Chapter 11
Geospatial AI Future Perspectives

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ABSTRACT

Geocomputation and geospatial artificial intelligence (GeoAI) play crucial roles in propelling geographic information science (GIS) and Earth observation into a new era. GeoAI has transformed conventional geospatial analysis and mapping, changing the approaches for comprehending and overseeing intricate human–natural systems. Nonetheless, challenges persist in multiple facets of geospatial applications concerning natural, built, and social environments, as well as in the integration of distinctive geospatial features into GeoAI models. At the same time, geospatial and Earth data play essential roles in geocomputation and GeoAI studies, as they can efficiently uncover geospatial patterns, factors, relationships, and decision-making processes. This chapter focuses on several topics related to geospatial AI, including advancements in this field and future perspectives of Geospatial AI.

INTRODUCTION

The fundamental concept of spatial prediction involves estimating the values of a geographic variable at locations that are not known, by utilizing values from known locations or through multivariate data analysis (for further details, refer to Zhu et al. 2018, mentioned under Spatially Explicit AI Models). Spatial interpolation represents a specific form of spatial prediction capability within GIS. Common approaches to spatial interpolation consist of Inverse Distance Weighting (IDW) and Triangulated Irregular Networks (TIN). The innovative application of machine learning and deep learning in spatial prediction encompasses various advancements. These include

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the development of spatial interpolation methods utilizing conditional generative adversarial neural networks, the interpolation and prediction of activity locations derived from sparsely sampled mobile phone location data, the classification of GPS noise levels through convolutional neural networks for precise distance estimation, the recognition of traffic signs to facilitate traffic rule updates, and the enhancement of trip distribution prediction. Furthermore, numerous human activities take place along road networks. Consequently, the prediction of traffic flows, urban mobility patterns, and crime occurrences over time and space has garnered significant interest (for further details, see Zhang et al. 2019; Zhao et al. 2019; Ren et al. 2020; and Zhang and Cheng 2020).

GeoAI, also known as geospatial artificial intelligence, represents a dynamic field of research that combines advanced AI technologies to address geospatial challenges (Li 2020). Over the last ten years, remarkable advancements have been achieved in the realm of AI, especially in the areas of machine learning and deep learning. The convolutional neural network (CNN) framework represents a significant advancement (Reichstein et al. 2019). The CNN framework utilizes the innovative idea of artificial neural networks (ANN) to create a computer model that simulates the biological neural network of the human brain, while also introducing transformative changes with the implementation of convolution modules (Li et al. 2012; Li 2021; Fukushima 2007; Zhang 1988). These modules are capable of performing information extraction, often referred to as feature extraction, where each feature is considered as the independent variable X in a regression process, directly from the raw data. CNN-based techniques can effectively engage with raw data, revealing concealed patterns through extensive mining and continuous learning processes. This type of analysis, grounded in data, alleviates the limitations found in conventional spatial analytics that rely on established rules or relationships between the input data and the desired outcome. It facilitates the direct discovery and recognition of patterns from the data itself. This is referred to as data-driven discovery (Yuan et al. 2004; Miller and Goodchild 2015). A significant advancement in CNN design is that each convolution layer (Albawi et al. 2017) executes local operations on the data, enabling the possibility of parallel computation. This design alleviates the computational limitations found in conventional artificial neural networks, which heavily rely on the interdependencies among artificial neurons within fully connected layers. The recent advancement of high-speed GPUs, featuring a few hundred to several thousand micro-processing units, enables the efficient training of CNNs, even those with intricate structures, utilizing their computing units in parallel. This also enables a deep learning model to handle large datasets, enhancing its capacity to identify new patterns, gather valuable information, and generate high-quality foundational datasets to support the clarification of significant scientific enquiries (Arundel et al. 2020). Additionally, deep learning models are often more effective

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