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Editorial

Geographic Complexity: Concepts, Theories, and Practices

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Geography is a fundamentally important discipline that provides a framework for understanding the complex surface of our Earth. This complexity can be interpreted from at least two points of view according to Malanson [1]. The first interpretation is the complex pattern of geographic features. These geographic features can be either natural, such as the coast of Britain, or manmade, such as the road networks of a metropolis. The second interpretation is the interacting processes of different geographic features. In essence, these are two sides of the same coin. Spatial complexity arises from geographic driving processes, and processes, in turn, are constrained and directed by spatial patterns [2]. The interactions of pattern and process produces scale-dependent complexity in geographical systems [3].

Due to these complex characteristics of Earth's surface, geographic research can benefit from theories and methods from complexity science (or sometimes complexity theory), which is the study of complex systems as "macroscopic collections of many basic but interacting units that are endowed with the potential to evolve in time" [4]. However, the use of complexity science in geographic research is somewhat limited, although several calls have been made and "geographic complexity" has been discussed, e.g., [5–9].

This Special Issue aspires to further advance the frontiers of geographic complexity. It contains a total of 13 papers, contributed by 46 authors from 24 institutes. These institutes include world-class universities, such as Purdue University and Tsinghua University, and national agencies such as the National Geomatics Center of China.

All contributions to this Special Issue have advanced our understanding of geographic complexity. Their brief introductions are as follows.

Cheng et al. [10] developed a social-media-data-based method for assessing the near-real-time intensity of the affected population. In the face of complex natural disasters, people affected are at risk of life and property and in need of help. However, it is sometimes challenging to efficiently and effectively coordinate emergency response. With the help of social media data about disasters, more useful information can be extracted to help relief operations.

Zhao et al. [11] proposed a data-mining model for exploring the regularities and patterns of human activities from complex spatiotemporal datasets. The model applies to a raster format of geospatial time-series data. They identified four typical patterns that are helpful to understand the land-use structure and commuting activities. In addition, their case study indicated that the proposed model is effective to explore and uncover spatiotemporal characteristics of public travel demand.

Zhang et al. [12] reduced the computational complexity of calculating the Boltzmann entropy of spatial data. In particular, they borrowed the idea of head/tail breaks to improve the computational efficiency of a method for calculating the Boltzmann entropy of numerical raster data. The improved method is capable of calculating both the absolute and the relative values of Boltzmann entropy, i.e., absolute and relative Boltzmann entropies.

The experimental results showed that the computation time can be reduced by the improved method to about 1% required by the original method.

Li et al. [13] proposed an archived multi-objective simulated annealing method (referred to as AMOSA-II) for complex geographical spatial sampling. The proposed method improved the computational efficiency of a traditional multi-objective optimization based on simulated annealing. The experiment results demonstrated that AMOSA-II is advantageous in terms of not only efficiency but also effectiveness in searching optimal solutions.

Wang et al. [14] developed a Global Similarity Measuring Algorithm for the Complex Trajectories (GSMCT), which quantifies the spatial proximity and topologic similarity among complex trajectories. GSMCT is highly effective in clustering complex trajectories. For example, GSMCT was effectively applied to cluster the trajectories of mesoscale ocean eddies from 1993 to 2016 in the South China Sea, deriving new, useful knowledge.

Zdena [15] presented a preliminary but important experiment of identifying similar cities through analyzing their land use data. The experiment covered nearly 800 European cities, whose urban atlas were derived from the Copernicus European Urban Atlas 2012. Behind the experiment was a machine learning-based method to discover patterns, structures, and shapes of land use in cities

Yuan et al. [16] employed the methods of social network analysis to investigate complex economic relationships. They analyzed the spatiotemporal evolution of the intra-regional trade community structures of the Indian Ocean Region, followed by a determination of fundamental factors impacting the formation of these structures. Their results indicated that the Indian Ocean Region exhibited different structures following 2015 from the preceding years.

Wang et al. [17] explored the complex changes in the rolling stock manufacturing industry (RSMI) within the Belt and Road Initiative (BRI) region from 2003 to 2017. To facilitate the exploration, social network analysis methods were applied. Many interesting findings were obtained, e.g., the connectivity of the rolling stock trade in this region increased significantly from 2003 to 2017.

Zhao et al. [18] analyzed the complex spatial pattern and flow field characteristics of the migration population of Egypt. To this end, they employed a fractal perspective, shifting the analysis from structural-fractal-based to spatial-fractal-based. Their results can be helpful to the formulation of population governance policies and to make decisions on spatial planning strategies of Egypt and other countries.

Xu et al. [19] proposed a method for evaluating landscape sustainability using spatial Boltzmann entropy, which is a fundamentally important and increasingly popular metric in landscape ecology. They established a quantitative relationship between spatial Boltzmann entropy and landscape sustainability. It was found that spatial Boltzmann entropy has great potential to evaluate the sustainability of diverse landscapes.

Yu et al. [20] developed a new Land Cover Complexity Index (LCCI) based on information theory. The index is useful for quantifying land cover heterogeneity in terms of both the composition and the configuration of a landscape, serving as a consistent and standardized framework for heterogeneity information extraction. Comparative experiments demonstrated that the index outperformed benchmarks in effectiveness.

Ma et al. [21] provided a novel understanding of the urban forms of 298 Chinese cities, through a fractal perspective to characterize the heavy-tailed distribution of street connectivity. They demonstrated that almost all 298 cities exhibited fractal structures in terms of street connectivity. More importantly, they found that the fractality of street networks is positively correlated with urban socioeconomic status and negatively correlated with energy consumption. In another study, Ma et al. [22] developed a useful tool, called PolySimp, for simplifying complex polygons based on the underlying scaling hierarchy of polygons. The tool's effectiveness has been demonstrated using British coastline data.

Overall, this Research Topic has presented a series of papers that address geographical complexity in novel and emerging ways. In particular, the big-data, social-network, economic analyses that are the focus of many of the papers are a topic of high emerging interest and a deep degree of complexity. While these papers often represent preliminary steps in developing these emerging fields, they are pioneering, and we have broken new ground with novel methods and ideas. The two papers on spatial entropy also are novel and groundbreaking, enabling vastly more efficient calculation of landscape entropy and, for the first time, a clear connection between landscape entropy and land use sustainability. Such a link has been anticipated for years [23], and demonstrating it quantitatively provides a major advance in the nascent field of landscape thermodynamics. In sum, the papers are a synergy of ideas and advances that provide a bold view of current thinking in geographical complexity science and novel pathways for the development of this important field of study.

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