

Spatiotemporal Data Analytics and the Modeling of Land Systems: Shaping Sustainable Landscape

Wenwu Tang ¹, Jianxin Yang ^{2,*}, Minrui Zheng ³ and Jingye Li ⁴

¹ Center for Applied GIScience, Department of Earth, Environmental and Geographical Sciences, School of Data Science, University of North Carolina at Charlotte, Charlotte, NC 28223, USA; wenwutang@charlotte.edu

² School of Public Administration, China University of Geosciences, Wuhan 430074, China

³ School of Public Administration and Policy, Renmin University of China, Beijing 100872, China; minruizheng@ruc.edu.cn

⁴ School of Public Administration, Hohai University, Nanjing 211100, China; jingye.li@hhu.edu.cn

* Correspondence: yangjianxin@cug.edu.cn

1. Introduction

Dynamics in land systems are pivotal in driving socioeconomic development, biodiversity protection, and the provision of ecosystem services. However, land use activities such as urban sprawl, deforestation, and agricultural practices may lead to a series of challenges across ecological, social, or economic dimensions [1–4]. The dynamics of land systems are often influenced by an interplay of biophysical and socioeconomic factors [5,6]. Biophysical factors relating to the climate, topography, or even soil provide foundational conditions for land use activities, while anthropogenic factors—including, but not limited to, population variability, economic development, and policy—play a driving role in the land uses and land cover changes that shape our landscape across varying spatiotemporal scales. Exploring the interactions among these factors and thereby gaining deeper insight into the complexity of land systems often requires the support of spatiotemporal data analysis and modeling capabilities. These capabilities are typically based on the integration of Geographic Information Systems (GIS), remote sensing, and computational models [7,8]. Computational models include generic approaches (e.g., statistics, optimization, simulation, or Artificial Intelligence (AI)) and domain-specific models. With this integration, we can obtain the high-resolution data that are becoming increasingly available to investigate spatiotemporal patterns and mechanisms related to land systems at various scales [9,10]. The use of spatiotemporal data analysis and modeling capabilities can enhance our understanding of how land systems respond to their internal drivers or external events (e.g., disasters), which is key to providing informed decision-making support for stakeholders such as policy makers [11,12].

The modeling of land systems allows for the projection of future land development dynamics in response to different scenarios, such as the impact of alternative policy interventions or external events. These land system models are often dynamic [13–15], empowering the study of the short- or long-term impact of land use activities driven by constraints from the population, economy, and environment. This aids in identifying potential challenges and opportunities associated with the development of land systems, which require sustainable land management and ecosystem resilience.

The aim of this Special Issue is to evaluate the role of spatiotemporal data analytics and modeling in the study of land systems, and thus to contribute to the resolution of current land development challenges. This Special Issue may offer insights into the development of sustainable landscapes in terms of scientific advances and practical implications. Our



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Special Issue includes 13 research papers, covering three thematic topics: (1) ecological and environmental functioning, (2) urban development, and (3) land change dynamics. Table 1 summarizes these papers in terms of their study region, model type, and factor type. A variety of models are noted, including statistical models, simulation models, and optimization models. The spatial statistics model is also highlighted [16], which is a special type of statistical model. Machine learning was also included in the table, as machine learning algorithms [17–19] can be used to support both statistical analysis (e.g., regression) and optimization (the search for optimal solutions). The factor type is determined based on a typology that includes biophysical factors, regulation and policy, infrastructure and accessibility, and socio-economic factors. Biophysical factors cover those drivers related to, for example, topographic, environmental, and ecological dimensions. Anthropogenic factors are more complicated, and are thus separated into regulation and policy, infrastructure and accessibility, and socio-economic categories.

Table 1. Summary of the types of models and factors used in the articles in this Special Issue.

Author (Year)	Study Region	Type of Models	Type of Factors
Shen and Gong (2024)	Qinghai–Tibet Plateau, China	Statistical Model, Machine Learning	Biophysical Factors Regulation and Policy, Infrastructure and Accessibility, Biophysical Factors
Zou, Fan et al. (2024)	Wanning City, China	Statistical Model	Biophysical, Socioeconomic Factors
Li, Yang et al. (2024)	Guiyang, China	Statistical Model, Spatial Statistics	Regulation and Policy, Socioeconomic Factors
Lin, Li et al. (2024)	Central Yunnan Urban Agglomeration, China	Statistical Model	Regulation and Policy, Socioeconomic Factors
Cai, Song et al. (2024)	Shanxi–Shaanxi–Inner Mongolia Energy Zone, China	Simulation, Spatial Statistics	Biophysical, Infrastructure and Accessibility
Wang, Zeng et al. (2024)	Urban Agglomerations of the Yellow River Basin, China	Spatial Statistics	Socioeconomic, Biophysical Factors
Zhang, Lin et al. (2024)	Guangdong-Hong Kong-Macao Greater Bay Area, China	Statistical Model, Spatial Statistics	Biophysical Factors
Wang, Wang et al. (2024)	Yangtze River Economic Belt, China	Machine Learning, Statistical Model	Infrastructure and Accessibility, Socioeconomic Factors
Zhao, Ni et al. (2024)	Mianning County, Eastern Edge of the Qinghai–Tibet Plateau, China	Statistical Model	Infrastructure and Accessibility, Biophysical Factors
Cai, Li et al. (2024)	Hangzhou City, China	Statistical Model, Machine Learning	Biophysical Factors
Zhang, Xia et al. (2024)	Wuhan City, China	Statistical Model, Simulation	Biophysical Factors, Regulation and Policy, Socioeconomic, Infrastructure and Accessibility Factors
Bilintoh, Pontius et al. (2024)	The Plum Island Ecosystems of northeastern Massachusetts, USA	Statistical Model	Biophysical Factors
Zhao, van Duynhoven et al. (2024)	Kelowna, BC, Canada	Statistical Model, Machine Learning	Biophysical, Infrastructure and Accessibility Factors

2. Topics

2.1. Ecological and Environmental Functioning

This theme encompasses studies of ecological or environmental functioning that investigate the interactions between biophysical mechanisms and anthropogenic activities at a landscape scale. Spatiotemporal analysis and modeling allow us to explore ecosystem dynamics and how these ecosystems adapt to ecological or environmental stressors [6,20,21]. For example, Shen and Gong (List of Contributions, 1) presented a space–time analytics framework to study how ecological quality on the Qinghai–Tibet Plateau varies over time due to the impact of climate change and anthropogenic activities, including policies. This space–time analytics framework drives the study of the ways in which this ecologically vulnerable region are modified by various dynamic processes. In Cai, Song et al.’s (List of Contributions, 2) study of ecosystems’ adaptive capacity, multi-scenario simulations were used to assess ecosystems’ response to different disturbances in the Shanxi–Shaanxi Inner Mongolia Energy Zone. Cai, Song et al. stressed the important role of resilience in the mitigation of environmental degradation in their study of ecosystems’ adaptive capacity. Li, Yang et al. (List of Contributions, 3) explored how ecosystem services are influenced by land change activities in Guiyang, China. With support from their spatiotemporal analysis, the impact of land cover change on the value of ecosystem services was quantified, further highlighting the importance of land management practices in ecosystem services’ valuation. In their ecological connectivity study, Zou, Fan et al. (List of Contributions, 4) investigated the ecological networks in Wanning city, China. A framework that identifies ecological corridors was developed by Zou et al. to evaluate ecological resilience in their study region. Landscape metrics such as the largest patch index and degree of landscape division were used to quantify landscape patterns in their study region. Cai, Li et al. (List of Contributions, 5) conducted an assessment of urban ecological health in Hangzhou, China. A suite of environmental indicators was combined in their assessment to guide the development of landscape management practices. These studies demonstrate that spatiotemporal data analytics are methodologically essential to the integration of multi-data sources and modeling capabilities, which can increase our understanding of ecological quality and resilience [21,22].

2.2. Urban Development

Urban development is another theme that receives considerable benefits from spatiotemporal analytics and modeling within the context of land systems [23–25]. Zhang, Lin et al. (List of Contributions, 6) conducted a study of urban development in the Guangdong–Hong Kong–Macao Greater Bay Area, focusing on the impact of biophysical factors, including topography, climate, soil, water bodies, and fault. Multicriteria evaluation and a spatial statistical model were used to evaluate the land suitability and carrying-capacity potential in their study region. Zhang, Xia et al. (List of Contributions, 7) delineated urban growth boundaries over time under different development scenarios. A cellular automata-driven urban simulation model was used in Zhang et al.’s study, which takes into account factors from the biophysical and socioeconomic dimensions (e.g., population, GDP, topography, proximity to transportation infrastructure, and land cover). Wang, Zeng et al. (List of Contributions, 8) assessed the impact of urban expansion on carbon emissions in urban agglomerations of the Yellow River Basin, China. The spatiotemporal patterns of urban development and carbon emissions from 2000 to 2020 were evaluated using kernel density estimation, Gini coefficient, landscape metrics (e.g., aggregation index, patch density, and landscape shape index), and a geographically temporally weighted regression model. Lin, Li et al. (List of Contributions, 9) investigated the spatially interacting dynamics of Central Yunnan Urban Agglomeration in China from 2000 to 2020 within the theoretical framework

of urban symbiosis. The functioning and interactions of urban development at the county level were evaluated in terms of production, living, and ecological functions. Each of these functions was characterized by an indexing system of relevant factors (similar to multicriteria evaluation) [26].

2.3. Land Change Dynamics

While urban development is a form of land change with a focus on urban dimensions, land change is a broader and more inclusive theme. Zhao, Ni et al. (List of Contributions, 10) analyzed spatiotemporal changes in construction land in Mianning county, located on the eastern side of the Qinghai–Tibet Plateau, China. The landscape expansion index and geographically weighted regression were used to investigate the changes in construction land from 1990 to 2020 by considering influential factors from five dimensions: geomorphology, geology, climate, river and vegetation environment, and socioeconomy.

Bilintoh, Pontius et al. (List of Contributions, 11) applied a Total Operating Characteristics (TOC) [27] approach to quantify temporal changes in one land cover type (marsh) in an ecological research site in Massachusetts, USA. Gains and losses of marsh, with reference to the distance-to-marsh boundary or elevation, were evaluated over three time periods (1938, 1972, and 2013). Bilintoh et al. demonstrated the importance of applying TOC to assess the spatiotemporal characteristics of land gain and loss.

Zhao, van Duynhoven et al. (List of Contributions, 12) discussed the use of three machine learning approaches (random forest, extreme gradient boosting, and support vector machine) to generate land suitability maps for the city of Kelowna, British Columbia, Canada. Land cover data in 2015 and land change data from 2015 to 2020 were used to train these machine learning models to estimate the weights of alternative criteria. These machine learning-derived land suitability maps were compared against traditional approaches, relying on expert knowledge such as the Analytical Hierarchy Process [28].

The study of land change dynamics can be conducted at the regional level. Wang, Wang et al. (List of Contributions, 13) proposed a framework that integrates meta-analysis, statistical analysis, and neural network modeling to estimate land demand for the transportation needs of the Yangtze River Economic Belt, China. Transportation land demands for 127 cities in the study region were predicted based on the use of a suite of influential factors related to socio-economic development (e.g., GDP, population). This analysis framework facilitates the exploration of spatiotemporal patterns of land demand for transportation and their driving mechanisms at the regional level.

3. Summary and Perspectives

The studies collected in this Special Issue highlight the use of spatiotemporal data analysis and modeling in the investigation of the dynamics in complex land systems. These studies concentrate on three themes: ecological and environmental functioning, urban development, and land change dynamics. Geospatial data at various spatial resolutions (e.g., 30 m, 1000 m, and 3.5 km) were used to study dynamics in land systems at various scales (from local to regional). A suite of nonspatial and spatial metrics (including landscape metrics) were extracted from these geographic data and used in their corresponding applications. The spatiotemporal analytics and modeling capabilities used in these studies include spatial statistics (e.g., spatial autocorrelation analysis, geographically weighted regression [29]), multicriteria evaluation, machine learning (e.g., neural networks, random forests), and spatial simulation [30,31].

Spatiotemporal data analytics and modeling serve as a data-intensive scientific approach to the exploration of land system dynamics across various scales [32]. Spatiotemporal data analytics and modeling allow us to document and analyze what happened in

the past and in various regions. Additionally, these capabilities (such as spatial simulation) provide spatially explicit modeling support for exploring what may happen in the future or in alternative scenarios [33–35]. Further, spatiotemporal data analytics and modeling capabilities hold great promise for representing and investigating the complexity of land systems, such as feedback loops, scale effect, emergence, and adaptation [36–39].

The use of AI [40,41] techniques such as neural networks or random forests is reported in this Special Issue. These AI techniques are applied in a traditional way and most AI techniques used in these studies remain conventional. As AI, exemplified by generative AI and agentic AI [42–44], continues to advance, modern AI techniques will highly likely catalyze a new wave of applications of spatiotemporal data analytics and modeling in the study of land systems in the near future. Modern AI techniques hold great potential in boosting the efficiency and effectiveness of spatiotemporal data analytics and modeling. Benefiting from the autonomy of emerging AI techniques, such as generative AI and agentic AI, the steps of spatiotemporal data analytics and modeling (e.g., preprocessing, model development and integration, post-processing, and evaluation) can be substantially automated. This will lead to a significant reduction in the time and cost required for modeling cycles cost, i.e., efficiency will increase. Furthermore, emerging AI techniques provide increasingly extensive support for new or novel modeling algorithms (e.g., foundation models; see [45]). These emerging AI algorithms may be of assistance when using spatiotemporal data analytics and modeling to obtain a better representation of the complex properties of land systems, such as nonlinearity, self-organization, scaling effects, and adaptation.

Conflicts of Interest: The authors declare no conflict of interest.

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