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VIEWPOINTS

Embracing geospatial analytical technologies in tourism studies

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Abstract
With the ongoing development of information and communications technology, geospatial technologies have become increasingly important in monitoring, managing, and predicting tourism activities. These tools can also uncover tourism's social, economic, cultural, environmental, and political impacts. In this viewpoint article, we discuss applications of cutting-edge geospatial analysis in tourism studies. Topics include opportunities from emerging geospatial data, a new typology of spatial analysis in tourism studies, spatial analysis with the 4-Ws approach, and humanistic geographic information systems. This paper offers methodological guidance for multi-scale geospatial analyses that are essential to tourism research.

Keywords Geospatial analysis · Big data · Geographic information systems · Mobility · Tourism

1 Introduction

Humans have not stopped moving after migrating from Africa roughly 70,000 years ago. Since the beginning of human history, people have observed, measured, and predicted mobility at levels ranging from personal to intercontinental. Contemporary human mobility research entails the modeling of movement (by individuals and groups) over space and time (Barbosa et al. 2018). Tourism is a key sector of modern society and is built on human mobility (Hall 2004). People often travel for leisure or business, prompting industries to accommodate visitors' transportation, accommodation, and entertainment needs. As travel is also highly spatial, a clear understanding of the geospatial aspects of tourism activities will provide vital insights for destina-

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tion marketing, planning, and management. Associated revelations can inform the industry's sustainable development.

Tourism embodies an immersive interaction between natural or constructed environments and visitors. This interaction is typically regulated by host communities, private entities, and governments. The quality of interaction hinges on sociocultural variables, including tourists' perceptions of attractions and residents' acceptance of visitors (Reisinger & Turner, 2012). Careful planning and control at attractions are integral to enhancing the tourist experience. Nearly all tourist sites and service facilities assume certain spatial forms. They can therefore be quantified using spatial data models for the purposes of inquiry, assessment, and reorganization. Such analysis allows for more deliberate planning and managerial decisions (Yang 2022). A data-driven approach is required to make these determinations. The penetration of spatial information and communications technology has generated myriad data sources for both researchers and the public. The popularity of personal digital gadgets such as smartphones, global positioning systems (GPS), Wi-Fi, and Bluetooth-enabled devices continues to expand in kind. Tourists' movement and spatial trajectories can now be monitored at unprecedentedly fine scales. The precision of these location-based datasets presents fresh opportunities for tourism scholars and practitioners to pursue a new data-driven research paradigm.

This data deluge cannot be fully harnessed without analytical technologies, primarily the geographic information system (GIS). This system complements information technologies to store, organize, visualize, analyze, and simulate geospatial data. Specifically, GIS provides tangible evidence—and thus actionable insights—for tourism scholars and practitioners to build a more sustainable industry. Despite fast-growing opportunities to embrace geospatial analysis in tourism, a knowledge gap precludes experts from truly capitalizing on relevant innovations. A host of intriguing topics discussed in the mainstream GIS and business geography literature remain primarily untapped in tourism. With more tourism scholars starting to conduct geospatial analysis for research and consulting purposes, it is crucial to outline advances in these technologies and their potential applications in the industry.

For this viewpoint paper, a group of researchers collaborated to describe the latest geospatial technologies available to tourism studies. The lead author has a background in geography and is working in the tourism domain; all other authors are faculty in prominent geography departments in the United States. This team possesses great interest and track records in tourism-related research. More importantly, the authors agree about the promise that evolving geospatial analytical technologies hold for tourism. This paper is not meant to be a literature review; rather, it represents a pioneering effort to scrutinize cutting-edge geospatial analytical methods and future research directions in tourism contexts. Doing so will diversify scholars' toolbox and contribute to related research, as tourism enjoys a reputation as a fertile ground for multi- and interdisciplinary studies.

2 Opportunities from emerging geospatial data

Tourism involves intensive movements between places. These movements, along with their interactions with the social and physical environments, cannot be captured without spatial data. In the parlance of GIS, two fundamental spatial data models are the vector data model and the raster data model (Longley et al. 2005). The vector data model represents spatial objects through discrete features, mainly three types of geometries: points, lines, and areas. These vector-based geometries can be employed to abstract discrete objects and activities in tourism that either have clear boundaries or can be precisely geocoded based on latitude and longitude (e.g., park boundaries, travel route networks, service facilities, movement trajectories, and activity locations). The raster data model is suited to dealing with continuous objects or attributes over a surface, where every location over the surface has a distinct value. Examples of raster data include land use data (which can also be vector-based on certain occasions), topographic data (e.g., slope, elevation), and climatic data (e.g., temperature, air quality). The vector- and raster-based data, even if not labeled as such, have been widely adopted to answer spatial and temporal questions of interest to tourists and industry stakeholders alike. Use cases have ranged from preliminary data visualization (e.g., creating maps) to complex spatial analytics (e.g., optimizing service placement).

Traditionally, questionnaire surveys have been used to collect detailed demographic, socioeconomic, and behavioral information about tourists (Crompton and Tian-Cole 2001). The swift development of information and communications technology and GPS-equipped smartphones have spawned advanced geospatial technologies that can gather data about users, environments, and their spatial interactions (Xu et al., 2020). Aside from traditional cartographical methods (e.g., land surveys), we discuss three emerging technologies that provide new sources of data to shed insights into future tourism research.

Mobile GIS extends traditional desktop GIS and enables people and organizations to acquire, localize, store, visualize, and analyze geospatial data in the field (Gao and Mai 2018). Mobile GIS can expedite tourism data collection by storing related datasets (e.g., locations, trajectories, images, texts, audio, videos) offline and can then upload them to a web server in the cloud in nearly real-time over cellular or wireless networks. Another unique application of mobile GIS is the geo-assisted tourist survey, which obtains digital survey responses via a geospatial platform. GPS tracking and travel surveys are accessible on mobile GIS platforms, which are helpful for understanding tourists' mobility patterns and time use (Sugimoto et al. 2019).

Location-based services (LBS) recognize the environments in which tourists are positioned and can adapt to location-based content accordingly. LBS-based mobile tourism platforms have been developed in different venues across countries (Liang et al. 2017; Panahi et al. 2013). A principal LBS attribute in tourism research is that users can customize their preferred attractions and plan tour routes both in advance and in real time. Sophisticated user modeling and profiling metrics can also be constructed to inform location-based tour recommendations. These models generally follow from collecting users' travel logs and analyzing their travel experiences on LBS platforms (Haris and Gan 2021).

Virtual reality/augmented reality (VR/AR) is an emerging means of geospatial data collection that complements the budding penetration of VR and AR equipment. VR presents a computer-rendered real-world environment and can be used to design immersive experiences. Accompanying technologies include eye tracking, which monitors a user's visual attention when using VR equipment, and such data are normally acquired via lab experiments (Scott et al. 2019). A potential application of VR/AR technologies is to enhance the tourist experience. Upon deploying AR in a real-world setting, tourist attractions can be converted into location beacons by placing virtual arrows and information panels throughout sites on mobile devices. These beacons can help visitors navigate their destinations with rich multimedia content (Safitri et al. 2017). Another application rests in digital tourism. By building an immersive virtual environment, advanced VR/AR technologies provide opportunities to promote attractions across space. This revolution can additionally accelerate digital tourism through a rapid epochal shift from conventional tourism (Liang et al. 2017).

Of these three emerging technologies, VR/AR as simulation technologies is most promising for revolutionizing future tourism. The existing AR-based applications are still in their infancy, as they are developed for marketing and communication purposes in the pre-trip phase (Jung et al. 2016). Another pressing issue is that there has been limited public awareness and acceptance of VR/AR on both tourism stakeholders' and travelers' ends (Yung and Khoo-Lattimore 2019). Reception hurdles include integrating VR/AR with real-time geospatial big data and the ever-growing complexity of GIS workflows to tackle real-world problems.

We envision future tourism studies will integrate new forms of geospatial data (Mobile GIS, LBS, and VR/AR) into human-centered and immersive tourism research. These datasets, which embody a rich set of environmental and social information, can only be acquired by fusing near real-time geospatial data, such as remote sensing and social sensing data. Among them, granular sources (e.g., mobile positioning information, social media sites, and app logs) are deemed especially relevant (Pan and Yang 2017). To integrate the multi-source data, the answer would lie in the field of geospatial cyberinfrastructure. Geospatial cyberinfrastructure is an interdisciplinary field aiming to marry advanced GIS, spatial analysis and modeling, VR/AR, text mining, and diverse geospatial domains to promote broad scientific advances (Li et al. 2020; Li and Zhang 2021; Wang, 2013; Zhang et al. 2021). For example, Li and Zhang (2021) proposed a geospatial cyberinfrastructure that incorporates social media and point-of-interest data into an AR system to improve awareness of travel situations. Future design of the AR-enabled geospatial cyberinfrastructure in tourism should tackle technical challenges, such as spatiotemporal data rendering and computing latency.

3 A new typology of spatial analysis

Geospatial data cannot be harnessed without analysis tools. The primary tool for such analysis refers to GIS (Goodchild and Longley 1999). This system, together with embedded operational tools, has been extensively employed in tourism (Bahaire and Elliott-White 1999). However, there has been limited research regarding the different types of GIS-aided spatial analysis. This framework, while setting the tone for positioning spatial analysis in tourism research, can be further elaborated based on the objective of the analysis. Based on GIS-related theoretical frameworks (Longley et al. 2005), we propose a new typology of spatial analysis applied to tourism research. These four types of analysis, listed in ascending order of complexity, include geovisualization, spatial query, pattern identification, and spatial optimization (see Table 1).

Geovisualization represents a set of techniques that visually represent geographical phenomena, process or simulation. Thus, visualizing data through choropleth mapping and advanced cartographic representation (e.g., spider diagrams and cartograms) is an important step toward improving data interpretability and facilitating information extraction. Geovisualization is a natural fit for tourism: information delivery in this industry is heavily contingent on spatial products, especially maps (including modern digital maps). The preferred geovisualization format mainly depends on the audience and map purposes. For instance, maps made for planners must prioritize scientific rigor, such as a meaningful classification scheme and an appropriate projection. Maps intended for tourists can be more subjective. The field of tourism geography has defined tourism mapping as not simply a mirror of reality; it can include social identities (Del Casino and Hanna 2000). Most tourist maps are thematic and target a specific audience, such as foodies, nightlife seekers, and commuters. The activity spaces encapsulated in such maps effectively translate spatial information into individualized mental maps. To promote this process, tourists' social identities, trip purposes, and motivations should be integrated into map design. Geovisualization in tourism studies will therefore vary with spatial data usage.

Table 1 A typology of spatial analysis in tourism studies

Type	Definition	Use cases
Geovisualization	Converting data into a spatial form, and visually representing geographical phenomena, processes or simulations	● Geocoding ● Visualizing travel trajectories ● Producing maps
Spatial query	Identifying spatial relationships between objects	● Demarcating regions suitable for tourism development ● Retrieving service facilities based on given criteria
Pattern identification	Identifying objects' spatial patterns	● Assessing site suitability ● Identifying tourists' space-time activity patterns for tourism management
Spatial optimization	Identifying optimal spatial solutions under given constraints	● Relocating tourism industries ● Relocating service facilities and sites ● Identifying optimal visit paths

Spatial query refers to identifying geospatial relationships among objects. In GIS terms, these spatial relationships include adjacency, contiguity, overlap, and proximity. Spatial querying, which GIS development has accelerated, has been employed in tourism site planning since the early 1990s (Bahaire and Elliott-White 1999). Primary tourism industry functions (i.e., services, attractions, infrastructure) are abstracted into spatial data models through a fairly reductionist approach (Farsari 2012). The spatial scope of environmental externalities and impacts overlaps with land use layers to identify candidate sites or regions that show promise for tourism development. The examples include identifying potential tourism development regions (Gunn 1994) and portraying landscapes of ecotourism development (Boyd & Butler, 1996). However, the early spatial querying attempts to frame site planning as a dichotomous spatial question while ignoring the roles of community involvement and social impacts in decision-making (Bahaire and Elliott-White 1999). The popularity of location-aware devices (e.g., GPS-enabled smartphones) and advances in mobile GIS technologies have since sparked individual-level spatial queries. This information can help practitioners identify and recommend travel destinations based on tourists' real-time locations, such as by retrieving a list of service facilities within a given distance (Noguera et al. 2012).

Pattern identification entails determining objects' spatial patterns through modeling. In tourism, this determination is based on measuring spatial objects' geometric properties (e.g., area and slope) and dimensions of tourism sustainability (e.g., business viability, waste management). Such attributes can be further consolidated within a geographic unit (e.g., ZIP code, census tract) or over a surface (e.g., kernel density surface) by sophisticated modeling techniques to support decision-making. Pattern identification is common in two tourism research streams. The first stream assesses site suitability for tourism development, generally by blending GIS with a decision-making model (Arbolino et al. 2021). Different from spatial querying, which only demarcates areas of suitability, decision-making models quantify sustainability variables along with expert knowledge to alleviate subjectivity and bias. The second stream seeks to identify space-time patterns in tourism activities to guide tourism planning. Overtourism can place pressure on the environment and indigenous communities. Monitoring tourist activities and pinpointing space-time patterns enhance managerial effectiveness. After more than two decades of refinement, pattern identification now relies on location-based mobility data (e.g., cellular data, georeferenced social media data, GPS-based mobility data, Wi-Fi probe data) (Li et al. 2022). Machine learning algorithms (e.g., neural networks, association rule mining, clustering models) have also revolutionized how space-time activity patterns are examined (Höpken et al. 2019).

Spatial optimization extracts optimal spatial solutions from a set of candidates based on certain constraints. This task has scarcely been applied in tourism planning but is theoretically rooted in the facility location problem (FLP) (Owen and Daskin 1998). Distance and its equivalents (e.g., travel time) are crucial to system efficiency. Therefore, minimizing travel distance or maximizing service areas is a primary objective in FLP-assisted planning issues. FLP models have numerous aims related to distance measures, such as the p-median model (minimizing total travel distance), the p-center model (minimizing maximum travel distance), the location-set-covering model (finding the smallest number of facilities to cover demand), and the maximal-covering-location problem (maximizing demand coverage within a service distance) (Klose and Drexl 2005). Subsequent spatial optimization models have introduced other planning scenarios and parameters, such as system dynamics, multiple objectives, and hierarchical structures (Chen et al. 2013). Spatial optimization in tourism planning largely follows this trend with the goal of improving facility, service, or resource utilization.

4 Strengthening spatial analysis with the 4-Ws approach

Since tourism is largely mobility-driven, pattern identification in the proposed typology is especially suited to mobility-related tourism research. Existing tourism studies, however, have yet to incorporate human mobility theories. To this end, we envision that future tourism should incorporate the different dimensions of human mobility from a new perspective, such as using the 4-Ws approach.

Tourism mobility involves information about a person (who), location (where), time (when), and context (what) (Jin et al. 2018). This 4-Ws approach promotes analyses of tourists' movement patterns and influencing factors. Discoveries are meant to improve service accessibility (Coppola et al. 2020), efficiency (Moyano et al. 2019), and sustainability (Verbeek and Mommaas 2008). Because tourism is pivotal to linking tourists' homes (origins) with their destinations (Hall 2005), the origin-destination connection (otherwise known as the "OD flow") is a central theme of tourism mobility studies. First, regarding the "where" and "when" components, scholars have summarized and geovisualized tourists' movement patterns at various geographic scales. Some researchers have detected popular attractions and tour routes (Hu et al. 2019); explored people's travel behavior during landmark events, such as the Great American Eclipse of 2017, on a national or global scale (Martín et al. 2021); and unraveled the impacts of catastrophic events (e.g., pandemics and hurricanes) on personal travel behavior (Martin et al., 2020a; Yang et al. 2023). Others have examined sequential movement patterns (Xu et al. 2021) and visualized space consumption (Shoval & Issacson, 2007). Second, along with tourists' physical movement across space and time, the "who" and "what" components cover tourist mobility in terms of traveler types and trip purposes.

The fusion of the 4-Ws cannot be accomplished without a multi-criteria decision-making (MCDM) system. MCDM is the process of making a decision when several criteria or objectives need to be evaluated to rank or choose among alternatives (Ishizaka and Nemery 2013). Popular MCDM methods include the analytical hierarchy process (AHP) (Saaty 1994), the technique for order preference by similarity to ideal solution (TOPSIS), simple additive weighting (Kaliszewski and Podkopaev 2016), and elimination and choice translating reality (ELECTRE) (Roy, 1991). Malczewski (2006) classified GIS-based MCDM into decision making under conditions of certainty and uncertainty. MCDM is often combined with fuzzy set theory to model ambiguities in spatial knowledge representation to inform spatial decisions (Tian and Peng 2020; Zhang et al. 2014; Zhang et al., 2018a). To substantiate the 4-Ws approach, we envision that the future design of the MCDM system should be extended to group decisions, such as by using participatory GIS to form a collaborative consulting system (Zhang et al. 2014; Zhang et al., 2018a, 2018b). For example, smartphone location data enable the collection of ample human mobility details. The ubiquitous GPS receivers embedded in smartphones can localize phone users within meters and furnish location data while users interact with installed applications (e.g., Google Maps) that have data-sharing permissions. These data can then reveal the 4-Ws of tourist mobility, such as how many people visited a park (destination), where they came from (origin), and how long they stayed. Crowdsourcing such GPS-enabled human mobility information in the 4-Ws dimensions, as a typical example of participatory GIS, is the foundation of developing a comprehensive MCDM system for tourism planning and management.

Another challenge for implementing the 4-Ws approach refers to the many uncertainties and the likely biases within the data collection. Tourism studies based on traditional census or survey data are limited in their topical breadth and depth due to cost and scalability constraints. For instance, survey data cannot capture dynamic and complex population movements amid heightened spatial mobility. However, these data are useful for identifying the "who" component: respondents' demographic and socioeconomic information is routinely solicited. These personal details are challenging to unveil with mobility data sources due to privacy concerns. Another pitfall of survey data, a lack of representativeness (Martin et al., 2020b), is particularly evident in mobility data owing to intrinsic large-scale sampling bias. For example, geotagged tweets tend to overrepresent youth, who constitute Twitter's primary users (Jiang et al. 2019). These restrictions suggest that no "perfect" mobility data exist for tourism research. Combining mobility datasets with traditional datasets offers a viable way to discern travel settings, refine mobility datasets, and mitigate data biases.

5 Humanistic GIS

Compared with most GIS approaches leveraging geospatial data, humanistic GIS is a relatively recent framework that stresses the system's evolution in mediating human experiences (Zhao 2021). Tourist activities are person-centered and experiential. Humanistic GIS therefore holds considerable potential for tourism research. Depending on the type of mediation, GIS can function as either embodiment GIS, hermeneutic GIS, autonomous GIS, or background GIS. Each provides a unique opportunity to analyze human movement over space and time.

Embodiment GIS applies in scenarios where individuals wear a GIS to perceive a place. When a person uses a smartwatch to travel to a tourist site, the smartwatch is an embodiment GIS because navigation information displayed on the watch mediates the wearer's local experience. VR goggles are another type of embodiment GIS: they immerse the wearer in a virtual environment (Yu and Gong 2012). This type of GIS can provide an augmented or even a surreal experience. Embodiment GIS can also capture biophysical responses as the wearer experiences a place. An electrocardiogram wrist strap can measure the wearer's pulse, whereas an electroencephalogram headset can detect nerve reflexes (Qin et al. 2013). Biophysical signals can shed light on the wearer's reactions to a tourist site and supplement existing means of tourist experience tracking, such as questionnaires and social media posts.

Hermeneutic GIS produces a representation of a place; that is, a person can only perceive the place through GIS mediation. A map is a typical hermeneutic GIS that delivers the maker's interpretation of the depicted place. Most conventional GIS instantiations are hermeneutic because any spatial analysis is derived from geospatial data, and data are specific numeric representations of a place. The digital twin is another common type, wherein a timely representation of a real-world physical system is produced and serves as a digital counterpart (Jones, 2020). Scholars can use digital twins to simulate, monitor, and maintain a geographical environment on the ground (e.g., a national park). Digital twins can also predict peak flows or analyze the impact of extreme weather without the need for real-world simulations. Although this representation is not identical to reality, information recipients can still process it. This GIS method can hence support numerous forms of spatial analysis and modeling.

Autonomous GIS relatedly behaves as an independent being. A climbing number of autonomous GIS instantiations provide services and support as people travel or visit tourist sites: self-driving vehicles transport passengers to a destination, food delivery bots bring meals to one's doorstep, and vacuum robots clean guestrooms. Autonomous GIS frees people from repetitive mechanical tasks. These tools can also be deployed for research purposes. For instance, when an autonomous GIS operates, interaction may provoke complex feelings for consumers. Imagine walking on a trail with and without delivery bots; the walker may feel varying levels of emotional intimacy toward bots and the surrounding environment (Rosenthal-von et al., 2013). Autonomous GIS can presumably transform tourists' emotional world; from a research perspective, it can make tourist sites and travel in general more pleasant and inclusive.

Background GIS becomes part of a place such that tourists barely notice its presence. The GIS continues to function normally and to influence tourist–site interaction in the meantime. A smart dashboard is a background GIS that collects, visualizes, and processes information from prepositioned sensors (i.e., the Internet of Things) across tourist attractions (Arasteh, 2016). Traffic information and weather data can be obtained spontaneously via sensors. These data enable decision makers to adaptively modify site operations, such as to avoid traffic congestion and prepare for extreme weather. GIS-driven operational adjustments can in turn accommodate travel behavior. In essence, background GIS produces real-time geographical data to inform decision making.

Humanistic GIS features an array of use scenarios involving spatial analysis and other GIS types in tourism studies. Humanistic GIS reorients the foundation of GIS from geographical data to the interactions between GIS instantiations and geographical phenomena of interest. These tools can process emplaced human experiences during travel or at tourist sites, revealing profound implications for human mobility in space and time.

6 Conclusions

This paper has presented several major applications of geospatial analytical technologies in tourism. Regarding data collection, mobile GIS, LBS, and VR/AR can support research at various geographic scales. Both demand- and supply-side analytical technologies have been described as well. Trajectory and mobility analyses dominate demand-side exploration, involving numerous datasets (e.g., smartphone location data and CDR data) and tools (e.g., SVM, DBSCAN, and LSTM). Supply-side investigations concern tourism supply patterns under a spatial analysis typology encompassing geovisualization, spatial query, pattern identification, and spatial optimization. Spatial decision support systems synchronize qualitative and quantitative data to perform MCDM. Lastly, humanistic GIS is a promising framework focusing on tourists' lived experiences. In Table 2, we summarize the specific future directions in applying geospatial analytical technologies in tourism studies.

This comprehensive discussion of geospatial analytical technologies summarizes many options to be embraced in research and practice. These tools will help stakeholders better manage, plan, and predict tourism activities from the demand and supply sides. Tourism and geography researchers should cooperate to encourage the use of these geospatial theories, data, toolsets, and philosophies. Top-tier tourism journals are beginning to see more publications from geography researchers. Meanwhile, many studies featuring tourism data are appearing in flagship geography outlets. Collaboration across these two disciplines can enrich graduate student supervision,

Table 2 Future directions of spatial analytics in tourism research

Areas	Future directions
Geospatial data collection	• Integrate geospatial technologies (Mobile GIS, LBS, and VR/AR) into human-centered and immersive tourism research • Access near real-time multi-source environmental and social information by fusing remote sensing and social sensing data.
Spatial analysis typology	• Add the spatial angles into traditional analysis in tourism (e.g., spatial statistics and spatial econometrics) • Leverage GeoAI to better recognize the pattern and conduct spatial optimization.
4-W approach in tourism application	• Develop tourism-specific geospatial cyberinfrastructure to marry advanced GIS, spatial analysis and modeling, VR/AR, text mining, and diverse geospatial domains to promote broad scientific advances in tourism research. • Design advanced visualization interfaces to support spatial decisions. • Integrate VR/AR with real-time geospatial big data and the ever-growing complexity of GIS workflows to tackle tourism-specific problems.
Humanistic GIS	• Provide more case studies to enable scholars and the public to understand the necessity of a humanistic approach. • Embrace a humanistic perspective when implementing geospatial analytical technologies in tourism studies.

funding applications, and consulting projects in academia, non-profit organizations, and industry. A productive line of tourism research leveraging geospatial analytical technologies is likely to benefit the tourism industry and society at large.

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