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Artificial intelligence and visual analytics in geographical space and cyberspace: Research opportunities and challenges

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A R T I C L E I N F O

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In recent decades, we have witnessed great advances on the Internet of Things, mobile devices, sensor-based systems, and resulting big data infrastructures, which have gradually, yet fundamentally influenced the way

Abbreviations: GeoAI, Geospatial Artificial Intelligence; GeoVA, Geovisual Analytics.

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Geographical space
Cyberspace
GeoAI
GeoVA

people interact with and in the digital and physical world. Many human activities now not only operate in geographical (physical) space but also in cyberspace. Such changes have triggered a paradigm shift in geographic information science (GIScience), as cyberspace brings new perspectives for the roles played by spatial and temporal dimensions, e.g., the dilemma of placelessness and possible timelessness. As a discipline at the brink of even bigger changes made possible by machine learning and artificial intelligence, this paper highlights the challenges and opportunities associated with geographical space in relation to cyberspace, with a particular focus on data analytics and visualization, including extended AI capabilities and virtual reality representations. Consequently, we encourage the creation of synergies between the processing and analysis of geographical and cyber data to improve sustainability and solve complex problems with geospatial applications and other digital advancements in urban and environmental sciences.

1. Introduction

The development of Information and Communication Technology (ICT) and hence the Internet of Things (IoT) have ushered our society in the digital era. The proliferation of personal computers, mobile phones, intelligent autonomous sensors such as those used in autonomous vehicles, and pervasive network connectivity facilitating interactions between individuals has led many human activities to shift gradually from offline to online. The digital transformation of human activities has transferred many human activities into cyberspace where people can perform collaborative activities, and where the role played by distance can at least be reconsidered (Cairncross, 2001). Cyberspace is generally considered "a global domain within the information environment consisting of the interdependent network of information technology infrastructures, including the internet, telecommunication networks, computer systems, and embedded processors and controllers" (England, 2008). This transformation brings opportunities and challenges to obtain valuable insights into the way these two spaces (geographical space and cyberspace) can be mapped onto each other, and interact. To face these challenges, current GIScience concepts, theories, and implementations should be revisited and extended to integrate the novel opportunities offered by cyberspace, including the way spatial and temporal properties are embedded in digital spaces. In recent years many efforts have been dedicated to exploring cyberspace and its associated activities. For example, through the analysis of mobile users' behavior connecting (physical) spatial locations and web environments, a strong correlation between human dynamics in geographical space and cyberspace is uncovered using a super linear statistical scaling model (Zhao et al., 2014). Through the analysis of social media data, another study reveals that geographical proximity still plays an important role in the interaction between humans in cyberspace, but spatial autocorrelation is significantly weaker than in physical space (Han et al., 2018). In fact, in online social networking (e.g., Facebook, Twitter, or Weibo), the interactions between people are not subject to the constraints of space and time as before, as individuals can communicate from anywhere without incurring travel costs, although time differences are still somewhat important for synchronous online meetings. Our work discusses the opportunities and challenges of geospatial artificial intelligence (GeoAI) and geovisual analytics (GeoVA) in geographical space and cyberspace, a challenging task as the theoretical and conceptual foundations that should be associated with them are still to be identified (Gao et al., 2019).

The continuous development of cyberspace generates a remarkable diversity of very large volumes of geospatial data at unprecedented rates of dissemination. Cyberspace data, whether voluntarily or involuntarily generated, originates from a variety of user communities, ranging from experts to the general public and different supports from social media to mobile users, but are not always well structured because they are most often not generated for further manipulation. This new cyberspace data space opens up a new field of interactions with that of geospatial data, thus offering novel application opportunities for many fields. However, this requires a preliminary study of the data modeling and processing principles associated with cyberspace data, and potential interoperability with geographical space. This leads us to specifically consider the potential contribution of GeoAI, which nowadays offers new methods for processing and reasoning on complex and time-related geospatial data, either structured or unstructured, and that of GeoVA, which provides cutting-edge visualization capabilities for the exploration of complex data. Together, GeoAI and GeoVA are well suited for providing a data processing framework associated with cyberspace in close connection with geographical space and humans-in-the-loop. The goal is to derive a series of conceptual data interaction principles that when considering together will bring new opportunities and synergies for urban, environmental, and earth sciences.

Given exciting recent developments in artificial intelligence (AI) that can provide novel computational solutions to mimic human intelligence to a certain degree, this paper proposes to recast GIScience in the era of cyberspace and envision its future characteristics. Based on a conceptual framework that identifies the respective intertwined roles of geographical space and cyberspace (Liu et al., 2022), we review current challenges and future directions offered by close interactions between the two spaces, as illustrated in Fig. 1. First, the data generation dimension covers a much larger information space, from geolocated smart sensors to human-generated geospatial data. Second, data modeling approaches are evolving, from well-structured data to the integration of very large heterogeneous datasets not always explicitly generated for further use. Third, the geographical space and geospatial data favor the exploration of novel AI data processing and visual explorations, where humans are directing different processing and interactive steps. Finally, the application scope is expanding at an unprecedented rate and reaching novel application areas. We specifically focus on geospatial artificial intelligence (GeoAI) and geovisual analytics (GeoVA) as these emergent fields in GIScience provide novel approaches and opportunities that enable analysis and exploration of the opportunities connecting geographical space and cyberspace. The following sections document the key opportunities and challenges offered by GeoAI and GeoVA in an era where geographical space is inextricably linked to cyberspace.

2. Geospatial data in the context of cyberspace

A large part of the world's population interacts and communicates in cyberspace daily. Cyberspace is an open, global, unregulated, and virtual area of decentralized human activities, social interactions, and application services in the information space transmitted by sensors and Internet communication channels, supported by cyberinfrastructure. Cyberinfrastructure provides a flexible integration of interdependent computing systems, data storage systems, advanced sensors powered by Industry 4.0, and data repositories, visualization environments and people, all linked together by software, high-performance networks, protocols, and computing resources not otherwise possible in the physical world. Cyberinfrastructures are constantly evolving and are even likely to soon integrate massive, decentralized sensors and robot devices with cognitive capabilities. A great deal of the data people are generating and transmitting in cyberspace includes geospatial elements. This raises many challenges related to data quality and trust, but as emerging data flows are generally massive, useful information can be inferred (Niu et al., 2017). Differences can be drawn between the large amount of physical Earth data (e.g., cartographic data, and satellite observations), human activities in geographical space (e.g., mobility), and those that happen in cyberspace (e.g., social media data). Although this classification gives a primal sense of the range of activities and potential geospatial data types, most human interactions in cyberspace are not isolated from events in geographical space, as they often influence and are influenced by one another. The degree of interaction between geographical space and cyberspace varies according to the nature of human activity. For instance, in many mobility services such as ridesharing, real-world interaction with cyberspace is intense. When requesting a ride, the client user will remain in contact with the backend system from the time they board the car until they arrive at their destination. In contrast, the interactions between cyber and geographical space when shopping online (i.e., delivery of goods through logistics and transport systems) can be much looser.

Geospatial data (e.g., location, identity, and semantics) that connect geographical space and cyberspace offers opportunities to better understand human behaviors at different scales with unprecedented spatial and temporal resolution (Lee et al., 2015). As human activity data is generated in real-time with high temporal frequency, monitoring and analysis of spatiotemporal dynamics for complex human activities in an urban context is enabled (Roche, 2016). Nonetheless, there is no doubt that big data creates challenges related to its characteristics (i.e., its dimensions) (Khan et al., 2017; L'heureux et al., 2017; Yang et al., 2017). In addition to the challenges of dimensionality and non-linearity in large amounts of generated data, GIScience and Cyberscience together may provide novel pathways for intelligent processing, while also raising new, complex challenges. Data standards, ethics, and modeling approaches can be reconsidered in light of these novel information spaces. The way physical space is related to cyberspace can raise data modeling challenges. For instance, a smart device connected to the Internet can have more than one IP address when using different networks, which may affect data accuracy. Additionally, with user-generated geospatial content, location spoofing can create data quality issues when users adopt these methods to improve proactive data privacy protection (Zhao and Sui, 2017). Moreover, cyberspace is a fertile environment for the growth of obsolete and useless data (e.g., junk email and bot spam), and the potential exists for cyberspace to be flooded with garbage data (Che et al., 2013). Therefore, it is imperative to envision and implement a sustainable and 'clean' cyberspace.

3. Modeling geographical space and cyberspace

GIScience was originally developed to address the fundamental theoretical issues behind the representation of the geographical world and a representation of places, activities and phenomena (Goodchild, 1992). However, rethinking GIScience from a cyberspace perspective requires data modeling beyond place (geographical space, context) and time (dynamics,) so a sound integration of digital interactions and data that emerge from cyberspace. In other words, conventional GIScience is concerned with the formulation of the geographical data model that has the potential to abstract reality or the real world and represents phenomena and feature attributes that are located in space, while cyberspace is rather oriented to the modeling of the digital space and the human interactions that happen in it. A specific peculiarity of cyberspace is that data is often recorded at a higher frequency than ever before. Early studies have discussed "virtual activity" and argued that the virtual environment can be regarded as a type of space (Batty, 1997; Yu and Shaw, 2008). Cyberspace has appeared due to the wide use of network infrastructure, continuous development of information, and sensor-based technologies that have greatly reduced geographical space constraints on people. Resembling geographical space, cyberspace is composed of virtual places (including identities, websites, and communication platforms) where people interact at an order of magnitude faster than in geographical space (Lü et al., 2018). In geographical space, the main modeling abstractions are derived from places and people, while in cyberspace they are derived from digital places and people, and overall cyberspace and geographical space are widely interacting and progressively integrated into a common modeling-based framework.

It is acknowledged that cyberspace cannot exist or function without geographical space, even though cyberspace has specific properties distinct from it (Batty, 1997; Mohebbi et al., 2020). Cyberspace is not considered a simple abstract virtual space, instead, it includes human activities and interactions that might be related to geographical space. First, human activities in cyberspace are mainly dependent on sensing and communications and network infrastructures (e.g., data servers and

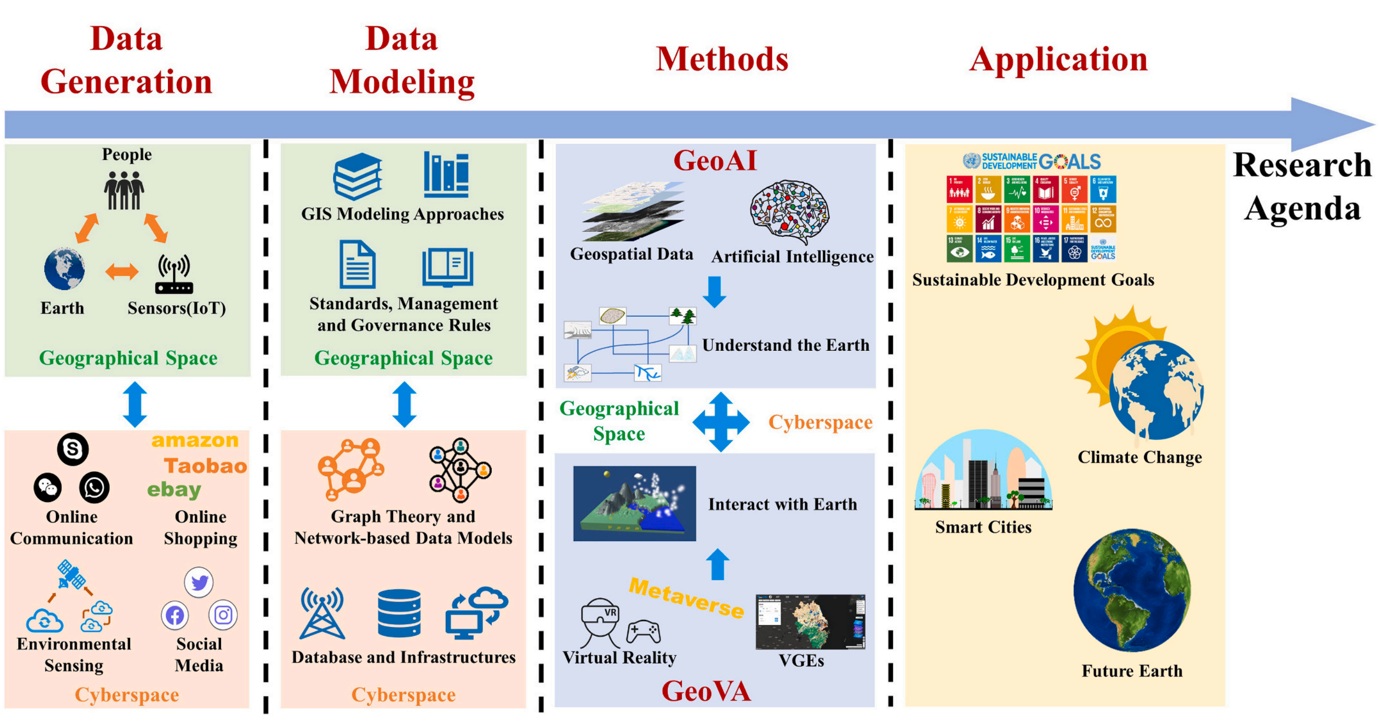

Fig. 1. An integrated view of GIScience and cyberspace, with perspectives offered by GeoAI and GeoVA

clients) deployed in the physical world. Second, geographical space and cyberspace have the same essential components (i.e., humans who exist and carry out physical activities) while humans themselves must exist and (so far) rely on the real geographical world. Third, many cyberspace services serve as an extension of physical-world activities rather than creating a new world. This indispensable relationship between cyberspace and geographical space sets an important foundation for future GIScience studies.

However, challenges remain in designing spatial data models that efficiently incorporate geographical space and cyberspace in an integrated framework to support the development of Geo-visualization capabilities and Geo-AI analytics. Their mutual interdependence and impact may also vary in different and unexplored scenarios. CyberGIS conceptual and logical models can supply reliable solutions to integrate various hardware and software systems and interact with end clients through layers such as cyberspace server and networking layers and with the presence of diverse and multi-type media data and its fit to initiatives in building smart and sustainable cities (Xing et al., 2020). For instance, there is a need to represent activities in cyberspace resulting in digital spatiotemporal trajectories (Shaw and Yu, 2009); when associated with geographical information, such spatially embedded digital trajectories have proven to be highly useful to predict human mobility (Pan et al., 2013), improve the identification of urban infrastructure (Xie and Ou, 2019), and support disaster management (Xiao et al., 2015). Various types of information beyond geospatial location can be used in cyberspace such as text, images, videos, website logs, and social media links. Another critical consideration is that activities in cyberspace are mostly characterized as flows, such as information transactions, telephone communications, and social media interactions; therefore, graph theory and network-based data models are often used to represent topological structures between entities (Çöltekin et al., 2020b). In practice, topological structures in cyberspace can be determined by spatial-social relations and flows from mobile phone and social media data which provide valuable insights into urban functions and structure in geographical space (Shen and Karimi, 2016; Tu et al., 2017). There is a clear interdependence across geographical space and cyberspace, which means that unified models and ontologies should be progressively defined. There are two similarities between human activities in cyberspace and geographical space (Hu et al., 2018):

(1) Cyberspace activities mimic physical activities, as Internet users navigate from one online community to another, explore different online communities, and often revisit communities they already know well, comparable to physical space (Kwan, 2001).

(2) Both cyberspace and geographical space have similarities that relate to locations (i.e., online platforms and places), such that some locations are more popular, and those places tend to attract more people. In contrast, other locations may attract only a limited number of people, and further locations may be authorized for only certain people to visit, such as private groups within online communities.

Because of these similarities, and as shown in Fig. 2, human activity patterns in cyberspace can be remodeled with the aid of sensing data in geographical space. A major constraint to take into account is that Euclidean distance is not the most suitable for analyzing relations and flows on networks. Though there is a large amount of research oriented to the modeling of human activities on the web, there is little research in the literature that has fully considered human activity in cyberspace as well as in geographical space so that we might understand human mobility patterns and their influence on movements in virtual spaces. Moreover, there is a need to revisit current GIS modeling approaches originally designed for well-designed models and applications whose data were mainly very well structured. In particular, data modeling and manipulation opportunities arising from knowledge graphs offer novel opportunities for a dynamic representation of geospatial phenomena (Del Mondo et al., 2021).

With the emergence of very diverse information sources resulting from cyberspace, most of the data is likely to be heterogeneous and unstructured, derived from diverse data processing algorithms, thus leading to a new generation of flexible data modeling approaches. The way geographical space and cyberspace data models should be designed and implemented also requires new thinking and integration of additional principles and constraints. In particular, there is a need to identify the most appropriate filtering and aggregation rules to conserve the minimum set of data that will be not only useful at a given time, but also possibly for the next generation, and with the difficulty of identifying these future needs that are not easily identifiable at present. This motivates the development of an integrated reference meta-model and data infrastructures for geographical space and cyberspace information. Cyberspace can be considered an interdependent network of data and global infrastructure. Data in cyberspace is captured from different sources, platforms, and users' actions, but a marginal amount of the data generated are generally stored and kept, thus generating the need for advanced real-time or live GeoAI capabilities. As cyberspace is physical distance free, and where people from different origins can interact, definitions of standards, management, and governance rules are difficult to implement. This leads to important vulnerability, transparency, security, and data protection issues that are difficult to resolve (Karim et al., 2019).

4. GeoAI: Geospatial artificial intelligence in geographical and cyberspace

4.1. Challenges and opportunities

Exploring spatiotemporal patterns attributed to natural or human-induced processes has been a vital part of the research agenda of GIScience for a long time. Through physical and virtual experiments, geographers and other spatial scientists derive knowledge on human-human and human-environment relationships and mechanisms,

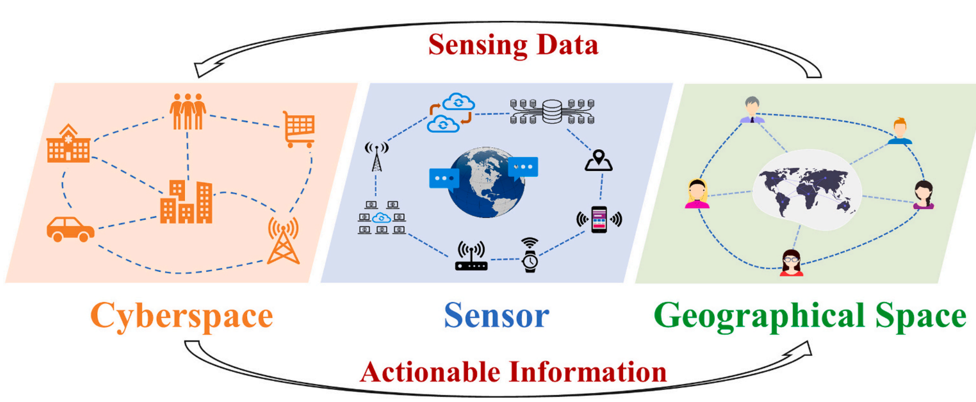

Fig. 2. Modeling geographical space and cyberspace.

forming theories for a wide range of benefits such as promoting sustainable living spaces (agricultural lands, cities). It is common to collect diverse data and adopt different approaches to obtain spatial knowledge, searching for appropriate spatial distributions, relationships, clustering, and dynamic processes (Goodchild, 2010). An early landmark contribution at the crossroads of GIScience and artificial intelligence (AI) is the book on Artificial Intelligence and Geography (Openshaw and Openshaw, 1997), which developed a series of computational approaches and parallel processing machines for searching for geographical patterns. AI also provides a novel form of exploration of human behaviors in the real world (Torrens, 2018). The ability and potentiality of AI for GIScience have been progressively strengthened with the availability of large databases and the search for novel data manipulation and exploration approaches. The emergence of data mining approaches (Miller and Han, 2009) and computational machine learning programs applied specifically to geographical data have been a rising trend in the past few years. Machine learning applied to geographical space encompasses a wide range of techniques from the discovery of spatial associations, clusters, and patterns to anomaly detection (Li et al., 2016). Neural network algorithms have been widely applied to the detection and extraction of objects in large images (Tang et al., 2021; Zhang et al., 2022a; Qian et al., 2022a), and trajectory prediction in urban environments (You et al., 2021; Qian et al., 2022b; Zhang et al., 2022b), although work to fully interpret the patterns and intrinsic mechanisms of these learning-based AI methods in a logical way that humans understand remains a major challenge.

GeoAI combines the strengths of GIScience and AI, which greatly improves the ability of dynamic perception, intelligent reasoning, and knowledge discovery of geographical phenomena and the accompanying processes (Li, 2020). With the support of the IoT, the Internet, 5G, VR, cloud computing, and other new technologies, the integration of GeoAI technologies and cyberspace can provide powerful methods and technical support for GIScience research (Janowicz et al., 2020). Meanwhile, this will open novel opportunities, or at least can be considered an integrative part of other emerging scientific and technological domains, and promote a transdisciplinary impact of GIScience. The recent convergence of social computing research over the Internet and geographical research opens a series of major opportunities for gaining additional information and insight from large data repositories whose initial objective was far away from offering such possibilities, such as inference of mobility patterns from social media activities in geographical space (Wakamiya et al., 2011). It has been shown that cyber-related big data is useful in classifying natural and human-induced spatial structures. For instance, the combination of social sensing big data and remote sensing technology can be well applied to observing actual human activities and obtaining more accurate imagery classification results (Deng et al., 2019).

For prediction tasks, GIS mainly relies on constructing linear-form models between historical hotspots and demographic factors. In this way, massive data and advanced data mining techniques enable us to build more versatile models that adopt high dimensional and complex features, while prediction has also become more accurate over time. Successful applications can be found in tourism and predictive policing (Shapiro, 2017; Williams et al., 2019; Cheng and Chen, 2021). Nevertheless, there are multiple challenges in the convergence of social and spatial relations. For instance, there are explicit (direct) interactions shown by changes in location and calls among people, and implicit (indirect) interactions indicated by co-locations and similar interests.

Other challenges include proactively identifying algorithm-driven behavior of the major platforms, such as overtly persuading and covertly manipulating behaviors. Effective initiatives decentralizing the power of social media platforms and ensuring accountable sovereignty of algorithms should be placed on the agenda focused on socio-economic issues, whereas now, data with a finer resolution in terms of human movement make it possible to gain knowledge about interactions from a mobility perspective. A further indication of mobility-induced spatial relations and structures represent the underlying foundational design of urban functions that drive the motivations for movement and travel.

Another challenging and promising work is to explore the composite impact of geographical and cyber human activities on classification and prediction tasks (Liu et al., 2022). This has attracted more attention as people are spending more time online and are more influenced by online content and relations; hence, the activities in cyberspace are not just additional features in Geo-AI models but should be combined with physical activity as a whole. There are numerous challenges and therefore opportunities in developing models with the advent of new cyber data and defined data representations.

4.2. GeoAI and collaborative cyberspace for current data science

The development of ICT introduces the concept of collaborative cyberspace, which enables different subjects (e.g., governments, organizations, communities, enterprises, and citizens) from different regions of the world to participate in cyberspace activities through cooperation. Because a considerable amount of data generated in cyberspace and geographical space is the consequence of people's passive or active participation in user-generated content (See et al., 2016), there are two major challenges. First, cyberspace is filled with data of unknown validity as previously stated. Second, maintaining active participation of people in cyberspace, which is easier in projects where people contribute passively, such as social networks, but more difficult when people are actively, knowingly, and voluntarily generating data, such as the OpenStreetMap project. GeoAI and collaborative cyberspace suggest approaches to addressing these challenges.

GeoAI can be employed to validate the quality of user-generated content in cyberspace. Computer vision, and particularly image recognition algorithms, have been widely used to evaluate user-generated information, such as in species identification applications (Wäldchen and Mäder, 2018), but there has been less emphasis on using AI to analyze geospatial user-generated content. GeoAI can help validate user-generated big data in cyberspace by training algorithms to model geographical space using other data sources such as sensors and satellite images and then using these trained models to validate data contributed by people. For example, using satellite imagery and deep learning algorithms to assess the positional accuracy or completeness of OpenStreetMap data (Xie et al., 2019). Another possibility is to utilize GeoAI to evaluate social media posts. For example, there has been research on how to evaluate fake news and misleading information on social networks such as Twitter during natural disasters (Rajdev and Lee, 2015; Torabi Asr and Taboada, 2019), but this work has primarily focused on textual analysis. One potential application of GeoAI may be to train models using sensor observations that forecast the likelihood of a natural disaster occurring to assess the accuracy of geo-tagged posts on social media about such events.

Furthermore, combining semantic information from big data in cyberspace with geographical data may improve the performance of AI algorithms, allowing for more accurate verification of future contributed data to cyberspace. For example, geo-tagged images of obstacles in streets, sidewalks, and parks, as well as textual information about the degrees of walkability and accessibility in a city, when combined with satellite and aerial imagery, can produce a more accurate classification map of a city's walkable/accessible areas than results using only one type of data. Another example project uses algorithms and collected images of lakes/seas to predict whether or not there are algae present, for the purpose of monitoring water quality (Biraghi et al., 2021). If the prediction is solely based on images, there is a risk of false positives (shadows, vegetation, etc.); however, if the images are combined with physical or social sensor data to build ensemble models trained on multi-type data, the water quality labeling can be more accurate, and thus more trusted data is generated in collaborative cyberspace. These more precise models can also be used to evaluate new data generated in cyberspace.

Another use of GeoAI in collaborative cyberspace is to infer the location of user-generated data by adding spatial information to non-geo-tagged content (Ajao et al., 2015; Stock, 2018). For example, there is a significant number of non-geotagged postings on social networks, but by utilizing existing geotagged posts, it may be possible to train algorithms that can predict the geolocation of non-geotagged posts, such as geolocating Tweets (Dutt and Das, 2021).

Besides data quality, GeoAI can propose potential solutions for the second challenge in collaborative cyberspace: sustaining people's contributions to cyberspace. As mentioned, the contributed data is either passive/involuntary (e.g., social media data, delivery applications, etc.) or active (e.g., crowdsourcing, VGI, citizen science, etc.). In active contributions, initiating and sustaining people's participation are known challenges (Lee et al., 2020; Lotfian et al., 2020). More specifically the main problems are to first reach out to the subjects that are potentially interested to contribute and second to provide motivational factors for them to continue contributing.

One way where GeoAI can help initiate participation is to use existing data to identify people's interests based on their location among other parameters and suggest they engage in a project of their interest. Thereby the advertisement for the project is targeting the interested community. This is similar to what is being done in Facebook News Feed, YouTube suggestions, etc. (Cotter et al., 2017; Roth et al., 2020), but for integrating the geographical space. Furthermore, receiving communication about the contributed data is another important key to sustaining participation. One possibility to address this is to provide people with automatic machine-generated feedback which is centered on the users' location. One example is the use of trained models on species distribution to provide feedback on the probability of observing a certain species in a particular location (Lotfian et al., 2021).

5. GeoVA: Geovisual analytics in geographical and cyberspace

5.1. Challenges and opportunities

Visual analytics (VA) frameworks leverage visual interfaces to support analytical reasoning and can bridge problem spaces where human decision-making and reasoning are superior to machines (e.g., semantic interpretation, object, and pattern recognition). In addition, VA can maximize advantages where machines are superior to humans (e.g., real-time advanced computations and infinite recall-on-demand) to support complex reasoning by humans. VA approaches are inherently those with humans-in-the-loop, a concept that frequently appears in the AI community in recent years (e.g., Zanzotto, 2019; Wu et al., 2022) and refers to the strengths of human cognition as an equal counterpart in analytical processes. This bridge between computational and visual methods is often constructed as a dynamic, coordinated-view visual interface (a 'dashboard') connected to a backend where a database and computational infrastructure supporting traditional statistics as well as machine learning/AI can be utilized. Users play a key role in directing VA, and this may depend on their desire to deduce, induce, or abduct hypotheses. Sometimes, users will rely on AI and computational methods to identify candidate patterns or anomalies (bottom-up analyses), and sometimes users approach the VA environment with a specific pattern already in mind that they seek to interrogate (top-down analyses) versus insights generated by visualization outputs and computational processes.

Visualization has always been an important part of GIScience, with roots of course in cartography. Geographical visualization (geovisualization) has played a crucial role in sophisticated workflows to leverage human sense-making and cognition (Andrienko et al., 2003). A challenge in the design of geovisualization is to craft intuitive representations of data that enable instant identification of patterns (or anomalies) related to certain phenomena in space and time (Çöltekin et al., 2020a). Considering the large volume and complexity of geographical data, the design of effective geovisualization and visual analytics approaches that integrate human strengths with computational tools (i.e., artificial intelligence that is critical to big data analytics) is also a core research aim within GIScience. In recent years, geovisual analytics (GeoVA) has emerged where computational analysis is directed by humans interacting with geospatial visual interfaces, and can also involve human assessment as a final step after automated pre-filtering. For example, automated methods to extract and visualize high-volume trajectories from GPS data have been proposed (Andrienko et al., 2007). Both two-dimensional (2D) map layouts and 3D visualization based on time geography are powerful approaches to analyzing human movements in geographical space (Çöltekin et al., 2020a). Various applications of extended (virtual, augmented, mixed) reality have also been proposed in GIScience as a potential paradigm shift in spatial knowledge acquisition and visual information processing (Slocum et al., 2001; Çöltekin et al., 2020b).

Since most of the geospatial data processing in modern society has spatial and temporal characteristics, GeoVA can combine visual and interactive methods and advanced computational techniques such as data mining, statistics, machine/deep learning, AI algorithms, and optimization to support human analytical reasoning, hypothesis building, and argumentation (Andrienko et al., 2009). While there are countless different opportunities to make use of GeoVA, a concrete (randomly selected) example could be as follows: To improve the classification accuracy of choropleth maps, a GeoVA environment can help users experiment with and evaluate different classification schemes involving multiple criteria interactively, thus better reflecting the spatial (and possibly temporal) distribution of phenomena (Sun et al., 2017).

The paradigm shift of activities to cyberspace has brought GIScience a wide range of information beyond human movement in geographical space or applications of extended reality. A prominent contemporary example is geotagged social media data, where documents not only include references to locations and time but also linguistic and social network relations (e.g., Straumann et al., 2014). It is challenging to extract knowledge and visualize information that is not solely related to its associated geographical space, and spatial references themselves may be vague or otherwise difficult to disambiguate. Since extracting knowledge in the social dimension is useful to better understand human societal behavior, some efforts have been made in urban studies to develop theoretical and more practical approaches for obtaining geo-social visual analytics (Luo and MacEachren, 2014: Gao et al., 2018). Contemporary big data may generate more knowledge than that of the social dimension mentioned above. An undeniable trend is that we have more opportunities to simultaneously observe both geographical and cyber systems. For example, in mobile phone data, visited websites are recorded along with geographical user positions. Thus, it is possible to gather high-resolution trajectories in both geographical space and cyberspace which may, in turn, improve current geovisual frameworks. Empirical research on how to properly define and present entities and personalize or customize visualizations to enhance the geo-visual explainability and amplify human cognition based on audience and context is still required.

5.2. GeoVA and extended reality (XR): immersive analytics

Along with the developments in AI, a new generation of display technologies such as extended reality (XR), i.e., augmented (AR), virtual (VR), and mixed (MR) reality systems open up new opportunities for VA (Çöltekin et al., 2020b), termed immersive analytics (Chandler et al., 2015; Simpson et al., 2016; Lochhead and Hedley, 2021). As a special case of immersive GeoVA, virtual geographic environments (VGEs), also referred to as geo-virtual environments, have been studied through several decades in GIScience dating back to the late 1990s (MacEachren et al., 1999; Lin et al., 2013a; Lin et al., 2013b; Chen et al., 2013a, 2013b). XR and VGEs have methodological and data-driven links to the digital twin concept, in which digital mirroring of both physical and social phenomena can be represented and interactively explored (Chen and Lin, 2018; Voinov et al., 2018). As digital twins provide real-time data from multiple sensors, the GeoVA dashboards, as well as their immersive versions, also referred to as embodied digital twins (Klippel et al., 2021), become potentially useful for big data applications. Concepts of in-situ visualization have been introduced for data analytics during runtime, e.g., of large ensemble simulations, allowing for model adaptation during simulation runtime for rapid prognostics (e.g., for extreme weather events). The newly enabled interactions between users and VGEs as the user can 'walk in the data' embody an example of the human-in-the-loop concept with added benefits of experience-based learning and life-like interactions, thus can increase the interest of public participation and feedback, and can further promote the development of VGEs (Lü et al., 2019).

After users enter a VGE that is based on collaborative cyberspace, IoT, and ICT, geospatial data can be displayed, processed, and shared in this virtual world, and then humans can realize omnidirectional interaction with computers and with each other. For instance, the Smart City Digital Twin (SCDT) paradigm (Michalik et al., 2022) was proposed and applied to increase the visibility of interactions between humans and urban infrastructures, where the spatiotemporal geographical data can be integrated into a platform with the powerful abilities of visual analytics.

Geospatial data (as available in cyberspace) offer many extraordinary opportunities enabled by the emergence of virtual and interactive communities such as 'the metaverse' (Stephenson, 2003). The metaverse concept is based on a large-scale network of three-dimensional virtual environments, which is born out of the real world and parallel to it. It is envisioned that there is an unlimited number of users and continuous dynamic geospatial data in the metaverse, which can as such create virtual spaces whose dynamic and semantic properties can be then explored and analyzed by GeoVA and GeoAI capabilities as we do in real-world geographical spaces (Ball, 2022). Therefore, the metaverse can be considered a virtual world based on geographical and collaborative cyberspace, where GeoVA can also be used to display and reason with geospatial data in real-time by users who can contact, interact with, and collaborate with each other.

As with all the geospatial sciences, earth sciences also benefit from the above-mentioned new paradigms (e.g., Gerloni et al., 2018, Moysey and Lazar, 2019, and Harknett et al., 2022). For example, mathematical and geoscience models, algorithms, and simulations can be shared in a lively and engaging way using dynamic interfaces and cyberinfrastructures, providing interaction capabilities and favoring methodology exchanges and replicability throughout different experts and disciplines (Shao et al., 2020; Goodchild and Li, 2021).

6. Perspectives

Geographical space and cyberspace, when combined in a common framework, offer a wide range of application opportunities in the urban, environmental, earth science, socioeconomic, and health domains. Not to mention the fact that in the era of urgent sustainable development objectives, the two should contribute to the development of a livable society. Smart cities provide a prominent example of the combined development of geographical space and cyberspace in that they rely on the full integration of the capabilities of the two information environments (Li et al., 2020). Cyberspace offers many opportunities for the development of advanced services in urban environments, from social to leisure to professional and resource-sharing activities. A substantial change came from the unprecedented data flow, transmission, and diffusion rates that produce large spatio-temporal-semantic data streams and sometimes data repositories. In urban environments, these big data sources can support the development of real-time data observation and processing applications at fine resolution and acceptable accuracy. By integrating multi-source heterogeneous data, GeoAI might favor the development of analysis, modeling, understanding, simulation, and prediction mechanisms that will take full advantage of the data sources generated in geographical space and cyberspace. GeoVA surpasses pictorial representations in visual effects as well as increases the quality and efficiency of understanding the geospatial data along with decision-making (Harbola and Coors, 2018). Utilizing GeoAI to reveal hidden patterns of big data of transportation networks and combining GeoVA to assist transportation management departments in understanding real-time traffic conditions can effectively achieve traffic monitoring in smart cities (Mortaheb and Jankowski, 2023). The emergence of the digital twin concept in urban environments provides a very close link between geographical space and cyberspace at an efficient and low cost (Scott, 2016). A digital city twin should reveal a bidirectional mapping between geographical space and cyberspace, thus enhancing the governance and policies of the entire urban system. In urban environments, specifically, the emerging field of autonomous driving, which is a typical and fundamental AI subject, when combined with sensors and large-scale geographical space and cyber-simulated worlds, opens revolutionary opportunities for the development of efficient autonomous driving solutions (Tu et al., 2021).

GeoAI is increasingly applied to model and capture the environment around us, which has certain advantages in exploring the internal links and interaction mechanisms between human activities and the living environment, especially in exploring its potential role in health research. The relationship between place and health was already recognized by Hippocrates more than two thousand years ago in his treatise "On Airs, Waters, and Places" (Nriagu, 2011). These associations between health and place form the foundations of modern health geography or geomedicine and are often exploited in the field of spatial epidemiology (Koch and Koch, 2005, and references therein, and Joost et al., 2018). But the recent advent of GeoAI opens new perspectives for research and applications in health, digital health, and related fields, for which the properties of the built, natural, or socio-economic environment plays a determining role (Brakefield et al., 2022). Indeed, integrating location-based information extracted from big geospatial data may allow us to better understand environmental risk factors and precisely identify new targets for tailored prevention efforts and treatment strategies (Kamel Boulos et al., 2019) considering places where the individual is living, working, or were traveling (Sirmaçek et al., 2022). Beyond spatial epidemiology and environmental health (VoPham et al., 2018), several disciplines may benefit from the contribution of GeoAI within the domains of public health. In particular, the use of the geographical dimension of the Internet of Things (IoT) makes it possible to enrich precision medicine with valuable additional information (Aravind and Maddikunta, 2022). During the COVID-19 pandemic, intelligent health monitoring frameworks were developed using wearable IoT and geofencing (El-Haleem et al., 2022) for susceptible patient monitoring and isolation and quarantine management (Ullah et al., 2021). The health domain is also likely to benefit from the further integration of Just-in-Time Adaptive Interventions (JITAIs) with GeoAI and IoT to understand, predict, and intervene in health behaviors at risk (Yang and Jankowska, 2019).

GeoAI applications to novel sources of spatial big data, such as social media, and electronic health personal sensors, have already advanced the science of population health in a significant way (Mohapatra and Mohanty, 2022). For instance, the automated HealthMap developed by the Boston Children's Hospital scans online and georeferenced news and social media reports for early warning signs of outbreaks. The system continuously (24/7) brings together distinct data sources to integrate, monitor, organize, and visualize online information about emerging diseases and facilitate their early detection (Cho, 2020). Besides, the mobile communication data of patients with infectious diseases can be well analyzed by GeoAI and an epidemic spread map can be produced and displayed by GeoVA, which can effectively assist government departments in early warning of epidemic transmission and epidemic prevention.

The combination of GeoAI with the advanced technologies recently developed in the field of the IoT and communications constitutes a unique chance to improve the quality of life of individuals and populations through the integration of different sources of environmental monitoring, health, and behavior data. But it should not be forgotten that the pooling of these data, which can only be achieved through the use of geographical information, also represents an important risk if it is carried out by health insurance companies or prospective employers, or lenders. Appropriate security measures, standards for securing and sharing data, and ethical frameworks (Kamel Boulos et al., 2019) for engagement are therefore key elements that must accompany any project in this area.

The United Nations Sustainable Development Goals (SDGs), issued by the United Nations in 2015, aim to solve 17 important social, economic, and environmental development issues from 2015 to 2030 in a comprehensive way and turn to the path of sustainable development. The implementation of the SDGs requires huge amounts of spatial-temporal data, and there is an urgent need for geographical information data, methods, frameworks, cyberspace tools, and platforms. With Earth observation and geospatial data as the main body, big Earth data can break through the constraints of statistical data administrative regions, cover different spatial and temporal scales and geographical location information, more accurately assess the progress of SDG indicators, and find problems on time (Guo, 2017). Since network infrastructure, behavioral agents, and network data have differences in spatial and regional characteristics, the methods of cyberspace geography (e.g., network data and geographical location high-precision automatic matching technique, spatiotemporal feature analysis, and knowledge map construction of network data) (Gao et al., 2019) can effectively realize the mapping from geographical space to cyberspace. The mapping from geographical space to cyberspace can help scholars more easily perceive, recognize, reason, and analyze the global forests, water resources, cultivated lands, cities, carbon fluxes and stocks, biodiversity, and human health conditions in combination with the models and methods of GeoAI and GeoVA, so as to obtain knowledge about the distribution of the global poor population, migration rates of wild animals, global forest area change, climate change, and so on. These results can provide geographical science decision-making support for the realization of the 2030 Sustainable Development Goals of the United Nations.

While geographical space and cyberspace are likely to provide an extraordinary range of application opportunities, cyberspace also brings avenues for cyber warfare, which can both disrupt cyber data infrastructures as well as the availability and security of critical data (Carlos Pedro, 2019). We should not underestimate the difficulties that await us. There is also a risk associated with the complexity of GeoAI and the wide range of possible human interactions which are likely to generate technical dead-ends as the level of expected maturity of many of the emerging application domains are still not well developed. This is likely to result in major difficulties associated with the explanation of data manipulation processes applied to geographical space and cyberspace and it will entail transparency challenges related to the explanation of so-called "black box" computational processes. Personal privacy and data access rights should be preserved and guaranteed by appropriate legal and technical mechanisms, and this at the global and individual levels, as the range of possible interactions in space and time is likely to generate data lakes where humans are likely to act upon these integrated geographical spaces and cyberspace, thus offering many opportunities for malicious actors to infer valuable information on the way humans behave in space and time.

7. Conclusions

Due to recent technological advances, we have witnessed a shift in human activities from geographical space to include cyberspace. This shift requires rethinking GIScience in the presence of new concepts and advances coming from cyberspace, such as placelessness, some aspects of timelessness, and the changing meaning of distance. Spatial concepts of place and distance are central to GIScience and modifying these from their traditional meaning calls for new thinking. Similarly, temporal analyses also take new meaning within cyberspace where we have abundant longitudinal data and a lack of transiency.

The shift of activities to cyberspace has been and will continue to be a key part of GIScience. The rich data flow in cyberspace has indicated that the dramatic changes in daily life transform human-environment relations. In future research, improved conceptual and computational data models should be proposed and empirically examined to reveal and understand, beyond human-environment relations, the complexity, and diversity of human-human, human-environment, and environment-environment relations in hybrid geographical space and cyberspace. Based on these data models, analysis of cyber-physical human activities is expected to extend current theories and methods in GIScience and have an even broader impact in other research fields that involve spatial analysis and visualization with geographical perspectives. For human geography, considering the cyberspace dimension in GIScience will be beneficial for improving the understanding of human well-being. For example, the assessments of social segregation require deep and detailed insights into human perception and social activities in cyberspace (Kwan, 2001) as well as the spatial patterns of static social attributes. For urban geography, hybrid models and analysis-based cyber-physical frameworks fit the complexity of reality and may result in superior prediction of mobility dynamics and enhanced interpretation of the functionality of urban places (Qian et al., 2020). This paper demonstrates how a re-thinking of GIScience, especially about GeoAI and GeoVA, from a cyberspace perspective, will profoundly motivate the innovation of theories and methods in traditional GIScience, as well as promoting interdisciplinary research, e.g., connecting to fundamental questions in geospatial knowledge acquisition and cognition, and extended (virtual, augmented, mixed) reality.

We have provided a brief overview of geospatial big data here and the associated challenges from a cyberspace perspective with a specific focus on GeoAI and GeoVA. To keep pace with developments in the Fourth Industrial Revolution, we call here for research attention to be focused on the GIScience research agenda from a cyberspace perspective. The more pressing needs include an appropriate ontology for geospatial data related to cyberspace, proposals outlining new virtual GIS capabilities, and the development of applications of GeoAI and GeoVA in cyberspace. We have supported our discussion with provocative and constructive ideas that will stimulate future work.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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