AM-21 - The Evolution of Geospatial Reasoning, Analytics, and Modeling

The field of geospatial analytics and modeling has a long history coinciding with the physical and cultural evolution of humans. This history is analyzed relative to the four scientific paradigms: (1) empirical analysis through description, (2) theoretical explorations using models and generalizations, (3) simulating complex phenomena and (4) data exploration. Correlations among developments in general science and those of the geospatial sciences are explored. Trends identify areas ripe for growth and improvement in the fourth and current paradigm that has been spawned by the big data explosion, such as exposing the 'black box' of GeoAI training and generating big geospatial training datasets. Future research should focus on integrating both theory- and data-driven knowledge discovery.

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Topic Description:

1. Introduction

The foundation of geospatial analytics and modeling is spatial reasoning. The evolution of human spatial reasoning appears to be closely related to the evolution of tools (technology) and language (Lewis 1987). Indeed, the field of spatial reasoning can be thought of as a scientific discipline subject to shifting paradigms throughout its development (Simpson 1989). It is difficult to isolate spatial reasoning from the discipline of cartography. Clearly, spatial reasoning occurs devoid of physical maps (in their various forms) through the use of the cognitive map (Lewis 1987). However, the use of maps and models as symbolic representations of spatial knowledge critically expands the essential abilities of spatial cognition (Vasilyeva and Lourenco 2012).

The progression of spatial thinking, although presumably improved by evolution in people, is likewise firmly identified with cultural needs, since certain societies today have neglected to move past the preoperational phase of cognition to the operational stage where logical organization of space arises (Blakemore 1981). Non-human animals can impart information about space, yet that information fails as enduring portrayals (Lewis 1987). Lewis (1987) proposed that advancing people would have needed a more persistent structure for capturing spatial knowledge to realize advanced spatial investigations and perpetuate their spatial consciousness across time and space. It is in those civilizations where projective and Euclidean geometries arose that map-production was first initiated (Lewis 1987).

Changes in how humans understand the world around them have been compelled throughout history by changing environments, advancing technological needs and developments (Simpson 1989; Barfield 2019). These innovations, in turn, often propelled further progress. The changes spurred by environmental changes appear to have eventually led through upright walking, which freed the hands for the early development of tools and the capture of fire, to larger brain size through added calories from cooking (Fabbro et al. 2019; Parker et al. 2016; Plummer et al. 2009). The availability of higher caloric intake appears to have increased the carrying capacity of the land, which likely led to larger groups of hominids living in an area (Fonseca-Azevedo and Herculano-Houzel 2012). Greater cooperation is required for the success of a denser population, resulting in the development of maps and language, and, hence, society (Khaitovich et al. 2008).

We suggest that geospatial analysis evolved through four critical discovery sets that follow the basic development of any science (see Gahegan 2020 for similar analysis) (Figure 1). First, basic spatial awareness evolved through the mobility and hunting needs of Homo erectus to understand direction and distance through empirical analysis by describing natural phenomena. Next, the cultural evolution of early, physically modern Homo sapiens led to the more theoretical questions of "what is nearby and why" through the development of generalization and the use of models reflected in advances in written language and cartography. As cultural evolution rapidly exceeded any physical changes in humans, the desire to simulate complex phenomena such as "where is the best place to relocate based on multiple layers or properties" led to the computational revolution, reflected in the geospatial sciences by the development of analytical cartography, GIS, and geostatistics. Today, we move into the fourth paradigm of GIScience to unify theory, experiment, and simulation through data exploration, on the road to answer questions such as “what spatial relationships are we missing” with Geospatial Artificial Intelligence (GeoAI) and related technologies. In the following paragraphs, we analyze in more detail the changing context of geospatial analytics and modeling through these four scientific paradigms. Specific emphasis will be placed upon the current data-driven revolution, its past, present and especially its future.

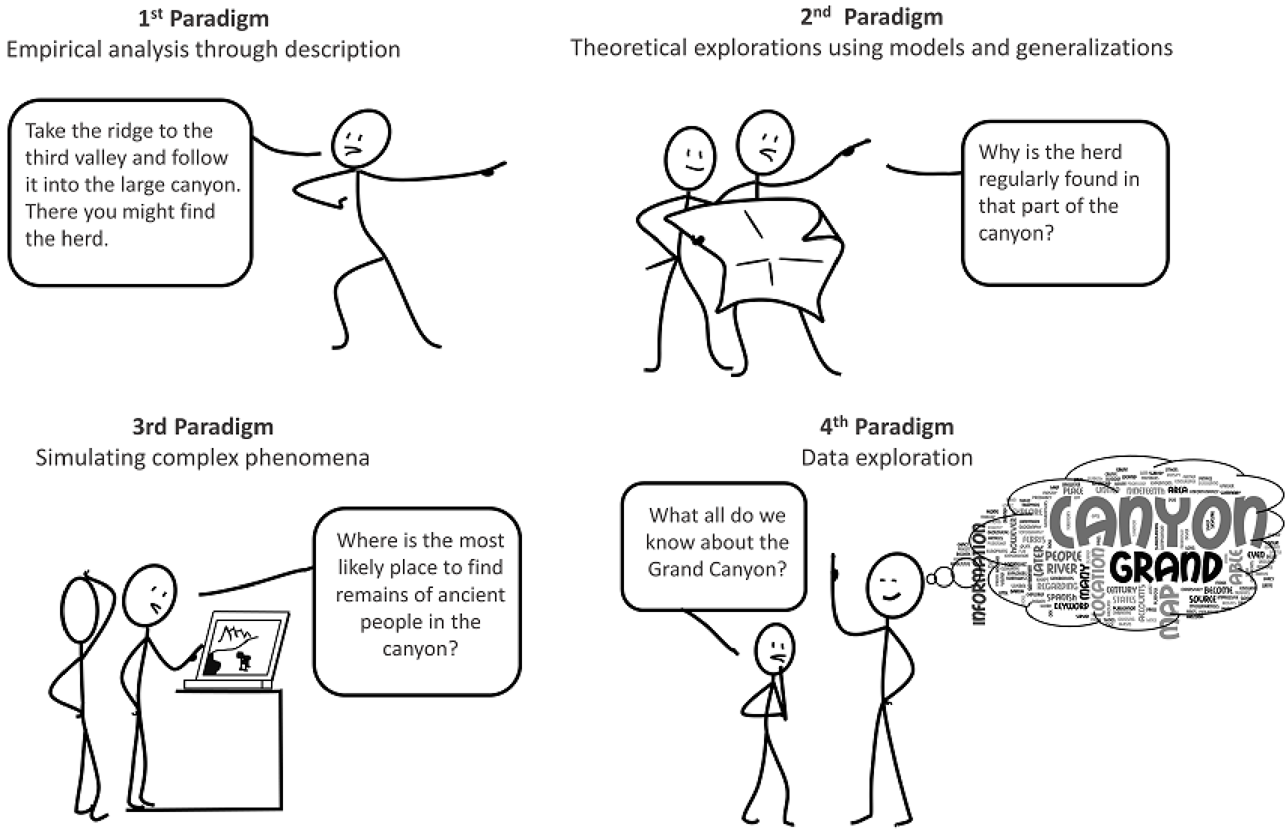

Figure 1. Geospatial Analysis and modeling changes through the four scientific paradigms. Source: authors.

2. The Four Scientific Paradigms as Related to Geospatial Analytics and Modeling

2.1. The First Paradigm: Empirical Analysis through Description

The hallmark of the first paradigm is empirical analysis, which is the description of the surrounding world in the spatial sciences, particularly in the form of locations, distances, and directions. Clearly, animals possess an innate form of spatial cognition. But early hominids would have moved beyond this basic capacity when around 6 million years ago natural selection began to encourage their upright ambulation (Melott and Thomas 2019), freeing their hands to develop tools as early as 2.6 million years ago (mya) (Semaw et al. 2003) and, eventually, to control fire (Parker et al. 2016). Homo erectus (and potentially other, earlier Homo species) may have exploited fire to prepare food as early as 1.9 million years ago (Organ et al. 2011), and butchered animals to cook at least 1.75 million years ago (Beyene et al. 2013). The nutrients available from cooked food, compared to the nutrients in raw food, are much easier to digest, a feature essential for brain evolution (Fonseca-Azevedo and Herculano-Houzel 2012). Essentially, cooking improved the digestibility of food, permitting hominids to better exploit the energy acquired from their consumption. Eventually, cooking food greatly reduced the time required to forage for the same number of calories, allowing Homo time to focus on other activities (Wrangham 2017). Certainly, small animal hunting and large game scavenging were common, evolving with stone age toolmaking, by the time of Homo erectus and by 1.5 mya, the hunting of large animals was probably common (Ferraro et al. 2013).

Big-game hunting compels the control of a vastly larger range than that needed to hunt small animals or required for foraging (DeVore and Washburn 1963; Peters 1978). To maintain such influence leading to a successful hunt, early hunters likely needed cognitive maps for efficient and effective travel across the region and a group communication system that permitted members to split into smaller numbers but also reunite again (Khaitovich et al. 2008). Hominids, missing the sensitive olfaction and powerful natural weapons including odors that other social carnivores such as wolves use to communicate, would have needed to acquire visual, vocal and intellectual methods instead (Peters 1978). Early communication of spatial analysis would have been in the form of describing natural phenomena (Brown 1949).

The shift to bipedalism appears to have also liberated hominid hands for gestural communication (Donald 1993). Corballis (2017) postulated that the movement of our bodies, particularly through hand and arm gestures, bestows a natural way to express phenomena in our primarily spatial environment. He concluded that the evolution of spatial awareness and language in hominids would have proceeded concurrently because the intellectual activities triggering nascent dialog probably had a substantial spatial element. This spatial element would have offered structure and function to the establishment of language. In fact, the communication required to plan the spatial logistics of a large-game hunt alone could provide the context for the development of early hominid language (Számadó and Szathmáry 2006).

It appears that natural selection favored distinctive voices that produced distinguishing vocalizations, rewarding the rapid recognition of hunting companions and initiating the predecessors of names (Lewis 1987). Once the use of names (or other symbols) arose to represent individual people, locations and events, cognitive maps and tactics would eventually meld into the capacity to easily build the framework for representing directions and positions (Peters 1978).

Correlates to the evolution of spatial reasoning can be made from studies of its development in primitive people alive today (Hallpike 1979; Lovett and Forbus 2011). Spatial concepts that dominate their thoughts include the notion of boundaries, as well as opposites such as open and closed, high and low and left and right (Lewis 1987). Lewis (1987) concluded that phenomena, ordered in a topological, as opposed to Euclidean, means, represent tangible natural elements of the physical world, providing testimony to the cognitive maps that inspired the development of recorded maps.

2.2 The Second Paradigm: Theoretical Explorations Using Models and Generalizations

As suggested earlier, basic spatial understanding is a precursor to mapmaking. The increased need to control a large region, as well as the development of language in its broader sense is reflected in the development of the map, arguably beginning in the Upper Paleolithic around approximately 25 thousand years ago (kya) through the desire to increase large game hunting kills (Svoboda 2017). In large areas, humans needed to evolve the displacement property of language, allowing them to describe experiences at other locations and points in time, in the past or future (Corballis 2017). The awareness of early Homo sapiens was focused on uncertainties and irregularities, whereas modern societies seek knowledge through the order and regularity of science (Lewis 1987).

In fact, Lewis (1987) argued that the need to communicate spatial knowledge and the development of human language appear to have developed concurrently, as both evolved to require a degree of permanence and three-dimensional representation. These characteristics, not supported in aural systems of speech and music or the visual systems of communication through gesture and dance, were realized in drawings, models and pictographs. He alleged that the development of teaching to support the expression of relationships between events, places and people required progress past simple imitation. Instruction is also enhanced when knowledge can be made less ephemeral.

Although it can be reasoned that cognitive maps embrace a conceptual understanding of the surrounding environment, and to communicate them in any form requires a kind of model, we focus on material representations of spatial knowledge, as they would be key to more advanced analysis simply via their relative permanence. Early models include carvings on animal parts and rock art and all varieties of the map, which can be defined as “graphic representations that facilitate a spatial understanding of things, concepts, conditions, processes, or events in the human world” (Harley and Woodward 1987a).

The second paradigm can be reflected in the spatial realm as the analysis of what is where and why it is there. It has been proposed that early Homo sapiens needed to understand why large game is found in certain locations and to predict its occurrence (Devore and Washborne 1963). Religious practice also would have spurred the creation of prehistoric maps. Smith (1987) believed their function was abstract and symbolic as opposed to practical and that their production was likely controlled by religious beliefs. Although information about early mapmaking is scarce, it is possibly the oldest form of primitive art (Brown 1949). The earliest examples involve carvings on animal tusks and other body parts (Smith 1987). Many maps were likely made and lost. Generally, those carved or painted on cave walls did not reflect elements of normal, mundane life, but instead those of religious beliefs, and they would have required extensive labor (Simpson 1989; Smith 1987). It is logical to assert that engravings on portable items such as tusks were used for hunt planning and execution, whereas those crafted on immobile structures characterized more artistic representations of ideas and beliefs (Svoboda 2017). Either way, the first prehistoric maps set the stage for more complex spatial analysis using graphic forms seen in historic times.

Almost 20,000 years after the first potential record of prehistoric map carvings in tusks and rocks, written cuneiform script arose in Sumer (Millard 1987). A probable function of Sumerian inscription was to compile lists of words by category, of which towns, mountains and rivers were an important part. Scribes were believed to have learned of their own and distant lands through the conquest of foreign lands, the trade industry, and taxation accounting (Dilke 1987). Mapmaking in the early historical age was highly influenced by the ancient cartography of Ancient Egypt and the Near East during the Bronze Age (~5 to 3.2 kya), responding to progress in the field of measurement, the need for surveys of conquered lands, and the rise of architectural design; the development of theoretical and applied cartographic thought in the classical period; and the concurrent presence in Medieval times of varied mapping traditions, such as those in local and regional cartography, the mappaemundi and portolan charts (Harley and Woodward 1987a). Maps evolved into tools used widely by scholars and the public in research and teaching as society began to contemplate the world in both a physical and social sense (Dilke 1987).

Cartographic phenomena arise at different times in space, and gaps in the historical record hinder its reconstruction (Woodward, Yee and Schwartzberg 1987). Although the timing of the appearance of cartographic phenomena across the world appears to have varied by tradition, common themes include celestial mapping, cosmography, maritime navigation, and geographic mapping of features such as rivers, roads and settlements (Harley and Woodward 1987b). It seems that far in advance of the sixteenth century rise of Europe, physical and cultural trade between Asia, Europe and the Mediterranean spheres united them into one great Old World system encompassing mapmaking traditions. For example, Islamic and South Asian cartographic traditions appear to have preserved many of their own distinctive characteristics while simultaneously embracing the cartographic practices of other premodern cultures (Harley and Woodward 1987b).

Societies beyond European influence probably preserved their own unique cartographic traditions (Woodward, Yee and Schwartzberg 1987). A dearth of literature describing traditional mapmaking, as well as the relative novelty of studies concerning non-European cartography and the social context of mapping and mapmaking, challenges interpretations of traditional Islamic and Indian mapping. These traditions appear to have touched many aspects of culture, including the arts and sciences, religion and magic, literature and philosophy, and even politics (Karamustafa 1987; Schwartzberg 1987). Interestingly, unlike other societies, the written text in these cultures appears to have provided the authoritative scholarship that contributed the subjects that became transformed in the maps that were subordinate to the literary treatise (Woodward, Yee and Schwartzberg 1987).

Traditional African, American, Arctic, Australian, and Pacific societies produced many relics that can arguably be described as maps, typically conveying a topological structure of some kind, often in the form of linear routes (Woodward and Lewis 1987). Most of these societies likely named physical and cultural elements of the landscape, whether settled or not, at a level of density and detail far outshining many modern traditions. Where it is unfeasible to separate secular and sacred mapmaking traditions in these societies, cartography may be conceived of as a model of the connections between the physical and spiritual world and between landscape and event, reflected in the concept of the "center" as a sacred place Woodward and Lewis, 1987).

It appears that the creation of maps during the European renaissance experienced an evolution like that in the literature and fine arts disciplines, related to the Scientific Revolution (Thrower 2008). Enormous technological changes through the rediscovery of classical mapping methods and the need for maps to manage growing trade routes powered a burst in the production and use of maps. Moreover, the acceptance of the abstract concept of coordinates as the fundamental map foundation and construction of orthogonal maps centered, framed and oriented maps through a geometric point of view that improved the public perception of map use and dependability worldwide (Woodward 2007).

Transformations in the theory of spatial representation and the implementation of that theory into models was paramount within this geospatial context. These developments likely guided early 20th century cadastral mapping, boundary surveying, and topographical and urban mapping (Woodward 2007). By 1912, Warren Manning had initiated the employment of spatial overlays to acquire a better understanding of complex environmental interactions. The analog-to-digital revolution, overhead mapping, warfare needs, and the tools of public administration boosted the availability of data, enhanced data resolution, and clarified data requirements and analytical techniques needed to solve issues related to the interactions between people and their environment (Simpson 1989). Overhead imaging spawned by warfare was especially influential with its resulting ‘big data,’ which required computational storage and digital analytical resources. Although modern spatial analysis dates at least as far back as 1832 when Charles Picquet created a map representing cholera outbreak across 48 districts of Paris, the inadequate accessibility to spatial data and tools for spatial analysis and visualization strictly limited the operative resolution of spatial issues (Marble 2015).

2.3 The Third Paradigm: Simulating Complex Phenomena

In the spatial realm, the third paradigm is embodied in analytical cartography, GIS and geostatistics. These technologies resolve questions such as “where is the ideal location based on multiple layers or properties?” and “what impact might a mining resource have on the local ecology?”

By the end of the twentieth century, the significance of spatial dynamics to numerous stages of personal and societal development and evaluation was established (Ormeling 2015). Pervasive applications of computer-based algorithms using geographic information science and related technologies to topics of human enterprise arose. This use contrasted sharply to the poor understanding of the impact of spatial elements in the early part of the century (Marble 2015).

Analytical cartography, originating in mathematical cartography with Waldo Tobler’s 1961 doctoral dissertation, has developed from the spatial data sciences in general, including computer graphics, computational geometry, geodesy, surveying, image processing and geography (Tobler, 2011; Moellering et al. 2000). Of specific interest to the field is the employment of mathematical transformations in geographic and cartographic spaces, integrating analytical theory with cartography (Moellering 2015). Its development was largely dependent upon cooperation among government, including the intelligence mapping community, academia, and industry (Clarke and Cloud 2000). Geographic information science, discussed below, has recently incorporated much of analytical cartography (Moellering et al. 2000).

Geostatistics, also referred to as spatial statistics, mainly concentrates on spatial extrapolation, but embraces other significant topics, such as spatial sampling strategy, sound model adoption, and the consequences of spatial clustering (Cressie 1991). Originally conceived in the mining disciplines (Matheron 1963), the "geo" in geostatistics initially denoted Earth-based statistics. Concurrently, Ganlin (1963) named his effectively indistinguishable structure for statistical analysis of spatially referenced (meteorological) data “objective analysis.” Since its inception, geostatistical techniques have been applied to a range of topics in engineering and science (Cressie 1991). Much of this framework has also been integrated into geographic information science, although some areas of expertise still rely on traditional statistical packages in which the spatial features are represented in columns of coordinate locations (Marble 2015) as compared to vector and raster datasets, which can offer additional data and data analysis techniques (for example, see Getis and Boots 1978).

In many areas, Geographic Information Systems developed through automated cartography and was driven by academic curiosity, the desire to use or improve data sources or techniques, or the recognition that some tasks could be accomplished only through employing computerized systems. Coppock (1991) recognized four phases of development of GIS from its beginning in the 60s to its almost modern maturity in the 90s. The first phase occurred approximately between 1960 and 1975 when individual personalities drove the inception of the field. When D.P. Bickmore published the Atlas of Great Britain and Northern Ireland it was criticized as being too dated and cumbersome. In addressing these criticisms, Bickmore concluded that the only viable approach to manage and analyze the data was with a computer, initiating the establishment of the Oxford System of Automated Cartography. The Canada Geographic Information System was similarly developed by R. Tomlinson to manage East African data after discovering that the cost of manual production was prohibitive. During the second phase, from 1973 to the early 80s, national agencies, especially in the United States, heavily fostered standardization of both experiment and application in GIS development and implementation. The U.S. Geological Survey and the Bureau of Census played key roles in the involvement. The third phase saw commercial entities such as ESRI, Intergraph, ComputerVision and Synercom dominate innovation from the early to late 1980s. Although advances in algorithms and data structures developed swiftly in the 1970s and 1980s, by the fourth phase in the 90s – the era of user dominance - many challenges remained related to data and error modeling, integration of spatial analysis, and institutional and managerial functions (Goodchild 1991).

The last decade of the 20th century and the first decade of the 21st century witnessed a transformation from the emphasis on Geographic Information Systems (software and hardware) to Geographic Information Science (GIScience) (Goodchild 2010). This shift was provoked by questions about the scientific viability of GIS when seeking funding in the mid-1980s, particularly from the National Science Foundation. In 1987, Ronald Abler and others, after broad dialogue with the research community, sponsored the formation of a national center in the United States based on five themes of GIScience research: spatial analysis and statistics; spatial relationships and database structures; artificial intelligence and expert systems; visualization; and social, economic, and institutional issues (Abler 1987). These themes united various distinct fields such as geography, cartography, computer science and statistics in what was at the time an innovative fusion of many disciplines (Goodchild 2010).

Entering the era of big data, traditional spatial analytical methods, such as geometric overlay and spatial statistics, have shown significant limitations in computation and algorithmic design when handling large, diverse datasets (Lee and Kang 2015). On the one hand, existing algorithms are mostly designed to run on a desktop leveraging a single computing core. These algorithms often lack effective strategies for managing computer memory to store data and intermediate results (Li et al. 2016). As data increase, these algorithms may result in software failure. On the other hand, traditional models and algorithms are better at handling smaller datasets with coarser resolution. For example, the stream flow analysis tool (available in ArcMap and other GIS software) functions well when extracting watersheds from coarse-resolution Digital Elevation Models (DEM) because the data present a relatively smooth surface to identify the stream flows. When leveraged to process high-resolution DEMs, which capture small details such as rocks or vegetation cover on the surface, the algorithm will create instead less meaningful results due to its inability to handle data uncertainties or "errors" caused by local data spikes. Moreover, the massive availability of observations of the physical and social world today has challenged traditional knowledge-driven research paradigms by asking and answering new questions based on these big data. A data-driven revolution is therefore urgently needed.

2.4 The Fourth Paradigm: Data Exploration

Addressing the above challenges has evolved the fourth research paradigm – data-driven discovery (Tansley and Tolle 2009) and data-driven GIScience (Gahegan 2020). There are three interconnected research themes for data-driven GIScience, namely data, models, and computation. Today's deluge of big data – extremely large datasets requiring non-traditional computing approaches - brings vast opportunities but also major challenges in the ready access of distributed geospatial datasets. With the explosion of the World Wide Web, the distribution of geospatial data has become increasingly dispersed, making effective discovery and utilization of the data extremely difficult. A familiar scientific concept is the 80-20 rule, which states that 80% of a scientist's time is used for data acquisition and only 20% is used for performing actual analysis and seeking new knowledge. Addressing this data issue requires novel ways of geospatial searches, especially for the data residing in the deep Web, i.e. hidden behind a firewall or within a database. PolarHub (Figure 2) is a solution that relies on large-scale web crawling, semantic-enabled data-filtering and high-performance computing to collect geospatial data and services across the globe (Li 2018). Such a solution offers a single access point for a diverse set of data covering environmental and social science domains and provides strong support to climate change, biodiversity, population and other studies.

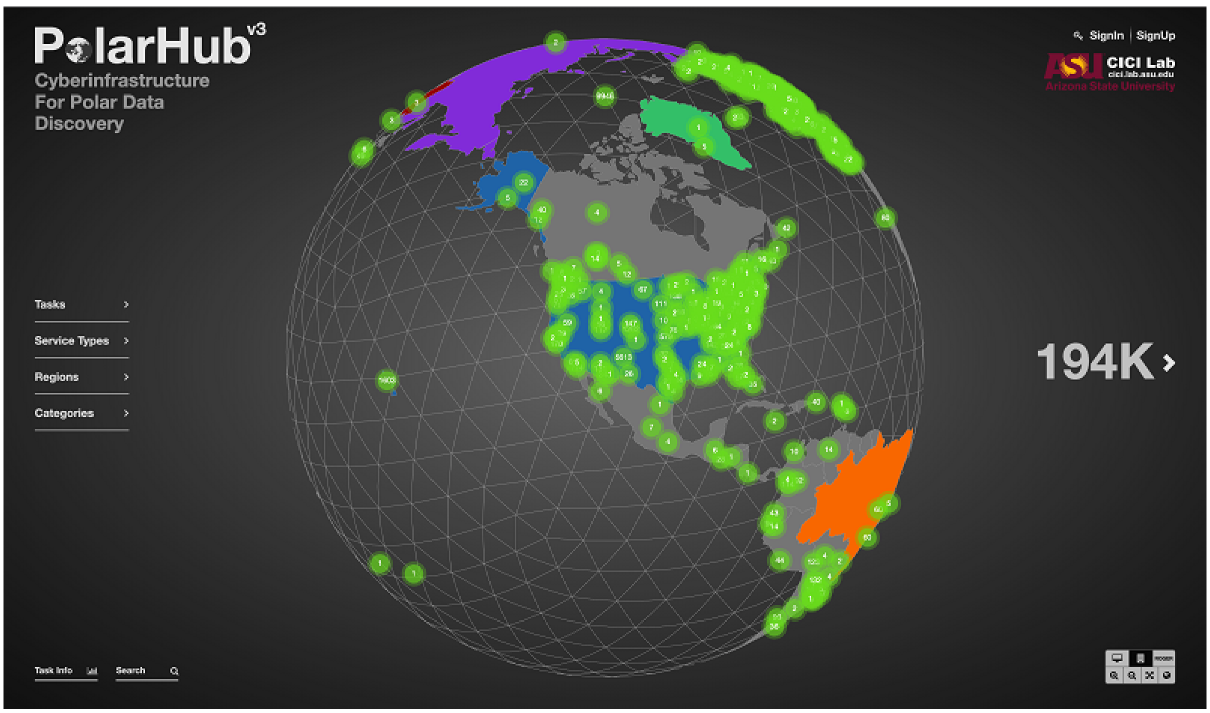

Figure 2. Web interface of PolarHub – a large-scale geospatial data discovery and search engine. Green dots show the global datasets from diverse data providers. Source: authors.

In parallel with solutions for data sharing and access, new data-driven analytical models, especially recent revolutionary developments in Artificial Intelligence (AI) such as deep learning offer new perspectives in advancing data-driven discovery. Compared to traditional knowledge-driven approaches, the deep learning model has the ability to automatically mine large datasets, both structured and unstructured, with little guidance or prior knowledge, to extract prominent features that help to discern objects and/or make more accurate predictions. Emerging GeoAI techniques (Li 2020), which offer thorough integration of spatial principles and AI, are more suited to handle geospatial data and problems. For instance, new models can be designed by incorporating fundamental spatial concepts, i.e. spatial autocorrelation to enable weakly supervised learning and object detection from fewer training data (Hsu and Li 2020; Arundel et al. 2020a). A geographically weighted artificial neural network (GWR) has the potential to tackle spatial heterogeneity, the inherent property of spatial phenomena (Anselin 1989), better than do general AI models (Hagenauer and Helbich 2021). As an extension of ordinary least squares, GWR estimates a weighted least squares regression at each spatial location. Observations that are closer to the regression location are given a higher weight than those farther away, reducing the impact of spatial heterogeneity on the results.

The success of analytical methods relies on rapid advances in computing technology. In the past decade, the establishment of national cyberinfrastructures on high performance computing platforms, such as XSEDE (Extreme Science and Engineering Discovery Environment; Towns et al. 2014) and Frontera (Stanzione et al. 2020) have offered critical computing resources to address data- and computation-intensive problems, helping to transform science and engineering fields. Distributed computing software platforms, such as cloud computing (Yang et al. 2019) and Spatial Hadoop (Eldawy and Mokbel 2015), have enabled the effective use of multiple computing nodes to tackle geospatial problems with collaboration and coordination. As real-time data and GIS have become the trending solutions for smart cities and environment monitoring (Li et al. 2020), streaming computing architectures, such as the Lambda framework (Kiran et al. 2015) and Storm (Cardellini et al. 2016), which offer high throughput and rapid processing of real-time geospatial data, are in great demand. In addition, the increasing capacity of GPUs (Graphical Processing Units) that integrate hundreds of parallel computing cores has served as the backbone of the above computing architecture in support of big data-driven analytics and visualization (Wang and Li 2019).

Despite exciting progress, the data-driven research paradigm has also been criticized in terms of lack of theory and its opacity in the learning process, which significantly challenges the model's ability to be explained and interpreted. To address this, Gahegan (2020) exploited the possibility of learning model
structure directly from the data and the use of inductive learning to accelerate the rate of theory advancement. In addition, to help the machine gain valuable insights, ground-truth training data are often needed. However, compared to the well-developed benchmark datasets in computer science, efforts for developing large-scale datasets for training GeoAI and other machine learning models especially those supporting environmental applications are still limited (Arundel et al. 2020b). Developing diverse and unbiased datasets and models that prompt trustworthy results is important for geospatial researchers and modelers. A more cohesive integration between traditional, theory-driven models and the emerging data-driven models may expose new research avenues for GIScience. Supporting technologies, such as visualization and other exploratory pattern analysis methods may also illuminate approaches to support the interactive and iterative process of geospatial knowledge discovery.

3. Summary and Conclusions

The physical and cultural evolution of spatial reasoning in humans has guided the changing context of geospatial analytics and modeling through the four scientific paradigms. Physical evolution propelled developments in spatial reasoning through the first paradigm of empirical analysis, as primates embarked on their journey to humanity. Bipedalism led to, among other advances, big game hunting, which required the understanding and control of large spatial ranges. The second paradigm marks rapid development of language and the generalization of spatial theory into models, particularly the map. The rise in analytical cartography, GIS and geostatistics during the third paradigm augmented progress in the simulation of complex spatial phenomena. The recent addition of big geospatial data to this environment has guided GIScience to the fourth and current paradigm, which centers around data-driven discovery of both the phenomena and the modeling process itself. Current challenges in this research arena include the need for large spatial datasets for GeoAI training, learning process opacity (the AI 'black box') and better integration of theory-driven and data-driven models. Undoubtedly, this work will escort GIScientists to more synergistic and continual ways to discover geospatial knowledge.

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Learning Objectives:

- Outline the general changes in geospatial analytics and modeling with each new scientific paradigm.
- List the two main driving forces behind the very first maps.
- List four societal practices of the early 20th century that stimulated the development of spatial models.
- Explain the needs that resulted in the development of analytical cartography, GIS and geostatistics.
- Explain the difference between Geographic Information Systems and Geographic Information Science.
- Define GeoAI.

Instructional Assessment Questions:

1. How is the field of cartography related to geospatial analytics and modeling?
2. How and why did GIScience arise from Geographic Information Systems?
3. What challenges in working with Big Data are specific to geographic information?
4. What are unique challenges in applying artificial intelligence to spatial data?

Related Topics:
- Epistemology

Keywords:

- GIScience
- spatial cognition
- GeoAI
- scientific paradigms
- knowledge discovery

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