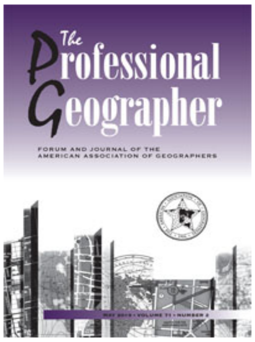

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Cyber Literacy for GIScience: Toward Formalizing Geospatial Computing Education

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The unprecedented availability of geospatial data and technologies is driving innovation and discovery but not without the risk of losing focus on the geographic foundations of space and place in this vast "cyber sea" of data and technology. There is a pressing need to educate a new generation of scientists and citizens who understand how space and place matter in the real world and who understand and can keep pace with technological advancements in the computational world. We define cyberliteracy for GIScience (cyberGIScience literacy) and outline eight core areas that serve as a framework for establishing the essential abilities and foundational knowledge necessary to navigate and thrive in this new technologically rich world. The core areas are arranged to provide multiple dimensions of learning ranging from a technological focus to a problem solving focus or a focus on GIScience or computational science. We establish a competency matrix as a means of assessing and evaluating levels of cyberGIScience literacy across the eight core areas. We outline plans to catalyze the collaborative development and sharing of instructional materials to embed cyberGIScience literacy in the classroom and begin to realize a cyberliterate citizenry and academe. **Key Words: big data, computational thinking, geographic education, GIS, spatial thinking.**

前所未见的地理空间数据与技术可及性, 正驱动着创新与发现, 但却无法避免在此般浩瀚的数据与科技之"网路海洋"中失去聚焦空间和地方的地理基础之危机。教育理解空间与地方在真实世界中的影响、并在计算的世纪中理解并能够跟上科技进步的新一代科学家与公民之需求相当迫切。我们为GIS科学定义网路素养 (网路GIS科学素养), 并概述建立在此一科技兴盛的新世界中航行并发展所需的核心能力和基础知识时提供作为架构的八大核心领域。本研究安排核心领域, 以提供聚焦技术、聚焦问题解决、抑或聚焦GIS科学或计算科学的多重学习面向。我们建立能力矩阵, 作为评价和é"定横跨八大核心领域的网路GIS科学素养之方法。我们拟定计画, 以催化合作发展与分享工具物质以在教室中深植网路GIS科学素养, 并着手实现具备网路素养的公民与学术。 **关键词: 大数据, 计算式思考, 地理教育, GIS, 空间思考。**

La disponibilidad sin precedentes de datos y tecnologías geoespaciales está jalonando la innovación y el descubrimiento, aunque no sin el riesgo de extraviar el foco en la fundamentación del espacio y lugar en este vasto "mar ciberal" de datos y tecnología. Hay una necesidad apremiante de educar una nueva generación de científicos y ciudadanos que entiendan cómo el espacio y el lugar importan en el mundo real, al tiempo que entiendan y mantengan el paso con los avances tecnológicos en el mundo computacional. Nosotros definimos la cibercompetencia en SIGciencia (competencia en ciber-SIGciencia) y esbozamos ocho áreas medulares que sirvan de marco para establecer las habilidades esenciales y conocimiento fundamental necesarios para navegar y prosperar en este nuevo mundo tecnológicamente enriquecido. Las áreas centrales están organizadas para proveer múltiples dimensiones de aprendizaje que se extienden desde un enfoque tecnológico hasta un foco con énfasis en solución de problemas, o un foco en SIGciencia o en ciencia computacional. Establecemos una matriz de competencia como medio de calcular y evaluar niveles de competencia en ciber-SIGciencia a través de las ocho áreas medulares. Esbozamos planes para catalizar el desarrollo en colaboración y compartir materiales instructivos con los cuales incrustar la competencia en ciber-SIGciencia en el aula y empezar a realizar una ciudadanía y una academia ciber-competentes. **Palabras clave: big data, educación geográfica, pensamiento computacional, pensamiento espacial, SIG.**

Technology is transforming the ways in which we undertake geographic problem solving. A myriad of systems and services are making geospatial tools and data accessible to broader audiences (Kraak 2004; Kugler et al. 2015; Liu, Padmanabhan, and Wang 2015; Yang et al. 2017). Nascent geospatial technologies from satellites and sensors to crowdsourcing platforms are introducing faster and easier ways to collect and disseminate geospatial data (Hart and Martinez 2006; Blaschke 2010; Loveland and Dwyer 2012; Zhao and Han 2016; Wulder et al. 2016; OpenStreetMap 2017). The unprecedented availability and openness of geospatial data and technologies is driving innovation and discovery (Yang et al. 2010; Kassen 2013; S. Wang et al. 2013), which is motivating an educational shift in geographic information systems (GIS) curricula (Bowlick, Goldberg, and Bednarz 2017; Ricker and Thatcher 2017). In the midst of change, however, we risk losing focus on the geographic foundations of space and place in this vast "cyber sea" of data and rapidly changing technologies. As a result, there is a pressing need to educate a new generation of scientists and citizens who understand how space and place matter in the real world and who understand and can keep pace with technological advancements in the digital era.

Thisarticle defines cyberliteracy for GIScience and outlines a set of eight core areas that are situated at the intersection of GIScience and computational science. By articulating this core literacy, along with strategies to help embed it within existing curricula, we provide context and direction for the acquisition of knowledge and skills needed for the practice of geospatial computing, which we define as being situated at the nexus of GIScience and computational science. This work fills a curriculum gap by integrating knowledge areas and skills that have historically been developed within departmental silos into a synergistic whole to begin educating a new generation of cyberliterate scientists and citizens who can use advanced technologies to make sense of massive geospatial data to solve problems facing the world and its inhabitants.

What Are Literacies and Why Do We Need Them?

Literacies broadly serve to outline essential abilities and foundational knowledge that are required to succeed in a scientific field, an occupation, or society in general (i.e., classic literacy, which is the ability to read and write). As technologies advance and scientific understanding evolves, what is considered an essential ability or foundational knowledge changes. Just as reading and writing became necessary to succeed in society in past generations, the ability to use digital technologies is becoming necessary to succeed today.

We build our definition of cyberliteracy for GIScience here on the definition of digital literacy by Gilster (1998), which is the "ability to understand and use information in multiple formats from a wide range of sources when it is presented via computers" (2). Digital literacy recognizes a shift in communication patterns and thought processes brought on by the Internet. Being digitally literate is considered vital in today's knowledge economy.

As GIS and geospatial computing expand beyond traditional desktop computers to Web GIS, cloud GIS, and cyberGIS, the essential abilities and foundational knowledge expected of GIScientists, GIS professionals, and those using geospatial technologies must also expand. What are the essential abilities and foundational knowledge for the next generation who will be using and advancing these new technologies to solve tomorrow's geographic problems? The remainder of this article defines cyberliteracy for GIScience, outlines eight topical areas as a framework for establishing the required abilities and knowledge areas, and provides a competency matrix to serve as a means of assessing and evaluating different literacy levels.

Cyberliteracy for GIScience

We define *cyberliteracy for GIScience* as the ability to understand and use established and emerging technologies to transform all forms and magnitudes of geospatial data into information for interdisciplinary problem solving. We posit that achieving cyberliteracy for GIScience requires learners to be knowledgeable in eight core areas (cyberinfrastructure, parallel computing, big data, computational thinking, interdisciplinary communication, spatial thinking, geospatial data, and spatial modeling and analytics) that bridge (1) GIScience and computational science and (2) technology and problem solving (Figure 1).

Cyberliteracy for GIScience (cyberGIScience literacy hereafter) highlights the importance of understanding and using cyberinfrastructure and geospatial technologies, the vital role of communication in interdisciplinary science, as well as the ability to think both spatially and computationally to tackle complex problems. Figure 1 shows how the core areas are arranged to provide multiple dimensions of learning ranging from a technological focus (i.e., spatial modeling and analytics, cyberinfrastructure, and parallel computing) to a problem-solving focus

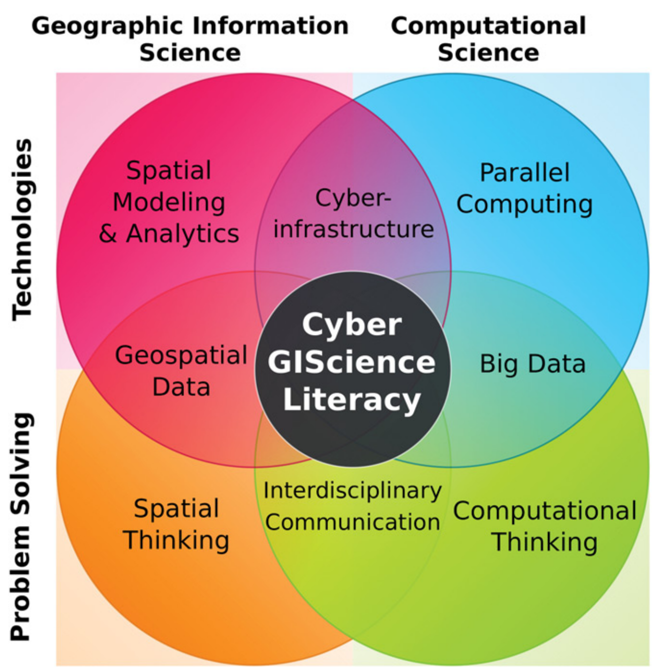

Figure 1 *Eight cyberliteracy for GIScience areas.*

(i.e., spatial thinking, interdisciplinary communication, and computational thinking). Learners might also focus on GIScience (i.e., spatial modeling and analytics, geospatial data, and spatial thinking) or computational science (i.e., parallel computing, big data, and computational thinking). These two disciplinary tracks are connected technologically using cyberinfrastructure and connected socially using interdisciplinary communication, thus forming eight core areas.

The following subsections summarize each area by providing a brief definition, contextual information, and key references. We outline four key themes in each area to provide a means to create learning objectives and structure sharable curriculum materials in geospatial computing. The themes are not meant to be comprehensive; in fact, we see many new themes, topics, and domains potentially intersecting cyberGIScience literacy. Rather, these key themes represent important concepts or skills within each area, which help to make each abstract area concrete. We begin with the technological bridge between GIScience and computational science—cyberinfrastructure—and progress clockwise around Figure 1.

Cyberinfrastructure

Cyberinfrastructure (CI), defined as "the comprehensive infrastructure needed to capitalize on dramatic advances in information technology" (Atkins et al. 2003, 4), includes such capabilities as high-performance and high-throughput computing, data management, visualization, and virtual organization support. Converging advances in these capabilities are changing the way research is being conducted, offering new modes of scientific discovery, and empowering a twenty-first-century knowledge economy.

Computational Infrastructures Computational infrastructures consist of hardware and software to provide computing capabilities. Massive computational capabilities can be achieved by connecting large numbers of compute nodes using low-latency and high-bandwidth network technologies to create high-performance computing (HPC) and cloud computing systems (Clarke 2003; Yang et al. 2011). These systems are generally designed to fit certain computational characteristics such as compute-intensive or data-intensive workloads. HPC and cloud computing systems often combine different processor technologies such as multicore processing units and accelerators such as graphics processing units (GPUs) with high-bandwidth networks and big data storage systems, and parallel processing software packages (Hennessy and Patterson 2011; Hwang and Jotwani 2011).

Spatial Data Infrastructures Many countries have recognized geospatial information as one of the most critical assets for improving economic, environmental, and societal outcomes, which has led to the development of the spatial data infrastructure (SDI). In a broad sense, SDI is intended to create an environment in which a wide range of stakeholders can access geographic information assets (Masser 2007). One common trait of SDI is the integration and use of spatial data at all scales from disparate sources, which is critical to the decision process (Williamson, Rajabifard, and Feeney 2003; Nebert 2004) and facilitates governance, interoperability, and availability of spatial data (Masser 2007).

Science Gateways Science gateways provide scholars, students, and citizen scientists easy access to specialized computational tools and data, thus reducing the barrier to entry and encouraging exploration (Wilkins-Diehr et al. 2008). Most science gateways provide easy-to-use Web-based interfaces, which can be designed for expert-level researchers or scientifically curious citizens to help researchers tap into the emerging area of citizen science to enable crowdsourcing or the collection of volunteered geographic information (VGI; Goodchild 2007; Haklay 2013; Zhao and Han 2016). Generic platforms such as HUBzero and Jupyter Notebooks make it increasingly easier to create science gateways that can leverage advanced cyberinfrastructure (McLennan and Kennell 2010; Kluyver et al. 2016).

CyberGIS and Other Spatial Cyberinfrastructures CyberGIS represents new-generation geographic information systems and science based on advanced computing and cyberinfrastructure and an emerging scientific field (S. Wang 2010). CyberGIS provides a solid foundation for tackling complex geographic problems and has contributed to the advancement of cyberinfrastructure. Other spatial cyberinfrastructures have also been developed to advance a specialized type of cyberinfrastructure from geospatial or spatial perspectives (Yang et al. 2010; Wright and Wang 2011). Here we focus on cyberGIS for brevity.

Parallel Computation

Parallel computing uses multiple processing resources to solve a computational problem by breaking it down into discrete parts to solve simultaneously, rather than the sequential execution of serial computing (Barney 2017). The combination of big data and more sophisticated analyses is driving the need for access to parallel computing. Nature is itself parallel, and parallel computing approaches are increasingly necessary for combining data analyses, computer simulations, and "what-if" models of geospatial phenomenon to identify possible solutions (S. Li et al. 2016).

Parallel Programming Parallel programming is a special type of programming that enables multiple tasks to be performed simultaneously. Parallel programming models that are in common use include shared memory, message passing, data parallelism, and task channel (Foster 1995; Wilkinson and Allen 1999). Understanding the trade-offs between parallel models (e.g., development effort, scalability, program complexity) is important when developing geospatial computing methods and models. Popular parallel programming libraries include Message Passing Interface (MPI) libraries and OpenMP.

Types of Parallelism Different parallel computing tasks can be matched to different parallel computing systems including multicore computing, distributed computing, and grid computing. Instruction-level parallelism enables instructions to be executed simultaneously, which is common in most modern processors (e.g., Intel and Advanced Micro Devices, Inc. microprocessors). Data parallelism enables data to be processed in parallel, whereas task parallelism enables a task to be decomposed into subtasks and processed in parallel (Culler, Singh, and Gupta 1999). Modern geospatial algorithms exploit multiple levels of parallelism to maximize performance gains.

Decomposition Many approaches exist to decompose a problem into subproblems to exploit parallel computing. Within geospatial computing, task decomposition and spatial domain decomposition are common (Guan and Clarke 2010). Task decomposition divides a process into subtasks that are distributed to multiple processing cores. Spatial domain decomposition—a special type of data decomposition—divides spatial data into subdomains and distributes the subdomains to be processed in parallel (Ding and Densham 1996).

Scalability The scalability of a parallel program generally refers to its ability to efficiently handle larger amounts of data or run on more processing cores. Strong scalability measures execution time as the number of processors increase for a fixed problem size, and weak scalability measures execution time as the number of processors increases with a fixed problem size per core (Kumar and Gupta 1994). Speed-up and efficiency are common measures to evaluate how well a parallel program is running on parallel computers. Amdahl's law models theoretical maximum speed-up for different task executions, which is governed by the percentage of a program not executing in parallel (Amdahl 1967).

Big Data

Big data "consists of extensive datasets—primarily in the characteristics of volume, variety, velocity, and/or variability—that require a scalable architecture for efficient storage, manipulation, and analysis" (NIST Big Data Public Working Group 2015). The first three characteristics are widely known as the "three Vs" owing to the increasing amount of data, range of representations, and speed at which they are produced (Laney 2001; Sagiroglu and Sinanc 2013) that can drive change in architectures and technologies (Yang et al. 2017). Many forms of sensors, networks, instruments, and constructs produce big data, from user-generated content on Twitter (Leetaru et al. 2013) to the data-rich and instrumentation-dense "smart city" (Kitchin 2014). Big data analytics might yield different approaches to scientific investigations (Kitchin 2016) and have growing literatures of theoretical and methodological approaches in geography and other fields (S. Li et al. 2016).

Data Storage Data storage becomes more complex as data sizes grow. Cost, capacity, and data access speed are important factors in data storage technologies (Hashem et al. 2015). Tiered data access that spans faster, short-term data storage using solid-state disks to slow, long-term archival storage on tape storage media are common. Many organizations facing massive data are trying to consolidate and centralize data storage, sometimes storing it "in the cloud," which can raise questions related to security and sustainability (Yang et al. 2017).

Data Management Data management has been defined as the process of "the development, execution and supervision of plans, policies, programs and practices that control, protect, deliver and enhance the value of data and information assets" (Mosley et al. 2010, §1.4). As with all data stores, privacy and security are considered important issues to take into account in geospatial data management (Bertino et al. 2008; S. Li et al. 2016). Data management needs innovations to accommodate big data (Agrawal, Das, and El Abbadi 2011), which might include NoSQL, parallel relational database management systems, and complex event processing systems.

Big Data Frameworks Big data frameworks include a range of technological solutions that help with management, modeling, analysis, and visualization of big data workflows (Assunção et al. 2015). To build an effective big data framework, it is necessary to understand the categories of analytics, types of data, data inputs, and processing technologies (Assunção et al. 2015). Information systems are often implemented with currently available frameworks including Apache Spark, HPCC System, Hive, and Impala.

Transforming Big Data into Information

Transforming big data into information is the first major step in the data life cycle that transforms raw data into actionable knowledge (NIST Big Data Public Working Group 2015). Sometimes called data wrangling or data munging (McKinney 2012), these processes clean, filter, and prepare raw data so that it can be input into analytical methods or models. This can be one of the most time-consuming and labor-intensive tasks of analytics (Assunção et al. 2015), which precede more in-depth analysis and modeling to create information.

Computational Thinking

Computational thinking is a way of problem solving that involves conceptualizing, formulating, and expressing a problem and its components in a way that makes it evaluable by humans, computers, or both (Wing 2006). Pertinent not just to computer systems but in scientific, mathematic, and other forms of inquiry, thinking computationally is a universally applicable skill (Grover and Pea 2013; Weintrop et al. 2016). Beyond a reworking of problem solving or critical thinking, computational thinking involves a distinct approach to analysis, design, and understanding (Wing 2008). This area and its components are a vital cyberGIScience literacy because the deconstruction of geographic problems and the identification of means to analyze components of them form a core competency in the fusion of geospatial and computational analysis.

Computational Abstraction Abstraction is a means of extracting value or meaning from a single example or problem and applying that extraction to other individual examples or making broader inferences (Gray and Tall 2007; Welling 2007). Computational abstraction seeks to extract the essence of a programming action from the syntax of the language or system of interaction (Touretzky et al. 2013). Because GIS is by its nature an abstraction of spatial data, the cyberliterate scientist must contend with multiple types of abstraction.

Computational Complexity Computational complexity refers to a theoretical approach in computer science for comparative classification of the difficulty of solving given problems (Arora and Barak 2009). Understanding the complexity of computational problems informs problem approach and the efficiency of analysis. This allows one to understand how computational requirements and calculation time of a given algorithm or method grow as the input data size grows, which is important for handling, manipulation, collecting, and processing spatial data.

Algorithms An algorithm is a set or sequence of actions to be performed in a computational problem-solving context. As a component of computational thinking, algorithmic understanding requires an awareness of how a problem can be decomposed into multiple steps (Seiter and Foreman 2013) and whether those steps can be solved simultaneously to invoke parallel and high-performance computing (Armstrong 2000; Shook et al. 2016). A literate algorithmic thinker pools and connects abilities to analyze and specify a solution to a problem, given its different cases and necessary basic actions (Futschek 2006). Algorithms such as plane-sweep, shortest-path, and nearest-neighbor continue to advance to meet the needs of spatial problems (Shekhar, Feiner, and Aref 2015), sometimes by exploiting the locality of spatial data to improve processing performance (Armstrong 2000). Designing algorithms, especially spatial algorithms, is a creative endeavor in the construction of efficient solutions to spatial and computational problems, which is a key skill for cyberliterate GIScientists.

Automation Automating tasks is a hallmark of computing. Developing automated workflows based on well-known workflow patterns (van der Aalst et al. 2003) improves overall work efficiency for frequently occurring tasks. Automation can play a role in improving replicability of scientific results (Mesirov 2010) by crystallizing the scientific process in computer code, and when it is combined with high-quality documentation, metadata, and provenance information it can communicate the process to scholars across disciplines.

Interdisciplinary Communication

Science is not a collection of silos. Tackling pressing problems facing the world and its inhabitants necessitates bridging scientific knowledge domains and thus requires interdisciplinary communication. CyberGIS and related technologies can play a role as a computational tool but also as a collaboration and communication tool to enhance interdisciplinary communication. The broad functionality of GIS, the advantages of cyberinfrastructure, and the applications of spatial thought and practice demand an integration of ontologies, epistemologies, and methodologies for actualization in an interdisciplinary manner (Winowiecki et al. 2011).

Shared Language Interdisciplinary research comes with certain challenges, including knowledge gaps and conflicts between disciplines (Rickles and Ellul 2015). A lack of familiarity with discipline-specific terms (e.g., symbology, extent) or overlapping definitions (e.g., scale in geography vs. computational science) can lead to misunderstandings. Therefore, it is important for a shared language to be established. Solutions include collaborative learning within the research team and building interdisciplinary partnerships (Rickles and Ellul 2015).

Communication Medium Interdisciplinary research benefits from common technology. GIS is often incorporated as a fundamental tool for research and decision making (Chen 1998). Like geography itself, which is considered to be an integrator of other disciplines (Baerwald 2010), GIS can be an integrating technology for interdisciplinary research. Interactive maps, dashboards, executable notebooks, and other technologies are also excellent mediums for communication.

Ethics, Privacy, and Intellectual Property As more data are collected in fine-grained detail from individuals (e.g., movement patterns and search histories) to the environment (e.g., locations of endangered species), issues of ethics and privacy are paramount. Geoprivacy or the locational privacy of individuals, in particular, must be protected, which has spurred robust research efforts aiming to balance privacy and analytical results (Armstrong and Ruggles 2006; Kwan, Casas, and Schmitz 2006; Richardson et al. 2015). In the era of hacking and data breaches, important questions include the following: What can be done with these data, how should they be protected, and who owns them and their derivatives? The digital divide can widen with issues related to inequality and representation (Elwood and Leszczynski 2011; Shelton, Poorthuis, and Zook 2015) as well as embedding discriminatory bias in big data analytics (Crawford and Schultz 2014; Podesta 2014), leading to questions of algorithmic transparency and accountability (Garfinkel et al. 2017).

Accessibility and Reproducibility Reproducibility is the hallmark of science. Yet, technical and social hurdles make reproducing computational research challenging (Peng 2011). Technologies such as science gateways can provide easy access to data and analytics through Web-based interfaces. Executable notebooks such as RStudio (Gandrud 2013) and Jupyter (Kluyver et al. 2016) enable code, results, and explanations to be combined into a single (executable) document. Virtualized containers such as Docker (Merkel 2014) provide transparent, consistent environments including operating system, software, and data. Combining these technologies with best practices (Sandve et al. 2013) will help make geocomputational results accessible and reproducible.

Spatial Thinking

Spatial thinking refers to the cognitive combination of representing and reasoning concerning the spatial relationship between objects, phenomena, and the background in which they exist (National Research Council 2006; Lee and Bednarz 2012). This literacy contains topics concerning the ability to consider and manipulate representations of spatial objects and relationships, skills that are vital in conceptualizing space, in working with spatial technologies, and in geographic thought (Lee and Bednarz 2009).

Spatial Cognition Mental spatial configurations represent objects as observed visually, aurally, and haptically, resulting in information for motor skills, language, and other cognitive tasks (Landau and Jackendoff 1993). These spatial actions and interpretations form the brain's capabilities for spatial cognition. This cognition influences many components of object recognition and operates across brain functions (Halligan et al. 2003; Montello, Grossner, and Janelle 2014). Examples of applied spatial cognition include wayfinding decision making and ability.

Spatial Relations Understanding how spatial relationships are manifested and how to represent them digitally is a necessity to adequately and accurately investigate spatial process in digital form. Topological relations have been formally specified (Egenhofer, Mark, and Herring 1994) and incorporated into many geospatial technologies. Other key spatial relations involve distance and direction. Further, it is important to recognize the role of time in determining spatial relationships.

Pattern Recognition Pattern recognition is a fundamental spatial cognition skill (Kastens and Ishikawa 2006). It is also a mature geospatial technology tool with origins in spatial analysis, air photo interpretation, and satellite image processing. Finding spatial patterns requires discovering spatial relations in data. Whereas it is a natural human ability, training computers to find patterns in massive quantities of unstructured data is still a challenge (Jain, Duin, and Mao 2000). With big data and cyberinfrastructure, the opportunities for object recognition, object extraction, and both supervised and unsupervised classification using machine and deep learning have expanded across many different fields and organizations (Bishop 2006; LeCun, Bengio, and Hinton 2015).

Modifiable Units and Uncertain Contexts As computation and data scale, it is important to acknowledge how spatial and temporal scale might influence our analytical and simulation results. The modifiable areal unit problem is a classic problem in geography and applies to data both big and small (Openshaw 1984). The modifiable temporal unit problem is similarly challenging and will grow in importance as more and more data become spatiotemporal (Cheng and Adepeju 2014). The uncertain geographic context problem applies to contextual units or neighborhoods and could influence results (Kwan 2012). Abstracting the spatial nature of objects for use in GIS is a difficult semantic task that can raise difficult problems for interoperability (Bishr 1998).

Geospatial Data

Geospatial data are raw geospatial facts, whereas information is the assemblage of data (Longley et al. 2015). An important aspect of cyberGIScience literacy is the ability to understand, work with, and manipulate geospatial data using a combination of knowledge and computational tools.

Capturing Geospatial Data and Information All digital information is captured, either manually or automatically, for representation as data (Bishr 1998). Manually captured data are recorded "by hand," meaning that someone types in, draws, or in some way expresses the data in a digital format. Vast quantities of automatically captured data are generated by imaging satellites, self-driving cars, smart cities, and sensor networks, among many others. Capturing, representing, and analyzing these new and continuously streaming data are becoming a significant challenge (Agrawal, Das, and El Abbadi 2011; Yang et al. 2017)

Representing Geospatial Data and Information Real-world phenomena are abstracted and represented as data, which are manipulated and transformed into meaningful representations or understandings and therefore transformed into information. Different spatial data models are used in this abstraction process, traditionally categorized into field and object models (Peuquet 1984; Worboys and Duckham 2004). The addition of time, flows, and other geographic characteristics has led to new spatial data models (Fisher and Unwin 2005; X. Li et al. 2014; J. Wang, Duckham, and Worboys 2016). For analyzing geospatial big data and running big, complex computational models, innovative spatial data models might be needed.

Transforming Geospatial Data to Information Geospatial data typically comprise individual numbers, text, symbols, and their associated spatial references. When spatial data are aggregated, transformed, analyzed, or woven together, they become information, which can be ascribed meaning. Information is distinguished from data by some degree of data selection, organization, and preparation; information is data transformed in some way to serve a purpose (Burrough, McDonnell, and Christopher 2015; Longley et al. 2015).

Geographic Information Systems GIS are designed to capture, store, manipulate, analyze, manage, and present all types of geospatial data. They combine data, technology, and people to describe, explain, and predict patterns and processes at geographic scales (P. Longley 2005). A systems viewpoint of GIS values the tools and technologies associated with solving spatial problems, especially as they are applicable to a given domain or problem (Wright, Goodchild, and Proctor 1997). GIS provide a rich integrative framework for many other geospatial technologies as well as the core technology used to transform geospatial data into information.

Spatial Modeling and Analytics

Geographers and GIScientists have long used computational procedures to understand spatial relationships and geographic phenomena. A firm grasp of classic spatial analytical models and methods will ensure we do not continuously reinvent the wheel and rediscover long-known principles. Yet, it is equally important to engage new technologies and methods such as parallel processing and machine learning that can help make sense of big spatial data and might shape the future of the field.

Spatial Analysis and Statistics Spatial analysis matured with the quantitative revolution in the geography of the 1960s (Chorley and Haggett 1967; Berry and Marble 1968). Early algorithms, however, were designed to find solutions given no or limited computing capabilities and therefore heuristics that could limit the set of potential solutions were necessary. With big data and parallel computing available, entirely new methods of spatial analysis are possible (Anselin 2012; Anselin and Rey 2012).

Spatial Analytic Models A spatial analytic model is a simplified representation of a system of spatial objects, their attributes (also known as state variables), processes, and interactions created for purposes of description, explanation, forecasting, or planning (e.g., Fotheringham and Rogerson 2002). These might be scale models, conceptual models, or mathematical models, varying with the level of abstraction and formalization (O'Sullivan and Perry 2013). The logic and mathematics of these models might be based on, for example, regression, simulation, or agent-based models, and these could be very simple, built from desktop software components, or very complex, involving parallel computation and big data stores (Parry and Bithell 2012; Westervelt and Cohen 2012).

Spatial Data Mining Spatial data mining is the process of exploring and discovering previously unknown but useful and interesting patterns from spatial data (Stolorz et al. 1995). It is more challenging to extract the useful patterns from geospatial big data than conventional data sets, due to not only intrinsic relationships and implicit autocorrelation but also heterogeneous data types including geo-tagged text and multimedia data (S. Wang and Yuan 2014). Many spatial data mining techniques have been proposed, including techniques of spatiotemporal data mining, text mining, geo-social network mining, and spatially savvy machine learning (Zafarani, Abbasi, and Liu 2014; Shekhar et al. 2015).

Machine and Deep Learning Machine and deep learning allow computational models to learn from data, sometimes using multiple layers of processing to capture multiple levels of abstraction (LeCun, Bengio, and Hinton 2015). These technologies are poised to disrupt geographic research by enabling computers to "learn" abstract geographic concepts for narrowly defined problems. Much like the early years of the quantitative revolution, most machine learning is not spatially aware, opening up many exciting research opportunities. These opportunities include data from the Internet of Things (IoT), which is beginning to produce so much data that it surpasses human sense-making abilities (Al-Fuqaha et al. 2015).

Cyberliterate Geospatial Citizens, Scientists, and Decision Makers

Having identified the eight core areas and associated themes, it is important to have a strategy for identifying how these can be operationalized in a curriculum to empower cyberliterate geospatial citizens, scientists, and decision makers. Modern curriculum design theory suggests that a backward design process (Wiggins and McTighe 2005) that starts with identification of tangible learning objectives tied to assessment will lead to better learning outcomes for students and be helpful for the instructors compared to a commonly used syllabus-centric specification (Boozer 2014).

The backward design process goes through three stages and starts with the identification of desired results in a way that is centered on articulating student learning outcomes. In this stage, it is informative to think about student learning as a progression of skills and abilities from basic recall to more substantive and deep understanding. This progression is often described by Bloom's taxonomy, which was originally published in 1956 and revised in 2001 (Bloom 1956; Anderson, Krathwohl, and Bloom 2001). The taxonomy identifies six such levels, and each of them can be characterized by a set of student-centered characteristic expressions of knowledge, skills, and abilities. Although Bloom's revised taxonomy sees basic recall as the lowest level of knowledge and creation as the highest, we cannot anticipate that learners will become experts or creators in all eight areas; rather, their expertise might be concentrated in a few areas while they maintain a more basic understanding in the remaining areas.

In the second stage, the curriculum designer will identify how students should demonstrate that they have reached these learning objectives. In other words, what assessments and activities will provide evidence of student learning? It is also important to identify by what criteria successful learning will be judged; for example, in terms of map qualities or software performance.

The third stage of the backward design process is to plan the actual instruction based on our objectives and assessment strategies. A guiding question at this stage is this: What do I need to provide students with for them to be able to complete assessment activities to my satisfaction? As educators, this is where we need to look at what facts and skills they need to be exposed to and how and in what sequence this information needs to be presented and taught.

To illustrate the backward design process, Table 1 lists example learning objectives for each literacy area. Table 1 identifies example learning objectives at three competency levels that roughly map to the six levels in Bloom's revised taxonomy: basic (remember and understand), intermediate (apply and analyze), and advanced (evaluate and create). Bloom's taxonomy levels are used as an example, but other frameworks, taxonomies, and levels (e.g., novice, advanced, expert) could be used depending on the particular curricular context (Hoffman et al. 2010).

To address diverse learner needs with multiple learner pathways, we propose that a *cyberGIScience literacy competency matrix*, examples of which are shown in Figure 2, can be used to convey, at a high level, what cyberGIScience literacy could be composed of for specific groups of learners. Once articulated for a specific group or domain, this matrix provides a framework for documenting necessary levels of cyberGIScience literacy and could be used to help evaluate the content of existing or proposed courses or curricula. Thus, the learning objectives along with a thoughtfully considered cyberGIScience literacy competency matrix will inform the second and third stages of the backward design process. This curriculum building and delivery process will begin cultivating cyberGIScience literacy for diverse learners by recognizing and embracing different learner pathways and achieving varied goals not only for GIS experts but also for domain scientists, decision makers, planners, engineers, and even citizen scientists (Baker et al. 2015).

The competency matrix can be used by both educators and learners. For example, an instructor of a geocomputing course might set competency goals for each key area when designing the curriculum in their course (illustrated as hashed bars in Figure 2A). Initial assessment of the students in the class might indicate several gaps in competency that are different depending on the students' background

Table 1 *Example learning objectives for each area at three competency levels: Basic (remember and understand), intermediate (apply and analyze), and advanced (evaluate and create)*

	Competency level		
CyberGIScience literacy Areas	**Basic (remember and understand)**	**Intermediate (apply and analyze)**	**Advanced (evaluate and create)**
Cyberinfrastructure	Identify an example of a spatial data infrastructure	Use cyberGIS to estimate deforestation from satellite imagery	Build a Web service to disseminate the latest Landsat 8 data
Parallel computation	Define speed-up and efficiency	Plot the speed-up curve for a parallel method scaling from 1 to 64 processing cores	Develop a parallel spatial method that uses the message passing interface
Big data	Explain the 3 Vs of big data	Compare and contrast big data with "traditional" data	Investigate a case where big data could lead to implicit bias
Computational thinking	Define algorithm	Sketch an algorithm to solve the TSP	Evaluate the computational complexity of your TSP algorithm
Interdisciplinary communication	Define boundary object	Demonstrate how GIS can be used to communicate one idea to a different discipline	Write a technical report for a domain-scientist detailing a computational method
Spatial thinking	Explain spatial relationships	Compare and contrast the use of fields and objects	Investigate how population density could affect global-scale data analyses
Geospatial data	Describe common cartographic elements on a map	Analyze population distribution using national census data	Create a viewshed from digital elevation model data
Spatial modeling and analytics	List 5 examples of spatial modeling	Differentiate spatial analysis from spatial modeling	Develop a kernel density estimation method

Note: TSP = traveling salesman problem; GIS = geographic information system.

and skill set (e.g., Figures 2B–2D). The instructor now has a high-level understanding of the competency goals for the course and gaps for the learners in the course. The matrix could be used across courses when designing curriculum to ensure that learners gain the right balance of competencies.

A learner, on the other hand, might use the competency matrix to self-identify knowledge and skills gaps and plan to take certain courses to address those gaps. For example, a GIS student might take the geocomputing course illustrated in Figure 2 to fill a computational science knowledge gap (Figure 2B), whereas a computer science student might take the same geocomputing course to improve his or her spatial modeling and analytics knowledge (Figure 2C). Although both students are taking the course to fill a knowledge gap, they each have different competencies and different learning goals, but both can be expressed in the competency matrix. In this way, the matrix provides a straightforward means to visualize the current competency levels of cyberliteracy as well as the goal competency levels across the eight core areas.

Because different professions across academia, industry, and government call for different abilities, we can expect there to be many different configurations of cyberGIScience literacy. For example, a developer creating a new Web-based spatial analytical tool will need to have a different composition of cyberGIScience literacy than a planner looking to use big spatial data to understand how a new urban high-rise will affect the surrounding citizens, businesses, and infrastructure. Yet, the fundamental process in terms of improving levels of competency in the eight core areas of cyberGIScience literacy is the same. It is important that our classes, training, and educational materials reflect these different needs and learner pathways by teaching to targeted learning outcomes, aligned with the assessment strategies used to verify the achievement of abilities and skills within each core area through the backward design process.

In summary, we highlight three primary contributions of this article. First, we establish a pedagogical framework called cyberliteracy for GIScience for educators and learners to capture and convey essential abilities and foundational knowledge that are necessary to navigate and thrive in this new technologically rich geospatial world, which are represented in eight core areas. Second, we identify four essential themes in each of the eight areas to structure curriculum development (Table 2). Third, we present a backward design process strategy to create sound assessments and curriculum materials surrounding these themes and areas. Together, these contributions provide the means to improve cyberGIScience literacy across a range of disciplines and fields.

Looking to the Future

To realize a cyberliterate citizenry and academe, the next step is to embed cyberGIScience literacy learning objectives, assessments, and instructional materials into a wide array of learning environments. Embedding cyberGIScience literacy into a classroom could take many forms. At the simplest level is microinsertion, which introduces one area or theme into a packed curriculum. It might be two slides on cyberinfrastructure, a five-minute activity discussing big data, or a homework question asking how programming and automation might affect a student's future (e.g., ESRI GeoInquiries; ESRI

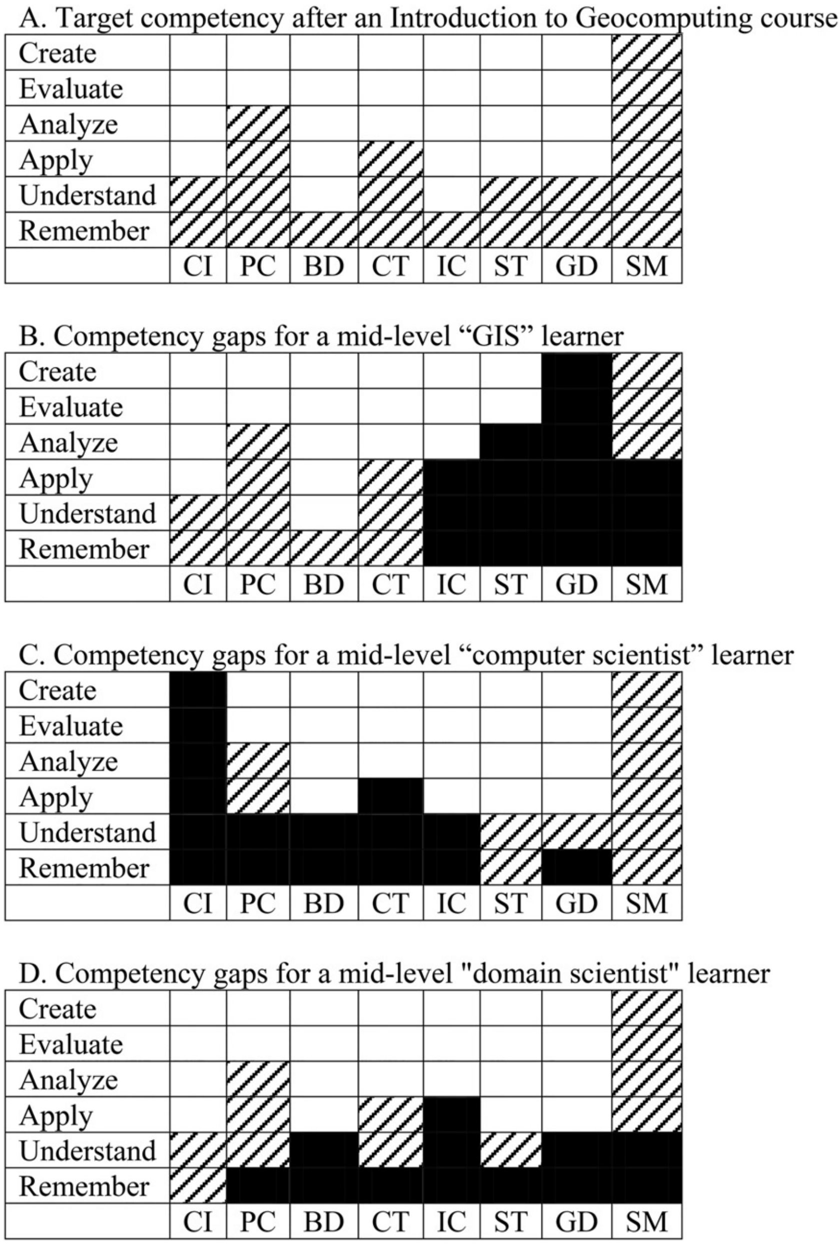

Figure 2 *The cyberGIScience literacy competencies matrix can be used to visualize the target competency for a specific learner audience and any gaps in competency for an individual. Figure 2A shows how it might be used to design an Introduction to Geocomputing course where hashed bars show the level of competency that students should achieve. Figures 2B–2D show how it can be used to highlight gaps (hashed bars) between existing competency (black bars) and target competency for three example learner categories. GIS = geographic information system; CI = cyberinfrastructure; PC = parallel computing; BD = big data; CT = computational thinking; IC = interdisciplinary communication; ST = spatial thinking; GD = geospatial data; SM = spatial modeling and analytics.*

2017); these are all excellent examples of microinsertion activities. At the next level, a full lecture or lab will allow for more depth. For example, a lecture on big data as part of geospatial data unit allows more time to explore concepts and issues. Replacing whole units will allow students to be immersed in an area such as computational thinking. They can be exposed to algorithms and try programming as a homework assignment. Finally, full courses and course sequences allow students to become expert creators in one or more cyberGIScience literacy area.

Table 2. *CyberGIScience literacy areas and themes*

Cyberinfrastructure	**Interdisciplinary communication**
a. Computational infrastructures	a. Shared language
b. Spatial data infrastructures	b. Communication medium
c. Science gateways	c. Ethics, privacy, and intellectual property
d. CyberGIS and other spatial cyberinfrastructures	d. Accessible software and data
Parallel computation	**Spatial thinking**
a. Parallel programming	a. Spatial cognition
b. Types of parallelism	b. Spatial relations
c. Decomposition	c. Pattern recognition
d. Scalability	d. Modifiable units and uncertain contexts
Big data	**Geospatial data**
a. Data storage	a. Capturing geospatial data and information
b. Data management	b. Representing geospatial data and information
c. Big data frameworks	c. Transforming geospatial data into information
d. Transforming big data to information	d. Geographic information systems
Computational thinking	**Spatial modeling and analytics**
a. Computational abstraction	a. Spatial analysis and statistics
b. Computational complexity	b. Spatial analytic models
c. Algorithms	c. Spatial data mining
d. Automation	d. Machine and deep learning

CyberGIScience literacy complements existing curriculum efforts and competency models. The University Consortium for GIScience (UCGIS) is creating a new GIS&T Body of Knowledge (UCGIS 2017) that includes new knowledge areas such as Computing Platforms and Programming and Development in addition to long-standing areas such as Cartography and Visualization and Foundational Concepts. A cyberGIScience literacy-focused curriculum could leverage many topics across these knowledge areas.

CyberGIScience literacy also complements the well-established geospatial technology competency model (GTCM; DiBiase et al. 2010). CyberGIScience literacy areas such as spatial modeling and analytics and some aspects of parallel computing could find analogs in the Analysis and Modeling and Software and Application Development industry-sector technical competencies. Big data, computational thinking, and cyberinfrastructure, however, do not cleanly map to a competency level. Future revisions of the GTCM might include new topics such as machine learning, providing a way to better align them.

To encourage the development of materials, we advocate for collaborative development and open sharing, because not all educators will have expertise in every cyberGIScience literacy area. An early effort in creating materials specifically for cyberGIS was initiated by the CyberGIS Center for Advanced Digital Studies at the University of Illinois in 2014. Under this project, seventeen CyberGIS Fellows developed teaching materials for a range of classes, which are freely available (CyberGIS 2018). Materials continue to be shared between interested individuals, but a mechanism to share more broadly is needed. One promising initiative supported by the UCGIS is the TeachGIS referatory, which might help in the development and dissemination of materials (TeachGIS 2017).

Just as the GIS community did in the 1990s under the National Center for Geographic Information and Analysis's (NCGIA) education initiatives (Goodchild and Kemp 1992), we aim to bring together educators to share experiences and practices, because we are entering uncharted territory with rapid changes in technologies and global problems. In early maps these uncharted territories were titled *Hic Sunt Dracones* or "Here Be Dragons" (Ruitenberg 2007), but that never stopped explorers from venturing into the unknown, nor should it stop us. ■

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