ABSTRACT

JACKSON, RODNEY DEWAYNE. Examining the Perspectives of Geospatial Professionals Toward the U.S. Department of Labor's Geospatial Technology Competency Model: A Q Methodology Approach (Under the direction of Dr. James Bartlett).

This research study used Q Methodology to determine the perceptions of geospatial professionals towards technical competencies located within the Geospatial Technology Competency Model (GTCM). The competency model is a result of two decades of time and effort to define the geospatial field as a distinct body and is a cornerstone of the domain. Geospatial competencies are a component within curriculum development, professional certification, and workforce requirements. The purpose of the study is to explore the viewpoints of geospatial professionals toward the GTCM and why they hold these views. By determining the viewpoints toward these competencies, the researcher can better understand how practitioners perceive the standard. Also, the identification of commonalities across viewpoints may reveal widely held beliefs within the field.

This study used Q Methodology as the research method. Q Methodology is an accepted approach to reveal individual subjectivity. Q Methodology is a mixed methods approach, combining both factor analysis and participant statements to develop viewpoints. Q Methodology has been used in studies to determine stakeholder perspectives and is valued for its ability to quantify viewpoints. In this study, participants were asked to sort 62 competency statements regarding the relevance of each competency to the geospatial field.

The results of this study could help to redefine the technical competencies receiving attention moving forward and assist in the professional preparation of our students as they transition into the workforce. The five themes developed during the analysis include Factor 1: Skeptical View of Remote Sensing, Factor 2: Programming is Critical, Factor 3: Leveraging

Location-based Data, Factor Four: No Room for Surveying in GIS, and Factor Five: Positive View of Land Surveying Operations. The study revealed only one consensus statement, and the scarcity of shared statements may be connected to the entrenched views expressed within the factors. The researcher investigated but did not find a relationship between various socio-demographic variables and the shared perspectives (factors).

This research study confirmed that a Q Methodological study is a practical approach to examine the statements within a competency model. Moreover, it supported the use of industry experts (as expressed in the General Theory of Expertise) to evaluate a conceptual model of competencies. The GTCM may be a conceptual model of competencies for the geospatial industry, but it continues to prove its value and applicability at reflecting the field of geospatial science. The results of this study may provide some feedback from employers regarding how the geospatial field views the technical competencies in the GTCM. Better sources of data, such as that found in this study, could enable institutions of higher education to more effectively engage industry partners and increase the value of their instruction to potential members of the geospatial workforce. The researcher hopes that others may find this study a suitable model for extracting the shared perspectives within a chosen field.

Keywords: competency model, geospatial, Q Methodology

Examining the Perspectives of Geospatial Professionals Toward the U.S. Department of Labor's Geospatial Technology Competency Model: A Q Methodology Approach

by
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DEDICATION

This study is dedicated to my wife, Mary Susan. Thank you for your sacrifices throughout this program. I would not have been able to complete my classes or this dissertation without your continued support during these past few years.

BIOGRAPHY

Rodney DeWayne Jackson was born in Elizabethtown, NC. He grew up in the Plain View Community of Sampson County, NC, and graduated from Midway High School. Rodney took a "gap year" between high school and college, choosing to enlist in the United States Army. He subsequently spent 33 years in the United States Army Reserves in both enlisted and officer roles. Rodney retired in 2017 as a Lieutenant Colonel in the Engineer Corps.

In 1985 Rodney began attending East Carolina University, where he attained his B.S. in Political Science and an M.A. in Geography. He worked in private industry and local government before arriving in higher education in 1998. Rodney has logged over two decades of service in numerous leadership roles in both the North Carolina Community College System and the University of North Carolina System. His love of Geography continues to this day, and he is active within the geospatial science community as an advocate and researcher.

In 2017, having recently retired from the U.S. Army and looking for the next great adventure, Rodney decided to put his GI Bill to good use and enrolled in the North Carolina State University Adult and Community College Education program. Rodney's interests revolve around enjoying the great outdoors, especially if there is fishing involved.

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There are many people that I would like to thank for their support. I must acknowledge the sacrifices made by my wife during these past three years as she had to take on additional responsibilities while I sat huddled in our office. Also, my in-laws, H.R. and Betsy Malpass, encouraged me (and provided me a place to sleep on those late Friday nights) every step of the way. I will take a moment to thank my parents, Jasper D. and Anna H. Jackson, both long passed away, for giving me the love for N.C. State and the grit necessary to accomplish my goals.

I must thank Dr. James Bartlett for his support and guidance during the dissertation process. His willingness to assist me in developing a project that I truly cared about was instrumental in my success. My committee members - Dr. Michelle Bartlett, Dr. Diane Chapman, and Dr. Travis Park – answered the call whenever I needed assistance, and I feel fortunate to have benefited from their knowledge.

I would also like to thank the 2017 Raleigh Cohort for being a great learning community. Additionally, the “A” Team was there on many occasions during this journey to offer perspective, and I appreciate the support and feedback. Finally, I want to thank Christine Nicodemus for the willingness to share her insights throughout the doctoral program.

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CHAPTER 1: INTRODUCTION

Background

The evolution of geospatial competencies mirrors the growth of the domain during the past 70 years. Most authors cite the Canada Geographic Information System (CGIS) of the mid-1960s as the first *geographic information system* (e.g., Foote, Bednarz, Monk, Solem, & Stoltman, 2012; Foote, Unwin, Tate, & DiBiase, 2012; Foresman, 1998), and its spread was initially very slow. The use of Geographic Information Systems (GIS) increased in the late 1970s and early 1980s with the declining cost of computers and corresponding increases in computational capacity. Subsequent advancements in desktop mapping and GIS software, as well as the spread of personal computers, spurred its continual growth into the 1990s (Fagin & Wikle, 2011).

The progression of the geospatial field was occurring at such a rapid rate during the 1990s that the U.S. Department of Labor (DOL) identified geotechnology as an emerging technological field (Annulis, Gaudet & Carr, 2004; Gewin, 2004; Horák, 2015). The events of September 11, 2001, and subsequent efforts to increase national security and improve emergency preparedness accentuated the value of location-based data (National Resource Council [NRC], 2006; NRC, 2013). A product of the growing recognition of the value of geospatial analysis was its inclusion in the DOL's High-Growth Job Training Initiative (HGJTI).

The DOL's report was consistent with the findings from Gewin (2004) and Gaudet, Annulis and Carr (2003), who saw an opportunity for significant expansion in the geospatial workforce. Numerous researchers saw the potential for a geospatial industry much earlier (Goodchild & Kemp 1992a; Huxhold, 1991; Obermeyer, 1993). Greenfeld (2006) noted that the Geographic and Land Information Society (GLIS) was established in 1993 "in response to the emergence of GIS from a conceptual idea with some sporadic implementations into a viable industry" (p. 119). Furthermore, Marble (1998) asserted that an expansion of the geospatial workforce was imminent and began evaluating its composition.

While the geospatial industry was only just recognized (Marble, 2006) as a distinct entity, the DOL Employment Training Administration (DOLETA) estimated that the geospatial workforce exceeded 857,000 (DiBiase et al., 2010). Furthermore, Henttu, Izaret, and Potere (2012) believe that geospatial services remain a growth industry, approaching $100 billion in annual revenues. The future also looks promising, as the industry is estimated to maintain a compound annual growth rate (CAGR) of between 15-20% and attain a market size approaching $500 billion by 2020 (Geospatial Media and Communications, 2018).

There has been an ongoing debate since the introduction of geographic information systems/science regarding how it should be defined. Many organizations, scholars, and governmental agencies have contributed to the discussion with as many questions asked as answered. In many ways, GIS represents something different to various people, contingent on the context. The Geospatial Information and Technology Association (GITA) asked their members to characterize GIS, but the group could not reach a consensus (Secilmis, 2005). They concluded that GIS could not be defined as a tool or profession, as the user would dictate its role depending on how central GIS was to their work. The tool versus science disagreement is representative of how geospatial science can be many things to different groups. As reasoned by DiBiase et al. (2010), "The breadth and diversity of geospatial has made it difficult to reach consensus about what the field entails, who geospatial professionals are, and what they should know and be able to do" (p. 55).

The argument for maintaining geospatial technology as a tool starts at its inception. In the beginning, geographic information systems (GIS) originated within the field of computer science, and many of the underlying components continue today. Horák (2015) submitted that GIS is understood as an applications-led technology, while Tomaszewski and Holden (2012) see it as a subset of information technology with shared technologies and aligned competencies. The reliance on tools within the field has caused concern for geographers, especially as more advanced applications remove the need for an underlying geographic understanding. Zhou, Smith, and Spinelli (1999) noted that GIS was pushing geography towards an applications-driven orientation, more aligned with computer technology than geography, and Marble (2006) recognized that GIS developed an extensive area of application that extended well beyond the traditional boundaries of geography.

The growth of GIS has made a tremendous impact on geography departments within higher education since the 90s. Dobson (1983) felt that *automated geography*, a precursor to GIS in many departments, would be a substantial extension of geography. By the late 1980s and early 1990s, GIS had gained a foothold in various academic programs at both undergraduate and graduate levels, and this, in turn, led to the explicit development of what Goodchild (1992) termed “geographic information science” (GISc or GIScience). The impact of GIScience on Geography Departments is becoming more pronounced, and the notion of credentialing programs or students has begun to take hold (Wikle, 2015). Golledge (2000) saw conflict between traditional academically-focused research with the need to develop GIS professionals and predicted that the discipline's response to the influence of GIS would "determine the viability, and ultimately the fate of geography" (p. 8). The effect of GIScience as an emerging discipline within a more extensive geographic field of study is inarguable, but its role within society may remain up for debate.

Geography and related academic programs have grown throughout higher education, and the impact of GIScience is visible through the growing number of courses relating to its content. Arrowsmith, Bagoly-Simó, Finchum, Oda, and Pawson (2011) attributed this expansion to an adjustment in the mission of institutions around the country towards workforce engagement, which is consistent with the development of an *employability* agenda in higher education (Harvey, 2000). There an increasing number of university-level credentials offered in a variety of GIS incarnations, and there is even a growing recognition of GIScience as a discipline unto itself (Prager & Plewe, 2009). Wikle (2017) supports this point when noting that some programs were transitioning to GIScience as a field of study. The continual growth of GIScience harkens back to a warning offered by Pickles (1993) when he asserted that "If it is to continue to claim that it is 'science,' then it must broaden its sphere of legitimation beyond method and application…" (p. 454).

The question of whether the geospatial area was a profession began in the 1990s (Goodchild & Kemp 1992a; Huxhold 1991; Obermeyer, 1994). While there is no consensus on all of the attributes that define a profession, however, many (DiBiase, 2007; Goodchild & Kemp, 1992a; Huxhold & Craig, 2003) have looked to Pugh's (1989) six attributes of a profession (self-awareness, a body of knowledge, an ideal of competence and expertise, ethical standards, formal organization, and a "hall of fame") as a guide. There appears to be a building consensus that a geospatial profession exits (DiBiase, 2012; Fagin & Wikle, 2011; Kemp, 2003; Obermeyer, 2009). The challenge then becomes the maintenance of standards for the profession (Gaudet et al., 2003) and the promotion of standards for competency (Mathews & Wikle, 2017).

A critical component for the geospatial profession to remain viable is the determination of the competency of its members. Ennis (2008) defines competency as "the capability of applying or using knowledge, skills, abilities, behaviors, and personal characteristics to successfully perform critical work tasks, specific functions, or operate in a given role or position" (p. 4). Many were concerned that the technological advances within geospatial technology would invite abuse from individuals lacking the necessary competencies (Goodchild & Kemp, 1992a; Kemp, 2003; Marble, 1998; Obermeyer, 1993). The capacity to define the competencies essential within the industry is of vital interest to higher education and employers. It is in the field's best interest to demonstrate the capabilities of its members, as Secilmis (2005) commented: "After all, competency is the ultimate workforce attribute" (p. 2).

Nature of the Problem

Various entities have attempted over the last 20 years to capture the skills needed for workers to be successful in the geospatial field. These efforts include an analysis of competencies found in higher education curricular documents (Schulze, Kanwischer & Reudenbach, 2013), professional geography competency models (Solem, Cheung, & Schlemper, 2008), DACUMs (Develop a Curriculum) built by the National Geospatial Technology Center (GeoTech), The University Consortium for Geographic Information Science's (UCGIS) Geographic Information Science and Technology (GIS&T) Body of Knowledge (BoK), and the Geospatial Technology Competency Model (GTCM) built by the U.S. Department of Labor Employment and Training Administration (DOLETA). All of the models represent an aspect of the geospatial field, but the GTCM represents a competency framework for the industry (Johnson, 2010) that captures the expertise which distinguishes and unites geospatial professionals (DiBiase et al., 2010).

Statement of Problem

The problem the geospatial domain faces is that a lack of external input from employers regarding how the geospatial field views the technical competencies in the GTCM handicaps colleges and universities. The lack of feedback inhibits higher education institutions from effectively engaging with industry partners and reduces the value of their instruction to potential members of the geospatial workforce. The creation of the GTCM capped years of struggle to build an industry model for geospatial occupations and is used, together with the BoK, as a foundation document for the GIS professional certification examination. Nevertheless, the GTCM is limited in what it can share regarding technical competencies in the field, as it was developed in 2010 using a panel of 12 professionals who demonstrated expertise within the industry (DiBiase et al., 2010). This panel worked to define the competencies within the model, and the proposed GTCM was distributed within the geospatial domain for comment. The GTCM was updated in 2014 and 2018 with input from the general public, subject matter experts (SMEs), and workforce panels. The survey was comprised of a five-point Likert scale asking the participants to evaluate the relevance of each competency. Unfortunately, the study did not require those respondents to evaluate each competency in comparison with the other competencies and rank them accordingly. Also, the survey was made available to geospatial practitioners and professionals alike without the benefit of a baseline competency requirement to participate.

Faculty are providing instruction with very little knowledge regarding how the geospatial field views the technical competencies in the GTCM. The lack of feedback inhibits higher education institutions from effectively engaging with industry partners and reduces the value of their instruction. A lack of external input from employers regarding how the geospatial field views the technical competencies in the GTCM inhibits higher education institutions from effectively engaging with industry partners and reduces the value of their instruction to potential members of the geospatial workforce. The ability to ascertain the competencies that are most important with the field would provide more information to higher education, professional societies, and certification organizations. Specifically, the GIS Certification Institute (GISCI) weights its Geospatial Core Technical Knowledge Exam®, in part, based upon the GTCM. The GISCI's decision is supported by Hong (2016), as he stated that "the GTCM developed by DOLETA is the most appropriate for use in identifying skills for GIS professionals, as it offers a wide range of in-depth technical and personal skill sets" (p. 148). A more informative evaluation of the GTCM's included competencies would provide the GISCI with the information needed to alter the representation of various knowledge areas and represent better the competencies found in the geospatial industry. The lack of feedback from employers regarding how the geospatial field views the technical competencies in the GTCM inhibits their relationship with industry partners and reduces the value of the instruction they provide to potential members of the geospatial workforce.

Purpose Statement

The purpose of the study is to explore the viewpoints of geospatial professionals toward the GTCM and why they hold these views. There are numerous challenges to assuring competence within the geospatial field due to the variety of applications and users in the field (Albrecht, 1998). By assessing the viewpoints toward these competencies, the researcher can better understand how practitioners view the standard. Also, the identification of commonalities across viewpoints may reveal widely held beliefs within the field. Attempts to regulate the discipline are progressing, but a connection between the learning outcomes achieved in academia and the practical knowledge demonstrated in the workplace is a reasonable path to establishing competency (Mathews & Wikle, 2017). It is feasible to assume that a certification model built upon a standard body of knowledge, field experience, and a competency-based exam is a valid approach to demonstrate competency.

Theoretical Framework

According to Merriam-Webster's dictionary, an expert is "one with the special skill or knowledge representing mastery of a particular subject"... ("Expert", 1986, p. 437). K. Anders Ericsson is a psychologist recognized as a leading researcher in the field of expertise research. Ericsson co-edited "Toward a General Theory of Expertise" (Ericsson & Smith, 1991) where the authors characterized the expertise approach as an "an attempt to describe the critical performance under standardized conditions, to analyze it, and to identify the components of the performance that make it superior" (p. 8). Early efforts at predicting outstanding performance involved an investigation of personality traits (Kuchinke, 1997). However, Ericsson offered that expertise was more dependent upon the knowledge gained, a skill developed through practice (Leonard, 2015), and learning experiences specific to a domain rather than to genetics (Woodard, Williamson, & Murphy, 2013). Posner (1988) advanced this idea when suggesting the *ordinary people*, given the right conditions, could develop expertise. Leonard (2015) saw Expertise Theory as a modern variation of behavioral learning theories that Billett, Harteis, and Gruber (2018) noted as having a focus on the structures and practices which support consistent superior performance. Unsurprisingly, Kuchinke (1997) noted there was significant difficulty arriving at a consistent definition of expertise. Ericsson and Smith (1991) conceded that a lack of unanimity regarding the description of the theory of expertise, but offered that the study of expertise differs from other approaches in that it holds that superior performance was primarily acquired.

Ericsson and Smith (1991) developed a more general study of expertise, building upon previous work evaluating the skills demonstrated by chess masters (Chase & Simon, 1973; de Groot, 1978), as they saw a need for a universal theory addressing the characteristics aligned with consistently high performance. Specifically, Ericsson and Smith (1991) noted that they had "seen that the more parsimonious theoretical approaches relying on stable inherited characteristics seem inadequate to account for outstanding and superior performance" (p. 7). Leonard (2015) posits that "Expertise Theory specifies how talent develops across specified fields or domains, focusing on cognitive task analysis (to map the domain), instruction and practice, and clearly specified learning outcomes against which one can objectively measure the development of expertise" (p. 1). The theory of expertise continued to develop, and Ericsson, Krampe, and Tesch-Römer (1993) held that their theoretical framework addressing expertise "explains expert performance in terms of acquired characteristics resulting from extended deliberate practice and that limits the role of innate (inherited) characteristics to general levels of activity and emotionality" (p. 363).

There is general agreement that while domain knowledge is a component of expertise (Germain & Tejeda, 2012), these terms were not synonymous. Other common attributes of expertise were problem-solving, experience, and the ability to repeatedly perform specified tasks (Herling, 2000; Mieg, 2001; Mockus & Herbsleb, 2002). In the expert performance approach, the reproducibility of superior performance on representative tasks that illustrate expertise in a domain should be the focus (Feltovich, Prietula, & Ericsson, 2018). These tasks are the foundation for standards within a domain, which may foster superior performance and advance the professionalization of a field (Mieg & Evetts, 2018). These considerations were the foundations for participants used in this research study. The pool of geospatial professionals for this study shared the typical characteristics of a history of critical thinking, domain knowledge, professionalism, consistently outstanding performance, and contributions to the field.

The use of content experts to conduct task analysis and evaluate work competencies is widely recognized (Hogan et al., 2010; Johnson, 2010; Russ-Eft, 1995; Weiss, & Shanteau, 2003) and promotes a more widespread acceptance of the work. While several approaches have been used for eliciting expertise (Lintern, Moon, Klein & Hoffman, 2018), the expectation is that an expert can judge between competing ideas and demonstrate their evaluative skill effectively (Weiss & Shanteau, 2003). Bereiter and Scardamalia (1993) accentuated the value of expert input when distinguishing between experts and non-experts. "The career of the expert is one of progressively advancing on problems constituting a field of work, whereas the career of the non-expert is one of gradually constricting the field of work so that it more closely conforms to the routines the non-expert is prepared to execute" (p. 11). The use of stakeholders who are closest to the core competencies enables the development of a model that benefits from their pooled experience (Grigoryev, 2006; McLagan, 1997; Russ-Eft, 1995). Perhaps Mirabile (1997) summed it up best, "The most important points about competency models is that the formats be governed by the collective wisdom of the people that need and build them" (p. 76).

Conceptual Framework

The term "competence" is connected to McClelland (1973), as he wrote the article, "Testing for Competence Rather than Intelligence" where he lamented that people were being evaluated based upon intelligence as opposed to their ability to perform tasks. He suggested that a customary intelligence test could not effectively predict future performance. Competence is more than knowledge and exists within a social context (Svensson, 2006). As offered by Gilbert (1978), "In order to convert measures of performance into measures of competence, we require a social standard" (p. 29). Furthermore, as competence is a measure of the application of knowledge against a standard, it may be noted by way of credentials (Gilbert, 1978; Svensson, 2006), and offers a method to judge performance. Conversely, Ashworth and Saxton (1990) found little evidence that the value of competence had been conclusively established or fully explored and believed that "*competence* is the embodiment of a mechanistic, technically-oriented way of thinking which is normally inappropriate to the description of human action, or the facilitation of the training of human beings" (p. 253). Regardless, available research contains numerous definitions that outline competence (Calenda & Tammaro, 2015; Lucia & Lepsinger, 1999; Mirabile, 1997; Svensson, 2006).

McClelland (1973) is credited with launching the competency movement by choosing to employ *criterion sampling* as opposed to intelligence to predict job performance. Unfortunately, McClelland (1973) did not define competency or competencies (Stevens, 2013). Some clarity has been provided by Hyneman (2013) who asserted that "competencies are generally defined as groupings of knowledge, skills, abilities, and other characteristics (KSAOs), often described in behavioral terms, which are theorized or empirically shown to be associated with job performance" (p. 4). Competencies were characterized by Lucia and Lepsinger (1999) as individual characteristics that acted as predictors of performance to aptitude and subject matter knowledge.

A key delineating factor in the literature relates to competence and competency, where the assumption is that a competency is the ability to apply knowledge, skills, abilities, and behaviors towards the accomplishment of goals (Campion et al., 2011; Ennis, 2008; Spencer & Spencer, 1993). As offered by Personnel Decisions Research Institutes, Inc. and Aguirre International, (2005), "Not to be confused with competence, a competency describes a behavior, but does not attempt to describe a level of performance" (p. 4). There is no unanimity on the limitation to describing or comparing performance, as research has shown competencies used to delineate between a variety of performance levels (Gaudet et al., 2003; Marrelli, Tondora & Hoge, 2005; Mirabile, 1997; Shippmann et al., 2000). Hyneman (2013) noted a lack of agreement on what constitutes a competency. The absence of consensus may be occurring due to what Campion et al. (2011) see when stating that the competency literature "consists mostly of writings based on practical experience (e.g., case studies, commentaries) because little empirical research exists" (pp. 225-226).

Prahalad and Hamel's (1990) introduction of core competencies was a catalyst for the development and growth of competency modeling practices. Core competencies were not viewed as individual-level attributes but seen as competencies unique to that model (Shippmann et al., 2000). From an industry perspective, core competencies are skills required of all workers are across similar occupations. Grigoryev's (2006) concept of competency modeling forged a connection between the desired outcomes of the model and the core competencies, which determined the behaviors linked to success. Core competencies are seen as fundamental components within a competency model (Prahalad & Hamel, 1990), and help to define a worker's professional competence (Spencer & Spencer, 1993).

While McClelland (1973) is credited with starting the competency modeling movement (Gaudet et al., 2003; Stevens, 2013), Spencer and Spencer (1993) defined the methodology to identify competencies and subsequent modeling efforts. Competency mapping performs this task by breaking a job, process, or occupation into its essential tasks and identifying the competencies required to be successful (Chouhan & Srivastava, 2014). The mapping process is built upon a set of core competencies (Prahalad & Hamel, 1990), which form the foundation in the development of the competency models (Shippmann et al., 2000). Lucia and Lepsinger (1999) continued the research into competency models and created a competency pyramid comprised of *aptitude*, *personal characteristics*, *skills*, and *knowledge*. The pyramid in Figure 1 is topped by *behaviors*, and Lucia and Lepsinger (1999) justified their decision stating "At the top of the pyramid is a specific set of behaviors that are the manifestation of all the innate and acquired abilities discussed earlier" (p. 6). This competency pyramid shares numerous similarities to the Building Blocks Competency Model built by DOLETA and used in this study.

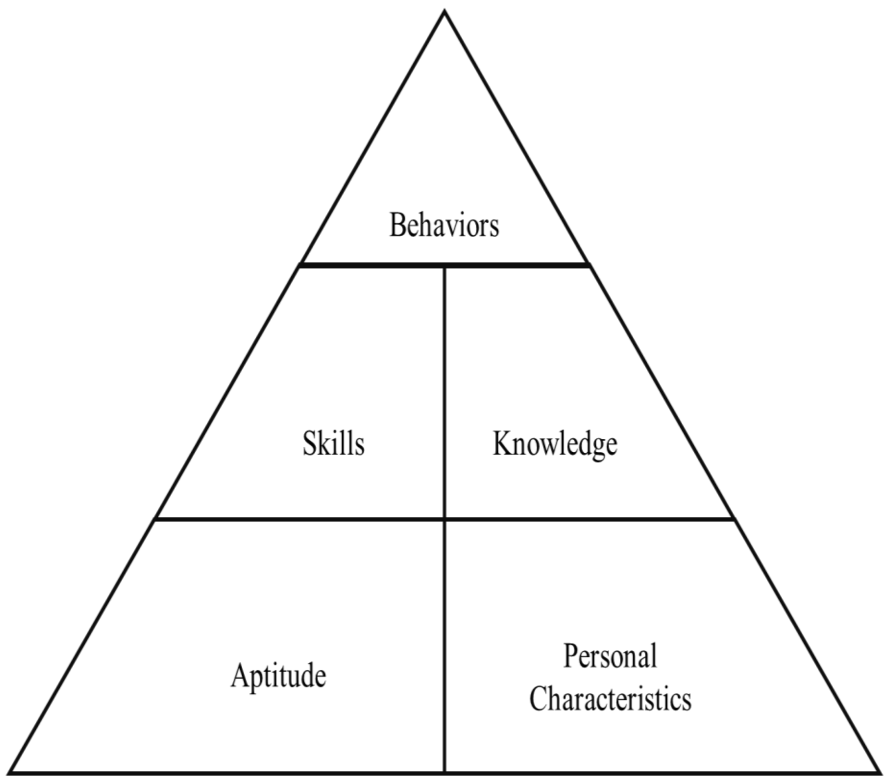

Figure 1: Competency Pyramid (Lucia & Lepsinger, 1999, p. 7)

A competency model is the specific combination of KSAOs that are needed for effective performance (competencies) in a role, occupation, or industry. Recent research (Campion et al., 2011; Shippmann et al., 2000) has created more consensus surrounding the construction and use of competency models. The view of the competency model's application will work to determine how comprehensively the KSAOs are defined. Determining the level of granularity of competencies is a balancing act between achieving the necessary detail while maintaining a level of simplicity (Mirabile, 1997; Shippmann et al., 2000). DiBiase et al. (2010) shared that reaching an agreement on the balance of competencies was one of the obstacles delaying the development of the DOLETA Geospatial Technology Competency Model (GTCM).

Competency models facilitate discussion, enable understanding, and provide an avenue for the application of the competencies within the workforce. Some researchers see the models applied more narrowly (Gaudet et al., 2003), while others look for broader uses (Zemke & Zemke, 1999). The models are used as benchmarks to delineate the competencies required for effective or superior performance (Chouhan & Srivastava, 2014; Lucia & Lepsinger, 1999) and can be used as guides or maps for professional development at the individual level, conduct a needs assessment within a company, or conduct a gap analysis of the industry (Ennis, 2008).

Competency modeling has many advantages as a tool for the evaluation of a task, occupation, organization, or industry. The use of cognitive task analysis to review the development of effective performance (Clark & Estes, 1996) coincided with the growth in the use of competencies as an approach to demonstrate effective work performance. Competency models have been used in place of traditional task analysis as they are less focused on specific duties and more interested in broad roles (Gaudet et al., 2003; Stevens, 2013). As offered by Marrelli et al. (2005), "The development and application of competency models is a proven approach for investing in human resources in order to achieve a more effective and productive workforce" (p. 559).

Organizations need a unifying framework for workforce development that captures the competencies required for successful performance in a cluster of associated tasks, processes, or industry. Gaudet et al. (2003) believed that "When competencies are identified, they should be organized and presented in a meaningful way" (p. 22). Hoge, Tandora, and Marrelli (2005) went further by stating that "A competency model is simply a conceptual framework or organizing scheme that details the competencies that are required for effective performance in a particular job" (p. 520). Stevens (2013) noted that typologies and hierarchies are approaches to competency modeling that have a sound theoretical base, adding that a hierarchal structure can act as an extension of the logic of typologies. The use of a hierarchical model is a common technique (Campion et al., 2011; Ennis, 2008; Lucia & Lepsinger, 1999), and Campion et al. (2011) suggested limiting the tiers in favor more highly-detailed competencies. Competencies in a hierarchical model tend to move from generic applications to increasingly specific technical capabilities.

The DOLETA GTCM model, shown in Figure 2, is a generic framework that depicts the competencies existing on tiers, with lower tiers (foundational competencies) serving as building blocks for the higher tiers. Having an extensive use in numerous industries (Ennis, 2008), these building blocks address personal effectiveness, academic, and workplace competencies. The second collection of competencies are explicitly connected to industry and are classified as industry-wide and industry-specific technical competencies. The final collection of competencies is occupation-related and beyond the scope of this study. While the pyramid portrays that competencies become more specific as one moves from foundational to occupation-related competencies (PDRI & Aguirre Int' l, 2005), this does not imply that competence attainment follows a particular sequence or that one competency is more valuable than another (DOLETA, 2019).

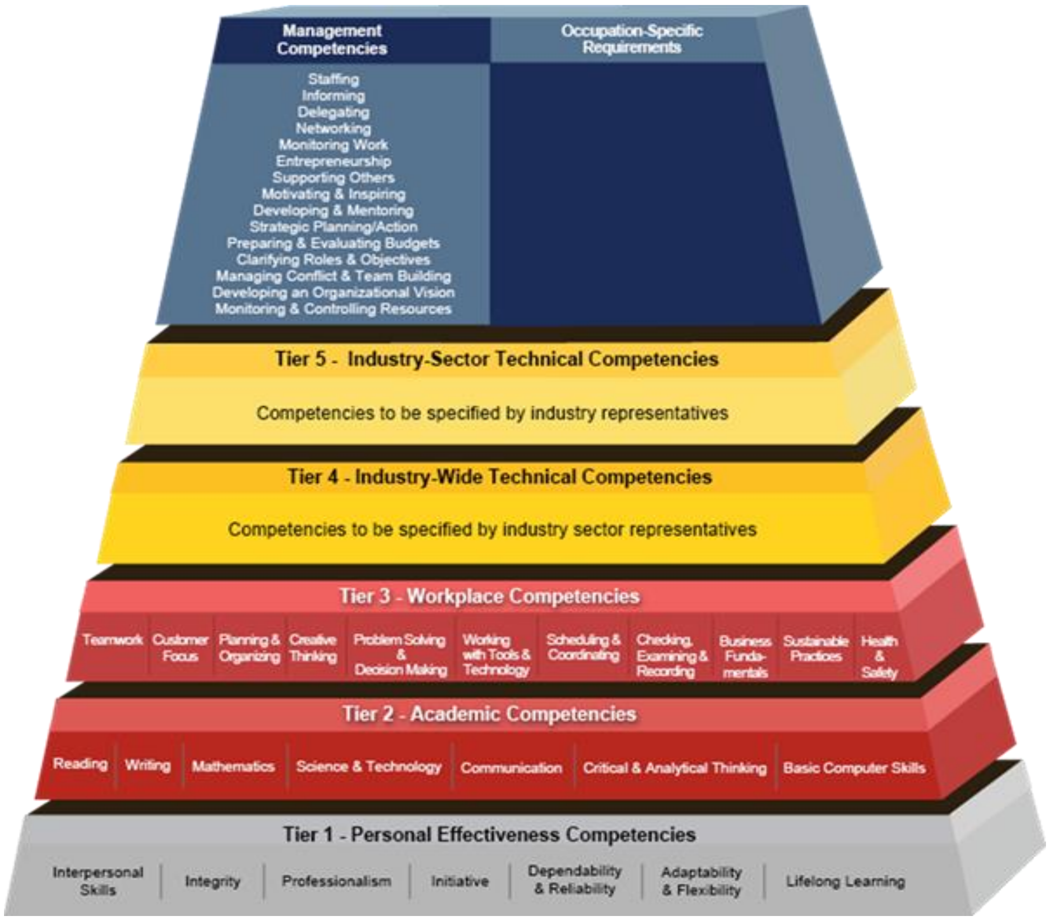

Figure 2: Building Blocks Competency Model (PDRI & Aguirre Int' l, 2005, p. 13)

The conceptual model in Figure 3 embodies the framework used in this study. Geospatial professionals active within the field comprised study participants. The concourse of technical competencies contains Tier 4 (Industry-Wide Technical Competencies) and Tier 5 (Industry-Sector Technical Competencies) of the GTCM. The researcher developed a set of statements, known as the Q-set, in a Q Methodological study from the technical competencies found in Tier 5, as these competency statements incorporate the accepted knowledge, skills, and abilities needed by geospatial practitioners. The statements located with Tier 4 are themed as addressing crosscutting geospatial abilities and represent the core geospatial competencies in the field. However, Tier 5 builds upon these statements and extends its application into three designated industry sectors of analysis and modeling, positioning and data acquisition, and software and application development. To include both tiers of the technical competencies would have been unnecessarily redundant and would not have advanced the research.

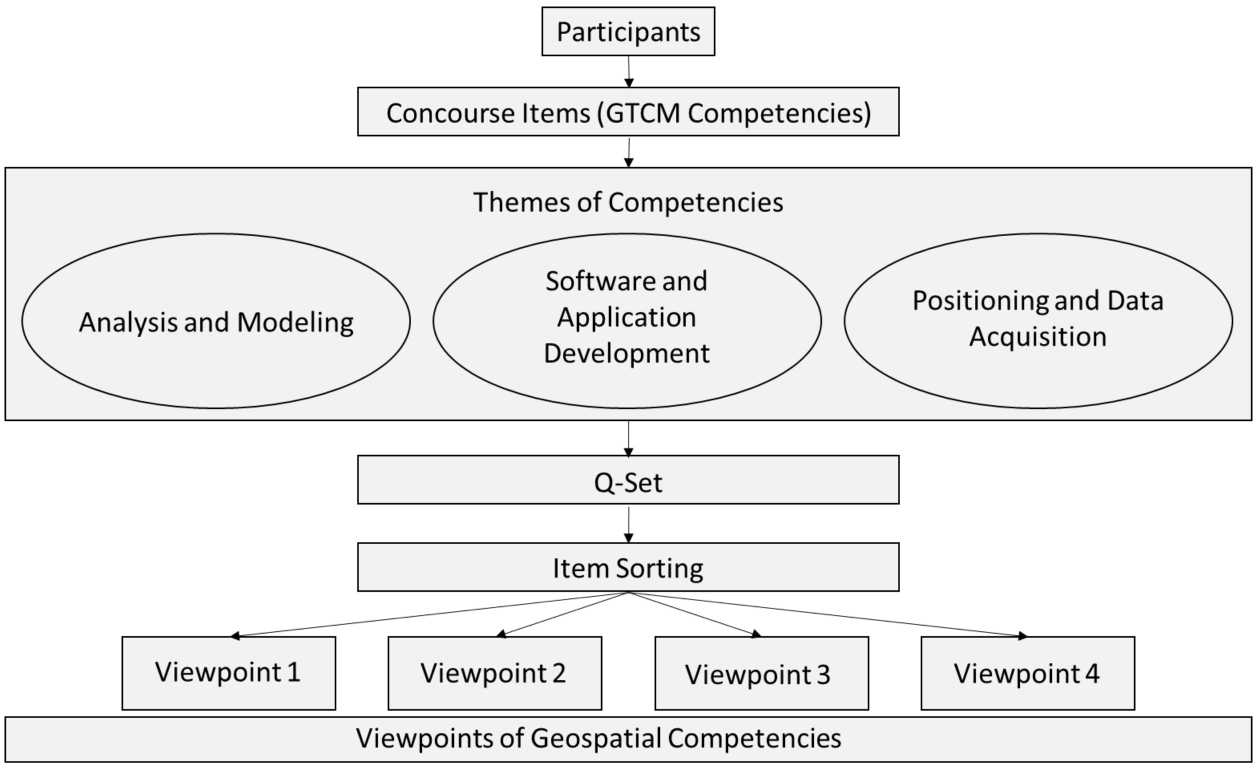

Figure 3: Conceptual Model for industry viewpoints of geospatial competencies

The Q-Set was constructed from these competency statements, and members of the P-Set sorted the statements based upon the determination of perceived relevance within the geospatial workforce. The result of the respondents' perspective acted to construct distinct viewpoints of the identified competency statements.

Research Question

The purpose of the study is to explore the viewpoints of geospatial professionals toward the Geospatial Technology Competency Model (DOLETA, 2019) and why they hold these views. The following research questions were used to develop the study:

1. How do Geographic Information Science Professionals view the technical competencies within the Geospatial Technology Competency Model and why?
2. Do perceptions of the geospatial competencies differ based upon the respondents' industry-sector, years of experience, method of certification, or education?

Significance of the Study

Educators must understand the geospatial industry by developing informed relationships and developing a well-educated workforce that is prepared to contribute immediately in the workforce. The ability to ascertain the competencies that are most important within the field would provide more information to higher education, professional societies, and certification organizations. Specifically, the GIS Certification Institute (GISCI) weights its Geospatial Core Technical Knowledge Exam®, in part, based upon the GTCM. An informative evaluation of the included competencies would provide the GISCI, the industry-recognized body for determining competence, with the information needed to alter the representation of various knowledge areas to represent better the competencies most needed in the geospatial industry.

There are numerous challenges to assuring competence within the geospatial field due to the variety of applications and users (Albrecht, 1998). Attempts at regulating the geospatial field are progressing, and a connection between the learning outcomes achieved in academia and the practical knowledge demonstrated in the workplace provide a reasonable path to establishing competency (Mathews & Wikle, 2017). Gaudet, Annulis, and Carr (2001) suggested that a geospatial technology competency model could be used to build a workforce. The first model developed at the University of Southern Mississippi was the most extensive workforce competency model to date, but it was not being referenced to the extent of the UCGIS's GIS&T Body of Knowledge (BoK) (Sullivan, 2007). DiBiase et al. (2010) added that USM's GTCM technical competencies were not sufficiently detailed to cover the broad range of aspects in the geospatial technology industry.

The US DOLETA recognized that an industry-wide framework was needed to define the field more accurately, assist educational institutions in preparing students for geospatial careers and so that the GTCM could provide the information necessary for the creation of new occupational titles at the DOL. The US DOLETA GTCM capped years of effort to develop an industry model framework for geospatial occupations and identified the foundational, industry-wide, and industry sector-specific expertise that distinguishes, and binds together, successful geospatial professionals (DiBiase et al. 2010). Expected uses of the GTCM include career guidance, curriculum development and assessment, recruitment and hiring, continuing professional development, criteria for voluntary certification, and outreach efforts intended to communicate characteristics of the geospatial field to the public.

Various entities have attempted to capture the skills needed to be successful in the geospatial field. These attempts vary from an analysis of GIS competencies found in higher education curricular documents (Schulze et al., 2013) to a professional geography competency model (Solem et al., 2008), which included both technical and general skills. The US DOLETA GTCM is seen as the most appropriate source for use in identifying skills for GIS professionals, as it offers a wide range of in-depth technical and personal skill sets (Hong, 2016). The US DOLETA GTCM is a foundational document in many activities aimed at establishing a competency baseline. The United States Geospatial Intelligence Foundation (USGIF) uses the GTCM as a source for its accreditation program. It has been promoted as a resource for the Open Source Geospatial Certification Model (Khan, Davis, & Behr, 2016). Its most significant impact can be found with the GIS Certification Institute's (GISCI) Geographic Information Science

Professional (GISP) certification. The GISP is the most widely used competency designation within the geospatial community. Unfortunately, the GISCI could not transition from a portfolio-based system for competency determination to a competency examination due to the absence of an accepted geospatial framework. The US DOLETA GTCM (along with GIS&T BoK) offers a source document from which to base exam questions. The lack of an exam called into question the value of a GISP certification, as a portfolio approach was seen as lacking rigor. The implementation of the Geospatial Core Technical Knowledge Exam® as an evaluation tool for competency has strengthened the profession.

Overview of Method

This study used Q Methodology as the research method. William Stephenson introduced Q Methodology in 1935 as a systematic approach to reveal an individuals' subjectivity (Brown,1993; Simons, 2013; Steelman & Maguire, 1999; Watts & Stenner, 2012). Cross (2005) asserts that "Q methodology is a more robust technique than alternative methods, for the measurement of attitudes and subjective opinion" (p. 206).

Q Methodology is neither a qualitative nor a quantitative approach but combines both analytical techniques (Brown, 1996; Dziopa & Ahern, 2011; McKeown & Thomas, 2013). Q Methodology has been used in studies to determine stakeholder perspectives (Cuppen, Bosch-Rekveldt, Pikaar & Mehos, 2016; Steelman & Maguire, 1999; Zabala, Sandbrook, & Mukherjee, 2018) and is valued for its ability to quantify viewpoints (McKeown & Thomas, 2013; Shemmings, 2006). In this study, participants were asked to sort 62 competency statements based upon their opinion regarding the relevance of competency to the geospatial field.

A five-step sequence is used to implement Q Methodology (Cuppen et al., 2016; McKeown & Thomas, 2013; Shemmings, 2006; Simons, 2013). The first step begins with the development of a comprehensive collection of possible statements regarding a given topic, otherwise known as a *concourse* (Cuppen et al., 2016; Dziopa & Ahern, 2011; van Exel & De Graaf, 2005). The next step is the selection of representative sample statements (Q-set) from the concourse to be evaluated during the Q-sort (Shemmings, 2006; Simons, 2013; van Exel & De Graaf, 2005). The administration of Q-sort then occurs where respondents (P-set) share their views, followed by factor analysis to determine correlations between perspectives (Simons, 2013; van Exel & De Graaf, 2005; Watts & Stenner, 2012). The final step in this approach is the interpretation of the factor loadings and subsequent findings (Cross, 2005; McKeown & Thomas, 2013; Watts & Stenner, 2012). More detail regarding the implementation of Q Methodology in this study can be found in Chapter 3.

Limitations

Q Methodology has received criticism, principally connected to the mixture of qualitative and quantitative methods. Directly, Simons (2013) notes that the application of factor analysis is a departure from its typical use. Further, studies using Q Methodology have been questioned regarding their reliability and generalization due to the inclusion of small sample sizes (van Exel & De Graaf, 2005), and there is also discussion regarding the replicability of Q-sorts within subsequent studies (Cross, 2005).

Participants for this study were be drawn from Geographic Information Science Professionals (GISPs). The experts used in this study are a minimal subset of a field that is estimated to contain more than 10,000 professionals and 500,000 practitioners. This limitation was applied to establish a minimum baseline of geospatial competency for the study.

Delimitations

There are other certifying and accrediting organizations that have members who have established a baseline of geospatial competency. These groups (e.g., American Society for Photogrammetry and Remote Sensing, United States Geospatial Intelligence Foundation, and the National Society of Professional Surveyors) evaluate some geospatial competencies found within the GTCM, but exist on the periphery of mainstream geospatial science. Also, only a tiny percentage of their membership perform the majority of tasks found within the GTCM. For this reason, the researcher did not solicit their members for participation.

Assumptions

This study is working under the assumption that participants were (a) willing to honestly and accurately shared their viewpoints, (b) able to perform the Q-sort without an issue, (c) able to understand the geospatial competencies as they have been provided, (d) able to discern the value of the role of the GTCM and the competencies contained therein, and (e) able to complete the sorting activity.

Definition of Terms

Competence is defined by Svensson (2006) as a "broader concept than knowledge, since it has emotional and social as well as cognitive components. Competence is based on ability in relation to the work, and is often expressed in terms of the credentials and merits of an individual" (p. 586).

Competency is defined by Ennis (2008) as "the capability of applying or using knowledge, skills, abilities, behaviors, and personal characteristics to successfully perform critical work tasks, specific functions, or operate in a given role or position" (p. 4).

Competency Model is defined by Campion et al. (2011) as "collections of knowledge, skills, abilities, and other characteristics (KSAOs) that are needed for effective performance in the jobs in question. The individual KSAOs or combinations of KSAOs are the competencies, and the set of competencies are typically referred to as the competency model" (p. 226).

Concourse is defined by Simons (2013) as "the sum of all things people say or think about the research question" (p. 29).

Expert is defined by Merriam-Webster (1986) as "one with the special skill or knowledge representing mastery of a particular subject" (p. 437).

Expertise is defined by Weiss and Shanteau (2003) as meeting two conditions, (1) the capacity to discriminate among similar but not identical stimuli within the domain and (2) the ability to demonstrate internal consistency (p. 107).

Expertise Theory is offered by Ericsson, Prietula and Cokely (2007) as the belief that experts are made, not born, and that "the development of genuine expertise requires struggle, sacrifice, and honest, often painful self-assessment and practice…practice that focuses on tasks beyond your current level of competence and comfort" (p. 2).

Geospatial Technology Competency Model (GTCM) is designated by Dibiase et al. (2010) as a competency model that "identifies the foundational, industry-wide, and industry sector-specific expertise that distinguishes, and binds together, successful geospatial professionals" (p. 55).

P-set is defined by Simons (2013) as "the group of participants that undertakes Q sorting" or the respondents to the Q-sort activity (p. 29).

Q Methodology is described by Bartlett and DeWeese (2015) as a technique to reveal subjectivity by gathering data in the form of opinions from participants' which are then grouped to reveal similar perspectives (p. 73). Stephenson (1935) offered this methodology as an inversion of traditional factor analysis where the participants are being correlated, not the tests.

Q-set is defined by van Exel and De Graaf (2005) as "a subset of statements is drawn from the concourse, to be presented to the participants" (p. 5).

Q-sort is defined by Cross (2005) as "a technique which conventionally involves the rank-ordering of a set of statements from agree to disagree…The Q-sort is usually a self-directed process" (p. 209).

Chapter Summary

This study investigates the perspectives held by geospatial science professionals towards the industry-wide and sector-specific competencies within the DOLETA GTCM. This study explores those views using the following questions:

1. How do Geographic Information Science Professionals view the technical competencies within the Geospatial Technology Competency Model and why?
2. Do perceptions of the geospatial competencies differ based upon the respondents' industry- sector, years of experience, or education?

This chapter provided a brief background on the geospatial field, including its current status, the need for a qualified workforce, and the critical role that a determination of the most crucial industry competencies plays in the geospatial field's future. The problem statement reveals a gap in practice between essential competencies needed by each industry sector and the competencies of those graduates entering the workforce. The purpose of the study is to explore the viewpoints of geospatial professionals toward the Geospatial Technology Competency Model (DOLETA, 2019) and why the geospatial professionals hold these views. The theoretical model is based upon Expertise Theory as experts are commonly used to construct and evaluate competency and competency models. The conceptual framework uses the competency model approach, as it is widely used in industry to define industry competency requirements and is the approach used for the DOLETA GTCM. Q Methodology is introduced as an appropriate method for this study. Limitations, delimitations, and assumptions were reviewed with a discussion of the potential biases found within the study. The chapter concludes with the definition of terms.

CHAPTER 2: LITERATURE REVIEW

Introduction

This chapter reviews how the determination and evaluation of competency have been a constant concern throughout the history of geospatial science. This study examined how the rise of geospatial science affected academic disciplines; the need to define technical competencies; the competency frameworks designed to harness the knowledge, skills, and abilities aligned with the field; the various roles assigned to geospatial technology; the need to define technical competencies (including a methodology for determining competence).; the impacts on the workforce; and the development of a profession built upon a foundation of distinguishing spatial capabilities. The research questions for this study:

1. How do Geographic Information Science Professionals view the technical competencies within the Geospatial Technology Competency Model and why?
2. Do perceptions of the geospatial competencies differ based upon the respondents' industry-sector, years of experience, method of certification, or education?

The ascension of geospatial science was connected with advances in computer hardware and software technology (Mathews & Wikle, 2019; Tate & Unwin, 2009) and there were initial concerns regarding the competency of individuals enabled by technological advances working in this emerging field (Dobson, 1983; Goodchild & Kemp, 1992a; Marble, 1998; Obermeyer, 1993). Several efforts were initiated to establish the academic topics taught (DiBiase et al., 2006; Goodchild & Kemp, 1992a; Marble, 1999; Prager & Plewe, 2009), expected workforce competencies (DiBiase et al., 2010; Gaudet et al., 2003; Johnson, 2010), and methods to evaluate technical competency (DiBiase, 2012; Huxhold & Craig, 2003; Quinn, 2015).

The purpose of the study is to explore the viewpoints of geospatial professionals toward the Geospatial Technology Competency Model (DOLETA, 2019) and why they hold these views. Determining the competencies viewed as most important within the field would provide more information to higher education, professional societies, and organizations awarding certifications. Believing that competence is a measure of the application of knowledge against a standard, this literature review captures the various evaluation models employed within the geospatial domain. A competency model is the specific combination of capabilities that are needed for effective performance in a role, occupation, or industry. The geospatial industry has selected the DOLETA GTCM as a unifying framework for workforce development, viewing it as the best approach to capturing the competencies required for successful performance.

Geospatial science emerged from the discipline of Geography, but new competencies continue to emerge as the science develops. The literature review that follows is organized by themes that demonstrate the essential role that competencies have played in the advancement of geospatial science. The themes convey competency development and its impact on academia, approaches to verifying competence, competency frameworks, the evolution of geospatial science from geography, workforce development geospatial competencies, and the development of a geospatial profession.

Impact on Academia

Today's geospatial science was first known as geographical information systems (GIS). GIS was strongly tied to computer science initially and was developed as a system for the collection, storage, and processing of location-based information (Foresman, 1998). The use of location information (geographical coordinates) is the distinctive characteristic separating GIS from other types of analysis. Sinton (2009) noted the strength of a spatial reference to assist a researcher in seeing a problem from a different perspective and assist in finding a solution. Most authors (e.g., Foote, Bednarz, Monk, Solem, & Stoltman, 2012; Foresman, 1998) cite the Canada system of the 1960s as the first 'GIS,' but the term did not gain much currency until the mid-1970s (Tate & Unwin, 2009) when innovative programs such as SYMAP, GRID, and IMGRID were being developed. Software advances and the subsequent distribution of software packages to a broader audience spurred the growth and exposure of GIS within the United States.

GIS instruction increased through the latter part of the 1980s as personal computers became more powerful, less expensive, and capable of running new desktop GIS software (Mathews & Wikle, 2019). The implementation of graphical user interfaces (GUIs) also made the software, which had previously been expensive to purchase and challenging to use, more user-friendly, and increased its practicality (Fagin & Wikle, 2011; Tate & Unwin, 2009). Lower hardware prices, higher storage capacity, and discounts offered by software vendors enabled the creation of GIS laboratories, providing greater access to GIS and spurring the demand for undergraduate GIS courses (Fagin & Wikle, 2011). Demand for instruction continued to grow, resulting in the initial development of courses, certificates, and later to degrees, as well. As offered by Foote et al. (2012), "there appears to be little doubt that technological developments have, on the one hand, allowed more people to access GIS and to ‘do GIS’ as well as on the other hand enabled new learning opportunities…. with and about GIS" (p. 5).

Geospatial science has historically been associated with two academic disciplines, computer science and geography, above all others (Samborski, 2006). The connection is based on its technological roots aligned with computer science and the theoretical constructs embedded in geography. Early on, Dobson (1983) recognized the impact of what he referred to as *automated geography* and saw it as a significant extension of geography. Pickles (1993) used

Dobson's "Automated Geography" article as a starting point to evaluate the extent and impact of computerization in the discipline. Geographers also viewed the rise of this new area of expertise as a way to demonstrate the field's value to both the private and public sectors of the economy (Sheppard, 1993). Departments of geography have an extensive history with geospatial science, where it continues to maintain a conspicuous position (Johnson & Sullivan, 2010; Sinton, 2012; Whalley et al., 2011).

Furthermore, Sinton (2009) noted a correlation in a renewed interest in the field of geography and the arrival of GIS. The impact of GIS was so significant in academia during the early 1990s that it was already being considered as a discipline unto itself (Obermeyer, 1994). The designation was confirmed later, due in part to its emphasis on technology, cross-disciplinary nature, and the development of competencies in addition to those found traditionally in geography (Foote et al., 2012). Fortunately, the early 1990s saw a spread of academic programs designed to teach the technology and supporting theory, which Goodchild (1992) referred to as *geographic information science* (GIS). The reference to a GIS as a *science* and not a *system* is significant as it created separation form the software and shifted focus, at least on the part of many in academia, to the importance of foundational knowledge.

One of the challenges associated with geospatial science is its application across a variety of disciplines. Such indistinctness allows many fields to offer instruction to their students in the use of the software, many times without the benefit of a deep theoretical foundation. The spread of geospatial education beyond the traditional geography departments is even more widespread at community colleges where programs are designed to fit specific local workforce needs. Johnson and Sullivan (2010) found that while geospatial techniques were most common in Geography Departments, there is an extensive distribution of programs providing instruction couched in terms of how geospatial techniques could be used within that discipline. The University Consortium for Geographic Information Science [UCGIS] (2003) noted a broadening of its focus well beyond the traditional boundaries of geography. The NRC (2006) has raised serious concerns between training students to use software without their understanding of the background rationale for selecting specific operations and the need to provide fundamental geospatial education. The NRC's concerns echoed Marble's (1999) warning years earlier, "The national impact of inadequate GIS education is substantial and growing" (p. 31).

Seeing the lack of a foundation curriculum document, the National Center for Geographic Information and Analysis (NCGIA) developed a teaching resource known as the Core Curriculum, which contained lecture materials to help educators teach GIS (Goodchild, 1992; Tate & Unwin, 2009). With the advances in technology, it was not long before the curriculum became outdated and was revised, expanding its scope into designing a Core Curriculum for Technical Programs (Johnson & Sullivan, 2010; Veenendaal, 2014) as well. In the time since the development of the Core Curriculum in GIS, the curriculum resources for geospatial education have grown significantly. The maturation of the discipline may make the Core Curriculum less relevant today, but its impact remains, as the resource acted as a precursor to the UCGIS BoK. This study will discuss the BoK later, but its influence is significant. As offered by Hong (2016), "The Body of Knowledge supports higher education to train students to become successful professionals in the field" (p. 148).

The presence of geospatial instruction in higher education (Whyatt, Clark, & Davies, 2011) continues to grow, and that appears unlikely to change. The growth in GIS began to impact geography departments as there was a split between traditional academic research and the production of geospatial graduates (Golledge, 2000). The most substantial influence came from an increase in the reliance on technology connected to GIS instruction. Sheppard (1993) felt that the technology was not neutral and could profoundly change the scholarly direction of geographic research. There has been unease regarding a technology-driven research agenda with a GIS focus, at the expense of core geospatial concepts (Tate & Unwin, 2009; Veenendaal, 2014). The lack of widespread focus on core geospatial competencies in higher education was noted by Marble (1999), who saw the problem as continuing to worsen as more of the workforce did not possess the skills necessary to be successful. Fagin and Wikle (2011) observed that this issue might even be more significant at community colleges who typically place less emphasis on theoretical considerations and focus on training and workforce development. However, Fagin and Wikle (2011) presuppose that students would not receive additional instruction related to the spatial concepts during the significant number of geospatial classes within an Associate's Degree. The problem had not abated years later when Marble (2006) wrote, "Presently, far too many academic programs concentrate on imparting only basic skills in the manipulation of existing GIS software to the near exclusion of problem identification and solving" (p. 1). Research continues to demonstrate less emphasis on core spatial competencies (Schulze et al., 2013), but there appears to be a growing recognition of the need for students to graduate with a solid geospatial foundation (Mathews & Wikle, 2019).

The ability of higher education to prepare students to meet labor market needs has been up for debate since the early 1990s (Solem, Kollasch & Lee, 2013). Additionally, there has been an increase in pressure in recent years to demonstrate that academic programs are enabling students to achieve their learning objectives and employability goals (Wikle, 2017). There is a connection between a renewed interest in professional certification practices and the lack of confidence that the geospatial industry has in the baseline level of graduate competence (Prager

& Plewe, 2009). Failing to provide competent workers would be unfortunate, given the improved standing of geospatial science within the general public (Prager, 2012) and the increased visibility of graduates. While higher education is progressively being assessed on its ability to provide graduates with the right skills (Solem et al., 2008), recent studies demonstrate a gap between the learning outcomes achieved in geospatial programs and the knowledge needed in employment (Mathews & Wikle, 2019; Wikle, 2017). Students have been attracted to the geospatial field, in part, due to their belief that it increases their marketability and enhances career opportunities (Sinton, 2012; Zhou et al., 1999); therefore, educators must provide the instruction needed to develop the geospatial skills of students (Hong, 2016).

The ability to make geospatial education more effective is based, in part, on identifying the educational competencies in need of improvement (Painho & Curvelo, 2012). Furthermore, Marble (2006) was concerned about the lack of consistency in geospatial instruction and shared that, "We are in a poor position to satisfy this demand for additional geospatial personnel since we have only a very vague notion of who we are and what—in the aggregate—we are currently doing" (p. 1). Part of the problem is due to academia's reluctance to admit how little they know about the competencies needed within the industry (Kemp, 2003) and that many programs are constructed with little contribution from the geospatial industry towards pinpointing the required knowledge, skills, and abilities (Marble, 2006).

In all situations, designing curricula so that it aligns with workforce needs, among other content-based learning outcomes, is an ongoing and critical challenge (DiBiase, 2007; Estaville, 2010; Sinton, 2012; Sullivan, Brase, & Johnson, 2008). Many institutions conduct a *Developing A CUrriculuM* (DACUM) task analysis with industry partners to identify geospatial knowledge, skills, and abilities (KSAs). Unfortunately, DACUMs tend to be very localized in nature and can only provide a limited amount of data at a national level. While the growth of geospatial science has been a great asset for a renewed appreciation for geography, educators must address the disconnect between higher education and workforce if there is hope to maintain this momentum (Foote et al., 2012).

Approaches to Verifying Competence

Barnhart (1997) differentiates between three approaches to professional certification: portfolio-based, competency-based, and curriculum-based. Barnhart's view of certification practices was very general and encompassed the three most widely used methods (certification, accreditation, and licensure) to deem someone competent. Each approach is in use within the geospatial profession, with varying degrees of success and applicability (Gaudet et al., 2003; Goodchild & Kemp, 1992b; Huxhold, 1991; Kemp, 2003; Obermeyer, 1993). Wikle (1998) supported the concept of establishing competency parameters for students but warned that "professional competency programmes must involve significant input from industry, academia, and professional associations" (p. 504).

There remains a need for skilled professionals in the geospatial industry (Davis, 2014), but there is a lack of consensus regarding the approach needed. Also, there have been concerns historically about the credentialing of GIS practitioners as well as how the lack of appropriately prepared workers would negatively affect the geospatial profession (Kemp, 2003; Obermeyer, 1994). This issue has only gotten worse as the use of geospatial tools has continued to expand (Burley, 1993). Much of the initial concern regarding academic preparation related to the variation in the design and content of courses or programs (NRC, 2006) as well as the lack of a geospatial standard that inhibits the ability of the industry to set competency guidelines. The most common geospatial credential awarded in higher education is a certificate, but these can range in learning objectives, structure, and subject matter (Wikle, 2015). Many have suggested that a third-party actor needs to create a baseline of competence for graduates of academic programs (Kemp, 2016; Obermeyer, 1993; Somers, 2000). Various actors within the geospatial industry have reviewed approaches to setting a minimum acceptable level of competence to distinguish professionals from practitioners, and many are seeing the benefits to the public and the profession (DiBiase, 2012).

There has been an increase in recognition of the validity of certification practices (Kemp, 2003; Prager & Plewe, 2009; Secilmis, 2005; Somers, 2000). Of the certification practices established by Barnhart (1997), the portfolio-based approach is seen as the weakest method and is no longer in use within the field; the competency-based approach is the most widely used within the industry, and one sector of the industry uses the curriculum-based technique. The establishment of competency baselines supports efforts to recognize individuals who maintain standards and is a component within the creation of a profession (DiBiase, 2012; Joffe, 2018), and for determining a minimum level of capability allows the geospatial industry the opportunity to demonstrate self-regulation. Somers (2000) captures the idea best when she offers that "The basic reasons for establishing certification and regulation for a profession are to protect the public and consumers and to benefit those in the profession" (p.22).

Licensure

A governmental body (within the context of this study, that entity would the individual states) usually manages licensure requirements to establish standards, manage the approved activities, and protect the public from harm (Harvey, 2003; Joffe, 2018; Kemp, 2003). Licensing is a high standard to meet and requires a significant amount of preparation, an examination, and continuous professional education. Some advocates for licensure see GIS as only a tool (Burley,

1993) to be used in a chosen discipline, fail to distinguish between licensure and certification, or believe that regulating bodies within each field should oversee its use. Others see the licensing of geospatial professionals as an effective bulwark against the potential for accreditation standards placed on their academic departments (Bralower et al., 2008).

There has been pressure from some within the field of surveying to bring geospatial professionals, or specifically, geospatial activities under the control of professional land surveying. Advances in locational technology permit operators to record data, once only the purview of surveyors, at very high levels of precision and accuracy. There is the potential for someone unfamiliar with critical geodetic considerations to create locational errors, doing great harm to the public (Harvey, 2003; Joffe, 2018). Also, some states now have professional land surveying designations that include a GIS component. The friction between surveyors and geographic information science professionals is most often connected at the dividing line between the practices allowed only for licensed surveyors (Joffe, 2018).

A case study that some geospatial advocates point to relates to the field of photogrammetry, which has been subsumed within professional land surveying. Photogrammetry is a science wherein measurements of objects can be calculated from photographs, typically aerial photographs of the earth's surface. Photogrammetry was self-regulated as a field and profession for many years and managed a rigorous certification program. Certified photogrammetrists can continue their work in their professions, as was previously the case, with the primary limitation being their inability to generate maps without the supervision of a licensed surveyor. A licensed surveyor must review any data or document produced by a certified photogrammetrists before it is released.

Accreditation

Accreditation is another approach to establishing standards for workers within the geospatial field. It would fall into the curriculum-based category of "certification" using the criteria established by Barnhart (1997). Quinn (2015) defines accreditation as "the process by which a nongovernmental agency grants a time-limited recognition to an institution or organization after verifying it has met predetermined, standardized criteria" (p. 17). Historically, external accreditation reviews tended to devote the most attention to facilities and faculty credentials to ensure that established standards are met (DiBiase, 2003; Obermeyer, 1993). As opposed to certification, accreditation is applied at the institutional level, typically educational institutions, where it has a long history (Obermeyer, 1993).

Advocates for accreditation note that it can set minimum requirements for institutions that could assist later certification efforts (Wikle, 2017). Others note that it would be more efficient to evaluate geospatial programs rather than individual applicants (Huxhold & Craig, 2003). Accreditation requirements tend to be costly, and there is a concern that the process would favor more substantially funded educational institutions. This concern grows larger when remembering that community college supply workers for a significant portion of the entry-level geospatial positions (DiBiase, 2003). Other concerns raised by those who assert that the restrictive nature of accreditations offers benefits to no one based upon a requirement to focus on specific content rather than develop critical thinking skills (Bralower et al., 2008).

The lack of educational standards or evaluation criteria stymied the development of an accreditation program for the geospatial field (Huxhold & Craig, 2003). The United States Geospatial Intelligence Foundation (USGIF) was tasked with academic accrediting in support of a growing geospatial intelligence field. The USGIF established guidelines and parameters for the knowledge, skills, and abilities required of geospatial intelligence professionals (Quinn, 2015). The GEOINT Essential Body of Knowledge (EBK) contains the requirements, which are based upon the GIS&T BoK and the DOLETA GTCM. Quinn (2015) defines the EBK as follows, "The body of knowledge and skills a professional must possess in order to perform successfully" (p. 19). The EBK enabled the USGIF to establish the standards for producing graduates from a geospatial intelligence accredited program, but the USGIF has awarded accreditation to only 16 programs thus far.

Certification

The geospatial industry uses a competency-based certification approach built around a knowledge examination of competencies derived from the DOLETA GTCM and the BoK. Obermeyer (1992) recognized the potential for certification in the geospatial field and later acknowledged its inevitability (Obermeyer, 1993) very early in the field's development. Quinn (2015) defines certification as:

> The voluntary process by which a non-governmental entity grants a time-limited recognition and use of a credential to an individual after verifying he or she meets predetermined, standardized criteria. It is often the vehicle a profession or occupation uses to differentiate among its members. (p. 18)

Certification is granted to someone by their colleagues or peers as recognition that they have been judged to possess sufficient knowledge, skills, and competences in their chosen profession (Kemp, 2016; Khan et al., 2016; Mathews & Wikle, 2017; Sullivan et al., 2008). Obermeyer (1994) also noted that certification could be used to limit entry into a profession, which is not the case within the geospatial domain, as certified professionals make up a small portion of the workforce. Somers (2004) sums the concept up well, "Advocates believe that GIS certification will protect the public, grow the GIS profession, increase and ensure competency of GIS professionals, instill ethical behavior, and provide assistance to employers" (p.37). Pugh (1989) asserted that certification is a precondition for the creation of a profession and that the field needed an organization to evaluate the technical competence of its practitioners (DiBiase, 2003).

The Urban and Regional Information Systems Association (URISA) led the effort to create an organization, later known as the Geographic Information Systems Certification Institute (GISCI), that would develop and implement a geographic information system (GIS) certification program in 2002 (Huxhold & Craig, 2003). The initial process was portfolio-based, one of Barnhart's (1997) recognized methods for certification. The portfolio approach was the GISCI's only option, as a standard for technical competence was not available. The GIS&T BoK arrived in 2007, followed by the GTCM in 2010 and provided sources to generate a technical competency exam. Support for the exam was not universal, but Mathews and Wikle (2017) offer the following insight, "the majority of comments about adding the written test expressed support. Many indicated that the examination requirement would improve the public stature of GIS certification by fostering greater confidence in GIS practitioners" (p. 9). The implementation of a competency exam was critical to the establishment of a geospatial profession; as peripheral fields were hard-pressed to argue for regulation of the geospatial domain. Regardless, Mathews and Wikle (2017) observed that less than 2% of the geospatial workforce were certified professionals. That value is consistent with the estimates of 500,000 workers in the industry and GISCI's database of just under 10,000 members. DiBiase's (2012) view that the certification effort was that "is finally taking root" (p. 4) appears to be accurate, but the fledgling profession had a long way to go.

Competency Frameworks

Determining the competencies needed in the geospatial field has been difficult due to an assortment of factors. Primary among these factors is the fact that the requisite set of skills has evolved during geospatial science's brief existence (NRC, 2006) due to its interdisciplinary history and the variety of applications of the technology (du Plessis & Van Niekerk, 2014; Wikle, 2010). Such a broad interpretation of the geospatial domain leads to difficulty in defining the knowledge, skills, and abilities required within the profession. Marble (2006) also noted that the field is limited due to the absence of a fully developed idea of the components within the industry, and the competencies needed to support those sectors. Not only does this lack of industry comprehension limit our understanding of the diversity of skills necessary for success, but also the depth of knowledge required (Wikle, 2010). The obstacles facing the geospatial workforce at the beginning of the 21st century were summed up by Marble (2006), "Without an operational, structural model of both the geospatial industry and its workforce, we find ourselves in a weak position from which to address either the geospatial industry's future development or its related future workforce needs" (p. 3).

Competency models define what employees should know and need to be able to do for success, and they have been used to establish employee educational guidelines and selection criteria (Hong, 2016; Khan et al., 2016). Specifically, competency models address technical competencies, interpersonal skills, academic requirements for a position, occupation, or industry (Ennis, 2008; Solem et al., 2008). Annulis (2004) states that "competency models define the knowledge, skills, and abilities that a person needs for success in the workplace" (p. 6). Competency modeling became critical for the newly forming field of geospatial science on the heels of the US Department of Labor, designating geotechnology as an emerging field (Gaudet et al., 2003; Horák, 2015). Several attempts have been made since the early 200s to capture the critical skills needed by geospatial workers (Hong, 2016) with varying levels of success. A widely recognized and accepted framework for geospatial competencies would create a better understanding of the skills needed by workers in different portions of the geospatial economy and allow researchers to perform gap analysis for the workforce as a whole (Marble, 2006; National Geospatial Advisory Committee, 2012).

There has been agreement that to understand the needs of the geospatial workforce, researchers have had to define "core" knowledge, skills, and abilities of all geospatial professionals (Huxhold & Craig, 2003; Marble, 2006). For this reason, the focus went first to defining core competencies as a starting point for creating an industry framework (Sullivan, 2007) in an attempt to establish a connection between instruction and application. One approach typically used at a local level is a job analysis technique known as developing a curriculum (DACUM). The DACUM approach benefits from receiving input directly from "expert" workers regarding the competencies for a specific occupation (Johnson, 2010). The DACUM method is limited due to its location-specific nature but can be bolstered by similar activities around the industry. The National Geospatial Technology Center of Excellence (GeoTech Center) implemented a national approach to capture geospatial core competencies. Executing multiples DACUMs within different geographic locations and industry sectors, the GeoTech Center aggregated core competencies into a Meta-DACUM (Johnson, 2010). While limited in application to specified occupations, DACUMs have been a valuable resource as the field has searched to define itself.

There are numerous sectors or communities within the geospatial field which maintain specific knowledge domains outside of or in addition to the generally recognized competencies.

Geospatial intelligence is an example of a portion of the economy in need of a competency model to meet its specific needs. The United States Geospatial Intelligence Foundation (USGIF) developed the GEOINT Essential Body of Knowledge (EBK) for the geospatial intelligence discipline in 2014. Quinn (2015) defines the EBK as “the body of knowledge and skills a professional must possess to perform successfully” (p. 17). The EBK is used to frame the USGIF’s accrediting guidelines as well as establish its certification parameters. Not surprisingly, the USGIF used Subject Matter Experts (SMEs) from the government, industry, and academia to construct the EBK. The GIS&T BoK (recognized as the model for geospatial knowledge areas) and the GTCM (the industry-standard work geospatial competencies) were both used as foundational pieces for the USGIF accreditation process.

The University of Southern Mississippi (USM) Geospatial Workforce Development Center (GWDC) led an effort to create the first geospatial competency model with funding from the National Aeronautics and Space Administration (NASA). NASA recognized a significant shortage of trained geospatial workers and supported the development of a competency model for geospatial professionals (DiBiase, 2007; Gaudet et al., 2003). A competency model aids in the translation of knowledge, skills, and abilities for success, which can be used to build a workforce (Annulis, 2004). Specifically, Annulis and Gaudet (2007) asserted that the USM GTCM “describes the kinds of geospatial workers (roles) required, the products and services they provide (outputs), and the required knowledge, skills, and abilities (competencies) that the industry needs” (p. 2). The USM GTCM was built from input provided by subject matter experts in the geospatial industry, working as focus groups within a series of workshop sessions (DiBiase, 2008; Hong, 2016). Gaudet et al. (2001) defended this approach by asserting the following:

> A common mistake during the design process is that management, without input from role experts, makes decisions about the skills necessary to perform a particular job. The expected outcomes model based on role expert contributions lends itself to flexibility. The model looks to the future rather than just the present, and the model is not job-specific. The nonspecific model can grow and develop with the changing needs of the company or industry (p. 3).

The focus group used in the development of the USM GTCM identified 12 roles fulfilled by geospatial professionals and derived 39 competencies (DiBiase, 2008; NRC, 2006).

The USM GTCM was the first geospatial competency model, and while it possessed some shortcomings relative to later models, it was the most comprehensive work on geospatial workforce competencies at that time (Samborski, 2006). One deficiency (DiBiase et al., 2010; Prager & Plewe, 2009; Sullivan, 2007) of the model was its limited number (39) and coverage of competency topics within the domain, especially when compared to those skills present within the industry. Other criticisms dealt with a lack of clarification of terms, the need for refinement, and the development of greater detail within the model (DiBiase et al., 2010; Samborski, 2006). Nevertheless, the USM GTCM delivered a valuable framework for developing workers with the necessary knowledge, skills, and abilities required for success (Johnson, 2010; Sullivan, 2007). Also, later models used elements of the USM GTCM in their geospatial frameworks (DiBiase et al., 2010; Hong, 2016).

Organizations affiliated with higher education recognized very early that a curriculum model would benefit the burgeoning area. One of the first efforts was led by the National Center for Geographic Information and Analysis (NCGIA), who began the development of a wide-ranging set of subjects in support of curriculum (Goodchild & Kemp, 1992b; Mathews & Wikle, 2019). The result of educational meetings and efforts to share materials was the NCGIA Core Curriculum in GIS, which was issued in 1990 and contained 75 one-hour units within a three-course sequence (Goodchild & Kemp, 1992b; Tate & Unwin, 2009). The model's value was recognized almost immediately as a framework for defining geospatial competencies needed to certify professionals. The Core Curriculum for Technical Programs was released even as the Core Curriculum in GIScience was revised again in 2000 to address technological advances (Johnson, 2010; Veenendaal, 2014). These early models constructed an environment amenable to a model curriculum in geographic information science which was intended to prepare students for the geospatial industry and contained a *body of knowledge* (Goodchild & Kemp, 1992b; Johnson & Sullivan, 2010; UCGIS, 2003; Prager & Plewe, 2009), which later followed as the GIS&T BoK.

In 1998 the UCGIS formed a Model Curricula Task Force intending to outline a comprehensive set of topics unique to the geospatial domain (UCGIS, 2003; Mathews & Wikle, 2019). The focus element of this project was the creation of the BoK for the geospatial realm, which was composed of 10 knowledge areas, 329 topics, and 1,600 educational objectives (DiBiase et al., 2007; DiBiase et al., 2006; Schulze et al., 2013). After years of discussion, the Association of American Geographers (AAG) published the UCGIS GIS&T Body of Knowledge in 2006 (DiBiase et al., 2006) with an inventory, categorized as knowledge areas, of the evolving intellectual content within the GIS&T field (Johnson & Sullivan, 2010; Prager, 2012).

The BoK is a collection of technical competencies found within the geospatial field (DiBiase et al., 2007; Sullivan et al., 2008), where Kemp (2012) notes that "topics are defined in terms of educational objectives" (p. 56). Johnson and Sullivan (2010) add that the BoK "represents an attempt to define parameters for the field of GIS&T, albeit from an academic rather than an industry-driven perspective" (p. 9). The GIS&T BoK is seen by many as the most successful effort as yet to create a comprehensive inventory of knowledge, skills, and abilities unique to the geospatial domain (NGAC, 2012; Schulze et al., 2013; Veenendaal, 2014).

The BoK is intended to be used for curriculum evaluation and planning, act as a model curriculum for geospatial academic programs, and assess student learning outcomes (DiBiase et al., 2006; Hong, 2016; Prager & Plewe, 2009). Also, the BoK was used to prepare the DOLETA GTCM and by multiple certification and accreditation bodies as an assessment tool (DiBiase, 2007). Detractors note that the BoK lacks a workforce focus, including an absence of individual personal competencies, and should be evaluated by working professionals regarding its real-world applicability (Johnson & Sullivan, 2010; Schulze et al., 2013; Sullivan et al., 2008).

In 2010, DOLETA issued a Geospatial Technology Competency Model (GTCM), documenting the specialized knowledge, skills, abilities, and educational preparation necessary to become a successful geospatial professional (Sinton, 2012; DOLETA, 2014). Researchers noted the absence of a competency model, translating the application of geospatial learning outcomes to the workforce (Solem et al., 2008). The National Geospatial Technology Center of Excellence (GeoTech Center) was formed in 2008, and one of its goals was to address the need for a comprehensive model. The GeoTech Center constructed a panel of 12 Subject Matter Experts (SMEs) representing a cross-section of the geospatial industry that provided the input needed for the construction of the initial DOLETA GTCM (DiBiase et al., 2010). The USM GTCM and the GIS&T BoK were also used as resources during the development of the DOLETA GTCM (DiBiase, 2007; DiBiase et al., 2010; Schulze et al., 2013). Johnson and Sullivan (2010) believed the DOLETA GTCM to be a critical step in the profession and stated, "The DOL's new GTCM represents a major milestone in the development of a coherent GST field" (p. 10).

The DOLETA GTCM is based on a standardized model framework of convertible building blocks representing domain-specific and generic competencies needed in the geospatial workforce (Schulze et al., 2013; Veenendaal, 2014). Specifically, it is a 9-tiered model that identifies general and specific competencies addressing the foundational, industry-wide, and industry sector-specific expertise that differentiates geospatial professionals. The 9-tiered model contains foundational competencies (Tiers 1-3) addressing personal effectiveness, academic preparation, and workplace behaviors. Next are technical competencies which contain knowledge and skills that occur within all sectors (Tier 4) and competencies specific to a sector (Tier 5). The remaining tiers are occupational (Tiers 6-8) and managerial (Tier 9) competencies (DiBiase et al., 2010).

The DOLETA GTCM applies to current or future workers as it contains a comprehensive set of competencies needed by a working geospatial professional and can be used to guide academic studies or professional development (DiBiase, 2012; DOLETA, 2014). The DOLETA GTCM is viewed as the most appropriate model currently available to identify the knowledge and skills needed by geospatial professionals regardless of occupation or industry sector and was written to meet the needs of the labor market (Hong, 2016; Veenendaal, 2014). The GISCI regarded the DOLETA GTCM enough that it announced that it would look into the development of a competency exam based, in part, on the technical competencies located within the model (Johnson & Sullivan, 2010). Both the GIS&T BoK and the DOLETA GTCM used expert-based processes and are significant contributors to defining the competencies located within the geospatial field (DiBiase et al., 2006; Gaudet et al., 2003; Prager, 2012; Prager & Plewe, 2009; Schulze et al., 2013).

The Evolution of Geospatial Science from Geography

There has been an ongoing debate since the beginnings of geospatial science regarding whether it should be defined as a tool (technology) or science (academic discipline). In many ways, GIS represents something different to various people, contingent on the context, and the variation in the user perception causes the use of terms interchangeably. The Geospatial Information & Technology Association (GITA) asked their members to characterize GIS, but they determined that GIS could not be defined as a tool or profession, as the user would dictate its role depending on how central GIS was to their work (Secilmis, 2005). The argument for maintaining geospatial technology as a tool has a long history. In the beginning, geographic information systems (GIS) originated within the field of computer science, and, even today, the systems maintained around the world are thought of in this manner. There is a shared history with information systems, and many of the underlying components relating to data management, queries, and programming languages continue today. Horák (2015) provides evidence of the view when he submits that "GIS is usually understood as an applications-led technology" (p. 1357). Tomaszewski and Holden (2012) take a different approach, seeing geospatial technology as a "specialized set of information technologies that handle georeferenced data" (p. 2). The reliance on tools within the field has caused concern for geographers, especially as more advanced applications remove the need for an underlying geographic understanding. Zhou et al. (1999) noted that GIS was pushing geography towards an application-driven orientation, more aligned with information technology than geography.

There is an increasing number of university-level degrees offered in a variety of forms, and there is a growing recognition of GIScience as a discipline unto itself (Prager & Plewe, 2009). During the past 20 years, geography programs have grown in size and number within universities, and geospatial programs have emerged in community colleges across the United States. Some of this growth can be attributed to an increasing number of students attending higher education, but the impact of GIScience is visible through the growing number of courses relating to its content. Arrowsmith et al. (2011) attribute this expansion to workforce engagement and an adjustment in the mission of institutions around the country. Golledge (2000) predicted that discipline's response to the influence of GIS would "determine the viability, and ultimately the fate of geography" (p. 8). The impact is becoming significant as the idea of credentialing programs or students continues to move forward (Wikle, 2015). Wikle (2017) supports this point when noting that many GIS programs were transitioning to GIScience as a field of study. The continual growth of GIScience harkens back to a warning offered by Pickles (1993) when he asserted that "If it is to continue to claim that it is "science," then it must broaden its sphere of legitimation beyond method and application…" (p. 454). The effect of GIScience as an emerging discipline within a more extensive geographic field of study is inarguable, but its role within society may remain up for debate.

Discussions will continue as to whether geospatial science is seen as a discipline or tool, but there is a growing recognition of a geospatial field and, by extension, a profession (NRC, 2013) driven in part by its ability to enhance spatial thinking (NRC, 2006). Geospatial science is fundamentally interdisciplinary, blending components from information science and geography (Tomaszewski & Holden, 2012), but it distinguishes itself from information technology through the application of spatial thinking (NRC, 2006). Geospatial science was initially characterized as technology in search of applications (Goodchild, 1992) but has grown from being viewed as a means to acquire knowledge to an end of scientific inquiry itself (Wright, Goodchild, & Proctor, 1997). Regardless, debates are likely to continue as reasoned by DiBiase et al. (2010) "The breadth and diversity of geospatial has made it difficult to reach consensus about what the field entails, who geospatial professionals are, and what they should know and be able to do" (p. 55).

Workforce Development and Geospatial Competencies

As early as the late 1990s, the geospatial industry was being acknowledged and the first significant research effort into workforce development led by the National Aeronautics and Space Administration (NASA). NASA realized that there would be a dearth of skilled geospatial professionals in the coming years, and, with their support, the initial emphasis launched a workforce development initiative beginning in 1997 (Gaudet et al., 2003). Much of the later workforce analysis originated in the early 2000s came on the heels of geospatial technology being recognized by the president's High Growth Job Training Initiative (HGJTI), which targeted industries for research and analysis which were identified as having high-growth potential and vital to the economy (Annulis, 2004; Gewin, 2004; Sullivan, 2007). The increased demand in the use of geospatial technologies and related growth of the industry triggered additional research in geospatial workforce development (Annulis et al., 2004).

The lack of an understanding of the industry contributed to the difficulties in determining the competencies needed within a geospatial workforce. DiBiase (2012) noted that DOLETA was concerned that the lack of a clear definition of the geospatial industry could limit the public's appreciation of its value and potentially limit its growth. Marble (2006) had more significant concerns and recognized the difficulty in securing a competent workforce without first understanding the industry. The DOLETA supported research targeting geospatial workforce development and commissioned a study. The report, “Defining and Communicating Geospatial Industry Workforce Demand,” sums up the study (Samborski, 2006) with the following determination; “The geospatial industry acquires, integrates, manages, analyzes, maps, distributes, and uses geographic, temporal and spatial information and knowledge” (p. 3).

Duane Marble (1998) wrote of a pyramid of geospatial skills and asserted that the majority of positions would need only to possess rudimentary geospatial skills. That view has continued (Estaville, 2010; Wikle & Fagin, 2015) as software applications have become more advanced. The continued need for entry-level positions provides an opportunity for two-year colleges to shoulder an essential role in meeting geospatial workforce needs (Allen, Beck, Brand, Johnson, & Johnson, 2006). Marble summed up the situation at the time:

> Currently, we are in the midst of a geospatial labor market shortage that shows every sign of growing more acute in the years to come. The explosive growth in the utilization of geospatial tools and data in nearly every sector of the global economy has been driven by dramatic increases in the capabilities of our tools and in the increased availability of better spatial data. (p. 1)

A driver for the geospatial industry’s growth has been the need for more accurate geospatial data with as much currency as possible. Wikle (2015) observed that many more citizens routinely use geospatial technology within a given day, which has also created greater geographic awareness (Sinton, 2009). An increased appreciation for geospatial technologies has promoted its use in a growing number of areas (Gewin, 2004).

While the U.S. Department of Labor expects the need for geospatial workers to continue its growth, researchers are noting the need for a higher level of expertise within the field (Vandenbroucke & Vancauwenberghe, 2016; Wikle, 2015) than previously required. The increase in the geospatial services industry and the related need for qualified workers is not new (Annulis, 2004; Gaudet et al., 2001; Gewin, 2004; Obermeyer, 1993), but the continuous inability to develop a workforce is concerning (DiBiase et al., 2006; Estaville, 2010; Marble, 2006; NRC, 2006; Solem et al., 2008). Even as researchers look ahead, the potential for future shortages continues (NGAC, 2012; NRC, 2013) as workers are either unprepared for the workforce or are unable to adapt to an evolving geospatial domain (Solem et al., 2008; Vandenbroucke & Vancauwenberghe, 2016). Defining the essential skills of a geospatial worker has evolved over time and differed from Gaudet et al. (2003) who stated that geospatial workers should possess "a blend of technical, business, analytical, and interpersonal competencies" (p. 25) to the NRC (2013) who argued that the geospatial workforce should be composed of a collection of skills that include "spatial thinking, scientific and computer literacy, math/statistics and professional ethics" (p. 74). Regardless of the era, it is apparent that workers must possess both the tangible and intangible skills valued by industry (Prager & Plewe, 2009).

Development of a Geospatial Profession

The question of whether geospatial information science was a profession began in the 1990s (Goodchild & Kemp, 1992a; Huxhold, 1991; Obermeyer, 1994), and still, there remains discussion on the need for a profession centered on geospatial competency (Wikle, 2017). While there is no consensus on all of the attributes that define a profession, many (DiBiase, 2007; Huxhold & Craig, 2003) have looked to Pugh's (1989) six attributes of a profession (self-awareness, a body of knowledge, an ideal of competence and expertise, ethical standards, formal organization, and a "hall of fame"). Some would argue that the final component needed was the formal creation of standards for a *GIS Professional* certification (Obermeyer, 2009), others waited until after the completion of a formal body of knowledge and related competency framework (DiBiase, 2012; Joffe, 2018; Quinn, 2015).

Applying Pugh's (1989) standard, there appears to be an emerging consensus that a geospatial profession exits (DiBiase, 2012; Fagin & Wikle, 2011; Kemp, 2003; Obermeyer, 2009). Once a profession has been established, members are expected to demonstrate professionalism (Kemp, 2016), which is based, in part, on its membership possessing expertise (Obermeyer, 1993). The test will be to require those operating in the geospatial domain to understand and apply the underlying geospatial science so that they may use the technology and associated tools to function in whatever role is appropriate within the geospatial field. The challenge then becomes the maintenance of standards for the profession (Gaudet et al., 2003) and the promotion of standards for competency (Mathews & Wikle, 2017). It is in the field's best interest to demonstrate the capabilities of its members, as Secilmis (2005) commented: "After all, competency is the ultimate workforce attribute" (p. 2).

The geospatial profession is a component within a developing industry that crosscuts many other workforce sectors (du Plessis & Van Niekerk, 2014; Gewin, 2004), and intersecting fields have challenged the need for a separate designation. Both land surveying and photogrammetry organizations, representing professions with long-standing histories of licensure or certification, have questioned the ability of the geospatial area to ensure competence among its members. DiBiase (2008) may have put it best when he said, "Broadly conceived, the GIS&T field occupies the intersection of accredited and non-accredited disciplines, regulated and unregulated professions, and old and new technologies. No wonder the field is contentious and confusing" (p. 1506). The geospatial industry needs a framework to define a competency standard for the field if there is hope to ensure that qualified geospatial professionals remain in the industry (Huxhold & Craig, 2003; Secilmis, 2005).

Chapter Summary

This chapter reviewed the relationship between competency determination and the evolution of geospatial science. The literature demonstrates the role that geospatial competency delineation has serves to distinguish the discipline, the need for competency evaluation, and how these considerations work to support a viable geospatial workforce. The literature reviewed demonstrated the emergence and separation of geospatial science from related disciplines, the models used to define learning outcomes and competencies, and evaluation methods developed to assure competence within the workforce. The literature provides evidence of the supportive nature of multiple models and the eventual acceptance of the industry-wide models detaining student learning outcomes (GIS&T Body of Knowledge) and workforce competencies (DOLETA Geospatial Technology Competency Model). Also, this review demonstrates how experts have been used to construct and evaluate competency models. The literature review shows that this study is the first to review the perception of geospatial competencies by requiring geospatial professionals to complete a sorting exercise within a Q Methodological study. The results of this study will contribute to the knowledge of how relevant geospatial professionals view the competencies contained within the model.

CHAPTER 3: METHODOLOGY

Introduction

The purpose of the study is to explore the viewpoints of geospatial professionals toward the Geospatial Technology Competency Model (DOLETA, 2019) and why they hold these views. By assessing the perceived relevance of these competencies, this study can isolate gaps in practice and better inform educational institutions as they prepare students for geospatial careers as well as facilitate the refinement of occupational titles at the DOL. The research questions below were used to develop the study:

1. How do Geographic Information Science Professionals view the technical competencies within the Geospatial Technology Competency Model and why?
2. Do perceptions of the geospatial competencies differ based upon the respondents' industry-sector, years of experience, method of certification, or education?

The methods section includes an overview of the research approach, research design, and research setting. The methods section described the methods in the steps in Q methodology, including the development of the question set from a concourse of statements, selection of a group of study participants, data collection, analysis of the data, and concluding with an explanation of the results.

Overview of the Research Approach

This study utilized Q Methodology, a mixed methods approach to research developed by William Stephenson in 1935 (Cuppen et al., 2016; Dziopa & Ahern, 2011; Simons, 2013). Q Methodology is a technique for studying human subjectivity with the facility to reveal shared subjectivities. (Brown, 1993; Cross, 2005). The methodology can provide qualitative detail regarding varied perspectives (Watts & Stenner, 2005; Zabala & Pascual, 2016), while still applying the structure found in quantitative techniques (Shemmings, 2006; Steelman & Maguire, 1999). Stephenson (1935) offered Q Methodology as an inversion of traditional factor analysis, where the analysis would correlate viewpoints instead of tests. He also stated:

> Whereas previously a large number of people were given a small number of tests, now we give a small number of people a large number of tests or test-items, or require a large number of responses from them. Previously individuals obtained scores; now the tests get them instead, due to the operation of the individuals upon them. By the present-day technique we obtain the factor saturations or loadings of tests, but by the new one we can obtain saturations for individuals. (pp. 18-19)

Watts and Stenner (2012) noted a strength of Q methodology as to be its capacity to reveal the intercorrelations of the data and their factor loadings, adding that "a well-delivered Q study reveals the key viewpoints extant among a group of participants and allows those viewpoints to be understood holistically and to a high level of qualitative detail" (p. 2).

Q Methodology has been used in previous research to gauge individual views and capture shared viewpoints (Cuppen et al., 2016; Flowers, 2017; Hatcher, 2010; Rogers, 2015; Steelman & Maguire, 1999; Varnadore, 2018). Therefore, it is appropriate to apply the methodology in this study to reveal individual beliefs of geospatial professionals regarding the relevance of technical competency statements found within the DOLETA GTCM.

Using Q Methodology in a research study is a five-step progression (Cuppen et al., 2016; Simons, 2013; van Exel & De Graaf, 2005). The process begins with the development of the Q-sample, which is the collection of statements sorted by the respondents. The Q-sample is developed from a "concourse," which was characterized by Wright (2013) as "a collection of statements that encompass all views about the subject under scrutiny" (p.154). The second step involves the selection of a group of study participants. The third step is the data collection, where respondents sort the statements and provide additional qualitative input. The fourth step involves the analysis of the data using a factor loading technique. The fifth and final step of the analysis involves the explanation of the results.

Research Setting

The ability to discover the geospatial competencies perceived as the most important within the field would provide more information to higher education institutions, professional societies, and certification organizations. As competence is a measure of the application of knowledge against a standard, a competency model is the specific combination of capabilities needed for effective performance. The demarcation of geospatial competency differentiates the discipline, allows for the emergence of geospatial science, and supports a viable geospatial workforce. The geospatial industry has selected the DOLETA GTCM as a unifying framework for workforce development, viewing it as the best approach to capturing the competencies required for successful performance. Experts have been used to evaluate geospatial competency models of one kind or another in the past, but this study is the first to review the perceptions of geospatial competencies within the DOLETA GTCM beyond a Likert scale approach. The results of this study will contribute to the knowledge of how relevant geospatial professionals view the competencies contained within the model.

Selection of Concourse and Q-sample (Q-set)

The concourse is an extensive collection of possible statements that capture individual viewpoints of topics within a domain (Bartlett & DeWeese, 2015; Cuppen et al., 2016; Dziopa & Ahern, 2011; Zabala & Pascual, 2016). Brown (1993) describes concourse theory as, “In Q, the flow of communicability surrounding any topic is referred to as a concourse…and it is from this concourse that a sample of statements is subsequently drawn for administration in a Q sort" (pp. 94-95). Wright (2013) added that in the concourse, "statements are usually sorted and thematically grouped" (p. 154). Determining when a concourse is complete can be challenging for researchers (Simons, 2013). This problem is less of a concern if the statements are representative of opinions held within the domain (van Exel & de Graaf, 2005). The DOLETA GTCM provided the initial statements found in the concourse. The DOLETA GTCM is recognized at the definitive model of geospatial workplace competencies and is a foundational document for the GISCI's certification examination. The DOLETA GTCM was developed in 2010 and has been revised in 2014 and 2018 to remain current with changes within the industry.

The concourse of communication is sampled to build a Q-set. The process of sampling from the concourse can present challenges (Simons, 2013) as the statements must be reduced to a reasonable number. McKeown and Thomas (1988) offer that researchers can use both unstructured and structured sampling to reduce the topics. The method does not matter, but the Q-sample must be typical of all statements and accurately represent a cross-section of the concourse (Brown, 1993). This idea was summarized by van Exel and De Graaf (2005), who wrote that "The concourse is thus supposed to contain all the relevant aspects of all the discourses. It is up to the researcher to draw a representative sample from the concourse at hand" (p.4). Regardless, there must be criteria and a process for reducing the selection of statements from the concourse to the Q-sample. This step is essential, as stressed by Zabala and Pascual (2016), "in order to conduct a Q study the researcher uses explicit criteria to select a set of statements from the concourse. The concourse is a hypothetical concept that conveys the infinite set of possible expressions that refer to a topic of concern" (p.3).

This study took several steps to meet the standard of a viable Q-sample representative of the concourse of communication. The DOLETA GTCM contains a total of 290 competencies. Cross (2005) suggests that the initial number of statements may be much larger than the final number of items and could be "reduced in number by pilot testing, the aim being to achieve optimum balance, clarity, appropriateness, simplicity and applicability" (p. 209). One hundred eighty-six of these competencies are not technical, not evaluated for GISP certification, and excluded from consideration. Of the remaining 104 technical competencies, 42 reside within Tier 4 (Industry-Wide Technical Competencies) and are a collection of *crosscutting geospatial abilities and knowledge*. Tier 5 (Industry-Sector Technical Competencies) contains the remaining 62 competencies distributed between the industry sectors of Positioning and Data Acquisition (25 competencies), Analysis and Modeling (18 competencies), and Software and Application Development (19 competencies). While some studies (Simons, 2013) cite that as many as 140 statements have been used in a Q-sample, the typical range would include between 40 and 80 statements (Simons, 2013; van Exel & De Graaf, 2005; Watts & Stenner, 2005; Zabala & Pascual, 2016). The concourse of technical competencies contained Tier 4 (Industry-Wide Technical Competencies) and Tier 5 (Industry-Sector Technical Competencies) of the GTCM. The researcher developed the Q-set (see Appendix A) from the specialized technical competencies found in Tier 5, as these competency statements incorporate the accepted knowledge, skills, and abilities needed by geospatial practitioners. The statements located with Tier 4 are themed as addressing crosscutting geospatial abilities and represent the core geospatial competencies in the field. However, Tier 5 builds upon these statements and extends its application into three designated industry sectors of analysis and modeling, positioning and data acquisition, and software and application development. To include both tiers of the technical competencies would have been unnecessarily redundant and would not have advanced the research. The result of the reduction process resulted in the creation of a 62 statement Q-sample.

Selection of P-sample (P-set)

The selection of a viable collection of respondents with geospatial expertise is necessary for conducting this Q Methodology study, particularly when considering the relatively low number of participants. Recognizing this need, the P-sample was built from a group of certified geospatial professionals. This decision is supported by Wright (2013), who stated that “P-set membership should reflect a body of participants who are ‘theoretically salient’ to the issue under study”(p.154). Specifying the parameters for determining inclusion in the P-set is critical, as the research is searching for representative perspectives. Watts and Stenner (2005) continued this argument by stating that “the exact constitution of the participant group must also be considered. In some contexts, it may be sensible to strategically sample participants” (p.79).

Perspective is at the center of this research, and the P-sample must be built upon a diverse collection of participants’ representative of the different sectors of the geospatial realm who are relevant to the statements under consideration (van Exel & De Graaf, 2005). As offered by Bartlett and DeWeese (2015), “The number of persons associated with a factor is of less importance than who they are” (p. 76). The point of Q Methodology is to reveal varied perspectives rather than generalize a population (Watts & Stenner, 2012). The use of purposeful sampling or what Watts and Stenner (2012) describe as “strategic sampling” (p. 71) is to elicit distinct views (van Exel & De Graaf, 2005). Cuppen et al. (2016) share a view of the value they find in the diversity of opinion, “This means that the fact that a person is expected to provide a different viewpoint as the other respondents is enough reason to include him/her in the P set” (p. 1351). Finally, Simons (2013) summed these concepts as follows, “the objective in Q is to be able to describe typical representations of different viewpoints rather than find the proportion of individuals with specific viewpoints" (p. 29).

The size of the P-sample is much smaller than needed in a typical survey. The P-sample is usually smaller than the Q-sample, and Simons (2013) notes that finding enough participants does not generally present a challenge. Also, Bartlett and DeWeese (2015) believe the "Q methodology does not require large samples to develop themes of subjectivity" (p. 76). The typical range of respondents varies from 40 to 60 (Dziopa & Ahern, 2011; Simons, 2013) individuals. Wright (2013) adds, "that the number of the participants rarely is greater than the number of statements in the Q sample" (p. 154). The relationship between the number of statements and the size of the participant group is optimized when four or five participants are loading on each respective viewpoint (van Exel & De Graaf, 2005; Wright, 2013). The ability of the GISCI to provide a participant group who are knowledgeable, invested, diverse, and of limited size enabled the use of a valid P-sample. The recruitment email (see Appendix B) was sent through the GISCI's Executive Director.

Selecting participants in a Q Methodology study is different in primarily two ways from traditional research. The first difference relates to the sampling of participants, and the sample size needed for a study (Cuppen et al., 2016). Participant selection can be driven by theory or opportunity (McKeown & Thomas, 1988), but Watts and Stenner (2012) explain that "perhaps the most important single message about participant recruitment in Q methodology is that opportunity sampling is rarely the best strategy" (p. 71). McKeown and Thomas (1988) add that "it is not the purpose of Q-method to explore idiosyncrasy at the expense of general principles" (p. 37). A goal of this study is to maximize the probability of revealing a variety of individual viewpoints (Stenner, Watts, & Worrell, 2017).

This study used the certification as a GISP as the primary criterion for selection to participate. The GISCI has approximately 10,000 members, but only a few hundred are active contributors. Using these members meets the standard of professional expertise and commitment to the field. A diverse population of respondents can provide a universal pool of the views within the domain. The instrument was appraised through field tests with a selected group of geospatial professionals not included in the study. The group evaluated the informed consent message, quality of procedural instruction, ease of the Q-sort exercise, and clarity of the qualitative questions. The researcher used the feedback to improve the activity.

North Carolina State University's Institutional Review Board (IRB) dictated that researchers follow a strict ethical code to protect those individuals who participate in the study. The NC State IRB approved this study (see Appendix C) requires that each participant must provide *informed consent* before participating in the research. The informed consent (see Appendix D) will be noted by the pressing of an *I AGREE* button by respondents before they begin the Q-sort. As part of the informed consent process, selected participants were provided information about the purpose of the study, the duration of the exercise, and the steps involved. Also, respondents were informed that the study was voluntary and that they could withdraw at any time. Participant confidentiality is a required component of ethical research (Creswell, 2014). Respondents were made aware that their information would not be anonymous but would be confidential, and that their privacy would be protected throughout the research study.

Construction of the Q-Sort

The foundation of Q Methodology is the Q-sort technique, which involves the rank-ordering of a set of statements along a range of values (Brown, 1996). The Q-sort is usually a self-directed process, with the participants using a set of instructions to guide the sorting process.

The Q-set is numbered randomly to reduce the potential for the introduction of bias (Cross, 2005), and the design permits the respondents to evaluate each statement against the others (Bartlett & DeWeese, 2015). Participants are provided statements which they sort based upon the level to which they *agree* or *disagree*, which express their subjectivity and models their perspective by rank ordering Q-sample statements (Brown, 1993; Zabala & Pascual, 2016). Zabala et al. (2018) state that the instruction can refer, for example, to an agreement with items, importance, acceptability, or closeness to the respondent's beliefs" (p. 1188).

The sorting process begins with a rough sorting of the statements into three piles: statements with which the participants generally agree, those items which they generally disagree with, and those about which they are undecided (Bartlett & DeWeese, 2015; van Exel & De Graaf, 2005). Participants are given a response grid to place their choices, the size and structure of which will be influenced by the number of statements being sorted (Cross, 2005). Respondents place their statements on the grid, which generally varies in size from 9 to 13 categories with values ranging from as low as 4 (+/-) to as high as 6 (+/-) depending on the number of statements located within the Q-sort (Bartlett & DeWeese, 2015; Cross, 2005; Simons, 2013; Steelman & Maguire, 1999). Zabala et al. (2018) elaborate, "Items placed in the same column receive the same ranking score. The sorting grid for this study ranged from -6 to +6 to support the 62 competencies under review, as there must be a spot in the matrix for every statement (Bartlett & DeWeese, 2015).

The Q-sort process is directed and organized to elicit accurate results, and Watts and Stenner (2012) discussed Stephenson's reasoning for his approach to the Q-sort:

> He also insinuates that his new and ingenious means of data collection might be enhanced by the imposition of a 'prearranged frequency distribution'. This distribution is another

> notable, and ultimately very famous, innovation known as the Q sort…Stephenson presumed this general shape – which evidently forces a relatively large number of items toward the midpoint of the distribution and permits far fewer at the peripheries – to be the (pre)arrangement of choice for gathering Q methodological data. (pp. 17-18)

The sorting grid is customarily shaped as a quasi-normal distribution, which will vary depending on the size of the Q-sample (Simons, 2013; van Exel & De Graaf, 2005; Watts & Stenner, 2005). In our study, the sorting grid was a normally distributed 13-point scale. The scaled grid (see Figure 4) measured perceptions regarding the ranking of the competence statements, from most relevant to least relevant. The quasi-normal distribution is based, in part, on the belief that fewer statements would naturally occur at the ends of the spectrum (Dziopa & Ahern, 2011; Simons, 2013; Wright, 2013; Zabala & Pascual, 2016). Brown (1993) notes that the shape of the distribution will not affect the statistical analysis.

The distribution is also characterized as "forced" due to the restrictions of the grid. The matrix is preset with a prescribed number of rows and columns with the aligned positive and negative values. The prescriptive nature of the model encourages respondents to reflect on their feelings more carefully and approach the exercise systematically (Steelman & Maguire, 1999; van Exel & De Graaf, 2005). Dziopa and Ahern (2011) note that many participants do not like forced sorting, but the advantage is that it prevents participants from remaining neutral and requires them to make value judgments (Wright, 2013). The Q-sort approach is similar to the Likert Scale for evaluating attitudes, but the key difference is that in a Q-sort, all statements are evaluated in comparison with other statements, rather than individually (Cross, 2005; Cuppen et al., 2016).

Typically, participants are asked some qualitative questions after the survey in an attempt to clarify their sorting decisions. The answers address the respondents' process for the ranking of statements, particularity those found at the ends of the distributions (Wright, 2013; Zabala et al., 2018). The information collected here will play an essential role in the analysis of the Q-sort and the subsequent factor loadings. The survey asked participants about (a) rationale for the competency statements placed at the extremes of the distribution, (b) the statements they had the most difficulty placing, and (c) any factors that played a significant role in the sorting process. Also, the researcher provided a series of demographic questions for the participants.

						0						
						0						
					-1	0	1					
				-2	-1	0	1	2				
				-2	-1	0	1	2				
			-3	-2	-1	0	1	2	3			
			-3	-2	-1	0	1	2	3			
		-4	-3	-2	-1	0	1	2	3	4		
	-5	-4	-3	-2	-1	0	1	2	3	4	5	
-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6

Figure 4. Q-sort Grid

Data Collection

The researcher collected data remotely using the Q Method Software product. The participants were sent a recruitment email describing the study and solicitation of their participation. Respondents followed the link provided and arrived at the entry point for the Q-sort activity (see Appendix E). They then reviewed the study description and then moved forward to the informed consent page where they reviewed a description of the study, and the role the NC State Institutional Review Board (IRB) plays in protecting their rights. They were given the option to *agree* or *not agree* to complete the activity, indicated by their selection of either button. If the respondents agreed to participate, they were taken to the next page where a protocol or instruction initiates them to the Q-sort activity. Videos were provided for reference and instruction, as needed. Also, a short video describing Q Methodology was available, should the respondents be interested. The next page provided an opportunity for the respondents to pre-sort the views of the technical competency statements into three categories as either least relevant, neutral, or most relevant to the geospatial industry. Upon completion, they were automatically moved to the sorting grid, where they made the final determinations. The software provided the option for respondents to change their decisions until they have resolved any concerns. Once complete, respondents submitted their responses and continue to a confirmation page. Upon completion, respondents were provided a summary of the study and a note sharing the researcher’s appreciation for their participation in the research study.

Data Analysis

Q Methodology conducts data analysis to identify constructs to which participants align themselves by applying an inverted form of factor analysis (Stephenson, 1935; Watts & Stenner, 2012; Wright, 2013; Zabala et al., 2018). Conducting a by-person factor analysis allows the researcher to recognize similarities and differences in viewpoints (Simons, 2013; van Exel & De Graaf, 2005; Watts & Stenner, 2005). The initial results of the Q-sort reveal factor characteristics such as the eigenvalues and percent of variance explained, which are used to decide on the initial factors generated (Watts & Stenner, 2005). Data analysis begins with a correlation matrix summarizing views, and factor extraction reveals the cluster of opinion (Steelman & Maguire, 1999).

Correlation Matrix

Data analysis begins with establishing the relationship between the variables, and this association between variables is revealed in a correlation matrix of Q-sorts. The correlation coefficients between the individual Q-sorts help to identify shared views held by respondents (van Exel & De Graaf, 2005). In discussing the correlation matrix, Bartlett and DeWeese (2015) offer the following summary, “This process represents the level of (dis)agreement between the individual sorts, otherwise known as the points of view that are demonstrated by each participant” (p. 79). The correlation matrix thereby reflects a relationship between the Q-sorts, not items found in the individual sorts (Watts & Stenner, 2012). Correlation statistics range between -1.00 (signifying a perfectly negative relationship) and +1.00 (signifying a perfectly positive relationship) between Q-sorts, while a 0.00 value would reflect a lack of association (Watts & Stenner, 2005). Q-sorts with values approaching 1.00 denote similar beliefs. Bartlett and DeWeese (2015) noted, “The goal of this process is to determine the variability of Q-sorts to determine how many shared factors are in evidence” (p. 79).

Factor Analysis

The researcher applies a data reduction technique known as factor analysis to the items found in the correlation matrix (Watts & Stenner, 2005), intending to explain as much variance as possible within the Q-sort (Wright, 2013). The factor analysis reduces the data to a few summarizing unrotated factors indicative of representative responses (Zabala & Pascual, 2016). These data are reduced using either centroid factor analysis (CFA) or principal components analysis (PCA). The primary difference between the two techniques is that PCA is purely mathematically-based, whereas CFA allows for decisions to be related to established theory (Wright, 2013). Watts and Stenner (2012) saw a distinction between the approaches:

> The key difference in the current context is simply that PCA will resolve itself into a single, mathematically best solution, which is the one that should be accepted. This may sound attractive of course, given the problem of infinite solutions we highlighted earlier, but it generally isn't attractive in Q methodology. It just deprives us of the opportunity to properly explore the data or to engage with the process of factor rotation in any sort of abductive, theoretically informed or investigatory fashion. (p. 97)

Watts and Stenner (2012) also stated that CFA was generally accepted as the preferred approach when compared to PCA.

The intent of using factor analysis is to identify underlying patterns within the data and reveal collections of like-minded respondents who similarly rank the statements based upon shared beliefs (Shemmings, 2006; Zabala & Pascual, 2016). Factor extraction groups Q-sorts from respondents who sorted the statements similarly, with each cluster representing an opinion (Cuppen et al., 2016; Steelman & Maguire, 1999). The task for the unrotated factors is to explain the variance found in the correlation matrix by loading as many Q-sorts as possible (Shemmings, 2006; Zabala et al., 2018). The first factor explains the most variance, with each subsequent factor explaining less (Bartlett & DeWeese, 2015; Watts & Stenner, 2012). The factors represent a hypothetical best-representative Q-sort, and, typically, only a few factors are selected (van Exel & De Graaf, 2005; Zabala & Pascual, 2016). The number of factors selected and rotated depends on the variability of the Q-sorts, but there are usually no more than seven factors (Dziopa & Ahern, 2011; Wright, 2013).

Factor Score Calculation

A factor loading is calculated for each Q-sort and is similar to correlation coefficients, as it denotes the degree to which a Q-sort aligned with each factor (Cross, 2005; Zabala et al., 2018). Individual Q-sorts with substantial loading on a factor are seen as *factor exemplars*, as their sort configuration is characteristic of that factor (Simons, 2013; Watts & Stenner, 2012). Eigenvalues are indicators of the extractors' ability to explain variance (Watts & Stenner, 2012). It is generally accepted that only factors with an eigenvalue greater than one (1.00) are seen as significant and selected for extraction and interpretation (Dziopa & Ahern, 2011; Shemmings, 2006). Watts and Stenner (2005) discuss their view on a cutoff value for eigenvalues, "A standard requirement is to select only those factors with an eigenvalue in excess of 1.00….it is generally accepted means of safeguarding factor" (p. 81). A researcher can also use a scree plot to support a decision on the number of factors selected. Watts and Stenner (2012) note that a scree plot can assist the researcher as it can "prevent the arbitrary retention of all factors with EVs greater than 1.00" (p. 117) by providing a visual display of the factors.

Factor Rotation

Factors are rotated after factor extraction in an attempt to get a better *fit* for the data and preserve the initial variance or increase the total variance explained (Bartlett & DeWeese, 2015). As clarified by McKeown & Thomas (1988), "The purpose is to maximize the purity of saturation of as many variates (Q-sorts) as possible on one or the other of the factors extracted initially" (p. 52). Factor rotation changes the viewpoint from where factors are observed and is a technique to make the output more understandable (Bartlett & DeWeese, 2015; Zabala et al., 2018). There are two options for factor rotation, varimax or judgmental, depending on the study. Varimax rotation is often used if the research is exploratory, whereas a judgmental rotation can be used if driven by prior research or theory (Cuppen et al., 2016; Wright, 2013). Watts and Stenner (2005) offered their position regarding rotation techniques, "it makes theoretical sense for us to pursue a rotated solution which maximizes the amount of variance explained by the extracted factors and as the Varimax procedure automatically seeks this mathematically superior solution, it also makes sense for us" (p. 81).

Rotated Factor Score Calculation

New factor scores are calculated once the rotation is complete, and the position of the evaluated statements provides an initial indication of the factor's viewpoint (Bartlett & DeWeese, 2015; Zabala & Pascual, 2016). Comparisons cannot be made between factors due to the different number of contributing Q-sorts (Watts & Stenner, 2012) loading upon the identified factors. The factor scores must first be standardized by converting them to a z-score before conducting any cross-factor analysis (Watts & Stenner, 2012 Zabala et al., 2018). A z-score defines a factor by illustrating a relationship between statements and factors which can be compared within a data matrix (Bartlett & DeWeese, 2015; Zabala & Pascual, 2016). The z-score is a continuous number representing the value assigned to a statement within each related factor and helps to define that factor's characteristics (Dziopa & Ahern, 2011; van Exel & De Graaf, 2005). The z-scores are then converted into whole numbers (e.g., -6 to +6 in the case of this study) to assist in cross-factor comparisons much like the values assigned during the sorting process (Bartlett & DeWeese, 2015; Dziopa & Ahern, 2011; McKeown & Thomas, 1988). Just as before, the sign of the score signifies a factor's agreement (or lack thereof) with each statement (Zabala & Pascual, 2016).

Factor Interpretation

Factor arrays, or the clustering of similar Q-sorts, are a strength of Q Methodology (Cuppen et al., 2016; Dziopa & Ahern, 2011). These arrays allow the researcher to interpret how the statements rank within each factor and begin theme development (Bartlett & DeWeese, 2015). A factor array represents a composite Q-sort for a conceptual best-fit of respondents loading predominantly on that factor (Dziopa & Ahern, 2011; McKeown & Thomas, 2013). A factor array plays a role in factor interpretation and theme development, as it can be seen as a typical Q-sort for the factor and is a generalization of a perspective (Bartlett & DeWeese, 2015; Cuppen et al., 2016; McKeown & Thomas, 2013). The factor scores allow the researcher to evaluate the configuration of all items within the array and the significance of specific statement locations (McKeown & Thomas, 1988; Watts & Stenner, 2012). The researcher developed *crib sheets*, as offered by Watts and Stenner (2012), to aid in the factor interpretation. The crib sheets (see Appendix F) used were modeled after one referenced by Watts and Stenner (2012).

Statements within the factor array with the highest and lowest scores are typically more useful for interpreting themes (Bartlett & DeWeese, 2015; Zabala et al., 2018). The analysis of statements that score the highest or lowest work to define a factor and distinguish it from another factor (Cuppen et al., 2016; Wright, 2013). A distinguishing statement will score significantly different on one factor as opposed to another, but consensus statements tend to align themselves similarly across the factors (Zabala & Pascual, 2016; Zabala et al., 2018). The results of the data analysis also provide a qualitative narrative, summarized in a title, which is derived from the most distinguishing characteristic of the perspective (Cuppen et al., 2016; Zabala et al., 2018). The title provides easy identification, and the narrative delivers an overview of the factor, highlighting various critical elements, including an ideal Q-sort (Cuppen et al., 2016; Simons, 2013). Many times the data collected in a post-sort questionnaire can provide valuable insight and assist in uncovering combinations of themes attached to a perspective (Bartlett & DeWeese, 2015; Watts & Stenner, 2005).

Validity and Reliability

Discussions surrounding validity and reliability are less prevalent in Q Methodology studies as they appear to be less relevant to the research than in similar research using R Methodology (Dziopa & Ahern, 2011; Watts & Stenner, 2012). Dziopa and Ahern (2011) offer that the lack of an external reference for an individual's perspective makes it impossible to evaluate validity. Watts & Stenner (2012) assert that validity, as it is understood in R Methodology, is meaningless due to the absence of a reference point. Also, Dziopa and Ahern (2011) note that the repeatability of results could be used to assess the reliability of a study. Watts and Stenner (2012) summarized the topic as follows,

> Reliability and validity, as understood in R methodology, are not applicable to Q methodology. One can, however, demonstrate that Q methodology delivers what it claims to deliver, i.e., the viewpoints of its participants, and hence that it is valid. This can be done by asking multiple participants to sort a set of items all from a single, imposed or primed viewpoint. (p.67)

Q Methodology is also different from other approaches regarding the number of participants. The typical range of respondents varies from 40 to 60 (Dziopa & Ahern, 2011, 2011; Simons, 2013) individuals and the relationship between the number of statements and size of the participant group is optimized when there four or five participants loading on each respective viewpoint (van Exel & De Graaf, 2005; Wright, 2013). There were 54 respondents in this study, which is consistent with acceptable standards. McKeown and Thomas (1988) explain the viability of a smaller number of survey respondents:

> In Q methodology, on the other hand, small numbers of respondents, including single cases, are psychometrically acceptable since the observational perspective is the respondent's own. Any interpretive accounts advanced by researchers, then, are subservient to the respondent's frame of reference as made operant by Q-sorting. It is for this reason that the validity and reliability tests so central to conventional scaling in mainstream attitude research are simply unessential within the psychometric framework of Q methodology. (p. 44)

The online Q-sort exercise forces respondents to place their statements in a normal distribution. The exact shape of the distribution is left to the researcher, but van Excel and de Graaf (2005) note,

> The kurtosis of this distribution depends on the controversiality of the topic: in case the involvement, interest or knowledge of the respondents is expected to be low...the distribution should be steeper in order to leave more room for ambiguity…in case respondents are expected to have strong, or well-articulated opinions on the topic at issue, the distribution should be flatter in order to provide more room for strong (dis)agreement with statements. (pp. 6-7)

This study used a normal distribution that is neither mainly flat nor peaked, as there has been no assessment of the respondents' investment or conviction before the study.

Limitations

The data capture window for this study does not align well with a national event filled with potential participants. Also, there is not a conference currently that allows participation to only geospatial professionals who have demonstrated a commitment to the field. Finally, if such an event occurred, this study would not be able to establish a history demonstrating expertise in the geospatial field or a particular commitment to its advancement.

Delimitations

The field of participants in this study is limited to those geospatial professionals who are certified or have demonstrated an exceptional level of commitment to the advancement of the profession. The data collection was conducted online in order to survey the chosen population. Unfortunately, there is no assurance that the respondents in the sorting activity equally represent the various divisions within the field.

Chapter Summary

This chapter provided the appropriateness of using Q Methodology to address perceptions of geospatial competencies. Also, the discussion explained the phases involved in a Q Methodological study and how this research conforms to the parameters established by previous researchers. Furthermore, the chapter delivered a broader conversation regarding the decisions made in the development of the concourse, Q-set, P-set, and Data Analysis. The culmination of the analysis of the decision to use Q Methodology in the study related to its suitability to answer the research questions while adhering to validity and reliability requirements.

CHAPTER 4: FINDINGS

This chapter describes the results of a research study consistent with Q Methodology, which attempts to reveal varied perspectives rather than generalize a population (Watts & Stenner, 2012). Upon receiving approval from the NC State Institutional Review Board to conduct the study, the researcher sent an email through the geographic information science certification institute (GISCI) soliciting geographic information science professionals (GISP) participation from their members. The members of the GISCI represent approximately 1% of the geospatial workforce and must complete an arduous certification process. The sampling of this limited population is supported by Wright (2013), who stated that "P-set membership should reflect a body of participants who are 'theoretically salient' to the issue under study" (p.154). 54 GISPs completed a Q-sort activity whereon they sorted 62 sector-specific technical competencies from Tier 5 of the Geospatial Technology Competency Model (GTCM).

The study results address the following research questions:

1. How do Geographic Information Science Professionals view the technical competencies within the Geospatial Technology Competency Model and why?
2. Do perceptions of the geospatial competencies differ based upon the respondents' industry-sector, years of experience, method of certification, or education?

P-set Demographics

The respondents are a varied and experienced group, averaging 22.9 years of experience with 20.2 years conducted within identified sectors of the geospatial field (see Table 1). The diversity of the geospatial industry was well represented, with 9% federal, 13% state, and 28% local government, respectively. The private industry was the highest contributor of respondents at 35%, other roles filling 9%, and post-secondary education held 6%. The participants have held their certification an average of 9 years, with 2015 as the most common certification year. Table 2 shows that the method of certification varied, but the portfolio approach held the majority of the processes (see Table 2).

Table 1. Industry sector representation (n =54)

Percentage of Industry Sector	Current Sector (%)	Majority of Career (%)
Analysis and Modeling	16.7 (9)	22.2 (12)
Positioning and Data Acquisition	5.6 (3)	11.1 (6)
Software & Application Development	11.1 (6)	7.4 (4)
A combination of the above	66.7 (36)	59.3 (32)

Table 2. Path to certification (n =54)

Path to Certification	n	%
Grandfathered	13	24.07
Portfolio	36	66.67
Knowledge Exam	5	9.26

The respondent group held an interesting combination of education in general, as well as concerning geospatial instruction (see Table 3). The occurrence of a certified professional holding an Associate's Degree as the highest level of general education suggests, and the data confirms, that the respondent received certification through the portfolio pathway. The other participant with an Associate's Degree as the highest level of general education is also reasonable, as they were "grandfathered" into their certification. Until recently, the minimum education requirement for a GISP created a barrier to certification for practitioners holding less than a Bachelor's Degree. The arrival of the Knowledge Exam in 2015 and subsequent reduction in education requirements represents an appreciation for the ability of certification applicants to demonstrated competency via an examination.

Table 3. Level of education (n = 54)

Level of Education	General (#)	Geospatial (#)
Associates	2	2
Bachelors	17	24
Masters	31	23
Doctorate	4	0
No Formal Education	0	5

Analysis of Research Question 1

The first research question seeks to explore the viewpoints of geospatial professionals toward the GTCM and why they hold these views. Q Methodology uses an inverted factor analysis technique with a forced distribution sorting grid to build the shared viewpoints of the participants.

Data Collection and Analysis

Q Methodology is an appropriate approach to reveal individual beliefs (Cuppen et al., 2016; Steelman & Maguire, 1999; Varnadore, 2018) and was used in this study to gauge the perceptions of geospatial professionals regarding the relevance of technical competency statements. The respondents ranked the 54 Q-set statements from most relevant (+6) to least relevant (-6). These data, in conjunction with answers from qualitative questions after the survey, are used to construct *themes* relating to shared views of the technical competencies' relevance.

The sorting grid is customarily shaped as a quasi-normal distribution, with a prescribed number of rows and columns, and is considered *forced* due to the restrictions of the grid. Dziopa and Ahern (2011) noted that many participants do not like forced sorting, but the advantage is that it prevents participants from remaining neutral and requires them to make value judgments (Wright, 2013). The prescriptive nature of the model encourages respondents to reflect on their feelings more carefully and approach the exercise systematically (Steelman & Maguire, 1999; van Exel & De Graaf, 2005).

Respondents completed an online sorting activity using a secure study portal from Q Method Software (qmethodsoftware.com). The participants sorted the 62 competencies, indicating the particular relevance of each competency statement from *most relevant* to *least relevant*. The point of Q Methodology is to reveal varied perspectives rather than generalize a population (Watts & Stenner, 2012). Unlike other methodologies, the number of participants is less critical than the opinions shared by the respondents. Perspective is at the center of this research, and the P-sample must be built upon a diverse collection of representatives within the geospatial realm who are relevant to the statements under consideration (van Exel & De Graaf, 2005). As offered by Bartlett & DeWeese (2015), "The number of persons associated with a factor is of less importance than who they are" (p. 76).

Correlation Matrix

The researcher analyzed the data collected from the Q-sort using Ken-Q Analysis Desktop Edition (KADE) (Banasick, 2019). Data analysis begins with a correlation matrix (see Appendix G), which establishes the relationship between two variables; the Q-sorts are the variables in this scenario. Correlation statistics range between -1.00 (signifying an entirely negative relationship) and +1.00 (signifying an entirely positive relationship) between Q-sorts, while a 0.00 value would reflect a lack of association (Watts & Stenner, 2005). The correlation matrix (see Appendix G) reveals a relationship between the Q-sorts (Watts & Stenner, 2012), while correlation coefficients between the individual Q-sorts help to identify shared views held by respondents (van Exel & De Graaf, 2005). Bartlett and DeWeese (2015) noted, "The goal of this process is to determine the variability of Q-sorts to determine how many shared factors are in evidence" (p. 79).

The KADE-generated correlation matrix revealed data regarding the relationships between individual sorts on 100 scale, where an entirely positive correlation is 100 (1.00), the absence of a correlation is 0, and an entirely negative correlation is -100 (-1.00). The highest correlation was a 70 (.70), shared between respondents 11 (received certification via the grandfathering approach and works in the analysis and modeling sector) and 42 (received certification via the knowledge exam and works in the analysis and modeling sector). Both participants loaded onto Factor 4, which is labeled *No Room for Surveying in GIS*. These individuals feel that a clear distinction exists between the competencies held by land surveyors and other geospatial professionals. The next highest correlation was a 65 (.65), shared between respondents 8 (received certification via the grandfathering approach and works in software and application development sector) and 23 (received certification via the knowledge exam and works in a combination of the industry sectors). Both participants loaded onto Factor 2, which is labeled "Programming is Critical." These individuals feel that the variations of programming, such as the automation of software routines, scripting, and application development, are a welcome addition to the geospatial field.

The lowest correlation value was a -39 (-.39), shared between respondent 27 (received certification via the portfolio approach and works in a combination of the industry sectors) and both Respondent 7 (received certification via the grandfathering approach and works in a combination of the industry sectors) and Respondent 34 (received certification via the portfolio approach and works in a combination of the industry sectors). Participant 27 initially loaded onto Factor 1 as a significant negative loading and was later removed from the analysis. Both participants 7 and 34 loaded onto Factor 1, which is labeled *Skeptical View of Remote Sensing*. These individuals feel that, while remotely sensed data can be useful as a way to provide visual context, it is not crucial for geospatial professionals to be conversant in its structure and composition. The -39 (-.39) correlation also occurred between Participant 18 (received certification via the grandfathering approach and works in the positioning and data acquisition sector) and Participant 20 (received certification via the portfolio approach and works in a combination of the industry sectors). Respondent 18 loaded onto Factor 2 *Programming is Critical* and Respondent 20 loaded onto Factor 5 *Positive View of Land Surveying Operations*. The next lowest correlation value of a -38 (-.38) existed between Participant 27 (received certification via the portfolio approach and works in a combination of the industry sectors) and 9 (received certification via the portfolio approach and works in positioning and data acquisition sector). Respondent 27 initially loaded onto Factor 1 as a significant negative loading and was later removed from the analysis. Respondent 9 did not significantly load into a factor.

Factor Analysis and Rotation

The researcher applied the factor analysis data reduction technique intending to explain as much variance as possible within the Q-sort (Wright, 2013). The factor analysis reduces the data to a few summarizing unrotated factors indicative of representative responses (Zabala & Pascual, 2016). Researchers reduce data using either centroid factor analysis (CFA) or principal components analysis (PCA). Watts and Stenner (2012) were concerned that PCA "deprives us of the opportunity to properly explore the data" (p. 97) and that CFA and was generally accepted as the preferred approach as it "leaves all possible solutions open" (p. 99). The researcher chose CFA as the data reduction technique for this analysis.

The task for the unrotated factors is to explain the variance found in the correlation matrix by loading as many Q-sorts as possible (Shemmings, 2006; Zabala et al., 2018). The first factor extracted explains the most variance, with each subsequent factor explaining less (Bartlett & DeWeese, 2015; Watts & Stenner, 2012). The factors represent a hypothetical best-representative Q-sort, and, typically, only a few factors are selected (van Exel & De Graaf, 2005; Zabala & Pascual, 2016). The number of factors selected depends on the variability of the Q-sorts, but there are usually no more than seven factors (Dziopa & Ahern, 2011; Wright, 2013). Watts and Stenner (2012) agree that starting with seven factors is reasonable and recommended beginning with one factor extracted per every 6-8 Q-sorts.

The researcher used the KADE analysis software to perform the analysis and began data reduction of the 54 submissions with seven factors. An Eigenvalue (EV) is calculated by summing the squared loadings of the Q-sorts defining a factor and are indicators of the extractors' ability to explain variance (Watts & Stenner, 2012). It is generally accepted that only factors with an eigenvalue greater than one (1.00) are seen as significant and selected for extraction and interpretation (Dziopa & Ahern, 2011; Shemmings, 2006). A researcher can also use a scree plot to support a decision on the number of factors selected. Watts and Stenner (2012) note that a scree plot can assist the researcher as it can "prevent the arbitrary retention of all factors with EVs greater than 1.00" (p. 117) by providing a visual display of the factors.

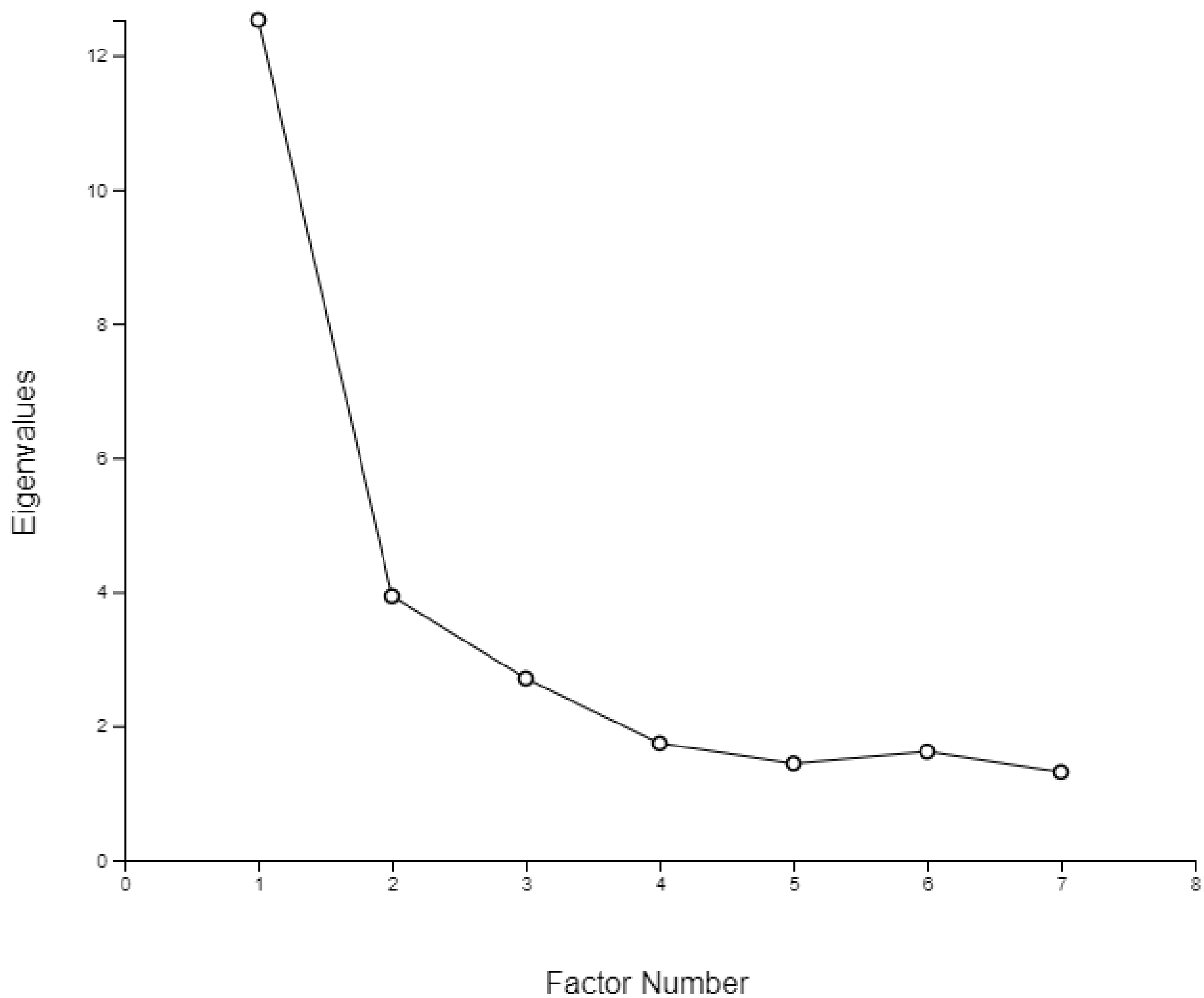

Figure 5: Scree Plot of the initial 7-Factor Solution

The researcher began with a 7-factor solution with an EV of 1.3, but Factors 5 and 6 had significant negative loadings ($p < 0.05$), and Factor 7 had only two participants loading at a significantly level ($p < 0.05$). A 6-factor solution provided an EV of 1.6, but Factors 5 and 6 had significant negative loadings ($p < 0.05$). The researcher moved to a 5-factor solution with an EV of 1.4, but Factor 1 had a significant negative loading ($p < 0.05$). The negative loading (-.5091), provided by Participant 27, was removed from the analysis. The 5-factor solution (EV=1.4) includes 33 participants, with not less than four significant loadings ($p < 0.05$) on any factor, explained 41% of the variance, and was accepted as the best solution. The researcher believes this final solution balances the competing needs to load as many participants as prudent onto each factor, cumulatively explain the most variance possible, and the development of a logical narrative of the expressed views (Wright, 2013; see Table 4).

Table 4. Factor Solutions

Factors	Significant Loads	Variance Explained	Eigenvalue	Reliability	Highest Factor Correlation	Range of People on Factors
7	28	46	1.31	0.92	0.67	1 - 7
6	34	44	1.62	0.95	0.65	1 - 8
5	33	41	1.44	0.97	0.68	4 - 9

Factor Characteristics

The general characteristics for each factor, including the number of Q-sorts loaded, eigenvalues, percentage of variance explained, composite reliability, and the standard error (*SE*) of the z-scores (see Table 5). Eigenvalues are signs of the extractors' ability to explain variance (Watts & Stenner, 2012). The composite reliability is an indication of a factor's strength (Zabala & Pascual, 2016), where "the value 0.8 is the customary value used in Q methodology for the average reliability coefficient, which is the expected correlation between two responses given by the same person" (p. 6). Watts and Stenner (2012) indicate that the standard error for z-scores can be calculated as 1 / (√ number of items in the Q-set). Using the aforementioned formula a *SE* of 0.13 can be calculated: $SE = 1 / (\sqrt{62})$; $SE = 1 / (7.874)$; $SE = 0.127$ (rounded to 0.13); $SE = 0.13$. The cross-product of a factor's two highest loadings must exceed the standard error. All of the extracted factors exceed the standard error value of 0.13 and are acceptable, as indicated by Watts and Stenner (2012).

Table 5. Factor Characteristics

Factor	Participants Loaded	Eigenvalues	Variance	Composite Reliability	*SE* of Factor Z-scores
1	8	12.5	23	0.97	0.17
2	9	3.9	7	0.97	0.16
3	5	2.7	5	0.95	0.22
4	7	1.7	3	0.97	0.18
5	4	1.4	3	0.94	0.24
Total variance			41		

The next step in data analysis is factor rotation. Factor rotation is an attempt to reveal the best combination of relationships between variables (Q-sorts) and maximize the explained variance (Watts & Stenner, 2012). McKeown and Thomas (1988) stated, "The purpose is to maximize the purity of saturation of as many variates (Q-sorts) as possible on one or the other of the factors extracted initially" (p. 52). There are two options for factor rotation, statistical or judgmental, depending on the study. Varimax rotation is often used if the research is exploratory, whereas a judgmental rotation is appropriate if driven by prior research or theory (Cuppen et al., 2016; Wright, 2013). The researcher applied a varimax rotation, which is supported by Watts and Stenner (2005) who state, "it makes theoretical sense for us to pursue a rotated solution which maximizes the amount of variance explained by the extracted factors" (p. 81).

Factor Correlation

The level of agreement or disagreement seen in the correlation matrix is represented similarly in factor score calculations, with values approach 1.00 showing increasing agreement and values nearing -1.00 revealing growing disagreement (Watts & Stenner, 2005). Highly correlated Q-sorts form the factors used in the analysis, standardized using z-score analysis, with the highest scoring statistically significant ($p < 0.05$) sorts flagged for inclusion in a factor. Initially, comparisons cannot be made between factors due to the different number of contributing Q-sorts (Watts & Stenner, 2012) loading upon the identified factors. The factor scores must first be standardized by converting them to z-scores (see Appendix H) before conducting any cross-factor analysis (Watts & Stenner, 2012 Zabala et al., 2018). A z-score defines a factor by illustrating a relationship between statements and factors which can be compared within a data matrix (Bartlett & DeWeese, 2015; Zabala & Pascual, 2016). The correlations between the factors, with Factors 2 and 4 having the highest level of agreement (.53), suggest that the five extracted factors are distinct and representative of views held within the respondents. Factors 2 and 5 held the lowest level of agreement (.00), followed closely by Factors 4 and 5 (.05). Z-scores for each competency statement divided into the five factors expressing a shared viewpoint (see Table 6).

Table 6. Correlations Between Factor Z-Scores

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1	1.00	0.46	0.39	0.33	0.24
Factor 2	0.46	1.00	0.32	0.53	0.00
Factor 3	0.39	0.32	1.00	0.39	0.35
Factor 4	0.33	0.53	0.39	1.00	0.05
Factor 5	0.24	0.00	0.35	0.05	1.00

Factor Loadings

The intent of using factor analysis is to identify underlying patterns within the data and reveal collections of like-minded respondents who similarly rank the statements based upon shared beliefs (Shemmings, 2006; Zabala & Pascual, 2016). Individual Q-sorts with substantial loading on a factor are seen as *factor exemplars*, as their sort configuration is characteristic of that factor (Simons, 2013; Watts & Stenner, 2012). A factor loading is calculated for each Q-sort and is similar to correlation coefficients, as it denotes the degree to which a Q-sort aligned with each factor (Cross, 2005; Zabala et al., 2018). While the number of factors will vary, van

Exel and De Graaf (2005) suggest there is an optimal amount of Q-sorts for each factor when stating, “The aim is to have four or five persons defining each anticipated viewpoint” (p. 6).

The researcher began the analysis with seven potential factors, with five retained. Initial factor analysis with 6 and 7 factors generated minimal Q-sorts (1 - 2) loading on various factors as well as multiple negative loadings. The researcher believed that the 5-factor solution was optimal, with the only significant negative loading (located on Factor 1) removed from the analysis. The five factors explained 41% of the variance, which Watts and Stenner (2012) viewed as acceptable when stating “anything in the region of 35–40% or above would ordinarily be considered a sound solution” (p. 107). Factor 1 explains 11% of the variance (Q-sorts 5, 7, 14, 17, 28, 34, 48, 49), Factor 2 explains 9% of the variance (Q-sorts 2, 8, 16, 18, 23, 25, 44, 47, 51), Factor 3 explains 7% of the variance (Q-sorts 1, 6, 35, 43, 54), Factor 4 explains 9% of the variance (Q-sorts 10, 11, 21, 24, 32, 40, 42), and Factor 5 explains 5% of the variance (Q-sorts 20, 37, 50, 52).

The five themes (see Table 7) developed from the analysis include Factor 1: *Skeptical View of Remote Sensing (significant loadings range in value from 0.683 to 0.4767),* Factor 2: *Programming is Critical (significant loadings range in value from 0.6669 to 0.3716)*, Factor 3: *Leveraging Location-based Data (significant loadings range in value from 0.549 to 0.372),* Factor 4: *No Room for Surveying in GIS (significant loadings range in value from 0.661 to 0.3178),* and Factor 5: *Positive View of Land Surveying Operations (significant loadings range in value from 0.5584 to 0.4533).* Additional descriptions of each factor were drawn from the associated distinguishing statements, the highest and lowest ranked items, and responses provided on the post-survey questionnaire.

Table 7. Factor Loadings with Significant Q-sorts

Participant	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
5	0.5299 *	0.1332	0.1863	0.2455	0.3569
7	0.6531 *	0.2435	-0.1688	-0.0907	0.204
14	0.5547 *	-0.2427	0.3049	0.1632	-0.1822
17	0.5303 *	0.4024	-0.0598	0.2358	0.1217
28	0.4861 *	0.0205	0.0469	0.1442	0.2894
34	0.683 *	0.0625	0.1223	0.197	0.233
48	0.4767 *	0.1289	0.1974	-0.0681	-0.1834
49	0.505*	0.142	0.1239	0.2751	0.2064
2	0.3229	0.5028 *	0.3395	0.1116	0.0999
8	0.3093	0.6401 *	0.0094	0.328	0.0127
16	0.2741	0.5128 *	0.1908	-0.0042	0.1092
18	0.1838	0.3716 *	0.0739	-0.084	-0.2346
23	0.4689	0.6669 *	0.0782	0.2238	0.023
25	-0.054	0.4207 *	0.0189	0.0788	0.0072
44	-0.1731	0.5867 *	0.1711	0.4129	-0.1269
47	-0.0126	0.4998 *	0.0659	0.2302	-0.1021
51	0.334	0.4287 *	0.0905	0.0065	-0.18
1	0.4673	-0.0457	0.5423 *	-0.0715	0.0905
6	0.2091	0.0939	0.5379 *	0.0778	0.2871
35	0.1234	0.1935	0.3799 *	0.2137	0.0972
43	-0.0633	0.1629	0.549 *	0.1161	-0.0526
54	0.0339	-0.0303	0.372 *	0.0687	0.0905
10	0.1733	-0.0581	0.1488	0.4367 *	0.1993
11	0.0641	0.2939	0.3154	0.5431 *	-0.085
21	0.0004	0.3025	0.3796	0.6002 *	-0.0583
24	-0.0015	0.0867	-0.0304	0.3178 *	-0.0654
32	0.0327	0.141	0.1229	0.3426 *	0.1408
40	0.0206	0.2216	0.1276	0.6451 *	-0.02
42	0.1044	0.2174	0.2819	0.661 *	0.0888
20	0.0208	-0.1925	0.0836	0.0729	0.5181 *
37	0.1722	0.0389	0.1186	-0.1034	0.4533 *
50	-0.0867	-0.1027	0.0936	-0.0534	0.5584 *
52	0.2908	0.1757	0.2458	-0.0861	0.5485 *

Note: Asterisk (*) Indicates Significance at $p < 0.05$

Factor Arrays

Factor array construction is the next phase in Q Methodology factor analysis. A factor array represents a composite Q-sort for a conceptual best-fit of respondents loading predominantly on that factor (Dziopa & Ahern, 2011). Factor arrays, or the clustering of similar Q-sorts, are a strength of Q Methodology (Cuppen et al., 2016), and allow the researcher to interpret how the statements rank within each factor and begin theme development (Bartlett & DeWeese, 2015). Factor arrays perform a role in factor interpretation and theme development, as the arrays can be seen as a typical Q-sort for the factor and are a generalization of a perspective (Bartlett & DeWeese, 2015; Cuppen et al., 2016; McKeown & Thomas, 2013). The factor scores allow the researcher to evaluate the configuration of all items within the array and the significance of specific statement locations (McKeown & Thomas, 1988; Watts & Stenner, 2012). In developing a factor array, a calculation of the weighted scores for each Q-sort that loads significantly on the factor are combined for a total weighted score for the factor (Watts & Stenner, 2012). The array is complete when the z-score is translated back to the initial scale used during the sorting exercise. In the case of this study, the converted values will range from -6 to +6 (see table 8). The researcher developed *crib sheets*, as offered by Watts and Stenner (2012), to aid in the factor interpretation. The crib sheets (see Appendix F) used were modeled after one referenced by Watts and Stenner (2012). Statements within the factor array with the highest and lowest scores are typically more useful for interpreting themes (Bartlett & DeWeese, 2015; Zabala et al., 2018). The analysis of statements that score the highest (see table 9) or lowest (see table 10) work to define a factor and distinguish it from another factor (Cuppen et al., 2016; Wright, 2013).

Table 8. Factor Arrays

Number	Statement	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
1	Use geospatial software to transform ellipsoid, datum, and/or map projection to georegister one set of geospatial data to another	1	1	1	2	1
2	Geocode a list of address-referenced locations to map data encoded with geographic coordinates and attributed with address ranges	3	1	4	3	2
3	Discuss examples of systematic and unsystematic land partitioning systems in the U.S. and their implications for land records	1	-3	-5	-3	1
4	Recognize that land records are administered differently around the world	1	0	1	-1	1
5	Explain the distinction between a property boundary and its representations, such as deed lines, lines on imagery, boundary depictions in cadastral (land records) databases	4	-1	1	-4	4
6	Plot a legal boundary description from a deed or plat	4	-1	0	-4	3
7	Design a system for acquiring, processing and integrating geospatial data from diverse sources	0	4	1	6	3
8	Identify sampling strategies for field data collection, including systematic, random, and stratified random sampling, and describe circumstances favorable to each	0	-1	0	1	4
9	Explain how spatial autocorrelation influences sampling strategies and statistics	-3	-2	-1	1	0
10	Perform requirements analysis for remotely sensed data acquisition using resolution concepts	-2	0	0	-2	-3

Table 8 (continued).

11	Explain the concept of "bit depth" and its implications for remotely-sensed image data	-6	-2	-1	-2	-1
12	Plan a remotely sensed data acquisition mission, including specifying an appropriate sensor and platform combination suited for particular project requirements	-5	-1	-3	-2	-2
13	Recognize the differences between ellipsoidal (or geodetic) heights, geoidal heights, and orthometric elevation	-1	0	0	0	3
14	Understand GNSS data post-processing (such as National Geodetic Survey's Online Positioning Service) and real time (such as Real Time Kinematic)	-1	-4	0	-5	1
15	Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets	-2	-5	-2	-5	3
16	Interpret the quality of GNSS data based on possible sources of error	-3	-2	-1	-3	2
17	Explain major GNSS error sources, such as ionospheric delay, clock error, ephemerides, and satellite health	-3	-6	-4	-3	0
18	Understand the process to produce an orthoimage data product with geometric accuracy suitable for project requirements	0	-2	-2	0	2
19	Understand how aerotriangulation contributes to data quality confidence and is applicable to completing related tasks	-2	-4	-3	-4	-3
20	Produce a metadata document that conforms to FGDC, ISO or other geospatial metadata standard	-1	0	5	2	0

Table 8 (continued).

21	Understand how to conduct primary research and implications of data privacy and confidentiality	1	-3	3	4	-4
22	Describe how information can be harvested and geocoded from social media	-1	-3	3	0	-4
23	Explain the process of acquiring and integrating large and heterogeneous datasets (spatial or nonspatial)	-2	2	2	5	4
24	Explain how a mobile device calculates location coordinates (e.g., GNSS, triangulation, trilateration, etc.)	-2	-1	2	-3	2
25	Compare differential GNSS and autonomous GNSS	-3	-4	-3	-6	1
26	Describe an example of a useful application of a buffer operation in GIS software	3	0	2	3	3
27	Perform a site suitability analysis using intersection and overlay functions of GIS software	2	1	3	4	2
28	Use GIS software to identify an optimal route that accounts for visibility, slope, and specified land uses	-1	0	1	0	0
29	Perform dynamic segmentation on transportation network data encoded in a linear reference system	0	-1	0	-2	-2
30	Explain how leading online routing systems work, and account for common geocoding errors	-1	-3	2	-1	-3
31	Use location-allocation software functions to locate service facilities that satisfy given constraints	-1	0	3	2	-1
32	Develop conceptual, logical, and physical models of a geospatial database designed in response to user requirements	3	2	4	4	-1

Table 8 (continued).

33	Understand how spatial data aggregation into different areal extents affects interpretation of results (Modifiable Areal Unit Problem)	-1	-5	-4	2	-3
34	Explain characteristics and appropriate uses of geospatial modeling techniques (e.g., artificial intelligence, machine learning, and deep learning)	0	0	-2	1	-2
35	Demonstrate familiarity with the existence of predictive models and their applications	0	1	-2	3	-3
36	Employ cartographic techniques to represent different kinds of uncertainty, including uncertain boundary locations, transitional boundaries, and ambiguity of attributes	1	0	3	3	6
37	Understand how to represent boundaries in plats, records, and descriptions, as stipulated in legal statute and precedent	5	-2	0	-3	2
38	Determine appropriate image data and image analysis techniques needed to fulfill project requirements	-4	2	5	-1	5
39	Explain the processes involved in geometric correction, radiometric correction, and mosaicking of digital remotely sensed data and the resulting errors	-3	-2	-2	-2	-2
40	Explain how to quantify the thematic accuracy of a land use/land cover map derived from remotely-sensed imagery	0	-1	0	0	0
41	Determine the thematic accuracy of a data product using ground verification methods	0	-2	-1	0	0

Table 8 (continued).

42	Explain the difference between pixel-based and object-based image classification	-4	-3	-1	-1	0
43	Perform object-oriented image classification	-4	-1	-2	-2	-2
44	Develop use cases for user-centered requirements analyses	1	3	-2	1	-2
45	Perform a feasibility study and cost/benefit analysis	2	1	1	2	5
46	Design a geospatial system architecture that responds to user needs, including desktop, server, and mobile applications	5	3	2	-1	-2
47	Communicate effectively with end-users to ensure that software applications meet user needs	6	3	4	1	2
48	Optimize geospatial system performance	3	3	0	0	-1
49	Identify appropriate software development tools for particular end uses	2	2	-3	1	1
50	Ensure that software code complies with industry standards, such as those promulgated by the Open Geospatial Consortium (OGC)	-5	1	-4	-1	0
51	Identify the factors that affect the interoperability of geospatial software applications	1	2	1	2	-1
52	Automate geospatial analysis such as transformation, raster analysis, and geometric operations	2	2	1	1	-1
53	Use scripting languages to automate repetitive tasks	3	5	0	3	1
54	Customize geospatial software using proprietary and open source software components	0	2	-5	0	-5
55	Use scripting languages or other tools to create web mapping applications	2	6	-1	0	-1

Table 8 (continued).

56	Employ query languages such as SQL to interrogate spatial data	2	5	2	5	-1
57	Work effectively in teams to plan and coordinate software and application development	4	3	-1	2	0
58	Stay informed about trends and best practices in information technology and software engineering, such as unit testing, version control, and continuous integration	2	4	6	-1	1
59	Evaluate open source software components for re-use and potential return contributions	-2	1	-3	1	-4
60	Realize opportunities to leverage positioning technology to create mobile end-user applications	1	1	-1	0	0
61	Explain how geospatial software in large enterprises fits into SOA (Service Oriented Architectures) and SaaS (Software as a Service)	-2	0	-6	-1	-6
62	Be able to leverage web architectural opportunities	0	4	2	-2	-5

Factor Interpretation

Factor interpretation involves the identification of statements useful in the analysis. Statements within the factor array with the highest and lowest scores are typically more useful for interpreting themes (Bartlett & DeWeese, 2015; Zabala et al., 2018), define a factor, and distinguish it from another factor (Cuppen et al., 2016; Wright, 2013). The statements with the highest and lowest scores (z-scores) for each factor also act as anchor statements and are located in Tables 10 and 11, respectively. Consensus statements tend to align themselves similarly across the factors (Zabala & Pascual, 2016; Zabala et al., 2018). The study revealed only one consensus statement (see Table 11), which is Statement 39. The range of ranking within the five factors was from -2 to -3, indicating a consistently negative view of the competency. The lack of shared statements may constrain a more nuanced interpretation of the factors. Conversely, a distinguishing statement will score at a statistically significant level on a factor and differentiate one factor from another.

This study identified five viewpoints held by geospatial professionals towards the technical competencies contained in Tier 5 of the GTCM. The factors representing these perspectives are Factor 1: *Skeptical View of Remote Sensing*, Factor 2: *Programming is Critical*, Factor 3: *Leveraging Location-based Data*, Factor 4: *No Room for Surveying in GIS*, and Factor 5: *Positive View of Land Surveying Operations*. The researcher used distinguishing statements, highest/lowest-ranked statements, and statements sorted higher/lower on particular factors to develop the factor narratives. The author used a *crib sheet* approach to organize the statement and facilitate factor interpretation. The crib sheet used is modeled after one referenced by Watts and Stenner (2012) and is located in Appendix F. Participant responses to the open-ended questions following the Q-sort, asking their rationale for choices made, assisted the researcher's interpretation of the factors.

Table 9. Highest Ranking Statement for Each Factor

Factor	Number	Statement	Z-score
1	47	Communicate effectively with end-users to ensure that software applications meet user needs	1.88
2	55	Use scripting languages or other tools to create web mapping applications	2.418
3	58	Stay informed about trends and best practices in information technology and software engineering, such as unit testing, version control, and continuous integration	2.023
4	7	Design a system for acquiring, processing and integrating geospatial data from diverse sources	2.078
5	36	Employ cartographic techniques to represent different kinds of uncertainty, including uncertain boundary locations, transitional boundaries, and ambiguity of attributes	1.96

Table 10. Lowest Ranking Statement for Each Factor

Factor	Number	Statement	Z-score
1	11	Explain the concept of "bit depth" and its implications for remotely-sensed image data	-2.473
2	17	Explain major GNSS error sources, such as ionospheric delay, clock error, ephemerides, and satellite health	-2.137
3	61	Explain how geospatial software in large enterprises fits into SOA (Service Oriented Architectures) and SaaS (Software as a Service)	-2.055
4	25	Compare differential GNSS and autonomous GNSS	-2.081
5	61	Explain how geospatial software in large enterprises fits into SOA (Service Oriented Architectures) and SaaS (Software as a Service)	-2.128

Table 11. Consensus Statement

Number	Statement	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
39	Explain the processes involved in geometric correction, radiometric correction, and mosaicking of digital remotely sensed data and the resulting errors	-3	-2	-2	-2	-2

Factor 1: Skeptical View of Remote Sensing

Factor 1 had eight Q-sorts and explained 11% of the variance in the study. This factor accounts for the most variance explained in the study. The factor's title is based upon the mostly negative views held by the participants towards digital imagery and remotely sensed data. Figure 6 is a model Q-sort for Factor 1. It is a composite representation of the idealized sorting response for the participants included in Factor 1 and serves as a generalization of their perspectives (McKeown & Thomas, 2013; van Exel & De Graaf, 2005). The researcher used the consensus statement in Table 11, distinguishing statements in Table 12, positive statements ranked higher in the factor array than in other factor arrays, negative statements ranked lower in the factor array than in other factor arrays, and responses in the post-sort questionnaire as data for this analysis.

Participants loading on this factor averaged 26 years of experience, 25 of which were in the geospatial field. The education levels were split between Masters (4) and Bachelor's Degrees (3), with the geospatial instruction divided between Bachelors (5) and Masters (2). Three of the participants work in local government, two in private industry, one in the federal government, one in the "other" category. All respondents indicated that the work in a combination of the industry sectors indicated in the GTCM (analysis and modeling, positioning and data acquisition, software, and application development).

Table 12. Distinguishing Statements for Factor 1

No.	Statement	Factor 1			Remaining Factors			
		Rank	Z-score	*S*	2	3	4	5
37	Understand how to represent boundaries in plats, records, and descriptions, as stipulated in legal statute and precedent	5	1.88	*	-2	0	-3	2
46	Design a geospatial system architecture that responds to user needs, including desktop, server, and mobile applications	5	1.72		3	2	-1	-2
55	Use scripting languages or other tools to create web mapping applications	2	0.82	*	6	-1	0	-1
21	Understand how to conduct primary research and implications of data privacy and confidentiality	1	0.42	*	-3	3	4	-4
62	Be able to leverage web architectural opportunities	0	0.09	*	4	2	-2	-5
7	Design a system for acquiring, processing and integrating geospatial data from diverse sources	0	-0.04		4	1	6	3

Table 12 (continued).

14	Understand GNSS data post-processing (such as National Geodetic Survey's Online Positioning Service) and real time (such as Real Time Kinematic)	-1	-0.59	*	-4	0	-5	1
28	Use GIS software to identify an optimal route that accounts for visibility, slope, and specified land uses	-1	-0.61		0	1	0	0
23	Explain the process of acquiring and integrating large and heterogeneous datasets (spatial or nonspatial)	-2	-0.71	*	2	2	5	4
38	Determine appropriate image data and image analysis techniques needed to fulfill project requirements	-4	-1.27	*	2	5	-1	5
42	Explain the difference between pixel-based and object-based image classification	-4	-1.55	*	-3	-1	-1	0
11	Explain the concept of "bit depth" and its implications for remotely-sensed image data	-6	-2.4 7	*	-2	-1	-2	-1

Note: $p < 0.05$: Asterisk (*) Indicates Significance at $p < 0.01$

Factor 1 was dominated by a dismissive view of digital imagery, a neutral perspective concerning data capture and manipulation, and a positive opinion for communication skills. Interestingly, two participants mentioned the importance of communication, but it was not highly ranked in the factor. The researcher attributes the inconsistency due to the existence of only two statements within the Q-set relating to communication, both of which focused on the information technology area. An example is statement 47, "Communicate effectively with end-users to ensure that software applications meet user needs." The lack of communication skills in Tier 5 (the origin of the Q-set) may be due to its presence in Tier 2 (Academic Competencies). Respondent 49 shares a comment emphasizing the need for communication, "As a consultant working with a variety of clients, I find that being able to understand or anticipate what they need and then be able to describe a particular solution is the most important thing that I do."

The Q-sorts loading onto Factor 1 held a distinctly positive attitude towards cadastral mapping. While only one distinguishing statement (37) related to the property mapping, it was the highest-scoring statement (+5) within the array. Statement 37 – "Understand how to represent boundaries in plats, records, and descriptions, as stipulated in legal statute and precedent" was supported by Statements 6 (+4), 5 (+4), 4 (+1), and 3 (+1) which were ranked higher in Factor 1 than in another array. The rankings could be connected to an appreciation for the land partitioning system combined with the reality that most property boundary operations occur outside of mainstream GIS. Participant 32 commented, "plotting legal boundaries - it is very important however, it may be (and was) done with other applications."

Factor 1 Q-sorts suggest a lack of enthusiasm towards data collection and integration, with generally low scores assigned to Statements 7 – "Design a system for acquiring, processing and integrating geospatial data from diverse sources" (0), 14 – "Understand GNSS data post-processing" (-1), and 23 – "Explain the process of acquiring and integrating large and heterogeneous dataset" (-2). Participant 49 commented that "Statements related to data quality were the most difficult to place." Statements 7 (0) and 23 (-2), which dealt with data integration competencies, also ranked lower in Factor 1 than in another array.

The Q-sorts loading onto Factor 1 clearly questioned the relevance of remote sensing and its contribution to the geospatial professional. The three lowest distinguishing statements were 38 – "Determine appropriate image data and image analysis techniques needed to fulfill project requirements" (-4), 42 – "Explain the difference between pixel-based and object-based image classification" (-4), and 11 – "Explain the concept of "bit depth" and its implications for remotely-sensed image data" (-6). Other related competencies, Statements 39 (-3), 43 (-4), and 12 (-5), ranked lower in Factor 1 than in another array. There are several potential reasons for the low scores assigned to raster-based data or imagery. One possible answer relates to the technical nature of some competencies. Also, the lack of contact or need for remote sensing technology by some participants might impact opinions. Participant 17 offered, "In my world, remote sensing is not that prevalent."

-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
11 Explain the concept of "bit depth" and its implications for	50 Ensure that software code complies with industry standards, such	38 Determine appropriate image data and image analysis techniques	39 Explain the processes involved in geometric correction,	15 Collect and integrate carrier phase (survey grade) GNSS positions	22 Describe how information can be harvested and geocoded from social	29 Perform dynamic segmentation on transportation network data	36 Employ cartographic techniques to represent different kinds	56 Employ query languages such as SQL to interrogate spatial data	32 Develop conceptual, logical, and physical models of a geospatial	6 Plot a legal boundary description from a deed or plat	37 Understand how to represent boundaries in plats, records,	47 Communicate effectively with end-users to ensure that software
	12 Plan a remotely sensed data acquisition mission,	43 Perform object-oriented image classification	25 Compare differential GNSS and autonomous GNSS	23 Explain the process of acquiring and integrating large and	30 Explain how leading online routing systems work, and account for	62 Be able to leverage web architectural opportunities	4 Recognize that land records are administered differently	52 Automate geospatial analysis such as transformation,	2 Geocode a list of ress-referenced locations to map data	5 Explain the distinction between a property boundary and	46 Design a geospatial system architecture that responds	
		42 Explain the difference between pixel-based and object-based	9 Explain how spatial autocorrelation influences sampling	10 Perform requirements analysis for remotely sensed data	31 Use tion-allocation software functions to locate service	41 Determine the thematic accuracy of a data product using ground	21 Understand how to conduct primary research and implications of	55 Use scripting languages or other tools to create web	26 Describe an example of a useful application of a buffer	57 Work effectively in teams to plan and coordinate software and		
			16 Interpret the quality of GNSS data based on possible sources of	61 Explain how geospatial software in large enterprises	14 Understand GNSS data post-processing (such as National	18 Understand the process to produce an orthoimage data product with	1 Use geospatial software to transform ellipsoid,	49 Identify appropriate software development tools for	53 Use scripting languages to automate repetitive			
			17 Explain major GNSS error sources, such as ionospheric	24 Explain how a mobile device calculates location coordinates	28 Use GIS software to identify an optimal route that accounts	34 Explain characteristics and appropriate uses of geospatial	60 Realize opportunities to leverage positioning technology to	58 Stay informed about trends and best practices in information	48 Optimize geospatial system performance			
				59 Evaluate open source software components for re-use and	13 Recognize the differences between ellipsoidal (or geodetic)	8 Identify sampling strategies for field data collection,	3 Discuss examples of systematic and unsystematic land	45 Perform a feasibility study and cost/benefit analysis				
				19 Understand how rotriangulation contributes to data quality	20 Produce a metadata document that conforms to FGDC, ISO or	7 Design a system for acquiring, processing and integrating	51 Identify the factors that affect the nteroperability of geospatial	27 Perform a site suitability analysis using intersection				
					33 Understand how spatial data aggregation into different	40 Explain how to quantify the thematic accuracy of a land use/land	44 Develop use cases for user-centered requirements analyses					
						54 Customize geospatial software using proprietary and open source						
						35 Demonstrate familiarity with the existence of predictive						

Legend

- Distinguishing statement at P< 0.05
- Distinguishing statement at P< 0.01
- Consensus statement

Figure 6: Model Sort for Factor 1 - Skeptical View of Remote Sensing

Factor 2: Programming is Critical

Factor 2 had nine Q-sorts and explained 9% of the variance in the study. This factor accounts for the largest number of participants in the study. The factor's title is based upon the typically positive views held by the participants towards the value and contributions that scripting, coding, and automation has within geospatial software applications. Figure 7 is a model Q-sort for Factor 2. It is a composite representation of the idealized sorting response for the participants included in Factor 2 and serves as a generalization of their perspectives (McKeown & Thomas, 2013; van Exel & De Graaf, 2005). The researcher used the consensus statement in Table 11, distinguishing statements in Table 13, positive statements ranked higher in the factor array than in other factor arrays, negative statements ranked lower in the factor array than in other factor arrays, and responses in the post-sort questionnaire as data for this analysis.

Participants loading on this factor averaged 27 years of experience, 23 of which were in the geospatial field. The education levels showed a majority of participants with a Master's (6) and the remainder holding Bachelor's Degrees (3). Geospatial instruction was split between Bachelor's (5) and Master's (3), and one respondent indicated that they had not received any formal geospatial instruction. The participants sharing an appreciation for computer programming work in private industry (3), the federal government (2), "other" category (2), and one representative each for post-secondary education and local government. Four respondents indicated that they work in a combination of the industry sectors, with an additional three located in software and application development, and one participant each is employed within positioning and data acquisition and analysis and modeling sectors.

Table 13. Distinguishing Statements for Factor 2

No.	Statement	Factor 2			Remaining Factors			
		Rank	Z-score		1	3	4	5
55	Use scripting languages or other tools to create web mapping applications	6	2.42	*	2	-1	0	-1
53	Use scripting languages to automate repetitive tasks	5	1.88		3	0	3	1
62	Be able to leverage web architectural opportunities	4	1.53		0	2	-2	-5
58	Stay informed about trends and best practices in information technology and software engineering, such as unit testing, version control, and continuous integration	4	1.47		2	6	-1	1
44	Develop use cases for user-centered requirements analyses	3	1.14	*	1	-2	1	-2
54	Customize geospatial software using proprietary and open source software components	2	0.89	*	0	-5	0	-5
2	Geocode a list of address-referenced locations to map data encoded with geographic coordinates and attributed with address ranges	1	0.33		3	4	3	2
26	Describe an example of a useful application of a buffer operation in GIS software	0	-0.12	*	3	2	3	3
5	Explain the distinction between a property boundary and its representations, such as deed lines, lines on imagery, boundary depictions in cadastral (land records) databases	-1	-0.73	*	4	1	-4	4
6	Plot a legal boundary description from a deed or plat	-1	-0.75		4	0	-4	3
41	Determine the thematic accuracy of a data product using ground verification methods	-2	-0.77		0	-1	0	0

Table 13 (continued).

21	Understand how to conduct primary research and implications of data privacy and confidentiality	-3	-0.99	1	3	4	-4
14	Understand GNSS data post-processing (such as National Geodetic Survey's Online Positioning Service) and real time (such as Real Time Kinematic)	-4	-1.32	-1	0	-5	1
15	Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets	-5	-1.53	-2	-2	-5	3
17	Explain major GNSS error sources, such as ionospheric delay, clock error, ephemerides, and satellite health	-6	-2.14	-3	-4	-3	0

Note: ($p < 0.05$: Asterisk (*) Indicates Significance at $p < 0.01$)

Factor 2 exhibited a decidedly positive view of computer programming in a variety of forms. Competency statements relating to computer science in general and programming specifically comprised the top four distinguishing statements. Statement 55 – "Use scripting languages or other tools to create web mapping applications" (+6), Statement 53 – "Use scripting languages to automate repetitive tasks" (+5), Statement 62 – "Be able to leverage web architectural opportunities" (+4), and Statement 58 – "Stay informed about trends and best practices in information technology and software engineering, such as unit testing, version control, and continuous integration" (+4) dominated the positive side of the factor. Respondent 44 stated, "Automation and scripting are the most important skills. These skills save an incredible amount of time and if a user knows how to automate a problem, then the work becomes reproducible." Also, seven additional statements (52, 51, 49, 60, 50, 59, 61) associated with programming and related activities loaded higher onto Factor 2 than in any other array. Participant 23 shared the opinion that "Web applications are the future of GIS." Multiple references to the application of scripting languages, especially by a wider audience than was historically the case, was a continuous theme.

The Q-sorts loading onto Factor 2 exhibited a generally negative view of land surveying activities. The three lowest distinguishing statements were 14 – "Understand GNSS data post-processing" (-4), 15 – "Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets" (-5), and 17 - "Explain major GNSS error sources, such as ionospheric delay, clock error, ephemerides, and satellite health" (-6). Respondent 44 offered that, "Knowledge of GNSS is very domain specific and not relevant to most scientific inquiry." Interestingly, none of the other statements (4, 5, 6, and 37) relating to property boundaries or GNSS operations (16, 24, and 25) ranked lower in Factor 2 than in another array. Especially when considering the comment from Respondent 51, "Systematic and unsystematic land positioning systems in the US has never had any relevance to anything I have ever done." An explanation could be that the lowest-ranked competencies are very technical.

-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
17 Explain major GNSS error sources, such as ionospheric	15 Collect and integrate carrier phase (survey grade) GNSS positions	19 Understand how rotriangulation contributes to data quality	42 Explain the difference between pixel-based and object-based	41 Determine the thematic accuracy of a data product using ground	8 Identify sampling strategies for field data collection,	36 Employ cartographic techniques to represent different kinds	60 Realize opportunities to leverage positioning technology to	38 Determine appropriate image data and image analysis techniques	47 Communicate effectively with end-users to ensure that software	7 Design a system for acquiring, processing and integrating	53 Use scripting languages to automate repetitive	55 Use scripting languages or other tools to create web
	33 Understand how spatial data aggregation into different	14 Understand GNSS data post-processing (such as National	30 Explain how leading online routing systems work, and account for	9 Explain how spatial autocorrelation influences sampling	43 Perform object-oriented image classification	28 Use GIS software to identify an optimal route that accounts	50 Ensure that software code complies with industry standards, such	54 Customize geospatial software using proprietary and open source	57 Work effectively in teams to plan and coordinate software and	62 Be able to leverage web architectural opportunities	56 Employ query languages such as SQL to interrogate spatial data	
		25 Compare differential GNSS and autonomous GNSS	21 Understand how to conduct primary research and implications of	39 Explain the processes involved in geometric correction,	29 Perform dynamic segmentation on transportation network data	61 Explain how geospatial software in large enterprises	59 Evaluate open source software components for re-use and	32 Develop conceptual, logical, and physical models of a geospatial	48 Optimize geospatial system performance	58 Stay informed about trends and best practices in information		
			22 Describe how information can be harvested and geocoded from social	11 Explain the concept of "bit depth" and its implications for	40 Explain how to quantify the thematic accuracy of a land use/land	10 Perform requirements analysis for remotely sensed data	1 Use geospatial software to transform ellipsoid,	23 Explain the process of acquiring and integrating large and	46 Design a geospatial system architecture that responds			
			3 Discuss examples of systematic and unsystematic land	16 Interpret the quality of GNSS data based on possible sources of	24 Explain how a mobile device calculates location coordinates	31 Use tion-allocation software functions to locate service	2 Geocode a list of ress-referenced locations to map data	52 Automate geospatial analysis such as transformation,	44 Develop use cases for user-centered requirements analyses			
				18 Understand the process to produce an orthoimage data product with	5 Explain the distinction between a property boundary and	26 Describe an example of a useful application of a buffer	35 Demonstrate familiarity with the existence of predictive	51 Identify the factors that affect the nteroperability of geospatial				
				37 Understand how to represent boundaries in plats, records,	6 Plot a legal boundary description from a deed or plat	34 Explain characteristics and appropriate uses of geospatial	45 Perform a feasibility study and cost/benefit analysis	49 Identify appropriate software development tools for				
					12 Plan a remotely sensed data acquisition mission,	20 Produce a metadata document that conforms to FGDC, ISO or	27 Perform a site suitability analysis using intersection					
						4 Recognize that land records are administered differently						
						13 Recognize the differences between ellipsoidal (or geodetic)						

Legend

- Distinguishing statement at P< 0.05
- Distinguishing statement at P< 0.01
- Consensus statement

Figure 7: Model Sort for Factor 2 - Programming is Critical

Factor 3: Leveraging Location-based Data

Factor 3 had five Q-sorts and explained 7% of the variance in the study. The factor's title is based upon the typically positive views held by the participants regarding the worth and utility of location-based data as value-added secondary data and information source. Figure 8 is a model Q-sort for Factor 1. It is a composite representation of the idealized sorting response for the participants included in Factor 1 and serves as a generalization of their perspectives (McKeown & Thomas, 2013; van Exel & De Graaf, 2005). The researcher used the consensus statement in Table 11, distinguishing statements in Table 14, positive statements ranked higher in the factor array than in other factor arrays, negative statements ranked lower in the factor array than in other factor arrays, and responses in the post-sort questionnaire as data for this analysis.

Participants loading on this factor averaged 27 years of experience, 21 of which were in the geospatial field. The education levels showed a majority of participants with a Master's (3) and the remainder holding Bachelor's Degrees (2), with the geospatial instruction split mirroring the primary education representation. Two of the participants work in local government, one in state government, one in post-secondary education, and one in private industry. Three respondents indicated that they work in a combination of the industry sectors, with the two remaining participants employed within analysis and modeling.

Table 14. Distinguishing Statements for Factor 3

No.	Statement	Factor 3			Remaining Factors			
		Rank	Z-score		1	2	4	5
58	Stay informed about trends and best practices in information technology and software engineering, such as unit testing, version control, and continuous integration	6	2.02		2	4	-1	1
20	Produce a metadata document that conforms to FGDC, ISO or other geospatial metadata standard	5	1.99	*	-1	0	2	0
22	Describe how information can be harvested and geocoded from social media	3	1.06	*	-1	-3	0	-4
30	Explain how leading online routing systems work, and account for common geocoding errors	2	0.98	*	-1	-3	-1	-3
62	Be able to leverage web architectural opportunities	2	0.84		0	4	-2	-5
5	Explain the distinction between a property boundary and its representations, such as deed lines, lines on imagery, boundary depictions in cadastral (land records) databases	1	0.6	*	4	-1	-4	4
6	Plot a legal boundary description from a deed or plat	0	-0.09		4	-1	-4	3
37	Understand how to represent boundaries in plats, records, and descriptions, as stipulated in legal statute and precedent	0	-0.16	*	5	-2	-3	2
49	Identify appropriate software development tools for particular end uses	-3	-1.09	*	2	2	1	1

Note: ($p < 0.05$: Asterisk (*) Indicates Significance at $p < 0.01$)

Factor 3 presented a positive view of the manipulation of location-based data and the creation of new datasets and information. Competency statements involving geospatial analysis comprised two of the top four distinguishing statements for Factor 3. Statement 22 – "Describe how information can be harvested and geocoded from social media" (+3) and Statement 30 – "Explain how leading online routing systems work, and account for common geocoding errors" (+2) provide a first look into the presence of geospatial analysis within the factor. Also, five additional statements (2, 31, 24, 30, 28) associated with location-allocation functions loaded higher onto Factor 3 than in any other array. Participant 35 explained the value of proper geospatial analysis, "You could have perfect date (sic) and use flawless analysis with museum quality maps or bleeding edge content delivery, but if the information you produce is not what the end user wanted then the effort was pointless…" An aberration in Factor 3 is the appearance of Statement 34 – "Explain characteristics and appropriate uses of geospatial modeling techniques (e.g. artificial intelligence, machine learning, and deep learning)" as a statement ranking lower (-2) in Factor 3 than in another array.

The Q-sorts used to construct Factor 3 display an ambivalence to land surveying and cadastral mapping. Statement 5 – "Explain the distinction between a property boundary and its representations, such as deed lines, lines on imagery, boundary depictions in cadastral (land records) databases" (+1), Statement 6 – "Plot a legal boundary description from a deed or plat" (0), and Statement 37 – "Understand how to represent boundaries in plats, records, and descriptions, as stipulated in legal statute and precedent" (0) support a neutral stance. The uncertainty demonstrated in the distinguishing statements is also seen in the absence of statements relating to property mapping appearing on Factor 3 higher than or lower than they appeared in any other array.

Factor 3 presented a fairly negative view of computer programming as well as geospatial application development. The lone negative distinguishing statement was Statement 49 –

“Identify appropriate software development tools for particular end uses” with a ranking of -3 on the array. However, numerous additional statements presented a view that scripting and software application development was not seen as important to the geospatial science field. The following statements, 53 (0), 60 (-1), 55 (-1), 54 (-5), and 61 (-6) were ranked lower in Factor 3 than in another array. It appears that the participants contributing to the factor’s construction questioned the value of computer programming as a relevant skill within the geospatial field.

-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
61 Explain how geospatial software in large enterprises	54 Customize geospatial software using proprietary and open source	33 Understand how spatial data aggregation into different	49 Identify appropriate software development tools for	18 Understand the process to produce an orthoimage data product with	41 Determine the thematic accuracy of a data product using ground	14 Understand GNSS data post-processing (such as National	5 Explain the distinction between a property boundary and	24 Explain how a mobile device calculates location coordinates	21 Understand how to conduct primary research and implications of	47 Communicate effectively with end-users to ensure that software	20 Produce a metadata document that conforms to FGDC, ISO or	58 Stay informed about trends and best practices in information
	3 Discuss examples of systematic and unsystematic land	50 Ensure that software code complies with industry standards, such	59 Evaluate open source software components for re-use and	15 Collect and integrate carrier phase (survey grade) GNSS positions	60 Realize opportunities to leverage positioning technology to	13 Recognize the differences between ellipsoidal (or geodetic)	1 Use geospatial software to transform ellipsoid,	26 Describe an example of a useful application of a buffer	27 Perform a site suitability analysis using intersection	2 Geocode a list of ress-referenced locations to map data	38 Determine appropriate image data and image analysis techniques	
		17 Explain major GNSS error sources, such as ionospheric	19 Understand how rotriangulation contributes to data quality	34 Explain characteristics and appropriate uses of geospatial	57 Work effectively in teams to plan and coordinate software and	48 Optimize geospatial system performance	28 Use GIS software to identify an optimal route that accounts	30 Explain how leading online routing systems work, and account for	36 Employ cartographic techniques to represent different kinds	32 Develop conceptual, logical, and physical models of a geospatial		
			12 Plan a remotely sensed data acquisition mission,	39 Explain the processes involved in geometric correction,	11 Explain the concept of "bit depth" and its implications for	29 Perform dynamic segmentation on transportation network data	7 Design a system for acquiring, processing and integrating	23 Explain the process of acquiring and integrating large and	31 Use tion-allocation software functions to locate service			
			25 Compare differential GNSS and autonomous GNSS	43 Perform object-oriented image classification	55 Use scripting languages or other tools to create web	8 Identify sampling strategies for field data collection,	45 Perform a feasibility study and cost/benefit analysis	62 Be able to leverage web architectural opportunities	22 Describe how information can be harvested and geocoded from social			
				44 Develop use cases for user-centered requirements analyses	42 Explain the difference between pixel-based and object-based	40 Explain how to quantify the thematic accuracy of a land use/land	52 Automate geospatial analysis such as transformation,	46 Design a geospatial system architecture that responds				
				35 Demonstrate familiarity with the existence of predictive	16 Interpret the quality of GNSS data based on possible sources of	6 Plot a legal boundary description from a deed or plat	4 Recognize that land records are administered differently	56 Employ query languages such as SQL to interrogate spatial data				
					9 Explain how spatial autocorrelation influences sampling	10 Perform requirements analysis for remotely sensed data	51 Identify the factors that affect the nteroperability of geospatial					
						37 Understand how to represent boundaries in plats, records,						
						53 Use scripting languages to automate repetitive						

Legend

- Distinguishing statement at P< 0.05
- Distinguishing statement at P< 0.01
- Consensus statement

Figure 8: Model Sort for Factor 3 - Leveraging Location-based Data

Factor 4: No Room for Surveying in GIS

Factor 4 had seven Q-sorts and explained 9% of the variance in the study. The factor's title is based upon the frequently negative views held by the participants towards legal boundaries, survey-related activities, and the Global Navigation Satellite System (GNSS). Figure 9 is a model Q-sort for Factor 1. It is a composite representation of the idealized sorting response for the participants included in Factor 1 and serves as a generalization of their perspectives (McKeown & Thomas, 2013; van Exel & De Graaf, 2005). The researcher used the consensus statement in Table 11, distinguishing statements in Table 15, positive statements ranked higher in the factor array than in other factor arrays, negative statements ranked lower in the factor than in other arrays, and responses in the post-sort questionnaire as data for this analysis.

Participants loading on this factor averaged 15 years of experience, 97% of which were in the geospatial field. The education levels were dominated by those holding Master's (6) and the remaining respondent holding a Bachelor's Degree. Geospatial instruction was more balanced with four representatives noting their instruction took place at the Master's level, with the remaining three participants acquiring the majority of their geospatial coursework at the Bachelor's level. Three of the participants work in private industry, with one in state government, the federal government, post-secondary education, and the "other" category, respectively. Five respondents indicated that they work in a combination of the industry sectors, with the two remaining participants employed within analysis and modeling.

Table 15. Distinguishing Statements for Factor 4

No.	Statement	Factor 4			Remaining Factors			
		Rank	Z-score		1	2	3	5
35	Demonstrate familiarity with the existence of predictive models and their applications	3	0.99	*	0	1	-2	-3
20	Produce a metadata document that conforms to FGDC, ISO or other geospatial metadata standard	2	0.82	*	-1	0	5	0
33	Understand how spatial data aggregation into different areal extents affects interpretation of results (Modifiable Areal Unit Problem)	2	0.67	*	-1	-5	-4	-3
9	Explain how spatial autocorrelation influences sampling strategies and statistics	1	0.65	*	-3	-2	-1	0
34	Explain characteristics and appropriate uses of geospatial modeling techniques (e.g. artificial intelligence, machine learning, and deep learning)	1	0.5		0	0	-2	-2
58	Stay informed about trends and best practices in information technology and software engineering, such as unit testing, version control, and continuous integration	-1	-0.32		2	4	6	1
38	Determine appropriate image data and image analysis techniques needed to fulfill project requirements	-1	-0.37	*	-4	2	5	5
62	Be able to leverage web architectural opportunities	-2	-0.77	*	0	4	2	-5
5	Explain the distinction between a property boundary and its representations, such as deed lines, lines on imagery, boundary depictions in cadastral (land records) databases	-4	-1.38	*	4	-1	1	4
6	Plot a legal boundary description from a deed or plat	-4	-1.48	*	4	-1	0	3
14	Understand GNSS data post-processing (such as National Geodetic Survey’s Online Positioning Service) and real time (such as Real Time Kinematic)	-5	-1.82		-1	-4	0	1

Table 15 (continued).

15	Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets	-5	-2.04		-2	-5	-2	3
25	Compare differential GNSS and autonomous GNSS	-6	-2.08	*	-3	-4	-3	1

Note: ($p < 0.05$: Asterisk (*) Indicates Significance at $p < 0.01$)

The organization of Factor 4 is substantially different from the other factors in this study. The highest positive value within the distinguishing statements is a +3, and there is very little neutral territory and dominated by a series of significant negative loadings. The relative rankings table includes many mildly positive values relating to geospatial analysis, positive statements connected to data management, and a continuation of a severe view relating to land surveying. The appearance of many statements in positive support of database competencies in the relative rankings after an absence within distinguishing statements seems odd to the researcher.

The Q-sorts loading onto Factor 4 held a slightly positive attitude towards geospatial analysis and modeling. The highest valued distinguishing statement was 37, “Demonstrate familiarity with the existence of predictive models and their applications,” but had a value of only +3. Other statements related to higher-order analysis were 33 (+2), 9 (+1), and 34 (+1), none of which demonstrated a strong degree of support for the area. Furthermore, there were no comments offered by the participants loaded onto this factor that demonstrated strong support for advanced analysis or predictive modeling. The lackluster support for analysis and modeling continued when reviewing the relative ranks of the statements, as no additional statements were ranked higher in Factor 4 than in another array.

As mentioned previously, no distinguishing statement addressed data manipulation operations. However, there were four statements ranked higher in Factor 4 than in another array.

Peculiarly, all of the database statements ranked higher in Factor 4's relative ranks than any of the statements regarding geospatial analysis and predictive modeling. The statements are 7 – "Design a system for acquiring, processing and integrating geospatial data from diverse sources" (+6), 56 – "Employ query languages such as SQL to interrogate spatial data" (+5), 23 – "Explain the process of acquiring and integrating large and heterogeneous datasets" (+5), and 32 – "Develop conceptual, logical, and physical models of a geospatial database designed in response to user requirements" (+4). Even more interesting is the general overlap of skills needed for a geospatial professional to conduct data manipulation and analysis, but the lack of highly viewed analysis competencies within Factor 4.

The statements comprising the negative values lacked any ambiguity, as land surveying occupied all of the lowest scores in the distinguishing statements as well as the relative ranks. The lowest five statements within the distinguishing statements for Factor 4 related to property boundaries or GNSS surveying, and included Statements 25 (-6), 15 (-5), 14 (-5), 6 (-4), and 5 (-4). Participant 21 explained their evaluation, "I felt that GNSS post-processing and RTK are very specific and detailed techniques, not especially relevant for a general knowledge of geospatial data." Also, Statements 19 (-4), 16 (-3), 37 (-35), and 24 (-3) ranked lower in Factor 4 than in another array. Participant 40 commented, "Having detailed knowledge of GNSS and even land survey methodology and practice is already an integral part of professional Land Surveying. There is no need or reason for GIS professionals to duplicate efforts that already have their own specialty." The opinion expressed by Participant 40 appears to summarize the beliefs held by other respondents loading onto Factor 4.

-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
25 Compare differential GNSS and autonomous GNSS	14 Understand GNSS data post-processing (such as National	5 Explain the distinction between a property boundary and	17 Explain major GNSS error sources, such as ionospheric	10 Perform requirements analysis for remotely sensed data	58 Stay informed about trends and best practices in information	13 Recognize the differences between ellipsoidal (or geodetic)	9 Explain how spatial autocorrelation influences sampling	1 Use geospatial software to transform ellipsoid,	2 Geocode a list of ress-referenced locations to map data	27 Perform a site suitability analysis using intersection	56 Employ query languages such as SQL to interrogate spatial data	7 Design a system for acquiring, processing and integrating
	15 Collect and integrate carrier phase (survey grade) GNSS positions	6 Plot a legal boundary description from a deed or plat	24 Explain how a mobile device calculates location coordinates	29 Perform dynamic segmentation on transportation network data	50 Ensure that software code complies with industry standards, such	41 Determine the thematic accuracy of a data product using ground	47 Communicate effectively with end-users to ensure that software	57 Work effectively in teams to plan and coordinate software and	26 Describe an example of a useful application of a buffer	32 Develop conceptual, logical, and physical models of a geospatial	23 Explain the process of acquiring and integrating large and	
		19 Understand how rotriangulation contributes to data quality	37 Understand how to represent boundaries in plats, records,	39 Explain the processes involved in geometric correction,	38 Determine appropriate image data and image analysis techniques	40 Explain how to quantify the thematic accuracy of a land use/land	52 Automate geospatial analysis such as transformation,	51 Identify the factors that affect the nteroperability of geospatial	53 Use scripting languages to automate repetitive	21 Understand how to conduct primary research and implications of		
			16 Interpret the quality of GNSS data based on possible sources of	43 Perform object-oriented image classification	4 Recognize that land records are administered differently	28 Use GIS software to identify an optimal route that accounts	34 Explain characteristics and appropriate uses of geospatial	20 Produce a metadata document that conforms to FGDC, ISO or	36 Employ cartographic techniques to represent different kinds			
			3 Discuss examples of systematic and unsystematic land	11 Explain the concept of "bit depth" and its implications for	42 Explain the difference between pixel-based and object-based	48 Optimize geospatial system performance	44 Develop use cases for user-centered requirements analyses	31 Use tion-allocation software functions to locate service	35 Demonstrate familiarity with the existence of predictive			
				62 Be able to leverage web architectural opportunities	61 Explain how geospatial software in large enterprises	60 Realize opportunities to leverage positioning technology to	49 Identify appropriate software development tools for	45 Perform a feasibility study and cost/benefit analysis				
				12 Plan a remotely sensed data acquisition mission,	46 Design a geospatial system architecture that responds	18 Understand the process to produce an orthoimage data product with	59 Evaluate open source software components for re-use and	33 Understand how spatial data aggregation into different				
					30 Explain how leading online routing systems work, and account for	54 Customize geospatial software using proprietary and open source	8 Identify sampling strategies for field data collection,					
						22 Describe how information can be harvested and geocoded from social						
						55 Use scripting languages or other tools to create web						

Legend

- Distinguishing statement at P< 0.05
- Distinguishing statement at P< 0.01
- Consensus statement

Figure 9: Model Sort for Factor 4 - No Room for Surveying in GIS

Factor 5: Positive View of Land Surveying Operations

Factor 5 had four Q-sorts and explained 5% of the variance in the study. The factor's title is based upon the somewhat positive views held by the participants towards the constructive impacts of understanding sampling strategies and the GNSS. Figure 10 is a model Q-sort for Factor 1. It is a composite representation of the idealized sorting response for the participants included in Factor 1 and serves as a generalization of their perspectives (McKeown & Thomas, 2013; van Exel & De Graaf, 2005). The researcher used the consensus statement in Table 11, distinguishing statements in Table 16, positive statements ranked higher in the factor array than in other factor arrays, negative statements ranked lower in the factor array than in other factor arrays, and responses in the post-sort questionnaire as data for this analysis.

Participants loading on this factor averaged 26 years of experience, 19 of which were in the geospatial field. The education levels were split between Bachelor's (2), Master's (1), and Doctoral (1) Degrees, with the majority (3) of their geospatial instruction taking place at the Bachelors' level. The majority (3) of the participants work in private industry, with the remainder (1) employed in the state government. All respondents indicated that they work in a combination of the industry sectors.

Table 16. Distinguishing Statements for Factor 5

No.	Statement	Factor 5			Remaining Factors			
		Rank	Z-score		1	2	3	4
36	Employ cartographic techniques to represent different kinds of uncertainty, including uncertain boundary locations, transitional boundaries, and ambiguity of attributes	6	1.96		1	0	3	3
45	Perform a feasibility study and cost/benefit analysis	5	1.69	*	2	1	1	2

Table 16 (continued).

8	Identify sampling strategies for field data collection, including systematic, random, and stratified random sampling, and describe circumstances favorable to each	4	1.3	*	0	-1	0	1
13	Recognize the differences between ellipsoidal (or geodetic) heights, geoidal heights, and orthometric elevation	3	1.21	*	-1	0	0	0
15	Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets	3	1.1	*	-2	-5	-2	-5
16	Interpret the quality of GNSS data based on possible sources of error	2	1.03	*	-3	-2	-1	-3
37	Understand how to represent boundaries in plats, records, and descriptions, as stipulated in legal statute and precedent	2	0.91	*	5	-2	0	-3
18	Understand the process to produce an orthoimage data product with geometric accuracy suitable for project requirements	2	0.88	*	0	-2	-2	0
25	Compare differential GNSS and autonomous GNSS	1	0.3	*	-3	-4	-3	-6
17	Explain major GNSS error sources, such as ionospheric delay, clock error, ephemerides, and satellite health	0	-0.25	*	-3	-6	-4	-3
56	Employ query languages such as SQL to interrogate spatial data	-1	-0.32	*	2	5	2	5
32	Develop conceptual, logical, and physical models of a geospatial database designed in response to user requirements	-1	-0.37	*	3	2	4	4
52	Automate geospatial analysis such as transformation, raster analysis, and geometric operations	-1	-0.4		2	2	1	1
51	Identify the factors that affect the interoperability of geospatial software applications	-1	-0.64	*	1	2	1	2

Table 16 (continued).

21	Understand how to conduct primary research and implications of data privacy and confidentiality	-4	-1.58		1	-3	3	4
62	Be able to leverage web architectural opportunities	-5	-1.59	*	0	4	2	-2

Note: ($p < 0.05$: Asterisk (*) Indicates Significance at $p < 0.01$)

The Q-sorts in Factor 5 reveals no strong opinions, but demonstrate an appreciation for the utility of land surveying as well as a negative view of information technology and associated skills. Most striking is the lack of consistency at the top of the Factor 5 array. The need for cartography (art) as a competency has diminished in the geospatial field as software (science) now permits users with limited traditional cartographic skills to produce beautiful maps. The ability to employ cartographic skills is still appreciated by some, as demonstrated by Participant 20 (referring to cartography), “Most important topic.... if a GISP doesn't understand this element, there are major issues.” Statements 36 – “Employ cartographic techniques to represent different kinds of uncertainty, including uncertain boundary locations, transitional boundaries, and ambiguity of attributes” (6). Interestingly, Statements 45 – “Perform a feasibility study and cost/benefit analysis” (5), and 8 – “Identify sampling strategies for field data collection, including systematic, random, and stratified random sampling, and describe circumstances favorable to each” (4) were the highest-ranking statements but are not related to cartography.

Factor 5 reflects a reasonably positive attitude towards land surveying, with an emphasis on GNSS operations. Seven statements appeared as distinguishing statements in support of land surveying. Statements 17 (0), 25 (+1), 37 (+2), 16 (+2), 15 (+3), and 13 (+3) all supported the relevance of land surveying and stood in stark contrast to the evaluation offered by Factor 4 (*No Room for Surveying in GIS*). Statement 15 is indicative of the competencies viewed positively in this factor, “Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets,” and encompasses the integration of traditional GIS skills and those displayed primarily by land surveyors. Reviewing the relative rankings of statements for Factor 5 revealed additional data to buttress the contributions of land surveying to the geospatial field, with Statements 14 (+1), 3 (+1), 4 (+1), and 5 (+4) revealing positive view of the activity. The perspective shared in Factor 5 is not overwhelming but does represent a broad-based acknowledgment of land surveying, especially in the context of GNSS missions, as a valuable contributor to the profession.

Factor 5 Q-sorts reveal a generally negative perception of information technology operations. Statements 51 – “Identify the factors that affect the interoperability of geospatial software applications” (-1), 52 – “Automate geospatial analysis such as transformation, raster analysis, and geometric operations” (-1), and 62 – “Be able to leverage web architectural opportunities” (-5) were the only statements associated with information technology located with the distinguishing statements for Factor 5. Statements 48 (-1), 55 (-1), 46 (-2), 59 (-4), 54 (-5), and 61 (-6) also ranked lower in Factor 5 than in another array. Interestingly, Statements 29 (-2), 34 (-2), and 35 (-3) are examples of competencies the act as a transition from information technology to geospatial analysis but are ranked lower in Factor 5 than in another array. Statement 34 demonstrates this bridge, “Explain characteristics and appropriate uses of geospatial modeling techniques (e.g., artificial intelligence, machine learning, and deep learning).” Many routine actions in geospatial analysis are automated through the development of models. The moderately lower evaluation of some scripting or programming routines, in conjunction with similar scores for modeling tasks, suggests that the participants represented have a less positive view of automated analysis.

-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
61 Explain how geospatial software in large enterprises	62 Be able to leverage web architectural opportunities	22 Describe how information can be harvested and geocoded from social	35 Demonstrate familiarity with the existence of predictive	46 Design a geospatial system architecture that responds	56 Employ query languages such as SQL to interrogate spatial data	50 Ensure that software code complies with industry standards, such	4 Recognize that land records are administered differently	16 Interpret the quality of GNSS data based on possible sources of	13 Recognize the differences between ellipsoidal (or geodetic)	5 Explain the distinction between a property boundary and	45 Perform a feasibility study and cost/benefit analysis	36 Employ cartographic techniques to represent different kinds
	54 Customize geospatial software using proprietary and open source	59 Evaluate open source software components for re-use and	10 Perform requirements analysis for remotely sensed data	39 Explain the processes involved in geometric correction,	32 Develop conceptual, logical, and physical models of a geospatial	57 Work effectively in teams to plan and coordinate software and	49 Identify appropriate software development tools for	24 Explain how a mobile device calculates location coordinates	6 Plot a legal boundary description from a deed or plat	23 Explain the process of acquiring and integrating large and	38 Determine appropriate image data and image analysis techniques	
		21 Understand how to conduct primary research and implications of	33 Understand how spatial data aggregation into different	44 Develop use cases for user-centered requirements analyses	52 Automate geospatial analysis such as transformation,	28 Use GIS software to identify an optimal route that accounts	3 Discuss examples of systematic and unsystematic land	2 Geocode a list of ress-referenced locations to map data	15 Collect and integrate carrier phase (survey grade) GNSS positions	8 Identify sampling strategies for field data collection,		
			19 Understand how rotriangulation contributes to data quality	43 Perform object-oriented image classification	31 Use tion-allocation software functions to locate service	40 Explain how to quantify the thematic accuracy of a land use/land	1 Use geospatial software to transform ellipsoid,	37 Understand how to represent boundaries in plats, records,	7 Design a system for acquiring, processing and integrating			
			30 Explain how leading online routing systems work, and account for	29 Perform dynamic segmentation on transportation network data	48 Optimize geospatial system performance	20 Produce a metadata document that conforms to FGDC, ISO or	14 Understand GNSS data post-processing (such as National	27 Perform a site suitability analysis using intersection	26 Describe an example of a useful application of a buffer			
				34 Explain characteristics and appropriate uses of geospatial	11 Explain the concept of "bit depth" and its implications for	41 Determine the thematic accuracy of a data product using ground	58 Stay informed about trends and best practices in information	18 Understand the process to produce an orthoimage data product with				
				12 Plan a remotely sensed data acquisition mission,	55 Use scripting languages or other tools to create web	60 Realize opportunities to leverage positioning technology to	53 Use scripting languages to automate repetitive	47 Communicate effectively with end-users to ensure that software				
					51 Identify the factors that affect the nteroperability of geospatial	9 Explain how spatial autocorrelation influences sampling	25 Compare differential GNSS and autonomous GNSS					
						42 Explain the difference between pixel-based and object-based						
						17 Explain major GNSS error sources, such as ionospheric						

Legend

- Distinguishing statement at P< 0.05
- Distinguishing statement at P< 0.01
- Consensus statement

Figure 10: Model Sort for Factor 5 - Positive View of Land Surveying Operations

Analysis of Research Question 2

The second research question seeks to determine if the views of geospatial professionals aligned with the five identified factors are independent of the level of education, years of experience, industry sector, or certification method. The hypothesis is that the participants will not reflect any differences in perception due to the level of education, certification method, years of experience, or industry sector. The researcher used Fisher’s Exact Probability Test, as opposed to the Chi-Square test, to investigate if a relationship existed. In discussing the value of row and column cross-classification tables, Mielke, Berry, and Zelterman (1994) determined that “Fisher’s exact probability test enjoys tremendous potential in educational and psychological research” (p. 98). Bower (2003) notes that “It’s appropriate to use Fisher’s exact test, in particular when dealing with small counts” (p. 37). The researcher based the decision to move forward with Fisher’s Exact Probability Test, as the data used in the study violated many of the conditions established by Swinscow (1997) for the Chi-Square Test of Independence. Swinscow (1997) observed the following regarding tests of independence:

> When the numbers in a 2 x 2 contingency table are small, the approximation becomes poor. The following recommendations may be regarded as a sound guide. In fourfold tables a test is inappropriate if the total of the table is less than 20, or if the total lies between 20 and 40 and the smallest expected (not observed) value is less than 5; in contingency tables with more than one degree of freedom it is inappropriate if more than about one fifth of the cells have expected values less than 5 or any cell an expected value of less than 1. An alternative to the test for fourfold tables is known as Fisher's Exact test.

The researcher conducted a Fisher's Exact Probability Test (see table 17) to determine if differences in perceptions were related to the participants' level of post-secondary education.

Table 17. Fisher's Exact Probability Test – Level of Education

		Bachelor	Masters	Doctoral	Total
Factor 1	Count	3	5	0	8
	Total %	9.09	15.15	0	24.24
	Column %	27.27	23.81	0	
	Row %	37.5	62.5	0	
Factor 2	Count	3	6	0	9
	Total %	9.09	18.18	0	27.27
	Column %	27.27	28.57	0	
	Row %	33.33	66.67	0	
Factor 3	Count	2	3	0	5
	Total %	6.06	9.09	0	15.15
	Column %	18.18	14.29	0	
	Row %	40	60	0	
Factor 4	Count	1	6	0	7
	Total %	3.03	18.18	0	21.21
	Column %	9.09	28.57	0	
	Row %	14.29	85.71	0	
Factor 5	Count	2	1	1	4
	Total %	6.06	3.03	3.03	12.12
	Column %	18.18	4.76	100	
	Row %	50	25	25	
	Total	11	21	1	33
		33.33	63.64	3.03	

Statistic: $X^2 = 9.953$, df = 8, $p = 0.2683$, Fisher Exact = 0.4549

*Note: 20% of cells have expected count less than 5; Chi-square value is suspect.

The researcher conducted a Fisher's Exact Probability Test (see table 18) to determine if differences in perceptions were related to the participants' industry sector. The variables used were the industry sectors (Analysis & Modeling, Positioning & Data Acquisition, Software & Application Development, and a combination). The results were not significant, with a $X^2 =$

17.782, df = 12, p = 0.1225, Fisher Exact = 0.1022. These results confirm the null hypothesis and the absence of a relationship between the industry sector and a shared perspective (factor).

Table 18. Fisher's Exact Probability Test – Industry Sector

		Positioning and Data Acquisition	Analysis and Modeling	Software and Application Development	A combination of Sectors	Total
Factor 1	Count	0	0	0	8	8
	Total %	0	0	0	24.24	24.24
	Column %	0	0	0	33.33	
	Row %	0	0	0	100	
Factor 2	Count	1	1	3	4	9
	Total %	3.03	3.03	9.09	12.12	27.27
	Column %	100	20	100	16.67	
	Row %	11.11	11.11	33.33	44.44	
Factor 3	Count	0	2	0	3	5
	Total %	0	6.06	0	9.09	15.15
	Column %	0	40	0	12.5	
	Row %	0	40	0	60	
Factor 4	Count	0	2	0	5	7
	Total %	0	6.06	0	15.15	21.21
	Column %	0	40	0	20.83	
	Row %	0	28.57	0	71.43	
Factor 5	Count	0	0	0	4	4
	Total %	0	0	0	12.12	12.12
	Column %	0	0	0	16.67	
	Row %	0	0	0	100	
	Total	1	5	3	24	33
		3.03	15.15	9.09	72.73	

Statistic: X^2 = 17.782, df = 12, p = 0.1225, Fisher Exact = 0.1022

Note: 20% of cells have expected count less than 5; Chi-square value is suspect.

The researcher conducted a Fisher's Exact Probability Test (see table 19) to determine if differences in perceptions were related to the participants' years of experience. The variables used were the years of experience grouped into categories (0-10, 11-20, 21-30, and 31-40). The results were not significant, with a X^2 = 6.908, df = 12, p= 0.8637, Fisher Exact = 0.9228. These results confirm the null hypothesis and the absence of a relationship between years of experience and a shared perspective (factor).

Table 19. Fisher's Exact Probability Test – Experience by Group

		0 - 10 Years	11 - 20 Years	21 - 30 Years	31 - Years	Total
Factor 1	Count	0	1	3	4	8
	Total %	0	3.03	9.09	12.12	24.24
	Column %	0	10	37.5	30.77	
	Row %	0	12.5	37.5	50	
Factor 2	Count	1	4	2	2	9
	Total %	3.03	12.12	6.06	6.06	27.27
	Column %	50	40	25	15.38	
	Row %	11.11	44.44	22.22	22.22	
Factor 3	Count	0	1	1	3	5
	Total %	0	3.03	3.03	9.09	15.15
	Column %	0	10	12.5	23.08	
	Row %	0	20	20	60	
Factor 4	Count	1	2	1	3	7
	Total %	3.03	6.06	3.03	9.09	21.21
	Column %	50	20	12.5	23.08	
	Row %	14.29	28.57	14.29	42.86	
Factor 5	Count	0	2	1	1	4
	Total %	0	6.06	3.03	3.03	12.12
	Column %	0	20	12.5	7.69	
	Row %	0	50	25	25	
	Total	2	10	8	13	33
		6.06	30.3	24.24	39.39	

Statistic: $X^2 = 6.908$, df = 12, $p = 0.8637$, Fisher Exact = 0.9228

Note: 20% of cells have expected count less than 5; Chi-square value is suspect.

The researcher conducted a Fisher's Exact Probability Test (see table 20) to determine if differences in perceptions were related to the participants' method of receiving GISP Certification. The variables used were the certification methods of grandfathered, knowledge exam, and portfolio. The results were not significant, with a $X^2 = 4.053$, df = 8, $p = 0.8523$, and

Fisher Exact = 0.9490. These results confirm the null hypothesis and the absence of a relationship between the method of receiving GISP Certification and a shared perspective (factor).

Table 20. Fisher's Exact Probability Test – Certification Method

		Grandfathered	Portfolio	Knowledge	Total
Factor 1	Count	3	4	1	8
	Total %	9.09	12.12	3.03	24.24
	Column %	37.5	18.18	33.33	
	Row %	37.5	50	12.5	
Factor 2	Count	2	6	1	9
	Total %	6.06	18.18	3.03	27.27
	Column %	25	27.27	33.33	
	Row %	22.22	66.67	11.11	
Factor 3	Count	1	4	0	5
	Total %	3.03	12.12	0	15.15
	Column %	12.5	18.18	0	
	Row %	20	80	0	
Factor 4	Count	2	4	1	7
	Total %	6.06	12.12	3.03	21.21
	Column %	25	18.18	33.33	
	Row %	28.57	57.14	14.29	
Factor 5	Count	0	4	0	4
	Total %	0	12.12	0	12.12
	Column %	0	18.18	0	
	Row %	0	100	0	
	Total	8	22	3	33
		24.24	66.67	9.09	

Statistic: $X^2 = 4.053$, df = 8, $p = 0.8523$, Fisher Exact = 0.9490

Note: 20% of cells have expected count less than 5; Chi-square value is suspect.

Chapter Summary

This chapter presented the results of the research study, which were used to address the two research questions. The researcher collected data from 54 certified GISPs, with 33 respondents loading onto five factors. The study gathered demographic, Q-sort (quantitative), and narrative (qualitative) data.

To address Research Question 1 (How do Geographic Information Science Professionals view the technical competencies within the Geospatial Technology Competency Model and why?), the researcher performed factor analysis on the Q-sort submissions and generated five factors. The post-sort questionnaire provided additional information and critical insight to the researcher who used the qualitative data to build the narratives for each factor. The five themes developed from the analysis include Factor 1: *Skeptical View of Remote Sensing*, Factor 2: *Programming is Critical*, Factor 3: *Leveraging Location-based Data*, Factor 4: *No Room for Surveying in GIS*, and Factor 5: *Positive View of Land Surveying Operations*. The analysis reveals distinct opinions relating to the inclusion of peripheral disciplines (computer programming, remote sensing, and land surveying). The study revealed only one consensus statement, and the scarcity of shared statements may be connected to the entrenched views expressed within the factors.

To address Research Question 2 (Do perceptions of the geospatial competencies differ based upon the respondents' industry-sector, years of experience, method of certification, or education?), the researcher used the Fisher's Exact Probability Test to discern whether a relationship exists between each variable and the five factors. The researcher discussed the findings and the implications found in this study in Chapter 5.

CHAPTER 5: DISCUSSION AND IMPLICATIONS

Introduction

This research study examined the viewpoints of geospatial professionals towards technical competencies located within the Geospatial Technology Competency Model (GTCM). The study began with a review of the geospatial industry and its use of competencies to define itself as a separate and distinct entity. Previous research has sought to determine the skills needed by a geospatial professional, but the absence of a study evaluating the relevance of the GTCM represented a gap in practice. The geospatial profession is built upon a defined set of workforce competencies, but the professionals within the industry have never been asked to rank the knowledge, skills, abilities, and other characteristics (KSAOs) within the GTCM. This chapter discusses the findings of the study and reviewed the nature of the identified factors.

The General Theory of Expertise is the foundation of this study's theoretical framework. Using the General Theory of Expertise premise, these experts who evaluate the KSAOs are expected to be stakeholders and heavily invested in the field. The contributors to this study are certified geographic information science professionals (GISP) who have signed a code of ethics, submitted a portfolio of work products, and averaged over 20 years of geospatial experience. The competency model approach, which has historically been built upon the input of industry experts, is the conceptual framework of the study.

Conclusions

The decision to use Q Methodology in the study relates to its suitability to answer the research questions while adhering to validity and reliability requirements.

The study results address the following research questions:

1. How do Geographic Information Science Professionals view the technical competencies within the Geospatial Technology Competency Model and why?

2. Do perceptions of the geospatial competencies differ based upon the respondents' industry-sector, years of experience, method of certification, or education?

This chapter describes the results of a research study consistent with Q Methodology, attempting to reveal varied perspectives as well as determine if relationships exist between the factors and socio-demographic variables.

Finding 1. This study revealed five viewpoints, which portray the different perspectives of GISPs participating in the research project. The five recognized factors represent a noteworthy variation in the perceptions of technical geospatial competencies. The researcher developed a title, compiled characteristics, and constructed a descriptive narrative for each factor. The emerging factors were Factor 1: Skeptical View of Remote Sensing, Factor 2: *Programming is Critical*, Factor 3: *Leveraging Location-based Data*, Factor 4: *No Room for Surveying in GIS*, and Factor 5: *Positive View of Land Surveying Operations*. The perspective shared in Factor 1 doubted the relevance of remotely sensing to the geospatial profession, with the three lowest distinguishing statements and statements ranked lower in Factor 1 than in another array all relating to remote sensing or imagery operations. The perspective shared in Factor 2 is supportive of information technology in the broader sense, with a specific appreciation for computer programming. There is an acknowledgment of the contribution of scripting, and similar programming activities with the top four distinguishing statements and seven additional statements loading higher onto Factor 2 than in any other array. The perspective shared in Factor 3 was a positive view of the manipulation of location-based datasets, with competency statements involving geospatial analysis comprising two of the top four distinguishing and five additional statements loaded higher onto Factor 3 than in any other array. Other statements selected displayed an uncertainty toward land surveying and cadastral mapping, with a slightly negative view of geospatial application development. The lack of a strong positive or negative position regarding competency statements differentiates this factor. The perspective shared in Factor 4 is substantially different from the other factors in this study. The highest positive value within the distinguishing statements is a +3, with some neutral statements, and led by a collection of negative significant loadings connected to land surveying undertakings. Another oddity is the appearance of several statements in support of database competencies in the relative rankings after their nonexistence within distinguishing statements. The perspective shared in Factor 3 revealed no strong opinions, but demonstrate an appreciation for the utility and value of land surveying. A positive outlook towards land surveying, with an emphasis on GNSS operations, is reflected in six positive distinguishing statements and four additional statements loading higher onto Factor 5 than in any other array. The perspective shared in Factor 5 represents an acknowledgment of land surveying, especially in the context of GNSS missions, as an appreciated contributor to the profession.

Finding 2. This study investigated if a relationship exists between perceptions of the geospatial competencies and the participants' industry-sector, years of experience, certification method, or education. The brief history of geospatial science contains an ongoing struggle to define the roles of each member within the community and whether the domain is entirely distinct. Arguments have been offered that portions of geographic information science should be included as a component within other fields (Tomaszewski and Holden, 2012), is redundant (Joffe, 2018), or is simply a software tool used by any field needing spatial analysis (Burley, 1993). With this level of disagreement within the geospatial workforce and the variety of routes someone could take to become a GISP, it seems reasonable to investigate a relationship between the five identified factors and the participants' industry-sector, years of experience, certification method, or education.

The researcher conducted a Fisher's Exact Probability Test, with the hypothesis that the participants would not reflect any differences in perception connected with each variable. These analyses confirm the null hypothesis of the lack of a relationship between years of experience, certification method, or education, and a shared perspective (factor). The researcher discovered a minimal correlation between industry sector and shared perspective. The origin of the relationship was not established, but it is reasonable to assume that participants might view their industry more favorably than other sectors. Also, the absence of a stronger association could be explained by the use of three broad industry sectors, when participants may work in much more narrowly defined occupations. Regardless, these results might suggest the applicability of the competency statements to all sectors of the geospatial workforce. The absence of a relationship between specific groups and the factors may indicate that the competencies used in the research are representative of the geospatial industry. Further study may be warranted, potentially using other variables to evaluate if potential relationships exist.

Finding 3. This study revealed a clear division of opinion among the participants regarding the relevance of remote sensing and land surveying activities. There has been pressure from some within the field of surveying to bring geospatial activities under the control of professional land surveying, noting a need to protect the public from harm (Harvey, 2003). The division between land surveyors and geographic information scientists is most often connected at the dividing line between the allowable practices, and some states have professional land surveying designations with a GIS component (Joffe, 2018; Somers, 2000).

There are seven statements aligned with the remote sensing field, and the highest-scoring statement garnering a 0.87 (Q-sort scale -6 to +6) and the average of all statements was -0.68. Land surveying and GNSS competencies scored much lower, with the highest rated statement appearing with a -0.55, and the average of all statements was -1.42. Furthermore, land surveying and GNSS had the three lowest-ranked statements in the Q-sort. The inconsistency appears when noticing that many of the competencies are related to “mapping grade” GNSS skills; skills which have been a tremendous benefit for the geospatial industry and fall within the accepted skillset of non-land surveyors. High accuracy GNSS falls within the domain of professional land surveying, which requires a license from each state (Joffe, 2018). Participant 41 offered, “Having detailed knowledge of GNSS and even land survey methodology and practice is already an integral part of professional Land Surveying. There is no need or reason for GIS professionals to duplicate efforts that already have their own specialty.”

A potential explanation for the scores may be connected to the preexisting external competency processes used in these sectors. Photogrammetry, a subcomponent of remote sensing, is a science wherein measurements of objects can be calculated from photographs, typically aerial photographs of the earth’s surface. The certification of photogrammetrists and remote sensing professionals predated the GISCI and continue today with several geospatial science designations (Khan et al., 2016). The GISCI was created from the Urban and Regional Information Systems Association (URISA). A significant portion of URISA’s and GISCI’s membership work in or support governmental GIS systems. Some of the competencies deemed less relevant by the participants are the peripheral activities (e.g., GNSS, photogrammetry, remote sensing, and land surveying), which collect or construct the data needed by geographic information science professionals.

Limitations

The study targeted a specific subset of the geospatial workforce. The participants were all certified GISPs, with a history of contributions to the community, education, and experience. Unfortunately, the group was not stratified to ensure that each industry sector had equal representation. Furthermore, the GISCI (who administers the GISP Certification) is a product of the Urban and Regional Information Systems Association (URISA), which has a significant local government population. Half of the respondents worked in governmental agencies, with 41 percent at the local or state government level. A P-set built to more accurately reflect a given professional geospatial workforce may prove more valuable.

The researcher completed factor extraction with a five-factor solution. The development of five factors is not necessarily a limitation, but additional factors would have explained more variance within the study. Recognizing that the number of factors selected and rotated depends on the variability of the Q-sorts (Dziopa & Ahern, 2011; Wright, 2013), the researcher chose five factors based upon the number of Q-sorts per factor, the additional variance explained, and the desire to avoid bipolar factors.

The study revealed only one consensus statement, Statement 39. Statement 39 read as follows, “Explain the processes involved in geometric correction, radiometric correction, and mosaicking of digital remotely sensed data and the resulting errors.” The range of ranking within the five factors was from -2 to -3, indicating a consistently negative view of the competency. The statement supports other findings regarding the views held toward the area of remote sensing. Statement 39 can act as an example of the value of consensus statements, and it also suggests that a deficiency of consensus statements could be a limitation in the study. The deficiency of common ground may be the result of the resolute views expressed within the factors. The lack of common viewpoints inhibits the production of additional information, which limits the researcher's ability to draw finer conclusions (Zabala et al., 2018).

The research instrument allowed participants to decline to answer the narrative comments relating to the rationale for the selection of the highest and lowest scores. Many respondents completed the narrative portion, but the lack of explanation for decisions made by some participants limited the ability of the researcher to understand the individual perspectives fully. The inability to capture all possible data at the individual level may have limited the potential accuracy of the complete analysis.

The researcher chose to use the 62 sector-specific competencies located in Tier 5 of the US DOLETA GTCM for this study. Tier 5 competencies are more granular in design than the Tier 4: Industry-Wide Technical Competencies. Tier 4 competency statements relate directly to *core* geospatial skills and reflect *crosscutting geospatial abilities and knowledge*. The specificity of many of the competency statements in Tier 5 may have unintentionally caused participants to react negatively to the competency statement with which they are unfamiliar.

Implications for Higher Education

The ability of higher education to prepare students for the labor market is a topic for debate (Solem et al., 2013), but there has been increased pressure to demonstrate that academic programs are enabling students to achieve their employability goals (Wikle, 2017). Recent studies demonstrate a gap between the learning outcomes and the knowledge needed in employment (Mathews & Wikle, 2019), which is reflected in a lack of confidence the geospatial industry has in the baseline level of competence of graduates (Prager & Plewe, 2009). Designing curricula so that it aligns with workforce needs is an ongoing challenge (Sinton, 2012), and the ability to make geospatial education more effective is based, in part, on identifying the educational competencies in need of improvement (Painho & Curvelo, 2012). A connection between the learning outcomes and the knowledge demonstrated in the workplace is a reasonable path to establishing competency (Mathews & Wikle, 2017). A difficulty associated with geospatial science is its application across a variety of disciplines, where it is the central analytical tool in many occupations. The extensive range of jobs makes it difficult for most graduates to receive the training they need, and academic programs should confirm that graduates can apply these skills in a variety of workforce settings.

The feedback generated by participants, who collectively have extensive experience and expertise, is the critical information needed within academia. If geospatial science faculty have a more accurate picture of the workforce, they will be better able to prepare students. Also, the information in this study could better prepare faculty and administrators for conversations with industry representatives. Previous studies have attempted to define the geospatial labor market through a content analysis of job advertisements (Hong, 2016), focus groups (Solem et al., 2008), surveys (Wikle & Fagin, 2015), an examination of job titles (Wikle, 2010), and other methods. Prior efforts have not evaluated a predefined set of competencies in an attempt to determine relevance in the workforce. The cataloging of existing geospatial workforce competencies, as well as emergent or obsolete skills, will allow educators to generalize about the comparative need for a specific combination of competencies in the geospatial industry. The information gained here may enable researchers to assert how geospatial skills are different in various geospatial workforce sectors and drive the modification of curricula.

Implications for the GIS Certification Institute (GISCI)

The GISCI manages the certification of approximately 1% of the geospatial workforce and is by far the largest certifying body in the field. The GISCI also is the most diverse population of certified geospatial professionals. The decision to collaborate with the GISCI was based upon its inclusivity, diversity, and the strict certification standards it employs. Also, Tier 8 (Occupation-Specific Requirements) of the GTCM addresses geospatial certification. The GISCI's Geospatial Core Technical Knowledge Exam® is based upon two competency models, the GIS&T BoK and the DOLETA GTCM. The GISCI may use the results of this study as an evaluative tool, among others, to determine if the exam needs to be modified. The exam's modification would most likely take two forms. First, the nature of the competencies would be modified to represent changes to the competencies needed in the industry. Secondly, the exam is comprised of ten knowledge categories, weighted differently based upon internal criteria. The exam intends to reflect the skills needed to be successful in the geospatial field, and the value placed upon each knowledge area may be adjusted based upon the research findings. The research will also provide to the GISCI a window into the opinions of their constituents, irrespective of the exam implications. Such knowledge could assist the body with a variety of decisions as it continues to lead the geospatial field.

Implications for the US Department of Labor

The US Department of Labor maintains the GTCM and conducts an update every four years to make sure that the competency model is an accurate reflection of the KSAOs needed within the field. The GTCM's first fiver tiers contain the designated skills needed within the workforce. The entire GTCM maintains nine tiers, of which Tier 6 is devoted to occupations, which are connected to standard job titles in the industry. The data from this research study can be used by DOLETA to update job titles, assess occupations, and evaluate the competencies within the model. The job tasks, descriptions, and titles within the geospatial field are varied and often change (Solem, 2008; Wikle, 2010), and input regarding the specific skills needed by geospatial professionals could inform future job tasks and related job descriptions. The geospatial job tasks, descriptions, and titles are the foundation for the DOL's occupations. The modification of these components could be used to alter outdated occupation titles. The GTCM is updated every four years through a survey of the geospatial community using a five-point Likert scale.

As mentioned previously, prior update efforts have used a five-point Likert scale in conjunction with focus groups to gauge the applicability of the competencies found in the GTCM. The surveys did not require those respondents to evaluate each competency in comparison with the other competencies and rank them accordingly. Also, the survey was made available to geospatial practitioners and professionals alike without the benefit of a baseline competency requirement to participate. The results from this research demonstrate the potential for the development of additional data, which could provide a better representation of the competencies needed within the geospatial field. A review of the research may modify the approach used during the next GTCM in 2021. A new approach would use Q Methodology to analyze a much broader and more diversified population. Within the factor analysis, different groups from the respondent population would be selected based upon a predefined set of criteria. These groups would act as a P-set, and their Q-sorts would be used to build factors (viewpoints). There may be significant value in examining the factors that emerge from the various subcultures within the geospatial domain. Outside of the factor analysis, there is significant value in examining a more generalized view of the competencies as well as anchor and consensus statements.

Recommendations for Future Research

This study investigated how a specific subset of the geospatial workforce, geographic information science professionals, viewed technical competencies within the GTCM. Other organizations, organized to address a specific set of geospatial competencies, could have a very different perspective regarding the GTCM. The United States Geospatial Intelligence Foundation (USGIF) accredits academic programs and is narrowly focused on geospatial intelligence (GEOINT), the American Society for Photogrammetry and Remote Sensing (ASPRS) certifies professionals (Certified Mapping Scientist), and the National Society of Professional Surveyors is a coalition of licensed surveyors evaluate some geospatial competencies found within the GTCM. Each of these groups could be targeted to learn how the members of that organization view the competencies within the GTCM or a domain-specific body of knowledge. Additional studies with the groups mentioned above could help to construct a complete picture of the geospatial workforce and the competencies needed to support the labor market.

This research restricted the competencies evaluated to a specified tier within the GTCM, focusing on technical expertise. Employers have noted the importance of other non-technical skills (Mathews & Wikle, 2019; Prager & Plewe, 2009; Solem et al., 2013; Wikle, 2017) within the profession. An evaluation of Tier 1 (Personal Effectiveness Competencies), Tier 2 (Academic Competencies), Tier 3 (Workplace Competencies), or some combination of these competencies could provide additional information about the skills needed to be successful in the geospatial profession. An investigation of the perceptions of Tier 4 (Industry-Wide Technical Competencies) competencies may prove more valuable than the current research study. The DOLETA recognizes the KSAOs in Tier 4 as representing crosscutting geospatial abilities and knowledge. The competencies are more general in design and elicit different responses due to the absence of sector divisions.

The University Consortium for Geographic Information Science's (UCGIS) Geographic Information Science and Technology (GIS&T) Body of Knowledge (BoK) is intended to be used for curriculum evaluation and planning, act as a model curriculum for geospatial academic programs, and assess student learning outcomes (DiBiase et al., 2006; Hong, 2016; Prager & Plewe, 2009). The BoK is a collection of technical competencies found within the geospatial field (DiBiase et al., 2007; Sullivan et al., 2008) and is one of the source documents for the GISCI's Geospatial Core Technical Knowledge Exam®. The BoK is a logical objective for future research relating to the geospatial profession, as it works to bridge the divide between learning outcomes and workforce competencies. The BoK was composed initially of 10 knowledge areas, 329 topics, and 1,600 educational objectives, and a study could be very valuable, given its breadth and depth.

The study used a forced distribution during the Q-sort activity. The forced distribution requires participants to be thoughtful during their evaluation, as they are comparing each competency statement within the sort. Unlike a Likert scale, participants must make difficult decisions during the ranking process and cannot assign an unlimited number of high or low scores to the competency statements. Participant 41 shared, "The sorting was difficult." Participant 53 added, "I understand what is being done, but I think that it is very difficult to bin tasks like these." These problematic choices have the potential to provide much more data and may potentially affect the rationale each respondent provides when justifying their decisions.

Recommendations for Future Q Studies

Future Q Methodology studies of the geospatial workforce who would benefit from more narrowly defining participant areas of employment. Moving beyond the job sector to a more granular identification, such as occupation or job title, will assist the researcher. Requiring answers to the post-sort questionnaire, as opposed to allowing them to be optional, would assist in interpreting the choices made by respondents. Finally, moving to the more general 42 competency statements in Tier 4 may provide a more accurate picture of respondent opinions. The combination of the previously mentioned modifications may prove to reveal even more information regarding shared perspectives in the field.

Another consistent application of a Q Methodological study could be as a feedback instrument. Regional focus groups within the geospatial industry are asked to define the tasks needed to support the local economy, typically in the form of developing a curriculum (DACUM) activity. The DACUM method is limited due to its location-specific nature, but the aggregation of multiple DACUMs from various regions (MetaDACUM) permits a national view core geospatial tasks. Personnel from the first focus groups could conduct a Q-sort to determine the applicability of a national DACUM. The researcher could evaluate what viewpoints emerge as well as if different industries, locations, or the number of years since the original DACUM affect the study results.

The future study with the potential to have the most significant impact may involve an update to the GTCM. Every four years, the US DOLETA updates the GTCM to ensure that it remains relevant. The Q-sort approach is similar to the Likert Scale for evaluating attitudes, but the critical difference, and advantage, is that in a Q-sort, all statements are evaluated in comparison with other statements. The researcher would have to modify the study's design to collect data from more participants, but there is the potential for an improved data solution. Using a forced distribution approach is an outstanding opportunity for additional data collected in round two from subject matter experts and in the final review by a workforce panel.

Conclusion

This research study used Q Methodology to examine the perspectives of 54 geospatial professionals the relevance of the 62 competencies located in Tier 5 of the GTCM. The participants sorted the Q-set into a forced distribution ranging in value from most relevant (+6) to least relevant (-6) to the geospatial field. 33 of the 54 respondents loaded onto five factors, each with a distinct set of characteristics that define a distinctive viewpoint. The identified views are: (1) *Skeptical View of Remote Sensing*; (2) *Programming is Critical*; (3) *Leveraging Location-based Data*; (4) *No Room for Surveying in GIS*; and (5) *Positive View of Land Surveying Operations*. The study also investigated whether perceptions of the geospatial competencies differ based upon the respondents' industry-sector, years of experience, method of certification, or education. The researcher conducted a Fisher's Exact Probability Test for each variable and found a weak relationship between the respondents' sector of the industry and the views expressed.

This research study confirmed that a Q Methodological study is a practical approach to examine the statements within a competency model. Moreover, it demonstrated a process using industry experts (as expressed in the General Theory of Expertise) to evaluate a conceptual model of competencies. The GTCM may be a conceptual model of competencies for the geospatial industry, but it continues to prove its value and applicability at reflecting the field of geospatial science.

The results of this study may provide some feedback from employers regarding how the geospatial field views the technical competencies in the GTCM. Better sources of data analysis, such as that found in this study, could enable institutions of higher education to more effectively engage industry partners and increase the value of their instruction to potential members of the geospatial workforce. The researcher hopes that others may find this study a suitable model for extracting the shared perspectives within a chosen field.

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APPENDICES

Appendix A: Geospatial Competencies in the Q-set

5.1 Positioning and Data Acquisition

5.1.1 Use geospatial software to transform ellipsoid, datum, and/or map projection to georegister one set of geospatial data to another

5.1.2 Geocode a list of address-referenced locations to map data encoded with geographic coordinates and attributed with address ranges

5.1.3 Discuss examples of systematic and unsystematic land partitioning systems in the U.S. and their implications for land records

5.1.4 Recognize that land records are administered differently around the world

5.1.5 Explain the distinction between a property boundary and its representations, such as deed lines, lines on imagery, boundary depictions in cadastral (land records) databases

5.1.6 Plot a legal boundary description from a deed or plat

5.1.7 Design a system for acquiring, processing and integrating geospatial data from diverse sources

5.1.8 Identify sampling strategies for field data collection, including systematic, random, and stratified random sampling, and describe circumstances favorable to each

5.1.9 Explain how spatial autocorrelation influences sampling strategies and statistics

5.1.10 Perform requirements analysis for remotely sensed data acquisition using resolution concepts

5.1.11 Explain the concept of "bit depth" and its implications for remotely-sensed image data

5.1.12 Plan a remotely sensed data acquisition mission, including specifying an appropriate sensor and platform combination suited for particular project requirements

5.1.13 Recognize the differences between ellipsoidal (or geodetic) heights, geoidal heights, and orthometric elevation

5.1.14 Understand GNSS data post-processing (such as National Geodetic Survey's Online Positioning Service) and real time (such as Real Time Kinematic)

5.1.15 Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets

5.1.16 Interpret the quality of GNSS data based on possible sources of error

5.1.17 Explain major GNSS error sources, such as ionospheric delay, clock error, ephemerides, and satellite health

5.1.18 Understand the process to produce an orthoimage data product with geometric accuracy suitable for project requirements

5.1.19 Understand how aerotriangulation contributes to data quality confidence and is applicable to completing related tasks

5.1.20 Produce a metadata document that conforms to FGDC, ISO or other geospatial metadata standard

5.1.21 Understand how to conduct primary research and implications of data privacy and confidentiality

5.1.22 Describe how information can be harvested and geocoded from social media

5.1.23 Explain the process of acquiring and integrating large and heterogeneous datasets (spatial or nonspatial)
5.1.24 Explain how a mobile device calculates location coordinates (e.g., GNSS, triangulation, trilateration, etc.)
5.1.25 Compare differential GNSS and autonomous GNSS

5.2 Analysis and Modeling

5.2.1 Describe an example of a useful application of a buffer operation in GIS software
5.2.2 Perform a site suitability analysis using intersection and overlay functions of GIS software
5.2.3 Use GIS software to identify an optimal route that accounts for visibility, slope, and specified land uses
5.2.4 Perform dynamic segmentation on transportation network data encoded in a linear reference system
5.2.5 Explain how leading online routing systems work, and account for common geocoding errors
5.2.6 Use location-allocation software functions to locate service facilities that satisfy given constraints
5.2.7 Develop conceptual, logical, and physical models of a geospatial database designed in response to user requirements
5.2.8 Understand how spatial data aggregation into different areal extents affects interpretation of results (Modifiable Areal Unit Problem)
5.2.9 Explain characteristics and appropriate uses of geospatial modeling techniques (e.g. artificial intelligence, machine learning, and deep learning)
5.2.10 Demonstrate familiarity with the existence of predictive models and their applications
5.2.11 Employ cartographic techniques to represent different kinds of uncertainty, including uncertain boundary locations, transitional boundaries, and ambiguity of attributes
5.2.12 Understand how to represent boundaries in plats, records, and descriptions, as stipulated in legal statute and precedent
5.2.13 Determine appropriate image data and image analysis techniques needed to fulfill project requirements
5.2.14 Explain the processes involved in geometric correction, radiometric correction, and mosaicking of digital remotely sensed data and the resulting errors
5.2.15 Explain how to quantify the thematic accuracy of a land use/land cover map derived from remotely-sensed imagery
5.2.16 Determine the thematic accuracy of a data product using ground verification methods
5.2.17 Explain the difference between pixel-based and object-based image classification
5.2.18 Perform object-oriented image classification

5.3 Software and Application Development

5.3.1 Develop use cases for user-centered requirements analyses
5.3.2 Perform a feasibility study and cost/benefit analysis

5.3.3 Design a geospatial system architecture that responds to user needs, including desktop, server, and mobile applications
5.3.4 Communicate effectively with end-users to ensure that software applications meet user needs
5.3.5 Optimize geospatial system performance
5.3.6 Identify appropriate software development tools for particular end uses
5.3.7 Ensure that software code complies with industry standards, such as those promulgated by the Open Geospatial Consortium (OGC)
5.3.8 Identify the factors that affect the interoperability of geospatial software applications
5.3.9 Automate geospatial analysis such as transformation, raster analysis, and geometric operations
5.3.10 Use scripting languages to automate repetitive tasks
5.3.11 Customize geospatial software using proprietary and open source software components
5.3.12 Use scripting languages or other tools to create web mapping applications
5.3.13 Employ query languages such as SQL to interrogate spatial data
5.3.14 Work effectively in teams to plan and coordinate software and application development
5.3.15 Stay informed about trends and best practices in information technology and software engineering, such as unit testing, version control, and continuous integration
5.3.16 Evaluate open source software components for re-use and potential return contributions
5.3.17 Realize opportunities to leverage positioning technology to create mobile end-user applications
5.3.18 Explain how geospatial software in large enterprises fits into SOA (Service Oriented Architectures) and SaaS (Software as a Service)
5.3.19 Be able to leverage web architectural opportunities

Appendix B: Survey Recruitment Email

Survey Recruitment

Date: 4/20/2020
To: Geographic Information Science Professionals
Re: Evaluating Perception of the Geospatial Technology Competency Model Using Q Methodology

Dear GISPs,

You are invited to participate in a research study on the perceptions of Geospatial Science Professionals towards the technical competencies from Tier 5 of the Geospatial Technology Competency Model (GTCM). The purpose of the study is to assess the attitudes held by geospatial professionals of sector-specific technical competencies within GTCM.

Data collection involves a sorting activity linked to this email message. There is a brief pre-survey socio-demographic survey, sorting activity (Tier 5 Competencies), and post-survey questionnaire. Once you have completed this activity, these data will be uploaded to a secure site and analyzed. Your involvement should take no more than 30 minutes. By assessing the perceived importance of these competencies, we can isolate gaps in practice and better inform educational institutions as they prepare students for geospatial careers as well as facilitate the refinement of occupational titles at the DOL.

The North Carolina State University, Institutional Review Board, has approved this study. I have also received approval from the Geographic Information Science Certification Institute (GISCI) to invite you to participate in the study. Your completion of the pre-survey socio-demographic survey, sorting activity, and post-survey questionnaire demonstrates consent to participate in this research project. You do not have to answer any question you do not want to answer. You may withdraw your participation at any time, and your data will not be saved. Please complete the sorting activity as requested and submit your answers.

Thank you for your attention and consideration. Please contact me if you have any questions or concerns. Please select this link: https://app.qmethodsoftware.com/study/4385 to arrive at the site. You will select **"NO – I DO NOT HAVE A PARTICIPATION CODE"** to begin the activity.

Regards,

Rodney D. Jackson
Ed.D. Candidate
North Carolina State University
rjackso8@ncsu.edu

Appendix C: Institutional Review Board Approval

Dear Rodney Jackson:

Date: April 14, 2020
IRB Protocol 20474 has been assigned Exempt status
Title: Evaluating Perception of the Geospatial Technology Competency Model Using Q Methodology
PI: Bartlett, James E

The research proposal named above has received administrative review and has been approved as exempt from the policy as outlined in the Code of Federal Regulations (Exemption: 46.101. Exempt d.2, d.3). Provided that the only participation of the subjects is as described in the proposal narrative, this project is exempt from further review. This approval does not expire, but any changes must be approved by the IRB prior to implementation.

1. This committee complies with requirements found in Title 45 part 46 of The Code of Federal Regulations. For NCSU projects, the Assurance Number is: FWA00003429.
2. Any changes to the protocol and supporting documents must be submitted and approved by the IRB prior to implementation.
3. If any unanticipated problems or adverse events occur, they must be reported to the IRB office within 5 business days by completing and submitting the unanticipated problem form on the IRB website: http://research.ncsu.edu/sparcs/compliance/irb/submission-guidance/.
4. Any unapproved departure from your approved IRB protocol results in non-compliance. Please find information regarding non-compliance here: http://research.ncsu.edu/sparcs-docs/irb/non-compliance_faq_sheet.pdf.

Please let us know if you have any questions.

****

NCSU IRB Office

Please contact ncsuirboffice@ncsu.edu if an official PDF approval letter with signature is required by your funding source.

Appendix D: Geospatial Science Professional Informed Consent Form

Title of Study: Evaluating Perception of the Geospatial Technology Competency Model Using Q Methodology **(eIRB #** 20474**)**
Principal Investigator: Rodney D. Jackson, rjackso8@ncsu.edu, 704-451-1720
Funding Source: None
Faculty Point of Contact: James E. Bartlett, jebartl3@ncsu.edu, 919-208-1697

What are some general things you should know about research studies?
You are invited to take part in a research study. Your participation in this study is voluntary. You have the right to be a part of this study, to choose not to participate, and to stop participating at any time without penalty. The purpose of this research study is to gain a better understanding of how Geospatial Science Professionals view the technical competencies within the Geospatial Technology Competency Model. We will do this through an online Q Methodology sorting exercise.

You are not guaranteed any personal benefits from being in this study. Research studies also may pose risks to those who participate. You may want to participate in this research because it will provide valuable data regarding the views of current geospatial professionals. You may not want to participate in this research because you do not wish to add to the understanding of how geospatial competencies are viewed by professionals within the workforce.

Specific details about the research in which you are invited to participate are contained below. If you do not understand something in this form, please ask the researcher for clarification or more information. A copy of this consent form will be provided to you. If, at any time, you have questions about your participation in this research, do not hesitate to contact the researcher(s) named above or the NC State IRB office. The IRB office's contact information is listed in the *What if you have questions about your rights as a research participant?* section of this form.

What is the purpose of this study?
The purpose of the study is to assess the perceptions held by geospatial professionals of sector-specific technical competencies within the geospatial technology competency model (GTCM). By assessing the perceived importance of these competencies, we can isolate gaps in practice and better inform educational institutions as they prepare students for geospatial careers.

Am I eligible to be a participant in this study?

There will be approximately 50-200 participants in this study. In order to be a participant in this study, you must agree to be in the study and provide an accurate representation of your views toward the competencies provided from the Geospatial Technology Competency Model. You cannot participate in this study if you do not want to be in the study or are not a geospatial professional.

What will happen if you take part in the study?

If you agree to participate in this study, you will be asked to do all of the following:

1. Respondents will rank (sort) 62 competencies in a Q-Sort activity (A Q-sort is used to examine perspectives by having participants sort a series of statements, typically on a scale from those with which they least to most agree. The activity forces respondents to make decisions between the competing statements during the ranking process.)
2. Optional, provide any additional comments to clarify your selections Respondents will be asked some clarifying questions at the end of the survey. These questions are:

   - Select a statement that you placed in the 6 column and share the reason for your decision.
   - Select a statement that you placed in the -6 column and share the reason for your decision.
   - Which statement did you have the most difficulty placing and why?
   - What factors helped to determine your sorting decisions?
   - Please share any additional thoughts not addressed by the questions above (these answers are used as data in determining how we characterize the cumulative perspective held within the geospatial industry).

The total amount of time that you will be participating in this study is approximately 30 minutes.

Risks and benefits:

There are minimal risks associated with participation in this research. The risks to you as a result of this research include the disclosure of raw data relating to individual Q-sorts.

There are no direct benefits to your participation in the research. The indirect benefits are a greater understanding within the geospatial community of the most valued competencies.

Right to withdraw your participation

You can stop participating in this study at any time for any reason. In order to stop your participation, please stop the Q-sort activity at any time. If you choose to withdraw your consent and to stop participating in this research, you can expect to your input and any related data you submitted will be removed.

Confidentiality, personal privacy, and data management

Trust is the foundation of the participant/researcher relationship. Much of that principle of trust is tied to keeping your information private and in the manner that we have described to you in this form. The information that you share with me will be held in confidence to the fullest extent allowed by law. Protecting your privacy as related to this research is of utmost importance to me.

How we manage, protect, and share your data are the principal ways that I protect your personal privacy. Data generated about you in this study will be de-identified.

> **De-identified.** Information that at one time could directly identify you, but that I have recorded this data so that your identity is separated from the data. I do not have a master list with your code and real name that connects your information to the research data. When the research concludes, there will be no way your real identity will be linked to the data I publish.

Compensation

For your participation in this study, you will receive: You will not receive anything for participating.

What if you have questions about this study?

If you have questions at any time about the study itself or the procedures implemented in this study, you may contact the researcher, Rodney D. Jackson, 422 Greenfern Court, Burlington, NC 27215, rjackso8@ncsu.edu, 704-451-1720. Faculty advisor: James E. Bartlett, 919-208-1697.

What if you have questions about your rights as a research participant?

If you feel you have not been treated according to the descriptions in this form, or your rights as a participant in research have been violated during the course of this project, you may contact the NC State IRB (Institutional Review Board) Office. An IRB office helps participants if they have any issues regarding research activities. You can contact the NC State IRB Office via email at irb-director@ncsu.edu or via phone at (919) 515-8754.

Consent To Participate

By signing this consent form, I am affirming that I have read and understand the above information. All of the questions that I had about this research have been answered. I have chosen to participate in this study with the understanding that I may stop participating at any time without penalty or loss of benefits to which I am otherwise entitled. I am aware that I may revoke my consent at any time.

Participant's printed name ____

I consent to research" <insert button>
I do not consent to research" <insert button>

Appendix E: Q-sort Protocol

Socio-Demographic Questions

1. How many years have you worked professionally?
2. How many years have you worked in a geospatial profession?
3. Are you a Certified Geographic Information Systems Professional (GISP)?
4. If so, in what year did you receive your GISP?
5. How did you receive your GISP?
    a. Portfolio
    b. Knowledge Exam
6. What is your highest level of education?
    a. Some college
    b. Associates
    c. Bachelors
    d. Masters
    e. Doctorate
7. At which level(s) did you receive geospatial instruction?
    a. Some college
    b. Associates
    c. Bachelors
    d. Masters
    e. Doctorate
8. In what sector do you currently work?
    a. Public
    b. Private
    c. Education
9. In what area of the industry do you currently work?
    a. Positioning and Data Acquisition
    b. Analysis and Modeling
    c. Software and Application Development
10. In what area of the industry have you spent the majority of your career?
    a. Positioning and Data Acquisition
    b. Analysis and Modeling
    c. Software and Application Development
11. What is the size of your current organization?
    a. 1-5 employees
    b. 6-20 employees
    c. 21-50 employees
    d. 51-100 employees
    e. 100+ employees
12. Are you a supervisor?

a. Yes
b. No

13. How many employees do you supervise?
    a. 0 employees
    b. 1-5 employees
    c. 6-20 employees
    d. 21-50 employees
    e. 51-100 employees
    f. 100+ employees
14. Are you a hiring manager?
    a. Yes
    b. No
15. Do you participate in hiring committees?
    a. Yes
    b. No
16. What is your job title?

Post Q-sort Qualitative Questions

1. Select a statement that you placed in the 6 column and share the reason for your decision.
2. Select a statement that you placed in the -6 column and share the reason for your decision.
3. Which statement did you have the most difficulty placing and why?
4. What factors helped to determine your sorting decisions?
5. Please share any additional thoughts not addressed by the questions above (these answers are used as data in determining how we characterize the cumulative perspective held within the geospatial industry).

Q-sort Instruction

You may select this Link, which can act as a reference as you are completing the Q-sort.

1. You will rank (sort) 62 competencies in a Q-Sort activity. A Q-sort is used to examine perspectives by having you sort a series of statements, typically on a scale from those with which they least to most agree. The activity forces you to make decisions between the competing statements during the ranking process. You will have an opportunity to pre-sort your view of the technical competency statements into three categories as either least relevant, neutral (undecided), and most relevant to the geospatial industry. Upon completion, you will move to the sorting grid, where you will make your final determinations. The matrix (sorting grid) is preset with a prescribed number of rows and columns with the aligned positive and negative values. The sorting grid measures perceptions regarding the ranking of the competence

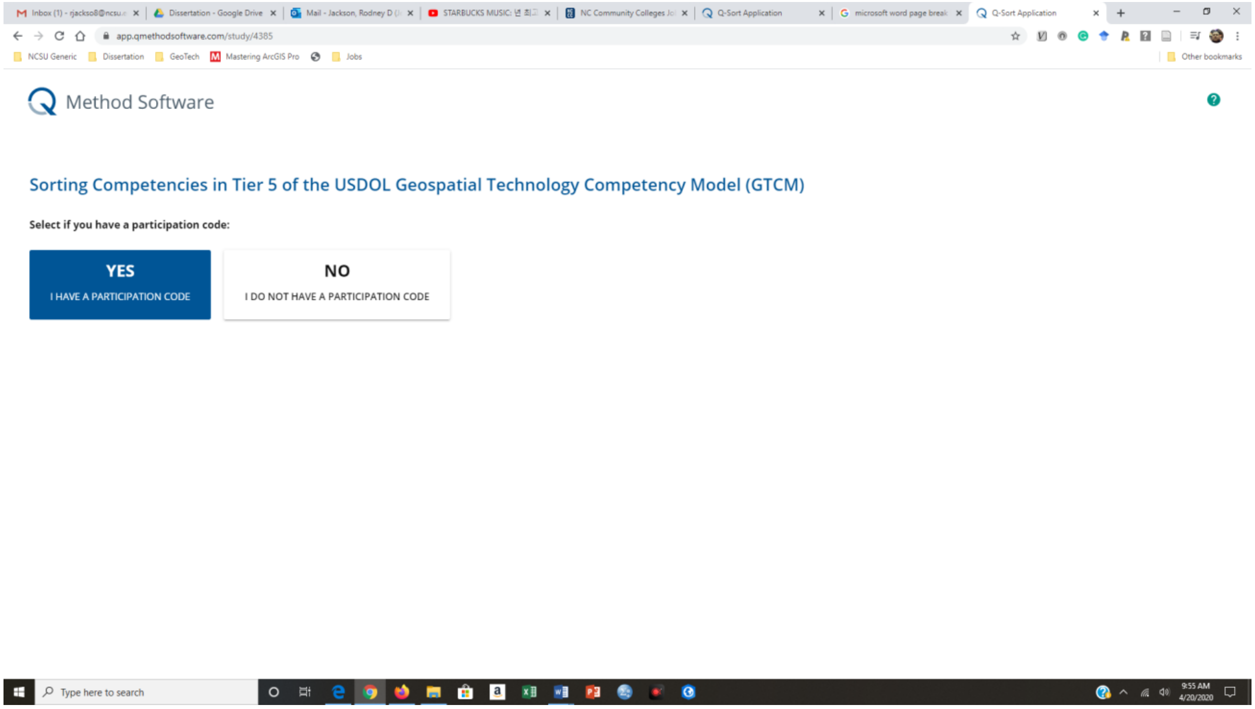
statements, from most relevant to least relevant. The sorting grid for this study will range from -6 to +6 to support the 62 competencies under review, with selections in each column having the same ranking (e.g., all -4s are equal, all +5s are equal, etc.). In our study, the sorting grid was a normally distributed 13-point scale and the shape of the distribution will not affect the statistical analysis. The software provides the option for you to change your decisions until you have resolved any concerns. Once complete, you will submit your responses and continue to the confirmation page.

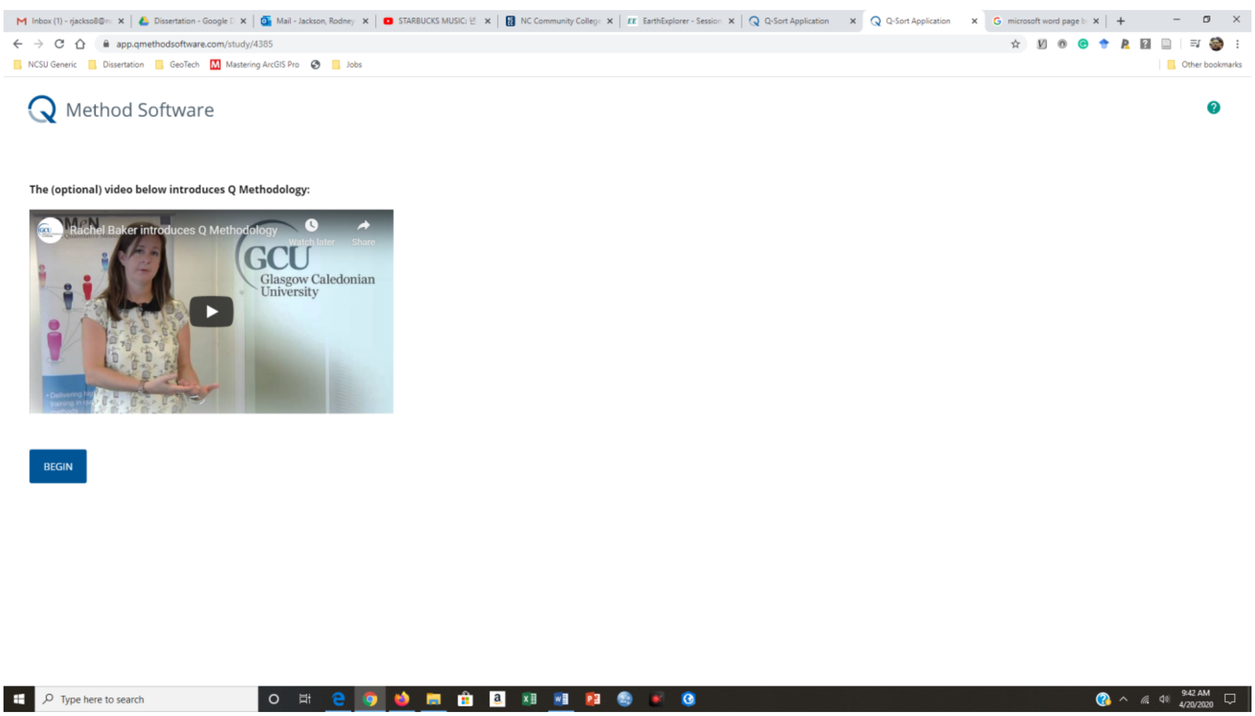
2. Next, you will provide any additional comments and be asked some clarifying questions at the end of the survey. These questions are:

- Select a statement that you placed in the "6" column and share the reason for your decision.
- Select a statement that you placed in the "-6" column and share the reason for your decision.
- Which statement did you have the most difficulty placing and why?
- What factors helped to determine your sorting decisions?
- Please share any additional thoughts not addressed by the questions above (these answers are used as data in determining how we characterize the cumulative perspective held within the geospatial industry).

Here are short videos demonstrating the steps involved in a Q-sort. You can bypass these videos, as desired.

1. Introduction to the Study
2. Presorting of Statements
3. Sorting Introduced
4. Sorting Exercise


app.qmethodsoftware.com/study/4385
Method Software
Sorting Competencies in Tier 5 of the USDOL Geospatial Technology Competency Model (GTCM)
Select if you have a participation code:
YES
I HAVE A PARTICIPATION CODE
NO
I DO NOT HAVE A PARTICIPATION CODE
Type here to search


app.qmethodsoftware.com/study/4385
Method Software
The (optional) video below introduces Q Methodology:
Rachel Baker introduces Q Methodology
GCU
Glasgow Caledonian University
BEGIN
Type here to search

app.qmethodsoftware.com/study/4385

Method Software

Title of Study: Evaluating Perception of the Geospatial Technology Competency Model Using Q Methodology (eIRB # 20474)

Principal Investigator: Rodney D. Jackson, rjackso8@ncsu.edu, 704-451-1720

Funding Source: None

Faculty Point of Contact: James E. Bartlett, jebartl3@ncsu.edu, 919-208-1697

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Specific details about the research in which you are invited to participate are contained below. If you do not understand something in this form, please ask the researcher for clarification or more information. A copy of this consent form will be provided to you. If, at any time, you have questions about your participation in this research, do not hesitate to contact the researcher(s) named above or the NC State IRB office. The IRB office's contact information is listed in the What if you have questions about your rights as a research participant? section of this form.

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Am I eligible to be a participant in this study?

There will be approximately 50-200 participants in this study. In order to be a participant in this study, you must agree to be in the study and provide an accurate representation of your views toward the competencies provided by the Geospatial Technology Competency Model. You cannot participate in this study if you do not want to be in the study or are not a geospatial professional.

What will happen if you take part in the study?

If you agree to participate in this study, you will be asked to do all of the following:

1. Respondents will rank (sort) 62 competencies in a Q-Sort activity. (A Q sort is used to examine perspectives by having participants sort a series of statements, typically on a scale from those with which they least to most agree. The activity forces respondents to make decisions between the competing statements during the ranking process.)

2. Optional, provide any additional comments to clarify your selections. Respondents will be asked some clarifying questions at the end of the survey. These questions are:

app.qmethodsoftware.com/study/4385

1. Respondents will rank (sort) 62 competencies in a Q-Sort activity. (A Q sort is used to examine perspectives by having participants sort a series of statements, typically on a scale from those with which they least to most agree. The activity forces respondents to make decisions between the competing statements during the ranking process.)

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- Select a statement that you placed in the "6" column and share the reason for your decision.
- Select a statement that you placed in the "-6" column and share the reason for your decision.
- Which statement did you have the most difficulty placing and why?
- What factors helped to determine your sorting decisions?
- Please share any additional thoughts not addressed by the questions above (these answers are used as data in determining how we characterize the cumulative perspective held within the geospatial industry).

The total amount of time that you will be participating in this study is approximately 30 minutes.

Risks and benefits: There are minimal risks associated with participation in this research. The risks to you as a result of this research include the disclosure of raw data relating to individual Q-sorts. There are no direct benefits to your participation in the research. The indirect benefits are a greater understanding of the geospatial community of the most valued competencies.

Right to withdraw your participation: You can stop participating in this study at any time for any reason. In order to stop your participation, please stop the Q-sort activity at any time. If you choose to withdraw your consent and to stop participating in this research, you can expect your input and any related data you submitted will be removed.

Confidentiality, personal privacy, and data management: Trust is the foundation of the participant/researcher relationship. Much of that principle of trust is tied to keeping your information private and in the manner that we have described to you in this form. The information that you share with me will be held in confidence to the fullest extent allowed by law. Protecting your privacy as related to this research is of utmost importance to me.

How we manage, protect, and share your data are the principal ways that I protect your personal privacy. Data generated about you in this study will be **de-identified**. **De-identified**. De-identified data information that at one time could directly identify you, but that I have recorded this data so that your identity is separated from the data. I do not have a master list with your code and a real name that connects your information to the research data. When the research concludes, there will be no way your real identity will be linked to the data I publish.

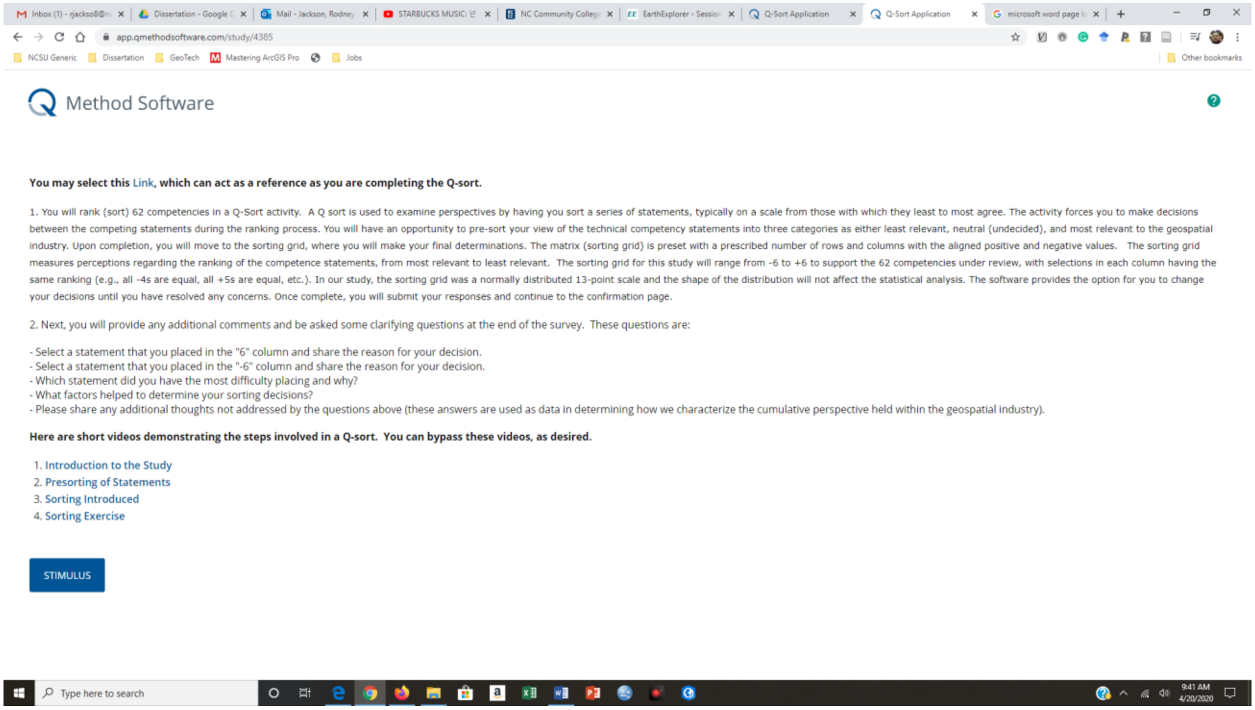
Compensation: For your participation in this study, you will receive: You will not receive anything for participating.

What if you have questions about this study? If you have questions at any time about the study itself or the procedures implemented in this study, you may contact the researcher, Rodney D. Jackson, 422 Greenfern Court, Burlington, NC 27215, rjackso8@ncsu.edu, 704-451-1720. Faculty advisor: James E. Bartlett, 919-208-1697.

What if you have questions about your rights as a research participant? If you feel you have not been treated according to the descriptions in this form, or your rights as a participant in research have been violated during the course of this project, you may contact the NC State IRB (Institutional Review Board) Office. An IRB office helps participants if they have any issues regarding research activities. You can contact the NC State IRB Office via email at irb-director@ncsu.edu or via phone at (919) 515-8754.

Consent to Participate: By selecting the "I AGREE" button, I am affirming that I have read and understood the above information. All of the questions that I had about this research have been answered. I have chosen to participate in this study with the understanding that I may stop participating at any time without penalty or loss of benefits to which I am otherwise entitled. I am aware that I may revoke my consent at any time.

I DO NOT AGREE | I AGREE



app.qmethodsoftware.com/study/4385

Method Software

You may select this Link, which can act as a reference as you are completing the Q-sort.

1. You will rank (sort) 62 competencies in a Q-Sort activity. A Q sort is used to examine perspectives by having you sort a series of statements, typically on a scale from those with which they least to most agree. The activity forces you to make decisions between the competing statements during the ranking process. You will have an opportunity to pre-sort your view of the technical competency statements into three categories as either least relevant, neutral (undecided), and most relevant to the geospatial industry. Upon completion, you will move to the sorting grid, where you will make your final determinations. The matrix (sorting grid) is preset with a prescribed number of rows and columns with the aligned positive and negative values. The sorting grid measures perceptions regarding the ranking of the competence statements, from most relevant to least relevant. The sorting grid for this study will range from -6 to +6 to support the 62 competencies under review, with selections in each column having the same ranking (e.g., all -4s are equal, all +5s are equal, etc.). In our study, the sorting grid was a normally distributed 13-point scale and the shape of the distribution will not affect the statistical analysis. The software provides the option for you to change your decisions until you have resolved any concerns. Once complete, you will submit your responses and continue to the confirmation page.

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1. Introduction to the Study
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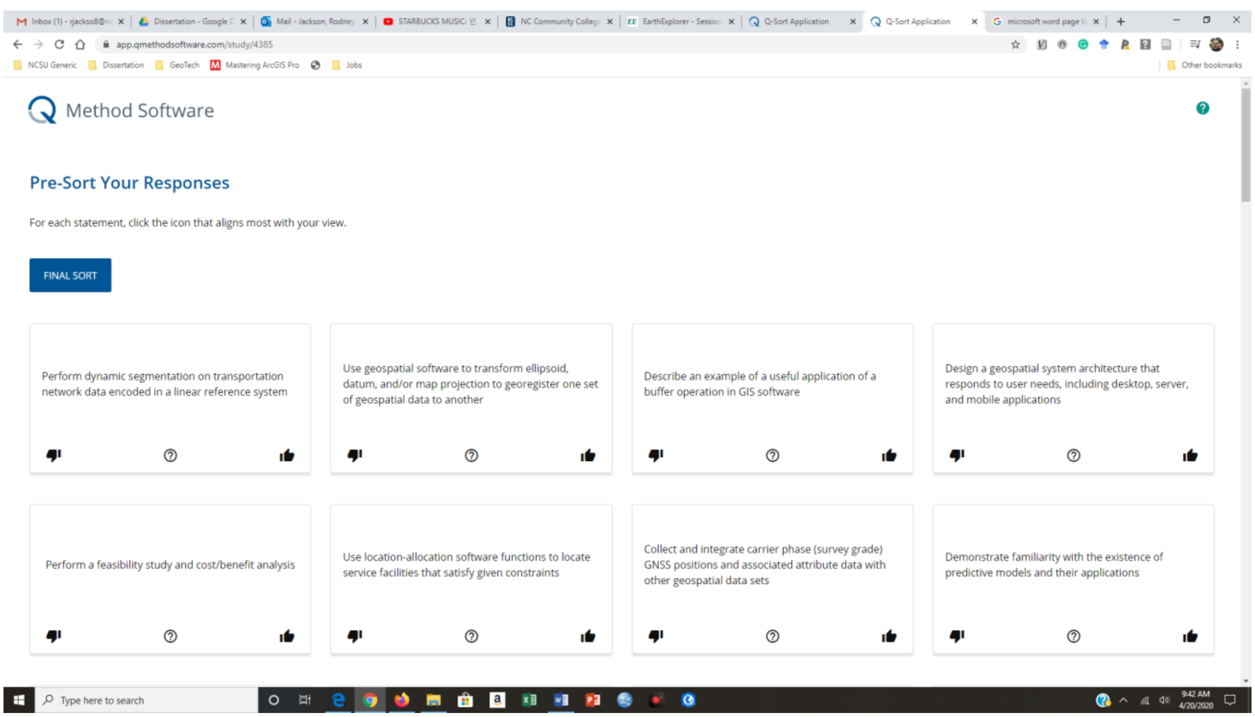
4. Sorting Exercise

STIMULUS



app.qmethodsoftware.com/study/4385

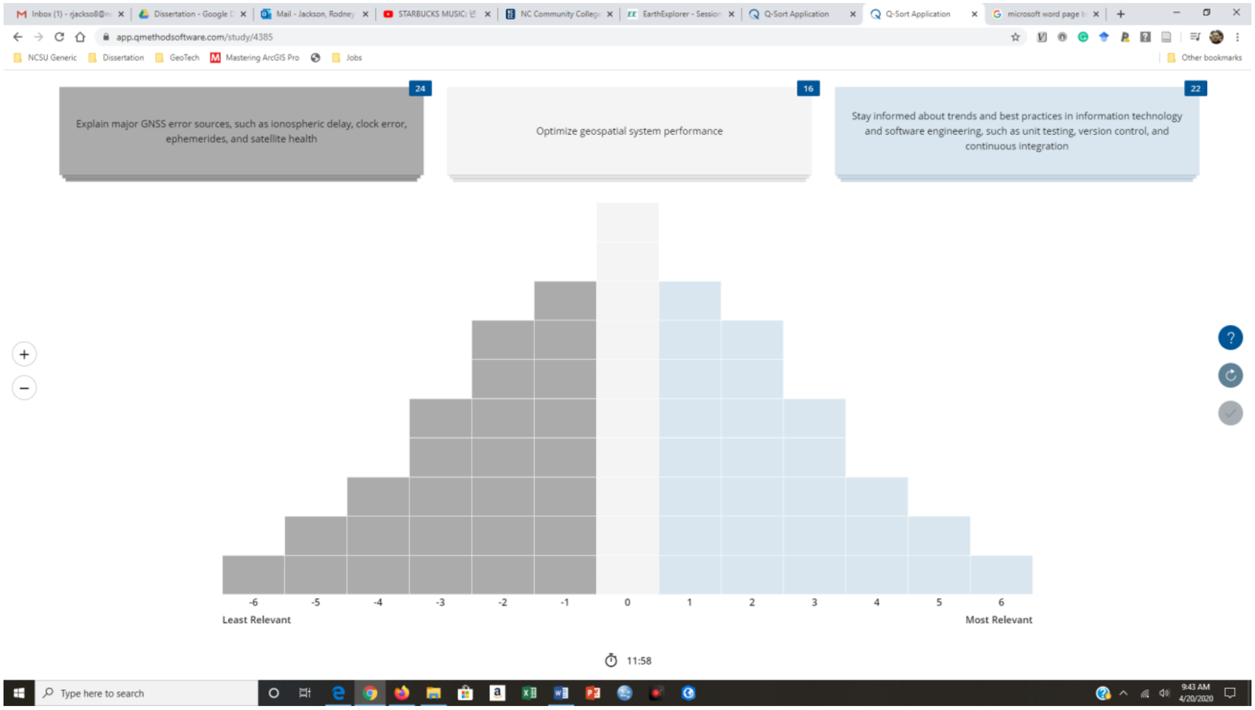
Method Software

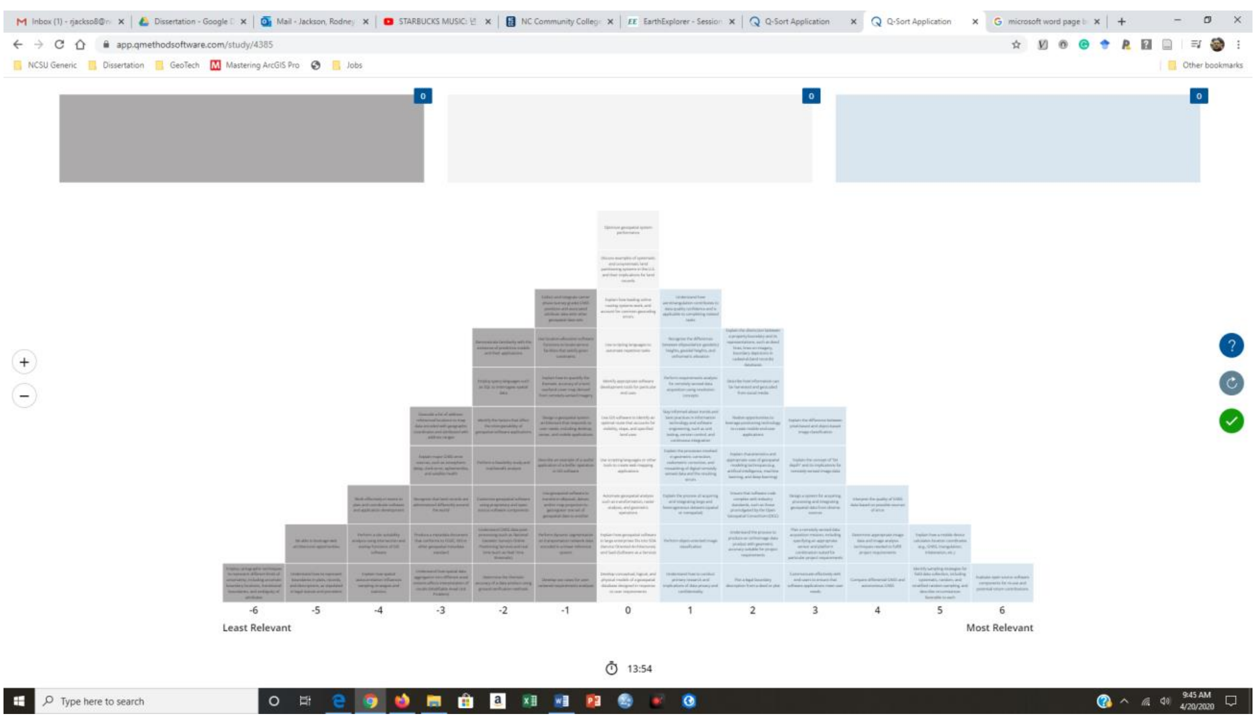
Pre-Sort Your Responses

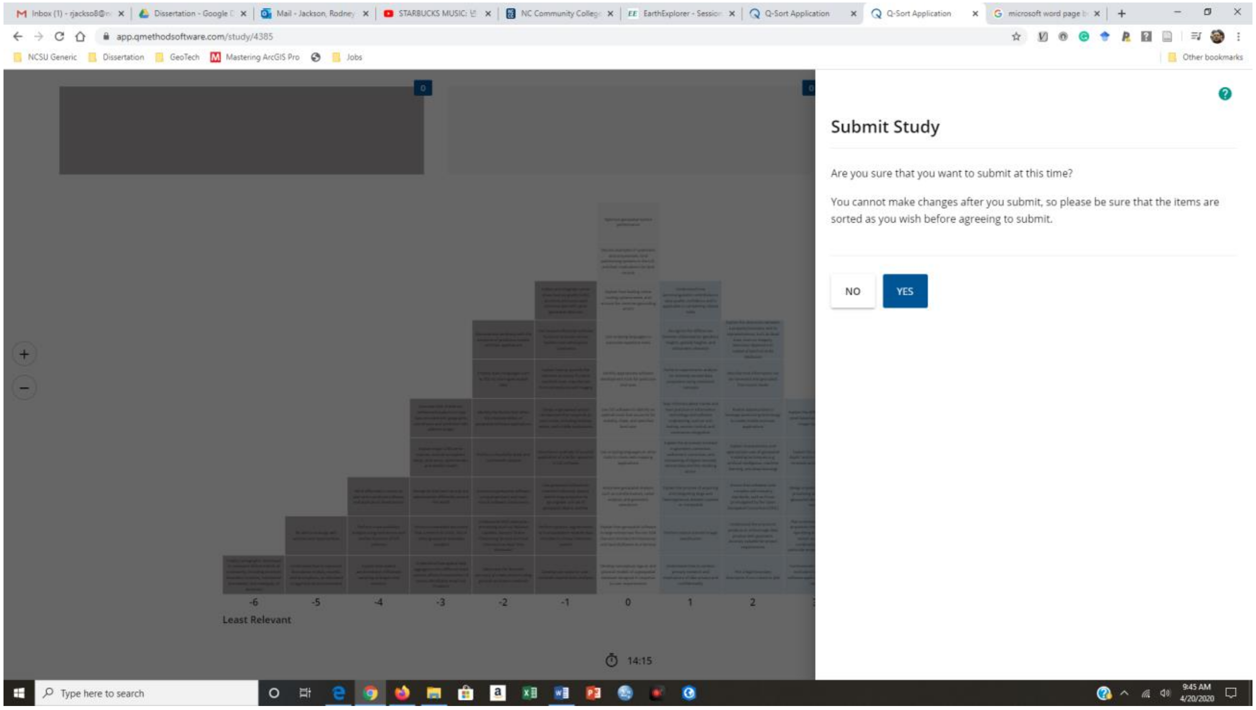
For each statement, click the icon that aligns most with your view.

FINAL SORT

- Perform dynamic segmentation on transportation network data encoded in a linear reference system
- Use geospatial software to transform ellipsoid, datum, and/or map projection to georegister one set of geospatial data to another
- Describe an example of a useful application of a buffer operation in GIS software
- Design a geospatial system architecture that responds to user needs, including desktop, server, and mobile applications
- Perform a feasibility study and cost/benefit analysis
- Use location-allocation software functions to locate service facilities that satisfy given constraints
- Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets
- Demonstrate familiarity with the existence of predictive models and their applications


app.qmethodsoftware.com/study/4385
24
Explain major GNSS error sources, such as ionospheric delay, clock error, ephemerides, and satellite health
16
Optimize geospatial system performance
22
Stay informed about trends and best practices in information technology and software engineering, such as unit testing, version control, and continuous integration
-6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6
Least Relevant
Most Relevant
11:58


app.qmethodsoftware.com/study/4385
0
0
0
-6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6
Least Relevant
Most Relevant
13:54


app.qmethodsoftware.com/study/4385
Submit Study
Are you sure that you want to submit at this time?
You cannot make changes after you submit, so please be sure that the items are sorted as you wish before agreeing to submit.
NO
YES
-6
-5
-4
-3
-2
-1
0
1
2
Least Relevant
14:15
Type here to search

Appendix F: Factor Crib Sheets

Crib sheet for Factor 1

Items ranked at +6 for Factor 1

47 Communicate effectively with end-users to ensure that software applications meet user needs

Items ranked higher in Factor 1 Array than in other factor arrays

37 Understand how to represent boundaries in plats, records, and descriptions, as stipulated in legal statute and precedent

46 Design a geospatial system architecture that responds to user needs, including desktop, server, and mobile applications

6 Plot a legal boundary description from a deed or plat

5 Explain the distinction between a property boundary and its representations, such as deed lines, lines on imagery, boundary depictions in cadastral (land records) databases

57 Work effectively in teams to plan and coordinate software and application development

26 Describe an example of a useful application of a buffer operation in GIS software

48 Optimize geospatial system performance

52 Automate geospatial analysis such as transformation, raster analysis, and geometric operations

49 Identify appropriate software development tools for particular end uses

4 Recognize that land records are administered differently around the world

60 Realize opportunities to leverage positioning technology to create mobile end-user applications

3 Discuss examples of systematic and unsystematic land partitioning systems in the U.S. and their implications for land records

29 Perform dynamic segmentation on transportation network data encoded in a linear reference system

41 Determine the thematic accuracy of a data product using ground verification methods

40 Explain how to quantify the thematic accuracy of a land use/land cover map derived from remotely-sensed imagery

Items ranked lower in Factor 1 than in other factors arrays

7 Design a system for acquiring, processing and integrating geospatial data from diverse sources

31 Use location-allocation software functions to locate service facilities that satisfy given constraints

28 Use GIS software to identify an optimal route that accounts for visibility, slope, and specified land uses

13 Recognize the differences between ellipsoidal (or geodetic) heights, geoidal heights, and orthometric elevation

20 Produce a metadata document that conforms to FGDC, ISO or other geospatial metadata standard

23 Explain the process of acquiring and integrating large and heterogeneous datasets (spatial or nonspatial)

39 Explain the processes involved in geometric correction, radiometric correction, and mosaicking of digital remotely sensed data and the resulting errors

9 Explain how spatial autocorrelation influences sampling strategies and statistics

16 Interpret the quality of GNSS data based on possible sources of error
38 Determine appropriate image data and image analysis techniques needed to fulfill project requirements
43 Perform object-oriented image classification
42 Explain the difference between pixel-based and object-based image classification
50 Ensure that software code complies with industry standards, such as those promulgated by the Open Geospatial Consortium (OGC)
12 Plan a remotely sensed data acquisition mission, including specifying an appropriate sensor and platform combination suited for particular project requirements

Items ranked at – 6 for Factor 1

11 Explain the concept of “bit depth” and its implications for remotely-sensed image data

Crib sheet for Factor 2

Items ranked at +6 for Factor 2

55 Use scripting languages or other tools to create web mapping applications

Items ranked higher in Factor 2 Array than in other factor arrays

53 Use scripting languages to automate repetitive tasks
56 Employ query languages such as SQL to interrogate spatial data
62 Be able to leverage web architectural opportunities
48 Optimize geospatial system performance
44 Develop use cases for user-centered requirements analyses
54 Customize geospatial software using proprietary and open source software components
52 Automate geospatial analysis such as transformation, raster analysis, and geometric operations
51 Identify the factors that affect the interoperability of geospatial software applications
49 Identify appropriate software development tools for particular end uses
60 Realize opportunities to leverage positioning technology to create mobile end-user applications
50 Ensure that software code complies with industry standards, such as those promulgated by the Open Geospatial Consortium (OGC)
59 Evaluate open source software components for re-use and potential return contributions
61 Explain how geospatial software in large enterprises fits into SOA (Service Oriented Architectures) and SaaS (Software as a Service)
10 Perform requirements analysis for remotely sensed data acquisition using resolution concepts

Items ranked lower in Factor 2 than in other factors arrays

36 Employ cartographic techniques to represent different kinds of uncertainty, including uncertain boundary locations, transitional boundaries, and ambiguity of attributes
26 Describe an example of a useful application of a buffer operation in GIS software
8 Identify sampling strategies for field data collection, including systematic, random, and stratified random sampling, and describe circumstances favorable to each
40 Explain how to quantify the thematic accuracy of a land use/land cover map derived from remotely-sensed imagery
41 Determine the thematic accuracy of a data product using ground verification methods
18 Understand the process to produce an orthoimage data product with geometric accuracy suitable for project requirements
30 Explain how leading online routing systems work, and account for common geocoding errors
19 Understand how aerotriangulation contributes to data quality confidence and is applicable to completing related tasks
15 Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets
33 Understand how spatial data aggregation into different areal extents affects interpretation of results (Modifiable Areal Unit Problem)

Items ranked at – 6 for Factor 2

17 Explain major GNSS error sources, such as ionospheric delay, clock error, ephemerides, and satellite health

Crib sheet for Factor 3

Items ranked at +6 for Factor 3

58 Stay informed about trends and best practices in information technology and software engineering, such as unit testing, version control, and continuous integration

Items ranked higher in Factor 3 Array than in other factor arrays

20 Produce a metadata document that conforms to FGDC, ISO or other geospatial metadata standard

38 Determine appropriate image data and image analysis techniques needed to fulfill project requirements

2 Geocode a list of address-referenced locations to map data encoded with geographic coordinates and attributed with address ranges

32 Develop conceptual, logical, and physical models of a geospatial database designed in response to user requirements

31 Use location-allocation software functions to locate service facilities that satisfy given constraints

22 Describe how information can be harvested and geocoded from social media

24 Explain how a mobile device calculates location coordinates (e.g., GNSS, triangulation, trilateration, etc.)

30 Explain how leading online routing systems work, and account for common geocoding errors

28 Use GIS software to identify an optimal route that accounts for visibility, slope, and specified land uses

4 Recognize that land records are administered differently around **the world**

29 Perform dynamic segmentation on transportation network data encoded in a linear reference system

40 Explain how to quantify the thematic accuracy of a land use/land cover map derived from remotely-sensed imagery

10 Perform requirements analysis for remotely sensed data acquisition using resolution concepts

Items ranked lower in Factor 3 than in other factors arrays

53 Use scripting languages to automate repetitive tasks

60 Realize opportunities to leverage positioning technology to create mobile end-user applications

57 Work effectively in teams to plan and coordinate software and application development

55 Use scripting languages or other tools to create web mapping applications

18 Understand the process to produce an orthoimage data product with geometric accuracy suitable for project requirements

34 Explain characteristics and appropriate uses of geospatial modeling techniques (e.g. artificial intelligence, machine learning, and deep learning)

44 Develop use cases for user-centered requirements analyses

49 Identify appropriate software development tools for particular end uses

54 Customize geospatial software using proprietary and open source software components

3 Discuss examples of systematic and unsystematic land partitioning systems in the U.S. and their implications for land records

Items ranked at – 6 for Factor 3

61 Explain how geospatial software in large enterprises fits into SOA (Service Oriented Architectures) and SaaS (Software as a Service)

Crib sheet for Factor 4

Items ranked at +6 for Factor 4

7 Design a system for acquiring, processing and integrating geospatial data from diverse sources

Items ranked higher in Factor 4 Array than in other factor arrays

56 Employ query languages such as SQL to interrogate spatial data
23 Explain the process of acquiring and integrating large and heterogeneous datasets (spatial or nonspatial)
27 Perform a site suitability analysis using intersection and overlay functions of GIS software
32 Develop conceptual, logical, and physical models of a geospatial database designed in response to user requirements
21 Understand how to conduct primary research and implications of data privacy and confidentiality
26 Describe an example of a useful application of a buffer operation in GIS software
35 Demonstrate familiarity with the existence of predictive models and their applications
1 Use geospatial software to transform ellipsoid, datum, and/or map projection to georegister one set of geospatial data to another
51 Identify the factors that affect the interoperability of geospatial software applications
33 Understand how spatial data aggregation into different areal extents affects interpretation of results (Modifiable Areal Unit Problem)
9 Explain how spatial autocorrelation influences sampling strategies and statistics
34 Explain characteristics and appropriate uses of geospatial modeling techniques (e.g. artificial intelligence, machine learning, and deep learning)
59 Evaluate open source software components for re-use and potential return contributions
40 Explain how to quantify the thematic accuracy of a land use/land cover map derived from remotely-sensed imagery
41 Determine the thematic accuracy of a data product using ground verification methods

Items ranked lower in Factor 4 than in other factors arrays

58 Stay informed about trends and best practices in information technology and software engineering, such as unit testing, version control, and continuous integration
4 Recognize that land records are administered differently around the world
29 Perform dynamic segmentation on transportation network data encoded in a linear reference system
24 Explain how a mobile device calculates location coordinates (e.g., GNSS, triangulation, trilateration, etc.)
37 Understand how to represent boundaries in plats, records, and descriptions, as stipulated in legal statute and precedent
16 Interpret the quality of GNSS data based on possible sources of error
5 Explain the distinction between a property boundary and its representations, such as deed lines, lines on imagery, boundary depictions in cadastral (land records) databases
6 Plot a legal boundary description from a deed or plat
19 Understand how aerotriangulation contributes to data quality confidence and is applicable to completing related tasks
14 Understand GNSS data post-processing (such as National Geodetic Survey's Online Positioning Service) and real time (such as Real Time Kinematic)

15 Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets

Items ranked at – 6 for Factor 4

25 Compare differential GNSS and autonomous GNSS

Crib sheet for Factor 5

Items ranked at +6 for Factor 5

36 Employ cartographic techniques to represent different kinds of uncertainty, including uncertain boundary locations, transitional boundaries, and ambiguity of attributes

Items ranked higher in Factor 5 Array than in other factor arrays

45 Perform a feasibility study and cost/benefit analysis
38 Determine appropriate image data and image analysis techniques needed to fulfill project requirements
5 Explain the distinction between a property boundary and its representations, such as deed lines, lines on imagery, boundary depictions in cadastral (land records) databases
8 Identify sampling strategies for field data collection, including systematic, random, and stratified random sampling, and describe circumstances favorable to each
13 Recognize the differences between ellipsoidal (or geodetic) heights, geoidal heights, and orthometric elevation
15 Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets
26 Describe an example of a useful application of a buffer operation in GIS software
16 Interpret the quality of GNSS data based on possible sources of error
24 Explain how a mobile device calculates location coordinates (e.g., GNSS, triangulation, trilateration, etc.)
18 Understand the process to produce an orthoimage data product with geometric accuracy suitable for project requirements
4 Recognize that land records are administered differently around the world
3 Discuss examples of systematic and unsystematic land partitioning systems in the U.S. and their implications for land records
14 Understand GNSS data post-processing (such as National Geodetic Survey's Online Positioning Service) and real time (such as Real Time Kinematic)
25 Compare differential GNSS and autonomous GNSS
40 Explain how to quantify the thematic accuracy of a land use/land cover map derived from remotely-sensed imagery
41 Determine the thematic accuracy of a data product using ground verification methods
42 Explain the difference between pixel-based and object-based image classification
17 Explain major GNSS error sources, such as ionospheric delay, clock error, ephemerides, and satellite health

Items ranked lower in Factor 5 than in other factors arrays

56 Employ query languages such as SQL to interrogate spatial data
32 Develop conceptual, logical, and physical models of a geospatial database designed in response to user requirements
52 Automate geospatial analysis such as transformation, raster analysis, and geometric operations
31 Use location-allocation software functions to locate service facilities that satisfy given constraints
48 Optimize geospatial system performance
55 Use scripting languages or other tools to create web mapping applications
51 Identify the factors that affect the interoperability of geospatial software applications

46 Design a geospatial system architecture that responds to user needs, including desktop, server, and mobile applications
44 Develop use cases for user-centered requirements analyses
29 Perform dynamic segmentation on transportation network data encoded in a linear reference system
34 Explain characteristics and appropriate uses of geospatial modeling techniques (e.g. artificial intelligence, machine learning, and deep learning)
35 Demonstrate familiarity with the existence of predictive models and their applications
10 Perform requirements analysis for remotely sensed data acquisition using resolution concepts
30 Explain how leading online routing systems work, and account for common geocoding errors
22 Describe how information can be harvested and geocoded from social media
59 Evaluate open source software components for re-use and potential return contributions
21 Understand how to conduct primary research and implications of data privacy and confidentiality
62 Be able to leverage web architectural opportunities
54 Customize geospatial software using proprietary and open source software components

Items ranked at – 6 for Factor 5

61 Explain how geospatial software in large enterprises fits into SOA (Service Oriented Architectures) and SaaS (Software as a Service)

Appendix G: Correlation Matrix

Participant	I12846	I12849	I12850	I12852	I12854	I12855	I12856	I12857	I12858	I12859	I12860	I12861	I12862	I12864	I12871	I12872	I12879	I12882	I12886	I12889	I12891	I12892	I12897	I12898	I12901
I12846	100	33	46	22	21	40	22	6	30	14	22	28	44	36	20	29	23	15	5	21	13	30	20	5	-12
I12849	33	100	31	37	34	28	23	41	30	19	37	27	52	21	31	49	31	29	34	0	41	30	53	9	20
I12850	46	31	100	28	54	37	18	36	47	40	29	43	37	28	22	28	52	31	31	4	30	39	40	2	-1
I12852	22	37	28	100	29	41	38	41	16	-8	36	39	44	13	18	37	42	25	15	7	23	36	54	11	29
I12854	21	34	54	29	100	40	36	31	58	31	21	40	26	41	13	23	53	13	25	9	24	30	46	8	10
I12855	40	28	37	41	40	100	22	20	49	11	15	40	29	16	11	2	20	9	-4	27	21	39	25	2	18
I12856	22	23	18	38	36	22	100	28	26	14	6	13	47	24	-5	29	39	7	29	10	-2	22	43	-10	23
I12857	6	41	36	41	31	20	28	100	23	19	32	29	21	2	53	34	57	35	51	-1	36	40	65	21	31
I12858	30	30	47	16	58	49	26	23	100	21	9	32	34	15	21	14	32	15	-2	7	7	37	25	-4	12
I12859	14	19	40	-8	31	11	14	19	21	100	21	29	17	4	10	-1	24	9	43	14	39	21	10	9	0
I12860	22	37	29	36	21	15	6	32	9	21	100	39	32	31	59	28	20	3	43	7	57	48	38	12	22
I12861	28	27	43	39	40	40	13	29	32	29	39	100	36	42	35	23	25	9	34	9	53	53	40	14	12
I12862	44	52	37	44	26	29	47	21	34	17	32	36	100	27	18	33	29	20	18	-10	27	40	35	-6	20
I12864	36	21	28	13	41	16	24	2	15	4	31	42	27	100	8	18	21	-10	18	22	17	23	13	-4	-10
I12871	20	31	22	18	13	11	-5	53	21	10	59	35	18	8	100	28	27	17	34	-9	50	43	47	17	25
I12872	29	49	28	37	23	2	29	34	14	-1	28	23	33	18	28	100	26	18	32	7	34	30	45	6	23
I12879	23	31	52	42	53	20	39	57	32	24	20	25	29	21	27	26	100	31	39	-5	10	39	59	10	6
I12882	15	29	31	25	13	9	7	35	15	9	3	9	20	-10	17	18	31	100	32	-39	10	12	29	11	0
I12886	5	34	31	15	25	-4	29	51	-2	43	43	34	18	18	34	32	39	32	100	-7	45	39	50	27	16
I12889	21	0	4	7	9	27	10	-1	7	14	7	9	-10	22	-9	7	-5	-39	-7	100	-8	-2	-9	-11	-7
I12891	13	41	30	23	24	21	-2	36	7	39	57	53	27	17	50	34	10	10	45	-8	100	39	34	28	20
I12892	30	30	39	36	30	39	22	40	37	21	48	53	40	23	43	30	39	12	39	-2	39	100	42	3	12
I12897	20	53	40	54	46	25	43	65	25	10	38	40	35	13	47	45	59	29	50	-9	34	42	100	16	28
I12898	5	9	2	11	8	2	-10	21	-4	9	12	14	-6	-4	17	6	10	11	27	-11	28	3	16	100	1
I12901	-12	20	-1	29	10	18	23	31	12	0	22	12	20	-10	25	23	6	0	16	-7	20	12	28	1	100
I12902	-20	-9	5	17	-2	-7	-14	-2	-4	7	7	6	-8	-12	-1	-23	-4	3	2	-15	3	-18	-9	30	5
I12903	-27	-20	-27	-10	-28	-21	-39	-21	-38	-3	5	-10	-23	-26	-6	-15	-36	-32	-23	23	2	-19	-33	-5	-11
I12906	18	26	28	23	45	11	30	21	29	-1	7	32	18	27	21	22	37	1	10	20	16	25	34	14	-17
I12909	43	52	53	41	35	47	37	41	28	7	31	31	44	30	40	39	37	22	24	8	30	40	57	2	6
I12913	1	29	26	36	36	4	27	47	5	27	47	27	13	34	33	33	48	11	54	-5	33	26	53	14	24
I12917	31	46	50	55	43	30	17	53	32	21	52	40	33	6	50	37	52	29	31	-9	55	54	56	22	21
I12919	-3	13	30	14	23	23	-4	26	22	23	18	33	21	6	7	5	20	0	27	-1	26	31	12	2	2
I12922	38	48	49	35	42	29	43	54	39	48	35	40	32	11	39	29	57	28	58	12	39	49	51	20	14
I12923	41	30	47	50	53	33	52	33	42	21	23	33	46	33	18	20	53	15	20	11	18	35	43	10	0
I12924	32	32	27	23	21	41	12	16	27	20	23	44	25	23	30	27	8	21	14	17	28	19	33	14	18
I12925	6	29	35	15	28	20	2	44	7	10	42	46	18	30	37	27	25	14	53	-8	50	39	42	24	14
I12934	25	12	32	16	24	21	21	4	41	7	2	18	19	-1	-10	14	7	11	1	14	3	18	11	-7	-26
I12935	13	13	19	6	23	18	13	10	31	-4	4	0	26	-11	18	19	12	3	-3	1	3	19	16	-5	25
I12938	33	29	36	16	34	20	23	13	17	47	29	43	30	32	20	11	22	-13	24	41	35	21	13	21	-4
I12945	3	21	27	15	20	23	0	36	17	36	36	39	9	2	46	11	20	-3	40	6	41	41	30	17	23
I12949	33	43	41	26	54	35	14	40	56	28	30	37	28	29	34	31	38	31	25	-1	29	50	37	18	14
I12951	16	37	31	46	32	30	10	39	24	19	70	43	19	22	52	20	37	-1	33	13	53	51	44	28	16
I12952	27	29	22	-2	8	31	3	11	22	29	21	32	33	8	27	13	-6	0	17	-6	39	46	20	-5	19
I12962	-7	42	1	34	15	5	-20	48	-3	0	51	37	12	3	46	27	21	9	34	-10	53	41	49	25	19
I12965	22	11	15	3	16	1	30	1	16	11	-7	-6	23	11	-8	18	16	4	10	6	-18	10	17	-8	6
I12968	25	20	39	18	32	34	-15	20	23	33	24	29	8	18	24	15	21	-10	5	27	33	33	18	4	-2
I12972	-9	38	30	19	9	3	10	41	7	11	29	14	14	-6	31	41	26	12	38	-11	28	35	43	-18	24
I12973	43	31	27	20	18	12	27	30	13	-1	12	7	26	37	18	26	25	16	8	-9	15	17	34	11	-11
I12974	28	37	31	32	35	32	48	31	25	17	27	38	37	23	27	12	34	-3	22	12	26	29	50	-4	16
I12975	11	5	7	-10	4	20	-1	-19	23	22	-15	17	0	-11	-20	19	-18	-19	-12	48	1	-9	-13	0	-7
I12977	12	30	25	16	20	10	7	47	25	3	13	19	22	13	36	16	44	40	42	-21	13	43	40	11	9
I12989	47	33	17	34	32	41	43	17	37	12	-3	34	41	16	2	35	13	-3	5	28	12	16	28	-5	10
I12994	9	6	10	-1	13	-4	21	6	11	-7	-30	-1	13	5	-27	21	8	13	1	7	-20	-9	-7	-1	-4
I12995	12	24	18	8	14	30	2	6	16	10	25	28	17	20	10	-1	3	-18	-8	8	26	33	6	-8	11

I12902	I12903	I12906	I12909	I12913	I12917	I12919	I12922	I12923	I12924	I12925	I12934	I12935	I12938	I12945	I12949	I12951	I12952	I12962	I12965	I12968	I12972	I12973	I12974	I12975	I12977	I12989	I12994	I12995
-20	-27	18	43	1	31	-3	38	41	32	6	25	13	33	3	33	16	27	-7	22	25	-9	43	28	11	12	47	9	12
-9	-20	26	52	29	46	13	48	30	32	29	12	13	29	21	43	37	29	42	11	20	38	31	37	5	30	33	6	24
5	-27	28	53	26	50	30	49	47	27	35	32	19	36	27	41	31	22	1	15	39	30	27	31	7	25	17	10	18
17	-10	23	41	36	55	14	35	50	23	15	16	6	16	15	26	46	-2	34	3	18	19	20	32	-10	16	34	-1	8
-2	-28	45	35	36	43	23	42	53	21	28	24	23	34	20	54	32	8	15	16	32	9	18	35	4	20	32	13	14
-7	-21	11	47	4	30	23	29	33	41	20	21	18	20	23	35	30	31	5	1	34	3	12	32	20	10	41	-4	30
-14	-39	30	37	27	17	-4	43	52	12	2	21	13	23	0	14	10	3	-20	30	-15	10	27	48	-1	7	43	21	2
-2	-21	21	41	47	53	26	54	33	16	44	4	10	13	36	40	39	11	48	1	20	41	30	31	-19	47	17	6	6
-4	-38	29	28	5	32	22	39	42	27	7	41	31	17	17	56	24	22	-3	16	23	7	13	25	23	25	37	11	16
7	-3	-1	7	27	21	23	48	21	20	10	7	-4	47	36	28	19	29	0	11	33	11	-1	17	22	3	12	-7	10
7	5	7	31	47	52	18	35	23	23	42	2	4	29	36	30	70	21	51	-7	24	29	12	27	-15	13	-3	-30	25
6	-10	32	31	27	40	33	40	33	44	46	18	0	43	39	37	43	32	37	-6	29	14	7	38	17	19	34	-1	28
-8	-23	18	44	13	33	21	32	46	25	18	19	26	30	9	28	19	33	12	23	8	14	26	37	0	22	41	13	17
-12	-26	27	30	34	6	6	11	33	23	30	-1	-11	32	2	29	22	8	3	11	18	-6	37	23	-11	13	16	5	20
-1	-6	21	40	33	50	7	39	18	30	37	-10	18	20	46	34	52	27	46	-8	24	31	18	27	-20	36	2	-27	10
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-15	23	20	8	-5	-9	-1	12	11	17	-8	14	1	41	6	-1	13	-6	-10	6	27	-11	-9	12	48	-21	28	7	8
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-18	-19	25	40	26	54	31	49	35	19	39	18	19	21	41	50	51	46	41	10	33	35	17	29	-9	43	16	-9	33
-9	-33	34	57	53	56	12	51	43	33	42	11	16	13	30	37	44	20	49	17	18	43	34	50	-13	40	28	-7	6
30	-5	14	2	14	22	2	20	10	14	24	-7	-5	21	17	18	28	-5	25	-8	4	-18	11	-4	0	11	-5	-1	-8
5	-11	-17	6	24	21	2	14	0	18	14	-26	25	-4	23	14	16	19	19	6	-2	24	-11	16	-7	9	10	-4	11
100	20	3	-12	11	4	13	-3	13	3	0	-14	-4	18	13	10	2	-13	-4	-1	-3	-6	0	7	-20	-1	-12	-9	-1
20	100	-18	-28	-23	-15	-7	-27	-39	-4	-25	-7	-3	1	-4	-37	0	6	10	-6	12	-7	-27	-18	10	-25	-11	-4	6
3	-18	100	31	13	31	1	32	43	2	33	35	18	46	7	24	21	-19	15	19	16	-3	17	47	6	26	19	11	18
-12	-28	31	100	20	44	25	38	33	39	36	10	24	28	27	38	35	11	13	20	15	20	43	36	-2	30	25	7	15
11	-23	13	20	100	34	18	30	31	14	50	-13	-2	13	31	26	30	-1	45	10	18	37	25	24	-23	30	10	0	-13
4	-15	31	44	34	100	30	57	44	25	28	19	12	19	27	54	60	17	50	12	35	30	15	35	-4	29	14	-9	26
13	-7	1	25	18	30	100	20	4	15	34	3	10	15	45	23	40	5	23	5	18	16	-10	16	14	11	11	-3	-9
-3	-27	32	38	30	57	20	100	53	44	27	17	16	45	44	50	46	30	27	1	17	23	25	52	1	35	30	1	6
13	-39	43	33	31	44	4	53	100	8	18	26	26	43	14	41	35	11	0	9	15	2	43	54	-6	22	35	5	17
3	-4	2	39	14	25	15	44	8	100	17	-8	23	25	35	34	21	35	16	-4	23	12	18	27	17	5	30	-4	-5
0	-25	33	36	50	28	34	27	18	17	100	-3	15	18	38	26	40	14	46	-7	15	25	21	30	-17	34	-6	-10	6
-14	-7	35	10	-13	19	3	17	26	-8	-3	100	18	13	-12	3	4	-4	0	16	16	4	-12	13	33	-1	39	15	7
-4	-3	18	24	-2	12	10	16	26	23	15	18	100	3	-5	6	0	8	0	8	5	-7	4	12	18	18	10	13	-4
18	1	46	28	13	19	15	45	43	25	18	13	3	100	31	30	31	15	3	10	31	-6	11	51	16	0	34	10	17
13	-4	7	27	31	27	45	44	14	35	38	-12	-5	31	100	27	55	26	29	-17	20	47	8	35	-5	14	7	-32	-4
10	-37	24	38	26	54	23	50	41	34	26	3	6	30	27	100	33	32	30	25	24	18	33	32	2	34	29	18	15
2	0	21	35	30	60	40	46	35	21	40	4	0	31	55	33	100	17	46	-16	33	27	10	37	-6	5	6	-36	24
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-4	10	15	13	45	50	23	27	0	16	46	0	0	3	29	30	46	22	100	-15	27	35	-1	13	-19	34	3	-11	16
-1	-6	19	20	10	12	5	1	9	-4	-7	16	8	10	-17	25	-16	-6	-15	100	2	-8	17	20	20	27	20	43	7
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-6	-7	-3	20	37	30	16	23	2	12	25	4	-7	-6	47	18	27	31	35	-8	13	100	7	18	-12	16	5	-11	6
0	-27	17	43	25	15	-10	25	43	18	21	-12	4	11	8	33	10	13	-1	17	10	7	100	32	-21	25	23	11	3
7	-18	47	36	24	35	16	52	54	27	30	13	12	51	35	32	37	17	13	20	9	18	32	100	6	11	35	-4	20
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-9	-4	11	7	0	-9	-3	1	5	-4	-10	15	13	10	-32	18	-36	-16	-11	43	0	-11	11	-4	31	20	30	100	-4
-1	6	18	15	-13	26	-9	6	17	-5	6	7	-4	17	-4	15	24	24	16	7	32	6	3	20	3	9	7	-4	100

Appendix H: Factor Z-Scores for Statements

No.	Statement	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
1	Use geospatial software to transform ellipsoid, datum, and/or map projection to georegister one set of geospatial data to another	0.42	0.34	0.57	0.99	0.64
2	Geocode a list of address-referenced locations to map data encoded with geographic coordinates and attributed with address ranges	1.33	0.33	1.35	1.24	0.99
3	Discuss examples of systematic and unsystematic land partitioning systems in the U.S. and their implications for land records	0.29	-1.07	-1.7	-1.24	0.66
4	Recognize that land records are administered differently around the world	0.49	-0.28	0.3	-0.43	0.69
5	Explain the distinction between a property boundary and its representations, such as deed lines, lines on imagery, boundary depictions in cadastral (land records) databases	1.48	-0.73	0.6	-1.38	1.45
6	Plot a legal boundary description from a deed or plat	1.7	-0.75	-0.09	-1.48	1.12
7	Design a system for acquiring, processing and integrating geospatial data from diverse sources	-0.04	1.63	0.53	2.08	1.08
8	Identify sampling strategies for field data collection, including systematic, random, and stratified random sampling, and describe circumstances favorable to each	-0.04	-0.34	-0.07	0.26	1.3
9	Explain how spatial autocorrelation influences sampling strategies and statistics	-1.08	-0.78	-0.59	0.65	-0.21
10	Perform requirements analysis for remotely sensed data acquisition using resolution concepts	-0.73	-0.05	-0.12	-0.6	-1.13

11	Explain the concept of “bit depth” and its implications for remotely-sensed image data	-2.47	-0.81	-0.31	-0.77	-0.45
12	Plan a remotely sensed data acquisition mission, including specifying an appropriate sensor and platform combination suited for particular project requirements	-1.76	-0.76	-1.31	-0.8	-0.98
13	Recognize the differences between ellipsoidal (or geodetic) heights, geoidal heights, and orthometric elevation	-0.63	-0.34	0.06	0.14	1.21
14	Understand GNSS data post-processing (such as National Geodetic Survey’s Online Positioning Service) and real time (such as Real Time Kinematic)	-0.59	-1.32	0.14	-1.82	0.61
15	Collect and integrate carrier phase (survey grade) GNSS positions and associated attribute data with other geospatial data sets	-0.7	-1.53	-0.78	-2.04	1.1
16	Interpret the quality of GNSS data based on possible sources of error	-1.16	-0.83	-0.49	-1.2	1.03
17	Explain major GNSS error sources, such as ionospheric delay, clock error, ephemerides, and satellite health	-1.26	-2.14	-1.47	-1.13	-0.25
18	Understand the process to produce an orthoimage data product with geometric accuracy suitable for project requirements	0.04	-0.85	-0.7	-0.02	0.88
19	Understand how aerotriangulation contributes to data quality confidence and is applicable to completing related tasks	-0.9	-1.11	-1.23	-1.82	-1.26
20	Produce a metadata document that conforms to FGDC, ISO or other geospatial metadata standard	-0.65	-0.24	1.99	0.82	0.03

21	Understand how to conduct primary research and implications of data privacy and confidentiality	0.42	-0.99	1.22	1.29	-1.58
22	Describe how information can be harvested and geocoded from social media	-0.15	-0.99	1.06	-0.13	-1.43
23	Explain the process of acquiring and integrating large and heterogeneous datasets (spatial or nonspatial)	-0.71	0.77	0.93	1.56	1.42
24	Explain how a mobile device calculates location coordinates (e.g., GNSS, triangulation, trilateration, etc.)	-0.78	-0.62	1.05	-1.19	1.02
25	Compare differential GNSS and autonomous GNSS	-1.04	-1.35	-1.34	-2.08	0.3
26	Describe an example of a useful application of a buffer operation in GIS software	1.31	-0.12	1	1.24	1.03
27	Perform a site suitability analysis using intersection and overlay functions of GIS software	0.61	0.18	1.21	1.48	0.88
28	Use GIS software to identify an optimal route that accounts for visibility, slope, and specified land uses	-0.61	0	0.53	0.1	0.13
29	Perform dynamic segmentation on transportation network data encoded in a linear reference system	0.18	-0.41	-0.04	-0.63	-0.89
30	Explain how leading online routing systems work, and account for common geocoding errors	-0.23	-0.97	0.98	-0.48	-1.31
31	Use location-allocation software functions to locate service facilities that satisfy given constraints	-0.35	-0.1	1.12	0.78	-0.41
32	Develop conceptual, logical, and physical models of a geospatial database designed in response to user requirements	1.4	0.88	1.27	1.31	-0.37

33	Understand how spatial data aggregation into different areal extents affects interpretation of results (Modifiable Areal Unit Problem)	-0.7	-1.65	-1.38	0.67	-1.15
34	Explain characteristics and appropriate uses of geospatial modeling techniques (e.g. artificial intelligence, machine learning, and deep learning)	-0.03	-0.16	-0.85	0.5	-0.91
35	Demonstrate familiarity with the existence of predictive models and their applications	-0.14	0.26	-1.09	0.99	-1
36	Employ cartographic techniques to represent different kinds of uncertainty, including uncertain boundary locations, transitional boundaries, and ambiguity of attributes	0.5	0.15	1.18	1	1.96
37	Understand how to represent boundaries in plats, records, and descriptions, as stipulated in legal statute and precedent	1.88	-0.93	-0.16	-1.2	0.91
38	Determine appropriate image data and image analysis techniques needed to fulfill project requirements	-1.27	1.09	1.78	-0.37	1.61
39	Explain the processes involved in geometric correction, radiometric correction, and mosaicking of digital remotely sensed data and the resulting errors	-0.9	-0.8	-0.88	-0.71	-0.75
40	Explain how to quantify the thematic accuracy of a land use/land cover map derived from remotely-sensed imagery	-0.04	-0.55	-0.08	0.1	0.07
41	Determine the thematic accuracy of a data product using ground verification methods	0.08	-0.77	-0.23	0.1	-0.13
42	Explain the difference between pixel-based and object-based image classification	-1.55	-0.94	-0.47	-0.43	-0.23
43	Perform object-oriented image classification	-1.45	-0.38	-0.9	-0.73	-0.89
44	Develop use cases for user-centered requirements analyses	0.2	1.14	-1.03	0.41	-0.84

45	Perform a feasibility study and cost/benefit analysis	0.72	0.26	0.4	0.68	1.69
46	Design a geospatial system architecture that responds to user needs, including desktop, server, and mobile applications	1.72	1.19	0.82	-0.45	-0.74
47	Communicate effectively with end-users to ensure that software applications meet user needs	1.88	1.46	1.42	0.65	0.84
48	Optimize geospatial system performance	0.96	1.25	-0.03	0.09	-0.44
49	Identify appropriate software development tools for particular end uses	0.79	0.59	-1.09	0.31	0.67
50	Ensure that software code complies with industry standards, such as those promulgated by the Open Geospatial Consortium (OGC)	-1.56	0.5	-1.42	-0.34	0.24
51	Identify th factors that affect the interoperability of geospatial software applications	0.24	0.61	0.27	0.96	-0.64
52	Automate geospatial analysis such as transformation, raster analysis, and geometric operations	0.84	0.71	0.38	0.58	-0.4
53	Use scripting languages to automate repetitive tasks	1.29	1.88	-0.17	1.01	0.33
54	Customize geospatial software using proprietary and open source software components	-0.1	0.89	-1.55	-0.06	-1.73
55	Use scripting languages or other tools to create web mapping applications	0.82	2.42	-0.35	-0.3	-0.63
56	Employ query languages such as SQL to interrogate spatial data	0.96	1.84	0.66	2.07	-0.32
57	Work effectively in teams to plan and coordinate software and application development	1.41	1.31	-0.27	0.97	0.2
58	Stay informed about trends and best practices in information technology and software engineering, such as unit testing, version control, and continuous integration	0.77	1.47	2.02	-0.32	0.39

59	Evaluate open source software components for re-use and potential return contributions	-0.89	0.46	-1.2	0.31	-1.52
60	Realize opportunities to leverage positioning technology to create mobile end-user applications	0.41	0.53	-0.24	0.01	-0.18
61	Explain how geospatial software in large enterprises fits into SOA (Service Oriented Architectures) and SaaS (Software as a Service)	-0.73	-0.01	-2.06	-0.43	-2.13
62	Be able to leverage web architectural opportunities	0.09	1.53	0.84	-0.77	-1.59