Examining the Perspectives of Practitioners and Educators toward a Geospatial Competency Matrix: A Q Methodology Approach

Rodney D. Jackson[1] and Thomas R. Mueller[2]*

[1] Department of Geography, Planning and Environment, East Carolina University, Greenville, NC, USA
[2] Geosciences Department, PennWest – California University, California, PA, USA

[*]Corresponding author: jacksonro22@ecu.edu

ABSTRACT

This study intended to provide insight into geospatial practitioners' and educators' viewpoints toward the National Geospatial Technology Center of Excellence (GeoTech Center) Geospatial Competency Matrix. These viewpoints are significant since educators and business professionals use workplace competencies for curriculum development, professional certification, and defining workforce requirements. The research question sought to determine the viewpoints toward the geospatial competencies and provides the field an understanding of how practitioners perceive these competency statements. Seventy participants sorted 72 cards (with Geospatial Competency Matrix Statements) on a scale of -6 to 6 and completed two short surveys with demographic and open-ended questions. The data was evaluated using factor analysis, descriptive statistics, and a crib sheet of high, low, and distinguishing statements to provide meaning to the viewpoints. This study found seven viewpoints toward a geospatial competency matrix: Factor 1: We are Cartographers (map evaluators); Factor 2: Vector Data are our Paramount Focus; Factor 3: Analysis is the Key to Addressing Geospatial Problems; Factor 4: Using Programming to Support Analysis; Factor 5: Where in the World is the Data; Factor 6: Data Refinements are a Critical Step in Spatial Analysis, and Factor 7: We have a Love/Hate Relationship with Data.
Keywords: competency, geospatial, Q Methodology, workforce

NATURE OF THE PROBLEM AND PROBLEM STATEMENT

Researchers have attempted to capture the skills needed for workers to succeed in the geospatial field. These studies include the analysis of learning outcomes found in higher education (Schulze, Kanwischer & Reudenbach, 2013), professional geography competency models (Solem, Cheung, & Schlemper, 2008), content analysis of job advertisements (Hong, 2016), surveys (Wikle & Fagin, 2015), and an examination of job titles (Wikle, 2010). The research efforts above represent an evaluation of competencies in the geospatial field, but they did not force participants to discriminate between the relevance of the competencies.

This research study uses Q Methodology to assess respondents' perceptions of the National Geospatial Technology Center of Excellence (GeoTech Center) Geospatial Competency Matrix. This study's results could help redefine the competencies receiving attention moving forward and assist in the professional preparation of students as they transition into the workforce. Q Methodology was chosen for the analysis given that the study's goal was to reveal varied perspectives rather than generalize a population (Watts & Stenner, 2012).

PURPOSE STATEMENT

The purpose of the study is to explore the viewpoints of practitioners and educators toward the GeoTech Center Geospatial Competency Matrix and why they hold these views. There are challenges to assuring competence within the geospatial field (Albrecht, 1998), but assessing viewpoints toward these competencies will enable a better understanding of the needs within the geospatial workforce. Also, identifying commonalities across viewpoints may reveal widely held beliefs within the field. Attempts to standardize the core competencies within the geospatial discipline are progressing, and developing a connection between the learning outcomes achieved in academia and the practical knowledge demonstrated in the workplace is a viable path to establishing competence (Mathews & Wikle, 2017).

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The study results address the following research questions:

1. How do practitioners and educators view the competency statements located within the GeoTech Center Geospatial Competency Matrix, and why?
2. Do perceptions of the geospatial competencies differ based on the respondents' industry- sector, experience in the geospatial profession, area of employment, or educational level where they received most of their geospatial instruction?

LITERATURE REVIEW

One of the challenges associated with geospatial science is its application across various disciplines. Johnson and Sullivan (2010) found that while geospatial techniques were most common in Geography Departments, many academic departments provide instruction couched regarding how geospatial techniques could be integrated within that discipline. 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 and can only provide a limited amount of data at a national level.

Competency models define what employees should know and need to do for success, and they have been used to establish employee educational guidelines and selection criteria (Hong, 2016). Determining the competencies needed in the geospatial field has been difficult due to various technology applications (Wikle, 2010). There has been general agreement that to understand the needs of the geospatial workforce, researchers had to define "core" knowledge, skills, and abilities of all geospatial professionals (Huxhold & Craig, 2003). For this reason, the focus went first to defining core competencies as a starting point for creating an industry framework (Sullivan, 2007) to establish a connection between instruction and application.

The University of Southern Mississippi (USM) led an effort to create the first geospatial competency model and built the most comprehensive work on the geospatial workforce competencies (Samborski, 2006) at the time. In 2010, the U.S. Department of Labor Employment and Training Administration (DOLETA) issued a Geospatial Technology Competency Model (GTCM), documenting the specialized KSAs and educational preparation necessary to become a successful geospatial professional (Sinton, 2012). 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 (Veenendaal, 2014).

After years of discussion, the Association of American Geographers (AAG) published the UCGIS Body of Knowledge (BoK) 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). Johnson and Sullivan (2010, 9) 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". The GIS&T BoK is seen by many as the most successful effort yet to create a comprehensive inventory of knowledge, skills, and abilities unique to the geospatial domain (Veenendaal, 2014).

METHODOLOGY

Selection of Concourse and Q-Sample (Q-Set)

A Q Methodology study begins with developing a comprehensive collection of possible statements regarding a given topic, otherwise known as a concourse (Dziopa & Ahern, 2011; van Exel & De Graaf, 2005). The concourse is an extensive collection of possible statements that capture individual viewpoints of topics within a domain (Cuppen et al., 2016; Zabala & Pascual, 2016) and is sampled to build a Q-set. The sampling process from the concourse can present challenges (Simons, 2013) as the statements must be reduced to a reasonable count and be typical of all statements and accurately represent a cross-section of the concourse (Brown, 1993).

The authors developed a set of statements, known as the Q-set, from the 190 competencies found in the GeoTech Center's Assessment Tool. These competency statements incorporate the accepted knowledge, skills, and abilities needed by geospatial practitioners. The assessment was selected as the concourse as it is designed to provide a system to evaluate the configuration of KSAs that geospatial professionals should possess. This study comprises the 72 geospatial competency statements from the GeoTech Center Geospatial Competency Matrix.

P-Set Demographics

The sampling of a limited population is supported by Wright (2013, 154), who stated that "P-set membership should reflect a body of participants who are 'theoretically salient' to the issue under study." The participant pool was comprised of attendees at the GeoTech Center's 2020 and 2021 annual conferences and educators participating in geospatial training during the same time. Seventy practitioners and educators completed a Q-sort activity for 72 competency statements in the GeoTech Center Geospatial Competency Matrix. The respondents are varied and knowledgeable, averaging 19.5 (SD = 11.6) years of experience with 12.9 (SD = 8.7) years within the geospatial field.

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 practitioners and educators regarding the relevance of competency statements. The 70 Respondents completed an online sorting activity indicating each competency statement's particular relevance from most relevant (+6) to least relevant (-6). In conjunction with qualitative questions after the survey, these data construct themes relating to shared views of relevance for the competencies. 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 grid's restrictions. The model's prescriptive nature encourages respondents to reflect on their feelings more carefully and approach the exercise systematically (Steelman & Maguire, 1999; van Exel & De Graaf, 2005). Perspective is at the center of this research. The P-set must be built upon a collection of representatives within the realm who can thoughtfully evaluate the statements under consideration (van Exel & De Graaf, 2005).

Correlation Matrix

The researchers analyzed the Q-sort data using Ken-Q Analysis Desktop Edition (KADE) (Banasick, 2019). Data analysis begins with a correlation matrix, which establishes the relationship between the Q-sorts. 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 highest correlation was 66 (.66), shared between Respondents 23 and 53, with the subsequent highest correlation being 65 (.65), which was shared between respondents 23 and 39. The lowest correlation was -37 (-.37) between Respondents 20 and 42, with the lowest correlation of -35 (-.35), which was shared between respondents 42 and 53. Correlation coefficients between the individual Q-sorts help identify shared views held by respondents (van Exel & De Graaf, 2005). Bartlett and DeWeese (2015, 79) noted, "The goal of this process is to determine the variability of Q-sorts to determine how many shared factors are in evidence".

Factor Analysis and Rotation

The researchers applied factor analysis to reduce 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) during factor analysis. Watts and Stenner (2012, 97) noted that PCA would "resolve itself into a single, mathematically best solution" and "deprives us of the opportunity to properly explore the data". The researchers used the KADE software to analyze and begin data reduction of the 70 submissions.

The unrotated factors' task is to explain the variance found in the correlation matrix by loading as many Q-sorts as possible (Zabala et al., 2018). The factors represent a hypothetical best-representative Q-sort, and, typically, only a few factors are selected (van Exel & De Graaf, 2005). The number of factors selected depends on the Q-sorts' variability, but there are usually no more than seven factors (Dziopa & Ahern, 2011; Wright, 2013). It is generally accepted that only factors with an eigenvalue higher than one (1.00) are selected for extraction and interpretation (Dziopa & Ahern, 2011; Shemmings, 2006). An eigenvalue (E.V.) is calculated by summing the squared loadings of the Q-sorts defining a factor and indicates the extractors' ability to explain variance (Watts & Stenner, 2012). A researcher can also use a scree plot (see Figure 1) to support a decision on the number of factors selected.

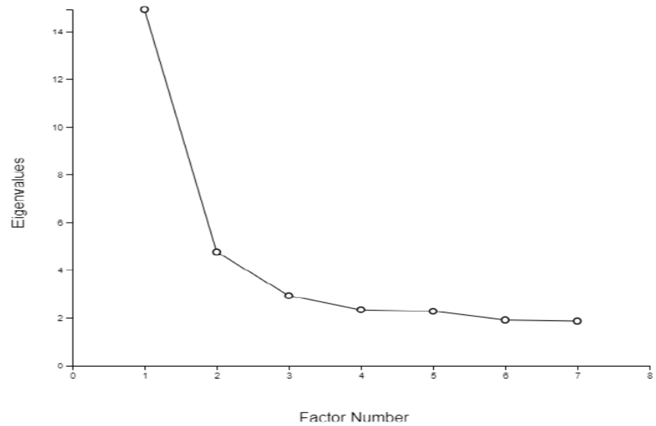

Figure 1: Scree Plot of the initial 7-Factor Solution

The researchers selected a 7-factor solution (EV=1.86) with 47 participants with no fewer than three loadings on any factor and explained 44% of the variance. The researchers believe the 7-factor solution balances the competing needs to load as many participants as prudent onto each factor, cumulatively explain the most variance possible, and develop a logical narrative of the expressed views (Wright, 2013; see Table 1).

Factor Characteristics

The general characteristics used in determining each factor include the number of Q-sorts loaded, eigenvalues, percentage of variance explained, composite reliability, and the standard error (S.E.) of the z-scores (see Table 2). 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, 6), 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". Watts and Stenner (2012) indicate that the standard error for z-scores can be calculated as 1 / (√ number of items in the Q-set). A *SE* of 0.12 was calculated: *SE* = 1 / (√72); *SE* = 1 / (8.485); *SE* = 0.117 (rounded to 0.12); *SE* = 0.12. Watts and Stenner (2012) prefer that the cross product of the two highest loadings of any factor double the standard error (0.24), which occurred in this study.

The next step in data analysis is factor rotation, which attempts to reveal the best combination of relationships between variables (Q-sorts) and maximize the explained variance (Watts & Stenner, 2012). There are two options for factor rotation,

Table 1. Factor Solutions

Factors	Significant Loads	Variance Explained (%)	Lowest Eigenvalue	Composite Reliability	Highest Factor Correlation	Range of Sorts
7	47	44	1.86	0.92	0.47	3 – 19
6	42	44	1.91	0.80	0.55	1 – 16
5	49	40	2.26	0.96	0.55	6 – 18

statistical or judgmental, depending on the study. A statistical 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 researchers applied a varimax (statistical) rotation, as this study was exploratory.

Factor Correlation

The level of agreement or disagreement seen in the correlation matrix is represented similarly in factor score calculations. 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 C) before conducting any cross-factor analysis (Zabala et al., 2018). A z-score defines a factor by illustrating a relationship between statements and factors, compared within a data matrix (Bartlett & DeWeese, 2015).

Factor Loadings

The intent of using factor analysis is to identify underlying patterns within the data and reveal collections of like-minded respondents who rank the statements based upon shared beliefs (Shemmings, 2006; Zabala & Pascual, 2016). Individual Q-sorts with a substantial loading on a factor are 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 comparable 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, 6) suggest there is an optimal number of Q-sorts for each factor when stating, "The aim is to have four or five persons defining each anticipated viewpoint".

The researchers began the factor extraction with centroid factor analysis. The 8-factor solution generated a factor without a Q-sort, and the 6-factor solution produced a negative loading on one factor and a single Q-sort loading on another. The 7-factor solution (EV=1.86) included 47 participants, with no fewer than three significant loadings ($p < 0.05$) on any factor and explained 44% of the variance. The authors determined that the 7-factor solution most effectively balances the competing needs to load as many participants as prudent onto each factor, cumulatively explain the most variance possible, and develop a logical narrative of the expressed views (Wright, 2013; see Table 1).

The seven themes developed from the analysis are Factor 1: We are Cartographers (significant loadings range in value from 0. 7221to 0. 4621) explains 21% of the variance (Q-sorts 2, 3, 4, 5, 7, 8, 10, 15, 16, 17, 18, 20, 21, 22, 23, 46, 52, 53, 69); Factor 2: Vector Data are our Paramount Focus (significant loadings range in value from 0.6747 to 0.3993) explains 7% of the variance (Q-sorts 11, 24, 25, 40, 62, 63, 65); Factor 3: Analysis is the Key to Addressing Geospatial Problems (significant loadings range in value from 0.6911 to 0.3952) explains 4% of the variance (Q-sorts 12, 13, 57, 59, 60); Factor 4: Using Programming to Support Analysis (significant loadings range in value from 0.628 to 0.4766) explains 3% of the variance (Q-sorts 26, 29, 32, 41, 47, 61); Factor 5: Where in the World is the Data (significant loadings range in value from 0.4989 to 0.2799) explains 3% of the variance (Q-sorts 31, 34, 64); Factor 6: Data Refinements are a Critical Step in Spatial Analysis (significant loadings range in value from 0.5014 to 0.4545) explains 3% of the variance (Q-sorts 33, 44, 48, 50); Factor 7: We have a Love/Hate Relationship with Data (significant loadings range in value from 0.5922 to 0.409) explains 3% of the variance (Q-sorts 14, 67, 68).

Factor Arrays

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 are a strength of Q Methodology (Cuppen et al., 2016) and allow the researchers to interpret how the statements rank within each factor (Bartlett & DeWeese, 2015). Factor arrays play a role in factor interpretation and theme development, as the arrays act like a typical Q-sort for the factor (Cuppen et al., 2016; McKeown & Thomas, 2013). The factor scores allow the researchers to evaluate the configuration of all items within the array and the significance of specific statement locations (McKeown &

Table 2. Factor Characteristics

Factor	Participants Loaded	Eigenvalues	Variance Explained	Composite Reliability	*SE* of Factor Z-scores
1	19	14.91	21	0.99	0.11
2	7	4.75	7	0.97	0.18
3	5	2.92	4	0.95	0.22
4	6	2.33	3	0.96	0.20
5	3	2.27	3	0.92	0.28
6	4	1.91	3	0.94	0.24
7	3	1.86	3	0.92	0.28
Total variance			44		

Thomas, 1988; Watts & Stenner, 2012). In developing a factor array, a calculation of each Q-sort's weighted scores that load 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 sorting exercise's initial scale. In this study, the converted values will range from -6 to +6 (see Table 3).

Factor Interpretation

Factor interpretation involves the identification of statements useful in the analysis. A distinguishing statement will score significantly different on one factor than another, but consensus statements tend to align themselves similarly across the factors (Zabala & Pascual, 2016). The study revealed no consensus statements. Statements within the factor array with

Table 3. Factor Arrays

No.	Statement	Factors						
		1	2	3	4	5	6	7
1	Explain what topology means in relation to geospatial data (i.e., adjacency, connectivity, containment, proximity)	1	-1	-2	0	0	-4	0
2	Identify spatial patterns; apply knowledge of how people and places are linked (spatial thinking and Tobler's First Law of Geography)	5	-4	3	4	0	4	2
3	Explain how to use geospatial technology to solve a problem	6	3	4	1	3	0	0
4	Describe how planar geometry (e.g., points, lines, polygons) are used to convert real-world features into digital representations of features	1	-3	-3	-2	2	3	-3
5	Define data's spatial reference	1	3	0	-1	1	2	2
6	Transform spatial data (e.g., reprojections, datums)	-2	3	2	2	3	2	-1
7	Apply appropriate map projections based on the type of analysis	1	1	3	-1	1	3	1
8	Describe the characteristics and appropriate uses of datums	-1	1	-1	-6	6	1	-5
9	Compare large-scale maps and small-scale maps	1	-1	-4	0	-1	-1	-4
10	Explain how interpretation and visualization of data in a map is influenced by the area of its boundary polygon (i.e., county versus state or state versus country, MAUP).	2	-2	-1	0	-5	-3	-5
11	Describe different map elements and how they may or may not be needed for different audiences or media	3	0	1	0	-4	-3	-4
12	Demonstrate knowledge of map interpretation	4	2	1	0	-1	2	2
13	Create charts, graphs, tables	1	1	-3	0	-4	-2	5
14	Critique the design of a given map in light of its intended audience and purpose	3	0	0	-1	2	-2	-1
15	Present results of an analysis using data visualization (cartography, charts, and graphs)	3	2	5	4	1	2	4
16	Create maps using cartographic principles (color, symbols, text, elements, etc.)	4	3	1	1	-1	0	1
17	Determine appropriate map scale	2	0	-1	-1	2	2	-2
18	Describe why acknowledgment of contributors and copyrights is necessary	2	-4	-2	-5	-2	-2	-1
19	Create a problem statement outlining the problem and ways to solve it using geospatial technology	5	-1	3	2	3	-1	6
20	Determine data needs and formats	4	3	0	2	0	1	-1
21	Compare basic analysis methods (point pattern analysis, cluster analysis, multi-criteria evaluation, and spatial process models)	0	-2	1	3	0	-1	-5
22	Perform buffer, slope, hillshade analysis	0	1	5	0	-3	-1	0
23	Derive new data (e.g., generate contours from DEM, data generalization, etc.)	-3	-2	3	-3	1	1	3
24	Perform overlay analysis	0	2	3	3	-2	0	2
25	Perform site selection	-1	-2	-2	-2	-3	-1	-2
26	Perform viewshed analysis	-3	-2	1	-2	-5	-4	-2

27	Interpret results from an analysis (is it appropriate/good)	3	1	4	5	5	6	3
28	Pre-process data (e.g., generalize, subset, reproject, clip, mosaic, etc.)	-2	1	-2	1	1	1	-1
29	Create elevation datasets (rasters) from vector data	-4	-1	3	-1	-2	-2	2
30	Perform network analysis (i.e., roads, streams, etc.)	-2	0	2	0	-1	-2	0
31	Create TINs from feature data	-5	-3	0	-4	-3	-6	-1
32	Describe different data formats (Vector, Raster, TIN, etc.)	2	0	-3	-3	-1	1	0
33	Apply appropriate data formats (Vector, Raster, TINs, Imagery)	0	1	2	-2	-2	4	0
34	Design database structure (e.g. schema)	-1	5	1	3	4	-1	-2
35	Create and maintain data dictionary	0	-2	-5	1	-1	-3	-2
36	Create database tables	0	5	-3	4	1	-1	1
37	Define data requirements to help solve a problem	5	2	5	3	4	-1	-3
38	Input data into a relational database	-2	0	-2	4	1	-4	0
39	Develop (construct) databases (e.g. define geometry & attributes)	-2	4	0	6	4	0	3
40	Apply different geoprocessing methods, including clip, buffering, and overlay	2	2	4	3	0	5	1
41	Edit and update attribute and spatial data geometry	0	5	1	2	-1	5	1
42	Demonstrate ability to carry out mathematical operations including addition, subtraction, multiplication, and division	-3	-3	-6	-2	-1	2	-3
43	Perform descriptive statistical analysis (mean, median, mode, etc.)	-2	-3	-5	0	3	5	3
44	Create programming code (i.e., Python or other languages)	-5	-1	-4	5	-5	0	2
45	Apply basic programming principles (SQL statements, Boolean logic, macros)	-3	-1	-4	5	-3	1	2
46	Perform data format conversions (vector to raster, raster to vector, raster to TIN)	-3	-1	6	-4	0	3	-3
47	Explain why map scale affects the resolution of data creation or acquisition for a given application	2	-1	-2	2	0	0	-4
48	Describe different methods of indicating locations (e.g., decimal degrees, UTM, military grid)	-1	-1	-3	-3	4	0	-3
49	Perform proximity analysis	1	3	2	2	-2	1	4
50	Describe how to geocode data	-1	0	-4	2	-4	-2	-2
51	Create and update attribute data	0	4	-1	3	0	4	4
52	Demonstrate how to create/update vector data	1	2	0	1	-2	3	3
53	Georeference data	0	6	0	1	5	2	5
54	Define data requirements (format, projections, scale, etc.)	3	4	1	-1	2	1	-2
55	Research and evaluate data sources	3	0	-1	0	2	1	0
56	Explain how to acquire data (create, purchase, locate)	2	1	-5	1	2	-3	-1
57	Demonstrate how to import/export data from various sources (e.g. spreadsheets)	1	2	-2	-2	0	2	4
58	Describe how to verify spatial data accuracy, quality, compatibility, and appropriateness for application	2	0	-1	1	3	3	1
59	Create/update metadata	0	0	-3	1	2	0	3
60	Perform spatial and non-spatial data table joins	-1	2	0	2	-3	4	0
61	Collect field data using GNSS (location and attribute)	-1	4	2	-2	-1	0	-1
62	Describe different data collection methods (e.g. GNSS, aerial, drones)	-1	-2	-1	-4	-4	0	-1
63	Conduct ground-truthing	-3	1	1	-4	5	-5	2
64	Describe basic remote sensing science concepts, including the electromagnetic spectrum, sensors, and bands	-1	-4	-1	-3	-3	-1	-3
65	Create composite images using imagery bands	-4	-3	2	-5	1	-5	0
66	Create index/ratio images (NDWI, NDVI, MSI, LAI, EVI, snow, etc.)	-6	-5	0	-2	-2	-3	-4

67	Perform change detection using imagery from different dates	-2	-2	2	-1	0	-5	1
68	Collect spectral signatures for imagery classification	-5	-6	-2	-5	-6	-4	1
69	Conduct image classification (e.g., supervised or unsupervised)	-4	-5	4	-3	-2	-2	1
70	Perform feature extraction from imagery	-4	-3	2	-1	1	-2	-2
71	Explain imagery resolutions (Spatial, Temporal, Radiometric, and Spectral)	-2	-5	-1	-3	3	-3	-6
72	Explain why ethics is important to the geospatial technology field	4	-4	0	-1	2	3	5

the highest and lowest scores are typically more helpful in interpreting themes (Bartlett & DeWeese, 2015; Zabala et al., 2018), defining a factor and distinguishing it from another factor (Cuppen et al., 2016; Wright, 2013). The statements with the highest and lowest scores (z-scores) for each factor are anchor statements in Tables 4 and 5, respectively. The authors used a crib sheet approach to organize the relative ranking of statements and facilitate factor interpretation. The crib sheet used is modeled after one referenced by Watts and Stenner (2012) and is in Appendix B.

Following the Q-sort, participant responses to the open-ended questions (see Appendix A) assisted the researchers' interpretation of the factors. The results provide a qualitative narrative, summarized in a title, derived from the most distinguishing characteristic of the perspective (Cuppen et al., 2016). The title offers easy identification, and the narrative delivers an overview of the factor, highlighting various critical elements (Cuppen et al., 2016; Simons, 2013). This study identified seven viewpoints held by practitioners and educators toward the Geospatial Competency Matrix's competencies. The factors representing these perspectives: The seven documented factors characterize a substantial variation in the perceptions of technical geospatial competencies. The emergent factors were Factor 1: We are Cartographers (map evaluators); Factor 2: Vector Data are our Paramount Focus; Factor 3: Analysis is the Key to Addressing Geospatial Problems; Factor 4: Using Programming to Support Analysis; Factor 5: Where in the World is the Data; Factor 6: Data Refinements are a Critical Step in Spatial Analysis, and Factor 7: We have a Love/Hate Relationship with Data.

RESULTS

Analysis of Research Question One

Factor 1: We Are Cartographers (Map Evaluators)

Factor 1 had 19 Q-sorts and explained 21% of the study's variance, accounting for the most variance explained in the study. The respondents are varied and experienced, averaging

Table 4. Highest Ranking Statement for Each Factor

Factor	Number	Statement	Z-score
1	3	Explain how to use geospatial technology to solve a problem	2.48
2	53	Georeference data	1.93
3	46	Perform data format conversions (vector to raster, raster to vector, raster to TIN)	2.03
4	39	Develop (construct) databases (e.g. define geometry & attributes)	2.15
5	8	Describe the characteristics and appropriate uses of datums	2.3
6	27	Interpret results from an analysis (is it appropriate/good)	2.28
7	19	Create a problem statement outlining the problem and ways to solve it using geospatial technology	2.24

Table 5. Lowest Ranking Statement for Each Factor

Factor	Number	Statement	Z-score
1	66	Create index/ratio images (NDWI, NDVI, MSI, LAI, EVI, snow, etc.)	-2.38
2	68	Collect spectral signatures for imagery classification	-1.98
3	42	Demonstrate ability to carry out mathematical operations including addition, subtraction, multiplication, and division	-2.35
4	8	Describe the characteristics and appropriate uses of datum	-1.85
5	68	Collect spectral signatures for imagery classification	-2.52
6	31	Create TINs from feature data	-2.02
7	71	Explain imagery resolutions (Spatial, Temporal, Radiometric, and Spectral)	-2.25

20.6 (SD=12.2) years of experience with 9.4 (SD=7.3) years spent in geospatial science. The following number of participants received formal geospatial instruction at the Associate's (1), Bachelor's (4), Masters (8), or Doctorate (0) level, with 6 possessing no formal geospatial education.

The Q-sorts loading onto Factor 1 demonstrated an appreciation for the skills needed by cartographers and map interpreters. The highest distinguishing statement (Table 6), Statement 11 (3), is representative of the factor and is supported by Distinguishing Statements 10 (2) and 18 (2), and 9 (1). Three of these, Statements 11, 10, and 18 were significant at p <0.01. Also, Statements 16 (4), 12 (4), 14 (3), and 17 (2) were ranked higher on Factor 1 than any other factor. The respondents held a generally negative view of remote sensing and competencies connected to manipulating datasets. The only distinguishing statement was Statement 66 (-6). The one remaining imagery competency, Statement 70 (-4), was a distinguishing statement and ranked lower in Factor 1 than any other factor. Numerous data handling competencies ranked lower on Factor 1 than any other factor, including Distinguishing Statements 29 (-4), 23 (-3), 6 (-2), and 28 (-2).

Factor 2: Vector Data Are Our Paramount Focus

Factor 2 had 7 Q-sorts and explained 7% of the variance in the study. The respondents are practitioners and educators with a wide range of years in the practice, averaging 22.4 (SD=12.2) years of experience with 16.3 (SD=7.9) years spent in geospatial science. The following number of participants received formal geospatial instruction at the Associate's (1), Bachelor's (3), Masters (2), or Doctorate (0) level, with 1 possessing no formal geospatial education.

The factor's title reflects respondents' opinion that the most relevant statements are those connected to competencies aligned to vector data processes. The competencies are a collection of database operations, spatial reference, and data transformation undertakings. Statement 61 (4), only one was distinguishing (Table 7). Regardless, all positive statements were ranked higher in Factor 2 than any other factor. Statements 53 (6), 61 (4), 6 (3), and 5 (3) are aligned with spatial referencing. Statements 41 (5), 54 (4), and 28 (1) address data manipulation. Finally, Statements 34 (5), 36 (5), and 51 (4) were connected to

database actions. The participants' negative views towards digital imagery and remote sensing competency areas are reflected in Distinguishing Statement 35 (-3). Also, Statements 64 (-4), 69 (-5), and 68 (-6) are ranked lower in Factor 2 than in another array.

Factor 3: Analysis Is the Key to Addressing Geospatial Problems

Table 6. Distinguishing Statements for Factor 1

No.	Statement	Factor 1 Q-SV	Factor 1 Z-score	S
3	Explain how to use geospatial technology to solve a problem	6	2.48	*
11	Describe different map elements and how they may or may not be needed for different audiences or media	3	1.07	*
10	Explain how interpretation and visualization of data in a map is influenced by the area of its boundary polygon (i.e., county versus state or state versus country, MAUP).	2	0.73	*
18	Describe why acknowledgment of contributors and copyrights is necessary	2	0.53	*
9	Compare large-scale maps and small-scale maps	1	0.27	

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

Table 7. Distinguishing Statements for Factor 2

No.	Statement	Factor 2 Q-SV	Factor 2 Z-score	S
61	Collect field data using GNSS (location and attribute)	4	1.3	
22	Perform buffer, slope, hillshade analysis	1	0.67	
45	Apply basic programming principles (SQL statements, Boolean logic, macros)	-1	-0.31	
65	Create composite images using imagery bands	-3	-0.97	
72	Explain why ethics is important to the geospatial technology field	-4	-1.27	*
2	Identify spatial patterns; apply knowledge of how people and places are linked (spatial thinking and Tobler's First Law of Geography)	-4	-1.7	*

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

Factor 3 had five Q-sorts and explained 4% of the variance in the study. The respondents are practitioners and educators with 18.0 (SD=4.2) years of experience with 12.2 (SD=5.3) years spent in geospatial science. The following number of participants received formal geospatial instruction at the Associate's (0), Bachelor's (1), Masters (2), or Doctorate (1) level, with 1 possessing no formal geospatial education.

Factor 3 was built from Q-sorts representing that spatial analysis is crucial to the geospatial field. Four of the five highest-scoring distinguishing statements (Table 8), Statements 22(5), significant at $p < 0.01$, 67(2), 30(2), and 26 (1), relating to the performance of various analyses. An additional competency, Statement 24 (3), was ranked higher in Factor 3 than any other factor. The competencies judged to have less relevance to the geospatial field were split between data acquisition and development. Statement 59 (-3) was the only negatively perceived distinguishing statement significant at $p < 0.01$ and related to data acquisition or data development. While not distinguishing statements, Statements 53 (0), 28 (-2), 36 (-3), 59 (-3), 50 (-4), and 35 (-5) related to data development and ranked lower in Factor 3 than in any other factor array. There were no distinguishing statements aligned with data acquisition, but Statements 51 (-1), 58 (-1), 55 (-1), 57 (-2), and 56 (-5) scored lower in Factor 3 than in any other array. Regardless of where data management activities fell within the spectrum, respondents held a dim view of this competency area, with 11 statements located lower in this array than in any other factor.

Factor 4: Using Programming to Support Analysis

Factor 4 had six Q-sorts and explained 3% of the variance in the study. The respondents are practitioners and educators with a wide range of years in the practice, averaging 15.5 (SD=12.9) years of experience with 14.2 (SD=12.9) years spent in geospatial science. Three respondents received formal geospatial instruction at the Bachelor's level, and the three remaining participants at the Master's level.

The factor's title reflects the appearance of numerous competencies connected to computer programming to facilitate spatial analysis. There are only two programming competencies within the matrix. Both were the highest-rated distinguishing statements (Table 9) within this factor, significant at $p < 0.01$, and ranked higher in Factor 4 than in any other array. The two highest-scoring distinguishing statements, Statements 45 (5) and 44 (5), are central to Factor 4 and supported by aligned competencies related to analysis. The connection between programming and spatial analysis is provided by Statement 21 (3), which is also a distinguishing statement significant at $p < 0.01$. Additionally, Statement 24 (3) is ranked higher in Factor 4 than any other array.

There was an absence of a dominant theme connected to irrelevant competency areas within Factor 4, but two competing collections of statements, geodesy, and data tasks, stood out. Respondents included within the factor appeared to devalue the maintenance of a dataset's spatial reference, as Statement 7 (-1) indicated, the lowest-ranked distinguishing statement in Factor 4. Furthermore, Statements 5 (-1), 7 (- 1), 48 (-3), and 8 (-6) were ranked lower in Factor 4 than in any other factor. The respondents loading upon Factor 4 exhibited a general aversion to activities relating to data formats, as represented by Statements 33 (-2) and 32 (-3), data conversion, Statements 23 (-3)

Table 8. Distinguishing Statements for Factor 3

No.	Statement	Factor 3 Q-SV	Factor 3 Z-score	S
46	Perform data format conversions (vector to raster, raster to vector, raster to TIN)	6	2.03	
22	Perform buffer, slope, hillshade analysis	5	1.63	*
69	Conduct image classification (e.g., supervised or unsupervised)	4	1.38	*
67	Perform change detection using imagery from different dates	2	0.93	
30	Perform network analysis (i.e., roads, streams, etc.)	2	0.67	
61	Collect field data using GNSS (location and attribute)	2	0.67	
34	Design database structure (e.g. schema)	1	0.2	
26	Perform viewshed analysis	1	0.14	
59	Create/update metadata	-3	-1.21	*
42	Demonstrate ability to carry out mathematical operations including addition, subtraction, multiplication, and division	-6	-2.35	*
46	Perform data format conversions (vector to raster, raster to vector, raster to TIN)	6	2.03	
22	Perform buffer, slope, hillshade analysis	5	1.63	*
69	Conduct image classification (e.g., supervised or unsupervised)	4	1.38	*
67	Perform change detection using imagery from different dates	2	0.93	

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

and 46 (-4), and data collection, as indicated by Statements 61 (-2), 57 (-2) and 62 (-4). Also, all the data-specific statements were ranked lower in Factor 4 than in any other factor.

Factor 5: Where in The World Is the Data

Factor 5 had three Q-sorts and explained 3% of the variance in the study. The respondents are practitioners and educators having various years in the practice, averaging 30.3 (SD=22.4) years of experience with 27.3 (SD=18.7) years spent in geospatial science. The following number of participants received formal geospatial instruction at the Bachelor's (1) or Doctorate (1) level, with one possessing no formal geospatial education.

Factor 5 was built from Q-sorts signifying that respondents believe that the accurate representation of spatial data location is essential in geospatial work. Distinguishing Statements 8 (6) and 48 (4), significant at the p <0.01, represent a focus on location determination (Table 10). Statement 58 (3) was an additional statement ranked higher in the array than any other factor. Closely related to these competencies were Statements 63 (5), significant at the p <0.01 level, 6 (3), and 28 (1) focused on getting data into the correct location and representative of real-world features.

The participant Q-sorts used to construct Factor 5 were split in their opinion between cartographic and analytical work as the least relevant competency areas. Distinguishing Statement 49 (-2) was the lowest-ranked distinguishing statement in Factor 5. Statement 49 (-2) was joined by Statements 24 (-2), 25 (-3), 22 (-3), and 26 (-5), all of which ranked lower on Factor 5 than in any other array. Competencies relating to the application of cartographic principles were also seen as lacking as Statements 12 (-1), 16 (-1), 13 (-4), and 11 (-4) are ranked lower in Factor 5 than in any other factor array.

Factor 6: Data Refinements Are a Critical Step in Spatial Analysis

Factor 6 had four Q-sorts and explained 3% of the variance in the study. The respondents are practitioners and educators having substantial years in the practice, averaging 14.8 (SD=7.5) years of experience with 12.8 (SD=6.7) years spent in geospatial science. Two of the respondents received formal geospatial instruction at the Bachelor's level, with another doing so at the Master's level and one possessing no formal

Table 9. Distinguishing Statements for Factor 4

No.	Statement	Factor 4 Q-SV	Factor 4 Z-score	*S*
45	Apply basic programming principles (SQL statements, Boolean logic, macros)	5	2.08	*
44	Create programming code (i.e., Python or other languages)	5	1.76	*
38	Input data into a relational database	4	1.58	*
21	Compare basic analysis methods (point pattern analysis, cluster analysis, multi-criteria evaluation, and spatial process models)	3	1.35	*
43	Perform descriptive statistical analysis (mean, median, mode, etc.)	0	-0.03	*
7	Apply appropriate map projections based on the type of analysis	-1	-0.52	

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

Table 10. Distinguishing Statements for Factor 5

No.	Statement	Factor 5 Q-SV	Factor 5 Z-score	*S*
8	Describe the characteristics and appropriate uses of datums	6	2.3	*
63	Conduct ground-truthing	5	2.01	*
48	Describe different methods of indicating locations (e.g., decimal degrees, UTM, military grid)	4	1.15	*
71	Explain imagery resolutions (Spatial, Temporal, Radiometric, and Spectral)	3	1.02	*
2	Identify spatial patterns; apply knowledge of how people and places are linked (spatial thinking and Tobler's First Law of Geography)	0	-0.08	
49	Perform proximity analysis	-2	-0.65	

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

geospatial education.

Factor 6 was assembled from Q-sorts, demonstrating the perception that the development, enhancement, and preservation of data are essential competencies. There were no distinguishing statements (Table 11) supporting data improvement activities, but six of the eight statements, Statements 41 (5), 40 (5), 60 (4), and 51 (4), 33 (4), 52 (3), and 28 (1) ranked higher in factor 6 than in any other factor array. The views regarding less relevant competencies were not nearly so united. Participants were split between seeing competencies focused on solving problems, Statements 3 (0) and 19 (-1), data operations Distinguishing Statements 1 (-4) and 38 (-4), and digital imagery, Distinguishing Statement 67 (-5) and Statement 65 (-5), as lacking consequence in the field. All the previously mentioned statements were ranked lower in Factor 6 than any other factor array.

Factor 7: We Have a Love/Hate Relationship with Data

Factor 7 had three Q-sorts and explained 3% of the variance in the study. The respondents are practitioners and educators having substantial years in the practice, averaging 16.7 (SD=14.0) years of experience with 10.0 (SD=13.1) years spent in geospatial science. One respondent received formal geospatial instruction at the Associate's level, with the remaining two possessing no formal geospatial education.

The factor's title refers to the bifurcated views of the Q-sorts loading onto the factor as they concern data competencies. Statements 51 (4), 57 (4), 23 (3), and 52 (3), associated with the creation or acquisition of data, were ranked higher in the array than any other factor. Conversely, Statements 20 (-1), 34 (-2), 54 (-2), and Distinguishing Statement 37 (-3) leaned toward defining the data needs for a project or scenario and ranked higher in the array than any other factor (Table 12). The paradoxes continue with Statements 19 (6) and 3 (0), Statements 68 (1) and 71 (-6), Statements 13 (5) and 9 (-4), Statements 49 (4) and 21 (-5). The only consistency with Factor 7 appeared to be the inconsistency of the shared opinions, as the statements were ranked higher or lower, depending upon the competency, in the Factor 7 array than in any other array.

Analysis of Research Question Two

The hypothesis for the second research question is that the participants will not reflect differences in opinion due to the respondents' experience in the geospatial profession, area of employment, industry-sector, or educational level. The re-

Table 11. Distinguishing Statements for Factor 6

No.	Statement	Factor 6 Q-SV	Factor 6 Z-score	*S*
46	Perform data format conversions (vector to raster, raster to vector, raster to TIN)	3	1.21	
53	Georeference data	2	1.01	
42	Demonstrate ability to carry out mathematical operations including addition, subtraction, multiplication, and division	2	0.89	*
37	Define data requirements to help solve a problem	-1	-0.31	
1	Explain what topology means in relation to geospatial data (i.e., adjacency, connectivity, containment, proximity)	-4	-1.29	
38	Input data into a relational database	-4	-1.33	
67	Perform change detection using imagery from different dates	-5	-1.4	

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

Table 12. Distinguishing Statements for Factor 7

No.	Statement	Factor 6 Q-SV	Factor 6 Z-score	*S*
13	Create charts, graphs, tables	5	1.88	*
44	Create programming code (i.e., Python or other languages)	2	0.61	
68	Collect spectral signatures for imagery classification	1	0.21	*
37	Define data requirements to help solve a problem	-3	-1.11	
47	Explain why map scale affects the resolution of data creation or acquisition for a given application	-4	-1.46	
21	Compare basic analysis methods (point pattern analysis, cluster analysis, multi-criteria evaluation, and spatial process models)	-5	-1.87	*

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

searchers conducted tests of Independence to determine if differences in perception were related to the participants' level of geospatial experience. The results were not significant, with an X^2 of 24.264, 24 degrees of freedom, a p-value of > .4466, and a Fisher's Exact two-sided probability of $p \leq .5384$ (Table 13).

The researchers conducted tests of Independence to determine if differences in perceptions were related to the participants' area of employment. The results were not significant, with an X^2 of 20.709, 18 degrees of freedom, a p-value of > .2943, and a. Fisher's Exact two-sided probability of $p \leq .1619$ (Table 14).

The researchers conducted tests of Independence to determine if differences in perceptions were related to the participants' industry sector. The results were significant, with an X^2 of 34.565, 18 degrees of freedom, a p-value of > .0107 (significance level of 0.05). Fisher's Exact Test yielded results that were also significant with a two-sided probability of $p \leq .0011$ and indicates that the association between the variables is statistically significant (Table 15). These results reject the null hypothesis of the absence of a relationship between the industry sector and a shared perspective (factor).

The researchers conducted tests of Independence to determine if differences in perceptions were related to the participants' level of geospatial education. The results were not significant, with an X^2 of 26.48, 24 degrees of freedom, a p-value of > .01, and a Fisher's Exact two-sided probability of $p \leq .4125$ (Table 16).

LIMITATIONS

The study did not require respondents to hold any credential indicating geospatial science proficiency. A P-set built to reflect a professional geospatial workforce more accurately may prove more valuable. The researchers completed factor extraction with a seven-factor solution. The development of seven factors is not a limitation, but two of the factors included only three Q-sorts, limiting the degree to which a shared perspective exists. The researchers used the 72 competencies gleaned from a more extensive 190 competency assessment tool constructed from numerous external sources. As such, the statements vary

Table 13: Test of Independence – Geospatial Experience

Experience	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Total
0 – 5 Years	8	1	1	2	0	0	2	14
6 – 10 Years	4	1	1	1	1	1	0	9
11 – 16 Years	3	1	2	0	0	2	0	8
17 – 22 Years	3	2	1	2	0	1	0	9
23+ Years	1	2	0	1	2	0	1	7
Total	19	7	5	6	3	4	3	47
Statistic	Value	df	Probability		Significant			
Chi-Square	24.264	24	$p >$ *.4466		No			
Fisher's Exact			$p \leq .5384$		No			

* Chi-Square (X^2) is not a reliable test with cell counts of less than 5.

Table 14: Test of Independence – Area of Employment

Employment	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Total
Private Industry	1	3	1	2	2	1	0	10
Public Sector	4	3	2	3	1	2	1	16
Secondary Education	10	1	1	0	0	0	1	13
Post-Secondary Education	4	0	1	1	0	1	1	8
Total	19	7	5	6	3	4	3	47
Statistic	Value	df	Probability		Significant			
Chi-Square	20.709	18	$p > .2943$*		No			
Fisher's Exact			$p \leq .1619$		No			

* Chi-Square (X^2) is not a reliable test with cell counts of less than 5.

Table 15: Test of Independence – Industry Sector

Sector	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Total
Analysis & Modeling	3	2	3	4	1	4	0	17
Positioning & Data Acquisition	1	2	0	0	1	0	0	4
Software & Application Development	1	2	0	2	0	0	1	6
Education	14	1	2	0	1	0	2	20
Total	19	7	5	6	3	4	3	47
Statistic	Value	df	Probability		*Significant*			
Chi-Square	34.565	18	*p* > .0107*		Yes			
Fisher's Exact			*p ≤ .0011*		Yes			

* Chi-Square (X^2) is not a reliable test with cell counts of less than 5.

Table 16: Test of Independence – Geospatial Education

Education	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Total
Associate	1	1	0	0	0	0	1	3
Bachelor	4	3	1	3	1	2	0	14
Master	8	2	2	3	0	1	0	16
Doctoral	0	0	1	0	1	0	0	2
No Formal Education	6	1	1	0	1	1	2	12
Total	19	7	5	6	3	4	3	47
Statistic	Value	df	Probability		Significant			
Chi-Square	26.48	24	*p* > *.3293		No			
Fisher's Exact			*p* ≤ .4125		No			

* Chi-Square (X^2) is not a reliable test with cell counts of less than 5.

in the level of granularity and focus. This variation may have influenced the behavior of the respondents.

FINDINGS

The geospatial profession is built upon a defined set of workforce competencies. Previous research has sought to determine the skills needed by geospatial professionals. However, the absence of a study evaluating the perceived relevance of geospatial competencies by practitioners and educators represented a gap in practice. This research study uses Q Methodology to assess respondents' perceptions towards the core competencies contained within the GeoTech Center Geospatial Competency Matrix. This article describes the results of a research study consistent with Q Methodology and attempts to reveal varied perspectives rather than generalize a population (Watts & Stenner, 2012).

Due to various applications and users, there are numerous challenges to assuring competence within the geospatial field (Albrecht, 1998). 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 an excellent path to establishing competency (Mathews & Wikle, 2017). The study results address the following research questions:

1. How do practitioners and educators view the geospatial competency statements within the GeoTech Center Geospatial Competency Matrix, and why?
2. Do perceptions of the geospatial competencies differ based on the respondents' industry- sector, experience in the geospatial profession, area of employment, or educational level where they received most of their geospatial instruction?

Finding 1. This study revealed seven viewpoints, representing the different perspectives of practitioners and educators participating in the research project. The seven documented factors characterize a substantial variation in the perceptions of technical geospatial competencies. The emergent factors were Factor 1: We are Cartographers (map evaluators); Factor 2: Vector Data are our Paramount Focus; Factor 3: Analysis is the Key to Addressing Geospatial Problems; Factor 4: Using Programming to Support Analysis; Factor 5: Where in the

World is the Data; Factor 6: Data Refinements are a Critical Step in Spatial Analysis, and Factor 7: We have a Love/Hate Relationship with Data.

Finding 2. The Chi-Square and Fisher's Exact Tests of Independence determined a relationship between the participants' industry sector and the factors. The analysis revealed an X^2 of 34.565, 18 degrees of freedom, and a p-value of > .0107 (significance level of 0.05). A Fisher's Exact Test yielded results having a two-sided probability of p ≤ .0011 and indicating a statistically significant association reject the null hypothesis of the absence of a relationship between the industry sector and a shared perspective (factor).

Finding 3. No competency cluster dominated the most relevant skills. However, positively viewed competency areas included using geospatial science to solve problems (Statements 3, 19, and 37, with a mean score of 0.83), spatial analysis (Statements 27, 49, and 24, with a mean score of 0.81), and database operations (Statements 39, 51, and 34), with a mean score of 0.65. The participants negatively viewed competency areas related to digital imagery and remote sensing, with seven statements falling in the bottom quarter of the array and three of the bottom four ranked statements. These competency statements, Statements 70, 69, 65, 64, 71, 66, and 68, were deemed less relevant to the geospatial field, with a mean value of -0.86.

CONCLUSION

This study represented the results of an investigation to address how practitioners and educators view the geospatial competency statements located within the GeoTech Center Geospatial Competency Matrix. The researchers collected data from 70 respondents, with 47 loading onto seven factors. The study found no consensus statements but revealed distinctly negative opinions connected with remote sensing competencies. Also, the research revealed a statistically significant relationship between the participants' industry sector and the factors. This research study validates using a Q Methodological study to examine the statements within a competency model. Moreover, it demonstrated a process to evaluate a conceptual model of competencies. Better data analysis sources, such as those found in this study, could enable educational institutions to engage industry partners more effectively.

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Dr. Rodney Jackson an adjunct geography faculty at East Carolina University, a Certified Geographic Information Systems Professional (GISP), and a Senior Researcher with the National Geospatial Center of Excellence.

Dr. Tom Mueller has been a geography professor at PennWest – California University since 1999. His interests include GIS, Crime Mapping, and geography education. His goal is to apply spatial theory to the real world, mainly using GIS.

APPENDIX A

POST-SORT QUESTIONS

Select a statement that you placed in the "6" column and share the reason for your decision. Please include what aspect of your education, experience, or expertise brought you to this determination (i.e., what made you make the decision?)

Select a statement that you placed in the "-6" column and share the reason for your decision. Please include what aspect of your education, experience, or expertise brought you to this determination (i.e., what made you make the decision?)

Which statement did you have the most difficulty placing and why? Please include as much detail as you feel is appropriate.

What factors helped to determine your sorting decisions? Please include as much detail as you feel is appropriate.

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).