# INNOVATION DIFFUSION IN GEOGRAPHIC INFORMATION SCIENCE RESEARCH

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INNOVATION DIFFUSION IN GEOGRAPHIC

INFORMATION SCIENCE RESEARCH

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## TABLE OF CONTENTS

## LIST OF TABLES

**Table** **Page**

## LIST OF FIGURES

## ABSTRACT

INNOVATION DIFFUSION IN GEOGRAPHIC INFORMATION RESEARCH

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Geographic Information Science (GIS) researchers analyze digital data to identify spatial patterns quantitatively. Following a similar approach, this thesis research reveals the diffusion dynamics of GIS research through analyzing the field's publications. A total of 985 GIS journal articles published between 1997 and 2007 in six different academic journals were examined. By assuming that each article was conducted at the institution listed as the primary author's affiliation, each journal article is evaluated using latent semantic analysis to reveal a set of correlations between the research themes of the articles year-by-year and location-by-location. With knowledge of the location and time of each publication, we show the spatial and thematic evolution of research activities in GIS.

# CHAPTER 1

# INTRODUCTION

Geographic Information Science (GIS) has a brief yet fruitful history. Geographic information science emerged in the past four decades as a growing field that affects communication, travel, transport, location services, mobile services, and other aspects of the economic, commercial, and academic activities. In this paper, we consider the thematic changes in GIS research over eleven years from an innovation diffusion point of view. Innovation diffusion research studies how ideas propagate through a society.

This thesis research uses latent semantic analysis (LSA) to measure the research changes in GIS from 1997 to 2007. LSA begins with the full text of research articles and quantifies the similarity of these articles. The result is a similarity index, a value from -1 to 1, of the similarity for each pair of articles. By grouping the articles according to author, author's affiliation location, year, or journal, LSA will quantify a similarity index among authors, locations, years, or journals. We also group articles by subject keywords in GIS to quantify the changes in research subjects over this eleven year period.

## UCGIS Research Priorities

The University Consortium of Geographic Information Science (UCGIS) formed in 1988 and has grown to include 67 academic institutional members, four representative professional organizations and ten government/non-profit/industry organizations (Eames, 2005). The organization has three purposes:

> "To serve as an effective, unified voice for the geographic information science research community;
>
> To foster multidisciplinary research and education;
>
> To promote the informed and responsible use of geographic information science and geographic analysis for the benefit of society."
>
> (UCGIS, 2003, page 2)

In 1996, UCGIS published their first set of white papers on research priorities for geographic information science (UCGIS, 1996). Since then, updates were published in 1998, 1999, 2000, 2002, and 2006. The consortium is a collaborative group of academic institutions, governmental organizations, and commercial GIS developers. In addition to recommending policy and legislation and setting goals for GIS education, the UCGIS advocates the advances in GIS research that are most important to its members. Listed in Table 1 are the research priorities (UCGIS, 1996; UCGIS, 2000).

**Table 1**. UCGIS Research Priorities (first year of publication).

| |
|---|
| Spatial data acquisition and integration. (1996) |
| Distributed computing. (1996) |
| Extensions to geographic presentations. (1996) |
| Cognition of geographic information. (1996) |
| Interoperability of geographic information. (1996) |
| Scale. (1996) |
| Spatial analysis in a GIS environment. (1996) |
| The future of spatial information infrastructure. (1996) |
| Uncertainty in geographic information and GIS-based analyses. (1996) |
| GIS and society. (1996) |
| Geospatial data mining and knowledge Discovery. (2000) |
| Ontological foundations for GIS. (2000) |
| Geographic visualization. (2000) |
| Remotely acquired data and information in GIScience. (2000) |

By updating their research priorities biennially, the UCGIS is providing the guideposts of future GIS research. Twelve years after their first publication, we can look back at the trends in the academic publications to see how the priorities define the subfields, advance the research, and pave the way for new advances in GIS.

# CHAPTER 2

# LITERATURE REVIEW

## History of Innovation Diffusion Research

Innovation diffusion is a multi-disciplinary research area that traces its roots to early twentieth century scientists in sociology and anthropology. Gabriel Tarde, a French lawyer and judge writing *The Laws of Imitation* in 1903, identified the adoption or rejection of an innovation as a crucial variable in analysis. At the same time, the sociologist Georg Simmel (active years: 1890-1918) in Berlin developed a key idea for diffusion research: that groups of individuals could act as a set of coordinates of affiliations. By using individuals as the key structural element, Simmel anticipated aspects of later social network research sixty years before it became formalized in literature (Rogers, 2003).

The paper, "The Diffusion of Hybrid Seed Corn in Two Iowa Communities" (Ryan and Gross, 1943), was the first to use sociometric data to determine the rate and causes of innovation diffusion (Rogers, 2003). Dr. Bryce Ryan and Neal C. Gross interviewed 345 farmers in two communities using surveys to find when and why they had chosen to use hybrid corn. During the interviews, they also noted from whom the farmer received the hybrid corn. By statistically analyzing when and from whom each farmer began adopting the new corn seed, Ryan and Gross showed the difference between when a farmer first heard about hybrid corn and when they adopted it (Ryan and Gross, 1943).

Ryan and Gross introduced several key principles of innovation diffusion. The *channels* of new information is often more important than the idea itself. Most farmers already knew about hybrid corn from salesmen, yet waited until several key early adopters tried the corn before adopting themselves. “The spread of knowledge and the spread of 'conviction' are, analytically at least, two distinct processes” (Ryan and Gross, 1943, page 21). They found that the rate of adoption over time was similar to the normal curve, where a slow acceptance by a few early adopters (also labeled 'opinion leaders') would be followed by the early majority of farmers, the late majority, and then the laggards who arrive last. This graph later became known as the *S-Shaped Adoption Curve* (Hägerstrand, 1953; Rogers, 2003), a theory in Innovation Diffusion that predicts the rate of acceptance based on character types of the individual. Quantitatively, they were able to show that diffusion itself is a social process that occurs over time. Using this methodology, Ryan and Gross developed the framework that led to innovation diffusion as a field of research.

Rural sociology was quick to adopt the innovation diffusion paradigm presented by Ryan and Gross, partly because technological innovation was seen as a key to successful development (Rogers, 2003). Since then, diffusion research has been included in the fields of economics, sociology, marketing, communications, management science, and not least of which, geography.

## Innovation Diffusion as a Spatial Process

Torsten Hägerstrand, working at the University of Lund in Sweden, broke new ground with his 1953 thesis, *Innovations förloppet ur korologisk synpunkt*, translated as *Innovation diffusion as a spatial process* by Allan Pred in 1967. Hägerstand was a geographer and therefore disposed to view diffusion as a spatial and temporal process. For his thesis, he studied the diffusion of the telephone, the automobile, and tuberculosis inoculations in the province of Östergotland in the 1920's, 1930's, and 1940's. Gathering data on soil conditions, population density, in- and out-migrations to the region, farming conditions, the road network, and money transfers, Hägerstrand was able to model in detail the effects that these indicators played on influencing innovation adoption (Hägerstrand, 1953).

Hägerstrand produced mathematical models using a Monte Carlo simulation to show which factors influenced diffusion using the laws of probability. A person's decision if and when to adopt an innovation is called the *innovation decision process* (Rogers, 2003). Hägerstrand's model includes *resistance,* or the factors that impede adoption. Modeling in both time and space, Hägerstrand produced a time-series of maps that expected the diffusion field based on the spread from central locations, similar to Walter Christaller's *Central Place Theory.* Central Place Theory in innovation diffusion posits that innovations are first adopted in core places (such as large cities, and then move outwards to rural areas (Hägerstrand, 1952; Rogers, 2003). In his theory, Hägerstrand could show geographically how the innovation would diffuse in the region depending on the variables present in the population, the location, and the innovation.

Further papers expanded on Hagerstrand's model to arrive at a formulaic description of the process of innovation diffusion at a group or regional level (Strang and Tuma, 1993). The unit of analysis in diffusion studies had, from the onset, been at the group or regional level. Everett M. Rogers suggests in *Diffusion of Innovations* that the unit of analysis should instead be the individual (Rogers, 2003). An individual's decision may depend on their social connections or other, external types of communication. As the social peers adopt a change, the individual may reach a *threshold*, or point where they will themselves accept the innovation (Valente, 1996). The threshold model of innovation diffusion analysis is the precursor to the social network analysis that has followed.

## Social Network Theory

A social network is a structure made of vertices of actors and interdependent linkages between them representing acquaintance. Actors are most often individuals, while the linkages can be various: exchanges of financial, informational, or technological means, markers of the spread of disease, and organizational structures, which can be both formal and informal groupings. Social networks are of interest because they represent the pattern of human interaction present in a social structure (Newman, 2000). The structure itself is of particular interest because it has implications for the spread of disease or information.

Social network experiments began in the 1960's (Newman, 2000). Stanley Milgram examined small world social networks where typical distances are comparable with those on a random graph (Watts and Strogatz, 1998). In his experiment, Milgram sent an misaddressed letter meant for a stockbroker in Boston to a person in Nebraska who was chosen at random (Travers and Milgram, 1969). The average number of steps for the letter to arrive from the first person to final recipient was six, leading to the phrase “six degrees of separation,” or the network distance between any two ends of the human community.

## Co-Citation and Co-authorship Networks

Citations were first used in the late 19th century by legal scholars (Kessler, 1963). In the early 1960's, Eugene Garfield and the Institute for Scientific Information began publishing the Scientific Citation Index (or, SCI), an index of paper-to-paper citations. A similar topic, bibliographic coupling, where one measures the amount that different papers cite the same sources, originated in 1963 (Kessler, 1963). The initial work drew few conclusions, but did present a methodology that would later be expanded (Small, 1973; Small, 2003). White and Griffith created the first co-citation map (White and Griffith, 1981).

The emphasis of co-citation analysis is to determine the subject similarity and association of key ideas in a field, also known as the specialty structure of science (Small, 1973.) A further relationship is established in the social structure of science, which can be determined by the co-authorship linkages in a science authorship network. An authorship network is a social network where vertices are authors and linkages are co-authorship status on one or more journal articles.

Co-authorship networks can be interpreted as structural representations of the collaborative nature of scientific research. The network structure of scientific collaborations has become an interest of great study, in part, because the data are easily available and complete. Several online databases, including MEDLINE (for biological research), NCSTRL (for computer science), and the Los Alamos e-Print Archive (for Physics), present large, easily accessible data sources for network researchers (Newman, 2000). Most importantly, the nature of the edges (connections) are clearly defined (Newman, 2000; Newman, 2001). This ensures a reliability in the structure and validates the connection.

The *clustering coefficient* is a measure of the local connectedness within a small part of a network. It is defined as “the average fraction of pairs that of a person's collaborators who have also collaborated with each other” (Strogatz and Watts, 1998, p. 441). The clustering coefficient, as a measure of local connectedness in a large network, is only a measure of local activity and does not define the boundaries of a locality. Discovering community groups in networks has become a key research area in recent years (Chen, 2005; Newman, 2006). The detection and definition of community structures, which are tightly connected subgroups with loose connections to the main network, is key to defining subgroups within the larger network of scientific collaborations.

Newman (2006) expands on the community finding problem by choosing communities based on probabilities. His method, *modularity,* is defined as the number of edges in a group minus the expected number in an equivalent random group (Newman, 2006). Using the eigenvalue and eigenvector for a modularity matrix generated from a network, each subnetwork can be iteratively checked for a positive modularity value. A positive value indicates that the subnetwork contribute to the total modularity; a zero or negative value indicates that the search can be stopped, as the subnetwork is not divisible further (Newman, 2006).

Newman has produced several studies based on co-authorship network analysis. One, entitled “Who is the best connected scientist?” (Newman, 2000), looks at the popular Erdös number phenomena. Paul Erdös was a Hungarian mathematician and frequent collaborator who produced over a thousand publications within his lifetime. Authors may assign an Erdös Number based on the shortest network distance away from Erdös in a co-authorship network. Therefore, persons who have coauthored a paper with Erdös have an Erdös number of one. Authors who have collaborated with an author who has an Erdös number of one would have a number of two, and so on.

## Knowledge Domain Visualization and Latent Semantic Analysis

Research in the field of information visualization has also approached the issues of innovation and knowledge diffusion, as well as citation analysis. Knowledge domain visualization (often shortened as “KDViz”) is the study of the dynamic, self-organized, and emergent complex intellectual system that underlies an emergent science (Chen, 2006). There are three key procedures in producing a visualization: extracting the salient structures from a set of data, detecting abrupt changes and emerging trends, and creating a visualization to coherently represent a set of complex information.

Latent semantic analysis (LSA, also known as LSI, latent semantic indexing) computes the singular value decomposition matrices of a matrix showing the number of occurrences of a keyword or phrase in columns by the sources (books, journal articles, etc) in the rows. A binary function (0 or 1) can be substituted for the number of occurrences if only the appearance of a keyword or phrase in a work is considered. Singular value decomposition (or SVD) is a technique in matrix computations that decomposes a matrix into three orthogonal matrices, one of which will be a truncated singular value matrix containing the factors that explain the variance across the rows (Golub and Van Loan, 1996).

Related pairings of articles or terms can be determined even when exact words or phrases do not match (Deerwester, Dumais, Furnas, Landauer, and Harshman, 1990). By representing the SVD results geographically in an n-dimensional space, the dot-product of two vectors represents their similarity. A network can then be built based on the measurement of similarities, which can then be used to visually represent the connections among journal articles.

Chen (1999; 2006) has provided examples of how co-citation analysis and document similarity can be used to create detail-rich models of knowledge domains. His work examines the Invisible Colleges, or scientists in a specialty group that may collaborate outside of normal geographic bounds. He digested the SCI (Scientific Citation Index) to find journal articles related to string theory in particle physics. Finding over 150,000 articles, he selected only those that had been cited 35 or more times. The resulting documents were weighted based on time, since more recent documents may not had as long as a time to become cited as older documents. A Pathfinder analysis was performed on the data to remove unimportant links. A network diagram was color-coded to pinpoint turning points in scientific research and visualized the knowledge relationships in the field of particle physics (Chen, 1999).

# CHAPTER 3

# METHODOLOGY

## Summary of Major Steps

- Collected journal articles from GIS journal websites, including full text, author names and author affiliations.
- Parsed data using small programs to collect names, dates (by year), place names, country, and affiliations from files and place them into a database.
- Verified names, affiliations for completeness and accuracy against the files and in the database.
- Ran initial latent semantic analysis to find secondary keywords highly correlated to the primary keywords derived from the UCGIS research themes.
- Created thirty-five textmatrices from articles, including matrices by author, location, country, article, year, journal, and place, and using full words, stemmed words, UCGIS keywords, weighted UCGIS keywords, and binary (1 or 0) word counts.
- Ran latent semantic analysis on each of the thirty-five textmatrices to generate correlated output matrices.
- Geocoded affiliation locations and calculate Euclidian distances between each

location point to every other location.

- Ran correlation analysis between the distances and the semantic relationship values for each paired publications.
- Arranged articles in time-order to find important "topic burst" points.
- Produced an aggregate map for each GIS research theme showing the ten highest correlated research sites.

## Data Collection, Processing, and Verification

The complete text of articles from the journals *Transactions in GIS*, *International Journal of Geographic Information Science*, *Cartography and Geographic Information Science*, *GeoInformatica*, and related GIS papers that appear in the *Annals of the Association of American Geographers* and the *Professional Geographer* constitute the sources of data. In total, there are 985 articles from the year 1997 to 2007. Also contained are the date of publication, the names of the authors and their affiliations at the time of the writing. Files were saved as PDF (portable document format) files and then converted to text.

Author affiliations, article titles, and date of publication were entered into a database using several small programs to check for completeness and accuracy. Checking accuracy begins by alphabetizing the list of author names and affiliations. Common discrepancies are capitalization choices in names, missing a middle initial, small differences in the naming of university departments, and the choice of complete names versus abbreviated named or nick-names. This can happen when one author appears under multiple names (“A. Smith”, “Alan Smith”, “Alan J. Smith”). Authors may have multiple affiliations in multiple locations. Affiliation to a given university does not guarantee that the author works only at one place. The common practice in research is to assign the first author status to the author that contributes the most substantial material to an article. While this is not always the case, there is no method known to divide article authorship appropriately. In all cases, the first address of the first author given in a paper was considered their affiliation location.

Articles require unique identifiers for analytical work and reference in this paper. We use a standard format accepted in bibliographic research. Articles are identified as "XY2000" or "XY2000_JOURNAL", where "X" is the primary author's first name initial, "Y" is the primary author's last name initial, "2000" is the year of publication, and "JOURNAL" is a shortened form of the journal name that published the article. The article "Error Propagation Modeling in Raster GIS: Adding and Ratioing Operations" by Giuseppe Ariba, Daniel Griffith, and Robert Haining and published in 1999 in *Cartography and Geographic Information Systems* would therefore be identified as "GA1999" or "GA1999_CAGIS."

## Geocoding

To derive geographic distance between author affiliation locations, the addresses of these institutions must be *geocoded*. Geocoding is the process of converting an address into geographical coordinates, usually done via a dictionary lookup of toponyms, or place names, to a set of coordinates. Tatsuhiko Miyagawa contributed a perl module[1] that uses Google Maps lookups to return geocoding data for a toponym. Addresses that do not return a set of coordinates are verified manually. To verify accuracy, all of the results were checked manually.

## Latent Semantic Analysis

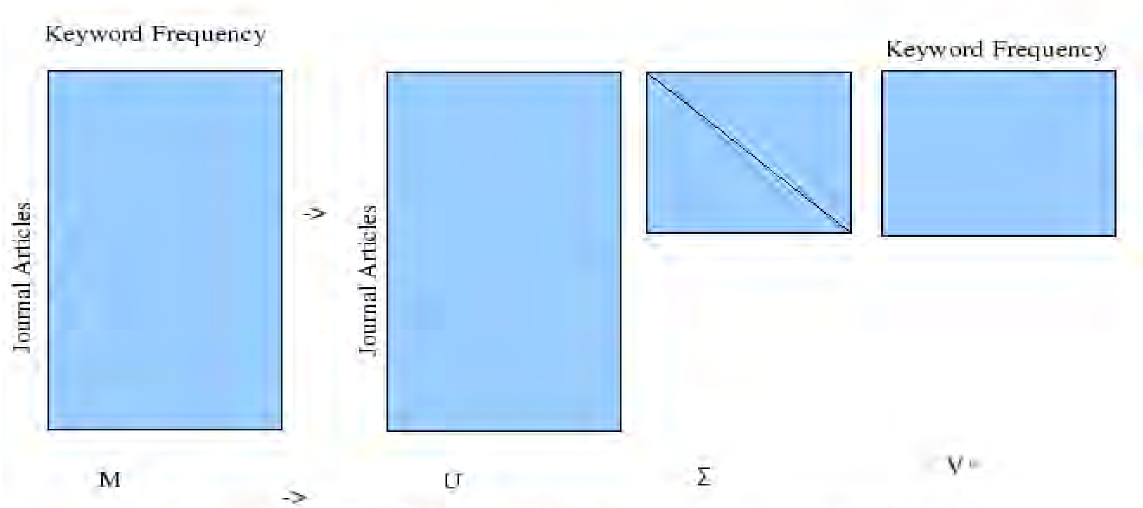
The programming language **R** has a latent semantic analysis module written by Fidolin Wild[2], which we used to run analysis[3]. For an example of LSA code, see *Appendix B: R code to Run Latent Semantic Analysis*. The input for latent semantic analysis is a matrix of article names as row headers and word counts as column headers (Deerwester et al, 1990). After creating a matrix of journal articles to words, a singular value decomposition (SVD) is performed to create three matrices: $X = T_0 . S_0 . D_0'$, where $T_0$ and $D_0$ have orthogonal columns, and $S_0$ is a diagonal matrix of $r$ x $r$, where $r$ is the rank of X. For a graphical example, see Figure 1.

The next step is to compute an approximate matrix $\chi$ that is generated from the largest $k$ values of $S_0$, $T_0$, and $D_0'$ into T, S, and D'. This matrix $\chi$ contains the independent associational structures in the matrix with the noise removed. The SVD can be interpreted geometrically in the same manner as principle component analysis. The result of the SVD is a $k$-dimensional vector representing the location of each keyword and

1 http://www.cpan.org/modules/by-module/Geo/Geo-Coder-Google-0.03.readme; accessed Saturday, February 9, 2008.
2 http://cran.r-project.org/src/contrib/Descriptions/lsa.html; accessed Tuesday, January 29, 2008.
3 http://www.r-project.org; accessed Tuesday, January 29, 2008.

journal article. In this space, the cosine or dot product between vectors corresponds to their estimated similarity.

This is a visual representation of a Singular Value Decomposition: $M = U\Sigma V^*$




An example might be where you have the matrix decomposition as follows:

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 2 \\ 0 & 0 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 4 & 0 & 0 & 0 \end{bmatrix} \rightarrow \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & -1 \\ 1 & 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} 4 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 \\ 0 & 0 & \sqrt{5} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \times \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ \sqrt{.2} & 0 & 0 & 0 & \sqrt{.8} \\ 0 & 0 & 0 & 1 & 0 \\ -\sqrt{.8} & 0 & 0 & 0 & \sqrt{.2} \end{bmatrix}$$

**Figure 1**. An Example Latent Semantic Analysis Calculation.

## Choosing UCGIS Thematic Keywords

To derive relationships among research themes, we must first choose keywords from the University Consortium of Geographic Information Science (UCGIS) research priorities. For each priority listed in Table 2, we identify one or two keywords to act as the primary search criteria. We do not need to find every exact, semantically-related term as each keyword is stemmed to a root word. Using stemming allows LSA to find plurals and alternate word forms of the keyword. The second step, below, ensures that alternate semantically-related terms are found and weighted.

**Table 2**. UCGIS Research Priorities (with primary keywords).

| |
|---|
| Spatial data acquisition and integration. (acquisition, integration) |
| Distributed computing. (distributed) |
| Extensions to geographic presentations. (representations) |
| Cognition of geographic information. (cognition) |
| Interoperability of geographic information. (interoperability) |
| Scale. (scale) |
| Spatial analysis in a GIS environment. (analysis) |
| The future of spatial information infrastructure. (infrastructure) |
| Uncertainty in geographic information and GIS-based analyses. (uncertainty) |
| GIS and society. (society) |
| Geospatial data mining and knowledge Discovery. (mining) |
| Ontological foundations for GIS. (ontological) |
| Geographic visualization. (visualization) |
| Remotely acquired data and information in GIScience. (remote) |

A second group of highly-correlated keywords related to the primary keywords are found and weighted by their Pearson correlation. After generating an initial latent semantic index of articles to stemmed words, we run Pearson product-moment correlations on each column-by-column, which contain the stemmed words of all articles. These provide a similarity index between each stemmed word. In Table 3, we have listed the word-stems that are most highly correlated to the word-stem "mobil-," used here to connote the word "mobile."

**Table 3.** Secondary keyword-stems Derived with a .5 or greater Pearson Correlation to Primary Keyword "mobil-."

| Word-stem | Correlation to "mobil-" |
|---|---|
| mobil- | 1 |
| phone | 0.95 |
| wireless | 0.84 |
| hyperlink | 0.81 |
| devic- | 0.72 |
| redirect | 0.71 |
| alert | 0.68 |
| hypertext | 0.64 |
| widespread | 0.62 |
| journey | 0.56 |
| schedul- | 0.54 |
| wayfind | 0.54 |
| envelop- | 0.53 |

In the Table 3 example, stemmed words are correlated to "mobil-", such as "phone", "wireless", or "hyperlink." Each word with a Pearson correlation of .5 or above is later used to generate weighted keywords textmatrices for input to the semantic analysis. For example, in Table 3, values of the keyword "mobile" will be equal to the number of occurrences of "mobil-" plus the number of occurrences of phone times 0.95 plus the number of occurrences of wireless times .84, and so on.

## Variations on Latent Semantic Analysis

The input matrix (journal articles vs. word counts; also known as the *semantic space*) is the standard term of analysis in LSA. Other matrix combinations are possible. In

Table 4, we enumerate five methods for grouping the columns and seven methods for grouping the rows.

**Table 4**. Variations of Input Matrices for semantic analysis.

| | *Words* | *Stemmed Words* | *Keywords* | *Weighted Keywords* | *Binary words* |
|---|---|---|---|---|---|
| *Journal Articles* | A1 | B1 | C1 | D1 | E1 |
| *Affiliations* | A2 | B2 | C2 | D2 | E2 |
| *Authors* | A3 | B3 | C3 | D3 | E3 |
| *Years* | A4 | B4 | C4 | D4 | E4 |
| *Journals* | A5 | B5 | C5 | D5 | E5 |
| *Countries* | A6 | B6 | C6 | D6 | E6 |
| *Places* | A7 | B7 | C7 | D7 | E7 |

- Journal Articles: Terms are extracted from each article (985 rows).
- Affiliations: Terms from articles written at the same location are combined into one row (398 rows).
- Authors: Terms from articles written by the same first author are combined into one row (823 rows).
- Years: Terms from articles written in the same year are combined into one row (11 rows).
- Journals: Terms from articles published in the same journal are combined into one row (6 rows).

- Countries: Term from articles with author locations in the same country are combined into one row (53 rows).
- Places: Terms from authors with the same university or professional affiliation are combined into one row (142 rows).
- Words: Word counts of words with five letters or more are used in the column-space (50371 columns).
- Stemmed words: Words with the same root, including plurals and verb forms, are combined into one column (34290 columns).
- Keywords: Words with a correlation greater than .5 to the UCGIS subject keywords are combined into one column per keywords (16 columns total). See "Correlation."
- Weighted Keywords: Words correlated to the UCGIS subject keywords are combined using the weighted, correlated value to the keyword. (16 columns total).
- Binary words: Instead of a word count, either a 1 or 0 (found or not found) is placed in the column for each word (34290 columns).

In total, thirty-five latent semantic analyses produced 105 output matrices - three per LSA. But which analytical method is best for producing results? By using five different weighting techniques, we can run analysis of variance on the output to see which technique explains the most variability. Each set of LSA results is compared using an F-test of variance.

## Presentation

Representations can capture the results visually. The first, and simplest, is a scatter plot of similarity of journal articles (the results from the latent semantic analysis) to the distances. This is a quick way to show the relationship (if any) between distance and correlation. To show examples of data flow, a map will be created showing articles with high (over .8) similarity indices.

A network diagram is also used to visualize the relationships among articles. Nodes in this network represent articles, locations, authors, journals, dates, or subjects, and links indicate the inverse similarity index. More similar articles have smaller network distances. A network diagram illustrates with simple clarity the density, number, and connectivity of highly-similar articles.

## CHAPTER 4

## RESULTS

Data Description

**Table 5**. Summary count of data types.

| | |
|---|---|
| Total articles | 985 |
| Total distinct first authors | 823 |
| Total locations | 398 |
| Total journals | 6 |

**Table 6.** Number of articles published in each journal.

| | |
|---|---|
| International Journal of Geographical Information Science | 325 |
| Transactions in GIS | 233 |
| Cartography and Geographic information Science | 215 |
| GeoInformatica | 137 |
| Annals of the Association of American Geographers | 40 |
| Professional Geographer | 35 |

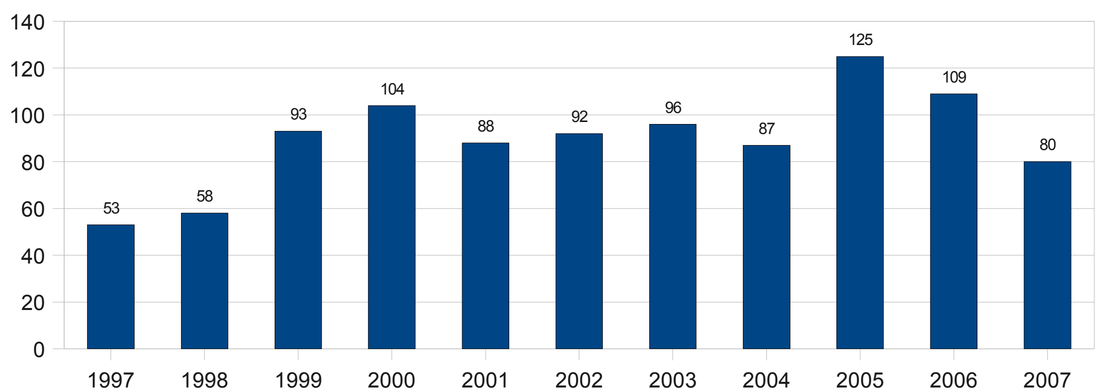



**Figure 2.** Articles Published as Year.

Latent Semantic Analysis: Correlating Similarity to Distance

GIS research is geographically diverse. Important research locations include North America, Asia, Europe, and Australia. Does distance correlate with article similarity? An initial scatterplot (Figure 3) of article similarity versus Euclidean distance appears to show no linear relationship between distance and similarity. The relationship is not a linear fit, as the $R^2$, or "goodness of fit", is .06 and does not meet the criteria for any linear explanation.

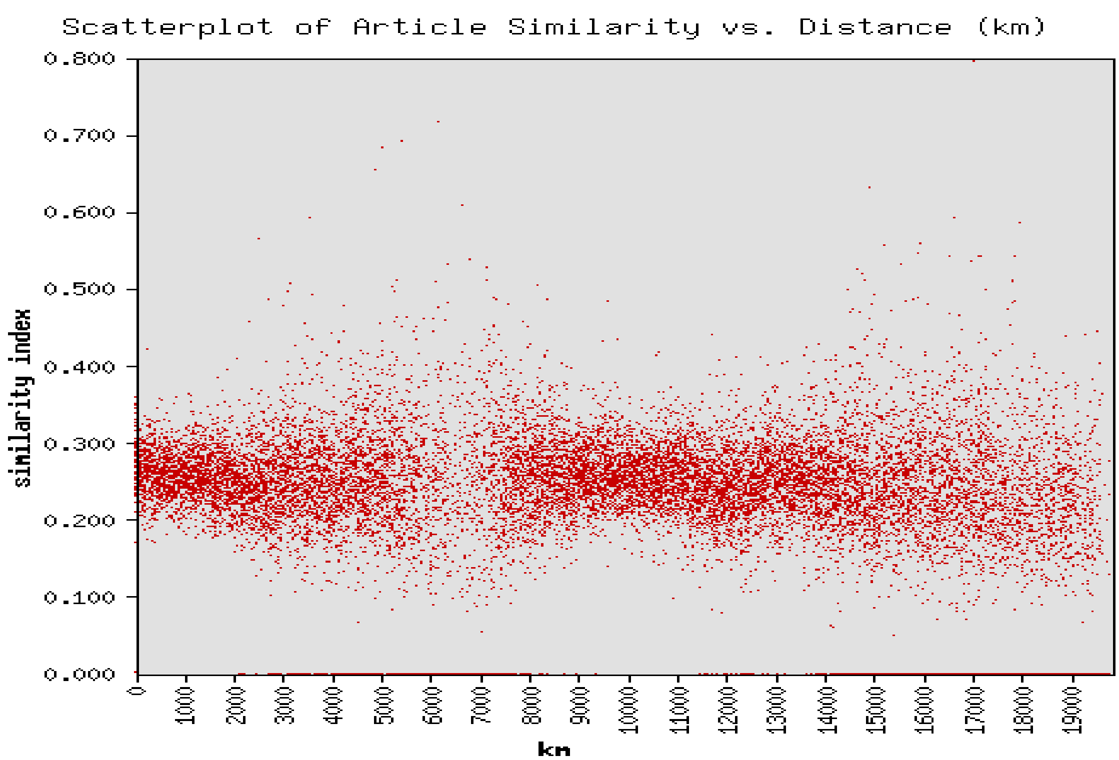



**Figure 3**. Scatterplot of Article Similarity (correlation) vs. Distance (km).

Figure 3 has a notable gap roughly between 6000 and 7000 kilometers where the number of articles reduces noticeably. The gap at these distances is due to the width of the Atlantic ocean. Distances larger than 7000 kilometers cross the Atlantic ocean, where distances less than 6000 kilometers are mostly intra-continental.

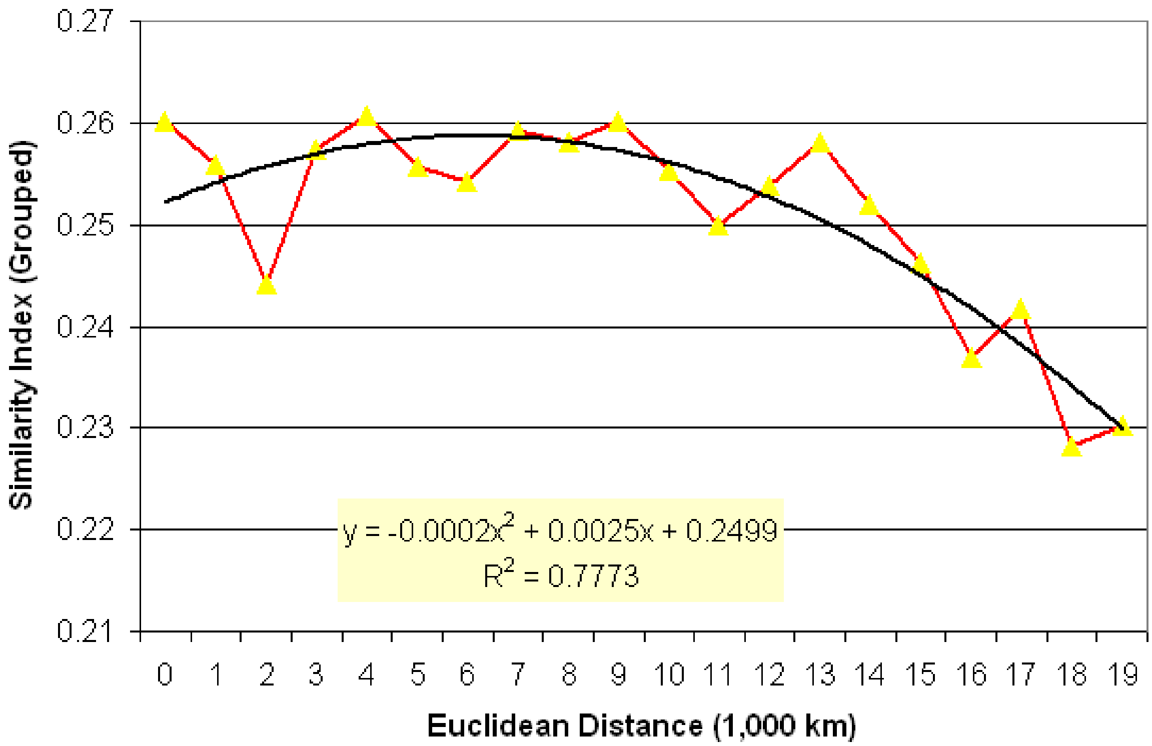



**Figure 4**. Article Similarity (Grouped) vs. Distance (1,000 km).

In Figure 4, we show grouped similarity indices versus Euclidean distance. After grouping articles into similar ranges, there is a trend showing an inverse relationship between distance and similarity. Two articles are, on average, more similar the closer the authors' affiliation locations. Figure 4 includes a polynomial regression formula that accounts for 77% of the values ($R^2 = .77$). In Chapter 5, we discuss some possible reasons for this relationship.

## Priorities Over Time

With the original textmatrix substituted for a year-by-keyword matrix, we can quantify the year-by-year research results against the UCGIS research priorities after running latent semantic analysis (Table 7). From this, we can see several trends in GIS research. Some areas, such as modeling, representation, and acquisition, remain highly active from year-to-year. Research in infrastructure has become less active over time. Mobile computing research trends upward in the years 2006 and 2007. The values for scale are small compared to its value in geographic research. In Chapter 5, we discuss possible reasons why research in scale issues appears small.

**Table 7**. Research quantified: results from LSA of the year-by-year research priorities as a percentage of that year's research.

| | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **modeling** | 23% | 23% | 23% | 23% | 23% | 23% | 23% | 23% | 24% | 23% | 23% |
| **data mining** | .5% | .5% | .5% | .5% | .6% | .5% | .6% | .6% | .6% | .5% | .6% |
| **ontology** | 3.0% | 1.8% | 5.3% | 2.8% | 6.6% | 5.2% | 7.0% | 7.2% | 8.6% | 6.6% | 8.1% |
| **acquisition** | 6.7% | 6.6% | 7.0% | 6.7% | 7.2% | 7.0% | 7.2% | 7.2% | 7.4% | 7.2% | 7.4% |
| **visualization** | 6.4% | 5.8% | 7.7% | 6.3% | 8.4% | 7.6% | 8.6% | 8.7% | 9.5% | 8.4% | 9.2% |
| **representation** | 9.4% | 9.4% | 9.4% | 9.4% | 9.3% | 9.4% | 9.3% | 9.3% | 9.3% | 9.3% | 9.3% |
| **society** | 11% | 12% | 9% | 11% | 7.5% | 8.8% | 7.2% | 7.0% | 5.7% | 7.5% | 6.1% |
| **analysis** | 14% | 14% | 11% | 14% | 10% | 12% | 10% | 9.9% | 8.6% | 10% | 9.0% |
| **infrastructure** | 3.0% | 3.4% | 2.2% | 3.0% | 1.8% | 2.2% | 1.7% | 1.6% | 1.1% | 1.8% | 1.3% |
| **interoperability** | 1.5% | 1.2% | 1.9% | 1.4% | 2.2% | 1.9% | 2.2% | 2.3% | 2.5% | 2.2% | 2.5% |
| **cognition** | 8.3% | 8.7% | 7.7% | 8.4% | 7.4% | 7.7% | 7.3% | 7.2% | 6.8% | 7.4% | 7.0% |
| **mobile** | 1.6% | 1.4% | 2.0% | 1.5% | 2.3% | 2.0% | 2.3% | 2.4% | 2.7% | 2.3% | 2.6% |
| **remote** | 3.6% | 3.7% | 3.4% | 3.6% | 3.3% | 3.4% | 3.3% | 3.3% | 3.1% | 3.3% | 3.2% |
| **distributed** | 5.9% | 6.1% | 5.5% | 6.0% | 5.2% | 5.5% | 5.2% | 5.1% | 4.9% | 5.2% | 4.9% |
| **scale** | .8% | .8% | .6% | .8% | .6% | .7% | .6% | .6% | .5% | .6% | .5% |
| **uncertainty** | 2.3% | 1.8% | 3.5% | 2.0% | 4.2% | 3.5% | 4.3% | 4.4% | 5.1% | 4.1% | 4.9% |

## Locational Analysis

By modifying the original article-word textmatrix, we can create a location-word textmatrix and preform the latent semantic analysis as well. Doing so, we can find which locations have a high correlation with a particular research theme. It is possible that locations with a high correlation to a subject area would be key innovative sites for that field. Figures 5 and 6 map primary research locations for some of the subject keywords.


**Figure 5**. Papers Published at North American Research Locations, 1997-2007.

With this, this paper answers the question of where the key centers of GIS research are. Further research may consider the ties between locations or the geographic network of each subfield. Knowing the relationship of the research locations in each subfield could assist in identifying sources of new research priorities. Outside of North America and Europe, GIScience research occurs in South Africa, New Zealand, Australia, Brazil, Hong Kong, Beijing, China, Taiwan, and South Korea.

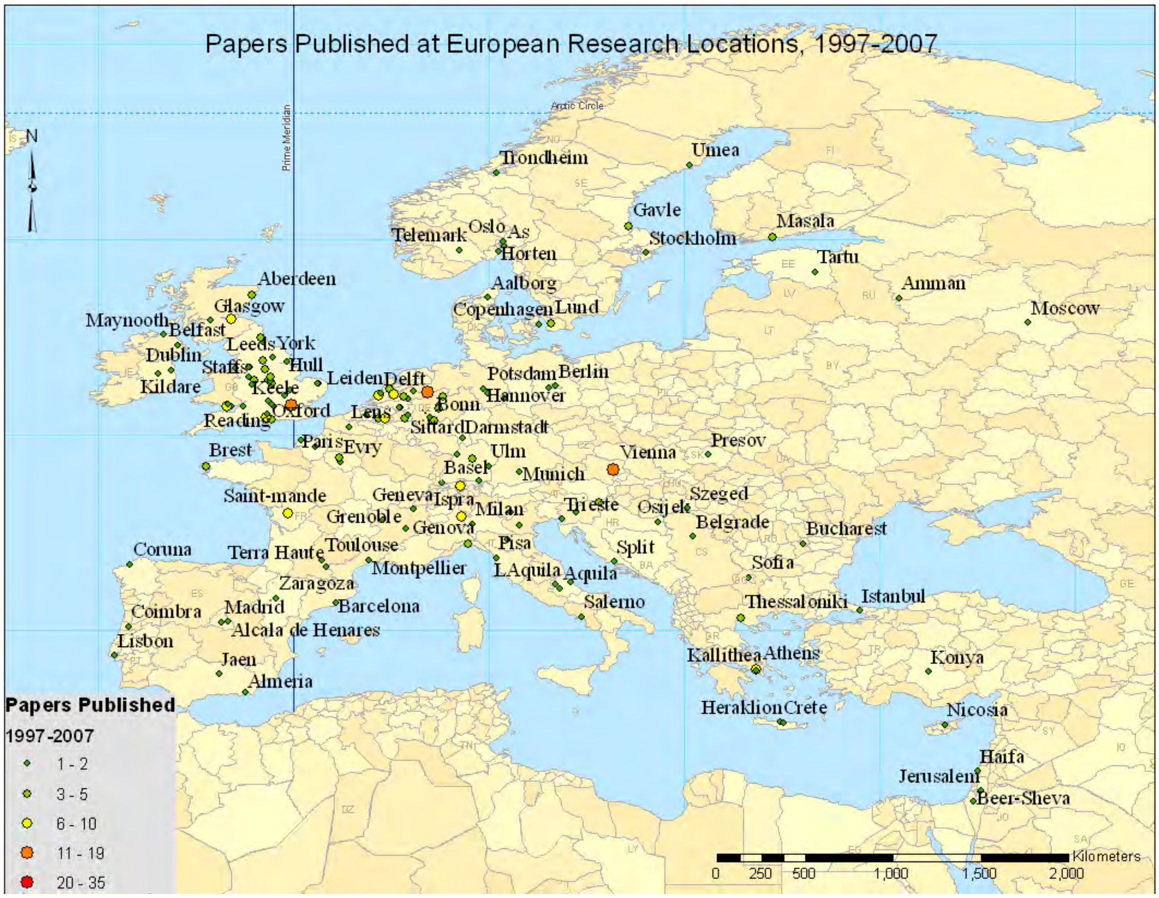



**Figure 6**. Papers Published at European Research Locations, 1997-2007.

After running a keyword-by-location semantic analysis, the ten locations with the highest weighted keywords counts have been found. For each UCGIS keyword, closely related keywords were found, with their correlations used as a weighting. The latent semantic index removes the noise from the textmatrix. The results, in Table 8, indicate which locations have the highest weighted keyword counts.

**Table 8.** The Ten Highest Correlated Locations Per Research Theme.

| **Cognition** | **Data Mining** | **Distributed Computing** | **Spatial Data Infrastructure** |
|---|---|---|---|
| Burnaby, BC | Beijing, China | Canberra, Australia | Columbus, OH |
| Columbia, SC | Burnaby, BC | Edinburgh, UK | Enschede, Netherlands |
| Columbus, OH | Hong Kong, China | Hong Kong, China | Hong Kong, China |
| Enschede, Netherlands | Ispra, Italy | Leuven, Belgium | Leeds, UK |
| Hong Kong, China | London, UK | London, UK | London, UK |
| Leeds, UK | Madison, WI | Madison, WI | Melbourne, Australia |
| Madison, WI | Orono, ME | Melbourne, Australia | San Diego, CA |
| Melbourne, Australia | Santa Barbara, CA | Orono, ME | Santa Barbara, CA |
| Munster, Germany | State College, PA | San Diego, CA | Seattle, WA |
| State College, PA | Vienna, Austria | Santa Barbara, CA | State College, PA |

| **Remote Computing** | **Representation** | **Scale** | **GIS and Society** |
|---|---|---|---|
| Canberra, Australia | Hong Kong, China | Canberra, Australia | Camden, NJ |
| Edinburgh, UK | Ispra, Italy | Edinburgh, UK | Columbus, OH |
| Hong Kong, China | Leeds, UK | Enschede, Netherlands | Enschede, Netherlands |
| London, UK | London, UK | Hong Kong, China | London, UK |
| Madison, WI | Madison, WI | London, UK | Melbourne, Australia |
| Melbourne, Australia | Orono, ME | Madison, WI | Minneapolis, MN |
| Orono, ME | Richmond, BC | Melbourne, Australia | San Diego, CA |
| Santa Barbara, CA | Santa Barbara, CA | San Diego, CA | Santa Barbara, CA |
| State College, PA | State College, PA | Santa Barbara, CA | Seattle, WA |
| Vienna, Austria | Vienna, Austria | State College, PA | State College, PA |

| **Interoperability** | **Mobile Computing** | **Uncertainty** | **Visualization** |
|---|---|---|---|
| Burnaby, BC | Camden, NJ | Canberra, Australia | Columbia, SC |
| Enschede, Netherlands | Colubus, OH | Edinburgh, UK | Columbus, OH |
| Hong Kong, China | Enschede, Netherlands | Hong Kong, China | Enschede, Netherlands |
| Leeds, UK | London,UK | Leuven, Belgium | Hong Kong, China |
| London, UK | Melbourne, Australia | London, UK | London, UK |
| Melbourne, Australia | Minneapolis, MN | Orono, ME | Madison, WI |
| Munster, Germany | San Diego, CA | Richmond, BC | Melbourne, Australia |
| Orono, ME | Santa Barbara, CA | Santa Barbara, CA | Santa Barbara, CA |
| Santa Barbara, CA | Seattle, WA | Vienna, Austria | State College, PA |
| State College, PA | Southampton, UK | Zurich, Switzerland | Stuttgart, Germany |

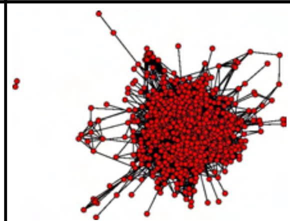
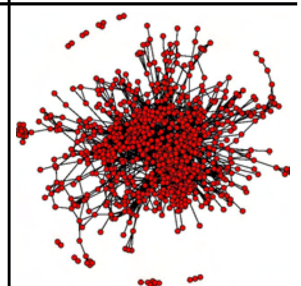
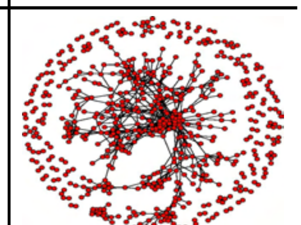
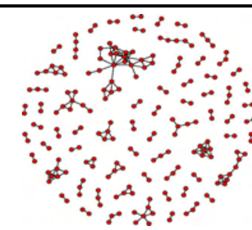
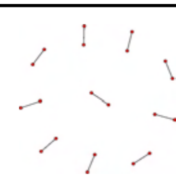
Table 8 shows the ten highest correlated locations per research area between the years 1997-2007. Some locations appear multiple times: Santa Barbara, London, Hong Kong, and State College, Pennsylvania, all appear in ten or more of the lists. Some locations, such as Zurich (uncertainty) and Stuttgart (visualization), appear only once. Sheer quantity of publishing will affect these results. Hong Kong is a frequent publisher and appears often. Imprecise language will also impact how the relationship between location and theme is determined. LSA infers semantic context, but language is never exact. Words have multiple meanings and multiple words can share a single meaning. The "looseness" of language will add noise to the data and affect the quality of the results.

## Determining the Correlation Cut-off for an Article-to-Article Network

Because language is not mathematically precise, the results of the semantic analysis are all correlated to each other at some level. In order to make sense of the relationships, some correlation cut-off is necessary. In Table 9, we show several potential cut-offs for a correlation value. At .5, the network of related articles is dense and rich. On the other end, .95 has no articles and .9 has a small network of only twenty.

For the purposes of this research, we choose .8 as a correlation to define highly-correlated links between articles. We do not need every link, only the most salient. At .8, the correlation links are both abundant and meaningful (see the "*Network Representations of Similar Articles*" section in Chapter 5). At lower cut-offs, the network is unwieldy to manage. A denser network would also require advanced network analysis techniques to find community structures which denote meaning. For these reasons, .8 is chosen as the correlation cut-off.

**Table 9**. Network Statistics for Correlation Cut-off Targets.

| Correlation Cut-off | Vertices (out of % possible) | Edges (Network Density) | Network Structure |
|---|---|---|---|
| 0.5 | 975 (99%) | 34880 (4%) |  |
| 0.6 | 886 (90%) | 10046 (1%) |  |
| 0.7 | 603 (61%) | 2284 (.2%) |  |
| 0.8 | 217 (22%) | 402 (.04%) |  |
| 0.9 | 20 (2%) | 20 (<1%) |  |
| 0.95 | 0 (0%) | 0 (0%) | |

# CHAPTER 5

# DISCUSSION

## The Research Priority Network: The Problem of Scale

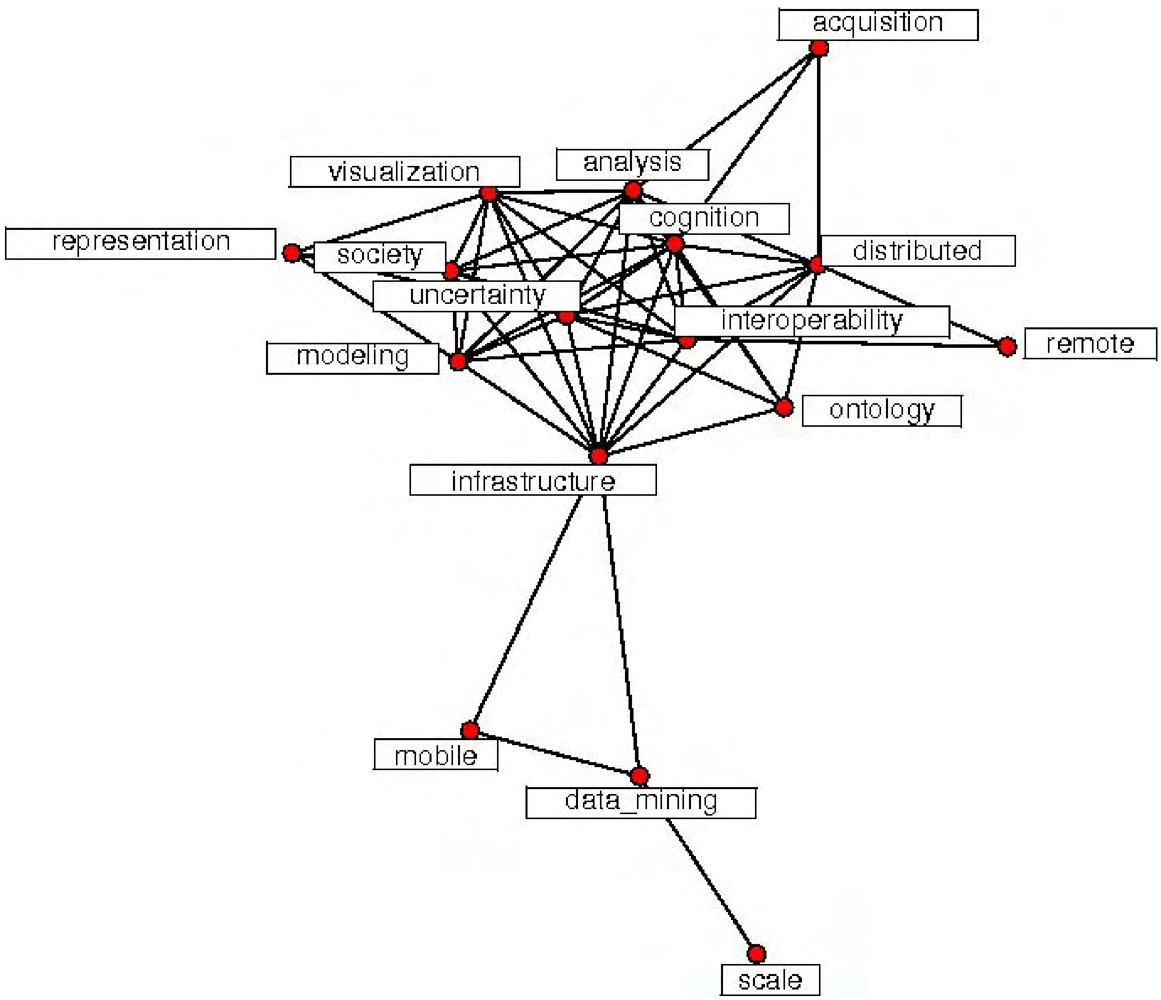



**Figure 7.** The knowledge domain network of the UCGIS priorities.

In Chapter 4, we found the terms that were highly correlated with the UCGIS subject keywords. To show how the subject keywords are related, we have correlated each keyword with each other keyword. In Figure 7, we link subjects that have a .8 Pearson correlation or higher. The network is a conceptual framework to demonstrate how the research priorities are thus related in the GIS knowledge domain.

Some areas of research are tightly coupled. Logically, "analysis" is linked to "visualization", "acquisition", "cognition", "distributed computing", "society", "uncertainty", "and "interoperability." "Representation" is linked to "visualization", "society", and "modeling." "Remote computing" is lined to "distributed computing."

"Scale", as a semantic subject, is loosely connected to the other terms and only directly connected to "data mining." At first, this appears counterintuitive. Many geographers would argue that scale is involved in many, if not all, types of geographical analysis. Scale has two particular characteristics that may explain its outsider status. If scale is, as theorized, involved in most geographic research, then the impact of the term "scale" may be deemed noise by the latent semantic algorithm. In a word frequency count, "scale" is the 53rd most frequently appearing term, excluding common words such as "the", "if", etc. Words that are universally pervasive will be considered noise by LSA.

The imprecise meaning of "scale" may also impact these results. The term "scale" has many definitions: "scale" can mean a fractional geographic representation, a set of musical notes, an instrument to measure weight, or the outer layer of a reptile or fish (See Figure 8). Latent semantic analysis depends on the meaning and context of the words in use. The lack of precise meaning in the English language will degrade the algorithm's ability to find correct correlations.

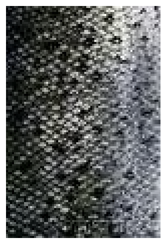
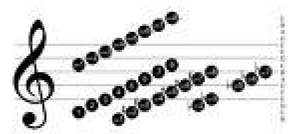
| | | |
|---|---|---|
|  |  |  |
| Scales are the outer layer of a fish. | Scale is a set of musical notes. | Scale is an instrument to measure weight. |

**Figure 8**. Different meanings of the word "scale."

Network Representations of Similar Articles

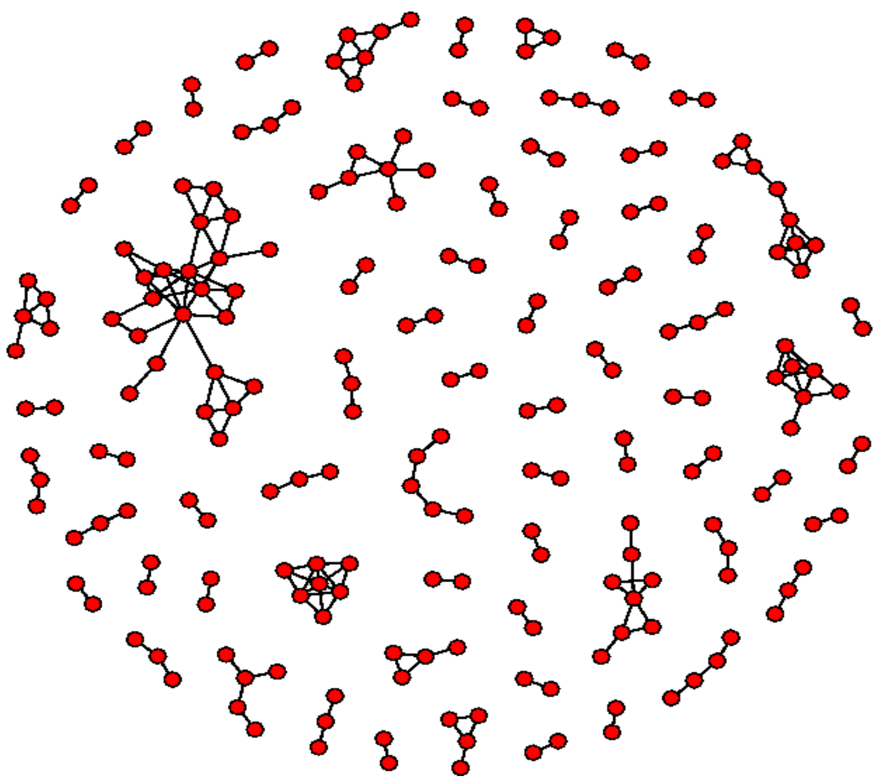


**Figure 9**. Network representation of similarity index between GIS articles, 1997-2007.

Each subnetwork is a representation of a group of articles, journals, or authors that have a Pearson correlation of .8 or greater. Each subnetwork is a possible route of knowledge or innovation. In the next section, we show a subnetwork in greater detail. Figure 10 is a network of authors with highly-similar articles. In total, there are 57 subnetworks with 215 nodes. The largest has 34 nodes (articles) and 146 linkages. The smallest has two nodes and one link. A key of authors is provided in Table 10.

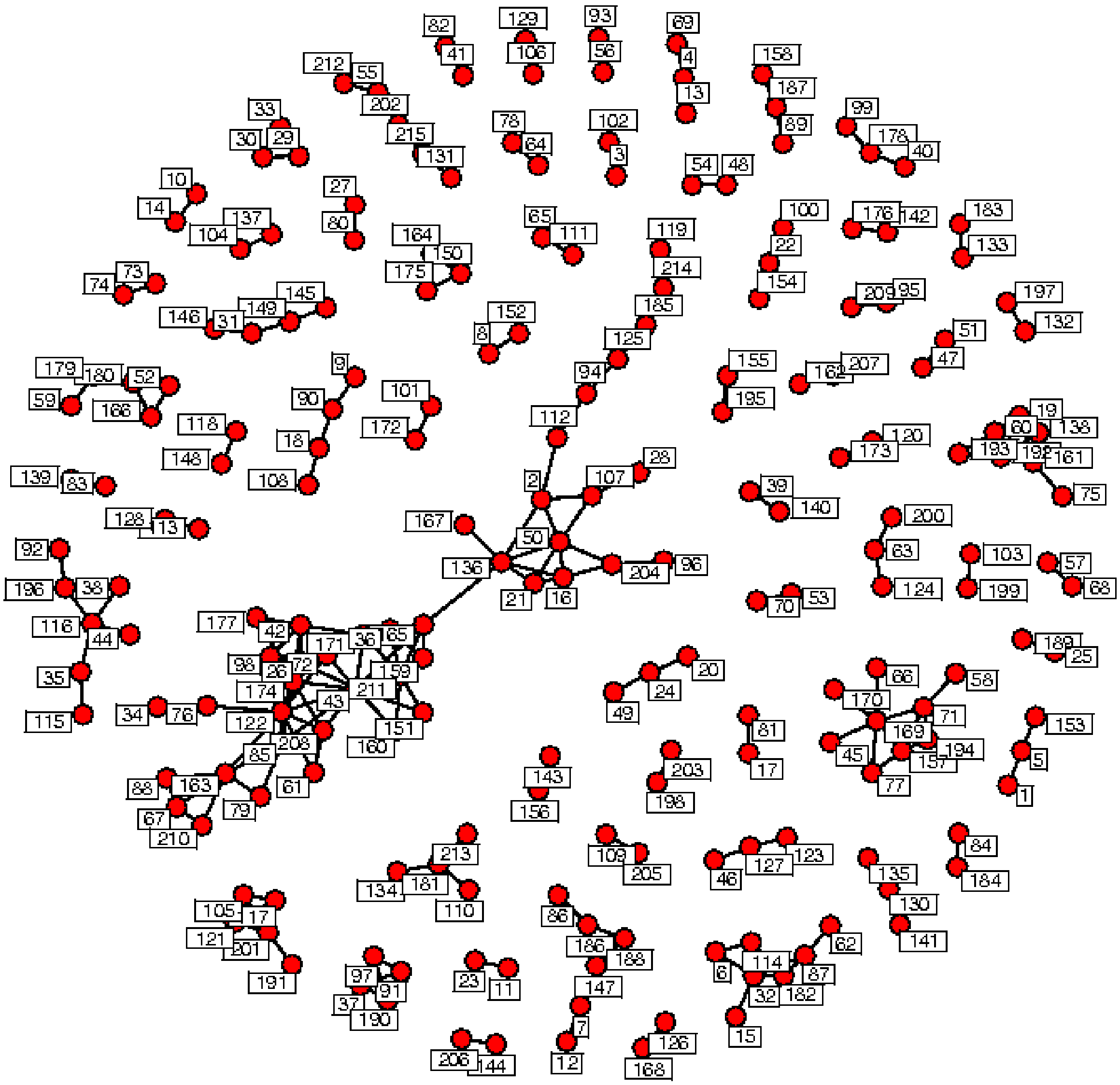



**Figure 10.** Network representation of authors with highly-similar publications, 1997-2007.

**Table 10.** Author key for Figure 10.

| | | | |
|---|---|---|---|
| 1 | Abhik Das | 41 | Demin Xiong |
| 2 | Jennifer Miller | 42 | Keven Roth |
| 3 | Anna Oldak | 43 | Melissa Lamont |
| 4 | Sabine Grunwald | 44 | Renee E Sieber |
| 5 | Anthony G Cohn | 45 | Theodore Saunders |
| 6 | Sanjiang Li | 46 | Boriana Deliiska |
| 7 | Anton J J Van Rompaey | 47 | P Agarwal |
| 8 | D Karssenberg | 48 | Bruce H Carlisle |
| 9 | Michele Crosetto | 49 | Howard Veregin |
| 10 | Antonio Corral | 50 | J Oksanen |
| 11 | Jun Zhang | 51 | Peter Fisher |
| 12 | Ashok Samal | 52 | Byong Nam Choe |
| 13 | Maria A Cobb | 53 | Olli Jaakkola |
| 14 | Aileen Buckley | 54 | Chaoqing Yu |
| 15 | Timothy Trainor | 55 | Walter Collischonn |
| 16 | Alan M Maceachren | 56 | Charles Dietzel |
| 17 | Menno Jan Kraak | 57 | Claire A Jantz |
| 18 | Alexey V Postnikov | 58 | Qingfeng Guan |
| 19 | Michael Heffernan | 59 | Xiaojun Yang |
| 20 | Allan Brimicombe | 60 | Cengizhan Ipbuker |
| 21 | Jessica Smith | 61 | Diederik Van Leeuwen |
| 22 | Allison Kealy | 62 | Fritz C Kessler |
| 23 | George Taylor | 63 | Ivan G Nestorov |
| 24 | Annu Maaria Nivala | 64 | John Cloud |
| 25 | Georg Gartner | 65 | Yang Cheng |
| 26 | Karen Wealands | 66 | Charles B Jackel |
| 27 | Anthony C Robinson | 67 | Matej Gombosi |
| 28 | Terry A Slocum | 68 | Ching Chien Chen |
| 29 | B Jiang | 69 | Sagi Filin |
| 30 | Bin Jiang | 70 | Christian Kiehle |
| 31 | Barry Smith | 71 | Rob Lemmens |
| 32 | Margarita Kokla | 72 | John Pickles |
| 33 | Barbara P Buttenfield | 73 | Chuanrong Zhang |
| 34 | Christine E Dunn | 74 | David J Coleman |
| 35 | Eric Sheppard | 75 | Z R Peng |
| 36 | Ian Masser | 76 | Claudio Paniconi |
| 37 | Michael F Goodchild | 77 | Puneet Srivastava |
| 38 | R E Sieber | 78 | Steve R Thorpe |
| 39 | W H Erik De Man | 79 | William Duane |
| 40 | Bastiaan Van Loenen | 80 | Claus Rinner |

**Table 10.** Author key for Figure 10 (continued).

| | | | |
|---|---|---|---|
| 81 | Robert D Feick | 121 | Eric Keys |
| 82 | Cory L Eicher | 122 | John Findley |
| 83 | Kevin Hawley | 123 | Eva Klien |
| 84 | Daniel Caldeweyher | 124 | I Budak Arpinar |
| 85 | Geoffrey Anderson | 125 | Florent Joerin |
| 86 | Iain M Brown | 126 | Luis A Bojorquez Tapia |
| 87 | Lysandros Tsoulos | 127 | Francois Lecordix |
| 88 | Daniel G Brown | 128 | Mahes Visvalingam |
| 89 | Martin Paegelow | 129 | S Mustiere |
| 90 | Daniel W Mckenney | 130 | Frederico Fonseca |
| 91 | Marcel Yri | 131 | Fulong Wu |
| 92 | David Martin | 132 | Xia Li |
| 93 | Nigel Walford | 133 | Fang Ren |
| 94 | David Puliar | 134 | Hongbo Yu |
| 95 | Lars Bernard | 135 | Feras M Ziadat |
| 96 | Soohong Park | 136 | J Gao |
| 97 | Marion Jones | 137 | Stefan Kienzle |
| 98 | Diansheng Guo | 138 | Geoffrey Blewitt |
| 99 | Vladimir Estivill Castro | 139 | Gertraud Peinel |
| 100 | Donggyu Park | 140 | Hui Lin |
| 101 | Leila De Floriani | 141 | Georg Stadler |
| 102 | Mahdi Abdelguerfi | 142 | Steven Van Dijk |
| 103 | Dan Lin | 143 | Steven Zoraster |
| 104 | K Raptopoulou | 144 | Tycho Strijk |
| 105 | Victor Teixeira De Almeida | 145 | Giuseppe Arbia |
| 106 | Danielle J Marceau | 146 | Wenzhong Shi |
| 107 | Tamas Abraham | 147 | Graeme Aggett |
| 108 | Darla K Munroe | 148 | Piotr Jankowski |
| 109 | J Crompvoets | 149 | Gregory Vert |
| 110 | James Boxall | 150 | Harold Moellering |
| 111 | John A Shuler | 151 | Max J Egenhofer |
| 112 | John Kelmelis | 152 | Helen Couclelis |
| 113 | Y Georgiadou | 153 | Sara I Fabrikant |
| 114 | Dawn J Wright | 154 | Robin G Fegeas |
| 115 | Denis J Dean | 155 | Isaac Karikari |
| 116 | E Lynn Usery | 156 | Steve Jacoby |
| 117 | Jeong Chang Seong | 157 | Wolfgang Hoeschele |
| 118 | E A De Kemp | 158 | Jason Dykes |
| 119 | Kevin B Sprague | 159 | J Lee |
| 120 | Trevor Harris | 160 | Jiyeong Lee |

**Table 10.** Author key for Figure 10 (continued).

| | | | |
|---|---|---|---|
| 161 | Jaakko Kahkonen | 191 | William Cartwright |
| 162 | Xuan Zhu | 192 | Melissa R Gilbert |
| 163 | Jan Chomicki | 193 | Michael J Shiffer |
| 164 | Stephane Grumbach Inria | 194 | Nancy J Obermeyer |
| 165 | John F Roddick | 195 | Michael Barndt |
| 166 | Raja Sengupta | 196 | Rina Ghose |
| 167 | Jack Shroder | 197 | William J Craig |
| 168 | Richard A Beck | 198 | Michael S Scott |
| 169 | Scott W Mitchell | 199 | Timothy Nyerges |
| 170 | Waldo Tobler | 200 | Oleg Balovnev |
| 171 | Jose Moreira | 201 | Werner Kuhn |
| 172 | Martin Erwig | 202 | Z Huang |
| 173 | Wei Zhang | 203 | Pip Forer |
| 174 | Karen K Kemp | 204 | Paul Robbins |
| 175 | Kenneth E Foote | 205 | S Fritz |
| 176 | Paul Heinrich | 206 | Paul Van Helden |
| 177 | Sarah W Bednarz | 207 | Thomas A Wikle |
| 178 | Tracey Morton Mckay | 208 | Pece V Gorsevski |
| 179 | Kent D Lee | 209 | S Lee |
| 180 | Lars Harrie | 210 | Qiang Cai |
| 181 | Lars E Harrie | 211 | Shuo Sheng Wu |
| 182 | M Bertolotto | 212 | Qingnian Zhang |
| 183 | Mark Gahegan | 213 | Serafino Cicerone |
| 184 | Marinos Kavouras | 214 | Sarah Elwood |
| 185 | Maria J P De Vasconcelos | 215 | Yanfen Le |
| 186 | Peng Ming | | |
| 187 | Matthew J Ungerer | | |
| 188 | Zhiqiang Zhang | | |
| 189 | Zeshen Wang | | |
| 190 | Matt Rice | | |

## Research Directions: Spatial Movement of Research

In this section, we begin with an example sub-network of related articles and explore them in depth. Knowledge is situated in place and time. A thought occurs, not at random in the ether, but in a person's mind while he is driving or she is chopping the onions. Published research is transmitted through the internet, libraries, papers, meetings, books, and journals.

**Table 11**. Similarity between articles. Numbers in Italics are below the .8 cut-off.

| | **BC2005** | **GA1999** | **JO2006** | **PF1998** | **WS2003** |
|---|---|---|---|---|---|
| **BC2005** | 1.000 | .738 | .856 | .832 | *.698* |
| **GA199** | *.738* | 1.000 | .821 | .840 | .826 |
| **JO2006** | .856 | .821 | 1.000 | .906 | *.780* |
| **PF1998** | .832 | 0.84 | .906 | 1.000 | .813 |
| **WS2003** | *.698* | .826 | *.780* | .813 | 1.000 |

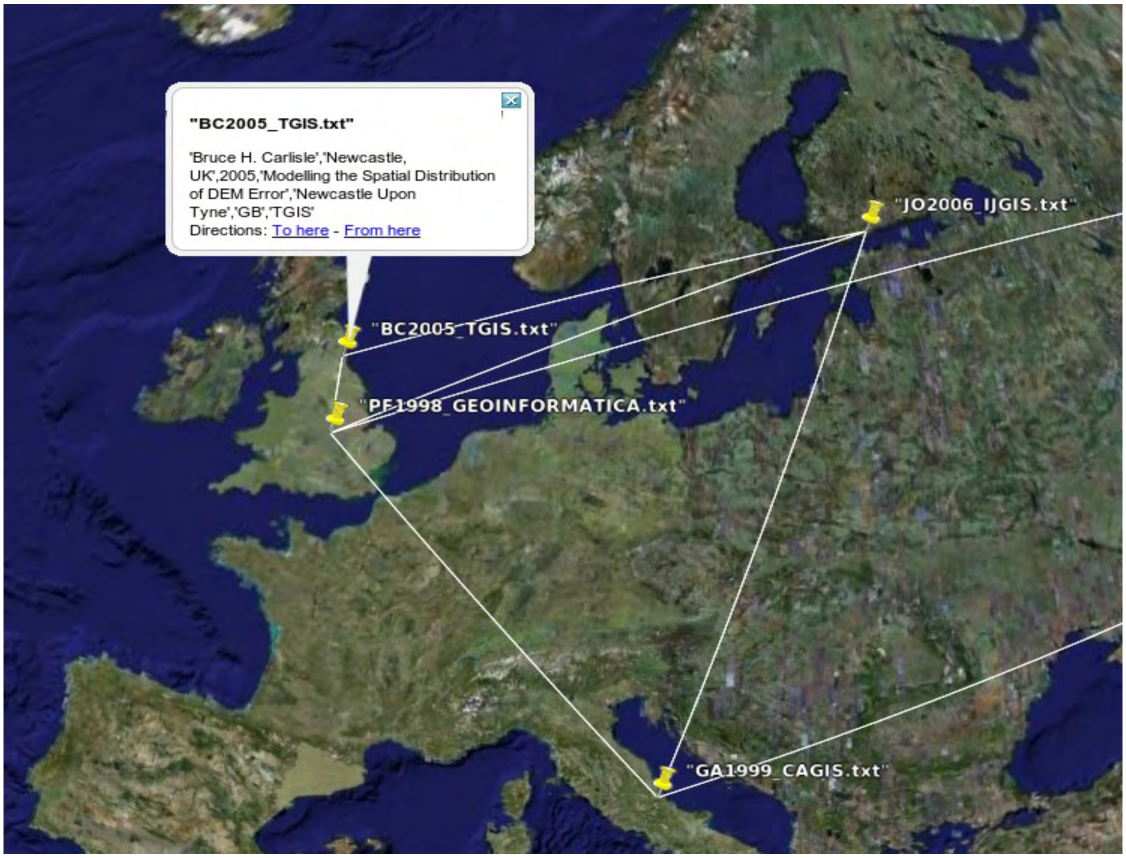



**Figure 11.** Map of one network of related articles.

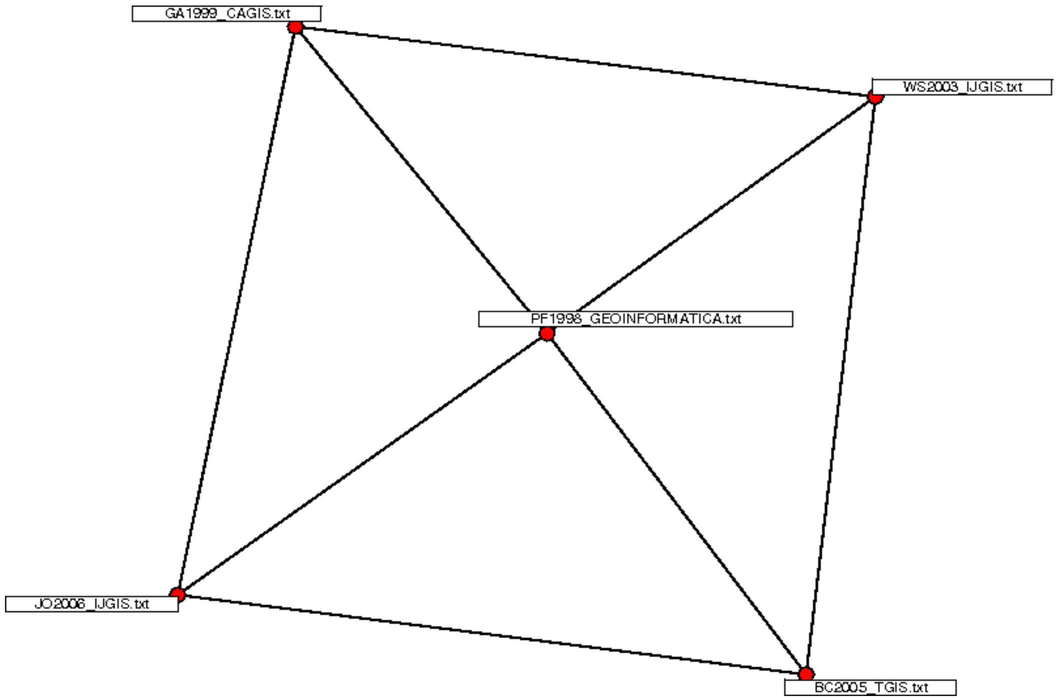



**Figure 12**. Network representation of some related articles.

Of the five articles in this network, two (BC2005 and JO2006) cite PF1998 in their references. The other articles may not cite each other, but they do hold common citations in their references. Using latent semantic analysis does reveal the connections between research. More importantly, LSA provides a quantitative measure between articles.

**Table 12**. Description of related networked articles.

| | |
|---|---|
| BC2005 | Title: Modeling the Spatial Distribution of DEM Error<br>Author: Bruce H. Carlisle (University of Northumbria)<br>Journal: Transactions in GIS, 2005<br>Location: Newcastle, UK |
| JO2006 | Title: Uncovering the statistical and spatial characteristics of fine toposcale DEM error<br>Authors: J. Oksanen, T. Sarjakoski (Finnish Geodesic Institute)<br>Journal: IJGIS, 2006<br>Location: Masala, Finland |
| PF1998 | Title: Improved Modeling of Elevation Error with Geostatistics<br>Author: Peter Fisher (University of Leicester)<br>Journal: GeoInformatica, 1998<br>Location: Leicester, UK |
| GA1999 | Title: Error Propagation Modeling in Raster GIS: Adding and Ratioing Operations<br>Authors: Giuseppe Arbia, Daniel Griffith, Robert Haining<br>Journal: Cartography and GIS, 1999<br>Location: Pescara, Italy |
| WS2003 | Title: Modeling error propagation in vector-based buffer analysis<br>Authors: Wenzhong Shi (Hong Kong Polytechnic), Chui Cheung, Changqing Zhu<br>Journal: IJGIS, 2003<br>Location: Hong Kong, China |

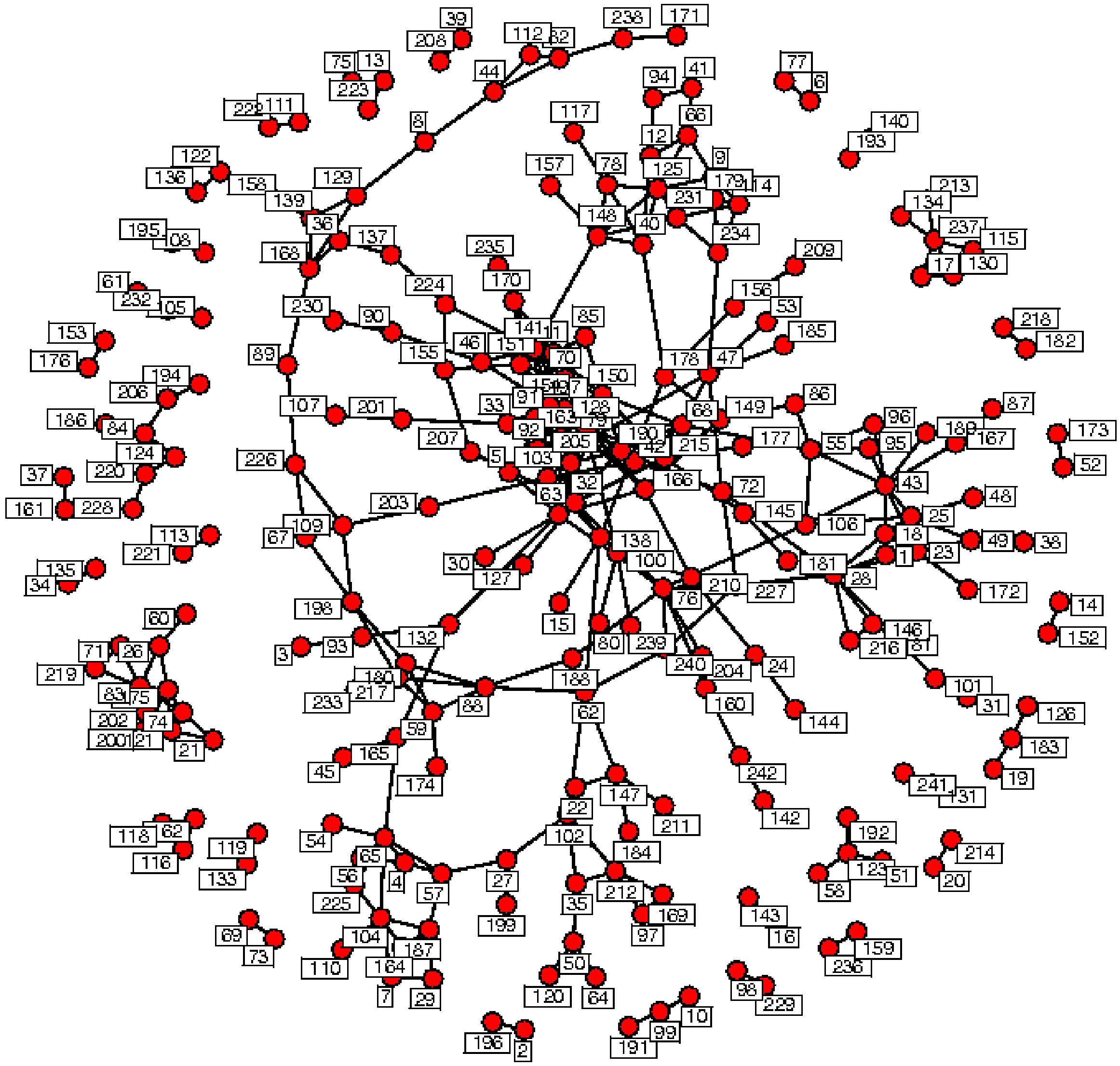


**Figure 13**. Network representation of highly-correlated locations, 1997-2007.

**Table 13**. Location key for Figure 13.

| | | | |
|---|---|---|---|
| 1 | Aalborg Denmark | 41 | Sault Ste Marie ON |
| 2 | Kallithea Greece | 42 | Silsoe UK |
| 3 | Porto Portugal | 43 | Belgrade Yugoslavia |
| 4 | Trondheim Norway | 44 | Deventer The Netherlands |
| 5 | University of South Australia | 45 | Frostburg MD |
| 6 | Aberdeen UK | 46 | Greenville NC |
| 7 | Crete | 47 | Istanbul Turkey |
| 8 | Accra Ghana | 48 | Jaen Spain |
| 9 | Rutgers NJ | 49 | Peterborough ON |
| 10 | Adelaide Australia | 50 | Belmont MA |
| 11 | Goulburn NSW Australia | 51 | Hull United Kingdom |
| 12 | Gyeonggi South Korea | 52 | Potomac MD |
| 13 | Maryville MO | 53 | Val Belair QC |
| 14 | Pisa Italy | 54 | Belo Horizonte Brazil |
| 15 | Salerno Italy | 55 | Brest France |
| 16 | Almeria Spain | 56 | Beltsville MD |
| 17 | Singapore | 57 | Madison WI |
| 18 | Amherst NY | 58 | Benin Nigeria |
| 19 | Modena Italy | 59 | Boulder CO |
| 20 | Santa Maria CA | 60 | Durham UK |
| 21 | Ann Arbor MI | 61 | Fayetteville AR |
| 22 | Toulouse France | 62 | Lexington KY |
| 23 | Arlington VA | 63 | Reston VA |
| 24 | Milan Italy | 64 | Winchester UK |
| 25 | As Norway | 65 | Berlin Germany |
| 26 | Glasgow UK | 66 | Canberra Australia |
| 27 | Ljubljana Slovenia | 67 | Bilthoven The Netherlands |
| 28 | Ashland OR | 68 | Canterbury New Zealand |
| 29 | Corvallis OR | 69 | Birmensdorf Switzerland |
| 30 | Athens Greece | 70 | Honolulu HI |
| 31 | Newcastle upon Tyne UK | 71 | Blacksburg VA |
| 32 | Austin TX | 72 | Pittsburgh PA |
| 33 | Veldhoven Netherlands | 73 | Bloomington IN |
| 34 | Bangkok Thailand | 74 | Brisbane Australia |
| 35 | Grenoble France | 75 | Windsor ON |
| 36 | Beijing China | 76 | Bonn Germany |
| 37 | LAquila Italy | 77 | Southport Queensland Australia |
| 38 | Belfast UK | 78 | Enschede Netherlands |
| 39 | Leuven Belgium | 79 | Melbourne |
| 40 | Parkersburg WV | 80 | Carbondale IL |

**Table 13.** Location key for Figure 13 (continued).

| | | | |
|---|---|---|---|
| 81 | Dunedin New Zealand | 121 | Mankato MN |
| 82 | Leicster UK | 122 | Clayton Victoria Australia |
| 83 | Lincoln New Zealand | 123 | Zaragoza Spain |
| 84 | Muenster Germany | 124 | Cologne Germany |
| 85 | Vancouver BC | 125 | Oslo Norway |
| 86 | Bristol England | 126 | Conway AR |
| 87 | Oak Ridge TN | 127 | Huntingdon UK |
| 88 | Research Triangle Park NC | 128 | Norwich UK |
| 89 | Santa Barbara CA | 129 | Nottingham UK |
| 90 | Suitland MD | 130 | Rolla MO |
| 91 | Woods Hole MA | 131 | Fairfax VA |
| 92 | Brookings SD | 132 | Sheffield UK |
| 93 | Presov Slovakia | 133 | Washington DC |
| 94 | Storrs CT | 134 | Curitiba Brazil |
| 95 | Brookville NY | 135 | Richmond BC |
| 96 | Butte MT | 136 | Darmstadt Germany |
| 97 | Bucharest Romania | 137 | London ON |
| 98 | East Lansing MI | 138 | Delft The Netherlands |
| 99 | Wolverhampton UK | 139 | Fredericton NB |
| 100 | Cagliara Italy | 140 | Karlsruhe Germany |
| 101 | East Midlands Airport | 141 | Milwaukee WI |
| 102 | Friedrichshafen Germany | 142 | Whitewater WI |
| 103 | Sao Paulo Brazil | 143 | Dublin Ireland |
| 104 | University of Ireland | 144 | Taipei Taiwan |
| 105 | Wernigerode Germany | 145 | Ulm Germany |
| 106 | Cambridge MA | 146 | Dusseldorf Germany |
| 107 | Nijimegen The Netherlands | 147 | Newcastle UK |
| 108 | Normal IL | 148 | Kildare Ireland |
| 109 | Terra Haute IN | 149 | Portsmouth UK |
| 110 | Iowa City IA | 150 | Sterling VA |
| 111 | Kingston upon Thames UK | 151 | Edinburgh UK |
| 112 | Tampa FL | 152 | Perth Australia |
| 113 | Casault Quebec | 153 | El Segundo CA |
| 114 | Corvalis OR | 154 | Haifa Israel |
| 115 | Seattle WA | 155 | St Louis MO |
| 116 | Champaign IL | 156 | Eugene OR |
| 117 | Kent State University | 157 | Greensboro NC |
| 118 | Lisbon Portugal | 158 | Fort Collins CO |
| 119 | North Shore New Zealand | 159 | Porto Alegre Brazil |
| 120 | Charlotte NC | 160 | Roorkee India |

**Table 13.** Location key for Figure 13 (continued).

| | | |
|---|---|---|
| 161 | Frankfort KY | 202 Masala Finland |
| 162 | Kirksville MO | 203 Leiden Netherlands |
| 163 | Gainesville FL | 204 Rockville MD |
| 164 | University of Queensland | 205 Lethbridge Canada |
| 165 | Geneva Switzerland | 206 University of Jordan |
| 166 | Mexico City Mexico | 207 Louvain Belgium |
| 167 | Split Croatia | 208 Toronto ON |
| 168 | Genova Italy | 209 London UK |
| 169 | Yangsan City South Korea | 210 Tallahassee FL |
| 170 | Glamorgan UK | 211 Ypsilanti MI |
| 171 | University of Keele | 212 Macomb IL |
| 172 | Gloucester Point VA | 213 Osijek Croatia |
| 173 | Grahamstown South Africa | 214 Maribor Slovenia |
| 174 | Mount Pleasant MI | 215 Memphis TN |
| 175 | Marquette MI | 216 Stennis Space Center MS |
| 176 | Guangzhou China | 217 Telemark Norway |
| 177 | Southampton UK | 218 Montevideo Uruguay |
| 178 | Hagen Germany | 219 Moscow ID |
| 179 | Le Chesnay France | 220 Moscow Russia |
| 180 | Thessaloniki Greece | 221 Winnipeg Manitoba |
| 181 | Hannover Germany | 222 New Delhi India |
| 182 | Konya Turkey | 223 Wallingford UK |
| 183 | Pontypridd UK | 224 New Orleans LA |
| 184 | Zurich Switzerland | 225 Newark DE |
| 185 | Heraklion Greece | 226 Pescara Italy |
| 186 | Leeds UK | 227 Otago New Zealand |
| 187 | Sofia Bulgaria | 228 Newcastle NSW Australia |
| 188 | Provo UT | 229 Townsville Australia |
| 189 | Horten Norway | 230 Tucson AZ |
| 190 | St Martin France | 231 Orono ME |
| 191 | Ithaca NY | 232 enschede Netherlands |
| 192 | State College PA | 233 Paris France |
| 193 | Jerusalem Israel | 234 Pensacola FL |
| 194 | Stillwater OK | 235 Pretoria South Africa |
| 195 | Keele University | 236 Redlands CA |
| 196 | Kent OH | 237 Wageningen Netherlands |
| 197 | Sankt Augustin Germany | 238 Richardson TX |
| 198 | University Park PA | 239 Syracuse NY |
| 199 | Knoxville TN | 240 Salt Lake City UT |
| 200 | Montreal QC | 241 Yokohama Japan |
| 201 | West Long Branch NJ | 242 Trento Italy |

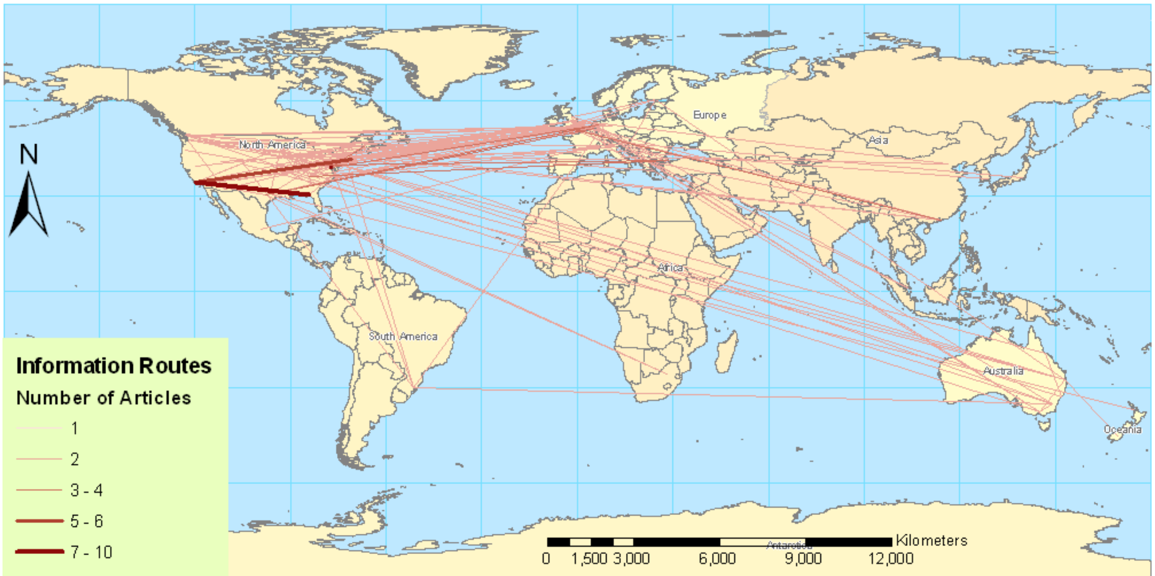



**Figure 14**. Information routes of highly-correlated articles.

In Figure 14, we present a route map of information flows, as represented by similar articles and the connections between them. Some striking patterns emerge. Clearly, many connections exist between North American and European locations, both within and between these continents. Even more striking is that other locations, such as those in Brazil, South Africa, China, and New Zealand, are more closely related to North American and European locations then they are to closer locations. Only in one case, in Australia, does a link occurs with both nodes locally in that country outside of North America or Europe.

These results may indicate a bias in language. As all of the publications are in English, this may limit information flows between countries of other native languages. Institutional funding and resources may also present challenges. North American and European institutions may be better funded or have more access to GIS literature.


**Figure 15**. Route map of information flows of three or more articles. One link, from Portsmouth, UK, to Hong Kong, is not shown.

## <u>The Impact of the UCGIS Research Priorities</u>

In measuring the research related to the UCGIS research priorities, we can determine the baseline of research in the geographic information science field. As the priorities have changed over the eleven year span of 1997-2007, so has the research changed as well. Trends in the research can be enumerated, providing guidance on current research priorities in the field. Given these results, the UCGIS can reconsider which research priorities need to be adjusted, encouraged, or removed.

The results do not speak to the quality of the research pursued. They do, however, provide the UCGIS with information on how research has changed, where different types of research are being performed, and how the knowledge domain is structured internally.

A graph of percent change in GIS research themes from 1997 is presented in Figure 16. One theme, infrastructure, is less prevalent in 2007 than in 1997. Some themes, such as society and analysis, are virtually identical in the amount of research in 2007 as they were in 1997. Ontology and data mining have risen significantly as the themes were lightly considered at the beginning of the study. The "stacking effect," where trends appear to move in unison, is an artifact. GIS themes are not completely independent, thus related themes will move in concert.

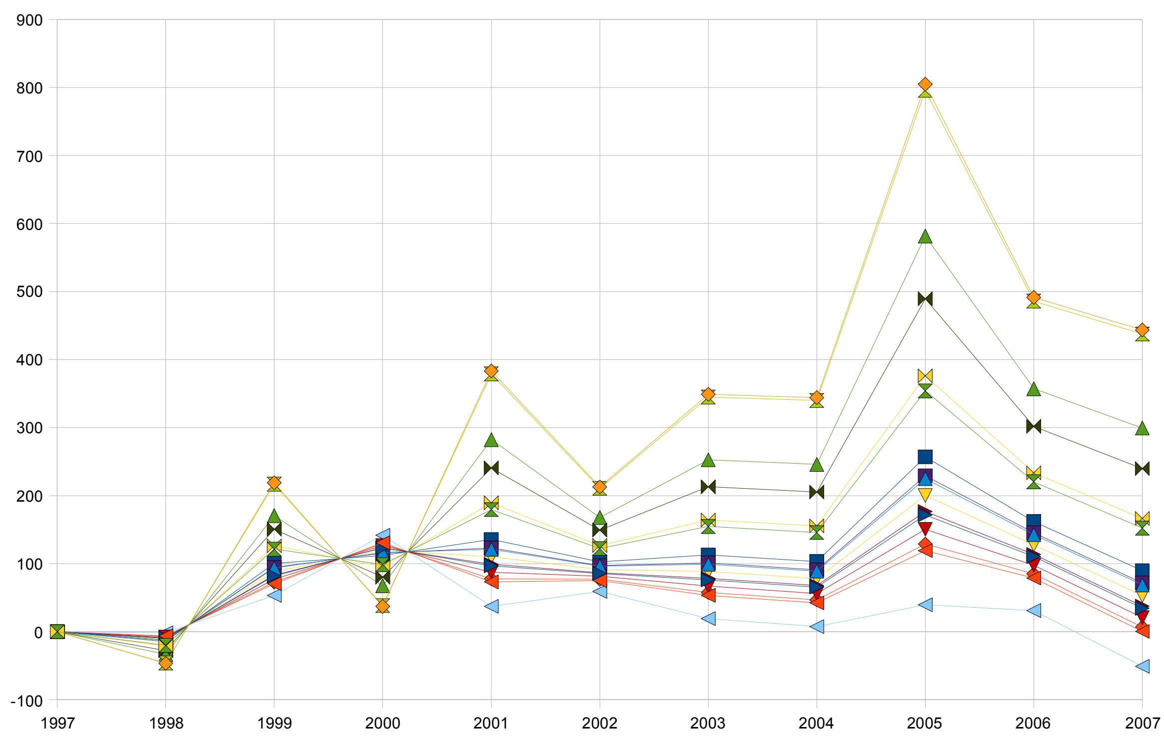



**Figure 16**. Percent Change in research themes, 1997-2007.

## Limitations and Key Assumptions

Inherent in most innovation diffusion studies is a process known as the pro-innovation bias (Rogers, 2003). *Pro-innovation bias* is the tendency to view only successful changes and adaptations in innovation and ignore failing ones. This study does not include unpublished or rejected manuscripts as these do not contribute to diffusion.

Because of cost restrictions, digital bibliographic data available to academic institutions is limited. Therefore, the data available were restricted to the years 1997 to 2007. During this period, a more complete snapshot of journal articles were available. Prior to 1997, easily available digital copies of research were not available. Therefore, the study was limited exclusively from 1997 to 2007. In some cases, the full text of research papers within these years were not available. In all cases, book reviews, editorials, and other non-research papers were excluded.

## Future Research

Semantic analysis provides a method to identify and quantify the relationship among published research. While it may not speak to the quality of the research, it can establish linkages between research, keywords, time, and space. This thesis has demonstrated several methods of analyzing the research changes over time (from 1997 to 2007) and over space. The analysis has identified words closely related to the subject keywords. Future research may explore how semantic alternatives are used in different locations.

Previous academic research has focused on the citation network as the structure of scientific connectivity (Small, 1973; White and Griffith, 1981; Newman, 2000; Newman, 2001). Citation networks are limited in that all citation values are binary: 1 for a work that is cited, 0 for a work that is not cited. Not all citations can be assumed to be of equal value, however. Latent semantic analysis could be used to find the similarity indices between journal articles and other published scholarly research. A similarity index may be a suitable replacement for the binary citation values.

Future research can expand on the networking analysis of latent semantic analysis (LSA) results. Options include optimizing the correlation cut-off values, finding community structure, or measuring the differences among multiple models of network types.

LSA is based on singular value decomposition, which uses two dimensions of analysis. Higher-order singular value decomposition (HOSVD) analyzes matrices in three or higher dimensions. A higher-order LSA could explore multiple dimensions of analysis, incorporating authorship, location, or other measures directly into the LSA. Doing so would provide a method to remove noise from several dimensions at the same time. Using thematic keywords in a higher-order LSA might remove some publication frequency noise.

Each-correlated article pair represents a spatial connection as well as thematic. The number of links between locations is an indicator of related research directions. Comparison subjects may include airplane flight networks. We could demonstrate the direction, and frequency of thematic connections between research locations on a map.

## Conclusion

Latent semantic analysis has proven to be a valuable tool to indicate similar articles. In this report, we have shown that it can be used to establish relationships between locations, authors, journals, and years. Using weighted keywords, we can show directions in research over time. Each of these methods has implications for understanding the specialty structure of a science and how that structure changes over time.

Researchers in GIScience are not isolated individuals, but rather a network of collaborators who work within organizations, departments, and professional groups to advance knowledge, cultivate relationships, and gain feedback on their work. Feedback on research is an integral part of the modern academic system; researchers are evaluated by peers, editors, and the public-at-large. Organizations such as the University Consortium of Geographic Information Science and the Association of American Geographers are catalysts that provide guidance and direction and foment these networks. This study suggests a methodology for quantifying and measuring what types of research are being produced where are by whom. Organizational networks should use these methods to establish directions of scientific research.

## APPENDIX A. R CODE FOR GENERATING TEXTMATRIX

The R code below creates a stemmed textmatrix from the directory "ALL_ARTICLES." The minimum word length is four letters, and all words are stemmed. The output is written into a comma separated values file.

```
#!/usr/bin/Rscript

library(lsa)

data(stopwords_en)

td = c("ALL_ARTICLES")
data(stopwords_en)
dtm = textmatrix(td, stopwords=stopwords_en, language="english",
stemming=TRUE, minWordLength=4,minGlobFreq=2)
write.table(dtm,file="DATA/wordsB.csv",row.names=TRUE,col.names=TRUE)


detach()
```

## APPENDIX B: R CODE TO RUN LSA

Below is computer code in the R programming language to run a Latent Semantic analysis on an input text matrix in the file *dtm.csv* with words in the columns and articles in the rows.

```
# Read in lsa library and textmatrix file
library(lsa)
dtm <- read.table("dtm.csv", sep=",")

# Run LSA, and return results into a textmatrix
landauerOriginalSpace = lsa(dtm, dims=dimcalc_share())
X = as.textmatrix(landauerOriginalSpace)
write.table(X,"lsa.csv",sep=",")

# Write word-to-word correlation
lsaCor2 = cor(X)
write.table(round(lsaCor2,3),file=paste("lsaA.csv", sep=",")

# write article-to-article correlation
lsaCor = cor(t(X))
write.table(round(lsaCor,3),file="lsaB.csv",sep=",")
detach()
```

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## VITA

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In addition to professional work as a computer programmer, systems analyst, and UNIX systems administrator from the years 1992 to 2008 at Texas Instruments, Dallas, Dallas Semiconductor, and the University of Texas at Austin, he has held a variety of odd jobs. These include a kindergarten teacher, radio disc jockey, goat herder, and celebrant. He has ordained two weddings in Texas and one in Missouri. He currently resides in Austin, Texas.

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