Mapping Library Lending:
Using GIS Technology to Explore ILL Lending Data

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Abstract:

Geographic Information System (GIS) technology can be employed by academic librarians to study interlibrary loan (ILL) lending patterns of circulating materials. The data collected and analyzed using GIS can apprise librarians about the efficacy of existing networks, assist them in making sound cost-saving choices, and inform collection development activities. In this article, the physical lending outputs at The University of Alabama are studied across five years to understand better and explore factors that impact lending activities within Alabama. The data retrieved elucidate stable patterns and highlight identifiable changes in usage that can inform subsequent lending network practices within the state. The totality of this data can aid toward the desired outcomes of enhanced resource sharing as it relates to ILL practices.

keywords: interlibrary loan (ILL), Geographic Information System (GIS), library lending, state and regional networks, temporal change

Introduction

Academic libraries lend their physical materials (print books, etc.) to users at borrowing institutions via interlibrary loan (ILL), based on a complex network of institutions that conduct reciprocal sharing via a lending string. The lending string usually represents ten to fifteen institutions that are linked in agreement to share resources. In recent years, regional storage facilities have begun lending items, but they do not borrow. Networks of institutions involved in these processes may be geographically, consortia, or academic conference-based, but are they the most efficient for getting materials to users? When considering ILL from a state-wide viewpoint, the goal is to provide users access to materials via an orderly system of networked libraries (Duggan, 2013).

This article examines how information obtained via Geographic Information System (GIS) might be harnessed to improve ILL networks of academic institutions. GIS can often explain information via maps and charts that does not come across as clearly in writing, and that visual-spatial component can nuance understanding (Arendt et al., 2018). Academic library users anticipate receiving their materials as quickly as possible, so reconsidering ILL through the lens of GIS may provide more efficiency to ILL lending.

To conduct this exploratory study, the lending outputs at The University of Alabama were examined within the state of Alabama for five years (2015-2019). The year 2019 was the end date because the data from the COVID-19 pandemic years (2020-2021) would be an anomaly in the dataset. By visually demonstrating these five-year lending trends, patterns emerged that helped form the understanding of ILL lending within the state. Following this study's lead, other academic libraries might use GIS to understand better their ILL lending within the state, region, or nation. It would also potentially increase their ability to make data-driven decisions about their ILL lending practices to decrease wait time for academic library users and save money and library employees' time.

Literature Review

The literature relating to the use of GIS in libraries spans decades. This is not surprising as libraries are heavily based on networks, and GIS can be employed for making maps, spatially measuring and analyzing these networks and the services offered within them, and reporting the results (Andris & O'Sullivan, 2021; Bishop & Mandel, 2010; Fortunato & Hric, 2016; Coyle, 2011). Existing research on GIS and libraries is associated with bibliographic citations, GIS stewardship for librarians, collection analysis, genealogy, service and staffing, wayfinding, and geospatial data as it relates to the Federal Depository Library Program (FDLP) (Adler, 1995; Arendt et al., 2018; Chang, 2018; Coyle, 2011; Frazer, 2001; Mandel et al., 2020; Pournaghi, 2017; Shen, 2018). Fewer research studies relate directly to using GIS for analyzing and interpreting geographical data to enhance comprehension of ILL lending patterns. In what follows, the literature on library use of networks and GIS will be reviewed to contextualize the present study's use of GIS toward understanding ILL lending patterns.

Why use GIS, networks, or graphs in the academic library?

The versatility of GIS and related technologies have promoted new ideas, methods, and approaches to its use in many different fields. Today, many institutions utilize GIS to effectively discover information, enhance decision-making, identify and share resources, and capitalize on economic benefits (Adler, 1995; Andris & O'Sullivan, 2021; Wei et al., 2015). Academic libraries are one type of institution that benefits from networks, sharing, and capitalizing on economic benefits when there are limited resources. GIS can help situate file structures, daily library operations, and inter-relationships in a meaningful visual context and remains an emerging research topic within libraries (Kraft et al., 1991; Luschow, 2022).

Proper use of GIS tools traditionally required training and a developed skillset, so simply having the technology could not endorse using it (Adler, 1995; Arendt et al., 2018; Bishop & Mandel, 2010). With many GIS technologies now available, however, simpler versions might allow librarians to teach themselves, and fewer software interfaces require a degree in geography or cartography to be used effectively (Kim, 2018; Mandel, 2021). This neogeography – the gap-closing between experts and non-experts – might facilitate using GIS for a more extensive understanding of purposes (Byrne & Pickard, 2016). The cost barrier continues, which usually manifests in the relationship between technology and physical space provisions in the library environment and between purchasing the software and having someone with the skill set to use it (Arendt et al., 2018).

Historically, GIS supported library and information sciences research in one of two ways. Either it was employed to inform the analysis of library service populations and facilities, or it served as a tool to allow for the analysis of collections and their usage (Bishop & Mandel, 2010; Coyle, 2011; Pournaghi, 2017; Shen, 2018). Beyond spreadsheets, only some software applications were specifically invented to help librarians in their collection analysis. GIS potentially fills this need by allowing greater statistical analysis to improve collections. (Coyle, 2011). Perhaps this is why a recent literature review found that articles by librarians using GIS to analyze service area populations are declining, and articles about librarians using GIS to manage facilities and collections have increased (Mandel et al., 2020).

Librarians have also used network science and graph theory to examine the relationships between authors, articles, subject matter, and institutions toward more precise bibliographic metrics and citation analysis (Powell et al., 2011). A growing body of research within libraries also exists wherein data are analyzed, and spatial display aids in establishing a future direction for services, spaces, and information discovery (Bishop & Mandel, 2010). With training, librarians can use GIS to explore and understand the ever-changing features of complex network environments (Powell et al., 2011).

Library Networks

The idea of libraries connecting, communicating, and interacting is familiar (Kraft et al., 1991). Considered in this way, the transfer of items and materials among libraries is an action capitalizing on an information network (Nance, 1970). As it is usually considered in terms of physical space, graph theory could assist in determining the placement of libraries understood as being "nodes" distributed among the area (in this instance, the state) served (Korfhage et al., 1972). Stated simply, potential lending library opportunities become accessible to the user within the network graph, increasing the likelihood of the person receiving their requested item.

Network analysis and GIS support the underlying ethos of ILL since ILL collaborations offer the potential to combine materials to achieve more than one library - situated in one location - could manage solo (Duggan, 2013). The converse of this is also true, however, as a library has, first and foremost, its own goals in mind (in this case, the ILL borrower's request). In contrast, a traditional network usually has the decision problem focused on the benefit of the entire group (Nance, 1970).

The challenge remains how to develop networks and parameters to facilitate ILL performance best as it relates to the goals of quick turn-around time, cost of filling the request, and quality as understood by patron satisfaction (Duggan, 2013). Lib-NAT (Library Network Analysis Theory) relates to some of these parameters and the methodology for understanding their efficacy (Duggan, 1971). These parameters are hindered by technical, financial, legal, administrative, and political scrutiny - particularly during the network design phase (Kraft et al., 1991). Network analysis allows researchers to examine relationship patterns between entities (in this instance, libraries) to understand the system better (Caldarelli & Catanzaro, 2012). One barrier to a perfect fitting of network analysis to ILL is that only some libraries can assist within the network; the transfer of information is predicated on just one lending library having the material to lend (Nance, 1970).

GIS and ILL

Businesses such as Google, Amazon, and Netflix have influenced library users' expectations surrounding immediacy concerning ILL (Sewell & Gaffney, 2017). Using GIS to map ILL interactions between libraries can draw attention to relationships within a complex network, and analysis of the data can reveal information about the materials moving from one library to another in terms of the number of volumes and even their content, if desired (Coyle, 2011; Shen, 2018). This information can give librarians a framework for better understanding fulfillment turn-around time to address user needs.

Outside of scanned documents, known as ILL document delivery services, shared print agreements for physical books, known as “returnables,” generally exist to increase discoverability via shared catalogs (such as OCLC), reduce costs of purchasing through reciprocal agreements, and save money on shipping via a mutual courier (Sewell & Gaffney, 2017). However, these returnables must also reach users quickly to be considered a successful transaction.

GIS became critical during the COVID-19 pandemic when libraries used it to demonstrate their continued value in the face of the crisis by supporting information sharing (Mandel, 2021). This information could then assist in drafting better-targeted lending agreements based on actual usage during the emergency. As is valid with the research using GIS to track circulating collections, using GIS with ILL records allows for visual mapping of which materials are being requested and where they are going outside the library (Coyle, 2011). In the face of the pandemic, librarians used GIS to visualize information at a distance while also discovering a novel usage for the technology during a global pandemic (Mandel, 2021).

Research Questions

GIS is familiar to the library environment, but opportunities for new and innovative uses abound. Within that framework, the researchers used GIS to better understand lending patterns in Alabama across five years. As researchers, we believe that the most elucidating research will come from the proper applications of GIS measures, methods, and models for the ILL-specific context (Andris & O'Sullivan, 2021). The following questions therefore guided the research:

1. Are there spatial-temporal patterns across existing lending networks?
2. When looking at contextual characteristics in conjunction with ILL data, can they help explain these patterns?
3. What cannot be - or is not - shown on the map?

Data & Methods

The data for this project was collected from three main sources across five years (2015, 2016, 2017, 2018, and 2019). The Integrated Postsecondary Education Data System (IPEDS) data from the National Center for Education Statistics (NCES, 2015-2019) informed several variables. They provided information about the colleges and universities within Alabama with whom reciprocal borrowing is conducted. The Public Libraries Survey (PLS) retrieved from the Institute of Museum and Library Services (IMLS, 2015-2019) provided statistical information about public libraries within the state. Lending data from OCLC's ILLiad and Ex Libris Group's RapidILL for The University of Alabama Libraries demonstrated which institutions were borrowing the most from this library, thereby providing this study's focal point of lending. KUDZU, a system of catalogs for the Association of Southeastern Research Libraries (ASERL), also provided supplemental ILL data. Data preparation was completed in R 4.3.1/RStudio 2023.06.2 using the "readxl" 1.4.3 package and Excel Microsoft 365. The collected data was mapped using Esri's ArcGIS Pro 3.1.0 with additional spatial statistics calculated in GeoDa 1.20.0.36 and R/RStudio using the "stats" 4.3.1 package.

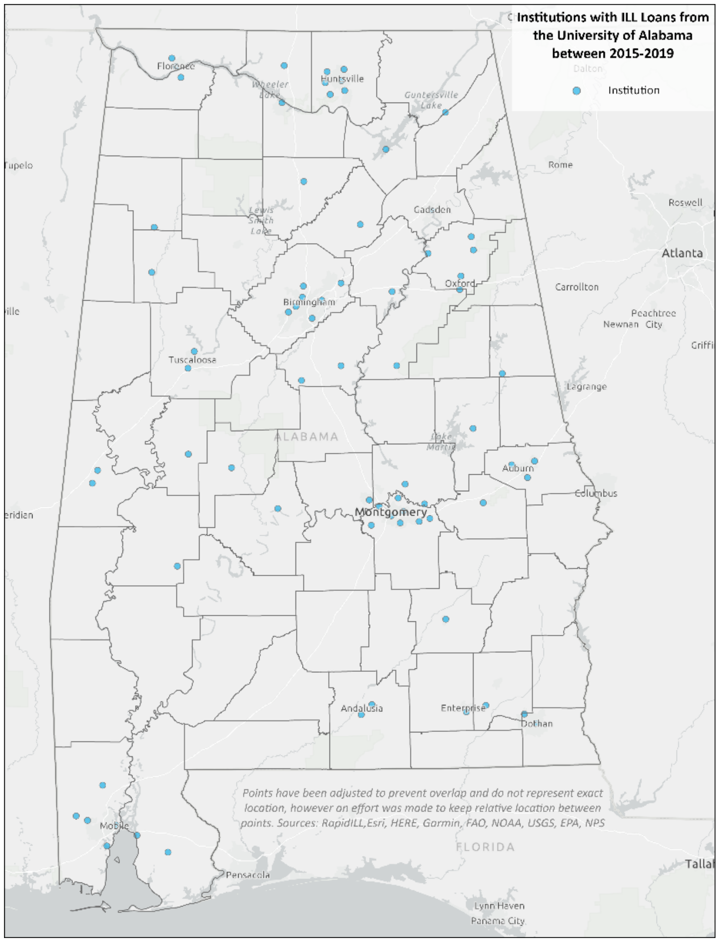


Figure 1 Study area and institutions

Variables

ALM Lending Statistics. The University of Alabama, Tuscaloosa's (ALM) lending records over the five years were exported from ILLiad and RapidILL for institutions in the state of Alabama (n=79) (Figure 1). Individual ILL records were then aggregated by Rapid ID for loans from ALM for each calendar year (January 1 – December 31). Libraries within the same academic institution were combined to allow a one-to-one join with IPEDS data as IPEDS reports at the institutional level, retaining the Rapid ID of the largest total ILL loans during the five years (n=71). For example, Lister Hill and Sterne Libraries at The University of Alabama Birmingham were included in our dataset and combined under the Rapid ID for Lister Hill "ABH". Each institution was manually classified by institution type as either UNIVERSITY (n=18), COLLEGE (n=11), TOWNSHIP (n=19), COUNTY (n=12), REGIONAL (n=1), GOVERNMENT (n=5), or OTHER (n=5) based on their stated service area and/or classification from IPEDS or PLS. Locations were then geocoded using Esri's geocoding service to gain latitude and longitude coordinates.

IPEDS variables. Within IPEDS, the variables that pertain to groups of people are the following. The variable "research FTE" (SFTERSRC) refers to the number of full-time research faculty an institution reported for the five years studied. These would be faculty members whose focus is primarily on conducting research. Another variable, "Librarians, Curators, and Archivists/Student and Academic Affairs and Other Education Services FTE" (SFTELCAI) contains the number of librarians or persons who work in information services at an institution. This study also considered the number of "graduate enrollment" (EFGRAD), which are noted as any full-time students enrolled in post-bachelor's degree programs, and "undergraduates" (EFUG), who are full-time students enrolled in degree-granting pre-bachelor's degree programs. "Total enrollment" (ENRTOT) represents a headcount of all students enrolled for credit in the fall of the academic year. "Total employees" are contained by the variable (EAPTOT). The derived variable, "service area," represents the sum of variable fields EAPTOT and ENRTOT.

IPEDS data related to this study's library collections are total "physical collections," including books and media (LPCLLCT). Another variable for this study is the total number of "electronic collections," including ebooks, databases, and electronic media (LECLLCT) for any institution. The variable "physical and electronic collections" (LTCLLCT) is employed to consider the sum of these groups.

To consider library circulation and ILL activities, the variables are total "library circulations" (LTCRCLT), which include physical as well as digital and electronic items. Total "interlibrary loans and documents provided" to other libraries (LILLDPR), also known as ILL lending. Total "interlibrary loans and documents received" (LILLDRC) is also known as ILL borrowing.

The data were summarized with an average across all five years for each institution. Years listed with "N/A" were not considered in the average. For example, if an institution closed in 2017, only three years of data were averaged. (See Appendix A for HTML query files). The data from IPEDS was then downloaded in comma-separated value (.csv) files. This data required cleaning as each institution examined needed its own data row for use in ArcGIS, which was not provided in the downloaded files. R, a computer language for statistics and mapping, was used to reformat and clean the data. Another issue was determining the number of employees at each institution since FTE can be reported in multiple ways (multiple variables) per institution within IPEDS.

PLS variables. The Administrative Entity (AE) PLS dataset, which includes individual statistics for main libraries, was retrieved from 2015-2019 from the IMLS website. As was true with the information from IPEDS, data tables were retrieved from PLS for each of the five years for this analysis. Variables extracted from the full PLS dataset included specific attributes about each library. Several codes to identify each library were utilized for this project. They are the "library identification code" assigned by IMLS (FSCSKEY), a "state identification code" assigned to the library (LIBBID), the "library name" code (LIBNAME), the "legal basis" code (C_LEGBAS) and the "geographic code" (GEOCODE).

Variables that describe each library's service area include the "population of the legal service area" (POPU_LSA), the "number of central libraries" (CENT_LIB), the "number of branches" (BRANLIB), as well as the "total number of paid full-time employees" (TOTSTAFF).

The collection-related variables from PLS are the number of "print materials" (BKVOL) including books and government documents, the number of "ebooks and digital resources" (EBOOK), "physical audio materials" (AUDIO_PH), "digital audio materials" (AUDIO_DL), "physical video units" (VIDEO_PH), and "digital audio units" (VIDEO_DL). There are also variables to capture "local and other electronic collections" (EC_LO_OT) and "state electronic collections" (EC_ST). "Serial subscriptions" are contained by the variable (SUBSCRIP).

For library circulation and ILL activities, the variables are "total annual circulation transactions" in the variable (TOTCIR), "interlibrary loans provided to other libraries," also known as ILL lending (LOANTO), and "interlibrary loans received from other libraries" also known as ILL borrowing (LOANFM).

The derived variable for "physical collection total" is the sum of print materials, physical audio units, and physical video units. The "electronic collection total" is the sum of ebooks, audio digital units, video digital units, local electronic collections, state electronic collections, and digital serial subscriptions.

Variable mapping between IPEDS and PLS. The data from IPEDS was combined with the PLS data for Alabama, averaging across five years. The datasets were combined based on similar or derived variables. Most variables, such as ILL Loans, ILL Borrows, Circulation, and collection totals, were easily paired for comparison. To compare variables not included in both datasets, an attempt was made to derive a similar comparable variable (see Table 1). For example, the variable “service population” was only reported for public libraries through the PLS; however, we can estimate the service population for an academic library as the sum of “Total Enrollment” and “Total Employees.” A crosswalk table was created between Rapid ID, PLS State-Assigned identification code (LIBID), and IPEDS Unit ID (UNITID). Finally, the PLS and IPEDS data were combined using a one-to-one join to the ALM Lending Statistics dataset and imported into ArcGIS Pro to create a single geospatial dataset for analysis.

IPEDS	**PLS**	**Definition**
ILLDPR	LOANTO	ILL loans provided to other libraires
ILLDRC	LOANFM	ILL loans received from other libraires.
Service Population*	POPLSA	Total (legal) service population. For academic libraires it was estimated as the sum of Total University Employees and Total Enrollment of students.
LTCRCLT	TOTCIR	Total circulation transactions
LPCLLCT	Toal Physical Collections*	Defined as physical media Derived as all PH collections in PLS
LECLLCT	Total Digital Collections*	Defined as all electronic, non-physical collections. Derived as all DL and electronic resource holdings.
LTCLLCT	Total Collections*	Defined as sum of Physical Collections and Digital Collections

*Table 1: Variable mappings between IPEDS and PLS datasets for comparison. * Indicates a derived variable.*

Exploratory Data Analysis

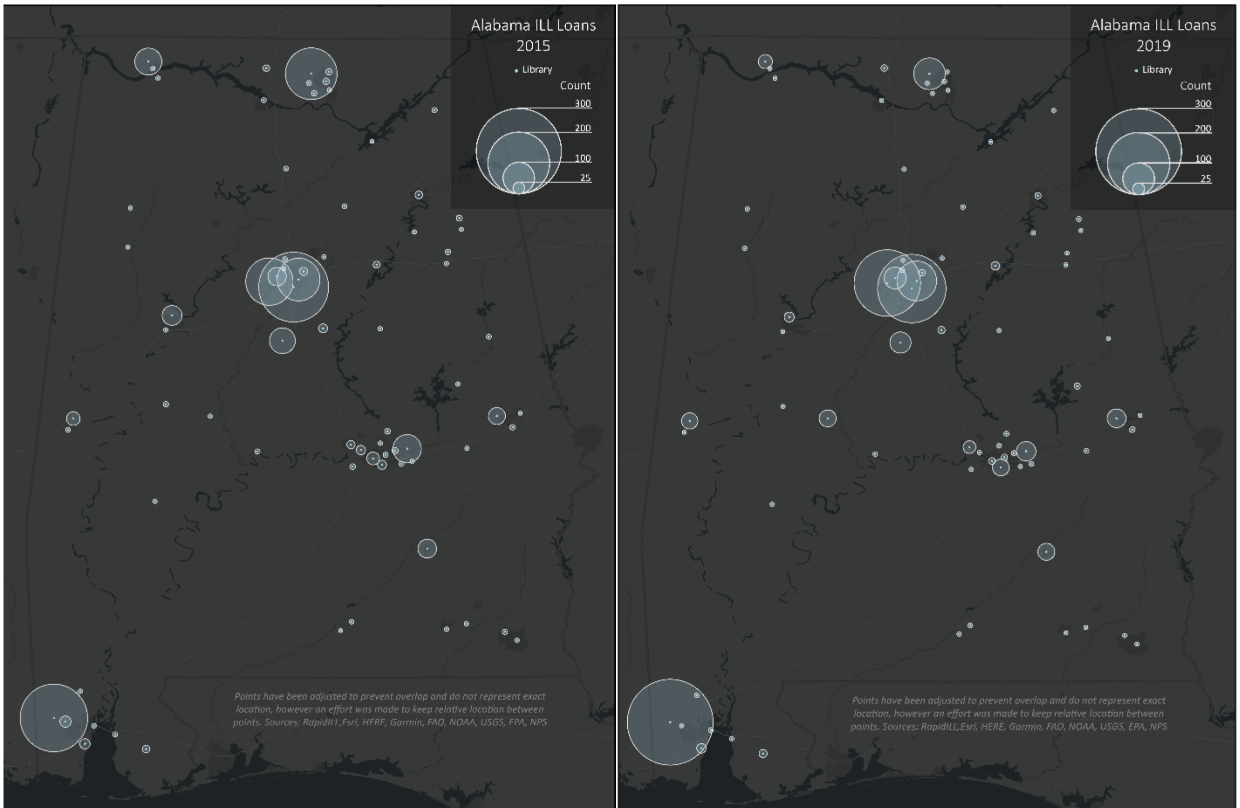
ALM lending data was positively skewed, causing issues with completing parametric statistics. Common solutions for correcting data skew, such as removing outliers, sub-setting, normalizing, and transforming (log, square root, reciprocal, etc.), failed to produce a symmetric distribution. Each method was applied to the dataset and tested using the Shapiro-Wilks test of normality. Since Pearson’s Correlation assumes normally distributed, parametric data, we were limited to using non-parametric statistics such as Spearman’s Rho and Kendall’s Tau-B.

Spearman's Rho assigns an average rank to all concordant values, whereas Kendall's Tau-B weights the result by considering the number of concordances and discordances. Both were included in the paper as Spearman's Rho is somewhat biased towards ties, and Kendall's Tau-B is more resilient and insensitive to errors.

GIS Mapping

To prepare the data, each institution included in the dataset was geolocated and manually checked to ensure accuracy. For institutions that have multiple libraries, the main library was selected as the location. The dataset was then projected to UTM Zone 16N to calculate the distance from Gorgas Library (located on The University of Alabama's main campus) to each institution in the dataset.

To explore the possibilities of geographic patterns, the total number of ILL Loans for each of the five years was plotted as proportional symbols (figure 2A) with varying point sizes consistently between years to allow for comparison. The change between years (figure 2B) was mapped similarly, showing the magnitude of change (point size) and percent change/direction (bivariant color). Additionally, the demographic variables from the PLS and IPEDs surveys were plotted similarly.



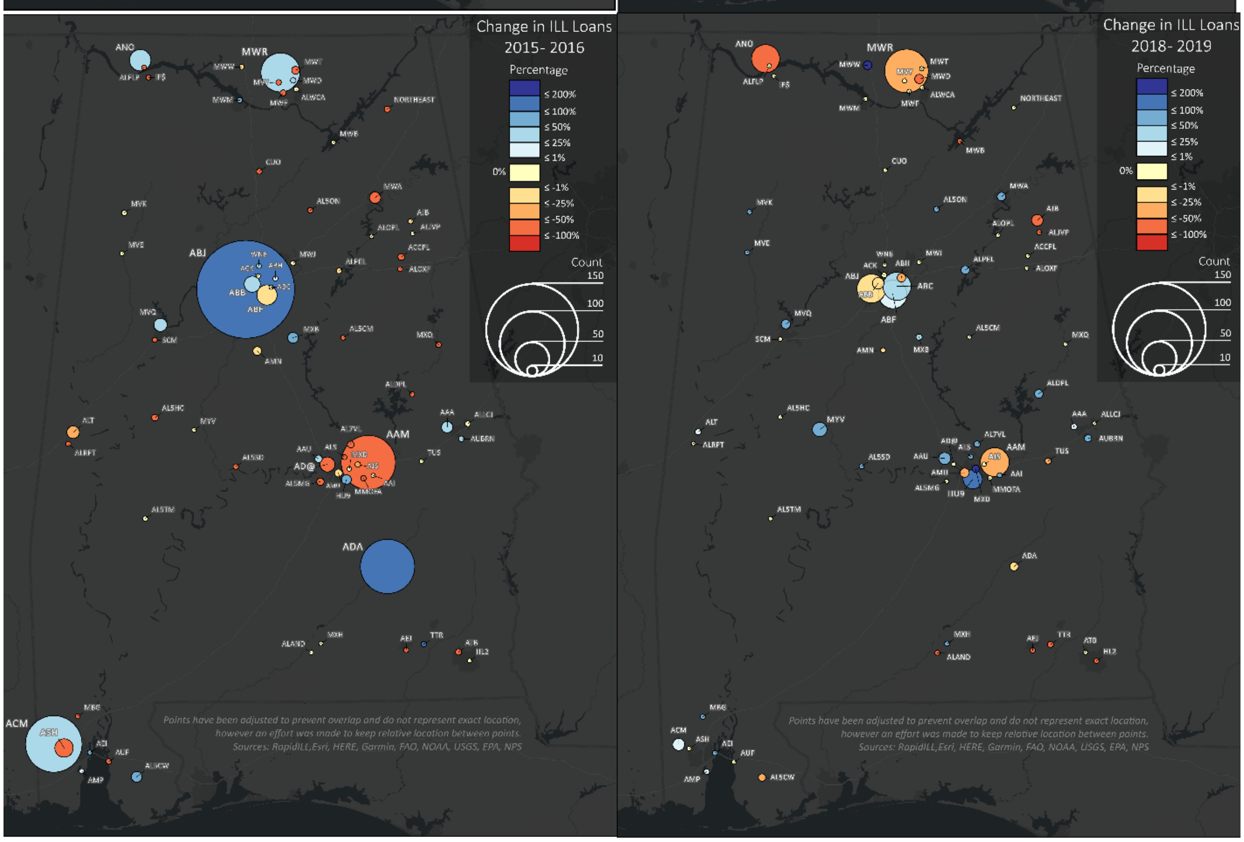
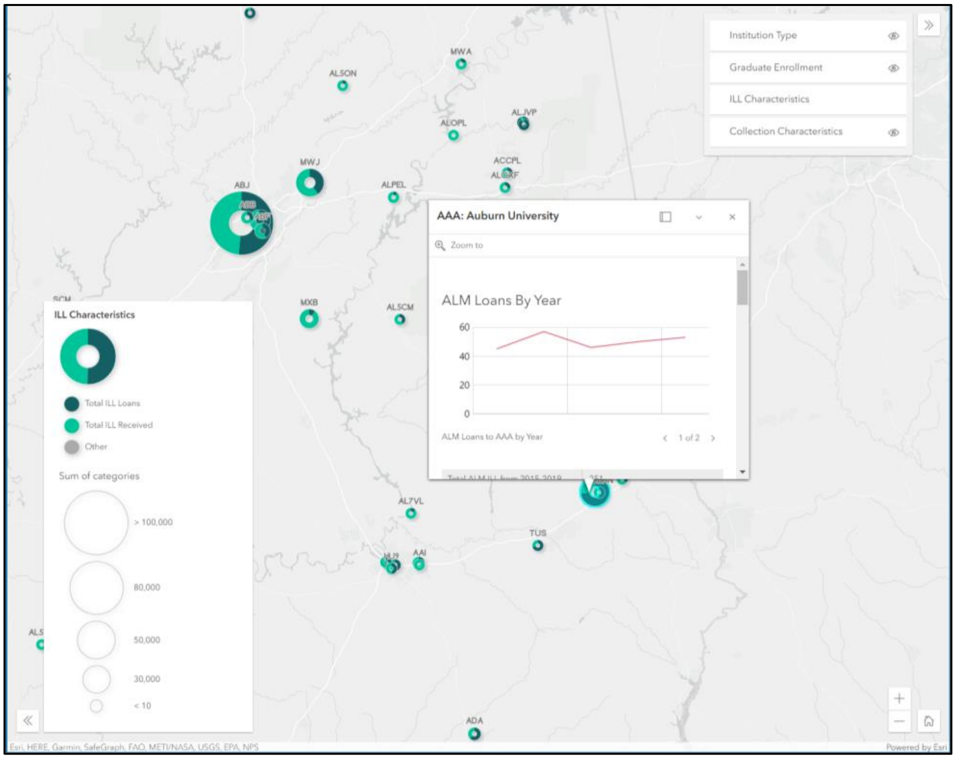


Figure 2A – The University of Alabama ILL Loans for 2015 and 2019, respectively.
Figure 2B – Change in the University of Alabama ILL Loans between 2015-2016 and 2018-2019

ALM loans, PLS, and IPEDs data were averaged over the five years. Initially, a scatterplot matrix was created in GeoDa to understand what variables may be interesting to map concerning the average loan for ALM. Variables with the highest suggested correlation were plotted on maps to investigate spatial patterns further. Additional combination statistics were plotted, such as the ratio of loaned to borrowed ILL transactions, percent of ALM loans to total received ILL loans, ILL loans per 1000 service population, etc.

Several ArcGIS Online maps (Figure 3A), dashboards (Figure 3B), and apps were created and utilized to explore possible patterns at both a state and individual scale. Pop-ups, graphs, linked views, and charts were used to display institutional-level information summarized across the five years. This allowed for a greater understanding of how one library's lending patterns fit contextually within regional and state trends.



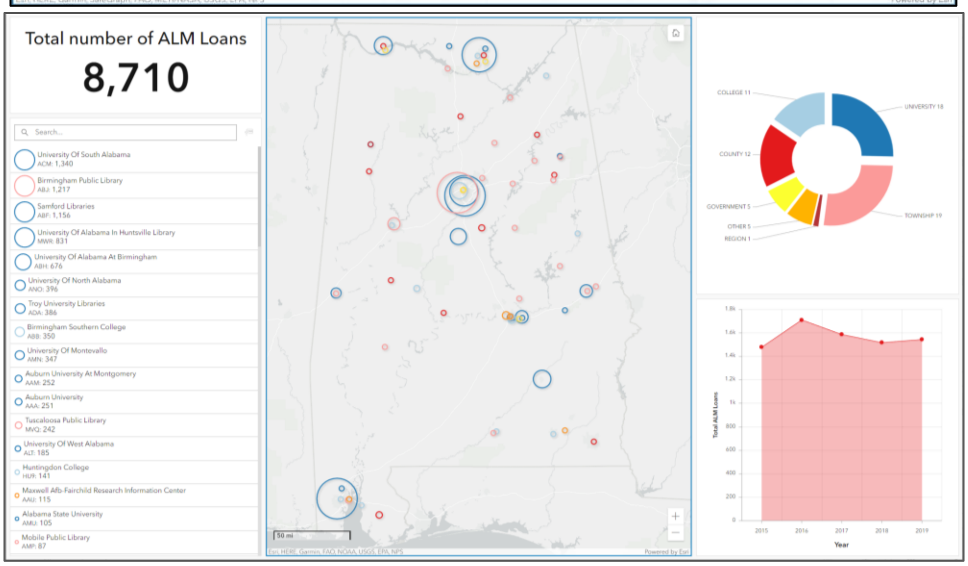


Figure 3A Screencap of an ArcGIS Online Map application shows the ratio of loaned and received ILL by institution (colors) and the number of ALM loans (size).
Figure 3B Screencap of an ArcGIS Online Dashboard allowing dynamic data interaction, including sorting by number of loans, filtering by institution type, and viewing the overall trend of loans.

Spatial Analysis

The field of geography has long tried to measure spatial patterns objectively by testing hypotheses generated through exploratory mapping. Visualization is a great way to explore data initially, but moving beyond just visual identification of spatial or data patterns is essential. Humans are prone to seeing patterns in random phenomena, so the additional step of applying spatial analysis measures can verify hypothesized patterns, highlighting the most robust patterns and finding other overlooked patterns. It is impractical to compare all elements in a dataset by hand, especially when GIS data often has hundreds of unique features. Thus, it is essential to have a systematic and automated way to highlight significant patterns and to direct researchers' efforts. This allows more time to evaluate the *practical* significance of the identified patterns.

One such spatial analysis measure used to identify clusters is spatial autocorrelation. The first law of geography states that "everything is related to everything else, but near things are more related than distant things," a phenomenon calculated as spatial autocorrelation (Tobler, 1970; Griffith, 2017). Elemental statistics assumes that all observations are independent, an assumption that is not true for most geospatial observations. Therefore, most elemental statistics may not capture the whole relationship between variables and may lead to false positives. Spatial autocorrelation attempts to measure the influence of neighboring entities on a location.

Spatial autocorrelation identifies clusters of high attribute values, clusters of low attribute values, highlights spatial outliers, and provides pseudo p-value for estimating statistical significance. Clusters of high or low values (often called "Hot spots" and "Cold spots") identify areas in which a feature is surrounded by similar values. Spatial outliers are classified as features that are surrounded by dissimilar values. With both global and localized versions of spatial autocorrelation, we can identify broader areas and individual institution patterns of ILL loans. Each feature also has a pseudo-p-value calculated to estimate the statistical significance of the outcome. A pseudo-p-value is calculated based on randomized trials used to create a probability distribution rather than using a known probability distribution. GeoDa, the software used for this analysis, uses a Monte Carlo Simulation by shuffling the neighboring features with others from the dataset and calculating spatial autocorrelation, thus simulating a random distribution. The observed spatial autocorrelation is compared to the randomized simulation to determine if they are different enough to verify that random processes do not cause the pattern.

Regarding this project, hot spots would indicate areas where our institution sends lots of returnables, and cold spots would indicate areas where we rarely send returnables. Identifying spatial outliers can help highlight institutions in a similar area but, for some reason, have a very different pattern of ILL usage. For high-value clusters and outliers, we can then investigate *why* ILL is used there more than in low-value clusters, identifying ways to provide targeted outreach to increase these areas of low usage.

Several methods to measure spatial autocorrelation offer global (summary of the entire dataset) and local (sometimes abbreviated LISA for Local Indicators of Spatial Autocorrelation) statistics. Spatial autocorrelation calculates A; a value <1 indicates a positive correlation creating hot and cold spots or that similar observations are near each other. A value of <1 indicates a negative spatial autocorrelation or that observations are near others that are dissimilar. Finally, a value of = 0 means no spatial autocorrelation or the spatial distribution of attribute values is random (Esri, n.d., A).

Global Moran’s I, local Moran’s I, and local median Moran’s I were calculated to measure our data's overall spatial patterns and localized trends. Additionally, all spatial autocorrelation methods were completed on the raw count of ALM Loans and the percent ALM Loans out of the total received. Both measures are helpful when considering ILL as the total number of ILLs sent to a location answers different questions than who gets most of their ILL materials from ALM.

Spatial autocorrelation was calculated using a univariate and bivariate local Moran's I to compare the spatial lag and ALM loans as well as ALM loans to the added PLS/IPED data. As noted earlier, due to the skew of our data, both a standard and median univariate local Moran's I were compared. Univariate median local Moran's I is more robust against neighborhood skewing to determine the impact. Choosing a model for the spatial relationships proved difficult due to the varied distribution of points across Alabama. It is recommended that each location have about eight neighbors and no points have all other points as neighbors (Esri, n.d., B).

Additionally, neighborhoods should not extend further than the conceptualized spatial relationship. The minimum distance to ensure one neighbor for each institution measured 42 miles (number of neighbors ranged from 1-16), where an estimated 25 miles (neighbors ranged from 0-9) seemed to be the natural radius of clusters. Three distances were used to determine neighbors (25 miles, 42 miles, and 50 miles), calculate spatial autocorrelation, and then compare (Figure 4).

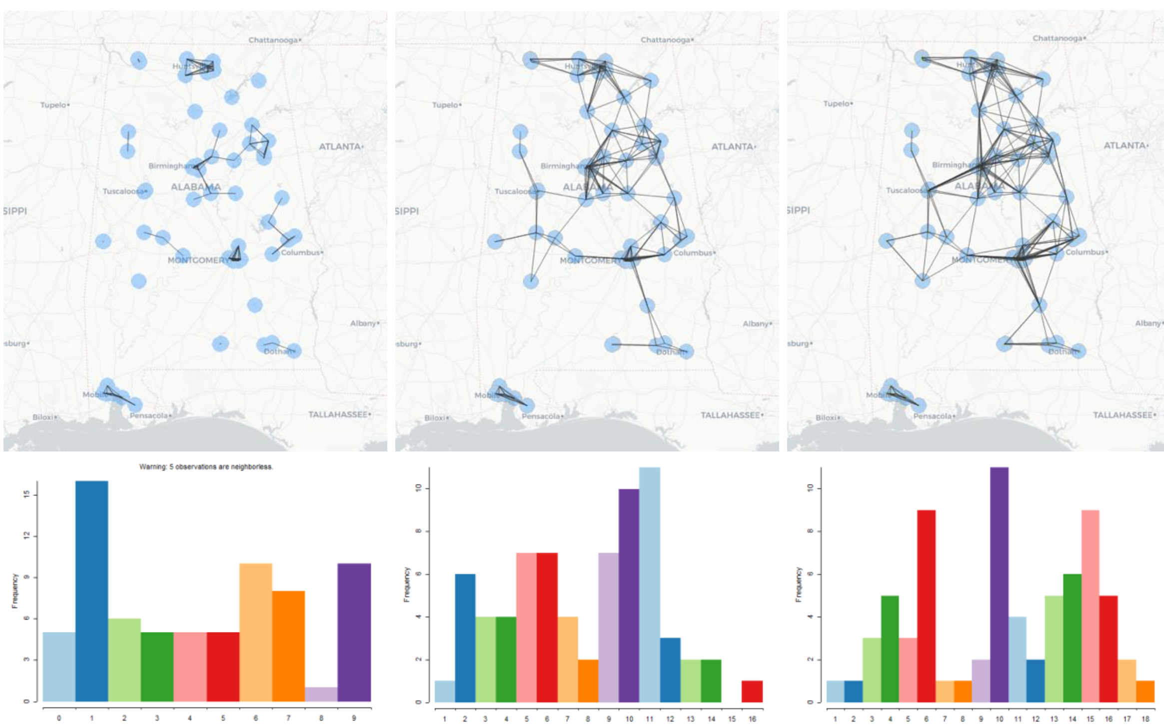


Figure 4 Maps showing neighbors to each institution at a 25, 42, and 50-mile radius and histograms of neighbors.

Although there is an extension of LISA that allows for multiple variable comparisons at a location, it was determined to be impractical to use with our data. As the name suggests, Bivariate Local Moran's I attempts to describe the relationship between a variable's value and neighboring values of another. However, the correlation between the two values at the given point is ignored. In our case, an example would be comparing the ALM loans of Birmingham Southern College with the graduate student enrollment of Samford, The University of Alabama Birmingham, the University of Montevallo, etc., without consideration of the institution's graduate student enrollment.

Findings

The dataset contained 71 institutions, over half (n = 55) with <100 ALM loans over the five years. Additionally, 25 institutions had 1 (n=14) or 2 (n=11) loans over five years. Of the remaining institutions, three exceeded 1,000 loans, two were between 500 and 999, and eleven were between 100 and 500. The three institutions with the highest total loans were the University of South Alabama (1340 loans), Birmingham Public Library (1217 loans), and Samford Libraries (1156 loans). Only 26 institutions received ILL from ALM all five years and had a relatedly large total of ALM loans.

The top 10 borrowers from ALM had varied lending patterns. The top 3 borrowers, University of South Alabama (1340 loans), Birmingham Public Library (1217 loans), and Samford Libraries (1156 loans), oscillated between years of substantial decrease and increase of up to 159 per year. Other changes of note include:

- Auburn University at Montgomery had a significant drop-off in borrowing during 2016 (ALM loans =0) and 2017 (ALM loans =14) despite the total over the five years being over 250.
- Judson College showed a substantial increase over the five years, growing from 0 ALM loans for 2015 and 2016 to 1, 30, and 47 ALM loans for 2017, 2018, and 2019, respectively.
- The University of Alabama in Huntsville Library had the largest overall decrease of 66 ALM loans from 2015 to 2019.
- Despite several large decreases, the University of South Alabama and Birmingham Public Library had an overall increase of 79 and 78 ALM loans, respectively.

Like Pearson's R, Spearman's Rho and Kendall's Tau are scaled between -1 and 1, where 1 indicates a perfect positive correlation and -1 a perfect negative correlation. Interestingly, service population and total circulation seemed to have little impact on ALM loans. In contrast, ILL Loans (rho = .75, tau =.59), ILL Received (rho=.75, tau=0.64), and size of digital, physical, and total collections (rho = 0.58, 0.60, 0.64; tau = 0.41, 0.65, 0.45 respectively) all demonstrated a strong correlation to number of ALM loans. Physical Collections, Electronic Collections, Total Collections, ILL Loans, and ILL Received were found to have moderately positive ranked spatial autocorrelation and were statistically significant for both Spearman's Rho and Kendall's Tau. Total enrollment, undergraduate enrollment, and several branch libraries remained statistically significant at lower alpha values with minor positive correlations (see Table 2). Service population, full-time research staff, total circulation, and distance to ALM were not statistically significant.

When comparing the results of the two tests, Spearman's Rho resulted in higher correlation values than Kendall's Tau. This is likely due to their differences in handling concordant values, as Rho is more resilient to ties. The variable of Graduate Student Enrollment best demonstrates this. Although Rho is over 0.67, the resulting Tau is 0.0003. Since many academic institutions have no graduate enrollment, there are many concordant values. Of the 29 academic libraries, nine were at universities with 0 graduate students, thus affecting the resulting Tau. Most of the concordant values are 0s in the dataset, so considering the practical significance of the ties in the dataset allows us to consider which statistic is more appropriate. Since it is common for institutions to have 0 graduate enrollment, Tau may be more representative of the correlation than Rho.

Variable	Spearman's Rho	Kendall's Tau
ILL Loans	0.7524 ***	0.601 ***
ILL Received	0.7426 ***	0.5971 ***
Graduate Enrollment +	0.6661 ***	0.000347***
Total Collections	0.6436 ***	0.4577 ***
FTE Library, Curators, +	0.6244***	0.4562***
Physical Collections	0.6022 ***	0.649625 ***
Electronic Collections	0.5831 ***	0.4148 ***
Total Employees	0.581***	0.4216***
Total Enrollment +	0.553 **	0.002297 **
Undergraduate Enrollment +	0.489**	0.011673 *
Number of Branches	0.3676**	0.2887**
Service Population	0.0977	0.0676
FTE Research +	-0.0907	-0.0692
Total Circulation	0.0666	0.0428
Distance to ALM	-0.0873	-0.0609

Table 2 + indicates only Academic Libraries were used in the analysis.

* Indicates level of significance, 0.1*, 0.01**, and 0.001***

Spatial Analysis

The Global version of Moran's I tries to summarize the spatial autocorrelation across the entire dataset which can lead to incorrect assumptions of the underlying local patterns (see Table 3). A value of -1 or +1 indicates that the whole dataset is positively or negatively spatially autocorrelated. However, if a dataset shows a mixture of positive and negative spatial autocorrelation, the global measure may not indicate the internal patterns. The univariate global Moran's I were low at 25, 42, and 50 miles (I = 0.08, 0.055, and 0.016) (Figure 5). Note that as we increase the distance (and therefore the number of neighbors), spatial autocorrelation decreases due to the inclusion of distant neighbors that, in theory, are less like the location. There is currently no global measure for median Moran's I available.

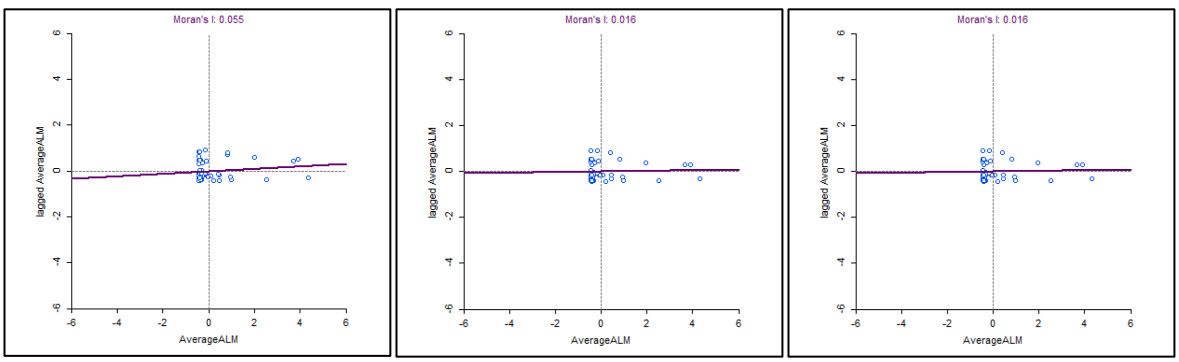


Figure 5: Global Moran's I scatterplots for neighbor distances of 25, 42, and 5 miles. Note that the Average ALM is standardized across the x-axis.

Adjacency Distance	Global Moran's I	Local Measure	Local Clusters
25 Miles	N/A	Median LISA	HH: Birmingham Southern College* LH: Rainsville Public Library, Southern Company, Birmingham Museum of Art* HL: Tuscaloosa Public Library*, University of North Alabama*
42 Miles	N/A	Median LISA	HH: Harrison Regional Library System HL: University of North Alabama*
50 Miles	N/A	Median LISA	HH: Harrison Regional Library System

			LH: Stillman College
25 Miles	0.08	Standard LISA	HH: Birmingham Southern College LH: Rainsville Public Library, Southern Company, Birmingham Museum of Art HL: Tuscaloosa Public Library*, University of North Alabama*
42 Miles	0.055	Standard LISA	LH: Harrison Regional Library System, Southern Company, Birmingham Museum of Art
50 Miles	0.016	Standard LISA	HH: Tuscaloosa Public Library LH: Stillman College, Harrison Regional Library System

Table 3: HH indicates high-value clusters (positive spatial autocorrelation)
LL indicates low-value clusters (positive spatial autocorrelation)
LH indicates low values surrounded by high values (negative spatial autocorrelation)
HL indicates high values surrounded by low values (negative spatial autocorrelation)
*Locations with p-values > 0.01, * indicates a p-value less than 0.001*

A total of 8 institutions were identified as spatial outliers, hot spots, or cold spots. General trends in the results indicate that the Birmingham area is a significant hotspot for ALM ILL loans with neighborhoods including The University of Alabama Birmingham, Birmingham Public Library, Samford Libraries, Birmingham Southern College, and University of Montevallo. Within this hotspot are several spatial outliers with low ALM ILL loans including the Birmingham Museum of Art, Southern Company, Harrison Regional Library System, and Rainsville Public Library. University of North Alabama was also identified as a high spatial outlier.

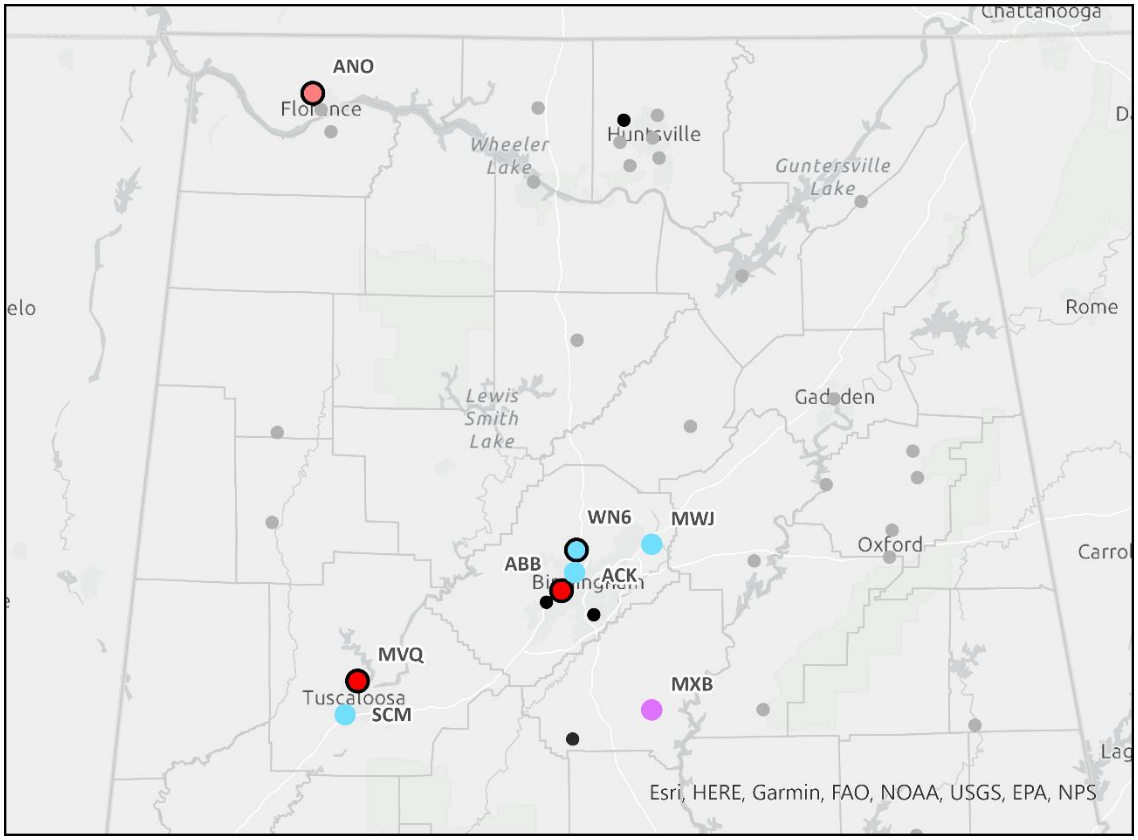


Figure 6 Map of significant clusters and spatial outliers.

When comparing median and standard LISA, several institutions were identified differently or were not significant. An interesting example is the case of Harrison Regional Library System, which was identified as both a high and low value. The mean of Harrison Regional is 75.88 average ALM loans, and the median is 39, indicating a large skew among its neighbors. The median LISA likely shows a more accurate result, labeling Harrison Regional as a hot spot around The University of Alabama at Birmingham, Birmingham Southern College, Samford Libraries, and Birmingham Public Library.

Another interesting discrepancy is with Tuscaloosa Public Library. At a 25-mile neighbor distance, Tuscaloosa Public Library was identified as a high value surrounded by low values (see Table 4). However, when using a neighboring distance of 50 miles, Tuscaloosa is identified as a part of the Birmingham area hot spot. With the smaller 25-mile neighborhood, Tuscaloosa Public

Library has only one neighbor – Stillman College – but with a 50-mile neighborhood, it is suddenly considered near most of the Birmingham area libraries with ten neighbors. This highlights the difficulty in choosing a neighboring distance as the question of "Is Tuscaloosa Near-by Birmingham?" depends on the context as it is much closer to Stillman College as they are in the same city.

Institution	**Frequency**
Birmingham Southern College	HH: 2
Rainsville Public Library	LH: 2
Southern Company	LH: 3
Birmingham Museum of Art	LH: 3
University of North Alabama	HL: 3
Tuscaloosa Public Library	HH: 1 HL: 2
Harrison Regional Library System	HH: 2 LH: 2 +
Stillman College	LH: 2

Table 4 + indicates that the identification may be impacted by neighborhood skew.

Discussion

Using GIS to explore ALM's ILL loan data both answered and created questions about how we structure and view ILL. Overall, the results indicate the complexity of how geography impacts ALM ILL patterns. At a state scale, there is a very minor impact, and both spatial and temporal data resemble random patterns. However, looking closer at an institutional or neighborhood scale shows there are underlying localized spatial patterns that are masked by a single statistic. Adding situational location data (such as information on their larger institutions) helps contextualize the trends we see spatially and leads to future work utilizing these insights.

Using these insights, institutional changes can be considered for future action. One possibility is to target outreach to public libraries, undergraduate populations, or institutions with no graduate program. Additionally, this spatial misalignment presents the opportunity to evaluate the distribution of ILL costs among institutions, such as shipping expense or reciprocal relationships, in terms of spatial location or pod association.

Are there spatial-temporal patterns across existing lending networks?

Over the five years of data, no clear overarching spatial and temporal patterns exist. A more nuanced look at ILL with data-driven web map applications can show more individualized or regional patterns. It is difficult to understand and identify patterns without interactive visualizations due to the very individualized institutions that use ILL services. Using this technology to identify local changes in borrowing behavior alongside spatial, demographic, institutional, and temporal information allows a greater understanding of our institution's ILL.

When looking at contextual characteristics in conjunction with ILL data, can they help explain these patterns?

Tuscaloosa Public Library was identified as a hotspot or high-value spatial outlier, making the significance of Stillman College as a low ALM loan spatial outlier interesting as both are in the same city as The University of Alabama. Additionally, Rainsville Public Library and Harrison Regional Library System likely identified as low spatial outliers as they are neighboring the Birmingham area but have a comparatively small service population themselves. University of Northern Alabama likely is identified as a high spatial outlier due to its relative isolation from other academic institutions and large urban areas.

Factors impacting the overall number of requested ILLs (use of the ILL system and graduate students) have a stronger suggested relationship to ALM loans. This is not surprising on further inspection, as ILL loans are placed somewhat randomly according to lending strings rather than by pairing close-by-distance institutions. Just by the likelihood of having more ILL requests, there is a greater chance of ALM filling the request. Contrary to what one might initially expect, results from our analysis indicate that direct distance from ALM has a minor impact on ILL.

What cannot be - or is not - shown on the map?

It can be challenging to distill what libraries do into a set of numbers and statistics. Through our institution's lens, it became apparent how limited a view our data provides of the larger patterns of ILL. Of the 112 public libraries in Alabama, only 22 had received at least one loan from ALM, a little under 20%. Ninety-nine of these libraries requested fewer than one book over the five years. The interconnectivity between other institutions remains a mystery and prevents further network analysis.

Limitations and Future Research

The use of GIS as a tool to better understand ILL is a relatively "green field" concept. There are ample opportunities for this academic library and others to consider conducting larger-scale projects to understand ILL service issues. The present study is certainly not comprehensive as to all the ways GIS might inform ILL activities. The choice to focus this study on lending relates to a previous study seeking an understanding of lending fill rates at this institution (Decker, 2021). A future study could consider which institutions in the state The University of Alabama Libraries borrow from to supplement its collections. Additionally, following that project and the one in this study, it would be worthwhile to conduct a research project looking at what did not get filled and why and where.

It is important to note that the dataset only contained institutions that borrowed from The University of Alabama between 2015 and 2019, not all institutions in Alabama. Our dataset accounts for approximately 12% of public libraries and 36% of academic institutions in

Alabama. Future work investigating the potential lack of ILL loans from The University of Alabama could yield additional locations of interest.

This study did not actively consider the geographic size of the service area, population density, and their impact on borrowing. It seems reasonable that the more compacted a population around a singular library, the more borrowing activities might transpire. This is especially true when considering areas within the state with larger academic institutions and new programs or smaller sections of collections that utilize ILL to bolster and support themselves.

Another future project might address the existing tenets of ILL, including reciprocal pods and distance. There is ample potential for modeling and comparing alternative lending strings and pod configurations based on geographic or social distance to optimize the time and cost of finding, filling, and shipping ILL requests. Additional inclusion of API catalogs, such as WorldCat, could also allow for dynamic lending strings based on request and location.

This study did not consider the COVID-19 pandemic and its influence on ILL lending. A future study for this academic library or another might compare pre-pandemic lending, for example, 2018-2019, and pandemic lending 2020-2021, to determine changes in lending patterns directly related to library closures, borrowing policies, and differences in re-opening dates.

Conclusion

This study represents a first foray at The University of Alabama Libraries into understanding how GIS technologies might be leveraged to identify trends related to ILL lending. It builds on the many ways that GIS has been used in academic libraries by focusing on the lending side of ILL within the state. As ILL is inherently based on geography and networks, it is a natural context for using GIS technology. Surprisingly, more literature is yet to be available on how libraries might benefit from adopting this technology to understand ILL better.

Sustainability is an increasingly important trend in academic libraries, and ILL employees' time and salaries must be considered finite resources. The information gleaned from studying ILL lending with GIS as a tool could help leverage limited resources toward their maximum impact. A user-centered approach begs for understanding lending needs and maximum efficiency in getting requested items to their desired locations in the least amount of time. In this way, information gleaned from GIS can visually and statistically inform ILL best practices.

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