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Validation of methods for adjusting construction cost estimates by project location

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VALIDATION OF METHODS FOR ADJUSTING CONSTRUCTION COST ESTIMATES BY PROJECT LOCATION

BY

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THESIS

Submitted in Partial Fulfillment of the
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ABSTRACT

Location factors are used to adjust conceptual cost estimates by project location. Presently, the construction industry has adopted a simple, proximity-based interpolation method which uses the “nearest neighbor” location factor to estimate unknown location factors. Although this approach is widely accepted, its validity has not been statistically substantiated. This study assessed the current method of adjusting conceptual cost estimates by project location. An evaluation of 14 alternative spatial estimation methods was also conducted. These methods were based on different approaches for combining 4 criteria: proximity, state boundary, home value, and income. This study used the 2006 RSMeans city cost index (CCI) dataset to conduct the evaluation. Geographic information systems (GIS) were used to visualize data and conduct spatial-statistical evaluations. The Global Moran’s I test was used to assess proximity-based spatial interpolation, which was implemented in the current method. In addition, comparisons of the current method and alternative methods were statistically assessed. The statistical analysis consisted of box plots, histograms, homogeneity of variance tests (Levene’s Statistic), and equality of sample distribution medians tests (Mann-Whitney). From interpretations of results, it was concluded that the Moran’s I test provided statistical justification for the current method. In addition, an alternative method was statistically proven to outperform the current method. This alternative method was the conditional nearest neighbor (CNN). Moreover, an additional alternative method which incorporated the ranking of proximity, median home values, and state boundaries could potentially outperform the current method as well as the CNN method. Future research is needed to fully substantiate the additional alternative method.

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CHAPTER 1.0 INTRODUCTION

1.1 Overview

Cost estimation is a fundamental practice which greatly contributes to the overall success or failure of construction projects. Cost estimates are projected regularly throughout the project lifecycle. In preliminary stages, such as pre-design and conceptual analysis, estimates help owners determine general financial feasibility including funding requirements. From the owner's perspective, these conceptual cost estimates are often used for budgeting and programming purposes and form the basis of project scope.

As there are various project stages in which cost estimates are produced, a recommend practice for their classification was established by the Association for the Advancement of Cost Engineering International (AACEI). This cost estimate classification system is summarized into a generic classification matrix, which was adapted in table 1.

Table 1. AACE Cost Estimate Classification System (adapted from Christensen & Dysert, 2003)

ESTIMATE CLASS	PROJECT DEFINITION	END USAGE	ACCURACY RANGE
CLASS 5	0% TO 2%	Screening or Feasibility	(+40% TO +200%) (-20% TO -100%)
CLASS 4	1% TO 15%	Concept Study or Feasibility	(+30% TO +120%) (-15% TO -60%)
CLASS 3	10% TO 40%	Budget, Control /Authorization	(+20% TO +60%) (-10% TO -30%)
CLASS 2	30% TO 70%	Control or Bid/Tender	(+10% TO +30%) (-5% TO -15%)
CLASS 1	50% TO 100%	Check Estimate or Bid/Tender	(+10%) (-5%)

Christensen & Dysert (2003) identified five cost estimate classes throughout the entire lifecycle of a project. Project definition was one of the most significant characteristics used to categorize the cost estimate class. Other factors included end usage and expected accuracy range. While results from this study may be applied to all classes of cost estimates, they are more beneficial to conceptual cost estimates (Class 4 and Class 5). According to the most prominent accuracy ranges in table 1, conceptual cost estimates are expected to be as much as +200% overestimated and even -100% underestimated. It can be inferred that these are highly inaccurate projections. There are many limitations that contribute to inaccuracy at this level of estimation including undefined project scope. Unfortunately, this is a problem that normally cannot be avoided. An owner may have an exact definition of project scope, but this is usually not the case, especially at the conceptual level. Typically, the owner only has a general idea of what they want to build. This affects the accuracy of conceptual costs because an estimator cannot accurately account for changes and consequent risks in an idea that has not been fully formulated. Accuracy of cost estimates is also limited by the accuracy of the adjustment methods used to develop the estimate. While there are multiple adjustments that are considered in conceptual cost estimation (date, location, complexity etc…), this research specifically evaluated the adjustment for geographic location. This is only one component of cost estimate adjustments. The research effort was to increase the potential accuracy of location adjustment, and therefore, the overall cost estimate itself. Current and alternative location adjustment methods were identified and evaluated. An alternative method was statistically proven to outperform the current method. Moreover, there is a need for future research to fully validate a combination of alternative methods that were identified in this research.

1.2 Background Information

A conceptual estimate is also referred to as a rough order of magnitude (ROM) according to Gould (2002). These estimates incorporate a gross unit cost which is adjusted for multiple project specific characteristics. Since the project characteristics are typically developed from a national average basis, they must be adjusted using corresponding adjustment factors. Gould (2002) concludes the ROM process by acknowledging that an appropriate contingency should be applied for economic or market conditions and scope adjustments. The method used for the adjustment of project specific characteristics can be considered as an input, which produces a preliminary cost estimate output. The quality of the input information vastly determines the degree of cost estimate accuracy (Christensen & Dysert, 2003). It is paramount to evaluate these project specific adjustment methods and the data used to produce them.

Cost estimation data sources can greatly influence estimate accuracy. Accordingly, consideration should be given to the reliability of the data sources. There are many data sources commercially available to the construction industry, many of which produce cost index guidelines for estimation. Researchers have indicated that estimation by cost index is a very common approach for all types of construction. In addition, a number of cost indices have been developed due to the popularity of this approach (McCabe et al., 2002). According to McCabe et al. (2002), the following are examples of cost sources available to estimators:

- Engineering News Record
- Hanscomb-Means International Construction Cost Index
- Hanscomb's Yardsticks
- Helyar Construction Cost Guide
- KPMG International Cost Comparison Analysis
- RSMeans Building Construction Cost Data
- Richardson Construction Cost Trend Reporter
- Richardson International Cost Index

This research used the *RSMeans Building Construction Cost Data* as a data source. It was assumed that the use of this source of construction information was considered a common industry practice for preliminary cost estimation.

Preliminary estimates are commonly prepared through the aid of historical cost data and have standard adjusting processes that take into account project specific characteristics such as construction date, geographical location, and project complexity. The focus of this research was on location adjustment. Location adjustment requires the use of location factors. Pietlock (2006) describes location factors as follows:

> A location factor is an instantaneous (i.e., current—has no escalation or currency exchange projection), overall total project factor for translating the total cost of the project cost elements of a defined construction project scope of work from one geographic location to another. This factor recognizes differences in productivity and costs for labor, engineered equipment, commodities, freight, duties, taxes, procurement, engineering, design, and project administration. The cost of land, scope/design differences for local conditions and codes, and differences in operating philosophies are not included in a location factor (p. 1).

Location factors are primarily used in class 4 and 5 estimates and are not intended to be used for higher quality estimates, such as class 3, 2, or 1. The RSMeans city cost index (CCI) and the Department of Defense area cost factor (ACF) index are two primary examples of location factor publications. The ACF index is primarily used for military projects, while the CCI is primarily used for commercial construction projects. RSMeans updates and publishes a CCI annually. It has demonstrated to be very useful because it provides location factor values for individual cities throughout the United States and Canada.

1.3 Research Question and Research Objectives

Cost factors distinguish a relationship between geographical locations of interest, usually represented as cities, and are used to predict cost implications. Although numerous sets of factors have been developed for many cities throughout the United States, not all cities have cost factors associated with them. With this in mind, the following primary research question for this study was established:

How should a cost estimate be adjusted for a location that does not have a location factor?

Phillip Waier, the LEED AP Principal Engineer for RSMeans, attempted to answer this primary research question. According to Waier (2006), "For a city not listed [in the RSMeans CCI], use the factor for a nearby city with similar economic characteristics" (p. 586). This mention of a "nearby city" indicated that proximity may be a key element in determining location factor interpolation. Proximity was one of the primary factors considered in this study. The mention to "similar economic characteristics" suggested the analysis of additional factors. These topics will be discussed in subsequent sections. In reference to the suggestion provided by RSMeans, it can be inferred as somewhat vague and left up to interpretation.

The most common interpretation of this suggestion is to use a simple, proximity-based interpolation method. In this study, the method was described as "nearest neighbor" interpolation and was considered the "current" method. To demonstrate the current method, it was assumed that an owner needed to build in a city which does not have a location factor. The owner's cost estimator would use the value of the nearest city with a location factor to perform the location adjustment. Although this method is commonly used, its validity has not been statistically substantiated. In answering the primary research question, the following secondary research questions were added to achieve the overall objective of improving accuracy of conceptual cost estimates:

- Can statistical analysis provide justification for the current, industry-suggested location adjustment interpolation method?
- What are possible alternatives to the current method that may potentially increase accuracy of location adjustments?
- Can these alternate methods be statistically proven to produce a more accurate estimate?

1.4 Project Justification

While this study will mostly benefit construction project owners, benefits extend to the construction industry as a whole. Recently, there has been a shortage of experienced estimators in the construction industry. The following statements are observations from Edward Walsh, Executive Director of the American Society of Professional Estimators (ASPE). These observations are based on the impact of the current shortage of estimators on his day-to-day activities. Walsh (2008) states:

> At a 2007 McGraw-Hill / ENR seminar I attended in Arlington, VA, a top shelf expert panel discussed the growing worker / management shortage in our industry, it isn't hard to see that estimators fall right into that mix. Baby boomer estimators are starting to retire and fewer candidates are there to step up into those jobs. The boomers are also taking their mentoring talents with them. With all the work there is to bid on these days, the shortage of experienced estimators seems to be having a significant impact (p. 1).

This shortage has caused a major problem in the construction industry. It ultimately forced industry stakeholders to rely on less experienced individuals for assessing critical project parameters, such as conceptual cost estimation location adjustment. Excessive error or significant miscalculations in these requirements could be detrimental to a project. From an owner's point of view, excessive error producing underestimated project costs may cause the owner to (1) search for additional sources of funding, (2) terminate the project in its entirety, or (3) reduce project scope to compensate for understated costs. All of these outcomes have serious detrimental implications. Similarly, while an overestimate is more favorable than its counterpart, it creates inefficiency of budget allocation, especially in a program where multiple construction projects are built simultaneously. If unnecessary funding is allocated to a certain project, this restricts budgeting for other projects that would otherwise be available. Inefficiency caused by overestimation is prevalent even for a single construction project. As an example, an owner may realize (during the construction phase) that higher quality building materials could have been used instead of lower quality building materials. Since the installation of lower quality materials has already been completed, it will cost additional time, money, and effort to compensate for removal and reinstallation. This inefficiency could have been avoided in the first place if projected costs were accurate. This demonstrates why the estimator's calculations of cost estimates and therefore, justification of the methods used to create them, are particularly important.

Furthermore, location adjustment research can be applied to other industries outside the realm of construction. For example, it can be useful to the human resource discipline to predict expected cost of living and compute salary equivalents for employee relocation situations. It can also be used in market analysis studies to evaluate higher verses lower costly areas to live. The results and implications of this research can benefit any industry in which location adjustment factors are necessary to formulate a projected cost.

1.5 Scope Limitations

Data from actual construction projects were not used in this study. This research used the 2006 RSMeans CCI dataset to compare location adjustment methods for conceptual cost estimates. The nearest neighbor interpolation method was evaluated as the current method. It was initially compared with state boundary and state average methods. Eventually, a comparison of 14 alternative spatial estimation methods was conducted. These methods were based on different approaches for combining 4 criteria: proximity, state boundary, home value, and income. Ultimately, a total of 15 different methods, including current and alternative methods, were statistically evaluated. Geographic information systems (GIS) were used to visualize data and conduct spatial-statistic evaluations. In addition, statistical analysis consisted of the following: box plots, histograms, tests for equality of variance (Levene's statistic), and tests for sample distribution medians (Mann Whitney). Although closely related, the following were not evaluated in this study:

- Time adjustment methods
- Scope adjustment methods
- Surface-based spatial prediction techniques

These may provide future exploratory topics of interest in construction cost management.

CHAPTER 2.0 REVIEW OF RELATED LITERATURE

2.1 Overview

The search for previous contributions on this topic found only few scholarly articles and most articles were not totally related to this research. Therefore, this study was considered as an exploratory investigation in the field of construction cost estimation. Research included the use of Geographic Information Systems (GIS) as a tool for visualizing and conducting spatial-statistic analysis of construction costs. More specifically, it included location adjustment method accuracy. It is important to broaden this distinctive topic to get a better understanding of pertinent literature. This chapter will discuss literature on the following topics, which are related to the research at hand:

- Cost Estimation
- Location Adjustment
- Geographic Information Systems

2.2 Cost Estimation

One of the most important factors of cost estimation is the actual person responsible for creating the estimate. According to Popescu et al. (2003), a good estimator should have a combination of knowledge, managerial talents, and construction experience. In addition, Popescu et al. (2003) describe skills of good estimator in the following:

- Ability to read and understand contract documents, with special skills in reading construction drawings for all specialties and related specifications

- Ability to accurately take off the quantities of construction work for which he or she is preparing the detail estimate

- Ability to visualize the future building from drawings, which usually requires some years of construction site experience

- Knowledge of arithmetic, basic geometry, and statistics

- Familiarity with estimation software in depth and with available building cost databases

- Knowledge of building construction methods

- Knowledge of labor productivity, crew composition, and impacts of various forecasted site conditions on crew output

- Possession of office managerial skills in organizing project related cost information

- Ability to work under pressure and meet all bid requirements and deadlines (p.47)

In this list, a familiarity with available building cost databases was mentioned. This could very well be one of the most important characteristics of a good cost estimator. Cost databases can be internal or external sources of information. Examples include internal company records and external published information. The research conducted in this thesis implemented the RSMeans city cost index as an external database source. Along with the estimator's familiarity with cost databases, another important characteristic of cost estimation is the actual methods used by the estimator in creating a cost estimate.

According to the editor for *Walkers Building Estimators Reference Book*, there are many different estimation methods (Ratner, 2002). The editor also proposed that if 20 different estimators were told to prepare a cost estimate, all using the same set of plans, not more than two resulting estimates would be prepared using the same basis. It is safe to say that cost estimation is a very subjective process, especially in preliminary stages when the project is not fully defined. This subjectivity can lead to inaccurate predictions of construction costs.

In this research, improving cost estimation accuracy and thus, meeting various cost estimation needs in relation to the project owner, was discussed. Carr (1989) mentioned that a cost estimate must be an accurate reflection of reality. This accurate reflection of reality is what cost estimators try to predict. The more detail included in the estimate, the more accurate the estimate should become. On the other hand, it can be very expensive for the owner to develop cost estimates, especially as the level of detail increases. This is primarily due to the time and effort required to produce detailed estimates. According to Carr (1989), the level of detail is based on two criteria: (1) whether a particular level of uncertainty is acceptable, and (2) if it is reasonably uniform for all components of the estimate. Owners should develop estimates with the appropriate level of detail relevant to each project stage.

In preliminary stages, the project is not completely defined. Most owners implement rapid cost estimation methods, which usually results in less accuracy in regards to total project costs. This lack of accuracy is carried over from preliminary estimates to sequential stages. If accuracy can be increased in preliminary stages, this should also increase in all sequential stages. Accuracy is directly affected by cost estimation methods. There are many kinds of cost estimation methods which can be implemented in construction costing. This chapter will discuss the various estimation methods published by researchers and how they are related to the research in this study. While not all methods apply specifically to conceptual cost estimation methods, they do all apply to construction or a related field of study.

Duverlie and Castelain (1999) studied the parametric method and the case based reasoning (CBR) method of cost estimation. They pointed out that the parametric method has the advantage of being made easily available within a project. Its major disadvantage is that it functions as a “black box” that does not allow users to verify the results or to ensure that they are not looking at a particular case. On the contrary, the CBR method has the capacity to accept unknown information and process particular cases, which makes it very useful for the designer. In a general manner, this allows for more precise results to be obtained than with the parametric method. However, its application in a project is more difficult because it requires a complete reasoning system based on individual projects. While Duverlie and Castelain’s research involved specific cost estimation methods, they were only applied during the design phase. In this aspect, their research differs from this study because estimation methods at the conceptual level (before the design phase) were not considered. Duverlie and Castelain (1999) mention and describe different cost evaluation methods in the following:

- *The intuitive method* is based on the experience of the estimator. The result is always dependent on the estimator's knowledge.

- *The analogical method* attempts to evaluate the cost of a set or a system from similar sets or systems.

- *The parametric method* seeks to evaluate the costs of a product from parameters characterizing the product but without describing it completely.

- *The analytical method* allows evaluation of the cost of a product from a decomposition of the work required into elementary tasks (p. 1).

In this research, cost estimation methods are discussed in relation to the experience of the estimator. This can be considered an intuitive method, as mentioned by Duverlie and Castelain. The current shortage of professional estimators in the construction industry (depicted by Edward Walsh in section 1.4 of this thesis) is forcing the construction industry to rely on a less experienced population of estimators. Therefore, it can be inferred that the intuitive method, which relies on the expert judgment of experienced estimators, is in jeopardy. The research effort of this study attempted to relieve this problem by determining a location adjustment method which is statistically proven. Findings from this study are expected to help inexperienced estimators who cannot rely on the intuitive approach for adjusting costs by location.

Continuing with cost estimation research methods, Kim et al. (2004) compared the accuracy of three cost estimating techniques including the following:

- Multiple Regression Analysis (MRA)
- Neural Networks (N-Net)
- Case-Based Reasoning (CBR)

Their research included data from 530 residential buildings projects built in 1997 in Seoul, Korea. MRA is an explanation of phenomena and prediction of future events. According to Kim et al. (2004), MRA uses a set of predictor variables $X_1, X_2, \ldots, X_n$ to explain variability of the criterion variable Y. N-Net is a computer system that simulates the learning process of the human brain. N-Nets are widely applied in many industrial areas, including construction. The last alternative, CBR, relies on rule-based reasoning and is based on experience or memory. While the cost estimation methods evaluated by Kim et al. (2004) were not specifically related to the research conducted in this study, the performance measurements used were specifically related. Kim et al. (2004) measured performance of their cost estimation techniques by respective variance and mean absolute error. These concepts were used in this study. In addition, this study also considered median, and standard deviation of error as a performance measurement of estimation methods.

In order to improve future cost estimation methods, the shortcomings of current estimation methods need to be considered. Intense competition and the demand for shorter completion times and lower costs have been driving innovative approaches within the construction industry. When considering the factors that contribute to project success in the construction industry today, it is clear that cost is as crucial as quality and functionality (Layer et al, 2002). Layer et al. researched three types of cost estimation methods including the following:

- statistical model
- analogous model
- generative-analytical model

According to Layer et al (2002), the shortcomings of these estimation methods include the following:

- There is a lack in accuracy. None of the methods mentioned is able to determine the costs with the required accuracy.
- The integration of cost calculation in the product development process and the possibility of design concurrent use are not solved satisfactorily.
- Thus far, the product development process is only partially supported. Existing methods cover only parts of the process, interrupting the cost calculation workflow.
- The increasing level of maturity during product development is not sufficiently considered. Not all the processes needed are taken into account, so that the costs calculated end up too low.
- Cost estimation using statistical and analogous models can be carried out only on the basis of historic data. Innovative technologies or new resources cannot be added.
- In rule-based systems, the acquisition and the maintenance of knowledge are difficult. The experience and the knowledge provided by experts do not carry enough weight (p. 507).

Accuracy is a key component in the shortcomings of cost estimate methods. If a new method can be introduced that can be statistically proven to increase accuracy, this will be a great contribution to construction cost estimation. This is one of the main research objectives within this study.

2.3 Location Adjustment

Cost estimate adjustments are performed during preliminary stages of a project. Adjustments are made for project specific characteristics such as project date, size, location, and complexity. Project costs can be adjusted based on the unit area, unit volume of a building, or occupancy units (number of parking spaces, number of beds, square footage, etc…). Popescu et al. (2003) describe a common procedure of applying cost estimate adjustments in the following:

- Determine the usable area of the building, volume, or number of occupant units.
- Select from the most recently published standards for the type of building that most closely matches the project, the unit area, unit volume, or occupancy unit standard cost.
- Adjust selected standard costs to a projects location using regional adjustment factors (p. 59).

Included in this procedure is project location adjustment. Location adjustments are performed using regional adjustment factors. The RSMeans city cost index (CCI) is an example of a published source of regional adjustment factors. The Area Cost Factor (ACF) index is another example. The RSMeans regional adjustment factors were an important component of this research. It provided the necessary data required to perform the different location adjustment methods evaluated in this research. This will be discussed in the methodology section of this study.

The United States of America Department of Defense created a unified facilities criteria design guide for location adjustment using location factors. The unified facilities represent the following organizations:

- U.S. Army Corps of Engineers
- U.S. Naval Engineers Facilities command
- U.S. Air Force Civil Engineer Center

The design guide makes reference to the ACF index. The United States of America Department of Defense (2005) states the following:

> The ACF index is used in adjusting estimated costs to a specific geographical area. The factors reflect the average surveyed difference for each location in direct costs between that location and the national average location.

In addition, the Air Force Civil Engineering Support Agency (2005) describes ACF considerations in the Historical Air Force Construction Cost Handbook:

> Location Factors or Area Cost Factors (ACF) are used by all DoD services to adjust average historical facility cost to a specific project location. This allows increased accuracy in identifying project costs during initial project submissions or when specific design information is not available. The area cost factor index takes into consideration the cost of construction material, labor and equipment, and other factors such as weather, climate, seismic conditions, mobilization, overhead and profit, labor availability, and labor productivity for each area (p. 73).

It is interesting that broad factors such as weather, climate, and labor productivity are reflected in the ACF index. The RSMeans CCI, which was used in this study, did not consider these items. The CCI reflects construction costs for material, labor and equipment only. A possible future topic may be to incorporate the same location adjustment methods evaluated in this research using the ACF index location factors.

Popescu et al. (2003) acknowledges location factors among several difficulties that may be encountered when creating a conceptual cost estimate:

- Published cost standards seldom represent 100% of the project under consideration.
- The location factor of adjusting a city or community is not accounted for in the published standard.
- The time factor involved in extrapolating future construction cost variations may differ (p. 59).

Research within this study focused on the location adjustment component of cost estimation. As mentioned, one of the problems that may be encountered in conceptual cost estimation location adjustment is that not all cities or communities are accounted for in published standard information. This contributes to the primary research question considered: How should an estimator adjust cost estimates for locations that do not have location factors? As mentioned before, minimal research has been conducted on this specific topic. Therefore, the remainder of this literature review section will discuss research related to location adjustment.

Johannes et al. (1985) introduced the concept of an "area cost factor" as an input decision for construction expansion. This cost factor can be described by the construction cost in new areas relative to the cost in another area. The primary purpose of this article was to explore how the economic theory of cost functions can be used to construct theoretically sound area cost factors. There are three major sections followed by conclusions that summed up the authors' findings.

The first section described the economic theory of cost functions and regional cost differentials. It considered the duality principle in economics and production technology, such as square footage. It claimed that by knowing the prices of inputs and the level of output, it was possible to derive the minimum cost of producing any amount of output, also known as a "cost function." Once a cost function has been developed, different regions can be compared using a cost factoring method to determine exactly what the regional cost differences are. An important assumption of the cost function is the functional form of the production technology. The article introduced and explained several popular production functions used in economics and engineering literature, including the Cobb-Douglass function. A useful application of the Cobb-Douglass function was that it allowed regional differentials to break down into regional factors. The regional cost factor depended on the level of output and factor prices across regions. According to Johannes et al. (1985), the area factor was dependent on the following: the relative price of labor across regions, the relative price of material across regions, and the amount of construction activity across regions.

The second section focused on the estimation of cost differences. The purpose of the section was to describe how this estimation was accomplished for a sample of US military construction projects. Data such as new housing units and the number of general contractors were collected. The article generalized the ordinary least squares (OLS) technique to produce cost function estimates.

According to Salvatore & Reagle (2002), OLS is a simple regression analysis technique for determining the "best" line of fit. Salvatore and Reagle also describe regression analysis as a tool for testing hypothesis and for prediction (2002). Regression analysis, including OLS may be beneficial in future research related to this thesis topic.

The third section of the research conducted by Johannes et al. explained the regional cost factors determined for the years 1975-1978 using individual cost factors for particular locations. The area cost factors were presented for each city for which a set of wage data and material price data was available or could be constructed. A standardized city and state cost index was constructed using this data. The article explained the steps taken for adjustment, which basically takes inputs and multiplies them by the cost factor for the closest city to derive the adjusted cost factor specific to the project under consideration. Differential changes in input factor prices were considered by adjusting for the rate of inflation.

Finally, the conclusion restated the goal of the study which was to employ economic theory of production and costs to generate construction project estimates which vary by project region. Under the Cobb-Douglass production technology, the regional cost factors are averages of the various input prices. Cost factors were computed for particular cities based on available data from 1975-1978. In general, assuming area factor price, inflation can be used to determine future cost factors. Furthermore, given the estimated function available in this study, it is possible to construct an area cost factor for a particular construction project assuming information about local factor prices and conditions are known. While the research conducted by Johannes et al. (1985) did not specifically pertain to this thesis study, it was interesting that ACF were determined. It is important to understand that this study does not evaluate how the RSMeans location factors were determined. These factors were simply used as a dataset to evaluate location adjustment methods. This concept will be explained in the methodology section of this research.

2.4 Geographic Information Systems

In all sciences there is an underlying aspiration to understand how the physical world works. Geographic information science is a discipline in which people try to understand how the world works by evaluating and describing human relationships with the Earth (Poku & Arditi, 2006). Basically, it explores the relationship between man and our physical environments. In relation to this science, geographic information systems (GIS) were created as tools to visualize and analyze these spatial relationships. GIS tools incorporate database files with geographically referenced thematic data, meaning a file can contain a geographic location as well as specific themes or attributes that pertain to the location. This is important because it allows us to quantitatively locate important features as well as the attributes of these features, which is a powerful analysis tool. GIS tools have been around since the early 1980's and were one of the fastest growing computer-based technologies of the 1990's (Bolstad, 2005). GIS have advanced technologically, and have been used in a multitude of industries as analytical, managerial, and visualization tools. For the purpose of this research, GIS tools were utilized for these exact characteristics. GIS were used to visualize the spatial relationships between US cities with RSMeans CCI location factors. In addition, statistical testing within GIS was used to test autocorrelation between proximity of cities and CCI values. This chapter will discuss literature on related research involving GIS.

GIS have been successfully implemented in various fields, including construction-related fields. Ashur and Crockett (1997) pointed out that GIS can be used to analyze cost data and improve cost estimation through the power of geographic management. A fundamental concept of GIS is the ability to integrate geographic systems and database spreadsheet information systems. Using GIS, information such as unit price data could be retrieved and displayed for each geographic point. Typically, state highway departments estimate construction project costs based on historical bid data. With the aid of GIS, a systematic information collection, organization, and storage process can be used so that relevant historical cost data can be retrieved. Traditional data collection and storage methods have been done for years, but because of the amount of time required to page through and assimilate compiled data, the process is not ideal. However, data collection and storage would be greatly simplified if one could visualize the data graphically. Using such technology would assist in easing the ever-increasing demand to analyze information to support more effective decision making.

While GIS has been more established in several aspects of construction project controls including scheduling, planning, and even material procurement, its contribution to cost estimation, especially at a conceptual level, has been minimal. Cheng & O'Connor (1996) evaluated the use of GIS for enhanced construction site layout. Similarly, Cheng & Yang (2001) studied GIS-based cost estimates integrated with material layout planning. Zhong et al. (2004) studied GIS-based visual simulation methodologies and their applications in concrete dam construction processes. Oloufa et al. (1994) integrated GIS for construction site investigation. Li et al. (2003) proposed an internet-based geographical information system for E-commerce applications in construction material procurement. Even with all these examples, the full potential of GIS in the construction industry has not been realized (Jeljeli et al., 1993). In addition, researchers have indicated that despite widespread application of GIS in the construction industry, project visualization involving GIS has not yet been used to its full potential (Bansal & Pal, 2007).

Bansal & Pal (2007) researched the effect of using the GIS environment for building cost estimation and visualization. They proposed a 5-step procedure for quantity takeoff cost estimation. In step 1, a single architectural drawing is divided into different themes. These themes act as the basis of the GIS-based cost estimate. In step 2, computer aided design (CAD) drawing files are converted into shape files and formatted for ArcMAP GIS software. In step 3, boundaries between adjacent polygons are dissolved. In step 4, attributes needed in quantity takeoff, such as shape, perimeter, area, height, length, and units are entered manually into the attributes table as new fields. Lastly, a new table is created as the bill of quantity (BOQ). The BOQ will have 8 fields that represent the attributes of each data theme. This process is used to create a quantity take off cost estimate. Although Bansal & Pal's research focused on how to create GIS-aided quantity take off cost estimates, which is unrelated to conceptual estimates, it is an example of how GIS have been used in construction cost estimation. This study involved conceptual cost estimation methods.

As technology is evolving, computer and information technology are developing rapidly. Yu et al. (1999) agree that the evolution of information technology and computing for architecture, engineering, construction, and facilities management fields (AEC/FM) will inevitably lead towards tools that collaborate through shared collections of information about AEC/FM projects. Past cost information is extremely important for cost estimating. It is very important that a system to collect and share cost information be developed. Industry Foundation Classes (IFCs) developed by the International Alliance for Interoperability (IAI) are general models of a building project that support project information sharing and exchange among different types of computer applications used in the project. Yu et al. (1999) agree that most Building Information Modeling (BIM) packages rely on IFC to improve data interoperability and the main focus has been on representing work plans, resources, and cost / schedule information. As cost information is included in this list, this suggests that cost estimation will eventually be improved by using some type of information technology. Since GIS is a form of information technology, it may potentially be the computer application that will lead to evolution in construction cost estimation.

GIS was utilized in this study mainly through its functionality of spatial estimation methods. Spatial estimation incorporates interpolation and prediction techniques. Interpolation and prediction techniques allow us to estimate variables at locations where they have not been measured. According to Bolstad (2005), spatial prediction differs from spatial interpolation because it uses a statistical fitting process. Spatial prediction uses rules and equations whereas interpolation only uses a set algorithm. Bolstad (2005) admits, “Our distinction between spatial prediction and interpolation is artificial, but it is useful in organizing our discussion, and highlights an important distinction between our data-driven models and our fixed interpolation methods" (p. 409). Due to the ambiguous distinctions between the two techniques, in this thesis there was no distinction between interpolation and prediction. Instead, the two terms were used interchangeably, both referring to spatial estimation.

Bolstad (2005) reveals that there are many spatial estimation methods, but the following are the most common:

- Thiessen (Nearest Neighbor) Polygon
- Local Averaging (Fixed Radius)
- Inverse Distance Weighted
- Trend Surface
- Kriging (p. 428)

Each respective method has inherent advantages and disadvantages and no method has been proven to continually outperform all others. This study utilized the nearest neighbor spatial estimation method as well as a similar version of the local averaging method. Bolstad (2005) conceptually defines nearest neighbor as the simplest method, in the sense that the mathematical function used is simply equality function and the nearest point is used to assign a value to an unknown location. In addition, local averaging may be viewed as slightly more complex than nearest neighbor but less complex than most other spatial estimation methods. In other words, local averaging may be considered a less complex method. According to Bolstad (2005), in local averaging cell values are defined based on the average of nearby samples. The number of samples depends on what search radius value is defined. In this study, a traditional search radius value was not defined. Instead, the state boundary was used to define the spatial extents of the search. To demonstrate this concept, all values within a state were averaged to estimate a collective value used for every potential project location within the state.

This study incorporated spatial auto-correlation measured within GIS. Bolstad (2005) concludes that spatial auto-correlation is the tendency of nearby objects to vary in concert, meaning high values are found near high values, and low values are found near low values. If auto-correlation between variables that affect location adjustment accuracy is studied, this knowledge can be incorporated into the estimation process. With this in mind, there is potential to greatly increase the chance of improving cost estimation accuracy.

CHAPTER 3.0 RESEARCH METHODOLOGY

3.1 Overview

The specific focus of this research was to assess and compare location adjustment spatial interpolation methods. It did not pertain to any other adjustment parameters affecting cost estimate accuracy such as project scope, size, date, or complexity. In addition, there was no data collected from actual construction projects. An overview of the research design framework implemented in this study can be explained using the flowchart in figure 1.

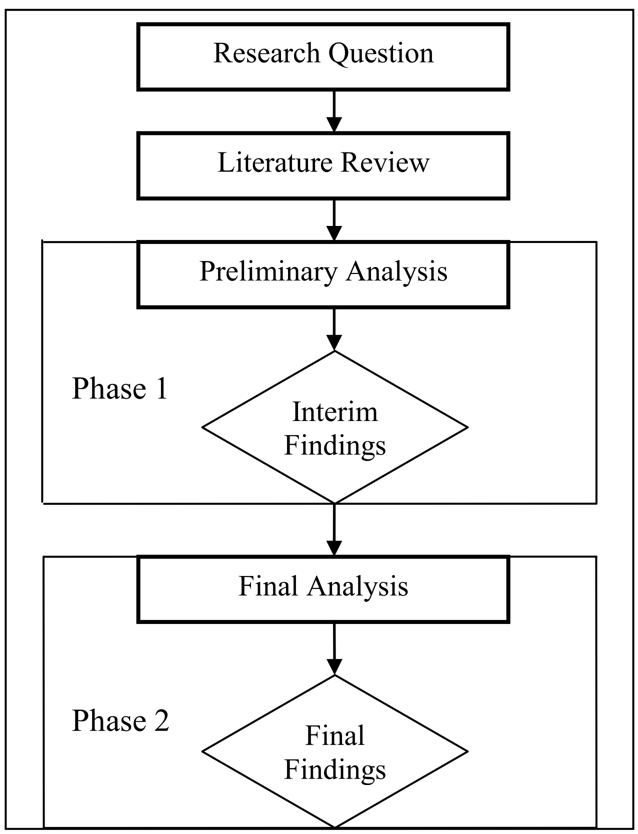


Figure 1. Flowchart of Research Steps

The first step was the research question. The following concepts were included in this step: frame research design, set project objectives, and identify scope limitations. These concepts were explained in chapter 1. The next research step was to conduct a literature review. The literature review was chapter 2 of this study. In regards to subsequent research steps shown in figure 1, there were two phases incorporated in this study. Phase 1 consisted of an exploratory study of initial methods in which a preliminary analysis was conducted, and interim findings were produced. Phase 2 consisted of an empirical study in which a final analysis was conducted, and final findings were produced. In phase 1, three initial location adjustment methods were evaluated. These initial methods included the following:

- Nearest Neighbor (NN)
- Conditional Nearest Neighbor (CNN)
- State Average (ST AVG)

For this study, NN was described as the "current" interpolation method. In addition, CNN and ST AVG were described as "alternative" methods. A comprehensive description of these methods will be discussed in chapter 5. An evaluation of current and alternative location adjustment interpolation methods were compared by the following techniques:

- Global Moran’s I Test Statistic
- Evaluation of NN Error as a Function of Distance
- Comparison of Overestimates and Underestimates
- Best Performance Comparison
- Comparison of Error Percentages
- Descriptive Statistics
- Histograms

Initial findings from these techniques were interpreted. As part of the findings, it was decided that the research design should be expanded. During phase 1 of this study, there were only three initial location adjustment interpolation methods evaluated. These methods were limited by the following criteria: proximity, and state boundaries. As part of phase 1 results, it was determined that additional location adjustment interpolation methods, involving socio-economic factors should be added to this study. Correspondingly, a Pearson’s correlation study involving various economic factors and the RSMeans CCI was conducted. From the Pearson correlation study findings, it was determined that two economic factors should be added to interpolation method criteria. This created the following list of criteria:

- Proximity
- State Average / State Boundaries
- Median Home Value
- Median Household Income

Additional alternative methods were developed using various combinations of these criteria. Ultimately, 15 different location adjustment methods (including the 3 initial methods from phase 1) were identified and described in this study.

In phase 2, an empirical comparison of all 15 location adjustment methods was conducted. Methods were classified by the number of criteria they considered. Single criterion and multiple criteria methods were identified. As these methods became more complex (combinations of three and four criteria), a ranking procedure was implemented. The ranking procedure was inspired by the Wilcoxon signed-rank test. Due to the complexity of the ranking procedure, parameters of this study were re-adjusted in order to meet research deadlines. This re-adjustment included decreasing the RSMeans CCI population sample size. Therefore, 2 different population sample sizes were considered. This included national-level, and regional-level samples. This topic will be thoroughly discussed in subsequent sections.

Descriptive and inferential statistical evaluations were also performed in phase 2 of this study. This included the following techniques:

- Comparisons of mean, median, standard deviation, and variance of error
- Histograms
- Box Plots
- Levene's Tests
- Mann-Whitney Tests

With this in mind, the remainder of this chapter will focus on the methods used to assess and compare the various cost estimate location adjustment interpolation methods evaluated in this study.

3.2 Performance Measurement: Error

This section will discuss how the performance of each interpolation method evaluated in this study was measured. Performance measurement took the form of an "error" value. According to Taylor (1997):

> All measurements, however careful and scientific, are subject to some uncertainties. Error analysis is the study and evaluation of these uncertainties, its two main functions being to allow the scientist to estimate how large his uncertainties are, and to help him to reduce them when necessary. The analysis of uncertainties, or "errors," is a vital part of any scientific experiment (p. xv).

While error analysis is an important research component, there are many methods of calculating error.

As mentioned earlier, the 2006 RSMeans CCI dataset was used in this research. From this dataset, a total of 649 cities were referenced as points on a map using ArcMap GIS software. The actual CCI location factor values pertaining to each city from the RSMeans dataset were added as attributes and spatially associated with each corresponding city. The cities were then exported as a new data layer and a map layout was created which displayed the United States and the cities with an RSMeans CCI value. This map is shown in figure 2.

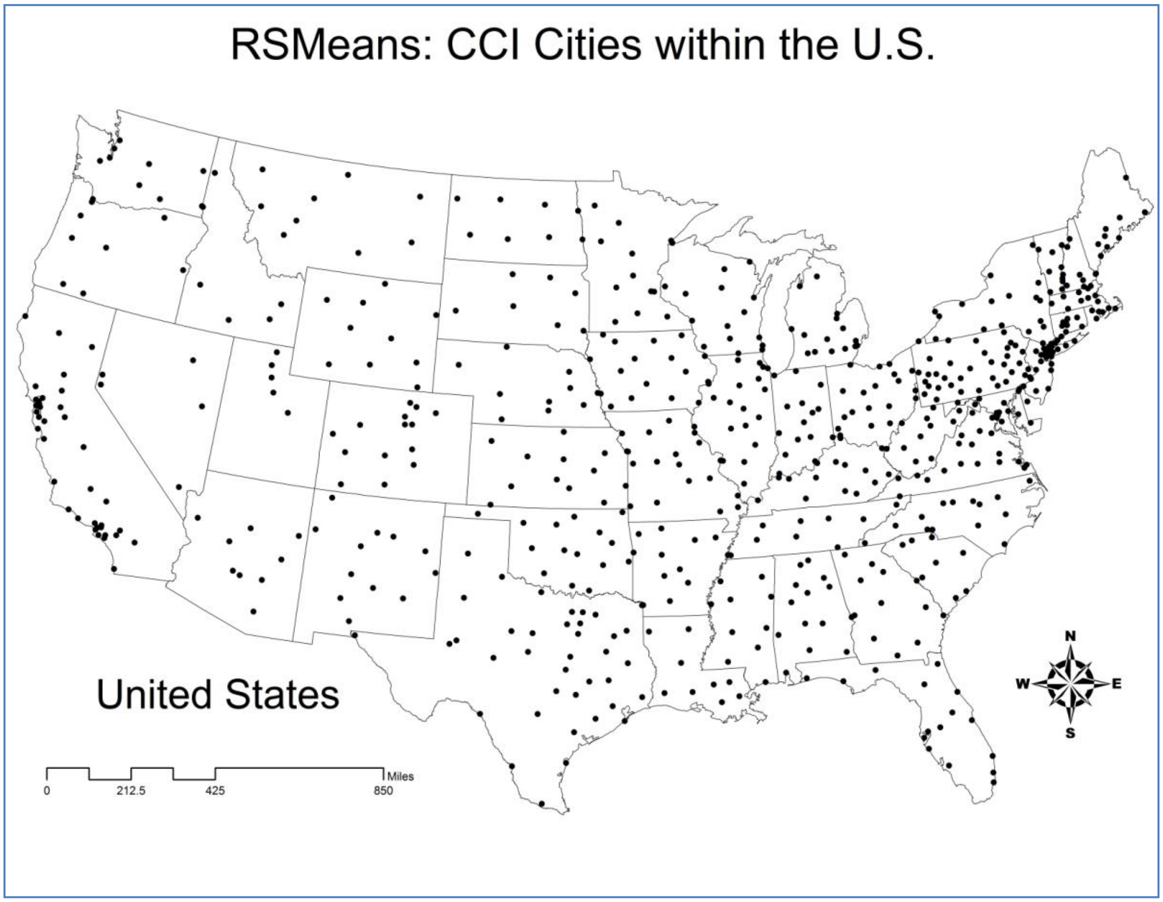


Figure 2. GIS Map of RSMeans CCI Cities

This map will be used to visualize how performance was measured for all location adjustment interpolation methods. Since the RSMeans CCI dataset was considered a reliable source and was readily available, it was used to conduct an internal validation to test if proximity-based spatial interpolation was a valid approach in relation to the primary research question discussed in section 1.3 of this study. An example of external validation would be to test the same spatial interpolation methods evaluated in this study using actual, “real life” project cost data. The implementation of actual project cost data could be the next step to this research and will be discussed in later chapters.

For each location adjustment method, a “twin location” was selected to represent each city within the RSMeans dataset. It is important to understand what is meant by twin location. This twin location (or twin) is the ideal alternative to an actual city. It varies depending on which interpolation method was considered. The CCI value for the twin city is what would be used if the original city did not have a CCI value. The method of selecting the twin location is what differentiates each interpolation method. The CCI value of the twin location was used as an estimated CCI value pertaining to each RSMeans city. Since each city has an actual known CCI value, the difference between estimated and actual values is what distinguishes the performance of the methods. This calculation produces an “error” between estimated and actual values. The following general remarks are from Ito (1987) in regards to error analysis:

> The data obtained by observations or measurements in astronomy …. and other sciences do not usually give exact values of the quantities in question. The error is the difference between the approximation and the exact value (p. 547).

It was inferred that this calculation of error was a common practice in many scientific research studies. In this study, error took the form of an overestimate or an underestimate. If the difference between estimated and actual data was positive this meant that the estimated value of the twin location was overestimated. Similarly, if the difference was negative this corresponded to an underestimate. Error was calculated for each city within the RSMeans dataset using the different interpolation methods evaluated in this study. This included both phase 1 and phase 2 of the research design. The following equations were used to calculate relative and absolute errors for each method.

$$E_{j,i} = P_{j,i} - A_i;$$

$$ER_j = \frac{\sum_{i=1}^{m} E_{j,i}}{m};$$

$$EA_j = \frac{\sum_{i=1}^{m} |E_{j,i}|}{m}$$

$i\ (1\ to\ m) = location\ ID$

$j\ (1\ to\ m) = location\ adjustment\ method\ ID$

$ER_j = Relative\ Error\ for\ method\ j$

$EA_j = Absolute\ Error\ for\ method\ j$

In these equations, $E_{j,i}$ depicts error for location i when using method j, $P_{j,I}$ depicts predicted value for location i when using method j, and $A_{j,i}$ depicts actual value for location i (which is independent from any method). $ER_{j\ I}$ is the average relative error and EA is the average absolute error when using method j. These are average errors across all m locations.

3.3 Phase 1 Analysis and Comparisons

This section will discuss analysis and the various comparisons of the initial interpolation methods evaluated in phase 1 of this study, which included the following:

- Global Moran’s I test statistic
- NN Error as a Function of Distance
- Comparison of Overestimates and Underestimates
- Best Performance Comparison
- Comparison of Error Percentages
- Descriptive Statistics
- Histograms
- Pearson Correlation Study

3.3.1 Global Moran’s I Test Statistic

The global Moran’s I test statistic, within ArcMap GIS software, was used to evaluate the degree of spatial auto-correlation between RSMeans CCI values and proximity. This testing method was specifically chosen because it was an established measure spatial auto-correlation. According to Banerjee et al. (2004) Morans’s I and Geary’s C are two standard statistics used to measure the strength of spatial association. A possible future topic relevant to this research may be to test spatial association or spatial auto-correlation using the Geary’s C statistic and compare results with those of this study.

The Moran’s I test statistic was conducted both statewide and nationwide. The statewide tests were conducted by selecting all the data points within a specified state or district and implementing the test statistic. This process was repeated for all territories within the United States (excluding Hawaii and Alaska) and the District of Columbia, meaning that 49 separate results were produced. The nationwide test was conducted by selecting all 649 RSMeans data points within the contiguous Unites States, and produced only 1 result. According to Bolstad (2005):

> Moran's I values approach a value of +1 in areas of positive spatial correlation, meaning large values tend to be clumped together, and small values clumped together. Values near zero occur in areas of low spatial correlation (pg. 412).

A negative correlation is shown as the Moran's I values approach a value of –1 and a positive correlation is shown as the Moran's I values approach +1. Correspondingly, a statistical Z score was calculated as part of the Moran's I test. The Z-score evaluated if the null hypothesis should be rejected. The null hypothesis in this research essentially stated that "there was no spatial clustering of cities with similar CCI values." Using a 95% confidence interval and a 0.05 significance level, the Z-score must be less than –1.96 or greater than 1.96 to reject the null hypothesis with statistically significant confidence. If evidence of significant auto-correlation results from the Moran's I tests, it will substantiate the validity of proximity based spatial-interpolation, and ultimately provide statistical justification of the NN interpolation method.

3.3.2 NN Error as a Function of Distance

As part of NN evaluation, research was conducted to evaluate if the nearest neighbor method became less reliable as the distance between CCI locations increased. To test this theory, error was measured as a function of distance. This took the form of an excel scatter plot. The "error" value, as described in section 3.2.1 of this study, was calculated and plotted according to the distance between the RSMeans city and its respective twin location. It is important to understand that absolute error values were used in this calculation.

3.3.3 Comparison of Overestimates and Underestimates

A comparison of overestimates and underestimates was also conducted. This took the form of a scatter plot which compared two variables. The scatter plot was chosen because it allowed for proper visualization of the data, which was needed in order to make resulting inferential decisions. In addition to the scatter plot a table was created which showed the actual number of overestimates and underestimates for each interpolation method. Relative error was used in the comparison of overestimates and underestimates. This analysis was conducted to determine if a set pattern could be observed. If a prominent pattern was observed this could possibly aid future studies involving location adjustment interpolation methods.

3.3.4 Best Performance Comparison

A comparison was conducted to evaluate performance of initial interpolation methods. As mentioned in earlier sections, there were 649 cities from which error was calculated. Each city produced an error value dependent upon which interpolation method was used. Out of the 3 initial methods, performance was quantified by which method worked best. A count of this measurement was performed, and a table was produced to compare results.

3.3.5 Comparison of Error Percentages

In addition, a comparison of different error percentages was also analyzed. Different levels of error were classified as the following: none, low, medium, high and very high. If the error for a city ranged from 0% to 1 %, it was concluded very low error. If the value ranged from 1% to 3%, it was concluded low error. If the value ranged from 3% to 5%, it was concluded medium error. If the value ranged from 5%, to 10% it was concluded high error. Finally, if the error was greater than 10%, it was concluded very high error. A count and percentage of how many cities were included in these levels was also calculated. Absolute error was used in this evaluation. This comparison was chosen because it contributed to evaluating performance of all initial interpolation methods.

3.3.6 Descriptive Statistics

Descriptive statistics, including calculations of mean, median, and standard deviation of error were considered for the initial location adjustment interpolation methods. Absolute error values were considered in all calculations. Various tables and charts were summarized to compare the statistical calculations. Descriptive statistic comparisons were used in order to determine if an alternative method could be statistically proven to outperform the current method.

3.3.7 Histograms

In addition, histograms of error from the initial methods evaluated in phase 1 of this study were compared and analyzed. The error considered in these histograms was relative, meaning positive and negative values. Histograms were incorporated because they can visually demonstrate statistical comparisons including the distribution of error and outliers.

3.3.8 Pearson Correlation

The final methodology considered in phase 1 of this research was to conduct a Person's correlation study. The goal of the study was to determine economic factors that were highly correlated with CCI values. Ultimately, this provided criteria which additional interpolation methods considered. Specific economic factors were evaluated to determine which had the most correlation with RSMeans CCI values. In performing this test, GIS data was obtained from the 2007 ESRI (Environmental Systems Research Institute) Data Source Book. This dataset contained economic information on all US cities. The 649 cities from RSMeans CCI dataset were selected and all other data removed, as they did not pertain to the research at hand.

The primary economic factors that were included in the data were the following: population, population density, median household income, median home value, and a national household income ranking. These were the initial economic characteristics that were considered to include in the alternative interpolation methods. They were used in this study primarily due to the availability of GIS data. Pearson's correlation test were conducted to narrow down potential economic factors considered and to avoid creating an overly complex alternative interpolation method.

3.4 Phase 2 Empirical Analysis and Comparisons

The following topics will be discussed in relation to phase 2 of this study:

- Ranking Procedure
- Population Sample Sizes
- General Statistical Analysis Techniques
- Levene's Tests
- Mann Whitney Tests

3.4.1 Ranking Procedure

Ranking involves establishing a numerical relationship between variables. In this research the ranking values ranged from 1 to N. The variable with the most similar value represented 1, and N represented the total number of variables within the selected dataset. N also represented the most dissimilar variable. Ranking was chosen as an analysis step because it facilitated an established evaluation technique. The ranking procedures used in this study was inspired by ranking tests developed by the statistician Frank Wilcoxon. Dunn & Clark (2009) identify Wilcoxon rank test in the following:

> Two rank tests were developed independently by Wilcoxon and Mann-Whitney to test the null hypothesis that two independent samples had the same distribution against the alternative hypothesis that one of the distributions is less than the other (one sided test) or that the two populations differ from each other (two sided test). This Wilcoxon is called the Wilcoxon rank sum test to distinguish it from the Wilcoxon test for paired data which is called the Wilcoxon signed ranks test (p. 195).

In addition, Gibbons and Chakraborti (2003) define the Wilcoxon signed ranks test in the following:

> This test [Wilcoxon signed rank test] is based on a special case of what are called rank-order statistics. The rank-order statistics for a random sample are any set constants which indicate the order of the observations… Rank-order statistics might then be defined as the set of numbers which results when each original observation is replaced by the value of some order-preserving function (p. 189).

The concept of rank-order statistics, as described by Gibbons and Chakraborti, was used in this study. Rank-order statistics can be very simple or very complex depending on the number of observations considered and the number of ranks considered. One, two, and three ranks were incorporated by the various interpolation methods considered in phase 2. A description of the interpolation methods, including the ranking procedures used in this study will be explained in chapter 5.0.

For the purposes of this research, equal weight was given to all ranking variables. This was chosen because it would be fairly arbitrary to decide how much consideration should be given to either variable. Should more weight be considered for income? Should more weight be considered for home value? How much weight should be given to each? Are the three closest cities or the five closest cities selected as ranking variables? These are all very subjective questions, and to avoid making a research mistake due to subjectivity, equal consideration was given to all ranking method variables.

In addition, ranking was performed on only three of the four criteria mentioned in section 3.1 of this study. As a review, location adjustment method criteria consisted of the following: proximity, state boundaries, income, and home value. While proximity, income, as well as home value can all be uniformly measured as a function of a domain, state boundaries cannot be equally measured. Ranking pertaining to state boundaries only has two outcomes, (1) city A is inside the state boundary of city B, or (2) city A is outside the state boundary of city B. This means that there are only two possible variables within the state boundaries ranking function domain (yes or no). There are 649 possible variables within the ranking function domains of all other methods. Therefore, state boundaries were not considered a ranking procedure, but were included in various interpolation methods that involved ranking. In other words, ranking was performed using two differing strategies. If the method included ranking and state boundaries, ranks were limited to the number of cities within the state boundaries. If the method did not include state boundaries, ranks were calculated using the entire dataset of 649 cities.

3.4.2 Population Sample Sizes

Sample size is the number of observations in a statistical sample. In this study, an initial sample of 649 observations, known as the "national-level" sample, was used. It was assumed that the statistical observations made using this national-level sample size was an accurate estimation of what should happen for the entire population. The entire population in this study was all cities within the contiguous United States, meaning approximately 40,000+ cities. According to proven statistical rules, such as the law of large numbers and the central limit theorem, it can be inferred that a larger sample size leads to increased precision in hypothesis tests. According to Lenth (2001), it is important that the sample size is "large enough" that an effect of such magnitude as to be scientifically significant will also be statistically significant. Lenth continues, "Sample size is important for economic reasons: An under-sized study can be a waste of resources for not having the capability to produce useful results, while an over-sized one uses more resources than are necessary" (p. 2). While sample size determination is a common statistical problem, there are many limitations in the research design itself affecting sample size outcomes. The following are examples of these limitations:

- Cost Considerations
- Complexity of the Design
- Research Deadlines
- Minimum Acceptable Level of Precision

From these limitations, it was inferred that sample size determination can be a subjective process. One thing that does hold true is that as the sample size increases, so does the precision of hypothesis test outcomes. In this research, there were two main limitations affecting the theoretical framework of the research design. These limitations included complexity of the design and research deadlines. Due to these limitations, a convention was assumed regarding how much data was "enough". A smaller sub-sample was randomly chosen to represent the national-level sample. This sub-sample was the "regional-level" sample which consisted of 82 observations. This was one of the research decisions that may be criticized. A defense for this research decision was found in the following statements from Lenth (2001):

> Sample-size problems are context-dependent. For example, how important it is to increase the sample size to account for such uncertainty depends on practical and ethical criteria. Moreover, sample size is not always the main issue; it is only one aspect of the quality of the study design (p. 10).

In review of the research design, complexity was added to location adjustment methods. Due to this complexity, sample size was reduced in order to meet certain research deadlines. While error for all 15 methods was calculated using the smaller, regional sample, error for only 7 methods was calculated using the larger, national sample. Future research efforts could assess all location adjustment methods using the whole national sample. Figure 3 shows a GIS map of the cities and states chosen to represent the regional-level sample.

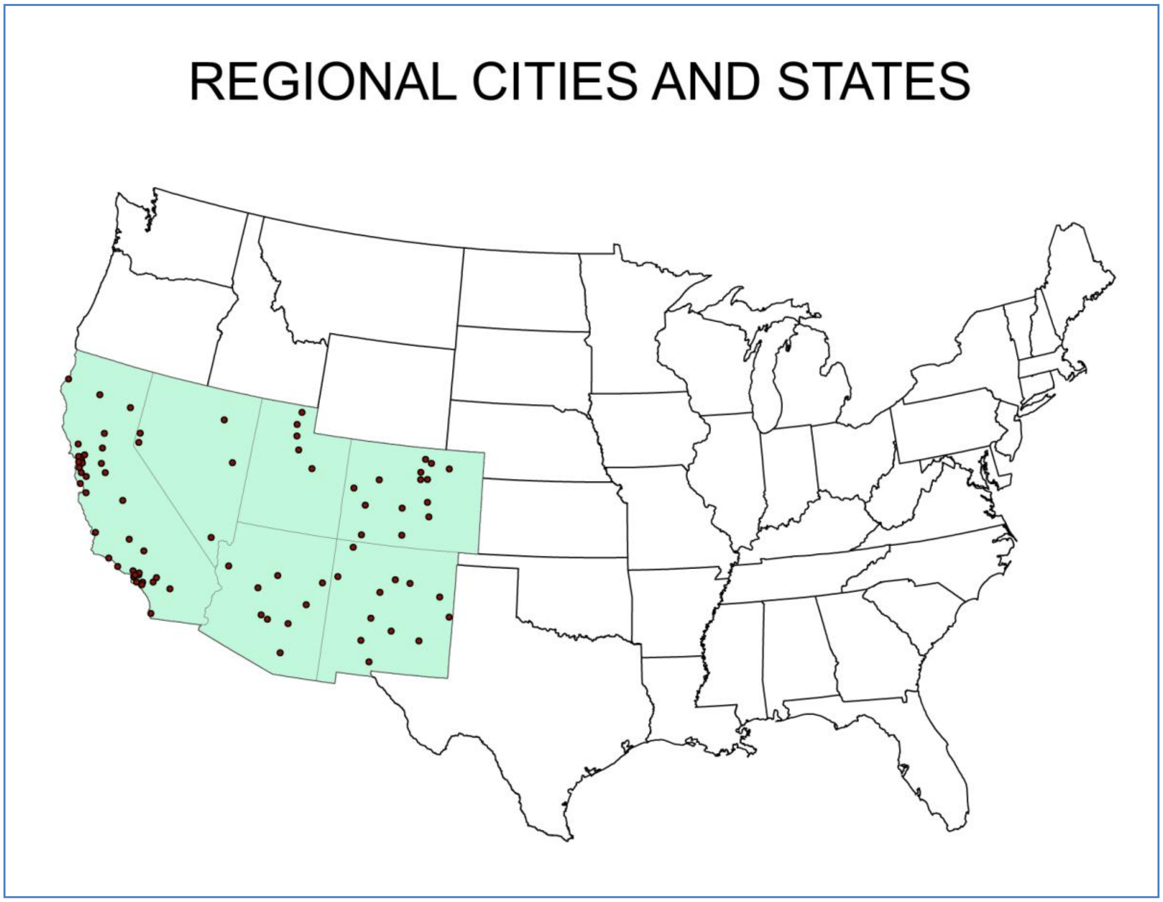


Figure 3. GIS Map of Regional Cities and States

Each point represents 1 of 82 total regional cities. The states included at this regional-level were the following: New Mexico, Colorado, Arizona, Utah, Nevada, and California. This region of states was selected randomly. There is a good mix of low and high autocorrelation as well as a low number and high number of cities within these states. It was assumed that regional-level sample should allow for a similar comparison of what results from the national-level dataset would determine. This assumption will be discussed later in this study.

3.4.3 General Statistical Analysis Techniques

General statistical techniques were used to analyze all 15 methods considered in phase 2 of this study. These techniques included mean, median, standard deviation and variance of error. Absolute value of error was used to calculate mean error. Relative error values were used to calculate median, standard deviation and variance. In addition, box plots and histograms were developed and analyzed in phase 2 of this study. Relative error was also used for box plot and histogram analyses. General statistical analysis techniques were implemented because they provided basic statistical information which was useful in determining location adjustment method performance.

3.4.4 Levene's Tests

Levene's tests were conducted in phase 2 of this study. Kault (2003) stated the following in reference to the Levene test:

> The common test for equal variance is called the Levene test. This test uses the principle that equal variances within each group by definition means equal values for the average of the square of the differences between each value and the group average… The Levene test then does a preliminary ANOVA to see if there is evidence against the assumption that the size of the difference between a value and its group average is on average the same in every group (p. 202).

The Levene's test was used in this study because it was considered a common approach to determine homogeneity of variance between groups. It did not determine which method outperformed other methods. It was used to determine what types of statistical tests were appropriate in this study. If the Levene's tests showed results that provided evidence of different variances, non-parametric tests were appropriate.

3.4.5 Mann-Whitney Tests

Mann-Whitney is a non-parametric test, which was used to test whether two independent samples of observations have statistically differing medians. According to Kinnear (2004):

> When there are serious violations of the assumptions of the *t*-test, nonparametric tests can be used instead…the comparable nonparametric test may lack the power to reject the null hypothesis…The Mann-Whitney test is an alternative to the independent samples *t*-test (p. 179).

These statements prove why the Mann-Whitney tests were used in this study. Non-parametric test were used in lieu of more traditional statistical tests (*t*-tests). One of the common *t*-test assumptions is that the data have the same variances. The Levene's test from section 3.4.4 determined that the initial interpolation methods had significantly different variances. Therefore, non-parametric tests such as Mann-Whitney were appropriate.

CHAPTER 4.0 PHASE 1 EXPLORATORY STUDY: ANALYSIS AND RESULTS

4.1 Overview

This section will report the findings from phase 1 analysis and results. As a review, the following analyses were considered in the exploratory study.

- Global Moran's I test statistic
- NN Error as a Function of Distance
- Comparison of Overestimates and Underestimates
- Best Performance Comparison
- Comparison of Error Percentages
- Descriptive Statistics
- Histograms
- Pearson Correlation Study

4.2 Global Moran's I Test Statistic

Moran's I tests were conducted nationally and for each individual state. This created national and state level results. Table 2 summarizes the state level tests. This included 48 states and 1 district within the contiguous Unites States. For each test, an index value and a Z-score value was determined. If the index value was positive, there was "clustering", meaning statistical evidence of spatial auto-correlation. If the index value was negative, there was statistical evidence of negative spatial auto-correlation. If the Z-score was greater than 1.96, auto-correlation results were statistically "significant". There were 3 instances in which the test did not successfully determine an index value or a Z-score. This was primarily due to the lack of input data within the test. In other words, there were not enough cities within the state or district for the test to measure spatial auto-correlation. This included Delaware, Washington D.C., and Rhode Island. For these instances, the results were "not applicable" as shown in table 2.

Table 2. Moran’s I Tests Results for State Level Analysis

Moran I Test Results for Individual States				
State/District	Moran's Index	CLUSTERED	Z Score	SIGNIFICANT
ALABAMA	-0.106245		-0.476793	
ARIZONA	-0.178088		-0.473334	
ARKANSAS	-0.115634		-0.426931	
CALIFORNIA	0.820966	YES	14.042334	YES
COLORADO	-0.115919		-0.560558	
CONNECTICUT	0.041086	YES	1.825827	NO
DELAWARE	NOT APPLICABLE			
DISTRICT OF COLUMBIA	NOT APPLICABLE			
FLORIDA	0.101853	YES	2.225169	YES
GEORGIA	-0.048505		0.773887	
IDAHO	-0.026602		0.861344	
ILLINOIS	0.498979	YES	8.72939	YES
INDIANA	-0.028556		0.875952	
IOWA	0.050944	YES	2.459729	YES
KANSAS	-0.047728		0.669308	
KENTUCKY	0.14384	YES	3.418235	YES
LOUISIANA	0.028915	YES	1.928826	NO
MAINE	-0.14854		-0.491829	
MARYLAND	0.057158	YES	1.255529	NO
MASSACHUSETTS	0.135946	YES	2.897366	YES
MICHIGAN	0.563173	YES	5.419719	YES
MINNESOTA	0.323685	YES	2.518224	YES
MISSISSIPPI	-0.054603		0.828869	
MISSOURI	-0.019038		0.754391	
MONTANA	-0.076468		0.53581	
NEBRASKA	0.016878	YES	1.21904	NO
NEVADA	0.031196	YES	0.658152	NO
NEW HAMPSHIRE	0.313499	YES	3.296673	YES
NEW JERSEY	0.093083	YES	2.015206	YES
NEW MEXICO	0.022073	YES	2.035047	YES
NEW YORK	0.625865	YES	8.04446	YES
NORTH CAROLINA	0.071429	YES	0.739861	NO
NORTH DAKOTA	-0.022863		0.428601	
OHIO	0.14973	YES	3.909278	YES
OKLAHOMA	-0.030998		0.940727	
OREGON	0.061146	YES	2.3324	YES
PENNSYLVANIA	0.144825	YES	5.507111	YES
RHODE ISLAND	NOT APPLICABLE			
SOUTH CAROLINA	-0.128443		0.157375	
SOUTH DAKOTA	-0.320901		-1.823682	
TENNESSEE	-0.201274		-0.784914	
TEXAS	-0.012473		0.489588	
UTAH	-0.080554		1.387565	
VERMONT	-0.028159		1.033033	
VIRGINIA	0.5849	YES	5.595534	YES
WASHINGTON	0.326007	YES	3.852031	YES
WEST VIRGINIA	0.085484	YES	2.788805	YES
WISCONSIN	0.323674	YES	4.112459	YES
WYOMING	-0.089586		0.353008	

From this table, it was prominent that no test showed evidence of significant, negative auto-correlation. This is apparent because there were no instances of a negative Moran's Index value and a Z-score greater than 1.96. In addition, 24 of 46 states showed results of positive Moran's Index values. Furthermore, 19 of these 24 states showed results of positive Moran's Index values, and Z-scores greater than 1.96. The 19 highlighted rows in table 2 shows results of positive, statistically significant spatial auto-correlation. This was evidence to reject the null hypothesis. The null hypothesis stated that RSMeans CCI values were not spatially auto-correlated with proximity. Consequently, there was evidence of positive, statistically significant auto-correlation between proximity and RSMeans CCI values for these states. These states were compiled and are shown in table 3.

Table 3. Positive Moran's Index and Significant Z-Score States

State	Moran's Index	Clustered	Z Score	Significant
CALIFORNIA	0.820966	YES	14.042334	YES
FLORIDA	0.101853	YES	2.225169	YES
ILLINOIS	0.498979	YES	8.729390	YES
IOWA	0.050944	YES	2.459729	YES
KENTUCKY	0.143840	YES	3.418235	YES
MASSACHUSETTS	0.135946	YES	2.897366	YES
MICHIGAN	0.563173	YES	5.419719	YES
MINNESOTA	0.323685	YES	2.518224	YES
NEW HAMPSHIRE	0.313499	YES	3.296673	YES
NEW JERSEY	0.093083	YES	2.015206	YES
NEW MEXICO	0.022073	YES	2.035047	YES
NEW YORK	0.625865	YES	8.044460	YES
OHIO	0.149730	YES	3.909278	YES
OREGON	0.061146	YES	2.332400	YES
PENNSYLVANIA	0.144825	YES	5.507111	YES
VIRGINIA	0.584900	YES	5.595534	YES
WASHINGTON	0.326007	YES	3.852031	YES
WEST VIRGINIA	0.085484	YES	2.788805	YES
WISCONSIN	0.323674	YES	4.112459	YES

Results of the Moran's I test statistic for the national-level returned a positive Moran's index value and a significant Z-score. These results are shown in figure 4.

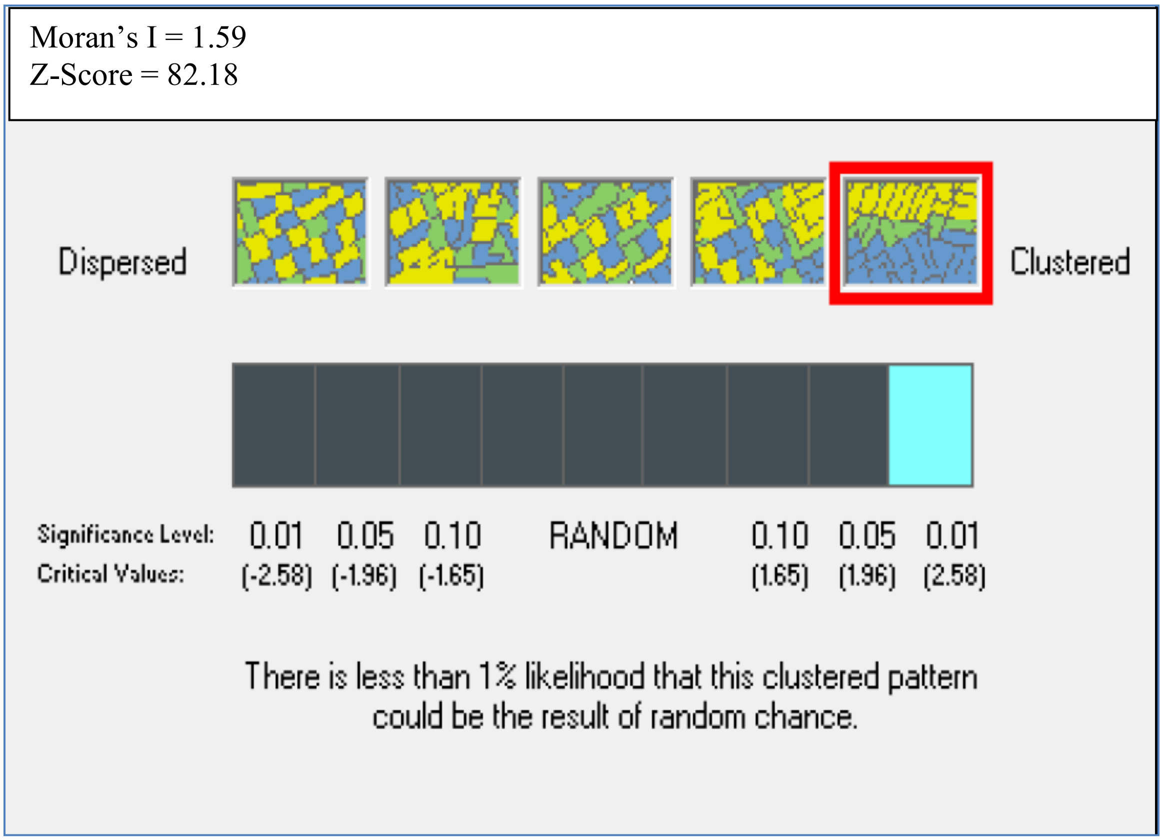


Figure 4. National-Level Moran's I Results

The Z-score of 82.18 indicated results were highly significant, and the Moran's index value of 1.59 indicated spatial clustering of CCI values across the entire nation. The tests results, both at the state and national-levels, act as an internal validation supporting proximity-based interpolation. The underlying assumption for proximity-based methods, including the current method, has been validated.

4.3 NN Error as a Function of Distance

The next step in this research tested if the NN method became less reliable as the distance between RSMeans CCI locations and their respective twin locations increased. To test this theory, error was measured as a function of distance. This is shown in figure 5.

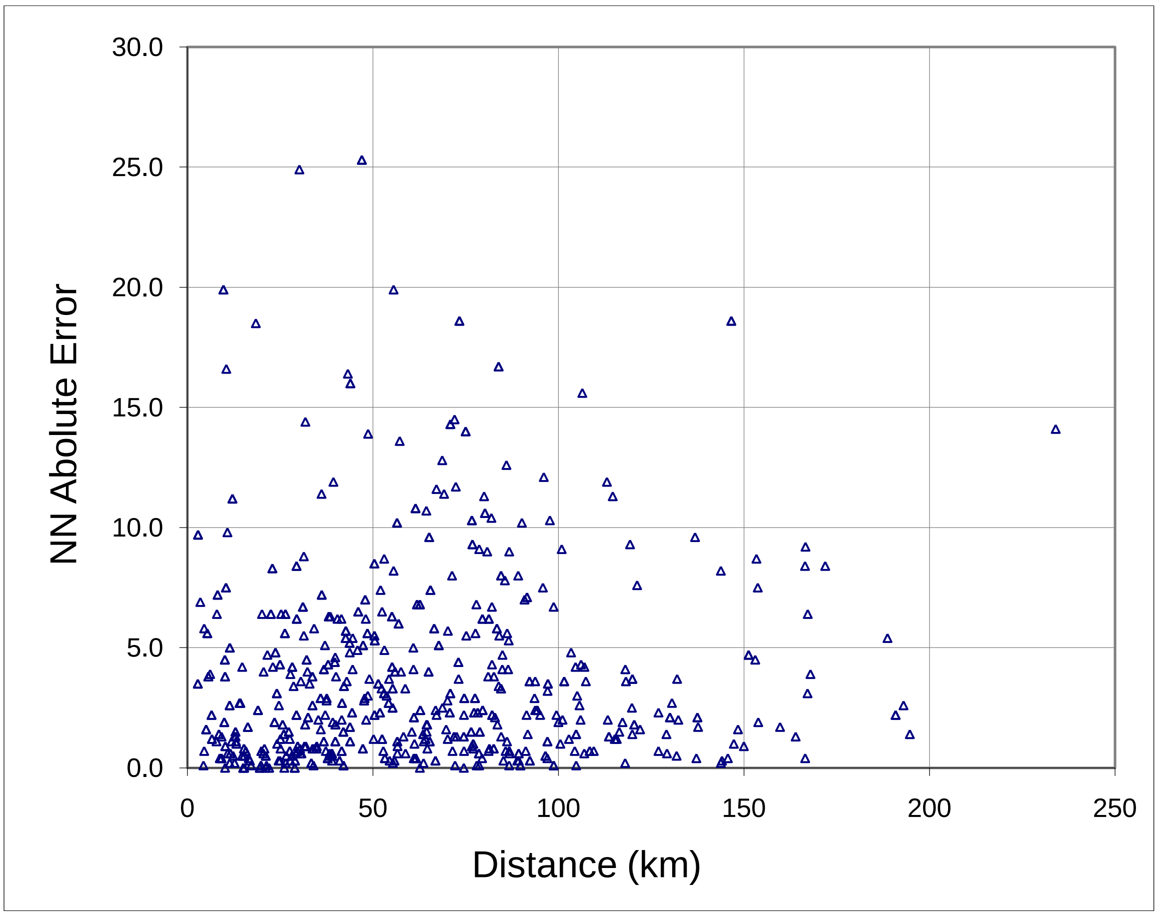


Figure 5. NN Error as a Function of Distance

Results from this figure indicated that many small errors occurred even at greater distances and many large errors occurred even at shorter distances. This suggested that the NN method did not become less reliable when proximity between actual and estimated CCI values increased. Unexpectedly, some odd patterns were found, such as greater errors (10 or greater) occurring at very short distances and smaller errors (5 or less) at greater distances.

4.4 Comparison of Overestimates and Underestimates

A comparison of error for NN and ST AVG methods was conducted. Error took the form of the difference between estimated CCI values less actual CCI values for each of the 649 cities. This created positive and negative differences or, simply stated, overestimates and underestimates. Figure 6 shows the comparison of overestimates and underestimates for both methods.

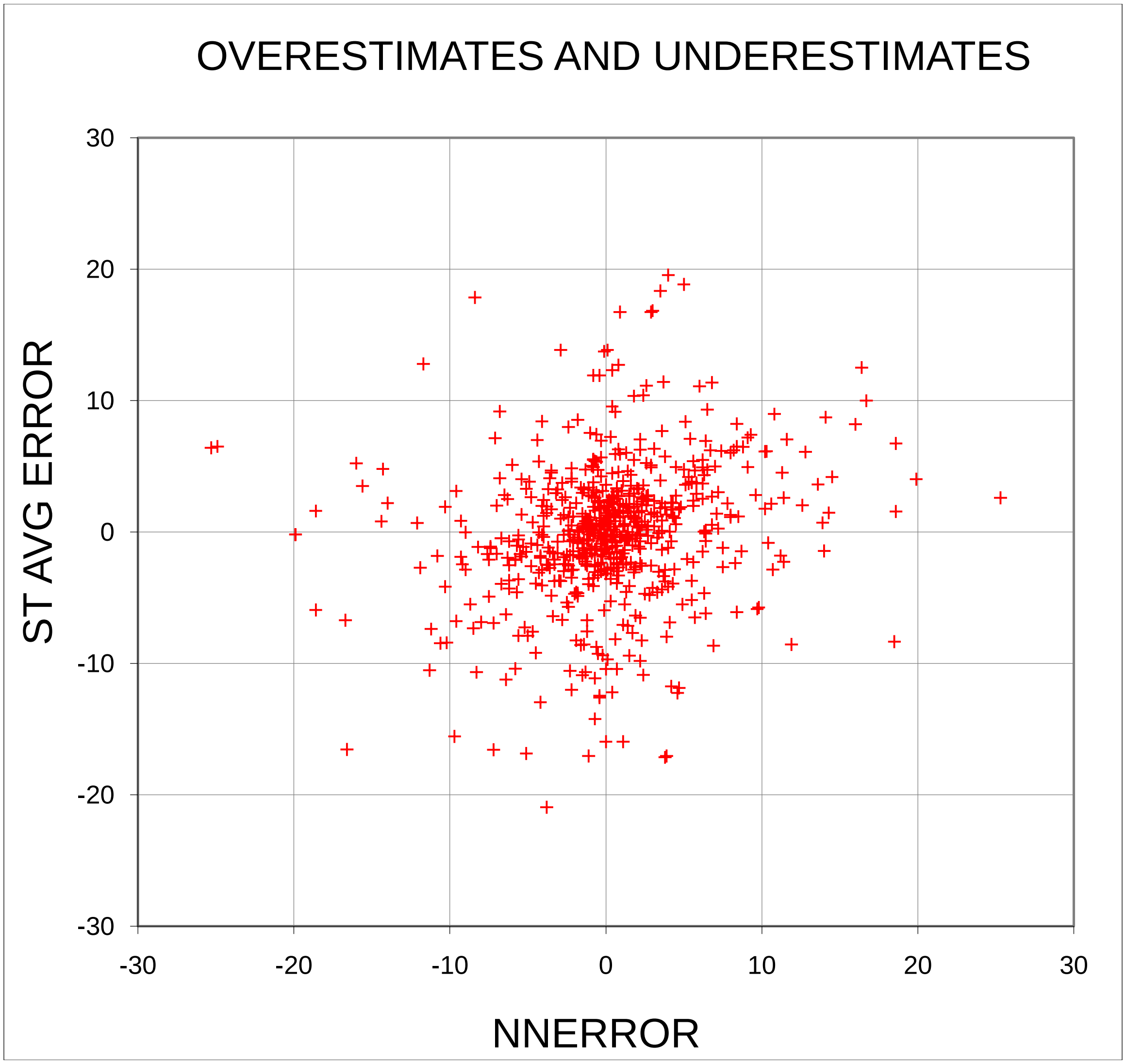


Figure 6. Scatter Plot Comparison of Overestimates and Underestimates

The results from this chart indicated that no apparent pattern or unique bias for either variable was found.

In addition, a comparison between CNN, NN, and ST AVG methods was conducted. Error classifications (overestimates, underestimates, or accurate estimates) were calculated for each method as shown in table 4.

Table 4. Error Classification Summary

Error Classification	Conditional Nearest Neighbor (CNN)	Nearest Neighbor (NN)	State Average (ST AVG)
Underestimates	332	333	327
Overestimates	301	303	314
Perfect estimates	15	13	7
Inconclusive	1	0	1
TOTAL	649	649	649

To understand this table, let's analyze results reported in the CNN column. At the bottom of the column, it shows that a total of 649 observations were conducted. Out of the 649, 332 were underestimated, 301 were overestimated, 15 were perfectly accurate, and 1 observation was inconclusive. Overall, results from the table indicated that underestimates were more prominent than overestimates in all three methods. Looking at the number of accurate estimates, there was a progression from least accurate to most accurate, with the conditional nearest neighbor having a slight advantage of more accuracy over the other two methods.

4.5 Best Performance Comparison

In this study, performance was measured by error. Error of NN and ST AVG methods were compared. To quantify the performance of these two variables, the absolute values of error for both methods were calculated. From these calculations, a spreadsheet was developed. This spreadsheet was used to determine which method provided more accuracy for each of the 649 data points. Results from the chart were as follows:

- Nearest neighbor proved to be more accurate in 319 cases
- State average also proved to be more accurate in 319 cases
- Equal results in 10 cases
- Inconclusive results in 1 case due to lack of data points within the boundary

When determining how many cases were more accurate for each method, these results indicated that there is basically an equal chance. Both NN and ST AVG methods performed equally. With this in mind, the state average method might be an acceptable alternative to the nearest neighbor interpolation method. Additional statistical evaluations were conducted to test this theory.

As a continuation, bi-variable comparisons of initial national-level methods were evaluated. Results are shown in table 5.

Table 5. Initial National-Level Bi-Variable Comparison

#	Comparison	Conditional Nearest Neighbor (CNN)	Nearest Neighbor (NN)	State Average (ST AVG)	Equal
1	CNN vs. ST AVG	355		282	11
2	CNN vs. NN	112	62		474
3	NN vs. ST AVG		319	319	10

This table will be explained in sections according to each row. Each row reports results of the comparison between two methods and shows the number of observations in which one method outperformed the other. Row 1 shows a comparison between CNN and ST

AVG. In comparing CNN and ST AVG, 355 observations were more accurate using the CNN method, 282 observations were more accurate using the ST AVG method, and 11 observations proved that both methods worked equally well. As a performance ratio, CNN outperformed ST AVG 355 to 282. In row 2, CNN and NN were compared. The performance ratio was 112 to 62 in favor of CNN. In row 3, NN and ST AVG were compared. The performance ratio was 319 to 319, meaning that both methods had an equal amount of more accurate observations. In other words, NN performed equally well as ST AVG and vice versa.

4.6 Comparison of Error Percentages

Continuing with the initial national-level methods analysis, various levels of absolute error were considered. The actual count and percentages of the various levels of error are shown in table 6 and a bar chart of these same results is shown in figure 7.

Table 6. Initial National-Level Methods Error Comparison

Interpolation Methods Error						
Interpolation Methods	Comparison	Very Low (0-1%)	Low (1%-3%)	Medium (3%-5%)	High (5%-10%)	Very High (>10%)
ST AVG	count	118	202	119	131	79
	percentage	18%	32%	18%	20%	12%
NN	count	156	186	104	137	66
	percentage	24%	29%	16%	21%	10%
CNN	count	178	218	93	110	50
	percentage	27%	34%	14%	17%	8%

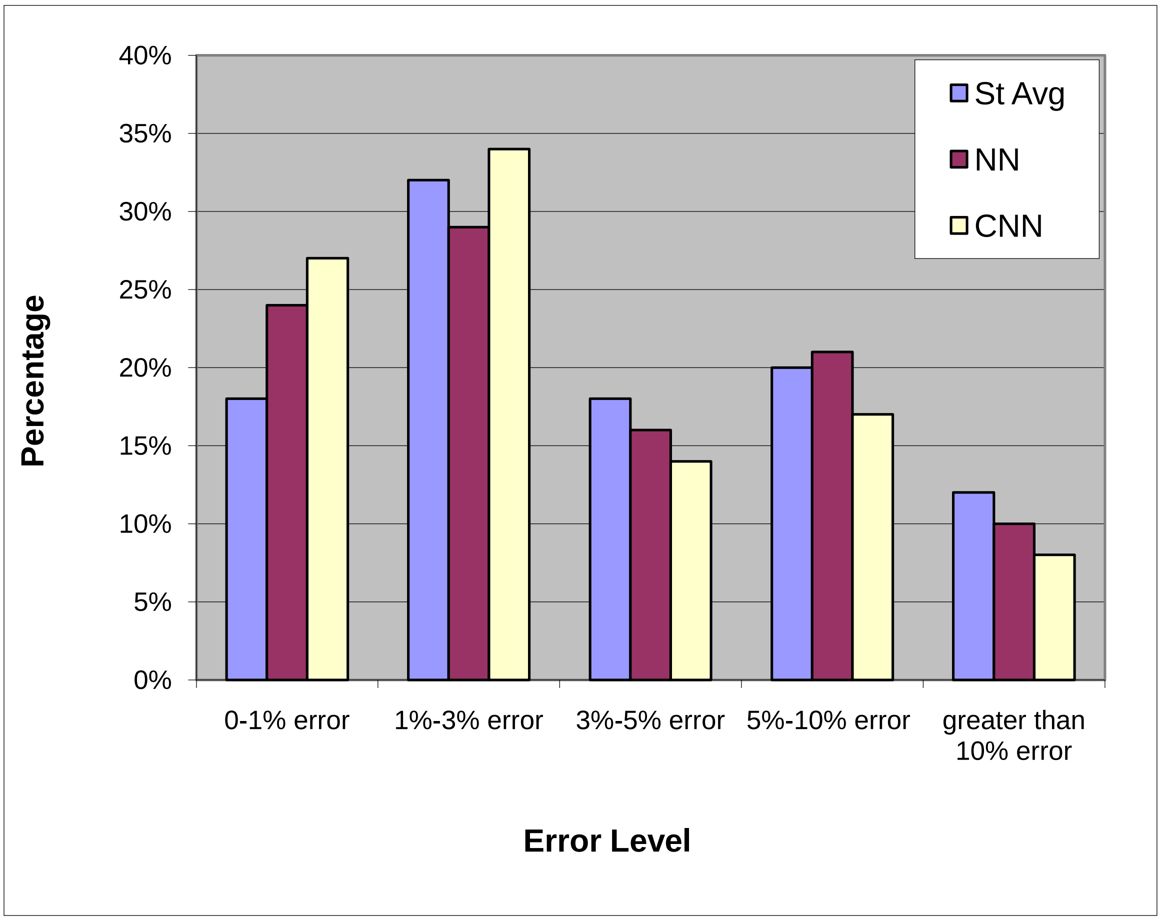


Figure 7. Initial National-Level Methods Error Comparison

Results based on the data presented in table 6 and figure 7 indicated that the CNN method had the least count and lowest percentage of the three methods at medium, high and very high error levels. Correspondingly, it also has the highest count and percentage at very low and low error amounts. It is important to mention that table 6 and figure 7 were calculated using absolute error.

4.7 Descriptive Statistics

Mean, median, and standard deviation of error values for all three methods were calculated and summarized in table 7.

Table 7. Summary of Median, Mean, and Standard Deviation of Error

	Conditional Nearest Neighbor (CNN)	Nearest Neighbor (NN)	State Average (ST AVG)
Median Error	1.95	2.30	2.56
Mean Error	3.07	3.78	3.80
Standard Deviation	3.09	4.08	3.77

The median and mean error for the NN method was less than ST AVG method, but greater than the CNN. In addition, standard deviation was highest in the NN method. Overall, results indicated that the CNN method had the least median, mean, and standard deviation of error.

4.8 Histograms

As an evaluation of the national-level methods, histograms were produced. Figure 8 shows the comparison of NN, CNN and ST AVG. Relative error was used for these histograms.

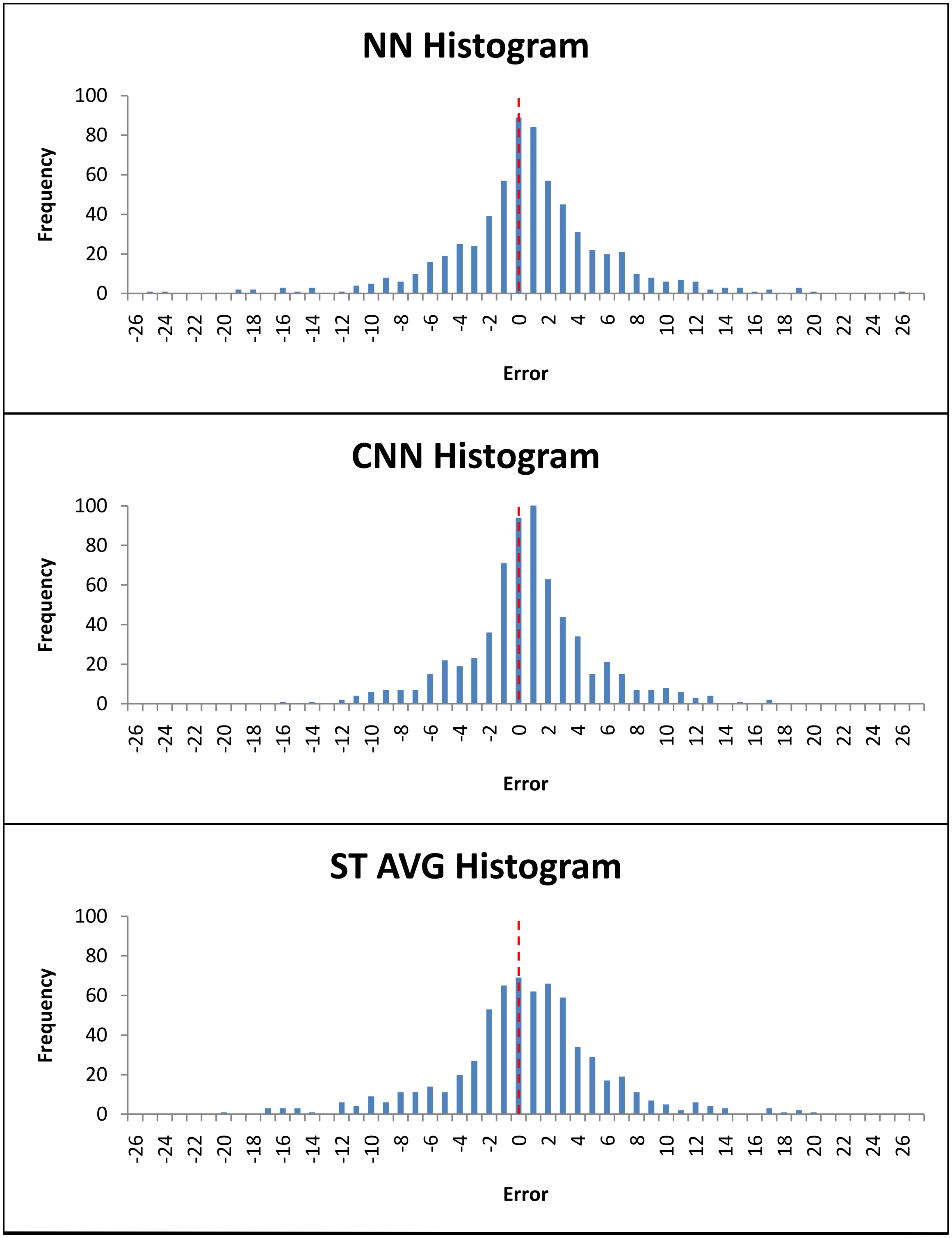


Figure 8. Histogram Comparison of NN, CNN and ST AVG

The dotted line in the middle of the histogram represents an error value of zero. In other words, it represents perfect accuracy in which there is no difference between estimated and actual CCI values. Results from the comparison of NN and ST AVG histograms indicated that there were more outliers in the NN method. There were also higher frequencies of low error amounts in the NN method. Comparing NN and CNN, histograms indicated that CNN had higher frequencies of lower error. In addition, CNN had lower outlier values. Similarly, comparing CNN to ST AVG, histograms indicated that CNN had higher frequencies of low error and lower outlier values again.

4.9 Pearson Correlation Study Results

Phase 1 of this research was considered as an exploratory study. As part of phase 1 results, it was determined that additional alternative methods should be considered in this research. Economic characteristics were a contributing factor to additional alternatives primarily due to the suggestion provided by RSMeans in section 1.3 of thesis. It was determined that a Pearson's correlation test should be conducted to determine economic variables that should be added to the research criteria. Economic variables were selected based on the availability of attainable data. Since there were innumerous economic variables which can be considered in alternative methods, future research may involve differing economic variables than those used in this study. Table 8 shows the various economic variables used in this study, and the Pearson's correlation results involving these variables..

Table 8. Pearson's Correlation

	CCI	pop 2007 (population)	pop 07 sq mi (population density)	mdhhinc_cy (median household income)	Hincrank (income ranking)	medval_cy (median home value)
CCI	1	0.331	0.43	0.551	-0.482	0.651
pop 2007 (population)	0.331	1	0.284	0.254	-0.273	0.446
pop 07 sq mi (population density)	0.43	0.284	1	0.16	-0.131	0.357
mdhhinc_cy (median household income)	0.551	0.254	0.16	1	-0.868	0.73
Hincrank (income ranking)	-0.482	-0.273	-0.134	-0.868	1	-0.554
medval_cy (median home value)	0.651	0.446	0.357	0.73	-0.554	1

Looking at the first row in the table, the CCI values from all RSMeans cities (denoted by CCI) was compared to each individual economic factor. The number in the first row under each heading is the degree of correlation between vertical and horizontal variables. In other words, this number represents the degree of correlation between location factors from RSMeans CCI cities and the individual economic factors of those same cities. This value can range from -1 to 1 showing 100% negative correlation to 100% positive correlation. The chart also shows correlation between all variables. Looking specifically at the first row, the economic factors with the highest correlation to CCI values are median household income (mdhhinc_cy) with a value of .551, and median home value (medval_cy) with a value of .651.

CH 5.0 PHASE 1 EXPLORATORY STUDY: DISCUSSION

5.1 Overview

A discussion of the following results will be addressed in this chapter:

- Global Moran's I test statistic
- NN Error as a Function of Distance
- Comparison of Overestimates and Underestimates
- Best Performance Comparison
- Comparison of Error Percentages
- Descriptive Statistics
- Histograms
- Pearson Correlation Study

Furthermore, a discussion of additional, alternative interpolation methods will be included. Finally, a detailed description of all 15 interpolation methods evaluated in this research will also be discussed in this chapter.

5.2 Discussion of Moran's I Tests Results

Based on the results from the Moran's I test statistic, it was determined that there was evidence of strong spatial auto-correlation between proximity and RSMeans CCI values. This was evident using the national-level dataset as well as individual state-level data. As a result of positive, national-level autocorrelation it was determined that the current, industry-adopted interpolation method (NN) was statistically valid. Location adjustments using this method along with the RSMeans CCI should produce substantial accuracy in regards to conceptual cost estimates for commercial building construction. On the contrary, alternative location adjustment methods may be statistically proven to outperform the current method.

Results from the Moran's I state-level tests also showed evidence of positive spatial autocorrelation between proximity and RSMeans CCI values. Since these tests were limited by the spatial extents of each individual state, it was inferred that there was statistical evidence which supported NN interpolation when restricted to state boundaries. As an alternative to NN, the "nearest neighbor within state boundaries" method was enveloped by this same limitation. Therefore, it was determined that the validity of this method was also substantiated. The nearest neighbor within state boundaries method was also referred to as the conditional nearest neighbor (CNN) method.

5.3 NN Error as a Function of Distance

Error for the NN method was measured as a function of distance to determine if the method became less reliable as the distance between CCI locations increased. The idea was to test observations of Waldo Tobler (1970). In Tobler's first law of geography he stated that "…everything in the universe is related to everything else, but closer things are more related to each other." Unexpectedly, it was determined that Tobler's first law did not entirely hold true for the NN interpolation method evaluated in this study. It was inferred that as the distance between a city and its respective twin location increased or decreased, there was no substantial evidence that the degree of error was proportional to the change in distance. In other words, error was not directly related to the distances between CCI locations and twin locations. Error did not become greater simply because of greater distances between a city and the twin location. Correspondingly, error did not become less due to shorter distances.

5.4 Comparison of Overestimates and Underestimates

Overestimates and underestimates were graphically compared in figure 6 from section 4.4 (Scatter Plot Comparison of Overestimates and Underestimates). It was inferred from this scatter plot that there were no apparent patterns or unique biases.

In addition, the comparison of overestimates versus underestimates in section 4.4 (table 4) revealed a slight increase in overestimates for all methods. However, there were no relatively significant or extreme differences between the number of overestimates and underestimates for each method. This implied that NN, ST AVG, and CNN location adjustments prepared solely using RSMeans CCI data might have a slight tendency to be underestimated. In comparing the number of accurate estimates it was determined that CNN significantly outperformed ST AVG but did not significantly outperform NN.

5.5 Best Performance Comparison

A best performance comparison was conducted for NN and ST AVG methods. This basically resulted in a 50/50 percentage tie. Based on this test alone, it was proposed that ST AVG might be substantially equivalent to the NN method. To further elaborate, median absolute error for both methods was calculated. Although it was conclusive that NN had a slight improvement over ST AVG, it was inconclusive if these results were just a matter of chance. Statistical testing methods helped to substantiate a conclusion. This will be discussed later in this chapter.

5.6 Comparison of Error Percentages, Descriptive Statistics, and Histograms

In all evaluations of error percentage comparison, descriptive statistics, and histograms, it was confirmed that CNN outperformed both ST AVG and NN methods. This implied that CNN had potential to be the most accurate interpolation method between the three initial methods. Surprisingly, the CNN was even potentially superior to the current method (NN). To fully conclude if the CNN could be proven statistically superior, relevant statistical assessments needed to be performed. As part of these statistical assessments, histograms were evaluated. Results indicated that the CNN had higher frequencies of observations with low error values. In addition, CNN outliers were less than those of ST AVG and even NN.

5.7 Discussion of Alternative Interpolation Methods

As a final result of phase 1, it was decided that additional alternative interpolation methods should be included in this research. In contemplating which additional alternative methods to consider, it was decided that contacting RSMeans would be beneficial. The following comments are from an email conversation between Adam Martinez (Construction Management Graduate Student), and Phillip Waier (P.E., LEED AP Principal Engineer for RSMeans): (P. Waier, Personal Communication, July, 2009).

Sunday, July 05, 2009 (Question)

Hello,
My questions involve the RSMeans city cost index. I think RSMeans provides location factors for approximately 900 cities within the US, but there are over 40000 cities in the US. How do you adjust an estimate for a location without a location factor?

Does state boundary play a role in this? Are there any specific economic factors that are considered? Are there any computer programs that are used to evaluate this decision, like Geographic Information Systems (GIS)? I am writing my thesis on this and would appreciate any direction you could give me.

Thank you
Adam Martinez,
Graduate Student, University of New Mexico

Monday, July 6th, 2009 (Response to question)

When the location does not exist on our published list the predominate methodology is to go to the nearest location. If your location is equidistant between several you might average. There are no hard and fast rules.

State boundaries are a consideration. The reason is that the wage rates used to calculate costs are often based upon Davis Bacon (Prevailing Wages) wages. These wages vary by state, therefore I would be more inclined to pick a location nearest mine in the same state.

The city cost indexes are based upon material, labor and equipment research at key locations. We cannot reflect competitiveness or lack thereof in the indexes.

Phillip Waier
P.E., LEED AP Principal Engineer for RSMeans

Note: See Appendix A for authorization of e-mail comments.

These comments show the professional opinions of Mr. Waier. It can be conferred that Mr. Waier may agree with alternative methods, including averaging and state boundaries. Averaging and state boundaries were the alternate methods considered in this phase 1 of this research. Mr. Waier did not mention any consideration for economic variables in this email. Waier (2006) does advocate the use of location factors with similar economic characteristics, but does not mention which economic characteristic to consider.

5.8 Pearson Correlation Study

From Pearson's correlation study results, it was interpreted that the following economic criteria should be included in possible alternative methods.

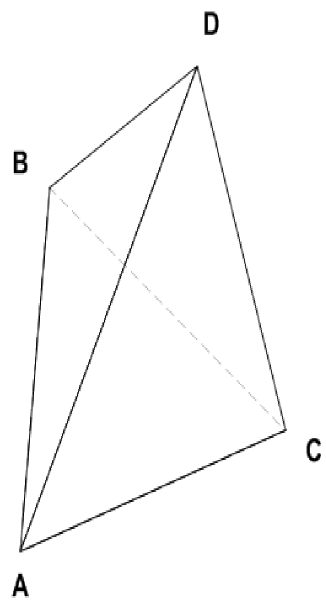
- Median Household Income
- Median Home Value

These factors had the highest degree of correlation to RSMeans CCI location factors. A detailed description of how these economic factors were considered in alternative methods will be discussed in sequential sections.

The criteria of alternative interpolation methods evaluated in this research included the following:

- Proximity
- State Boundary / State Average
- Median Home Value
- Median Household Income

Figure 9 is a graphical representation of a triangular based pyramid. It was used to identify possible combinations of methods resulting from the criteria above. With this in mind, it facilitated a naming convention for the interpolation methods. This is shown in the ID column in Figure 9. With the exceptions of, CNN, NN, and ST AVG, the remainder of this study will use this naming convention to identify the interpolation methods. Single-criterion and multi-criteria methods were compared in this study. A total of 15 different combinations of methods were evaluated in this research. This included the current method, the initial alternative methods from phase 1 of this study, and the additional alternative methods analyzed in phase 2 of this study.



#	ID	Method
1	A	Proximity (P)
2	B	State Boundaries (SB)
3	C	Median Home Value (MHV)
4	D	Median Household Income (MHI)
5	AB	P + SB
6	BC	SB + MHV
7	AC	MHV + P
8	AD	P + MHI
9	BD	SB + MHI
10	CD	MHV + MHI
11	ABC	P + SB + MHV
12	ABD	P + SB + MHI
13	BCD	SB + MHV + MHI
14	ACD	P + MHV + MHI
15	ABCD	P + SB + MHV + MHI

Figure 9. All Methods Evaluated

Point A represents proximity, point B represents state boundaries, point C represents median home value, and point D represents median household income. These were the four single criterion methods evaluated in this research. In addition, multi-criteria methods were also considered. Segment AB represents a combination of proximity and state boundaries. Segment BC represents a combination of state boundaries and median home value. Segment AC represents a combination of proximity and median home value. Segment AD represents a combination of proximity and median household income. Segment BD represents a combination of state boundaries and median household income. Segment CD represents a combination of median household income and median home value. Area ABC represents a combination of proximity, state boundaries, and median home value. Area ABD represents a combination of proximity, state boundaries, and median household income. Area BCD represents a combination of state boundaries, median home value, and median household income. Area ACD represents a combination of proximity, median home value, and median household income. The final area, ABCD, represents a combination of proximity, state boundaries, median home value, and median household income.

5.9 Single Criterion Methods Under Analysis

According to figure 9, there are four single-criterion methods evaluated in this research including the following:

- Proximity
- State Boundaries
- Median Household Income Method
- Median Home Value Method

5.9.1 Proximity

Some of the most prevalent methods of location adjustment for cities that do not have location factors include the use of proximity to other cities with location factors. Although there are many possible proximity methods, there was only one method evaluated in this research based solely on proximity. This was the current industry suggested interpolation method known as the nearest neighbor (NN). It is important to understand that linear distance was used for all calculations involved in the NN method. Linear distance was used due the simplicity of calculations from multiple geographic locations throughout the U.S. A possible continuation of this study may focus on distance based on other factors such as highway and road travel.

The NN Method selects the nearest available CCI location factor regardless of state boundaries to interpolate for unknown CCI factors. This process will be demonstrated in the GIS map of Arizona and New Mexico shown in figure 10.

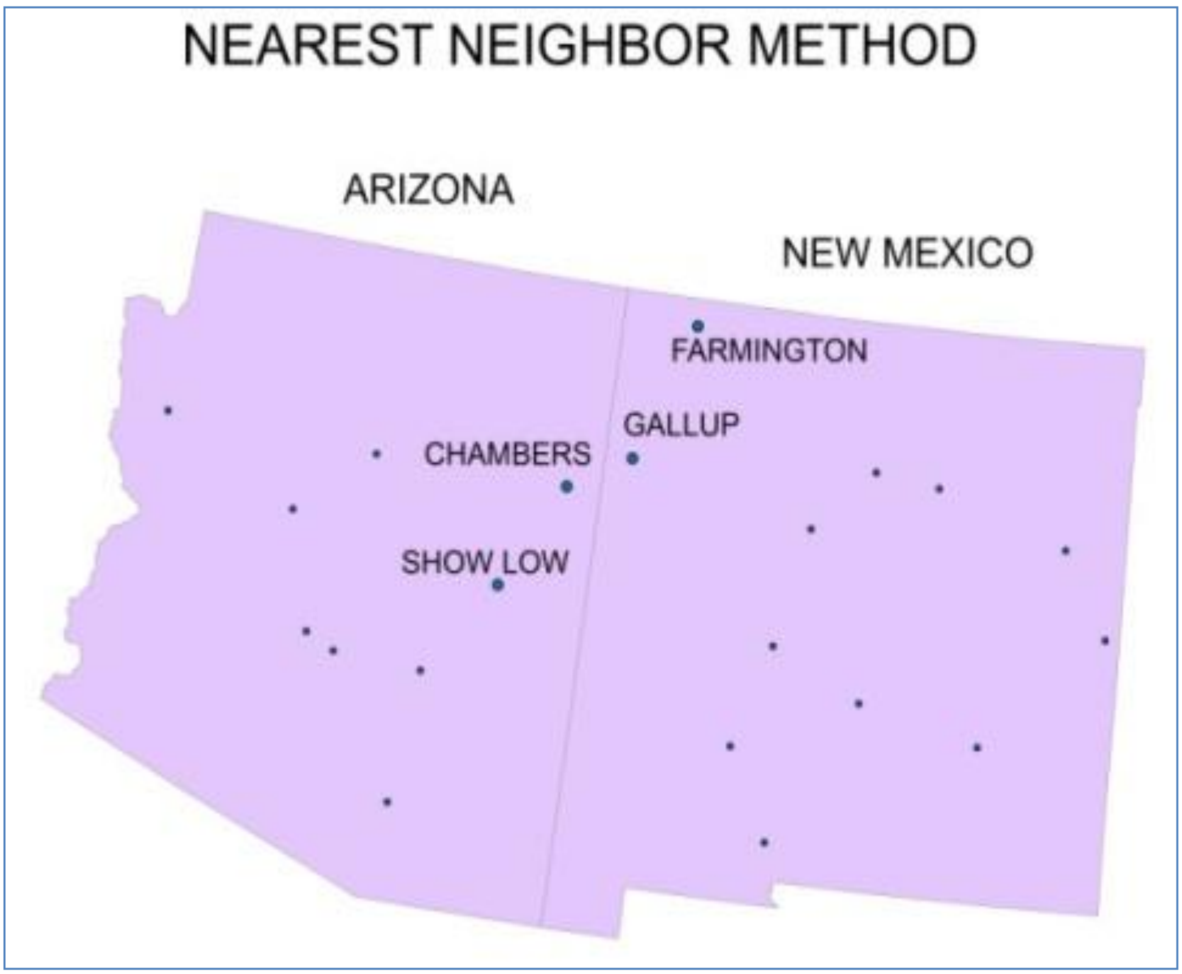


Figure 10. GIS Map of Arizona and New Mexico

The map shows the cities within Arizona and New Mexico that have a 2006 RSMeans location factor. These cities are shown as points within the states. It also has four cities labeled including Farmington, Gallup, Chambers, and Show Low. As an example, an owner wants to build their next commercial construction project in Chambers, AZ, and this city does not have a location factor. Chambers, AZ does in fact have a location factor, but for this example, it was assumed that it does not. The owner wants to perform a conceptual cost estimate for this location. To perform this estimate, a location adjustment factor must be identified. Given the presumed lack of location factor for Chambers, the nearest neighbor method will identify the closest known location factor as a suggested location factor value for Chambers, AZ. Looking at Chambers, the estimator calculates the closest location to this city. Using linear distance, Gallup is approximately 73 kilometers away, and Show Low is approximately 119 kilometers away. Therefore, the closest geographical location to Chambers, AZ with a known factor is Gallup, NM. According to the NN method, Gallup is the "twin location" for Chambers. This means that the CCI value for Gallup, NM would be the logical choice for the estimator to use as a value for Chambers, AZ. In this example, Chambers did not have a CCI value in the first place. One of the underlying assumptions in this method is that state boundary does not play a significant role in the nearest neighbor selection process. In other words, the estimator is looking for the closest known location factor regardless of state boundary. Obviously, this assumption can be disputed, and this will be addresses in later methods.

The nearest neighbor method can be visualized using Geographic Information Systems (GIS). Within ArcMAP GIS software, there is a feature known as Thiessen

Polygon Interpolation. This is used as a visual representation of the nearest neighbor concept. A thiessen polygon would represent the area of influence of one of the CCI values. Basically, all the locations within a city's area of influence are those that would select the given location when the NN method is used. Figure 11 is a GIS map of the United States sectioned into thiessen polygons.

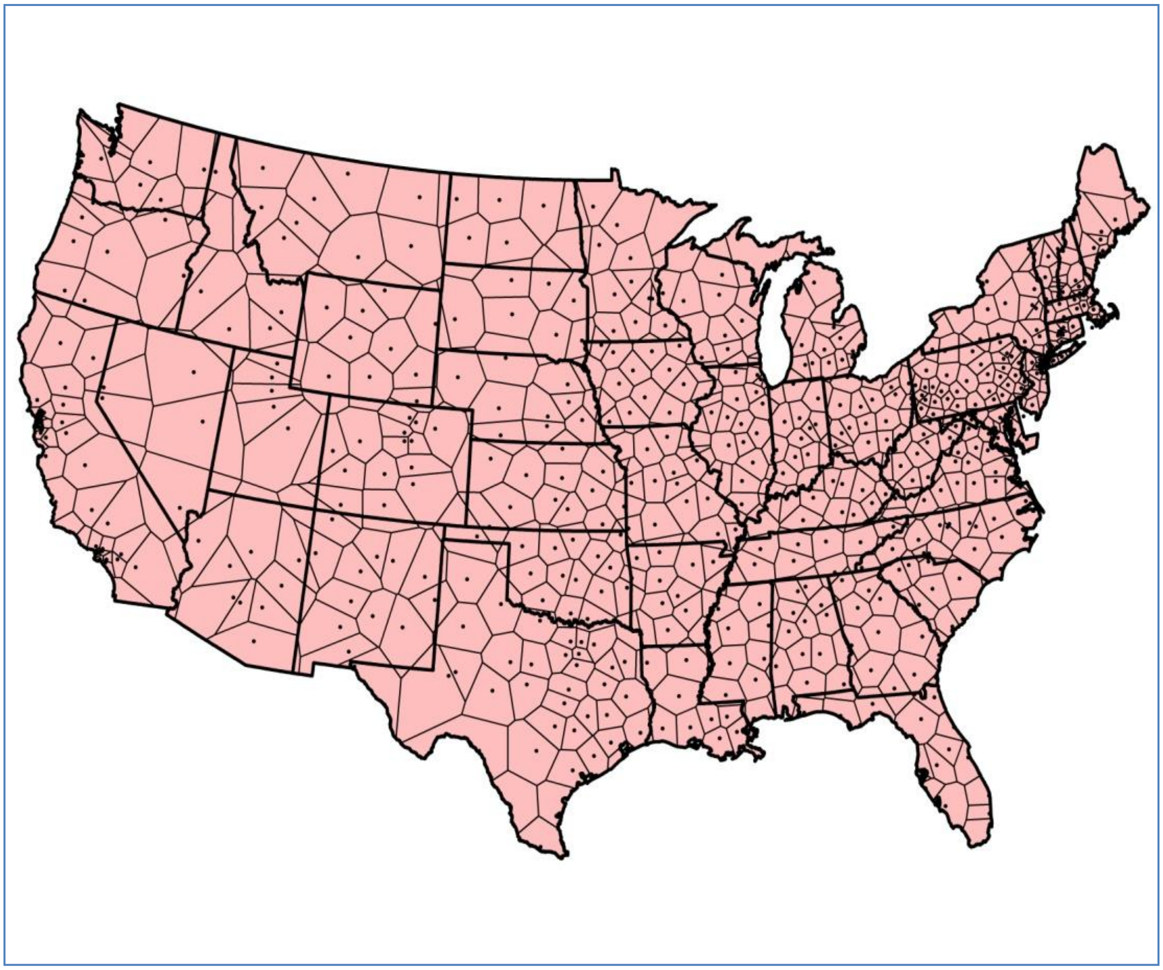


Figure 11. GIS Map of National-Level Thiessen Polygons

The points in figure 11 represent US cities with a known location factor from the RSMeans CCI. There are a total of 649 cities with these known location factors. The Thiessen polygons create a boundary and every location within that boundary has an equal value for a Z variable. The Z variable can be any variable of interest that can be measured. In this instance, the Z variable is the CCI value. The Z variable changes from one value to the next at the Thiessen polygon boundary. According to Bolstad (2005), the polygons define a region surrounding a sampled point that has a value equal to that of the sampled point. The sampled point is the known CCI city and the defined region is all the area surrounding that city which is geographically closer to that sampled point than to any other sampled point. It is important to understand that linear distance was used to define this boundary. As the sampled population density increases, the polygons become smaller. Similarly, in areas of low density sampled points, the polygons within the points become larger. Figures 12 and 13 show the thiessen polygons for New Mexico. The first (Figure 12. NN Thiessen Polygons) shows polygons which are not limited by state boundary. The second (Figure 13. CNN Thiessen Polygons) shows polygons which are limited by state boundary. Figure 13 will be useful in explaining the CNN method which will be discussed in later sections of this study.

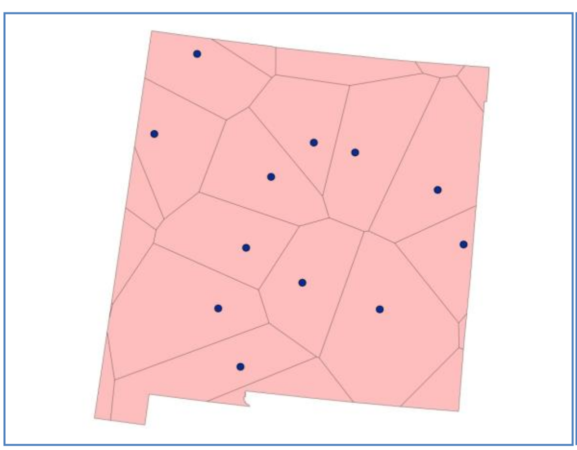


Figure 12. NN Thiessen Polygons

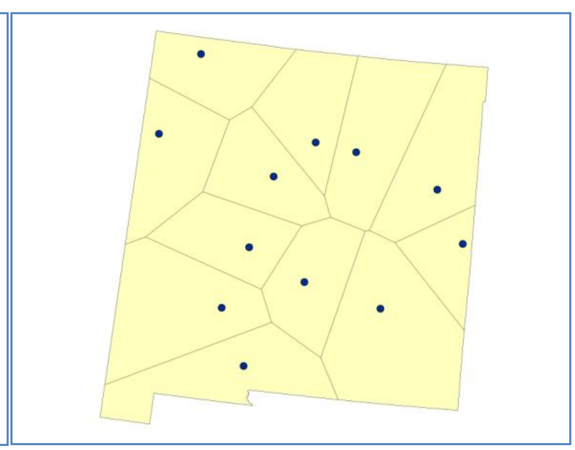


Figure 13. CNN Thiessen Polygons

New Mexico has 12 cities with a known CCI value. These are the sampled points found near the center of each polygon. Each polygon shows all the areas in which the CCI value is defined as equal to that of the pertaining sampled point. In other words, a polygon shows the area that should have the same CCI value using the NN method. This is useful to an estimator because it eliminates having to calculate distances of cities with location factors to construction sites. For example, an owner wants to build a new commercial building within New Mexico, but does not know exactly where. There are several potential areas spread throughout the state in which the owner has an interest. A conceptual estimate with location adjustment is needed for each potential area. The estimator can mark the areas, possibly by using longitude and latitude coordinates. The estimator will then know which location adjustment factor to use simply by evaluating which polygon corresponds to each potential location. One of the underlying questions related to this example includes the following: what if a potential location lies directly on a polygon boundary? First off, the distances from the potential location to two or more sampled points must be exact. Secondly, the probability for this to occur on an actual construction project is minimal, but if it were to happen, it would be up the estimator to choose which location factor to use or what alternative method to use. Lastly, there is no proper way to handle this situation using the nearest neighbor method or any other method discussed in this research. A possible solution suggested by RSMeans (see e-mail conversation from section 5.7) would be to average the two equal-distant CCI values. The key concept associated with NN interpolation is that although this method is commonly used, its validity has not been statistically substantiated.

5.9.2 State Boundaries

The State boundaries criterion used in this study was unique. When implemented as the only factor in a single-criterion method, it actually referred to averaging within state boundaries. When used in a multi-criteria method it literally referred to a state boundaries limitation. With this in mind, state boundaries as a single criterion method was actually the ST AVG method mentioned in phase 1.

The ST AVG method takes an average of all CCI values within each state and uses this value for every location within the state. Figure 14 is a GIS map of Colorado, which will be used to demonstrate the ST AVG method.

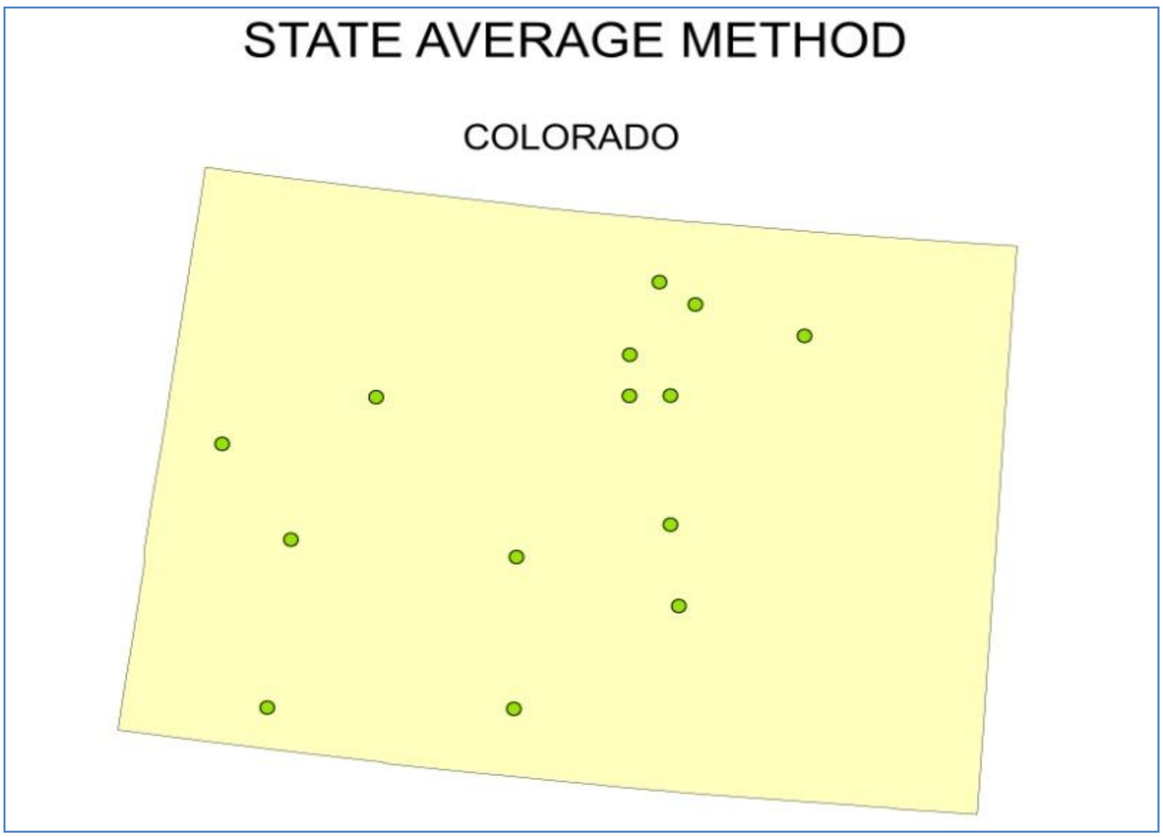


Figure 14. GIS Map of Colorado

Looking at the map, there are several points spread all over the state. These points represent locations of cities with known RSMeans CCI location factors. The average value of the CCI values for all locations within the state is calculated. This average value is used for all location adjustments within the state.

Obviously, there are enormous differences in costs to build at different locations throughout the state, but it will be interesting to see how this method compares to more time-consuming methods. What gives this method its defining characteristic is its simplicity. To demonstrate this, an owner wants to build in multiple locations throughout the state. Using this method the estimator has the same location adjustment value for each potential location. This saves a lot of time and effort in identifying the factor needed for the preparation of a conceptual cost estimate. While the estimator is gaining valuable time and effort, he may be giving up accuracy. Although unrelated to this study, it would be interesting to see if this trade off is significantly legitimate.

To further demonstrate how the ST AVG method is calculated, a GIS attribute table for Colorado is shown in table 9.

Table 9. GIS Attributes Table

FID	Shape *	NAME	ST	STATE	CCI
0	Point	ALAMOSA	CO	COLORADO	91.7
1	Point	BOULDER	CO	COLORADO	92.7
2	Point	COLORADO SPRING	CO	COLORADO	93.9
3	Point	DENVER	CO	COLORADO	95.8
4	Point	DURANGO	CO	COLORADO	92.7
5	Point	FORT COLLINS	CO	COLORADO	92.8
6	Point	FORT MORGAN	CO	COLORADO	92.8
7	Point	GLENWOOD SPRING	CO	COLORADO	93.2
8	Point	GOLDEN	CO	COLORADO	93.6
9	Point	GRAND JUNCTION	CO	COLORADO	91.7
10	Point	GREELEY	CO	COLORADO	86.1
11	Point	MONTROSE	CO	COLORADO	91.1
12	Point	PUEBLO	CO	COLORADO	92.5
13	Point	SALIDA	CO	COLORADO	91.9

Looking at the table, there is a total of 14 points within Colorado that have a CCI value. The CCI values are shown on the far right column. These values range from a minimum of 86.1 to a maximum of 95.8. The average value is 92.3; therefore, this is the value the estimator would use for location adjustment of any potential project within the state. Now that the actual procedure associated with ST AVG has been explained, it is important to understand why this alternative was initially considered.

As part of the initial evaluation process, the current interpolation method was compared with initial alternative methods in an effort to determine the most accurate location adjustment methodology. Recalling that, in this research, the NN method was considered the current method, it was compared with the first alternative method. With this in mind, the first initial alternative interpolation method considered was the ST AVG method. Using GIS, average RSMeans CCI values within states were calculated and associated as attributes of each state. Correspondingly, a graduated color map was produced. This is shown in figure 15.

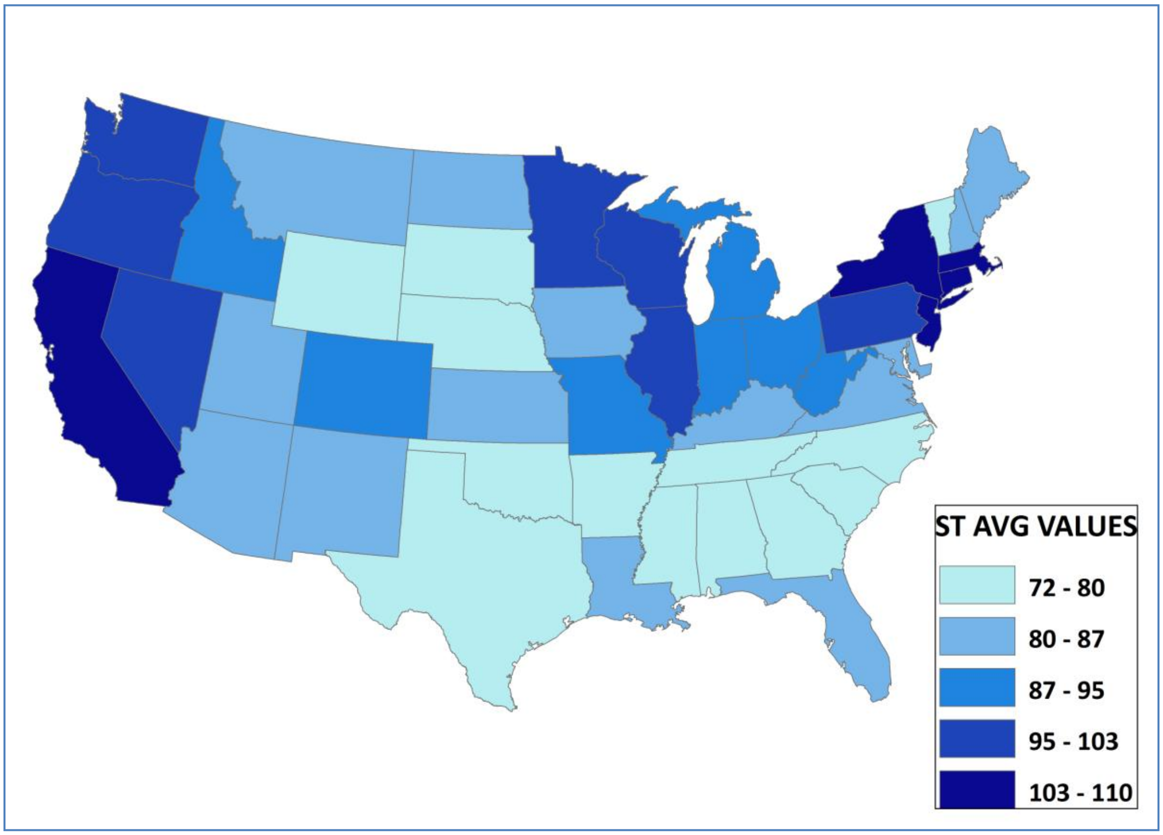


Figure 15. GIS Graduated Color Map of ST AVG Values

The map indicated clusters of areas with similar state average CCI values. These clusters provided evidence that proximity and state average CCI values might be correlated. Due to this, it was inferred that the ST AVG method would be a logical choice as a potential alternative to the current method.

5.9.3 Median Household Income Method

The median household income method selects the city with the most similar household income as the twin location. This selection is not contingent on state boundaries, meaning that the most similar income value to that of the desired city is selected regardless of what state it is located. For example, an owner wants to build in Albuquerque, NM and this city did not have a location adjustment factor. Assuming that Albuquerque has a median household income of $55,000.00, and the most similar income to this value is in Denver, Colorado with a value of $55,000.01. Using the median household income method, the CCI value for Denver would be selected to represent a location adjustment factor for Albuquerque. In other words, Denver would be selected as the twin location to Albuquerque.

If the situation arises that more than one city has the same most similar income then all of these cities would be considered as "multiple twin locations" and the CCI values of these cities are averaged together and used as the estimated CCI for the unknown value. To demonstrate this "multiple twin locations" situation let's consider the Albuquerque and Denver example previously mentioned. In this example, Albuquerque does not have a location factor and an estimator need to adjust for this unknown location factor value. Albuquerque has a median income of $55,000.00; Denver as well as Santa Fe has median incomes of $55,000.01. In this case, both Denver and Santa Fe have the most similar income to Albuquerque. Therefore, the CCI for Denver and Santa Fe are averaged together and used as the estimated CCI for Albuquerque. This is the "multiple twin CCI averaging technique". It is used in this, and all sequential methods in which more than one twin exists.

5.9.4 Median Home Value Method

The fourth and final interpolation method based solely on one criterion is the median home value method. Conceptually, this method is very similar to the median household income method. The twin location is selected by calculating the most similar median home value. The "multiple twin CCI averaging technique" is also used in this method. This concludes the interpolation methods base on one characteristic including the current, industry suggested method as well as alternative methods.

5.10 Two Criteria Methods Under Analysis

Continuing with alternative methods, this section will explain two criteria methods. There are a total of 6 possible combinations which include the following:

- Proximity and State Boundaries
- Median Household Income and State Boundaries
- Median Home Value and State Boundaries
- Median Household Income and Median Home Value
- Proximity and Median Household Income
- Proximity and Median Home Value

5.10.1 Proximity / State Boundaries

The first two criteria method was the CNN method describe in phase 1 of this study. It is similar to the nearest neighbor method because the closest known location factor is selected to represent the unknown location factor, but a boundary is added to restrict extending the selection process from across state lines. Figure 16 shows a GIS map of New Mexico and Texas.

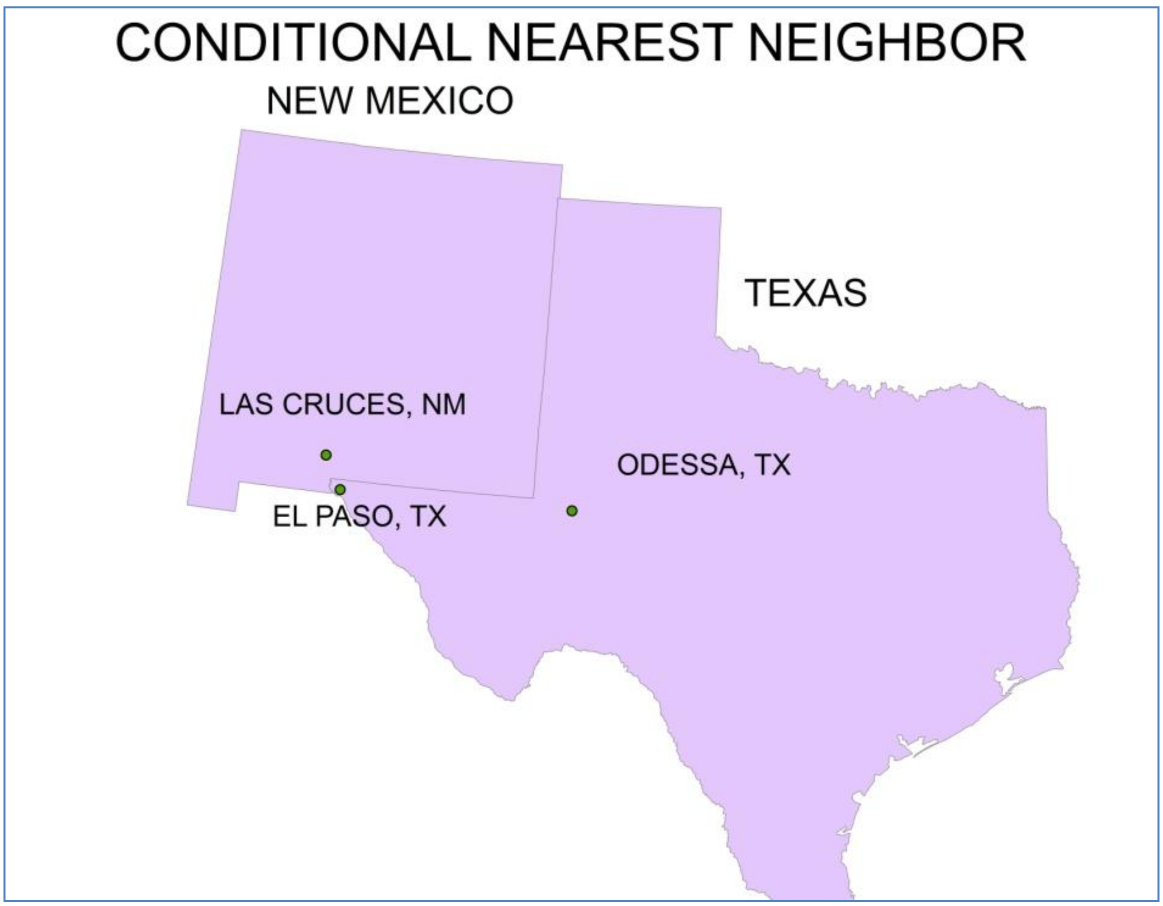


Figure 16. GIS Map of Map of New Mexico and Texas

Three cities with location factors were selected from these states; these cities included Las Cruces, El Paso, and Odessa. For this example, an owner wants to build a new facility in El Paso, TX and this city does not have a location factor. Using the CNN method, the estimator would use the location factor from Odessa, TX instead of Las Cruces, NM. Although Las Cruces is in fact closer to El Paso than Odessa, the estimator cannot use the Las Cruces location factor as a comparable to El Paso because of the state boundary restriction. Since Odessa is geographically the closest city to El Paso, with a known location factor within the state of Texas, this would be the optimal choice as a replacement value for the unknown location factor for El Paso. The underlining assumption in this example is that El Paso did not have a location factor.

Figure 17 shows a GIS map of California and Nevada, which will demonstrate the CNN process.

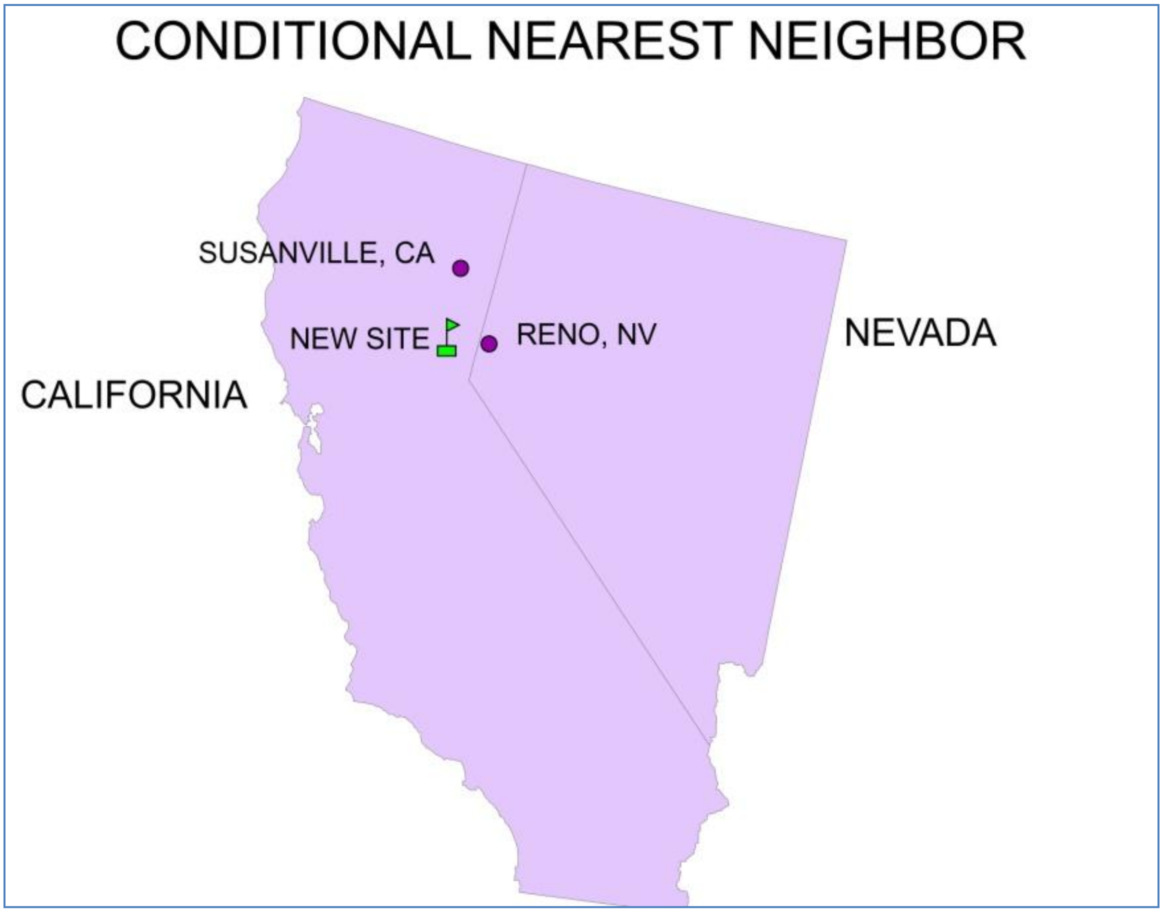


Figure 17. GIS Map of Map of California and Nevada

Looking at the map, there are two cities, Susanville, CA and Reno, NV. Both of these cities have a location factor from RSMeans 2009. There is also a flag that represents a new location in which an owner wants to build a commercial building. The cities are the two closest geographical cities from the new site. The distance from the new site to Reno, NV is approximately 60 kilometers whereas the distance from the new site to Susanville, CA is approximately 100 kilometers. Using the CNN method the logical choice to use as a location factor for the new site is Susanville, CA even though it is further. If the estimator were using the NN approach, this would not be the case. The logical choice using the NN approach would be Reno, NV. This shows how the different interpolation methods have vastly different outcomes.

5.10.2 Median Household Income / State Boundaries Method

The second two criteria interpolation method is the median household income / state boundaries method. There are 649 total locations within the RSMeans CCI dataset. Using ArcMap GIS both economic factors (median household income and median home value) were added as attributes for each corresponding location. All data was then sorted by state using Microsoft excel. This created a spreadsheet with 649 variables separated by state showing data that included economic factors for each RSMeans city. From this point, the data for all cities within a single state was selected and sorted by the median household income. For each city, the difference between its respective median household income and those of all other cities within the state was calculated. Using the absolute value of this difference, the lowest value was selected as the counterpart for the selected city. In other words, an RSMeans city is selected and using this process the next city with the most similar household income within the same state was calculated.

5.10.3 Median Home Value / State Boundaries Method

The median home value / state boundaries method is very similar to the median household income / state boundaries method. It included the same procedure, but median home value was used in lieu of income. Table 10 shows data used in calculating the median home value / state boundaries ranking method.

Table 10. Median Home Value / State Boundaries Ranking Method

CITY FID	CITY NAME	MEDIAN HOME VALUE	ACTUAL CCI VALUE	MOST SIMILAR HOME VALUE WITHIN STATE	FID OF LOCATION WITH SIMILAR HOME VALUE
86	PRICE	114913	77.6	142883	85
85	OGDEN	142883	85.5	163970	84
84	LOGAN	163970	86.4	142883	85
87	PROVO	192264	86.7	201075	88
88	SALT LAKE CITY	201075	87.7	192264	87

The data for all 649 variables was sorted by state, and then by median home value. This table is a section of the data for the state of Utah. Looking at the far left of the table there is a “city fid” column. This is the numerical identification for the individual RSMeans city with a location factor. The city name and state is mentioned and there is also a median home value and CCI value that pertains to this city. For Price, Utah the fid number is 86, the median home value is $114,913 and the actual CCI value is 77.6. From this information the next similar home value can be calculated. The next similar value to $114K is $142K. The two columns on the right are the most important part of this table. They display the actual amount of the next similar home value within the state and the identification number of the city with the next similar home value. For Price, the next similar city in home value is Ogden. This process was repeated not only for the state of Utah but for all 649 variables throughout 48 states. This concludes the interpolation methods based solely on economic factors.

5.10.4 Median Household Income / Median Home Value

The fourth two criteria method involved socio-economic variables. This is where the concept of ranking (explained in section 3.4.2) was introduced. The median household income / median home value method involves assigning a rank to each economic variable and using the lowest combined rank to select a twin location. For example, an owner wants to build commercial office in Austin, TX. Assuming that this city did not have a CCI value, what location adjustment factor does the estimator use for Austin? Using the median household income / median home value method, a ranking for each city's income related to that of Austin is established. Then a similar ranking for home value is established. The values for both ranks are combined, and the city pertaining to the lowest combined rank is selected as the twin location. It is important to explain that state boundaries are not considered in this method and therefore, a city in another state may be the twin. This parameter can definitely hinder the accuracy of the method and therefore, the additions of state boundary and proximity will be discussed later in this chapter.

5.10.5 Proximity / Median Household Income

This section discusses the ranking method based on proximity and median household income. Proximity between cities was determined using ArcGIS. Then a ranking was established for a selected city from the RSMeans CCI dataset. A second ranking was established for income. The city with the lowest combined rank is selected as the twin location.

5.10.6 Proximity / Median Home Value Method

The final two criteria interpolation method is based on proximity and median home value. Proximity between cities was determined using ArcGIS. Then a ranking was established for a selected city from the RSMeans CCI dataset. A second ranking was established for home value. The city with the lowest combined rank is selected as the twin location. Although there is less probability for a city in a different state to be selected as the twin location, it is still a possibility using this method.

5.11 Three Criteria Methods Under Analysis

Three criteria methods will be discussed in this section. There are four possible combinations of methods at this level including the following:

- Proximity / Median Household Income / State Boundaries Method
- Proximity / Median Home Value Method / State Boundaries Method
- Median Household Income / Median Home Value/ State Boundaries Method
- Proximity / Median Household Income / Median Home Value Method

It is important to mention that the multi-criteria methods involving ranking were not calculated for all 649 RSMeans cities. This is where the regional-level sample size (explained in section 3.4.2) was applied.

5.11.1 Proximity / Median Household Income / State Boundaries

For this method, a GIS spatial join was created between an individual city and all the cities within the same state. This created an attribute column which calculated distances in meters. The median income values were attained from the same dataset used in economic methods that was discusses earlier. Table 11 is a GIS attributes table which will be used to explain the proximity/income/St. boundaries ranking procedure.

Table 11. GIS Attributes Table

CITY FID	CCI	NAME	MED INCOME	INCOME DIFF	RANK 1	DIST IN METER	RANK 2	SUM RANKS
541	84.1	CHAMBERS	27152	NA	NA	NA	NA	NA
548	84.8	SHOW LOW	34684	7532	1	119211	1	2
544	83.6	KINGMAN	40043	12891	3	417422	8	11
543	83.6	GLOBE	38556	11404	2	233936	3	5
549	85.6	TUCSON	46500	19348	5	358111	7	12
547	84.3	PRESCOTT	44092	16940	4	283164	4	8
542	87.9	FLAGSTAFF	48197	21045	6	198514	2	8
545	85.0	MESA	57460	30308	7	288743	5	12
546	87.6	PHOENIX	57460	30308	8	303081	6	14

This table shows data from cities within Arizona. Starting from the left, the following is displayed: city FID, which is the identification value, actual RSMeans CCI value for the city, city name and state, median income, and other factors which will be explained later.

We can see that the Chambers, AZ row has been highlighted. This means that all data in the right half of the table pertains to Chambers. These columns include the following: income difference, rank 1, distance, rank 2, and summary of ranks. The income difference column shows the difference between the median income of Chambers and all other cities. Show Low has a median income of $34,684. When the median income of Chambers is subtracted from that of Show Low the difference is $7,532. Since this is the lowest value, which also means the most similar value, it attains a ranking of 1. This value is shown in the rank 1 column. Similarly, all other ranking values in this column were established from the degree of similarity to the median income for Chambers. We can see that the city with the most difference is Phoenix; this city has value of 8 in the rank 1 column. Continuing with the columns, the next heading is distance. This column displays the varying distances in meters from Chambers. Looking at the Flagstaff row, the city is approximately 198 kilometers (198,514 meters) away from Chambers. Since this is the second lowest value it attains a ranking of 2 in the rank 2 column. This ranking is completed by measuring the degree of proximity from Chambers. The last column shows a summation of the two ranking columns. The lowest combined rank has a value of 2 and pertains to Show Low. This would be the city selected as the twin location to Chambers. The process was repeated for each city evaluated with this method.

5.11.2 Proximity / Median Home Value Method / State Boundaries

This method involves ranking of proximity and median home value within a state. It is conceptually similar to other ranking methods. The only difference is a change in the characteristics evaluated. For each city, similar median home values within the state are ranked. Then a secondary ranking is established for proximity within state to the same city. The sum of both ranks is calculated, and the lowest combined rank is considered as the twin location to the original city.

5.11.3 Median Household Income / Median Home Value/ State Boundaries Method

The third three criteria method is the Median Household Income / Median Home Value/ State Boundaries method. It also used a ranking procedure. Ranking was established by state based on both economic factors. The lowest combined rank was calculated and used as the twin location.

5.11.4 Proximity / Median Household Income / Median Home Value Method

The final three criteria method is based on proximity and both economic factors. Ranks were established based on each of these variables. The lowest combined rank was calculated and used as the twin location. This method is the only three criteria method that does not consider state boundaries. Table 12 shows the 7 methods calculated at the national-level.

Table 12. National-Level Methods

ID	NATIONAL LEVEL METHODS
A(NN)	Nearest Neighbor
B(ST AVG)	State Average
AB(CNN)	Nearest Neighbor within State Boundary
D	Most Similar Median Household Income
C	Most similar Median Home Value
CD	Median Household Income / State Boundaries Method
BC	Median Home Value / State Boundaries Method

Microsoft excel was used to calculate error for all methods. Error was calculated for both relative numbers and absolute numbers. Once the error (relative or absolute) for all variables considered was in a single column, it was manipulated to create basic statistical information such as mean, median, standard deviation and variance. In comparing this information, the method with the least amount of mean, median, standard deviation and variance or absolute error was theoretically considered the most accurate. This method could theoretically produce the most accurate location adjustment and ultimately the most accurate conceptual cost estimate.

5.12 Four Criteria Methods Under Analysis

The final method evaluated in this research incorporated all criteria which included the following:

- Proximity
- State Boundaries
- Median Household Income
- Median Home Value

5.12.1 Proximity / Median Household Income / Median Home Value / State Boundaries Method

The final multi-criteria method is similar in theory to other multi-criteria methods which used ranking, but added another level of complexity. Data from earlier methods was used. Table 13 will be used to demonstrate the proximity/income/home value/St. boundaries method.

Table 13. Four Criteria Method Data

NAME	INCOME RANK 1	PROXIMITY RANK 2	MED HOME VALUE	HOME VALUE DIFF	HOME VALUE RANK 3	RANK TOTALS
CHAMBERS	NA	NA	82793	NA	NA	NA
SHOW LOW	1	1	125777	42984	1	3
KINGMAN	3	8	148717	65924	2	13
GLOBE	2	3	150052	67259	3	8
TUCSON	5	7	181978	99185	4	16
PRESCOTT	4	4	201518	118725	5	13
FLAGSTAFF	6	2	207275	124482	6	14
MESA	7	5	241112	158319	7	19
PHOENIX	8	6	241112	158319	8	22

Chambers, AZ is highlighted and both ranking values from income and proximity are shown. The addition to this table is shown on the 4 right columns and included the following: median home value, home value difference, home value ranking 3, and ranking totals. The median home value data was the same data used in prior multi-criteria methods. This table was sorted by the home value rank 3 column. The most similar home value to Chambers is that of Show Low, therefore the "rank 3" value is 1. The city with the most dissimilar home value was Phoenix. The city with the lowest combined ranks was also Show Low, which is highlighted. Therefore this would be the twin location to Chambers. Assuming Chambers did not have a CCI value, the estimator would use the CCI value from Show Low for Chambers. This may be the same outcome as other approaches. It will be interesting to see if this similarity is shown in the results from other methods. This was the final method evaluated in this research.

CHAPTER 6.0 PHASE 2 EMPIRICAL COMPARISON OF METHODS: ANALYSIS AND RESULTS

6.1 Overview

This chapter will discuss phase 2 analysis and results. It is important to understand that phase 2 comparisons included initial methods from phase 1. In addition, there were results pertaining to different sample sizes. Furthermore, error was calculated using both relative values (positive and negative) and absolute values. This was done in order to evaluate methods using various statistical testing techniques. The statistical testing techniques included descriptive statistics, box plots, Levene's tests, and Mann-Whitney tests. Results from all of these topics will be discussed in this chapter.

6.2 Descriptive Statistics

In this research, descriptive statistics referred to calculations for mean, median, standard deviation, and variance of error for all groups including the following:

- Single Criterion Methods
- Two Criteria Methods
- Three Criteria Methods
- Four Criteria Methods
- All Methods

6.2.1 Single Criterion Methods Results

There were 4 single criterion methods evaluated in this research. These methods included the following:

- Nearest Neighbor Method
- State Average Method
- Median Household Income Method
- Median Home Value Method

Error was calculated for all these methods at both national and regional-levels. Table 14 shows the results for mean, median, standard deviation, and variance of error for these methods at the national-level.

Table 14. Single Criterion National-Level Relative Error Statistics

METHOD CRITERIA	NATIONAL ERROR (RELATIVE VALUES)			
	MEAN	MED	ST DEV	VAR
Nearest Neighbor (NN)	0.23	0.10	5.56	30.87
State Average (ST AVG)	0.00	0.11	5.36	28.68
Most Similar Median Household Income	0.66	0.20	14.29	204.27
Most similar Median Home Value	0.10	0.25	12.42	154.16
MIN	0.00	0.10	5.36	28.68
MAX	0.66	0.25	14.29	204.27

Error for this chart was determined using relative differences between estimated and actual CCI values. Results indicated that the ST AVG method produced the lowest mean, standard deviation and variance of relative error. On the contrary, the median household income method produced the highest mean, standard deviation and variance of relative error. In addition, the NN method produced the lowest median relative error, and the median home value method produced the highest median relative error.

Single criterion methods were also evaluated at the regional-level. Table 15 shows the regional-level results for mean, median, standard deviation, and variance of error for these methods.

Table 15. Single Criterion Regional-Level Relative Error Statistics

METHOD CRITERIA	REGIONAL ERROR (RELATIVE VALUES)			
	MEAN	MED	ST DEV	VAR
Nearest Neighbor (NN)	-0.03	-0.05	4.15	17.23
State Average (ST AVG)	0.00	0.08	4.00	16.02
Most Similar Median Household Income	-2.39	-1.00	13.39	179.37
Most similar Median Home Value	0.25	0.35	8.27	68.39
MIN	-2.39	-1.00	4.00	16.02
MAX	0.25	0.35	13.39	179.37

Error for this chart was determined using relative differences between estimated and actual CCI values. Results indicated that the ST AVG method produced the lowest standard deviation and variance of relative error. On the contrary, the median household income method produced the highest standard deviation and variance of relative error. These regional-level relative error results were identical to the national-level results.

Absolute error descriptive statistics for single criterion methods at both national and regional-levels were also calculated. Results are shown in table 16.

Table 16. Single Criterion Regional/National-Level Absolute Error Statistics

METHOD CRITERIA	NATIONAL ERROR (ABSOLUTE VALUES)				REGIONAL ERROR (ABSOLUTE VALUES)			
	MEAN	MED	ST DEV	VAR	MEAN	MED	ST DEV	VAR
Nearest Neighbor	3.78	2.30	4.08	16.62	2.62	1.70	3.21	10.30
State Average	3.80	2.56	3.77	14.18	2.92	1.99	2.71	7.36
Most Similar Median Household Income	10.52	7.80	9.68	93.77	9.68	6.80	9.50	90.29
Most similar Median Home Value	9.63	8.15	7.83	61.29	6.15	4.25	5.49	30.15
MIN	3.78	2.30	3.77	14.18	2.62	1.70	2.71	7.36
MAX	10.52	8.15	9.68	93.77	9.68	6.80	9.50	90.29

Error for this chart was determined using differences between estimated and actual CCI absolute values. Results indicated that the NN method produced the lowest mean absolute error. On the contrary, the median household income method produced the highest mean absolute error.

6.2.2 Two Criteria Methods Results

There were 6 two criteria methods evaluated in this research including:

- Proximity / State Boundaries Method (CNN)
- Median Household Income / State Boundaries Method
- Median Home Value / State Boundaries Method
- Median Household Income / Median Home Value Method
- Proximity / Median Household Income Method
- Proximity / Median Home Value Method

While all 6 methods were evaluated at the regional-level, only 3 of these methods were calculated at the national-level. The two criteria national-level methods included the following:

- Proximity / State Boundaries Method (CNN)
- Median Household Income / State Boundaries Method
- Median Home Value / State Boundaries Method

Table 17 shows the results of absolute error descriptive statistics for all two criteria methods at the national and regional-levels.

Table 17. Two Criteria Regional/National-Levels Absolute Error Statistics

METHOD CRITERIA	NATIONAL ERROR (ABSOLUTE VALUES)				REGIONAL ERROR (ABSOLUTE VALUES)			
	MEAN	MED	STD DEV	VAR	MEAN	MED	STD DEV	VAR
Proximity / State Boundary (CNN)	3.07	1.95	3.09	9.57	1.98	1.40	2.03	4.14
Median Household Income / State Boundaries Method	3.98	2.50	4.75	22.60	2.24	1.20	2.23	4.99
Median Home Value / State Boundaries Method	3.69	2.50	3.75	14.08	2.29	1.40	2.12	4.48
Median Household Income / Median Home Value Method	NA	NA	NA	NA	6.46	3.73	6.45	41.57
Proximity / Median Household Income Method	NA	NA	NA	NA	4.20	3.10	4.08	16.61
Proximity / Median Home Value Method	NA	NA	NA	NA	3.36	2.60	2.93	8.58
MIN	3.07	1.95	3.09	9.57	1.98	1.20	2.03	4.14
MAX	3.98	2.50	4.75	22.60	6.46	3.73	6.45	41.57

This table indicated that CNN produced the lowest mean, median, standard deviation, and variance. On the contrary, the income / state boundaries method produced the highest mean, median, standard deviation, and variance. At the regional-level, CNN still had the lowest mean, standard deviation and variance and one of the lowest median values. On the contrary, income / home value method had the highest mean, median, standard deviation, and variance.

Relative error statistics were also calculated. Table 18 shows the results of relative error descriptive statistics for two criteria methods included in their respective national and regional-levels.

Table 18. Two Criteria Regional/National-Level Relative Error Statistics

METHOD CRITERIA	NATIONAL ERROR (RELATIVE VALUES)				REGIONAL ERROR (RELATIVE VALUES)			
	MEAN	MED	STD DEV	VAR	MEAN	MED	STD DEV	VAR
Proximity / State Boundary (CNN)	0.16	0.10	4.36	19.00	0.04	0.20	2.85	8.11
Median Household Income / State Boundaries Method	0.15	0.05	6.20	38.48	0.11	0.25	3.17	10.06
Median Home Value / State Boundaries Method	-0.01	0.00	5.27	27.74	0.24	0.35	3.12	9.74
Median Household Income / Median Home Value Method	NA	NA	NA	NA	-0.32	-0.45	9.15	83.67
Proximity / Median Household Income Method	NA	NA	NA	NA	-1.42	-0.75	5.69	32.39
Proximity / Median Home Value Method	NA	NA	NA	NA	-0.39	0.00	4.46	19.87
MIN	-0.01	0.00	4.36	19.00	-1.42	-0.75	2.85	8.11
MAX	0.16	0.10	6.20	38.48	0.24	0.35	9.15	83.67

At the national-level, results from this table indicated that CNN produced the lowest standard deviation, and variance. On the contrary, income / state boundaries method produced the highest standard deviation, and variance. At the regional-level, CNN still had the lowest standard deviation and variance. On the contrary, the income / home value method had the highest standard deviation, and variance. These results are consistent with national-level results.

6.2.3 Three Criteria Methods Results

There were 4 three criteria methods evaluated in this research. All 4 methods were evaluated only at the regional-level. These methods included the following:

- Proximity / Median Household Income / State Boundaries Method
- Proximity / Median Home Value Method / State Boundaries Method
- Median Household Income / Median Home Value / State Boundaries Method
- Proximity / Median Household Income / Median Home Value Method

Table 19 shows descriptive statistics for relative and absolute regional-level error values.

Table 19. Three Criteria Regional-Level Relative/Absolute Error Values Statistics

METHOD CRITERIA	REGIONAL ERROR (ABSOLUTE VALUES)				REGIONAL ERROR (RELATIVE VALUES)			
	MEAN	MED	STD DEV	VAR	MEAN	MED	STD DEV	VAR
Proximity / Median Household Income / State Boundaries Method	2.16	1.30	2.18	4.77	0.23	0.20	3.07	9.44
Proximity / Median Home Value Method / State Boundaries Method (ABC)	1.99	1.40	1.75	3.07	0.36	0.40	2.63	6.93
Median Household Income / Median Home Value/ State Boundaries Method	2.61	1.87	2.51	6.30	-0.17	-0.10	3.63	13.15
Proximity / Median Household Income / Median Home Value Method	3.78	2.60	3.63	13.17	-0.97	-0.40	5.17	26.70
MIN	1.99	1.30	1.75	3.07	-0.97	-0.40	2.63	6.93
MAX	3.78	2.60	3.63	13.17	0.36	0.40	5.17	26.70

Regional-level, absolute value results indicated that the proximity / home value / state boundaries method (denoted by “ABC” from section 5.8, figure 9) produced the lowest mean, standard deviation, and variance, and one of the lowest median values. On the contrary, the proximity / income / home value method (denoted by "ACD" from section 5.8, figure 9) produced the highest mean, median, standard deviation, and variance. In accordance, regional-level statistics produced the same results. ABC produced the lowest standard deviation, and variance, and method ACD produced the highest standard deviation, and variance.

6.2.4 Four Criteria Methods Results

There was only one four criteria method evaluated. It was the only method that considered all criteria considered in this study: proximity, state boundaries, median home value, and median household income. Table 20 shows the results for mean, median, standard deviation and variance for absolute and relative error values.

Table 20. Four Criteria Regional-Level Relative/Absolute Error Values Statistics

METHOD CRITERIA	REGIONAL ERROR (RELATIVE VALUES)				REGIONAL ERROR (ABSOLUTE VALUES)			
	MEAN	MED	ST DEV	VAR	MEAN	MED	ST DEV	VAR
Proximity / Median Household Income / Median Home Value / State Boundaries	0.36	0.33	2.85	8.11	2.06	1.20	1.98	3.93

6.2.5 All Methods

As part of the empirical comparison, descriptive statistics for all methods were produced for both regional and national-levels. This was calculated in order to determine which method produced the lowest statistical error results. Table 21 shows absolute error results of regional and national levels.

Table 21. Absolute Error Values Statistics for All Methods

ID	METHOD CRITERIA	NATIONAL ERROR (ABSOLUTE VALUES)				REGIONAL ERROR (ABSOLUTE VALUES)			
		MEAN	MED	ST DEV	VAR	MEAN	MED	ST DEV	VAR
A	NN	3.78	2.30	4.08	16.62	2.62	1.70	3.21	10.30
B	ST AVG	3.80	2.56	3.77	14.18	2.92	1.99	2.71	7.36
AB	CNN	3.07	1.95	3.09	9.57	1.98	1.40	2.03	4.14
D	Most Similar Median Household Income	10.52	7.80	9.68	93.77	9.68	6.80	9.50	90.29
C	Most similar Median Home Value	9.63	8.15	7.83	61.29	6.15	4.25	5.49	30.15
BD	Median Household Income / State Boundaries Method	3.98	2.50	4.75	22.60	2.24	1.20	2.23	4.99
BC	Median Home Value / State Boundaries Method	3.69	2.50	3.75	14.08	2.29	1.40	2.12	4.48
CD	Median Household Income / Median Home Value Method					6.46	3.73	6.45	41.57
AD	Proximity / Median Household Income Method					4.20	3.10	4.08	16.61
AC	Proximity / Median Home Value Method					3.36	2.60	2.93	8.58
ABD	Proximity / Median Household Income / State Boundaries Method					2.16	1.30	2.18	4.77
ABC	Proximity / Median Home Value Method / State Boundaries Method					1.99	1.40	1.75	3.07
BCD	Median Household Income / Median Home Value/ State Boundaries Method					2.61	1.87	2.51	6.30
ACD	Proximity / Median Household Income / Median Home Value Method					3.78	2.60	3.63	13.17
ABCD	Proximity / Median Household Income / Median Home Value / State Boundaries					2.06	1.20	1.98	3.93

National-level results indicated that CNN produced the lowest mean, median, standard deviation, and variance. Method D produced some of the highest values. Looking at regional-level results CNN produced the lowest mean and method ABC produced the second lowest mean with a difference of only .01. In addition, method ABC produced the lowest standard deviation and variance. Method D produced the highest mean, median, standard deviation, and variance. In addition, CNN had one of the lowest median, standard deviation, and variance of error at the regional-level.

Table 22 shows relative error results of regional and national levels.

Table 22. Relative Error Values Statistics for All Methods

ID	METHODS	NATIONAL ERROR (RELATIVE VALUES)				REGIONAL ERROR (RELATIVE VALUES)			
		MEAN	MED	ST DEV	VAR	MEAN	MED	ST DEV	VAR
A	NN	0.23	0.10	5.56	30.87	-0.03	-0.05	4.15	17.23
B	ST AVG	0.00	0.11	5.36	28.68	0.00	0.08	4.00	16.02
AB	CNN	0.16	0.10	4.36	19.00	0.04	0.20	2.85	8.11
D	Most Similar Median Household Income	0.66	0.20	14.29	204.27	-2.39	-1.00	13.39	179.37
C	Most similar Median Home Value	0.10	0.25	12.42	154.16	0.25	0.35	8.27	68.39
BD	Median Household Income / State Boundaries Method	0.15	0.05	6.20	38.48	0.11	0.25	3.17	10.06
BC	Median Home Value / State Boundaries Method	-0.01	0.00	5.27	27.74	0.24	0.35	3.12	9.74
CD	Median Household Income / Median Home Value Method					-0.32	-0.45	9.15	83.67
AD	Proximity / Median Household Income Method					-1.42	-0.75	5.69	32.39
AC	Proximity / Median Home Value Method					-0.39	0.00	4.46	19.87
ABD	Proximity / Median Household Income / State Boundaries Method					0.23	0.20	3.07	9.44
ABC	Proximity / Median Home Value Method / State Boundaries Method					0.36	0.40	2.63	6.93
BCD	Median Household Income / Median Home Value/ State Boundaries Method					-0.17	-0.10	3.63	13.15
ACD	Proximity / Median Household Income / Median Home Value Method					-0.97	-0.40	5.17	26.70
ABCD	Proximity / Median Household Income / Median Home Value / State Boundaries					0.36	0.33	2.85	8.11

At the national-level, CNN still produced the lowest standard deviation and variance. At the regional-level, method ABC still produced the lowest standard deviation and variance. On the contrary, method D produced the highest standard deviation and variance for both national and regional-levels. In addition, CNN had one of the lowest median, standard deviation, and variance of error at the regional-level.

6.3 Histograms

Histograms of the most prominent regional-level methods were created to show the comparison between CNN and ABC. Figure 18 shows this comparison. As with earlier mentioned histograms, the dotted line represents an error value of zero. Looking at figure 18 it is apparent that the histograms of CNN and ABC are similar, but higher outliers are present in the CNN method. In addition, the frequency of observations with accurate estimates (zero error) was slightly higher in ABC. With this in mind, it can be implied that ABC may have a slight advantage over CNN, but it is important to mention that sample selection may impact this result. If one or two outlier observations were removed from the sample, the histograms would be nearly identical. Therefore, looking at the histograms comparison in figure 18, it was determined that ABC did not outperform CNN. Histograms showing comparisons of other methods were not evaluated because results from the descriptive statistics for all methods determined a degree apparent similarity between ABC and CNN only. This apparent degree of similarity was not present in other methods.

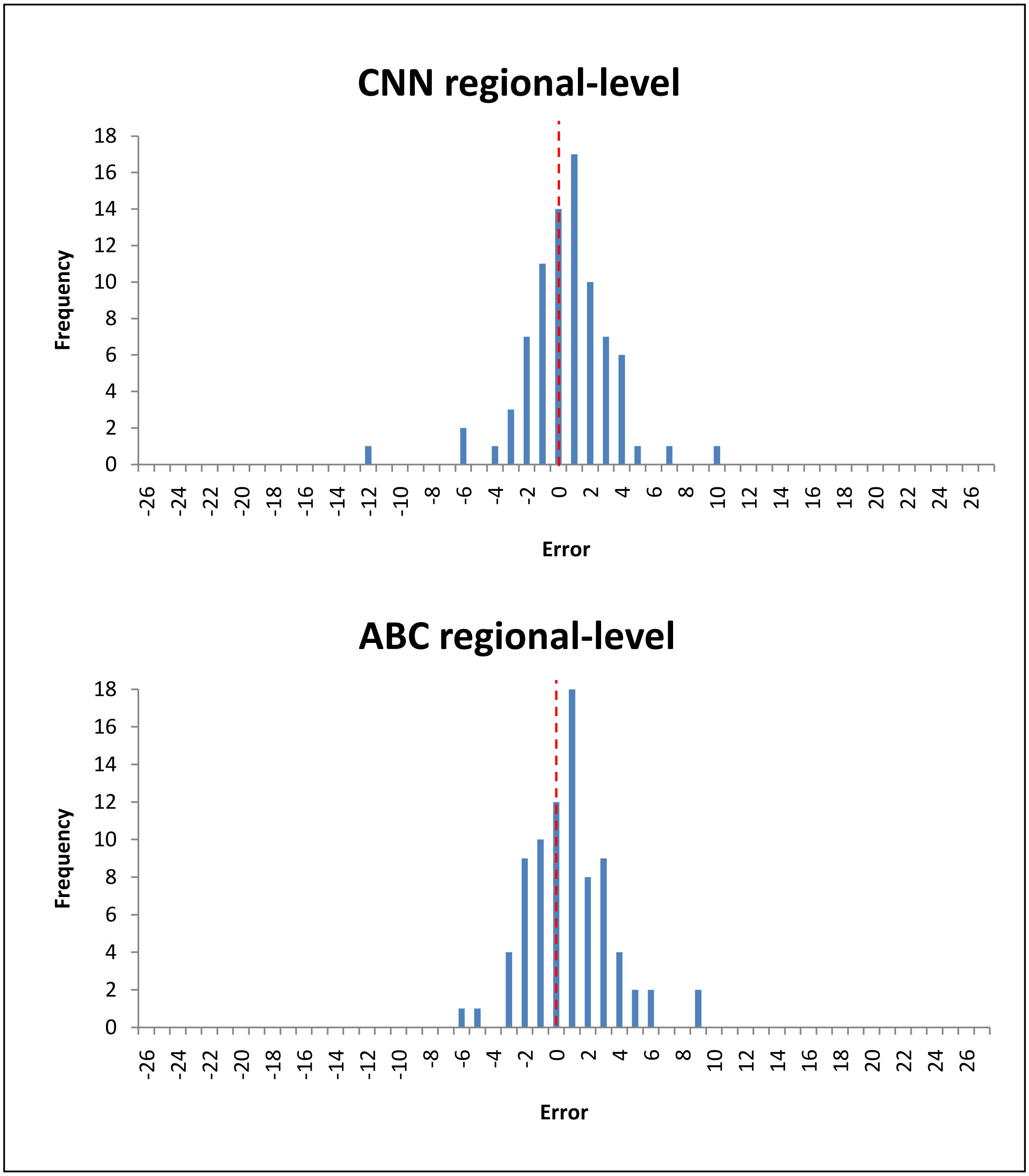


Figure 18. Histogram Comparison of CNN and ABC

6.4 Box Plots

Continuing with the statistical results, box plots showing relative error for various methods were evaluated. Figure 19 shows box plots of all national-level methods.

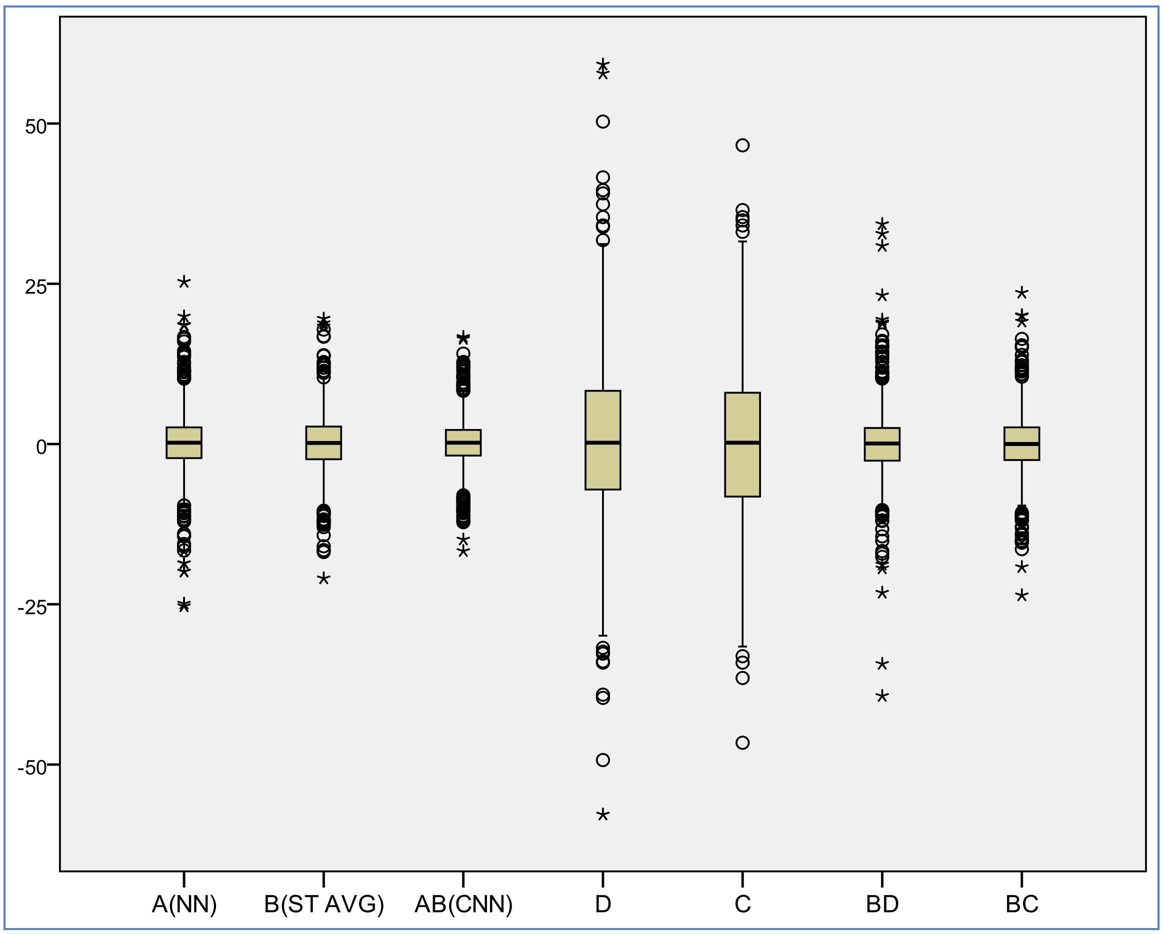


Figure 19. Box plots of National-Level NN, ST AVG, and CNN Error

Results indicated that all methods showed evidence of outliers. These are the extreme values that deviate significantly from the rest of the data. Essentially, these are the circles or asterisks found above and below the whiskers.

Box plots of the most prominent regional-level methods were also evaluated. These methods included the following:

- A(NN)
- B(ST AVG)
- AB(CNN)
- ABC

Results are shown in figure 20.

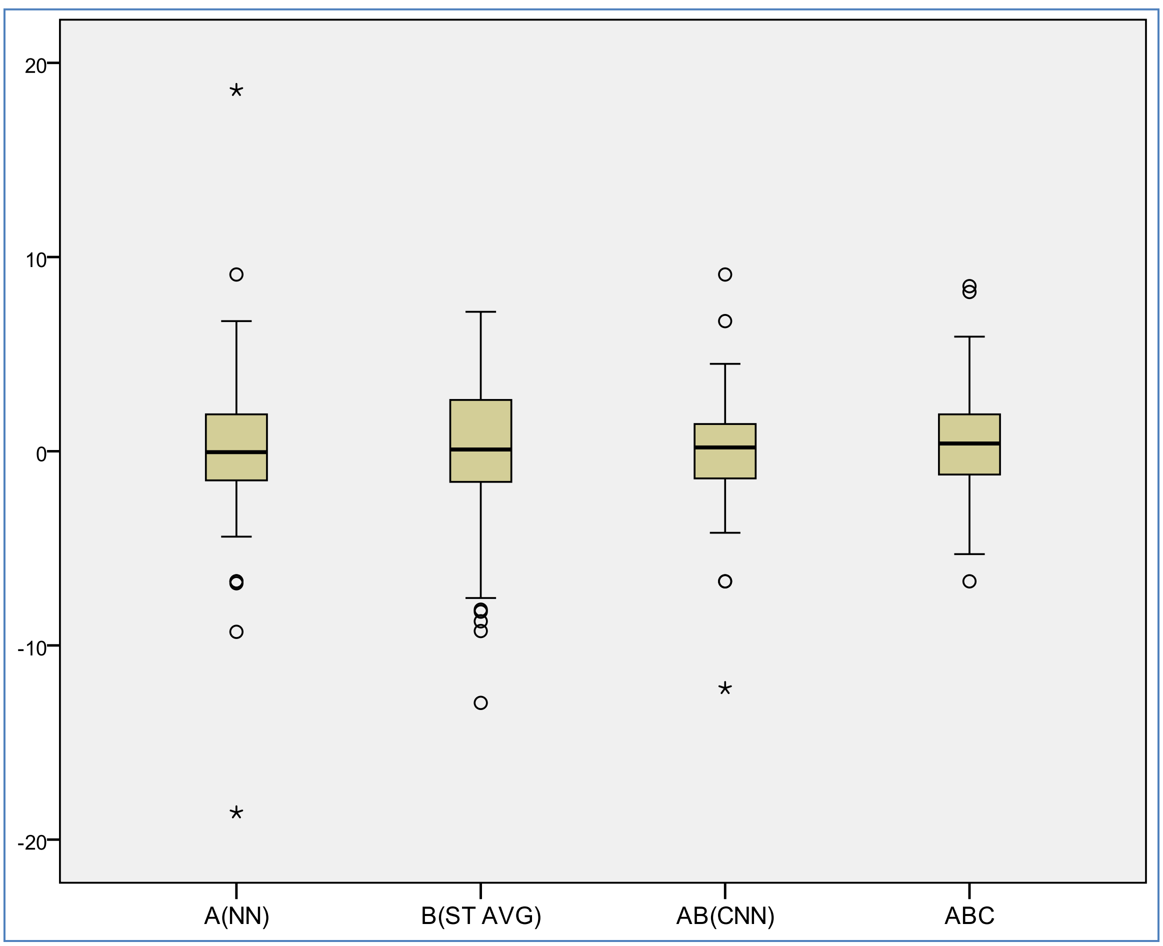


Figure 20 Box Plots of Most Prominent Regional-Level Methods

There did not appear to be a large difference in the medians of these methods. CNN had the least spread between whiskers, but also had high outlier values.

6.5 Levene’s Test

The Levene’s Test for equality of variance was conducted for the initial national-level methods. Results are shown in figure 21.

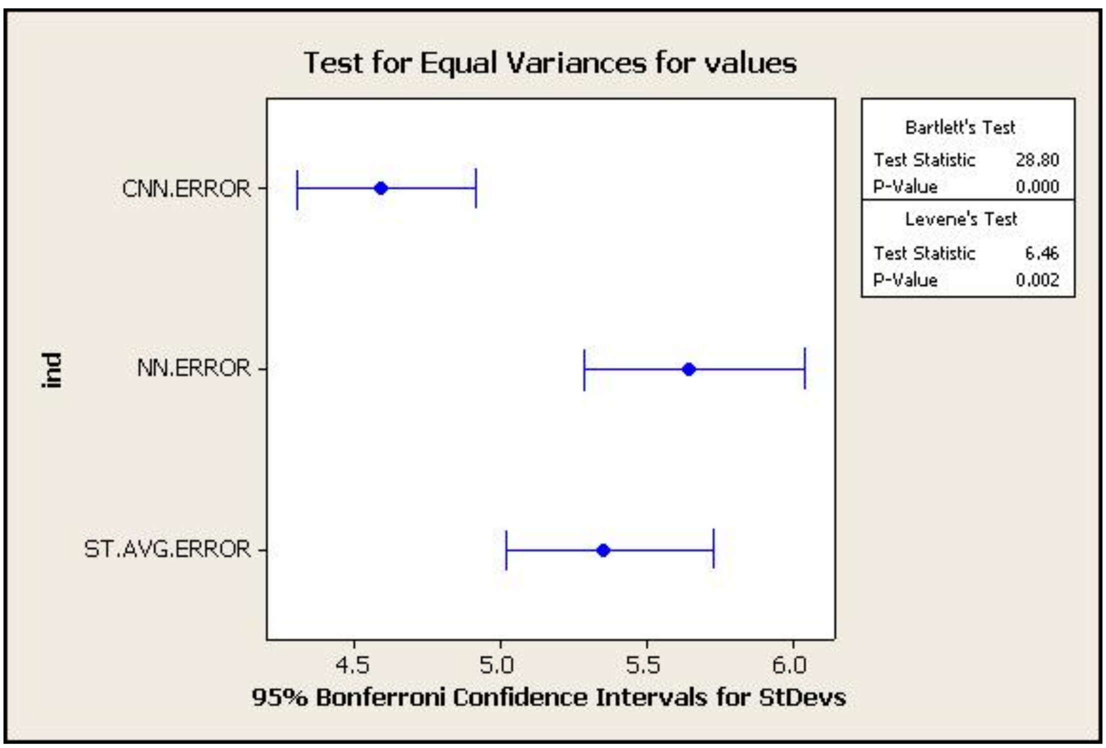


Figure 21. Levene’s Test Results for CNN, NN, and ST AVG

Results indicated that the P value (.002) was less than the significance level (.05) therefore there is evidence to reject null hypothesis that the variance between methods are the same. As part of the test, Bonferroni confidence intervals (CI) were shown. The CI for CNN was well separated from the other two methods, also showing evidence to reject the null hypothesis. Table 24 shows bi-variable Levene's tests results for initial national-level methods.

Table 23. Levene's Test Results for NN, ST AVG AND CNN National Error

Test of Homogeneity of Variances

	Levene Statistic	df1	df2	Sig.
AB(CNN) versus A(NN)	12.391	1	1295	.000
AB(CNN) versus B(ST AVG)	14.727	1	1294	.000

Results indicated that there is significance less than .05 between CNN versus NN and respectively between CNN versus ST AVG. There is a statistically significant difference between the variances of these methods.

The Levene's test for homogeneity of variances was also calculated for the most prominent regional-level methods. This is shown in Table 24. The most prominent regional-level methods were defined in section 6.4 of this thesis.

Table 24. Levene's Test Results for the Most Prominent Regional-Level Methods

	Levene Statistic	df1	df2	Sig.
AB(CNN) versus ABC	.007	1	162	.933
AB(CNN) versus A(NN)	2.316	1	162	.130
AB(CNN) versus ST AVG	6.372	1	162	.013
B(ST AVG) versus A(NN)	.437	1	162	.509
ABC versus A(NN)	2.701	1	162	.102
ABC versus B(ST AVG)	7.402	1	162	.007

There were two comparisons that resulted in significance less than .05. These comparisons included CNN versus ST AVG and ABC versus ST AVG. There was a statistically significant difference between the variances of these comparisons.

6.6 Mann-Whitney

The Mann-Whitney test was evaluated at national and regional-levels. Table 25 shows the results for the prominent, national-level methods (CNN, NN, and ST AVG).

Table 25. Mann-Whitney Test Results for Prominent, National Methods Error

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of national relative error for CNN vs NN is the same across categories of national level sample size.	Independent-Samples Mann-Whitney U Test	.742	Retain the null hypothesis.
2	The medians of national relative error for CNN vs NN are the same across categories of national level sample size.	Independent-Samples Median Test	.978	Retain the null hypothesis.
3	The distribution of national relative error for CNN vs ST AVG is the same across categories of national level sample size.	Independent-Samples Mann-Whitney U Test	.893	Retain the null hypothesis.
4	The medians of national relative error for CNN vs ST AVG are the same across categories of national level sample size.	Independent-Samples Median Test	.912	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

For all methods, the null hypothesis was retained meaning there was no significant difference between the medians.

Table 26 shows results for the prominent, regional-level methods including CNN, NN, ST AVG, and ABC. In comparing these methods, the null hypothesis also was retained, meaning there was no significant difference found between the median errors of all regional methods.

Table 26. Mann-Whitney Test Results for Prominent, Regional Methods Error

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distribution of national relative error for CNN vs ABC is the same across categories of regional level sample size.	Independent-Samples Mann-Whitney U Test	.640	Retain the null hypothesis.
2	The medians of national relative error for CNN vs ABC are the same across categories of regional level sample size.	Independent-Samples Median Test	.349	Retain the null hypothesis.
3	The distribution of national relative error for CNN vs NN is the same across categories of regional level sample size.	Independent-Samples Mann-Whitney U Test	.845	Retain the null hypothesis.
4	The medians of national relative error for CNN vs NN are the same across categories of regional level sample size.	Independent-Samples Median Test	.876	Retain the null hypothesis.
5	The distribution of national relative error for CNN vs ST AVG is the same across categories of regional level sample size.	Independent-Samples Mann-Whitney U Test	.762	Retain the null hypothesis.
6	The medians of national relative error for CNN vs ST AVG are the same across categories of regional level sample size.	Independent-Samples Median Test	.876	Retain the null hypothesis.
7	The distribution of national relative error for ST AVG vs NN is the same across categories of regional level sample size.	Independent-Samples Mann-Whitney U Test	.617	Retain the null hypothesis.
8	The medians of national relative error for ST AVG vs NN are the same across categories of regional level sample size.	Independent-Samples Median Test	1.000	Retain the null hypothesis.
9	The distribution of national relative error for ABC vs NN is the same across categories of regional level sample size.	Independent-Samples Mann-Whitney U Test	.533	Retain the null hypothesis.
10	The medians of national relative error for ABC vs NN are the same across categories of regional level sample size.	Independent-Samples Median Test	.274	Retain the null hypothesis.
11	The distribution of national relative error for ABC vs ST AVG is the same across categories of regional level sample size.	Independent-Samples Mann-Whitney U Test	.878	Retain the null hypothesis.
12	The medians of national relative error for ABC vs ST AVG are the same across categories of regional level sample size.	Independent-Samples Median Test	.349	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

CHAPTER 7.0 PHASE 2 EMPIRICAL COMPARISON OF METHODS: DISCUSSION

7.1 Overview

This chapter will discuss interpretations of actual observations mentioned in chapter 6.0. In other words, this section will discuss how phase 2 results were interpreted.

7.2 Discussion of Descriptive Statistics Results

As a continuation of the statistical assessment, the mean, median, standard deviation, and variance of error for all 15 methods were calculated. This included absolute and relative error values as well as regional and national methods. Methods were grouped by the number amount of criteria they included (single criterion and multi-criteria). Descriptive statistics from these groups were compared individually. Finally, all methods from all groups were compared collectively.

7.2.1 Single Criterion and Multi Criteria Methods

Based on the results from single criterion methods, it was inferred that NN had the highest possibility of being the most accurate single criteria method. For the two criteria methods, it was inferred that CNN had the highest possibility of being the most accurate method. In regards to three criteria methods, it was inferred that method ABC had the highest possibility of being the most accurate method. There was only one four criteria method evaluated. Error for this method was only calculated at the regional-level. Due to a lack of alternatives at this level, a "most accurate" four criteria method was not determined. Instead, error for this method was compared with all other respective criteria groups.

7.2.2 Discussion of All Method Results

From a comparison of all 15 regional-level methods, it was determined that CNN and method ABC had the highest possibilities of creating the most accurate location adjustments. Because standard deviation and variance from method ABC was less than CNN and mean error was basically the same between the two, method ABC was considered to have a slight advantage over CNN. Unexpectedly, it was concluded that method ABC might actually outperform the current interpolation method (NN) as well as the CNN method. Statistical tests were conducted to determine if this conclusion could be substantiated.

In regards to the national-level, a comparison of all 7 methods was also evaluated. Method ABC was not included in this evaluation due to time limitations and the complexity of calculating results using the national-level sample. It was determined that mean, median, standard deviation, and variance of error was less using the CNN method, therefore, it was deemed the "most accurate" national-level method. Again, statistical testing determined if this conclusion was substantial. Statistical comparisons of CNN and ABC were conducted to fully substantiate if one method could be statistically proven to outperform the other.

7.3 Discussion of National-Level Statistical Testing Methods

As a final evaluation, statistical testing methods were implemented using national-level error. These methods included the following:

- Box Plots for graphical examination
- Levene's test for homogeneity of variance
- Mann-Whitney test for sample distribution equality of median

7.3.1 Box Plots

Box plots of all national-level methods were first analyzed. With this in mind, the following was determined: CNN seemed to have the lowest value of outliers, there did not appear to be large differences in the medians, the box sizes were larger for methods D and C (meaning their respective kurtosis should be dissimilar from other methods), and spread between whiskers was lower for, NN, CNN, and ST AVG methods.

Box plots for the national-level phase 1 methods (NN, CNN, and ST AVG) were then analyzed. The following was determined: Outliers for the CNN method seemed to be lower than the other methods, there was essentially no difference between the medians, the box seemed centered between the whiskers in all cases (meaning that the data seemed to be normally distributed), there seemed to be little to no difference between box sizes (meaning their respective kurtosis should be similar), and spread between whiskers was less for the CNN method. From these interpretations, it was apparent that CNN was the most accurate national-level method. This meant that CNN could be a superior alternative to the current interpolation method (NN) and the ST AVG method. The Levene's test and Mann-Whitney test were evaluated at the national-level to substantiate this claim.

7.3.2 Levene's and Mann Whitney Tests

The Levene's test was first run on all three national-level methods to assess the equality of variance between the samples. The null hypothesis that "the sample variances were equal" was rejected, therefore, it was determined that statistical testing methods based on equal variances (such as ANOVA or even T-tests) would not be substantial and thus, would not be used. Other testing methods based on differing variances (such as the Mann-Whitney Test), were appropriate. While the Mann-Whitney tests proved no statistical differences across any comparison of any sample medians throughout this study, the Levene's test did prove more useful and provided valuable statistically evidence.

Using SPSS software, bi-variable Levene's tests comparisons of the phase 1 national-level methods were conducted. In other words, the Levene's test was used to compare two methods at a time. Results showed significant differences in variances between CNN vs. ST AVG and likewise between CNN vs. NN. Therefore, it was inferred that the amount of variation within error for the CNN method was significantly less than that of ST AVG and NN. According to this result from Levene's testing, CNN statistically outperformed ST AVG and NN. With this in mind, CNN was the best national-level method and should ultimately produce the most accurate location adjustment compared to other national-level methods evaluated in this study.

In other words, an alternative to the current industry practice for location adjustment (NN) was statistically proven to produce a more accurate cost estimate. This alternative was the CNN method.

7.4 Discussion of Regional-Level Statistical Testing Methods

As the final steps in this study, research was conducted to test if results from the national sample would be prevalent even at the smaller sample population (the regional-level). Accordingly, tests were conducted to determine if other alternatives (in addition to CNN) proved to be more accurate than the current method (NN) at the smaller sample population. Ultimately, similar statistical testing methods used at a national-level were applied to the regional-level.

7.4.1 Histograms

Histograms were used to compare CNN and method ABC at the regional-level. From this comparison, it was determined that frequency of lower error values seemed comparable between methods, but higher outliers existed in the CNN method. From this, it was inferred that method ABC could be equivalent to the CNN method.

7.4.2 Box Plots

Box plots of the most prominent regional-level methods were then analyzed. These methods included NN, ST AVG, CNN, AND ABC. The following was interpreted: There did not appear to be a large difference in the medians of these methods, CNN had the lowest spread between whiskers followed by method ABC, CNN still had higher outliers than ABC, ST AVG had the largest box meaning the respective kurtosis should be dissimilar from other methods, and NN had the highest outlier values. Box plots for only the CNN and method ABC were then compared. The same interpretation was still determined; CNN might have a slightly lower spread between whiskers but also has slightly higher outliers.

7.4.3 Mann Whitney Tests

As mentioned in section 7.3.2, the Mann-Whitney tests proved no statistical differences across any comparison of any sample medians throughout this study. In other words, from the Mann Whitney tests, it was concluded that there was no evidence to reject the null hypothesis that sample medians were equal. Therefore, a conclusion as to method performance was not obtainable using the Mann-Whitney tests.

7.4.4 Levene's Tests

Levene's tests were conducted on the most prominent regional-level methods. These methods were identified in section 6.5. A total of six different tests were conducted each comparing two different combinations of samples. CNN was compared to all other prominent methods. In the same manner, method ABC was also compared to all other prominent methods. Interestingly, only two of the comparisons rejected the null hypothesis that variances were equal including the following:

- CNN versus ST AVG
- ABC versus ST AVG

It was inferred that there was a statistical difference between the variances for only these comparisons. CNN and ABC did not show significant differences between variances. Therefore, it was not concluded that either was statistically the "best" method. Furthermore, both showed statistical improvement only against the ST AVG method. They did not show differences between variances for the current method (NN). Looking back at results from the national-level, it was indicated that CNN statistically outperformed ST AVG and NN. At the regional-level this was not the case. Regionally, CNN only outperformed ST AVG. This led to the belief that the sample size used at the regional-level might have been too small to realistically demonstrate what would happen using the entire population. A future research topic could evaluate the theoretical framework of this study to determine sample size requirements.

CHAPTER 8.0 CONCLUSIONS

8.1 Summary of Study Results

Moran's I analysis provided evidence of strong spatial auto-correlation between proximity and RSMeans CCI values. Person's correlation analysis provided evidence that economic factors including home value and household income should be included in determining alternative location adjustment interpolation methods. Statistical testing analysis included the following: descriptive statistics calculations, histograms, box plots, Levene's tests, and nonparametric tests using differing samples. These analyses provided evidence that the CNN method outperformed all other methods at the national level. At a regional level, CNN and ABC performed equally well and in some instances ABC actually outperformed CNN. Future research should be conducted to prove the validity of the ABC method as a new location adjustment interpolation method for construction cost estimation.

8.2 Research Questions

As a review of the problems under consideration, the following questions were thoroughly addressed throughout this study:

- Can statistical analysis provide justification for the current, industry-suggested location adjustment interpolation method?
- What are possible alternatives to the current method that may potentially increase accuracy of location adjustments?
- Can these alternate methods be statistically proven to produce a more accurate estimate?

8.3 Research Rational and Findings

Each research question mentioned in section 8.2 was evaluated. The following sections will discuss the findings of each of the 3 individual questions. In addition, the research rational behind all findings will also be explained.

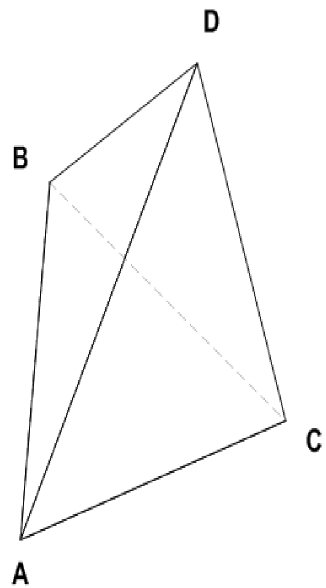
8.3.1 Research Rational and Findings for Question 1

To answer the first question under consideration, an understanding of what was meant by "the current method", is needed. A common problem in the construction industry today involves cost estimate location adjustment for locations that do not have location adjustment factors. This study evaluated the current interpolation method used for estimating these unknown location adjustment factors. The current method referred to "nearest neighbor" interpolation, which was a spatial estimation technique based on linear distance and proximity. This technique basically estimated a variable for a city solely based on the same variable of the closest proximate city. The variable in this study was the 2006 RSMeans CCI.

Moran's I tests, within ArcMAP GIS software, was conducted to measure spatial auto-correlation between RSMeans CCI values and proximity. Results indicated significant spatial auto-correlation, therefore, the underlying assumption for proximity-based interpolation methods was validated. The current method was based solely on proximity. It was concluded that statistical analysis can provide justification for the current, industry-suggested location adjustment interpolation method.

8.3.2 Research Rational and Findings for Question 2

In reference to the second problem under consideration, 14 possible alternatives to the current method were identified. In all, 15 different methods were evaluated in this research. Methods were distinguished by the number of criteria they included. Figure 22 shows a triangular based pyramid which represents all possible methods resulting from combinations of these criteria.



#	ID	Method
1	A	Proximity (P)
2	B	State Boundaries ($B)
3	C	Median Home Value (MHV)
4	D	Median Household Income (MHI)
5	AB	P + $B
6	BC	$B + MHV
7	AC	MHV + P
8	AD	P + MHI
9	BD	$B + MHI
10	CD	MHV + MHI
11	ABC	P + $B + MHV
12	ABD	P + $B + MHI
13	BCD	$B + MHV + MHI
14	ACD	P + MHV + MHI
15	ABCD	P + $B + MHV + MHI

Figure 22. All Methods Evaluated

8.3.3 Research Rational and Findings for Question 3

The third and final problem under consideration involved statistical comparisons of the 15 methods. This entailed identifying a performance measurement and applicable statistical testing techniques. The performance measurement used in this study was an "error" value calculated by taking the estimated CCI value and subtracting the actual CCI value. Correspondingly, the statistical testing techniques evaluated in this study included the following

- Histograms
- Box Plots
- Tests for Homogeneity of Variance (Levene's Statistic)
- Tests for Equality of Sample Distributions and Medians (Mann-Whitney)

As error calculation became more complex, especially using multi criteria estimation methods, it was decided to use reduce the evaluation level in order to maximize time and effort. With this in mind, two evaluation levels were established in this study. This consisted of the national-level and the regional-level. Table 27 shows all methods compared in this study, and the level from which they were evaluated.

Table 27. All Methods Evaluated

ID	METHOD NAME	EVALUATION LEVEL
A	Nearest Neighbor (NN)	NAT & REG
B	State Average (ST AVG)	NAT & REG
AB	Nearest Neighbor within State Boundary (CNN)	NAT & REG
D	Most Similar Median Household Income	NAT & REG
C	Most similar Median Home Value	NAT & REG
BD	Median Household Income / State Boundaries Method	NAT & REG
BC	Median Home Value / State Boundaries Method	NAT & REG
CD	Median Household Income / Median Home Value Method	REGIONAL
AD	Proximity / Median Household Income Method	REGIONAL
AC	Proximity / Median Home Value Method	REGIONAL
ABD	Proximity / Median Household Income / State Boundaries Method	REGIONAL
ABC	Proximity / Median Home Value Method / State Boundaries Method	REGIONAL
BCD	Median Household Income / Median Home Value/ State Boundaries Method	REGIONAL
ACD	Proximity / Median Household Income / Median Home Value Method	REGIONAL
ABCD	Proximity / Median Household Income / Median Home Value / State Boundaries Method	REGIONAL

The evaluation level referred to the size of the population sample from which statistical assessments were conducted. The national-level population included all 649 cities within the contiguous United States which RSMeans provided a CCI location factor. The regional-level was a smaller sample which was randomly chosen. This consisted of a region of 82 cities from the 649 national-level cities. As the table shows, all methods were evaluated from the regional-level sample and only 7 were evaluated from the national-level sample. Error was calculated at different sample sizes due to time limitations and the complexity of calculating results for the 649 cities at the national-level.

Due to the performance measurements and statistical testing results from the national-level sample, it was concluded that CNN was the “best” method. It statistically outperformed all other national-level methods. CNN was an alternative to the current method. Therefore, it was concluded that an alternative method was statistically proven to produce a more accurate location adjustment estimate.

Due to the performance measurements and statistical testing results from the regional-level sample, it was concluded that the CNN did not outperform the current method, but did perform equally well as the current method. Since the regional-level results did not completely coincide with the national-level, it was concluded that the sample size from the regional-level may have been too small to significantly estimate what should happen at the national-level sample size.

While the regional-level results did not completely coincide with the national-level, there were some concurring results. For example, CNN statistically outperformed ST AVG at both the regional and national-levels. This provided evidence that there may be some “truth” to other results that occurred at the regional-level. One of the most interesting results that was concluded at the regional-level was that method ABC could be statistically equivalent or even slightly superior to CNN. If it could be statistically proven to outperform CNN at the national-level this could provide the construction industry with an entirely new method that would statistically improve cost estimation. Ultimately, this new method could become the new industry standard. Future performance evaluations and statistically testing is needed to fully validate this conclusion.

8.4 Limitations of the Study

This study could be considered as limited by a number of possibilities. The most prevalent factors include the following:

- RSMeans CCI Dataset
- Economic Data
- Interpretation of Proximity
- Regional-Level Population Size
- External Validation

Each of these topics will be discussed in this chapter.

8.4.1 RSMeans CCI Dataset

The city cost index dataset used in this study was published by RSMeans in the 2006 Building Construction Cost Data book. There are various generalizations in regards to the published costs associated with this data source. It was assumed that the RSMeans CCI was a valid predictor of construction costs. In addition, the types of projects are limited to commercial or industrial projects that cost $1,000,000.00 or more. This does not include residential or civil applications such as bridges, dams, or highways. The type of construction is limited to new construction which does not include renovations or minor alterations. Because these limitations exist for the internal data used within this research, these same limitations apply to the research findings.

8.4.2 Economic Data

Data for the GIS economic factors used in this study came from the 2007 Environmental Systems Research Institute (ESRI) data source book. While ESRI is considered by many to be the leader in GIS modeling and mapping software and technology, the data did not exactly coincide with the annual publication from RSMeans. RSMeans data was from 2006, and economic data was from 2007. The reason for this slight limitation was due to the availability of the data. It was assumed that this did not significantly affect the overall research findings. In addition, economic factor were considered in alternative methods evaluated in this study due to their availability from ESRI. As there are numerous economic factors available from widespread sources, additional research may incorporate alternative interpolation methods based on differing economic variables as those considered in this study.

8.4.3 Interpretation of Proximity

Proximity was calculated using linear distance. A possible alternative to linear distance could be actual road travel distance. The possible reasoning behind the use of travel distance could be that in many circumstances, especially rural areas, the major costs affecting construction (labor, equipment, and materials) might come from the closest city using travel distance in lieu of linear distance. The use of travel distance in determining the "twin" city could have a significant difference in calculation of error.

8.4.4 Regional-Level Population Size

All prevalent findings concluded from the national-level sample were not concluded from the regional-level sample. This caused a limitation to the study because results from the regional-level may not be entirely consistent. In this manner, method ABC may not be equivalent or superior to method CNN. To statistically prove if there is a superior method to CNN, error for ABC should be calculated using the national-level sample size.

Finally, this study was limited to an internal validation of location adjustment methods. It did not prove results would be the same using actual construction project data. This could be a possible continuation of the study. This study was limited to concluding that, using the RSMeans CCI, the CNN method should theoretically produce the most accurate location adjustment for conceptual cost estimates. It would be interesting to see if the same results would still take place using "real life" applications.

8.5 Implications for Future Research

Future studies involving GIS spatial estimation and location adjustment interpolation are to follow. The most beneficial possible future research topics may involve method ABC. Future research efforts could assess all location adjustment methods evaluated in this study, including ABC, using the national sample. If performance measurements and statistical testing at the national-level were completed, there is a possibility that ABC will outperform not only the current interpolation method (NN), but also the CNN interpolation method. Some organizations have already begun to implement the CNN method, but ABC is still unknown because it is an entirely new method that has not been introduced to the industry. If ABC was statistically proven to provide more accuracy then CNN, this would be a great benefit to the construction industry as a whole. It could provide more accuracy to location adjustment cost estimates, potentially making a difference of thousands of dollars for project stakeholders.

Other possible continuations of this study may involve testing the use of city-specific correction factors and alternative geo-statistical interpolation methods. Alternative interpolation methods could include data from various economic variables not considered in this study, such as county level taxation basis, cost of living, or wages. In addition, alternative location factors publications, such as the ACF, could be used instead of RSMeans. Regression analysis and OLS may be an alternative to the spatial prediction method used in this study. Geary's C could be used in lieu of Moran's I to test for spatial autocorrelation. Travel distance could be used in lieu of linear distance.

Finally, the Moran's I test statistic proved that proximity-based interpolation for location adjustment was valid, in theory. A comparison of the theoretical framework of this study and actual preliminary cost data from "real-life" projects would be an interesting future topic.

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APPENDIX A: AUTHORIZATION OF E-MAIL COMMENTS

Below are comments from an email conversation between Adam Martinez (Construction Management Graduate Student), and Phillip Waier (P.E., LEED AP Principal Engineer for RSMeans):

Friday, Sept 25th, 2009 (Question)

Mr. Waier,
Thank you for your input. I was wondering if you would mind me publishing this information in my thesis, I will make reference that it was your comment. Please let me know if you are ok with this. I can send you a copy of what I am writing and how I incorporate your comments if you would like.

thank you

Adam Martinez,
Graduate Student, University of New Mexico

Thursday, Sept 24th, 2009 (Response to question)

Adam,
Feel free to include my response in your thesis. And yes I would like a copy.

Thanks

Phillip Waier
P.E., LEED AP Principal Engineer for RSMeans

In this conversation, Phillip Waier specifically authorized the publication of his email response. His email response is shown in section 5.7 of this study.