MOBILE POSITIONING DYNAMICS IN AN IMAGE-BASED HYBRID GEOCROWDSOURCING SYSTEM

by

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A Thesis
Submitted to the
Graduate Faculty
of
George Mason University
in Partial Fulfillment of
The Requirements for the Degree
of
Master of Science
Geographic and Cartographic Sciences

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A Thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at George Mason University

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DEDICATION

This accomplishment is dedicated first to my children: Travis, TJ, and Nate to show them that one never stops learning and improving. If you want it, go out and get it. To my wife, Sara for her support through this process, for being my sounding board for ideas, my caffeinator on late nights, and my wake-up call to get me back on track when I got lazy. Finally, to my parents, Don and Lisa, thank you for always believing in me and always pushing me to be better. Your pride in me is a constant source of encouragement. Thank you for showing me the bell buoys.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank Dr. Matt Rice for guiding me through this process and making himself available at all hours to answer my questions. I am sure by the end, he regrets ever giving me his cell phone number. Next, a sincere thank you to the National Geospatial-Intelligence Agency for affording me the opportunity and time to complete the requirements for this degree.

Additionally, thank you to the following who had significant impact:

- Han Qin for the countless hours in helping to develop and improve the mobile contribution software.
- Manzhu Yu for her python coding prowess.
- Sam Ober for developing the final phase of the software application used in this research.
- Joshua Lane for copy/edit and objective viewpoints.
- My two other committee members Dr. Dieter Pfoser and Dr. Ruixin Yang who worked to ensure I could complete this project in the compressed timeframe.
- Samantha Cooke for the scheduling, wrangling, and organizing that was required to get this project to completion.

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LIST OF ABBREVIATIONS

Americans with Disabilities Act……………………………………………….………..ADA
Coefficient of Determination……………………………………………………….R^2
Department of Defense…………………………………………………………..DOD
Digital Elevation Model…………..……………………………………………….….DEM
Geocrowdsource Data…………………………………………………………….…...GcD
Geographic Information Systems……………….…………………………….………..GIS
George Mason University Geocrowdsourcing Testbed………………………...GMU-GcT
George Mason University……...……………………………………………………..GMU
Global Positioning Service……………...………………………………………………..GPS
International Atomic Energy Agency……………………………..…………….IAEA
Light Detection and Ranging…………………………………………………LiDAR
Minimum Points Number……...…………………………………………………MinPts
National Oceanographic and Atmospheric Administration…….……………………..NOAA
National Standards for Spatial Data Accuracy……………………….……………NSSDA
Non-Government Organization……………………………………………………NGO
Participatory Mapping…………………….………………………………………….....PM
Public Participatory Geographic Information Systems.……………………………..PPGIS
Predefined Neighborhood Radius……………………………………………………Eps
Quality Assessment…………..………………………………………………………QA
Root Mean Square Error…………………...……………………………………..RMSE
United States Geological Survey…………………………………………………USGS
Volunteered Geographic Information………………………………………………VGI

ABSTRACT

MOBILE POSITIONING DYNAMICS IN AN IMAGE-BASED HYBRID GEOCROWDSOURCING SYSTEM

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George Mason University, 2018

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Geocrowdsourced data (GcD), also known as volunteered geographic information, has proven to be an invaluable resource to the geospatial science community. From a United States National Security perspective, GcD has become a force-multiplier for the Department of Defense aiding in nuclear counterproliferation efforts; at a humanitarian level it was used to aid first responders reaching earthquake victims in Haiti. Despite the potential benefits, research has shown GcD to be unreliable unless moderated with quality assessment methods applied to the data. However, circumstances may prevent moderation and new quality assessment methods must be designed. This research demonstrates a correlation between the number of GcD contributors and the level of positional accuracy of information contributed to the George Mason University Geocrowdsourcing Testbed (GMU-GcT). A mobile-phone, image-based data contribution tool from the GMU-GcT was developed and distributed to student volunteers at GMU who provided information regarding pre-defined locations on

campus. Findings showed that the positional accuracy characteristics of the data contributions to the GMU-GcT improved with added contributors, reaching a level comparable to previously-studied accuracy threshholds reached with a significantly more detailed and heavily moderated data contribution workflow. Undermoderated reports from single contributors averaged 8.55m in positional error. With an increasing number of contributors, positional error of reports for the same item dropped to 3.89m (n=20). The most common positional error threshold for geocrowdsourced data, referred to in previous work as the Haklay distance (approximately 6.0 meters) was reached with two contributors, and after four contributors, the positional error rate stayed fairly constant. This research demonstrated that a fully moderated crowdsourced data contribution process, used in previous incarnations of the GMU-GcT, is unnecessary for producing data with adequate fitness-for-use, including common routing and obstacle avoidance algorithms.

CHAPTER 1 - GEOCROWDSOURCING AND ITS UBIQUITIOUS SOURCES AND USES

In a 2006 Wired magazine piece discussing new sources of revenue for business, Jeffrey Howe coined the term “crowdsourcing” as a word play on the existing employment-related term outsourcing, which was responsible for thousands of jobs being sent to cheaper labor markets in countries such as China, India and Vietnam. Howe’s concept of “crowdsourcing” was the generation of new ideas, new content, and new business intelligence from the public, who at the time were using the Internet and had just begun using social media platforms such as MySpace to generate content. Just a year later, Goodchild (2007) noted the emergence of nascent map-based crowdsourcing activity, and described the concept as volunteered geographic information, and in a later publication (2009) outlined the costs, benefits, advantages, and possible future of this emerging activity. A decade later, it is safe to conclude that this activity has truly had a dramatic impact on the way geographic data is captured, collected, curated, analyzed, and displayed. Daniel Sui also underscores the significance of this phenomena. He describes the emergence of a citizen-centric, web-based data collection paradigm as a “profound transformation on how geographic data, information, and knowledge are produced and circulated” (Sui et al. 2014, 1), and part of an emergence of vast volumes of geographic data from sensors, archives, media, text, and the public, which he characterized as an “exaflood of digital data growth” (ibid.).

The term used in this thesis to describe the collective phenomena of citizen-centric, web-based geographic data collection is geocrowdsourcing, which harkens back to Howe (2006), with the acknowledgement to many other authors, such as Goodchild and Sui, who have provided useful commentary on the terminology for this phenomenon. While the various differences in meaning and nuances for the terminology are outside the scope of this thesis, the primary body of work and research focus remains consistent with interests expressed by the same researchers. This thesis focuses on the way that the public contributes geographic information to a web-based data collection system. Specifically, this thesis explores the growth of mobile data collection for geographic information systems (GIS) and the individual and collective positioning dynamics of mobile geocrowdsourcing activities. The primary conduit for public data collection for GIS is the mobile phone. Understanding the limitations, dynamics, and positioning characteristics of mobile devices (discussed in detail by Rice et al. 2015) is paramount to understanding the critical quality and reliability facets of geocrowdsourced data, which are acknowledged by Goodchild and others as being the single largest weakness of this phenomena. This thesis research adds critical information about this dynamic to the larger body or research, and helps answer the questions posed by Haklay (2010a, 2010b) and many others: "How good is geocrowdsourced data?", and "How many volunteers does it take to map an area well?". The answers to these questions are provided in this thesis. This thesis is part of a larger body of work conducted by GMU Researchers in the Department of Geography and Geoinformation Science, where several ongoing research efforts are exploring the dynamics of geocrowdsourcing and methods for quality assessment, as discussed in Qin et al. (2016), Rice et al. (2012b, 2013b, 2014, 2015) and Aburizaiza et al. (2016).

This first chapter provides an introduction of geocrowdsourcing and various methods of application and areas of interest to the author and sets the stage for the remainder of the thesis. Subsequent chapters review relevant literature, discuss the data and methodology used in this thesis, followed by results, conclusions, and suggestions for future work.

1.1 Varying Methods of Application

The applications of crowdsourced geospatial information are potentially limitless. Researchers at George Mason University are examining methods of utilizing a micro-level campus geocrowdsourcing database to create an alert system for mobility and visually impaired students, informing them of areas along their routes that may be impassible or hazardous to traverse (Rice, et. al, 2013a). At a macro level, the Department of Defense (DOD) has examined applications of using crowdsourced data to supplement battlefield situational awareness systems and to aid in nuclear counterproliferation efforts (Leno and Miller, 2015). Furthermore, geocrowdsourced data was used to augment search as rescue operations after national disasters such as during the Haiti Earthquake recovery effort in 2010 (Yates & Paquette, 2011) and to discover the benefits of using geocrowdsourced information for wildfire evacuation planning during the California wildfires of 2007-2009 instead of waiting for official or authoritative information (Goodchild & Glennon, 2010).

1.1.1 Nuclear Counter-Proliferation

As early as 1998 scientists began to realize that non-state actors and non-governmental organizations (NGO) could play a vital role in the discovery, monitoring, and reporting of clandestine nuclear materials. Researchers found that when providing some type of incentives for contributions, or disincentives for those who did not contribute, governments were able to tap into a reporting stream far greater and with fewer restriction than those available to state actors alone (Mitchell, 1998). By 2010 scientists had expanded upon that premise by allocating resources into scouring news media, social media and crowdsourced information for the purposes of discovering and tracking nuclear sites and materials allowing for stricter monitoring and enforcement of International Atomic Energy Agency (IAEA) safeguards (Pabian, 2010).

1.1.2 Haiti Earthquake

Many case studies have been conducted on the usability and efficacy of user generated content in response to disaster relief, recently and chiefly among those studies was the Haiti earthquake of 2010. Research led by Zook et al. (2010) displayed the benefits of Haitian citizens and others on the ground in Haiti providing local knowledge data from the savaged areas of Haiti as well as volunteers worldwide mapping previously uncharted areas of Haiti thanks in part to freely available commercial satellite imagery of Haiti provided by Google, Digital Globe and GeoEye (Zook et al., 2010). The updated imagery allowed the volunteer mappers to trace new roads and buildings into OpenStreet map with higher degrees of precision due to the higher spatial resolution of the imagery. The imagery also provided a means to map out areas where buildings collapsed or where roads were impassible due to the earthquake. In Figure 1 below is a set of four side by side images showing the before and after earthquake commercial imagery for a portion of Haiti. One can clearly see the fineness of the spatial resolution of the imagery as well as the issues that first responders would have encountered when conducting search and rescue operations.

Figure 1 Before and After Satellite Images in Haiti (Zook et al (2010), Source Google (2010). Screenshot of Google website, allowed use)

The combination of freely available information, citizens on the ground in Haiti (who in-turn are local area experts) and hundreds of volunteers worldwide, allowed within two weeks of the earthquake over 10000 new contributions to be entered into OpenStreetMap for Haiti which provided first responders and disaster relief organizations a better understanding of the scope of the damage and how best to manage the emergency (Zook et al., 2010). Figure 2 shows a popular example of the amount of effort poured into OpenStreetMap immediately following the earthquake displaying the increase in richness of data available after volunteers began tracing the new routes and locations.

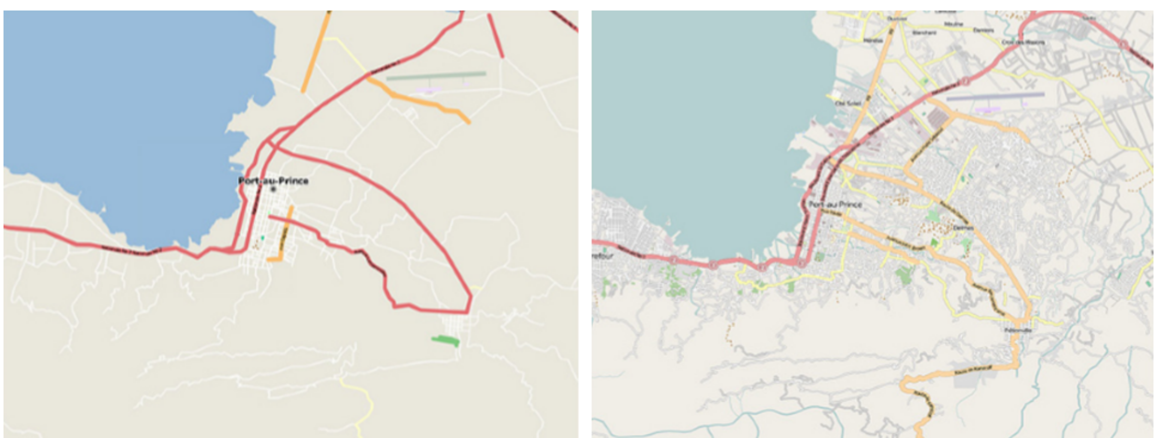


Figure 2 OpenStreetmap screenshot of Port Au Prince before and after the earthquake (Zook et al (2010), Source Maron (2010). Screenshot of Brainoff website, allowed use)

1.1.3 California Wildfires

Goodchild and Glennon (2010) researched the benefit of using crowdsourced geospatial data instead of authoritative or official data in response to evacuation planning during the four massive California wildfires from 2007-2009. Just as with the “fire alarm" approach over a decade earlier by Mitchell (1998) increased the number of reporting sources, the crowdsourcing approach for evacuation planning dramatically increased the number of reports regarding the size and speed of expansion of the wildfires. While authoritative information provided a high level of accuracy, the information could have taken days to complete the process of collection, exploitation, and dissemination back to the public. By this time, the size and speed of expansion of the wildfires could have drastically changed. Goodchild and Glennon found that with the expanded contributor base reporting on the boundaries of the fires, even if positional accuracy of the reporting was less accurate, the contributions were accurate enough to provide a level of understanding about the size and speed of expansion to assist officials in determining whether or not to commence evacuations in certain areas. Goodchild and Glennon also agreed that the costs of an unneeded evacuation due to less precise information (a false positive) were far less than those of waiting days to receive an evacuation order that could potentially had been provided sooner to move citizens to safety (Goodchild and Glennon, 2010).

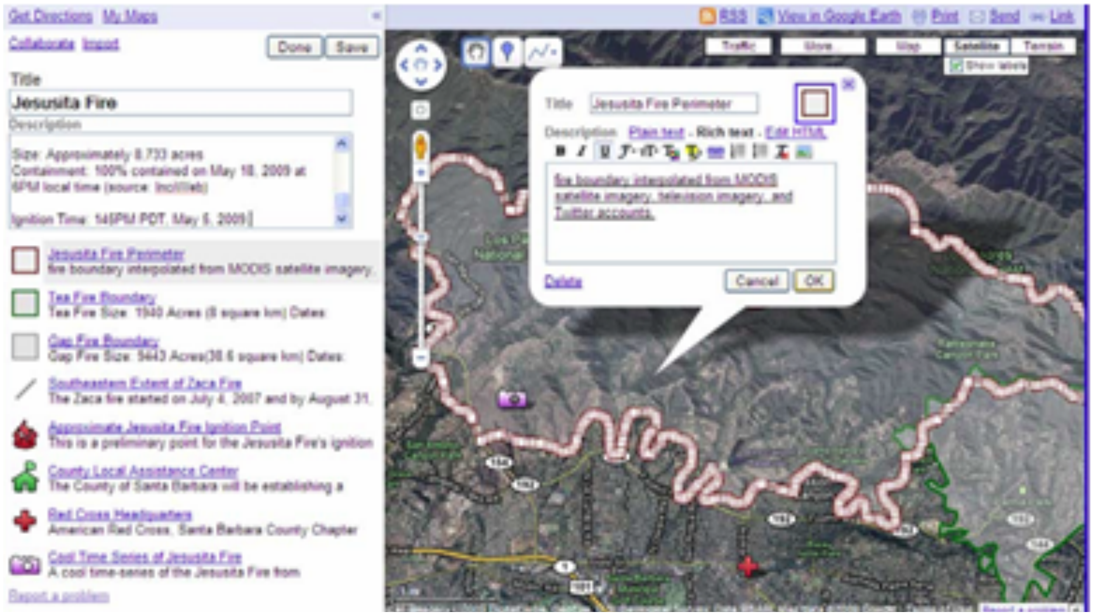


Figure 3 Screenshot of webpage of amateur wildfire reporter (Goodchild and Glennon, 2010)

1.2 A Brief History of GcD/VGI

The following sections discusses the evolution of geocrowdsourced data (GcD) and volunteered geographic information (VGI) and their relationship to the rapid increase in unstructured and semi-structured digital data, referred to by Sui et al. (2014) as an exaflood of digital information.

1.2.1 Evolution

As previously stated, the emergence of citizens as sensors is not a new concept. Throughout history, human reporting has long been sought out by intelligence organizations as a valuable source of information about an adversary. Persons conducting corporate espionage, the stealing and sharing confidential research or methods of one institution with another, continues today. A recent evolution of the concept of citizen sensors however has been used to raise public awareness on social issues and affect change in regards to public safety concerns. Until recently however, this was mostly accomplished through the use of email, web blogs, and social media platforms. These methods, while effective, required an individual to actively create information that was to be shared with others. With the advent of smart devices however, the evolution of citizen contributions became a revolution of new ideas and methods and resulted in exponential increases in publicly available information. Goodchild et al. (2005) presaged this revolution, describing the emergence of a social-media driven, web-connected information sharing community, which they termed the Spatial Web.

1.2.2 Revolution

The emergence of smartphones and gps-enabled devices that allow user input and collection of locational data are now pervasive in society and can be used in virtually every aspect of our daily lives both personally and professionally. Unlike previous generations of citizen contributions which required some form of manual input, smart devices allow for passive collection and distribution of information, much of which is geospatially referenced, by almost anyone anywhere. This data, most of which is unstructured data stored in a myriad of databases, requires only that an interested party with access to the data conduct searches of the plethora of information to discover what he or she is looking for. It can be used for as benign a purpose as finding the fastest route to work to a more vital purpose such as assisting first responders in search and rescue operations. In the figure below, one can see the dramatic exponential increase in the amount of unstructured data, trillions of gigabytes worth, available on the web. Current research at George Mason University is using a combination of passive information collection along with manual user input to accomplish a variety of scientific goals. Stefanidis et al. (2013a, 2013b, 2013c) use large volumes of passively collected geosocial data to study social protest movements, monitor earthquakes, and to look at the changing nature of political boundaries, as defined by members of online social communities. Gkountouna et al. used multiple data sources to study trajectories and movement (2017). Yang et al. (2017) are developing high-performance computing infrastructure to deal with the challenges of large volumes of data (2017), while Curtin et al. (2014) explore the quality of solutions to data-rich and combinatorily complex optimization problems. Camelli et al. (2012) use complex computational models and big data to study GIS-based dispersion modeling. This explosion of data is a significant scientific opportunity, and an important part of the future geospatial landscape. The development of scientific frameworks and geocomputational approaches is equaly important in making sense of this new, data-rich geospatial landscape. This thesis hopes to extend research and illuminate certain issues wtihin this domain.

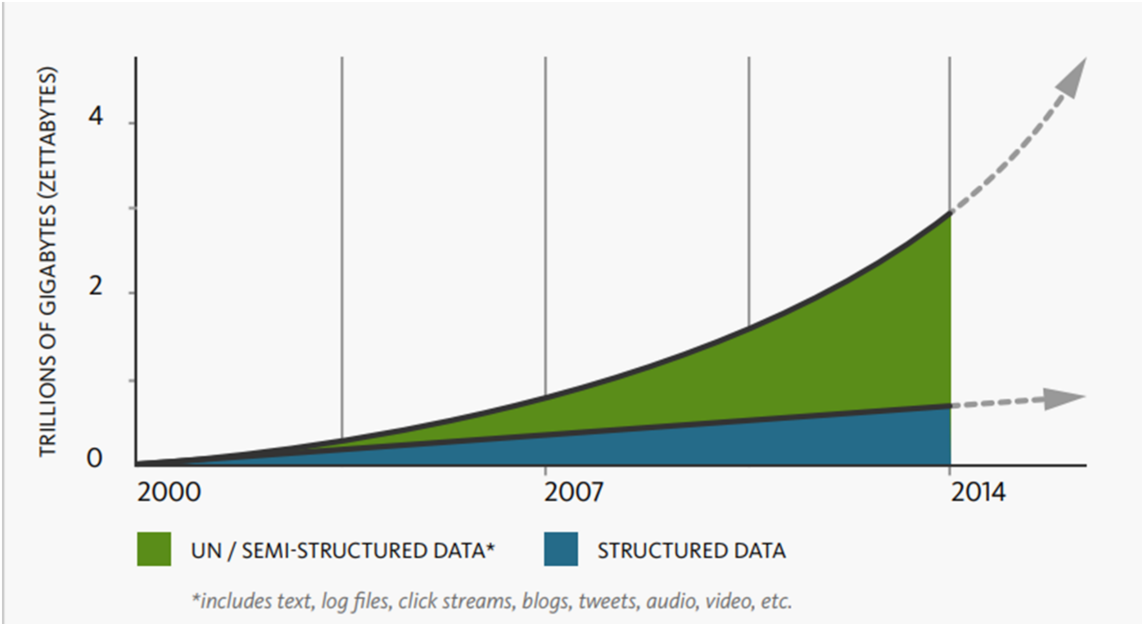


Figure 4 Big Data: Amount of available unstructured data on the web (N.D. Why NoSQL. Retrieved from www.couchbase.com)

The following chapter reviews important research and concepts as a way of building a conceptual framework for this thesis. This past research provides insight into quality assessment dynamics in geocrowdsourced data, and reviews ways that crowdsourcing techniques can be used in a simplified geocrowdsourcing testbed to accomplish specific data generation and data fitness-for-use goals.

CHAPTER 2 - LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

2.1 Quality Assessments and Positional Accuracy

This thesis looks closely as the issue of quality assessment in geocrowdsourced data – an issue frequently described as the principle weakness of geocrowdsourcing, and identified by researchers such as Goodchild (2007) and Girres et al. (2010) as a major priority. Quality assessment has been a major theme within the GMU Geocrowdsourcing Testbed (GMU-GcT), and this thesis continues the recent work in this area (Rice et al. 2018) by exploring a simplification of the GMU-GcT and an image-centric contribution workflow.

2.1.1 Quality Assessment Criteria

Many factors affect the reliability and accuracy of GcD. To achieve higher levels of accuracy and reliability, crowdsourced data must undergo quality assessments (QA) for at least three important variables: positional accuracy, temporal accuracy and attribute accuracy (Rice et al. 2014). These three quality assessment items are based on the "atomic element" view of geographic information espoused in chapter 3 of Longley et al. (2015), where all geographic information is described as an associated triple of [location (x,y), time and attribute]. The most thorough views of geospatial data accuracy contain additional factors (Guptill et al. 1995, Hunter et al. 1992, and Veregin 1999), such as lineage, completeness, logical consistency, and fitness-for-use (usage), but a predominate focus of recent studies (e.g., Haklay 2010, and Girres et al., 2010) is positional accuracy. Positional accuracy is best described as the horizontal and vertical spatial accuracy of the collected data. The National Standard for Spatial Data Accuracy (NSSDA), developed by the Subcommittee for Base Cartographic Data is the most relevant accuracy measurement method for GcD (Rice, et al. 2014). This method uses root mean square error (RMSE) calculations (or the square root of the group of distances of points of collection) from a single point of interest. By using the NSSDA standards, one does not need to discard data because they do not meet a preset threshold, rather, the researcher can set the threshold, generally at the 95% confidence level, and then describe those characteristics in the accompanying research (FGDC, 1998).

The second quality assessment element, temporal accuracy, is a composite measure of the consistency of the data collected with regard to the collection and observations times. Temporal accuracy suggests that the data collected and reported represent the time period asserted by the collector, and that the data are not out-of-date. Whether it be from a GPS-enabled device or a social media platform, a time stamp is generally associated with the submitted information, both during collection (and often saved as embedded meta-data) and during submission to a crowdsourcing system. Interestingly, with temporal accuracy, the currency of collection may, in some cases, become more important than a formal temporal accuracy measurement. As Goodchild describes in relation to the 2009 wildfires in Santa Barbara, California, having large amounts of data submitted quickly may be more valuable than awaiting formal, authoritative data that could take much longer to produce and disseminate (Goodchild and Glennon 2010). On the Haitian earthquake, Zook et al. (2010) concurs the advantage of quickly-produced GcD. However, without any means of verification for the data being produced, the substantial number of GcD contributions in a crisis event may not always be a positive situation. As Starbird et al. (2014) describe in relation to the Boston Marathon bombing in 2013, submissions of inaccurate or even false information resulted in delays in discovering the true identities of the perpetrators and false identification of innocent, uninvolved people. They also discovered that once the incorrect information was submitted, subsequent corrections did little to diminish people's initial determinations (Starbird et al. 2014). While this particular example is not strictly geospatial in nature, it remains a cautionary example of the dangers of inaccurate information being used for public awareness purposes, particularly for time-sensitive events.

The final measure in the quality assessment procedure described is one of attribute accuracy, which measures the agreement between the characteristics of an event reported by a contributor, and the true characteristics of the same object, as determined through ground-truth measurements or by some other more accurate process. Attribute accuracy is often measured through techniques such as a confusion matrix and Kappa statistics. Attribute accuracy addresses the subjective nature of feature naming in geospatial datasets and underscores the difficulties in having untrained, non-expert contributors, who may be unfamiliar with the data collection software or with scientific principles underlying the geospatial disciplines (Rice et al. 2014). The difficulty in achieving high accuracy in attribute data entry was especially apparent during the Haiti earthquake emergency response effort where 73% of over 3400 reclassified messages from Haitians that were received and translated by GcD contributors failed to convey the message intent, and 50% of the messages were miscategorized altogether (Camponovo and Freundshuh 2014).

2.1.2 Quality Assessment Approaches

In addition to knowing what variables are needed for a quality assessment of GcD, one must also know how to conduct the quality assessment. Goodchild and Li (2012) divide geocrowdsourcing QA methods into three “approaches”: the crowdsourcing approach; the social approach; and the geographic approach. The crowdsourcing approach, describes methodological approaches from three interpretations of the term. In this first interpretation of the crowdsourcing approach, the authors discuss the dynamic where large volumes of people are used to problem solve a problem. This interpretation suggests if a problem exists and needs to be solved, the more people one has addressing the problem, the more likely it is to be solved. Secondly, the crowdsourcing approach refers to the strength of spatial clustering. As mentioned earlier with the Santa Barbara wildfires, many people reporting on a topic from an initial report lends credence to the event upon which is being reported. Goodchild and Li (2012) use the example of Wikipedia, on which a person contributes unmoderated information that is incorrect. The drive of people will be to correct information that they either know or perceive to be incorrect, therefore Wikipedia with its millions of contributors essentially becomes self-correcting and generally accurate because of its users (Goodchild and Li

2012). The third interpretation is based on the need for people to find the truth. This interpretation follows results based on Linus's Law that if many eyes look at something then someone will find the error. The law states that people will strive to find truth and correct errors, therefore, the more people who look at something, the more likely it is that errors will be found (Goodchild and Li 2012).

The second method for conducting QA is known as the social approach. Rice et al. (2013b) describe this approach as one which uses experienced moderators as "gatekeepers" who work in a hierarchical structure to ensure that data that are being contributed is both accurate and relevant. As mentioned earlier, having a moderator for the contributions is a method to ensure a higher level of accuracy for the contributed data. GMU MS student Rebecca Rice explored the moderated quality assessment workflow of the GMU-GcT in her thesis from 2015, and in a subsequent publication (Rice et al. 2016). Rice discovered, in her thesis research, that moderated ground truth in the GMU-GcT has an absolute positional accuracy between 2.12 and 5.55 meters, depending on whether the item being measured is small (~1m square) or larger.

In articulating the social approach for quality assessment, Goodchild again uses Wikipedia as an example. As moderators also tend to be contributors, about a tenth of a percent of total contributors are moderators of the information. This is why Wikipedia can fit into both categories since 1500 moderators cannot possibly moderate 15 million users efficiently. The moderators validate and assess the data they are able to assess, and then the crowd of users is expected to find the remaining errors (Goodchild and Li 2012). In her thesis research, Rice notes that this quality assessment approach is considered an expensive, resource-intensive approach, and that it works well in small projects without the benefit of a large number of contributors that would make the crowdsourced quality assessment approach feasible and logical.

The final method for quality assessment discussed by Goodchild and Li (2012) is the geographic approach. Rice et al. (2013) describe this approach as a comparison of contributions to known geographic facts and phenomena of an area. One would look for inconsistencies between the two which would lead to conflict resolution for the inconsistencies. For example, if one were interested in the location of all sidewalks on the GMU campus and one of the contributions was located in the Mason Pond (an actual example cited by Rice et al. 2013), then the comparison of known geographic facts and phenomena to contributed data would be a red flag that an error in collection or data entry has occurred. This quality assessment approach is a law-seeking or nomothetic approach for data quality, and assumes that there are natural geographic laws and facts that can form a basis for comparison.

While moderation is an effective way to mitigate inaccurate or incomplete geocrowdsourced data, what options are available if moderation is not available due to time, personnel, or monetary costs? The answer to this question is the crux of the research topic being discussed. In 2010, GMU researchers began exploring methods to aid mobility and vision impaired students in navigation of the GMU campus (Rice et al. 2011. The initial research goals and project funding resulted in the development of a strictly-moderated geocrowdsourcing system where contributors would enter up to 15 separate locations or attribution characteristics of anything the contributor perceived as an impediment to safe movement along predefined pedestrian corridors. This was a cumbersome and time-consuming process both for the contributor and the moderator. Fewer than expected contributors used the system, with 12 active contributors out of the 40-50 that were needed to maintain adequate temporal and spatial coverage (Rice, et al, 2013). To alleviate the inconveniences of the desktop contribution tool, Rice et al (2014) developed a mobile version of the tool that had fewer categories of information for contributors to enter, however the data still required moderation to ensure accuracy of the entries. Additionally, the mobile version required the contributor to enter subjective categories such as "Describe the obstacle" and "Duration" as well as "Urgency". As these categories could be and were answered differently by different contributors it again became a cumbersome chore for the moderator to sort through the data to attempt to discern why a contributor may have marked something as high urgency or what a contributor meant by "a hole in the sidewalk" (Qin et al., 2015, and Paez 2014). Again, between the requirement for moderation of the data and the amount of data required to be entered by the contributors, few students became regular contributors to the project. A general review of the developing project from the early phases is contained in Rice et al. (2012a) and Qin et al. (2015)

2.1.3 Positional Accuracy without Moderation

A focus of this research is to simplify the input mechanism for the contributor and forgoing strict moderation of the geospatial data being contributed. The goal is to greatly increase the number of contributors which can be done by creating an input platform similar to that of Instagram. Therefore, the only information the contributor would need to provide is a picture and brief description of what they see. The three required atomic elements for geospatial data presented by Longley et al. (2015) -- location, time, and attribute, can be provided by a simplified system. Time and location are provided by the GPS and time metadata from the data collection tool itself, and attribute (image and description) is provided by the contributor. The benefit of increasing the number of contributors with such a tool is that it may do away with the need for strict moderation of the data. By coding the application to find location-relative clusters of entries from the many contributions, one may enable algorithms to relate the entries within these clusters to detect probable like objects, and then calculate a spatial mean from the clustered observations. This would lower the overall error of the reported location and thus achieve a desired accuracy level for obstacles that pose an impediment to mobility. The research presented in subsequent chapters of this thesis did not approach the clustering in an automated or semi-automated fashion, but gathered intentionally tagged observations about specific pre-defined locations on the local college campus. The automation of this clustering process is a matter for future work.

With assistance from GMU faculty, research collaborators, volunteers, and new data collection tools, this research will show that an increased number of contributions to the simplified user interface as a phone application will result in increased accuracy when measuring the position of collection to the ground truth location of the target being collected upon

2.2 Threshold of Contributions to Reach Acceptable Positional Accuracy

Foody et al (2015) understood the value of crowdsourced data but also understood the limitations of that data, namely positional accuracy. To address this concern, research was conducted to attempt to correlate the level of positional accuracy of contributions to the number of contributors and contributions. To obtain a measurable result, the study was conducted by selecting 299 satellite images along with an open call for volunteers to participate which resulted in 65 persons. The objective given to the volunteers was to review the satellite images and from a predefined set of choices, select the land cover of the image (Foody et al., 2015). As the participants were all volunteers, their levels of experience, motivation and completeness of the task were varied. This allowed for researches to not only calculate accuracy rates solely on the number of contributions versus the accuracy of contributions, but also to calculate at what threshold for the number of individual contributors was needed to achieve certain accuracy thresholds. Foody et al (2015) calculated the R-square value of overall accuracy of land cover classification as it related to increasing numbers of contributors but who contributed differing amounts of information. As shown clearly in Table 1, the more contributors who participated, the higher the overall accuracy.

Number of Volunteers	R^2
5	0.0009
10	0.8194

15	0.8594
25	0.8579
35	0.7279
65	0.9359

Table 1 Correlation between number of contributors and R^2 of accuracy (Foody et al., 2015)

A second area of focus in the study was to determine if only using the "best volunteers" contributions would result in an increase in accuracy. However, as illustrated in Figure 3, in this particular instance, when evaluating the contributions of 14 volunteers who contributed the same amount (all 199 images) and their individual accuracy rates for classification, the research revealed that after 11 volunteers, no further significant increase in accuracy was gained, showing that a continuing increase volunteers does not always equal higher quality information (Foody et al., 2015).

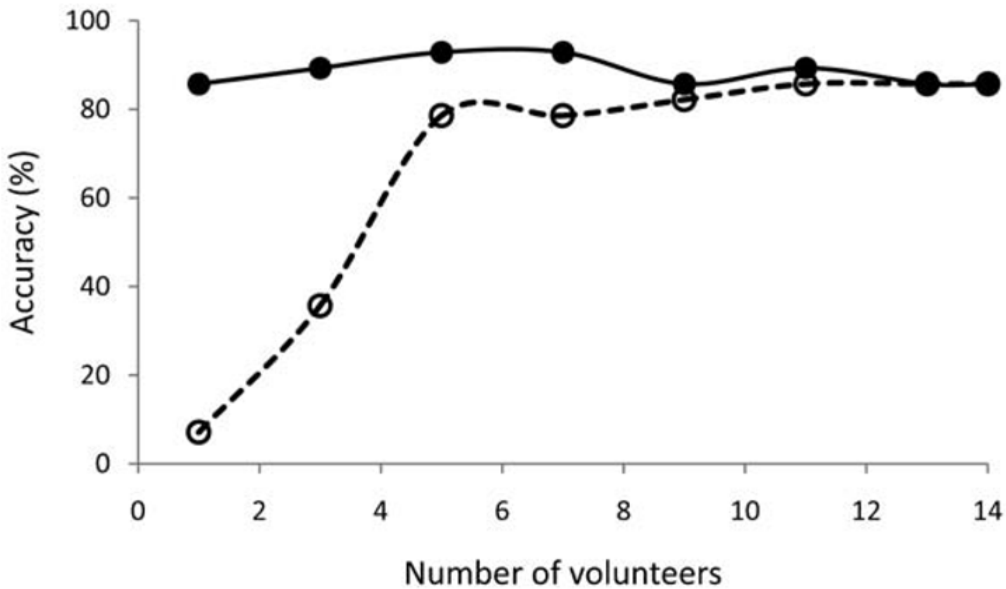


Figure 5 Correlation between number volunteers and level of accuracy (Foody et al., 2015)

Research conducted by Haklay, et al. (2010) provided more credence to the studies by Foody et al. (2015) by showing the correlation between Linus' Law and GcD. Haklay et al. (2010) intended to prove that Linus' Law – which states that as the number of contributors increases so does the quality of the contributions – was relevant when relating GcD contributions quality (by measurement of positional accuracy) to OpenStreetMap by testing the correlation with three studies conducted earlier by Zulfiqar (2008), Ather (2009) and Basiouka (2009). Haklay determined that the earlier studies collectively demonstrated the validity of Linus's Law, at least in regard to positional accuracy of features. Haklay noted that the assumption of increased contributors leads to quality improvements is true in the areas analyzed. The study areas analyzed by Haklay were based on a $25km^2$ region. This study in this thesis will be a smaller, approximately1km^2 region, and follows up on future research suggestions from Haklay et al. advocating a similar research study on a smaller areas.

Additional research was conducted by Rohrbach et al. (2015) which examined the effect sample size had on spatial data quality as it related to mapping areas for land use. The premise of the study is to enable to the concept of participatory mapping (PM) in the form of questionnaires on which the participants have a myriad of fields to complete to describe land use of an area over the previous 20 years. The form of PM implemented in this study was public participatory GIS (PPGIS) upon which Rohrbach explains that "sampling effects and data quality are key issues" and set forth answer to the following issues:

- We assess the data quality of PM past land use based on the correctness and completeness of the data. .
- We propose a procedure for estimating the correlation between sample size and data quality through a resampling approach.
- We display and discuss the influence of participants' individual performance on aggregated groups' PM outcome.
- We test the sensitivity of the suggested procedures to different mapping scales (Rohrbach et al., 2016, pp 682-683).

The sampling in this study was not a random sampling but a carefully researched and specifically selected group of 23 local farmers (15-16 of whom ultimately provided completed responses to the survey) who had thorough knowledge of the landscape and history of their border town in Switzerland. The data collection portion of the study began with the researches providing the sample group with aerial images of three different scales: 1:500, 1:12,500, 1:25,000. The participants were directed to mark where they believed their land was located in the present day, followed by marking the areas they believed were arable lands in 1990. Researchers then scanned and georeferenced and the images to overlay the famers' estimates to enable processing in GIS software. Three sources providing aerial imagery from 1986, federal statistical data from 1985-1995 and a study recording the state of the area were used as a ground-truth area of approximately 117 hectares that would be used for comparison against the participants' survey responses (Rohrbach et al., 2016). This ground-truth measurement would be used to compare to the present day measurements to determine the level of change in arable land. The resulting comparison from the data processing portion of the research is shown in Figure 6.

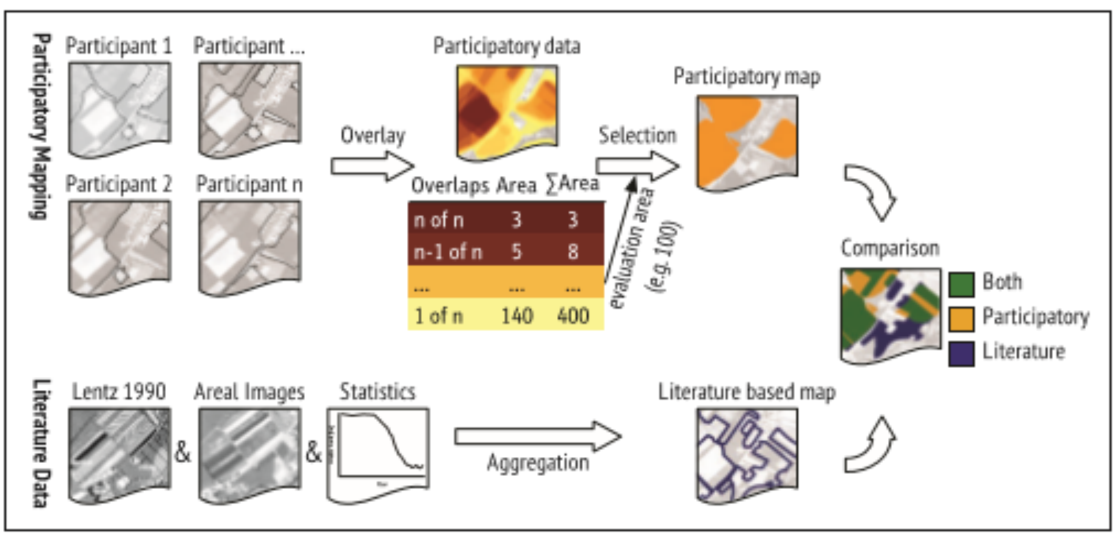


Figure 6 Overview of data processing of participatory mapping data (Rohrback, Anderson, & Laube, 2016)

The findings, much as in the findings from Haklay et al. (2010), showed that after a certain number of contributors, no significant increase in accuracy was achieved. The results of this survey showed that the more areas an individual respondent mapped, the higher his or her individual accuracy became. However, as a group measurement, diminishing returns presented after 10 participants (Figure 7) and no significant increase in overall accuracy was achieved (Rohrbach et al., 2016).

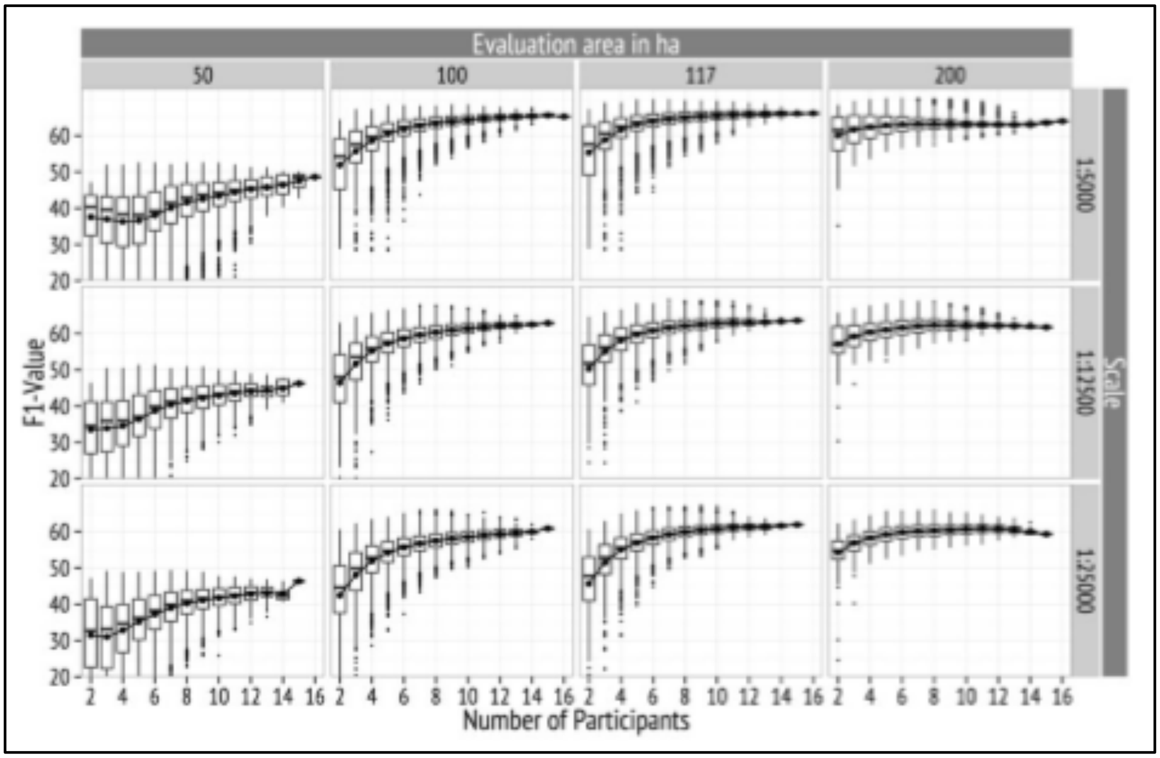


Figure 7 FI-values of different sample sizes, areas evaluation and scales (Rohrback, Anderson, & Laube, 2016)

The relationship between the number of contributors to a particular issue and the level of positional accuracy and the diminishing returns of the increase in accuracy as the number of contributors increases will be addressed in more detail specific to the issue of obstructions to mobility later in this research.

2.3 Research Problem and Hypothesis

Multiple research studies noted above have shown that repeated observation, through crowdsourcing, can reduce positional and attribute errors, whether the subject is road geometry in OpenStreetMap, or land cover mapping from imagery. The GMU Geocrowdsourcing Testbed (GMU-GcT) has undergone a simplification. This thesis tests the larger research idea noted above, through the vehicle of the GMU-GcT. Specifically, this thesis will test the hypothesis that an increase in the number of observations for a specific geographic object will lead to a lower positional error, and that this reduction will have some converging property, as shown in Figure 5 (from Foody 2015). The Rebecca Rice thesis from 2015 found the average positional error associated with moderated ground truth to be in the range 2.12m to 5.55m, depending on the size of the object being reported. This earlier thesis work suggests that moderated geocrowdsourcing systems such as GMU-GcT can result in object positional accuracies in this range. This thesis hopes to prove that a hybrid geocrowdsourcing system built on simple image capture can result in similar accuracies, but without the cost and expense of the social moderation process used previously in the GMU-GcT.

CHAPTER 3 – METHODOLOGY AND DATA

3.1 Methods of Collection

Between 2011 and 2016, GMU researchers developed and maintained a geocrowdsourcing system called the GMU Geocrowdsourcing Testbed (GMU-GcT), which was a cumbersome desktop-centered system with a moderated quality assessment workflow built on the ‘social’ approach discussed by Goodchild and Li. The evolution of the system is documented in research reports and papers, including Qin et al. (2016), Rice et al. (2012b, 2013b, 2014, 2015) and Aburizaiza et al. (2016).   In 2015 and 2016, this system adopted a mobile incarnation, and later, and experimental image-based contribution tool that will be the subject of this proposed research.

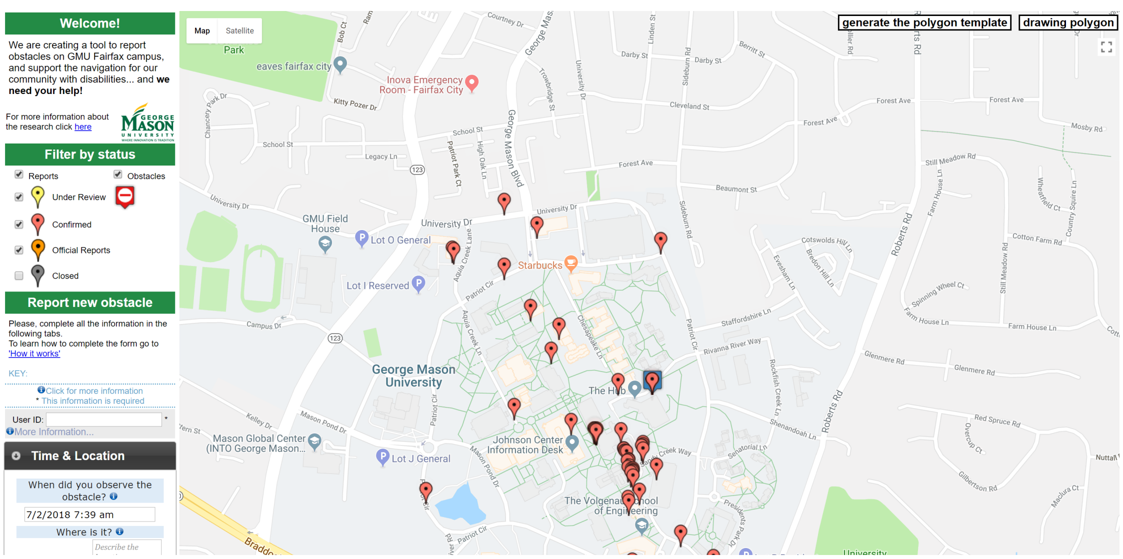


Figure 8 Screenshot of desktop version of GMU-GcT application (retrieved from http://geo.gmu.edu/vgi)

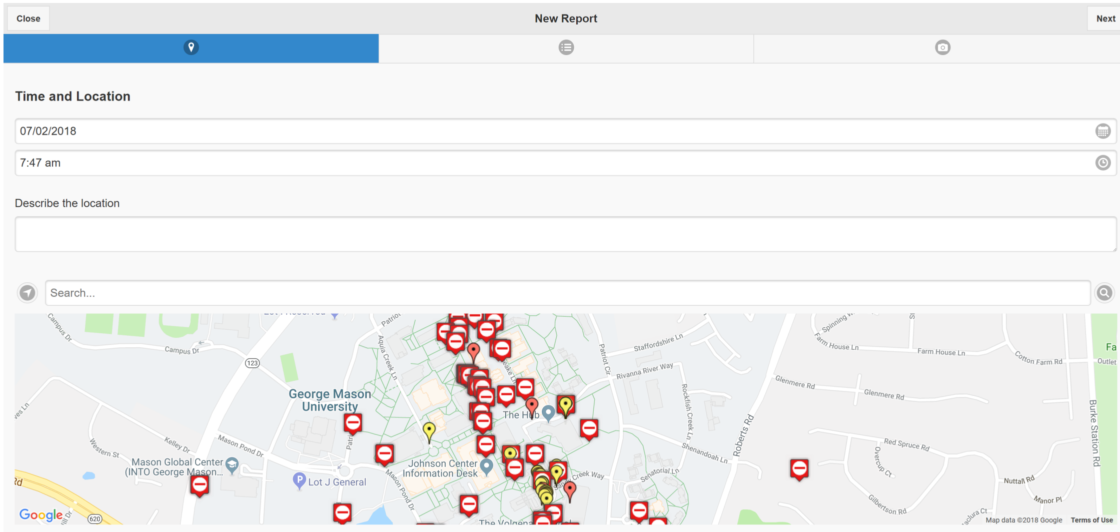


Figure 9 Screenshot of mobile version of GMU-GcT application (http://geo.gmu.edu/vgi/m)

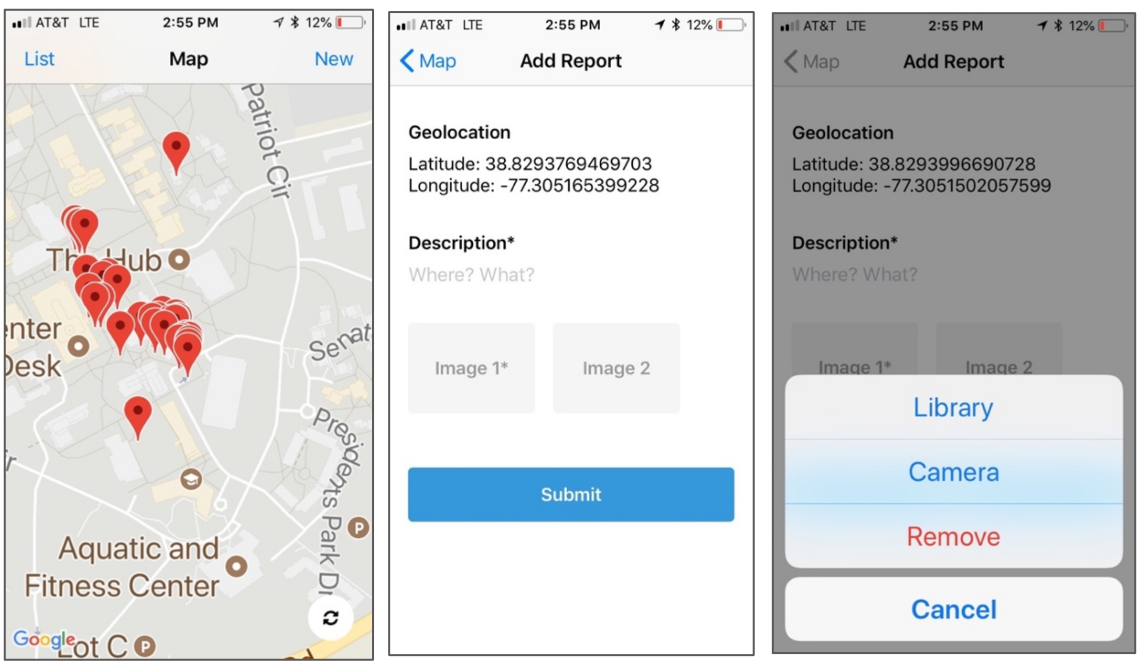


Figure 10 Screenshot of smartphone version of GMU-GCT application (retrieved from geo.gmu.edu/cgd2018)

In an effort to explore the updated quality assessment dynamics discussed in section 2.1 of this thesis, a study comprised of two distinct phases was conducted to compare the data collection workflow of the contributors to the GMU-GcT using the strictly moderated GMU-GcT, the mobile version of the GMU-GcT, and the image-based contribution tool. Phase 1(P1) consisted of a cohort of volunteers comprised of undergraduate students from the Geography and Geoinformation Science Department at GMU who completed tasks assigned to them to determine accuracy and precision levels of contributions. The purpose of this initial phase was to explore the contribution dynamics and positional characteristics of a web-application revision of the GMU-GcT, to be used in fine-tuning the subsequent updates to the GMU-GcT contribution tools.

The first step of P1 involved researchers pre-staging markers within a pre-defined bounding box on the GMU campus. Besides being placed along walkways and in the open, some markers were placed in environments with differing characteristics to provide a variety of measurement challenges such as: near tall buildings, on extremely sloped surfaces, and under tree canopy. Markers were also placed at locations to represent either a point or areal features. Area locations for instance were marked by being placed off of a main path in a grassy area in a configuration of multiple cones forming a polygon. Each of the point and area markers were labeled and the precise location of each marker recorded. Control coordinates for the area locations were determined by the center of the location shape.

Figure 11 Examples of markers for volunteers to locate in Phase 1

To begin the second step of P1, the general locations of the marker positions were placed on maps of the bounding box area. The maps were distributed to student volunteers who were instructed to find the markers and record their locations using the above-mentioned image-based contribution tool. Example photographs taken from the image-based software were provided to the students to provide examples of marker appearance. Examples images were comprised of multiple images from various look-angles and distances so as not to bias the students' perceptions of how they should capture an image of the markers. Before beginning their search for the markers, students were given specific instructions on how to use the contribution tool and to what settings (wi-fi and location services) to set their phones. An example of the student instructions can be found in Appendix A.

Figure 12 Example photographs given to volunteers showing an object of interest from many viewing angles to prevent collection bias

The student volunteers were sent out in small groups rather than en masse to prevent bias in the collection process, and more specifically in the standing or observing location in relation to the object of interest. While volunteers collected on the two targets, a researcher marked their position with chalk. Once all the volunteers had completed the task, the distance in meters from the chalk markings to the targets was measured to provide insight into collection positions and variations in distance from the point of collection to point and area targets. Upon one group's return, the next group of student volunteers completed the same task. Roughly 30 students comprised this study group and the task was be performed for three weeks.

Phase 2 (P2) of the experiment occurred in the final two weeks of this study. The specific reasoning for P2 collection will be discussed in greater detail in Chapter 4. Similar to P1, P2 also began with using pre-defined locations throughout the GMU campus. However, instead of using markers, P2 locations were chosen from pre-existing landmarks and features on the campus. As was the case in P1, some locations were applicable as point targets and some were better suited as area targets. Following location selections, reference handouts were produced which included an overview map of the study area with the target locations alphabetically labeled on the map. Additionally, photographs were taken of each locations from various angles to mitigate any bias as to the angle from which the collection should be performed. The reference handouts were then distributed to volunteers for them to review and to ask questions should they have any. In contrast to P1, P2 volunteers comprised a combination of students, research assistants and non-academic volunteers. Prior to being released for the collection, specific instructions were given to the volunteers as to how to complete the task (see Appendix A). Each volunteer in this phase was randomly assigned an identification number which was included on his or her handout. Volunteers were instructed to include that number on each contribution. Also, they were instructed that there was no particular order in which they needed to collect the target locations; that the alphabetical designations of each location were not representative of an order of collection, but only to provide reference as to the location of each target. In a similar fashion to P1, two researchers pre-staged at a point and an area target and recorded chalk markings for the positions from which the volunteers completed collection. Following the task completion by all volunteers, the distances in meters to the targets from the chalk markings were measured.

Figure 13 Example of obstacles for Phase 2 collection

Along with user sentiment and user feedback, captured in surveys, this research project examined the quality assessment capabilities and possibilities of each phase. The quality assessment comparison showed workflows for each tool and provided comparison to see if a simplified, Instagram-style contribution system produced the same basic quality estimates for location, time, and attribute. Additionally, project researchers were able to determine if a larger number of contributions and an increased rate of contributions was possible with a simpler tool, as projected during future project planning in 2015 and 2016 (Rice et al. 2015). The procedures in P2 were designed around the hypothesis of this research stated in Section 2.3: An increase in the number of observations for a specific geographic object will lead to a lower positional error, and that this reduction will have some converging property.

3.2 Data

3.2.1 Student and Volunteer Data Contributions

The Phase1 collection period took place over two weeks and was comprised of undergraduate student volunteers from GMU who completed the assigned tasks in conjunction with current coursework requirements. Each volunteer was randomly assigned an identification number to keep track of individual observations and to alleviate any privacy concerns of collecting personal information from students in conjunction with their collected information. Week 1 of the P1 was comprised of 24 student volunteers and Week 2 was comprised of 14 student volunteers. Two locations were assigned for collection for a planned 38 individual observations. Information collected during P1 included: phone type and model, geolocational data, date and time, manually measured collected distance away from the assigned location, and a free text description submitted by volunteers at the time of collection, and various exif data from the volunteers' phones.

Phase 2 collection was completed over several days and volunteers were comprised of GMU students and non-academic volunteers from a wide range of ages and backgrounds. Each student was randomly assigned an identification number to keep track of individual observations and ensure all volunteers collected all targets. Twenty-one volunteers provided contributions for 13 targets for a total of 273 distinct observations. Along with geolocations provided by the volunteers through the collection application; date and time, images taken by volunteers, and free-text descriptions written by the volunteers were collected, along with various exif data from the volunteers' phones. Furthermore, two of the locations (one a point location and the other an area location) were observed by researchers during the collection period. As volunteers completed his or her submission, the researcher marked the collection location and measured the distance between the target location and collection location.

Phone type. Phase1 was completed using a web application to which any volunteer could access to provide contributions. No restrictions for the type of phone for P1 were enforced, which led to various models of iPhones and Android devices being used for the phase.

Phase 2 was designed as a mobile application and was implemented using constraints for applications which are to be approved by Apple AppStore for wide distribution. At the time of the study, the application had not been approved by the Apple thus the beta version of the application was still under development. Only iPhone models 6, 7, 8, and X were used for collection during this phase.

Location Information. Phase 1 was developed as a web application. Because of this, multiple issues negatively affected the collection and submission of data and inconsistent measures for locations resulted over the two weeks. The second week of collection, for example, with 14 volunteers participating, only seven of the collected and submitted reports made it into the database. Of the seven reports that resulted, location error from the point of collection ranged from as accurate as 5 meters to as non-sensical as 600 meters away. The collection errors under the P1 development model could not be remedied in the time allotted. The errors possibly resulted from a combination of HTML5 coding issues as well as google location privacy restrictions in conjunction with the locations being on the edge of wi-fi signal on campus and the location services moving from wi-fi to tower location calculations during the collection process.

Figure 14 Phase 1 Collection of two points with inconsistent locational returns

As show in Figure 16, two example points are displayed on map of the GMU campus. Distance errors ranged between 10 meters and over 600 meters from the point of collection. Despite exhaustive editing of code and troubleshooting the errors could not be corrected. With no remedy being developed, the P1 collection plan was suspended and the P2 development of a smartphone-based application began. Phase 2 collection provided accurate locational data for the testing period with 100 percent of the submitted collections being added to the database. The data gleaned from the study will be explained in further detail in Chapter 4.

Data Collection/Submission Methods. For P1 the volunteers used their phones to directly log into the developed web application which was both slow and cumbersome sometimes requiring volunteers to wait several minutes for confirmation that their location report was submitted. Additionally, irrespective of what phone type or model was being used, some volunteers were unable to connect to the web application at all, therefore none of their attempts to provide contributions were successful. As a result, no usable results were to be gleaned from Phase 1 collection, other than general information about standing location/position and general feedback used to fine-tune the future updates to the GMU-GcT.

The P2 smartphone application allowed volunteers direct access to the contribution system which provided an Instagram-style display. After permissions were granted and volunteers logged into the application, all submissions attempted by volunteers were successfully submitted to the GMU geocrowdsource database and provided nearly instant submission confirmation after a location was collected.

Because of the software errors and contribution anomalies involved with Phase 1, Chapter 4 will only include results from the Phase 2 collection.

CHAPTER 4 - ANALYSIS OF RESULTS

4.1 Results

As discussed in Chapter 3.1, Phase 2 collection consisted of 21 volunteers who provided contributions for 13 pre-defined locations on the GMU campus for a total of 273 distinct contributions to the GMU-GcT database. These locations were comprised of six point targets and seven targets with areal qualities. The average observation distance between the volunteer's collection location and the target was 4.64 meters. The average distance of collection from point targets was 4.31 meters and from area targets was 4.98 meters. Specific data on volunteer location during collection will be discussed later in this chapter.

The 273 collection points were downloaded from the GMU-GcT database and imported into ArcGIS Pro where the data were converted from a Microsoft Excel CSV file into shapefiles to provide a visual interpretation of the data collected. Unlike Phase 1 collection, most of the data collected in Phase 2 remained clustered in the appropriate areas near the targets upon which were being collected, as seen in Figure 15.

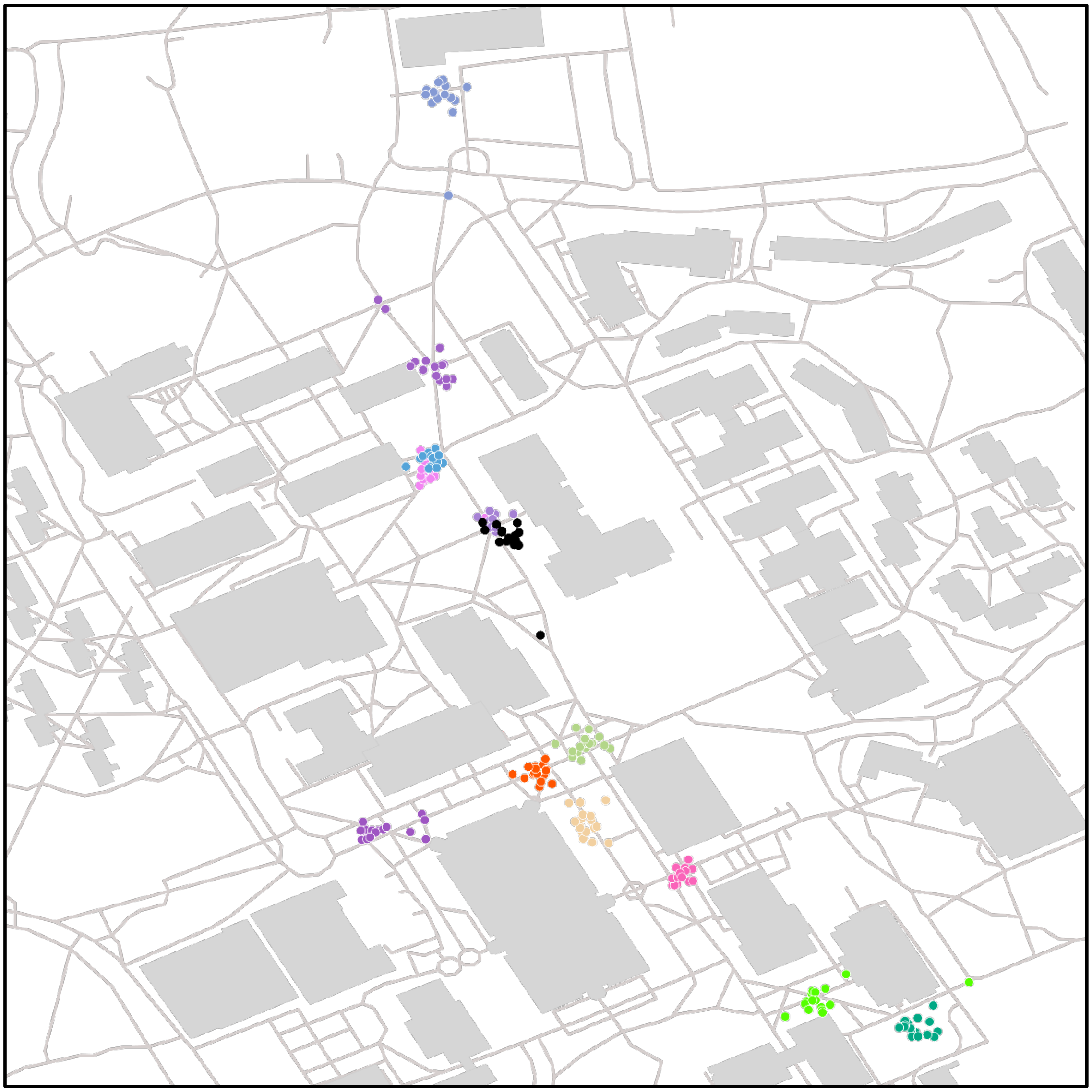


Figure 15 Depiction of all 273 points collected during Phase 2

Despite the marked improvement in the accuracy of data from Phase 1 to Phase 2, issues such as human error or software issues resulted in several observations not falling within their expected collection areas as seen in Figure 15. This issue was addressed by determining the need to assign upper and lower limits of distance from the objects of collection to the contributor. Any contributions outside of those limits would be disregarded as outliers. To capture the most relevant data possible a three standard deviation upper and lower limit was implemented against the data. Three standard deviations, 27.23 meters, and a mean collection distance error across all contribuions of 8.55 meters, meant that any contributions greater than 35.78 meters from the points of collection would be disregarded. As such, six observations were eliminated from consideration, resulting in 267 usable contributions. Removing these six outliers from the collection measurements, resulted in the reduction of the overall mean distance of all collection error to 7.17 meters. The trimmed set of contributions is shown in Figure 16 below.

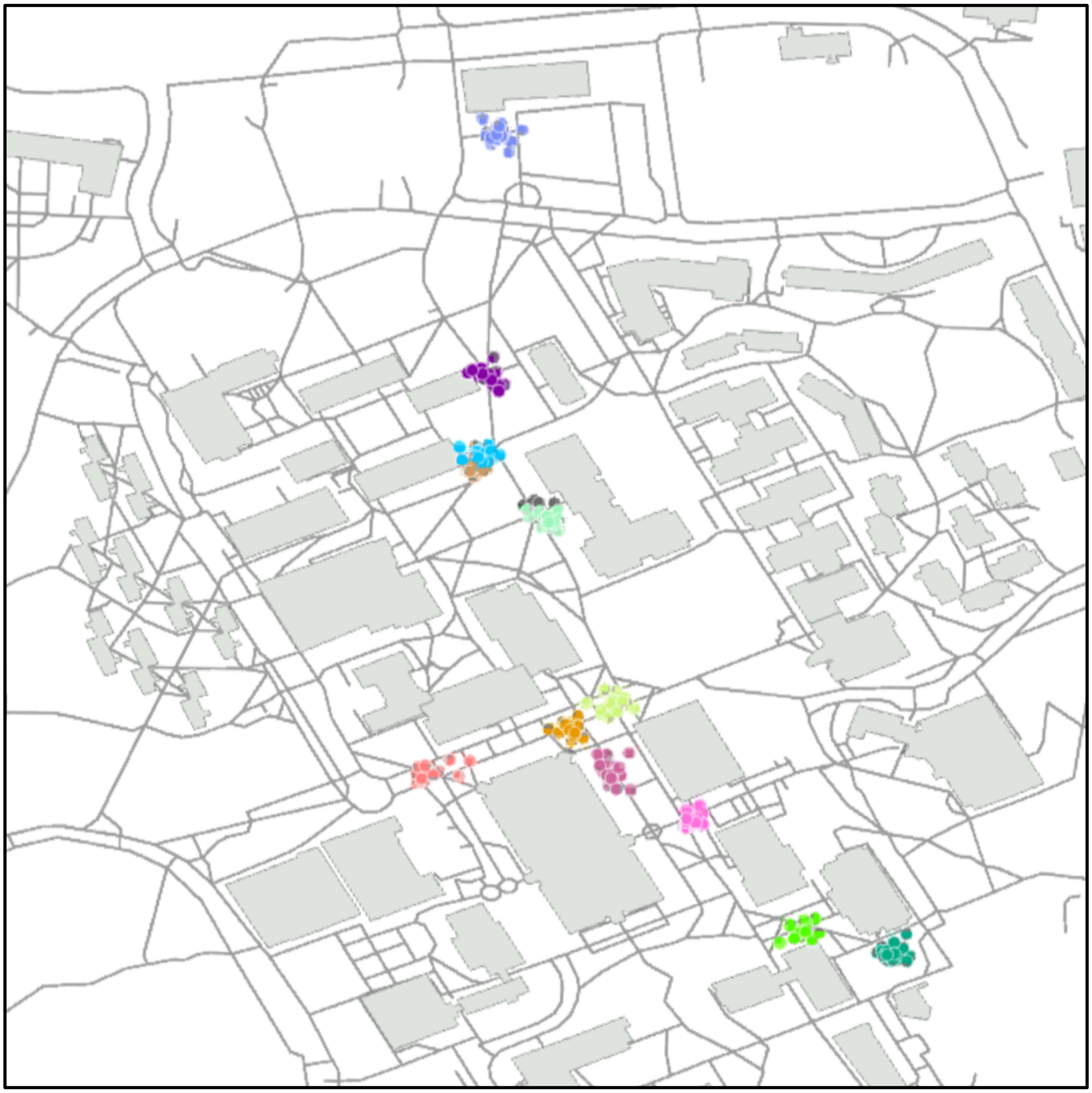


Figure 16 All collected observations except outliers

To effectively measure the distance from the volunteer to the obstacle, an accurate location for the centerpoint of the obstacles was needed. Several measures of accuracy were examined to find the most precise measurement of a centerpoint to each obstacle. The first measurement used was the mean of contributions per each target to determine a centerpoint using the data from the application for this research. As that centerpoint measurement was only as accurate as the medium from which it was collected, and the average error across all collection points was 7.17 meters, this method was not deemed the best choice for a centerpoint measurement. Next, researchers utilized Google Maps using a combination of visual observations on the Google Maps application in addition to local knowledge of the study area to determine the centerpoints. The issue of accuracy of reporting even with moderators providing “ground truth” locations was addressed by Rice 2015 in which she calculated the average reporting errors of moderators who provided ground checking on obstacle reports submitted by volunteers. What she found was, even with three moderators and visual confirmation of where an obstacle was located, the three moderators’ average distance error from the obstacle was still 5.55 meters if including areal targets and 2.12 if only considering point targets (Rice, 2015). Since the Google Maps imagery of the GMU campus was collecting during a leaf-on timeframe, many of the locations were obscured by tree canopy and researchers had to use relational methods to determine where some obstacles were located. The combination of leaf-on photo-correlation along with the built in error of determining ground truth through visual observations even with moderators led to the decision that this method would not be the most accurate means of determining ground truth in this study. Lastly, the Virginia Base Mapping Program (VBMP) data was used. Image tiles were downloaded from the VBMP website and ingested to ArcGIS Pro. The image tiles represented high resolution aerial imagery (as fine as 1 foot) obtained during a leaf-off timeframe which allowed for an easier and more accurate interpretation of where the ground truth locations of obstacles were located through both local knowledge and photo-correlation of locations of interest relative to obstacles on which were being reported. This method proved to be the most reliable method for determining the ground truth locations and was used as the centerpoints for distance calculations and constraints. This method also has the related benefit of being done with a reference base layer used by virtually all the municipal City, County, and state-level GIS offices. This suggests that it is likely the most consistent with common infrastructure data produced by the same agencies. The use of VBMP base imagery in ArcGIS for locating ground truth locations is repeatable within the Commonwealth and will allow GMU-GcT project partners in the region to contribute data with consistent positional characteristics. The VBMP-derived centerpoints and the trimmed set of contributions is shown in Figure 17, below.

The distances from all observations to the VBMP centerpoints were entered into a spreadsheet. From this spreadsheet an average mean distance from observer to target across all observations was able be determined. Additionally, using computationally-intensive python script, every possible permutation of 1 through 21 collections for each target was completed and summarized[1]. The results, shown in Figure 18 below, support a hypothesis that with more contributions for each target, the average mean error distance away from the target also decrease across all targets.

[1] The number of possible combinations of observations in a thorough analysis of 21 observations is enormous. There are 21 possible sets of 1 observation, and 210 possible pair-wise combinations of 21 observations. The number of possible sets of 11 observations, from a population of 21, is a little more than 51 quadrillion (5.1090942×10^{19}. In order to create a summary of all possible permutations, researchers from GMU's Spatiotemporal Innovation Center assisted with the calculations, led by GMU postdoctoral researcher Dr. Manzhu Yu.

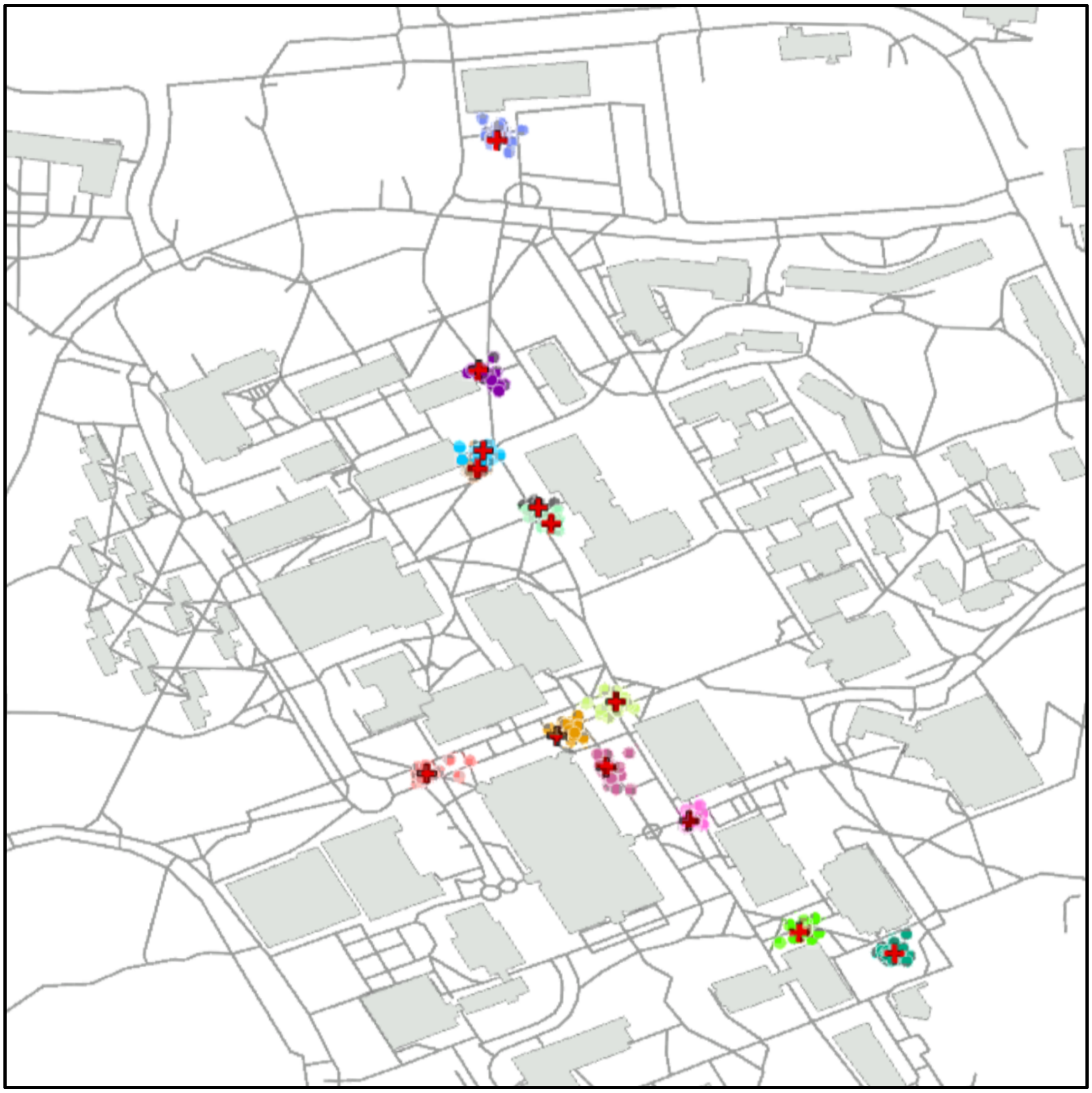


Figure 17 Collected observations along with VBMP centerpoints

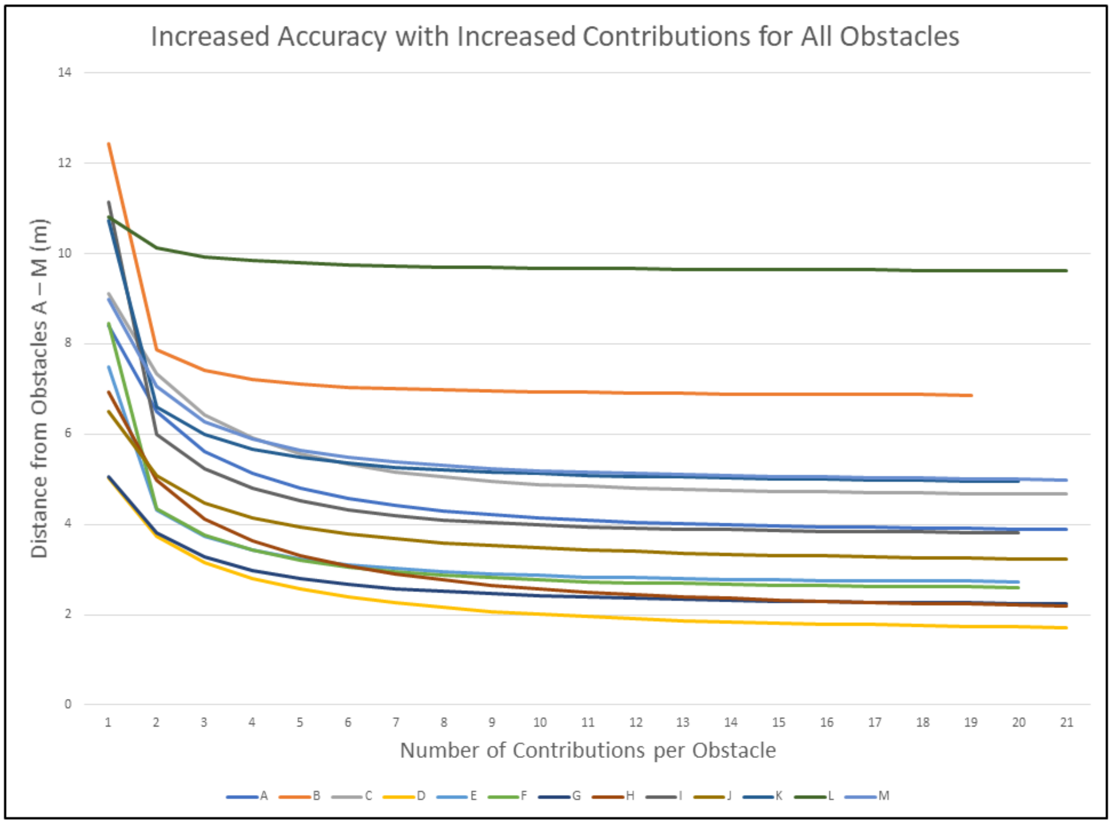


Figure 18 An increase in contributions resulted in an increase in accuracy across all obstacles

In Figure 19 below, one can see a line chart which has all the location means combined into one line which easily displays how the mean distance error from the target, which begins at 8.55 meters with only 1 contribution per target, decreases to 4.07 meters with 21 contributors per target.

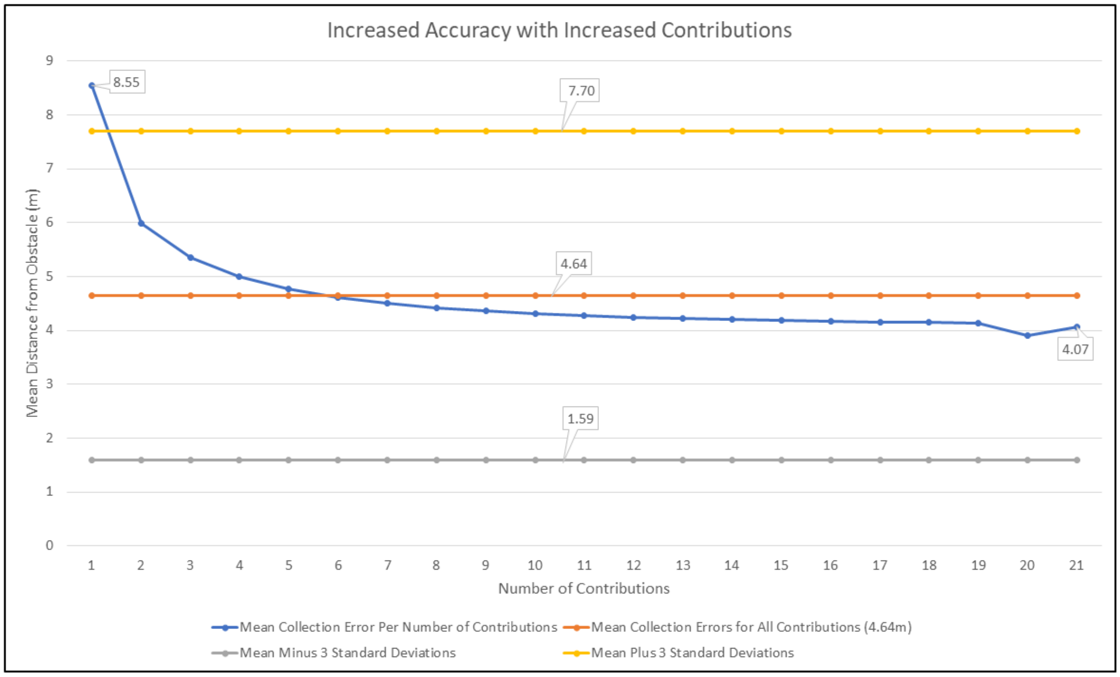


Figure 19 Mean of average distances from all targets decreased with increase number of contributions

This correlation is easily seen when examining the effects of the number of contributions against a single target. Location I, a bench near a sidewalk on campus, shows the marked decrease in accuracy error. Using the permutations discussed earlier, averaging the error of all single contributions for the location, the mean distance error from the bench was 11.15 meters; by adding only two additional contributions and averaging all 3 contribution possibilities, the mean error distance was reduced to 5.24 meters; and by averaging all 13 contribution possibilities, the error decreased even more to 3.90 meters. This decreases in positional error, shown in Figure 18 as one of the descending lines on the chart, is alternatively shown with error ellipses in Figure 20. The outermost error ellipse ("average error (n=1): 11.1m") represents the mean error of each individual observation taken one at a time. Figure 21 shows the same location but with concentric error ellipses shrinking as the number of contributions increases from n=1 to =13. The inner error ellipse (“average error (n=12): 3.9m”) represents the positional error of all 21 observations as a group. Similar diagrams for the complete set of locations for this study are contained in **Appendix D**.

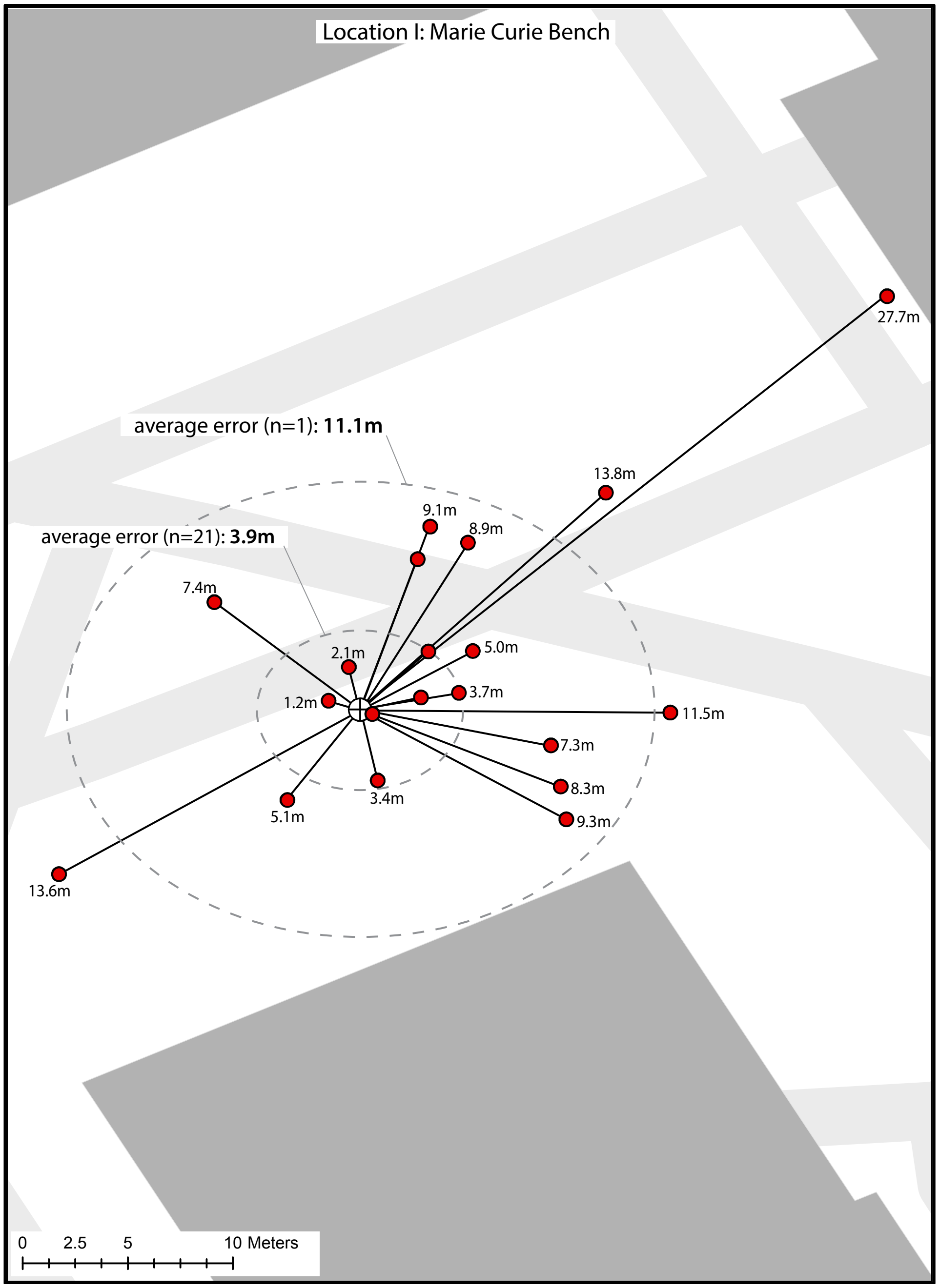


Figure 20 Distribution of contributed points for Location I: Marie Curie Bench

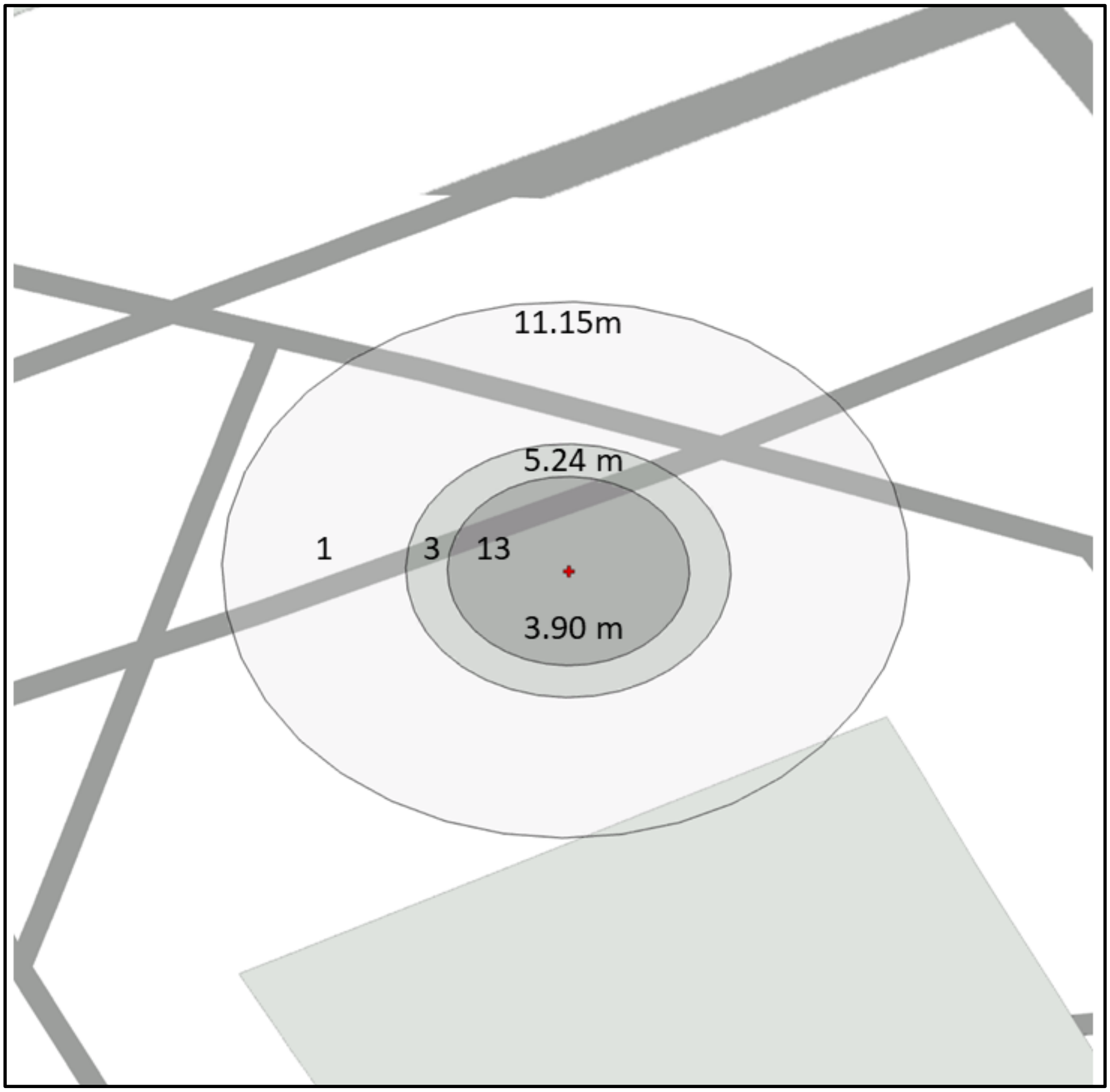


Figure 21 Ellipses showing the decrease in distance error with increase of contributions for Location I: Marie Curie Bench

In the table below, is a sample of additional examples of the decline in overall distance error from each location that was collected upon. Shown in the table are the resulting declines using 1, 3, 5, 10 and 19 contributions per location. The complete spreadsheet for all permutations and all locations can be found in Appendix B.

Target ID	Number of Contributions Per Target 1	3	5	10	19
A	8.404878	5.624724	4.80367	4.150466	3.909318
B	12.43118	7.426769	7.113164	6.935107	6.86699
C	9.113295	6.437562	5.569164	4.892386	4.688177
D	5.044272	3.162249	2.57089	2.006842	1.741693
E	7.484104	3.750794	3.240984	2.865521	2.738884
F	8.456489	3.761861	3.209103	2.771038	2.613505
G	5.050245	3.280812	2.800155	2.420288	2.259263
H	6.939243	4.129228	3.313699	2.572921	2.232124
I	11.1492	5.241142	4.512444	3.982599	3.82151
J	6.506087	4.480755	3.93358	3.479624	3.24966
K	10.74241	5.985105	5.477512	5.124576	4.965037
L	10.82337	9.937404	9.786422	9.678217	9.628248
M	8.997032	6.284767	5.643509	5.194343	5.011088

Table 2 Sample of decline in overall distance error as number of contributions increases

Additional data obtained during collection through both phases included distance measurements of the volunteer from the object he or she was collecting. Both targets in Phase 1 were measured and two targets in Phase 2 were measured. A point and area representative point were measured in each phase. As seen in Figures 22-25 below, the mean error distance from the point of collection to the object of interest was farther away for area targets than for point targets. One would expect these means show a greater disparity the larger and/or higher the area targets being collected.

Week 1 Measurement Stats	
Mean	1.706033333
Standard Error	0.122117574
Median	1.778
Mode	2.3622
Standard Deviation	0.598251492
Sample Variance	0.357904848
Kurtosis	-0.628804253
Skewness	-0.141301835
Range	2.159
Minimum	0.5588
Maximum	2.7178
Sum	40.9448
Count	24
Conf. Lvl (95.0%)	0.25261945

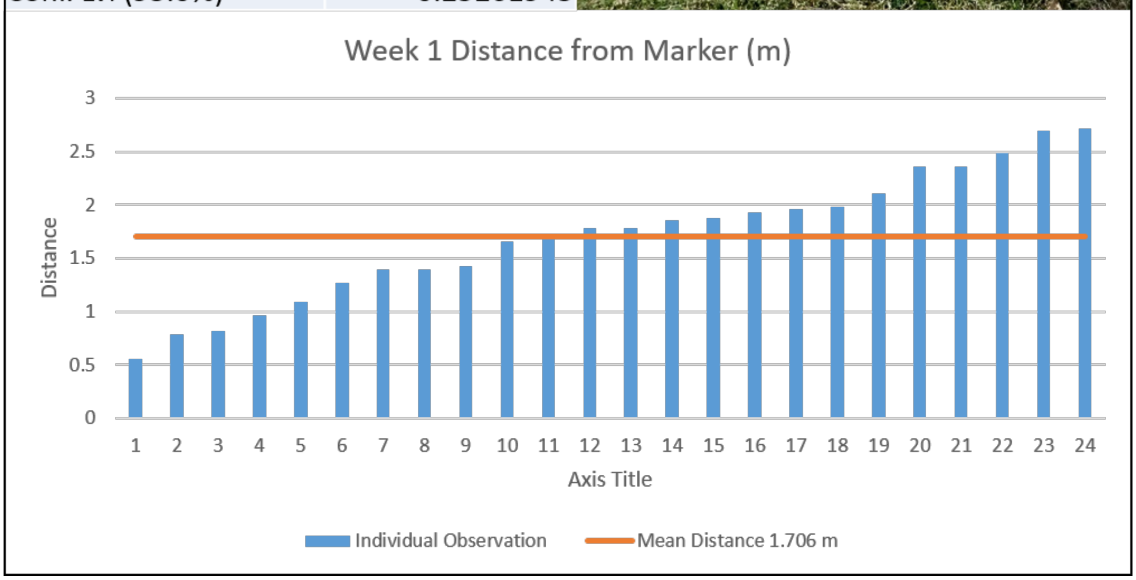


Figure 22 Phase 1, Week 1 Distance of Collection Statistics for Area Collection

Week 2 Measurement Stats	
Mean	1.17348
Standard Error	0.130064252
Median	1.0922
Mode	1.0922
Standard Deviation	0.503736682
Sample Variance	0.253750645
Kurtosis	3.554341333
Skewness	1.364524366
Range	2.1082
Minimum	0.4572
Maximum	2.5654
Sum	17.6022
Count	15
Confidence Level(95.0%)	0.278960076

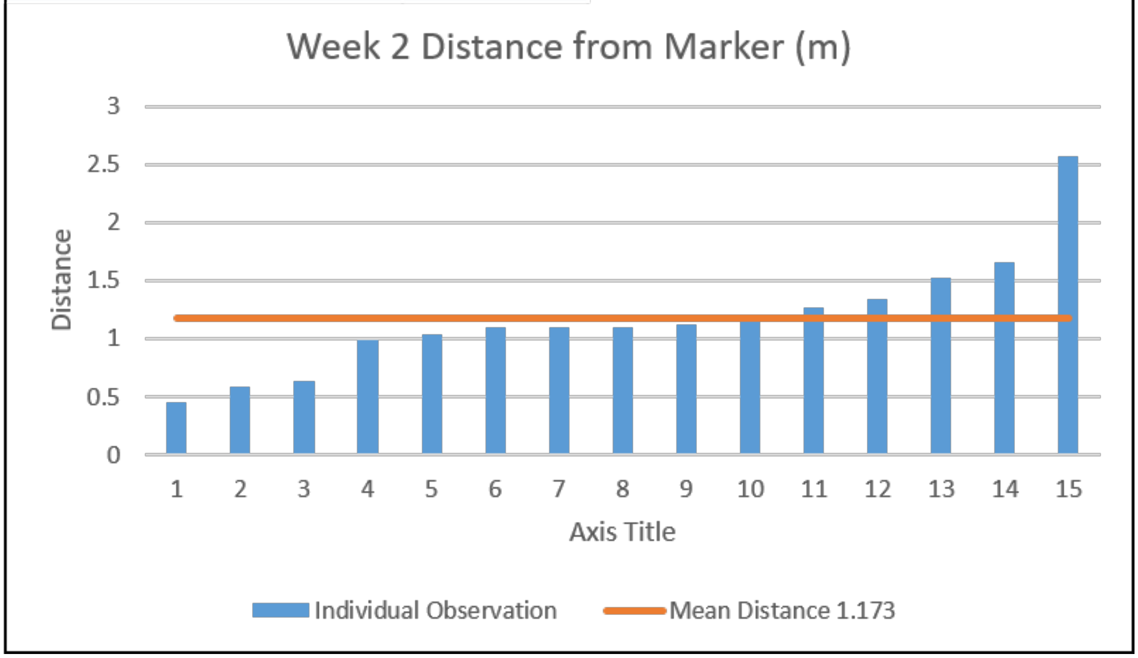


Figure 23 Phase 1, Week 2 Distance of Collection Statistics for Point Collection

Krug Hall Collection Distance (meters)	
Mean	4.985657143
Standard Error	0.474806116
Median	4.1148
Mode	4.1148
Standard Deviation	2.175834969
Sample Variance	4.734257813
Kurtosis	-0.543938937
Skewness	0.733944362
Range	7.4676
Minimum	1.9812
Maximum	9.4488
Sum	104.6988
Count	21
Confidence Level(95.0%)	0.990428203

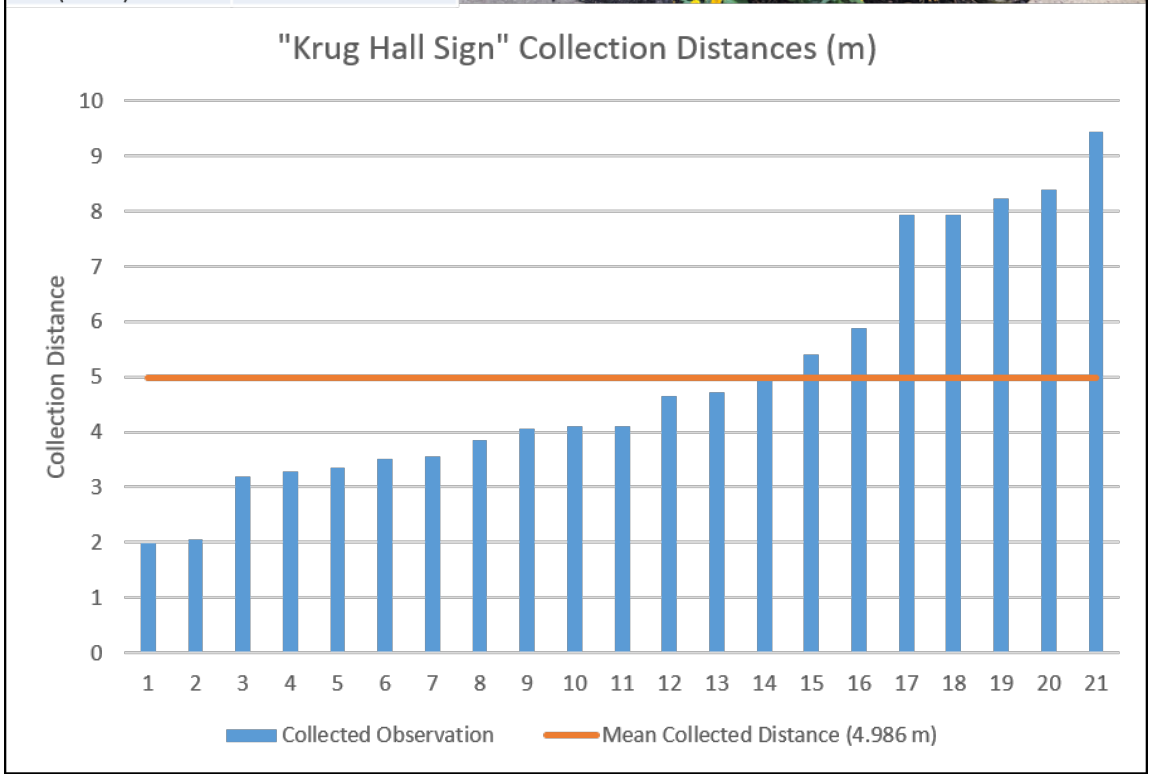


Figure 24 Phase 2 Distance of Collection Statistics for Area Collection

Sandwich Board Distance (Meters)	
Mean	2.442633333
Standard Error	0.348094459
Median	1.8288
Mode	1.0668
Standard Deviation	1.595169208
Sample Variance	2.544564803
Kurtosis	-0.655378267
Skewness	0.736367803
Range	5.3086
Minimum	0.3048
Maximum	5.6134
Sum	51.2953
Count	21
Confidence Level(95.0%)	0.726112318

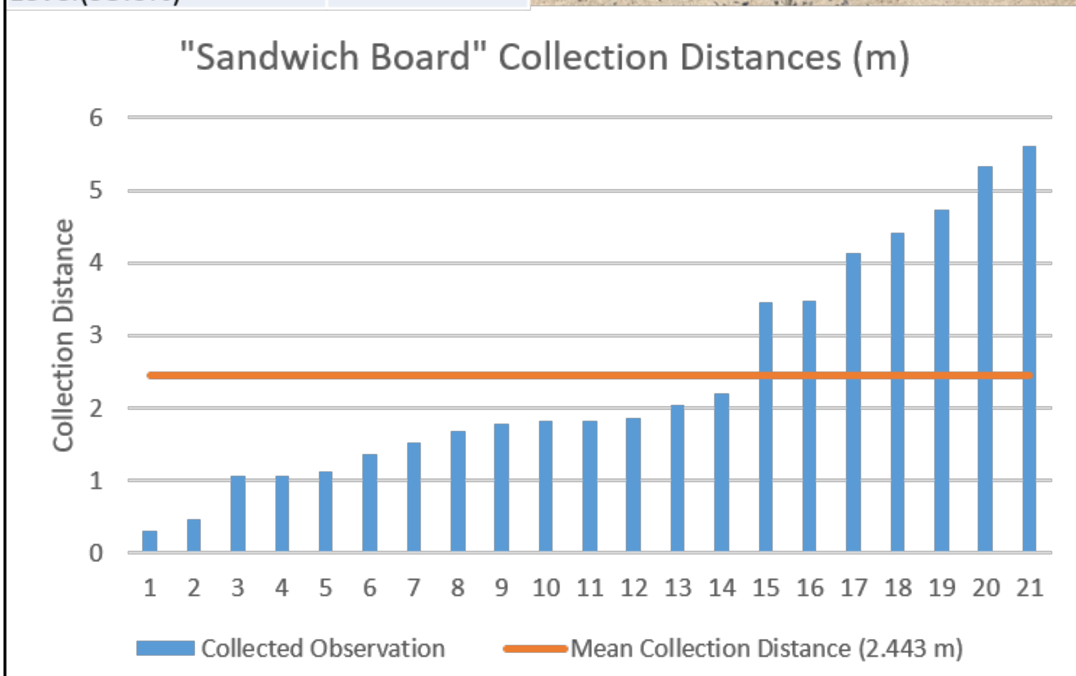


Figure 25 Phase 2 Distance of Collection Statistics for Point Collection

CHAPTER 5 - CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

As mentioned in Chapter 4.1, the mean distance error between the point of collection and the obstacle on which is being collected decreased from 8.55 meters to 3.68 meters with 1 to 21 contributors respectively. This decrease represents a 56.91% decrease in overall error by increasing the number of contributions submitted against an individual object when including the outliers. With the outliers removed, the decrease is from 8.54 meters to 4.07 meters still represents an impressive decrease in overall distance collection error of 52.34%. These results support the hypothesis that more contributions to a geocrowdsourcing system will decrease the overall distance error in the reporting of obstacles. The number of contributors needed to meet an acceptable error threshold of less than five meters, or the previously mentioned "Haklay Distance" of six meters, depends on multiple factors, not the least of which is whether the obstacle being collected upon is a point target or area target. However, if only the average of all collected distances across all targets in this study are being used as the determining factor, then only 4 contributions per target were needed to result in attaining that threshold at 4.99 meters. After only 4 contributions per target, the accuracy error decreased by 41.64 %. While modest decreases in overall error continued with further contributions, the fact that only 4 were needed to provide an error distance of under 5 meters, means that the goal of developing a real time reporting system for obstacle reporting and routing may be attained with only minimal participation by users of the system.

Another interesting measurement obtained in this study was that of the overall distance from the target that contributors collected observations. Using two examples from Chapter 4.1, in which researchers measured the ground distance from the point of collection to the object being collected upon, for the Sandwich Board point target, the mean distance of collection was 2.44 meters; while the Krug Hall area target had a mean collection distance of 4.98 meters. This represents an increase of 104.1%. Likely as the size or height of the area target increased, the distance of collection would also increase.

5.2 Ideas for Future Work

While the methodologies introduced in this research were proven to be successful, there remain several avenues of improvements and continuations of this research to be pursued and applied.

5.2.1 Utilization of Contributions for Routing and Obstacle Avoidance

The methodologies developed in this research can be used to further improve the a system of mobility access awareness on the GMU campus. The Phase 2 application could be used in conjunction with real time reporting to provide obstacle avoidance notices to those with mobility impairments to assist them in determining the best alternative routes available to them.

The GMU-GcT has been a focal point for much research involving pedestrian routing techniques and route optimization. Research conducted by Qin et al. (2018) was focused on the optimization of repairing pedestrian pathways through an area containing obstacles to movement for persons with mobility impairments. Using cost maximization concepts incorporating variables including: budget, cost of repair, benefit and proximity of needed repairs to other needed repairs, models were developed displaying the most efficient methods to conduct repair based on which constraints (if any) were imposed. Another main consideration in the previous studies conducted by the GMU-GcT research team was how to quickly provide this information to GMU students in a near real time method so that persons with mobility impairments could be made aware of obstacles to movement as soon as possible. This real-time communication process would be a vast improvement over the GMU Accessibility Map which is updated about once a year. The research conducted by Qin, Curtin, Rice and others is the foundational research upon which current research using the GMU-GcT is based.

Rodgers, 2016 conducted research regarding slope also using the GMU-GcT. Rodgers compared various resolutions of elevation datasets using DEMs obtained from the USGS and Fairfax County as the elevation measurement function which were accurate to within 1/3 (approx. ten meters), five meters, 1/9 arc second (approx. three meters) and one meter. As Rodgers surmised and as one may suspect, a ten or five-meter positional accuracy may provide resolution fine enough for large linear features such as major highways and secondary roads; the 1/9 arc second DEMs may be of resolution fine enough to provide good fidelity on small roads and alleys; however, for features as narrow as sidewalks and walking paths, the resolution for all of the DEMS except the 1m DEM were too course to be useable for accurate measurements. In Rogers' experiments then, the 1m DEM was chosen for use overlaying elevation data onto a pedestrian network (Rodgers, 2016). Rodgers chose to use DEMs from the USGS because they was freely available and easily available and chose 1m DEMs because the LiDAR data, which can be used to conduct more precise measurements of elevation at GMU only became available after the research had begun; this was unfortunate because Rodgers states that per measurements conducted by NOAA, LiDAR met accuracy rates within tolerances set forth in the Geometric Geodetic Accuracy Standards and Specifications published by the Federal Geodetic Control Committee (Rodgers, 2016). Meeting this standard meant that LiDAR measurements could in fact be used as ground-truth measurements in the absence of known ground control points whereas the USGS DEMs used in the research were not precise enough to be used for accuracy assessments without using ground control points for validation (FGDC, 1998).

Rodgers overlayed the DEMs onto the GMU Physical Accessibility Map from 2014 and using vector shapefiles of the GMU pedestrian network, campus spot elevations and elevation contour intervals, As demonstrated in Figures 26 and 27, Rodgers was able to visualize both the network and elevations throughout campus using ArcGIS. In the research described later in this paper, the benefits of using high resolution LiDAR elevation data will be compared to those lower resolution DEMs to display the benefit of continuing to find higher resolution data sets to conduct research (Rodgers, 2016).

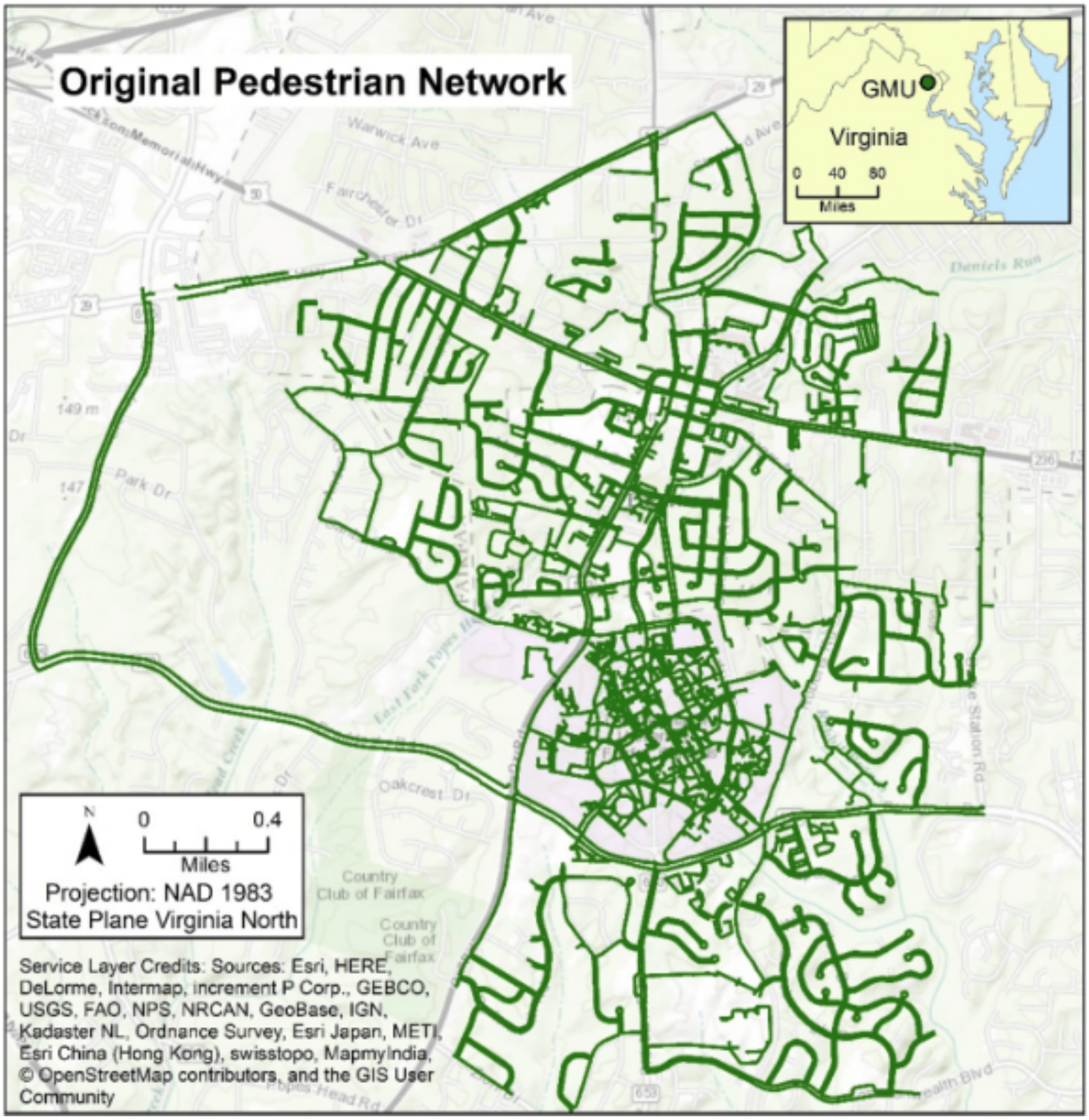


Figure 26 GMU network (Rodgers, 2016)

Figure 27 Accessibility route outputs at various DEM resolutions (Rodgers, 2016)

An example of how to improve upon both Rodgers' research and the research discussed in this paper would be to develop a method to not only consider mobility routes based on slope, but to also have volunteer reports of obstacles along routes of interest to be automatically updated into a database that would provide alerts to anyone using the applications. Many software applications are available to determine routing options. In the figure below, with only minimal python coding and the use of Model Builder, a route between two points was developed in ESRI’s ArcPro. An example of the code used and the model built can be found in Appendix C.

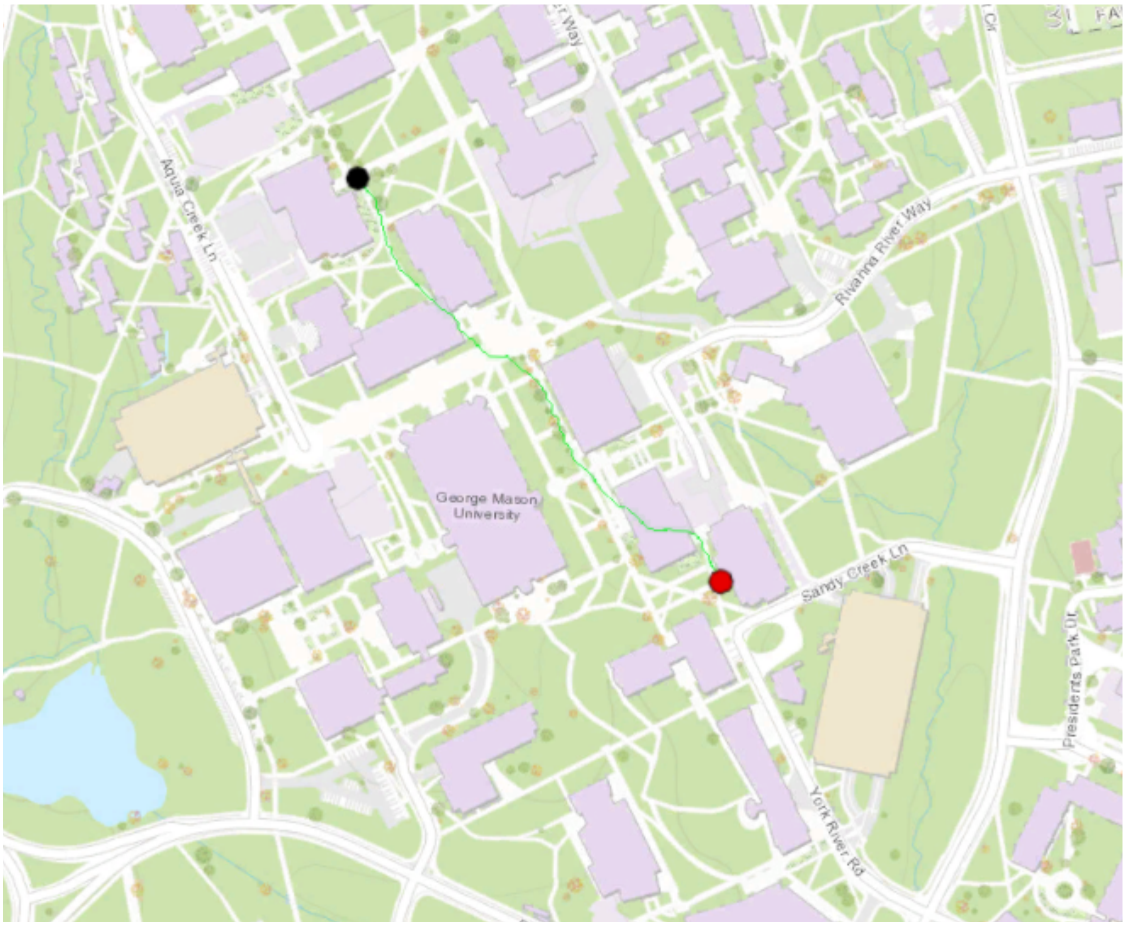


Figure 28 Least cost path calculation using only DEM

In Figure 28 a least cost path model was constructed in ArcPro that only considered the DEM of the area when calculating the path between two points. As on can see, the path intersects buildings and does not follow walkways that persons with mobility impairments would likely be able to traverse.

However, in Figure 29 the model was constrained by not only the DEM but also to only use walkways on the GMU campus. The result shows a route that closely follows a pathway between the two points.

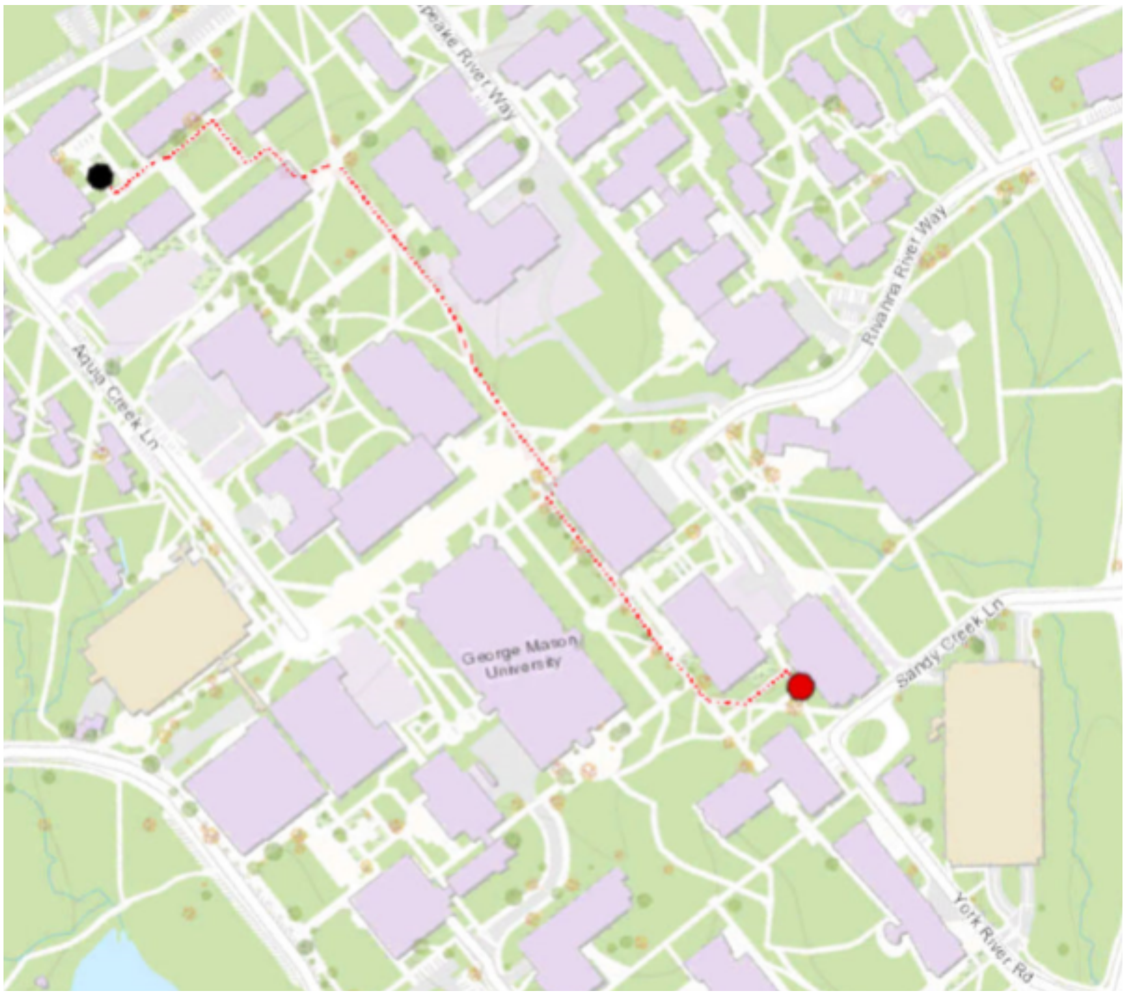


Figure 29 Constrained least cost path calculation using DEM and pedestrian walkways

With further modifications to the code, notional obstacles could be added into the path that would result in the new route needing to be calculation but still follow the paths. A methodology that could combine the functionality of ArcPro with the handheld applications developed in this research could provide a near real time version of route optimization and obstacle avoidance for students with mobility issues on the GMU campus.

5.2.2 Spatio-temporal Clustering

As evidenced by Figure 30 below, some items of interest, or reports submitted to the GMU-GcT may be close in proximity to each other. The items shown below have centerpoints that are 14.2m apart. This usually results in an overlapping of contributed point locations. As seen in the figure some contribution points (e.g., green points) are closer in distance to the other reported obstacle (red obstacle) than to the (green) one they are associated with. Without some means of distinguishing one set of contributions from another, there would be little in the way of knowing which contributions were related to which targets.

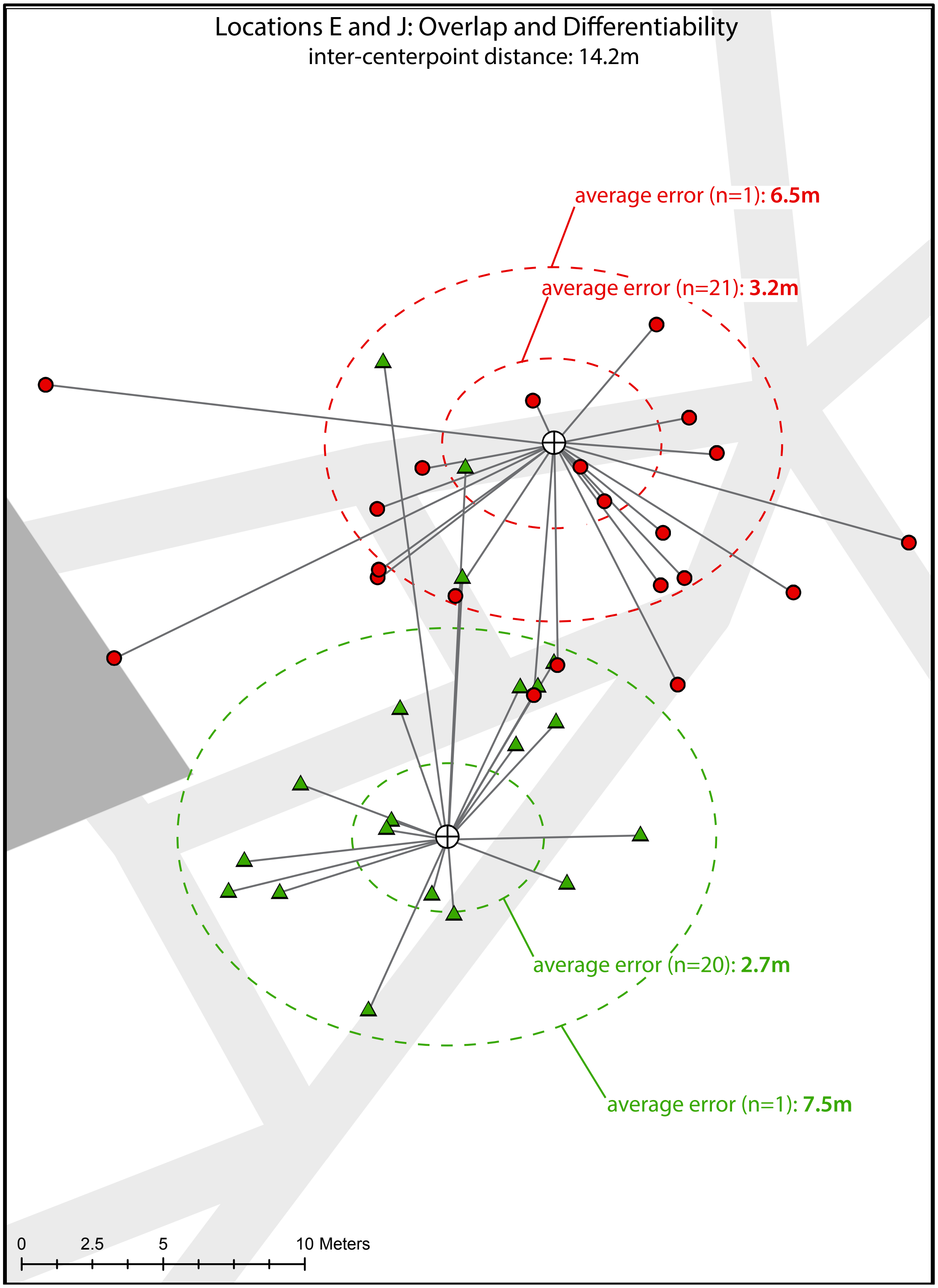


Figure 30 Example of overlapping points with no clear distinguishing characteristics

Manual methods for creating a contrast between points is a straightforward way of separating one set of collection points from another, however this is will only assist a researcher who already knows which points were collected by whom and for what. Without that background knowledge on the collection points, manually color coding or separating observations would be a tedious or perhaps unattainable task. This could be addressed by developing a spatio-temporal clustering algorithm that could scan contributions by geo-location, free-text comments, and submitted images to determine if a group of collected contributions are related. Also, if orientation vectors could be derived from the contributions, those in conjunction with other spatio-temporal attributes could be used to decrease the error in defining the clusters.

A significant amount of research has been undertaken to develop ways to use GcD in conjunction with other types of spatial data to discover new methods of using the positions and contributions of the GcD to find road networks, structures, etc…Specifically, Yang, Zhang, & Lu (2014) used GcD contributions to map road networks using clustering algorithms. This method would follow closely to the attribute entries by the participants in the GMU research when describing obstructions. The process developed by Yang et at (2014) was comprised of several stages. The first involved finding clusters of linear contributions and constructing line segments between the clusters. The researchers used a linear clustering algorithm developed by Ester et al (1996) which "predefined a neighborhood radius *Eps* and the minimum points number *MinPts* to detect a set of core points (initial clusters) and then expands the initial clusters by searching *Eps*-neighborhood points" (Yang, Zhang, & Lu, 2014). Similarly to research conducted by Yang, Zhang, & Lu (2014) in which a clustering mechanism was developed to relate point of interest contributions from volunteered geographic information to road networks mapped by official agencies, this study attempted to cluster GcD contributions regarding obstacles to mobility on a predefined and pedestrian sidewalk network on the George Mason University Campus. In addition to the algorithmic spatial relationship between point of interest contributions and road networks, the study also implemented the use of semantic alignment, whereby they attributional information such as the road name was used to determine the location of roads (Yang, Zhang, & Lu, 2014).

While the methodology developed by Yang et al. touches upon the means to cluster points along linear features, much work would need to be done to find a way to adapt this clustering algorithm to account for image submissions into a Instagram-style contribution system.

5.2.3 Dimensionality and its Effects on Collection Position

While some data were collected regarding contributor location when collecting on a target, no specific research into how the dimensionality in size or height of a target would affect the collection position of contributors. Two examples on a small scale in this research that would be a good starting point for this analysis would be comparing Points A (Clock Tower) and G (Sandwich Board). As shown in the figure below, the clock is a tall object, approximately 3m while the Sandwich Board is less than a meter. The resulting collection distances between the two show a stark contrast in the average distance of collection, with the sandwich board having a much lower collection distance and average error.

Figure 31 Comparison of Clock Tower and Sandwich Board

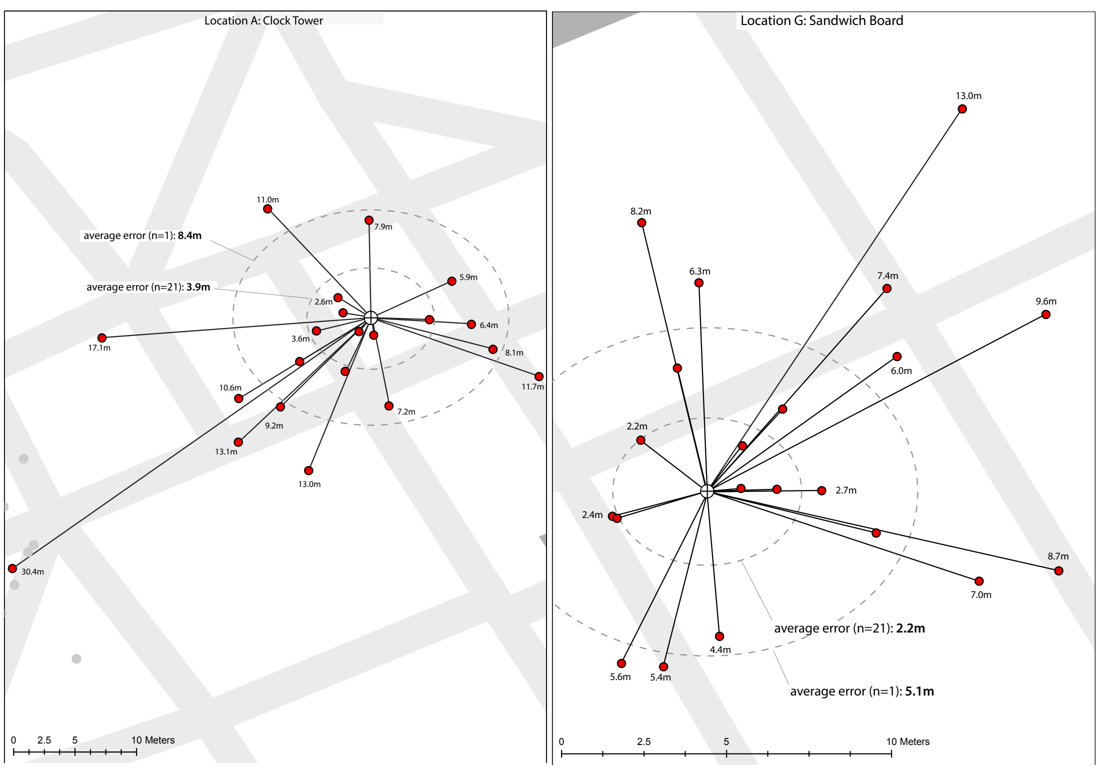


Figure 32 Comparison of Collection Locations of Clock Tower and Sandwich Board

5.3 Synopsis

In conclusion, this thesis discussed the history of Geocrowdsourced data, and explained that while implementing GcD as a discipline is not new, emerging technologies and an an exponential increase in the amount of data that are available has led to a revolution in how GcD is and can be used. While GcD is generally incumbent upon quality assessment by moderators to ensure accuracy, this research demonstrated a correlation between the number of GcD contributors and the level of positional accuracy of information contributed to the GMU-GcT by using a mobile-phone, image-based data contribution tool. Findings showed that the positional accuracy characteristics of the data contributions to the GMU-GcT improved with added contributors, reaching a level comparable to previously-studied accuracy thresholds reached with a significantly more detailed and heavily moderated data contribution workflow and reducing the average positional error of contributions from 8.55m to 3.89m with 20 contributions. In fact, to exceed the most common positional error threshold for geocrowdsourced data, referred to in previous work as the Haklay distance (approximately 6.0 meters), only two contributors were required. This research demonstrated that a fully moderated crowdsourced data contribution process, used in previous incarnations of the GMU-GcT, is unnecessary for producing data with adequate fitness-for-use, including common routing and obstacle avoidance algorithms.

APPENDIX A

Phase 1 Collection Instructions

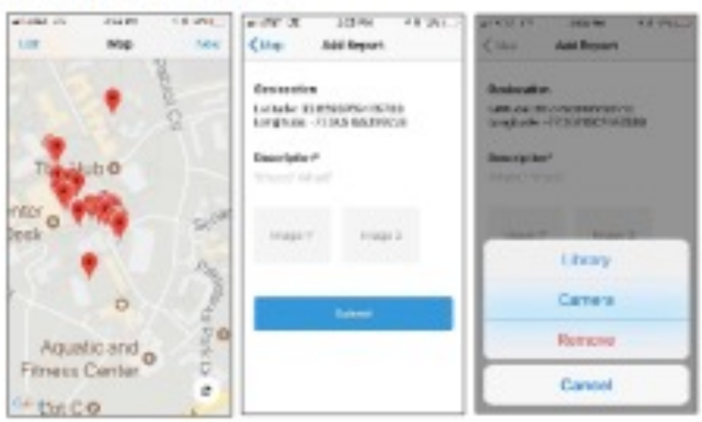
Phase 2 Collection Instructions

GMU Geocrowdsourced Data Collection Instructions
Iteration 2: CGD Mobile Application

Purpose: Collect all thirteen points on the attached pages with a mobile data collecifon application. Collection consists of 1) an image or images of a pre-defined point of interest, and 2) a (What? Where?) description of the same points of interest.

1. Read these instructions completely before beginning, and ask questions as needed.
2. Your numeric participant ID for this learning exercise is: ____93____
3. Using the phone provided, open the CGD application, and give permission to use location and photos/camera if or when prompted.
4. **In any order** of your choosing, visit each location shown on the printed map and attached identification images, and use the following reporting procedures at each location.
5. Click on the "New" report in the upper right corner (see images below)
6. Enter a (Where? What?) text description in the Description Field, for the item you are reporting.
7. Use your assigned numeric participant ID (printed above) and the alphabetic map ID (on the attached map) to start your description: For Subject #99 and Map item Z, the description could be "99Z: obstacle Z in walkway near building XX". Please remember to use the numeric ID assigned to you and the map index number for the item you are reporting.
8. Tap "Image 1" and take a photo using the "camera" option. If you want, take and submit a second image for the same report submission, using the "Image 2" button (see below)
9. Click on the Submit button at the bottom of the app and wait for a confirmation of your submission.
10. You are **NOT** instructed to stand in a particular relative location or at a specific distance. Approach the object from any angle or direction, at any distance. Report them in any order.
11. If you have collected all 13 points, and feel inclined to do so, submit reports of your own. These reports should be of navigation obstacles on or near the walkways on campus. Any item which could pose an accessibility hazard can be reported with the same steps mentioned above. Common hazards reported with our system include tripping hazards, slippery or uneven walkway surfaces, barricades, obstacles to movement, steeply sloped walkways, broken sidewalk pavers, etc. . . .

This learning exercise is now complete. Return to the starting point and return the phone and this set of directions to Dr. Rice or Toby Williams.



APPENDIX B

Table of Permutations for Distance Error

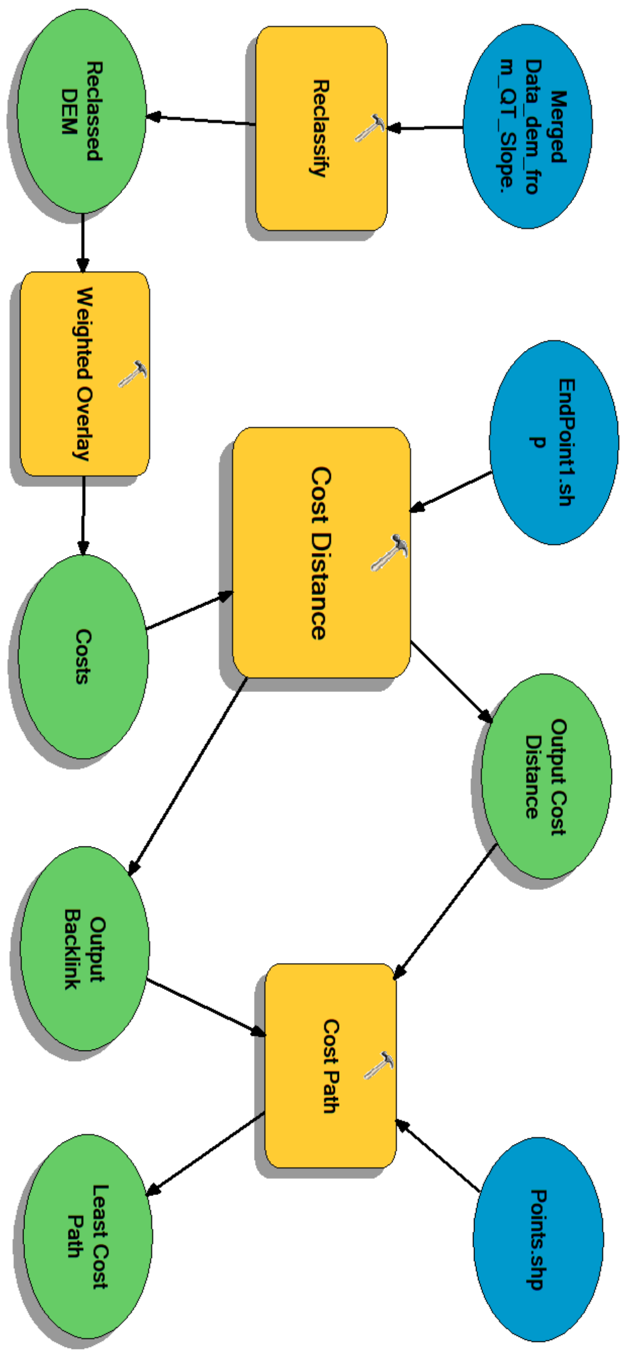
	Number of Contributions Per Target										
Target ID	1	2	3	4	5	6	7	8	9	10	11
A	8.40487777	6.50748178	5.62472363	5.12408433	4.80367014	4.58339965	4.4251851	4.30790714	4.21898362	4.1504663	4.09696163
B	12.4311762	7.86338181	7.42676873	7.22320292	7.11316351	7.04741378	7.00461493	6.97460371	6.95232418	6.93510687	6.9213944
C	9.11329506	7.32824193	6.43756196	5.91089899	5.56916376	5.33472449	5.16843878	5.04782089	4.95886103	4.89238587	4.84218316
D	5.04427235	3.72633054	3.16224934	2.81209826	2.57089036	2.39407602	2.25979614	2.155414	2.07291736	2.0068424	1.95329376
E	7.48410424	4.32337841	3.75079378	3.43637585	3.24098415	3.11038074	3.01856608	2.95215267	2.9028019	2.86552133	2.83680458
F	8.45648881	4.33889509	3.76186098	3.42559163	3.20910325	3.06027757	2.95370928	2.87519535	2.81615525	2.77103829	2.73607229
G	5.05024515	3.81073439	3.28081196	2.98688443	2.80015468	2.67283045	2.58132264	2.51320809	2.46109251	2.42028793	2.38768786
H	6.93924333	4.98360349	4.12922823	3.63968051	3.31369858	3.0797378	2.90410303	2.7678147	2.65981638	2.57292147	2.50231407
I	11.149198	6.00099632	5.24114212	4.79655904	4.51244431	4.32196497	4.19026081	4.09739825	4.03094996	3.9825994	3.94656969
J	6.50608678	5.07381941	4.48075465	4.14724477	3.93358042	3.7858613	3.67816538	3.596229	3.53175195	3.47962441	3.43654987
K	10.742405	6.61508751	5.985105	5.66486293	5.47751163	5.3561891	5.27192139	5.20998779	5.16238868	5.12457635	5.0937768
L	10.8233665	10.1403758	9.93740399	9.84205109	9.78642204	9.74992359	9.72412239	9.7049128	9.69005363	9.67821684	9.66856523
M	8.99703246	7.05668134	6.28476734	5.88331921	5.64350854	5.48707989	5.37871681	5.30004329	5.24066553	5.1943426	5.15722957

Table of Permutations for Distance Error (cont)

Target ID	Number of Contributions Per Target (cont.)								
	13	14	15	16	17	18	19	20	21
A	4.02071429	3.99313216	3.97036959	3.95132036	3.93517103	3.92132017	3.90931759	3.89882238	3.88957217
B	6.90091603	6.89306581	6.88634763	6.8805327	6.87545008	6.87096945	6.86698973		
C	4.77442439	4.75146624	4.7333561	4.71880927	4.70685183	4.69680396	4.68817665	4.68063323	4.67395777
D	1.87303044	1.84246402	1.81642338	1.79391939	1.77428572	1.7570115	1.74169303	1.72801262	1.7157183
E	2.79648808	2.78203307	2.77017753	2.76032607	2.75203786	2.74497598	2.73888375	2.73356919	
F	2.68663298	2.66878318	2.65398667	2.64150203	2.63081285	2.62156917	2.61350457	2.60640931	
G	2.339171	2.32065906	2.30483678	2.29114559	2.279179	2.2686302	2.25926277	2.25089083	2.24336515
H	2.39699317	2.35753553	2.32439225	2.29619574	2.27188031	2.25071019	2.23212368	2.21568043	2.2010324
I	3.89681317	3.87872141	3.86357033	3.85068761	3.83960003	3.82996101	3.82150963	3.81404571	
J	3.3694045	3.34269518	3.31937942	3.29884256	3.2806114	3.26431541	3.24966014	3.23640846	3.22436719
K	5.04657775	5.02808617	5.01208189	4.99809509	4.98576753	4.9748211	4.96503651	4.95623853	
L	9.65377409	9.64798222	9.6429712	9.63859308	9.63473509	9.63130974	9.62824811	9.6254952	9.62300655
M	5.10170728	5.08050477	5.06244443	5.04689721	5.03338638	5.02154531	5.0110882	5.00178958	4.99346951

APPENDIX C

ArcPro Model Builder for Least Cost Path

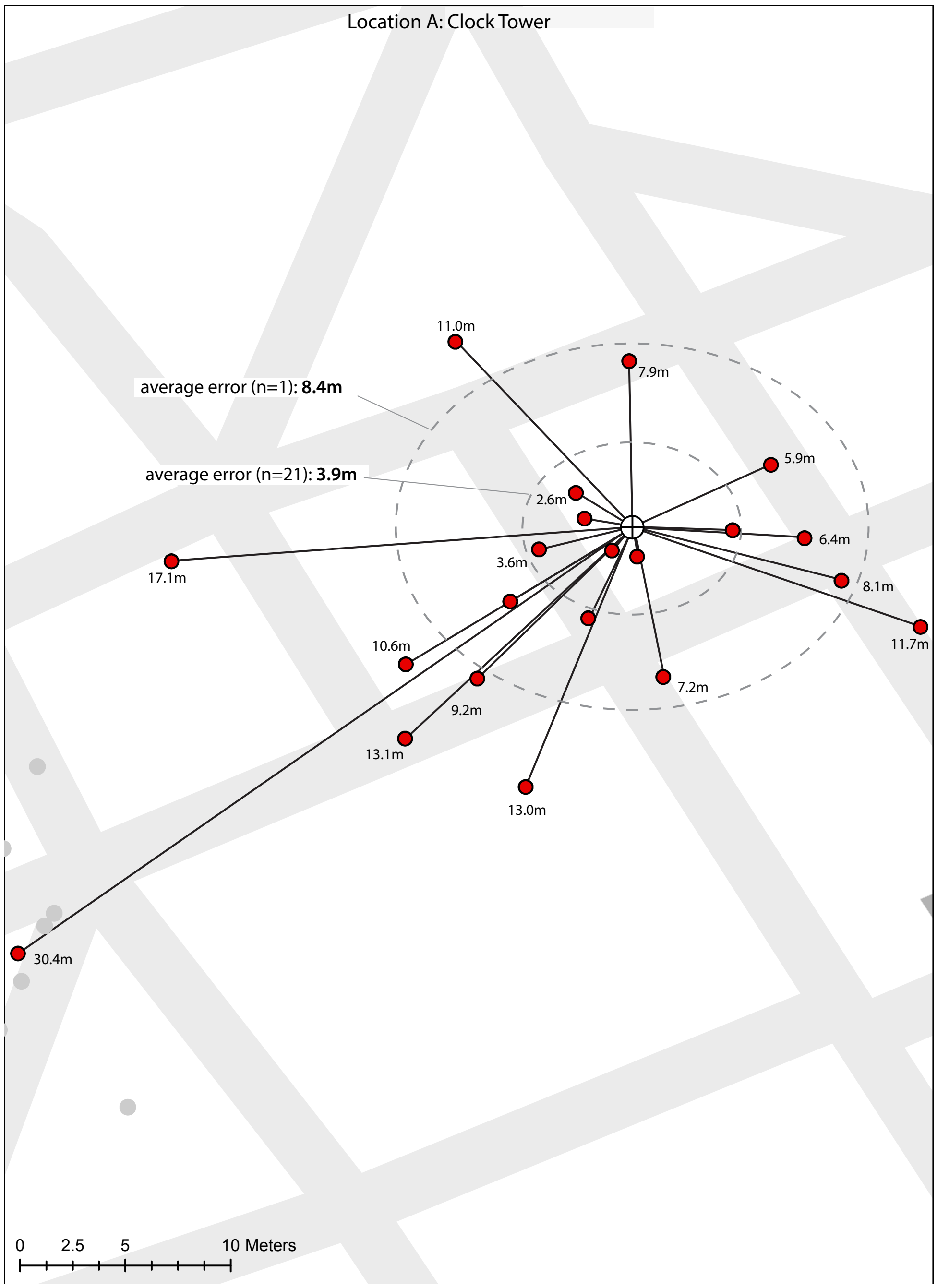


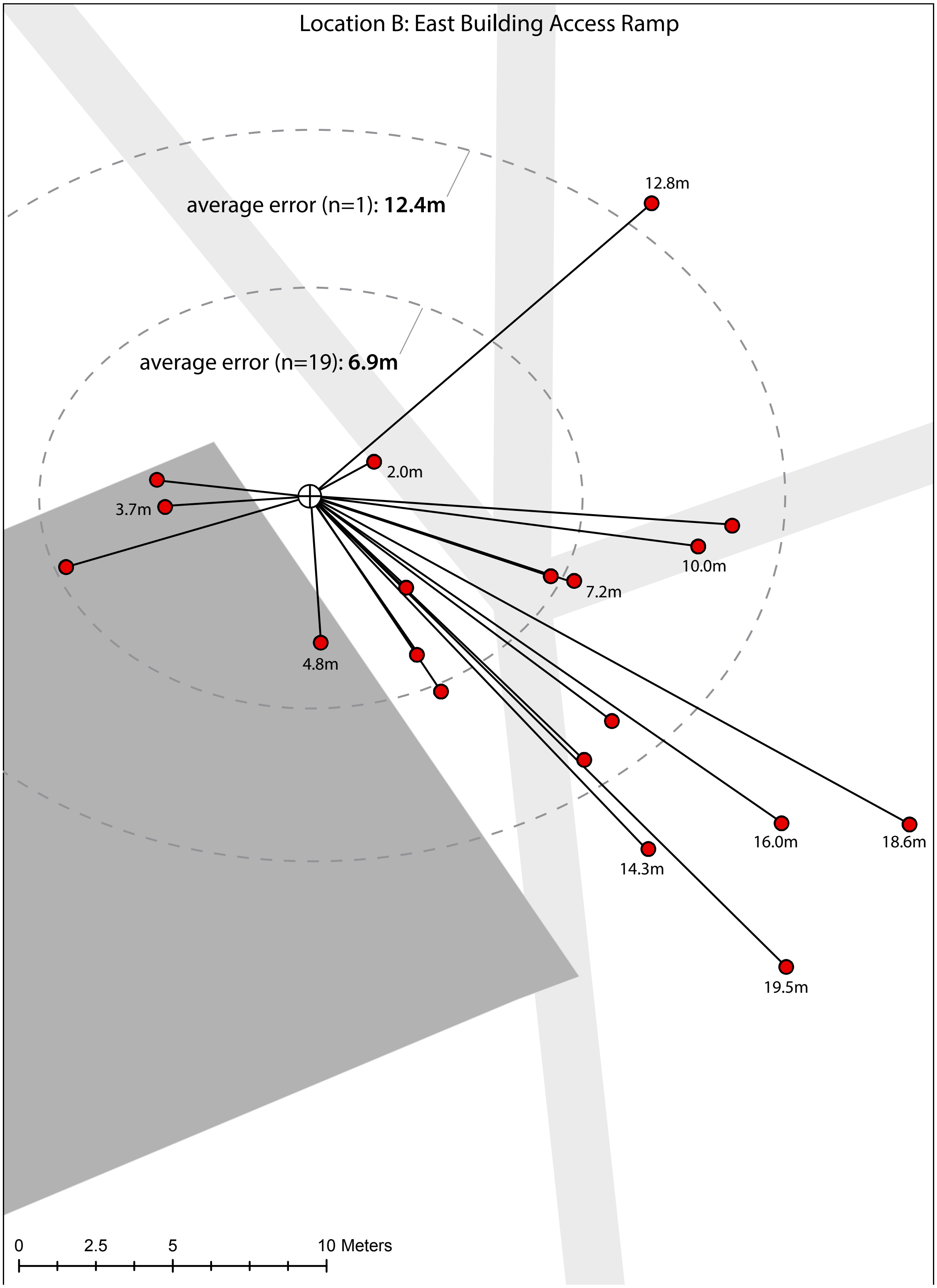
ArcPro Python Code for Least Cost Path

```
# Import arcpy module
import arcpy


# Local variables:
Points_shp = "E:\\Thesis\\Crowdsourcing Thesis\\Data\\Point Features\\Points.shp"
EndPoint1_shp = "E:\\Thesis\\Crowdsourcing Thesis\\Data\\Point Features\\EndPoint1.shp"
Merged_Data_dem_from_QT_Slope_tif = "Merged Data_dem_from_QT_Slope.tif"
Reclassed_DEM = "C:\\Users\\toby\\Documents\\ArcGIS\\Projects\\Least_Cost\\Least_Cost.gdb\\Reclass_tif3"
Costs = "C:\\Users\\toby\\Documents\\ArcGIS\\Projects\\Least_Cost\\Least_Cost.gdb\\Weighted_Recl_DEM"
Output_Cost_Distance = "C:\\Users\\toby\\Documents\\ArcGIS\\Projects\\Least_Cost\\Least_Cost.gdb\\CostDis_shp_test1"
Output_Backlink = "C:\\Users\\toby\\Documents\\ArcGIS\\Projects\\Least_Cost\\Least_Cost.gdb\\cst_dst_bcklnk_test1"
Least_Cost_Path = "C:\\Users\\toby\\Documents\\ArcGIS\\Projects\\Least_Cost\\Least_Cost.gdb\\CostPat_shp1_to_1_test1"

# Set Geoprocessing environments
arcpy.env.scratchWorkspace = "C:\\Users\\toby\\Documents\\ArcGIS\\Default.gdb"
arcpy.env.snapRaster = "Merged Data_dem_from_QT.tif"
arcpy.env.extent = "DEFAULT"
arcpy.env.cellSize = "0.75"
arcpy.env.mask = "QT_Ped_BB_Split_Join_Pro_Slo"
arcpy.env.workspace = "C:\\Users\\toby\\Documents\\ArcGIS\\Default.gdb"

# Process: Reclassify
arcpy.gp.Reclassify_sa(Merged_Data_dem_from_QT_Slope_tif, \
                       "VALUE", "0 1.054621 1;1.054621 1.757702 2;1.757702 2.460783 3;2.460783 3.163864 4;\
                       3.163864 3.866945 5;3.866945 4.921566 6;4.921566 6.327727 7;6.327727 8.085430 8;\
                       8.085430 11.249293 9;11.249293 89.994347 10", Reclassed_DEM, "DATA")

# Process: Weighted Overlay
arcpy.gp.WeightedOverlay_sa("('C:\\Users\\toby\\Documents\\ArcGIS\\Projects\\Least_Cost\\Least_Cost.gdb\\ \
                            Reclass_tif3' 100 'VALUE' (1 1; 2 2; 3 3; 4 4; 5 5; 6 6; 7 7; 8 8; 9 9; 10 10;\
                            NODATA NODATA));1 10 1", Costs)

# Process: Cost Distance
arcpy.gp.CostDistance_sa(EndPoint1_shp, Costs, Output_Cost_Distance, "", Output_Backlink, "", "", "", "", "")

# Process: Cost Path
arcpy.gp.CostPath_sa(Points_shp, Output_Cost_Distance, Output_Backlink, Least_Cost_Path, "EACH_CELL", "Id")
```

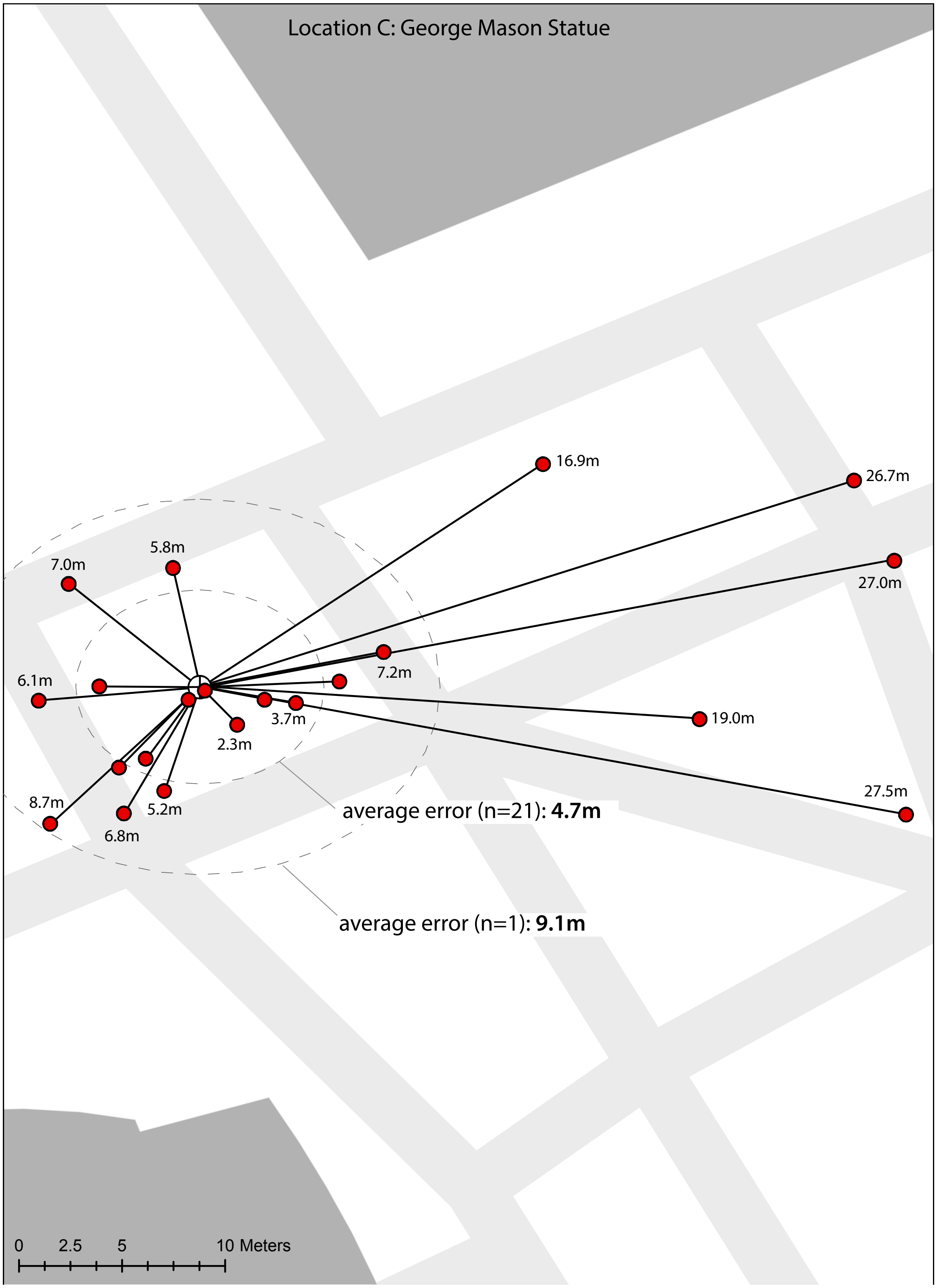
APPENDIX D

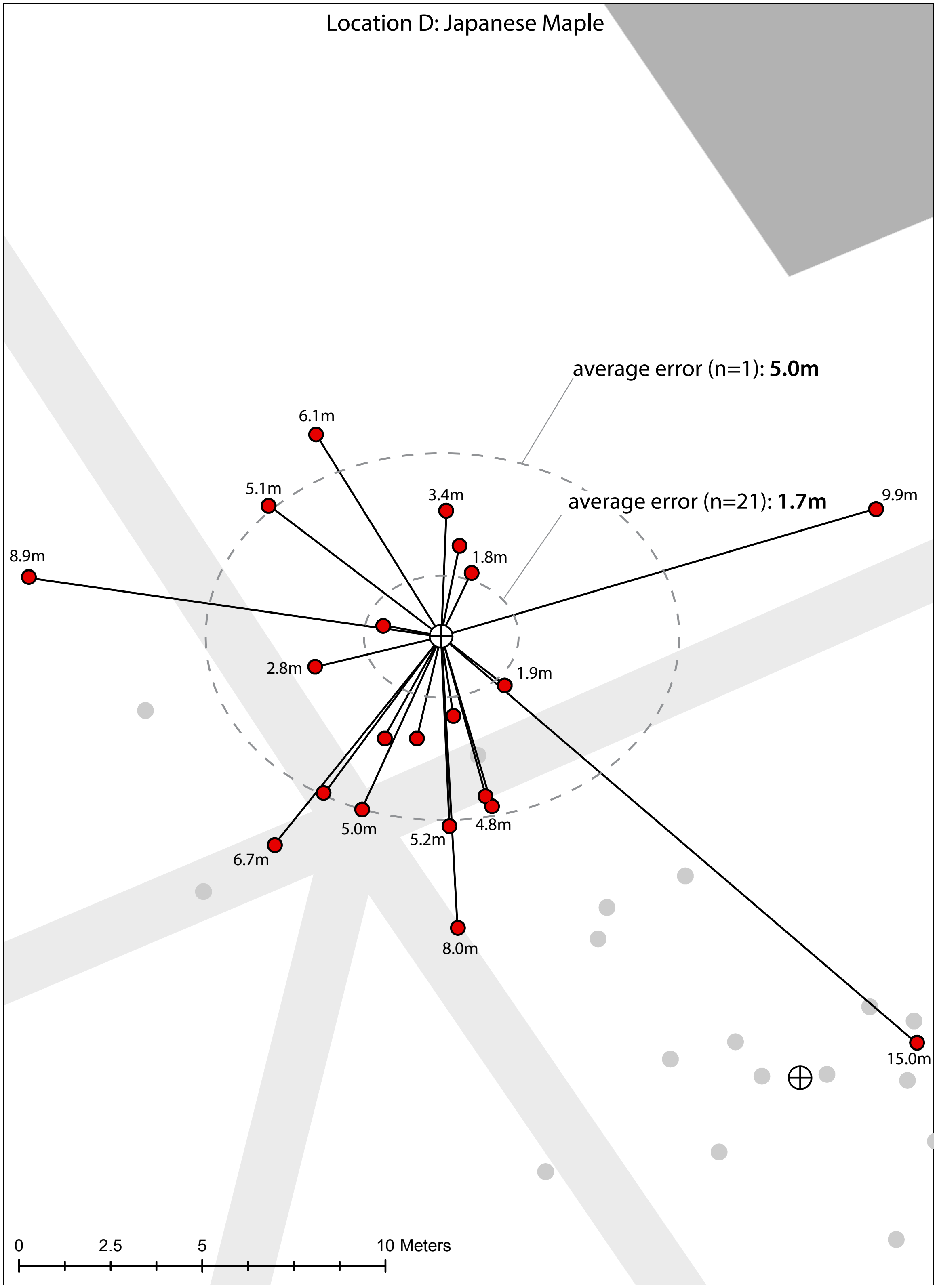
Spider Diagrams

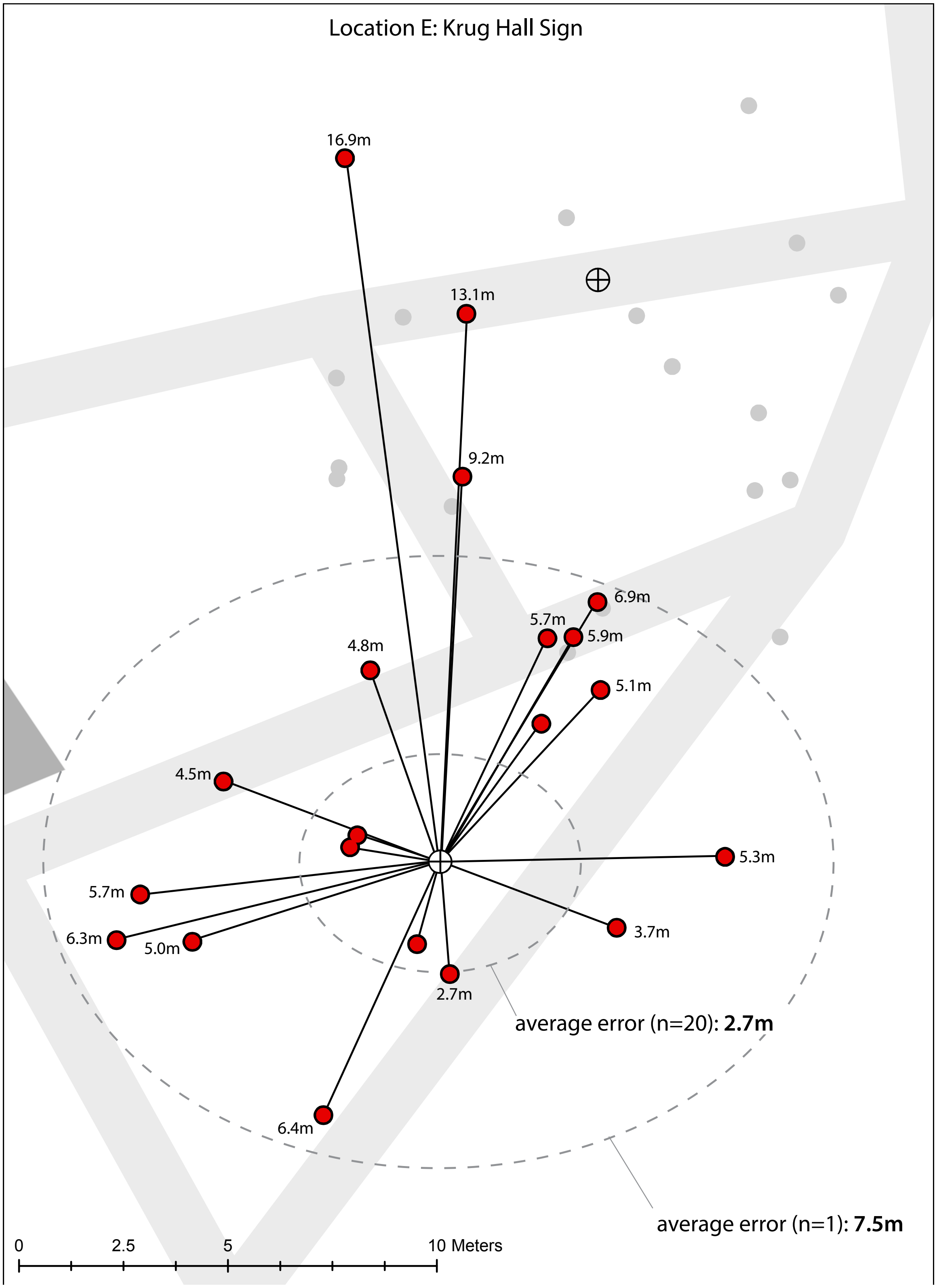




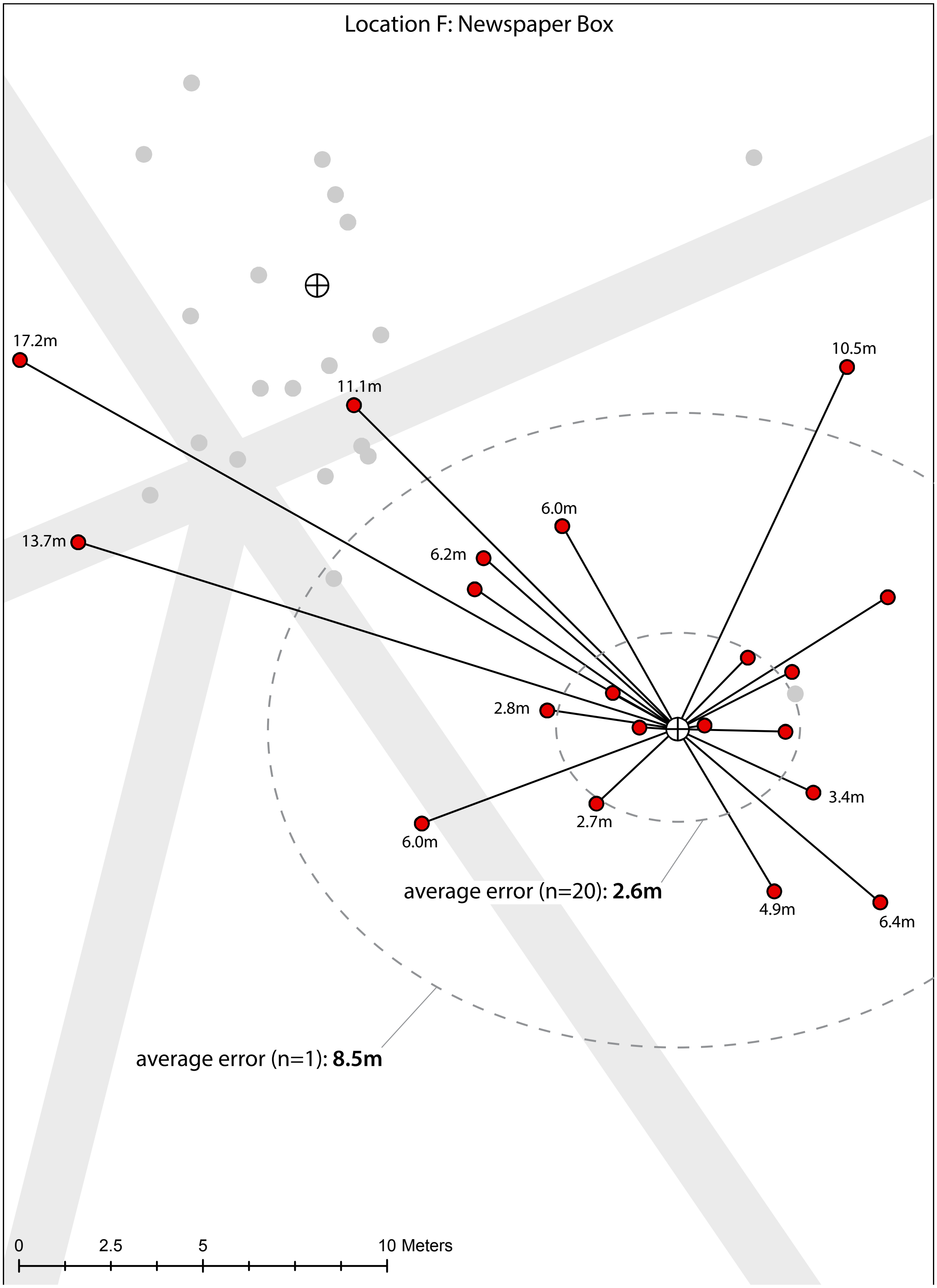
Location B: East Building Access Ramp
average error (n=1): **12.4m**
average error (n=19): **6.9m**
12.8m
2.0m
3.7m
4.8m
7.2m
10.0m
14.3m
16.0m
18.6m
19.5m
0
2.5
5
10 Meters

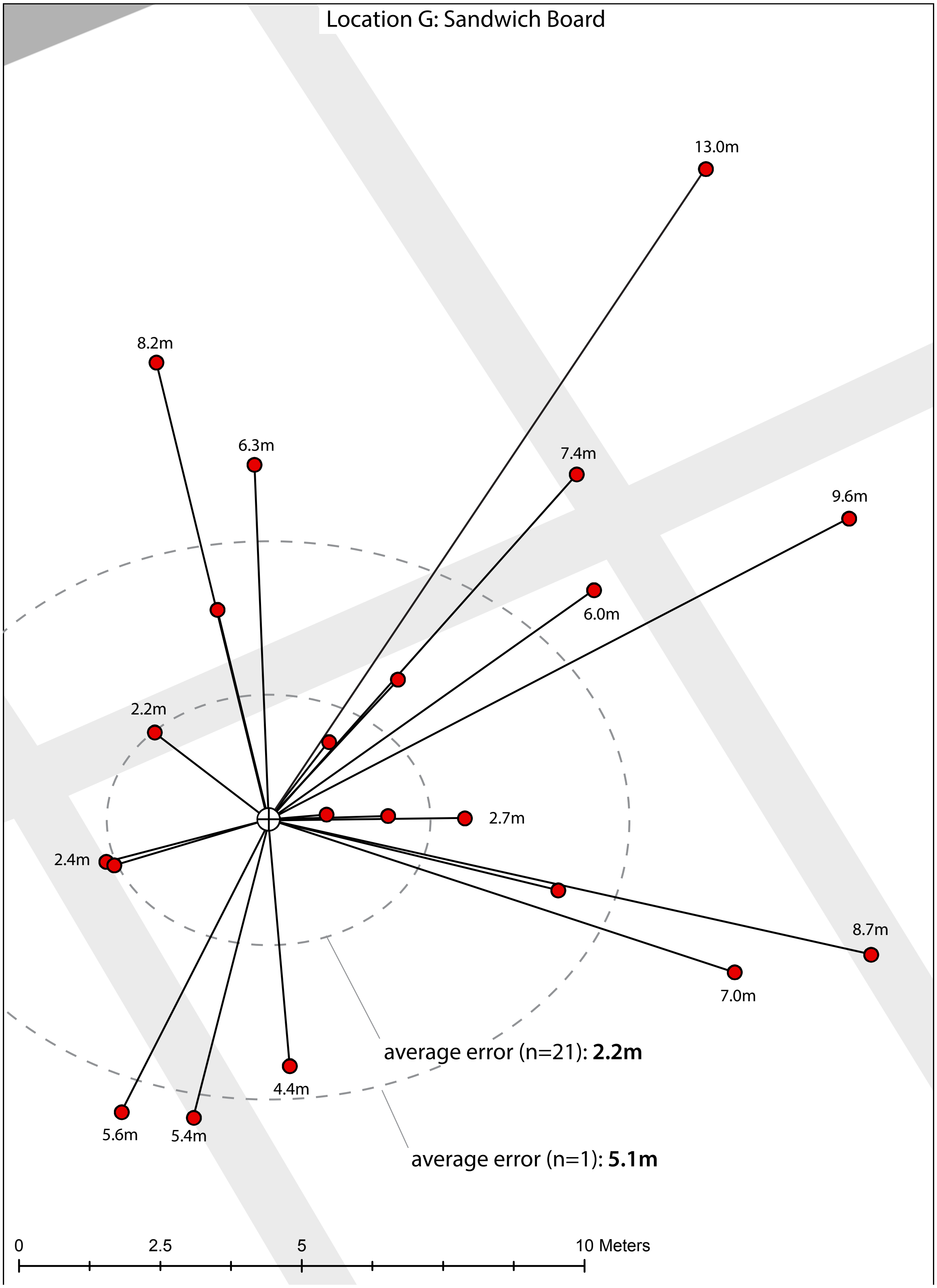

Location C: George Mason Statue
16.9m
26.7m
27.0m
5.8m
7.0m
7.2m
6.1m
3.7m
19.0m
2.3m
27.5m
8.7m
5.2m
6.8m
average error (n=21): **4.7m**
average error (n=1): **9.1m**
0 2.5 5 10 Meters

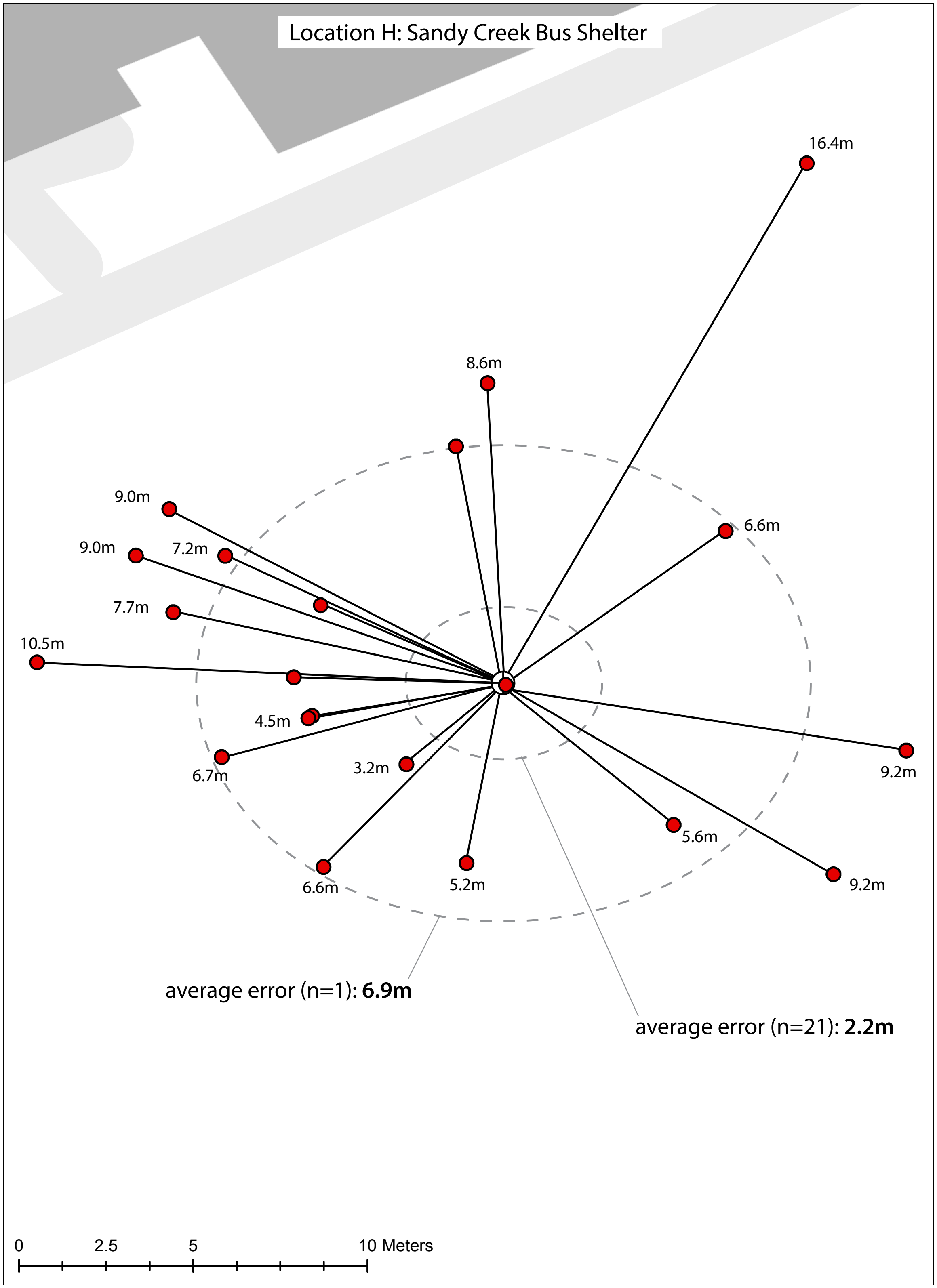

Location D: Japanese Maple
average error (n=1): **5.0m**
average error (n=21): **1.7m**
6.1m
5.1m
3.4m
9.9m
8.9m
1.8m
2.8m
1.9m
5.0m
5.2m
4.8m
6.7m
8.0m
15.0m
0
2.5
5
10 Meters

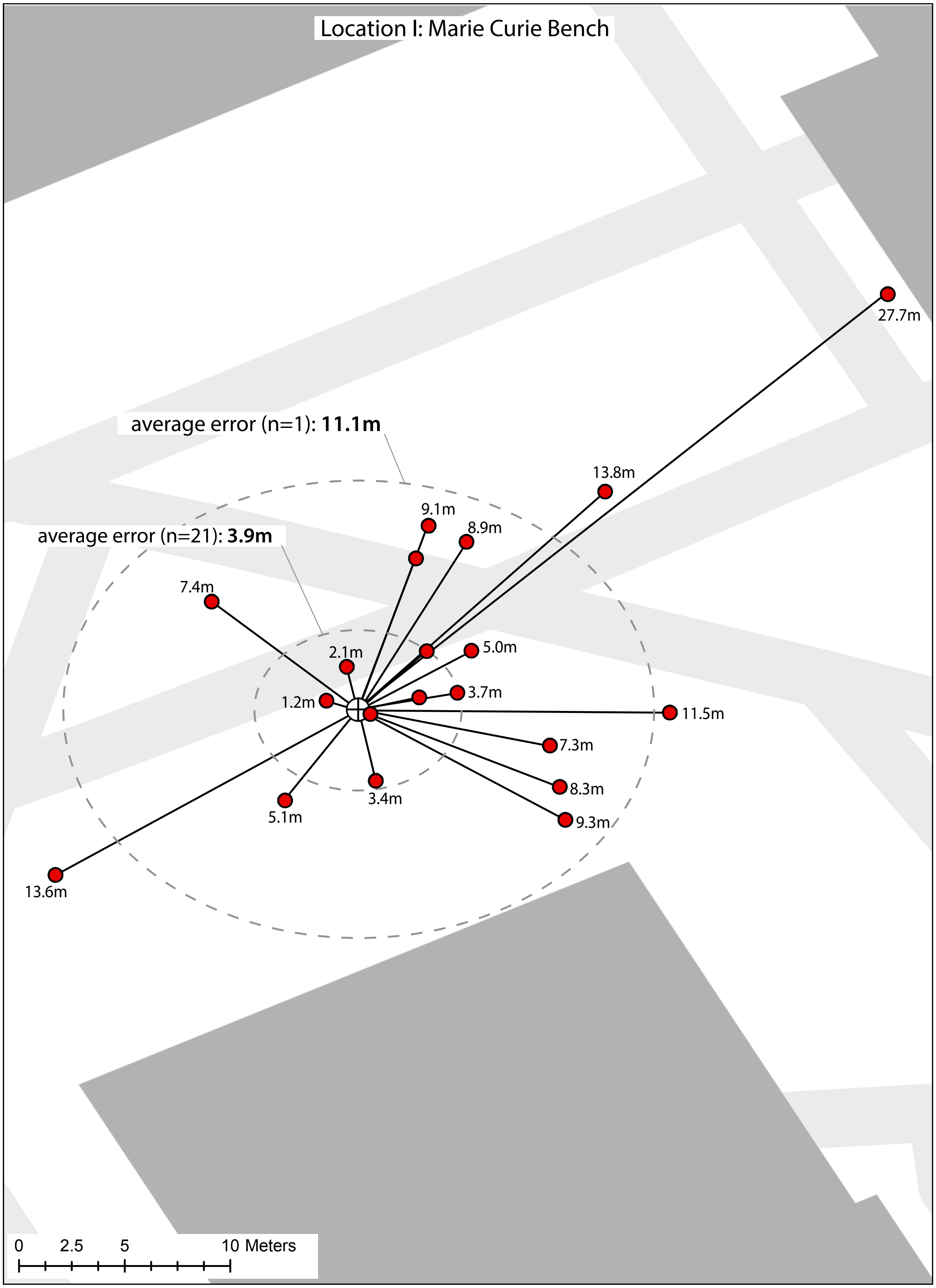


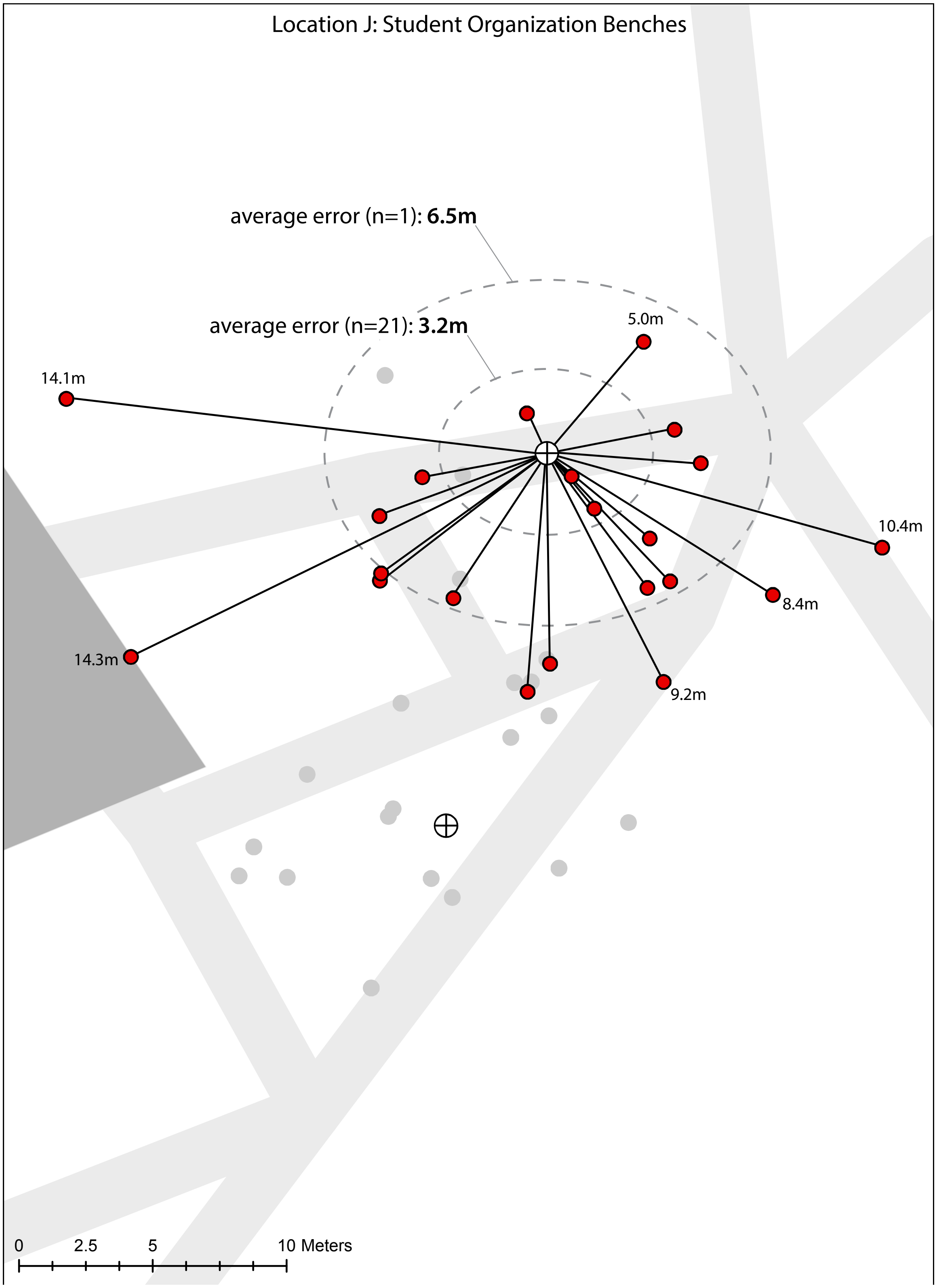
Location E: Krug Hall Sign
16.9m
13.1m
9.2m
6.9m
5.7m
5.9m
4.8m
5.1m
4.5m
5.3m
5.7m
6.3m
5.0m
3.7m
2.7m
average error (n=20): **2.7m**
6.4m
average error (n=1): **7.5m**
0
2.5
5
10 Meters

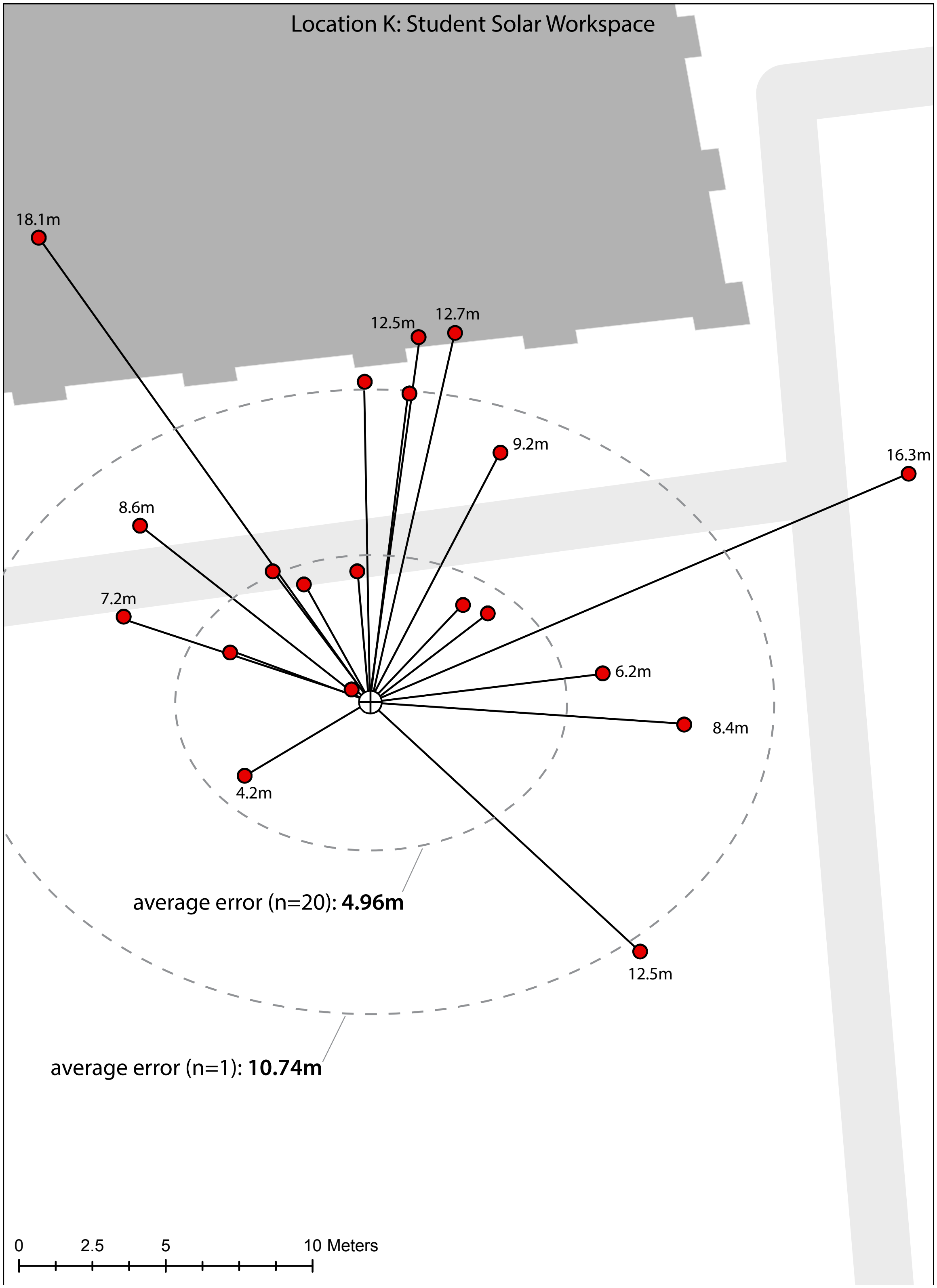

Location F: Newspaper Box
17.2m
10.5m
11.1m
6.0m
6.2m
13.7m
2.8m
3.4m
2.7m
6.0m
average error (n=20): **2.6m**
4.9m
6.4m
average error (n=1): **8.5m**
0
2.5
5
10 Meters

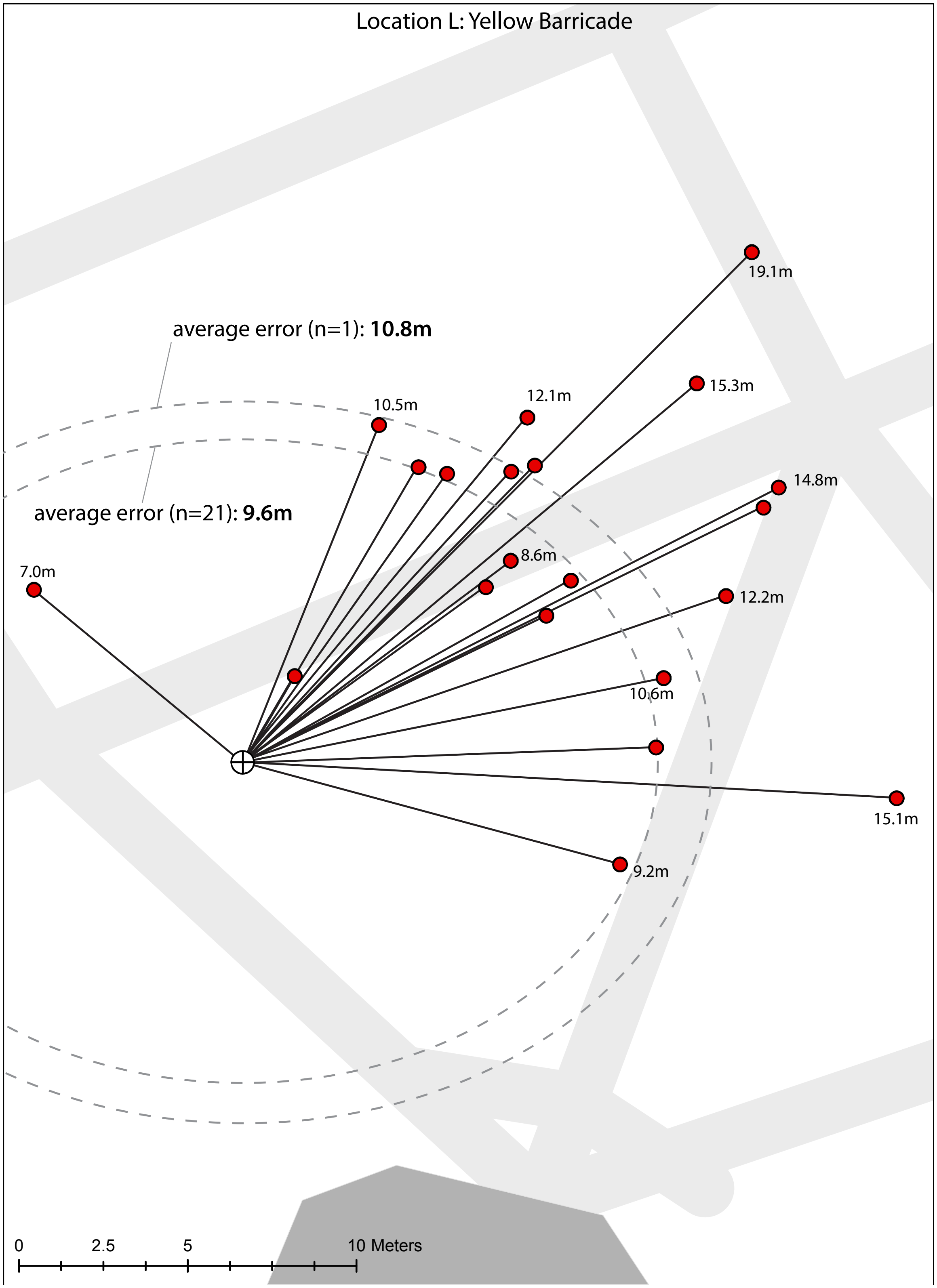

Location G: Sandwich Board
13.0m
8.2m
6.3m
7.4m
9.6m
6.0m
2.2m
2.7m
2.4m
8.7m
7.0m
average error (n=21): **2.2m**
4.4m
5.6m
5.4m
average error (n=1): **5.1m**
0
2.5
5
10 Meters

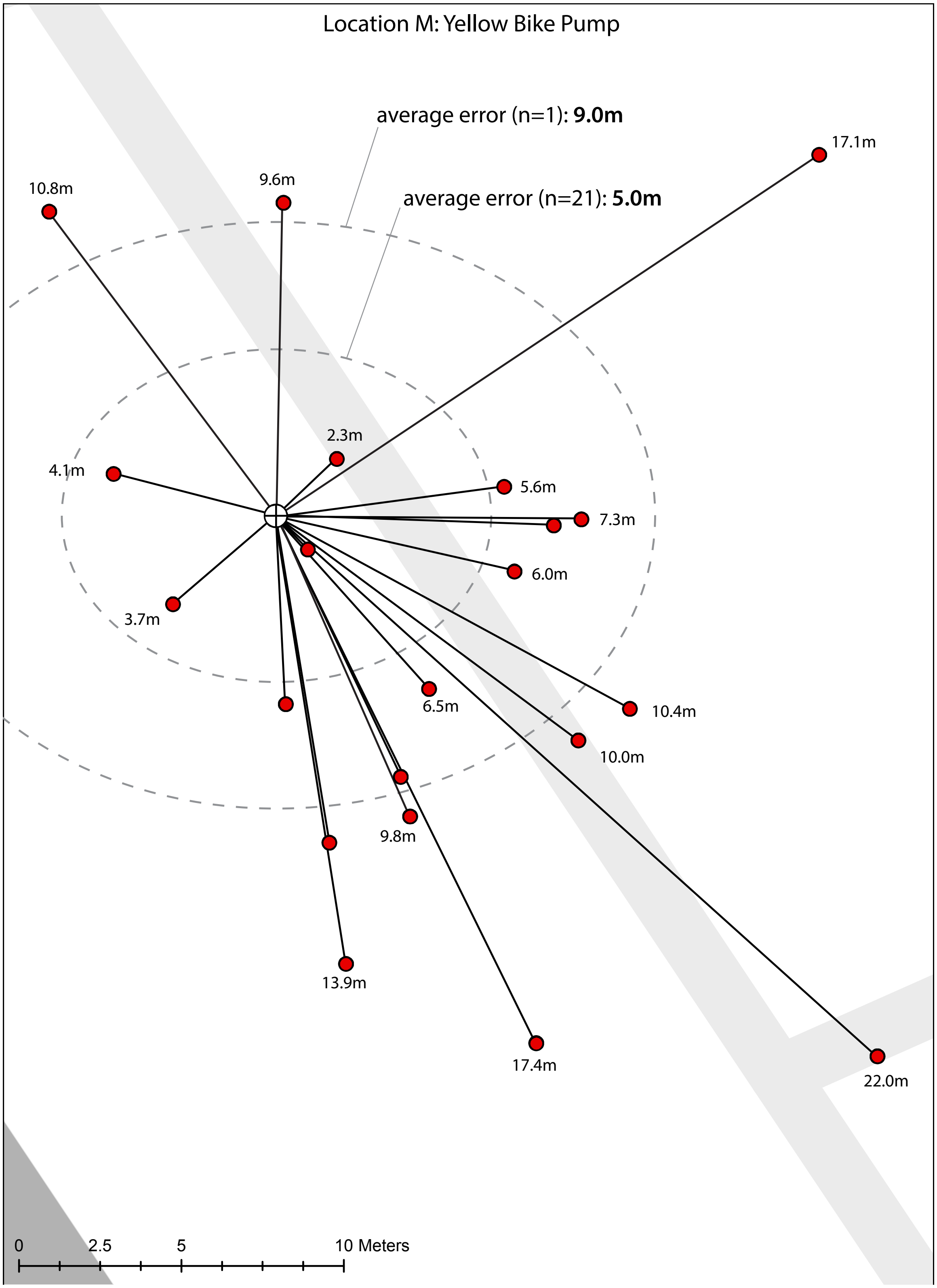

Location H: Sandy Creek Bus Shelter
16.4m
8.6m
9.0m
6.6m
9.0m
7.2m
7.7m
10.5m
4.5m
3.2m
6.7m
9.2m
5.6m
6.6m
5.2m
9.2m
average error (n=1): **6.9m**
average error (n=21): **2.2m**
0
2.5
5
10 Meters


Location I: Marie Curie Bench
27.7m
average error (n=1): **11.1m**
13.8m
9.1m
8.9m
average error (n=21): **3.9m**
7.4m
5.0m
2.1m
3.7m
1.2m
11.5m
7.3m
8.3m
3.4m
9.3m
5.1m
13.6m
0
2.5
5
10 Meters


Location J: Student Organization Benches
average error (n=1): **6.5m**
average error (n=21): **3.2m**
5.0m
14.1m
10.4m
8.4m
14.3m
9.2m
0
2.5
5
10 Meters


Location K: Student Solar Workspace
18.1m
12.5m
12.7m
9.2m
16.3m
8.6m
7.2m
6.2m
8.4m
4.2m
12.5m
average error (n=20): **4.96m**
average error (n=1): **10.74m**
0
2.5
5
10 Meters


Location L: Yellow Barricade
19.1m
average error (n=1): **10.8m**
15.3m
12.1m
10.5m
14.8m
average error (n=21): **9.6m**
8.6m
7.0m
12.2m
10.6m
15.1m
9.2m
0
2.5
5
10 Meters


Location M: Yellow Bike Pump
average error (n=1): **9.0m**
average error (n=21): **5.0m**
17.1m
10.8m
9.6m
2.3m
4.1m
5.6m
7.3m
6.0m
3.7m
6.5m
10.4m
10.0m
9.8m
13.9m
17.4m
22.0m
0
2.5
5
10 Meters

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