Benefit-Cost Analysis to Use Big Data via Data Service – A Focused Study Using Aerial Imagery Data to Improve Pedestrian and Bicycle Safety

Final Report

Project No. **BED25-977-16**

Submitted to:

Florida Department of Transportation
Emmeth Duran, P.E., RSP$_{2I}$ (PM)

Prepared by:

USF Center for Urban Transportation Research
Pei-Sung Lin, Ph.D., P.E., PTOE, FITE (PI)
Achilleas Kourtellis, Ph.D. (Co-PI)
Can Cui, Ph.D.

April 2025

2025

Disclaimer

The opinions, findings, and conclusions expressed in this publication are those of the authors and are not necessarily those of the Florida Department of Transportation.

Metric Conversion

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC

Technical Report Documentation

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle Benefit-Cost Analysis to Use Big Data via Data Service – A Focused Study Using Aerial Imagery Data to Improve Pedestrian and Bicycle Safety		**5. Report Date** April 2025 **6. Performing Organization Code**
7. Author(s) Pei-Sung Lin, Achilleas Kourtellis, Can Cui		**8. Performing Organization Report No.**
9. Performing Organization Name and Address Center for Urban Transportation Research (CUTR) University of South Florida 4202 E Fowler Avenue, CUT100 Tampa, FL 33620-5375		**10. Work Unit No.** **11. Contract or Grant No.** BED25-977-16
12. Sponsoring Agency Name and Address Florida Department of Transportation 605 Suwannee Street, MS 30 Tallahassee, FL 32399-0450		**13. Type of Report and Period Covered** Final Report, November 2023 – April 2025 14. **Sponsoring Agency Code**
15. Supplementary Notes		

This research project explored the use of big data technologies and aerial imagery to enhance transportation safety and efficiency in Florida. The project evaluated the effectiveness of big data applications by comparing traditional assessment methods, such as the FDOT Maintenance Rating Program (MRP), with automated approaches enabled by artificial intelligence (AI) and machine learning (ML) tools. Aerial imagery was used to extract key roadway features such as crosswalks, pavement markings, ADA-compliant facilities, and bicycle lanes, while condition assessments helped identify faded markings and areas in need of maintenance prioritization. These efforts demonstrated the potential of using big data and associated AI tools to complement and enhance traditional methods.

The analysis revealed significant relationships between crash frequency, injury severity, pavement marking visibility, and annual average daily traffic (AADT). Findings showed that intersections with faded markings and higher traffic volumes experienced increased crash risks, highlighting the need for proactive maintenance strategies. Additionally, the study conducted a benefit-cost analysis, which confirmed the economic viability of adopting big data technologies to improve safety and efficiency in transportation systems.

The recommendations from this research provide actionable guidance for transportation agencies. These include prioritizing intersections with high crash risks for marking improvements, integrating big data tools with existing systems, and fostering collaboration between public and private sectors to scale data-driven solutions. By addressing critical challenges and leveraging innovative technologies, this project underscores the transformative potential of big data in improving roadway safety and operational efficiency.

17. Key Words Big Data, Artificial Intelligence (AI), Machine Learning (ML), Aerial Imagery, Roadway Assessment, Pavement Markings, Cost-Benefit Analysis, Safety		**18. Distribution Statement**	
19. Security Classif. (of this report)	**20. Security Classif. (of this page)**	**21. No. of Pages** 101	**22. Price**

Acknowledgments

The research team at the Center for Urban Transportation Research (CUTR) at the University of South Florida (USF) sincerely thanks FDOT Project Manager Emmeth Duran, P.E., RSP_{21}, for his full support, guidance, and assistance in this important research. Our appreciation also goes to FDOT Research Center Manager Darryll Dockstader, Research Development Coordinator Jennifer Clark, Performance and Workforce Coordinator Jason Tuck, and Business Systems Coordinator Ta'rika Green for their support and assistance.

Executive Summary

The rapid advancements in big data technologies have revolutionized how organizations collect, analyze, and leverage data for decision making. This report provides a comprehensive exploration of the applications, challenges, and potential of big data in diverse domains, emphasizing its transformative impact on industries, research, and public policy.

Big data enables precise trend analysis, improved customer engagement, and operational efficiencies in sectors such as healthcare, finance, transportation, and education. Advanced predictive analytics powered by big data has been instrumental in addressing real-world problems, including disease outbreak predictions, fraud detection, and supply chain optimization. Despite its potential, big data adoption faces significant challenges. Data privacy and security remain critical concerns, with the potential for breaches and misuse of sensitive information. The scalability and interoperability of big data systems present technical hurdles in integrating disparate data sources. Furthermore, a shortage of skilled professionals in data analytics and management hampers organizations from fully leveraging big data’s potential.

Innovations in artificial intelligence (AI) and machine learning (ML) are driving new applications for big data, enabling automated and real-time insights. The adoption of cloud computing solutions facilitates scalable and cost-effective data storage and analysis. At the same time, ethical considerations and regulatory frameworks are evolving to address the societal implications of big data usage. Big data also informs evidence-based policymaking, allowing governments to design targeted interventions and measure outcomes effectively. Collaboration between public and private sectors enhances data sharing and utilization while ensuring accountability and transparency.

To fully leverage big data, organizations must invest in scalable, secure infrastructure to manage increasing data volume and complexity. Educational institutions and businesses should prioritize training programs to build a skilled workforce in data science and analytics. Implementing strong data governance frameworks and encryption technologies is crucial for safeguarding privacy. Collaboration between academia, industry, and government can maximize big data’s potential through shared expertise and resources. Clear guidelines and oversight mechanisms are essential to ensuring responsible, ethical, and equitable use of big data across sectors.

This research explored big data and aerial imagery to enhance Florida’s pedestrian safety. It compared traditional and AI-driven assessments, analyzed crash risks linked to pavement markings and traffic volume, confirmed economic viability, and recommended data-driven maintenance strategies for improved roadway safety and efficiency. This report underscores the transformative power of big data and highlights the need for strategic investments and policy measures to address challenges and maximize its benefits. By adopting a forward-looking approach, stakeholders can harness big data to drive innovation, improve efficiencies, and address critical societal challenges.

Table of Contents

List of Figures

List of Tables

1 Introduction

The rapid development and adoption of big data technologies have transformed various sectors by enabling the collection, analysis, and application of vast amounts of data. Recent advancements in artificial intelligence (AI) and machine learning (ML) have further revolutionized the field, allowing swift processing of complex and traditional time-consuming tasks. These technologies enable the integration of data from various sources, such as cameras, sensors, and roadside devices, to provide actionable insights and recommendations for transportation agencies. Big data, combined with AI and ML, has unlocked the potential to address critical challenges in transportation, particularly in improving safety and operational efficiency.

In terms of transportation, pedestrian and bicycle safety are areas of significant concern. Pavement markings play a crucial role in ensuring safe navigation for pedestrians, bicyclists, and drivers by providing clear guidance on roadways. High-quality, highly visible markings are essential for reducing the risk of crashes and injuries, while faded or low-visibility markings can lead to misunderstandings or misinterpretations, increasing the likelihood of crashes. By leveraging big data and advanced analytics, transportation agencies can monitor the quality of pavement markings, identify high-risk locations, and prioritize maintenance efforts to enhance safety and mobility.

The purpose of this section is to provide an overview of the context and significance of big data, set the stage for the discussions in subsequent sections, and introduce the main themes explored in this report. It begins with a discussion of the background and importance of big data and is followed by an outline of the scope and objectives of this study.

1.1 Overview

“Big data” refers to the large, diverse sets of information that grow at ever-increasing rates. It encompasses the *volume* of information, the *velocity* or speed at which it is created and collected, and the *variety* or scope of the data points being covered (known as the "three v's" of big data) [1]. Big data often comes from data mining, arrive in multiple formats, and can be categorized as unstructured or structured. Structured data consists of information already managed by the organization in databases and spreadsheets and are frequently numeric. Unstructured data is information that is unorganized and does not fall into a predetermined model or format. They include data gathered from social media sources, which help institutions gather information on customer needs.

Big data availability and gathering are at the forefront of many global industries, including transportation. Large volumes of big data have been accessible in the transportation sector, and these data provide important details about traffic, route conditions, and activities from a variety of sources. Therefore, some questions need to be answered, outlined as follows:

- What are the main benefits that big data can bring to the transportation industry?
- Who can supply huge amounts of data and how do you utilize them?

- Is the cost reasonable?
- What is big data's benefit-to-cost ratio?

These kinds of questions can be answered by the growing availability of big data, prompting the need for transportation agencies to investigate whether it is feasible to purchase the data needed for analysis and create proactive crash prevention plans that increase safety, save lives, avoid fatalities and injuries, and lessen the non-recurring traffic congestion that results from crashes. Conducting this research study can offer valuable insights into the topic.

Improving pedestrian and bicycle safety relies significantly on the existence of pavement markings dedicated to these modes of travel. The markings are intended to provide cars, cyclists, and pedestrians with unambiguous directions, making it easier for all to navigate and share the road safely. The safety of all road users, including bicyclists and pedestrians, is significantly impacted by the quality and visibility of these markings. Moreover, ensuring well-maintained, highly visible markings enables pedestrians and bicyclists to safely cross roads, thereby reducing the probability of crashes and injuries. Conversely, worn-out, fading, or inadequately visible pavement markings for bicyclists and pedestrians can lead to confusion, potentially causing vehicles, cyclists, and pedestrians to misinterpret one another. These misunderstandings may contribute to crashes, serious injuries, and fatalities among pedestrians and cyclists.

With the goal of eliminating fatalities and decreasing serious injuries on public roads, Florida is aligned with the national traffic safety vision known as "Target Zero" [2]. Protecting bicyclists and pedestrians is one of the top priorities for the Florida Department of Transportation (FDOT). Aligned with the principles outlined in FDOT's Strategic Highway Safety Plan (SHSP) [3], Florida's Pedestrian and Bicycle Strategic Safety Plan (PBSSP) [4], last revised in October 2021, promotes pedestrian and bicyclist safety by encouraging safe practices. With a five-year rolling average of fewer non-motorized fatalities and severe injuries, the primary objective of the PBSSP is to eradicate pedestrian and bicyclist fatalities as well as serious injuries caused by traffic crashes on public roads. One proactive strategy is to routinely address identified deficiencies, such as addressing wide turning radii at crossings, missing crosswalks, and faded paint markings, by taking necessary actions.

Conducting a benefit-cost analysis through a targeted examination utilizing high-resolution imagery big data to assess its capacity, accessibility, and cost-effectiveness in enhancing pedestrian and bicycle safety is practical, beneficial, and essential, particularly for FDOT. The findings of this study may offer a clear evaluation of the viability of utilizing big data and high-resolution imaging to enhance bicycle and pedestrian safety in Florida. The findings may also shed light on creative ways to leverage big data to boost productivity, safety, and mobility.

1.2 Project Objectives

This research study aims to explore how FDOT may improve safety and efficiency by leveraging big data that is now publicly and privately accessible. The following are among the specific project objectives:

- Research big data applications in transportation and the availability of data from big data service providers by conducting extensive literature research.
- Examine the qualitative and quantitative connections between traffic volume, crashes involving bicycles and pedestrians, and high-resolution image data and extracted features.
- Use data collection, analysis, and benefit-cost analysis to assess the type of service's suitability, accessibility, and affordability for transportation agencies. Additionally, implement long-term data retention and storage following Florida Department of State and FDOT guidelines.
- Assist transportation agencies by offering suggestions on when and how to leverage big data from data service providers to increase road user safety.

More importantly, the Center for Urban Transportation Research (CUTR) at the University of South Florida (USF) is working with a vendor that offers big data and the capacity to extract information from pictures linked to infrastructure for bicyclists and pedestrians. The vendor is one of the biggest distributors of aerial data and uses AI and ML algorithms to identify, extract, process, and evaluate elements from gathered high-resolution aerial images, and other data from at least two perspectives. To enhance the safety of bicyclists and pedestrians, it gathers high-resolution imagery every two years, or more frequently if necessary. It then uses AI and ML-powered technologies to extract relevant data. When pavement markings—such as crosswalks, stop bars, bike lanes, bike symbols, green bike lanes, etc.—need to be repainted because they are faded, worn out, or difficult to see, the data service can detect them and offer rankings. Additionally, in the future, the program could detect turning radii at intersection approaches (this is in development), sidewalk width and gaps, refuge islands, and curb ramps that comply with the Americans with Disabilities Act (ADA). If detected, the curb ramps are recognized based on the truncated dome mats. The program does not measure height or any ADA compliance on the height or slope of the curb ramp.

1.3 Organization of Report

The rest of this report is organized as follows: Section 2 provides a review of the existing literature and state of practice, focusing on the applications of big data and aerial imagery in transportation, along with their implications for pedestrian and bicycle safety. Section 3 outlines the methodologies used in the project, including the use of aerial imagery with AI/ML tools and the FDOT Maintenance Rating Program (MRP) for assessing roadway conditions, as well as the processes for data acquisition and evaluation. Section 4 presents the analysis of the relationship between crash data, pavement marking visibility, and traffic volume (AADT), identifying key safety priorities. Section 5 evaluates the feasibility of using big data, emphasizing its ability, availability, and affordability for transportation agencies. Section 6 conducts a detailed benefit-cost analysis, assessing the economic and operational advantages of adopting big data solutions. Finally, Section 7 summarizes the findings and offers recommendations for future applications and research directions.

2 Literature Review and State of Practice

This section contains a comprehensive literature review that focuses on the usage of big data received from service providers for transportation research, as well as the data availability from big data service providers. The literature review also investigates the state's present techniques for inspecting pavement markings, as well as the timetable for detecting, identifying, and correcting fading markings. The literature review provides valuable information to support this FDOT research project on benefit-cost analysis to use big data via data service. It supports the focused study in this FDOT research project using aerial imagery data to improve pedestrian and bicycle safety. The results and findings from the literature review are beneficial for researchers to assess the ability, availability, and affordability of using big data to effectively improve transportation safety and reduce fatalities, injuries, and crashes for all road users.

2.1 Overview of Big Data Application in Transportation

Big data plays a crucial role in transportation operations by providing insights into traffic patterns, route optimizations, and predictive maintenance. It enables better decision-making, enhances efficiency, and improves overall transportation management. Also, big data has been classified into different ranges, from operations to planning, research, and traveler information.

2.1.1 Big Data in Operations, Planning, and Research

The prominence of big data collection and accessibility is a significant focus in numerous global industries, specifically in the transportation sector, ranging from operations to planning to research. Within the transportation sector, substantial volumes of big data have become accessible, encompassing valuable insights about traffic, road conditions, and various activities from various sources. As the abundance of big data continues to grow, transportation agencies must explore the possibility of procuring essential data from providers for analysis and crafting proactive measures to prevent crashes, thereby enhancing safety, preserving lives, mitigating fatalities and injuries, and diminishing the traffic congestion that arises due to crashes.

Big data has been extensively studied in the field of transportation. Neilson et al. [5] conducted a comprehensive assessment of the literature on big data in transportation to examine and comprehend the state of the art, as well as the opportunities and challenges associated with the application of big data and analytics in transportation. They demonstrated how big data and analytics may be used to analyze data from many sources, including social media, connected vehicles (CV), traffic monitoring systems, and crowdsourcing, to gain insights and enhance transportation systems. More importantly, they covered a variety of storage, processing, and analytical methods, as well as platforms and software architecture for the transport domain, which resulted in finding the difficulties involved in implementing big data and analytics.

Torre-Bastida et al. [6] analyzed the latest research efforts revolving around big data for the transportation and mobility industry, its applications, baseline scenarios, fields and use cases such as routing, planning, infrastructure monitoring, and network design, among others. Also, this analysis was done strictly from the big data perspective, focusing on those contributions gravitating toward techniques, tools, and methods for modeling, processing, analyzing, and visualizing the transport and mobility of big data.

Griffin et al. [7] investigated the sources of bias and methods for mitigating them through a review of published studies and interviews with experts. Topical comparisons and reliability measures were made possible through the coding of qualitative data. Their findings revealed four areas of bias and mitigation measures that are important to transportation academics and practitioners: sampling, measurement, demography, and aggregation. This paradigm for understanding and dealing with bias in big data contributed to research by providing practical techniques for quickly growing transportation data sources.

Mohandu et al. [8] noted considerable growth, data analytics, and the identification of Intelligent Transportation Systems (ITS), in which an effective structure for ITS data analytics has been investigated. Many ITS data analytics platforms have been handled, as well as route optimization, traffic congestion forecasts, fatal crash analysis, huge transit organization, private route design, and transportation infrastructure management.

In another study, Shukla et al. [9] showed how big data analytics can be applied to the development of a smart transportation system. The researchers discovered that smart transportation mobility can be simply implemented because most citizens own smartphones, and it can be easily linked to smart traffic signals to meet the goal of smart transportation. Smart mobility is an important component in attracting enterprises since it leads to better services, corporate planning, environmental support, and social behavior.

Kaffash et al. [10] examined the literature to provide a bibliography, a comprehensive evaluation of ITS applications, and a review of the most known big data models utilized in the context of ITS. During the review, the researchers analyzed 586 publications from 1997 to 2019, resulting in a deep understanding of the applications of big data methods in ITS and disclosing distinct regions of those applications, as well as integrating models and applications. In a similar study, Jan et al. [11] developed a layered architecture for leveraging the benefits of Hadoop (a collection of open-source tools that can store and process large amounts of data) and SPARK (an open-source data processing engine that can process a wide range of data) for analyzing massive amounts of real-time transportation data with the support of multiple algorithms and techniques. They also tested a proposed strategy on a variety of transportation datasets from diverse legitimate databases. The Hadoop ecosystem, in collaboration with SPARK, produced highly accurate results that could be shared instantly with the public, enabling them to monitor real-time road traffic conditions, thus optimizing travel time and ensuring on-time arrivals.

Similarly, Wang et al. [12] examined more than 50 scientific articles affirming the significant and growing influence of urban big data in travel behavior research, as well as its advantages over traditional survey data. In this manner, they constructed a typology of four important categories of urban big data—social media, GPS log, mobile phone and location-based service, and smart card—using this body of published work, focusing on the features and applications of each type in the context of travel behavior research. They also made recommendations for researchers to gain data science knowledge and programming skills for analyzing big urban data, for public and private sector agencies to collaborate on the collection and sharing of big urban data, and for legislators to enforce data security and confidentiality.

Zeyu et al. [13] investigated the feasibility of conducting a model study based on noisy trajectory data collected by a cell phone for ITS. A real-time modeling method based on trajectory data is provided, and experiments for analysis are devised. The least-square approach is used to calibrate parameters in an upgraded Gazis–Herman–Rothery (GHR) car-following model. Sensitivity analysis and cross-calculation are used to determine whether the modeling approach is sufficiently trustworthy and resilient. Lastly, the results demonstrated the realistic use of noisy data in data-driven modeling as well as the viability of employing cell phone trajectory data for dynamic modeling for ITS.

Ghofrani et al. [14] implemented a novel taxonomy framework to survey and offer a complete overview of contemporary big data applications in the domain of railway engineering and transportation. In addition, the survey examined three aspects of railway transportation where big data analysis was used, namely operations, maintenance, and safety. Furthermore, the level of big data analytics, types of big data models, and a range of big data methodologies were evaluated and summarized, resulting in the identification of existing research gaps, and finding a future research direction in big data analytics in railway transportation systems. Similarly, Zhu et al. [15] reviewed the history and characteristics of big data and ITS before discussing the framework for conducting big data analytics in ITS, which summarized data source and collection methods, data analytics methods and platforms, and big data analytics application categories. Several case studies of big data analytics applications in ITS are presented, including road traffic crash analysis, traffic flow prediction, public transportation service planning, personal travel route planning, rail transportation management and control, and asset maintenance.

2.1.2 Big Data in Transportation Safety

“Big data” can be used in transportation safety in several ways, such as improving predictive models, identifying potential crash locations, finding hidden patterns, understanding and enhancing traffic safety, and reducing travel time. Additionally, other applications of big data to improve transportation safety are through tasks such as crash detection or prediction, discovering contributing factors to crashes, driving behavior analysis, and crash hotspot identification. For example, Das et al. [16] examined the significance of big data in ensuring transportation safety. Using semi-structured interviews with big data professionals, the researchers performed a quantified analysis of topic frequency and an evaluation of idea reliability using two independently trained coders. The research team created a text-mining pipeline to uncover trends, patterns, and biases in unstructured textual materials. Significant terms used by experts when explaining the role of big data in transportation safety, how the terms relate to the big data professionals' language via network plots, and how clustering demonstrates the need to focus on big data sources, quality, analysis, and implementation were also discovered.

In a similar study, Lian et al. [17] examined big data applications in ITS and connected and automated vehicle safety. The researchers considered subjects such as crash detection or prediction, finding contributing factors to crashes, driving behavior analysis, crash hotspot identification, and so on. Furthermore, it was discovered that using advanced analytics with large data has a high potential for understanding and improving traffic safety. More crucially, big data applications in traffic safety combined and processed huge multisource data, breaking through the restrictions of traditional data analytics, and discovering and solving problems that traditional safety analytics could not. Amin et al. [18] explored the role of big data in shaping the ITS with a focus on the road safety sector and discussed the limitations of existing studies.

Abdel-Aty et al. [19] presented a Web-based proactive traffic safety management (PATM) and real-time big-data visualization tool based on an award-winning system that won the U.S. Department of Transportation for safety visualization challenge. Based on the data, it was discovered that several modules, including real-time crash and secondary crash prediction, closed-circuit television-based expedited detection, PATM recommendations, data sharing, and report creation, had been built. At the front end, both real-time data and system outputs are represented using interactive maps and various types of figures to depict data distribution and efficiently expose hidden patterns.

Hoseinzadeh et al. [20] addressed safety issues in pathfinding difficulties by establishing a methodological framework that takes both safety and mobility into account. To do that, the authors used the concept of volatility as a surrogate safety performance measure to quantify route safety and driver behavior, with the suggested framework calculating safety indices and journey times using CV big data and real-time traffic data. It was also found that the assessed safety indices had a five-year collision history, route speed and acceleration volatility, and driver volatility, while travel time and safety shaped a cost function known as route impedance. Finally, the suggested routes for numerous scenarios were displayed to showcase the study's findings, which resulted in different routes being advised when safety indices were considered rather than just trip time.

To lessen the initial load of data collecting and descriptive analytics for statistical modeling and risk-associated route optimization, Mehdizadeh et al. [21] undertook a study by analyzing a data-driven bibliometric, where they were able to demonstrate how the literature could be classified into two distinct research streams: (a) explanatory or predictive models that aim to comprehend and measure crash risk concerning various driving conditions, and (b) optimization techniques that concentrate on reducing crash risk by choosing the best routes and paths and scheduling rest periods. To address this problem, the authors made high-quality data sources—such as various study designs, outcome variables, and predictor variables—publicly available. The researchers also provided code to enable practitioners and researchers to collect and explore data, as well as descriptive analytic techniques—such as data summarization, visualization, and dimension reduction more easily. Additionally, Mannering et al. [22] employed and assessed four different modeling approaches for safety data to implement a trade-off between prediction and causality. Additionally, the authors discussed the issues surrounding the use of real-time safety data and data from observed crashes.

2.1.3 Affordability of Big Data in Transportation

The affordability of big data in transportation is influenced by various factors, including the cost of data collection, storage, processing, and analysis, which have been discussed below.

Data collection costs:

- Sensors and devices: The cost of deploying sensors, GPS devices, cameras, and other data-collecting devices on vehicles, infrastructure, or through mobile apps can vary.
- Connectivity: Costs associated with establishing and maintaining a reliable network for data transmission from vehicles to central servers.

Data storage costs:

- Cloud services: Storing large volumes of data, especially if utilizing cloud-based solutions, involves expenses related to storage space, data transfer, and other associated services.

Data processing and analysis costs:

- Computational resources: The complexity of processing and analyzing vast amounts of transportation data may require significant computing power. This can be achieved through on-premises servers or cloud-based solutions.
- Software and algorithms: Developing or licensing algorithms for data analysis, machine learning, and predictive modeling can contribute to costs.

Integration costs:

- Bringing together data from diverse sources may require integration efforts and investments in interoperable systems.

Data quality and cleaning costs:

- Ensuring the quality of collected data and cleaning it for accuracy and consistency can involve additional expenses.

Security and privacy measures:

- Implementing robust security measures to protect sensitive transportation data and ensuring compliance with privacy regulations can add to the overall cost.

Training and skills development:

- Training staff or hiring professionals with the skills required for handling big data in the transportation sector may involve additional costs.

Regulatory Compliance:

- Complying with regulations related to data collection, storage, and privacy might require investments in compliance management systems.

Scale of Deployment:

- The scale at which transportation big data solutions are deployed, whether on a city-wide or regional level, can impact costs significantly.

Advancements in Technology:

- The affordability landscape is subject to change with advancements in technology. As technology evolves, new, more cost-effective solutions may become available.

It is important to note that as technology advances and the adoption of big data solutions in transportation becomes more widespread, economies of scale and increased competition may contribute to the reduction of overall costs. Additionally, collaboration between public and private sectors can play a role in making big data solutions in transportation more affordable and accessible.

Even though big data in transportation has been discussed and used for the last few years, the research team could not identify specific projects or studies that have presented benefit-cost analysis (BCA) or return-on-investment (ROI) for specific uses cases. This project performs a specific BCA based on the pavement markings and other roadway feature identification in maintenance and prevention.

2.2 Overview of Aerial Imagery Data in Transportation

Recently, many research studies utilized aerial imagery data in the transportation domain to provide some insightful results to the stakeholders, transit agencies, and related organizations. One study done by Francis et al. [23] utilized unsupervised machine learning techniques, due to the reason that supervised learning requires training datasets, which are not always available or easy to construct with aerial imagery. Using the case study of traffic crashes in three United Kingdom cities, the authors offered an innovative pipeline to show how readily available aerial imagery might be utilized to strengthen the provision of services connected to the built environment. It also demonstrated how latent elements of the built environment can be extracted from top-down photos' simple visual portrayal by using aerial imagery. Using these latent picture features to reflect the urban structure, the researchers showed how dangerous road segments can be clustered to give road safety professionals a data-augmented tool to improve their understanding of the causes and locations of various types of traffic collisions.

Using satellite imagery and a transfer learning approach, Brewer et al. [24] expand on the literature review by estimating road quality and the associated information about travel speed. Specifically, a convolutional neural network architecture is first trained on data collected in the United States and then “fine-tuned” on an independent, smaller dataset collected from Nigeria. Additionally, the authors employed an open, cellphone-based measuring platform to assess and contrast eight distinct convolutional neural network architectures on a dataset comprising 53,686 photos of 1,500 miles of U.S. roads, classifying each road segment as "low," "middle," or "high" quality. These classes were estimated to be 80 percent accurate using satellite photography, and 99.4 percent of the predictions fell into the actual or nearby class.

To build strong deep models from raw satellite imagery, Najjar et al. [25]presented a deep learning-based mapping strategy that uses open data. This approach has the potential to predict accurate city-scale road safety maps at a reasonable cost. The authors trained a deep model on satellite photos derived from more than 647,000 traffic-crash records gathered over four years by the New York City Police Department to empirically validate the suggested approach. With 78 percent accuracy, the best model predicted road safety from raw satellite photos. A city-scale map showing three levels of road safety for Denver using the New York City approach was also forecasted. When the map produced from raw satellite images is compared to one created using three years' worth of data from the Denver City Police Department, the accuracy of the former is 73 percent.

The status of unpaved roads can be measured using high-resolution optical satellite imagery, according to a novel approach proposed by Workman et al.[26]. This data is crucial for maintenance planning, which was tested on 83 routes totaling 131.7 kilometers in Tanzania. The testing results showed that, when compared to ground truth data, the condition may be approximated with 71.9 percent accuracy by examining variations in the road surface's pixel intensity. Moreover, the authors tested the system's ability to forecast road conditions using machine learning techniques on the same network. The accuracy obtained with a hybrid classifier technique was 88 percent. More significantly, the suggested structure gave Local Road Authorities (LRAs) the ability to specify the information they get by their own priorities, providing a quick, impartial, reliable, and possibly economical mechanism that helps LRAs get over their current difficulties.

An unmanned aerial system (UAS) was employed by Azari et al. [27] to improve industry awareness and stakeholders' knowledge base about bridge inspection procedures. The authors made use of the aircraft and sensors to support or enhance inspections, whereby the owners of the bridges received the data they required via UAS, as well as the means and techniques by which the owners of the bridges, or the organization that provides support to them, could handle the massive volume of data gathered by UAS-deployed sensors during an inspection. Butila et al. [28] used UAS to track and examine traffic in a related investigation. The researchers carried out a methodical analysis of UAS applications in civil engineering in this fashion, particularly those about traffic monitoring. Thirty-four papers were found in five scientific databases. They discovered that while the field was still in its infancy, advances in sophisticated image processing techniques and technologies used in the development of UAS had resulted in an explosion of applications and increased benefits for society, lowering unpleasant situations like traffic jams and collisions in the world's largest cities.

Goel et al. [29] presented an innovative method that identified trucks and buses from Google Earth satellite photos to estimate the traffic volume of these vehicles. Considering the Indian state of Rajasthan, a total of 44,000 of these vehicles were geo-located and manually identified on national highways without any differentiation between trucks and buses. The authors also fitted a spatial-temporal Bayesian regression model with the district-level number of traffic fatalities as the outcome variable. This led to the discovery of a strong Pearson correlation between the counts of freight vehicles reported by a national-level study for various road sections and Google Earth estimates of heavy vehicles, which was 0.84 ($p < 0.001$). Finally, the regression analysis revealed a positive correlation between the districts' mortality risk and the number of heavy vehicles and rural residents living close to highways.

To identify safety-related anomalies from traffic video data, Yang et al. [30] introduced a novel functional technique that directly models the time series of a variation of the time-exposed time-to-collision safety indicator. They used about an hour's worth of traffic video footage captured by a UAS at signalized intersections to compile a summary of nine common functional anomaly detection techniques. By personally going over the camera footage, ground truth safety-related abnormalities are found and reviewed. This process is utilized to verify the effectiveness of anomaly detection techniques. It has been discovered that there is a good separation between non-anomalies and safety-related anomalies. Table 2-1 displays the research studies and technical reports published and implemented in an aerial case study.

Table 2-1. Literature Review References vs. Data Types

Reference	Type of Data		
	Big data in operations, planning, and research	Big data in transportation	Aerial imagery data
[5]	X		
[6]	X		
[7]	X		
[8]	X		
[9]	X		
[10]	X		
[11]	X		
[12]	X		
[13]	X		
[14]	X		
[15]	X		
[16]		X	
[17]		X	
[18]		X	
[19]		X	
[20]		X	
[21]		X	
[22]		X	
[23]			X
[24]			X
[25]			X
[26]			X
[27]			X
[28]			X
[29]			X
[30]			X

2.3 Impact of Pavement Marking Quality on Pedestrian and Bicycle Crashes

The impact of pavement marking quality on pedestrian and bicycle crashes is a significant consideration in the realm of transportation safety. Pavement markings play a crucial role in guiding and managing traffic flow, and their quality can influence the behavior and safety of pedestrians and cyclists. There are several ways in which the quality of pavement markings can affect the frequency and severity of pedestrian and bicycle crashes as described below.

High-quality pavement markings are essential for ensuring visibility, especially in low-light or adverse weather, enabling pedestrians and cyclists to navigate intersections, crosswalks, and bike lanes safely. Well-maintained crosswalks and bike lanes reduce the risk of collisions by guiding road users and minimizing conflicts with motor vehicles. At intersections, clear markings like stop lines and lane divisions manage traffic flow and prevent hazards. In school zones and high-foot-traffic areas, visible markings enhance safety by alerting drivers to pedestrians, particularly children. Additionally, pavement markings support traffic signal compliance and speed control, ensuring safer conditions for all road users. Faded or poorly maintained markings increase confusion, reduce safety, and elevate crash risks.

In addition, some studies investigated how well-marked pavement affects driver behavior and road safety. Babic et al. [31] carried out a comprehensive analysis of the most important research studies to date on the effects of road markings indicating hazard locations, both longitudinally and transversely, on driver behavior and overall road safety. In a related study, Carlson et al. [32] gathered some research to show a fresh viewpoint on the advantages of pavement markings and, when data is available, to outline the advantages of certain pavement marking features. This paper highlights regions where results are accessible but show inconsistent and occasionally conflicting outcomes, as well as places where definite conclusions are available. The authors discovered that the existence of pavement markings, lane widths, functional classification, curve presence, and volume, including state and local roadways—were important characteristics to consider when analyzing the crashes. The findings of a comprehensive analysis might be utilized to justify revisions to the handbook on uniform traffic control device policy, which would offer safety-justified guidelines for pavement marking application timing.

Two pavement markings, a backward pointing herringbone pattern and transverse rumble strips, were studied by Arien et al. [33] for their impact on lateral control and speed in and around curves. The speed and lateral control of the curves varied, as demonstrated by the results; these behavioral variations were most likely caused by variations in the geometric alignment, cross-sectional design, and speed limit of the curves.

The effects of broader longitudinal pavement markings on safety were examined by Hussein et al. [34]. This study used information gathered from 38 treatment sites (highway segments) throughout three Canadian jurisdictions (British Columbia, Alberta, and Quebec) to conduct a before and after safety review. After the broader longitudinal pavement markings were put in place, the results showed a significant overall reduction in both total crashes and target collisions (i.e., run-off-the-road collisions) by 12.3 percent and 19.0 percent, respectively. The percentage of total collisions decreased in Alberta, British Columbia, and Quebec, respectively, by 11.1%, 27.5%, and 1.1%. In the same way, the three jurisdictions saw a decrease in run-off-road collisions, which varied from 22.7% to 28.9%. Wider longitudinal pavement markings may be able to lower crash rates and raise safety standards on Canadian roadways, according to the findings.

Johnson et al. [35] investigated the theory that inadequate geometric arrangement, signage, and pavement markings, together with driver bewilderment and information overload, are the root causes of the increased frequency of property-damage-only crashes at some multi-lane roundabouts in the United States. Then, using accepted traffic engineering concepts, the authors examined research papers, investigated the best practices for pavement marking and roundabout signage, and discussed parts of the 2009 handbook on uniform traffic control devices that would go against these guidelines.

3 Use of Aerial Imagery and FDOT Maintenance Rating Program (MRP)

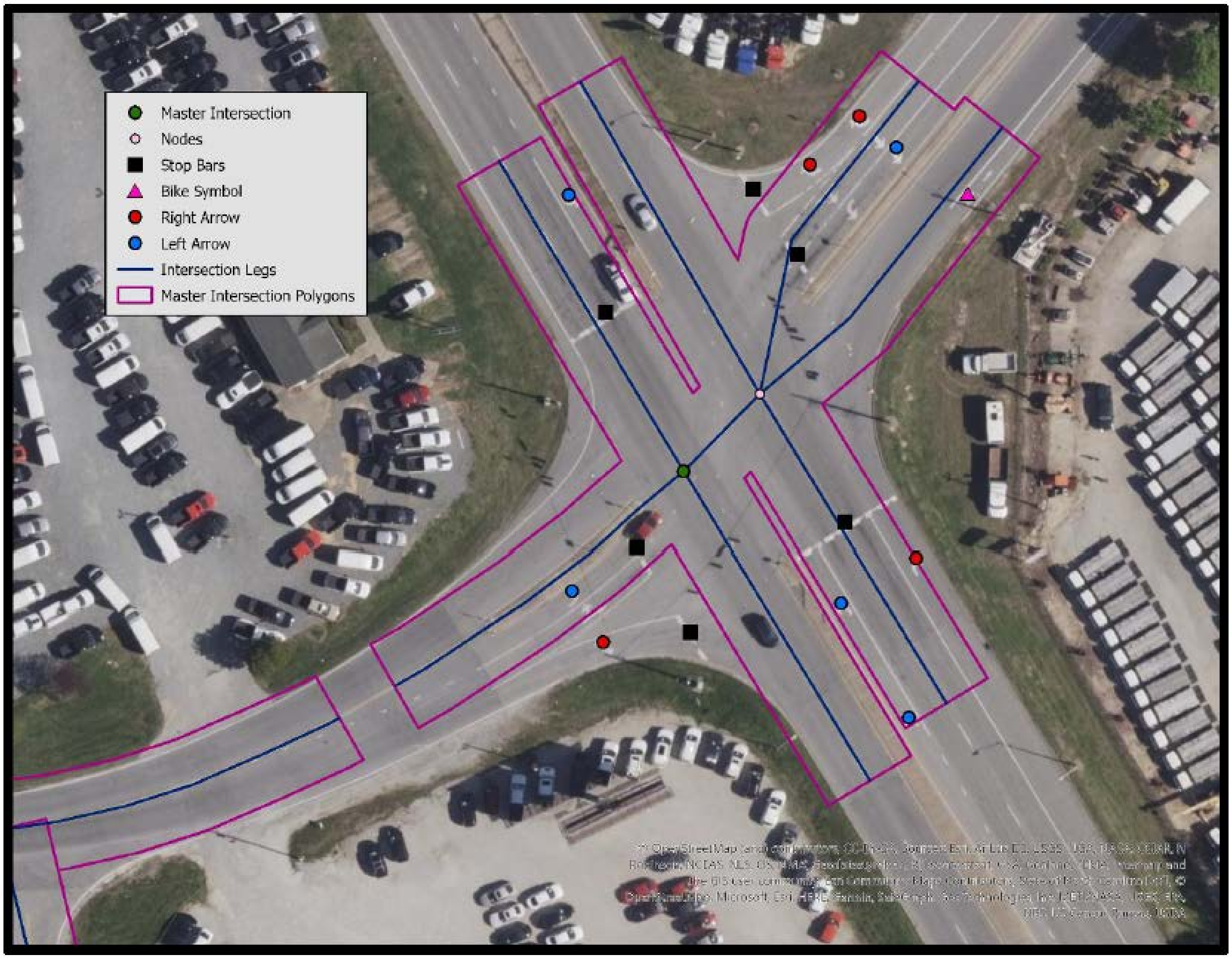
The project team has partnered with Vexcel Imaging, Inc., which is a leading provider of optics and sensor technology enabling geospatial accuracy in imaging collection.

3.1 Use of Aerial Imagery for Roadway Assessment

Vexcel uses AI and ML algorithms to analyze the images collected, and provide the following roadway data elements in large scale coverage:

1. Roadway Inventories for Bike and Pedestrian Facilities
    a. Crosswalks (standard and high visibility) at intersections and midblock.
    b. Bicycle lanes (symbols, words, and green painted lanes).
    c. ADA detectable curb ramps and pedestrian refuge islands.
    d. Dedicated left turn and right turn lanes using roadway arrow markings and words (e.g., ONLY).
    e. Sidewalks + width measurements.
    f. Curb extensions and corner radii.
2. Condition Assessment of Road Markings for Maintenance Prioritization
    a. Identification of faded or worn pavement markings.
    b. Development of prediction models based on historic and ongoing imagery.
3. ADA Compliance Assessment
    a. Mapping of required detectable warnings on curb ramps per DOT ADA standards.
4. Confirm and Document Installation of Countermeasures
    a. Creation of as-builts for FHWA proven pedestrian and bicyclist countermeasures (e.g., high visibility crosswalks, advance stop and yield lines, pedestrian refuge islands) using annual, semiannual (in urban areas) and disaster event (e.g., hurricane, wildfire, tornados) imagery.

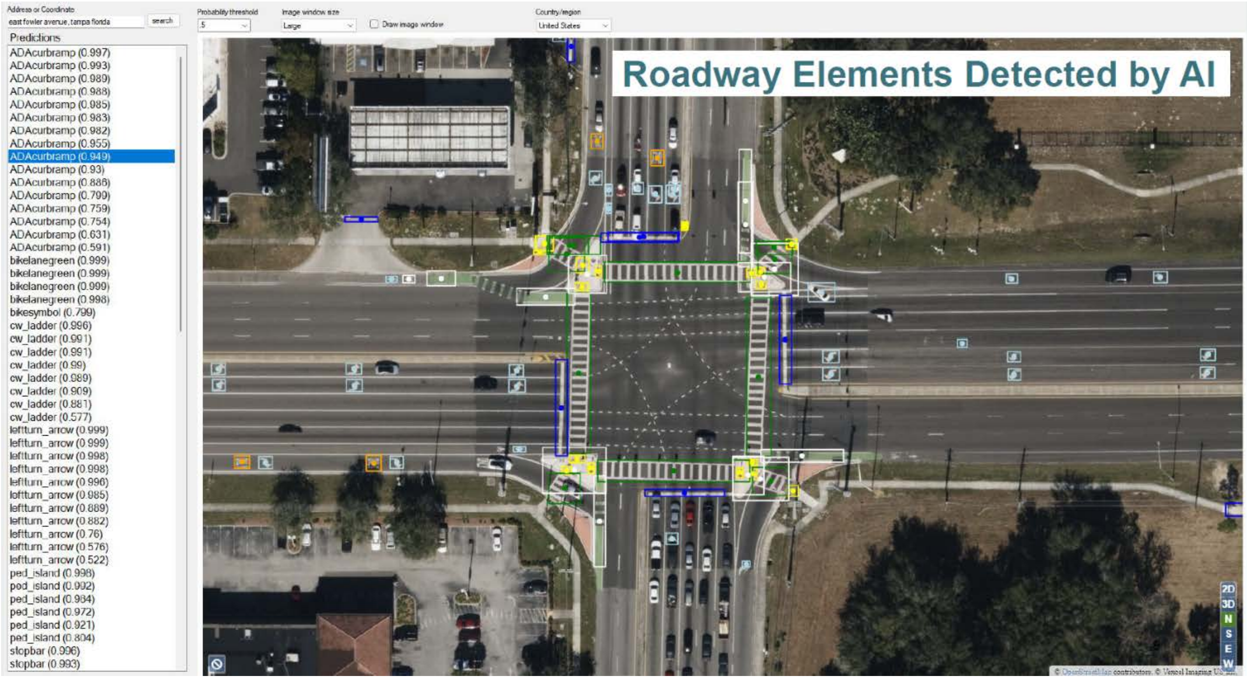
The Vexcel data analytics team has worked with other DOTs to provide services like the data and service provided for this project with USF/CUTR and FDOT. The use case is a project with the FHWA Data and Analysis Technical Assistance team to assist the North Carolina DOT (NCDOT) by piloting a method for acquiring intersection-related model inventory of roadway elements (MIRE) attributes. The team tested a sample of data features that were extracted from images of the City of Greensboro, City of Goldsboro, and City of Marion in NC. Figure 3-1 shows an example of the roadway elements extracted from the imagery for the study with NCDOT. The study concluded that the findings illustrate the scope of potential updates that could be made to North Carolina’s intersection inventory based on three representative municipal locations in the state.



Source: Vexcel Imaging, Inc.

Figure 3-1. NCDOT intersection inventory feature displayed with Vexcel roadway elements

For the purposes of the current project with FDOT, the team extracted roadway features from the District 7 (D7) coverage area, to identify markings in poor conditions. Figure 3-2 shows an example of the ML/AI tool that was used to extract roadway elements for this study. In addition, the service can differentiate between types of crosswalks and how worn they are. Figure 3-3 shows an example of different types of crosswalk markings at signalized intersections.



Source: Vexcel Imaging, Inc.

Figure 3-2. Aerial view of a major intersection with AI-detected roadway elements

Source: Vexcel Imaging, Inc.

Figure 3-3. Standard vs. high visibility crosswalks

3.2 FDOT Maintenance Rating Program (MRP)

In addition to protecting public facilities by maintaining the current infrastructure, FDOT oversees the delivery of regular and consistent maintenance of the state highway system in a safe state to customers. Maintenance field supervisors are tasked with upholding specified conditions by maintenance engineers, who in the past prescribed service levels for various highway features, such as roadway, roadside, traffic services, drainage, and vegetation. These ideal maintenance parameters were not set as a minimum or maximum; rather, they represented a service level that considered several factors, including comfort, safety, economics, the impact on the environment, aesthetics, and, finally, financial limitations on the resources that were available, such as equipment, personnel, and materials. Generally, maintenance staff, such as field supervisors, make these decisions on an informal basis, deciding which elements should be allowed to regress and which should be kept at a desired level of service. As a result of these numerous and intricate variables, inconsistent choices were made, which inadvertently led to reduced maintenance levels.

A rigorous, systematic process for determining the appropriate levels of maintenance was created because of these inconsistencies and the ensuing decrease in maintenance levels. In April 1985, this technique, now known as the Maintenance Rating Program (MRP) was put into practice. This program considers the previously mentioned variables and permits various service levels for maintenance tasks and roadway categories.

The type of maintenance required determines the classification of a particular facility. There are currently four facility type classifications: urban restricted access, urban arterial, rural limited access, and rural arterial. Additionally, the five components of each type of highway facility—roadway, roadside, traffic services, drainage, and vegetation/aesthetics—are separated for each type. The characteristics that are unique to each of these aspects are included in further categories. For example, the roadside element consists of the following sub elements: sidewalk, fence, slope pavement, unpaved shoulder, and front slope [36]. The personnel responsible for conducting the MRP survey uses the MRP handbook which outlines the methods and procedures for all elements rated by the MRP.

3.2.1 Service Sample Selection

According to the Maintenance Rating Program Handbook [37], the information gathered is stored by the MRP using the department's data processing system. The gathered data are compared to the intended maintenance conditions or levels. The samples of highways to be surveyed are also created by data processing. These samples are chosen from the department's inventory of roadway features, which is created by classifying all facilities according to their length and use (e.g., urban limited access), and then using a random number generator program to generate survey locations. Selection by facility type, county, maintenance area (yard), district, or state level is possible due to the random number generator's adaptability.

3.2.2 Survey Sample List

The computer printout that serves as the survey sample list includes the county part and subsection, state road number, maintenance area, facility type number, and sample location per milepost. Thirty samples per facility type, or at least three samples per available mile, are typically required for each maintenance area. No samples are produced for assessment if the mileage for any type of facility is less than three. If the initial sample is deemed unsuitable for assessment, there are backup samples available for utilization.

3.2.3 Survey Frequency

A listing of samples required to be surveyed is provided to each district by the Office of Maintenance at the following frequencies:

- "Scheduled Sample Period: By the final working day of the scheduled period, the district must have finished surveying those samples within the district. By the last day of the rating period, the district will ensure that all data has been confirmed to be accurate and submitted into the Department's data processing system in the correct location. Regular entry of the obtained data into the data processing system is advised. If needed, the computer file will offer a secure location for storing information along with a rapid way to access it. While interim and preliminary reports could be needed for planning, status, or interpolated data, statistically speaking, partial data cannot be used until all samples have been finished and entered."
- "As Required: Occasionally, it will be necessary to survey a specific stretch of road (such as the one next to or heading into a well-known tourist destination). Surveys may be needed on other occasions for a specific facility type (such as urban limited access), by section, by grouping of sections, by county, by maintenance area, or by any combination of facility types by sections, counties, districts, or the entire state. These additional requests will typically be given priorities and completion deadlines, which may need some adjustment of current and other workloads [37]."

3.2.4 Data Collection

To preserve the program's credibility, the data is gathered thoroughly and precisely. Additionally, ratings could be utilized by other sections and divisions within the Department, other state agencies in Florida, and even by federal and other state authorities.

There must be a minimum of two members on an MRP survey team. The MRP is implemented and maintained by each district. It is required that the MRP survey team's top priority be their own safety as well as the protection of other drivers and pedestrians. To ensure adequate safety, it might be necessary to schedule the survey of samples with high traffic density during periods of low traffic. It could be required to ask the maintenance area where the survey is being conducted for a safety crew (flag persons, cones, signs, flashing directional arrow, etc.). The survey team assesses each sample while walking in a group and facing traffic. The survey team faces traffic to ensure their safety and avoid missing any items that one person might overlook, thus enabling precise measurements. Following is a discussion of the specific elements that this project addressed using the Vexcel Imaging, Inc. service.

- Striping

The MRP Handbook page 55 [37] , outlines that for striping, 90% of the length and width of each line must be reflective and functions as intended.

  - Pavement Striping: It is a six-inch-wide centerline, skip line, or edge line.

- Evaluation: Daylight and nighttime inspections shall be done. Each line is evaluated independently.
- Solid Lines: Determine the length and width of each solid line in the sample point. A minimum of 5.4 inches of each line width should be present, visible, and reflective at night with low-beam headlights. Determine if the lines are reflective at night for a distance of 160 feet. Due to changes in Standard Plans, striping may have been installed at certain locations on some roadways whereas no striping is installed at similar locations on other roadways. Do not evaluate striping at locations where it has not been installed.
- Skip Lines: Determine the length and width of each skip line in the sample point. A minimum of 5.4 inches of each line width should be present, visible, and reflective at night with low-beam headlights. Only evaluate the stripe and not the skip.
- Contrast Lines: Black lines are used for contrast only and should not be evaluated for reflectivity. They are rated for length and width only, if present and maintained.

Refer to Standard Plans for interchange markings and special marking areas.

Striping does not meet MRP standards when any of the following exist:

1. If more than 10% of the length of any line is less than 5.4 inches wide during daylight inspection.
2. If more than 10 % of the length and width of any line is not visible for a distance of 160 feet at night.
3. If more than 10% of the length of any line is missing.
4. If more than 10% of the length of any line is covered by soil, grass, debris, staining, or skid marks.

- Pavement Symbols

The MRP Handbook page 60 [37] outlines that 90% of existing symbols should function as intended and 50% or greater of any one symbol should function as intended to meet MRP standards:

- Pavement Symbol: Pavement symbols are used to communicate certain meanings at specific locations. Included in this characteristic are gore area markings, shoulder markings, word, and symbol markings, stop bars, all crosswalk lines within the R/W, parking space markings (does not include edge lines that delineate parking), curb markings, painted medians, radius markings, turning guidelines and others.
- Evaluation: The total square footage of all symbols within the sample point should be determined. Symbols that appear to be abandoned should be verified as such by the area engineer and not be evaluated if determined to be abandoned. Curb markings and crosswalks on connecting side streets are not to be evaluated for nighttime reflectivity. The Standard Plans or the MMS Handbook can be referenced to determine the square footage of symbols.

Pavement Symbols do not meet MRP standards when any of the following exist:

1. If more than 10% of the cumulative symbol area is not functioning as intended during daylight observation.
2. If more than 10% of cumulative symbol area is not reflective for a distance of 160 feet using low beam headlights during nighttime observation.
3. If more than 50% of one symbol is missing or not reflective for a distance of 160 feet use low-beam headlights during nighttime observation.
4. If symbols are not installed according to the Standard Plans.

4 Acquisition and Assessment of Aerial Imagery Data for Roadway Analysis

As organizations across various sectors increasingly rely on geospatial information for planning, analysis, and decision support, the significance of acquiring accurate, up-to-date aerial imagery cannot be overstated. Whether for urban planning, environmental monitoring, infrastructure development, or disaster response, the quality of the acquired data directly influences the efficacy of subsequent analyses and decision-making processes.

This section provides the process the CUTR team used for high-resolution aerial imagery data acquisition, providing a roadmap for future use by FDOT. As per the task objectives, CUTR acquired data from Vexcel, including roadway feature extraction via the data service. Figure 4-1 shows the four steps used to obtain the data. First, a study area and data quantity were determined, followed by the acquisition and review of a sample, the suitability of the feature extraction was evaluated for the project, and finally, the CUTR team acquired a complete dataset. Each of the first three steps is explained in detail in the following subsections. The description of Step 4 on the acquisition of complete dataset is provided in Section 3.

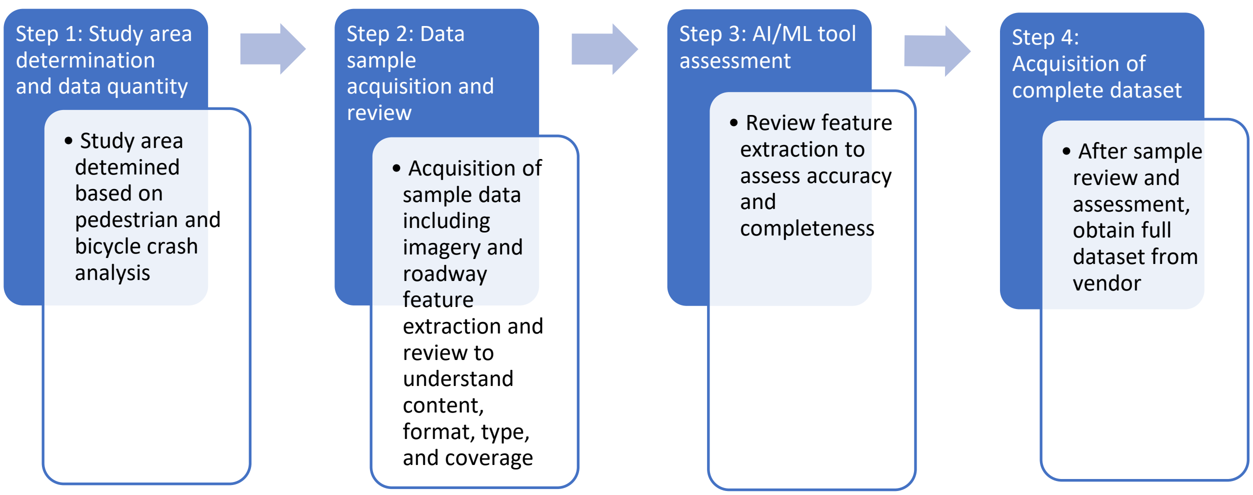


Figure 4-1. Procedure used to acquire and review data from Vexcel

4.1 Study Area Determination and Data Quantity

Selecting an appropriate study area is a critical foundation, influencing the project's outcomes and the effectiveness of the acquired aerial imagery data in the analysis. This section delves into the rationale, methodology, and criteria employed to meticulously define the boundaries of the study, ensuring that the data collected aligns seamlessly with the project objectives.

Because the project focuses on pedestrian and bicyclist crashes that occur at intersections, GIS visualization tools are used to produce high crash frequency maps. Initially, the information was obtained from the Signal Four (S4) Analytics webpage developed by the University of Florida. S4 includes a Target Zero inquiry that yields various results depending on parameters, such as crash severity, emphasis area, and numerous other factors.

The CUTR team utilized S4 to download and import pedestrian and bicyclist-related crash data from January 1, 2018, through December 31, 2022, into ArcGIS Pro. This data, including the most recent five-year crash data to obtain trends, was filtered, processed, and reviewed in the preceding stage. The focus narrowed to Hillsborough County and Pinellas County, which exhibited the highest frequency of pedestrian and bicycle crashes within FDOT District 7. It is important to note that crashes occurring only at intersections were used for the high frequency crash (heat) maps. Figure 4-2 displays the flowchart of this procedure.

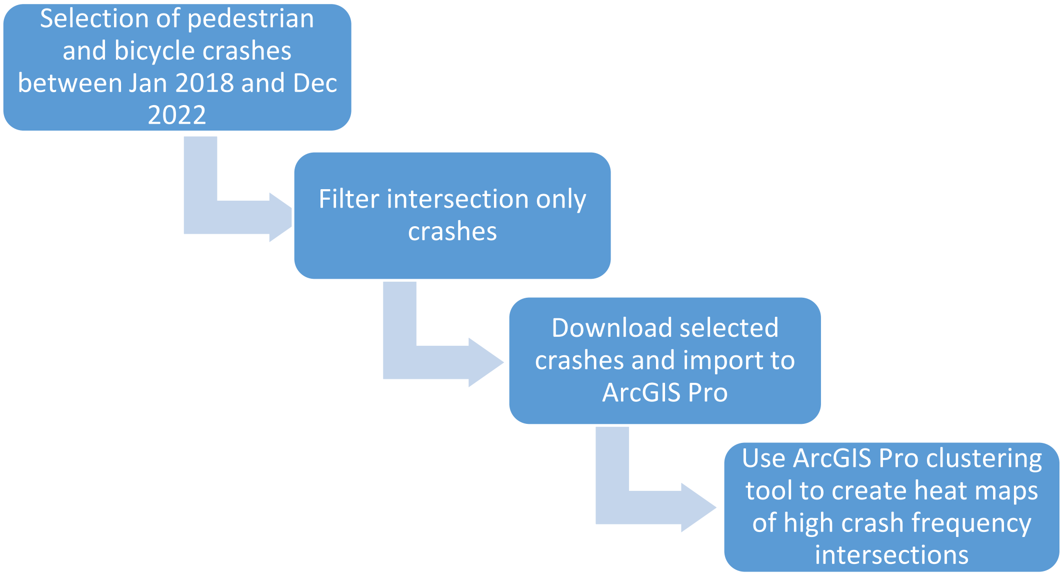
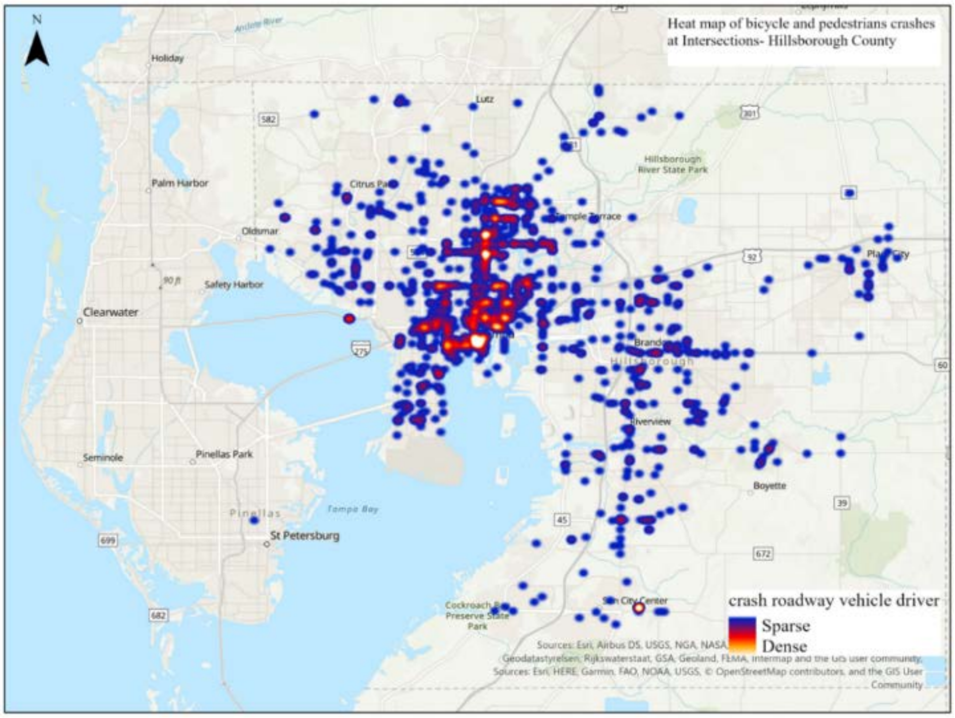


Figure 4-2. Flowchart of crash selection and heat map generation using ArcGIS Pro

In terms of the results, Figure 4-3 shows the heat map of pedestrian and bicyclist crashes for Hillsborough County, and Figure 4-4 shows the heat map for Pinellas County. Based on the heat maps produced, the areas where the highest frequency of crashes occurred were identified as a focus for the study area.

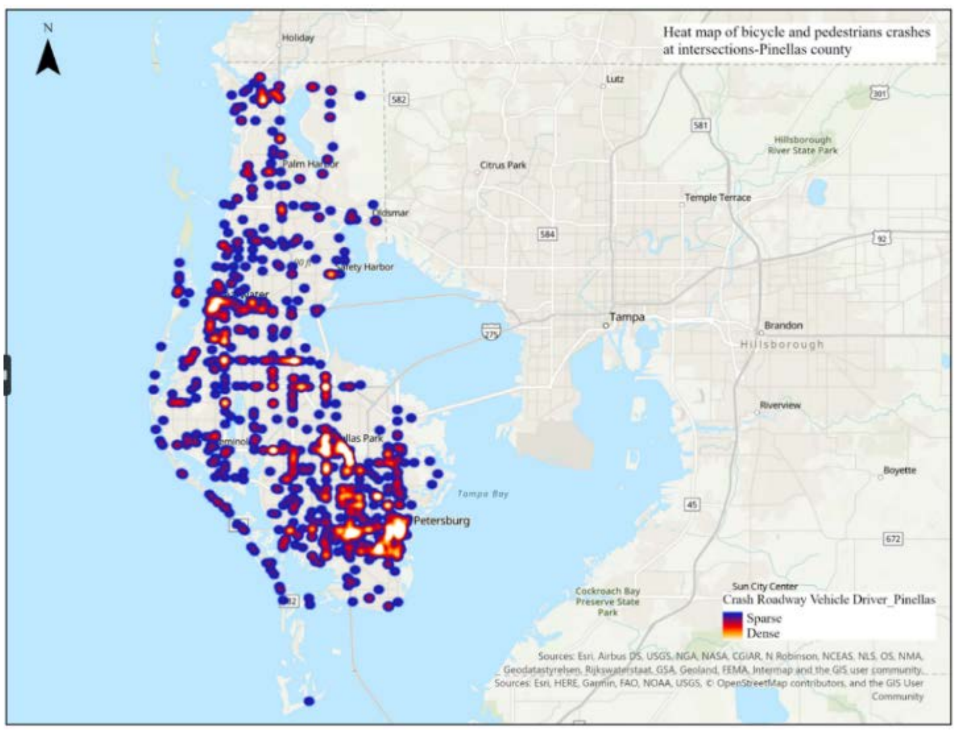
Due to the difference in image resolution from Vexcel, an additional analysis for two counties was also conducted to identify urban versus rural area crashes. Figure 4-5 displays the heat map of pedestrian and bicyclist crashes at intersections for rural and urban areas for Hillsborough County and Figure 4-6 for Pinellas County. Based on this analysis, crashes in urban areas occur more frequently than crashes in rural areas.

Finally, the CUTR team investigated the quantity of data needed to be obtained. The Vexcel service provides roadway feature extraction for all roads, intersections, and other locations inside the study area. The CUTR team identified that it would acquire the roadway feature extraction and images from the latest images available. At the time of this report, the most recent images are from February 2023. The team has assessed that this quantity of data is adequate for this focus study.



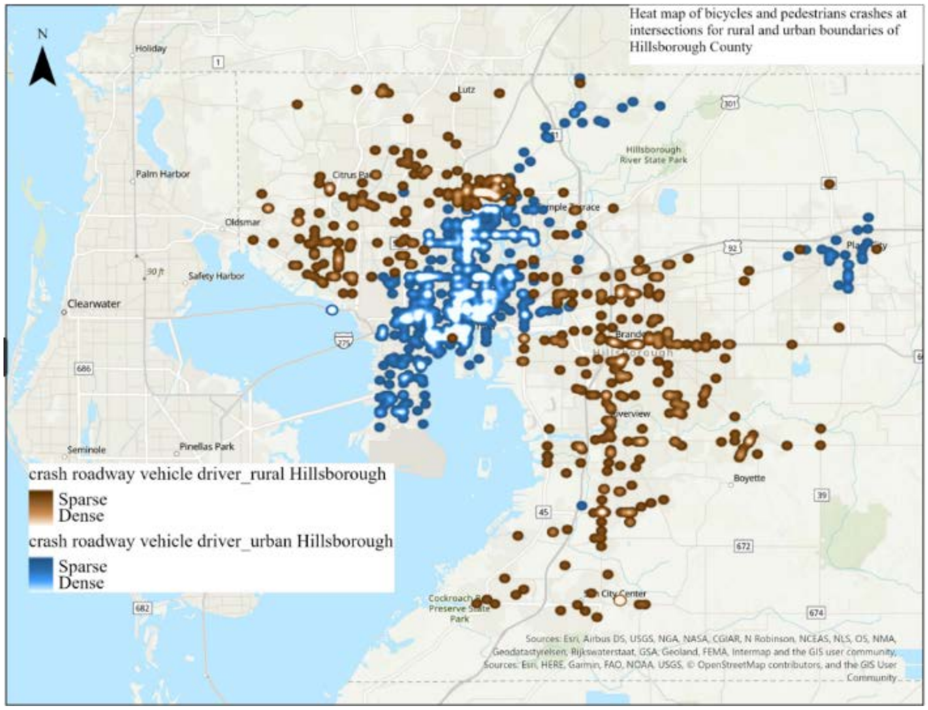
Source: CUTR

Figure 4-3. Hillsborough County pedestrian and bicycle crash heat map



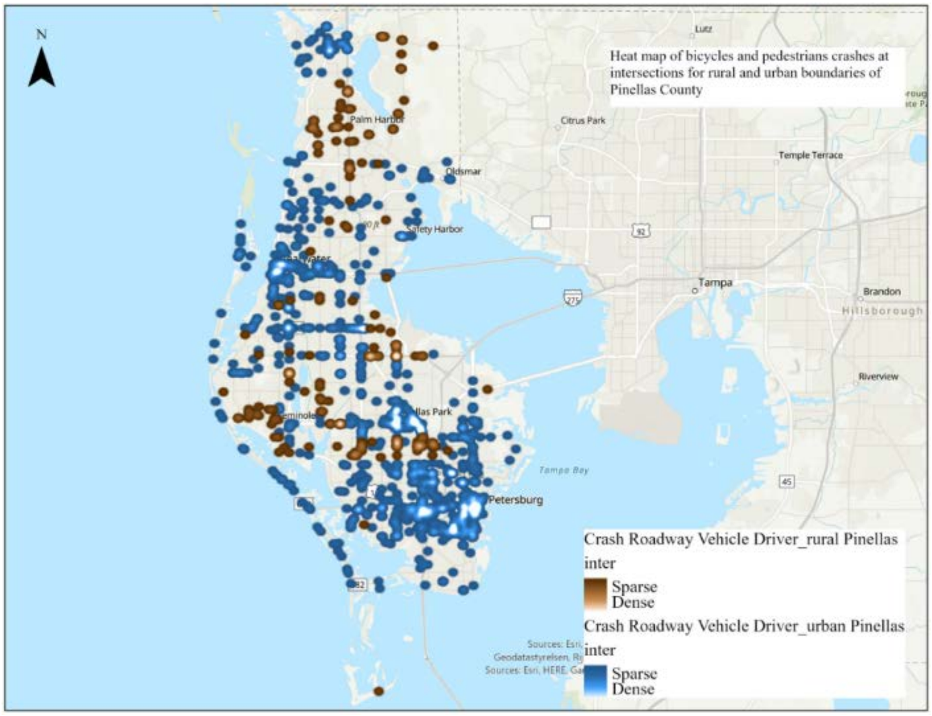
Source: CUTR

Figure 4-4. Pinellas County pedestrian and bicycle crash heat map



Source: CUTR

Figure 4-5. Hillsborough County heat map of pedestrian and bicycle crashes at intersections for rural and urban areas



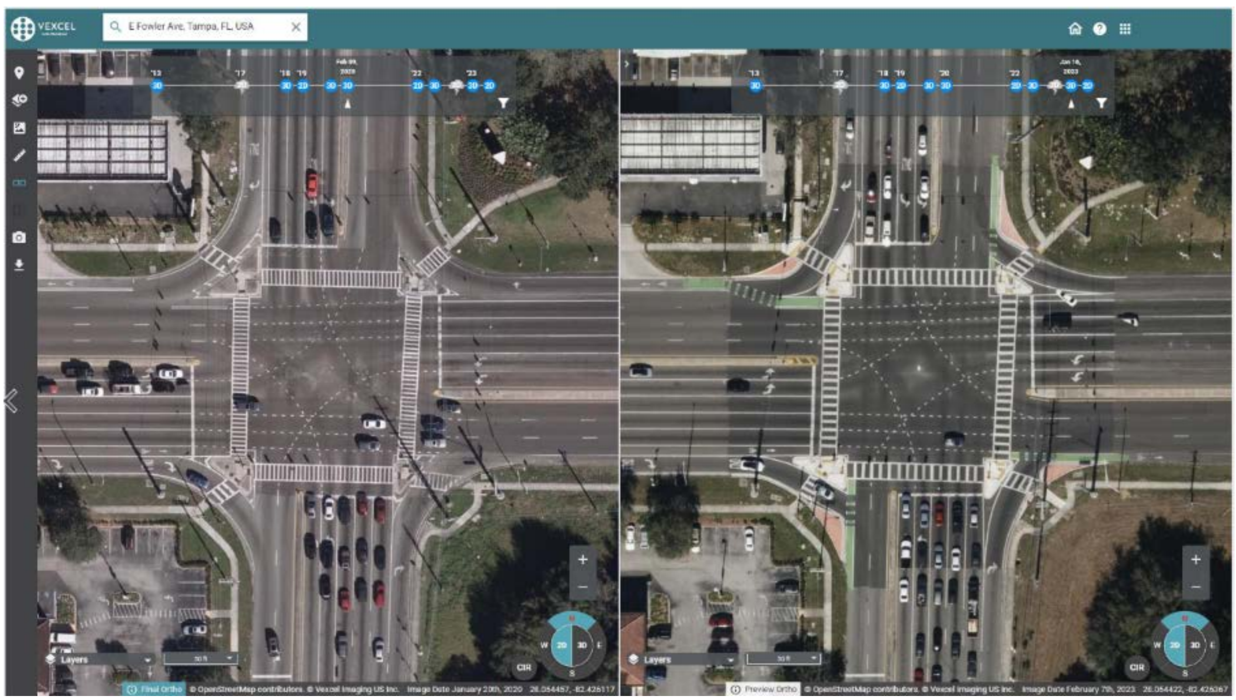
Source: CUTR

Figure 4-6. Pinellas County heat map of pedestrian and bicycle crashes at intersections for rural and urban areas

In summary, the urban versus rural crash analysis provides insights into the distribution of pedestrian and bicycle crashes across the two counties at intersections in both rural and urban areas. The color-coded representation helps to distinguish the frequency of crashes in different boundary types for each county. Based on this analysis, the area covering much of Hillsborough and Pinellas Counties was provided to Vexcel in a polygon to extract the roadway features using the AI tool.

4.2 Data Sample Acquisition and Review

The CUTR team commenced by reviewing a sample of data obtained from the chosen data service provider, including raw imagery and extracted roadway features. Figure 4-7 shows the raw imagery data at the intersection of E Fowler Ave and Bruce B. Downs Blvd in the City of Tampa, in which the objective was to understand the data's content, format, type, and coverage. The figure shows the Vexcel Viewer, a Web-based image service where the images can be reviewed and used for analysis. The image on the left shows the intersection of E Fowler Ave and Bruce B. Downs Blvd in 2013, and the image on the right shows the same intersection in 2023.



Source: Vexcel Imaging, Inc.

Figure 4-7. The imagery data viewer from Vexcel Imaging, Inc.

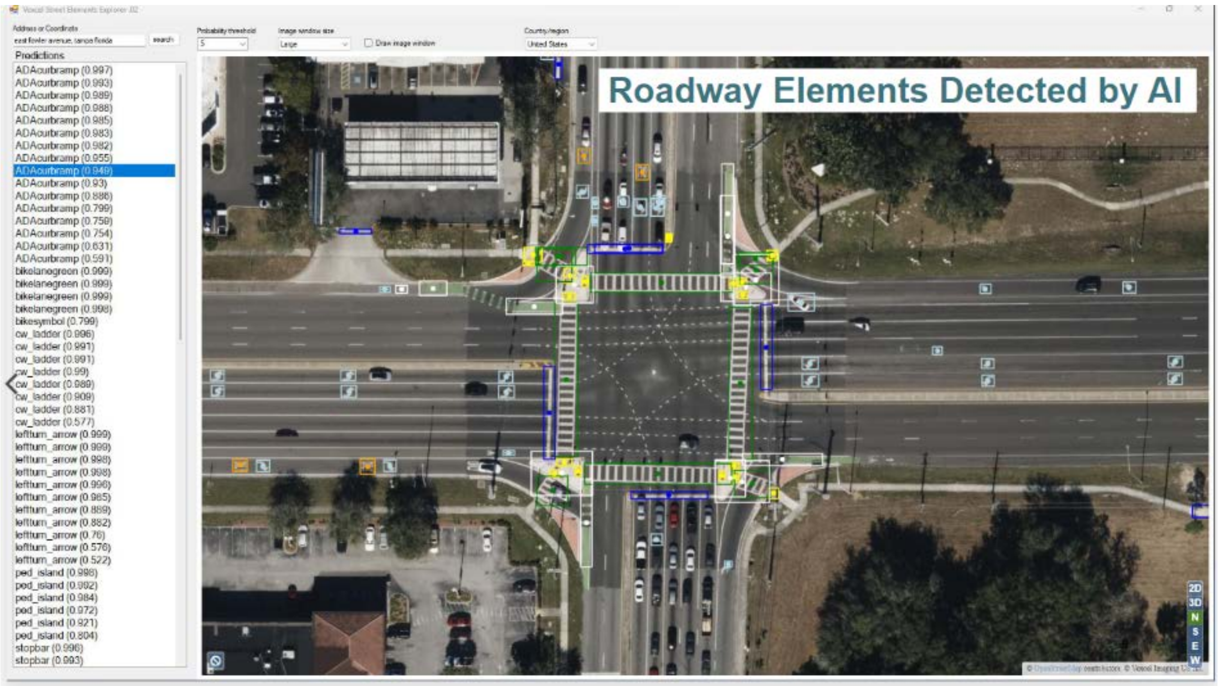
Because this task concerns roadway pavement markings, its elements information is primarily managed and visualized utilizing geospatial databases and GIS software with road features described by polylines, points, and polygon objects. The data scheme for roadway elements is to provide vector geometry and associated attribute information about an AI-detected element and the source imagery used for analysis. Table A-1 shows the data dictionary for roadway elements, including longitude, latitude, ID number, categories, name, types, quality scores, confidence, area, crossing distance, and collection method. The complete data dictionary is shown in Appendix A [38].

The roadway element dataset is an AI-based product that provides essential data for inventorying roadways for reporting, compliance, and safety analysis. The dataset identifies and maps the location of roadway features, including ADA curb mats, roundabouts, and pedestrian islands, as well as crosswalks, stop lines, word, symbol, and arrow pavement markings. The data is delivered as a CSV file, which can be used in various applications. The file contains a table of extracted roadway features with attributes for each feature, such as location, name, description, area, and others. Up to two types of geometry data (Point and Polygon) are available for each element. Crosswalk elements contain an additional geometric attribute (Line String) for calculated crossing distances. Each of these geometry types can be displayed in GIS applications, which is demonstrated in Figure 4-8. Full descriptions of attribute fields can be found in the Data Dictionary, located in Table A-1.

Source: Vexcel Imaging, Inc.

Figure 4-8. Crosswalk element displaying bounding box polygon, bounding box centroid point, and crossing distance (line string)

Figure 4-9 displays the roadway elements overlayed with the imaging layer at the intersection of E Fowler Ave and Bruce B. Downs Blvd in the City of Tampa. Figure 4-10 lists all the categories described in Table A-1.



Source: Vexcel Imaging, Inc.

Figure 4-9. Roadway elements detected by Vexcel' s AI tool

Foundational Roadway Elements

CATEGORY	GROUPING	ELEMENT	PEDESTRIAN/BICYCLE SPECIFIC	CONDITION ASSESSMENT AVAILABLE
Pavement Markings	Arrows	Three Way Arrow		
Pavement Markings	Arrows	Right Turn Arrow		X
Pavement Markings	Arrows	Left Turn Arrow		X
Pavement Markings	Arrows	Right + Left Arrow		
Pavement Markings	Arrows	Straight Arrow		
Pavement Markings	Arrows	Straight + Left Arrow		
Pavement Markings	Arrows	Straight + Right Arrow		
Pavement Markings	Bicycle Lane	Green Bicycle Lane	X	
Americans with Disabilities Act	Crosswalks	ADA Detectable Curb Ramp	X	
Pavement Markings	Crosswalks	Diagonal Crosswalk	X	X
Pavement Markings	Crosswalks	Ladder Crosswalk	X	X
Pavement Markings	Crosswalks	Solid Crosswalk	X	
Pavement Markings	Crosswalks	Standard Crosswalk	X	X
Pavement Markings	Crosswalks	Zebra Crosswalk (Continental)	X	X
Pedestrian	Crosswalks	Pedestrian Refuge Island	X	
Pavement Markings	Stop and Yield Lines	Stop Bar		X
Pavement Markings	Stop and Yield Lines	Yield Bar		
Pavement Markings	Symbols	Bicycle Symbol	X	
Pavement Markings	Symbols	Handicap (wheelchair) road marking	X	
Pavement Markings	Symbols	Railroad Crossing		
Pavement Markings	Symbols	Speed Hump road marking		
Pavement Markings	Word	AHEAD road marking		
Pavement Markings	Word	BIKE road marking	X	
Pavement Markings	Word	BUS road marking		
Pavement Markings	Word	CLEAR road marking		
Pavement Markings	Word	KEEP road marking		
Pavement Markings	Word	LANE road marking		
Pavement Markings	Word	MERGE road marking		
Pavement Markings	Word	ONLY road marking		
Pavement Markings	Word	PED road marking	X	
Pavement Markings	Word	SCHOOL road marking		
Pavement Markings	Word	SLOW road marking		
Pavement Markings	Word	STOP road marking		
Pavement Markings	Word	TAXI road marking		
Pavement Markings	Word	XING road marking	X	
Pavement Markings	Word	YIELD road marking		

Source: Vexcel Imaging, Inc.

Figure 4-10. The functional roadway elements extracted by Vencel's AI tool

The tool is, therefore, an important element in the extraction of useful information from aerial images. The processing is fast and can provide accurate information on the pavement marking conditions on Florida's roadways. To extract all roadway features for the selected area, Vexcel required five days to provide the dataset for the Feb 2023 images.

4.3 Examination and Assessment of AI and ML Tools

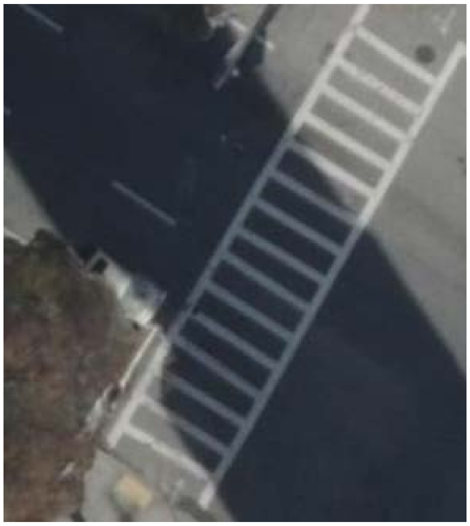
With the ability to swiftly process vast amounts of data from diverse sources such as camera systems, sensors, and roadside devices, AI and ML algorithms empower transportation agencies to gain valuable insights into traffic patterns, road conditions, and overall infrastructure performance. This real-time data processing capability enhances the speed of decision-making and enables the timely implementation of adaptive strategies to address dynamic challenges. Furthermore, the application of AI and ML extends beyond mere data processing; it allows for identifying predictive patterns, enabling transportation agencies to manage and optimize their resources proactively. As a result, these technological advancements streamline traditional time-consuming tasks and pave the way for a more responsive, adaptive, and intelligent transportation ecosystem. This transformative impact positions AI and ML as indispensable tools in shaping the future of transportation management and infrastructure optimization.

The CUTR team assessed the capabilities of the vendor's AI and ML-powered tools in extracting features of interest. As mentioned earlier, the data is provided in CSV and shapefile formats. As such, due to the nature of the data, it was imported into a GIS tool and reviewed for accuracy. In addition, a comparison between the data extracted from the big-data services versus FDOT's pavement marking program is as follows.

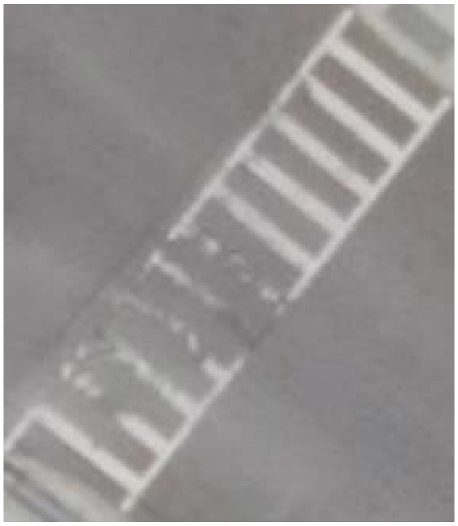
4.3.1 Pavement Marking Assessment by Vexcel

One innovative feature of this data service is that pavement roadway markings are assigned a quality score value that ranks the marking quality using subjective criteria, which ranges from 1 (poor) to 4 (good) based on the visibility of defects. Figure 4-11 displays all four conditions that have been described in Table A-1. As shown, the quality of the crosswalk ranges from good to poor to help determine when the markings need to be repainted.

a. Good condition (4)



b. Acceptable condition (3)



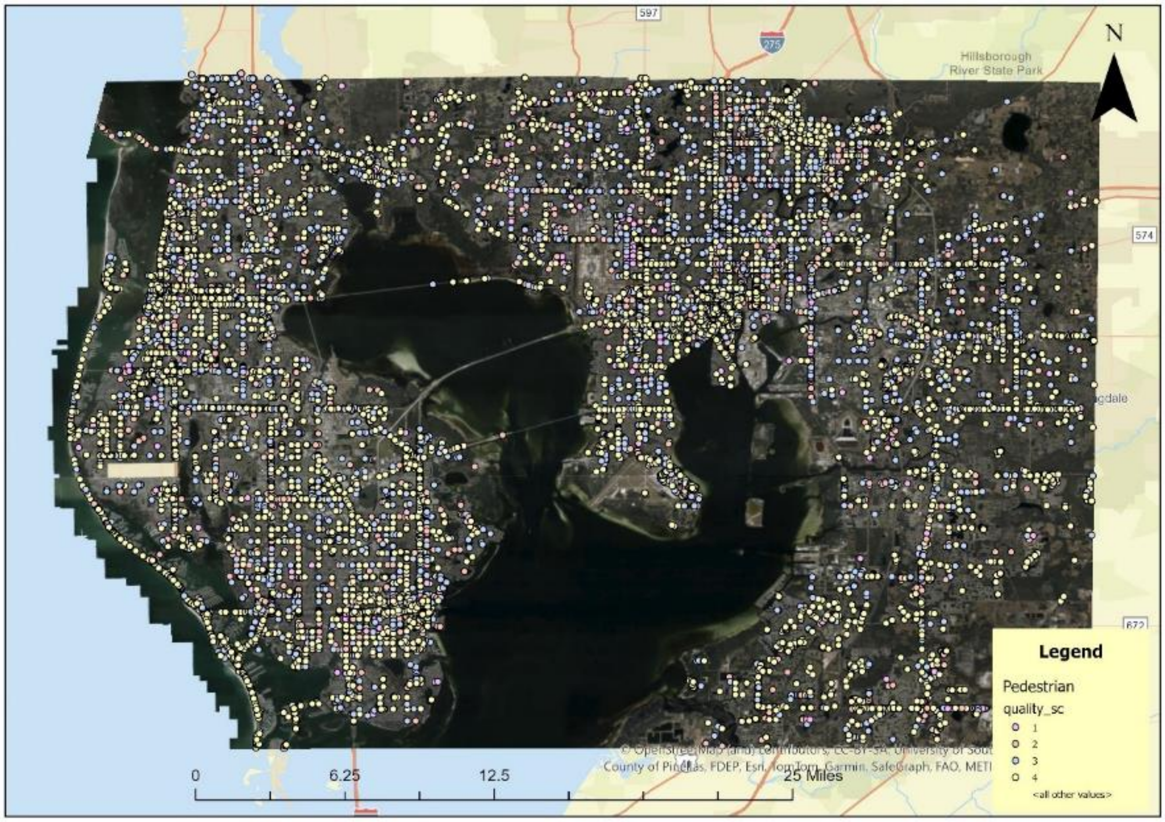
c. Fair condition (2)

d. Poor condition (1)

Source: Vexcel Imaging, Inc.

Figure 4-11. Crosswalk illustration with quality scores based on pavement marking visibility, wear, and overall condition

This data allows pavement markings to be quickly filtered by category and quality score to identify markings for further review. Figure 4-12 shows the study area map (Hillsborough and Pinellas Counties) with the locations and quality scores of all marked crosswalks.



Source: Vexcel Imaging, Inc.

Figure 4-12. Crosswalk pavement markings with a quality score of 1 – 4

4.3.2 Pavement Marking Assessment by FDOT

To ensure customer safety, FDOT is also in charge of maintaining the state highway system with continuous and dependable care, which led to the creation of a program known as the Maintenance Rating Program (MRP). This responsibility also includes maintaining public facilities through the upkeep of existing infrastructure. Maintenance field supervisors are responsible for maintaining specified conditions set by maintenance engineers. Historically, these engineers would determine service levels for various highway features such as roads, roadside amenities, traffic services, drainage systems, and vegetation. These ideal maintenance standards were not rigidly defined as minimum or maximum requirements but represented a benchmark considering factors like safety, comfort, economic viability, environmental impact, aesthetics, and the availability of equipment, personnel, and materials. Typically, maintenance personnel, including field supervisors, make decisions on an ad-hoc basis, prioritizing which aspects can degrade and which need to be maintained at a desired level. However, due to the complexity of these factors, inconsistent decisions have been made, inadvertently resulting in lowered maintenance standards.

Pavement symbols are used to communicate certain meanings at specific locations. Included in this characteristic are gore area markings, shoulder markings, word and symbol markings, stop bars, all crosswalk lines within the right of way, parking space markings (does not include edge lines that delineate parking), curb markings, painted medians, radius markings, turning guidelines, and others.

To evaluate the pavement markings, FDOT determines the total square footage of all symbols within the sample point. Symbols that appear to be abandoned should be verified as such by the area engineer and not evaluated if they are determined to be abandoned. Curb markings and crosswalks on connecting side streets are not to be evaluated for nighttime reflectivity.

Pavement symbols do not meet MRP standards when any of the following exist:

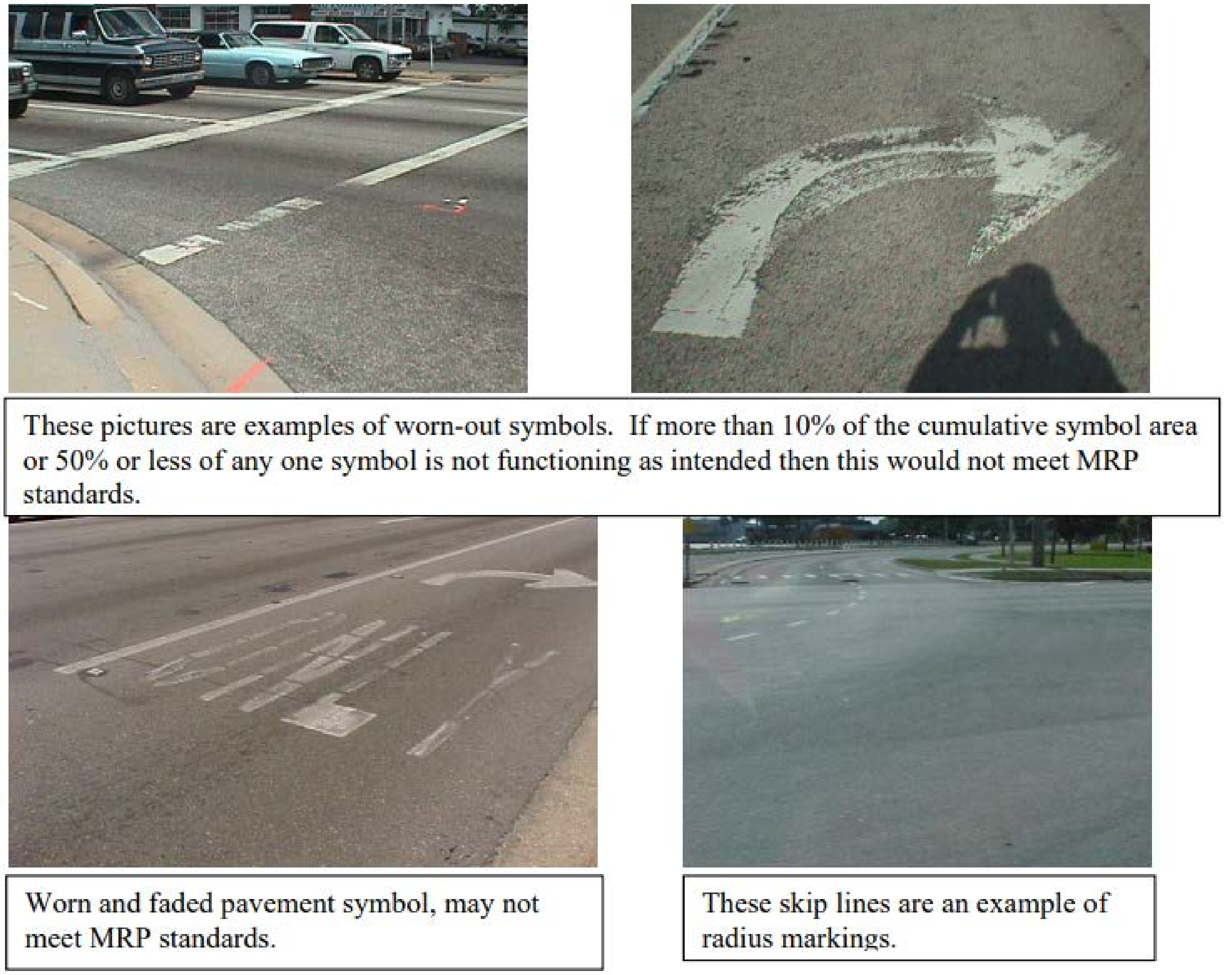
- If more than 10% of the cumulative symbol area is not functioning as intended during daylight observation.
- If more than 10% of the cumulative symbol area is not reflective for a distance of 160 feet using low beam headlights during nighttime observation.
- If more than 50% of one symbol is missing or not reflective for a distance of 160 feet using low beam headlights during nighttime observation.
- If symbols are not installed according to the Standard Plans.

In Figure 4-13, the top two pictures show that the pavement symbol is in good condition, which means the symbol meets the FDOT's MRP standards. The four remaining pictures require repainting to enhance the quality of that street and make it acceptable according to the defined conditions discussed earlier by FDOT.

Pavement symbols in good condition, meets MRP standards.

Pavement symbols in good condition, meets MRP standards.

Figure 4 - 13. Examples of pavement symbol conditions relative to MRP standards



Source: FDOT MPR Manual

Figure 4-13. Examples of pavement symbol conditions relative to MRP standards, continued

4.3.3 Comparing Vexcel and FDOT Assessments

Two pavement marking assessments have been presented in the previous sections. The first is a new assessment using AI and ML tools from high visibility imaging, and the second is the current method used by FDOT, which requires a crew to visit the site and take samples of pavement markings to assess their quality. Even though the two assessments differ in collection, they produce similar results. The most significant difference, however, is that Vexcel's service provides the features for all available markings in the area in a matter of days. FDOT's method requires a rolling selection of random sites, manual inspection from a crew, and quality assessment of only that sample.

While both assessments aim to improve road safety through accurate pavement marking assessments, their methodologies offer complementary perspectives. Vexcel emphasizes automated analysis, while FDOT focuses on a blend of manual and automated inspections.

It is possible, therefore, to establish a service where the output of the feature extraction service from imaging matches the quality assessment conducted by FDOT crews, thereby eliminating the need to do manual inspections or reducing the need dramatically. In addition, the quality score and location of the feature extraction service from Vexcel can complement the MRP survey because crews can assess the quality of pavement markings and symbols more efficiently and ensure that only markings that are worn or faded are repainted.

4.4 Feature Extraction Sample Assessment

To better understand the sample data provided by Vexcel and their accuracy on feature extraction, the feature list was reviewed for a total of 20 intersections (10 in Hillsborough County and 10 in Pinellas County). The process required the use of GIS software to view the extracted features and the Vexcel Imaging service to view the image collected via their imaging service. Based on the provided feature list, the service does not provide information on turning radii at intersections or sidewalk gaps at this time. These features are in the process of future development from the service provider. In addition, the ADA-compliant curbs are assessed by the presence of truncated dome mats and not by their height or slope.

The reviewed features were focused on pedestrian and bicycle users. For pedestrians, the following features were reviewed:

- Detectable warning mats (truncated dome mats),
- ladder crosswalks, longitudinal bar crosswalks, solid crosswalks, and transverse crosswalks, and
- pedestrian islands.

For bicyclists, the following features were reviewed:

- Bike text,
- bike symbol,
- green colored pavement, and
- shared bicycle lane.

Table 4-1 shows the analysis results for the 10 intersections in Hillsborough County. In the table, all possible features are listed, but not all intersections have those features. The features that are not available have a zero in the “feature present” column. The numbers in the columns indicate the sum of the features at each intersection for all approaches. In addition, Vexcel identifies four different types of crosswalks which are not present everywhere. Most intersections in Florida have either a ladder type crosswalk or the transverse line crosswalk. The ratio of the number of detected versus present features is the percent accuracy. The accuracy results vary from zero percent detected to 117 percent (detected more than present), which shows some mislabeling. As shown in Table 4-1, most features were detected with 100% accuracy.

Table 4-1. Hillsborough County Feature Analysis

Intersecting Roads	Feature Type	Feature Present	Detected	Accuracy %
E Fowler Ave & B.B. Downs Blvd	Pedestrian Features			
	Detectable warning mat	15	8	53%
	Ladder crosswalk	8	8	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	4	4	100%
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Features			
	Bike text	0		
	Bicycle symbol	3	3	100%
	Green-colored pavement	4	4	100%
	Shared lane (bicycle)	0		
E Fowler Ave & N Nebraska Ave	Pedestrian Feature			
	Detectable warning mat	8	6	75%
	Ladder crosswalk	4	4	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	0		
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	5	0	0%
	Green-colored pavement	2	1	50%
	Shared lane (bicycle)	0		
E Serena Dr & N 46th St	Pedestrian Feature			
	Detectable warning mat	5	4	80%
	Ladder crosswalk	4	4	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	0		
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	0		
	Green-colored pavement	0		
	Shared lane (bicycle)	5	5	100%

Table 4-1. Hillsborough County Feature Analysis, Continued

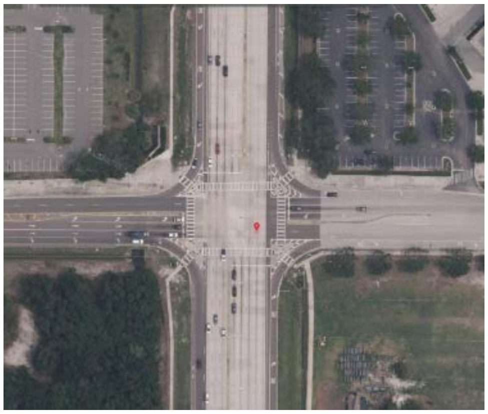
Intersecting Roads	Feature Type	Feature Present	Detected	Accuracy %
E Fowler Ave & N 56th St	Pedestrian Feature			
	Detectable warning mat	16	9	56%
	Ladder crosswalk	8	8	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	4	4	100%
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	6	7	117%
	Green-colored pavement	4	1	25%
	Shared lane (bicycle)	0		
W Waters Ave & Sheldon Rd	Pedestrian Feature			
	Detectable warning mat	8	5	63%
	Ladder crosswalk	4	4	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	0		
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	5	4	80%
	Green-colored pavement	2	2	100%
	Shared lane (bicycle)	0		
W Tampa Bay Blvd & N Dale Mabry Hwy	Pedestrian Feature			
	Detectable warning mat	16	15	94%
	Ladder crosswalk	8	8	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	4	4	100%
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	4	4	100%
	Green-colored pavement	0		
	Shared lane (bicycle)	2	2	100%

Table 4-1. Hillsborough County Feature Analysis, Continued

Intersecting Roads	Feature Type	Feature Present	Detected	Accuracy %
N Ashley Dr & E Polk St	Pedestrian Feature			
	Detectable warning mat	6	5	83%
	Ladder crosswalk	5	5	100%
	Longitudinal bar crosswalk	1	1	100%
	Pedestrian island	2	2	100%
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	0		
	Green-colored pavement	0		
	Shared lane (bicycle)	0		
W Hillsborough Ave & Sheldon Rd	Pedestrian Feature			
	Detectable warning mat	4	0	0%
	Ladder crosswalk	6	3	50%
	Longitudinal bar crosswalk	0	3	
	Pedestrian island	2	2	100%
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	0		
	Green-colored pavement	0		
	Shared lane (bicycle)	0		
E Brandon Blvd & Kingsway Rd	Pedestrian Feature			
	Detectable warning mat	4	2	50%
	Ladder crosswalk	4	4	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	0		
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	2	2	100%
	Green-colored pavement	0		
	Shared lane (bicycle)	0		

Table 4-1. Hillsborough County Feature Analysis, Continued

Intersecting Roads	Feature Type	Feature Present	Detected	Accuracy %
US-41 & E College Ave	Pedestrian Feature			
	Detectable warning mat	8	0	0%
	Ladder crosswalk	4	4	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	0		
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	5	5	100%
	Green-colored pavement	0		
	Shared lane (bicycle)	0		

A similar analysis was conducted for Pinellas County with an accuracy of feature extraction varying from 50% to 100%. The majority of feature types were detected with 100% accuracy. Table 4-2 presents the results of this analysis. Based on the sample analysis conducted at 20 intersections, the feature extraction service from Vexcel shows promising results. It can be used to identify pavement markings with a low-quality score that need immediate repainting.

Table 4-2. Pinellas County Feature Analysis

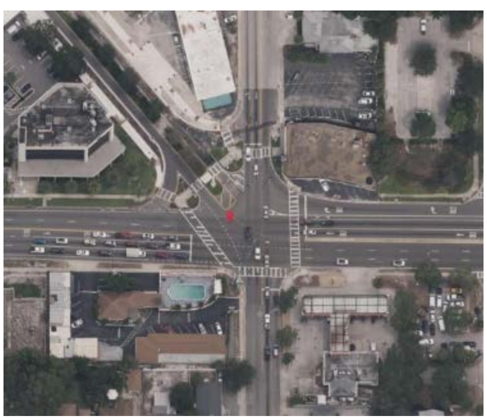
Intersecting Roads	Feature Type	Feature Present	Detected	Accuracy %
Gulf to Bay Blvd & Court St	Pedestrian Feature			
	Detectable warning mat	14	13	93%
	Ladder crosswalk	8	8	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	3	3	100%
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	2	2	100%
	Green-colored pavement	0	1	
	Shared lane (bicycle)	0		

Table 4-2. Pinellas County Feature Analysis, Continued

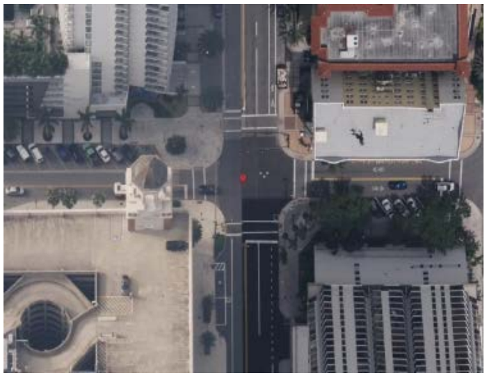
Intersecting Roads	Feature Type	Feature Present	Detected	Accuracy %
Central Ave & 1st St E	Pedestrian Feature			
	Detectable warning mat	8	6	75%
	Ladder crosswalk	0		
	Longitudinal bar crosswalk	0		
	Pedestrian island	0		
	Solid crosswalk	0		
	Transverse crosswalk	4	4	100%
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	2	1	50%
	Green-colored pavement	0		
	Shared lane (bicycle)	4	4	100%
Central Ave & 31st St N	Pedestrian Feature			
	Detectable warning mat	8	7	88%
	Ladder crosswalk	0		
	Longitudinal bar crosswalk	0		
	Pedestrian island	0		
	Solid crosswalk	4	2	50%
	Transverse crosswalk	0	2	
	Bicycle Feature			
	Bicycle symbol	0		
	Green-colored pavement	0		
	Shared lane (bicycle)	2	2	100%
Gulf Blvd & 5th Ave	Pedestrian Feature			
	Detectable warning mat	6	5	83%
	Ladder crosswalk	4	4	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	0		
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	2	2	100%
	Green-colored pavement	1	1	100%
	Shared lane (bicycle)	0	0	

Table 4-2. Pinellas County Feature Analysis, Continued

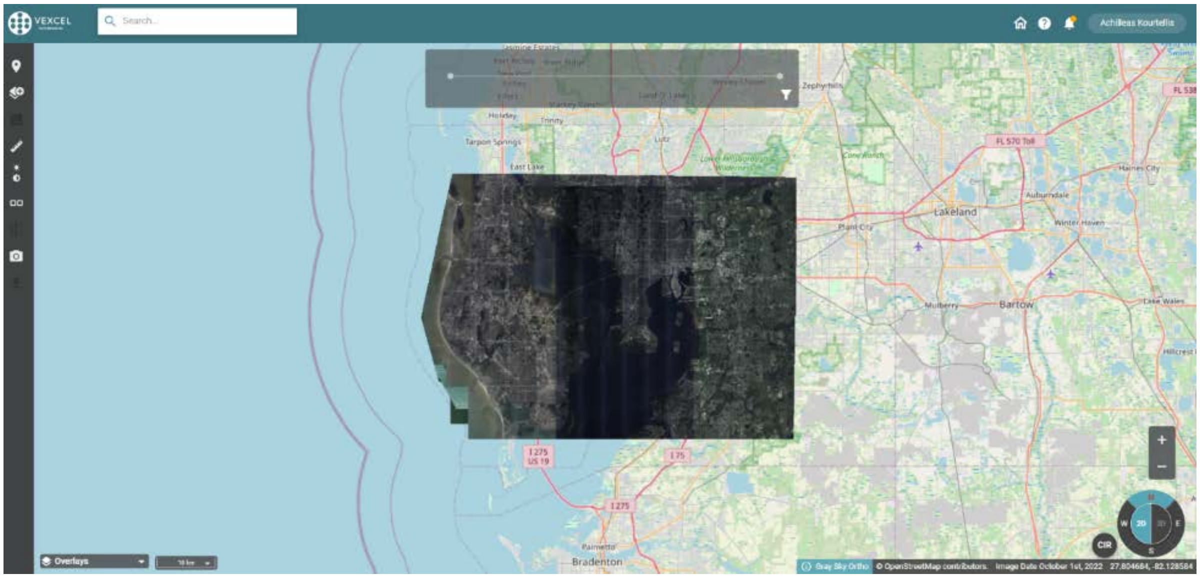
Intersecting Roads	Feature Type	Feature Present	Detected	Accuracy %
Court St & S Missouri Ave	Pedestrian Feature			
	Detectable warning mat	12	7	58%
	Ladder crosswalk	6	6	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	2	2	100%
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	3	3	100%
	Green-colored pavement	0		
	Shared lane (bicycle)	0		
SR 580 & US Hwy 19 N	Pedestrian Feature			
	Detectable warning mat	16	12	75%
	Ladder crosswalk	10	10	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	4	4	100%
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	8	8	100%
	Green-colored pavement	0		
	Shared lane (bicycle)	0		
5th Ave N & 4th St N	Pedestrian Feature			
	Detectable warning mat	9	5	56%
	Ladder crosswalk	5	4	80%
	Longitudinal bar crosswalk	0		
	Pedestrian island	1	1	100%
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	0		
	Green-colored pavement	0		
	Shared lane (bicycle)	0		

Table 4-2. Pinellas County Feature Analysis, Continued

Intersecting Roads	Feature Type	Feature Present	Detected	Accuracy %
Seminole Blvd & Ulmerton Rd	Pedestrian Feature			
	Detectable warning mat	8	8	100%
	Ladder crosswalk	4	4	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	0		
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	0		
	Green-colored pavement	0		
	Shared lane (bicycle)	0		
Curlew Rd & US19N	Pedestrian Feature			
	Detectable warning mat	4	4	100%
	Ladder crosswalk	4	3	75%
	Longitudinal bar crosswalk	0		
	Pedestrian island	0		
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	9	9	100%
	Green-colored pavement	0		
	Shared lane (bicycle)	0		
SR 580 & Race Track Rd	Pedestrian Feature			
	Detectable warning mat	7	4	57%
	Ladder crosswalk	3	3	100%
	Longitudinal bar crosswalk	0		
	Pedestrian island	1	1	100%
	Solid crosswalk	0		
	Transverse crosswalk	0		
	Bicycle Feature			
	Bike text	0		
	Bicycle symbol	6	6	100%
	Green-colored pavement	1	1	100%
	Shared lane (bicycle)	0		

4.5 Acquisition of Complete Aerial Imagery Dataset

Following the work described in Section 2 and review of the acquired data sample, the CUTR team acquired the entire aerial imagery dataset and all roadway features inside the study area shown in Figure 4-14.



Source: Vexcel Imaging, Inc.

Figure 4-14. Study area coverage based on acquired aerial imagery

The final dataset extracted from images collected in February 2023 included 173,362 roadway features, out of which 55,781 are relevant for the focused study on pedestrian and bicycle features as described in the previous section. The highlighted cells in Table 4-3 show the features the CUTR team used for this study.

Table 4-3. Full Dataset Roadway Feature Count

Feature Category	Count
ADA	**30,705**
Accessibility symbol (wheelchair)	5,562
Detectable warning mat	25,143
Arrow	**62,677**
Lane reduction arrow	865
Left turn arrow	28,155
Left/right arrow	140
Right turn arrow	10,558
Straight arrow	20,771
Straight/left arrow	922
Straight/right arrow	1,037
Three-way arrow	61
U-turn arrow	168

Table 4-3. Full Dataset Roadway Feature Count, Continued

Feature Category	Count
Bicycle	**11,089**
Bicycle symbol	7,963
Green-colored pavement	529
Shared lane (bicycle)	2,597
Crosswalk	**18,481**
Ladder crosswalk	11,498
Longitudinal bar crosswalk	3,096
Solid crosswalk	1,277
Transverse line crosswalk	2,610
Intersection-junction	**1,539**
Pedestrian island	1,068
Roundabout	471
Railroad	**711**
Railroad crossing	664
Railroad crossing extended	47
Stop	**31,498**
Stop line	31,283
Yield line	215
Symbol	**302**
Double chevron	81
Other symbol	221
Text	**16,360**
BIKE text	33
BUS text	389
ONLY text	4,401
Other text	7,372
SCHOOL text	1,494
SCHOOL text extended	403
STOP text	2,199
YIELD text	69
Grand Total	**173,362**

In addition, based on the quality score provided by Vexcel, Table 4-4 shows the breakdown of four types of crosswalks and their quality score based on the Vexcel methodology presented in section 3.1. From the preliminary analysis, six percent of crosswalks have poor condition, 22 percent have fair condition, 34 percent have acceptable condition, and 38 percent have good condition.

Table 4-4. Crosswalk Quality Ranking in Vexcel Dataset

Feature Type/Name	Poor Condition (1)	Fair Condition (2)	Acceptable Condition (3)	Good Condition (4)	Grand Total
Crosswalk					
Ladder crosswalk	495	2,436	4,162	4,405	11,498
Longitudinal bar crosswalk	251	826	880	1,139	3,096
Solid crosswalk	126	284	486	381	1,277
Transverse line crosswalk	233	520	731	1,126	2,610
Grand Total	**1,105**	**4,066**	**6,259**	**7,051**	**18,481**
Percent of Total	**6%**	**22%**	**34%**	**38%**	**100%**

The Vexcel service can provide data for all available image timelines between 2013 and 2023.

4.6 Summary

In this task, the CUTR team set out to obtain aerial imagery data via a data service with feature extraction using AI and ML tools. Leveraging aerial imagery data from Vexcel Imaging, Inc., the CUTR team employed their AI- and ML-powered tools to identify the presence of roadway elements, including crosswalks, detectable curb mats, pedestrian islands, bike text, bicycle symbol, green-colored pavement (bicycle lanes), and shared bicycle lane. In addition, the crosswalks include a quality score ranging from 1 to 4, which indicates the condition of the paint. Worn or faded markings have a poor-quality score and indicate a need for immediate remediation.

The CUTR team first performed a crash analysis to identify the area required for feature extraction and worked with the vendor to obtain a data agreement and a sample of the data. Analysis of a sample of intersections (10 in Hillsborough County and 10 in Pinellas County) showed the accuracy of the feature extraction. The results showed that the crosswalk detection had the highest accuracy (100%) and was suitable for quality analysis. Other features vary in accuracy.

The CUTR team also reviewed the data for quality and to understand its content, format, type, and coverage, in collaboration with the big data service provider.

The CUTR team used the acquired data to proceed with an in-depth analysis in subsequent tasks and conduct a benefit-cost analysis of acquiring, using, and retaining this type of big data for future FDOT use.

5 Data Analysis and Crash-Marking-AADT Relationship

In this section, the research team at CUTR works on developing an approach to enhance road safety by delving into pedestrian and bicycle crash data alongside examining faded markings. The initial phase involves data preparation, where datasets undergo rigorous cleaning and organization to ensure accuracy and reliability. Following this, the CUTR team develops data analysis methods and modeling techniques tailored to discern the patterns and trends within the collected data. This analytical framework facilitates a comprehensive comparison of the characteristics in pedestrian and bicycle crash data against faded markings, shedding light on potential correlations and disparities that may influence road safety outcomes.

Three separate subtasks are included in the main objective and are crucial to the research project. Initially, the CUTR team performed a thorough analysis of the features present in crash data involving bicycles and pedestrians to identify the main contributing variables to these incidents. The faded markings were examined in detail, and their effect on road safety, as well as any trends or correlations with crash data were assessed. To provide insights that can guide targeted actions and legislative activities aimed at enhancing pedestrian and bicyclist safety on roadways, the CUTR team researches the relationship between these two crucial sets of safety data. With a careful combination of modeling, data preparation, and analysis, this task seeks to deliver practical insights that can lead to the development of a more sustainable and safe transportation infrastructure.

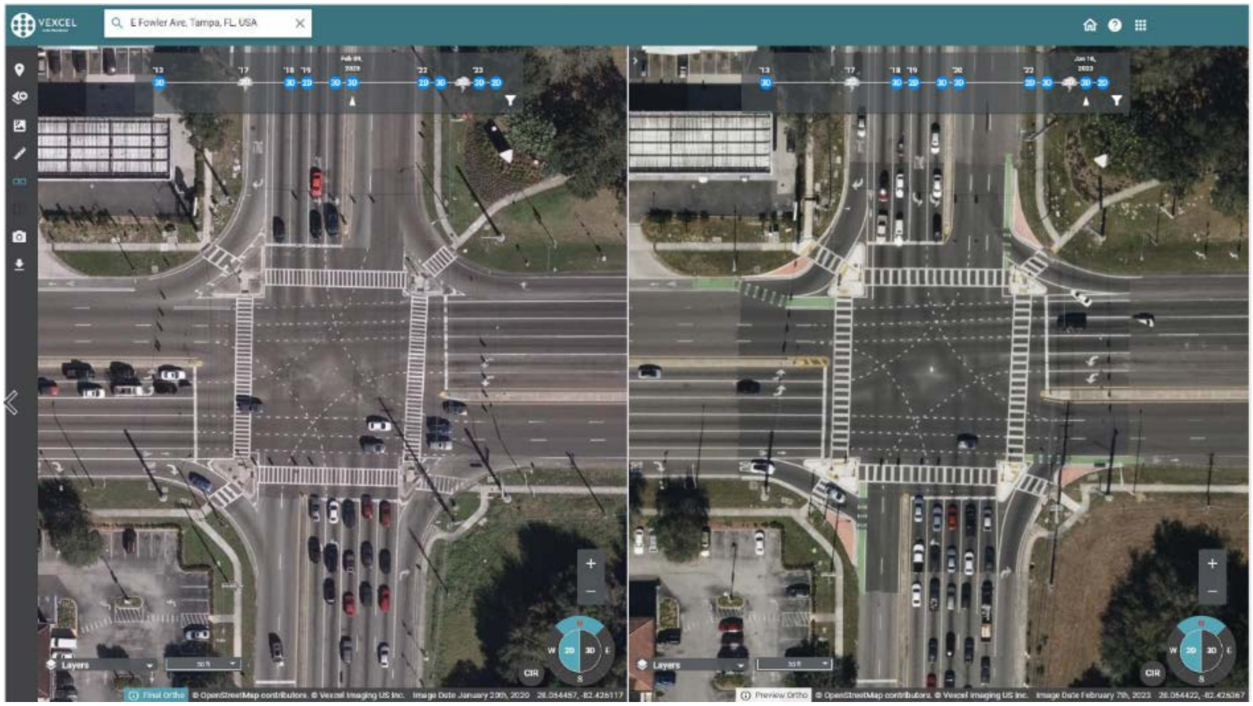
5.1 Data Preparation

To complete the analysis, the CUTR team followed a thorough collection and organizing process, using information from various sources to improve the analysis. This section outlines the data collected and the procedures followed to prepare the data for analysis.

5.1.1 Roadway Features

As mentioned in the previous task deliverable, the CUTR team utilized roadway feature data extracted from aerial imagery collected from Vexcel Imaging, Inc. The data service provider uses machine learning to extract roadway features from the images they take. The team reviewed a sample of this data and established an understanding on the format, coverage, and accuracy.

Figure 5-1 displays an example of the raw imaging data viewer. The image shows two different timelines at the intersection of E. Fowler Ave and Bruce B. Downs Blvd in the City of Tampa. The web-based Vexcel Viewer allows users to examine and analyze images, such as this example from 2020 (left) and 2023 (right). This tool allows users to compare differences between the two timelines and observe changes that have occurred over time.



Source: Vexcel Imaging, Inc.

Figure 5-1. The imagery data viewer from Vexcel Imaging, Inc.

As part of this project, the team acquired roadway features for the study area shown in Figure 5-2.

Table 5-1 displays the selected pedestrian and bicycle features extracted from Vexcel in February 2023. To enable a comparison, data from both 2020 and 2023 were collected for the analysis. The difference in the counts is likely due to additional features in the year 2023 or due to the accuracy of the feature extraction algorithm.

Table 5-1. Roadway Feature Count

Feature Category	2020 Count	2023 Count
Bicycle	10,688	11,089
Bicycle symbol	8,048	7,963
Green-colored pavement	164	529
Shared lane (bicycle)	2,476	2,597
Crosswalk	16,734	18,481
Ladder crosswalk	9,150	11,498
Longitudinal bar crosswalk	3,275	3,096
Solid crosswalk	1,926	1,277
Transverse line crosswalk	2,383	2,610

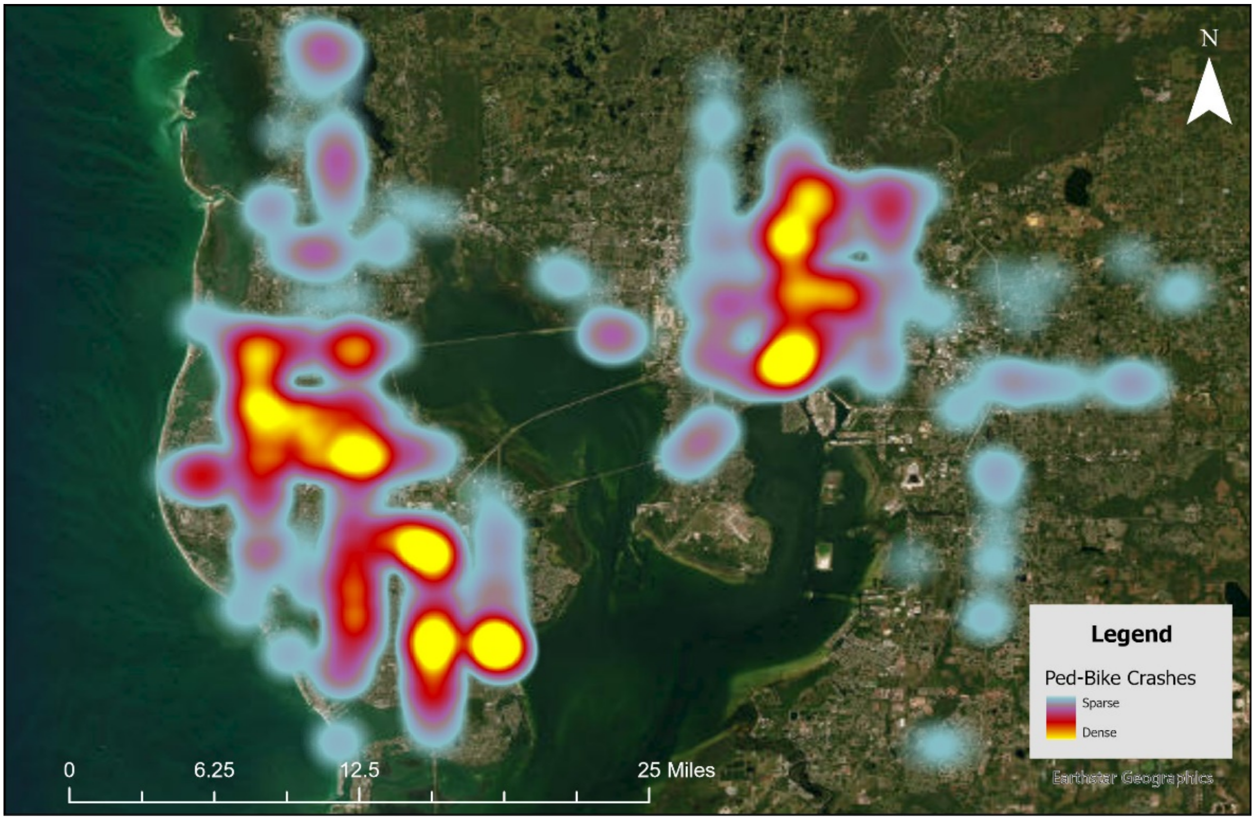
5.1.2 Crash Data

Crash data involving pedestrians and bicyclists were extracted from Signal 4 Analytics for 2020 and 2023. These two years had available roadway features, allowing the use of consistent crash data for analysis and comparison between the two timelines.

After filtering pedestrian and bicycle crashes to include only those at intersections within the study area, 665 crashes were identified—278 in Pinellas County and 387 in Hillsborough County. The highest percentage of crashes resulted in non-incapacitating injuries (39.9%), followed by possible injuries (31.9%). Incapacitating injuries and fatal crashes together accounted for 14.4% of all crashes. Table 5-2 provides a breakdown of crash locations and injury severity, while Figure 5-3 presents a heat map of pedestrian and bicyclist crashes.

Table 5-2. Pedestrian and Bicycle Crashes Included in Analysis

Year	2020	2023	Total
Pinellas County	144	183	327
Hillsborough County	134	204	338
Total	278	387	665 (100%)
No Injury	41	51	92 (13.8%)
Possible Injury	95	117	212 (31.9%)
Non-Incapacitating Injury	101	164	265 (39.9%)
Incapacitating Injury	31	45	76 (11.4%)
Fatal	10	10	20 (3.00%)



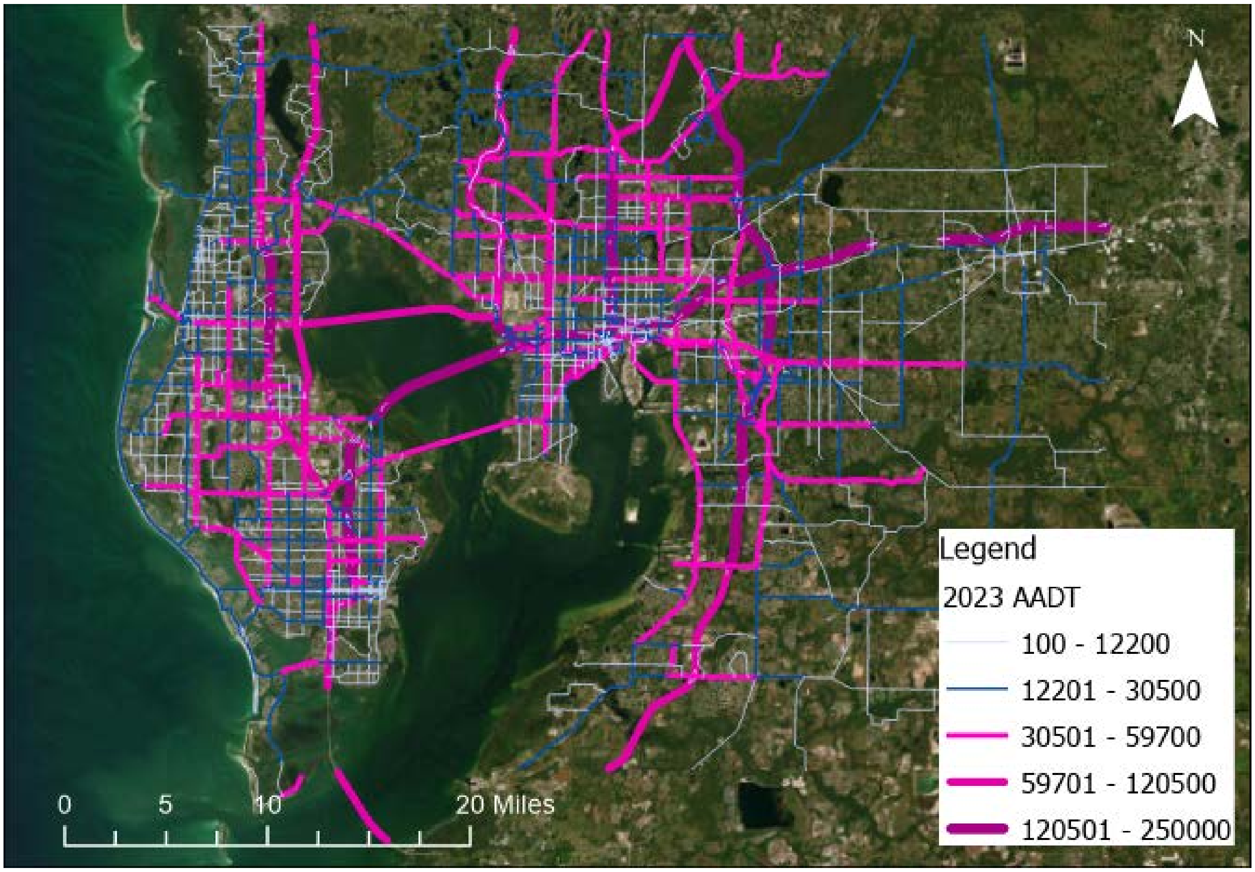
Source: CUTR

Figure 5-2. Heat map of pedestrian and bicycle crashes used in the analysis

5.1.3 Annual Average Daily Traffic

As mentioned in the scope, it is expected that the roadway markings (especially crosswalks that traverse the direction of travel) are worn when a large volume of vehicles travel over them. To add this dimension to the analysis, the annual average daily traffic (AADT) values for 2020 and 2023 for all major roads in the study area were extracted from FDOT's Data Hub AADT layer[1]. Figure 5-3 displays the color-coded 2023 AADT values for roadways in the study area. A similar map was created for the 2020 AADT values.

[1] https://gis-fdot.opendata.arcgis.com/datasets/ceb698fb86d446c08f0b8e54acab6293/explore?location=27.665932%2C-83.790008%2C6.77



Source: CUTR

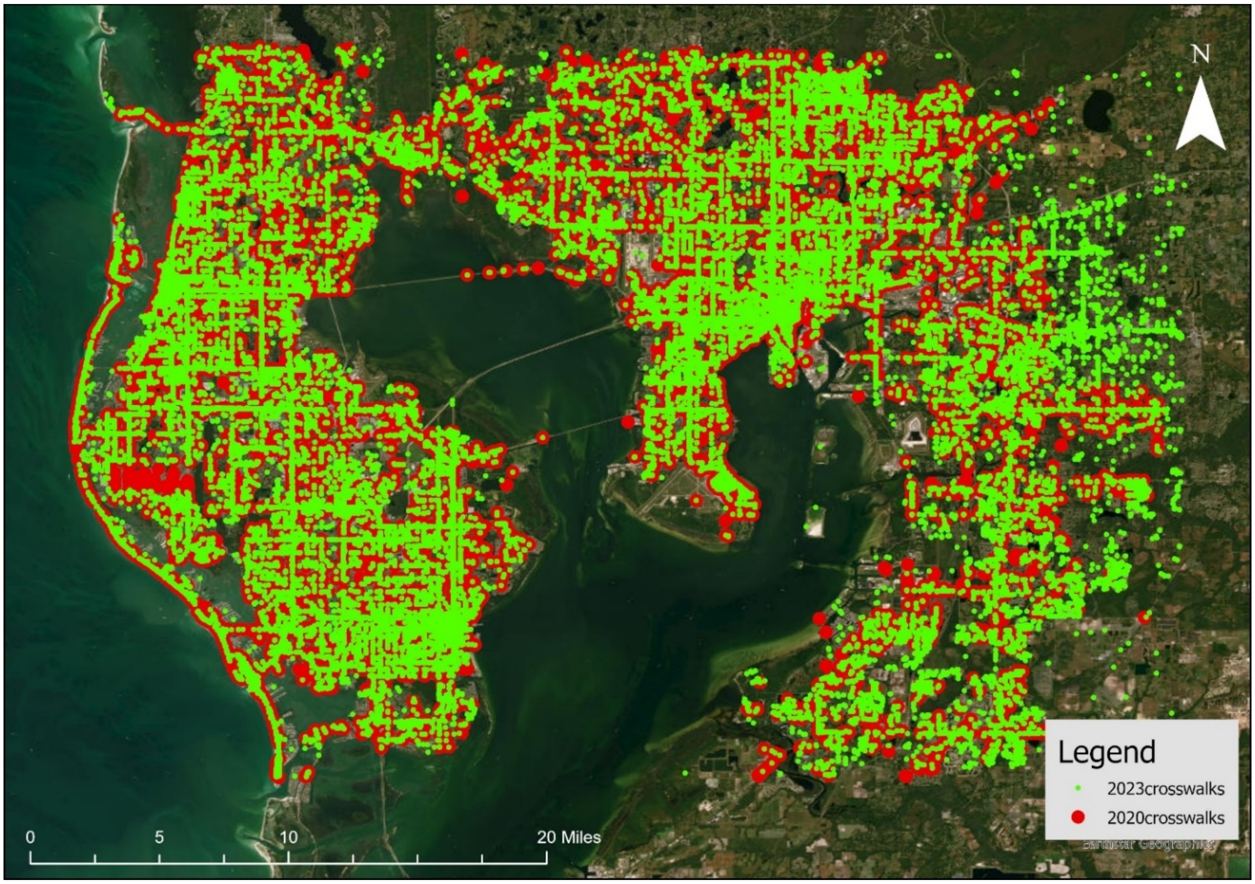
Figure 5-3. Map of 2023 AADT data used in the analysis

5.2 Analysis of Relationship between Crashes and Marking Visibility and AADT

Determining the relationship between pavement markings and crash data involving pedestrians and bicycles requires an organized method for analyzing and interpreting data. The CUTR team assessed the characteristics of bicycle and pedestrian crash data against pavement marking conditions to identify any relationships. This investigation looks at the location, type, and crash severity against pavement marking quality.

5.2.1 Methodology

The process began by identifying the crosswalks common to both 2020 and 2023 datasets. As shown in Figure 5-4, not all crosswalks were consistently identified across the two years. This discrepancy can be attributed to the imagery captured by Vexcel and the precision of the feature extraction algorithms. A total of 16,734 crosswalks were identified exclusively in 2020 and 18,481 in 2023. Following the matching procedure between the two years, 13,638 crosswalks were identified as common between the 2020 and 2023 datasets.



Source: CUTR

Figure 5-4. Crosswalks identified using Vencel's feature extraction service

After identifying the crosswalks common to both years, the change in pavement marking quality ratings was calculated. As mentioned in the Task 2 deliverable, Vexcel provides a quality marking rating to the crosswalks on a scale of 1 to 4, where 1 indicates poor, 2 indicates fair, 3 indicates acceptable, and 4 indicates good. By subtracting the 2020 quality ratings from the 2023 ratings, a scale of three possible outcomes was generated: negative, no change, and positive change. An example of the crosswalk quality rating change is shown in Table 5-3. It is important to acknowledge that some degree of error exists due to the limitations in the accuracy of the algorithm when assigning pavement marking quality ratings.

Table 5-3. Examples of Crosswalk Quality Rating Changes

Value in 2020	Value in 2023	Quality Rating Change
4 – good	1 – poor	-3 (decreased 3 units of quality)
4 – good	4 – good	0 (no change in quality)
1 – poor	4 – good	+3 (increased 3 units of quality)

The three categories are explained below with examples:

1. If a crosswalk had a 4 – good quality in 2020 and a 1 – poor quality in 2023, it means the change is a loss of three units of quality between the three years and is associated with a negative change. This can happen with any combination of values.
2. If a crosswalk had a 4 – good quality in 2020 and a 4 – good quality in 2023, it means the crosswalk remained with the same quality and is associated with a change of zero. This can happen with other values.
3. If a crosswalk had a 1 – poor quality in 2020 and a 4 – good quality in 2023, it means it increased by three units, possibly due to a repainting of the crosswalk, and is associated with a positive change. This can happen with any combination of values.

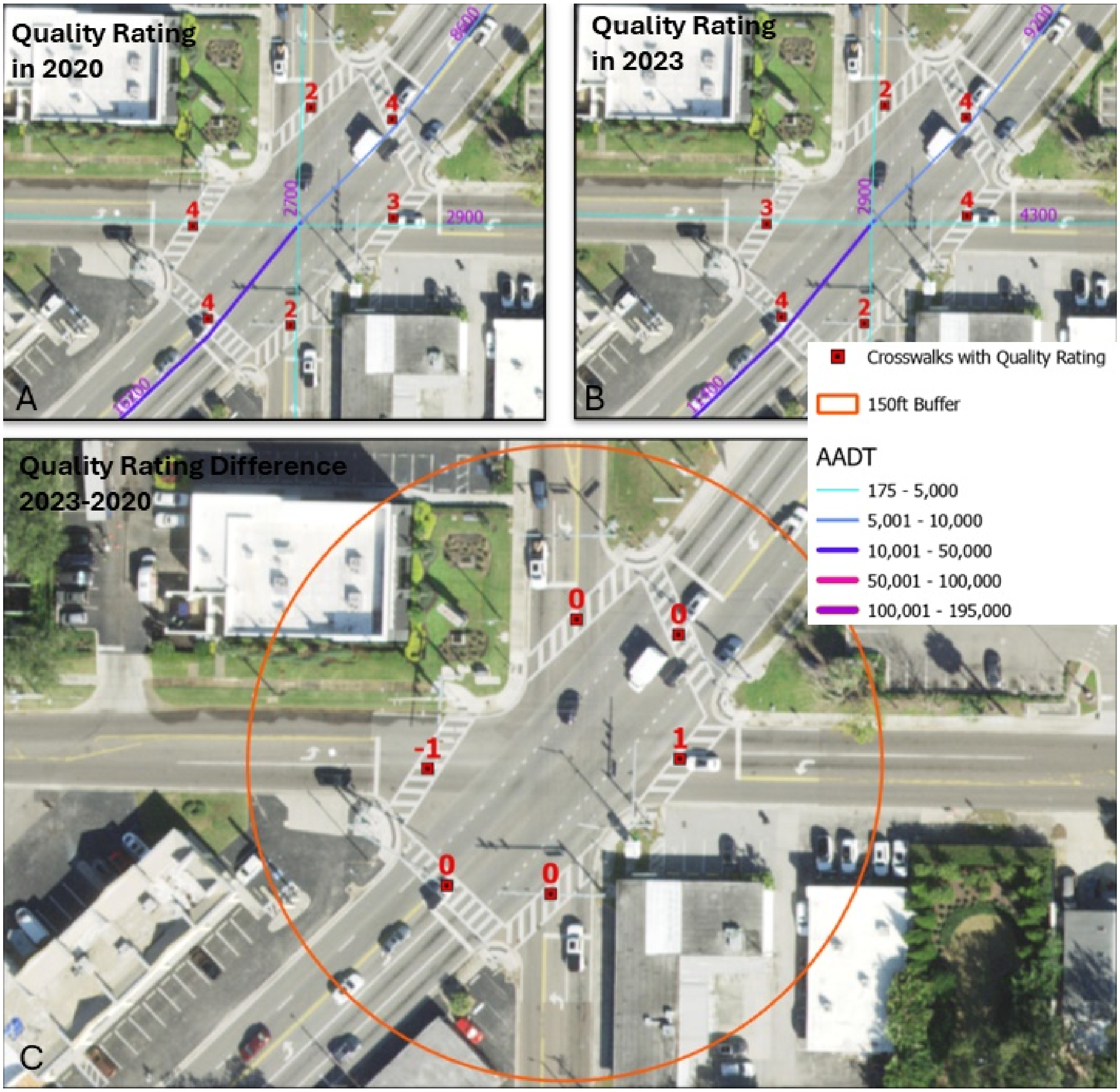
Among 13,638 crosswalks identified in 2020 and 2023, approximately 48% showed no change in quality, 35.4% experienced a decrease in quality (marking faded), and 16.4% showed an increase in quality (marking improved). A significant portion of the changes were minor, with 27.3% of crosswalks decreasing by only one point and 11.2% increasing by one point. Altogether, 86.6% of the crosswalks either showed no change or had a minimal one-point difference. Detailed statistics are provided in Table 5-4.

Table 5-4. Crosswalk Quality Change between 2020 and 2023

Crosswalk Marking Quality Change	Change in Quality Rating (2023-2020)	Count	%
Marking faded	-3	94	0.7
	-2	1,012	7.4
	-1	3,726	27.3
Marking remained the same	0	6,566	48.1
Marking improved (likely repainted)	1	1,525	11.2
	2	613	4.5
	3	102	0.7
	Total	**13,638**	**100**

After the 2020 and 2023 crosswalk matching process, AADT values for both years were assigned to the corresponding crosswalks. Crosswalks that could not be matched to a roadway with AADT data were excluded from the analysis. Additionally, crosswalks located in parking lots were also excluded to ensure that only relevant roadway crosswalks were considered.

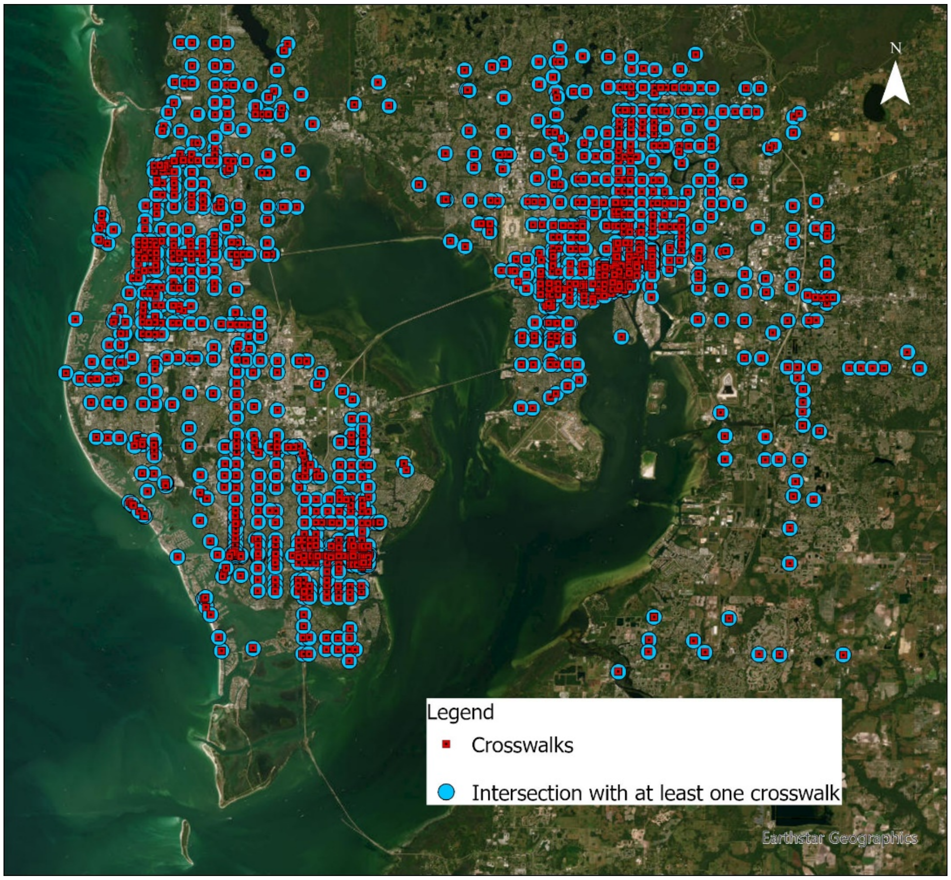
The identified crosswalks were assigned to the intersections. Each crosswalk was linked to an intersection if it was located within a 150-foot radius of that intersection. Figure 5-5 shows crosswalks quality rating and AADT for 2020 (Figure A), 2023 (Figure B), and the changes in quality ratings between the two years and a 150-foot buffer used to assign crosswalks to the intersection (Figure C).



Source: CUTR

Figure 5-5. Example of an intersection with crosswalk quality rating and AADT: (A) 2020 AADT and crosswalk quality rating, (B) 2023 AADT and crosswalk quality rating (C) Quality rating change (2023-2020) and 150-foot buffer

In this process, 1,211 intersections with at least one crosswalk were identified. Figure 5-6 presents the location of these intersections and 3,927 crosswalks.



Source: CUTR

Figure 5-6. Location of intersections and crosswalks used in the study

Next, the maximum AADT for 2020 and 2023 at each intersection, along with the minimum pavement quality rating, was calculated using the Summary Statistics tool. This step identified the highest traffic volume and the lowest pavement quality rating change for crosswalks at each intersection.

Following this, the total number of crashes occurring within a 250-foot radius of each intersection was summarized and assigned to intersections with at least one crosswalk. Additionally, the maximum injury severity for these crashes was recorded for each intersection. The workflow of this process is illustrated in Figure 5-7.

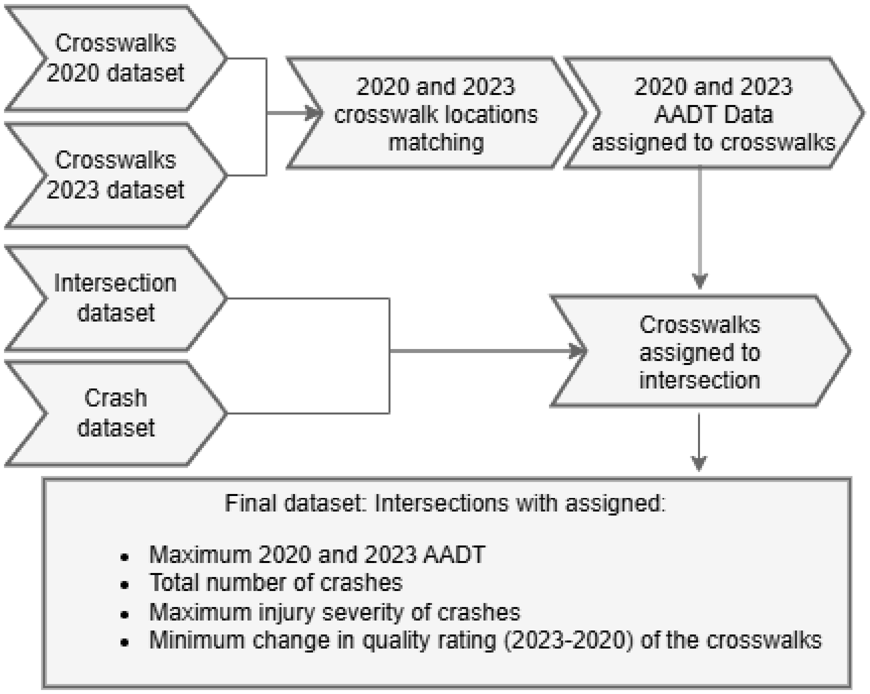


Figure 5-7. Datasets and process workflow

To ensure a comprehensive analysis, the dataset was structured at the intersection level, rather than at the individual crosswalk level. Specifically, for each intersection, the following attributes were recorded: the lowest quality change of all crosswalk markings, the maximum of AADT across all road segments, and the total number of crashes.

The final dataset includes 1,211 intersections with at least one crosswalk. Of these intersections, 436 experienced at least one pedestrian or bicyclist crash. Considering the minimum crosswalk markings quality change, 765 intersections recorded a negative change in pavement rating (faded markings), 350 intersections had no change (no change in marking appearance), and 96 intersections showed a positive change in pavement rating (markings improved).

Next, correlations between the maximum 2020 and 2023 AADT, the minimum crosswalk markings quality change, and number of 2020-2023 crashes were calculated to investigate and understand the relationships between traffic volume, crosswalk safety, and crash occurrences. A categorical variable was created to split the crosswalk ratings into three groups: negative ratings (indicating deteriorated crosswalk conditions in 2023 compared to 2020), positive ratings (indicating improved crosswalk conditions), and ratings with a quality rating value of zero (indicating unchanged crosswalk conditions). This categorization enabled separate correlation analyses for each crosswalk condition group, aiming to identify any relationship between crosswalk quality ratings, crashes, and AADT. The goal was to gain deeper insight into how changes in crosswalk conditions may influence safety and traffic patterns.

5.3 Results

The correlation matrix for each of the three categories of pavement marking quality change (negative, zero, positive) was constructed and plotted to examine the relationship between the investigated parameters.

Among the 1,211 analyzed intersections, 765 included at least one crosswalk with a negative change in quality markings (they faded between 2020 and 2023). The correlation results show a weak positive but not statistically significant correlation between pavement quality marking change and crash number. A positive and significant correlation exists between the maximum 2020 and 2023 AADT and crash numbers. A strong positive and significant correlation exists between the maximum injury severity and crash number. The correlation results indicate that with an increase in the AADT, there is an increase in the number of crashes. While the number of crashes increases, the injury severity rises, too. Additionally, there is a strong positive correlation between AADT from 2020 and 2023. A positive correlation also exists for AADT in both years and crash injury severity and a very weak positive correlation between injury severity and crosswalk marking quality rating. Table 5-5 shows the results for crosswalks with a negative quality marking change.

Table 5-5. Pearson Correlation for Faded Pavement Markings

	AADT 2020	AADT 2023	Quality Rating	Injury Severity	Number of Crashes
AADT 2020	1				
AADT 2023	0.978**	1			
Quality Rating	0.037	0.032	1		
Injury Severity	0.193**	0.191**	0.073**	1	
Number of Crashes	0.248**	0.243**	0.071	0.817**	1

**. Correlation is significant at the 0.01 level (2-tailed)

*. Correlation is significant at the 0.05 level (2-tailed)

For 350 intersections with a minimum quality pavement marking rating change of zero (no change between 2020 and 2023), the correlation analysis indicates a positive and significant relationship between maximum AADT (2020 and 2023) and crash numbers and a very strong correlation between the number of crashes and crash maximum injury severity. This correlation aligns with expectations, as roads with higher AADT typically experience more crashes. Additionally, a correlation analysis suggests a very strong positive correlation between AADT for 2020 and 2023 and a positive correlation between injury severity and AADT for 2020 and 2023. The results are shown in Table 5-6.

Table 5-6. Pearson Correlation for Unchanged Pavement Markings

	AADT 2020	AADT 2023	Quality Rating	Injury Severity	Number of Crashes
AADT 2020	1				
AADT 2023	0.976**	1			
Quality Rating	a	a	a		
Injury Severity	0.283**	0.271**	a	1	
Number of Crashes	0.291**	0.273**	a	0.833**	1

**. Correlation is significant at the 0.01 level (2-tailed)
*. Correlation is significant at the 0.05 level (2-tailed)
a. Cannot be computed because at least one of the variables is constant

Finally, for 96 intersections with positive quality marking changes, there is a strong positive correlation between injury severity and the number of crashes and a positive and significant correlation between the maximum AADT for 2020 and 2023 and the number of crashes. There is also a negative, not significant correlation between the pavement markings quality change and the number of crashes, indicating that with the decrease in the pavement quality the number of crashes increases. Additionally, there is a strong positive correlation between AADT values for 2020 and 2023 and a positive correlation between crash injury severity and AADT for 2020 and 2023. Table 5-7 presents the correlation analysis results.

Table 5-7. Pearson Correlation for Repainted Pavement Markings

	AADT 2020	AADT 2023	Quality Rating	Injury Severity	Number of Crashes
AADT 2020	1				
AADT 2023	0.962**	1			
Quality Rating	-0.019	0.017	1		
Injury Severity	0.531**	0.568**	-0.022	1	
Number of Crashes	0.495**	0.532**	-0.057	0.870**	1

**. Correlation is significant at the 0.01 level (2-tailed)
*. Correlation is significant at the 0.05 level (2-tailed)

5.4 Summary and Recommendation

During this task, the research team collected and prepared the data necessary to examine the relationship between crosswalk marking quality in the study area, pedestrian and bicycle crashes, and AADT. The analysis reviewed 1,211 intersections, 3,927 crosswalks, and 665 pedestrian/bicycle crashes in the Tampa Bay area.

The process involved a methodology that started with careful data preparation to guarantee the dependability and quality of the dataset. The CUTR team used mapping and data correlation analysis approaches to examine the relationship between the three variables. Even though the two variables (AADT and crash data) have been examined in the past, the new variable of crosswalk marking quality provided by Vexcel Imaging data service adds an additional layer of investigation. A summary of the relationship between the three variables is provided below.

All intersections including faded, no change, and repainted crosswalk markings:

- A very strong positive correlation between the number of pedestrian/bicycle crashes and crash injury severity, indicating that as the number of pedestrian crashes increases, the severity of injuries in those crashes also tends to increase significantly. In other words, locations or conditions with more pedestrian crashes are strongly associated with higher injury severity levels.
- A very strong positive relationship between AADT in 2020 and AADT in 2023, indicating that as AADT in 2020 increases, AADT in 2023 also increases in nearly the same proportion. In other words, locations with higher traffic volumes in 2020 generally continued to have higher traffic volumes in 2023, and vice versa for lower volumes.
- A moderate (for repainted crosswalk markings) and weak (for faded and no change crosswalk markings) positive correlation between the number of pedestrian/bicyclist crashes and the maximum AADT, suggesting a tendency for the number of crashes to increase as AADT increases.

Intersections with faded crosswalk markings:

- Positive and significant correlation between faded markings and injury severity; in other words, as crosswalks experience faded markings, the injury severity increases.
- Positive but not significant correlation between faded markings and crashes; in other words, the more faded markings, the more crashes might be experienced.

Intersections with repainted crosswalk markings:

- A very weak negative correlation between repainted crosswalks and number of pedestrian/bicycle crashes, indicating that the intersections with repainted crosswalks might experience slightly fewer crashes.

The team recommends that FDOT use the marking quality data to target crosswalks that need immediate repainting. The method can target specific crosswalks or intersections that have faded markings for over two cycles and is accurate enough to represent only the crosswalks and intersections that need attention. This approach allows for quicker and more timely rehabilitation of the crosswalk markings.

Repainting pavement markings is crucial for the effective operation of autonomous vehicles (AVs) and advanced driving assistance systems (ADAS). These systems rely heavily on clear, visible road markings to navigate safely and accurately. Faded or poorly maintained markings can lead to misinterpretation of the road layout, potentially causing navigation errors or unsafe driving conditions. By ensuring that pavement markings are consistently repainted and highly visible, FDOT can provide well maintained roads, which in turn enhance traffic safety, reduce human error, and pave the way for a future with more reliable and efficient autonomous transportation.

Moreover, clear and well-maintained road markings contribute to a sense of order and safety for all road users. They make the road look well-cared-for and professionally managed, which can boost drivers' confidence and comfort. When people see crisp, bright markings, they are more likely to feel secure and trust that the road is safe to travel on, enhancing the overall driving experience.

Providing practical recommendations for FDOT is a key goal of this project. The research findings help guide focused infrastructure upgrades and safety precautions by identifying regions of poor or subpar pavement markings that are associated with increased crash rates. The team intends for the findings to be used in future FDOT restriping planning.

6 Evaluating Big Data for Transportation Applications

In this section, the research team investigated the ability, availability, and affordability of using big data to address safety issues cost-effectively and proactively for transportation agencies and provided findings and recommendations. The evaluation of the use of imagery data with AI tools can be used as a case study as described below.

6.1 Investigating the Ability of Big Data

Section 4.3 illustrates how big data, specifically aerial imagery combined with AI and ML tools, demonstrates the ability to detect critical roadway features accurately. AI tools provided by Vexcel Imaging were able to analyze pavement marking quality (rated on a scale of 1 to 4), detect crosswalks, and evaluate intersections for ADA compliance. This capability allows transportation agencies to proactively identify high-risk areas where faded or missing markings might pose significant safety risks to pedestrians and cyclists. Section 5 demonstrated that intersections with poor-quality crosswalk markings often had higher crash rates, particularly at high-traffic intersections, thus confirming the ability of imagery data to pinpoint safety vulnerabilities. Specifically:

- **Crosswalk Identification and Quality Scoring**: The imagery data enabled accurate identification of crosswalks, stop bars, and bicycle lanes, key elements for pedestrian and bicycle safety. Task 2 found that AI tools provided quality scores for these features, helping assess crosswalk marking conditions on a scale from 1 (poor) to 4 (good). This rating system allowed for a clear, quantitative method to prioritize repainting, or maintenance based on the degradation of markings, thus enabling proactive safety measures.
- **Detection of ADA-Compliance Features**: The AI-powered feature extraction highlighted ADA compliance elements such as detectable warning mats and pedestrian refuge islands. This capability allows FDOT to identify areas where ADA-compliant facilities might need improvement, directly supporting safer pedestrian crossings, especially for individuals with disabilities.
- **Risk Identification Based on Marking Conditions**: Section 4 used GIS tools to overlay imagery data with crash statistics, which revealed that intersections with faded or low-visibility markings were correlated with higher rates of pedestrian and bicycle crashes. This insight underscores the ability of big data to identify high-risk locations and target those for maintenance, helping FDOT address safety concerns cost-effectively.
- **Broad Coverage with Consistent Data Quality**: The Vexcel service collects data across wide geographic areas bi-annually or more frequently, ensuring that intersections and high-traffic locations are consistently monitored. This systematic data collection approach supports FDOT’s ability to maintain an up-to-date overview of roadway conditions, which is critical for proactive safety interventions.

6.2 Investigating the Availability of Data

The availability of high-resolution aerial imagery data was thoroughly assessed in Task 2, focusing on its quality, frequency, and geographical coverage. The findings indicate that this data is sufficiently comprehensive to support FDOT's needs for pedestrian and bicycle safety analysis across a broad area of interest.

The Vexcel Imaging service provided expansive coverage tailored to high-crash areas in Hillsborough and Pinellas Counties. Section 4 and 5 findings show that this imagery data can be strategically targeted to cover both high-density urban areas and critical rural intersections, ensuring comprehensive data availability in locations with elevated pedestrian and bicycle activity. This flexibility allows FDOT to focus on areas most in need of safety analysis, enhancing the relevance of data collection for infrastructure improvement efforts.

Vexcel Imaging's bi-annual data collection frequency, with options for more frequent updates, ensures that FDOT has access to up-to-date visual information on pavement markings, crosswalks, and other roadway features. Sections 4 and 5 highlighted that the semi-annual updates are sufficient to monitor changes in pavement and marking conditions over time, enabling FDOT to detect feature degradation promptly. This data frequency supports proactive maintenance by allowing for timely identification and intervention at critical locations, minimizing the likelihood of potential safety hazards for vulnerable road users.

The high resolution (7.5 cm or better GSD) of Vexcel' s imagery data allows for precise analysis of roadway elements. Task 2 found that the detail captured by this data supports the identification of small but critical features, such as various crosswalk types, ADA compliance elements, and bicycle lane markings. The high quality of these images ensures that FDOT can rely on accurate, detailed data to make informed decisions about maintenance priorities and infrastructure updates, enhancing the reliability of transportation safety strategies.

While FDOT maintains its own data sources, Sections 4 and 5 demonstrated that Vencel's high-resolution imagery serves as a valuable supplement to existing in-house data. The enhanced level of detail, regular updates, and specific targeting capabilities of Vexcel' s data bridge potential gaps in FDOT's traditional data collection. This integration of external imagery with internal datasets ensures a more comprehensive and current overview of roadway conditions, especially in high-priority areas where data is crucial for proactive safety management.

6.3 Data Integration with FDOT Systems

The previous sections assessed the compatibility and integration potential of high-resolution imagery data and AI-powered feature extraction with FDOT's existing data systems. Findings indicate that the data format, structure, and attributes provided by Vexcel Imaging are well-suited for integration with FDOT's geographic information systems (GIS) and maintenance programs, facilitating seamless data incorporation and enhanced functionality. Key points include:

Vexcel Imaging provides data in widely compatible formats, including JSON and CSV files, as well as GIS-ready shapefiles. These standardized formats allow for straightforward import into

FDOT’s GIS platforms, such as ArcGIS, which is routinely used for transportation analysis and roadway management. The use of these formats minimizes the need for data conversion, thereby reducing processing time and maintaining data accuracy during integration.

The imagery data includes detailed attribute fields that align with FDOT’s data requirements. These fields contain essential information such as location coordinates, feature type, condition ratings, and ADA compliance indicators. This level of detail allows FDOT to incorporate the data directly into existing roadway databases, supporting efficient categorization, filtering, and analysis. Additionally, this alignment with FDOT’s attribute requirements ensures that new data can be layered with in-house datasets for a unified view of roadway conditions.

Vencel’s data includes a quality scoring system for pavement markings and other critical features, using a scale of 1 to 4 that reflects the current condition and visibility of crosswalks, stop bars, and bicycle lane markings. This scoring aligns well with FDOT’s MRP which prioritizes roadway elements based on visibility and wear. Findings from previous tasks suggest that this compatibility allows FDOT to use Vexcel’ s data to complement and enhance the MRP’s manual inspection process, reducing the need for on-site evaluations and enabling more focused, data-driven maintenance planning.

Previous tasks demonstrated that the data integrates well with GIS tools, allowing FDOT to conduct spatial analysis and generate heat maps to visualize high-risk areas, particularly intersections with degraded crosswalk markings or high crash rates. This capability enhances FDOT’s ability to map, track, and analyze pedestrian and bicycle safety across the state, supporting targeted interventions based on data-driven insights.

The structured nature of Vencel’s data, with clearly defined geometry and attribute fields, supports scalability as FDOT’s data needs evolve. Additional features, such as future development of automated assessments for turning radii and sidewalk gaps, could be incorporated into FDOT’s systems with minimal adjustments. This adaptability positions FDOT to expand its data-driven initiatives, including integration with new technologies like automated vehicles and ADAS, which rely on precise, well-maintained roadway markings.

6.4 Investigating the Affordability of Big Data

This section provides an initial assessment of the affordability of using high-resolution aerial imagery and AI/ML tools compared to traditional data collection methods. Both approaches have distinct advantages, and this analysis examines cost, scalability, and operational implications to identify the most effective solution for FDOT’s needs.

- Initial Cost Overview: Big data solutions, such as those offered by Vexcel Imaging, require an upfront investment in data acquisition, subscription fees for periodic updates, and integration costs. These costs enable regular and detailed data collection without the need for manual inspections. In contrast, traditional data collection typically involves ongoing expenses related to field inspections, including personnel, travel, and equipment costs. While traditional methods may have lower initial technology costs, they require sustained funding over time to cover repeated fieldwork and data processing.

- Operational Cost Efficiency: Big data offers the advantage of minimizing field operations by allowing remote assessments of roadway features. AI-driven analysis reduces labor and travel requirements, potentially lowering operational costs in the long term. Traditional methods, however, provide on-the-ground insights that can capture details not always visible in aerial imagery. Field personnel can directly evaluate physical features, which may be essential for certain complex assessments. Although big data solutions present a streamlined approach, traditional methods retain the advantage of firsthand inspection and adaptability to real-time observations.
- Scalability and Geographic Coverage: Big data is highly scalable, covering large or multiple regions without the proportional increase in costs typical of traditional field-based methods. This makes it a viable option for broad coverage, especially in urban areas where transportation infrastructure requires frequent monitoring. Traditional data collection, on the other hand, allows for targeted inspections in specific locations, which may be advantageous for smaller-scale studies or focused safety assessments. The scalability of big data provides extensive reach, while traditional methods offer flexibility for tailored assessments as needed.
- Potential for Proactive Maintenance: Frequent updates from big data providers enable proactive maintenance strategies by identifying early signs of wear in roadway features. This predictive approach supports long-term cost savings by reducing the likelihood of costly repairs due to delayed intervention. Traditional methods, which rely on scheduled inspections, may offer advantages in terms of comprehensive site evaluations but can be limited in their ability to track rapid changes in feature quality. Both methods offer value: big data for ongoing monitoring and traditional approaches for in-depth evaluations at specified intervals.

Both big data and traditional methods have affordability benefits, depending on the scope and objectives of the data collection. Big data upfront costs may be offset by operational savings and proactive maintenance capabilities over time, making it a cost-effective option for large-scale or high-frequency monitoring. Traditional methods, while requiring recurring expenses, provide FDOT with flexibility and on-site verification capabilities that remain critical for certain types of inspections. The following benefit-cost analysis delves further into the quantitative and qualitative aspects, offering a comprehensive view of the long-term financial and operational impacts of each approach.

7 Benefit-Cost Analysis of Using Big Data

This analysis provides a detailed comparison of big data versus traditional methods, considering direct and indirect costs, ROI, and qualitative improvements to transportation safety.

7.1 Cost Analysis

7.1.1 FDOT MRP

The FDOT MRP conducts sample surveys three times a year to assess roadway and roadside conditions. The surveys focus on five main components of limited rural access roadways: roadway conditions, traffic services, roadside features, drainage systems, and vegetation management.

These surveys ensure that infrastructure within the region meets established standards for safety and functionality.

For Fiscal Year 2023-2024, the 2nd Period Report for District 7 (D7) highlights a total coverage mileage of 1,893.82 miles. The mileage is distributed across the district as follows: 737.53 miles in Tampa, 737.476 miles in Brooksville, and 403.824 miles in Pinellas.

$$\text{Per mile cost}=\frac{Total\ Annual\ Cost}{Total\ Miles} \qquad (1)$$

Each survey round incurs a lump-sum cost of $36,500, resulting in an annual cost of $109,500 for three survey rounds. Based on equation (1), the average maintenance evaluation cost is **$19.27** per mile per year.

7.1.2 Aerial Imagery Data

The aerial imagery data service provides a solution at a rate of $10 per mile per year. This service focuses on detailed assessments of bicycle and pedestrian facilities, offering high-resolution data and mapping capabilities for critical infrastructure elements.

The key areas of focus for this service include:

- Identification of Crosswalks: Accurately detects and categorizes crosswalks, including standard and high-visibility markings, at intersections and midblock crossings.
- Bicycle Lane Mapping: Captures and maps bicycle lane infrastructure, including lane symbols, directional words, and green-painted segments to ensure compliance and visibility.
- ADA Compliance and Pedestrian Facilities: Identifies and maps ADA-compliant curb mats, pedestrian refuge islands, and other features designed to enhance accessibility and safety.

This aerial imagery-based approach provides detailed and reliable data that supports infrastructure planning, maintenance, and compliance with safety standards, particularly for non-motorized road users. With its cost-efficient structure, this service complements traditional survey methods by delivering comprehensive, large-scale coverage tailored to modern transportation needs.

The pricing information was obtained from the Vexcel Imagery vendor, as summarized in Table 7-1. Vexcel’ s services offer two imagery resolutions:

- 7.5-cm imagery is updated annually and primarily targets urbanized areas classified by the U.S. Census.
- 15-cm imagery is updated on a 12–30 month cycle and provides broader coverage across the United States.

Table 7-1. Cost and Features Comparison of Vexcel Imagery Products for Roadway Analysis

Product	Annual Subscription Price (2600 km²)	Single Run Cost (960 miles2)	Notes
Vexcel Wide Area 15-cm Imagery (3- and 4-Band Orthos)	$12,740	N/A	Collected every 12–30 months for the entire U.S.; less accurate due to building lean effects.
Vexcel Urban Area 7.5-cm Imagery (4-Band TrueOrtho)	$50,960	N/A	Collected annually for urban areas; it provides the best AI results with True Ortho accuracy.
Vexcel Elements (Roadway Features)	N/A	$9,408	Perpetual license; elements can be run on both 7.5-cm and 15-cm imagery for QA.

Note: 960 miles^2=2486.39 km^2

The 7.5-cm imagery delivers superior AI analysis capabilities due to its higher accuracy, utilizing True Ortho technology. The pricing structure includes access to both historical and newly acquired imagery within the subscription term, ensuring comprehensive and up-to-date data coverage.

The 15-cm imagery, while offering broader coverage due to its 12–30 month collection cycle across the entire U.S., provides a balance between resolution and geographic extent. Although it lacks the True Ortho properties of the 7.5-cm imagery, the 15-cm imagery still maintains higher absolute positional accuracy (X/Y RSME) compared to standard aerial or satellite imagery. This makes it a practical solution for areas where 7.5 cm imagery is not available or required.

Despite detecting fewer elements due to building lean effects, 15-cm imagery remains suitable for general roadway analysis, offering sufficient detail for applications like network-level asset management, intersection prioritization, and broad maintenance planning. The pricing structure for 15-cm imagery includes access to both historical and newly collected datasets, similar to the 7.5-cm imagery, enabling users to analyze trends and changes over time.

In scenarios where cost or coverage is a primary concern, the 15-cm imagery provides an economical alternative, allowing for greater regional analysis without significantly compromising data accuracy for less critical applications. This imagery is especially advantageous for projects requiring large-scale area monitoring, such as rural roadway assessments or statewide transportation planning, where ultrahigh resolution may not be essential.

7.1.3 Data Storage Cost

This section analyzes the estimated data storage costs associated with managing aerial imagery for a study area of approximately 1000 square miles. Depending on the image resolution, the required storage capacity ranges from 1 TB to 4 TB. To determine the most cost-effective storage solution, we compare pricing across three major cloud providers: Google Cloud Storage [39], Amazon S3 [40], and Azure Blob Storage [41].

This analysis evaluates the monthly storage costs, data retrieval fees, and network egress charges for each provider. Additionally, we provide a breakdown of long-term storage costs over a five-year period to guide decision making for large-scale, long-duration projects.

Table 7-2 provides a detailed comparison of monthly storage costs for 1 TB and 4 TB across three major cloud providers: Google Cloud, Amazon S3, and Azure Blob Storage. The table also includes additional fees for data retrieval and network egress to provide a comprehensive view of potential costs.

Table 7-2. Comparison of Cloud Monthly Storage Costs for 1 TB to 4 TB across Major Providers

Provider	Storage Tier	Cost for 1 TB	Cost for 4 TB	Data Retrieval Cost (per GB)	Network Egress Cost (per GB)
Google Cloud	Standard	$26.62	$106.48	$0.01	$0.12 for the first 1 TB
Amazon S3	Standard	$23.55	$94.20	$0.01	$0.09 for the first 10 TB
Azure Blob	Hot	$18.43	$73.72	$0.01 (Cool Tier)	$0.087 for the first 5 GB

To evaluate long-term costs, Table 7-3 and Table 7-4 provide a detailed comparison of five-year incremental storage costs for three major cloud providers, under two distinct data growth scenarios: incremental addition of 1 TB per year and 4 TB per year. Azure Blob Storage consistently offers the lowest total costs over five years.

Table 7-3. Five-Year Incremental Storage Costs for 1 TB Added Annually across Cloud Providers

Year	Data Stored	Google Cloud (Cost)	Amazon S3 (Cost)	Azure Blob (Cost)
1st Year	1 TB	$319.44	$282.60	$221.16
2nd Year	2 TB	$638.88	$565.20	$442.32
3rd Year	3 TB	$958.32	$847.80	$663.48
4th Year	4 TB	$1,277.76	$1,130.40	$884.64
5th Year	5 TB	$1,597.20	$1,413.00	$1,105.80
Total	15 TB	$4,791.60	$4,239.00	$3,317.40

Table 7-4. Five-Year Incremental Storage Costs for 4 TB Added Annually across Cloud Providers

Year	Data Stored	Google Cloud (Cost)	Amazon S3 (Cost)	Azure Blob (Cost)
1st Year	4 TB	$1,277.76	$1,130.40	$884.64
2nd Year	8 TB	$2,555.52	$2,260.80	$1,769.28
3rd Year	12 TB	$3,833.28	$3,391.20	$2,653.92
4th Year	16 TB	$5,111.04	$4,521.60	$3,528.56
5th Year	20 TB	$12,777.60	$11,304.00	$8,846.40
Total	60 TB	$25,555.20	$22,608.00	$17,692.80

7.1.4 Cost and Service Comparison

In this section, the overall cost-effectiveness and service offerings of the FDOT MRP Survey and Vexcel Imagery methods are analyzed, incorporating storage costs and evaluating their suitability for various project requirements.

The price for Vexcel with the study areas is 2600 km^2, an assumed road density of two miles of road per square mile[42], This density is a general estimate for regions with typical U.S. urban infrastructure. To estimate the total road mileage within the study area, multiply the total area (in square miles) by the road density:

Estimated road mileage=1,003 (mi^2) ×2 (miles/mi^2) =2,006 miles

Table 7-5 compares the annual costs, mileage covered, and cost per mile for three methods: FDOT Survey, Vexcel 15-cm imagery, and Vexcel 7.5-cm imagery.

Table 7-5. First Year Cost Comparison of FDOT Survey and Vexcel Imagery Methods

Method	Annual Cost (USD)	Mileage Covered	Cost Per Mile (USD)
FDOT MRP Survey	$109,500	1,893.82 miles	$57.82
Vexcel (15 cm)	$12,961	2,006miles	$6.46
Vexcel (7.5 cm)	$51,844	2,006 miles	$25.85

Table 7-6. Five-Year Cost Comparison of FDOT Survey and Vexcel Imagery Methods

Method	Five-year Cost (USD)	Mileage Covered	Cost Per Mile (USD)
FDOT MRP Survey	$547,500	1,893.82 miles	$57.82
Vexcel (15 cm)	$64,805	2,006miles	$6.79
Vexcel (7.5 cm)	$259,000	2,006 miles	$27.59

The results clearly demonstrate that the Vexcel 15-cm imagery method is the most cost-efficient, offering significant savings compared to the FDOT survey method, with a lower cost per mile and expanded coverage. On the other hand, the Vexcel 7.5-cm imagery offers enhanced precision but at a higher cost, making it suitable for projects where accuracy is critical.

Depending on project needs, 15-cm imagery is recommended for broader roadway assessments, while 7.5-cm imagery is ideal for projects requiring highly detailed analysis. The FDOT survey method, although more expensive, remains a viable option for specific manual evaluation scenarios.

Table 7-7 highlights the differences in coverage and capabilities between the traditional MRP Method and the modern Vexcel Imagery (7.5 cm and 15 cm resolutions). The comparison focuses on the ability of each method to identify and assess key roadways, traffic service, roadside, drainage, and vegetation elements.

Table 7-7. Comparison of Elements Covered by MRP, 7.5-cm, and 15-cm Imagery

Category	Element	MRP Method	Vexcel 7.5 cm Imagery	Vexcel 15 cm Imagery
Roadway	Flexible Pavement Conditions	✓	✓	✓
	Rigid Pavement Conditions	✓	✓	✓
Traffic Services	Raised Markers	✓	✓	✗
	Striping	✓	✓	✓
	Pavement Symbols	✓	✓	✓
	Bicycle lanes (Symbols, Green Lanes)	✗	✓	✓
Traffic Services	Signs	✓	✓	✗
	Object Markers		✓	✗
	Lighting	✓	✓	✗
Roadside	Unpaved Shoulders	✓	✓	✓
	Front Slope Maintenance	✓	✓	✓
	Fences	✓	✓	✗
	Sidewalks	✓	✓	✓

Table 7-7. Comparison of Elements Covered by MRP, 7.5 cm, and 15 cm Imagery, Continued

Category	Element	MRP Method	Vexcel 7.5 cm Imagery	Vexcel 15 cm Imagery
Roadside	Pedestrian Refuge Islands	✗	✓	✓
	Crosswalk Identification	✓	✓	✓
Drainage	Side/Cross Ditches	✓	✓	✓
	Inlets	✓	✓	✗
	Miscellaneous Drainage	✓	✓	✗
	Sweeping	✓	✓	✓
Vegetation	Roadside Mowing	✓	✓	✓
	Slope Mowing	✓	✓	✓
	Landscaping	✓	✓	✓
	Tree Trimming	✓	✓	✓
	Litter Removal	✓	✓	✓
	Turf Condition	✓	✓	✓

The table demonstrates how each method is suited to different project needs:

- **MRP Method**: Best for comprehensive manual assessments across smaller areas.
- **7.5-cm Imagery**: Best for detailed, high-precision projects in urbanized areas.
- **15-cm Imagery**: Best for large-scale, cost-efficient evaluations with moderate detail.

The Vexcel 15-cm imagery offers broader geographic coverage and is the most cost-efficient solution, with a cost of $6.35 per mile per year. However, it lacks the precision of 7.5-cm imagery and struggles with elements that require detailed visual clarity, such as guardrails, signs, and lighting. This makes it ideal for large-scale assessments where cost and coverage take priority over granular detail.

Utilizing the most effective option, assuming Azure Blob Storage for 4 TB (for 7.5-cm imagery) and 1 TB (for 15-cm imagery) over a five-year storage period, Table 7-8 presents a detailed comparison of the five-year costs associated with the FDOT MRP Survey and Vexcel Imagery methods, including subscription and storage costs.

Table 7-8. Five-Year Cost Comparison of FDOT MRP Survey and Vexcel Imagery Methods

Method	Subscription Cost (5 years)	Storage Cost (5 years)	Total Cost
FDOT MRP Survey	$547,500	N/A	$527,500
Vexcel (15 cm)	$63,700	$1,105.8	$64,805.8
Vexcel (7.5 cm)	$254,800	$4,423.2	$259,223.2

Ultimately, the selection of the appropriate method depends on project needs. The MRP method remains suitable for traditional evaluations requiring manual accuracy, while the Vexcel 7.5-cm imagery is the preferred choice for high-resolution urban projects. The Vexcel 15-cm imagery is a practical, cost-effective option for broader roadway assessments with moderate accuracy requirements. Decision-makers can leverage this comparison to balance cost, coverage, and detail in roadway evaluation strategies.

7.2 Benefit Analysis

The benefit analysis evaluates the efficiency, accuracy, coverage, and cost-effectiveness of the three methods (MRP, 7.5-cm Imagery, and 15-cm Imagery) to help decision-makers identify the optimal approach for their specific requirements.

In Task 3, the CUTR team conducted the correlation analysis for AADT, marking quality, and number of crashes; the results show that quality crosswalk marking has a strong positive correlation with AADT, higher traffic volumes, and injury severity are associated with an increase in crashes. Therefore, an increase in marking quality can lead to reduced crashes, improved safety, and cost savings.

In the Tampa AOI analysis area, there are a total of 1,211 intersections. Among these, 246 intersections experienced a quality score (QS) level increase, 462 intersections faced a QS level decrease, and 503 intersections remained unchanged in their QS levels. The crash reduction by QS level is illustrated in Figure 7-1, which captures the relationship between QS level changes and crash reduction values. It displays a heatmap illustrating the change in crash frequency across intersections with varying pavement marking Quality Score (QS) levels between 2020 and 2023. The vertical axis indicates the QS level in 2020, while the horizontal axis shows the QS level in 2023. Each cell represents the average change in the number of crashes, calculated as:

Crash Reduction=Average crash count (2020–2022) −Crash count in 2023

Positive values (shaded in red) reflect a reduction in crashes in 2023 relative to the earlier average, while negative values (shaded in blue) indicate an increase. For example, intersections with a QS improvement from level 1 in 2020 to level 3 in 2023 show an average reduction of approximately 0.19 crashes. In contrast, some QS transitions (e.g., level 3 to 3) show negative values, suggesting more crashes occurred in 2023. The Tampa AOI crash dataset contains a total of 2,404 crashes from 2020–2023. Crash reduction values range from approximately -0.2 to +0.2across the 1,211 intersections.

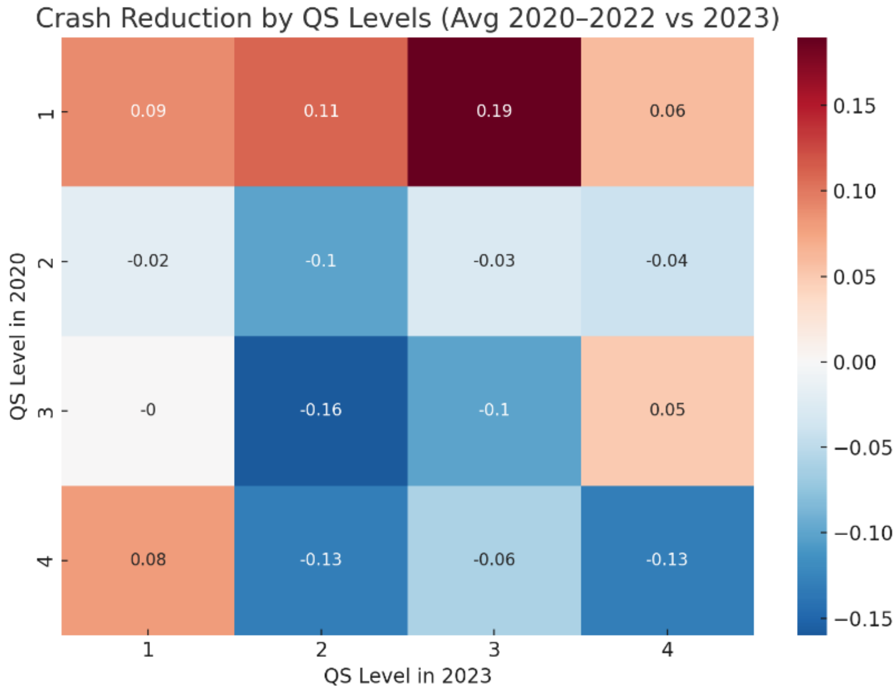


Figure 7-1. Crash reduction by QS level

While the analysis demonstrates a general relationship between marker quality improvements and crash reduction, it is important to recognize several limitations: (1) Not all intersections with QS level increases underwent repainting or upgrades in 2023. Improvements may have occurred earlier, in 2021 or 2022, meaning their effect on the crash number might not fully align with the analyzed timeframe, (2) Some intersections with QS level increases still show higher crash numbers in 2023. This may be due to external factors such as traffic growth, changes in roadway geometry, or increased pedestrian and cyclist activity. This highlights the complexity of isolating QS-related safety effects and the need to consider broader contextual factors when interpreting the results.

A positive crash reduction value (fewer crashes in 2023 compared to the 2020–2022 average) represents a benefit, while a negative crash reduction value (more crashes in 2023) represents a disbenefit. This value is used to monetize crash reduction benefits and disbenefits associated with QS transitions. This however can be skewed since during 2020 the COVID-19 pandemic reduced volume of traffic and crashes.

To estimate the benefit of crash reduction resulting from QS level improvements, this study adopted comprehensive cost values from the National Safety Council [43]. These values include not only direct economic losses (such as medical costs and productivity losses), but also account for quality-of-life impacts. When injury severity breakdowns were not available at the intersection level, national average proportions based on FHWA and NHTSA guidance were used to estimate crash outcomes. Table 7-9 summarizes the average comprehensive cost by injury severity level along with the nationally recommended distribution for crashes.

Table 7-9. Crash Cost and Severity Distribution Reference

Injury Severity	Code	Comprehensive Cost (2023)	Suggested National Proportion
Death	K	$13,705,000	0.004
Disabling	A	$1,112,000	0.05
Evident	B	$242,000	0.15
Possible	C	$132,000	0.25
No Injury	O	$18,000	0.546

By weighing the comprehensive cost per injury type using these proportions, the average comprehensive cost per crash was estimated to be $189,548.

Figure 7-2 and Figure 7-3 illustrate how benefits and disbenefits are distributed across QS transitions and intersection categories, respectively.

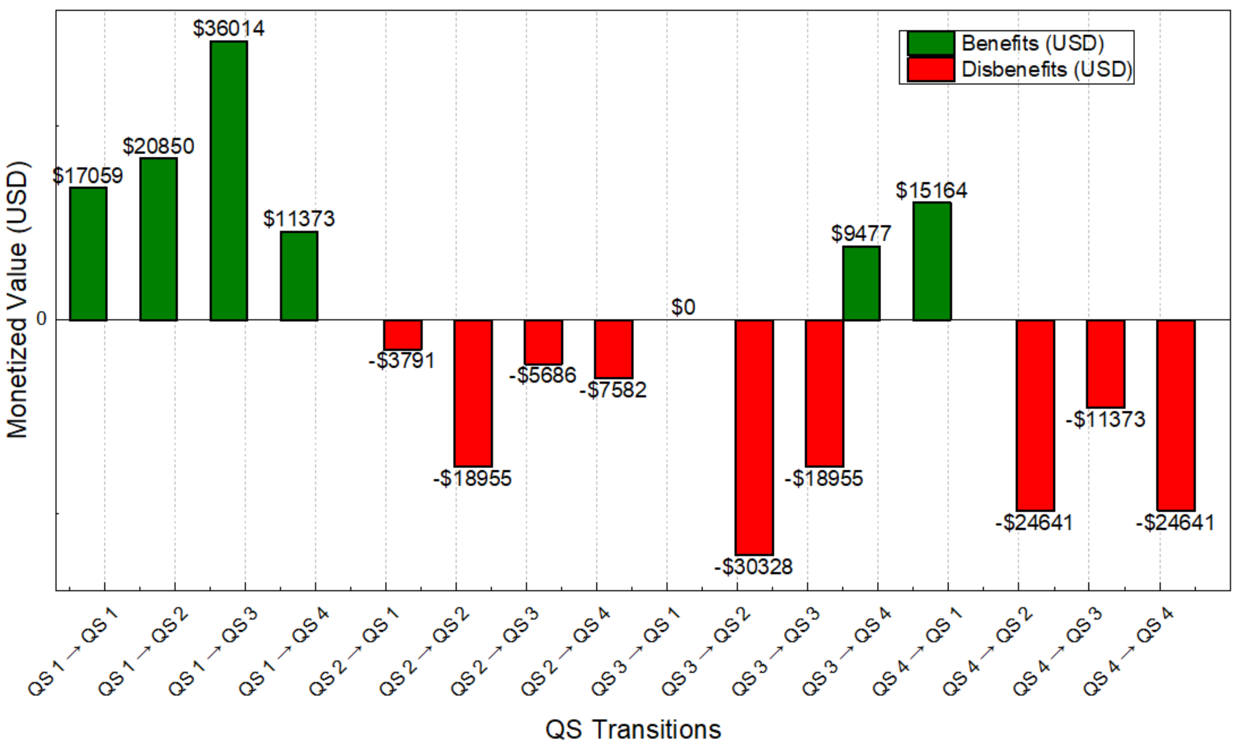


Figure 7-2. Comparison of benefit and disbenefit by QS transitions

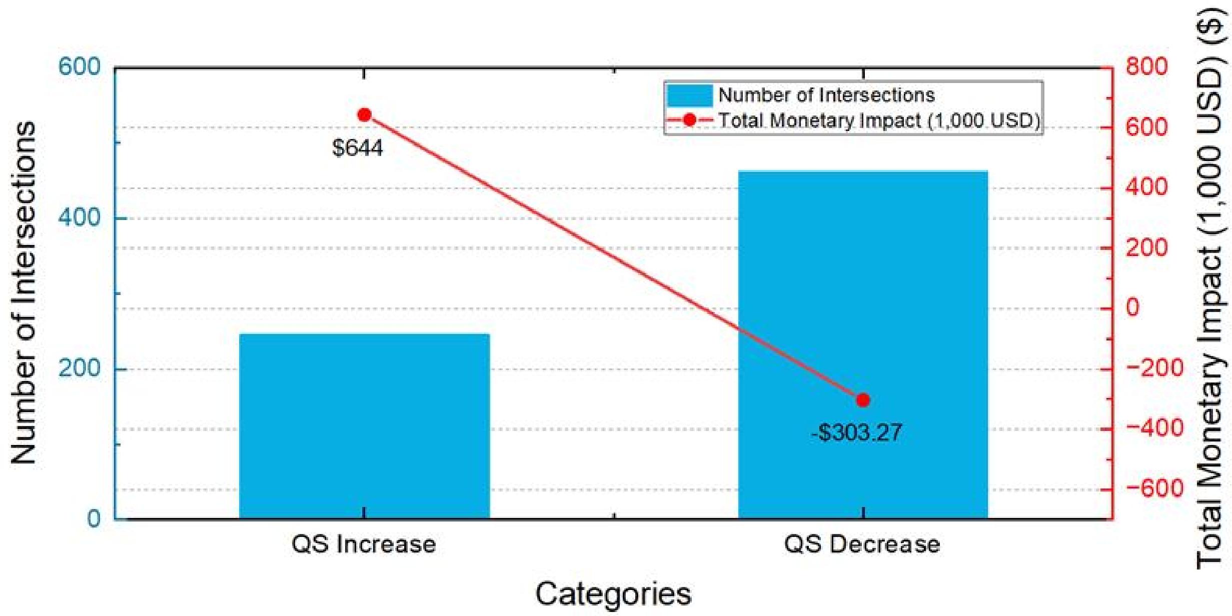


Figure 7-3. Comparison of benefit and disbenefit by intersection QS transition categories

As shown in Figure 7-3, the total monetary benefit from positive QS transitions is $644,000, while the total disbenefit from negative QS transitions is $303,270. This results in a net monetary impact of:

$$\text{Net Impact} = \$644{,}000 - \$303{,}270 = \$340{,}730 \text{ (USD)}$$

QS level increases generally correspond to crash reductions, indicating the effectiveness of marker quality improvements. QS level decreases often lead to higher crash numbers, suggesting a direct relationship between deteriorating marker quality and increased crash risks.

7.3 Benefit-Cost Ratio (B/C) or ROI Calculation

This section compares the benefit-cost ratio and return on Investment (ROI) for three methods—FDOT Survey, Vexcel (15 cm), and Vexcel (7.5 cm)—to assess the financial effectiveness of each approach. A positive ROI indicates the investment generates more benefits than its costs.

Table 7-10 provides a five-year cost, Benefit-Cost Ratio (B/C), and ROI comparison for the FDOT Survey and Vexcel Imagery methods, focusing solely on the monetary savings from crash reduction.

Table 7-10. Five-Year Cost, Benefit-Cost Ratio, and ROI for FDOT Survey and Vexcel Imagery Methods

Method	Cost (USD)	Benefit-Cost Ratio (B/C)	ROI (%)
FDOT Survey	$547,500	2.01	100.73 %
Vexcel (15 cm)	$63,700	17.25	1,625.27 %
Vexcel (7.5 cm)	$254,800	4.31	331.32 %

The Vexcel (15 cm) imagery demonstrates the highest cost-effectiveness, with a B/C ratio of 17.25 and an ROI of 1,625.27 %, indicating that the benefits from crash-related cost savings far exceed the method's cost. The Vexcel (7.5 cm) imagery also performs well, achieving a positive ROI of 331.32 % and a B/C ratio of 4.31, making it a viable option for higher-resolution data needs. In contrast, the FDOT MRP Survey shows a B/C ratio of 2.01 and an ROI of 100.73%, although positive—is significantly lower than those achieved using Vexcel imagery.

While this benefit analysis is based on past crash data related to the improvement in marker QS levels, the inclusion of Vexcel imagery services offers additional advantages beyond crash prevention. These include:

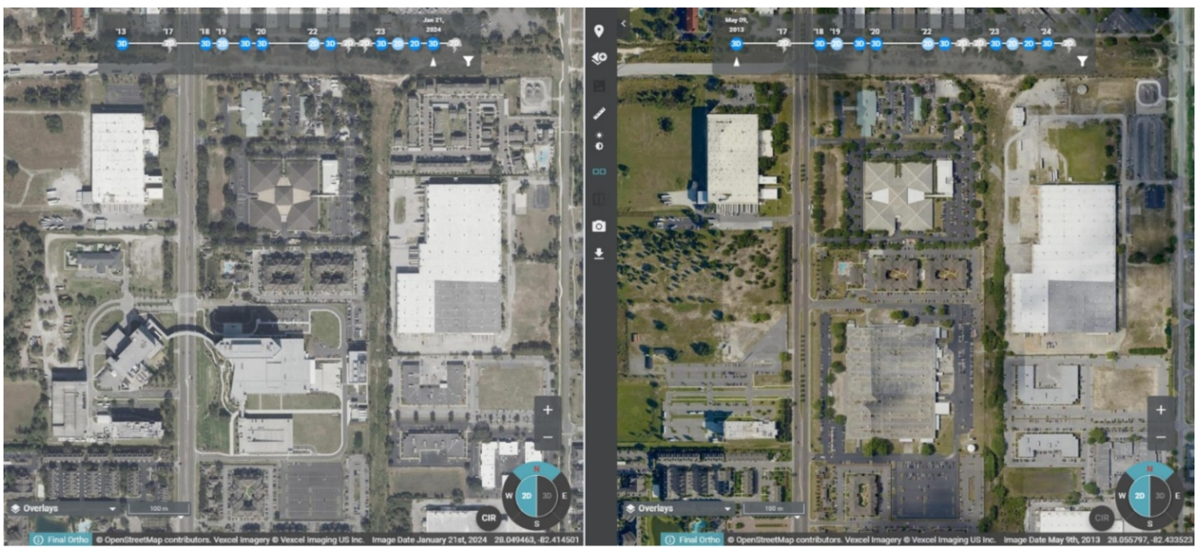
- The platform automatically detects, and outlines features such as buildings, roads, and vegetation. These outputs can be used for land use analysis, property assessments, and change detection (Figure 7-4).
- Vexcel' s vegetation analysis capabilities offer valuable insights into road safety and environmental management by assessing vegetation coverage, monitoring sight distance obstructions, and analyzing changes over time. The platform helps identify areas where vegetation encroaches on roads, obstructs sightlines at intersections or curves, and monitors vegetation growth or reduction through time-series analysis (Figure 7-5).
- Vexcel enables users to compare imagery from different years, making it possible to track changes in infrastructure, urban development, and environmental conditions over time (Figure 7-6).

Source: Vexcel Imaging, Inc.

Figure 7-4. High-resolution aerial imagery with object detection and land use analysis from Vexcel platform

Source: Vexcel Imaging, Inc.

Figure 7-5. Infrared aerial imagery for vegetation and land use analysis from Vexcel platform



Source: Vexcel Imaging, Inc.

Figure 7-6. Comparison of historical and current aerial imagery using Vexcel platform's time-series analysis

Integrating advanced imagery services like Vexcel (15 cm) not only enhances safety outcomes by supporting data-driven decisions but also reduces costs associated with traditional survey methods. Its high B/C ratio and ROI make it a compelling choice for agencies aiming to maximize the efficiency of their investments while improving roadway conditions. Furthermore, the ability to address multiple areas of infrastructure—beyond safety—positions Vexcel as a strategic tool for holistic urban and transportation management.

7.4 Summary and Recommendations

To address problematic QS level decreases, FDOT District 7 can focus on improvement at intersections where marker quality has deteriorated because these areas are associated with increased crashes and significant disbenefits, amounting to $303,270. Implementing targeted interventions such as repainting, upgrading markers, or other safety improvements and prioritizing high-traffic and high-crash locations will maximize the impact of these measures and effectively reduce crash risks.

Intersections with QS level increases have shown notable safety benefits, with total benefits amounting to $644,000. To sustain these positive outcomes, it is essential to maintain and monitor these intersections regularly. Continued maintenance of marker quality will ensure that safety improvements are preserved over time, supporting the long-term effectiveness.

Adopting cost-effective methods, such as Vexcel (15 cm) imagery, can significantly enhance the efficiency of safety assessments and intervention planning. This method demonstrated a higher B/C ratio, and ROI compared to others, making it a valuable tool for broader-scale analysis. Utilizing advanced imagery technologies can help agencies identify areas needing improvement and optimize resource allocation for maximum impact.

8 Conclusion and Recommendations

This research highlights critical insights into using big data and associated AI tools via data service to improve roadway safety in a cost-effective manner. This research not only showed a positive correlation between Average Annual Daily Traffic (AADT) and both crash frequency and severity, but also revealed a positive correlation between faded pavement markings and increased crash severity. Furthermore, the monetary benefits of maintaining high-quality markings over faded ones underscore the economic importance of proper maintenance.

In this research project, the focused study using aerial imagery data to improve pedestrian and bicycle safety, serves as a valuable case study for transportation agencies using big data. It offers a practical exploration of the ability, availability, and affordability of using big data to tackle safety challenges. By leveraging affordable technologies, such as Vexcel imagery with 15 cm resolution, agencies can greatly enhance the accuracy and efficiency of safety assessments and intervention strategies. Advanced imagery tools also enable more precise identification of areas requiring improvement, supporting more effective and optimized resource allocation.

The evaluation of big data solutions, particularly through Vexcel Imagery services, highlights their superior cost-effectiveness and scalability for transportation safety and infrastructure assessment. The Vexcel (15 cm) imagery offers the highest benefit-cost ratio (B/C) at 7.94, indicating an exceptional return on investment, with substantial coverage at a cost of $6.35 per mile. This method outperforms traditional FDOT surveys and Vexcel (7.5 cm) imagery in terms of affordability while still providing adequate detail for broader roadway analysis.

Improvements in marker quality scores (QS) demonstrate a clear correlation with crash reductions, affirming the impact of high-quality roadway features on transportation safety. Despite some limitations, the use of advanced imagery technologies has enabled data-driven decisions to prioritize maintenance and upgrades. Positive monetary impacts from the QS level increases further underscore the effectiveness of these interventions, even as challenges from QS level decreases highlight areas requiring targeted safety improvements.

To maximize benefits, the study recommends adopting cost-efficient solutions like Vexcel (15 cm) imagery for large-scale assessments while utilizing Vexcel (7.5 cm) imagery for projects requiring detailed analysis. Furthermore, maintaining and improving QS levels at intersections is critical to sustaining safety gains, with targeted interventions to address areas of decline. The integration of these advanced data solutions into routine FDOT operations can enhance decision-making and resource allocation, ensuring long-term safety and efficiency benefits.

In addition to pavement markings, FDOT may consider to harness big data to address a variety of other infrastructure challenges. Property inventory tracking, roadway element condition assessments, and vegetation management can all benefit from advanced data analytics and imagery-based evaluation methods. Integrating big data into these operational areas can improve asset visibility, streamline decision-making, and support the development of predictive maintenance models, ultimately leading to more resilient and cost-effective transportation infrastructure.

References

[1] B. Lutkevich and I. Wigmore. "3 V's (volume, velocity and variety)." TechTarget. https://www.techtarget.com/whatis/definition/3Vs#:~:text=Ivy%20Wigmore-,What%20are%20the%203%20V's%20of%20big%20data%3F,number%20of%20types%20of%20data. (accessed February 1, 2025).

[2] Florida Department of Transportation. "Target Zero Initative." https://www.fdot.gov/agencyresources/target-zero (accessed February 21, 2025).

[3] Florida Department of Transportation, *Strategic Highway Safety Plan*. Tallahassee, FL: Florida Department of Transportation, 2025.

[4] Florida Department of Transportation, *Florida's Pedestrian and Bicycle Strategic Safety Plan (PBSSP)*. Tallahassee, FL: Florida Department of Transportation, 2021.

[5] A. Neilson, I. Indratmo, B. Daniel, and S. Tjandra, "Systematic Review of the Literature on Big Data in the Transportation Domain: Concepts and Applications," *Big Data Research,* vol. 17, pp. 35-44, September 2019, doi: 10.1016/j.bdr.2019.03.001.

[6] A. I. Torre‐Bastida, J. Del Ser, I. Laña, M. Ilardia, M. N. Bilbao, and S. Campos‐Cordobés, "Big Data for transportation and mobility: recent advances, trends and challenges," *IET Intelligent Transport Systems,* vol. 12, no. 8, pp. 742-755, October 2018, doi: 10.1049/iet-its.2018.5188.

[7] G. P. Griffin, M. Mulhall, C. Simek, and W. W. Riggs, "Mitigating Bias in Big Data for Transportation," *Journal of Big Data Analytics in Transportation,* vol. 2, no. 1, pp. 49-59, April 2020, doi: 10.1007/s42421-020-00013-0.

[8] A. Mohandu and M. Kubendiran, "Survey on Big Data Techniques in Intelligent Transportation System (ITS)," *Materials Today: Proceedings,* vol. 47, pp. 8-17, 2021, doi: 10.1016/j.matpr.2021.03.479.

[9] S. Shukla, K. Balachandran, and V. S. Sumitha, "A framework for smart transportation using Big Data," in *2016 International Conference on ICT in Business Industry & Government (ICTBIG)*, 2016: IEEE, pp. 1-3, doi: 10.1109/ICTBIG.2016.7892720.

[10] S. Kaffash, A. T. Nguyen, and J. Zhu, "Big data algorithms and applications in intelligent transportation system: A review and bibliometric analysis," *International Journal of Production Economics,* vol. 231, pp. 107868-107868, January 2021, doi: 10.1016/j.ijpe.2020.107868.

[11] B. Jan, H. Farman, M. Khan, M. Talha, and I. U. Din, "Designing a Smart Transportation System: An Internet of Things and Big Data Approach," *IEEE Wireless Communications,* vol. 26, no. 4, pp. 73-79, August 2019, doi: 10.1109/MWC.2019.1800512.

[12] C. Wang and D. B. Hess, "Role of Urban Big Data in Travel Behavior Research," *Transportation Research Record: Journal of the Transportation Research Board,* vol. 2675, no. 4, pp. 222-233, April 2021, doi: 10.1177/0361198120975029.

[13] J. Zeyu, Y. Shuiping, Z. Mingduan, C. Yongqiang, and L. Yi, "Model Study for Intelligent Transportation System with Big Data," *Procedia Computer Science,* vol. 107, pp. 418-426, 2017, doi: 10.1016/j.procs.2017.03.132.

[14] F. Ghofrani, Q. He, R. M. P. Goverde, and X. Liu, "Recent applications of big data analytics in railway transportation systems: A survey," *Transportation Research Part C:*

Emerging Technologies, vol. 90, pp. 226-246, May 2018, doi: https://doi.org/10.1016/j.trc.2018.03.010.

[15] L. Zhu, F. R. Yu, Y. Wang, B. Ning, and T. Tang, "Big Data Analytics in Intelligent Transportation Systems: A Survey," *IEEE Transactions on Intelligent Transportation Systems,* vol. 20, no. 1, pp. 383-398, January 2019, doi: 10.1109/TITS.2018.2815678.

[16] S. Das and G. P. Griffin, "Investigating the Role of Big Data in Transportation Safety," *Transportation Research Record: Journal of the Transportation Research Board,* vol. 2674, no. 6, pp. 244-252, June 2020, doi: 10.1177/0361198120918565.

[17] Y. Lian, G. Zhang, J. Lee, and H. Huang, "Review on big data applications in safety research of intelligent transportation systems and connected/automated vehicles," *Accident Analysis & Prevention,* vol. 146, pp. 105711-105711, October 2020, doi: 10.1016/j.aap.2020.105711.

[18] M. A. Amin, S. Hadouej, and T. S. J. Darwish, "Big Data Role in Improving Intelligent Transportation Systems Safety: A Survey," 2019, pp. 187-199.

[19] M. Abdel-Aty, O. Zheng, Y. Wu, A. Abdelraouf, H. Rim, and P. Li, "Real-Time Big Data Analytics and Proactive Traffic Safety Management Visualization System," *Journal of Transportation Engineering, Part A: Systems,* vol. 149, no. 8, August 2023, doi: 10.1061/JTEPBS.TEENG-7530.

[20] N. Hoseinzadeh, R. Arvin, A. J. Khattak, and L. D. Han, "Integrating safety and mobility for pathfinding using big data generated by connected vehicles," *Journal of Intelligent Transportation Systems,* vol. 24, no. 4, pp. 404-420, July 2020, doi: 10.1080/15472450.2019.1699077.

[21] A. Mehdizadeh *et al.*, "A Review of Data Analytic Applications in Road Traffic Safety. Part 1: Descriptive and Predictive Modeling," *Sensors,* vol. 20, no. 4, pp. 1107-1107, February 2020, doi: 10.3390/s20041107.

[22] F. Mannering, C. R. Bhat, V. Shankar, and M. Abdel-Aty, "Big data, traditional data and the tradeoffs between prediction and causality in highway-safety analysis," *Analytic Methods in Accident Research,* vol. 25, pp. 100113-100113, March 2020, doi: 10.1016/j.amar.2020.100113.

[23] J. Francis, J. Bright, S. Esnaashari, Y. Hashem, D. Morgan, and V. J. Straub, "Unsupervised feature extraction of aerial images for clustering and understanding hazardous road segments," *Scientific Reports,* vol. 13, no. 1, pp. 10922-10922, July 2023, doi: 10.1038/s41598-023-38100-1.

[24] E. Brewer, J. Lin, P. Kemper, J. Hennin, and D. Runfola, "Predicting road quality using high resolution satellite imagery: A transfer learning approach," *PLOS ONE,* vol. 16, no. 7, July 2021, doi: 10.1371/journal.pone.0253370.

[25] A. Najjar, S. i. Kaneko, and Y. Miyanaga, "Combining Satellite Imagery and Open Data to Map Road Safety," in *Proceedings of the AAAI Conference on Artificial Intelligence*, February 2017, vol. 31, no. 1, doi: 10.1609/aaai.v31i1.11168.

[26] R. Workman, P. Wong, A. Wright, and Z. Wang, "Prediction of Unpaved Road Conditions Using High-Resolution Optical Satellite Imagery and Machine Learning," *Remote Sensing,* vol. 15, no. 16, pp. 3985-3985, August 2023, doi: 10.3390/rs15163985.

[27] H. Azari, D. O'Shea, and J. Campbell, "Application of Unmanned Aerial Systems for Bridge Inspection," *Transportation Research Record: Journal of the Transportation*

Research Board, vol. 2676, no. 1, pp. 401-407, January 2022, doi: 10.1177/03611981211031896.

[28] E. V. Butilă and R. G. Boboc, "Urban Traffic Monitoring and Analysis Using Unmanned Aerial Vehicles (UAVs): A Systematic Literature Review," *Remote Sensing,* vol. 14, no. 3, pp. 620-620, January 2022, doi: 10.3390/rs14030620.

[29] R. Goel, J. J. Miranda, N. Gouveia, and J. Woodcock, "Using satellite imagery to estimate heavy vehicle volume for ecological injury analysis in India," *International Journal of Injury Control and Safety Promotion,* vol. 28, no. 1, pp. 68-77, January 2021, doi: 10.1080/17457300.2020.1837886.

[30] D. Yang, K. Ozbay, K. Xie, H. Yang, F. Zuo, and D. Sha, "Proactive safety monitoring: A functional approach to detect safety-related anomalies using unmanned aerial vehicle video data," *Transportation Research Part C: Emerging Technologies,* vol. 127, pp. 103130-103130, June 2021, doi: 10.1016/j.trc.2021.103130.

[31] D. Babić, M. Fiolić, D. Babić, and T. Gates, "Road Markings and Their Impact on Driver Behaviour and Road Safety: A Systematic Review of Current Findings," *Journal of Advanced Transportation,* vol. 2020, pp. 1-19, August 2020, doi: 10.1155/2020/7843743.

[32] P. J. Carlson, E. S. Park, and C. K. Andersen, "Benefits of Pavement Markings," *Transportation Research Record: Journal of the Transportation Research Board,* vol. 2107, no. 1, pp. 59-68, January 2009, doi: 10.3141/2107-06.

[33] C. Ariën *et al.*, "The effect of pavement markings on driving behaviour in curves: a simulator study," *Ergonomics,* vol. 60, no. 5, pp. 701-713, May 2017, doi: 10.1080/00140139.2016.1200749.

[34] M. Hussein, T. Sayed, K. El-Basyouny, and P. de Leur, "Investigating safety effects of wider longitudinal pavement markings," *Accident Analysis & Prevention,* vol. 142, pp. 105527-105527, July 2020, doi: 10.1016/j.aap.2020.105527.

[35] M. T. Johnson, "Safety Impacts of Signing and Pavement Markings on Property-Damage-Only Crashes at Multi-Lane Roundabouts," *Transportation Research Record: Journal of the Transportation Research Board,* vol. 2673, no. 2, pp. 477-488, February 2019, doi: 10.1177/0361198118823738.

[36] Florida Department of Transportation (FDOT). "Maintenance Rating Program." https://www.fdot.gov/maintenance/maintratingprogram.shtm (accessed February 15, 2025).

[37] Florida Department of Transportation, *Maintenance Rating Program (MRP) 2024 Handbook*. Tallahassee, FL: Florida Department of transportation, 2025.

[38] Vexcel Imaging Inc. "Getting Started with Vexcel Elements Roadway." https://vexcel.atlassian.net/servicedesk/customer/portal/15/topic/6e08c583-d8f3-4774-98fa-f63adc41e195/article/2870673475 (accessed February 13, 2025).

[39] Google Cloud. "Cloud Storage pricing." https://cloud.google.com/storage/pricing (accessed February 10, 2025).

[40] Amazon Web Services Inc. "Amazon S3 pricing." https://aws.amazon.com/s3/pricing/?utm_source=chatgpt.com (accessed February 15, 2025).

[41] Microsoft. "Azure Blob Storage Pricing." Microsoft. https://azure.microsoft.com/en-us/pricing/details/storage/blobs/ (accessed February 1, 2025).

[42] US Forest Service Road Management, *Road Density as an Indicator of Road Hazard*. Washington, D.C.: USDA Forest Service, 2000.
[43] National Safety Council. *Guide to calculating costs: Costs of motor-vehicle injuries*. Injury Facts. https://injuryfacts.nsc.org/all-injuries/costs/guide-to-calculating-costs/, 2023. (accessed April 25, 2025).

Appendices

Appendix A – Data Dictionary

Table A-1. Data Dictionary: Roadway Elements

Parameter	Data Type	Description	Example
Long	Number	Longitude of bounding box centroid.	long=-118.12998220 324516
Lat	Number	Latitude of bounding box centroid.	lat=34.01481565143 788
Id	String	Unique feature id.	id=b790977e-9038-11ee-afd0-2552c67c4ca1
Category	String	ADA - Accessibility features such as detectable warnings and pavement markings related to requirements of Title II of the ADA.	Category: crosswalk
		arrow - Arrow pavement markings as listed in the Manual on Uniform Traffic Control Devices (MUTCD) 11th Edition.	
		bicycle - Pavement markings were installed to guide bicyclists traveling on the roadway.	
		crosswalk - Pavement markings installed to guide pedestrians who are crossing roadways. In conjunction with signs and other measures, crosswalk markings help to alert road users to a designated pedestrian crossing point.	
		intersection-junction - Curbs and other roadway elements commonly installed to define or improve safety at an intersection or junction.	
		railroad - Grade crossing pavement markings.	
		stop - Stop and yield line pavement markings.	
		symbol - Symbol pavement markings such as route shields.	
		text - Word pavement markings.	
Name	String	Category ADA A. Accessibility symbol (wheelchair): International symbol of accessibility parking space marking, with or without a blue background. B. Detectable warning mats: Detectable warning mats (truncated domes) are used for ADA compliance to indicate the boundary between pedestrian and vehicular routes where there is a flush instead of a curbed connection.	Name: transverse crosswalk

Table A-1. Data Dictionary: Roadway Elements, Continued

Parameter	Data Type	Description	Example
Name	String	Category arrow C. Lane reduction arrow: lane reduction arrow D. Left turn arrow: Left turn lane-use arrow. E. Right/left arrow: Right and left turn lane-use arrow. F. Right turn arrow: Right turn lane-use arrow. G. Straight arrow: Through lane-use arrow. H. Straight/left arrow: Left turn and through lane-use arrow. I. Straight/right arrow: Right turn and through lane-use arrow. J. Three-way arrow: Right, left, and through lane-use. K. Uturn arrow: Uturn arrow.	
		Category bicycle L. Bicycle symbol: Bicycle symbol and helmeted bicycle symbol markings. M. Green-colored pavement (bicycle): Green-colored asphalt or concrete, or paint or other marking materials applied to the surface of a road to indicate a bicycle facility. N. Shared lane (bicycle): Bicycle symbol marking with double chevrons indicating a shared use lane.	
		Category crosswalk ➢ Transverse crosswalk: Marked crosswalk with longitudinal lines parallel to traffic flow. ➢ Ladder crosswalk: High visibility marked crosswalk with longitudinal and transverse line markings. ➢ Longitudinal bar crosswalk: - High visibility marked crosswalk with longitudinal line markings parallel to traffic flow, including bar pair designs. ➢ Solid crosswalk: Marked crosswalk with colored pavements between longitudinal line markings.	

Table A-1. Data Dictionary: Roadway Elements, Continued

Parameter	Data Type	Description	Example
Name	String	Category intersection-junction ➢ Pedestrian islands: islands or medians placed in the center area of a street that can serve as a place of refuge for pedestrians who are attempting to cross at a midblock or intersection location. ➢ Roundabout: The central island of a circular intersection design where traffic travels around a central island. Common circular intersection types including roundabouts, rotaries, and traffic circles are detected.	
		Category railroad ➢ railroad crossing: railroad crossing (X) symbol.	
		Category stop ➢ Stop line - Solid white lines extending across approach lanes to indicate the point at which the stop is intended or required to be made. ➢ Yield line - Yield line (triangular) marking.	
		Category symbol ➢ Double chevron: Double chevron markings are generally used to denote the continuation or direction of travel for a bicycle lane. ➢ Other symbols: Route shield and other markings. Speed hump - Speed hump (triangular) marking.	
		Category text ➢ BIKE text. ➢ BUS text ➢ ONLY text. ➢ SCHOOL text ➢ STOP text. ➢ YIELD text. ➢ OTHER text	

Table A-1. Data Dictionary: Roadway Elements, Continued

Parameter	Data Type	Description	Example
Type	String	Type options. ➢ pavement marking: Pavement markings and colored pavements. ➢ Infrastructure: Structural roadway elements.	Type: pavement marking
Quality score	Number	Quality score options ➢ Poor (1): Pronounced signs of defects that can significantly affect the function of the pavement marking. ➢ Fair (2): Pronounced signs of defects that can affect the function of the pavement marking. ➢ Acceptable (3): Minimal visible signs of defects. ➢ Good (4): No visible signs of defects.	Number = 1
Confidence	Number	The range is between 0 and 1.	Confidence = 0.72
Area	Number	Bounding box area (square meters)	Area = 489.95
Crossing distance	Number	Pedestrian crossing distance (meters)	Crossing distance = 30.6
Method	String	➢ curb2curb - Length calculated from a line drawn between opposing ADAcurbmat bounding box centroids. ➢ curb2center - Length calculated from a line drawn across the road starting at an ADAcurbmat centroid and through a crosswalk centroid, clipped by the crosswalk bounding box. ➢ center - Length calculated using a crossing line drawn through the crosswalk bounding box centroid and perpendicular to a street centerline LineString, clipped by the crosswalk bounding box. ➢ diagonal - Length of a line drawn between opposing corners on the longest sides of the crosswalk bounding box.	Method = center

Table A-1. Data Dictionary: Roadway Elements, Continued

Parameter	Data type	Description	Example
Source	String	Source of imagery and feature extractions.	source=©2024 Vexcel Imaging US, Inc.
Layer	String	Vexcel image product used for analysis. Layer options: ➢ bluesky-ultra - TrueOrtho 7.5 cm GSD imagery. ➢ urban-r - Urban Ortho 7.5 cm GSD imagery. ➢ bluesky-high - Wide Area Ortho 15 cm GSD imagery.	layer=bluesky-ultra
Coverage Type	String	Type of image product	Coverage-type=final-ortho
Camera Technology	String	Vexcel camera model and version used for data collection.	camera technology= UltraCam_Osprey_4.1_f120
aoi	String	Vexcel data collection parent area name.	aoi=us-ca-losangeles-2023
child_aoi	String	Vexcel data collection child area name.	child_aoi=us-ca-losangeles-2023
min_gsd	Number	Minimum ground sampling distance (meters) of image tile.	min_gsd=0.0507
max_gsd	Number	Maximum ground sampling distance (meters) of image tile.	max_gsd=0.0765
min_capture_date	Date	The start date of image capture for the child_aoi (m/d/yyyy h:mm).	capture_date_min=11/24/2022 20:59
max_capture_date	Date	The end date for image capture for the child_aoi (m/d/yyyy h:mm).	capture_date_max=2/02/2023 18:04
estimated_date	Date	The collection date of the nadir image most centered over the road element location.	estimated_date=1/17/2023 21:13
process_date	Date	Date imagery analyzed by Vexcel algorithms (m/d/yyyy h:mm).	process_date=12/01/2023 10:59

Table A-1. Data Dictionary: Roadway Elements, Continued

Parameter	Data type	Description	Example
bbox_wkt	String	Bounding box geometry in Well-known text (WKT) format.	bbox_wkt=POLYGON ((-118.13014313578606 34.01474117134329, -118.12982194125652 34.01474117134329, -118.12982194125652 34.01489013153246, -118.13014313578606 34.01489013153246, -118.13014313578606 34.01474117134329))
crossing_wkt	String	Line string geometry in Well-known text (WKT) format.	crossing_wkt=LINESTRING (-118.1301431357860565 34.0148506073785413, -118.1298219412565231 34.0147808407089798)

Appendix B – Data Agreement with Vexcel-USF

AMENDMENT TO

INTEGRATOR LICENSE AGREEMENT NO. 1

This Amendment (this "***Amendment***") to the Integrator License Agreement No. 1 ("***Agreement***") dated November 28, 2023, between Vexcel Imaging US, Inc., a Delaware corporation ("***Vexcel***"), and The University of South Florida Board of Trustees, a public body corporate acting on behalf of the Center for Urban Transportation Research at the University of South Florida ("***Integrator***," and together with Vexcel, the "***Parties***"), is entered between the Parties effective as of January 29, 2024 (the "***Amendment Effective Date***"). Capitalized terms used herein but not defined have the meanings ascribed to in the Agreement.

WHEREAS, the Parties would like to extend the term of the Agreement.

NOW, THEREFORE, in consideration of the mutual promises and covenants contained in the Agreement (as modified by this Amendment), the adequacy of which is acknowledged by each Party, the Parties agree as follows:

1. Section 4.1 of the Agreement shall be deemed deleted in its entirety and replaced with the following:

"Term. The term of the License Agreement will run from the License Effective Date until February 1, 2025, unless terminated early pursuant to Section 11.2 of the Framework Agreement (the "***License Term***").

2. Except as modified by this Amendment, all other terms of the Agreement remain in full force and effect (and apply to the rights granted pursuant to this Agreement).

[Signature page follows.]

IN WITNESS WHEREOF, the Parties hereto have caused this Agreement to be executed as of the Amendment Effective Date.

Vexcel Imaging US, Inc.	**University of South Florida Board of Trustees, a public body corporate**
By: DocuSigned by: Rob Agee 1C16AD089FDB44D...	By: DocuSigned by: Brieanne Matier 0F8FBF06ED8F4F2...
Name: Rob Agee	Name: Brieanne Matier
Title: Chief Operating Officer	Title: Associate Director, USF Procurement
1/30/2024 | 15:00 PST	1/30/2024 | 14:35 EST

INTEGRATOR LICENSE AGREEMENT NO. 1

This Integrator License Agreement No. 1 (the "***License Agreement***") is governed by the Integrator Framework Agreement dated November 28, 2023 (the "***Framework Agreement***"), between Vexcel Imaging US, Inc., a Delaware corporation ("***Vexcel***"), and The University of South Florida Board of Trustees, a public body corporate acting on behalf of the Center for Urban Transportation Research at the University of South Florida ("***Integrator***," and together with Vexcel, the "***Parties***"), and is entered into as of November 28, 2023 (the "***License Effective Date***"), between the Parties. Capitalized terms used herein but not defined shall have the meaning ascribed to them in the Agreement.

1. DEFINITIONS

"***Customer Record***" means an assessment or report derived from Integrator's Internal Use of the Product with respect to a customer of Integrator. A Customer Record may contain Derivatives and a few images of Product or Modified Product relevant to the report or analysis.

"***Customer***" has the meaning set forth in the Framework Agreement, provided that, for purposes of this License Agreement, the term "***Customer***" as referred to in the terms and conditions of the Framework Agreement is further limited to the Government Sponsor, to which the requirements for and related to Customers in the Framework Agreement apply.

"***Derivatives***" means works that are created by analyzing the Product and extracting features and attributes from the Product to update and improve Integrator's intersection database, specifically excluding any portion of the images or pixels themselves.

"***Framework Agreement***" has the meaning set forth in the introductory paragraph.

"***Government Sponsor***" means the Florida Department of Transportation.

"***Integrator***" has the meaning set forth in the introductory paragraph.

"***Integrator Offering***" has the meaning set forth in Section 2.1 of this License Agreement.

"***License Agreement***" has the meaning set forth in the introductory paragraph.

"***License Effective Date***" has the meaning set forth in the introductory paragraph.

"***License Term***" has the meaning set forth in Section 4.1 of this License Agreement.

"***Upfront Fee***" has the meaning set forth in Section 3.1 of this License Agreement.

"***Modified Product***" has the meaning set forth in Section 2.1(b) of this License Agreement.

"***Party***" has the meaning set forth in the introductory paragraph.

"***Product***" means the off-the-shelf digital imagery, metadata, and geospatial information (if any) set forth in Exhibit A of this License Agreement that are generally made available to Vexcel's customers.

"***Product License***" has the meaning set forth in Section 2.1 of this License Agreement.

"***Vexcel***" has the meaning set forth in the introductory paragraph.

2. LICENSE TERMS

2.1. License Grant. Vexcel grants Integrator during the License Term a non-exclusive, non-transferable right to (a) create Derivatives; (b) subject to Section 2.2(b) of the Framework Agreement (No Adverse Impact on Images), resample the Product to a smaller size and/or modify the Product to overlay graphics, text, and/or other content (collectively, "***Modified Product***"); (c) sublicense the Derivatives and a reasonable amount of related Product or Modified Product to the Government Sponsor for: (i) the purpose of conducting safety analysis research with the Integrator for vulnerable road users for the Internal Use of the Integrator and the Government Sponsor and (ii) publishing a report analyzing the usefulness of the Product in such research (the "***Integrator Offering***"), which in each case, for such Customer's use, and the license granted in this Section 2.1, the "***Product License***").

3. FEES AND PAYMENT

3.1. Upfront Fee. Integrator shall pay Vexcel a upfront, non-refundable annual fee of $15,000 (the "***Upfront Fee***"), due upon execution of this License Agreement.

3.2. Payment Terms. All amounts due under this License Agreement shall be invoiced and paid in U.S. dollars net 30 days from date of invoice.

4. TERM AND TERMINATION

4.1. Term. The term of the License Agreement will run for one year from the License Effective Date unless terminated early pursuant to Section 11.2 of the Framework Agreement (the "***License Term***").

4.2. Termination of License. The Product License terminates upon termination of this License Agreement. Upon termination of the Product License, Integrator may not continue to use and must delete all Imagery Product (as defined in Exhibit A) delivered pursuant to this License Agreement and any Modified Product created under this License Agreement from such Imagery Product, except to the extent the same has been incorporated into the Integrator Offering. Customers may retain the Elements Product (as defined in Exhibit A) and the Integrator Offering for the purpose permitted in Section 2.1, subject to the terms of the Framework Agreement and this License Agreement.

4.3. Payment of Outstanding Fees. Upon termination of this License Agreement, Integrator shall immediately pay to Vexcel all amounts owing under the License Agreement.

License Effective Date.

Vexcel Imaging US, Inc.	**University of South Florida Board of Trustees, a public body corporate**
By: DocuSigned by: Rob Agee 1C16AD089FD844D...	**By:** DocuSigned by: Brie Matier 0F8F0F0B6D8F4F2...
Name: Rob Agee	**Name:** Brie Matier
Title: Chief Operating Officer	**Title:** Associate Director, Procurement Services

EXHIBIT A

PRODUCT DESCRIPTION AND SPECIFICATIONS

Products:

Imagery Product:

Urban True Ortho Imagery

- *Image type*: Orthorectified imagery with 7.5cm GSD or better
- *Image format*: 3-band (RGB or CIR) imagery JPEG Q95
- *Spatial reference system*: Spherical Mercator/WGS84 (EPSG:3857)
- *Access*: Vexcel Viewer and API
- *Collection date*: All currently available

Elements Product:

Elements: Roadway Attributes (Up to 2 datasets from image library)

- *Product description*: Information on the existence and quality of roadway features including pavement markings and select infrastructure such as pedestrian refuge islands
- *Data format*: JavaScript Object Notation (JSON) with key-value pairs and geometric Well-Known Text (WKT)
- *Spatial reference system*: Geographic/WGS84 (EPSG:4326)

Imagery collection date: To be selected by customer from available vintages

For the following AOIs:

Tampa Bay Metro Area, FL
Total area of ~2600 square kilometers covering ~1915 centerline road miles.

Appendix C – Complete Dataset Roadway Feature Count

Table C-1. Complete Roadway Feature Dataset Counts

Feature Category	2020 Count	2023 Count
Americans with Disabilities Act (ADA)	**34,631**	**30,705**
Accessibility symbol (wheelchair)	7,287	5,562
Detectable warning mat	27,344	25,143
Arrow	**69,441**	**62,677**
Lane reduction arrow	952	865
Left turn arrow	29,757	28,155
Left/right arrow	163	140
Right turn arrow	11,162	10,558
Straight arrow	25,218	20,771
Straight/left arrow	995	922
Straight/right arrow	1,059	1,037
Three-way arrow	43	61
U-turn arrow	92	168
Bicycle	**10,688**	**11,089**
Bicycle symbol	8,048	7,963
Green-colored pavement	164	529
Shared lane (bicycle)	2,476	2,597
Crosswalk	**16,734**	**18,481**
Ladder crosswalk	9,150	11,498
Longitudinal bar crosswalk	3,275	3,096
Solid crosswalk	1,926	1,277
Transverse line crosswalk	2,383	2,610
Intersection-Junction	**1,538**	**1,539**
Pedestrian island	1,010	1,068
Roundabout	528	471
Railroad	**853**	**711**
Railroad crossing	797	664
Railroad crossing extended	56	47
Stop	**30,520**	**31,498**
Stop line	30,308	31,283
Yield line	212	215
Symbol	**265**	**302**
Double chevron	101	81
Other symbols	164	221

Table C-1. Complete Dataset Roadway Feature Count, Continued

Feature Category	2020 Count	2023 Count
Text	**22,699**	**16,360**
BIKE text	27	33
BUS text	205	389
ONLY text	4,494	4,401
Other text	12,705	7,372
SCHOOL text	1,875	1,494
SCHOOL text extended	439	403
STOP text	2,920	2,199
YIELD text	34	69
Grand Total	**187,369**	**173,362**