DEPARTMENT OF TRANSPORTATION

# Assessing the Deterioration of Pedestrian Assets

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Pedestrian assets, particularly sidewalks, are highly susceptible to aging, adverse weather conditions, and suboptimal construction practices, often leading to rapid deterioration. This deterioration is often ignored due to the widespread misconception that pedestrian assets are low risk, resulting in many deteriorated sidewalks being left untreated or inadequately maintained. A comprehensive deterioration modeling framework that integrates advanced spatial and temporal data sources, advanced data analytics, and predictive modeling would enable infrastructure managers to predict the aging process of pedestrian assets and ultimately prioritize investments, plan maintenance schedules, and allocate budgets efficiently.

This project developed assessment frameworks and deterioration models for pedestrian assets that support reliable and informed decision-making regarding funding needs and asset design and maintenance. Various data sources and modeling and analysis procedures were explored, and a pedestrian asset assessment methodology was developed and evaluated. The research demonstrated a scalable and cost-effective approach to assessing sidewalk conditions, providing actionable insights for proactive maintenance. The quantifiable benefits, including construction savings, improved life-cycle costs, reduced risk, and safety enhancements, position this methodology as a valuable tool for sustainable infrastructure management.

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# ASSESSING THE DETERIORATION OF PEDESTRIAN ASSETS

## FINAL REPORT

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# EXECUTIVE SUMMARY


Pedestrian assets, particularly sidewalks, are vital for ensuring safe and accessible mobility in urban infrastructure systems. However, these assets are highly susceptible to aging, adverse weather conditions, and suboptimal construction practices, often leading to rapid deterioration. This deterioration is often ignored due to the widespread misconception that pedestrian assets are low risk, resulting in many deteriorated sidewalks being left untreated or inadequately maintained. Consequently, maintenance backlogs grow and service levels decline.

The current pedestrian asset management approach in the United States is largely reactive, relying on subjective judgment and limited condition data. Maintenance and rehabilitation activities often lack the support of well-established condition rating systems or predictive deterioration models that could estimate the short- and long-term performance of pedestrian assets. This reactive approach hinders the ability to prioritize investments effectively, plan maintenance schedules, and allocate budgets efficiently.

Deterioration modeling is critical for overcoming these challenges, enabling infrastructure managers to predict the aging process of sidewalks and other pedestrian assets. There is a significant gap in using advanced data sources for pedestrian asset modeling that are available at low or no cost. Although these sources could provide valuable spatial and temporal data, their potential remains underexplored for sidewalk condition monitoring.

Given these unexplored resources, there is a need for a comprehensive framework that integrates advanced data analytics and predictive modeling to address gaps in current pedestrian asset management practices. This framework must leverage existing data sources effectively, account for the complex nature of deterioration, and provide actionable insights for proactive maintenance and resource optimization.

The goal of this project was to develop performance measures, deterioration models, and assessment frameworks for pedestrian assets that support reliable and informed decision-making regarding funding needs and asset design and maintenance. Various data sources and modeling and analysis procedures were explored, and a pedestrian asset assessment methodology was developed and evaluated.

The research demonstrates a scalable and cost-effective approach to assessing sidewalk conditions, providing actionable insights for proactive maintenance. The quantifiable benefits, including construction savings, improved life-cycle costs, reduced risk, and safety enhancements, position this methodology as a valuable tool for advancing sustainable infrastructure management.

# CHAPTER 1: INTRODUCTION

## 1.1 PROJECT BACKGROUND

Pedestrian assets are vital components of urban infrastructure systems because they provide residents with safe access and active mobility (Zegeer et al. 2010). Like any other transportation asset, these are vulnerable to aging, severe weather, and inadequate construction practices that may lead to rapid deterioration. For instance, sidewalks are typically designed for a service life of 20 to 40 years, and they are often reported to fail prematurely, one to five years after they are opened for service (Huber et al. 2013). Generally, pedestrian assets are mistakenly perceived as low-risk assets, and therefore many deteriorated assets are left untreated or are treated inadequately, resulting in unsatisfactory service levels and maintenance backlogs (Espada et al. 2018). As such, pedestrian networks require new and more appropriate approaches for condition assessment and budget allocation (Makarewicz et al. 2018). Under Title II of the Americans with Disabilities Act (ADA), the Minnesota Department of Transportation (MnDOT) is obligated to keep an inventory of pedestrian assets including sidewalks and curb ramps. MnDOT reports on the compliance of assets each year.

Although condition rating is one measure of compliance, deterioration of the condition of pedestrian assets is not well understood or documented. Understanding how, why, and at what rate pedestrian assets deteriorate will significantly improve MnDOT's ability to forecast funding needs and will improve project scoping and delivery. Compared to the management of major transportation assets such as pavements or bridges, pedestrian asset management is still at its early stage. While inventory and condition data have provided a solid foundation, developing performance measures and deterioration models is essential for reliable and informed decision-making.

The primary goal of the project was to develop a deterioration framework for pedestrian assets that supports performance tracking. This framework will help guide funding decisions, improve asset design and maintenance, and ultimately ensure more informed, data-driven decision-making in managing pedestrian infrastructure, paving the way for its integration into the transportation asset management program. In addition, this research aimed to address the critical knowledge gaps in pedestrian asset deterioration, enabling transportation agencies to make more informed decisions regarding comprehensive asset management and funding allocation and ultimately ensuring safer and more sustainable pedestrian networks.

## 1.2 RESEARCH ACTIVITIES

The following activities were undertaken for this research project.

### 1.2.1 Survey of Agencies

A survey of state departments of transportation (DOTs) and select local agencies was conducted to gather information on their current assessment frameworks for pedestrian assets. This survey assessed the integration of these frameworks into risk-based transportation asset management plans as well as the agencies' investments in data collection technologies and changes in maintenance practices. The findings provided valuable insights into the current state of pedestrian asset management and identified gaps and opportunities for improvement.

### 1.2.2 Data Processing and Integration

A critical aspect of the research was the integration and processing of MnDOT's historical data on pedestrian assets. This involved identifying data gaps, such as missing variables necessary for deterioration modeling and imputing missing information using available datasets. In addition, supplementary data from external sources, including land use, population, weather, and climate data, were integrated to build a more robust dataset for analysis.

### 1.2.3 Field Data Collection

Field data collection involved obtaining baseline data from selected study sites using an automated condition rating methodology developed by the research team. This methodology was used to assess the condition of pedestrian assets in comparison to data previously collected by MnDOT, enabling the team to establish correlations and validate the data for subsequent analysis.

### 1.2.4 Development of Deterioration Framework

This activity focused on developing a methodology for a statewide deterioration model and condition assessment framework for pedestrian assets, particularly sidewalks, in Minnesota by leveraging various data sources, including high-resolution aerial imagery, Google Street View imagery, and lidar data. The process involved analyzing sidewalk conditions across multiple years using digital number (DN) values to track changes in surface characteristics. Key steps included data acquisition, preprocessing, feature extraction, temporal analysis, and predictive modeling to identify deterioration trends. The research also explored the integration of these data sources into a comprehensive framework that aids in proactive maintenance planning and resource optimization, ensuring sustainable and safe pedestrian infrastructure management.

### 1.2.5 Evaluation and Testing of Deterioration Methodology

To evaluate and test the developed deterioration framework, the research team used multiple temporal datasets that provided 15 cm resolution aerial imagery of urban and suburban areas. Temporal analysis of DN values from the imagery identified deterioration trends, and a linear regression model was applied to quantify the rate of deterioration. This activity demonstrated the feasibility of using DN metrics for cost-efficient sidewalk condition assessments, validating the data-driven framework for long-term maintenance planning and resource optimization.

# CHAPTER 2: LITERATURE REVIEW

## 2.1 ASSET MANAGEMENT OVERVIEW

Asset management is a complex, multifaceted discipline that serves as the backbone of organizational efficiency and long-term sustainability. Defined as an integrated process, it involves planning, organizing, controlling, and disposing of assets to meet the diverse needs of organizations, governmental agencies, and individuals (El-Akruti et al. 2013a, Haldane 2014, Petchrompo and Parlikad 2019, Dix et al. 2023). The scope of asset management is broad, encompassing both tangible assets like buildings and equipment as well as intangible ones such as intellectual property and goodwill (Davis n.d.). Moreover, assets can be functionally categorized into operating assets, which are essential for day-to-day business, and financial assets, which represent future cash flows like stocks and bonds (Amadi-Echendu et al. 2010).

The complexity of asset management is further heightened by its life-cycle approach. Unlike a one-time activity, asset management is a continuous process that spans the entire life cycle of a product or project (Davis n.d.). This necessitates a comprehensive, systematic approach that involves a series of steps from identifying and classifying to validating, optimizing, and monitoring assets (Vanier 2001). Given its cross-functional nature, asset management requires collaborative inputs from various departments and stakeholders, including investors, managers, and end-users (Van der Lei et al. 2012).

Risk assessment is another integral facet of asset management, aimed at protecting all stakeholders from unexpected risks. This becomes increasingly challenging as the number, locations, and conditions of assets grow, adding layers of complexity to the management process (Petchrompo and Parlikad 2019). Therefore, asset management is not just about managing assets in isolation but involves a holistic approach that considers multiple variables such as asset types, locations, and conditions as well as organizational goals.

### 2.1.1 Transportations Assets

Transportation assets are the physical resources that enable the movement of humans and goods (Markow 2007, Nemmers 1997). They are vital for the economic and social development of any nation, as they play an important role in trade, commerce, employment, health care, and education (Markow 2007, Meyer et al. 2010, Nemmers 1997).

The value of the transportation infrastructure and other assets in the United States, such as vehicles and equipment, was estimated at $10 trillion in 2021. The public sector owned 56.2% of these assets, while the private sector owned 43.8%. These statistics reflect the importance and role of transportation assets in the United States (BTS 2021).

### 2.1.2 Asset Management in the Transportation Industry

According to the Federal Highway Administration (FHWA), "[t]ransportation asset management is a strategic and systematic process of operating, maintaining, upgrading, and expanding physical assets effectively throughout their life cycle. It focuses on business and engineering practices for resource allocation and utilization, with the objective of better decision making based upon quality information and well-defined objectives" (FHWA 2017).

Transportation asset management serves as a conduit between the expectations of end-users regarding the system's condition, performance, and availability and the overarching systems management and business strategies. The core principles of transportation asset management are as follows (TRB 2006):

- **Policy-Driven Resource Allocation**: Decisions about resource allocation are guided by clearly established policy goals and objectives, ensuring alignment with broader strategic aims.
- **Performance-Based Management**: Policy objectives are converted into tangible system performance metrics, which are then employed for both day-to-day and long-term strategic management.
- **Analysis of Options and Trade-Offs**: The allocation of funds—whether among different types of investments, like preventive maintenance versus rehabilitation, or among different asset categories, like pavements versus bridges—is determined through a rigorous analysis of how each allocation contributes to the attainment of policy objectives.
- **Data-Driven Decision Making**: The evaluation of various options is conducted using credible, up-to-date information, ensuring that decisions align with an agency's policy goals effectively.
- **Monitoring for Accountability and Feedback**: Performance outcomes are systematically monitored and reported, providing a transparent mechanism for accountability and enabling continuous improvement through feedback.

## 2.2 PEDESTRIAN ASSETS

Pedestrian assets are the physical infrastructure specifically designed to facilitate safe and efficient pedestrian movement (Li et al. 2018). These assets play a crucial role in enhancing pedestrian convenience and reducing vehicular traffic congestion (Markow 2007). Moreover, they contribute to creating a more walkable and livable urban environment while also improving air quality by encouraging walking over driving (Baumgartner et al. 2016, Marshall et al. 2021, Vehmas et al. 2006).

The landscape of pedestrian assets is diverse, encompassing sidewalks, crosswalks, pedestrian bridges, and traffic signals (Markow 2007). Despite this variety, there are common and essential factors that must be prioritized to ensure that these assets are both convenient and effective. These factors include design, maintenance, and public education (Marshall et al. 2021).

**Design Considerations:** Proper design is paramount for safety and convenience. For instance, sidewalks should be sufficiently wide to accommodate comfortable walking; crosswalks need to be well-marked, well-lit, and strategically located where pedestrian traffic is high; pedestrian bridges should be universally accessible; and traffic signals must be clear, easy to understand, and timed to allow safe crossing (Baumgartner et al. 2016, Chang and Vavrova 2016, Loewenherz 2010, Vehmas et al. 2006).

**Maintenance Aspects:** Regular and effective maintenance is essential for the functionality and safety of pedestrian assets. For example, sidewalks should be promptly repaired and regularly swept to remove debris. Crosswalks need to be repainted as they fade and must be kept free from obstructions. Pedestrian bridges should undergo regular inspections and necessary repairs, while traffic signals must be consistently checked to ensure that they are operating correctly (Chang and Vavrova 2016, Haldane 2014, Peraka and Biligiri 2020, Vehmas et al. 2006).

**Public Education:** Educating both pedestrians and drivers is crucial for enhancing pedestrian safety. Drivers should be trained to yield to pedestrians in crosswalks and to avoid speeding or tailgating in pedestrian-heavy areas. Similarly, pedestrians need to be educated about road safety rules and should take precautions like using sidewalks, obeying crosswalk signals, and staying alert to their surroundings (Vehmas et al. 2006, Chang and Vavrova 2016).

### 2.2.1 Enhancing the Pedestrian Assets

In an increasingly urbanized world, the role of pedestrian assets—ranging from sidewalks and crosswalks to pedestrian bridges and traffic signals—has never been more critical. These assets are not just conveniences; they are essential components of urban infrastructure that contribute to public safety, environmental sustainability, and overall quality of life. As cities continue to grow and evolve, so too does the need to focus on enhancing these pedestrian assets. This section explores various strategies and considerations that can guide urban planners, policymakers, and communities in improving the design, accessibility, and sustainability of pedestrian assets. By adopting a multifaceted approach, we can create urban environments that are not only more walkable but also more inclusive and sustainable.

**Widening Sidewalks and Increasing Crosswalks:** Expanding the width of sidewalks can significantly improve pedestrian safety and convenience. Narrow sidewalks are not only uncomfortable but also pose safety risks, especially in high-traffic areas (Li et al. 2018). Additionally, increasing the number of crosswalks can alleviate traffic congestion and encourage walking, reducing the community's overall reliance on automobiles (Li et al. 2018, Lin et al. 2020).

**Accessibility for People with Disabilities:** It is imperative that pedestrian assets are designed with inclusivity in mind. Sidewalks should be wide enough to accommodate wheelchairs and other mobility devices. Crosswalks should be level and easily navigable for people with disabilities. Pedestrian bridges should feature wide elevators and voice-assisted instructions to ensure safety and accessibility for all (Baumgartner et al. 2016, Chang and Vavrova 2016, Loewenherz 2010).

**Additional Accessibility Features:** Further enhancements can include the installation of curb ramps, tactile paving, audible signals, and countdown timers. These features not only make pedestrian assets more accessible but also significantly improve safety for individuals with visual or hearing impairments (Chang and Vavrova 2016, Loewenherz 2010, Petchrompo and Parlikad 2019).

**Sustainability Considerations:** Sustainable design is crucial for the long-term viability of pedestrian assets. Using durable, eco-friendly materials can reduce environmental impacts and improve the overall health and well-being of pedestrians (Lin et al. 2020, Marshall et al. 2021, Nemmers 1997, Petchrompo and Parlikad 2019, Vehmas et al. 2006).

**Inclusive Design:** Inclusion should be a cornerstone in the design and implementation of pedestrian assets. Facilities should be accessible and safe for all citizens, regardless of age or physical ability. This includes considerations for children, the elderly, and those with health conditions (Baumgartner et al. 2016, Loewenherz 2010, Vehmas et al. 2006).

**Technological Advancements:** Recent innovations like geographical information systems (GIS), computer-aided design (CAD), and smart sensors offer new avenues for improving pedestrian asset management. Real-time traffic data can be used to optimize traffic signals, while wayfinding systems can assist pedestrians in navigating urban landscapes more efficiently (Vanier 2001, Davis n.d., Schneider et al. 2006).

### 2.2.2 Costs and Benefits of Pedestrian Assets

The financial implications of pedestrian assets can vary widely depending on the scope and complexity of a given project. However, a comprehensive cost-benefit analysis often reveals that the long-term benefits substantially outweigh the initial costs. To maximize these benefits, community engagement is crucial. Public meetings, workshops, and feedback from local residents and businesses can provide invaluable insights into the specific needs of the community where the assets will be implemented (Day et al. 2014, Gadsby et al. 2021, Li 2018).

Pedestrian asset projects are not without their challenges, the most prominent of which is funding. The construction, operation, and maintenance of these assets can be financially demanding (Vanier 2001). Maintenance presents another significant challenge; the constant exposure to weather conditions and wear and tear from usage can lead to quicker degradation, necessitating frequent repairs (Khambatta and Loewenherz 2012).

Several projects across the United States serve as compelling case studies for the efficacy and benefits of well-managed pedestrian assets. For example, New York City has seen a significant reduction in traffic fatalities since the installation of protected bike lanes. In Portland, Oregon, the development of a pedestrian-friendly downtown area has revitalized the city’s core, benefiting not just pedestrians but also drivers and policymakers (City Life Org 2023, U.S. DOT 2019).

## 2.3 STATE OF PEDESTRIAN ASSET MANAGEMENT

This section provides a summary of two National Cooperative Highway Research Program (NCHRP) projects that investigated the state of pedestrian asset management in the United States. In addition, it summarizes the state of pedestrian asset management in the United States and internationally and provides a comparative analysis of both.

### 2.3.1 NCHRP Synthesis 371

The 2007 synthesis report titled *Managing Selected Transportation Assets: Signals, Lighting, Signs, Pavement Markings, Culverts, and Sidewalks* (Markow 2007) paints a picture of a pedestrian asset management system that is still evolving and faces several challenges. One of the most glaring issues is the lack of comprehensive and consistent data. Unlike the well-established management systems for pavements and bridges, pedestrian asset management often lacks the analytic tools and data inventories needed for effective planning and maintenance. This data deficiency is not merely a technical issue; it is a significant roadblock that hampers the ability of agencies to make informed decisions.

Resource constraints add another layer of complexity. Agencies are often forced into a reactive mode, focusing on immediate concerns like safety and liability to the detriment of long-term, system-based planning. This emergency and ad hoc approach is far from optimal and does not align with the principles of comprehensive asset management. Another challenge is the fragmented responsibility for pedestrian assets, which is often spread across multiple public and private organizations. This diffusion of responsibility complicates efforts to develop a unified, comprehensive approach to asset management. It also makes it difficult to get a complete picture of the state of pedestrian assets, further complicating planning and investment decisions.

In summary, the document highlights the urgent need for a more structured and unified approach to pedestrian asset management. This includes the development of robust data collection methods, the implementation of comprehensive management plans, and a shift from reactive to proactive management strategies (Markow 2007).

### 2.3.2 NCHRP Synthesis 558

The 2020 synthesis report titled *Availability and Use of Pedestrian Infrastructure Data to Support Active Transportation Planning* (Louch et al. 2020) discusses the state of pedestrian asset management in the United States in terms of the various topics listed below.

**Current State of Data Collection:** The document emphasizes the importance of understanding the current state of pedestrian infrastructure data collection efforts in the United States. Data are often collected for specific, isolated purposes rather than as part of a comprehensive plan that covers the entire transportation network. This piecemeal approach is problematic because it does not provide a complete picture of existing infrastructure. This is inconsistent with emerging perspectives on asset management and transportation performance management (TPM), which advocate for a more holistic approach to data collection.

**Importance of Comprehensive Data:** The report argues that having comprehensive data on pedestrian infrastructure is crucial for effective and efficient planning for pedestrians in the United States. The current practice of limited data collection is neither cost-effective nor in line with FHWA policies. These policies recommend a more comprehensive approach to asset management, suggesting that a more thorough data collection strategy is needed to ensure effective planning for pedestrian infrastructure.

**Data Maintenance and Update Strategy:** The document highlights the importance of maintaining and updating data on the condition of existing pedestrian infrastructure. Accurate data are essential for future planning and recommendations. Some inventories even specify that data maintenance be conducted by staff from public entities, indicating a level of institutional involvement in keeping the data current.

**State Practices:** The objective of the synthesis is to summarize the practices of various state departments of transportation (DOTs) in the United States for storing, collecting, and sharing pedestrian infrastructure data. This information aims to help agencies tailor their data collection processes to build data infrastructure that supports multiple uses. This, in turn, would lead to more consistent and efficient planning and management of pedestrian infrastructure.

**Survey Results:** The report includes the results from a survey of DOT staff across 40 states. The survey reveals that 12 states (or 39% of the respondents) have a data maintenance plan in place. This suggests that while some states are ahead in terms of planning and data management, there is still room for improvement in others.

**Types of Data Collected:** The types of data collected for pedestrian asset management vary in scope and focus, according to the document. ADA-related planning takes precedence, largely due to federal mandates requiring the maintenance and implementation of ADA transition plans. State DOTs commonly gather counts and collision data, as well as information on shoulders and sidewalks, particularly at the project level and along state roadways. However, there are gaps in the data collection; trail data are often overlooked, and crossing and signal data are collected less frequently. Some states are exploring innovative approaches, such as using lidar technology, to gather more comprehensive data on pedestrian counts and collisions. Overall, the data collection practices reflect a mix of regulatory compliance, safety concerns, and emerging technological applications.

**Purposes of Data Collection:** The data collected for pedestrian asset management serve multiple purposes, each with its own set of priorities and objectives. The most prevalent use of the data is for planning related to ADA compliance, followed closely by project-level planning. These two categories often take precedence due to regulatory requirements and immediate project needs. Safety analysis is another significant area where the data are applied, focusing on assessing and mitigating risks associated with pedestrian infrastructure. Beyond these, the data are used for connectivity analysis and maintenance tracking, providing insights into the overall network efficiency and the state of the assets. Specialized planning initiatives also benefit from the data, including the development of active transportation plans, safe routes to school programs, and the strategic placement of traffic signals. Overall, the data play a multifaceted role, aiding in both compliance and proactive planning for safer and more efficient pedestrian environments.

**Methods of Data Collection:** The methods employed for collecting data on pedestrian assets are diverse and leverage both traditional and modern technological approaches. Initial data collection often starts with digital tools like Google Earth and vans equipped with 360° cameras, providing a broad overview of the existing infrastructure. However, these digital methods are often supplemented by physical verification through site visits to ensure data accuracy. GIS applications play a crucial role in feature creation, particularly for crosswalks and sidewalks, allowing for a more detailed and spatially accurate representation of assets. Additionally, video logs and aerial imagery are used to capture real-time conditions and offer another layer of data for analysis (Louch et al. 2020).

### 2.3.3 Summary of the Domestic Landscape

The responsibility for planning, funding, and maintaining pedestrian assets in the United States falls on various levels of government—federal, state, and local—as well as different agencies such as transportation, public works, and parks and recreation. For example, Minnesota has a comprehensive Transportation Asset Management Plan (TAMP) that includes pedestrian infrastructure among its asset classes (MnDOT 2012). However, the absence of a national standard results in a wide disparity in the quality and availability of pedestrian infrastructure across the country.

Cities like Portland, Seattle, New York, and San Francisco have made significant strides in enhancing their pedestrian asset management systems. These cities have adopted innovative approaches to promote walking as a viable mode of transportation. However, many other cities face challenges such as aging infrastructure, insufficient funding, competing priorities, and low public awareness (Aoun et al. 2015). Each initiative, whether it is in New York or California, has its unique set of goals and strategies, but they all aim to make walking safer, more accessible, and more efficient for everyone.

Nationally, organizations like the American Pedestrians Association (APA) and the American Public Works Association (APWA) provide valuable resources such as the APA's *Pedestrian Asset Management Toolkit* and APWA's *Pedestrian Asset Management Guide* that offer comprehensive guidance on how to manage pedestrian assets effectively, including inventorying assets, assessing their condition, and developing maintenance plans.

### 2.3.4 International Perspectives

In contrast, Europe has been a frontrunner in adopting advanced and comprehensive pedestrian asset management systems. Cities like Copenhagen, Amsterdam, Zurich, and Barcelona have integrated pedestrian infrastructure with land use, transport, and urban design policies (ITDP 2011). These cities have also implemented effective systems that monitor and improve pedestrian assets using various tools and techniques.

### 2.3.5 Comparative Analysis

The US approach to pedestrian asset management appears fragmented when compared to international best practices. While the federal government provides some funding and guidance, it neither mandates nor monitors the implementation or performance of pedestrian projects. State and local governments have varying degrees of authority and capacity to manage pedestrian assets. Moreover, the public sector often collaborates with the private sector or nongovernmental organizations to provide or advocate for pedestrian facilities and programs. The level of public awareness and demand for walking as a transportation option is also notably lower in the United States than in many other countries (Aoun et al. 2015).

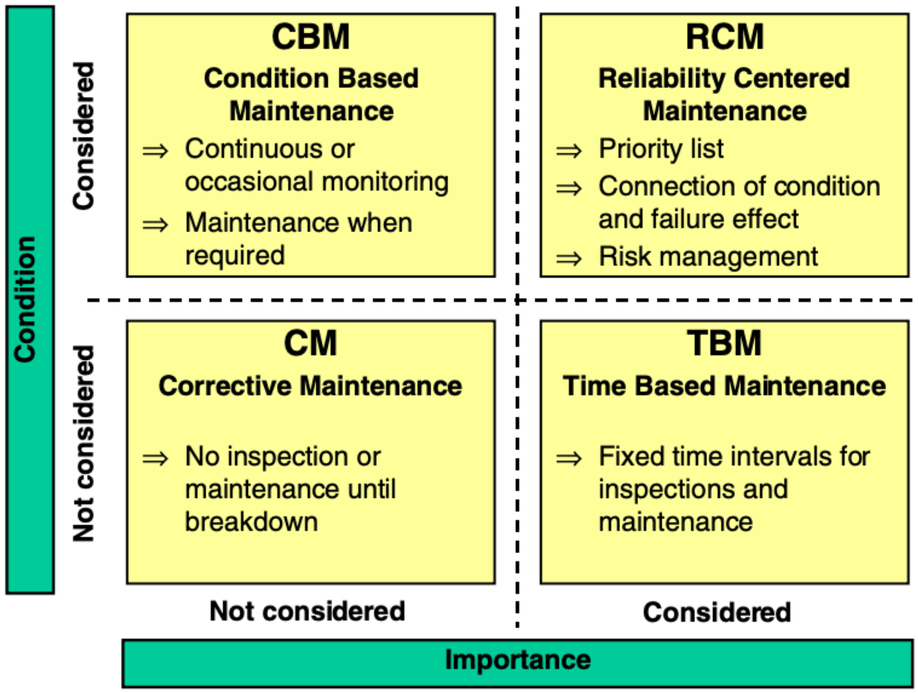
The state of pedestrian asset management in the United States is a complex issue that requires multilevel governance and multisectoral collaboration. While some cities have made significant progress, the lack of a national vision and coordination hampers the overall development of pedestrian infrastructure in the country.

## 2.4 PEDESTRIAN ASSET DETERIOATION

The deterioration of pedestrian assets, defined as a gradual decline in their condition due to both normal and abnormal wear and tear, poses significant risks to public safety. These risks range from minor inconveniences like stumbling on uneven sidewalks to more severe consequences such as fatal accidents caused by malfunctioning traffic signals or poorly lit crosswalks (Lin et al. 2022, Tee and Ekpiwhre 2019).

While it is virtually impossible to entirely prevent such deterioration, there are proactive measures that can mitigate its impact. These include identifying high-risk assets, developing targeted maintenance plans, allocating necessary resources, and engaging with community stakeholders for timely interventions (Li 2018, U.S. DOT 2019, Lin et al. 2022, Marshall et al. 2021).

Schneider et al. (2006) offer a classification of maintenance strategies, as shown in Figure 2-1, based on the condition and importance of the assets, which in turn influences both costs and asset availability. For example, assets that are both crucial and in poor condition should be subject to regular inspections at fixed intervals, while less important assets in acceptable condition may only require maintenance upon breakdown. This prioritization is especially crucial when resources are limited, allowing for immediate attention to the most severely damaged assets. However, this approach is not without its pitfalls, as neglecting minor issues can lead to more significant, costlier problems over time (FHWA 2017, Lin et al. 2022, Schneider et al. 2006).




*Schneider et al. 2006*

**Figure 2-1. Classification of maintenance strategies**

Periodic maintenance is generally the norm, but this should be aligned with the broader objectives of the managing agencies (Davis n.d.). A well-crafted maintenance plan requires the collection of specific data, such as inspection frequency, types of repairs needed, and resource allocation. These data not only help in the systematic upkeep of pedestrian assets but also aid in predicting future maintenance needs (Haldane 2014, Lin et al. 2020, Petchrompo and Parlikad 2019). However, the effectiveness of any maintenance plan should be continually monitored to identify gaps and areas for improvement (El-Akruti et al. 2013a, Peraka and Biligiri 2020).

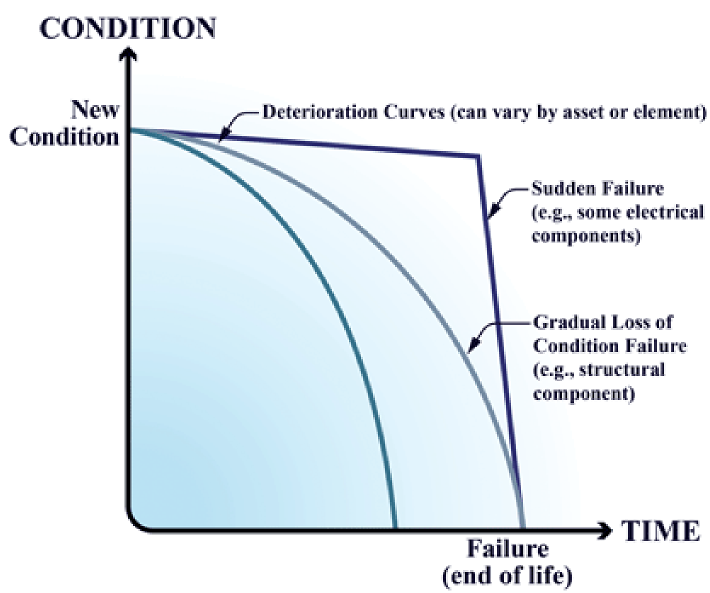
Effective communication with stakeholders is indispensable for the successful management of pedestrian assets. Feedback on asset performance and maintenance effectiveness can provide valuable insights for continual improvement. Moreover, educating pedestrians about the risks associated with damaged or deteriorated infrastructure is essential for public safety (Amadi-Echendu et al. 2010, Schneider et al. 2006).

### 2.4.1 Factors Driving Pedestrian Asset Deterioration

Several factors contribute to the deterioration of pedestrian assets, some of which are beyond human control, such as weather conditions, aging, and natural disasters, while others, like lack of maintenance and traffic volume, can be managed proactively (Lin et al. 2022, Tee and Ekpiwhre 2019). Aging is an inevitable factor; as pedestrian assets age, they naturally develop more cracks, damage, and uneven surfaces. Weather conditions, varying from region to region, also play a significant role. Assets exposed to harsh weather like rain, snow, and ice are more susceptible to damage and require special design considerations to extend their lifespan and minimize future maintenance costs (Khambatta and Loewenherz 2012, Baumgartner et al. 2016, Haldane 2014).

Conversely, factors like maintenance and traffic volume are somewhat within our control. Regular, periodic maintenance can mitigate severe damage and address minor issues before they escalate. Traffic volume, whether from vehicles or pedestrians, also impacts the wear and tear on these assets. While the design phase usually accounts for this, real-world conditions often differ from design assumptions, necessitating post-construction interventions (Markow 2007, TRB 2006).

To help decision-makers understand these dynamics, FHWA has proposed a graph, as shown in Figure 2-2, that illustrates the relationship between an asset's condition and its life cycle. This graph shows that assets are at their best when new and deteriorate to a near-zero condition by the end of their life cycle. The graph also distinguishes between different types of deterioration curves. For instance, gradual loss of condition is more common in structural components like sidewalks, while sudden failures are more likely in electrical components like traffic signals. This graphical representation serves as a valuable tool for understanding the behavior of assets over time, emphasizing the importance of strategic maintenance and life-cycle planning (FHWA 2017).




*FHWA 2017*

**Figure 2-2. Asset deterioration graph**

### 2.4.2 Pedestrian Asset Deterioration Implications

The deterioration of pedestrian assets has wide-ranging consequences that affect various stakeholders, including pedestrians, governmental agencies, DOTs, and decision-makers (TRB 2006). From a safety standpoint, worn-out assets pose significant risks, such as falls and trips, particularly for vulnerable populations like children and individuals with disabilities. Functionally, these deteriorated assets compromise accessibility, making it challenging for people with disabilities to navigate safely (Petchrompo and Parlikad 2019, TRB 2006).

Financial repercussions are also significant; the cost of maintaining deteriorated assets often far exceeds initial budget estimates, placing a strain on public resources (Davis n.d.). On a social level, the decline in the condition of pedestrian assets can lead to a decrease in property values in the surrounding areas. Over time, residents may come to view neighborhoods with poorly maintained pedestrian infrastructure as less livable, prompting them to relocate and thereby increasing the burden on services in other areas (El-Akruti et al. 2013, Lin et al. 2020, Nemmers 1997).

### 2.4.3 Pedestrian Asset Deterioration Assessment

The assessment of pedestrian asset deterioration is a comprehensive process that aims to evaluate the current state of these assets and identify both existing and potential future damage (Khambatta and Loewenherz 2012, Lin et al. 2022, Marshall et al. 2021). Various methods are employed for this assessment, including visual inspection, nondestructive testing, destructive testing, and condition monitoring (Gadsby et al. 2021, Li 2018, Lin et al. 2022).

Visual inspection is the most commonly used method and involves the examination of visible signs of damage such as cracks, potholes, and uneven surfaces. While effective for identifying surface-level issues, this method falls short in detecting internal damage that could escalate into costly repairs down the line (Khambatta and Loewenherz 2012, Marshall et al. 2021, Tee and Ekpiwhre 2019).

In contrast, nondestructive testing employs advanced technologies like ultrasonic scans, ground-penetrating radar, and radiography to assess asset conditions without causing any damage. Destructive testing, on the other hand, involves methods that do cause damage to the assets, such as coring, sampling, and destructive load testing. Condition monitoring, often facilitated by sensors and other technological tools, offers real-time insights into the asset's state, allowing for early identification of those at risk of deterioration (Gagliardi et al. 2023, Tosti et al. 2021).

A thorough assessment of asset deterioration is crucial for the development of a maintenance plan. Such a plan is instrumental in preemptively identifying issues before they escalate into more significant damage or pose risks to pedestrian safety. However, the assessment process is not without challenges. Barriers such as the cost and time required for the assessment, the expertise of the assessors, data availability, and the need for stakeholder input can all impede the effective utilization of pedestrian asset deterioration assessment (Day et al. 2014, Khambatta and Loewenherz 2012, Li 2018).

### 2.4.4 Benefits of Pedestrian Asset Deterioration Assessment

Assessing the deterioration of pedestrian assets serves multiple purposes, one of which is guiding decision-makers in selecting the most appropriate construction materials. For example, opting for more sustainable materials not only enhances asset performance during the operational phase but also minimizes environmental impact, particularly when constructing in green areas. The use of high-quality materials can significantly reduce future maintenance needs, thereby lowering the overall indirect costs associated with the operation and maintenance of these assets throughout their life cycle. This, in turn, improves the cost-benefit ratio of the assets (Day et al. 2014, Gadsby et al. 2021, Li 2018).

A systematic approach to assessing asset deterioration also allows for more accurate tracking and quantification of the rate of deterioration over the asset's life cycle. This enables the development of predictive models that can guide decision-makers in estimating potential future maintenance costs. Such an approach makes financial planning more accurate and effective (Amadi-Echendu et al. 2010, Nemmers 1997).

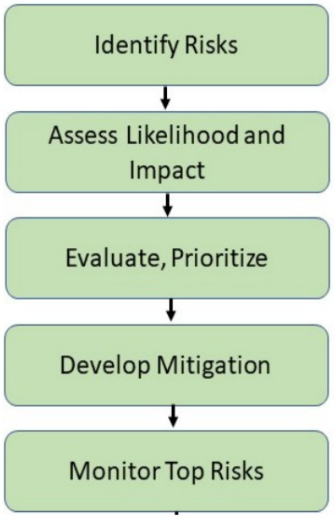
Moreover, proactive assessment creates valuable databases that can be integrated into a comprehensive data framework. This framework can track both current and anticipated deterioration, allowing for the development of data-driven, strategic mitigation strategies over time (Gadsby et al. 2021, Lin et al. 2022, U.S. DOT 2019).

From a legal standpoint, advanced assessment techniques can significantly reduce the risk of accidents, thereby minimizing tort liability and exposure to complaints under the ADA (Loewenherz 2010). A reduction in pedestrian exposure to accidents due to well-maintained assets will likely result in fewer legal consequences. This, combined with the potential for reduced future maintenance costs—especially when considering the high initial costs of design and construction—means that the total cost of pedestrian assets over their life cycle could be significantly lower than with traditional approaches (Baumgartner et al. 2016, Marshall et al. 2021, U.S. DOT 2019).

## 2.5 DATA COLLECTION FOR PEDESTRIAN ASSET ASSESSMENT

While ADA compliance remains a significant driver for state agencies in collecting data on pedestrian assets, as noted in NCHRP Synthesis 558, it is crucial to recognize that pedestrian asset management is a far more nuanced and multidimensional undertaking. The scope extends well beyond the boundaries of ADA requirements, encompassing a broader range of factors that contribute to the overall quality, safety, and efficiency of pedestrian environments. Data collection in this context is not merely a regulatory obligation; it is the linchpin for a host of activities that shape the urban pedestrian landscape. These data serve as the foundational element for planning, implementing, and continually evaluating the state of pedestrian infrastructure. They inform decisions that range from immediate safety interventions, such as installing more pedestrian-activated crosswalks, to long-term urban planning strategies that consider pedestrian flow, economic activity, and environmental sustainability.

FHWA has established a risk management process, as depicted in Figure 2-3, that serves as a globally recognized framework for assessing potential damage, including that arising from severe weather and climate change. This process begins with risk identification, followed by estimating the likelihood and impact of these risks based on historical data and prior experience. Subsequently, the evaluation and prioritization process allocates resources and efforts towards the most urgent maintenance needs. Continuous monitoring is essential to ensure that the risk management process aligns with project objectives and delivers value to all stakeholders (Dix et al. 2023). This process cannot be sustained in the absence of data.




*Dix et al. 2023*

**Figure 2-3. Steps in the FHWA risk management process**

### 2.5.1 Types of Data Collected

The data required for assessing pedestrian assets can vary depending on the type of asset and the purpose of the data collection. However, there are common types of data that are generally essential, and they fall into one of the following three categories: spatial data, material and structural data, and usage and safety metrics.

**Spatial Data**: One of the primary types of data collected pertains to the availability, location, and geometry of pedestrian infrastructure. This includes sidewalks, crosswalks, signals, signs, and lighting. Collecting these data is crucial for identifying gaps in the existing pedestrian network and planning for new or improved facilities. For instance, a lack of crosswalks in a high-traffic area could be a significant gap that needs immediate attention.

**Material and Structural Data**: Another critical aspect is the collection of data on the material, thickness, width, slope, cross slope, and overall condition of pedestrian infrastructure. These data are invaluable for assessing the quality and performance of existing facilities. They help urban planners prioritize maintenance activities and rehabilitation projects. For example, sidewalks made of substandard material that deteriorates quickly might need to be replaced with more durable options. For specific tasks like repair history tracking, additional data such as the type of repair used, estimated repair costs, and repair priority are indispensable for achieving optimal outcomes (Petchrompo and Parlikad 2019, Van der Lei et al. 2012, Vanier 2001).

**Usage and Safety Metrics**: The third pillar of data collection focuses on the usage, demand, and safety of pedestrian infrastructure. This involves gathering data on pedestrian traffic, accident rates, and other safety metrics (Hastings 2010, Meyer et al. 2010, Nemmers 1997). Such data can help evaluate the effectiveness and efficiency of pedestrian facilities and services, thereby identifying potential issues or risks that need to be addressed. For instance, a high number of pedestrian accidents at a particular intersection could indicate the need for better signage or lighting.

The quality and accuracy of the collected data are paramount for making informed decisions. Data should not only be accurate and reliable but also comprehensive, capturing all relevant aspects rather than just what is easily available. Timely data collection is equally important; gathering data soon after an asset is constructed or renovated allows for early identification and resolution of issues. Delaying data collection until defects appear can significantly increase repair costs and may even necessitate asset demolition and reconstruction. Therefore, data collection should be both thorough and cost-effective to ensure a successful assessment (BTS 2021, Schneider et al. 2006, TRB 2006).

## 2.6 UTILIZING ARTIFICIAL INTELLIGENCE IN PEDESTRIAN ASSET ASSESSMENT

The integration of artificial intelligence (AI) into the realm of pedestrian asset management is still in its nascent stages, but the potential for transformative change is evident. AI can serve multiple functions in this context, from automating data collection to developing sophisticated condition monitoring systems and aiding in decision-making processes. When properly deployed, AI technologies can significantly enhance the efficiency, accuracy, and overall effectiveness of pedestrian asset assessments.

One of the most promising applications of AI in this field is its ability to analyze images and videos to identify signs of asset deterioration. This not only automates the data collection process but also increases its efficiency and accuracy. Beyond mere data collection, AI can also develop condition monitoring systems capable of tracking the state of pedestrian assets over various time frames. Such systems are invaluable for early identification of assets at risk of deterioration. AI can further assist by creating risk assessment models that categorize assets based on their likelihood of deterioration, thereby enabling more targeted and efficient allocation of maintenance and inspection resources.

The insights generated by AI can be invaluable for decision-makers. For example, AI algorithms can suggest the most effective courses of action for repair work, prioritize maintenance activities, or even recommend the replacement of irreparably damaged assets. This level of decision-making support can lead to more optimized and cost-effective asset management strategies.

In the United States, various DOTs and universities are increasingly exploring the utility of AI in pedestrian asset management. For example, the University of California, Berkeley, has developed an AI-based system designed to predict the risk of pedestrian accidents. This innovative system integrates data on asset conditions, traffic patterns, and weather conditions to make its predictions (Griswold et al. 2019). Similarly, the city of Seattle has utilized AI and computer vision technologies to identify and prioritize pedestrian assets in need of repair (Packer 2016). The Massachusetts Department of Transportation is also leveraging AI to detect crosswalk locations statewide and to classify them by type (continental, parallel lines, or solid) and location category (intersection, midblock, or driveway) (Apostolov et al. 2024).

### 2.6.1 Limitations of Using Artificial Intelligence in Pedestrian Asset Assessment

While AI offers transformative potential in the field of pedestrian asset management, it is crucial to address several concerns and challenges associated with its deployment. These range from issues of data accuracy and scalability to ethical considerations and user accountability.

First, the effectiveness of AI is heavily dependent on the quality of the data it is trained on. Inaccurate or outdated data can lead to flawed models, which in turn can result in poor decision-making. Therefore, human oversight remains indispensable for reviewing the performance of AI models to ensure their accuracy and reliability. This is a critical step in mitigating the risks associated with AI's inherent limitations (Kour et al. 2022, Lee 2021).

Scalability is another significant concern. AI models can be computationally expensive to run, and it is essential to match the complexity of the AI model to the problem at hand. Over-engineering solutions for minor issues can result in financial inefficiencies, while overly simplistic models may not adequately address more complex challenges in pedestrian asset management (Cunningham et al. 2019, Hou and Ai 2020, Lee 2021).

The interpretability of AI models is also a key issue. Complex models that are not easily understood can create barriers to effective decision-making. For AI to be truly useful, its results must be interpretable and easily communicated to stakeholders, including those without technical expertise (Chen and Zhou 2019).

Ethical considerations are paramount, especially given that the data processed by AI models often pertain to human activities. Ensuring ethical use of these data is critical, as is maintaining transparency in how AI is deployed in pedestrian asset management. This includes clarity about how data are collected, processed, and used to build AI models, as well as how the results of these models are presented to decision-makers (Cunningham et al. 2019, Hou and Ai 2020, Kour et al. 2022).

Lastly, accountability is crucial when it comes to the deployment of AI in this context. Whether governmental authorities, stakeholders, researchers, or citizens, all parties involved should be held accountable for the ethical and effective use of AI. This includes responsibility for the accuracy of AI models, ethical considerations, and the broader impact of AI on pedestrians and other stakeholders (Abduljabbar et al. 2019, Mcmahon et al. 2020, Ushakov et al. 2022).

## 2.7 GAPS IN THE LITERATURE

The existing literature on pedestrian asset deterioration assessment reveals several significant gaps that warrant further research and exploration. These gaps range from the absence of standardized assessment methods to the underutilization of emerging data science concepts like business intelligence (BI), AI, and machine learning (ML).

**Lack of Standardized Assessment Methods:** One of the most glaring gaps is the absence of a unified method for assessing the condition of pedestrian assets. While various studies have attempted to create general frameworks, there is still no standardized approach that allows for the measurement and comparison of asset conditions on a numerical scale. This lack of standardization hampers effective maintenance planning and risk assessment.

**Insufficient Databases:** Another major gap is the lack of comprehensive databases that document the condition of pedestrian assets at both network and project levels. The absence of such databases makes it challenging to identify assets at risk, thereby leading to ineffective maintenance plans. A network database could facilitate comparisons between areas with similar conditions, providing a more robust scale for asset assessment and future problem prediction.

**Neglect of Social Aspects:** The literature also tends to focus predominantly on the technical aspects of pedestrian asset deterioration, often neglecting its social implications. This oversight can result in a disconnect between social needs and theoretical assumptions, reducing public awareness and involvement in the decision-making process.

**Imbalance in Damage Assessment:** Most existing assessment methods focus primarily on external or physical damage, largely ignoring internal damage that could be equally crucial. This imbalance calls for the development of advanced methods capable of detecting both external and internal damage to provide a more comprehensive assessment.

**Underutilization of Data Science Concepts:** Lastly, the literature has yet to fully leverage evolving data science concepts like BI, AI, and ML. Utilizing these technologies could lead to the development of comprehensive frameworks that draw on data from diverse sources. Such frameworks could not only improve predictive modeling for asset behavior but also document valuable lessons learned.

In summary, these gaps in the literature highlight the need for a more holistic approach to pedestrian asset deterioration assessment—one that incorporates standardized methods, comprehensive databases, social considerations, balanced damage assessments, and the latest advancements in data science.

# CHAPTER 3: SURVEY REPORT

## 3.1 INTRODUCTION

This chapter presents the comprehensive findings of a survey conducted to understand the current practices in the management of pedestrian assets across various organizations. The survey, divided into four parts, aimed to gather a broad spectrum of data.

Part 1 delves into some information about the respondents, including their organizational type, state representation, and job roles. A crucial aspect of this part was to understand the pedestrian asset data collection efforts within these organizations.

Part 2 focused on the methodologies adopted by organizations in managing pedestrian assets. It sought to understand the various strategies employed and their approach towards future data collection plans.

Part 3 was designed to gather information on the types of pedestrian assets managed by the organizations, the methods used for their assessment, the specific data collected, and the criteria for rating these assets. This section provided insights into the most commonly evaluated assets and the frequency and methodology of these evaluations.

Part 4, the final part of the survey, explored the technologies employed in collecting data on pedestrian assets and the methods used for managing and storing these data. This section aimed to understand the technological landscape of pedestrian asset data collection and management among the participating organizations.

This chapter analyzes the responses to each survey question, presenting the data through illustrative figures and charts to facilitate a clear understanding. It encapsulates the diversity in management practices and technological adoption, providing a panoramic view of the current state of pedestrian asset management. The insights gleaned from the survey not only offer a comprehensive overview of existing practices but also illuminate the various ways organizations are navigating the challenges and opportunities in pedestrian asset management.

### 3.1.1 Part 1

Part 1 enquired about the respondents' identifying information, which included the type of organization each respondent worked in, the state they represented, their job title and how many years they had been serving in that role. Additionally, Part 1 inquired about the data collection efforts related to pedestrian assets within their respective organizations.

**Q1 - What type of organization do you work in?**

The survey findings indicated that the largest portion (65%) of the participating organizations consisted of state DOTs. Figure 3-1 displays the distribution of the remaining types of organizations.

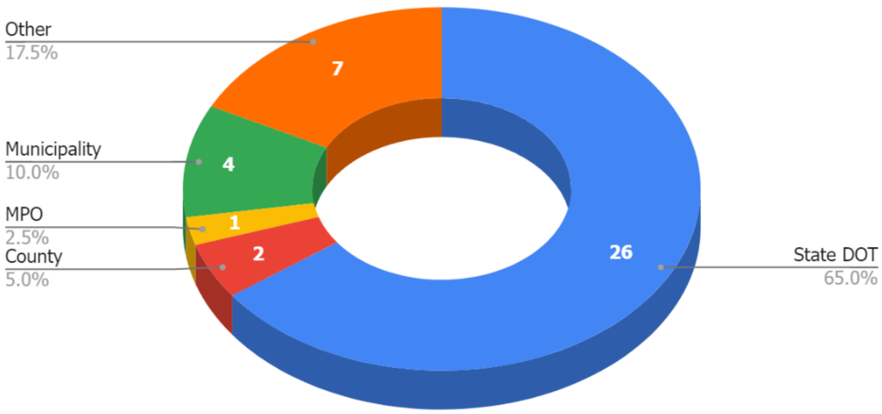



**Figure 3-1. Type of organization**

When respondents selected the “Other” option, they were prompted to manually input organizations that were not included in the provided list. The following is a list of answers entered by the respondents:

- Consultant
- Regional development commission
- Nonprofit NGO [nongovernmental organization]
- Regional development organization

**Q2 - 50 States, DC, and Puerto Rico**

The survey had representation from 25 out of the 50 states, along with the District of Columbia. Figure 3-2 illustrates the states that participated in the survey.

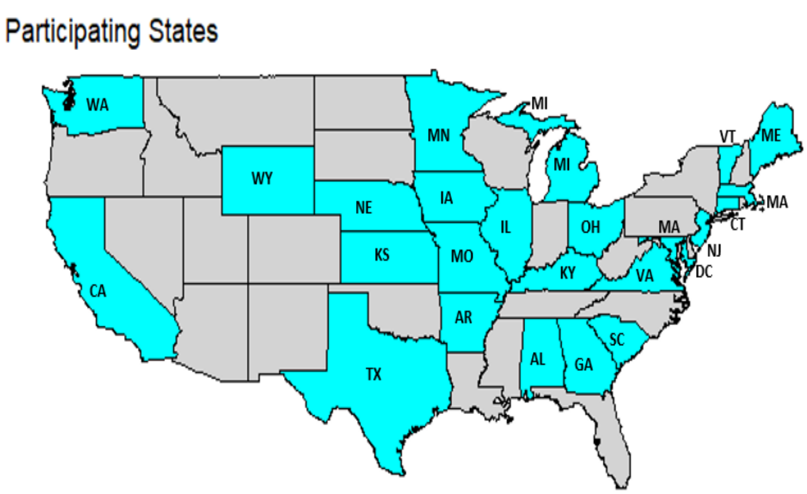



**Figure 3-2. Participating states**

**Q4 - What part of your organization do you work in (e.g., asset management, planning, maintenance, etc.)**

Responses to this question were categorized according to the section or department to which the respondent belonged within their respective organizations. The top categories included the following:

- Planning
- Asset Management
- Safety
- Design

In addition, the word cloud depicted in Figure 3-3 graphically summarizes the responses. This visual illustrates the multifaceted approach that state DOTs are employing to oversee pedestrian assets and the varied emphasis placed on these responsibilities across the country. Central to the visualization is "planning" and "asset management," which are significantly emphasized, indicating that these units are often at the core of pedestrian infrastructure management.


**Figure 3-3. Word cloud showing parts of the organization respondents belong to**

Surrounding these units are other relevant areas such as "safety," "design," "engineering," "traffic operations," and "transit," each contributing to the management of pedestrian assets in more specialized ways. Their presence in the word cloud, albeit with smaller font sizes, suggests that while these units are less frequently reported as the primary managers, they still play a critical role in the overall stewardship of pedestrian infrastructure.

The inclusion of more specific terms like “bicycle and pedestrian programs” points to specialized divisions within some state DOTs that focus on nonmotorized forms of transportation, reflecting an emerging recognition of the importance of pedestrian-centric planning.

Additionally, the word cloud reveals a diversity of focus areas, including “research,” “advocacy,” and “implementation of the transition plan.” These terms suggest an inclination towards embracing research-driven, advocacy-informed, and transition-focused methodologies in pedestrian asset management.

In essence, Figure 3-3 captures a nuanced picture of the organizational landscape within state DOTs concerning the management of pedestrian assets. It reveals a trend toward the integration of pedestrian asset management within the more traditional frameworks of planning, yet it also emphasizes the integral roles of other departments. This reflects a growing understanding that the management of pedestrian assets is not confined to a single unit but is a cross-sectional task that benefits from the collaboration of multiple departments within state DOTs, each bringing a unique perspective and expertise to the collective effort of making pedestrian infrastructure safe, efficient, and accessible.

**Q6a - Does your agency collect any data on pedestrian assets (for e.g. sidewalks, crosswalks, curb ramps, bike paths, trails, parking areas, bus stops, pedestrian bridges, signalized crosswalk, pedestrian refuge islands, pedestrian countdown timers, pedestrian-activated crosswalks, tactile paving, braille crosswalk signs, accessible seating, shared-use path, etc.)?**

Out of the 40 participating agencies, 36 of them (representing approximately 90%) indicated that they collected data on pedestrian assets, while the remaining 4 (about 10%) indicated otherwise. Figure 3-4 shows this distribution.

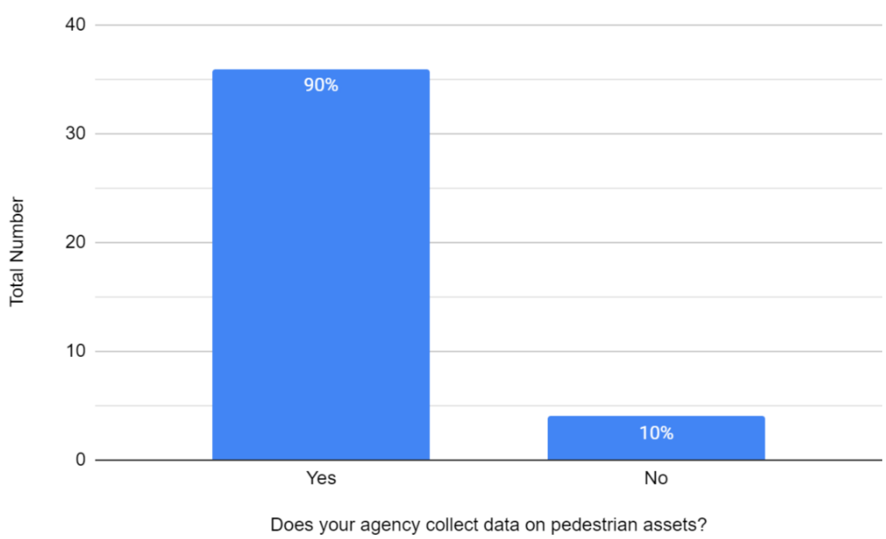



Figure 3-4. Collection of pedestrian data

**Q6b - Do you plan to in the future?**

Among the remaining 4 agencies that do not currently collect data on pedestrian assets, 50% of them indicated having plans to gather such data in the future.

### 3.1.2 Part 2

Part 2 focused on the approach adopted by organizations in managing their pedestrian assets.

**7. How would you best describe your organization's approach to managing pedestrian assets?**

The survey revealed that the most prevalent approaches to managing pedestrian assets, as reported by the respondents, were "Inventory" and "Condition assessment," each comprising approximately 27% of the results. The next most common approach was "Using condition to prioritize projects," making up about 16%. The least popular approach was "Pedestrian assets are part of our TAMP," accounting for only 5% of the responses. Figure 3-5 provides a visual summary of these approaches.

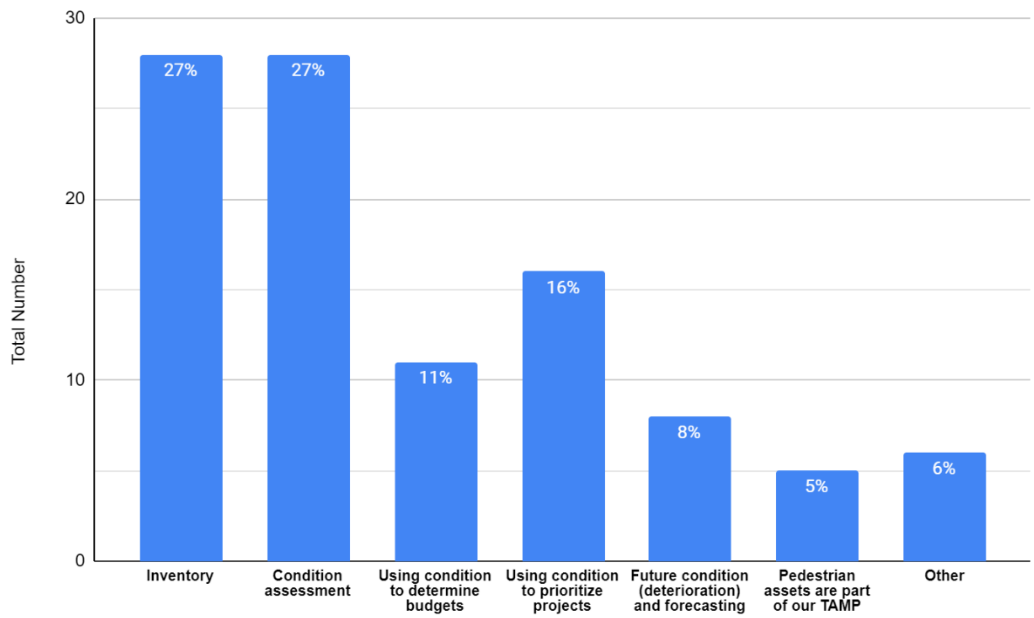



**Figure 3-5. Approach to managing pedestrian assets**

Approximately 6% of the respondents chose the "Other" option, which allowed them to manually input their approach to pedestrian asset management. The following is the list of those responses:

- On a project basis
- ADA Transition Plan prioritization for upgrades
- Managing with adjacent road and bridge assets
- Currently we have inventories of our curb ramps for ADA compliance, and we have mapped our sidewalks.

- Rely on Regional Planning Commissions to collect condition data for sidewalks. The state has records of assets locations such as pedestrian signals, signs and markings. Emphasize that municipalities own and maintain sidewalks.

**8. Various factors can prompt the inspection of an asset. Please rank the following reasons based on their frequency in prompting an inspection within your organization. Drag the options, placing the most common reason at the top and the least common at the bottom.**

Factors that can prompt the inspection of an asset were assigned scores based on their ranking in each response, with a factor receiving 10 points for being ranked 1st, 9 points for 2nd, 8 points for 3rd, and so on. According to the survey results, "User complaints" was the top factor that prompted an asset inspection. Figure 3-6 displays the ranking of these factors.

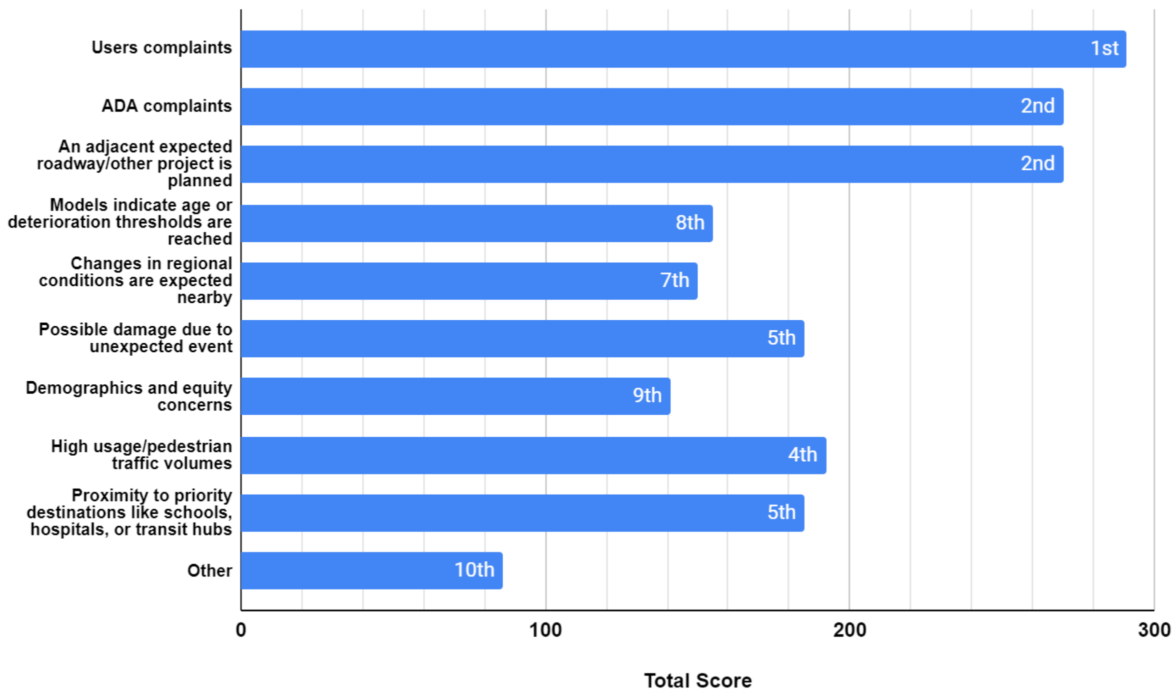



Figure 3-6. Factors that prompt inspection of pedestrian assets

When respondents selected the "Other" option, they were prompted to describe factors that were not included in the provided list. The following is a list of answers manually entered by the respondents:

- Project modifying asset completed
- We do not maintain or inspect sidewalks. The following does not apply to the state’s sidewalk inspection process at this time. We update curb ramps and pedestrian signals as part of agency projects.
- 5-year frequency
- At the time of this survey, the systemwide pedestrian asset inventory program is under development and its methodology is in a pilot stage. Outside of this pilot program, the condition of pedestrian assets may be assessed if they are part of the purpose and need of a project.

- Sidewalks are maintained by municipalities.
- ADA compliance

### 3.1.3 Part 3

This part focused on gathering information about the organizations' inventory of pedestrian assets, the methods used to assess each asset, the specific data collected for each asset, and the criteria employed to assign ratings to individual assets.

**9. Below is a list of potential pedestrian assets. Please check all pedestrian assets that are evaluated as part of your pedestrian asset management approach:**

The survey findings indicate that among the participating agencies' pedestrian asset management approaches, the most commonly included pedestrian asset was "Sidewalk," comprising approximately 17% of the responses. Following that, "ADA ramps and coverings" accounted for about 15%, while the least common inclusion was "Pedestrian barrier and rails," making up only about 4%. Figure 3-7 provides the distribution of the pedestrian assets.

Only two organizations evaluated all listed asset types as part of their pedestrian asset management approach. Most organizations manage a small to moderate number of pedestrian assets, with two peaks at two and six assets. Figure 3-8 shows this distribution. This could suggest that there is a common capacity for pedestrian asset management that most organizations are comfortable with, and only a few organizations have the resources or mandate to manage a larger number of assets.

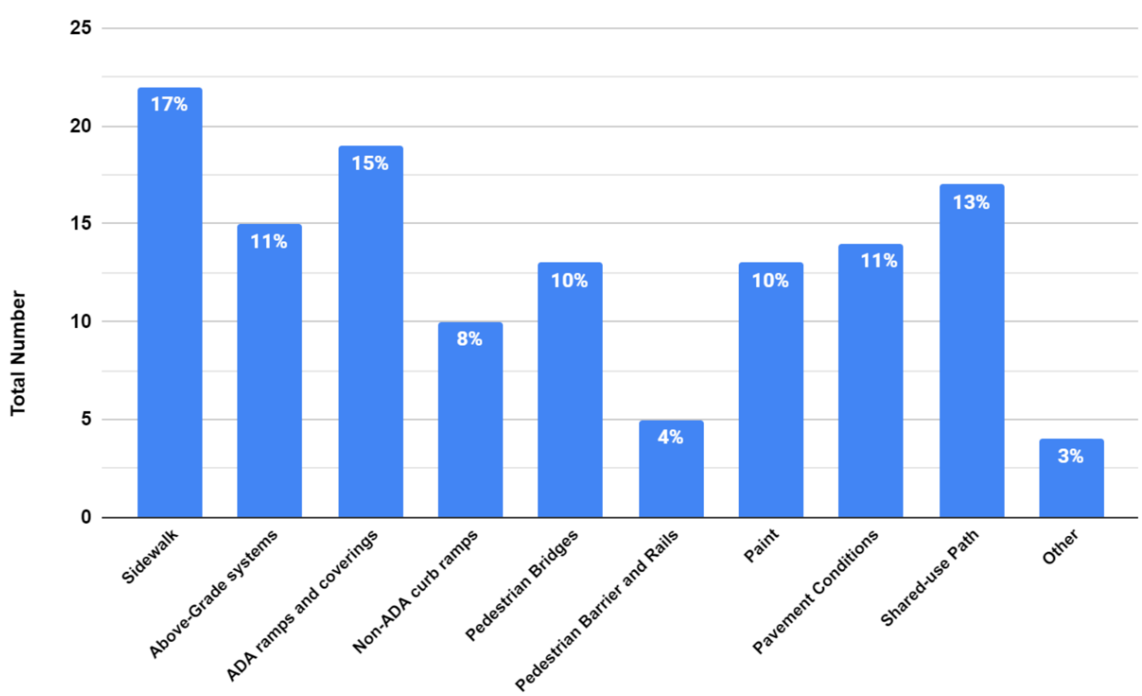



Figure 3-7. Potential pedestrian assets

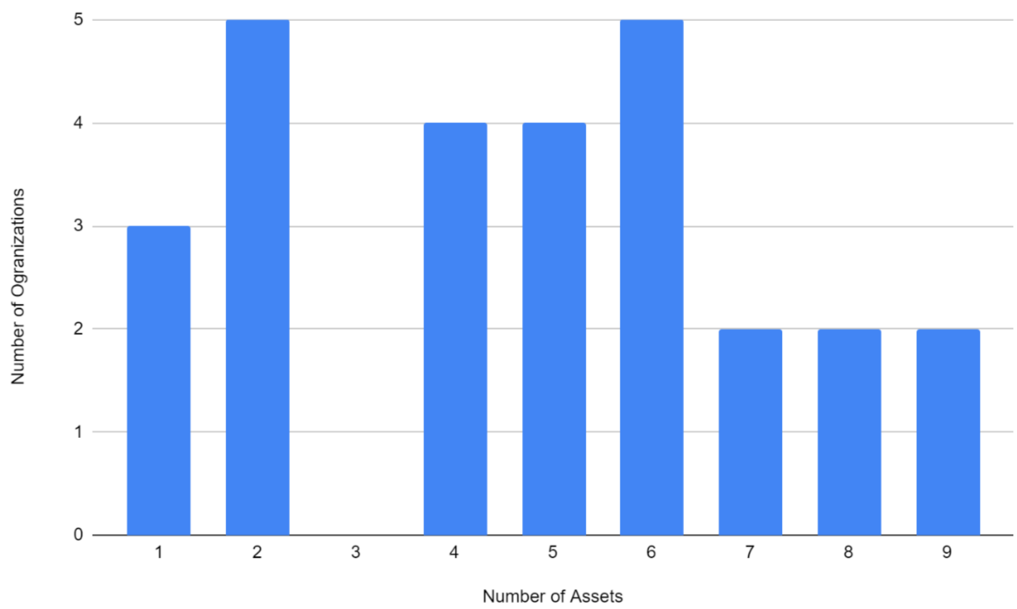



**Figure 3-8. Count of different assets that organization manage**

When respondents selected the "Other" option, they were prompted to manually input additional pedestrian assets that were not included in the provided list. The following is a list of answers manually entered by the respondents:

- Sidewalks, curb ramps, and pedestrian signals are evaluated with adjacent road and bridge improvement.
- Transit stops
- Bicycle facilities
- Above-grade systems (e.g., signage, signals, pedestrian-level lighting) may be assessed if within the purpose and scope of the project.

**9a. How do you typically evaluate this asset? (select all that applies)**

The survey results reveal the typical evaluation methods employed for each pedestrian asset, with each asset being evaluated using a minimum of two methods. Figure 3-9 visually illustrates the methods used for evaluating each asset according to the respondents.

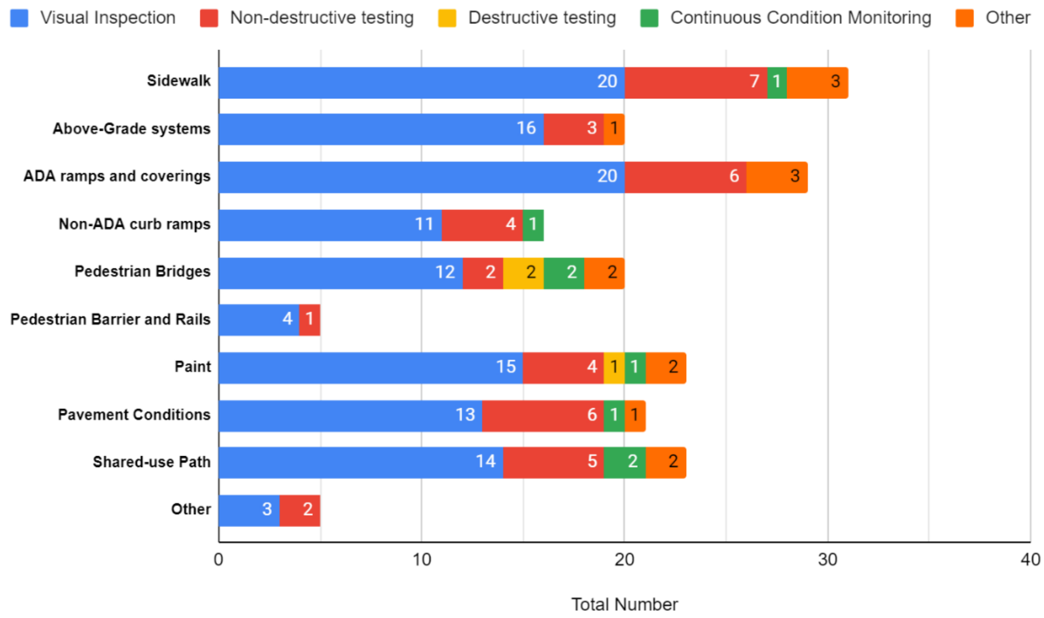



**Figure 3-9. How assets are typically evaluated**

The "Other" option, when selected, enabled respondents to manually input methods for evaluating each asset that were not originally provided as options in the survey. The following are lists of additional methods for evaluating the assets, grouped by the respective asset type.

Sidewalk:

- Virtual tracking
- Ultra lite inertial profiler
- Virtual inspection through road video log

Above-Grade Systems:

- Year installed

ADA Ramps and Coverings:

- GPS inventory collection on projects
- We incorporate upgrades and improvements during projects.
- Lidar scanning and condition assessment has been introduced in our DOT. This scanning of ramps will be undertaken as below.

Pedestrian Bridges:

- Depends on who owns the bridge and if the bridge is part of our network
- Part of the state bridge inspector’s responsibility for state-owned bridges
- MnDOT dataset

Paint:

- Crosswalks and markings are the responsibility of the municipality. We only paint when it is part of the contract.
- Markings are updated on an annual basis or bi-annual basis independent of an evaluation.
- This is on an automatic cycle.

Pavement Conditions:

- Part of pavement condition assessments
- Pavement analysis through pavement management

Shared-Use Path:

- Utilize counters to identify traffic use. Visual inspection of condition being the most common.
- Accelerometer readings from iPhone

The most prevalent method for evaluating pedestrian assets, as determined by the survey, was Visual Inspection, accounting for approximately 65% of the responses. Nondestructive testing was the next most common method at about 20%, while Destructive testing was the least utilized method, representing only about 2% of the responses. Figure 3-10 provides a graphical representation of the distribution of these evaluation methods.

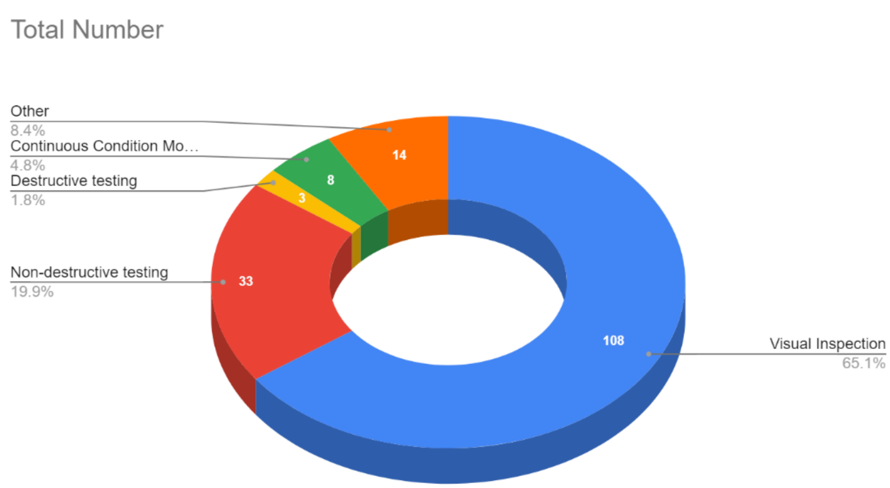



**Figure 3-10. Methods of evaluating assets**

**9b. How often do you perform this evaluation?**

The survey results illustrate the frequency with which each pedestrian asset is typically evaluated, with evaluation periods ranging from less than every 10 years to multiple times a year. Figure 3-11 visually displays the evaluation periods for each asset according to the responses from the participants.

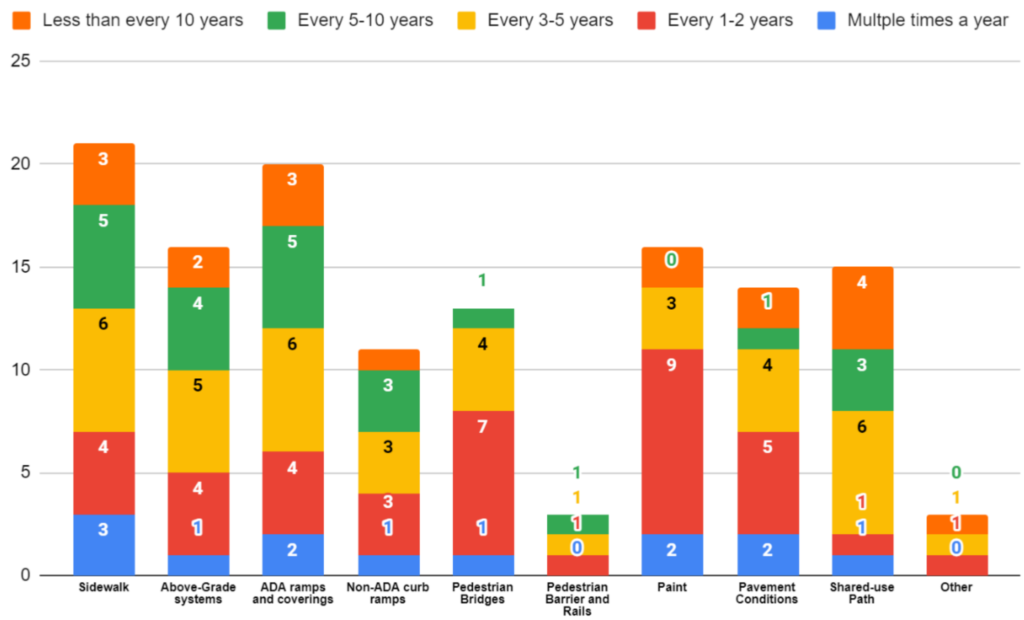



Figure 3-11. How often assets are evaluated

The most common evaluation frequency for pedestrian assets, as indicated by the survey results, was found to be "Every 3-5 years," accounting for approximately 31% of the responses. The next most common frequency was "Every 1-2 years," at about 28%, while the least frequent evaluation period was "Multiple times a year," with approximately 8%. Figure 3-12 visually presents the distribution of these different evaluation time periods.

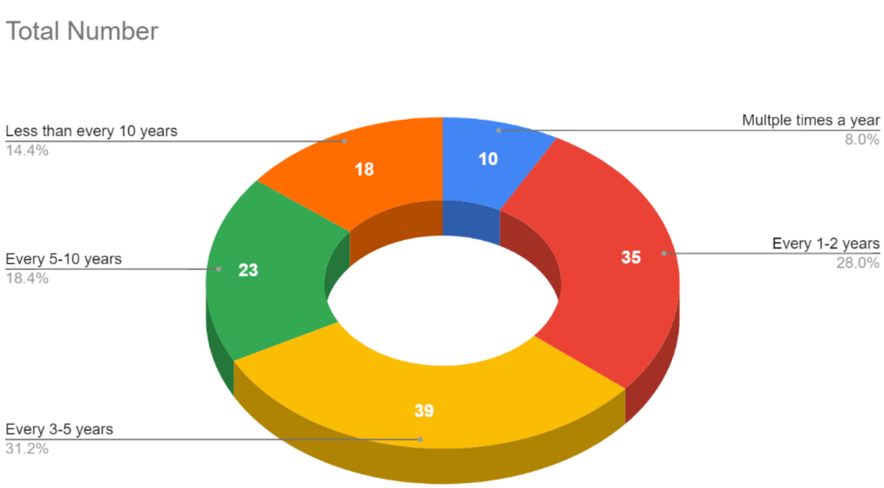



Figure 3-12. Frequency of asset evaluation

**10. The following matrix outlines pedestrian assets and the type of information collected. Please check the box for each type of asset and the information collected for that asset. For example, if location, material type, and pedestrian traffic are collected for an asset, check all three. If no data is collected for an asset, please check "We do not collect information" only. If other is selected, you will be asked to provide the information collected on that asset in the follow up question.**

The survey results provide insights into the type of information collected for each type of pedestrian asset. Figure 3-13 provides a comprehensive visual representation of this information.

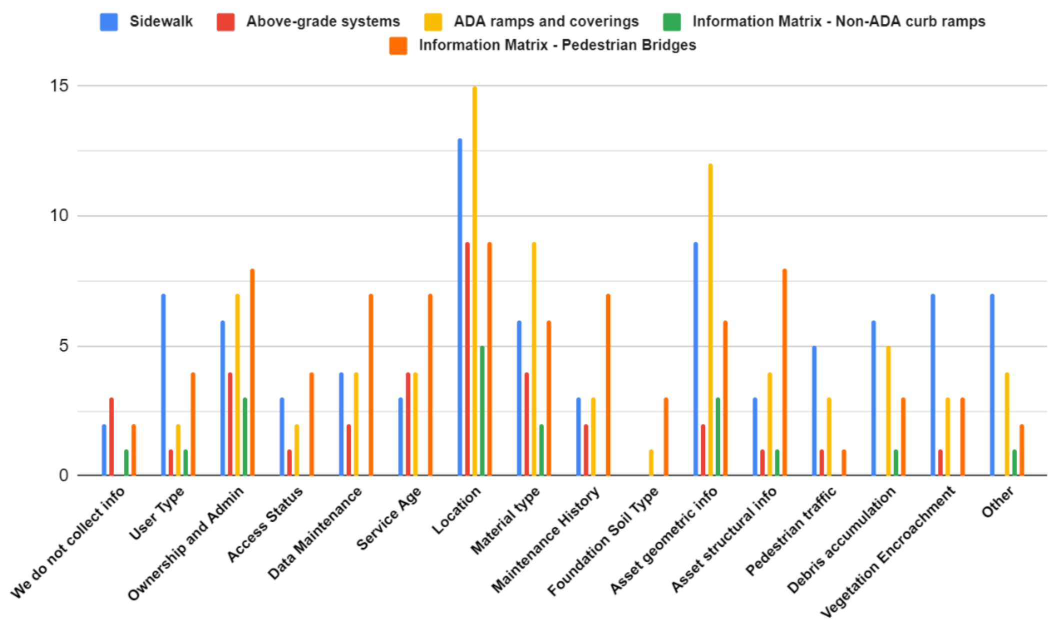



Figure 3-13. Information collected for each asset type

According to the survey results, data related to the "Location" of pedestrian assets is the most commonly collected type of information, accounting for 17.4% of the responses. Following that, data concerning "Ownership and Administration" and "Asset geometric information" each represent 9.8% of the responses. The least common type of data collected is "Foundation soil type and other parameters," which is reported at less than 1%. Figure 3-14 visually displays the distribution of the types of data collected.

The most common combinations are unique to individual agencies, with no repeating pattern found across multiple agencies. This emphasizes the tailored approach agencies take towards data collection based on their specific needs and operational contexts.

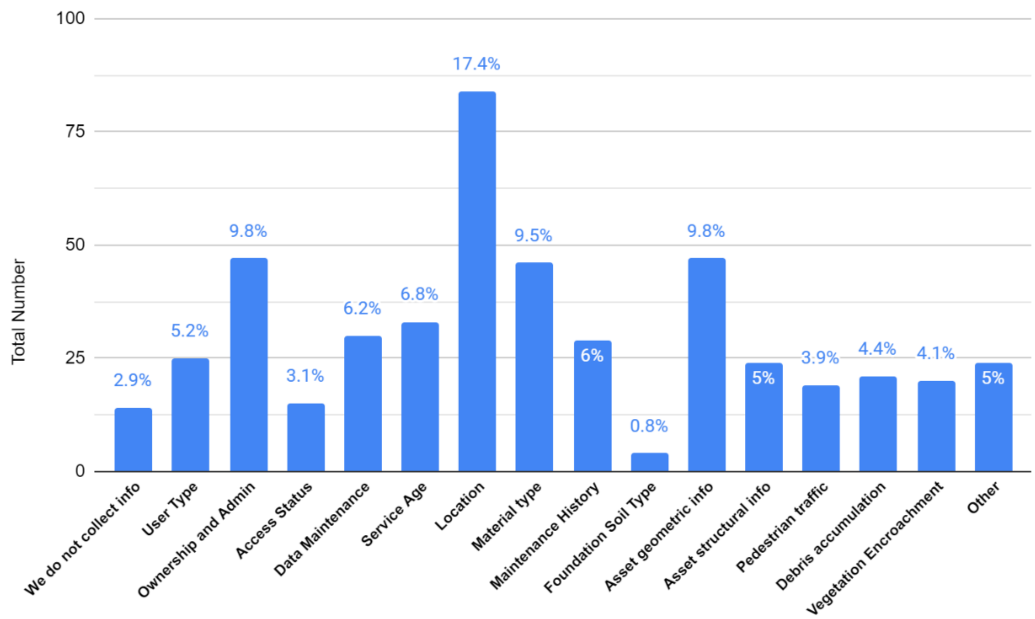



**Figure 3-14. Types information collected for assets**

The "Other" option, when selected, enabled respondents to manually input types of data collected for each asset that were not originally provided as options in the survey. The following are lists of additional methods for evaluating the assets, grouped by the respective asset type.

Sidewalk:

- Lidar scanning for ADA compliance (width, slope) and condition is currently being undertaken through a study that will evaluate all sidewalks.

ADA Ramps and Coverings:

- Within projects 200 - 400 curb ramps a year are incorporated, bringing them into compliance with accessibility.
- Lidar scanning for ADA compliance (width, slope) and condition is currently being undertaken through a study that will evaluate all sidewalks.

Pedestrian Bridges:

- MassDOT collects information on ALL bridges, pedestrian and vehicular, in order to comply with all federal requirements for safety inspection, funding, and repair.

Pavement Conditions:

- None

Shared-Use Path:

- Surface condition

**Q11 - After gathering information on your assets, do you assign a rating to each type of asset?**

The survey findings indicate that only 45% of the agencies assign ratings to pedestrian assets after data collection. Figure 3-15 shows the distribution of this information.

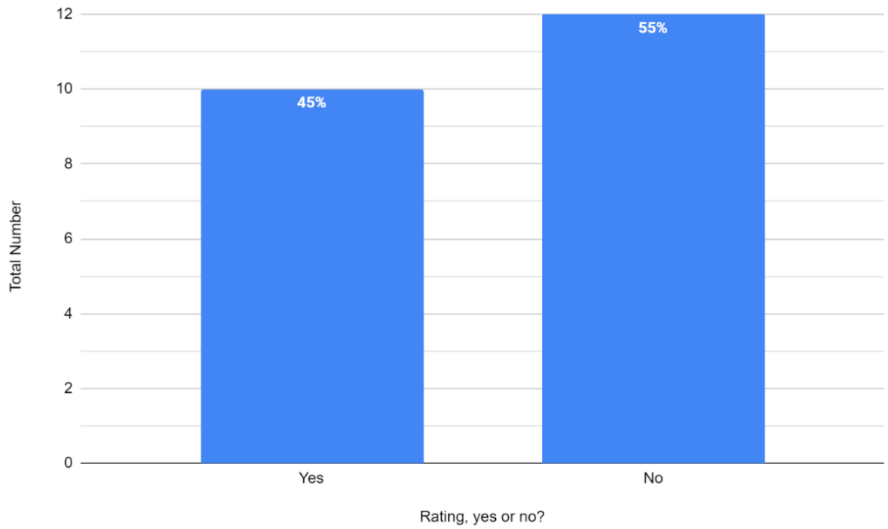



Figure 3-15. Are assets assigned ratings

**12. What criteria do you use to assign a rating to each type of asset? Please check the applicable boxes for each asset type. If other is selected, you will be asked to provide the criteria for assigning a rating for that asset in the follow up question.**

The survey results provide insight into the criteria used by participating agencies to assign ratings to each type of pedestrian asset. Figure 3-16 visually illustrates these criteria for reference.

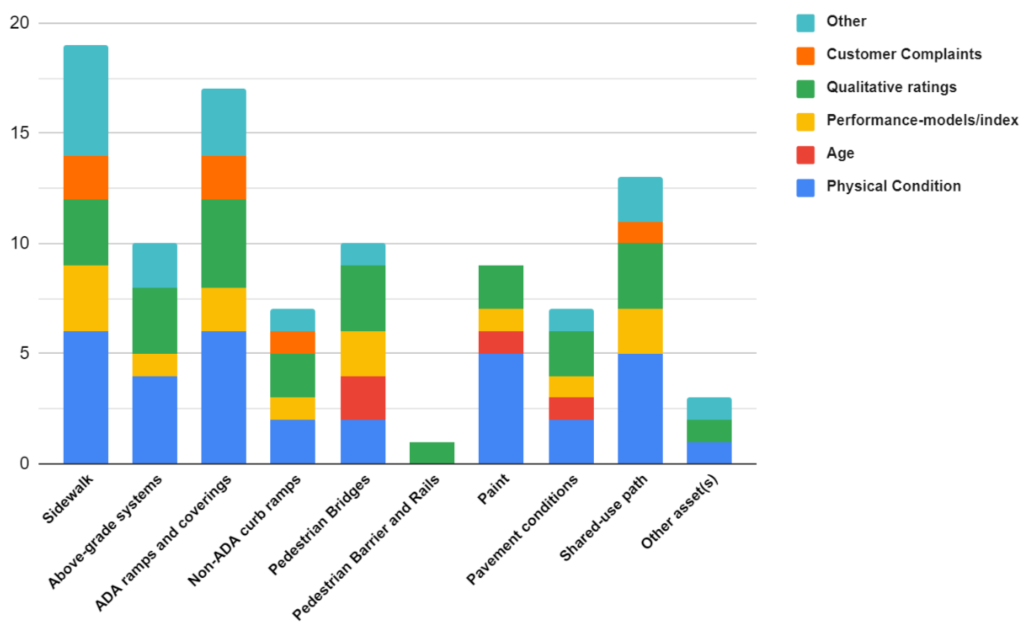



Figure 3-16. Criteria for assigning ratings to each type of asset

According to the survey results, the most common criteria for rating pedestrian assets is the "Physical condition," accounting for approximately 34% of the responses. Following that, "Qualitative ratings" represent 25% of the criteria used for assigning ratings. "Age" is the least common criterion, making up about 4% of the responses. Figure 3-17 visually depicts the distribution of these criteria for assigning ratings to each pedestrian asset type.

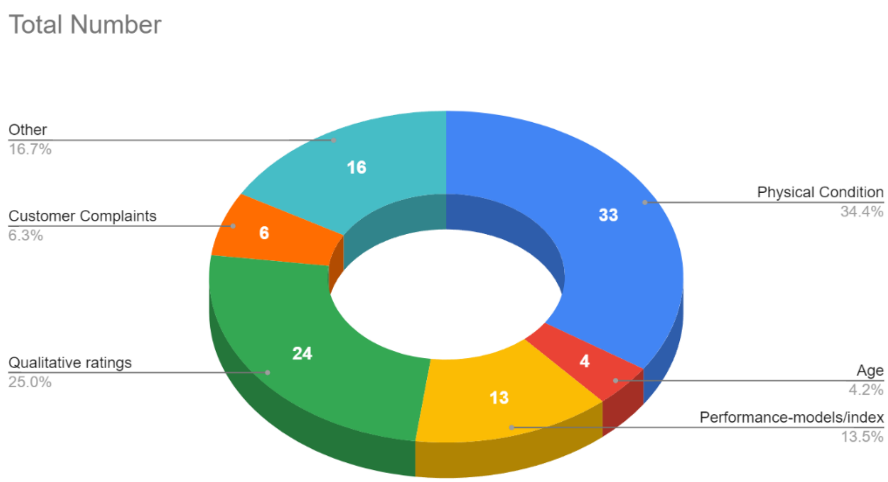



**Figure 3-17. Criteria for assigning ratings**

The following are lists of the “Other” selection entries grouped by the respective asset type.

Sidewalk:

- Activity score - i.e., how likely it will be subject to traffic
- Priority ranking is set by location and usage and total locations.
- ADA compliance on width and slope

Above-Grade:

- Typical push button signals are owned and maintained by the local municipality.
- Different measurements compliance

ADA Ramps and Coverings:

- Activity score - i.e., how likely it will be subject to traffic
- Priority ranking is set by location and usage and total locations.
- ADA compliance on width and slope

Non-ADA curb ramps:

- Priority ranking is set by location and usage and total locations.

Pedestrian Bridges:

- Condition and safety are ranked to prioritize bridge repair.

Shared-Use Path:

- Priority ranking is set by location and usage divided by total locations.
- Traffic volume of particular SUPs assists in prioritizing repairs and/or expansion of the network.

Other:

- Visual condition and complaints by the community.

### 3.1.4 Part 4

This portion of the survey focused on gathering information about the technologies that organizations employ to collect data on their pedestrian assets, as well as the methods for managing and storing these data.

**13. For each asset type, please check all the applicable technologies used for data collection. If other is selected, you will be asked to provide the applicable data collection technology for that asset in the follow up questions.**

The survey results provide insights into the applicable technology criteria used by participating agencies to collect data for each type of pedestrian asset. Figure 3-18 visually represents these technology criteria for reference.

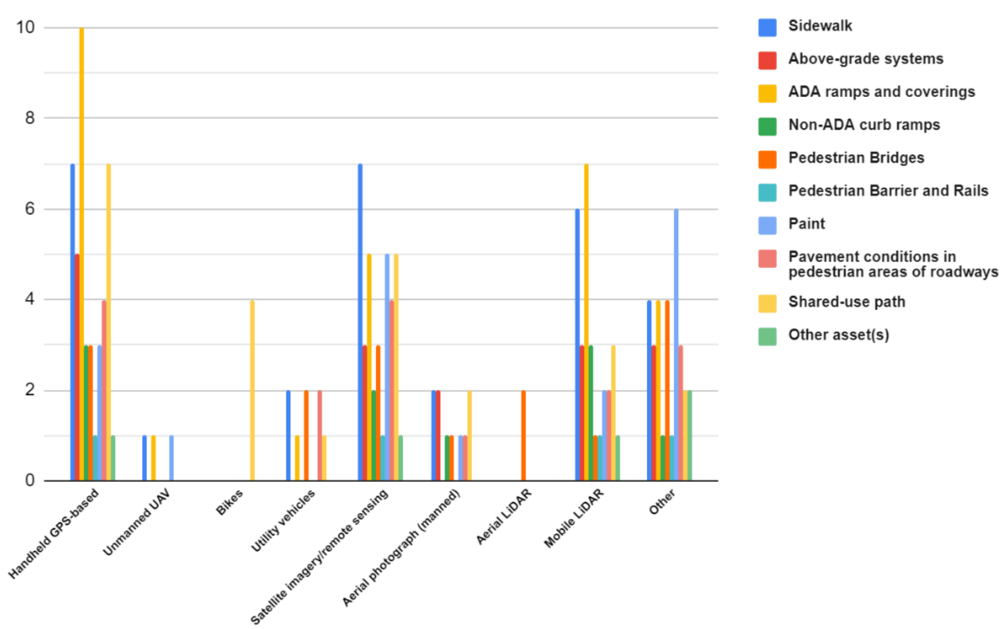



Figure 3-18. Technologies used for data collection for each asset type

The survey results indicate that the most used technology for collecting pedestrian data is a "Handheld GPS-based device," comprising approximately 27% of the responses. Following that, "Satellite imagery/remote sensing" is the next most frequently employed technology, representing about 22% of the responses. The least used technology for data collection is "Aerial LiDAR," accounting for approximately 1.2%. Figure 3-19 visually displays the distribution of these technologies used for data collection.

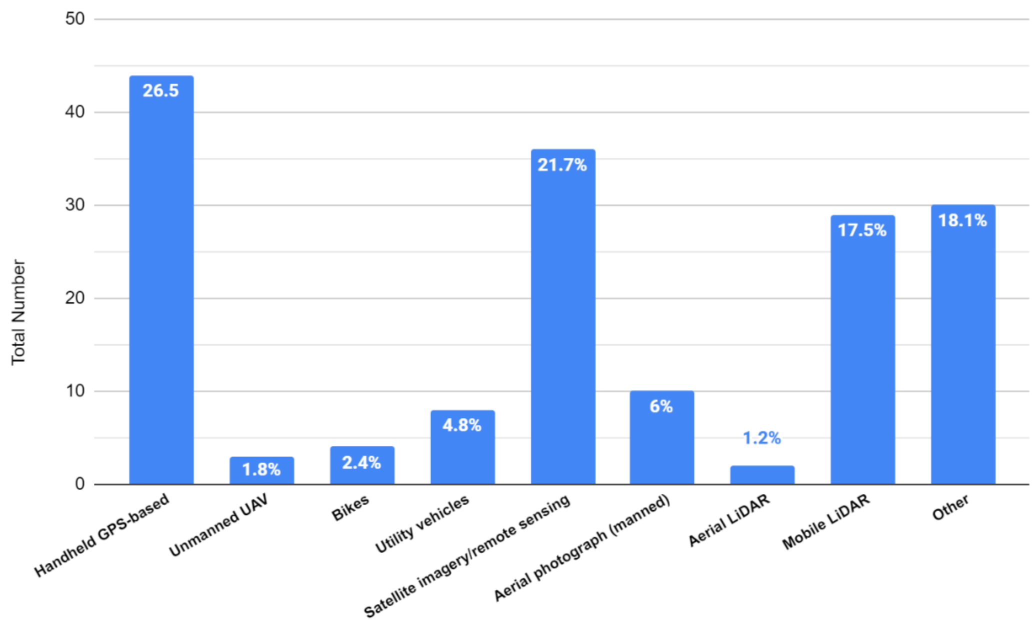



**Figure 3-19. Technologies used for data collection**

The following are lists of the “Other” technologies grouped by the respective asset type.

Sidewalk:

- Visual inspection
- Virtual inspection
- None

Above-Grade:

- We develop a neural network to identify, classify and locate roadway signs.
- As-builts
- Field investigation

ADA Ramps and Coverings:

- In 2005, VTrans utilized its existing video inventory to identify the location of all curb ramps on the state system. In addition to the location, each ramp was analyzed to determine if it contained the required detectable warnings. The reason this particular ADA feature was designed and implemented as a project catalogue to ensure that the geometric requirements of the ADA were being met and also to identify at what locations the required detectable warnings were not present. In 2009, VTrans, utilizing Federal stimulus funds, reassessed prior upgrades made to all curb ramps on the state system and to ensure that previous improvements complied with ADA design standards. The 2005 inventory was used as a starting point to identify the ramp locations. Field visits to all curb ramp sites ensured comprehensive inventory review and site inspection. Upon site inspection, some sites were removed from the inventory citing prior upgrades, while others were added as visual identification of compliance-related issues, most notably the absence of detectable warnings, was noted. When that project was completed in 2010, all curb ramps on the state system had been identified, scheduled for necessary improvements, and/or were compliant with the current ADA curb ramp regulations.

- Visual inspection
- Virtual inspection and field inspection using mobile application ArcGIS FIELDMAP
- Field investigation

Non-ADA Curb Ramps:

- Field investigation

Pedestrian Bridges:

- Written inspections on plan sets/paper
- Bridges and rail trail bridges are inspected every two years as part of our bridge inspection team.
- Field investigation
- MnDOT dataset

Pedestrian Barrier and Rails:

- Written inspections on plan sets/paper

Paint:

- Written inspections on plan sets/paper
- Pavement marking has an annual cycle for maintenance.
- Visual inspection
- As-builts
- Field investigation

Pavement Conditions:

- Roadway condition is monitored from centerline to fog line, the shoulder condition considered as part of this condition review.
- Visual inspection

Shared-Use Path:

- Visual inspection
- Field investigation

Other:

- MassDOT will introduce vehicle mounted lidar scanners to collect data through an outside vendor, and MassDOT will buy a similar vehicle to update the data.
- Visual inspection

**Q14 - How do you manage and store data related to your pedestrian assets? Please check all that apply.**

According to the survey results, the most used method for managing and storing pedestrian asset data is the "Spatial GIS system," accounting for approximately 20% of the responses. Following that, "Excel spreadsheet" is the next most frequently used method, with about 16%. "PDFs, drawings, or paper maps" make up the top three methods, representing about 14%. Interestingly, the survey revealed that none of the participating agencies used building information modeling (BIM) to manage and store pedestrian asset data. Figure 3-20 visually presents the distribution of these methods used for data management and storage.

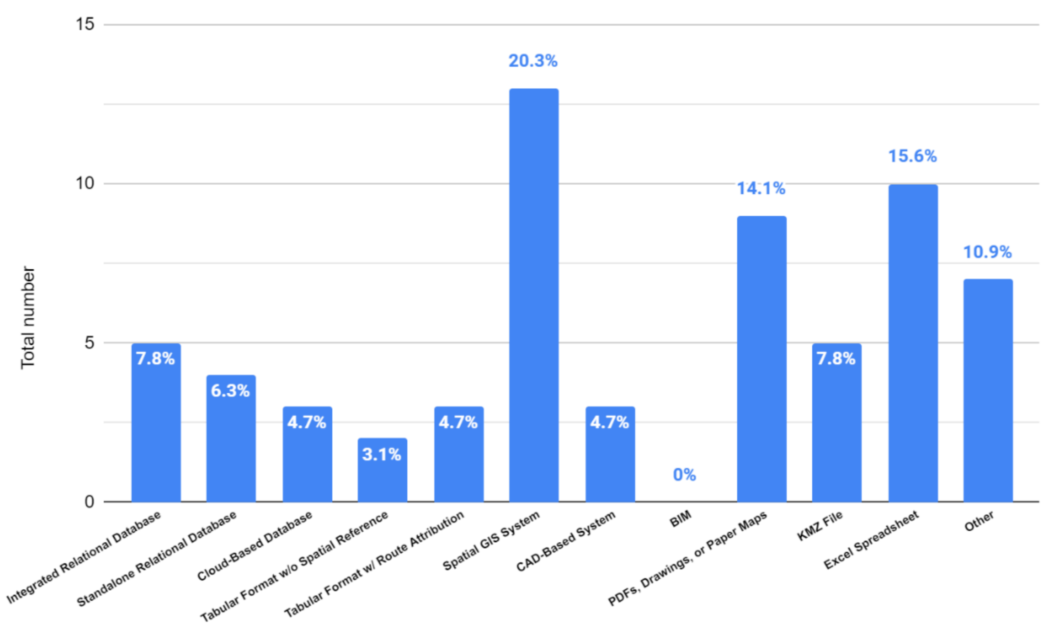



**Figure 3-20. Database for data storage and management of pedestrian assets**

Approximately 11% of the respondents chose the "Other" option, which allowed them to manually input other data management technologies used by their organization. The following is a list of those responses:

- Lidar stored on cloud and imported into AutoCAD
- We are working on populating a GIS layer to inventory where sidewalks exist and where gaps exist.

The results suggest that state DOTs are the most comprehensive in their use of various data management and storage methods, particularly favoring integrated relational databases alongside spatial and traditional mapping tools. Municipalities and metropolitan planning organizations (MPOs), while also utilizing a variety of tools, lean more towards spatial GIS and basic document-based storage methods.

These patterns indicate a potential correlation between the scale and scope of the organizations' responsibilities and their choice of data management strategies. State DOTs, with presumably larger-scale operations, opt for a broader array of tools, including more sophisticated database solutions.

To further explore the patterns, some data management and storage formats selected by agencies were matched with associated selected formats. Table 3-1 shows some selected data formats and their associated data management and storage formats.

For example, agencies using KMZ files also chose integrated relational databases, cloud-based databases, tabular formats with route and milepost attribution, spatial GIS, CAD-based systems, PDFs, drawings, or paper maps, as well as Excel for managing and storing data.

**Table 3-1. Associated data management and storage formats**

| Formats | Associated Data Management and Storage Formats |
|---|---|
| KMZ | Integrated relational database, cloud-based database, tabular format with route and milepost attribution, spatial GIS, CAD-based system, PDFs, drawings, or paper maps, Excel spreadsheet |
| Excel | Integrated relational database, spatial GIS, PDFs, drawings, or paper maps, KMZ file |
| Tabular Format without Spatial Reference | Spatial GIS, PDFs, drawings, or paper maps |
| Tabular Format with Route and Milepost Attribution | Integrated relational database, standalone relational database, cloud-based database, spatial GIS, CAD-based system, PDFs, drawings, or paper maps, KMZ file, Excel spreadsheet |

**Q15 - The research project includes three to five examples to illustrate representative use case studies. Involvement includes a follow up interview and a review of use case writeup. Please let us know if you are interested in participating as a use case example agency. Are you interested in participating as a case example study for this project?**

Only 4 out of 24 respondents expressed their willingness to participate in a follow-up interview. Figure 3-21 shows the distribution of this willingness among the survey participants.

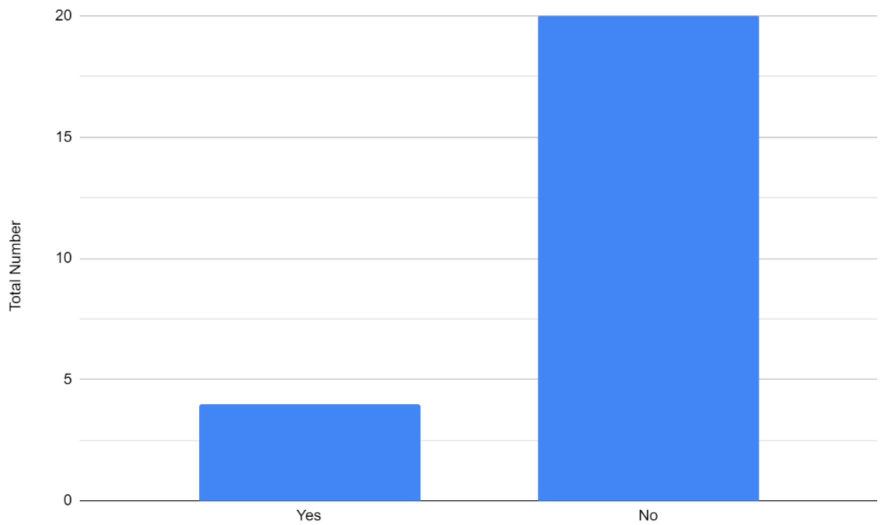



Figure 3-21. Willingness to participate in follow-up interview

## 3.2 MASSACHUSETTS DEPARTMENT OF TRANSPORTATION TARGETED INTERVIEW

### 3.2.1 Maintenance Strategy

The Massachusetts Department of Transportation (MassDOT) employs a cloud-based GIS database to manage comprehensive data on its road network, with plans to expand this database to include sidewalk inventories and their conditions. The data gathered through various assessments significantly shape the maintenance strategies for pedestrian assets. This strategic focus has led to an increased frequency in preventive maintenance and has guided the allocation of funds for both deferred maintenance and capital construction projects. The criteria used for prioritization are as follows:

1. **ADA Compliance**: Priority is given to ensuring that assets meet ADA requirements, which mandate accessibility for individuals with disabilities. This means that any pedestrian assets that are not in compliance with ADA standards are prioritized for maintenance to ensure accessibility.
2. **Condition of the Asset**: The second criterion is the condition of the asset, where assets in poorer condition are given higher priority for maintenance. This ensures that the most deteriorated or damaged assets are addressed promptly to maintain safety and functionality for pedestrians.

Currently, MassDOT prioritizes the development of in-house performance models for sidewalk assessment, although existing models primarily gauge sidewalk condition based on age. However, literature-based models are also integrated into the assessment processes. For pedestrian bridges, age and visual inspection rankings are pivotal in determining their maintenance needs.

Pedestrian asset maintenance projects within budget constraints are ranked based on this order:

1. Environmental justice (EJ) communities and transit zones
2. ADA requirements
3. Density of need (areas with a high density of low scores/high need are prioritized) based on the analysis of the data collected
4. Sidewalks and curbs to be made compliant as part of a roadway reconstruction project per MassDOT directive

### 3.2.2 Collaborations

MassDOT is collaborating with a research team from the University of Massachusetts Amherst to perform network-level sidewalk condition assessment. The project aims to enhance pedestrian infrastructure data for informed maintenance and construction planning by applying mobile lidar technology for inventory and condition assessment of MassDOT-managed sidewalks, covering approximately 1,300 miles.

The scope of work details five primary tasks:

1. **Data Preprocessing and Consolidation**: Supplying mobile lidar data for processing and integration into a centralized repository.
2. **Sidewalk Extraction and Condition Assessment**: Utilizing an algorithm to extract ADA compliance features from the data, assessing conditions like cross slope, sidewalk width, and surface roughness.
3. **Curb Ramp Inventory and Condition Assessment**: Extracting detailed features of curb ramps, including ADA compliance, ramp defects, and material types.
4. **Miscellaneous Data Extraction**: Identifying and extracting additional pedestrian infrastructure features from the lidar data.
5. **Reporting of Results**: Summarizing research efforts and presenting the final deliverables.

### 3.2.3 Types of Data Extracted

A developed sidewalk extraction algorithm is applied to the consolidated, centralized data repository to extract the following detailed ADA compliance features:

- Cross slope (measurements at 10 ft intervals)
- Longitudinal slope (measurements at 50 ft intervals)
- Sidewalk width (measurements at 10 ft intervals and coordinates of the locations with limited passing clearances or obstructions)

Investigations are ongoing to leverage additional video log images together with the mobile lidar point cloud data to extract the following features:

- Surface roughness (measurement for at 10 ft intervals)
- Surface conditions (cracking, missing panels, spalling, and settlement)
- Surface material types (e.g., concrete, pavement, brick, stone)

A developed curb ramp extraction and assessment algorithm is also applied to the consolidated, centralized data repository to extract the following detailed features:

- Missing ramps (coordinates of the locations)
- ADA compliance for each ramp (e.g., ramp dimension, running slope, top landing slope, and the presence of detectable warning)
- Ramps at driveways (coordinates of the locations)

In addition, additional video log images are leveraged together with the mobile lidar point cloud data to extract the following features:

- Ramp cracking and other defects
- Ramp material types (e.g., concrete, pavement, brick, stone)

The goal is to develop a GIS layer containing all the sidewalk and curb ramp features.

MassDOT is also investigating additional pedestrian infrastructure features that can feasibly be extracted from mobile lidar data and the companion video log images and develop corresponding point cloud processing algorithms for automated feature extraction.

## 3.3 SUMMARY

This chapter outlines the findings from a survey aimed at understanding the management practices for pedestrian assets within various organizations. Divided into four parts, the survey focused on respondent information, management methodologies, asset types and evaluation methods, and technological tools for data collection and management.

Key findings include the following:

- The survey findings indicate significant participation from state DOTs, with responses from 25 states and the District of Columbia. Although many agencies actively collect data on pedestrian assets, the survey revealed that there is no dedicated unit specifically tasked with managing these assets.
- The survey also reveals substantial data collection efforts on pedestrian assets like sidewalks, ADA ramps and coverings, and shared-use paths. Most organizations reported being able to manage between two and six types of pedestrian assets.
- Regarding asset management strategies, the survey showed a preference for inventory and condition assessments. Visual inspections for condition assessments were identified as the most

prevalent evaluation methods, with most organizations conducting evaluations every three to five years. User complaints and ADA compliance were cited as the primary reasons prompting asset inspections.

- Location and ownership information emerged as the most collected data type, with handheld GPS-based devices and satellite imagery or remote sensing identified as the predominant technologies for data collection. About half of the organizations assign ratings to the assets after information is collected, and these ratings are commonly based on the physical condition of the asset. The survey shows diverse data management practices, with spatial GIS system being the most common method.

The survey's insights reveal a landscape of pedestrian asset management that is both diverse and dynamic, with organizations employing a variety of strategies, technologies, and practices to meet their unique challenges and opportunities. The findings underscore the critical role of comprehensive data collection and analysis in facilitating informed decision-making and effective asset management, ultimately contributing to the development of safer, more efficient, and more accessible pedestrian environments.

# CHAPTER 4: DATA PROCESSING OF HISTORIC BASELINE DATA FOR PEDESTRIAN ASSETS

## 4.1 INTRODUCTION

Following the identification of key data gaps and challenges in the literature review and survey of state and local agencies, this chapter delves into the critical process of data processing and integration for pedestrian assets. The literature review highlighted the importance of accurate and comprehensive data for effective pedestrian asset management, while the survey of agencies revealed that a significant gap exists in the consistency and quality of data used across jurisdictions. To address the identified challenges, the research summarized in this chapter focused on the integration of historical baseline data from MnDOT, alongside supplementary datasets. The goal was to create a robust, comprehensive dataset that has the capability to support predictive analysis and enhances the understanding of pedestrian asset deterioration. This chapter describes the methods used for data cleaning, validation, and enrichment, all of which ensure that the resulting dataset can be leveraged to enhance decision-making and maintenance strategies for pedestrian infrastructure.

This chapter delineates the comprehensive methodology implemented for the processing of historic baseline data pertinent to pedestrian assets within the state of Minnesota. It emphasizes the integration and analysis of data collected by MnDOT, particularly within a GIS. The focus is to establish a foundational dataset that can be utilized to model the deterioration of pedestrian assets effectively.

The historic data described here represent an intricate and expansive dataset detailing the pedestrian access routes (PAR) across the state of Minnesota. The collection of these data began in 2018, and the data have been meticulously updated, with the most recent update noted in November 2023. The dataset is a rich repository of information, serving as a crucial tool for urban planners, accessibility coordinators, and transportation officials in the management and enhancement of pedestrian infrastructure.

## 4.2 STRUCTURING OF THE PEDESTRIAN INVENTORY

The PAR inventory is methodically segmented into various line data types, each signifying a distinct component of the pedestrian network:

- **Typical Sidewalks**: The conventional walkways along streets and roads.
- **Driveways**: Points of vehicular entry and exit that intersect with pedestrian pathways.
- **Crosswalks**: Designated pedestrian crossings that enhance safety at intersections and other road crossings.
- **Typical Bridges**: Structures that facilitate pedestrian movement over physical obstacles like rivers and highways.
- **Pedestrian Bridges and Approaches**: Specialized bridges and their access points explicitly designed for pedestrian use.

- **Trails**: Paths that may be used for walking, biking, and other nonmotorized traffic, often located along streets and roads.
- **Railroad Crossings**: Intersections where pedestrian pathways cross railway lines.
- **Gaps**: Unaccounted or missing segments within the pedestrian network.
- **Other**: Miscellaneous categories that do not fit into the standard classifications but are part of the pedestrian framework.

## 4.3 THE ASSESSMENT LAYERS

Crucial to the dataset are the three interrelated layers, each offering additional depth and context to the pedestrian routes as captured in Figure 4-1:

1. **Cross Slopes and Condition Assessment Points**: This collection of data points provides vital information on the gradient and surface condition of the PARs. These data points are collected in increments of 25 ft, offering a granular perspective of the paths pedestrians' traverse, which is essential for accessibility and maintenance planning.

2. **Obstructions**: The dataset includes a catalog of obstructions encountered along pedestrian routes. These impediments are meticulously classified and documented, indicating the real-world challenges to accessibility and mobility within the pedestrian network. Table 4-1 shows the list of obstruction types collected, and each obstruction type has been categorized by the research team as either distress or inventory type. The term "distress" can be used to indicate an obstruction that likely causes damage or deterioration to the sidewalk, potentially causing a hazard. On the other hand, "inventory" could refer to obstructions that that should be placed outside of the PAR and are part of the normal streetscape or built environment and do not necessarily indicate damage.

3. **Bus Stops**: This segment of the data records the location and type of bus stops found within the MnDOT right-of-way. The data here are not limited to stops owned by MnDOT but include all that are found within its jurisdiction. Detailed measurements of the boarding areas are taken to ensure compliance with ADA standards.

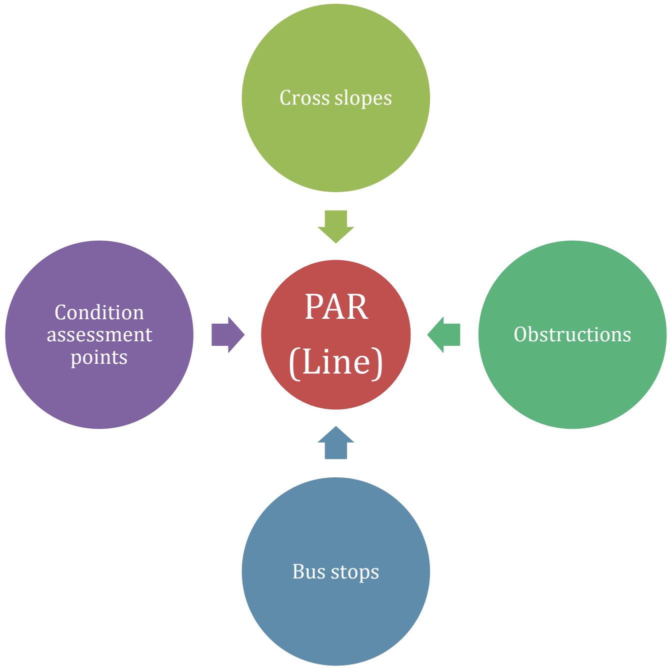



**Figure 4-1. Relationship of the assessment layers to the PAR**

**Table 4-1. Obstruction types and category**

| Obstruction Type | Category |
|---|---|
| Bridge joint | Distress |
| Broken panel | Distress |
| Cross slope | Distress |
| Electrical box | Inventory |
| Foliage | Inventory |
| Heaved/sunken panel | Distress |
| Hydrant | Inventory |
| Light post | Inventory |
| Manhole | Inventory |
| Narrow surface | Distress |
| Other | Inventory |
| Panel gap | Distress |
| Running slope | Distress |
| Sign | Inventory |
| Stairs | Inventory |
| Street furniture | Inventory |
| Traffic pole | Inventory |
| Tree trunk | Inventory |

## 4.4 DATA INTEGRATION

Figure 4-2 illustrates a streamlined five-step data processing workflow. This workflow is integral to transforming raw data into a finished deliverable. Each stage is designed to systematically refine and enhance the data, ensuring that the final output is both accurate and actionable.

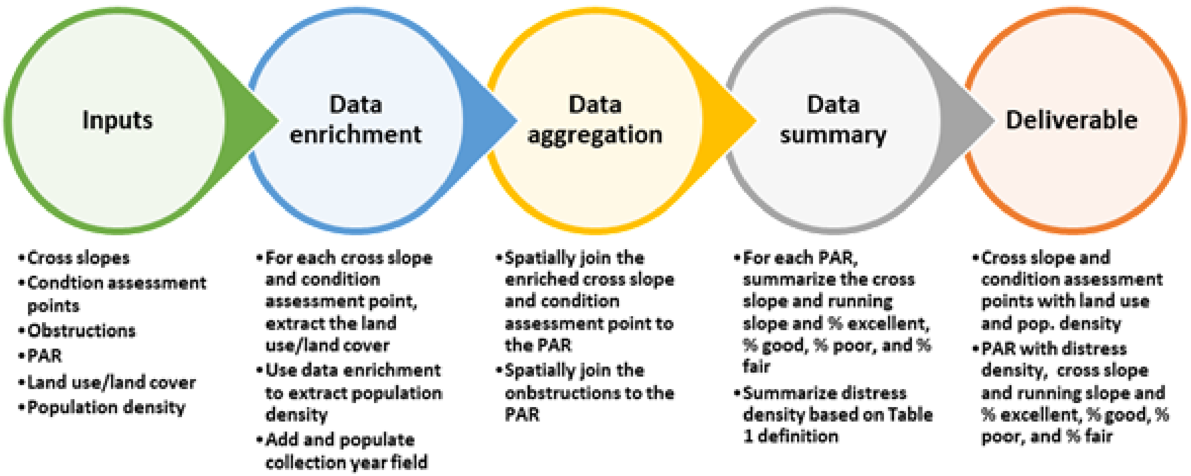



Figure 4-2. Data integration workflow

## 4.5 DETAILED WORKFLOW STEPS

### 4.5.1 Step 1. Inputs

This step includes all of the assessment layers referenced in Figure 4-1. In addition, land use/land cover and population density are also included. The land cover data were obtained from the U.S. Geological Survey (USGS) National Land Cover Database (NLCD), which is a comprehensive, nationwide land cover dataset that utilizes a 16-class land cover classification system. This system is adapted from the Anderson Level II classification scheme and, as illustrated in Figure 4-3, categorizes land surface characteristics such as urban areas, agricultural lands, forests, water bodies, ice/snow, and impervious surfaces. The most recent epoch of the data is 2021, and the data can be downloaded from the USGS website (USGS 2023). The population density was obtained from ESRI 2023 population estimates (population per square mile).


Figure 4-3. Anderson Level II classification scheme

### 4.5.2 Step 2. Data Enrichment

This step involves cleaning, validating, and integrating the data with additional datasets to provide a more comprehensive context. The objective here is to enhance the quality and depth of the information, preparing it for more complex analysis. Data cleaning of the assessment layers involved adding a field to track the year of the data collection. The Enrich tool from ArcGIS Pro (ESRI n.d.-a) enriches data by adding demographic and landscape facts about the people and places that surround or are inside data locations. The output is a duplicate of the input with additional attribute fields. This tool requires an ArcGIS Online organizational account or a locally installed Business Analyst dataset. The Enrich tool was used to extract the population density for each cross slope and condition assessment point. To extract the land cover for the assessment layers, the Extract Values to Points spatial analyst tool (ESRI n.d.-b) was utilized.

### 4.5.3 Step 3. Data Aggregation

This aggregation serves to consolidate the information, potentially reducing it to a more concise format that highlights the most critical data points for easier handling and analysis. Part of the goal was to provide a pedestrian asset management section as the aggregation layer. However, the PAR was already delineated in the lowest common denominator, so the research team adopted it as the aggregation layer. All of the enriched data were aggregated to the PAR. The research team created a new unique identifier for the PAR to consolidate the multiple years of collection into one uniform database.

### 4.5.4 Step 4. Data Summary

This step involves extracting relevant insights and trends from the dataset. The focus is on condensing the data into a more palatable and informative summary without losing essential details. Hence, each PAR record summarizes the cross slope and running slope and the percent of the asset in excellent, good, poor, and fair condition and summarizes the distress density based on the definition in Table 4-1.

### 4.5.5 Step 5. Deliverable

In this stage, the data integration process culminates in a unified and cohesive GIS dataset. Having been enriched with demographic and land cover data, the dataset offers a multidimensional view of pedestrian assets across Minnesota. This deliverable can be customized to meet stakeholder needs and effectively communicate the findings, with formats ranging from a detailed report to a visual presentation to an interactive GIS dashboard. This dashboard enables users to explore the data both spatially and temporally. The key features of this deliverable are as follows:

- **Detailed Statistical Analysis**: The GIS data for each PAR record and collection year are aggregated to provide insightful statistics. These statistics encapsulate the following:
    1. Minimum, mean, and maximum values for cross slope, running slope, and population density, offering a comprehensive view of these measurements over time.

2. Mode calculation for land cover, which yields insights into the most prevalent land use/land cover types associated with each PAR record. This GIS-based analysis enriches the dataset with environmental context, which is important for planning and conservation efforts.

- **Pavement Condition Assessment**: A central element of the research focuses on the condition of pedestrian assets, which is assessed for each PAR record and collection year within the GIS framework. This assessment includes the following:
  1. Calculation of the percentage distribution of condition ratings—excellent, good, fair, and poor. This distribution provides a nuanced portrayal of pavement quality, reflecting the variability across different locations and over various time periods.
  2. Determination of distress frequency and count per linear foot of PAR, as defined in Table 4-1. The GIS dataset allows for the spatial visualization of these conditions, offering an intuitive understanding of infrastructure health and aiding in predictive maintenance.

This GIS deliverable goes beyond the mere tabulation of data by facilitating spatial analysis and visualization, which are essential for comprehensive urban and transportation planning. The integration of statistical analysis within the GIS environment allows for a more dynamic and actionable understanding of pedestrian asset conditions, supporting informed decision-making and effective communication with all relevant stakeholders.

## 4.6 RECOMMENDATIONS

The MnDOT pedestrian asset inventory is an extensive dataset that encompasses various elements related to pedestrian infrastructure. While this inventory is a valuable resource for a myriad of applications, including the evaluation and management of pedestrian assets, if combined with other datasets, it can provide more opportunities for enhanced decision making. The following is a list of recommendations for MnDOT to consider:

1. **Data integration**: The MnDOT inventory is not currently integrated with additional datasets that create a more comprehensive assessment of pedestrian assets. Data reflecting traffic patterns, environmental conditions such as weather and climate impacts, and the effects of urban development are important for a full understanding of the stressors impacting pedestrian infrastructure. The absence of these data leads to an incomplete picture of the assets' condition and the factors contributing to their deterioration.
2. **Life-cycle data:** In order to predict the life cycle of pedestrian infrastructure, construction materials, age of assets, and historical maintenance records are needed. MnDOT will be capturing lidar and asset age annually moving forward and will be importing the most current pedestrian infrastructure in 2024 into a maintenance management system to capture maintenance activities.
3. **Data comparability**: The temporal span over which the data were collected introduces variability in terms of the mapping methods and classification systems used. As a result, comparing data across different years can be challenging, making it difficult to assess the rate and patterns of deterioration over time. This is especially instructive because the data were collected by various MnDOT districts and personnel.

4. **Temporal Data:** With over 80% of the pedestrian assets subjected to data collection only once, there are not enough data to predict deterioration, and the ability to establish baseline conditions and monitor changes over time is hampered. Data condition and compliance is ever changing, and therefore setting up cyclical data collection frequencies will ensure that data are kept up to date. MnDOT is pursuing innovative ways to collect pedestrian data through satellite imagery and lidar.
5. **Additional Safety-Related Data:** While not the focus of this research project, other identified datasets focus on the safety aspects of pedestrian asset management. These are presented in Table 4-2 and are categorized according to specific pedestrian assets.

**Table 4-2. Data combination summary**

<table>
<tr><th>Pedestrian Asset</th><th>MnDOT Table Schema</th><th>Additional Data for Integration</th></tr>
<tr><td rowspan="15">Intersections</td><td>Intersection ID</td><td rowspan="15">Pedestrian volume (Allsopp and Smith 1997)<br>Crossing time (Lin et al. 2020)<br>Waiting time (Lin et al. 2020, Tan et al. 2007)<br>Crossing patterns (Li et al. 2018, Tan et al. 2007)<br>Safety Accidents (Tan et al. 2007)<br>Driver behavior (Hubert et al. 2020)<br>Pedestrian satisfaction (Hubert et al. 2020)<br>Pedestrian demographics<br>Surrounding land use (Hubert et al. 2020)<br>Condition (extract from the pavement management program)</td></tr>
<tr><td>Shape</td></tr>
<tr><td>Current Status</td></tr>
<tr><td>Construction Status</td></tr>
<tr><td>Flatwork Contractor</td></tr>
<tr><td>MnDOT Maintenance District</td></tr>
<tr><td>Owning Agency</td></tr>
<tr><td>Nearest Mainline Roadway (Highway)</td></tr>
<tr><td>Intersecting Road</td></tr>
<tr><td>County Name</td></tr>
<tr><td>City/Other Municipality Name</td></tr>
<tr><td>Construction Year</td></tr>
<tr><td>General Comments</td></tr>
<tr><td>QA/QC Comments</td></tr>
<tr><td>Record Retirement Date</td></tr>
</table>

| Pedestrian Asset | MnDOT Table Schema | Additional Data for Integration |
|---|---|---|
| **Pedestrian Ramps** | SHAPE | Tactile indicators (Lin et al. 2020)<br>Obstructions (Allsopp and Smith 1997)<br>Material and surface texture<br>Curb height (Lin et al. 2020)<br>Handrails availability (Hubert et al. 2020)<br>Usage pattern (Allsopp and Smith 1997)<br>User feedback (Hubert et al. 2020) |
| | Parent Intersection ID/FK | |
| | Pedestrians Ramp Status (Condition) | |
| | Quadrant of Intersection | |
| | Ramp Location in Intersection | |
| | Ramp Type | |
| | Pedestrian Activity | |
| | What Rd/Hwy is Ramp Crossing? | |
| | Truncated Domes Present? | |
| | Width of Ped Ramp (in.) | |
| | 4’ Wide PAR Maintained? | |
| | Pedestrian Landing at least 4’x4’? | |
| | Landing(s) Present and in Correct Locations? | |
| | Is Vertical Change > Quarter Inch? | |
| | Specifications 2521.3 Compliant? (Inspectors) | |
| | Landing 1 Running Slope (%) | |
| | Landing 1 Cross Slope (%) | |
| | Ramp 1 Cross Slope (%) | |
| | Ramp 1 Running Slope (%) | |
| | Landing 2 Running Slope (%) | |
| | Landing 2 Cross Slope (%) | |

| Pedestrian Asset | MnDOT Table Schema | Additional Data for Integration |
|---|---|---|
| | Landing 3 Running Slope (%) | |
| | Landing 3 Cross Slope (%) | |
| | Ramp 2 Running Slope (%) | |
| | Ramp 2 Cross Slope (%) | |
| | Ramp 3 Running Slope (%) | |
| | Ramp 3 Cross Slope (%) | |
| | Ramp and Landing(s) Condition | |
| | Gutter Flowline (%) | |
| | Gutter In slope (%) | |
| | Gutter Condition | |
| | Adequate Drainage? | |
| | Pedestrians Ramp Comments | |
| | Built to Plan? (Inspectors) | |
| | Curb Ramp Compliant? (Inspectors) | |
| | Complaints? (Inspectors) | |
| | Reason Ramp Not Compliant (Inspectors) | |
| | QA/QC Comments | |
| **Pedestrian Signals** | OBJECTID | Crossing time (Allsopp and Smith 1997) |
| | Shape | Pedestrian volume (Hubert et al. 2020) |
| | Parent Intersection Unique ID | Waiting time (Lin et al. 2020) |
| | Signal Status | Button usage (Lin et al. 2020) |
| | Signal Type | Pedestrian behavior (Allsopp and Smith 1997) |
| | | Safety incidents (Hubert et al. 2020) |

| Pedestrian Asset | MnDOT Table Schema | Additional Data for Integration |
|---|---|---|
| | Pedestrian Activity | Compliance with signals (Allsopp and Smith 1997)<br>Accessibility (Allsopp and Smith 1997)<br>Signal malfunctions (Hubert et al. 2020)<br>User satisfaction (Allsopp and Smith 1997)<br>Peak usage time (Hubert et al. 2020)<br>Emergency response (Allsopp and Smith 1997)<br>Pedestrian density (Allsopp and Smith 1997)<br>Age (Lin et al. 2020)<br>Condition (Button wear, Bulb, post) |
| | Pedestrian signal tone | |
| | Walk Signal? | |
| | Countdown Present? | |
| | PEDSIG_PHASE | |
| | Button Location | |
| | Pole Location | |
| | Button Landing Area? | |
| | Button Landing Slope | |
| | Button Landing Slope Perp | |
| | Button Oriented in Direction of Ped Travel? | |
| | Button Height (in.) | |
| | Button Side-Reach (in.) | |
| | Distance to Curb (ft) | |
| | Distance to Walkway (ft) | |
| | Distance between buttons (ft) | |
| | Hand hole within PAR? | |
| | 2’ Distance from Back of Walk and Grade Breaks? | |
| | 6’ Maintenance Access Route Maintained? | |
| | Pedestrian signal Comments | |
| | Complaints (Inspectors) | |

| Pedestrian Asset | MnDOT Table Schema | Additional Data for Integration |
|---|---|---|
| | Built to Plan? (Inspectors) | |
| | Signal Compliant? (Inspectors) | |
| | Noncompliance Reason (Inspectors) | |
| | QA/QC Comments | |
| | Record Retirement Date | |
| **Pedestrian Crossing** | Parent Intersection ID | Pedestrian volume (Hubert et al. 2020) |
| | Cross Walk Status | Crossing time (Allsopp and Smith 1997) |
| | Marking Type | Waiting time (Lin et al. 2020) |
| | Crosswalk Material | Pedestrian speed (Hubert et al. 2020) |
| | Rd/Hwy Crossed | Crossing patterns (Allsopp and Smith 1997) |
| | Part of Trail? | Accessibility (Lin et al. 2020) |
| | Side of Intersection | Safety Accidents (Allsopp and Smith 1997) |
| | Pavement Condition | Driver behavior (Hubert et al. 2020) |
| | Ramp within Crosswalk? | Pedestrian satisfaction (Allsopp and Smith 1997) |
| | Walkway Width (ft) | Pedestrian Demographics (Allsopp and Smith 1997) |
| | Running Slope (%) | Surroundings land use (Lin et al. 2020) |
| | Cross Slope (%) | Condition of material |
| | Crosswalk Comments | Retro-reflectivity |
| | Complaints? (Inspectors) | |
| | Crosswalk Compliant? (Inspectors) | |
| | Reason Not Compliant (Inspectors) | |
| | QA/QC Comments | |

| Pedestrian Asset | MnDOT Table Schema | Additional Data for Integration |
|---|---|---|
| | Record Retirement Date | |
| **Sidewalk** | Length | Foot traffic (Allsopp and Smith 1997)<br>Pedestrian speed (Lin et al. 2020)<br>Accessibility (Rating) (Allsopp and Smith 1997)<br>Current condition (Periodically)<br>Number of safety accidents (Allsopp and Smith 1997)<br>Using of surrounding areas (Allsopp and Smith 1997)<br>Lighting and visibility (Lin et al. 2020)<br>Public amenities (Benches, Trash bins, aesthetic treatments etc.,)<br>Vegetation and obstructions (Lin et al. 2020)<br>Weather conditions (Allsopp and Smith 1997)<br>Usage trends (events) (Allsopp and Smith 1997)<br>Obstructions (distance-clearance) (Lin et al. 2020)<br>Weather maintenance (winter)<br>Sidewalk design |
| | Sidewalk/PAR Status | |
| | Sidewalk/PAR Type | |
| | Driveway Type | |
| | Driveway Control Signal? | |
| | Sidewalk/PAR Construction Status | |
| | MnDOT District | |
| | County | |
| | City/Municipality | |
| | Owning Agency | |
| | Pedestrian Activity | |
| | Nearest Mainline Route | |
| | Nearest Side Street(s) | |
| | Sidewalk/PAR Material | |
| | Walkway Width (In.) | |
| | Boulevard Material | |
| | Boulevard Width (In.) | |
| | Wheel-Measured Length (ft) | |
| | Sidewalk Comments | |
| | SP Number (Inspectors) | |
| | Construction Year (Inspectors) | |

| Pedestrian Asset | MnDOT Table Schema | Additional Data for Integration |
|---|---|---|
| | Sidewalk/PAR Section Complaints? (Inspectors) | |
| | Sidewalk/PAR Section Compliant? (Inspectors) | |
| | PAR Noncompliance Reason (Inspectors) | |
| | QA/QC Comments | |
| | Record Retirement Date | |
| | Crosswalk Marking Type | |
| | Ramp Within Crosswalk? | |
| | Part of Trail? | |
| **Cross Slopes** | SHAPE | Material and textures |
| | Cross Slope Status | |
| | Cross Slope Type | |
| | Driveway Type | |
| | Control Signal Present? | |
| | Cross Slope (%) | |
| | Running Slope (%) | |
| | Pavement Condition at Cross Slope | |
| | Complaints? (Inspectors) | |
| | QA/QC Comments | |
| | Record Retirement Date | |
| **Obstruction** | Obstruction Status | |
| | Obstruction Type | |

| Pedestrian Asset | MnDOT Table Schema | Additional Data for Integration |
|---|---|---|
| | Obstruction Comments | |
| | Complaints? (Inspectors) | |
| | QA/QC Comments | |
| | Record Retirement Date | |
| **Bus Stop** | Parent Sidewalk ID/FK | Amenities availability (Hubert et al. 2020)<br>Lighting (Allsopp and Smith 1997)<br>Usage data (Allsopp and Smith 1997)<br>Demographics (Lin et al. 2020)<br>Bus arrival information (Hubert et al. 2020)<br>Condition of amenities |
| | Bus Stop Status | |
| | Bus Stop Construction Status | |
| | Bus Stop Type | |
| | Connected to PAR? | |
| | Boarding Area Present? | |
| | Domes or Other Detectable Surface on Boarding Area? | |
| | Boarding Area Width (ft) | |
| | Boarding Area Depth (ft) | |
| | Boarding Slope Perp. (%) | |
| | Boarding Slope Para. (%) | |
| | Condition Rating | |
| | Bus Stop Comments | |
| | Complaints? (Inspectors) | |
| | Bus Stop Compliant? (Inspectors) | |
| | Reason Not Compliant (Inspectors) | |
| | QA/QC Comments | |
| | Record Retirement date | |

## 4.7 DATA MANAGEMENT AND QUALITY CONTROL

The data have incremental and ongoing quality assurance and validation processes. However, it is noted that there may be areas within the right-of-way still lacking data, and some records may be overlapping or outdated, reflecting changes before and after specific projects. This indicates an active, ongoing effort to capture the dynamic nature of the pedestrian landscape.

Data are added and updated by MnDOT personnel and contracted staff, primarily during the warmer months when field conditions are favorable. Simultaneously, data stewards regularly review the dataset, updating, retiring, or deactivating records to maintain the dataset's accuracy and relevance.

**Future Transition**

Looking ahead, there are plans to integrate the PAR into the Transportation Asset Management System (TAMS), which will centralize and streamline the management of transportation assets. With this transition, the current public-facing version of the data in ArcGIS Online will be phased out.

## 4.8 CONCLUSION

The MnDOT pedestrian asset inventory, while a significant starting point for understanding pedestrian infrastructure, can be enhanced and/or combined with other data to fully manage and understand the assets' deterioration. The recommendations require a multifaceted approach, including the integration of diverse data sources, the standardization of data collection methods, and the development of comprehensive documentation practices that capture the condition of assets over time. Enhancing the inventory with this critical information would greatly improve the reliability of deterioration assessments and bolster the overall strategy for maintaining pedestrian infrastructure in Minnesota.

# CHAPTER 5: DATA COLLECTION PLAN

## 5.1 OBJECTIVE

The primary aim of this data collection phase was to deploy a specialized data bike system to gather comprehensive sample data that reflect the current state of selected sidewalk segments. This mobile data-gathering approach provided high-resolution surface images and detailed vertical motion metrics that served as indicators of the sidewalks' condition. Upon collection, the data were systematically compared with existing historical records to assess changes in the sidewalk conditions. The comparison also served to model sidewalk condition degradation.

## 5.2 SCOPE OF TASKS

### 5.2.1 Site Selection

The sites were selected based on the availability of two key types of data: two historical snapshots and a variety of condition categories. Given that the objective was to monitor deterioration over time, priority was given to collecting data from sites that are currently in good condition. This was followed by sites in fair, excellent, and poor condition, respectively. Figure 5-1 illustrates the start points of the data collection clusters, while Figure 5-2 shows the condition distribution of the proposed sites. Table 5-1 details the geographic coordinates in decimal degrees for these sites. In total, 16 sites were chosen, with the majority located in the Minneapolis-St. Paul area.

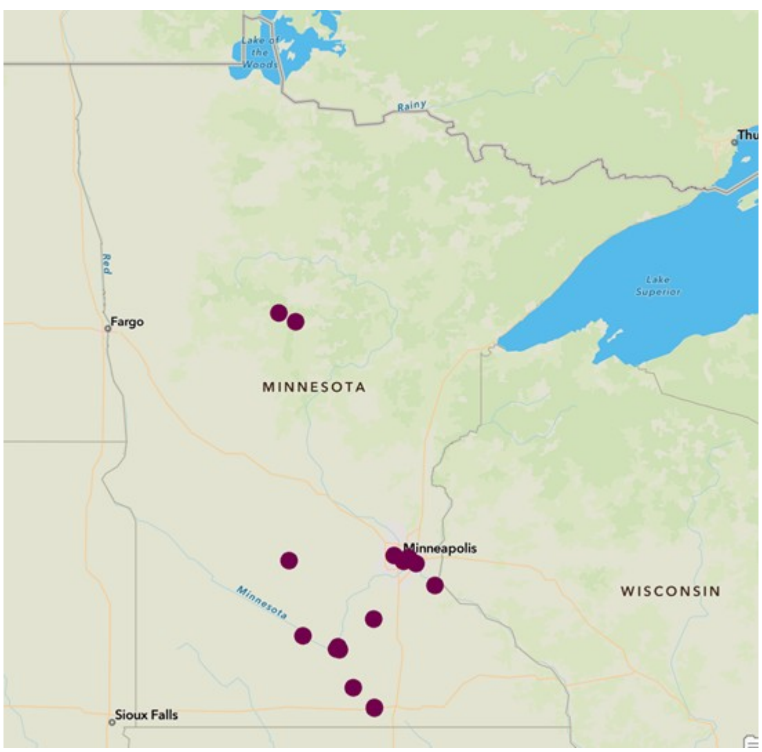



Figure 5-1. Data collection sites

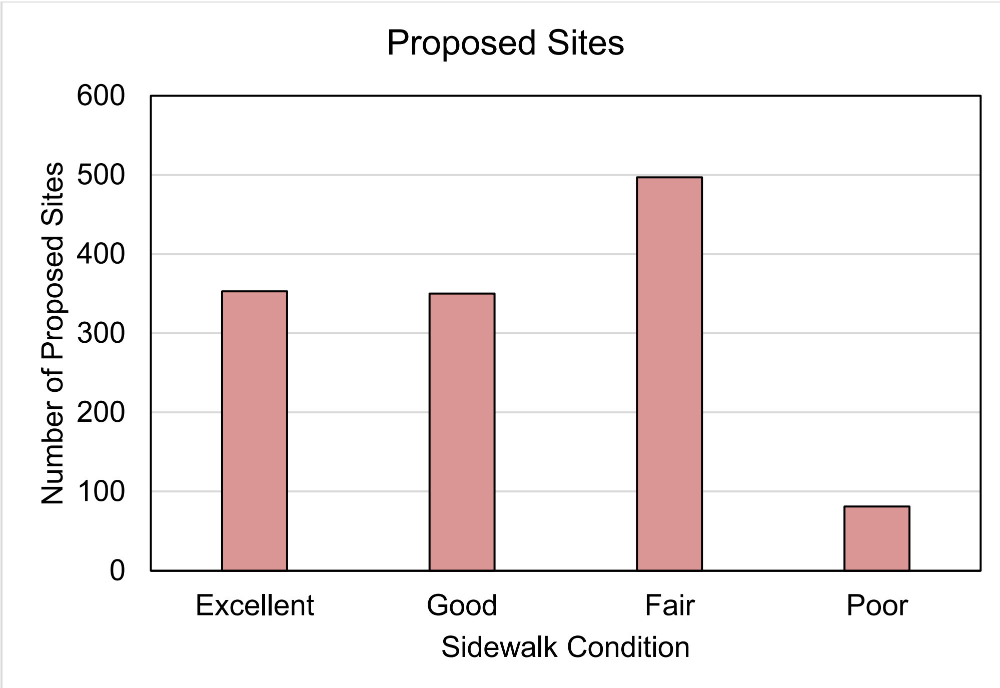



**Figure 5-2. Condition distribution of the proposed sites**

**Table 5-1. Geographic coordinates of selected sites**

| Site ID | Start_X | Start_Y | End_X | End_Y |
|---|---|---|---|---|
| 1 | -93.57685775 | 43.66868605 | -93.57509535 | 43.67266988 |
| 2 | -93.575066 | 43.67274247 | -93.58078897 | 43.67593626 |
| 3 | -94.43981976 | 44.29196277 | -94.44492149 | 44.29604882 |
| 4 | -93.22510388 | 44.92862167 | -93.24658453 | 44.95981671 |
| 5 | -93.08050288 | 44.90709401 | -93.08052783 | 44.91016564 |
| 6 | -93.16684702 | 44.96027858 | -93.16686907 | 44.97363776 |
| 7 | -93.34111381 | 44.97735306 | -93.34831447 | 44.97780134 |
| 8 | -94.52213072 | 46.92649585 | -94.5204656 | 46.93138649 |
| 9 | -92.852361 | 44.72491564 | -92.85238416 | 44.73153676 |
| 10 | -93.83126577 | 43.84478669 | -93.83025769 | 43.84372916 |
| 11 | -94.00398155 | 44.17017677 | -94.00736652 | 44.18149293 |
| 12 | -94.02028716 | 44.1985768 | -93.98283314 | 44.18958733 |
| 13 | -94.60704698 | 44.9336333 | -94.37475832 | 44.89681253 |
| 14 | -93.58559527 | 44.43287946 | -93.58538536 | 44.4466545 |
| 15 | -94.73191015 | 47.00264651 | -94.72714516 | 46.99857821 |
| 16 | -94.03414246 | 44.18021812 | -94.02047633 | 44.18997956 |

In addition, one site was selected because it was part of the MnDOT mobile lidar collection in 2023. Part of the objective of the field data collection was to assess the various technologies that can be leveraged for pedestrian asset data collection.

# CHAPTER 6: FIELD DATA COLLECTION REPORT

## 6.1 INTRODUCTION

Building upon the insights gained from the literature review and the survey of state and local agencies, this chapter delves into alternative methods for assessing the condition of pedestrian assets, particularly sidewalks. While traditional visual inspections remain the most common approach, recent advancements in technology—such as remote sensing, computer vision, and sensor-based systems—offer promising alternatives for more efficient and comprehensive assessments. The literature highlighted a growing interest in these innovative approaches, which are being adopted globally to improve the accuracy, consistency, and cost-effectiveness of pedestrian asset evaluations. Similarly, the survey responses from various transportation agencies revealed a shift towards incorporating emerging technologies in their asset management practices. This chapter explores these alternative methods, discussing their potential applications, benefits, and challenges in the context of pedestrian asset management. By considering these new tools alongside traditional methods, this chapter aims to provide a comprehensive understanding of how best to assess pedestrian assets in a way that supports proactive maintenance and long-term infrastructure planning.

In the United States, current pedestrian asset management and budgeting practices are mostly dependent on experience and subjective judgment supported by limited physical condition data. Maintenance and rehabilitation activities are mainly based on a reactive approach due to a lack of well-established condition rating methods or deterioration models that can be used to estimate the long-term or short-term performance of pedestrian assets (Lin et al. 2022). To develop a data-driven condition assessment system, the project team and the Des Moines Area Metropolitan Planning Organization have made significant efforts to collect surface images and roughness data using a bicycle-based data collection system (Des Moines Area MPO 2019). Up until now, there has been no substantial progress in effectively analyzing these data and rating the condition of pedestrian assets through automated means. This study aims to bridge this gap by employing mathematical and computer vision models to analyze the collected data, thereby reducing human intervention in capturing the condition of these assets.

As described in this chapter, selected sample test sites were used for the collection of images and accelerometer data using a data bike system. The collected accelerometer data was then processed through a mathematical model to estimate the surface roughness. Additionally, an advanced computer vision model was deployed to the imagery to automatically extract information on distress. This data-driven condition assessment system is expected to facilitate effective decision-making in the maintenance of pedestrian infrastructure.

## 6.2 OBJECTIVE

The primary aim of this data collection phase was to deploy a specialized data bike system to gather comprehensive sample data that reflects the current state of selected sidewalk segments. This mobile data-gathering approach provided high-resolution surface images and detailed vertical motion metrics that served as indicators of the sidewalks' condition. Upon collection, the data were systematically compared with existing historical records to assess changes in the sidewalk conditions. The comparison also served to model sidewalk condition degradation.

## 6.3 DATA COLLECTION METHODS

### 6.3.1 Data Bike System

A notable innovation in infrastructure assessment has emerged through the development of a specialized data bike system (Alatoom et al. 2024) designed for efficient data collection across an extensive sidewalk network. By leveraging this data collection system, it is possible to reduce the need for field inspections for trail condition assessment, as the system can travel at a bicycle's speed, suitable for collecting data on pedestrian infrastructure. Initially, the system was developed to complement, rather than replace, comprehensive physical inspections.

The data bike system is comprised of two major components: an iPhone and a GoPro camera, mounted on the back of the data bike as shown in Figure 6-1. The iPhone is equipped with an accelerometer sensor. The SensorLog app, installed on the iPhone, captures the accelerometer data while the bike is ridden at cycling speed. Additionally, the GoPro camera mounted on the back of the bike is capable of capturing continuous geo-tagged imagery while riding.


**Figure 6-1. Iowa data bike system**

### 6.3.2 Data from Accelerometer Sensor

Employing an iPhone-equipped data bike developed for a study sponsored by the Des Moines Area Metropolitan Planning Organization (https://intrans.iastate.edu/research/in-progress/development-of-a-trail-management-program/), an evaluation of sidewalk roughness was undertaken. The smartphone's onboard sensors, including Global Positioning System (GPS) sensors for location tracking and an accelerometer for measuring acceleration, played a pivotal role in data acquisition. Notably, the z-axis acceleration data from the accelerometer was utilized to characterize sidewalk roughness, aligning with the vertical motion experienced during traversal. These data were synchronized with the corresponding latitude and longitude coordinates obtained from the GPS sensors, facilitating precise spatial mapping of roughness variations along the sidewalk routes. Figure 6-2 shows a simplified illustration of how the accelerometer sensor collects the acceleration data.

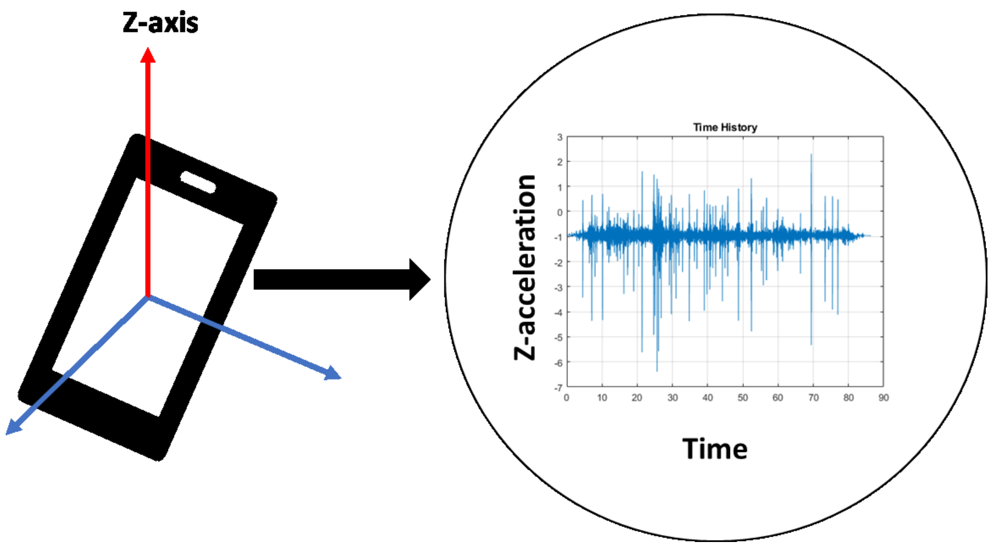



Figure 6-2. Acceleration data collected from smartphone accelerometer

### 6.3.3 Vision Data

For the purpose of collecting vision data, we employed the GoPro Hero 10 Black, which features a 23 MP camera equipped with a GP2 processor, enabling the collection of continuous georeferenced photos. The GoPro camera was strategically mounted on the back of the data bike, positioned at a downward 45$^{o}$ angle to capture the full width of the sidewalk surface. We set the camera to "wide angle" mode to capture the adjacent features of the sidewalks. The images were captured in time-lapse mode at 1-second intervals. To ensure clarity in the captured images, the bike’s speed was maintained between 7 to 8 mph. Figure 6-3 presents some sample photos collected from the test sites.


Figure 6-3. Images captured by GoPro camera

### 6.3.4 Reference Profiler

A walking profiler (shown in Figure 6-4) is typically used as a reference profiler to calibrate inertial profiler measurements of surface roughness. The accuracy of roughness measurements taken by a walking profiler is expected to range between 94% and 99%, and this varies based on the speed of walking during data collection (ARRB Group Ltd. 2017). A walking profiler consists of an inclinometer, mounted on the measuring foot, which assesses either the gradient or the azimuth. A computer program computes a new reference height for each new step, which is updated by adding the relative height of the previous step. The relative height is determined based on the foot's inclination towards the vertical axis and the length of the section being measured. The device continuously records the pavement surface's longitudinal profile through a constantly lowered metal foot, recalculating and logging the cumulative height for each measuring section in reference to the starting point. An electronic walking profiler is capable of graphically displaying the results of profile measurements and automatically calculating the International Roughness Index (IRI) value.

**Figure 6-4. Walking profiler used as the reference profiler**

## 6.4 DESCRIPTION OF THE TEST SITES

The sites were selected based on the availability of two key types of data: two historical snapshots and a variety of condition categories. Given that the objective was to monitor deterioration over time, priority was given to collecting data from sites that are currently in good condition. This was followed by sites in fair, excellent, and poor condition, respectively. Figure 6-5 illustrates the start points of the data collection clusters, while Figure 6-6 shows the historical condition distribution of the data collection sites. Table 6-1 details the geographic coordinates in decimal degrees for these sites. In total, 13 sites were collected, with the majority located in the Minneapolis-St. Paul area. Sites where data were collected on both sides of the road were identified as A and B, respectively.

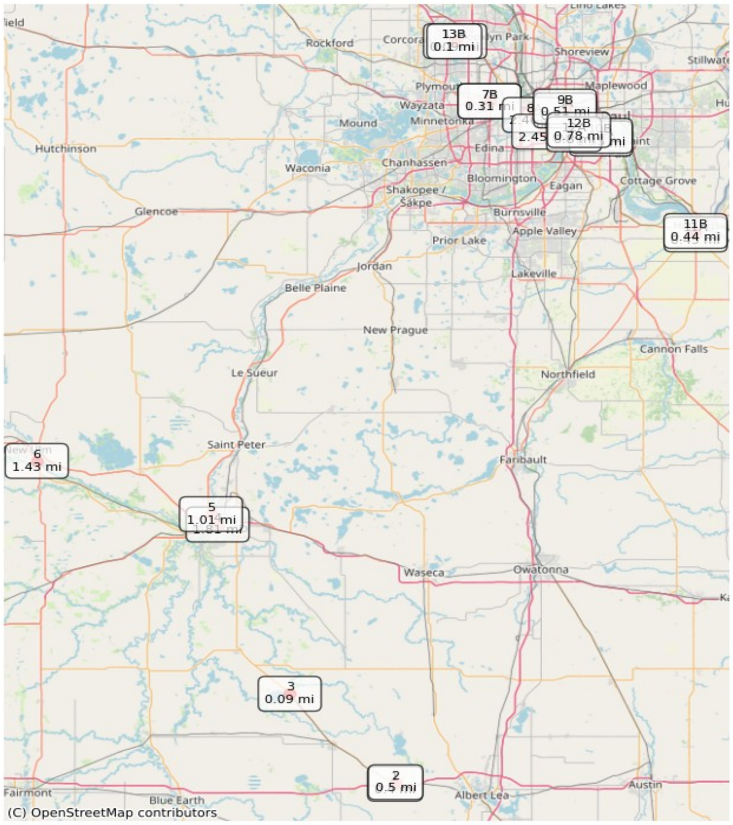


Figure 6-5. Data collection sites


Figure 6-6. Historical condition distribution of the data collection sites

Table 6-1. Geographic coordinates of field collection sites

| Id | SiteID | Length (miles) | Start_X | Start_Y | End_X | End_Y |
|---|---|---|---|---|---|---|
| 1 | 1 | 0.39999 | -93.5766 | 43.66963 | -93.5750 | 43.67266 |
| 2 | 2 | 0.49999 | -93.575066 | 43.6727427 | -93.5807 | 43.67593 |
| 3 | 3 | 0.088364 | -93.8302 | 43.84375 | -93.8314 | 43.84473 |
| 4 | 4 | 1.807148 | -94.004 | 44.17002 | -94.0126 | 44.19457 |
| 5 | 5 | 1.005714 | -94.02 | 44.18988 | -94.0342 | 44.18009 |
| 6 | 6 | 1.434993 | -94.4396 | 44.29189 | -94.4567 | 44.30846 |
| 7 | 7A | 1.131202 | -93.349 | 44.97797 | -93.3263 | 44.97782 |
| 7 | 7B | 0.314282 | -93.3491 | 44.97784 | -93.3428 | 44.97727 |
| 8 | 8A | 2.463214 | -93.2412 | 44.95181 | -93.219 | 44.91982 |
| 8 | 8B | 2.449553 | -93.2187 | 44.92003 | -93.2405 | 44.9519 |
| 9 | 9A | 0.570409 | -93.1666 | 44.96024 | -93.1669 | 44.96847 |
| 9 | 9B | 0.511943 | -93.1672 | 44.96764 | -93.1672 | 44.96027 |
| 10 | 10A | 0.35609 | -93.0805 | 44.9071 | -93.0805 | 44.91225 |
| 10 | 10B | 0.354541 | -93.0808 | 44.91229 | -93.0808 | 44.90716 |
| 11 | 11A | 0.445481 | -92.8523 | 44.72472 | -92.8524 | 44.73115 |
| 11 | 11B | 0.438115 | -92.8527 | 44.73118 | -92.8527 | 44.72484 |
| 12 | 12A | 0.800065 | -93.1454 | 44.91517 | -93.1337 | 44.92319 |
| 12 | 12B | 0.782296 | -93.1335 | 44.92312 | -93.1449 | 44.91531 |
| 13 | 13A | 0.085504 | -93.4319 | 45.09136 | -93.4336 | 45.09126 |
| 13 | 13B | 0.09623 | -93.4337 | 45.09098 | -93.4317 | 45.09079 |
| **Total miles** | | **15.72** | - | - | - | - |

## 6.5 SURFACE ROUGHNESS

Surface roughness is a critical factor in the planning and maintenance of sidewalks used for various forms of transportation, including bicycles (AASHTO 2012, Landis et al. 2004). It significantly affects the safety and comfort of cyclists (Bíl et al. 2015) and can lead to discomfort and reduced enjoyment for riders, potentially decreasing sidewalk usage. IRI is a widely recognized metric used for assessing pavement quality, performance, and roughness (Al-Suleiman (Obaidat) and Alatoom 2022, Hosseini and Smadi 2021). Initially developed for evaluating road surfaces, the IRI methodology, based on the quarter-car system, is adaptable to other types of surfaces, including sidewalks. By simulating a vehicle traveling at a standardized speed, typically 49.71 mph (80 km/h), the vertical displacements of a simulated spring are measured to quantify surface roughness (Sayers et al. 1986).

### 6.5.1 Roughness Estimation Based-on Accelerometer Readings

Following data collection, rigorous analysis procedures were employed to enhance data quality. Noise filters were applied to the acceleration data, followed by signal processing techniques to convert the filtered data into a quantifiable Bike Roughness Index (BRI). This process provided a comprehensive measure of sidewalk roughness. The methodology for sidewalk roughness evaluation is presented in Figure 6-7. The preprocessing step included applying a high-pass filter based on bike velocity and removing stationary data points using GPS speed measurements. The sidewalk was then segmented based on GPS coordinates to enable location-specific analysis (Alatoom et al. 2024).

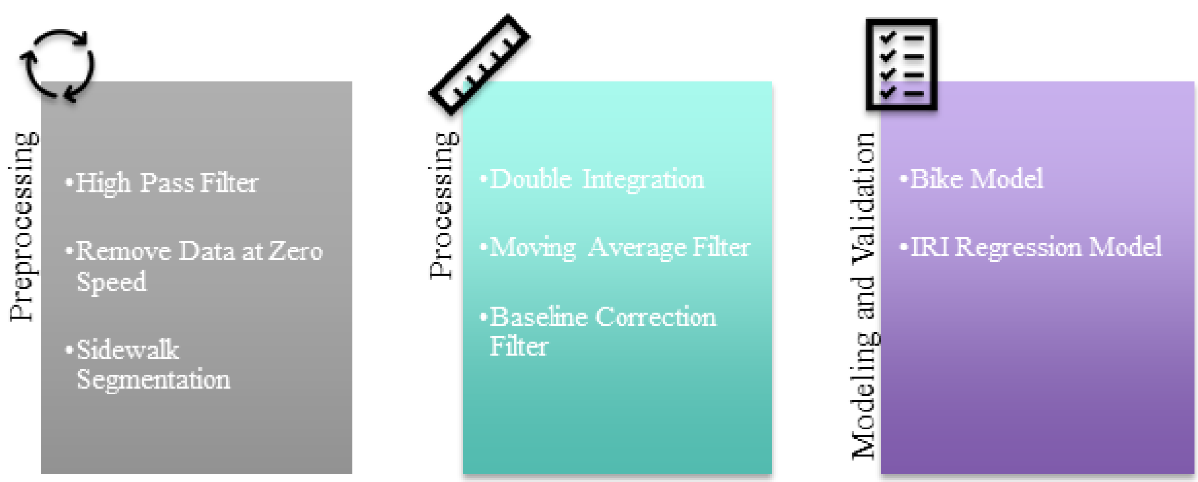



**Figure 6-7. Sidewalk roughness evaluation using the data bike method**

The processing step involved converting accelerometer data into meaningful measurements through various filtering techniques to reduce noise and systematic biases. This refined data provided insights into sidewalk conditions, supporting infrastructure maintenance decisions. Finally, the evaluation underwent validation using the walking profiler IRI. Comparing measurements between the smartphone-based evaluation and walking profiler IRI established a correlation, validating the effectiveness of the smartphone-based approach for assessing sidewalk conditions (Alatoom et al. 2024).

In the processing step of the sidewalk roughness evaluation, several techniques were employed to refine the accelerometer data and derive meaningful insights into sidewalk conditions. Double integration was utilized to convert the filtered accelerometer data into displacement measurements, offering a quantifiable representation of vertical movements experienced during sidewalk traversal. This was complemented by the application of a moving average filter to smooth the displacement data, reducing noise and fluctuations caused by surface irregularities or sensor inaccuracies. Additionally, a baseline correction filter was implemented to mitigate systematic biases and ensure that the analysis focused solely on variations in sidewalk roughness. These techniques collectively enhanced the accuracy and reliability of the data, facilitating a more comprehensive understanding of sidewalk conditions and supporting informed decision-making for infrastructure maintenance and improvement efforts.

Following the processing step, the sidewalk roughness evaluation underwent modeling and validation procedures to assess its accuracy and reliability. Validation was conducted using the walking profiler IRI. By comparing the roughness measurements obtained from the smartphone-based evaluation with those from the walking profiler IRI, a correlation was established, validating the effectiveness of the smartphone-based approach in assessing sidewalk conditions.

### 6.5.2 Verification of BRI

To validate the derived roughness parameter, comparisons were made with established IRI data obtained through a walking profiler. The IRI data, collected through systematic surveys utilizing specialized equipment, served as a reference for sidewalk condition assessment. By correlating the BRI with the established IRI values, the accuracy and reliability of the smartphone-based method were evaluated as shown in Figure 6-8. Figure 6-8 is based on more than 2,000 data points aggregated to the six sites where the walking profiler IRI was collected. The goodness of fit ($R^2$) between IRI and BRI was high, reaching 0.82. This indicates a good correlation between the two methods. Table 6-2 shows information about the data collected from the sections used to calibrate the data bike method. The root mean square (RMS) of the vertical acceleration is another roughness indicator could be used to describe the sidewalk roughness. V is the average velocity used to collect the data using the data bike, and it is used to determine the cutoff frequency for filtering the acceleration data. These data were utilized to calculate BRI and estimate IRI.

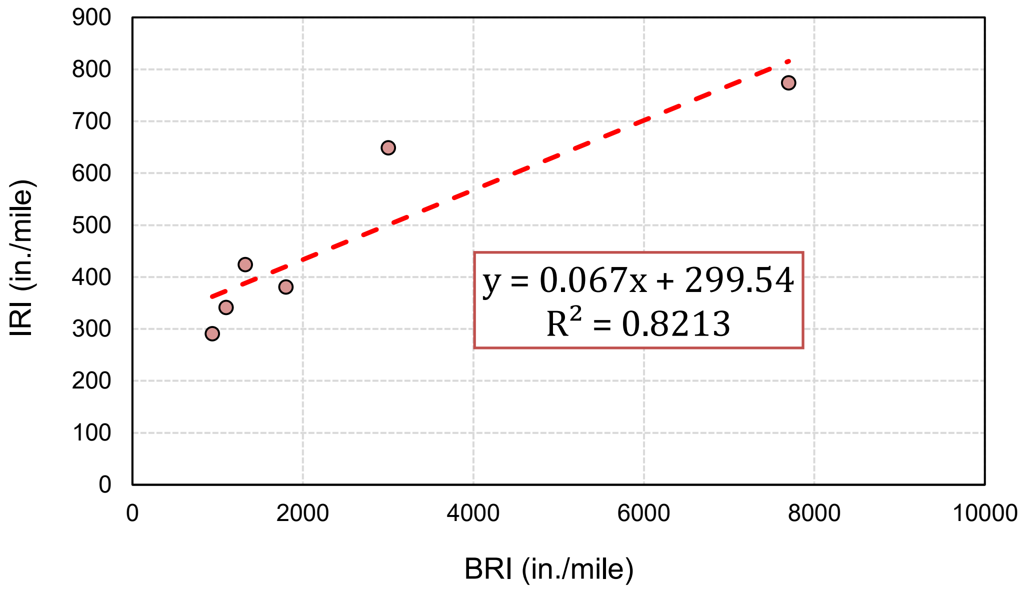



**Figure 6-8. Correlation between BRI and IRI**

**Table 6-2. Information about the data collected to calibrate the data bike method for IRI**

| RMS ($m/sec^2$) | V (mph) | Section Length (mi) | BRI (in./mi) | IRI (in./mi) | Section ID | Surface Type |
|---|---|---|---|---|---|---|
| 1.0850 | 6.8393 | 0.07 | 1323.7 | 423.9 | Section 6 | PC |
| 1.7201 | 6.52386 | 0.190392 | 3001.1 | 649.1 | Section 7A-1 | PC |
| 2.4619 | 6.85164 | 0.186490 | 7697.9 | 773.9 | Section 7A-2 | PC |
| 2.3245 | 6.94895 | 0.168121 | 1099.9 | 341.6 | Section 8 A | PC |
| 1.4104 | 6.64797 | 0.079311 | 1802.4 | 380.8 | Section 13 A | PC |
| 1.3377 | 7.13665 | 0.314743 | 936.7 | 290.9 | Section 5 | AC |

Table 6-3 presents the IRI estimated using the data bike method for various sections within the sidewalk network. Each row corresponds to a specific section identified by its Section ID, with accompanying average $IRI_{DI}$ (double integration method) values after using the calibration equation in Figure 6-8 and average BRI values (before calibration).

Table 6-3. IRI estimated using the data bike method for the whole network

| Section ID | Avg. $IRI_{DI}$ | Avg. BRIs |
|---|---|---|
| 1 | 374.8 | 1123.4 |
| 2 | -- | -- |
| 3 | 425.9 | 1887.2 |
| 4 | 357.4 | 863.7 |
| 5 | 336.2 | 548.0 |
| 6 | 366.9 | 1006.8 |
| 7A | 376.2 | 1145.4 |
| 7B | 375.4 | 1132.3 |
| 8A | 361.0 | 917.4 |
| 8B | 351.7 | 779.6 |
| 9A | 353.5 | 806.3 |
| 9B | 369.7 | 1048.6 |
| 10A | 435.6 | 2030.9 |
| 10B | 371.0 | 1067.4 |
| 11A | 361.6 | 927.0 |
| 11B | 367.7 | 1018.1 |
| 12A | 370.0 | 1052.8 |
| 12B | 377.3 | 1161.7 |
| 13A | 368.1 | 1023.5 |
| 13B | 467.0 | 2500.2 |

## 6.6 AUTOMATED DISTRESS ASSESSMENT

### 6.6.1 Vision-Based Surface Distress Assessment

This study implemented an automated computer vision system, as shown in Figure 6-9, designed to localize, classify, and segment surface distress from high-resolution GoPro images. The data acquisition process involved mounting GoPro cameras on vehicles, capturing detailed images that served as input for the distress detection model. This model is a convolutional neural network tailored to identify various distress types such as transverse and longitudinal cracking, interconnected cracking, sealed longitudinal cracking, potholes, patching, and spalling, with precise localization and classification. The segmented distresses are then quantified to provide measurable data, which is crucial for the assessment of the pavement condition. The model is suitable for network-level deployment, allowing for the assessment of pavement distress over large areas.

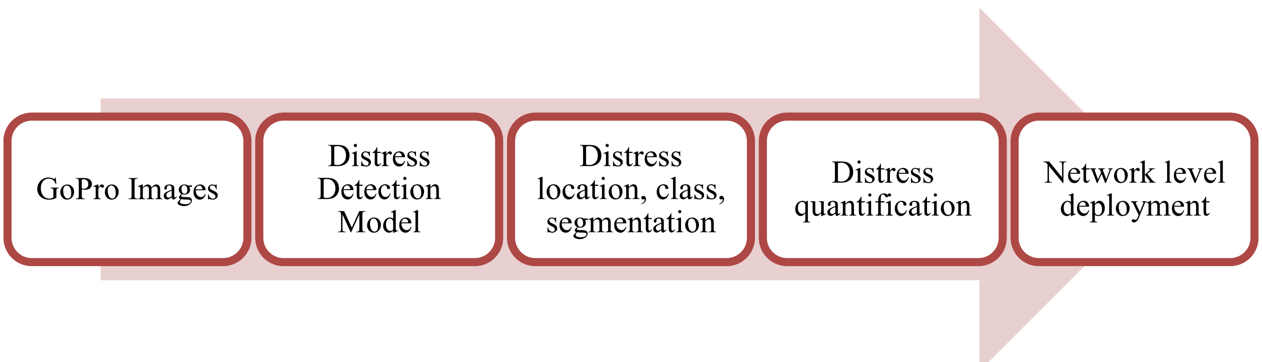
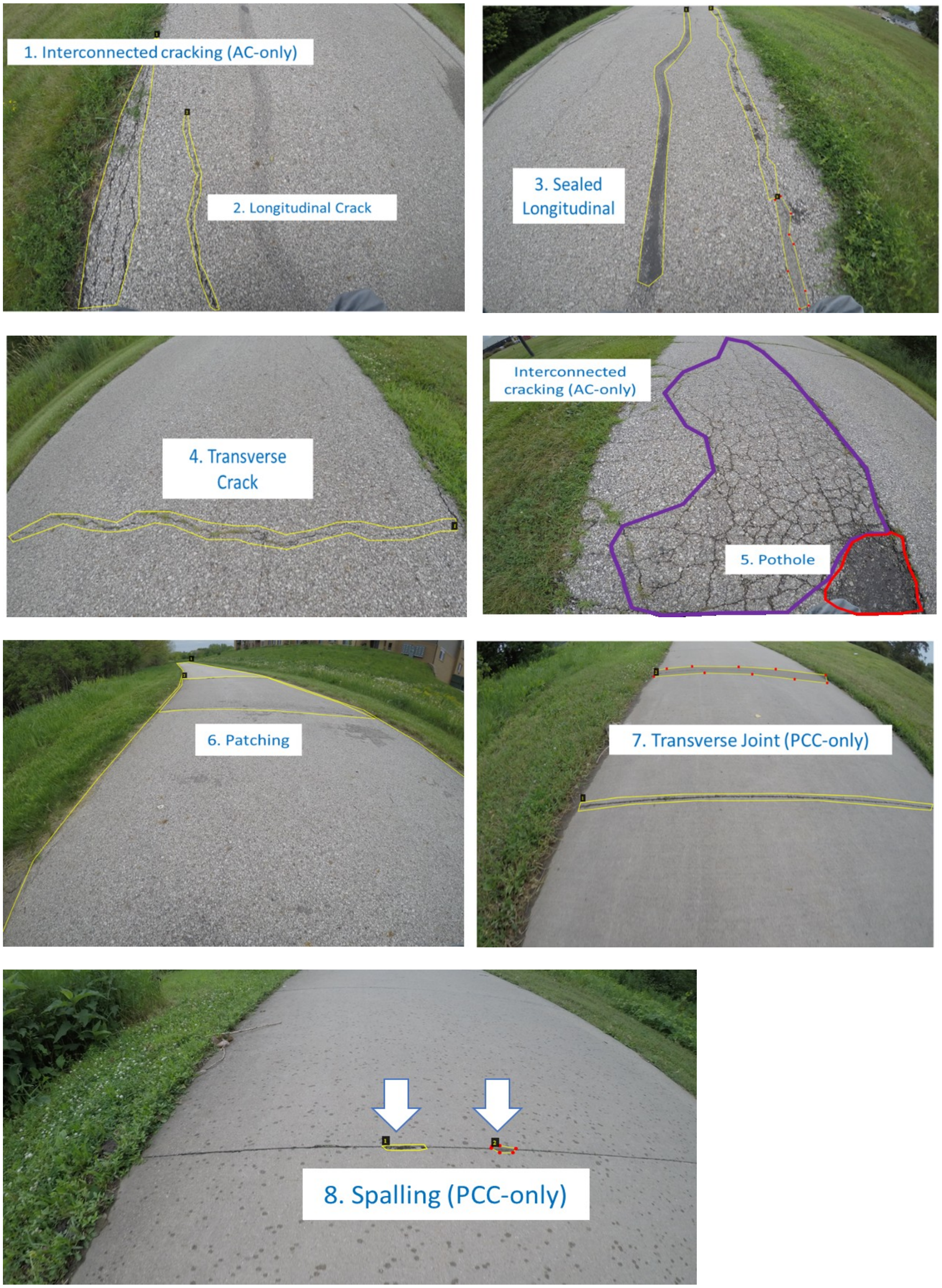



**Figure 6-9. Flowchart of the distress assessment process**

The model was implemented utilizing an open-source Mask-R-CNN architecture, and it was trained and validated using a dataset that was annotated with expert-verified distress classifications. To train the Mask R-CNN model, we compiled a dataset comprising 4,500 images. This dataset includes images depicting eight types of surface distresses, as shown in Figure 6-10, specifically (1) interconnected cracking, (2) longitudinal cracking, (3) sealed longitudinal cracking, (4) transverse cracking, (5) transverse joints, (6) spalling, (7) potholes, and (8) patching. The characteristics of most of these distresses are widely recognized within the pavement management community. Notably, we defined interconnected cracking as instances where multiple longitudinal cracks intersect with one another. Training the Mask R-CNN model required the annotation of these distress classes with polygons precisely outlining each distress. We manually annotated these distresses within our training dataset to use as input to the Mask R-CNN model.




*From a study sponsored by the Des Moines Metropolitan Planning Organization titled Development of a Trail Management Program*

**Figure 6-10. Eight types of surface distresses identified and annotated for model training**

The methodology employed by the computer vision model consists of a series of interconnected steps, as shown in Figure 6-11. Initially, a backbone neural network generates feature maps from the input images, which are then processed by a region proposal network to identify potential distress locations. These are subsequently refined through ROIAlign to ensure accurate feature extraction. The model utilizes fully connected layers to predict distress classifications and bounding boxes, coupled with a parallel network for mask prediction. This process results in a final output that annotates the original GoPro images with detailed information on each identified distress type.

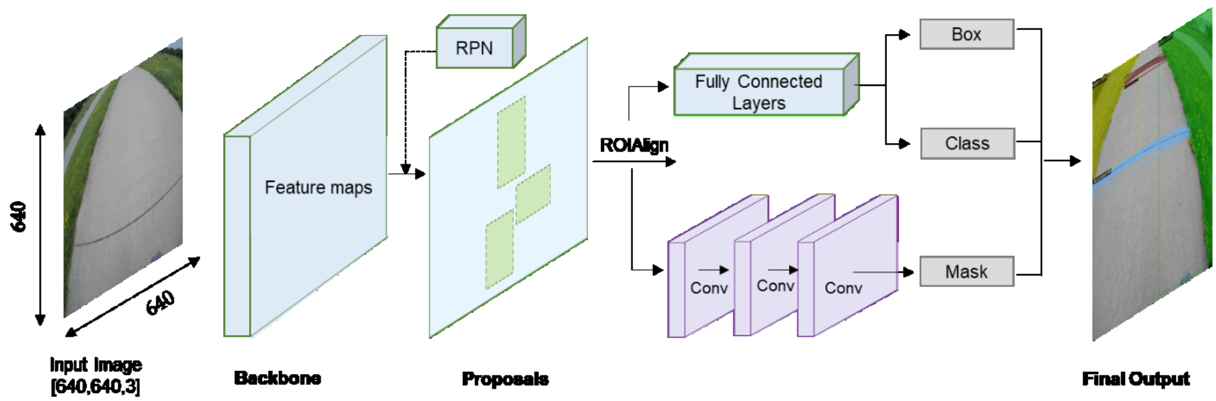


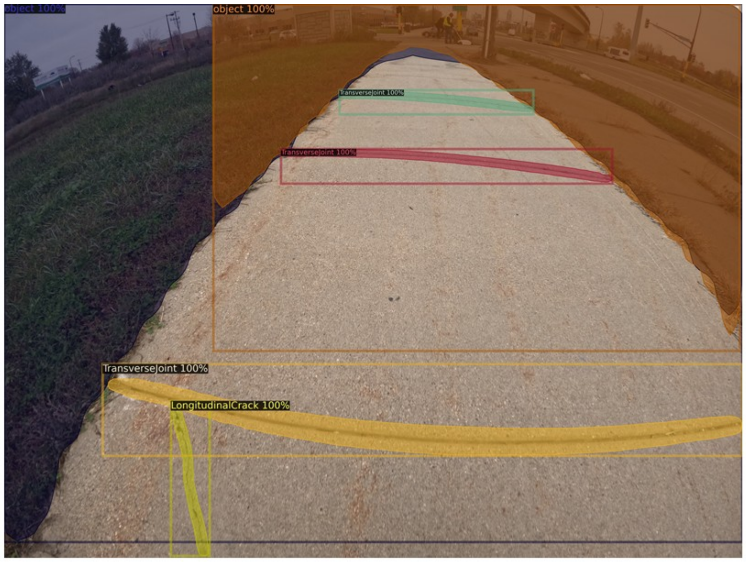

Figure 6-11. Mask-R-CNN model architecture

To achieve network-level deployment, the model was scaled and optimized for processing large datasets, enabling comprehensive pedestrian network assessments. The distress segmentation and quantification capabilities of our system are essential for obtaining valuable condition information, facilitating the prioritization of maintenance efforts. By leveraging this automated assessment tool, agencies can significantly enhance the efficiency of pedestrian asset inspections and the overall management of pedestrian infrastructure.

### 6.6.2 Quantification of Surface Distress

The predicted masks from the computer vision models were processed and analyzed to quantify the actual extent of surface distresses on the ground. Capturing images with GoPro cameras, which often result in distorted, wide-angle, and oblique-view images, posed a significant challenge in accurately measuring the length or area of the surface distress. To overcome this, we employed a scaling factor derived from extensive experimentation with GoPro cameras. This process involved capturing images of objects with predetermined lengths, designed to simulate longitudinal and transverse cracks located at different parts of the images. After that, we were able to establish a reliable scale by comparing the predicted masks from the computer vision models with these known dimensions (i.e., the ground truth). This scaling factor is essential for converting the dimensions within the predictive masks into real-world measurements. Figure 6-12 illustrates an example in which the depicted image reveals the detection of three transverse joints. These joints were recorded as a count and incorporated into the distress database. In addition, a longitudinal crack was identified, spanning 1,167 pixels within the image. To calculate the actual length of the longitudinal crack, a scaling factor was applied. This factor considers the position of the crack from the bottom of the image and the number of pixels occupied by the crack.

In this case, the true length was estimated to be approximately 1.48 ft. Based on visual inspection, this estimated length was considered to be accurate.




**Distress Quantification**

| Distress Type | Predicted number of pixels | Count | Actual length from SCALE MODEL(ft) |
|---|---|---|---|
| **T-Joint** | **4824** | 1 | -- |
| **T-Joint** | **2498** | 1 | -- |
| **T-Joint** | **1461** | 1 | -- |
| **Longitudinal Cracking** | **1167** | -- | 1.48 |

**Figure 6-12. Example of distress quantification algorithm**

Table 6-4 shows a comprehensive overview of pavement distress across the test sites, obtained through the automated assessment system. For instance, Site 4 exhibits a significant extent of interconnected cracking, covering an area of approximately 4,970.9 ft$^2$, along with longitudinal cracking measured at 1,671.1 ft. On the other hand, Site 8A shows a high degree of transverse cracking, measured at over 20,371 ft. The variation across sites indicates diverse pavement conditions.

Table 6-4. Site-level surface distress data

| Site ID | Length (miles) | No. of images | Interconnected Cracking (ft$^2$) | Longitudinal (ft) | Patching (ft$^2$) | Pothole (count) | Sealed Longitudinal (ft) | Spalling (count) | T-Joint (count) | Transverse (ft) |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.39 | 97 | - | 35.4 | - | 0 | 9.1 | 0 | 296 | 7.5 |
| 2 | 0.49 | 153 | 1.7 | - | - | 0 | - | 0 | 502 | 8.3 |
| 3 | 0.08 | 55 | - | 18.7 | - | 0 | 7.2 | 0 | 122 | - |
| 4 | 1.80 | 794 | 4970.9 | 1671.1 | 0.7 | 0 | - | 0 | 2 | 4057.9 |
| 5 | 1.00 | 492 | 159.5 | 93.5 | 37.7 | 0 | 21.6 | 0 | 0 | 6156.2 |
| 6 | 1.43 | 692 | 84.3 | 301.2 | 0.2 | 0 | 17.7 | 14 | 2146 | 1327.6 |
| 7A | 1.13 | 597 | 147.1 | 1156.3 | 0.3 | 0 | 26.8 | 10 | 1020 | 2314.7 |
| 7B | 0.31 | 176 | 33.1 | 424.5 | - | 0 | 48.9 | 0 | 396 | 251.2 |
| 8A | 2.46 | 1157 | 135 | 3524.8 | 2.1 | 0 | 9.5 | 34 | 3546 | 20371 |
| 8B | 2.44 | 1108 | 39.6 | 839.1 | - | 2 | - | 14 | 3558 | 669.8 |
| 9A | 0.57 | 153 | - | 495.7 | 1.4 | 0 | 212.6 | 4 | 458 | 153.7 |
| 9B | 0.51 | 259 | 88.8 | 1108.4 | 10.9 | 0 | - | 2 | 734 | 702.9 |
| 10A | 0.35 | 177 | 5.8 | 268.3 | - | 0 | 1.9 | 2 | 662 | 14.6 |
| 10B | 0.35 | 200 | 37.3 | 233.7 | - | 0 | 9 | 0 | 700 | 34.8 |
| 11A | 0.44 | 260 | 117.9 | 206.2 | - | 0 | - | 6 | 814 | 514.8 |

| Site ID | Length (miles) | No. of images | Interconnected Cracking ($ft^2$) | Longitudinal (ft) | Patching ($ft^2$) | Pothole (count) | Sealed Longitudinal (ft) | Spalling (count) | T-Joint (count) | Transverse (ft) |
|---|---|---|---|---|---|---|---|---|---|---|
| 11B | 0.43 | 238 | 14.3 | 288.8 | - | 0 | 31.7 | 14 | 654 | 810.1 |
| 12A | 0.80 | 389 | 109.3 | 572.4 | 61.4 | 4 | 55.4 | 6 | 462 | 1481.9 |
| 12B | 0.78 | 373 | 123.3 | 1083.4 | 0.9 | 2 | 302 | 16 | 578 | 1969.8 |
| 13A | 0.08 | 44 | 6.4 | 18.8 | - | 0 | - | 0 | 66 | 18 |
| 13B | 0.09 | 45 | 2 | - | - | 0 | - | 2 | 114 | 329 |

## 6.7 COMPARISON WITH HISTORICAL DATA

The roughness and surface distress metrics collected by the data bike were compared with historical condition data acquired through visual inspections. While the comparison was done by comparing surface distress metrics and roughness measures separately, integrating these metrics into a single, unified condition index could provide a more comprehensive and meaningful evaluation of condition. This index would offer a holistic view of the pedestrian asset, taking into account both its physical integrity and the smoothness of the ride it provides. Nevertheless, conducting an initial correlation analysis should significantly aid in validating the metrics obtained from the data bike. For segments with multiple years of historical data, the condition data from the most recent year was chosen for analysis.

The Pearson correlation coefficient was calculated to quantify the linear correlation between various road distress metrics and the historically recorded condition of road surfaces. This statistical measure ranges from -1 to 1, where 1 indicates a perfect positive linear relationship, -1 indicates a perfect negative linear relationship, and 0 suggests no linear correlation. The calculation involves comparing the distress metrics, such as the extent of interconnected cracking, longitudinal and transverse cracking, potholes, and spalling, against the percentages of roads classified into condition categories (excellent through poor). This method assesses how changes in distress metrics relate to variations in road quality.

As shown in Figure 6-13, a positive correlation coefficient implies that as the distress metric increases (e.g., more potholes or a greater length of cracking), the condition of the road is more likely to be rated as poor. Conversely, a negative correlation suggests that increases in the distress metric are associated with a higher likelihood of the road being classified as excellent. For example, a strong negative correlation between "Pothole (count)" and excellent roads indicates that fewer potholes are associated with better road conditions. Meanwhile, a positive correlation between the same metric and poor road conditions suggests that an increase in potholes aligns with roads being in worse condition. These correlations provide critical insights into the effectiveness of automated distress assessments in predicting road quality, emphasizing the significance of targeted maintenance and the potential for predictive analytics in infrastructure management.

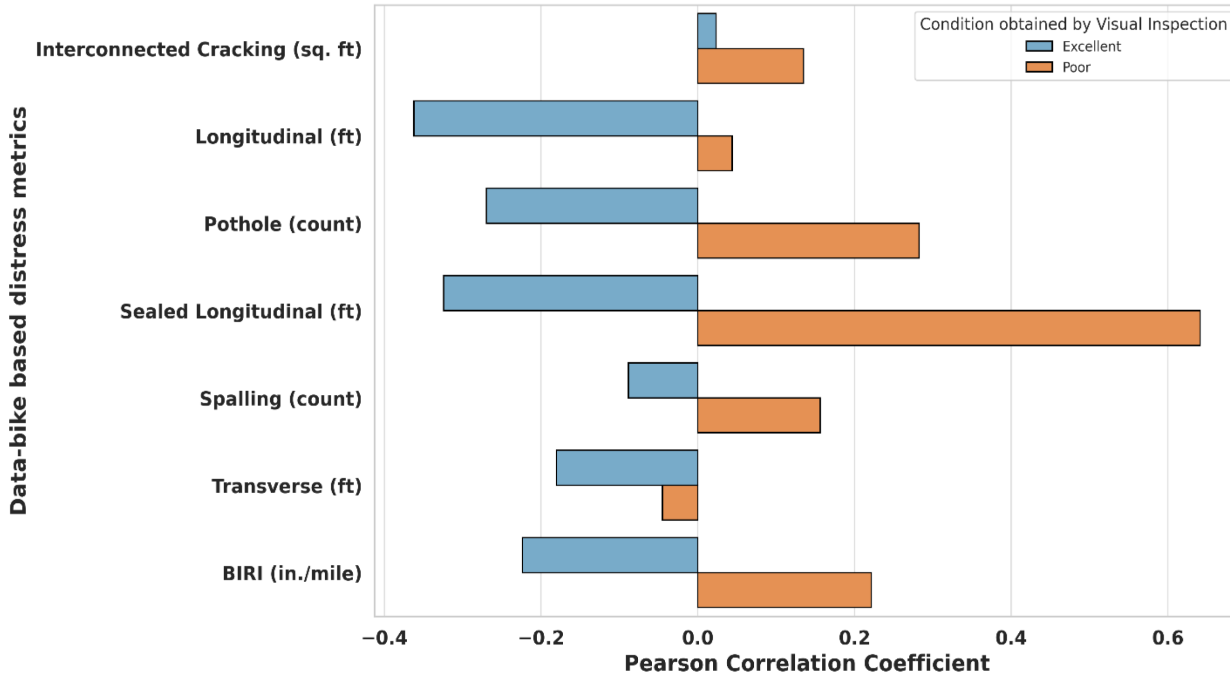



**Figure 6-13. Correlation of data bike–based distress metrics with historical condition**

## 6.8 SUMMARY AND DISCUSSION

This report describes the data collection methodology, which utilized the data bike system equipped with an iPhone and a GoPro camera across selected test sites in Minnesota. The accelerometer data obtained were processed through a mathematical model to determine surface roughness, while a cutting-edge computer vision model was deployed to evaluate the collected imagery to autonomously extract distress information. Our findings suggest that this data-driven approach, integrating mathematical and computer vision models, can greatly reduce human intervention in the condition assessment process. Preliminary analysis suggests a good correlation between the distress metrics obtained from the data bike system and historically recorded condition through visual inspection. The successful application of this technology demonstrates its potential for wider adoption in the management of pedestrian infrastructure.

### 6.8.1 Potential Data Acquisition Systems for Pedestrian Assets

Referring to the data acquisition system discussed in the previous sections, which collects vertical motion data via an accelerometer sensor and vision data using a GoPro camera, this section explores other potential systems for gathering similar data for pedestrian asset condition assessment on a network level. Although a Class-1 e-bike was utilized in our study, alternative types of e-bikes could also serve as suitable substitutes. Moreover, there is significant potential in leveraging crowdsourcing programs to acquire this type of data.

#### 6.8.1.1 E-Bike Type

Switching from a Class 1 e-bike to a Class 2 e-bike can provide possible benefits for this type of data collection. It is understood that a Class 2 e-bike can offer better control over maintaining a consistent speed, improved stability at lower speeds, and possibly more accurate data collection. This would only impact the roughness data. The bike type does not impact the distress data, which are based on the images from the GoPro camera. However, transitioning to a different bike type for data collection would require recalibration of our existing algorithms to accommodate the new data acquisition system.

#### 6.8.1.2 Crowdsourcing Program

The concept of a bike-agnostic data collection approach through a crowdsourcing program has also shown promise (Wage and Sester 2021). However, when considering the implementation of a crowdsourcing program for our purposes, several challenges need to be addressed to ensure the reliability of the data collected. The primary concern would be the variability in bike specifications, sensor (mobile device) positioning, and riding speeds among participants. These factors could significantly affect the consistency and comparability of the data.

To mitigate these issues, extensive preprocessing of the collected data would be necessary. Additionally, the nature of crowdsourcing may lead to uneven coverage of pedestrian assets, with some areas being more frequently reported than others, introducing bias in the data collected. Another mitigation option to accommodate this variability would be the development of a phone app that would preprocess the data based on a well-defined guideline to ensure consistency.

In summary, a crowdsourced data collection approach offers a promising avenue for enhancing our data collection capabilities. Formalizing it as a private-public stakeholder collaboration will greatly enhance its coverage because there is a stable niche interest in the space.

# CHAPTER 7: METHODOLOGY FOR STATEWIDE DETERIORATION MODEL AND CONDITION ASSESSMENT FRAMEWORK

## 7.1 PROBLEM STATEMENT

Pedestrian assets, particularly sidewalks, are vital for ensuring safe and accessible mobility in urban infrastructure systems. However, these assets are highly susceptible to aging, adverse weather conditions, and suboptimal construction practices, often leading to rapid deterioration. Although sidewalks are typically designed for a service life of 20 to 40 years, they frequently fail prematurely, with deterioration reported as early as 1 to 5 years after service initiation (Huber et al. 2013). This premature degradation is ignored due to the widespread misconception that pedestrian assets are low risk, resulting in many deteriorated sidewalks being left untreated or inadequately maintained. Consequently, maintenance backlogs grow, and service levels decline, underscoring the urgent need for more effective condition assessment and management practices (Espada et al. 2018).

The current pedestrian asset management approach in the United States is largely reactive, relying on subjective judgment and limited condition data. Maintenance and rehabilitation activities often lack the support of well-established condition rating systems or predictive deterioration models that could estimate the short- and long-term performance of pedestrian assets (Lin et al. 2022). This reactive approach hinders the ability to prioritize investments effectively, plan maintenance schedules, and allocate budgets efficiently.

Deterioration modeling is critical for overcoming these challenges, enabling infrastructure managers to predict the aging process of sidewalks and other pedestrian assets. There is a significant gap in utilizing advanced data sources for pedestrian asset modeling that are available at low or no cost. Although these sources could provide valuable spatial and temporal data, their potential remains underexplored for sidewalk condition monitoring. Given these unexplored resources, there is a need for a comprehensive framework that integrates advanced data analytics and predictive modeling to address gaps in current pedestrian asset management practices. This framework must leverage existing data sources effectively, account for the complex nature of deterioration, and provide actionable insights for proactive maintenance and resource optimization.

## 7.2 OBJECTIVE

The primary objective of this phase was to develop reliable performance measures and deterioration models for pedestrian assets, particularly sidewalks, through the following key steps:

- Identify strategies and organizational goals related to pedestrian asset condition and ensure that findings support proactive maintenance planning and organizational priorities for sustainable pedestrian infrastructure.
- Assess available data sources for completeness, resolution, and temporal consistency to determine their suitability for condition modeling.

- Analyze sidewalk conditions using performance metrics derived from high-resolution imagery.
- Develop a framework suitable for deterioration model based on already existing data sources.

## 7.3 STRATEGIES AND ORGANIZATIONAL GOALS

This section outlines the results of an engagement exercise conducted between the research team and stakeholders with expert knowledge of pedestrian assets. The primary objective was to explore organizational strategies and goals for promoting the sustainability, safety, and efficient management of pedestrian infrastructure over the next 5 to 10 years. Stakeholders were convened by the Technical Advisory Panel (TAP) for this project to share insights and provide guidance. The primary findings include the following:

- Data Integration and Utilization
    - *Data Collection and Management*: One of the foremost goals is to integrate pedestrian infrastructure data into the TAMS. This involves data collection through various stages of construction, scoping, and inspector assessments to ensure that the data are comprehensive and up to date.
    - *Analytics and GIS*: Utilizing analytics and GIS is important for making the data available for informed decision-making and strategy development.
- Rebuilding and Maintenance
    - *Rebuilding Phase*: The organization is currently in a rebuilding phase, focusing on updating and maintaining pedestrian assets that have suffered from years of underinvestment. This includes ensuring compliance with modern design standards and addressing noncompliance issues due to deterioration.
    - *Curb Ramps and Sidewalks*: Regular updates of curb ramps and sidewalks during pavement projects are prioritized to ensure that they meet current standards, particularly for accessibility and safety.
- Work Order and Interim Work Tracking
    - *Work Order Elements*: Implementing a robust system is important for capturing and tracking interim work on pedestrian environments. This is crucial for identifying problem areas and designs that may contribute to the deterioration of pedestrian assets.
- Maintenance Agreements and Responsibilities
    - *Challenges in Maintenance Tracking*: Maintaining and tracking responsibilities across state and local agencies involves significant challenges. Clear maintenance agreements are essential to ensure consistency and accountability, particularly for sidewalks and pedestrian facilities managed by local agencies.
    - *Statewide Maintenance Agreement Proposal*: A master maintenance agreement across the state could clarify roles and responsibilities between state and local agencies. This approach would help align data collection, maintenance practices, and investments with the goals of a unified TAMS.
    - *Data Integration for Maintenance*: Integrating maintenance data into the TAMS is critical. This includes capturing information on interim repairs, the life-cycle impacts of maintenance

activities, and the effectiveness of various repair strategies. Workflows that allow local agencies to contribute data to the TAMS can enhance decision-making and promote alignment with state objectives.
    - *Strategic Tracking and Analysis*: Selecting representative projects or districts to systematically track maintenance practices and their outcomes can provide valuable insights. Evaluating the long-term impacts of maintenance interventions can inform policy decisions and optimize pedestrian asset management practices.
- Comparative Analysis:
    - *Piecemeal versus Complete Replacements*: The long-term effectiveness of piecemeal repairs versus complete replacements of sidewalk segments should be analyzed. This involves studying the life cycle and deterioration rates of different repair strategies to optimize maintenance and replacement practices.
- Strategic Project Selection:
    - *Project Prioritization*: Pedestrian projects should be selected based on a combination of factors, including ADA compliance, overall condition, and usage data. The aim is to ensure that investments are directed towards areas with the highest need and potential impact.
    - *Legislative Compliance*: Adhering to state regulations, such as the inventory requirements outlined in state guidelines, is important for maintaining a comprehensive inventory of pedestrian infrastructure.
- Resiliency and Adaptation:
    - *Climate Resilience*: Considerations for climate resilience should be incorporated into pedestrian asset management. This includes understanding the impact of flooding and other climate-related events on pedestrian walkways and designing infrastructure to withstand these challenges.
- Collaboration with Local Agencies:
    - *Local Agency Integration*: The importance of local agencies in maintaining pedestrian infrastructure should be recognized. The goal is to collaborate with local agencies to align data collection and maintenance practices, ensuring a unified approach to managing pedestrian assets across different jurisdictions.

By focusing on these strategies, the organization aims to create sustainable, safe, and well-maintained pedestrian infrastructure that meets current needs and anticipates future challenges.

## 7.4 DATA SOURCES FOR DETERIORATION MODELING

This section outlines the various data sources evaluated for this study. Several key characteristics were considered when selecting datasets to ensure that they would be suitable for analyzing pavement and sidewalk condition over time:

1. Is the dataset available across multiple years to enable the study of historic condition degradation over time?
2. Does the dataset provide extensive coverage of the MnDOT's sidewalk network?

3. Is there consistency in the dataset over time? For imagery data, are consistent resolution and acquisition methods maintained across different years?
4. Does the dataset have sufficient spatial resolution to capture desired details of pavement distress, such as cracks and potholes?
5. Does the dataset meet high standards of quality and accuracy, with minimal noise and artifacts, ensuring its suitability for quantitative analysis?
6. Is the dataset accessible and compatible with the study's processing capabilities, including computational and software requirements?

Data sources such as aerial imagery at different spatial resolutions, Google Street View imagery, and lidar datasets were identified for the preliminary evaluation.

### 7.4.1 Aerial Imagery

Aerial imagery, obtained through various means such as manned and unmanned aerial vehicles, satellites, and lidar technology, has become a valuable tool for asset monitoring across different fields. The applications of aerial imagery are diverse and include areas such as agriculture, forestry, urban planning, disaster response, and environmental monitoring. Aerial imagery provides high-resolution data that can be used for tasks like land cover classification, crop monitoring, forest health assessment, and infrastructure monitoring (White 2012, Sari et al. 2021, Kubišta and Surový 2021, Pricope et al. 2019). The fusion of aerial imagery with lidar data enhances the accuracy of ground object classification and enables detailed land cover surveys (Mo et al. 2019). Moreover, aerial imagery has been proven effective in monitoring spatial variations in crop conditions and yields, making it a valuable tool for precision agriculture (Zhang et al. 2014, Sari et al. 2021).

The advantages of using aerial imagery for asset monitoring are numerous. Aerial imagery allows for the rapid collection of data over large areas, reducing the time required for analysis and decision-making processes. It also facilitates better organization of fieldwork, lowers costs, improves work quality, and eliminates subjective factors associated with manual inspection (Budnik 2023). However, despite its advantages, aerial imagery also has limitations. The spatial resolution of the imagery, influenced by factors such as processing conditions and sensor capabilities, can impact the quality and detail of the data collected (Kubišta and Surový 2021). Furthermore, challenges exist in selecting the most suitable imaging asset for a given mission, especially when multiple assets with varying capabilities are available (Gilleron et al. 2019). Ensuring the accuracy and quality of aerial imagery data also requires attention to factors like processing parameters and data collection methods (Pricope et al. 2019).

### 7.4.2 Google Street View Imagery

Google Street View imagery has gained significant attention in various research fields due to its extensive geographical coverage, high resolution, and standardized images of urban environments (Stubbings et al. 2019). Researchers have leveraged Google Street View for diverse applications such as urban forest indexing (Stubbings et al. 2019), transport object detection (Bai 2024), neighborhood auditing (Bader et al. 2016), utility pole identification (Zhang et al. 2018), and the derivation of neighborhood-built environments for health outcome studies (Yue et al. 2022). The use of Google Street View has also extended to urban land use classification by integrating aerial and street view images (Cao et al. 2018). Moreover, Google Street View has been employed for fine-grained orientation of street-view images by cross-view matching with satellite imagery (Hu et al. 2022).

The utility of Google Street View utility lies in its ability to provide panoramic views with accurate geolocation information, making it a valuable resource for asset monitoring and assessment (Zhang et al. 2018). The advantages of Google Street View include its ability to offer a resource-efficient and reliable alternative to physically auditing neighborhood attributes associated with walking and cycling (Badland et al. 2010). It has been noted that Google Street View images provide a viable alternative to field audits, improving efficiency and expanding the geographic and temporal scope of audits (Kelly et al. 2012). However, Google Street View also has limitations. While it offers extensive coverage, its distribution and spatial representation are influenced by corporate orientations and resource allocations, leading to uneven coverage in certain areas (Quinn and León 2019). Despite these limitations, Google Street View remains a valuable tool for asset monitoring and assessment due to its high-quality imagery and geolocation information.

## 7.5 DETERIORATION METHODOLOGY USING AERIAL IMAGERY

### 7.5.1 Research Hypothesis and Study Design

This research focused on modeling pavement deterioration using properties derived from aerial imagery captured through photogrammetric methods. A few studies have explored remote sensing data for transportation infrastructure condition assessment, primarily from satellite-based imagery due to its broad and consistent coverage. One such study by Bashar (2022) demonstrated that satellite data can be leveraged to assess the existing surface roughness of pavements by analyzing pixel brightness and texture metrics from panchromatic imagery. Panchromatic imagery refers to grayscale images captured across a wide range of wavelengths, typically covering the visible light spectrum (blue, green, and red). Such images are created by combining the light intensity from all of these wavelengths into a single channel, producing high-resolution detail. This makes panchromatic images valuable for detecting and analyzing fine spatial features in remote sensing. For example, a panchromatic band in satellite imagery is often used to sharpen multispectral images through a process called pan-sharpening (Jensen 2007). In this context, higher roughness levels correlated with lighter pixel intensities in panchromatic images, indicating increased surface irregularity. Deteriorated pavements exhibited a wider range of intensity values, greater variance, and higher entropy, suggesting a loss of surface uniformity (Bashar 2022). Similarly, Pan et al. (2016) utilized multispectral imagery to classify pavement aging into three categories (light, medium, and heavy) based on the reflectance and slope of the spectral signature across wavelengths from 0.35 to 2.5 µm. This approach revealed that aging pavements exhibit distinctive spectral features, although it did not conclusively differentiate specific distress types.

Aerial imagery often lacks the resolution required for detailed distress-level pavement assessments. Despite this limitation, these data sources offer frequent and extensive coverage, which can contribute to a holistic understanding of pavement condition and serve as a basis for deterioration modeling.

Changes in intensity values correspond to variations in surface conditions, which can be detected and analyzed. For pavements and sidewalks, deteriorated areas would exhibit different reflectance characteristics than surfaces in good condition.

To evaluate these changes systematically, this study incorporated the analysis of DN values, which represent the intensity of reflected light captured by sensors. DN values are the scaled radiometric values of an image pixel, typically ranging from 0 to 255 in an 8-bit imagery format (Jensen 2007). These values are calculated as follows:

$$\mathrm{DN} = \frac{Radiance - Offset}{Gain}$$

where *radiance* is the amount of light energy received by the sensor from a specific surface area and *offset* and *gain* are sensor-specific calibration parameters that normalize the radiance values for consistent analysis.

Based on insights from the literature and the intensity characteristics of pavement distress in imagery data, we hypothesized that the development of new distresses or increased surface roughness will lead to a decrease in pixel brightness for damaged pavement segments. Distress features, such as cracks, potholes, joint faulting, and vegetation growth, would typically appear as darker pixels, reflecting the degraded condition and increased roughness. The conceptual framework of this hypothesis is illustrated in Figure 7-1. Part (a) shows a distress-free surface with uniform pixel values, representing a pavement segment in good condition. Part (b) depicts the development of distress, including cracks and potholes, where distressed pixels appear darker than surrounding areas. This distinction between distress-free and distressed pixels supports the hypothesis that deteriorated areas exhibit unique reflectance characteristics, making them identifiable through changes in pixel brightness.

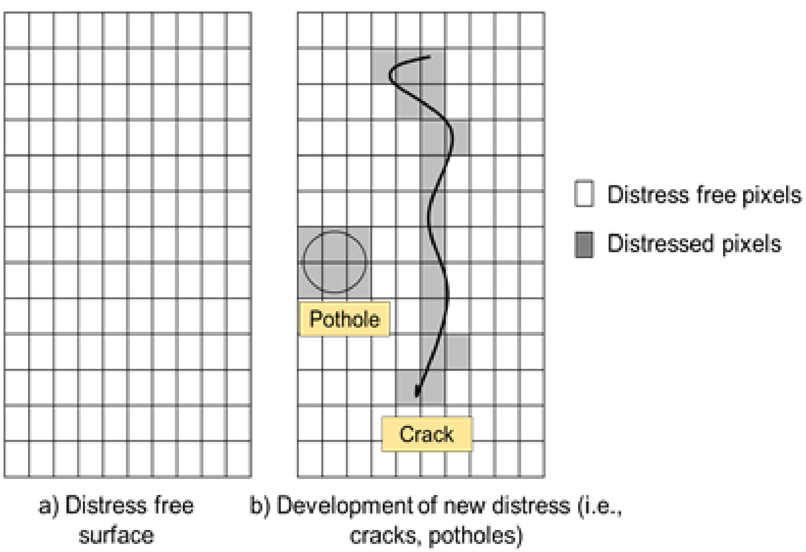



**Figure 7-1. Illustration of research hypothesis**

### 7.5.2 Data Description

Aerial imagery was acquired at varying resolutions using different equipment, reflecting the diverse technologies employed in data collection. Aerial imagery encompasses various technologies designed for diverse applications in remote sensing and mapping. Panchromatic imagery provides high-resolution black-and-white images, is sensitive to visible light (0.4 to 0.7 µm), and is widely used for photogrammetry and detecting surface textures. Color imagery (true color) captures red, green, and blue wavelengths, closely resembling human visual perception, making it effective for mapping and general visual assessments. Infrared imagery includes black-and-white and color infrared (false color) images, sensitive to green, red, and near-infrared wavelengths (0.5 to 1.0 µm). These are invaluable for analyzing vegetation health, detecting water pollution, and studying crop conditions. Multispectral imagery captures data across multiple spectral bands, enabling detailed analyses for applications such as resource management and environmental monitoring. Angular coverage further classifies imagery into narrow, normal, wide, and super-wide angles, depending on the camera's focal length, with applications ranging from intelligence to resource mapping. Additionally, oblique imagery, captured at angles like 30° (low oblique) and 60° (high oblique), provides familiar perspectives for reconnaissance and aeronautical mapping, while stereoscopic imagery uses overlapping photographs to allow 3D terrain analysis, essential for topographical mapping. Together, these types of aerial imagery offer comprehensive tools for understanding and analyzing the Earth's surface (Dr. Shyama Prasad Mukherjee University, n.d.).

#### 7.5.2.1 NAIP Aerial Imagery

The National Agricultural Imagery Program (NAIP) provides aerial imagery at a resolution of up to 30 cm that is critical for various applications in environmental monitoring, land use classification, and resource management. NAIP imagery is collected through aerial photography, typically during the agricultural growing season, which allows for the capture of seasonal variations in vegetation and land use (Zhang et al. 2019). One of the primary advantages of NAIP imagery is its accessibility and cost-effectiveness. The imagery is available at low or no cost, which facilitates its use in various research and operational contexts (Zhang et al. 2019). Furthermore, the high spatial resolution of NAIP imagery enables detailed feature extraction and change detection, which is crucial for monitoring environmental changes and managing natural resources. NAIP imagery has been utilized in a wide array of studies, including forest inventory assessments (Hogland et al. 2018), urban planning, and ecological monitoring (Fraser and Congalton 2021).

One significant issue is the potential for propagated errors during change analysis, particularly when assessing dynamic landscapes such as wetlands and forests (Campbell and Wang 2019). Additionally, the variability in image quality due to atmospheric conditions, such as haze and smoke, can adversely affect classification accuracy (Wickramarathna et al. 2021).

To capture temporal changes and understand the progression of sidewalk deterioration, NAIP aerial imagery data from different years was retrieved and compiled. In this study, imagery with a resolution of 60 cm was obtained for a selected site and analyzed over a timespan of four years (2019–2023). These historical data are essential for providing insights into how the condition of sidewalks has evolved over time, highlighting trends and identifying areas of concern. The data preparation involved segmenting the sidewalks by defining and creating polygons that accurately represented the boundaries of the sidewalks within the images, as shown in Figure 7-2. This process included mapping the exact locations and extents of the sidewalks, ensuring that the analysis was based on precise and clearly defined areas. Initially, six sidewalk segments from NAIP were chosen for analysis (Sites 01 through 06). Efforts were made to ensure the consistency and suitability of the imagery for various analytical applications, enabling reliable temporal analysis of the sites' condition.

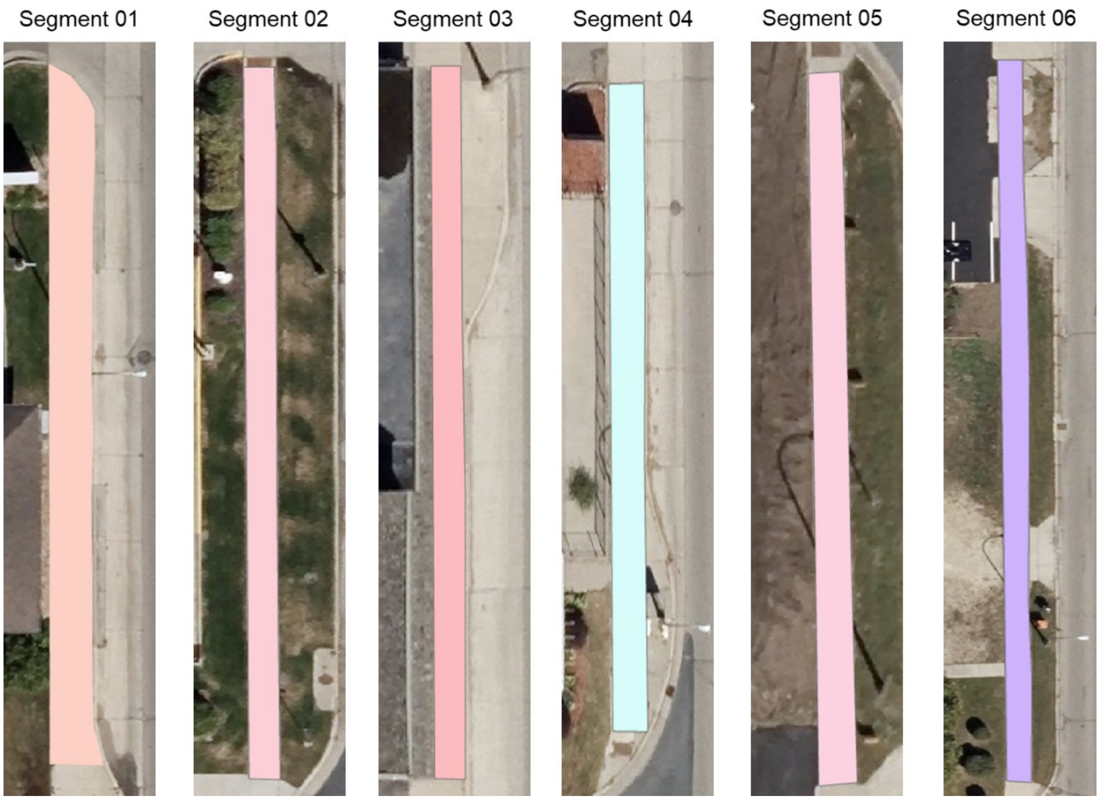



**Figure 7-2. Selected sidewalk segments for detailed assessment**

#### 7.5.2.2 Analysis of NAIP Data

Once the historical aerial imagery data had been compiled, a comparative analysis was conducted to quantify the extent of deterioration, identify patterns, and assess the rate at which sidewalks are degrading. DN values were analyzed for six sites across three years (2019, 2021, 2023) to understand temporal changes in surface characteristics. Key statistical metrics, including mean, median, and standard deviation, were calculated to capture central tendencies and variability. To demonstrate the change in the mean and median of DN values from this imagery, the percent change was calculated using equation 7-1. Additionally, cumulative distribution function (CDF) plots were generated to observe shifts in probability distributions over time, enabling a comprehensive evaluation of surface condition changes.

$$\text{Percent change (\%)} = \left(\frac{\text{DN value in later year - DN value in earlier year}}{\text{DN value in earlier year}}\right)*100 \tag{7-1}$$

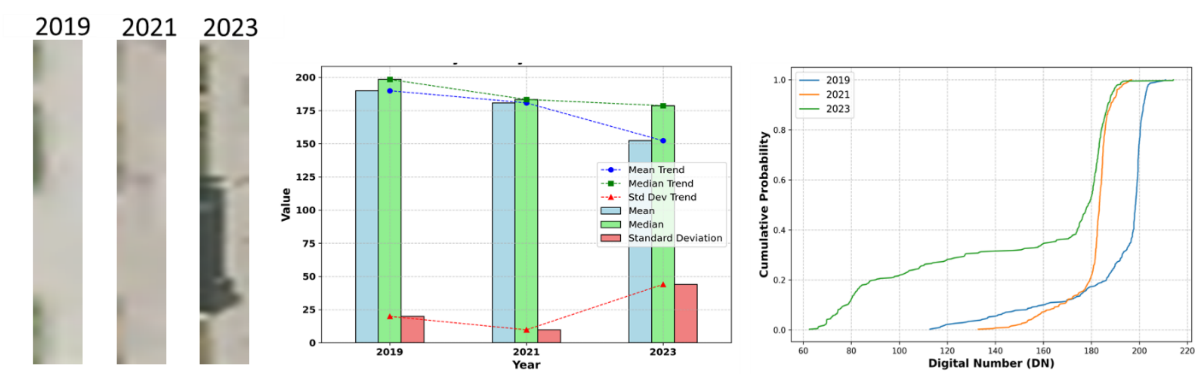
The changes in DN values over time are shown in Table 7-1 and Figures 7-3 through 7-8. The hypothesis proposed that either the mean or median DN values would decrease over time, indicating surface deterioration, and that the standard deviation could help identify the impact of shadows or other artifacts. From 2019 to 2021, all six sites showed a consistent decrease in both the mean and median DN values, aligning with the hypothesis. This trend continued from 2021 to 2023 for the majority of sites, except for Sites 02 and 04, where the mean and median values stabilized or slightly increased. These exceptions suggest minimal surface degradation in these segments or the influence of other factors, such as improved reflectance or less imaging noise during data acquisition.

The standard deviation provided critical insights into the role of shadows and imaging artifacts. Sites 01 and 03 exhibited significantly higher standard deviations in 2023 compared to earlier years, coinciding with sharp declines in the mean and median DN values from 2021 to 2023. This pattern indicates that these sites were likely impacted by shadows, which introduced greater variability and contributed to the steep declines in the mean and median metrics. In contrast, sites with lower standard deviations generally exhibited more stable trends, supporting the interpretation that shadowed images can be identified by higher standard deviations.

Overall, the analysis revealed that the majority of the segments showed a declining trend in both mean and median DN values, consistent with surface aging or deterioration. High standard deviations at specific sites, such as Sites 01 and 03, highlighted the confounding effects of shadows, which can be distinguished from actual surface changes through this variability. These findings underscore the importance of accounting for imaging artifacts, such as shadows, vegetation, pedestrians, etc., when interpreting DN trends.

Table 7-1. DN changes over time: NAIP data

| Site ID | Mean % Change_ 2019 to 2021 | Mean % Change_ 2021 to 2023 | Median % Change_ 2019 to 2021 | Median % Change_ 2021 to 2023 | Std. Dev. % Change_ 2019 to 2021 | Std. Dev. % Change_ 2021 to 2023 |
|---|---|---|---|---|---|---|
| Site 1 | -4.83 | -15.55 | -7.59 | -2.35 | -5.05 | +17.12 |
| Site 2 | -7.13 | 0.08 | -6.93 | 5.62 | -0.07 | +7.78 |
| Site 3 | -6.23 | -33.10 | -7.21 | -46.04 | -1.25 | +20.13 |
| Site 4 | -6.49 | -2.55 | -6.79 | 0.10 | -1.56 | +5.03 |
| Site 5 | -9.62 | 0.82 | -7.09 | -0.41 | +5.67 | -1.33 |
| Site 6 | -9.21 | -0.18 | -7.02 | 2.16 | +3.51 | +1.58 |

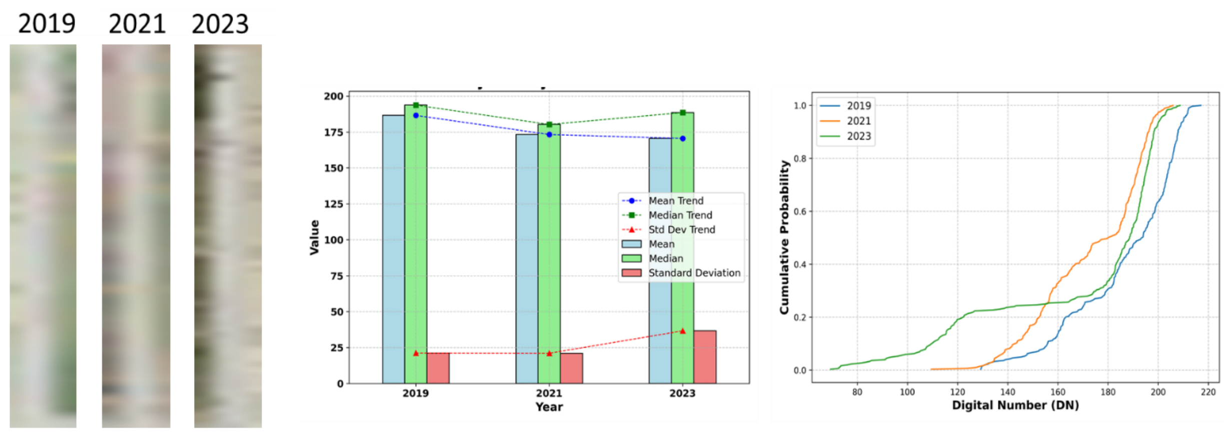



a) Aerial imageries over the years

b) Statistical Trends of DN Values Over Time

c) Cumulative Distribution Function (CDF) of DN Values Over the Years

Figure 7-3. DN changes in Site 01

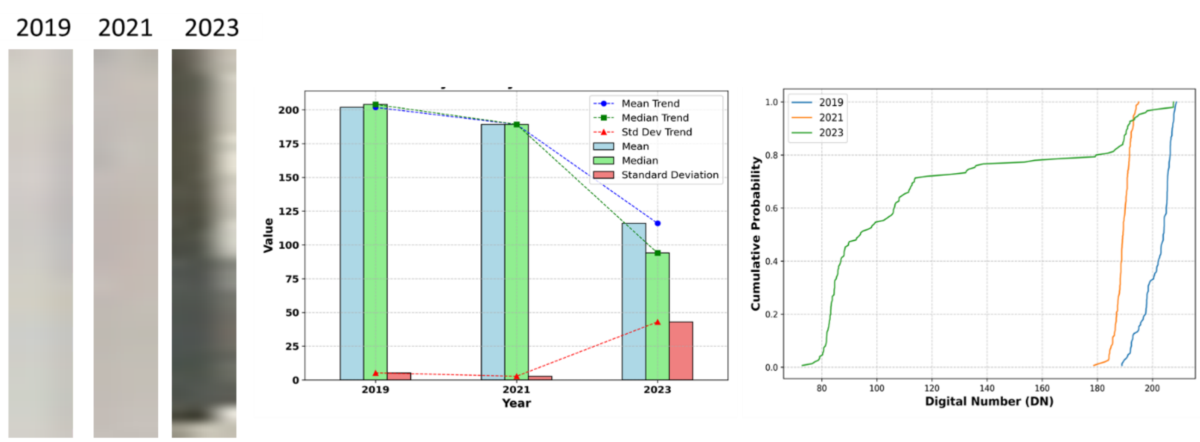



a) Aerial imageries over the years

b) Statistical Trends of DN Values Over Time

c) Cumulative Distribution Function (CDF) of DN Values Over the Years

**Figure 7-4. DN changes in Site 02**

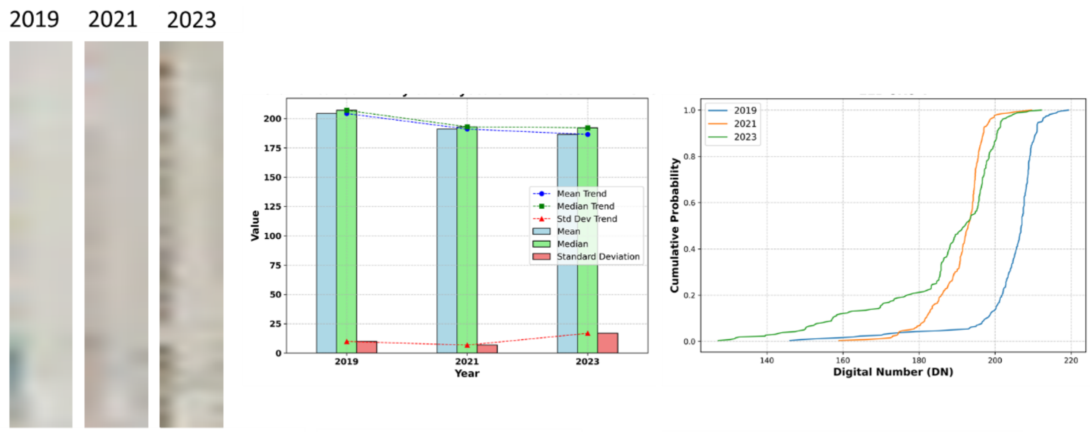



a) Aerial imageries over time

b) Statistical Trends of DN Values Over Time

c) Cumulative Distribution Function (CDF) of DN Values Over the Years

**Figure 7-5. DN changes in Site 03**

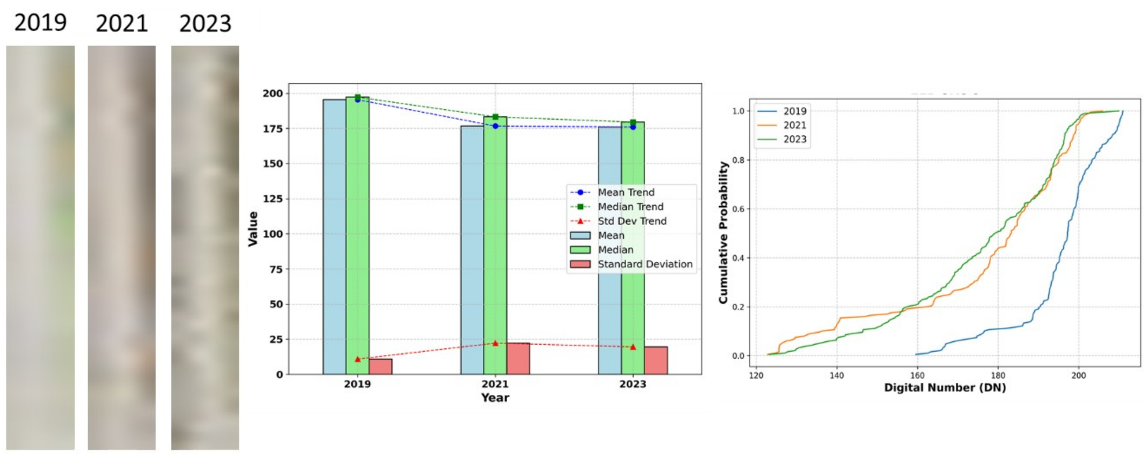



a) Aerial imageries over time

b) Statistical Trends of DN Values Over Time

c) Cumulative Distribution Function (CDF) of DN Values Over the Years

**Figure 7-6. DN changes in Site 04**

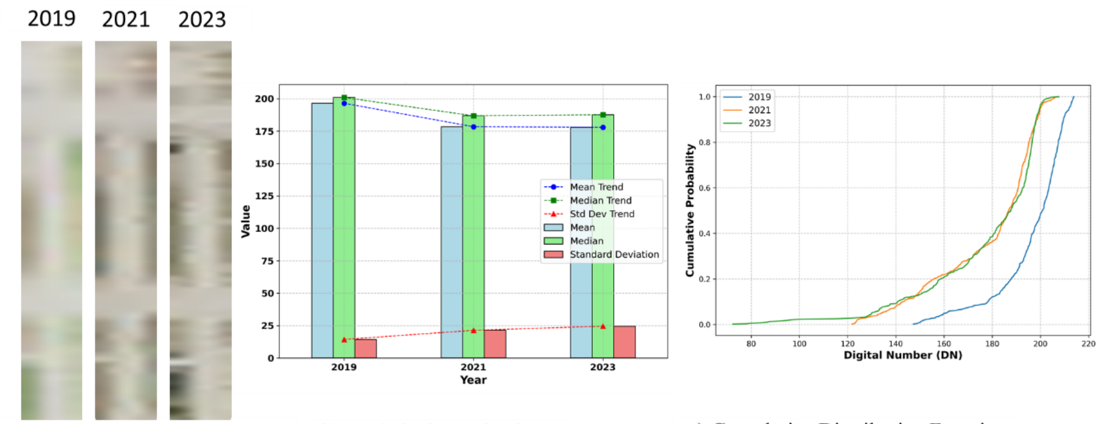



a) Aerial imageries over time

b) Statistical Trends of DN Values Over Time

c) Cumulative Distribution Function (CDF) of DN Values Over the Years

**Figure 7-7. DN changes in Site 05**




a) Aerial imageries over time

b) Statistical Trends of DN Values Over Time

c) Cumulative Distribution Function (CDF) of DN Values Over the Years

**Figure 7-8. DN changes in Site 06**

#### 7.5.2.3 MnGeo Aerial Imagery

To accurately assess the condition of sidewalks and model their deterioration, aerial imagery datasets from the Minnesota Geospatial Information Office (MnGeo) were employed. These high-resolution images, available at a resolution of 15 cm, provide a detailed view of sidewalk areas, crucial for this analysis. The 15 cm resolution means that each pixel in the image corresponds to a 15 cm by 15 cm square area on the ground. In other words, the image captures details at a level where features that are 15 centimeters apart can be distinguished. This resolution is considered high enough to observe relatively fine details, such as small objects, variations in surface texture, or the outline of specific features. The 15 cm resolution data used in this evaluation were from 2020, 2022, and 2023 (Figure 7-9). This comprehensive temporal coverage allowed for the assessment of changes and deterioration over multiple years. All imagery data were georeferenced to the coordinate system "WGS 1984 Web Mercator (auxiliary sphere)," ensuring consistent and accurate geographic alignment.


Figure 7-9. MnGeo aerial imagery at a resolution of 15 cm

The MnGeo aerial images' high spatial resolution enables detailed observation of small features, such as cracks and surface wear, essential for identifying and quantifying deterioration accurately. Additionally, the imagery's multiple spectral bands (e.g., visible, infrared) help detect various material properties and surface conditions. The georeferenced accuracy of the images ensures precise mapping and comparison over time, and their compatibility with GIS software facilitates efficient data integration and analysis. The regular updates and consistent quality of MnGeo imagery provide a reliable basis for longitudinal studies and the development of robust deterioration models.

The evaluation site was selected because of the availability of multiple complementary datasets, including lidar and data bike data, collected as part of this project. These datasets provided an opportunity to compare and validate findings derived from aerial imagery with other sources. The segmentation process began by defining the total length of the sidewalk using geospatial tools and aerial imagery. This total length was then divided into equal intervals, with each segment corresponding to a specific portion of the sidewalk. Figure 7-10 shows the segmentation process applied to the network-level imagery to create segments of consistent length. The site was systematically divided into 23 uniform sidewalk segments, each representing a length of 0.01 mile, as shown in Figure 7-10, to enable detailed spatial analysis of surface conditions. This segmentation approach enabled a localized assessment of deterioration and allowed for consistent comparisons across the entire sidewalk length.

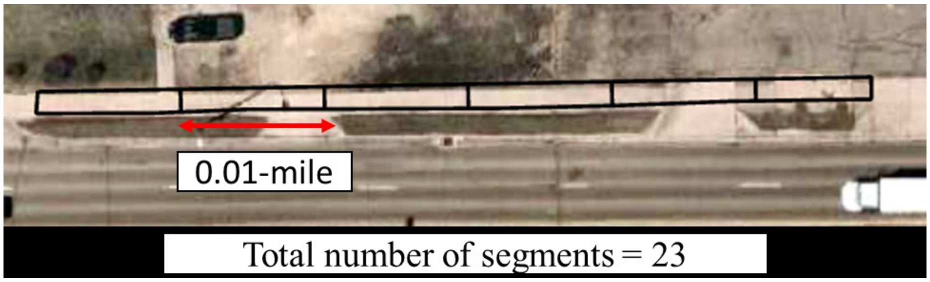



**Figure 7-10. Sidewalk segments of 0.01-mile length**

#### 7.5.2.4 Analysis of MnGeo Data

The analysis of DN trends and variability across the dataset highlights the ability to identify shadowed imagery and assess overall consistency with the established hypothesis of declining mean and median DN values due to surface deterioration. Shadowed images can often be identified by a significant year-to-year decline in mean and median DN values, coupled with a significant increase in standard deviation for a specific year. As shown in Table 7-2, Site 0 exhibited a significant decline in mean (-55.4%) and median (-71.1%) values from 2020 to 2022, followed by a sharp rebound (+176.0% in mean and +255.3% in median) in 2022–2023. Similarly, Site 3 showed steep declines (-41.0% in mean and -56.3% in median) followed by substantial increases (+76.8% in mean and +122.0% in median). These extreme fluctuations are characteristic of shadowed images.

**Table 7-2. DN changes over time: MnGeo imagery**

| Site ID | Mean % Change 2020-2022 | Mean % Change 2022-2023 | Median % Change 2020-2022 | Median % Change 2022-2023 | Std. Dev. % Change_ 2020 to 2022 | Std. Dev. % Change_ 2022 to 2023 |
|---|---|---|---|---|---|---|
| Site_0 | -55.4 | 176.0 | -71.1 | 255.3 | -30.76 | -82.86 |
| Site_1 | 33.8 | 17.8 | 130.4 | -2.3 | -5.36 | -87.75 |
| Site_2 | -3.7 | -1.6 | -2.9 | -2.2 | 54.60 | -31.63 |
| Site_3 | -41.0 | 76.8 | -56.3 | 122.0 | 31.70 | -75.56 |
| Site_4 | -8.7 | 96.4 | -33.6 | 219.1 | 62.84 | -75.12 |
| Site_5 | -2.2 | -1.6 | -1.7 | -3.3 | -15.87 | -29.99 |
| Site_6 | -3.1 | -1.8 | -3.1 | -2.2 | -12.17 | -29.80 |
| Site_7 | -3.3 | -2.5 | -3.1 | -3.8 | 4.24 | -37.67 |
| Site_8 | -3.4 | -2.0 | -1.6 | -4.6 | 42.12 | -44.80 |

| Site ID | Mean % Change 2020-2022 | Mean % Change 2022-2023 | Median % Change 2020-2022 | Median % Change 2022-2023 | Std. Dev. % Change_ 2020 to 2022 | Std. Dev. % Change_ 2022 to 2023 |
|---|---|---|---|---|---|---|
| Site_9 | -4.0 | 0.5 | -4.7 | -0.3 | -18.41 | -37.44 |
| Site_10 | -4.4 | 4.1 | -7.8 | 4.4 | -22.23 | -44.83 |
| Site_11 | -7.5 | 7.3 | -4.5 | 3.5 | 51.55 | -74.59 |
| Site_12 | 29.2 | -2.2 | 107.9 | -28.9 | -48.77 | 46.51 |
| Site_13 | 16.3 | 70.9 | -14.0 | 79.1 | 778.27 | 55.94 |
| Site_14 | 2.2 | 97.6 | -13.7 | 89.9 | 135.47 | 118.56 |
| Site_15 | 6.7 | 0.3 | 2.3 | -1.1 | -47.49 | -37.06 |
| Site_16 | 4.0 | 0.0 | 1.6 | -1.2 | -34.37 | -49.87 |
| Site_17 | 0.3 | 2.8 | 0.9 | -0.2 | 38.11 | -51.79 |
| Site_18 | -32.2 | 68.8 | -42.8 | 94.5 | 34.99 | -61.27 |
| Site_19 | -7.0 | 25.7 | -33.7 | 69.2 | -6.35 | -9.17 |
| Site_20 | 35.6 | 81.5 | 34.7 | 139.9 | 97.19 | 33.85 |
| Site_21 | 12.6 | 9.1 | 5.1 | 3.5 | -23.68 | -67.93 |
| Site_22 | 3.4 | 4.9 | 4.7 | 4.5 | 69.47 | -29.06 |

On the other hand, sites such as Site 2, Site 5, Site 6, Site 7, Site 8, Site 9, Site 10, Site 11, Site 15, Site 16, and Site 17 demonstrated no shadows in their images, as evidenced by consistent trends in DN values, with gradual declines and lower variability. Within these clear sites, further analysis of year-to-year percentage changes in mean and median values revealed that the majority of the sites experienced a negative change. Sites such as Site 2 and Site 5 showed steady reductions in mean and median values across both intervals, with Site 2 exhibiting -3.7% (2020–2022) and -1.6% (2022–2023) changes in mean and -2.9% and -2.2% changes in median. Similarly, Site 7 displayed consistent declines, with -3.3% (2020–2022) and -2.5% (2022–2023) changes in mean and -3.1% and -3.8% changes in median.

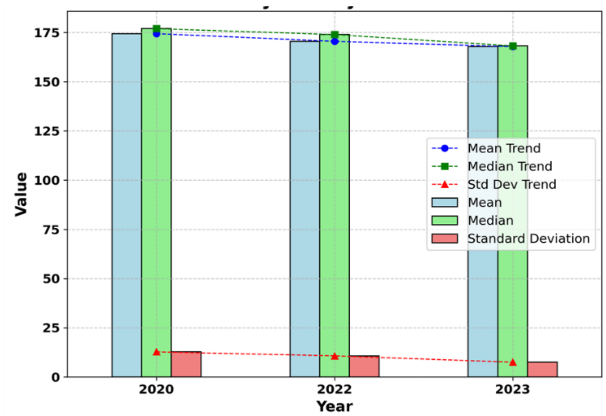
Specifically, 8 of the 11 non-shadowed sites (Site 2, Site 5, Site 6, Site 7, Site 8, Site 9, Site 10, and Site 11) exhibited declines in both mean and median DN values over at least one of the two intervals analyzed (2020–2022 and 2022–2023). Figure 7-11 shows the detailed assessment process, where the extracted imagery is shown alongside the trend in mean and median DN values and standard deviation. Figure 7-11 also shows the respective slope of the trend, which was calculated as shown in equation 7-2. The slope pattern observed in these sites aligns well with the hypothesis that DN values tend to decline over time as surface conditions deteriorate, further supporting the reliability of the data for assessing surface degradation.

$$Slope = \frac{\text{DN value in later year - DN value in earlier year}}{\text{Later year - Earlier year}} \tag{7-2}$$

Overall, the results confirm the hypothesis that DN values decline over time due to surface aging or deterioration, with shadowed sites contributing to variability through extreme changes in DN values and standard deviation. The consistency of the observed trends across non-shadowed sites further reinforces the robustness of this framework for assessing surface deterioration, while the identification of shadowed imagery highlights the importance of accounting for variability in surface condition assessments.

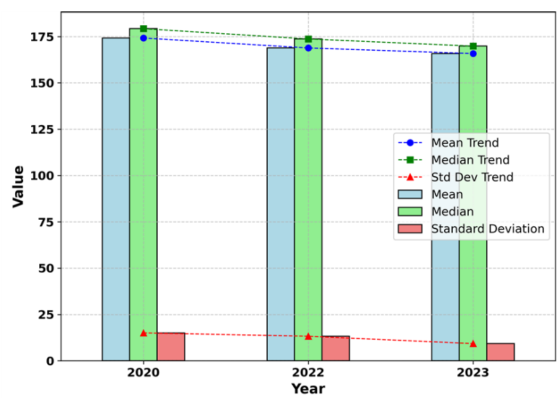

| Statistical Measure | Change 2020 to 2022 | Change 2022 to 2023 |
|---|---|---|
| Mean | -3.32 | -2.77 |
| Median | -2.70 | -3.94 |
| Standard Deviation | 2.72 | -4.88 |

# Site 05

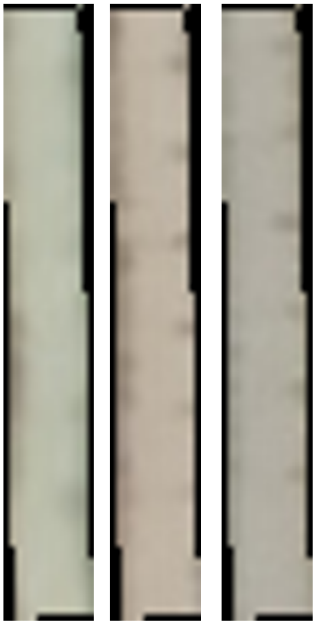

| Statistical Measure | Change 2020 to 2022 | Change 2022 to 2023 |
|---|---|---|
| Mean | -1.94758 | -2.7161 |
| Median | -1.5052 | -5.7499 |
| Standard Deviation | -1.01271 | -3.22058 |

# Site 06

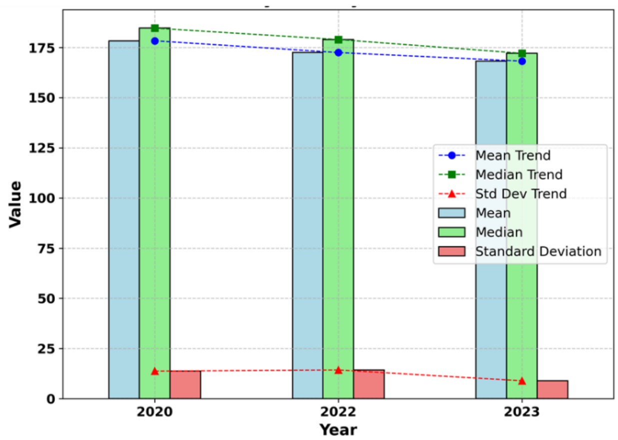




| Statistical Measure | Change 2020 to 2022 | Change 2022 to 2023 |
|---|---|---|
| Mean | -2.68 | -3.00 |
| Median | -2.77 | -3.85 |
| Standard Deviation | -0.92 | -3.94 |

2020 2022 2023

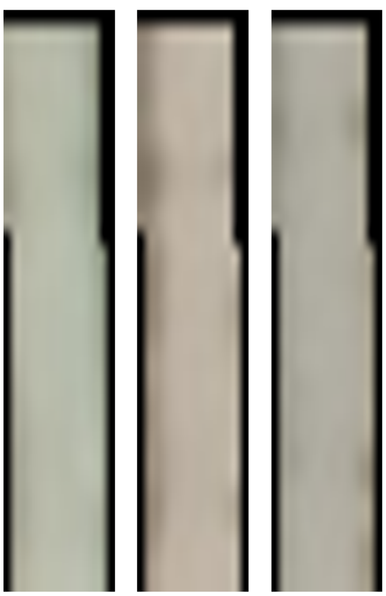


# Site 07

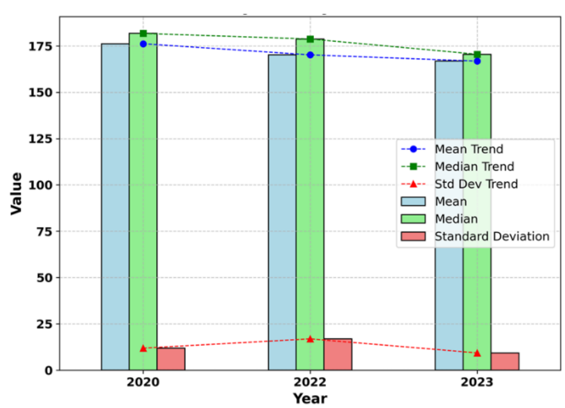



| Statistical Measure | Change 2020 to 2022 | Change 2022 to 2023 |
|---|---|---|
| Mean | -2.92 | -4.29 |
| Median | -2.83 | -6.86 |
| Standard Deviation | 0.29 | -5.39 |

2020 2022 2023



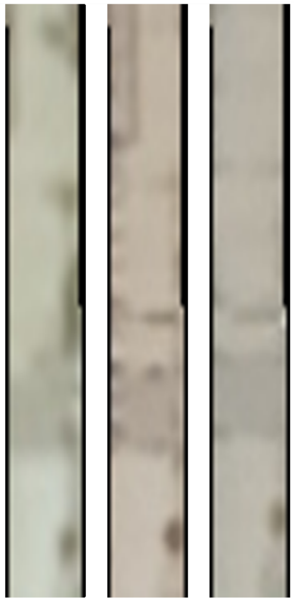
# Site 08

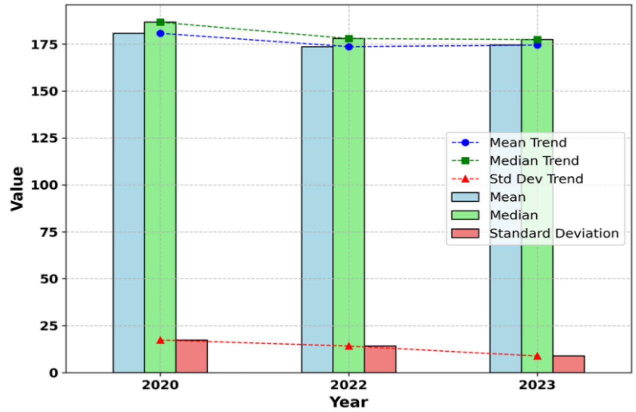



| Statistical Measure | Change 2020 to 2022 | Change 2022 to 2023 |
|---|---|---|
| Mean | -3.00 | -3.38 |
| Median | -1.49 | -8.23 |
| Standard Deviation | 2.51 | -7.58 |

# Site 09

2020 2022 2023

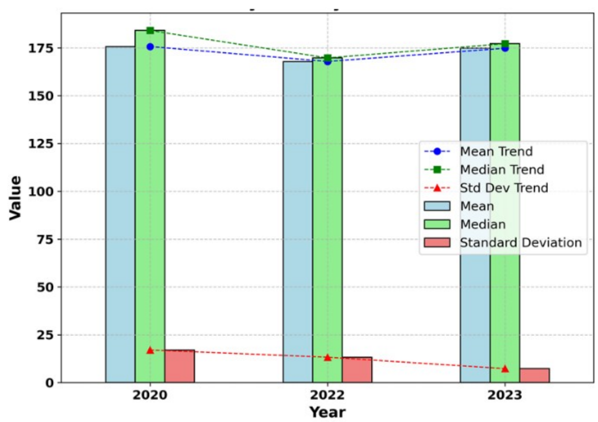





| Statistical Measure | Change 2020 to 2022 | Change 2022 to 2023 |
|---|---|---|
| Mean | -3.57 | 0.84 |
| Median | -4.34 | -0.53 |
| Standard Deviation | -1.60 | -5.31 |

# Site 10

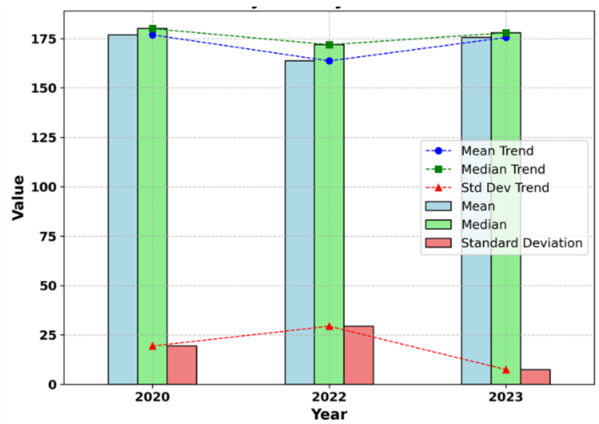
2020 2022 2023




| Statistical Measure | Change 2020 to 2022 | Change 2022 to 2023 |
|---|---|---|
| Mean | -3.91 | 6.93 |
| Median | -7.16 | 7.43 |
| Standard Deviation | -1.89 | -5.94 |

# Site 11

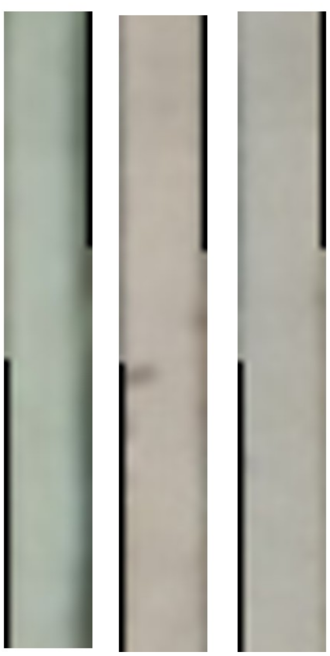
2020 2022 2023

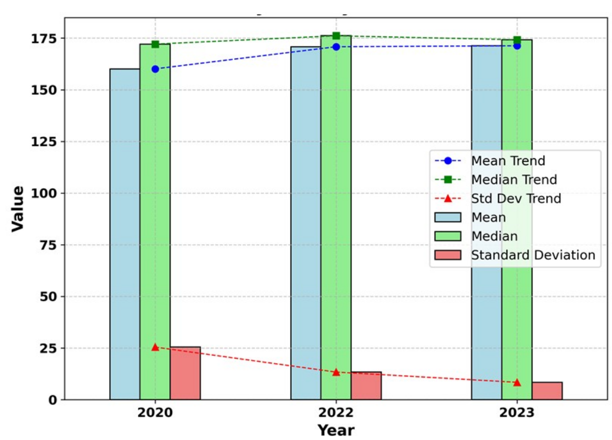



| Statistical Measure | Change 2020 to 2022 | Change 2022 to 2023 |
|---|---|---|
| Mean | -6.59 | 11.87 |
| Median | -4.06 | 6.01 |
| Standard Deviation | 5.00 | -21.94 |

# Site 15

2020 2022 2023

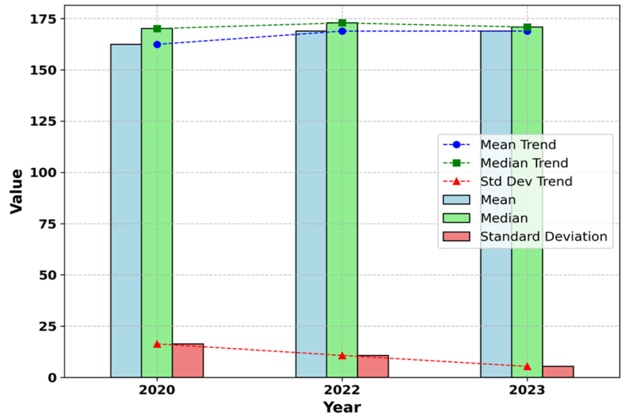





| Statistical Measure | Change 2020 to 2022 | Change 2022 to 2023 |
|---|---|---|
| Mean | 3.23 | 0.02 |
| Median | 1.40 | -2.05 |
| Standard Deviation | -2.81 | -5.36 |

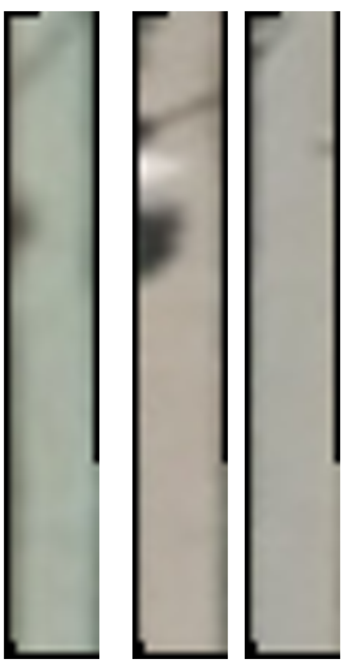
2020 2022 2023

## Site 16

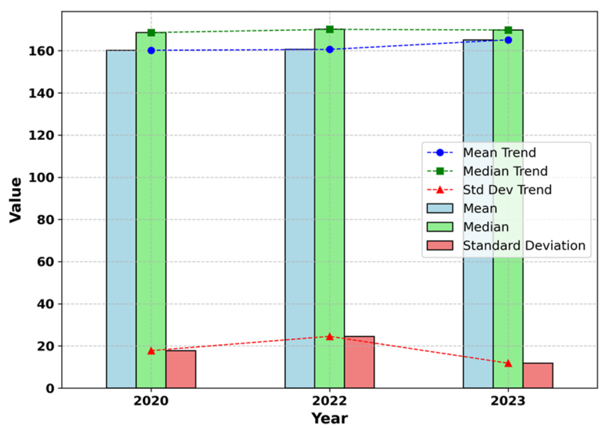



| Statistical Measure | Change 2020 to 2022 | Change 2022 to 2023 |
|---|---|---|
| Mean | 3.23 | 0.02 |
| Median | 1.40 | -2.05 |
| Standard Deviation | -2.81 | -5.36 |

2020 2022 2023



## Site 17




| Statistical Measure | Change 2020 to 2022 | Change 2022 to 2023 |
|---|---|---|
| Mean | 0.20 | 4.55 |
| Median | 0.76 | -0.28 |
| Standard Deviation | 3.39 | -12.72 |

**Figure 7-11. Sites that were not impacted by shadows or artifacts demonstrating an overall declining trend**

### 7.5.3 Implications of Using Aerial Imagery

The use of aerial imagery for sidewalk deterioration assessment provides an innovative approach to infrastructure condition monitoring. By leveraging aerial imagery datasets with adequate resolution, it becomes possible to analyze surface changes across extensive networks, enabling proactive maintenance and resource optimization. Aerial imagery offers the potential for longitudinal studies, allowing infrastructure managers to track deterioration trends and predict future conditions. However, the methodology has some limitations as well. Below are listed specific advantages and disadvantages of using aerial imagery for sidewalk deterioration monitoring:

**Advantages**

- Aerial imagery allows for the assessment of large areas, providing network-wide coverage that is not feasible with traditional ground surveys. It facilitates consistent and uniform data collection across urban and suburban regions.
- Aerial imagery offers a cost-efficient alternative for periodic assessments, especially when datasets like NAIP are freely available. Historical datasets, such as NAIP and MnGeo, enable the analysis of long-term trends in sidewalk deterioration, aiding in the identification of aging patterns and progression over time.
- Georeferenced aerial imagery integrates seamlessly with Geographic Information Systems (GIS) for mapping, segmentation, and analysis.
- Automated or semi-automated analysis of aerial imagery minimizes human bias, providing objective assessments of sidewalk conditions. Extracted metrics, such as DN values, can serve as inputs for predictive models for condition and deterioration quantification.

**Disadvantages**

- Lower-resolution datasets, such as NAIP’s 60 cm imagery, may not capture fine-grained features such as small cracks or surface-level defects, reducing accuracy for detailed assessments.
- Shadows, lighting variations, and atmospheric conditions can introduce noise and distort DN values, complicating the interpretation of results. Shadowed or artifact-heavy images require additional preprocessing, increasing analysis time.
- Aerial imagery lacks three-dimensional detail, making it challenging to identify vertical surface deformations like slope, sidewalk heaving, or trip hazards.
- Aerial imagery is typically collected at fixed intervals, limiting its ability to provide real-time assessments or capture sudden deterioration events.
- Datasets like NAIP or MnGeo, which may have gaps in temporal or spatial coverage, reducing its applicability in some regions.
- While some datasets are freely available, such as NAIP, high-resolution imagery like MnGeo or specialized acquisitions may involve substantial costs, especially for custom needs.
- Findings from aerial imagery often require ground-based validation to confirm accuracy, adding to the overall effort and cost.

## 7.6 DETERIORATION METHODOLOGY USING GOOGLE STREET VIEW IMAGERY

In this section, two methodologies are proposed for acquiring sidewalk condition data based on manual assessment, each utilizing Google Street View, but through different platforms: Google Earth Pro and Google Maps. Both methods leverage 360° imagery to assess and document surface distresses, though they differ in their capabilities and limitations.

### 7.6.1 Methodology 1: Utilizing Google Street View via Google Earth Pro

The first approach involves using Google Street View through the Google Earth Pro platform. This method allows for the digitizing of visible surface distresses captured in the 360° images provided by Google Street View. The primary advantage of this method is its ability to accurately map the approximate location, spatial extent, and geometry of each distress. This includes features such as crack length, potholes, and spalling areas.

#### 7.6.1.1 Implementation

The validation process used six sample sidewalks in Minneapolis, as shown in Figure 7-12, and Figure 7-13 shows higher resolution imagery for sidewalk 1 specifically.

**Figure 7-12. Validation sidewalks**


Figure 7-13. Sidewalk 1

In this section, the practical implementation of the first methodology is detailed, followed by a presentation and discussion of the resulting outputs.

Figure 7-14 shows how to start Google Street View within the Google Earth Pro platform. This step can be done by dragging the “pegman” and dropping it at the nearest point to the desired sidewalk along the adjacent street. After Google Street View is initiated, the distress digitizing process can be done.

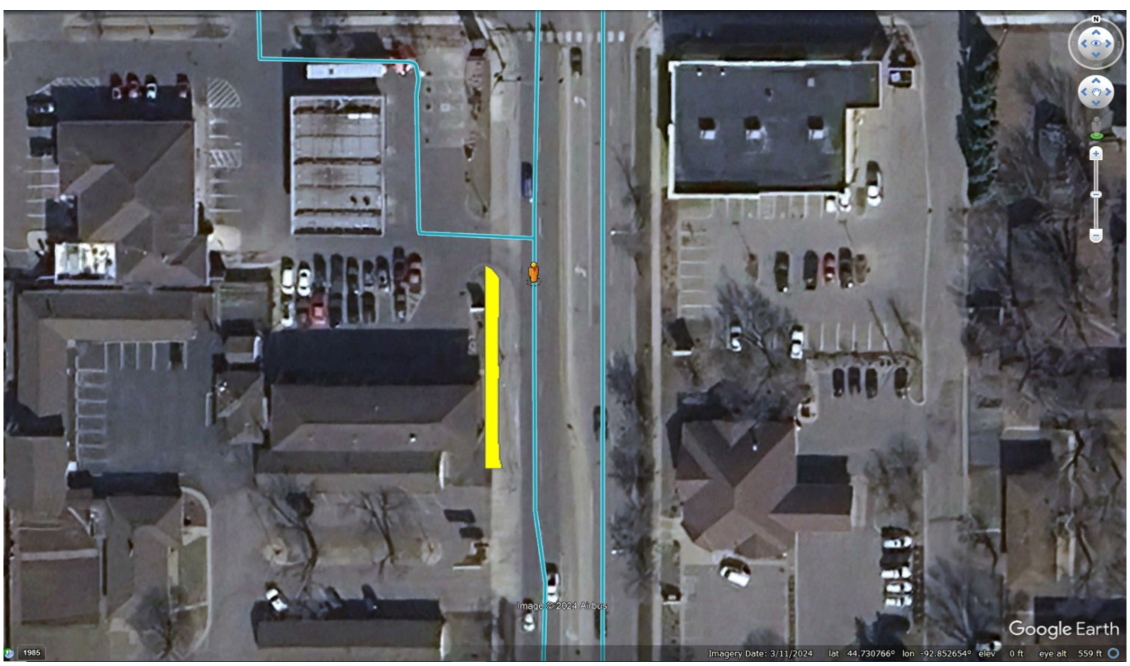



Figure 7-14. Starting Google Street View within Google Earth Pro platform

Digitizing in Google Earth Pro is a straightforward process. The "Add Placemark" tool is used to digitize point features such as potholes, manholes, and spalls. For linear distresses, such as longitudinal and transverse cracking, the "Add Path" tool is employed. Additionally, the "Add Polygon" tool is utilized to digitize areal features like patches.

Figure 7-15 illustrates the digitizing of spalling on a sidewalk, while Figure 7-16 demonstrates the digitizing of longitudinal cracks. When digitizing similar types of distresses, they can either be assigned the same “name” with different numbers or organized into a folder named after the distress type. As shown in Figure 7-17, a separate folder can be created for each type of distress, containing all digitized features for the six sidewalks.

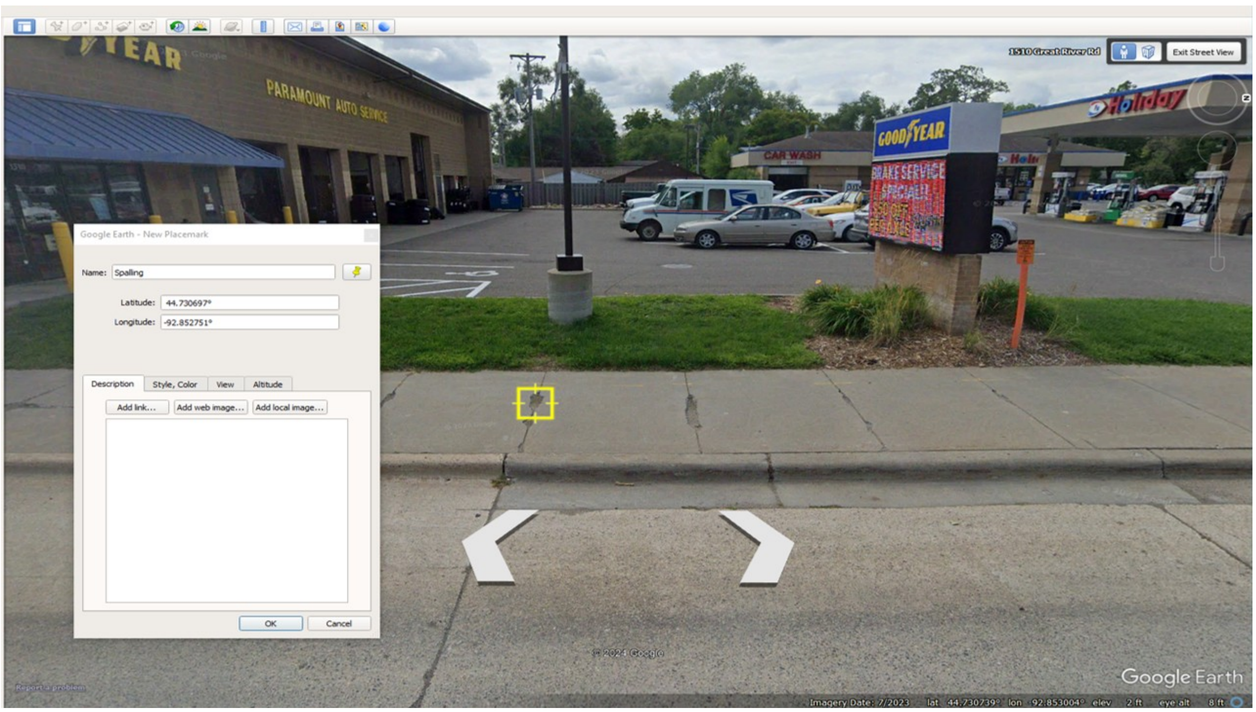



**Figure 7-15. Digitizing spalls**

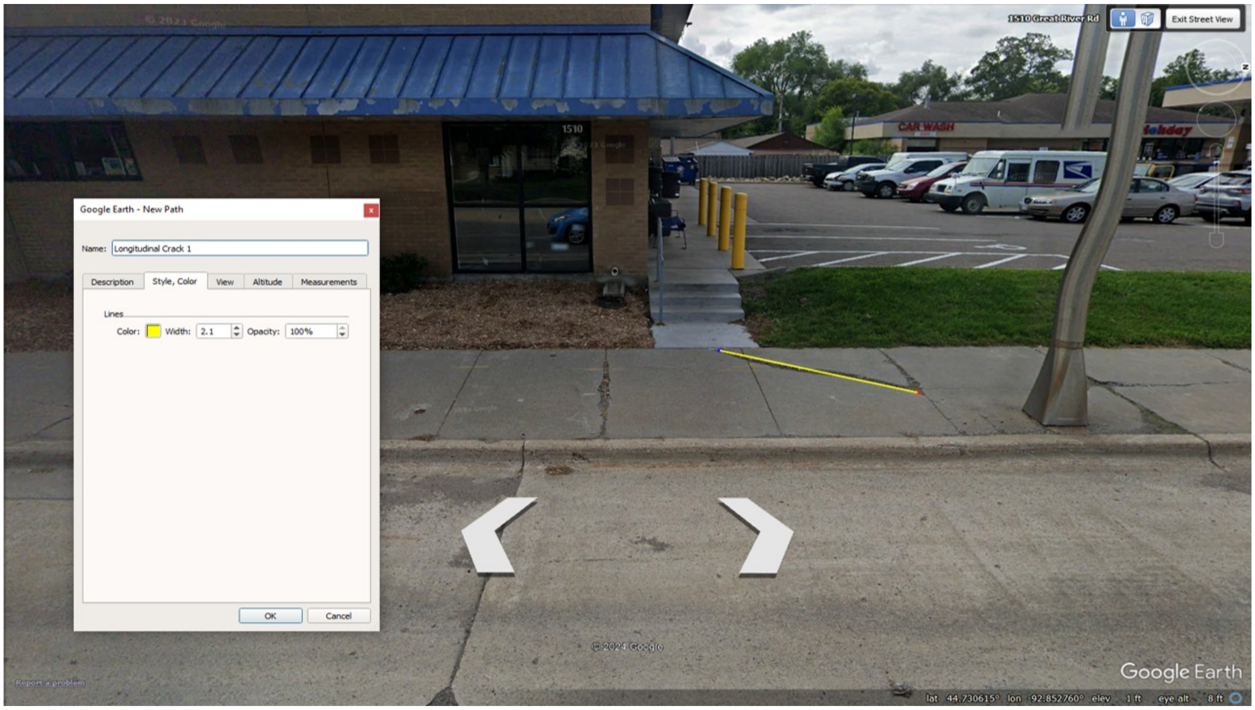



**Figure 7-16. Digitizing longitudinal cracks**

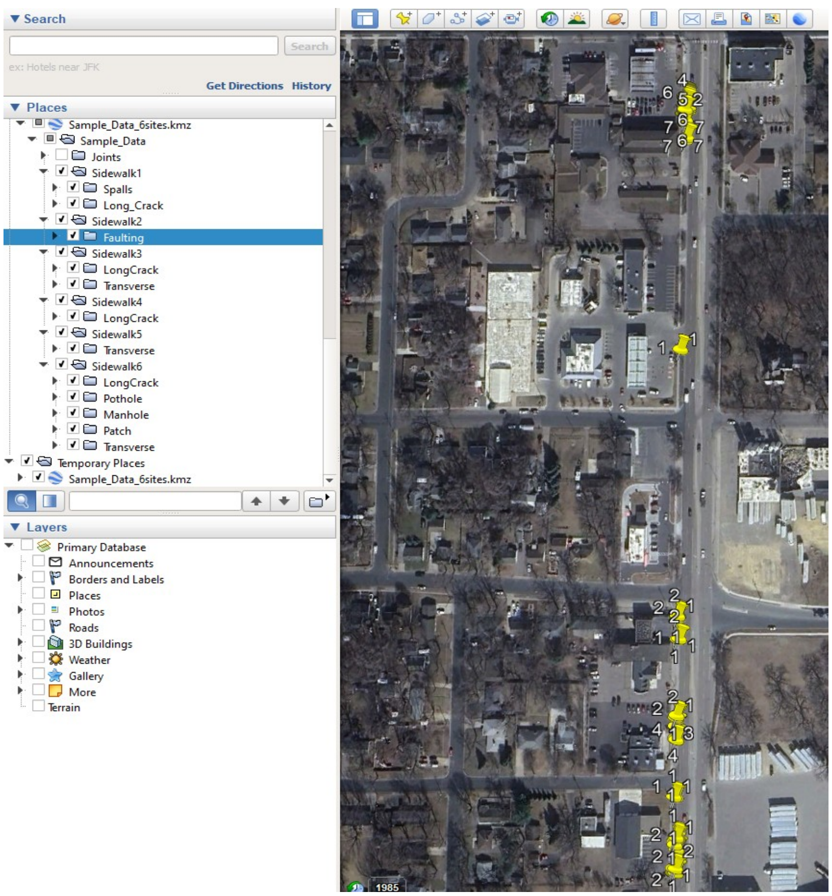



**Figure 7-17. Digitized distresses for the six sidewalks**

It is recommended to save the digitized features as a KML/KMZ file for import into GIS platforms, such as ESRI ArcGIS, which will facilitate generating distress summaries for each sidewalk, as shown in Figure 7-18. Then, the distresses can be spatially joined to the sidewalks so that condition summaries for each sidewalk can be obtained, as shown in Figure 7-19.


**Figure 7-18. Sidewalk data imported to ArcGIS Pro**

| | OBJECTID * | Shape * | Id | Spalling | Pothole | Faulting | Patching | Transverse_Count | Transverse_Leng | Long_count | Long_leng | Manhole | Shape_Length | Shape_Area |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | Polygon | 1 | 12 | 0 | 0 | 0 | 0 | 0 | 7 | 31 | 0 | 112.403446 | 173.717902 |
| 2 | 2 | Polygon | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 132.3227 | 136.049596 |
| 3 | 3 | Polygon | 3 | 0 | 0 | 0 | 0 | 1 | 4 | 0 | 0 | 0 | 86.322074 | 78.675467 |
| 4 | 4 | Polygon | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 4.5 | 0 | 93.177441 | 140.160484 |
| 5 | 5 | Polygon | 5 | 0 | 0 | 0 | 0 | 1 | 4.5 | 0 | 0 | 0 | 80.647225 | 79.881206 |
| 6 | 6 | Polygon | 6 | 1 | 2 | 0 | 2 | 2 | 9 | 2 | 9 | 2 | 191.733629 | 237.552455 |

**Figure 7-19. Condition summaries of the sample sidewalks**

**Advantages:**

- **Digitizing Capability**: The method allows for precise digitizing of sidewalk distresses, enabling the creation of detailed records of each defect's location and dimensions.
- **Spatial Information**: The extent and geometry of distresses can be documented, providing valuable data for condition assessments and maintenance planning.

**Limitations:**

- **Lack of Historical Data**: Google Earth Pro only provides the most recent imagery, meaning that historical sidewalk condition data cannot be obtained. This limits the ability to analyze changes or deterioration over time.
- **Time-Consuming**: Variable outputs are provided depending on human extraction.

### 7.6.2 Methodology 2: Utilizing Google Street View via Google Maps

The second approach leverages Google Street View through the Google Maps platform. Unlike Google Earth Pro, Google Maps offers access to historical imagery, allowing users to view all 360° images captured for a specific sidewalk segment over time. This feature is particularly useful for tracking changes in sidewalk conditions and assessing the progression of distresses.

#### 7.6.2.1 Implementation

This approach is implemented using the Google Maps platform, which provides access to 360° images from multiple years, as illustrated in Figure 7-20. It is important to note that historical images are useful for identifying distresses, particularly cracks, provided that the resolution is sufficient. Generally, images captured in 2011 and later offer adequate resolution for this purpose.

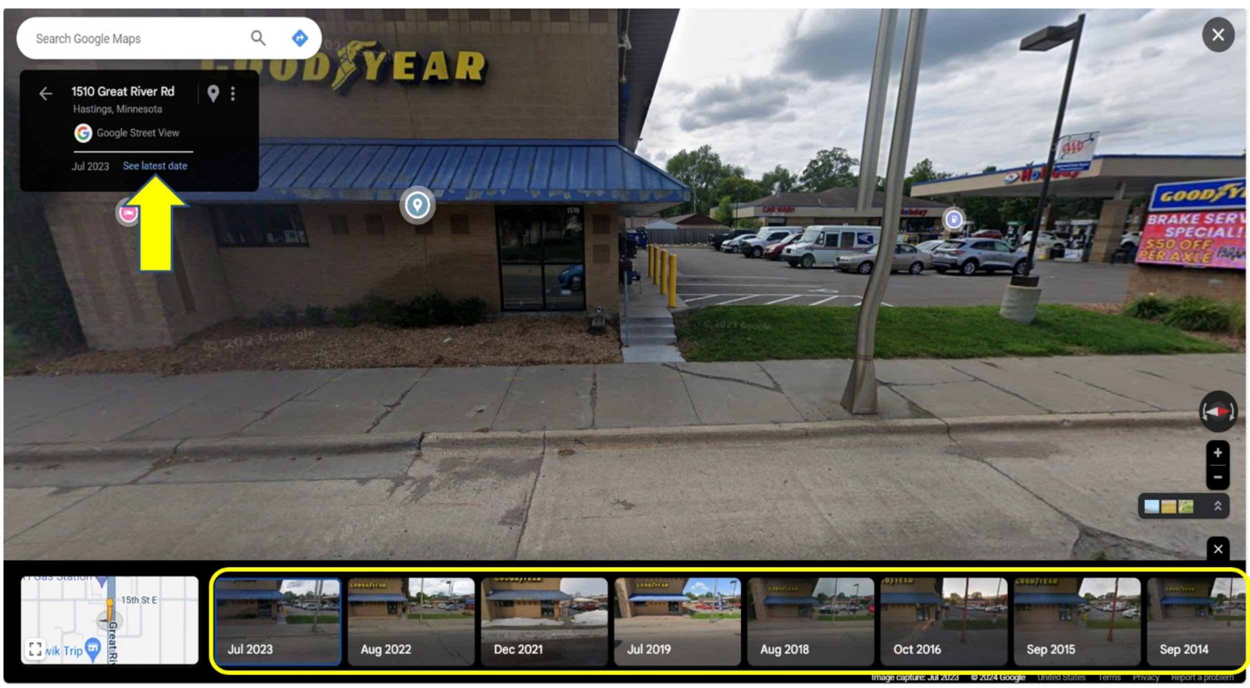



**Figure 7-20. Google Street View through Google Maps**

Since Google Maps does not offer digitizing capabilities, data must be manually collected and stored in an Excel sheet. Distresses such as spalls and potholes can be recorded as a count per sidewalk segment. For transverse cracking, the total length can be calculated by multiplying the number of transverse cracks by the sidewalk width. In cases where a transverse crack does not span the entire width of the sidewalk, such as when a crack extends from one edge to the middle, a fractional value (e.g., 0.5) can be used to approximate the crack length. Similarly, longitudinal cracks can be counted and multiplied by the slab length of the respective sidewalk. If the slab width or length is unknown, these dimensions can be measured using the distance measuring tool in Google Earth and then applied to this approach.

This approach was used to obtain the distress data for the six sidewalks (i.e., the sample for the implementation) for the years 2011, 2016, and 2022, and the results are summarized in Table 7-3. It can be seen from the condition summaries that the sidewalks are deteriorating slowly over time. For example, it took about 11 years for the longitudinal cracks on Sidewalk 1 to grow from 12.25 ft in 2011 to 31 ft in 2022. Meanwhile, many other distresses did not show at all on Sidewalk 1 in the period from 2011 to 2022, such as transverse cracking and potholes.

Table 7-3. Condition summaries for the sidewalks for the years 2011, 2016, and 2022

| Sidewalk | Year | Spalling | Pothole | Patching | Transverse Count | Transverse Length | Long Count | Long Length |
|---|---|---|---|---|---|---|---|---|
| 1 | 2011 | 5 | 0 | 0 | 0 | 0 | 3 | 12.25 |
| | 2016 | 10 | 0 | 0 | 0 | 0 | 3 | 12.25 |
| | 2022 | 12 | 0 | 0 | 0 | 0 | 7 | 31 |
| 2 | 2011 | 0 | 0 | 0 | 4 | 20 | 1 | 2.5 |
| | 2016 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 2022 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 2011 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 2016 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 2022 | 0 | 0 | 0 | 1 | 4 | 0 | 0 |
| 4 | 2011 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 2016 | 0 | 0 | 0 | 0 | 0 | 1 | 4.5 |
| | 2022 | 0 | 0 | 0 | 0 | 0 | 1 | 4.5 |
| 5 | 2011 | 0 | 0 | 0 | 1 | 4.5 | 0 | 0 |
| | 2016 | 0 | 0 | 0 | 1 | 4.5 | 0 | 0 |
| | 2022 | 0 | 0 | 0 | 1 | 4.5 | 0 | 0 |
| 6 | 2011 | 3 | 0 | 2 | 2 | 9 | 2 | 9 |
| | 2016 | 1 | 2 | 2 | 2 | 9 | 2 | 9 |
| | 2022 | 1 | 2 | 2 | 2 | 9 | 2 | 9 |

**Advantages:**

- **Access to Historical Data:** This method allows for the examination of sidewalk conditions over time, providing a more comprehensive understanding of deterioration patterns.
- **Condition Assessment Over Time:** Historical imagery can be used to study the progression of distresses, which is valuable for long-term asset management.

**Limitations:**

- **Lack of Digitizing Tools:** Google Maps does not support the digitizing of distresses, meaning that the precise location and spatial extent of each distress cannot be directly obtained. Instead, this method proposes an alternative approach where the number of cracked slabs is counted, and the crack lengths are estimated by multiplying the count by the slab dimensions. This estimation, however, is less accurate compared to the digitizing possible in Google Earth Pro.
- **Estimation Errors:** The reliance on manual counting and estimation introduces potential inaccuracies, especially for complex or irregularly shaped distresses.
- **Time-Consuming**: This approach takes more time to process and can have cost and coverage implications.

### 7.6.3 Common Drawbacks

Both methodologies share a significant limitation: the difficulty in automating the data collection and analysis processes. The reliance on manual interpretation and digitizing of distresses makes these methods time-consuming and potentially inconsistent, especially across larger datasets. Moreover, both methods depend heavily on the quality and availability of the Google Street View images, which may vary in resolution, coverage, and update frequency.

In conclusion, while both approaches offer valuable tools for sidewalk condition assessment, the choice of method depends on the specific requirements of the project, such as the need for historical data versus the need for precise spatial documentation.

### 7.6.4 Evaluation of Data Sources

The evaluation of available data sources for sidewalk condition and deterioration modeling reveals distinct advantages and limitations for each, determined by key factors such as temporal coverage, spatial resolution, consistency, and data quality. Aerial imagery, Google Street View, and lidar were critically assessed as primary sources to capture surface deterioration trends over time. These data sources can be likened to a set of diagnostic tools, each suited for different scales and levels of detail in sidewalk condition modeling.

Aerial imagery serves as a valuable source for network-wide condition monitoring, providing extensive spatial coverage and historical data availability. The MnGeo datasets, with a spatial resolution of 15 cm, offer sufficient detail to detect surface-level changes and broader deterioration trends. However, similar to using a wide-angle lens to observe a landscape, aerial imagery is limited in its ability to identify finer details, such as cracks or small potholes, particularly when the resolution (e.g., NAIP's 60 cm) exceeds the dimensions of the distress being analyzed. Temporal coverage, a key strength of aerial imagery, facilitates trend analysis over multiple years, but atmospheric artifacts, shadows, and temporal inconsistencies introduce potential distortions. While aerial imagery sets a strong foundation for determining network-wide deterioration rates, distress-level accuracy still requires verification through ground-based surveys or high-resolution supplementary imagery.

Google Street View complements aerial imagery by offering ground-level perspectives with high-resolution panoramic images. This data source may enable localized assessments of condition changes. However, Google Street View lacks the precision tools required for distress measurement, and its availability and resolution can vary significantly across locations. As a result, while Google Street View is valuable for visual inspections and localized assessments, it is not yet a robust alternative for precise, quantitative analysis at the network level.

In this study, lidar data were also considered for an evaluation that enhances aerial imagery by providing 3D surface information, capturing fine vertical details and surface roughness. However, the lack of historical lidar datasets limits lidar's application in this study, as deterioration modeling depends on temporal data consistency. Additionally, lidar's high cost presents a significant barrier to its widespread adoption for large-scale networks. Despite these limitations, the integration of lidar with aerial imagery holds promise for future research, particularly for validating surface conditions in critical or high-priority segments.

Based on these evaluations, aerial imagery—particularly the MnGeo datasets—was identified as the viable data source for assessing sidewalk conditions due to its higher spatial resolution, wide temporal coverage, and compatibility with GIS for analysis. However, its limitations highlight the importance of integrating additional data sources like Google Street View and lidar for specific tasks. Aerial imagery provides a high-level "map" for network-wide assessments, but ground-based tools like Google Street View or lidar are necessary for assessing specific details, validating trends, and enabling distress-level assessments. Together, these tools offer a multiscale approach that balances coverage, resolution, and cost-effectiveness for sidewalk condition modeling.

### 7.6.5 Proposed Deterioration Modeling Framework

The proposed framework for modeling sidewalk deterioration leverages high-resolution aerial imagery integrated with advanced analytics to predict the deterioration of surface conditions. The framework comprises the following key steps:

- **Data Acquisition and Preprocessing:**
    - Gather aerial imagery data across multiple years with a consistent spatial resolution and georeferencing (e.g., MnGeo 15 cm resolution or better).
    - Perform preprocessing to address imaging artifacts, such as shadow correction and atmospheric normalization, ensuring data consistency.
- **Segmentation and Feature Extraction:**
    - Divide sidewalks into uniform segments (e.g., 0.01-mile intervals) for consistent data representations.
    - Extract key features, including pixel brightness, texture metrics, and spatial variability, to quantify surface conditions.
- **Temporal Analysis:**
    - Analyze the mean, median, and standard deviation of DN values for each segment over time to detect trends.

    - Identify anomalies, such as sharp declines or high variability, to differentiate between true deterioration and artifacts like shadows.
- **Predictive Modeling:**
    - Utilize statistical and machine learning models to forecast deterioration based on extracted features and historical trends.
    - Integrate environmental factors (e.g., weather, traffic load) for a holistic prediction of surface deterioration.
- **Validation and Calibration:**
    - Compare predicted deterioration trends with field measurements and ground-truth data to validate the model.
    - Calibrate the model iteratively to enhance prediction accuracy.
- **Decision Support:**
    - Develop visualizations and GIS-based tools to aid decision-making for maintenance planning and budget allocation.
    - Identify priority areas requiring immediate interventions and optimize resource allocation for rehabilitation efforts.

By employing this framework, asset managers can systematically assess and predict sidewalk conditions, ensuring proactive maintenance and resource optimization. While the framework focuses on modeling surface deterioration trends, it does not currently account for specific compliance-related issues, such as sidewalk tipping, trip hazards, or other localized safety concerns that may arise. Incorporating additional features, such as 3D elevation models or high-resolution point cloud data, could enhance the framework's ability to detect these hazards and ensure compliance with accessibility standards, such as the ADA. This approach not only improves infrastructure management but also enhances pedestrian safety and accessibility.

# CHAPTER 8: EVALUATION AND TESTING OF METHODOLOGY AND IMPLEMENTATION OF A DATA WAREHOUSE

## 8.1 PROPOSED FRAMEWORK

The proposed framework for modeling sidewalk deterioration integrates high-resolution aerial imagery by analyzing the image properties to estimate the surface condition of sidewalks over time. The methodology begins with a robust data acquisition and preprocessing phase, where aerial imagery spanning multiple years, such as MnGeo imagery with a 15 cm resolution, is gathered with consistent spatial resolution and georeferencing. Preprocessing steps are then applied to address imaging artifacts, including shadow correction and atmospheric normalization, ensuring consistency across datasets and preparing the imagery for analysis.

The next stage involves segmentation and feature extraction, where sidewalks are divided into uniform segments, such as 0.01-mile intervals, to facilitate structured data representation. In the temporal analysis phase, the framework computes statistical metrics, such as the mean, median, and standard deviation of DN values, for each sidewalk segment over multiple time points. This step allows for the detection of long-term deterioration trends. Anomalies, such as sudden declines or high variability in these metrics, are identified to distinguish true surface deterioration from imaging artifacts like shadows or other external influences. Predictive modeling leverages these extracted features and historical trends to forecast future deterioration of sidewalk conditions. Statistical models are employed to predict these changes, to create a holistic predictive framework.

## 8.2 OBJECTIVE

The primary objective of this study was to develop and evaluate a robust methodology for assessing the deterioration of sidewalk conditions using high-resolution aerial imagery. By leveraging DN values derived from photogrammetric data, this study aimed to establish a data-driven framework for predicting sidewalk deterioration trends over time. The proposed methodology integrates advanced preprocessing techniques, feature extraction, and statistical modeling to quantify surface conditions, identify distress patterns, and forecast future deterioration. The ultimate goal of the methodology is to provide a scalable and reliable tool for supporting proactive maintenance planning and sustainable infrastructure management.

## 8.3 DATA ACQUISITION

### 8.3.1 Aerial Imagery: MnGeo

MnGeo provides high-resolution aerial imagery essential for geospatial analyses and infrastructure assessments. Offering resolutions of 7.5 cm and 15 cm, MnGeo’s datasets enable detailed evaluations of urban and rural landscapes, supporting applications such as asset monitoring, urban planning, and environmental studies (MnGeo n.d.). MnGeo acquires aerial imagery through periodic flights over

Minnesota, ensuring up-to-date and comprehensive coverage. These images are georeferenced using advanced ground control techniques, ensuring spatial accuracy critical for integration with GIS. The imagery encompasses various landscape features, including sidewalks, roads, and vegetation, making it a versatile resource for urban planning and infrastructure management.

MnGeo datasets are frequently utilized in the public and private sectors due to their comprehensive temporal and spatial coverage. The ability to analyze high-resolution imagery with precise georeferencing underlines MnGeo's critical role in advancing data-driven decision-making processes, particularly in urban and environmental contexts (MnGeo 2020).

### 8.3.2 Site Selection Criteria for Evaluation

The study sites were carefully chosen based on specific criteria to ensure the quality and consistency of the data used for analysis. One of the primary requirements was the availability of at least three temporal snapshots of aerial imagery from the MnGeo aerial imagery database. The inclusion of multiple time points allowed for the longitudinal analysis of sidewalk conditions, facilitating the detection of trends and changes over time. This temporal resolution was essential to develop a robust framework for monitoring sidewalk deterioration. Another critical criterion was the presence of bike-based data for the selected sites that was collected as part of the project. This supplementary ground data provided a potential validation dataset, which may strengthen the reliability of the results and insights derived from the imagery. The final criterion focused on ensuring the unobstructed visibility of sidewalks in the aerial imagery. Sites with significant visual obstructions, such as tree canopies or extensive shadowing, were excluded to maintain the quality of feature extraction and analysis. Unobstructed imagery was critical for accurately segmenting sidewalks and quantifying their condition without the confounding effects of external artifacts.

Based on these carefully defined criteria, two counties in Minnesota were selected for applying the study's methodology: Dakota County and Hennepin County. These counties were ideal due to their comprehensive temporal imagery coverage, the availability of bike-based validation data, and minimal obstructions in the selected sidewalk segments. Figure 8-1 illustrates the geographic extent of the selected sites across these two counties, highlighting the distribution of the study areas.

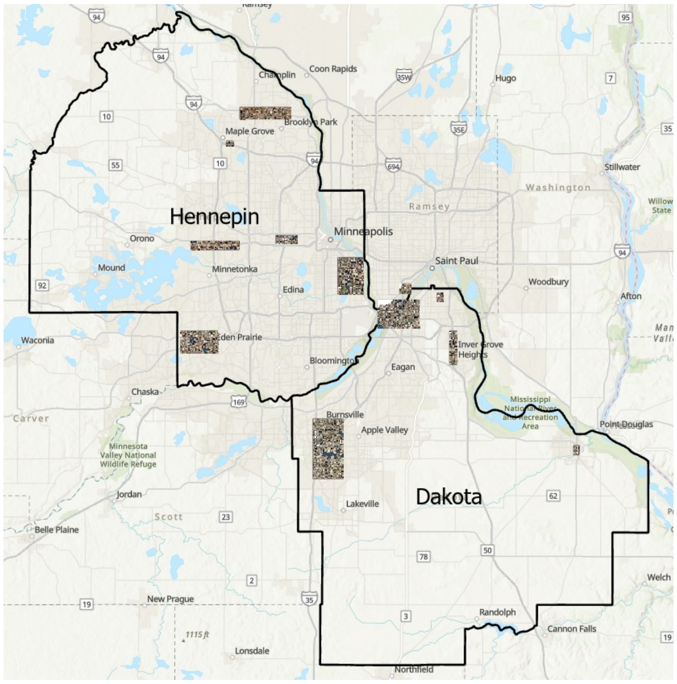



**Figure 8-1. Aerial imagery obtained for two counties: Hennepin and Dakota**

As shown in Table 8-1, both counties provided sufficient temporal coverage of aerial imagery. Dakota County offered six sites with data spanning five time points: 2010, 2013, 2019, 2021, and 2023. Similarly, Hennepin County contributed six sites with imagery available for 2018, 2021, and 2022. The selection of these counties provided diverse urban and suburban settings for analysis, which is important for making the findings generalizable to various settings.

**Table 8-1. Dataset description**

| Location | Number of sites | Available Image Data (Year) |
|---|---|---|
| Dakota County | 6 | 2010-2013-2019-2021-2023 |
| Hennepin County | 6 | 2018-2021-2022 |

## 8.4 DETERIORATION MODELING

### 8.4.1 Data Preparation

The data preparation process for deterioration modeling was aimed at transforming raw aerial imagery into a structured and analyzable dataset. This process involved manual annotation of sidewalks, polygon conversion, segmentation into uniform intervals, and feature extraction to ensure accurate representation of sidewalk conditions. The workflow is illustrated in Figures 8-2 and 8-3, while Table 8-2 provides a quantitative summary of the dataset used in this study.

### 8.4.2 Segmentation and Feature Extraction

The initial step in the data preparation involved the manual annotation of sidewalks. Using high-resolution aerial imagery, sidewalk areas were carefully delineated to create precise polygon features, as shown in Figure 8-2. Each polygon represented a unique sidewalk segment, ensuring accurate spatial definition. This conversion was critical for integrating the annotated data with geospatial tools, enabling accurate calculations and measurements in subsequent steps. Some quality assurance measures were applied to ensure the accuracy of the annotations, including the exclusion of non-sidewalk features that could introduce errors into the analysis.

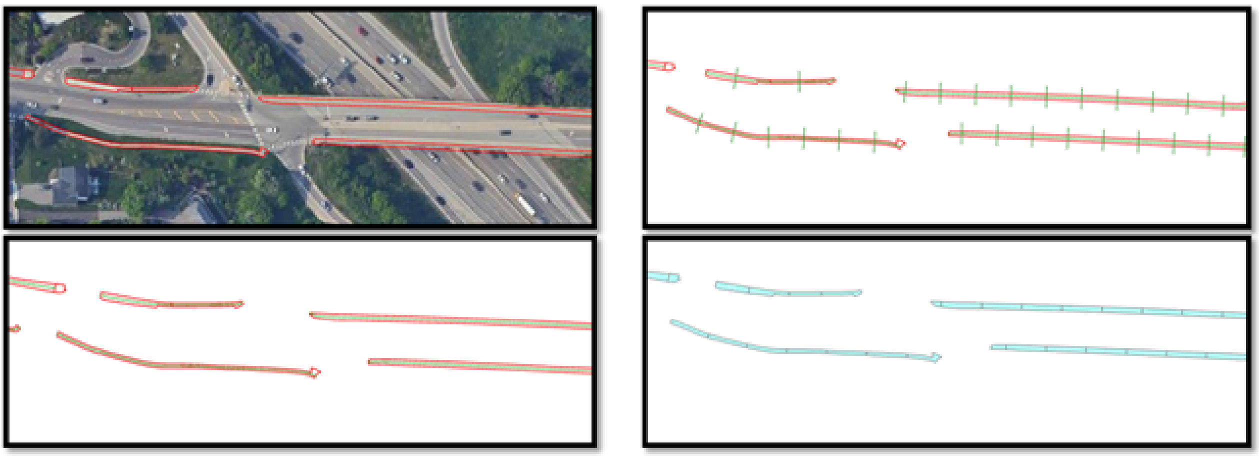


**Figure 8-2. Sidewalk annotation and sample extraction**

After the polygons were created for large sidewalk segments, they were then divided into uniform segments of 0.01 miles in length, as shown in Figure 8-3. This segmentation ensured consistent data representation across the entire study area and allowed for a structured approach to analyze the spatial and temporal characteristics of sidewalks while maintaining the granularity needed for deterioration modeling. Segmentation at this scale aligns with standard treatment lengths commonly utilized in maintenance planning.

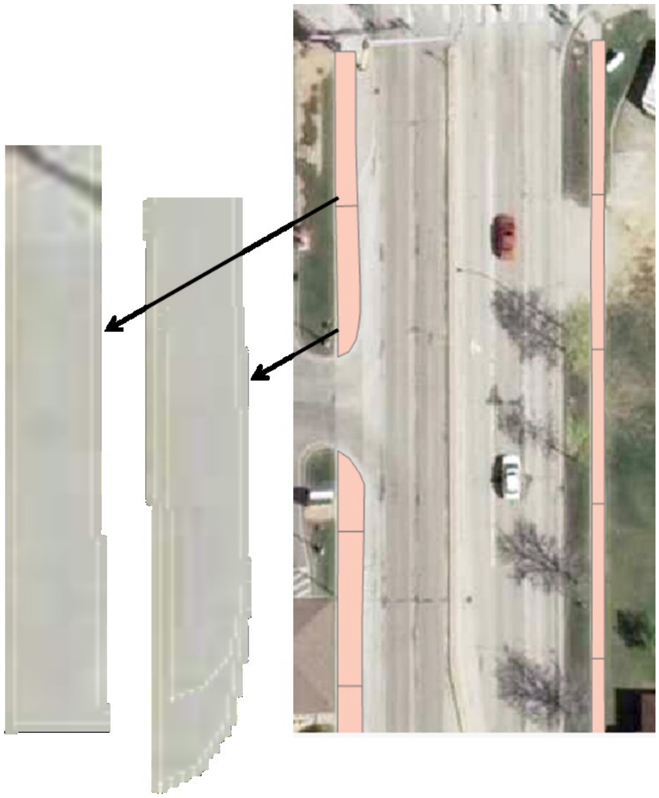


Figure 8-3. Sidewalk extraction

As shown in Table 8-2, the dataset prepared for this study consisted of 12 sites, encompassing 171 sidewalks, which were segmented into 1,514 0.01-mile intervals. This structured dataset formed the basis for extracting quantitative features required for modeling.

Table 8-2. Initial dataset for deterioration modeling

| | |
|---|---|
| **Number of sites** | 12 |
| **Number of sidewalks** | 171 |
| **Number of 0.01-mile segments** | 1,514 |

### 8.4.3 Temporal Analysis

The temporal analysis of image properties involved evaluating critical metrics such as the mean, median, and standard deviation of DN values across multiple time points for each sidewalk segment. DN represents the pixel intensity values in a digital image and is directly related to the reflectance of the surface captured by the imaging sensor. DN values quantify the amount of light reflected or emitted by a surface, with brighter surfaces corresponding to higher DN values and darker surfaces to lower DN values. These values are integral to interpreting the physical characteristics of surfaces and detecting changes over time. This step provided a quantitative basis for detecting trends and identifying changes in surface conditions over time, which are essential for understanding and predicting deterioration patterns.

#### 8.4.3.1 Calculate Image Properties

As discussed in the proposed framework for this study, DN values potentially serve as an indicator of sidewalk surface conditions. Pavement surfaces in good condition without distresses or surface anomalies would typically exhibit higher and more uniform pixel intensity, reflecting consistent material and texture characteristics. Conversely, deteriorated segments, such as those with cracks, potholes, vegetation, or other forms of distress, tend to have lower DN values due to darker pixel intensities. Therefore, this study explored the utility of DN values in monitoring sidewalk deterioration.

To standardize the analysis, the aerial imagery was converted into grayscale images. This conversion ensured that the images would be represented by a single intensity value per pixel, simplifying the computation of statistical summaries while preserving the visual and quantitative characteristics of the original image. The following grayscale conversion formula was applied (Poynton 1996, Scikit-image 2023):

$$\text{Grayscale DN} = 0.2125 * \text{Red band} + 0.7154 * \text{Green band} + 0.0721 * \text{Blue band} \tag{8-1}$$

For each segment, the following key metrics were calculated based on the grayscale pixel intensities:

- **Mean DN**: Represents the average pixel intensity within each segment, providing a baseline for overall surface reflectance.
- **Median DN**: Acts as a robust central tendency measure and is less sensitive to extreme values, which is particularly useful in segments affected by shadows or bright reflections.
- **Standard Deviation of DN**: Captures the variability in pixel intensities, indicating heterogeneity in the surface condition. Higher variability may point to distress or inconsistencies in the surface texture.

The computation of these metrics over time allowed for the identification of trends, such as consistent declines in mean DN values indicative of surface degradation or spikes in variability suggesting the emergence of localized distress or shadows.

#### 8.4.3.2 Dataset Filtering

The dataset filtering process was a critical step in ensuring the accuracy of derived metrics by identifying and removing anomalies introduced by shadows, image artifacts, or extreme reflectance conditions. This multistep process involved setting thresholds for standard deviation and mean-median difference, as well as removing entirely shadowed and overexposed segments (DN = 0 and DN = 255, respectively). Figures 8-4 through 8-7 illustrate the impact of these artifacts and the filtering process.

### 8.4.4 Impact of Shadows and Artifacts on DN Metrics

Shadows and image artifacts such as trees, people, or vehicles significantly impact the metrics derived from DN values, often distorting key indicators like the mean, median, and standard deviation. Figure 8-4 provides a clear depiction of how these factors impact temporal DN trends. As evident in Figure 8-4, shadows introduce variability and skew the intensity distributions, complicating the differentiation between genuine deterioration and artifacts caused by lighting conditions or environmental factors.

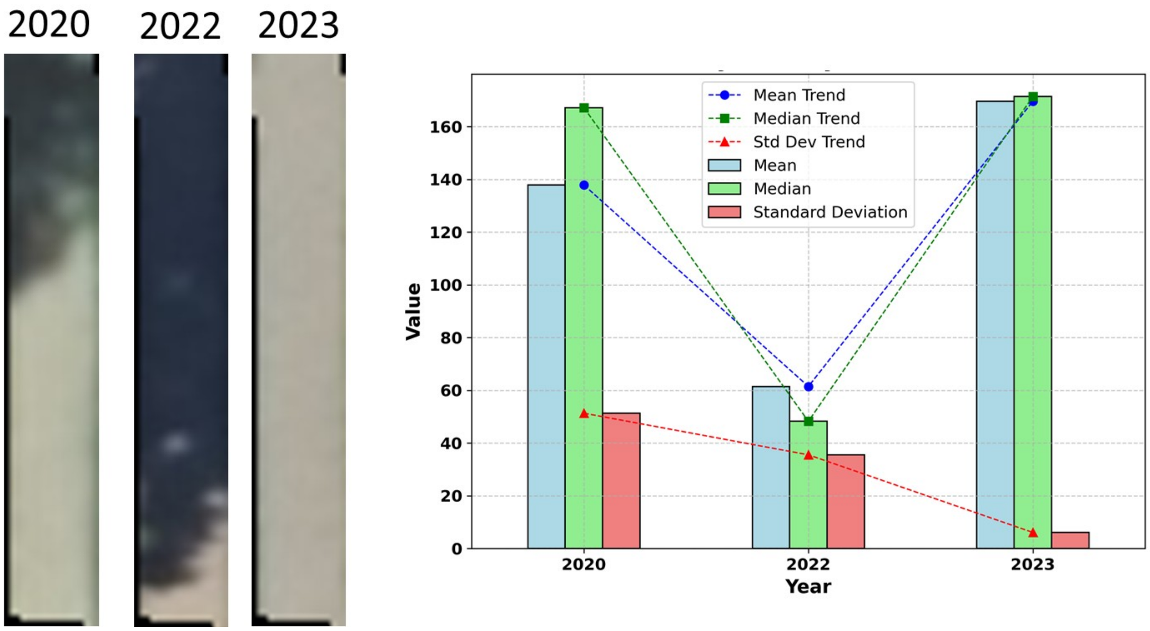



Figure 8-4. Impact of shadows on metrics derived from DN values

The relationship between shadows and standard deviation is not straightforward, requiring a more careful approach to identify and remove shadowed images systematically. Observing the DN metric trends over the years, an image filtering strategy can be developed for deterioration modeling. For instance, Figure 8-4 shows that in 2020, partial shadowing resulted in the highest standard deviation among the three years. The partial coverage introduced heterogeneity in the pixel intensities within the image, with darker areas corresponding to shadowed regions and brighter areas to non-shadowed regions. This increased variability is captured by the elevated standard deviation. By contrast, in 2023, the absence of shadows led to a uniform distribution of DN values, resulting in the lowest standard deviation. These two cases demonstrate the expected relationship, where shadowed images generally exhibit higher variability compared to shadow-free images. However, the scenario in 2022 challenges this relationship. In this case, shadows almost entirely covered the image, resulting in a relatively moderate standard deviation. The lack of a significant difference between shadowed and non-shadowed areas within the same image reduced variability, even though the image itself was entirely affected by lighting conditions. This nonlinear relationship highlights that standard deviation alone is insufficient as a reliable indicator for shadow detection, as it depends on the spatial distribution and extent of the shadow's presence in an image.

Hence, the mean-median difference was explored as a complementary metric. Unlike standard deviation, the mean-median difference demonstrated a more consistent relationship with shadow presence. In 2023, where shadows were absent, the mean-median difference was the lowest, reflecting the uniform distribution of pixel intensities. By contrast, in 2022 and 2020, where shadows were present in varying degrees, the mean-median difference was higher due to the skew introduced by shadowed regions. This consistent behavior suggests that the mean-median difference could serve as a complementary metric for detecting shadowed images.

Therefore, a systematic approach to removing shadowed images involves the combined use of standard deviation and mean-median difference. Images with high standard deviation values likely contain partial shadows, as observed in 2020. Meanwhile, images with a high mean-median difference, as seen in both 2020 and 2022, indicate skewed DN distributions caused by shadows. By applying thresholds for both metrics, it is possible to identify and filter out images significantly affected by shadows, ensuring that the dataset represents genuine surface conditions.

The filtering stage focuses on identifying and removing images impacted by shadows and lighting variations to ensure that the dataset reflects artifact-free sidewalk surfaces. The filtering process employs two key metrics—standard deviation and mean-median difference—to systematically detect and eliminate affected images.

High standard deviation values in DN metrics are indicative of substantial variability within an image, often caused by partial shadows or highly heterogeneous surface conditions. Figure 8-5 demonstrates the application of a standard deviation threshold of 30 to filter out such segments. In the histogram of the original data (left), a long tail is evident, representing images with elevated variability due to shadows or artifacts. By setting the standard deviation threshold at 30, segments exceeding this value are flagged and removed from the dataset. After filtering, as shown in the right panel of Figure 8-5, the histogram displays a more uniform distribution, with the removal of outliers. This step reduces the influence of extreme variability, ensuring that the dataset captures genuine surface characteristics rather than artifacts caused by inconsistent lighting.

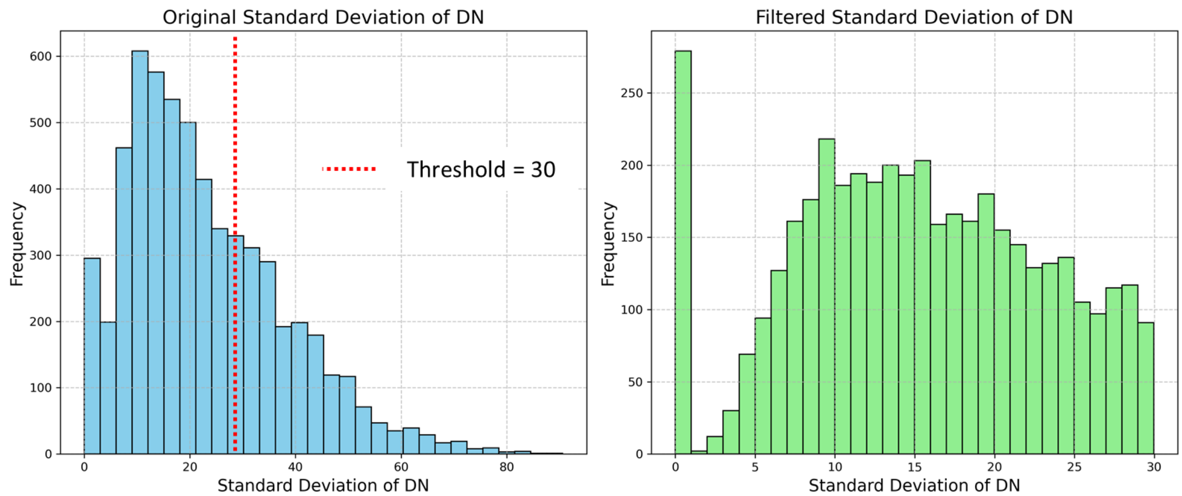



**Figure 8-5. Filtering based on standard deviation of DNs within the images**

While standard deviation effectively identifies high variability, it may not fully capture cases where shadows or lighting introduce skewness in DN distributions. For such scenarios, the mean-median difference is a complementary metric. A high mean-median difference suggests a skewed intensity distribution, often caused by partial shadows or bright reflections. Figure 8-6 illustrates the filtering process using a threshold of 15 for the mean-median difference.

In Figure 8-6 (left), the histogram of the original data shows a broad spread of values, indicating significant skewness in some segments. By applying the threshold, segments with extreme mean-median differences are removed, resulting in the filtered histogram Figure 8-6 (right). This step ensures that images with skewed DN distributions, likely affected by shadows or inconsistent lighting, are excluded from the analysis.

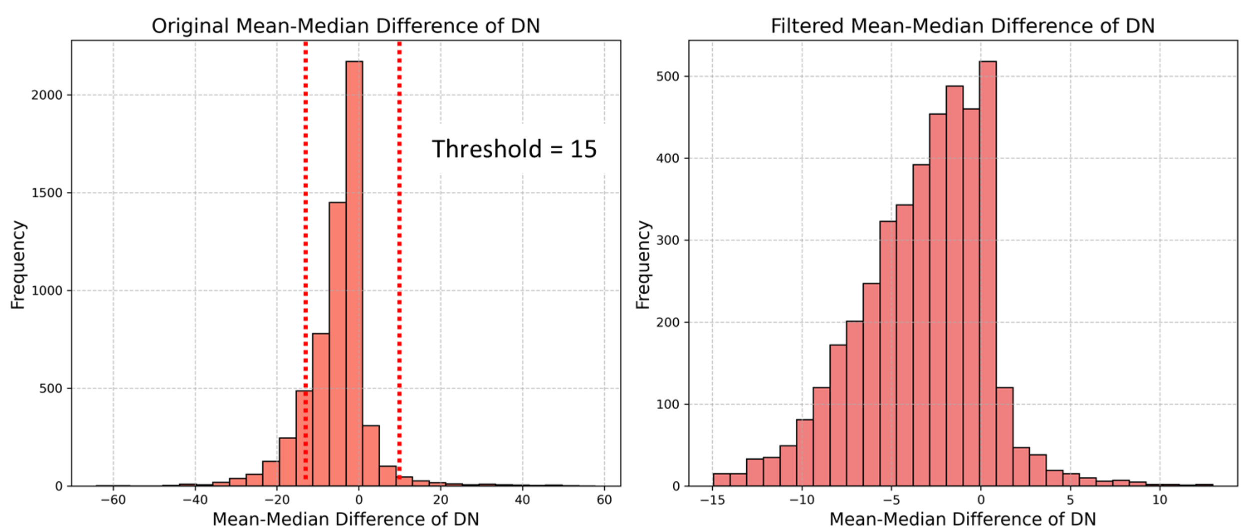



**Figure 8-6. Filtering based on difference between mean and median of DNs**

In addition to filtering images based on high standard deviation and mean-median differences, an essential step involves identifying and removing completely shadowed segments that might not be captured by the previously established thresholds. A standard deviation of zero in DN values indicates an entirely uniform pixel intensity across the segment. In shadowed images, this uniformity arises because no significant reflectance is captured, resulting in a consistent DN value (often near zero) throughout the image. These segments provide no variability, making them unsuitable for analysis of surface conditions. Similarly, low but nonzero standard deviations close to zero may also represent near-completely shadowed areas. In Figure 8-7 (left), the original distribution of standard deviation values shows a noticeable spike at zero, representing completely shadowed images. These images cannot be removed using thresholds for high standard deviation or mean-median difference, necessitating this additional step. Figure 8-7 (right) shows the distribution of standard deviation values after this filtering step. The spike at zero has been eliminated, reflecting the removal of completely shadowed images. The resulting dataset now contains only segments with reasonable variability, ensuring that all remaining data can contribute to the analysis of surface conditions.

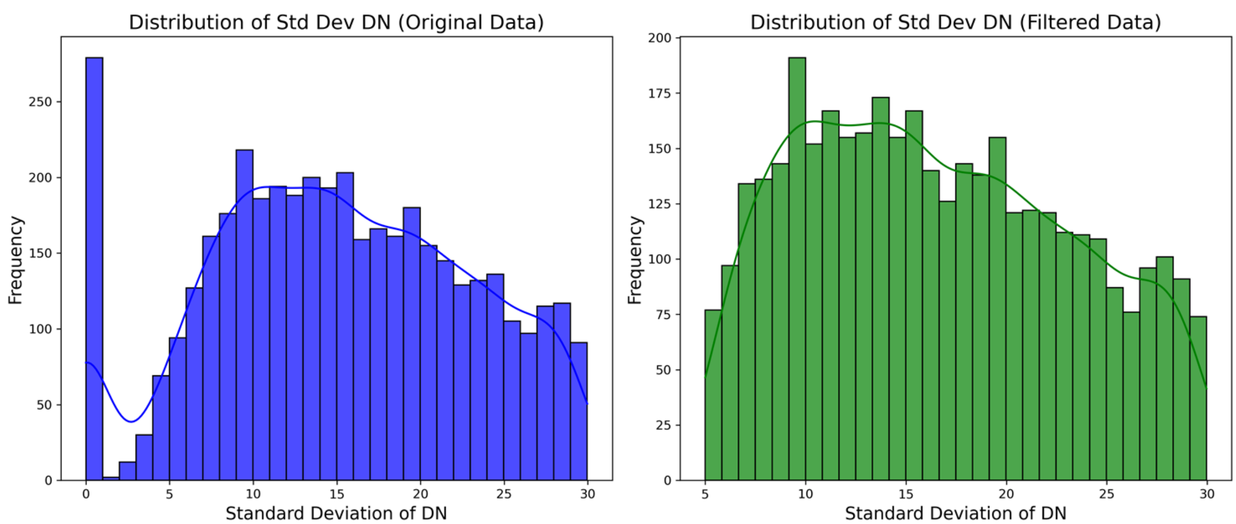



**Figure 8-7. Filtering completely shadowed images**

### 8.4.5 Linear Regression Model

Before fitting a linear regression model to the filter data, a few preprocessing steps were carried out on the dataset. For instance, the presence of spikes in mean DN values across consecutive years can distort trend analyses and impact the reliability of deterioration modeling. These anomalies are typically caused by temporary conditions, such as inconsistent lighting, seasonal vegetation changes, or surface treatments, that do not reflect actual surface deterioration. To address this, a two-step process was employed: detecting an increase in DN values through a year-to-year comparison (Figure 8-8) and normalizing the data by pavement age to fit a linear deterioration trend (Figure 8-9).

By analyzing the direction of changes in mean DN values for consecutive years, cases where the direction of change contradicted the expected trend of gradual deterioration were identified. An expected trend would be a negative slope in DN values between two consecutive years. When a positive slope was observed between years, the latter year's data were removed. The data cleaning process prioritized maintaining the overall deterioration pattern, ensuring that genuine variations due to surface degradation were preserved. Figure 8-8 shows the retained datapoints after all of the filtering steps.

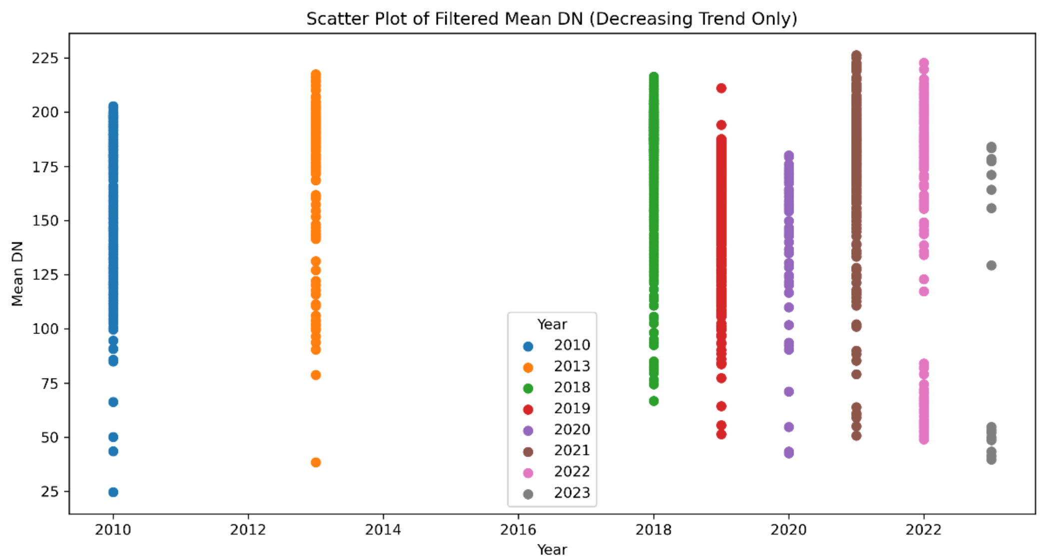



**Figure 8-8. Cleaned data after filtering**

To refine the cleaned dataset and establish a consistent trend, the data were normalized by pavement age, defined as the time elapsed since the baseline year for each segment. A linear regression model was subsequently fitted to the normalized data, as shown in Figure 8-9. The regression equation is expressed as follows:

$$y = -2.63 * x + 174.58 \quad (2)$$

where $y$ represents the DN value as a function of age ($x$). The slope of the equation (−2.63) signifies the rate of deterioration derived from the DN-based condition analysis. This deterioration rate provides a rough understanding for assessing the progressive deterioration in surface quality over time. The deterioration rate can be integrated with an initial condition index to predict the future condition of a segment for a specified age. The initial condition index can be quantified using DN values derived from high-resolution aerial imagery or ground-truth measurements collected via bicycle-based frameworks, both of which were employed in this study. This approach allows for the practical application of the model to forecast sidewalk conditions, enabling proactive maintenance planning.

By coupling the initial condition index with the deterioration rate, infrastructure managers can estimate the expected condition of a segment over its life cycle. This methodology provides a data-driven framework for anticipating when maintenance or rehabilitation may be necessary. The linear regression model, developed through this task, serves as a foundational tool for predicting future conditions based on historical DN trends.

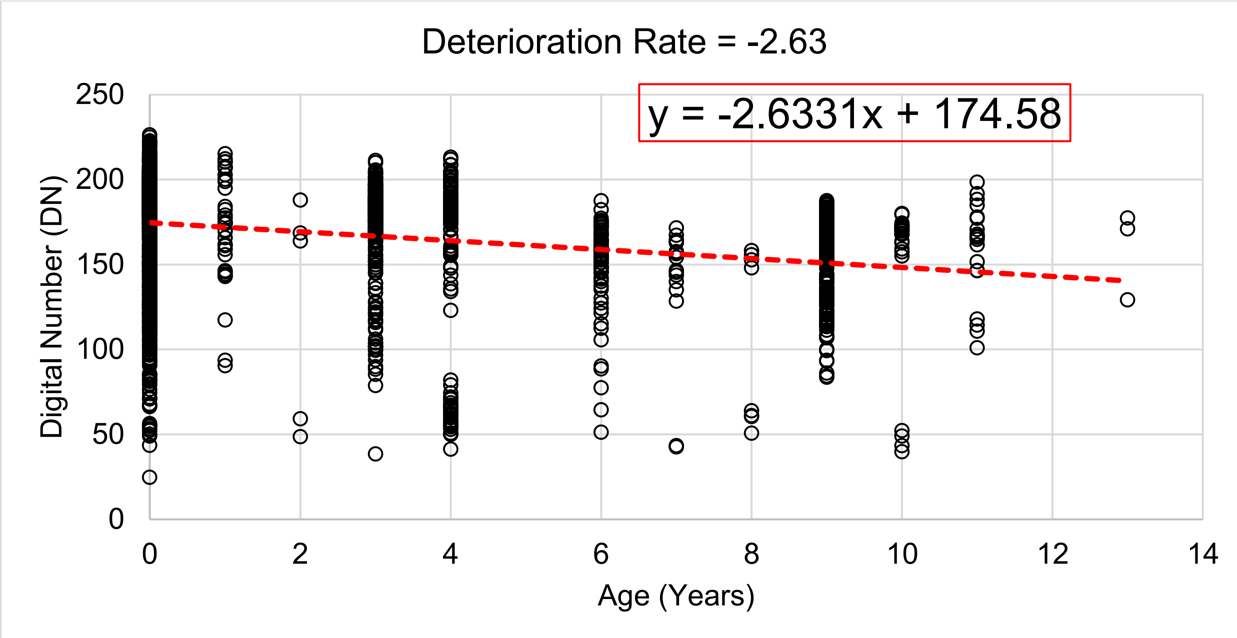



Figure 8-9. Deterioration model

## 8.5 SUMMARY

The findings of this study highlight the potential of using aerial imagery and DN-based metrics for cost-efficient sidewalk condition assessments. Analysis of DN values revealed clear correlations between surface conditions and metrics such as mean, median, and standard deviation. The study also demonstrated few filtering steps to address anomalies caused by shadows, lighting conditions, and extreme reflectance. Shadows, in particular, posed challenges, as their relationship with DN variability was found to be nonlinear. The combined use of standard deviation and mean-median difference thresholds effectively removed shadowed segments, ensuring a clean dataset for analysis. This filtering process was validated through temporal trends that consistently showed progressive deterioration in DN values over time.

The deterioration rate was quantified through linear regression from the DN trends. The fitted linear regression model established a deterioration rate of −2.63, which could be coupled with the initial condition index derived from DN values or ground-truth measurements to predict of surface degradation over time. These projections can be integrated into a TAMP, supporting life-cycle planning by predicting future maintenance needs and guiding budget allocation. This approach allows for long-term planning by forecasting the timing of necessary repairs and replacements based on the predicted deterioration rates.

It is important to note that deterioration rates may vary across different regions of the state due to factors such as climate, traffic volume, and local environmental conditions. For example, urban areas with higher foot traffic and more extreme weather conditions may experience faster deterioration than rural areas. By incorporating region-specific data into the model, this approach can provide more accurate and localized projections, ensuring that maintenance efforts are prioritized effectively according to the unique needs of each area.

The proposed methodology offers a scalable solution for pedestrian infrastructure maintenance planning, helping to optimize resource allocation, extend the lifespan of assets, and improve overall infrastructure management.

# CHAPTER 9: SUMMARY, CONCLUSIONS, AND IMPLEMENTATION STEPS

## 9.1 SUMMARY

This project focused on developing a comprehensive methodology for assessing the deterioration of pedestrian assets, particularly sidewalks, to improve decision-making in asset management and maintenance. The research began with a detailed literature review that explored existing practices in pedestrian asset management both within the United States and internationally. The review highlighted the importance of effective data collection, evaluation techniques, and the growing use of emerging technologies in assessing the condition of pedestrian infrastructure.

A survey of state and local agencies was conducted to understand current practices in data collection and the evaluation and maintenance of pedestrian assets. The survey revealed a reliance on traditional methods, such as visual inspections, although some agencies have begun to explore advanced technologies like sensors and computer vision to enhance assessment accuracy and efficiency.

The project then focused on the data processing and integration of historical data from MnDOT, enriching the dataset with additional information such as land use and climate data. This step was essential for creating a robust dataset that could support predictive analysis, offering a more accurate understanding of asset deterioration by accounting for various influencing factors.

Field data collection was carried out using advanced tools, including a data bike system equipped with sensors and cameras to capture detailed information on sidewalk conditions. This effort was specifically aimed at exploring alternative methods for condition rating that could provide quantitative data for modeling the deterioration of pedestrian assets, in contrast to traditional visual inspections.

The methodology for the statewide deterioration model was developed by integrating high-resolution aerial imagery, Google Street View data, and field data. The model was designed to quantify the rate of deterioration of pedestrian assets and predict future conditions based on various factors.

Finally, the evaluation and testing of the methodology demonstrated that the model provided a reliable framework for predicting sidewalk deterioration. The testing confirmed that the methodology could be effectively applied to forecast deterioration, guiding future asset management and maintenance strategies, and supporting informed decision-making for the management of pedestrian assets.

## 9.2 CONCLUSIONS

The research developed a comprehensive methodology for assessing the deterioration of pedestrian assets, particularly sidewalks, that was aimed at improving asset management and maintenance strategies. The research successfully integrated traditional evaluation methods with advanced technologies, providing a more robust framework for understanding and managing pedestrian infrastructure. Central to this effort was the development of a statewide deterioration model, which combines high-resolution aerial imagery and field data to quantify the rate of deterioration, hence providing the basis to predict future asset conditions.

Field data collection was a critical part of this project and involved the use of advanced tools like the data bike system equipped with sensors and cameras to capture detailed information on sidewalk conditions. This effort focused on exploring alternative methods for condition rating that provided more precise, quantitative data for modeling deterioration, offering a significant improvement over traditional visual inspections. By integrating these innovative data collection methods, the project ensured that the deterioration model was built on a comprehensive, reliable dataset.

The model developed through this research offers a predictive framework for forecasting the future condition of pedestrian assets. Through the integration of various data sources, the model can account for factors influencing asset deterioration and provide actionable insights for maintenance planning. Evaluation and testing of the methodology confirmed its effectiveness, validating its ability to reliably predict sidewalk deterioration. The results demonstrate that the model can be used as a tool to guide decision-making in asset management, optimize resource allocation, and improve the prioritization of maintenance activities.

In addition, the project emphasizes the importance of establishing a robust data management framework for pedestrian asset data. This framework includes integrating historical baseline data and using a data warehouse for more efficient data processing, storage, and access. The integration process followed a structured workflow, ensuring that the data were cleaned, validated, and enriched with supplementary information such as land use and population density. This enriched dataset will be essential for creating more accurate deterioration models. By consolidating and aggregating the data into a central system, agencies will be better equipped to monitor asset conditions continuously, assess deterioration trends over time, and make informed decisions based on the most up-to-date information. This proactive approach will help streamline maintenance planning and resource allocation, ultimately supporting the long-term sustainability and safety of pedestrian infrastructure.

Ultimately, this project provides transportation agencies with a powerful, data-driven tool to improve pedestrian infrastructure management. By combining predictive models with advanced data collection techniques, the research offers a pathway to more sustainable, efficient, and proactive management of pedestrian assets, ultimately enhancing the safety, accessibility, and longevity of infrastructure for the communities they serve.

## 9.3 RESEARCH BENEFITS

The research highlights substantial benefits for infrastructure managers:

1. **Construction Savings:**
    - Early detection of deterioration minimizes the need for extensive repairs, reducing construction costs.
    - Prioritized maintenance helps extend the service life of assets, deferring the need for costly full reconstruction.

2. **Improved Life-Cycle Costs:**
    - Proactive maintenance planning extends the life cycle of sidewalk assets, reducing the overall expenditure over their lifespan.
    - Proactive maintenance planning also enables targeted repairs aligned with pavement and other programmed projects, optimizing resource allocation and efficiency.
3. **Reduced Risk:**
    - Early identification of high-risk areas mitigates liability risks associated with trips, falls, or injuries on deteriorated sidewalks.
    - Early identification of high-risk areas also provides a reliable mechanism for risk assessment and prioritization, aligning with municipal safety goals.
4. **Safety Enhancements:**
    - Regular monitoring ensures timely maintenance of hazardous segments, enhancing pedestrian safety.
    - Regular monitoring also supports compliance with ADA standards, ensuring safe and accessible infrastructure for all users.
5. **Cost-Effectiveness:**
    - Replacing manual inspection with aerial imagery and automated analytics reduces assessment costs.
    - Aerial imagery and automated analytics enable large-scale assessments without the need for extensive field surveys.
6. **Scalability and Reliability:**
    - The segmentation approach (0.01-mile intervals) ensures consistent data representation across networks.
    - Compatibility with GIS supports seamless integration with asset management platforms.
7. **Environmental Benefits:**
    - Proactive maintenance reduces the environmental impacts of construction activities, such as material use and emissions from heavy machinery.

## 9.4 IMPLEMENTATION STEPS

To operationalize the proposed methodology, the following steps are recommended:

1. **Data Collection Partnerships:**
    - Partner with MnGeo to ensure ongoing access to high-resolution aerial imagery and geospatial data, minimizing data access costs while maximizing long-term benefits such as a reduced need for additional data collection and improved decision-making for proactive maintenance.
    - Establish data sharing agreements with local agencies to leverage additional data sources.
2. **Pilot Deployment:**
    - Test the framework in additional counties to validate generalizability.
    - Use ground-truth validation (e.g., bike-based data) to refine predictions.
3. **Model Calibration:**

- Use lidar data and data bike measurements to validate and calibrate the deterioration model.
- Compare DN-based deterioration trends with high-resolution lidar data to refine surface condition predictions.
- Integrate data bike ground-truth measurements for enhanced accuracy and precision in model calibration.
- Leverage local expertise to validate findings and tailor the model to specific regional characteristics.

4. **Model Application:**
   - Apply the calibrated model to forecast future sidewalk conditions based on DN trends and use the projections to assess future maintenance requirements and capital investment needs.
5. **Integration with Asset Management Systems:**
   - Integrate the deterioration model into existing TAMS and TAMP.
6. **Training and Knowledge Sharing:**
   - Develop training programs on leveraging aerial imagery and predictive analytics for infrastructure management.
7. **Scaling to Other Asset Types:**
   - Adapt the methodology for other pedestrian infrastructure assets (e.g., curb ramps, crosswalks, sidepaths).

## 9.5 NEXT STEPS FOR FURTHER RESEARCH

1. **Incorporation of Additional Data Sources:**
   - Use lidar and Google Street View to enhance spatial and temporal resolution.
   - Explore integration with climate and traffic data to improve model robustness.
2. **Automation and AI Integration:**
   - Integrate with an ongoing MnDOT research project on the use of machine learning algorithms for automated feature extraction and anomaly detection.
3. **Policy Development:**
   - Work with policymakers to establish standardized protocols for using aerial imagery in infrastructure planning.

## 9.6 FINAL WORD

The research demonstrates a scalable and cost-effective approach to assessing sidewalk conditions, providing actionable insights for proactive maintenance. The quantifiable benefits, including construction savings, improved life-cycle costs, reduced risk, and safety enhancements, position this methodology as a valuable tool for advancing sustainable infrastructure management.

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