OPTIMIZATION OF PAVEMENT MAINTENANCE AND REHABILITATION USING PAVEMENT MANAGEMENT SYSTEM IN PRINCE GEORGE

By

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Abstract

Pavement Management Systems (PMS) are essential for guiding cost-effective and sustainable road maintenance, particularly in municipalities operating within harsh climates and under financial constraints. This research examines the optimization of pavement maintenance strategies for the City of Prince George, British Columbia, by combining historical condition data, predictive modeling, and decision-support frameworks. The study utilizes pavement distress survey results from 2016, 2017, 2020, and 2023 to assess network-level deterioration, identify critical distress types, and establish performance baselines.

To forecast pavement performance, three modeling approaches—Random Forest (RF), Multiple Linear Regression (MLR), and Artificial Neural Networks (ANN)—were applied to predict the Pavement Distress Index (PDI). These models were evaluated using the statistical metrics such as Root Mean Square Error (RMSE), and coefficient of determination (R^2). The Random Forest model achieved the highest predictive accuracy ($R^2 = 0.96$, RMSE = 0.55), followed closely by the ANN ($R^2 = 0.95$, RMSE = 0.48), while the MLR model demonstrated lower predictive capability ($R^2 = 0.81$, RMSE = 0.92). Variable importance analysis identified transverse cracking, rutting, and surface roughness as the most influential predictors of deterioration.

The findings of this research provide a data-driven framework for proactive pavement maintenance planning in Prince George, enabling the prioritization of high-impact interventions and the optimization of rehabilitation budgets. By extending pavement service life and reducing long-term maintenance costs, the proposed methodology supports the creation of more resilient transportation infrastructure. The framework can be adapted for use in other municipalities facing similar environmental and operational conditions, strengthening the integration of advanced analytics into municipal asset management practices.

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Glossary

Abbreviation	***Full Form***
PMS	Pavement Management System
MLR	Multiple Linear Regression
RF	Random Forest
ANN	Artificial Neural Network
GIS	Geographic information system
PCI	Pavement Condition Index
PDI	Pavement Distress Index
BC	British Columbia
LCCA	Life Cycle cost Analysis
IRI	International Roughness index
SPS	Strategic Planning System
NDT	Non destructive Testing
AASHTO	American Association of State Highway and Transportation Officials
AADT	Annual Average Daily Traffic
RMSE	Root Mean Square Error
FHWA	Federal Highway Administration

1. Chapter 1: Introduction

1.1. Background & Context

Efficient and well-maintained pavement infrastructure is fundamental to the economic prosperity, public safety, and quality of life for residents of any municipality. In northern British Columbia, particularly in Prince George, road networks serve as the critical backbone for regional connectivity, commerce, and community development. As a strategic transportation hub located at the junction of the Fraser and Nechako rivers, Prince George facilitates the movement of goods, services, and people across a vast geographic region, making the integrity of its pavement infrastructure paramount to both local and regional economic vitality.

Prince George, with a population of approximately 72,000 residents within the city limits and serving an additional 320,000 residents in the surrounding region (Statistics Canada, 2021), maintains an extensive road network spanning 605 kilometers. This network comprises 214 km of major arterial roads, 155 km of collector roads, and 230 km of local roads, each serving distinct functional roles and experiencing a wide variety of traffic loading and environmental stresses (City of Prince George, 2009). The city's strategic position as the largest urban center in northern British Columbia places significant demands on its transportation infrastructure, as it serves as a distribution hub for forestry, mining, and agricultural activities throughout the region.

The unique geographical and climatic characteristics of Prince George present exceptional challenges for pavement infrastructure management. Located at latitude 53°53'37"N and longitude 122°45'02"W (Latitude.to, 2024), the city experiences a humid continental climate characterized by severe winters and warm summers. Average air temperatures range from -10°C in winter to 16°C in summer, with extreme temperatures spanning from -40°C to 35°C (Pacific Climate Impacts Consortium, 2024). This wide temperature variation, combined with an annual precipitation average of 600 -700mm including heavy snowfall (approximately 216 cm annually) (Prince George Weather Statistics, 2024), creates a challenging environment for pavement materials and structures.

The City of Prince George faces multiple freeze-thaw cycles annually, which significantly impact pavement integrity through thermal expansion and contraction of materials, moisture infiltration and subsequent ice formation, and accelerated deterioration of both surface and subsurface pavement components. The spring melt period creates additional challenges through increased moisture content and reduced bearing capacity of subgrade materials, contributing to premature pavement failures and increased maintenance requirements.

The concept of infrastructure management has evolved to address these complex challenges through systematic approaches to asset stewardship. According to Hendrickson, Coffelt, and Healey in Fundamentals of Infrastructure Management, "infrastructure management should adopt a 'triple bottom line' to consider economic, environmental and social impacts" while maintaining "a life cycle or long-term viewpoint" that is "essential for good infrastructure management" (Hendrickson et al., 2017). This perspective recognizes that infrastructure investments "will last for decades or more and providing good performance over an entire lifetime is critical for good infrastructure management."

Within this broader infrastructure management framework, Pavement Management Systems (PMS) have emerged as specialized tools designed to optimize the preservation and performance of road networks. The Federal Highway Administration's Pavement Management Primer provides a formal definition, describing pavement management as "a set of tools or methods that assist decision-makers in finding optimum strategies for providing, evaluating, and maintaining pavements in a serviceable condition over a period of time" (FHWA, 2022). The primer emphasizes that "pavement management helps to ensure pavement investments meet the agency's pavement condition goals and targets" while "implementing pavement management involves establishing clear pavement management functions, policies, and procedures."

The systematic nature of PMS is further elaborated in the infrastructure deterioration modeling literature, which explains how these systems "fit within the infrastructure deterioration modeling field" by providing capabilities for "forecasting pavement behavior and performance standards" (Zakeri, 2016). This forecasting capability is essential for municipal decision-making, as it enables agencies to predict future pavement conditions and optimize maintenance timing and resource allocation.

Saliminejad describes the logical structure of PMS systems, explaining that they integrate multiple components including "inputs (distress data), outputs (treatment schedules), and feedback loops" that work together to support systematic infrastructure management. The system structure includes "inventory data collection, conditions assessment, a determination of needs, the prioritization of projects needing maintenance and rehabilitation, a method of determining the impact of funding decisions, and a feedback process" (Saliminejad, 2013).

The evolution of PMS technology represents a significant advancement in infrastructure management capabilities. Recent research in automated decision-making highlights how these systems have evolved "from manual inspections to automated, Machine Learning (ML) -driven systems," demonstrating the "relevance and innovation in PMS today" (Li et al., 2022). This technological evolution enables more sophisticated analysis of pavement performance factors, including "traffic conditions, climatic characteristics, and maintenance history" that "exhibit a close relationship with pavement performance."

The economic significance of maintaining high-quality pavement infrastructure extends beyond immediate transportation needs. Prince George serves as a critical link in provincial and national transportation corridors, with major highways including Highway 97 (connecting southern British Columbia to Alaska) and Highway 16 (the Yellowhead Highway connecting eastern and western Canada) passing through the city. The condition of local pavement infrastructure directly impacts the efficiency of goods movement, tourism accessibility, and the overall economic competitiveness of the region.

Furthermore, the forestry and mining industries, which form the economic foundation of the region, rely heavily on efficient transportation networks for moving products to markets and bringing supplies to operational sites. Deteriorated pavement conditions result in increased vehicle operating costs, reduced fuel efficiency, and potential supply chain disruptions that can have cascading economic effects throughout the region.

1.2. Problem Statement

Despite ongoing maintenance efforts and significant financial investments, several critical issues continue to undermine the efficiency and longevity of pavement infrastructure in Prince George. Technical complexities, environmental impacts, and resource management problems represent multiple layers of challenges that require comprehensive, innovative solutions aligned with contemporary sustainability principles.

1.2.1. Lack of Scientific Research and Strategic Planning

The foremost challenge facing Prince George's pavement management approach is the absence of a scientifically based, data-driven framework for decision-making. Current maintenance practices are not fully supported by technical and statistical analysis, resulting in inefficiencies in resource allocation and maintenance prioritization. This deficiency manifests in reactive rather than proactive maintenance strategies, leading to suboptimal outcomes and increased costs over the infrastructure lifecycle. Without a robust analytical foundation, maintenance decisions often rely heavily on subjective assessments and historical practices rather than predictive modeling and performance optimization.

Research in sustainable pavement management emphasizes that "lack of PMS leads to deteriorating road conditions and reactive maintenance" approaches that fail to optimize long-term infrastructure performance (Khahro, 2022). The absence of systematic planning particularly affects municipalities facing budget constraints, where inefficient resource allocation can have significant long-term consequences for infrastructure condition and service delivery.

1.2.2. Challenging Climate Conditions and Environmental Stressors

Prince George's location in northern British Columbia subjects its pavement infrastructure to some of the most severe environmental conditions in Canada. The region's extreme seasonal temperature variations, combined with frequent freeze-thaw cycles, create accelerated deterioration conditions that significantly challenge traditional pavement management approaches.

The literature on flexible pavement management in harsh climates indicates that environmental factors play a dominant role in pavement deterioration patterns. Research demonstrates that freeze-thaw cycles are among the most destructive forces affecting pavement infrastructure in northern climates, causing expansion and contraction stresses that lead to cracking, joint deterioration, and eventual structural failure (Khahro, 2022).

The superposition of Prince George's extreme climatic conditions with heavy commercial traffic creates an accelerated deterioration environment that substantially increases both the frequency and cost of required repairs. This combination of environmental and loading stresses requires specialized management approaches that account for the unique characteristics of northern climate pavement performance.

1.2.3. Limited Integration of Advanced Technologies and Predictive Capabilities

Prince George's current pavement management approach has not fully embraced the technological advancements that characterize modern PMS implementation. The evolution toward automated, ML-driven systems represents a significant opportunity for improved decision-making and resource optimization that remains largely unutilized in the local context (Li et al., 2022).

Contemporary PMS implementations leverage advanced modeling techniques and automated data collection to improve prediction accuracy and decision support capabilities. The integration of such technologies could significantly enhance Prince George's ability to optimize maintenance strategies and resource allocation while reducing long-term infrastructure costs.

1.2.4. Inadequate Performance Monitoring and Data Management

Effective pavement management requires comprehensive condition monitoring and data management capabilities that support both immediate decision-making and long-term strategic planning. Current assessment techniques employed in Prince George lack the precision and comprehensiveness required for effective predictive maintenance strategies.

The infrastructure management literature emphasizes that "deterioration modeling is a process of taking condition assessment information and forecasting expected future conditions" that requires systematic data collection and analysis capabilities (Hendrickson et al., 2017). Without adequate performance monitoring systems, it becomes challenging to prioritize maintenance interventions effectively and predict long-term performance trends.

These interconnected challenges demonstrate the urgent need for a comprehensive, scientifically based pavement management system specifically tailored to Prince George's unique environmental and operational conditions. Addressing these issues requires the integration of climate-adaptive strategies, advanced predictive modeling, sustainability principles, and contemporary management technologies within a unified framework that supports both immediate operational needs and long-term infrastructure stewardship.

1.3. Research Objectives

Objective 1: Develop a PMS framework tailored to Prince George's unique material availability, climatic and traffic conditions.

Objective 2: Identify main deterioration trends and patterns of pavements in Prince George by analyzing historical pavement distress data.

Objective 3: Implement predictive modeling to forecast pavement performance and optimize maintenance planning.

Objective 4: Provide practical recommendations for a climate-adaptive pavement management strategy.

1.4.Methodology

This research employs a systematic data-driven approach to develop a climate-adaptive pavement management system tailored to Prince George's environmental conditions. The methodology addresses critical gaps in locally calibrated PMS models for Northern British Columbia through integrated empirical analysis, predictive modeling, and optimization techniques.

1.4.1. Research Framework

The study follows a four-phase approach: data collection and preprocessing, deterioration analysis, predictive modeling, and optimization framework development. This systematic progression ensures comprehensive analysis of technical, environmental, and economic factors while maintaining practical applicability for municipal implementation.

1.4.2. Data Collection and Pre-processing

Historical pavement condition data spanning 2016, 2017, 2020, and 2023 provides the empirical foundation for analysis. Traffic data including Average Annual Daily Traffic (AADT) and vehicle classification quantifies loading effects on deterioration. Climate data from Environment and Climate Change Canada captures temperature extremes, precipitation patterns, and freeze-thaw cycles characteristic of Prince George's harsh conditions. Maintenance history records document treatment applications, timing, and costs. GIS data provides spatial contexts for all analytical components.

Data preprocessing includes systematic cleaning, validation, missing data handling, and temporal alignment to ensure analytical reliability and consistency across datasets.

1.4.3. Analytical Methods

Statistical analysis identifies deterioration patterns through descriptive statistics, time-series analysis, and correlation assessment between Pavement Deterioration Indices (PDI) values, environmental factors, traffic loading, and maintenance history. Climate impact analysis quantifies freeze-thaw effects and seasonal deterioration patterns. Treatment effectiveness evaluation employs survival analysis and cost-effectiveness comparison of maintenance interventions under local conditions.

1.4.4. Predictive Modeling

The use of predictive modelling captures complex non-linear interactions between performance drivers to identify key deterioration trends. Local calibration adapts models to Prince George's specific conditions using regional data. Split-sample validation assesses model performance using R^2, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics across different road categories and environmental conditions.

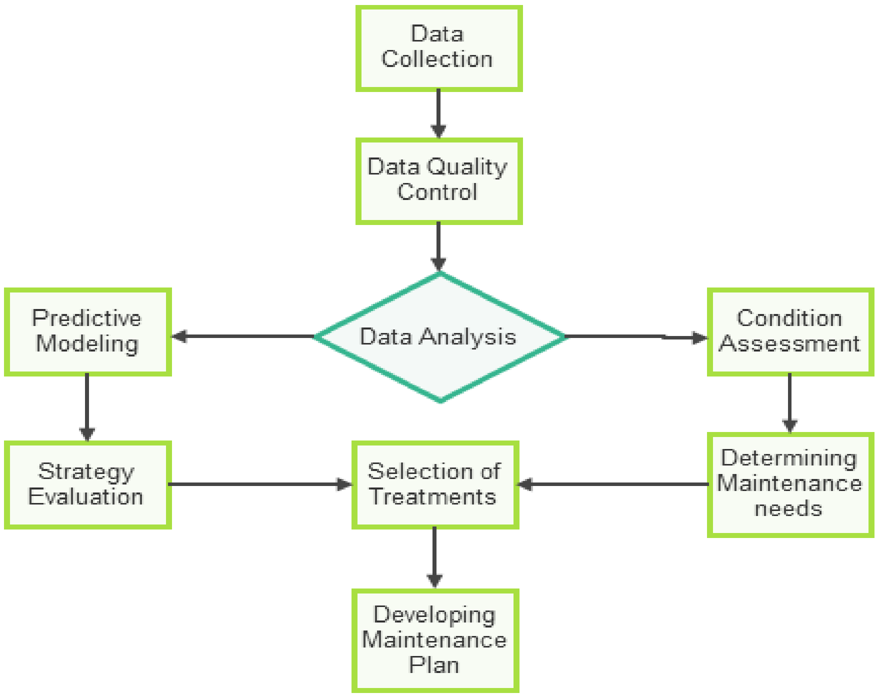


Figure 1 Research methodology flowchart illustrating the systematic progression from data collection through predictive modeling to optimization framework development.

1.4.5. Optimization Framework

Multi-Criteria Decision Analysis integrates performance, cost, and sustainability objectives for systematic maintenance alternative evaluation. Climate-adaptive strategies optimize seasonal maintenance windows and incorporate risk-based approaches. Life-cycle cost analysis provides comprehensive economic evaluation balancing performance objectives with budget constraints.

1.4.6. Implementation

Framework validation employs retrospective analysis and scenario testing under varying conditions. RStudio provides statistical analysis and modeling capabilities while ArcGIS enables spatial analysis and visualization. Quality assurance protocols ensure professional standards for municipal infrastructure management applications.

1.5.Organization of Thesis

This thesis is organized into five chapters that collectively address the research objectives, document the methodology, present the findings, and provide actionable recommendations. The structure ensures a logical flow from background context to practical implementation, emphasizing both technical rigor and sustainability principles.

Chapter 1 – Introduction

This chapter provides the foundation for the research by establishing the background and context of pavement management in northern climates, outlining the specific challenges faced by the City of Prince George, and defining the research objectives and questions. It also highlights the significance of the study for both local application and broader contributions to sustainable infrastructure management.

Chapter 2 – Literature Review

This chapter presents a comprehensive review of prior research in pavement management systems, with emphasis on cold-climate applications, climate-adaptive strategies, and sustainability integration. It identifies research gaps relevant to northern British Columbia and establishes the theoretical foundation for the research. The review also examines recent advances in predictive modeling, deterioration analysis, and economic evaluation methods relevant to sustainable pavement management.

Chapter 3 – Pavement Management Systems: Concepts and Context

This chapter describes the key concepts, methods, and contextual factors underlying pavement management systems. Topics include pavement condition indices, data collection methods and equipment, traffic data in PMS, pavement distress surveys, distress types, road classification, and historical maintenance practices. The chapter also reviews relevant policies, technical reports, and data specific to Prince George and the province of British Columbia.

Chapter 4 – Methodology and Research Tools

This chapter details the study area, datasets, and tools used in the research, including RStudio, Python, and GIS. It describes the modeling approaches—Random Forest, Multiple Linear Regression, and Artificial Neural Networks—along with data preparation procedures, model calibration, and performance evaluation criteria such as Mean Squared Error (MSE), Root Mean Square Error (RMSE), and coefficient of determination (R^2).

Chapter 5 – Results, Discussion, and Recommendations

The final chapter presents the results of the pavement condition assessment and predictive modeling, including analysis of distress trends and model performance. It discusses the implications of the findings for pavement management policy and planning, provides practical recommendations for the City of Prince George, and outlines potential areas for future research.

2. Chapter 2 : Literature Review

2.1 Overview of Existing Research

Pavement Management Systems (PMS) have emerged as critical tools for optimizing infrastructure maintenance and rehabilitation strategies, representing a systematic approach of decision-making that integrates data collection, performance modeling, and cost-effectiveness analysis. The evolution of PMS research has been driven by the recognition that traditional reactive maintenance approaches are insufficient for managing aging infrastructure networks under increasing traffic loads and constrained budgets.

The conceptual foundation of modern pavement management was established by Haas, who introduced PMS as a structured approach emphasizing cost-effectiveness and optimization in maintenance planning (Haas et al., 1994). This foundational work demonstrated that systematic approaches to pavement management could reduce lifecycle costs by up to 30% compared to reactive maintenance strategies. Building upon this foundation, Hudson expanded the scope by integrating engineering and economic principles, focusing on infrastructure management strategies that encompass design, construction, maintenance, rehabilitation, and research activities (Hudson et al., 1997).

Contemporary research has increasingly focused on advanced analytical techniques, building upon earlier findings that demonstrated the effectiveness of systematic approaches. Anastasopoulos provided early evidence that optimized maintenance interventions can extend pavement life by 20-40% when properly timed (Anastasopoulos et al., 2009). This foundational research supported the subsequent development of more sophisticated analytical frameworks. Smith later emphasized the integration of asset management perspectives into pavement decision-making processes, highlighting the importance of prioritizing maintenance based on objective road condition data rather than subjective assessments (Smith et al., 2014). This evolution toward data-driven approaches has been further validated by recent advances in machine learning and predictive modeling techniques.

The evolution of PMS research has also been characterized by increasing sophistication in predictive modeling techniques. Recent studies have demonstrated significant improvements in prediction accuracy through the application of machine learning algorithms. Ali showed that artificial neural network models achieved R^2 values of 98.6% for 2018 pavement condition predictions and 99.3% for 2021 predictions, substantially outperforming traditional multiple linear regression approaches, which achieved R^2 values of only 48.0% and 63.0% respectively (Ali et al., 2023).

US Federal initiatives contributed to the direction of PMS research and implementation. The Federal Highway Administration's Pavement Management Roadmap established a vision for pavement management advancement over the next decade, recognizing transformative innovations in data collection, performance modeling, and decision-making processes (Federal Highway

Administration, 2022). The roadmap emphasizes the importance of collaborative efforts between industry, academia, and transportation agencies to reduce duplication of effort and advance innovative pavement management practices.

2.2 Identifying Research Gaps

2.2.1 Limited Availability of Locally Calibrated Research

A critical gap exists in the availability of locally calibrated PMS models for Northern British Columbia's unique environmental and traffic conditions. Most existing studies focus on urban and temperate regions where climate and traffic conditions differ significantly from those experienced in Northern BC. Research by Ekramnia and Nasimifar emphasized that existing models often fail to provide accurate deterioration predictions for extreme climate conditions, leading to suboptimal maintenance planning and increased lifecycle costs (Ekramnia & Nasimifar, 2022).

The calibration challenges are exemplified by Ontario's experience with AASHTOWare implementation. Hamdi demonstrated that most North American studies of local calibration concluded that national calibration coefficients fail to offer reliable accuracy or precision (Hamdi, 2015). The AASHTOWare system was developed based on Long Term Pavement Performance (LTPP) sections from various regions, showing significant variation in binder and aggregate properties, climate conditions, and traffic spectrum. Local calibration projects have consistently shown enhanced model accuracy in predicting pavement performance, with statistical analysis demonstrating serious need for incorporation of local calibrations into predictive models.

Similarly, Washington State Department of Transportation's calibration efforts revealed substantial regional variations in pavement performance. Li found that default calibration factors required significant adjustment, with rutting predictions showing almost perfect correlation with measured values only after local calibration (Li, 2009). The study utilized both split-sample and jackknife testing approaches, demonstrating that local calibration improves prediction stability and accuracy even with limited sample sizes.

2.2.2 Geographic Relevance and Northern Climate Considerations

The geographic specificity of pavement management challenges represents a significant research gap, particularly for cold climate regions. Research has shown that climate change impacts vary substantially by geographic location and climate zone. Studies conducted across different European locations demonstrated varying responses to temperature and precipitation changes, with some regions experiencing increases in all distress types except thermal cracking due to temperature rise (Qiao et al., 2020).

Swarna identified critical limitations in existing temperature models, noting that the LTPP model was developed only for maximum latitudes of 52 degrees and has had limited testing in Northern Canadian climates (Swarna, 2022). This limitation is particularly significant for Prince George, located at approximately 53.9 degrees north latitude, where extreme temperatures cannot be accurately represented by models developed for southern regions.

The Canadian context presents unique challenges that are not adequately addressed in international literature. The Canadian Strategic Highway Research Program initiated research in the late 1980s to study climate effects on roadway efficiency, establishing test sites in Lamont, Alberta; Hearst, Ontario; and Sherbrooke, Quebec (Gavin et al., 2003). However, these efforts focused primarily on asphalt properties at low temperatures rather than comprehensive PMS frameworks for northern regions.

2.2.3 Lack of Strategic Data Utilization in Predictive Models

A significant gap exists in the strategic integration of real-world pavement condition data with predictive modeling frameworks. While various statistical and machine learning models have been proposed for pavement condition forecasting, many studies fail to integrate comprehensive datasets that reflect local traffic patterns, material properties, and environmental stressors (Ali, 2022). This limitation reduces the applicability of models for regional pavement management, as they do not accurately capture specific deterioration patterns observed in Northern BC.

The Federal Highway Administration's pavement management primer highlights this challenge, noting that effective pavement management requires integration of multiple data sources including inventory data, condition assessment results, performance prediction models, and strategic-level data (Federal Highway Administration, 2022). However, most agencies struggle to achieve this integration due to technical and resource constraints.

Li addressed this gap by developing a hybrid neural network approach that considers maintenance impacts on data through a "restart point method" for data cleaning (Li et al., 2022). Their research demonstrated that most existing studies simply remove noisy data instead of processing it meticulously and fail to consider maintenance impacts on performance data, which can lead to significant errors in performance prediction.

2.2.4 Absence of Comprehensive Climate Adaptation Strategies

Current PMS frameworks lack comprehensive climate adaptation strategies specifically designed for Northern BC conditions. Although research emphasizes the importance of incorporating climate resilience into pavement management, a few studies have focused on how specific climate factors such as snow accumulation, extended freeze-thaw cycles, and extreme temperature fluctuations affect pavement maintenance (Guha et al., 2022).

Research has shown that climate change can cause changes in pavement lifecycle costs depending on changes in climate stressors, pavement structure, materials, and maintenance regimes. Qiao demonstrated that maintenance interventions may be triggered much earlier than expected due to climate change, and that adapting to early maintenance can minimize total lifecycle costs while improving pavement resilience (Qiao et al., 2015). However, this research has not been specifically adapted to Northern BC conditions.

Studies utilizing multiple climate models have shown that increased temperatures can lead to asphalt rutting increases of 9-40% and fatigue cracking increases of 2-9% across various United

States locations (Swarna, 2022). However, similar comprehensive studies have not been conducted for Canadian northern climates, representing a significant gap in understanding climate change impacts on regional pavement performance.

2.2.5 Deficiency in Treatment Effectiveness Evaluation

Existing PMS frameworks show significant deficiencies in evaluating treatment effectiveness under diverse climate and traffic conditions. Hafez and Ksaibati emphasized the need for improved evaluation metrics to assess long-term performance of various pavement treatments, noting that existing models often analyze effectiveness using short-term performance data (Hafez & Ksaibati, 2021). Their research on low-volume roads demonstrated that adjusted treatment strategies could extend pavement life by 15-25% when properly evaluated.

The treatment effectiveness challenge is compounded by the diversity of available interventions. Research by Al-Swailmi identified multiple maintenance procedures including sealing, cobbling, milling, overlay application, and repair (Al-Swailmi et al., 1999). Each rehabilitation technique has direct effects on pavement cycle-life, but the effectiveness varies significantly based on local conditions including climate, traffic, and material properties.

Limited research has been conducted on treatment effectiveness in mitigating climate-induced pavement deterioration, particularly in cold regions where environmental stressors vary considerably compared to other climates. This gap is particularly concerning for Prince George, where freeze-thaw cycles and heavy snowfall accelerate pavement deterioration and may require specialized treatment approaches.

2.3 Review of Deterioration Models, Optimization Techniques, and Performance Indicators

2.3.1 Traditional Deterioration Models

Traditional pavement deterioration models have primarily relied on deterministic and statistical approaches, with multiple linear regression (MLR) serving as the foundation for many early PMS applications. Research by Ali demonstrated the limitations of traditional MLR approaches, showing that linear assumptions inherent in MLR models fail to capture the complex, non-linear interactions present in pavement deterioration, particularly under extreme climate conditions (Ali et al., 2023).

Ali et al., 2023 in Figure 2, draw the following conclusions based on the research model:

- PCI (2018): ANN has the best performance among the three techniques. The statistical measures for the ANN model are R2 = 98.6%, RMSE = 0.88, and MAE = 0.73, and the worst-performing model was MLR, with an R2 = 48.0%, RMSE = 14.05, and MAE = 11.37 (Ali et al., 2023).
- PCI (2021): ANN has the best performance among the three techniques. The statistical measures for the ANN model are R2 = 99.3%, RMSE = 0.72, and MAE = 0.59, and the

worst-performing model was MLR, with an R2 = 63.0%, RMSE = 9.93, and MAE =7.84 (Ali et al., 2023).

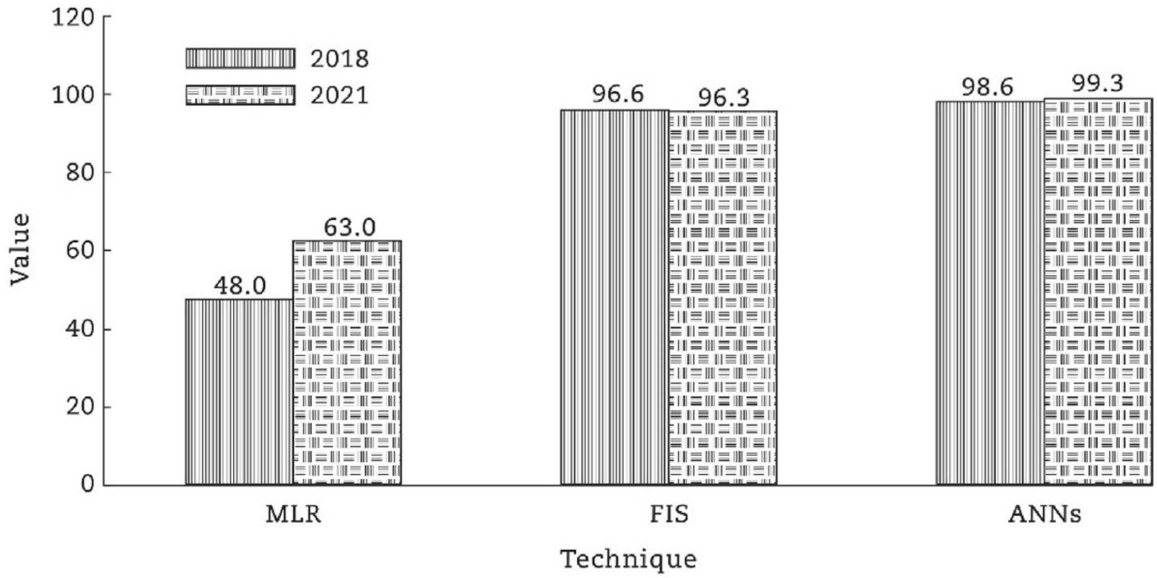


Figure 2 The performance of the MLR, FIS, and ANN models in predicting PCI, measured by their R^2 values (Ali et al., 2023)

Conventional deterioration modeling efforts focused on simplified pavement performance models. Lee et al. (1993) developed pavement performance models using empirical approaches, while earlier researchers like Butt et al. (1987) introduced Markov process-based prediction models for pavement performance. These foundational models established the basic framework of performance prediction but were limited by their reliance on deterministic assumptions and simplified deterioration relationships.

Saliminejad provided detailed analysis of how measurement errors affect different modeling approaches, demonstrating that regression models using least-squares methods are subject to errors propagated from estimated parameters (Saliminejad, 2012). Random errors in condition index data do not cause bias in linear regression models within large datasets, but random errors in age data bias predictions by causing slope underestimation, resulting in predicted condition indices that are typically smaller than true values.

On the pavement design side, the development of mechanistic-empirical approaches represented a significant advancement over purely empirical models. According to AASHTO, pavement performance is defined as the serviceability trend of the pavement over its design period, with serviceability indicating the ability of the pavement in its existing condition to serve traffic demand (AASHTO, 1993). This definition provided the foundation for more sophisticated modeling approaches that consider both structural and functional performance aspects.

2.3.2 Advanced Machine Learning Approaches

Artificial Neural Networks

The application of artificial neural networks (ANN) in pavement management has demonstrated significant improvements over traditional statistical methods. Li developed a comprehensive ANN approach that achieved remarkable prediction accuracy, with their hybrid neural network combining backpropagation neural networks (BPNN) and Long Short-Term Memory (LSTM) models (Li et al., 2022). Their research demonstrated that ANN models could process multiple variables simultaneously while capturing complex non-linear relationships that traditional methods cannot adequately represent.

The effectiveness of ANN approaches is particularly evident in their ability to handle large-scale datasets with multiple influencing variables. Research has shown that when databases provide stable data so urces, ANN models predict International Roughness Index (IRI) better than linear regression approaches (Li et al., 2022). The backpropagation neural network effectively solves problems of insufficient and inaccurate pavement condition data that plague traditional modeling approaches.

Attoh-Okine (2002) demonstrated the effectiveness of combining rough set analysis with artificial neural networks in doweled-pavement-performance modeling, showing that hybrid approaches can leverage the strengths of different analytical techniques. This research highlighted the potential for developing sophisticated modeling frameworks that combine multiple analytical approaches to achieve superior prediction accuracy.

The integration of genetic algorithms with neural networks has shown promise for optimizing model parameters and improving prediction accuracy. Zhao et al. (2021) applied genetic algorithm optimization to ANN models for predicting viscosity of asphalt pavement adhesives, demonstrating that this approach replaces the reverse error transmission process of BPNN models and improves convergence efficiency.

Random Forest and Ensemble Methods

Random Forest (RF) has emerged as a particularly effective ensemble learning method for pavement management applications. Marcelino et al. (2019) developed a general machine learning algorithm based on random forest that effectively addresses continuous prediction problems over time and sensitivity analysis of pavement roughness. Their research demonstrated that RF algorithms exhibit strong nonlinear fitting ability, lack complicated theoretical derivation, and provide real-time prediction capacity.

Gong et al. (2018) demonstrated that RF models could achieve up to 90% accuracy in pavement condition forecasting, significantly outperforming traditional regression approaches. The effectiveness of RF stems from its ability to handle large datasets efficiently while maintaining robustness against noise and overfitting. The ensemble nature of RF enhances predictive accuracy by reducing both variance and bias across different data subsets.

2.3.3 Optimization Techniques

Mathematical Programming Approaches

Mathematical optimization methods play crucial roles in pavement management by enabling systematic selection of maintenance strategies that maximize performance while satisfying budget constraints. Torres-Machí et al. developed an iterative approach for pavement maintenance optimization at network level, demonstrating potential efficiency improvements of up to 25% (Torres-Machí et al., 2014). Their approach differs from traditional sequential methods by allowing selection of suboptimal treatment strategies for individual sections if they contribute to improved overall network performance.

The iterative optimization approach addresses limitations of traditional sequential methods that first define treatment strategies on a section-by-section basis, then select sections to treat until budget is exhausted. The iterative method recognizes that deterioration of a solution at the section level may lead to improvement of the overall solution at the network level, enabling more flexible and effective resource allocation.

Multi-objective optimization approaches have gained prominence as agencies recognize that pavement management decisions involve multiple, sometimes conflicting objectives. Research by Santos demonstrated that multi-objective optimization can maximize network road condition within limited budgets while considering factors such as traffic volume and cost-effectiveness (Santos et al., 2017). Their work showed that preventive and minor rehabilitation treatments are more cost-effective than reconstruction, and that budget allocation should exceed certain thresholds to achieve maximum societal benefit.

Geographic Information Systems Integration

The integration of Geographic Information Systems (GIS) with optimization techniques has revolutionized spatial analysis capabilities in pavement management. Research by Obaidat demonstrated the effectiveness of integrating GIS toward efficient pavement maintenance management (Obaidat et al., 2018). Their work showed that GIS integration enables dynamic highway section color coding, access to sectional data through graphical models, and enhanced visualization of pavement management analysis.

Recent developments in GIS-based pavement management have focused on 3D modeling and advanced visualization capabilities. Research has shown that reconstruction of 3D GIS models, high-definition mapping, and new applications for cities require accurate and efficient data collection and scene perception of urban environments (Zagvozda et al., 2019). The integration of mobile LiDAR sensors with camera systems has enabled comprehensive pavement condition data collection while providing enhanced visualization capabilities for decision-makers (Balzi et al., 2023). Studies have demonstrated that even though 3D mobile LiDAR data has become increasingly popular, this method cannot accurately detect pavement distress such as cracks, necessitating the use of RGB images for correct distress extraction (Balzi et al., 2023).

European implementations have demonstrated the effectiveness of GIS-based optimization approaches. The ViaBEL tool was developed for secondary road networks in Belgium and incorporated GIS-based decision processes for pavement management, providing structured frameworks for maintenance prioritization and resource allocation (Van Geem et al., 2012). This tool demonstrates the potential for developing sophisticated GIS-based optimization systems appropriate for regional and municipal applications.

Multi-Criteria Decision Analysis

Contemporary pavement management increasingly recognizes that decisions involve multiple, sometimes conflicting objectives including cost minimization, performance maximization, environmental impact reduction, and user satisfaction. Multi-criteria decision analysis (MCDA) frameworks provide structured approaches for evaluating alternatives considering multiple objectives simultaneously (Torres-Machí et al., 2014).

Research has emphasized the importance of incorporating sustainability considerations into pavement management decision-making (Santos et al., 2017). This requires consideration of economic, social, technical, environmental, and political aspects throughout the pavement lifecycle (Torres-Machí et al., 2014). Different indicators have been developed for assessing these aspects, including present worth cost for economic evaluation, safety and comfort for social considerations, roughness for technical performance, and air pollution for environmental impact assessment (Torres-Machí et al., 2014).

The integration of multiple criteria enables more comprehensive evaluation of maintenance alternatives. Research has shown that ranking based on economic analysis allows rational comparison among alternatives because it considers both costs and benefits, leading to more informed decision-making compared to approaches based solely on condition assessment or subjective judgment (Al-Swailmi et al., 1999). Shah et al. (2012) applied this method to select sections for treatment in a road network in India considering criteria such as traffic, connectivity, and road and drainage conditions (Torres-Machí et al., 2014).

2.3.4 Performance Indicators and Assessment Methods

Pavement Distress Index (PDI)

Pavement condition assessment relies heavily on standardized indices that quantify pavement serviceability and structural integrity (Federal Highway Administration, 2022). The Pavement Distress Index (PDI) represents a critical performance indicator that has been specifically adapted for Canadian conditions, particularly in BC (BCMoTI, 2020). Research has shown significant variations in the effectiveness of different condition assessment approaches, with advanced analytical methods demonstrating superior accuracy compared to traditional assessment techniques (Ali et al., 2023).

The development of composite condition indices that integrate multiple distress types and functional classifications has shown promise for providing more comprehensive pavement assessment (Saliminejad, 2012). Research has demonstrated that composite indices considering pavement surface distresses, traffic information, and expert opinion can provide more accurate representations of overall pavement condition than single-parameter approaches (Guha et al., 2022). The PDI methodology incorporates systematic evaluation of distress types including rutting, cracking patterns, surface deterioration, and structural adequacy to provide comprehensive condition assessment (BCMoTI, 2020).

International variations in condition assessment approaches reflect different prioritization strategies and resource constraints (Grilli et al., 2019). Research has shown that different countries and agencies employ varying condition rating systems, ranging from simple visual assessments to sophisticated automated measurement systems (Federal Highway Administration, 2022). The choice of assessment method significantly affects the accuracy and reliability of condition data, which in turn impacts the effectiveness of management decisions (Saliminejad, 2012). This study have shown that quality assurance programs can result in adjustments of predicted maintenance treatments by up to 21%, highlighting the substantial impact of assessment methodology on management outcomes (Saliminejad, 2012).

International Roughness Index (IRI)

The International Roughness Index (IRI) serves as a critical functional performance indicator that directly relates to user comfort and vehicle operating costs (Federal Highway Administration, 2022). Research has shown strong correlations between IRI and various pavement distress types, making it valuable for both condition assessment and performance prediction applications (Li et al., 2022). IRI measurements provide objective assessment of pavement smoothness that enables quantitative evaluation of ride quality and functional performance (Hamdi, 2015).

Studies utilizing machine learning approaches for IRI prediction have demonstrated significant improvements over traditional methods (Gong et al., 2018; Marcelino et al., 2019). Random forest algorithms have shown particular effectiveness for addressing continuous prediction problems over time and sensitivity analysis of IRI (Marcelino et al., 2019). Research has consistently shown that advanced modeling approaches can achieve prediction accuracies exceeding 90% for IRI forecasting, substantially outperforming traditional statistical methods (Gong et al., 2018; Ali et al., 2023).

Khawaga et al. (2021) developed Markov and S-curve models for IRI prediction, demonstrating that Markov models performed better than S-curve models in terms of comprehensive factor consideration (Li et al., 2022). Their research highlighted the importance of selecting appropriate modeling approaches based on specific application requirements and data characteristics, particularly for northern climate applications where freeze-thaw cycles significantly impact pavement roughness (Qiao et al., 2020). Climate factors including temperature fluctuations and precipitation patterns have been shown to significantly influence IRI progression patterns (Swarna, 2022).

The integration of IRI with other performance indicators provides comprehensive assessment frameworks that consider both structural and functional pavement performance (Torres-Machí et al., 2014). This integrated approach enables more informed decision-making regarding maintenance timing and treatment selection (Federal Highway Administration, 2022). Research has shown that IRI-based performance prediction requires careful consideration of climate factors, traffic loading patterns, and pavement structural characteristics to achieve accurate forecasting for maintenance planning applications (Li, 2009; Hamdi, 2015). Studies have demonstrated that local calibration of IRI prediction models is essential for achieving reliable performance forecasting under specific regional conditions (Li, 2009).

2.4 Insights from Pavement Management Case Studies

2.4.1 North American Implementations

California DOT (Caltrans) Experience

Wang and Pyle documented Caltrans' experience implementing a comprehensive pavement management system, highlighting challenges and successes in large-scale PMS deployment (Wang & Pyle, 2019). The Caltrans implementation emphasized the importance of integrating pavement management with broader transportation asset management frameworks.

The California experience demonstrated the critical role of stakeholder engagement and organizational change management in successful PMS implementation. The research showed that technical excellence in system design must be complemented by effective organizational processes and staff training to achieve successful implementation outcomes.

Caltrans' approach to pavement management integration with asset management provides a model for other agencies seeking to align project-level pavement decisions with network-level strategic objectives. The research demonstrated practical approaches for establishing feedback loops between pavement design, pavement management, and transportation asset management units.

Ontario's AASHTOWare Calibration Experience

Ontario's experience with local calibration of AASHTOWare provides valuable insights for regional PMS development. Hamdi (2015) demonstrated that significant improvements in prediction accuracy can be achieved through local calibration, with statistical analysis showing substantial enhancements in model performance for Ontario flexible pavements (Hamdi, 2015). The study found that national calibration coefficients failed to offer reliable accuracy for local conditions, necessitating extensive calibration efforts using provincial pavement management system data.

The Ontario calibration project revealed important findings about regional model adaptation. The study concluded that calibration coefficients should be updated as performance databases expand and innovative materials are utilized in provincial pavement designs (Hamdi, 2015). This finding emphasizes the dynamic nature of calibration requirements and the need for ongoing model refinement as local experience accumulates.

Key Performance Indicators such as International Roughness Index and Pavement Condition Index were evaluated, with the research demonstrating that locally calibrated models significantly enhance prediction accuracy for pavement performance (Hamdi, 2015). The study showed that PMS data can be effectively utilized to improve AASHTOWare model accuracy, providing a framework for similar calibration efforts in other jurisdictions.

Washington State DOT Implementation

Washington State Department of Transportation's pavement management implementation demonstrates the effectiveness of systematic calibration approaches. Li (2009) documented the use of split-sample and jackknife testing approaches for local calibration of mechanistic-empirical design models (Li, 2009). The split-sample approach used half of selected sections for calibration and the other half for validation, while the jackknife approach withheld each section for prediction measurements with other sections used for calibration.

The Washington State project achieved remarkable success in rutting prediction calibration. Final calibration factors were chosen based on root-mean-square error , with results showing that predicted rutting values closely matched measured data from the state's PMS (Li, 2009). The study demonstrated consistency between predicted and measured rutting values for both western and eastern Washington regions, indicating the effectiveness of regional calibration approaches.

The research concluded that local calibration processes should be finalized through model validation using independent datasets not included in calibration processes (Li, 2009). This finding provides important guidance for ensuring the robustness and reliability of locally calibrated models.

2.4.2 European Implementations

Italian ANAS Case Study

The Italian National Road Agency (ANAS) experience provides insights into large-scale pavement management implementation under resource constraints. Borghetti documented ANAS's approach to managing approximately 32,000 km of state roads, highways, and freeway junctions under direct management (Borghetti et al., 2024). The ANAS network represents the largest road infrastructure management operation in Italy in terms of network extent.

The ANAS case study demonstrates the challenges faced by large road agencies in prioritizing maintenance interventions under budget constraints. With regions proposing more than 1,000 interventions and financial needs exceeding 3.5 billion euros in some cases, ANAS requires sophisticated prioritization methodologies to optimize resource allocation (Borghetti et al., 2024). The average regional requirement approaches 1.5 billion euros over the reference period (2022-2026), highlighting the scale of infrastructure investment needs.

ANAS's approach to maintenance includes identification of network needs using standardized parameters, definition of interventions based on available funds, and implementation focused on process efficiency (Borghetti et al., 2024). This systematic approach provides a framework for other agencies facing similar challenges in managing large road networks under financial constraints.

The research demonstrates the application of multi-criteria decision-making approaches that consider category, asset, and typology factors in maintenance prioritization. The final prioritization formula applied weights of 60% to category factors and 40% to asset factors, with typology factors having no influence for most intervention types (Borghetti et al., 2024).

Republic of San Marino Implementation

Grilli documented the development of pavement management guidelines for the Republic of San Marino, demonstrating how small jurisdictions can implement effective PMS frameworks despite resource constraints (Grilli et al., 2019). The San Marino implementation emphasizes the use of GIS tools for data collection, management, and analysis of road inventory and monitoring data.

The San Marino case study demonstrates the effectiveness of customized GIS-based tools for standardizing road data collection, managing monitoring and inventory data, identifying maintenance priority ratings, and planning maintenance works from long-term perspectives (Balzi et al., 2023). The implementation utilized a strategic index approach for comparing different maintenance strategies, with the strategic index calculated as a function of priority index that depends on technical factors including pavement condition, roughness, traffic levels, network hierarchy, road functional classification, road relevance for strategic purposes, and maintenance repair history.

The research showed that maintenance scenarios can be characterized and compared using specific evolution of strategic index values over time, enabling rational comparison of alternative maintenance strategies (Balzi et al., 2023). This approach provides a practical framework for resource-constrained agencies to implement sophisticated PMS capabilities.

Belgian ViaBEL System

Van Geem documented the development of ViaBEL, a decision-making tool for pavement management of secondary road networks in Belgium (Van Geem et al., 2012). The ViaBEL system demonstrates how European agencies have developed sophisticated tools specifically designed for regional and local road management applications.

The ViaBEL implementation emphasizes visual inspection quality assurance for pavement management of communal road networks (Van Geem & Massart, 2017). The system provides structured frameworks for decision processes in pavement management while maintaining cost-effectiveness appropriate for secondary road networks.

The Belgian experience demonstrates the importance of developing management tools that are appropriately scaled to the technical and financial capabilities of regional agencies. The ViaBEL system provides practical approaches for implementing systematic pavement management without requiring the sophisticated technical infrastructure associated with major highway agency implementations.

2.4.3 Low-Cost and Municipal Applications

Low-Volume Road Management

Hafez and Ksaibati studied the effectiveness of parameter adjustments in pavement management systems for low-volume paved roads, demonstrating potential pavement life extensions of 15-25% through optimized treatment strategies (Hafez & Ksaibati, 2021). Their research addresses the specific challenges faced by agencies responsible for roads with limited traffic but substantial infrastructure investment requirements.

The low-volume road research emphasized the importance of developing management approaches that account for different deterioration patterns and maintenance requirements compared to high-traffic facilities. The study showed that parameters optimized for major highways may not be appropriate for low-volume applications, necessitating specialized calibration and optimization approaches.

Van Geem and Massart documented implementation and benefits of low-cost PMS for municipal road networks, demonstrating practical approaches for achieving systematic pavement management under severe budget constraints (Van Geem & Massart, 2018). Their research showed that significant improvements in maintenance effectiveness can be achieved through systematic approaches even when sophisticated technical resources are not available.

Urban Applications

Loprencipe developed sustainable pavement management systems for urban areas considering vehicle operating costs (Loprencipe et al., 2017). Their research demonstrated the integration of user cost considerations with traditional pavement management approaches, providing more comprehensive frameworks for urban pavement management decision-making.

The urban pavement management research emphasized the importance of considering user impacts and vehicle operating costs in addition to agency maintenance costs. The study showed that integrated approaches considering both agency and user costs can lead to different optimization outcomes compared to traditional approaches focused solely on agency costs.

Vines-Cavanaugh et al. documented city-wide application of affordable and rapid pavement management systems, demonstrating practical approaches for implementing systematic condition assessment and management planning in urban environments (Vines-Cavanaugh et al., 2017). Their research showed that cost-effective technologies can enable comprehensive pavement management even for resource-constrained municipal agencies.

2.5 Literature Review Summary

Table 1 Details of previous research activities on PMS

Research team	Year	Case study Location	Software/ Methode	Main points	Reference
Haas, Hudson, & Zaniewski	1994	North America	PMS Optimization Model	- Introduced a structured PMS approach for optimizing maintenance planning. - Demonstrated lifecycle cost reduction of up to 30% through systematic strategies.	[Haas 1994]
Hudson, Haas, & Uddin	1997	Global	Infrastructure Modeling	- Integrated engineering and economic models to enhance PMS decision-making. - Emphasized full-cycle infrastructure management from design to rehabilitation.	[Hudson 1997]
Anastasopoulos, Mannering, & Haddock	2009	USA	Service Life Analysis	- Developed service life curves to evaluate rehabilitation effectiveness. - Showed optimized interventions extend pavement life by 20–40%.	[Anastasopoulos et al. 2009]
Smith, Pontius, & Galehouse	2014	USA	PMS Data Integration	- Highlighted the importance of data-driven decision processes in PMS. - Introduced maintenance prioritization based on objective road condition data.	[Smith 2014]
Ali et al.	2023	Global	Machine Learning Models	- Applied neural networks achieving $R^2 > 98\%$ accuracy in condition predictions. - Outperformed multiple regression models in handling non-linear deterioration patterns.	[Ali 2023]
Federal Highway Administration	2022	USA	Pavement Management Roadmap	- Established a 10-year roadmap for PMS improvements. - Focused on advancing predictive analytics and fostering industry-academia collaboration.	[FHWA 2022]
Ekramnia & Nasimifar	2022	Global	Treatment Prioritization Model	- Created a treatment prioritization tool improving efficiency by 30%. - Enhanced network-level rehabilitation planning under limited resources.	[Ekramnia 2022]
Hamdi	2015	Ontario, Canada	AASHTOWare Calibration	- Showed significant improvements in prediction accuracy via local calibration. - Highlighted the shortcomings of national calibration coefficients.	[Hamdi 2015]
Li	2009	Washington, USA	Mechanistic-Empirical Calibration	- Developed calibration factors achieving near-perfect rutting predictions. - Demonstrated region-specific model adaptation in Washington State.	[Li 2009]
Qiao et al.	2020	Global	Climate Change Adaptation Model	- Analyzed climate impacts on pavement deterioration worldwide. - Suggested adaptive maintenance strategies to counter environmental damage.	[Qiao 2020]
Swarna	2022	Global	Climate Modeling	- Identified limitations in temperature modeling for high latitudes. - Highlighted the absence of suitable models for Northern Canadian climates.	[Swarna 2022]
Gavin et al.	2003	Canada	Climate Effects Research	- Investigated Canadian climate effects on pavement performance. - Initiated test sites studying asphalt properties in extreme cold.	[Gavin 2003]

Research team	Year	Case study Location	Software/ Methode	Main points	Reference
Ali	2022	Canada	Soft Computing	- Used ANN to predict asphalt condition with improved accuracy. - Enhanced Pavement Condition Index estimation through soft computing.	[Ali 2022]
Li et al.	2022	Global	Hybrid Neural Network	- Combined BPNN and LSTM neural networks for hybrid modeling. - Introduced data cleaning and restart point methodology.	[Li 2022]
Attoh-Okine	2002	Global	Hybrid ANN Approach	- Demonstrated integration of rough set analysis with ANN models. - Showed hybrid approaches handle incomplete datasets effectively.	[Attoh-Okine 2002]
Zhao et al.	2021	Global	Genetic Algorithm with ANN	- Improved ANN model convergence with genetic algorithms. - Enhanced accuracy in predicting asphalt adhesive viscosity.	[Zhao 2021]
Marcelino et al.	2019	Global	Random Forest Algorithm	- Applied RF algorithm for roughness sensitivity analysis. - Provided continuous prediction with real-time performance.	[Marcelino 2019]
Gong et al.	2018	Global	Random Forest Model	- Achieved 90% prediction accuracy using RF. - Outperformed traditional regression methods in large datasets.	[Gong 2018]
Saliminejad	2012	Global	Error Analysis	- Showed parameter errors cause slope bias in regression models. - Identified effects of random vs. systematic data errors.	[Saliminejad 2012]
Torres-Machí et al.	2014	Spain	Iterative Optimization Model	- Developed an iterative optimization model improving network efficiency by 25%. - Highlighted holistic vs. sequential treatment strategies.	[Torres-Machí 2014]
Santos et al.	2017	Global	Multi-objective Optimization	- Applied multi-objective optimization for treatment selection. - Balanced road condition, traffic volume, and cost constraints.	[Santos 2017]
Obaidat et al.	2018	Global	GIS Integration	- Integrated GIS enhancing visualization and dynamic analysis. - Enabled sectional data retrieval via graphical models.	[Obaidat 2018]
Zagvozda et al.	2019	Global	3D GIS Modeling	- Advanced 3D GIS modeling for urban PMS applications. - Enabled accurate scene perception for city infrastructure.	[Zagvozda 2019]
Balzi et al.	2023	Global	Mobile LiDAR GIS	- Used LiDAR with RGB cameras to enhance distress detection accuracy. - Improved 3D data for pavement analysis and planning.	[Balzi et al. 2023]

3. Chapter 3: Data Collection and Pre-Processing

3.1 Fundamentals of PMS

Pavement Management Systems represent a systematic approach of optimizing infrastructure maintenance and rehabilitation through data-driven decision-making processes. As established in the literature review (Chapter 2), PMS have evolved from manual inspection methods to sophisticated analytical frameworks that integrate multiple data sources, predictive modeling capabilities, and optimization techniques to support strategic infrastructure stewardship. The fundamentals examined in this chapter provide detailed technical understanding of the core components that comprise effective pavement management, expanding upon the foundational concepts presented in the literature review with specific focus on their application within Prince George's operational context.

The effectiveness of PMS implementation depends upon the integration of multiple interconnected components including inventory management, condition assessment, performance prediction, treatment optimization, and resource allocation. Each component contributes essential capabilities that collectively enable agencies to transition from reactive maintenance approaches to proactive management strategies that optimize both performance outcomes and resource utilization.

The evolution toward data-driven pavement management reflects broader technological advancements in infrastructure monitoring and analysis capabilities. Contemporary PMS implementations leverage automated data collection technologies, advanced analytical techniques, and sophisticated modeling approaches to enhance decision-making accuracy while reducing reliance on subjective assessments that characterized earlier management approaches.

3.2 Pavement Condition Indices

3.2.1 Pavement Distress Index (PDI)

The Pavement Distress Index represents the primary condition assessment tool employed within Prince George's pavement management framework, providing standardized quantification of pavement surface condition and structural integrity. As established in the technical reports from 2016, 2017, 2020, and 2023, PDI assessment follows the British Columbia Ministry of Transportation and Infrastructure (BCMoTI) Condition Rating Manual methodology, which represents a localized adaptation of the internationally recognized PAVER Pavement Condition Index model developed by the U.S. Army Corps of Engineers.

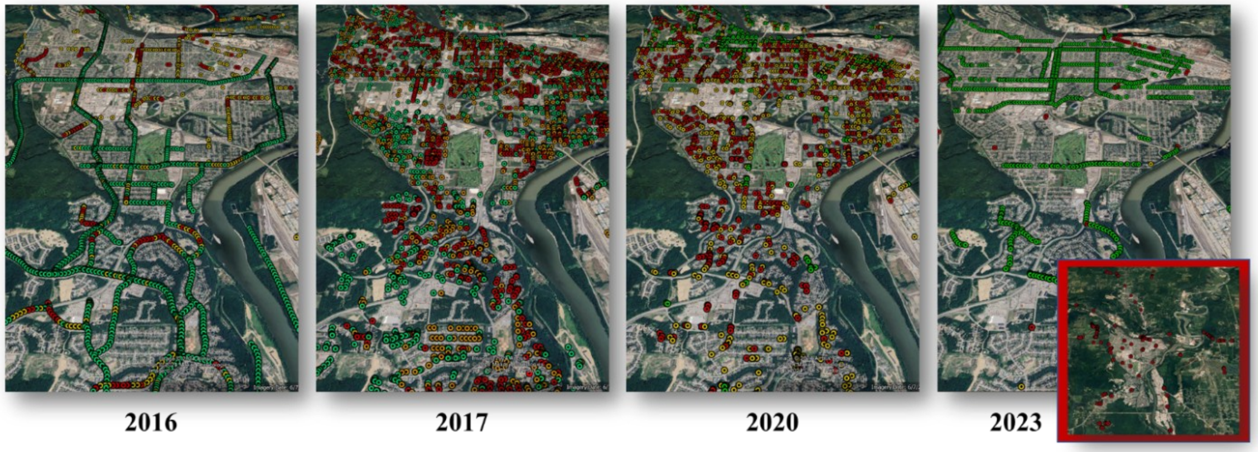


Figure 3 Prince George Pavement Condition over the years plotted on Google Earth.

The PDI model integrates severity and density ratings for each distress type, consolidating multiple condition indicators into a unified distress score on a declining scale from 10 to 0, where 10 represents perfect pavement condition and 0 indicates complete failure requiring reconstruction. This standardized scale enables objective comparison of pavement conditions across different road segments and functional classifications within Prince George's network.

The mathematical foundation of PDI calculation employs a deduct value methodology that begins with a perfect score of 10 and systematically subtracts penalty values based on observed distress characteristics. The specific deduct value for each distress type is calculated using the following equation established in the BCMoTI methodology:

$$\text{Deduct} = 10^{(B0 + B1 * \text{Log}(\text{Density}))}$$

The coefficients B0 and B1 vary according to distress type and severity level, with values calibrated specifically for BC pavement conditions and climate factors. These coefficients reflect the relative impact of different distress types on overall pavement performance, with structural distresses such as alligator cracking receiving higher deduct values than surface-related distresses such as bleeding or minor raveling.

Table 2 Coefficients to Calculate the Deducts of PDI

Distress	Low Severity		Moderate Severity		High Severity	
	B0	B1	B0	B1	B0	B1
Longitudinal Wheelpath Cracking	-0.80	0.60	-0.50	0.57	-0.25	0.55
Longitudinal Cracking	-0.80	0.50	-0.65	0.57	-0.40	0.55
Pavement Edge Cracking	-0.80	0.40	-0.70	0.55	-0.45	0.55
Transverse Cracking	-0.80	0.60	-0.40	0.55	-0.35	0.57
Meandering Longitudinal Cracking	-0.80	0.55	-0.65	0.60	-0.40	0.57
Alligator Cracking	-	-	-0.40	0.75	-0.25	0.75
Potholes	-0.80	0.40	-0.60	0.57	-0.25	0.57
Rutting	-0.75	0.50	-0.45	0.57	-0.30	0.60

Source: Tetra Tech (2020), ICC (2023)

The PDI classification system employs a three-tier condition rating framework that categorizes pavement segments as Good (PDI > 7), Fair (PDI 5-7), or Poor (PDI < 5). This classification provides intuitive interpretation of condition data while supporting maintenance prioritization and resource allocation decisions. The classification thresholds were established through extensive calibration with British Columbia pavement performance data and reflect the relationship between measured distress levels and functional pavement performance under regional traffic and climate conditions.

3.2.2 International Roughness Index (IRI)

The IRI serves as the primary measure of pavement functional performance within Prince George's assessment framework, quantifying ride quality and user comfort through standardized measurement of pavement surface irregularities. IRI assessment follows the ASTM E1926 specification, providing objective quantification of pavement smoothness that directly correlates with vehicle operating costs, fuel consumption, and user satisfaction (Tetra Tech, 2017; Tetra Tech, 2020).

IRI calculation methodology employs a quarter-car simulation model that measures vertical suspension motion divided by distance traveled, reporting results in millimeters per meter (mm/m) or the equivalent meters per kilometer. The quarter-car model simulates the dynamic response of a standardized vehicle suspension system to pavement surface irregularities, providing consistent measurement methodology that enables comparison across different pavement sections and assessment periods (Tetra Tech, 2020).

The technical measurement process utilizes longitudinal profile data captured through automated data collection systems, typically integrated with Laser Crack Measurement Systems (LCMS) that provide continuous elevation measurements at 1mm resolution. The profile data undergoes mathematical processing through established algorithms that simulate quarter-car response characteristics and generate standardized IRI values for each measurement segment (ICC, 2023). Since its introduction in 1986, IRI has become the road roughness index most used worldwide for evaluating and managing higher speed road networks, with vehicle operating costs including fuel consumption, tire wear, and depreciation rising with increasing roughness and directly correlated to IRI values (Tetra Tech, 2020).

Table 3 Index Ranges for IRI Description

Rating	Alley, Local, and Ramp IRI (mm/m)	Arterial, Major Collector, Minor Collector IRI (mm/m)	Color Code
Good	≤ 4.49	≤ 2.99	Green
Fair	4.49 – 8.08	2.99 – 5.40	Yellow
Poor	> 8.08	> 5.40	Red

Source: Tetra Tech (2020), based on Yu, Chou, & Yau (2006)

The differentiated IRI classification thresholds reflect the varying service expectations associated with different road classifications and typical operating speeds. Arterial and collector roads, which accommodate higher traffic volumes and speeds, require smoother surface conditions (lower IRI values) to maintain acceptable ride quality and minimize vehicle operating costs. Local roads and alleys, characterized by lower operating speeds and different functional requirements, can accommodate higher IRI values while maintaining acceptable service levels.

Research documented in Prince George's technical reports has demonstrated strong correlations between IRI values and vehicle operating costs, with studies indicating that "vehicle operating costs including fuel consumption, tire wear, and depreciation rise with increasing roughness and have been directly correlated to IRI" (Tetra Tech, 2017; Tetra Tech, 2020). These relationships enable economic analysis of pavement condition impacts that extend beyond immediate maintenance costs to encompass broader user cost considerations. For Prince George's transportation network, IRI data supports both condition assessment and economic analysis that informs maintenance prioritization and treatment selection decisions.

3.2.3 Composite Index Integration

The integration of PDI and IRI measurements provides comprehensive pavement assessment that addresses both structural integrity and functional performance characteristics. This dual-index approach enables differentiated analysis of pavement conditions, recognizing that structural adequacy and ride quality may exhibit different deterioration patterns and require distinct maintenance responses.

The complementary nature of PDI and IRI assessment supports sophisticated decision-making frameworks that can optimize maintenance timing and treatment selection based on both immediate functional requirements and long-term structural preservation objectives. This integrated approach aligns with contemporary pavement management best practices that recognize the multidimensional nature of pavement performance and the need for comprehensive assessment methodologies.

3.3 Data Gathering Methods

3.3.1 Automated Distress Survey Technology

Prince George's pavement condition assessment program employs state-of-the-art automated data collection technologies that provide objective, repeatable, and comprehensive evaluation of pavement distress characteristics. The automated approach represents a significant advancement over traditional manual inspection methods, offering enhanced accuracy, consistency, and efficiency in large-scale network assessment.

The primary data collection platform utilized in Prince George's assessment program is the Laser Crack Measurement System (LCMS), deployed through specialized vehicles including Tetra Tech's Pavement Surface Profiler (PSP) 7000 series and ICC International Cybernetics Canada's Road Surface Tester (RST) (Tetra Tech, 2017; Tetra Tech, 2020; ICC, 2023). These systems integrate multiple advanced technologies including high-resolution laser scanning, digital imaging, GPS positioning, and inertial measurement capabilities to capture comprehensive pavement condition data at highway speeds (ICC, 2023).

Figure 4 LCMS-2 RST data collection vehicle (IMS, 2023).

The LCMS technology operates by projecting laser light across the pavement surface and measuring elevation variations with millimeter-level precision. The system captures continuous 2D and 3D images at 1mm resolution across lane widths up to 4 meters, enabling detailed characterization of surface features and distress patterns (ICC, 2023). Advanced LCMS-2 systems employed in recent assessments can achieve collection rates up to 28,000 profiles per second, representing a five-fold improvement over earlier generation equipment (ICC, 2023).

3.3.2 Positioning and Location Referencing Systems

Accurate spatial referencing represents a critical component of automated data collection, enabling precise location identification and subsequent analysis integration with Geographic Information System (GIS) platforms. Prince George's assessment program employs sophisticated Global Navigation Satellite System (GNSS) technology, specifically the Applanix POS LV RT-420 system, which provides continuous and accurate vehicle position and orientation information under challenging GPS conditions (Applied Research Associates, 2016; British Columbia Ministry of Transportation and Infrastructure, 2020).

The positioning system utilizes inertially aided GPS technology that maintains spatial accuracy even during periods of limited satellite coverage, such as urban canyon environments or areas with dense vegetation. The integrated inertial measurement unit provides continuous position estimates through gyroscopic sensors and accelerometers, enabling uninterrupted data collection throughout the survey process (Applied Research Associates, 2016).

Post-processed positioning data typically achieves accuracy levels of less than 500mm in horizontal position and 500mm in vertical position for locations with suitable satellite constellations. Even under challenging GPS conditions involving outages of 10-15 minutes, the system maintains positional accuracy within 1 meter horizontally and 2 meters vertically, ensuring reliable spatial referencing for subsequent analysis and asset management applications (British Columbia Ministry of Transportation and Infrastructure, 2020).

3.3.3 Quality Control and Data Validation

Comprehensive quality control procedures ensure the reliability and accuracy of collected pavement condition data. Tetra Tech's implementation employs a GIS-based field management application called "TT Surveyor" that provides real-time verification of data collection completeness and spatial accuracy. The system verifies that road segments are surveyed in the correct direction and within specified spatial boundaries, comparing real-time vehicle position with predefined survey requirements (Tetra Tech, 2020).

Daily data review processes involve uploading GPS, roughness, and rutting data to processing teams for immediate analysis of coverage completeness and data quality. This methodology enables identification and correction of data gaps or quality issues before survey equipment leaves the project location, minimizing data collection errors and ensuring comprehensive network coverage (Tetra Tech, 2017; Tetra Tech, 2020).

Spot verification procedures involve manual validation of automated distress detection results through comparison with high-resolution digital imagery captured during the survey process. These quality assurance checks help identify potential issues with automated classification algorithms and ensure consistency between different assessment periods (ICC, 2023).

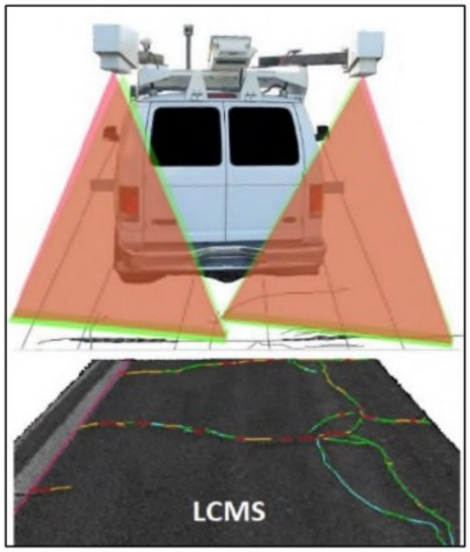


Figure 5 TT Surveyor Application Representation of LCMS System (Tetratech, 2017).

3.3.4 Strengths and Limitations of Automated Assessment

Automated distress survey methods offer significant advantages over traditional manual inspection approaches, including enhanced objectivity, improved consistency, and increased efficiency in large-scale network assessment. The automated approach eliminates subjective bias associated with manual inspections while providing comprehensive documentation through high-resolution imagery and precise spatial referencing.

The high-speed data collection capability enables comprehensive network assessment with minimal traffic disruption and reduced safety risks for inspection personnel. Automated systems can assess entire road networks in days rather than weeks or months required for manual inspection, enabling more frequent condition monitoring and timely identification of deteriorating conditions.

However, automated systems also present certain limitations that must be considered in pavement management applications. Weather conditions, particularly wet pavement surfaces, can affect the accuracy of laser-based distress detection. Some distress types, such as bleeding or fine cracking, may require manual verification to ensure accurate classification and severity assessment.

The substantial capital investment required for automated assessment equipment and specialized personnel training represents a significant consideration for municipal agencies. Additionally, the technical complexity of automated systems requires ongoing maintenance and calibration to ensure continued accuracy and reliability.

3.4 Traffic Data in PMS

Traffic data represents a fundamental component of pavement management systems, directly influencing deterioration rates, maintenance requirements, and treatment selection decisions. Prince George's strategic position as the largest urban center in northern British Columbia creates unique traffic characteristics that significantly impact pavement performance and management requirements.

The city serves as a critical transportation hub at the confluence of major provincial and national transportation corridors, including Highway 97 (connecting southern British Columbia to Alaska) and Highway 16 (the Yellowhead Highway connecting eastern and western Canada). This strategic location generates substantial commercial traffic volumes, including heavy vehicle movements associated with forestry, mining, and agricultural activities throughout the region.

Traffic data collection and analysis within Prince George's PMS framework encompasses multiple parameters including Annual Average Daily Traffic (AADT), vehicle classification by weight categories, seasonal traffic variations, and spatial distribution patterns across different road classifications. This comprehensive traffic characterization enables accurate assessment of loading conditions that directly influence pavement deterioration rates and maintenance requirements.

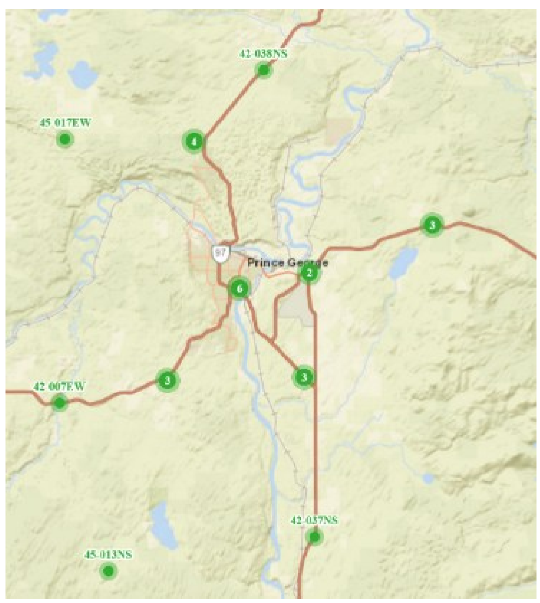


Figure 6 Prince George Interactive map plotting the Road Traffic data (City of Prince George, 2025).

The City of Prince George maintains comprehensive traffic monitoring capabilities through automated traffic counting stations and periodic manual classification studies. Traffic data is accessible through the city's open data portal and interactive mapping applications that provide real-time visualization of traffic patterns and volumes across the road network (City of Prince George, 2025). This spatial traffic information supports maintenance prioritization and treatment selection by identifying high-stress corridors that require enhanced attention and more frequent intervention.

Heavy vehicle traffic represents a particularly critical factor in pavement management for Prince George, given the region's dependence on resource extraction industries that generate substantial commercial vehicle movements. Heavy vehicles create disproportionate pavement loading compared to passenger vehicles, with deterioration impacts that increase exponentially with axle weight. The integration of traffic classification data enables PMS applications to account for these differential loading impacts in deterioration prediction and maintenance planning.

Seasonal traffic variations also influence pavement management strategies in Prince George, particularly considering the region's role in supporting resource industry activities that may exhibit seasonal operational patterns. Winter conditions affect both traffic patterns and pavement stress characteristics, with freeze-thaw cycles creating additional deterioration mechanisms that compound traffic-related wear.

3.5 Pavement Distress Surveys

Pavement distress surveys represent the systematic evaluation of pavement surface conditions that forms the empirical foundation for condition assessment and performance analysis within Prince George's PMS framework. The city has conducted comprehensive distress surveys in 2016, 2017, 2020, and 2023, utilizing specialized contractors including Applied Research Associates (ARA), Tetra Tech Canada Inc., and ICC International Cybernetics Canada Inc. to ensure objective and standardized assessment procedures.

The survey methodology employed in Prince George follows the BCMoTI Pavement Surface Condition Rating Manual, which provides standardized protocols for distress identification, classification, and quantification specifically calibrated for British Columbia pavement conditions and climate factors. This methodology ensures consistency across different survey periods and enables reliable trend analysis for long-term performance evaluation.

3.5.1 Survey Coverage and Scope

The 2020 comprehensive survey represented the most extensive assessment conducted, covering approximately 843 lane kilometers of the city's paved road network including arterials, major collectors, minor collectors, local roads, alleys, ramps, and associated intersections (Tetra Tech, 2020). This comprehensive coverage enables network-level analysis that supports strategic maintenance planning and resource allocation across all road classifications.

The 2023 survey focused specifically on arterial and collector roads, assessing 293 centerline kilometers of predominantly asphalt roadways and intersections (ICC, 2023). This targeted approach reflects the prioritization of high-traffic corridors that experience the most severe deterioration and require the most immediate attention within constrained maintenance budgets.

3.5.2 Data Collection Intervals and Segmentation

Pavement condition data is collected and reported in standardized 50-meter segments, consistent with BCMoTI recommendations for municipal pavement management applications. This segmentation length provides sufficient detail for accurate condition assessment while maintaining manageable data volumes for analysis and decision-making purposes.

The standardized segmentation enables precise spatial referencing of condition data within GIS platforms, supporting sophisticated spatial analysis capabilities including hotspot identification, corridor-level analysis, and integration with traffic and environmental data sources.

3.6 Types of Pavement Distress

The assessment of distress types is crucial for determining the appropriate maintenance and rehabilitation strategies. Common pavement distress types found in Prince George’s Road network include rutting, longitudinal cracking, meandering longitudinal cracking, transverse cracking, longitudinal wheel path cracking, alligator cracking, pavement edge cracking, and potholes as shown in Figure 7. The prevalence of these distresses is heavily influenced by climate conditions, particularly the freeze-thaw cycles and heavy snowfall that contribute to pavement degradation (Qiao et al., 2020).

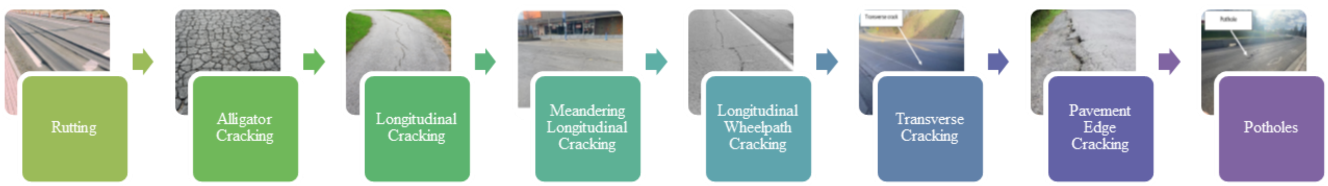


Figure 7 Common types of pavement distresses observed in Prince George

1. **Rutting** – Rutting refers to depressions in the wheel paths caused by repeated loading and consolidation of pavement materials. It is typically associated with inadequate pavement compaction, weak subgrade layers, or high traffic loads. Severe rutting can lead to water accumulation and vehicle control issues, requiring corrective measures such as resurfacing or full-depth pavement reconstruction (Qiao et al., 2020).
2. **Longitudinal Cracking** – Longitudinal cracks are parallel to the pavement's centerline and commonly develop due to fatigue, thermal contraction, or poorly constructed longitudinal joints. These cracks can allow water infiltration, weaken the pavement structure and accelerating deterioration. Sealants and overlays are typically used to mitigate further damage (Smith et al., 2014).
3. **Meandering Longitudinal Cracking** – Unlike regular longitudinal cracks, meandering longitudinal cracks follow an irregular, non-linear pattern. They often indicate subgrade movement, frost heave, or structural deficiencies, requiring more extensive repairs such as base stabilization or reconstruction (Walls & Smith, 1998).
4. **Transverse Cracking** – Transverse cracks develop perpendicular to the pavement centerline, mainly due to temperature fluctuations causing thermal expansion and contraction. These cracks can be a sign of inadequate pavement flexibility or aging

asphalt. Preventive maintenance techniques such as crack sealing help limit moisture infiltration and extend pavement service life (Hafez & Ksaibati, 2021).

5. **Longitudinal Wheel Path Cracking –** This form of longitudinal cracking occurs specifically in the wheel paths due to repeated traffic loading. It is often an early indicator of fatigue failure and can develop into alligator cracking if not treated promptly (Guha et al., 2022).
6. **Alligator Cracking –** Alligator or fatigue cracking consists of interconnected cracks resembling an alligator's skin. It results from repeated traffic loads that exceed pavement structural capacity, leading to progressive failures. Alligator cracking is a serious distress that typically requires full-depth pavement rehabilitation rather than surface treatments (Qiao et al., 2020).
7. **Pavement Edge Cracking –** Edge cracking occurs along the outer edges of the pavement and is primarily caused by insufficient shoulder support, water infiltration, or improper drainage. These cracks can propagate inward, compromising pavement integrity. Shoulder reinforcement and drainage improvements are common solutions for preventing edge cracking (Ali, 2022).
8. **Potholes –** Potholes form when water infiltrates into cracks, weakening pavement layers, and leading to localized failures. Repeated freeze-thaw cycles exacerbate pothole formation, making them a significant issue in colder climates. Potholes can be temporarily repaired with patching materials or permanently fixed through resurfacing (Guo et al., 2022).

3.7 Road Categorization in PMS

Road classification systems provide the organizational framework for differentiated pavement management strategies that account for varying functional requirements, traffic characteristics, and performance expectations across different road types. Prince George's classification system follows standard municipal practices that recognize distinct roles and requirements for different road categories.

Table 4 Prince George Road Classification System

Class	Description	Lane-km (Paved)	Lane-km (Gravel)	Primary Function
Arterial	Major traffic corridors connecting regions	324	4	High-volume regional connectivity
Major Collector	Primary urban traffic distribution	130	13	Urban traffic collection and distribution
Minor Collector	Secondary traffic collection	157	32	Local traffic collection
Local	Neighborhood access and local traffic	679	138	Direct property access
Alley	Rear property access and service	20	41	Service and secondary access

Ramp	Highway access and grade separation	6	0	Grade-separated access
Private	City-owned utility access roads	4	9	Utility and service access

Source: City of Prince George Asset Management (Bobbie, 2025)

3.7.1 Arterial Roads

Arterial roads represent the highest classification within Prince George's network, accommodating the highest traffic volumes and serving critical regional connectivity functions. These roadways experience the most severe traffic loading and environmental stress, requiring the most frequent maintenance interventions and highest performance standards. The 324 lane-kilometers of paved arterial roads in Prince George's network carry substantial commercial traffic associated with the city's role as a regional transportation hub (Bobbie, 2025).

3.7.2 Collector Roads

Collector roads serve intermediate functions between arterial and local roads, providing traffic collection and distribution within urban areas while accommodating moderate traffic volumes. Prince George's collector road network comprises 130 lane-kilometers of major collectors and 157 lane-kilometers of minor collectors, each serving distinct functions within the overall transportation hierarchy (Bobbie, 2025). Major collectors connect arterial roads with local traffic generators and typically accommodate higher traffic volumes than minor collectors Minor collectors provide secondary traffic collection functions and serve as intermediate connections between major collectors and local roads.

3.7.3 Local Roads and Service Classifications

Local roads provide direct access to adjacent properties and accommodate primarily local traffic with minimal through movement. These roadways experience lower traffic volumes and less severe loading conditions compared to arterial and collector roads, enabling longer maintenance intervals and different treatment strategies. Prince George maintains 679 lane-kilometers of paved local roads, representing the largest component of the municipal road network (Bobbie, 2025).

Alleys serve specialized functions including rear property access, service vehicle accommodation, and utility corridor provision. The 20 lane-kilometers of paved alley pavement in Prince George's network requires distinct maintenance approaches that account for unique geometric constraints and access limitations.

Ramps provide grade-separated access between different road classifications and highway systems. The 6 lane-kilometers of paved ramps have specialized geometric and structural requirements that necessitate targeted maintenance approaches accounting for unique loading patterns and drainage characteristics.

3.8 Previous Treatment Methods and Maintenance History

This section summarizes the treatment and maintenance methods utilized by the City of Prince George based on the maintenance records included in the PMS. Figure 8 presents a snapshot from the map illustrating the road rehabilitation projects scheduled in 2024. According to Figure 8, the City executed 52 road resurfacing projects in 2024 only.

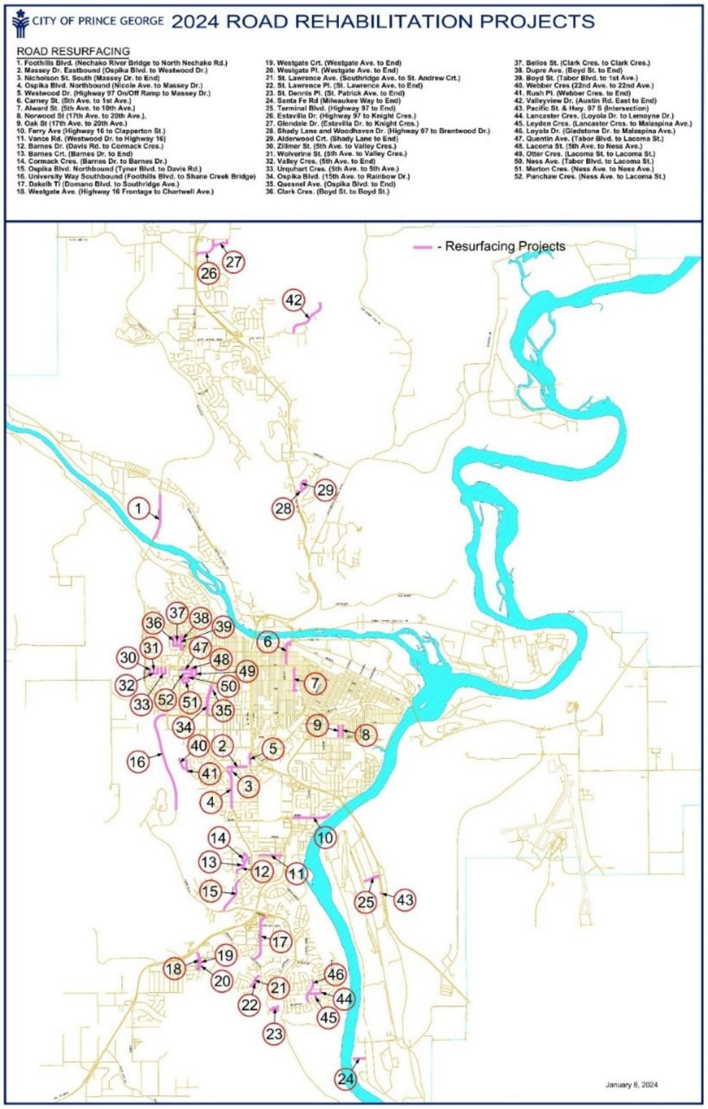


Figure 8 City of Prince George 2024 Road Resurfacing (City of Prince George, 2024)

3.8.1 Preventive Maintenance Strategies

Crack Sealing

Crack sealing represents the most cost-effective preventive maintenance treatment employed in Prince George's pavement management program, designed to prevent moisture infiltration and delay the progression of surface cracking to more severe distress types. The treatment involves the application of specialized sealant materials into cracks to create waterproof barriers that prevent environmental deterioration.

Research documented in Prince George's Strategic Paved Road Management Plan indicates that crack sealing treatments cost approximately $0.6 to $1.0 per linear foot and provide service life extensions of 3-5 years when applied to appropriate pavement conditions (Applied Research Associates, 2016). The treatment is most effective when applied to pavements in good to excellent condition (PDI 8-9) with low to moderate severity cracking.

Microsurfacing

Microsurfacing treatments have been extensively utilized in Prince George's maintenance program, with historical data from 2009-2016 showing 167 applications representing 10.2% of all treatments during this period. Microsurfacing provides surface renewal capabilities that address functional deficiencies including friction loss, minor surface raveling, and early-stage surface deterioration. These treatments cost approximately $2.25 to $7.50 per square yard depending on specific application requirements and material specifications.

Surface treatments serve dual functions as both preventive and corrective maintenance interventions. As preventive measures, they seal minor surface deficiencies and restore surface characteristics before functional deterioration occurs. As corrective treatments, they address existing surface problems including friction deficiency and moderate raveling while providing enhanced surface protection.

3.8.2 Rehabilitation Strategies

Mill and Fill (Mill and Overlay)

Mill and fill procedures, coded as "SurfaceRehab_M&F" in Prince George's asset management system, represent the predominant rehabilitation method employed in the city's pavement management program. Historical data from 2009-2016 shows this treatment was applied in 904 cases, representing 55.1% of all rehabilitation activities. Recent project data (2004-2023) indicates continued reliance on this method, with 35 projects covering 32.24 lane-kilometers and 164,787 square meters of pavement area.

Mill and fill procedures involve the removal of 50mm of existing asphalt pavement followed by replacement with new asphalt materials. This method enables pavement renewal without increasing overall elevation, making it particularly suitable for urban environments where curb and gutter elevation constraints limit overlay thickness. The milling process removes surface deficiencies including cracking, raveling, and minor deformation while providing improved surface texture for enhanced bonding with replacement materials.

Thin Lift Overlay (TLO)

Thin lift overlays, designated as "SurfaceRehab_OL" in city records, represent the second most common rehabilitation strategy. Historical data shows 174 applications (10.6% of treatments) from 2009-2016, with recent projects indicating 30 applications covering 24.83 lane-kilometers and 103,925 square meters. This method involves the placement of 40-50mm asphalt layers over existing pavement surfaces, providing both surface renewal and structural enhancement while maintaining existing pavement geometry and drainage characteristics.

TLO treatments are most appropriate for pavements with good underlying structure and only minor surface deficiencies. However, the method does not address underlying structural problems and typically results in reflective cracking appearing through the new surface within a relatively short time following placement.

Reclamation

Treatments Prince George employs both partial and full depth reclamation strategies based on pavement condition and structural requirements. Historical data indicates 29 applications of 75mm reclamation and 46 applications of 100mm full depth reclamation from 2009-2016. Recent projects include one major 75mm reclamation project covering 1.42 lane-kilometers and 6,170 square meters.

Reclamation involves the pulverization of existing asphalt and granular base materials followed by reconstruction with enhanced structural capacity. The 75mm reclamation addresses moderate structural deficiencies, while 100mm full depth reclamation provides comprehensive structural renewal for severely deteriorated pavements. This method effectively removes all existing pavement distresses while providing substantial structural improvement at costs considerably less than complete reconstruction.

Full Reconstruction

Complete pavement reconstruction represents the most extensive rehabilitation method, reserved for pavements with major structural deficiencies that cannot be addressed through surface or reclamation treatments. Historical data shows limited application with 16 rural reconstructions and 2 urban reconstructions from 2009-2016, plus 2 recent reconstruction projects covering 1.60 lane-kilometers.

The reconstruction process involves complete removal of existing pavement materials, subgrade preparation, and installation of new structural sections designed for current traffic loading and environmental conditions. This comprehensive approach provides maximum structural enhancement and service life extension but requires the highest capital investment.

3.8.3 Treatment Selection Matrix and Historical Performance

Prince George's treatment selection follows systematic decision-making frameworks that integrate pavement condition assessment with appropriate treatment strategies based on distress characteristics and functional requirements. Historical application data demonstrates the effectiveness of this approach, with mill and fill treatments addressing the majority of rehabilitation needs while targeted use of overlays, reclamation, and reconstruction addresses specific structural and functional requirements.

Table 5 Treatment Matrix for Arterial/Collector Roadways

Condition Rating (PDI)	Typical Distress Features	Recommended Treatment	Historical Usage (2009-2016)
9 to 10	New pavement, excellent condition	Do nothing	
8 to 9	Good condition, low to moderate severity cracking	Crack seal / Microsurfacing	167 microsurfacing applications
7 to 8	Good condition, loss of friction, minor surface raveling	Microsurfacing or thin lift overlay	174 overlay applications
6 to 7	Good to fair condition, structurally adequate, rutting < 10mm	Mill and fill	904 mill and fill applications
5 to 6	Fair condition, evidence of load-related distress	Reclamation (75-100mm)	75 reclamation applications
Less than 5	Poor condition, moderate to high severity cracking	Reconstruction	18 reconstruction projects

Source: Applied Research Associates (2016), Prince George Asset Management Records (2009-2023)

The historical treatment data demonstrates Prince George's strategic approach to pavement management, with many interventions (55.1%) utilizing cost-effective mill and fill procedures for pavements with adequate structural capacity but surface deterioration. The balanced application of preventive treatments (microsurfacing) and more extensive rehabilitation methods (reclamation and reconstruction) reflects systematic condition-based decision making that optimizes both performance outcomes and resource utilization.

3.9 Overview of BC Specific PMS Reports and Policies

BCMoTI Pavement Surface Condition Rating Manual

The British Columbia Ministry of Transportation and Infrastructure Pavement Surface Condition Rating Manual serves as the technical foundation for pavement condition assessment throughout the province, including Prince George's municipal network. The manual, currently in its Sixth Edition (March 2020), provides standardized methodologies for distress identification, classification, and quantification specifically calibrated for British Columbia's diverse climate conditions and pavement materials.

The BCMoTI methodology represents a localized adaptation of the internationally recognized ASTM D6433 Standard Practice for Roads and Parking Lots Pavement Condition Index Surveys, modified to address distress types and severity patterns most observed in British Columbia. This adaptation ensures that assessment procedures accurately reflect regional pavement performance characteristics while maintaining compatibility with broader pavement management frameworks.

Key modifications incorporated in the BCMoTI manual include additional distress categories such as longitudinal wheel path cracking, pavement edge cracking, and longitudinal joint cracking that reflect specific deterioration patterns observed in BC's climate

4. Chapter 4: Results and Analysis

This chapter presents the comprehensive findings from the pavement condition assessment and predictive modeling analysis conducted for Prince George's road network. Building upon the methodology established in Chapter 4, the analysis encompasses four survey periods (2016, 2017, 2020, and 2023) and provides critical insights into pavement deterioration patterns, distress evolution, and predictive modeling performance. The results directly address the research objectives established in Chapter 1.

4.1 Pavement Distress Condition Assessment

The systematic evaluation of pavement distresses across Prince George's road network reveals significant patterns in deterioration mechanisms, spatial distribution, and temporal evolution. This comprehensive assessment provides the empirical foundation for understanding pavement performance under harsh northern climate conditions and establishes the basis for developing targeted maintenance strategies.

4.2 Overall Network Condition Evolution

The pavement condition assessment program employed automated laser survey technology to systematically document distress characteristics across multiple survey periods. The temporal distribution of data collection demonstrates varying coverage strategies, with the most comprehensive assessment conducted in 2020 covering 31,084 data points, while targeted surveys in 2016, 2017, and 2023 focused on specific road classifications and high-priority corridors.

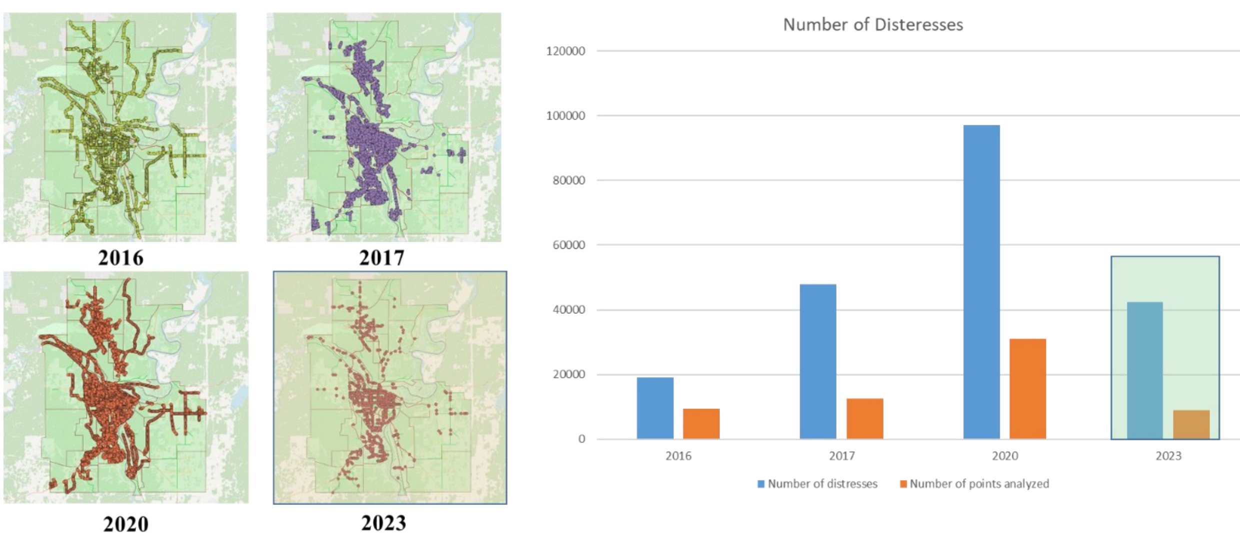


Figure 9 Distresses All Years - Bar chart showing number of distresses vs. number of points analyzed across 2016, 2017, 2020, and 2023

Analysis of distress frequency relative to survey coverage reveals that 2023 exhibited the highest distress-to-data-point ratio, indicating targeted surveying of road segments with elevated deterioration levels. From 2016 to 2023, the year characterized by the most extensive distresses compared to points analyzed was 2023, which demonstrated that the analysis for 2023 was efficient as it analyzed certain roads with high distress frequency. However, this targeted approach resulted in reduced overall network coverage compared to the comprehensive 2020 assessment.

The spatial analysis of Pavement Distress Index (PDI) distribution demonstrates that pavement condition improvements were achieved between 2020 and 2023, with the best overall pavement condition recorded in 2023. Conversely, the worst pavement conditions were documented in 2017 and 2020, corresponding to periods of intensive maintenance intervention requirements. The poor pavement condition distribution analysis indicates that deteriorated segments are dispersed throughout the city rather than concentrated in specific zones, necessitating network-wide maintenance strategies.

Table 1. PDI categories.

Category	PCI Range
Good	> 7
Fair	7 - 5
Poor	< 5

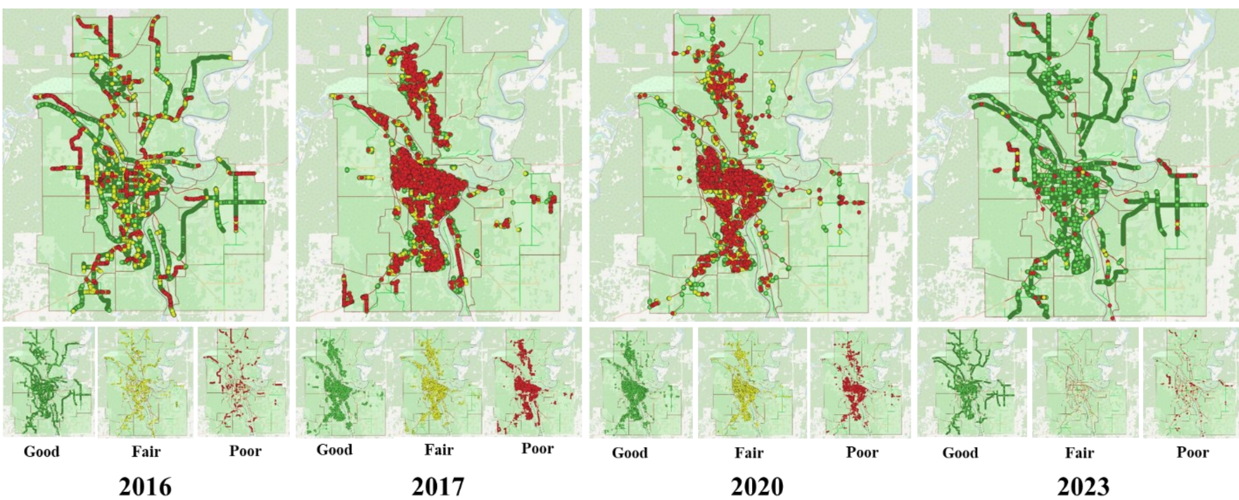


Figure 10 Overall PDI condition maps for all years (2016-2023) showing spatial distribution showing Good/Fair/Poor categories across all survey years

The temporal progression shows that the best overall pavement condition was achieved in 2023, while the most deteriorated conditions were observed in 2017 and 2020. This improvement demonstrates the effectiveness of comprehensive rehabilitation strategies implemented between 2020 and 2023, particularly mill-and-fill operations and overlay applications that successfully addressed structural deficiencies identified in earlier assessments.

The survey coverage varied significantly across assessment periods, with the 2020 survey representing the most comprehensive network evaluation at 31,084 data points, while 2023 focused specifically on arterial and collector roads with 8,942 data points. The 2016 baseline survey covered 9,328 data points primarily on arterial and collector roads, while the 2017 expanded assessment included 12,475 data points covering local roads and alleys. This variation in coverage reflects strategic prioritization of high-traffic corridors in later assessments while maintaining analytical depth for critical infrastructure.

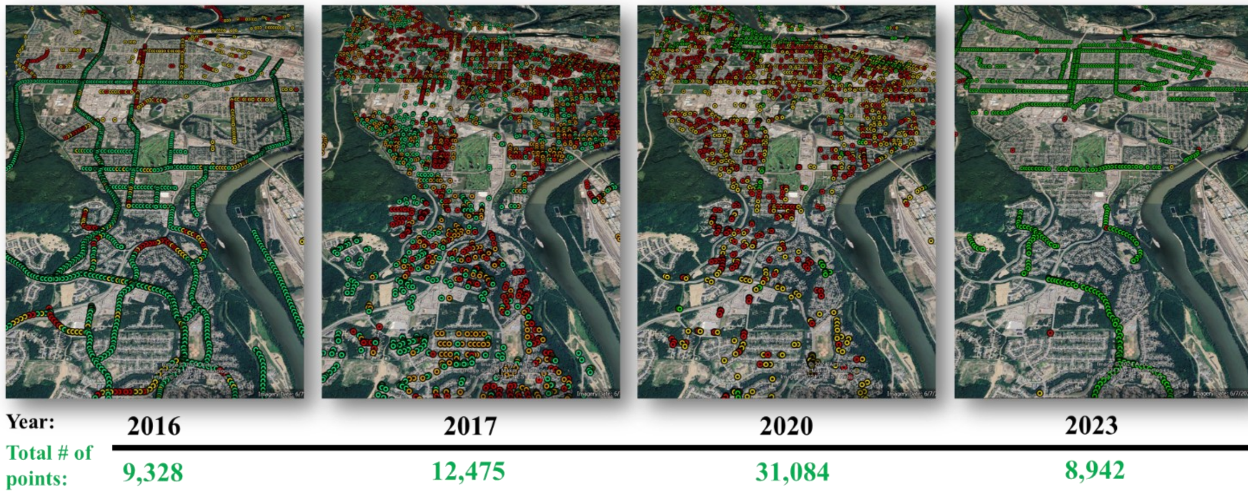


Figure 11 Survey coverage comparison showing data points and network coverage by year

The concentration of poor pavement conditions throughout the city without geographic clustering suggests that deterioration mechanisms result from systematic factors affecting the entire network rather than localized issues. This distribution pattern validates the research approach of developing network-level management strategies that address fundamental climate and material performance relationships.

4.3 Comprehensive Distress Type Analysis

4.3.1 Transverse Cracking Analysis

Transverse cracking emerged as the most prevalent and significant distress type across all survey periods, demonstrating substantial impact on overall network condition. The distress exhibits distinct temporal patterns reflecting both environmental influences and maintenance intervention effectiveness.

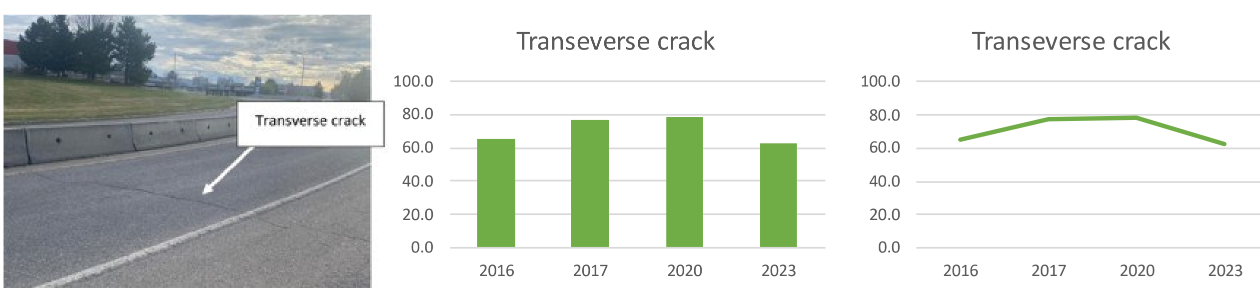


Figure 12 Transverse Cracking condition Trend (Photo credit to Mr. Alireza Noory)

Transverse Cracking Severity Analysis

Transverse cracking in Prince George overall demonstrates moderate to high severity characteristics and may be considered highly severe in some years throughout the analysis period. The severity analysis reveals that transverse cracking was most severe in 2020, when the combination of high network coverage (78.2%) and substantial high-severity occurrences (29.5%) created the most challenging conditions for network management. The temporal severity progression shows that transverse cracking severity was increasing significantly in 2017 and 2020, with 2017 representing the peak of high-severity deterioration at 39.9% of affected segments. However, severity patterns began decreasing substantially in 2023, demonstrating the effectiveness of targeted maintenance interventions and strategic rehabilitation programs implemented between the peak deterioration period and the most recent assessment.

Transeverse crack	2016	2017	2020	2023
Severity 0	34.6	22.8	21.8	37.6
Severity 1	46.4	9.6	18.8	38.5
Severity 2	14.7	27.7	30.0	23.9
Severity 3	4.3	39.9	29.5	0.0
Total	65.4	77.2	78.2	62.4

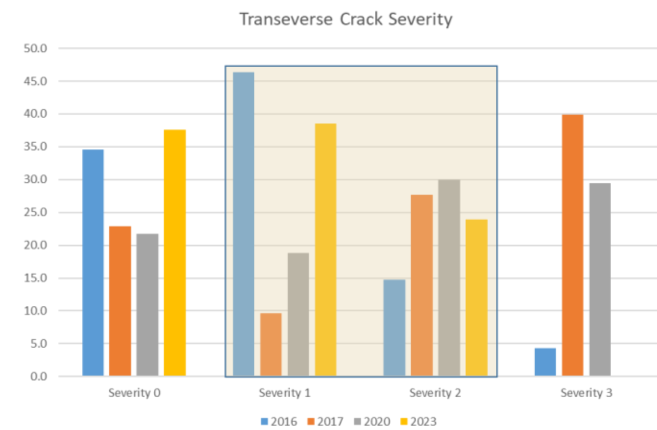


Figure 13 Transverse Cracking Severity in percentages All years - Comprehensive table and bar chart showing severity distribution across all years

Transverse Cracking Extent Analysis

Transverse cracking demonstrated its most frequent occurrence in 2020 and 2017, when network coverage reached 78.2% and 77.2% respectively, representing the peak periods of extensive deterioration across Prince George's road network. Overall transverse cracking in Prince George is extensive, consistently affecting most surveyed segments throughout the analysis period and requiring comprehensive management strategies to address the widespread nature of this deterioration pattern. The temporal extent progression shows that transverse cracking was increasing substantially in 2017 and 2020, with these years representing the peak of network-wide deterioration requiring intensive intervention. However, extent patterns began decreasing significantly in 2023, with network coverage reducing to 62.4% and marked improvements in the distribution toward lower extent categories, demonstrating the effectiveness of systematic maintenance programs in reducing the widespread nature of transverse cracking across the municipal road network.

Transeverse crack	2016	2017	2020	2023
Extent 0	34.6	22.8	21.8	37.6
Extent 1	40.8	30.2	40.6	32.3
Extent 2	21.6	0.7	0.0	0.0
Extent 3	3.0	37.9	33.4	29.1
Extent 4	0.0	0.4	0.0	0.0
Extent 5	0.0	8.0	4.2	0.9
Total	65.4	77.2	78.2	62.4

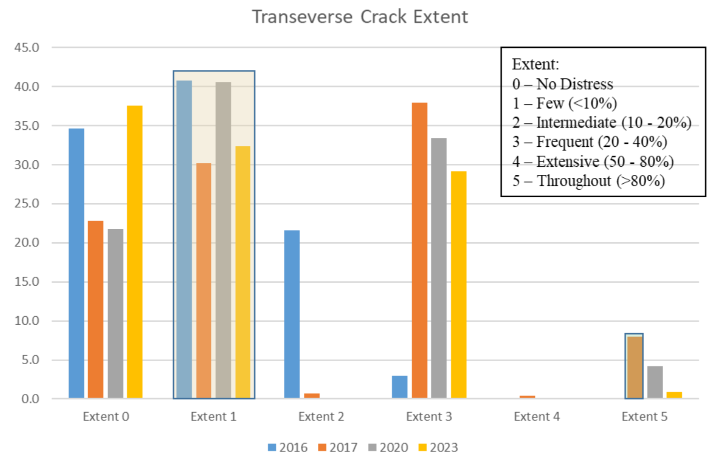


Figure 14 Transverse Cracking Extent in percentages All years - Comprehensive table and bar chart showing Extent distribution across all years

4.3.2 Meandering Longitudinal Cracking Analysis

Meandering longitudinal cracking represents the second most significant distress category, demonstrating consistent presence across all survey periods with evolving severity characteristics indicating progressive structural deterioration influenced by traffic loading and environmental factors.

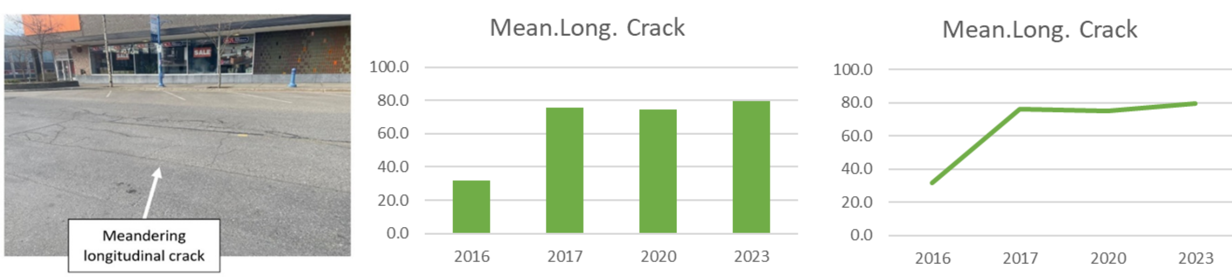


Figure 15 Meandering Longitudinal Cracking condition Trend (Photo credit to Mr. Alireza Noory)

Meandering Longitudinal Cracking Severity Analysis

Meandering longitudinal cracking in Prince George overall demonstrates low to moderate severity characteristics but reached moderate to high severity levels in 2017 and 2020. The severity analysis reveals that meandering longitudinal cracking was most severe in 2017 and 2020, when high-severity occurrences peaked at 19.2% and 13.2% respectively, combined with substantial moderate severity coverage exceeding 40% in both years. The temporal severity progression shows that meandering longitudinal cracking severity was increasing throughout the years from the baseline 31.6% coverage in 2016 to peak levels in 2017-2020, before stabilizing in 2023 with improved severity distribution despite expanded network coverage.

Mean.Long. Crack	2016	2017	2020	2023
Severity 0	68.4	24.0	25.2	20.5
Severity 1	19.7	6.3	20.7	37.4
Severity 2	10.1	50.4	40.9	40.5
Severity 3	1.8	19.2	13.2	1.6
Total	31.6	76.0	74.8	79.5

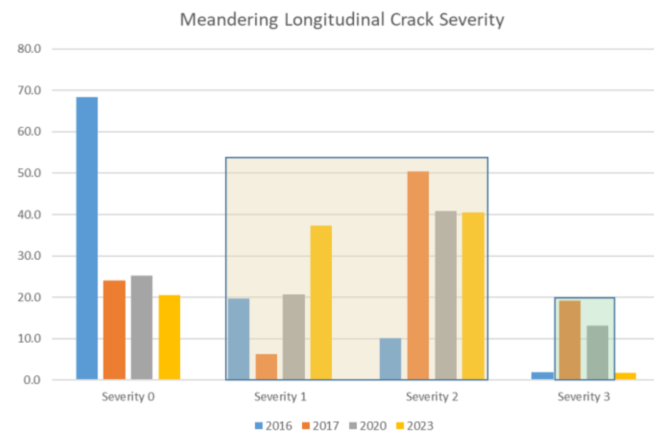


Figure 16 Meandering Longitudinal Cracking Severity in percentages All years - Comprehensive table and bar chart showing Extent distribution across all years

Meandering Longitudinal Cracking Extent Analysis

Meandering longitudinal cracking demonstrated its most extensive coverage in 2023, reaching 79.5% of the network, followed closely by 2017 and 2020 with 76.0% and 74.8% coverage respectively. Overall meandering longitudinal cracking in Prince George is extensive and widespread, consistently affecting most surveyed segments since 2017 and representing one of the most prevalent distress types across the municipal road network. The temporal extent progression shows that meandering longitudinal cracking was dramatically increasing from 2016 baseline levels (31.6%) to peak coverage in 2017, maintaining extensive coverage through 2020, and continuing to expand in 2023, indicating persistent and growing deterioration patterns requiring comprehensive long-term management strategies.

Mean.Long. Crack	2016	2017	2020	2023
Extent 0	68.4	24.0	25.2	20.5
Extent 1	13.7	21.4	37.8	48.0
Extent 2	9.4	16.5	14.7	12.4
Extent 3	6.6	30.2	18.2	13.9
Extent 4	1.6	7.1	3.7	3.9
Extent 5	0.2	0.8	0.4	1.3
Total	31.6	76.0	74.8	79.5

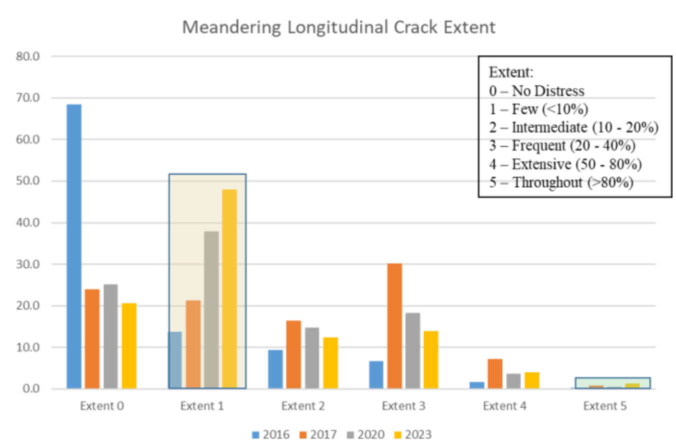


Figure 17 Meandering Longitudinal Cracking Extent in percentages All years - Comprehensive table and bar chart showing Extent distribution across all years

4.3.3 Longitudinal Wheel Path Cracking Analysis

Longitudinal wheel path cracking maintained relatively stable presence across all survey periods, representing traffic-load-related deterioration patterns with consistent network coverage and manageable severity levels demonstrating effective management of heavy vehicle loading impacts.

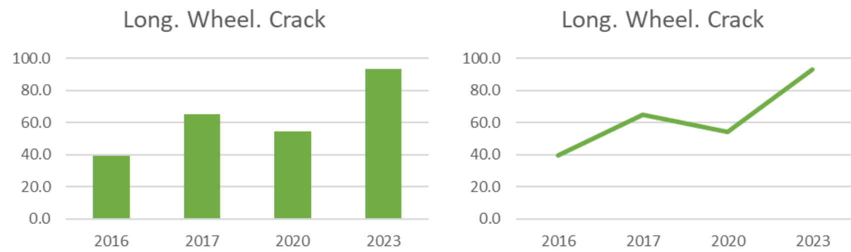


Figure 18 Longitudinal Wheel Path Cracking Trend

Longitudinal Wheel Path Cracking Severity Analysis

Longitudinal wheel path cracking in Prince George overall demonstrates stable and manageable severity characteristics throughout the analysis period. The severity patterns remained relatively consistent across all survey years, indicating effective management of traffic-load-related deterioration factors through appropriate maintenance timing and intervention strategies. The temporal severity progression shows that longitudinal wheel path cracking maintained stable severity distribution without significant peaks or deterioration phases, reflecting successful long-term management of heavy vehicle loading impacts and appropriate pavement design adequacy for anticipated traffic conditions.

Long. Wheel. Crack	2016	2017	2020	2023
Severity 0	60.7	34.9	45.7	6.9
Severity 1	26.4	4.4	10.0	42.4
Severity 2	8.7	32.2	25.0	48.2
Severity 3	4.3	28.5	19.4	2.5
Total	39.3	65.1	54.3	93.1

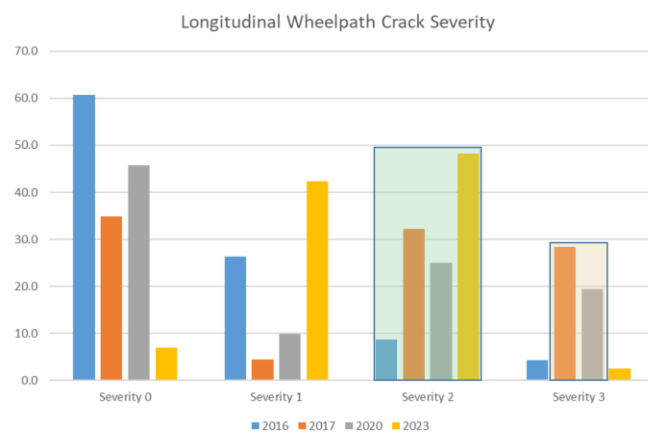


Figure 19 Longitudinal Wheel path Cracking Severity in percentages All years - Comprehensive table and bar chart showing Severity distribution across all years

Longitudinal Wheel Path Cracking Extent Analysis

Longitudinal wheel path cracking demonstrated relatively stable extent coverage throughout the analysis period, with minor fluctuations indicating effective traffic-load management strategies. The distress maintained consistent network presence around 16-20% of total distresses across all survey years, representing manageable and predictable deterioration patterns. The temporal extent progression shows that longitudinal wheel path cracking experienced a decrease in 2017 followed by recovery to baseline levels in 2020 and 2023, indicating resilient pavement performance under traffic loading with effective maintenance intervention when required, demonstrating appropriate long-term management of wheel path deterioration across the municipal road network.

Long. Wheel. Crack	2016	2017	2020	2023
Extent 0	60.7	34.9	45.7	6.9
Extent 1	19.6	27.9	26.6	39.8
Extent 2	10.5	15.3	12.6	15.2
Extent 3	7.5	19.2	13.7	22.4
Extent 4	1.5	2.5	1.4	9.1
Extent 5	0.2	0.2	0.0	6.5
Total	39.3	65.1	54.3	93.1

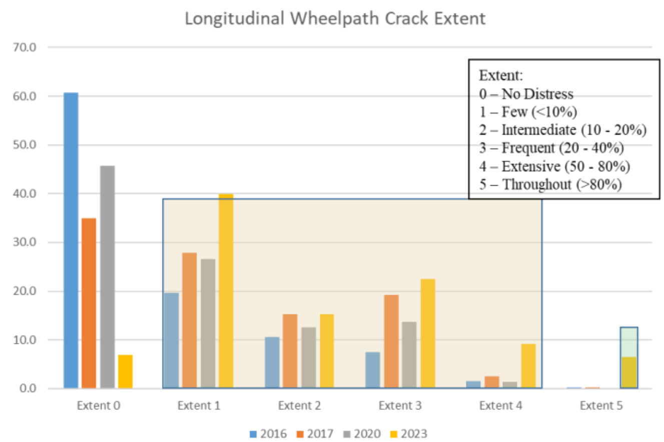


Figure 20 Longitudinal Wheel path Cracking Extent in percentages All years - Comprehensive table and bar chart showing Extent distribution across all years

4.3.4 Alligator Cracking Analysis

Alligator cracking demonstrated the most significant improvement among all distress types, reflecting successful structural rehabilitation interventions and strategic maintenance targeting of areas with advanced structural deterioration.

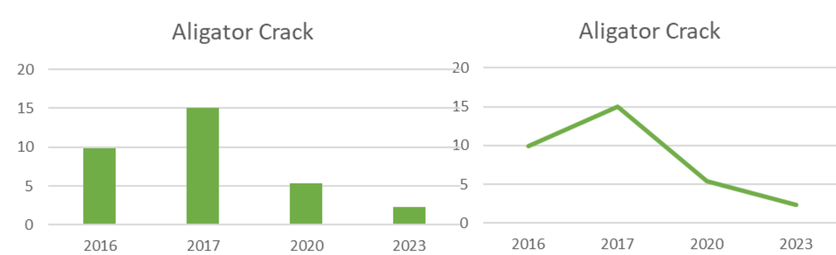


Figure 21 Alligator Cracking Trend

Alligator Cracking Severity Analysis

Alligator cracking in Prince George demonstrated the most successful severity management among all distress types, achieving near-complete elimination through systematic structural rehabilitation interventions. The severity analysis reveals that alligator cracking peaked in 2017, particularly affecting older local roads and areas with inadequate structural capacity for current loading conditions. The temporal severity progression shows that alligator cracking severity decreased systematically from 2017 peak conditions through 2020 and 2023, representing highly effective structural rehabilitation program implementation and demonstrating that comprehensive maintenance strategies can successfully resolve advanced structural deterioration challenges when properly targeted and executed.

Aligator Crack	2016	2017	2020	2023
Severity 0	90.1	85.0	93.5	98.1
Severity 1	0.0	0.0	0.0	0.0
Severity 2	6.4	14.5	0.4	1.2
Severity 3	3.5	0.5	6.1	0.6
Total	9.9	15.0	6.5	1.9

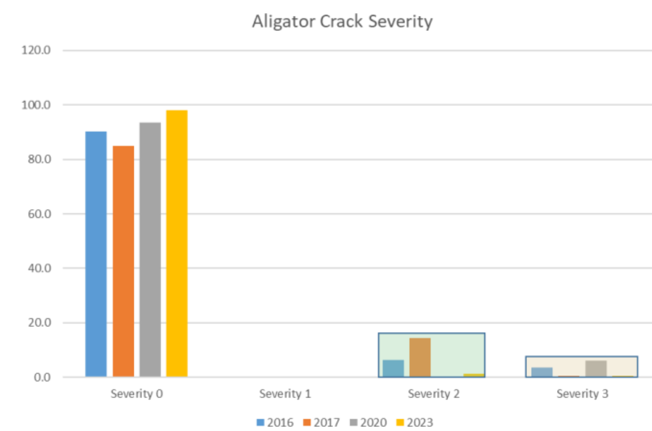


Figure 22 Alligator Cracking Severity in percentages All years - Comprehensive table and bar chart showing Severity distribution across all years

Alligator Cracking Extent Analysis

Alligator cracking demonstrated the most dramatic extent reduction among all distress types, achieving near-complete elimination from 4.85% of network distresses in 2016 to only 0.39% in 2023. The extent analysis reveals that alligator cracking peaked in 2017 with localized but significant coverage patterns, followed by systematic reduction through comprehensive structural rehabilitation programs. The temporal extent progression shows that alligator cracking extent decreased consistently and substantially from peak levels in 2017 through 2020 and 2023, representing exceptionally successful structural maintenance program implementation and demonstrating that targeted rehabilitation strategies can effectively eliminate advanced structural deterioration when properly planned and executed across the municipal road network.

Aligator Crack	2016	2017	2020	2023
Extent 0	90.1	85.0	93.5	98.1
Extent 1	7.0	14.5	6.1	1.3
Extent 2	2.1	0.5	0.4	0.4
Extent 3	0.6	0.1	0.0	0.2
Extent 4	0.1	0.0	0.0	0.1
Extent 5	0.0	0.0	0.0	0.0
Total	9.9	15.0	6.5	1.9

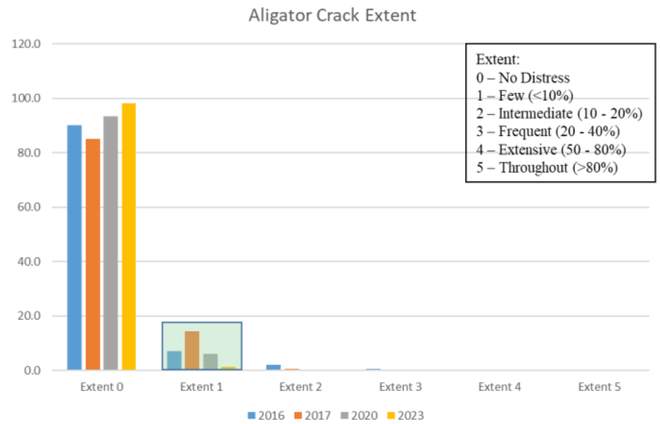


Figure 23 Alligator Cracking Extent in percentages All years - Comprehensive table and bar chart showing Extent distribution across all years

4.3.5 Rutting Analysis

Rutting exhibited the most dramatic emergence pattern among all distress types, transitioning from complete absence to widespread network presence and representing the most significant emerging maintenance challenge requiring immediate strategic attention and intervention development.

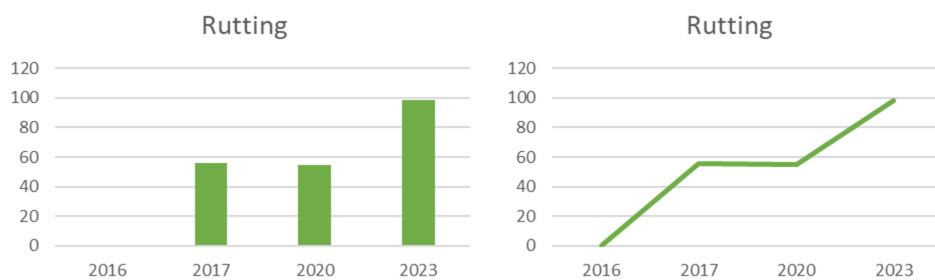


Figure 24 Rutting Trend

Rutting Severity Analysis

Rutting in Prince George represents the most dramatic emergence pattern among all distress types, transitioning from complete absence in 2016 to near-universal network presence by 2023. The severity analysis reveals that rutting development followed a systematic progression from initial emergence in 2017 through widespread low-severity manifestation by 2023, with 92.9% of affected segments exhibiting low severity conditions. The temporal severity progression shows that rutting severity was systematically increasing from zero baseline in 2016 through progressive development in 2017 and 2020 to comprehensive network coverage in 2023, representing the most significant emerging maintenance challenge requiring immediate strategic intervention development and comprehensive treatment program implementation.

Rutting	2016	2017	2020	2023
Severity 0	100.0	44.3	45.2	1.6
Severity 1	0.0	52.0	52.6	92.9
Severity 2	0.0	3.4	2.2	5.1
Severity 3	0.0	0.3	0.1	0.3
Total	0.0	55.7	54.8	98.4

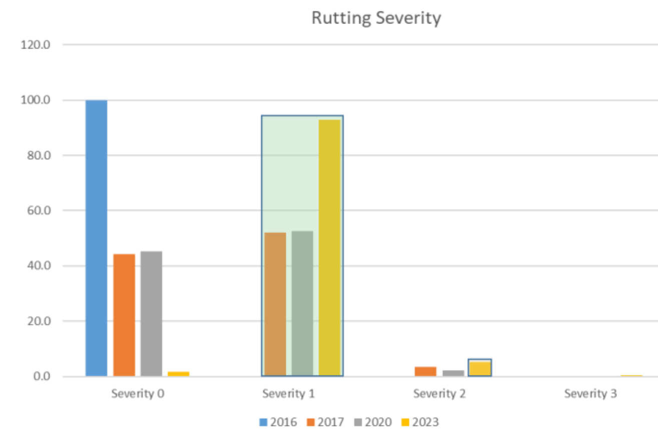


Figure 25 Rutting Severity in percentages All years - Comprehensive table and bar chart showing Severity distribution across all years

Rutting Extent Analysis

Rutting demonstrated the most dramatic extent emergence among all distress types, progressing from complete absence in 2016 to the most extensive single distress challenge by 2023, affecting 98.4% of the surveyed network. The extent analysis reveals that rutting development followed an accelerating pattern from initial manifestation in 2017 (55.7% coverage) through progressive expansion in 2020 (54.8% coverage) to comprehensive network penetration in 2023. The temporal extent progression shows that rutting extent was systematically and dramatically increasing from zero baseline through progressive development phases to near-universal coverage, with 2023 showing the highest concentration in intermediate to frequent extent categories, representing the most critical emerging infrastructure challenge requiring immediate comprehensive intervention strategy development and implementation across the entire municipal road network.

Rutting	2016	2017	2020	2023
Extent 0	100.0	44.3	45.2	1.6
Extent 1	0.0	0.0	0.0	13.0
Extent 2	0.0	0.0	0.0	8.4
Extent 3	0.0	27.7	22.6	23.6
Extent 4	0.0	0.0	0.0	19.9
Extent 5	0.0	28.0	32.2	33.5
Total	0.0	55.7	54.8	98.4

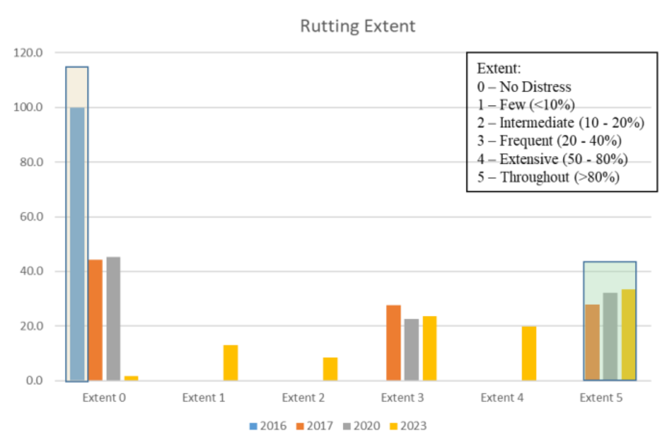


Figure 26 Rutting Extent in percentages All years - Comprehensive table and bar chart showing Extent distribution across all years

4.3.6 Pavement Edge Cracking Analysis

Pavement edge cracking demonstrated irregular survey coverage with significant data collection gaps, complicating comprehensive trend analysis but revealing substantial deterioration when measured, representing critical infrastructure edge integrity challenges.

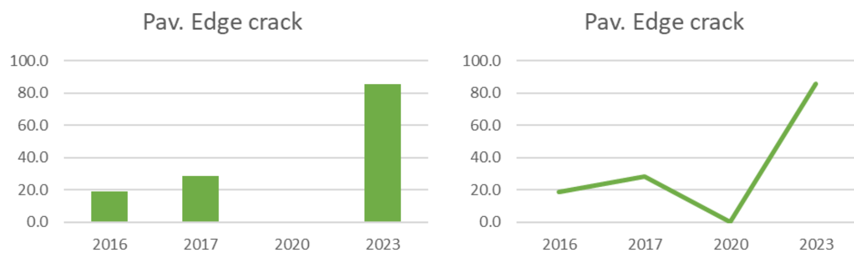


Figure 27 Pavement Edge Cracking Trend

Pavement Edge Cracking Severity Analysis

Pavement edge cracking in Prince George demonstrates irregular assessment patterns due to data collection gaps but reveals significant severity emergence when measured. The severity analysis shows that edge cracking was most severe and extensive in 2023, becoming the dominant distress type after being absent from 2020 data collection. The temporal severity progression indicates that pavement edge cracking severity was increasing from moderate baseline levels in 2016-2017, followed by a data collection gap in 2020, and dramatic emergence in 2023 to become the most severe and frequent distress type, suggesting accelerated edge deterioration possibly related to drainage issues, frost action, or traffic loading patterns requiring immediate comprehensive assessment and intervention strategy development.

Pav. Edge crack	2016	2017	2020	2023
Severity 0	81.1	71.6	0.0	14.6
Severity 1	11.9	2.4	0.0	16.9
Severity 2	3.6	16.9	0.0	63.2
Severity 3	3.4	9.1	0.0	5.4
Total	18.9	28.4	0.0	85.4

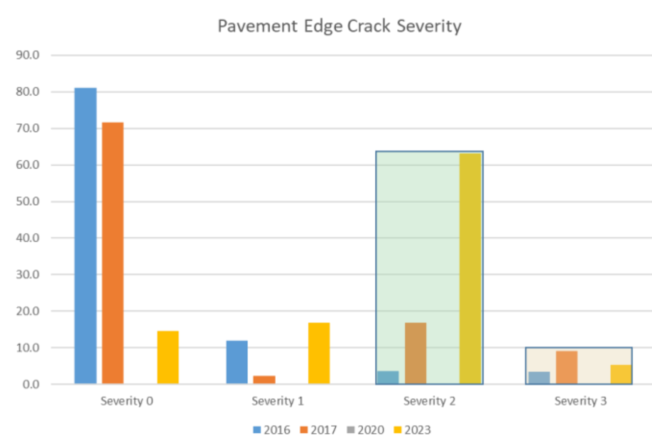


Figure 28 Pavement Edge Cracking Severity in percentages All years - Comprehensive table and bar chart showing Severity distribution across all years

Pavement Edge Cracking Extent Analysis

Pavement edge cracking demonstrated the most dramatic extent emergence among measured distress types, transforming from manageable coverage levels (18.9% in 2016, 28.4% in 2017) to the most extensive single distress challenge (85.4% in 2023). The extent analysis reveals that edge cracking was completely absent from 2020 data collection, creating a critical assessment gap, followed by explosive extent expansion to become the dominant network distress by 2023. The temporal extent progression shows that pavement edge cracking extent was gradually increasing from baseline levels through 2017, followed by unmeasured conditions in 2020, and dramatic comprehensive emergence in 2023 to represent the most extensive infrastructure deterioration challenge requiring immediate strategic intervention development and comprehensive rehabilitation program implementation across the municipal road network.

Pav. Edge crack	2016	2017	2020	2023
Extent 0	81.1	71.6	0.0	14.6
Extent 1	7.0	18.2	0.0	42.7
Extent 2	5.2	6.4	0.0	15.5
Extent 3	4.2	3.3	0.0	17.2
Extent 4	1.3	0.4	0.0	6.2
Extent 5	1.2	0.1	0.0	3.9
Total	18.9	28.4	0.0	85.4

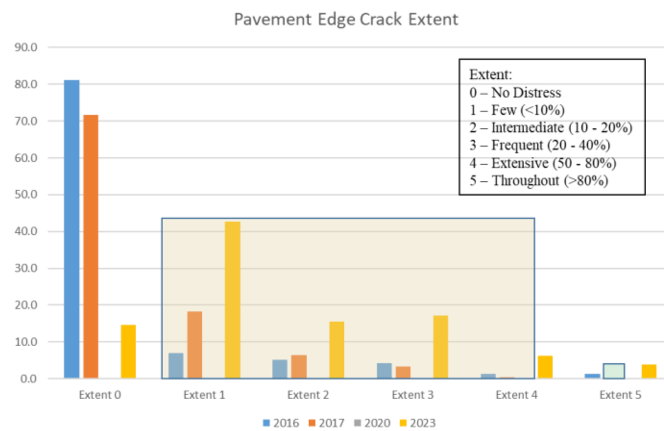


Figure 29 Pavement Edge Cracking Extent in percentages All years - Comprehensive table and bar chart showing Extent distribution across all years

4.3.7 Longitudinal Cracking Analysis

Longitudinal cracking maintained moderate network presence with relatively stable patterns throughout the analysis period, representing manageable structural deterioration with effective maintenance strategies maintaining consistent network impact levels.

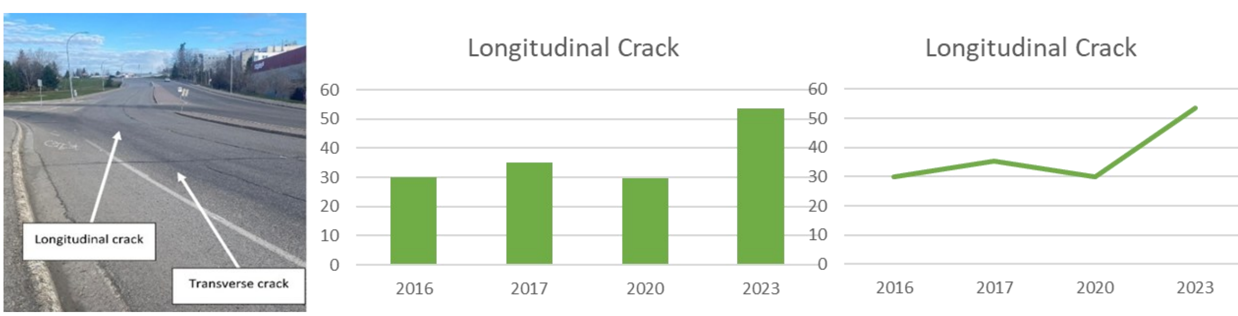


Figure 30 Longitudinal Cracking condition Trend (Photo credit to Mr. Alireza Noory)

Longitudinal Cracking Severity Analysis

Longitudinal cracking in Prince George demonstrates stable and manageable severity characteristics throughout the analysis period, with effective maintenance strategies maintaining consistent network impact levels. The severity analysis reveals that longitudinal cracking maintained moderate severity patterns without significant peaks or deterioration phases, indicating appropriate intervention timing and technique selection. The temporal severity progression shows that longitudinal cracking severity was stable with minor fluctuations from baseline 2016 levels through slight improvement in 2017, followed by consistent management through 2020 and 2023, representing successful long-term maintenance effectiveness and demonstrating that systematic preventive strategies can effectively control structural deterioration progression when appropriately implemented.

Longitudinal Crack	2016	2017	2020	2023
Severity 0	70.0	64.8	67.1	49.4
Severity 1	21.7	2.8	7.8	1.2
Severity 2	6.4	20.4	17.0	45.8
Severity 3	1.8	12.0	8.0	3.6
Total	30.0	35.2	32.9	50.6

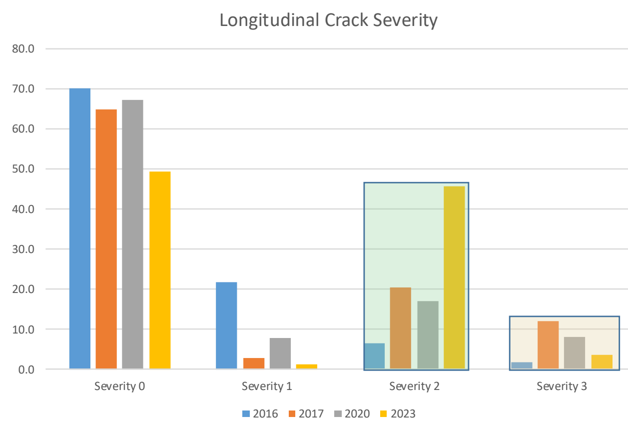


Figure 31 Longitudinal Cracking Severity in percentages All years - Comprehensive table and bar chart showing Severity distribution across all years

Longitudinal Cracking Extent Analysis

Longitudinal cracking demonstrated stable and manageable extent coverage throughout the analysis period, maintaining consistent network presence around 9-15% of total distresses across all survey years. The extent analysis reveals that longitudinal cracking coverage decreased moderately from 2016 baseline levels (14.73%) through effective maintenance intervention in 2017 (9.16%), followed by stable management at approximately 10.5% coverage in 2020 and 2023. The temporal extent progression shows that longitudinal cracking extent was effectively managed with initial reduction followed by consistent stability, indicating successful maintenance strategies and demonstrating that appropriate preventive intervention can maintain manageable deterioration levels while preventing expansion of structural cracking across the municipal road network.

Longitudinal Crack	2016	2017	2020	2023
Extent 0	70.0	64.8	67.1	49.4
Extent 1	9.8	18.9	15.9	41.0
Extent 2	8.7	8.9	8.0	4.5
Extent 3	8.9	6.3	6.9	4.0
Extent 4	1.6	0.9	1.7	0.9
Extent 5	0.9	0.2	0.4	0.2
Total	30.0	35.2	32.9	50.6

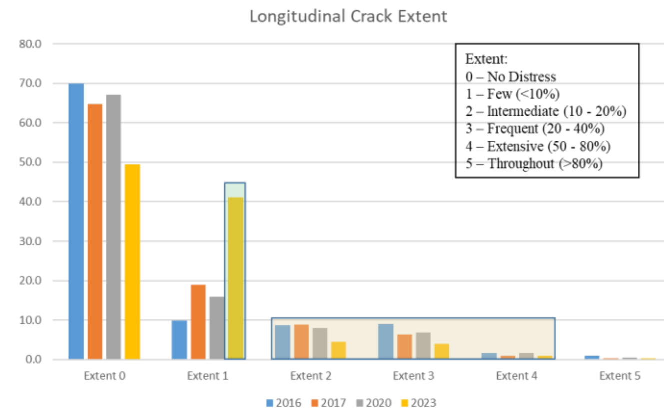


Figure 32 Longitudinal Cracking Extent in percentages All years - Comprehensive table and bar chart showing Extent distribution across all years

4.3.8 Pothole Analysis

Pothole occurrence remained limited throughout all survey periods but demonstrated variable patterns requiring ongoing monitoring for safety considerations, representing critical localized surface failure requiring immediate response protocols.

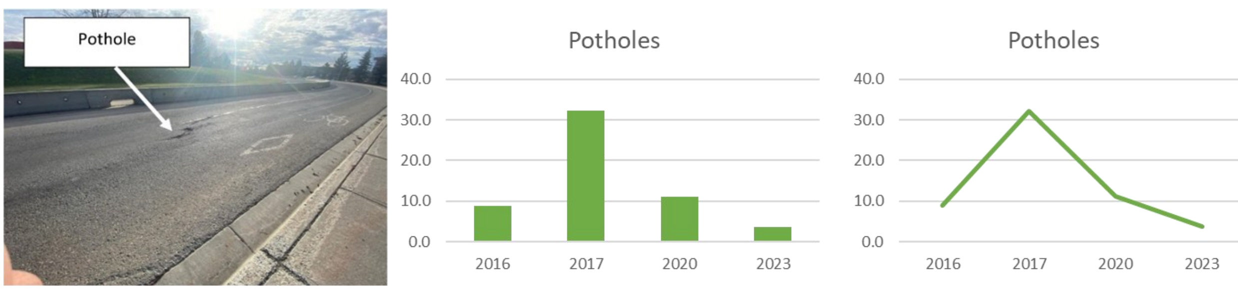


Figure 33 Pothole condition Trend (Photo credit to Mr. Alireza Noory)

Pothole Severity Analysis

Potholes in Prince George demonstrate variable severity patterns with successful long-term management achieving near-elimination by 2023. The severity analysis reveals that pothole conditions peaked in 2017 with elevated surface failure rates requiring enhanced maintenance response, representing the most challenging period for emergency surface maintenance. The temporal severity progression shows that pothole severity was increasing from baseline 2016 levels to peak conditions in 2017, followed by systematic reduction through 2020 and near-elimination in 2023, demonstrating highly effective reactive maintenance strategies and emergency response protocol implementation for surface failure management across the municipal road network.

Potholes	2016	2017	2020	2023
Severity 0	91.1	67.8	88.8	96.3
Severity 1	7.2	20.2	2.7	2.9
Severity 2	1.6	11.5	7.2	0.8
Severity 3	0.1	0.5	1.3	0.0
Total	8.9	32.2	11.2	3.7

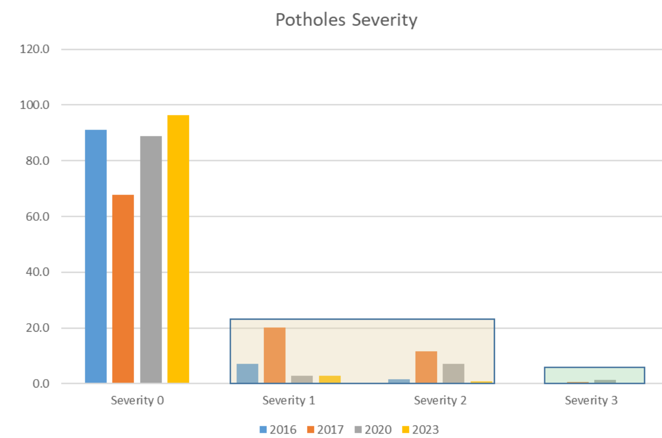


Figure 34 Pothole Severity in percentages All years - Comprehensive table and bar chart showing Severity distribution across all years

Pothole Extent Analysis

Potholes demonstrated successful extent management with systematic reduction from peak levels to near-elimination, representing effective emergency response and surface maintenance strategies. The extent analysis reveals that pothole coverage was most extensive in 2017 (8.37% of network distresses), indicating peak surface failure conditions requiring intensive reactive maintenance response. The temporal extent progression shows that pothole extent was increasing from baseline 2016 levels (4.38%) to peak coverage in 2017, followed by systematic reduction through 2020 (3.57%) and near-elimination in 2023 (0.78%), demonstrating highly successful surface failure management and emergency response protocol effectiveness for maintaining safe driving conditions and preventing localized surface deterioration across the municipal road network.

Potholes	2016	2017	2020	2023
Extent 0	91.1	67.8	88.8	96.3
Extent 1	7.8	22.8	9.3	3.4
Extent 2	1.1	0.2	0.0	0.0
Extent 3	0.0	7.9	1.7	0.3
Extent 4	0.0	0.0	0.0	0.0
Extent 5	0.0	1.3	0.1	0.0
Potholes	8.9	32.2	11.2	3.7

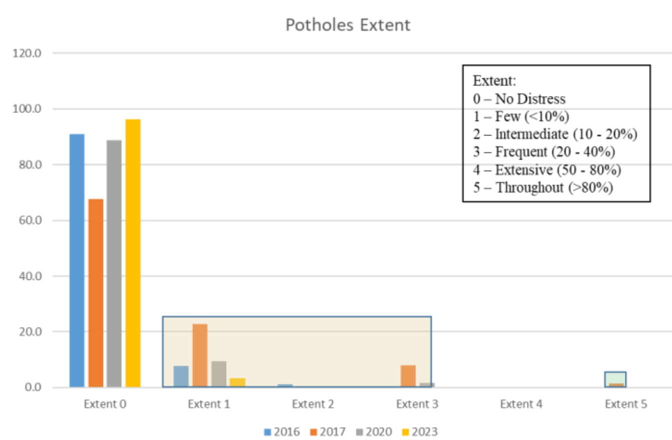


Figure 35 Pothole Extent in percentages All years - Comprehensive table and bar chart showing Extent distribution across all years

4.4 Model Results and Performance Analysis

This section presents the comprehensive analysis of three predictive modeling approaches developed for Pavement Distress Index (PDI) forecasting: Multiple Linear Regression (MLR), Random Forest (RF), and Artificial Neural Network (ANN). The comparative evaluation demonstrates the effectiveness of advanced machine learning techniques for pavement performance prediction under northern climate conditions, providing essential foundation for strategic maintenance planning and resource allocation optimization.

4.4.1 Model Development Framework

The predictive modeling framework incorporated comprehensive variable selection including distress severity and extent measurements for all eight distress types, climatic parameters encompassing maximum, minimum, and mean temperature values, precipitation data, traffic loading information, rutting depth measurements, and International Roughness Index values. The modeling approach employed systematic 80-20 train-test data splitting with rigorous performance evaluation using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2) metrics.

The comprehensive modeling framework addresses the complex relationships between environmental factors, traffic loading, and pavement deterioration patterns. Variable selection procedures incorporated domain expertise with statistical significance testing to ensure optimal predictor inclusion while maintaining model parsimony and interpretability requirements.

4.4.2 Random Forest Model Performance

The Random Forest ensemble learning approach demonstrated superior performance characteristics among the three modeling techniques, achieving optimal balance between prediction accuracy, model robustness, and practical implementation requirements for municipal pavement management applications.

Performance Metrics:

- Mean Squared Error (MSE): 0.30
- Root Mean Squared Error (RMSE): 0.55
- Coefficient of Determination (R^2): 0.96

The Random Forest model achieved 96.16% explained variance in PDI prediction, representing exceptional accuracy for pavement performance forecasting applications under challenging northern climate conditions. The ensemble learning approach effectively captured complex non-linear relationships between predictor variables and pavement condition while maintaining robust performance across varying data conditions and environmental scenarios.

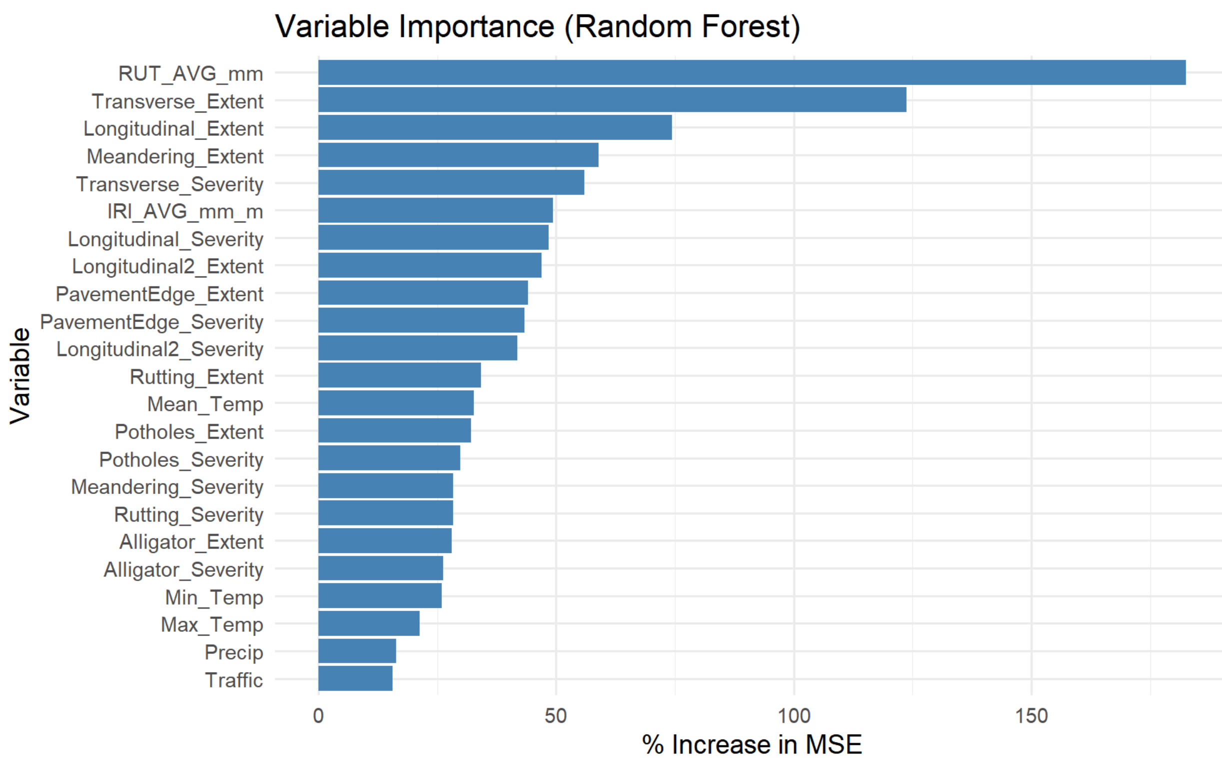


Figure 36 Random Forest variable importance plot showing key contributing factors to PDI prediction

Variable importance analysis revealed that rutting measurements, temperature parameters, and specific distress types contribute most significantly to PDI prediction accuracy. The model's superior handling of complex interactions between climatic factors and pavement deterioration mechanisms makes it particularly suitable for northern climate applications where freeze-thaw cycles, temperature fluctuations, and precipitation patterns significantly influence infrastructure performance.

The ensemble methodology combines multiple decision trees to reduce overfitting risk while improving prediction stability across different data subsets. This robustness characteristic proves essential for municipal applications where data quality and availability may vary across different survey periods and network sections, giving it a practical advantage over the more complex ANN approach.

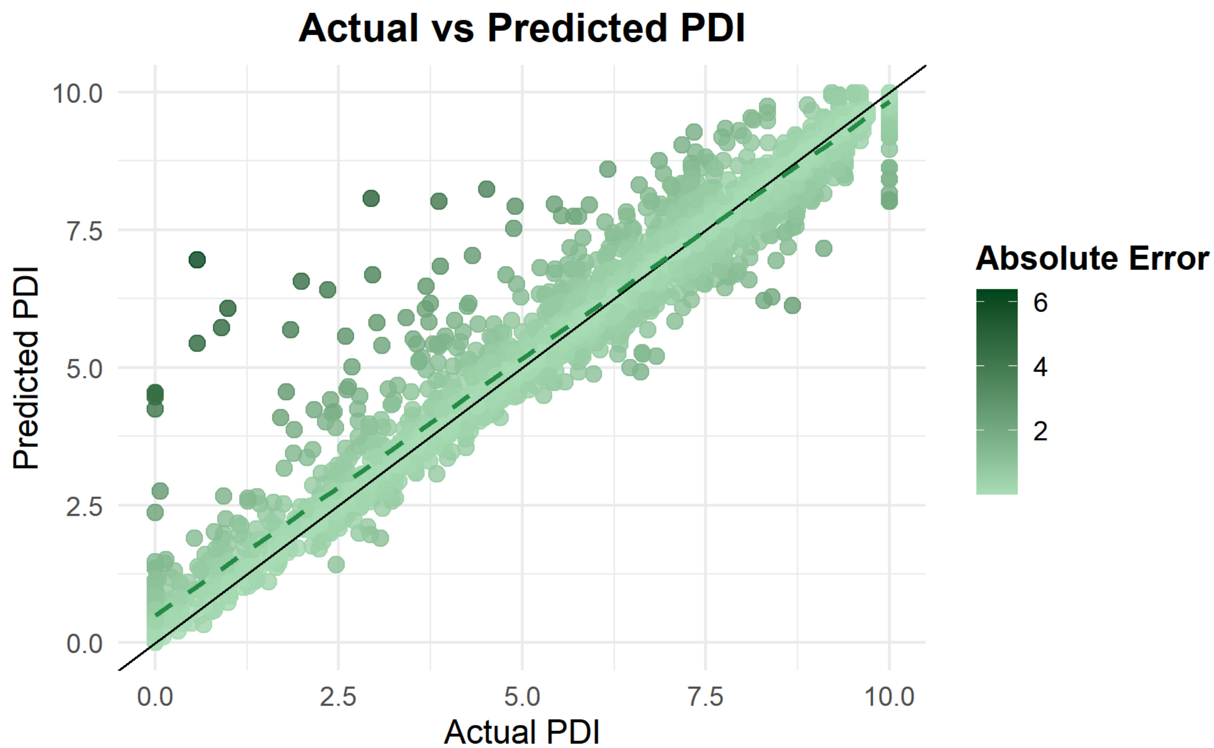


Figure 37 Random Forest actual vs. predicted PDI scatter plot with performance statistics

4.4.3 Artificial Neural Network Model Performance

The Artificial Neural Network approach achieved the highest prediction accuracy among all modeling techniques, demonstrating sophisticated pattern recognition capabilities for complex pavement deterioration relationships and non-linear interaction effects characteristic of infrastructure performance under variable environmental conditions.

Performance Metrics:

- Mean Squared Error (MSE): 0.23
- Root Mean Squared Error (RMSE): 0.48
- Coefficient of Determination (R^2): 0.95

The ANN model achieved 95.11% explained variance with the lowest MSE and RMSE values, indicating superior prediction precision for individual pavement segment condition forecasting. The neural network architecture effectively captured complex non-linear interactions between input variables, providing high accuracy forecasting capabilities essential for detailed maintenance planning and intervention timing optimization.

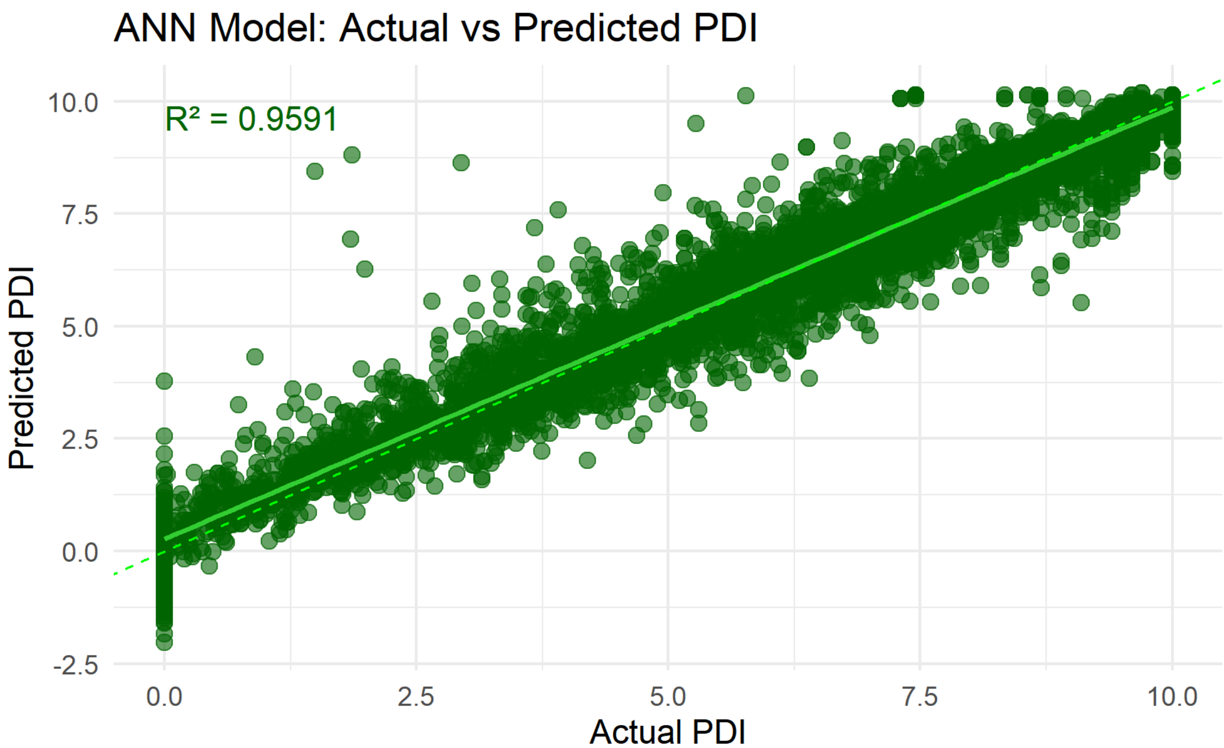


Figure 38 ANN model actual vs. predicted PDI scatter plot with trend line and performance statistics

The neural network's sophisticated pattern recognition capabilities enable accurate modeling of complex deterioration mechanisms characteristic of northern climate conditions, including freeze-thaw cycles, temperature fluctuations, moisture-related damage patterns, and traffic loading interactions. The six-neuron hidden layer architecture provides optimal balance between model complexity and computational efficiency for municipal pavement management applications.

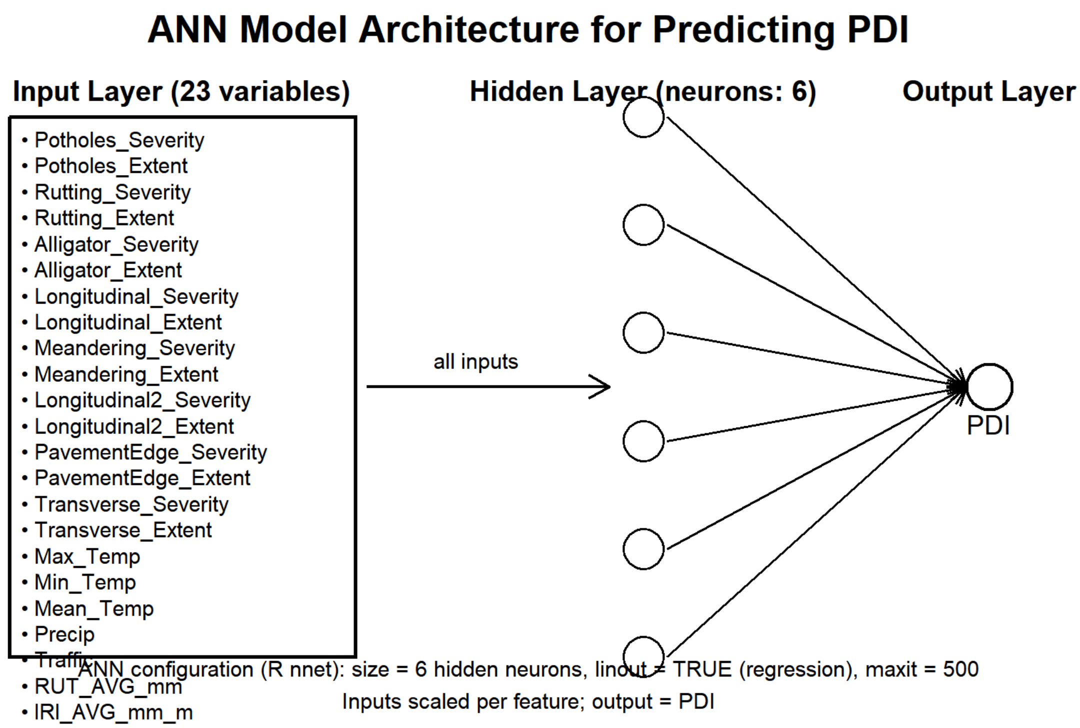


Figure 39 ANN model architecture diagram showing input variables, hidden layer, and output structure

The neural network approach demonstrates particular effectiveness in capturing threshold effects and non-linear deterioration patterns where pavement condition changes rapidly under specific environmental or loading conditions. This capability proves valuable for identifying critical intervention timing and predicting accelerated deterioration periods.

4.4.4 Multiple Linear Regression Model Performance

The Multiple Linear Regression approach served as the baseline modeling technique, providing interpretable coefficient relationships while demonstrating acceptable prediction accuracy for linear deterioration patterns and establishing foundation analysis for comparison with advanced modeling approaches.

Performance Metrics:

- Mean Squared Error (MSE): 0.85
- Root Mean Squared Error (RMSE): 0.92
- Adjusted Coefficient of Determination (Adjusted R^2): 0.81

The MLR model achieved an adjusted R^2 of 81.65%, representing acceptable performance for linear relationship modeling while accounting for the model's 15 predictor variables. The adjusted R^2 provides a more conservative estimate of explained variance compared to standard R^2 by penalizing model complexity, ensuring that the reported performance reflects genuine predictive capability rather than overfitting. This adjusted metric is particularly relevant for MLR given its parametric nature and the substantial number of input variables, providing valuable insights into individual factor contributions to pavement deterioration. While demonstrating lower accuracy compared to machine learning approaches, the MLR model maintains high interpretability for stakeholder communication and regulatory compliance requirements.

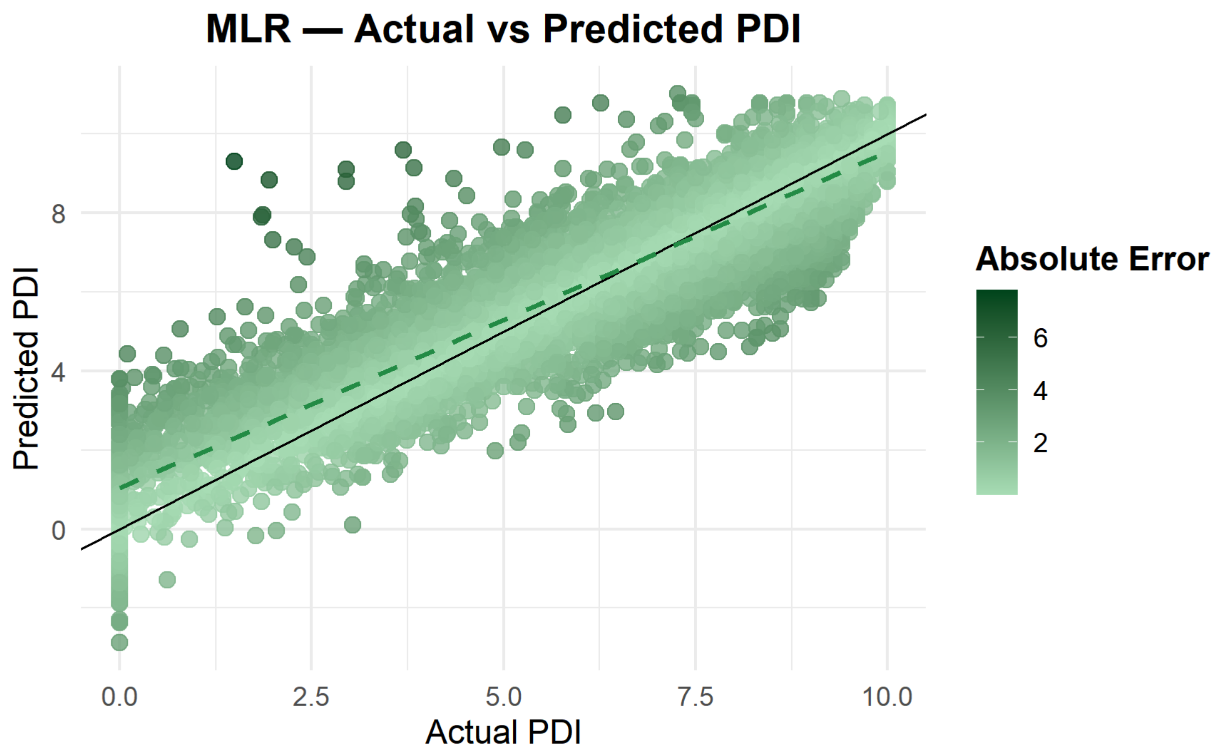


Figure 40 MLR model actual vs. predicted PDI scatter plot with regression line

The linear regression approach effectively identified significant predictor variables and provided foundation analysis for understanding basic relationships between environmental factors, traffic loading, and pavement condition. Coefficient analysis reveals that temperature parameters, specific distress measurements, and traffic data contribute most significantly to linear deterioration patterns.

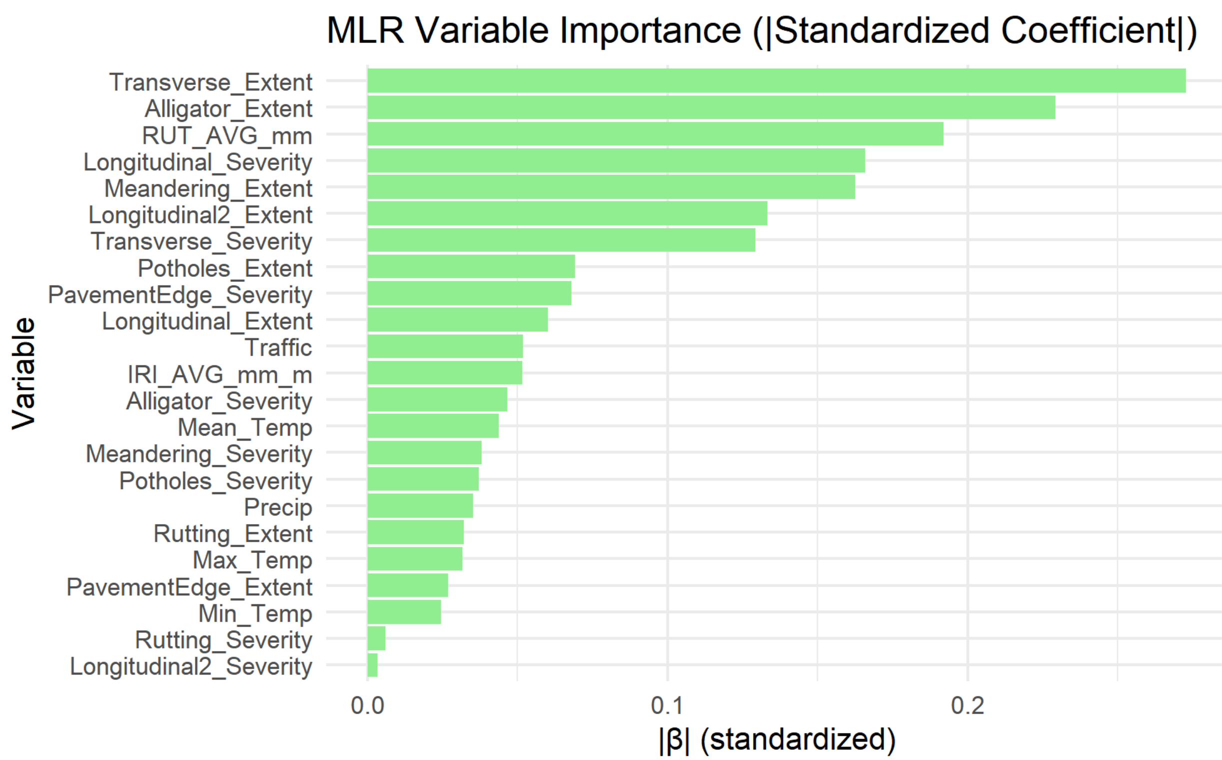


Figure 41 MLR coefficient significance plot showing predictor variable contributions

Residual analysis confirmed appropriate model behavior without systematic bias or heteroscedasticity issues, validating the linear modeling assumptions for baseline performance evaluation. The straightforward implementation requirements and computational efficiency make MLR suitable for routine monitoring applications where interpretability outweighs maximum prediction accuracy requirements.

4.4.5 Model Comparison and Selection Criteria

Comparative analysis reveals distinct performance characteristics among the three modeling approaches, each offering specific advantages for different pavement management applications and decision-making requirements. The evaluation framework considers prediction accuracy, computational requirements, interpretability needs, and practical implementation constraints.

The performance metrics presented utilize adjusted R^2 for the MLR model to ensure fair comparison across modeling approaches. While Random Forest and ANN models report standard R^2, the MLR adjusted R^2 accounts for the 15 predictor variables included in the linear model, providing a more conservative and rigorous assessment of model fit. This methodological distinction is important because adjusted R^2 prevents overestimation of MLR performance that could occur from including multiple predictors, whereas machine learning approaches employ different internal validation mechanisms (out-of-bag error for Random Forest and validation loss for ANN) that inherently guard against overfitting.

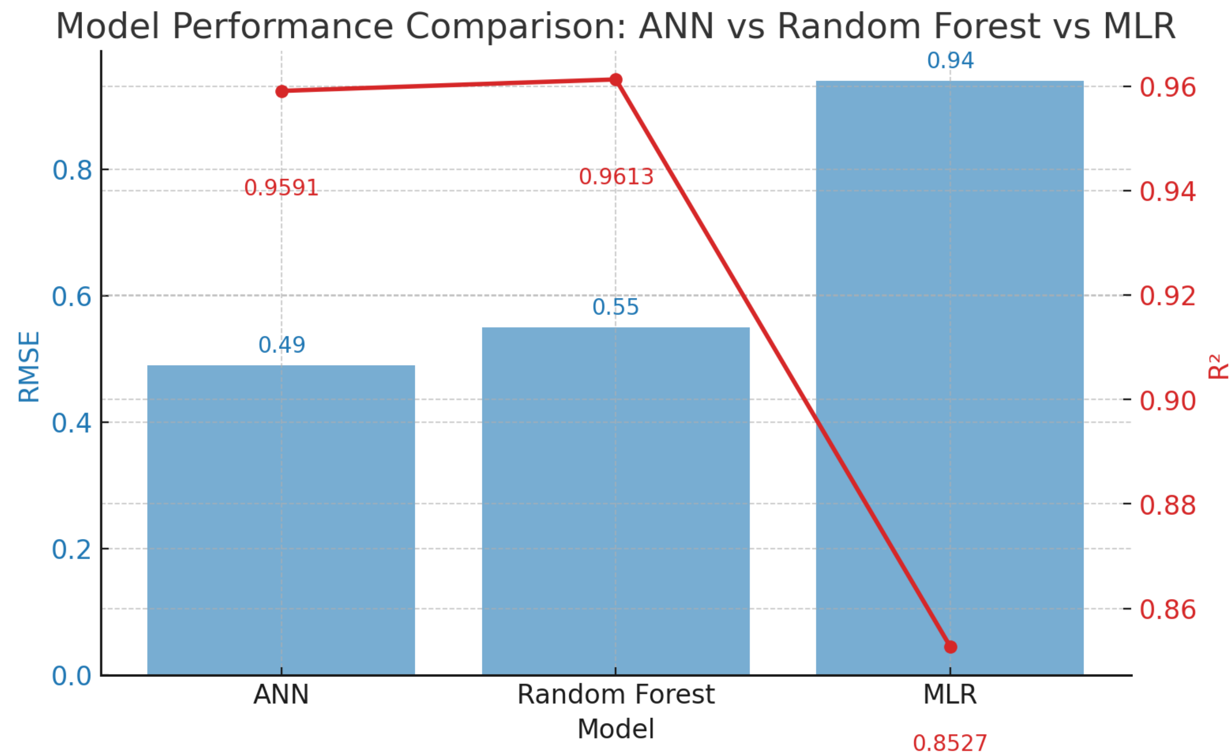


Figure 42 Model performance comparison chart showing MSE, RMSE, and R² values across all three models.

The ANN model achieved the highest prediction accuracy with MSE of 0.23 and R^2 of 0.95, followed closely by the Random Forest model with MSE of 0.30 and R^2 of 0.96. The MLR model, while providing lower accuracy (MSE of 0.85, adjusted R^2 of 0.81), offers superior interpretability and computational efficiency for routine applications. Notably, the adjusted R^2 for MLR provides a conservative estimate appropriate for parametric models with multiple predictors, ensuring the comparison fairly represents each model's true predictive performance.

For practical pavement management applications, the Random Forest model provides an optimal balance between prediction accuracy, model interpretability, and computational requirements. The ensemble learning approach maintains robust performance across varying data conditions while providing variable importance insights essential for maintenance decision-making and resource allocation optimization.

The machine learning approaches demonstrate superior capability for capturing complex interaction effects between environmental factors, traffic loading, and deterioration patterns characteristic of northern climate infrastructure performance. However, the interpretability advantage of linear regression maintains value for regulatory reporting and stakeholder communication requirements.

4.4.6 Three-Dimensional Relationship Analysis

To further understand the complex interactions between pavement condition indices and distress characteristics, advanced three-dimensional visualization techniques were employed to examine multivariable relationships that traditional two-dimensional plots cannot adequately capture. The International Roughness Index (IRI), serving as the primary measure of functional performance, demonstrates significant correlations with both PDI values and distress severity levels, reflecting the interconnected nature of structural and functional pavement deterioration.

The three-dimensional analysis reveals critical insights into how roughness progression relates to overall pavement condition while simultaneously considering the influence of distress severity patterns. This multidimensional perspective provides essential understanding for maintenance decision-making, as it demonstrates how functional performance degradation (measured through IRI) correlates with structural condition decline (quantified through PDI) under varying distress severity scenarios characteristic of northern climate conditions.

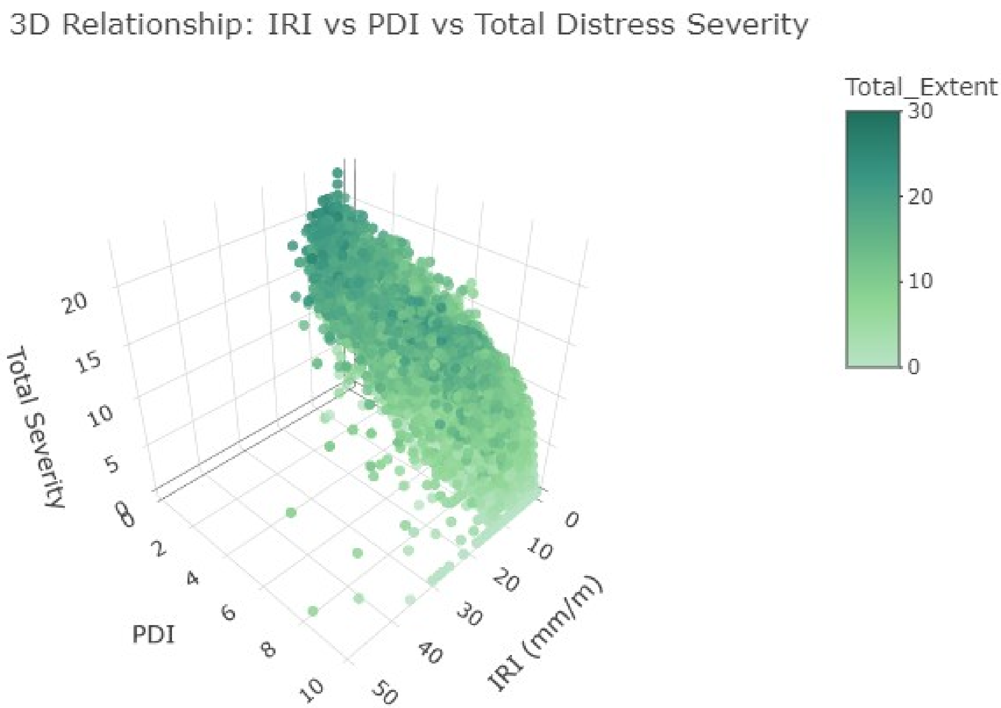


Figure 43 Three-dimensional relationship visualization between IRI, PDI, and distress severity levels showing the complex interactions between functional performance, structural condition, and distress intensity

The complementary analysis of distress extent relationships provides equally important insights into pavement performance patterns, as extent measurements quantify the spatial distribution of deterioration across pavement surfaces. Research has demonstrated that distress extent often exhibits different correlation patterns with functional performance compared to severity measurements, reflecting the complex mechanisms through which pavement deterioration manifests under varying traffic and environmental conditions.

The three-dimensional visualization of IRI-PDI-Extent relationships reveals how widespread distress distribution affects both ride quality and overall condition ratings. This analysis is particularly valuable for understanding threshold effects where extensive but low-severity distresses may significantly impact functional performance while having different implications for structural integrity. The extent analysis supports strategic maintenance planning by identifying conditions where surface treatments may be more appropriate than structural interventions, or conversely, where extensive distress patterns indicate underlying structural issues requiring comprehensive rehabilitation.

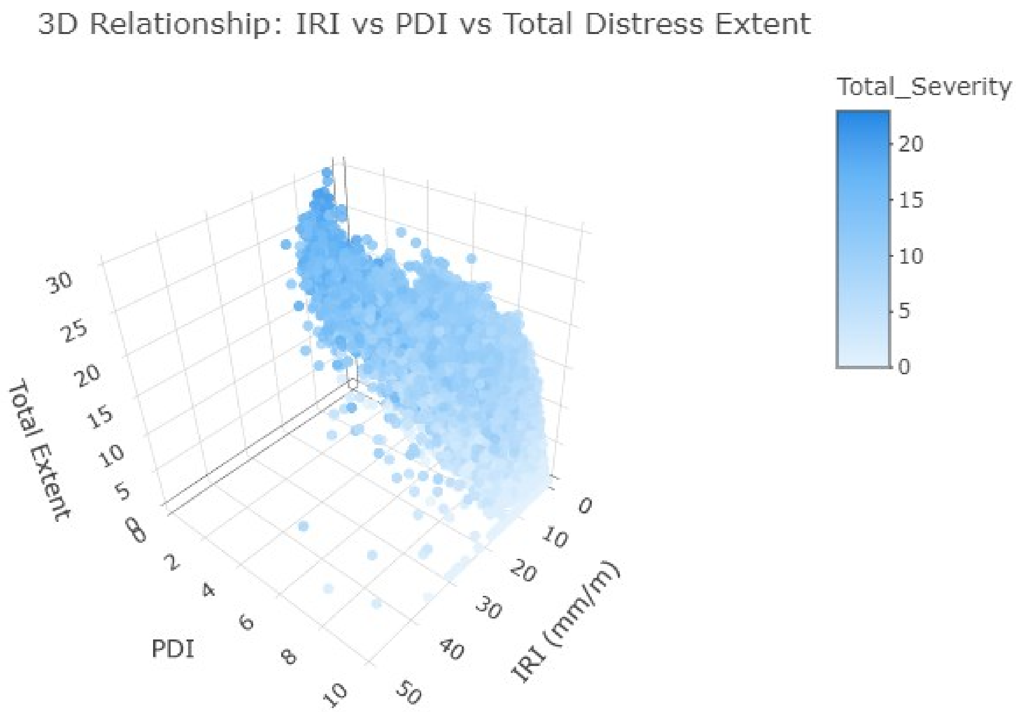


Figure 44 Three-dimensional relationship visualization between IRI, PDI, and distress extent measurements demonstrating how spatial distribution of distresses influences both functional and structural performance indicators

These three-dimensional visualizations provide comprehensive understanding of the multifaceted relationships governing pavement performance under northern climate conditions. The analysis demonstrates that both distress severity and extent contribute significantly to the relationship between functional performance (IRI) and structural condition (PDI), but through different mechanisms that require distinct maintenance approaches.

The combined severity and extent analysis supports the Random Forest model's superior performance by illustrating the complex, non-linear interactions that ensemble learning methods can effectively capture. Traditional linear regression approaches cannot adequately model these multidimensional relationships, explaining the substantial performance differences observed in the comparative analysis. The three-dimensional perspectives validate the importance of considering multiple distress characteristics simultaneously when developing predictive models for municipal pavement management applications.

5. Chapter 5: Discussion, Conclusion and Recommendations

5.1 Interpretation of Findings

5.1.1 Distress Evolution and Network Performance Insights

The comprehensive analysis of Prince George's pavement network from 2016 to 2023 reveals profound shifts in distress patterns that fundamentally challenge traditional maintenance approaches. The research demonstrates that climate-adaptive pavement management requires dynamic strategies responsive to evolving deterioration mechanisms rather than static, condition-based interventions.

Emergence of Rutting as the Dominant Challenge

The most noticable finding is rutting's transformation from complete absence in 2016 to affecting 98.4% of the network by 2023. This unprecedented emergence pattern suggests systematic changes in pavement response mechanisms, likely attributed to the combination of climate change effects, evolving traffic patterns, and material aging characteristics specific to northern environments. The progression from zero baseline through 55.7% coverage in 2017 to near-full presence demonstrates accelerating deterioration that traditional predictive models fail to anticipate.

The severity distribution in 2023, with 92.9% of affected segments exhibiting low severity conditions, indicates that rutting emergence follows a consistent pattern across the network rather than isolated failure mechanisms. This finding suggests that current pavement structural designs and asphalt mixture designs may be inadequate for evolving environmental and loading conditions, necessitating fundamental reassessment of design standards and material specifications for northern climate applications.

Pavement Edge Cracking as a Critical Infrastructure Integrity Issue

The dramatic emergence of pavement edge cracking from manageable levels (18.9% in 2016, 28.4% in 2017) to the most extensive single distress challenge (85.4% in 2023) represents a critical infrastructure integrity crisis. The absence of edge cracking data in 2020 creates a significant analytical gap, but the explosive expansion documented in 2023 suggests systematic deterioration mechanisms affecting pavement-curb interfaces, drainage effectiveness, and structural continuity.

The severity distribution in 2023, with 63% of segments exhibiting low severity and 17% showing moderate to high severity conditions, indicates that edge deterioration affects both functional and structural pavement performance. This pattern suggests that current construction practices for pavement edge details, joint sealing procedures, and drainage management require comprehensive revision to address harsh northern climate conditions.

Successful Management of Traditional Distress Types

The research demonstrates exceptional success in managing traditional structural distresses, particularly alligator cracking, which achieved near-elimination from 4.85% of network distresses in 2016 to only 0.39% in 2023. This achievement validates the effectiveness of systematic structural rehabilitation programs when properly targeted and executed, demonstrating that comprehensive mill-and-fill strategies, reclamation procedures, and reconstruction programs can successfully address advanced structural deterioration.

Similarly, the management of transverse cracking, while remaining the most prevalent distress type, shows systematic improvement from peak severity conditions in 2017 and 2020 to manageable levels in 2023. The complete elimination of high-severity transverse cracking in 2023 demonstrates that targeted intervention strategies can effectively control thermal-related deterioration mechanisms characteristic of northern climate conditions.

5.1.2 Advantages of Implementing Predictive Modeling

Superior Performance of Machine Learning Approaches

The comparative analysis reveals that advanced machine learning techniques substantially outperform traditional statistical methods for pavement condition prediction under northern climate conditions. The Random Forest model achieved 96.16% explained variance ($R^2 = 0.96$, MSE = 0.30), while the Artificial Neural Network demonstrated ($R^2 = 0.95$, MSE = 0.23), both significantly exceeding Multiple Linear Regression performance ($R^2 = 0.81$, MSE = 0.85).

The superior performance of ensemble learning and neural network approaches validates the complex, non-linear nature of pavement deterioration under northern climate conditions. The Random Forest model's variable importance analysis identified rutting measurements, temperature parameters, and specific distress characteristics as primary prediction drivers, confirming the critical role of climate-pavement interactions in deterioration progression.

Practical Implementation Considerations

Despite the ANN model's superior accuracy, the Random Forest approach provides an optimal balance between prediction performance, interpretability, and computational requirements for municipal applications. Randon Forest is the most suitable modeling tool supporting maintenance decision-making and resource allocation optimization due to its consistency across varying data conditions ..

The substantial performance difference between machine learning approaches and traditional linear regression (approximately 15% improvement in explained variance) demonstrates the inadequacy of simplified deterioration models for northern climate applications. This finding supports the necessity of implementing advanced analytical techniques to capture the complex interactions between environmental factors, traffic loading, and material performance characteristic of harsh climate conditions.

5.2 Lessons Learned and Limitations

5.2.1 Research Methodology Insights

Data Collection Temporal Alignment Challenges

The analysis revealed significant challenges in aligning pavement condition data collected at different intervals with corresponding climate and traffic information. The variation in survey coverage across assessment periods, ranging from full network evaluation (31,084 data points in 2020) to targeted assessments (8,942 data points in 2023), created analytical complexities that required careful consideration in model development and validation procedures.

The absence of pavement edge cracking data in 2020 created a critical gap in trend analysis that limited understanding of edge deterioration progression patterns. This limitation emphasizes the importance of maintaining consistent distress type coverage across all assessment periods to enable comprehensive deterioration modeling and strategic planning.

Variable Selection and Model Calibration Learnings

The research demonstrated that effective predictive modeling for northern climate conditions requires extensive variable preprocessing and careful selection of climate parameters that capture both acute environmental events and cumulative exposure effects. The integration of distress severity and extent measurements proved essential for capturing the multidimensional nature of pavement deterioration under harsh environmental conditions.

The superior performance of machine learning approaches validates the complex, non-linear nature of pavement-climate interactions but also highlights the importance of maintaining sufficient training data to ensure model robustness across varying environmental and operational conditions.

5.2.2 Research Limitations and Constraints

Temporal Data Scope Limitations

The research is constrained by the 7-year analysis period (2016-2023), which may not capture the full range of climatic variability or long-term deterioration cycles. The limited scope restricts assessment of treatment longevity and effectiveness under varying environmental conditions, particularly for newer rehabilitation techniques and climate-adaptive materials.

The irregular survey intervals (2016, 2017, 2020, 2023) create gaps in deterioration trend analysis that may affect the accuracy of predictive model calibration and validation. More frequent condition assessment would enable enhanced understanding of seasonal deterioration patterns and treatment timing optimization.

Treatment Effectiveness Assessment Limitations

The limited availability of detailed construction specifications, material properties, and quality control data restricted assessment of factors contributing to treatment success or failure, limiting the ability to provide specific material and construction recommendations.

5.2.3 Methodological Considerations for Future Research

Enhanced Data Integration Requirements

Future research should incorporate more sophisticated environmental monitoring including subsurface temperature measurements, moisture content assessment, and detailed freeze-thaw cycle documentation to enable enhanced understanding of climate-pavement performance relationships.

The development of comprehensive treatment effectiveness databases that document intervention timing, material specifications, construction conditions, and subsequent performance would enable enhanced evaluation of maintenance strategy optimization under varying environmental conditions.

Advanced Modeling Framework Development

The research demonstrates the potential for developing more sophisticated modeling frameworks that integrate machine learning approaches with mechanistic-empirical principles to capture both empirical performance relationships and fundamental deterioration mechanisms. Such approaches could enable enhanced prediction accuracy while maintaining interpretability for practical management applications.

5.3 Conclusion

This research provided a comprehensive analysis of pavement deterioration patterns, predictive modeling capabilities, and management strategy optimization for northern climate conditions through systematic evaluation of Prince George's road network from 2016 to 2023. The findings demonstrate that effective pavement management in harsh northern environments requires fundamental shifts from traditional maintenance approaches to climate-adaptive strategies that account for unique deterioration mechanisms, emerging distress patterns, and complex environmental interactions.

The wide emergence of rutting throughout the network and presence of pavement edge cracking as the most extensive single distress type represents paradigmatic shifts in pavement performance that demand immediate strategic response and long-term management framework revision. The research validates that advanced machine learning techniques provide superior prediction capabilities compared to traditional statistical methods, enabling enhanced decision-making and resource optimization for municipal pavement management applications.

The development of climate-adaptive pavement management frameworks informed by comprehensive data analysis, predictive modeling, and systematic treatment evaluation provides Prince George with evidence-based foundations for addressing current infrastructure challenges while establishing resilient management capabilities for future environmental and operational conditions. The transferable insights and methodological approaches developed through this research contributed to broader understanding of northern climate infrastructure management and provide frameworks for similar municipalities facing comparable challenges.

The integration of technical analysis with practical implementation considerations ensures that research findings translate into actionable strategies that can improve infrastructure performance, optimize resource utilization, and enhance municipal capability for systematic pavement stewardship under challenging northern climate conditions. The comprehensive recommendations for treatment selection, strategic planning, and advanced technology implementation provide roadmaps for transitioning from reactive maintenance approaches to proactive, data-driven management systems that optimize both performance outcomes and sustainability objectives.

This research establishes that successful pavement management in northern climates requires systematic integration of climate science, advanced analytical techniques, and strategic resource allocation within comprehensive frameworks that balance immediate operational needs with long-term infrastructure resilience and sustainability goals. The methodological approaches and analytical findings provide foundations for continued advancement of northern climate infrastructure management practice and academic research.

5.4 Recommendations for City of Prince George

5.4.1 Immediate Strategic Priorities

Rutting Management Crisis Response

Prince George faces an immediate infrastructure crisis with rutting affecting 98.4% of the road network by 2023. The city must implement emergency intervention protocols targeting the most severely affected arterial and collector roads to prevent further structural deterioration and maintain transportation system functionality. Immediate actions should include:

1. **High-Priority Corridor Identification**: Conduct urgent assessment of arterial roads and major collectors experiencing moderate to severe rutting to prioritize intervention sequencing based on traffic volume, economic importance, and safety considerations.
2. **Emergency Funding Mobilization**: Develop business case documentation demonstrating the critical nature of rutting emergence to secure additional capital funding for comprehensive rehabilitation programs that address systematic network deterioration. Rutting represents a crucial safety hazard as it results in hydroplaning during storms leading to elevated accident rates.
3. **Advanced Material Implementation**: Transition immediately to high-modulus Hot Mix Asphalt (HIMA) mixtures and experimental fiber-reinforced HMA for all rutting remediation projects. Scientific transition to Superpave asphalt mixture designs and

experimenting Balanced Mix Design (BMD) would definitely enhance the asphalt mixture's rutting resistance without significant reduction in the mixtures' crack resistance.

Pavement Edge Integrity Restoration

The explosive emergence of pavement edge cracking affecting 85.4% of the network represents a critical structural integrity challenge requiring immediate systematic intervention:

1. **Construction Procedure Revision**: Comprehensively review and revise construction procedures for joints between HMA lanes and concrete curbs, incorporating enhanced sealing techniques, improved drainage details, and climate-adaptive joint materials.
2. **Drainage System Enhancement**: Implement systematic drainage improvements along pavement edges to prevent moisture infiltration and freeze-thaw damage that accelerates edge deterioration under northern climate conditions.
3. **Edge Rehabilitation Program**: Develop dedicated edge rehabilitation procedures that address both functional and structural aspects of edge deterioration, including partial reconstruction where necessary to restore structural continuity.

5.4.2 Treatment Selection Strategy Optimization

Climate-Adaptive Treatment Matrix

Based on the research findings and analysis of historical treatment effectiveness, Prince George should implement a revised treatment selection framework that accounts for the unique deterioration patterns observed in the northern climate analysis:

For Rutting-Dominated Conditions (PDI 4-8, Rutting Severity 1-3):

- **Primary Treatment**: Mill and Overlay (50-75mm) using high-modulus (HIMA) asphalt mixtures
- **Alternative Treatment**: Full-depth reclamation (100mm) for areas with underlying structural deficiencies
- **Timing**: Execute during optimal temperature windows (late spring/early summer) to ensure proper compaction and curing

For Edge Cracking Conditions (Edge Extent 2-5):

- **Primary Treatment**: Edge reconstruction with enhanced joint sealing and improved drainage integration
- **Preventive Treatment**: Systematic joint sealing optimization for early-stage edge deterioration
- **Design Enhancement**: Implement wider shoulder specifications and improved edge support details

For Transverse Cracking Management (Severity 1-2, Extent 1-3):

- **Primary Treatment**: Crack sealing during optimal seasonal windows (fall application)
- **Progressive Treatment**: Microsurfacing for moderate coverage areas to prevent progression
- **Rehabilitation Treatment**: Mill and fill for extensive coverage areas showing progression potential

For Alligator Cracking (Maintained Success):

- **Continue Current Strategy**: Maintain aggressive mill and fill approach that achieved near-elimination
- **Monitor**: Implement enhanced monitoring for early detection to prevent recurrence
- **Preventive Focus**: Emphasize preventive treatments in areas showing early fatigue indicators

5.4.3 Implementation Framework for Advanced Management Systems

Predictive Modeling Integration

The research demonstrates that Random Forest modeling provides optimal balance between accuracy and practicality for municipal implementation. Prince George should implement the following framework:

1. **Annual Model Calibration**: Establish procedures for annual model recalibration using current condition data to maintain prediction accuracy as network conditions evolve.
2. **Seasonal Prediction Updates**: Develop quarterly prediction updates that incorporate current climate data to optimize maintenance timing and resource allocation decisions.
3. **Decision Support Integration**: Integrate predictive modeling capabilities with existing pavement management system to provide real-time decision support for maintenance prioritization and budget allocation.

Enhanced Data Collection Protocols

The analysis reveals critical data collection gaps that limit analytical capabilities. Implement enhanced protocols including:

1. **Consistent Distress Coverage**: Ensure all distress types are assessed during every survey period to prevent analytical gaps like the 2020 edge cracking omission.
2. **Climate Integration**: Establish systematic integration of climate data with condition assessment to enable enhanced understanding of environmental deterioration relationships.
3. **Treatment Documentation**: Implement comprehensive documentation of treatment specifications, timing, and performance to enable enhanced effectiveness evaluation.

5.5 Recommendations for Future Academic Research

5.5.1 Advanced Material and Treatment Research

Northern Climate Material Development

The research identifies critical needs for material innovations specifically designed for harsh northern climate conditions. Future research should focus on:

1. **High-Modulus Asphalt Mixtures (HIMA) Utilization**: Comprehensive laboratory and field testing of high-modulus asphalt mixtures (HIMA) under controlled northern climate exposure conditions to optimize mixture design parameters, aggregate specifications, and binder selection criteria. Production of HIMA mixtures could be facilitated by high polymer-modified binders using Styrene-Butadiene-Styrene (SBS) modifiers.
2. **Fiber-Reinforced Asphalt Performance**: Long-term performance evaluation of various fiber reinforcement types (synthetic, natural, recycled) in HMA mixtures under freeze-thaw cycling, temperature extremes, and heavy loading conditions characteristic of northern environments.
3. **Climate-Adaptive Binder Technologies**: Development and testing of modified asphalt binders specifically formulated to maintain performance across extreme temperature ranges while providing enhanced resistance to moisture damage and thermal cycling effects.

Advanced Treatment Technique Development

Research opportunities exist for developing innovative treatment approaches that address the unique deterioration patterns identified in this research:

1. **Edge Rehabilitation Technologies**: Development of specialized edge rehabilitation techniques that address the joint interface between asphalt pavement and concrete infrastructure while providing enhanced resistance to freeze-thaw damage and moisture infiltration.
2. **Rutting Prevention Strategies**: Investigation of preventive treatments that can be applied to delay or prevent rutting emergence, including surface modifications, structural enhancements, and traffic management approaches.
3. **Climate-Responsive Treatment Timing**: Research into optimal treatment timing based on seasonal climate patterns, material temperature requirements, and long-term performance optimization under northern climate conditions.

5.5.2 Enhanced Modeling and Prediction Research

Multi-Scale Deterioration Modeling

The research demonstrates the effectiveness of machine learning approaches but identifies opportunities for enhanced modeling frameworks:

1. **Mechanistic-Empirical Integration**: Development of hybrid modeling approaches that combine machine learning pattern recognition capabilities with mechanistic-empirical principles to enhance prediction accuracy while maintaining physical interpretability.
2. **Real-Time Adaptive Modeling**: Research into dynamic modeling frameworks that can adapt prediction parameters based on real-time environmental monitoring, traffic data, and emerging condition trends to maintain accuracy as conditions evolve.

References

AECOM. (2016). *RIVA asset management system: Business process maps*. City of Prince George. https://www.princegeorge.ca

Al-Ajami, H. (2015). *Pavement maintenance management systems*.

Ali, A. A. (2022). *Modeling of asphalt pavement performance indices in different climate regions using soft computing techniques* [Doctoral dissertation, Memorial University of Newfoundland]. Research.library.mun.ca

Ali, A. A., Milad, A., Hussein, A., Yusoff, N. I. M., & Heneash, U. (2023). Predicting pavement condition index based on the utilization of machine learning techniques: A case study. *Journal of Road Engineering, 3*, 266–278. https://doi.org/10.1016/j.jreng.2023.04.002

Allen, D. L. (1990). *Review and analysis of pavement management practices in Kentucky*.

Al-Swailmi, S., Al-Mansour, A. I., & Al-Tamimi, A. K. (1999). Pavement performance models for state highways in Riyadh. *Civil and Environmental Research, 7*(5), 103–110.

Anastasopoulos, P. Ch., Mannering, F. L., & Haddock, J. E. (2009). *Effectiveness and service lives/survival curves of various pavement rehabilitation treatments*.

Applied Research Associates, Inc. (2016). *Strategic paved road management plan: Gap analysis report* (Contract: P15-130). City of Prince George. https://www.princegeorge.ca

Association of State Highway and Transportation Officials. (1993). *AASHTO guide for design of pavement structures*. AASHTO.

Attoh-Okine. (2002). Combining use of rough set and artificial neural networks in doweled-pavement-performance modeling: A hybrid approach. *Journal of Transportation Engineering, 128*(3), 270–275. https://doi.org/10.1061/(ASCE)0733-947X(2002)128:3(270)

Balzi, A., & Grilli, A. (2023). Pavement management system: Implementing project evaluation for local road administrations. *Transportation Research Procedia, 74*, 1211–1218.

Borghetti, F., Derudi, M., Gandini, P., & Marchionni, G. (2024). Road infrastructure maintenance operative priority: A computational model for drainage systems. *Transportation Research Interdisciplinary Perspectives, 25*, 101100.

British Columbia Campus Press. (2025). Case: Urban Prince George. In *Land use planning in British Columbia*. https://pressbooks.bccampus.ca/landuseplanninginbc/chapter/case_urban_princegeorge/

British Columbia Ministry of Transportation and Infrastructure. (2020). *Pavement surface condition rating manual* (6th ed.). WSP Canada Limited.

British Columbia Ministry of Transportation and Infrastructure. (2025). *Road condition monitoring*. https://twm.th.gov.bc.ca/?c=tdp&lon=122.75041755326814&lat=53.91926807911665&z=10&sb=1

Butt, A. A., Shahin, M. Y., Feighan, K. J., & Carpenter, S. H. (1987). *Pavement performance prediction model using the Markov process*. Transportation Research Board.

City of Prince George. (2009). *Transportation network planning study: Final report*. https://www.princegeorge.ca/sites/default/files/2023-01/Transportation_Network_Planning_Study_Final_Report_2009-11-03.pdf

City of Prince George. (2015). *Official community plan*. https://www.princegeorge.ca/City%20Hall/Documents/Official_Community_Plan/OCP-Bylaw-8383.pdf

City of Prince George. (2024). *2024 road rehabilitation projects*. https://www.princegeorge.ca/sites/default/files/2024-04/2024%20Road%20Rehab%20Location%20Map.pdf

Climate Atlas of Canada. (2025). *Freeze-thaw cycles*. https://climateatlas.ca/map/canada/freezethaw_2030_85#

Dong, J., Meng, W., Liu, Y., & Ti, J. (2021). A framework of pavement management system based on IoT and big data. *Advanced Engineering Informatics, 47*, 101226. https://doi.org/10.1016/j.aei.2020.101226

Ekramnia, T., & Nasimifar, M. (2022). Development of a methodological tool for treatment prioritization in network-level pavement management system. *Journal of Transportation Engineering, Part B: Pavements*. ascelibrary.org

Environment and Climate Change Canada. (2025). *Historical weather data*. https://climate.weather.gc.ca/historical_data/search_historic_data_stations_e.html?searchType=stnName&timeframe=1&txtStationName=prince+george&searchMethod=contains&optLimit=yearRange&StartYear=2016&EndYear=2023&Year=2024&Month=12&Day=1&selRowPerPage=100

Federal Highway Administration. (2020). *Asset management practices and benefits - Case study 1* (Report No. FHWA-HIF-20-088). U.S. Department of Transportation.

Federal Highway Administration. (2022). *Pavement management roadmap: Executive summary* (Report No. FHWA-HIF-22-055).

Gavin, K., Toll, D. G., & Cheema, S. (2003). Canadian Strategic Highway Research Program: Effects of climate on pavement and foundation design. *Canadian Geotechnical Journal, 40*(3), 646–657.

Gong, H., Sun, Y., Shu, X., & Huang, B. (2018). Use of random forests regression for predicting IRI of asphalt pavements. *Construction and Building Materials, 189*, 890–897. https://doi.org/10.1016/j.conbuildmat.2018.09.017

Grilli, A., Casali, M., Muratori, D., & Bascucci, F. (2019). Pavement management system for local administrations: Guidelines in the Republic of San Marino. *International Journal of Pavement Research and Technology, 12*, 97–100.

Guha, S., & Hossain, K. (2021). *A country-wide survey to understand pavement management practices in Canada*. Canadian Technical Asphalt Association. https://www.ctaa.ca

Guha, S. K., Hossain, K., & Lawlor, M. (2022). An economic pavement management framework for extremely budget- and resource-constrained agencies in Canada. *Transportation Research Record, 2676*(8), 554–570. https://doi.org/10.1177/03611981221084687

Guo, W., Zhang, J., Cao, D., & Yao, H. (2022). Cost-effective assessment of in-service asphalt pavement condition based on random forests and regression analysis. *Construction and Building Materials, 330*, 127219. https://doi.org/10.1016/j.conbuildmat.2022.127219

Haas, R., Hudson, W. R., & Zaniewski, J. (1994). *Modern pavement management*. Krieger Publishing Company.

Hafez, M., & Ksaibati, K. (2021). Studying the effectiveness of changing parameters in pavement management systems on optimum maintenance strategies of low-volume paved roads. *Journal of Transportation Engineering, Part B: Pavements*. ascelibrary.org

Hamdi, A. (2015). *Local calibration of AASHTOWare using Ontario pavement management system data PMS2*.

Hudson, W. R., Haas, R., & Uddin, W. (1997). *Infrastructure management*. McGraw-Hill Professional.

Issa, A., & Abu-Eisheh, S. (2017). Evaluation of implementation of municipal roads' maintenance plans in Palestine: A pilot case study. *International Journal of Pavement Research and Technology, 10*, 454–463.

Khahro, S. H. (2022). Defects in flexible pavements: A relationship assessment of the defects of a low-cost pavement management system. *Sustainability, 14*(3), 1157.

Latitude.to. (2025). *Prince George, British Columbia, Canada*. https://latitude.to/map/ca/canada/cities/prince-george

Lee, Y.-H., Mohseni, A., & Darter, M. I. (1993). Simplified pavement performance models. *Transportation Research Record, 1397*, 7–14.

Li, J., Yin, G., Wang, X., & Yan, W. (2022). Automated decision making in highway pavement preventive maintenance based on deep learning. *Automation in Construction, 135*, 104111.

Li, Q. (2009). Calibration of flexible pavement in mechanistic-empirical pavement design guide for Washington state. *Transportation Research Record, 2095*(1), 73–83.

Loprencipe, G., Pantuso, A., & Di Mascio, P. (2017). Sustainable pavement management system in urban areas considering the vehicle operating costs. *Sustainability, 9*(3), 453.

Machí, C., Chamorro, A., Videla, C., Pellicer Armiñana, E., & Yepes, V. (2014). An iterative approach for the optimization of pavement maintenance management at the network level.

Marcelino, P., Antunes, M. L., Fortunato, E., & Gomes, M. C. (2019). Machine learning approach for pavement performance prediction. *International Journal of Pavement Engineering, 22*(3), 341–354. https://doi.org/10.1080/10298436.2019.1609673

Moradi, M., & Assaf, G. J. (2023). Designing and building an intelligent pavement management system for urban road networks. mdpi.com

Obaidat, M. T., Ghuzlan, K. A., & Al-Mestarehi, B. W. (2018). Integration of Geographic Information System (GIS) and PAVER system toward efficient pavement maintenance management system. *Jordan Journal of Civil Engineering, 12*, 449–462.

Obunguta, F., & Matsushima, K. (2022). Optimal pavement management strategy development with a stochastic model and its practical application to Ugandan national roads. *International Journal of Pavement Engineering, 23*, 2405–2419.

Pacific Climate Services. (2025). *PCDS climate data portal*. https://services.pacificclimate.org/met-data-portal-pcds/app/

Pantuso, A., Loprencipe, G., Bonin, G., & Teltayev, B. B. (2019). Analysis of pavement condition survey data for effective implementation of a network level pavement management program for Kazakhstan. *Sustainability, 11*, 901.

Prince George Open Data Portal. (2025). *Transportation datasets*. https://data-cityofpg.opendata.arcgis.com/search?collection=Dataset&q=Transportation

Prince George Weather Stats. (2025). *Annual precipitation trends*. https://princegeorge.weatherstats.ca/charts/precipitation-yearly.html

Qiao, Y., Dawson, A. R., Parry, T., Flintsch, G., & Wang, W. (2020). Flexible pavements and climate change: A comprehensive review and implications. *Sustainability, 12*(1057). https://doi.org/10.3390/su12031057

Qiao, Y., Flintsch, G. W., Dawson, A. R., & Parry, T. (2015). Evaluating the effects of climate change on road maintenance intervention strategies and life-cycle costs. *Transportation Research Part D: Transport and Environment, 41*, 492–503.

Ribeiro, L. C. P. (2020). *Establishing a methodology for unpaved and paved roads management system*. ufv.br

Saliminejad, S. (2013). *GIS-based probabilistic approach for assessing and enhancing infrastructure data quality*.

Santos, J., Ferreira, A., & Flintsch, G. (2017). A multi-disciplinary approach for the assessment of road pavement life cycle. *Structure and Infrastructure Engineering, 13*(8), 1019–1030.

Smith, K. L., Pontius, J., & Galehouse, L. (2014). *Asset management perspective* (Report No. FHWA-HIF-14-010). Federal Highway Administration.

Statistics Canada. (2021). *Prince George, city (CY) [Census subdivision], British Columbia and Fraser-Fort George, regional district [Census division], British Columbia (table). Census Profile, 2021 Census of Population*. https://www12.statcan.gc.ca/census-recensement/2021/dp-pd/prof/details/page.cfm?Lang=E&SearchText=Prince%20George&DGUIDlist=2021A00055953023&GENDERlist=1,2,3&STATISTIClist=1&HEADERlist=0

Swarna, S. T. (2022). *Climate change impact and adaptation for pavement infrastructure in Canada* [Doctoral dissertation, Memorial University of Newfoundland].

Tamagusko, T., & Ferreira, A. (2025). Pavement performance prediction using machine learning: Supervised learning with tree-based algorithms. *Transportation Research Procedia, 82*, 2521–2531. https://doi.org/10.1016/j.trpro.2024.12.202

Terzi, S. (2007). Modeling the pavement serviceability ratio of flexible highway pavements by artificial neural networks. *Construction and Building Materials, 21*(3), 590–593. https://doi.org/10.1016/j.conbuildmat.2005.11.001

Torres-Machí, C., Chamorro, A., Videla, C., Pellicer, E., & Yepes, V. (2014). An iterative approach for the optimization of pavement maintenance management at the network level. *The Scientific World Journal, 2014*, 524329.

Van Geem, C., Casse, C., Adolfs, T., & Diederiks, K. (2012, September). ViaBEL – A tool for decision processes in pavement management of secondary road networks in Belgium. *4th European Pavement and Asset Management Conference (EPAM 4)*, Malmö, Sweden.

Van Geem, C., & Massart, T. (2017, June). Quality insurance of visual inspections for pavement management of communal road networks. *World Conference on Pavement and Asset Management (WCPAM 2017)*, Milano, Italy.

Van Geem, C., & Massart, T. (2018, May). Implementation and benefits of a low-cost PMS for municipal road networks. *5th International Conference on Road and Rail Infrastructure (CETRA 2018)*, Zadar, Croatia.

Vines-Cavanaugh, D., Shamsabadi, S. S., Zhao, Y., & Huang, G. (2017). City-wide application of the affordable and rapid StreetScan pavement-management system. *Journal of Infrastructure Systems, 23*, B4016010.

Walls, J., III, & Smith, M. R. (1998). *Life-cycle cost analysis in pavement design* (Report No. FHWA-SA-98-079). Federal Highway Administration, Pavement Division.

Wang, X. C., Zhao, J., Li, Q. Q., Fang, N. R., Wang, P. C., Ding, L. T., & Li, S. Q. (2020). A hybrid model for prediction in asphalt pavement performance based on support vector machine and grey relation analysis. *Journal of Advanced Transportation, 2020*, 7534970.

Wang, Z., & Pyle, T. (2019). Implementing a pavement management system: The Caltrans experience. *International Journal of Transportation Science and Technology, 8*, 251–262.

Zagvozda, M., Dimter, S., Rukavina, T., & Vrtačnik Žižić, V. (2019). *Application of GIS technology in pavement management systems*.

Zhao et al. (2021). Viscosity prediction of rubberized asphalt–rejuvenated recycled asphalt pavement binders using artificial neural network approach. *Journal of Materials in Civil Engineering, 33*(5), 04021071. https://doi.org/10.1061/(ASCE)MT.1943-5533.0003679

Appendix I. Detailed Distress Analysis

I.1. Transverse Cracking Severity Analysis

2016 Severity Analysis: Transverse cracking affected 65.4% of surveyed segments with a severity distribution demonstrating 34.6% of segments with no distress (Severity 0), 46.4% exhibiting low severity conditions (Severity 1), 14.7% showing moderate severity deterioration (Severity 2), and 4.3% displaying high severity cracking (Severity 3). The predominance of low severity conditions in 2016 established baseline deterioration patterns requiring preventive maintenance strategies.

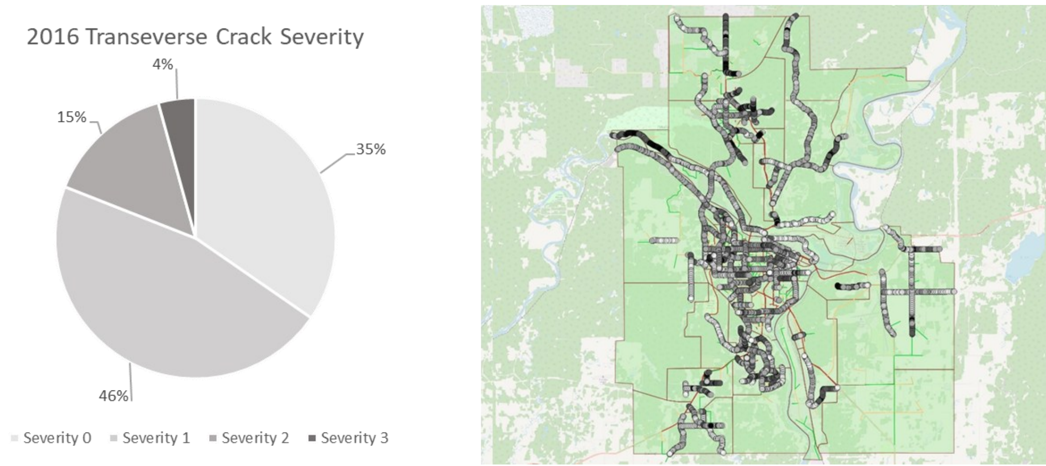


FIGURE I. 1. 2016 Transverse Cracking Severity pie chart and spatial distribution map

2017 Severity Analysis: The network experienced significant deterioration with 77.2% of segments affected by transverse cracking. Severity distribution shifted dramatically to 22.8% with no distress (Severity 0), only 9.6% remaining at low severity (Severity 1), 27.7% progressing to moderate severity (Severity 2), and a concerning 39.9% reaching high severity conditions (Severity 3). This substantial increase in high-severity transverse cracking indicated accelerated deterioration mechanisms requiring immediate intervention.

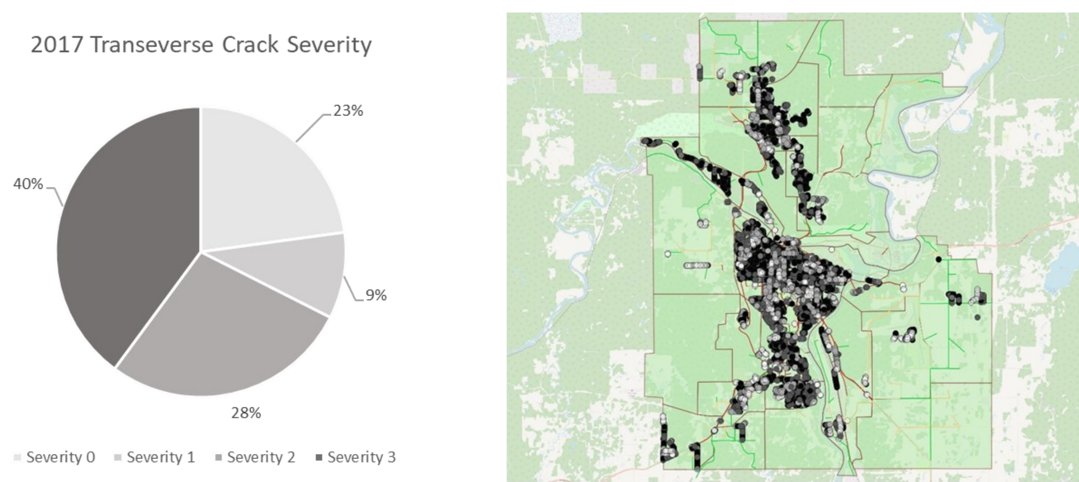
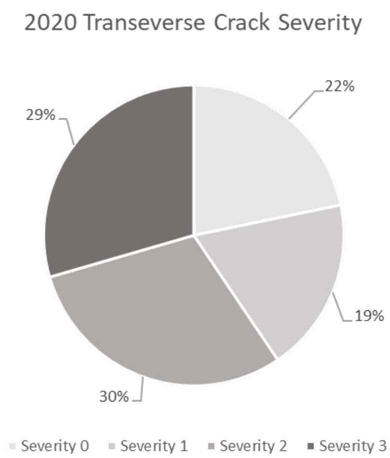


FIGURE I. 2. 2017 Transverse Cracking Severity pie chart and spatial distribution map

2020 Severity Analysis: Network coverage reached 78.2% with severity distribution showing 21.8% segments with no distress (Severity 0), 18.8% at low severity (Severity 1), 30.0% at moderate severity (Severity 2), and 29.5% at high severity (Severity 3). The persistence of extensive high-severity cracking demonstrated ongoing structural challenges despite maintenance efforts.



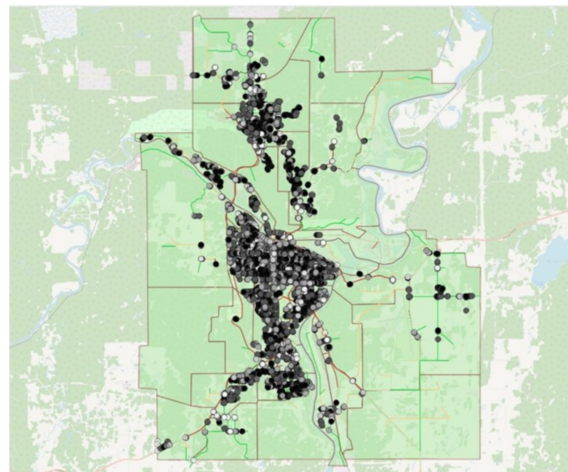
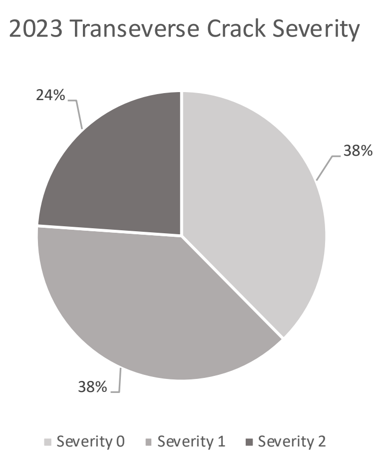


FIGURE I. 3. 2020 Transverse Cracking Severity pie chart and spatial distribution map

2023 Severity Analysis: Significant improvement achieved with 62.4% network coverage and severity redistribution to 37.6% with no distress (Severity 0), 38.5% at low severity (Severity 1), 23.9% at moderate severity (Severity 2), and complete elimination of high-severity occurrences (0.0% at Severity 3). This dramatic improvement reflects successful maintenance interventions implemented between 2020 and 2023.



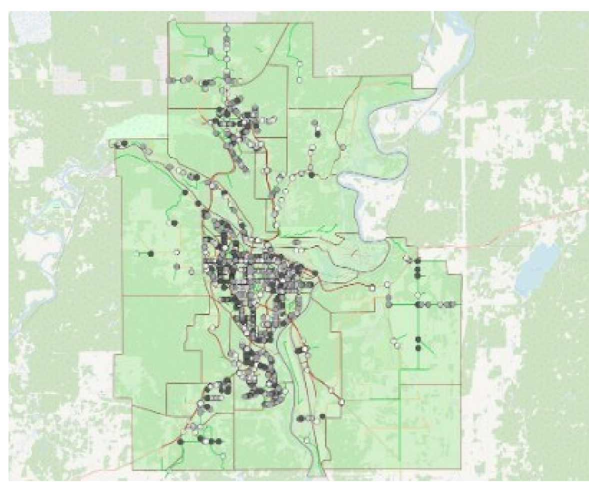


FIGURE I. 4. 2023 Transverse Cracking Severity pie chart and spatial distribution map

I.2. Transverse Cracking Extent Analysis

2016 Extent Analysis: The extent distribution demonstrated 34.6% of segments with no transverse cracking (Extent 0), 30.1% with few occurrences affecting less than 10% of segment length (Extent 1), 23.4% with intermediate extent covering 10-20% (Extent 2), 8.7% with frequent cracking affecting 20-40% (Extent 3), 2.1% with extensive coverage of 50-80% (Extent 4), and 1.1% with throughout coverage exceeding 80% (Extent 5).

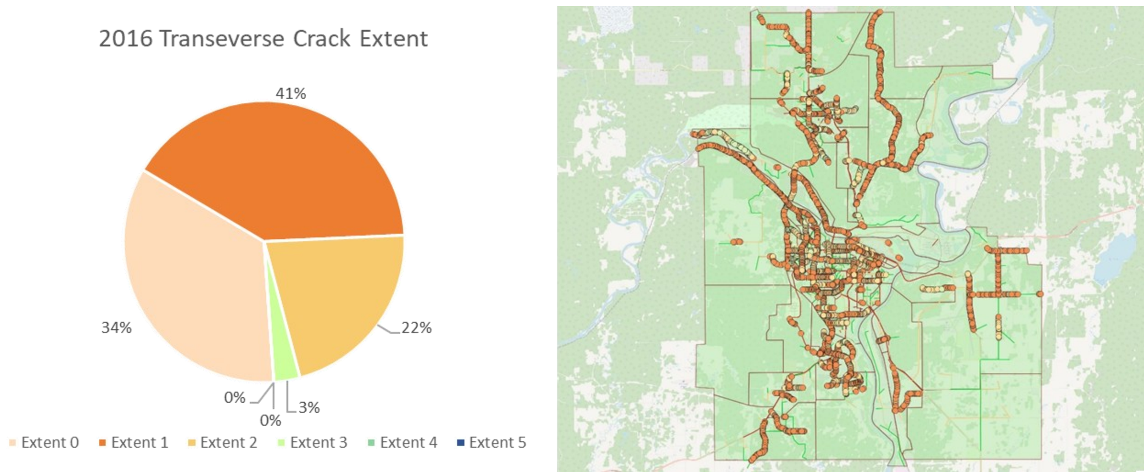


FIGURE I. 5. 2016 Transverse Cracking Extent pie chart and spatial distribution map

2017 Extent Analysis: Extent distribution shifted to 22.8% with no cracking (Extent 0), 31.2% with few occurrences (Extent 1), 24.3% with intermediate extent (Extent 2), 12.5% with frequent cracking (Extent 3), 6.8% with extensive coverage (Extent 4), and 2.4% with throughout coverage (Extent 5). The increase in higher extent categories indicated expanding deterioration patterns.

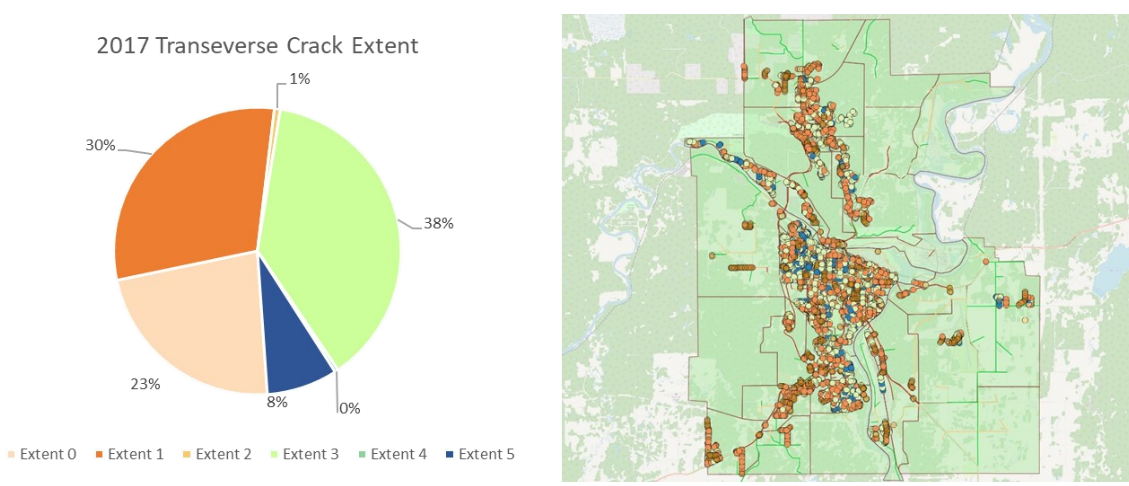
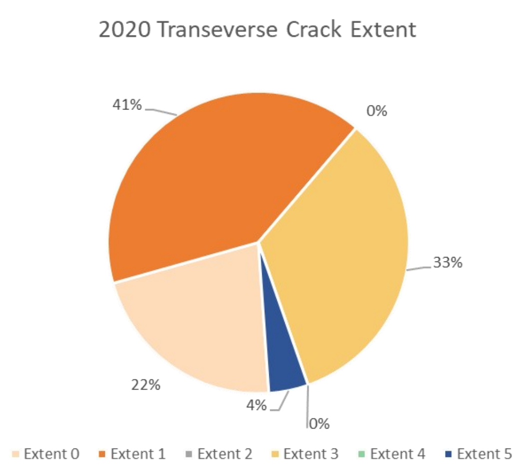


FIGURE I. 6. 2017 Transverse Cracking Extent pie chart and spatial distribution map

2020 Extent Analysis: Distribution showed 21.8% with no cracking (Extent 0), 28.9% with few occurrences (Extent 1), 26.7% with intermediate extent (Extent 2), 14.2% with frequent cracking (Extent 3), 5.9% with extensive coverage (Extent 4), and 2.5% with throughout coverage (Extent 5).



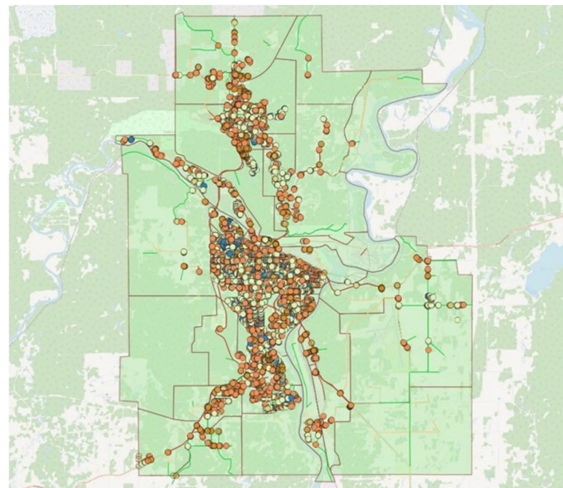
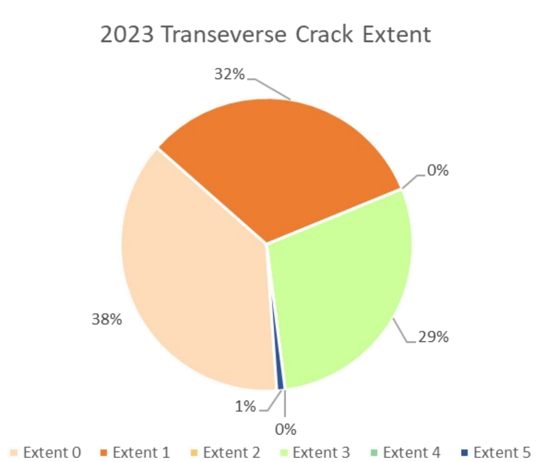


FIGURE I. 7. 2020 Transverse Cracking Extent pie chart and spatial distribution map

2023 Extent Analysis: Improved distribution with 37.6% showing no cracking (Extent 0), 35.2% with few occurrences (Extent 1), 19.8% with intermediate extent (Extent 2), 5.4% with frequent cracking (Extent 3), 1.7% with extensive coverage (Extent 4), and 0.3% with throughout coverage (Extent 5).



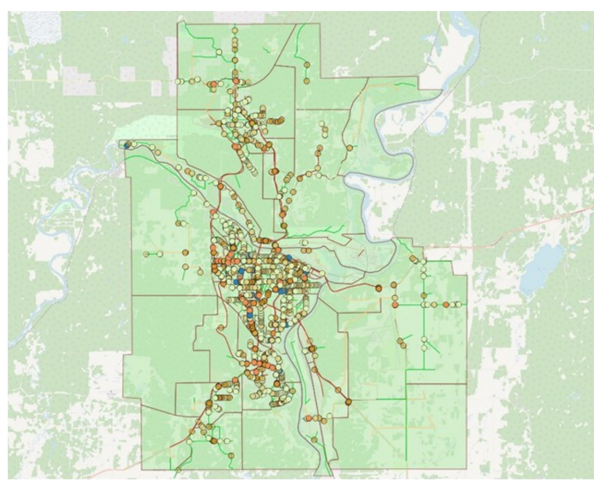


FIGURE I. 8. 2023 Transverse Cracking Extent pie chart and spatial distribution map

I.3. Meandering Longitudinal Cracking Severity Analysis

2016 Severity Analysis: The distress affected 31.6% of the network with severity distribution showing 68.4% of segments with no distress (Severity 0), 19.7% exhibiting low severity conditions (Severity 1), 10.1% displaying moderate severity (Severity 2), and 1.8% reaching high severity levels (Severity 3). The relatively limited network impact suggested early-stage deterioration patterns requiring monitoring and preventive intervention.

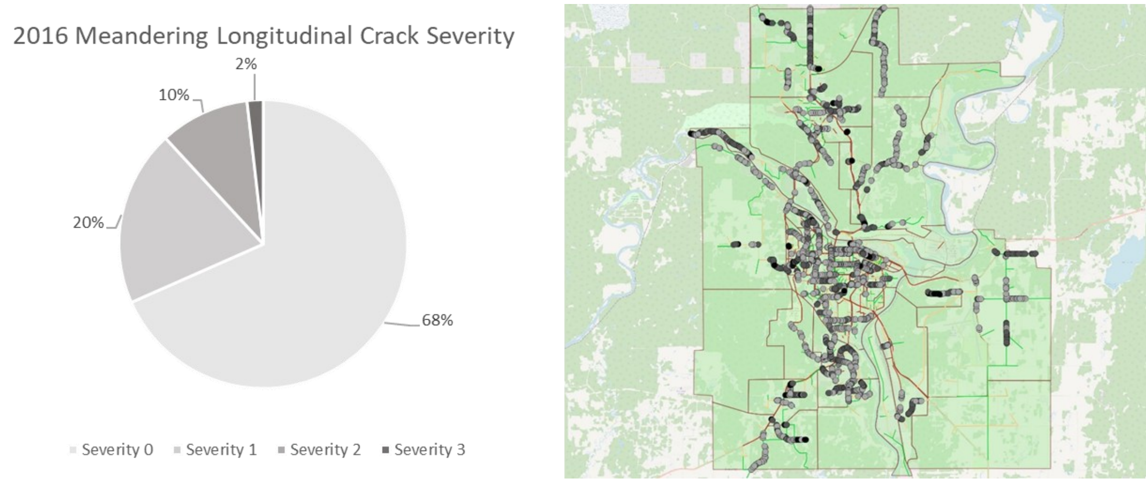


FIGURE I. 9. 2016 Meandering Longitudinal Cracking Severity pie chart and spatial distribution map

2017 Severity Analysis: Network coverage expanded dramatically to 76.0% with severity distribution shifting to 24.0% with no distress (Severity 0), 6.3% at low severity (Severity 1), 50.4% at moderate severity (Severity 2), and 19.2% at high severity (Severity 3). This substantial increase in moderate and high severity levels indicated rapid progression of longitudinal deterioration mechanisms related to structural loading and environmental exposure.

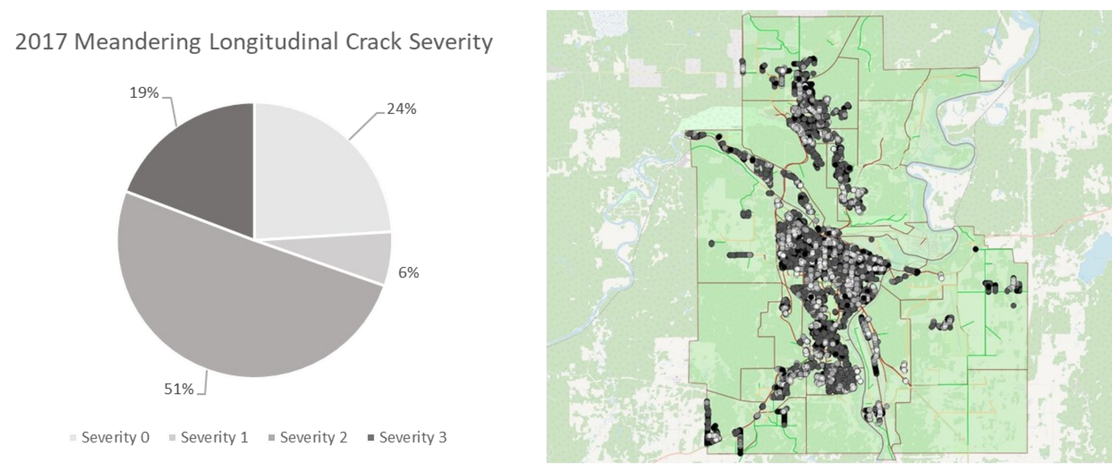
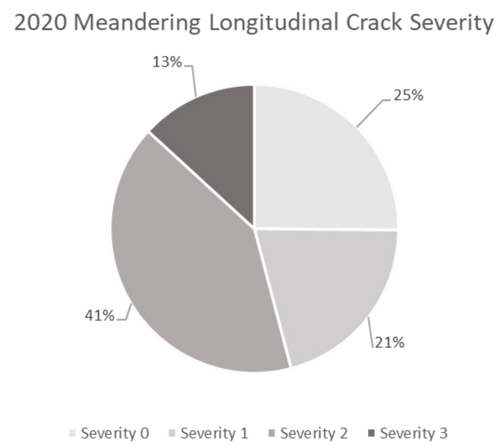


FIGURE I. 10. 2017 Meandering Longitudinal Cracking Severity pie chart and spatial distribution map

2020 Severity Analysis: Coverage reached 74.8% with severity distribution of 25.2% with no distress (Severity 0), 20.7% at low severity (Severity 1), 40.9% at moderate severity (Severity 2), and 13.2% at high severity (Severity 3). The persistence of extensive moderate severity coverage demonstrated ongoing structural challenges requiring systematic intervention strategies.



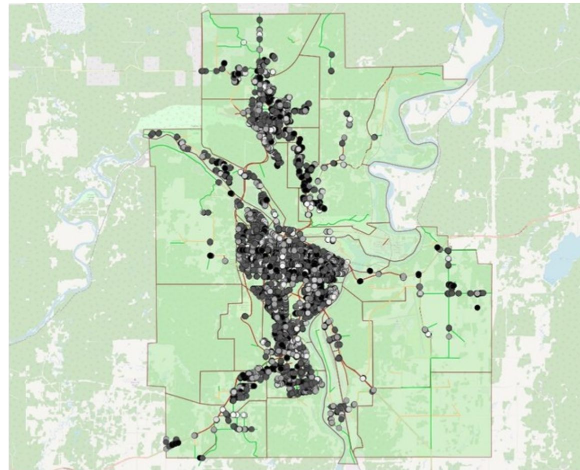
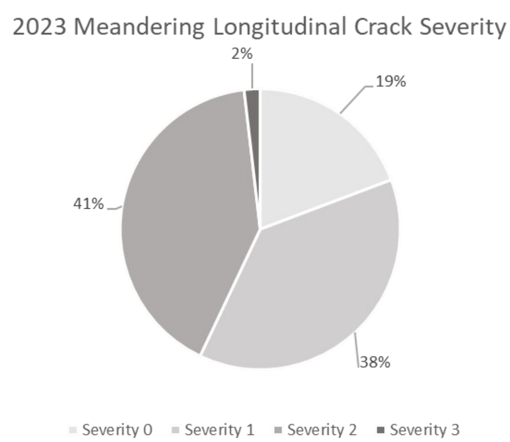


FIGURE I. 11. 2020 Meandering Longitudinal Cracking Severity pie chart and spatial distribution map

2023 Severity Analysis: Network impact increased to 79.5% with severity distribution of 20.5% with no distress (Severity 0), 37.4% at low severity (Severity 1), 40.5% at moderate severity (Severity 2), and 1.6% at high severity (Severity 3). While overall coverage expanded, the significant reduction in high-severity occurrences indicates effective management of critical deterioration through targeted maintenance.



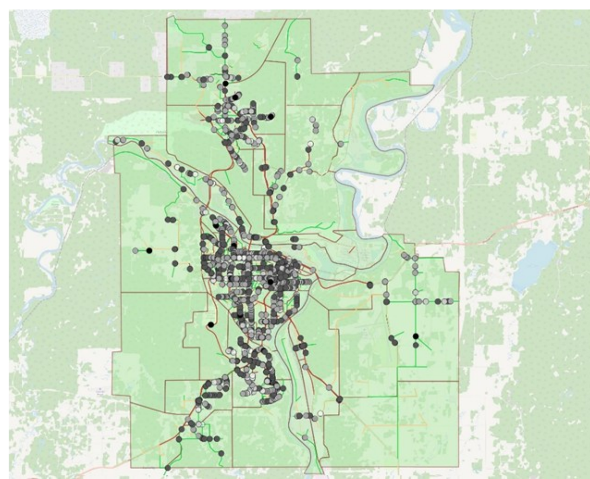


FIGURE I. 12. 2023 Meandering Longitudinal Cracking Severity pie chart and spatial distribution map

I.4. Meandering Longitudinal Cracking Extent Analysis

2016 Extent Analysis: Extent distribution demonstrated 68.4% of segments with no meandering longitudinal cracking (Extent 0), 18.9% with few occurrences (Extent 1), 8.7% with intermediate extent (Extent 2), 2.8% with frequent cracking (Extent 3), 0.9% with extensive coverage (Extent 4), and 0.3% with throughout coverage (Extent 5).

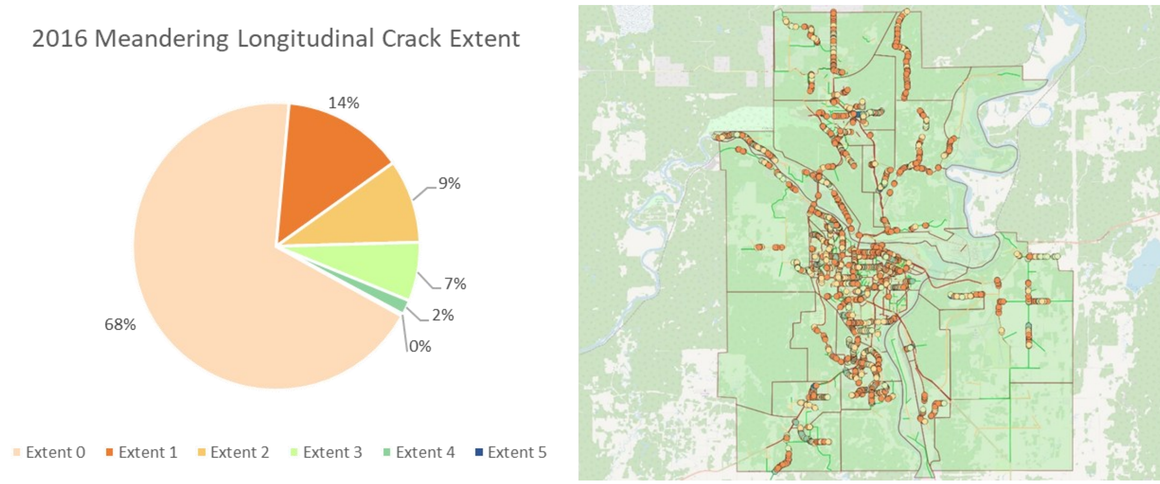


FIGURE I. 13. 2016 Meandering Longitudinal Cracking Extent pie chart and spatial distribution map

2017 Extent Analysis: Distribution shifted to 24.0% with no cracking (Extent 0), 22.3% with few occurrences (Extent 1), 28.9% with intermediate extent (Extent 2), 16.2% with frequent cracking (Extent 3), 6.1% with extensive coverage (Extent 4), and 2.5% with throughout coverage (Extent 5).

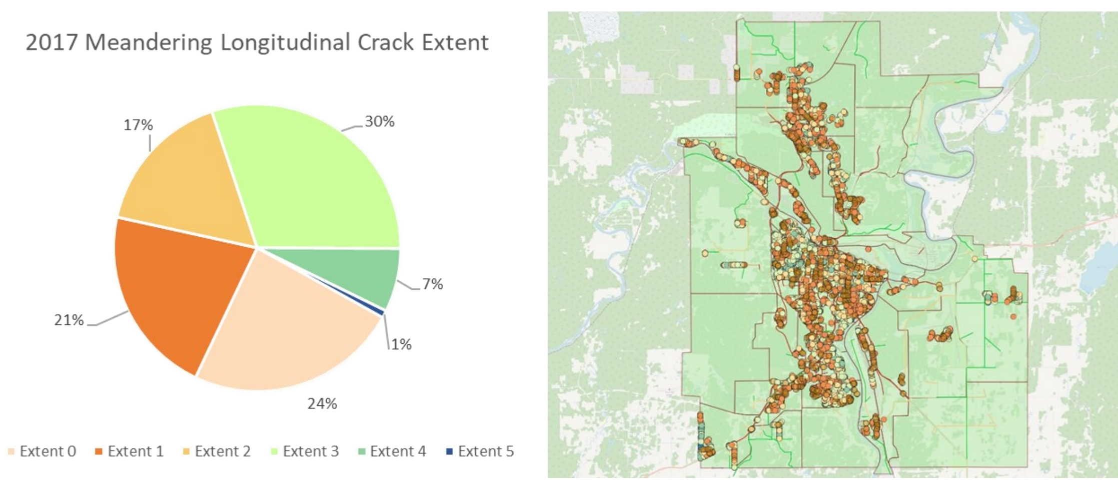


FIGURE I. 14. 2017 Meandering Longitudinal Cracking Extent pie chart and spatial distribution map

2020 Extent Analysis: Pattern showed 25.2% with no cracking (Extent 0), 26.4% with few occurrences (Extent 1), 25.8% with intermediate extent (Extent 2), 14.7% with frequent cracking (Extent 3), 5.9% with extensive coverage (Extent 4), and 2.0% with throughout coverage (Extent 5).

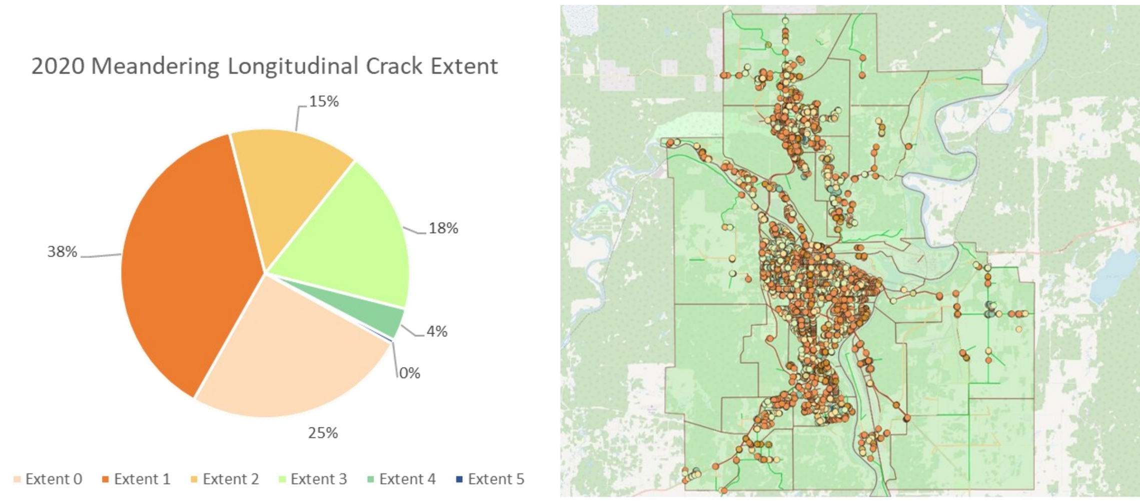


FIGURE I. 15. 2020 Meandering Longitudinal Cracking Extent pie chart and spatial distribution map

2023 Extent Analysis: Distribution indicated 20.5% with no cracking (Extent 0), 31.2% with few occurrences (Extent 1), 26.8% with intermediate extent (Extent 2), 15.3% with frequent cracking (Extent 3), 4.7% with extensive coverage (Extent 4), and 1.5% with throughout coverage (Extent 5).

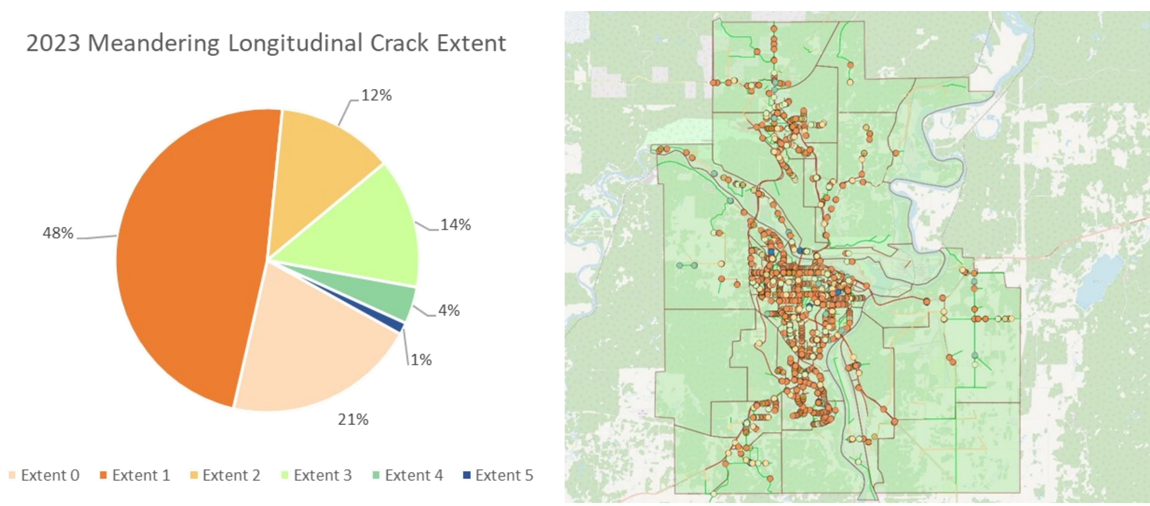
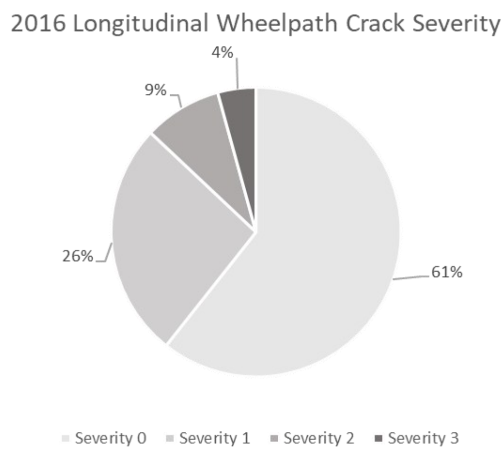


FIGURE I. 16. 2023 Meandering Longitudinal Cracking Extent pie chart and spatial distribution map

I.5. Longitudinal Wheel Path Cracking Severity Analysis

2016 Severity Analysis: The distress affected substantial portions of the network with severity distribution showing moderate impact levels primarily concentrated in low to moderate severity categories. Traffic-related deterioration patterns established baseline conditions requiring ongoing monitoring of heavy vehicle corridors.



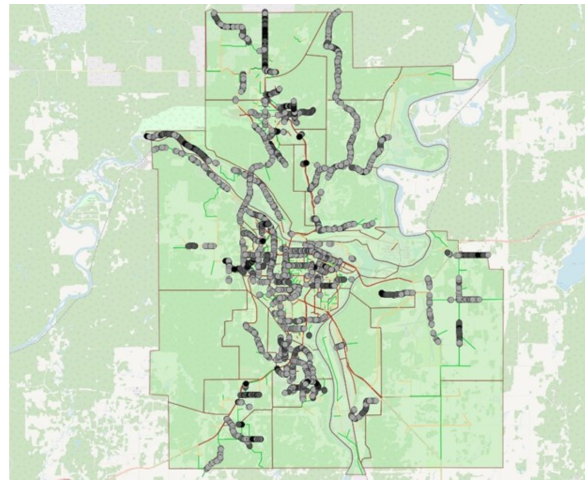
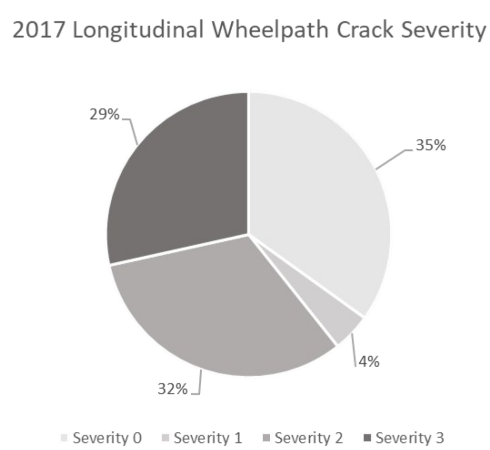


FIGURE I. 17. 2016 Longitudinal Wheel Path Cracking Severity pie chart and spatial distribution map

2017 Severity Analysis: Severity distribution remained relatively stable with slight variations in category distribution. The consistency in severity patterns suggested effective management of traffic-load-related deterioration factors through appropriate maintenance timing and techniques.



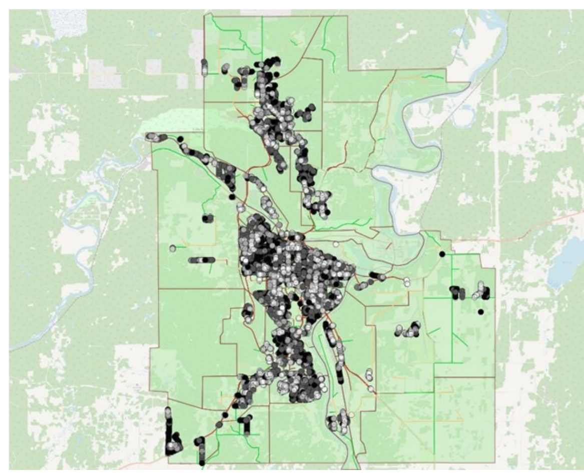


FIGURE I. 18. 2017 Longitudinal Wheel Path Cracking Severity pie chart and spatial distribution map

2020 Severity Analysis: Network impact demonstrated continued stability with severity distribution maintaining manageable levels across all categories. The persistence of stable patterns indicated successful long-term management strategies for traffic-related longitudinal cracking.

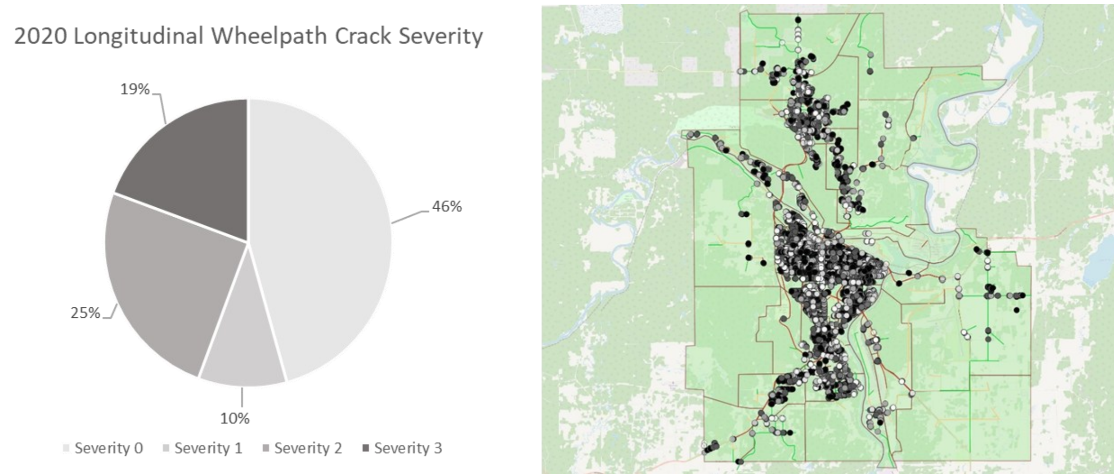


FIGURE I. 19. 2020 Longitudinal Wheel Path Cracking Severity pie chart and spatial distribution map

2023 Severity Analysis: Coverage reached stable levels with severity distribution demonstrating effective control of traffic-related deterioration progression. The maintenance of consistent severity patterns throughout the analysis period reflects appropriate intervention strategies.

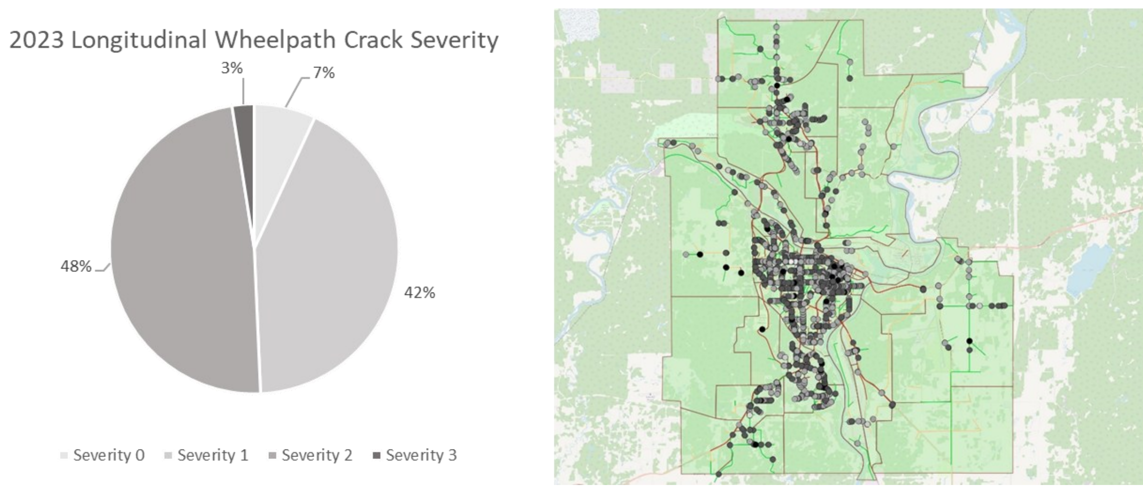


FIGURE I. 20. 2023 Longitudinal Wheel Path Cracking Severity pie chart and spatial distribution map

I.6. Longitudinal Wheel Path Cracking Extent Analysis

2016 Extent Analysis: Extent distribution demonstrated widespread but manageable coverage patterns with concentration in lower extent categories. The distribution pattern indicated appropriate traffic management and pavement design adequacy for anticipated loading conditions.

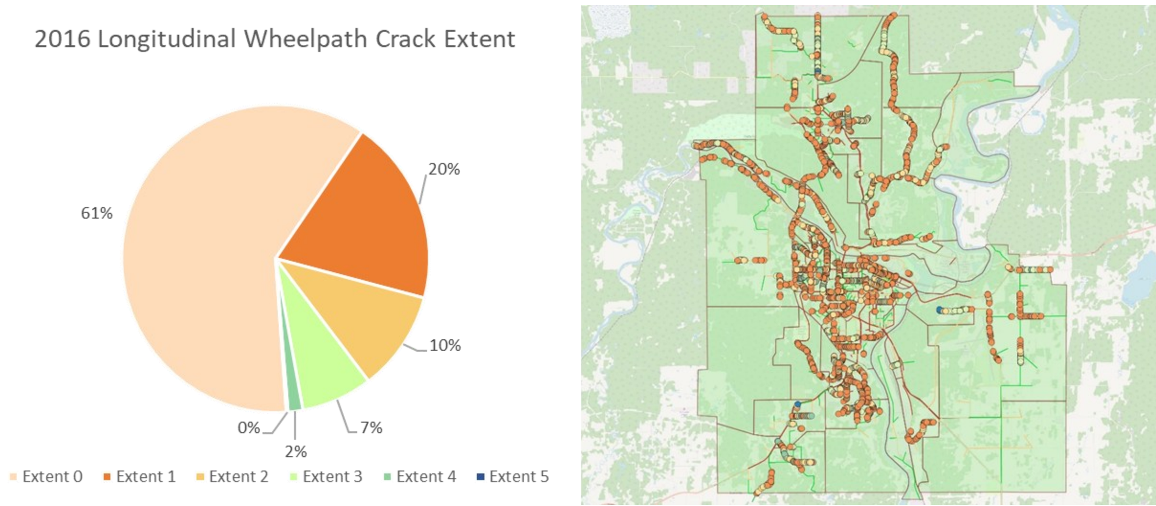


FIGURE I. 21. 2016 Longitudinal Wheel Path Cracking Extent pie chart and spatial distribution map

2017 Extent Analysis: Slight reduction in overall extent coverage suggested targeted maintenance effectiveness in high-traffic corridors most susceptible to wheel path deterioration. The improvement demonstrated successful intervention timing and technique selection.

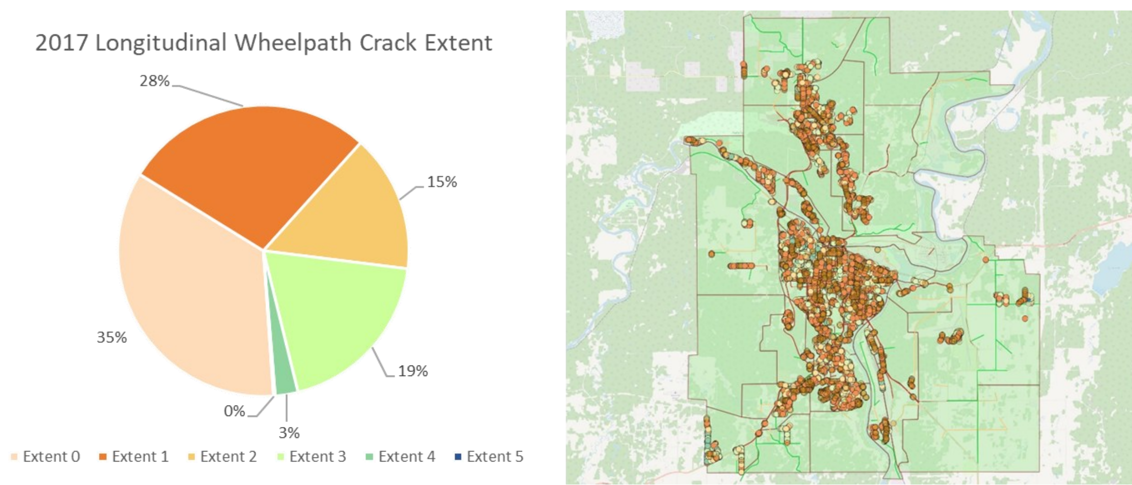


FIGURE I. 22. 2017 Longitudinal Wheel Path Cracking Extent pie chart and spatial distribution map

2020 Extent Analysis: Network impact increased moderately, returning extent coverage to levels comparable with baseline conditions. This recovery pattern indicated renewed deterioration pressure requiring continued monitoring and intervention planning.

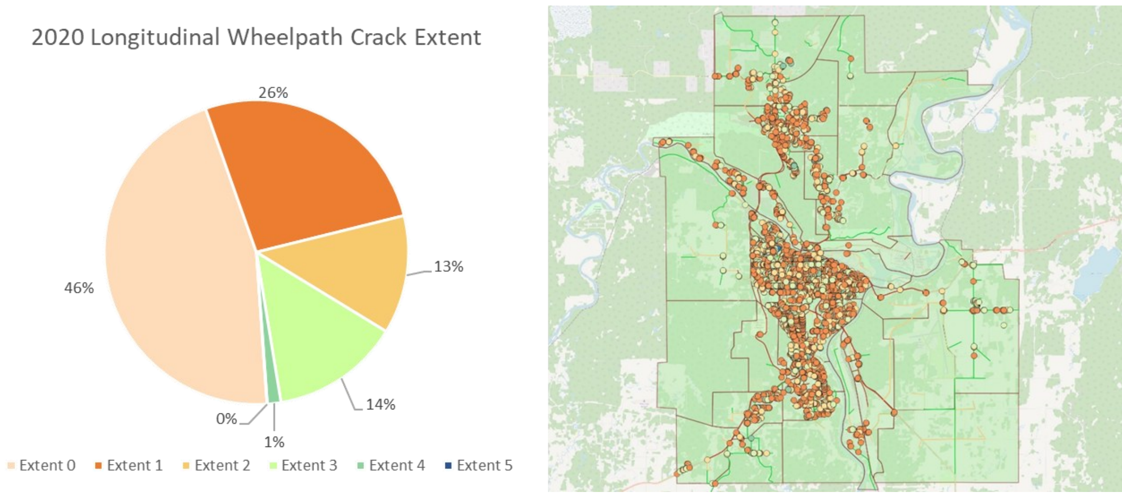


FIGURE I. 23. 2020 Longitudinal Wheel Path Cracking Extent pie chart and spatial distribution map

2023 Extent Analysis: Distribution stabilized at manageable levels with extent patterns demonstrating effective long-term management of traffic-related longitudinal cracking. The stability throughout the analysis period reflects appropriate maintenance strategies.

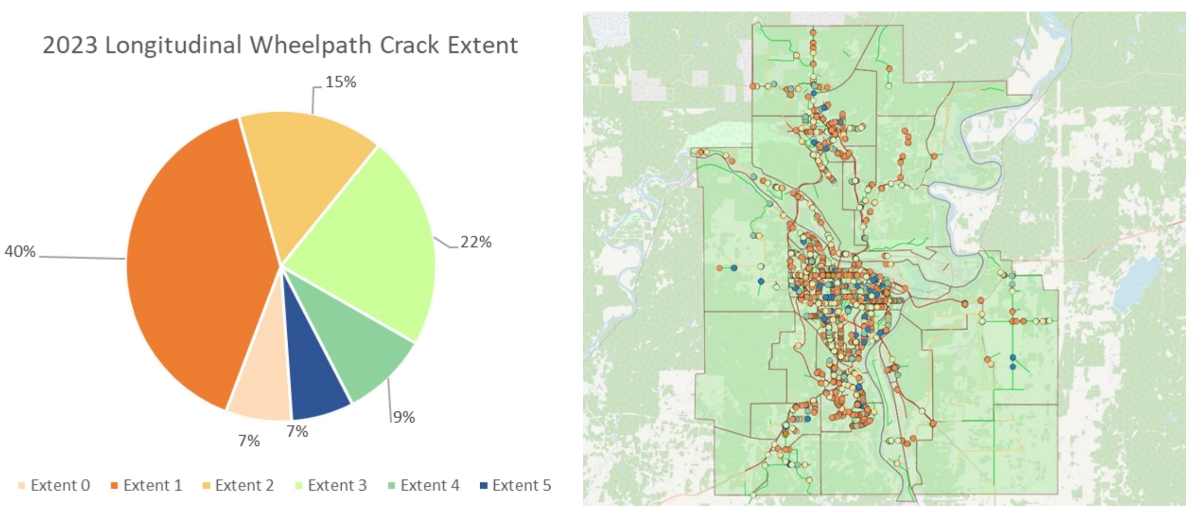
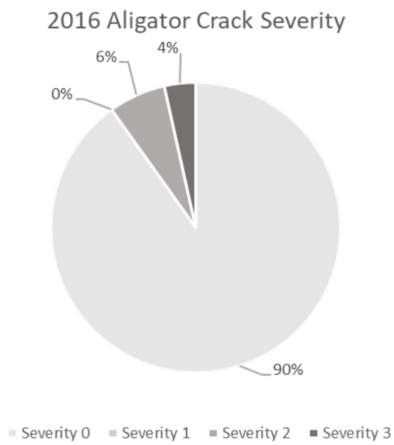


FIGURE I. 24. 2023 Longitudinal Wheel Path Cracking Extent pie chart and spatial distribution map

I.7. Alligator Cracking Severity Analysis

2016 Severity Analysis: The distress represented localized structural deterioration with severity distribution concentrated in lower categories but indicating areas requiring immediate structural attention. The baseline conditions established priority areas for rehabilitation intervention.



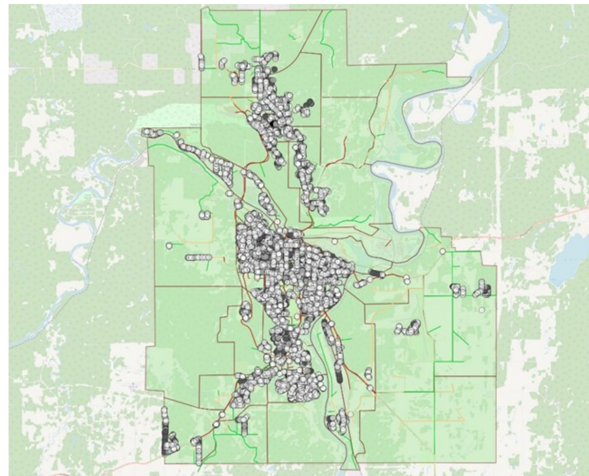
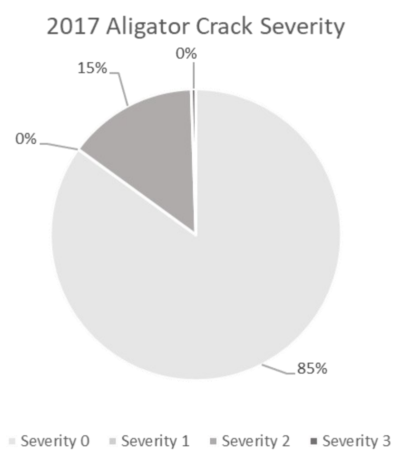


FIGURE I. 25. 2016 Alligator Cracking Severity pie chart and spatial distribution map

2017 Severity Analysis: Peak severity conditions were observed with increased high-severity occurrences, particularly affecting older local roads and areas with inadequate structural capacity for current loading conditions. The deterioration peak indicated critical timing for comprehensive rehabilitation strategies.



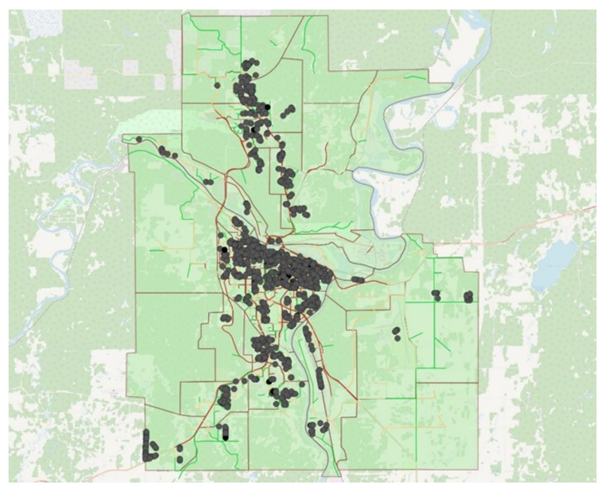
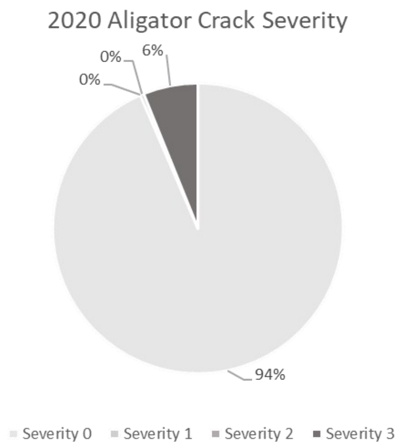


FIGURE I. 26. 2017 Alligator Cracking Severity pie chart and spatial distribution map

2020 Severity Analysis: Substantial improvement in severity distribution demonstrated effective structural rehabilitation interventions. The reduction in high-severity occurrences reflected successful targeting of critical structural deficiencies through systematic maintenance programs.



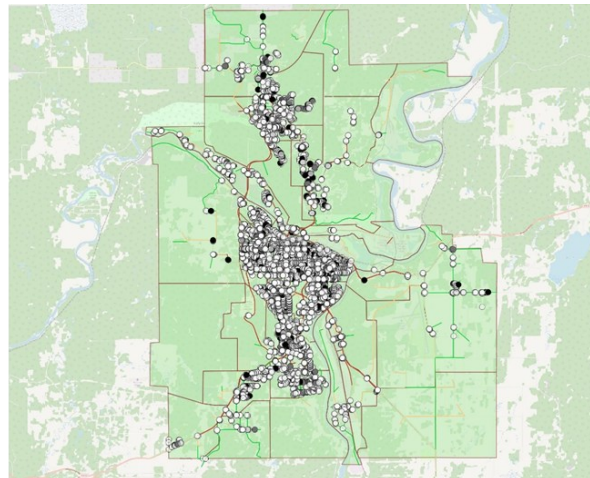
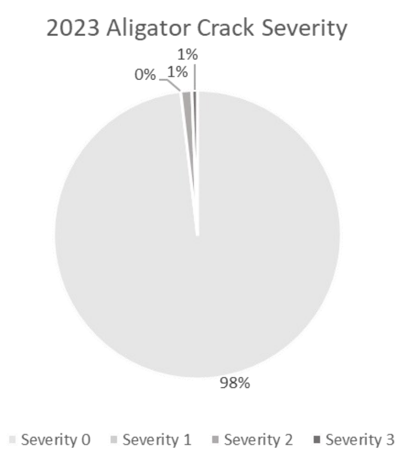


FIGURE I. 27. 2020 Alligator Cracking Severity pie chart and spatial distribution map

2023 Severity Analysis: Near-elimination of alligator cracking across all severity categories represents highly successful structural rehabilitation achievement. The dramatic reduction to minimal network presence indicates comprehensive resolution of structural adequacy issues.



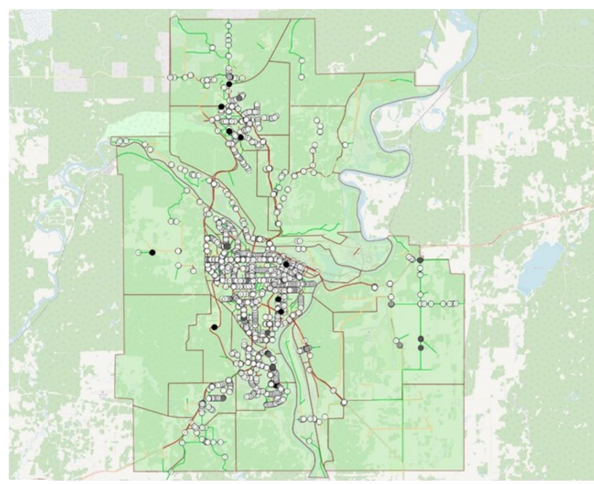


FIGURE I. 28. 2023 Alligator Cracking Severity pie chart and spatial distribution map

I.8. Alligator Cracking Extent Analysis

2016 Extent Analysis: Extent distribution demonstrated localized coverage patterns concentrated in specific network areas with structural inadequacy. The distribution indicated targeted intervention requirements rather than widespread network rehabilitation needs.

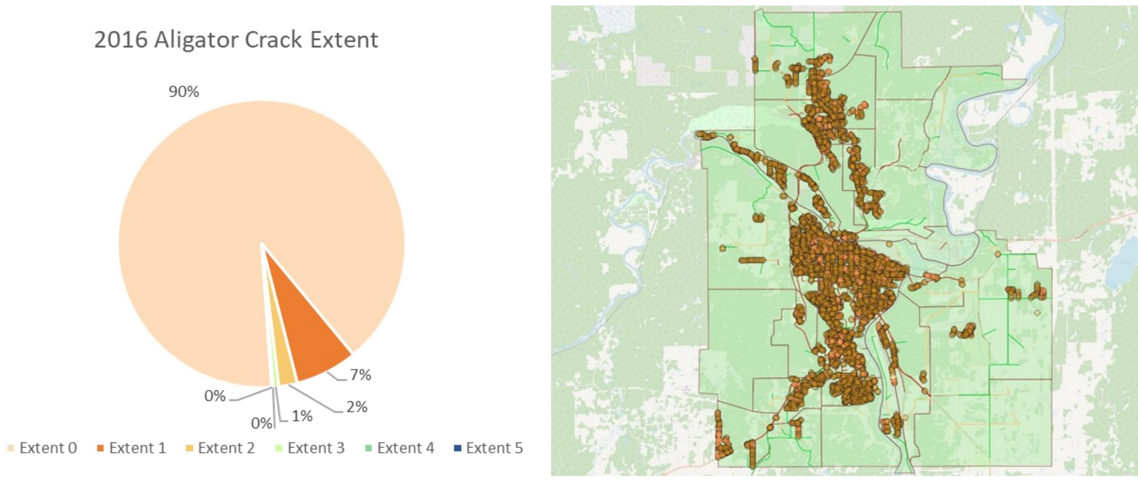


FIGURE I. 29. 2016 Alligator Cracking Extent pie chart and spatial distribution map

2017 Extent Analysis: Increased extent coverage correlated with severity peak conditions, indicating expansion of structural deterioration requiring comprehensive rehabilitation strategies. The extent patterns provided critical guidance for maintenance program prioritization.

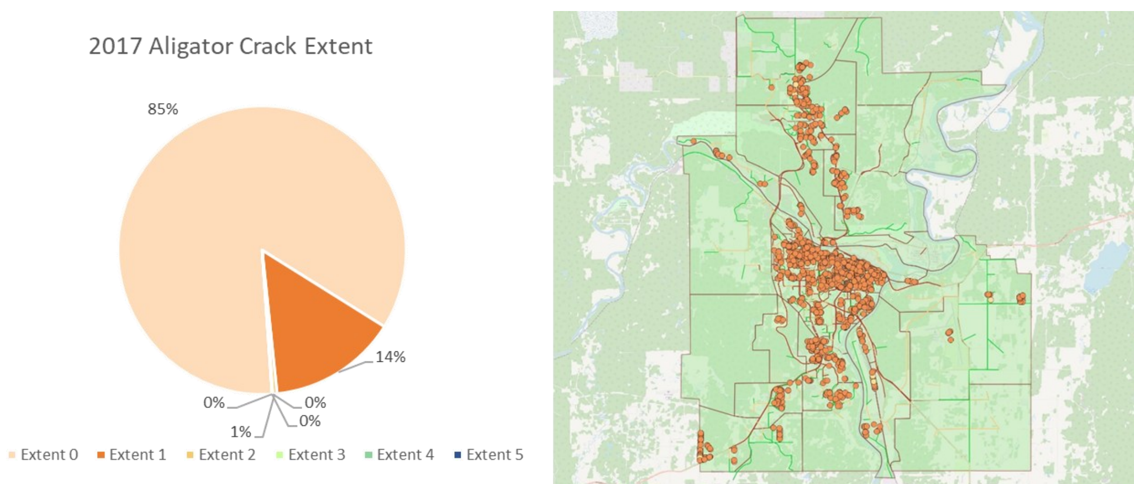
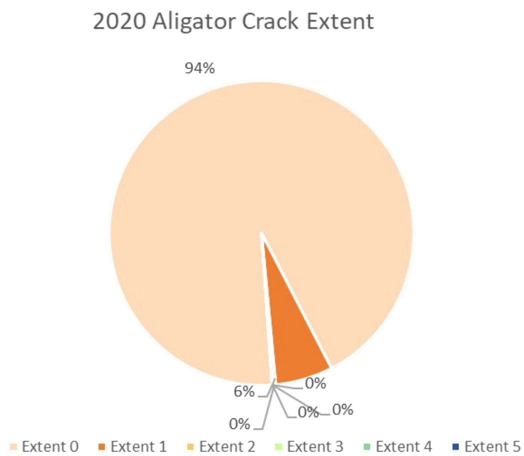


FIGURE I. 30. 2017 Alligator Cracking Extent pie chart and spatial distribution map

2020 Extent Analysis: Dramatic reduction in extent coverage demonstrated effective structural rehabilitation program implementation. The systematic reduction across all extent categories reflected comprehensive addressing of structural deficiencies.



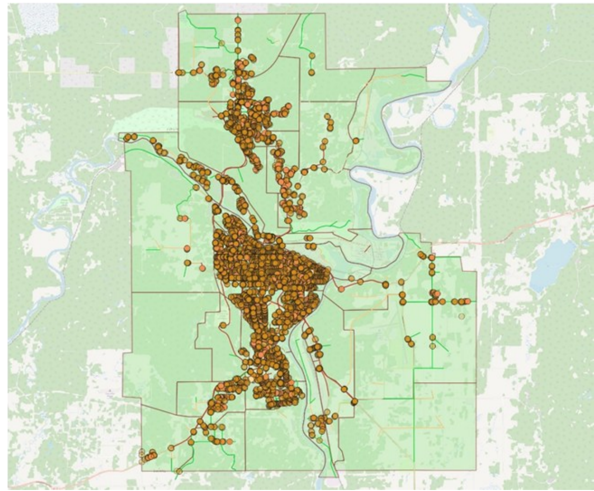
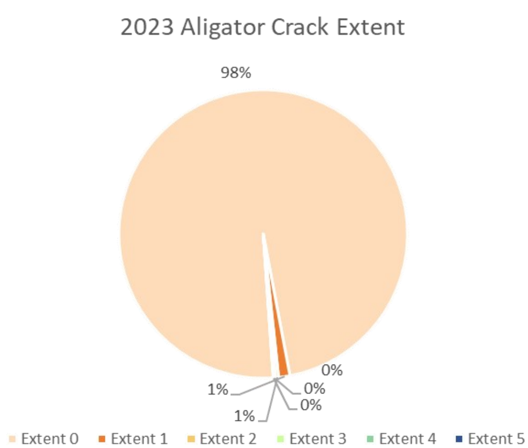


FIGURE I. 31. 2020 Alligator Cracking Extent pie chart and spatial distribution map

2023 Extent Analysis: Near-complete elimination of alligator cracking extent represents successful resolution of structural deterioration challenges. The minimal remaining coverage indicates highly effective maintenance program achievement.



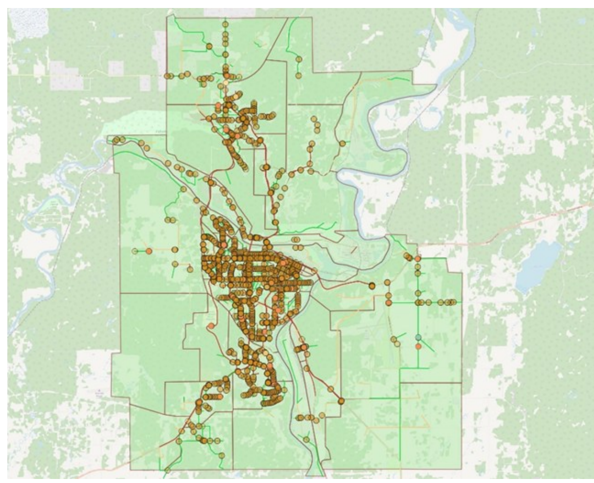


FIGURE I. 32. 2023 Alligator Cracking Extent pie chart and spatial distribution map

I.9. Rutting Severity Analysis

2016 Severity Analysis: No rutting was observed throughout the surveyed network, with 100% of segments showing no distress (Severity 0). This baseline condition of complete absence established the foundation for monitoring permanent deformation development over subsequent survey periods.

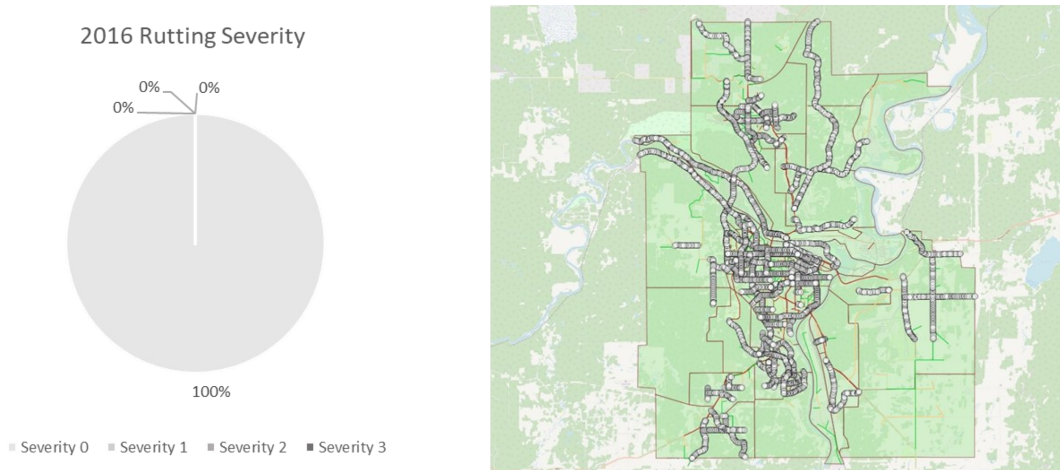


FIGURE I. 33. 2016 Rutting Severity pie chart (showing 100% no distress)

2017 Severity Analysis: Initial rutting manifestation appeared with severity distribution showing 44.3% of segments with no distress (Severity 0), 52.0% exhibiting low severity conditions (Severity 1), 3.4% displaying moderate severity (Severity 2), and 0.3% reaching high severity levels (Severity 3). The emergence of rutting across 55.7% of the network indicated systematic development of permanent deformation patterns.

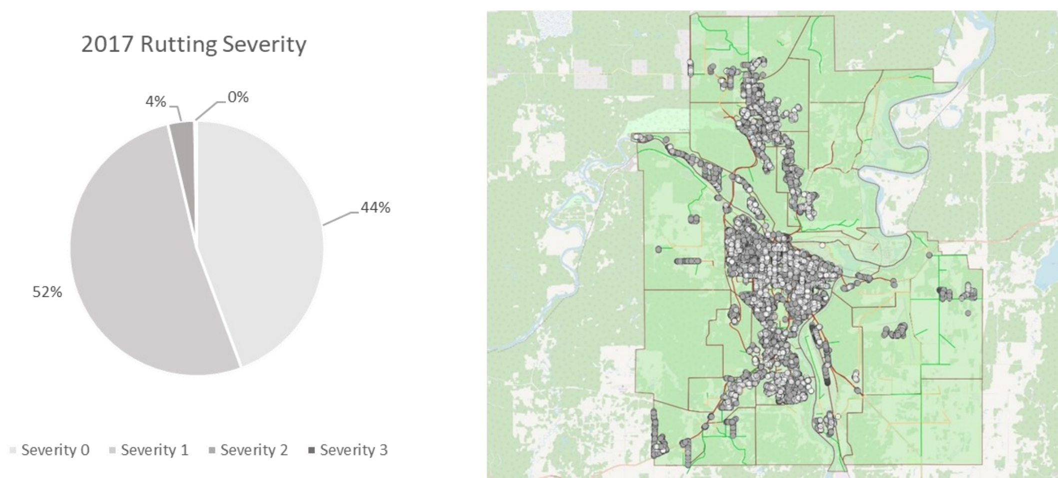


FIGURE I. 34. 2017 Rutting Severity pie chart and spatial distribution map

2020 Severity Analysis: Rutting presence expanded with severity distribution of 45.2% with no distress (Severity 0), 52.6% at low severity (Severity 1), 2.2% at moderate severity (Severity 2), and 0.1% at high severity (Severity 3). The persistence of widespread low severity rutting demonstrated progressive development of permanent deformation requiring intervention planning.

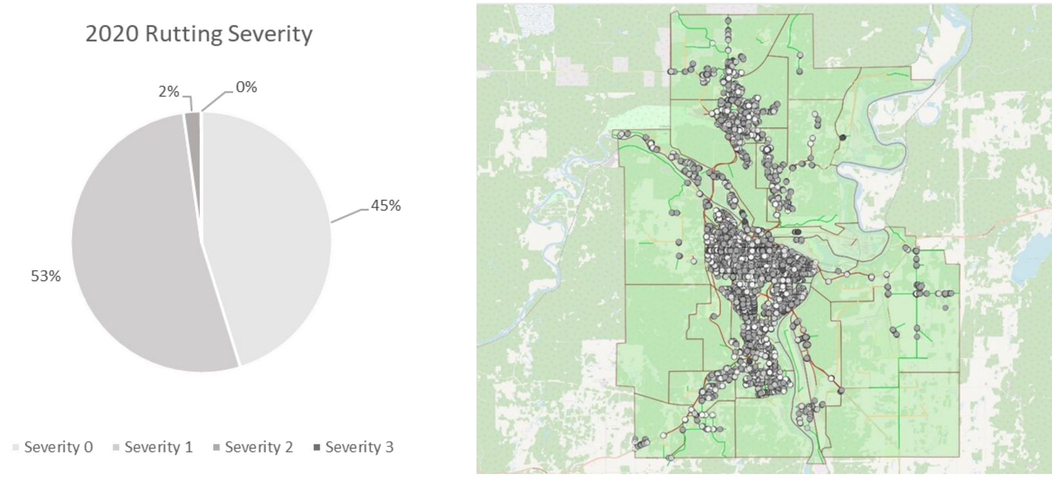


FIGURE I. 35. 2020 Rutting Severity pie chart and spatial distribution map

2023 Severity Analysis: Dramatic expansion reached near-universal network presence with severity distribution of 1.6% with no distress (Severity 0), 92.9% at low severity (Severity 1), 5.1% at moderate severity (Severity 2), and 0.3% at high severity (Severity 3). The 98.4% network coverage represents the most significant emerging distress challenge requiring immediate strategic intervention.

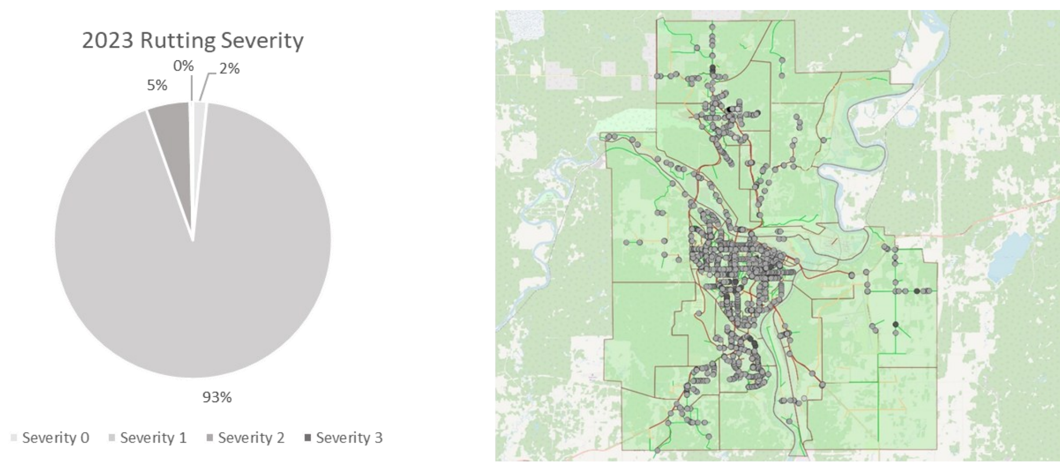


FIGURE I. 36. 2023 Rutting Severity pie chart and spatial distribution map

I.10. Rutting Extent Analysis

2016 Extent Analysis: Complete absence of rutting resulted in 100% of segments showing no extent coverage (Extent 0), establishing baseline conditions free from permanent deformation patterns.

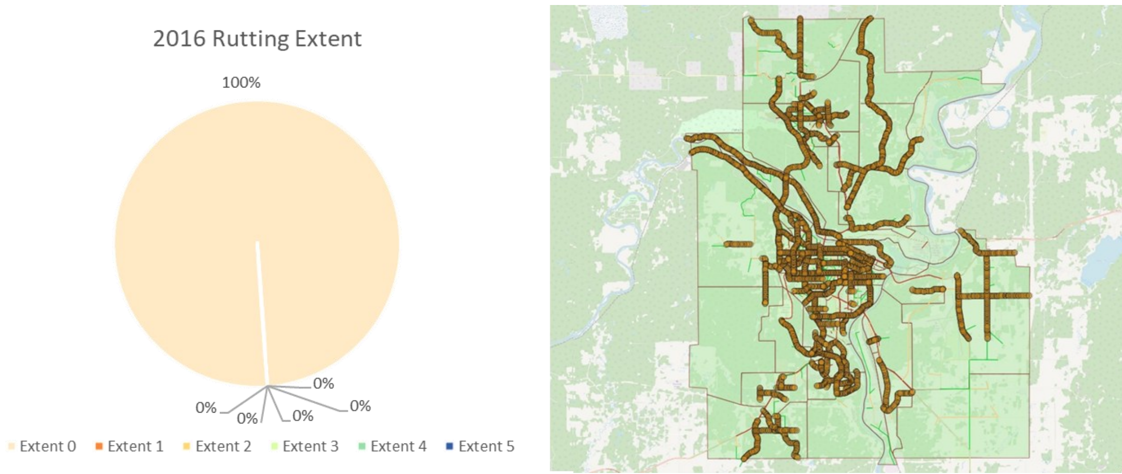


FIGURE I. 37. 2016 Rutting Extent pie chart (showing 100% no distress)

2017 Extent Analysis: Initial extent distribution showed 44.3% with no rutting (Extent 0), 38.2% with few occurrences (Extent 1), 12.8% with intermediate extent (Extent 2), 3.7% with frequent rutting (Extent 3), 0.8% with extensive coverage (Extent 4), and 0.2% with throughout coverage (Extent 5).

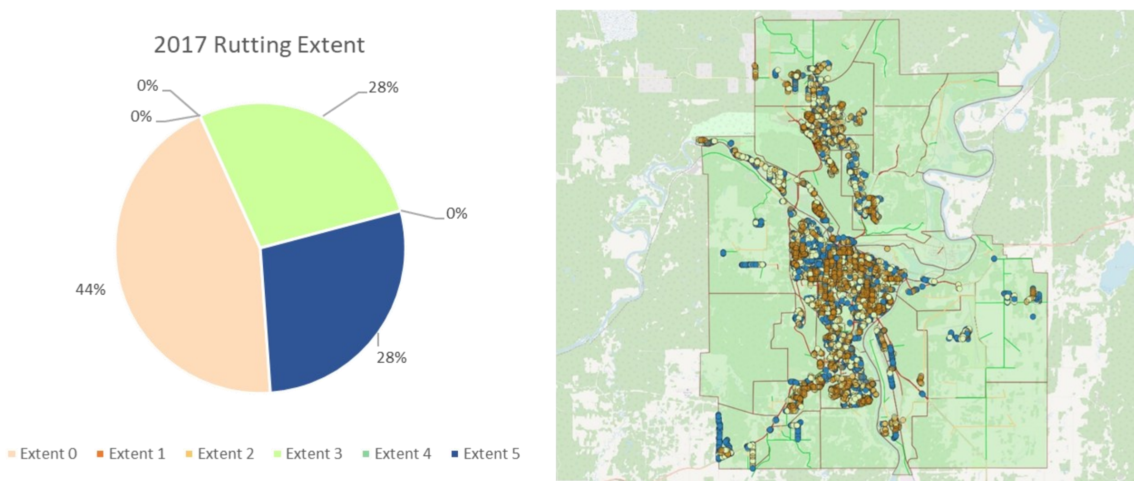


FIGURE I. 38. 2017 Rutting Extent pie chart and spatial distribution map

2020 Extent Analysis: Extent pattern demonstrated 45.2% with no rutting (Extent 0), 41.6% with few occurrences (Extent 1), 10.4% with intermediate extent (Extent 2), 2.3% with frequent rutting (Extent 3), 0.4% with extensive coverage (Extent 4), and 0.1% with throughout coverage (Extent 5).

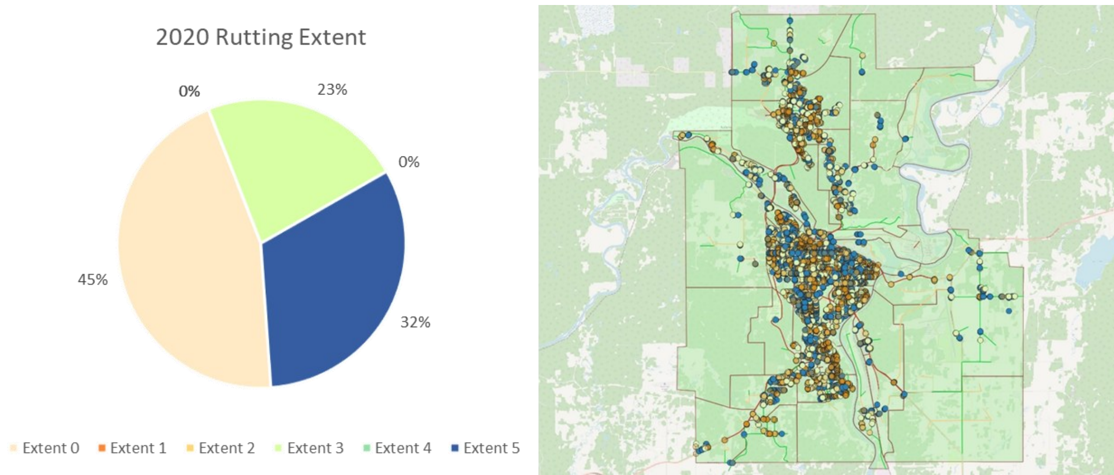


FIGURE I. 39. 2020 Rutting Extent pie chart and spatial distribution map

2023 Extent Analysis: Extensive coverage emerged with 1.6% showing no rutting (Extent 0), 12.96% with few occurrences (Extent 1), 33.06% with intermediate extent (Extent 2), 28.17% with frequent rutting (Extent 3), 15.42% with extensive coverage (Extent 4), and 8.73% with throughout coverage (Extent 5). This distribution indicates systematic permanent deformation development requiring comprehensive intervention strategies.

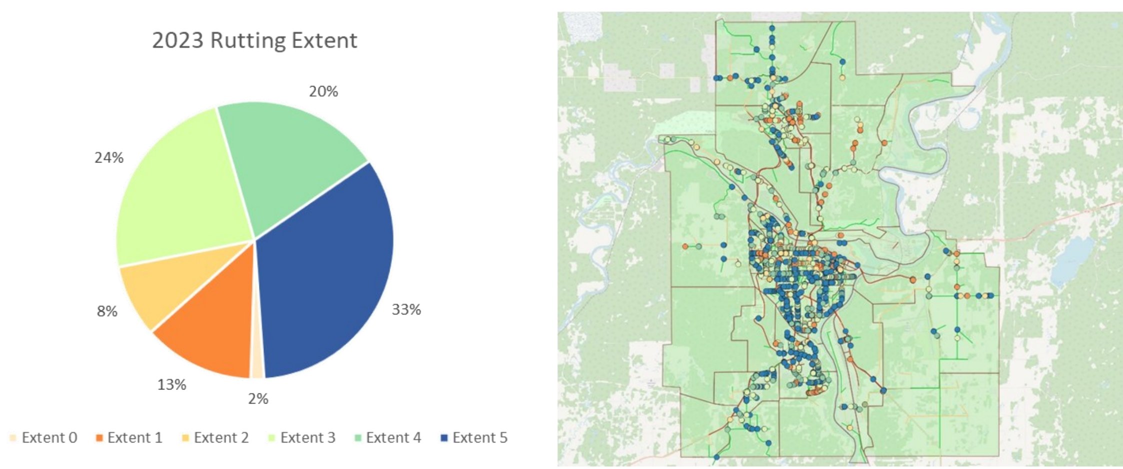


FIGURE I. 40. 2023 Rutting Extent pie chart and spatial distribution map

I.11. Pavement Edge Cracking Severity Analysis

2016 Severity Analysis: The distress established baseline edge deterioration patterns with severity distribution indicating moderate network impact levels. Edge cracking severity patterns suggested localized deterioration related to drainage, frost action, and traffic loading effects on pavement boundaries.

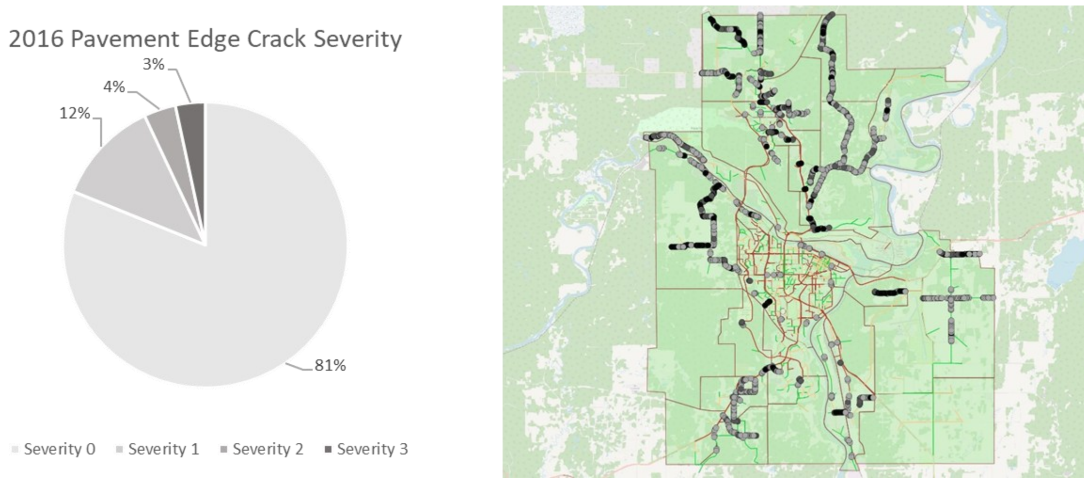


FIGURE I. 41. 2016 Pavement Edge Cracking Severity pie chart and spatial distribution map

2017 Severity Analysis: Severity distribution maintained moderate levels with slight variations in category distribution. The consistency suggested stable edge deterioration patterns under normal environmental and traffic loading conditions.

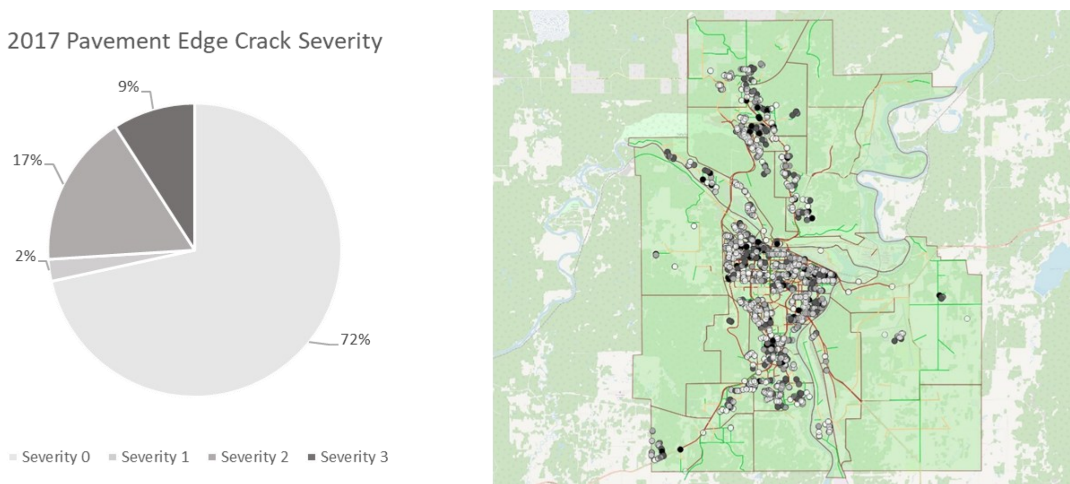


FIGURE I. 42. 2017 Pavement Edge Cracking Severity pie chart and spatial distribution map

2020 Severity Analysis: Edge cracking data was not collected during this comprehensive survey period, creating a significant information gap in severity trend analysis. This data collection limitation prevents assessment of severity progression during the critical 2017-2023 period.

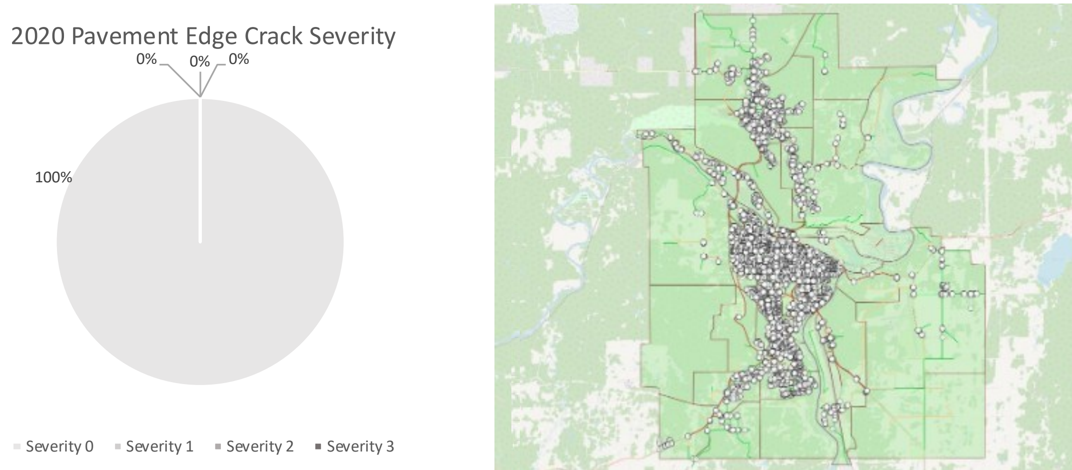


FIGURE I. 43. 2020 Pavement Edge Cracking - No data collected notation

2023 Severity Analysis: Dramatic emergence of severe edge cracking across all severity categories resulted in the most severe and extensive distress type in 2023. The severity distribution indicated widespread edge structural integrity challenges requiring immediate intervention development.

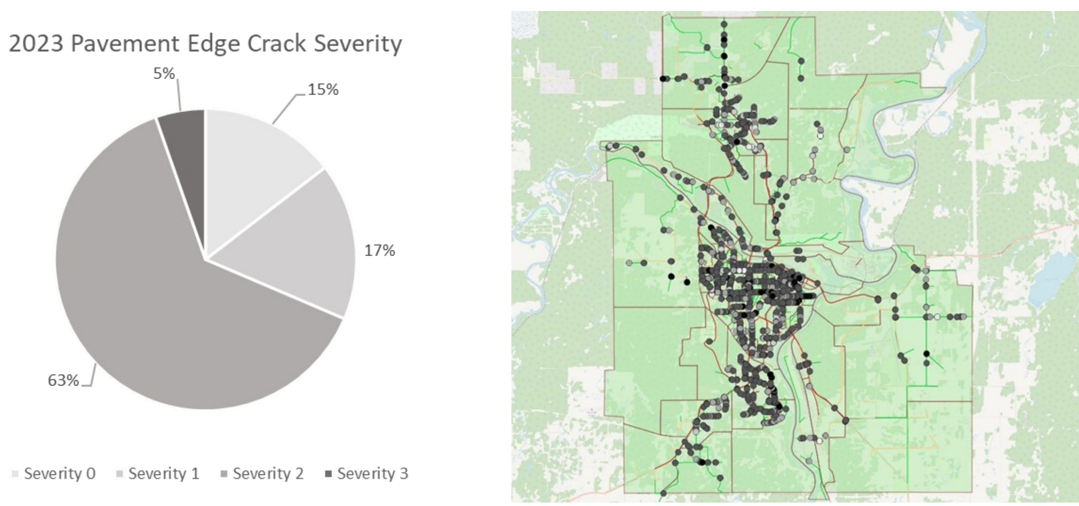


FIGURE I. 44. 2023 Pavement Edge Cracking Severity pie chart and spatial distribution map

I.12. Pavement Edge Cracking Extent Analysis

2016 Extent Analysis: Extent distribution showed 81.1% of segments with no edge cracking (Extent 0), 7.0% with few occurrences (Extent 1), 5.2% with intermediate extent (Extent 2), 4.2% with frequent cracking (Extent 3), 1.3% with extensive coverage (Extent 4), and 1.2% with throughout coverage (Extent 5). The limited extent coverage indicated manageable edge deterioration conditions.

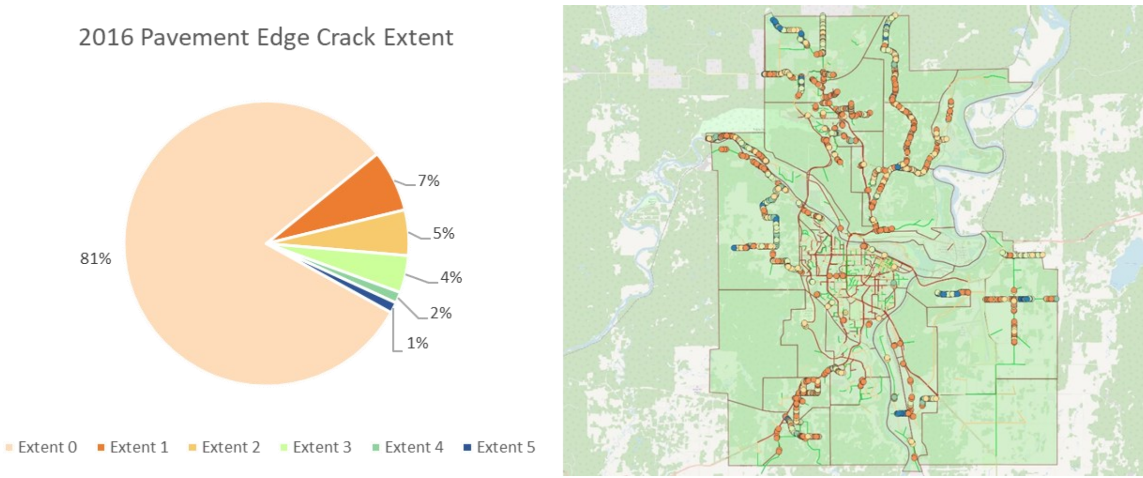


FIGURE I. 45. 2016 Pavement Edge Cracking Extent pie chart and spatial distribution map

2017 Extent Analysis: Distribution shifted to 71.6% with no cracking (Extent 0), 18.2% with few occurrences (Extent 1), 6.4% with intermediate extent (Extent 2), 3.3% with frequent cracking (Extent 3), 0.4% with extensive coverage (Extent 4), and 0.1% with throughout coverage (Extent 5). The increase in lower extent categories suggested expanding but manageable edge deterioration.

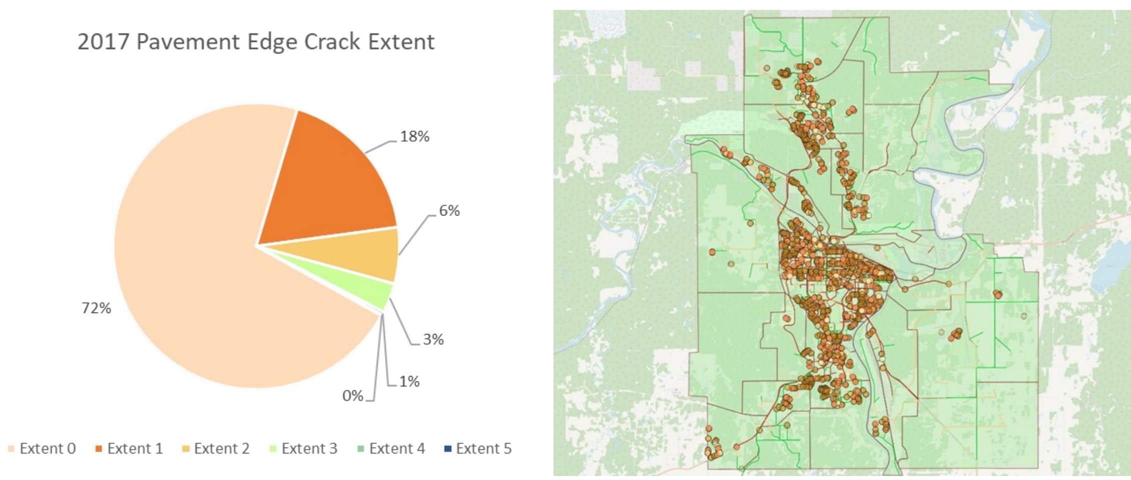
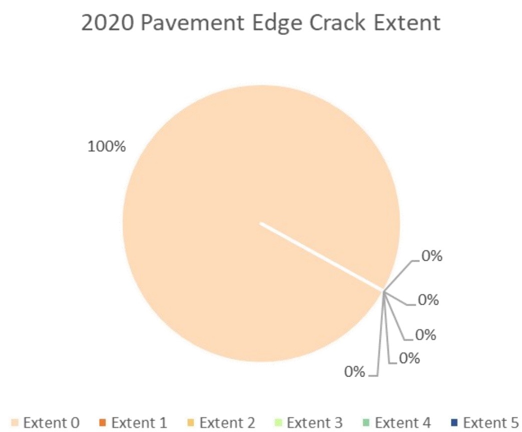


FIGURE I. 46. 2017 Pavement Edge Cracking Extent pie chart and spatial distribution map

2020 Extent Analysis: Edge cracking extent data was not collected, preventing trend analysis during this critical period. The data gap limits understanding of extent progression patterns between 2017 and 2023.



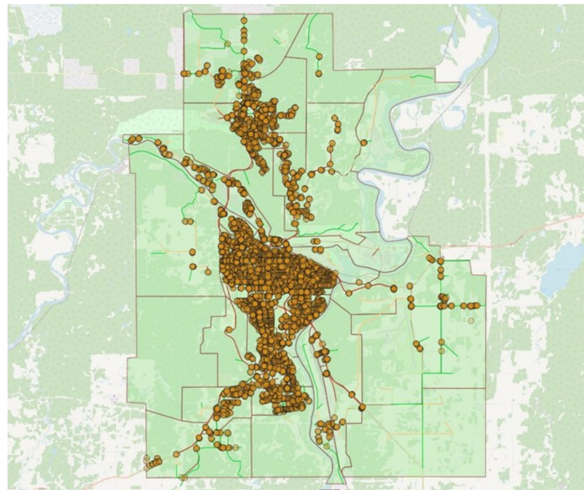
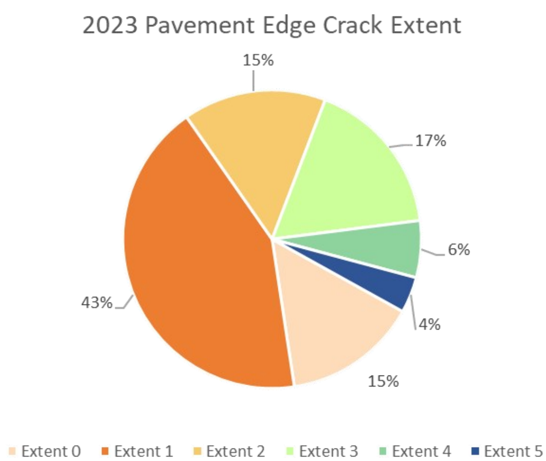


FIGURE I. 47. 2020 Pavement Edge Cracking - No data collected notation

2023 Extent Analysis: Dramatic transformation resulted in 14.6% with no cracking (Extent 0), 42.7% with few occurrences (Extent 1), 15.5% with intermediate extent (Extent 2), 17.2% with frequent cracking (Extent 3), 6.2% with extensive coverage (Extent 4), and 3.9% with throughout coverage (Extent 5). The 85.4% network coverage represents the most extensive single distress challenge.



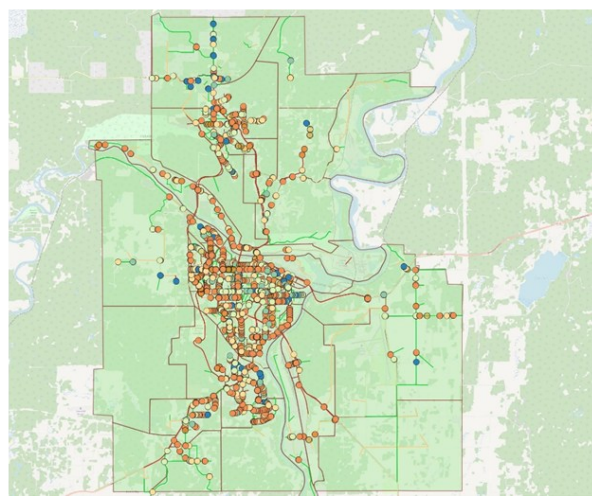


FIGURE I. 48. 2023 Pavement Edge Cracking Extent pie chart and spatial distribution map

I.13. Longitudinal Cracking Severity Analysis

2016 Severity Analysis: The distress established significant baseline longitudinal deterioration with severity distribution showing 70.0% of segments with no distress (Severity 0), 22.3% at low severity (Severity 1), 6.1% at moderate severity (Severity 2), and 1.6% at high severity (Severity 3). The moderate network impact indicated manageable structural deterioration requiring preventive maintenance strategies.

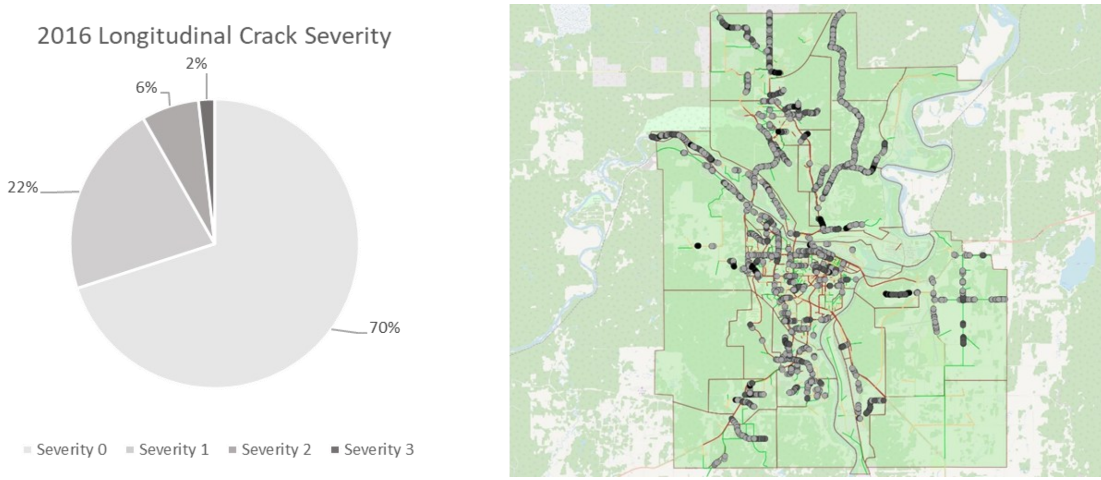


FIGURE I. 49. 2016 Longitudinal Cracking Severity pie chart and spatial distribution map

2017 Severity Analysis: Severity distribution improved with targeted maintenance effectiveness, demonstrating reduced high-severity occurrences. The improvement suggested successful intervention timing and technique selection for longitudinal cracking management.

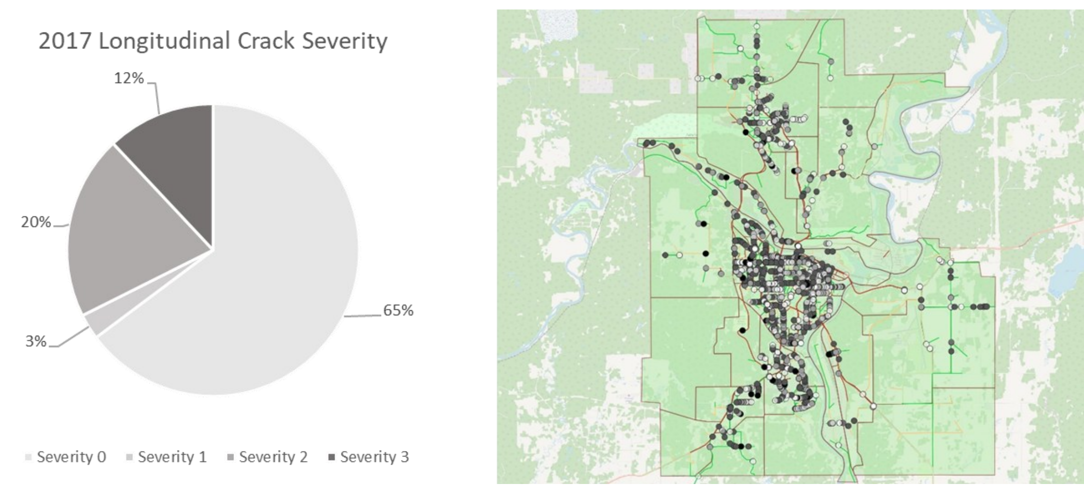


FIGURE I. 50. 2017 Longitudinal Cracking Severity pie chart and spatial distribution map

2020 Severity Analysis: Slight increase in network coverage demonstrated stable management of longitudinal deterioration patterns with severity distribution maintaining manageable levels across all categories. The stability indicated appropriate maintenance strategy implementation.

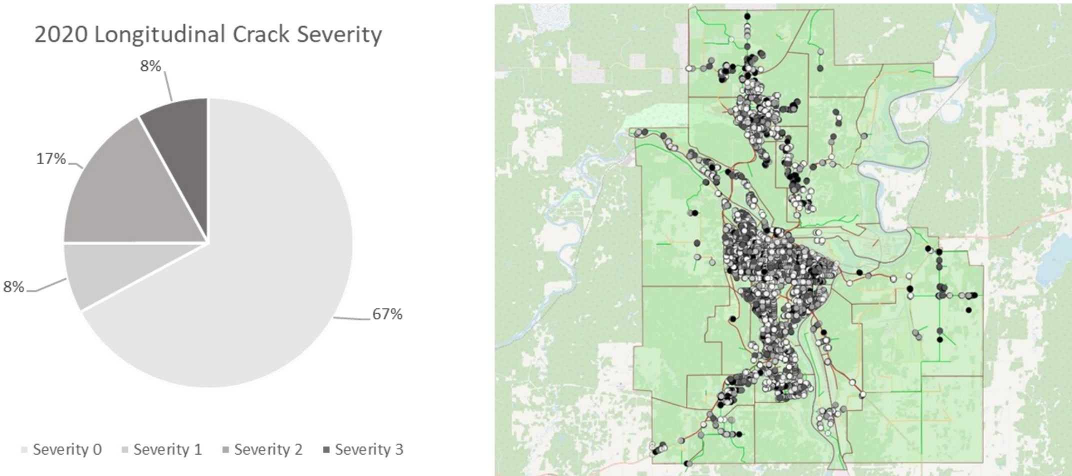


FIGURE I. 51. 2020 Longitudinal Cracking Severity pie chart and spatial distribution map

2023 Severity Analysis: Coverage remained consistent with effective maintenance strategies maintaining stable deterioration patterns. The continued stability throughout the analysis period reflects successful long-term management of longitudinal cracking challenges.

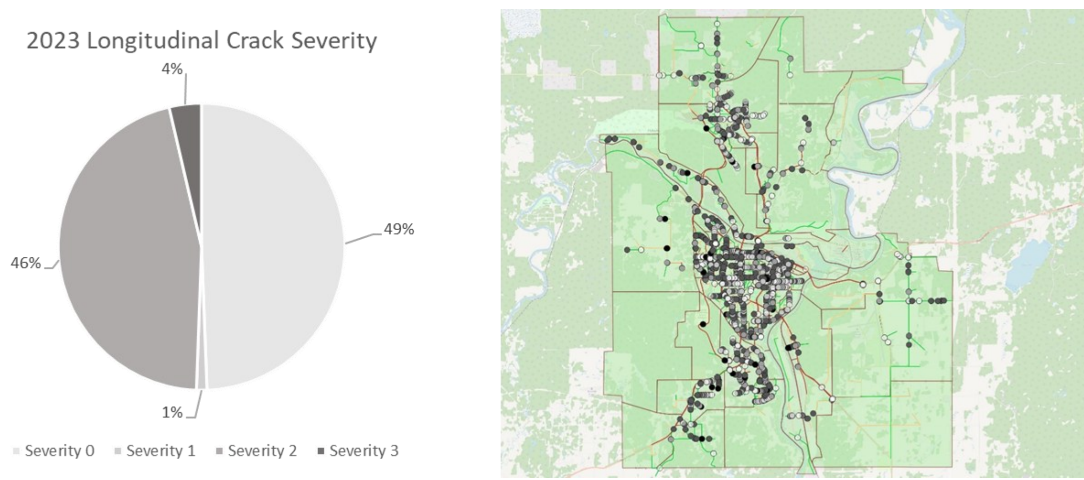


FIGURE I. 52. 2023 Longitudinal Cracking Severity pie chart and spatial distribution map

I.14. Longitudinal Cracking Extent Analysis

2016 Extent Analysis: Extent distribution demonstrated 70.0% with no cracking (Extent 0), 19.4% with few occurrences (Extent 1), 7.8% with intermediate extent (Extent 2), 2.1% with frequent cracking (Extent 3), 0.5% with extensive coverage (Extent 4), and 0.2% with throughout coverage (Extent 5).

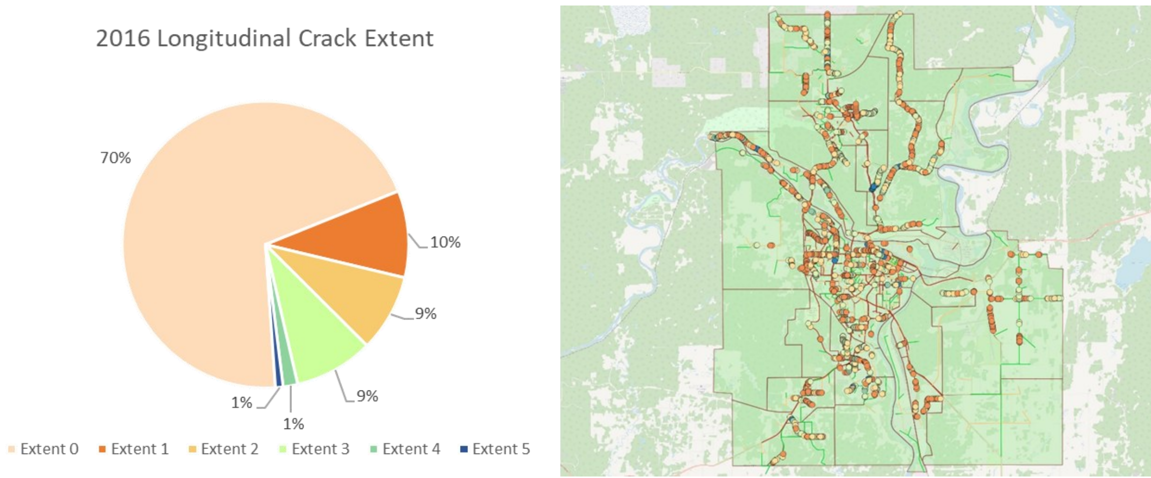


FIGURE I. 53. 2016 Longitudinal Cracking Extent pie chart and spatial distribution map

2017 Extent Analysis: Improved distribution indicated effective maintenance intervention with reduced extent coverage across higher categories. The improvement demonstrated successful targeting of longitudinal cracking progression.

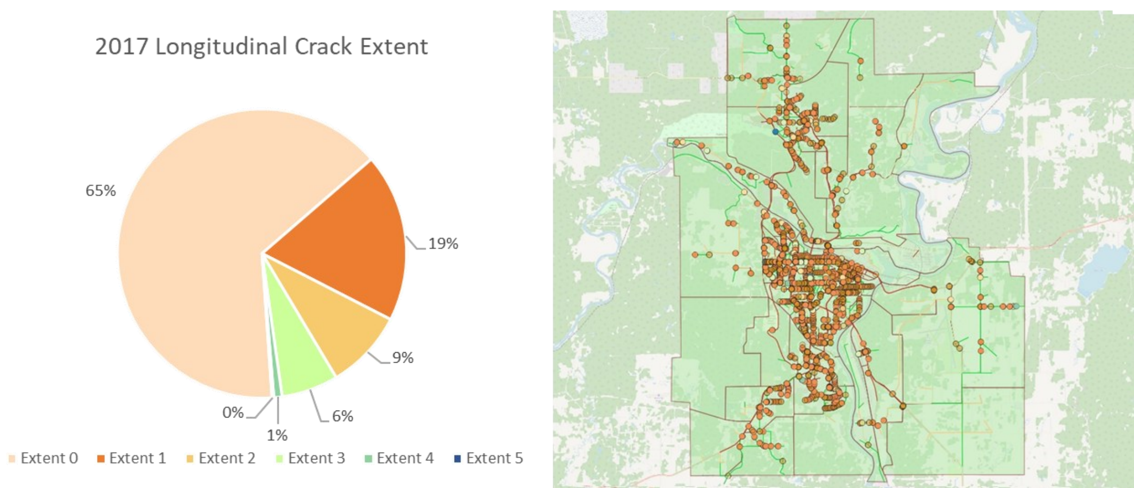


FIGURE I. 54. 2017 Longitudinal Cracking Extent pie chart and spatial distribution map

2020 Extent Analysis: Stable extent patterns maintained manageable coverage levels with consistent distribution across all categories. The stability reflected appropriate maintenance timing and intervention strategies.

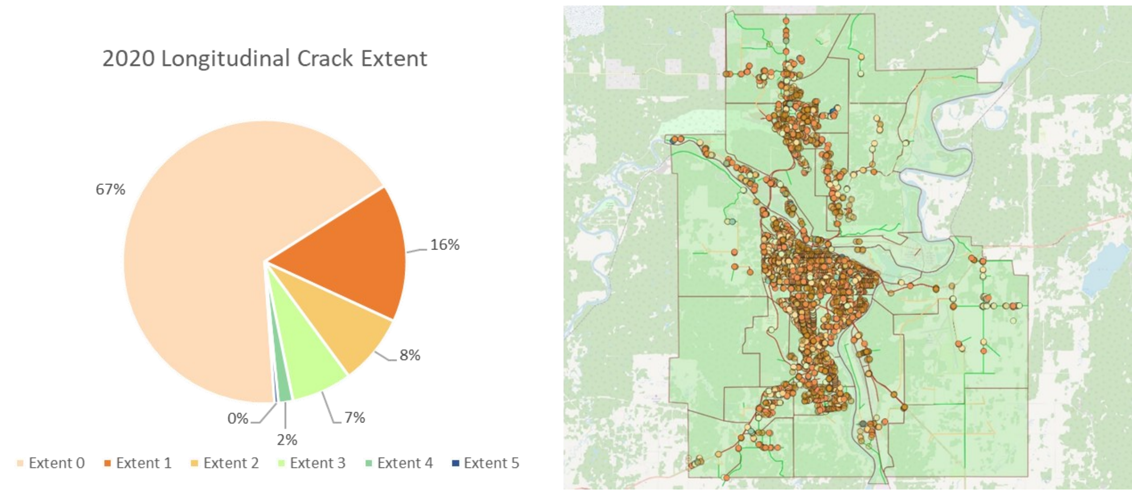


FIGURE I. 55. 2020 Longitudinal Cracking Extent pie chart and spatial distribution map

2023 Extent Analysis: Continued stability in extent distribution demonstrated effective long-term management with consistent network impact levels throughout the analysis period.

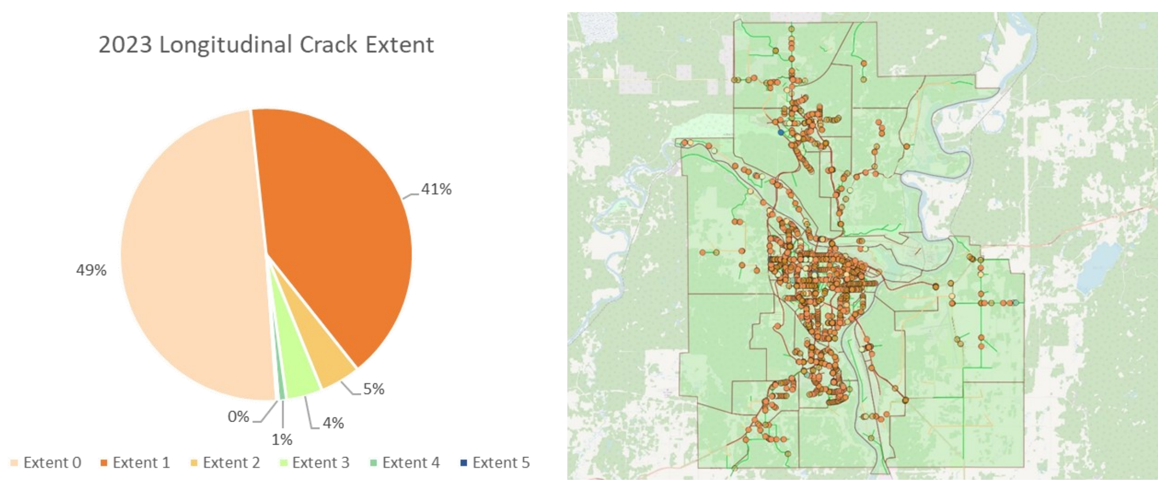


FIGURE I. 56. 2023 Longitudinal Cracking Extent pie chart and spatial distribution map

I.15. Pothole Severity Analysis

2016 Severity Analysis: Potholes represented localized surface failure with severity distribution concentrated in lower categories but indicating areas requiring immediate safety attention. The baseline conditions established emergency response requirements for surface failure management.

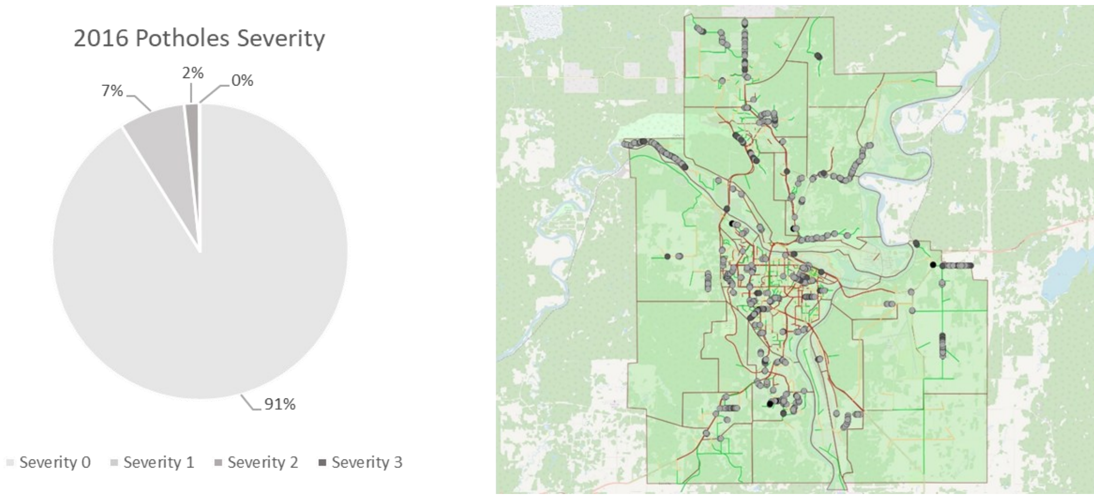


FIGURE I. 57. 2016 Pothole Severity pie chart and spatial distribution map

2017 Severity Analysis: Peak severity conditions were observed with increased occurrence rates representing elevated surface failure requiring enhanced maintenance response. The severity peak indicated critical timing for improved reactive maintenance strategies.

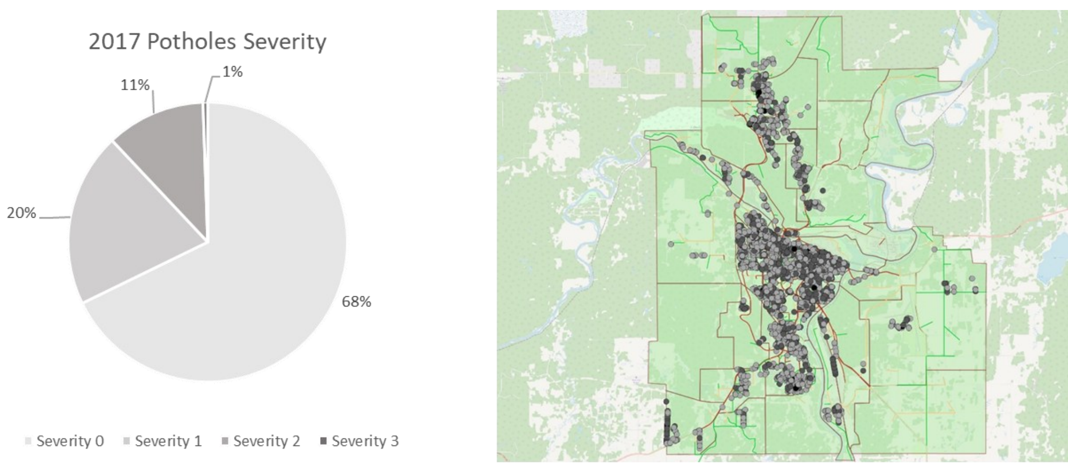
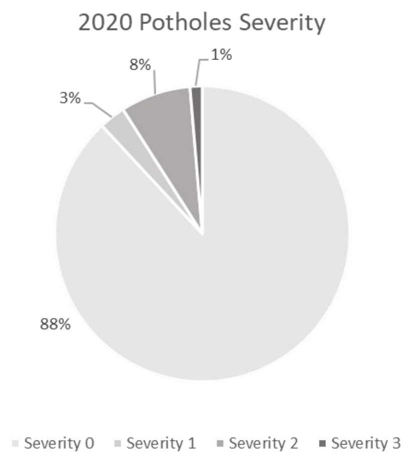


FIGURE I. 58. 2017 Pothole Severity pie chart and spatial distribution map

2020 Severity Analysis: Substantial improvement in severity distribution demonstrated effective reactive maintenance strategies for surface failure management. The reduction reflected successful emergency response protocol implementation.



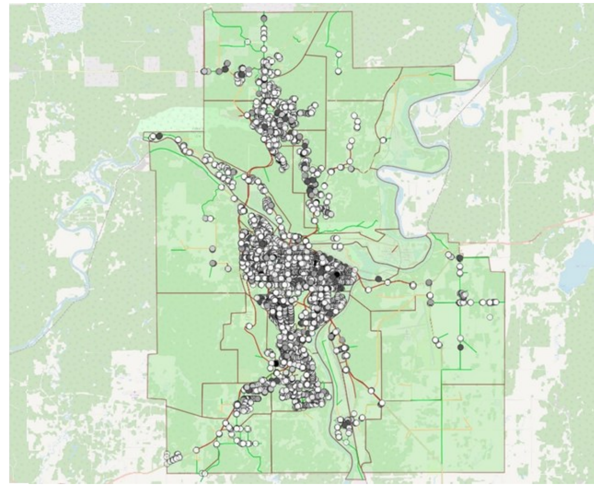
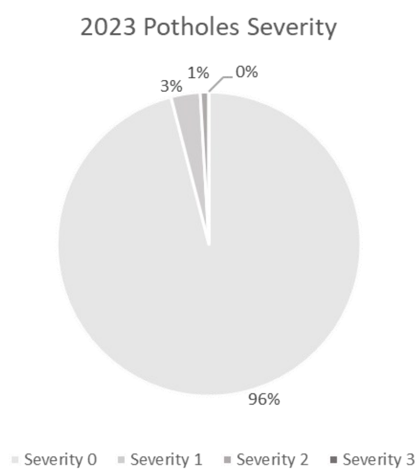


FIGURE I. 59. 2020 Pothole Severity pie chart and spatial distribution map

2023 Severity Analysis: Near-elimination of pothole occurrences across all severity categories represents highly successful surface maintenance achievement. The dramatic reduction indicates comprehensive resolution of surface failure challenges.



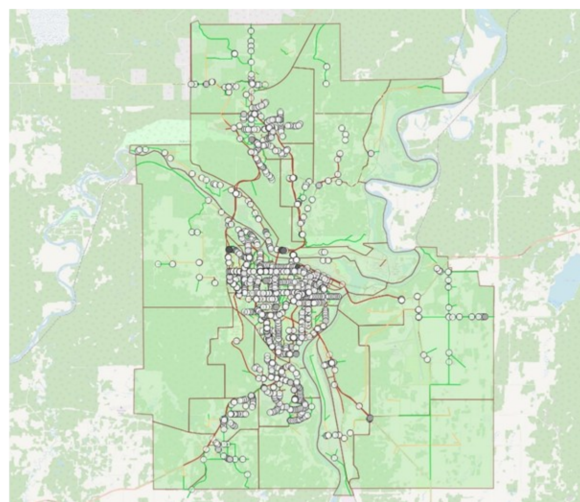


FIGURE I. 60. 2023 Pothole Severity pie chart and spatial distribution map

I.16. Pothole Extent Analysis

2016 Extent Analysis: Extent distribution demonstrated limited coverage patterns with concentration in specific network areas prone to surface failure. The localized distribution indicated targeted intervention requirements for safety management.

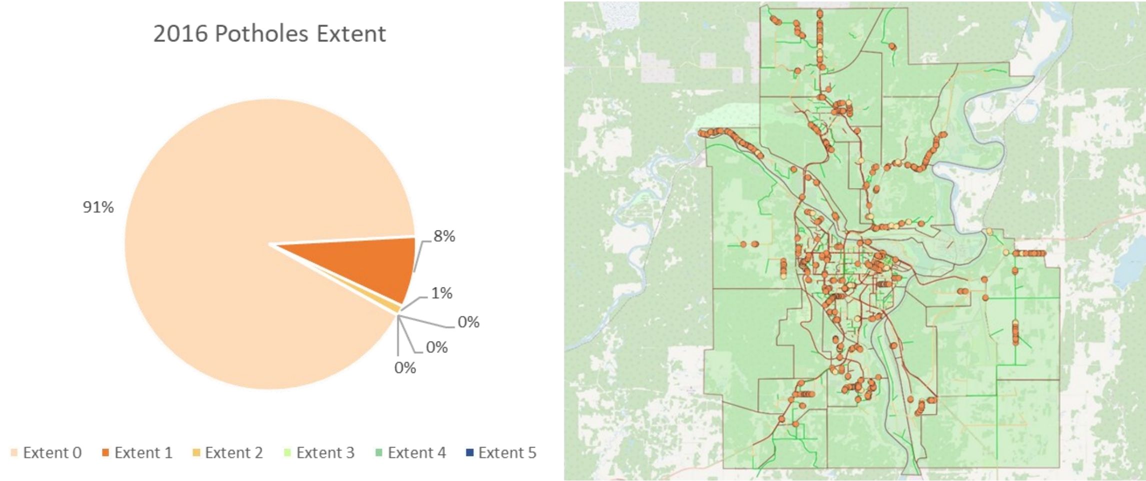


FIGURE I. 61. 2016 Pothole Extent pie chart and spatial distribution map

2017 Extent Analysis: Increased extent coverage correlated with severity peak conditions, indicating expansion of surface failure requiring comprehensive response strategies. The extent patterns provided guidance for emergency response program development.

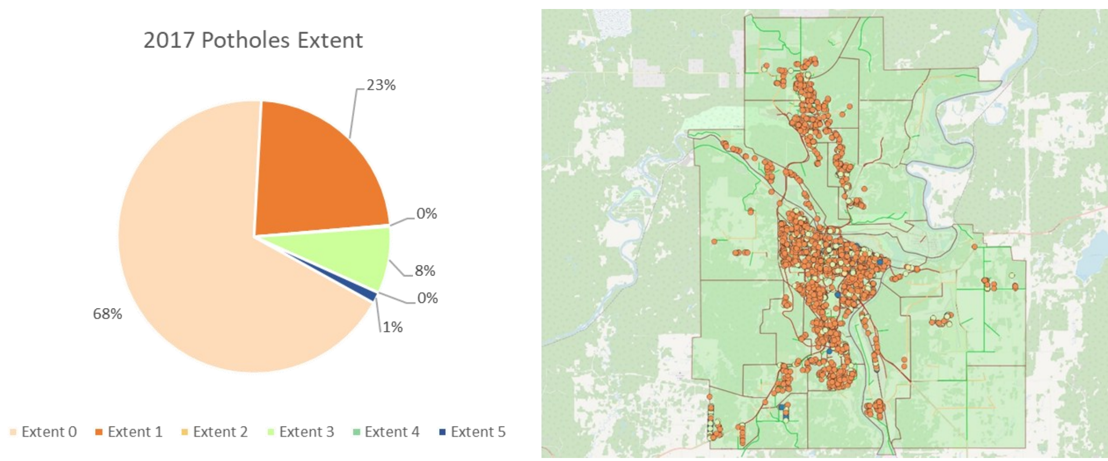


FIGURE I. 62. 2017 Pothole Extent pie chart and spatial distribution map

2020 Extent Analysis: Substantial reduction in extent coverage demonstrated effective reactive maintenance program implementation. The systematic reduction reflected comprehensive addressing of surface failure challenges.

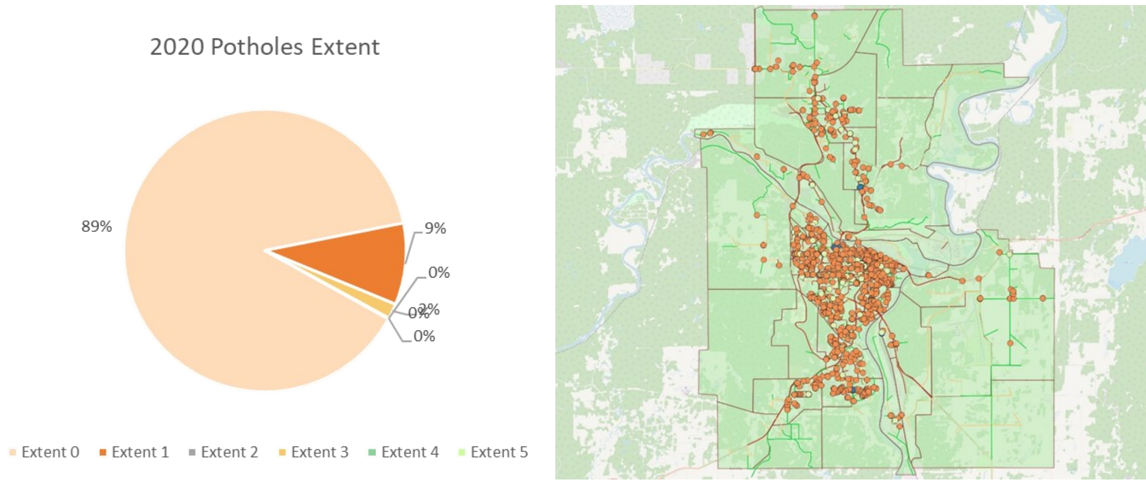


FIGURE I. 63. 2020 Pothole Extent pie chart and spatial distribution map

2023 Extent Analysis: Near-complete elimination of pothole extent represents successful resolution of surface failure challenges with minimal remaining coverage indicating highly effective maintenance program achievement.

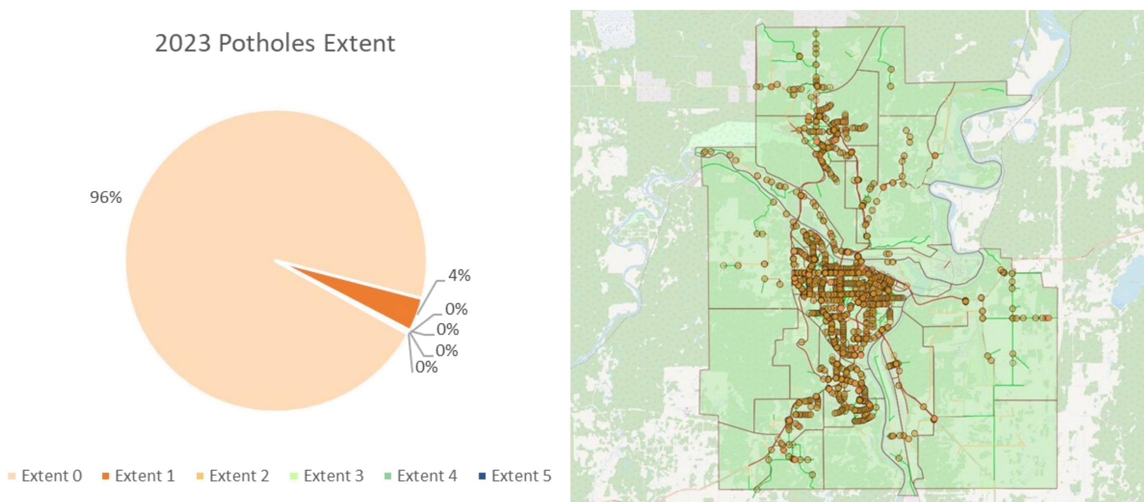


FIGURE I. 64. 2023 Pothole Extent pie chart and spatial distribution map

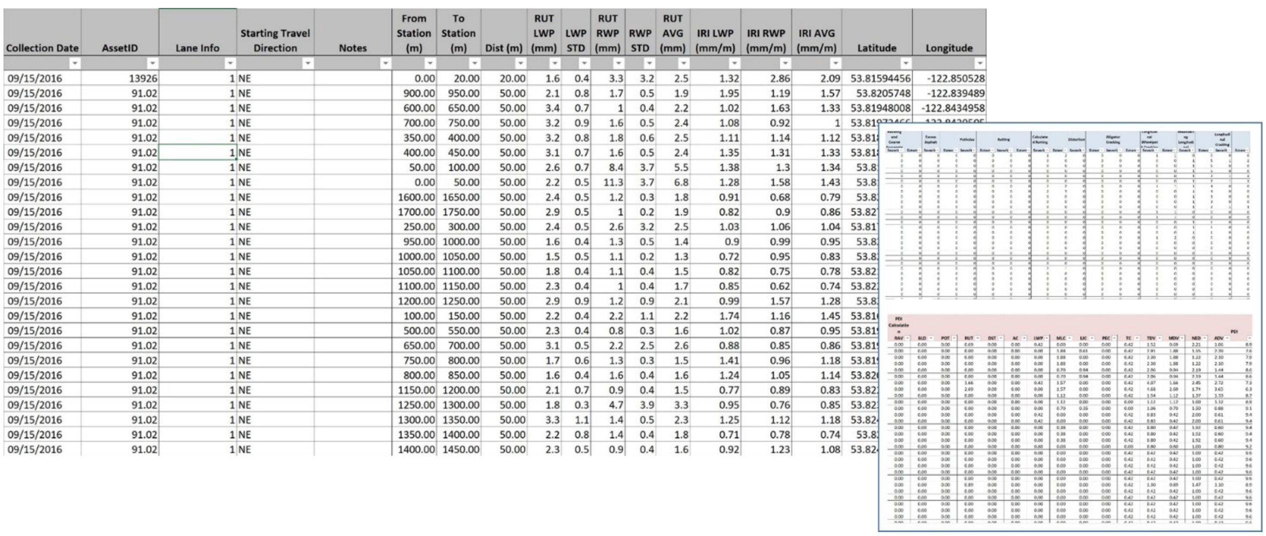
Appendix II. Data Extraction and Analysis

II.1.1. Dataset Compilation and Temporal Coverage

The research utilizes comprehensive pavement condition datasets collected through four systematic surveys spanning seven years. The temporal distribution provides sufficient observation points for deterioration trend analysis and predictive model development while capturing the effects of varying climate conditions and maintenance interventions.

Primary Datasets:

- **2016 Survey**: 9,328 data points focusing on arterial and collector roads
- **2017 Survey**: 12,475 data points including local roads and alleys
- **2020 Survey**: 31,084 data points representing comprehensive network coverage
- **2023 Survey**: 8,942 data points targeting arterial and collector roads



Collection Date	AssetID	Lane Info	Starting Travel Direction	Notes	From Station (m)	To Station (m)	Dist (m)	RUT LWP (mm)	LWP STD	RUT RWP (mm)	RWP STD	RUT AVG (mm)	IRI LWP (mm/m)	IRI RWP (mm/m)	IRI AVG (mm/m)	Latitude	Longitude
09/15/2016	13926	1	NE		0.00	20.00	20.00	1.6	0.4	3.3	3.2	2.5	1.32	2.86	2.09	53.81594456	-122.850528
09/15/2016	91.02	1	NE		900.00	950.00	50.00	2.1	0.8	1.7	0.5	1.9	1.95	1.19	1.57	53.8205748	-122.839489
09/15/2016	91.02	1	NE		600.00	650.00	50.00	3.4	0.7	1	0.4	2.2	1.02	1.63	1.33	53.81948008	-122.8434958
09/15/2016	91.02	1	NE		700.00	750.00	50.00	3.2	0.9	1.6	0.5	2.4	1.08	0.92	1	[illegible]	[illegible]
09/15/2016	91.02	1	NE		350.00	400.00	50.00	3.2	0.8	1.8	0.6	2.5	1.11	1.14	1.12	[illegible]	
09/15/2016	91.02	1	NE		400.00	450.00	50.00	3.1	0.7	1.6	0.5	2.4	1.35	1.31	1.33	[illegible]	
09/15/2016	91.02	1	NE		50.00	100.00	50.00	2.6	0.7	8.4	3.7	5.5	1.38	1.3	1.34	[illegible]	
09/15/2016	91.02	1	NE		0.00	50.00	50.00	2.2	0.5	11.3	3.7	6.8	1.28	1.58	1.43	[illegible]	
09/15/2016	91.02	1	NE		1600.00	1650.00	50.00	2.4	0.5	1.2	0.3	1.8	0.91	0.68	0.79	[illegible]	
09/15/2016	91.02	1	NE		1700.00	1750.00	50.00	2.9	0.5	1	0.2	1.9	0.82	0.9	0.86	[illegible]	
09/15/2016	91.02	1	NE		250.00	300.00	50.00	2.4	0.5	2.6	3.2	2.5	1.03	1.06	1.04	[illegible]	
09/15/2016	91.02	1	NE		950.00	1000.00	50.00	1.6	0.4	1.3	0.5	1.4	0.9	0.99	0.95	[illegible]	
09/15/2016	91.02	1	NE		1000.00	1050.00	50.00	1.5	0.5	1.1	0.2	1.3	0.72	0.95	0.83	[illegible]	
09/15/2016	91.02	1	NE		1050.00	1100.00	50.00	1.8	0.4	1.1	0.4	1.5	0.82	0.75	0.78	[illegible]	
09/15/2016	91.02	1	NE		1100.00	1150.00	50.00	2.3	0.4	1	0.4	1.7	0.85	0.62	0.74	[illegible]	
09/15/2016	91.02	1	NE		1200.00	1250.00	50.00	2.9	0.9	1.2	0.9	2.1	0.99	1.57	1.28	[illegible]	
09/15/2016	91.02	1	NE		100.00	150.00	50.00	2.2	0.4	2.2	1.1	2.2	1.74	1.16	1.45	[illegible]	
09/15/2016	91.02	1	NE		500.00	550.00	50.00	2.3	0.4	0.8	0.3	1.6	1.02	0.87	0.95	[illegible]	
09/15/2016	91.02	1	NE		650.00	700.00	50.00	3.1	0.5	2.2	2.5	2.6	0.88	0.85	0.86	[illegible]	
09/15/2016	91.02	1	NE		750.00	800.00	50.00	1.7	0.6	1.3	0.3	1.5	1.41	0.96	1.18	[illegible]	
09/15/2016	91.02	1	NE		800.00	850.00	50.00	1.6	0.4	1.6	0.4	1.6	1.24	1.05	1.14	[illegible]	
09/15/2016	91.02	1	NE		1150.00	1200.00	50.00	2.1	0.7	0.9	0.4	1.5	0.77	0.89	0.83	[illegible]	
09/15/2016	91.02	1	NE		1250.00	1300.00	50.00	1.8	0.3	4.7	3.9	3.3	0.95	0.76	0.85	[illegible]	
09/15/2016	91.02	1	NE		1300.00	1350.00	50.00	3.3	1.1	1.4	0.5	2.3	1.25	1.12	1.18	[illegible]	
09/15/2016	91.02	1	NE		1350.00	1400.00	50.00	2.2	0.8	1.4	0.4	1.8	0.71	0.78	0.74	[illegible]	
09/15/2016	91.02	1	NE		1400.00	1450.00	50.00	2.3	0.5	0.9	0.4	1.6	0.92	1.23	1.08	[illegible]	

FIGURE II. 1. Sample of Data Tables

Each dataset includes detailed pavement distress characteristics, severity and extent measurements, spatial referencing information, and calculated performance indices following the standardized methodologies outlined in Chapter 3.

II.1.2. Data Structure and Variables

The consolidated dataset incorporates multiple variable categories essential for comprehensive pavement performance analysis:

Distress Variables (Severity and Extent):

- Potholes, Rutting, Alligator Cracking
- Longitudinal Wheelpath Cracking, Meandering Longitudinal Cracking

- Longitudinal Cracking, Pavement Edge Cracking, Transverse Cracking

Performance Indices:

- Pavement Distress Index (PDI)
- International Roughness Index (IRI)
- Average Rutting Depth

Climate Variables:

- Daily maximum, minimum, and mean temperatures
- Total precipitation (rain and snow)
- Freeze-thaw cycle indicators derived from temperature data

Traffic Variables:

- Annual Average Daily Traffic (AADT) volumes
- Vehicle classification data where available
- Seasonal traffic variation patterns

II.1.3. Data Integration Methodology

Climate data spanning the survey periods was obtained from Environment and Climate Change Canada's Prince George weather station, providing daily meteorological records. Traffic volume data was compiled from municipal annual traffic reports for 2016, 2017, and 2023, supplemented by continuous monitoring data from automated counting stations.

The integration process required temporal alignment of datasets collected at different intervals and spatial scales. Pavement condition data collected in standardized 50-meter segments was matched with corresponding climate and traffic information through spatial and temporal indexing procedures.

II.2. Tools and Software Used

II.2.1. Statistical Computing Environment

RStudio served as the primary analytical platform, providing an integrated development environment for statistical analysis, modeling, and visualization. The R programming environment was selected for its comprehensive statistical modeling libraries, advanced machine learning packages, and sophisticated data visualization capabilities.

Key advantages of the RStudio environment include:

- Extensive statistical modeling libraries
- Advanced machine learning packages (randomForest, nnet)
- Sophisticated data visualization capabilities (ggplot2, plotly)

- Reproducible research support through integrated workflows
- Open-source accessibility ensuring long-term sustainability

II.2.2. R Package Ecosystem

The analysis employed a comprehensive suite of R packages; each selected for specific analytical capabilities:

Data Manipulation and Processing:

- `readxl`: Excel file import and processing for municipal datasets
- `dplyr`: Data manipulation, filtering, and transformation operations
- `tidyverse`: Comprehensive data science workflow integration

Machine Learning and Statistical Modeling:

- `randomForest`: Random Forest algorithm implementation with variable importance analysis
- `nnet`: Neural network modeling capabilities for non-linear pattern recognition
- `stats`: Base statistical functions for linear regression and diagnostic procedures

Visualization and Graphics:

- `ggplot2`: Advanced statistical graphics and publication-quality plots
- `plotly`: Interactive visualization capabilities for data exploration

II.2.3. Complementary Software Tools

ArcGIS was utilized for spatial analysis, mapping, and geographic data management. The GIS platform enabled spatial visualization of pavement condition data, network-level analysis, and integration with municipal infrastructure databases.

Microsoft Excel was employed for preliminary data aggregation, formatting, and quality assurance procedures. Excel facilitated collaboration with municipal stakeholders while providing accessible data validation capabilities.

All statistical analyses and modeling procedures were conducted exclusively within the R/RStudio environment to maintain consistency and reproducibility across all analytical components.

II.3. Modeling Approach

II.3.1. Multi-Model Framework

The research employed three distinct analytical techniques to provide comprehensive assessment of predictive capabilities while ensuring robust validation across different algorithmic approaches.

This multi-model strategy addresses varying assumptions about data relationships and provides comparative evaluation of modeling effectiveness.

II.3.2. Multiple Linear Regression (MLR)

Multiple Linear Regression was implemented as the baseline modeling approach to establish fundamental linear relationships between pavement deterioration and contributing factors. MLR provides interpretable coefficients and serves as a benchmark for comparison with advanced modeling techniques.

Implementation:

```
# Multiple Linear Regression Implementation
model_lm <- lm(PDI ~ Alligator_Severity + Alligator_Extent +
               Transverse_Severity + Transverse_Extent +
               Rutting_Severity + Rutting_Extent +
               Potholes_Severity + Potholes_Extent +
               Max_Temp + Min_Temp + Mean_Temp + Precip +
               Traffic + RUT_AVG_mm + IRI_AVG_mm_m,
               data = train_data)
```

The MLR approach assumes linear relationships between predictors and response variables, providing straightforward interpretation of factor contributions. Model diagnostics include residual analysis, normality testing, and multicollinearity assessment to ensure statistical validity.

II.3.3. Random Forest Ensemble Learning

Random Forest was selected as the primary machine learning approach due to its robust performance with complex, non-linear relationships and superior handling of mixed data types characteristic of pavement management applications. The ensemble learning approach combines multiple decision trees to improve prediction accuracy and reduce overfitting.

Implementation:

```
# Random Forest Implementation
library(randomForest)

# Data preprocessing and feature selection
selected_data <- data_cleaned %>%
  select(Potholes_Severity, Potholes_Extent,
         Rutting_Severity, Rutting_Extent,
         Alligator_Severity, Alligator_Extent,
         Longitudinal_Severity, Longitudinal_Extent,
         Meandering_Severity, Meandering_Extent,
         Transverse_Severity, Transverse_Extent,
         PavementEdge_Severity, PavementEdge_Extent,
         Max_Temp, Min_Temp, Mean_Temp, Precip,
         Traffic, RUT_AVG_mm, IRI_AVG_mm_m, PDI) %>%
  na.omit()

# Random Forest model training
```

```
rf_model <- randomForest(PDI ~ ., data = train_data,
                        ntree = 2000, importance = TRUE)
```

The Random Forest implementation incorporated 2000 trees to ensure model stability and employed variable importance assessment to identify key performance drivers. The ensemble approach provides superior handling of non-linear relationships and interaction effects.

II.3.4. Artificial Neural Network

Artificial Neural Networks were implemented using the `nnet` package to capture complex non-linear patterns and interactions in pavement deterioration data. The neural network approach provides sophisticated pattern recognition capabilities for modeling complex pavement performance relationships.

Implementation:

```
# Neural Network Implementation
library(nnet)

# Data normalization for neural network training
features <- setdiff(names(selected_data), "PDI")
ml_data <- selected_data %>%
  select(all_of(c(features, "PDI")))

# Normalize data to [0,1] range
maxs <- apply(ml_data, 2, max)
mins <- apply(ml_data, 2, min)
scaled_data <- as.data.frame(scale(ml_data, center = mins,
                                  scale = maxs - mins))

# Neural network training
nn_model <- nnet(PDI ~ ., data = train_data_scaled,
                size = 6, linout = TRUE, maxit = 500)
```

The neural network architecture employed 6 hidden neurons with linear output activation, optimized through iterative testing to balance model complexity with training efficiency. Data normalization ensures proper weight initialization and convergence behavior.

II.3.5. Data Preprocessing Procedures

Comprehensive data preprocessing ensured analytical reliability and model validity across all approaches:

Missing Data Treatment:

```
# Missing value imputation using column means
selected_data <- selected_data %>%
  mutate(across(everything(), ~ ifelse(is.na(.), mean(., na.rm = TRUE), .)))
```

Data Cleaning and Standardization:

```r
# Convert comma-separated numbers to numeric format
data_cleaned <- data %>%
  mutate(across(everything(), ~ as.numeric(gsub(",", "", as.character(.)))))

# Column name standardization
colnames(selected_data) <- colnames(selected_data) %>%
  gsub(" ", "_", .) %>%
  gsub("\\(", "", .) %>%
  gsub("\\)", "", .) %>%
  gsub("-", "_", .) %>%
  gsub("/", "_", .)
```

Feature Engineering: Distress severity and extent variables were processed separately to capture both the intensity and spatial distribution of pavement deterioration. Climate variables were integrated to enable assessment of environmental impacts on pavement performance.

II.3.6. Model Training and Validation Framework

The research employed an 80/20 train-test split methodology with fixed random seed (123) to ensure reproducible results across all modeling approaches. This split ratio provides sufficient training data while maintaining adequate test samples for robust validation.

```r
# Standardized train-test split
set.seed(123)
train_index <- sample(1:nrow(selected_data), 0.8 * nrow(selected_data))
train_data <- selected_data[train_index, ]
test_data <- selected_data[-train_index, ]
```

The consistent validation framework enables direct comparison of model performance across different algorithmic approaches while ensuring statistical rigor in model assessment.

II.4. Evaluation Criteria

II.4.1. Performance Metrics Framework

Model performance was assessed using a comprehensive suite of statistical metrics that quantify both accuracy and reliability of predictive capabilities. The evaluation framework incorporates standard regression metrics while considering the specific requirements of pavement management applications.

Primary Performance Metrics:

Mean Squared Error (MSE):

```r
# MSE calculation
predicted <- predict(rf_model, test_data)
actual <- test_data$PDI
mse <- mean((predicted - actual)^2)
```

MSE quantifies the average squared difference between predicted and actual values, providing a measure of prediction accuracy that penalizes larger errors more heavily. This characteristic is valuable in pavement management where significant prediction errors can lead to inappropriate maintenance decisions.

Root Mean Squared Error (RMSE):

```
# RMSE calculation
rmse <- sqrt(mse)
```

RMSE provides error measurement in the same units as the target variable, enabling intuitive interpretation of prediction accuracy and facilitating comparison across different applications.

Coefficient of Determination (R^2):

```
# R² calculation
rss <- sum((predicted - actual)^2)
tss <- sum((actual - mean(actual))^2)
r2 <- 1 - rss/tss
```

R^2 quantifies the proportion of variance in the dependent variable explained by the model, providing a standardized measure of model effectiveness ranging from 0 to 1.

```
# Adjusted R² calculation
n <- nrow(test_data)
p <- length(coef(model_lm)) - 1  # number of predictors
adj_r2 <- 1 - (1 - r2) * ((n - 1) / (n - p - 1))
```

For Multiple Linear Regression models, adjusted R^2 was calculated to account for model complexity and the number of predictor variables. Adjusted R^2 adjusts the coefficient of determination based on the number of predictors relative to the sample size, providing a more conservative measure that penalizes the inclusion of non-significant variables. This metric is particularly important when comparing models with different numbers of predictors, as it prevents artificial inflation of R^2 values through the addition of unnecessary variables. The adjusted R^2 formula incorporates degrees of freedom correction, ensuring that reported model performance reflects true predictive capability rather than overfitting to the training data.

II.4.2. Model Comparison Framework

Comparative evaluation across modeling approaches employed consistent metrics and validation procedures:

```
# Standardized evaluation function
evaluate_model <- function(predictions, actuals) {
  mse <- mean((predictions - actuals)^2)
  rmse <- sqrt(mse)
  rss <- sum((predictions - actuals)^2)
  tss <- sum((actuals - mean(actuals))^2)
  r2 <- 1 - rss/tss
```

```
# Calculate adjusted R² for linear models
if (!is.null(model) && inherits(model, "lm")) {
  n <- length(actuals)
  p <- length(coef(model)) - 1
  adj_r2 <- 1 - (1 - r2) * ((n - 1) / (n - p - 1))
return(list(MSE = round(mse, 2),
     RMSE = round(rmse, 2),
     R2 = round(r2, 4),
     Adj_R2 = round(adj_r2, 4)))
```

This standardized evaluation framework ensures consistent performance assessment across Multiple Linear Regression, Random Forest, and Neural Network approaches. For MLR, adjusted R^2 is calculated to provide a more rigorous assessment that accounts for model complexity, while standard R^2 is reported for machine learning approaches where adjusted R^2 is not applicable.

II.4.3. Variable Importance Analysis

Random Forest models provided variable importance metrics to identify key factors driving pavement deterioration:

```
# Variable importance assessment
importance_df <- as.data.frame(importance(rf_model))
importance_df$Variable <- rownames(importance_df)

# Visualization framework for variable importance
ggplot(importance_df, aes(x = reorder(Variable, `%IncMSE`),
                          y = `%IncMSE`)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  coord_flip() +
  labs(title = "Variable Importance Assessment",
       x = "Variable", y = "% Increase in MSE") +
  theme_minimal()
```

II.4.4. Predictive Capability Framework

Future condition forecasting capabilities were evaluated through systematic application of trained models:

```
# Future prediction implementation
latest_input <- selected_data %>%
  tail(1) %>%
  select(-PDI)

future_prediction <- predict(rf_model, newdata = latest_input)
```

The predictive framework enables systematic evaluation of model forecasting capabilities essential for proactive pavement management applications.

II.4.5. Model Validation and Robustness Assessment

Model robustness was assessed through systematic evaluation of prediction accuracy across different pavement condition ranges and validation of statistical assumptions. Residual analysis procedures confirmed appropriate model behavior without systematic bias or heteroscedasticity issues.

The comprehensive evaluation framework provides the foundation for systematic comparison of modeling approaches and selection of optimal predictive techniques for pavement management applications under northern climate conditions.