GEORGIA DOT RESEARCH PROJECT 23-25

Final Report

LEVERAGING PROBE DATA FOR IMPROVING INCIDENT MANAGEMENT PRACTICE IN RURAL AREAS

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16. Abstract

Traffic data are essential for decision-making by state departments of transportation in planning, designing, operating, maintaining, and rehabilitating transportation systems. However, collecting traffic counts at numerous portable sites in rural areas demands significant time and resources. In response, the Georgia Department of Transportation (GDOT) has been exploring alternative data acquisition technologies to efficiently gather traffic data across Georgia's rural road network. With the increasing availability and use of probe data in various transportation applications, this study examines the feasibility of leveraging probe data for two key purposes: (1) improving vehicle miles traveled (VMT) reporting and (2) enhancing incident management practices in rural areas. To evaluate the feasibility of VMT reporting, traffic volumes estimated from probe data on rural state roads were compared to traffic volumes from GDOT's portable count sites, which served as the ground truth. Using a sample of 500 portable count sites in rural South Georgia, probe-derived traffic volumes yielded an overall estimation error of 21 percent and 29 percent for daily vehicle miles traveled (DVMT) based on data from Vendor 1 and Vendor 2, respectively. Notably, the most stable traffic estimates occurred on Wednesdays; estimating DVMT using only Wednesday's data reduced the error to −4 percent for Vendor 1 and 5 percent for Vendor 2. To enhance incident management, event data from the Regional Integrated Transportation Information System (RITIS) were employed to model both the risk and duration of incidents on interstate highways in rural South Georgia, patrolled by Georgia's Coordinated Highway Assistance and Maintenance Program (CHAMP). Incident risk and duration were treated as binary classification problems, utilizing a state-of-the-art gradient-boosting tree method. The incident risk model achieved an F1 score of 0.65 with a recall of 0.74. For incident duration, a 30 min threshold yielded the best classification performance, with an F1 score of 0.72. Feature importance analysis, combined with spatiotemporal heatmaps, uncovered specific patterns that can inform and optimize incident management practices.

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DISCLAIMER STATEMENT

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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EXECUTIVE SUMMARY

Probe data have emerged as a valuable resource for enhancing various transportation practices, with a strong focus on urban transportation management. This study seeks to explore the utility of probe data in two key areas within the rural setting: vehicle miles traveled (VMT) estimation and incident management.

For VMT estimation, the study assesses the feasibility of using probe-based data by comparing it to Georgia Department of Transportation (GDOT) portable counts, which serve as the ground truth. For incident management, probe-based event data are analyzed to uncover spatiotemporal patterns of incidents, with the goal of improving GDOT's Coordinated Highway Assistance and Maintenance Program (CHAMP) program, particularly for rural interstates beyond the Atlanta Metropolitan area. Key findings from the study include:

- Estimation of VMT

  This study evaluates traffic volumes estimated using probe-derived traffic data from two selected market vendors. The results indicate notable variability across different facility types and days of the week. However, estimates for Wednesdays showed improved consistency, yielding overall estimation errors of −4 percent and 5 percent for daily vehicle miles traveled (DVMT) based on data from Vendor 1 and Vendor 2, respectively.

- Incident Management

  To gain a deeper understanding of spatiotemporal patterns on rural interstates in South Georgia, event data were analyzed to model the risk and duration of incidents. The results reveal critical features and unique spatiotemporal patterns that can inform and enhance incident management strategies on these rural interstates.

CHAPTER 1. INTRODUCTION

Traffic data are fundamental to decision making by state departments of transportation for planning, design, operations, maintenance, and rehabilitation of transportation systems. The Office of Transportation Data (OTD) at the Georgia Department of Transportation (GDOT) has over 300 permanent continuous count stations (CCSs) and more than 9000 portable count sites [1]. The CCSs are primarily located on major roadways in urban and suburban areas, whereas the portable count sites are spread out to cover the majority of the statewide road network, including the expansive rural areas in Georgia. Given the large number of portable sites, OTD collects data at these sites over a 3-year cycle with about 3000 sites being collected each year. Considering the excessive time and resources required for collecting traffic counts at the large number of portable sites, OTD has been continually seeking alternative data acquisition technologies to efficiently collect traffic data for the bulk of the rural road network in Georgia. The emergence and increasing penetration of connected vehicles and devices provide tremendous probe data and offer a great opportunity for acquiring traffic data in an effective and non-traditional way.

Probe data can be collected from a diverse range of entities, including a full range of vehicles (e.g., passenger cars, transit vehicles, freight carriers, etc.) as well as any person with a smartphone [2]. This continually growing probe data (Big Data) has fueled many data service companies to deliver valuable data and data-driven products that assist transportation agencies with informative and objective decision making.

Use of probe data can be beneficial in certain application contexts (e.g., traffic operations and management) as compared to traditional sensors installed at fixed locations. Knowing that the two sources of data (i.e., the probe data from mobile objects and the data from stationary count stations) are largely geospatially complementary and can be correlated or cross-referenced for data quality verification, there are tremendous opportunities for leveraging both data sources to enhance current practices at GDOT. For example, with a proper quality control process, OTD can supplement the spatially limited CCS data with high-quality probe data. This can potentially eliminate or significantly reduce data collection effort at 9000+ portable sites. Additionally, the operators at Transportation Management Centers (TMCs) will be able to leverage this new data source to more effectively manage emerging or developing events, such as incidents, in a proactive fashion.

Particularly, the advantages of using probe data are obvious for rural areas, where sensors are extremely sparse or nearly nonexistent. Installing and maintaining a large sensor network to cover the expansive rural areas will be cost-prohibitive and resource-demanding. The probe data can be readily obtained to cover the rural road network in Georgia. However, the quality of the various sources of probe data and their suitability in different application contexts need to be carefully evaluated before OTD can adopt any of them in practice. This proposed study serves as the first step for OTD to evaluate the feasibility of using probe data to (1) estimate vehicle miles traveled (VMT), and (2) improve GDOT's Coordinated Highway Assistance & Maintenance Program (CHAMP) in South Georgia.

CHAPTER 2. LITERATURE REVIEW

Traffic incidents, being unexpected events, can lead to fatalities, injuries, or property damage; disrupt traffic flow; and create significant risks such as secondary crashes. These incidents not only endanger responders and the traveling public but also affect travel reliability, commercial activities, and the overall efficiency of transportation systems. Traffic incident management (TIM) is a critical responsibility of transportation and public safety agencies, aimed at ensuring the safe and swift clearance of traffic incidents [3]. Effective TIM minimizes the duration and impact of traffic incidents; enhances the safety of motorists, crash victims, and emergency responders; and reduces the likelihood of secondary crashes.

Although urban areas have been the focus of much TIM research and practice, rural areas, despite their lower traffic volumes and populations, present unique challenges due to factors such as an aging population, longer travel distances, limited network connectivity, and constrained resources. Consequently, incidents in these areas often experience delayed detection and response times. Additionally, rural roads typically traverse expansive natural landscapes, feature higher posted speeds, and have different geometric and surface conditions, which contribute to specific types of incidents, such as run-off-road crashes and wildlife collisions [4]. This literature review delves into the current state of TIM, with a particular emphasis on the challenges faced in rural areas. It explores response strategies, case studies, and best practices to provide a comprehensive understanding of how TIM can be improved in these contexts.

TRAFFIC INCIDENT MANAGEMENT CHALLENGES IN RURAL AREAS

TIM activities are generally divided into five interrelated functional areas: detection and verification, traveler information, response, scene management and traffic control, and quick clearance and recovery. Actions within these areas often occur simultaneously. For example, while public information officers continuously disseminate traveler information, scene management and clearance efforts are being carried out at the incident site. Each functional area in TIM presents unique challenges, particularly in rural settings.

(1) **Detection and Verification:** In rural areas, challenges in detection and verification include inconsistent notification of public safety agencies, inaccuracies in incident reports (often provided by motorists), overwhelmed dispatchers with limited attention, and slow detection times. In nonurban or remote areas, where passing vehicles are infrequent, incidents may go unnoticed for extended periods [5]. Early detection is crucial to ensure prompt medical assistance and reduce the likelihood of secondary incidents.

(2) **Traveler Information:** Providing accurate traveler information in rural areas is hampered by several factors. First, the lack of advanced monitoring systems often leads to poor information quality. Miscommunication and lack of coordination among responding agencies, dispatchers, and the media can degrade information accuracy as it is relayed to third parties, making it difficult to provide clear and consistent updates. Additionally, the use of dynamic message signs (DMSs) presents its own set of challenges. Some argue that DMSs should be reserved exclusively for emergencies to ensure motorists pay attention when necessary, while others believe regular non-incident messages help familiarize drivers with checking DMSs, increasing their reliance on them during incidents. Balancing these approaches is essential to maintain drivers' attentiveness without desensitizing them to critical messages [6].

(3) **Response:** Challenges in response within rural TIM include:

- *Achieving Optimum Response*: Rural areas often struggle with both under-response and over-response during incident management. Under-response occurs when insufficient or inappropriate resources are dispatched, leading to delays as additional resources are requested. For example, state patrol units in rural areas may be limited, covering vast territories with lengthy response times. Similarly, tow truck response times can be significantly delayed. Conversely, over-response, where too many resources are deployed, can exacerbate congestion and reduce the efficiency of emergency services. Achieving the right balance requires improved incident verification and a better understanding of the specific needs and capabilities of different responding agencies.
- *Difficult Scene Access*: Limited access to incident scenes in rural areas is often caused by traffic congestion and roadway design, such as limited sight distance due to curves and hills, constrained geography caused by ditches adjacent to the roadway, and limited areas to park response vehicles and perform work. At the same time, congestion complicates the ability of responders to reach the scene, and the lack of wide shoulders that are often converted to traffic lanes in some areas further restricts emergency access, making it challenging to navigate around blocked or slowed traffic [7].

(4) **Scene Management and Traffic Control:** Several challenges are prominent in rural TIM.

- *Confusion over Authority/Roles*: disagreements over decisions like road closures can cause confusion and strain interagency relationships due to differing priorities.

- *Difficult On-Scene Maneuverability*: Congestion from emergency vehicles at the scene complicates access and can lead to delays when vehicles need to be moved. In rural areas, responders frequently deal with incidents involving livestock, slow-moving farm vehicles, and horse-drawn carriages [8]. These incidents necessitate specialized responses, particularly in the case of livestock collisions, where standard operating procedures must be adapted.
- *Responder Safety*: Responders face high risks of being struck by passing vehicles, with significant fatalities reported among law enforcement, rescue, and towing personnel.
- *Secondary Incidents*: Secondary incidents often occur due to motorists being unaware of the primary incident, increasing injury severity and congestion, accounting for 14–18 percent of incidents.
- *Excess Delay*: Incidents can significantly reduce road capacity, leading to substantial delays and economic losses, although TIM efforts help mitigate some of these impacts.

(5) **Quick Clearance and Recovery:** Key challenges in rural TIM related to quick clearance and recovery include the following:

- *Abandoned Vehicle Hazards*: Vehicles left on roadways for extended periods pose significant safety risks, with enforcement difficult due to large coverage areas and infrequent patrols.
- *Lengthy Minor Incident Clearance*: Delays in clearing minor incidents stem from low prioritization, lack of dedicated patrols, and restrictive removal policies. Misclassification of incidents can also cause unnecessary delays.

- *Lengthy Major Incident Clearance*: Major incidents face delays due to the slow mobilization of specialized personnel and equipment, and poor coordination among agencies, leading to severe impacts.
- *Liability Concerns*: Hesitation to expedite clearance due to liability fears can increase the risk of secondary incidents, which often pose greater dangers than potential damage to vehicles or cargo [9].

CASE STUDIES AND BEST PRACTICES

To effectively respond to traffic incidents in rural areas, transportation systems management and operations (TSMO) typically employ two primary strategies. The first involves quick clearance policies and procedures designed to swiftly remove disabled vehicles from the roadway. The second strategy includes TIM programs that offer courtesy patrols or service patrols to assist stranded motorists and manage traffic flow around the incident site [7]. Many state departments of transportation (DOTs) have implemented targeted practices to address the unique challenges of rural incident management. These efforts primarily aim to reduce the duration and impact of traffic incidents; enhance the safety of motorists, crash victims, and emergency responders; improve the allocation and deployment of limited resources and equipment; and minimize delays and road closures. The best practices adopted are generally focused on five aspects: (1) multi-agency collaboration, (2) communication and technology, (3) resource allocation and pre-positioning, (4) incident scene safety, and (5) data collection and analysis.

Multi-Agency Collaboration

The literature consistently emphasizes the critical role of multi-agency collaboration in effective TIM in rural areas. Research underscores the importance of close coordination among various stakeholders, including law enforcement, fire departments, emergency medical services (EMS), transportation agencies, and towing services. Formal agreements and established communication protocols are highlighted as essential components to streamline coordination and ensure a unified response. Moreover, regular joint training exercises, incorporating both tabletop simulations and field drills, are recommended to prepare all agencies for the complexities of incident response in rural settings. The *Georgia Traffic Incident Management Guidelines* [10] provide a good example and are summarized in table 1.

Table 1. Georgia TIM guidelines.

Project Description	The project was initiated by the GDOT and the Traffic Incident Management Enhancement (TIME) Task Force. The primary goal is to establish a standardized approach for managing traffic incidents, ensuring the safety of responders and the public while minimizing disruptions to traffic flow. The guidelines were developed to support quick clearance of incidents, improve responder safety, and reduce the likelihood of secondary crashes. They provide a broad framework that can be adapted to local conditions, ensuring that all stakeholders, including law enforcement, fire and rescue personnel, EMS, and towing and recovery teams, work together effectively.
Benefits	The multi-agency collaboration fostered by the Georgia TIM guidelines offers numerous benefits: • Improved Safety: The guidelines prioritize the safety of both responders and the public by promoting best practices in incident

	management, such as proper vehicle positioning and the use of high-visibility apparel. • Faster Incident Clearance: By establishing clear protocols and encouraging cooperation among different agencies, the guidelines help to reduce the time required to clear incidents, thereby minimizing traffic disruptions. • Enhanced Communication: The project promotes the use of reliable communication systems and joint training exercises, which improve coordination and ensure that all responders are prepared to work together efficiently. • Resource Optimization: By facilitating the strategic placement of resources and encouraging mutual aid agreements, the guidelines help to ensure that the right resources are available where and when they are needed.
Challenges	• Geographic Diversity: The wide-ranging geographic coverage of rural areas in Georgia presents logistical challenges in ensuring timely response and effective communication across different regions. • Resource Limitations: Rural areas often have limited resources, making it difficult to implement all aspects of the guidelines uniformly. Pre-positioning resources and coordinating with neighboring jurisdictions are essential but can be challenging to manage.

	• Interagency Coordination: Ensuring consistent communication and collaboration among multiple agencies with different operational protocols and priorities can be difficult, particularly in complex or large-scale incidents.
Lessons Learned	• The Importance of Training: Regular, joint training exercises are crucial to ensure that all responders are familiar with the guidelines and can work together effectively during real incidents. • Adaptability: The guidelines need to be adaptable to local conditions. No two incidents are the same, and responders must be able to assess each situation and apply the guidelines in a way that makes sense given the specific circumstances. • Continuous Improvement: The guidelines are intended to be a living document, with regular updates based on feedback from the field and changes in technology and legislation. This approach ensures that the guidelines remain relevant and effective over time.

Communication and Technology

The challenge of maintaining robust communication systems in rural areas is well documented, with scholars advocating for the deployment of reliable technologies such as satellite phones and extended-range two-way radios. These systems are crucial for ensuring that all responders are equipped to communicate effectively across vast and often remote areas. Furthermore, the literature points to the growing importance of incident detection and notification technologies, including automated crash notification systems, closed-circuit television (CCTV) cameras, and mobile applications, which can expedite the reporting and response to incidents. Global information systems (GISs) are also identified as valuable tools for managing and dispatching resources efficiently, given the geographic challenges inherent in rural areas. For instance, the Federal Highway Administration (FHWA) has introduced unmanned aircraft systems (UAS) for TIM [11], as summarized in table 2.

Table 2. UAS in TIM (FHWA project).

Project Description	The project focuses on the integration of UAS into TIM strategies, particularly in rural areas. The goal is to leverage UAS technology to improve the speed and accuracy of traffic crash investigations, reduce roadway clearance times, enhance the safety of incident responders, and minimize the impact of incidents on traffic flow. FHWA has been actively promoting the national deployment of TIM programs, with UAS being identified as a promising tool to enhance these efforts.

Benefits	The adoption of UAS in rural TIM offers several significant benefits: • Faster Incident Clearance: UAS allows for quicker documentation of crash scenes, which in turn reduces the time required to clear roadways. Studies have shown that UAS can reduce roadway closure times by as much as 80 percent, leading to substantial economic savings and improved traffic flow. • Enhanced Safety: UAS reduces the need for responders to be on the roadway for extended periods, thereby lowering the risk of secondary crashes and improving overall responder safety. • Cost-Effectiveness: Compared to traditional methods like total station and 3D scanners, UAS are less expensive to operate and maintain. The technology also offers scalable solutions, enabling agencies to deploy multiple units across different locations. • Improved Data Collection: UAS provides high-resolution aerial imagery and accurate measurements, which enhance the quality of crash investigations and make it easier to understand the dynamics of incidents.
Challenges	• Weather and Environmental Conditions: UAS operations can be hindered by adverse weather conditions such as fog, precipitation, and strong winds, which are common in rural areas. These factors can limit the effectiveness of UAS and require alternative methods for incident documentation.

	• Privacy Concerns: The use of UAS by law enforcement agencies has raised concerns among the public regarding privacy and the potential misuse of surveillance capabilities. Agencies must navigate these concerns through community engagement and transparent communication. • Regulatory and Operational Hurdles: UAS operations are subject to strict regulations by the Federal Aviation Administration (FAA), including restrictions on flying in certain airspaces and obtaining necessary waivers. Additionally, agencies must develop comprehensive policies and procedures to ensure the proper use and management of UAS.
Lessons Learned	• Importance of Training: Proper training for UAS operators is crucial to ensure the safe and effective use of the technology. Agencies must invest in ongoing training programs to keep operators proficient and up to date with regulatory requirements. • Community Engagement: Proactively engaging with the public and addressing privacy concerns is essential for gaining community support for UAS programs. Transparency in how UAS will be used and the safeguards in place to protect privacy can help build trust. • Program Evaluation: Regular evaluation of UAS programs is necessary to assess their effectiveness and identify areas for improvement. Agencies should track metrics such as incident

	clearance times, cost savings, and safety outcomes to demonstrate the value of UAS in TIM.

Resource Allocation and Pre-Positioning

Studies highlight the necessity of strategic resource placement to reduce response times in rural areas, where distances between resources and incident sites can be significant. Pre-positioning of critical resources such as tow trucks, ambulances, and hazardous material response teams at strategic locations is often cited as best practice. Additionally, mutual aid agreements between neighboring jurisdictions are recommended to facilitate resource sharing during major incidents, thereby enhancing the overall response capability. The *State of New Jersey Traffic Incident Management Strategic Plan* [12] showcased an example of resource management, as summarized in table 3.

Table 3. New Jersey TIM Strategic Plan.

Project Description	The New Jersey TIM Strategic Plan aims to enhance the management of traffic incidents across the state, including rural areas. The plan's primary goals are to reduce incident duration, improve safety for both responders and motorists, and ensure the quick clearance of incidents to minimize traffic disruptions. This is achieved through a coordinated, multidisciplinary approach that involves various stakeholders, including law enforcement, fire and rescue services, EMS, towing and recovery, and transportation agencies.

Benefits	The implementation of the New Jersey TIM Strategic Plan in rural areas offers several key benefits: • Improved Safety: The plan enhances the safety of responders and motorists by promoting best practices in incident management, including the use of protective equipment and proper vehicle positioning. • Reduced Incident Duration: By establishing clear protocols and encouraging interagency cooperation, the plan helps reduce the time required to clear incidents, leading to fewer traffic disruptions. • Efficient Use of Resources: The strategic allocation and pre-positioning of resources, such as emergency vehicles and towing services, ensure that the right resources are available when needed, improving overall response efficiency.
Challenges	Despite its benefits, the TIM Strategic Plan faces several challenges in rural areas: • Geographic Challenges: Rural areas often have vast and varied terrains, making it difficult to ensure the timely arrival of resources at incident scenes. • Resource Limitations: Often, a limited number of resources are available in rural areas, which can complicate the management of incidents, especially those requiring a significant response.

	• Interagency Coordination: Ensuring consistent and effective communication and cooperation among multiple agencies with different operational protocols can be challenging, particularly in rural settings where infrastructure may be lacking.
Lessons Learned	Several important lessons have emerged from the implementation of the New Jersey TIM Strategic Plan: • Importance of Training: Regular, joint training exercises are crucial for ensuring that all responders are familiar with TIM protocols and can work together effectively during incidents. • Data-Driven Decision Making: The use of data to identify high-risk areas and optimize resource allocation has proven essential for improving incident management outcomes in rural areas. • Flexibility and Adaptability: The ability to adapt strategies in real-time based on evolving incident conditions and traffic patterns is critical for maintaining the effectiveness of the TIM program.

Incident Scene Safety

The literature on incident scene safety in rural areas emphasizes the importance of implementing appropriate traffic control measures to protect both responders and motorists. Research indicates that deploying detours, portable message signs, and temporary rumble strips can significantly enhance safety at incident scenes. Additionally, specialized training for responders' on scene safety is essential, particularly in addressing the unique challenges of low-visibility conditions and high-speed rural roads. Minnesota Department of Transportation has demonstrated effective practices in this regard, notably with the use of changeable message signs (CMSs) [13], which have proven beneficial for TIM, as outlined in table 4.

Table 4. Minnesota Department of Transportation CMS project.

Project Description	The primary goal is to provide real-time, accurate information to motorists about traffic incidents, road conditions, and other relevant information to improve safety and manage traffic effectively. The project aims to standardize the use of CMSs across various scenarios, including traffic incidents, work zones, and adverse weather conditions, ensuring that motorists receive timely warnings and instructions that help prevent secondary accidents and ensure the safety of both drivers and incident responders.
Benefits	The implementation of CMSs in rural TIM offers several significant benefits: • Enhanced Motorist Safety: By providing timely warnings and information, CMSs helps reduce the risk of secondary accidents, particularly in low-visibility or high-speed rural environments. • Improved Incident Response: CMSs enable better communication of incident details, allowing for more effective traffic management and quicker incident clearance. • Versatility in Application: CMSs can be used in a wide range of scenarios, including during construction, maintenance activities, and special events, in addition to traffic incidents.

Challenges	The deployment and effective use of CMSs in rural areas face several challenges: • Geographic Limitations: The vast and often remote nature of rural areas can make it difficult to deploy CMSs at strategic locations, especially where power and communication infrastructure are limited. • Maintenance and Operation: Keeping CMSs operational and updated in rural areas can be challenging due to the need for regular maintenance, which can be complicated by distance and environmental factors. • Driver Comprehension: Ensuring that messages are simple, clear, and easily understood by motorists traveling at high speeds is critical, yet challenging, especially in environments where drivers might not expect or be accustomed to encountering CMSs.
Lessons Learned	The use of CMSs in rural TIM has provided several valuable lessons: • Message Simplicity is Key: Messages must be clear, concise, and easy to understand within the few seconds a driver has to read them. Overly complex messages can confuse drivers and reduce the effectiveness of CMSs. • Regular Maintenance is Essential: Keeping CMSs functional and up to date requires a robust maintenance plan, particularly in rural areas where environmental conditions can be harsh.

	• Training for Consistent Usage: Operators must be adequately trained to use CMSs effectively, ensuring that messages are consistent and follow established guidelines for clarity and impact.

Data Collection and Analysis

The literature consistently underscores the importance of systematic data collection and analysis in enhancing rural TIM. Standardized processes for incident data reporting, including metrics such as response times, outcomes, and contributing factors, are recommended to drive continuous improvement. Additionally, conducting after-action reviews following significant incidents is highlighted as a crucial practice for capturing lessons learned and identifying areas for future enhancement. For instance, as shown in table 5, the New York State Department of Transportation funded a project [14] that utilized social media feeds as a data resource to support TIM, aiding in early detection and management.

Table 5. New York State Department of Transportation incident management support tool.

Title	*Reducing Incident-Induced Emissions and Energy Use in Transportation: Use of Social Media Feeds as an Incident Management Support Tool*
Objective	The project aims to explore the use of social media platforms, specifically Twitter, as a tool for early detection and management of traffic incidents. By leveraging user-generated content, the study seeks to enhance TIM practices; reduce traffic delays, emissions, and fuel consumption; and

	ultimately improve overall transportation efficiency for both local and rural roads.
Goals	• Early Incident Detection: Utilize social media, particularly Twitter, to detect traffic incidents earlier than traditional methods. • Reduction of Traffic Delays: Analyze the potential of social media to reduce vehicle-hours of delay during incidents. • Emission Reduction: Quantify the reduction in harmful emissions (CO, NO_x, PM2.5) as a result of quicker incident detection and management. • Fuel Savings: Estimate fuel savings due to decreased delay times associated with incident management. • Recommendations: Provide guidelines for the efficient use of social media in TIM, including keyword strategies and partnership suggestions.
Benefits	• Improved Incident Response Time: The use of social media feeds allows for quicker detection of incidents, which in turn reduces response times. • Environmental Benefits: Significant reductions in emissions and fuel consumption are observed because of quicker incident clearance. • Cost Savings: The project demonstrates potential monetary saving of approximately $75,600 due to reduced delays and fuel savings.

	• Enhanced Information Sharing: Social media provides supplementary information that is not always captured by traditional methods, offering a broader picture of traffic incidents.
Challenges	• Data Quality and Relevance: Extracting relevant and accurate information from the vast amounts of unstructured data available on social media poses a significant challenge. • Inconsistency in Data: The accuracy of the data varies widely, particularly with personal tweets, which often contain colloquial language and informal grammar. • Limited Geographic Information: Only a small percentage of tweets contain geolocation data, making it difficult to precisely determine the location of incidents. • Safety Concerns: The use of social media while driving raises concerns about distracted driving, which the project does not encourage.
Lessons Learned	• Importance of Specialized Keywords: The study emphasizes the need for carefully selected and tested keywords tailored to the nature of the tweets, especially when extracting data from personal accounts. • Potential of Structured Hashtags: Introducing structured hashtags could enhance the specificity and reliability of information gathered from social media, particularly for location data.

	• Necessity of Partnerships: Collaborations with social media platforms and data providers are identified as essential for gaining real-time access to relevant data. • Future Research Directions: Further studies are needed to explore the application of social media data for TIM on a larger scale and in different geographic locations, particularly in areas with less existing infrastructure.

CHAPTER 3. DATA ACQUISITION AND PROCESSING

DATA ACQUISITION

We collected data from multiple sources, as summarized in table 6. Traffic counts from the portable sites are obtained from GDOT. Two sources of probe data were used, including event data extracted from the Regional Integrated Transportation Information System (RITIS) and traffic volumes obtained from two identified vendors in the market. The GDOT traffic counts and probe data were obtained over 3 years (2021–2023). The GDOT roadway ArcGIS shapefile was utilized for event data mapping and spatial analysis.

Table 6. Data formats and sources.

Data	Time	Format	Source
Roadway	2021	ArcGIS shapefile (line feature)	GDOT
CCS	2021–2023	CSV, shapefile (point feature)	GDOT
Portable	2021–2023	CSV, shapefile (point feature)	GDOT
Probe data – event data	2021–2023	Exported as CSV	RITIS
Probe data – traffic volume	2021–2023	CSV	Vendors

Note: CSV: comma-separated values format.

DATA FUSION AND PROCESSING

For VMT estimation, the sampled portable sites were spatially paired with vendor data based on site coordinates and road-related features, such as functional class (FC), number of lanes, and road name. For meaningful comparison, temporal pairing by day of week (DOW) and month of year (MOY) was also enforced. For incident analysis and modeling, three interstates in the rural region of South Georgia (i.e., I-16, I-95, and I-75) were identified for the case study. All event data associated with the rural sections of the three interstates were filtered out based on their coordinates in reference to the roadway ArcGIS shapefile. The event data were further aggregated by hourly windows for temporal analysis and modeling. The format of compiled data is shown in table 7.

Table 7. Examples of compiled data.

Segment ID	Time	Road Name	Segment Length (mile)	Func Class	Urban Code	County Code	AADT	AADT_Single	PCT_Peak_Single	AADT_Combo	PCT_Peak_Combo
10541	12/2/2023 18:00	I-75	0.088	1	99999	185	51,700	2,068	0.83	1,913	3.70
10903	12/2/2023 20:00	I-75	0.103	1	89974	185	56,400	290	0.90	662	1.17
10914	12/7/2023 3:00	I-16	0.115	1	99999	175	23,900	685	9.20	6,225	26.05
10168	12/6/2023 13:00	I-95	0.122	1	99999	191	57,500	1,394	14.80	12,392	21.55
12166	12/9/2023 2:00	I-16	0.105	1	99999	289	23,300	932	0.37	248	1.06
11124	12/10/2023 21:00	I-95	0.033	1	79768	29	60,600	1,796	0.97	420	0.69
10519	12/1/2023 0:00	I-75	0.057	1	99999	93	52,900	2,132	0.01	604	1.14
10519	12/1/2023 1:00	I-75	0.057	1	99999	93	52,900	2,132	0.01	604	1.14
10333	12/1/2023 0:00	I-95	0.003	1	99999	191	61,100	2,444	0.98	12,392	20.28
10333	12/1/2023 1:00	I-95	0.003	1	99999	191	61,100	2,444	0.98	12,392	20.28
10805	12/1/2023 11:00	I-16	0.086	1	99999	31	32,300	1,292	0.65	892	2.76
10805	12/1/2023 12:00	I-16	0.086	1	99999	31	32,300	1,292	0.65	892	2.76

Segment ID	Time	Week	Weekend	Season	Holiday	Peak hour	Incident	Duration	Duration (< 20 min)	Duration (20-60 min)	Duration (> 60 min)
10541	12/2/2023 18:00	Saturday	1	Winter	0	1	1	18	1	0	0
10903	12/2/2023 20:00	Saturday	1	Winter	0	0	1	29	0	1	0
10914	12/7/2023 3:00	Thursday	0	Winter	0	0	1	53	0	1	0
10168	12/6/2023 13:00	Wednesday	0	Winter	0	0	1	2	1	0	0
12166	12/9/2023 2:00	Saturday	1	Winter	0	0	1	1	1	0	0
11124	12/10/2023 21:00	Sunday	1	Winter	0	0	1	55	0	1	0
10519	12/1/2023 0:00	Friday	0	Winter	0	0	0	0	0	0	0
10519	12/1/2023 1:00	Friday	0	Winter	0	0	0	0	0	0	0
10333	12/1/2023 0:00	Friday	0	Winter	0	0	0	0	0	0	0
10333	12/1/2023 1:00	Friday	0	Winter	0	0	0	0	0	0	0
10805	12/1/2023 11:00	Friday	0	Winter	0	0	0	0	0	0	0
10805	12/1/2023 12:00	Friday	0	Winter	0	0	0	0	0	0	0

Notes: AADT_Single: annual average daily traffic for single-unit trucks; AADT_Combo: AADT for combination trucks; PCT_Peak_Single: percent of single-unit trucks during the peak hour; PCT_Peak_Combo: percent of combination trucks during the peak hour.

CHAPTER 4. FEASIBILITY STUDY OF PROBE DATA FOR VMT REPORTING

FHWA requires states to report annual VMT as part of the Highway Performance Monitoring System. Typically, VMT is reported by context (rural versus urban) and functional classification [15]. Besides FHWA reporting, the information obtained from statewide traffic monitoring programs is also the primary information resource for almost all general queries about road use in a state. These data provide a critical framework for effective decision making. Many users, both inside and outside of state highway agencies, periodically need basic traffic statistics, and those statistics should be readily available and comparable throughout the state and between states. Requests for statewide data can range from how VMTs are changing to compute carbon emissions to whether specific roads carry enough volume to warrant new construction activity. A comprehensive statewide counting program allows an agency to confidently and effectively answer a wide range of key policy and business questions[16].

GDOT's current traffic monitoring program relies on traffic data gathered from 300+ CCSs strategically placed on interstates and 9000+ portable count stations throughout the state's road network, most of which are on rural roads [1]. The portable counts are conducted manually on selected dates, which is resource demanding and time consuming. GDOT is considering alternative technologies or data sources to replace or supplement these portable counts. Probe data are a potential option for this purpose. However, it is critical for GDOT to understand and know the quality aspects of the data. Two common parameters to characterize data quality are accuracy and biases. This study aims to assist GDOT with data quality testing and review based on sound statistical methodologies, following established traffic engineering methods as applicable [16].

SAMPLING OF PORTABLE SITES

A total of 500 portable count sites were sampled in the rural region of South Georgia, as shown in figure 1. The sampling considers spatial coverage as well as budget constraint. Traffic counts were extracted from these sites and compared with corresponding traffic volume estimates from two identified vendors.

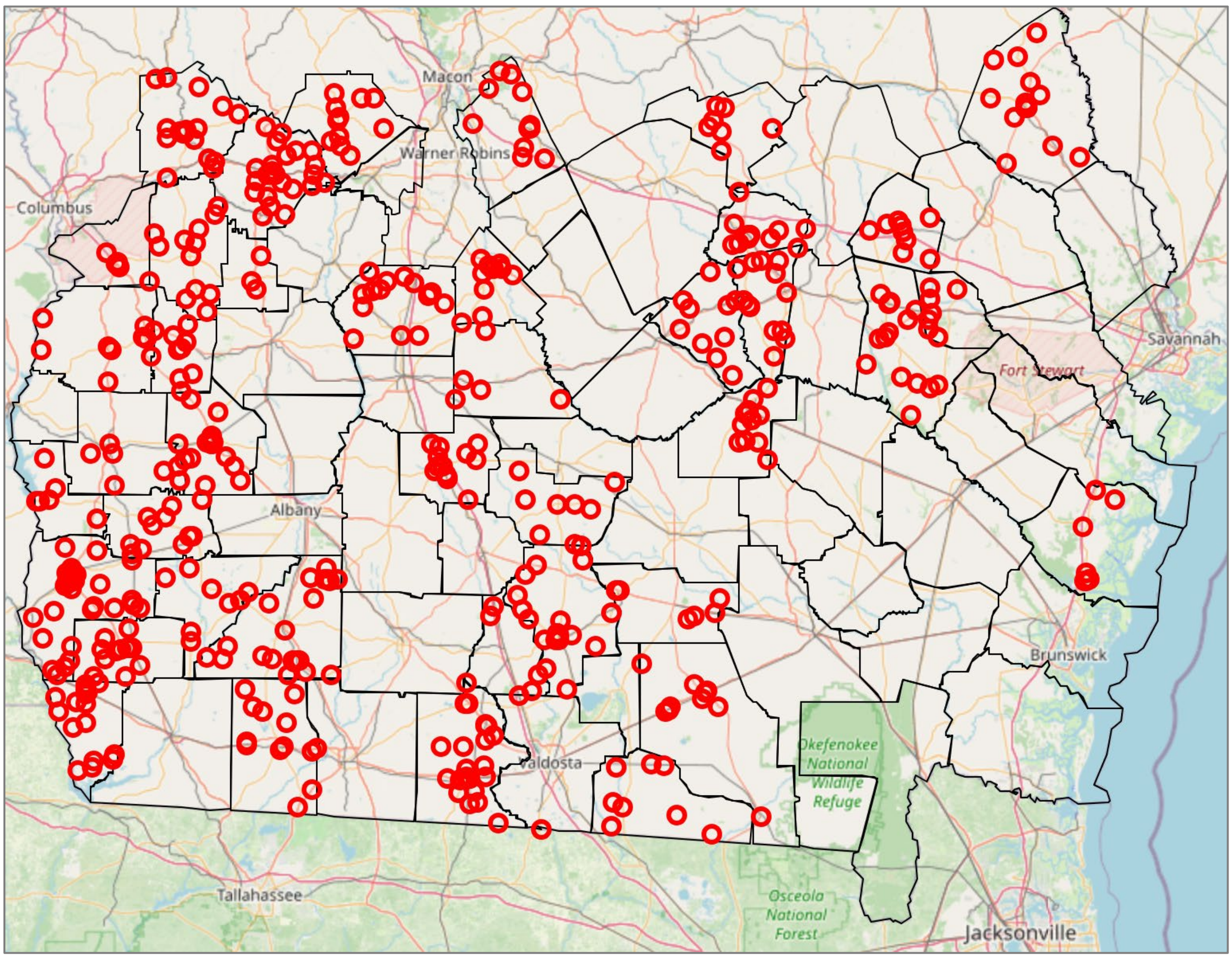

Figure 1. Graph. Sampling of portable count sites.

COMPARISON OF TRAFFIC VOLUMES

To evaluate the consistency of probe-based traffic volume estimates against actual counts from GDOT's portable sites, analysis of variance (ANOVA) and paired t-tests were applied to compare traffic volume estimation errors across FC and DOW.

Analysis of Variance

ANOVA was conducted to identify factors contributing to variability in traffic volume estimation error. The results for FC and DOW are presented in table 8 and table 9 using data from Vendor 1 and Vendor 2, respectively. DOW was found to be highly significant, with a *p*-value of less than 0.001, while FC showed significance at the 0.1 level for Vendor 1 data and at the 0.01 level for Vendor 2 data.

Table 8. ANOVA (FC and DOW) for Vendor 1 Data.

	SSE	df	F	*p*-value
FC	618.98	4	2.093	0.079
DOW	4,629.86	4	15.656	0.000
FC *DOW	906.67	16	0.766	0.725
Residual	126,792.44	1,715		

Notes: SSE: sum of squares for errors; df: degrees of freedom; F: F-statistic.

Table 9. ANOVA (FC and DOW) for Vendor 2 data.

	SSE	df	F	p value
FC	2,000.61	4	3.896	0.004
DOW	7,882.43	4	15.350	0.000
FC *DOW	2,030.12	16	0.988	0.467
Residual	220,428.95	1,717		

Notes: SSE: sum of squares for errors; df: degrees of freedom; F: F-statistic.

Paired *t*-Test

Given the significance of FC and DOW in explaining variance in traffic volume estimation error, paired *t*-tests were conducted to assess the consistency of traffic volume data across FCs and DOWs. The results, summarized in table 10 and table 11, reveal significant differences between the portable site counts and vendor-estimated volumes, marked in red to indicate a significance level of at least 0.05. Overall, the DOW patterns show better consistency for Wednesdays.

Table 10. Paired *t*-test by FC and DOW (Vendor 1).

Functional Class	Day of Week	Count	Percent Error		Paired t-Test		Portable Site Volume		Vendor 1 Volume	
			mean	std	t stat	p-value	mean	std	mean	std
Principal Arterial (3)	1	29	3.459	5.306	3.510	0.002	2,063	2,082	4,624	2,962
	2	68	1.631	5.152	2.610	0.011	3,874	3,408	4,404	2,849
	3	81	0.159	0.628	2.286	0.025	4,955	3,556	5,063	3,153
	4	51	2.720	14.617	1.329	0.190	4,731	4,159	5,925	3,909
	5	12	4.028	3.357	4.156	0.002	2,663	1,517	11,195	5,466
Minor Arterial (4)	1	56	4.986	13.541	2.755	0.008	1,203	1,226	2,563	1,757
	2	144	3.350	11.180	3.595	0.000	2,152	2,118	2,463	1,649
	3	165	0.007	0.430	0.201	0.841	2,684	1,903	2,489	1,692
	4	107	1.930	14.579	1.369	0.174	2,168	1,674	2,647	1,823
	5	20	4.471	8.087	2.472	0.023	1,079	902	2,965	2,341
Major Collector (5)	1	118	5.886	20.696	3.089	0.003	368	512	814	880
	2	246	0.985	2.872	5.380	0.000	755	880	806	779
	3	271	0.051	0.625	1.333	0.184	868	821	809	783
	4	151	0.694	2.871	2.971	0.003	693	617	878	803
	5	22	5.518	17.911	1.445	0.163	277	203	948	1,052
Minor Collector (6)	1	15	4.089	9.171	1.727	0.106	81	79	216	283
	2	30	0.459	1.720	1.460	0.155	224	216	257	371
	3	34	-0.291	0.483	-3.516	0.001	451	685	465	998
	4	21	0.342	1.332	1.178	0.253	581	1,267	629	1,318
	5	4	3.714	2.837	2.619	0.079	615	907	2,324	2,846
Local (7)	1	16	0.333	1.567	0.851	0.408	140	206	168	268
	2	32	-0.271	0.942	-1.627	0.114	258	316	171	291
	3	31	-0.475	0.508	-5.204	0.000	291	307	179	298
	4	15	-0.282	0.825	-1.322	0.207	209	233	190	337
	5	1	-0.500	-	-	-	6	-	3	-

Table 11. Paired *t*-test by FC and DOW (Vendor 2).

Functional Class	Day of Week	Count	Percent Error		Paired t-Test		Portable Site Volume		Vendor 2 Volume	
			mean	std	t stat	p-value	mean	std	mean	std
Principal Arterial (3)	1	29	3.054	5.062	3.250	0.003	2,063	2,082	3,968	2,885
	2	68	1.781	5.218	2.815	0.006	3,874	3,408	4,006	2,834
	3	81	0.062	0.650	0.852	0.396	4,955	3,556	4,253	2,914
	4	51	2.121	12.903	1.174	0.246	4,731	4,159	4,475	2,992
	5	12	2.028	2.222	3.163	0.009	2,663	1,517	6,812	3,650
Minor Arterial (4)	1	56	6.145	13.584	3.385	0.001	1,203	1,226	3,158	2,208
	2	144	4.628	14.233	3.902	0.000	2,157	2,121	3,173	2,162
	3	166	0.257	0.536	6.175	0.000	2,685	1,896	3,103	2,095
	4	108	2.439	16.842	1.505	0.135	2,187	1,703	3,121	2,097
	5	21	6.556	13.743	2.186	0.041	1,127	906	3,565	2,422
Major Collector (5)	1	119	7.926	18.017	4.799	0.000	366	511	1,020	912
	2	246	2.596	15.889	2.563	0.011	755	880	1,027	868
	3	272	0.524	1.259	6.867	0.000	855	805	972	808
	4	151	1.188	3.117	4.683	0.000	673	574	951	744
	5	23	5.827	17.419	1.604	0.123	275	198	869	548
Minor Collector (6)	1	15	7.472	8.922	3.244	0.006	98	87	370	155
	2	34	3.253	5.905	3.212	0.003	233	219	395	243
	3	38	0.678	0.709	5.894	0.000	431	650	610	1,201
	4	23	2.044	2.018	4.860	0.000	537	1,217	763	1,550
	5	4	3.541	0.678	10.449	0.002	615	907	2,691	3,871
Local (7)	1	16	9.359	17.535	2.135	0.050	153	205	443	329
	2	25	7.773	24.288	1.600	0.123	310	345	465	315
	3	27	3.622	7.768	2.423	0.023	304	322	440	290
	4	11	8.346	21.227	1.304	0.221	254	258	432	268
	5	2	30.887	15.480	2.822	0.217	12	8	307	70

COMPARISON OF DAILY VEHICLE MILES TRAVELED

For reporting purposes, VMT are typically summarized by FC. In this evaluation, daily vehicle miles traveled (DVMT) are reported by FC and presented in table 12 and table 13 for Vendor 1 data and Vendor 2 data. The DVMT was calculated using a standardized length of 0.2 mi for each portable site, a value chosen to ensure the consistent traffic volume, which has no effect on the error estimation. Both table 12 and table 13 include the DVMT values derived from portable site counts and vendor-estimated volumes, along with the corresponding percentage estimation errors. The overall DVMT estimation error is 21 percent for Vendor 1 data and 29 percent for Vendor 2 data.

Table 12. DVMT estimation by FC (Vendor 1; weekdays).

Functional Class	Sample Size	DVMT_P(1)	DVMT_V1(2)	Error (%)
Principal Arterial (3)	241	199,577	256,031	28
Minor Arterial (4)	492	214,721	250,257	17
Major Collector (5)	808	115,029	133,381	16
Minor Collector (6)	104	7,585	9,855	30
Local (7)	95	4,532	3,311	−27
Total	**1,740**	**541,443**	**652,835**	**21**

Notes:
(1) DVMT computed based on traffic counts of the portable sites.
(2) DVMT computed based on estimated traffic volumes by Vendor 1.

Table 13. DVMT estimation by FC (Vendor 2; weekdays).

Functional Class	Sample Size	DVMT_P(1)	DVMT_V2(2)	Error (%)
Principal Arterial (3)	241	199,577	208,384	4
Minor Arterial (4)	495	216,709	312,149	44
Major Collector (5)	811	113,981	160,380	41
Minor Collector (6)	114	8,114	14,090	74
Local (7)	81	4,246	7,188	69
Total	**1,742**	**542,626**	**702,192**	**29**

Notes:
(1) DVMT computed based on traffic counts of the portable sites.
(2) DVMT computed based on estimated traffic volumes by Vendor 2.

Notably, the most stable traffic volume estimates occurred for Wednesdays, which aligns well with general observations that Wednesdays, as midweek days, reflect more consistent travel patterns compared to other weekdays. Consequently, the VMTs were recalculated using only Wednesday volumes, with the results presented in table 14 and table 15 for Vendor 1 and Vendor 2, showing reduced overall errors of −4 percent and 5 percent, respectively.

Table 14. DVMT estimation by FC (Vendor 1; Wednesdays).

Functional Class	Sample Size	DVMT_P(1)	DVMT_V1(2)	Error (%)
Principal Arterial (3)	81	80,274	82,024	2
Minor Arterial (4)	165	88,559	82,126	-7
Major Collector (5)	271	47,054	43,839	-7
Minor Collector (6)	34	3,066	3,161	3
Local (7)	31	1,805	1,111	-38
Total	**582**	**220,757**	**212,261**	**-4**

Notes:
(1) DVMT computed based on traffic counts of the portable sites.
(2) DVMT computed based on estimated traffic volumes by Vendor 1.

Table 15. DVMT estimation by FC (Vendor 2; Wednesdays).

Functional Class	Sample Size	DVMT_P(1)	DVMT_V2(2)	Error (%)
Principal Arterial (3)	81	80,274	68,893	-14
Minor Arterial (4)	166	89,150	103,024	16
Major Collector (5)	272	46,534	52,861	14
Minor Collector (6)	38	3,276	4,634	41
Local (7)	27	1,641	2,375	45
Total	**584**	**220,875**	**231,786**	**5**

Notes:
(1) DVMT computed based on traffic counts of the portable sites.
(2) DVMT computed based on estimated traffic volumes by Vendor 2.

CHAPTER 5. INCIDENT MODELING AND INFERENCE

GDOT has two patrol programs, the Highway Emergency Response Operator (HERO) program and CHAMP. The HERO program serves the Metro Atlanta region, whereas CHAMP covers interstates in Georgia (except I-59 and I-24) and outside Metro Atlanta. For this study, the focus is on identifying the process to improve CHAMP in rural South Georgia, as indicated by the rectangle in figure 2. CHAMP operators patrol 7 days/week, 16 hours/day, and are on call the remaining hours. Each CHAMP operator patrols an average 50-mile section of the interstate during an 8-hour shift and is on call up to 4 hours. The top two priorities that CHAMP aims to address are lane-blocking and shoulder-blocking incidents. CHAMP operators detect, verify reports, and provide assistance with traffic incidents to ensure safe, quick clearance and efficient traffic flow.

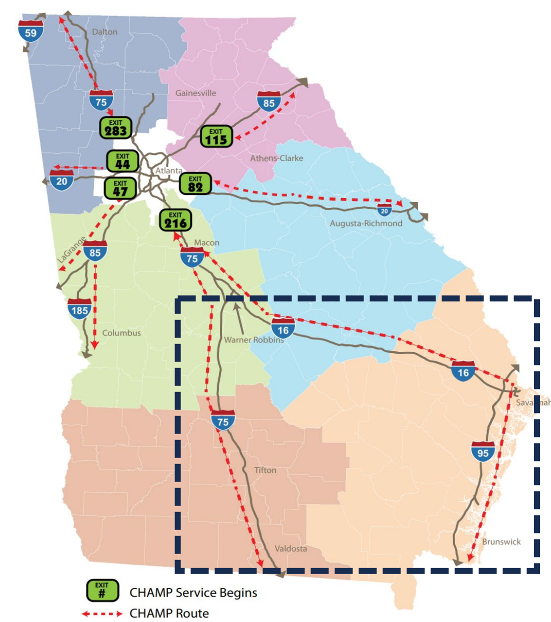

Figure 2. Map. Study area of CHAMP.

INCIDENT RISK MODELING

We approached incident risk prediction as a classification task, where the risk is modeled as the probability of an incident occurring on a road segment within a specified time window (e.g., 1 hour). The hourly temporal partition provides a framework to define the problem as a binary classification: a value of 0 indicates that no incidents occurred during the hour, and a value of 1 indicates that an incident did occur.

Given the tabular nature of the event data, we employed CatBoost [17], a state-of-the-art gradient boosting algorithm that effectively handles categorical features through target statistics and uses ordered boosting to avoid target leakage in subsequent boosting. The algorithm builds simple, oblivious trees, which helps to prevent overfitting and allows for parallelization, leading to faster computation. To address the challenge of modeling rare events like incidents, we applied negative (non-incident) sampling for effective model training, as illustrated in figure 3.

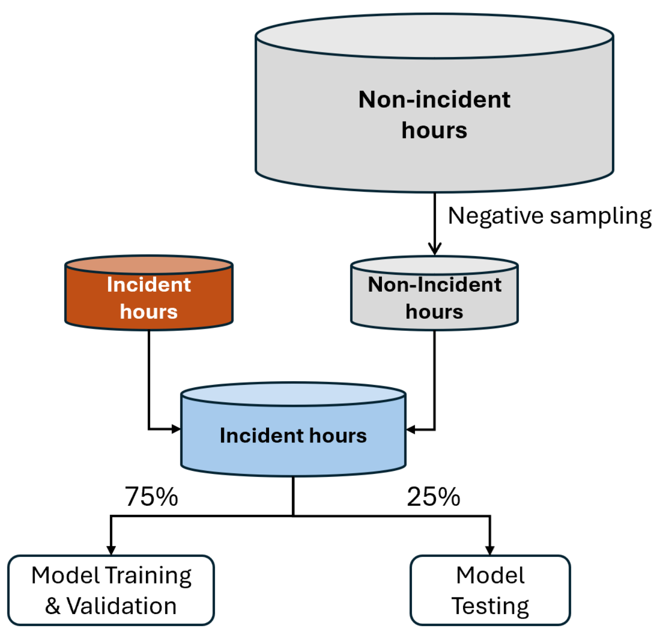

Figure 3. Flowchart. Illustration of negative sampling.

Model Training and Evaluation

For this incident classification task, the dataset consisted of 73,194 samples, with 44,282 (~60 percent) randomly selected for training, 11,071 (~15 percent) for validation, and the remaining 17,841 (~25 percent) reserved for testing. The best hyperparameters identified are a tree depth of 8, a learning rate of 0.06, and 850 iterations. The training and validation losses of the incident risk model are plotted in figure 4.

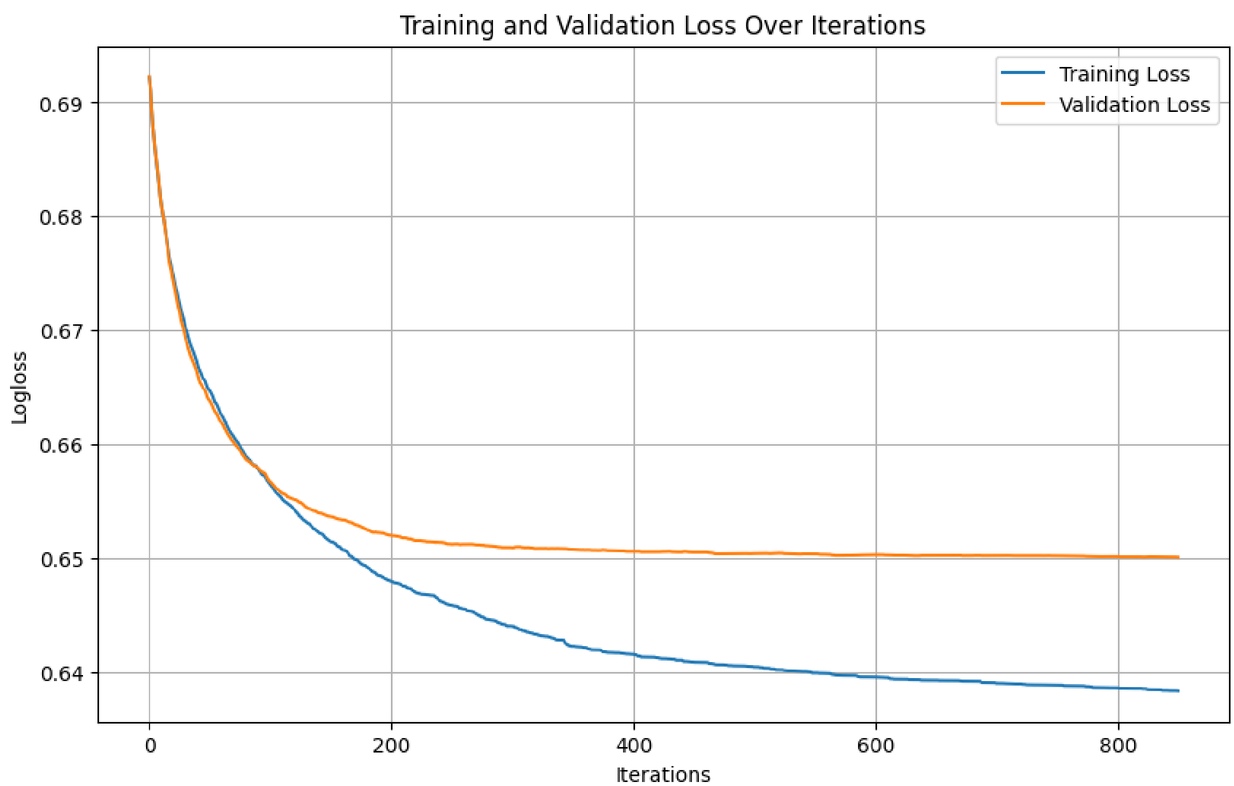

Figure 4. Chart. Training progression of the incident risk model.

As shown in figure 4, the training and validation losses consistently decrease over iterations, indicating a smooth convergence. The validation loss stabilizes after approximately 600 iterations. The lowest validation loss achieved is approximately 0.6496. The consistent gap between the training and validation losses is typical. For model evaluation, the test dataset was used. The test results are shown in figure 5.

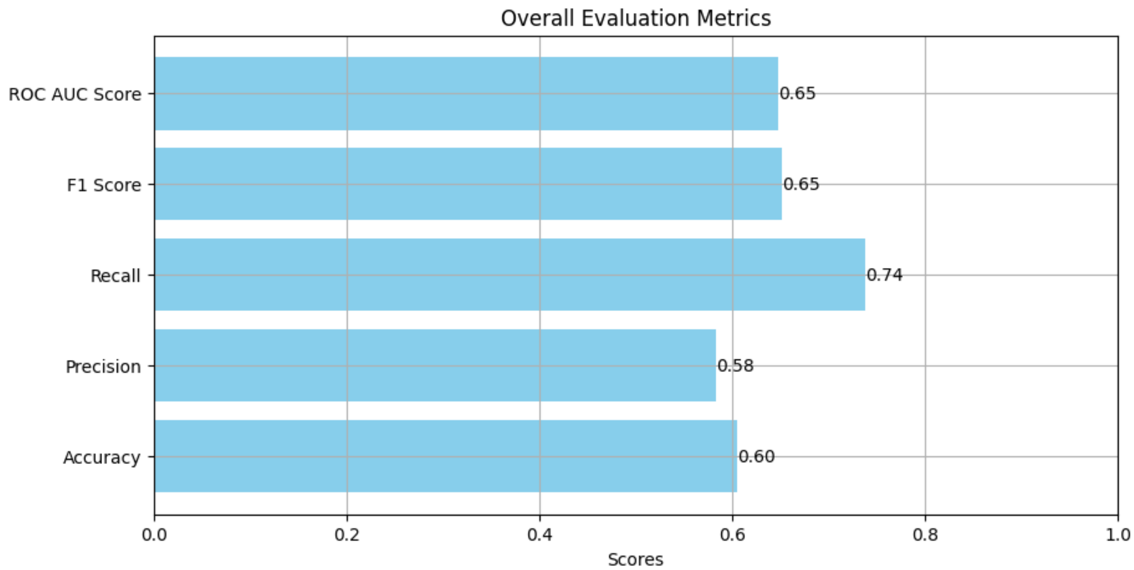

Figure 5. Chart. Performance evaluation of the incident risk model.

The model achieved a receiver operating characteristic (ROC) area under the curve (AUC) score of 0.65, an overall F1 score of 0.65, an accuracy of 60.5 percent, a precision of 0.58, and a recall of 0.74. The high recall indicates that the model can successfully identify 74 percent of all actual incidents, a critical metric for incident management. The relatively lower precision suggests a potential for false positives. Overall, the model is more sensitive to detecting incidents, making it valuable in scenarios where identifying potential risks is prioritized, even at the cost of a higher false positive rate.

Model Interpretation

For model interpretation, we utilized SHapley Additive exPlanations (SHAP) [18]. The SHAP plot offers a detailed analysis of the features influencing the prediction outcome, specifically for incident classification in our case. Figure 6 displays the SHAP values for the top 20 features.

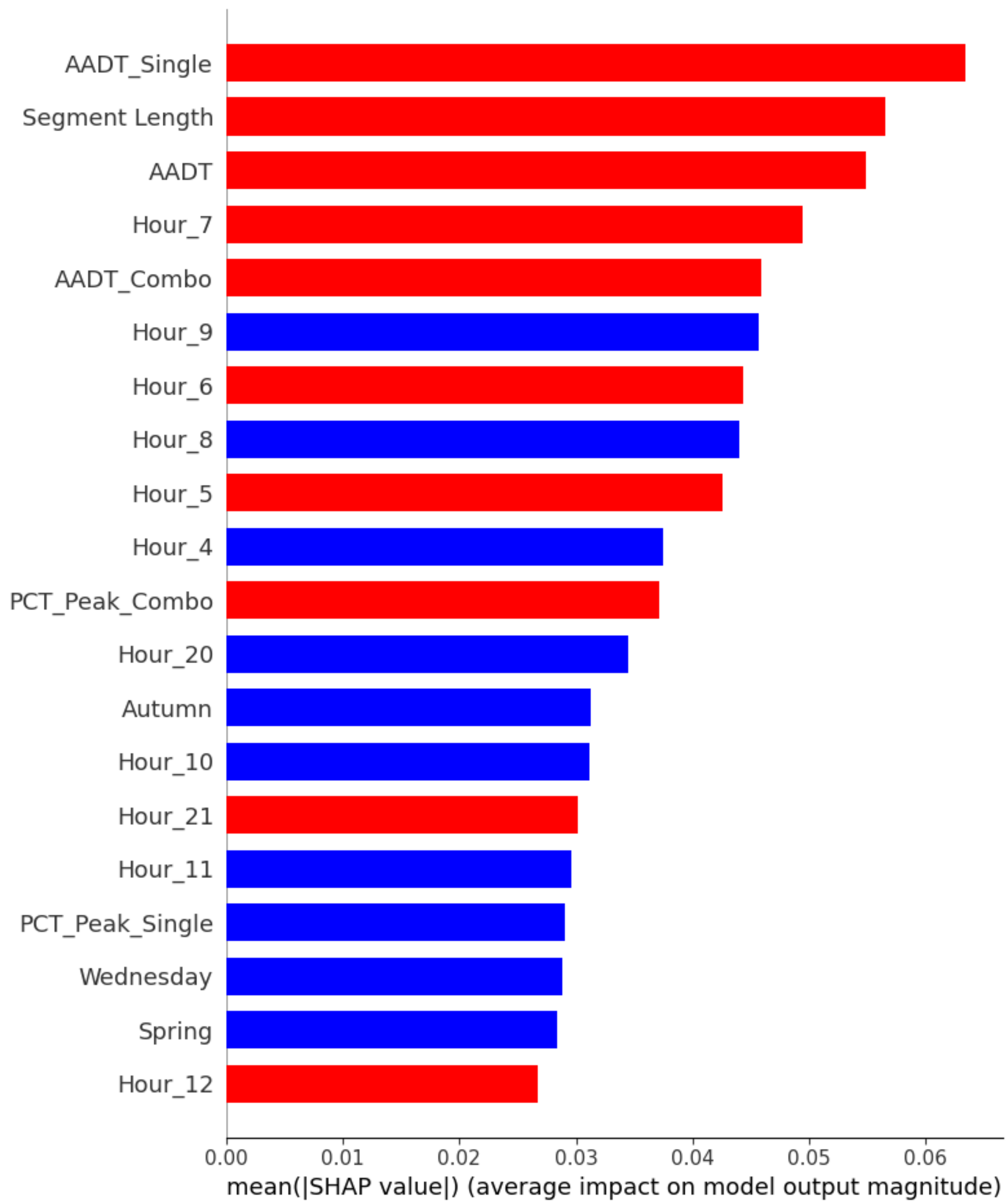

Figure 6. Chart. Feature importance of the incident risk model.

The length of each horizontal bar indicates the overall importance of a feature on the model prediction outcome. The color of the bar represents the direction of influence, where red signifies a positive influence (i.e., higher feature values increase incident risk) and blue indicates a negative influence (i.e., higher feature values decrease incident risk). As shown in figure 6, the most impactful features are AADT_Single, Segment Length, and AADT, all of which generally increase incident risk as their values rise. The time of day also plays a significant role, with elevated incident risk observed during the early morning hours (5–8 am), noon (12–1 pm), and night (9–10 pm). Interestingly, a higher percentage of combination trucks correlates with increased incident risk, whereas a higher percentage of single-unit trucks is associated with a lower risk. Incident risk also varies by season, with lower risk during Autumn and Spring. Additionally, Wednesdays are associated with a reduced risk of incidents. These insights suggest that incident risk is primarily influenced by traffic volume and segment length and exhibits temporal patterns by time of day, day of week, and season.

To gain more detailed understanding on a particular incident and associated factors, we included a SHAP force plot (figure 7) for a particular incident case with correct model prediction.

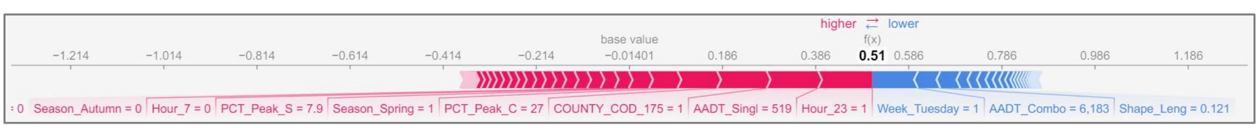

Figure 7. Chart. SHAP force plot: inference of an example by the incident risk model.

For this particular incident, the model predicted a score of 0.51. Features such as the late-night hour (11 pm–12 am), AADT_Single, the county location, and the percentage of combination trucks during peak periods all contributed to increasing the predicted score (indicated by red arrows), thereby raising the incident risk. Conversely, factors like Tuesday, AADT of combination trucks, and Segment Length pushed the predicted score lower (shown by blue arrows), reducing the incident risk. The final prediction represents a balance of these influences, resulting in a score of 0.51, which is higher than the base value.

INCIDENT DURATION MODELING

The extent or severity of an incident is modeled by its duration. Given the occurrence of an incident, the duration (in minutes) can be approached as either a regression or classification task, depending on the problem's formulation and practical considerations. However, our experiments indicate that classification is a better fit, given the lack of fine-grained features and the predominance of categorical data. As a result, we focused on modeling incident duration as a classification problem. The histogram of duration is shown in figure 8. The cumulative distribution of distinct duration thresholds is presented in table 16, revealing that the majority of incidents (92.16 percent) have durations less than 100 min.

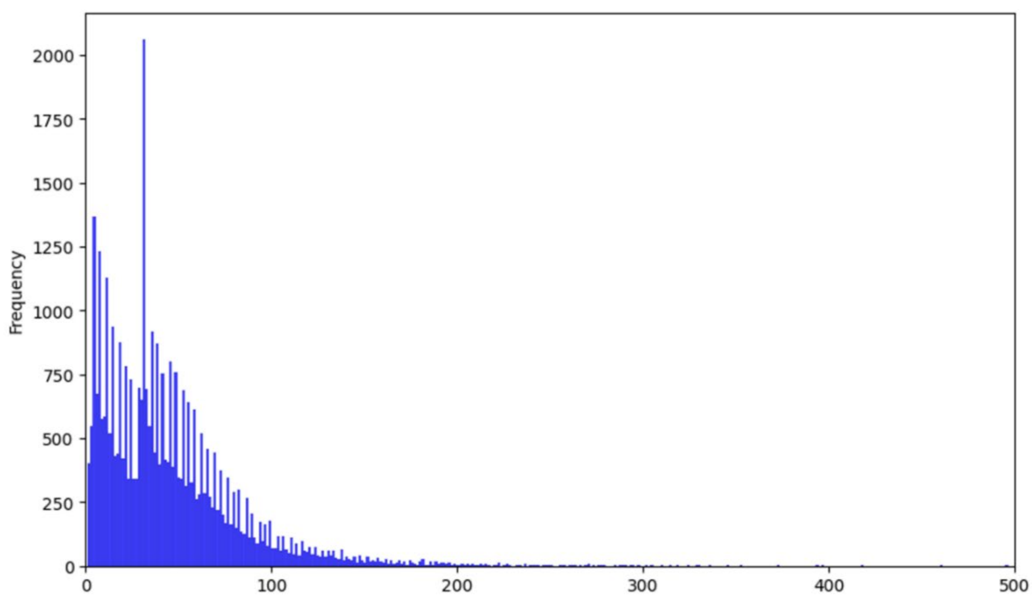

Figure 8. Graph. Histogram of incident duration.

Table 16. Cumulative distribution by duration threshold.

Threshold (min)	Percentage of Data below Threshold
30	36.95
45	59.51
60	73.92
100	92.16

Model Training and Evaluation

A CatBoost model was trained for the binary classification task using various duration thresholds. Although the class imbalance is less severe than in incident risk modeling, the duration dataset remains imbalanced depending on the chosen threshold. To address this, we utilized CatBoost's "auto_class_weights" feature, set to "SqrtBalanced." We tested different thresholds, including 30, 40, and 60 min, to classify incidents as "Low duration" versus "High duration." The total dataset consisted of 36,187 samples, with 21,711 (~60 percent) randomly selected for training, 7,238 (~20 percent) for validation, and the remaining 7,238 (~20 percent) reserved for testing.

To optimize the CatBoost model's performance, we conducted a hyperparameter search, resulting in a learning rate of 0.01, a tree depth of 13, and 2000 iterations. These hyperparameters were then used for model training. The training progress is shown in figure 9. The test results, summarized in table 17, indicate that a 30 min threshold yielded the best performance, with an F1 score of 0.72 and an accuracy of 0.75 for incidents with durations greater than 30 min.

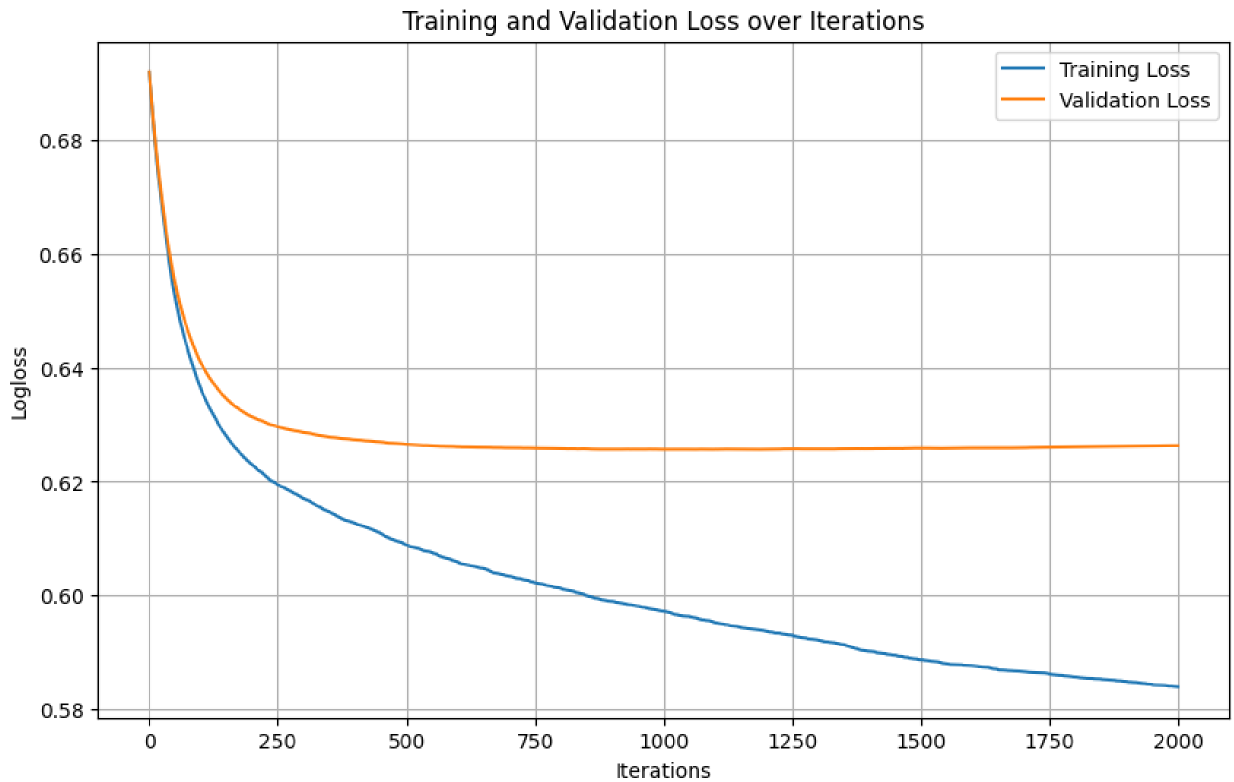

Figure 9. Graph. Model training progress.

Table 17. Classification performance of incident duration

Duration Class		Accuracy	F1 score	Class "Low" accuracy	Class "High" accuracy
Low	High				
≤30 min	>30 min	**0.63**	**0.72**	0.43	**0.75**
≤45 min	>45 min	0.58	0.39	0.74	0.33
≤60 min	>60 min	0.73	0.15	**0.94**	0.09

Model Interpretation

Similar to the incident risk model, the SHAP plot for the incident duration model (with the 30 min threshold) is shown in figure 10.

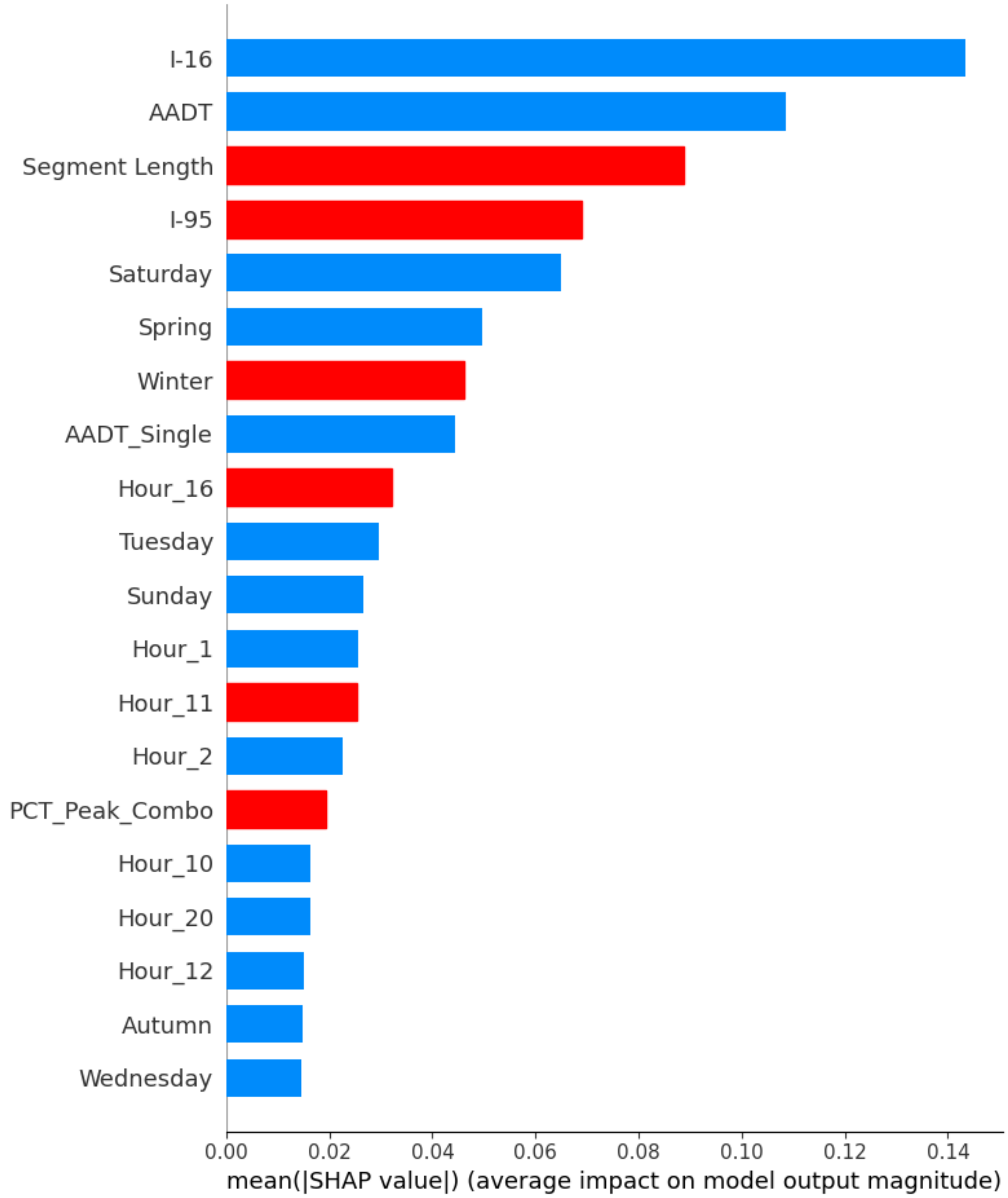

Figure 10. Chart. Mean (|SHAP value|) of CatBoost (30 min threshold).

Features in red are positively associated with longer incident duration (over 30 min). Conversely, features in blue are negatively associated with longer incident durations. The top features in terms of importance are I-16, AADT, and Segment Length, signifying the large influence of these features on incident duration. Focusing on the time-related features, the SHAP plot reveals some interesting patterns regarding the impact of specific hours, days of the week, and seasons on incident duration. The incidents with longer durations (greater than 30 min) are experienced over the noon hour (11 am–12 pm) and the afternoon peak hour (4 pm–5 pm). Incidents occurring on weekends (Saturday and Sunday) are generally shorter. Seasonal effects are also notable, with Winter being positively correlated with incident duration, likely due to adverse weather conditions. Conversely, Spring is negatively correlated with incident duration. These temporal patterns of incident duration can be leveraged for more effective incident management practices.

To provide further insights, figure 11 displays the SHAP force plot for a sampled incident where the model correctly predicted a longer duration. For this incident, the model predicted a score of 0.70, exceeding the base value. The most significant positive influence on the prediction came from the incident occurring on a Tuesday, whereas the most significant negative influence was from the incident not occurring on I-16.

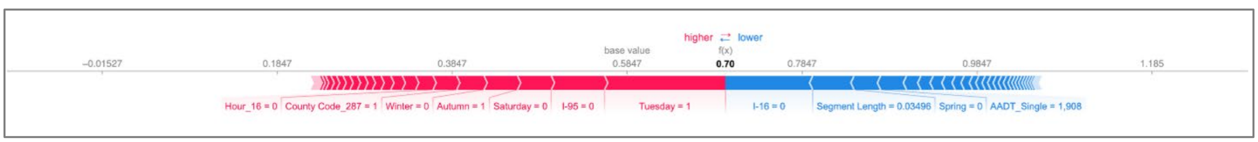

Figure 11. Chart. SHAP force plot: inference of an example by the incident duration model.

CHAPTER 6. SPATIOTEMPORAL ANALYSIS

HOT SPOTS

In this section, we analyze and visualize hot spots using the Getis-Ord Gi* statistic for the study sections of I-16, I-75, and I-95 based on the frequency of incidents, floods, and animal strikes over the 3-year period (2021–2023). The identified hot spot locations, indicating higher risks of incidents, floods, and animal strikes, are shown in figure 12, figure 13, and figure 14, respectively.

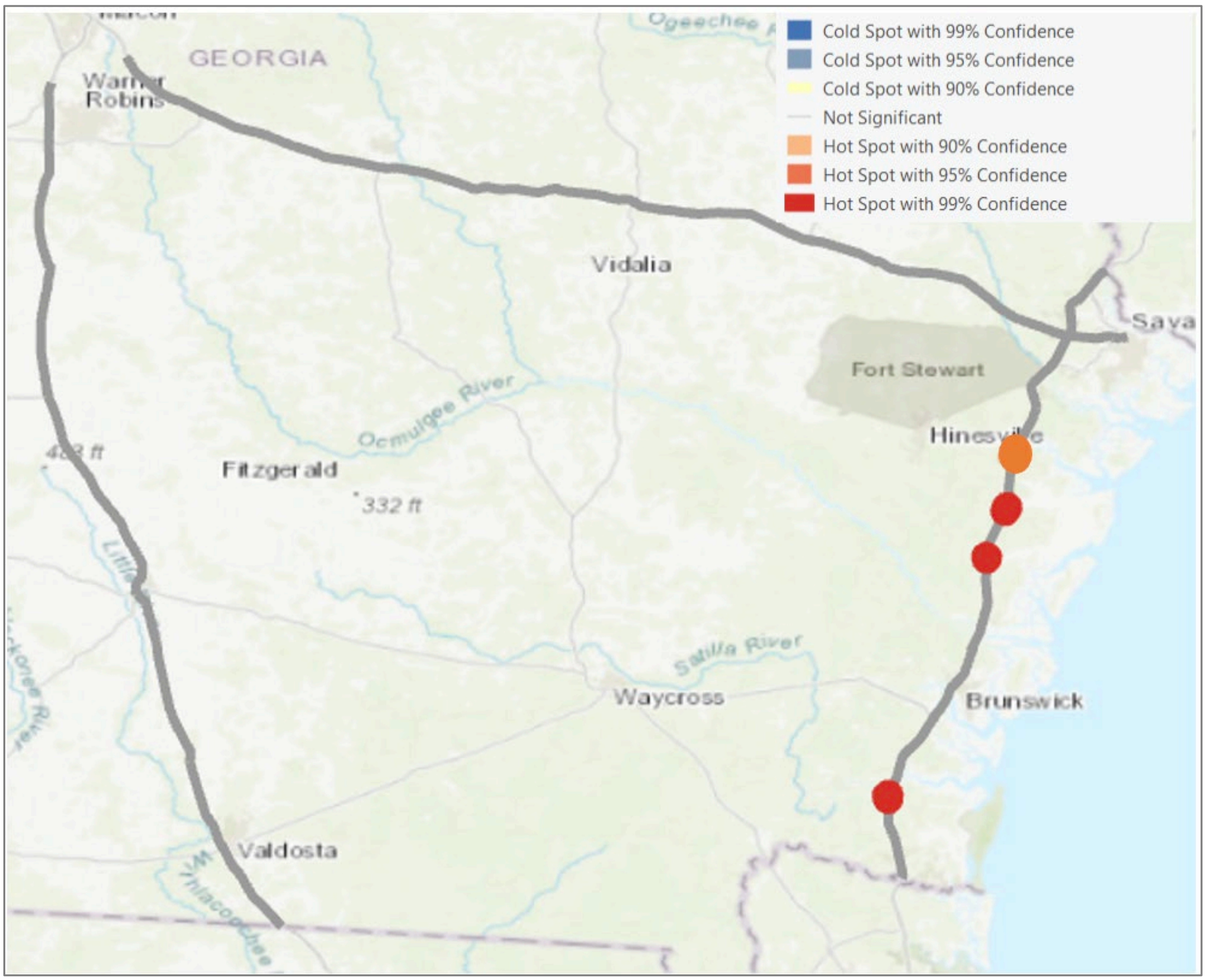

Figure 12. Map. Hot spots analysis for incidents.

As shown in figure 12, the red and orange circles represent "hot spots" with a higher concentration of incidents, with varying degrees of confidence indicated by different shades of red. These hot spots are predominantly located on I-95, where incidents are more frequent. Notably, the southern section of I-95 in Camden County reveals overlapping hot spots for incidents, floods, and animal strikes, warranting further investigation to understand the underlying causes.

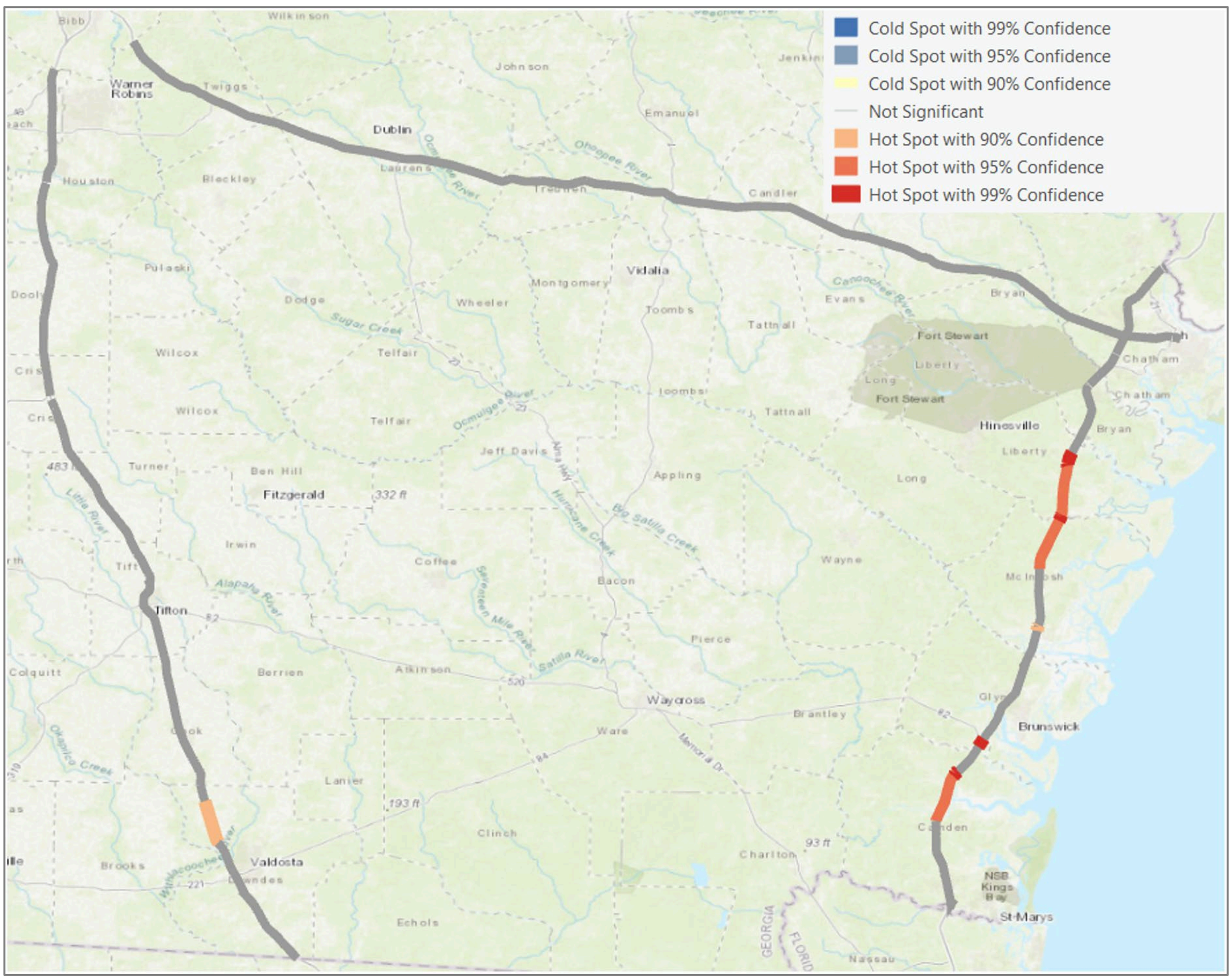

Figure 13. Map. Hot spots analysis for floods.

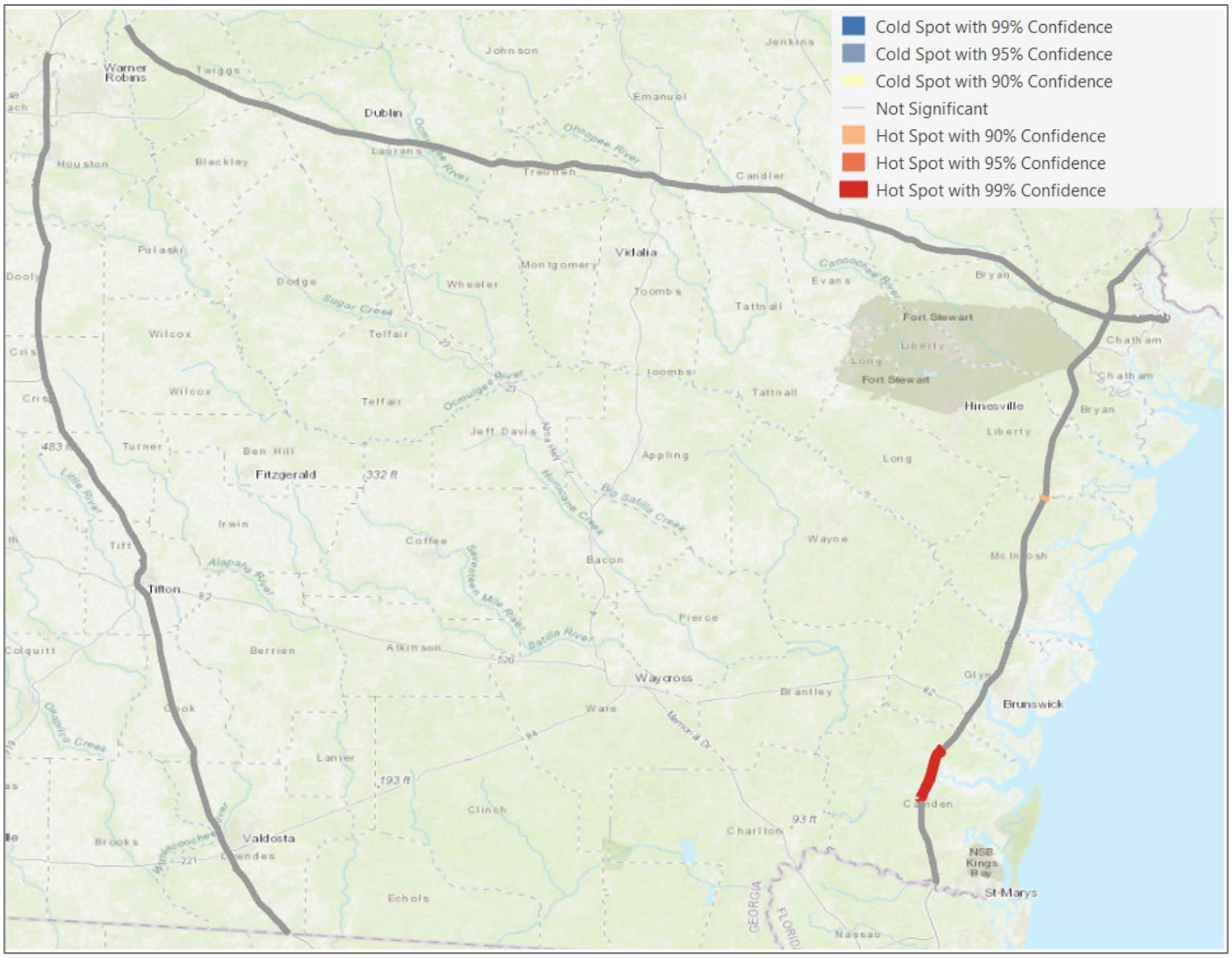

Figure 14. Map. Hot spots analysis for animal strikes.

SPATIOTEMPORAL HEATMAPS

To visulize spatiotemporal patterns, we plotted incident heatmaps for the study sections of I-16, I-75, and I-95 across different time scales: hourly, day of the week, and season. These heatmaps are displayed in figure 15, figure 16, and figure 17, respectively. Recognizing the significant socioeconomic and safety impacts of long-duration incidents, we also generated separate heatmaps to highlight the spatiotemporal patterns of incidents lasting longer than 1 hour, as shown in figure 18, figure 19, and figure 20. These heatmaps can serve as valuable tools to guide incident management practices on these rural insterstates.

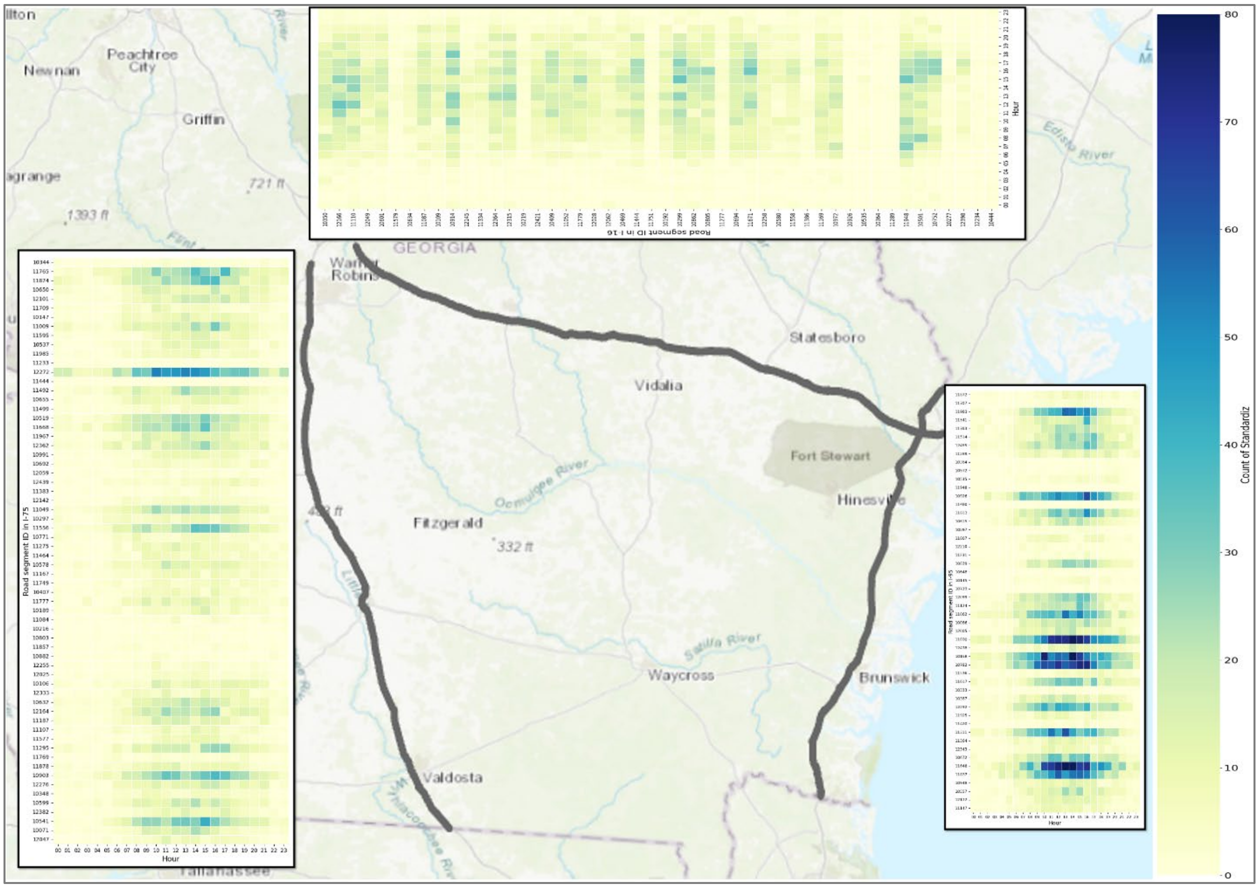

Figure 15. Map. Spatiotemporal heatmap per the frequency of incidents (temporal resolution: hour).

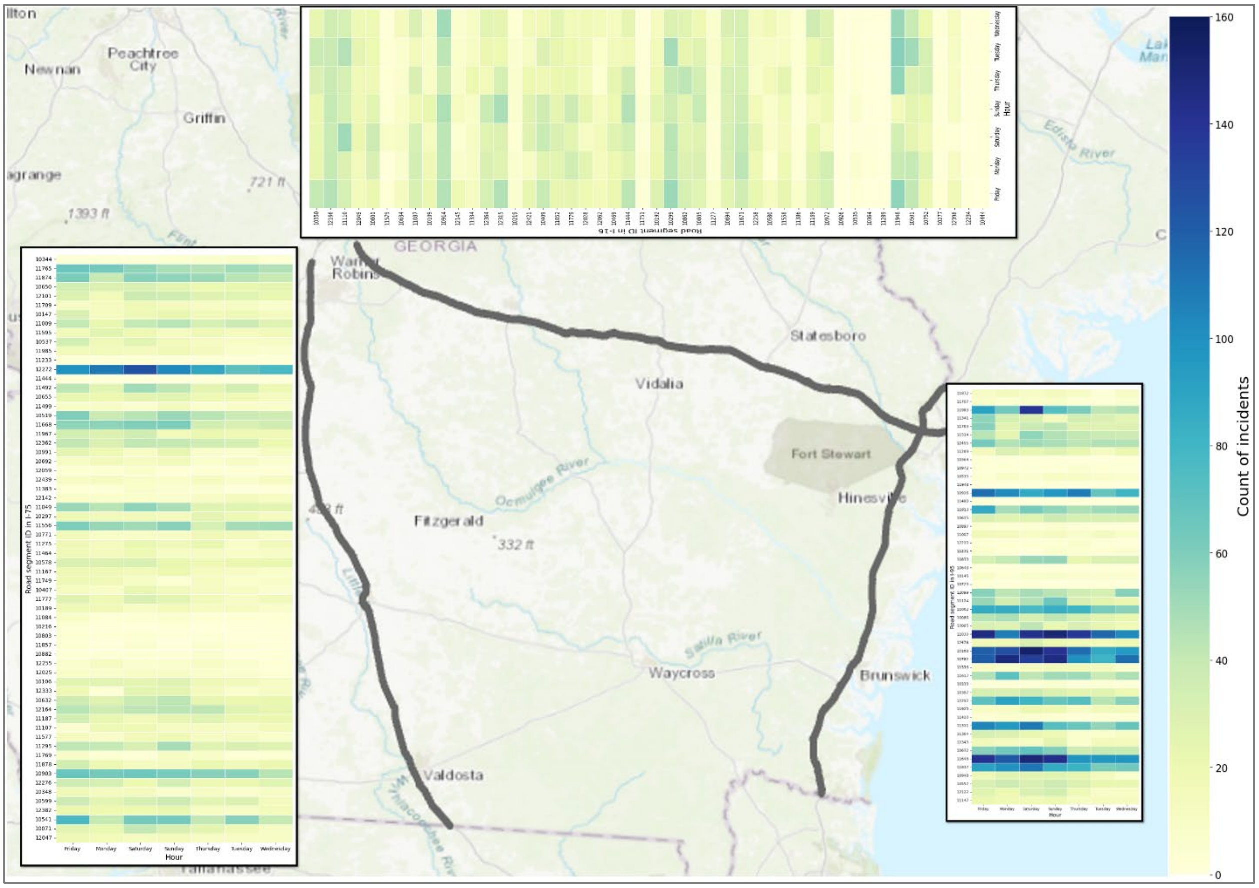

Figure 16. Map. Spatiotemporal heatmap per the frequency of incidents (temporal resolution: day of week).

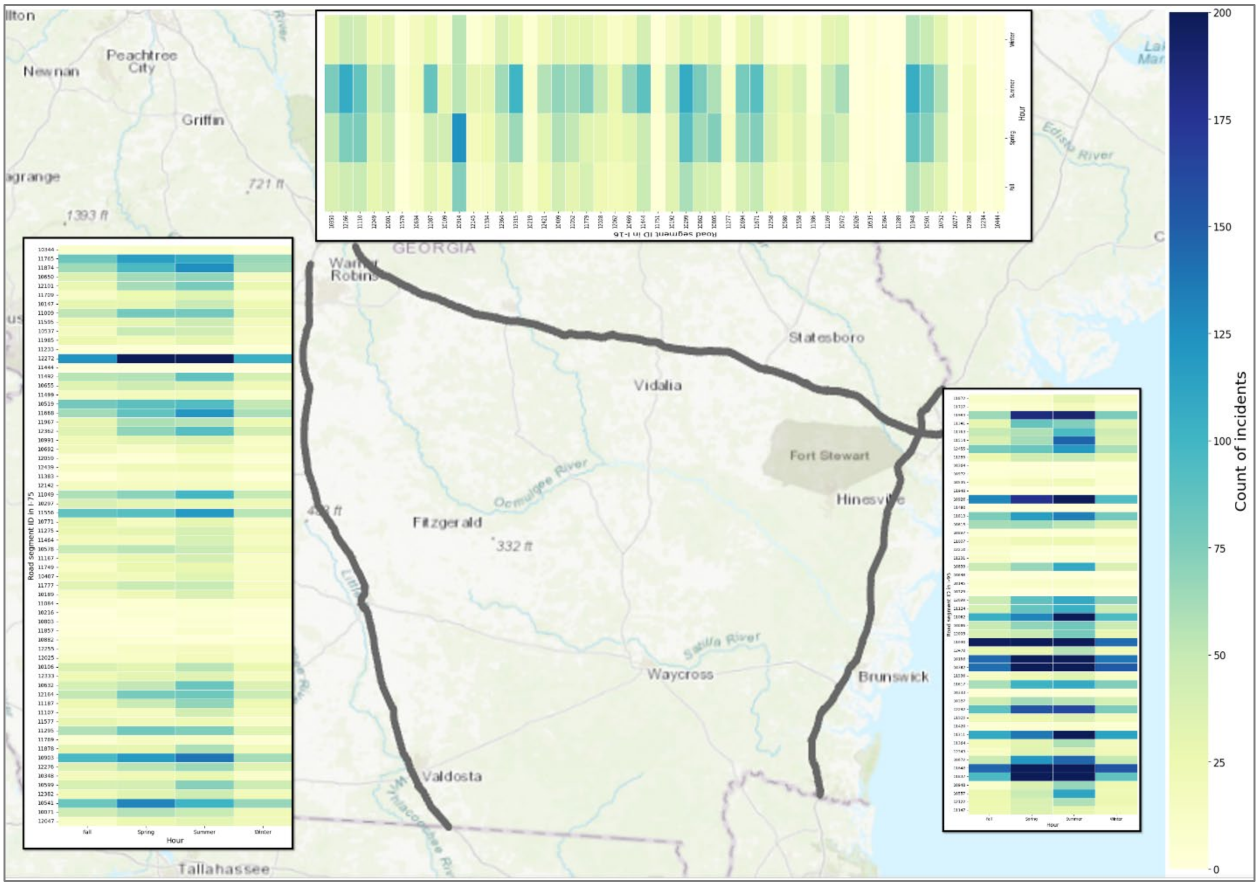

Figure 17. Map. Spatiotemporal heatmap per the frequency of incidents (temporal resolution: season).

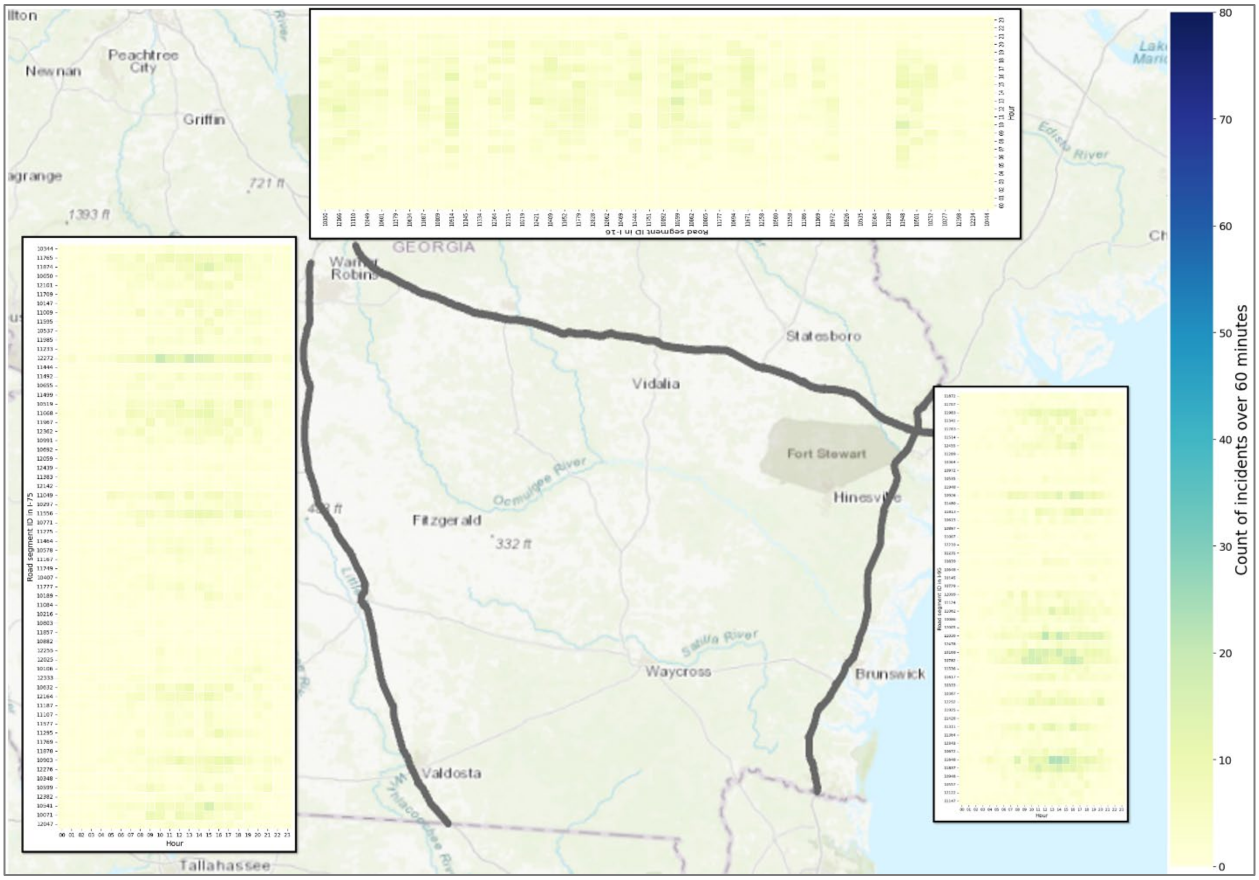

Figure 18. Map. Spatiotemporal heatmap per the frequency of incidents with duration over 60 min (temporal resolution: hour).

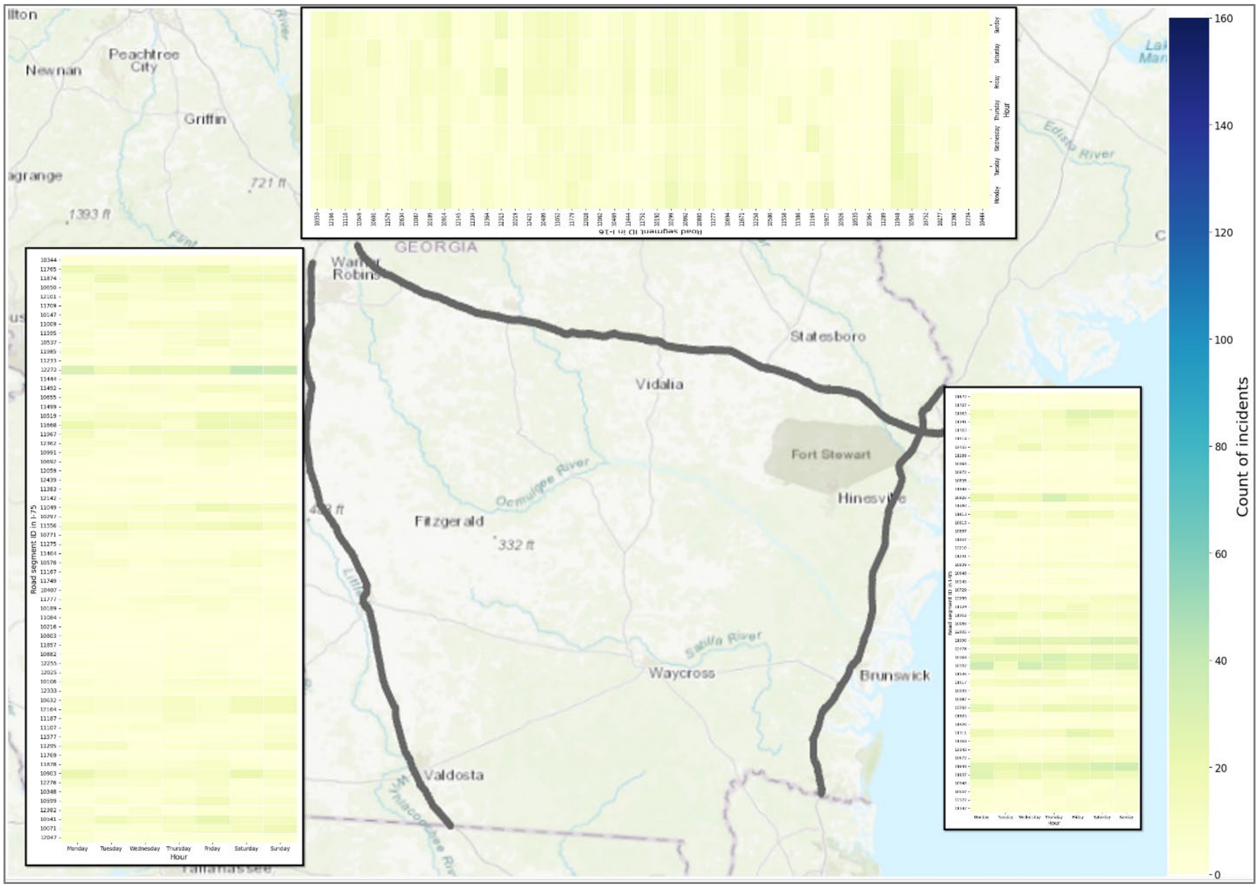

Figure 19. Map. Spatiotemporal heatmap per the frequency of incidents with duration over 60 min (temporal resolution: day of week).

Figure 20. Map. Spatiotemporal heatmap per the frequency of incidents with duration over 60 min (temporal resolution: season).

CHAPTER 7. CONCLUSIONS AND RECOMMENDATIONS

In conclusion, this study explored the utility of probe data in two critical applications in rural areas: (1) VMT reporting and (2) incident management practices. We first evaluated the feasibility of using probe data for VMT reporting by comparing probe-derived traffic volumes with ground truth traffic counts from GDOT's portable count sites in rural South Georgia. ANOVA was employed to analyze the variance in estimation error across different functional classes and temporal patterns, including variations by day of the week and month of the year. The findings reveal that both FC and DOW significantly influence error variance, with paired *t*-tests indicating relatively stable volume estimates for Wednesdays. Notably, using Wednesday volumes results in DVMT estimation errors of −4 percent and 5 percent for Vendor 1 and Vendor 2, respectively.

We then examined the potential of probe event data to enhance incident management practices, with a specific focus on GDOT's CHAMP program. As a case study, we analyzed incidents on three major interstates (I-16, I-75, and I-95) in rural South Georgia. Two gradient-boosting tree models were trained to predict incident risk and classify incident duration, uncovering key influential factors and emphasizing the impact of situational context on both incident risk and duration.

Additionally, we conducted a spatiotemporal analysis to identify hot spots and patterns that can directly inform incident management practices by targeting specific road sections, times of day, days of the week, and seasons. This approach can enhance patrol efficiency, reduce incident durations, and mitigate negative impacts.

Although the results highlight the potential benefits of enhanced patrol practices in rural areas, several limitations were noted, particularly concerning data sources. Firstly, the highway network shapefile used for visualization does not account for travel direction. Developing a connected, directional highway network with enhanced segmentation could improve modeling accuracy. Secondly, the absence of fine-grained road geometry (e.g., curvature) and weather data limits the models' predictive power. Incorporating these features is expected to further enhance the accuracy and effectiveness of the models.

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REFERENCES

[1] Georgia Department of Transportation (GDOT). (2018). *Georgia's Traffic Monitoring Guide*. GDOT, Office of Transportation Data, Atlanta, GA. Available online: https://www.dot.ga.gov/DriveSmart/Data/Documents/Guides/2018_Georgia_Traffic_Monitoring_Program.pdf.

[2] Federal Highway Administration (FHWA). (2024). "EDC-6 Crowdsourcing for Advancing Operations." FHWA, Washington, DC. https://www.fhwa.dot.gov/innovation/everydaycounts/edc_6/crowdsourcing.cfm.

[3] Farradyne, P.B. (2000). *Traffic Incident Management Handbook*. Federal Highway Administration, Office of Travel Management, Washington, DC.

[4] Al-Bdairi, N.S.S., Hernandez, S., and Anderson, J. (2018). "Contributing Factors to Run-Off-Road Crashes Involving Large Trucks Under Lighted and Dark Conditions." *Journal of Transportation Engineering A Systems*, *144*(1), 04017066. American Society of Civil Engineers. Available online: http://dx.doi.org/10.1061/JTEPBS.0000104.

[5] Ozbay, K.M.A., Xiao, W., Jaiswal, G., Bartin, B., Kachroo, P., and Baykal-Gursoy, M. (2009). "Evaluation of Incident Management Strategies and Technologies Using an Integrated Traffic/Incident Management Simulation." *World Review of Intermodal Transportation Research*, *2*(2–3), pp. 155–186. Inderscience Publishers. Available online: http://dx.doi.org/10.1504/WRITR.2009.023305.

[6] Finley, M.D., Durkop, B.R., Wiles, P.B., Carvell, J.D., and Ullman, G.L. (2001). *Practices, Technologies, and Usage of Incident Management and Traveler Information Exchange and Sharing in Texas*. Report 7-4951-1, Texas Department of Transportation, Research and Technology Implementation, Austin, TX. Available online: http://tti.tamu.edu/documents/4951-1.pdf.

[7] Birriel, E., Mitchell, D., Sullivan, V., and Peters, J. (2022). *Applying Transportation Systems Management and Operations (TSMO) to Rural Areas*. Report FHWA-HOP-22-026, U.S. Department of Transportation, Federal Highway Administration, Washington, DC. Available online: https://ops.fhwa.dot.gov/publications/fhwahop22026/fhwahop22026.pdf.

[8] Carson, J.L. (2010). *Best Practices in Traffic Incident Management*. Report FHWA-HOP-10-050, U.S. Department of Transportation, Federal Highway Administration, Office of Transportation, Washington, DC. Available online: https://ops.fhwa.dot.gov/publications/fhwahop10050/fhwahop10050.pdf.

[9] Carson, J.L. (2008). *Traffic Incident Management Quick Clearance Laws: A National Review of Best Practices*. U.S. Department of Transportation, Federal Highway Administration, Office of Operations, Washington, DC. Available online: https://ops.fhwa.dot.gov/publications/fhwahop09005/quick_clear_laws.pdf.

[10] Georgia Department of Transportation (GDOT) (2024). *Georgia Traffic Incident Management Guidelines*. Georgia Traffic Incident Management Enhancement Task Force, GDOT, Atlanta, GA. Available online: https://timetaskforce.com/time-initiatives/tim-guidelines/.

[11] Carrick, G. and Burgess, L. (2022). *Unmanned Aircraft Systems for Traffic Incident Management.* Report No. FHWA-HOP-20-063, U.S. Department of Transportation, Federal Highway Administration, Washington, DC. Available online: https://ops.fhwa.dot.gov/publications/fhwahop20063/fhwahop20063.pdf.

[12] New Jersey Department of Transportation. (2022). *State of New Jersey Traffic Incident Management Strategic Plan – Version 2*, New Jersey Department of Transportation, Ewing, NJ.

[13] Minnesota Department of Transportation. (2012). *Changeable Message Sign (CMS) Manual of Practice*. Report No. MN/RC 2012-32, Minnesota Department of Transportation, St. Paul, MN. Available online: https://mdl.mndot.gov/items/201232.

[14] Yazici, M.A., Kamga, C., Mudigonda, S., and Almotahari, S. (2018). *Reducing Incident-Induced Emissions and Energy Use in Transportation: Use of Social Media Feeds as an Incident Management Support Tool*. Report No. C-14-11, New York State Energy Research and Development Authority (NYSERDA), New York State Department of Transportation, Albany, NY.

[15] Federal Highway Administration (FHWA). (2015). *Highway Performance Monitoring System (HPMS)*. U.S. Department of Transportation, FHWA, Washington, DC. Available online: https://highways.dot.gov/safety/data-analysis-tools/rsdp/rsdp-tools/highway-performance-monitoring-system-hpms.

[16] Federal Highway Administration (FHWA). (2022). *Traffic Monitoring Guide.* U.S. Department of Transportation, FHWA, Washington, DC. Available online: https://www.fhwa.dot.gov/policyinformation/tmguide/2022_TMG_Final_Report.pdf.

[17] Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A.V., and Gulin, A. (2017). CatBoost: Unbiased Boosting with Categorical Features. arXiv, https://doi.org/10.48550/arXiv.1706.09516.

[18] Lundberg, S.M., Erion, G.G., and Lee, S.I. (2019). Consistent Individualized Feature Attribution for Tree Ensembles. arXiv, https://doi.org/10.48550/arXiv.1802.03888.