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Statewide Non-Motorized Traffic Monitoring Study

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13. Abstract
The growing emphasis on creating a multimodal transportation system in the U.S. requires high-quality multimodal traffic data for planning success. This research investigated strategies for integrating non-motorized (i.e., bicyclist and pedestrian) traffic monitoring into routine motorized traffic monitoring practices in Louisiana. Key objectives included exploring data consolidation possibilities, refining adjustment factors, evaluating emerging data sources, and investigating count location expansion opportunities. The literature/practice review results suggest that program institutionalization, QA/QC procedure implementation, local agency collaboration, open data access, and network expansion with data support are potential strategies for statewide implementation success. Throughout the project, the research team: (1) developed a draft data transmission, management, and maintenance protocol; (2) refined adjustment factor calculations by comparing different methods and data sources; (3) evaluated third-party mobility data from different sources

with a method proposed to mitigate data bias for practical use (i.e., Virtual Network Sensors); and (4) investigated how to leverage third-party mobility data to systematically identify road segments with similar temporal activity patterns for strategic placement of counters (i.e., two-stage spatial-temporal clustering framework). Overall, hybrid data collection and use can better support a monitoring network with limited existing data by creating reliable baseline data and enabling ground-truth validation. Ultimately, establishing a standardized, scalable non-motorized traffic monitoring framework aligned with national practices will allow Louisiana to effectively support robust long-term multimodal transportation planning.

Project Review Committee

Each research project will have an advisory committee appointed by the LTRC Director. The Project Review Committee is responsible for assisting the LTRC Administrator or Manager in the development of acceptable research problem statements, requests for proposals, review of research proposals, oversight of approved research projects, and implementation of findings.

LTRC appreciates the dedication of the following Project Review Committee Members in guiding this research study to fruition.

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Implementation Statement

This research reviewed best state practices for non-motorized traffic monitoring to date, conducted stakeholder surveys in Louisiana to better understand local practices and expectations, and summarized emerging technologies and data sources to identify how their potential may contribute to future practices. Overall, the research has shown that ongoing, sustained state-level support for data collection is highly valuable for promoting high-quality, consistent data that can be used for planning and evaluation.

Figure 5 provides a draft data transmission chart that involves multiple agencies for collaborative data collection and management. This conceptual collaboration model describes the following potential activities from each entity, which need to be tested and agreed upon in practice through follow-up implementation:

- Local entities are expected to propose counting locations of interest and complete equipment installation and maintenance in the field.
- MPOs are expected to serve as a conjunction to coordinate regional interests, perform data QA/QC, transmit cleaned data to LTRC personnel (likely on a quarterly basis), etc.
- LTAP is expected to deliver relevant training courses (e.g., equipment selection and data collection) to local entities and MPOs.
- LTRC is expected to apply the accumulated research experience in practice by developing training resources to support LTAP, formatting the data transmitted from MPOs, uploading the formatted data to DOTD's GIS development/production portal, performing the GIS database maintenance work on a continuous basis, etc.
- DOTD is expected to facilitate LTRC's access to its GIS development/production portal, work with local and regional agencies to identify funding opportunities for data collection activities, and comment and approve data collection and management protocols, which will be finalized during the implementation process.
- DOTD is expected to serve a statewide leadership role in the implementation process so that local agencies have clear guidance about funding opportunities available to begin this process (e.g., formula and competitive funds for which count equipment and activities are eligible expenses; how to collect high-quality, useful data; and information about how to use data once it is collected). Ideally, it will be helpful to establish an initial point of contact at DOTD who is knowledgeable about active transportation planning to serve as

the primary coordinator overseeing implementation and directing inquiries to the most suitable individual or entity.

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Introduction

The Louisiana Department of Transportation and Development (DOTD) has funded several research activities in the last five years to better understand the increasing walking and biking activities in the state:

- **LTRC Project 16-4SA:** Pedestrians and Bicyclists Count: Developing a Statewide Multimodal Count Program [1]
- **LTRC Project 17-2SA:** ITS Support for Pedestrians and Bicyclists Count: Developing a Statewide Multimodal Count Program [2]
- **LTRC Project 19-1SA:** Evaluation of Counting Device for Pedestrians and Bicyclists [3]
- **LTRC Project 19-3SA:** Pedestrians and Bicyclists Count, Phase 2: Implementing and Applying Multimodal Demand Data [4]

In a recent report published by the Federal Highway Administration (FHWA), "improve data collection and analysis to advance safety for all users" is also identified as one of five key opportunities as FHWA advances its Complete Streets efforts [5]. Including non-motorized traffic (i.e., bicyclist and pedestrian) counting in routine motorized traffic counting practice will help state DOTs understand non-motorized users' travel patterns; select and prioritize projects improving multimodal access; ensure projects will be designed to balance multimodal travel needs for communities' benefits; and evaluate outcomes achieved from invested projects from multiple perspectives. The following paragraphs outline several critical problems in existing practice that need to be addressed.

First, public agencies (e.g., LTRC/DOTD, MPOs, and cities) have, to date, set up their own non-motorized traffic counters and collected data under their own rules. This phenomenon results in data being collected and stored in different formats, increases the risk of overlapping work (e.g., collecting data at the same time and location by different agencies), and creates barriers to data sharing and knowledge transfer. Is it possible to consolidate all or most of the non-motorized traffic data collected in Louisiana to date? Would statewide collaboration and coordination in data collection among public agencies be feasible in the future?

Second, installing non-motorized traffic counters to cover all roads in a state is costly and unrealistic, even when multi-agency data-collection collaborations are considered. A typical solution is to install permanent counters at strategic locations and deploy a rotating set of temporary counters across the network. What strategies should DOTD use to rotate its owned temporary counters in scenarios with/without multi-agency collaboration? Could the existing adjustment factors be further improved with data from other sources?

Third, new technologies and data products for non-motorized traffic counting continue to emerge. These technologies and products need to be evaluated for their implementation feasibility and data accuracy before deployment. Additionally, data fusion techniques have shown promise in expanding the utility of observed counts rather than replacing them. It is likely that big data sources (e.g., mobile phone data) could make counting data even more critical to the accurate analysis of active transportation demand.

Literature Review

This section provides a review of emerging data sources that provide non-motorized traffic volume (e.g., fitness applications and passive data collection), object detection technologies applied in other fields that could be adapted for non-motorized traffic counting purposes, existing non-motorized traffic monitoring practices in the U.S., and adjustment factor use in non-motorized traffic monitoring.

Emerging Data Sources for Non-Motorized Traffic Counting

The purpose of this review is to understand third-party data products, select those that fit the current study scope (i.e., providing network-level non-motorized traffic counts), and proceed with those that offer greater potential, accessibility, and affordability to support in-depth count data comparisons in the next step.

Strava Metro

Strava Metro launched in 2014 and has relied on its app users to log their activities without taking any Location-Based Service (LBS) data as input [6]. With logged activities, Strava Metro provides OD flow and network-level volume data at hourly/daily temporal resolutions. County-level datasets are currently made available to local government agencies and research partners at no cost for non-commercial purposes through an application for a user account.

Strava Metro data is stated to correlate with the number of walking/biking commuters in block groups as reported in the American Community Survey [7]. Some research even found that its data representation improved during the COVID-19 lockdowns [8]. Their platform provides data from 2019 and is free for public agencies and their partners, encouraging its widespread use in research and practice. Strava Metro data has been used to understand biking activities [9], estimate visitors to natural open spaces [10], improve urban trails, prioritize investment in bicycle infrastructure, support active transportation planning [11], and more. In 2021, Lee and Sener provided a review regarding how Strava Metro data has been used in monitoring bicyclist activities [12].

LBS Data Products

The following subsections review data product vendors that process raw Location-Based Service (LBS) data to provide non-motorized traffic counts. LBS data is considered to have greater spatial precision and accuracy than cellular data [13]. These data product vendors may collect raw LBS data in-house and/or receive it from other companies, such as Cuebiq, Gravy Analytics, Quadrant, and TomTom. This review focuses on data product vendors instead of raw data providers. This study starts with a long list of data product providers, but narrows to focus on those who provide non-motorized traffic count data; see Table 1. It is noted that this area has been growing rapidly in recent years, with new data vendors and data products emerging often. The following subsections provide detailed introductions to those providing network-level non-motorized traffic counts.

Table 1. Overview of data product vendors

Company	Non-motorized traffic	Spatial resolution	Temporal resolution
AirSage	Yes	OD flow and activity density	Hourly, Daily
Habidatum	Yes	Network	Hourly, Daily
Replica	Yes	OD flow and network	Hourly, Daily
StreetLight	Yes	Network and census zone	Hourly, Daily

Note: "OD" stands for Origin-Destination

Habidatum. One of Habidatum's products (i.e., Location Risk Score) indicates that the company conducts travel mode inference [14]. Their methodology counts each user passing a biking/walking road segment only once per hour, regardless of how many times they pass it in that hour. All of the hourly counts are aggregated to produce the daily count. Daily averages for workdays and weekends are computed separately.

Replica. Replica provides trip tables for various travel modes, Annual Average Daily Traffic (AADT), travel speed, turning movement counts, and spend data [15]. Active transportation (i.e., biking and walking) is included in their trip tables and listed among their use cases [16]. Example use cases include supporting road diet projects, providing better access to transit service, understanding the impacts of e-bikes, identifying high-risk areas for pedestrians, etc.

Replica active transportation trip data is available from 2019. Each record in the active transportation table represents an individual biking/walking trip. The following attributes are available for each trip record: travel mode, trip/tour purpose, time stamp, network link ID, and origin/destination block group, land use, and building use. The data attributes can help generate origin-destination tables and network volumes, and support other customized analyses [15].

Overall, Replica's bicycle trip count data appears to offer significant opportunities for practitioners in the following cases:

- Identifying network chokepoints with probable latent demand due to constraints of the transportation grid, regardless of current use and/or facility suitability;
- Observing apparent patterns in the distribution of users from key connections (e.g., Lafitte Greenway) to neighborhood streets; and
- Identifying segments which may serve as key neighborhood connections for bicyclists and pedestrians, but have been missed in previous planning efforts, and/or where future counts should be collected.

At the area-wide network level, the data offer useful insights into route choice that are likely to be valuable to planners in identifying investment opportunities. However, users should interpret the data cautiously and in combination with other data sources, not relying on reported trip counts as a substitute for either actual user volumes or, in some cases, for segment-level relative demand when data anomalies appear to inflate or underreport actual activity levels. As these observations indicate, there are several recurrent anomalies in which the model used to generate these values appears to lack critical contextual information, resulting in erroneous outputs that could negatively impact planning efforts if not carefully vetted against local data and knowledge.

StreetLight. StreetLight publishes national trend reports regarding how biking and walking activities change from year to year in the U.S. [17]. Data have been available since 2019 and were initially provided at the census tract level on their platform, with a recent release of segment-level data in 2026. Its data have been used to support road diet proposals, design a bicyclist/pedestrian bridge for destination access, inform active transportation safety analysis, run before-and-after analyses to observe biking trip variations related to infrastructure built, etc.

Their travel mode inference methodology is a multi-pass algorithm to identify various modes of travel, such as vehicles, buses, rails, bikes, and walking trips, by combining both heuristic and probabilistic approaches [18] [19] [20]. For example, all rail trips are separated from others based on a series of heuristic rules, with the fact that all trips occur along a uniquely identifiable rail network. Walking or stationary trips are identified and grouped into points. The remaining, unassigned LBS pings are assigned with mode probabilities for vehicle, bike, and bus based on their movement patterns and spatial features. Machine learning (i.e., random forest) is used to separate vehicles, bikes, and bus trips from one another.

Emerging Data Review Summary

Data product vendors that currently provide non-motorized traffic counts also provide motorized traffic counts. It is not surprising to find that many other data product vendors are contributing to motorized traffic count areas, such as HERE, INRIX, TomTom, Unacast, and Wejo. Thinking optimistically, this may indicate the potential for more data product vendors to contribute to non-motorized traffic counts in the future as interest in active transportation grows. More products are under development by data product vendors, raw data providers, and/or their collaborators in academia. For example, Cuebiq collaborates with Spectus.ai in supporting research activities ("Data for Good" movement) [21]. The Spectus platform contains a set of built-in algorithms to infer travel modes from raw LBS data. A general idea of travel mode inference is related to travel speed. As a part of this research, a polygon surrounding the LSU campus was selected on the Geojson.ai platform to extract sample data from October 2022. A total of 7,258 travel trajectories passed through the polygon area during the specified period. Of these, 1,396 had a maximum speed below 12 mph and were inferred by the platform to be walking, running, or cycling activities. This type of raw trajectory data being open to the research community provides flexibility to develop more advanced algorithms for travel mode inference in the future.

Non-Motorized Traffic Detection Algorithms

LTRC Projects 16-4SA and 19-3SA provided an in-depth review of mechanical non-motorized detection technologies (i.e., sensors) and developed an inventory of technology and vendors relevant to these methods of data collection, including an exploratory review of video-based detection methods, encompassing both manual review and algorithmic data extraction. Sensor-based methods of data collection (e.g., inductive loops, infrared, pneumatic tubes, etc.) are still in regular use across the U.S., with no major changes in technology or usage identified since the previous review. This study builds on previous projects by exploring in greater depth the technologies and methods used in automated data processing for detecting and classifying non-motorized traffic, an area of rapid growth and innovation in recent years.

Video and Image-Based Detection

Video-based detection remains the most extensively studied approach for automated bicyclist and pedestrian monitoring. Early work relied on hand-crafted feature descriptors. Dalal and Triggs [22] introduced the Histogram of Oriented Gradients (HOG), which computes normalized gradient-orientation histograms across local image cells and, when combined with a linear Support Vector Machine (SVM), established a strong benchmark for pedestrian detection in outdoor scenes. Lowe [23] introduced the Scale-Invariant Feature Transform (SIFT), which improved robustness to changes in scale, rotation, and viewpoint, making it useful for object matching under partial occlusion and varying camera perspectives. These methods demonstrated that reliable feature-based detection in complex traffic environments was feasible, but their performance was limited relative to later deep learning approaches.

The development of convolutional neural network (CNN)-based object detectors substantially improved detection accuracy and operational efficiency. Faster R-CNN [24] introduced a two-stage architecture combining a Region Proposal Network with a shared convolutional detection framework. The YOLO (You Only Look Once) family further improved computational speed by framing detection as a single-stage regression problem. The original YOLO model [25] enabled real-time object detection, while YOLOv3 improved multi-scale prediction and small-object recognition [26]. More recent developments, such as YOLOv10, have emphasized end-to-end real-time detection and reduced reliance on post-processing, thereby improving performance in crowded scenes where overlapping users may otherwise lead to undercounting [27]. Transformer-based detectors have extended this progression: DEtection TRansformer (DETR) introduced an end-to-end set-prediction framework that eliminates anchor design and non-maximum suppression [28], while Real-Time DEtection TRansformer (RT-DETR) demonstrated that transformer-based detection can achieve real-time performance suitable for operational deployment [29].

For non-motorized traffic counting, detection is typically paired with multi-object tracking to avoid duplicate counts and preserve trajectories across frames. Deep Simple Online and Realtime Tracking (SORT) incorporates appearance features to improve re-identification under occlusion [30], while ByteTrack improves robustness by associating both high- and low-confidence detections, reducing missed objects in dense or partially obstructed scenes [31]. Modern video pipelines can therefore provide not only count totals but also direction, dwell time, and trajectory data. Their primary limitations remain sensitivity to lighting conditions, camera placement, and weather, as well as privacy considerations associated with image capture in public spaces.

Radar-Based Detection and Classification

Radar-based systems offer a privacy-preserving alternative to cameras for operational field conditions, as they do not capture visual imagery and perform reliably under low-light conditions, glare, and many adverse weather scenarios. Millimeter-wave (mmWave) and frequency-modulated continuous-wave (FMCW) radar systems estimate object position and velocity from reflected signals and Doppler information. Zhao et al. [32] demonstrated that point-cloud features derived from mmWave radar, combined with a kernel SVM classifier, can distinguish pedestrians from vehicles based on reflected signal geometry and motion patterns. Nimac et al. [33] applied FMCW radar at crosswalks using a group-tracking algorithm to estimate pedestrian counts, group size, and travel direction, illustrating its practical relevance for transportation monitoring.

Separating pedestrians from bicyclists is a more difficult challenge that depends on micro-Doppler signatures generated by periodic limb movement (e.g., arm swing in pedestrians and leg rotation in bicyclists). Although micro-Doppler analysis adds useful discriminatory information, reliable pedestrian-bicyclist separation using radar alone remains difficult in operational field conditions because signatures can overlap under similar speeds and movement patterns [34]. This limitation is important for agencies that require mode-specific counts rather than aggregate non-motorized volumes.

LiDAR-Based Detection and 3-D Point Cloud Processing

LiDAR (Light Detection and Ranging)-based systems provide a third approach for automated non-motorized traffic detection. By emitting laser pulses and measuring time-of-flight returns, LiDAR generates three-dimensional (3-D) point clouds that directly represent object geometry. Unlike camera-based systems, LiDAR performance is not dependent on ambient lighting, making it well-suited for continuous monitoring under variable day and night conditions. PointNet was the first deep learning architecture to process raw, unordered 3-D point clouds directly [35], and PointNet++ extended this framework through hierarchical feature learning at multiple spatial scales, improving performance for sparse and small objects [36]. PointPillars further improved computational efficiency by encoding point clouds into pseudo-image pillars, which are processable with 2-D CNN architectures, making near-real-time deployment more feasible [37].

For pedestrian and bicyclist counting, LiDAR's primary strength is its ability to detect small and spatially compact targets while providing accurate 3-D location and trajectory information. Recent work has shown that deep learning models can improve small-target detection in sparse LiDAR point clouds, which is especially relevant for non-motorized users at longer distances [38]. Primary limitations include higher equipment costs relative to cameras or radar and degraded performance in heavy rain or fog due to reduced point-cloud density.

Implications for Non-Motorized Traffic Counting

Across all three sensing modalities, the literature reflects a clear shift from hand-crafted and rule-based approaches toward data-driven detection and tracking frameworks. Video-based systems currently provide the richest classification capability and are best suited for applications requiring simultaneous bicyclist and pedestrian detection, trajectory extraction, and detailed behavioral analysis. Radar-based systems offer important advantages in privacy protection and low-light performance but remain limited when mode-specific classification is required. LiDAR-based systems provide strong geometric accuracy and lighting independence, with growing promise for small-target detection, though higher cost remains a practical constraint.

No single modality is universally optimal for all non-motorized monitoring applications; system selection depends on the monitoring objective, required classification detail, site conditions, privacy considerations, and budget. Increasingly, the autonomous vehicle perception literature from which many of these algorithms are drawn points toward sensor fusion, combining camera with radar or LiDAR, as a means of offsetting the limitations of any single modality, and this approach merits consideration for high-priority non-motorized traffic monitoring sites. A continuing gap across all modalities is the limited emphasis on standardized evaluation frameworks that focus on counting accuracy under real-world field conditions, including temporal consistency, sensitivity to occlusion, and robustness across weather and lighting conditions. Addressing this gap will be essential to translating algorithmic advances into reliable operational non-motorized traffic-monitoring programs.

Practice of Other State DOTs in Non-Motorized Traffic Data Collection and Management

At the national level, there have been few significant updates to guidance pertaining to non-motorized data collection in the last few years, with the exception of a 2022 update to FHWA's *Traffic Monitoring Guide (TMG),* which for the first time fully integrates active modes (e.g., biking, walking, and other micro-mobility modes) throughout, including discussion of video-based counts and other emerging technology opportunities [39]. The updated TMG outlines several key differences between standard motorized vehicle monitoring and micromobility traffic monitoring:

- Scale of data collection and limited number of samples for active modes;

- Scope of data collection, with data collection for active modes prioritized on shared-use paths and lower functional class roads, whereas data collection for motor vehicles prioritizes higher functional class roads and interstates;
- Wider variation in technologies used and sample durations for active modes; and
- Ongoing evolution of monitoring technology and lack of well-established error rates and associated management protocols

The TMG also references supporting documentation from state-level agencies as examples of further information on specific topics, reflecting recent efforts around the country to implement federal guidance and advance the state of the practice by expanding active transportation monitoring and providing relevant resources to support state and local efforts.

Recent advancements by peer state DOTs provide a roadmap for scaling and institutionalizing non-motorized monitoring programs. A review of existing and emergent leaders in statewide non-motorized monitoring practice reveals that while some of the previous leaders (e.g., Colorado, Washington, and North Carolina; see LTRC Project 19-3SA) continue to provide a useful template for developing and applying data, new leaders (e.g., Florida, Michigan, and Texas) have emerged providing resources and insight into practical applications for collecting and disseminating bicyclist and pedestrian demand data. This section summarizes recent publications and advances in the state of the practice among each of these states, with a focus on better understanding the following aspects of program implementation, as well as the overall size and scope of each state's activities; see Table 2.

Table 2. Approximate scale and funding of statewide non-motorized count programs

State	Continuous count sites	Short-duration count sites	Data platform/ repository	Identified funding source(s)	Notable scale characteristics	Key documents/plans
Colorado Department of Transportation	33 permanent sites (primarily urban/suburban; majority on trails)	Corridor-based tube counts and one-month infrared deployments	Non-Motorized Traffic Data dashboard	Initial $50,000 Kaiser Permanente grant; ongoing state planning and research funds (not guaranteed)	Basic-stage program; limited staffing; working toward 50 representative sites	Non-Motorized Monitoring Program and Implementation Plan

State	Continuous count sites	Short-duration count sites	Data platform/ repository	Identified funding source(s)	Notable scale characteristics	Key documents/plans
Texas Department of Transportation	Part of 175 permanent sites statewide (DOT + local combined)	1,005 short-duration sites statewide	BP | CX centralized exchange platform (direct user uploads)	Not specified in available documentation	Direct access to data platform supports local involvement	Improving the Amount and Availability of Pedestrian and Bicyclist Count Data in Texas
North Carolina Department of Transportation	72+ continuous sensors statewide	Used strategically to develop expansion factors	EcoVisio (API-integrated), managed by ITRE	Sustained NCDOT funding since 2014 (specific source not detailed)	Long-running program (10+ years); Collaborative Agency Model outlines roles for local-led data collection	State-of-the-Art Approaches to Bicycle and Pedestrian Counters; North Carolina Non-Motorized Volume Data Program (NC NMVDP) Phase 2 Final Report
Florida Department of Transportation	Expanded to 272 continuous counters (major growth in 2025)	Statewide short-term count program + loan equipment	TDMS + Non-Motorized Traffic Monitoring Program Data Dashboard	Initial FHWA State Transportation Innovation Council (STIC) grant; ongoing FDOT program support	Rapid expansion; integrated into Traffic Monitoring program; priority safety network focus	State Transportation Innovation Council (STIC) Grant Final Report 2023 Traffic Monitoring Handbook
Washington State Department of Transportation	60+ permanent sites	Recommends ~30 short-term count locations per 100 centerline miles (three-year cycle, aspirational)	Public count portal + AADB estimation tool	Not specified in available documentation	Mature guidance; emphasizes network-wide extrapolation and modeling	Collecting Network-Wide Bicycle and Pedestrian Data
Michigan Department of Transportation	20+ identified continuous locations (planned/early stage)	60+ short-duration locations	MS2 Non-motorized Database System	Funding levels not specified; implementation plan projected annual capital costs ($18k to $66k)	Early-stage coordinated expansion; strong planning framework, but unclear implementation scale	Non-Motorized Data Collection and Monitoring Program Guide and Implementation Plan

Additionally, the review of these states' current practices highlights the following themes:

1. **Institutionalizing the Program**

The clearest distinction between mature and emerging programs is sustained institutional commitment. North Carolina's long-term investment, supported by contracted technical expertise, allowed iterative refinement of QA/QC, factor development, and reporting, although challenges sustaining the current Collaborative Agency Model are apparent. Florida similarly embedded non-motorized monitoring within its broader Traffic Monitoring framework, prioritized installations on high-crash corridors, and accelerated program impact.

Implication for Louisiana: Formal integration within DOTD's Traffic Monitoring structure is critical. Clear role definition and dedicated staffing—or at minimum, an identified point of contact, potentially supplemented initially by contracted support—will help institutionalize non-motorized data collection into practice.

2. **Building a Representative Network**

Colorado and Washington emphasize developing factor groups (e.g., commute, recreation, mixed; regional distinctions) and building representative index sites within each group. Rather than dispersing counters opportunistically, both states move toward statistically defensible expansion.

Implication for Louisiana: Define factor groups early (e.g., urban commuter corridors, shared-use recreational trails, small-city mixed-use facilities, rural highways). Build continuous counters strategically to represent each category.

3. **Flexible and Scalable QA/QC**

Texas's platform-based QA/QC walkthrough, in which users adjust thresholds based on local context, provides a practical model. Colorado and North Carolina demonstrate tiered validation processes that evolve as programs mature.

Implication for Louisiana: QA/QC procedures for an emerging count program should include basic automated flags (e.g., zeros, spikes, directional imbalance, transmission gaps); clear documentation of validation decisions; and adjustable thresholds for local variation (e.g., festival events, weather). Advanced correction factors and expansion modeling can be implemented once sufficient historical data is available.

4. Supporting Local Agencies Through Structure and Tools

Several practices stand out:

- Equipment loan programs (Texas, Florida)—maintain an inventory of mobile count units that local agencies may borrow to collect data for project development and/or basic benchmarking.
- Formal short-duration count request process (Colorado)—in lieu of or in addition to loaned equipment, DOTs may directly respond to data requests, particularly for projects on state routes.
- Centralized database platform/management (Texas, North Carolina, Florida, Washington, Michigan)—provide a user-friendly process and platform for sharing data, including technical support.
- Outreach and training (Florida, North Carolina, Texas)—provide ongoing support to encourage coordinated local data collection, such as FDOT's annual Statewide Non-Motorized Traffic Monitoring Program meetings.

Implication for Louisiana: Develop a centrally managed loaner counter inventory and/or a standardized request form for short-term counts, particularly for DOTD-involved projects. Develop a data-sharing agreement enabling local uploads, if desired (e.g., TxDOT BP|CX platform) and/or a designated agency point of contact for integrating local data into statewide databases. Provide annual, continuing-education-approved training workshops, modules, or meetings to build capacity.

5. Leveraging Supplemental Data Sources

Colorado's structured comparison of Strava Metro data with permanent counter data provides a pragmatic approach to crowd-sourced data. While not suitable for absolute volume estimates without calibration, such data support relative demand and route choice analysis.

Implication for Louisiana: Use third-party datasets to identify high-use corridors lacking counters; support network prioritization; and estimate relative demand patterns, particularly where permanent counters are limited. As monitoring expands, inform priority locations to fill gaps in network understanding.

6. Transparency and Data Access

Texas, Florida, and Washington all emphasize public dashboards and export functionality. Open data improves program visibility, supports local planning, and builds stakeholder buy-in.

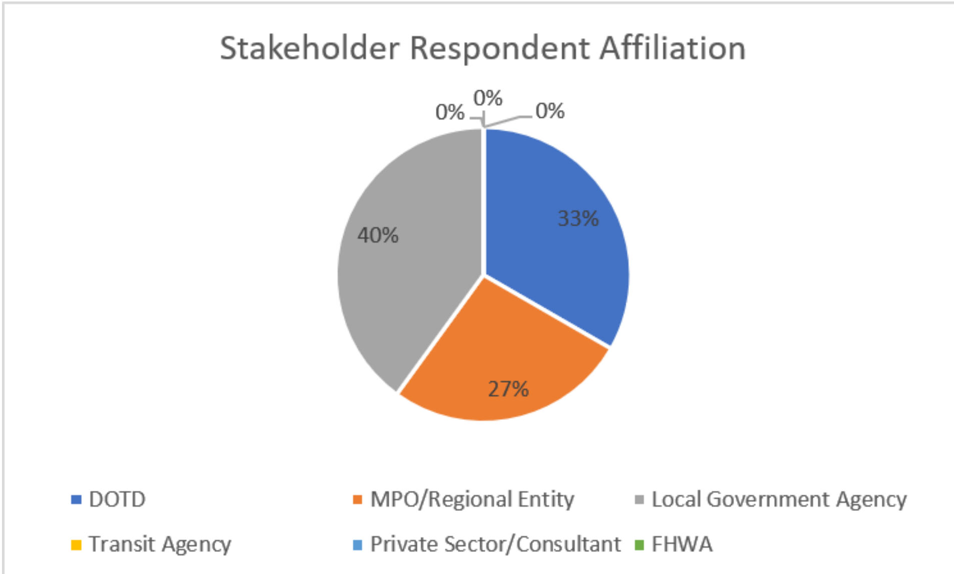
Implication for Louisiana: Develop a publicly accessible dashboard with filterable site information, downloadable summary data, clear disclaimers regarding validation status, and potentially, API and/or login access for advanced users.

Practice of DOTD Districts and MPOs in Louisiana

To better understand current practices, opportunities, and needs, as a prerequisite to encouraging the expansion of active transportation data collection across the state, the researchers developed a survey for DOTD Districts, MPOs, and local transportation planning agencies. This survey aimed to understand current non-motorized traffic monitoring practices, the level of interest in non-motorized traffic counting, current staff capacity, and the scope of planning and data needs for non-motorized road users among public organizations in Louisiana. The survey questionnaire (Appendix A) was distributed to 22 DOTD employees (District Engineers for each District, as well as various Department leaders), 56 MPO staffers involved in relevant programs and roles, and 29 planning directors, transportation planners, public works directors, or chief engineers at municipal agencies, between September 1, 2023, and October 20, 2023, with intermediate reminders.

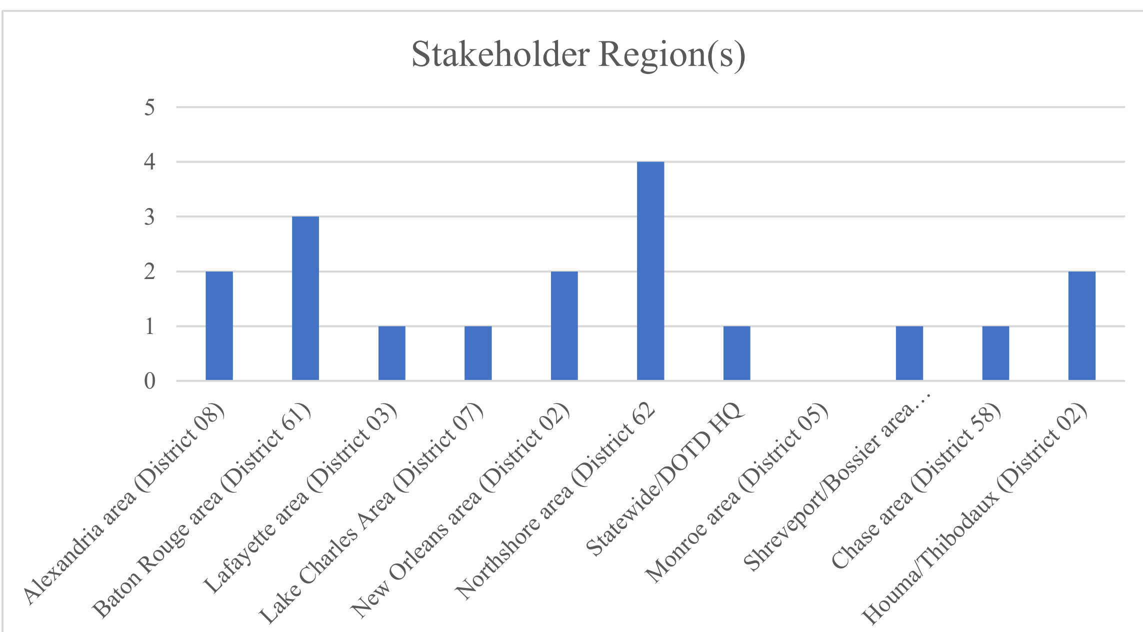
The survey was substantively completed by 15 respondents, representing a roughly equal mix of DOTD District Engineers, MPO staff, and local government agencies; see Figure 1.

Figure 1. Stakeholder diagnostic survey respondent affiliation



Respondents represented expertise in planning, design and engineering, and administration or operations, and at least one respondent participated from each DOTD District, with the exception of District 05; see Figure 2.

Figure 2. Stakeholder diagnostic survey respondent region



The majority of those who chose to participate already collect, or have collected in the past, some form of non-motorized count data. This included respondents at DOTD Headquarters and with the District 08, District 07, and District 04 offices, as well as at Capital Region Planning Commission, South Central Planning and Development Commission, and New Orleans Regional Planning Commission. Among these respondents, the largest share reported collecting manual, short-term counts. Three respondents reported previous use of pneumatic tubes to count bicycles, two reported manual review of video-based counts, and one reported a count type or technology not known or listed. Specific vendors noted included counters by EcoCounter, Jamar Technologies, and Count Cam/Spack Solutions. Most respondents indicated a small number (i.e., five or fewer) of known short- or long-term automated count locations, while several reported a larger number of manual count locations. Where prompted, some of these locations were noted, generally identified as project-specific count samples collected for Stage 0 studies, safety analyses, crosswalk requests, etc.

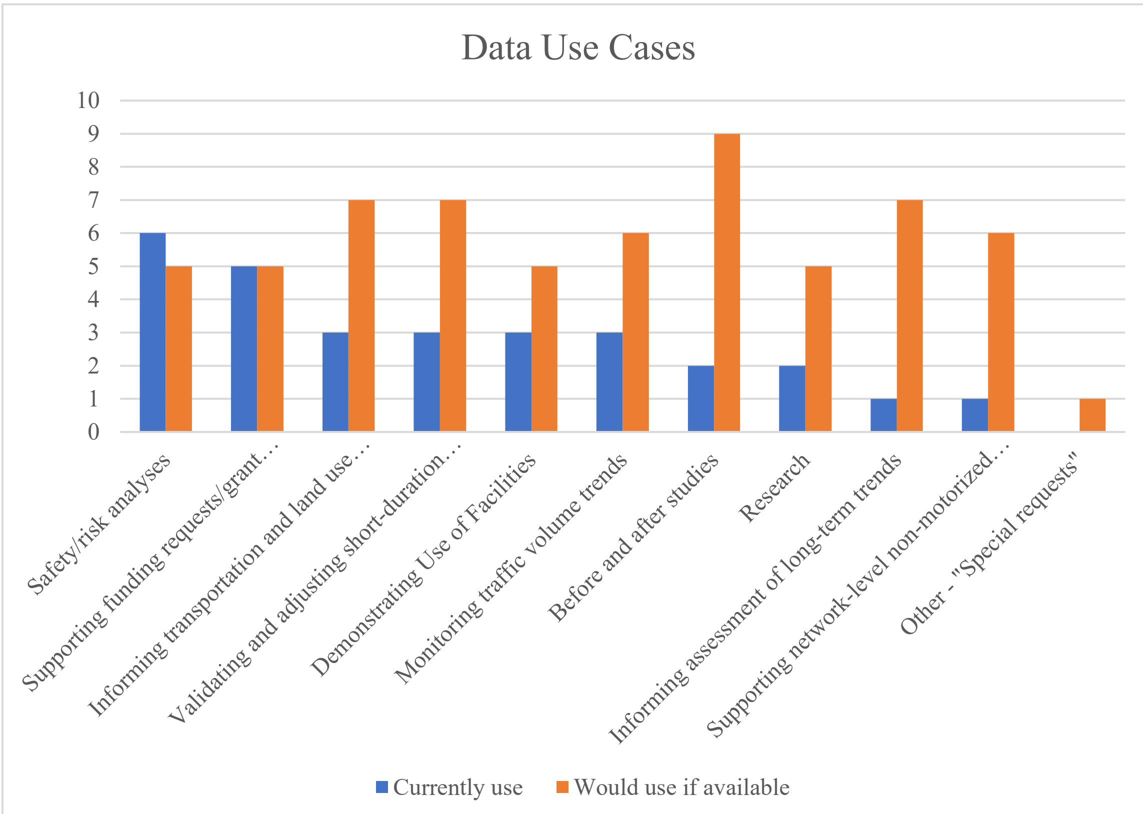
Responses pertaining to data storage and management clearly reflect a lack of coordination and do not suggest that consolidation of data for future use beyond the project or initiative for which it was collected has previously been a priority; counts are embedded in project documentation, rather than compiled with other, related data. Some data is only available in PDF or hard-copy file formats.

Among respondents who did not report any previous non-motorized count activities, inadequate staff time and a lack of knowledge about available counting technologies were cited as the top barriers to conducting such activities. One respondent observed that a lack of bicyclist and pedestrian facilities to monitor and/or a lack of reported crash history disincentivizes multimodal monitoring.

A second block of questions pertained to interest in, and capacity for, non-motorized traffic monitoring. While most respondents indicated one or more staff members fully or partly responsible for activities related to active transportation planning or programs, and all respondents indicated at least one full-time equivalent (FTE) staff person focused on traffic count collection or management generally, no respondents indicated existing staff capacity for non-motorized monitoring specifically.

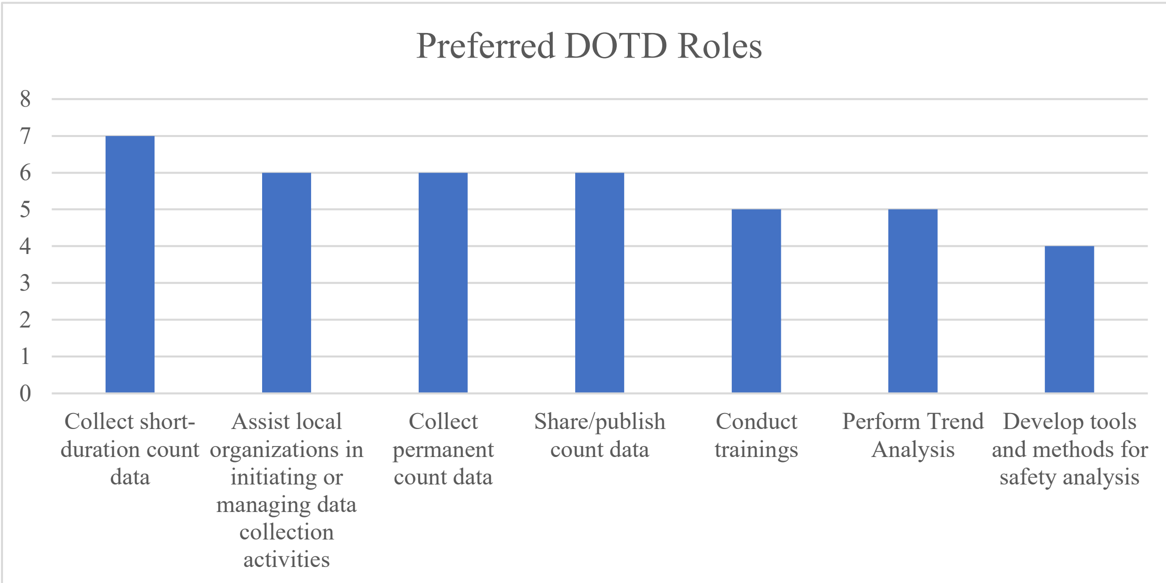
Currently, the collected count data is primarily used for safety analyses, supporting funding requests, and, to a lesser extent, informing transportation and land-use feasibility studies, validating and adjusting short-term counts collected as part of feasibility or traffic studies, and demonstrating facility use. Most respondents indicated moderate or strong interest in initiating or expanding such activities, however, and suggested a range of potential use cases, most notably before-and-after studies, identifying long-term trends, informing feasibility studies, and validating and adjusting short-term counts; see Figure 3.

Figure 3. Stakeholder diagnostic survey current and potential data use cases



Respondents indicate a desire for DOTD leadership to collect both short- and long-term count data, assist local organizations in initiating or managing data collection activities, and share and publish count data. Training, analyses, and tools for safety analysis were also cited as appropriate by some respondents; see Figure 4.

Figure 4. Stakeholder diagnostic survey preferred DOTD non-motorized count program roles



Several respondents provided contact information for further follow-up and/or indicated interest in sharing existing count data with DOTD for a statewide database. The research team followed up with several of these individuals to learn more about the extent and nature of existing count data, where applicable. In some jurisdictions, upcoming active transportation planning efforts were expected to provide an opportunity for revisiting this topic. At least one MPO reported using supplemental datasets, such as Strava Metro, to inform demand analysis, but found this to be of limited utility in their area due to small user samples. In some cases, samples of local count data, representative of the range of data types currently collected (e.g., manual screenline counts, turning movement counts, pneumatic tube counts, and manually reviewed video counts) were provided to inform development of standard templates and data integration protocols. Although these sample datasets were generally temporally limited (e.g., less than 24 hours) or missing critical site information or QA/QC documentation, and thus have not been integrated into the Active Transportation Information Site, they provided valuable information about current practices and potential guidance needed to encourage the alignment of local data collection efforts with statewide standards, while preserving flexibility for local agencies to collect data appropriate for local needs and via a range of technologies and methods.

Adjustment Factors

Non-motorized traffic is inherently more variable than motorized traffic; for this reason, more data is generally required to conduct inferential statistical analyses of count and/or crash data. Permanent or long-term count locations are invaluable for understanding how short-term counts fit into overall annual trends for a given jurisdiction, climate, and/or built environment context [1]. Setting up non-motorized traffic counters to cover all roads in a state is costly and unrealistic, even when multi-agency data collection collaborations are considered; a typical solution is to install permanent counters at a strategic set of fixed locations and deploy a rotating set of temporary counters more widely across the network (e.g., counts collected before and after a project is completed, or annual or seasonal counts for broader network monitoring).

A primary use of continuous non-motorized count data is to extrapolate these short-term counts into Annual Average Daily Non-Motorized Traffic (AADNT) estimates. Reliably adjusting short-term data generally requires at least one full year of clean data from one or more comparable sites; multiple years of data allow for continual refinement of adjustment factors and serve as a critical barometer of overall trends [4].

LTRC Project 19-3SA developed preliminary factor groups for all available bicyclist and pedestrian counters for data collected from July 2020 through July 2022 [4]. Note that the study excluded an initial four-month period from March 2020 to June 2020 for counters installed in New Orleans due to unusually elevated volumes and anomalous patterns resulting from COVID-19. The current study seeks to re-evaluate these initial adjustment factors, develop additional methods to expand and interpret data, and apply preliminary adjustment factors to short-term counts in comparable locations to assess the extent and limitations of their applicability.

The 2013 Traffic Monitoring Guide (TMG) was the first edition of this document to explicitly discuss non-motorized data collection and use [40]. It recommends following a similar process for adjusting non-motorized traffic volumes as is used for motor vehicle volume adjustment, with two important caveats: first, the TMG recognizes that few agencies have collected sufficient data to clearly establish unique traffic factor groups, and consequently, few agencies had at that time systematically applied seasonal or daily adjustment factors to short-term counts, preferring instead to collect data at times that are perceived to be “typical” and thus in less need of adjustment. The 2013 TMG recommends shifting from this approach toward one based on seasonal adjustment, as more permanent count locations are installed.

The 2022 update of the TMG largely integrates recommendations for non-motorized and micro-mobility users into overall recommendations for monitoring, based on an assumption of moving toward such an integrated approach. It does, however, recognize the continuing gap in the scale of data collection and the number of monitoring locations typical in any geographic area, relative to motor vehicle counts. Ideally, a given jurisdiction would have at least three to five counters per identified, distinct factor group [41] [42]. Where sufficient numbers of permanent counters exist, a variety of methods for matching short-term counts to long-term count stations with similar characteristics or usage patterns can be applied, including land use characteristics, facility types, activity profiles, or empirical clustering methods [43] [44]. In practice, most jurisdictions have permanent monitoring stations at only a limited range of facilities representing a narrow range of factor groups. Thus, the ability to develop reliable estimates for short-term counts across a network is more limited.

However, temporal and environmental adjustments, even based on limited data, can still be valuable for understanding typical trends within a city or region and for filling data gaps.

Monthly Adjustment Factor

The TMG recommends developing monthly or seasonal adjustment factors for non-motorized/micro-mobility volume counts to estimate annualized daily traffic for short-term counts, especially those collected at times of the year not considered typical for a given climate (note: in most regions, spring and fall counts are considered most representative). Monthly or seasonal factors can also be used to fill future data gaps (e.g., due to power failures, obstructions, etc.) at this specific location using imputed data. Such temporal adjustment factors can be based on as few as one permanent count location, though more locations representing a variety of activity profiles are recommended in NCHRP Report 797 [44]. Review and refinement of data from more sites, and over a longer period of time, helps establish predictable activity profiles that can more reliably factor short-term counts [44].

Using multiple years of count data helps mitigate the effects of unusual conditions from year to year [44]. At the same time, seasonal adjustment factors should be updated periodically to reflect actual changes in typical patterns. Moreover, the 2022 TMG observes, primarily with respect to motorized traffic, that temporal adjustment factors are most accurately developed annually and applied to data from that same year to account for economic and environmental conditions. Non-motorized traffic volumes may be less sensitive to broad economic trends but more subject to environmental conditions and generally more volatile [45]. Therefore, a balance between timeliness and the breadth of data used to develop factors needs to be considered. Monitoring shifts in seasonal patterns over time and identifying data volatility is likely to be important in considering appropriate applications of the data.

Weekly Adjustment Factor

The 2022 TMG and NCHRP Report 797 also provide general guidelines for developing day-of-week (DOW) and hourly adjustment factors. While they can also be used, to some extent, to expand very short counts (i.e., hours or days, rather than weeks) into annualized daily averages, the principal purpose of DOW and hourly factors is to fill in data gaps for specific missing periods of time. For instance, if a few days of data are missing from a permanent count station due to power loss, relatively precise imputed values may be calculated using monthly and DOW adjustment factors to interpolate a typical value for that period. Likewise, if a pneumatic tube counter installed for two weeks is temporarily obstructed (e.g., by a parked car), these factors may be used to infer missing data for a few hours.

This is an optional step that may be valuable when comparing sites to provide similar volume estimates for a specific period. In all cases where imputed values are calculated, these should be clearly flagged in source datasets and noted in data reporting. Note that adjustment factors for very low-volume periods (e.g., overnight hours) should generally not be used, as near-zero counts can exaggerate the adjustment factor and yield unreliable estimates. A null or default value (e.g., 5% of ADT) may be substituted when late-night estimates are desired, based on an initial review of data patterns.

As with seasonal adjustment factors, DOW factors may be averaged across multiple locations (ideally among sites in like factor groups) to derive a general adjustment factor for interpreting data from similar locations. Because daily patterns vary more widely from site to site depending on land use context and facility type, generalized DOW factors should be applied with caution; a commuter-oriented downtown bike lane, for instance, will likely not have the elevated average user volumes observed on recreation-oriented trails.

In the same way, hourly adjustment factors may vary widely from site to site and by facility type, particularly in one-way facilities. Thus, in most cases, it will not be appropriate to generalize broadly until more robust factor group datasets are available. However, hourly patterns from one or more contextually similar locations may be judiciously used to expand data from short counts (e.g., manual counts) to derive an estimated 24-hour volume.

Day-of-Year Expansion Factors

Where a minimum of 12 months of continuous data, with few or no significant gaps, is available for at least one site per factor group within a study area, day-of-year (DOY) expansion factors may be developed to adjust short-term counts at similar sites during the same year. Researchers have found this method to provide greater overall accuracy [46] [47] [48], as the method inherently accounts for weather, rather than trying to derive and apply adjustment factors for specific weather characteristics and other day-specific variables. Mean error rates of 14 to 21% have been documented with as little as one day of short-term count data, compared to 24 to 40% using seasonal or day of week methods [48].

Expansions of data from sites geographically proximate to one another are found to perform better in terms of accuracy than those more distant from the reference count location [48]. However, the use of this method is only feasible where robust, relatively complete data exists, and adjustment factors must be recalculated annually. Researchers still recommend, where possible, the use of at least seven days of short-term count data to minimize error using DOY expansion factors [46] [47] [48]. Additionally, limited research comparing the accuracy of an averaged DOY expansion factor across sites within a factor group, versus simply using the geographically closest relevant count site as a reference, has been conducted to guide refinement of this method [48].

Impact of Weather on Activity Patterns

The TMG states that "overall climate conditions will strongly influence seasonal patterns. Day-to-day weather conditions will also influence specific daily or weekly patterns" [45]. Collection of detailed weather data for continuous counters may be used to develop adjustment factors to account for temperature, precipitation, humidity, or other variables presumed to significantly impact bicyclist and pedestrian activity [47]. Moreover, adjustment factors that incorporate weather factors have been found to outperform traditional methods applied to motor vehicles, which are less sensitive to weather conditions [47].

A significant body of research has examined the relationships between active transportation and various weather factors (e.g., temperature, precipitation, humidity, wind speed). The majority of such studies have focused on cities in temperate or cold climates (e.g., northern U.S., Canada, New Zealand, and northern Europe) and have emphasized cycling activities [47] [49] [50] [51] [52] [53]. These studies typically found that: (1) cycling tends to increase as temperature increases, up to a certain point, and (2) precipitation and humidity are often significant negative predictors. Other potential weather-related variables include maximum daily dew point depression and hours of daily sunshine.

Variations in the impact of weather based on user group and/or trip purpose are also explored, with the common finding that recreational bicyclists tend to be more weather-sensitive than commuters or utilitarian bicyclists [52] [53]. However, Wu et al. found that the quality of cycling infrastructure (i.e., physically separated facilities) mitigated the negative impact of weather factors on ridership for certain user groups (e.g., men and recreational riders) [54]. The presence or absence of alternative modes of access (e.g., public transit) was also identified as an important influence; when there are multiple convenient options for getting to work or other destinations, bicyclists may be more likely to switch modes during inclement weather.

Research on the impact of weather on pedestrian activity specifically is somewhat sparse. A study of modally separated user volumes on trail facilities in 13 cities across a variety of U.S. climate regions found a parabolic relationship of counts to weather factors, with temperature being the most important variable [55]. An analysis of the impacts of weather factors, including high temperatures, on pedestrian activity in Utah showed that temperatures above 90 degrees affected pedestrian activity and underscored the need to consider user needs at both ends of the weather spectrum when designing and operating infrastructure [56]. A study in Doha, Qatar, using short-term, dash-cam observations to fill an identified gap in research on hot climates found seasonal and temporal variation (e.g., more pedestrian activity in the evenings during hot weather) [57].

Overall, a variety of relationships between activity levels and weather variables have been tested and identified. However, gaps in the literature remain regarding active mobility, particularly in climate regions where policy goals encouraging multimodal travel may interact with the realities of escalating extreme weather. Incorporation of weather factors into the analysis of activity data overall, as well as into the development of local adjustment factors, will improve both the reliability of data outputs and the utility of their interpretation.

Objective

This project aimed to identify opportunities to integrate non-motorized traffic data (e.g., bicyclist and pedestrian) into routine motorized traffic counting practice in Louisiana. The specific objectives of the research included:

- Consolidating non-motorized traffic data collected to date by LTRC and DOTD onto a GIS platform;
- Exploring the possibilities of consolidating non-motorized traffic data collected by other public agencies onto the same GIS platform;
- Refining adjustment factors for short-term counters with additional data;
- Evaluating emerging data products by comparing them with the counting data collected to date in Louisiana; and
- Evaluating opportunities for and needs pertaining to expanding counting locations to support DOTD's needs.

Scope

This research primarily focused on managing non-motorized traffic data collected by LTRC and DOTD to date, but also considered data collected by other public agencies in anticipation of developing multi-agency collaborations in the future.

- **Data type**: Non-motorized traffic data refers to pedestrians (including wheelchairs, scooters, and other mobility devices) and bicyclists (including e-bikes).
- **Geographic scope**: The geographic scope of the data collection and analysis is intended to be statewide. However, permanent counters have been installed in four parishes in Louisiana to date, so the corresponding analysis was mostly completed for these four parishes, with the methodology applicable to a broader geographic scope.
- **Temporal scope**: Permanent count data from existing devices was compiled from 2020 through 2025 to support this project. Additionally, short-term count data representing a minimum of seven complete days of continuous hourly data collected by UNOTI through previous studies between 2017 and 2025 was integrated into the count database. Permanent counter data from 2021 to 2023 were used to develop adjustment factor calculations and to compare with Strava Metro data. When data from Replica was introduced in studying the fourth research objective, the temporal analysis scope was reduced to one year (i.e., 2023) due to data quality (e.g., missing network links in earlier years) and data availability at the study time. Finally, data from the most recent years (i.e., 2023, 2024, and 2025) were collected from Strava Metro and Replica to support counter location expansion analysis.

Methodology

This section introduces the methodologies the research team used to meet the research objectives outlined above.

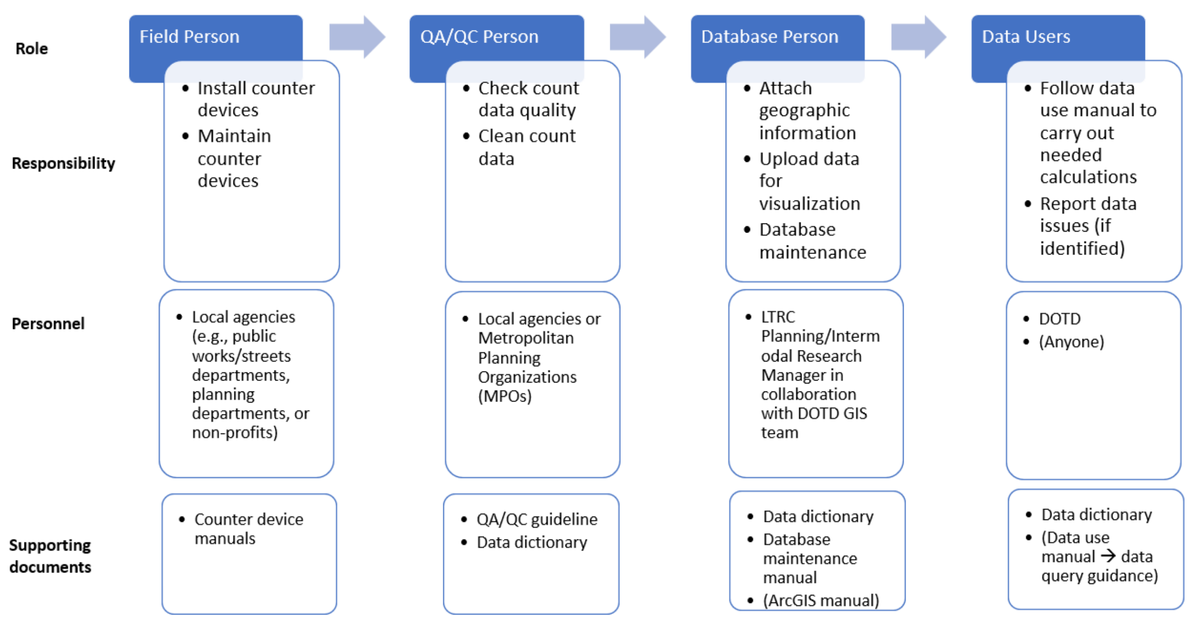
Counter Data Transmission, Management, and Maintenance

This subsection documents the research team's solution in meeting two of the research objectives: (1) consolidating non-motorized traffic data collected by LTRC and DOTD to date onto a GIS platform, and (2) exploring the possibilities of consolidating non-motorized traffic data collected by other public agencies onto the same GIS platform.

Data Transmission

Figure 5 is a draft of a potential data transmission plan that describes the major stakeholders and their responsibilities. This conceptual model needs to be tested in practice through implementation.

Figure 5. Draft data transmission chart



Data Management and Visualization

This section introduces the count database developed in compliance with federal guidelines and the QA/QC procedure.

Database Development

Data coding follows the *Coding Nonmotorized Station Location Information in the 2016 Traffic Monitoring Guide Format,* published by FHWA in November 2016 [58]. Appendix B provides a data dictionary that explains each data layer and field.

QA/QC Procedures

Data quality assurance/quality control (QA/QC) is essential to any traffic monitoring activity. All automated counting equipment has inherent errors; adjusting for these errors and validating data require well-defined protocols and standards established by the managing agency, as well as routine maintenance. As discussed above, a variety of factors can affect data quality, and the existing procedures for QA/QC for motor vehicles cannot be directly transferred to non-motorized datasets due to lower average volumes and much greater variability in bicyclist and pedestrian activity. Standard processes for eliminating data that falls outside two standard deviations of the mean, for example, would likely result in the deletion of many hours or days of accurate, valid activity reflecting local conditions at a given facility.

A more nuanced, localized approach to data review and processing is required to ensure valid results. Methods of cleaning, processing, and applying continue to evolve as additional cities and states develop more robust inventories of count locations and additional years of data for testing, analysis, and modeling. However, the general framework for assessing data quality always consists of several basic steps:

1. Chart and visually inspect data.
2. Determine criteria for assessing outliers.
3. Utilize professional judgment and context knowledge/research to make decisions about which data to include and exclude from the dataset.
4. Document all editing decisions and retain a copy of the raw dataset.

First, daily and hourly data must be downloaded for the specified time period, including directional information by mode, where applicable. Charting the data by hour (for shorter count durations) and by day (for longer count durations) typically reveals the most significant data gaps, spikes, or irregularities. When unusual data is observed at the daily level, further investigation of hourly data is warranted. As discussed above, reasons for irregular data are myriad, ranging from blocked sensors to equipment malfunction to special events and holidays. Not all unusual data is erroneous. Thus, particularly where counters are new, and no historical data exists against which to compare results, it is important to perform an initial review of atypically low or high counts to identify dates corresponding to major events or disruptions.

Once at least three months of uninterrupted data have been collected, with validation counts confirming equipment reliability, a series of conditional and statistical quality assurance tests may be applied to the data to identify and, if needed, filter invalid data from statistical calculations. Recommended tests for flagging and/or excluding data vary and should not be applied uniformly across sites without consideration of overall site characteristics and user volumes (i.e., lower volume sites require looser thresholds to account for high inherent variability). Table 3 outlines the series of recommended tests applied to the current permanent counter datasets to systematically assess large volumes of data, based on an initial review of at least 12 months of data. As a starting point, the count locations are classified based on total daily volumes. Parameters for thresholds (e.g., number of standard deviations, percentage of daily total) should be tailored to the specific site based on preliminary manual review of data (three months or more) and/or factor group classification, where comparable count sites exist. Initial parameters should be defined using professional judgment, be presumed to be preliminary, and be revised following the collection of the first 12 months of data and/or major changes in context, such as significant land use changes or facility upgrades.

Table 3. Basic QA/QC flagging framework for continuous counters

Test	**Description**	**Name**	**GENERIC High volume facility (> 500 per day)**	**GENERIC Moderate volume facility (100-500 per day)**	**GENERIC Low volume facility (<100 per day)**	**Comments**
Initial analysis period	Dates of data from which initial flag thresholds are set					
Gaps	Identify the number of hours in a day for which no data is available (no transmission)	Max_Exp_NoData	1	1	1	Preliminary exception; calculate data completeness % after all flags reviewed

Test	Description	Name	GENERIC High volume facility (> 500 per day)	GENERIC Moderate volume facility (100-500 per day)	GENERIC Low volume facility (<100 per day)	Comments
Zero counts	Determine how many intervals (hours, days) in a row with zero counts recorded	Max_Exp_0_Count	4 hours	8 hours	12 hours	Flagged values principally constituted of overnight hours are usually ok
Daily maximum	Exclude data that exceeds a determined upper threshold above which volumes are not physically reasonable. Parameters may vary by day of week/month of year.	Daily_Max	2000	800	200	Calculate by mode
Hourly maximum	Exclude data that exceeds a determined upper threshold above which volumes are not physically reasonable. Parameters may vary by day of week/month of year.	Hourly_Max	200	100	20	Calculate by mode
Overnight hourly	Test if any hours between 12:00 a.m. and 5:00 a.m. exceed a maximum expected value for low-volume hours	Max_Exp_12-5am	20	15	10	May differ if near nightlife or high early morning recreation usage
Overnight total	Test if total volume of users recorded between 12:00 a.m. and 5:00 a.m. exceed a maximum expected percentage of daily total	Night_%	10%	10%	10%	May need differing weekday/weekend values

Test	Description	Name	GENERIC High volume facility (> 500 per day)	GENERIC Moderate volume facility (100-500 per day)	GENERIC Low volume facility (<100 per day)	Comments
IN/OUT ratio	Where applicable, test if daily in:out ratio exceeds expected value (in either direction, assuming bi-directional design)	In_Out	60%/40%	70%/30%	70%/30%	Adjust for systemic sensor directional error (typically overcount IN values)
Standard deviation (above mean)	Flag data that is more than X standard deviations above the mean (by direction if applicable)	St_Dev_abovemean	2 standard deviations	2 standard deviations	2 standard deviations	Flag only to check for concurrent anomalies; data likely valid where variability is high
Standard deviation (below mean)	Flag data that is more than X standard deviations below the mean (by direction if applicable)	St_Dev_belowmean	2 standard deviations	1.5 standard deviations	n/a	Low-volume, high-variability sites may not use this metric
Standard deviation (direction)	Flag data that is more than X standard deviations above or below the mean of opposite-direction volumes	St_Dev_Direction	2 standard deviations	2 standard deviations	2 standard deviations	Needs further analysis; does not appear to work for lower bounds in most locations
IQR	Identify outliers based on interquartile range of all counts of a particular type (including direction, weekday vs. weekend, etc.), excluding any previously flagged data	IQR_Outliers	(varies)	(varies)	(varies)	Calculate on an as-needed basis, depending on notable site characteristics

Data exceeding determined parameters may be flagged for further review, omission, and/or correction. Flagged data should again be cross-checked against special events and extreme weather conditions. Note that low-user-volume count locations will often experience greater volume volatility and require additional review. Data strongly suspected to be incorrect should be scrubbed, and, if necessary, sources of potential error should be investigated if they are not apparent. In some cases, hourly data may be scrubbed, and daily totals must be recalculated, either as-is or by imputing hourly averages in place of the omitted data.

Data cleaning for LTRC permanent count sites utilized the above flagging framework, along with professional judgement, to review data for the initial analysis period (i.e., from installation through July 2022, as presented in Project 19-3SA) and develop customized flag thresholds (i.e., using conditional formatting tools in Excel to clearly mark data entries outside of threshold values) for each location, based on observed patterns and anomalies associated with each site. See Appendix C for an example of this process for a high- and low-volume count site using one year of test data. Subsequent data periods were cleaned by setting flag thresholds to these values to automatically identify potentially erroneous counts.

As data availability expands and confidence in parameters for a given site increases, data processing may be primarily automated. However, some targeted manual review is still required, particularly if data is used to develop expansion factors or in advanced analytic applications where errors may significantly impact outcomes. As a final step, a manual review of flagged data, based on professional judgment and local insight, was conducted to complete the initial cleaning of count data prior to data expansions and adjustments.

Database Maintenance

The database maintenance manual, included in Appendix D, covers the steps needed to transfer a count data sheet (.xlsx) into a spatial data sheet and save the spatial data sheet in a geodatabase file/folder (.gdb). The purpose of these steps is to reserve essential data information for data visualization and query on a shared data platform for public access. Detailed steps are included in the Appendix to address various needs to strengthen multi-agency collaboration on data management.

Adjustment Factor Calculation

This section describes the research team's approach to meeting the third research objective: refining adjustment factors for short-term counters with additional data.

A previous LTRC project (19-3SA) developed a set of multipliers for all count locations [4]. The calculation was based on a minimum of eight hours of manual validation counts to account for net sensor errors (i.e., sensor correction factor) as well as contextual errors (i.e., context correction factor) to derive an overall site-specific correction factor intended to estimate total bicyclist and/or pedestrian usage within the right-of-way. These correction factors are not expected to change significantly from year to year unless there are modifications to either the equipment or the facility being monitored, in which case additional manual validation counts should be completed. Whether to apply only a sensor correction factor, both a sensor and contextual correction factor, or no correction factor at all depends on the intended data use and audience.

The current research focuses on calculating monthly and weekly adjustment factors using the method recommended by FHWA in its most recent Traffic Monitoring Guide (TMG) [40] and considers the impacts of weather.

FHWA Method

The monthly adjustment factor is the ratio of Annual Average Daily Traffic (AADT) to Monthly Average Daily Traffic (MADT), while the weekly adjustment factor is the ratio of AADT to Weekly Average Daily Traffic (WADT). Therefore, the first step is to calculate AADT, MADT, and WADT. There have been various methodologies for such calculations with three basic procedures: simple average, AASHTO method, and FHWA method. The 2022 TMG recommends the last calculation method (i.e., FHWA method) over the other two [40]. Limitations of the first two methods are recorded in the 2022 TMG [40]. The following equations present how to calculate AADT, MADT, and WADT using the FHWA method.

$$MADT_m = \frac{\sum_{j=1}^{7} w_{jm} \sum_{h=1}^{24} \left[\frac{1}{n_{hjm}} \sum_{i=1}^{n_{hjm}} VOL_{ihjm} \right]}{\sum_{j=1}^{7} w_{jm}} \qquad [1]$$

$$AADT = \frac{\sum_{m=1}^{12} d_m * MADT_m}{\sum_{m=1}^{12} d_m} \qquad [2]$$

where,

$AADT$ = annual average daily traffic;

$MADT_m$ = monthly average daily traffic for month m;

VOL_{ihjm} = total traffic volume for the i-th occurrence of the h-th hour of day within j-th day of week during the m-th month;

n_{hjm} = the number of times the h-th hour of day within j-th day of week during the m-th month has available traffic volume. Its number ranges from 1 to 5 depending on hour of day, day of week, month, and data availability;

w_{jm} = the weighting for the number of times the j-th day of week during the m-th month (either 4 or 5); the sum of the weights in the denominator is the number of calendar days in the month (i.e., 28, 29, 30, or 31); and

d_m = the weighting for the number of days (i.e., 28, 29, 30, or 31) for the m-th month in a particular year.

Calculation example using the FHWA method. The equations presented above may appear complex at first glance. Here is a step-by-step calculation example with daily count data. Take January as an example. Table 4 is an example monthly calendar for January. Assume that daily counts are available for all the days in the January (indicated by X in Table 4). The first step is to calculate the day-of-week averages for January. For example, Avg_{Mon} equals the sum of the daily volumes observed on Mondays in January divided by five, the number of Mondays in the example month. Replicating this calculation for all weekdays in January will give the values shown on the last row in Table 4.

Table 4. An example monthly calendar

Mon	Tue	Wed	Thu	Fri	Sat	Sun
X	X	X	X	X	X	X
X	X	X	X	X	X	X
X	X	X	X	X	X	X
X	X	X	X	X	X	X
X	X	X				
Avg_{Mon}	Avg_{Tue}	Avg_{Wed}	Avg_{Thu}	Avg_{Fri}	Avg_{Sat}	Avg_{Sun}

The second step is to calculate MADT using Equation [1], which corresponds to Steps 5 and 6 in the FHWA AADT calculation example (see pages 3-70 in TMG 2022). The calculation using our example for January is as follows:

$$MADT_{Jan} = \frac{5 * (Avg_{Mon} + Avg_{Tue} + Avg_{Wed}) + 4 * (Avg_{Thu} + Avg_{Fri} + Avg_{Sat} + Avg_{Sun})}{5 * 3 + 4 * 4}$$

The last step is to calculate AADT using Equation [2], which corresponds to Steps 7 and 8 in the FHWA AADT calculation (see pages 3-70 in TMG 2020). This calculation is as follows:

$AADT = [31 * (MADT_{Jan} + MADT_{Mar} + MADT_{May} + MADT_{July} + MADT_{Aug} + MADT_{Oct} + MADT_{Dec}) + 30 * (MADT_{Apr} + MADT_{June} + MADT_{Sep} + MADT_{Nov}) + 28 * MADT_{Feb}]/(31 * 7 + 30 * 4 + 28)$

Calculating WADT. The calculation approach is similar to that shown in Equation [1]. The only difference is to sum by m (e.g., adding the number of Mondays across all the calendar months in a year) instead of by j:

$$WADT_j = \frac{\sum_{m=1}^{12} w_{jm} \sum_{h=1}^{24} \left[\frac{1}{n_{hjm}} \sum_{i=1}^{n_{hjm}} VOL_{ihjm} \right]}{\sum_{m=1}^{12} w_{jm}} \qquad [3]$$

where,

$WADT_j$ = weekly average daily traffic for j-th day of week;

VOL_{ihjm} = total traffic volume for the i-th occurrence of the h-th hour of day within j-th day of week during the m-th month;

n_{hjm} = the number of times the h-th hour of day within j-th day of week during the m-th month has available traffic volume. Its number ranges from 1 to 5 depending on hour of day, day of week, month, and data availability; and

w_{jm} = the weighting for the number of times the j-th day of week during the m-th month (either 4 or 5); the sum of the weights in the denominator is the number of calendar days in the month (i.e., 28, 29, 30, or 31).

Finally, it should be noted that complete data may not be available for all days, weeks, or months in a year in practice. A solution is to pool data collected from multiple years to support AADT, MADT, and WADT calculations.

Leveraging the Power of Emerging Data Sources for Non-Motorized Traffic Monitoring: Virtual Counters

This section documents the research team's method in meeting the fourth research objective: evaluating emerging data products by comparing them with counting data collected to date in Louisiana.

The 2022 TMG states: "One of the most important tasks of the continuous count program is the monitoring of traffic volume trends and the tracking of temporal patterns around the state. Temporal patterns are used by the agencies to group continuous count sites together for the development of traffic volume adjustment factors for factoring data from short-term count sites. Foremost among these trends is the monitoring of AADT at specific highway locations" [40]. Apparently, it is impossible to install permanent counters on all the routes. Third-party mobility data, such as Strava and LBS data, has the potential to fill in the gap since they have continuously tracked human activities throughout the years. That data could potentially serve as virtual, permanent counters installed across the entire road network. Past studies using this approach have compared non-motorized traffic volume from mobility data sources directly with that from permanent counters [9] [59]. Such comparisons were typically made annually for metropolitan areas and, in most cases, were limited to correlation tests. Some studies also seek to predict observed counts by using the third-party mobility data, built environment-related factors, socio-demographic factors, and weather-related factors [59]. The approach is straightforward, but its pitfall lies in criticisms of the third-party mobility data's representativeness [60]. The internal data representativeness bias could potentially be reduced when mobility data are compared against themselves to present patterns and trends [61]. Such an operation is performed during the calculation of adjustment factors. Therefore, another approach for broader applications might be to use collected counter data to calibrate adjustment factors calculated with third-party mobility data. The current study aimed to answer the following three questions:

- Q1: How large is the raw count discrepancy between counter data and human mobility data products?
- Q2: Will the discrepancy be reduced if raw counts from human mobility data are used to generate adjustment factors?
- Q3: Can human mobility data from multiple sources help improve the practice of relying on permanent counters for adjustment factor calculation?

The first two questions can be answered by conducting visual observations from plots and making simple correlation tests. The third question can be answered by estimating a spatial-temporal model based on the following equation. Here, a linear relationship with potential explanatory variables is used as an illustration:

$$AdjustmentFactor_{Counter}^{it} = Constant + b_1 * AdjustmentFactor_{MobilityData}^{it} + b_2 * BuiltEnvironment^{i} + b_3 * SocioDemographics^{i} + b_4 * NearbyActivity^{it} + b_5 * TemporalFactor^{t} \quad [4]$$

where,

$AdjustmentFactor_{Counter}^{it}$ = weekly/monthly adjustment factors calculated by using counter data for location i for time t (i.e., Monday to Sunday in the weekly case; January to December in the monthly case);

$AdjustmentFactor_{MobilityData}^{it}$ = weekly/monthly adjustment factors calculated by using mobility data for location i at time t (i.e., Monday to Sunday in the weekly case; January to December in the monthly case);

$BuiltEnvironment^{i}$ = built environment factors at location i, such as land use and characteristics of other transportation facilities;

$SocioDemographics^{i}$ = socio-demographic factors at location i, such as population density;

$NearbyActivity^{it}$ = human activities in nearby places, such as the number of people visiting nearby points-of-interests (POIs). This type of data could be collected from other mobility data vendors that provide place-based insights, such as SafeGraph and Advan [62]; and

$TemporalFactor^{t}$ = temporal factors could be weekday/month/season indicators. This could also be temporal lags (such as adjustment factors calculated in a previous time period).

The parameters estimated from the model (i.e., $constant, b_1, b_2, b_3, b_4, and\ b_5$) will help ensure the adjustment factors calculated from mobility data are close to those calculated from counter data.

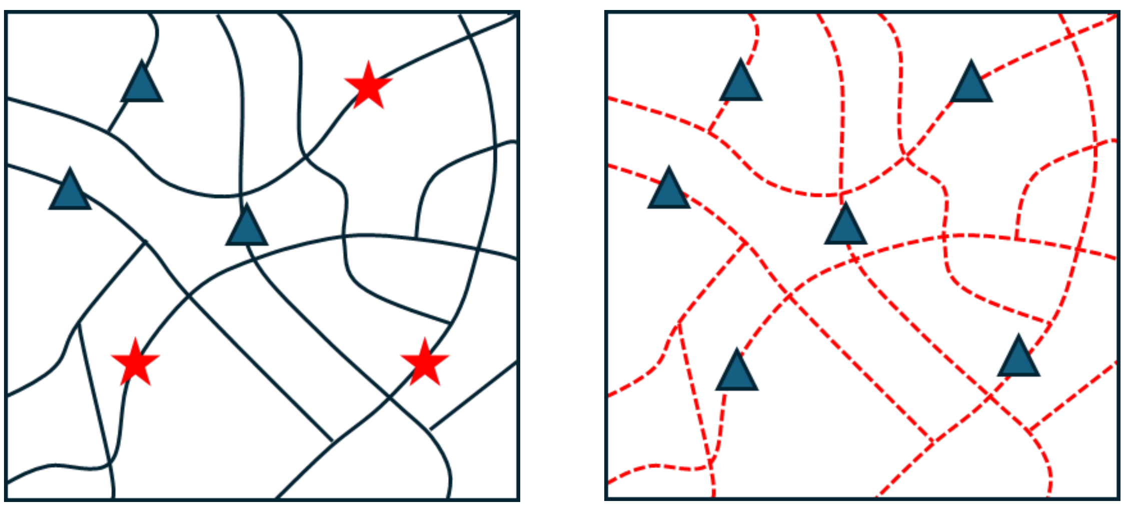
It is expected that mobility data can help generate adjustment factors across the entire road network with data passively collected on a continuous basis in a wide spatial scope. Additionally, the adjustment factors can be calibrated using the above-estimated parameters for any location on the road network, since the required input data are generally available. This characteristic makes the approach useful for expanding short-term counts to generate AADNT for a location or for predicting future activities at that location when a permanent counter is absent. That is, AADNT estimates will be possible for places where only short-term counts exist (i.e., not for out-of-sample predictions). The ultimate purpose of the whole process is to leverage human mobility data for network-wide traffic predictions and monitoring, which are called Virtual Network Sensors in short. The following equation illustrates the process described above. This process should especially benefit areas with limited resources by enabling an extensive set of permanent counters to be installed in practice. Figure 6 is a conceptual illustration of the traditional and future counting practice.

$$\widehat{AdjustmentFactor}_{Counter}^{it} = \widehat{Constant} + \hat{b}_1 * AdjustmentFactor_{MobilityData}^{it} + \hat{b}_2 * BuiltEnvironment^{i} + \hat{b}_3 * SocioDemographics^{i} + \hat{b}_4 * NearbyActivity^{it} + \hat{b}_5 * TemporalFactor^{t} \quad [5]$$

where,

$\widehat{AdjustmentFactor}_{Counter}^{it}$ = adjustment factors estimated for location i for time t (e.g., January to December in the monthly case).

Figure 6. Conceptual illustration of non-motorized traffic monitoring (traditional vs future)



(a) Traditional: road network with permanent counters (in red star) installed at strategic locations and short-term counters (in blue triangle) rotated

(b) Future: road network with Virtual Network Sensors (in red dashed line) covering the entire region with short-term counters (in blue triangle) rotated

Validation Process

Validating the estimated parameters for the approach is related to the use cases described in the previous paragraph. Assume short-term count data were collected at the same location but for two different time periods (e.g., January 2021 and July 2023). The following equation is used to predict the number of trips in July 2023 at that location, which can be compared with the actual observations for validation.

$$\widehat{ShortCount}^{July,2023} = ShortCount^{January,2021} * YearlyGrowthFactor * \frac{\widehat{AdjustmentFactor}_{Counter}^{January}}{\widehat{AdjustmentFactor}_{Counter}^{July}} \quad [6]$$

where,

$\widehat{AdjustmentFactor}_{Counter}^{January}$ and $\widehat{AdjustmentFactor}_{Counter}^{July}$ = monthly adjustment factors estimated for location i for January and July, respectively;

$ShortCount^{January,2021}$ = short-term count data collected for location i in January 2021;

$\widehat{ShortCount}^{July,2023}$ = number of predicted activities for location i in July 2023; and

$YearlyGrowthFactor$ = annual growth factor.

The following equation takes weather factors into consideration to test whether they could further improve the predictions and address the impacts from extreme weather events and climate change:

$$\widehat{ShortCount}^{July,2023} = ShortCount^{January,2021} * YearlyGrowthFactor * \frac{\widehat{AdjustmentFactor}_{Counter}^{January}}{\widehat{AdjustmentFactor}_{Counter}^{July}} * \frac{Weather^{January,2021}}{Weather^{July,2023}} \quad [7]$$

where,

$Weather^{January,2021}$ and $Weather^{July,2023}$ = weather factors (e.g., precipitation and temperature) for location i in January 2021 and July 2023, respectively.

Developing Counter Location Selection Strategy for Statewide Non-Motorized Traffic Monitoring

The final objective of this research was to provide methodological guidance on strategically expanding data collection to optimize the utility of these data for network-level analysis, planning, and performance measurement. Most communities in Louisiana currently lack the foundational data on which to base such an analysis. For agencies or groups interested in initiating new data collection activities where no or few permanent counters currently exist, site selection strategies will vary based on program goals and the type and extent of active transportation facilities available. Most jurisdictions begin by collecting permanent counts at one or more key locations where site conditions are conducive to installation and maintenance, where relatively robust non-motorized activity is expected, and/or where a new active transportation facility has been installed. The data frameworks and applications described within this study are intended to be flexible; any count technology (i.e., mechanical sensors, video-based, etc.) which collects data at a suitable level of temporal granularity (i.e., hourly data or smaller) and which can reliably collect data continuously for a long period of time (ideally, multiple years) may be used to initiate and/or expand a permanent count program.

As programs expand beyond the initial sites, identification of locally relevant typical usage patterns or contexts (i.e., factor groups) is suggested to determine priority areas for expansion. For additional information about site selection and non-motorized count program initiation, please refer to LTRC Project 16-4SA: Pedestrians and Bicyclists Count [63], LTRC Project 19-3SA: Pedestrians and Bicyclists Count Phase II [64], and the TMG [45] for site selection criteria, guidance on basic factor group identification, and initial counter planning, installation, and validation protocols.

The approach and related findings described in this section reflect an effort to explore methods for moving from a small set of permanent count locations representing two or more factor groups to a larger, more representative sample of contexts, using supplementary datasets that provide network-level data. This study proposes a two-stage spatial-temporal clustering framework to identify groups of network segments that have similar spatial characteristics and temporal activity patterns. The clustering results are then used to identify representative monitoring locations within each cluster.

Data Preparation

This part of data analysis used bicyclist and pedestrian activity data obtained from Strava Metro and Replica from the most recent years (i.e., 2023, 2024, and 2025). The temporal coverage ranged specifically from Spring 2023 to Spring 2025. Data for Fall 2025 was not available at the time of collection and were therefore excluded from the analysis. Replica data were available across the entire state, whereas Strava Metro data were available for four parishes: East Baton Rouge Parish, Lincoln, St. Tammany, and Orleans Parishes. As a preliminary analysis, only roadway segments located within these four parishes were considered to ensure that observations from both data sources could be included. Roadway segments from the two datasets were matched based on the OpenStreetMap segment identifier (osmId). The unique identifier allows observations from the two sources to be merged into one dataset.

Next, seasonal or weekly adjustment factors were calculated for each roadway segment i by using data from the two different data sources, respectively. Here, adjustment factors, rather than raw counts, are used in the analysis because findings from the previous tasks show that converting raw counts from mobility data sources into adjustment factors can help reduce discrepancies. Due to data granularity, seasonal adjustment factors can only be calculated to distinguish fall from spring, while weekly adjustment factors can only be calculated to distinguish Saturday (i.e., weekend) from Thursday (i.e., workday).

$$X_{ij}^{Mode} = \{AF_{ij}^{S}, AF_{ij}^{R}\} \quad [8]$$

where,

X_{ij}^{Mode} = a set of seasonal/weekly adjustment factors developed for a travel mode (i.e., bicyclist and pedestrian) on a road segment i;

AF_{ij}^{S} = a set of seasonal/weekly adjustment factors (i.e., $AF_{i,Fall}^{S}$, $AF_{i,Spring}^{S}$, $AF_{i,Thu}^{S}$, $AF_{i,Sat}^{S}$) calculated based on data from Strava Metro (S); and

AF_{ij}^{R} = a set of seasonal/weekly adjustment factors (i.e., $AF_{i,Fall}^{R}$, $AF_{i,Spring}^{R}$, $AF_{i,Thu}^{R}$, $AF_{i,Sat}^{R}$) calculated based on data from Replica (R).

Two-Stage Spatial-Temporal Clustering Framework

A two-stage clustering framework was implemented to identify representative road segments with similar spatial characteristics and temporal activity patterns.

Stage 1: Spatial Clustering Using DBSCAN

The first stage of clustering groups roadway segments was based on their geographic proximity using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm [65]. DBSCAN identifies clusters of observations that are spatially close while labeling isolated points as noise. Unlike partitioning methods, DBSCAN does not require the number of clusters to be specified in advance and can identify clusters of arbitrary shapes, making it suitable for road network datasets.

Each roadway segment i in the dataset was represented spatially using the midpoint of its geometry. The midpoint coordinate was calculated from the longitude and latitude of the segment's starting and ending nodes. The geographic coordinates were then transformed into a planar coordinate system using a Universal Transverse Mercator (UTM) projection to support accurate spatial distance calculations [66]. After projection, each segment is represented by planar coordinates (x_i, y_i), where x_i and y_i denote the projected coordinates measured in meters.

Spatial clustering was then performed based on the Euclidean distance between segment locations. The ϵ-neighbourhood of observation p is defined as:

$$N_\varepsilon(p) = \{q \in D \mid dist(p, q) \leq \varepsilon\} \qquad [9]$$

where,

D = the set of observations (i.e., road segments) whose midpoint falls within distance ε of segment p;

ε = 1500m in bicycle analysis and 500m in pedestrian analysis, which are the smallest values achieving a noise rate below 15%; and

$dist(p, q)$ = the Euclidean distance (i.e., $\sqrt{(x_p - x_q)^2 + (y_p - y_q)^2}$) between two observations p and q.

A point p is classified as a core point if the number of observations within its ϵ-neighborhood is greater than or equal to the minimum points threshold (i.e., $minPts$). A core point represents an observation located in a high-density region of a spatial dataset.

$$\mid N_\varepsilon(p) \mid \geq minPts \qquad [10]$$

Core points therefore represent observations located in relatively high-density areas of the spatial dataset. The neighborhood radius parameter, ϵ, was determined through sensitivity testing of multiple candidate values, considering the number of clusters formed, the proportion of noise observations, and the distribution of cluster sizes. The output of this stage assigns each roadway segment to a spatial cluster S_i.

Stage 2: Temporal Clustering of Activity Patterns

While spatial clustering groups geographically proximate roadway segments, segments within the same spatial cluster may exhibit different temporal patterns. Therefore, a second clustering stage was conducted to identify temporal activity patterns within each spatial cluster. Prior to clustering, temporal variables were standardized using z-score normalization:

$$z_{ij} = \frac{X_{ij}^{Mode} - \mu_j}{\sigma_j} \quad [11]$$

where,

X_{ij}^{Mode} = the set of seasonal or weekly adjustment factors developed for a travel mode (i.e., bicyclist and pedestrian) on a road segment i, as defined previously; and

μ_j, σ_j = the mean and standard deviation of a time period.

Temporal clustering was performed using the k-means algorithm, which groups observations into k clusters by minimizing the sum of squared distances within a group. The optimal number of temporal clusters was determined by using silhouette analysis [67].

Final Spatial-Temporal Cluster Representation

The final classification of roadway segment i combines both spatial ($S_{i \in n}$) and temporal ($T_{i \in k}$) clustering results. The temporal clusters are nested within spatial clusters, allowing spatial clusters within the same geographic region to be further differentiated by their temporal activity patterns. The resulting spatial-temporal clusters represent roadway segments with similar geographical characteristics and temporal activity patterns. These clusters will further guide the selection of permanent and temporary counter locations for the non-motorized traffic study by ensuring that monitoring locations capture the diversity of activity patterns across transportation networks.

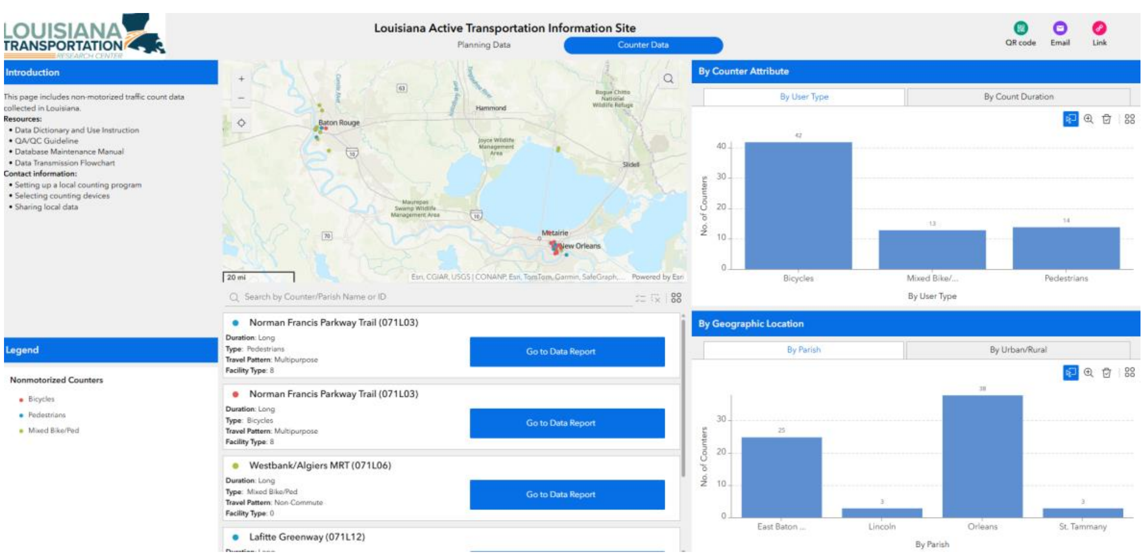
Discussion of Results

This section documents the results of applying the methodologies described in the previous section to meet the research objectives.

Data Collected to Date in Louisiana

A dashboard prototype was created and is now hosted on the DOTD GIS production portal for quick data access (i.e., the Active Transportation Information Site); see Figure 7. The list of permanent and short-term counters is presented geographically on a map, with their major attributes listed below the map. Several charts are included on the right side to provide an overview of counters by user type, count duration, parish, or urban/rural. The dashboard is currently hosted on both the DOTD GIS development portal, accessible to all DOTD employees, and the DOTD GIS production portal, accessible to a limited group of users and eventually expected to be accessible to the entire public.

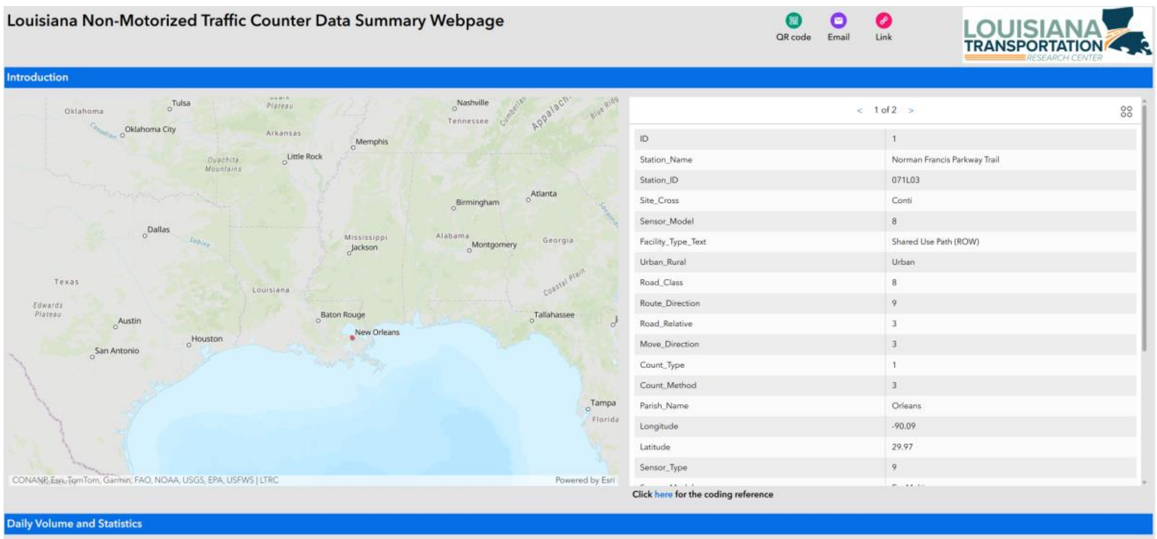
Figure 7. Dashboard prototype appearance (main page)



Permanent Counters

The dashboard currently hosts information for 29 permanent counters installed to date across 18 sites in Louisiana. These counters are intended for data collection for a period of one year or more. A count data summary page was developed to show daily volume and statistics (i.e., average daily volume by year, month, and day of week) and hourly volume and statistics; see Figure 8.

Figure 8. Dashboard prototype appearance (permanent count data summary page)



Of the original 18 count sites, seven have remained operational throughout the project period. Previous research (LTRC Project 23-5SS) summarized data through July 2022, which was used to develop preliminary factor groups and adjustment factors as discussed above. Most of the permanent counters were originally installed in 2020 or 2021, when active transportation activities were still significantly influenced by well-documented shifts in travel patterns related to COVID-19. While the developed dashboard provides detailed, site-level insights into hourly, daily, and seasonal patterns, this section provides a broad overview of longitudinal data across count sites with multiple years of post-COVID data to assess general trends and implications for planning. Appendix E outlines mean daily user averages for each site, by year and mode, where applicable. These averages are not adjusted and do not include imputed values for missing data. When there are significant data gaps, mean values may not fully represent complete annual averages.

Short-Term Counters

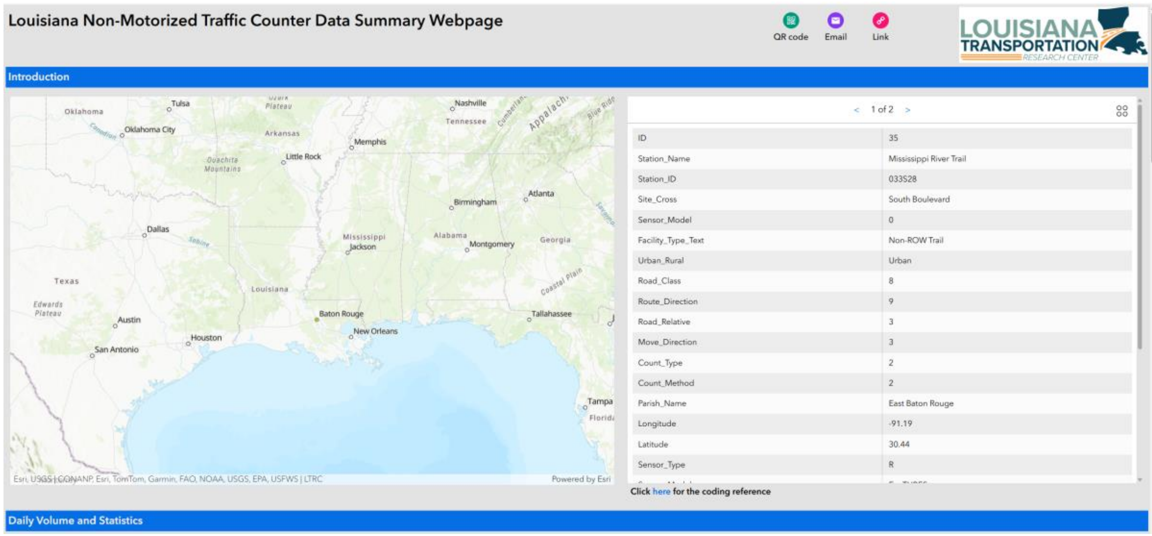
In addition to the ongoing maintenance of equipment and data from permanent counters, this study incorporated data from automated short-term counts collected by UNO Transportation Institute from 2017 through 2025, including two additional counts collected specifically for this study to supplement data collected at those sites (Tulane Avenue and Martin Luther King, Jr Blvd) in previous years. This included a total of 54 counts across 21 sites, with up to four sensors installed per site (e.g., to capture two sidewalk facilities and bicycle lanes on either side of a roadway) and some sites visited in multiple years. Only sites for which a minimum of seven complete days of data were available were included in the dashboard. Although these counts were collected across several projects and for different sponsors, all counts were collected in accordance with the guidance outlined in LTRC Project 16-4SS [68].

The average (mean) count duration was 24 days per counter, with a median of 19 days, including partial beginning and ending days. Nine of the count locations were in Baton Rouge, and 12 were in New Orleans. Thirty-seven of the counts captured bicycles (i.e., pneumatic tube counters); 11 were intended to count pedestrians on sidewalks, though these may also have counted bicycles traveling on sidewalks; and six counted all users on shared-use trails. A full list of short-term counts collected by site is available in Appendix E.

Through the diagnostic stakeholder survey, additional samples of local data were solicited and reviewed. However, none of these were determined to be sufficiently granular (i.e., hourly data bins or smaller) and/or of adequate length (i.e., a minimum of seven days of continuous data) to comply with minimum viable data standards and warrant inclusion in the database at this time. These counts, collected using pneumatic tubes, manual review of video data, or manual field observation, are indicative of typical project-based data collection practices and highlight an opportunity to outreach to local and regional agencies and their contractors to support enhanced, coordinated multimodal count practices that provide compatible data.

The dashboard currently hosts information for short-term counters installed to date in Louisiana; see Table 17 in Appendix E. A separate count data summary page is developed to show daily volume and statistics (i.e., average daily volume by day of week) and hourly volume and statistics; see Figure 9.

Figure 9. Dashboard prototype appearance (short-term count data summary page)



Adjustment Factors

Table 5 shows whether adjustment factors can be calculated for all permanent counters in Louisiana using three years of data from January 2021 to December 2023. It is noted that calculating adjustment factors for each year, as recommended in the TMG, is not feasible in the current situation due to data shortages.

Table 5. Adjustment factor calculation overview

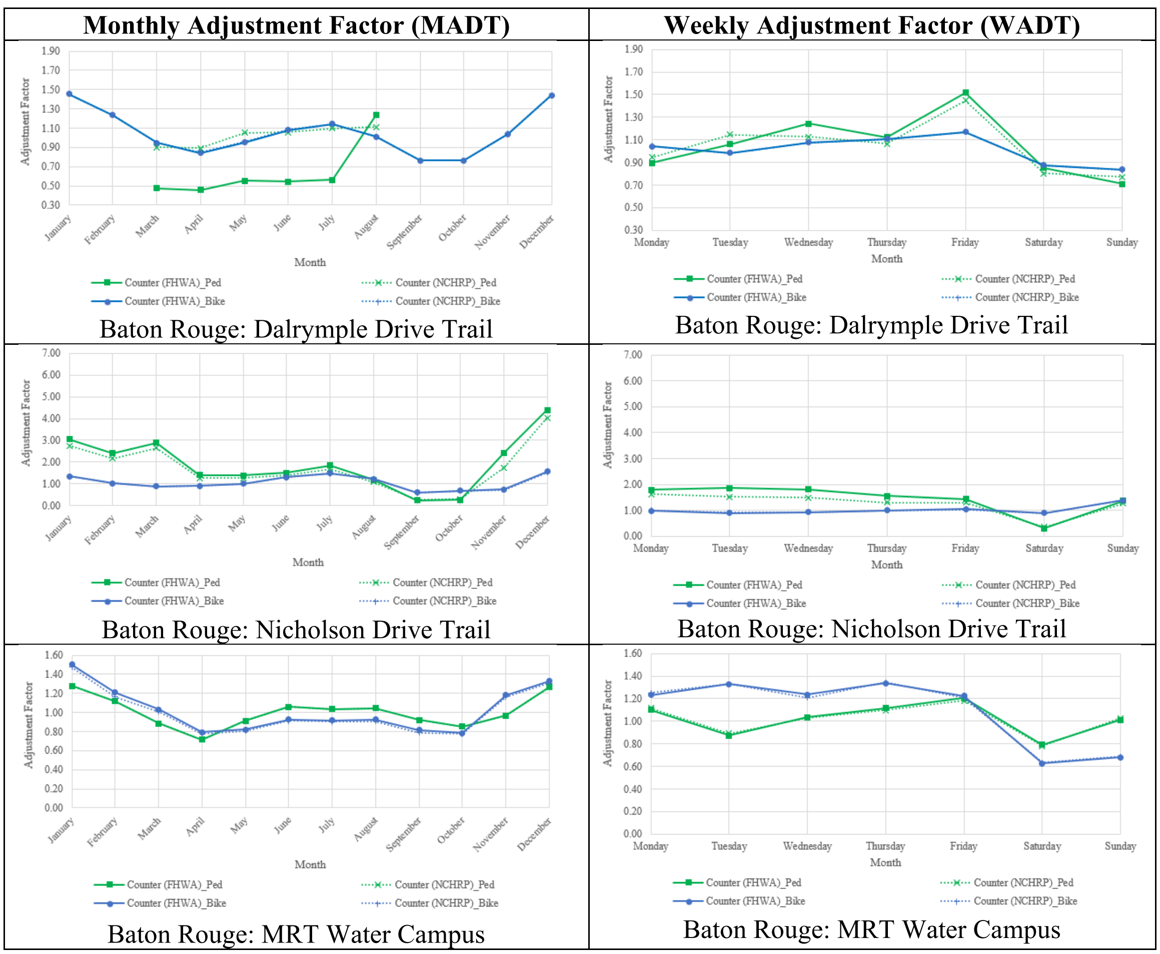
City name	Counter name	Monthly		Weekly	
		Ped	Bike	Ped	Bike
Baton Rouge	Dalrymple Drive Trail	Partial	Complete	Complete	Complete
Baton Rouge	Nicholson Drive Trail	Complete	Partial	Complete	Partial
Baton Rouge	MRT Water Campus	Partial	Complete	Partial	Complete
Baton Rouge	Government Street	No	Complete	No	Complete
Baton Rouge	Capital Heights Avenue	No	Partial	No	Complete
New Orleans	Norman Francis Parkway Trail	Complete	Complete	Complete	Complete
New Orleans	Lafitte Greenway	Complete	Complete	Complete	Complete
New Orleans	Baronne Street	No	Complete	No	Complete
New Orleans	Wisner Trail	Complete	Complete	Complete	Complete
New Orleans	Esplanade Avenue	No	Complete	No	Complete
Mandeville	Tammany Trace	Complete	Complete	Complete	Complete

Note: "No" means adjustment factors are not available. "Partial" means adjustment factors are available for certain months/weekdays but not all. "Complete" means adjustment factors are available for all the months/weekdays.

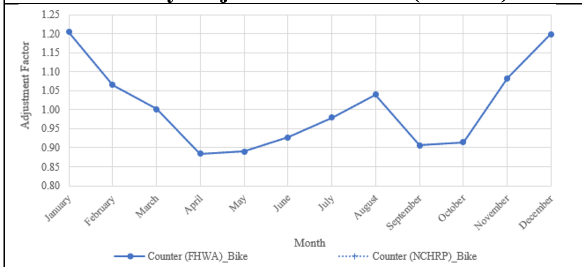
Comparing Previous Results with FHWA Calculations for Permanent Counters

Figure 10 shows monthly and weekly adjustment factors calculated by using both the FHWA and NCHRP methods for permanent counters in Louisiana. Pedestrian activities are shown in green, while bicyclist activities are shown in blue. The solid lines represent adjustment factors calculated by using the FHWA method. The dotted lines represent adjustment factors calculated by using the NCHRP method (i.e., used in LTRC Project 19-3SA). When the collected counts are more complete, the two calculation methods produce similar adjustment factor values. When the number of observations is insufficient for certain months/weekdays, the two calculation methods yield quite different adjustment factor values (e.g., MADT for pedestrian activities on Dalrymple Drive Trail and MADT for bicyclist activities on Capital Heights Avenue).

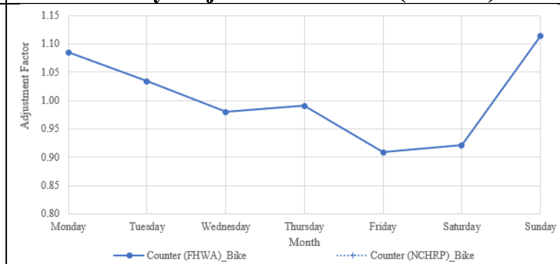
Figure 10. Monthly and weekly adjustment factors for permanent counters in Louisiana



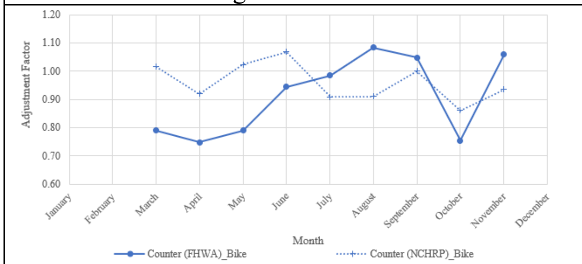
Monthly Adjustment Factor (MADT)	Weekly Adjustment Factor (WADT)



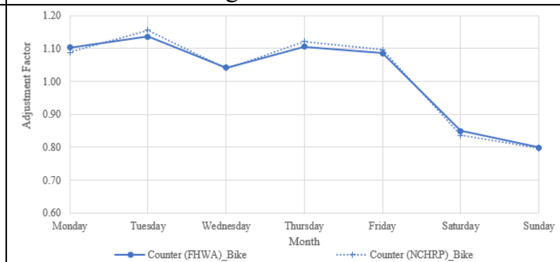
Baton Rouge: Government Street



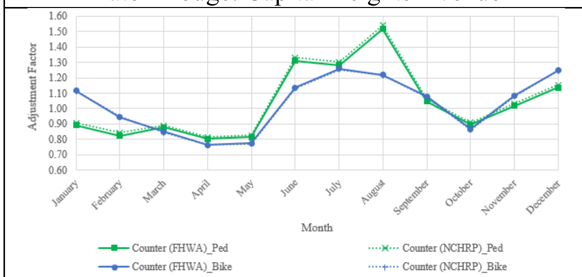
Baton Rouge: Government Street



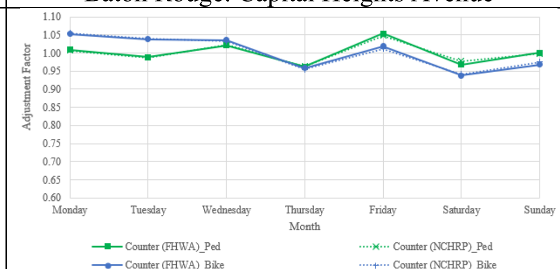
Baton Rouge: Capital Heights Avenue



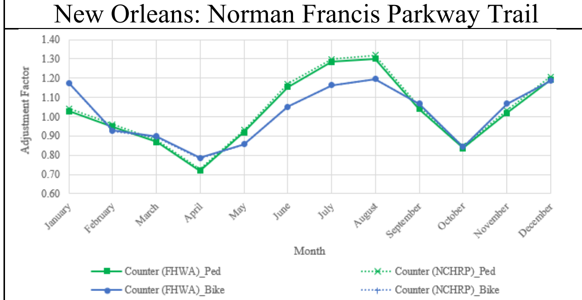
Baton Rouge: Capital Heights Avenue



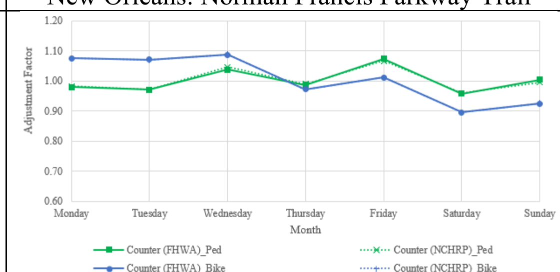
New Orleans: Norman Francis Parkway Trail



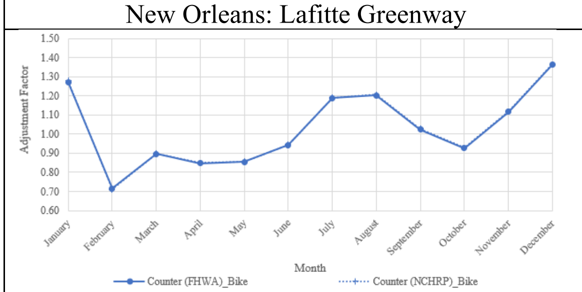
New Orleans: Norman Francis Parkway Trail



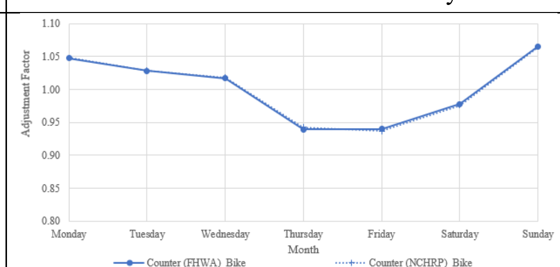
New Orleans: Lafitte Greenway



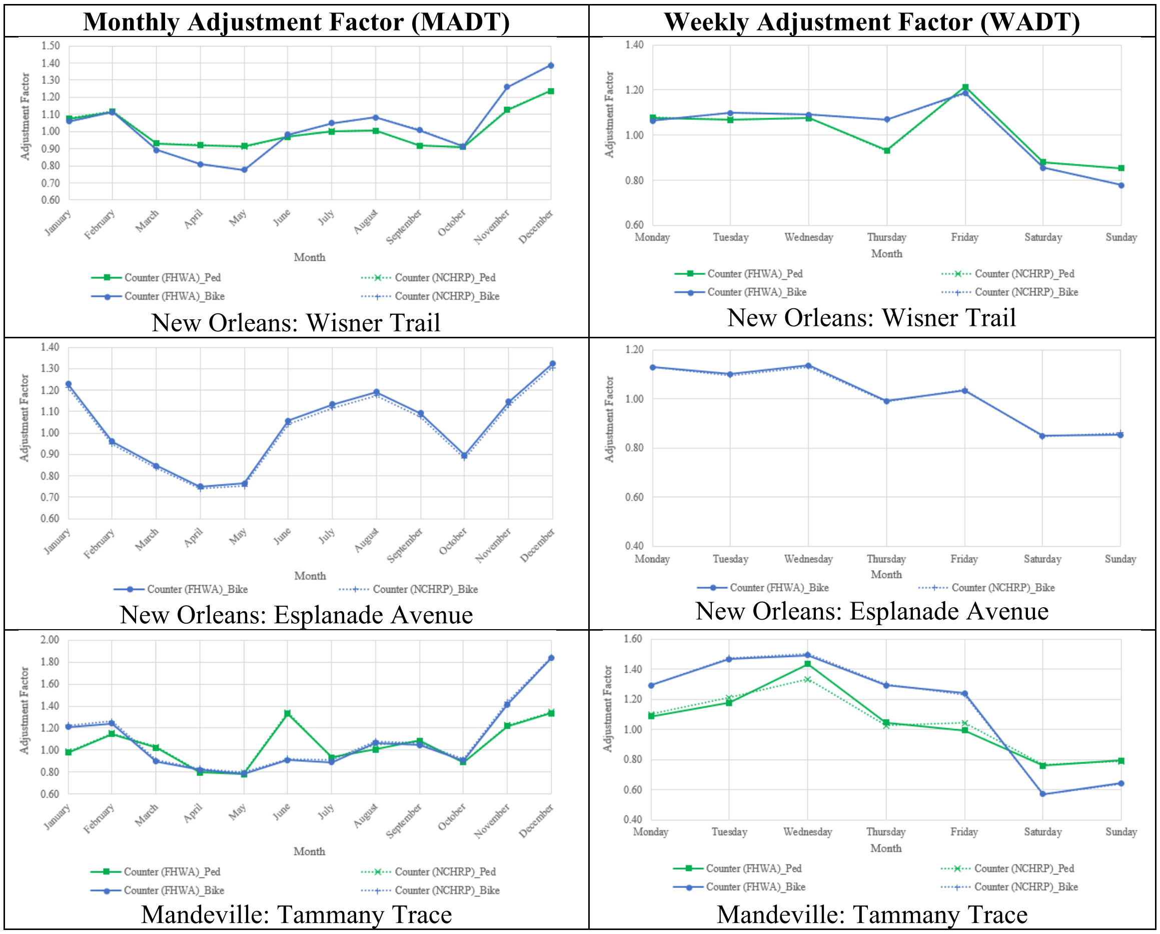
New Orleans: Lafitte Greenway



New Orleans: Baronne Street



New Orleans: Baronne Street



Comparing Factors Calculated by Emerging Data Sources with Those by Counter Data

Counter vs. Strava Metro

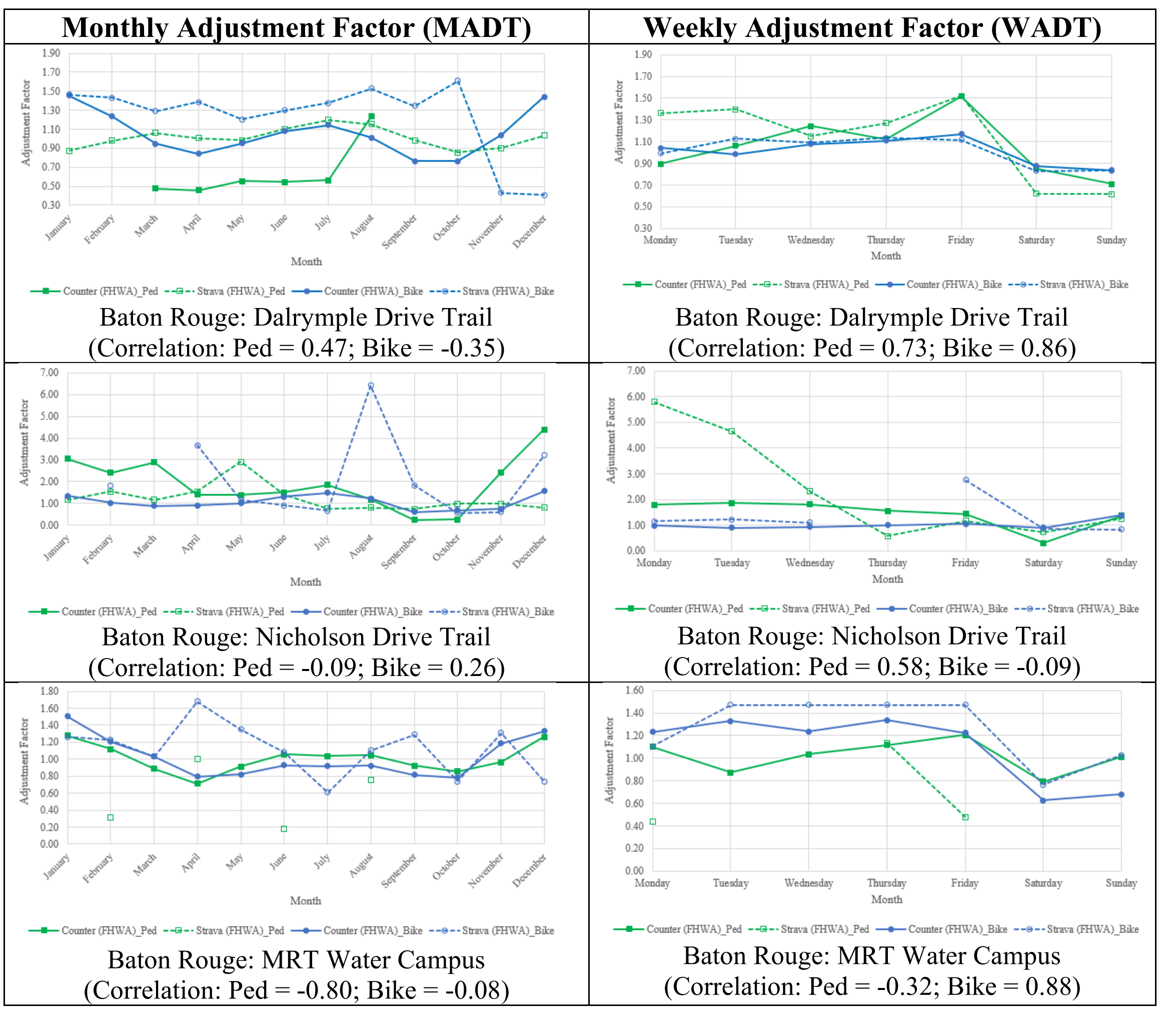
Figure 11 shows monthly and weekly adjustment factors calculated using the FHWA method, with data from permanent counters in Louisiana and third-party data (Strava Metro). Pedestrian activities are shown in green, while bicyclist activities are shown in blue. The solid lines represent adjustment factors calculated by using the FHWA method with counter data. The dashed lines represent adjustment factors calculated by using the FHWA method with Strava Metro data.

First, the adjustment factors calculated with the two different data sources are at least within a similar range. This observation suggests that third-party data may be more useful for adjustment factor calculations, with additional calibrations, than as a direct source to replace count data.

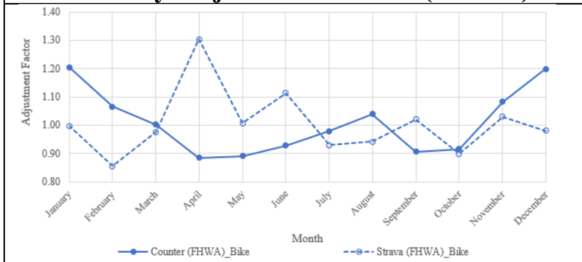
Second, adjustment factors calculated from the two data sources are very close in some cases, such as WADTs for bicyclist activities on Dalrymple Drive Trail and for pedestrian activities on Wisner Trail. Among the 36 cases, 12 have absolute correlation values of 0.8 or greater, while another 12 have values between 0.4 and 0.8.

Among the remaining 12 cases, their adjustment factors were calculated using the two different data sources, which differed from each other (i.e., correlation was lower than 0.4). Additionally, Strava data sometimes could not produce adjustment factors for a particular month or week. For example, MADT for pedestrian activities on the facility associated with the MRT Water Campus count site is only available for four calendar months. This phenomenon may relate to how Strava coded its count data and the availability of count observations, as explained in the literature review section.

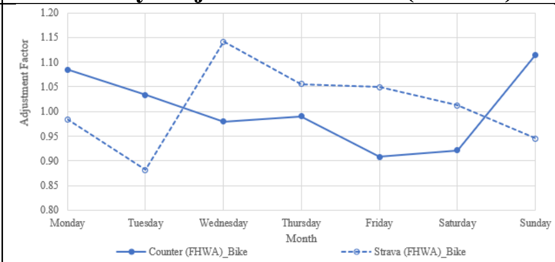
Figure 11. Monthly and weekly adjustment factors calculated with counter and Strava data



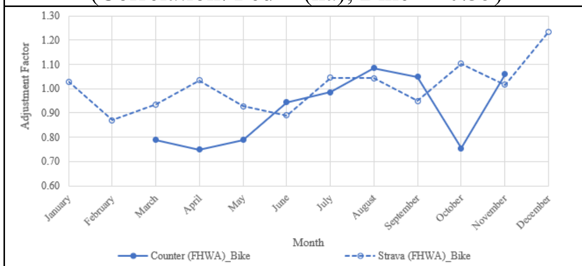
Monthly Adjustment Factor (MADT)	Weekly Adjustment Factor (WADT)



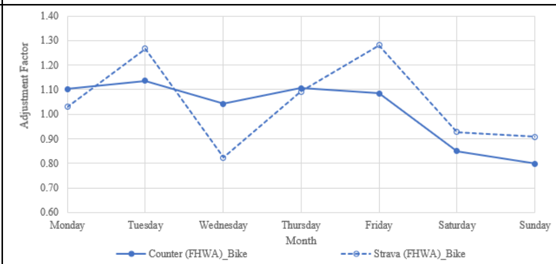
Baton Rouge: Government Street
(Correlation: Ped = (na); Bike = -0.35)



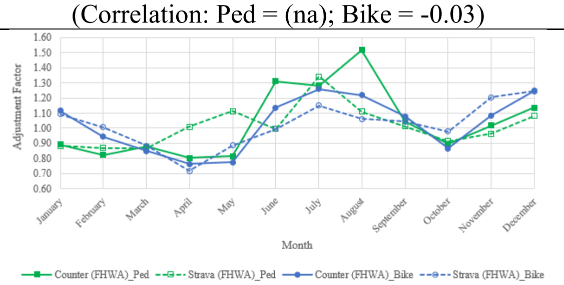
Baton Rouge: Government Street
(Correlation: Ped = (na); Bike = -0.53)



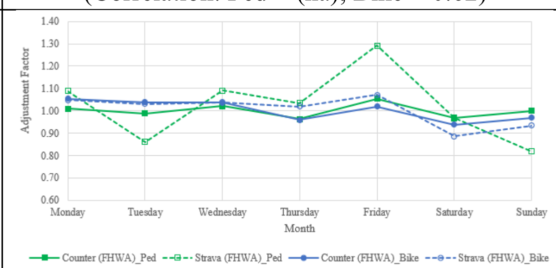
Baton Rouge: Capital Heights Avenue
(Correlation: Ped = (na); Bike = -0.03)



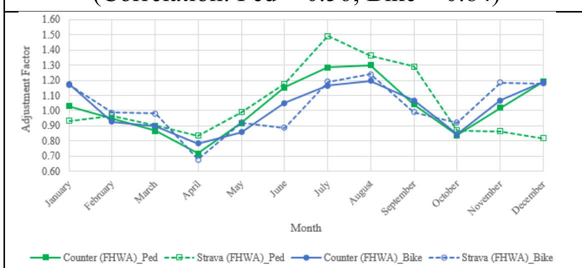
Baton Rouge: Capital Heights Avenue
(Correlation: Ped = (na); Bike = 0.62)



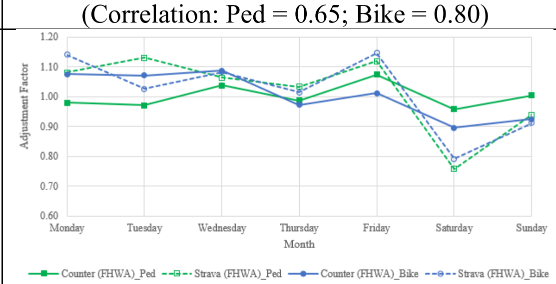
New Orleans: Norman Francis Parkway Trail
(Correlation: Ped = 0.56; Bike = 0.84)



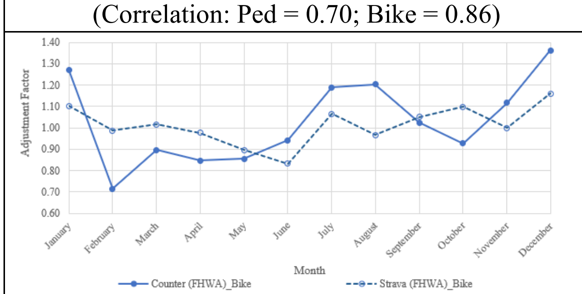
New Orleans: Norman Francis Parkway Trail
(Correlation: Ped = 0.65; Bike = 0.80)



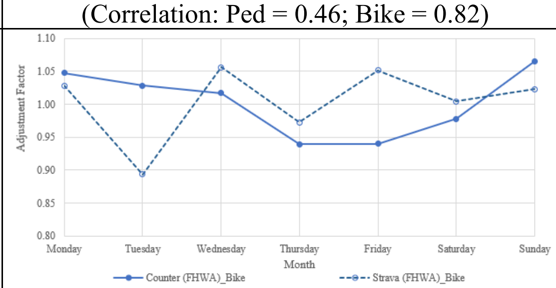
New Orleans: Lafitte Greenway
(Correlation: Ped = 0.70; Bike = 0.86)



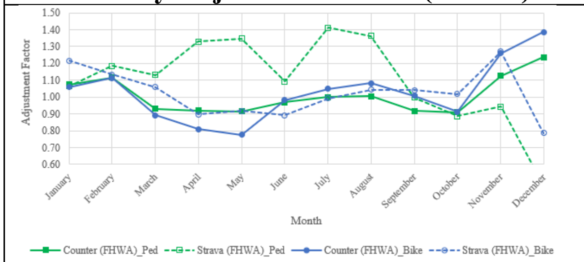
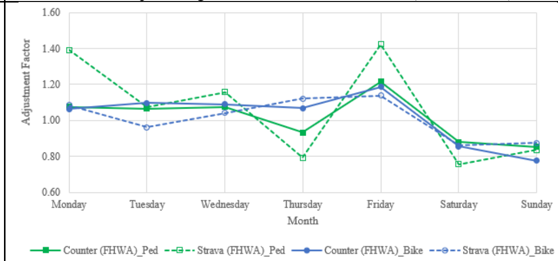
New Orleans: Lafitte Greenway
(Correlation: Ped = 0.46; Bike = 0.82)



New Orleans: Baronne Street
(Correlation: Ped = (na); Bike = 0.56)

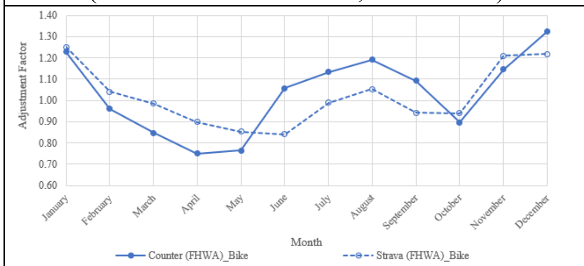


New Orleans: Baronne Street
(Correlation: Ped = (na); Bike = -0.05)

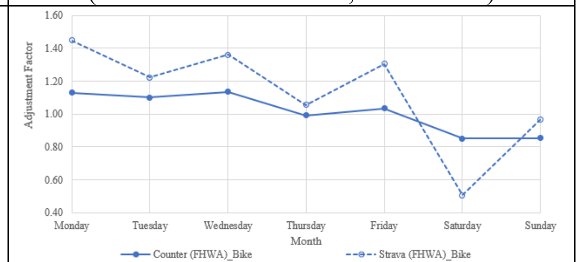
Monthly Adjustment Factor (MADT)	Weekly Adjustment Factor (WADT)
	

New Orleans: Wisner Trail
(Correlation: Ped = -0.56; Bike = 0.16)

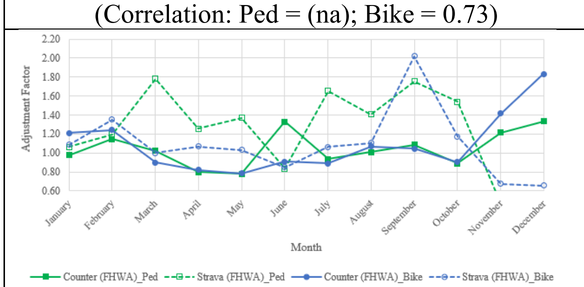
New Orleans: Wisner Trail
(Correlation: Ped = 0.92; Bike = 0.85)



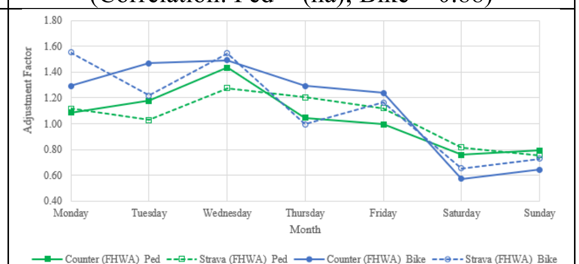
New Orleans: Esplanade Avenue
(Correlation: Ped = (na); Bike = 0.73)



New Orleans: Esplanade Avenue
(Correlation: Ped = (na); Bike = 0.88)



Mandeville: Tammany Trace
(Correlation: Ped = -0.64; Bike = -0.32)



Mandeville: Tammany Trace
(Correlation: Ped = 0.84; Bike = 0.86)

Note: “na” means not available.

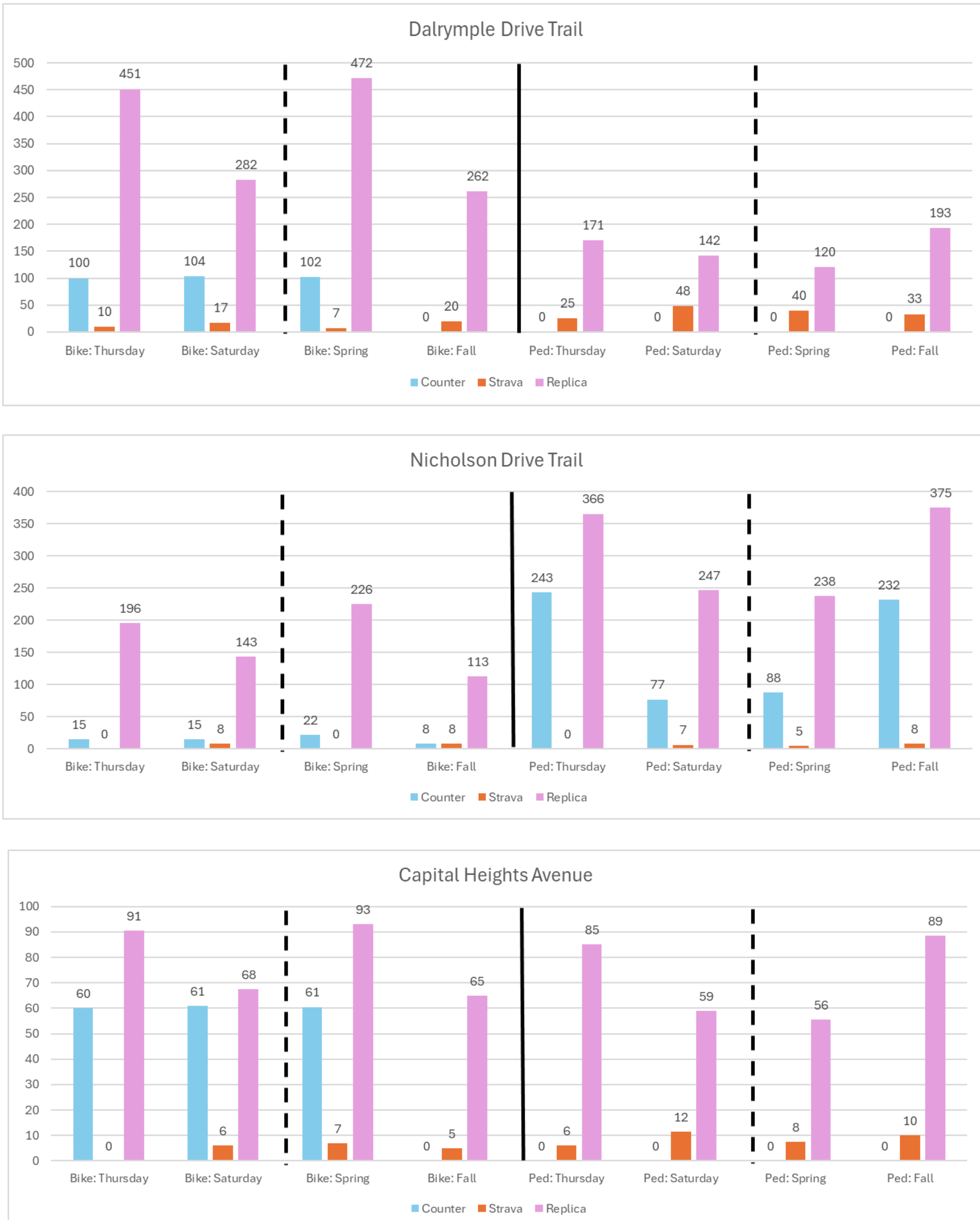
Counter vs. Multi-Source

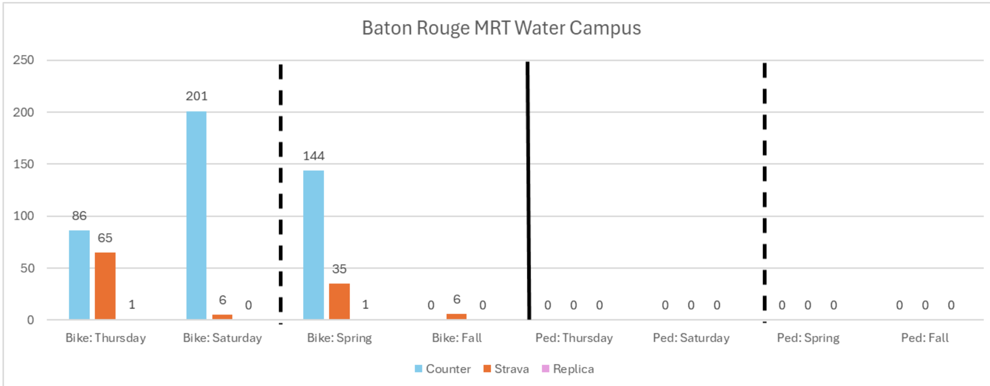
This section aims to address how well third-party data (i.e., Strava Metro and Replica) align with one another and with the counter data collected in Louisiana. Counter data was collected from 11 permanent counters installed in Louisiana, with daily data ranging from January to December 2023. Strava Metro data were collected at the same time for the available Strava edges near each counter location. Similarly, network-level Replica data was collected for the same time for the nearby network link ID for each counter location. Replica offers calibrated and disaggregated trip data that represent typical travel behavior on a typical workday (i.e., Thursday) and a typical weekend day (i.e., Saturday) in two seasons (i.e., spring and fall) at the network link level. In Replica data, spring spans March to May, while fall spans September to November. Further, daily counts from counters and Strava Metro were fused in the same format as Replica data, making four datasets for comparison: bike weekly, bike seasonal, pedestrian weekly, and pedestrian seasonal. For example, the bike weekly dataset contains data from each source but only on Thursdays and Saturdays, spanning the fall and spring months of 2023.

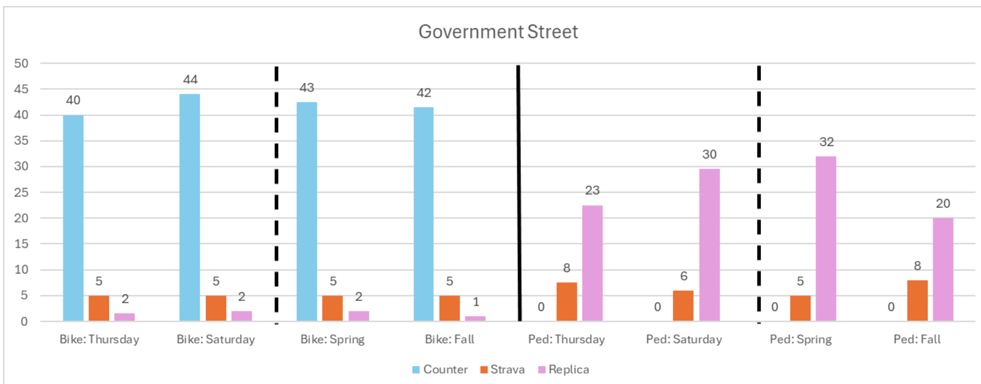
Raw count data collected and organized on a weekly and seasonal basis were used to generate a clustered bar chart with four categorical groupings. Figure 12 shows the data distribution by counting location. This comparative analysis reveals substantial discrepancies in non-motorized volume estimates across the three data sources, with Strava Metro consistently reporting the lowest counts, particularly for pedestrian activity. This is expected because the data inherently reflects only a subset of users. Across all locations, Strava Metro volumes are significantly lower than those recorded by the counters and Replica, and the data exhibits limited sensitivity to variations by location, season, or day. The limited variation in Strava Metro data suggests it does not fully reflect overall non-motorized travel. Prior studies have found that the data are biased toward recreational, fitness-focused users and often miss commuting activity, especially in lower-income areas [69].

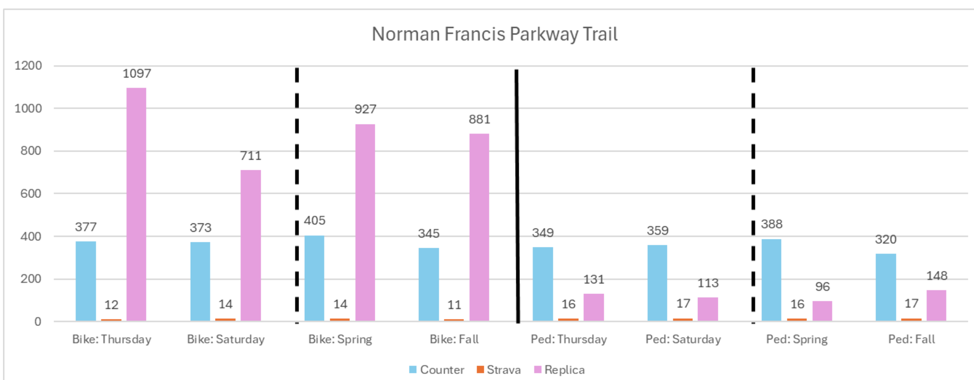
Replica shows mixed results across the 11 monitoring locations, with patterns of overestimation, underestimation, and mixed accuracy. Notable overestimation is observed at Dalrymple Drive Trail, Nicholson Drive Trail, Capital Heights Avenue, and Baronne Street, where both bicyclist and pedestrian volumes reported by Replica substantially exceed those recorded by permanent counters. Mixed results appear in Norman Francis Parkway Trail and Wisner Trail, where bicyclist volumes are overestimated but pedestrian volumes are underestimated. These differences are likely due to Replica using broad location and population data, which can overestimate activity near busy roads or in crowded city areas. Consistent underestimates appear at Baton Rouge MRT Water Campus, Lafitte Greenway, Esplanade Avenue, and Tammany Trace. The underestimation may reflect gaps in input data or challenges in accurately modeling travel behavior in settings that are in their own right-of-way, well outside of the motorized street network. Collectively, these findings highlight the importance of validating modeled and crowdsourced data against empirical observations, particularly in environments where local travel patterns deviate from regional modeling assumptions.

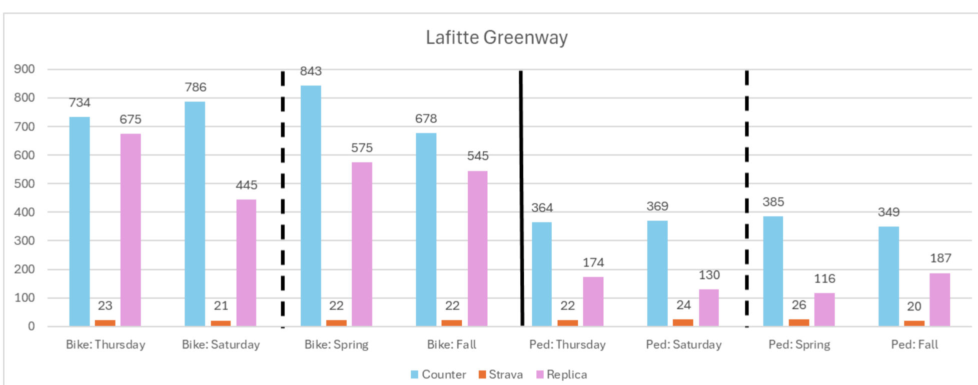
Figure 12. Grouped clustered bar chart: raw count

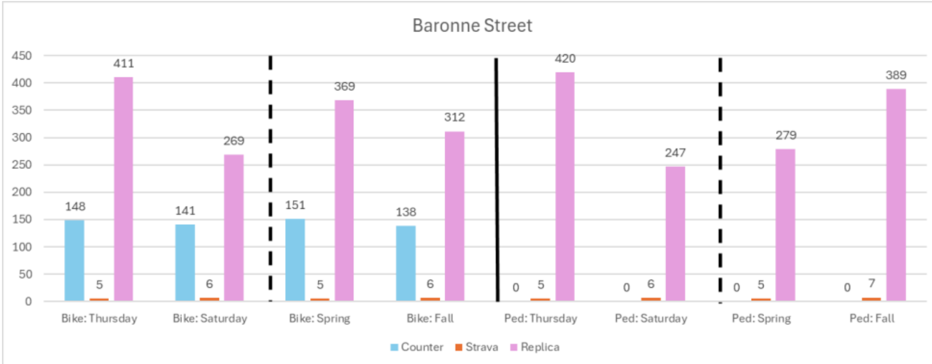


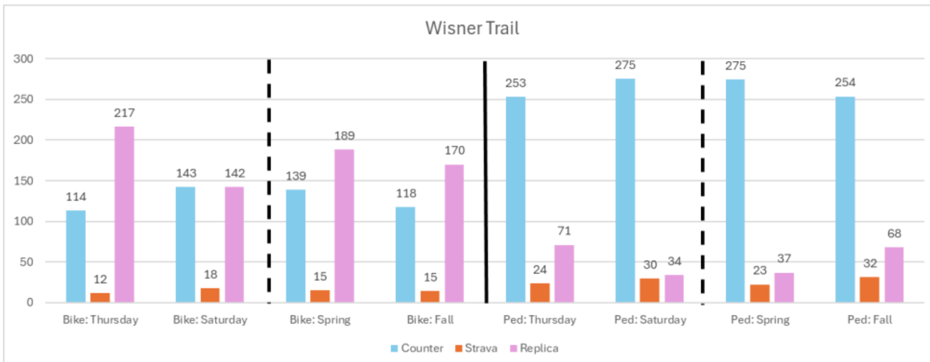

Baton Rouge MRT Water Campus
250
200
150
100
50
0
86
65
1
201
6
0
144
35
1
0
6
0
0 0 0
0 0 0
0 0 0
0 0 0
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica

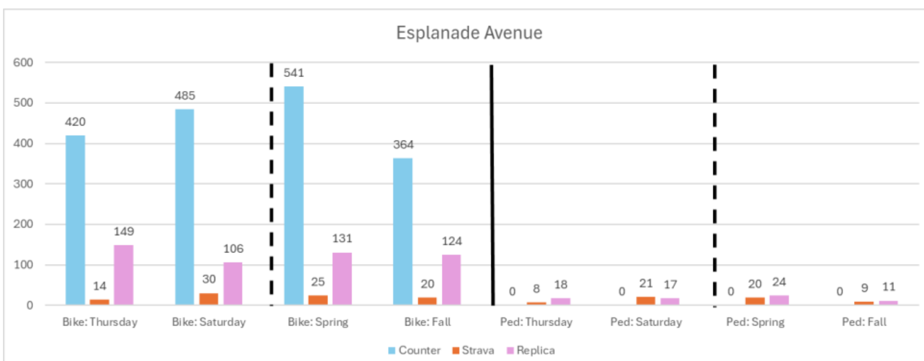

Government Street
50
45
40
35
30
25
20
15
10
5
0
40
5
2
44
5
2
43
5
2
42
5
1
0
8
23
0
6
30
0
5
32
0
8
20
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica


Norman Francis Parkway Trail
1200
1000
800
600
400
200
0
377
12
1097
373
14
711
405
14
927
345
11
881
349
16
131
359
17
113
388
16
96
320
17
148
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica


Lafitte Greenway
900
800
700
600
500
400
300
200
100
0
734
23
675
786
21
445
843
22
575
678
22
545
364
22
174
369
24
130
385
26
116
349
20
187
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica


Baronne Street
450
400
350
300
250
200
150
100
50
0
148
5
411
141
6
269
151
5
369
138
6
312
0
5
420
0
6
247
0
5
279
0
7
389
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica


Wisner Trail
300
250
200
150
100
50
0
114
12
217
143
18
142
139
15
189
118
15
170
253
24
71
275
30
34
275
23
37
254
32
68
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica


Esplanade Avenue
600
500
400
300
200
100
0
420
14
149
485
30
106
541
25
131
364
20
124
0
8
18
0
21
17
0
20
24
0
9
11
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica

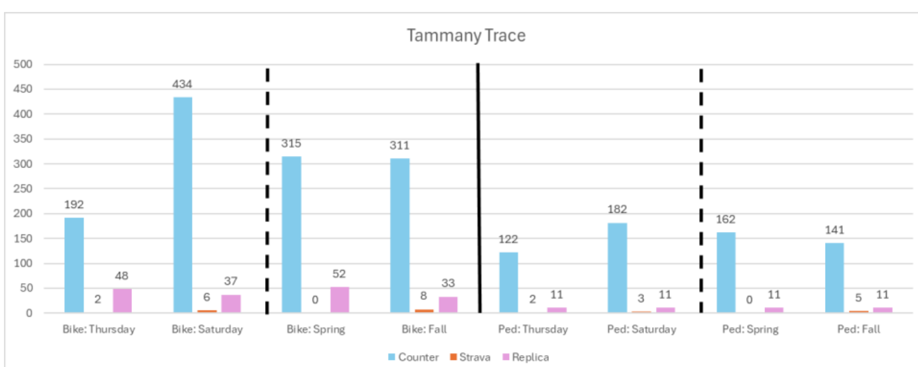

Tammany Trace
500
450
400
350
300
250
200
150
100
50
0
192
2
48
434
6
37
315
0
52
311
8
33
122
2
11
182
3
11
162
0
11
141
5
11
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica

Table 6 shows the percentage discrepancy summary for the raw data from Strava Metro and Replica. First, Strava Metro consistently underreports bicyclist and pedestrian volumes with a discrepancy rate of approximately 90%. Second, Replica overreports bicyclist volumes, with a discrepancy rate exceeding 100%, while it performs much better in presenting pedestrian volumes, with an error rate under 36%. This result corresponds to the fact that most existing travel mode detection algorithms largely depend on travel speed.

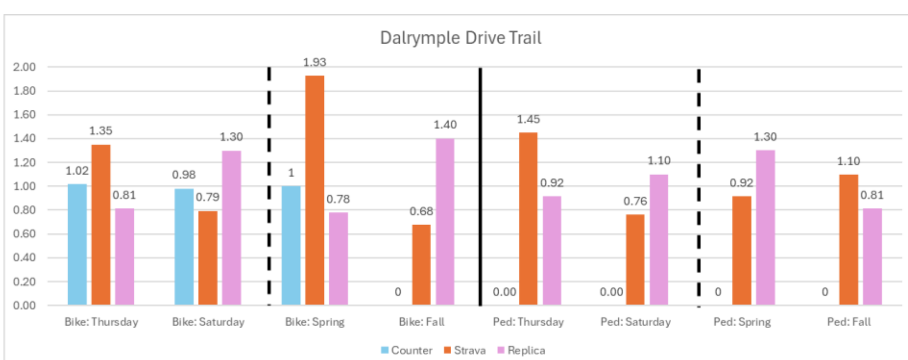
Table 6. Percentage discrepancy summary: raw count

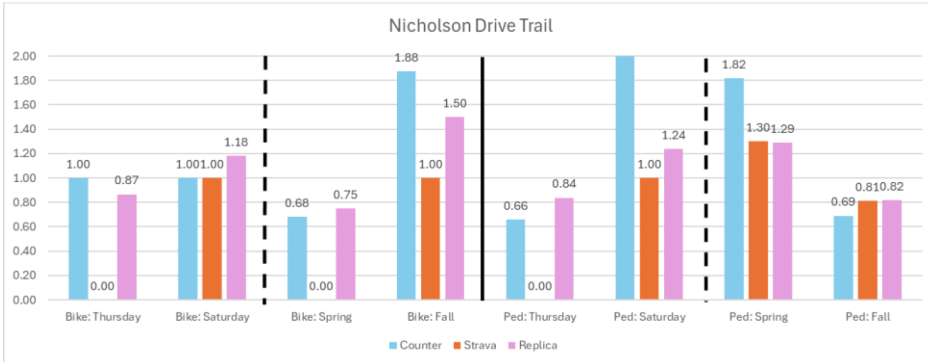
Data Source	Bike		Pedestrian	
	Weekly	Seasonal	Weekly	Seasonal
Strava Metro	-87.69	-86.93	-94.08	-94.46
Replica	+125.56	+185.81	-32.20	-35.84

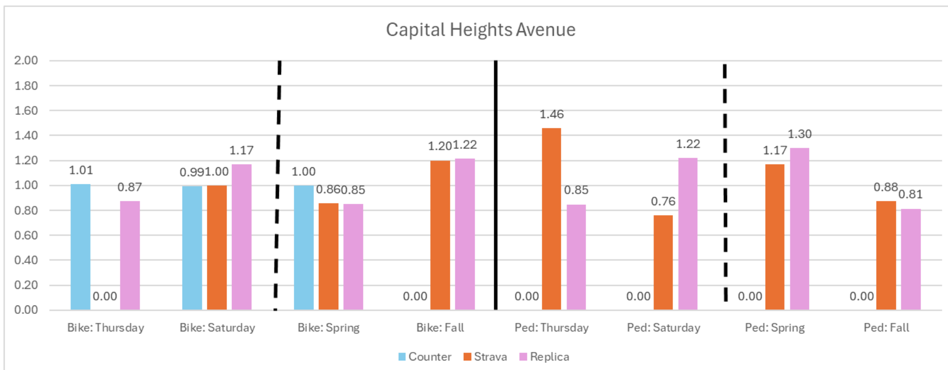
Raw count data from each source were then transformed into average daily non-motorized traffic by computing the mean across weekly and seasonal observations for both bicyclist and pedestrian counts. Adjustment factors were subsequently derived for each data source, separately for both weekly and seasonal patterns. A clustered bar chart was then generated for each counting location to visualize the resulting adjustment factors, as shown in Figure 13, which follows the same formatting as Figure 12.

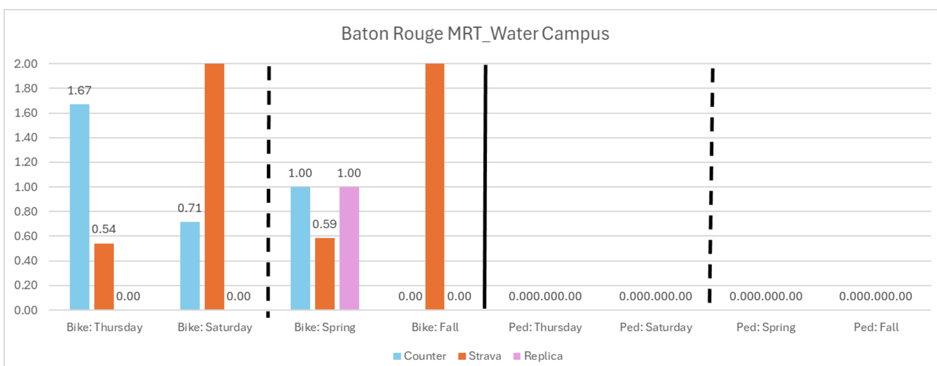
The adjustment factors chart across all 11 stations in Louisiana shows improved alignment among data sources: counters, Strava Metro, and Replica, particularly for bicycle modes. An integrated analysis across all four datasets (i.e., Bike Weekly, Bike Seasonal, Pedestrian Weekly, and Pedestrian Seasonal) reveals data differences between Strava Metro, Replica, and observed counter data. Stations such as Dalrymple Drive Trail, Government Street, and Norman Francis Parkway Trail consistently show low percentage discrepancies across both sources, suggesting reliable alignment with ground-truth counts. Conversely, Baton Rouge MRT Water Campus exhibits exceptionally high discrepancies in Strava Metro and widespread data unavailability in Replica, underscoring the limitations of modeled data in low-volume or recently developed areas. Other locations, including Nicholson Drive Trail and Esplanade Avenue, show mixed results across temporal scales and modes, reflecting source-specific biases or incomplete coverage. These findings show that while human mobility data can help improve non-motorized traffic monitoring, their accuracy depends on location, travel mode, and time of year, making careful, location-specific validation essential.

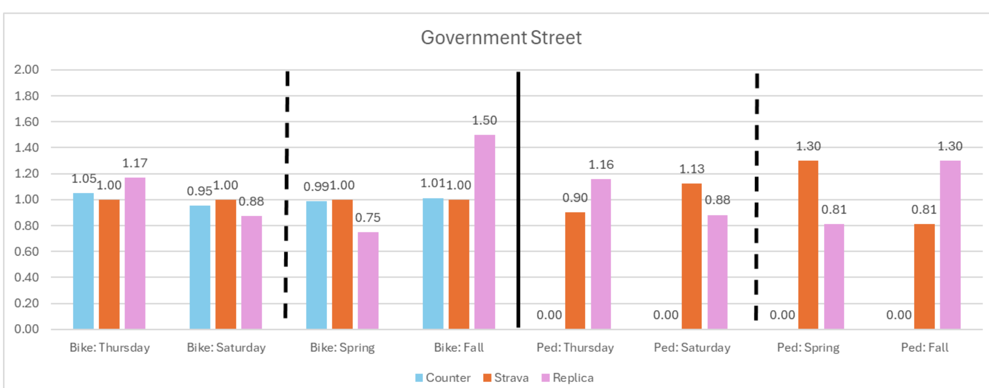
Figure 13. Grouped clustered bar chart: adjustment factor

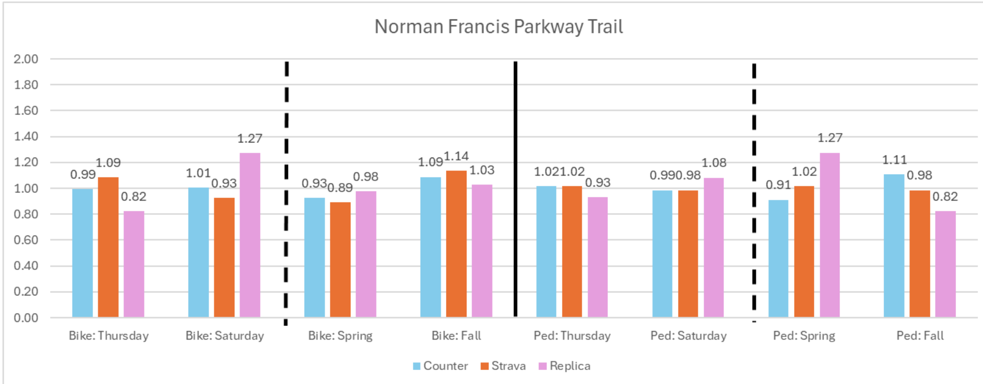


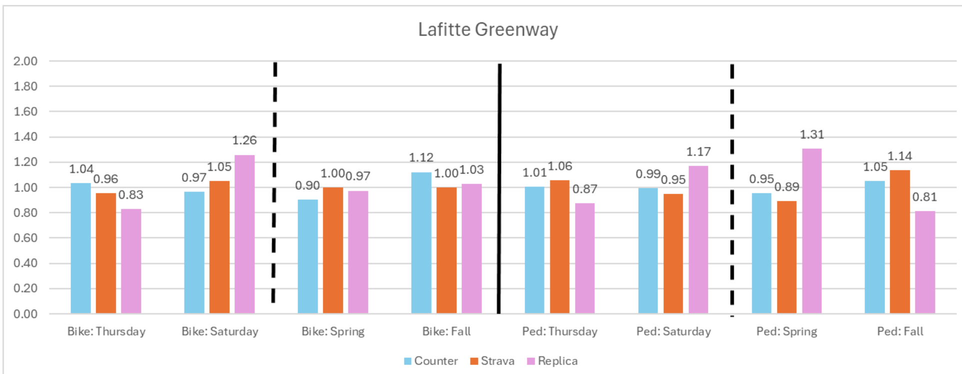

Nicholson Drive Trail
2.00
1.80
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
1.00
0.00
0.87
1.00
1.00
1.18
0.68
0.00
0.75
1.88
1.00
1.50
0.66
0.00
0.84
1.00
1.24
1.82
1.30
1.29
0.69
0.81
0.82
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica

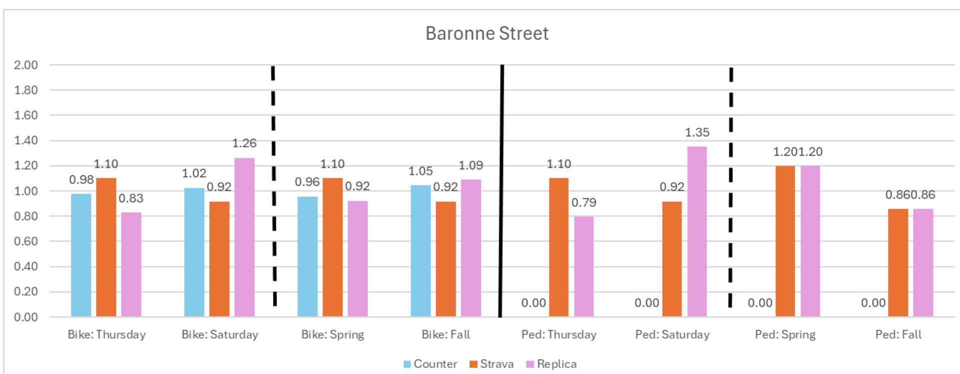

Capital Heights Avenue
2.00
1.80
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
1.01
0.00
0.87
0.99
1.00
1.17
1.00
0.86
0.85
0.00
1.20
1.22
0.00
1.46
0.85
0.00
0.76
1.22
0.00
1.17
1.30
0.00
0.88
0.81
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica

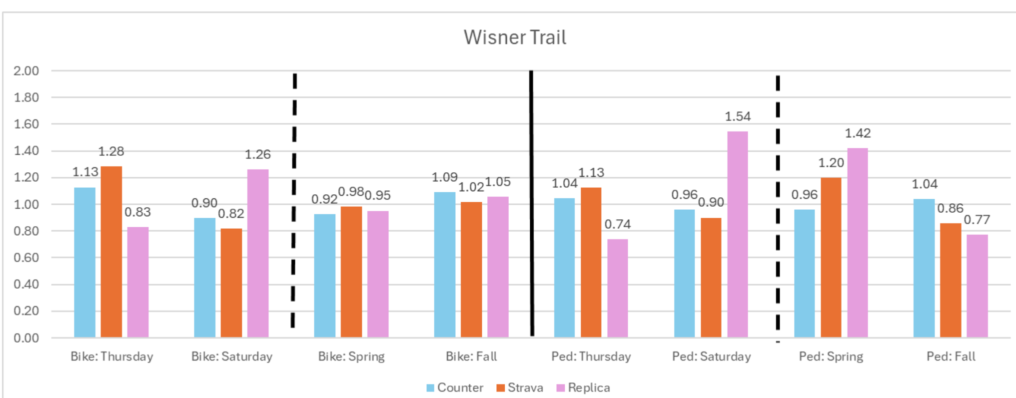

Baton Rouge MRT_Water Campus
2.00
1.80
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
1.67
0.54
0.00
0.71
0.00
1.00
0.59
1.00
0.00
0.00
0.000.000.00
0.000.000.00
0.000.000.00
0.000.000.00
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica

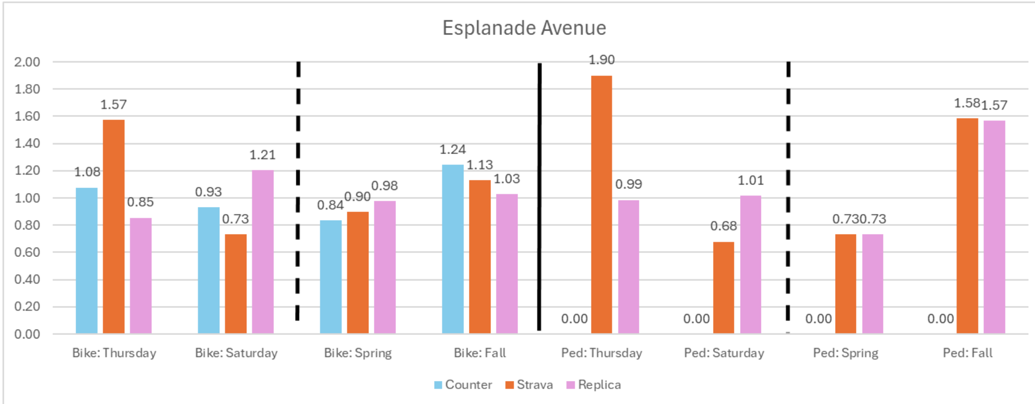

Government Street
2.00
1.80
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
1.05
1.00
1.17
0.95
1.00
0.88
0.99
1.00
0.75
1.01
1.00
1.50
0.00
0.90
1.16
0.00
1.13
0.88
0.00
1.30
0.81
0.00
0.81
1.30
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica

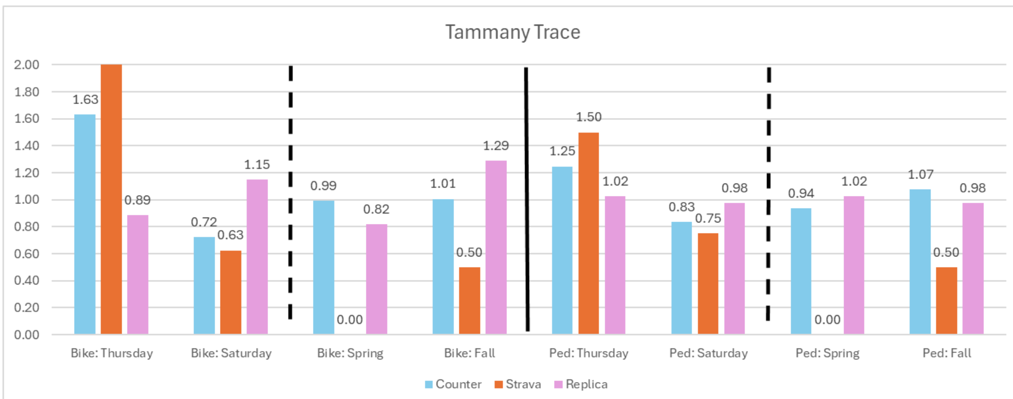

Norman Francis Parkway Trail
2.00
1.80
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
0.99 1.09 0.82
1.01 0.93 1.27
0.93 0.89 0.98
1.09 1.14 1.03
1.02 1.02 0.93
0.99 0.98 1.08
0.91 1.02 1.27
1.11 0.98 0.82
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica


Lafitte Greenway
2.00
1.80
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
1.04 0.96 0.83
0.97 1.05 1.26
0.90 1.00 0.97
1.12 1.00 1.03
1.01 1.06 0.87
0.99 0.95 1.17
0.95 0.89 1.31
1.05 1.14 0.81
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica


Baronne Street
2.00
1.80
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
0.98 1.10 0.83
1.02 0.92 1.26
0.96 1.10 0.92
1.05 0.92 1.09
0.00 1.10 0.79
0.00 0.92 1.35
0.00 1.20 1.20
0.00 0.86 0.86
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica


Wisner Trail
2.00
1.80
1.60
1.40
1.20
1.00
0.80
0.60
0.40
0.20
0.00
1.13 1.28 0.83
0.90 0.82 1.26
0.92 0.98 0.95
1.09 1.02 1.05
1.04 1.13 0.74
0.96 0.90 1.54
0.96 1.20 1.42
1.04 0.86 0.77
Bike: Thursday
Bike: Saturday
Bike: Spring
Bike: Fall
Ped: Thursday
Ped: Saturday
Ped: Spring
Ped: Fall
Counter
Strava
Replica





Further, percentage discrepancies were summarized as shown in Table 7. The discrepancy rate drops after converting raw counts to adjustment factors, and Strava Metro-based adjustment factors perform relatively well in three categories except Bike Weekly. This inconsistency appears to be due to limited and inconsistent Strava Metro data availability at some counter locations.

Table 7. Percentage discrepancy summary: adjustment factors

Data Source	Bike		Pedestrian	
	Weekly	**Seasonal**	**Weekly**	**Seasonal**
Strava Metro	+45.72	-3.79	+1.58	-6.01
Replica	+4.43	+1.47	+2.27	+4.02

The following work helps address the third research question: "*Q3: Can human mobility data from multiple sources help improve our practice of relying on permanent counters for adjustment factor calculation?*" Two regression models are used to assess how well adjustment factors derived from Strava Metro and Replica can explain counter-based adjustment factors. First, a simple regression model without interception is used, and the results are summarized below in Table 8.

The high R^2 and adjusted R^2 values indicate that it is worthwhile to leverage human mobility data from multiple sources to calculate adjustment factors. The coefficients are statistically significant (p-value < 0.1) for Bike Weekly, Bike Seasonal, and Pedestrian Weekly. This suggests that a weighted combination of crowd-sourced (Strava Metro) and LBS (Replica) mobility data can better reflect temporal variations in non-motorized traffic volumes. Additionally, it should be noted that the Pedestrian Seasonal model has less significant coefficients. This is attributed to both data sparsity and high variability in pedestrian seasonal counts. Several stations (e.g., Dalrymple Drive Trail, Government Street, Baronne Street, and Esplanade Avenue) only collect bicycle counts, not pedestrian volumes, thus reducing the sample size. Among stations with available data, discrepancies vary widely. For example, Wisner Trail shows a +25.00% difference in Strava Metro data in spring and a -17.31% difference in fall, while Tammany Trace shows a -53.27% difference in spring and a -8.41% difference in fall. These inconsistencies make it difficult for the model to identify stable relationships, leading to weaker, less significant coefficients.

Table 8. Simple regression results

Model	R^2	Adj_R^2	Strava Metro (Xit)		Replica (Zit)	
			Coefficient	P-value	Coefficient	P-value
Bike Weekly	0.990	0.990	0.525	<0.001	0.421	<0.001
Bike Seasonal	0.980	0.980	0.564	<0.001	0.441	0.002
Ped Weekly	0.990	0.990	0.738	<0.001	0.230	0.008
Ped Seasonal	0.940	0.920	0.800	0.09	na	na

A second series of models were estimated to include categorical variables to observe differences across counter locations. Specifically, three counter attribute variables were considered: the city where a counter is located, the travel pattern of users at that site, and the type of facility (e.g., bike lane or shared-use path). Table 9 lists these attributes for all counters. Among the three categorical variables evaluated, travel pattern is the only one that shows statistically significant impacts. The travel pattern variable includes two subcategories (i.e., multi-purpose and non-commute) in the dataset.

Table 10 shows that the multi-source regression models fit very well, with $R^2 > 0.97$ for all four datasets. Weekly models performed well for both bicyclist and pedestrian models across two travel categories (multi-purpose and non-commute), indicating that both Strava Metro and Replica adjustment factors contribute to the models. For the seasonal models, non-commute bike patterns are captured well by Strava Metro and Replica, whereas only Strava Metro's multi-purpose data is statistically significant for pedestrians. This suggests that Strava Metro may better capture seasonal variation patterns across locations, even if its overall accuracy is slightly lower. It may highlight that a lower average error does not necessarily imply stronger explanatory power in regression analysis.

Table 9. Classification of counters by facility type, city, and travel pattern

Station name	Bike			Pedestrian		
	Facility type	City	Travel pattern	Facility type	City	Travel pattern
Dalrymple Drive Trail	Shared Use Path (ROW)	Baton Rouge	Non-commute	Shared Use Path (ROW)	Baton Rouge	Non-commute
Nicholson Drive Trail	Shared Use Path (ROW)	Baton Rouge	Multi-purpose	Shared Use Path (ROW)	Baton Rouge	Non-commute
Baton Rouge MRTWater Campus	Non-ROW Trail	Baton Rouge	Multi-purpose	Non-ROW Trail	Baton Rouge	Non-commute
Government Street	Bike Lane	Baton Rouge	Non-commute	NA	Baton Rouge	NA
Capital Heights Avenue	Bike Lane	Baton Rouge	Non-commute	NA	Baton Rouge	NA
Norman Francis Parkway Trail	Shared Use Path (ROW)	New Orleans	Multi-purpose	Shared Use Path (ROW)	New Orleans	Multi-purpose
Lafitte Greenway	Non-ROW Trail	New Orleans	Non-commute	Non-ROW Trail	New Orleans	Multi-purpose
Baronne Street	Bike Lane	New Orleans	Multi-purpose	NA	New Orleans	NA
Wisner Trail	Shared Use Path (ROW)	New Orleans	Non-commute	Shared Use Path (ROW)	New Orleans	Multi-purpose
Esplanade Avenue	Bike Lane	New Orleans	Non-commute	NA	New Orleans	NA
Tammany Trace	Non-ROW Trail	Mandeville	Non-commute	Non-ROW Trail	Mandeville	Non-commute

Note: "NA" means not available.

Table 10. Multisource regression results

Model	R^2	Adj_ R^2	Strava Metro: Multi-purpose (Xit)		Strava Metro: Non-commute (Xit)		Replica: Multi-purpose (Zit)		Replica: Non-commute (Zit)	
			Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Bike Weekly	0.995	0.993	0.657	<0.001	0.518	<0.001	0.322	0.040	0.422	<0.001
Bike Seasonal	0.990	0.985	(na)	(na)	0.597	0.002	(na)	(na)	0.415	0.01
Ped Weekly	0.990	0.990	0.846	<0.001	0.537	<0.001	0.142	0.006	0.436	0.001
Ped Seasonal	0.975	0.956	1.111	0.03	0.348	0.57	(na)	(na)	(na)	(na)

Counter Expansion Study Results

The number of road segments that have sufficient and complete observations for clustering analysis are 2,945 (bicyclist) and 4,879 (pedestrian) across four Louisiana parishes. Table 11 and Table 12 present a summary of the study results from implementing the two-stage clustering framework. Each table includes the number of road segments in a cluster (i.e., segs(n)), temporal clustering statistics (i.e., best k average silhouette and silhouette class), roadway type, and land use context.

Table 11. Bicyclist spatio-temporal cluster

Label	Segs (n)	Best k	Avg. silhouette	Sil. class	Primary OSM type	Land use context
East Baton Rouge						
S1	472	7	0.263	Moderate	Tertiary, residential, secondary	Mixed-use arterials and residential streets near Southern University and LSU corridors; diverse land-use generating seven temporal sub-clusters
S9	27	2	0.274	Moderate	Footway, residential, path	West EBR off-street paths and residential streets
S10	50	3	0.305	Moderate	Secondary, service	South EBR commercial and service-road corridors
S16	17	-	-	No split	Secondary (100%)	Northern EBR exurban roads; temporal; clustering not possible because 100% of Strava Thursday were missing

Label	Segs (n)	Best k	Avg. silhouette	Sil. class	Primary OSM type	Land use context
Orleans						
S3	1595	4	0.303	Moderate	Tertiary, secondary, residential	Dense New Orleans cycling network; 54% of all bicycle segments; mixed arterials and neighborhood streets throughout the historic grid
S7	36	-	-	No split	Tertiary, primary	Eastern Orleans waterfront arterials; 58% Strava Thursday missing
S8	43	2	0.326	Moderate	Secondary, tertiary	Algiers/West Bank arterials and cross-river connector roads
Lincoln						
S2	77	3	0.267	Moderate	Residential, secondary, cycleway	Louisiana Tech University area; campus residential streets, secondary arterials, and designated cycleways
St. Tammany						
S4	30	2	0.289	Moderate	Cycleway, tertiary, residential	Northshore multi-use path network near Covington; dedicated cycleways connecting residential neighborhoods
S5	75	2	0.319	Moderate	Residential, tertiary, cycleway	Slidell-area suburban residential streets and shared-use paths
S6	20	2	0.323	Moderate	Cycleway, secondary, residential	Dedicated cycleway segments in Slidell; higher cycleway share than S5
S11	32	2	0.539	Strong	Cycleway, residential	Covington recreational trail (Tammany Trace); only bicycle cluster to achieve strong silhouette
S14	15	2	0.447	Moderate	Cycleway, residential	Eastern St. Tammany greenway; dedicated cycleway with adjacent residential access
S13	10	-	-	No split	Cycleway, residential, tertiary	Isolated cycleway node near Abita Springs; no feasible k ≥ 2 under the minimum cluster size requirements
S12, S15, S17 (St. Tammany, 10 segments each) have no split due to all Strava Metro Thursday data being missing. These clusters represent isolated exurban secondary road nodes with insufficient usable Strava Metro data for temporal clustering.						

Note: Segs (n) = number of non-noise road segments within the spatial cluster, excluding DBSCAN noise. Best k = optimal number of temporal sub-clusters selected from K-means solutions evaluated across k = 2 to 15. Avg. Silhouette = average silhouette width at best k, Silhouette classification: Strong ≥ 0.50; Moderate 0.25–0.49; Weak < 0.25. No split indicates a spatial-only assignment retained without temporal subdivision. "- "denotes that no temporal clustering can be performed. Clusters S12, S15, and S17 (St. Tammany, ten segments each) are reported as a single grouped row because all three share the same no-split reason (i.e., complete absence of observations for Thursdays in Strava Metro data) and the same land-use characterization as isolated exurban trail nodes; reporting them separately would not provide additional analytical information.

Table 12. Pedestrian spatial-temporal cluster

Label	Segs (n)	Best k	Avg. silhouette	Sil. class	Primary OSM type	Land use context
East Baton Rouge						
S1	970	2	0.686	Strong	Footway, residential, tertiary	Urban core and university zone; footways and residential streets spanning LSU, Southern University, and adjacent neighborhoods; strongest silhouette score in the study
S2	102	7	0.231	Weak	Residential, cycleway, footway	South EBR fragmented residential corridors; diverse infrastructure mix generating seven temporal sub-clusters
S6	62	2	0.214	Weak	Residential, service	Southeast EBR low-density residential and service roads
S14	18	2	0.274	Moderate	Residential, footway	Mid-EBR residential streets; includes S14_T17, where extreme Strava Metro values indicate a probable athletic training loop and recreation—user bias
S8	15	2	0.33	Moderate	Path, footway	West EBR off-street paths and shared-use footways
Orleans						
S5	2727	—	—	No split	Footway, residential, tertiary	Dense New Orleans pedestrian grid; 55.9% of all pedestrian segments; retained as a spatial-only cluster because no temporal split met the silhouette criterion, indicating genuine temporal homogeneity rather than a data limitation
S9	82	—	—	No split	Tertiary, footway, secondary	Uptown/Mid-City Orleans mixed arterial sidewalks
S7	16	—	—	No split	Tertiary, footway	Mid-City Orleans arterial sidewalks
Lincoln						
S3	130	2	0.358	Moderate	Footway, residential, cycleway	Louisiana Tech campus pedestrian zone; footway-dominant with campus residential streets; dual-semester seasonality (Fall = 1.28, Spring = 1.17)
St. Tammany						
S21	21	2	0.193	Weak	Residential, tertiary, cycleway	Mandeville-area neighborhood paths and local connector streets with mixed residential and recreational access

Label	Segs (n)	Best k	Avg. silhouette	Sil. class	Primary OSM type	Land use context
S4	39	—	—	No split	Residential, cycleway, tertiary	Northshore suburban paths near Covington; 51% Strava Thursday missing

Note: Several small spatial clusters across all parishes did not support temporal subdivision ($k \geq 2$), indicating internally homogeneous temporal behavior. In EBR, clusters S11 (n = 18), S15 (n = 16), S16 (n = 16), S17 (n = 10), and S18 (n = 14) were all composed of residential streets and showed temporally homogeneous activity patterns. In Orleans, clusters S10 (n = 21), S12 (n = 10), S13 (n = 10), and S19 (n = 17), represent residential and mixed street types, similarly remaining unsplit. In St. Tammany, clusters S20 (n = 12), S22 (n = 10), and S23 (n = 10) also showed no feasible temporal split, with S20 identified as a cycleway and characterized by 42% missing Strava data, which may have reduced the potential for temporal separation.

The spatial cluster structure is highly uneven in both modes. In the bicycle network, cluster S3 in Orleans Parish contains 54% of all segments, while in the pedestrian network, cluster S5 in Orleans Parish contains 56% of all segments. This concentration reflects the dense and continuous street network of the New Orleans urban core. In contrast, St. Tammany Parish is divided into many small and geographically isolated clusters, consistent with its more dispersed suburban bikeway system and recreational trail network.

Temporal split performance differs substantially by parish. East Baton Rouge (EBR) Parish shows nearly complete temporal differentiation in both bicycle and pedestrian modes. This pattern likely reflects its diverse land-use context, including university areas, mixed-use corridors, and suburban residential streets, which generate distinct weekday and seasonal activity patterns. The strongest temporal separation in the study occurs in EBR Parish pedestrian cluster S1, which achieved the highest silhouette score (i.e., 0.686) [67]. This result indicates a clear division between a weekend-oriented recreational sub-network and a workday-dominant sub-network, suggesting that Replica and Strava Metro provide a consistent and complementary temporal signal within the same geographic area.

A different pattern is observed in Orleans Parish pedestrian cluster S5. Although this cluster retained 2,462 complete eight-factor observations, no temporal split produced an acceptable silhouette score across the full range of tested k values. The Replica adjustment factors also vary only slightly within this cluster (Thursday = 0.91, Saturday = 1.18, fall = 1.06, spring = 1.03), indicating that pedestrian activity across much of the Orleans Parish street grid is relatively stable across weekdays and seasons. This temporal stability itself is an important finding, as it suggests that a single well-placed permanent counter may provide representative adjustment factors for a large share of pedestrian segments in Orleans Parish. Under the combined-data condition, an additional limitation is the substantially higher variability in Strava Metro Thursday factors compared with Replica (standard deviation of

1.77 versus 0.12), which adds noise to the feature space and reduces the clustering algorithm's ability to identify well-defined temporal subgroups [12] [70].

In St. Tammany Parish, several bicycle clusters could not be evaluated temporally because Strava Thursday observations were entirely missing. This reflects a limitation in data coverage rather than true temporal homogeneity. The result is consistent with lower usage of crowdsourced GPS applications on isolated and low-volume trail facilities [12] [70]. Unlike the Orleans Parish pedestrian case, where the no-split result reflects genuine temporal stability, the St. Tammany Parish outcome likely reflects insufficient data rather than stable behavior. These clusters may reveal meaningful temporal structure if analyzed using Replica-only variables or if Strava coverage improves in lower-density areas.

Lincoln Parish is represented by a single spatial cluster for both bicycle and pedestrian modes, consistent with its compact university-town characteristics centered on Louisiana Tech University in Ruston. Although the number of segments is relatively small, both modes still show meaningful temporal splits. The bicycle cluster reflects a mix of campus residential streets, secondary roads, and cycleways around the Louisiana Tech area. The pedestrian cluster shows the clearest temporal split outside of EBR Parish and suggests a semester-based seasonal pattern, with higher activity in both fall and spring. This indicates that pedestrian demand in Lincoln Parish is strongly influenced by the academic calendar and the institutional role of the Louisiana Tech campus. Strava Metro also shows weaker seasonality than Replica, suggesting that it may capture a smaller subgroup of users rather than the broader student-related pedestrian activity.

Overall, bicycle temporal cluster quality is mostly moderate, with 81.6% of segments falling within a silhouette range of 0.263 to 0.447. This indicates acceptable temporal patterns, though not strongly separated. One likely explanation is the behavioral and demographic difference between the two data sources. Strava Metro tends to overrepresent weekday fitness and commuter users, whereas Replica reflects a broader travel population. When both sources are combined into a single feature vector, these differences can reduce within-cluster consistency. Future work should consider source-weighted or Replica-only clustering for segments with weak Strava coverage and should also test additional temporal indicators, such as peak-hour ratios or weather sensitivity measures, which prior studies suggest may improve the discriminatory power of non-motorized temporal clustering frameworks [71] [72].

Temporal Factor Group Analysis

An examination of the cluster centroid profiles revealed five distinct temporal behavior patterns across the bicyclist and pedestrian networks in the four study parishes. These patterns are interpreted here as study-specific, data-driven factor groups derived from the joint spatial–temporal clustering results and are conceptually aligned with the flexible factor-group framework described in the FHWA TMG [39], which recommends grouping monitoring locations with similar temporal variation to support development of adjustment factors and transferability of short-count expansion factors. Consistent with prior non-motorized monitoring research, the identified factor groups reflect meaningful differences in day-of-week and seasonal behavior that are directly relevant to representative counter placement, count expansion, and interpretation of source-specific bias [73] [74]. In this study, factor-group assignments are based on three complementary dimensions: (1) weekly orientation, measured using the Saturday/Thursday ratio in both data sources; (2) seasonal orientation, measured using the fall/spring ratio in both data sources; and (3) the degree of cross-source divergence between Replica and Strava Metro defined as the absolute difference between the Replica and Strava Saturday to Thursday ratios. Divergence is classified as low (below 0.25), moderate (0.25 to 0.50), high (0.50 to 1), or extreme above (1.00), adopting the same 0.25 and 0.50 breakpoints established by Kaufman and Rousseeuw for silhouette-based cluster interpretation [67]. Table 13 summarizes the revised five-factor-group framework, including the defining temporal characteristics, cross-source relationships, representative examples, and monitoring implications. Table 14 provides the representative centroid values that support each group assignment.

The five factor groups represent distinct monitoring environments. Factor Group A captures clusters with stable weekly and seasonal behavior and relatively low divergence between Replica and Strava Metro, making them the strongest candidates for representative factor transfer and permanent counter placement. Factor Group B identifies weekend-recreational environments, where Saturday activity substantially exceeds Thursday activity in Replica, and where unstratified short counts could overestimate typical weekday demand. Several Group B clusters also exhibit high cross-source divergence, as Strava Metro primarily captures weekday fitness bicyclists and commuters who record their trips using the app, while casual recreational users who travel predominantly on weekends are largely absent from its user base [12] [70].

Factor Group C reflects weekday-utilitarian environments, characterized by balanced or weekday-dominant weekly profiles consistent with commuter, school-access, or routine utilitarian travel, and represents the group where Replica and Strava Metro are closely aligned. Factor Group D captures clusters where seasonal sensitivity is more pronounced than weekly contrast, suggesting the influence of academic calendars, institutional activity, or other seasonally structured demand. Finally, Factor Group E includes source-divergent or anomalous clusters, where Replica and Strava Metro exhibit substantially different weekly or seasonal patterns, indicating that these locations require additional contextual validation before being used for count expansion or representative counter selection.

Together, Table 13 and Table 14 provide both the conceptual and numerical bases for the factor group interpretation. Table 13 summarizes the study-specific classification logic and monitoring implications, while Table 14 links that interpretation directly to representative centroid values from both bicyclist and pedestrian clusters. Complete centroid results for all clusters, including the full set of weekly and seasonal values and derived ratios, are provided in Appendix F (Table 19 and Table 20) for reference and reproducibility.

Table 13. Joint Replica-Strava factor group classification based on weekly and seasonal centroid profiles

FG	Revised factor group name	Defining weekly pattern	Defining seasonal pattern	Cross-source relationship (Replica vs. Strava)	Typical interpretation	Representative examples	Monitoring implication
A	Stable Cross-Source Baseline	Replica and Strava Saturday/Thursday ratios are balanced or only mildly weekend-elevated	Replica and Strava fall/spring ratios are near 1.0 (seasonally stable)	Low divergence: both sources tell a broadly similar temporal story	Stable, broadly representative non-motorized activity with limited temporal distortion	Ped: S11, S18, S2_T3, Bike: S1_T7,	Best candidates for representative continuous counters; strongest transferability of adjustment factors
B	Weekend Recreational	Replica Saturday/Thursday clearly above 1.40, Strava Sat/Thu is frequently lower, producing cross-source divergence	Seasonal effect is secondary, while weekly contrast dominates	Low to extreme divergence; Strava frequently under-represents weekend recreational demand relative to Replica	Leisure-oriented, trail, scenic, or discretionary weekend activity	Ped: S2_T5, S2_T7, S7 Bike: S1_T4, S11_T28, S3_T12, S11_T29	Should be separated from utilitarian corridors; weekend short counts may overestimate annualized weekday demand if no temporal adjustment is applied
C	Weekday Utilitarian	Saturday/Thursday ratio is near 1.0 or <1.0, indicating balanced or weekday-dominant activity	Fall often exceeds spring, but the seasonal contrast is moderate	Usually low to moderate divergence; sources are more aligned than in recreational groups	Commuter, school-access, institutional, or regular utilitarian travel	Ped: S17, S8_T15, S6_T13 Bike: S3_T14, S6_T19, S2_T9	Weekday counting timing is critical; these are good candidates for weekday-focused monitoring and adjustment

FG	Revised factor group name	Defining weekly pattern	Defining seasonal pattern	Cross-source relationship (Replica vs. Strava)	Typical interpretation	Representative examples	Monitoring implication
D	Seasonal / Institutional Sensitivity	Weekly patterns may be mixed, balanced, or weakly directional	Fall/spring or spring/fall imbalance is the dominant signal in at least one source	Moderate to high divergence possible, especially where one source is more sensitive to localized institutional activity	Campus, school-year, event, or season-sensitive environments where institutional calendars govern temporal behavior	Ped: S3_T10, S3_T11, S20 Bike: S1_T3, S14_T30, S6_T20	Spatial proximity alone is insufficient; seasonal stratification is needed in factor transfer and counter placement
E	Source-Divergent / Anomalous	Weekly direction may differ sharply between Replica and Strava, including directional reversals	Seasonal direction or magnitude may also diverge between sources	High to extreme divergence (above 0.50); sources do not describe the same temporal behavior	Fitness-user bias, organized athletic activity, context-specific corridors, low-baseline data instability, or localized anomalies	Ped: S14_T17, S1_T1, S22, S15 Bike: S3_T13, S10_T27,	Requires explicit caution; should be flagged before using in count expansion or assigning representative counters

Table 14. Representative bicyclist and pedestrian centroid ratios used for joint factor group assignment

FG	Mode	Representative cluster	Segs (n)	Replica Sat/Thu	Strava Sat/Thu	Replica Fall/Spring	Strava Fall/Spring	Divergence level	Basis for assignment
A	Ped	S11 (EBR)	18	1.03	1.01	0.97	1.02	Low	Stable cross-source baseline with balanced weekly and seasonal behavior in both sources
A	Bike	S1_T7 (EBR)	55	1.02	0.84	1.16	1.01	Low	Near-flat weekly profile in both sources with minimal seasonal variation; consistent with a utilitarian cycling corridor where demand is stable year-round
B	Ped	S2_T5 (EBR)	9	2.73	0.98	1.18	0.91	Extreme	Strongest recreational pedestrian signal in dataset; Replica captures weekend recreational public largely absent from Strava Metro user base

FG	Mode	Representative cluster	Segs (n)	Replica Sat/Thu	Strava Sat/Thu	Replica Fall/Spring	Strava Fall/Spring	Divergence level	Basis for assignment
B	Ped	S2_T7 (EBR)	24	1.84	0.8	0.82	0.9	Extreme	Strong weekend elevation in Replica with spring-peak seasonal pattern; Strava Metro under-represents recreational weekend pedestrians on these segments
B	Bike	S1_T4 (EBR)	24	2.37	0.83	1.18	1.13	Extreme	Waterfront and greenway corridors; extreme Replica weekend elevation confirms recreational public not captured by fitness app data
B	Bike	S11_T28 (St. Tammany)	20	1.96	0.47	0.76	1.01	Extreme	Tammany Trace recreational trail; strongest cross-source inversion in the dataset, recreational public largely invisible to Strava Metro
B	Bike	S3_T12 (Orleans)	296	1.67	0.58	1.14	0.85	Extreme	Same behavioral profile as S11_T28; recreational weekend elevation in Replica with weekday Strava Metro orientation on dense Orleans cycling network
B	Bike	S11_T29 (St. Tammany)	7	1.56	0.91	1.21	1.06	High	Replica shows clear weekend peak consistent with recreational cycling on the Northshore trail network
C	Ped	S17 (EBR)	10	0.92	0.89	1.03	0.86	Low	Weekday-dominant activity in both sources with low divergence; consistent with utilitarian pedestrian travel
C	Bike	S3_T14 (Orleans)	129	0.9	0.79	1.55	1	Low	Clearest weekday-utilitarian result in the dataset; fall-semester commuter arterial with strong source alignment between Replica and Strava
D	Ped	S3_T11 (Lincoln)	23	1.28	0.32	0.58	0.6	High	Spring-dominant Replica seasonal combined with fall weekday Strava surge; reflects end-of-year outdoor campus activity and fall-semester fitness behavior, respectively
D	Bike	S1_T3 (EBR)	12	1.17	0.83	4.39	1.09	Moderate	Extreme Replica fall concentration; likely institutional or event-driven seasonal demand; flag for site verification before operational use
E	Ped	S14_T17 (EBR)	9	1.09	0.16	0.91	9.01	High	Extreme Strava fall and weekday factors with stable Replica values; Strava reflects a narrow athletic subgroup, not general pedestrian demand; verify site before use
E	Bike	S3_T13 (Orleans)	9	1.65	2.93	1.17	0.37	Extreme	Two sources describe different temporal patterns in the same segments and cannot be explained by a single behavioral interpretation

Applications for Counter Location Selection

The joint spatial and temporal clustering results show that combining Replica and Strava Metro adjustment factor profiles can identify distinct, study-specific factor groups that are not apparent from spatial proximity alone. Across the bicyclist and pedestrian networks in the four study parishes, the five-factor-group framework indicates that road segments located near one another may still exhibit different weekly, seasonal, and cross-source temporal patterns. This finding has important implications for representative counter placement and short-count expansion. Rather than selecting monitoring locations only to maximize geographic coverage, agencies should also consider whether candidate locations represent different temporal behavior types.

The five factor groups identified in this study suggest different monitoring strategies. Factor Group A (Stable Cross-Source Baseline) represents the most efficient condition for permanent counter placement, in which a single well-placed counter can provide representative adjustment factors across many behaviorally similar segments. Factor Group B (Weekend Recreational) identifies facilities where Saturday short counts would systematically overestimate annualized weekday demand if the temporal pattern were not accounted for. This indicates that recreational facilities should be distinguished from more utilitarian corridors when developing adjustment factors. Factor Group C (Weekday Utilitarian) includes corridors where weekday-focused monitoring is appropriate and where both data sources provide consistent adjustment factors. Factor Group D (Seasonal and Institutional Sensitivity) captures segments governed by academic calendars or institutional activity cycles, requiring count coverage across multiple seasons rather than a single representative period. Factor Group E (Source-Divergent and Anomalous) includes clusters where Replica and Strava Metro show substantially different temporal patterns, indicating that these locations require additional verification before being used for adjustment factor applications or counter selection.

An important finding is the variation in source agreement across factor groups. Replica and Strava Metro are most closely aligned in weekday-utilitarian environments (Group C) and most divergent in recreational and anomalous environments (Groups B and E). This pattern is consistent with previous research showing that crowdsourced fitness-based data may reflect a narrower user population than broader modeled mobility data. The degree of divergence between the two sources, therefore, has direct implications for monitoring practice. Where Replica and Strava Metro are closely aligned, adjustment factors derived from third-party sources can be applied with greater reliability. Where divergence is substantial, the site should be treated with caution and reviewed against local land use context before adjustment factors are used for count expansion.

Overall, the factor group framework shifts the counter placement question from where counters should be located to which temporal behavior patterns should be represented and in what sequence they can be identified from available field data. This interpretation is consistent with the FHWA TMG, which emphasizes grouping monitoring locations with similar temporal variation when developing and applying adjustment factors [39].

While the factor group label tells an agency which monitoring strategy to use, the actual adjustment factor for count expansion should be derived from the specific cluster that best matches the candidate site, not from a single average value for the general factor group. Two sites in the same factor group can have different adjustment factors depending on their type. For example, both the EBR Parish cluster S1_T4 and the Orleans Parish cluster S3_T12 are Group B recreation sites, but their Saturday/Thursday ratios are different, 2.37 in EBR Parish and 1.67 in Orleans Parish. The EBR Parish site is a dedicated waterfront trail, whereas the Orleans Parish site is within the right-of-way of a busy street where some weekday travel still occurs even within the recreation cluster. Using the wrong cluster's adjustment factor at a new site would lead to errors in the annual traffic estimate. In practice, this means that when an agency identifies a candidate counter site as Group B, they should look up the clusters in Tables 13 and 14 whose land use description most closely matches their site and use that cluster's centroid values for count expansion.

Counter Placement Sequence by Factor Group

The factor groups identified in this study support a practical, phased strategy for non-motorized counter deployment. A seven-day or greater short count that includes both weekday and weekend days provides a useful first-step screening tool through the Saturday/Thursday ratio, consistent with the minimum count duration recommended by the FHWA TMG for non-motorized data collection [39] and supported by prior research on short-count error minimization [73]. In this study, Group B recreational sites had a mean Saturday/Thursday ratio of 1.61, while Group C utilitarian sites had a mean ratio of 0.99. A threshold of approximately 1.20 on the Saturday/Thursday ratio provides a practical first-order tool for distinguishing likely recreational from utilitarian sites, consistent with the day-of-week classification framework established by Miranda-Moreno et al. [74]. By contrast, full classification of all factor groups requires longer observation periods or additional data. Group A can only be identified after confirming stability across a full annual cycle [73]. Group D requires at least two seasons of data to detect the fall/spring imbalance that defines it [75] [76]. Group E depends on disagreement between passive mobility data sources rather than physical count data alone. The practical implication is a two-phase strategy: agencies should first use short counts to identify likely Group B and Group C sites for early permanent counter installation, then refine Group A and Group D classifications after one year of continuous data. Sites that later show Group E-like behavior should be reviewed rather than prioritized for permanent deployment.

For local agencies in the four study parishes, the maps produced by this study can be used directly to support counter site selection. Agencies can identify the likely factor group for a candidate site by matching it to the nearest classified road segment. Group B and Group C sites should be prioritized for early permanent counter installation because they can be screened from a single seven-day or greater short count. Sites near Group D clusters should be counted in both fall and spring, while sites near Group E clusters should be reviewed carefully against local land use before investment.

For Louisiana DOTD, full replication of the joint Replica and Strava Metro framework is not necessary for statewide guidance. Where Replica data is available statewide, a Replica-only approach can provide a practical first step in parishes where Strava Metro coverage is unavailable. Using the Thursday, Saturday, fall, and spring adjustment factors, this approach can support preliminary identification of likely recreational, utilitarian, and season-sensitive patterns. These preliminary classifications should be refined as permanent counter data or additional passive mobility data become available.

For local agencies in other parishes, the recommended first step is to apply for the same seven-day or greater short-count screen. Consistent with findings from prior Louisiana counting programs, hourly peak-period ratios are not reliable indicators of utilitarian cycling in this region because Louisiana cycling activity does not exhibit the same morning and evening commute peaks observed in other cities [63] [64]. Candidate sites with a Saturday/Thursday ratio above 1.20 are likely recreational corridors, while sites below 1.10 are likely utilitarian corridors. This allows agencies to make the most important early distinction in the framework without requiring passive mobility data or clustering analysis. For agencies that already have two or three initial counters, the next counter should be placed to fill any missing behavior type, typically ensuring that the network includes at least one likely recreational site and one likely utilitarian site. After one year of continuous data, sites can be refined into Group A or Group D based on seasonal patterns. Group D is most relevant in parishes with universities or other major institutional activity or other land use specific contexts, such as special event venues, which may or may not be institutional in nature and may not be necessary in every parish. Group E should not be selected as a planned counter target. If strong disagreement between data sources appears later, the site should be reviewed before it is used for broader factor application.

Future work should validate these factor group assignments using additional permanent counter observations as the statewide non-motorized monitoring program expands. Priority should be given to confirming the distinction between Group A and Group B, C and D, since this separation requires at least two seasons of continuous data per site. Future work should also evaluate the performance of the Replica-only pathway in parishes outside the current Strava Metro coverage area.

Outreach Work and Future Plan

Stakeholder outreach has been a core component of this study and related prior efforts focused on improving bicyclist and pedestrian volume monitoring in Louisiana. The outreach activities conducted across multiple projects were designed to build awareness of emerging methods for multimodal counting, understand the needs and capacity of state and local partners, and reduce barriers to establishing sustainable counting programs.

Prior research and implementation initiatives (e.g., LTRC Projects 16-4SA and 19-3SA) established an important foundation for statewide outreach and capacity-building. These studies developed key resources and initiated engagement with agencies responsible for multimodal planning and data collection. Most notably, this includes *Pedestrian and Bicycle Count Data Collection and Use: A Guide for Louisiana* [68], which provides practitioners with practical guidance on count technologies, methodologies, and applications. Additionally, the team designed and delivered a consultant-focused training program demonstrating how to collect short-term bicyclist and pedestrian counts using infrared and pneumatic tube counters. This training introduced practitioners to standardized approaches for data collection and helped build technical familiarity with emerging counting technologies.

The research team also collaborated with the New Orleans Regional Planning Commission (NORPC) to initiate a multi-parish outreach effort designed to gauge interest in establishing bicycle and pedestrian counting programs. Through this “road show,” the team engaged local agencies, such as planning and public works departments, to discuss potential applications of count data and to identify preliminary candidate locations for future counting efforts. These early outreach activities provided an initial understanding of statewide interest and capacity, which informed the approach used in the current research.

Outreach Activities Conducted During This Project

During the current project, outreach efforts focused primarily on documenting existing practices, strengthening relationships with key agencies, and developing implementation resources that could support future statewide deployment of counting programs.

The research team first conducted a diagnostic survey (Appendix A) and follow-up engagement with Metropolitan Planning Organizations (MPOs), local governments, and the Louisiana Department of Transportation and Development (DOTD) District offices to better understand current approaches to bicyclist and pedestrian data collection. Follow-up discussions were held with several agencies to obtain more detailed insights into their practices, constraints, and data needs. These discussions included the Rapides Area Planning Commission (RAPC), South Central Planning and Development Commission (SCPDC), Capital Region Planning Commission (CRPC), St. Tammany Parish Planning and Development, Lafayette Consolidated Government, and other stakeholders.

Through these discussions, the research team documented a range of existing practices and needs. For example, RAPC shared sample vulnerable road user (VRU) count data previously collected on LA 28E in Pineville and described prior experience using third-party mobility datasets. SCPDC provided documentation of earlier manual count studies and noted constraints related to staffing and funding. St. Tammany Parish shared information about existing trail and park visitation data and expressed interest in expanding systematic monitoring. Several agencies, including Lafayette Consolidated Government and stakeholders in Baton Rouge, indicated interest in developing more formalized counting programs but noted that guidance, funding, and technical support would be helpful to initiate these efforts.

In parallel with these outreach discussions, the research team worked closely with NORPC to develop a pilot implementation framework for multimodal counting. This work included integrating multimodal count requirements into consultant procurement scopes of work and reviewing proposals to ensure contractors understood the data collection objectives. The team also collaborated with NORPC to develop a draft use-case document outlining the goals, technical requirements, and potential applications of bicyclist and pedestrian count data. Additional materials prepared as part of the project included a draft workshop presentation and a handout packet for local and regional agencies, a draft demonstration presentation for the Louisiana Active Transportation Information website/dashboard, and draft technical guidance on people-counting equipment specifications, installation procedures, and maintenance practices.

The research team also coordinated with DOTD staff to clarify key implementation questions raised by regional partners, including project funding pathways, procurement processes, equipment selection considerations, and installation responsibilities. This coordination helped address several uncertainties that had previously slowed implementation discussions and helped ensure that the guidance being developed through the research aligned with DOTD processes and expectations.

Collectively, these outreach activities were intended to reduce friction points for agencies interested in initiating bicycle and pedestrian counting programs, regardless of scale, by providing both technical guidance and examples of feasible implementation approaches.

Planned Outreach Activities Deferred to the Implementation Phase

At the outset of the project, the research team developed a broader outreach plan intended to support statewide adoption of the tools and resources produced through the research. However, the timing of several project components, most notably the public launch of the Louisiana Active Transportation Information dashboard, delayed the implementation of this outreach strategy. Because the dashboard had not yet been released publicly during the research phase, several planned engagement activities were postponed to ensure that outreach could include a demonstration of the full system and associated resources.

The planned outreach strategy included hosting a statewide webinar introducing the dashboard and associated research outputs to MPOs, DOTD Districts, and local agencies. The webinar was intended to demonstrate how agencies could access and interpret available data, explain how organizations could contribute data to the system, and outline pathways for initiating new counting programs. Following the statewide webinar, the team planned to offer targeted workshops tailored to the needs and capacity of specific agencies and regions identified through the diagnostic survey and outreach conducted during the project.

These workshops were envisioned as more detailed technical sessions covering topics such as defining data use cases, selecting appropriate count locations and technologies, navigating permitting and procurement processes, installation and calibration practices, and establishing long-term operations and maintenance procedures. Additionally, the outreach plan included follow-up discussions with DOTD District staff and selected regional partners to clarify roles, identify support needs, and determine how the research outputs could be integrated into ongoing planning and project development processes.

Although these activities were not implemented during the research phase due to factors beyond the project team's control, they remain a critical next step in translating the research findings into practice. As such, these outreach efforts are recommended for implementation following the completion of the research phase and the public release of the dashboard and related tools.

Conclusions

The findings of this research indicate that while the state of practice for bicyclist and pedestrian data collection is evolving rapidly, it remains grounded in a set of consistent, proven approaches. While emerging technologies, particularly video-based detection and automated data processing, offer increased flexibility and analytical potential, most agencies with mature multimodal monitoring programs continue to rely on networks of permanent or semi-permanent mechanical counters to generate reliable, continuous baseline data. These systems provide the temporal depth and consistency needed to understand trends, calibrate short-term counts, and support long-term planning decisions. For Louisiana to keep pace with national best practices, it will be important to adopt a similarly hybrid approach, leveraging new technologies where appropriate, while prioritizing the establishment of a core network of permanent counters on key facilities to anchor the statewide data system.

At the same time, the growing emphasis on multimodal transportation planning across the United States underscores the increasing importance of high-quality data. As communities invest in bicyclist and pedestrian infrastructure, the need to understand usage patterns, seasonal variation, and network performance becomes more critical. This is especially true as agencies increasingly turn to third-party datasets (e.g., app-based or passively collected mobility data) to supplement traditional data sources. While these datasets can provide valuable insights, they are inherently limited by sampling bias and incomplete coverage and must therefore be validated against ground-truth count data to ensure reliability. In this context, Louisiana has an opportunity to position itself at the forefront of practice by developing an integrated data ecosystem that combines permanent count data, short-term counts, and third-party datasets in a complementary manner.

Finally, this research demonstrates that regardless of the specific technologies deployed, the fundamental data needs and the systems required to support them are largely consistent across jurisdictions. Agencies require standardized, high-quality data that can be collected continuously, validated, stored, and shared in a consistent format. A key contribution of this study is the development of a framework for standardized data collection, management, and transmission that aligns with national guidance and is compatible with Traffic Monitoring Analysis System (TMAS) requirements. By advancing this framework and supporting its implementation through coordinated outreach, technical guidance, and institutional support, Louisiana can establish a scalable, sustainable approach to multimodal monitoring that supports statewide planning, safety analysis, and investment decision-making.

The principal challenge of developing, expanding, and maintaining such a program is ongoing equipment maintenance, as well as local capacity and funding to sustain activities over time. Of the original 18 count sites, only seven have remained operational throughout this study. In late 2023, many counters installed began losing data transmission capabilities due to a gradual national shift away from 3G wireless technology, necessitating a costly upgrade of all units. Additionally, numerous counters were partially or fully disabled due to vandalism and/or equipment damage from vehicle collisions, particularly in units that include an infrared sensor in a post. In other cases, environmental conditions (e.g., water intrusion from flooding) gradually damaged even “waterproof” components, resulting in unreliable data and necessitating their removal.

While these count units have been repaired and replaced where feasible, in some cases, re-initiation of count sites is on hold pending local partner cooperation and/or identification of funds for ongoing collection and maintenance. Costs for automatic data transmission from the equipment vendor have also increased, presenting a greater burden for local partners interested in collecting or continuing to collect count data.

To encourage local partnership in coordinated data collection, incentivizing and supporting the inclusion of one or more count devices as part of state project funding, particularly for discretionary grants, presents an opportunity to expand, provided that it is coupled with a corresponding data-sharing agreement to ensure transmission of resulting data in support of statewide planning.

Counters consisting solely of an inductive loop sensor have proven to be the most resilient to damage and failure, as well as delivering the greatest overall accuracy. Where feasible (i.e., on dedicated bikeways and trails), this represents an opportunity to expand data at relatively low maintenance, thereby reducing installation costs, particularly if installed as part of facility construction or resurfacing.

For short-term counts, encouraging local agencies to align any data collected, whether systematic in nature or related to specific infrastructure projects or studies, with minimum standards for database inclusion (i.e., at least seven days of continuous data and hourly data intervals) can help increase the quality, utility, and opportunity for advanced data analytics outlined by this study.

Finally, the findings of this project highlight several conclusions about how passive human mobility data, the conversion of raw data into adjustment factors, and network-level clustering can advance non-motorized traffic monitoring in Louisiana. For example, adjustment factors calculated from human mobility data substantially reduce discrepancies between third-party data and permanent counter observations compared with using raw counts directly. In practice, it may be more useful for agencies to use those adjustment factors rather than raw counts. Additionally, the two-stage spatial-temporal clustering framework developed in this project demonstrates that human mobility adjustment factor groups can help systematically identify groups of road segments with similar temporal behavior, patterns that are not visible from geographic location alone. This provides a practical, data-driven foundation for counter location guidance consistent with the FHWA Traffic Monitoring Guide's (TMG) recommendations for factor-group-based site selection in non-motorized monitoring programs. The value of this approach, however, depends on the connectivity of the active transportation network being analyzed. In well-connected urban networks, the clustering framework produces stable and transferable factor groups, allowing human mobility data to represent many segments with minimal counter investment, as demonstrated by the Orleans Parish pedestrian network in this project. In contrast, fragmented networks, where isolated trails, greenways, and neighborhood paths cannot form coherent spatial clusters, are less amenable to this approach, and direct counts at individual facilities are more likely to be required. For Louisiana, this distinction is particularly relevant given the difference between the dense, connected street networks of New Orleans and East Baton Rouge Parish and the dispersed trail and greenway infrastructure of St. Tammany Parish. This should inform how agencies in different local contexts prioritize and sequence the expansion of their non-motorized monitoring programs.

Recommendations

The following actions are recommended based on the work completed throughout this project:

- **Establish a shared equipment loan program**. When funding is available, DOTD or LTRC may want to procure a small pool of user-friendly counting equipment, including pneumatic tube counters, infrared counters, and portable video-based systems, and make them available for loan to local agencies, MPOs, and District offices. This would enable partners to initiate data collection efforts without significant upfront investment and help build statewide familiarity with different technologies.
- **Develop a regular statewide gathering on active transportation data**. Organize an annual (or initially biennial) bicyclist and pedestrian workshop that focuses on data collection, monitoring practices, and data applications. This could begin as a modest workshop-style event and expand over time, providing a forum for knowledge sharing and peer exchange.
- **Designate a centralized point of contact for multimodal counting**. Establish a clear, accessible point of contact within DOTD responsible for advising on bicyclist and pedestrian data collection. This role should include dedicated capacity to provide technical assistance to local agencies, MPOs, and District offices in developing and sustaining data collection programs.
- **Finalize and disseminate technical guidance and specifications**. Provide clear, finalized technical specifications and supporting guidance from DOTD regarding acceptable counting equipment, data formats, and management practices, including guidance on the use of third-party datasets. This will help ensure consistency, clarify funding eligibility, and reduce uncertainty for agencies seeking to implement counting programs.
- **Leverage funding mechanisms to expand counting programs**. Explore the use of the State Transportation Innovation Council (STIC) grant program or similar funding sources to support the deployment of permanent counters and expansion of short-term data collection efforts, including equipment loan programs. This may also include updating grant guidance to encourage inclusion of count data collection, in conjunction with data sharing agreements to facilitate transmission of locally

collected data for regional and state planning use, in programs that support new active transportation projects (e.g., Recreational Trails, Safe Routes to Public Places, Transportation Alternatives).

- **Promote standardized short-term count practices**. Encourage local agencies to conduct systematic short-term counts, with a recommended duration of 14 days (minimum seven days) to the greatest extent feasible, to support consistent and comparable data collection across jurisdictions.
- **Integrate multimodal data collection into consultant scopes of work**. Require that traffic data collection conducted as part of DOTD- or MPO-funded studies include robust bicyclist and pedestrian counts where applicable. Scopes of work should clearly define expectations for multimodal data collection, and contractors should be required to demonstrate appropriate training and competency to ensure data quality and consistency.
- **Implement a coordinated outreach and training program**. Deliver a statewide introductory webinar to present available tools, including the dashboard, and outline pathways for beginning data collection. This could be followed by targeted, regionally tailored workshops to provide more detailed technical guidance based on agency needs and capacity.
- **Use of the third-party data for hybrid data collection.** It is recognized that different human mobility sources capture different user populations; crowdsourced fitness app data tends to reflect a narrower demographic of regular cyclists and fitness users, while calibrated population models, such as Replica, represent a broader cross-section of the traveling public. For this reason, officials should select or combine sources accordingly based on the planning question being addressed. Despite the discrepancy, it is still valuable for public agencies to leverage their current access to data platforms (e.g., Strava Metro) and use adjustment factors derived from this data, rather than raw counts, for network monitoring and potential short-term counter location selection. For future research, it would be worthwhile to expand the clustering framework to cover the entire state of Louisiana to further validate the method's applicability and result in a statewide scope.

Acronyms, Abbreviations, and Symbols

Term	Description
AADB	Annual Average Daily Bicyclists
AADNT	Annual Average Daily Non-Motorized Traffic
AASHTO	American Association of State Highway and Transportation Officials
API	Application Programming Interface
Cm	centimeter(s)
CNN	Convolutional Neural Network
CRPC	Capital Region Planning Commission
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DETR	Detection Transformer
DOTD	Louisiana Department of Transportation and Development
DOW	Day of Week
DOY	Day of Year
FHWA	Federal Highway Administration
FMCW	Frequency-Modulated Continuous-Wave
FTE	Full-Time Equivalent
ft.	foot (feet)
GIS	Geographic Information System
GPS	Global Positioning System
HOG	Histogram of Oriented Gradients
in.	inch(es)
ITRE	Institute for Transportation Research and Education
lb.	pound(s)
LBS	Location-Based Service
LiDAR	Light Detection and Ranging
LTRC	Louisiana Transportation Research Center
M	meter(s)
MADT	Monthly Average Daily Traffic
mmWave	Millimeter-Wave
MPO	Metropolitan Planning Organization

Term	Description
NC NMVDP	North Carolina Non-Motorized Volume Data Program
NCHRP	National Cooperative Highway Research Program
NORPC	New Orleans Regional Planning Commission
OD	Origin-Destination
OSM	OpenStreetMap
osmId	OpenStreetMap segment identifier
POI	Point of Interest
RAPC	Rapides Area Planning Commission
RT-DETR	Real-Time Detection Transformer
SCPDC	South Central Planning and Development Commission
SIFT	Scale-Invariant Feature Transform
SORT	Simple Online and Realtime Tracking
STIC	State Transportation Innovation Council
SVM	Support Vector Machine
TMG	Traffic Monitoring Guide
UNOTI	UNO Transportation Institute
UTM	Universal Transverse Mercator
VRU	Vulnerable Road User
WADT	Weekly Average Daily Traffic
YOLO	You Only Look Once

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Appendix A: Non-Motorized Counting Diagnostic Survey Instrument

The Louisiana Transportation Research Center (LTRC) has been sponsoring research projects related to the collection and use of non-motorized traffic data. This survey is to understand current non-motorized traffic monitoring practices, level of interest in non-motorized traffic counting, current staff capacity, and the scope of planning and data needs pertaining to non-motorized road users among public organizations in Louisiana.

If you are affiliated with DOTD (e.g., District offices and DOTD sections/offices/programs), please contact the project investigators Ruijie "Rebecca" Bian (rbian1@lsu.edu) and Tara Tolford (tmtolfor@uno.edu) to discuss data collection.

More information about this research project may be found here.

Q1 Stakeholder Respondent Role:

- ☐ USDOT / Federal agency (11)
- ☐ State Department of Transportation (DOT) (2)
- ☐ Metropolitan Planning Organization (MPO) or other regional entity (3)
- ☐ Local government agency (4)
- ☐ Non-governmental stakeholder: Consultant/Private Sector (7)
- ☐ Non-governmental stakeholder: Advocate/Non-Profit Organization (8)
- ☐ Transit agency (5)
- ☐ Other (specify) (6)

____

Q2 Which of the following best describes your role?

- ▢ Design/Engineering (1)
- ▢ Administration (2)
- ▢ Planning (3)
- ▢ Project Management (4)
- ▢ Operations (5)
- ▢ Consultant (6)
- ▢ Research/Education (8)
- ▢ Other (Describe) (7) ____

Q3 Which of the following best describes the region(s) in which you work? (select all that apply)

- ▢ Statewide/DOTD HQ (1)
- ▢ New Orleans area (District 02) (2)
- ▢ Lafayette area (District 03) (3)
- ▢ Shreveport/Bossier area (District 04) (4)
- ▢ Monroe area (District 05) (5)
- ▢ Lake Charles Area (District 07) (6)

- ☐ Alexandria area (District 08) (7)
- ☐ Chase area (District 58) (8)
- ☐ Baton Rouge area (District 61) (9)
- ☐ Northshore area (District 62) (10)
- ☐ Other - Outside of Louisiana (11)

1. Current Traffic Monitoring Practices

Q4 Does your organization currently collect any non-motorized count data? This can include systematic count programs, before/after counts, data collected through Stage 0/feasibility studies, etc.

- ☐ Yes—both bicyclists and pedestrians (4)
- ☐ Yes—pedestrians only (5)
- ☐ Yes—bicyclists only (6)
- ☐ No (7)
- ☐ Unsure (8)

Display This Question:

If 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Unsure

Q5 Pedestrian and bicycle volume or count data is sometimes collected as part of a systematic evaluation or monitoring program, and is sometimes collected at the individual project level, such as by contractors conducting a traffic study or feasibility/alternatives analysis. Are you aware of any data which your organization

may possess that includes information about the number or characteristics of pedestrians and bicyclists at a given location?

☐ Yes—my organization collects pedestrian and/or bicycle volume data of some kind, such as a component of traffic or feasibility studies (1)

☐ No—there is unlikely to be any relevant data within my organization (2)

☐ Unsure (3)

Display This Question:

If 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = No

Or Pedestrian and bicycle volume or count data is sometimes collected as part of a systematic evalua... = No - there is unlikely to be any relevant data within my organization

Q6 In your understanding, why does your organization not collect non-motorized count data? (select all that apply)

☐ Inadequate staff time (4)

☐ Lack of knowledge of available counting technologies (5)

☐ Unsure on the best methods (6)

☐ Equipment and/or maintenance costs (7)

☐ Benefits are unclear (8)

☐ Other (please specify) (9)

____

Display This Question:

If 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - both bicyclists and pedestrians

Or 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - pedestrians only

Or 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - bicyclists only

Or Pedestrian and bicycle volume or count data is sometimes collected as part of a systematic evalua... = Yes - my organization collects pedestrian and/or bicycle volume data of some kind, such as a component of traffic or feasibility studies

Q7 What kind of equipment has your agency previously used to collect non-motorized counts? (select all that apply)

- ☐ Short-duration—manual counts (no equipment or handheld counter) (4)
- ☐ Short-duration—infrared sensors (5)
- ☐ Short-duration—pneumatic tubes (6)
- ☐ Short-duration—video counts (manually reviewed) (7)
- ☐ Short-duration—video counts (automatically processed) (8)
- ☐ Short-duration—other or unknown method (9)
- ☐ Long-duration/permanent counts—infrared sensors (10)
- ☐ Long-duration/permanent counts—pneumatic tubes (11)
- ☐ Long-duration/permanent counts—inductive loops (12)
- ☐ Long-duration/permanent counts—other or unknown method (13)

Display This Question:

If 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - both bicyclists and pedestrians

Or 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - pedestrians only

Or 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - bicyclists only

Or Pedestrian and bicycle volume or count data is sometimes collected as part of a systematic evalua... = Yes - my organization collects pedestrian and/or bicycle volume data of some kind, such as a component of traffic or feasibility studies

Q8 What vendors and equipment models have you or your organization worked with? (if known)

Display This Question:

If 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - both bicyclists and pedestrians

Or 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - pedestrians only

Or 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - bicyclists only

Or Pedestrian and bicycle volume or count data is sometimes collected as part of a systematic evalua... = Yes - my organization collects pedestrian and/or bicycle volume data of some kind, such as a component of traffic or feasibility studies

Q9 At how many locations has your organization collected count data?

	N/A (1)	1 to 2 locations (2)	3 to 5 locations (3)	6 to 10 locations (4)	More than 10 locations (5)
Short-duration—manual counts (4)	▢	▢	▢	▢	▢
Short-duration—automated counts (infrared, pneumatic tubes, etc) (5)	▢	▢	▢	▢	▢
Short-duration—video counts (either manually or automatically processed) (6)	▢	▢	▢	▢	▢
Long-duration or permanent counts (7)	▢	▢	▢	▢	▢

Display This Question:

If 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - both bicyclists and pedestrians

Or 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - pedestrians only

Or 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - bicyclists only

Or Pedestrian and bicycle volume or count data is sometimes collected as part of a systematic evalua... = Yes - my organization collects pedestrian and/or bicycle volume data of some kind, such as a component of traffic or feasibility studies

Q10 Please list the location and year(s) (with as much specificity as possible) of any counts previously collected (or provide reference or contact info to follow up for more info). [OPTIONAL]

Display This Question:

If 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - both bicyclists and pedestrians

Or 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - pedestrians only

Or 1.Current Traffic Monitoring Practices Does your organization currently collect any non-motorized... = Yes - bicyclists only

Or Pedestrian and bicycle volume or count data is sometimes collected as part of a systematic evalua... = Yes - my organization collects pedestrian and/or bicycle volume data of some kind, such as a component of traffic or feasibility studies

Q11 How and where is non-motorized data stored (file format, responsible office, etc.)?

2. Capacity and Interest in Non-Motorized Traffic Monitoring

Q12 How many full-time equivalent (FTE) staff persons does your agency employ who are responsible for:

- ☐ Activities relating to active transportation planning or programs (walking, bicycling, and/or transit) (1) ____
- ☐ Activities relating to traffic count collection and/or management (all travel modes) (2) ____

Q13 Please rate your agency's level of interest in initiating or expanding non-motorized data collection activities in the next 1-5 years:

- ☐ Extremely interested (19)
- ☐ Very interested (20)
- ☐ Moderately interested (21)
- ☐ Slightly interested (22)
- ☐ Not at all interested (23)

Q14 For what purposes would you or do you currently use bicycle and pedestrian count data? (select all that apply)

	Currently use (1)	Would use if available (2)
Demonstrating use of facilities (1)	▢	▢
Supporting funding requests/grant proposals (2)	▢	▢
Monitoring traffic volume trends (3)	▢	▢
Before and after studies (4)	▢	▢
Safety/risk analyses (5)	▢	▢
Research (6)	▢	▢
Informing transportation and land use feasibility studies (7)	▢	▢
Informing assessment of long-term trends (8)	▢	▢
Supporting network-level non-motorized demand models or estimates (9)	▢	▢

Validating and adjusting short-duration counts collected as part of feasibility or traffic studies (10)	▢	▢
Other (specify) (11)	▢	▢

Q15 What role would your organization like to see the Department of Transportation and Development (DOTD) to play in non-motorized count data collection? (select all that apply)

▢ Share/publish count data (1)

▢ Collect permanent count data (2)

▢ Conduct trainings (3)

▢ Assist local organizations in initiating or managing data collection activities (4)

▢ Perform trend analysis (5)

▢ Collect short-duration count data (6)

▢ Develop tools and methods for safety analysis (7)

▢ Other (specify) (8) ____

Q16 Would you be interested in sharing your non-motorized count data with DOTD in the future, as part of a statewide database?

- ☐ Yes (1)
- ☐ No (2)
- ☐ Not applicable (4)
- ☐ Maybe, but I have the following questions or concerns (3)

____

Q17 If your organization would potentially be willing to share pedestrian and bicycle count data previously collected with us for research purposes and/or inclusion in the statewide count database, please provide contact information and we'll reach out to discuss further.

- ☐ Name (4) ____
- ☐ Organization (5) ____
- ☐ Email (6) ____

Appendix B: Counter Data Dictionary

The data dictionary explains pedestrian and bicyclist count data collected in Louisiana from 2010. The coding follows the "Coding Non-Motorized Station Location Information in the 2016 Traffic Monitoring Guide Format" published by FHWA in November 2016, which is referred as "TMG—Nonmotorized" in the following texts.

Feature layer name	**Feature type**	**Data source**	**Data sharing**	**Layer and attribute description**
Disaggregate data				
Count Station	Point	Refer to the "Notes" column for more information	Online dashboard	This layer presents the location of the count station and its associated attributes. • ID • Station_Name: name of a counting station. • Station_ID: ID of a counting station. This "six-character identifier" only contains letters and numbers. The first three characters refer to FIPS county/parish code (i.e., Parish_ID). The fourth character refers to count duration (i.e., Count_Duration_Class; M for Manual, L for Long, and S for Short). The last two characters refer to a unique ID within each parish. (Page 11 in TMG—Nonmotorized). One Station ID may represent multiple individual but related count device installation locations and/or facilities. For example, two infrared sensors counting sidewalks and two pneumatic tube sensors counting bike lanes on either side of a roadway. • Site_Cross_Street: name of the cross street. • Facility_Type_Code: facility type code. Please refer to the shared coding file for more information. (Page 17-21 in TMG—Nonmotorized) • Facility_Type_Text: facility type with short description. • Urban_Rural: whether a station is in an urban or rural context as defined by current U.S. Census Urbanized Area classification. • Road_Class: functional classification of the roadway (in text). Please refer to the shared coding file for more information. (Page 11-12 in TMG—Nonmotorized). Where available, functional classification is retrieved from this DOTD resource. • Route_Direction: direction of a route. Please refer to the shared coding file for more information. (Page 12-13 in TMG—Nonmotorized).

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				• Road_Relative: count location relative to the Direction of Route and records which "side" of the road the counted facility is on (same or opposite). Please refer to the shared coding file for more information. (Page 14-15 in TMG—Nonmotorized) • Move_Direction: the direction of movement of the users being counted, relative to Route_Direction. Please refer to the shared coding file for more information. (Page 15-17 in TMG—Nonmotorized). • Count_Type: Indicates what type of user is being counted. Please refer to the shared coding file for more information. (Page 22-23 in TMG—Nonmotorized) • Count_Method: Indicates the method used to conduct the count, whether by a human observation (=1), portable traffic recording device (=2), or permanent count station (=3). (Page 23-24 in TMG-Nonmotorized) • City: name of the city where a counting station is located • Parish_Name: name of the parish where a counting station is located • Parish_ID: the FIPS county/parish code. • Latitude • Longitude • Sensor_Type: Generic type of sensor used to conduct count. Please refer to the shared coding file for more information. (Pages 24-25 in TMG—Nonmotorized) • Sensor_Model: Refers to manufacturer name for sensor unit, currently includes EcoMulti, EcoPyro, EcoTUBES, and EcoZelt. Please refer to Appendix B from LTRC Project 16-4SA for detailed counter information. • User_Type_Text: user types include Bicycles, Mixed Bike/Ped, and Pedestrians. (Page 22-23 in TMG—Nonmotorized) • Count_Duration_Class: count duration classes include Manual (i.e., human observation), Long (i.e., long-term/continuous/permanent counts) and Short (i.e., short-term counts). (Page 23-24 in TMG—Nonmotorized) • Date_Begin: date which data at this station was first collected (in MM/DD/YYYY format). • Date_End: date which data at this station was discontinued (in MM/DD/YYYY format). • ADT: average daily traffic • ADT_Period: time period considered in calculating ADT. • Data_Report: link to access counting report of a site. • Travel_Pattern: travel patterns include Multipurpose, Non-Commute, and Recreational.

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				• Data_Owner: sponsor of a counting project and the entity that owns the counting data. • Notes: data source
Count Data	Tables on dashboard	Refer to the "Notes" column for more information	Online dashboard	Count data file includes count station information and count data information. Count station information corresponds to data entries in "Count Station" file: • Station_ID: ID of a counting station. • Station_Name: name of a counting station. • Parish_Name: name of the parish where a counting station is located. • Parish_ID: the FIPS county/parish code. • Latitude • Longitude • Route_Direction: direction of a route. Please refer to the shared coding file for more information. (Page 12-13 in TMG—Nonmotorized). • Road_Relative: count location relative to the Direction of Route and records which "side" of the road the counted facility is on (same or opposite). Please refer to the shared coding file for more information. (Page 14-15 in TMG—Nonmotorized) • Move_Direction: the direction of movement of the users being counted, relative to Route_Direction. Please refer to the shared coding file for more information. (Page 15-17 in TMG—Nonmotorized). • Facility_Type_Text: facility type with short description. When one Station ID represents multiple individual but related count device installation locations and/or facilities, it includes all facility types in one field. For example, two infrared sensors counting sidewalks and two pneumatic tube sensors counting bike lanes on either side of a roadway. In this case, "Facility_Type_Text" equals "Sidewalks; Bike lanes". Count data information uses the template from LTRC Project 19-3SA (Appendix E). • Date: expressed in the format "2/13/2020" in the daily count data. • Full_Date: expressed in the format like "Thursday, February 13, 2020". • DateTime: expressed in the format like "2/13/2020 9:00:00" for daytime hours or "2/13/2020 21:00:00" for nighttime hours in the hourly count data. • Year: expressed in the format like "2020" (i.e., YYYY). • Month: expressed in the format like "2" (i.e., MM). • Day: expressed in the format like "13" (i.e., DD). • Hour: expressed in the format like "9" for daytime hours or "21" for nighttime hours in the hourly count data.

Feature layer name	Feature type	Data source	Data sharing	Layer and attribute description
				• Day_of_Week: expressed by number from 1 (which stands for Monday) to 7 (which stands for Sunday). • Weekend: whether the date is a weekend day (TRUE or FALSE) • Total_Users: the total number of bicyclists and pedestrians observed in both directions, which equals Total_IN + Total_OUT (when both modes are detected and with no missing data). • Total_IN: the total number of bicyclists and pedestrians observed in the first direction, which equals Peds_IN + Bikes_IN (when both modes are detected and with no missing data). • Total_OUT: the total number of bicyclists and pedestrians observed in the second direction, which equals Peds_OUT + Bikes_OUT (when both modes are detected and with no missing data). • Peds_IN: the total number of pedestrians observed in the first direction. • Peds_OUT: the total number of pedestrians observed in the second direction. • Total_Peds: the total number of pedestrians observed in both directions, which equals Peds_IN + Peds_OUT. • Bikes_IN: the total number of bicyclists observed in the first direction. • Bikes_OUT: the total number of bicyclists observed in the second direction. • Total_Bikes: the total number of bicyclists observed in both directions, which equals Bikes_IN + Bikes_OUT. **Note 1**: <Null> means count data was not collected; Zero means no bike/ped activity was observed. **Note 2**: Total_Users, Total_IN, and Total_OUT may not be <Null> even when Peds_IN, Peds_OUT, Total_Peds, Bikes_IN, Bikes_OUT, and Total_Bikes are <Null>. This only means the installed counter cannot distinguish pedestrians from bicyclists, so both activities are counted combined.
Count Data Report	Figures on dashboard	Refer to the "Notes" column for more information	Online dashboard	The dashboard presents the following information based on users' queries: • Site introduction • Average daily volume by year • Average daily volume by calendar month • Average daily volume by day of week • Average hourly volume by time of day

Count data file naming protocol (V1: by station):

This naming protocol may work better for local data management.

Case 1: When one Station ID represents one count device installation location and/or facility, we only distinguish count records by hour and day. For example, we have “count_data_cleaned_daily_033L28.xlsx” and “count_data_cleaned_hourly_033L28.xlsx” for “Baton Rouge MRT—Casino Site”.

Case 2: When one Station ID represents multiple individual but related count device installation locations and/or facilities, we distinguish count records by: (1) hour and day and (2) roadway direction. For example, two infrared sensors counting sidewalks and two pneumatic tube sensors counting bike lanes on either side of a roadway of north/south direction. Take “Tulane Avenue—LA-61” as an example; we have the following files:

- count_data_cleaned_daily_071S14N.xlsx
- count_data_cleaned_daily_071S14S.xlsx
- count_data_cleaned_hourly_071S14N.xlsx
- count_data_cleaned_hourly_071S14S.xlsx

Count data file naming protocol (V2: merged/appended data):

This naming protocol complies with DOTD data management needs.

For daily counts, the file name is “count_data_cleaned_daily.xlsx”. Similarly, the file name becomes “count_data_cleaned_hourly.xlsx” for hourly counts.

Appendix C: QA/QC Sample Workbook

[See the attached Excel workbook]

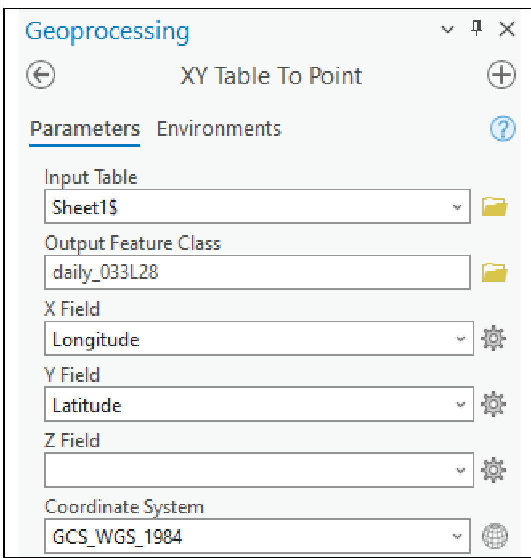
Appendix D: Database Maintenance Manual

This section explains how to convert a count data sheet (.xlsx) into a spatial data sheet and save the spatial data sheet in a geodatabase (.gdb). The purpose of these steps is to reserve essential data information for data visualization and query on a shared data platform for public access. The following steps use the “count_data_cleaned_daily_033L28.xlsx” file as an example. If you are asked to keep only one spatial data sheet for all counters, merge all the count data sheets into one data sheet (.xlsx) before taking the steps below.

Step 0: Check data quality. No cell in the Excel data sheet should have (blanks), especially in the following columns. If you observe (blanks), check the QA/QC Guideline (see Appendix B) and work with the QA/QC person to fill in correct values (even if the value is <Null>) before proceeding to the next step.

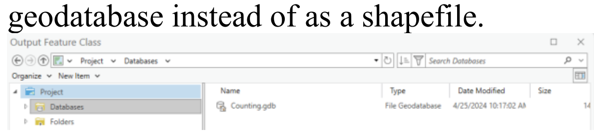
Total_Users	Total_IN	Total_OUT
Peds_IN	Peds_OUT	Total_Peds
Bikes_IN	Bikes_OUT	Total_Bikes

Step 1: In ArcGIS Pro, use “Map → Add Data → XY Point Data” and save the output feature in a geodatabase file/folder (instead of as a shapefile). Here, the geodatabase file/folder is named “Counting_033L28.gdb” to host all the spatial data sheets related to this counter. If you do not have a geodatabase file/folder, please create one by opening the “Catalog View” pane and clicking “New File Geodatabase.”



Input Table: Select the Excel sheet you want to import data from, which is “count_data_cleaned_daily_033L28.xlsx” in this case.

Output Feature Class: Select “Databases” instead of “Folders” to save your data in a geodatabase instead of as a shapefile.



Enter a proper name for the imported data, which is “daily_033L28” in this case.
Hit the “Run” button.

Step 2: Check data attributes for the following columns to make sure their data type is “Double” instead of “Text.”

Total_Users	Total_IN	Total_OUT
Peds_IN	Peds_OUT	Total_Peds
Bikes_IN	Bikes_OUT	Total_Bikes

Figure 14. An example of correct data types

☑ Visible	■ Read Only	Field Name	Alias	Data Type	☑ Allow NULL	☐ Highlight	Number Format	Domain	Default	Length
☑	☐	Total_Users	Total_Users	Double	✓	☐	Numeric			
☑	☐	Total_IN	Total_IN	Double	✓	☐	Numeric			
☑	☐	Total_OUT	Total_OUT	Double	✓	☐	Numeric			
☑	☐	Peds_IN	Peds_IN	Double	✓	☐	Numeric			
☑	☐	Peds_OUT	Peds_OUT	Double	✓	☐	Numeric			
☑	☐	Total_Peds	Total_Peds	Double	✓	☐	Numeric			
☑	☐	Bikes_IN	Bikes_IN	Double	✓	☐	Numeric			
☑	☐	Bikes_OUT	Bikes_OUT	Double	✓	☐	Numeric			
☑	☐	Total_Bikes	Total_Bikes	Double	✓	☐	Numeric			

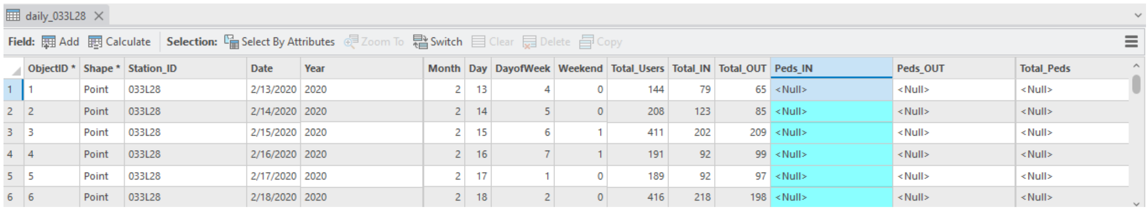
Figure 15. An example of wrong data types

☑	☐	Total_Users	Total_Users	Double	✓	☐	Numeric			
☑	☐	Total_IN	Total_IN	Double	✓	☐	Numeric			
☑	☐	Total_OUT	Total_OUT	Double	✓	☐	Numeric			
☑	☐	Peds_IN	Peds_IN	Text	✓	☐				255
☑	☐	Peds_OUT	Peds_OUT	Text	✓	☐				255
☑	☐	Total_Peds	Total_Peds	Text	✓	☐				255
☑	☐	Bikes_IN	Bikes_IN	Text	✓	☐				255
☑	☐	Bikes_OUT	Bikes_OUT	Text	✓	☐				255
☑	☐	Total_Bikes	Total_Bikes	Text	✓	☐				255

The wrong data types appear because the way ArcGIS Pro/Portal recognizes a <Null> value differs from Excel. Therefore, you need to transfer <Null> values into the data type that ArcGIS Pro/Portal can recognize. Without this step, columns including “<Null>” will still be recognized as “Text,” which will prevent online data query in the next step.

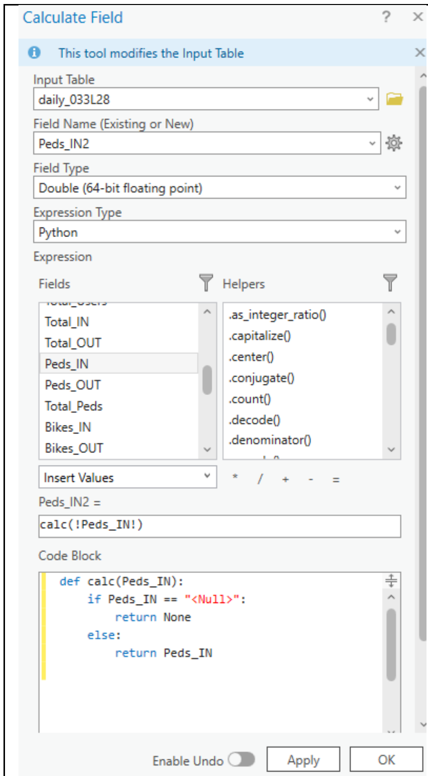
Right click on a data column that is marked as “Text” in their Data Type → Hit the “Calculate Field.”

Figure 16. An example of “calculate field”



	ObjectID *	Shape *	Station_ID	Date	Year	Month	Day	DayofWeek	Weekend	Total_Users	Total_IN	Total_OUT	Peds_IN	Peds_OUT	Total_Peds
1	1	Point	033L28	2/13/2020	2020	2	13	4	0	144	79	65	<Null>	<Null>	<Null>
2	2	Point	033L28	2/14/2020	2020	2	14	5	0	208	123	85	<Null>	<Null>	<Null>
3	3	Point	033L28	2/15/2020	2020	2	15	6	1	411	202	209	<Null>	<Null>	<Null>
4	4	Point	033L28	2/16/2020	2020	2	16	7	1	191	92	99	<Null>	<Null>	<Null>
5	5	Point	033L28	2/17/2020	2020	2	17	1	0	189	92	97	<Null>	<Null>	<Null>
6	6	Point	033L28	2/18/2020	2020	2	18	2	0	416	218	198	<Null>	<Null>	<Null>

Use “Peds_IN” as an example. Apply the following settings in “Calculate Field.”



Input Table: Automatically filled in by ArcGIS Pro.

Field Name: Create a new field name to save your data, which is “Peds_IN2” in this case for simplification.

Field Type: Select “Double (64-bit floating point)” to keep consistency with other data columns that enable online data query.

Fields: Select “Peds_IN,” which is the field you are working on in this case.

Peds_IN2=: Enter “calc(!Peds_IN!)”

Code Block: Enter the following code

```
def calc(Peds_IN):
    if Peds_IN == "<Null>":
        return None
    else:
        return Peds_IN
```

Hit “OK” to complete the calculation.

Repeat the calculation for all the data columns that have “Text” as their Data Type. The following is a set of calculation codes that may be needed in the process. They are kept here to save time for typing code. Remember to select the correct code for the data column you are working on.

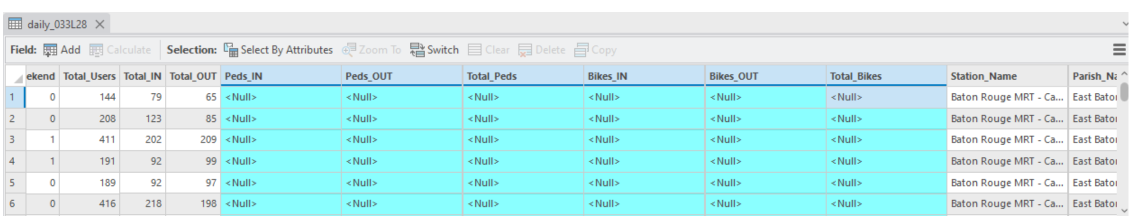
calc(!Total_Users!)
Code block
def calc(Total_Users):
    if Total_Users == "<Null>":
        return None
    else:
        return Total_Users
	calc(!Total_IN!)
	Code block
	def calc(Total_IN):
	    if Total_IN == "<Null>":
	        return None
	    else:
	        return Total_IN
		calc(!Total_OUT!)
		Code block
		def calc(Total_OUT):
		    if Total_OUT == "<Null>":
		        return None
		    else:
		        return Total_OUT

calc(!Total_Peds!)
Code block
def calc(Total_Peds):
    if Total_Peds == "<Null>":
        return None
    else:
        return Total_Peds
	calc(!Peds_IN!)
	Code block
	def calc(Peds_IN):
	    if Peds_IN == "<Null>":
	        return None
	    else:
	        return Peds_IN
		calc(!Peds_OUT!)
		Code block
		def calc(Peds_OUT):
		    if Peds_OUT == "<Null>":
		        return None
		    else:
		        return Peds_OUT

calc(!Total_Bikes!)
Code block
def calc(Total_Bikes):
    if Total_Bikes == "<Null>":
        return None
    else:
        return Total_Bikes
	calc(!Bikes_IN!)
	Code block
	def calc(Bikes_IN):
	    if Bikes_IN == "<Null>":
	        return None
	    else:
	        return Bikes_IN
		calc(!Bikes_OUT!)
		Code block
		def calc(Bikes_OUT):
		    if Bikes_OUT == "<Null>":
		        return None
		    else:
		        return Bikes_OUT

Step 3: Remove fields you no longer need to save storage space. In this case, you need to remove the following fields: Peds_IN, Peds_OUT, Total_Peds, Bikes_IN, Bikes_OUT, and Total_Bikes. Select those fields → Right click on them → Hit "Delete"

Figure 17. An example of fields to be removed


daily_033L28

Field: Add Calculate Selection: Select By Attributes Zoom To Switch Clear Delete Copy

	ekend	Total_Users	Total_IN	Total_OUT	Peds_IN	Peds_OUT	Total_Peds	Bikes_IN	Bikes_OUT	Total_Bikes	Station_Name	Parish_Na
1	0	144	79	65	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	Baton Rouge MRT - Ca...	East Bato
2	0	208	123	85	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	Baton Rouge MRT - Ca...	East Bato
3	1	411	202	209	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	Baton Rouge MRT - Ca...	East Bato
4	1	191	92	99	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	Baton Rouge MRT - Ca...	East Bato
5	0	189	92	97	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	Baton Rouge MRT - Ca...	East Bato
6	0	416	218	198	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	Baton Rouge MRT - Ca...	East Bato

Step 4: Rename fields that we created in Step 2 so that they can be understood easily without confusion. Right click on a data column → Hit "Fields" → Rename fields as shown below. We need to make revisions under both the "daily_033L28" and "Data Source" tabs.

Figure 18. Data appearance before taking Step 4

(a) "daily_033L28" tab

daily_033L28 | *Fields: daily_033L28

Current Layer: daily_033L28

Visible	Read Only	Field Name	Alias	Data Type	Allow NULL	Highlight	Number Format	Domain	Default	Length
✓	☐	Facility_Type_Text	Facility_Type_Text	Text	✓	☐				255
✓	☐	Peds_IN2	Peds_IN2	Double	✓	☐	Numeric			
✓	☐	Peds_OUT2	Peds_OUT2	Double	✓	☐	Numeric			
✓	☐	Total_Peds2	Total_Peds2	Double	✓	☐	Numeric			
✓	☐	Bikes_IN2	Bikes_IN2	Double	✓	☐	Numeric			
✓	☐	Bikes_OUT2	Bikes_OUT2	Double	✓	☐	Numeric			
✓	☐	Total_Bikes2	Total_Bikes2	Double	✓	☐	Numeric			

(b) "Data Source" tab

daily_033L28 | Fields: daily_033L28

Current Layer: Data Source

Field Name	Alias	Data Type	Allow NULL	Domain	Default	Length
Longitude	Longitude	Double	✓			
Route_Direction	Route_Direction	Double	✓			
Road_Relative	Road_Relative	Double	✓			
Move_Direction	Move_Direction	Double	✓			
Facility_Type_Text	Facility_Type_Text	Text	✓			255
Peds_IN2	Peds_IN2	Double	✓			
Peds_OUT2	Peds_OUT2	Double	✓			
Total_Peds2	Total_Peds2	Double	✓			
Bikes_IN2	Bikes_IN2	Double	✓			
Bikes_OUT2	Bikes_OUT2	Double	✓			
Total_Bikes2	Total_Bikes2	Double	✓			

Figure 19. Data appearance after taking Step 4

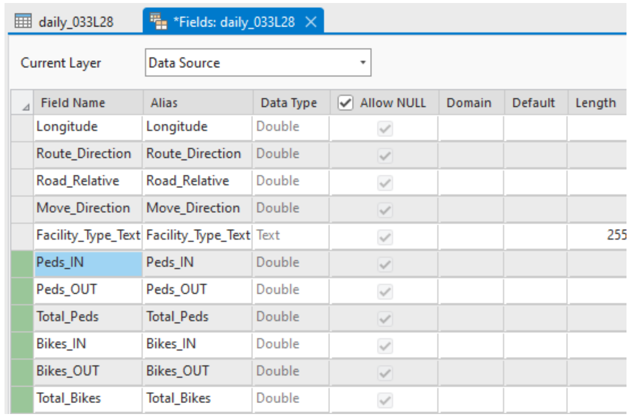
(a) "daily_033L28" tab

daily_033L28 | *Fields: daily_033L28

Current Layer: daily_033L28

Visible	Read Only	Field Name	Alias	Data Type	Allow NULL	Highlight	Number Format	Domain	Default	Length
✓	☐	Facility_Type_Text	Facility_Type_Text	Text	✓	☐				255
✓	☐	Peds_IN	Peds_IN	Double	✓	☐	Numeric			
✓	☐	Peds_OUT	Peds_OUT	Double	✓	☐	Numeric			
✓	☐	Total_Peds	Total_Peds	Double	✓	☐	Numeric			
✓	☐	Bikes_IN	Bikes_IN	Double	✓	☐	Numeric			
✓	☐	Bikes_OUT	Bikes_OUT	Double	✓	☐	Numeric			
✓	☐	Total_Bikes	Total_Bikes	Double	✓	☐	Numeric			

(b) “Data Source” tab


daily_033L28 | *Fields: daily_033L28

Current Layer: Data Source

Field Name	Alias	Data Type	Allow NULL	Domain	Default	Length
Longitude	Longitude	Double	✓			
Route_Direction	Route_Direction	Double	✓			
Road_Relative	Road_Relative	Double	✓			
Move_Direction	Move_Direction	Double	✓			
Facility_Type_Text	Facility_Type_Text	Text	✓			255
Peds_IN	Peds_IN	Double	✓			
Peds_OUT	Peds_OUT	Double	✓			
Total_Peds	Total_Peds	Double	✓			
Bikes_IN	Bikes_IN	Double	✓			
Bikes_OUT	Bikes_OUT	Double	✓			
Total_Bikes	Total_Bikes	Double	✓			

Please make sure that the following fields all have “Double” as their data type as shown in the figure attached above: Total_Users, Total_IN, Total_OUT, Peds_IN, Peds_OUT, Total_Peds, Bikes_IN, Bikes_OUT, and Total_Bikes. This is to ensure that the webpage query module summarizes numeric values rather than text characters.

Other critical fields to ensure the success of online data query are: Year, Month, Day, and Hour. Double-check those fields to make sure: (1) they do not have any missing values; (2) they follow the field format described in the data dictionary; and (3) their data type is not “Text” and preferably should be “Double.”

Hit “Save” to save your results. Then you have completed the data transfer task for one Excel sheet in ArcGIS Pro. Repeat Steps 1 to 4 for all the Excel (.xlsx) data sheets you have for this counter. The last step is to compress the “Counting_033L28.gdb” file/folder to save it as a ZIP file for data upload.

Common Questions in Data Maintenance

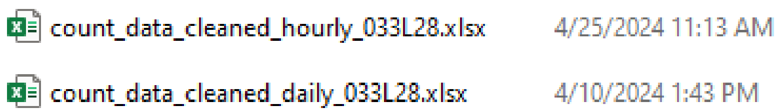
Question 1: How do the input and output files appear?

Answer: There are two cases, as described below.

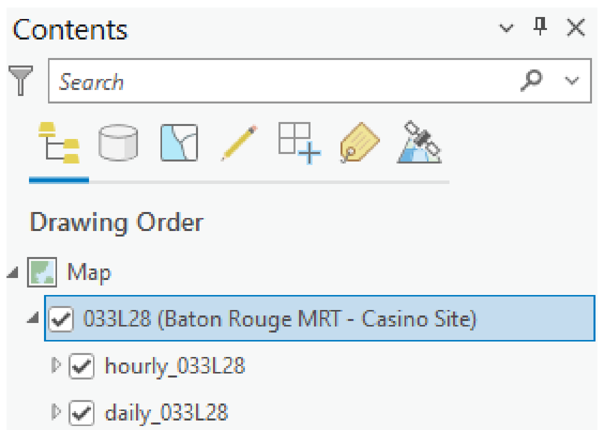
Case 1: One geodatabase file represents one counting location. This happens when a counter is installed on a road segment to count non-motorized traffic in both directions. Such a geodatabase file contains two counting files (i.e., one for hourly counts and another for daily counts).

Figure 20. Input and output data files (Case 1)

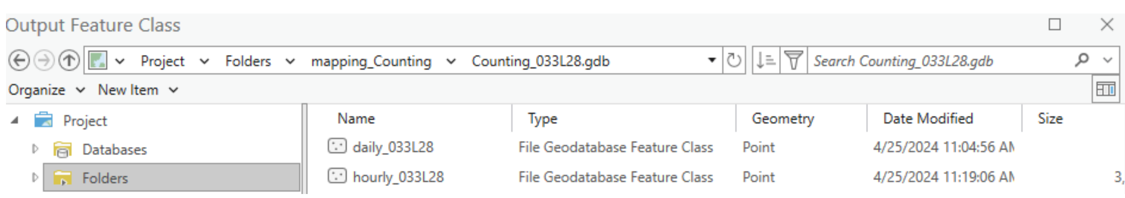
(a) Input files (.xlsx) for one counter



(b) Organizing counting files (.gdb) in ArcGIS Pro



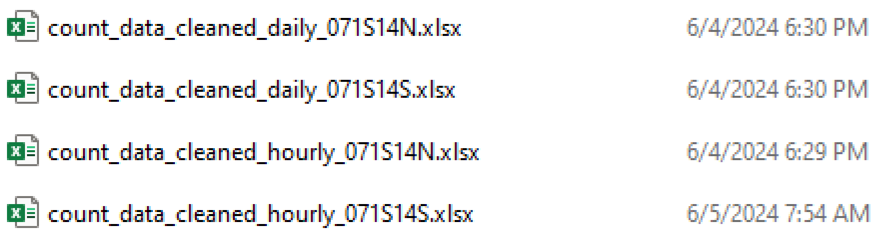
(c) Output files (i.e., counting files [.gdb] in one geodatabase) for one counter



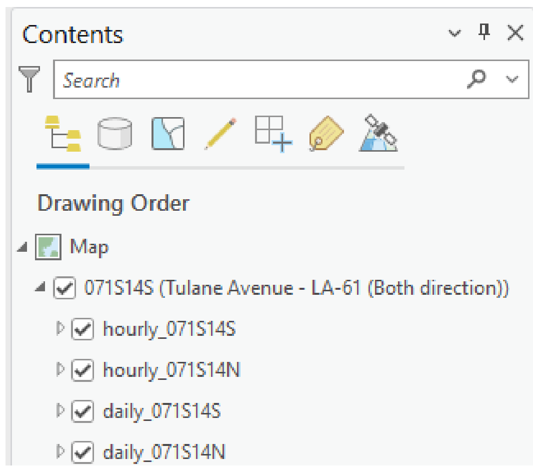
Case 2: One geodatabase file may include two counting locations that are closely related to each other. This happens when two counters are installed on either side of a road segment. For example, motorized travel lanes may have sidewalks/bike lanes built on two sides. Note that a sidewalk/bike lane on each side may also have both IN and OUT counts, since people could walk/bike in either direction on those facilities.

Figure 21. Input and output data files (Case 2)

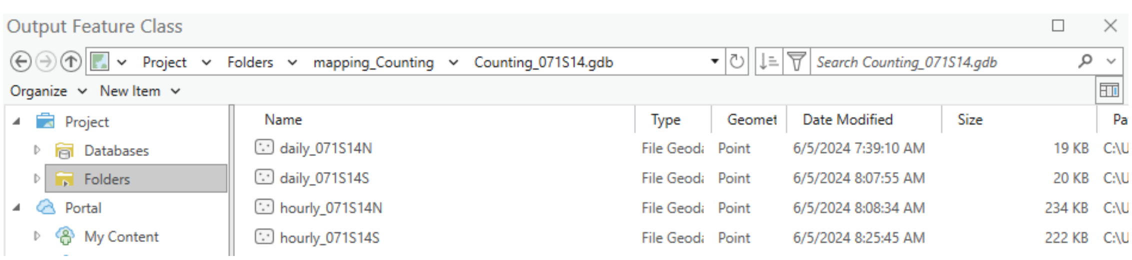
(a) Input files (.xlsx) for one counter



(b) Organizing counting files (.gdb) in ArcGIS Pro



(c) Output files (i.e., counting files [.gdb] in one geodatabase) for one counter



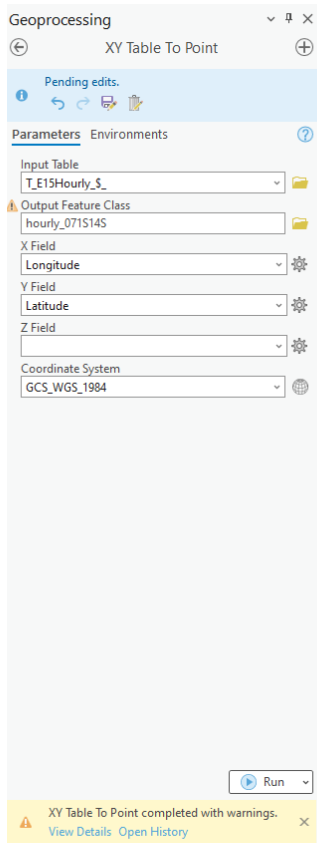
Question 2: Does it matter if I encountered warnings when I conducted “XY Table To Point” in ArcGIS Pro? What do I need to do to make things look right?

Answer: One situation where the warning is observed is that the Excel file contains unnecessary rows (i.e., hidden data). This situation makes your counting file (in .gdb format) look like the second figure shown below (full of <Null> values). The solution is to clean the

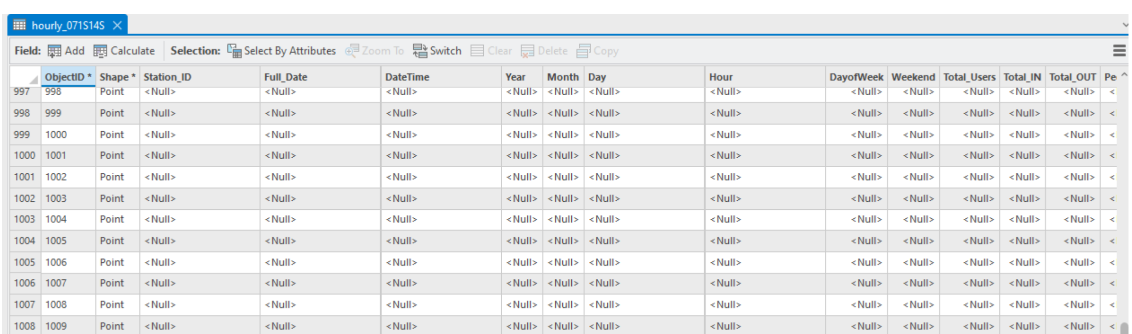
Excel file by ONLY copying and pasting the rows of data you need into a new Excel file before you conduct "XY Table To Point" in ArcGIS Pro.

Figure 22. Warning shown in "XY Table To Point"

(a) Warning



(b) Rows of <Null> values in your output .gdb file when encountering a warning



	ObjectID *	Shape *	Station_ID	Full_Date	DateTime	Year	Month	Day	Hour	DayofWeek	Weekend	Total_Users	Total_IN	Total_OUT	Pe
997	998	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<
998	999	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<
999	1000	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<
1000	1001	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<
1001	1002	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<
1002	1003	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<
1003	1004	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<
1004	1005	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<
1005	1006	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<
1006	1007	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<
1007	1008	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<
1008	1009	Point	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<Null>	<

Question 3: Does it matter how I name the output files?

Answer: Yes. Please make sure the output files are named as indicated above. The naming protocol is also explained below. Keeping file formatting and naming consistent will ensure the success of online data queries in the next step, which becomes even more important when we are managing a large volume of data collected from different sources. Multi-agency collaborations and continuous training are needed in this process to build mutual understanding.

Case 1 (i.e., when count data are saved individually for each counter):

A map geodatabase file is named as “Counting_[Station ID].gdb.” For example, it looks like “Counting_033L28.gdb” for “Baton Rouge MRT—Casino Site.” This is also true when one Station ID represents multiple individual but related count device installation locations and/or facilities. For example, it looks like “Counting_071S14.gdb” for “Tulane Avenue—LA-61.”

A map geodatabase file contains several count data map layers/files. A count data map layer/file is named as “hourly_[Station ID]” or “daily_[Station ID]” to distinguish hourly counts from daily counts for one counter. When one Station ID represents multiple individual but related count device installation locations and/or facilities, the naming rule is a bit different, with roadway direction added. That is, “hourly_[Station ID]_[N/S/E/W]” or “daily]_[N/S/E/W].” Using “Tulane Avenue—LA-61” as an example, you have the following map layers/files: daily_071S14N, daily_071S14S, hourly_071S14N, and hourly_071S14S.

Case 2 (i.e., when count data are merged and saved for all counters):

This is the approach preferred by the DOTD GIS team. Only two geospatial files can be uploaded: “count_data_cleaned_daily” and “count_data_cleaned_hourly.”

Appendix E: Counter Longitudinal Data Summary

Count Site Summary

Table 15. Permanent count site inventory and installation dates

Station ID	Site name	Facility type	City	Equipment	Modes	Install date	Decommission date/ last data reported	Comments
071L03	Norman Francis Parkway Trail	Shared-Use Trail	New Orleans	EcoMulti	Peds, Bikes	3/3/2020	12/31/2025	ONGOING
071L06	Algiers MRT	Shared-Use Trail	New Orleans	EcoPyro	All	3/16/2020	3/31/2022	Removal due to data quality issues
071L12	Lafitte Greenway	Shared-Use Trail	New Orleans	EcoMulti	Peds, Bikes	3/7/2020	12/31/2025	ONGOING
071L20	Baronne St Bike Lane	Protected Bike lane	New Orleans	EcoTubes	Bicycles	9/28/2017	12/31/2025	ONGOING
071L25	Wisner Trail	Shared-Use Trail	New Orleans	EcoMulti	Peds, Bikes	3/4/2020	1/22/2024	Removed due to damage
071L39	Esplanade Ave Bike Lanes	Bike Lanes	New Orleans	EcoZelt	Bikes	3/13/2020	12/31/2025	ONGOING
071L40	Morris FX Jeff (Behrman) Park Trail	Shared-Use Trail	New Orleans	EcoMulti	Peds, Bikes	11/6/2020	3/26/2023	Removed due to damage
103L41	Tammany Trace	Shared-Use Trail	Mandeville	EcoMulti	Peds, Bikes	8/26/2020	5/16/2024	Undiagnosed data transmission problem
103L42	Mandeville Lakefront Path	Shared-Use Trail	Mandeville	EcoPyro	All	8/27/2020	3/14/2023	Removal due to data quality issues
061L48	Rock Island Greenway—Phase 1	Shared-Use Trail (Unpaved)	Ruston	EcoMulti	Peds, Bikes	8/24/2021	8/25/2022	Local partner failure to repair/reinstall
061L49	Rock Island Greenway—Phase 2	Shared-Use Trail	Ruston	EcoPyro	All	3/17/2021	6/15/2024	Local partner failure to maintain
033L44	Dalrymple Drive Trail	Shared-Use Trail	Baton Rouge	EcoMulti	Peds, Bikes	3/11/2021	3/31/2023	Removed due to damage
033L45	Nicholson Drive Trail	Shared-Use Trail	Baton Rouge	EcoMulti	Peds, Bikes	3/10/2021	12/31/2025	ONGOING (Mixed Users)
033L46	Capital Heights Bike Lanes	Bike Lanes	Baton Rouge	EcoZelt	Bicycles	3/11/2021	12/31/2025	ONGOING
033L47	Gardere Lane Sidewalk	Sidewalk	Baton Rouge	EcoPyro	All	3/10/2021	10/19/2025	Ongoing data quality issues
033L28	Baton Rouge MRT (Casino)	Shared-Use Trail	Baton Rouge	EcoPyro	All	2/13/2020	7/21/2021	Planned removal

Station ID	Site name	Facility type	City	Equipment	Modes	Install date	Decommission date/ last data reported	Comments
033L56	Baton Rouge MRT (Water Campus)	Shared-Use Trail	Baton Rouge	EcoMulti	Peds, Bikes	7/19/2021	6/28/2025	Reinstalled 2024, Removed due to damage
033L57	Government St Bike Lanes	Bike Lanes	Baton Rouge	EcoZelt	Bicycles	7/18/2021	12/31/2025	ONGOING

Figure 23. Permanent count data availability by site, mode, and month

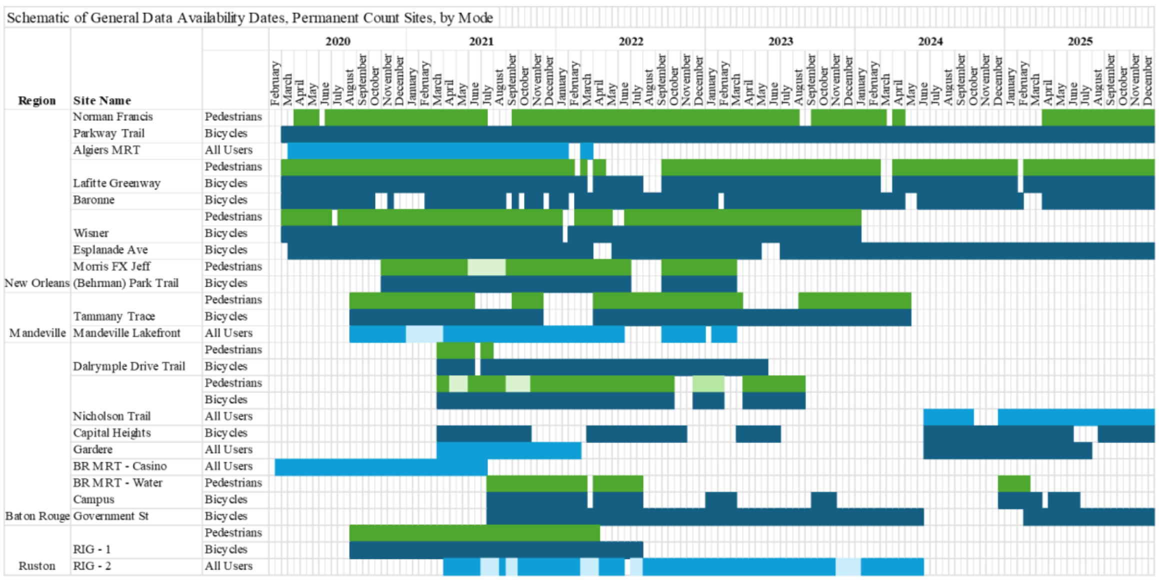


Table 16. Mean daily user volumes (permanent counters)

Site ID	Site Name	Mean Daily Users (Unadjusted)																	
		2020			2021			2022			2023			2024			2025		
		Ped	Bike	All	Ped	Bike	All	Ped	Bike	All	Ped	Bike	All	Ped	Bike	All	Ped	Bike	All
071L03	Norman Francis Parkway Trail	391*	546*	937*	326	417	743	326*	355*	682*	313*	333	649*	366*	316	730*	243*	325	570*
071L06	Algiers MRT			876*			555			463*									
071L12	Lafitte Greenway	378*	722*	1100*	335	601	936	337	627	964	312	648	960	356	599	953	410	611	1013
071L20	Baronne St Bike Lane		151*			132*			133			130			105*			127*	
071L25	Wisner Trail	327*	294*	614*	210	166	374	252*	113*	338*	219	108	327						
071L39	Esplanade Ave Bike Lanes		530*			382			351*			365			324*			308	
071L40	Behrman Park Trail	40*	21*	61*	73	29	101	99	24	123	72*	20*	92*						
103L41	Tammany Trace	125*	269*	394*	116*	209*	330	148*	203*	358*	121*	213	310*	138*	198*	335*			
103L42	Mandeville Lakefront Path			865*			743			760*			720*						
061L48	Rock Island Greenway—Phase 1	108*	8*	116*	113*	6	119		7*	120*									
061L49	Rock Island Greenway—Phase 2						32*			34			28			37*			
033L44	Dalrymple Drive Trail				312*	123*	435*		99			99*							
033L45	Nicholson Drive Trail				29*	24*	51*	91*	21*	111*	89*	17*	103*			99*			133
033L46	Capital Heights Bike Lanes					54*			65*			60*			62*			57*	
033L47	Gardere Lane Sidewalk						96*			89*						78*			86*
033L28	Baton Rouge MRT (Casino)			502			371*												
033L56	Baton Rouge MRT (Water Campus)				124*	131*	256*	123*	110*	241*		104*					90*	91*	164*

Site ID	Site Name	Mean Daily Users (Unadjusted)																	
		2020			2021			2022			2023			2024			2025		
		Ped	Bike	All	Ped	Bike	All	Ped	Bike	All	Ped	Bike	All	Ped	Bike	All	Ped	Bike	All
033L57	Government St Bike Lanes					32*			35			39			36*			42*	
	*Partial data, may not be representative of annual averages																		

Table 17. Short-term count location summary

Station ID	Site Name	Parish	Direction	Facility Type	Equipment	Modes	Begin Date	End Date	Count duration (days)
033S18	Government Street	East Baton Rouge	Eastbound	Sidewalk	EcoPyro	Pedestrians	10/4/2017	11/8/2017	35
			Westbound	Sidewalk	EcoPyro	Pedestrians	10/4/2017	11/8/2017	35
033S26	Capital Heights Ave	East Baton Rouge		Bike Lane	EcoTUBES	Bicycles	7/16/2019	8/1/2019	16
033S27	Downtown Greenway	East Baton Rouge		Shared Use Path (ROW)	EcoPyro	All	7/16/2019	8/1/2019	16
				Shared Use Path (ROW)	EcoTUBES	Bicycles	7/16/2019	8/1/2019	16
033S28	Mississippi River Trail	East Baton Rouge		Non-ROW Trail	EcoPyro	All	7/16/2019	8/1/2019	16
				Non-ROW Trail	EcoTUBES	Bicycles	7/16/2019	8/1/2019	16
033S29	BREC I-110 Trails—Scotlandville	East Baton Rouge		Non-ROW Trail	EcoPyro	All	8/1/2019	8/20/2019	19
				Non-ROW Trail	EcoTUBES	Bicycles	8/1/2019	8/20/2019	19
033S30	BREC I-110 Trails—Airline Terrace	East Baton Rouge		Non-ROW Trail	EcoPyro	All	8/1/2019	8/20/2019	19
				Non-ROW Trail	EcoTUBES	Bicycles	8/1/2019	8/20/2019	19
033S36	Dalrymple Dr	East Baton Rouge		Non-ROW Trail	EcoPyro	All	11/15/2019	12/8/2019	23
033S37	Gardere Ln	East Baton Rouge		Sidewalk	EcoPyro	Pedestrians	11/15/2019	12/8/2019	23
033S38	Nicholson Dr	East Baton Rouge		Shared Use Path (ROW)	EcoPyro	All	2/13/2020	3/18/2020	34

Station ID	Site Name	Parish	Direction	Facility Type	Equipment	Modes	Begin Date	End Date	Count duration (days)
071S14	Tulane Avenue—LA-61	Orleans	Northbound	Bike Lane	EcoTUBES	Bicycles	6/11/2017	7/17/2017	36
			Southbound	Bike Lane	EcoTUBES	Bicycles	6/11/2017	7/17/2017	36
			Northbound	Sidewalk	EcoPyro	Pedestrians	6/11/2017	7/17/2017	36
			Southbound	Sidewalk	EcoPyro	Pedestrians	6/11/2017	7/17/2017	36
071S15	Esplanade Avenue (Northbound)	Orleans	Northbound	Bike Lane	EcoTUBES	Bicycles	8/18/2017	9/27/2017	40
			Southbound	Bike Lane	EcoTUBES	Bicycles	8/18/2017	9/27/2017	40
			Northbound	Sidewalk	EcoPyro	Pedestrians	8/18/2017	9/27/2017	40
			Southbound	Sidewalk	EcoPyro	Pedestrians	8/18/2017	9/27/2017	40
071S21	Basin St	Orleans		Separated Bike Lane	EcoTubes	Bicycles	6/29/2018	10/31/2018	124
				Separated Bike Lane	EcoTubes	Bicycles	10/21/2021	12/16/2021	56
071S35	Macarthur Blvd	Orleans		Bike Lane	EcoTubes	Bicycles	12/4/2019	12/20/2019	16
				Separated Bike Lane	EcoTubes	Bicycles	10/23/2021	11/6/2021	14
071S50	St. Bernard Avenue	Orleans	Northbound	Bike Lane	EcoTubes	Bicycles	10/23/2020	11/21/2020	29
							10/28/2023	11/12/2023	15
			Southbound	Bike Lane	EcoTubes	Bicycles	10/23/2020	11/21/2020	29
							10/28/2023	11/12/2023	15
071S51	Marconi Drive	Orleans	Northbound	Separated Bike Lane	EcoTUBES	Bicycles	3/11/2021	3/28/2021	17
							10/6/2023	10/27/2023	21
			Southbound	Separated Bike Lane	EcoTUBES	Bicycles	3/11/2021	3/21/2021	10
							10/6/2023	10/27/2023	21
071S54	N Peters	Orleans		Separated Bike Lane	EcoTubes	Bicycles	4/25/2021	5/16/2021	21
							5/15/2023	5/24/2023	9
071S60	Lakeshore Drive	Orleans		Separated Bike Lane	EcoTUBES	Bicycles	11/20/2021	12/5/2021	15
							12/3/2023	12/19/2023	16
071S61	MLK Jr Blvd	Orleans	Northbound	Separated Bike Lane	EcoTubes	Bicycles	11/17/2023	12/3/2023	16
							4/27/2025	5/11/2025	14
			Southbound	Separated Bike Lane	EcoTubes	Bicycles	4/27/2025	5/11/2025	14
							4/27/2025	5/11/2025	14
			Northbound	Sidewalk	EcoPyro	Pedestrians	4/27/2025	5/11/2025	14
			Southbound	Sidewalk	EcoPyro	Pedestrians	4/27/2025	5/11/2025	14

Station ID	Site Name	Parish	Direction	Facility Type	Equipment	Modes	Begin Date	End Date	Count duration (days)
071S64	Elysian Fields	Orleans	Northbound	Separated Bike Lane	EcoTubes	Bicycles	4/1/2021	4/24/2021	23
							4/1/2021	4/24/2021	23
			Southbound	Separated Bike Lane	EcoTubes	Bicycles	4/1/2021	4/24/2021	23
							4/30/2023	5/15/2023	15
071S66	Tulane Avenue—Medical District	Orleans	Northbound	Separated Bike Lane	EcoTubes	Bicycles	9/10/2023	10/1/2023	21
							4/12/2025	4/27/2025	15
			Southbound	Separated Bike Lane	EcoTubes	Bicycles	9/10/2023	10/1/2023	21
							4/12/2025	4/27/2025	15
			Northbound	Sidewalk	EcoPyro	Pedestrians	4/12/2025	4/27/2025	15
			Southbound	Sidewalk	EcoPyro	Pedestrians	4/12/2025	4/27/2025	15

New Orleans—Annual Trends

In New Orleans, trend analysis includes data from counters at current permanent count sites installed as early as 2010, providing a longer-term view of overall trends and the impacts of COVID-19. In general, these older count locations (Norman Francis Parkway, Lafitte Greenway, and Baronne St) indicate steady, year-over-year upward growth through 2019 across all user groups. For the Norman Francis Parkway Trail and Lafitte Greenway, 2020 marked a high point in observed user activity; see Figure 24 andFigure 25. In the subsequent years, user counts at Norman Francis Parkway Trail have failed to recover to pre-COVID volumes, although 2025 averages are artificially depressed by missing data during peak spring activity months. On Lafitte Greenway, meanwhile, user volumes have held roughly steady or grown modestly since 2021.

Figure 24. Norman Francis Parkway Trail

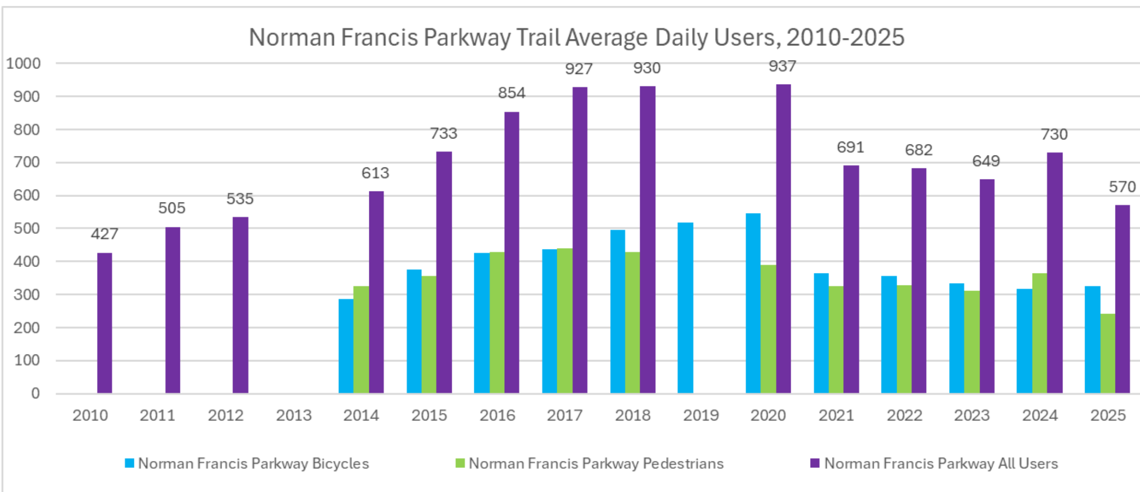
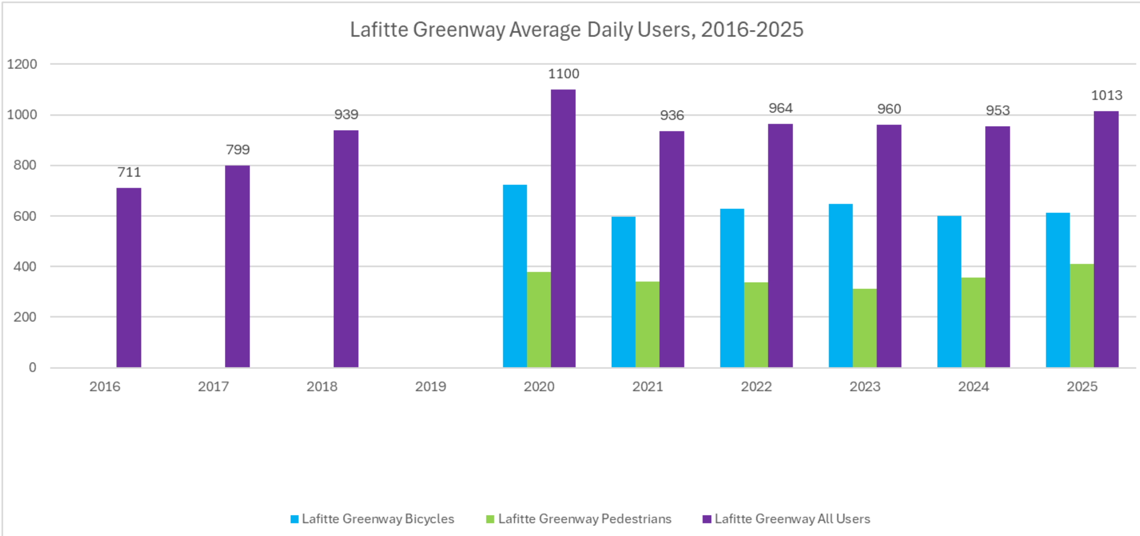
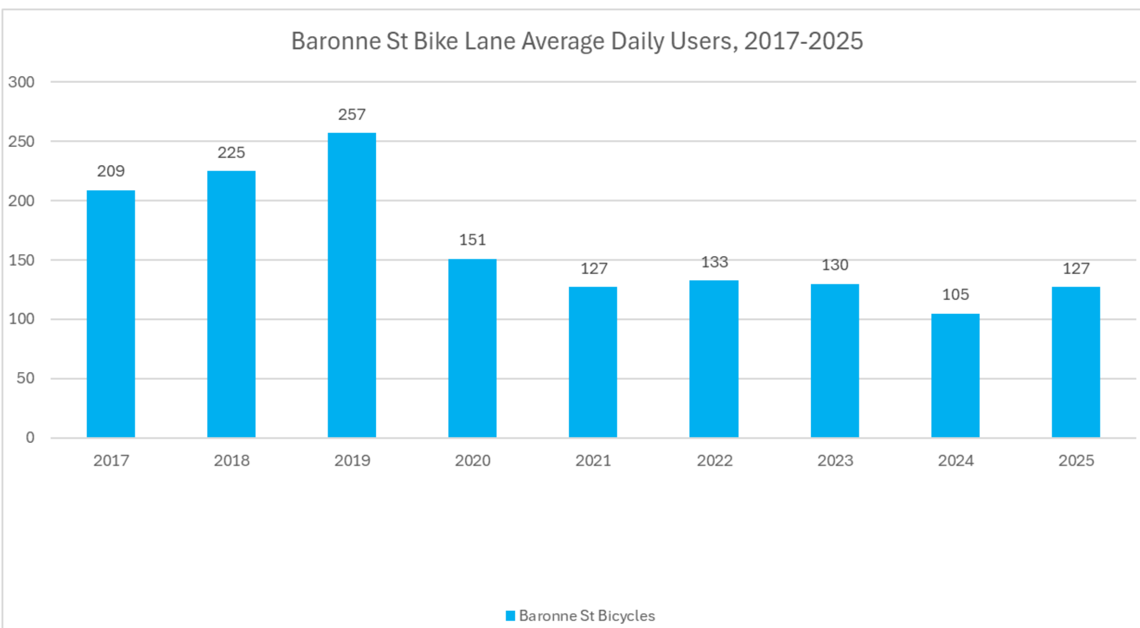


Figure 25. Lafitte Greenway



Meanwhile, on Baronne St, a bike lane in the Central Business District, 2020 represented a steep drop-off in user counts after two years of growth, followed by fairly stable averages (though still well-below pre-COVID volumes) from 2021 to 2025; see Figure 26.

Figure 26. Baronne Street



The new permanent count locations installed in March 2020 (Esplanade Avenue bike lanes, Wisner Trail) initially reflected a boost in recreational activity, followed by a substantial drop in 2021 and a gradual, modest decline in subsequent years; see Figure 27 andFigure 28. The counter installed in Morris FX Jeff Park (formerly Behrman Park) in late 2020 was only in operation for two full years, with increased counts in 2022 suggesting an increase in activity on the new trail connection, though additional data is not available to verify this outcome; see Figure 29.

Figure 27. Esplanade Avenue

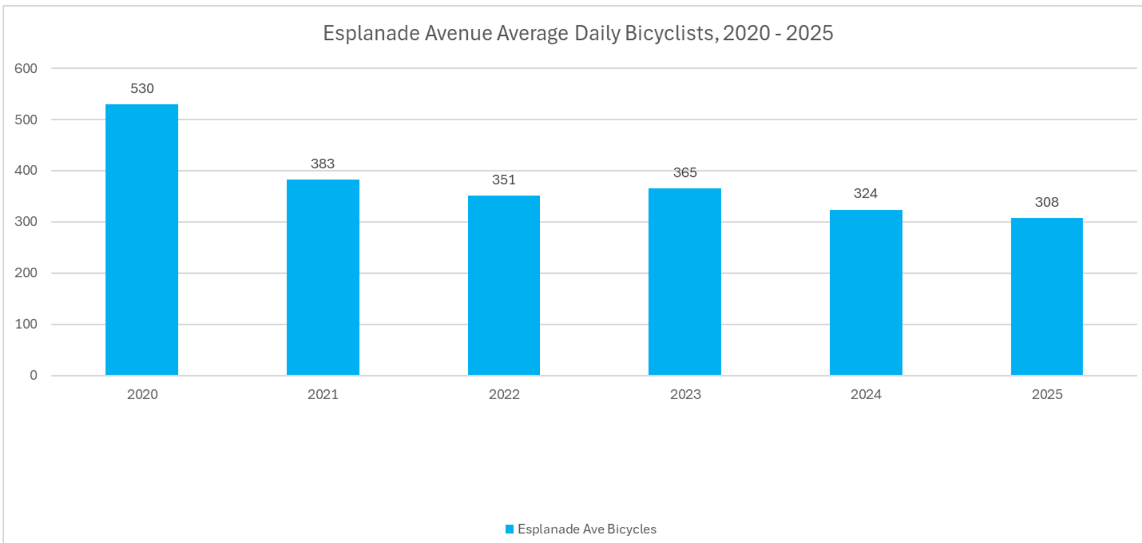


Figure 28. Wisner Trail

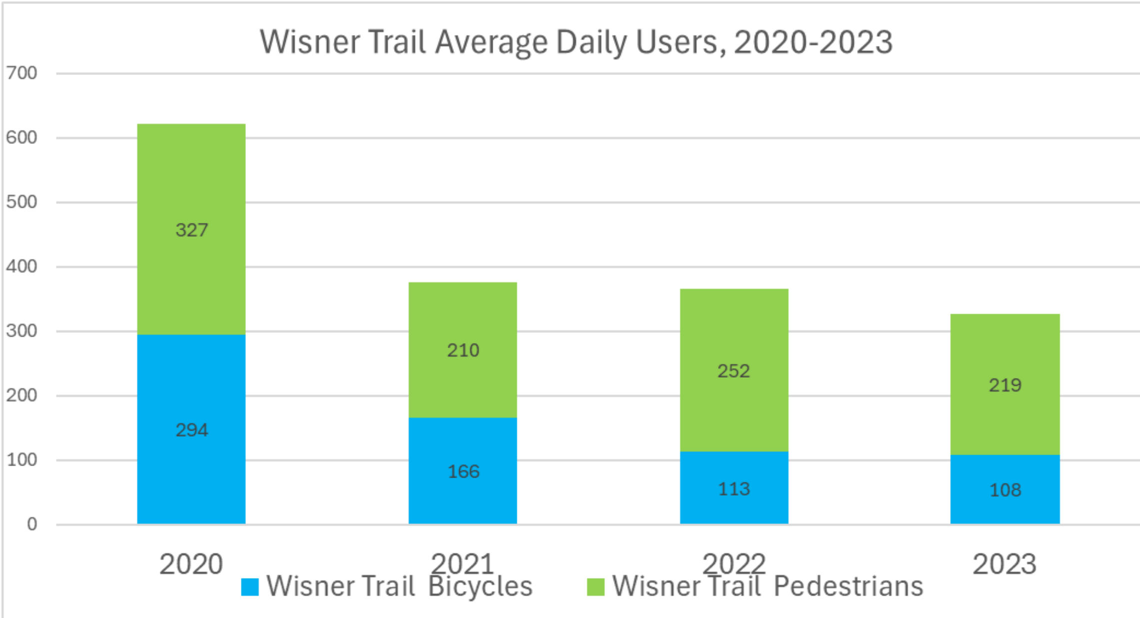
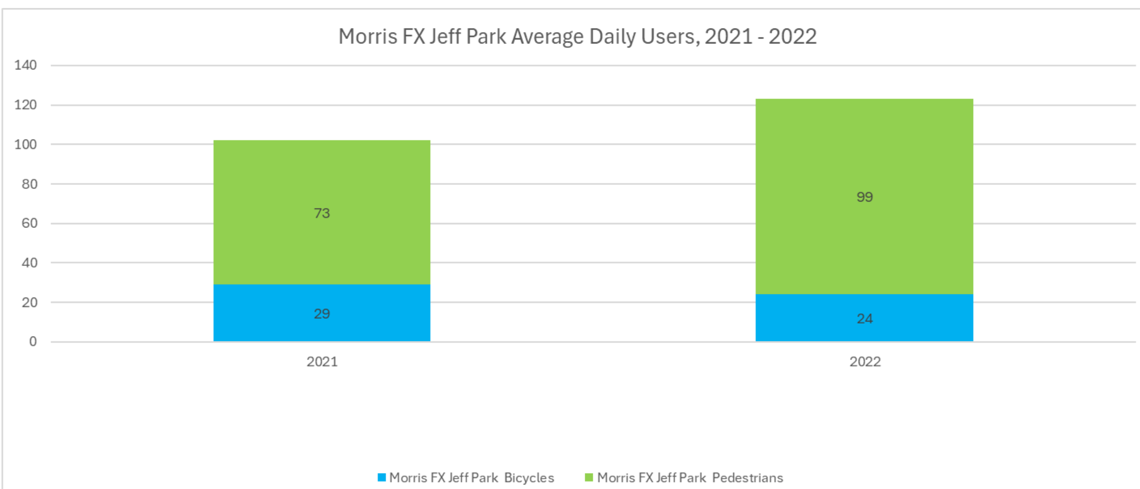


Figure 29. Morris FX Jeff Park



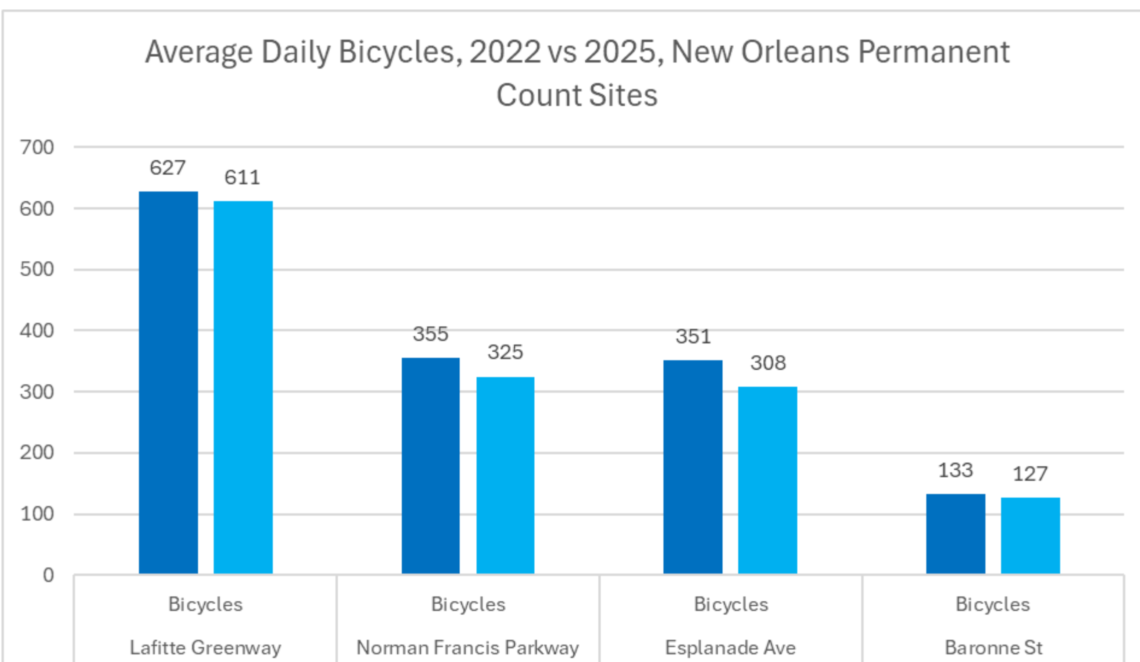
Overall, the data suggests a relatively stable "new normal" for active transportation activity levels across monitoring sites in New Orleans, following a period of pre-COVID growth, with activity remaining steady (or growing slightly) on high-quality shared-use trails. Notably, Orleans Parish lost over 20,000 residents between 2020 and 2025, reflecting broader trends that may impact activity volumes. Simultaneously, the share of people who walk, bicycle, or take transit to work dropped by over 6,000 between 2019 and 2024 (see Table 18), suggesting that a shift toward remote work, coupled with population loss and a decline in overall work-related trips, may have contributed to these findings. The decrease in bicycle commuting in particular (a 53% decrease in the estimated total of regular bike commuters) is likely reflected in observed bicycle counts, which have continued to decline slightly at all ongoing count sites in New Orleans since 2022; see Figure 30.

Table 18. Mode of transportation to work

	2019		2024	
	#	%	#	%
Drove Alone	125,311	67.2%	109,757	64.5%
Carpooled	18,469	9.9%	15,966	9.4%
Public Transit	9,425	5.1%	6,934	4.1%
Bicycle	4,908	2.6%	2,299	1.4%
Walked	11,503	6.2%	10,349	6.1%
Other	4,211	2.3%	3,536	2.1%
Worked from Home	12,680	6.8%	21,330	12.5%
Total	186,534		170,171	

(Data source: American Community Survey 1-year estimates Table B08006)

Figure 30. Average daily bicycles (New Orleans)



Baton Rouge—Annual Trends

In Baton Rouge, the first permanent counters were installed in 2021, except for a portable counter installed for over one year on the Mississippi River Trail in 2020. For this reason, longitudinal data is more limited. Compared to New Orleans, year-over-year patterns appear to be less consistent, with relatively stable user volumes observed on the Capital Heights and Government Street bike lanes as well as the Gardere Lane sidewalk (see Figure 31 andFigure 32), and notable growth on the Nicholson Drive Trail following the elimination of COVID-related restrictions in 2022 (see Figure 33). The final two sites (Dalrymple Drive Trail and the Mississippi River Trail) experienced significant data loss, making interpretation more challenging; see Figure 34 andFigure 35. See Table 15 for detailed information about operational dates for each count location.

Figure 31. Capital Heights

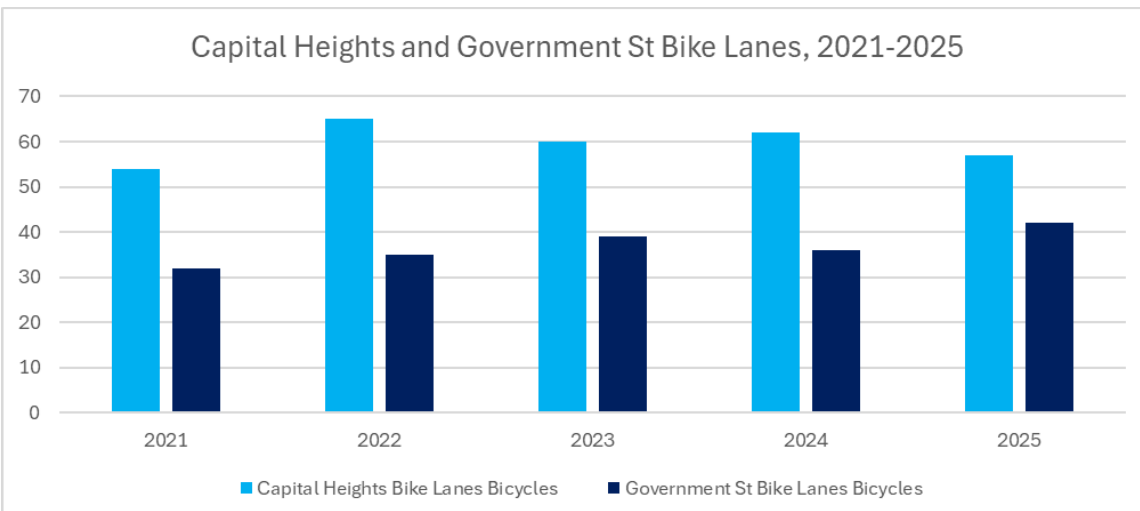


Figure 32. Gardere Lane

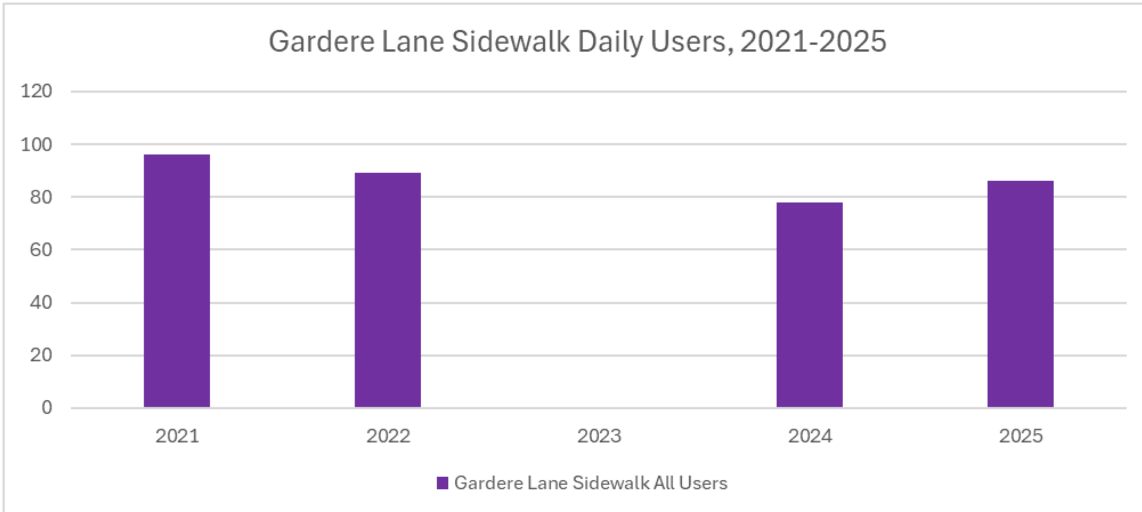


Figure 33. Nicholson Drive Trail

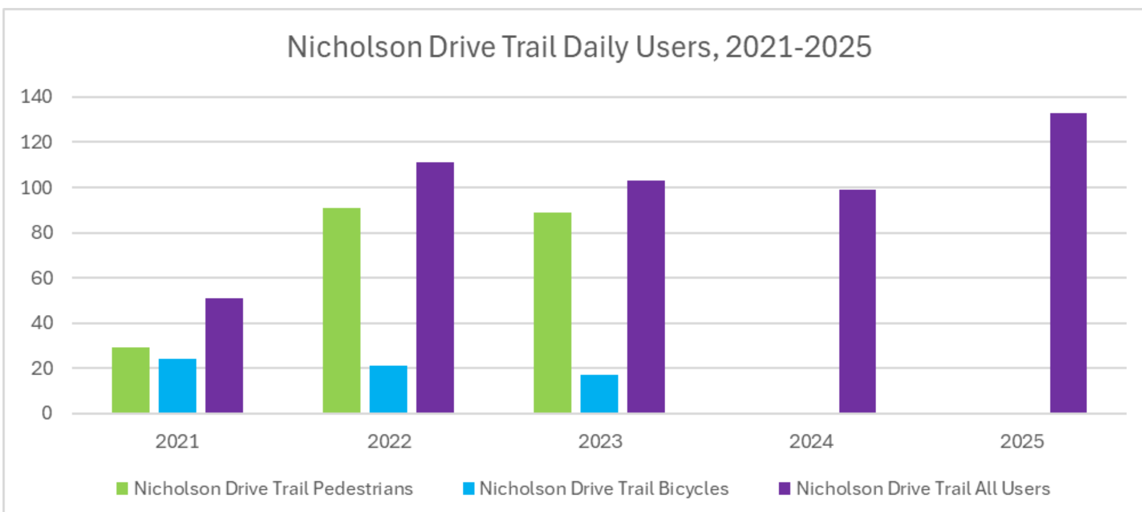


Figure 34. Dalrymple Drive Trail

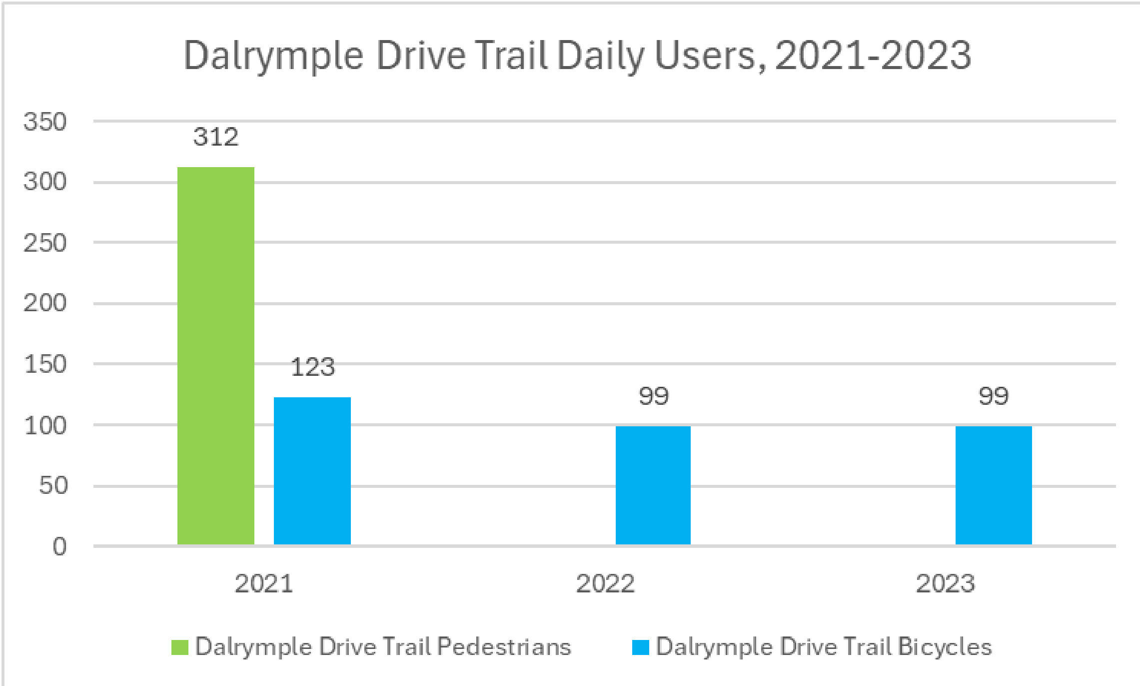
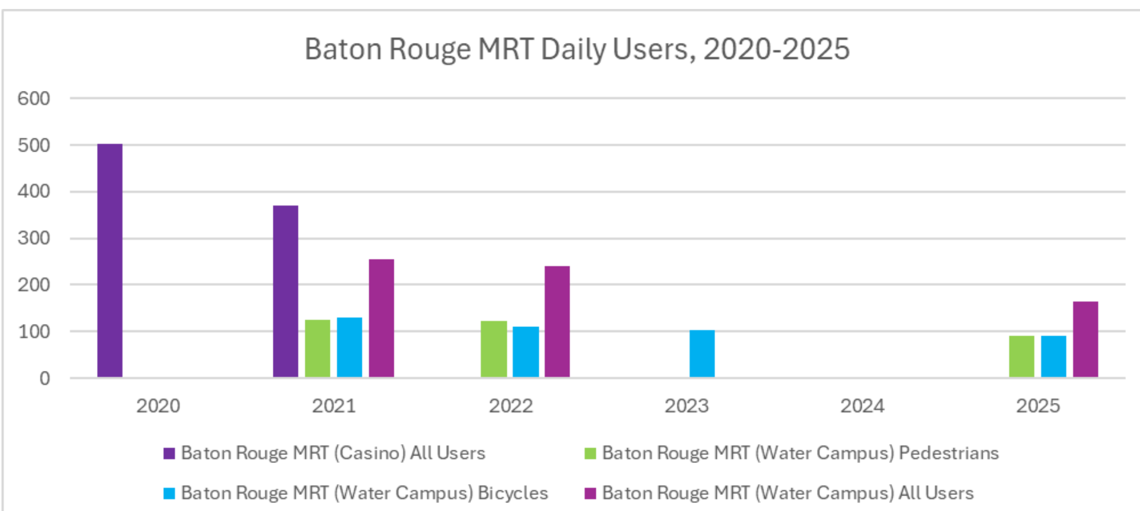


Figure 35. Mississippi River Trail



Mandeville and Ruston—Annual Trends

Finally, permanent counters installed in Mandeville and Ruston (see Figure 36 and Figure 37), none of which are currently operational, reflect relatively stable annual trends between installation and decommission date, suggesting that extrapolations from this data, including analysis involving third-party datasets, are likely to be reasonably reflective of ongoing patterns for these facilities.

Figure 36. Tammany Trace and Mandeville Lakefront

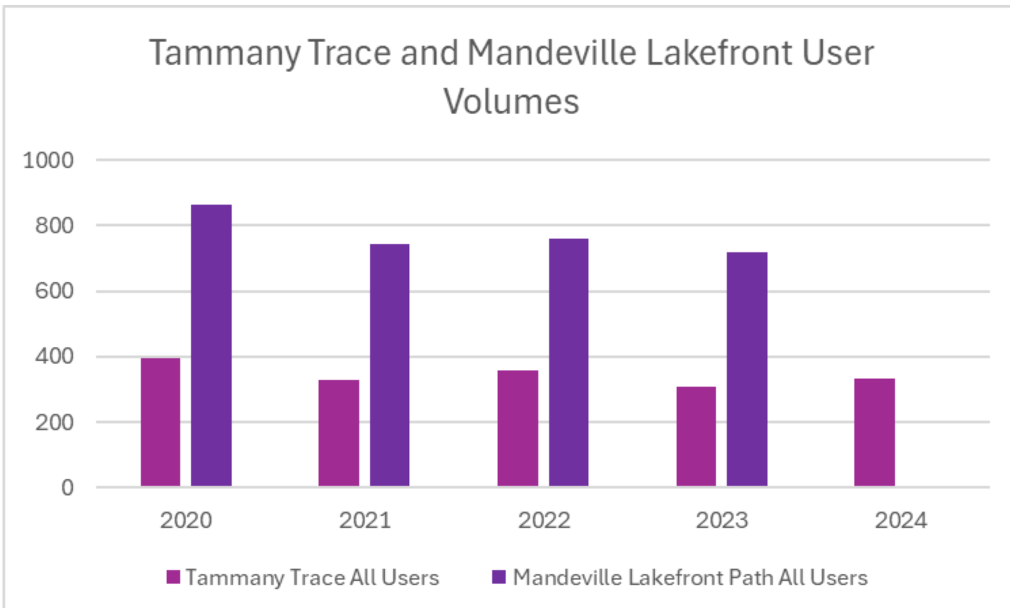
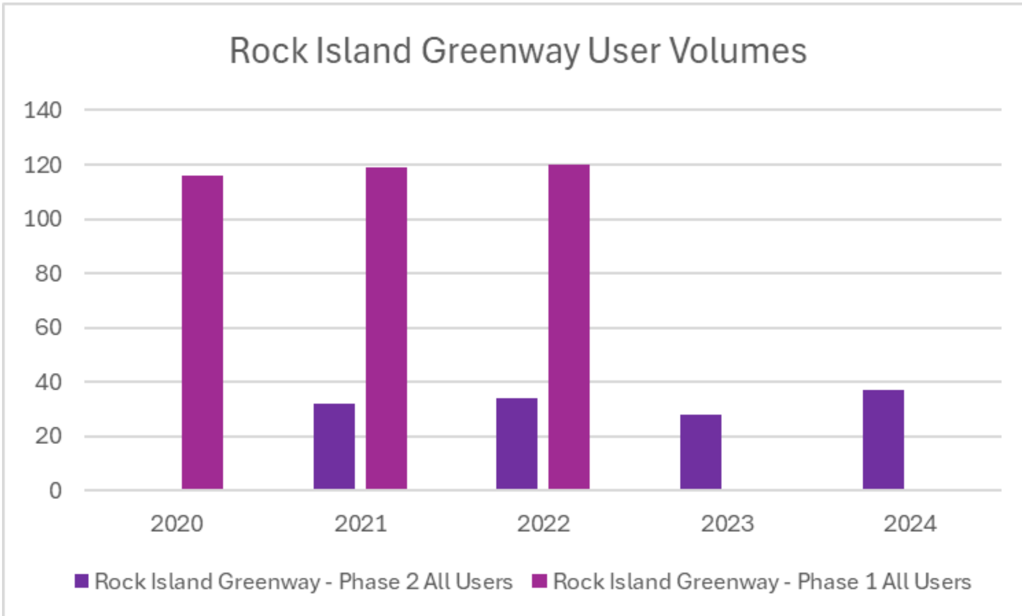


Figure 37. Rock Island Greenway



Appendix F: Cluster Centroid Table for Bicyclists and Pedestrians

Table 19. Bicyclist cluster centroid

Spatial_label	Temporal_label_global	Final_cluster	Segment_Count	Replica_Bike_Thu	Replica_Bike_Sat	Replica_Bike_Fall	Replica_Bike_Spring	Strava_Bike_Thu	Strava_Bike_Sat	Strava_Bike_Fall	Strava_Bike_Spring
S1		S1	50	0.919	1.200	1.306	1.011	1.215	0.984	1.160	0.963
S10		S10	4	0.788	1.375	0.903	1.140	NA	1.000	0.626	2.773
S10	T25	S10_T25	5	0.854	1.227	1.616	0.752	1.376	0.887	0.859	1.060
S10	T26	S10_T26	28	0.933	1.162	0.966	1.071	1.341	0.826	0.991	1.007
S10	T27	S10_T27	13	0.872	1.198	1.369	0.869	2.962	0.606	1.016	0.981
S11		S11	5	0.846	1.419	1.036	1.000	NA	1.000	1.313	0.987
S11	T28	S11_T28	20	0.760	1.485	0.885	1.163	1.592	0.743	1.000	0.995
S11	T29	S11_T29	7	0.856	1.336	1.149	0.946	1.062	0.963	1.038	0.977
S12		S12	10	0.804	1.561	1.056	1.003	NA	1.000	1.274	0.839
S13		S13	10	1.030	1.118	0.913	1.175	1.414	0.815	1.125	1.027
S14	T30	S14_T30	10	0.869	1.180	2.071	0.660	1.262	0.873	1.041	0.986
S14	T31	S14_T31	5	1.055	1.029	1.997	0.835	1.001	1.290	1.154	1.192
S15		S15	10	0.724	1.813	1.012	1.065	NA	1.000	1.536	0.846
S16		S16	17	0.775	1.471	1.033	0.985	NA	1.000	0.848	1.500
S17		S17	10	0.779	1.438	0.988	1.024	NA	1.000	1.134	0.878
S1	T1	S1_T1	198	0.830	1.285	1.149	0.914	1.064	0.966	1.040	0.979
S1	T2	S1_T2	56	0.854	1.248	1.146	0.917	1.366	0.808	1.092	0.928
S1	T3	S1_T3	12	0.946	1.107	2.977	0.678	1.120	0.935	1.045	0.959
S1	T4	S1_T4	24	0.735	1.742	1.160	0.984	1.114	0.922	1.071	0.947
S1	T5	S1_T5	16	0.904	1.178	0.859	1.416	1.175	0.898	0.971	1.021
S1	T6	S1_T6	61	0.827	1.281	1.152	0.918	1.307	0.838	0.911	1.104
S1	T7	S1_T7	55	1.018	1.039	1.121	0.965	1.115	0.932	1.006	0.993
S2		S2	6	0.836	1.363	0.984	1.130	1.042	0.975	1.301	0.804
S2	T10	S2_T10	41	0.861	1.267	1.025	1.176	1.077	0.960	1.074	0.934
S2	T8	S2_T8	25	0.823	1.337	1.137	0.943	1.188	0.901	0.901	1.087
S2	T9	S2_T9	5	1.261	0.947	1.504	1.077	1.174	0.934	1.114	0.921
S3		S3	125	0.839	1.336	1.190	0.953	1.164	1.009	1.014	1.112
S3	T11	S3_T11	1036	0.825	1.295	1.055	0.987	1.048	0.978	1.016	1.003
S3	T12	S3_T12	296	0.808	1.350	1.103	0.969	1.409	0.815	0.921	1.087
S3	T13	S3_T13	9	0.815	1.346	1.087	0.932	0.711	2.081	0.723	1.945
S3	T14	S3_T14	129	1.095	0.988	1.453	0.939	1.159	0.920	1.006	1.007
S4		S4	4	0.737	1.747	1.049	0.993	NA	1.000	0.993	1.031

Spatial_label	Temporal_label_global	Final_cluster	Segment_Count	Replica_Bike_Thu	Replica_Bike_Sat	Replica_Bike_Fall	Replica_Bike_Spring	Strava_Bike_Thu	Strava_Bike_Sat	Strava_Bike_Fall	Strava_Bike_Spring
S4	T15	S4_T15	9	0.882	1.312	1.077	0.996	1.158	0.951	1.060	0.944
S4	T16	S4_T16	17	0.795	1.408	0.935	1.114	1.413	0.829	1.040	0.977
S5		S5	4	0.826	1.907	1.362	0.935	0.925	1.057	0.955	1.135
S5	T17	S5_T17	12	1.037	1.170	1.793	0.826	1.328	0.813	1.061	0.965
S5	T18	S5_T18	59	0.897	1.347	1.238	0.968	1.091	0.964	0.997	1.032
S6	T19	S6_T19	8	1.112	0.953	1.299	1.011	1.011	1.029	1.018	0.984
S6	T20	S6_T20	12	0.940	1.206	2.107	0.712	1.466	0.804	1.036	0.978
S7		S7	36	0.755	1.580	1.082	0.979	1.122	1.006	1.062	1.025
S8	T21	S8_T21	22	0.843	1.268	1.006	1.024	0.836	1.335	0.876	1.146
S8	T22	S8_T22	21	0.863	1.229	1.038	0.992	0.998	1.027	1.110	0.957
S9		S9	1	0.856	1.203	1.163	0.880	1.122	0.944	1.000	NA
S9	T23	S9_T23	9	1.018	1.089	1.389	0.880	0.967	1.071	1.062	0.985
S9	T24	S9_T24	17	0.810	1.416	1.126	0.961	1.145	0.911	0.977	1.052

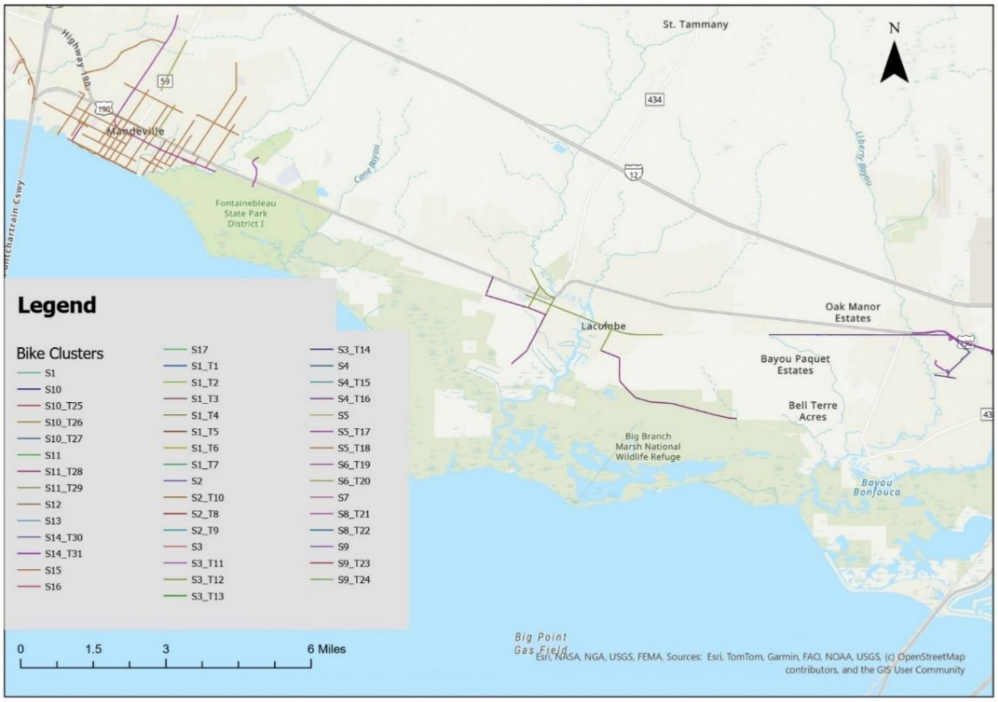
Table 20. Pedestrian cluster centroid

Spatial_label	Temporal_label_global	Final_cluster	Segment_Count	Replica_Ped_Thu	Replica_Ped_Sat	Replica_Ped_Fall	Replica_Ped_Spring	Strava_Ped_Thu	Strava_Ped_Sat	Strava_Ped_Fall	Strava_Ped_Spring
S1		S1	120	0.885	1.246	1.033	1.050	1.283	1.215	1.108	1.038
S10		S10	21	0.958	1.094	1.031	0.993	1.230	0.960	1.006	1.024
S11		S11	18	1.026	1.053	1.033	1.069	1.006	1.021	1.029	1.004
S12		S12	10	0.915	1.196	1.301	0.888	1.187	0.938	1.022	0.982
S13		S13	10	0.919	1.116	1.026	0.990	1.518	1.199	0.877	1.583
S14	T16	S14_T16	9	0.890	1.408	1.042	1.033	1.157	1.102	1.451	1.110
S14	T17	S14_T17	9	1.055	1.152	1.018	1.115	4.155	0.646	6.490	0.721
S15		S15	16	0.832	1.286	0.955	1.109	2.236	0.752	2.241	0.962
S16		S16	16	0.966	1.131	1.152	0.947	1.235	0.934	1.014	1.212
S17		S17	10	1.067	0.982	1.036	1.004	1.099	0.976	0.916	1.068
S18		S18	14	0.951	1.099	1.016	1.029	1.055	0.986	0.960	1.044
S19		S19	17	0.900	1.238	1.134	0.951	1.014	1.149	0.945	1.099
S1	T1	S1_T1	19	0.846	1.311	1.099	0.947	0.592	4.941	0.722	6.801
S1	T2	S1_T2	831	0.887	1.246	1.015	1.083	1.318	0.915	0.990	1.108
S2		S2	3	0.987	1.082	1.039	0.998	0.800	1.111	1.171	0.943
S20		S20	12	0.857	1.255	0.824	1.555	1.376	0.907	0.840	1.127
S21		S21	1	0.853	1.249	0.942	1.067	NA	1.000	1.250	0.939
S21	T18	S21_T18	12	1.030	1.041	1.043	1.049	1.239	0.878	0.912	1.217
S21	T19	S21_T19	8	0.898	1.316	0.931	1.136	1.098	0.961	1.015	1.033
S22		S22	10	0.987	1.117	1.110	0.946	0.914	3.296	0.850	4.090

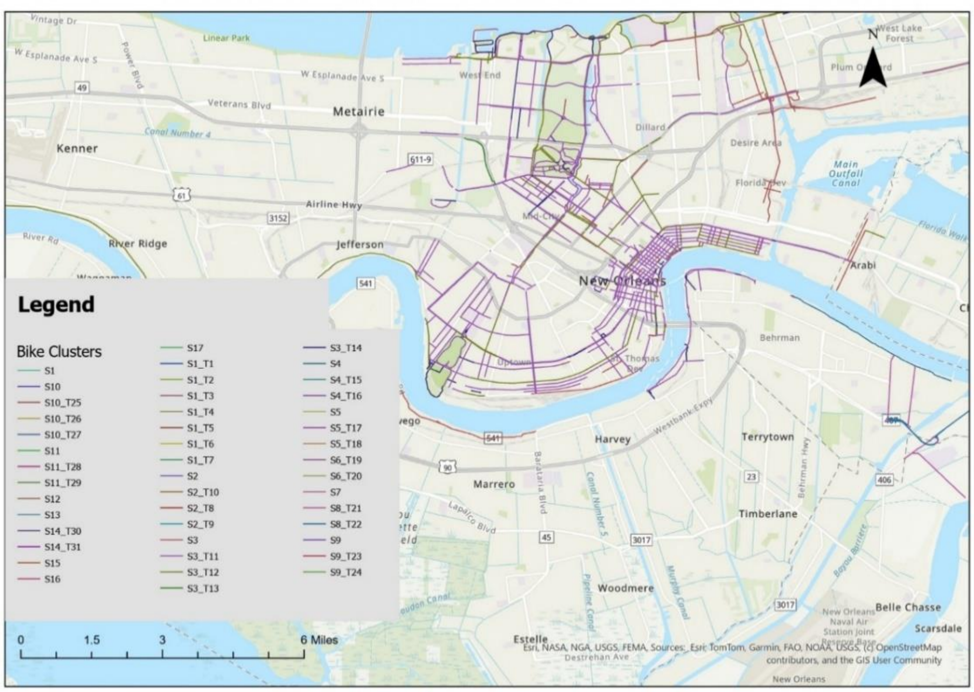
Spatial_label	Temporal_label_global	Final_cluster	Segment_Count	Replica_Ped_Thu	Replica_Ped_Sat	Replica_Ped_Fall	Replica_Ped_Spring	Strava_Ped_Thu	Strava_Ped_Sat	Strava_Ped_Fall	Strava_Ped_Spring
S23		S23	10	0.943	1.188	1.026	1.095	1.193	0.891	0.952	1.085
S2	T3	S2_T3	27	0.911	1.180	1.053	0.986	1.042	0.997	1.063	0.977
S2	T4	S2_T4	5	0.982	1.180	0.907	1.168	0.750	1.457	1.539	0.808
S2	T5	S2_T5	9	0.713	1.951	1.109	0.938	1.050	1.031	0.985	1.088
S2	T6	S2_T6	6	0.928	1.221	0.895	1.172	1.911	0.804	1.839	0.897
S2	T7	S2_T7	24	0.788	1.452	0.936	1.148	1.154	0.918	0.962	1.071
S2	T8	S2_T8	6	0.891	1.428	1.167	0.927	0.794	1.360	0.750	1.338
S2	T9	S2_T9	22	0.975	1.099	0.861	1.234	1.005	1.042	1.138	0.932
S3		S3	12	0.909	1.421	2.110	1.086	1.396	0.958	1.077	1.107
S3	T10	S3_T10	95	0.943	1.175	1.276	1.171	1.143	0.976	1.105	0.977
S3	T11	S3_T11	23	0.912	1.168	1.045	1.794	2.413	0.767	0.786	1.313
S4		S4	39	0.875	1.290	1.067	1.026	1.361	1.911	0.913	2.211
S5		S5	2727	0.914	1.176	1.058	1.030	1.522	0.939	1.057	1.102
S6		S6	5	0.867	1.338	1.116	1.031	0.938	1.014	1.069	0.953
S6	T12	S6_T12	26	0.854	1.321	0.993	1.046	1.067	0.966	1.017	1.040
S6	T13	S6_T13	31	1.014	1.043	1.209	0.925	1.096	0.965	0.973	1.052
S7		S7	16	0.815	1.478	0.953	1.132	1.050	0.985	1.000	1.022
S8	T14	S8_T14	6	1.018	1.051	0.926	1.212	1.011	1.036	1.098	1.006
S8	T15	S8_T15	9	1.075	0.947	0.944	1.122	1.183	0.875	0.930	1.062
S9		S9	82	0.868	1.311	1.099	1.028	2.295	0.934	2.295	1.142

Figure 38. Bicyclist cluster map

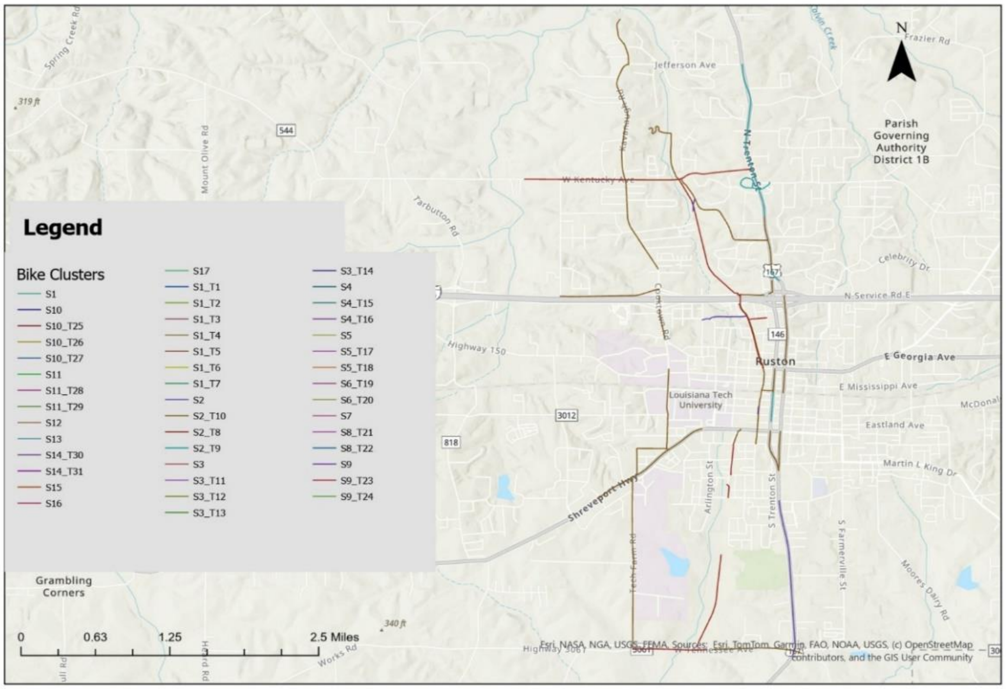
a) St Tammany Parish



b) Orleans Parish



c) Lincoln Parish



d) EBR Parish

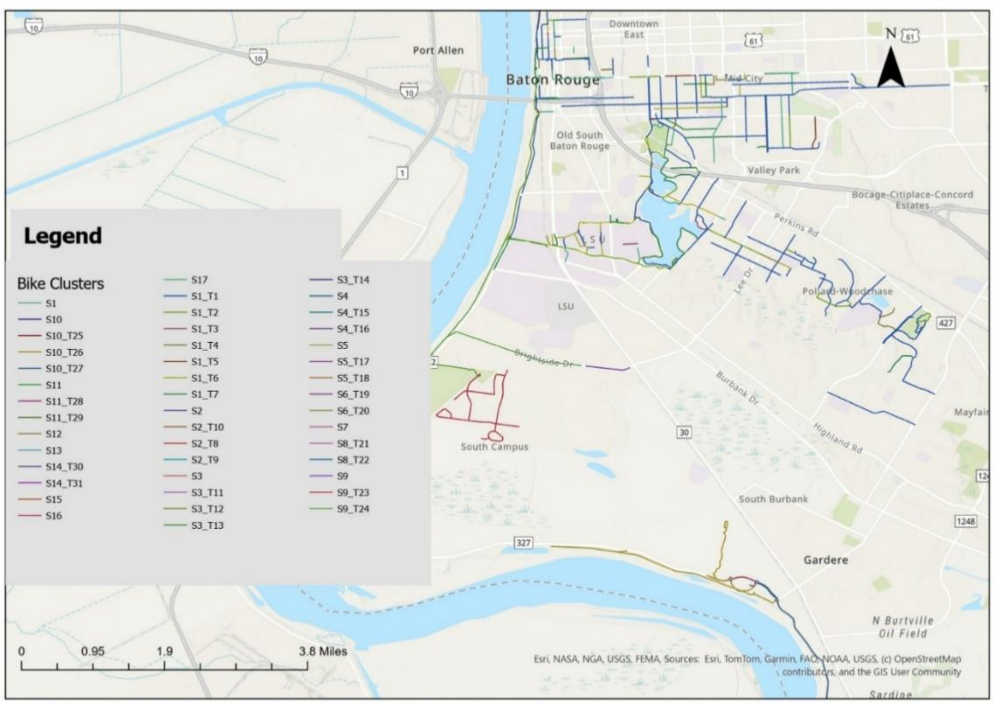
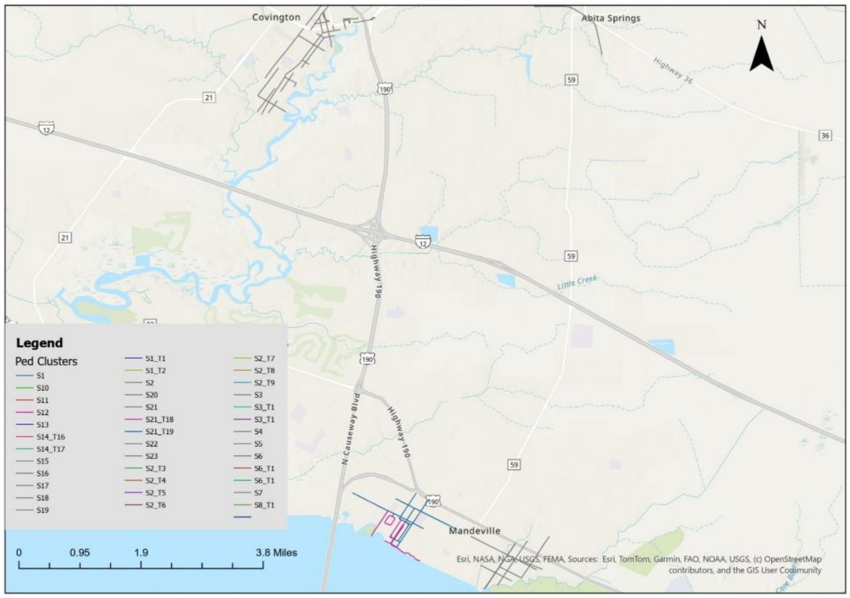
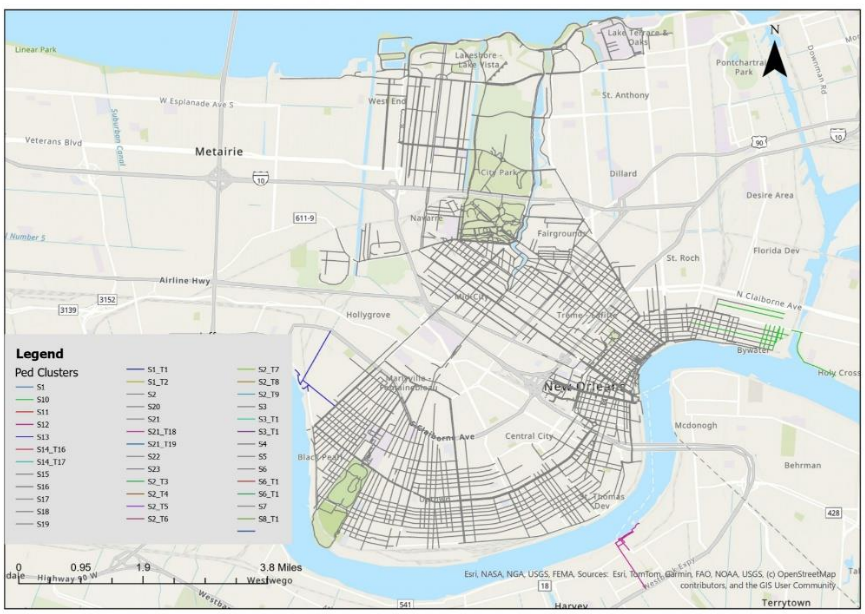


Figure 39. Pedestrian clusters map

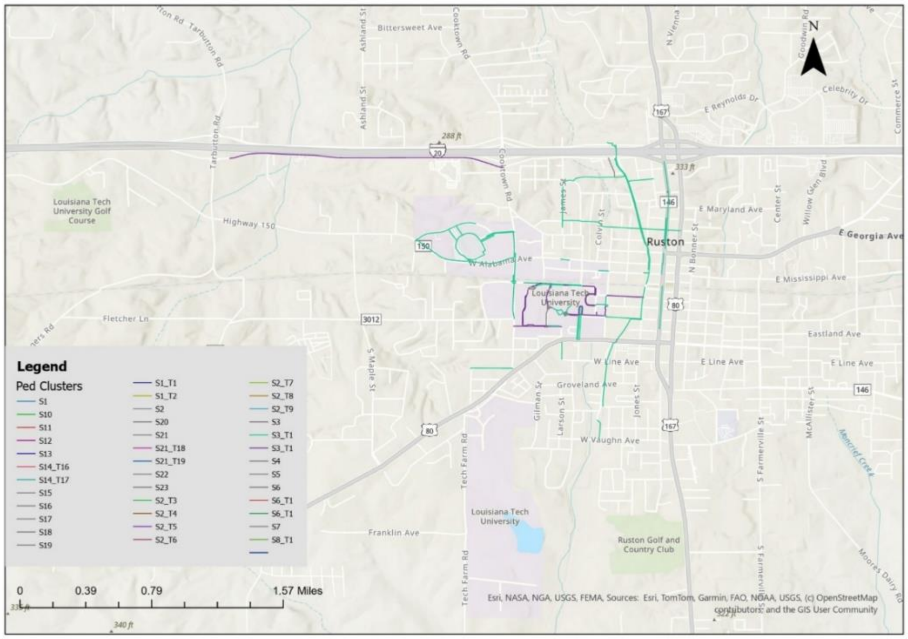
a) St Tammany Parish



b) Orleans Parish



c) Lincoln Parish



d) EBR Parish