Appendix C: Modeling Shared-Use Path Volumes

MODELING SHARED PATH VOLUMES

Final Report

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1. INTRODUCTION

User volumes from shared paths provide important information for planning, infrastructure, mobility, safety, environmental, and public health considerations. Greater Madison Metropolitan Planning Organization (MPO) partnered with the Wisconsin Traffic Operations and Safety Laboratory (TOPS Lab) to conduct this research project and evaluate shared paths' temporal trends, types of users, quantify the effect of weather conditions, and estimate user volumes. The objectives of this research were to evaluate the accuracy of existing automated counts (infrared and inductive loop sensor counters), incorporate crowdsource data (Strava), provide models to estimate hourly and daily pedalcycle counts, and provide recommendations for the implementation of model estimates on shared paths in the Madison area.

2. METHODOLOGY

The methodological approach consisted of selecting sites of interest, video field data collection and processing (ground truth data), historical data collection from different sources, evaluation of the accuracy of automatic counters, development of volume models, model validation, and assessment of model transferability. Figure 1 provides an overview of the methodology.

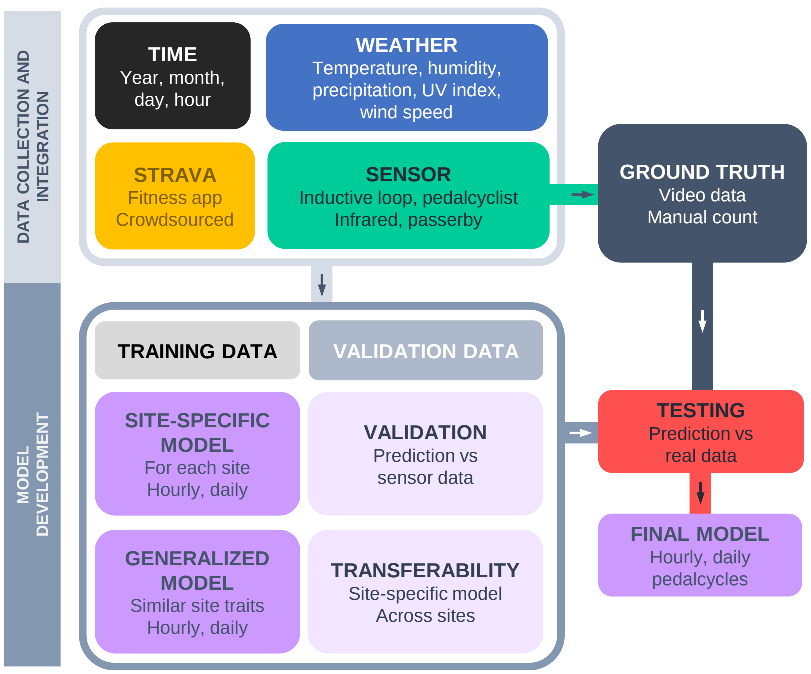

Figure 1. Overview of project methodology

2.1. Sites of Interest

The following four sites were strategically selected to cover shared paths with different attributes and availability of data:

Site 1. Southwest Commuter Path at Monroe St, Madison, WI
Site 2. Capital City Trail at John Nolen Dr and North Shore Dr, Madison, WI
Site 3. Capital City Trail at Syene Rd, Fitchburg, WI
Site 4. Hank Aaron State Trail at S 76th St, West Allis, WI

Figure 2 illustrates the locations of the selected sites. Site 1 is located on the University of Wisconsin – Madison campus by the Camp Randall Stadium. Site 2 is located near Lake Monona and Monona Bay. Sites 1 and 2 are only 1.4 mi apart and located on popular recreational and commuting routes, with connectivity and accessibility from multiple sidewalks, shared paths, and are surrounded by densely populated areas. Sites 3 and 4 were selected as sites with different characteristics. Site 3 is located further apart from the other two sites (approx. 3.4 mi) in the Madison area with lower population density and reduced access points from sidewalks or other paths. Site 4 is located in the City of West Allis in the Milwaukee area (approx. 73 mi from the City of Madison). Historical bicycle counts from Eco-counters (inductive loop sensor) were available for Sites 1 and 2 since 2014 and 2015, respectively. Passerby count data from infrared sensor counters at Site 3 (Eco-Counter and TRAFx) and Site 4 (TRAFx) were available between 2022 and 2023.

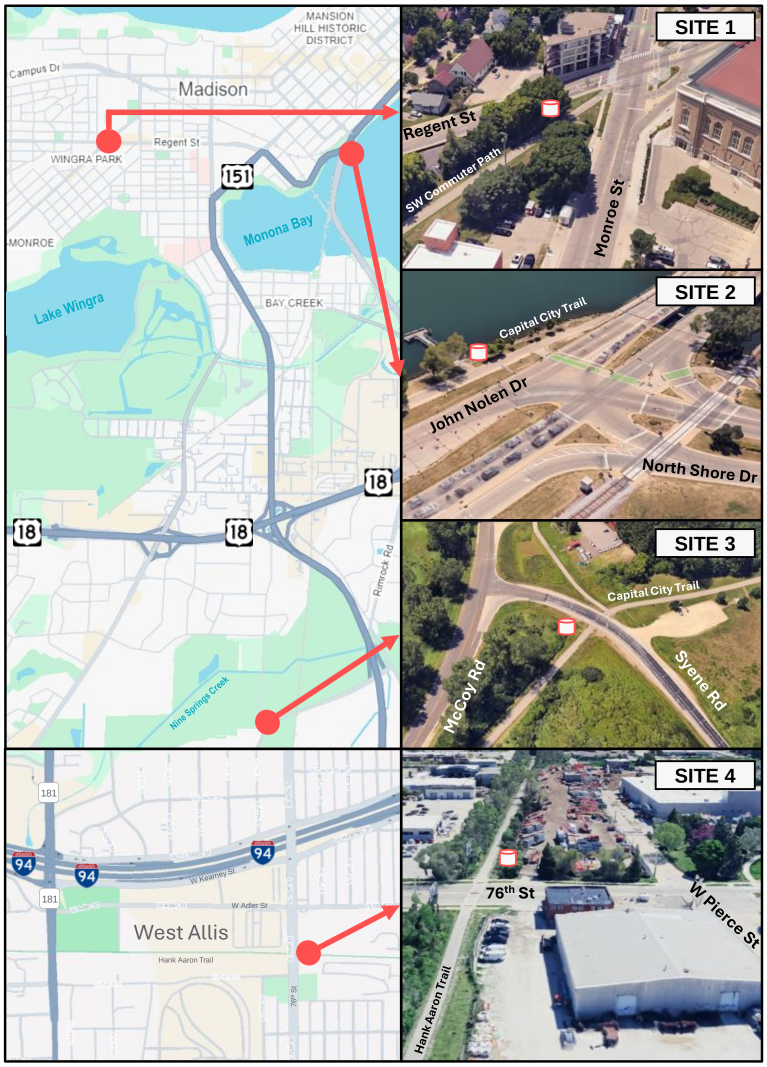

Figure 2. Study sites

2.2. Data Collection

Data collection consisted of gathering field video data, historical count data, crowdsourced data, and weather data from different sources.

2.2.1. Field Video/Ground Truth Data Collection

Equipment was specifically assembled to have the capacity to record video for 12 hours a day. The 12-hour video recording equipment consisted of portable cabinets with camcorders powered by battery banks. Figure 3 illustrates screenshots of camera recording and data collection equipment at the different sites.

Field video data was collected for 12-hour periods during daytime for seven days in August including all days of the week at Sites 1, 2, and 3. At Site 4, data was collected for four days in August including two weekdays and two weekend days. Table 1 provides the specific dates of data collection and amount of video data collected.

(a) Site 1, Southwest Commuter Path at Monroe St

(b) Site 2, Capital City Trail at John Nolen Dr and North Shore Dr

(c) Site 3, Capital City Trail at Syene Rd

(d) Site 4, Hank Aaron State Trail at 76th St

Figure 3. Field data collection camera views and sensor

2.2.2. Sensor Count Data

Permanent pedalcycle sensor data collection was available from inductive loop Eco-Counters since 2014 and 2015 at Sites 1 and 2, respectively. Inductive loop counters are electrified wired loops embedded in the pavement that detect pedalcycles by measuring changes in electromagnetic inductance when a metal object passes over them.

Sites 3 and 4 had passersby infrared count sensors that detect pedalcycles and other shared path users. Passersby count data at these sites was available between 2022-2023. Infrared sensors detect users by measuring changes in infrared radiation as users pass through a detection zone. These sensors usually involve an active emitter and receiver technology creating an invisible beam that is interrupted when a user crosses it, or passive technology which detects changes in heat as users pass through.

Sensor count data was requested from the City of Madison, City of Fitchburg, Dane County, and Wisconsin Department of Natural Resources (DNR). Table 1 provides details of the sensor and video data at the four sites.

Table 1. Video and sensor data by site

Site		1	2	3	4
Description		Southwest Commuter Path at Monroe St, Madison, WI	Capital City Trail at John Nolen Dr and North Shore Dr, Madison, WI	Capital City Trail at Syene Rd, Fitchburg, WI	Hank Aaron State Trail at S 76th St, West Allis, WI
Video	Dates	08/07-13/2023	08/07-13/2023	08/21-27/2023	08/17-20/2023
	Days	Monday-Sunday	Monday-Sunday	Monday-Sunday	Thursday-Sunday
	Hours	84	84	84	48
Sensor	Period	2014-2023	2015-2023	2022-2023	2022-2023
	User	Pedalcycle	Pedalcycle	Passerby	Passerby
	Type	Eco-Counter (inductive loop)	Eco-Counter (inductive loop)	TRAFx and Eco-Counter (infrared)	TRAFx (infrared)

2.2.3. Strava Data

Strava is a popular fitness application that allows users to record and analyze their activities, such as cycling, running, and hiking, using smartphones or other geolocation wearable devices. Strava provides route mapping features, activity statistics, and performance tracking, while also enabling social interactions by allowing users to share their activities, compare results, and be ranked in leaderboards (Strava 2024). The TOPS Lab has a research license to access Wisconsin Strava data, which was used for this project. Since the data from Strava primarily comes from fitness activities and not all shared path users use the application, the data is biased towards this specific type of user and market penetration, representing only a small subset of the overall population of shared path users. However, Strava does provide valuable information to be considered in modeling, especially at locations without permanent counting stations or with limited trail user volume information. Strava hourly count data were available between 2019-2024. Since Strava is a smartphone application, market penetration and number of active users over time must be considered in modeling.

2.2.4. Weather Data

Weather data was collected from the National Aeronautics and Space Administration (NASA) Prediction of Worldwide Energy Resources (POWER) database. NASA POWER is a publicly available data source that provides satellite-derived meteorological and solar data. Several NASA satellite missions and global climate models are integrated to offer long-term historical weather data (NASA POWER 2025). Weather variables of interest included temperature, humidity, wind speed, precipitation, and UV index. Weather data was collected at the hourly level at the sites of interest between 2019-2024.

2.3. Video/Ground Truth Data Processing

Approximately 268 hours of video were processed manually to record the date and time stamp in which a user passed by the sites of study. Users were classified by type: pedalcyclist, pedestrian, and others. Pedalcyclists consisted of recumbent, tandem, trailer, cargo, elliptical, traditional bicycles, and tricycles. Pedestrians consisted of users walking, running, accompanied by a dog on a leash or pushing a stroller. Other users included people on scooters, skateboards, rollerblades, or roller skis. The direction of travel was also coded in the data. The video hourly count data is interchangeably referred to as the ground truth or test data. The ground truth data was used to evaluate the accuracy of hourly counts from sensors, determine user type distribution, directional travel trends, and serve as test data for model predictions.

2.4. Data Management

All data variables were available between 2019-2023 (five years) for Sites 1 and 2. Sensor count data were available for the period of 2022-2023 (two years) for Sites 3 and 4. Since data originated from diverse sources, data linkage was required to consolidate variables into integrated datasets for each site. Thus, consolidated observations were defined by hour and date with corresponding weather, sensor, Strava and ground truth count data variables, if available for the given period of analysis. For daily observations, hourly observations were aggregated by date. Since the hourly and daily count data follow seasonal and temporal variations, to remove outliers, mean and standard deviations of hourly and daily sensor counts were evaluated by month of the year. For example, the mean and standard deviation of the 12 PM hour from all days of the month in January were evaluated. Similarly, for daily count evaluations, the mean and standard deviation of daily counts as a function of the month were evaluated. Sensor counts that exceeded plus or minus three times the standard deviation (±3σ) of the reference hour or day, according to the month, were considered outliers and removed from the data (450 hourly observations were removed). After outliers' removal, there were approximately 42,000 hourly or 1,800 daily observations from each site with five years of data (Sites 1 and 2).

The available data was partitioned into training, validation, and test (ground truth) data. The training data was used to develop models, and the validation data was used to assess the performance of the models when comparing predictions with observations not considered in the model training. Training and validation data included Strava, sensor, and weather data. For modeling hourly volumes at sites with five years of data, approximately 39,000 hourly observations were randomly selected for model training and the remaining 3,000 hourly observations were used for model validation. Similarly, for modeling of daily volumes, approximately 1,500 daily observations were randomly selected for model training and the remaining 300 daily observations were used for model validation. The validation sample size for count models was around 7% (hourly) and 17% (daily) of the overall data in each site, and it provided a representative number of observations to capture diverse observations at randomly selected times of the day, month, and year.

For the final evaluation (test) of the performance of the model, hourly predictions were compared to the observed ground truth data. Thus, the test data consisted of the ground truth data that was obtained from manual processing of videos which included 45 to 77 hourly counts by site. Ground truth data for daily (24-hour) counts was not available since data was collected in 12-hour periods.

2.5. Model Development

Model development consisted of model training, validation, assessment of transferability, model generalization, and testing. Negative Binomial (NB) regression modeling was implemented since the hourly and daily count data displayed overdispersion (variance was greater than the mean). The NB is appropriate to model response count data over a period of time such as the number of shared path users in an hour or day as a function of other factors, in this case, temporal and weather variables. The NB regression model form with a log link function is:

$$E(Y_i) = \mu_i \tag{E.1}$$

$$Var(Y_i) = \mu_i + \frac{{\mu_i}^2}{\theta} \tag{E.2}$$

$$Y_i = NB(\mu_i, \theta) \tag{E.3}$$

$$\ln(\mu_i) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_n X_{in} \tag{E.4}$$

$$\mu_i = e^{(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_n X_{in})} \tag{E.5}$$

Where,

$E(Y_i)$ = expected value for the i-th observation,
μ_i = mean or predicted value of the i-th observation,
$Var(Y_i)$ = variance of the i-th observation,
θ = dispersion term,
β_0 = intercept or constant term,
$\beta_1 \ldots \beta_n$ = regression model coefficients,
$X_{i1} \ldots X_{in}$ = predictor variables.

Table 2 provides the details of the variables explored for modeling. The response or predicted variable was sensor count. Predictor variables to capture the effect of temporal and weather variations were explored. Temporal variables explored included the hour of the day, weekday, week or weekend day, month, and year. Weather variables explored included temperature, humidity, precipitation, wind, and UV index.

Table 2. Summary of data variables

Data		Variable	Units	Values	Type
Count	Strava	STR	hourly, daily	0-max	Discrete
	Sensor	SEN	hourly, daily	0-max	Discrete
	Ground truth	GT	hourly, daily	0-max	Discrete
Temporal	Hour of the day	HR	24 hours	0-23	Ordinal
	Day of the week	DYW	Monday to Sunday	1-7	Ordinal
	Weekday	DY	Week or weekend day	0-1	Categorical
	Month of the year	MO	January to December	1-12	Ordinal
	Year	YR	5 years	2019-2023	Ordinal
Weather	Temperature	TEMP	°F, hourly	Min-max	Continuous
	Minimum temperature	minTEMP	°F, daily	Min-max	Continuous
	Maximum temperature	maxTEMP	°F, daily	Min-max	Continuous
	Average temperature	aTEMP	°F, daily	Min-max	Continuous
	Humidity	HUM	%, hourly	0-100	Continuous
	Average humidity	aHUM	%, daily	0-100	Continuous
	Precipitation	PR	inch	0-max	Continuous
	Precipitation accumulation	cPR	inch, daily	0-max	Continuous
	Precipitation > 0.1 in	RN	Rain or no rain	0-1	Ordinal
	Hours with precipitation > 0.1 in	cRN	Hour count, daily	0-24	Discrete
	Wind speed	WD	mph	0-max	Continuous
	Average wind speed	aWD	mph	0-max	Continuous
	UV index	UV	index, hourly	0-max	Continuous
	Average UV index	aUV	index, daily	0-max	Continuous

Predictor variables were specified according to the hourly or daily resolution of models. For daily models, the min, max, and average of temperature, accumulation of precipitation, number of hours with rain, average humidity, average wind speed, and average UV index were considered.

2.6. Model Validation, Transferability, and Testing

To evaluate the models' performance, estimates were produced with predictor variables corresponding to observations from subsets of data that were not included in the model training. Thus, the predicted hourly or daily estimates were compared to actual observations of sensor counts (validation) or ground truth (testing) data. A linear regression model was fitted in which the predicted data was the dependent variable, and the independent variable was the observed data. Depending on the application and data, from the linear relationship, the slope estimate close to the value of one represents an adequate model. The intercept of the linear relationship may also be evaluated to analyze error or bias. Statistical significance of the linear model coefficients was also considered. Also, the coefficient of determination (R^2) of the linear relationship helped assess how well the models explain the variation between the predicted and observed data. The closer the value of R^2 is to one, there would be an optimal fit of the linear regression model which provides confidence in the relationship between predicted and observed data.

Models were developed and validated using data from each site. Model transferability was evaluated by comparing the predictions of the transferred model to the alternate site observed and ground truth data. For instance, the model developed with data from Site 1 was used to produce estimates for Site 2. The linear relationship of estimates and observed data was evaluated to assess performance of model transferability. If models displayed optimal transferability across particular sites, a unified model was developed with all data from the identified sites that shared similar attributes for application across those sites. Validation and test for unified models were also conducted with the combined data of the sites sharing similar attributes and site-specific model transferability.

3. RESULTS

3.1. User Type and Hourly Trends

Using 268 hours of processed field video data (ground truth), the hourly count trends were evaluated according to the site, user type, direction of travel, and day of the week. Results are provided in Table 3 and Figure 4.

The sites in the study showed a distribution of users between 78-87% of pedalcyclists, 12-21% of pedestrians, and 1-2% of others. Thus, the main users of the shared paths were pedalcyclists. Pedestrians' path use increased over the weekends compared to weekdays. For instance, Site 2 had 18% of pedestrians during the week and 27% during weekend days. Sites 1 and 3 showed similar trends of 16 to 18% and 10 to 13%, respectively. On the contrary, Site 4 showed a significant drop in pedestrians during weekends (9%) compared to weekdays (20%).

Table 3. Summary of ground truth count data by site

Site	Description		Weekday	Weekend day	All days
1	Period	Days	5 (71.4%)	2 (28.6%)	7 (100.0%)
		Hours	54 (70.1%)	23 (29.9%)	77 (100.0%)
	Count by user type	Pedalcyclists	5,899 (82.8%)	2,492 (81.4%)	8,391 (82.3%)
		Pedestrians	1,150 (16.1%)	541 (17.7%)	1,691 (16.6%)
		Other	78 (1.1%)	30 (1.0%)	108 (1.1%)
	Count by direction	→ EB	3,315 (46.5%)	1,543 (50.4%)	4,858 (47.7%)
		← WB	3,812 (53.5%)	1,520 (49.6%)	5,332 (52.3%)
	All user counts		**7,127 (100.0%)**	**3,063 (100.0%)**	**10,190 (100.0%)**
2	Period	Days	5 (71.4%)	1 (14.3%)	7 (100.0%)
		Hours	47 (68.1%)	22 (31.9%)	69 (100.0%)
	Count by user type	Pedalcyclists	7,942 (81.0%)	4,462 (72.7%)	12,404 (77.8%)
		Pedestrians	1,720 (17.5%)	1,631 (26.6%)	3,351 (21.0%)
		Other	144 (1.5%)	41 (0.7%)	185 (1.2%)
	Count by direction	↑ NB	5,283 (53.9%)	3,102 (50.6%)	8,385 (52.6%)
		↓ SB	4,523 (46.1%)	3,032 (49.4%)	7,555 (47.4%)
	All user counts		**9,806 (100.0%)**	**6,134 (100.0%)**	**15,940 (100.0%)**
3	Period	Days	5 (71.4%)	2 (28.6%)	7 (100.0%)
		Hours	55 (71.4%)	22 (28.6%)	77 (100.0%)
	Count by user type	Pedalcyclists	1,011 (87.8%)	1,119 (85.6%)	2,130 (86.6%)
		Pedestrians	115 (10.0%)	168 (12.9%)	283 (11.5%)
		Other	26 (2.3%)	20 (1.5%)	46 (1.9%)
	Count by direction	→ EB	587 (51.0%)	627 (48.0%)	1,214 (49.4%)
		← WB	565 (49.0%)	680 (52.0%)	1,245 (50.6%)
	All user counts		**1,152 (100.0%)**	**1,307 (100.0%)**	**2,459 (100.0%)**
4	Period	Days	2 (50.0%)	2 (50.0%)	4 (100.0%)
		Hours	23 (51.1%)	22 (48.9%)	45 (100.0%)
	Count by user type	Pedalcyclists	571 (77.6%)	1,289 (89.6%)	1,860 (85.5%)
		Pedestrians	147 (20.0%)	129 (9.0%)	276 (12.7%)
		Other	18 (2.4%)	21 (1.5%)	39 (1.8%)
	Count by direction	→ EB	369 (50.1%)	857 (59.6%)	1,226 (56.4%)
		← WB	367 (49.9%)	582 (40.4%)	949 (43.6%)
	All user counts		**736 (100.0%)**	**1,439 (100.0%)**	**2,175 (100.0%)**
Count of all users at all sites			**18,821 (61.2%)**	**11,943 (38.8%)**	**30,764 (100.0%)**

Weekdays were characterized by reaching peak counts during the morning (8-11 AM) and late afternoon (4-5 PM). Weekend days were characterized by having high peaks between 9 AM to 1 PM. Higher counts were observed during the weekend. Directional travel showed higher volumes in the morning peak hours for one direction and higher volumes in the opposite direction in the afternoon peak hours during weekdays, as illustrated in Figures 4(a) (Site 1), 4(c) (Site 2), and 4(g) (Site 4). Sites 1, 2, and 4 are located in areas that connect suburban areas with downtown or university campus areas which are widely used for commuting purposes, reflecting peak hour volumes by direction and time of the day during weekdays. Site 3 is located in a more isolated area in which volumes peak late afternoon during weekdays. It should be noted that ground truth data was collected during specific time periods in August of 2023. Additional details of ground truth data by site are provided in Appendix A.

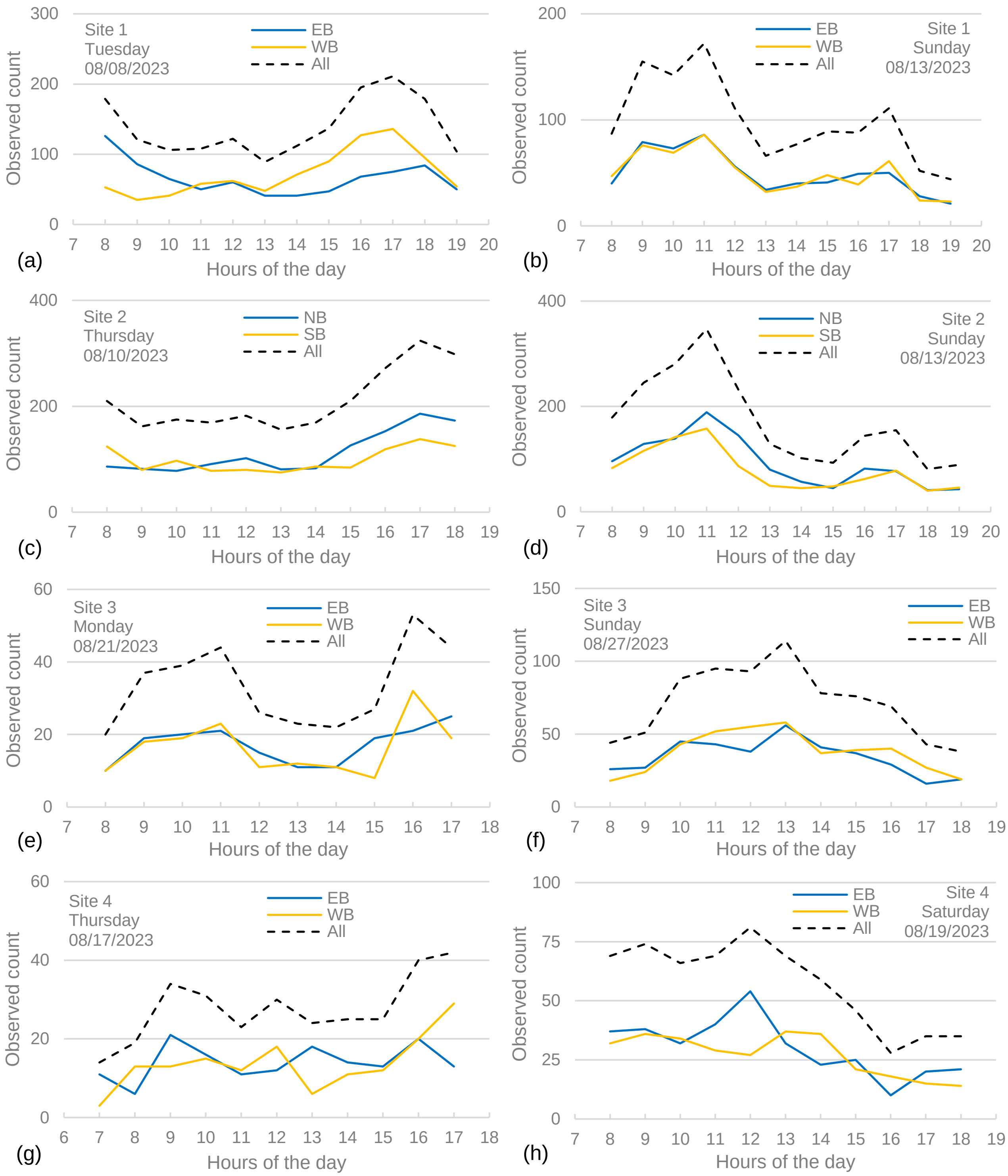

Figure 4. Selected directional and total hourly user ground truth count data by site

3.2. Accuracy of Automatic Counters

Inductive loop sensors at Sites 1 and 2 count pedalcyclists with a high degree of accuracy of 90.9% (9.1% error) and 92.1% (7.9% error), respectively. Figures 5(a) and 5(b) provide an analysis of the linear relationship between ground truth observed data (GT_{hr}) and inductive loop sensor counts (SEN_{hr}). Results show a statistically significant slope coefficient equal to 0.92 (Site

1) and 0.90 (Site 2), and R^2 equal to 0.99 for both sites. The intercept was very small (close to 0) and not statistically significant for both sites. Count data from the inductive loop sensors have been proven to be very effective at counting pedalcyclists and some of the undercounting errors may be associated with pedalcyclists passing side by side, on the edge of the path, reduced metal parts, or other variations.

Infrared sensors at Sited 3 and 4 count passersby with a reduced degree of accuracy of 53.8% (46.2% error) and 66.5% (33.5% error), respectively. Figures 5(c) and 5(d) provide an analysis of the linear relationship between ground truth data and infrared sensor counts. Results show a moderate linear relationship with a slope coefficient equal to 0.42 and intercept equal to -0.65 for Site 3 (R^2=0.54). The linear relationship for Site 4 was poor with slope coefficient equal to -0.12 and intercept equal to 37.94 (R^2=0.08). Infrared sensors can be triggered by many moving objects, can be sensitive to surface reflection and temperature fluctuations, or may not detect small or quick moving objects. Also, infrared sensors are subject to vandalism or being stolen.

Due to the limited accuracy of infrared sensors and reduced data available (2 years, 2022-2023) from Sites 3 and 4, models were only developed using data from Sites 1 and 2.

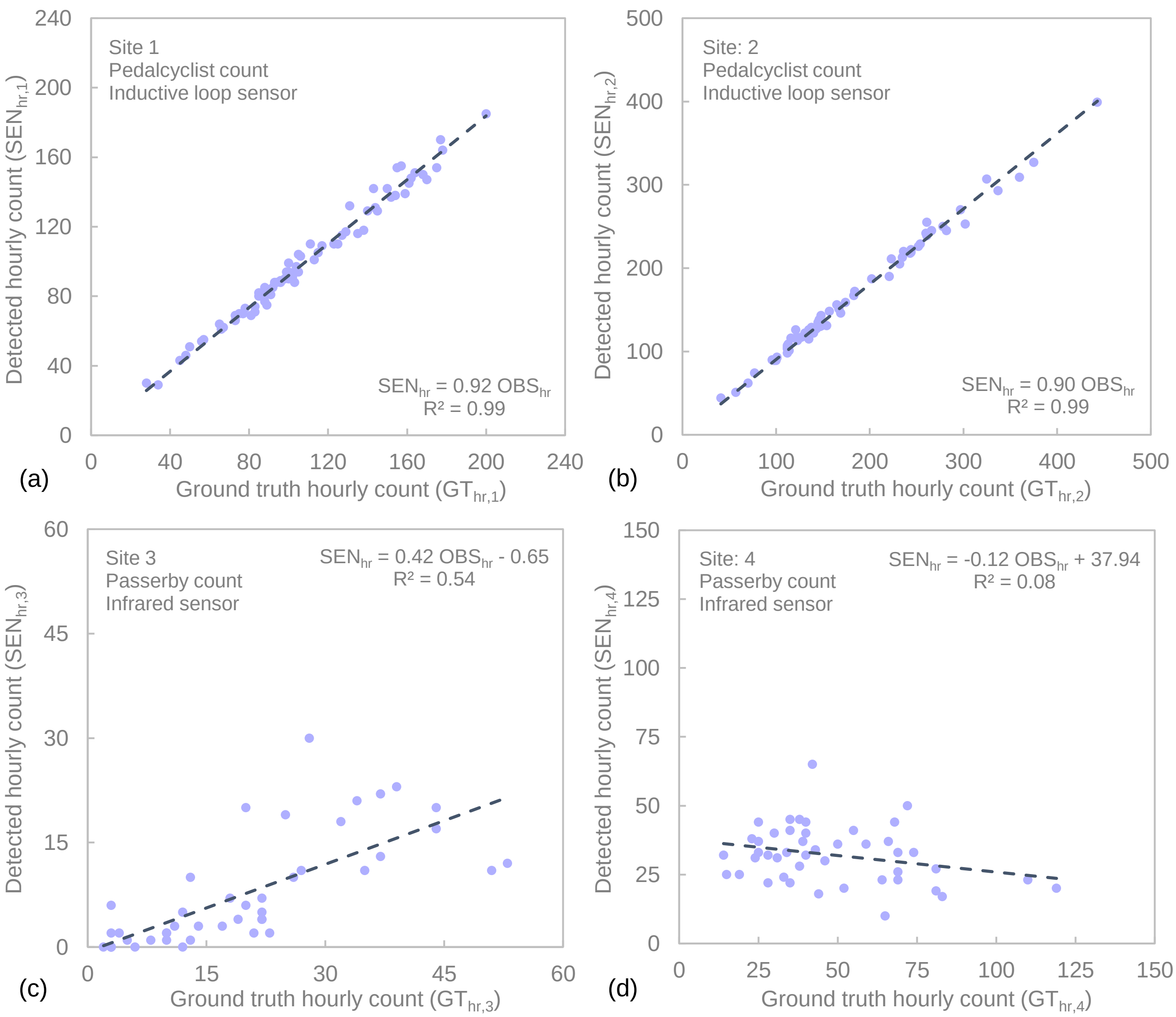

Figure 5. Linear relationship between detected sensor and ground truth hourly count data

3.3. Shared Path User Volume Models

Since data from inductive loop sensors from Sites 1 and 2 proved to have high degree of accuracy with pedalcycle counts, hourly and daily pedalcycle volume models were developed at the site-specific and aggregated level after verification of transferability. Models were validated with randomly selected data (not included in training) and tested with ground truth data.

3.3.1. Exploratory Data Analysis

Before modeling, variables were evaluated to assess the distribution of data, correlation (r), and shape of functional forms. Figure 6 provides scatterplots of hourly sensor versus Strava counts for each site. There is a clear distinction among the count volumes across sites, with Sites 1 and 2 having up to 300 and 500 hourly counts compared to Sites 3 and 4 with lower volumes no greater than 150 hourly counts. Hourly sensor counts showed larger values with increasing Strava counts and strong correlations between 0.70 to 0.89. Based on the distribution of the variable STR, exponential, power, and Hoerl functions were explored in modeling.

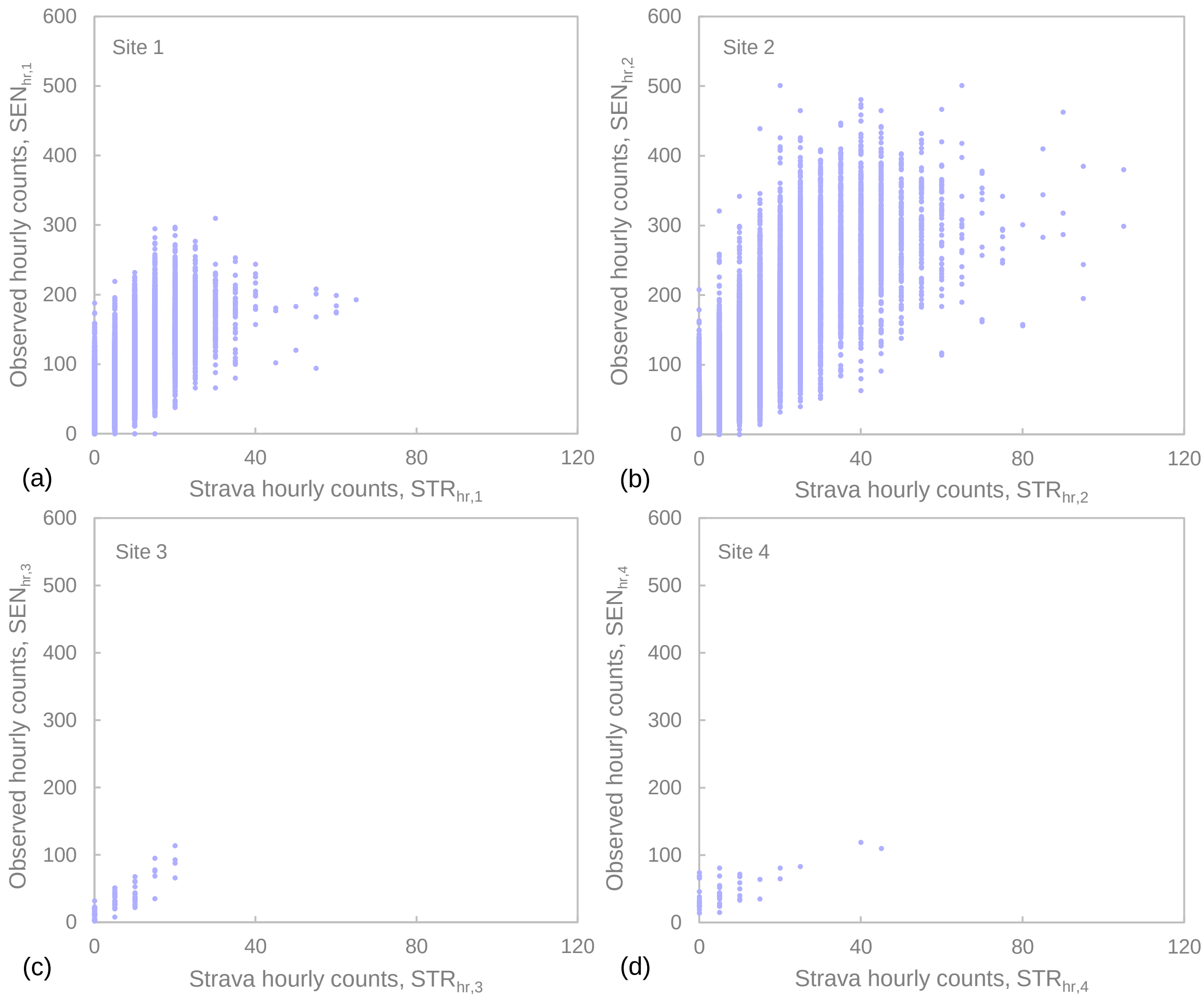

Figure 6. Sensor versus Strava counts by site

The monthly (MO) and hourly (HR) variables had a similar temporal distribution with a bell shape distribution with most of the observations concentrated during warmer months and daytime hours, and reduced counts during cold months and nighttime hours, as shown in Site 1 with Figures 7(a) and 7(b). Polynomial functions were explored for the MO and HR variables.

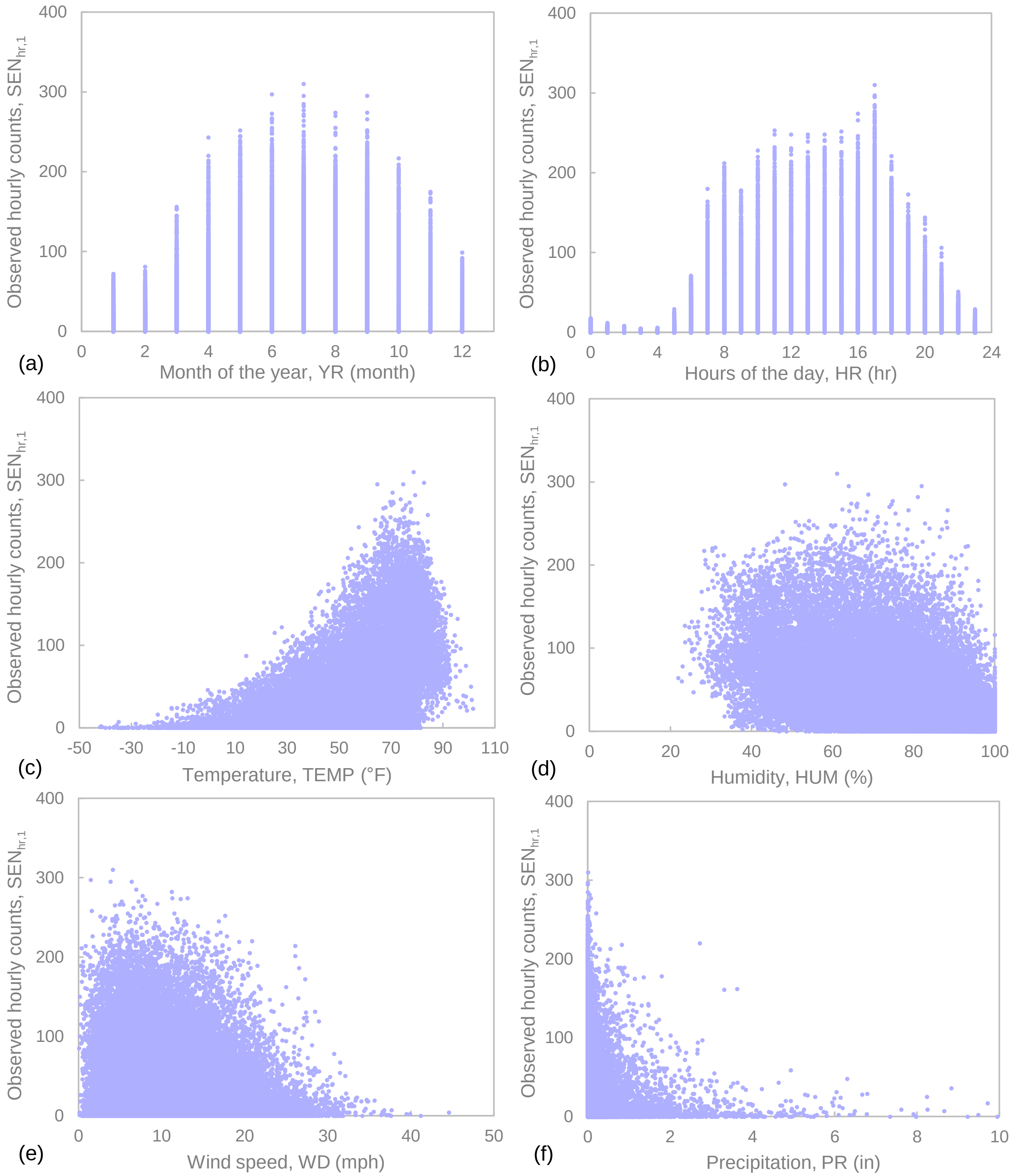

Figure 7. Site 1 sensor hourly counts versus predictor variable (a) month, (b) hour of the day, (c) temperature, (d) humidity, (e) wind speed, and (f) precipitation

The temperature variable showed an increasing trend in counts as temperature increased (r=0.58). Small hourly counts were observed even in negative temperatures since these paths are maintained during the winter season. Exponential and polynomial functions were explored for the TEMP variable. The humidity variable concentrated near the values of 40-100%. The relationship of the humidity variable with counts was not clear and was correlated with the temperature (r=0.41) and precipitation (r=0.18) variables. Rescaling and transformations were implemented with the HUM variable, and several linear, exponential, or power functions were explored. The wind speed variable had a particular skewed distribution. Polynomial functions were explored for the WD variable. Precipitation was highly concentrated with values near zero and decreasing counts with increasing inches of precipitation by hour. The variable PR was explored as a continuous variable with an exponential function and as binary variable RN. The RN variable indicated rain if the precipitation in an hour exceeded 0.1 inches.

For daily observations, hourly data was aggregated to the corresponding date, and minimum, maximum, and average values of predictor variables were used. Similar temporal distributions were observed with daily observations and the same functional forms as hourly observations were explored.

The models were developed incrementally as each predictor variable was introduced in the model with an optimal functional form. Goodness of fit was assessed at each step of exploration of functional forms and addition of predictor variables. Measures evaluated included the model coefficients' statistical significance, dispersion term, log-likelihood, Akaike information criterion (AIC), and residuals.

3.3.2. Hourly Site-specific Models

Hourly models were developed for Sites 1 and 2 with corresponding data. The model equation form is presented in Equation E.6, and Table 4 provides model coefficients and statistical measures.

Hourly Predictor Variables. Statistically significant (p-value < 0.050) variables for estimating hourly sensor counts were Strava counts, year, month, day of the week, hour, temperature, and rain. The Strava count variable optimal functional form was a power function, polynomial functions for the month and hour variables, and the rest of the variables had exponential functional forms. The predictor variables reflected intuitive increasing, decreasing, and bell shape trends in relation to sensor hourly counts.

$$SEN_{hr,j} = e^{\beta_0} \times \left(STR_{hr,j} + 1\right)^{\beta_1} \times e^{\left(\beta_2 YR + \beta_3 MO + \beta_4 MO^2 + \beta_5 DY + \beta_6 HR + \beta_7 HR^2 + \beta_8 TEMP + \beta_9 RN\right)} \quad [pedalcycles/hour] \qquad \text{(E.6)}$$

Where,

$SEN_{hr,j}$	= predicted sensor hourly pedalcycle count for site j,
STR_{hr}, j	= Strava hourly pedalcycle count for site j,
YR	= year (2019-2023),
MO	= month of the year (1-12),
DY	= weekday (week = 0, weekend = 1),
HR	= hour of the day (0-23),
$TEMP$	= hourly temperature (°F),
RN	= hourly rain, precipitation > 0.1 in (0,1),
$\beta_0 \dots \beta_9$	= regression model coefficients.

Each predictor variable made significant contributions to goodness of fit measures as each variable was introduced into the model. Other variables such as wind, humidity, or UV index were explored, but contributions to model prediction were not significant.

Table 4. Site-specific hourly model coefficients and measures of goodness of fit

Description	Hourly coefficient (p-value)	
	Site model 1	Site model 2
Sample	39,881	39,489
β_0	55.344 (< 0.001)	100.500 (< 0.001)
β_1	0.410 (< 0.001)	0.477 (< 0.001)
β_2	-0.028 (< 0.001)	-0.050 (< 0.001)
β_3	0.307 (< 0.001)	0.193 (< 0.001)
β_4	-0.020 (< 0.001)	-0.013 (< 0.001)
β_5	-0.256 (< 0.001)	-0.175 (< 0.001)
β_6	0.532 (< 0.001)	0.408 (< 0.001)
β_7	-0.019 (< 0.001)	-0.015 (< 0.001)
β_8	0.016 (< 0.001)	0.019 (< 0.001)
β_9	-0.353 (< 0.001)	-0.351 (< 0.001)
θ	2.676 (< 0.001)	3.134 (< 0.001)
AIC	290,895	310,332
Log-likelihood	-290,873	-310,310

Hourly Model Validation. Models from Sites 1 and 2 were validated with the validation dataset, a subset of 3,000 randomly chosen observations from each site. Figure 8 and Table 5 include the validation results by site. The linear fit of predicted and observed hourly counts showed that site-specific models from Sites 1 and 2 have slopes of 0.97 and 0.89, intercepts equal to 3.73 and 5.76, and R^2 equal to 0.76 and 0.82, respectively. Thus, validation slopes are close to the value of one (similar magnitude between predicted and observed hourly counts), small intercepts (no major systemic bias or error), and large coefficient of determination R^2, which indicates that there is a strong linear relationship between predicted and observed hourly counts.

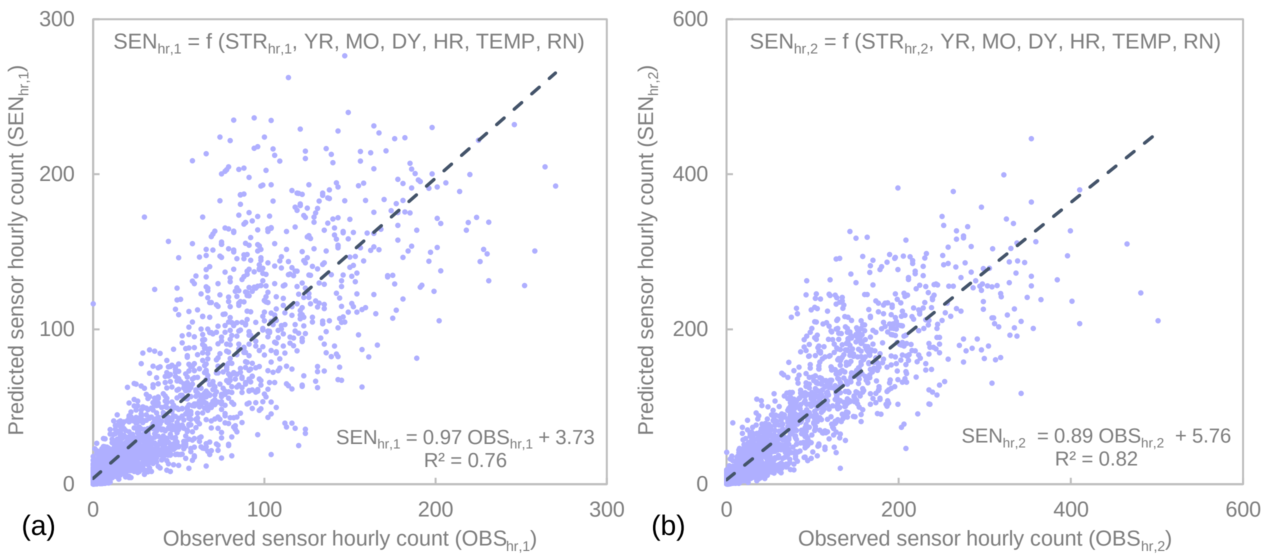

Figure 8. Site-specific hourly model validation for (a) Site 1 and (b) Site 2

Hourly Model Transferability. Site-specific hourly models' transferability were assessed by using Site 1 and Site 2 models across all potential sites to compare predicted and observed counts using validation or ground truth data. The linear relationship between predicted (site model) and observed (site transfer) hourly counts were assessed, and results are provided in Table 5. Using the corresponding validation data from each site, results indicate that site specific models from Sites 1 and 2 have similar model performance between each other with small intercepts, slopes close to one, and large R^2. Since infrared sensor data showed very low levels of accuracy, ground truth data was used with Sites 3 and 4 to assess the transferability of models from Sites 1 and 2. Results showed that models from Sites 1 and 2 prediction accuracy did not transfer to Sites 3 and 4 because there was systemic bias or error between 22-74 hourly counts, predictions with magnitudes of up to 2.3 times of the value of observed hourly counts, and R^2 less than 0.5, showing moderate to low strength with linear relationships between predicted and observed hourly counts.

Sites 1 and 2 shared similar characteristics and volumes whereas Sites 3 and 4 had different features and lower volumes. Thus, data from Sites 1 and 2 were aggregated and generalized hourly models were developed. The generalized models provide valuable prediction capabilities at other locations with specific site characteristics to estimate counts where Strava counts and weather data are available, despite the lack of historical sensor counts.

Table 5. Validation and transferability results of site-specific pedalcycle hourly models

Site model[1]	Description	Validation site[2] or site transfer[3]			
		1	2	3	4
1	Sample	3,000*	3,000*	77+	45+
	Intercept	3.73 (< 0.001)	6.29 (< 0.001)	73.93 (< 0.001)	39.03 (0.014)
	Slope	0.97 (< 0.001)	0.75 (< 0.001)	1.16 (< 0.001)	1.69 (< 0.001)
	R^2	0.76	0.78	0.31	0.39
2	Sample	3,000*	3,000*	77+	45+
	Intercept	3.49 (< 0.001)	5.76 (< 0.001)	66.01 (< 0.001)	22.19 (0.204)
	Slope	1.10 (< 0.001)	0.89 (< 0.001)	1.53 (< 0.001)	2.28 (< 0.001)
	R^2	0.78	0.82	0.42	0.48

Notes: [1] Site-specific model, [2] validation site results, [3] sites with transferred models to assess prediction performance, * validation sample data, + ground truth data, R^2 = coefficient of determination.

3.3.3. Daily Site-specific Models

Daily models were developed for Sites 1 and 2 with corresponding data. The model equation form is presented in Equation E.7, and Table 6 provides model coefficients and statistical measures.

Daily Predictor Variables. Statistically significant (p-value < 0.050) variables for estimating daily sensor counts were daily Strava counts, year, month, day of the week, average daily temperature, and the number of hours a day with rain. Similar predictor variables' functional form than hourly models were found optimal for daily models—power function (STR_{dy}), polynomial (MO), and exponential functions (YR, DY, aTEMP, cRN).

$$SEN_{dy,j} = e^{\beta_0} \times \left(STR_{dy,j} + 1\right)^{\beta_1} \times e^{\left(\beta_2 YR + \beta_3 MO + \beta_4 MO^2 + \beta_5 DY + \beta_6 aTEMP + \beta_7 cRN\right)} \quad [pedalcycles/day] \qquad \text{(E.7)}$$

Where,

$SEN_{dy,j}$	= predicted sensor daily pedalcycle count for site j,
$STR_{dy,j}$	= Strava daily pedalcycle count for site j,
YR	= year (2019-2023),
MO	= month of the year (1-12),
DY	= weekday (week = 0, weekend = 1),
$aTEMP$	= average daily temperature (°F),
cRN	= hours in a day with precipitation > 0.1 in (0-24),
$\beta_0 \ldots \beta_7$	= regression model coefficients.

Table 6. Site-specific daily model coefficients and measures of goodness of fit

Description	Daily coefficient (p-value)	
	Site model 1	Site model 2
β_0	67.828 (< 0.001)	128.747 (< 0.001)
β_1	0.312 (< 0.001)	0.375 (< 0.001)
β_2	-0.032 (< 0.001)	-0.062 (< 0.001)
β_3	0.191 (< 0.001)	0.062 (< 0.001)
β_4	-0.012 (< 0.001)	-0.004 (< 0.001)
β_5	-0.194 (< 0.001)	-0.072 (< 0.001)
β_6	0.015 (< 0.001)	0.021 (< 0.001)
β_7	-0.019 (< 0.001)	-0.026 (< 0.001)
θ	10.984 (< 0.001)	7.527 (< 0.001)
AIC	20010	21447
Log-likelihood	-19992	-21429

Daily Model Validation. Models from Sites 1 and 2 were validated with the validation dataset, a subset of 300 randomly chosen observations from each site. Figure 9 and Table 7 include the validation results by site. The linear fit of predicted and observed daily counts showed that site-specific models from Sites 1 and 2 have slopes of 0.97 and 0.92, and R^2 equal to 0.95, respectively. The intercept was set to zero because the linear relationship was stronger for smaller counts (< 1,000 for Site 1, and < 2,000 for Site 2) and had an improved overall fit. Thus, validation slopes are close to the value of one (similar magnitude between predicted and observed daily counts), and large coefficient of determination R^2, which indicates that there is a strong linear relationship between predicted and observed daily counts.

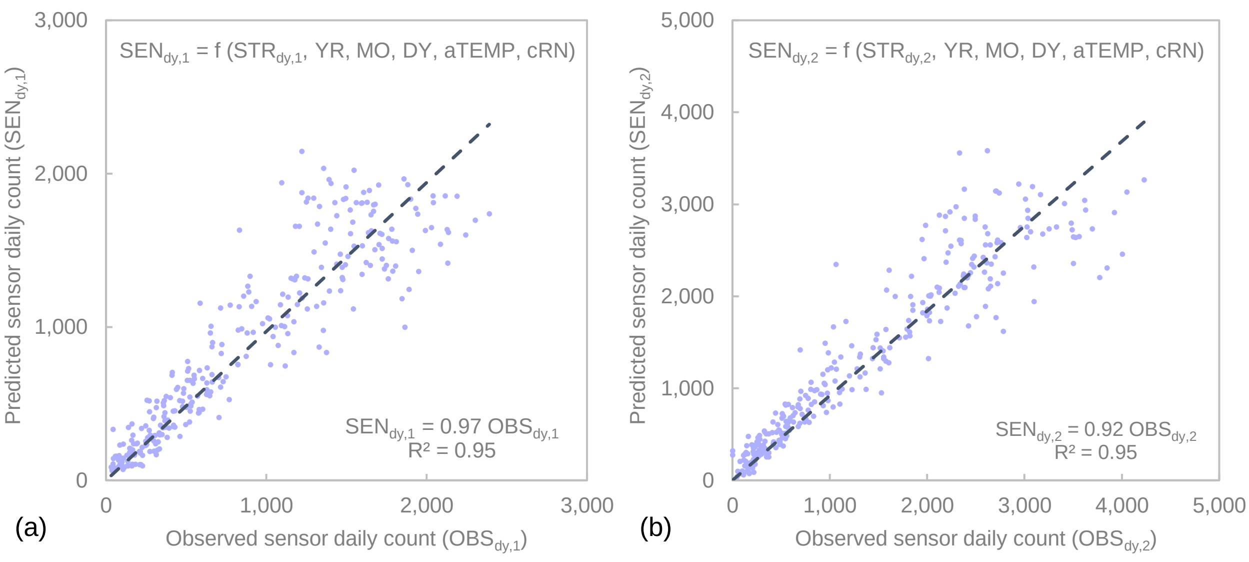

Figure 9. Site-specific daily model validation for (a) Site 1 and (b) Site 2

Daily Model Transferability. Site-specific daily models' transferability was assessed by using Site 1 and Site 2 models across each other to compare predicted and observed counts using validation data. Since sensor data was unreliable for Sites 3 and 4, and there was no complete ground truth daily data available, assessment of the transferability of daily models was not possible for Sites 3 and 4. The linear relationship between predicted (site model) and observed (site transfer) daily counts were assessed, and results are provided in Table 7. Using the corresponding validation data from each site, results indicate that site specific models from Sites 1 and 2 have similar model performance between each other with small intercepts, slopes close to 1, and large R^2. Sites 1 and 2 shared similar characteristics and volumes, so data from Sites 1 and 2 were aggregated and generalized daily models were developed.

Table 7. Site-specific daily model coefficients and measures of goodness of fit

Site model[1]	Description	Validation site[2] or site transfer[3]	
		1	2
1	Sample	300*	299*
	Slope	0.97 (< 0.001)	0.72 (< 0.001)
	R^2	0.95	0.93
2	Sample	300*	299*
	Slope	1.18 (< 0.001)	0.92 (< 0.001)
	R^2	0.95	0.95

Notes: [1] Site-specific model, [2] validation site results, [3] sites with transferred models to assess prediction performance, * validation sample data, R^2 = coefficient of determination.

3.3.4. Generalized Hourly and Daily Models

Generalized models were developed with sites that share similar attributes and have proven site-specific model transferability. Sites 1 and 2 share similar count volumes, user type distribution, located in neighboring areas, and serve as recreational and commuting routes. Thus, generalized models were developed by combining data from Sites 1 and 2. Equations E.8 and E.9 provide model equations for the hourly and daily sensor counts. Since there is a small error (undercount) with inductive loop sensor counts compared to ground truth data between 8-9%, an adjustment factor (φ) was estimated with the mean error difference of hourly observations which were assumed to translate to daily observations in the same proportion provided in Equations E.10 and E.11.

$$SEN_{hr} = e^{\beta_0} \times (STR_{hr} + 1)^{\beta_1} \times e^{(\beta_2 YR + \beta_3 MO + \beta_4 MO^2 + \beta_5 DY + \beta_6 HR + \beta_7 HR^2 + \beta_8 TEMP + \beta_9 RN)}\ [pedalcycles/hour] \quad \text{(E.8)}$$

$$SEN_{dy} = e^{\beta_0} \times \left(STR_{dy} + 1\right)^{\beta_1} \times e^{(\beta_2 YR + \beta_3 MO + \beta_4 MO^2 + \beta_5 DY + \beta_6 aTEMP + \beta_7 cRN)}\ [pedalcycles/day] \quad \text{(E.9)}$$

$$N_{hr} = \varphi \times SEN_{hr}\ \ [pedalcycles/hour] \quad \text{(E.10)}$$

$$N_{dy} = \varphi \times SEN_{dy}\ \ [pedalcycles/day] \quad \text{(E.11)}$$

Where,

N_{hr} = predicted hourly pedalcycle count,
N_{dy} = predicted daily pedalcycle count,
SEN_{hr} = predicted sensor hourly pedalcycle count,
SEN_{dy} = predicted sensor daily pedalcycle count,
STR_{hr} = Strava hourly pedalcycle count,
STR_{dy} = Strava daily pedalcycle count,
YR = year (2019-2023),
MO = month of the year (1-12),
DY = weekday (week = 0, weekend = 1),
HR = hour of the day (0-23),
$TEMP$ = hourly temperature (°F),

$aTEMP$ = average daily temperature (°F),
RN = hourly rain, precipitation > 0.1 in (0,1),
cRN = hours in a day with precipitation > 0.1 in (0-24),
φ = sensor error adjustment factor (in reference to ground truth data),
$\beta_0 \dots \beta_9$ = regression model coefficients.

Model Coefficients. Table 8 provides the model coefficients for generalized hourly and daily models. Some differences in the models can be noted, the daily model does not include the hour of the day variable (HR) which reduces the number of coefficients in the model, uses the average daily temperature (aTEMP) and the number of hours in a day with precipitation greater than 0.1 in (cRN). For model training, 79,370 (hourly) and 2,989 (daily) observations were used. Optimal functional forms were the same as site-specific models with a power function for the Strava count variable, polynomial functions for the month and hour variables, and exponential functions for the rest of the variables.

Table 8. Generalized hourly and daily model coefficients and measures of goodness of fit

Description	Coefficient (p-value)	
	Hourly model	Daily model
Sample	79,370	2,989
φ	1.089 (< 0.001)	1.089 (< 0.001)
β_0	79.070 (< 0.001)	97.253 (< 0.001)
β_1	0.459 (< 0.001)	0.360 (< 0.001)
β_2	-0.040 (< 0.001)	-0.046 (< 0.001)
β_3	0.241 (< 0.001)	0.116 (< 0.001)
β_4	-0.016 (< 0.001)	-0.007 (< 0.001)
β_5	-0.212 (< 0.001)	-0.132 (< 0.001)
β_6	0.460 (< 0.001)	0.017 (< 0.001)
β_7	-0.017 (< 0.001)	-0.021 (< 0.001)
β_8	0.018 (< 0.001)	NA (NA)
β_9	-0.348 (< 0.001)	NA (NA)
θ	2.761 (< 0.001)	8.284 (< 0.001)
AIC	604,024	41,730
Log-likelihood	-604,002	-41,712

Model Validation. The generalized models were validated with a separate subset data of 6,000 hourly and 599 daily observations, combined from Sites 1 and 2. Figure 10(a) (hourly) and 10(b) (daily) illustrate the validation of the generalized models by comparing the predicted and observed sensor counts. The results show a strong linear association between hourly and daily predicted and observed values with slopes of 0.95 and 0.90, and R^2 equal to 0.86 and 0.94, respectively. There was no major systemic bias or error. Thus, the models predict pedalcycle sensor counts under diverse periods and weather conditions.

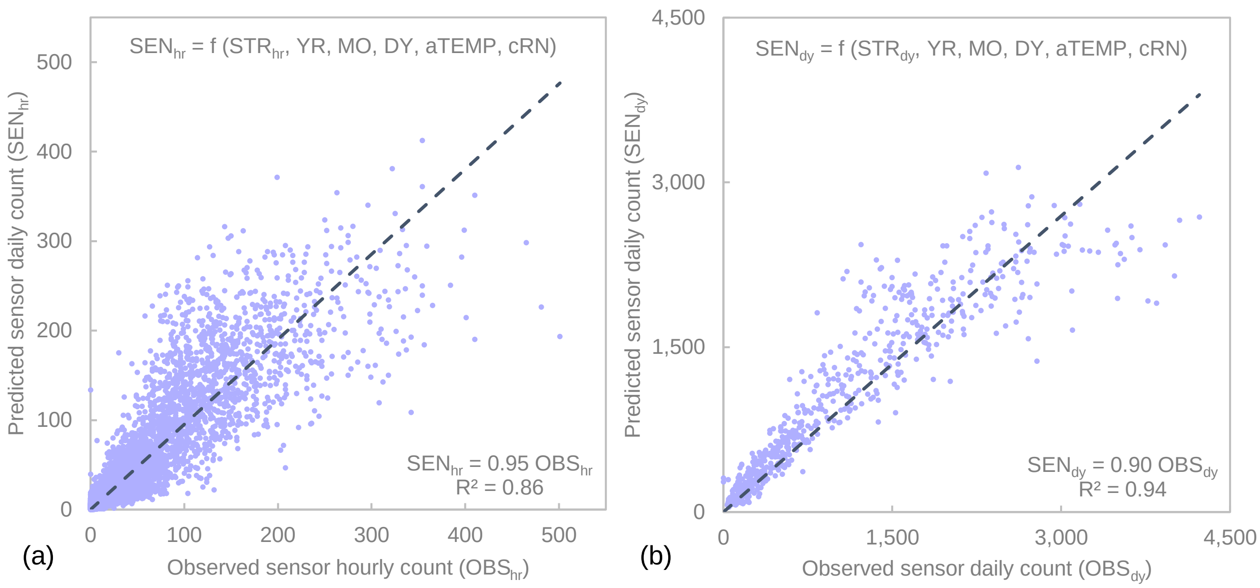

Figure 10. Linear relationship between predicted and observed sensor counts at the (a) hourly and (b) daily level

Sensor Error Adjustment and Model Testing. The generalized models showed optimal levels of performance with validation data. Further testing and sensor error adjustment were required to accurately estimate ground truth observations. In the final step of the model development, the sensor predictions were adjusted for the small error (undercounting) of pedalcycles with inductive loop sensors. By adjusting the error, the adjusted prediction can be directly compared to the ground truth data. Since ground truth data is available for 12-hour periods, there is no daily ground truth data for testing daily models. Thus, only hourly model adjusted predictions were compared to 146 hourly ground truth data. Figure 11 provides the results of the test. Results show that hourly adjusted predictions also had a strong linear relationship with hourly ground truth data with a slope of 1.16 and R^2 equal to 0.92.

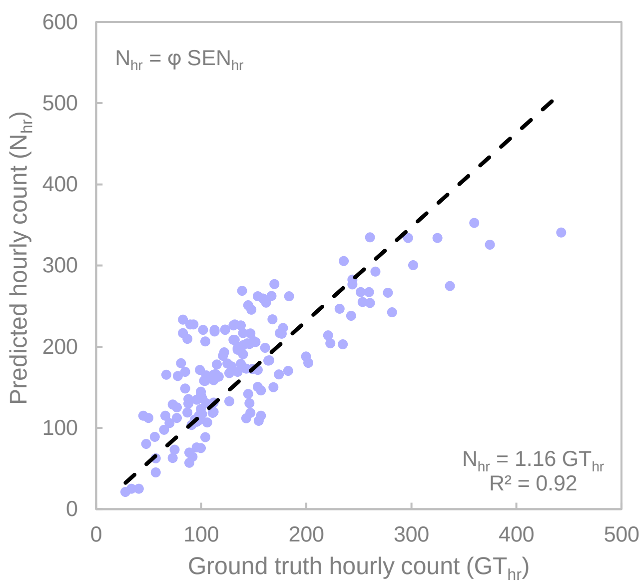

Figure 11. Linear relationship between predicted and ground truth hourly counts

4. DISCUSSION AND RECOMMENDATIONS

Modeling of shared path users' volume is very difficult to conduct due to the lack of historical count data and counting technology accuracy. Weather variables have a major and significant temporal impact on path counts. Short term ground truth data provided valuable insight into the type and distribution of path users and assessment of the accuracy of sensor counts. In this study, pedalcycles were the main user on shared paths (78-87%). Inductive loops showed high level of pedalcycle count accuracy (91-92%). With the availability of five years (2019-2023) of pedalcycle sensor counts, modeling of pedalcycle hourly and daily counts was pursued.

Temporal variables such as hour of the day, weekday, month, and year had a significant effect on counts. Weather variables such as temperature and precipitation were highly associated with pedalcycle counts. Strava count data significantly improves model prediction accuracy. Since Strava is a smartphone application, temporal variation of registered and active users need to be considered. The year and month variables capture the temporal variations in pedalcycle activity, Strava user market penetration and other effects such as the pandemic impact.

Site-specific models were transferable to sites with similar volumes and traits; however, they did not transfer well to sites with vastly lower volumes and different land use characteristics. Thus, models were generalized by combining data from sites sharing similar traits. Based on the available data, generalized hourly and daily pedalcycle count models were developed, validated, and tested (using ground truth data). Models showed optimal levels of accuracy.

Due to the lack of reliable long-term pedestrian and other user count data (not pedalcycles), development of count models for these users was not possible. However, assuming that the distribution of shared path users remains the same over time, pedestrian and other users' distribution may be used to estimate counts as a function of pedalcycles counts. However, distributions from short term (12 hours for 4-7 days) observations of pedestrians and other users are representative of the month of August of 2023, and further investigation may be required to verify if these distributions hold over different seasons of the year.

Count models can be used to obtain estimates for different applications including planning, maintenance, safety and emergency response, event planning, tourism or recreational information, public health and wellness initiatives, and education. Specific recommendations for application of the models developed and future efforts include the following:

- The generalized hourly and daily models can be applied to estimate pedalcycle counts on sections of shared paths (without sensor counts) that have high volumes, serve as commuting and recreational routes, and are surrounded by densely populated areas.
- The models can be applied using temporal, weather, and Strava count data on the:
  - Capital City trail between E Lakeside St and E Wilson St.
  - Southwest Commuter Path between Commonwealth Ave and Main St.
- Model count estimates can be used as a measure of exposure for safety analysis between trail users and vehicles at trail crossings.
- Model count estimates can be used to assess if countermeasures or treatments are warranted to reduce risks on trails (signage, illumination, winter storms) and among trail users (interactions between pedalcycles and pedestrians, crowded trails), bird migration (near lakes), or special events.
- Hourly count estimates can also be used to optimize signal timing plans at trail crossings near or at signalized intersections.
- Explore new video detection technologies for permanent user counting and classification stations.
- Installation of permanent counting stations (inductive loop sensors) at strategic locations would significantly contribute to expand the coverage of historical count data and model estimates filling in the gaps in the network without count data.

5. CONCLUSIONS

The present study provides a scalable and transferable approach to estimate shared path usage, leveraging a combination of automated sensor, crowd-sourced, ground truth video, and weather data with advanced statistical modeling. The robust approach is used to develop models estimating hourly and daily pedalcycle volumes. The findings highlight the importance of temporal and weather variables in predicting shared path usage, reinforcing the impact of seasonal variations, time of day, temperature, and precipitation. The results demonstrate that Strava data, despite its inherent bias toward fitness-oriented users, significantly improves model predictions and can serve as a valuable data source to model and estimate counts in sites where there are not permanent counting stations available. Inductive loop sensors count pedalcycles accurately and provide valuable count data.

The findings of this study have significant implications for transportation planning, infrastructure development, and safety improvements. The ability to estimate shared path user volumes enables planners to make data-driven decisions regarding maintenance scheduling, facility design, and safety interventions. The integration of these models into trail management systems will enhance the ability of agencies to allocate resources efficiently, ensuring that shared paths continue to serve as safe, accessible, and well-maintained facilities for all users.

Key challenges and limitations identified in this study were the limited accuracy of infrared-based passerby counters and model transferability. The issues associated with these sensors, along with the lack of long-term passerby count data, prevented the development of a dedicated pedestrian volume model. However, this study provided insights into pedestrian distribution trends with ground truth data of 12-hour periods over four to seven days at four sites. Transferability of pedalcycle volume models was possible across sites that share similar traits and volumes. Thus, more sites with reliable count sensors would be required to expand the coverage across the shared path network in the Madison area to estimate volumes with specific attributes and conditions.

Future efforts and research should expand the installation of inductive loop pedalcycle counters across strategic sites in the network and explore alternative passerby counting technologies, such as video-based or AI-assisted detection systems, to improve data reliability for pedestrian counting and modeling.

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APPENDIX A

Table A1. Ground truth data summary for Site 1, Southwest Commuter Path at Monroe St, Madison, WI

Description		Count										Distribution		
		Mon 08/21/2023	Tue 08/22/2023	Wed 08/23/2023	Thu 08/24/2023	Fri 08/25/2023	Sat 08/26/2023	Sun 08/27/2023	Weekday	Weekend	All	Weekday	Weekend	All
Data	Period (AM-PM)	11-20	8-20	8-18	8-19	8-20	8-19	8-20	NA	NA	**NA**	NA	NA	**NA**
	Hours	9	12	10	11	12	11	12	54	23	**77**	NA	NA	**NA**
Users	Pedalcyclists	988	1,402	1,148	1,242	1,119	1,618	874	5,899	2,492	**8,391**	82.8%	81.4%	**82.3%**
	Pedestrians	226	238	187	258	241	230	311	1,150	541	**1,691**	16.1%	17.7%	**16.6%**
	Other	10	23	9	14	22	21	9	78	30	**108**	1.1%	1.0%	**1.1%**
Direction	← WB	710	870	721	796	715	923	597	3,812	1,520	**5,332**	53.5%	49.6%	**52.3%**
	→ EB	514	793	623	718	667	946	597	3,315	1,543	**4,858**	46.5%	50.4%	**47.7%**
All		**1,224**	**1,663**	**1,344**	**1,514**	**1,382**	**1,869**	**1,194**	**7,127**	**3,063**	**10,190**	**100.0%**	**100.0%**	**100.0%**

Table A2. Ground truth data summary for Site 2, Capital City Trail at John Nolen Dr and North Shore Dr, Madison, WI

Description		Count										Distribution		
		Mon 08/21/2023	Tue 08/22/2023	Wed 08/23/2023	Thu 08/24/2023	Fri 08/25/2023	Sat 08/26/2023	Sun 08/27/2023	Weekday	Weekend	All	Weekday	Weekend	All
Data	Period (AM-PM)	11-20	8-19	8-19	8-19	8-13	8-18	8-20	NA	NA	**NA**	NA	NA	**NA**
	Hours	9	11	11	11	5	10	12	47	22	**69**	NA	NA	**NA**
Users	Pedalcyclists	1,661	1,951	1,811	1,936	583	2,949	1,513	7,942	4,462	**12,404**	81.0%	72.7%	**77.8%**
	Pedestrians	461	406	324	367	162	1,086	545	1,720	1,631	**3,351**	17.5%	26.6%	**21.0%**
	Other	36	41	39	24	4	22	19	144	41	**185**	1.5%	0.7%	**1.2%**
Direction	↑ NB	1,240	1,248	1,184	1,241	370	1,979	1,123	5,283	3,102	**8,385**	53.9%	50.6%	**52.6%**
	↓ SB	918	1,150	990	1,086	379	2,078	954	4,523	3,032	**7,555**	46.1%	49.4%	**47.4%**
All		**2,158**	**2,398**	**2,174**	**2,327**	**749**	**4,057**	**2,077**	**9,806**	**6,134**	**15,940**	**100.0%**	**100.0%**	**100.0%**

Table A3. Ground truth data summary for Site 3, Capital City Trail at Syene Rd, Fitchburg, WI

Description		Count										Distribution		
		Mon 08/21/2023	Tue 08/22/2023	Wed 08/23/2023	Thu 08/24/2023	Fri 08/25/2023	Sat 08/26/2023	Sun 08/27/2023	Weekday	Weekend	All	Weekday	Weekend	All
Data	Period (AM-PM)	8-18	7-18	7-18	7-18	7-19	8-19	8-19	NA	NA	**NA**	NA	NA	**NA**
	Hours	10	11	11	11	12	11	11	55	22	**77**	NA	NA	**NA**
Users	Pedalcyclists	301	237	102	83	288	432	687	1,011	1,119	**2,130**	87.8%	85.6%	**86.6%**
	Pedestrians	29	31	15	5	35	73	95	115	168	**283**	10.0%	12.9%	**11.5%**
	Other	5	8	2	2	9	13	7	26	20	**46**	2.3%	1.5%	**1.9%**
Direction	← WB	163	133	54	40	175	268	412	565	680	**1,245**	49.0%	52.0%	**50.6%**
	→ EB	172	143	65	50	157	250	377	587	627	**1,214**	51.0%	48.0%	**49.4%**
All		**335**	**276**	**119**	**90**	**332**	**518**	**789**	**1,152**	**1,307**	**2,459**	**100.0%**	**100.0%**	**100.0%**

Table A4. Ground truth data summary for Site 4, Hank Aaron State Trail at S 76th St, West Allis, WI

Description		Count							Distribution		
		Thu 08/17/2023	Fri 08/18/2023	Sat 08/19/2023	Sun 08/20/2023	Weekday	Weekend	All	Weekday	Weekend	All
Data	Period (AM-PM)	7-18	6-18	8-19	7-18	NA	NA	**NA**	NA	NA	**NA**
	Hours	11	12	11	11	23	22	**45**	NA	NA	**NA**
Users	Pedalcyclists	223	348	556	733	571	1289	**1,860**	77.6%	89.6%	**85.5%**
	Pedestrians	78	69	63	66	147	129	**276**	20.0%	9.0%	**12.7%**
	Other	6	12	12	9	18	21	**39**	2.4%	1.5%	**1.8%**
Direction	← WB	152	215	299	283	367	582	**949**	49.9%	40.4%	**43.6%**
	→ EB	155	214	332	525	369	857	**1,226**	50.1%	59.6%	**56.4%**
All		**307**	**429**	**631**	**808**	**736**	**1,439**	**2,175**	**100.0%**	**100.0%**	**100.0%**