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Article

Correcting Bias in Crowdsourced Data to Map Bicycle Ridership of All Bicyclists

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Abstract: Traditional methods of counting bicyclists are resource-intensive and generate data with sparse spatial and temporal detail. Previous research suggests big data from crowdsourced fitness apps offer a new source of bicycling data with high spatial and temporal resolution. However, crowdsourced bicycling data are biased as they oversample recreational riders. Our goals are to quantify geographical variables, which can help in correcting bias in crowdsourced data and to develop a generalized method to correct bias in big crowdsourced data on bicycle ridership in different settings in order to generate maps for cities representative of all bicyclists at a street-level spatial resolution. We used street-level ridership data for 2016 from a crowdsourced fitness app (Strava), geographical covariate data, and official counts from 44 locations across Maricopa County, Arizona, USA (training data); and 60 locations from the city of Tempe, within Maricopa (test data). First, we quantified the relationship between Strava and official ridership data volumes. Second, we used a multi-step approach with variable selection using LASSO followed by Poisson regression to integrate geographical covariates, Strava, and training data to correct bias. Finally, we predicted bias-corrected average annual daily bicyclist counts for Tempe and evaluated the model's accuracy using the test data. We found a correlation between the annual ridership data from Strava and official counts ($R^2 = 0.76$) in Maricopa County for 2016. The significant variables for correcting bias were: The proportion of white population, median household income, traffic speed, distance to residential areas, and distance to green spaces. The model could correct bias in crowdsourced data from Strava in Tempe with 86% of road segments being predicted within a margin of ± 100 average annual bicyclists. Our results indicate that it is possible to map ridership for cities at the street-level by correcting bias in crowdsourced bicycle ridership data, with access to adequate data from official count programs and geographical covariates at a comparable spatial and temporal resolution.

Keywords: bias correction; LASSO; active transportation; big data; crowdsourcing

1. Introduction

Lack of physical activity is identified as one of the primary factors leading to increased risk of chronic diseases, including obesity, cardiovascular diseases [1], and type 2 diabetes [2] as well as cancer [3]. The World Health Organization recommends a minimum of 150 min of moderate physical activity per week [4]. Active transportation modes (bicycling and walking) help to incorporate routine physical activity among adults with a sedentary lifestyle to reduce health risks. Consequently, public health and urban planning agencies are increasingly recognizing the importance of active transportation [5] in their pursuit of broader public health goals [6], creating a demand for a better

understanding of the influences on bicycle ridership. Previous studies [7,8] have used empirical methods to inform policymakers about necessary infrastructure changes using origin-destination surveys to help increase physical activity levels among adults.

Unfortunately, there are large gaps in the data resolution, coverage, and quality for active transportation at the street segment level. Existing approaches to bicycle counting result in data with poor spatial detail and/or limited temporal coverage [9]. The three most common ways to collect bicycle ridership data are manual counts [10], temporary, and continuous counters [9]. Manual counts, often conducted by volunteers, typically enumerate the number of cyclists at major street intersections during peak commuting periods for a few days of the year [11], and lack dense spatial coverage and temporal detail [12]. Temporary counts (i.e., tube counters set out for a week or two) provide a snapshot of ridership at a location over time, but, typically, the spatial coverage is limited. Automated counters (counting bicyclists crossing a specific street intersection continuously) [13] have great temporal detail, but often lack spatial coverage.

Crowdsourcing has, therefore, emerged as a tool of interest for collecting data on bicycling ridership [14–16], comfort mapping for bicyclists [17], understanding the effects of the built environment on ridership [18], and promoting safety among riders [19]. The emergence of crowdsourced data generated by fitness apps (e.g., [Strava.com](https://www.strava.com)) has provided a new source of ridership data with enhanced spatial and temporal resolutions [20]. With the proliferation of smartphones, fitness apps, such as Strava, have emerged as one of the most popular and rich sources of data for physical activity tracking; Strava records an average of 2.5 million GPS routes weekly by users across 125 cities all over the world [21].

However, the primary concern with crowdsourced data is the bias towards recreational riders, who are frequent users of GPS-enabled fitness apps. Thus, there is a need to quantify and correct the inherent bias in crowdsourced data [22] for a better representation of the ridership patterns of all riders, across varying ages and abilities. A generalized bias correction approach across all spatial and temporal scales is desirable to facilitate mainstream usage of crowdsourced fitness app data from platforms, such as Strava, for public health and urban planning. Most studies on bias in crowdsourced data [23] focus on characterizing the nature of the bias [24,25]. We hypothesize that crowdsourced data in urban settings can be used to map bicycling ridership [20,26]. Here, we move the research forward by developing a generalized approach to bias correction that combines traditionally collected ridership data with crowdsourced data to fill gaps in the spatial and temporal detail.

Our goal is twofold—first, to quantify which geographical variables can help in correcting bias in crowdsourced data; and second, to develop a generalized method to correct bias in big crowdsourced data on bicycle ridership in different settings to generate maps representative of all bicyclists at a street-level spatial resolution. Maps were created with enhanced spatial and temporal detail given the ‘big data’ provided by crowdsourced fitness apps. Bias correction was framed as using crowdsourced fitness app user counts along with additional geographic covariates to predict average annual daily bicyclist (AADB) counts on a street network. The result is a map that shows the ridership of bicyclists of all ages and abilities, even those that do not use the app.

2. Materials and Methods

2.1. Study Area

Our study area was the Maricopa County in the state of Arizona, USA, and covers 9200 square miles (Figure 1). Maricopa County includes 27 cities anchored by Phoenix [27]. With a population of over 3.3 million people, it is the fourth most populous county in the USA [28]. The weather is mostly arid with summer temperatures ranging from 50 °F (10 °C) to 108 °F (42 °C) and winter temperatures between 35 °F (1 °C) and 90 °F (26 °C), with an average precipitation of 132 mm in summer and 236 mm in winter. The city of Tempe, within Maricopa County, specifically has more than 175 miles of

bikeways and the highest percentage of residents commuting by means of bicycles at 4.2%, far higher than the Maricopa County average of 0.8% [29].

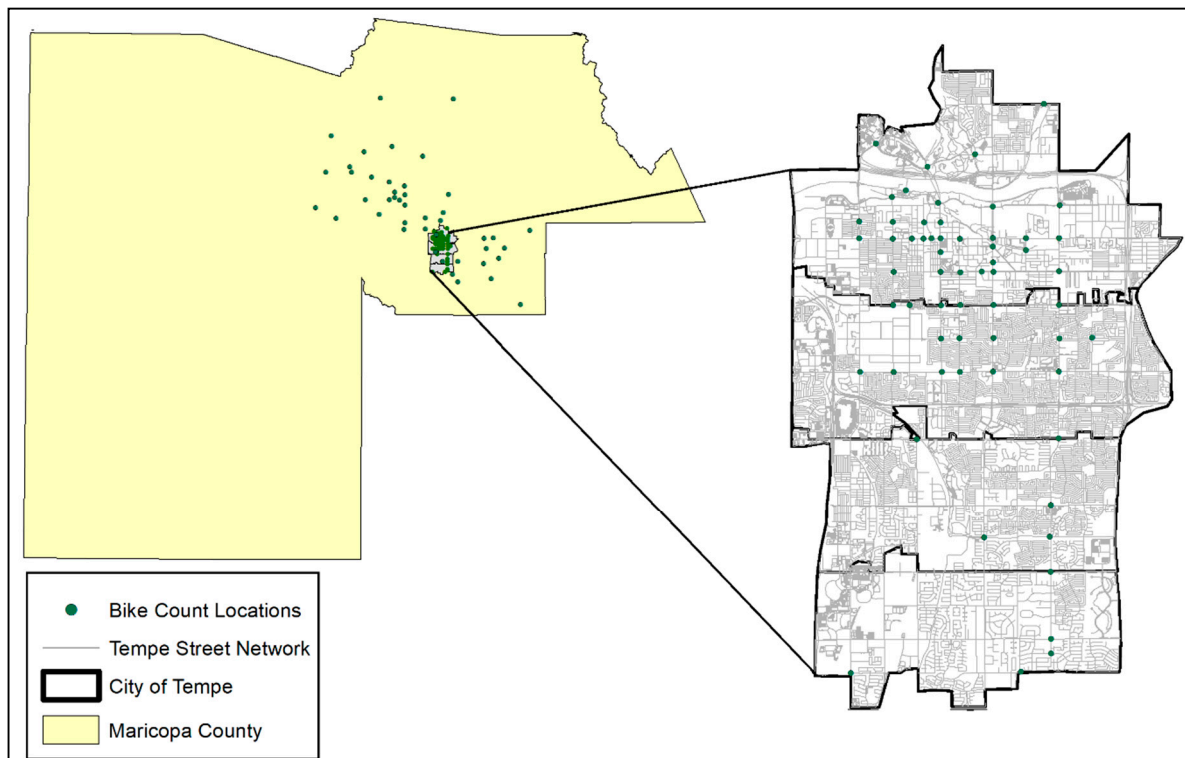


Figure 1. Study area in Maricopa County, AZ, USA.

2.2. Data Sources

2.2.1. Official Bicycle Counts

Two official count data sets were used, the first to train the model and the second to test the model. To train the model, we used temporary, automated bicycle counts completed by the Maricopa Association of Governments (MAG) at 44 locations in 2016 (Figure 2). We used the commonly reported time period, the annual average daily bicyclist (AADB) count, for the official counts as provided by the MAG. Bicyclists were counted by the MAG using automated counters with pneumatic tubes over a span of eight continuous two-week periods in the months of April, May, October, and November to understand and capture the variation in seasonal cycling volumes.

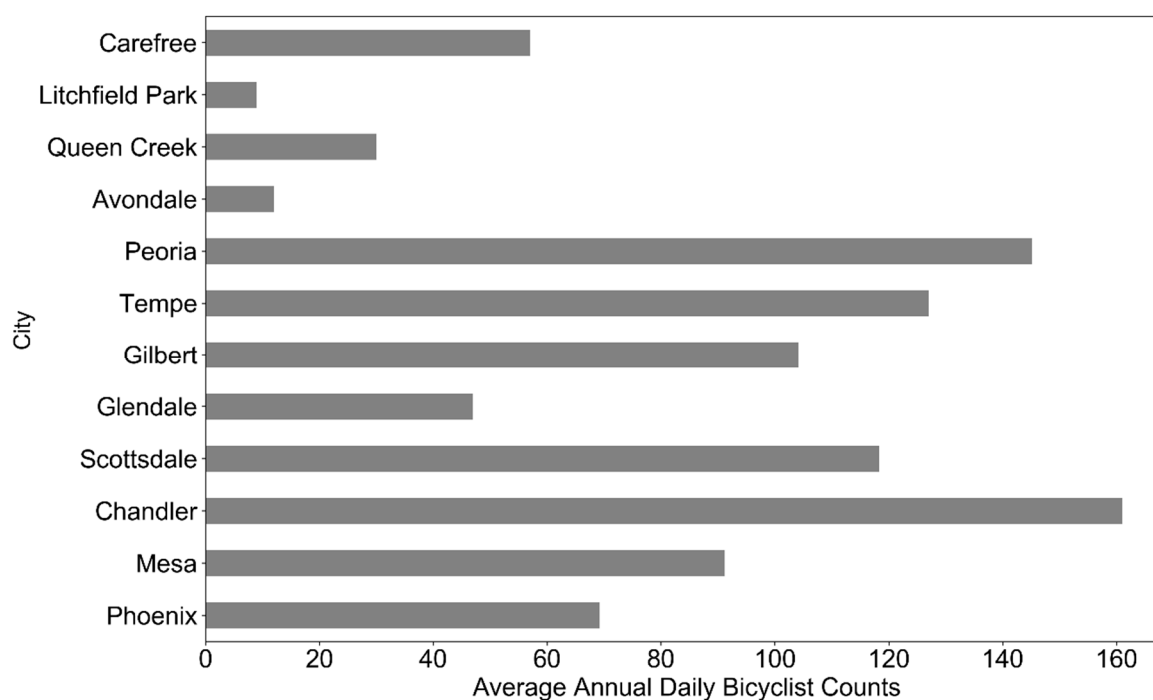


Figure 2. Average annual daily bicyclist counts in Maricopa County in 2016.

The count locations covered the most populated regions within Maricopa County and spanned 12 major cities, including Avondale, Carefree, Chandler, Gilbert, Glendale, Litchfield Park, Mesa, Peoria, Phoenix, Queen Creek, Scottsdale, and Tempe. Figure 2 shows the AADB counts in order of the population density of each city within Maricopa County. The counters were located across a range of locations, including freeways and arterials with and without bike facilities, as well as bike paths, such as near canals and trails. The AADB counts were extrapolated based upon the 2-week period counts. Also, owing to the extreme weather conditions, overall ridership is generally lower in the study area compared to other North American cities.

We used an independent test dataset to evaluate the model prediction accuracy, from the city of Tempe, where manual bicyclist counts across 60 locations were available. These manual counts were conducted by a non-profit organization, the Tempe Bicycle Action Group (TBAG), at peak periods in the morning (0700–0900) and evening (1600–1800) on weekdays in the months of April to May and October to November in 2016, and 12,345 cyclists were recorded. The bicycle ridership data collected by the TBAG were used to evaluate the global model accuracy at a smaller spatial scale, just for the city of Tempe.

2.2.2. Crowdsourced Data from Fitness App

The Maricopa Association of Governments distributed Strava bicycling data for 2016 for the entire Maricopa County. Strava data included street network shapefiles with anonymized bicyclist count information along with each street segment as well as at street intersections, at a one-minute temporal resolution. The high spatial and temporal coverage of the Strava data in Maricopa County allowed for counts to be obtained in the same locations and time periods as those collected through automated count stations. The total number of Strava riders throughout Maricopa County in 2016 is shown in Figure 3.

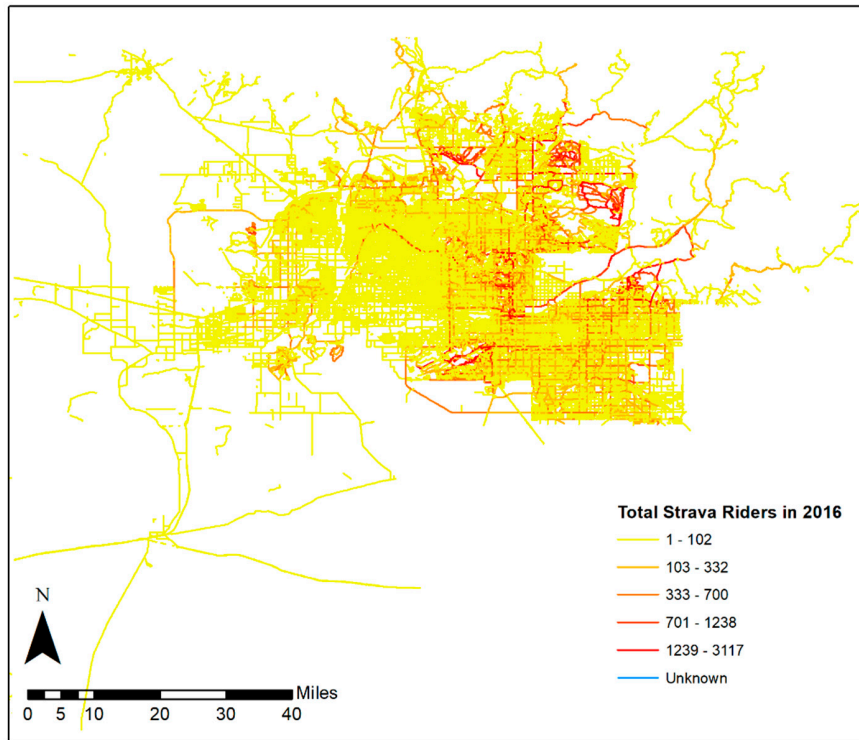


Figure 3. Distribution of Strava riders in Maricopa County for 2016.

Among all the Strava riders, nearly 76.5% of Strava riders in 2016 in Maricopa County were male, 17.6% were female, and 5.9% did not specify a gender, as shown in Figure 4, which indicates Strava riders were not fully representative of the entire population and there was an inherent bias in the ridership data, which requires correction.

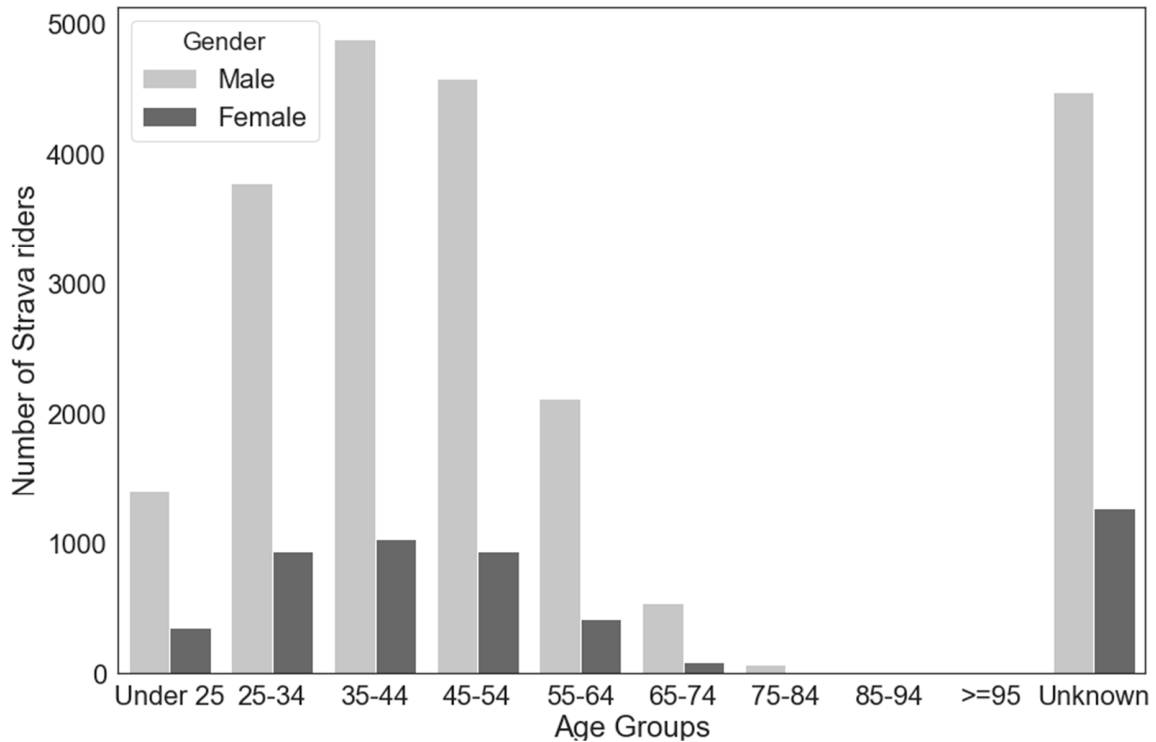


Figure 4. Age-gender distribution of Strava riders in Maricopa County for 2016.

2.2.3. Explanatory Geographical Covariates

In Table 1, we list the explanatory geographical covariates used in our model along with their potential relationship with bicycling. The geographical covariates were provided by the MAG for each census block group in Maricopa County. We identified those census block groups which were intersected by a unique street segment and assigned the mean of all the variables in the intersected polygons to the respective street segment. We also used the shortest distance technique to compute the proximity to green spaces, residential areas, and commercial areas for each individual street segment. The shortest distance is the Euclidean or straight-line distance from the nearest land-use polygon of a specific type (e.g., green space/residential area/commercial area) to the street segment. The MAG also provided the shapefiles on land-use classes, which were used to categorize green spaces, residential, and commercial areas.

Table 1. Geographical covariates influencing ridership in Maricopa County (2016).

Description	Measure	Source	Year	Resolution	Relevance
Crowdsourced Fitness App	Bicyclist count across street segments grouped by location and timestamp	Strava Metro	2016	Street Segment	Crowdsourced cycling data help predict categories of cycling volumes in urban environments [15,20].
Built Environment	(a) Average daily traffic volume (b) Average segment speed limit	(a) USDOT Federal Highways Administration (b) OpenStreetMap	2016	Street Segment	Built environment has a significant influence on active transportation choices [1,18,30,31]. Improving traffic promotes bicycling [32].
Demographics	(a) Population density (b) % white population (c) Median age (d) % veterans (e) % high school educated	Maricopa Association of Governments Open Data Portal	2010	AZ Census Block Group	Densely populated areas have higher number of cyclists [33,34]. Ethnicity variations affect bicycle ridership levels [35].
Land Use Mix	(a) Proximity to greenspace (b) Proximity to residential areas (c) Proximity to commercial areas	Maricopa Association of Governments Land Use Data	2016	Street Segment	Nearness to residential areas and green open spaces has shown positive associations with an increase in physical activity [1,36].
Socio-Economic	(a) Median household income	Maricopa Association of Governments Open Data Portal	2010	AZ Census Block Group	Areas with lower income levels tend to bike more [10,37,38].
Commute Patterns	(a) % of population who commute to work with bicycles	Maricopa Association of Governments Open Data Portal	2010	AZ Census Block Group	Frequent bicycle commuters are more likely to have a higher level of education [39].

2.3. Model Design and Analysis

Our approach for bias correction employed a multi-step approach as shown in Figure 5. We performed the following steps for correcting bias in the Strava data:

- (i) The relationship between the Strava ridership data and official counts across 44 locations in Maricopa County (train data) was quantified using ordinary least squares regression.
- (ii) Additional geographic data from multiple disparate sources (Table 1) were then aligned, controlling for variable multicollinearity, with ridership data from Strava, and a variable selection

technique—LASSO—was used to identify the most significant geographical variables from all the listed variables in Table 1.

- (iii) A generalized linear model with a Poisson distribution was fitted using the observed AADB counts as a dependent variable and the Strava ridership data along with the geographical covariates selected by LASSO, which were outcomes of step (ii), at comparable spatial and temporal scales as independent variables. Using this model, we corrected the bias in the crowdsourced bicycle ridership data by age and ability across Maricopa County using a 10-fold cross-validation across the 44 locations.
- (iv) The coefficients of the model fitted in step (iii) were then used to explain the variation in the AADB counts and the bias-corrected predictions.
- (v) The best-fitted model from step (iii) was cross-validated, which is a technique used to test the model fit by holding out 10% of the data and training the model with 90% of the data in multiple iterations, and the model with least cross-validation error was used to predict the observed AADB at unknown locations and to create a street-level map of bias-corrected AADB counts in Tempe.
- (vi) Finally, the prediction accuracy of the model, shown in step (iii), was evaluated in Tempe across 60 locations where ground truth data for the AADB counts were available (test data).

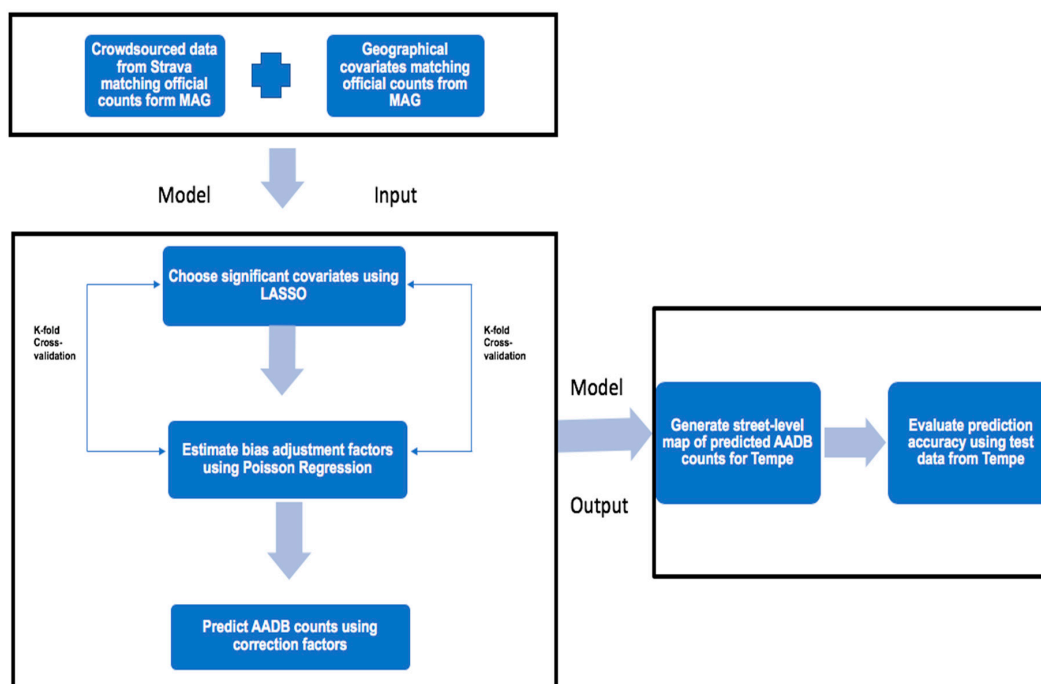


Figure 5. Model design for bicycle ridership prediction using Poisson regression.

Each of the steps is explained in further detail in the sections that follow. The exploratory analysis and data preprocessing were performed using Jupyter Notebooks [40]. Spatial analyses were undertaken in ESRI® ArcGIS 9.3 and the model was partly built using both Python 3.5 [41] and R 3.4 [42]. For more details on the code used in the steps (i) to (vi), please refer the Supplementary Materials.

2.3.1. Comparison of Official and Crowdsourced Bicyclist Counts

To quantify how the bicycle ridership of all riders is represented by sampling the crowdsourced app ridership, we compared the ridership counts from Strava with official counts from automated bike counter systems installed by the MAG [27] across 44 locations in Maricopa County for a two-week period in the months of April, May, October, and November. The Python package, PANDAS (Python

data analysis library) [43], was used to summarize, match, and extract crowdsourced data counts for each individual road segment in Maricopa County to account for ridership estimates.

Comparisons between the two datasets were made at daily, monthly, and annual levels. We used regression analysis to quantify how much of the variation in bicycle ridership was explained by the crowdsourced data. To do this, we matched counts from Strava, aggregated into hourly intervals, and matched those to the time windows when official counts were conducted by the MAG. Once counts were matched temporally, we compared both datasets at daily, monthly, and annual levels. We obtained R^2 values using simple linear regression for each time period and retained the volumes with the highest R^2 for further analyses.

2.3.2. Variable Selection for Bias Correction Using LASSO

In order to correct for the bias in the crowdsourced ridership data, we included the geographical covariates from Table 1. Variable multicollinearity, which is the state of high inter-correlations among independent variables, was limited by retaining only those variables which had a variance inflation factor (VIF) below 7.5 [44]. If the variance inflation factor of a predictor variable was 7.5, this meant that the standard error for the coefficient of that predictor variable was 2.73 ($\sqrt{7.5}$) times as large as it would be if that predictor variable was uncorrelated with the other predictor variables. These covariates were hypothesized to influence bicycle ridership at a geographic scale comparable to that of the Strava data. Spatial joins from the Python library, Geopandas [45], were used to link bicycling counts data with the geographical covariates.

We used an average of the geographical covariates for all the census block groups that a particular street segment intersected. The distance variables were calculated in ArcGIS using a simple Euclidean distance measured in miles. Since the number of independent variables for our analysis was 15, even after accounting for inter-correlations through VIF, we used a statistical method to select only those variables that explained most of the variance in the overall bicycle ridership. A variable selection technique using LASSO (least absolute shrinkage and selection operator) [46] was applied to select covariates that best explained the bias in the Strava data, while accounting for the bias–variance tradeoff [46].

The purpose of LASSO is to apply a constraint on the sum of the absolute values of the model parameters with a fixed upper bound. To do so, the method applies a shrinkage process (also known as regularization), where it penalizes the coefficients of the independent variables, shrinking some of them to zero. The variables that still have a non-zero coefficient after the shrinkage were selected to be inputs of the final Poisson regression model. By using LASSO, we intended to minimize the prediction error of the final AADB counts. The LASSO can be thought of as an additional step, which can help transportation planners choose, from a large set of variables in a study area, only those which can in effect help improve the prediction results and contribute significantly in explaining variation in the overall bicycle ridership.

Given the set of explanatory variables, $x_1, x_2 \dots x_p$, and the outcome, y , the observed bike counts, LASSO fits the linear model:

$$\hat{y} = \beta_0 + \beta_1 \cdot x_1 + \dots + \beta_p \cdot x_p \quad (i), \quad (1)$$

by minimizing the following criterion:

$$\sum_{i=1}^n (y - \hat{y})^2 + \lambda \sum_{j=1}^p |\beta_j|. \quad (2)$$

In doing so, the non-contributing geographical covariates are shrunk to zero. We ran 200 iterations of the LASSO on our training data using a 10-fold cross-validation approach to obtain the optimal value for λ (tuning parameter), which yielded the minimum cross-validation error on the training dataset for all iterations. The variable selection was performed using the randomized LASSO scores provided by

the scikit-learn Python library based on the stability function proposed by [47]. For a cut-off, π_i , with $0 < \pi_i < 1$ and a set of regularization parameters, Λ , the set of stable variables is defined as:

$$\hat{\mathcal{S}}^{stable} = \{k : \max_k \left(\prod_k^{\hat{\lambda}} \right) \geq \pi_i\}. \quad (3)$$

With the chosen λ , we retained the variables with a high selection probability and disregarded those with low selection probabilities using a score function, which provided the coefficient of determination, R^2 , of the prediction ranging from 0 to 1. The coefficient, R^2 , is defined as $(1 - u/v)$, where u is the residual sum of squares and v is the total sum of squares of the variables retained with the chosen value of λ . The LASSO module from the Python machine learning library, scikit-learn, was used to perform variable selection.

2.3.3. Estimating Bias-Corrected Bicycle Volumes from a Crowdsourced Fitness App and Geographical Covariates

We fitted the geographical covariates selected by LASSO to a generalized linear model following a Poisson distribution to explore the relationships among the selected covariates, and the bicycle ridership counts in Maricopa County using Equation (3). We chose the Poisson model as it generates non-negative predictions, which are appropriate for modeling count data.

As shown in Figure 2, the geographical variables as well as the official counts and counts from the crowdsourced app were provided as inputs to the model. The LASSO variable selection algorithm determined the stable covariates that best replicate the bicyclist counts. Following variable selection, the Poisson model predicted the AADB counts along all street segments in Maricopa County. The regression model was specified as a Poisson distribution with a log-link function [48] as follows:

$$Y_i \sim \text{Poisson}(\mu_i), \log(\mu_i) = \beta_i X_i, \quad (4)$$

where:

Y_i = the AADB counts at site i

β_i = vector of parameters for count site i

X_i = vector of the observed geographical covariates for count site i .

The AADB counts were generated by the model across the entire road network in Maricopa County, including paved streets with and without bike facilities. The segments from Strava that were matched in spatial and temporal resolution to the official MAG counts were used in fitting the Poisson model. Hence, we could compare the counts from both sources at only those locations, where both counts were available, which were then used to train our model. The remaining segments that only had Strava counts were used to test the predictive power of the model. The average annual counts from Strava along with the geographical covariates were the independent variables for the model. The significant variables were those with a p -value < 0.001 . Since we assumed that our dependent variables (the MAG counts) follow a Poisson distribution with a mean that depends on some covariates, we used a generalized linear model that takes into account the heteroscedasticity in the data.

2.3.4. Predicting Ridership Using Poisson Model Coefficients

The Poisson model coefficients were used to predict ridership at all street segments in Tempe. A k -fold cross-validation technique [49] was used to determine the best fit for our training data using the Poisson model, and Akaike's information criterion (AIC) was computed at each step to determine the best-fitting model for our training data. The bias-corrected ridership estimates were then classified using a histogram into five different categories—very low, low, medium, high, and very high.

2.3.5. Mapping Predicted Bicyclist Counts

For ease of visualization and to support our validation of the prediction accuracy with independent data, we generated a map for a smaller area and compared the bias-corrected map with the annual Strava ridership map for the city of Tempe, where ground truth data were available from the TBAG. Results were visualized across the city of Tempe with a uniform color scheme representing each category with varying widths of street segments.

2.3.6. Bias Correction Model Prediction Accuracy

As the ultimate goal of the model was to predict bicycling volumes that were corrected for sampling bias, we applied the model to spatially continuous data from 60 locations across the city of Tempe and predicted annual bicycle ridership across all street segments. The bicycle counts provided by the TBAG were used to determine the prediction accuracy.

We verified our model using a 10-fold cross-validation approach in order to account for overfitting. We performed 100 iterations of the model, splitting the dataset into a train-test sample ranging from 15% to 85%, and chose the model with minimum cross-validation error as the best fit. We then calculated the differences between the predicted and observed AADB counts and analyzed the variation of the differences with the percentage of segments predicted.

3. Results

The crowdsourced data from Strava captured 642,298 trips for 28,571 unique bicyclists across Maricopa County for the entire year of 2016. A total of 24,917 riders were captured using automated counters in Maricopa County in 2016. The AADB counts ranged from 0 to 522 with the highest ridership in the city of Chandler and the lowest in Litchfield Park. The average number of daily Strava cyclists at the same locations ranged from 0 to 34 when compared with the Strava data. The manual counts from the TBAG comprised of 60 locations within Tempe with a total of 12,151 riders.

3.1. Strava and the MAG Count Comparisons

The ordinary least squares regression analysis between the AADB counts from the MAG and Strava accounted for 76% of the variation between the two datasets.

3.2. Variables Selected for Correcting Bias Using LASSO

In Table 1, the geographical covariates along with the month and day of count used for determining the most significant variables to use as input for the Poisson model are shown. The tuning parameter, λ , was 1.85, based on the minimum cross-validation error of 0.014 on the training set. In Table 2, all input variables used by LASSO are listed. The most significant variables which were not shrunk to zero ($\lambda = 1.85$) and had a score above 0.65 were: Distance to residential areas, distance to green spaces, percentage of white population, median household income, average segment speed limit, and average number of Strava riders.

Table 2. Variable importance based on LASSO variable selection ($\lambda = 1.85$).

Covariates	LASSO Scores
Distance to residential areas	1.00
Distance to green spaces	1.00
% white population	1.00
Median household income	1.00
Average segment speed limit	0.98
Strava counts	0.96
Average daily traffic volume	0.59
% veterans population	0.43
Population density	0.4
% population who commute with bicycles	0.05
Distance to commercial areas	0.02
Median age	0
% Population with at least high school education	0
Count month	0
Count day	0

3.3. Poisson Model Results for Bias-Corrected Bicyclist Volumes

In Table 3, a list of the parameter estimates of the Poisson regression on the six variables chosen from Table 2 through LASSO is provided. The model had an AIC of 1832.9 and yielded the lowest mean-squared error of 0.0045 after 100 iterations of cross-validation. The pseudo- R^2 of the fitted model was 0.59. In Table 3, the standard errors and 95% confidence intervals of the associated parameter estimates are also highlighted. The variables, distance to green spaces, distance to residential areas, median household income, and traffic speed, have an overall negative impact on ridership while the number of Strava riders and the percentage of white population have an overall positive influence on bicycle ridership.

Table 3. Parameter estimates using Poisson regression.

Dependent Variable: AADB Counts from MAG					
Explanatory Variables (x_i)	Estimate(log) (β_i)	Std. Error	p -Value	95% CI	
				Lower	Upper
Strava counts	0.17	0.01	<0.001	0.15	0.18
Average segment speed limit	-0.09	0.01	<0.001	-0.11	-0.08
Distance to residential areas	-0.51	0.01	<0.001	-0.59	-0.43
Distance to green spaces	-0.74	0.07	<0.001	-0.88	-0.59
Median household income	-0.09	0.01	<0.001	-0.01	-0.08
% white residents	0.11	0.01	<0.001	0.09	0.14
Intercept	3.78	0.08	<0.001	3.63	3.92

The in-sample fit for the entire Maricopa County (where ground truth was available from the MAG) using the Poisson model resulted in an R^2 of 0.64 between the observed and predicted counts (Figure 6).

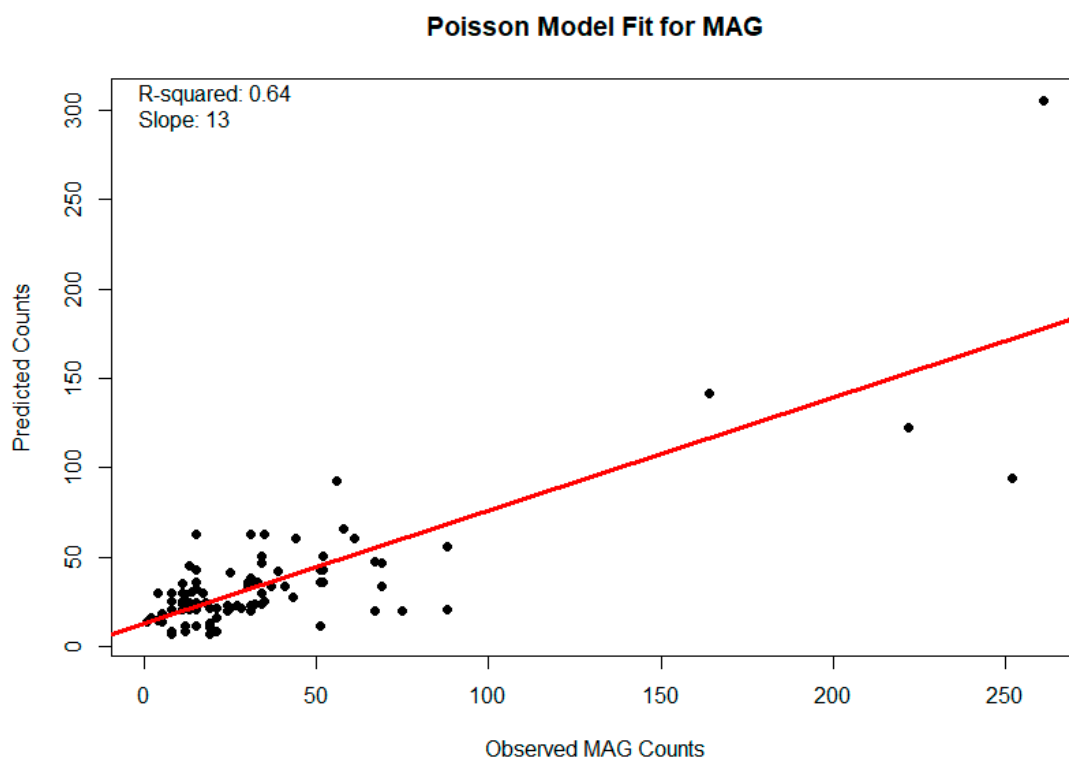


Figure 6. Poisson model predicted vs. actual AADB counts for Maricopa County (2016).

3.4. Predicted Ridership Estimates Using Poisson Model Coefficients

Changes in the predicted ridership volume relative to changes in each of the covariates in the model help to demonstrate the contribution of geographic covariates in correcting bias in the overall ridership volume estimates. To provide a baseline for comparison, the intercept of the Poisson model alone provides an estimate of the mean observed counts on a street segment, independent of all other covariates. Table 4 shows the factor by which each covariate influences overall ridership.

Table 4. Variation in predicted AADB counts for each variable, with all other attributes held constant, when the variable is changed by a factor, e^{β_i} .

Variables (x_i)	Scale (per unit)	Change Factor (e^{β_i})	Change in Observed Bicyclist Counts (y) (all other Variables Held Constant at Their Mean)
Intercept	-	43	-
Strava riders	1 rider	1.18	18% increase
Distance to residential areas	1 mile	0.6	40% decrease
Distance to green spaces	1 mile	0.48	52% decrease
Average segment speed limit	10 mph	0.91	9% decrease
Median household income	\$10,000	0.91	9% decrease
% white population	10%	1.12	12% increase

In this study, the mean AADB count on each street segment represents 43 bicyclists. The parameter estimate for the average number of Strava riders was 1.18 (Table 4), which indicates that if the average number of Strava riders on a particular street segment increases by 1, given that all other variables were held at their respective average values, the estimated ridership on that segment would increase

to approximately 50.74. In other words, Strava counts account for 1 in every 50 bicyclists along a particular street segment.

The proximity of a street segment to a residential neighborhood and green spaces was found to impact overall ridership significantly. With every 1 mile increase in the shortest distance of a street segment from a residential neighborhood, the predicted number of bicyclists decreases by 40% (Table 4). Similarly, for every 1 mile increase in the shortest distance between a street segment and green space, the observed bicyclist counts decreases by 52%, *ceteris paribus*. Ethnicity is a weaker, but still significant, contributing factor to ridership volumes, with ridership counts being positively related to the percentage of white population in the neighborhood of a street segment. The number of observed bicyclists on a street segment that is located in a neighborhood with a 60% white population will have 12% more observed bicyclists than if it is located in a neighborhood with a 50% white population, *ceteris paribus*.

Additionally, high values of median household income and increased speed limits were found to be associated with low overall ridership. The parameter estimates show that the observed number of bicyclist counts decreases by 9% for every \$10,000 increase in average income whereas for every 10 mph increase in the average speed limit on a particular street segment, the predicted number of bicyclists decreases by 9%, *ceteris paribus*.

3.5. Mapping Predicted Ridership Volumes in Tempe

Based on our model, we predicted bias-corrected ridership volumes across the city of Tempe, shown in Figure 7, classified using Jenks' classification into five categories: Very low (0–25), low (25–100), medium (100–750), high (750–2500), and very high (2500+). The thin lines indicate streets with a low volume of bicyclists while the thicker lines indicate streets with a high volume of bicyclists.

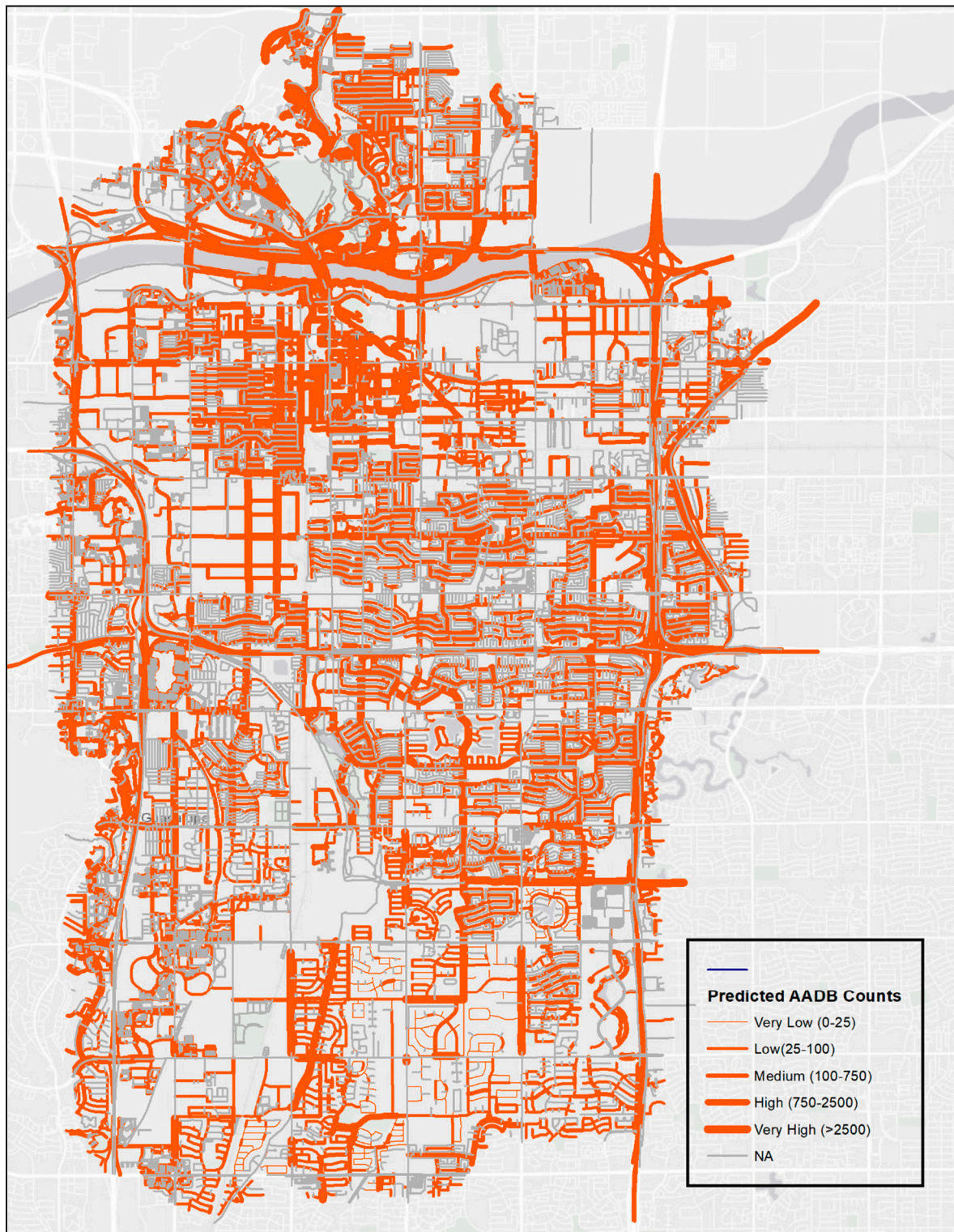


Figure 7. Predicted bicycle AADB counts for the entire street network of Tempe in 2016.

3.6. Prediction Accuracy of the Bias Correction Model in Tempe

In Figure 8, the result of the prediction accuracy as a function of the difference in the predicted AADB counts from the observed counts across 60 count locations in Tempe is given.

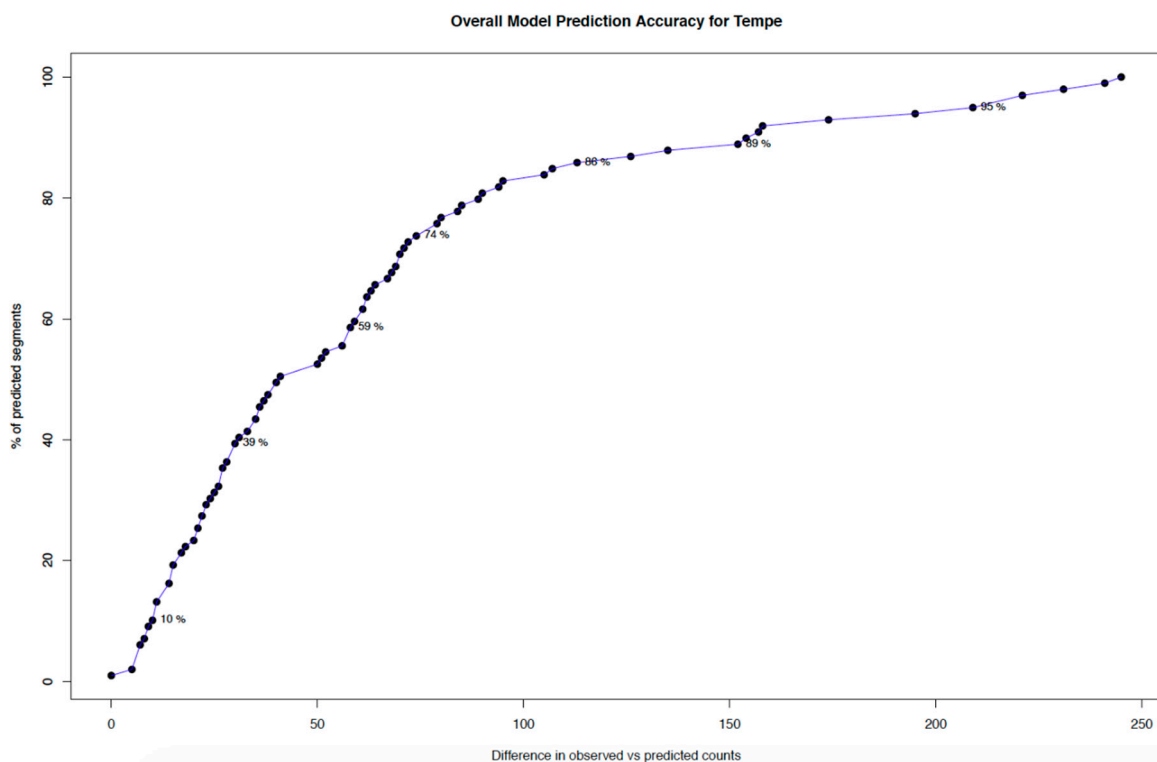


Figure 8. Model Prediction Accuracy for Tempe in 2016.

Overall, for 59% of the segments, we predicted ridership volumes within ± 50 AADB, 86% of the segments were within a ± 100 AADB, and 95% within ± 200 AADB.

4. Discussion

We were able to correct the bias in crowdsourced data from Strava using a set of covariates describing the street location and from this we were able to generate maps representative of all bicyclists at a street-level spatial resolution. The correlation between the Strava and official counts alone can explain nearly 52% of the variation in overall bicycle ridership, however, we were limited by the availability of ground truth data, which could help improve the R^2 further. Our goal in combining geographic covariates with Strava counts was to account for additional factors that influence bicycle ridership and may not be captured solely by crowdsourced sampling. These variables helped in making necessary adjustments for the estimation of observed counts of all bicyclists, including those not using the Strava app, thereby correcting bias in crowdsourced data from Strava.

The Poisson regression approach has frequently been used in bicycle crash analysis by [10,35] as well as for exposure measurement of accidents by [50]. A probabilistic joint analysis approach has been used for correcting sampling bias in species distribution models by [51]. Using the mixed-model approach, this paper proposes a new technique in the bias correction of crowdsourced data for physical activity mapping from bicycle ridership.

The results of our study indicate that bias correction of crowdsourced data may prove to be a useful method for the estimation of bicycle ridership in North American cities. Our results for the city of Tempe (Figure 7) indicate that for 80.3% of road segments, where ground truth data were available, estimated bicycle counts were correct to within 25% of the observed counts (± 50 riders). Our findings are in alignment with recent research by [15,20], who found strong relationships between Strava and all bicycling ridership in North American cities.

As expected, the proximity of a street segment to a residential neighborhood had a significant influence on the overall bicycle ridership. Most segments that are close to a residential area in Tempe have better road infrastructure, including paved sidewalks and dedicated bike lanes. This encourages

inexperienced bicyclists to ride safely and also adds comfort to the overall bicycling experience in general for riders of all ages and abilities. Hence, transportation planners should pay more attention to the use of wider streets with dedicated bike lanes in residential areas to help increase active transportation among riders irrespective of their age and ability. Similarly, a closer proximity to green space also had a positive influence on ridership. One reason for the relationship between bicycling and green space may be that green corridors, which connect the bicycle network within a city, facilitate increased overall bicycle ridership.

The positive coefficients for Strava counts and the white population percentage are in alignment with the fact that ethnicity influences ridership and that in urban areas, generally, a higher proportion of white residents ride bicycles than non-white residents. Previous studies by [32,52] have shown that positive relationships exist between ethnicity (white, non-white) and physical activity. Our model results also show that ethnicity is an important factor to use when correcting bias Strava sampled bicycle ridership volumes.

Median household income was also significant in influencing overall bicycling ridership. It has been found in previous research [53] that people from lower economic backgrounds are less likely to adopt an active lifestyle and our results also indicate a similar trend. Bicycling should be made more cost-effective for daily use by commuters in order to promote active transportation.

High speed limits are often correlated with roads having greater concentrations of larger-sized vehicles and more traffic, both of which are major deterrents to bicycling in general [32,39] and often result in crashes [54]. These results suggest policy directions for the safety of bicyclists by means of the reduction of speed limits on busy traffic corridors, and the provision of dedicated bike lanes or green zones on major streets connecting areas of interest (schools, business centers, parks, shopping complex, etc.) to attract riders of all ages and abilities.

The model framework proposed in this study can be used for correcting bias in Strava riders from other cities or bicyclist counts comparable in space and time obtained from other bicycling apps. However, our study has a few limitations. The official counts from the MAG were collected at 44 locations scattered across the whole of Maricopa County. As the segments containing available ground truth data were mostly within the city limits, data from open spaces on the outskirts of cities were sparse. The choice of geographic covariates was specific to the study area and might vary for different geographic settings, depending upon their relevance. The model could have been improved in terms of the prediction accuracy if more ground truth data were available across diverse locations to train the model. Street conditions with a low prediction accuracy can be targeted for future sampling and organized data collection efforts can be proposed for better quality data, which could help in the improvement of the model. With the availability of sufficient data, further studies could examine the spatial heterogeneity of bias-corrected ridership across varying geographies using localized regression on more realistic conditions across larger spatial scales.

5. Conclusions

Big crowdsourced data from fitness apps, like Strava, on bicycling volumes can be used to make informed decisions on factors that influence ridership in urban areas on a much finer spatial scale. We introduced a new method for correcting bias in crowdsourced data with the help of a three-step mixed-model approach by quantifying crowdsourced data and official counts in a specific geographic region, using LASSO to choose the most significant geographic variables that could correct bias, and finally, fitting the covariates along with the crowdsourced data by means of Poisson regression to predict and map overall ridership in the region. The method developed in this study is broadly applicable for correcting bias in crowdsourced bicycling data when official counts and geographical data are available at comparable spatial and temporal resolution. Based on the results of this paper, in the future, it is suggested that local transportation authorities should work closely with researchers to improve the coverage of official count data, helping them to identify locations to place counters so that a denser spatial coverage as well as more ground truth data are obtained to improve the model's

performance. The proposed bias correction model, with detailed data that is continuous through space and collected repeatedly in time, can help transportation planners in making informed decisions related to bicycle infrastructure planning to promote healthier lifestyles among urban residents of all ages and abilities. Detailed maps of bicycling ridership are critical to professionals in making decisions regarding infrastructure investment and policy changes that support active transportation. The framework developed in this paper can be used as a generalized risk assessment and exposure modeling tool to benefit accident prevention among bicyclists, with sufficient availability of accident data from crowdsourced platforms, like Bikemaps.org [19], and provide an estimate of bias-corrected bicyclist volumes for infrastructure planning to enhance comfort among bicyclists and promote active modes of transportation for healthier lifestyles among wider demographics.

Supplementary Materials: The following are available online at <http://www.mdpi.com/2413-8851/3/2/62/s1>.

Author Contributions: A.R. developed the algorithms and code, analyzed and interpreted the Strava and MAG data regarding the bicyclist counts, and performed the modeling and analyses. T.A.N. organized the data collection effort, identified the research gap, contributed to the verification of the results, and was a major contributor in writing the manuscript. A.S.F. was a major contributor in developing robust analytical methods, interpreting the results, and editing and writing the manuscript. M.W. helped in the overall organization of the manuscript and contributed in reviewing the results and communicating the context. All authors read and approved the final manuscript.

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Abbreviations

MAG	Maricopa Association of Governments
TBAG	Tempe Bicycle Action Group
LASSO	Least absolute shrinkage and selection operator
PANDAS	Python data analysis library
AADB	Average annual daily bicyclists
VIF	Variance Inflation Factor

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