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FORECASTING BICYCLE FACILITY DEMAND

Final Report

By

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DISCLAIMER

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EXECUTIVE SUMMARY

Executive Order 12898: Environmental Justice in Minority Populations and Low-Income Populations was officially issued on February 11, 1994 by President Clinton. This order “requires each federal agency to identify and address, as appropriate, disproportionately high and adverse human health or environmental effects of its programs, policies and activities on minority and low-income populations” (Federal Register, 1994).

Mitigation efforts to address the problem of environmental injustice include the incorporation of bicycle facilities into an infrastructure due to its’ well-known positive impacts upon health, food availability, employment access and ultimately regional sustainability. The placement of bicycle facilities within the infrastructure and the health benefits that come with these facilities will be accessible for utilization by the whole population, including the minorities and low-income population. Some of the health benefits include decrease in air pollution, increased cardiovascular fitness, increased muscle strength and flexibility, and decrease in the stress levels.

In order to begin the process of identifying all the positive impacts that could come with the implementation of bicycle facilities one must estimate how many users these bicycle facilities will attract. There has been some work done in estimating the impacts of bicycle facilities, yet very little has been done to examine the impacts upon minorities or other specific population segments. Furthermore, research forecasting the number of bicycle users, much less, estimation of the impacts is relatively scarce. Most predictive models for bicycle facility usage are developed by the combination of bicycle facility user counts, origin-destination surveys and demographic data.

The objective of this report is to (1) evaluate current and past predictive models that are used for forecasting off-street bicycle facility demand; (2) create a statistical model from locally sourced data that is able to connect bicycle facility counts to time, demographic data, and weather data; (3) conclude if the statistical model can be applied to different bicycle facilities. If all objectives are met then the statistical model and findings can be used to estimate the impacts of bicycle facilities upon health, food availability, employment access and ultimately regional sustainability for any given area. To accomplish this goal, the research team will use multilinear regression to correlate the relationship between local off-street bicycle facilities count data and demographic/socioeconomic data that will enable a model that is able to accurately predict bicycle facility usage within any environment.

Chapter 1. Introduction

1.1 Problem Statement

Minorities and low-income individuals frequently perceive that they have not been provided easy access to off-street bicycle facilities. This disproportion in accessibility disallows this population the numerous health benefits that come with the implementation of off-street bicycle facilities. Traffic laws in most states provide bicyclists the rights to operate on street lanes shared with automobiles or in what AASHTO calls “wide outside lanes” or in marked bike lanes and in off-street bike trails. Conversion costs for shared lanes or marked bike lanes are minimal, however construction costs of off-street trails are much greater. Bike facility researchers have developed several concepts to describe “rider comfort and safety” associated with the various facility types, however, all tend to agree that the best comfort and safety levels are provided by off-street bike facilities. Due to the small costs of providing on-street bike facilities, forecasts for numbers of users is usually not a high priority. However, due to the much larger costs of off-street facilities, despite much greater comfort and safety, forecasts of numbers of likely users is a very high priority but a difficult task. To address the issue of identifying potential impacts of bicycle facilities upon minorities and other specific population segments, numbers and types of people that will use a proposed bicycle facility must be identified. Numbers of users for existing bicycle facilities can be counted, however, forecasts of numbers of users for planned (but not yet built) facilities must be developed through the creation of a demand model. Desirably, such a demand model should be able to produce reasonably accurate forecasts for any type of off-street bicycle facility in any type of environment.

1.2 Objectives

The objective of this work is to (1) evaluate current and past predictive models that are used for forecasting off-street bicycle facility demand; (2) create a statistical model from locally sourced data that is able to connect bicycle facility counts to time, demographic data, and weather data; (3) conclude if the statistical model can be applied to different bicycle facilities.

1.3 Expected Contributions

To accomplish these objectives, several tasks have been undertaken. These tasks include reviewing scientific reports that coincide with the subject of forecasting bicycle facility demands, collecting and cleaning necessary count, demographic/socioeconomic, and weather data for the creation of a demand model, and the creation of a statistical model that is able to accurately predict bicycle facility demand. Each of these contributions were essential for the completion of this report.

1.4 Report Overview

The remainder of this report is organized as such: Chapter 2 provides a summarized and synthesized literature review over the current and past methods that have been used for forecasting off-street bicycle facilities demand. Chapter 3 is the solution methodology for the creation of three different demand models. This methodology provides the data that is used for the creation of each demand model, and an explanation of the results from the demand model.

Chapter 4 is the summary of the research results, and the direction that should be taken toward future research.

Chapter 2. Literature Review

2.1 Introduction

This chapter provides a summarized and synthesized literature review over current and past methods that have been used to forecast off-street bicycle facilities demand. The information that is collected for this literature review will provide insight on how many studies have been conducted to test off-street bicycle facilities demand, what types of models and methods have been used, and the results of these models. The purpose for focusing on off-street bicycle facilities is to fill a need for improved demand estimation techniques for this most desirable but most expensive and therefore most divisive bicycle facility class.

2.2 Off-Street Bicycle Facility Demand Models

Off-street bicycle networks are defined as trails that are separated from any roadway. Off-street facilities are able to boost accessibility to valued destinations and also create recreation and utilitarian travel demand (Gobster, 1995). With the realization of the many benefits that come with off-street bicycle facilities, cities and metropolitan areas across the United States have been looking for accurate demand models for off-street bicycle facilities. Yet, despite the widely accepted importance of off-street bicycle facilities, or as some call it non-motorized paths, local advocates and agencies lack adequate tools for estimating the demand of these facilities. Tools like continuous counting systems, that are typically used for motorized facilities, could be used to track the long-term quantity of bicyclists and pedestrians using bicycle facilities and contribute to development of accurate demand models. Not only is there a lack in tools, but the need for the understanding of how non-motorized entities travel can vary extremely based on external factors such as the weather, the environment, or the season, and how all these variables can drastically effect demand models. So far, there has been very little research done on predicting the demand of on-street bicycle facilities, let alone, off-street bicycle facilities, but the research that has been done utilizes different types of solution methodologies. The proceeding section will review different types of demand models that stem from two different types of data collection (long-term and short-term pedestrian and bicyclist counts) and the results from these models.

2.2.1 Long-Term Off-Street Counts

There have been demand models that utilize long-term (continuous counting systems) and short-term bicycle and pedestrian count programs to predict the number of users for off-street bicycle facilities. The data that is gathered from continuous counting systems are known to be more reliable and provide concrete evidence for the reasons behind changes in bicycle and pedestrian volumes. For example, continuous counters are able to capture the change in the number of bicycle facilities that occurs with the change in the seasons. One study collected long-term pedestrian and bicyclist counts by using continuous infrared monitors that were placed along 33 miles of multiuse greenway trails in Indianapolis, Indiana (Lindsey, Wilson, Rubchinskaya, Yang, & Han, 2007). These counters monitored traffic 24 hours/day, 7 days per week, and stopped after collecting three years of count data. Researchers then connected the bicycle and pedestrian counts to demographic variables including population, age, and ethnicity. The resulting multilinear regression model showed that off-street trail “traffic is higher in neighborhoods with higher proportions of minorities” which was not expected because field observations have indicated that people of white ethnicity use the trails disproportionately (Lindsey et al., 2007).

2.2.2 Short-Term Off-Street Counts

Instead of collecting data for many years, short-term data collection efforts count the number of pedestrians and bicyclists through a certain area for time durations of a few hours to several days. Short-term data is convenient for agencies who are unable to utilize continuous counting systems that are more expensive due to the price of the equipment and the need for individuals to keep track of the data and the system maintenance. Once short-term count data has been collected, like the long-term count data, researchers can use these counts to develop regression models to predict future demand. Variables within the regression model can contain weather, neighborhood socio-demographics, built environment characteristics, presence of bus line or bicycle facility type. A report written by Steve Hankey, Greg Lindsey, et al., used ordinary least squares and negative binomial regressions to estimate future non-motorized traffic usage for on-street and off-street locations in Minneapolis, Minnesota. Although it is known that long-term counts provide more reliable results, this study proved that “1- or 2-h bicycle and pedestrian counts can predict reasonable estimates of ‘daily’ (12-h) counts” for both on-street and off-street bicycle facilities, this study also found that there was a positive correlation between the number of counted bicyclists and percentage of non-whites, college degree holders, and percentage of people over the age of 65 or under the age of 5 (Hankey et al., 2012). Furthermore, there was a negative correlation between the number of counted bicyclists and median household income, crime, and population density (Hankey et al., 2012).

2.3 Summary

This section provides insight on how other studies have conducted and tested off-street bicycle facilities demand. This section focuses on demand models that were created from the collection of long-term and short-term off-street counts.

Long-term counts are considered off-street counts of bicyclists or pedestrians that are collected from continuous counting systems. The data that is gathered from continuous counting systems are known to be more reliable and provide concrete evidence for the reasons behind changes in bicycle and pedestrian volumes. By connecting local demographics to long-term off-street counts with a multilinear regression model, one study found that off-street trail “traffic is higher in neighborhoods with higher proportions of minorities” which was not expected because field observations have indicated that people of white ethnicity use the trails disproportionately (Lindsey et al., 2007).

On the other hand, short-term counts may have durations as short as several hours. Short-term counts are considered more convenient for agencies who are unable to utilize continuous counting systems and has been proven to provide reasonable demand models. One study found that there was a positive correlation between the number of counted bicyclists and percentage of non-whites, college degree holders, and percentage of people over the age of 65 or under the age of 5 (Hankey et al., 2012). Furthermore, there was a negative correlation between the number of counted bicyclists and median household income, crime, and population density (Hankey et al., 2012).

Although short-term counts can be used to create reasonable demand models, obtaining long-term counts should still be an agencies primary goal. The Federal Highway Administration claims that the common practice of conducting short-term counts and extrapolating them, while understood for practical reasons, is often insufficient and has the potential to produce skewed interpretations of the level of bicycling and or walking occurring in a community (FHWA, 2011). At a minimum, agencies should install a select few permanent counters in order to provide validation toward the short-term counting systems.

Chapter 3. Solution Methodology

3.1 Introduction

This chapter will describe the methodology for creation of a demand estimation model using counts from 10 different permanent counting stations that are located throughout several City of Austin off-street trails. There will be three statistical models, the first model uses long-term count data of bicyclists to create a time series analysis, the second model is also created by the collection long-term count data of bicyclists and their correlation to the surrounding socio-demographics, and the third will also correlate the long-term count data to the City of Austin's weather data. Each model is able to provide another piece to the story of who is currently utilizing and predicted to utilize the City of Austin off-trails. The creation of these three models will not only benefit the City of Austin for future planning but may also be useful to other cities that are attempting to quantify off-street bicycle facility impacts.

The following sections for each demand model will be organized as such: description of the data used within the model, the resultant regression model, and a summary of the model's results. Section 3.2 provides all the information related to the times series analysis model, Section 3.3 the socio-demographic model, and lastly, Section 3.4 the weather model.

3.2 Time Series Analysis Model

The section will serve to provide the details of the data that is being used for this model. Details include the Eco-Visio count system that was used to collect the long-term count data, the location of the counters, and their average daily counts.

3.2.1 Eco-Visio Count Data

The City of Austin is currently using Eco-Visio to capture long-term pedestrian and bicyclist counts. The Eco-Visio counting system is a permanent counting system called Urban Multi, which can monitor and differentiate between pedestrians and bicyclists. This system operates by combining PYRO (passive infrared sensors), ZELT inductive loops, and a smart connected subsystem in order to seamlessly transfer the collected count data to the Eco-Counter Server (Eco-Visio, n.d.). The count data is collected at a 15 minute or 1-hour time interval and is then displayed onto the Eco-Visio online Eco-Counter Server. There are 16 permanent counters and 21 short duration counters currently operating and running within the City of Austin. Shown in **Error! Reference source not found.** is the permanent and short duration counter locations, the permanent stations being the blue boxes, and the short duration stations being the orange boxes.

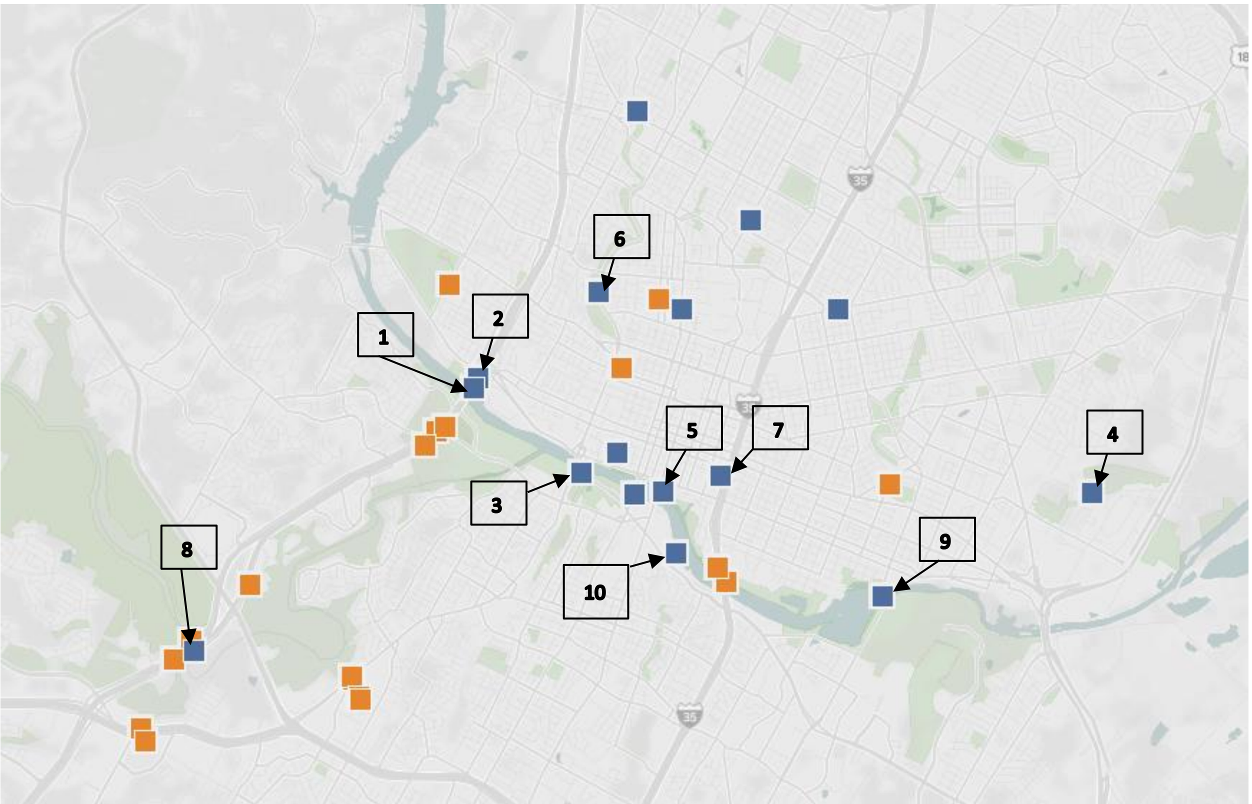

Figure 1: Permanent and Short Duration Counter Locations Within the City of Austin

Only 10 of the permanent counters were used for the demand model because the remaining 6 permanent counters had an error that did not allow the counts to be extracted during the defined time-range. This list of the 10 permanent counter locations that were used are found in Table 1. The number that is designated to each counter can be matched to the map of the counter locations found in Figure 1 above.

Table 1: Permanent Counters Locations and Names

Number	*Counter Location and Name*
1	Johnson Creek Trail at Mopac W 5th, St W 6th St Interchange
2	Ann and Roy Butler Trail at Mopac Crenshaw Bridge
3	Butler Trail at S Bank Colorado River E of Pflueger Bridge
4	Walnut Creek Trail N of Jain Ln
5	Butler Trail at N Bank of Colorado River E of Congress Ave Bridge
6	Shoal Creek Blvd N of W 24th St
7	Lance Armstrong Bikeway at Waller Creek
8	Mopac at Barton Creek
9	Pleasant Valley Road over Colorado River West Side
10	Ann and Roy Butler Trail at E Bouldin Creek

The count data from each location listed above collected both weekday and weekend counts from a range of around 1-5 years. Unfortunately, the time range was inconsistent per counter due to technical malfunctions, nevertheless the samples that were collected for each counter went well beyond 365 days. A weekday date is considered a date that falls on or between a Monday and Friday. On the other hand, a weekend date is a date that falls on a Saturday or Sunday. Both are needed due to the large discrepancy in the number of counted bicyclists that ride during the week and on the weekend. Furthermore, it should be noted that this analysis only utilized bicyclist counts.

The bicyclist count data for the 10 permanent counters were collected and averaged and graphed for each day of the week and each month of the year in order to understand the current seasonal trends. For Johnson Creek Trail (counter #1), the average daily bicyclist counts can be found Figure 2 while the monthly averages can be found in Figure 3. This trail was chosen as an example due to the fact that it encapsulates the basic trends and behaviors of most of the off-trails.

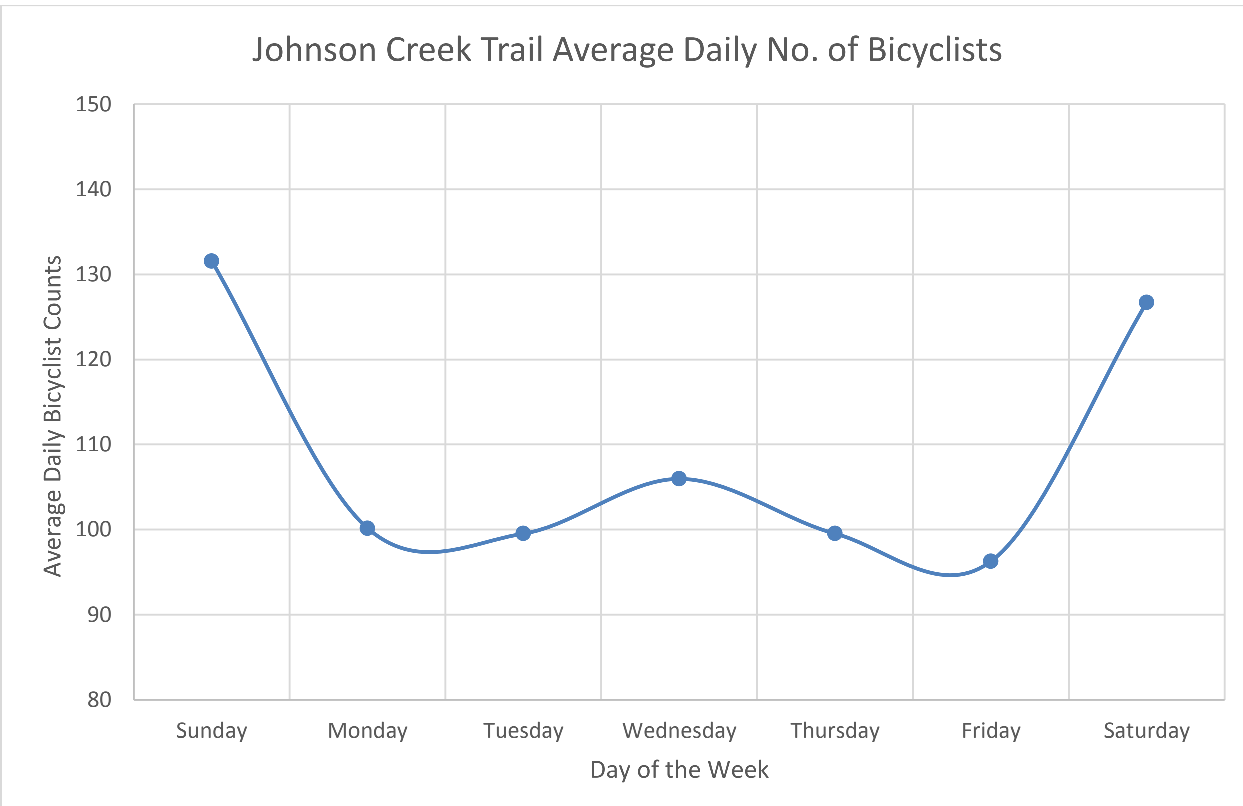

Figure 2: Johnson Creek Trail Average Daily Bicyclist Counts

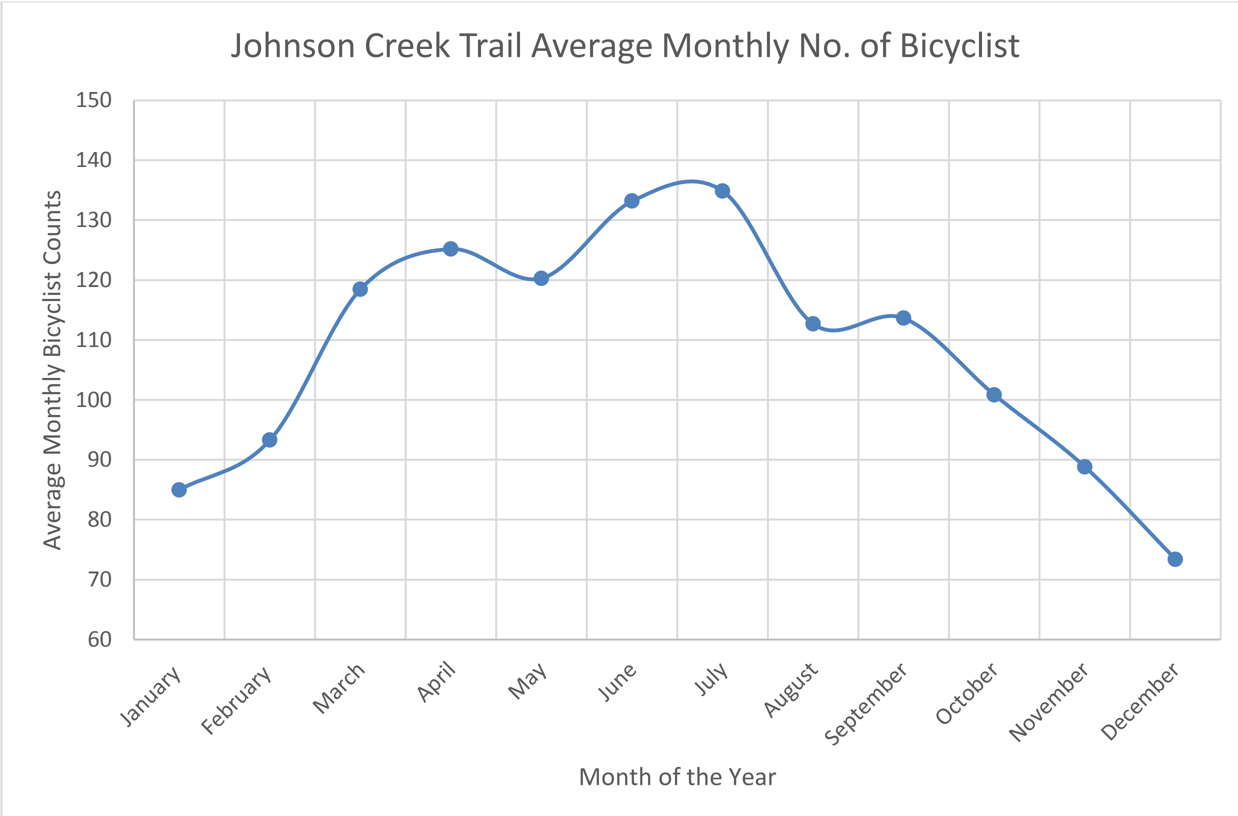

Figure 3: Johnson Creek Trail Monthly Average Bicyclist Counts

Figure 2 reveals that the highest number of bicyclists throughout the week can be found on Sunday, while the lowest number of bicyclists found on the Johnson Creek Trail is on Friday. Throughout the week, from Monday to Friday, the number of bicyclists rises and peaks on Wednesday, but then drops back down on Friday. Throughout the weekend, Saturday and Sunday have extremely close numbers of bicyclists, but it is Sunday that has more counted bicyclists. From the daily averages, it can be concluded that most bicyclists who use Johnson Creek Trail are recreational users due to the high number of Saturday and Sunday bicyclist counts. This statement holds true for most of the observed trails.

Figure 3 showed that the highest number of bicyclists throughout the months of the year are found during the month of July. The month that has the lowest number of bicyclists for Johnson Creek Trail is during the month of December. The second highest number of bicyclists was June. Both June and July are considered one of the hottest months of the year in Austin, Texas, while December is one of the coldest, this shows that off-trail cyclists are more likely to ride Johnson Creek Trail (and most off-trails throughout Austin) during the hotter months of the year.
Each counter has somewhat unique daily and monthly patterns and the rest of the graphs for the other counter locations can be found in the Appendix Observing each counter location's current number of bicyclist users is the main component the statistical models that will be presented throughout this paper.

3.2.2 Data Analysis

A time series model is a method of forecasting that is able to make predictions of future values based on previously observed timewise trends. The goal of creating a time series analysis model is to predict the number of future bicyclists that will use the off-trails throughout the City of Austin. Time series does not incorporate other variables such as demographics, but rather bases its' forecasting on the apparent seasonal trends that are found throughout the historical data.

Due to the time gaps for the collection of bicycle counts the locations that were found to have more than 1000 data points (days) and did not have large data gaps were the locations chosen for the time series analysis. By following these constraints, the time series analysis will be able to more accurately predict the future demand trends of bicyclists. The three locations that fell within these restrictions are:

- **Counter No .1**: Johnson Creek Trail at Mopac W 5th, St W 6th St Interchange
- **Counter No. 2:** Ann and Roy Butler Trail at Mopac Crenshaw Bridge
- **Counter No. 4:** Walnut Creek Trail N of Jain Ln

Creating a time series model for these three locations provides a view of the current and future seasonal similarities or differences across locations. The software Prophet, which is a package within R, was used to capture and produce the current and future seasonal number of bicyclists for each location. Although there were no significant gaps in data points for these three locations, there were still some missing dates. Fortunately, Prophet is robust enough to handle outliers, missing data points, and any major changes in the time series, therefore, initial smoothening of the raw data set was unnecessary.

The two graphs that are shown in the proceeding pages for each location are (1) the resultant time series forecast model and (2) the time series forecast general trend. The time series forecast model reveals the historical bicycle counts, and the Yhat values for each location. The Yhat values are the blue points along Figure 4 representing the time series model composed of three components: trend, seasonality, and holidays. These components are combined in the following equation:

$$Yhat = y(t) = g(t) + s(t) + h(t) + \epsilon_t$$

Here g(t) is the trend function which models non-periodic changes in the value of the time series (represented in Figure 5), s(t) represents periodic changes (e.g., weekly and yearly seasonality), and h(t) represents the effects of holidays which occur on potentially irregular schedules over one or more days. The error term ϵ_t represents any idiosyncratic changes which are not accommodated by the model; it is assumed that ϵ_t is normally distributed (Taylor & Letham, n.d.).

The variable g(t) within the equation above is graphically represented within the time series forecast general trend graph which is first shown in Figure 5. The general trend line graph is composed of straight-line segments that were created by a piecewise linear function, while the variable g(t), whose units of measurement are the number of bicyclists per day, was produced by the piecewise logistic growth equation.

The resultant time series forecast model and its general trend for Johnson Creek Trail can be seen in Figure 4 and Figure 5 below. The start and end dates of the collected bicyclist counts for Johnson Creek Trail is 05/31/2015-02/09/2020 and was programmed to forecast 365 days into the future (02/09/2021).

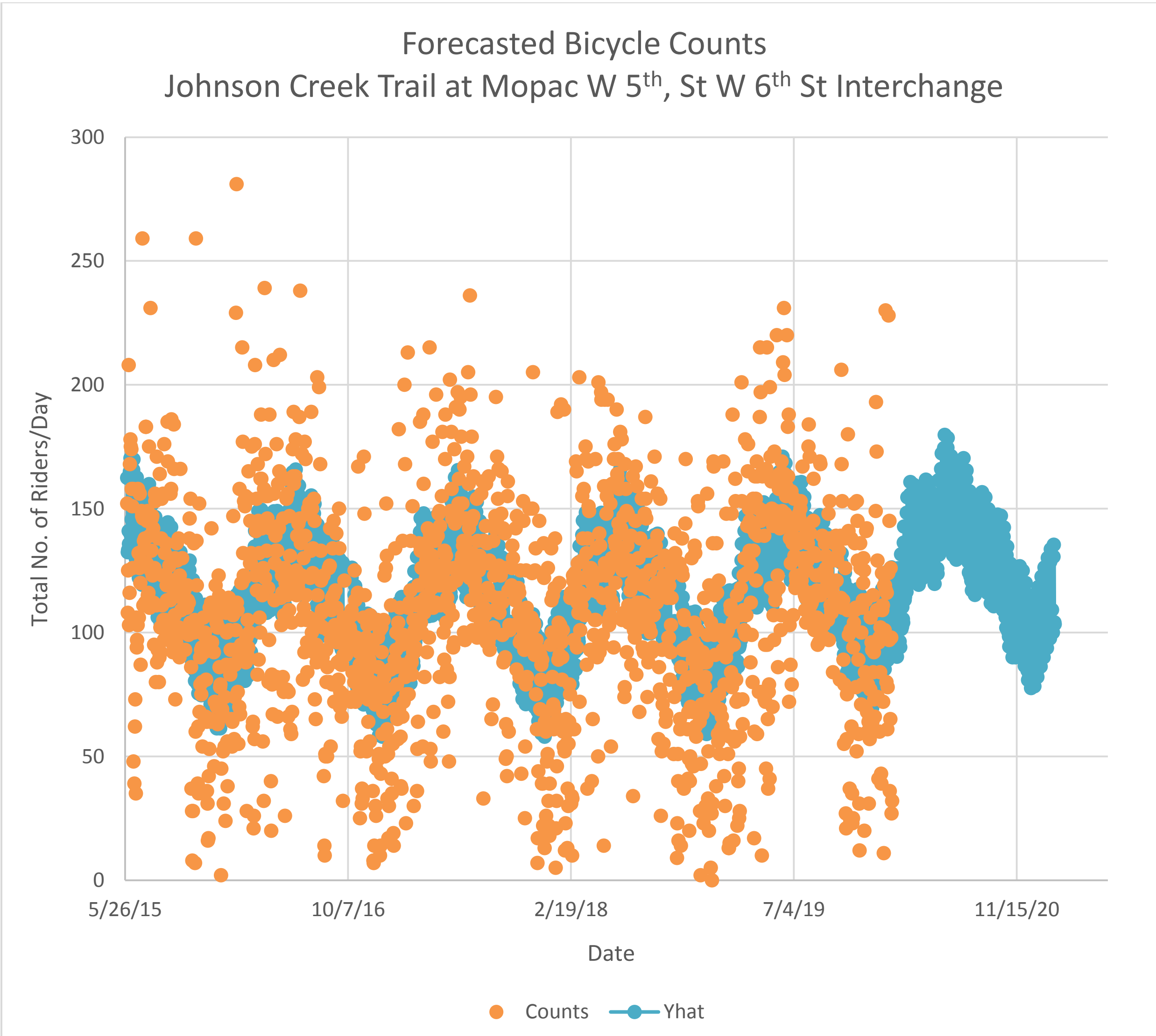

Figure 4: Johnson Creek Trail Time Series Demand Forecast

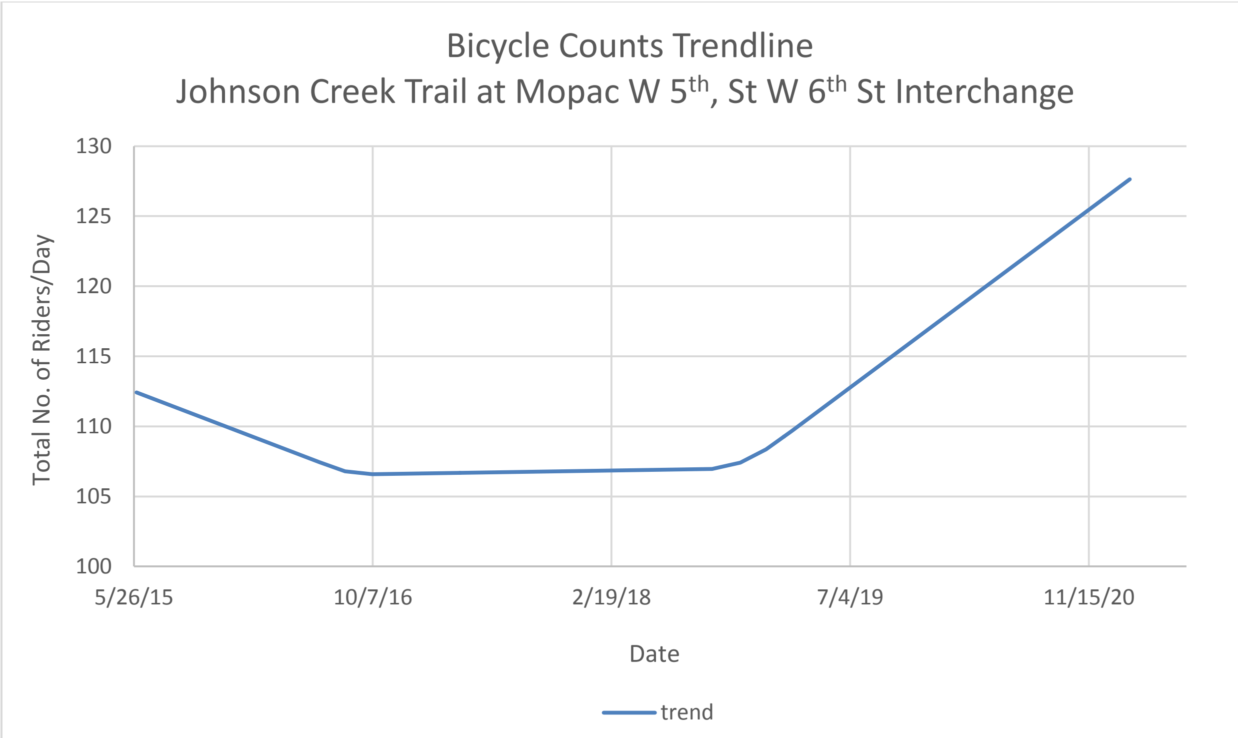

Figure 5: Johnson Creek Trail General Trendline

The resultant time series forecast model and its general trend for Ann and Roy Butler Trail at Mopac Crenshaw bridge can be seen in Figure 11 and Figure 7 below. The start and end dates of the collected bicyclist counts for this trail is 02/18/2016-06/01/2020 and was programmed to forecast 365 days into the future (06/01/2021).

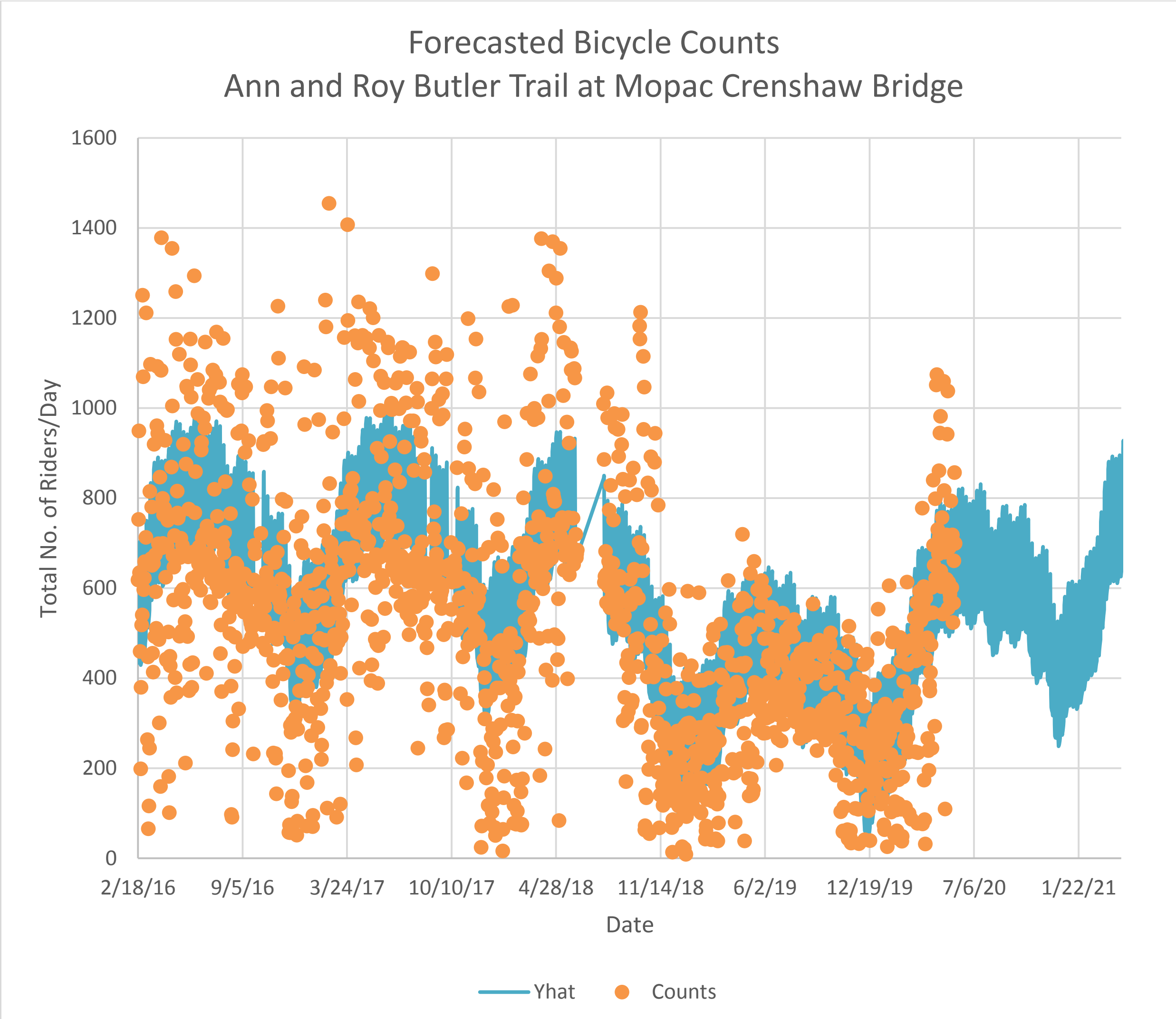

Figure 6: Ann and Roy Butler Trail at Mopac Crenshaw Bridge Time Series Demand Forecast

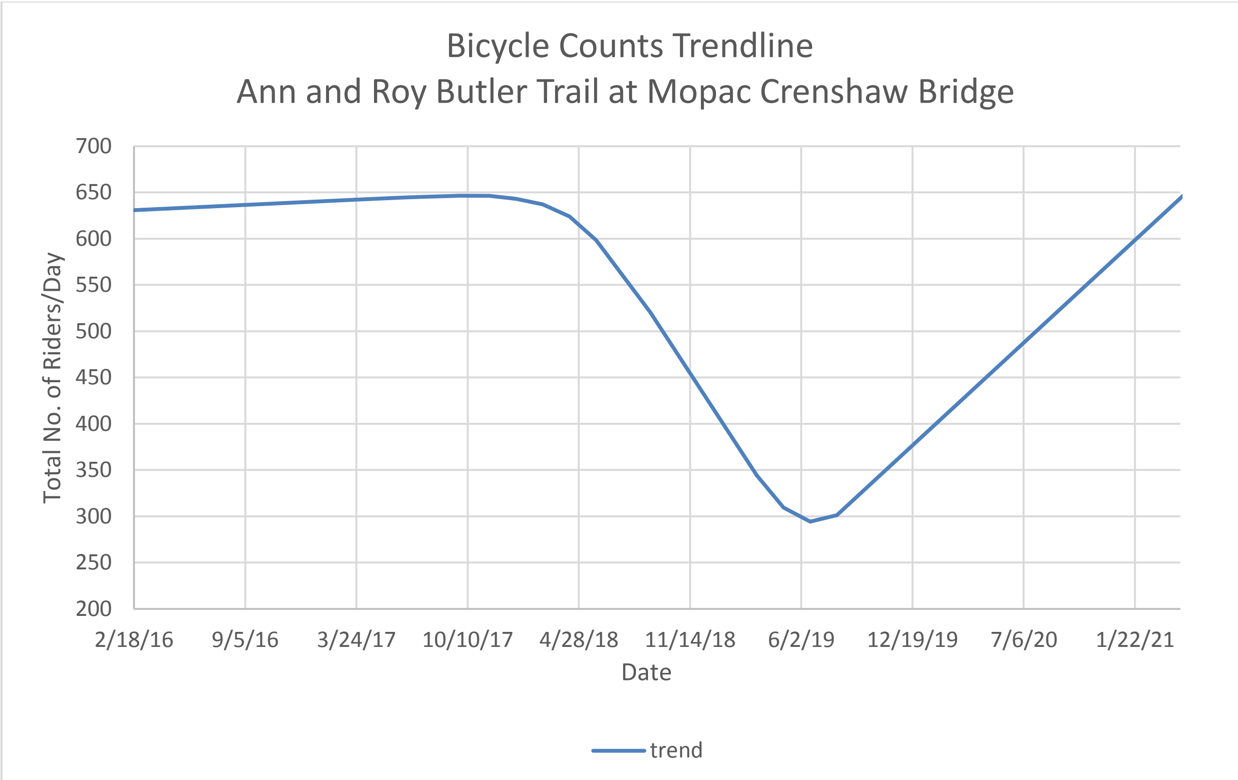

Figure 7: Ann and Roy Butler Trail at Mopac Crenshaw General Trendline

The resultant time series forecast model and its general trend for Walnut Creek Trail N of Jain Ln can be seen in Figures 8 and 9 below. The start and end date of the collected bicyclist counts for this trail is 05/31/2015-02/10/2020 and was programmed to forecast 365 days into the future (02/10/2021).

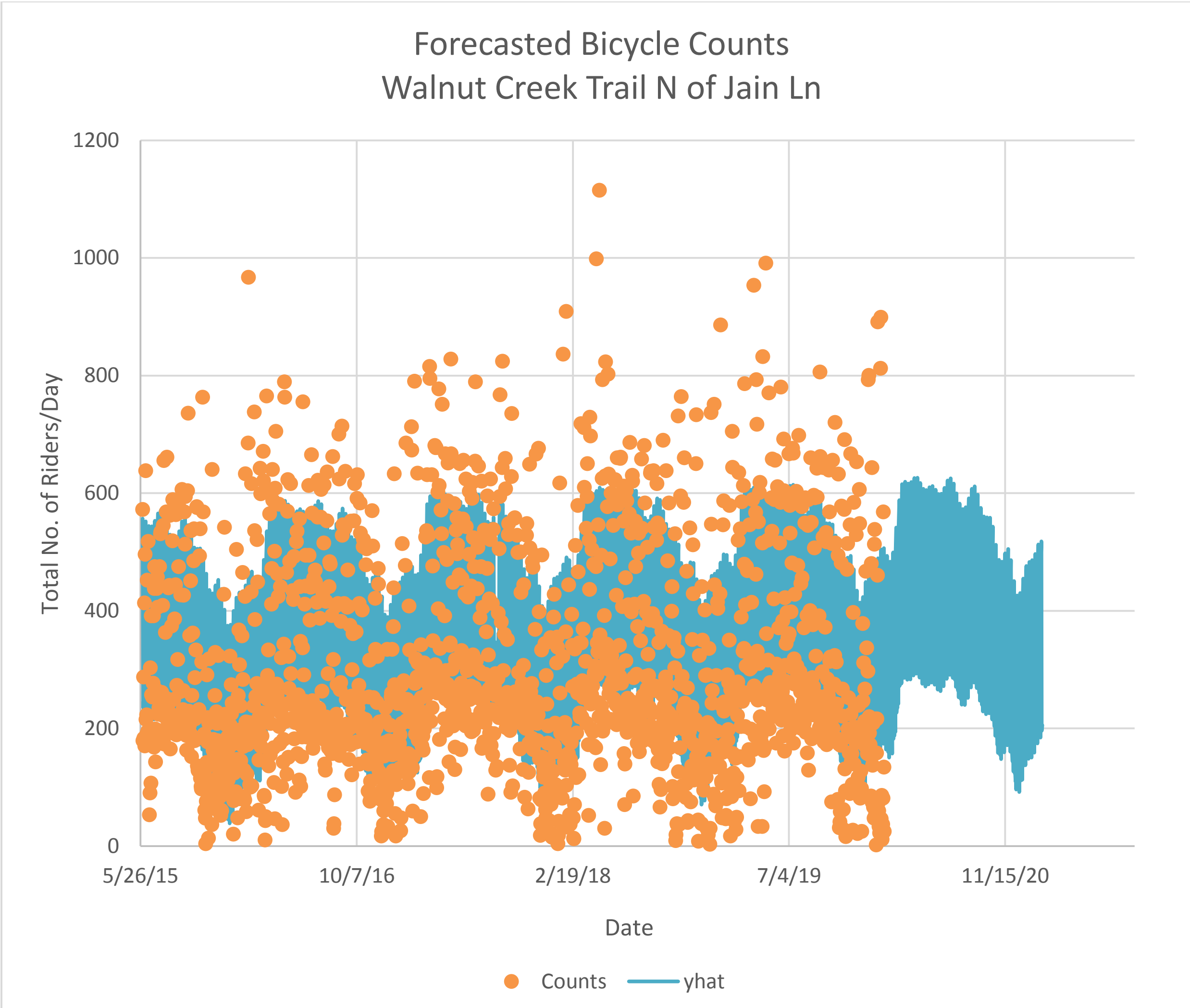

Figure 8: Walnut Creek Trail N of Jain Ln Time Series Demand Forecast

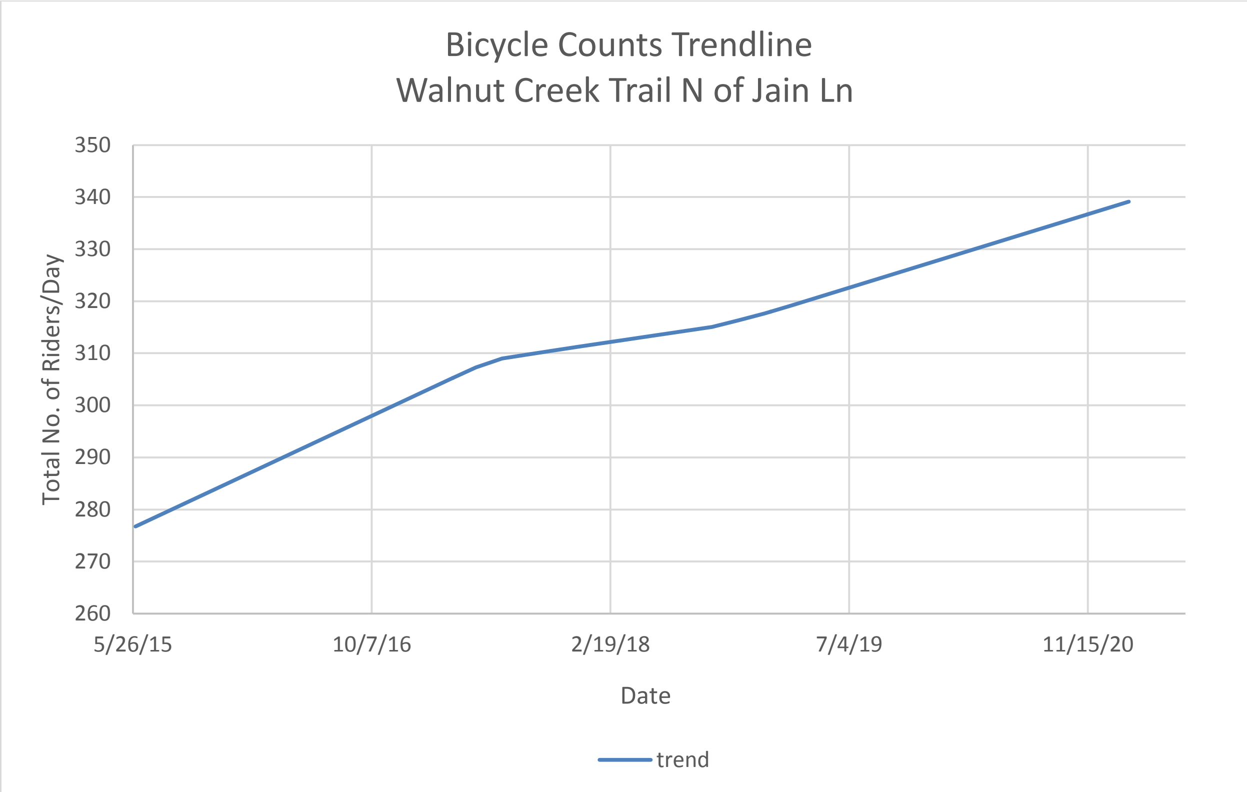

Figure 9: Walnut Creek Trail N of Jain Ln General Trendline

3.2.3 Summary

Each forecast model for the three different locations all rise and fall with the heavy and light biking seasons throughout the years. The arcs within each model peak during the months of springtime (March, April, and May), and dip around the months of winter (December, January, and February). Figure 4 for Johnson Creek Trail shows a steady oscillation between the peak and low periods of the seasons throughout the past. It is hard to locate overall trend of time series model and that is why Figure 5 was provided. As mentioned before, start and end dates of the collected bicyclist counts for Johnson Creek Trail are 05/31/2015-02/09/2020 and was programmed to forecast 365 days into the future (02/09/2021). According to Figure 5, the general trend of the number of bicyclists utilizing this particular trail was decreasing from year 2015-2016, flattened to a steady state from 2016-2018, then began to increase from 2018-2020. The general trendline graph also includes the forecasted trend for 2021 and is shown to continue its' increase from 2020-2021. The decrease in ridership from 2015-2016 could be because a variety of impacts. The increase in ridership from 2018 to 2021 could be a combination between the overall population increase within the City of Austin in the past couple of years, the enactment of the plans set forth in the 2014 Austin Bicycle Master Plan that was created in 2014, and the COVID-19 pandemic. The City of Austin's comprehensive bicycle master plans goal was to create a bicycle network that serves people of all ages and abilities, providing direct and comfortable connections to where people live, work and play (City of Austin, 2014). These networks would improve overall bicycle safety by increasing off street bike lanes which are a physically separated from motor vehicle. One of the main types of protected bike lanes are urban trails, or off-street trails, as the ones that are being analyzed within this paper. The COVID-19 pandemic spread to the United States in January 2020 and is still rampaging throughout the world. COVID-19 caused Texas to begin the process of shutting down businesses and schools, and recommended isolating in one's home in order to stop the spread of the virus in March 2020. Self-isolation has caused many people to look to the outdoors as a new source of entertainment, exercise, or even travel in order to avoid exposure to other people. The result of this is a boom in bicycle sales. Sales of adult leisure bikes tripled in April while overall U.S. bike sales, including kids' and electric-assist bicycles, doubled from the year before, according to market research firm NPD Group, which tracks retail bike sales (Sharp & Chan, 2020). Unfortunately, Johnson Creek Trail does not have day to day bicycle counts during the COVID-19 pandemic, therefore, there is no way to tell how accurate the 2020-2021 forecast is for this location.

Ann and Roy Butler Trail at Mopac Crenshaw Bridge also showed a steady oscillation between the spring and winter seasons of the number of bicyclists. Figure 6 shows that there was a possible malfunction with the counter between the months of 06/01/2018 and 08/01/2018 which can be seen in the jump between the datapoints. Figure 6 also shows a glimpse into a decrease in ridership on the trail beginning around springtime (04/01/2018). This decrease in reaffirmed after looking at Figure 7, where the steady state of decent in number of riders begins at 04/01/2018 and ends at 06/02/2019. The date of the decrease in ridership coincides with the moment when electric scooters were released in the City of Austin. The rise in popularity of electric scooters could have caused the decrease in bicycle ridership as more riders choose to use electric scooters rather than ride their bikes. Furthermore, at the date of 06/02/2019, a steady rise in riders begins and continues into 2021.This increase could also be the result of the general increase in the population, the implementation of the 2014 Austin bicycle master plan, and the COVID-19 pandemic. The counter for this location was able to gather bicycle counts during the time that COVID-19 began its spread to Texas, which has allowed an analysis to check on how accurate the time series was in predicting the change in the number of bicyclists due to COVID-19. Figure 10 compares two trendlines, one being the forecast that was based on the actual COVID-19 counts, and the second trendline being the forecast that did not include the actual COVID-19 counts. Figure 6, that was shown previously, includes the COVID-19 counts in its' forecast trendline, and is represented as the dark blue Yhat2 within Figure 10. The light blue trendline within Figure 10 is Yhat1 which is the forecast trendline that did not include the COVID-19 counts. As seen in the graph, COVID-19 has indeed encouraged ridership throughout Ann and Roy Butler Trail at Mopac Crenshaw Bridge. The dark blue trendline (Yhat2) shows a slighter larger forecast in ridership that is closer to the true bicycle counts during COVID-19 than the light blue trendline (Yhat1). Yet, both lines are not perfect at capturing the true effects of COVID-19 upon ridership. Based on this graph it can be concluded that predications that are being made with COVID-19 datapoints are not as easy to capture and should be handled with care.

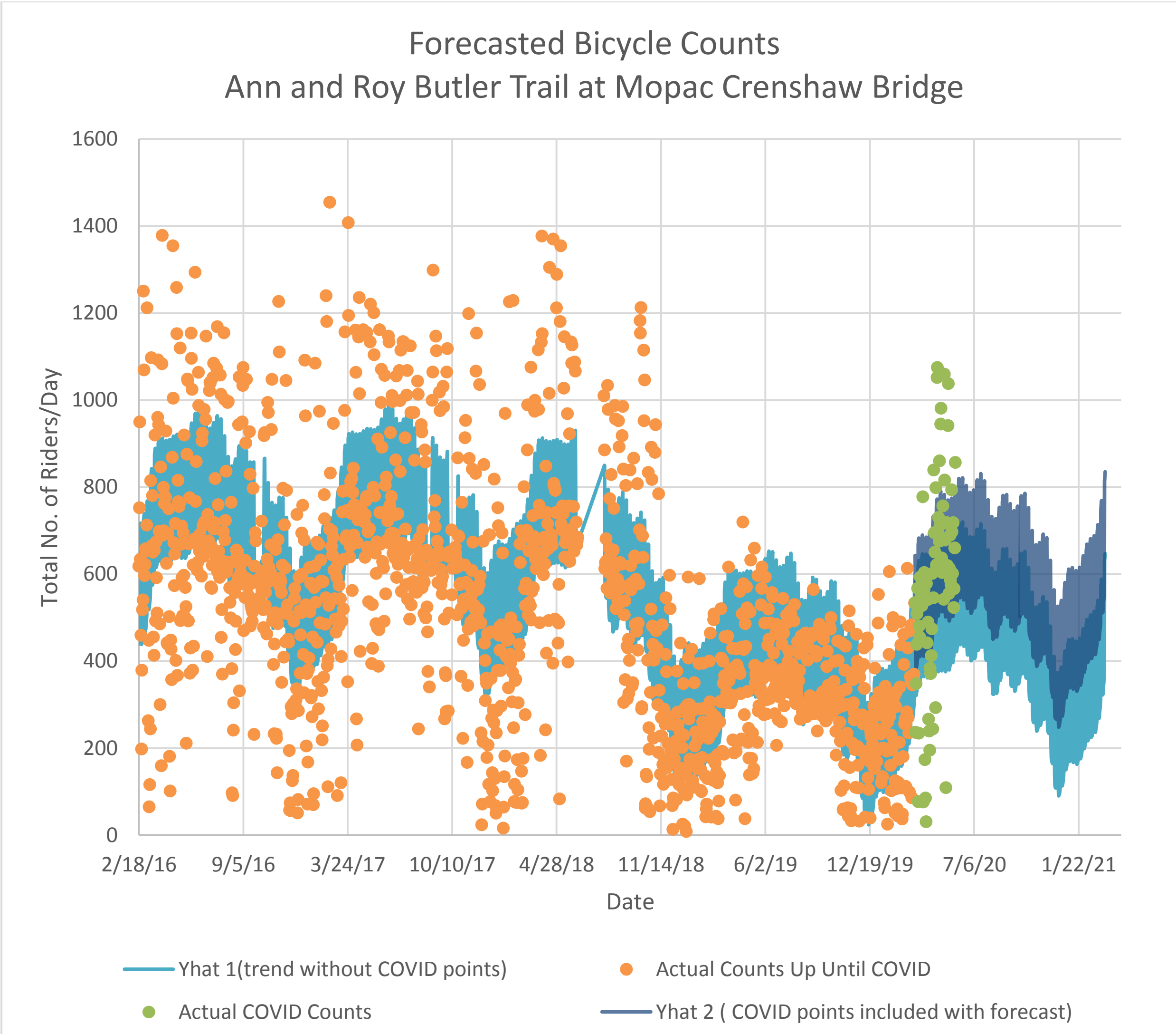

Figure 10: Ann and Roy Butler Trail at Mopac Crenshaw Bridge COVID-19 Graph

Lastly, the time series forecast graph (Figure 8) for Walnut Creek Trail N of Jain Ln revealed the seasonal oscillation, but there were many outliers that caused the Yhat trend to have a large upper and lower bound. The larger the distance between an upper and lower bound on a time series forecast, the less accurate its' predictions. The outliers could be a malfunction of the counter not being able to completely capture all the bicyclists who pass by the counter location. The general trendline (Figure 9) shows an overall increase in ridership from 2015-2021. As mentioned before, the general trendline increase in ridership that is shown in Figure 9 could be due to the population increase, 2014 Austin bicycle master plan, and/or COVID-19. Yet due to the fact that this location was unable to capture bicyclist counts during COVID-19, the accuracy of the 2020-2021 forecasts really is somewhat questionable.

3.3 Socio-Demographic Models

The section will provide the details of the socio-demographic model development process. Details include use of the American Community Survey (ACS) socio-demographic data and the same long-term count data that was used in the previous section. If needed, review Section 3.2.2 for descriptions of the long-term count data.

3.3.1 Demographic Data

The two data sources used for this analysis are the Eco-Visio counting system, and the American Community Survey demographic data.

The local demographic data was taken from the American Community Survey (ACS) between the years of 2014-2019. The ACS demographic data was placed into ArcGIS and then extracted from a 1-mile radius area around each counter's plotted location. This assumption is significant because it implies that bicyclists traveling through each counter location are beginning or ending their trip within one mile of this point. Refer to Figure 11 below for a visual of the 1-mile radius circles that were created for each one of the 10 permanent counters.

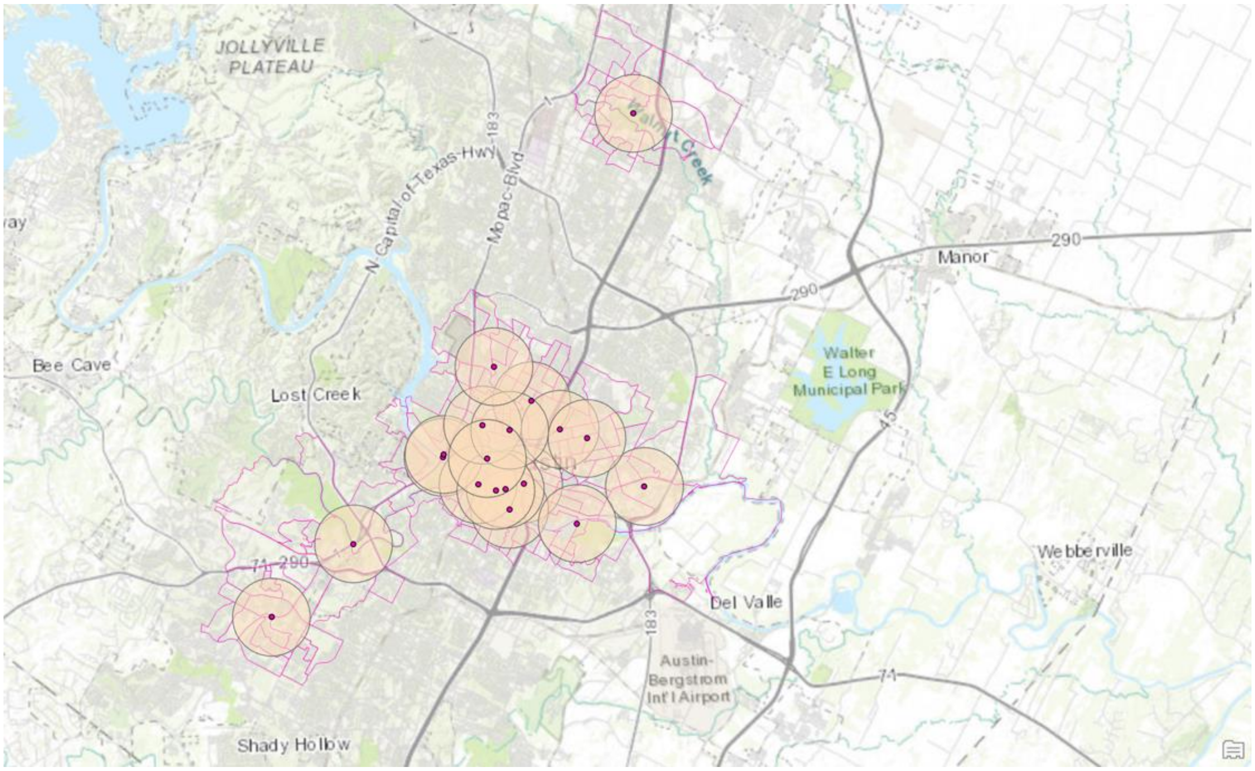

Figure 11: ArcGIS Counter Circles

The demographic variables from ACS that were extracted for each 1-mile radius circle are as follows:

1. **Other Race:** Counted number of people who are of the population's minority races such a Black, Asian, etc.
2. **White:** Counted number of people who are racially white

3. **Hispanic:** Counted number of people who are Hispanic
4. **Females:** Counted number of females
5. **Males**: Counted number of males
6. **Average Age:** The average age of the people residing within the circle
7. **Population/Square mile:** The population per square mile within the circle
8. **Average Family Size:** The average family size within the circle

3.3.2 Data Analysis

This section will provide the weekday and weekend resultant off-street demand models.

3.3.3 Off-Street Demand Model

The demand models are negative binomial regression models that were created using Statistical Analysis (SAS) software. Negative binomial regression models are for modeling count variables, usually for over-dispersed count outcome variables. Also, the negative binomial model, as compared to other count models (i.e., Poisson or zero-inflated models), is assumed to be the more appropriate model. In other words, we assume that the dependent variable is ill-dispersed (either under- or over- dispersed) and does not have an excessive number of zeros (SAS, n.d.).

The first negative binomial model's dependent variable utilizes the 5-year weekday average counts, while the second negative binomial model's dependent variable utilizes the 5-year weekend average counts. The independent variables, or the x-variables, are the same for both models and are the ACS demographic variables that were referenced in the previous section.

In an attempt to confirm that every independent variable was correlated with the weekday and weekend counts each variable was individually placed into a negative binomial regression model. For simplicity the table below reveals the negative binomial regression results for each demographic variable and the weekday bicyclist counts. Keep in mind that each demographic variable was placed into its' own negative binomial model as the independent variable for the weekday bicyclist counts (dependent variable) in order to see if the two are correlated. The independent variable will be considered correlated to the dependent variable when the Pr value is less than the chosen alpha value of 10%, in other words the null hypothesis must be rejected. Also, the form of the model equation for a negative binomial regression is the same as that for Poisson regression, meaning the log of the outcome is predicted with a linear combination of the predictors:

$$Log(y) = Intercept + b1(x1) + b2(x2) \dots bn(xn)$$

Which further implies:

$$y = \exp\big(Intercept + b1(x1) + b2(x2) \dots + bn(xn)\big)$$
$$= \exp(Intercept) + \exp(b1 * x1) + \exp(b2 * x2) \dots + \exp(bn * xn)$$

Noting the fact that the estimates are multiplied by the exponential function will help with the understanding of the resultant estimates. Understanding the estimates will aid in knowing how they affect the relationship between the independent and dependent variables.

Table 2: Weekday Demographic Model

Parameter	*DF*	*Estimate*	*Standard Error*	*Pr > Chi Sq*
Intercept	1	7.5768	0.6246	<.0001
Other Race	1	-0.0003	0.0025	0.9031
Dispersion	1	0.5177	0.2125	
Intercept	1	6.4330	1.0829	<.0001
White	1	0.0008	0.0008	0.3219
Dispersion	1	0.4734	0.1976	
Intercept	1	7.5538	0.4024	<.0001
Hispanic	1	-0.0001	0.0008	0.8853
Dispersion	1	0.5114	0.2124	
Intercept	1	10.1159	2.0053	<.0001
Females	1	-0.0034	0.0026	0.1840
Dispersion	1	0.4435	0.1859	
Intercept	1	5.7910	0.9964	<.0001
Males	1	0.0018	0.0011	0.0895
Dispersion	1	0.4093	0.1724	
Intercept	1	6.5405	3.8085	0.0859
Average Age	1	0.0284	0.1122	0.7998
Dispersion	1	0.5096	0.2117	
Intercept	1	6.6322	0.7249	<.0001
Population/Sq. Mile	1	0.0001	0.0001	0.2243
Dispersion	1	0.4563	0.1909	
Intercept	1	8.6684	1.6390	<.0001
Average Family Size	1	-0.4178	0.5780	0.4698
Dispersion	1	0.4919	0.2048	

The weekend negative binomial regression model statistical results are represented in the same fashion in Table 4.

Table 3: Weekend Demographic Model

Parameter	*DF*	*Estimate*	*Standard Error*	*Pr > Chi Sq*
Intercept	1	6.9510	0.5512	<.0001
Other Race	1	-0.0000	0.0022	0.9872
Dispersion	1	0.4739	0.2089	
Intercept	1	6.4999	1.0176	<.0001
White	1	0.0003	0.0008	0.6592
Dispersion	1	0.4661	0.1951	
Intercept	1	6.9030	0.3737	<.0001
Hispanic	1	0.0001	0.0007	0.8975
Dispersion	1	0.4732	0.1978	
Intercept	1	9.1773	1.8910	<.0001
Females	1	-0.0029	0.0024	0.2282
Dispersion	1	0.4196	0.1767	
Intercept	1	5.6724	1.0264	<.0001
Males	1	0.0014	0.0011	0.2181
Dispersion	1	0.4179	0.1761	
Intercept	1	6.2798	3.5055	0.0732
Average Age	1	0.0195	0.1032	0.8499
Dispersion	1	0.4724	0.1975	
Intercept	1	6.6163	0.7249	<.0001
Population/Sq. Mile	1	0.0001	0.0001	0.6421
Dispersion	1	0.4653	0.1947	
Intercept	1	7.2644	1.5349	<.0001
Average Family Size	1	-0.1148	0.5408	0.8319
Dispersion	1	0.4721	0.1974	

3.3.4 Summary

The objective of this section was to provide the methodology for creation of statistical models that will be able to predict the demand of ten off-street bicycle facilities that are located within the City of Austin. Several weekday and weekend statistical models were created from the collection of long-term count data of bicyclists and their correlation to the surrounding demographics. The models are eight negative binomial regression models created for both the weekend bicyclist counts and the weekend bicyclist counts. Results from the sixteen models showed that only the demographic variable labeled as 'Males' was correlated to the weekday bicyclist counts. Unfortunately, no other demographic variable was found to be correlated to the bicyclist count data. The Pr value from the weekday 'Males' model was 0.0895, which is less than the defined alpha value of 10%. This allowed the null hypothesis of "no correlation" to be rejected meaning the number of males in the area is correlated to the number of off-street bicyclists. To break down this relationship more, Figure 12 shows that with an increase in the number of males within the 1-mile circle there will then be an increase in the number of off-street bicyclists. For example, Figure 12 shows that 800 males will create a predicted value of 1300 off-street bicyclists. Keep in mind that the bicyclist count data was collected from 2014-

2019, meaning that as the number of men within the area increase the number of off-street bicyclists will also increase in the next five years.

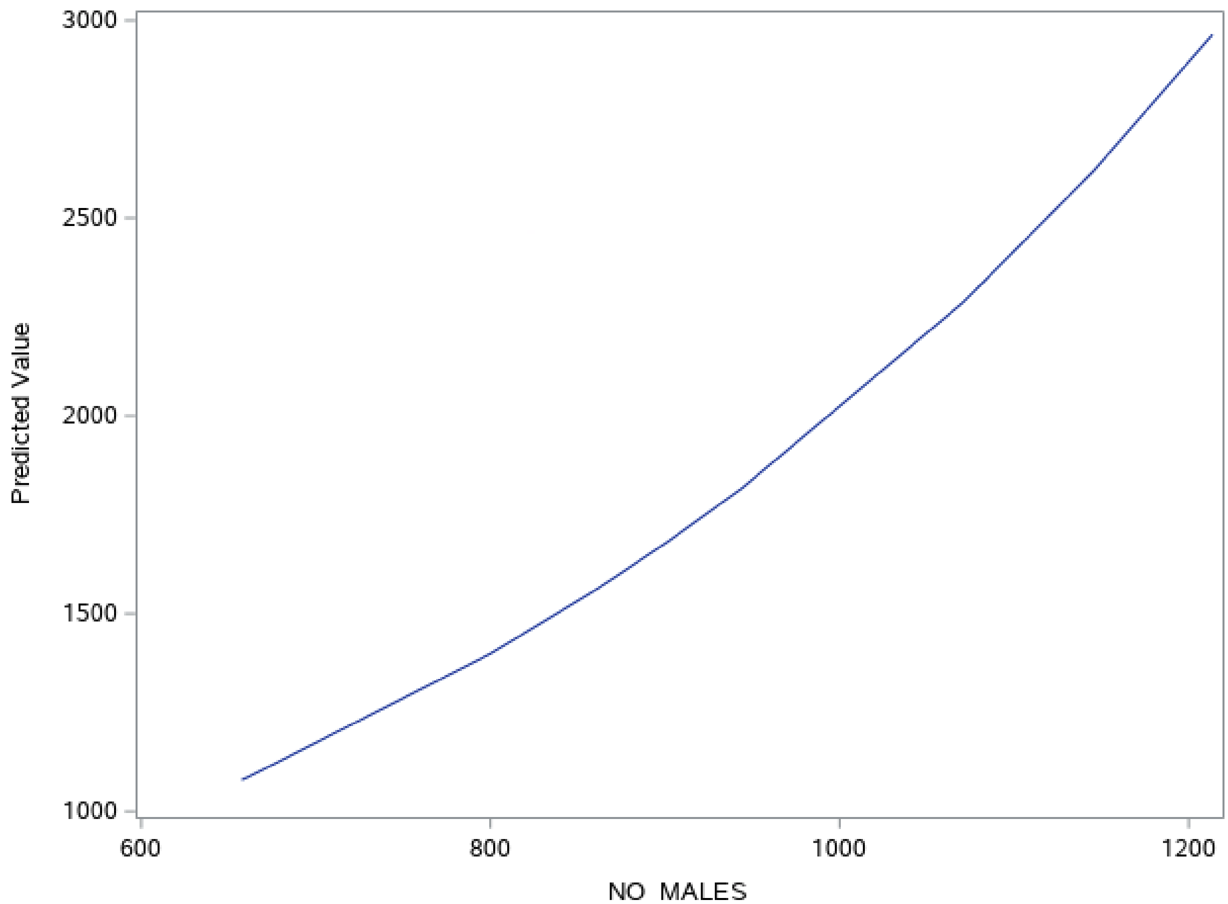

Figure 12: Males to Predicted Number of Off-street Cyclists

3.4 Weather Model

The section provides details of the data and proposed models for describing relationships between bicycle activity and weather conditions. Details include the stations for which the weather data was taken, the weather variables used and the fact that this model uses the same long-term count data that was described earlier. If needed, review Section 3.2.2 for information over the long-term count data.

3.4.1 NOAA Weather Data

Weather may have significant influence on the demand of bicyclists, especially for off-trail riders. For example, bicyclists are more likely to utilize an off-trail while the weather is hot and sunny. On the other hand, if it is raining then a bicyclist is less likely to go riding on one of the off-trails. In order to confirm these theories, local weather data was taken from the National Centers for Environmental Information database. This database provided daily weather data for the City of Austin from the "Austin Camp Mabry" weather station. This station represents the entire City of Austin and has been capturing daily weather data from 1938 to present day 2020. The location of the "Austin Camp Mabry" station can be found on Figure 13 below.

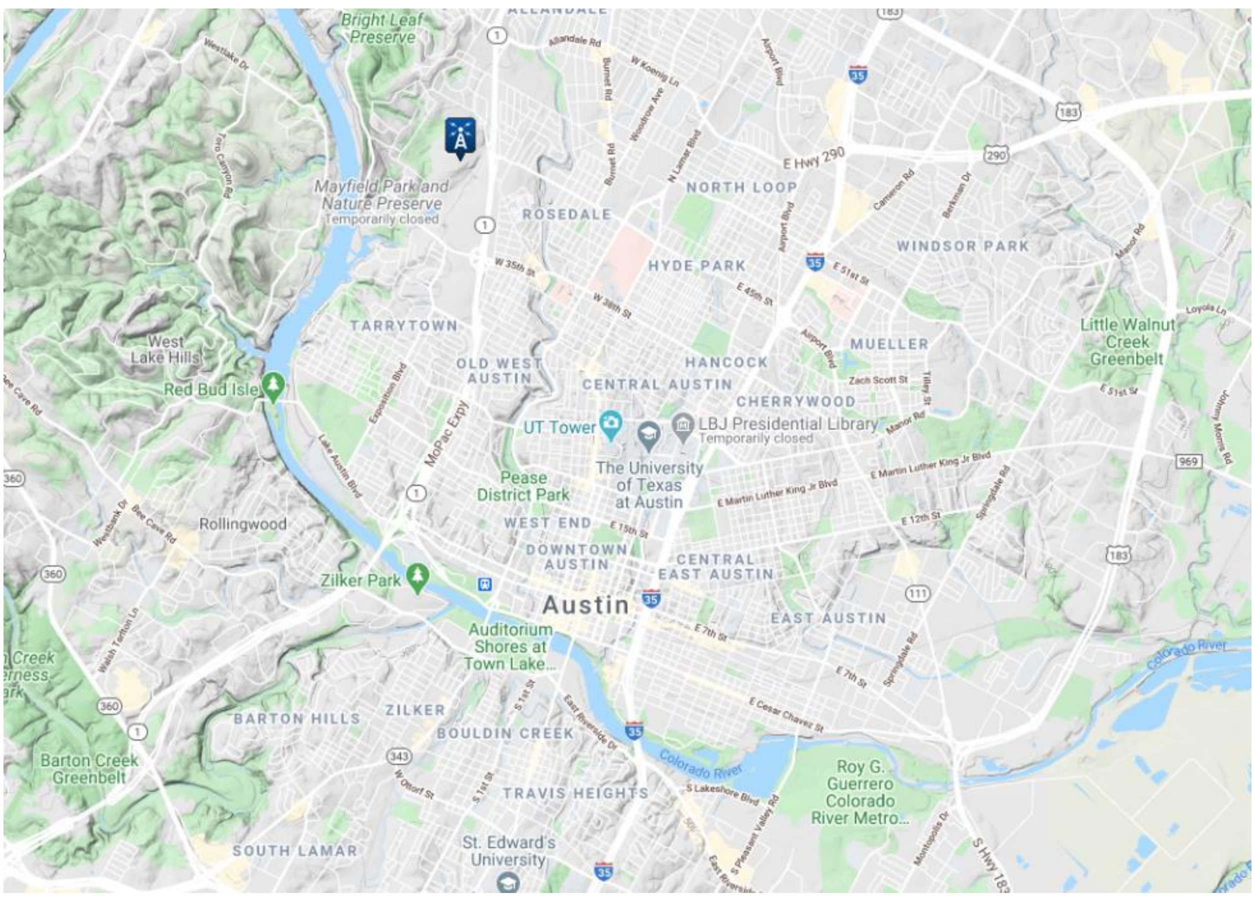

Figure 13: Austin Camp Mabry Weather Station Location

Daily data on the precipitation, maximum temperature, minimum temperature, average wind speed and presence of haze/fog are used as the independent variables for the negative binomial models. These dates match each day for the collected bicyclist counts.

3.4.2 Data Analysis

Like the demographic model, these demand models are negative binomial regression models that were created using Statistical Analysis (SAS) software.

Two negative binomial models were created for each counter, one for weekday bicyclist counts, and one for weekend bicyclist counts. For the weekday bicycle models, the daily weekday number of bicycles are the dependent variables (y-variables), while for the weekend model, the daily weekend number of bicycles are the depend variables. For further explanation, all the daily collected bicycle count dates that fell on and within Monday-Friday would be used within the weekday, while all the daily bicycle count dates that fell on or within Saturday-Sunday would be used within the weekend model. The independent variables, or the x-variables, are the same for both weekday and weekend models which are the weather variables (precipitation, maximum temperature etc.) that were referenced in the previous section.

Unlike the demographic model, each independent variable was placed into each model (one weekday and weekend) due to each counter dataset meeting the one in ten rule requirements. The one in ten rule is a rule of thumb for how many predictor parameters can be used when doing a regression analysis. This rule states that one predictor variable for every ten outcomes should be used in order to avoid the risk of overfitting. Both weekday and weekend negative binomial regression results can be found in Table 4 and Table 5. Both tables provide the significance and estimate value for each independent weather variable. A breakdown of the meaning behind the results will found in the following section.

Table 4: Weekday Weather Demand Model

Dependent Variable: Weekday Bicycle Counts

Counter ID Number		Independent Variable						
		Intercept	*Precipitation*	*Minimum Temperature*	*Maximum Temperature*	*Average Wind Speed*	*Presence of Haze/Fog*	*Dispersion*
1	Estimate	2.9666	-0.4231	-0.013	0.0299	-0.0011	-0.066	0.081
	Pr > Chi Sq	<.0001	<.0001	<.0001	<.0001	0.8021	0.0019	0
2	Estimate	3.7739	-0.3756	-0.0152	0.0402	-0.0054	-0.05	0.1906
	Pr > Chi Sq	<.0001	<.0001	<.0001	<.0001	0.429	0.1161	0
3	Estimate	4.0072	-0.3745	-0.0205	0.0378	0.0054	-0.0238	0.2851
	Pr > Chi Sq	<.0001	<.0001	<.0001	<.0001	0.6299	0.6534	0
4	Estimate	4.1243	-0.0683	-0.0006	0.0162	-0.001	-0.0829	0.2607
	Pr > Chi Sq	<.0001	0.0895	0.8152	<.0001	0.8911	0.0207	0
5	Estimate	4.7803	-0.4574	-0.0152	0.0288	0.0055	-0.0182	0.1111
	Pr > Chi Sq	<.0001	<.0001	<.0001	<.0001	0.5244	0.6675	0
6	Estimate	3.0088	-0.1847	-0.0045	0.0231	-0.0077	-0.0853	0.1141
	Pr > Chi Sq	<.0001	0.0011	0.1729	<.0001	0.4327	0.0649	0
7	Estimate	6.158	-0.237	-0.0026	0.0114	-0.008	-0.0624	0.0641
	Pr > Chi Sq	<.0001	<.0001	0.1227	<.0001	0.1015	0.0063	0
8	Estimate	2.888	-0.4539	-0.0125	0.0283	-0.0111	-0.0864	0.1206
	Pr > Chi Sq	<.0001	<.0001	<.0001	<.0001	0.1384	0.0159	0
9	Estimate	3.8713	-0.3616	-0.0102	0.0294	-0.0094	-0.0145	0.1242
	Pr > Chi Sq	<.0001	<.0001	0.0004	<.0001	0.2786	0.7223	0
10	Estimate	4.9842	-0.4225	-0.0144	0.0285	0.0007	-0.0254	0.0619
	Pr > Chi Sq	<.0001	<.0001	<.0001	<.0001	0.9229	0.4229	0

Table 5: Weekend Weather Demand Model

Dependent Variable: Weekend Bicycle Counts

Counter ID Number		Intercept	Precipitation	Minimum Temperature	Maximum Temperature	Average Wind Speed	Presence of Haze/Fog	Dispersion
1	Estimate	3.3107	-0.4959	-0.0179	0.0327	-0.0037	-0.0442	0.1052
	Pr > Chi Sq	<.0001	<.0001	<.0001	<.0001	0.6622	0.2355	0
2	Estimate	4.6511	-0.4349	-0.0096	0.0309	-0.0042	-0.0128	0.2057
	Pr > Chi Sq	<.0001	<.0001	0.0099	<.0001	0.7316	0.8036	0
3	Estimate	4.8466	-0.2284	-0.0302	0.0397	0.013	-0.0792	0.1593
	Pr > Chi Sq	<.0001	0.0074	<.0001	<.0001	0.3544	0.2103	0
4	Estimate	5.5425	-0.1181	-0.0055	0.0135	-0.0084	-0.1047	0.2113
	Pr > Chi Sq	<.0001	0.0221	0.1327	0.0001	0.4335	0.0368	0
5	Estimate	5.2522	-0.1961	-0.0246	0.0354	-0.0021	-0.0734	0.0972
	Pr > Chi Sq	<.0001	0.0083	<.0001	<.0001	0.8728	0.2145	0
6	Estimate	3.1475	-0.3772	-0.0026	0.0203	-0.0089	-0.103	0.1754
	Pr > Chi Sq	<.0001	0.0589	0.7016	0.0016	0.6714	0.2439	0
7	Estimate	6.1612	-0.1955	-0.0051	0.0133	-0.0203	-0.0533	0.0849
	Pr > Chi Sq	<.0001	<.0001	0.0822	<.0001	0.0356	0.2185	0
8	Estimate	3.7097	-0.4616	-0.0115	0.0262	-0.0354	-0.0718	0.1107
	Pr > Chi Sq	<.0001	<.0001	0.0026	<.0001	0.0028	0.1645	0
9	Estimate	4.5964	-0.2997	-0.0189	0.0313	-0.0076	-0.0211	0.1368
	Pr > Chi Sq	<.0001	0.0004	<.0001	<.0001	0.6112	0.7502	0
10	Estimate	5.3539	-0.6355	-0.0172	0.0322	-0.0144	-0.0763	0.0942
	Pr > Chi Sq	<.0001	<.0001	0.0004	<.0001	0.3213	0.2437	0

3.4.3 Summary

The same requirement that was used in the Demographic models was also used in the weather models, whereas the independent variables (weather) will be considered correlated to the dependent variable (bicycle counts) when the Pr value is less than the chosen alpha value of 10%, in other words the null hypothesis must be rejected. The breakdown of the weekday results for the off-trail bicycle counts are as followed:

- **Precipitation**
  - The precipitation variable is the measured inches of rain during the defined time range. The Pr values for each counter location are all less than 0.10, and therefore are found to be correlated to the bicycle counts. The estimate for each counter is negative which means that there is a negative correlation of bicyclists using the off-trails and rain. In other words, with the increase in inches of precipitation there will be a decrease in the number of bicyclists that utilize the off-trails. The weather was not restrained by a 1-mile radius like the demographic models; therefore, this behavior applies to all the residents within the City of Austin.
- **Minimum Temperature**
  - The minimum temperature is the lowest temperature in Fahrenheit that occurred throughout the day. Eight out of ten of the counters had Pr values that were less than 0.10, meaning eight out of the ten were significantly correlated to the bicycle counts while counter locations six and seven had Pr values that were slightly above 0.10. These two locations are Shoal Creek Blvd N of W 24th and Lance Armstrong at Waller Creek. The estimates for the counters that were significantly correlated are all negative, meaning the lower/colder the minimum temperature is during the day fewer bicyclist will choose to ride on the off-trails.
- **Maximum Temperature**
  - The maximum temperature is the highest temperature in Fahrenheit that occurred throughout the day. All counters locations were found to be significantly correlated to the bicycle counts. The estimate values were all positively correlated, meaning that the higher the maximum temperature is throughout the day then the greater number of bicyclists will choose to ride on the off-trails.
- **Average Wind Speed**
  - The average wind speed is the average wind speed that was measured throughout each day in miles per hour. All of the counter locations are not correlated to average wind speed, but counter location seven was close to 0.10 at 0.1015 (Lance Armstrong at Waller Creek). This means that wind speed does not affect the number of bicyclist's choosing to ride on the off-trails within the City of Austin. This result makes sense due to the fact that Austin does not typically have high wind speeds.
- **Presence of Haze/ Fog**

    - The presence of haze and fog was not measured in mathematical units, rather as 1's and 0's where 1 represents haze/fog being present throughout the city and 0 representing no haze/fog. Half of the counter locations were found to not be correlated to the presence of haze/fog. The locations that are found to be correlated are locations 1, 4, 6, 7, and 8. These locations are spread out from one another and are not all near Lake Austin (refer back to Figure 1).

The weekend results for the off-trail bicycle counters are as follows:

- **Precipitation**
    - Like the weekday results, all counter locations are found to be correlated to the amount of precipitation in the area. The estimates for each counter are also negative meaning that with there is a negative correlation of bicyclists using the off-trails and rain.
- **Minimum Temperature**
    - Except for locations 4 and 6 the rest of the counter locations were significantly correlated to the minimum temperature. The estimates of the correlated count locations have negative correlations meaning that the lower the minimum temperature, the smaller number of people will choose to ride their bicycles on the off-trails.
- **Maximum Temperature**
    - All counter locations were correlated to the maximum temperature throughout the day. Like the weekday results, the estimates were positive values meaning the maximum temperature is positive correlated to the number of bicyclists throughout the day. More bicyclist will choose to ride on the off-trails if the temperature is hotter.
- **Average Wind Speed**
    - Locations 7 and 8 are correlated to the average wind speed, which is Lance Armstrong at Waller Creek and Mopac at Barton Creek. The estimates of the two locations have a negative value which means that the greater the wind speed the less likely people will choose to ride on these trails. Both counters are located off of two major highways, Lance Armstrong at Waller Creek is located off of I-35 and Mopac at Barton Creek is located off of Mopac Expressway. Due to both these counters being located near major highways, the wind may have a wind tunnel affect that causes discomfort when riding.
- **Presence of Haze/Fog**
    - The presence of haze/fog is not correlated to any of the counter locations except for counter location 4. Location 4 is Walnut Creek Trail N of Jain Ln which is the farthest eastern counter. The estimate for this location is negative, therefore, less people will choose to ride on Walnut Creek Trail when there is haze/fog presence. This counter is located within the Greenbelt which is a wooded park area that is prone to more moisture that could then become trapped within the wooded area. This would make it hard for bicyclists to navigate throughout the densely wooded area safety.

Chapter 4. Summary and Conclusions

4.1 Introduction

Several statistical models were created to capture the future bicyclist demand of off-trails throughout the City of Austin. The first set of models utilized a time series analysis which successfully captured the future number of bicyclists for three out of the ten counter locations. The second set of models used negative binomial regression models to capture the demographic makeup of the bicyclists along the off-trails. Lastly, the third model set also utilized negative binomial regression models to correlate local City of Austin weather data to the number of off-trail bicyclists. Each set of statistical models were able to capture a different piece of the puzzle that makes up the current and future off-trail riders. Bringing these models together will reveal a clearer image of what is and will be seen along these City of Austin bicycle trails.

This chapter will further interpret and break down this image/story that is being told by the set of statistical model results and disclose the directions that should be taken for future research in order to improve bicycle facilities demand models.

4.2 Summary and Conclusions

The first statistical model was a time series analysis. This analysis purely provided the predicted number of bicyclists for three off-trails. All three locations showed that there is an increase in ridership during the months of spring, and a decrease in ridership during the winter months. All three locations predicted an increase in ridership from 2020-2021. The hypothesis for reason behind these increases could be a combination of the population increase within the City of Austin, the implementation of the 2014 Austin bicycle master plan, and/or the COVID-19 pandemic. Only one of the counters captured bicycle counts during the pandemic which then allowed a cross-check on how accurate Prophet was in predicting ridership during the COVID-19 pandemic. Based on those forecasts, it was concluded that there was indeed an overall increase in ridership during the pandemic, yet even with the COVID-19 data points being included in the forecast Prophet was still unable to fully capture the effects of COVID-19. This showed that forecasting with COVID-19 datapoints is not easy and should be handled with care.

The second set of statistical models was the demographic negative binomial regression models. The results from the models forecasted that with the increase in the number of males there will be an increase in the number of off-street bicyclists during the weekday for the next five years. Although these results are truthful, these models were unable to identify strong relationships between demographics and numbers of bicycle users. Therefore, there will be a new approach taken in order to properly capture the demographic makeup of off-street bicyclists. This approach will be further explained in the Directions for Future Research section.

Lastly, the third set of models was the weather models that also utilized negative binomial regression. The results from both the weekday and weekend models are very similar in the sense that most of the weather variables were found to be significantly correlated to the number of counted off-trail bicyclists. The essence of the results for both the weekday and weekend models are that bicyclists are less likely to ride on the off-trails if it is raining or if it is cold. On the other hand, bicyclists are more likely to ride on the off-trails if it is hotter. The remaining variables, average wind speed and the presence of haze/fog, did not show significant correlation to the number of bicyclists. These models show that weather has and will continue to have a significant effect on bicyclist demand.

Together these models provide these main takeaways:

- Bicyclist demand along the off-street trails will **increase** during the spring season (March, April, and May)
- Bicyclist demand along the off-street trails will **decrease** during the winter season (December, January, and February)
- Bicyclist demand **rose** during the COVID-19 pandemic, and is predicted to continue this behavior into 2021
- The number of male bicyclists will **increase** along the off-street trails during the weekday for the next five
- During both the weekday and weekend, bicyclists demand will **decrease** along the off-trails if it is raining or cold outside
- During both the weekday and weekend, bicyclists demand will **increase** along the off-trails if it is hotter outside

Each statistical model that was created could indeed be applied to different bicycle facilities only if that bicycle facilities local data is acquired. Unfortunately, the demographic data did not correlate well to the Austin off-street bicycle counts, which in turn, could not provide concrete evidence regarding low-income and/or minorities using off-street trails.

4.3 Directions for Future Research

The weekday and weekend models for the demographic demand model was created from only 10 permanent counters. It is not recommended that negative binomial models be applied to small samples, therefore, utilizing only 10 observations is not nearly enough. Yet, the City of Austin does not have enough permanent counters in order to recreate a proper negative binomial demand model. With that in mind, future research and resources should go toward implementing more permanent counters throughout the City of Austin in order to capture the demographic makeup of off-trail bicyclists throughout the city.

Furthermore, future work can also include the utilization of Smart Location Mapping to create new demand models. Created by the United State Environmental Protection Agency (EPA), Smart Location Mapping is interactive maps and data for measuring location efficiency and built environment. More specifically, using Smart Location Mapping will allow demand estimation models to include measurements such as density of development, diversity of land use, street network design, and accessibility to destinations as well as various demographic and employment statistics. Most attributes are available for all U.S. block groups (EPA, n.d.). One study that compared Travis County, Texas's street network design, taken from the Smart Location Mapping database, to the Strava Metro app found that cyclists riding to track statistics for fitness may be less sensitive to bicycle-specific infrastructure. They may ride at a speed closer to that of the automotive traffic in urban areas, and they may choose routes that are less congested by vehicles in general as well (Griffin & Jiao, 2014).

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Appendix

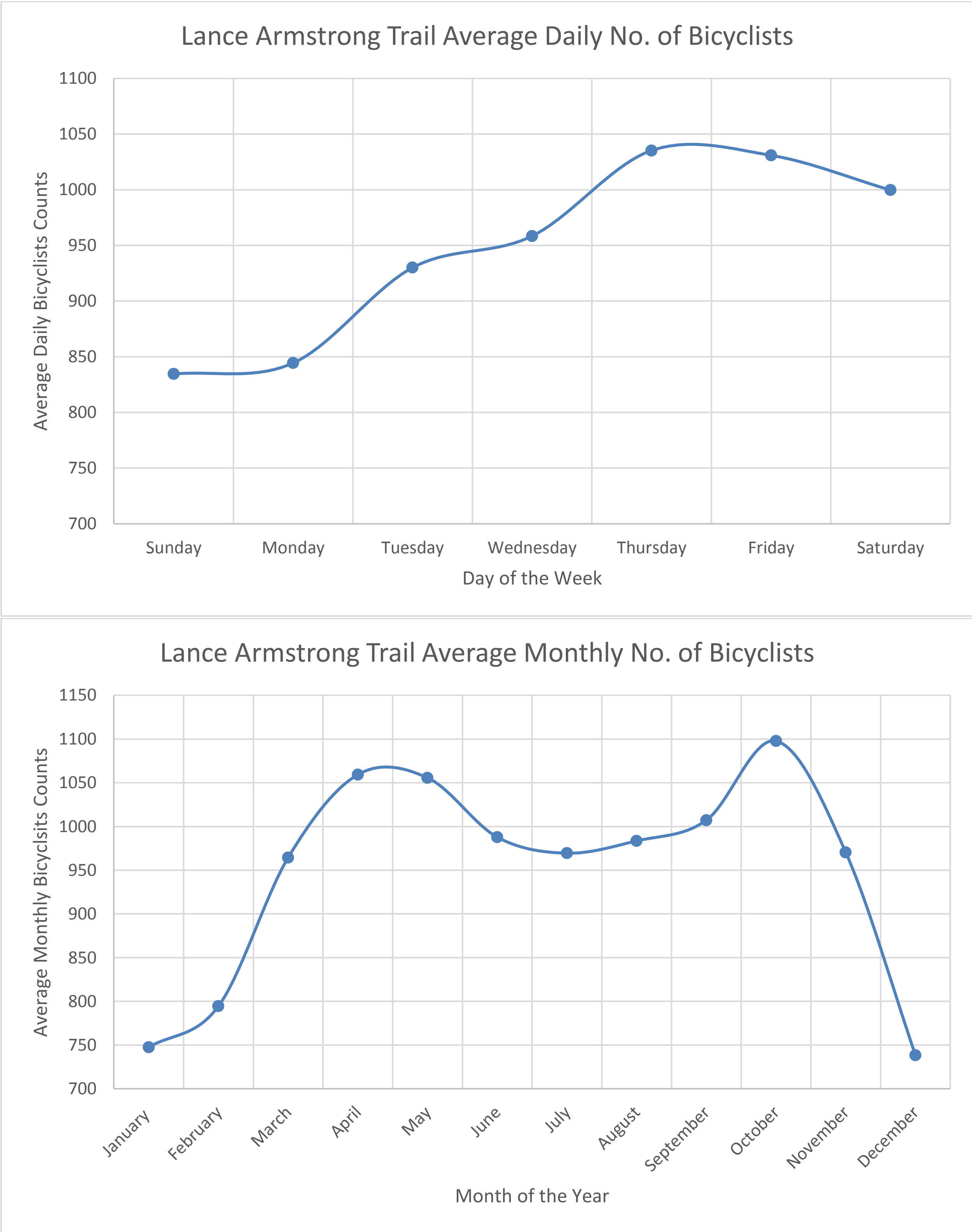


Figure 14: Lance Armstrong Bikeway at Waller Creek Avg. Monthly and Daily No. of Bicyclists

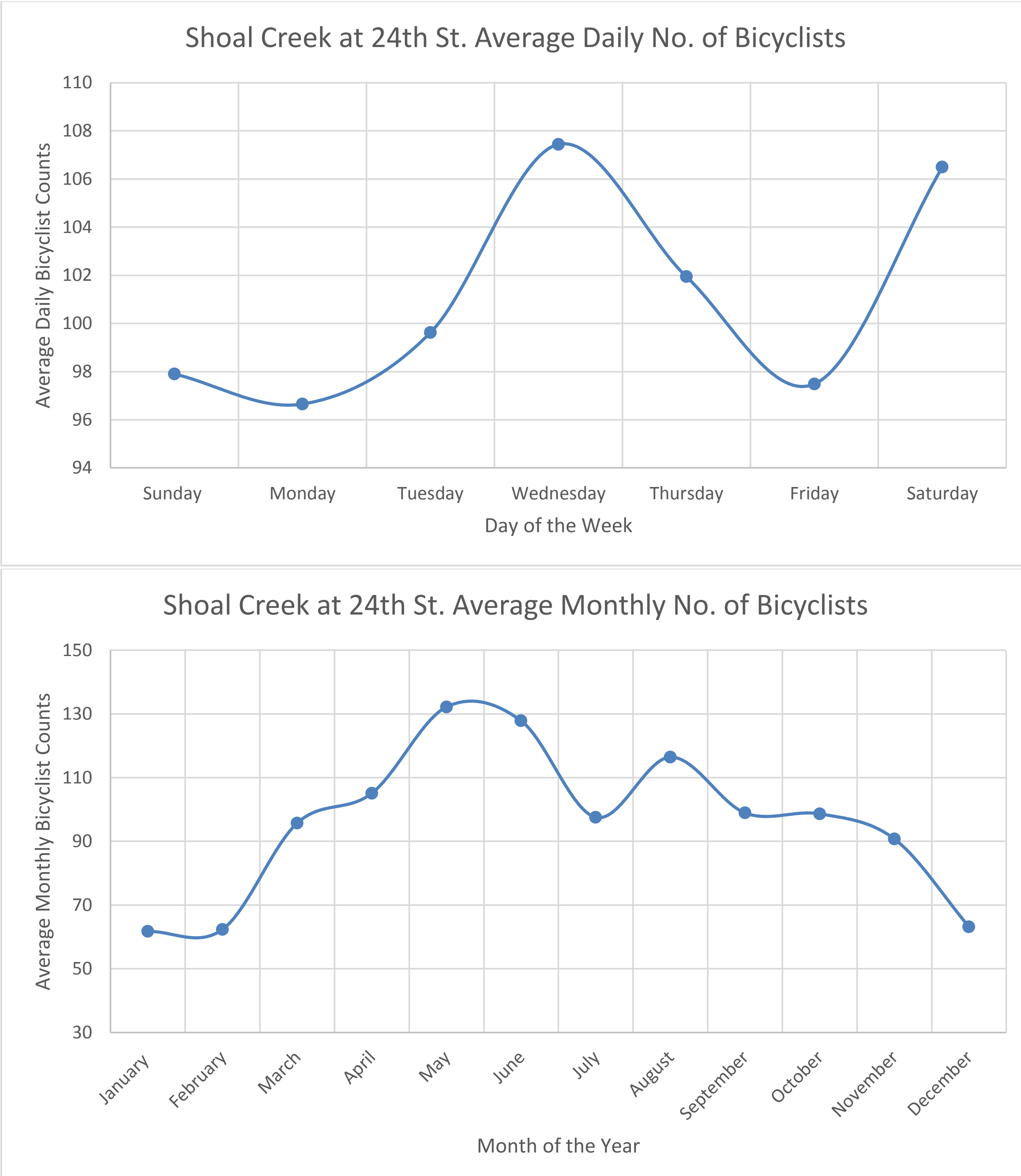


Figure 15: Shoal Creek Blvd N of W 24th St. Avg. Monthly and Daily No. of Bicyclists

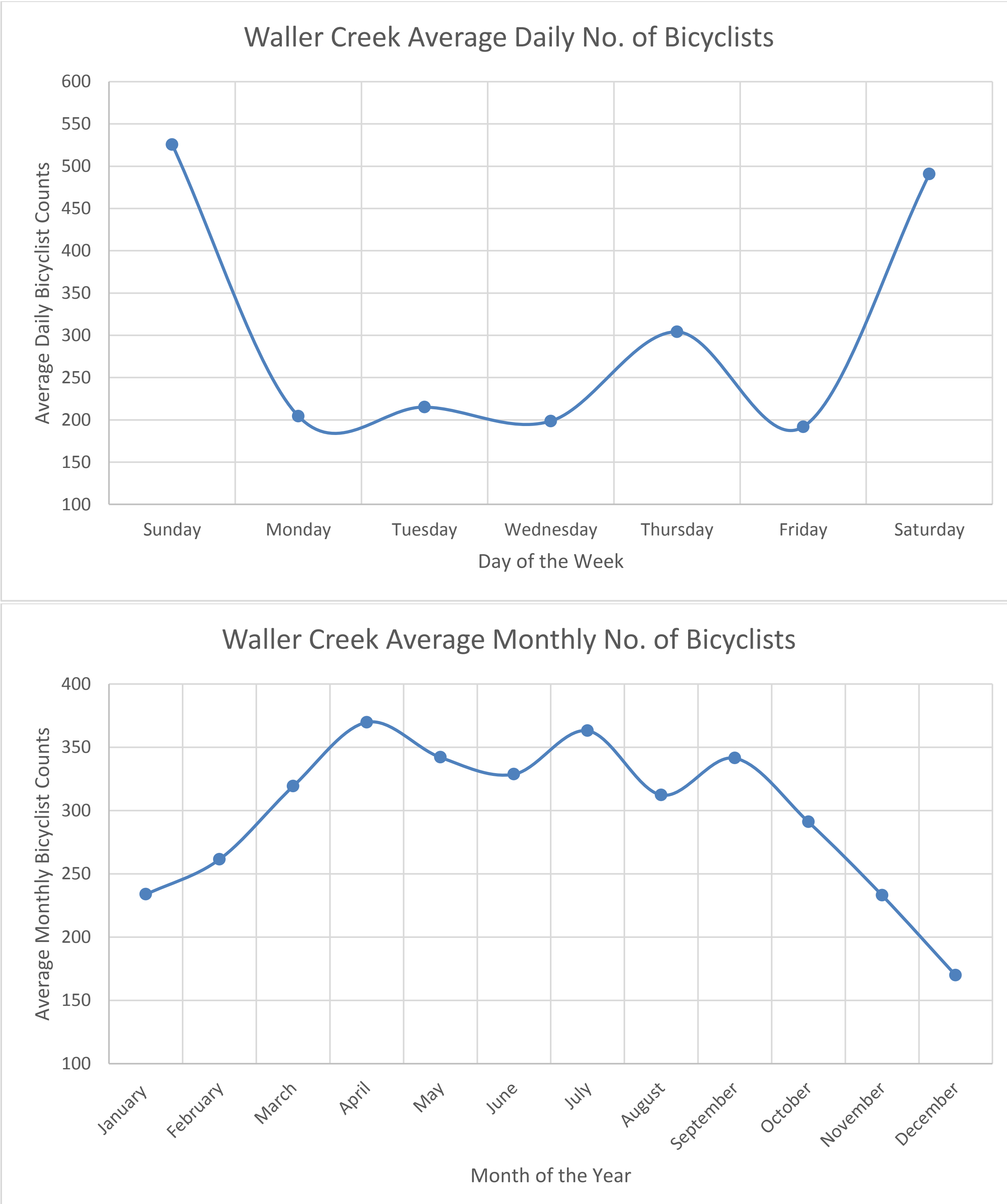
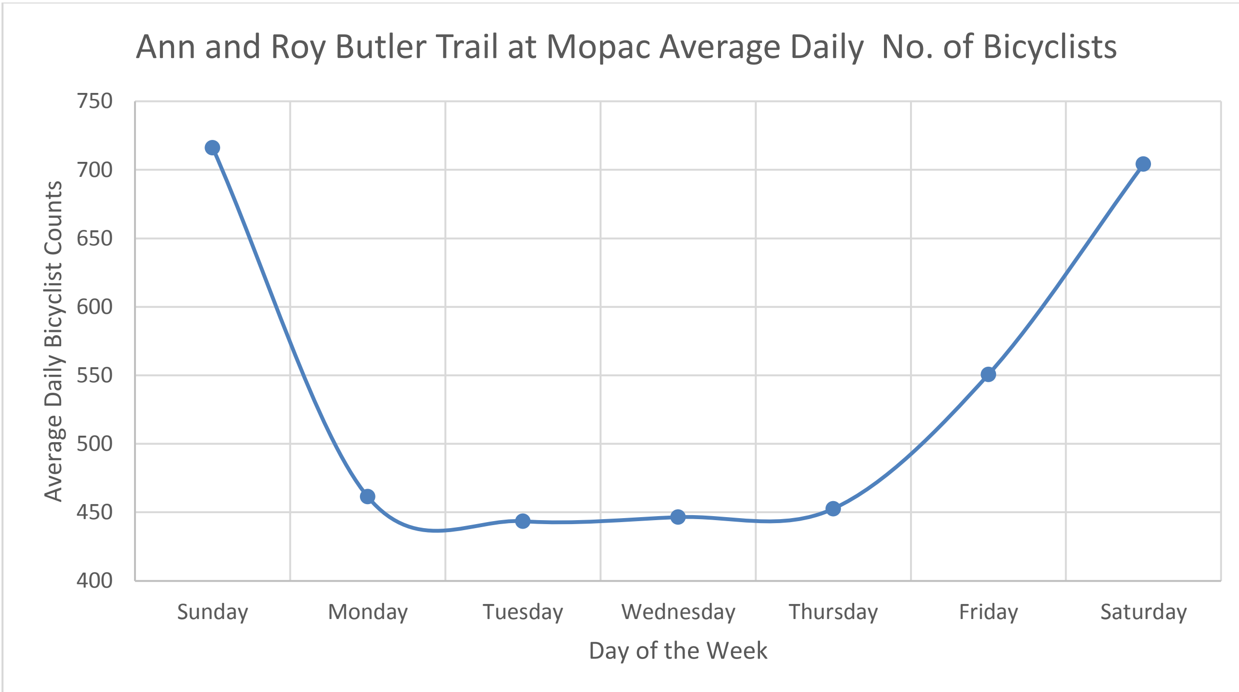


Figure 16: Waller Creek Trail N of Jain Ln Avg. Monthly and Daily No. of Bicyclists



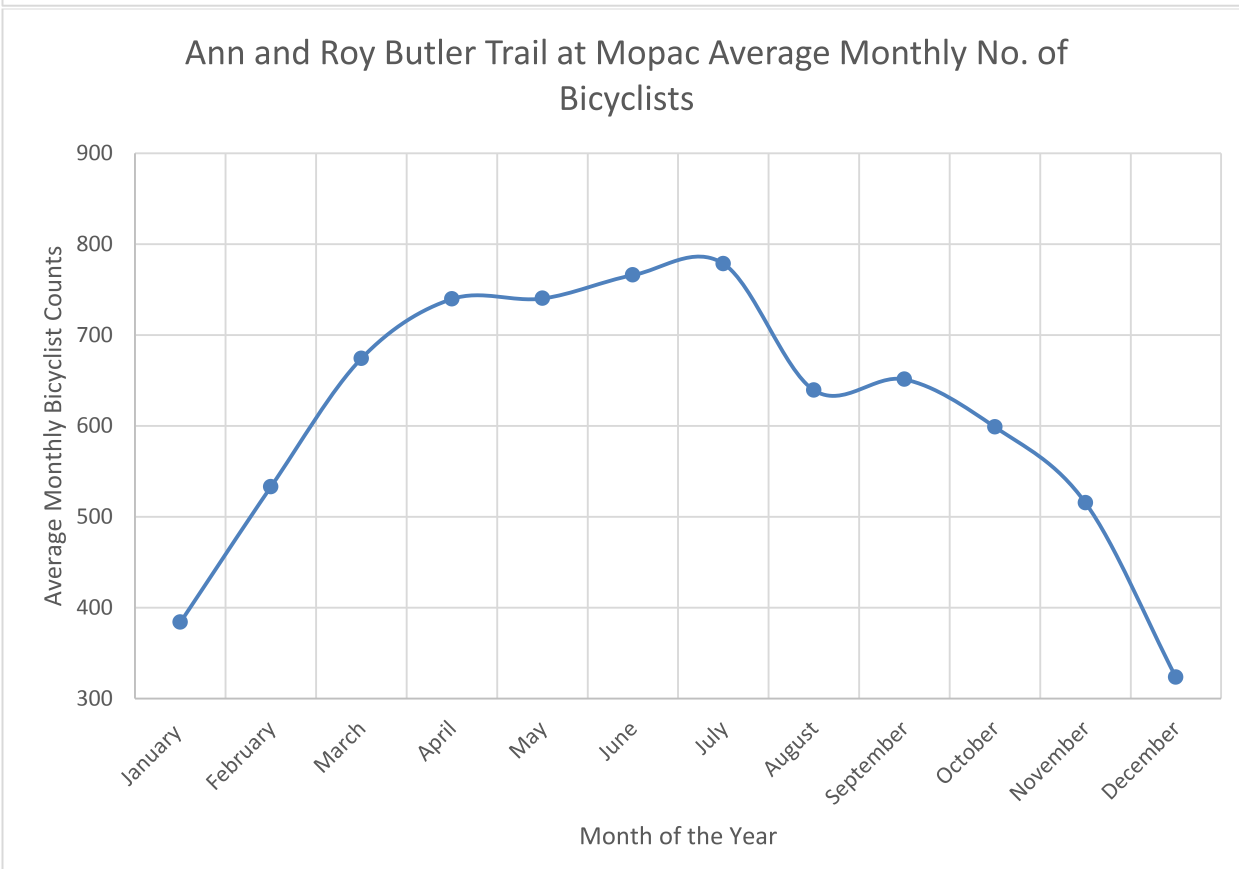
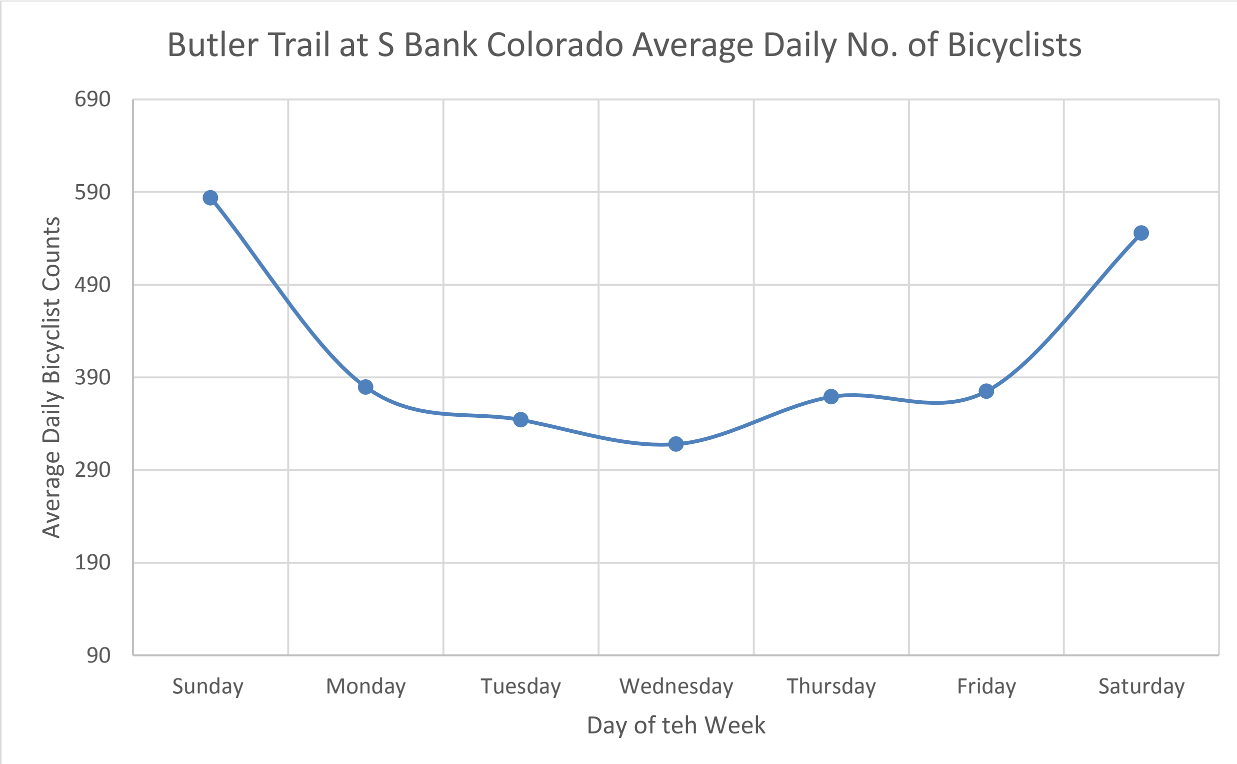


Figure 17: Ann and Roy Butler Trail at Mopac Crenshaw Bridge Avg. Monthly and Daily No. of Bicyclists



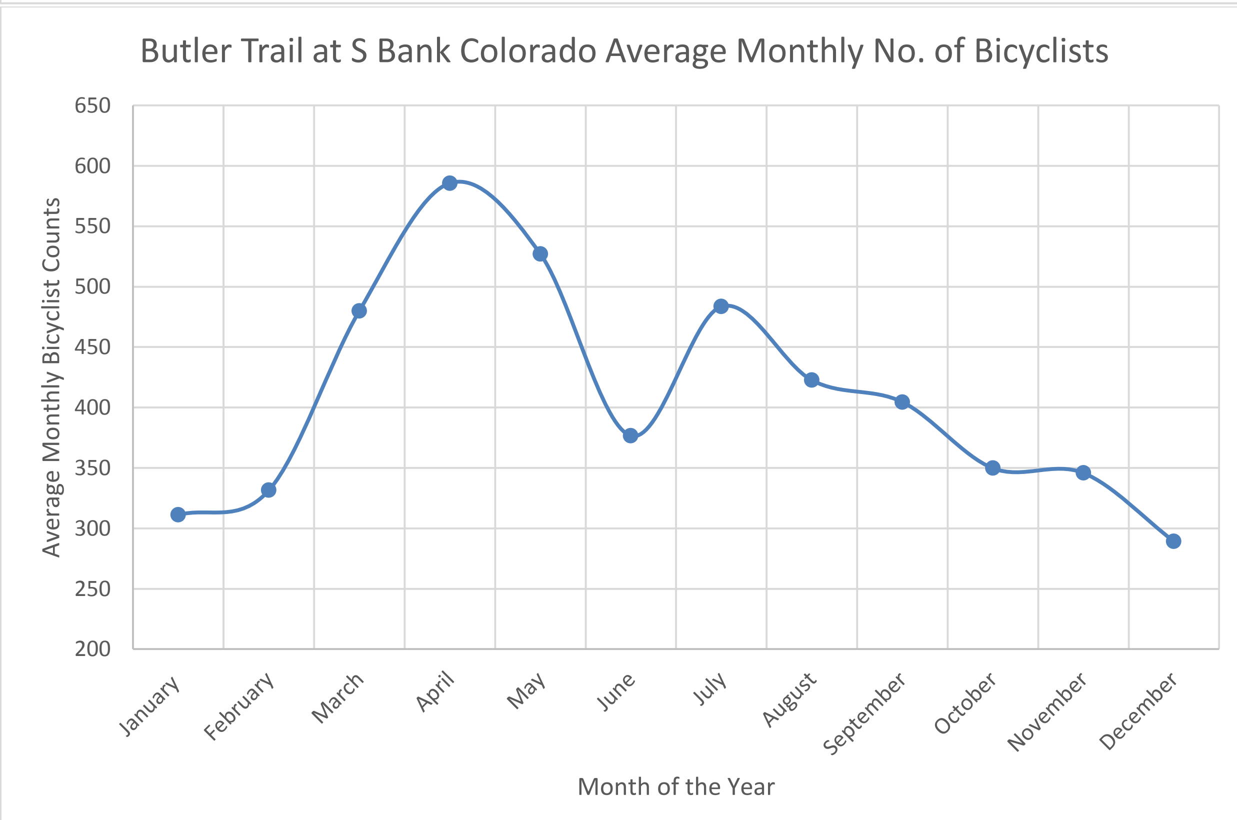


Figure 18: Butler Trail at S Bank Colorado River E of Pflueger Bridge Avg. Monthly and Daily No. of Bicyclists

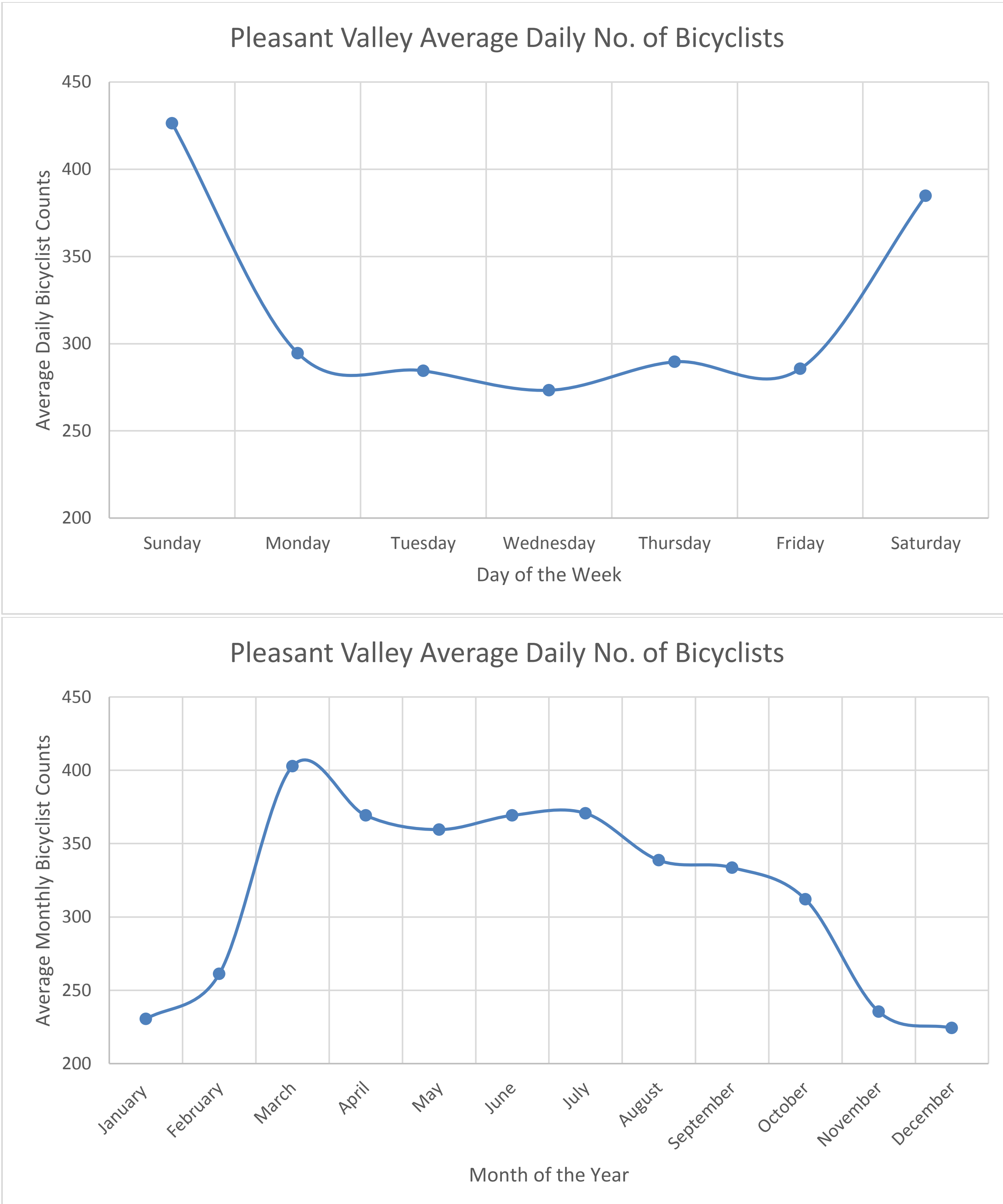
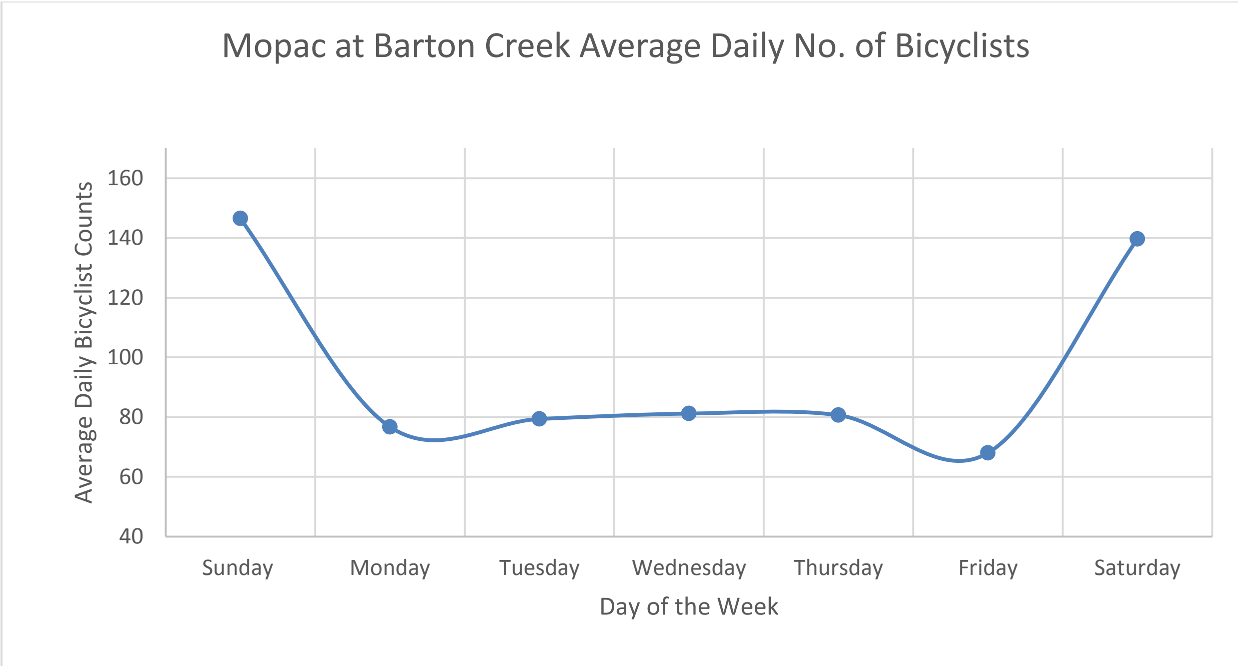


Figure 19: Pleasant Valley Road over Colorado River West Side Avg. Monthly and Daily No. of Bicyclists



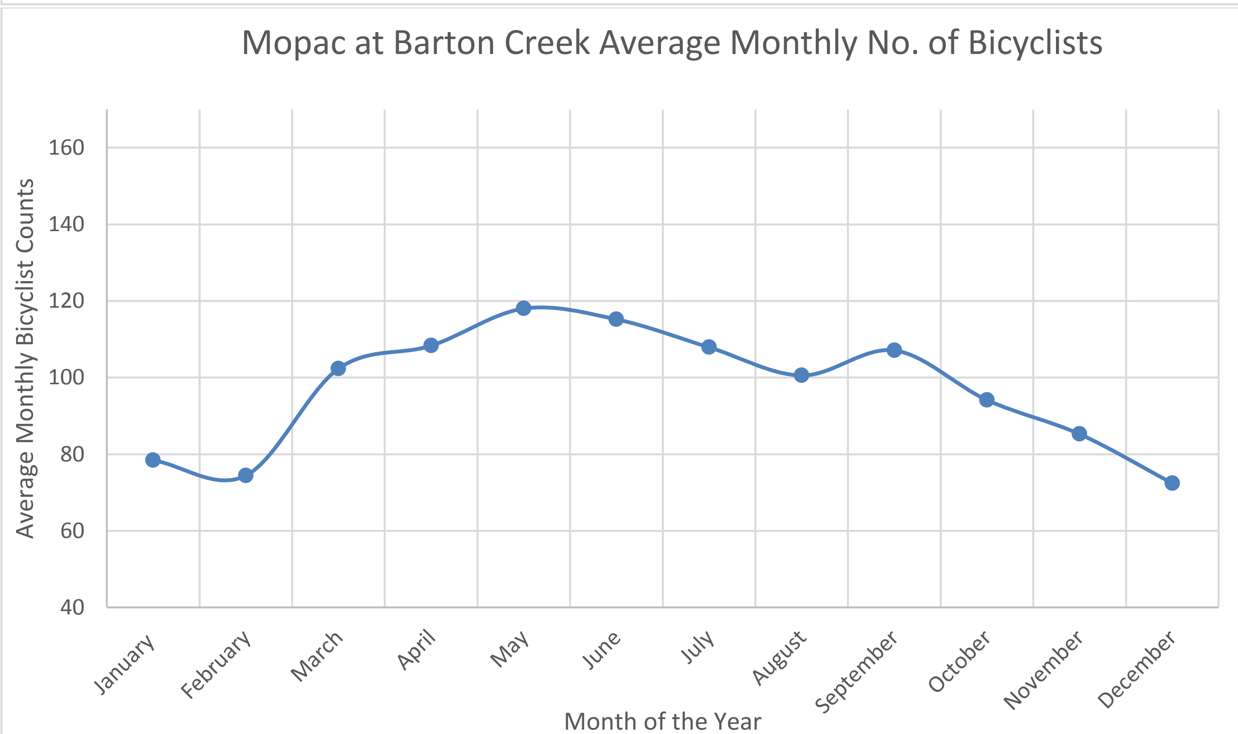
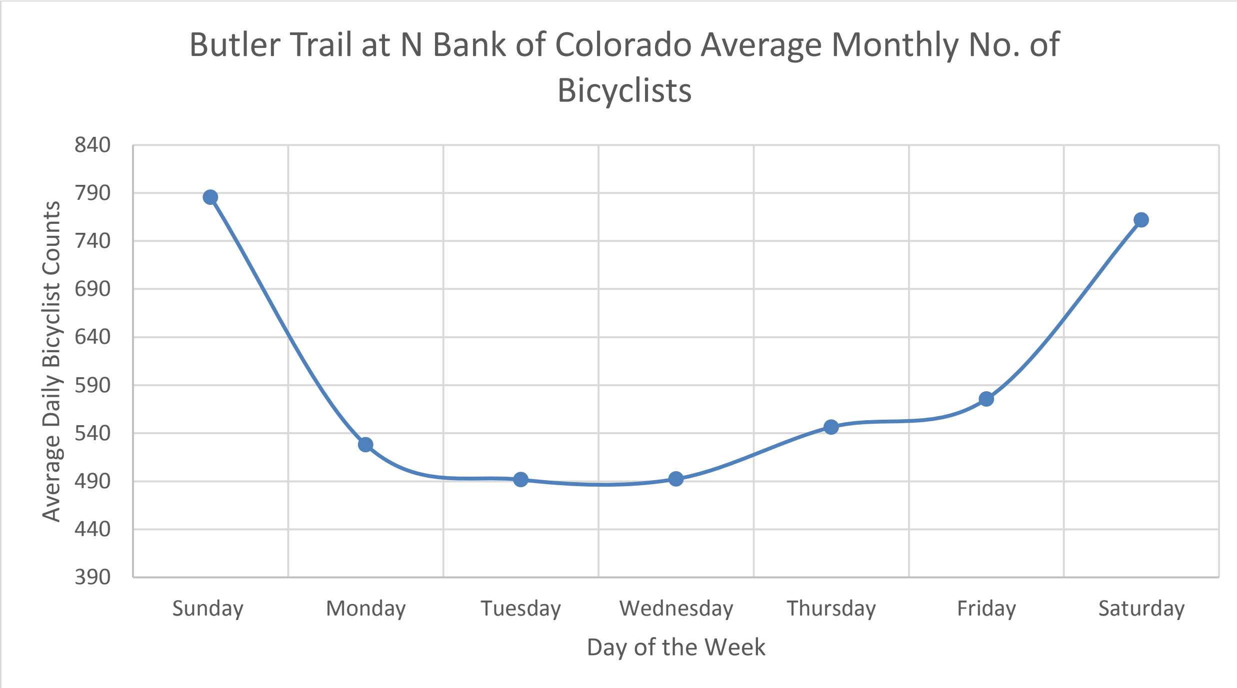


Figure 20: Mopac at Barton Creek Avg. Monthly and Daily No. of Bicyclists



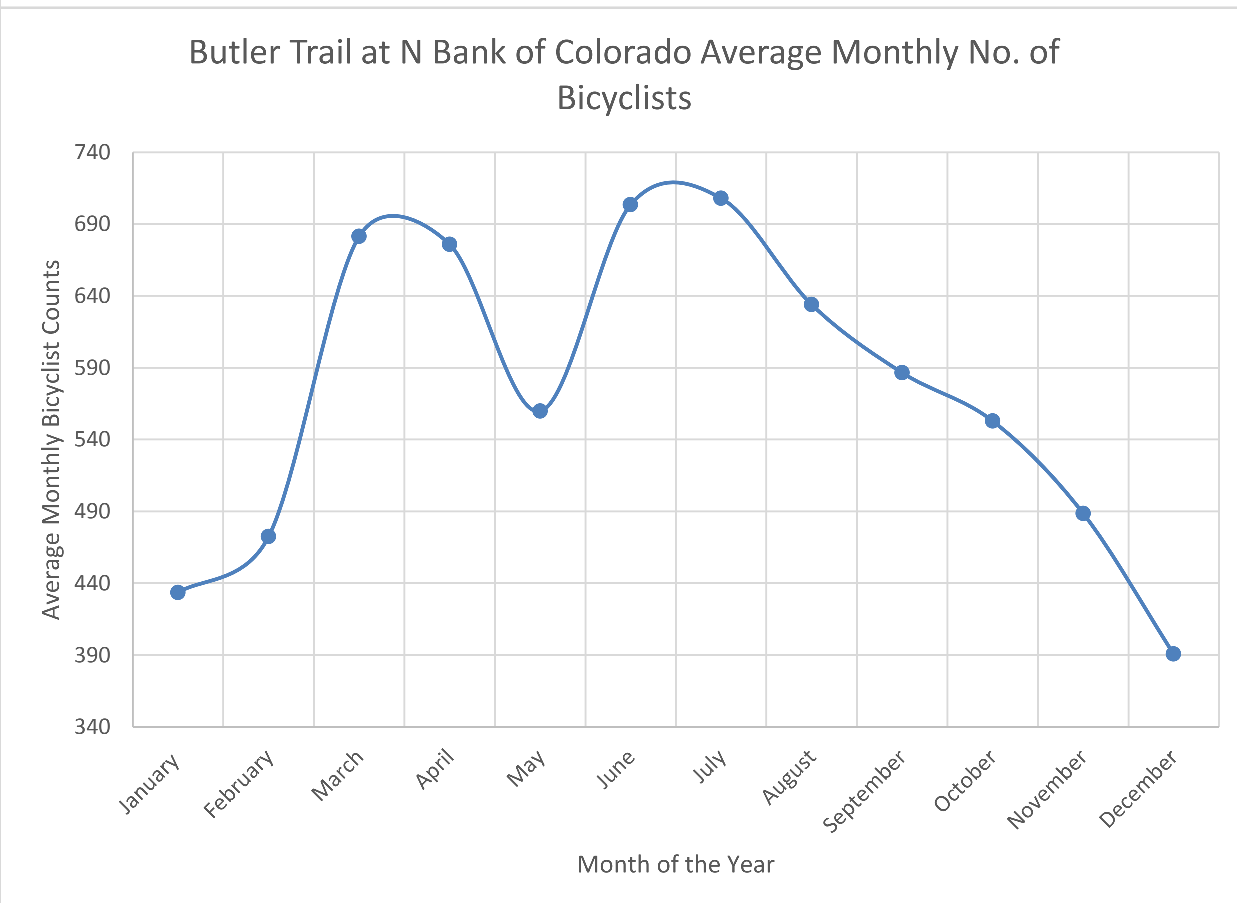
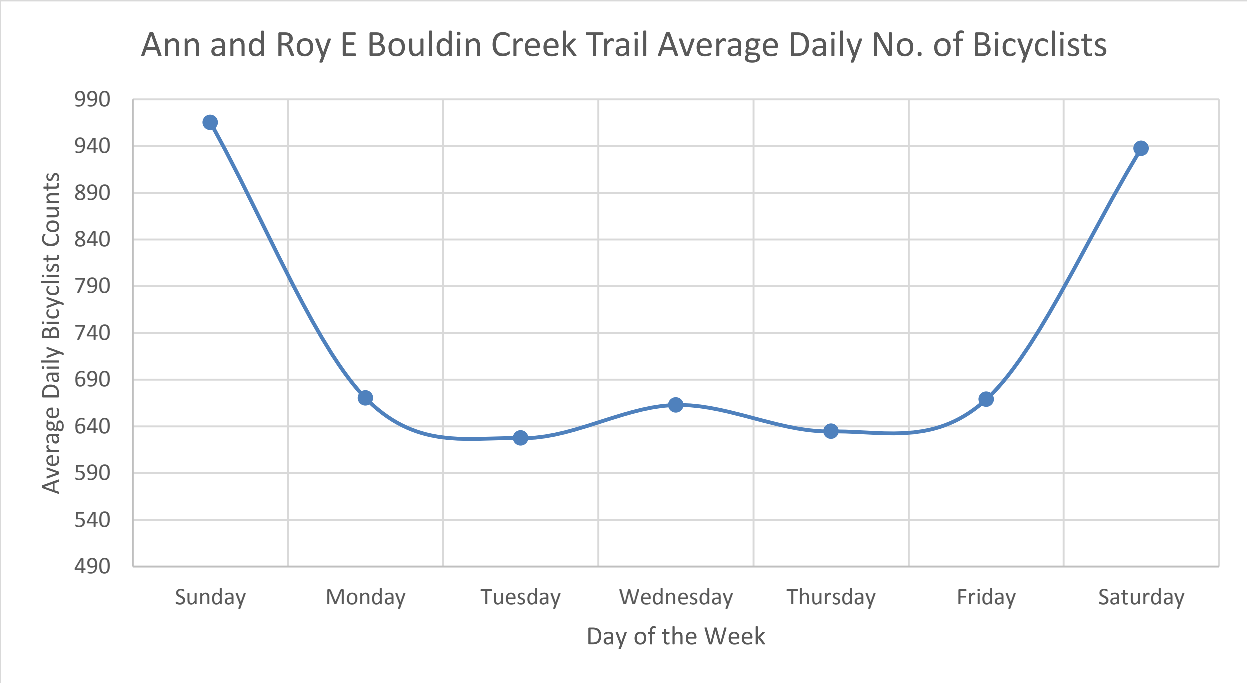


Figure 21: Butler Trail at S Bank Colorado River E of Pflueger Bridge Avg. Monthly and Daily No. of Bicyclists



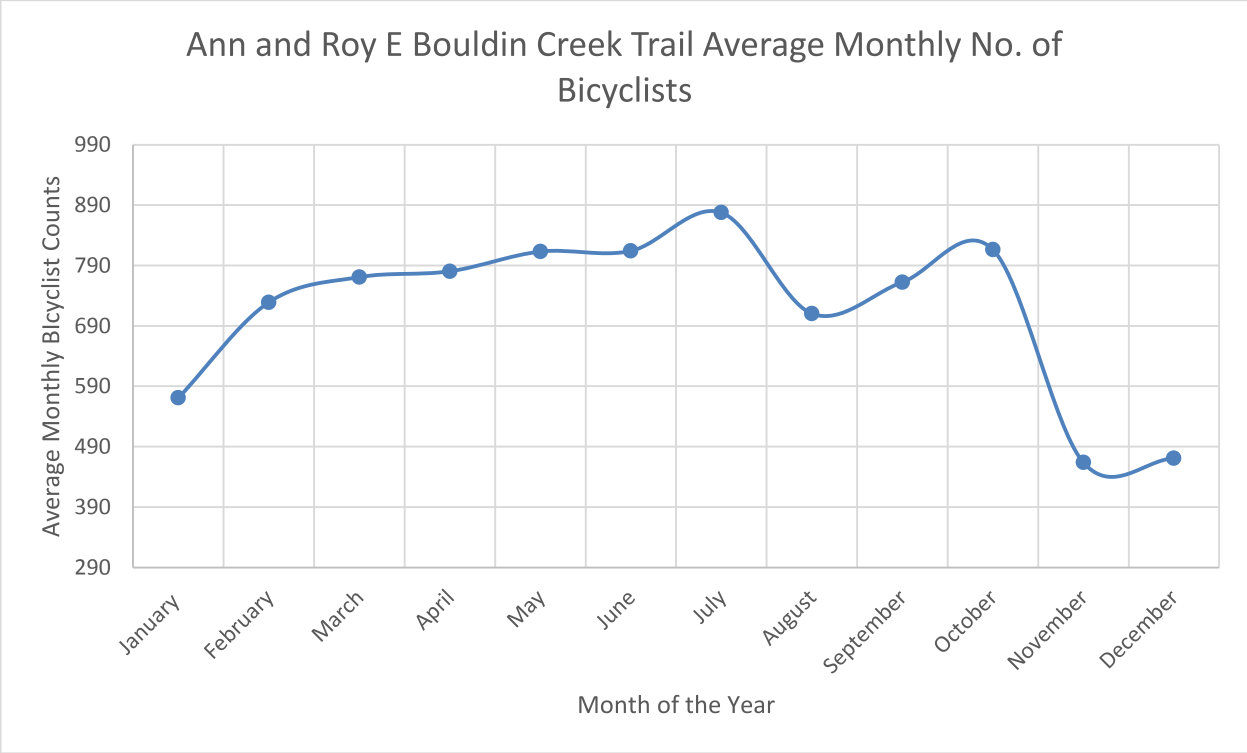


Figure 22: Ann and Roy Butler Trail at E Bouldin Creek Avg. Monthly and Daily No. of Bicyclists