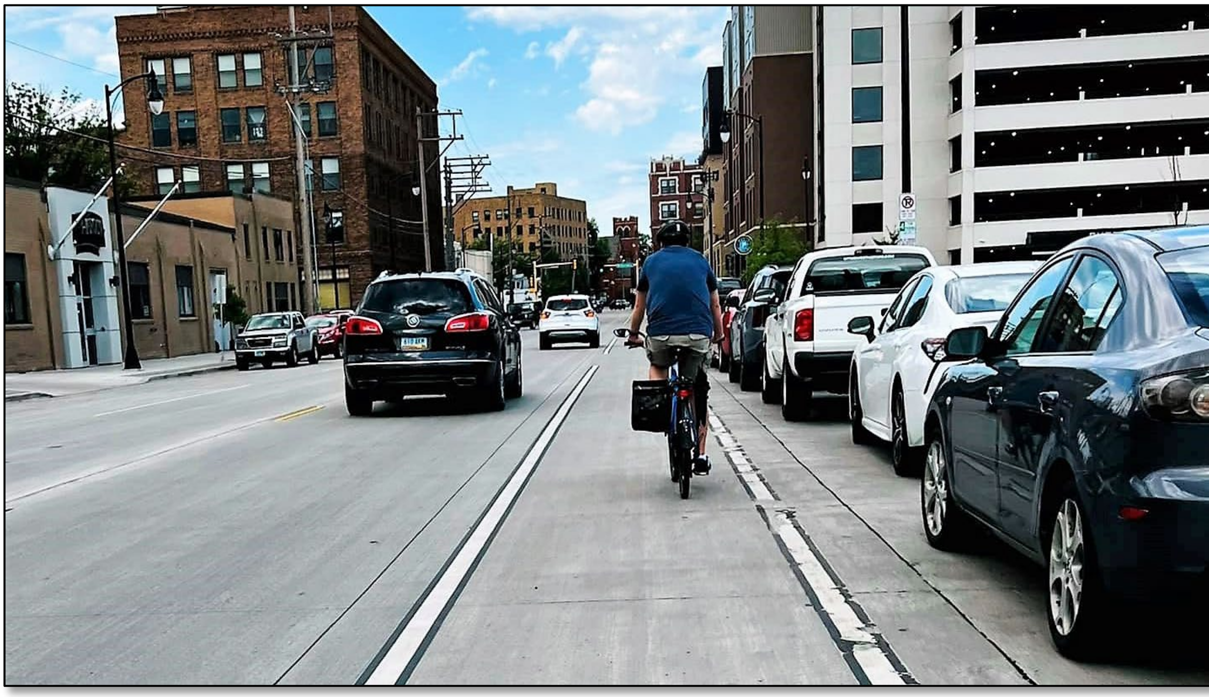
SURTCOM 22-14

Effects of Bicycle Facility Characteristics and the Built Environment on Bicycle Use: Case Study of Fargo-Moorhead



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ABSTRACT

This study developed a level of traffic stress (LTS) map for Fargo-Moorhead and used crowdsourced bicycle use data from Strava to show relationships between the built environment and bicycle use. The LTS map is useful for showing how friendly and encouraging areas are toward bicycle use, as well as for showing the connectivity of low-stress pathways, and the bicycle ridership model shows how the development of bicycle facilities and other changes to the built environment are associated with bicycle use, as measured using Strava count data. The results of the bicycle use model show that the existence of bicycle facilities is positively associated with bicycle use. This suggests that bicyclists are using the roadway design features that are meant to accommodate them, including shared-use paths, bike lanes, buffered lanes, shared-lane markings, signed-only routes, and shoulders. Other significant predictors of bicycle use included industrial employment density, which was negative, proximity to downtown or to water, low-stress connectivity, traffic volume and speed, which had unexpected positive effects, and median age.

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1. INTRODUCTION

In recent years, cities across the country have been designing new bicycle facilities, or making improvements to existing ones, to provide additional transportation options to residents and encourage increased bicycling. Types of bicycle facilities include shared-lane markings, striped paved shoulders, bike lanes, buffered bike lanes, sidepaths, bicycle boulevards, cycle tracks, and multi-use trails. While providing new or improved bicycle facilities may encourage increased bicycling, design characteristics of the street and the built environment are also important. Streets with higher traffic volumes and faster vehicles speeds, for example, may discourage bicycle use.

To measure how bicycle facility and street design characteristics affect bicycle users, Mekuria et al. (2012) developed the Level of Traffic Stress (LTS) ratings. LTS is a 1-4 rating given to a road segment or crossing indicating the level of stress it imposes on bicyclists. Criteria for rating street segments include proximity to traffic, interaction with traffic, traffic speed, and street width. A bicycle facility that is physically separated from traffic would have an LTS of 1 (lowest stress), while the LTS for bike lanes or for riding in mixed traffic can vary from 1 to 4 depending on bike lane width, bike lane blockages, street width, and vehicle speed.

The LTS rating is a theoretical model for predicting bicycling. The factors used to calculate LTS may be important for predicting bicycle use, but other factors may also be important, such as population density, employment density, land use mix, proximity to destinations, connectivity, and demographics. The objective of this research is to study how each of these factors are associated with bicycle use. The research will also show if bicyclists are using roadway design features that are meant to accommodate bicyclists.

One of the limitations for conducting this type of research is a lack of data on bicycle use. Wang et al. (2016) attempted to validate the LTS model using census data, mode choice data, and regional household travel survey data. Their results were mixed. Their study relied on survey data rather than actual bicycle count data. Recently, studies have begun using crowdsourced GPS data on bicycle use to gain a better understanding of bicycle ridership patterns across the city. One popular source of such data is Strava Metro. This study takes advantage of bicycle count data available from Strava Metro and analyze bicycle use in the Fargo-Moorhead metropolitan area.

Specific research objectives are as follows:

- Review the literature on bicycle LTS and other measures of bicycle level of service or suitability, the determinants of bicycle use, and the use of crowdsourced data for bicycle use.
- Develop an LTS map for Fargo-Moorhead
- Estimate the relationship between bicycle facility characteristics and bicycle usage.
- Identify the importance of street design characteristics on bicycle usage.
- Determine the importance of other built-environment or land-use characteristics on bicycle usage.

The remainder of this report is organized as follows. The literature review is provided in section 2. In section 3, the LTS map for Fargo-Moorhead is developed and presented. This section describes the methodology and data used and presents the results. The model for bicycle use is provided in section 4. This includes the description of the data and modeling procedure and a discussion of the results. Finally, section 5 provides a summary, conclusions, recommendations, and limitations.

2. LITERATURE REVIEW

This section reviews previous research on factors influencing bicycle mode choice and route choice, bicycle use models, level of traffic stress for bicyclists, bicycle level of service, and the use of crowdsourced data and Strava for bicycling studies.

2.1 Measures of Roadway Bicycle Use Suitability

2.1.1 Bicycle Level of Traffic Stress

Various studies have attempted to measure how comfortable or stressful an environment is for bicycling. The Geelong Bikeplan Team first developed the bicycle tension rate in Australia in 1978, as described by Harkey et al. (1998) and Sorton and Walsh (1994). The classification was used to describe how acceptable the roads were from a cycling point of view, given that they would like to reduce not just the physical effort during their cycle ride but also the mental action or tension of sharing the road with other vehicles. They described the top three crucial factors that affect their stress levels when riding a bicycle: the curb lane width, the motor vehicle's speed, and traffic volume. Multiple combinations of these variables were classified between 1, referring to a very low-stress level, and 5, a very high-stress level. These qualitative values for the same three factors were re-evaluated by Sorton and Walsh (1994). They applied the definition to ordinary cyclists, grouped into three classifications: youth, casual, and experienced riders.

More recently, the Level of Traffic Stress (LTS) rating was developed by Mekuria et al. (2012) to measure how bicycle facility and street design characteristics affect bicycle users. LTS is a 1-4 rating given to a road segment or crossing indicating the level of stress it imposes on bicyclists. Criteria for rating street segments include proximity to traffic, interaction with traffic, traffic speed, and street width. A bike facility that is physically separated from traffic would have an LTS of 1 (lowest stress), while the LTS for bike lanes or for riding in mixed traffic can vary from 1 to 4 depending on bike lane width, bike lane blockages, street width, and vehicle speed. The four levels of LTS refer to the road conditions workable for the four types of cyclists suggested by Geller (2009). Segments categorized as LTS 1 are convenient for all kinds of cyclists, while LTS 4 segments are optimal only for the most advanced cyclist; intermediate-level segments of LTS are considered suitable for moderately experienced cyclists. The LTS rating has been used in several studies to identify and select infrastructure interferences for creating low-stress routes for cyclists.

2.1.1.1 Measuring Level of Traffic Stress

LTS for a street segment is measured based on street and traffic characteristics (e.g., road width, traffic level, the existence of a parking lane) and if the bicycles are in mixed traffic, on bike paths, or separate routes, as outlined in Tables 2.1 to 2.3 (Mekuria, Furth, and Nixon 2012). A low level of stress could be reached in mixed traffic on local roads with low traffic rates. As the number of lanes, the speed of traffic, and traffic volume grow, preserving a low degree of stress demands more safety measures – designated cycle lanes and, finally, physically separated bike lanes (Mekuria, Furth, and Nixon 2012).

Table 2.1 LTS Criteria for Bike Lanes Alongside a Parking Lane

Lane factor	LTS ≥ 1	LTS ≥ 2	LTS ≥ 3	LTS ≥ 4
Through lanes per direction	1	no effect	≤2	no effect
Speed limit	25 mph or less	30 mph	35 mph	45 mph or more
Traffic Volume (AADT)	≤6300	> 6300–≤14,000	> 14,000–≤27,000	> 27,000
Functional Class	Local	Major or Minor Collector	Minor Arterial	Principal Arterial
Sum of the bike lane and parking lane width	15 ft. or more	15 ft. or more	15 ft. or more	15 ft. or more
Bike lane blockage	rare	no effect	frequent	no effect

Source: Mekuria et al. (2012) and Bearn et al. (2018)

Table 2.2 LTS Criteria for Bike Lanes Not Alongside a Parking Lane

Lane factor	LTS ≥ 1	LTS ≥ 2	LTS ≥ 3	LTS ≥ 4
Through lanes per direction	1	2, if directions are separated by a median	more than 2, or 2 without a separating median	no effect
Speed limit	30 mph or less	no effect	35 mph	40 mph or more
Traffic Volume (AADT)	≤3000	> 3000–≤6300	> 6300–≤14,000	> 14,000
Functional Class	Local	no effect	Major or Minor Collector	Minor Arterial
Bike lane width	6 ft. or more	5.5 ft. or less	no effect	no effect
Bike lane blockage	rare	no effect	frequent	no effect

Source: Mekuria et al. (2012) and Bearn et al. (2018)

Table 2.3 Target Population of LTS Criteria in Mixed Traffic

LTS Levels	LTS ≥ 1	LTS ≥ 2	LTS ≥ 3	LTS ≥ 4
Target	Safety-aware children	Most of the adult population	Confident cyclists	Fearless cyclists
Criteria for mixed traffic	2-3 lanes AND speed limit up to 25 mph	2-3 lanes AND speed limit up to 30 mph	4-5 lanes AND speed limit up to 35 mph	Any street width if speed limit 35 + mph OR Any speed limit if 6 + lanes OR Street width: 4-5 lanes AND speed limit 30 + mph

Source: Mekuria et al. (2012)

The original LTS categorized all segregated cycling facilities (shared-use paths, sidepaths) as LTS 1 (Mekuria, Furth, and Nixon 2012). However, this approach does not incorporate the possible stress of bike and motor vehicle interactions at roadways, small intersections, and loading areas. Protected bike facilities, such as side lanes, one- and two-way cycle tracks, and raised cycle tracks, are categorized as LTS 2 due to motor vehicles and cyclists' possible interaction at mid-block roadways, crossings, and loading bays.

The LTS 2 criteria are based on Dutch bike facilities planning and design criteria. Criteria for other traffic stress levels need either more isolation from traffic (for LTS 1) or increasingly less isolation (for LTS 3 and 4) (Mekuria, Furth, and Nixon 2012).

LTS also addresses intersections. The original LTS criteria included measures such as the curb radius and the right-hand turn lane length. A crossing is categorized as low stress (LTS < 3) if the method is low stress and the crossing has a short right turn lane (< 150 ft. with a pocket bike lane and <75 ft. without a pocket bike lane) (Mekuria, Furth, and Nixon 2012).

2.1.1.2 Using OpenStreetMap Data

Obtaining the data discussed in the previous section to build an LTS network could be challenging, but OpenStreetMap (OSM) could be a useful alternative. OpenStreetMap (OSM) is a crowdsourced database of geographic characteristics that include administrative borders, route centerlines, structure footprints, and physical and natural features. OSM is continually updated and provides a useful source of network data for coordination and multimodal accessibility initiatives. This resource helps millions of users worldwide who can use OSM data without limitations. The data can be used to build a base map of bicycle networks.

Some studies assessed the completeness of OSM tags and used OSM data to add LTS on networks. Hochmair et al. (2015) examined the integrity and accuracy of OSM tags linked to the bike infrastructure. They discovered a significant increase in the provision of information on cycling facilities within the OSM, and that the accuracy of this information is equal to or surpassing other datasets in Portland, Florida, Miami, and Oregon. Wasserman et al. (2019) found that OSM can create a successful LTS network with considerably less effort than traditional approaches. Murphy and Owen (2019) used OSM data to measure the utility of bicycle networks for real-world cyclists. They performed a national overview of low-stress bicycle connectivity through the use of OSM data to create low-stress bicycle networks in Minneapolis-St. Paul, Miami, Seattle, and Washington, D.C.

2.1.1.3 Use of LTS Data

LTS has been used and modified to assess bicycle network connectivity, biking behavior, accessibility, and bicycle safety. Table 2.4 shows studies that used the LTS model to identify and select infrastructure interferences for creating low-stress routes for cyclists and placing new bicycle facilities. No study, to our knowledge, has specifically validated LTS as a metric of cycling experience, but research has demonstrated a link between LTS and biking behavior. Prabhakar and Rixey (2017) studied the relationship between the level of traffic stress (LTS) and bike-share ridership in Montgomery County, Maryland. They demonstrated the effectiveness of the LTS measures in defining the impact of low-stress cycling links on ridership. They showed that the pairs of bike-share stations linked by a higher percentage of low-stress facilities had more bike-share trips. Linear regression was utilized to forecast the relationship between bike riding and low-stress bike interactions between stops, accounting for demographics, and built environment factors describing the regional context (Prabhakar and Rixey 2017). Wang et al. (2016) attempted to validate the LTS model using census data, mode choice data, and regional household travel survey data. Their results were mixed. Their study relied on survey data rather than actual bicycle count data.

Table 2.4 Studies That used LTS Model

Study	Location	Goal
Geller (2009)	Portland, Oregon	Suggest that the four levels of LTS refer to the road conditions workable for the four types of cyclists.
Mekuria et al. (2012)	California	Develop the LTS ratings.
Vogt (2015)	New Hampshire	Modify LTS to evaluate its relationship with bicycle crashes.
Wang et al. (2016)	Salem and Keizer, Oregon	Measure the link between LTS and bike mode share and trip rates.
Boettge et al. (2017)	St. Louis, Missouri	Use LTS to specific cyclists' stress experiences.
Chen et al. (2017)	Concord, Manchester, Nashua, Portsmouth, New Hampshire	LTS with bicycle injury seriousness.
Semler et al. (2017)	Washington, D.C.	Make an LTS network map as a baseline to highlight potential bicycle infrastructure investments.
Moran et al. (2018)	Philadelphia, Pennsylvania	Level street network links matching to their capacity to contribute to low-stress connectivity.
Wang et al. (2020)	Ohio, Franklin County	Analyze the interaction between bicycle network design and sharing mode.

Two studies in New Hampshire evaluated the performance of LTS in estimating bike crash risk. Vogt (2015) modified LTS to evaluate its relationship with bicycle crashes in four cities in New Hampshire. She provided a new model for assessing bicycle safety using LTS, adding bicycle crashes as an additional layer to LTS maps. Chen et al. (2017) compared LTS dimensions and crash sites using GIS. They created a bike accident severity model, which integrates LTS measurements, using a mixed logit modeling framework. Visual mapping findings suggested a geospatial association between higher LTS roads and bicycle-type accidents. They found that LTS was correlated with the severity of cycling collisions and that high LTS may have differing effects on the accident's severity. However, more analyses were suggested to better understand the statistical importance and impact of LTS on accident severity (C. Chen et al. 2017).

Other studies have used LTS to measure accessibility by bicycle. Pérez et al. (2017) and Semler et al. (2017) applied various LTS adaptations in Washington D.C. Semler et al. (2017) assessed the accessibility of cyclists in the district by using the LTS model to identify places that could benefit from bike infrastructure and attract a more significant percentage of cyclists on a low-stress network.

Semler et al. focused on data needs. They minimized the amount of data that generally need field-work collection. Their findings provided a comprehensive inventory of the road's characteristics. They suggested their approach as a creative method of classifying the bicycle network into LTS that could be adopted by other places in the United States.

Connectivity affects how convenient it is for a person to travel across a transportation system (Twaddell et al. 2018). A low-stress bicycle path is less useful and convenient if it is disconnected from other low-stress paths. Examining the level of stress for an entire route from origin to destination requires examining the network elements that make up the trip and identifying the most stressful element along that route. A route is limited by the weakest connection rule, which means that its most stressful connection measures the route's stress. The route's stress level, therefore, is not determined by the sum or average of stress levels along the route but rather the most stressful connection (Mekuria, Furth, and Nixon 2012). Stressful connections may be avoided by detours, but long detours indicate a poorly connected cycling network.

Cyclists' may be reluctant to ride their bikes for transport if a low-stress network involves a significant detour, considering their sensitivity to distance (Furth, Mekuria, and Nixon 2016). According to Schoner and Levinson (2014), the lack of a connected network can have consequences such as forcing the cyclist into mixed traffic roads, requiring longer routes to avoid a mixed traffic road, or stopping cycling altogether.

Greenways and recreational cycling paths provide a high degree of safety but often do not connect homes to critical destinations such as schools, offices, shopping centers, and entertainment facilities. If such pathways are linked, they often need long detours relative to a street network and higher stress connections. Thus, to promote cycling, high-quality, well-connected, and direct infrastructures are needed. When a network is categorized using the LTS model, different metrics can be used to evaluate connectivity. By isolating LTS-level network connections, it is possible to calculate how connectivity varies for groups with varying stress tolerances. LTS 2 and LTS 1 connections are placed in the network representation to evaluate "low-stress" connectivity.

Mekuria et al. (2012) considered that two points are connected if they can be accessed using only connections of a provided stress level while restricting the route to less than 25% beyond the shortest possible route. Two connectivity measures are established from percent of the trip linked, including a trip table, and percent of the nodes linked, which is a rougher approach if a trip table is not available.

Furth et al. (2016) developed a rating method for visualizing and assessing the deficiency of connectivity in a low-stress bicycle network. They suggested a measure for connectivity, which is the fraction of the origin-destination pairs connected without high tension or unnecessary detour, with the origin-destination pairs weighted by the travel demand. Moran et al. (2018) applied LTS connectivity analysis to assess potential connectivity improvements from individual street-level projects.

Research on low-stress connectivity can also be extended to show bicycle access to jobs or other destinations. Faghih Imani et al. (2019) built a city-wide stress cycling network for the city of Toronto and found a low level of cycling connectivity to employment (< 5000 jobs) across the city at lowstress levels (LTS≤2). The relation between low-stress access to work and the decision to cycle from home was explored using a binary logit model. The findings show that the measure of cycling accessibility, particularly low-stress access, has a significant impact on cycling as a mode of transportation (Faghih Imani, Miller, and Saxe 2019). Wang et al. (2020) similarly analyzed the effect of the LTS network on bicycle mode shares for commuting to work. They found that increasing the proportion of LTS 2 road segments was positively associated with the share of bicycle commuters, but no relationship was found between the proportion of LTS 1 road segments and bicycle mode shares, and social and cultural factors were found to be more significant predictors of decreases in automobiles.

Other studies have focused on perceived factors to evaluate and place new bicycle facilities. Boettge et al. (2017) suggested that active cyclists should be consulted to integrate users' site-specific information into cycling infrastructure evaluations. They conducted an approach that surveys cyclists' stress levels along the roads in St. Louis, MO. They found stress associations with speed limit, highway classification, and the number of lanes. The survey prioritizes streets with bike lanes to roads with shared lane markings or no infrastructure. The existence of cycling infrastructure did not correlate with the documented levels of stress (Boettge, Hall, and Crawford 2017).

In addition to these studies based on LTS rating, many studies have incorporated geographic information systems (GIS) in their analysis. A new study proposed an information approach for road classification based on LTS, which relied on a clustering component combined with statistically tuned models and easily accessible road network data. Huertas et al. (2020) used the clustering component, which provided a quick and effective way of separating related road network segments. They merged government data with open-access repositories utilizing geographic information systems (GIS) to identify road segments. The interpretative component accounts for assigning the LTS classification to the road segments) considering the location-specific context. They introduced their LTS-based classification technique in Bogotá, Columbia, applying LTS divisions low, medium, high, and extremely high, compatible with this Latin American metropolis's characteristics.

Bearn et al. (2018) proposed an adapted LTS measure in terms of traffic, highway, and bikeway attributes to the data applicable to most planning and engineering organizations. The adapted LTS was used to identify and assess the bike network's connectivity in two case studies in Atlanta to test the technique and illustrate realistic implementations for infrastructure management. The research was performed in ArcGIS and offered findings that can be readily understood by the public and decision-makers while focusing on quantifiable road and route characteristics.

To understand the route preferences and the level of low-stress cycling link between origins and destinations, Crist et al. (2019) evaluated GPS trip data from utilitarian bikers, who are those riding bicycle for transportation purposes rather than leisure or recreation. GPS data were gathered from adult cyclists over several days. The LTS score was allocated to all bikeable road segments in the network. The shortest routes between origin and destination along bikeable roads and low-stress routes (LTS 1 or 2) were determined. They connected road paths to the LTS network, and the LTS and distances observed were compared to the shortest and lowest stress roads. LTS maps were created to demonstrate the shortage of low-stress links (Crist et al. 2019).

Some studies have analyzed the effects on bicyclists from riding in high-stress conditions. Physiological factor-based methodology studies used technologies to evaluate biological responses to conditions experienced by the bikers. To assess the effect of cycling on physical and mental health, Jones et al. (2016) studied 240 participants in U.K. cities. The galvanic skin response (GSR) data revealed that high tension levels relate to video observations and rider accounts of pedestrian disputes in many cases. They discovered that the GSR baselines varied considerably depending on the subject, and to address this problem, the participant data are distributed in three bands of different colors for high, medium, and low measurements. Locations where participants displayed elevated GSR values corresponded to intersections where participants suggested that they had safety issues (Jones, Chatterjee, Spinney, Street, van Reekum, et al. 2016). Another study closely related to this research quantified traffic and bicycle facilities' effect on average stress levels. Caviedes and Figliozzi (2018) suggested an innovative approach: real-world, on-road physiological stress assessments as bicycles ride through various types of cycling facilities at peak and off-peak traffic hours. By comparing videos with stressful activities, it was possible to observe the conditions of these stressful events.

2.1.2 Bicycle Level of Service and Other Measures

The LTS rating is one measure of the compatibility of street segments to bicycle use, but various similar measures have been developed over the years. One such alternative is the Bicycle Level of Service (BLOS), described in the Highway Capacity Manual (HCM). This model is based on 10 features (including speed, geometric characteristics, and volume) used to produce a numeric ranking, then converted into a letter rating to describe bicycling convenience and safety (M. Lowry et al. 2012). The HCM-based LOS is a qualitative method used to measure the ease of adaptability of the traffic flow, primarily from the point of view of traffic service. However, the biker-perceived LOS puts a great deal of focus on the safety of bikers, in addition to the organizational criteria (Turner, Shafer, and Stewart 1997). This method is based on 10 features: 1) width of outside lane, 2) width of bicycle path, 3) width of shoulder, 4) quantity of busy on-street parking, 5) vehicle traffic volume, 6) vehicle speeds, 7) percent heavy vehicles, 8) pavement condition, 9) existence of curb, and 10) quantity of through lanes (M. Lowry et al. 2012). Table 2.5 identifies examples of studies using the BLOS model

Table 2.5 Studies That Used LOS Model

Study	Location	Method
Dowling (2008)	Several different metropolitan areas of the United States	Highway Capacity Manual 2010 LOS
Landis et al. (1997)	Different urban sections of the United States	Bicycle level of service (BLOS)
Jensen (2007)	Denmark	Danish BLOS
Dixon (1996)	Gainesville, Florida	Gainesville bicycle LOS
Foster et al. (2015)	Chicago, Illinois; Portland, Oregon; and San Francisco, California	LOS for protected bike lanes
Kang and Lee (2012)	South Korea	BLOS

Several studies have developed comprehensive measures to assess the bicycle level of service (BLOS), comfort, and roadway safety. They used different approaches to assess the satisfaction of bikers with the street environment. Approaches involved field surveys (e.g., volunteers taking a prescribed course), video labs, and web-based interest surveys. Many studies have developed strategies that forecast the mean level of service that would be listed by bikers. Most of the studies estimate the level of service of bicycles for street segments between signaled intersections. A few studies are based on forecasting the overall level of service on the arterial route. Petritsch et al. (2007) produced an arterial LOS method for bikers focused on a combination of video lab and field surveys. LOS reports were collected from 63 volunteers who took the 20-mile course in Florida in November 2005.

Examples of segment LOS methods based on field surveys or video lab are Landis et al. (1997) and Jensen (2007). Landis et al. (1997) produced the earliest statistically calibrated BLOS method for road segments depending on real observations of 145 bikers worldwide. They designed cycling safety in terms of traffic flow, the number of lanes, speed limits, the proportion of heavy traffic, accessibility to land use, the outside lane's width, and pavement. The safety and comfort levels for the different road segments were measured from A to F. Jensen (2007) produced a BLOS method under Danish conditions. The Danish BLOS uses a cumulative-logit method that estimates the percentage of consumers in each of the six BLOS grades from "very satisfied" to "very dissatisfied." The Danish BLOS method is more detailed than the HCM BLOS and BCI; the Danish BLOS model weighted the effect of on-road bicycle roads and bike tracks separately (Jensen 2007). Foster et al. (2015) sought to create the first BLOS method for protected cycle paths.

Dowling et al. (2008) developed LOS models in National Cooperative Highway Research Program (NCHRP) Report 616. They established a model for evaluating how well an urban street addresses the needs of all its travelers: car owners, bus travelers, bike riders, and pedestrians. Four different LOS methods (one for each mode) were inserted into the data of the video lab and field survey. The methods integrate the interactions of the other street users, both consciously and implicitly. They recommended an Integrated Multimodal LOS Model Framework for urban street users. The National Cooperative Highway Research Program Bicycle Level of Service (NCHRP BLOS) was written as a spreadsheet software engine and delivered to assist analysts in applying the LOS methods (Dowling et al. 2008).

Griswold et al. (2018) argued that the quality of bicycle level of service measures could be enhanced based on empirically measured cyclist choices and expectations. They studied cycling patterns, interests, and user experience in the San Francisco Bay Area. They matched the facility preferences collected from a survey to the scores from the National Cooperative Highway Research Program Bicycle Level of

Service (NCHRP BLOS) and level of traffic stress (LTS). By combining statistics and behavioral analysis, they could improve the quality of bicycle level of service measures.

Lowry et al. (2016) developed a new method for classifying bicycle stress based on the economic concept of the marginal rate of substitution (MRS), which is the rate at which a consumer is willing to give up one good in exchange for another. For bicyclists, MRS values can be evaluated based on analyses of route choices. For example, analysis of bicycle behavior may show that a bicyclist is willing to travel a certain distance farther in a bike lane than on a similar street without a bike lane. How much father they would be willing to travel to take that route provides information about how much less stressful, or more comfortable, it is to travel in a bike lane. Lowry et al. (2016) used these MRS values, along with the number of lanes and the speed limit, to reflect bicycle stress.

Although the BLOS approach may, in theory, be used to rank the streets, it has some functional weaknesses. One is that it needs traffic volume and lane width data that are often inaccessible. The second is that there is no direct correspondence between the level of BLOS and the tolerance of the user; that is, the method does not seek to define a specific level of service as the minimum needed to support the majority population (Mekuria, Furth, and Nixon 2012).

The Bicycle Compatibility Index (BCI) developed by Harkey et al. (1998) is another alternative. This index enables engineers to assess how appropriate a roadway is for bikes and motor vehicles' efficient operation simultaneously. This approach was developed based on speed, geometric data, and traffic volume. The BCI represents the variations between urban and suburban road segments. The sites chosen for the research were situated in five cities, reflecting various geographical conditions found in the United States. They watched a videotape of multiple road segments and assessed how comfortable they would feel traveling on each segment. The BLOS method and the BCI discuss the comfort of the bicycle along the road. The BCI method includes several additional aspects that may influence bikers' perceived comfort and safety level. This approach takes into account the existence of a bicycle lane or paved shoulder, the width of the bicycle lane or pavement shoulder, the width of the lane, the volume of the lane in one direction, the volume of the opposite lane, the 85th percentile speed of traffic, the existence of a parking lane of more than 30% occupation, the style of roadside construction and a modification factor for the volume of trucks, the turnover of parking spaces, and right-turn volumes.

2.1.3 Summary

The level of traffic stress (LTS) method was created to measure, track, and enhance bicycle networks' suitability. To properly reflect the acceptable tolerances of different types of riders, experts have established the LTS method. Due to its relative ease of data collection, LTS has rapidly become a standard used by researchers to calculate, track, and improve the bicycle network. The idea of bicycle stress levels was first created in 1978 by the Geelong Bikeplan Group in Australia (Harkey et al., 1998; Sorton & Walsh, 1994). A bicycle facility that is separated from traffic would have an LTS of 1 (lowest stress), while the LTS for bike lanes or for riding in mixed traffic can vary from 1 to 4 depending on bike lane width, bike lane blockages, street width, and vehicle speed (Mekuria, Furth, and Nixon 2012).

The Bicycle Level of Service (BLOS) method is focused on the level of comfort provided by subjects who have completed a course involving a variety of bike paths and traffic situations. By linking those comfort levels to the characteristics of the different areas, they established a method for estimating the comfort rating that a person would assign to a road connection based on features such as traffic speed, traffic volume, the existence of a bike lane, the existence of a parking lane, whether the area is residential or not, and the volume of operating space accessible to bikes. Predicted levels are then classified into six levels of service, from A (best) to F (worst).

The LOS models could be used to compare the trade-offs between various street cross-sections from the viewpoint of each mode. LOS measurement is utilized as a traffic management system technique to establish project guidelines and goals but could also be useful for parallel and long-range transportation planning. A variety of methods were used to develop the various modal LOS models (Table 2.5).

2.2 Determinants of Bicycle Use

Bicycle use can be influenced by the characteristics or presence of bicycle facilities, characteristics of the street or street network, the built environment, and individual characteristics. Several studies have analyzed how these various factors are related to bicycle use.

First, research has shown the relationship between bicycle facilities and bicycle use. Studies have shown that bike lanes have a positive effect on bicycling (Pucher, Dill, and Handy 2010; P. Chen, Shen, and Childress 2018; Zhao 2014; Buehler and Dill 2016). The characteristics of bike lanes can be important. Some research has shown greater comfort for bicyclists with wider lanes or buffered lanes because of the greater separation from traffic and from opening doors of parked cars (Buehler and Dill 2016). Studies have also shown a greater preference for separated facilities (Buehler and Dill 2016; Watkins et al. 2020). Watkins et al. (2020) found separated lanes with no curb parking as being rated the most comfortable.

Connectivity of bicycle infrastructure is also important. While individual bike lanes or paths may be useful, encouraging bicycle use requires a network of connected bicycle facilities. Studies have shown that a dense network of connected bicycle facilities helps increase bike trips (Buehler and Dill 2016).

In addition to bicycle infrastructure, the characteristics of streets and the street network are also important determinants of bicycle use. A network with greater street density, intersection density, and connectivity is easier to navigate by bicycle. Cervero et al. (2009) found that street density is positively associated with bicycling, and other research has shown the importance of connectivity (Zhao 2014; Y. Wang et al. 2016).

The width of streets and the speed and volume of automobile traffic can also play a role. Neighborhood streets with low volumes of automobile traffic are more attractive for bicycle use. While studies have shown that adding bike lanes to busier streets increases bicycle comfort and use on those streets, these bike lanes are not necessarily any more attractive than bicycling on a low volume street (Broach, Dill, and Gliebe 2012).

Research has shown that traffic calming efforts and reduced automobile speeds have had positive effects on bicycling (Pucher, Dill, and Handy 2010; P. Chen, Shen, and Childress 2018; Buehler and Dill 2016; Cui, Mishra, and Welch 2014). Cyclists have also been found to be sensitive to traffic volumes (Broach, Dill, and Gliebe 2012; Buehler and Dill 2016; Cui, Mishra, and Welch 2014), slope (Broach, Dill, and Gliebe 2012; P. Chen, Zhou, and Sun 2017; P. Chen, Shen, and Childress 2018; Cervero et al. 2009; Fraser and Lock 2011), intersection control (Broach, Dill, and Gliebe 2012), turn frequency (Broach, Dill, and Gliebe 2012), and distance (Broach, Dill, and Gliebe 2012; P. Chen, Shen, and Childress 2018; Fraser and Lock 2011). Additional vehicle lanes also tend to decrease cyclist comfort in most cases (Watkins et al. 2020). Focus groups conducted by Watkins et al. (2020) revealed that curbside parking was one of the biggest deterrents to bicycling. Bicyclists may be less likely to choose a route that has more traffic signals or, to a lesser extent, stop signs, unless conflicting traffic volumes are high, in which case signals are preferred (Broach, Dill, and Gliebe 2012; Buehler and Dill 2016).

Sensitivity to many of these factors vary between individuals. Inexperienced bicyclists have greater fear of motorized traffic (Buehler and Dill 2016). Experienced bicyclists tend to prefer on-street lanes to bike paths (Pucher, Dill, and Handy 2010). Bike commuters are less sensitive to car traffic volume and speeds (Buehler and Dill 2016). Preferences may also differ depending on the purpose of the bicycle trip. For example, cyclists are more sensitive to distance for commute or utilitarian trips (Broach, Dill, and Gliebe 2012).

Studies of bicycle use often control for demographics, including age, gender, income, education, car ownership, and employment status, and some also control for psychological factors, such as attitudes and perceptions (Buehler and Dill 2016). Watkins et al. (2020) found that age and education had significant effects on comfort, safety, and willingness to try using bicycle routes. Some research has shown greater bike use in neighborhoods with a higher percentage of white population and younger adults (P. Chen, Zhou, and Sun 2017). Studies have also found that attitudes are important in predicting bicycling behavior (Ma and Dill 2015). Watkins et al. (2020) found that attitudes regarding car dependence, bike enjoyment, active travel, and risk-taking were important.

Areas with higher employment density have also been found to have greater bicycle use (P. Chen, Zhou, and Sun 2017; Cui, Mishra, and Welch 2014), as have areas with mixed land use (P. Chen, Shen, and Childress 2018; Zhao 2014; Y. Wang et al. 2016). Some research has also shown increased bicycling in areas with greater population density, household density, and school enrollment density (Cui, Mishra, and Welch 2014). Cyclists may also prefer routes near water, parks, and trees (P. Chen, Shen, and Childress 2018; Fraser and Lock 2011).

2.3 Crowdsourced Bicycle Use Data

One of the major challenges to bicycle research and understanding bicycle usage is a lack of bicycle count data. Collecting bicycle count data manually or with automatic counters can be time consuming or expensive, so the number of locations for which bicycle count data are available is limited in most cities. This is especially true in smaller cities.

In Fargo-Moorhead, the Metropolitan Council of Governments (Metro COG) has placed a total of five automated counters at various locations. These counters count passersby throughout the year, but they have several drawbacks. They are limited to just five locations; they may undercount the number of people traveling in a group, counting two people as one; and most importantly for bicycle analysis, they do not differentiate between bicycles and pedestrians. In addition to these five automatic counters, there is one automatic counter installed by the Minnesota Department of Transportation (MnDOT) that is able to differentiate between bicycles and pedestrians, but having just one counter is of limited use for bicycle analysis and is certainly not capable of helping us understand how bicycle volume varies through the city and the factors that contribute to that variation.

Metro COG supplements the automated counters with manual counts conducted at 16 locations in the Fargo-Moorhead metro area. These counts are conducted once a year for a four-hour period on a typical weekday in September (some locations are counted for two consecutive weekdays, depending on availability of staff and resources). These counts differentiate between pedestrians, bicyclists on the path/sidewalk, and bicyclists on the street. The manual counts are more useful for bicycle research because they differentiate between bicycles and pedestrians and they cover a larger number of locations, but the data are still limited in that they are collected over a short period of time, and 16 locations is insufficient for detailed analysis. Understanding how variations in bicycle facilities, street design, and other factors influence bicycle use requires much more extensive count data.

One potential solution to this data problem is the use of crowdsourced data. In recent years, researchers have begun using crowdsourced data to study various problems relating to bicycle use. This includes crowdsourced data to map ridership, assess safety, map infrastructure, and track attitudes (Nelson et al. 2020). Crowdsourced ridership data can be obtained through fitness apps that collect data by using GPS-enabled smartphones or other GPS devices. One of the more popular of these apps is Strava. Strava also provides a data product, called Strava Metro, that has emerged recently as a new data source for analyzing bicycle ridership. Strava data have been shown to have potential for identifying travel patterns, estimating travel demand, and analyzing route choice (Lee and Sener 2020; Alattar, Cottrill, and Beecroft 2021). The data have also been used to study bicycle safety (Ugan et al. 2022; Fischer et al. 2022), gender inequality (Battiston et al. 2022), bicyclist exposure to air pollution (Lee and Sener 2019), and behavioral changes during and following the COVID-19 pandemic (Venter et al. 2021; Schweizer et al. 2021).

Strava users track their bicycle trips with their phone or GPS device and share that data with the Strava app. Strava Metro removes any identifiers from the data, aggregates the data, and provides the data to transportation planners. Researchers have shown that, while the data have limitations, Strava Metro data can be used to analyze ridership and evaluate the impact of infrastructure changes. These data have the advantage of extensive coverage, providing far more data than could be collected using traditional methods. Griffin et al. (2020) argued that while big data, such as crowdsourced data, has potential biases, it should be used to address transportation challenges not solvable using traditional methods, including planning for bicycling, pedestrian, and emerging transportation modes.

2.3.1 Bias in Strava Data

One potential concern in using crowdsourced data such as Strava is that the data may not be representative and could be biased. This bias could be expected because only a small percentage of bicycle riders use Strava. Strava users are limited to those with access to the technology and the motivation to use it. If transportation decisions are based on the behavior of those who use a particular technology the most, others could be excluded, and urban equity issues could worsen (Nelson et al. 2020).

Lee and Sener (2020) reviewed studies that have applied Strava data and found that these data typically represent 1-5% of total bicycle volume. Bias could occur if certain groups of people are more likely to use Strava or if Strava is more likely to be used for certain types of trips. Both sources of bias could be concerns. Research on the degree or seriousness of the bias is mixed.

Studies indicate Strava users are more likely to be male and aged 25-44 (Lee and Sener 2020). However, bicycle users, in general, are also more likely to be male and younger. Children are not represented in the Strava data, because Strava policy restricts users to those who are 16 or older. Nelson et al. (2020) concluded that despite demographic bias, the spatial patterns may be representative.

Because Strava is a fitness app, it may be more likely to be used for exercise or recreational trips and less for utilitarian or commute trips. Garber et al. (2019) found that fitness app users, not specifically Strava users but users of any smartphone app for recording rides, rode proportionately more for leisure. These apps are not exclusively used for leisure or fitness, as Garber et al. (2019) found most users commonly report utilitarian trips, and Lee and Sener (2020) found that about 20-40% of Strava cycling is for commuting, but Garber et al. (2019) concluded that the app data may over-represent recreational rides. Kwayu et al. (2021) also recommended that data from fitness apps be complemented with other data sources to capture travel behaviors of both commuting and recreational riders.

Bicyclists riding for recreation may choose different routes or use different types of facilities than those riding for utilitarian purposes. Those riding for utilitarian purposes may be more likely to choose the shortest route, avoid hills, and use on-street facilities, while recreational riders may be more likely to use separated paths and may seek challenging terrain (Garber, Watkins, and Kramer 2019; Griffin and Jiao 2015). While some research found that Strava users prefer steeper terrain (Griffin and Jiao 2015), other research found that Strava users prefer flatter segments (Lin and Fan 2020b).

Sultan et al. (2017) analyzed crowdsourced data in the Netherlands and Germany and found bicyclists commonly prefer longer routes through safe, more attractive, and popular areas. While Strava data could be biased toward recreational, off-street trails, Hochmair et al. (2019) found just the opposite. They found that Strava under-counted ridership on these trails, which they speculated could be due to Strava users wanting to ride at a faster pace and therefore selecting on-street riding. Some research, such as that by Sanders et al. (2017) in Seattle, has found no discernible bias in the Strava data toward recreational riding. Garber et al. (2019) also concluded that at the individual level, app users and non-app users had similar infrastructure preferences. Jestico et al. (2016) concluded that in urban areas, recreational riders and commuters may use the same routes.

Based on this review of the literature, there is a possibility of demographic and spatial bias within the Strava data. However, the evidence regarding the size and seriousness of the bias is inconclusive and mixed.

2.3.2 Correlation Between Strava Counts and Official Bicycle Counts

Despite potential bias, some studies have shown that the Strava counts are significantly related to observed bicycle counts (Jestico, Nelson, and Winters 2016; Dadashova and Griffin 2020). Jestico et al. (2016) concluded that even though Strava users represent a small portion of all cyclists, the crowdsourced data may be a good proxy for estimating cycling volumes. Research has shown strong correlations between Strava counts and observed count data. Lee and Sener (2020) reviewed several studies that found correlations greater than 0.75 between Strava data and actual count data. Conrow et al. (2018) found a correlation of 0.79 in Sydney, Australia. They found the correlation to be higher in areas with lower population density, greater social disadvantage, and lower ridership overall.

Lee and Sener (2020) concluded that Strava data can be generalizable to the entire population, but the validity of the results may depend on temporal aggregation and the analysis site. Large enough time and spatial frames should be used to improve the validity of the results. One potential problem with the Strava data is that Strava does not report counts on segments with fewer than three users, for privacy reasons, which could result in ridership not being counted on some segments. The sampling issues with Strava could be corrected by using a longer time frame or larger spatial aggregation (Lee and Sener 2020).

2.3.3 Modeling with Strava Data

A few studies have developed models to understand the effects of the types of bicycle facilities, road network characteristics, land use characteristics, demographics, terrain, and other factors on bicycle use, as measured by the count of Strava users (Dadashova and Griffin 2020; Griffin and Jiao 2015; Hochmair, Bardin, and Ahmouda 2019; Jestico, Nelson, and Winters 2016; Lin and Fan 2020b; Orellana and Guerrero 2019; Garber et al. 2022; Munira and Sener 2020). These studies developed regression models using the Strava counts as the dependent variable (Table 2.6). Some of these studies aggregated Strava data at the census block group level (Griffin and Jiao 2015; Hochmair, Bardin, and Ahmouda 2019). Others used street segments as the unit of analysis (Lin and Fan 2020b; Orellana and Guerrero 2019).

Table 2.6 Studies That Have Modeled Strava Bicycle Counts

Study	Location	Explanatory Variables
Dadashova and Griffin (2020)	Texas	Roadway facility, household income, demographics, population density, weather conditions
Griffin and Jiao (2015)	Travis County, Texas	Gross activity density, regional diversity, average percent slope, bike lanes, bike paths, roadway shoulder > 1.2 meters
Hochmair et al. (2019)	Miami-Dade County, Florida	Road network characteristics (functional class, bicycle facility type, off-street paths, intersections, network impedance, betweenness centrality), built environment characteristics (bicycle park, bridge, distance to central business district, distance to ocean or bay, near university, mixed density index, greenness), socio-demographics (income, race, gender, number of jobs, median age, car ownership)
Jestico et al. (2016)	Victoria, British Columbia	Slope, population density, pavement widths, on-street parking, posted speed limits, bicycle facilities
Lin and Fan (2020b)	Charlotte, North Carolina	Temporal variables, road characteristics (length of road segment, number of lanes, one-way), sociodemographic characteristics (household income, total households), geometry (slope), bicycle facilities (off-street paths, bike lanes, signed bike lanes, suggested bike routes)
Orellana and Guerrero (2019)	Cuenca, Ecuador	Social-economic and land use conditions (household density, living conditions index, and land use mix), infrastructure variables (road hierarchy, existence of segregated bike lane, number of intersections), physical conditions (slope)
Munira and Sener (2020)	Austin, Texas	Age, education, income, frequency of schools and office establishments, distance from transit hub, number of transit stops, sidewalks, and trails

These studies found significant associations between Strava counts and bicycle facilities, roadway characteristics, and other factors. Griffin and Jiao (2015) found greater bicycle volumes for roads with bike lanes, shoulders, and paths, and bike use was found to be greater in and near populated places with businesses. They also found greater volumes on roads with challenging terrain, likely because of Strava users seeking the challenge, though other studies have found that slope has a negative effect. Orellana and Guerrero (2019) found that the road hierarchy and segregated cycle paths had a strong influence on bicycle use. Hochmair et al. (2019) showed that on-road cycling facilities on low-traffic roads and off-road trails are associated with an increase in bicycle use for Strava users, and that bicycle facilities on arterial roads did not affect bike use. Lin and Fan (2020b) concluded that variables associated with providing higher safety and comfort levels, such as off-road paths and suggested bike routes, are positively associated with bike use.

Chen et al. (2017) examined the correlation between Strava data and the bicycle level of traffic stress (LTS). They found that roadways with LTS 2 have the most total Strava trips and those with LTS 4 have the least. In general, they found Strava users tended to choose routes with lower LTS, which is expected as those roadways with higher LTS are less safe for bicyclists.

Some research has used Strava data to examine the impacts of new bicycle infrastructure (Boss et al. 2018; Heesch et al. 2016). Boss et al. (2018) used Strava data to compare changes in ridership following three infrastructure projects in Ottawa-Gaineau, Canada, and they found cyclists shifted their routes to take advantage of the new infrastructure.

Spatial autocorrelation needs to be considered when modeling with Strava data (Griffin and Jiao 2015; Hochmair, Bardin, and Ahmouda 2019; Lee and Sener 2020). Griffin and Jiao (2015) employed a geographically weighted regression. Hochmair et al. (2019) used a spatially filtered regression model, and they noted that several coefficients that were significant in other studies and in their nonspatial models became insignificant in the spatially filtered regression model.

Using Strava data in conjunction with other data sources could provide improved bicycle ridership estimates. Some studies have attempted to correct for biases in the Strava data and provide improved estimates of bicycle use. These studies developed models of bicycle use with the official bike counts at counting locations as the dependent variables and Strava counts as one of the independent variables. For example, Sanders et al. (2017) modeled bicycle use in Seattle as a function of land use variables, transportation system variables, and Strava counts. They found that the model fit improved by adding the Strava data. Lin and Fan (2020a), similarly modeled bicycle manual counts as a function of Strava counts along with road network characteristics, slope, socio-demographic data, zoning, temporal data, and bicycle facility data in Charlotte, North Carolina. Nelson et al. (2021) found that Strava data can be used as an input to map bicycle ridership across a city. They modeled official bike counts in several North American cities as a function of the number of Strava riders and several variables for safety and design, land use, demographics, socio economics, topography, and climate. Livingston et al. (2020) studied Strava data in Scotland and concluded that the crowdsourced data could be used to predict the order of magnitude of cycling flows but that it lacks precision, making it unable to detect small changes bicycle use.

Roy et al. (2019) showed that models such as these could correct for biases in the Strava data and provide reasonably accurate estimates of bike use. They modeled bicycle counts in Maricopa County, Arizona, as a function of Strava data along with built environment measures, demographics, land use mix, socio-economic factors, and commute patterns. They found that the most significant variables for correcting bias were the proportion of the population that is white, median household income, traffic speed, distance to residential areas, and distances to green spaces. In testing their model, Roy et al. (2019) found the estimated counts were correct to within 25% of observed counts in 80% of road segments. While using such a model to correct the bias in Strava data could be useful, it also requires a sufficient number of official counts to build and test the model.

3. LEVEL OF TRAFFIC STRESS MAP FOR FARGO-MOORHEAD

Following the methods developed in previous studies, a level of traffic stress (LTS) map was developed for the Fargo-Moorhead metropolitan area. This section describes the methods used for categorizing the level of traffic stress, the data sources, and the results.

3.1 LTS Methodology

3.1.1 Criteria Used for Categorizing the Level of Traffic Stress

Based on geometric design and traffic factors, this section provides the criteria for classifying road segments and separating bicycle facilities by the level of traffic stress. These criteria are proposed based on traffic features such as road width, traffic speed, annual average daily traffic volume, functional class, and the presence of or lack of on-street motor vehicle parking, and whether bikes are in mixed traffic, bike lanes, or on segregated routes. Road segments and bike facilities are classified as LTS 1, LTS 2, LTS 3, and LTS 4. LTS 1 roads and bikeways are the least stressful, with low traffic levels and speed restrictions, whereas LTS 4 roadways and bikeways are the most stressful, with high traffic volumes and speed limitations. To categorize the Fargo-Moorhead area in terms of the level of traffic stress, the area was divided into three classes of bikeways: paths that are physically separated from traffic, on-street bikeways, and mixed traffic streets. Figure 3.1 shows the workflow to prepare the data for bike level of traffic stress classification.

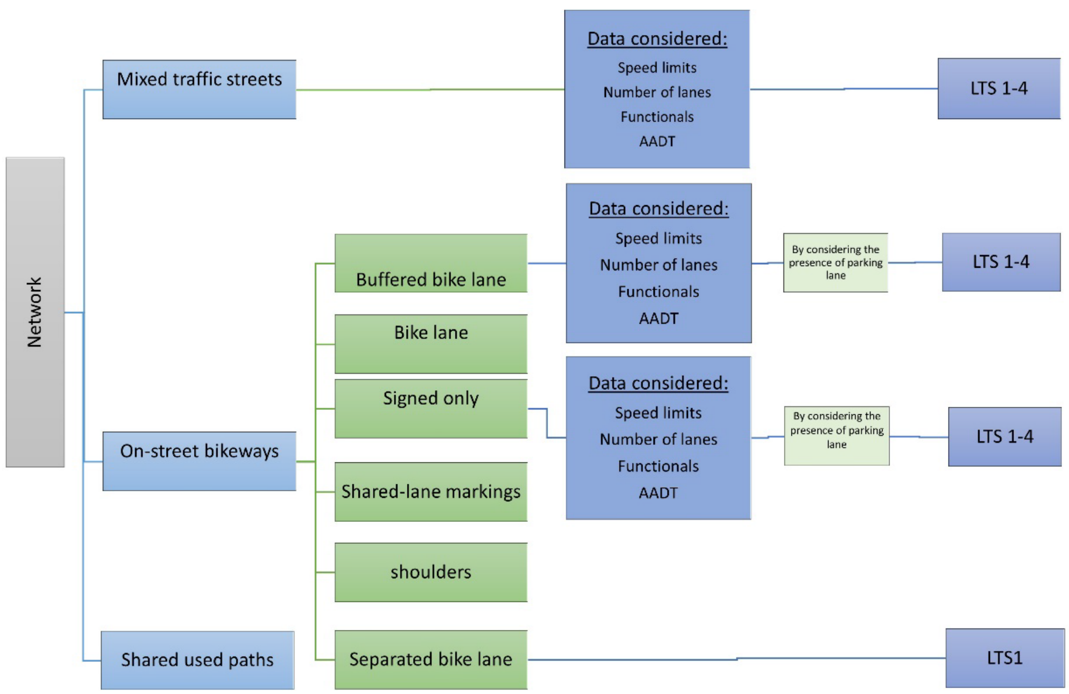

Figure 3.1 Workflow for Bike Level of Traffic Stress Classification

3.1.1.1 Criteria for separated bicycle facilities

According to research, people prefer riding on segregated bicycle infrastructure (Broach, Dill, and Gliebe 2012). Physically separated bikeways, multi-use pathways, walkways in parks, and trails are given the lowest level of traffic stress, LTS 1. So, all separated cycling facilities (shared-use pathways and protected cycle tracks) were categorized as LTS 1 in the original LTS.

This category does not include sidewalks unless they are designated for biking or shared-use pathways. Therefore, in this study, separated cycling facilities and shared-use routes that are the most segregated from motor vehicle traffic are classed as LTS 1.

3.1.1.2 Criteria for bikeways

All facilities where a bicycle is permitted such as roadways, shared-use pathways, or greenways are considered part of the bicycle network. In the United States cyclists are allowed to travel on bicycle-exclusive and shared facilities, including any unrestricted roadway. Bike lanes can experience the whole spectrum of traffic stress (Mekuria, Furth, and Nixon 2012). If bike lanes are wide enough and are located on a road with moderate and straightforward traffic, they can create a low-stress riding environment. However, if bike lanes are located on roads with high speeds or aggressive traffic, or close to high-turnover parking lanes with insufficient clearance, they can create a high-stress environment.

For the purposes of bikeways LTS analysis, the features that were considered in this study are the type of bikeways, annual average daily traffic volume, speed limits, functional class of roads, number of road lanes, and other bikeways characteristics, such as whether the facility is alongside a parking lane or not. On-street bikeways in the Fargo-Moorhead area are categorized as buffered bike lanes, signed only, shared-lane markings (commonly referred to as sharrows), shoulders, and separated bike lanes. In addition, the presence of parking lanes alongside bikeways were extracted from Google Earth.

This study used different criteria for bikeways alongside a parking lane and those not alongside a parking lane. As mentioned before, bikeways separated from traffic were considered LTS 1, and the other types of bikeways, such as bike lanes, signed only, shared-lane markings, and shoulders (except buffered bike lanes which have specific criteria in this study), were categorized through these criteria as LTS 1 to LTS 4 after determining whether they were alongside a parking lane or not. Tables 3.1 and 3.2 were provided by Bearn et al. (2018) which define the four LTS categories used in this research regarding speed limits, the number of lanes, functional class, and traffic volume.

Table 3.1 Criteria for Bikeways Not Alongside Parking Lane

	LTS≥1	LTS≥2	LTS≥3	LTS≥4
Through lanes per direction	1	(No effect)	≤2	(No effect)
Traffic Volume (AADT)	≤6300	>6300–≤14,000	>14,000- ≤27,000	>27,000
Functional Class	Local	Major or Minor Collector	Minor Arterial	Principal Arterial
Speed Limit	≤25mph	30 mph	35 mph	≥40mph

Table 3.2 Criteria for Bikeways Alongside Parking Lane

	LTS≥1	LTS≥2	LTS≥3	LTS≥4
Through lanes per direction	1	(No effect)	≤2	(No effect)
Traffic Volume (AADT)	≤3000	>3000–≤6300	>6300- ≤14,000	>14,000
Functional Class	Local	(No effect)	Major or Minor Collector	Minor Arterial
Speed Limit	≤25mph	30 mph	35 mph	≥40mph

3.1.1.3 Number of through lanes per direction

Street width has a major impact on cyclists' perception of security, which is evaluated in this study by the number of through lanes per direction. Multilane highways, as opposed to those with a single lane in each direction, promote faster traffic speeds and more "turbulent" traffic since they are less restricted and predictable. At driveways and junctions, a multilane environment reduces a cyclist's visibility to left-turning and cross-traffic (Mekuria, Furth, and Nixon 2012). In the Fargo-Moorhead area, most local streets are one lane in each direction, which could be the best reason for classifying them as LTS1.

The LTS based its criterion for the number of lanes on the Dutch CROW Design Manual but amended the Dutch requirements to allow for additional lanes per direction if the route featured a median. Because of the lack of data on the placement of medians in the case study area and data on the impact of medians on speeds and bike collisions, this study did not include medians.

It would be preferable to consider if the bicycle lane and parking lane width were adequate to reduce perceived stress due to the potential of a car door opening in the path of a bicyclist, referred to as "dooring." Therefore, this study evaluated less traffic volume on the streets with bikeways alongside parking lanes than those not. However, because data on parking and bicycle lane width is generally unavailable, this study confined data collection to the presence or lack of on-street parking close to bike lanes. Therefore, data on parking lanes alongside the bikeways for Fargo and Moorhead were obtained manually from Google Earth, as the data was not available.

3.1.1.4 Speed limit

The comfort of bikers is affected by traffic speed, and bicycling is discouraged by high motor vehicle traffic speeds. When available, measurements of observed speed are the best data to utilize, especially when observed traffic speed and the posted speed limit vary. However, in general, measurements of observed speed are not widely available, so speed limit could be a good alternative, especially in cities where speed cameras control speeds, making actual speeds conform with the speed limits. In this study, due to lack of data, speed limits were considered instead of actual speeds.

In Fargo, although speed limits differ, they are generally 25 mph on residential and local streets and higher on higher-order roads. These speed limits generally correspond with actual traffic speeds. But in Moorhead, the speed limit may not be a good alternative to actual speed because the speed limit of 30 mph is used in residential and local streets. In some local streets, traffic runs at speeds of 25 mph, and on some roads like arterials where actual speeds can exceed 35 mph. But due to the lack of data, we considered speed limits instead of prevailing speed, which was the main reason that most of the local streets in Fargo are categorized as LTS1. However, most Moorhead streets are classified as LTS2.

3.1.1.5 Traffic volume or Annual Average Daily Traffic (AADT) and functional class

When categorizing facilities, the original LTS did not consider traffic volume or functional class. However, according to studies, most people who wish to ride their bikes more frequently see "too much traffic" as the most significant environmental barrier. As a result, this study covered traffic volume and functional class. According to the USDOT FHWA Highway Functional Classification Concepts, Criteria, and Procedures, the number of travel lanes and functional class are closely related: "roadways are built and constructed according to their expected function." Most travel takes place on a network of interconnected roads, with each roadway segment moving traffic through the system toward destinations. The idea of functional categorization outlines the role that a certain highway segment performs in servicing the network's traffic flow. Roadways are classified in one of many functional classes within a hierarchy based on the type of transport service they provide (U.S. Department of Transportation Federal Highway Administration, 2013). An arterial, for example, is meant to be a high-capacity road with more travel lanes, but a collector has fewer travel lanes than an arterial, and a local road has even fewer travel lanes than a collector. When comparing the shortest route to the actual path, bicycles used arterial highways substantially less frequently than predicted by the shortest route model and used local roads significantly more frequently (Winters et al. 2010).

The AADT information for Fargo was manually extracted from an interactive map from Metro COG for 2015, and 2018 AADT data for Moorhead was extracted from Metro COG's shapefile.

3.1.1.6 Criteria for buffered bike lanes with and without on-street parking

A buffer can be placed in a buffered bike lane between the bicycle lane and the motor vehicle lane and between the bicycle lane and the motor vehicle parking lane or curb. In addition, Fees et al. (2015) described research showing that a buffered bike lane eliminates or reduces the threat of “dooring” when the lane travels alongside on-street parking. Some bikeways are buffered in the Fargo-Moorhead area, so we need to set the specific criteria for these kinds of bike lanes. Tables 3.3 and 3.4 show the criteria for buffered bike lanes with and without on-street parking (Bearn, Mingus, and Watkins 2018).

Table 3.3 Criteria for Buffered Bikeways Not Alongside Parking Lane

	LTS≥1	LTS≥2	LTS≥3	LTS≥4
Through lanes per direction	1	(No effect)	≤2	(No effect)
Traffic volume (AADT)	≤6300	>6300–≤14,000	>14,000- ≤27,000	>27,000
Functional class	Local or Major or Minor Collector	(no effect)	Minor Arterial	Principal Arterial
Speed limit	≤30mph	35 mph	40 mph	(no effect)

Table 3.4 Criteria for Buffered Bikeways Alongside Parking Lane

	LTS≥1	LTS≥2	LTS≥3	LTS≥4
Through lanes per direction	1	(No effect)	≤2	(No effect)
Traffic volume (AADT)	≤3000	>3000–≤6300	>6300- ≤14,000	>14,000
Functional class	Local	Major or Minor Collector	Minor Arterial	Principal Arterial
Speed limit	≤25mph	30 mph	35 mph	≥40mph

3.1.1.7 Criteria for mixed traffic streets

The level of traffic stress is considered unaffected by signs, shared-lane markings, or a wide outer lane where bikes share space on the road with motor vehicles. Studies have proven that shared-lane markings offer a little advantage, but nothing close to the benefit of defining an exclusive biking zone by marking a bike lane. Studies of wide-lane conversions (when a wide lane is divided into a travel lane and a bike lane) have consistently shown that bicyclists experience less stress when a bike lane line formally separates the bicycling zone, as evidenced by a shift in cyclist position away from right side hazards. Beyond the effect of the operational area provided by the bike lane, bike lane stripes improve the level of traffic stress by nearly one level (e.g., 3 to 2 or 2 to 1) (Mekuria, Furth, and Nixon 2012).

This study considered that level of traffic stress when riding in a mixed traffic street depends on the number of lanes, speed limits, traffic volume, and functional class; related criteria are illustrated in Table 3.5 from the Bearn et al. (2018) study. For example, in multilane traffic with 40 mph or greater speeds and traffic volume of 14000 vehicles per day or greater, LTS is 4.

Table 3.5 Criteria for Mixed Traffic Streets

	LTS≥1	LTS≥2	LTS≥3	LTS≥4
Through lanes per direction	1	(No effect)	≤2	(No effect)
Traffic volume (AADT)	≤2000	>2000–≤6000	>6000- ≤14,000	>14,000
Functional class	Local	(No effect)	Major or Minor Collector	Minor Arterial
Speed limit	≤25mph	30 mph	35 mph	≥40mph

3.1.1.8 Criteria for mixed traffic in the presence of right-turn lanes

Bicyclists will be in a high-stress situation if there is an auxiliary right lane and no bike lane, either because the street does not have bike lanes or because the bike lane is dropped to make room for an auxiliary lane. Unless the right-turn lane is so little used and has low traffic speeds, cyclists can share it as a de facto bike lane with right-turn cars. When a roadway has a bike lane for part of the block but not on a junction approach, the block is classified as having no bike lane. As a result, the requirement to ride in mixed traffic will be factored into the base segment's traffic stress level (Mekuria, Furth, and Nixon 2012). Table 3.6 from Mekuria et al. (2012) study shows the level of traffic stress criteria related to mixed traffic in the presence of a right-turn lane.

Table 3.6 Level of Traffic Stress Criteria Related to Mixed Traffic in the Presence of a Right-Turn Lane

Configuration	Level of Traffic Stress
Single right-turn lane with length < 75 ft. and intersection angle and curb radius limit turning speed to 15 mph	(no effect on LTS)
Single right-turn lane with the length between 75 and 150 ft., and intersection angle and curb radius limit turning speed to 15 mph	LTS > 3
Other	LTS = 4

The data required to apply these criteria for the Fargo-Moorhead area was unavailable, and it was provided manually from shapefiles, So, it was only used in a few right-turn lanes. However, most streets with right-turn lanes were multilane arterials with a stress level of 3 or 4, so this step did not significantly impact the results.

3.1.1.9 Criteria for Unsignalized Intersections

Auxiliary turn lanes are frequently created as roadways approach signalized junctions. The effect of additional left-turn lanes on bicycles may be ignored because cyclists typically keep to the right. However, additional right-turn lanes challenge a cyclist's regular position and create a weaving problem. Following the "weakest link" concept, the stress level associated with an intersection approach should be aggregated with the stress level previously allocated to a segment. As a result, the features of an intersection approach might worsen rather than improve a segment's LTS (Mekuria, Furth, and Nixon 2012). Unsignalized crossings can be risky, especially if they require crossing several lanes and include fast traffic. When a segregated path crosses a roadway or ends at an intersection, there is a high possibility for motor vehicle and bicycle conflict. Bicyclists using a protected cycling facility, bicycle lane, or shared travel lane are also more likely to suffer increased perceived stress at unsignalized crossings, especially if the roadway being crossed has several lanes and a higher posted speed limit (Bearn, Mingus, and Watkins 2018). Therefore, in this study, the traffic stress associated with unsignalized crossings was calculated by Bearn's LTS, calculating the intersection LTS as the LTS level of the highest-stress street. So, if a low-stress street crossed a high-stress artery, the intersection was classified as high-stress. For example, if a street is considered LTS 3 while a crossing approach on either end of the street has LTS 2, the combined stress level remains LTS 3; but if the approach has LTS 4, the combined stress level for the road will be LTS 4.

3.1.1.10 Criteria for signalized intersections

The original LTS guideline defines a set of design requirements for signalized junctions with right-turn lanes. In addition, the original LTS methodology needs particular design parameters such as curb radius and right turn lane length, which are not available for the case study.

Signalized crossings are not often a barrier to riding and so were not included in the criteria used in this study. Long crossings on roadways where the bicycle's signal period is too short for a slow rider to cross before conflicting traffic is receives a green signal might be added as an exemption (Mekuria, Furth, and Nixon 2012). However, because data on signal timings correlated with crossing length are not widely available, this aspect was not addressed in this study. Consequently, the signalized junction LTS criterion did not affect the overall network connectivity.

3.1.2 Data

Shapefiles were obtained from the Fargo-Moorhead Metropolitan Council of Governments (Metro COG) for roadways, bikeways, and shared-use paths. They include a comprehensive inventory of roadways and road characteristics. Data sources used for this study were from Metro COG, the Minnesota Department of Transportation, and Google Earth:

- Roads shapefiles for Fargo and Moorhead (Clay_Road_CLs, Fargo_Road_Centerline) from Metro COG include data on each street segment, including its geographical coordinates, number of lanes, speed limit, functional class, and shape length.
- A bikeways shapefile (Bikeways_08192020) from Metro COG for the Fargo-Moorhead area includes data on each bikeway, including its geographical coordinates, type of bikeways, and shape length.
- A shared-use-paths shapefile (Shared_Use_Paths_08192020) from Metro COG for the Fargo-Moorhead area includes data on each shared-use-paths, including its geographical coordinates, pavement, width, and shape length.
- A traffic signal shapefile for Fargo from Metro COG indicating which intersections have traffic signals.

- Traffic signal data for Moorhead from Google Earth indicating which intersections have traffic signals.
- An annual average daily traffic volume (AADT) 2015 sub-area interactive map for Fargo from Metro COG.
- An AADT 2018 shapefile for Moorhead from Minnesota Department of Transportation.

3.1.3 Methodology

3.1.3.1 Bikeways

Information on bicycle facilities, including buffered lanes, bike lanes, signed-only routes, shared-lane markings, and shoulders was obtained from Metro COG and combined with the information about speed limits, number of lanes, and functional class from the Clay County and Fargo roadway shapefiles. The traffic volume information was manually extracted from an AADT 2015 interactive map from Metro COG, and those for Moorhead were manually inserted from an AADT shapefile from the Minnesota Department of Transportation. The location of on-street parking on roads with bike lanes, signed-only routes, shared-lane markings, and shoulders was manually coded in Excel by utilizing Google Earth imagery. Then bikeways were divided into two categories: bikeways alongside the parking lanes and those not alongside the parking lanes. According to the criteria for bikeways not alongside parking lane and criteria for bikeways alongside parking lane (Table 3.1 and 3.2), bike lanes, signed-only routes, shared-lane markings, and shoulders were categorized as LTS 1 to LTS 4. According to the criteria for buffered bikeways not alongside parking lanes and alongside parking lanes, they were classified as LTS 1 to LTS 4. According to the criteria, all physically separated bike facilities were classified as LTS 1.

3.1.3.2 Mixed traffic

To classify mixed traffic roads, data from Metro COG for speed limits, number of lanes, and functional class of road segments for the Fargo-Moorhead area were used. Information related to traffic volume was manually inserted from the AADT 2015 interactive map for Fargo from Metro COG and the AADT 2018 shapefile for Moorhead from the Minnesota Department of Transportation. Road segments were given an LTS classification according to the criteria for mixed traffic street (Table 3.5).

As mentioned, because of the lack of actual speed data, speed limits were considered the speed feature of this study. The speed limit on residential and local streets of Fargo was 25 mph, which means with 1 through lane per direction and traffic volume of less than 2,000 AADT, these streets were categorized as LTS1. However, in Moorhead, the speed limit on residential and local streets was 30 mph, and in the same situation, with 1 through lanes per direction and traffic volume less than 2,000 AADT, these streets were categorized as LTS2. These differences between speed limits in these two areas resulted in different levels of traffic stress for similar streets, which made these areas' LTS analysis more complicated.

3.1.3.3 Applying the presence of right-turn lane effects on segments

If a roadway has a bike lane for part of the block but drops it on a junction approach, that block is categorized as having no bike lane. As a result, the necessity to ride in mixed traffic will be factored into the degree of traffic stress in the base section. The presence of right-turn lanes in Fargo-Moorhead segments was manually extracted by utilizing Google Earth imagery. In streets where there was a right-turn lane, the length of that was measured by using ArcMap. Regarding related criteria for mixed traffic (Table 3.6) in the presence of right-turn lanes, the effect was applied to the segment in GIS by changing the LTS code. In streets where the segment had single right-turn lanes with a length < 75 ft, this right-turn lane had no impact on the segment's LTS. In streets where the segment had single right-turn lanes with a length between 75 and 150 ft, the LTS of that segment was modified to LTS 3. And in other situations, the LTS of that segment was changed to LTS 4. The data required to apply these criteria in the Fargo-Moorhead area were not consistently accessible and were extracted manually from Google Earth in only a few situations. However, most roadways with right-turn lanes are multilane arterials with base segment stress levels of 3 or 4.

3.1.3.4 Applying the crossing effect to segments

For analyzing the level of traffic stress in segments with a crossing, where a low-traffic-stress-level segment like LTS 2 intersects a high-traffic-stress-level roadway like LTS 3 at an unsignalized intersection, the stress level for crossing the low-traffic-stress-level street was adjusted to the high traffic stress level. Stress levels caused by a crossover are coupled with stress levels caused by other variables in the standard "weakest link" manner, which means they determine the amount of stress only if they are worse than the stress caused by the connection (Mekuria, Furth, and Nixon 2012).

For Fargo, the presence of a traffic signal was checked by overlapping the traffic signal shapefile from Metro COG on the LTS map of the segments. For Moorhead, because of the lack of GIS data, this was manually extracted from Google Earth images.

It is critical to define the effect of stressful crossings on path choice because if paths are chosen solely on the stress associated with links, shortest-path logic will attempt to connect low-stress segments that meet on opposite sides of a wide street without accounting for the stress involved in the crossing.

3.2 Results

Using GIS, a level of traffic stress was allocated to each road segment and pathway in the Fargo-Moorhead area based on the parameters outlined in the previous section. Colors show the level of traffic stress as LTS1: Green, LTS2: Blue, LTS3: Purple, and LTS4: Brown. Figure 3.2 shows the level of traffic stress in the Fargo Moorhead area.

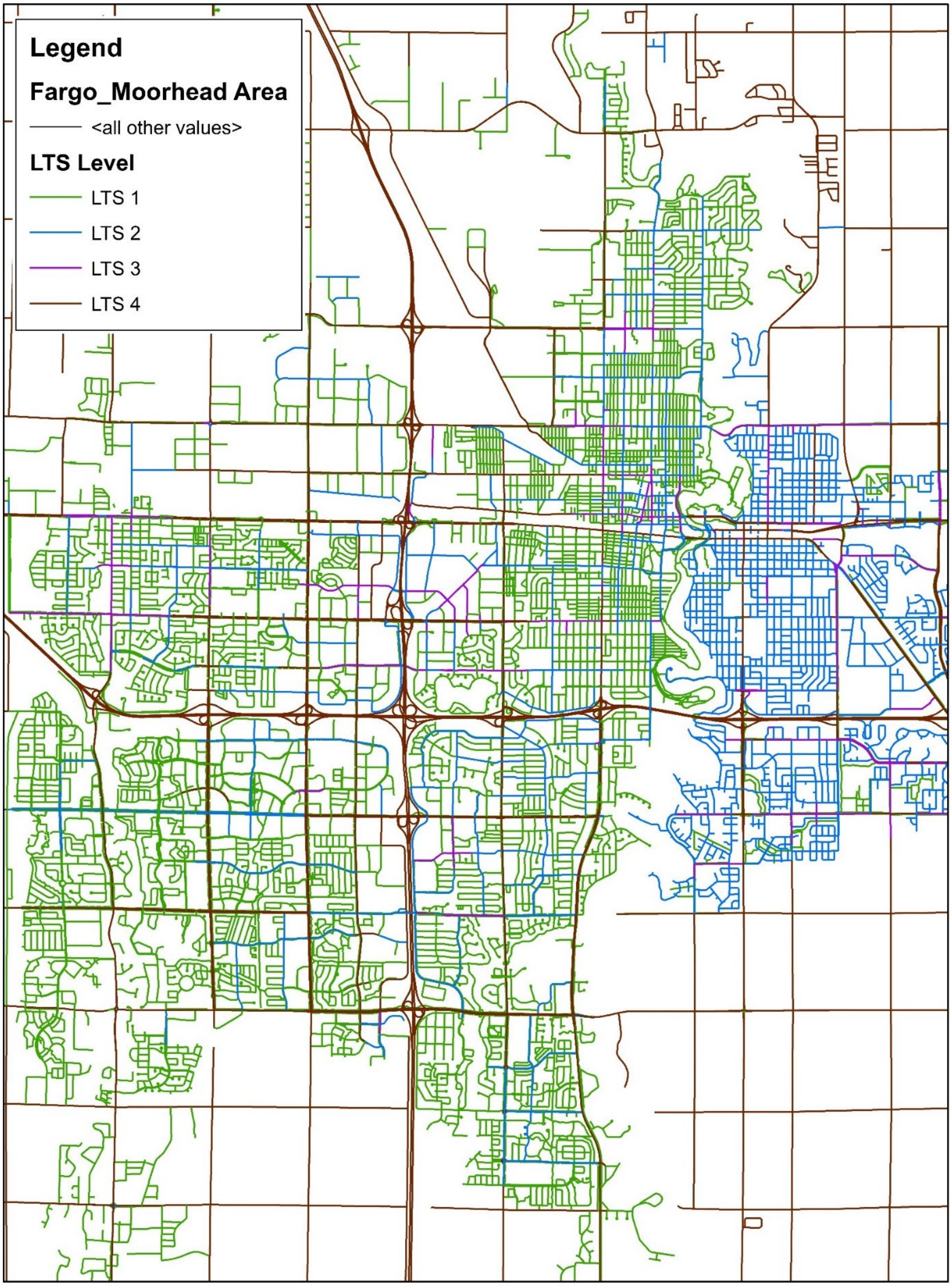

Figure 3.2 The Level of Traffic Stress Map of Fargo Moorhead Area

3.2.1 Distribution of Traffic Stress Levels

As shown in the LTS map, green lines occupy a large part of the study area because residential streets account for most of the area. For example, 56% of the Fargo-Moorhead segments and pathways are classified as LTS 1 (mostly residential streets) and 24% as LTS 4 (higher speed arterials). The distribution of segment miles by the intensity of traffic stress is shown in Table 3.7.

Table 3.7 Distribution by Level of Traffic Stress

LTS	Stress	Miles	Percent
1	Lowest	1079.16	56.1%
2	Low	317.05	16.5%
3	Medium	56.3	2.9%
4	High	471.23	24.5%
Total		1923.74	100 %

Table 3.8 shows the results of the LTS map based on the road types and bike lanes. As mentioned before, all separated bike lanes and shared-used paths facilities are considered LTS 1. As you can see in the table, all the shoulder bike lane facilities, after considering their AADT (Annual Average Daily Traffic), the number of lanes, speed limits, and functions categorized as LTS 4, which could be because of existing shoulder facilities alongside the highways with two or more lanes each way and speed limits of 45 mph or more.

Table 3.8 Distribution Different Types of Facilities by Level of Traffic Stress

LTS	Shared travel lanes	Shared-used path	Bike lane	Buffered bike lane	Separated bike lane	Shoulder	Shared-lane Markings	Signed only
1	794.9	271.6	0.7	0	0.2	0	4.0	7.8
2	302.7	0	0.1	3.2	0	0	6.5	4.5
3	45.1	0	9.5	0.7	0	0	1.1	0
4	215.6	0	1.0	0	0	253.2	0	1.5
Total	1358.4	271.6	11.23	3.9	0.2	253.2	11.6	13.8

For greater detail and better understanding, Figure 3.3 zooms in on a portion of the city to show level of stress. As these maps show, the principal and minor arterial network can be visualized as a grid of mostly brown (LTS 4) streets. Some arterials have shared-used paths or bike lanes alongside the roads, shown by blue lines that indicate LTS 2. However, most of the area was covered by the local streets shown as LTS 1 by green lines, with speed limits of 25 mph or less and a traffic volume of 6,300 AADT or less, and the major collectors with speed limits of 30 mph are categorized LTS 2. There are some blue lines alongside the brown lines, which indicates there are bike lanes alongside but separated from the highways with LTS 4.

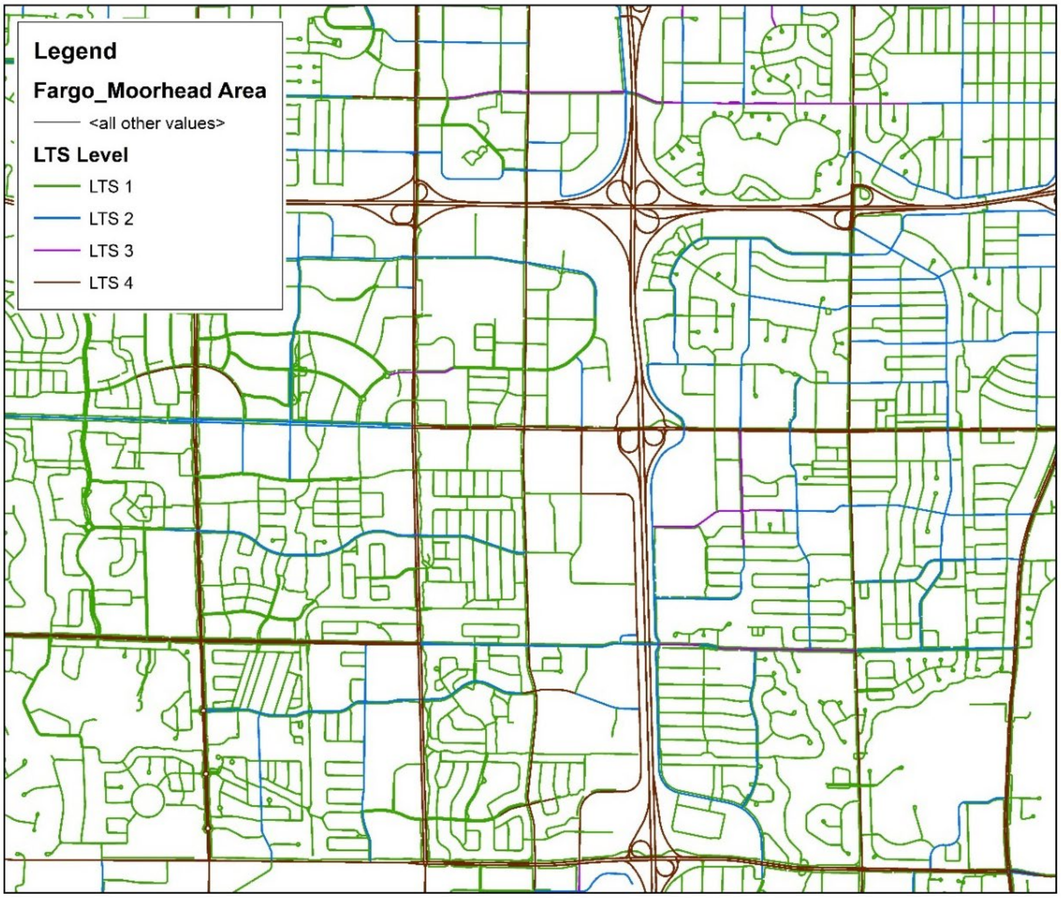

Figure 3.3 Zooming in on the Level of Traffic Stress Map for an Area of the City

3.2.2 Connectivity

Figure 3.4 shows a map of only the LTS 1 and 2 linkages. The Moorhead area that emerges from the map's right side is the connected blue lines. And the curvy green line in the middle of the map is the shared-used path network along the Red River. There are some connected clusters in Fargo, which show the local streets with speed limits of 30 mph or less.

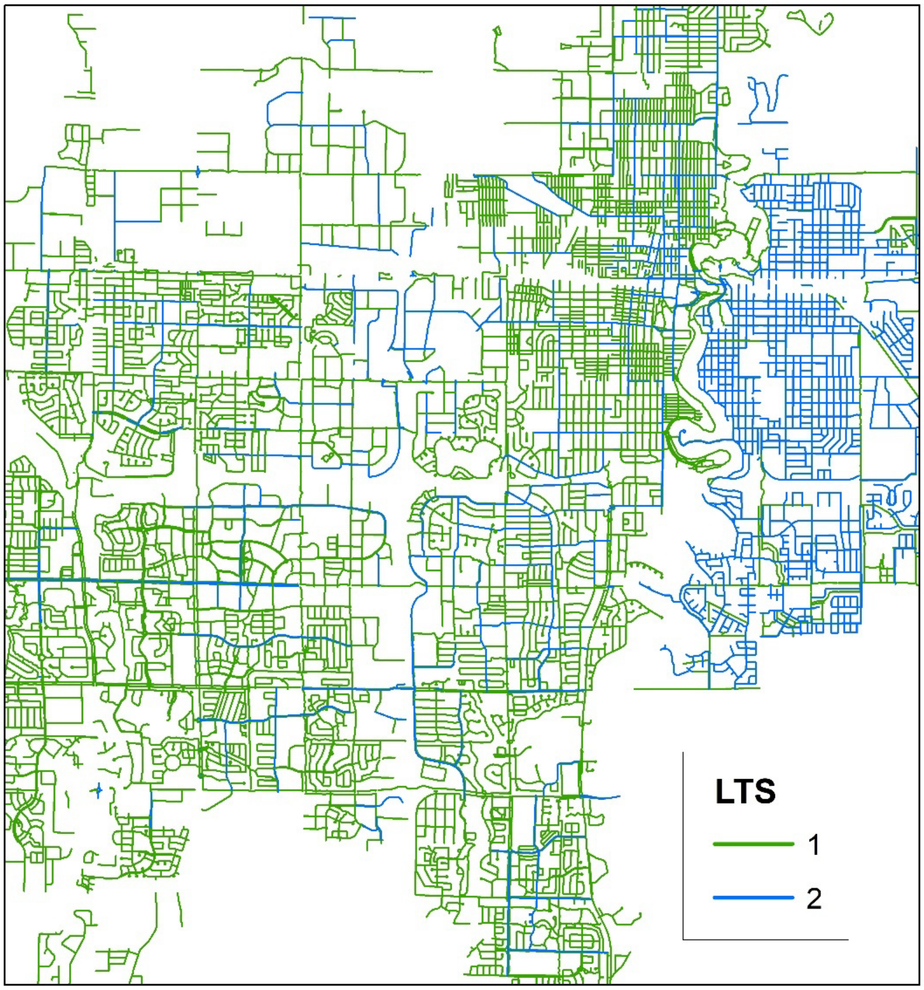

Figure 3.4 Level of Traffic Stress Map Showing Only LTS 1 and LTS 2 Links

To illustrate the connectivity of low-stress networks, Figure 3.5 shows clusters of LTS 1. Each cluster represents connected LTS 1 facilities. The edges of clusters are barriers with no LTS 1 connectivity. Each color represents a different cluster, and the largest clusters are shown in the map. As you can see there is a good connection between the bike paths alongside the Red River and the local streets close to that. Analysis of connectivity cluster maps reveals that there is a barrier, which is the arterial streets. A high-stress artery divides the smaller streets on each side of it from one another, causing them to become isolated. Unsafe crossings can prohibit local streets from connecting with arterial roads, even if they meet at an unsignalized 4-way intersection. Because of the high demand at signalized intersections of arterials and secondary roads, the secondary roads are typically enlarged on the blocks that approach arterials, with bike lanes often removed or shifted in a way that causes high-stress merging conditions for cyclists.

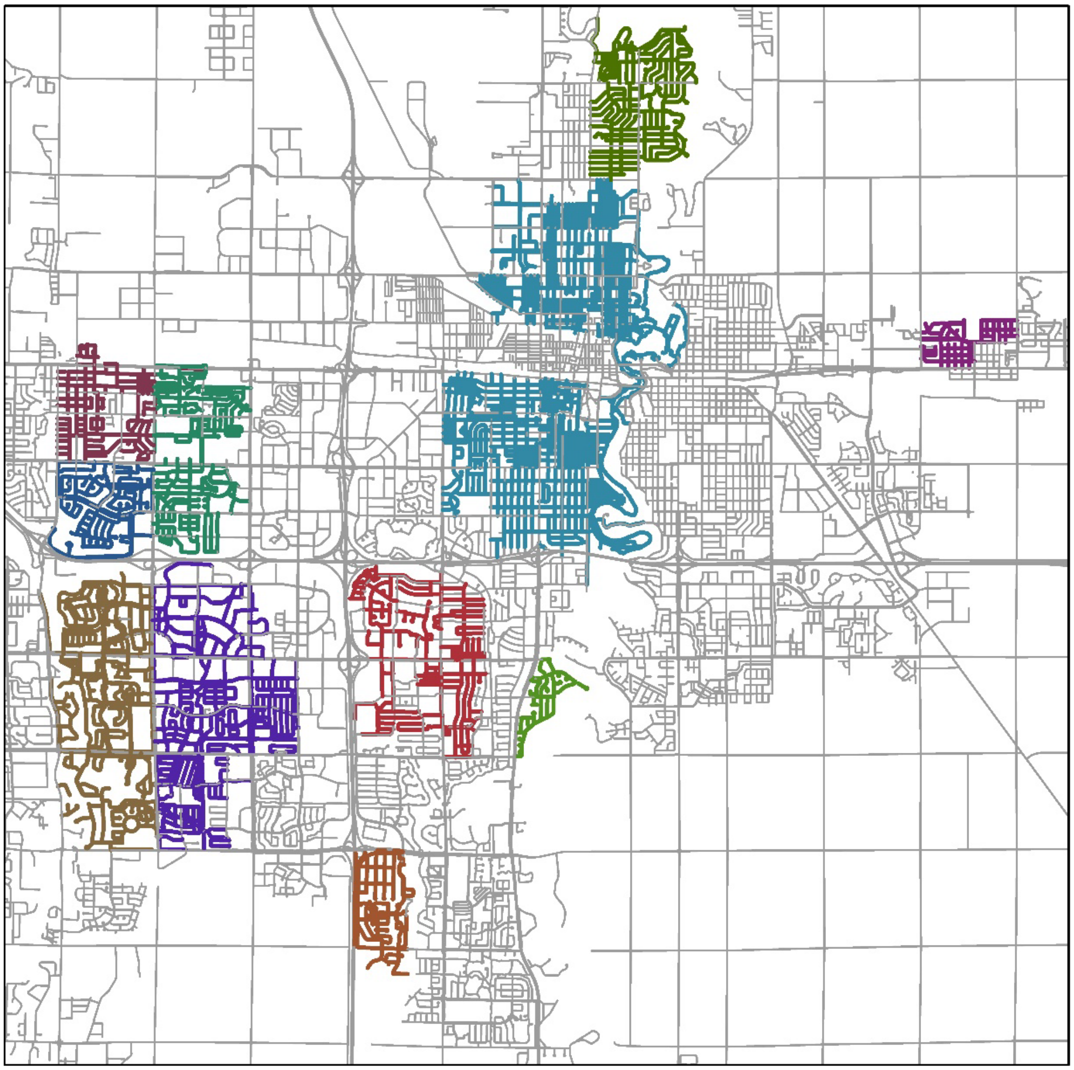

Figure 3.5 Clusters of LTS 1 Connectivity

The clusters are expanded to include LTS 2 in Figure 3.6, which shows the largest connected clusters of LTS 1 or 2. Barriers are created by LTS 3 or 4 facilities. The map shows there are some large clusters of low-stress networks, but their utility is limited if they lack low-stress interconnecting links. Highways, railways, and rivers, which need grade-separated crossings, are examples of natural and artificial barriers.

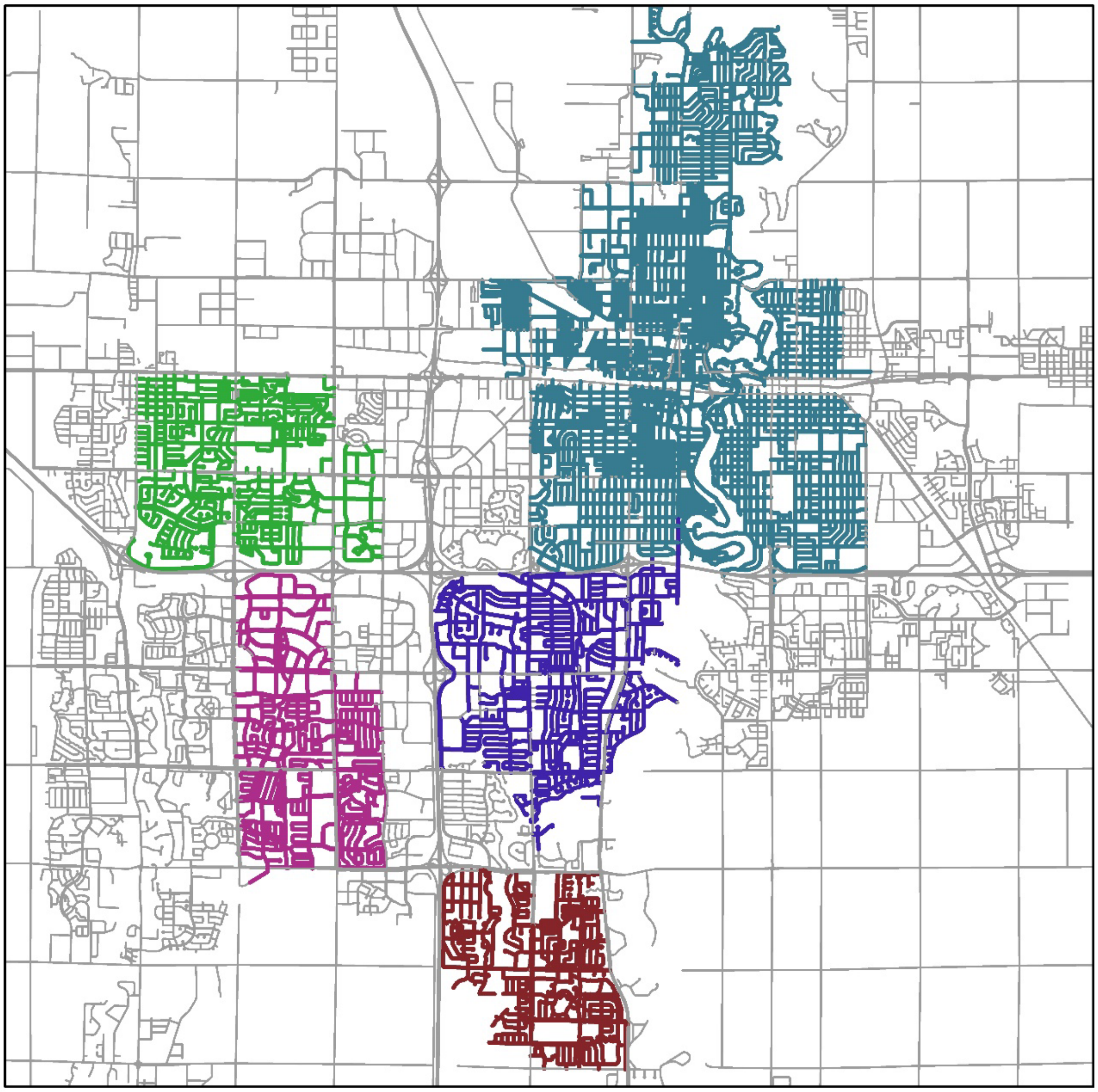

Figure 3.6 Clusters of LTS 1 and 2 Connectivity

4. MODEL FOR BICYCLE USE

The level of traffic stress is important because it influences how comfortable someone is likely to feel riding a bicycle, which can determine whether they decide to ride their bicycle, influencing the overall level of bicycle use in the city. The components of LTS are related to the design of the street and bicycle networks. Along with these design characteristics, other elements of the built environment may also influence bicycle use. Cervero et al. (2009) defined five dimensions of the built environment: density, diversity, design, destination accessibility, and distance to transit. These dimensions, along with sociodemographic characteristics, can be used as a theoretical framework for modeling bicycle use.

Measures of density used in the study include population density and employment density, and land use mix is used as a measure of diversity. Increases in density and land use mix are expected to be positively related to bicycle use, because they indicate a greater number of people or trip attractors, and land use mix suggests the possibility of shorter distance trips that could be made by bicycle.

Several design factors are considered in this study. These include barriers in the roadway network, bicycle facility type and width, connectivity, intersection density, number of lanes, street classification, street density, traffic speed, and traffic volume. Previous studies have found many of these factors to be related to bicycle use, as discussed in Section 2.

Destination accessibility refers to the proximity or accessibility of trip attractors. If there are major destinations nearby, individuals may be more likely to use their bike as a means of transportation. This study considers the proximity to downtown, which can be a major trip attractor. The proximity to water is also considered, as previous research suggested cyclists prefer trips near water, parks, and trees.

The last of the five dimensions of the built environment is the distance to transit. Distance to transit could have either a positive or negative relationship with bicycle use, depending on if the relationship is complementary or substitute. Transit and bicycling may complement each other if transit riders use a bicycle to access the transit service. On the other hand, if they are substitutes, proximity to transit would be negatively related to bicycle use, as transit riders could use transit for making a trip instead of bicycling. In that case, bicycle trips would be more likely in areas with poor or no transit service, as those trips could not be easily made by transit, if at all. Of course, proximity to transit could also be related to other built environment factors that could also influence bicycle use, such as density, land use mix, street design, and destination accessibility, so its inclusion in the model would need to be examined for potential multicollinearity. Despite the potential relationship between transit and bicycle use, distance to transit was not considered in this study because of the nature of the bicycle data. As noted from other studies, Strava users are more likely to ride for recreational purposes and may have higher incomes. Therefore, the location of transit stops is less likely to have an effect, particularly in Fargo-Moorhead where automobile ownership and accessibility is high.

In addition to the five dimension of the built environment, demographic characteristics are also likely related to bicycle use, as suggested by previous research reviewed in Section 2. This study examines neighborhood demographics, including median age, median household income, minority population percentage, and percentage of population that is male, as potential determinants of bicycle use.

4.1 Data

Several measures of density, diversity, and design, as well as demographic data, were obtained from the Smart Location Database, provided by the U.S. Environmental Protection Agency. The Smart Location Database provides data at the Census block group level for several measures of housing and population density, diversity of land use, neighborhood design, destination accessibility, transit service, employment, and demographics.

Data for bicycle infrastructure and the roadway network that were used for creating the LTS maps are also included for modeling bicycle use. This includes locations of bicycle facilities across the metro area, including bike lanes, buffered lanes, shared-lane markings, signed-only bicycle routes, and shared-use paths, as well as data for speed, AADT, and number of lanes.

The dependent variable in the model is the count of bike trips from Strava summed over the two-year period of 2019-2020. The data were aggregated over this time period, as suggested by Lee and Sener (2020), to reduce the number of segments without any trips recorded and to have a larger sample of data. Figure 4.1 maps the number of bicycle trips recorded by Strava over these two years across the Fargo-Moorhead metro area. Areas with the greatest number of trips include the trails near the river, streets in or near downtown, various shared-use paths, and popular routes for recreational cyclists who are riding out of town. The number of trips recorded by Strava is a small sample of the total number of bicycle trips taken.

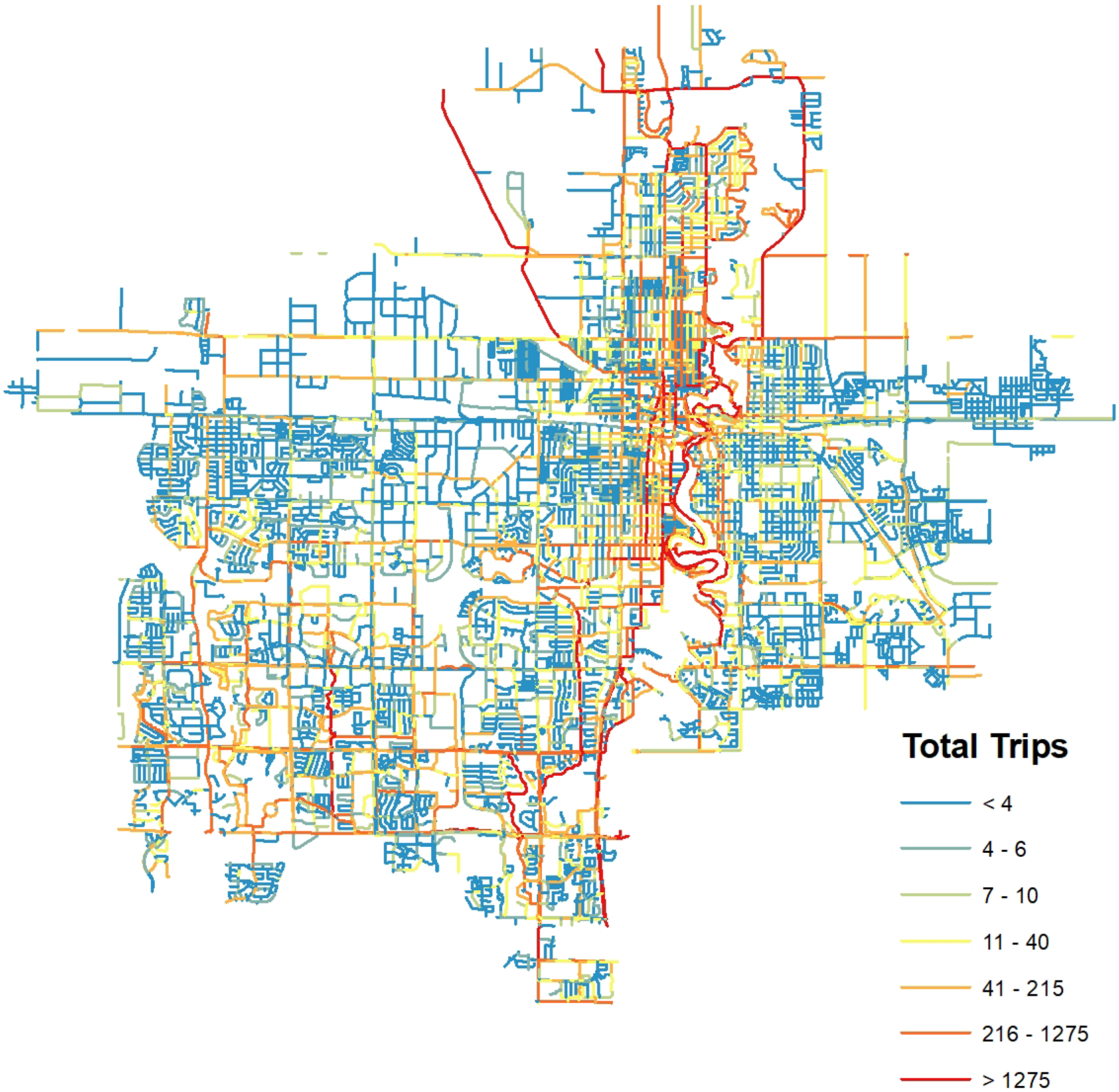

Figure 4.1 Map of Strava Bicycle Trips for Fargo-Moorhead, 2019-2020

Merging the Strava data with the GIS data for the street network and bicycle facilities created difficulties because the GIS data collected from Strava did not match the other GIS files. For example, the locations of the streets did not completely match, and the datasets did not include a common field to allow them to be joined. Further, the Strava shapefile included sidewalks and paths in some places, but not in others, and the accuracy of the GPS data in determining if a trip occurred on the street or an adjacent path or sidewalk could be questionable. Merging these two datasets proved to be a challenge. Attempts to use a spatial join created several errors. Therefore, to address this problem, the Fargo-Moorhead metro area was divided into a grid, and data from the separate GIS files were joined to the grid. The square cells in the grid are 500 feet long by 500 feet wide, which is approximately the size of a city block. They are small enough to capture the effects of bicycle infrastructure and the built environment, but large enough to avoid errors in joining data from different data sources. In each cell of the grid, the number of bicycle trips was calculated as the maximum number of trips recorded by any Strava segment within that cell. Figure 4.2 maps the grid and the number of bicycle trips in each cell. Cells in the grid were removed if they did not contain any streets or bicycle facilities or were not located within city limits. Interstate highways were also removed because no bicycle traffic is possible on those highways. This resulted in 6,490 cells with data.

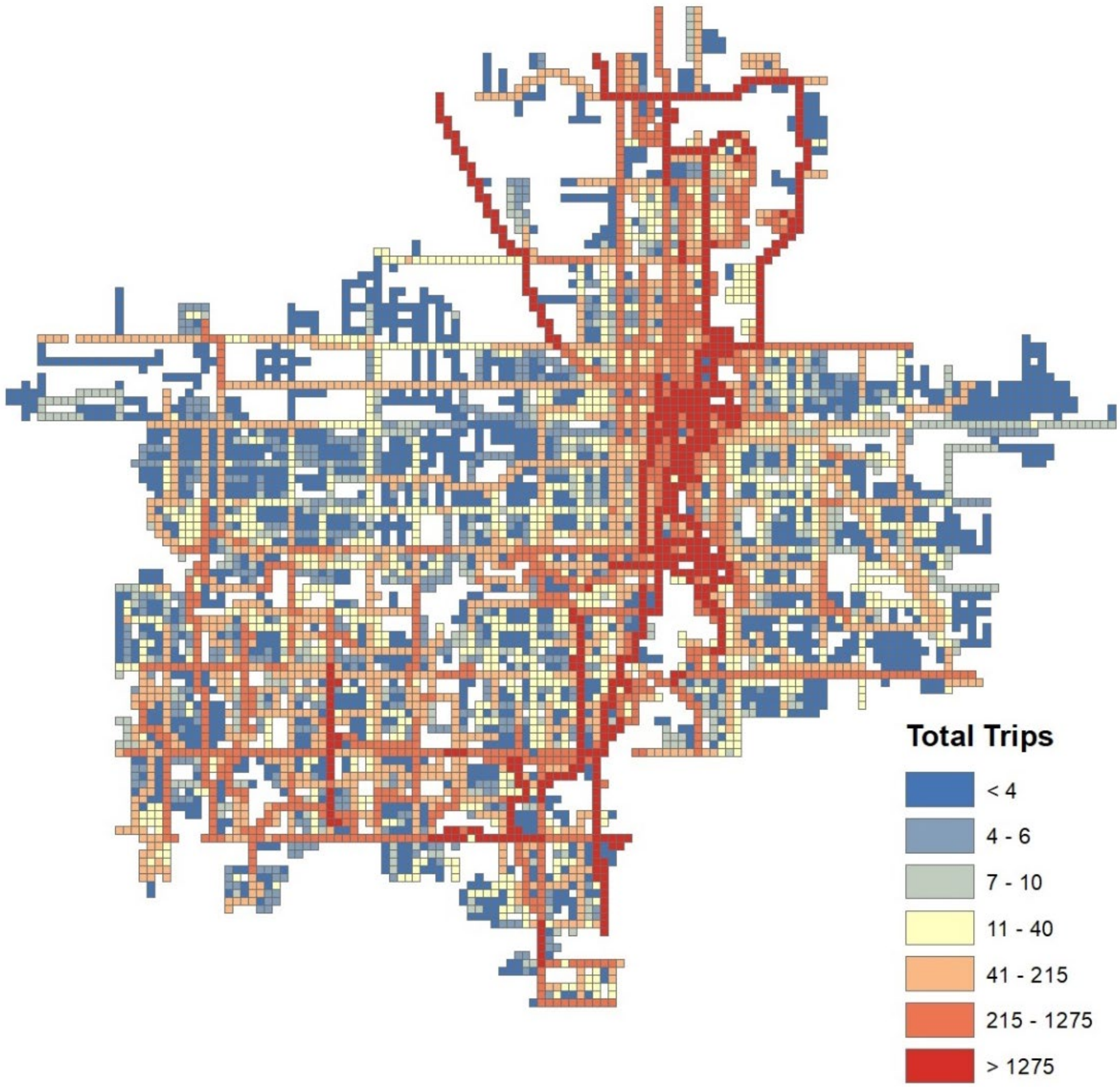

Figure 4.2 Grid Map of Strava Bicycle Trips for Fargo-Moorhead, 2019-2020

Table 4.1 shows explanatory variables that were considered in this study. Population density was obtained from the American Community Survey and employment density from the Smart Location Database. Both were measured at the Census block group level. Further, employment density data were obtained separately for retail, office, industrial, service, and entertainment jobs. Different types of jobs may affect bicycle use differently. For example, areas with a high density of retail or entertainment jobs may attract trips, whereas industrial areas may be less attractive for bicycle use. The calculation of each of the measures used from the Smart Location Database are described by Chapman et al. (2021).

Table 4.1 Potential Explanatory Variables for Bicycle Use

Variable	Data Source
Density	
Population density	American Community Survey
Employment density: Total, retail, office, industrial, service, entertainment	Smart Location Database
Diversity	
Employment and household entropy	Smart Location Database
Household workers per job equilibrium index	Smart Location Database
Employment entropy	Smart Location Database
Design	
Road network density: Total, auto-oriented, multi-modal, pedestrian-oriented	Smart Location Database
Street intersection density: Total, auto-oriented, multi-modal, pedestrian-oriented (3 or 4 legs)	Smart Location Database
Bike lane	Metro COG GIS data
Buffered lane	Metro COG GIS data
Shared-use path	Metro COG GIS data
Shared-lane markings	Metro COG GIS data
Signed-only bike route	Metro COG GIS data
Shoulder	Metro COG GIS data
Low-stress connectivity	Derived
Number of lanes	Metro COG GIS data
Speed	Metro COG GIS data
AADT	Metro COG GIS data
Destination Accessibility	
Distance to downtown	Derived
Distance to water	Derived
Demographics	
Median age	American Community Survey
Median household income	American Community Survey
Percentage population male	American Community Survey
Percentage population white	American Community Survey
Percentage population low wage	Smart Location Database
Percentage population no vehicles	American Community Survey
Other	
Highway 81 dummy variable	Derived
Highway 3 dummy variable	Derived

Three measures of diversity from the Smart Location Database were considered: employment and household entropy, household workers per job equilibrium index, and employment entropy. The first two measures attempt to quantify the mix of employment and residential development within the area, and the third measures the mix of employment types. See Chapman et al. (2021) for more details.

Road network and street intersection density data were also obtained from the Smart Location Database. Increased density of streets and intersections indicates greater connectivity. The Smart Location Database provides several measures of network and intersection density. Total road network density is provided, as well as network density specifically for auto-oriented links, multi-modal links, and pedestrian oriented link. Density is measured as facility miles per square mile. Intersection density is similarly available for total intersections excluding auto-oriented intersections, auto-oriented intersections, multi-modal intersections, and pedestrian-oriented intersections. Density is measured as intersections per square mile.

Pedestrian-oriented facilities are defined as having lower speeds. Chapman et al. (2021) provides more detail about how each of these are defined and measured.

The design characteristics also include several variables used to calculate the level of traffic stress, as described in Section 3. These include the locations of bicycle facilities – bike lanes, buffered lanes, shared-use paths, shared-lane markings, signed-only bike routes, and shoulders. It also includes speed, measured as the speed limit, the number of lanes, and AADT.

The study also considered another measure of connectivity that was derived from the LTS maps developed in Section 3. The low-stress connectivity measure is based on the LTS 1 and 2 clusters shown previously in Figure 3.6. A few potential measures were considered. One was a dummy variable indicating if the area was part of one of these clusters. Dummy variables were also created for each individual cluster. Finally, a measure was created which quantified the size of the cluster. Cluster size was measured as the number of grid cells that belong to an individual cluster. If a grid cell belonged to one of these clusters, the cluster size indicates the size of the cluster to which it belongs.

Distance to downtown and to water were considered as two measures of destination accessibility. A boundary area for downtown Fargo and Moorhead was identified, and the distance from each grid cell to that boundary was measured in GIS. Within downtown, distance was measured as being equal to zero. Distance to water was measured for two rivers in the metro area: the Red River and the Sheyenne River. The distance was measured to whichever river was the closest.

Demographic data for median age, median household income, and percentage of population that is male, white, low wage, or in a household without a vehicle were obtained from the American Community Survey or the Smart Location Database.

Lastly, two dummy variables were created for two roadways that might be expected to have higher levels of bicycle use than would otherwise be expected based on the variables included in the model. These are for U.S. Highway 81 and Clay County Highway 3, which are roadways that connect the city to rural areas and are popular routes for recreational cyclists.

Each of the variables obtained from the Smart Location Database and the American Community Survey were measured at the Census block group level. This provides some level of variation throughout the metro area, which includes 188 block groups. However, this is far fewer than the 6,490 grid cells developed for this study, which is the unit of observation for the ridership model. The data captures some variation across the metro area but not block-to-block variation in density or demographics. For the model, each individual grid cell was assigned the values for the Census block group to which it belongs.

Each of the bicycle facility variables are represented by dummy variables equal to 1 if the grid cell contains such a facility and 0 if not. Number of lanes, speed, and AADT for each cell was determined by the street segment located within that cell. If more than one street segment was located in a cell, the largest value was used. AADT data were not available for all low-volume residential streets. Therefore, the AADT variable was converted to a 1-16 scale, and the streets without AADT data were considered to have the lowest volume of traffic (AADT=1).

4.2 Model Development

As shown in Table 4.1, there are several potential independent variables to explain variations in bicycle trips. However, some of these variables may be correlated, creating multicollinearity issues, and some may be better predictors than others. An exploratory regression was first conducted in ArcGIS to identify independent variables that provide the greatest fit, and the variance inflation factor (VIF) was calculated for each variable to identify multicollinearity problems.

The exploratory regression tool in ArcGIS Pro 2.8 was used to help specify the model. It is a data mining tool that tries all possible combinations of explanatory variables and determines which models provide the greatest fit and passes all of the necessary OLS diagnostics. The exploratory regression tool was run using models with 2-4 explanatory variables. The tool then considered all possible combinations of explanatory variables. The model was limited to four variables, because including more would have created too many possible combinations for the tool to analyze within a reasonable time. The dependent variable was the log of bicycle trips. Each model was assessed based on the adjusted R^2, coefficient p-values, and other diagnostics. Models were tested for spatial autocorrelation using Global Moran's I, which is a measure of the overall clustering of the spatial data. The existence of spatial autocorrelation would violate the assumptions of an OLS model and require the use of a spatial regression model, such as a spatial error or spatial lag model.

4.3 Results

The results of the exploratory regression showed that the models with the highest adjusted R^2 included some combination of the shared-use path dummy variable, proximity to water, proximity to downtown, cluster size or cluster dummies indicating connectivity, AADT, speed, and the dummy variable for U.S. Highway 81.

Table 4.2 shows a summary of the significance of each independent variable in the exploratory regression. It shows the percentage of models in which the variable was statistically significant, and the percentage of models in which the estimated coefficient was negative or positive. Several of the variables were significant 99% or 100% of the time, with coefficients that consistently had the same sign, either positive or negative. This indicates that these results are robust. In particular, bicycle facilities are shown to have a positive effect. The dummy variables for bike lanes, buffered lanes, shared-lane markings, sign-only paths, and shoulders are all consistently significant and positive.

Table 4.2 Exploratory Regression: Summary of Variable Significance

Variable	% Significant	% Negative	% Positive
Bike lane	100	0	100
Buffered lane	100	0	100
Shared-lane markings	100	0	100
Signed-only	100	0	100
Shared-use path	100	0	100
Distance to water	100	100	0
Shoulder	100	0	100
AADT	100	0	100
U.S. Highway 81	100	0	100
Clay County Highway 3	100	0	100
Cluster 3	100	100	0
Worker-job mix	100	100	0
Cluster size	100	0	100
Median age	100	0	100
Speed	100	0	100
Percentage population white	100	0	100
Industrial employment density	99	100	0
Employment and household entropy	98	100	0
Service employment density	95	1	99
Distance to downtown	95	90	10
Cluster	95	2	98
Cluster 1	95	4	96
Office employment density	94	1	99
Pedestrian-oriented intersection density (4-leg intersections)	93	13	87
Multi-modal network density	93	99	1
Pedestrian-oriented network density	92	10	90
Cluster 2	91	4	96
Cluster 5	91	7	93
Retail employment density	91	91	9
Median household income	89	8	92
Percentage population male	88	12	88
Street intersection density	85	18	82
Total road network density	85	16	84
Auto-oriented network density	81	92	8
Population density	78	18	82
Percentage population aged 25-49	77	96	4
Pedestrian-oriented intersection density (3-leg intersections)	76	17	83
Auto-oriented intersection density	73	76	24
Multi-modal intersection density (3-leg intersections)	72	96	4
Percentage low-wage workers	70	55	45
Entertainment employment density	70	12	88
Percentage households no vehicles	69	15	85
Gross employment density	69	21	79
Multi-modal intersection density (4-leg intersections)	64	54	46
Percentage population aged 18-24	55	73	27
Employment entropy	44	54	46
Cluster 4	39	20	80
Number of lanes	27	15	85

Population density is often found to be significant, and the effect is usually positive, as expected, but the result is not as robust, as it is sometimes insignificant or negative. Employment density tends to be significant and positive, but the results are not as robust and tend to differ depending on the type of employment. Industrial employment density is consistently significant and negative, indicating fewer bike trips in industrial areas. On the other hand, office and service employment density are found to have consistently positive effects on bicycle use. Results for retail and entertainment density are less consistent, though retail density tends to be negative and entertainment density positive.

The diversity measures, including the worker-job mix and the employment and household entropy, have unexpected negative relationships with bicycle use. This might be explained by Strava trips being biased more toward recreational trips rather than commuting or utilitarian trips. Employment entropy, which measures the mix of employment types, appears to have no relationship with bicycle use.

Among the design variables, as previously noted, bicycle facilities are important. Connectivity is also important. The pedestrian-oriented intersection and density variables are often statistically significant and in most models are shown to have a positive relationship with bike use. Conversely, the auto-oriented network and intersection density are often found to have negative relationships. Overall street intersection density and road network density tend to have positive effects. Connectivity is also measured by belonging to a large low-traffic stress cluster. Belonging to such a cluster is shown to have a significant and positive relationship with bicycle use, and bicycle use is also positively related to the size of the cluster. The dummy variables for the individual clusters have varying effects. AADT and speed were unexpectedly found to have positive relationships with bicycle use, and the number of lanes appears to be insignificant. It is likely that increased AADT and speed are correlated with other factors that attract bicycle use.

Destination accessibility variables are also significant. Distance to water is consistently significant and negative, which indicates that bicycle use increases closer to water. Similarly, distance to downtown is usually found to be significant, with a negative effect, indication bicycle use is greater closer to downtown, though the results are not as robust.

Some demographic variables appear to be important, while the results for others are inconsistent. Notably, median age and the percentage of the population that is white are consistently significant with positive effects. Results also suggest median household income tends to be positively related to bicycle use, and the percentage of the population that is male is often found to have a positive relationship. Other demographic variables have inconsistent and often insignificant results. Lastly, the dummy variables for U.S. Highway 81 and Clay County Highway 3 are significant and positive in every model.

Multicollinearity and spatial autocorrelation need to be addressed before specifying a final model. The calculation of VIFs show that many of the independent variables are correlated. For example, gross employment density is correlated with some of the other employment density variables. Many of the measures of intersection and network density are correlated, and the cluster size and cluster dummy variables are correlated. A second exploratory regression was run using five independent variables, with some of the correlated variables removed, and the results were largely the same as shown in Table 4.2, which was based on models with 2-4 independent variables.

Global Moran's I shows that these models exhibit spatial autocorrelation. None of the models tested with the exploratory regression passed the spatial autocorrelation test. A model with spatial autocorrelation violates the assumption about the independence of residuals, resulting in inflated test statistics.

A final model was selected consisting of independent variables found to be highly significant in the exploratory regression, excluding variables that were correlated with other independent variables (VIF > 5). The regression was estimated using a spatial error model, which accounts for spatial dependence in the error terms. Results from the spatial error regression model are shown in Table 4.3.

Table 4.3 Results of Spatial Error Regression Model of Bicycle Use

Variable	Coefficient	p-value
Constant	2.9313	0.016*
Density		
Population density	0.0088	0.726
Employment density	0.0001	0.994
Industrial employment density	-0.2878	0.004**
Diversity		
Worker-job mix	-0.3236	0.153
Design		
Bike lane	2.1920	0.000**
Buffered lane	1.1150	0.004**
Shared-lane markings	2.0747	0.000**
Signed-only	0.8015	0.000**
Shared-use path	2.3099	0.000**
Shoulder	1.2215	0.000**
Pedestrian-oriented intersection density	-0.0014	0.689
Cluster size	0.0003	0.016*
AADT	0.2133	0.000**
Speed	0.0259	0.000**
Destination Accessibility		
Distance to downtown	-0.0001	0.000**
Distance to water	-0.0003	0.000**
Demographics		
Percentage population white	0.1107	0.900
Median household income	0.0000	0.634
Percentage population male	-1.2790	0.362
Median age	0.0223	0.000**
Other		
U.S. Highway 81	5.6938	0.000**
Clay County Highway 3	4.2543	0.000**
Lambda	0.7362	0.000**
$R^2 = 0.617$		
n = 6490		

*p<0.05, **p<0.01

The population density and total employment density variables are not statistically significant. However, industrial employment density is significant with a negative effect. This shows that bicycle use is lower in industrial areas, everything else equal. The one diversity variable in the model, worker-job mix, is not significant.

Many of the design variables are statistically significant. The dummy variables for bike lane, buffered lane, shared-lane markings, signed-only, shared-use path, and shoulder are all significant with positive effects. These results show that bicycle use is greater where these bicycle facilities exist. Each of these types of bicycle facilities are shown to be positively related to bicycle use. The magnitude of the effect is greatest for the shared-use path and bike lanes, suggesting these are most effective in increasing bicycle use, and the effect is smallest for signed-only routes and shoulders, but results still suggest that these are also effective in increasing bicycle use.

The cluster size variable is significant and positive, suggesting that connectivity is also important. This result means that areas that are part of a larger, connected cluster of low stress facilities have increased bicycle use. Many of the intersection and network density variables were correlated, so only the pedestrian-oriented density variable was included in the model, but it was not found to be significant. Cluster size is shown to be a better predictor of bicycle use than intersection density.

The results also show AADT and speed to be significant and positive. This is the opposite of what was expected. However, there may be a confounding factor that explains the positive relationship. Areas with higher levels of traffic and speed may be desirable routes to cyclists for other reasons. Perhaps they provide more direct routes or better access to destinations. The result could also be caused by a potential bias in the data, due to the demographics and riding preferences of Strava users. Strava users may be less fearful of higher-stress roadways, and therefore, may be more inclined than the average rider to use high-volume, high-speed roadways. This could be especially true if they are attempting to maintain a certain speed, which would lead them to prefer higher speed routes with less traffic control.

Distance to downtown and distance to water are both negative and significant. This indicates that as distance from downtown or water increases, bicycle use decreases. In other words, bicycle use increases closer to downtown or closer to the water. The magnitude of the effect is greater for water. Many of the areas with the greatest bicycle usage are trails near the Red River.

Among the demographic variables, only age was found to be statistically significant. Bicycle use was found to be positively related to median age. Income, gender, and race were not found to be significant.

Lastly, the dummy variables for U.S. Highway 81 and Clay County Highway 3 are significant and positive, and the magnitude of the effect is large. This shows that bicycle use on these highways is greater than would be expected based solely on the other variables in the model. Bicycle use is likely greater on these highways because they are parts of popular routes used by recreational cyclists for making longer, out-of-town rides. The large positive effect of these variables could show some bias in the Strava data toward recreational trips, because these routes are not likely to be used as significantly for commuting or utilitarian trips.

5. CONCLUSIONS

This study developed a level of traffic stress (LTS) map for Fargo-Moorhead and used crowdsourced bicycle use data from Strava to show relationships between the built environment and bicycle use. The LTS map is useful for showing how friendly and encouraging areas are toward bicycle use, as well as for showing the connectivity of low-stress pathways, and the bicycle ridership model shows how the development of bicycle facilities and other changes to the built environment are associated with bicycle use.

The constructed LTS map shows that much of the Fargo-Moorhead area consists of low-stress (LTS 1 or 2) facilities, mostly low-volume residential streets and shared-use paths that are separated from traffic. However, higher-speed and higher-volume roadways often create barriers for the low-stress network. The maps of the connected low-stress clusters show that some areas are well connected by low-volume residential streets and separated paths, but the boundaries of these clusters show where there are barriers to bicycle use. Areas outside these clusters tend to be in more auto-oriented neighborhoods where there are more barriers to bicycle use. Overcoming these barriers often requires lower-stress options for crossing an LTS 3 or 4 roadway. This could require reducing speeds, reducing the number of lanes to cross, or creating a grade-separated crossing. Low-stress interconnecting links are necessary to create a more connected network.

The greatest low-stress connectivity is shown to exist in neighborhoods along the Red River and in the older parts of the metro area, including downtown and areas near downtown. The separated path along the river provides a connection to several neighborhoods, and these neighborhoods are built on a grid network that offers greater connectivity. The area has a more urban development pattern with fewer of the wide arterials to create barriers. Even within this cluster, there are areas of poor connectivity. For example, traveling between north and south Moorhead on a low-stress network could only be done by traveling on the separated path along the river.

There are some limitations to the LTS map. Calculations were made using speed limit data instead of actual vehicle speeds. The use of actual vehicle speeds could provide different results. Low-volume residential streets were classified as LTS 1 if their speed limit was 25 mph. However, if actual speeds are greater than 25 mph, then they should be classified as LTS 2. Low-volume residential streets in Moorhead were all classified as LTS 2 because the speed limit is 30 mph, even though traffic speeds may be no different than on similar streets in Fargo. The methodology provides support for speed limits being no higher than 25 mph on these streets, because those lower speeds are necessary to create a network that is more supportive of bicycle use.

The LTS method is less useful for classifying roadways that travel outside the city. The method makes no distinction between a multilane highway with a 70-mph speed limit and a two-lane roadway with a wide shoulder and a 45-mph speed limit. Both would be classified as LTS 4, but they offer tremendously different experiences for bicyclists. Even gravel roads are categorized as LTS 4, using this methodology. A different method is needed to categorize roadways that travel outside the city.

The results of the bicycle use model provide some expected results and some surprising results. First, the model shows that the existence of bicycle facilities is positively associated with bicycle use. This suggests that bicyclists are using the roadway design features that are meant to accommodate them, and it suggests that investments in these facilities have been useful. The model cannot say whether investments in bicycle facilities has led to an increase in bicycle use, rather it shows that areas where those investments have occurred have greater bicycle use. That greater bicycle use could be because of an increase in bicycle use or it could be because those facilities are simply influencing route choice. It likely could be a combination of increased bicycle use and route choice, but the model cannot say. Regardless, the results show bicyclists are more likely to travel where those facilities exist.

Results also show that each type of bicycle facility has had a positive effect, even shared-lane markings, signed-only routes, and shoulders, although the effect is greatest for shared-use paths and bike lanes. It may be expected that buffered bike lanes would have a greater impact than regular bike lanes with no separation or buffer. However, there are too few buffered bike lanes in Fargo-Moorhead to show that distinction. Separated lanes were not included in the model because there are very few instances of such lanes in the metro area. Connectivity was also shown to be important. Areas within a larger cluster of connected, low-stress streets or bike paths had higher levels of bicycle use.

Bicycle use was also found to be greater in or near downtown and in areas near the Red River or Sheyenne River. These are popular attractors for bicycle use. The findings, therefore, support the development of bicycle infrastructure in these areas.

The results for AADT and speed were unexpected. Areas with higher AADT and speed had greater bicycle use, even though these are higher stress areas that would be expected to discourage bicycle use. This result may be because arterials and collector streets with higher speeds and traffic volumes may provide better access to destinations and more direct routes for cyclists. It could also be due to bias in the data, as Strava users may be more confident bicyclists who are less deterred by the higher-stress routes. The results are not showing specifically that the bicycle traffic is occurring on the streets, but rather it could be on adjacent paths or sidewalks. Some of these streets have separated paths to accommodate bicyclists. The findings suggest that these higher stress streets should have facilities to accommodate bicyclists, particularly separated paths, because there is higher demand for bicycle use.

Bicycle use was also found to be higher for two highways, U.S. Highway 81 and Clay County Road 3, leading out of town, even though they are classified as LTS 4. Clay County Highway 3 currently has a wide shoulder to accommodate bicycle traffic, while U.S. Highway 81 has no accommodations. Findings suggest that the greater demand for bicycle use on these roadways could justify improved bicycle infrastructure.

There are some limitations to the model of bicycle use. The Strava data represent only a small portion of bicycle use, and there is potential for bias regarding the types of trips being made or the types of users, as discussed in the literature review. Although, as other studies have suggested, the results can still be useful and fairly representative of the use of bicycle infrastructure. Existing bicycle count data in the Fargo-Moorhead metro area is sparse, so it is difficult to validate the Strava data. The Strava data show some positive correlation to the official count data, but it is not a strong correlation. Additional count data is needed to validate the results. As shown by other studies, the combination of official count data with crowdsourced data from Strava or other sources can be useful for mapping bicycle use across the metro area.

The study aggregated Strava data for 2019 and 2020 to provide a greater number of observations. This study did not attempt to identify any trends in bicycle use over time, but there were more than twice as many Strava trips reported in 2020 than in 2019. However, that increase could be because of either an increase in bicycle use or an increase in the popularity of Strava, or both of those factors. The Covid-19 pandemic of 2020 appeared to result in significant increases in bicycling across the world (Venter et al. 2021; Schweizer et al. 2021). However, it is possible that the share of bicyclists using Strava has also increased, and if Strava or other crowdsourced apps are capturing a larger share of bicycle use, then future data may prove to be more useful. The combination of future crowdsourced data with an increase in official counts could be used to map bicycle use more accurately across the metro area, and the data could be studied further to identify specific barriers in the network.

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