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Estimating Isochrone Map Uncertainty for an Individual Cycle Commuter at Okanagan College, Kelowna, British Columbia, and Its Impact on Available Housing Choice

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Abstract

Identification of variables that influence differences between predicted and observed cycling times for one cyclist commuting to Okanagan College (OC) was performed using principal components analysis. These data were used to create a personalized predictive time algorithm, which was subsequently applied in an isochrone map format centered on OC. A 29% difference in the area within the 20-minute commuting time was estimated, suggesting that potential residential location choices made with inaccurate isochrone maps are inaccurate. A comparison with an isochron cycling map for Trinity College Dublin was made to emphasise differences in the impact/implications of this type of map in the promotion of sustainable transportation for a post-secondary institution. It is determined that these maps may misinform new community members as to areas of residential location choice.

Keywords

Principal Components Analysis, Cartography, Residential Choice, Bicycle, Campus Sustainability Planning

1. Introduction

Bonham and Koth identify that cycling culture in a university setting is an important component of a post-secondary institution's sustainability, despite differing investments in dedicated cyclist infrastructure on campuses [1]. Risk factors were identified as limitations to cycling to campus adoption in Massachusetts, USA [2]. Zhou suggests a number of factors may contribute to student travel mode choice, with gender, age and status being important in opting for cycling [3]. Wuerzer and Mason found that university students would cycle a distance of about 5 - 6 km as an optimal value [4]. Decreased travel time was identified as a motivating factor for riding at the University of Tennessee [5]. Temperate climates also negatively affect the adoption of cycling [6] [7], though weather conditions were also cited as constraints in Malaysia [8]. Existing modes may also be a barrier to the adoption of cycling to campus [9]. Zhou *et al.* [10] purport that the nature of the community, *i.e.* college town vs. urban university, affects cycling choices. This difference in culture has been recognized within the EU-funded PASTA—Physical Activity Through Sustainable Transport Approaches—project, which identified the "social environment", or cycling culture, as an important facet in the adoption of active transport [11].

Cycling maps have long been a facet of cycling culture [12]. Cartographers create isochrone (also known as radius or concentric ring) maps depicting expected movement times from a central point to out-lying destinations, sometimes using coloured bands to represent specific blocks of time. This approach for predicting cycling times has been adopted by Trinity College Dublin, Ireland (https://www.tcd.ie/collegehealth/promotion/travel/Cycling.php). This type of map is somewhat limited in its usefulness, as it is not intended for route selection such as a cycling map, *i.e.*, similar to one generated for Cincinnati [13], but rather to provide an imprecise indication of travel time from zones of origin to a single destination. Ultimately, the isochrone map may be limited in its usefulness to one's initial exposure to a city or in an exclusionary choice application, delimiting the areas for residential choice when relocating, as one often does when one "goes to university". Thereafter, the cyclist is shown to experiment with route choice and time to find a suitable route [14]. For university students, the proximity between institution and residence is a significant factor in transportation mode choices [10] [15], and may affect performance outcomes [16] or the feeling of connectedness to an institution [17]. Co-location is an important element within residential choice [18], and consideration of commute modes is part of residential location discrete choice modelling [19] [20]. Decisions regarding co-location and travel mode choices are made prior to or immediately after an individual first arrives in a community [21]. Thus an accurate isochrone map centered upon a post-secondary institution for the purposes of residential choice may be valuable for prospective university students and faculty or staff. Despite its apparent limited period of usefulness, having such a map available may contribute to promoting campus cycling culture.

Currently, the KLO campus of Okanagan College, Kelowna, British Columbia, has no isochrone map for cycling times. Generating an accurate map is one of many steps to encourage cyclo-commuting to campus [22]. This is especially important as there is a large number of international students arriving each year in the community. Like many Canadian post-secondary institutions, Okanagan College has increased the number of international students from 359 full-time equivalent students in 2005-2006 to 1467 in 2019-2020 [23]. It also makes use of precariously employed faculty to fill short-term contract teaching positions (personal experience). These temporary staff and international students require housing during their stay in the community, which means commute times and modes may be a consideration in where they choose to live. They also may reside in Kelowna only for a short duration whilst connected to the institution [24] [25], thus electing to rent rather than purchase a home. As housing choice is made when an individual first arrives in the city, having an isochrone map may be useful, if it's accurate, for planning transportation mode [26] or in residential choice [27].

An accurate map, one that neither overestimates nor underestimates riding times, requires a valid, representative cycling time-distance algorithm. Interactive mapping applications, such as Google Maps, can also be used to predict the duration of cycling trips from origin to destination, providing what may be an accurate estimate of time required. Cyclo-commuters could potentially use these estimates of cycling time to choose routes to select or avoid infrastructure or traffic situations with a corresponding variation in travel time [28].

Manum *et al.* identify numerous components to determine the most accurate means of estimating cycling time, including "route geometry, intersection impedance, type of bicycle route, kind of surface, and density of entrances to buildings along route" [29]. Crowd-sourced data can also be useful in incorporating real-world, real-rider data, averaged for weather conditions [30] [31]. However, riders employing this technology may not be representative of the diversity of cyclists, particularly novices. Unlike algorithms generated for motor-vehicle traffic, where cell phone data can be included [32] and velocity is controlled with speed limits, cycling speeds may be significantly more variable [33]. For any one particular rider on any one particular route, there is likely a significant deviation from an application's (*i.e.* Google Maps) predicted value. This variation may be due to the unique "rider and bicycle" combination on that route. For example, heavier, less fit riders may have compounded slower times, especially uphill, in comparison to lighter, fitter riders. Conversely, riders with more weight and confidence might have much faster times on a net downhill route. Also unknown is the effect of limited endurance, that is to say, if riders gradually go slower as trip length increases. Bicycle type may also play a significant role in determining the route time—a high-performance road bike would likely be significantly faster than a heavy, knobbly-tire-equipped mountain bike. Note that the use of an e-bike (electrically assisted bicycle) would likely yield much more consistent estimates, such as those for motor vehicles, as maximum speeds are often attainable even on uphill routes. Thus the deviation from the predicted time could be substantial for any individual using a conventional, pedal-powered bicycle. For individuals choosing a residence location based on trip duration, a cycling time map based on generic algorithm results may be significantly misleading.

An isochrone map using riding times generated from Google Earth for commutes of 20 minutes or less (the average local commute time within the City of Kelowna [34]) shows a maximum distance of <6 km (a cycling speed of about 18 km/hr) from the campus (**Figure 1(a)**). The 27 km^2 area contained within the 20-minute concentric ring consists of much of the relatively flat and densely populated urban areas of the city, and given the proximity to waterfront, some of the least affordable neighbourhoods [35] [36]. It does not extend to the more affordable residential neighbourhoods of Rutland or Glenmore, located to the NE and NNE of Okanagan College, respectively. Precisely how different a map can appear for one rider vs another, and thus affect the area of potential locations for residence choice within the 20-minute commute if representative data were used, is currently unknown.

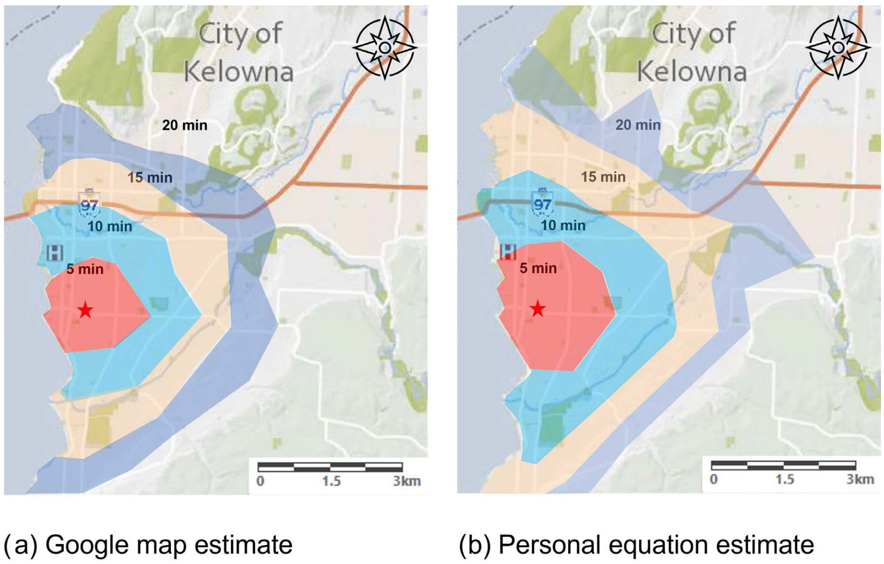


Figure 1. Isochrone map estimates from the KLO campus, Okanagan College, using (a) Google Earth to estimate riding time, and (b) a personal equation estimate generated in this manuscript.

Here, an examination of cycling time variation to predicted Google Maps times for one rider is presented. Cycling time predictions were explored on generally uphill routes from Okanagan College with conventionally human-powered bicycles, with the ultimate purpose of generating an accurate, personalized isochrone map outbound from the KLO campus. A personal algorithm is used to generate a comparison isochrone map, illustrating a change in the area of potential residential choices for one individual. Air quality factors may also be highly co-variable [37], and knowledge of the effect on cycling time/speed is limited [38], so values for air temperature and particulate matter were included in this study. A principal components analysis was used to identify significant variables that may be included in the derivation of the personal algorithm.

2. Methods

2.1. Location

Kelowna is situated in the central Okanagan region of British Columbia, Canada.

The Okanagan valley runs primarily north-south through the interior plateau of the province. Elevations at the valley bottom are approximately 350m asl, with much of the developed road infrastructure on or near the valley bottom. The top of the plateau rises roughly 1000m above that, with few roads accessing the slopes. It is an ideal community in which to ride a bicycle with its generally warm temperatures and dry conditions from spring through autumn. Monthly means of daily temperatures in Kelowna from May through to September are 12.8˚C, 16.6˚C, 19.5˚C, 19.1˚C, and 13.9˚C, respectively. Mean maximum temperatures are 20.2˚C, 24.2˚C, 27.9˚C, 27.6˚C, and 21.7˚C for the same period. The average rainfall for May to September is 40.2, 45.9, 37.2, 32.1, and 31.7 mm, respectively, with 2.8, 3.3, 2.6, 2.2, and 2.1 days of rain receiving more than 5 mm [39].

The city itself has a population of approximately 146,000 residents and the regional district about 223,000 [40], distributed in areas of 212 km^2 and 2900 km^2, respectively. Benchmark pricing for single-family homes in the central Okanagan is $1,001,500 for March 2022 [41]. The overall majority of roads within the city are paved, with the exception of a few sections leading to higher elevations exiting the city, e.g. June Springs Road, Little White Forest Service Road, etc. There are approximately 140 traffic lights on a total of about 900 km of roadway, yielding a light density of 0.16 light/km (or 6.4 km/light). The city claims 300 km of on-street bike lanes and 40 km of separated, shared-use paths [42]. On-street bike lanes, shared pathways, and roadways were used in this study, all of which (except for a short 50 m segment used once) were paved. The road infrastructure is rated as bicycle-friendly [43]. Cycling promotion is supported by the city (https://www.kelowna.ca/sites/files/1/docs/related/pbmp_final_draft.pdf), with infrastructure improvements established when upgrading utilities, e.g. Ethyl Street corridor (https://getinvolved.kelowna.ca/ethel-street-active-transportation-corridor-phase-6). Dedicated cycling paths to connect various regions of the city have been a priority for the past decade, including access points to the KLO campus of Okanagan College (https://getinvolved.kelowna.ca/casorso-active-transportation-corridor). However, the city has traditionally been auto-centric, with less than 2% of trips made by bicycle [44] [45].

The KLO campus of Okanagan College reflects this car dependency, with approximately 900 car parking spaces available for its student body of just over 5000 full-time individuals over all programs. Additionally, there are 450 parking spots available for staff, and 50 short-term or visitor spots on campus (https://www.okanagan.bc.ca/sites/default/files/2020-06/Kelowna%20Parking%20Map.pdf), with an additional 250 spots available at a parking lot 0.5 km off campus. Similar to Trinity College, Dublin, Ireland, which lies in the low elevation coastal area of Dublin, the KLO campus is situated on the lowest elevation area of the city of Kelowna near the shoreline of Okanagan Lake, approximately 346 m asl). Thus rides to the campus would either be flat or downhill from most areas of the city, whereas ride times outbound from the college will likely increase because of the increase in elevation. Okanagan College currently does not have an official cycling-to-campus strategy, though bicycle racks and lockers are located outside of most buildings.

2.2. Data Collection

The riding time and distance from or near the KLO campus to various locations in the city was recorded in the period from May to August, 2021 and the duration of rides was limited to one hour or less. Three different types of bicycles were employed in this study: an older (approx. 2001) Norco Sasquatch mountain bike with 26" wheels and tire width of 1.125", a 2006 Cannondale CAAD8 road bike with 700C wheels and 23 mm tires, and a 2017 Kona Dew Deluxe commuter bike with 700C wheels and 35 mm tires. Cycling clothing was generally adapted to the bicycle, with casual cotton shorts worn with the mountain bike and sport-specific, spandex (elastane)-based cycling bib/jersey with the road bike. Either a backpack or pannier bag was used to carry extra items on trips with the Norco Sasquatch and Kona Dew Deluxe. Only a spare tube and pump were carried when riding the Cannondale.

Time, distance, elevation, and temperature data were collected using a Garmin Forerunner 10 or Garmin Edge 25 and manually transferred to Microsoft Excel using Garmin Connect. No rides were completed during "rain days" during this study. Air quality (PM2.5) was downloaded from the BC Air Data Archive for the Kelowna KLO Road station. Rider weight, measured using a household-variety Taylor digital scale, and date ridden were similarly recorded. Each route's distance and predicted time were estimated using Google Maps with the "directions" and cycling feature. Traffic lights were included if they were triggered by vehicle proximity, but not by pedestrians only, and were included even with a right-hand turn where stopping may not have occurred.

The rider was an approximately 60-year-old male recreational cyclist with average fitness. He typically rides about 100 km/week in the summer but does not ride a bicycle competitively. Using the identities outlined by Dill and McNeil [46], he may fall into the "Strong and Fearless" category, or the "terminal" phase of the transtheoretical model [47]. If asked, he would state that he rides assertively in traffic, but generally doesn't like to exert himself at any point while riding, thus effort on most rides was considered more or less consistent. A power meter was not used, though it would be a worthwhile consideration in a future study.

2.3. Data Analyses

A multiple regression analysis using Vasser Stats Online (http://vassarstats.net) was performed to determine if relationships exist between the following variables: day number, rider weight (kg), Garmin time taken (minutes, rounded upwards to the nearest whole value), Garmin distance (km), Garmin elevation (m), Garmin temp (˚C), Garmin time of day at start of ride (converted to decimal), tire width (mm), air pollution (PM2.5 (ug/m^3)), traffic light count, vs. the Google/Garmin time ratio. The three different bikes were changed from categorical to numerical variables by considering tire widths, as wider tires with less air pressure have greater rolling resistance, a significant factor in bike speed vs. effort [48] [49].

To visualize potentially important relationships, single linear regression analyses were plotted between the variables listed above and the ratio of predicted riding time relative to the actual time. Also plotted were weight, temperature and air pollution vs. day number, to characterize these expected relationships. Temperature and time of day were also plotted, however correlation was estimated using a logarithmic function.

A singular value decomposition (SVD) principal component analysis (PCA) was performed on normalized, ln (x) transformed data using ClustVis [50] to determine the strongest determinants in the data set. PCA are based on imaginary axes that can be understood by the variables found on their extremes, or loadings. A three-dimensional plot of the three principal components was generated using Excel 3D Scatter Plot [51]. Maps were based on the city of Kelowna's interactive base map (https://www.kelowna.ca/city-services/maps-open-data/interactive-maps).

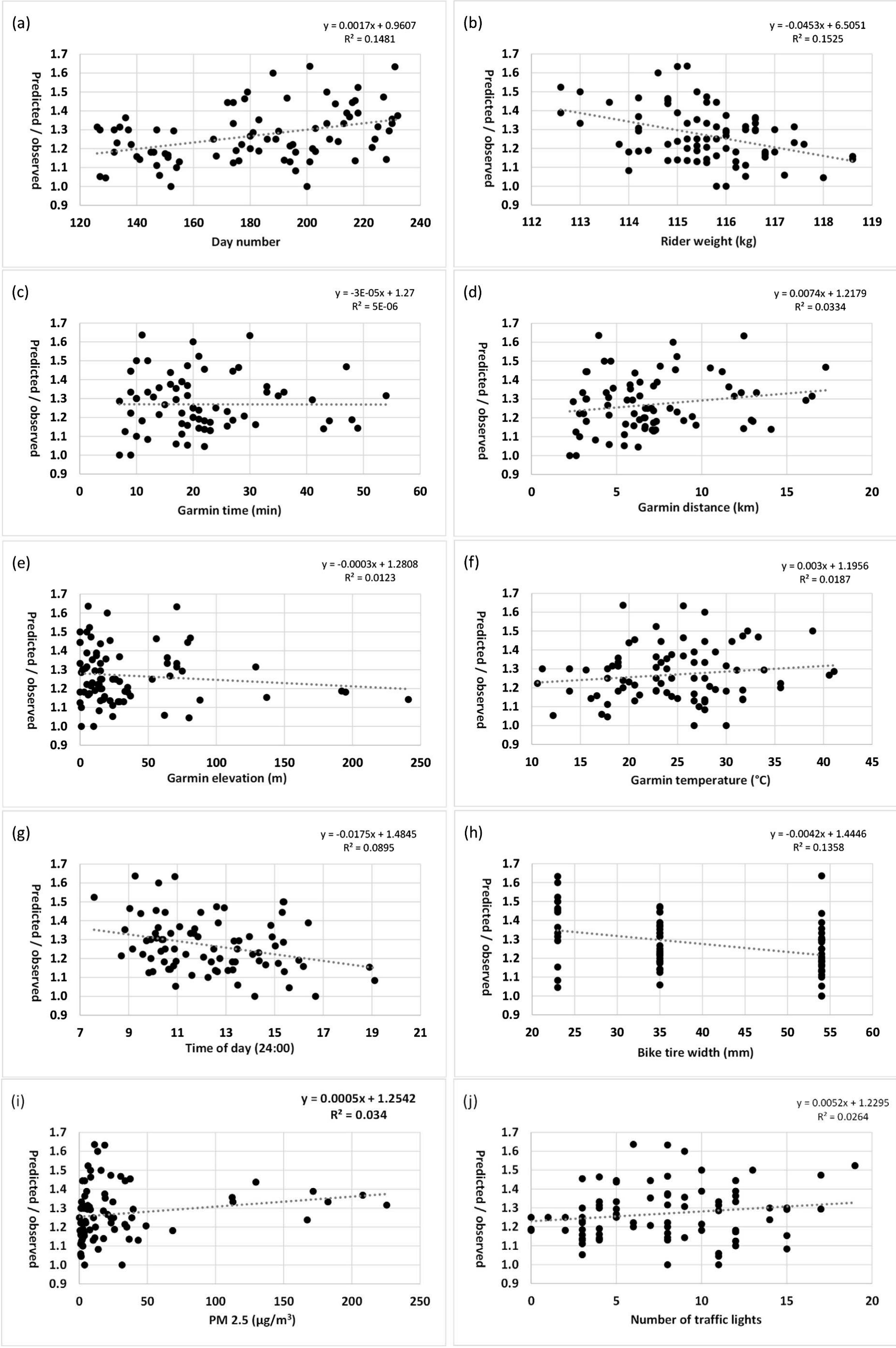
3. Results

A total of 81 rides were completed in the four-month period, having an average distance of 7.0 km, ranging between 2.3 - 17.3 km. The average ride time was 20.8 minutes (range: 7 - 54 min), with an average elevation gain of 33 m (range: 0 - 241 m). The road bike was used on 15 rides, where the hybrid was used for 29 and the mountain bike for 37. An average number of 1.14 traffic lights per km were encountered (range: 0 - 19). Air temperatures experienced ranged from 10.6 - 41.1˚C, and air quality (PM2.5) varied from 0.2 - 225.5 μg/ml.

3.1. Regression Analyses

The simple linear plots (**Figure 2**) and the multiple regression matrix (**Table 1**) show several relationships that were expected to be strongly correlated and thereby of little interest to this study, e.g., at $r = 0.959$, the longer the distance ridden the greater the amount of time taken. The relationships "of interest" are those affecting the predicted vs observed time, expressed as the ratio (RAT) between Google Maps's time vs that measured with a Garmin device.

Positively correlated with the ratio (faster than predicted) was day number ($r = 0.389$, **Figure 2(a)**) and, to a lesser degree, air quality ($r = 0.189$, **Figure 2(i)**) and distance ridden ($r = 0.179$, **Figure 2(d)**). Day number may be important only because as the summer progressed, the rider was likely fitter. This effect may be confirmed with the rider's weight decreasing ($r = -0.39$) over the duration of the summer (**Figure 2(k)**). The apparent increase in speed with increased air pollution ($r = 0.189$, **Figure 2(i)**) may be confounded by increased temperatures and particulate matter that occurred later in the summer (**Figure 2(l)**, **Figure 2(m)**). Accumulated heat during the summer period and unusual heat dome [52] [53] led to more frequent and severe wildfire regionally, resulting in more smoke occurring in the valley as summer progressed, reflected in the correlation between day number and air pollution ($R^2 = 0.2607$, r = 0.511). The correlation between aridity and fire has been observed in similar ecosystems in the southwest US [54]. On longer distance rides, the rider was able to ride faster (r = −0.41) due to the faster bike *i.e.*, the road bike with narrower tire width, being chosen (**Figure 2(d)**, **Figure 2(h)**, **Table 1** Bike-GAD r = −0.414). Air quality was not a factor in cycling time variation; however, this may be due to a predisposition (*i.e.*, males over 30 years) to ignore discomfort [55] associated with the sub-optimal conditions.



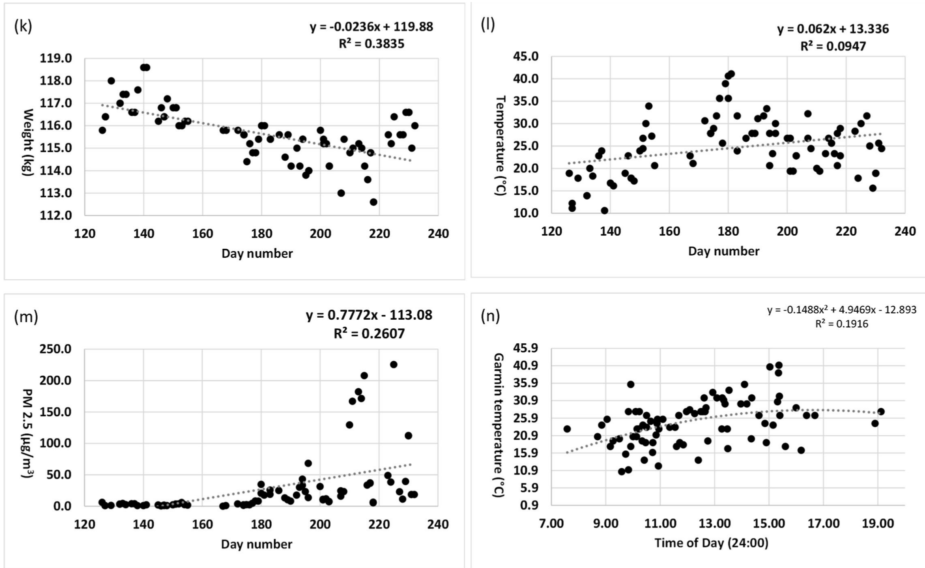


Figure 2. (a)-(j) Regression analyses between the differences between Google Earth predicted and observed riding time. (k)-(n). Regression analyses between variables of interest collected in this study, (k) rider weight vs day number, (l) temperature vs day number, (m) air pollution reflected by PM2.5 vs day number, and (n) Garmin temperature vs time of day.

Negatively correlated with the ratio was rider weight (r = −0.391, Figure 2(b)), bike type (r = −0.363, Figure 2(h)), and time of day (r = −0.297, Figure 2(g)). Rider weight decreased by about 3 kg (Figure 2(k)) over the summer period, likely with an increase in fitness resulting in faster riding times. Bike type was expected to influence the time ratio and was deliberately included as a variable in this study. Time of day likely reflects rider fatigue that occurred later in the day more so than comfortable cycling temperatures in the morning, as temperature itself had little effect on the ratio (Figure 2(f)). Temperatures were warmer later in the day (r = 0.406, Figure 2(n)) and warmer later in summer (r = 0.308, Figure 2(l)).

Elevation change was only weakly negatively correlated with the ratio (r = −0.114, Figure 2(e)). Elevation increases only occur the further the ride from the college (r = 0.695) due to the city's topography, and thus correlate with a longer ride time (r = 0.818). As none of the rides were greater than one hour or 20 km (Figure 2(c)-(d)), an "endurance effect" was not considered to have taken place. With an increase in the number of traffic lights, the ratio was slightly positive but not significant (r = 0.16, Figure 2(j)). Non-causal relationships also appear in the data, for example, the correlation between rider weight and temperature (r = −0.42), likely due to the fact that warmer temperature days occurred later in the summer.

Table 1. Multiple regression, where DN = day number, KG = rider weight (kg), GAT = Garmin time (min), GAD = Garmin distance (km), GE = Garmin elevation (m), GT = Garmin temp (˚C), TOD = time of day at the start of ride, BIKE = tire width (mm), PM2.5 = air pollution reflected by PM2.5 (ug/m³), TL = number of traffic lights, and RAT = Google/Garmin time ratio.

	DN	KG	GAT	GAD	GE	GT	TOD	BIKE	PM2.5	TL	RAT
DN	1	**−0.62**	−0.046	0.09	−0.171	**0.308**	−0.123	−0.102	**0.511**	0.121	**0.389**
KG		1	0.001	−0.165	0.167	**−0.42**	0.104	**0.269**	−0.155	−0.159	**−0.39**

Continued

GAT	1	**0.959**	**0.818**	−0.043	−0.044	**−0.33**	0.005	−0.204	**−0.01**
GAD		1	**0.695**	0.02	−0.102	**−0.41**	0.062	−0.14	**0.179**
GE			1	−0.079	0.047	**−0.36**	−0.059	−0.139	**−0.11**
GT				1	**0.406**	**−0.25**	0.031	0.123	**0.141**
TOD					1	−0.123	−0.047	0.136	**−0.3**
BIKE						1	−0.059	−0.337	**−0.36**
PM2.5							1	0.014	**0.189**
TL								1	**0.16**
RAT									1

3.2. Principal Components Analysis

The first axis (Table 2(a), Figure 3) explains 47% of the variation in the data set, with tire width (BIKE, load = −10) at one end of axis 1 and distance (GAD) and traffic light number (TL) with loadings of 6.7 and 6.5, respectively on the opposite end of this axis (Table 2(b)). The second axis explains a further 24% of the variation, with elevation (GE) at −9 and the remainder of variables except distance on the positive side of this axis. However, when viewing the third axis, which contains 23% of the variation, air pollution (PM2.5) and elevation are on the positive axis (loadings of 8.7 and 2.2, respectively, Figure 3(b)), with the remainder of the variables on the negative side. Elevation and air quality appear as important variables when comparing the second and third axes (Figure 3(c)). A three-dimensional plot of this data (Figure 3(d)) shows the most important measured factors explaining variation in the data set (bike choice, distance, elevation, traffic lights, and air pollution), separated in space at the extremes of these three axes.

Table 2. (a) Percent of variation explained by each principal component axis. (b) Percent of variation explained by each principal component axis.

(a)

	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Individual	0.470	0.241	0.227	0.037	0.015	0.010	0.000
Cumulative	0.470	0.711	0.938	0.975	0.990	1.000	1.000

(b)

	PC axis 1	PC axis 2	PC axis 3
GAD	−6.7	−2.0	−1.8
GE	1.0	−9.1	2.2
GT	5.6	1.3	−1.1
TOD	−0.8	1.0	−2.6
BIKE	10.0	1.9	−1.3
PM2.5	−2.7	4.0	8.7
TL	−6.5	2.8	−4.1

Table 3. Area of polygons shown in **Figure 1**, as determined using GoExplore Consulting Ltd software (https://www.goexplore.consulting/powerpoint-polygon-areas).

Isochrone (min)	Google Earth Estimate Area (km²)	Google Earth estimate cumulative area (km²)	Personal estimate area (km²)	Personal equation cumulative area (km²)
5	3.0	3.0	4.8	4.8
10	6.3	9.3	9.7	14.5
15	7.9	17.2	10.7	25.2
20	10.2	27.4	10.2	35.4

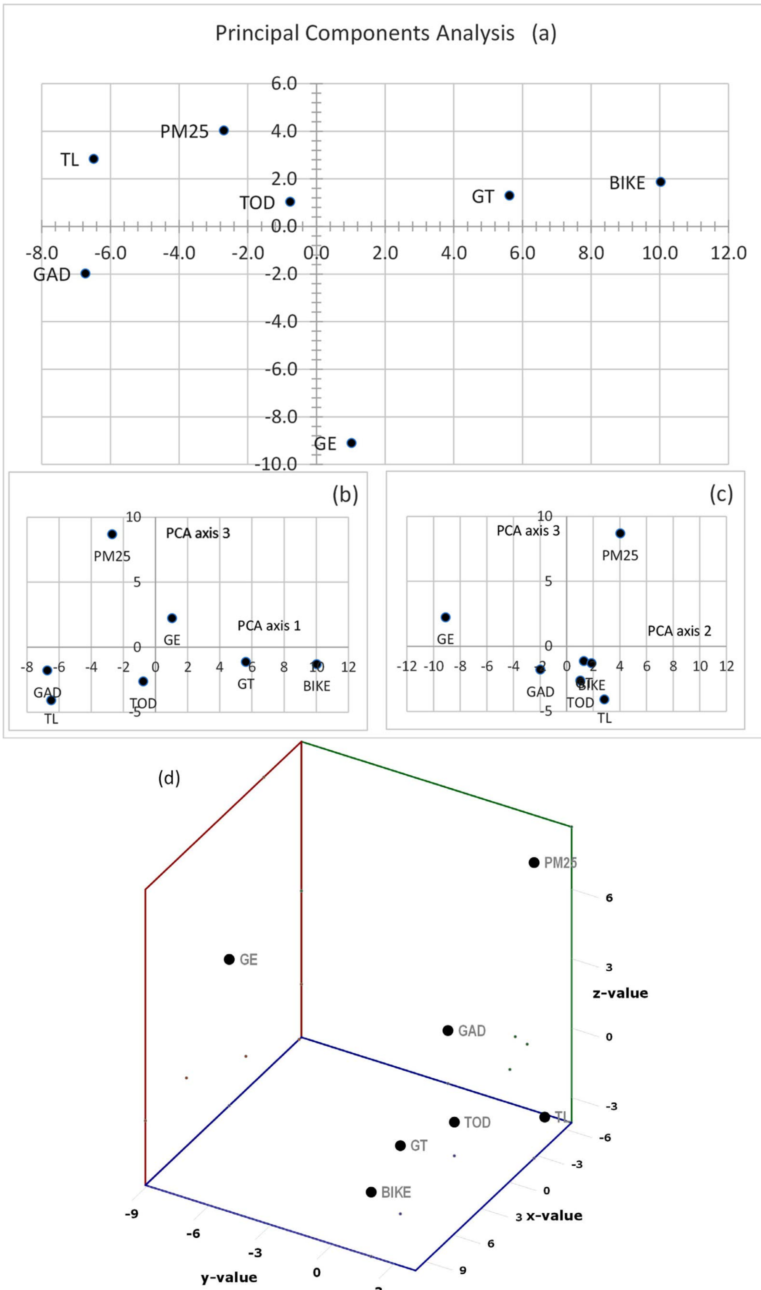


Figure 3. Principal component analysis of (a) axes one vs two, (b) axes one vs three, (c) axes two vs. three, and (d) a three-dimensional representation of axes one, two and three.

3.3. Personal Equation Generation

A multiple variable linear regression model was generated based on the variables easily obtained using Google Maps identified in the PCA. Air quality is excluded from the model, as a prediction on any given day is essentially impossible [56]. Traffic light numbers were also excluded, as the number of lights on the route is not available in the Google Maps description. This personal equation uses distance, elevation change, and bike tire width to adjust the Google Maps predicted ride time to a potentially more accurate estimate. The following equation:

$$\text{Estimated time} = \text{Predicted time}/[(0.015176 * \text{distance}) + (-0.00159 * \text{elevation}) + (-0.00456 * \text{bike tire width}) + 1.405675]$$

where distance is in km, elevation in m, and bike tire width in mm, is based on the entire ride data set and has an R squared value of 0.272. To illustrate the application of this equation, an isochrone map generated from these values centred on the KLO campus of Okanagan College is shown in **Figure 1(b)**, with the value of 23 mm selected for bike tire width.

The personalized map contains larger areas within each of the five-minute time divisions (**Table 3**), with an overall area increase of 29% as compared with the Google Maps predicted area. This results in several neighbourhoods where extensive residential development and housing opportunities become available within the 20-minute commute time, particularly in the north Glenmore and Rutland neighbourhoods. Fewer differences in area are observed with higher elevation neighbourhoods, particularly in southeast Kelowna, an elevated region situated on former glacial lake bottoms [57], and those on Dilworth Mountain.

4. Discussion

All Google map estimates of cycling time exceeded those of the actual ride times, regardless of the bicycle type chosen in this study. Variables affecting ride times were identified using multiple linear regression and principal components analyses; traffic light number and air quality were subsequently dropped, leaving bike choice, distance, and elevation as significant variables from which a personal equation to adjust Google Maps' predicted ride time could be generated. An isochrone map was subsequently created with this personal equation that showed a 29% larger area from which a 20-minute commute could be achieved. These cycling variables were previously reviewed by Manum *et al.* [29], and none should be surprising to people who have either used the Google Maps application and ridden a bicycle for commuting. What appears significant is the magnitude of difference in time for one individual from a predicted value. The potential difference in commuting distance may affect members of the college community in terms of transportation mode choice or, more importantly, location of residence choice. A post-secondary institution adopting this type of map potentially misinforms its community.

Trinity College displays on its website an isochrone map with ride times up to one hour, covering an area of approximately 400 km^2; the 20- and 30-minute cycling areas are approximately 55 and 125 km^2. Irishcycle.com [58] reports the average commute distance for Dublin is 5.88 km (straight line distance) and an average speed of 14 km/hr, resulting in an average cycling commute of just under 25 minutes, suggesting the area available to reside within this average commute time would be 75 km^2. The 2016 overall commute time, which includes public and private transportation, averages 28.9 minutes [59]. As there is a vast difference in areas between the 1-hour and the 30-minute map, is displaying a one-hour commute time map optimistic or deceptive, to encourage those living 15 km or more distant to consider cycling? Caulfield shows that only ~5% of commuters in 2011 cycle within the 30-minute area, and <4% in the 50 - 60-minute areas [60]. As this institution is located at approximately sea level, most outbound rides will also increase in elevation, though there will generally be less than 100 m elevation difference to outlying regions an hour's distance away [61]. Would return trips be more than an hour? How many college members would consider cycling more than two hours per day, every day of the week? Without on-campus vehicle parking for students and less than 1% of faculty using personal vehicles [62], perhaps there is acceptance of this notion. Vale *et al.* [63] suggest that institutional infrastructure makes a greater impact on travel mode than distance; that is to say, available car parking may discourage cycling. This may explain the difference in the numbers of people commuting by bicycle between OC, which has abundant parking and Trinity College Dublin, which has no available student parking on campus.

It was unexpected that traffic lights were an identified factor in the PCA, given that Kelowna has 78% fewer lights per km than Dublin. The traffic lights that Kelowna does have appear concentrated within the 20-minute ring (**Figure 1(a)**), as the average number of lights encountered (1.14 lights/km) was similar or greater than that of Dublin. With a population of about 540,000 people, Dublin has about 820 traffic lights [64] on about 1146 km of roads (road authority), yielding a light density of 0.72 lights/km (or 1.4 km/light). Traffic lights have been previously recognized as a factor in route choice [31] [65], and data from Amsterdam shows that cyclists often detour from the shortest route [66] to avoid them. Romanillos and Gutierrez [67] also found that traffic light density is negatively correlated with cycling speed. Proposals for optimizing speed for cyclists relative to traffic lights in urban areas have been modeled by Anagnostopoulos *et al.* [68] in Finland, however, no such system has been considered for Kelowna.

Confounding variables to Google Earth's prediction of cycling times goes beyond the measured values of Manum *et al.* [29]. Here, rider and bicycle type are shown to be major variables in prediction error. The question of whether rider effort changed on any ride is valid. Without the use of a power meter, little can be objectively compared; however, from rider feedback, effort per ride was generally considered to be consistent. The use of a power meter to follow or limit effort may improve predictive times; however, this remains untested. Note that Google Earth doesn't appear to delimit their predictions over longer riding distances (*i.e.* four 100 km segments provide the same time as one 400 km segment).

It is noted that all rides here were done during the months of May through August, where normal average temperatures are 13˚C and 20˚C, approximately. The rider was able to wear minimal cycling clothing, avoiding bulky or uncomfortable rain/cold weather gear. It is obvious that riding the same routes in winter would take significantly more time as the road surfaces are, at times, icy, snowy, wet, or slushy. Additional layers of clothing make shifting gears, use of brakes, and pedaling less efficient. Future research should examine the role of weather, such that a "winter climate conditions" variable can also be applied to determine the decrease in area available for residence choice.

It is unlikely that an isochrone map is sufficient for an active mobility cultural promotional measure to increase active transportation mode choice for OC commuters. A responsible approach, like for all post-secondary institutions, would be to adopt a sustainable transportation plan [69]. The University of Minnesota's cycling strategy plan sets forth the goal to "…encourage and support bicycling as a sustainable and equitable transportation mode…" and includes growth strategies, monitoring technology, maps, and education priorities [70]. It should be noted that the continental-type climate of Minnesota ranges from −9˚C in Jan to 23˚C in July [71]. If winter weather isn't a deterrent in Minnesota, it also shouldn't be a concern in Kelowna. Several Canadian post-secondary institutions also have official plans, e.g. The University of Victoria [72], and the University of British Columbia [73], though both of these institutions are found in maritime climates, suitable for year-round cycling. At OC, with a relatively mild winter climate, a sustainable, active transportation plan should be feasible.

Kelly *et al.* [22] review many of the Canadian schemes utilized to increase the share of cycling trips, with infrastructure as the dominant consideration. The City of Kelowna's plan to increase cycling infrastructure is considered an equitable step forward [74], a "carrot" in the motivation strategy to push active transport [75]. The benefits of increased infrastructure have been noted elsewhere [76]. Bicycle counters in the city of Kelowna (e.g., that at the Rail Trail at Bernard Avenue) show a generally increasing trend in the number of bicycles passing by [77]. A process to promote active transport options was considered by the Interior Health Authority, when relocating their facilities in downtown Kelowna, where car parking is not available [78]; there, a mode shift to cycling was incentivized. Okanagan College has made limited progress with the promotion of cycling—participating in an annual promotional activity and building a bicycle storage compound. Doran *et al.* [74] recognize that participation in active transport may reflect socio-economic realities rather than a choice, particularly for low-income migrant individuals. Nash and Mitra suggest that socio-demographic characteristics determine how students commute to their post-secondary institutions [79]. For British Columbia, where pickup truck sales increased dominance in a growing number of vehicles (70% of 237,092 new vehicles in 2017 to 77% of 202,677 vehicles in 2021, along with an increase in registered vehicles provincially from 3,268,655 in 2017 to 3,512,196 in 2021 [80]), it can be safely assumed that Okanagan residents remain unaffected by the "stick" of increased carbon taxes or price of fuel to reduce automobile dependency [81] which has been successful elsewhere [82]. However, Orvin *et al.* suggest that with the convenient location of OC, near the lake and with relatively good cycling infrastructure, it may be possible to take advantage of this to promote active commuting [83].

5. Conclusion

A sizeable portion of the city of Kelowna is within a 20-minute cycling time of Okanagan College. Depending on the individual, this may be greater or larger in area compared to that predicted by Google Earth maps. For one rider, a personalized isochrone map generated a 29% greater area of the city from which to choose a residential location for a 20-minute commute. A personalized isochrone cycling map, such as the one presented here, based upon an individual's choice of bicycle (tire width as proxy for efficiency of bicycle) and elevation, can be useful when first choosing a residential location from which to commute to Okanagan College. This principle is applicable to other post-secondary institutions nationally, if not internationally. An average campus-based isochrone map, because of its uncertainty for all riders, may potentially misinform new college community members when choosing a residential location. As part of a sustainable transportation plan, isochrone maps for cycling routes may be of limited value. However, a plan to increase bicycle commuting to campus is recommended. Future research should investigate whether or not isochrone maps are consulted by new college community members when considering residential locations.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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