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Impact of environment on bicycle travel demand—Assessment using bikeshare system data

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ABSTRACT

The paper aims to quantify the daily bicycle traffic volume based on the data from bicycle automatic counters and bikeshare system (BSS) trip data taking into account the impact of weather conditions. Changes in bicycle traffic were assessed based on coefficient of variation of bicycle volume and number of BSS trips. The research was conducted in the city of Cracow (Poland) for 2 years. The volume at 13 locations with bicycle automatic counters and a daily number of trips on public bicycles were avaialble. Data on daily weather conditions were collected from a weather station located in the city.

The monthly coefficients of variation of the number of BSS trips and cyclists' volume in analyzed locations are not statistically significantly different. It means data from BSS, easily to obtain, can be used to assess variation in cyclists volume. Mean daily air temperature, daily rainfall, public and school holidays had a statistically significant impact on bicycle volume. Models have shown that BSS trip data can be successfully used to evaluate the impact of weather conditions on bicycle volume. Additionally, based on the developed models, reliable coefficient of variations for Annual Average Daily Bicycle Traffic of BSS users and all cyclists were indicated.

1. Introduction

Bicycle volume data aggregated at daily basis are needed in road safety analysis (estimation of bicycle volume as risk exposure), planning, design, and management of bicycle infrastructure (estimations of bicycle traffic performance, calculations of infrastructure capacity, etc.) (Bullock, Brereton, & Bailey, 2017). When planning or designing road infrastructure, traffic volume has to represent traffic conditions in the long-term period. Therefore, the impact of weather conditions and the environment on bicycle volume in this type of analysis is not as significant as it is when road safety or infrastructuremanagement is concerned. On the other hand, everyday usage of a bicycle is strongly affected by weather conditions (Ermagun, Lindsey, & Loh, 2018). According to Thomas, Jaarsma, and Tutert, (2013)) the daily fluctuation of bicycle volume is 80 % described by weather conditions. Therefore, any significant weather changes may have a not negligible effect on daily bicycle volume.

However, bicycle traffic data (e.g. speed, bike volume) is difficult to obtain and push researchers and practitioners to plan the implementation of bikeshare system (BSS), by using models which not include the observed bike volumes (Soriguera & Jiménez-Meroño, 2020). On the other hand, disaggregated bike volume data at hourly level are not useful in road safety analysis: crashes are rare and random events and it would led to zero inflated datasets (short segments and short period of observation) (Cafiso, D'Agostino, & Persaud, 2018), unuseful for prediction models calibrations, as happens to the vehicle accidents modeling (D'Agostino, Cafiso, & Kiec, 2019).

Bicycle trips can be made on the roadway, sidewalk, bicycle infrastructure, which makes automatic counters difficult to use. On the other hand, manual measurements are time-consuming, inaccurate and relatively expensive. In recent years, GPS technology has become an increasingly popular method of traffic parameter estimation. This type of bicycle traffic data can be collected from the BSS and analyzed (Joo, Oh, Jeong, & Lee, 2015; Woodcock, Tainio, Cheshire, O'Brien, & Goodman, 2014; Fishman & Schepers, 2016; Buck et al., 2013; Fournier, Christofa, & Knodler, 2017; Imani, Eluru, El-Geneidy, Rabbat, & Haq, 2014; Pogodzinska, Kiec, & D'Agostino, 2020). However, applying this type of data in the analysis requires describing the relationship between parameters of trips made by BSS users and the actual bike volume. This relationship can change also based on environmental and weather conditions (Eren & Emre Uz, 2020). Besides in certain weather conditions, bicycle volume, as well as the number of BSS trips, can be different

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during School Holidays (SH) and Public Holiday (including weekends) (PH) than in other days because of the bicyclist attitude and behavior are different (Ma, Zhang, Xin Li, Wang, & Zhao, 2019; Zhao, Guo, Zhang, Guo, & Palmer, 2019).

The paper aims to quantify the daily bicycle traffic volume based on the data from bicycle automatic counters and BSS trip data. BSS called "Wavelo", operates in Cracow since 1 st March 2017 and consists of around 1500 bikes and 168 rent stations. Similar to bicycle volume data, data of a daily number of public bicycle loans (trips) in analyzing periods were available at the Cracow Road Administration website. The evaluation has taken into account the variation due to the impact of weather conditions. This condition can already provide information about the future use of the bike infrastructure due to climate change and allow more proper management and aware development of transport planning and traffic safety assessment. To provide transferable and practical results the changes in bicycle traffic were assessed based coefficient of variation of bicycle volume and number of BSS trips.

2. Literature Review

The impact of weather conditions on bicycle volume was previously estimated based on a questionnaire survey and observed data (mainly automatic counters). There were a few research where the impact of weather conditions on BSS users volume was analyzed (Ashqar, Elhenawy, & Rakha, 2019; Corcoran, Li, Rohde, Charles-Edwards, & Mateo-Babiano, 2014; Gebhart & Noland, 2014). However, authors do not know any research where differences in the influence of weather conditions on BSS users and other cyclists were evaluated. According to (Bergström & Magnusson, 2003; Brandenburg, Matzarakis, & Arnberger, 2007; Gebhart & Noland, 2014; Sabir, 2011; Thomas et al., 2013; Hanson & Hanson, 1977) weather's effect varies between different cyclist groups (different levels of experience and trip motivation, age, gender). Impact of weather conditions on bicycle use was previously described in reference to daily number BSS trips (Gebhart & Noland, 2014; Noland & Ishaque, 2006), daily and/or hourly bicycle volume (Flynn, Dana, Sears, & Aultman-Hall, 2012; Gallop, Tse, & Zhao, 2012; Miranda-Moreno & Nosal, 2011), the likelihood of bicycle commuting (Flynn et al., 2012), time spend on cycling (Gebhart & Noland, 2014; Winters, Friesen, Koehoorn, & Teschke, 2006), average daily bicycle trip rate (Saneinejad, Roorda, & Kennedy, 2012; Winters, Davidson, Kao, & Teschke, 2011).

More in detail the weather parameters found to have a significant impact on cyclists' volume are the following: air temperature, precipitation, sunshine (Noland & Ishaque, 2006; Phung & Rose, 2007; Tin, Woodward, Robinson, & Ameratunga, 2012) cloud cover (Gallop et al., 2012; Saneinejad et al., 2012), humidity (Gallop et al., 2012; Gebhart & Noland, 2014), and wind strength (Flynn et al., 2012; Sabir, 2011; Tin et al., 2012).

Particularly, an increase in temperature leads to an increase in bicycle use. Research conducted by (Noland & Ishaque, 2006) indicated that on days with maximum temperature up to 15 °C and above 20 °C 10 % and 50 % of daily bicycle trips were taken respectively. Each 1 °C increase in temperature resulted in an increased in daily bicycle volume and hourly bicycle volume by 2.6 % and 3.2 % respectively (Tin et al., 2012), and an increase in the likelihood of bicycle commuting by 3% (Flynn et al., 2012). In (Gallop et al., 2012) increase of 1 °C from the mean temperature was found to increase bicycle volume by 1.65 %. Time spend on cycling decrease by 9% for every 30-day increase in freezing temperatures (Winters et al., 2006). Sabir (2011) found that, compared with temperature 0–10 °C, the number of individual daily bicycle trips and average daily distance traveled per person decrease by 7.76 % and 13.04 % when the temperature did not exceed 0 °C and increase by 21.95 % and 57.83 % in temperature above 25 °C, respectively. Miranda-Moreno and Nosal (2011) calculated that when temperature doubled, bicycle volume could be expected to increase by 43–50 %.

Also, the temperature was found to have a non-linear effect on bicycle volume, which means that when the temperature exceeds the threshold value cyclist volume decreases. In (Miranda-Moreno & Nosal, 2011) temperature had a negative effect on bicycle volume when it was higher than 28 °C. The ideal temperature for bicycle riding was identified to be about 25 °C in (Richardson, 2000) and (Böcker, Uteng, Liu, & Dijst, 2019), 28 °C in (Phung & Rose, 2007), and 32.2 °C in (Gebhart & Noland, 2014) and (Lewin, 2011). Winters et al. (2011) calculated that average daily bicycle trip rate increase from 1.68 work trips/person for temperatures below 0 °C, up to 1.73 work trips/person for temperatures 16–20 °C. Higher temperature (above 20 °C) resulted in a decrease in the average daily bicycle trip rate to 1.72 work trips/person.

Together with temperature, another factor influencing significantly on bicycle volume is rain. Nankervis (1999) concluded that heavy rain is the biggest deterrent for cyclists to ride. Additionally, Winters et al. (2011) found that rainfall deterred cyclists from bicycle use more than hot and humid weather. Results reported in (Gebhart & Noland, 2014) showed that the impact of precipitation differs between registered users of BSS (monthly or annual membership) and casual users (1–5 day membership). Compared to no rain conditions, in the rain registered users and casual users made respectively 48.5 % and 68.3 % fewer bike trips/hour. At the same time, trip duration decreased by 10.1 % and 22.4 % in the rain and by 9.4 % and 12.1 % in the snow for registered users and casual users respectively.

Research conducted by Noland and Ishaque (2006) showed that 70 % of bikeshare trips were made in days with no rainfall. For comparison, Corcoran et al. (2014) calculated that on rainy days the number of BSS trips decrease by 31 % compared with days with no rain. According to Flynn et al. (2012) the likelihood of bicycle commuting increased by 91 % in the absence of rain and decreased by 10 % during the snow. Tin et al. (2012) calculated that daily bicycle volume and hourly bicycle volume decreased by 1.5 % and 10.6 % for a 1 mm increase in rainfall during that day or hour respectively. Sabir (2011) was noticed that precipitation greater than 0.1 mm resulted in a decrease in the number of individual daily bicycle trips and average daily distance traveled on the bike per person by 7.89 % and 11.74 % respectively.

Previous studies show that weather's effect varies between different cyclist groups (different levels of experience and trip motivation, age, gender), however, there was no research where differences in the influence of weather conditions on BSS users and other cyclists were evaluated. This type of analysis is needed to evaluate whether a change in bicycle volume due to changing weather conditions can be estimated based o BSS trip data. The results can be generalized to deliver a starting point in the planning and management of the cities facing climate change and provide information about the future usage of bicycle infrastructures. Additionally, modeling of the variability of bicycle volume can support the assessment of risk exposure in road safety analysis and management.

3. Data

The analyzing period was 2 years (from 1st January 2018 to 31st December 2019). The analysis was made regarding daily bicycle volume, due to bicycle count data which was aggreagated for days and hourly date were not available. This approach seems to be useful because daily bicycle volume data is the basis for road safety, traffic operation analysis, transport planning, and traffic management. For each day of the analyzing period observed bicycle volume in 9 locations, a number of BSS trip taken, and weather conditions were gathered. In certain weather conditions, bicycle volume, as well as the number of BSS trips, can be different during School Holidays (SH) and Public Holiday (including weekends) (PH) than in other days. Therefore, the occurrence of those days in 2018 and 2019 was also specified. To develop regression models, data for the 2018 year was used. The validation of models was conducted on data from 2019.

3.1. Bicycle volume and BSS data

In Cracow (Poland), automatic bicycle counters are located in various sites covering all city with different traffic characteristics (recreational, commuter). The analysis was made regarding the 9 available locations where bicycle volume data was available and were homogenous in terms of users type and terrain (Sun, Chen, & Jiao, 2018) for all 2018 and 2019 and 4 control locations where data was available for all 2019. Data on daily bicycle volume was downloaded from the Cracow Road Administration website. These data are free and updated every day.

Table 1 presents the minimum, maximum and average value of daily bicycle volume in the 9 analyzed locations and the daily number of BSS trips taken in 2018.

3.2. Weather conditions data

According to Gallop et al. (2012) 58 % of cyclists consider the weather when deciding whether to bike, and 77 % of them base their decision on current rather than forecasted or recent weather. Therefore, in the analysis data of daily weather conditions registered by a weather station located in the city rather than forecasted data was used. Parameters available by the weather station and considered in the analysis are listed in Table 2.

4. Methodological Approach and results

4.1. Seasonal variation of bicycle volume

Monthly coefficients of variation of bicycle volume for each of the 9 analyzed locations, as well as of the number of BSS trips taken were calculated and gathered in Table 3.

Firstly, Analysis of Variance (ANOVA) was used to calculate, whether the monthly variation of bicycle volume differs statistically significant between 9 analyzed locations. The results of the analysis are presented in Table 4. No statistically significant differences were noticed. Therefore, all locations with automatic bicycle counters were treated like one group. Then, ANOVA was used likewise to determine whether the monthly variation of bicycle volume (average for 9 locations) is statistically significantly different from a monthly variation of a number of BSS trips taken (Table 4). No statistically significant differences were noticed.

Average monthly variability of bicycle volume and number of BSS trips taken are presented in Fig. 1.

4.2. Impact of weather conditions on daily bicycle volume

To analyze changes in bicycle volume in a shorter period, Ordinary Least Squares (OLS) regression models describing the impact of weather conditions on BSS users and all cyclists were developed.

The dependent variable in developed models was the daily coefficient of variation of bicycle volume (for locations with automatic counters) and daily coefficient of variation of the number of bicycle trips taken (for BSS). The reason was that the level of daily bicycle volume differs significantly between analyzed locations (AADBT ranges from 729 Bicycles/24 h up to 1994 Bicycles/24 h). Additionally, for BSS number of bicycle trips taken (trips/24 h) was analyzed, which is a different variable than bicycle volume (bicycles/24 h). Therefore, to make results for BSS and automatic counters comparable, there was a need to standardize the dependent variable in developed models.

The group of independent variables included both qualitative and quantitative ones, describing the weather conditions and public and school holidays. An OLS regression models with non-linear estimation were calibrated using the data from 2018. The models' form is reported in Eq. 1.

$$AADBT_{coeff} = \exp(\alpha + \beta * \textit{weather parmeters} + \gamma * \textit{Bin}) \tag{1}$$

where:

$AADBT_{coeff}$ – daily coefficient of variation of bicycles volume or daily number of BSS trips taken [-];

α – Intercept

β – regression term of numerical variables i.e. weather parameters [-];

γ – regression terms of binary variables (*Bin*) i.e. pH and SH (equal to 1 there is public or school holidays, and 0 if it is not)

Additionally, data from 2019 for 4 control locations (where automatic bicycle counters were implemented during 2018), was used for models' validation. It was made by comparison of the observed and predicted values of the daily coefficient of variation of bicycle volume and a daily number of BSS trips taken.

Based on descriptive statistics (Table 2) and Spearman correlation analyses, the number of weather parameters taken into account in developed models was narrowed down. Coefficients of variations for a maximum value of humidity and mean, maximum and minimum values of atmospheric pressure are lower than 0.2. Because of the small variation of those parameters, it was decided not to consider them in the developed models. As expected, mean air temperature, humidity, and atmospheric pressure were correlated with their maximum and minimum values. However, strong correlations between other weather parameters were also noticed. Finally, weather parameters that were decided to be analyzed are the following: mean air temperature Tmean (^{o}C), maximum wind speed Wmax (kph), daily rainfall Rday (mm). In previous studies, the temperature was found to have a non-linear effect on bicycle volume (Gebhart & Noland, 2014; Lewin, 2011; Miranda-Moreno & Nosal, 2011; Phung & Rose, 2007; Richardson, 2000; Saneinejad et al., 2012). Therefore, only non-linear models were tested. It was noticed that in developed relationships maximum wind speed coefficient had a positive value, which means that an increase in maximum wind speed increases the number of BSS trips taken or bicycle volume. That relationship seemed to be doubtful, and therefore other models without Wmax were built.

It is worth mentioning that the function of location (recreational for locations 1 and 7 and commuting for other locations) was tested as an independent variable in models for automatic bicycle counters data. However, it was not statistically significant.

Regression models describing the relationship between the coefficient of variation of the daily number of BSS trips taken and daily bicycle volume (Table 5) and weather parameters, as well as school holidays and public holidays (including weekends), were calibrated using the data from 2018. All independent variables included in the model (Eq. 2) were significant with over 99th percentile confidence level.

$$AADBTcoeff = \exp(a0 + a1 * Tmean\char`^2 + a2 * Tmean + a3 * Rday + a4 * PH + a5 * SH) \tag{2}$$

Table 1
Minimum, maximum and average annual daily bicycle traffic (AADBT) [bicycle/day] and a daily number of BSS trips taken [trips/day] in 2018.

	Location									BSS "Wavelo"
	1	2	3	4.	5	6	7	8	9	
Min	22	13	0	41	30	30	37	17	17	54
Max	5329	2345	4148	5252	3117	1344	6341	2802	1749	7427
AADBT	1520	866	1455	1994	1238	598	1258	841	729	2676

Table 2
Descriptive statistics for weather parameters.

Weather parameter	Unit	Symbol used	Mean	Minimum	Maximum	Std dev.	Coeff. of variation
Minimum air temperature	°C	Tmin	7.3	−15.3	20.8	8.313	1.138
Maximum air temperature	°C	Tmax	15.9	−9.9	34.5	10.755	0.676
Mean air temerature	°C	Tmean	11.5	−11.6	26.5	9.316	0.811
Minimum humidity	%	Hmin	60.1	25.0	97.0	17.897	0.298
Maximum humidity	%	Hmax	91.0	61.0	100.0	6.145	0.068
Mean humidity	%	Hmean	76.8	43.0	99.0	11.694	0.152
Minimum atmospheric pressure	hPa	Pmin	1014.3	992.1	1036.1	7.707	0.008
Maximum atmospheric pressure	hPa	Pmax	1019.9	1002.0	1039.9	7.140	0.007
Mean atmospheric pressure	hPa	Pmean	1017.1	996.4	1038.1	7.338	0.007
Maximum wind speed	kph	Wmax	8.4	0.0	35.2	9.292	1.101
Mean wind speed	kph	Wmean	1.6	0.0	18.0	2.481	1.530
Daily rainfall	mm	Rday	1.6	0.0	41.2	4.440	2.705

Table 3
Average monthly coefficient of variation of bicycle volume and number of BSS trips.

Month	Location									BSS „Wavelo"
	1	2	3	4.	5	6	7	8	9	
1	0.174	0.325	0.253	0.295	0.270	0.397	0.170	0.247	0.211	0.158
2	0.121	0.253	0.193	0.226	0.185	0.308	0.117	0.207	0.149	0.124
3	0.323	0.395	0.347	0.378	0.353	0.468	0.334	0.446	0.291	0.293
4	1.784	1.365	1.555	1.498	1.572	1.315	1.793	1.329	1.431	1.733
5	2.059	1.617	1.819	1.682	1.776	1.544	2.142	1.455	1.665	2.038
6	1.689	1.607	1.133	1.639	1.619	1.545	1.440	1.556	1.509	1.936
7	1.451	1.408	1.560	1.444	1.487	1.295	1.531	1.703	1.462	1.544
8	1.536	1.561	1.761	1.578	1.665	1.403	1.709	1.639	1.754	1.550
9	1.291	1.405	1.469	1.380	1.379	1.373	1.409	1.534	1.488	1.202
10	0.931	1.079	1.035	1.015	0.927	1.147	0.816	0.905	1.097	0.834
11	0.469	0.675	0.607	0.593	0.537	0.777	0.399	0.715	0.638	0.436
12	0.172	0.309	0.268	0.271	0.230	0.429	0.140	0.265	0.305	0.152

Table 4
Results of ANOVA analysis.

ANOVA for 9 locations				
	df	Mean Square	F-test	Sig.
Intercept	1	3257.720	12940.812	0.000
Location	8	0.000	0.001	1.000
Month	11	102.931	408.877	0.000
Location x Month	88	0.595	0.363	0.000
Error	3177	0.252		
Total	3285			
Corrected Total	3284			
ANOVA for all locations and BSS				
	df	Mean Square	F	Sig.
Intercept	1	722.595	5006.453	0.000
Locations	1	0.079	0.549	.459
Month	11	27.933	193.535	0.000
Locations x Month	11	0.698	4.837	0.000
Error	692	0.144		
Total	716			
Corrected Total	715			

where:

$AADBT_{coeff}$ – daily coefficient of variation of Annual Average Daily Bicycle Traffic (AADBT) (i.e. bicycle volume or number of BSS trips taken) [-];

Tmean – mean daily air temperature [°C];

Rday – daily rainfall [mm]

PH – public holidays together with weekends (PH = 1 for public holidays and/or weekends; PH = 0 for the business day);

SH – school holidays (SH = 1 for school holidays; SH = 0 for other days); and

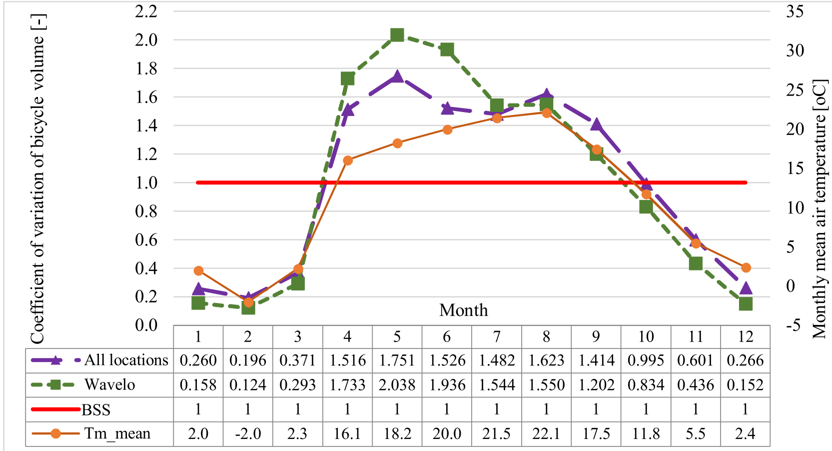
a_i are regression terms.

Bicycle volume data from automatic counters and the number of BSS trips taken as well as weather conditions data from 2019 were used for models' validation. Validation of developed models presented in Fig. 2 indicates that the model for BSS trips is slightly better fitted ($R^2 = 0.849$) than a model for bicycle volume from automatic counters ($R^2 = 0.704$). A comparison of predicted values for both models indicates that they can be used alternatively depending on the availability of data ($R^2 = 0.982$).

Data from 2019 for 4 control locations (where automatic bicycle counter were implemented during 2018) were used for models' validation. Results presented in Fig. 3 show, that developed models can be both used to bicycle volume estimation considering impact weather in other locations in the city ($R^2 = 0.814$ and $R^2 = 0.797$ for automatic counters model and BSS model respectively).

5. Discussion

BSS users are a special group of cyclists. They may be less sensitive to weather changes during the day. For example, they may rent a bike in the morning for a commute trip and change mode of transportation for a comeback trip if it starts to rain It was also noticed by (Sun et al., 2018), who found a substitutional relationship between public transit and BBS during rainy weather.. On the other hand, private bike ensures "door to door" trip. BSS users may have to rent and leave the bicycle at a station, which can be located away from their destination. During the rain or colder temperature, this additional trip which has to be made e.g. by foot may discourage cyclists to use the system. Public bicycles may be often used by tourists. In the summer, when the number of tourists in the city grows, the increase in public bicycle volume can be more dynamic than the increase in the volume of other cyclists. However, the number of bikes in the system is limited. As a result, an increase in the volume of public bicycles is also limited. Moreover, in the colder months, the number of bicycles in the system may be reduced. It can be caused also by the lack of annual city visitors, who are one potential contributor to the failure of the city's BBS program (Sun et al., 2018),. For example, in Cracow (Poland) from 1st December 2018 to 28th February 2019, only 1/3 of public bicycles were available. As a consequence, even there was a warmer and sunny week in that period, the increase in public bicycle



	1	2	3	4	5	6	7	8	9	10	11	12
All locations	0.260	0.196	0.371	1.516	1.751	1.526	1.482	1.623	1.414	0.995	0.601	0.266
Wavelo	0.158	0.124	0.293	1.733	2.038	1.936	1.544	1.550	1.202	0.834	0.436	0.152
BSS	1	1	1	1	1	1	1	1	1	1	1	1
Tm_mean	2.0	-2.0	2.3	16.1	18.2	20.0	21.5	22.1	17.5	11.8	5.5	2.4

Fig. 1. Average monthly variability of bicycle volume, number of BSS trips and monthly mean air temperature.

Table 5
Regression coefficients for developed BSS model (R2 = 0.858) and automatic bicycle counters model (R2 = 0.707).

BSS							
Parameter		Estimated	Error	t	p-value	Upper CI	Lower CI
Intercept	a0	−2.30286	0.175573	−13.1162	<0.001	−2.64819	−1.95753
Tmean^2	a1	−0.00567	0.000578	−9.8090	<0.001	−0.00680	−0.00453
Tmean	a2	0.26770	0.020185	13.2624	<0.001	0.22800	0.30740
Rday	a3	−0.02113	0.003764	−5.6135	<0.001	−0.02853	−0.01373
PH	a4	−0.26202	0.032644	−8.0266	<0.001	−0.32623	−0.19782
SH	a5	−0.20879	0.033328	−6.2646	<0.001	−0.27434	−0.14323
Automatic bicycle counters							
Parameter		Estimated	Error	t	p-value	Upper CI	Lower CI
Intercept	a0	−1.52742	0.054213	−28.1745	<0.001	−1.63371	−1.42113
Tmean^2	a1	−0.00355	0.000199	−17.8148	<0.001	−0.00394	−0.00316
Tmean	a2	0.18062	0.006549	27.5793	<0.001	0.16778	0.19346
Rday	a3	−0.03439	0.002118	−16.2409	<0.001	−0.03854	−0.03024
PH	a4	−0.27250	0.015161	−17.9737	<0.001	−0.30222	−0.24277
SH	a5	−0.09616	0.015060	−6.3856	<0.001	−0.12569	−0.06664

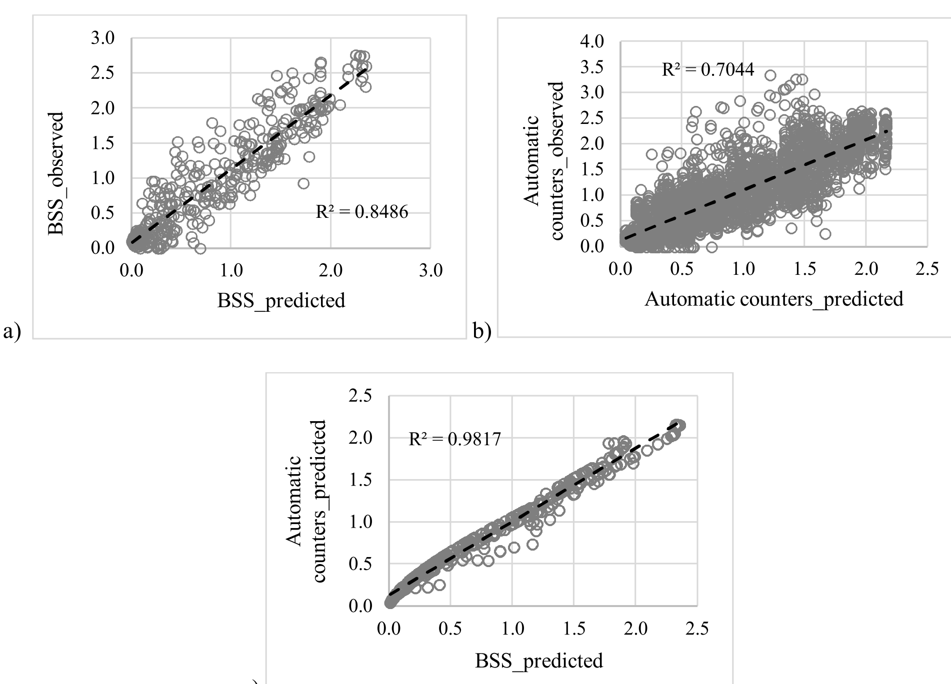


Fig. 2. Relationship between the observed and predicted value of the daily coefficient of variation for: a) number of BBS trips, b) bicycle volume from automatic counters c) predicted values for both models.

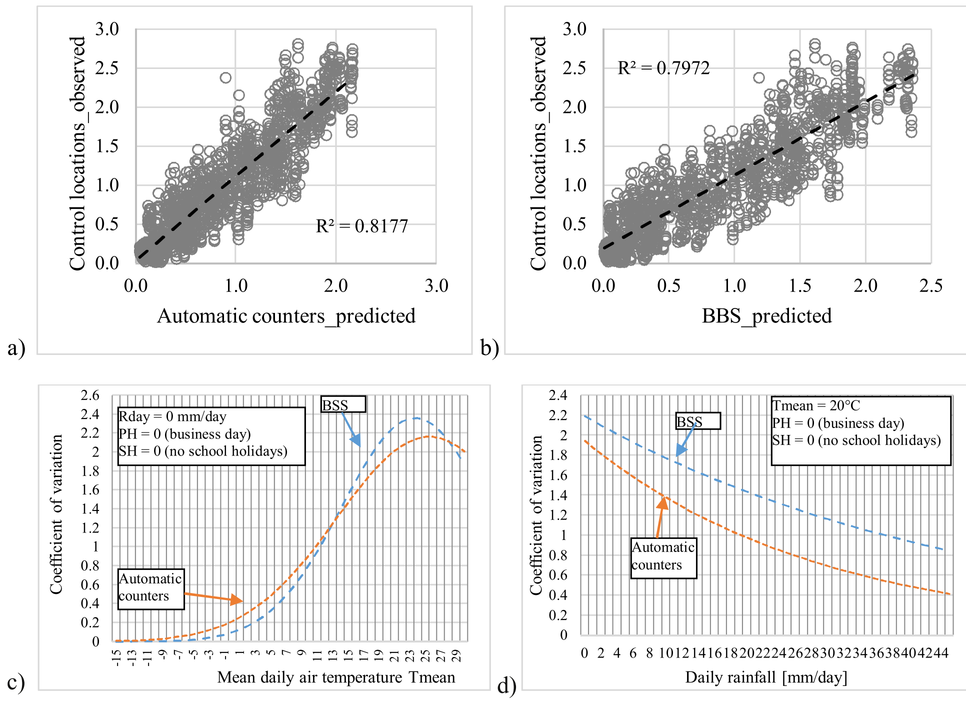


Fig. 3. Relationship between the two values of daily coefficient of variation in control locations: observed and a) predicted based on automatic counters model, b) predicted based on BSS model. Change of coefficient of variation of bicycle volume and number of BSS trips taken due to: a) changing mean daily air temperature, b) changing daily rainfall.

volume was limited. Considering this the bicycle volume, as well as a number of BSS trips taken, are the lowest in February and the highest in May. In February bicycle volume is by 80 % lower and in May by 75 % higher than AADBT. The number of BSS trips taken is by 88 % lower and by 104 % higher in February and May respectively. In October, when the coefficient of variation is 0.995, bicycle volume is the closest to AADBT.

In previous studies, it was found that daily fluctuation of bicycle volume was 80 % described by weather conditions (Thomas et al., 2013). Similar results were obtained regarding the number of BSS taken. A variation of bicycle volume from automatic counters, based on the results of the regression model, in 71 % was described by weather conditions. It suggests that for automatic bicycle counters other factors than weather (eg. area development), may have a significant impact on bicycle volume. The function of location (recreational for locations 1 and 7 and commuting for the other two) was tested as an independent variable in the model. However, it was not statistically significant.

In Fig. 3a change of coefficient of variation of bicycle volume and number of BSS trips taken due to changing mean daily air temperature was shown. It was assumed that there was no rainfall (Rday = 0 mm/day), no school holidays (SH = 0) and that it was a business day (PH = 0). The maximum value of the coefficient estimated by models is around 2.16 in temperature 25 °C and 2.36 in temperature 24 °C for automatic counters and BSS respectively. These results are comparable with those obtained by Richardson (2000), who found the ideal temperature for bike riding to be 25 °C. In temperature 13 °C estimated coefficient of variation is the same for bicycle volume and BSS trips. In temperatures up to 13 °C coefficient of variation of bicycle volume is higher than the coefficient of variation of the number of BSS trips taken. Analyzed coefficients are equal to 1 (AADBT) in temperatures 11.3 °C and 10.7 °C for BSS and automatic counters respectively. In October, when the coefficient of variation of bicycle volume is 0.995, monthly mean air temperature (Tm_mean) is 11.8 °C, which is very close to reliable temperatures for AADBT estimated from the model (Fig. 1). BSS users are more sensitive to lower temperatures than all population of cyclists. An increase in the number of BSS trips taken is relatively slow in freezing temperatures. It may suggest that BSS is mainly used in warmer months or it may be an effect of a limited number of public bicycles available in February with the lowest mean air temperature equal -2.0 °C (Fig. 1).

In Fig. 3b change of coefficient of variation of bicycle volume and number of bikeshare trips taken due to changing daily rainfall was shown. It was assumed that mean daily air temperature was 20 °C (Tmean = 20 °C), that it was a business day (PH = 0) during the school year (SH = 0). Rainfall has less impact on BSS users than on all population of cyclists, which suggests that they are less sensitive to rainfall (e.g. they may rent a bike in the morning for a commute trip and change mode of transportation for comeback trip when it starts to rain).

The impact of public holidays (PH) and weekends on bicycle volume and the number of BSS trips taken were presented in Fig. 4a. Y-axis represents the difference in coefficient of variation on business days (PH = 0) and public holidays together with weekends (PH = 1) for different mean daily air temperatures. It was assumed that there is no daily rainfall (Rday = 0 mm/day) and no school holidays (SH = 0). In public holidays and weekends, bicycle volume and number of bicycle trips taken are lower than in business days. However, the described impact is not significant in freezing temperatures. A similar effect was obtained concerning school holidays (SH) (Fig. 4b). During school holidays bicycle volume and number of bicycle trips taken is lower than during school year, but generally, the effects of temperature have negligible effects in freezing temperatures when bicycle volume and number of bikeshare system trips taken are relatively low. These results confirmed that there is a generally commuting use of the bike in the city.

6. Conclusions

In the present research work, a new approach to the estimation of bicycle traffic volume has been explored by using data from BSS and automatic counters. The added value of the paper is the use of already available and low-cost resources to give a reliable estimation of bicycle traffic (in its daily average value and its variation based on exogenous variables) which is base planning activities at a city level, including traffic safety management.

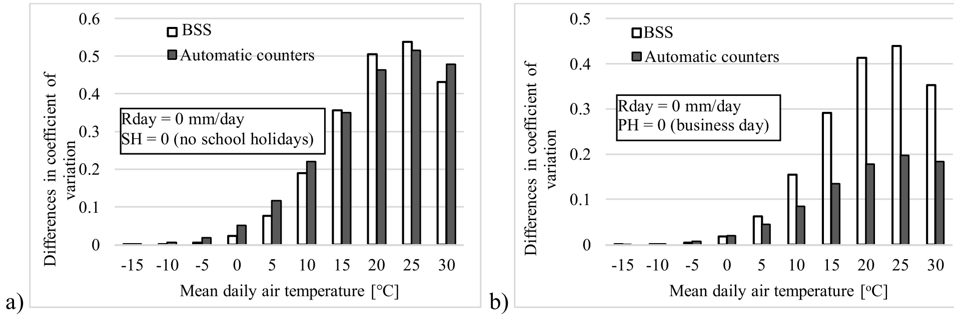


Fig. 4. Differences in the coefficient of variation of bicycle volume and number of BSS trips taken: a) in business days (PH = 0) and public holidays together with weekends (PH = 1), b) during holidays (SH = 0) and school year (SH = 1) for different mean daily air temperatures.

Results clearly have shown that weather parameters similarly affect BSS users and all population of cyclists including the bicyclist attitudes considered by separating holidays by working days. Therefore, the impact of weather conditions on bicycle volume can be estimated based on BSS trip data. In fact, the analysis resulted to be very effective in the estimation of the exposure measure variations based on the rain, as shown by the validation carried out on the second year, which allows excluding the presence of confounding factors and uncontrollable bias in the estimation. The variation of bike volume exposure based on weather conditions provides an insight on how the bike mobility will change over time according to the climate changes, and provide the basis for the management of the future infrastructure at the city level.

It should be noticed, the present results are limited in relation to:

- data collection (relatively small sample – 9 locations used to model calibration);
- autocorrelation problem can commonly be observed in bicycle volume (Chen, Zhou, and Sun, (2017)); Noland, Smart, and Guo, (2016)) and Sun et al. (2018)) but data did not allow a proper inference which account for this issue (although expected collinearity woud not bias the results);.
- bike traffic data were avaialbe per day not for hours, therefore high changes in weather conditions during the day could not be included,

Future research direction should point the transferability of the proposed models and methodology including the elimination of confounding factors which could have not taken into account in the present research work. As further development similar models for other transport modes sensitive for weather conditions (e.g. electric scooters) should be tested and developed following a similar approach. Despite those limitations, results are valuable for practitioners and decision-makers.

Declaration of Competing Interest

The authors report no declarations of interest.

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