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Effects of meteorology on bike-sharing: Cases of 13 cities using non-linear analyses

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ABSTRACT

Bike-sharing system (BSS) provides bicycle rental services for short-term use. The association of BSS with meteorological factors has not been studied sufficiently using nonlinear analysis. To bridge these gaps, this study explored the impact of meteorological conditions on bike-sharing system (BSS) usage in 13 cities in Europe and North America, using a combination of nonlinear analyses to avoid the limitations of linear analyses used traditionally. Specifically, self-organizing map (SOM) and decision tree analyses were used. The SOM results revealed six meteorological profiles (clusters). Kruskal–Wallis test was applied to determine the main effect of the cluster on the input variables. The decision tree indicated temperature (34.4 %), followed by clusters (23.3 %), and cities (17.5 %) as the most influential factors on BSS usage. These findings demonstrated the need to generate nonlinear analyses to understand the dynamic interaction of meteorological variables and BSS usage, providing insights for developing sustainable urban transportation policies.

1. Introduction

Bike-sharing systems (BSS) are active transport (AT) services that provide facilities to rent bicycles for short-term use, thereby enabling convenient and cost-effective travel within a city. With increasing demand for sustainable transportation options, understanding the factors that influence the use of BSS is crucial for optimizing their effectiveness and promoting their integration into urban transportation networks (O'Brien et al., 2014; Rydin et al., 2012). This knowledge can contribute to the sustainable use of urban spaces.

Analyzing BSS datasets can improve the urban cycling experience and increase the knowledge of the urban cycling (Beecham, 2015). Furthermore, the international scientific community is currently focused on identifying the factors that affect BSS usage patterns (Guo et al., 2022; Torrisi et al., 2021). Among the several influencing factors, meteorological conditions play a significant role in understanding the patterns of BSS usage (Eren & Uz, 2020). Temperature, atmospheric pressure, humidity, wind speed, precipitation, and snowfall influence the decision-making processes of considering BSS as a viable transportation option (Eren & Uz, 2020; Fishman et al., 2015). Meteorological research has often focused on one or a few cities, which limits the generalizability of the results, with an exception of some studies that have assessed the relationships between meteorological conditions and BSS usage in a large number of cities (Bean et al., 2021). Furthermore, previous studies predominantly employed linear analyses to investigate these relationships, limiting our understanding of the complex interplay between weather characteristics and their relationship with BSS usage. To date, only a few recent studies have analyzed these relationships using nonlinear analysis (Quach & Malekian, 2020; Villarrasa-Sapiña et al., 2023). This was a breakthrough in understanding the influence of weather on BSS use, but these studies were only conducted in one city considering its specific weather characteristics, and thus, the findings could not be extrapolated to the world.

Therefore, to address these research gaps, the present study used a combination of nonlinear analysis techniques, particularly self-organizing map (SOM) and decision tree analyses, to explore the associations between meteorological conditions and BSS usage across multiple cities in Europe and North America, as well as their relevance.

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These continents were selected because they share common interests in addressing the climate crisis, advancing the protection of the planet, and conserving the environment for future generations (Council of the European Union, 2016; European Commission, 2023).

Against this backdrop, the combination of SOM and decision tree allowed us to capture the interaction between meteorological variables and BSS through high-dimensional and non-linear relationships, which is the main objective of this study. Overall, this study provides a more holistic and comprehensive understanding of weather factors that affect BSS usage.

2. Literature review

BSS has emerged as an increasingly popular form of AT, providing an eco-friendly alternative to traditional commuting methods in urban areas (Chiariotti et al., 2018; DeMaio, 2009). It has several advantages as a sustainable transportation mode, such as the promotion of public transport through multi-modality transport connections, reduction of automobile dependency, and contribution to a healthy lifestyle (Oja et al., 2011; Pérez et al., 2017).

Empirical studies are being increasingly conducted on the relationship between weather conditions and BSS; however, the geographic scope and methodological approaches remain unclear (Corcoran et al., 2018). Given the looming threat of climate disruption, investigating the association between weather conditions and urban transportation more meticulously is becoming crucial. Cycling, which is arguably the most sustainable mode of urban transport available for short- and medium-distance travel (Pucher & Buehler, 2008, 2017), is likely to be more susceptible to weather fluctuations than driving or using public transport, because cyclists are exposed to the full impact of climate conditions. In certain cities, weather conditions serve as a pivotal determinant of considering whether to cycle or not (Ahn et al., 2022). Therefore, the relationship between weather and BSS use has been studied for more than a decade, but the techniques used thus far remain similar, as they are all based on linear analyses. Regression analysis is the most common linear analysis that is conditioned by the beta value established for each variable studied, which may cause an estimation error if any data are outside the analyzed range. Therefore, extrapolation of these data was limited to the geographical points and contexts studied. Furthermore, these analyses did not observe variations that may be caused by interactions among themselves; that is, they did not consider the interrelationships among different factors. Lu et al. (2014) conducted a systematic review and concluded that these analyses can lead to multicollinearity, instability, and incorrect results with statistically significant differences.

Particularly, previous studies have found that the number of bicycle users is higher when the temperature is between 20 and 30 °C (Eren & Uz, 2020). Additionally, in certain geographical regions, temperatures above 30 °C are considered favorable (Sanmiguel-Rodríguez & Arufe-Giráldez, 2019). Contrastingly, low temperatures (Eren & Uz, 2020) and precipitation (Gebhart & Noland, 2014; Hyland et al., 2018; Kim, 2018; Rixey, 2013; Yang, 2018) reduce the likelihood of using BSS, while mild temperatures and scarce precipitation are associated with the greater use of BSS (Sanmiguel-Rodríguez & Arufe-Giráldez, 2019). These results are supported by the results reported by Quach and Malekian (2020), who demonstrated that temperature, followed by precipitation, were the most relevant variable for predicting BSS use. Nevertheless, excessive heat during certain periods of the year and a lack of familiarity with precipitation could affect BSS usage (Sanmiguel-Rodríguez & Arufe-Giráldez, 2019). However, some cyclists may still prefer ride in unfavorable conditions because these variables do not exhibit a uniform global impact (Chibwe et al., 2021; Pazdan et al., 2021; Rixey, 2013). For instance, the optimal temperatures for using BSS were 34.3 and 10.8 °C in New York and San Francisco, respectively (Ahn et al., 2022). According to Curriero et al. (2002), these variations in temperature could be attributed to variances in weather across the respective locations, in conjunction with the populations' varying levels of heat tolerance and acclimation.

Humidity is another factor affecting BSS usage. High humidity reduces both the likelihood of cycling and the duration of trips (Ashqar et al., 2019; Gebhart & Noland, 2014; Miranda-Moreno & Nosal, 2011). This could be because of the increased body thermal sensation generated by high humidity, especially when the temperature is high (Monforte & Ragusa, 2022). Because of its relationship with atmospheric pressure, different studies have selected this variable as a predictor for BSS usage alongside other meteorological characteristics; however, this relationship of atmospheric pressure with BSS usage did not gain sufficient importance in analysis (Chibwe et al., 2021; Pazdan et al., 2021). The impact of wind speed on AT, such as BSS, has frequently been regarded as unfavorable (Fishman et al., 2015). However, recent studies have indicated that its effect is contingent upon its interplay with other weather variables, such as temperature and precipitation (Böcker et al., 2019; Helbich et al., 2014). Furthermore, snow negatively affects bicycle use (de Kruijf et al., 2021). Yang (2018) indicated that snow reduced the number of BSS trips in Boston, although no corroborating research has been published thus far on other sites.

3. Methods and data

3.1. Data collection

BSS data from 13 cities of Europe and North America were obtained by different forms of data mining from 2015 to 2022 (Table 1) as follows: Washington DC (Unlimited Biking), Toronto (Bike Share Toronto), Los Angeles (Metro Bike Share), Oslo (Oslo City Bike), Munich (Bike Share Map), Montreal (Montreal Bike Rental), Madrid (BiciMAD), San Francisco (SFMTA Bike Share), Chicago (Divvy Bikes), London (Santander Cycles), New York (Citi Bike NYC), Santa Monica (Metro Bike Share), and València (Valenbisi). The data included BSS trips, which included the date, start time, and end time of each trip. In each city, the total time of trips using BSS per day was calculated using the start and end times. The data for València were obtained from JCDecaux and the data for other cities were acquired from open data. Information on the meteorological variables were acquired from the Open Weather Map.

The shaded cells are the years of the cities with data.

3.2. Methodology

After the raw data were collected, the daily summation of the total time spent using BSS in each city was calculated. The cities studied were different because they had specific population sizes. Therefore, to equate the use of BSS between them, the percentage of daily use in each city was calculated (Eq. 1).

$$\text{Percentage of daily BSS use} = \frac{\text{Total daily time} \times 100}{\sum \text{Total time per year}} \tag{1}$$

A comprehensive data matrix was formulated by incorporating the aforementioned information wherein every row corresponded to a distinct day per city (i.e., case) and every column represented an individual variable to be scrutinized. The daily variables considered were as follows:

- Percentage of use: daily percentage of BSS usage (%).
- Temperature: daily average temperature (°C).
- Atmospheric pressure: daily average atmospheric pressure (mb).
- Humidity: daily average relative humidity (%).
- Wind: daily average wind speed (m/s).
- Precipitation: daily average precipitation (l/m^2).
- Snow: daily average snow (l/m^2).

Table 1
Total data recompilation.

City	2015	2016	2017	2018	2019	2020	2021	2022
Washington DC	■	■	■	■	■	■	■	■
Toronto		■	■	■	■	■	■	■
Los Angeles		■	■	■	■	■	■	■
Oslo					■	■	■	■
Munich	■	■	■	■	■	■	■	
Montreal	■	■	■	■	■	■	■	■
Madrid			■	■	■	■	■	
San Francisco				■	■	■	■	■
Chicago	■	■	■	■	■	■	■	■
London			■	■	■	■	■	■
New York			■	■	■	■	■	■
Santa Monica		■	■	■	■	■	■	■
València	■	■	■	■	■	■	■	

3.3. Data analysis

A technique based on unsupervised artificial neural networks, known as SOM, was executed to include the study variables as input variables. The purpose of this analysis was to classify days based on their similarities to the input variables. Consequently, the SOM generated day profiles for these meteorological conditions and BSS use. This analysis was performed using MATLAB R2022b (MathWorks Inc., Natick, MA, USA) and the SOM toolbox (Version 2.0 beta) for MATLAB (Vesanto et al., 2000). The SOM construction process can be illustrated in three steps: 1) construction of a neural network, 2) initialization, and 3) SOM training (Pellicer-Chenoll et al., 2015; Seifert et al., 2023). Notably, this classification method obtained better results than other conventional methods, such as principal component analysis, when many variables and big data are employed (Astel et al., 2007; Li et al., 2018).

3.4. SOM analysis procedure

The main goal of SOM analysis is to transform an input signal pattern of arbitrary dimensions into a discrete two-dimensional map in a topologically ordered manner (Dragomir et al., 2014). This type of analysis can be used to classify or detect the relationships between a series of variables related to a problem.

3.4.1. Construction of a neural network

The initial step is to build a neural network composed of nodes, also known as neurons, whose dimensions depend on the number of cases being examined. In this case, through 26,860 cases (i.e., days) and the proportion of the two main eigenvalues of the dataset, the network or grid had a rectangular shape with a size of 32 × 25 neurons in height and width, respectively. A hexagonal shape was selected for representation; thus, each central neuron had six neighbors (i.e., adjacent neurons).

3.4.2. Initialization

A value was assigned to each node or neuron for each input variable. SOMs were initialized in two different ways. On the one hand, in the randomized initialization, small random values were assigned to each neuron's weight vector. On the other hand, linear initialization was applied when the weight vectors were initialized in an orderly manner along the linear subspace spanned by the two principal eigenvectors of the input dataset. The assigned weights were modified during the training. In this study, two different training algorithms were applied (sequential and batch).

3.4.3. SOM training

Before starting the training process, the values of the variables were normalized between 0 and 1 such that the scale of the variables would not affect SOM training. This normalization was applied using Eq. 2, where z_i is the normalized value and x_i is the original value.

$$z_i = \frac{x_i - min(x)}{max(x) - min(x)} \tag{2}$$

Every neuron present in the lattice was in a state of competition with the other neurons for each of the n cases in the sample. The data vector assignment (i.e., the value vector of every day in the total sample) was executed by comparing the values of the input with the weights of each neuron in the lattice. The neuron that emerged as the winner in every case was the one that has the smallest Euclidean distance between its vector of weights and the input vector.

After allocating the input data vector to a neuron, the competitive process was succeeded by an adaptive process wherein the weights of the winning neuron and its adjacent neurons were modified and structured in a topological pattern (i.e., the ordering and convergence phases).

To understand this modification of the neurons, Eq. 3 provides the calculations used to train the neural network. After each iteration (n) the weights were modified according to the differences between the initial weights and the input vector, neighborhood function, and learning ratio, as shown in Fig. 1. This process was developed by the researchers that conducted this study to represent SOM analysis (Seifert et al., 2023).

In Eq. 3, the weight vector of the jth neuron is represented by w_j, while η denotes the learning rate, $h_{j,\ i(x)}$ represents the neighborhood function, and x is the input vector. The neighborhood function was employed to enable the winning neuron and its nearest neighbors to adjust their weights to resemble the input vector more closely than the neurons distant from the winning neuron. In the present study, we tested four different neighborhood functions: Gaussian, cut Gaussian, Epanechnikov, and Bubble. The learning ratio was high during the first iteration, and then gradually decreased to extremely low values. Hence, at the onset of training, extensive modifications in the weight of the neurons were initiated and subsequently underwent more subtle alterations as the process advanced.

$$w_j(n+1) = w_j(n) + \eta(n) h_{j,\ i(x)}(n) \left(x - w_j(n)\right) \tag{3}$$

The described process was repeated 100 times to obtain a conclusive analysis result because of its dependence on certain stochastic procedures, including the initialization and entry order of the input vector. The odds of discovering the optimal solution to the problem were augmented by repeating the process 100 times. Owing to the implementation of dual training techniques, four distinct neighborhood functions, and a pair of initialization methods, 1600 SOMs were successfully generated (i.e., 100 × 2 × 4 × 2).

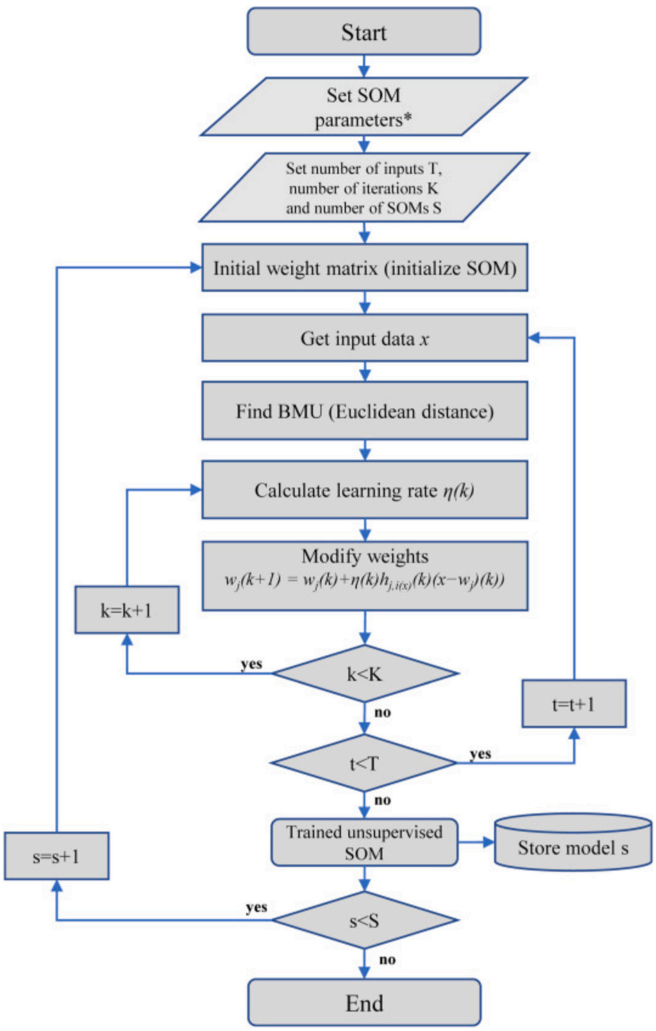

Fig. 1. Flowchart for the unsupervised SOM algorithm. *We used the following parameters in constructing SOMs: initialization = linear vs. random; training methods = sequential vs. batch; neighborhood functions = Gaussian vs. cut Gaussian vs. Epanechnikov vs. Bubble.
Figure has been extracted from Seifert et al. (2023).

After the SOM analysis, a k-means method was used to classify the neurons into large clusters according to their characteristics. The number of clusters was selected to be between 1 and 10 to avoid excessive number of profiles. The final number of clusters was established using the Davies–Bouldin index (Davies & Bouldin, 1979). These clusters were used to describe the weather characteristics and the percentage of BSS usage on the analyzed days.

3.5. Statistical analysis

The days that constituted each cluster were acquired, and subsequently, the centrality data of all the input variables were computed. These data were used to determine the impact of cluster membership on the attributes of the days (i.e., weather variables and the percentage of BSS usage). To achieve this, a statistical analysis was conducted using SPSS v28 software (SPSS Inc., Chicago, IL, USA). The distribution of variables was analyzed using the Kolmogorov-Smirnov test. As the variables did not follow a normal distribution, a non-parametric test, namely Kruskal-Wallis test, was applied to determine the effect of the cluster on the weather and percentage of BSS use variables. The Dunn-Bonferroni post-hoc test was then applied to each pair of clusters. A p value of 0.05 was selected as the level of significance for all statistical analyses.

3.6. Decision tree analysis procedure

A decision tree was applied to obtain a prediction model for BSS use using meteorological variables and clusters obtained by SOM analysis, as well as to determine the relevance of the study variables. To conduct this analysis, the BSS usage percentage variable was first categorized into high- and low-BSS usage days. For this purpose, the median daily percentage of BSS usage was used. Days with lower and higher percentage than the median were labelled as “low use” and “high use” of BSS, respectively.

A matrix was then generated by combining the meteorological variables and those resulting from the previous analyses, where the rows represent the days analyzed and the columns represent the variables used, namely, the daily use of BSS, meteorological variables, cities, and clusters. The first was used as the response variable, and the remaining were used as the input variables (i.e., predictors). This matrix was fed into the R-studio software (R 4.3.0), and a decision tree analysis was performed using the CART algorithm. The observations (i.e., rows) of the matrix were randomly divided into two groups, 80 % and 20 %, which were used for the training tree and to calculate the cross-validity, respectively. The tree was pruned using the prune function to avoid overfitting of the resulting model. Once the tree was generated, the performance values and relevance percentage of each variable within the analysis were calculated.

4. Results

Table 2 presents the centrality data for the variables studied in each city. Each row represents the city and each column contains a variable studied using the mean and standard deviation of all data collected. Additionally, the first column includes the Köppen Geiger climate group for each city, based on recent updates (Beck et al., 2023, 2020).

4.1. Description of SOM results

SOMs were represented by seven component maps corresponding to each input variable, as illustrated in Fig. 2 (left). This approach facilitated the establishment of crucial links and topological relationships between these maps. The distribution of each variable is shown in the maps. Specifically, lower and higher values were observed in blue and yellow neurons, respectively. To understand how the maps present the relationships, an example is provided below: In the first map, the percentage of BSS use is shown in color, with the left-side neurons (yellow) showing higher values than the right-side neurons (blue). In addition to temperature (i.e., the second map), the map shows a similar distribution of the BSS percentage of the use of neuron values. In this case, the high values (yellow neurons) are on the bottom-left side, and, in the diagonal direction, the low values are on the upper-right side. The high values coincided in both maps with the neurons on the left side, whereas the lower values coincided with the upper-right side. In other words, high temperatures showed a topological relationship with a high percentage of BSS use and vice versa.

According to this example, the general topological relationships between every studied variable can be observed through the maps. Beyond the relationship between temperature and the percentage of BSS use shown previously, the following associations were also observed:

i) Intermediate atmospheric pressure values were associated with the highest percentage of BSS use. Conversely, extreme values (highest and lowest) appeared to be negatively related to low values of BSS use.
ii) High humidity values were related to low values of BSS use, although these values (i.e., percentage use) were not the lowest on the map.

Table 2
Descriptive data of each city.

City (Köppen Giger climate)	Use percentage (%)	Temperature (°C)	Atmospheric pressure (mb)	Humidity (%)	Wind (m/s)	Precipitation (l/m^2)	Snow (l/m^2)
Washington DC (Cfa)	0.47 (0.53)	13.09 (9.66)	1017 (7)	65 (15)	3.89 (1.52)	0.46 (0.95)	0.03 (0.17)
Toronto (Dfb, bordering on Dfa)	0.32 (0.29)	10.18 (10.09)	1016 (7)	70 (12)	4.73 (2.08)	0.39 (0.72)	0.06 (0.27)
Los Angeles (Csa)	0.27 (0.16)	19.05 (4.65)	1015 (4)	62 (15)	0.93 (0.46)	0.11 (0.38)	0 (0)
Oslo (Dfb)	0.32 (0.21)	9.38 (7.36)	1006 (13)	51 (22)	3.52 (1.75)	0.44 (1.15)	0.06 (0.47)
Munich (Cfb)	0.31 (0.29)	9.92 (7.43)	1016 (11)	77 (11)	1.99 (1.02)	0.32 (0.49)	0.04 (0.17)
Montreal (Dfb)	0.48 (0.2)	16.29 (6.69)	1015 (7)	67 (13)	4.85 (1.65)	0.55 (1.01)	0.01 (0.11)
Madrid (Bsk)	0.34 (0.46)	15.61 (7.75)	1017 (7)	57 (18)	3.63 (1.68)	0.61 (3.79)	0.00 (0.05)
San Francisco (Csb)	0.29 (0.13)	14.82 (3.42)	1016 (5)	79 (11)	2.3 (1.33)	0.14 (0.47)	0 (0)
Chicago (Dfa)	0.29 (0.37)	11.33 (10.59)	1017 (7)	67 (12)	5.23 (2.51)	0.4 (0.77)	0.04 (0.19)
London (Cfb)	0.29 (0.15)	12.44 (5.61)	1016 (11)	74 (11)	4.2 (1.6)	0.27 (0.39)	0.01 (0.08)
New York (Cfa)	0.28 (0.15)	13.93 (9.31)	1017 (7)	65 (14)	5.74 (1.95)	0.57 (1.33)	0.04 (0.4)
Santa Monica (Csa)	0.3 (0.23)	17.37 (3.57)	1015 (4)	70 (17)	3.65 (0.94)	0.15 (0.8)	0 (0)
València (Bsh)	0.32 (0.17)	18.27 (6.03)	1017 (7)	64 (13)	3.45 (1.64)	0.21 (1.14)	0 (0)

Data are expressed as mean (standard deviation).
Koppen Giger climate groups: Bsk, Cold semi-arid climate; Bsh, Hot semi-arid climate; Cfa, Humid subtropical climate; Cfb, Marine west coast climate; Csa, Hot summer Mediterranean climate; Csb, Warm summer Mediterranean climate; Dfa, Hot summer humid continental climate; and Dfb, Warm summer humid continental (Beck et al., 2023, 2020).

iii) High snow values were related to low BSS use values, but precipitation did not always have a negative relationship with BSS use because its highest values were located in the same map place as both high and low percentages of BSS use values.

4.2. Cluster classification and their differences

The neurons were grouped into six clusters (Fig. 2 — Cluster map) because the Davies-Bouldin index was stable between 6 and 10 clusters (i.e., similar error) and provided the simplest solution. Therefore, six clusters were determined as the best option, because adding more clusters reduced this index only slightly, making it difficult to capture and understand the results. The hit map shows the density of the number of days assigned to each neuron (Fig. 2 — Hit map). Once the six clusters were generated, measures of centrality and dispersion were obtained for each (Fig. 2, right panel).

Through statistical analysis, a cluster main effect was found for each analyzed variable ($p < 0.01$), both for weather variables and the percentage of BSS usage (Table 3). The pairwise comparisons are presented in Table 4.

4.3. Distribution of clusters and cities

The number of days per city in each cluster was also determined (Fig. 3). Using this information, the percentages of each city in the clusters were calculated, highlighting those with the highest representation in each cluster (>10 % of the total cluster days) (Fig. 4). In this way, which cities had the most representation in each cluster were observed.

The number of days and percentage of each city per cluster were calculated to determine which clusters were predominant in each city (Fig. 5). Specifically, clusters with percentages >20 % in each city were highlighted.

Finally, the number and percentage of days with rain or snow were obtained for each cluster. Table 5 shows that Cluster 2 had the highest percentage of rainy days, and Clusters 3 and 5 had the fewest rainy days. However, Clusters 2 and 3 had the most snow days, while Clusters 1, 4, and 5 had the fewest snow days.

4.4. Decision tree results

As shown in Fig. 6, the trained decision tree had 21,487 d, which were divided into two main branches and 14 terminal nodes (5 for high BSS use and 9 for low BSS use). The left branch (days with <12 °C) had 5 terminal nodes. Node 5 of this branch showed that, in Washington DC, Oslo, Montreal, Madrid and Valencia, if the temperature on days was between 6.8 and 12 °C, humidity was <76 % and precipitation (if any) was <0.14 l/m^2, BSS use was high. Contrastingly, for all other conditions in all cities studied, if the temperature was below 12 °C, BSS use was low (Nodes 1, 2, 3, and 4).

The right branch (days with ≥12 °C) included nine terminal nodes. On the one hand, in Los Angeles and Santa Monica, if the temperature was ≥17 °C and the characteristics were similar to those in Clusters 4 and 6, BSS use was high. On the other hand, if the characteristics were similar to those in Clusters 1 and 5 or the temperature was <17 °C, BSS use was low.

Conversely, in San Francisco and Valencia, which showed <0.3 l/m^2 precipitation and a temperature range of 12–25 °C, BSS use was high. However, if rainfall was ≥0.3 l/m^2 or the temperature was >25 °C, BSS use was low.

Finally, continuing the right-hand branch (days with ≥12 °C), Washington DC, Toronto, Oslo, Munich, Montreal, Madrid, Chicago, London, and New York presented low BSS use if days showed characteristics of Clusters 2 or 6 and ≥0.34 l/m^2 precipitation. Contrastingly, if the precipitation in these clusters was low or the days exhibited characteristics of Clusters 1, 3, 4, or 6, BSS use was high.

Table 6 shows the performance of the decision tree in classifying days in the training and validation datasets. The order of relevance of the studied input variables, from highest to lowest, was temperature (34.4 %), cluster (23.3 %), city (17.5 %), atmospheric pressure (5.9 %),

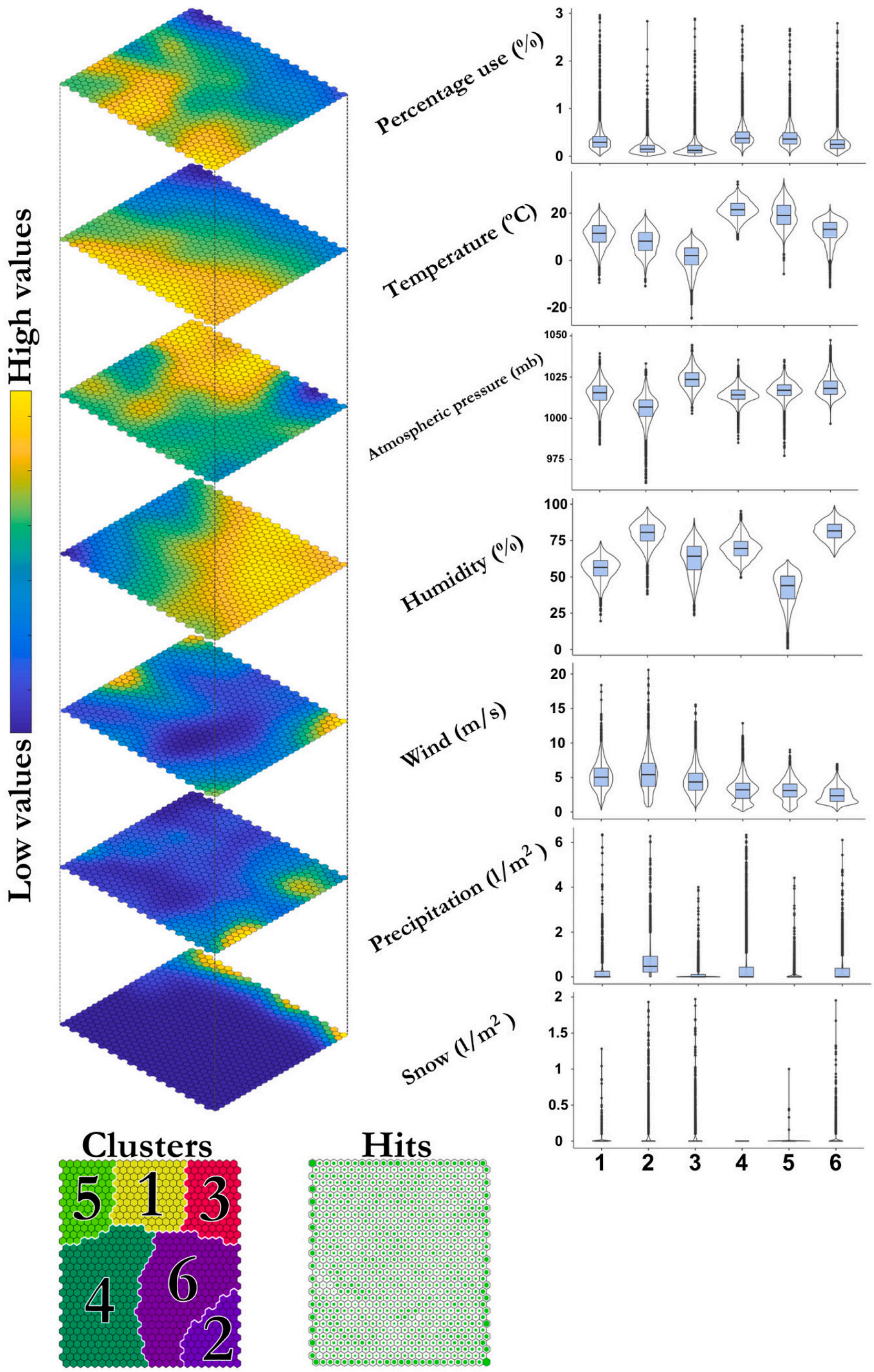

Fig. 2. Hit and cluster maps have been shown at the bottom. The hit map represents the distribution of the days. Every neuron contains several days. The cluster map represents the neuron's groups generated by days characteristics. At the top, each row represents a variable by means of a component map and a distribution graph (combination of box and violin plot), to understand the values of the neurons in each cluster. The component maps show a color representation of the values of the days corresponding to each neuron. In the graphs, outliers have been removed for better display of the graph.

wind (5.8 %), precipitation (4.7 %), snow (4.5 %), and humidity (3.8 %).

5. Discussion

5.1. Weather profiles and bike-sharing use

Six profiles of days (i.e., clusters) were obtained by studying the meteorological characteristics and use of BSS in all cities. In general, three BSS levels as AT use were observed. There were four profiles that favored BSS use, although two stand out from the rest (high and moderate levels of use). Contrastingly, the two profiles were significantly detrimental to a low level of BSS use.

First, the profiles with the highest usage, C4 and C5, were described. Both had the highest temperatures of all clusters, intermediate atmospheric pressure, light wind speed, and no snow. These profiles differed in a few variables. Specifically, C4 showed moderately high humidity and half of the days had light precipitation (Table 5). However, on some days, they experienced heavy precipitation (see IR in Table 4).

Table 3
Effect of the clusters on the variables.

Variable	H_5	*p*-Value
Percentage use (%)	7,047.27	<0.001
Temperature (°C)	18,207.44	<0.001
Atmospheric pressure (mb)	9,090.75	<0.001
Humidity (%)	18,743.13	<0.001
Wind (m/s)	6,834.84	<0.001
Precipitation (l/m^2)	3,891.21	<0.001
Snow (l/m^2)	3,012.48	<0.001

Contrastingly, C5 showed moderately low humidity and a few rainy days, although these days may have experienced extremely heavy precipitation. These profiles showed the relevance of days with temperatures close to 20 °C, without high humidity, without extreme atmospheric pressure, or wind speed (i.e., neither high nor low), and without snow. However, precipitation was not as relevant.

As shown in Fig. 5, C4 was the predominant cluster in most of the cities studied. This was because the day profile was the most common. Oslo, Madrid, San Francisco, and London do not usually have this climate (i.e., >20 % days/year). Likewise, of all these cities, Los Angeles, València, and Washington DC stood out as they contributed the most days to C4 (Fig. 4). By contrast, in C5, this was only observed as a common profile in Oslo and Madrid (Fig. 5). However, together with these cities, València, Santa Monica and Los Angeles were also prominent cities within the cluster (Fig. 4).

Second, C2 and C3 profiles had the lowest usage. Both had the lowest temperatures and heavy snowfall. However, there were a few differences. C2 had the lowest temperature (warmer than C3), lowest atmospheric pressure of all clusters, extremely high humidity, highest wind speed of the clusters, light to heavy precipitation, and light to heavy snow on some days. Contrastingly, C3 had very cold temperatures, highest atmospheric pressure among the clusters, comfortable humidity, moderate wind speed, light to moderate rain for few days, and most days with snow (some days with severe snowfall). The C2 profile was common in Toronto Oslo, Munich and London (Fig. 5), although Chicago stood out in the number of days in this profile among the rest of the cities (Fig. 4). In this profile, cities with Hot and Warm summer humid continental climates, and Marine west coast climate (Dfa, Dfb, and Cfb climates, respectively) predominate due to their low temperatures (see

Table 4
Comparison of the different variables between clusters.

	Use percentage (%)	Temperature (°C)	Atmospheric pressure (mb)	Humidity (%)	Wind (m/s)	Precipitation (l/m^2)	Snow (l/m^2)
Cluster 1	0.37* (0.36)	11.10* (5.09)	1015* (7)	56* (8)	$5.19^{C3,C4,C5,C6}$ (2.11)	0.27* (1.53)	$0.01^{C2,C3,C4,C6}$ (0.05)
Cluster 2	$0.19^{C1,C4,C5,C6}$ (0.3)	7.91* (5.1)	1006* (9)	80* (8)	$5.55^{C3,C4,C5,C6}$ (2.65)	0.7* (0.84)	0.08* (0.3)
Cluster 3	$0.20^{C1,C4,C5,C6}$ (0.38)	1.17* (5.53)	1024* (6)	63* (11)	4.54* (2)	0.13* (0.7)	0.09* (0.49)
Cluster 4	0.42* (0.24)	21.47* (3.83)	1014* (5)	70* (7)	$3.22^{C1,C2,C3,C6}$ (1.7)	$0.42^{C1,C2,C3,C5}$ (1.09)	$0^{C1,C2,C3,C6}$ (0)
Cluster 5	0.41* (0.25)	19.27* (5.45)	1017* (6)	42* (12)	$3.14^{C1,C2,C3,C6}$ (1.48)	0.21* (1.99)	$0^{C2,C3,C6}$ (0.02)
Cluster 6	0.29* (0.26)	12.23* (5.1)	1019* (6)	81* (6)	2.52* (1.19)	$0.3^{C1,C2,C3,C5}$ (0.92)	0.01* (0.09)

Data are expressed as the mean (standard deviation).
* Significant differences among clusters. C1, C2, C3, C4, C5, and C6 indicate significant differences from Clusters 1, 2, 3, 4, 5, and 6, respectively.

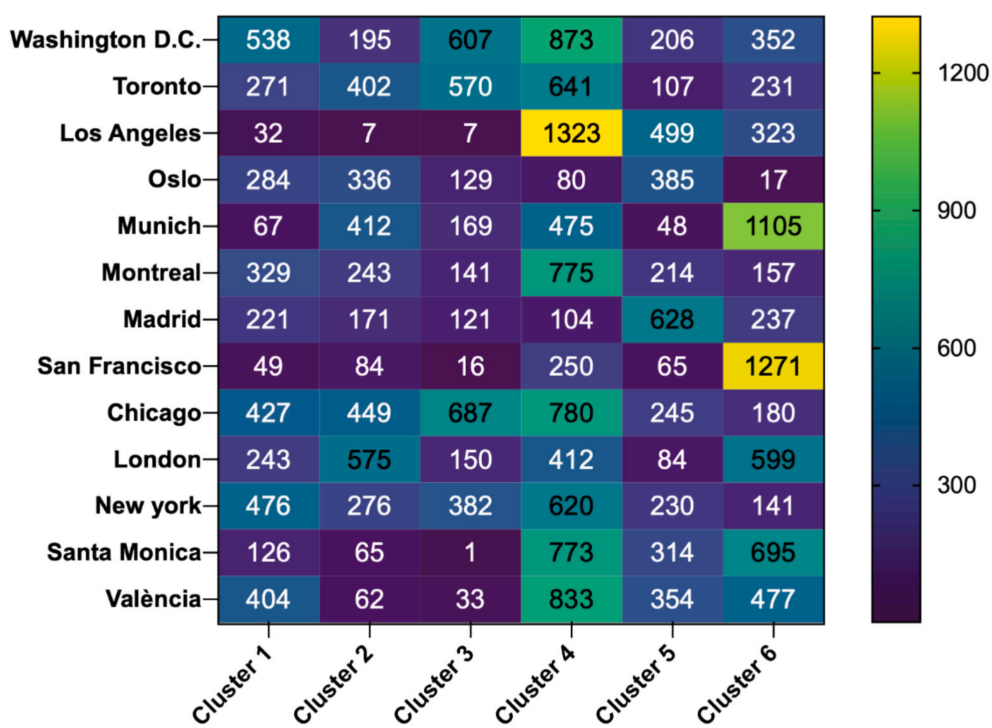

Fig. 3. Distribution of total days between cities and clusters.

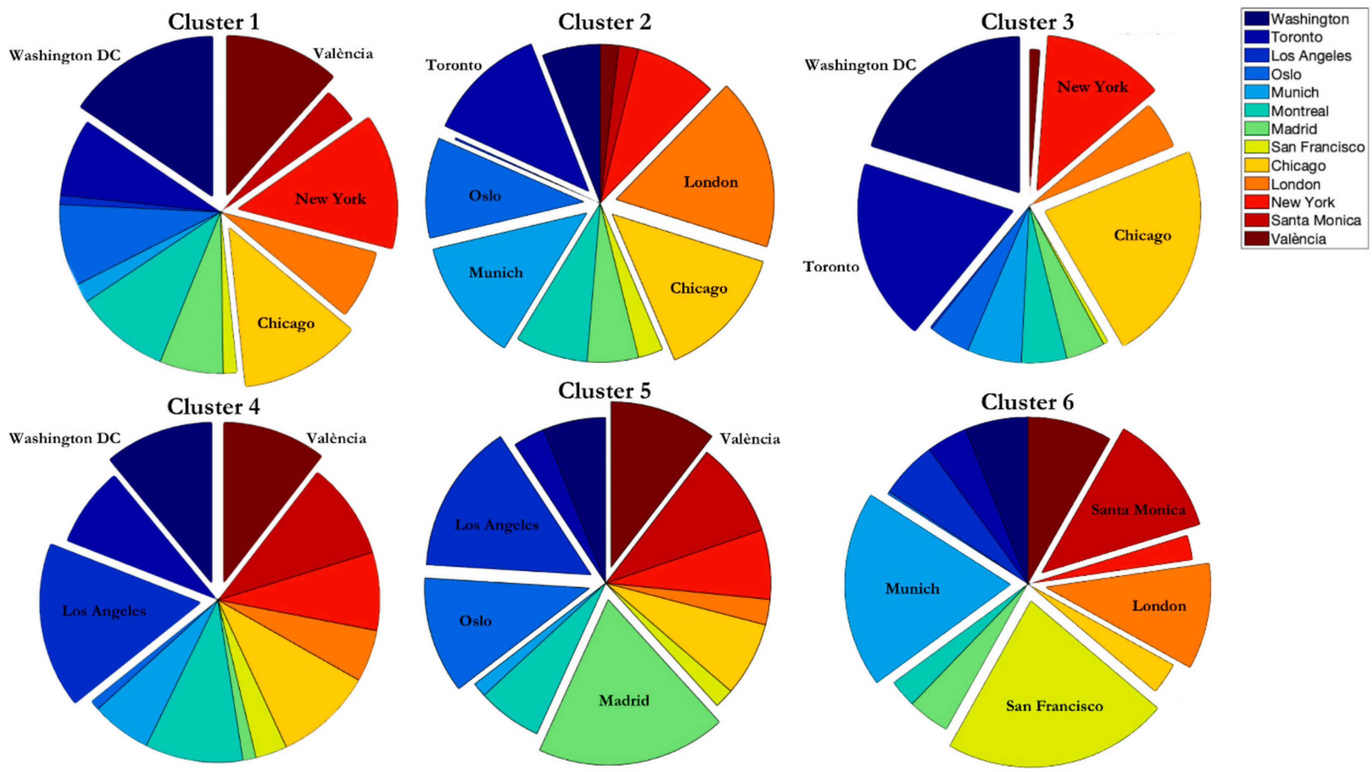

Fig. 4. Distribution of cities in the clusters. The percentage of days of each city in clusters has been shown. Cities with >10 % of the days in each cluster are separated.

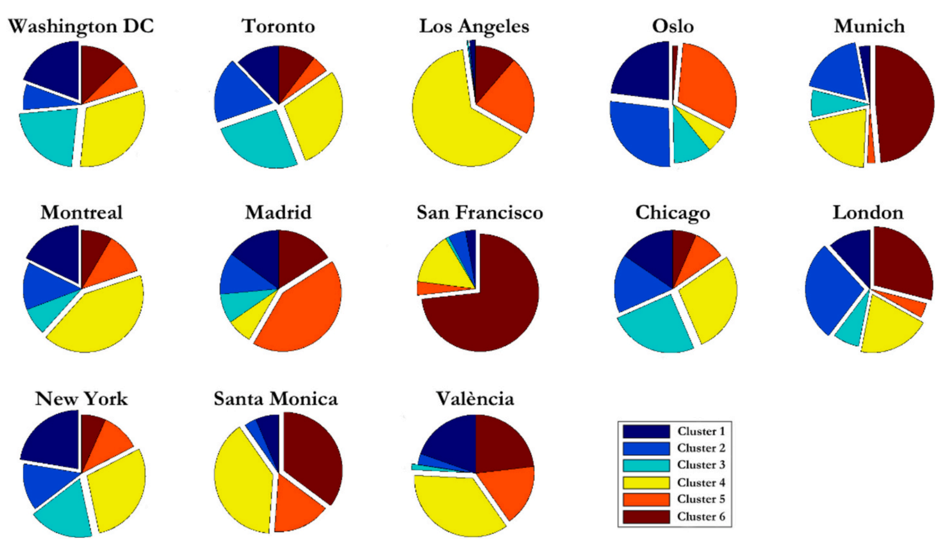

Fig. 5. Distribution of clusters in the cities. The percentage of days of each cluster in cities has been shown. Clusters with >20 % of the days in each city are separated.

Table 5
Number and percentage of days with rain and snow in each cluster.

	Total days	Rain days		Snow days	
	n	n	%	n	%
Cluster 1	3467	1394	40.21	58	1.67
Cluster 2	3277	2735	83.46	476	14.53
Cluster 3	3013	772	25.62	656	21.77
Cluster 4	7939	3627	45.69	0	0
Cluster 5	3379	639	18.91	5	0.15
Cluster 6	5785	2640	45.64	191	3.3

Table 2). Profile C3 was typical in Washington DC, Toronto, Chicago, and, with a similar amount, in New York (Figs. 4 and 5). The predominant climates profile in this cluster are Humid subtropical climate and Hot summer humid continental climate (Cfa and Dfa, respectively), characterized by frequent precipitation and hot summers. Toronto, although classified as Warm summer humid continental climate (Dfb in Table 2), is transitioning towards a Dfa climate.

Third, C6 was also important because it is a common profile in the cities studied, including Munich, San Francisco (for most of the year), London, Santa Monica, and València (Figs. 4 and 5). Commonly, C6 showed a moderate to high level of BSS use and was characterized by

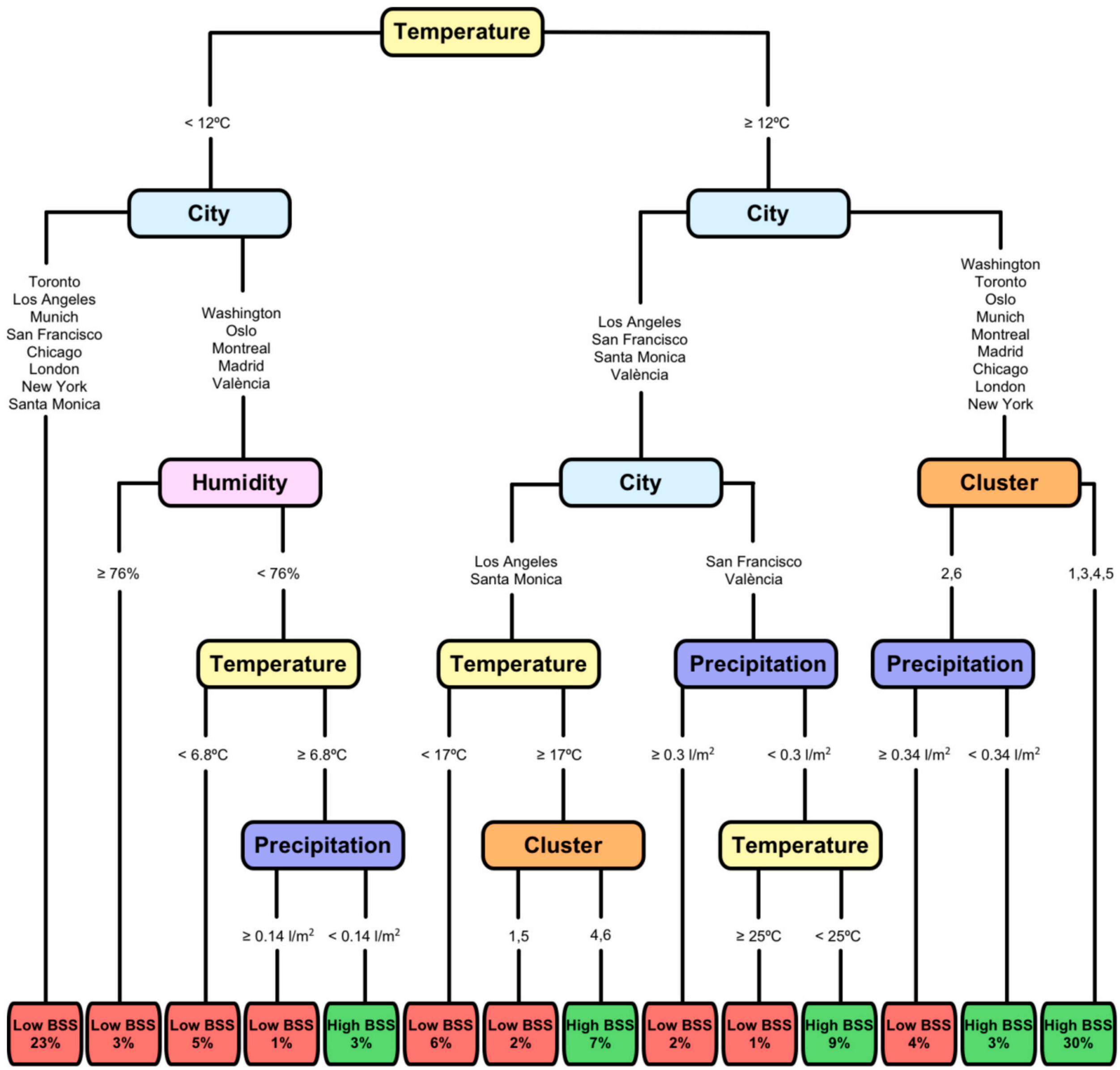

Fig. 6. Classification tree for days with high or low BSS use.

Table 6
Performance variables of the decision tree in both training and validation datasets.

	Decision tree	
	Training	Validation
Accuracy (%)	0.77	0.76
Sensitivity	0.74	0.73
Specificity	0.81	0.80
Positive prediction value	0.79	0.78
Negative prediction value	0.76	0.74
Precision	0.79	0.78
F1	0.76	0.75

moderate temperature, intermediate atmospheric pressure, extremely high humidity, and extremely light wind speed; half of the days had light to extremely heavy rain, and a few days had light to heavy snow. As can be seen in the right main branch of the decision tree (Fig. 6), in most of the cities studied, days with ≥ 12 °C in this cluster negatively affected BSS use if it had sufficient precipitation (0.34 m/l^2). Therefore, among the cities with unique day, Munich and London were the most affected, as San Francisco, Santa Monica, and València did not exhibit this condition (see the decision tree, Fig. 6). These results demonstrate that precipitation during C6 days only impacts the use of BSS in cities with a Marine west coast climate (Cfb). This refers to climates without dry seasons and with warm summers (Beck et al., 2020).

Finally, the characteristics of C1 were moderate temperatures, intermediate atmospheric pressure, comfortable humidity, and higher wind speed than most clusters; almost half of the days had light to extremely heavy rain, but a few days had moderate snow. This profile was characteristic of Washington DC, Oslo, Montreal and New York (Fig. 5) (cities with Cfa and Dfb climates), although it was predominant in Washington, DC, València, New York, and Chicago (Fig. 4). This may be because only Oslo contributed the fewest days to the analysis (see Fig. 3) and both Oslo and Montreal close their BSS stations during the winter months. Specifically, this profile is characteristic of cities with humid climates, including those with hot summers.

These profiles indicated that temperature is a relevant factor for using BSS because, when comfortable, factors that a priori are negative (such as precipitation, humidity, or wind) do not affect it if the negative factor is not abundant. This is supported by the decision tree results and relevance of the variables. Indeed, the type of climate can significantly affect precipitation patterns. As illustrated in the right branch of the decision tree (Fig. 6), precipitation affects the four coastal cities with lowest annual precipitation differently than the other cities. This conclusion has not been reached until now, as a recent review concluded that precipitation affects BSS use, although the day has a comfortable temperature (Eren & Uz, 2020). Moreover, precipitation is considered to be the most relevant meteorological factor while studying many cities (Bean et al., 2021). This discrepancy may be due to the new perspective of analysis used in our study, in which the dynamic interaction of variables can be examined. Previous studies were based on linear relationships, and they did not observe the amount of rainfall needed, relative to other factors (such as temperature), to influence BSS use. However, excessive cold has always reported to have a negative influence, although at each geographical point, people's sensitivity to cold varies (Bean et al., 2021).

Humidity has previously been considered an important factor (Ashqar et al., 2019) and, although it was not relevant in this study, its interaction with other factors had a negative effect on BSS use. This study corroborates that when humidity is comfortable or low, it does not affect AT; however, when humidity is high, it negatively affects BSS use (Eren & Uz, 2020; Miranda-Moreno & Nosal, 2011; Villarrasa-Sapiña et al., 2023). Similarly, precipitation by itself does not influence BSS usage but depends on other variables, such as temperature and humidity. However, BSS use is affected by heavy rain, which could explain why previous studies reported negative correlations between BSS use and precipitation (Kim, 2018; Rixey, 2013).

Wind speed did not appear to have a significant influence if it was not accompanied by extremely cold temperatures. This result was consistent with that of a recent study that applied the same analysis (Villarrasa-Sapiña et al., 2023) and highlights the controversy generated by the study of this variable (He et al., 2019). Contrastingly, snow was also found to negatively affect BSS, corroborating the results of a previous study (Yang, 2018). This has also been proven in other sustainable means of transportation, such as e-scooters (Abouelela et al., 2023), and other ATs, such as walking (de Montigny et al., 2012).

Finally, this study highlighted that atmospheric pressure influenced BSS use. Specifically, atmospheric pressure can have a negative effect at extremely low or high values. This could be explained by the fact that low atmospheric pressure may imply that less oxygen is available; therefore, blood oxygen is reduced and people feel tired (Correa et al., 2015). This result is the first to indicate the influence of weather on AT, which may be due to the applied analysis. In fact, along with temperature, atmospheric factor showed the most relevance in this study (see the results of the decision tree, 5.9 %). However, further scientific evidence is required to confirm this relevance.

These results indicated that there are cities with similar profiles, even though they are in different geographic areas (Fig. 5). The first highlighted profile was created by Washington, DC, Toronto, Chicago, and New York. These cities gained attention for having many C3 and C4 days, followed by a few C1 and C2 days. Montreal could also be included in this profile, although it did not have as many C3 days. All these cities are characterized by subtropical or continental climate, with high humidity, consistent precipitation, cold winters and hot summers, although according to the decision tree, in Washington DC and Montreal, days with <12 °C seem to be conditioned by other meteorological variables. The second profile was formed by Los Angeles, València, and Santa Monica, which had a large part of the year in C4 and a few days in C5 and C6. According to the decision tree, these North American cities were more temperature-sensitive than València and required warmer temperatures to use BSS. They are characterized by a Mediterranean climate with hot summers and mild winters, Although the observed differences in BSS usage may be attributed to recent Köppen-Geiger climate updates, which have reclassified Valencia from a Mediterranean climate to an Arid and hot climate due to a reduced number of precipitation days (Beck et al., 2020). The third profile was formed by Munich and London (Marine west coast climate, Cfb), which had many days between C2, C4, and C6. San Francisco was similar to these cities (Warm summer Mediterranean climate, Csb), although it had many days in C6; therefore, it could also be part of this profile or a previous one. In fact, according to the decision tree results, the estimation of BSS use during warm days in San Francisco was similar to València, unlike Munich or London. San Francisco, London, and Munich were characterized by comfortable summers and cold winters. The main difference is that San Francisco experiences dry summers, unlike Munich or London. Finally, according to the clusters, Oslo and Madrid showed no similarities to the other cities. However, looking at the decision tree, the coldest days (<12 °C) were estimated as those in Washington DC, Montreal, and València, although their warm days were estimated like most of the cities studied (i.e., by clusters).

5.2. Policy implications

Meteorological conditions can prompt citizens to switch between different modes of transport. For example, negative weather conditions may cause a shift from the use of bicycles to private cars (Wadud, 2014). Accumulation of individual decisions of this type have significant consequences for transportation systems in terms of traffic congestion, pollution, and overall trip experience (Böcker et al., 2016; Koetse & Rietveld, 2009). Therefore, having knowledge of the days with a higher probability of motorized traffic congestion is important to apply public policies to improve this situation. Specifically, we extracted the most relevant weather profile of each city so that their governments could adapt specific transport and sustainability policies to reduce pollution.

Therefore, each city should attend to the profiles of days that most negatively affected BSS use (i.e., C2 and C3), especially if their number of days stand out among the profiles (Fig. 4). Additionally, which days of the year have these characteristics (e.g., very cold, cold with precipitation, or snow) should be examined. Once these profiles are identified in a year, policies can be implemented to facilitate AT and reduce private motorized transport, as it is feasible under these weather conditions (Dybdalen & Ryeng, 2022).

In these profiles, some cities may have several days during which weather conditions can be dangerous for the AT of citizens, particularly if they are cycling. As a policy measure, public transport should be substantially increased, as people prefer public modes of transport to cycling when it is cold or raining (Böcker et al., 2016), and even facilitate its access (e.g., by clearing snow, increasing the number of bus and subway lines, number of stations, and reducing or removing the price of access to public transport) to avoid the collapse of private motor vehicles. Weather conditions and AT have led to different policy strategies for reducing the probability of motor vehicle accidents, traffic congestion, and pollution (Godavarthy & Rahim Taleqani, 2017).

Owing to their characteristics, cities with practically no C2 or C3 days should consider C1 and C6. In this way, the meteorological characteristics that can most negatively affect the use of BSS will be known. This can provide information to understand how they affect their population, with an objective for designing policies that favor its use. Additionally, these cities tend to be hot. When analyzed independently, some cities showed a negative association between excess heat and BSS usage. Therefore, in cities prone to high temperatures, these days should be given attention, especially if they usually have high humidity (Eren & Uz, 2020). For example, the study conducted by Villarrasa-Sapiña et al. (2023) in València using the same methodology can be used. They observed that BSS use reduced at temperatures >25 °C if the humidity was moderate or >23 °C if the humidity was high. Cities that exhibit these characteristics for several days in a year should implement green policies; that is the amount of green area with drought-resistant trees (e.g., *Ficus benjamina* in wide spaces and *Acer campestre* in narrow streets) should be increased to provide more shade and reduce temperature (Gutiérrez et al., 2021; Langenheim et al., 2020) and public transport stations should be provided with shades (Lanza & Durand, 2021).

5.3. Limitations

Cities that contributed more days to the analysis were assigned greater importance in this study. Oslo and Madrid contributed the least, while Washington DC and Chicago contributed the most to the analysis. However, the study included many cities with different weather types and considered a long study period to overcome any limitations and provide a holistic scenario. BSS is not operational in Oslo and Montreal during the winter months, which should be considered before drawing conclusions about these cities because the percentage of BSS use during this period is zero. However, the peak seasons of BSS use can be compared between the cities. Future studies should analyze other ATs to determine whether these profiles follow the same pattern.

Moreover, in the future, in addition to meteorological conditions, other factors (e.g., sociodemographic or environmental variables) that may influence the use of BSS may be studied, such as the price of renting the BSS, the number of bike lanes in the cities, the number of kilometers of segregated or non-segregated cycle lanes, the percentage slope of the terrain between BSS stations (both positive and negative), or the amount of time that each city has promoted cycling as an AT (both with infrastructure and by culture). However, although the variables mentioned were not included in this study, our decision tree has produced high, stable, and consistent performance metrics (i.e., without overfitting between training and validation) (see Table 6). Therefore, it can be concluded that the meteorological factors examined alone are sufficient to achieve a reliable prediction of bicycle use for commuting.

6. Conclusions

To the best of our knowledge, this study is the first to investigate how weather conditions affect BSS usage, covering 13 cities of international relevance over different years and using more robust and advanced nonlinear analyses, such as SOM and decision tree analyses. This provides a broad new perspective on how weather characteristics affect (positively and negatively) AT by BSS.

Based on these analyses, weather profiles were generated, allowing us to understand the dynamic interactions between weather variables and the use of BSS. Thus, we attempted to avoid the methodological limitations of linear predictive analysis.

In conclusion, the results of this study indicated that the most relevant variables are temperature (34.4 %), clusters (23.3 %), and geographic area (i.e., cities) (17.5 %). The sum of the percentages of their relevance contributed 75.1 % of the total information. Therefore, these three variables were sufficient to predict the use of BSS. Contrastingly, the remaining variables contributed a small percentage of information (<5.9 %). Specifically, all meteorological variables, except temperature, were of marginal relevance for independently forecasting the use of BSS. In other words, a combination of these factors, including snow and rain, is required to understand their interactions and estimate BSS use.

These results supported the need to generate clusters or employ more advanced, nonlinear analyses to forecast the use of BSS. Moreover, the importance of understanding the characteristics of the geographical areas under study was highlighted to determine where the obtained results can be extrapolated.

Additionally, this study also characterized cities based on the profiles generated in such a way that each city could be analyzed independently and by comparison. The information obtained allows the collaboration of different cities with similar profiles in developing and implementing policies that promote AT in general and BSS in particular, or public transport, to mitigate the consequences of the profiles that negatively affect the use of BSS as a specific AT.

Abbreviations

BSS	bike-sharing system
AT	active transport
SOM	self-organizing map

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CRediT authorship contribution statement

Israel Villarrasa-Sapiña: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Jose-Luis Toca-Herrera:** Writing – review & editing, Supervision, Software, Methodology, Investigation. **Maite Pellicer-Chenoll:** Writing – original draft, Visualization, Data curation. **Karolina Taczanowska:** Writing – original draft, Software, Investigation. **Pilar Rueda:** Writing – review & editing, Resources, Project administration, Formal analysis. **José Devís-Devís:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no competing financial interests or personal relationships that may have influenced the work reported in this study.

Data availability

Data will be made available on request.

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