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Environment

Application of the K-Means method to classify climatic regions of asphalt pavements in Brazil

Aplicação do método K-Médias para classificação de regiões climáticas de pavimentos asfálticos no Brasil

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ABSTRACT

Climatic conditions significantly impact the behavior and performance of flexible pavements. The Brazilian territory is known for its continental dimensions, which leads to enormous climate variability. As a result, national asphalt pavements are subject to different climatic conditions, according to the regions in which they are located. Thus, the present study aims at identifying climatic regions with homogeneous climatic characteristics that affect the performance of flexible pavements in Brazil, using the K-Means clustering method. The methodology proved to be adequate, dividing the country into 5 climatic regions, namely: region 1 is characterized by high temperatures, radiation, and low precipitation; region 2, by the large thermal amplitude and high temperatures; region 3, by smaller thermal amplitudes, higher wind speeds, and high radiation; region 4, by milder temperatures, high temperature range, and considerable precipitation; and region 5, by high volumes of precipitation and high humidity, in addition to high temperatures.

Keywords: Climate; K-Means clustering; Asphalt pavements; Climatic regions; Brazil

RESUMO

As condições climáticas impactam significativamente o comportamento e o desempenho dos pavimentos flexíveis. O território brasileiro é conhecido por suas dimensões continentais, o que acarreta enorme variabilidade climática. Com isso, os pavimentos asfálticos nacionais estão sujeitos a diferentes condições climáticas de acordo com cada região em que estão inseridos. Assim, o presente estudo tem como objetivo identificar regiões climáticas com características climáticas homogêneas que afetam o desempenho de pavimentos flexíveis no Brasil, utilizando o método de clusterização K-Médias. A metodologia mostrou-se adequada, dividindo o país em 5 regiões climáticas: a região 1 é caracterizada por altas temperaturas e radiação, e baixa precipitação; a região 2 pela grande amplitude térmica e altas temperaturas; a região 3 por menores amplitudes térmicas, maiores velocidades de vento e alta radiação; a região 4 por temperaturas mais amenas, alta amplitude térmica e precipitação considerável; e a região 5 pelos elevados volumes de precipitação e alta umidade, além de altas temperaturas.

Palavras-chave: Clima; Agrupamento K-Médias; Pavimentos asfálticos; Regiões climáticas; Brasil

1 INTRODUCTION

The pavement performance depends on many factors, including traffic, weather conditions, and material properties. Climatic conditions are relevant factors in the behavior of asphalt pavements and, consequently, in the performance and service life of these structures (Hasan et al., 2015; Haslett et al., 2021; Qiao et al., 2020; Wistuba & Walther, 2013).

Titus-Glover (2021) summarized, based on several studies on pavement deterioration climate impact, the main climate parameters, namely: solar radiation and cloud cover; air temperature; precipitation and humidity; and wind speed. These variables influence pavement temperature, water damage to the structure, and aging. The difference in climatic conditions has a significant influence on the bearing capacity and performance of asphalt pavement, being related to rutting, cracking, aging, and other deteriorations on asphalt pavements (Gopisetti et al., 2021; C. Wang et al., 2019).

Temperature is one of the most important aspects that affects the design and performance of flexible pavements, exerting influence on asphalt materials in particular (Ramadhan & Al-Abdul Wahhab, 1997). Higher temperatures can reduce the materials’ stiffness, changing the pavement response to traffic loads, thus reducing the structure service life. In addition, their ability to resist rutting also decreases (Faccin, Specht et al., 2021). It is also observed that temperature, as well as its spatial and temporal variation, is a major factor in fatigue life prediction of asphalt pavements (Kim, 2009; Moreno-Navarro et al., 2015).

Another important degradation mechanism to asphalt pavements is moisture damage. Precipitation can impact the asphalt overlay or other pavement layers by changing their water content (Gubler et al., 2005). For unbound materials, the increase in the water level has a significant effect on the responses of the structure with decreased resilient modulus and increased rate of accumulation of permanent deformation (Rokitowski et al., 2021; Saevarsdottir & Erlingsson, 2013). Therefore, the asphalt mix degradation in flexible pavement structures service life is directly related to the deleterious action of water (Brondani, Faccin et al., 2022; Brondani, Menezes Vestena et al., 2022). The cohesion of the mixture changes by the detachment of aggregates from the asphalt binder, bringing up changes of important properties, such as flexibility, tensile resistance, and stiffness. According to other studies (Júnior et al., 2019; Kakar et al., 2015; Omar et al., 2020; W. Wang et al., 2019), the presence of moisture in the asphalt mixture can cause a series of damage that end up by reflecting the service life of the asphalt coating, demanding severe levels of interventions and maintenance.

Climatic conditions also affect the aging process of asphalt mixtures in the field, which results in chemical changes, rheological and material performance (e.g., volatilization of bitumen fractions, increased stiffness, and brittleness), leading to the development of premature failure due to fatigue and thermal cracking (P. O. B. de A. Júnior et al., 2023).

In this scenario, some researchers have developed a way to regionalize the asphalt pavements in their countries, based in climate variables, creating climatic regions, that is, regions with homogeneous conditions. Most of the studies rely on asphalt binder Performance Grades (PG) classification for this purpose (Balushi et al., 2020; Delgadillo et al., 2017, 2018; Lee et al., 2018), as it considers the maximum and minimum pavement temperatures. For Brazilian context, Leite and Tonil (Leite, L. F. M.; Tonial, 1994), following the SUPERPAVE specifications, performed a PG map classification for Brazil; subsequently, Cunha et al. (Cunha et al., 2007) reviewed the PG map adopting the same database used in Leite and Tonial (1994), but applying different equations for the calculation of pavement temperatures. Recently Faccin et al. (Faccin, Schuster, et al., 2021) presented a new PG map using updated data, different models, and reliabilities for the Brazilian climate.

However, besides temperature influence, it is also worth noting the impact of moisture damage effect and aging. Thus, other studies, such as Long-term Pavement Performance Program (LTPP), indicate proposals for climate regions by considering precipitation parameters in addition to temperature (Schwartz et al., 2015). For instance, the climate zoning of asphalt pavements in China is based on three weather factors, which include high temperature, low temperature, and precipitation (Zhao et al., 2022). Wang et al. (C. Wang et al. (2019), as another example, divided Tibet into 5 climatic regions considering solar radiation, high temperature, low temperature, and large temperature difference. Another illustration comes from Dong et al. (Dong et al., 2021) that classify different climatic regions for the US considering 16 climate variables from the Long-term Pavement Performance (LTPP) database, which is composed by annual temperature, freezing, thawing, precipitation, snowfall conditions, and the use of a cluster analysis.

Homogeneous climatic zones are expected to indicate similar behavior of asphalt pavements. Yang et al. (Y. Yang et al., 2020) adopted the K-means clustering algorithm to partition Liaoning Province (China) into four regions, bearing in mind the following factors: high temperature, low temperature, precipitation, and solar radiation. The results of the climatic regionalization were compared with those from field investigations. It was observed that pavement degradation in each climatic zone was related to the respective region’s climatic characteristics.

Clustering methods have been frequently used to partition a domain of interest into distinct climatic zones, for different areas of interest (Araujo, 2020; X. Yang et al., 2018), being one of them the paving area (Dong et al., 2021; Y. Yang et al., 2020). Cluster analysis is a method widely used to classify data samples or variables into different groups based on their similarity (Seidel et al., 2008). Distance metrics (e.g., Euclidean distance) are commonly used to measure the similarity between samples.

These clustering techniques are useful for dealing with large, multivariate, and multidimensional data that are difficult for human perception; for instance, weather data (Doan et al., 2023). The K-Means clustering (MacQueen, 1967) is the most frequently used clustering algorithm, as it classifies n samples into k clusters, based on distance. It was proposed by MacQueen (1967); (Li & Wu, 2012; Tripathi et al., 2018; Wu, 2012), and considered an unsupervised machine learning method.

When large amounts of data are analyzed for clustering, it is necessary to adopt multivariate data analysis techniques in order to remove the multicollinearity of the variables, by transforming a set of original intercorrelated variables into a new set of uncorrelated variables. For example, this is the case with the PCA (Principal Component Analysis) used in other studies (Dong et al., 2021; Finkler et al., 2016; Yang et al., 2020).

After defining climate regions, as already done in research in other areas of knowledge, one should seek to validate the separation of clusters through statistical tests of multiple comparison, making it possible to assess whether the groups (climatic regions) are homogeneous and representative (Aprilina et al., 2023; Doan et al., 2023).

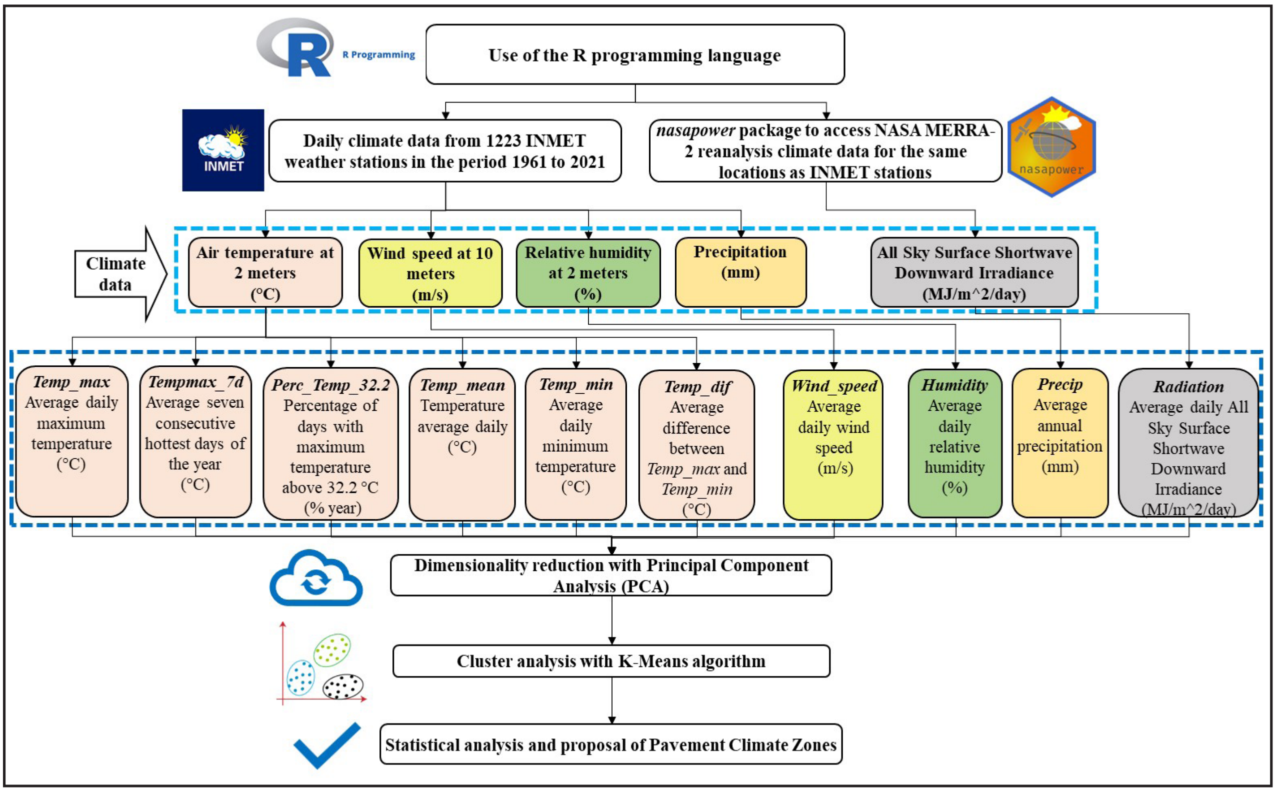
Due to the importance of the climate in the behavior/performance of flexible pavements, it is necessary to understand the climatic parameters in the design stage and selection of materials in paving works, especially in the context and reality of Brazil. The Brazilian territory is continental, with a high climate variability, spanning from an equatorial climate in the northern of the country, with more than 3100 mm of year precipitation, to a semiarid climate in some northeastern regions, with less than 700 mm. Besides that, annual mean air temperature can range from 12ºC to higher than 26°C (Alvares et al., 2013).

Thus, inserted in the Brazilian scenario, this study aims to identify climatic regions with homogeneous climatic characteristics that affect the performance of flexible pavements in Brazil, based on 10 climatic variables from 1223 weather stations, through unsupervised machine learning method K-Means clustering and statistical analysis. Furthermore, it is expected to evaluate the characteristics of each region by indicating the main climatic agents that act on the asphalt pavements in each area.

2 METHODOLOGY

Figure 1 presents the methodology adopted in this work, identifying the main steps necessary to achieve the proposed objective.

Figure 1 – Flowchart on the methodology



Source: Authors (2023)

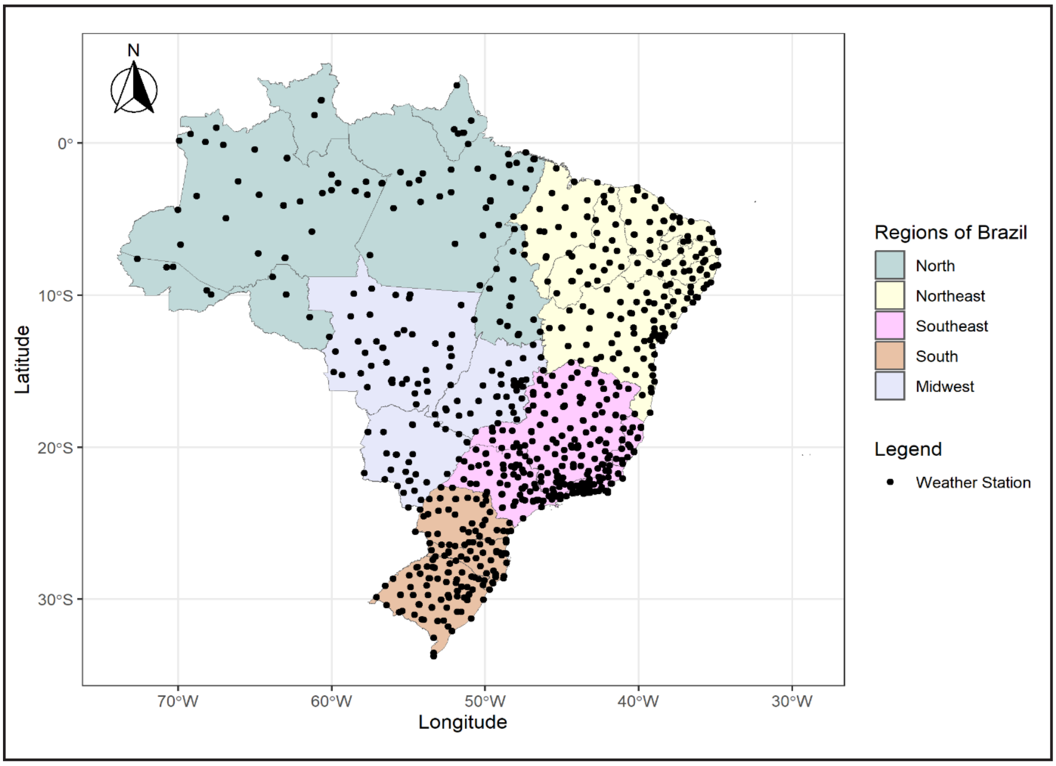
2.1 Climate data and parameters

In the first stage, the national climate data were collected from the website of the National Institute of Meteorology of Brazil (INMET, Portuguese acronym) (INMET, 2021). A total of 1223 weather stations were used and distributed in all regions of Brazil. Due to the lack of solar radiation data available for all INMET stations, data from the MERRA-2 reanalysis (Gelaro et al., 2017) were used to obtain radiation. The climatic variables indicated in Figure 1 were chosen for analysis in this work because several aforementioned publications indicate that they are the most relevant in the behavior and performance of asphalt pavements.

For all weather stations, the daily climate data listed in Figure 01 were collected from 1961 to 2021. Using the R software (R Core Team, 2021), these climatic variables were considered in the cluster analysis. Due to the lack of data at INMET stations, which was already reported in other studies (de Souza et al., 2022; Faccin, Schuster et al., 2021), it was adopted as a criterion to disregard the years with more than 15% of data missing data for each climate variable, and a minimum of 5 years of valid data.

Thus, out of the 1223 stations initially evaluated, a total of 900 of them remained with valid data for the cluster analysis (Figure 2).

Figure 2 – Location of the 900 Brazilian meteorological stations considered



Source: Authors (2023)

The climate parameters considered in cluster analysis were calculated according to Equations (1-10).

$$Temp\_max = \frac{1}{n}\sum_{i=1}^{n} Temp\_max_{,\text{average,year}} \quad (1)$$

$$Tempmax\_7d = \frac{1}{n}\sum_{i=1}^{n} Tempmax\_7d_{,year} \quad (2)$$

$$Perc\_Temp\_32.2 = \frac{1}{n}\sum_{i=1}^{n} T_{\%>32.2,year} \quad (3)$$

$$Temp\_mean = \frac{1}{n}\sum_{i=1}^{n} Temp\_mean_{,average,year} \quad (4)$$

$$Temp\_min = \frac{1}{n}\sum_{i=1}^{n} Temp\_min_{,average,year} \quad (5)$$

$$Temp\_dif = \frac{1}{n}\sum_{i=1}^{n} Temp\_dif_{,average,year} \quad (6)$$

$$Wind\_speed = \frac{1}{n}\sum_{i=1}^{n} Wind\_speed_{,average,year} \quad (7)$$

$$Humidity = \frac{1}{n}\sum_{i=1}^{n} Humidity_{,average,year} \quad (8)$$

$$Precip = \frac{1}{n}\sum_{i=1}^{n} Precip_{,sum,year} \quad (9)$$

$$Radiation = \frac{1}{n}\sum_{i=1}^{n} Radiation_{,average,year} \quad (10)$$

Where:
Temp_max is the average daily maximum temperature over a span of n years (°C);
$Temp\_max_{,average,year}$ is the average daily maximum temperature per year (°C);
Temp_max_7d is the average seven consecutive hottest days over a span of n years (°C);
$Temp\_max\_7d_{,year}$ is the seven consecutive hottest days of the year (°C);
Perc_Temp_32.2 is the percentage average of days when daily maximum air temperature was above 32.2 °C for n years (%);
T%>32.2, year is the percentage of days when daily maximum air temperature was above 32.2 °C for a year (%);
Temp_mean is the average daily temperature over a span of n years (°C);
$Temp\_mean_{,average,year}$ is the average daily temperature per year (°C);
Temp_min is the average daily minimum temperature over a span of n years (°C);
$Temp\_min_{,average,year}$ is the average daily minimum temperature per year (°C);
Temp_dif is the average difference between Temp_max and Temp_min over a span of n years (°C);
$Temp\_dif_{,average,year}$ is the average daily difference between Temp_max and Temp_min per year (°C);
Wind_speed is the average daily wind speed over a span of n years (m/s);
$Wind\_speed_{,average,year}$ is the average daily wind speed per year (m/s);
Humidity is the average daily humidity over a span of n years (%);
$Humidity_{,average,year}$ is the average daily humidity per year (%);
Precip is the annual average precipitation over a span of n years (mm);
$Precip_{,sum,year}$ is the sum precipitation per year (mm);
Radiation is the average daily All Sky Surface Shortwave Downward Irradiance over a span of n years (MJ/m^2/day);
$Radiation_{,average,year}$ is the average daily All Sky Surface Shortwave Downward Irradiance per year (MJ/m^2/day).

2.2 Climate regionalization method using the K-Means algorithm and statistical analysis

Among multivariate techniques, the Principal Component Analysis (PCA) is one of the most used statistical techniques in data analysis in several areas of knowledge. PCA is a statistical technique of multivariate analysis that linearly transforms an original set of variables, initially correlated with each other, into a substantially smaller set of uncorrelated variables that contain most of the information of the original set, named principal components (Hongyu et al., 2016).

To obtain the principal components, the “stats” package was used, available in the R software (Abdi & Williams, 2010). According to Rencher (Rencher, 2002), at least 70% of the total variance must be explained by the first and second main components. When the cumulative contribution rate exceeds 85%, the core components chosen cover most of the information from the original variables (Y. Yang et al., 2020). Furthermore, such limits were adopted as a criterion in the selection of the main components.

The K-Means algorithm requires the number of clusters as input. There are several approaches for selecting the number of groups, and it is often complex to identify the best alternative for the database in use. In view of this, an alternative consists on executing various statistical methods and obtaining the number of clusters with greater acceptance (that is, finding consensus). This can be carried out through the “parameters” package (Lüdecke et al., 2020), available for use in the R software.

To perform the segmentation, the R software was used (R Core Team, 2021), through the ‘factoextra’ package (Mundt, 2020). The K-Means Clustering Algorithm (MacQueen, 1967) is an unsupervised learning method. The software selects the K initial centroids specified according to the number of previously defined clusters. Each point in the data is then assigned to the nearest centroid, and each collection of points assigned to a centroid form a cluster. The centroid of each cluster is then updated based on the points assigned to that cluster. This process is repeated until no points change groups (Wu, 2012).

The K-Means clustering method classifies objects within multiple groups, so that intra-cluster variation is minimized by the sum of squares of the Euclidean distances between items and their centroids, according to Equation 11.

$$W(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2 \tag{11}$$

In this way, xi is the point that belongs to the Ck cluster and μk represents the mean of the value attributed to the Ck cluster. Each observation (xi) is assigned to a cluster such that the sum of squares of the observation›s distance from its central cluster (μk) is minimal. Also, to define the intra-cluster variation, the formula below is used, and it should be as low as possible (Equation 12). More details about the K-Means algorithm can be found in (MacQueen, 1967; Mundt, 2020; Wu, 2012).

$$tot.intracluster = \sum_{k=1}^{k} W(C_k) = \sum_{k=1}^{k} \sum_{x_i \in C_k} (x_i - \mu_k)^2 \tag{12}$$

After defining the clusters, multiple comparison tests were performed to assess whether there is statistical difference between the groups, considering 95% confidence.

The Shapiro-Wilk normality test will be performed for the data, to assess whether they meet the normal distribution. As a result of that, it will be possible to verify the validity of the cluster analysis through dispersion tests, depending on whether parametric or non-parametric tests will be used. Analysis of variance, or ANOVA, as it is parametric, requires variables with normal distribution, independent samples taken at random, and similar sample variances. The Kruskal-Wallis test is the non-parametric equivalent of the ANOVA in which the assumptions of normality and homogeneity of variances are not met. Depending on the type of test to be used to verify the clusters (ANOVA or Kruskal-Wallis), post hoc tests (ex: Dwass-Steel-Critchlow-Fligner) will be used to identify which of the pairs of groups differ after performing the cluster analysis. The next step is to compare the clusters using measures of central tendency and dispersion for the analytical characterization of the groups, presenting the results in box plots and tables.

3 RESULTS AND DISCUSSIONS

In order to explain the results obtained through the study, the following sections discuss, respectively, the cluster analysis and the climate regions characteristics.

3.1 Climatic variables and data preparation

Table 1 summarizes the statistical descriptions of the variables considered in the cluster analysis, for all meteorological stations. It is possible to observe considerable differences in Brazil for the considered parameters, such as an average temperature ranging from 11°C to 29°C, and places with average annual precipitation from 299 mm to 3484 mm.

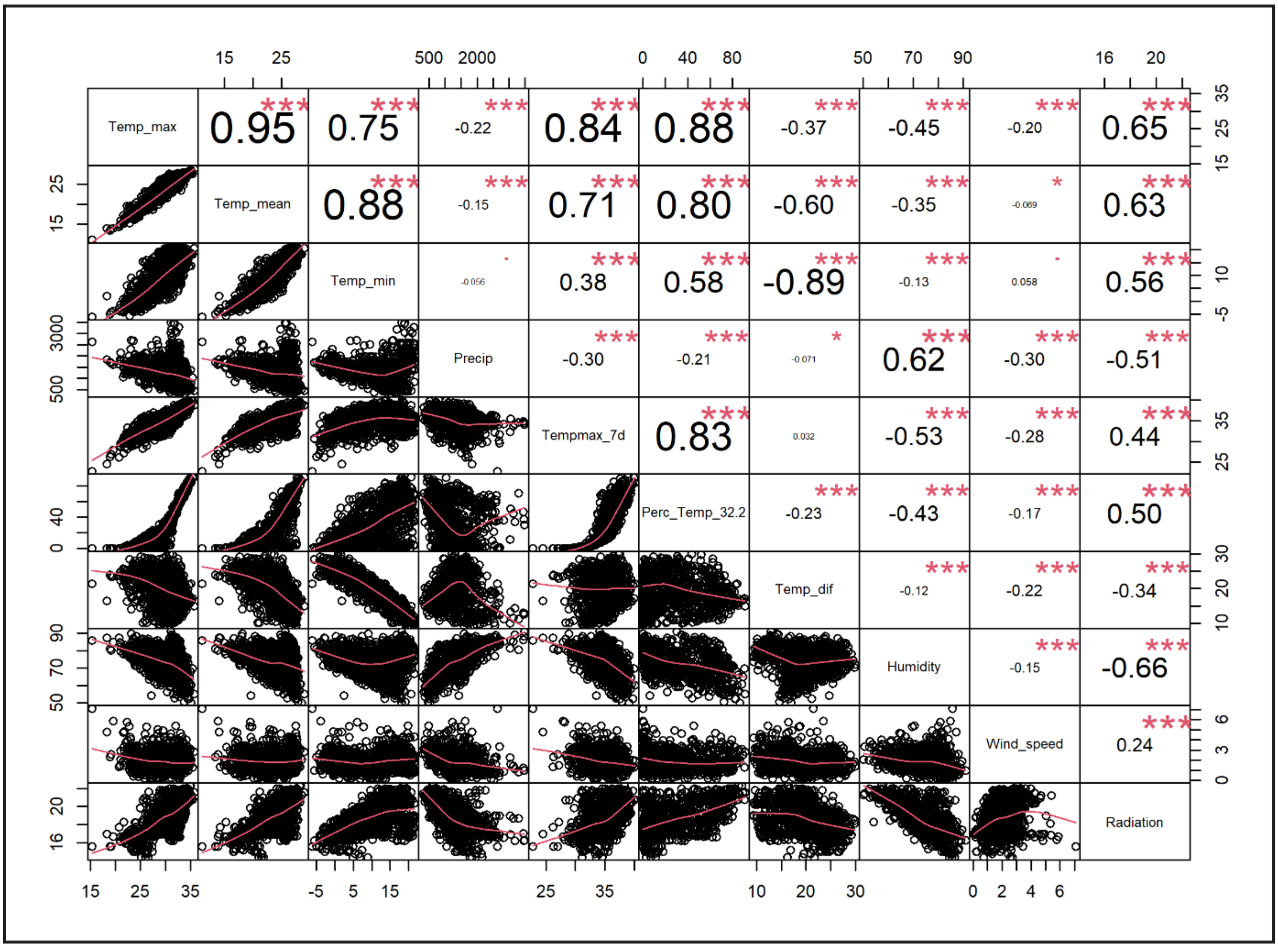
Table 1 – Statistical descriptions of the climatic data for all meteorological stations

Climate parameters	Mean	Median	Standard deviation	Minimum	Maximum
Temp_max (°C)	29.4	29.8	3.28	15.3	35.7
Tempmax_7d (°C)	34.8	35	2.46	22.8	40.1
Perc_Temp_32.2 (%)	29.1	22.5	24.6	0	91.3
Temp_mean (°C)	23.1	23.5	3.18	11	29
Temp_min (°C)	9.49	9.76	6.8	-6.17	21.6
Temp_dif (°C)	19.9	20	4.86	9.28	30
Wind_speed (m/s)	1.94	1.79	0.939	0.042	7.09
Humidity (%)	73.7	74.5	7.64	50.1	91
Precip (mm)	1356	1328	495	299	3484
Radiation (MJ/m^2/day)	18.6	18.6	1.66	14.4	22.3

Source: Authorship (2023)

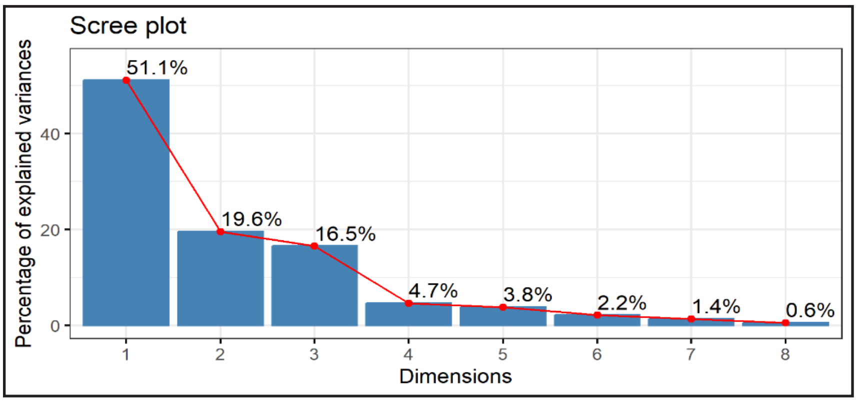
Figure 3 presents the Pearson correlation matrix for the available variables considered to assess the multicollinearity of the data (the degree to which any variable effect can be predicted or explained by other variables and is a basic assumption in cluster analysis). The multicollinearity between the variables can change the grouping patterns because these variables are implicitly weighted with greater weight (J. F. Hair et al., 2005). It is possible to observe high values of correlation between parameters related to air temperature, thus justifying the use of the principal component analysis (PCA) statistical technique.

Figure 3 – Correlation matrix chart



Source: Authors (2023)

Figure 4 – Screen plot

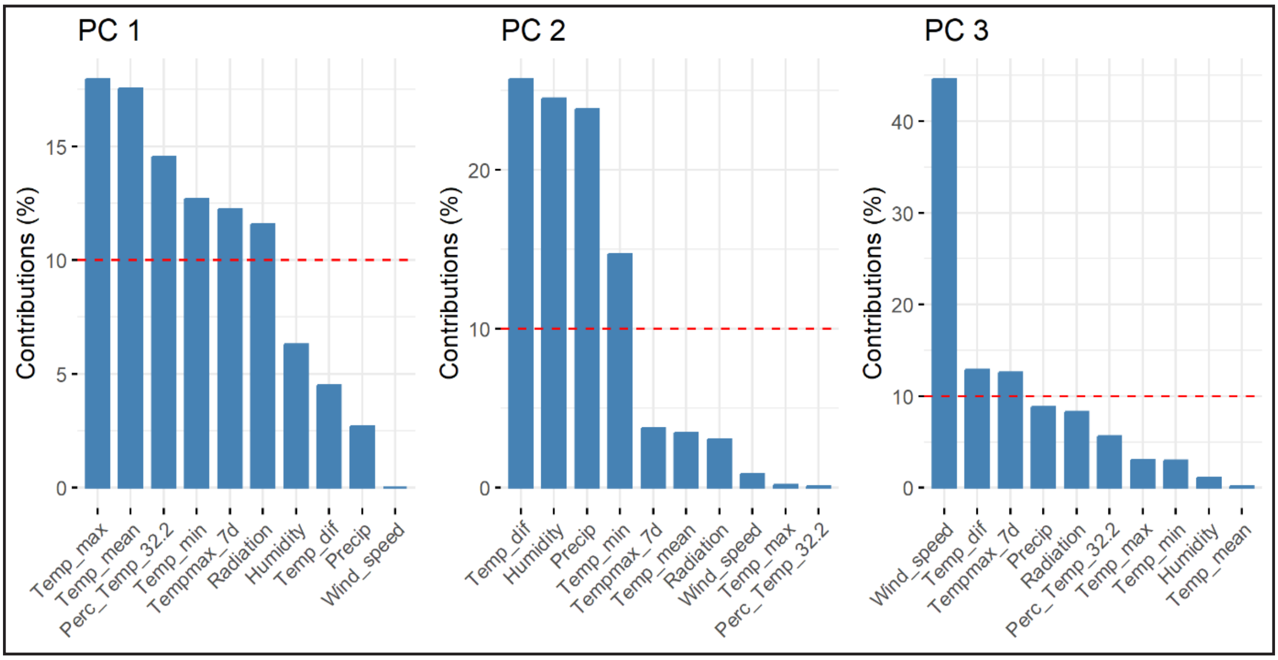


Source: Authors (2023)

Based on the results obtained by using the principal components technique, the percentages of variance explained by each dimension are shown in Figure 4. The first two principal components were responsible for 70.7% of the total data variation, meeting the recommendation of Rencher (Rencher, 2002). The contribution rate of the cumulative variance of the first three factors reached 87.2%, exceeding the general requirement of 85%. Therefore, the first three principal components effectively summarize the total sample variance and can be used to represent the 10 climatic factors considered initially.

Figure 5 demonstrates the contribution of each climate variable to the first three principal components (PC). The first component is primarily related to the 5 parameters related to air temperature and radiation. The second component is mainly related to precipitation and humidity, in addition to thermal amplitude. The third component is mostly related to wind speed.

Figure 5 – Contribution of the variables to the first three PCs



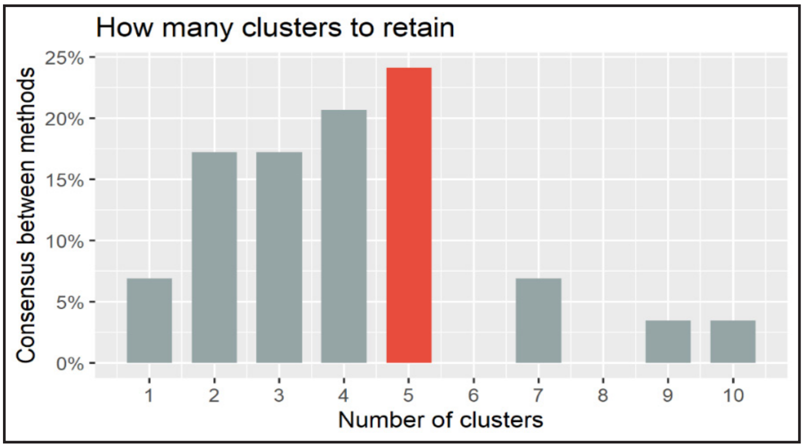
Source: Authors (2023)

3.2 Cluster analysis using k-Means

For the definition of the number of clusters, considering the 3 principal components, as shown in Figure 6, the choice of 5 clusters is supported by 7 (24.14%)

methods among the 29 evaluated in the parameters package (Gap_Dudoit2002, Ch, Hartigan, Rubin, DB, PtBiserial, Mixture (VEV)).

Figure 6 – Optimal cluster number by K-means clustering and "parameters" package

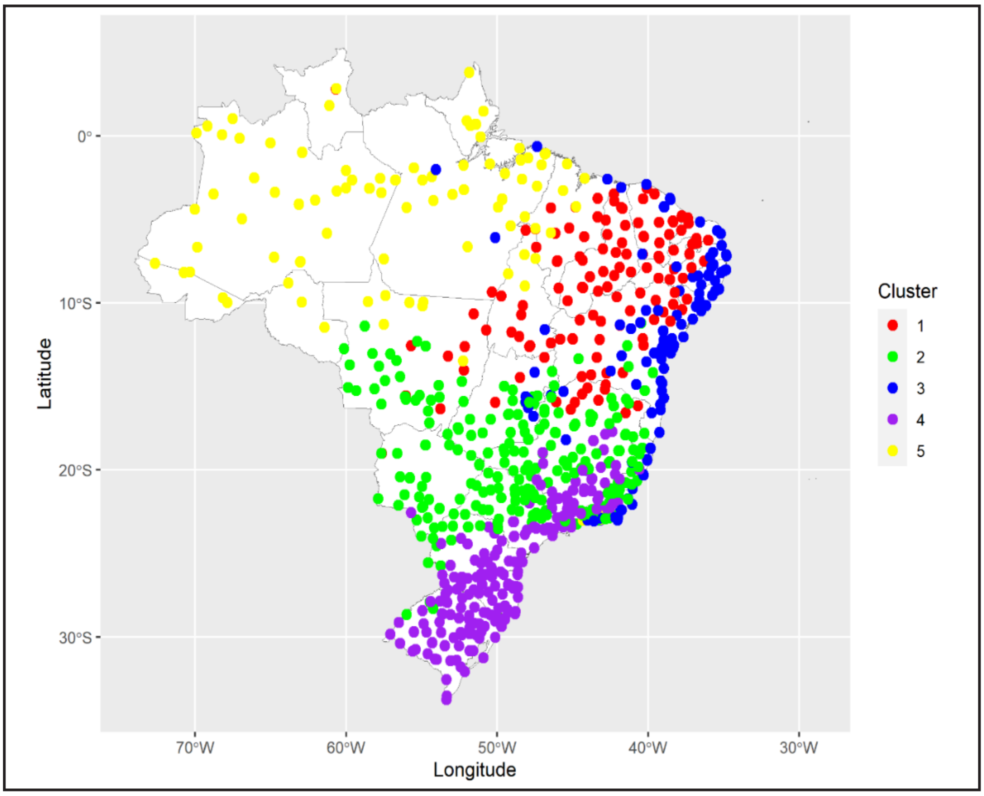


Source: Authors (2023)

The cluster classification for each climatic station is show in Figure 7. According to it, it is possible to notice the five climate regions. In order to facilitate the understanding during the work, the clusters are identified by colors, as follows: Cluster 1 - red; Cluster 2 – green; Cluster 3 – blue; Cluster 4 – purple; and Cluster 5 – yellow.

As shown in Figure 7, the 900 weather stations in the research area were divided into five regions (i.e., clusters) in accordance to the dispersion factors obtained with K-Means algorithm. Region 1 covers mainly the northeast region of Brazil, characterized by a semi-arid climate for the most part. Region 2 includes, in general, places in the Southeast and Midwest of the country, a region with a tropical climate. Region 3 is located mainly in the coastal region, in places with a coastal tropical climate. Region 4 is located in the south of the country, with a subtropical climate, and part of the southeast (where the higher altitude tropical climate predominates). Region 5, on the other hand, includes places with an equatorial climate, with the Amazon rainforest located in this area.

Figure 7 – Cluster classification for each climatic station by K-Means Clustering



Source: Authors (2023)

Some regions (e.g., the one numbered as 5) appear well delimited on the map; however, others (e.g., the one numbered as 3) have points dispersed with other regions. This situation can be justified due to the specific characteristics of certain places (e.g., higher altitudes). Therefore, it is necessary to evaluate other grouping techniques in future studies. According to Souza et al. (de Souza et al., 2022), understanding tropical climates is difficult due to the scarcity of data, but also because studies on climate classification are scarce. In this context, the evaluation of climate data from atmospheric reanalyzes, such as NASA's MERRA-2, can be an interesting alternative, due to better spatial coverage and data availability. In addition, the climatic regions can be evaluated separately, to understand whether it makes sense to make subdivisions according to microclimates.

3.3 Comparison between clusters using statistical tests

The tests presuppose the hypothesis of data normality (Ho), returning a p-value > 0.05 if they result in adherence to the normality parameters. Thus, the comparison between the clusters was carried out using non-parametric analysis of variance, as there were violations in the assumption of normality of the data, according to the results of the Shapiro-Wilk normality test (Shapiro & Wilk, 1965) presented in the Table 2 (p-value less than a significance level of 0.05 – in red).

Table 2 – Shapiro Wilk test applied to cluster data (p-value)

Climate parameters	Cluster				
	1	2	3	4	5
Temp_max (°C)	0.041	0.028	0.032	< .001	< .001
Tempmax_7d (°C)	0.108	0.139	0.173	< .001	0.87
Perc_Temp_32.2 (%)	< .001	< .001	< .001	< .001	0.001
Temp_mean (°C)	< .001	0.078	0.045	< .001	< .001
Temp_min (°C)	0.092	0.025	0.27	0.002	< .001
Temp_dif (°C)	0.009	0.011	0.008	< .001	< .001
Precip (mm)	< .001	0.211	0.004	< .001	0.001
Humidity (%)	0.095	0.436	< .001	0.011	0.055
Wind_speed (m/s)	< .001	0.071	< .001	< .001	0.007
Radiation (MJ/m^2/day)	< .001	< .001	0.002	0.029	< .001

Source: Authors (2023)

Thus, subsequently, the Kruskal-Wallis test (Kruskal & Wallis, 1952) was implemented, which is a non-parametric method of analysis of variance, allowing the comparison of three or more groups in independent samples. The results are shown in Table 3.

Table 3 – Kruskal-Wallis analysis of variance

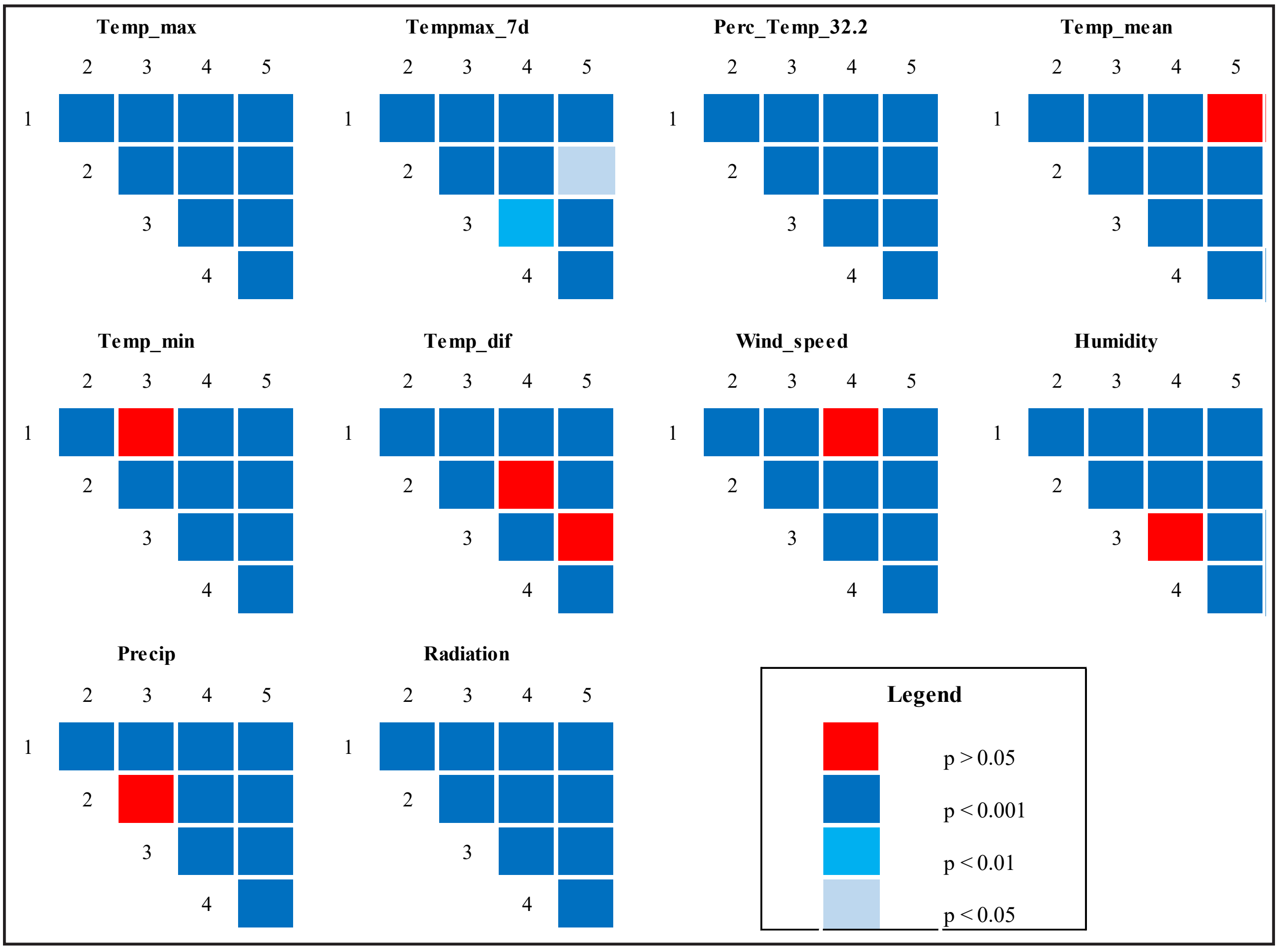
Climate parameters	p-value
Temp_max (°C)	< .001
Tempmax_7d (°C)	< .001
Perc_Temp_32.2 (%)	< .001
Temp_mean (°C)	< .001
Temp_min (°C)	< .001
Temp_dif (°C)	< .001
Wind_speed	< .001
Humidity (%)	< .001
Precip (mm)	< .001
Radiation (MJ/m^2/day)	< .001

Source: Authors (2023)

As shown in Table 3, the Kruskal-Wallis test p-values are less than 0.05 (less than a significance level of 0.05), which leads us to reject the null hypothesis that there is no difference between the clusters for each of the different variables.

To compare the groups and obtain a result that indicates whether there is a significant difference between the groups, we used the Dwass-Steel-Critchlow-Fligner test (Hollander et al., 2015). It is a test for multiple comparisons that allows the comparison of clusters two by two to verify which clusters differed from each other. These results are presented in Figure 8, in which the blue squares represent statistically significant differences, while the the red ones show no difference between the groups. For most comparisons, significant differences are observed between clusters.

Figure 8 – Dwass-Steel-Critchlow-Fligner test applied to clusters



Source: Authors (2023)

For variables related to air temperature, the high temperature parameters (Temp_max, Tempmax_7d and Perc_Temp_32.2) indicate significant differences between groups. For the Temp_mean parameter, there is no statistically significant difference only between clusters 1 and 5, indicating that the two regions have similar average daily air temperatures. In regard to Temp_min, the same situation occurs when comparing groups 1 and 3, as well as for the Temp_dif parameter and groups 2-4 and 3-5.

In relation to wind speed (Wind_speed), there is no statistically significant difference between clusters 1 and 4, despite being located far from each other on the map. Regarding humidity, there is also no statistically significant difference between groups 3 and 4, and for precipitation (Precip), there is not between 2 and 3. For radiation, there are significant differences between all groups.

The results indicate that the methodology used in this investigation can define regions with similar climatic parameters that influence flexible pavements, based on historical climatic series.

3.4 Climate regions: characteristics

In order to assess the characteristics of each region obtained through cluster analysis, Table 4 presents the statistical descriptions of the climatic variables for each region, and the main pavement climatic parameters are presented in box plots for each area in Figure 9.

Due to Brazil's continental dimensions, a high variability of climatic parameters is expected. Because of this, each of the five climate regions are described differently, as it follows.

Region 1 (Cluster 1) is characterized by high temperatures and radiation, as well as low levels of humidity and precipitation. In this region, mostly located in a semi-arid climate, the highest air temperatures in Brazil occur and they persist for a large part of the year. The minimum temperatures are similar to those from region 3, as already identified in the multiple comparison tests. The average thermal amplitude, obtained by the difference between Temp_max and Temp_min, indicates values from 11.8 to 25.4 °C. Wind speed does not present a significant difference with cluster 4, as already observed in the statistical tests. The area has the lowest relative humidity and precipitation levels, with average annual precipitation less than 350 mm in some locations. In addition, in such area, there are the highest average daily radiation levels in the country. Such climatic conditions indicate that the region has the highest pavement temperatures in Brazil. As a result, paving projects in this area demand binders and asphalt mixtures with high resistance to permanent deformation. Moreover, aging caused by radiation is more severe than in other regions of the country, which may influence cracking in the field. Water damage is milder compared to other regions due to low humidity and precipitation.

Region 2 (Cluster 2) is characterized by high thermal amplitude and high temperatures. The data indicate places with high temperatures, but lower and with reduced occurrence in relation to region 1. In these points, high thermal amplitudes occur during the year, caused by lower minimum temperatures in relation to groups 1, 2 and 3. Higher levels of precipitation are measured in relation to region 1, showing no significant difference with cluster 3, as already observed in the statistical tests. In general, the radiation is high, however, lower than regions 1 and 3. These meteorological conditions require high performance from paving materials, demanding materials that meet high, medium and low temperatures throughout the year, with high resistance to both permanent deformation and fatigue.

Region 3 (Cluster 3) is characterized by smaller thermal amplitudes, higher wind speeds and high radiation. This region covers a large part of the Brazilian coast. The winds are higher, with a predominance of high temperatures, but lower than in zones 1, 2 and 4. Due to its location close to the coast, with higher wind speed and humidity than in regions 1 and 2, maximum air temperatures above 32.2°C occur less frequently over the years. The minimum temperatures are similar to those of region 1, and the average thermal amplitude is smaller than in regions 1, 2, and 4. The levels of precipitation are higher compared to region

1 and show no statistical differences compared to region 2. High values of radiation are measured at these points. These results indicate more constant temperatures throughout the year, which may facilitate the development of materials for the region. However, higher levels of humidity are identified compared to regions 1 and 2, demanding extra attention.

Region 4 (Cluster 4) is mainly depicted by low temperatures and high thermal amplitude. Although high air temperatures also occur in this region, it includes points with the lowest values of maximum temperatures, and with the lowest frequencies during the year. It is worth noting that the lowest temperatures in the country are measured in this region, and as well as in region 2, high thermal amplitudes occur during the year. The region has high levels of relative humidity and precipitation. In addition, in general, the lowest radiation values are identified at these points compared to other regions. These climatic data demonstrate that the materials to be used in this area require good performance in terms of fatigue cracking, due to the lower temperatures. In addition, some locations register high temperatures and a high temperature range, demanding materials with good resistance to permanent deformation as well. Water damage also deserves attention because of humidity and precipitation levels.

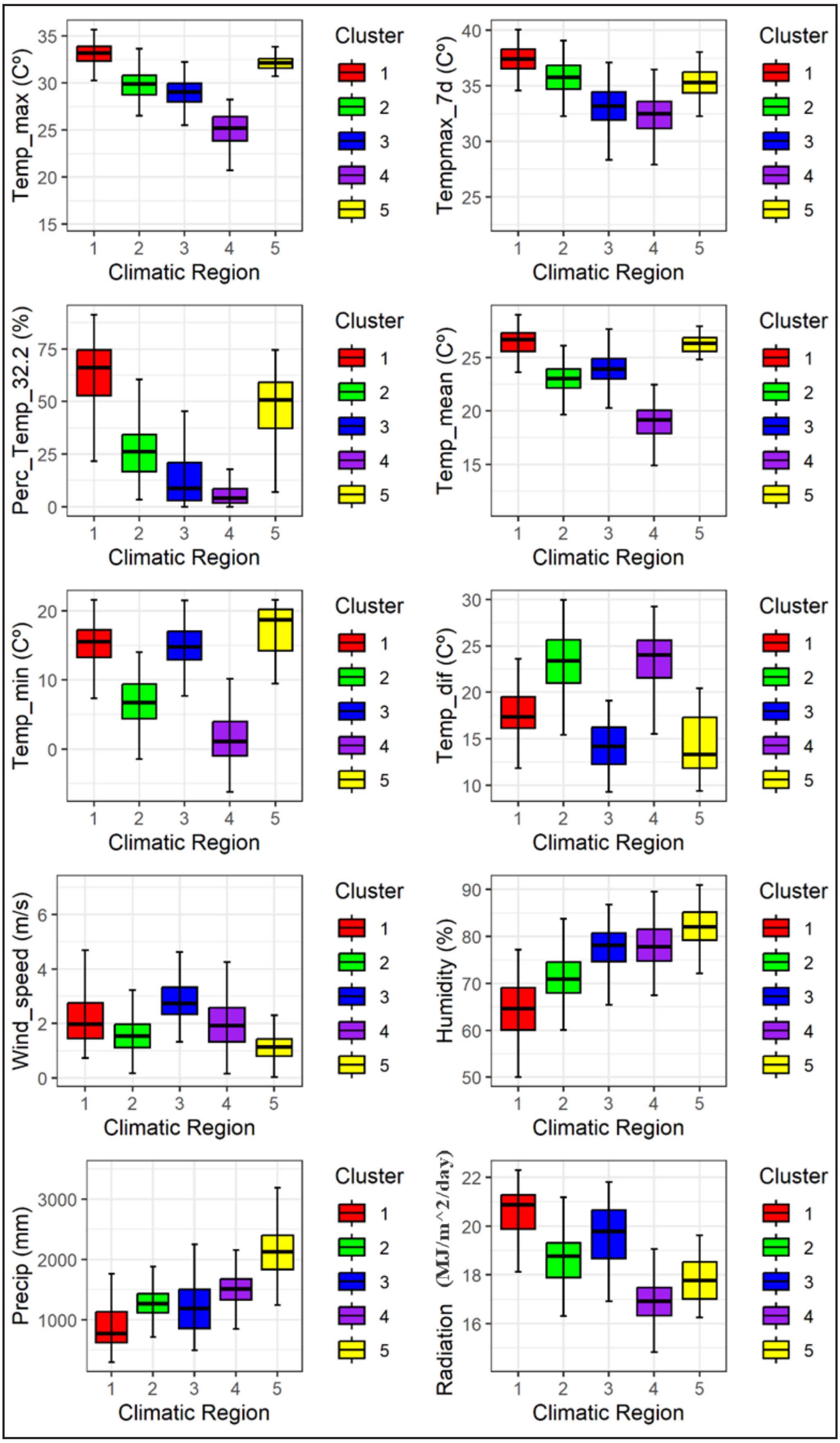
Region 5 (Cluster 5) is characterized by high volumes of precipitation and high humidity, in addition to high temperatures. The region has high values of air temperature, which extend for a good part of the year in most places. Due to these high temperature values, low values of thermal amplitude are observed, as well as in region 3. The locations record, on average, the lowest values of wind speed. In relation to humidity and precipitation, the highest rates in the country are measured, largely due to the local climate that includes a significant portion of the Amazon Forest. Radiation levels lower than regions 1, 2 and 3 are identified in this area. In this zone, high pavement temperatures predominate, with permanent deformation being the main concern. Furthermore, due to the high levels of precipitation and humidity, damage caused by water deserves special attention from the designer for works in the region.

Table 4 – Statistical descriptions of the climatic data for each climate region

Statistical measures	Climate Region (Cluster)	Temp_max	Tempmax_7d	Perc_Temp_32.2	Temp_mean	Temp_min	Temp_dif	Wind_speed	Humidity	Precip	Radiation
Mean	1	33.1	37.4	62.9	26.4	15.2	17.9	2.14	64.3	882	20.6
	2	29.9	35.7	27.8	23	6.78	23.1	1.57	71.3	1273	18.6
	3	28.9	33.1	12.6	23.9	14.8	14.1	2.86	76.7	1222	19.6
	4	24.9	32.3	5.5	18.8	1.47	23.5	2.03	78.3	1531	16.9
	5	31.9	35.3	47.8	26.1	17.5	14.4	1.18	81.8	2147	17.8
Median	1	33.2	37.4	66.2	26.7	15.5	17.3	1.97	64.6	765	20.9
	2	29.9	35.8	26	23.1	6.73	23.4	1.53	70.9	1267	18.8
	3	29.1	33.2	8.71	23.9	14.7	14.2	2.74	78.1	1188	19.8
	4	25.2	32.5	3.94	19.1	1.09	24	1.91	77.8	1509	16.9
	5	32.2	35.3	50.7	26.3	18.7	13.3	1.14	82	2124	17.8
Standard deviation	1	1.11	1.16	14.8	1.17	2.83	2.45	0.844	5.94	357	0.949
	2	1.44	1.37	14.9	1.31	3.16	3.06	0.588	4.83	246	0.95
	3	1.5	1.66	11.8	1.82	3.12	2.55	0.833	5.94	439	1.31
	4	1.98	2.08	4.96	1.75	3.38	2.93	1.03	4.3	291	0.934
	5	1.23	1.2	16	1.17	3.28	3.1	0.551	4.23	467	0.868
Minimum	1	30.3	34.6	21.6	23.6	7.32	11.8	0.727	50.1	299	18.1
	2	26.5	32.3	3.31	19.6	-1.43	15.4	0.168	54.1	593	16.3
	3	25	28.3	0	19.6	7.69	9.28	1.33	61.2	495	16.9
	4	15.3	22.8	0	11	-6.17	14.1	0.151	67.4	850	14.4
	5	26.9	32.3	3.99	21.7	9.49	9.35	0.042	72.1	1244	16.2
Maximum	1	35.7	40.1	91.3	29	21.5	25.4	4.69	77.1	1760	22.3
	2	33.7	39.1	72.7	26.1	14	30	3.28	83.8	1989	21.2
	3	32.2	37.1	45.4	27.7	21.5	19.1	5.4	86.8	2698	21.8
	4	28.2	36.5	21.5	22.5	10.2	29.2	7.09	89.6	2697	19.1
	5	33.8	38.1	74.4	27.9	21.6	20.4	3.12	91	3484	19.6

Source: Authors (2023)

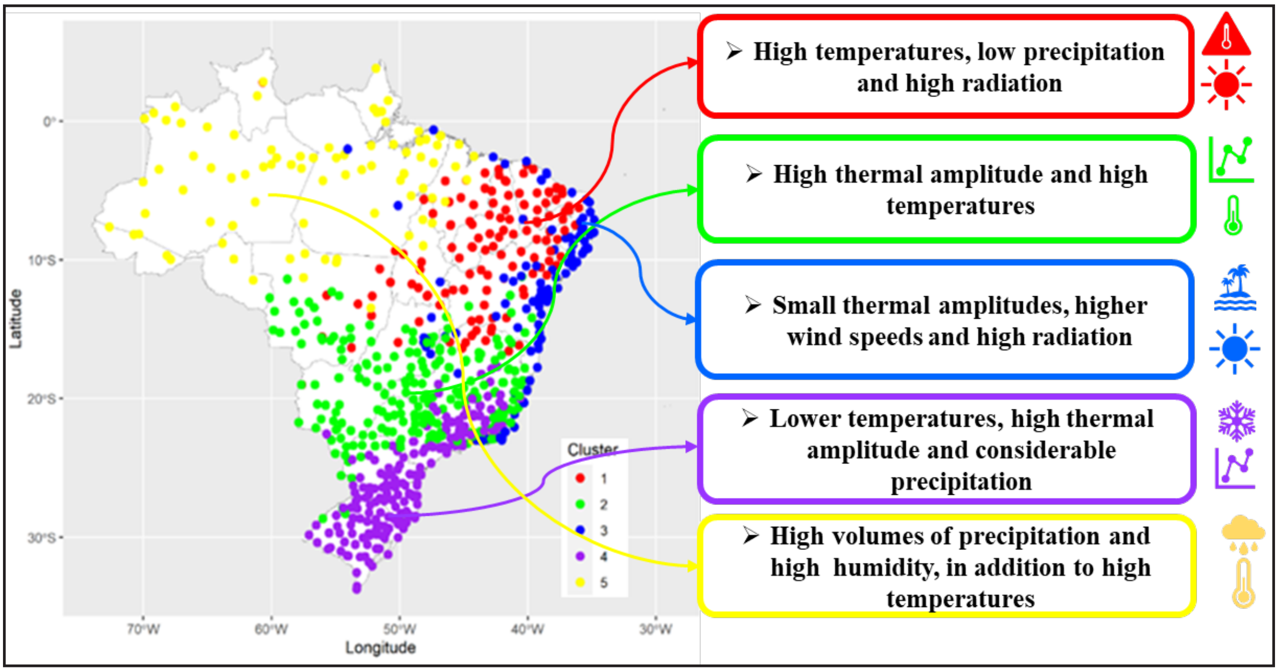
Figure 9 – Box Plots for all climate parameters and respective clusters



Source: Authors (2023)

It should be noted that all pavement degradation mechanisms must be evaluated and deserve attention in the design phase. In this context, a robust field research to validate these assumptions is necessary for future studies, although it is not the objective of this research. However, based on the climatic data presented, some special care must be taken depending on the region, as highlighted in Figure 10. This information seeks to help designers and companies that develop materials in relation to the climatic conditions of each region.

Figure 10 – Key features by region based on climate data



Source: Authors (2023)

4 CONCLUSIONS

This study used six decades of climate data from a large number of Brazilian weather stations to identify climatic regions with homogeneous characteristics and to evaluate the variables affecting the performance of flexible pavements in Brazil. The identified aforementioned regions are understood differently from each other, based on statistical analyses. Therefore, according to the methodological design established in this study, the following conclusions and recommendations are made:

1) The climate regions, considering climatic data that impact flexible pavements, divided Brazil into 5 different areas, based on the K-Means clustering analysis method and statistical analyses. Region 1 is especially characterized by high temperatures, radiation and low precipitation; Region 2, by high thermal amplitude and high temperatures; Region 3, by smaller thermal amplitudes, higher wind speeds, and high radiation; Region 4, by milder temperatures, high thermal amplitude, and considerable precipitation; and Region 5, by high volumes of precipitation and of humidity, in addition to high temperatures;

2) The K-Means cluster analysis has been proven to be adequate for classifying climate regions. An adequate separation of the clusters can be observed by indicating significant differences between the five zones proposed based on the statistical tests of multiple comparison;

3) Based on the characteristics described for each region, some recommendations can be made to designers and material manufacturers in the area of asphalt paving: for Region 1, the main care is to select binders and asphalt mixtures resistant to permanent deformation; for Region 2, special attention must be given to fatigue, in addition to permanent deformation, due to the high thermal amplitude; for Region 3, the main concern is also permanent deformation, however, less severe than in Regions 1 and 2; in Region 4, the damage caused by fatigue and humidity deserves to be highlighted; and finally, for Region 5, in addition to permanent deformation, great attention must be paid to damage caused by water and drainage.

Finally, it can be concluded that the methodology contributed to a better understanding of the climatic characteristics that impact the performance of asphalt pavements.

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