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Predicting climate types for the Continental United States using unsupervised clustering techniques

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Abstract

The problem of clustering climate data observation sites and grouping them by their climate types is considered. Machine learning–based clustering algorithms are used in analyzing climate data time series from more than 3,000 climate observation sites in the United States, with the objective of classifying climate type for regions across the United States. Understanding the climate type of a region has applications in public health, environment, actuarial science, insurance, agriculture, and engineering.

In this study, daily climate data measurements for temperature and precipitation from the time period 1946–2015 have been used. The daily data observations were grouped into three derived data sets: a monthly data set (daily data aggregated by month), an annual data set (daily data aggregated by year), and a threshold exceeding frequency data set (threshold exceeding frequency provides the frequency of occurrence of certain climate extremes). Three existing clustering algorithms from the literature, namely, *k*-means, density-based spatial clustering of applications with noise, and balanced iterative reducing and clustering using hierarchies, were each applied to cluster each of the data sets, and the resulting clusters were assessed using standardized clustering indices. The results from these unsupervised learning techniques revealed the suitability and applicability of these algorithms in the climate domain. The clusters identified by these techniques were also compared with existing climate classification types such as the Köppen classification system. Additionally, the work also developed an interactive web and map-based data visualization system that uses efficient big data management techniques to provide clustering solutions in real time and to display the results of the clustering analysis.

KEYWORDS

big data, climate data, clustering, computational geosciences, machine learning

1 | INTRODUCTION

Data analytics and data-driven machine learning techniques are important for the discovery of valuable insights from large high-dimensional data sets. Data mining techniques such as clustering algorithms (Duda, Hart, & Stork, 2012; Jain, Murty, & Flynn, 1999) help in discovering clusters that may have gone undetected. The clusters can offer important clues on similarities, correlations, and relationships within a large data set. It can also help in outlier detection.

Climate is a critical component of the Earth's ecosystem and is an important aspect of people's daily lives, industrial production, and agricultural output. Climate is defined as long-term averages and variations in weather measured over a period of several decades (Melillo, Richmond, & Yohe, 2014). The Continental United States has the advantage of a having a rich source of voluminous climate data observations. The daily climate data records go back about a hundred years. These large climate data repositories are housed in national, operational data centers such as the NOAA Regional Climate Centers (the NOAA Southern Regional Climate Center [http://www.srcc.lsu.edu] is housed at Louisiana State University) and the National Center for Environmental Information (http://www.ncei.noaa.gov). Programmatic access to these large, distributed data repositories is made available using enterprise-grade web services and an application programming interface (http://www.rcc-acis.org; DeGaetano, Noon, & Eggleston, 2015) that was developed by the IT staff at the Regional Climate Centers. Recently, a new data set, the threshold exceeding frequency (TEF; Huang, Sathiaraj, Wang, & Keim, 2017), was created from such observational data archives. Using historical climate data measurements at individual sites, climate scientists have developed more generic, broader, region-based climate classification types. The rich climate data source is a good foundation for the application of clustering algorithms to derive unsupervised learning–based climate types or clusters.

2 | BACKGROUND

Clustering analysis is an unsupervised learning technique that finds applications in several fields, including pattern recognition, machine learning, image processing, and information retrieval. Clustering is the unsupervised classification of patterns (observations, data items, or feature vectors) into groups (Jain et al., 1999). Clustering does not need prior knowledge about the data set. Clustering techniques partition a data set into clusters so that objects in the same cluster are more similar to each other than objects in different clusters. These objects are also referred to as data points or points. A commonly used clustering algorithm is the *k*-means clustering method (MacQueen et al., 1967) that tries to minimize a squared error criterion (Jain et al., 1999). Nonparametric methods for density-based clustering have also been developed (Jain et al., 1999). A widely used density-based clustering method is density-based spatial clustering of applications with noise (DBSCAN; Ester et al., 1996), which groups dense and nearby points to form clusters. Balanced iterative reducing and clustering using hierarchies (BIRCH; T. Zhang, Ramakrishnan, & Livny, 1996) is another hierarchical clustering technique. This study evaluates the performance of three clustering algorithms—*k*-means, DBSCAN, and BIRCH—in grouping climate measurement sites into climate types or clusters.

In climate science, Köppen classification (KC) is used to spatially group regions based on the predominant climate of that region. The spatial distribution of this classification is shown in Figure 1. Using empirical observations, Köppen (Köppen & Geiger, 1930) pioneered and established a climate classification system that uses monthly air temperature and rainfall to define boundaries (clusters) of different climate types around the world (Chen & Chen, 2013).

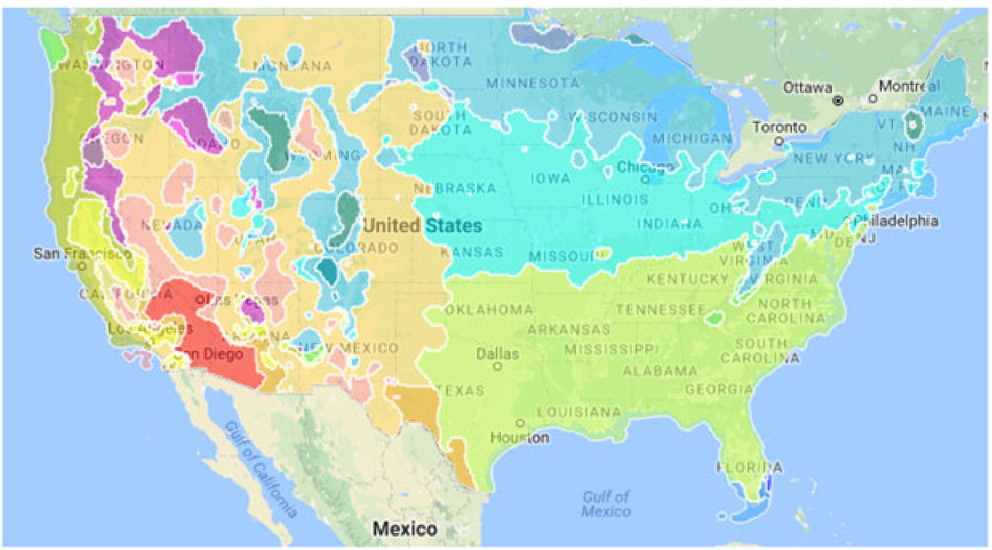


FIGURE 1 A screenshot of Köppen Climate Classification from goo.gl/2mU2qr

In this work, unsupervised, predictive learning techniques are used to predict climate classification types, and each of the clustering solutions is evaluated using the KC system. Prior work on climate classification includes that of Fovell and Fovell (1993), which used principal component analysis to generate climate zones. The work of Zscheischler, Mahecha, and Harmeling (2012) has explored the use of unsupervised clustering techniques such as *k*-means to explore the feasibility of such techniques as compared to the empirical rule–based KC system. Some differentiating factors between the work of Zscheischler et al. (2012) and our work were that the former used gridded data sets and remotely sensed vegetation indices and ours uses actual ground truth data from climate observation sites. The time period studied was also a shorter time span from 2001 to 2007, whereas this work spans a 70-year window from 1946 to 2015. Gridded data sets are typically derived using interpolation processes and, hence, can be prone to inaccurate estimations due to lack of accounting for topographical climate variations (Mourtzinis, Edreira, Conley, & Grassini, 2017; such as in mountainous regions) or approximating in areas that have poor coverage of measurement sensors. Since this work uses observational data sets, the data being fed to the clustering algorithms are of better quality and are void of any inaccurate estimations or approximations. Some of the challenges involved in this work included the extensive data preprocessing and management of the *big data* sets (processing nearly 50 million points of information) and the ability to derive clusters in real time as new observations come in.

Recent work such as that of Netzel and Stepinski (2016) has used similar clustering approaches to derive climate classification types on a global scale. Again, in this case, gridded data sets were used as compared to actual climate station measurements as in this work. There was difference also in the clustering algorithms deployed to generate the climate type classes and the area of focus (this work focused on the Continental United States as compared to the global study by Netzel & Stepinski, 2016). A similarity between the work of Netzel and Stepinski (2016) and our work is that the proposed clustering will not predict KC types, but instead, alternative climate type classifications are provided. The reason for this is that unsupervised clustering techniques are initiated using a random seed and the clusters obtained do not have a cluster type label. Our map-based visualization system, described later, provides a spatial mapping of the clusters, which enables the effective inferring of clusters. These predicted climate classifications can also be used as a more dynamic representation of a climate type in a changing climate scenario as compared to the rule-based, empirical KC technique. The visualization system developed also provides the ability for a spatial comparison between the predicted clusters and KC types. The work of X. Zhang and Yan (2014) highlights the importance of cluster analysis in classifying climate types in the context of climate change especially when KC is less able to reflect variations in climate classifications. The work of X. Zhang and Yan (2014) also used a global gridded data set and only the *k*-means algorithm to derive climate types. The focus was to look for temporal and geographical shifts in climate types. In Liss, Koch, and Naumova (2014), machine learning techniques were used to define climate regions, but the focus was solely in the context of public health. The work of Mahlstein and Knutti (2010) involved using cluster analysis to look at regional climate change patterns, but the analysis did not involve comparing the clusters with KC types.

KC consists of five major climate type groups and a number of climate type subtypes under each major group, as listed in Table 1. The Continental United States, which is our study area, has four main types. The tropical climate type A is determined when the monthly mean temperature for every month is equal to or higher than 18°C, and the four subtypes under A are determined based on their annual and monthly mean precipitation values. The dry climate type B is defined by very low precipitation. The monthly mean temperature of the coldest month lies between −3°C and 18°C for mild temperate C type, and the different seasonal precipitations result in four subtypes. The continental climate D has at least one month with temperatures equal to or lower than −3°C, and the subtypes are decided according to the seasonal precipitation. Finally, the polar climate E is for regions that have their warmest monthly mean temperature of any month to be equal to or lower than 10°C (Chen & Chen, 2013).

This climate classification system has been widely used by geographers and climatologists around the world. The system is powerful in linking climate and natural vegetation (Bailey, 2009) and to evaluate climate change impacts (Diaz & Eischeid, 2007; Fovell & Fovell, 1993; Kottek, Grieser, Beck, Rudolf, & Rubel, 2006; Liss et al., 2014).

This work uses machine learning–based clustering algorithms to generate clusters or climate classification types. These clusters are evaluated using standardized metrics for clustering algorithms and comparing the classification types revealed by the empirical, deterministic KC technique.

This work is structured as follows. First, information regarding sources for the daily climate data and metadata for the 3,000 climate stations in the Continental United States is provided. The data preprocessing routines used to transform raw climate data observations into derived annual, monthly, and TEF data sets (Huang et al., 2017) are explained and how machine learning techniques are applied to generate clusters. Secondly, a real-time data visualization system and a user interface to visualize the clustered solutions are described. Lastly, computational results and analysis are provided.

TABLE 1 As provided in Chen and Chen (2013): Main characteristic of Köppen climate major groups and subtypes

Major group	Subtypes
A: Tropical	Tropical rain forest: Af
	Tropical monsoon: Am
	Tropical wet and dry savanna: Aw or As
B: Dry	Desert (arid): BWh, BWk
	Steppe (semiarid): BSh, BSk
C: Mild temperate	Mediterranean: Csa, Csb, Csc
	Humid subtropical: Cfa, Cwa
	Oceanic: Cfb, Cfc, Cwb, Cwc
D: Snow	Humid: Dfa, Dwa, Dfb, Dwb, Dsa, Dsb
	Subarctic: Dfc, Dwc, Dfd, Dwd, Dsc, Dsd
E: Polar	Tundra: ET
	Ice cap: EF

3 | PROBLEM DESCRIPTION

Figure 2 depicts a flowchart for the data processing involved. First, the daily climate data sets from 1946 to 2015 are obtained from the Applied Climate Information System (ACIS). The data are then grouped by month or year to generate the annual climate data set, monthly climate data set, and TEF climate data set. The three derived time series (annual, monthly, and TEF) are stored in a memory-based cache (Redis, http://redis.io) for fast access and analysis. Then, these three climate time-series data sets are utilized for unsupervised learning. Three unsupervised learning–based clustering algorithms, namely, *k*-means, DBSCAN, and BIRCH, are used to derive clusters. The clusters formed (nine sets of clusters) are evaluated using clustering metrics and also compared with existing KC types.

3.1 | Data sources

The study used the daily climate data from ACIS (DeGaetano et al., 2015), an Internet-based system designed to facilitate the generation and dissemination of climate data products to users. ACIS is developed by the NOAA Regional Climate Centers (DeGaetano et al., 2010) to manage the complex flow of information from climate data collectors to end users of climate data information.

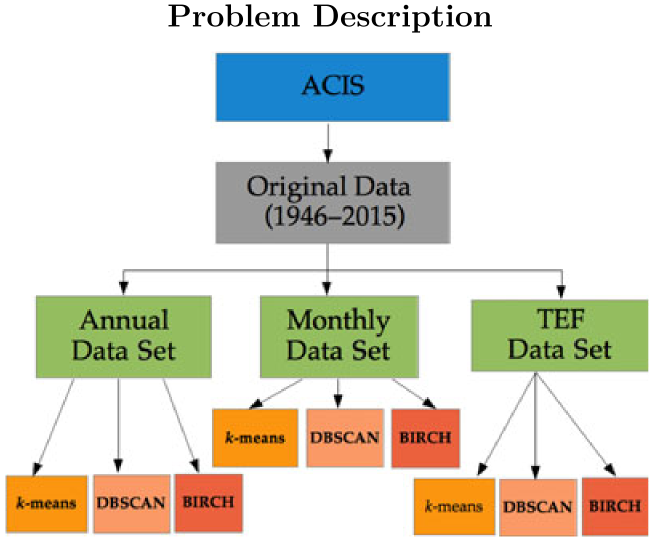


FIGURE 2 Flowchart for data processing. ACIS = Applied Climate Information System; BIRCH = balanced iterative reducing and clustering using hierarchies; DBSCAN = density-based spatial clustering of applications with noise; TEF = threshold exceeding frequency

ACIS accepts and returns climate information in JavaScript Object Notation, which uses structures that are similar to those used in many coding languages, including C, C++, Java, JavaScript, Perl, and Python. For each call, users specify a set of parameters to describe the data being requested. After passing these parameters to the server and accessing these climate data, a climate data product is returned to users.

For vegetation and ecosystems, the climate of a region involves the following elements: temperature, precipitation, humidity, wind, and radiation. However, most climate analyses use near-surface air temperature and precipitation as the two major variables (Fovell & Fovell, 1993; Kottek et al., 2006; Liss et al., 2014). In this study, the climate elements used were maximum temperature, minimum temperature, and precipitation.

There are more than 26,000 Global Historical Climatology Network climate data measurement sites. However, not all span the entire time period of 1946–2015. Additional criteria used for this data analysis included the following: allow for less than 10% missing values for a station per year and every climate division should have at least three climate measurement sites. Once these criteria were applied, the number of valid stations that fit these rules reduced to 3,210, as shown in Figure 3. These 3,210 stations were well distributed and covered most parts of the Continental United States.

3.2 | Data set generation

Data from ACIS are on a daily time scale. Data were processed to derive three data sets. The three data sets derived were annual, monthly, and TEF.

Annual and monthly climate data sets were derived by grouping and averaging by year and month, respectively. The TEF provides the frequency of occurrence of extreme climate events. To establish the TEF data set, some climate extremes thresholds were chosen. Generation of the TEF data set was first described in the work of Huang et al. (2017). The thresholds used in generating the data set were based on a combination of thresholds used in the *CLIMDEX—Data sets for Indices of Climate Extremes* (Donat, 2013) and the Southeast chapter of the *National Climate Assessment* document, released in 2014 (Melillo et al., 2014). The chosen extremes are provided in Table 2.

The TEF data set was generated by using the defined thresholds and the daily climate data set to estimate the annual frequency of days that either exceeded or fell below a certain threshold. This was carried out for each climate measurement site. As an example, for threshold *Minimum Temperature* ≤ 75, the number of occurrences where the minimum temperature was less than or equal to 75 was tallied by year and calculated for each of the years in the time period 1946–2015. This process was repeated for all 3,210 climate measurement sites and for each of the thresholds to obtain the derived TEF data set. This threshold-based data set provides a representation of climate extremes at each site and is a useful application resource for clustering sites that experience similar climate trends and extremes.

FIGURE 3 Spatial distribution of climate data observing stations

TABLE 2 Threshold values to generate the threshold exceeding frequency data set

Element	Thresholds
Maximum temperature (in °F(°C))	≥105(41), ≥100(38),
	≥95(35), ≥85(29)
Minimum temperature (in °F(°C))	≥80(27), ≥75(24), ≥70(21),
	≥65(18), ≤36(2), ≤32(0),
	≤28(−2), ≤24(−4), ≤15(−9),
	≤10(−12), ≤5(−15), ≤0 (−18)
Precipitation (in in.(mm))	≥2 (50), ≥4 (100)

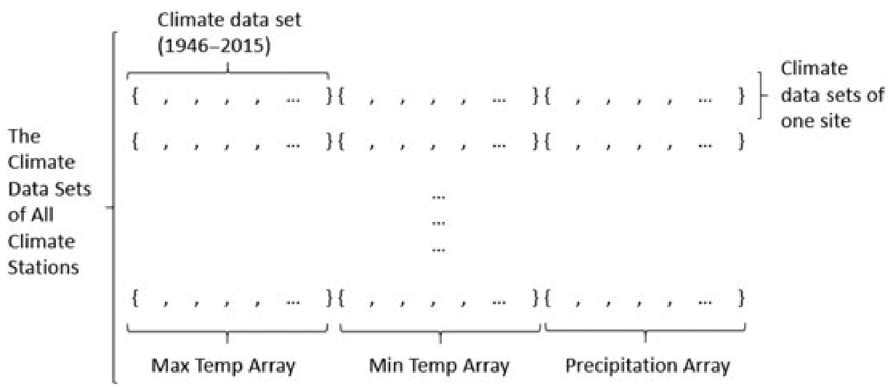


FIGURE 4 Input data structure after preprocessing

The input data structure for the clustering algorithm is described in Figure 4. The input data of any climate measurement site are divided into three arrays: maximum temperature array, minimum temperature array, and precipitation array (each array comprises data from 1946 to 2015). Each row corresponds to a climate measurement site, and all rows correspond to all the climate measurement sites. In addition, to ensure a serially complete data set, climate stations had no more than 10% missing values per year or month. A climate observation site that contained more than 10% missing values was removed from the analysis. In cases where missing values were less than 10%, missing data were imputed using an average value of nearby climate measurement sites. Moreover, to eliminate the effects of different units between precipitation, maximum temperature, and minimum temperature, the pertinent data columns were normalized as follows: $X' = (X - E)/\sigma$, where X is the original value, E is the mean of the data column, and σ is the standard deviation of the data column.

4 | CLUSTERING ALGORITHMS AND METRICS USED

4.1 | *k*-means

The *k*-means clustering algorithm (MacQueen et al., 1967) is a commonly used clustering algorithm and comes under the category of partitioning-based clustering techniques. In *k*-means, *a priori* knowledge of the number of clusters is important. The *k*-means algorithm can be applied over continuous data as noted in the works of Fukunaga (2013) and Duda and Hart (1973). The *k*-means algorithm calculates its centers iteratively. A detailed survey of data clustering algorithms—particularly *k*-means—can be found in the work of Jain (2010). The formation of clusters using this methodology can be mathematically defined as follows: Given a data set $D = \{d_1, \ldots, d_N\}$ with N points that need to be clustered into, for example, K clusters. Clusters can be considered as $C = c_1, c_2, \ldots, c_K$. The *k*-means algorithm forms clusters such that a clustering criterion is optimized. A commonly used clustering criterion is the sum of squared Euclidean distances between each data point d_N and the centroid m_K (cluster center) of the subset c_K, which contains d_N. This criterion is called clustering error E and depends on the cluster centers $m_1, \ldots, m_M$ (this corresponds to an a priori defined number of clusters). The error for each cluster c_K can be denoted as: $E(c_K) = \sum_{d_N \in c_K} ||d_i - m_K||^2$.

The goal is to minimize the sum of the squared errors across all clusters. The k-means algorithm is a locally optimal algorithm. It is an iterative algorithm that initially selects arbitrary cluster centers and a set of clusters around each center. It then iteratively reassigns cluster centers to make the sum of squared errors minimal. The main disadvantage of the method lies in its sensitivity to initial starting positions of the cluster centers. Therefore, in order to obtain near-optimal solutions using the k-means algorithm, several runs of the algorithm are conducted by varying the initial positions of the cluster centers.

4.2 | DBSCAN

DBSCAN is a density-based clustering technique (Ester et al., 1996) that can identify clusters of arbitrary shapes. Density-based clustering techniques define a cluster as a region comprised of high-density objects. A cluster is described as a linked region that exceeds a given density threshold (Biçici & Yuret, 2007). DBSCAN uses two predefined parameter values: the size of the neighborhood denoted as ϵ and the minimum number of points in a cluster denoted as $N_{\min}$. In DBSCAN, a random point x is chosen, and it finds all the points that are density reachable from x while ensuring that the minimum points criterion of $N_{\min}$ is met. If x is a core point, then the formation of a cluster is completed with respect to ϵ and $N_{\min}$. If x is a border point, then no points are density reachable from x. DBSCAN then begins with an unclassified point to repeat the same process. The two parameters, ϵ and $N_{\min}$, direct the operation of DBSCAN and ensure the quality of clusters. The two parameters are adopted universally in the functioning of DBSCAN. In most cases, DBSCAN explores each point of the database multiple times.

4.3 | BIRCH

The BIRCH algorithm was introduced by T. Zhang et al. (1996). As compared to DBSCAN (density-based clustering) and k-means (partition-based clustering), BIRCH is a hierarchical clustering algorithm that scans the data once and develops an in-memory tree representation for clusters. Two key features in BIRCH include a data structure for each cluster called the *clustering feature (CF)* and an in-memory tree representation denoted as the *CF-tree*.

The *CF* is a compact data structure that allows for easy merging of subclusters. A *CF* is a tuple that summarizes information about the cluster. Given N d-dimensional data points in a cluster $\{\vec{X_i}\}$ where $i = 1, 2, \ldots, N$, *CF* is defined as a triple, that is, $CF = (N, \vec{LS}, \vec{SS})$, where N is the number of data points in the cluster, $\vec{LS}$ is the sum of the N data points, and $\vec{SS}$ is the square sum of the N data points. A *CF-tree* has two additional parameters: branching factor B for nonleaf nodes in the tree and threshold T for the leaf nodes.

4.4 | Homogeneity and V-measure

The notions of homogeneity and V-measure were first introduced by Rosenberg and Hirschberg (2007), with the objective that any clusters formed will have two properties—homogeneity and completeness. Homogeneity, H, is an objective that the cluster contains only members of a single class and the score is a value between 0 and 1, with higher values (closer to 1) representing higher homogeneity. Completeness, C, is the notion that all members of a given class are assigned to the same cluster. V-measure is then defined as $2 \times \frac{H*C}{H+C}$. The V-measure also yields scores between 0 and 1, with higher scores indicating greater completeness.

4.5 | Data visualization

To demonstrate the computational analysis, a data visualization system was developed. The data visualization system contains a low-latency database, a real-time interactive machine learning system for generating clusters, and an interactive user interface for map-based visualizations and setting clustering parameters. The visualization system provides a web-based visual interface to compare predicted clusters (from k-means, DBSCAN, and BIRCH) with the classification types of the KC system. The site is hosted at http://climext.srcc.lsu.edu. The technologies used in this study include **Scikit-learn** (Pedregosa et al., 2011; a Python module for machine learning, particularly clustering and classification), **Tornado** (a Python web framework and asynchronous networking library), **Redis** (an in-memory database cache), **Pandas** (a data analysis toolkit for Python), **React** (a JavaScript library for building user interfaces), **GraphQL** (a query language for application programming interfaces), **WebGL** (a JavaScript library for rendering 2D and 3D graphics), and **D3** (a JavaScript visualization library).

5 | COMPUTATIONAL RESULTS AND ANALYSIS

The computational analysis involves evaluating the performance of the three clustering algorithms on the three climate time series data sets (annual, monthly, and TEF). The evaluation used the above outlined metrics, namely, homogeneity and V-measure (Rosenberg & Hirschberg, 2007), to evaluate the quality of the clusters formed. A diagnostic explanation between KC and the derived clusters is also provided. It is important to note that the predicted clusters cannot be directly compared with KC types (as outlined in Table 1). Clustering algorithms generate clusters in a random order and provide cluster labels that are numeric. However, when the climate measurement sites along with their predicted cluster labels are plotted on a map, the spatial visualization provides specific groupings or polygons that closely resemble the spatial distribution of the KC system. These visual groupings provide a strong case for the use of unsupervised clustering models that rely on purely climate data and are computationally nimble as compared to KC that relies on additional vegetation and remotely sensed data to derive climate types.

5.1 | Analyzing clusters formed by *k*-means

The *k*-means method worked well when applied to all three data sets. Table 3 provides homogeneity and V-measure scores for varying cluster sizes (ranging from 4 to 12). One can observe from Table 3 that the homogeneity scores for the TEF data set are higher than those for the monthly and annual data sets. Secondly, as the number of clusters increases, the homogeneity scores show an increasing trend.

Figures 5(a), 5(b), and 6(a) display eight predicted clusters after applying *k*-means clustering on the annual, monthly, and TEF data sets, respectively. In the map, the different colors of points represent different clusters. Figure 6(b) displays a spatial distribution for KC.

5.2 | Analyzing clusters formed with DBSCAN

When DBSCAN was applied to each of the three data sets, degenerative results emerged, such as all climate sites were merged into one or two clusters. After a gridded search of optimal parameters, the parameters used in DBSCAN were as follows: $\epsilon = 21$ and the minimum points in a cluster set $N_{\min}$ set to 2. Only one example of such a degenerative solution is provided as Figure 7(a), when DBSCAN was applied on the TEF data set. The gray points represent the noisy samples.

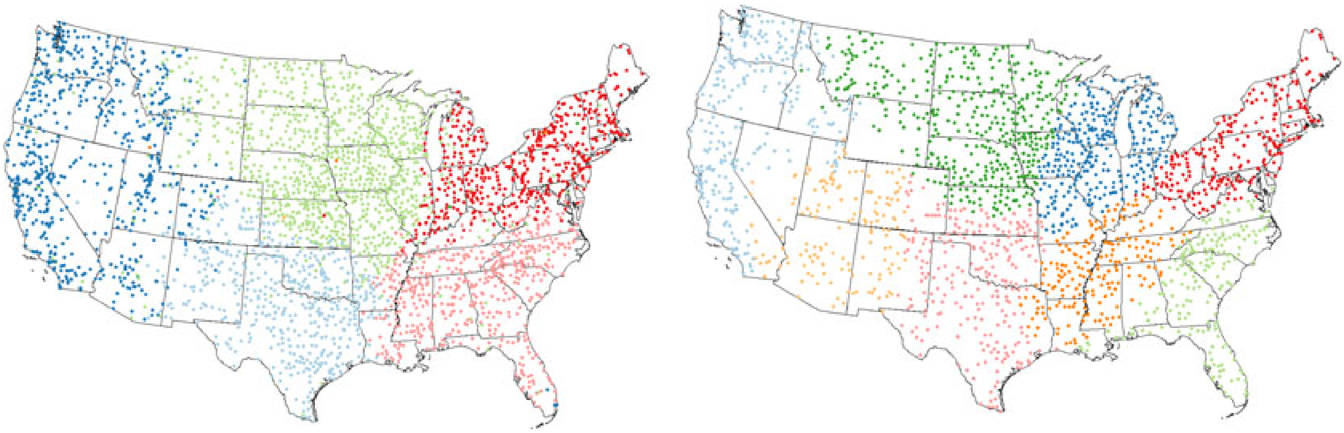
5.3 | Analyzing clusters formed with BIRCH

Table 4 depicts homogeneity and V-measure scores for BIRCH.

TABLE 3 Homogeneity and V-measure scores of *k*-means for different numbers of clusters and the three data sets (a higher score is better)

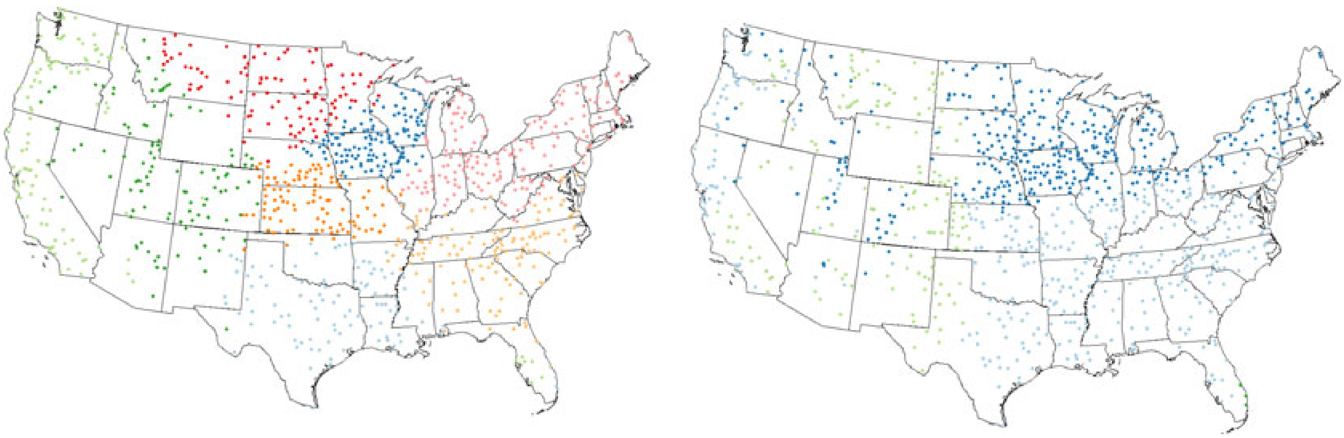
	Homogeneity			V-measure		
No. of clusters	**Annual**	**Monthly**	**TEF**	**Annual**	**Monthly**	**TEF**
4	0.202	0.231	0.315	0.180	0.211	0.279
5	0.201	0.274	0.306	0.180	0.228	0.250
6	0.207	0.277	0.344	0.184	0.217	0.265
7	0.240	0.326	0.425	0.201	0.244	0.310
8	0.217	0.379	0.464	0.180	0.270	0.325
9	0.266	0.382	0.433	0.208	0.262	0.293
10	0.269	0.422	0.476	0.219	0.281	0.311
11	0.235	0.425	0.533	0.185	0.274	0.340
12	0.328	0.432	0.574	0.232	0.274	0.357

Note. TEF = threshold exceeding frequency.



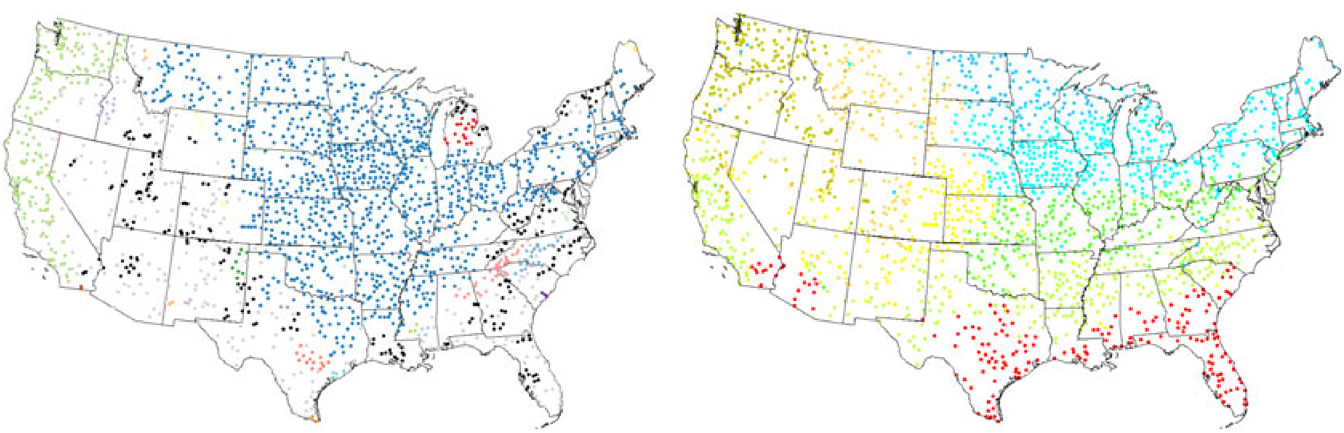
(a) (b)

FIGURE 5 *k*-means on annual and monthly time series. (a) Clustering using *k*-means on the annual time series. (b) Clustering using *k*-means on the monthly time series



(a) (b)

FIGURE 6 *k*-means on threshold exceeding frequency (TEF) and the spatial distribution using Köppen classification (KC) labels. (a) Clustering using *k*-means on the TEF data set. (b) KC types or labels



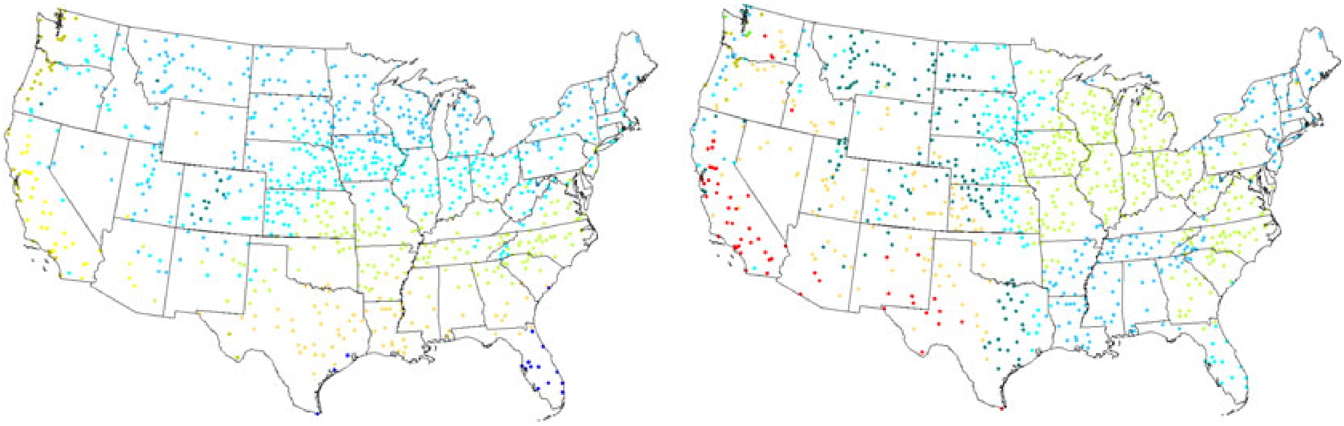
(a) (b)

FIGURE 7 Clustering result using balanced iterative reducing and clustering using hierarchies (BIRCH) and density-based spatial clustering of applications with noise (DBSCAN) on the monthly data set. (a) Clustering using DBSCAN with parameters $\epsilon = 21$ and $N_{\text{min}} = 2$. (b) Clustering using BIRCH on the monthly data set

TABLE 4 Homogeneity and V-measure scores using balanced iterative reducing and clustering using hierarchies (BIRCH) with different numbers of clusters and data sets (BIRCH parameters: a threshold of 1 and a branching factor of 50) (higher scores are better)

	Homogeneity			V-measure		
No. of clusters	**Annual**	**Monthly**	**TEF**	**Annual**	**Monthly**	**TEF**
4	0.099	0.187	0.264	0.107	0.174	0.234
5	0.142	0.236	0.289	0.133	0.201	0.238
6	0.142	0.241	0.384	0.133	0.197	0.298
7	0.142	0.246	0.438	0.133	0.192	0.323
8	0.193	0.324	0.460	0.168	0.233	0.324
9	0.194	0.342	0.471	0.168	0.235	0.322
10	0.242	0.384	0.492	0.191	0.257	0.328
11	0.242	0.388	0.542	0.191	0.252	0.350
12	0.242	0.409	0.544	0.191	0.261	0.337

Note. TEF = threshold exceeding frequency.



(a) (b)

FIGURE 8 Clustering result using balanced iterative reducing and clustering using hierarchies (BIRCH) on the annual and threshold exceeding frequency (TEF) data sets. (a) Clustering using BIRCH on the annual data set. (b) Clustering using BIRCH on the TEF data set

BIRCH has approximately the same results as *k*-means, and most of the homogeneity and V-measure scores of BIRCH are slightly lower than *k*-means.

Figures 7(b), 8(a), and 8(b) show the spatial distribution of eight predicted clusters using BIRCH clustering on the monthly, annual, and TEF data sets, respectively. The parameters used were a threshold of 1 and a branching factor of 50.

5.4 | Summary of analysis

The clustering results from *k*-means and BIRCH are compared with KC types using the climate stations that are part of each cluster. (Results using DBSCAN were not reported due to its poor performance in producing degenerative clusters.) Since clustering algorithms are unsupervised by nature, they yield clusters in a random order. They also do not predict the KC types. Hence, a new approach is explored by grouping the climate stations by KC types (using inherent spatial information such as latitude and longitude) and then comparing the groups to the clusters generated. Percentages of stations that are part of a generated cluster will provide clues on the similarities of the cluster and a KC type. For the eight-cluster solution, a summary comparison has been provided in Table 5. To interpret the Table, eight KC types are represented in rows, and the columns represent combinations of the three data sets and two clustering algorithms. Along each row, each value represents the percentage of climate stations that are part of a cluster as compared to the number of stations that are part of a KC category.

TABLE 5 Comparing clustering results with Köppen classification (KC)

	k-means			BIRCH		
Köppen (KC) type	**Annual**	**Monthly**	**TEF**	**Annual**	**Monthly**	**TEF**
Cfa	37%	52.8%	39.2%	45.5%	35.3%	47.8%
BSk	54.1%	38.8%	34.8%	45.9%	31.5%	10.0%
Dfb	42.0%	67.4%	72.8%	42%	31.3%	90.0%
Dfa	32.8%	65.3%	50%	36.7%	84.4%	72.7%
Csb	19.3%	58.3%	70.2%	26.3%	59.0%	70.2%
Cfb	9.5%	4.5%	5%	4.7%	29.5%	5.3%
Dsb	20%	48.7%	33.3%	20%	48.7%	44.4%
Csa	5%	43.2%	66.7%	38.9%	15.4%	66.7%

Note. BIRCH = balanced iterative reducing and clustering using hierarchies; TEF = threshold exceeding frequency.

From Table 5, we can infer that *k*-means and BIRCH provide dissimilar or alternative climate types as compared to the KC system. There are a few observations with high similarities, as follows: for classification type *Dfb* and BIRCH on TEF yielding a 90% match rate, *Dfb* and *k*-means on TEF yielding a 72.8% rate, *Csb* and *k*-means on TEF yielding a match rate of 70.2%, and *Dfa* on BIRCH and monthly yielding a match rate of 84.4%. However, most match percentage numbers in Table 5 hover below 50%. On the whole, the TEF and monthly data sets yielded more similar clusters to the KC clusters. The level of dissimilarity also suggests value in considering alternative classification types that may be more pertinent to climate data records as compared to the empirical KC types.

6 | CONCLUSIONS AND FUTURE WORK

Overall, by analyzing the climate data from more than 3,000 climate stations in the Continental United States between 1946 and 2015, *k*-means and BIRCH offered better clustering solutions as compared to DBSCAN. This conclusion was formed after evaluating clusters using standardized metrics for clustering such as V-measure and homogeneity scores and by comparing the cluster compositions (climate stations) with the original KC types. *k*-means and BIRCH had approximately similar results. DBSCAN failed to provide effective clusters partly due to its known difficulties of scaling to high-dimensional databases (Gan, Ma, & Wu, 2007). The derived data set, TEF (Huang et al., 2017), provided similar clustering solutions to the KC system as compared to the monthly and annual climate data sets. A possible reason for this is that the empirical KC technique (used for evaluation) is designed around extreme climate data values, and hence, the TEF data set, which is a climate extremes–based data set, fits that description. On the whole, a new clustering-based approach based on actual climate station data has been proposed and implemented, and the clusters generated provided for alternative climate type configurations. An intuitive, dynamic climate clustering web-based tool has also been created to interactively generate climate clusters for the Continental United States and to visually compare the clustering solution with that proposed by the KC system. In addition, a number of possible directions for future research can be stated. One can apply the same clustering algorithms to evaluate how the climate classification types are changing over time and space. This can help geographers and meteorologists evaluate and assess a changing climate using machine learning algorithms. One can also extend the area of study beyond the Continental United States to North America and to the entire world. This will enable comparisons on a large scale between machine learning–derived clusters and those derived from empirical climatology-based classification techniques. The work can be extended to incorporate future climate model scenarios spanning the time period 2020–2070 and evaluate how clusters and climate classification types change over time.

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REFERENCES

Bailey, R. G. (2009). *Ecosystem geography: From ecoregions to sites*. New York, NY: Springer Science & Business Media.

Biçici, E., & Yuret, D. (2007). Locally scaled density based clustering. In *Adaptive and Natural Computing Algorithms. ICANNGA 2007*. *Lecture Notes in Computer Science: Vol. 4431* (pp. 739–748). Berlin, Germany: Springer.

Chen, D., & Chen, H. W. (2013). Using the Köppen classification to quantify climate variation and change: An example for 1901–2010. *Environmental Development*, *6*, 69–79.

DeGaetano, A. T., Brown, T. J., Hilberg, S. D., Redmond, K., Robbins, K., Robinson, P., … McGuirk, M. (2010). Toward regional climate services. *Bulletin of the American Meteorological Society*, *91*(12), 1633–1644.

DeGaetano, A. T., Noon, W., & Eggleston, K. L. (2015). Efficient access to climate products using acis web services. *Bulletin of the American Meteorological Society*, *96*(2), 173–180.

Diaz, H. F., & Eischeid, J. K. (2007). Disappearing alpine tundra of Köppen climatic type in the western United States. *Geophysical Research Letters*, *34*(18).

Donat, M. (2013). Climdex: Climate extremes indices. https://www.climdex.org/indices.html. (Accessed on 05/02/2018).

Duda, R. O., & Hart, P. E. (1973). Pattern classification and scene analysis. *A Wiley-Interscience Publication*. New York, NY: Wiley.

Duda, R. O., Hart, P. E., & Stork, D. G. (2012). *Pattern classification*. New York, NY: John Wiley & Sons.

Ester, M., Kriegel, H. P., Sander, J., & Xu, X. (1996). A density-based algorithm for discovering clusters in large spatial databases with noise. *Kdd*, *96*(34), 226–231.

Fovell, R., & Fovell, M. (1993). Climate zones of the conterminous United-States defined using cluster-analysis. *Journal of Climate*, *6*(11), 2103–2135.

Fukunaga, K. (2013). *Introduction to statistical pattern recognition*. San Diego, CA: Elsevier.

Gan, G., Ma, C., & Wu, J. (2007). *Data clustering: Theory, algorithms, and applications* (Vol. 20). Philadelphia, PA: Siam.

Huang, X., Sathiaraj, D., Wang, L., & Keim, B. (2017). *Deriving data-driven insights from climate extreme indices for the continental US*. Paper presented at the 2017 IEEE International Conference on Data Mining Workshops, ICDM Workshops 2017, New Orleans, LA.

Jain, A. K. (2010). Data clustering: 50 years beyond k-means. *Pattern Recognition Letters*, *31*(8), 651–666.

Jain, A. K., Murty, M. N., & Flynn, P. J. (1999). Data clustering: A review. *ACM Computing Surveys*, *31*(3), 264–323.

Köppen, W., & Geiger, R. (1930). *Handbuch der klimatologie* (Vol. 3). Berlin, Germany: Gebrüder Borntraeger.

Kottek, M., Grieser, J., Beck, C., Rudolf, B., & Rubel, F. (2006). World map of the köppen-geiger climate classification updated. *Meteorologische Zeitschrift*, *15*(3), 259–263.

Liss, A., Koch, M., & Naumova, E. N. (2014). Redefining climate regions in the United States of America using satellite remote sensing and machine learning for public health applications. *Geospatial Health*, *8*(3), S647–S659.

MacQueen, J., et al. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability*, Oakland, CA.

Mahlstein, I., & Knutti, R. (2010). Regional climate change patterns identified by cluster analysis. *Climate Dynamics*, *35*(4), 587–600.

Melillo, J. M. (2014). *Climate change impacts in the United States, highlights: US national climate assessment*. Washington, DC: Government Printing Office.

Mourtzinis, S., Edreira, J. I. R., Conley, S. P., & Grassini, P. (2017). From grid to field: Assessing quality of gridded weather data for agricultural applications. *European Journal of Agronomy*, *82*, 163–172.

Netzel, P., & Stepinski, T. (2016). On using a clustering approach for global climate classification. *Journal of Climate*, *29*(9), 3387–3401.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., … Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

Rosenberg, A., & Hirschberg, J. (2007). *V-measure: A conditional entropy-based external cluster evaluation measure*. Paper presented at EMNLP-CoNLL.

Zhang, T., Ramakrishnan, R., & Livny, M. (1996). Birch: An efficient data clustering method for very large databases. In *Proceedings of the ACM Sigmod Record International Conference on Management of Data* (pp. 103–114).

Zhang, X., & Yan, X. (2014). Spatiotemporal change in geographical distribution of global climate types in the context of climate warming. *Climate Dynamics*, *43*(3–4), 595–605.

Zscheischler, J., Mahecha, M. D., & Harmeling, S. (2012). Climate classifications: The value of unsupervised clustering. *Procedia Computer Science*, *9*, 897–906.

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