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Spatiotemporal Outlier Detection: Did Buoys Tell Where the Hurricanes Were?

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ABSTRACT
Data points that exhibit abnormal behavior, either spatially, temporally, or both, are considered spatiotemporal outliers. Spatiotemporal outlier detection is important for the discovery of exceptional events due to the rapidly increasing amount of spatiotemporal data available, and the need to understand such data. A tropical cyclone system or a hurricane can be considered an abnormal activity of the atmosphere system. Discovery of such an abnormality usually leverages data from a satellite or radar. Not many people have thought about using a weather buoy, a floating device that provides meteorological and environmental information in real time for open ocean and coastal zones. The aim of this research is to see if a spatiotemporal outlier approach can help to discover the evolution and movement of the hurricane system from weather buoy observations. This article leverages an algorithm, spatiotemporal local density-based clustering of applications with noise (ST-LDBCAN), which has been developed and used by the authors to detect outliers in various scenarios. The ST-LDBCAN has a novel way of defining spatiotemporal context and can handle multivariate data, which is its advantage over existing algorithms. The results show a good correlation between detected spatiotemporal outliers and the paths and evolution of Hurricanes Katrina and Gustav.

KEYWORDS
Buoy; data mining; hurricanes; outlier detection; spatiotemporal

Outliers (anomalies) are often referred to as data points that are significantly different from others in the same data set (Grubbs 1969; Barnett and Lewis 1994; Chandola, Banerjee, and Kumar 2009). Hawkins's (1980) definition of outliers raised the possibility that outliers could be generated by a different mechanism, such as equipment malfunction. Because such data errors can be easily filtered out by data cleansing in a data preprocessing phase, the outliers discussed in this article are specifically referred to as those detectable in cleaned data. Outlier detection is the problem of finding data points or patterns in data that do not conform to expected normal behavior (Chandola, Banerjee, and Kumar 2009). In many cases, the data have a "normal" model and the outliers are identified as deviations from this normal model.

Spatial outliers are objects that behave significantly differently from their surrounding spatial neighbors (Aggarwal 2013). Spatial continuity is the key to understanding the identification of spatial outliers if applying Tobler's first law of geography (Tobler 1970), which pointed out that "everything is related to everything else, but near things are more related than distant things."

The world can be seen as a continuously varying across space. Good examples for this view are earth surface elevation and temperatures. *Spatial continuity* refers to ideas that every location in the field has a value and such value varies with distance; in other words, you do not expect vertical

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cliffs from a field representing the height of the earth's surface (O'Sullivan and Unwin 2010). Attributes of geographic objects can have two dimensions or characteristics: behavioral and contextual (Aggarwal 2013). The behavior attribute is the attribute of interest that is measured for each object such as surface temperatures, wind speeds, disease outbreak numbers, and so on. The contextual attribute is the location of interest at which the behavioral attribute is measured, typically in two- or three-dimensional coordinates. Sometimes the contextual attributes might be expressed at the spatial scale of interest (Aggarwal 2013), such as county, census tract, or zip code, among other possible scales. Abrupt changes in the behavioral attribute could provide useful information about the underlying contextual outliers because it tends to disrupt spatial continuity. For instance, unusually low air pressure in a very small localized area could suggest the early formation of a cyclone. In spatiotemporal data, both spatial and temporal continuities are considered for outlier detection. Spatiotemporal methods for outlier detection are significantly more challenging because they require the joint modeling of the spatial and temporal components as well as detecting outliers integrally from both perspectives (Roddick and Spiliopoulou 1999; Cheng and Li 2006; Ng *et al.* 2010; Wu, Liu, and Chawla 2010). Data points that exhibit abnormal behavior either spatially, temporally, or both are considered spatiotemporal outliers.

Spatiotemporal outlier detection is gaining substantial popularity in geographic information science (GIScience) due to the pervasiveness of numerous kinds of location-based or environmental devices that record position, time, or environmental properties of an object or set of objects in real time. Example applications include research in areas of ocean sea surface temperature (Birant and Kut 2006, 2007), precipitation (Abraham and Tan 2009; Wu, Liu, and Chawla 2010), epidemiology (Buckeridge 2007; Robertson *et al.* 2010), traffic (Shekhar, Lu, and Zhang 2003), crime (Aggarwal and Yu 2001; Lin and Brown 2006; Rogers, Barbara, and Domeiconi 2009), and terrorism (Gao *et al.* 2013). Spatiotemporal outlier detection aims to find spatial outliers; however, instead of just looking at a single snapshot in time, it considers the behavior of these outliers over several time periods. Generally, all methods that work for spatial outlier detection can be extended to handle spatiotemporal outliers. There are two mechanisms for detecting spatiotemporal outliers (Aggarwal 2013): (1) find spatial and temporal outliers separately and then combine the results, and (2) use both spatial and temporal attributes simultaneously as contextual attributes to detect outliers. The disadvantage of the former approach is that the solution is suboptimal. The latter mechanism is more general, integrated, and meaningful. Different weights can be assigned to spatial and temporal attributes to reflect the relative importance of spatial continuity or temporal continuity relevant to the application at hand. In this research the latter mechanism was applied with weighting options to detect spatiotemporal outliers from weather buoy data sets.

A buoy is a floating device that can have many purposes. A weather buoy is usually equipped with sensors used to measure weather parameters and report collected data via satellite radio links or commercial satellite phone networks to meteorological centers for forecasting and other studies (Sprigg and Bosart 1998). The National Data Buoy Center (NDBC), a part of the National Weather Service (NWS), operates and maintains a network of data-collecting buoys that provide real-time information on ocean and coastal zones surrounding the United States. Historical weather buoy data archived by the NDBC enables researchers to rebuild the meteorological perspectives for ocean distant from land. Buoy data also have the ability to capture large-scale meteorological systems, such as tropical cyclones.

Instead of forecasting, this research tries to investigate retrospectively to see if historical buoy data are capable of indicating where hurricanes were by means of spatiotemporal outlier detection. Hurricanes usually span from hundreds to thousands of miles in terms of the radius of wind, and are easily captured by satellite images. Hurricanes and other tropical cyclones are rapidly rotating storm systems characterized by strong winds, heavy rainfall, and a low-pressure center, or eye (National Hurricane Center 2015). They presumably challenge the "normal" pattern of weather data recorded by buoy stations. The purpose of this research is to see if the outliers detected from historical buoy data are related to the hurricanes in the spatiotemporal context.

The remainder of this article is organized as follows. The next section reviews related work in outlier detection. We then detail data source, research area, and methodology. After we present our experiment's results and further discussion, the final section concludes this article and discusses future work.

Literature review

Anselin (1995) used Moran's test to detect local autocorrelation. Moran's test is able to identify spatial outliers over local clusters (areas where adjacent data points have similar values); however, this test is designed for univariate data and is not applicable to multivariate data. Shekhar, Lu, and Zhang (2003) proposed a unified approach to detect outliers against traffic data. Their approach used directed graph neighborhoods for outlier detection. They also compared the attribute value of a data object to the average attribute value of its neighbors. This work only investigated one nonspatial attribute, however. A spatial weighted approach of Kou, Lu, and Chen (2006) highlighted a function that is able to represent the outlierness of an object effectively. The outlierness can be viewed as the difference between a single nonspatial attribute and its neighbors. The aforementioned approaches handle univariate data well, but have difficulties in analyzing multiple nonspatial variables. The key challenge is how to define a general distance function in a multiattribute data space (Shekhar, Lu and Zhang 2003).

The peer group analysis (PGA) discussed in Ferdousi and Maeda (2006) was used to detect outliers in time series data (stock exchange data). Wu, Liu, and Chawla (2010) used the outstretch algorithm to detect outliers in the precipitation data. The top-*k* outliers (*k* is a predefined number) need to be identified and this algorithm was applied to the top-*k* outliers for each time period. Developed by Leung and Leckie (2005), the fpMAFIA algorithm was a density-based and grid-based clustering algorithm suitable for unsupervised (no training is necessary) outlier detection with applications in identifying network intrusions. Its benefit of being an unsupervised approach is compromised, however, by the necessity of predetermining parameters: One still needs to find heuristic ways to determine the input parameters. Rogers, Barbara, and Domeiconi (2009) used a statistics-based approach for spatiotemporal outlier detection by applying the stroud (strangeness outlier detection) algorithm. They calculated a measurement called *strangeness factor* for every object, which is the summation of the weighted distance of spatial, temporal, and thematic attributes from one object to its nearest neighbors. This multimodal distance measure was called the kernel of the nearest *k* neighbors. After this, Rogers, Barbara, and Domeiconi (2009) used a statistical method to compare the strangeness of an object to some of the baseline, or normal objects. If the difference was significant, they termed the object a spatiotemporal outlier. The question of weighting options among different attributes (thematic, spatial, and temporal attributes) remained unsolved and highly depended on prior knowledge of the data.

Ester *et al.* (1996) introduced an algorithm of clustering and detecting outliers with arbitrary shapes—the density-based spatial clustering of applications with noise (DBSCAN)—that specialized in spatial data. DBSCAN is an unsupervised approach that does not need previously labeled data for training and only requires two input parameters. Breunig *et al.* (2000) introduced the local outlier factor (LOF), which quantifies each object based on its locality, rather than just assigning a binary value for an object whether it belongs to a cluster or not. There are many variations of LOF that have evolved since its introduction, such as the connectivity-based outlier factor (COF; Tang *et al.* 2002), the local correlation integral (LOCI; Papadimitriou *et al.* 2002), and the cluster-based local outlier factor (CBLOF; He, Xu, and Deng 2003). Both the DBSCAN and the LOF treat behavioral, spatial, and temporal attributes the same way, which raises concerns about the spatiotemporal neighborhood definition in those approaches. An appropriate neighborhood (context) is very important for outlier detection because the neighborhood represents the normality of the data and outliers are supposed to deviate from that normality. Key attributes of aforementioned outlier detection methods are summarized in Table 1.

A new spatiotemporal outlier detection approach, the spatiotemporal local density-based clustering of applications with noise (ST-LDBCAN), developed by Duggimpudi *et al.* (2016) was

Table 1. Summary of key attributes of applied methods surveyed in this article (in chronological order).

References	Methods	Key attributes	Outlier types
Anselin (1995)	Local Moran's I	Designed for univariate data	Spatial outlier
Ester *et al.* (1996)	Density-based spatial clustering of applications with noise (DBSCAN)	Unsupervised approach, only need one parameter	Spatial outlier
Breunig *et al.* (2000)	Local outlier factor (LOF)	Quantitative measure of outlierness	General outlier
Bolton and Hand (2001)	Break point analysis (BPA)	Time series data (credit card transactions)	Temporal outlier
Tang *et al.* (2002)	Connectivity-based outlier factor (COF)	Variation of LOF, works well in low-density situation	General outlier
Papadimitriou *et al.* (2002)	Local correlation integral (LOCI)	Variation of LOF, work for both local density and multiple granularity, has data-dictated cutoff for outlier determination	General outlier
He, Xu, and Deng (2003)	Cluster-based local outlier factor (CBLOF)	Variation of LOF, detect cluster-based local outlier	General outlier
Shekhar, Lu, and Zhang (2003)	Unified approach	Only one nonspatial attribute	Spatial outlier
Leung and Leckie (2005)	pfMAFIA	Unsupervised approach, many parameters need to be predetermined	Sequence-based outlier
Ferdousi and Maeda (2006)	Peer group analysis (PGA)	Time series data (stock exchange data)	Temporal outlier
Kou, Lu, and Chen (2006)	Spatial weighted approach	Only works well for univariate data	Spatial outlier
Duan *et al.* (2007)	Local-density based spatial clustering algorithm with noise (LDBSCAN)	Integration of LOF and DBSCAN	Spatial outlier
Quah and Sriganesh (2008)	Self organization map (SOM)	Time series data (credit card transactions), prior knowledge required	Temporal outlier
Rogers, Barbara, and Domeiconi (2009)	Strangeness outlier detection (stroud)	Weighted approach, prior knowledge required	Spatiotemporal outlier
Wu, Liu, and Chawla (2010)	Outstretch algorithm	Top-*k* approach	Spatiotemporal outlier

applied in this research. The ST-LDBCAN is able to detect spatiotemporal outliers because the metric it uses to assess outlierness is based on spatiotemporal continuity. The key contribution of the ST-LDBCAN approach is the introduction of a spatiotemporal contextual metric of outlierness called the spatiotemporal–local outlier factor (ST–LOF). The ST–LOF is especially effective for detecting contextual collective outliers like the ones the authors tried to detect from the weather buoy data sets in this article. Contextual collective outliers are a collection of data instances that are anomalous in a specific context, such as spatiotemporal context, over a period of time (Chandola, Banerjee, and Kumar 2009). A hurricane system reflected in the weather buoy data set can be regarded as contextual collective outliers, which are different from contextual point outliers. The latter generally considers its neighbors as normal instances whereas the former's neighbors might be outliers as well (Chandola Banerjee, and Kumar 2009). The ST–LOF score of a data instance is computed with respect to its local spatiotemporal neighborhood (continuity) so that an outlier can be compared to another outlier in the neighborhood. This capability makes detecting collective outliers in an intuitive spatiotemporal context possible. This is the main reason why the ST-LDBCAN algorithm was chosen for this research.

The ST-LDBCAN algorithm is explained in the following section and more details can be found in Duggimpudi *et al.* (2016). A performance comparison of the ST–LOF, the spatiotemporal metric of outlierness of the ST-LDBCAN algorithm, and the LOF, the global metric of outlierness without spatiotemporal context, out of the experiments with weather buoy data sets, is presented later. The quantitative comparison confirms the ST–LOF is superior to the LOF in detecting contextual collective outliers.

Data and method

Data source

The NDBC has been archiving weather buoys data since the mid-1970s. Historical weather buoy observation data have gone through quality check processes to verify the validity of readings, and those readings generated by equipment malfunction have already been excluded. The availability of such information varies significantly by time and station. It is possible that some buoys might not have any readings for several months or longer due to damage caused by strong winds. It usually takes NDBC significant time and effort to regain functionality of those damaged buoys. Each buoy station's location (latitude and longitude) and the reading time are reported with reading frequency varying from every hour to every six minutes. Hourly data were selected for the purpose of this research. The acquisition time is archived in UTC (Coordinated Universal Time) format, which is normally five or six hours ahead of local Daylight Saving Time in the Gulf of Mexico.

NDBC Gulf of Mexico buoy data in 2005 and 2008 were used in this research. All numeric values of historical data are normalized by subtracting the mean and dividing by standard deviation, so that the contributions from different attributes can be comparable. Buoy data, attributes of wind direction, wind speed, sea-level air pressure, air temperature, and water temperature from 2005 were selected to match the approach of Rogers, Barbara, and Domeiconi (2009). The expectation is that the results from this research should produce similar results to theirs. In terms of the data in 2008, the wind direction and water temperature variables were excluded because of availability issues for the majority of buoys. The wind gust (peak five- or eight-second gust speed) variable was added because high-speed gusts are usually one of the most damaging effects of hurricanes. The variables used in this study are listed in Table 2. In the situation where there was missing data for the selected variables, the whole data point was deleted from the database. To make the analysis meaningful, historical hurricane tracks for Katrina and Gustav were used in this research and were downloaded from the National Weather Service GIS Data Portal (NWS 2015).

Study area

The area of study for this research (see Figure 1) is the Gulf of Mexico and surrounding ocean where the huge and intense cyclonic activities prevailed historically. The paths of Hurricanes Katrina and Gustav and buoys in the Gulf of Mexico in 2005 and 2008 are also included in Figure 1. For the studied region, there are data from a total of thirty buoys in 2005 (nine damaged during Hurricane Katrina) and sixty-eight in the months of August and September in 2008 (six damaged). It is clear from Figure 1

Table 2. Variables of National Data Buoy Center weather buoy data (2005 and 2008) used in this research.

Variables	Description	Availability in 2005	Availability in 2008
Latitude	Latitude of the buoy location	Yes	Yes
Longitude	Longitude of the buoy location	Yes	Yes
Time	Reading time in UTC (Coordinated Universal Time)	Yes	Yes
WDIR	Wind direction (the direction the wind is coming from in degrees clockwise from true north) during the same period used for WSPD	Yes	Significant portion missing
WSPD	Wind speed (m/s) averaged over an eight-minute period for buoys and a two-minute period for land stations, reported hourly	Yes	Yes
GST	Peak five- or eight-second gust speed (m/s) measured during the eight-minute or two-minute period; the five- or eight-second period can be determined by payload	No	Yes
PRES	Sea level pressure (hPa); for C-MAN sites and Great Lakes buoys, the recorded pressure is reduced to sea level using the method described in NWS Technical Procedures Bulletin 291 (11/14/80)	Yes	Yes
ATMP	Air temperature (Celsius) for sensor heights on buoys	Yes	Yes
WTMP	Dewpoint temperature taken at the same height as the air temperature measurement	Yes	Significant portion missing

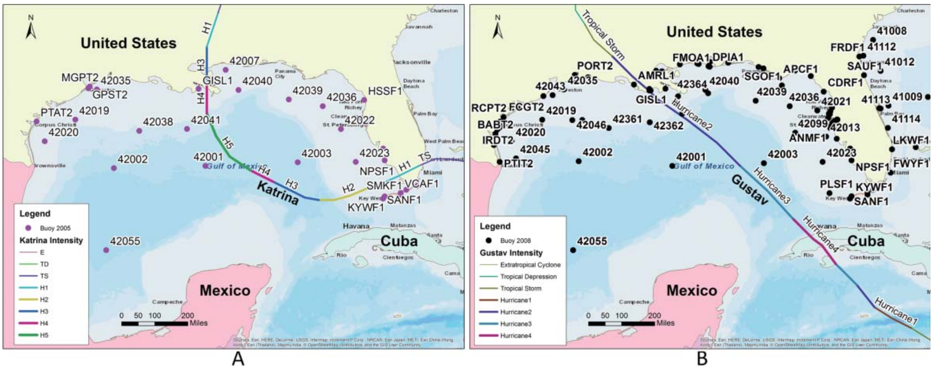


Figure 1. Study area: The paths and intensities of hurricanes and the National Data Buoy Center weather buoys in the Gulf of Mexico: (A) Buoys in 2005 and Hurricane Katrina; (B) buoys in 2008 and Hurricane Gustav.

that most of them are located along the U.S. coastline and very few are in the open ocean. Most of the additional buoys in 2008, compared to 2005, were added in areas that are close to the coastlines of the Gulf of Mexico., The new addition helps to provide timely weather information for coastal communities when they need it most.

Method

Outlier detection

The parallelized approach for spatiotemporal outlier detection developed by Duggimpudi *et al.* (2016) was based on the ideas of the LOF (Breunig *et al.* 2000) and the DBSCAN (Ester *et al.* 1996) with consideration of spatiotemporal context and locality. This approach is explained briefly later. Readers are also encouraged to check out the references for a better understanding of the LOF and the DBSCAN algorithms.

The basic idea of the LOF algorithm is that every data point has a score of its outlierness. An outlier is expected to be a point in a low-density area compared to its nearest neighbors. LOF score is the average of the ratio of the local reachability density between a point and its nearest neighbors. Local reachability density of a point p is the inverse of the average reachability distance based on the *MinPts* nearest neighbor's distance. It only requires one parameter, *MinPts*, the number of nearest neighbors used in defining the local neighborhood of the point of interest. The value of LOF of point p can be calculated by

$$LOF_{MinPts}(p) = \frac{1}{|N_{MinPts}(p)|} \sum_{o \in N_{MinPts}(p)} \left(\frac{LRD_{MinPts}(o)}{LRD_{MinPts}(p)} \right) \tag{1}$$

where p is the point of interest, *MinPts* is the number of nearest neighbors to define the neighborhood for p, N denotes the neighborhood of point p, o is an individual data point in p's neighborhood, and *LRD* is the local reachability density of a point. Points belonging to a cluster should have an LOF value close to 1, and outliers should have high LOF values (normally larger than 1.5, or 2, or even higher; see Breunig *et al.* 2000 for more details). Practically it might be challenging sometimes to determine a cutoff LOF value to differentiate outliers from inliers.

In the LOF calculation, each attribute is treated equally. Rogers, Barbara, and Domeiconi (2009) found that behavioral attributes make the greatest contribution to a data point's outlierness in spatiotemporal data, whereas very small weights are needed for spatial and temporal attributes. Duggimpudi *et al.* (2016) adopted this idea and extended the LOF definition to the ST–LOF by modifying the LOF formulas to only use the spatial and temporal attributes to define the neighborhood of a point, then calculating the outlierness score by only using the behavioral attributes. Intuitively, if an object p has a high ST–LOF score (> 1), then p could potentially be an outlier. If p has a low ST–LOF score (< 1), then p lies deep inside a cluster. Compared with the LOF, the ST–LOF has two parameters, *MinPts* and k. *MinPts* defines the number of nearest neighbors required in the regional query to make sure the spatiotemporal neighborhood is correct. k is the number of neighboring points included in the reachability density calculation. The ST–LOF score of an object p reveals how much p is similar or different in its behavioral (nonspatio-temporal) attributes to its spatiotemporal neighbors, and is given by

$$ST-LOF_{MinPts,k}(p) = \frac{1}{|\,ST-N_{MinPts}(p)\,|} \sum_{o \in ST-N_{MinPts}(p)} \left(\frac{ST-LRD_{MinPts,k}(o)}{ST-LRD_{MinPts,k}(p)} \right) \quad (2)$$

The DBSCAN (Ester *et al.* 1996) is a clustering algorithm with the capability of detecting outliers (as noises). The basic idea is that (1) clusters are high-density areas that are surrounded by low-density areas, and (2) noises (outliers) are points not assigned to any cluster. The DBSCAN has two parameters, *Eps*—radius of region query, and *MinPts*—a threshold for defining density. Both of the mentioned parameters are global (applied to the whole data set) and do not consider locality (continuity of a data instance's neighborhood), as the density threshold is applied on all data despite the fact that some clusters might have considerably higher density than other clusters. This leads to problems such as the merging of clusters that should be separate, or the labeling of a whole low-density cluster as noises (outliers). Another issue is the binary nature of outliers (noise or not) and the fact that there is no quantitative measurement for outlierness. The local-density based spatial clustering algorithm with noise (LDBSCAN; Duan *et al.* 2007) is an algorithm that integrated the locality from the LOF into the density-based definition of cluster and noise of the DBSCAN. The LDBSCAN has three parameters: (1) *MinPts*, for nearest neighbor queries; (2) *LOFUB*, a threshold to define clusters (core points); and (3) *PCT*, a threshold to separate clusters. The limitation of the LDBSCAN algorithm is that it does not have special consideration for spatial or temporal context, and the context is the key of the research at hand.

The ST-LDBCAN algorithm extends the idea of LDBSCAN by having an intuitive way to construct the spatiotemporal context for data objects using a novel metric of spatiotemporal outlierness—the ST–LOF. The ST-LDBCAN algorithm has five parameters (two for ST–LOF, three for clustering): (1) *MinPts* for ST–LOF generating appropriate neighborhood; (2) kth nearest neighbor for ST–LOF, local reachability density calculation; (3) *LOFUB* for defining cluster, (4) *PCT*, the threshold to separate clusters; and (5) *MPC*, the minimum number of points in the spatiotemporal neighborhood to check when the algorithm tries to expand the cluster. In addition, the ST-LDBCAN algorithm enforces the cluster definition by setting a minimum number of points for a cluster as a low number (*e.g.*, 4; this is not a user input parameter, though), to avoid the low cardinality cluster and using the ST–LOF instead of the LOF to have a more meaningful spatiotemporal neighborhood for the outlier detection.

The algorithm starts with calculating the ST–LOF value for all points and each point is marked as unclassified; then for each unclassified point, the algorithm checks to see if the point is qualified to be assigned to any existing cluster; if not, the point is assigned as noise. At the end, both the cluster information and the ST–LOF value will be presented. Those points that (1) are labeled as noise, and (2) have a high ST–LOF value are strong outliers; points that only meet one of these two conditions are considered weak outliers.

For different data sets the optimized algorithm parameters will be different. Generally, the recommended range for *MinPts* is 10 to 45 and that of k is 3 to 9 (Breunig *et al.* 2000); the recommendations for *LOFUB, PC*, and *MPC* are [1.5, 2.5], [0.2, 0.5], and larger than 5, respectively (Duan *et al.* 2007). Discussion about how to choose parameters is explained in Breunig *et al.* (2000), Duan *et al.* (2007), and Duggimpudi *et al.* (2016). These preceding are general guidelines and the recommended range might not work for some cases. For example, the recommended range of *MinPts* might not work for the problems investigated in this research because such a recommendation is for problems of detecting contextual point outliers. A larger number of *MinPts* are needed to define the right spatiotemporal context when detecting contextual collective outliers like the one in this research. The parameters selected for this study are listed in Table 3 based on experiments.

Quantitative evaluation of outliers

A comparison of the resultant outliers between the proposed spatiotemporal approach, the ST–LOF, and the original global approach, the LOF, were performed to evaluate the quality of outliers detected. A quantitative measure, the outliers association with hurricane intensity index (OAHII), was developed for this purpose. The OAHII is a measure of correlation between the resultant outlierness scores and the estimated actual impact of the hurricane (ground truth). The ground truth was presented by the actual hurricane path (NWS 2015), which included information about latitude, longitude, time, and maximum wind speed around hurricane eyes. The data are recorded at six-hour intervals so they have to be interpolated to make them hourly to match the buoys' readings.

The impact of a hurricane on a certain buoy k at a time t is modeled as

$$impact_{k,\,t} = w_t / d_{k,t} \tag{3}$$

where w_t is the maximum sustained wind speed of the hurricane at time t, and $d_{k,t}$ is distance between the buoy k and the hurricane eye location at time t. This simple model captures the intuition that the impact depends on both intensity of the hurricane and the closeness of the buoy. The measurement introduced here is able to compare results of the two approaches.

The OAHII is the average, over time, of Pearson's correlation between two vectors: the estimated impact of the hurricane, using the model described earlier, and the outlierness scores LOF, which means either the ST–LOF or the LOF scores as in Equation 4:

$$OAHII = \frac{\sum_{t=1}^{T} Cor(IMPACT_t,\ LOF_t)}{T} \tag{4}$$

where T is the length of the time period, and $IMPACT_t = [impact_{1,t}, \ldots, impact_{n,t}]^t$ is the vector of hurricane impact on all of the buoys at time t. Similarly, $LOF_t = [LOF_{1,t}, \ldots, LOF_{n,t}]^t$ is the vector of outlierness scores assigned to all the buoys at the same time t, and n is the number of buoys. The OAHII is normalized between −1 and 1. Positive or negative values indicate a positive or negative correlation between these two vectors, respectively. The quantitative evaluation results are discussed next.

Results and discussion

Outlier detection results

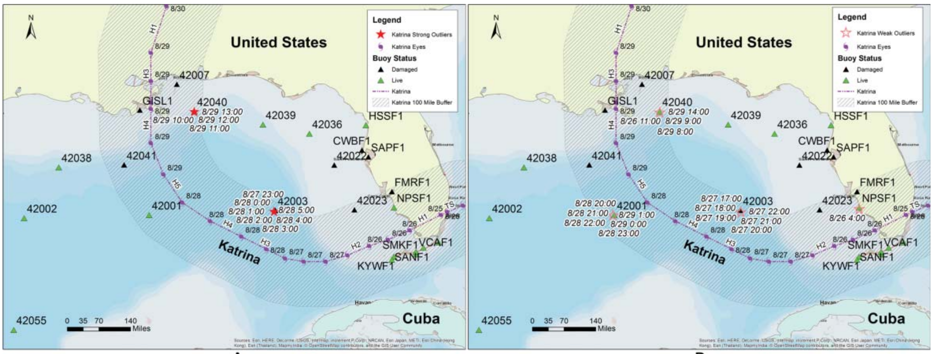
Hurricane katrina

The outlier detection results for Hurricane Katrina can be seen in Figure 2. Strong outliers were detected at two buoys at multiple times (see Table 4 and Figure 2A for details) and each data object

Table 3. Spatiotemporal local density-based clustering of applications with noise parameters selected in this research.

MinPts	k	LOFUB	PCT	MPC
200	4	2.8	0.4	125

Note: MinPts = the number of nearest neighbors used in defining the local neighborhood of the point of interest; *k* = number of neighboring points included in the reachability density calculation; *LOFUB* = a threshold to define clusters; *PCT* = a threshold to separate clusters; *MPC* = the minimum number of points in the spatiotemporal neighborhood to check.



A B

Figure 2. Outliers detected between August 25 and 30, 2005, from National Data Buoy Center weather buoy data in the Gulf of Mexico: (A) Strong outliers; (B) weak outliers.

with a different time stamp is considered a single outlier. One of the buoys, 42003, is located about 300 miles offshore in the Gulf of Mexico. Its closest distance to the eye of Hurricane Katrina was about 80 miles when the hurricane intensified from Category 3 to Category 4 in the early morning of August 28, 2005 (Knabb, Rhome, and Brown 2005). The authors were able to detect seven consecutive readings as strong outliers for this buoy during the time period of August 27 23:00 p.m. to August 28 5:00 a.m. Detailed information indicated that this buoy was eventually damaged on the same day after the last outlier was detected. Another buoy detected, 42040, is located about 70 miles offshore and 50 miles east of southeastern Louisiana. Its closest distance to the hurricane eye was about 84 miles, which occurred immediately prior to when the hurricane made landfall with Category 4 intensity near Buras-Triumph, Louisiana at 11:10 a.m. on August 29, 2005 (Knabb, Rhome, and Brown 2005; see Figure 2A). The authors were able to detect four consecutive readings from 10:00 a.m. to 13:00 p.m. on August 29, 2015 at buoy 42040 as shown in Table 4.

In Figure 2A, a 100-mile buffer along Hurricane Katrina's path was overlaid on top of the buoys to visualize the proximity of the hurricane system. If we take a close look at those buoys in the buffer zone after Katrina intensified to a Category 2 hurricane early on August 27, 2005, in Figure 2A (seven buoys in total in this case), we can see four out of the seven buoys were damaged (Buoy 42023, 42041, GISL1, and 42007). For those damaged buoys, we do not have any readings for this period of investigation; therefore, they were excluded from this research. If those damaged sensors were able to survive and provide useful readings, most likely some outliers would be captured there as well. Among the remaining three live buoys out of the seven, two captured consecutive strong outliers as discussed

Table 4. Details of strong outliers detected between August 25 and 30, 2005, from National Data Buoy Center weather buoy data in the Gulf of Mexico.

Sensor ID	Latitude	Longitude	Time (UTC)	Wind direction (degree)	Wind speed (m/s)	Pressure (millibar)	Air temperature (Celsius)	Water temperature (Celsius)	LOF	Cluster ID
42003	26.007	−85.648	8/27 23:00	68	23.8	991.6	27.9	30.3	3.25	−1
42003	26.007	−85.648	8/28 0:00	65	25.2	989.9	26.8	30.2	3.54	−1
42003	26.007	−85.648	8/28 1:00	68	28.6	988.7	27.0	30.2	4.19	−1
42003	26.007	−85.648	8/28 2:00	77	25.6	988.8	26.7	30.1	3.62	−1
42003	26.007	−85.648	8/28 3:00	89	26.0	989.3	26.7	30.0	3.71	−1
42003	26.007	−85.648	8/28 4:00	96	26.6	987.8	26.7	29.9	3.84	−1
42003	26.007	−85.648	8/28 5:00	105	26.3	987.9	27.2	29.9	3.77	−1
42040	29.212	−88.207	8/29 10:00	127	28.1	979.3	26.2	29.0	3.05	−1
42040	29.212	−88.207	8/29 11:00	139	27.3	979.3	26.2	28.9	2.89	−1
42040	29.212	−88.207	8/29 12:00	147	27.1	979.3	26.1	28.5	2.85	−1
42040	29.212	−88.207	8/29 13:00	159	28.0	981.8	25.8	28.4	2.96	−1

Note: LOF = local outlier factor.

earlier and one captured a series of weak outliers (Buoy 42001; see details in Table 5 and Figure 2B for weak outliers detected). All three live buoys out of the seven have some weak outliers being detected (hollow stars on Figure 2B) at moments when the hurricane intensities were not as high as those being detected as strong outliers at the same buoy.

It is not surprising that some of the other readings for Buoys 42003 and 42040 were also captured as weak outliers based on the earlier discussion about their proximity to the hurricane system. The open ocean buoy 42001 also captured six sequential readings as outliers late on August 28 when Katrina reached its highest power as a Category 5 hurricane and the neighboring buoy 42041 was eventually damaged (see Figure 2B). From Table 5, one can observe two weak outliers out of the seventeen that might not have been relevant to Hurricane Katrina. Buoy 40240 had a weak outlier detected on August 26 when Katrina was still over the Florida peninsula. During this time, there was a significant change in wind direction from 66 degrees in the previous hour to 263 degrees in this reading, and there was also an air temperature drop from 29.6°C to 27.5°C. It indicates that this reading is a legitimate outlier, although it might not relate to Hurricane Katrina because the air pressure was not low (1015 mb); however, it might be caused by local events, such as thunderstorms. The next weak outlier was detected on August 26 at station NPSF1, located on the west shore of the Florida peninsula (see Figure 2B). During this time, the eye of Hurricane Katrina was passing the area where this buoy is located. Detailed information shows that there were significant changes from this reading to the next reading (four previous readings on the same day were missing): Wind directions changed from 270 degrees to 7 degrees and wind speed increased from 0 m/s to 8.4 m/s. The change in wind direction is the most probable reason the buoy was selected as an outlier, and it also makes sense because it was close to the eye of the hurricane both in space and time. At the time of the reading, Hurricane Katrina was considered to be between a tropical storm and a Category 1 hurricane and the air pressure recorded was not very low (1007 mb; Knabb, Rhome, and Brown 2005).

The aforementioned results prove that the proposed approach was able to detect collective outliers in the weather buoy data, and most of the time, the outlier detected was relevant to the hurricane within the spatiotemporal context. There were some challenges in this research as well. It warrants further discussion because peer researchers might face similar challenges and the multitude of ways those challenges were confronted in this research could inspire further innovative approaches.

Table 5. Details of weak outliers detected between August 25 and 30, 2005, from National Data Buoy Center weather buoy data in the Gulf of Mexico.

Sensor ID	Latitude	Longitude	Time (UTC)	Wind direction (degree)	Wind speed (m/s)	Pressure (millibar)	Air temperature (Celsius)	Water temperature (Celsius)	LOF	Cluster ID
42040	29.212	−176.414	8/26 11:00	263	3.5	1013	27.5	30.0	2.45	300005
npsf1	26.132	−81.807	8/26 4:00	270	0.0	1007	26.5	30.5	2.13	−1
42003	26.007	−85.648	8/27 17:00	62	19.6	999	27.9	30.3	2.51	300005
42003	26.007	−85.648	8/27 18:00	65	20.8	998	28.1	30.3	2.72	300005
42003	26.007	−85.648	8/27 19:00	66	20.7	997	28.0	30.3	2.70	300005
42003	26.007	−85.648	8/27 20:00	68	20.0	996	27.0	30.3	2.60	300005
42003	26.007	−85.648	8/27 21:00	64	20.7	994	27.8	30.3	2.73	300005
42003	26.007	−85.648	8/27 22:00	64	21.0	993	27.1	30.3	2.76	300005
42001	25.888	−89.658	8/28 20:00	282	24.3	981	27.0	29.6	2.63	300005
42001	25.888	−89.658	8/28 21:00	279	23.4	982	28.1	29.6	2.51	300005
42001	25.888	−89.658	8/28 22:00	268	23.0	983	28.1	29.5	2.48	300005
42001	25.888	−89.658	8/28 23:00	262	23.1	984	27.8	29.5	2.51	300005
42001	25.888	−89.658	8/29 0:00	260	23.6	985	28.9	29.5	2.61	300005
42001	25.888	−89.658	8/29 1:00	255	22.3	988	28.8	29.5	2.40	300005
42040	29.212	−88.207	8/29 14:00	166	25.2	984	26.8	28.2	2.64	300005
42040	29.212	−88.207	8/29 8:00	111	25.5	984	27.4	29.2	2.66	300005
42040	29.212	−88.207	8/29 9:00	128	25.1	983	26.7	29.2	2.60	300005

Note: LOF = local outlier factor.

One challenge in applying the LOF-like algorithm is where to set the LOF cutoff value to differentiate outliers from inliers (a data instance considered as a normal case). If some kind of a benchmark exists (e.g., published research using the same data set), then the job of picking the cutoff value becomes much easier. Rogers, Barbara, and Domeiconi (2009) applied a statistics-based spatiotemporal outlier detection method (stroud algorithm) into the 2005 NDBC weather buoy data from the Gulf of Mexico (the same data set we used in this research). Rogers, Barbara, and Domeiconi (2009) reported a total of 437 outliers detected in their most aggressive approach. They put all weights on the thematic attributes while placing no weights on the spatial and temporal attributes to get this result, which is similar to the idea in this research—excluding the spatial and temporal attributes in the outlierness calculation. We went a step further than Rogers, Barbara, and Domeiconi, however, and used the spatial and temporal attributes to generate a data point's neighborhood, which ensures that the outliers detected are contextually appropriate. Using the number of outliers in Rogers, Barbara, and Domeiconi (2009) as the benchmark, a cutoff LOF value at 2.39 produced 429 outliers in the 2005 whole year data set in this research. Among those 429 outliers in 2005, there are 11 strong outliers and 17 weak outliers detected (as discussed earlier and shown in Tables 4 and 5 and Figure 2) between August 25 and August 30, 2005, when Hurricane Katrina wreaked havoc in the Gulf of Mexico (Knabb, Rhome, and Brown 2005). Rogers, Barbara, and Domeiconi (2009) also reported a strong outlier at buoy 40240 at 7:00 a.m. (local time, 12:00 UTC) on August 29, which was one of the four strong outliers we detected at this buoy.

Another challenge often encountered in multidimensional data research is how to treat data from different dimensions. The challenge is whether to treat them as being equally important or to assign related weights to different attributes, and ultimately, how to justify the decision being made. In hurricane-related research, damage intensity scales such as the Saffir-Simpson Hurricane Potential Damage Scale (Simpson 1974) and the Freeman/Hasling Hurricane Damage Potential Scale (Hasling 2011) recognize that maximum sustained wind speed, the central pressure, storm surge scale, storm speed, and the radius of high winds are all important factors contributing to the overall damage of a hurricane. Based on such understanding, among the five behavioral attributes available, a relative weight of 1, 5, 3, 1, and 1 was assigned to wind direction, wind speed, air pressure, air temperature, and water temperature (see Table 2). Although this is a normative decision based on the idea that more weight should be placed on wind speed and air pressure, one could easily make a different decision.

One more practical challenge is how to get comparable spatial neighbors and temporal ones in the regional spatiotemporal neighboring query. In other words, you want to have a good combination in any regional query instead of just one kind of neighbor. This is a common challenge for spatiotemporal analysis in sensory data because you tend to have much denser temporal data than spatial data. A temporal scaling factor (TSF) of fifty was applied for the 2005 data set to get a balanced spatial and temporal density. The weighting and scaling mentioned earlier was accomplished in a data preprocessing phase by multiplying the weight or scale after the original data were normalized.

Overall, the experiments on 2005 buoy data produce very promising results about telling the story of Hurricane Katrina through outliers. Most of the time, the outlier detected was relevant to the hurricane within the spatiotemporal context. The detected collective outliers were able to reflect highlight moments of Hurricane Katrina even with very limited data available (open ocean buoys vs. coastal buoys). Four out of the seven buoys within the 100-mile buffer of Hurricane Katrina's path were damaged during the time when it was a Category 2 hurricane or higher. This research was able to detect a series of outliers (strong or weak) from the remaining three live buoys as well as some weak outliers elsewhere when the storm system was weaker.

Hurricane gustav

Applying the same set of algorithm parameters and LOF cutoff at 2.39 as used in the case study of Hurricane Katrina, we were able to produce seven strong outliers (Table 6) and eight weak outliers (Table 7) during the time period of August 31 to September 1, 2008, when Hurricane Gustav swept

Table 6. Details of strong outliers detected between August 31 and September 1, 2008, from National Data Buoy Center weather buoy data in the Gulf of Mexico.

Sensor ID	Latitude	Longitude	Time (UTC)	Air temperature (Celsius)	Pressure (millibar)	Gust (m/s)	Wind speed (m/s)	LOF	Cluster ID
42001	25.888	−89.658	8/31 22:50	28.4	1000.5	22.9	17.0	2.95	−1
42003	26.007	−85.648	8/31 11:49	28.6	997.8	30.3	20.6	3.11	−1
42003	26.007	−85.648	8/31 12:49	27.6	996.6	30.3	21.2	3.23	−1
42003	26.007	−85.648	8/31 13:49	26.0	994.8	30.0	24.0	3.73	−1
42003	26.007	−85.648	8/31 14:49	26.2	993.4	35.3	26.8	4.39	−1
pstl1	28.932	−89.407	9/1 8:00	25.6	986.4	48.2	34.1	2.90	−1
pstl1	28.932	−89.407	9/1 9:00	25.5	978.9	49.4	38.5	3.43	−1

Note: LOF = local outlier factor.

the Gulf (Beven and Kimberlain 2009; see Figure 3). In this data set, we used four behavioral attributes instead of five. Attributes for wind direction and water temperature were missing for a significant portion of the buoy readings in the research area; therefore, these two attributes were excluded from the Hurricane Gustav investigation. One additional attribute, the wind gust—a sudden, brief increase in the speed of wind, was available in the 2008 NDBC weather buoy data. Gust is a useful measure in capturing the varying peaks and lulls of wind speed and was included as the fourth behavioral attribute. A slightly different weighting schema was applied on the four behavioral attributes (1, 5, 2, and 4 were assigned to air temperature, air pressure, gust, and wind speed) based on test runs. One of the lessons that we learned from the experiments in Hurricane Katrina was that too much weight on wind speed might introduce outliers associated with local events, such as thunderstorms. Assigning a high enough weight on air pressure helps to filter out such local events so that the resultant collective outliers will be more relevant to the hurricane system under investigation. As a side note, wind speed was still assigned the highest weight (wind speed and gust combined). Because more buoys were available in 2008, a reduced TSF (ten, based on experimental runs) was given.

Among the seven strong outliers (see Table 6 and Figure 3A), four were detected consecutively at open ocean Buoy 42003 between 11:49 and 14:49 on August 31, 2008. Its closest distance to the eye of Hurricane Gustav was about 53 miles, when the hurricane maintained its intensity as a Category 3 storm on August 31, 2008, prior to its downgrade to Category 2 late on August 31, 2008 (Beven and Kimberlain 2009). Another open ocean buoy, Buoy 42001, captured one strong outlier at 22:50 on August 31, 2008. Its closest distance to the hurricane eye was about 134 miles, while the hurricane's intensity was a Category 2. When compared to the situation at Buoy 42003, a smaller amount of strong outliers were captured at Buoy 42001 due to the larger distance and

Table 7. Details of weak outliers between August 31 and September 1, 2008, from National Data Buoy Center weather buoy data in the Gulf of Mexico.

Sensor ID	Latitude	Longitude	Time (UTC)	Air temperature (Celsius)	Pressure (millibar)	Gust (m/s)	Wind speed (m/s)	LOF	Cluster ID
42001	25.888	−89.658	8/31 16:50	26.3	1006.0	19.5	15.8	2.51	600000
42001	25.888	−89.658	9/1 0:50	27.2	998.9	18.8	14.8	2.48	600000
42001	25.888	−89.658	9/1 1:50	27.7	999.1	21.0	16.0	2.73	600000
42001	25.888	−89.658	9/1 5:50	28.4	998.8	19.4	15.2	2.49	600000
42001	25.888	−89.658	9/1 6:50	27.4	998.9	19.0	15.2	2.46	600000
42003	26.007	−85.648	8/31 8:49	26.6	1001.3	22.4	19.5	2.67	600000
42003	26.007	−85.648	8/31 10:49	27.4	998.5	23.4	18.1	2.57	600000
pstl1	28.932	−89.407	9/1 11:00	26.2	978.3	39.9	31.1	2.60	600000

Note: LOF = local outlier factor.

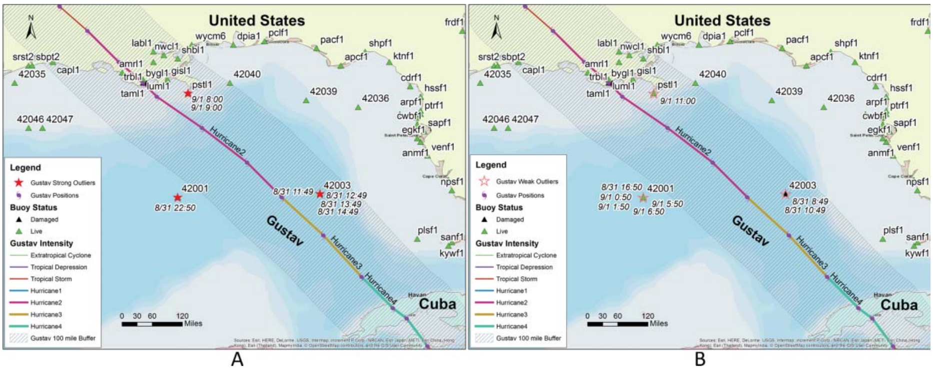


Figure 3. Outliers detected between August 31 and September 1, 2008 from National Data Buoy Center weather buoy data in the Gulf of Mexico: (A) Strong outliers; (B) weak outliers.

weaker intensity. The third buoy that captured strong outliers was station pstl1, which is about 2.5 miles offshore of the Mississippi River estuary (Figure 3A) and is not a real costal buoy. Its closest distance to the hurricane eye was about 40 miles, when the storm system was a Category 2 hurricane and prior to its landfall on the afternoon of September 1, 2008. Two consecutive strong outliers were detected at 8:00 and 9:00 September 1, 2008 at this station. The neighboring buoys of station pstl1 were either further away from the hurricane eye (e.g., Buoy 42040, about 100 miles away from the hurricane eye) or experienced less powerful winds after the hurricane's landfall. It is worth mentioning that after the last outlier was detected, Buoy 42003 was damaged again.

Five out of eight weak outliers detected in this event were from Buoy 42001 (Table 7 and Figure 3B) late on August 31 and early on September 1, 2008, when the air pressure was relatively low with significant wind speed. The two weak outliers detected at Buoy 42003 early on August 31, 2008, were pretty similar (relatively low air pressure and significant wind speed). The weak outliers detected at station pstl1 at 11:00 a.m. on September 1, 2008, were a little bit different, as they had a lower air pressure and stronger wind in comparison to others in the table.

In the case study of Hurricane Gustav, both strong and weak outliers detected reflect the proximity of the affected buoys to the hurricane eye in the spatiotemporal context, as well as the variation of the intensity of the hurricane. To get a glimpse at the quality of the work accomplished in this research, a quantitative evaluation of the work of outlier detection for Hurricanes Katrina and Gustav, which compares the outliers with ground truth (estimated impact from the hurricane), is discussed in the next section.

Quantitative evaluation of detection results

As discussed earlier, the method of OAHII was used to quantitatively evaluate the outlier detection results of ST–LOF and the LOF approach. The results were based on weather buoy data during the period of Hurricanes Katrina and Gustav and are presented in Figure 4. The horizontal axis represents time t in hours between August 25 and August 30, 2005, for Hurricane Katrina in Figure 4A and 4B, and August 31 and September 1, 2008, for Hurricane Gustav in Figure 4C and 4D. The vertical axis represents the correlation between two vectors: the estimated impact of the hurricane as defined in Equation 3 and the outlierness scores (either the LOF scores or the ST–LOF scores) for the hurricane. Each circle in the plot represents, at a time t, the correlation between the outlierness scores of all buoys at time t, and the estimated impact of the hurricane (ground truth) of the same buoys at the same time. Plots in Figure 4 show that the ST–LOF algorithm has better correlations with ground truth for both hurricanes, as there are much less negative correlation values (if any) for the ST–LOF than the LOF. Overall, the ST–LOF correlation values are higher than those

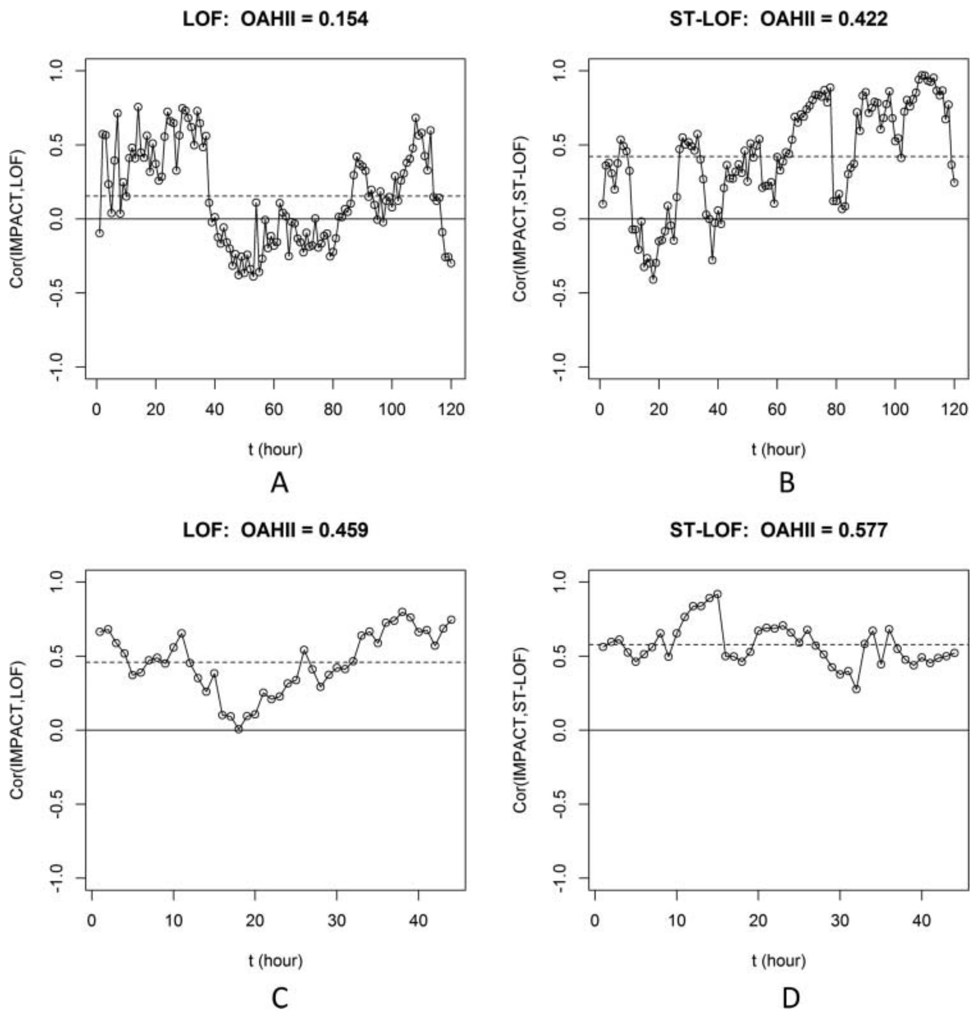


Figure 4. Performance comparison using outliers association with hurricane intensity index (OAHII) method: (A) The local outlier factor (LOF) approach for Hurricane Katrina; (B) the Spatiotemporal–local outlier factor (ST–LOF) approach for Hurricane Katrina; (C) the LOF approach for Hurricane Gustav; (D) the ST–LOF approach for Hurricane Gustav.

of the LOF. This trend is evident in the value of the OAHII for both hurricanes, as shown in Table 8. The OAHII values in these two case studies show the superiority of the proposed ST–LOF approach over the original nonspatiotemporal LOF approach, as the new approach is able to establish intutive spatiotemporal context.

Table 8. The overall performance comparison of the LOF and the ST–LOF approaches for Hurricanes Katrina and Gustav based on OAHII method.

	OAHII value	
Use cases	LOF	ST–LOF
Hurricane Katrina	0.154	0.422
Hurricane Gustav	0.459	0.577

Note: LOF = local outlier factor; ST–LOF = spatiotemporal–local outlier factor; OAHII = outliers association with hurricane intensity index.

Conclusion

The ST-LDBCAN algorithm is an unsupervised approach that does not require training or prior knowledge and has proven its ability to generate a meaningful spatiotemporal neighborhood for outlier detection. Spatiotemporal outlier detection using the ST-LDBCAN algorithm on NDBC weather buoy data in this research produced promising results of revealing where the strong force of a hurricane system was located. The buoys that experienced strong winds and were in close proximity to the hurricane were either destroyed or were detected as outliers. Due to the low density of open ocean weather buoys and frequent damage caused by strong storms, the outliers detected from NDBC weather buoy data might not reflect the whole picture of the hurricane system, such as trajectory and size of the system, and so on. Other data sets such as satellite imagery and weather reconnaissance data are considered to be a useful complement to portray the hurricane's trajectory. The proposed approach is also applicable to other regions if sufficient observation data are available. Naturally, this approach is also extendable to detecting outliers for land weather observation data, as the density of weather stations on land is much higher than that of open ocean buoys. The outliers from land weather observation data might point to those localized events, such as tornadoes and thunderstorms.

The contextual approach of outlier detection, the ST–LOF, of the ST-LDBCAN algorithm was not only able to detect the abrupt changes in readings but also to capture the momentum of hurricanes at space and time. The success of detecting contextual collective outliers in both case studies shows that appropriate spatiotemporal context is crucial in detecting such outliers; otherwise only a few point outliers will be detected, and the collective outliers like those consecutive records at a single station will most likely be missed. This is because a noncontextual approach typically treats those collective outliers as new normality as they are dominant in a small period of time or a small region.

One limitation of this approach is that more input parameters are required than the original LOF, DBSCAN, and LDBSCAN. This is the kind of sacrifice required to get a more meaningful neighborhood. Weighting and scaling might help with outlier detection but it is still a heuristic approach. Most of the time, the approach of weighting and scaling still requires some domain knowledge of the application at hand and many assumptions have to be made. This is another limitation of the proposed approach.

Despite the limitations just discussed, this research provides a new perspective when looking at historical buoy data and can benefit other climatic and meteorological researchers (typically historical buoy data are used for meteorological model validation and calibration). The spatiotemporal collective outlier detection approach presented in this article can have broad applications in areas of epidemiology, disease surveillance, crime prevention, environmental monitoring, and others, wherever spatially distributed sensory data are abundant. The discovery of abnormality in those areas helps to identify underlying causes of the abnormality and counter the problems. Future work needs to focus on reducing the number of parameters required because an unsupervised approach is supposed to have a minimal number of parameters. Another enhancement could be developing machine learning methods for weighting recommendations.

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