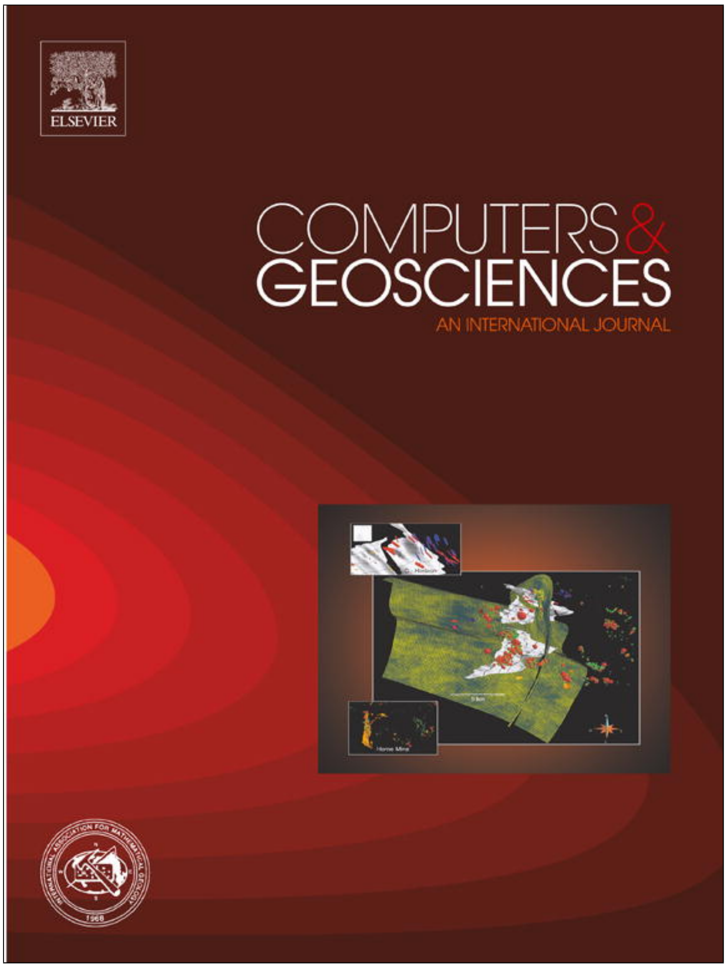
ELSEVIER
COMPUTERS &
GEOSCIENCES
AN INTERNATIONAL JOURNAL

Computers & Geosciences 52 (2013) 126–131

Contents lists available at SciVerse ScienceDirect

Computers & Geosciences

journal homepage: www.elsevier.com/locate/cageo

Polyline averaging using distance surfaces: A spatial hurricane climatology

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ARTICLE INFO

Article history:
Received 10 May 2012
Received in revised form
10 October 2012
Accepted 17 October 2012
Available online 26 October 2012

Keywords:
Hurricane
Linear tracks
Geovisualization
Distance surfaces
Climate study

ABSTRACT

The US Gulf states are frequently hit by hurricanes, causing widespread damage resulting in economic loss and occasional human fatalities. Current hurricane climatologies and predictive models frequently omit information on the spatial characteristics of hurricane movement—their linear tracks. We investigate the construction of a spatial hurricane climatology that condenses linear tracks to one-dimensional polylines. With the aid of distance surfaces, an average hurricane track is calculated by summing polylines as part of a grid-based algorithm. We demonstrate the procedure on a particularly vulnerable coastline around the city of Galveston in Texas, where the tracks of the closest storms to Galveston are also weighted by an inverse distance function. Track averaging is also applied as a means of interpolating possible paths of historical storms where records are sporadic observations, and sometimes anecdotal. We offer the average track as a convenient regional summary of expected hurricane movement. The average track, together with other hurricane attributes, also provides a means to assess the expected local vulnerability of property and environmental damage.

1. Introduction

The US Gulf states are habitually hit by tropical storms and hurricanes, causing widespread environmental damage, economic loss, and occasional human fatalities. Much of the existing research is focused on devising models that search for consistency in hurricane frequency to predict future hurricane occurrences. These models, many stochastic in design, create what are called hurricane climatologies, and are built from data on storm intensity, size, and return rate from past events; in addition to climate variables that are known to be favourable for hurricane activity (inter ala Jagger et al., 2001; Elsner and Jagger, 2006; Landsea et al., 2006; Watson and Johnson, 2008; Lin et al., 2010). In a sense, a hurricane climatology is built to characterize the expected time and place for hurricanes to occur, which may be conditional on environmental conditions. Some research has used track clusters or spatial groups of tracks to estimate a hurricane's spatial behaviour (Elsner, 2003; Camargo et al., 2007; Froude, 2008). However, hurricane climatologies frequently omit spatial information on the tracks when measuring hurricane movement. In other words, geometric data relative to the track that a hurricane takes across space is seldom incorporated (Scheitlin and Elsner, 2010). A more complete, track-relative, spatial hurricane climatology would facilitate greater awareness of hurricane behaviour by improving our abilities to measure the likelihood and trajectory of the next occurrence.

Track-relative spatial hurricane climatology is built from data on past hurricanes. Past hurricane tracks are recorded by the National Hurricane Center (NHC) in Miami, Florida. The NHC monitors the movement of hurricanes and collects information on their location, intensity, and areal size at regular six-hour intervals gained from reconnaissance flights, remotely sensed images, and surface observations. The data are initially plotted as individual points (the centre or eye of the hurricane), which are connected in chronological order to form a linear track. From a geocomputational standpoint, these single storm tracks can be condensed into one-dimensional polylines, fixed with starting and end points corresponding to the hurricane's origin as an organized storm through to ultimate dissipation. As polylines, the single tracks are amenable to statistical analysis when searching for spatial patterns, in particular the relative frequency and likelihood of hurricane occurrence. One statistical measure is to calculate the average track from a set of polylines for a given geographic area. The average track would represent the expected hurricane path and would provide a basis for projecting future paths along with a level of uncertainty.

Average tracks, like all averages, are excellent for visualizing trends. From a mass of hurricane tracks, the average produces a single and convenient summary that demarcates the most likely geometric path. And like all averages, the more observations the stronger the degree of confidence and reliability. We demonstrate the calculation of the average track by using hurricane data from

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0098-3004/$ - see front matter
http://dx.doi.org/10.1016/j.cageo.2012.10.012

the North American hurricane database (HURDAT) collected by the NHC and the concept of distance surfaces. Focusing on the city of Galveston in Texas, USA, we generate grid-based distance surfaces for the paths of each of the hurricanes that have passed by Galveston. The average track is the hypothetical route that passes along the centre of the mass of observed hurricanes. In addition, access to a second database provides historical records of hurricane activity between 1700 and 1855 (Chenoweth, 2006, 2007). Given the age of when this database was created it has very few observations; all are of when hurricanes made landfall. The averaging technique is applied to these historical records as a potential means to reconstruct the expected track (Scheitlin et al., 2010). Both databases facilitate the generation of more complete spatial hurricane climatologies by measuring the temporal frequency of hurricane events over much longer time periods and hence provide evidence to determine which coastal strips have had the most impact from hurricane activity. We first explore the rational for using polylines to represent hurricane tracks, as well as the computational benefits of distance surfaces, before demonstrating the technique in more detail.

2. Polylines and distance surfaces

Geographic features are frequently represented by polylines. Multi-segment polylines form crisp cartographic boundaries that facilitate the demarcation of convenient discrete objects—from which various spatial metrics may be calculated. They can also be used to represent discrete linear features, including the paths hurricanes have made and are predicted to make. Polylines are standard objects in GIS, but where a research challenge lies is in the handling and visualization of large quantities of polylines, especially multiple sets representing the same geographic feature (Siirtola, 2000; Wentz et al., 2003a; Kuijpers et al., 2006). This is because spatial data models typically produce large quantities of output after every iteration, particularly if their dependent variables are allowed to fluctuate. Some output from GIS is in the form of vector polylines predicting the location of areal boundaries or the most optimal linear path if iterations measure flow processes. Many examples are evident from transportation optimization to measuring flood risks from hydrological discharge. When applied to models forecasting hurricane movement large sets of polylines are typically generated to represent the full range of track possibilities. Sometimes multiple polylines are generalized, for example in the search for a single polyline that 'best' represents the others. This best polyline can be the average or weighted average of the entire set. Averaging is less computationally demanding than other reductionist methods, such as hierarchical clustering, and provides a dynamic, interactive approach to the geo-visualization of the overall tendency in complex spatial data. A useful analogy may be to imagine skiers leaving tracks behind on a mountain slope, and where the goal is to find the most frequent or favourable pathway taken by the skiers.

Research on polyline averaging is mostly restricted to exploratory visual analysis of environmental and social science data, including general hurricane climatic data (Steed et al., 2009), summaries of health statistics (Edsall, 2003), and the handling of generic two-dimensional parallel spatial coordinates (Inselberg and Dimsdale, 1990). Indeed, parallel coordinates are another useful way for visualizing large data sets in a space-efficient and interactive manner. Their downside is that they frequently consist of a computationally overwhelming number of individual line segments. This often presents a problem for differentiating between complete polylines, and means that it may be simpler to calculate the average trend of the set of polylines rather than the entire parallel coordinate set. Nevertheless, the averaging of parallel coordinates is relatively simple because a set consists of line segments with an identical range of values (Siirtola, 2000). Geographic polyline data, on the other hand, are often of variable length scattered throughout space. This means that unlike parallel coordinates there are no common starting points, end points, or connections between polylines. The goal of our work is to provide an algorithm for averaging spatial polylines that may not have any commonalities other than they exist on a similar geographic plane. However, a simple vertical stacking of these polylines is insufficient to calculate a spatial average. What is needed is a means with which the horizontal distances between polylines can be consistently measured and an accurate average calculated.

The technique is illustrated by three hypothetical polylines in Fig. 1a, where the lateral distances between the polylines represented by the solid line, dashed line and dotted line need to be summed and divided by three. We chose distance surfaces, or distance maps (Mather, 1944; Hirata, 1995) to create a boundless Cartesian plane for each polyline. Each surface represents increasing Euclidean distance away from the location of one of the polylines (Fig. 1b). They are identical to regular-interval buffering techniques in most GIS software packages. Both are capable of calculating continuous distances, but for visualization purposes, isolines or buffer zones are employed to represent regular intervals. Distance surfaces have been used in a variety of techniques, including the generation of shortest paths between points, cluster analysis, skeletonization (Danielsson, 1980; Russ, 1989), watershed analysis, transport proximity, and the risk of natural disasters. Once distance surfaces are created for each polyline, their distance values may be averaged to provide an average distance surface, thus giving way to an average polyline.

3. Polyline averaging

The calculation of an average polyline using distance surfaces may at first appear obvious. Yet it is absent from the GIS and meteorological literatures. Existing studies instead focus predominantly on individual count data to represent hurricane activity, which are sometimes aggregated into cumulative tracks. A recent example by Zandbergen (2009) analyzed the spatial patterns of hurricane tracks as count data for evaluating the level of exposure at the local scale to various hurricane intensities. Thus, count data may be sufficient for describing how often coastlines experience storms at various intensities over time, but count data are limited to recording discrete observation points over fixed time intervals. Instead severe storms travel along continuous space; and as such the entire length of their tracks needs to be represented, starting from where they begin as organized storms to when they finally dissipate over land.

Returning to Fig. 1, the three hypothetical polylines occur in a similar geographic area and have a range of [0,1] and a value x at every 0.01 y; this is where $x=y+a$, and where a is normally distributed with mean of 0 and standard deviation of 0.1. For each polyline a distance surface is generated using grid-based isolines to represent Euclidean distances in units of x (Fig. 1b). The polylines themselves are coded to 0. Calculating the average is then a matter of aggregating all three distance surfaces, and for each grid summing the total Euclidean distances and dividing by 3 (Fig. 1c). Mathematically, a value of some number ν indicates that the three polylines are, on average, ν units of x away from that point. For instance, shorter distance values have the most agreement between the polylines, and a value of zero means that all of the polylines intersect at that point. The final stage involves identifying the linear route of the sequence of points that are

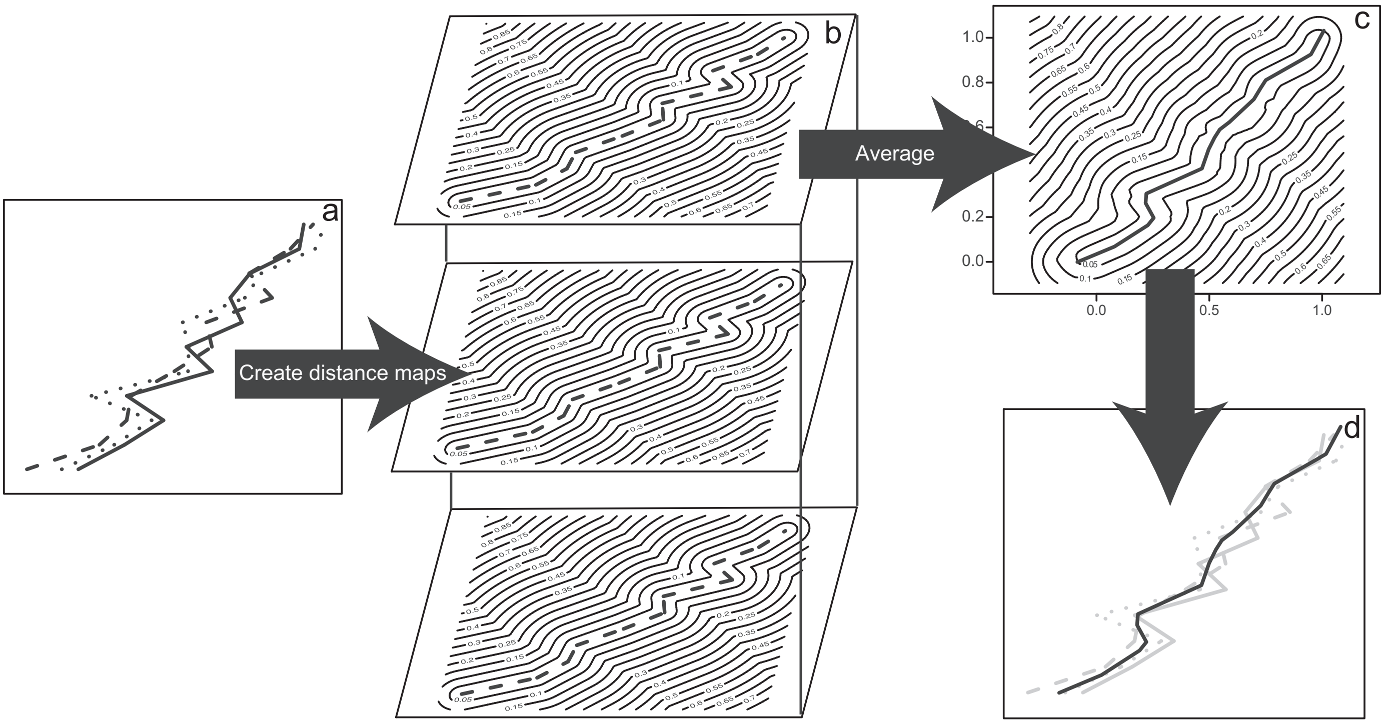

Fig. 1. Steps for polyline averaging using distance surfaces: (a) three polylines to be averaged, (b) a distance surface is created for each polyline. Isolines are the shortest distance from that point to the polyline in units of x, (c) the distance surfaces are averaged, creating an average-distance surface, (d) the average polyline (black), and the original set of polylines (grey).

coded with the lowest numbers. A line is digitized manually and is considered the average polyline (Fig. 1d). The result is akin to a typical least-cost route on a cost-density surface.

The generation of distance surfaces and the calculation of the average were performed using the open source statistical software *R*. Some modifications to our technique include a heavier weighting for polylines closer to the average. That is because they are considered to have a greater impact on the overall trend, and is the typical assumption used in hurricane research when determining the likelihood of storm impacts. As such, we have added a distance–decay parameter to our averaging technique and this will be demonstrated by our case study in the next section.

4. Hurricane averaging: The case study of Galveston

Known for its vulnerable location in the Gulf of Mexico, Galveston in the US state of Texas experiences relatively frequent hurricane activity, and is an exemplar location for the creation and application of a spatial hurricane climatology. The first step is to aggregate data from past Galveston hurricanes. Since hurricane tracks are being created by connecting point observations of the storms, it is beneficial to use points at the smallest possible interval. To this end, we employ the HURDAT database collected by the NHC since 1851 at hourly-interpolations (Jagger and Elsner, 2006). From these data, 10 major hurricane tracks (wind speeds $>50\,\mathrm{m\,s^{-1}}$) that passed within $\sim$100 km of Galveston between 1851 and 2009 were accessed from the HURDAT dataset (NHC) (Fig. 2). Distance surfaces were generated for each of the 10 polylines representing the tracks and then combined to calculate the average (Fig. 3). However, instead of taking the simple average an inverse distance weighting (IDW) component is added to adjust for diminishing importance of the track with increasing distance from Galveston.

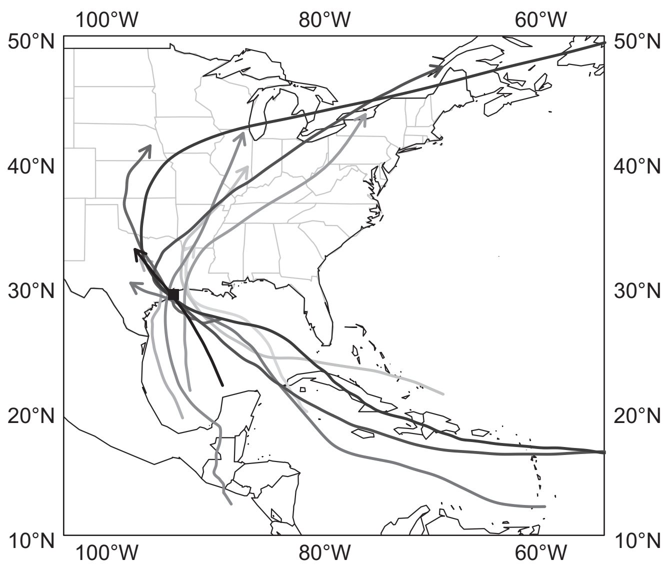

Fig. 2. Major hurricane tracks (wind speeds >50 m/s) passing within 100 km of Galveston, TX, 1851–2009. The darker tracks passed closest to the city.

In other words, hurricane tracks that passed closer to Galveston were given a heavier statistical weighting—the darker tracks in Fig. 2 represent hurricanes that passed closer to the city. The formula for the average distance surface $D(s)$ now becomes:

$$D(s) = \frac{\sum_{k=1}^{10} w_k D_k(s)}{\sum_{k=1}^{10} w_k} \quad (1)$$

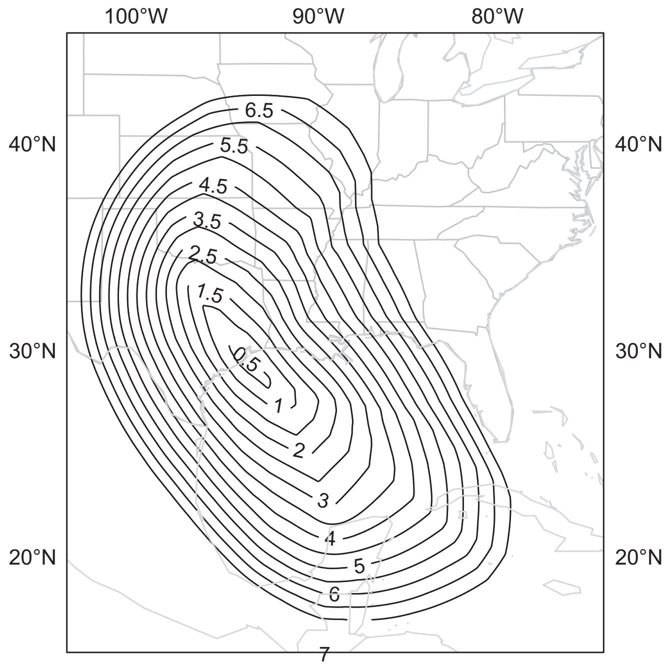

Fig. 3. IDW average distance surface of the major Galveston hurricane tracks shown in Fig. 2. Isolines are lines of average distance and shown in degrees of latitude. Hurricanes passing nearest Galveston (the darkest tracks in Fig. 2) are weighted most heavily.

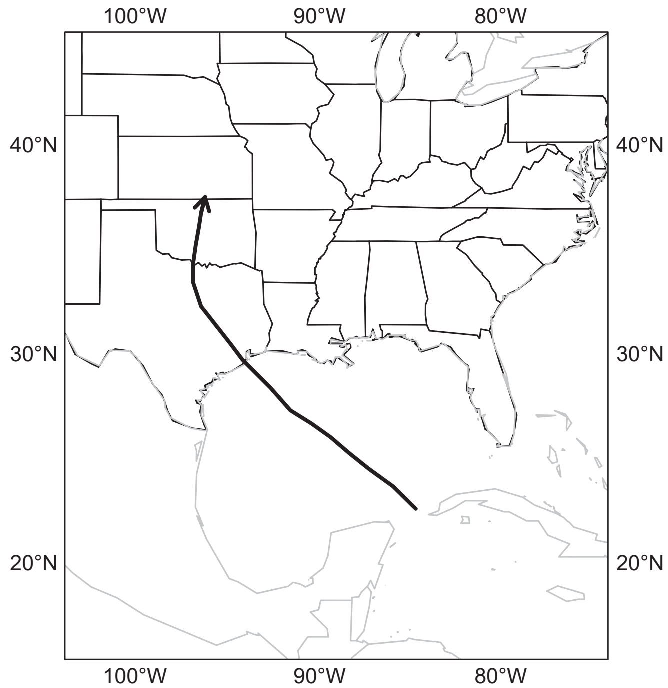

Fig. 4. The average major Galveston hurricane track. The track is based off of the IDW average of the 10 closest major hurricanes from 1851 to 2009.

where $w_k = 1/d(e,t_k)$, and $d(e,t_k)$ is the great-circle distance from the track (t_k) to Galveston and $D_{k(s)}$ is the distance surface for track k. With an IDW assumption the entire database of tracks may theoretically be used to calculate the average. However, those that are very far away will have little effect, and in any case, a smaller sample is computationally simpler and produces nearly identical results.

The result of applying Eq. (1) on the 10 distance surfaces representing the 10 hurricane tracks is shown in Fig. 3. Isolines are used to illustrate the average distances which tend to form a bullseye pattern around Galveston. Beyond, distance values increase in all directions, but the gradient is steeper longitudinally than latitudinally showing the tracks are more similar in the north and south directions. The major difference between the average-track distance surface and those representing the individual 10 tracks is that the average track does not have a value of zero. Instead it connects the lowest values of average distance, forming a linear path, which is represented by a crisp line in Fig. 4. Because hurricanes vary in length, it is important to limit this line to within the immediate vicinity of landfall. This is because from a meteorological standpoint, there is little interest in the track hundreds of kilometres north over land where the hurricanes have significantly decayed and perhaps transitioned into extratropical cyclones. Thus, choosing an appropriate limit may well be determined by intent. In the Galveston example, a threshold at approximately 4° isoline may be sufficient to summarize average hurricane movement across the Gulf of Mexico, with storms typically organizing somewhere between Cuba and the Yucatan Peninsula. In sum, the average track adds a spatial dimension to create a more complete Galveston hurricane climatology. And in combination with current meteorological conditions the average track may provide valuable spatial information for many stochastic models designed to predict future storm activity, economic loss, and even global climatic change.

5. Hurricane averaging: Historical records

As seen by the previous example, information from past hurricanes may guide our knowledge of future events. To this end, hurricanes prior to 1851 are being reconstructed to extend our database and thus augment hurricane models. One such source of past records is the one compiled by Chenoweth (2006, 2007) for hurricane activity occurring between 1700 and 1855 using qualitative historical documents. In the archive, a narrative for each hurricane describes one or a few locations where the effects of its activity were observed and documented. Some of the locations are specific (i.e., latitude and longitude coordinates) while others much broader (e.g., Gulf of Mexico). The rest of the hurricane's journey is, not surprisingly, unreported. Our work on calculating the average track has important ramifications for improving the utility of such historical records in hurricane research. In particular, the ability to add a spatial component to isolated observations, and as a result interpolate a continuous line of probable hurricane movement. This is similar to more abstract space–time geography problems where algorithms are used to create continuous tracks for moving objects where there are missing data (Wentz et al., 2003b; Gregory and Ell, 2006). Hurricanes provide a unique example because they are known to take regular paths across space relative to presiding climate conditions (Elsner, 2003). Moreover, the assumption is that hurricanes that strike the same landmarks tend to have similar paths, at least locally.

We demonstrate how our track averaging method is able to interpolate hurricane paths by focusing on one storm as an example. Storm 25 from the Chenoweth (2006) archive has two observations; one on the island of Jamaica and one in the US state of Louisiana, both during September 1722. The first step involves assigning latitude and longitude coordinates to the geographic centroid of Jamaica and to the midpoint of Louisiana's coastline. These may seem overly general but hurricanes typically cover wide areas, and besides, the goal is to interpolate an approximate linear path between waypoints and not to be too precise with the location of archival records that may have many intrinsic errors anyway. The next step is to gather as many hurricanes from the 1851 to 2009 HURDAT database that may have had similar trajectories with Storm 25 between the waypoints of Jamaica and Louisiana. Ten hurricanes passing nearest were selected, and ranked by their great-circle distance away from the waypoints. This is represented in Fig. 5 where the darker shaded tracks passed closest to the waypoints; all 10 passed within 100 km. Distance surfaces are then created for each of the 10 tracks, stacked, and IDW-averaged in relation to each hurricane's distance from the waypoints. For instance, the track shaded black in Fig. 5 has the heaviest weighting and greatest impact when calculating average distances. The result of applying the spatial average to the 10 HURDAT storms using our technique of summing the 10 individual distance surfaces is displayed in Fig. 6 as degree isolines. Note that the lowest averages, and hence greatest agreement between the ten tracks, are located at the two waypoints. This is the expected outcome because, recall, the choice of the 10 storms was made on their proximity to both

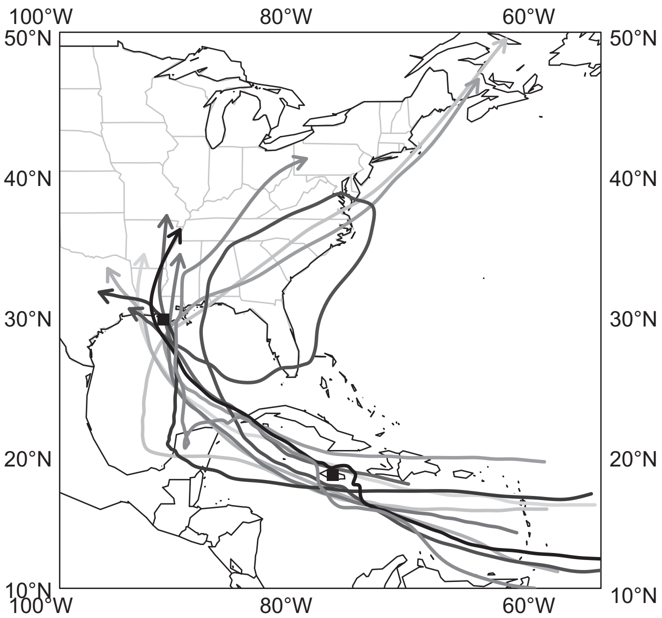

Fig. 5. Ten hurricanes from 1851 to 2007 passing nearest the points representing Jamaica and Louisiana. The darkest tracks passed closer, on average, to the two points.

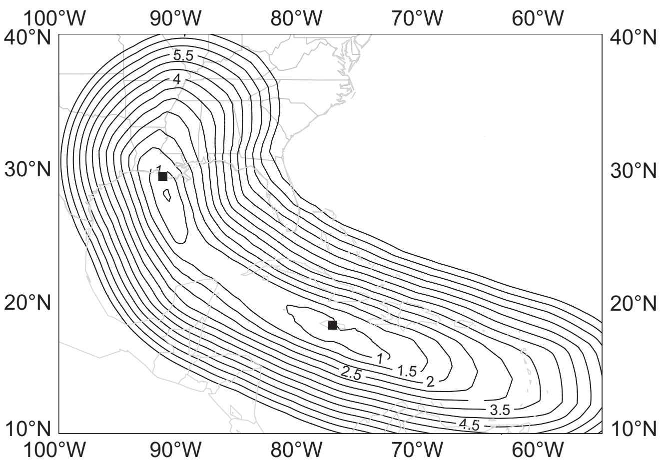

Fig. 6. Average distance surface of hurricanes passing nearest Jamaica and Louisiana. Isolines are degrees of latitude.

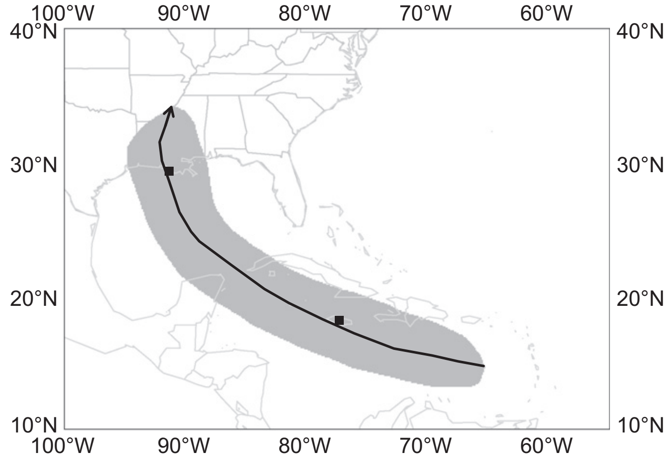

Fig. 7. The average track and pathway of hurricanes passing near Jamaica and Louisiana. This is a probable pathway and track for Storm 25 during September 1722 in the Chenoweth (2006) archive.

Jamaica and the midpoint of Louisiana's coastline. Finally, as in the Galveston case, the final most likely track that Storm 25 may have taken is represented by a polyline that connects the sequence of grids with the lowest average values, and labelled as the average track (Fig. 7). In addition, and as reminder that our averaging technique may be affected by overly generalized waypoint locations, we are recommending caution and advocating the use of a zone as well as a line. The zone represents the possible path of Storm 25 within the 3° longitude isoline. The choice of a threshold at 3° is based on the zone covering both the whole island of Jamaica and the entire Louisiana coastline. If the spatial averaging technique was applied to other historic storms the threshold may vary according to the locational precision of their waypoints.

Admittedly the process of using modern storm tracks to assess a likely path of a historical storm has limitations. First, errors are inherent in the historical catalogues. These include misinterpretations and exaggerations of the locations, dates, and storm intensities observed and reported in historical newspapers and other sources. Although Chenoweth (2006) describes how the archive was carefully checked to avoid such errors it is not unreasonable to assume that there may be errors associated with Chenoweth's interpretation of the newspapers and ship logs. In any case, many of the sources were in other languages or partly illegible. Some may have been vague or confusing. Moreover, Chenoweth only included tropical cyclones for which he had reasonable confidence in the source documents and omitted others. Of course assigning coordinates to approximate locations, some as vague as "Gulf of Mexico" also limits the utility of our averaging technique. Finally, the interpolated path based on averaging recent storms may, in the worst case scenario, be as imprecise as the length of the Louisiana coastline. However, if waypoints are more geographically exact there is stronger confidence in the interpolation process simply because hurricanes are largely controlled by presiding climatic conditions, dictated by concentrations of high pressure steering hurricanes in a fairly predictable manner. And above all, averaging provides a valuable means with which historical records can be incorporated into models that evaluate long-term climatological changes.

6. Conclusions

Hurricane tracks can be represented as simple one-dimensional polylines. This allows tracks to be spatially analyzed when searching for geographic patterns. It also adds a valuable spatial component to hurricane climatologies designed to measure past frequencies and predict possible future occurrences. Our work demonstrates how a spatial averaging technique based on distance surfaces can distil a set of polylines representing hurricane tracks into one single polyline that summarizes the most spatially frequented track. We demonstrated the technique when calculating the average track from a set of hurricanes recorded over the city of Galveston in Texas, as well as a means to improve the spatial trajectory of an historical storm that had been observed at only two locations. In both examples, the averaging technique is important for a number of reasons. First, it identifies the most vulnerable coastal strips that may be damaged by hurricanes; this in itself helps in developing effective mitigation policies. Second, from a computationally reductionist standpoint, an average track, like all averages, condenses multiple tracks into a convenient single-track summary. And like all averages, the more observed frequencies the stronger the relevance and confidence of the average. In a sense it is also a way to visualize simple expectations from complex data. Third, the spatial component it adds to existing hurricane climatologies and predictive models provides a more complete framework with which to study the climatic factors responsible for fuelling hurricane activity. And lastly, the calculation of an average may also be used to augment, strengthen and to complete historical records by helping fill gaps in missing years.

Possible improvements to the spatial averaging method based on polylines include estimating levels of error, where information on uncertainty would be obtained from polyline similarity testing (along the lines of work by Kuijpers et al., 2006). This is where similarity across the whole set of polylines would provide information regarding the relevance of the average polyline. If the polylines have little similarity then the average polyline may not have as much spatial relevance. Once an average polyline is created, similarity testing can provide information about the difference between the average and the original set. Calculating standard distances from the average polyline to the set is another way to obtain similar information. Such testing should also help determine a reasonable range of values within which the average polyline is finally identified.

Admittedly hurricanes occupy far more areal space than the zero width of polylines. However, this should not detract from the usefulness of the averaging technique which is strictly designed to measure the linear movement of hurricanes over geographic space. Nevertheless, we are currently investigating modifications that would incorporate some measure of width as well as length. Experiments are underway to explore a range of spatial tessellations that would add a variable width dimension to linear objects according to storm intensities. An areal tessellation may also become an alternative to distance surfaces and interpolated isolines, although a trade-off remains between statistical expediency and visual communication. By incorporating wind speed, work is also underway on the benefits of vectorizing the polylines; in other words, add magnitude to their direction. In the meantime the current method of averaging polylines serves an immediate purpose for summarizing hurricane tracks. Whether it is applicable for summarizing spatial patterns in other severe atmospheric phenomena or as perhaps animal migratory routes, and maybe even traffic and pedestrian flows, remains a research challenge.

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