



Hurricane track forecast cones from fluctuations

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Trajectories of tropical cyclones may show large deviations from predicted tracks leading to uncertainty as to their landfall location for example. Prediction schemes usually render this uncertainty by showing track forecast cones representing the most probable region for the location of a cyclone during a period of time. By using the statistical properties of these deviations, we propose a simple method to predict possible corridors for the future trajectory of a cyclone. Examples of this scheme are implemented for hurricane Ike and hurricane Jimena. The corridors include the future trajectory up to at least 50 h before landfall. The cones proposed here shed new light on known track forecast cones as they link them directly to the statistics of these deviations.

Tropical Cyclones (TCs), otherwise known as hurricanes or typhoons, are extreme atmospheric events which can be devastating upon landfall in populated areas. Several schemes are used to predict their trajectories^{1,2}. Some predictions are based on the knowledge of previous hurricane tracks in the geographical area of interest and others use full scale numerical simulations¹. Different statistical analyses are also carried out on the nature of the trajectory (i.e. linear versus recurved) for different basins, on the mean velocity and the deviations from predicted tracks, and on the landfall probability for different regions^{3–8}. Since trajectories of TCs show large deviations from a generally predictable mean trajectory (which could be linear or recurved), prediction schemes can be imprecise, giving the statistical approaches a legitimate place. These deviations are difficult to predict as they are due to different factors such as the proximity of land and its topography, variations in the surrounding large scale flow, or modifications of the vortex structure itself¹. In fact, track predictions usually include an estimate of the deviation of the trajectory from the predicted track in the form of so called track forecast cones which are based on error statistics from previous hurricane tracks as compared to predictions.

Here we show that the statistical properties of these deviations, from say a predictable simple linear track, can be used to determine possible corridors or track forecast cones for TCs. This is based on recent observations suggesting that the deviations of the trajectory of generic vortices or TCs from a mean trajectory can be modeled with a universal law⁹ for their so called mean square displacement. This law appears for the random movement of generic vortices in two dimensions as has been shown in experiments and numerical simulations^{9–11}. In particular we suggest that track forecast cones available today can be linked directly to this measure of the trajectory deviations around a mean and that unless these deviations can be understood, and the factors giving rise to them are fully taken into account in models and simulations, reducing such uncertainty will be a difficult task.

The mean square displacement (MSD), a notion borrowed from statistical physics and the study of Brownian motion, is a measure of the deviation from a mean trajectory. A classical example where this notion has gained all its importance is that of a colloidal particle in a simple fluid. In the absence of flow, the particle, subject to thermal agitation of the surrounding fluid, will have a position which fluctuates in time. If this position is denoted X , the MSD is defined as follows: $\langle (X(t + t') - X(t'))^2 \rangle$ (the brackets denote an average over time t') where $X(t)$ is the instantaneous position of the particle at time t . As this position varies erratically in time, the particle will explore a certain area which is given by the MSD. According to statistical mechanics $\langle (X(t + t') - X(t'))^2 \rangle = Dt$ where D is the so called diffusion coefficient which depends on the temperature, the radius of the particle and the viscosity of the fluid. This is known as normal Brownian diffusion. If a mean flow of constant velocity V_X steers the particle in a particular direction, the position of the particle will have a fluctuating component $\delta X(t)$ and a deterministic part given by the mean flow: $X(t) = V_X t + \delta X(t)$. In this case, the fluctuating part will have a MSD given by the previous expression while the mean position increases as $V_X t$. While normal diffusion describes a large set of random movements, anomalous diffusion may occur under certain conditions. Perhaps the most famous example is random movement in the presence of so called Levy flights^{12,13} where the particle exhibits large jumps



from time to time in its trajectory. A general form of the MSD is suggested by the expression $\langle (X(t+t') - X(t'))^2 \rangle \sim t^\alpha$ where the exponent α may take values smaller (subdiffusion) or larger (superdiffusion) than 1. Several examples of superdiffusion have been observed experimentally such as the case of an object in a turbulent flow for example. Superdiffusive behavior can be related to the interaction between the object and the medium^{12,13}. Examples of entities that interact with the medium itself have been illustrated in the case of passive beads in a bath of self-propelling bacteria¹⁴, and the movement of passive beads in a laminar rotating flow¹⁵. The isolated vortices, discussed below to illustrate the role of fluctuations, are randomly kicked by the turbulent agitation of the flow. These vortices must have an important reaction on the medium itself. The movement of vortices is also sensitive to the sign of vorticity variations¹⁶ which in a turbulent medium may show a complicated spatial and temporal distribution giving rise to a non trivial interaction with the moving vortex. TCs are also entities that interact with the surrounding flow, the topography, and that may change structure in the course of their movement giving possible reasons for changing course and engendering deviations from a simple track.

Results

As a way to introduce the concept of mean square displacement and show how it can be implemented for TCs, we illustrate this behavior using experiments on soap bubbles first. Indeed when half a soap bubble, deposited on a plate that is heated from below at temperatures in the range 35 to 60°C, thermal convection can be observed around the equator of this half bubble^{9,17}. As the temperature increases, the thermal plumes emitted from the heated part of the half bubble start to reach higher heights. This agitation produces, from time to time, single vortices of a few centimeters in diameter and that wander around the bubble as shown in the inset of figure 1 where the trajectory of this vortex presents noticeable fluctuations around a mean position. This can be seen for both longitude and latitude. When this signal is analyzed to extract the MSD of the vortex versus time, $\langle (X(t+t') - X(t'))^2 \rangle$, we obtain a well-defined dependence in the form of a power law with an exponent that is higher than 1 as seen in figure 1. Note that the longitude and latitude (denoted Y and X) show roughly equal amplitudes for the MSD meaning that the fluctuations are isotropic. Also, the exponent coming out of this analysis turns out to be independent of temperature

and soap concentration and has a value around $\alpha = 1.6^\circ$. The fact that the exponent is higher than 1 indicates that these vortices exhibit so called superdiffusion attributed to large and random jumps⁹.

It is this observation that has guided us to look for such a behavior in the movement of TCs, which are large scale single vortices. Indeed, for generic vortices in two dimensional turbulent flows^{10,11} and for TCs⁹, the trajectory shows important deviations from a mean track. In the case of TCs, a displacement along a preferred direction with a non zero velocity is usually present. However, the MSD of the fluctuating part due to the deviations from a mean trajectory (when the mean drift has been subtracted) turns out to increase with time following a well-defined power law versus time⁹. This MSD can be written as: $\langle (\delta X(t+t') - \delta X(t'))^2 \rangle = A_c(t/t_c)^\alpha$ (the brackets are an average over time t'). Here δX is the deviation from the mean trajectory in either longitude or latitude, A_c is the value of the MSD at $t = t_c$, and t_c is a characteristic time. The exponent α has a value near 1.65 indicating superdiffusion.

Here, we show through an analysis of an extended set of TC trajectories in different basins¹⁸ that this law is obeyed very well by the great majority of TCs and for different basins. For each TC, and in order to extract the deviations from a mean track, the longitude and latitude coordinates were plotted versus time separately. A linear fit was carried out to estimate the constant drift velocity of the TC in the longitude and latitude directions. This linear dependence of the position versus time defines the mean trajectory of the cyclone. When this mean linear trajectory is subtracted from the data, we obtain what we call the fluctuating part of the trajectory as shown in the example of figure 2 and in the lower inset to this figure for hurricane Jimena. At times, the variation of the longitude or latitude versus time cannot be approximated correctly using a linear law: This happens routinely when the TC is close to the coast for example. In such cases, we remove the few points that deviate strongly from a linear dependence. Basically the model we are using supposes that the TCs move along a straight mean trajectory with superimposed deviations or fluctuations. Such a simple model has also been proposed by⁷. The linear approximation of the mean trajectory is not the rule. However, a recent classification has found significant clusters of linear trajectory cyclones⁸. For the sake of comparison we have also tested a parabolic fit to the track data of the example of figure 2. Once this mean parabolic trend is subtracted from the trajectory, the deviations are again recovered as shown in the lower inset of figure 2. Note that

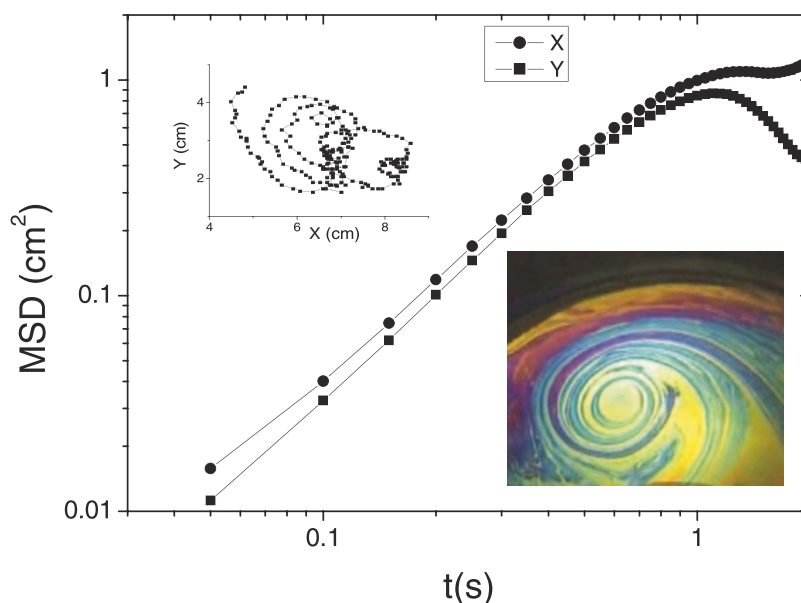


Figure 1 | Mean square displacement versus time for a single vortex in a soap bubble heated from below. Insets: photo of a vortex and its trajectory.

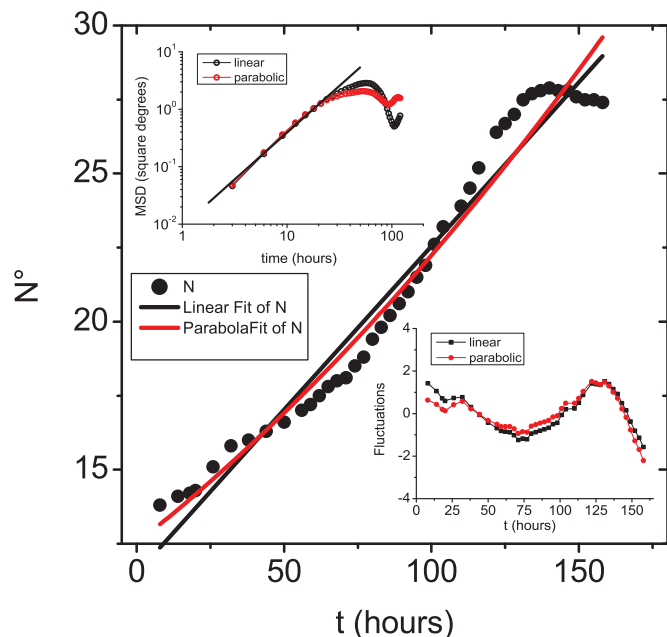


Figure 2 | Latitude versus time for hurricane Jimena. The solid line is a linear fit to the trajectory. The lower inset shows the fluctuating part after subtracting the linear part. Subtraction of a parabolic fit is also shown. The upper inset shows the MSD calculated using the the linear and parabolic trajectory.

these deviations though different from the previous ones, obtained by subtracting the linear dependence, bear much resemblance to them. Note that the MSD of the example of figure 2, shown in the upper inset, for both the linear and parabolic mean trajectories are superimposed for the short times showing that the parameters of the power law regime are hardly affected in this example by the use of a linear or parabolic model. For this study however, and for the simplicity of implementing our analysis, we have only considered the linear track approximation despite its limitations. From such linear fits to the data (see figure 2), we extract the mean velocity of the TC. Once this is achieved, the MSD is calculated using the fluctuating part of the trajectory (see lower inset of figure 2). Examples of the MSD for a few TCs are shown in figure 3a and b for the longitude and latitude respectively. Note that the MSD follows the power law stated above as delimited by the dashed lines and as has been suggested previously. Here the latitude shows less fluctuations than the longitude indicating anisotropy of the calculated deviations. At long times, the MSD no longer follows a power law and seems to either flatten out or go through a broad maximum. This effect may be simply due to a lack of statistics at long times but it may also signal a lack of correlation at these times which is the most probable cause.

We now determine the parameters of the power law for each TC. By fixing the amplitude $A_c = 10$ square degrees, the only free parameter for the power law is the time constant. We determine the time constant t_c from such graphs as shown in figure 3 by simply reading off the time for which the amplitude is A_c . This time constant is then extracted for a large number of TCs in different basins (over 500 trajectories have been examined for the purpose of this study). In addition to this time constant we also extract the exponent of the power law dependence of the MSD using a best fit method. We now have the three parameters characterizing our simple model: the drift velocity, the time constant, and the exponent. One may then look at the statistics of these quantities for each basin separately or for all basins analyzed and examine the validity of this simple model.

The global result can be illustrated in the form of histograms of the quantities extracted. Let us first take a look at the histogram of exponents. This histogram, shown in figure 4 a and b for the

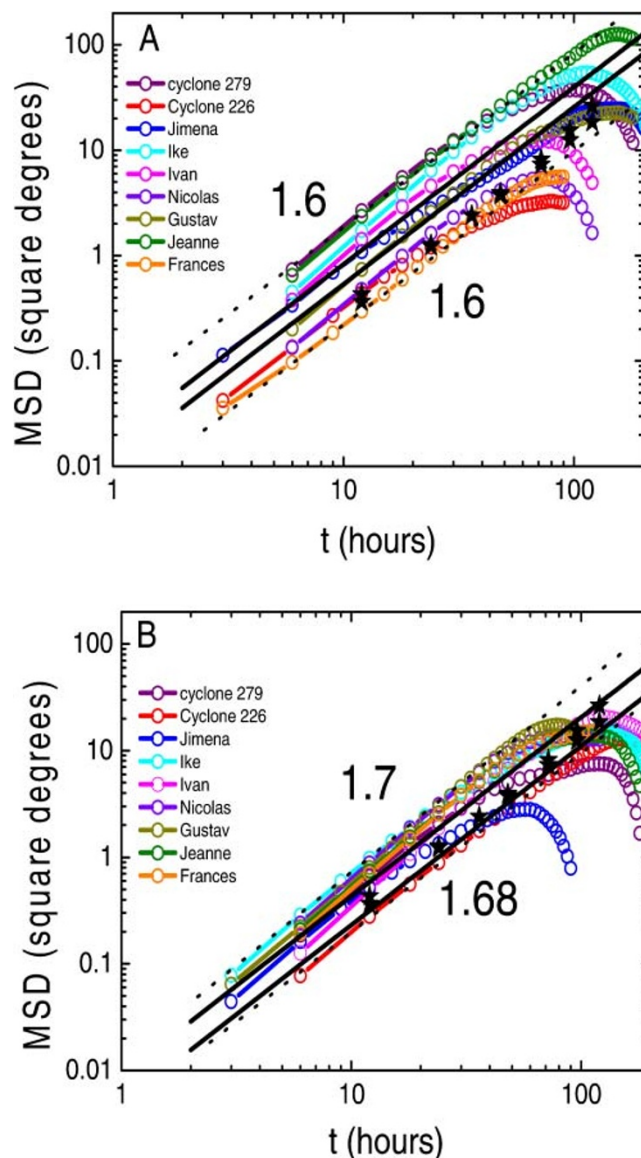


Figure 3a and 3b | Mean square displacement of longitude and latitude respectively for 9 different TCs versus time. Cyclones noted 226 and 279 are in the Indian Ocean dated 27/05/2005 and 08/05/2003 respectively. The black stars on this graph indicate the square of the circle radii (in square degrees) used to predict track forecast cones of the National Hurricane Center. The dashed lines indicate power laws with the indicated exponent to delimit the observed behavior. The solid lines use t_c extracted from the peak of the histograms (upper curve) of figure 4 or the mean value (lower curve).

longitude and latitude, shows a well-defined peak at a value of 1.65. Despite the spread in values most cyclones (see cumulative probabilities in the insets), over 70%, are well described by an exponent between 1.5 and 1.8. No difference is observed between the longitude and latitude analyses nor for the different basins examined. Most TCs therefore show deviations characterized by a power law for the MSD.

Let us now take a look at the characteristic times. Here again the histograms of figure 5a and b (for all basins with no distinction) show a well defined peak for each component with a difference between the longitude and latitude components (indicating anisotropy) and again despite the spread in values, a well defined peak is clearly seen for both components. This peak is at 40 hours for the longitude and 60 hours for the latitude. The mean value of t_c is 55 h for the longit-

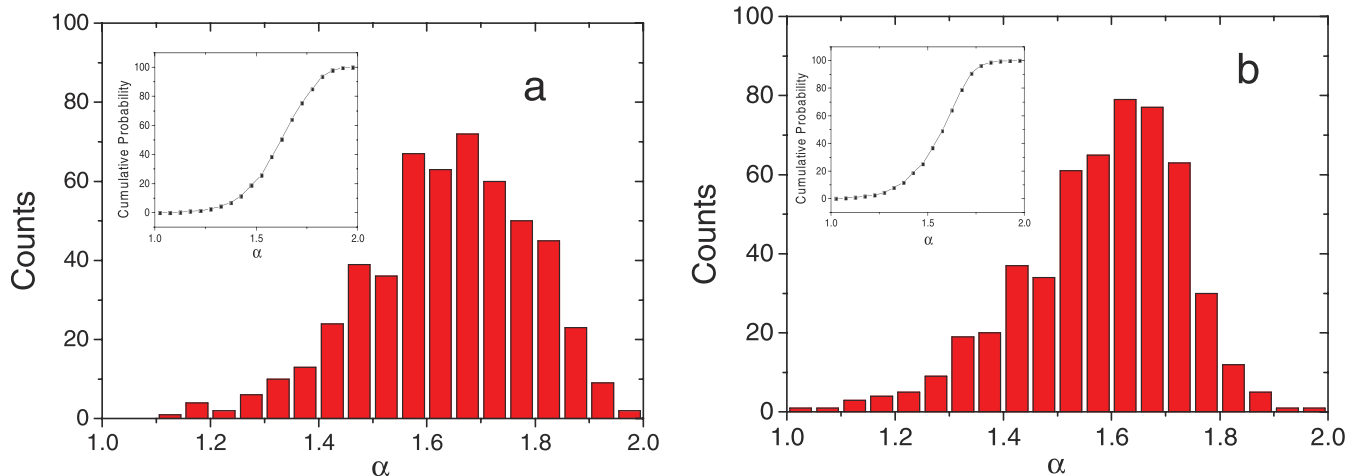


Figure 4 | histograms of the exponent α along with the cumulative probability. a is for longitude and b is for latitude.

ude and near 100 h for the latitude. From the cumulative probability, about 60% of TCs have characteristic times between 20 and 80 hours for longitude and 40 and 100 hours for latitude. Note that differences between basins can also be detected in this measure with the Atlantic basin giving the smallest times. Figure 6 shows histograms by basin along with the mean values found. Note that different basins show variations in the mean value of t_c and in the position of the peak. The Atlantic basin shows the smallest characteristic times indicating stronger deviations than other basins. In general, longitude shows stronger deviations than latitude.

In figure 3, showing the MSDs, we show the computed average MSD using the mean values extracted from our histograms (for all basins) for the exponent and the time constant. These are the solid lines in this graph. The upper one uses the characteristic time from the peak position of the histogram while the lower line uses the mean value of t_c . Note that the computed MSDs are in good agreement with the general trend. A surprising result comes from comparing the MSD calculated to the mean deviation from the predicted trajectories used to estimate track forecast cones. This data, obtained from the National Hurricane Center web site¹⁹, is displayed as black stars in figure 3, which shows that this mean deviation also follows a power law as for the MSD suggesting that the error in forecasting as represented by the track forecast cones seems to be related if not given by the MSD calculated here.

Discussion

We suggest that the power law we have uncovered here through an extensive analysis of TC trajectories, can be used to predict, in a simple, quick, and cheap way, corridors for the movement of these structures. The principle of this prediction scheme is as follows and an illustration is shown in figure 7. This estimate assumes that the hurricane follows a smooth mean trajectory around which deviations occur with statistics that are well described by the power law stated above for the MSD. Suppose now that some previous positions are known. We first determine a mean tendency for the later movement of the structure based on these previously known positions. The simplest possible tendency is that the structure will just continue along a straight line at a velocity V_X given by the last known positions versus time. Our tests of this hypothesis turned out to be reasonably correct for most cyclones analyzed (see figure 2). Since the future trajectory will deviate from the mean track, supposed to be linear here, the MSD is used as a measure of this deviation by writing the displacement $X(t) = V_X t \pm \sqrt{A_c((t-t_0)/t_c)^{\alpha}}$. Here $X(t)$ refers to either longitude or latitude. The first term is the mean linear trajectory with a constant speed V_X and the second term measures the deviation from this assumed trajectory with t_0 being the time at which the prediction starts. As we have shown above, the majority of TCs we have analyzed show such a tendency as they exhibit a mean trajectory with superimposed deviations. Figure 7 shows the result of

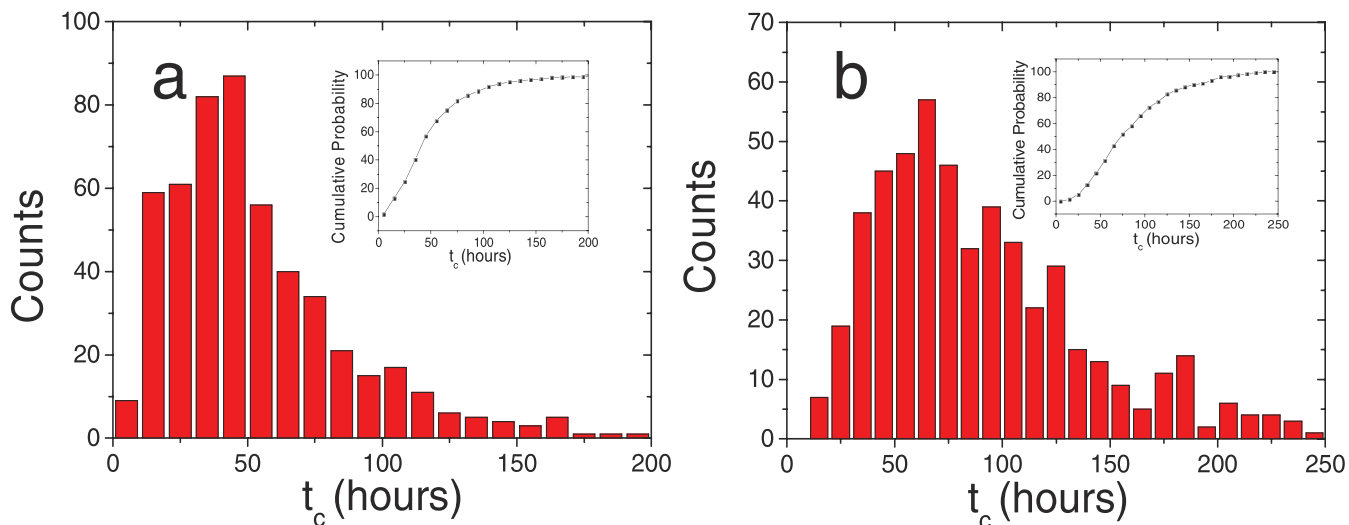


Figure 5 | histograms of t_c for all basins along with the cumulative probability. a is for longitude and b is for latitude.

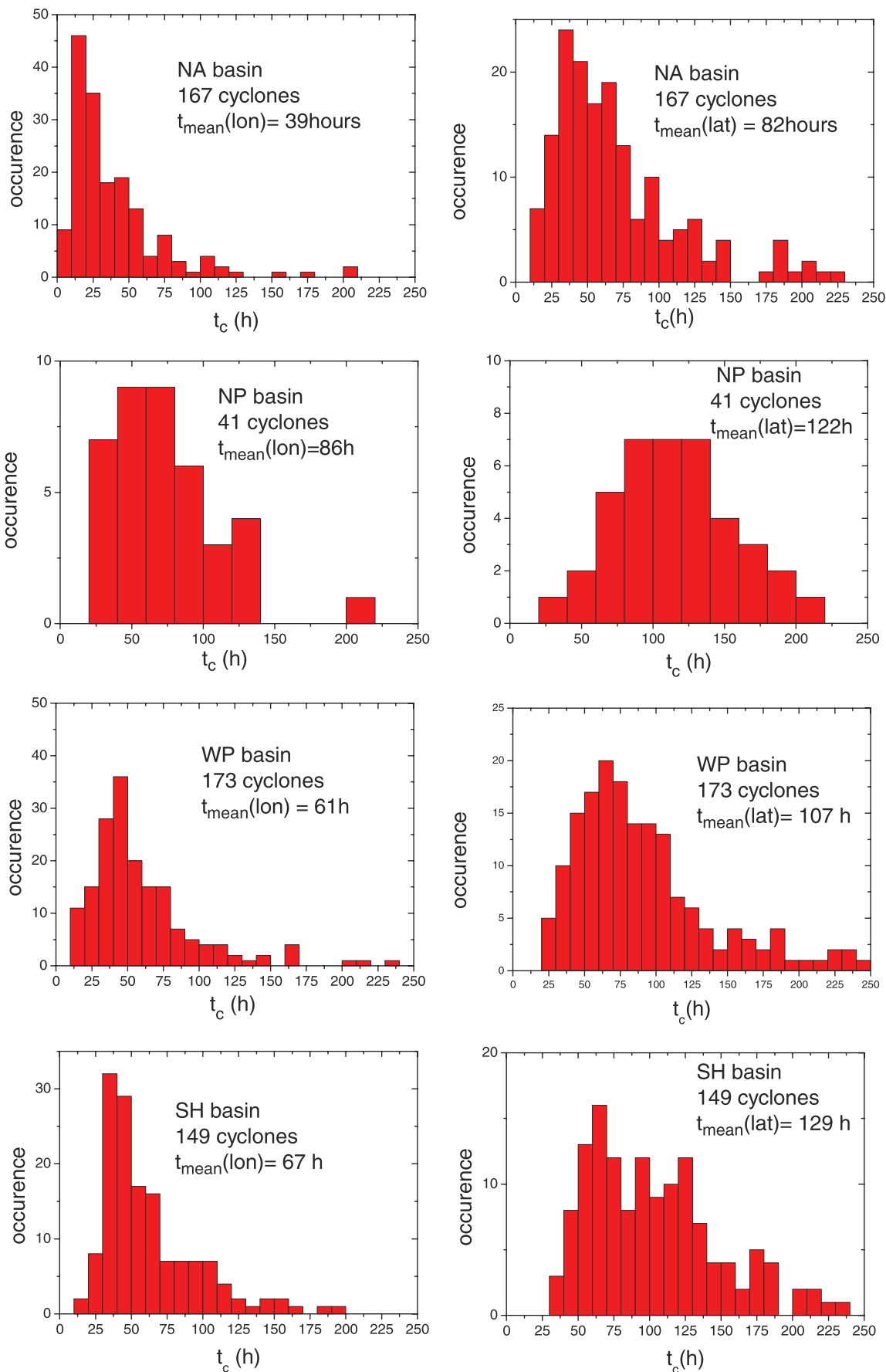


Figure 6 | histogram of t_c for different basins, longitude on the left and latitude on the right: NA= North Atlantic; NP= northeast Pacific; WP= western North Pacific.

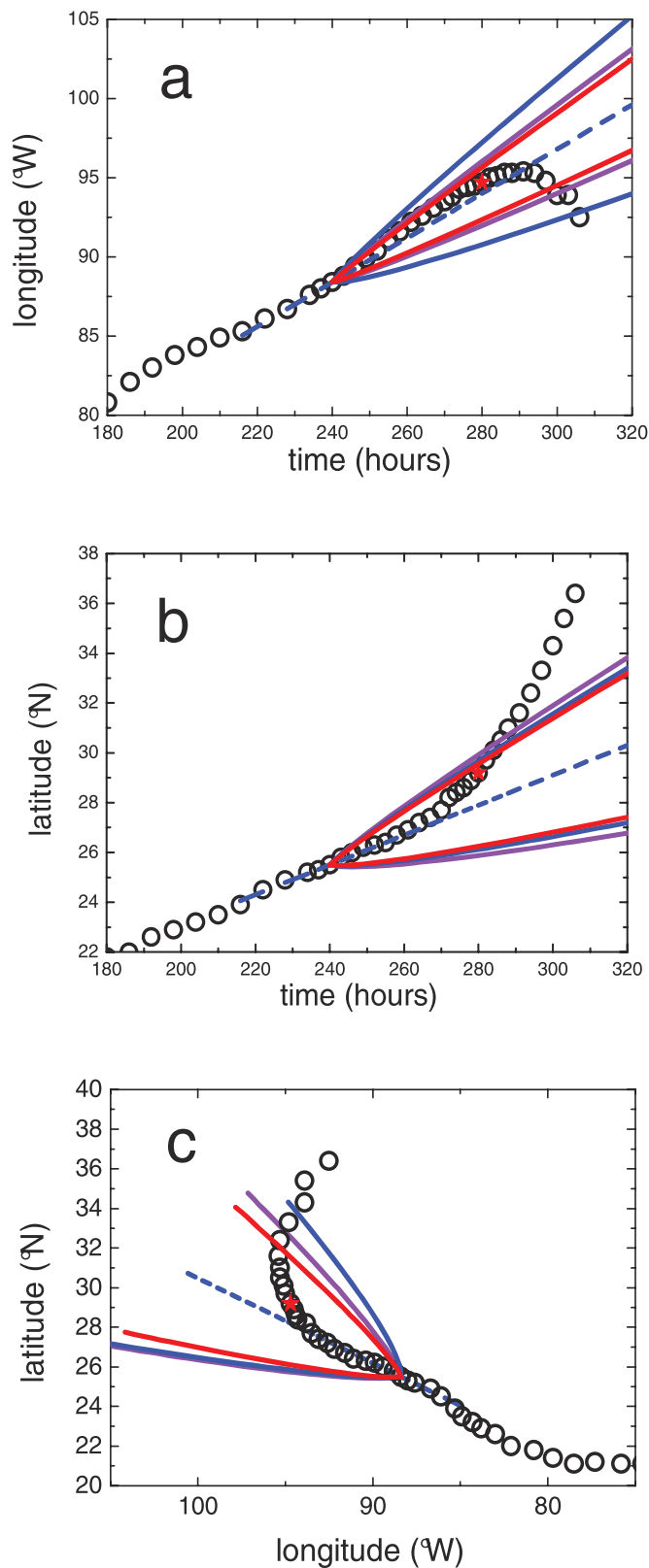


Figure 7 | Implementation of the proposed scheme for hurricane Ike (2008): a) longitude b) latitude (open circles) versus time near landfall (red dot). The blue dashed line is the linear prediction 40 hours before landfall. The blue solid lines delimit the predicted cone using the mean values of t_c for the Atlantic basin. The magenta line uses the t_c calculated from the MSD of the trajectory before the prediction point, the red line is the NHC forecast cone. Panel c shows the trajectory in a latitude versus longitude plot (same symbols as a and b). The hurricane trajectory is obtained from the National Hurricane Center web site.

this corridor prediction for hurricane Ike (2008), which hit the coast of Texas at Galveston. The corridor prediction is started 40 hours before landfall. Actually, the prediction can be restarted after each new data point by simply recalculating the velocity V_x and using the new t_0 to obtain a new cone. This figure shows the full trajectory of the cyclone in the form of circles. The dashed line is the supposed linear trajectory with a velocity determined using the last known positions; this is the supposed linear path if the hurricane were to continue along a straight track with a constant velocity. The full lines represent the predicted cone using the expression above. The prediction starts at the intersection between the two full lines (i.e. at $t = t_0$). An important feature here is that the future trajectory of the hurricane remains confined within this cone for a time comparable to but smaller than the time period for which the power law above is valid as panels a and b of figure 7 show for longitude and latitude versus time. Beyond this time scale (which is typically between 60 and 100 hours, see figure 3), the power law for the MSD is no longer valid so the corridor estimate breaks down. Figure 7c shows the corridor in a latitude versus longitude graph. Note that the landfall location, marked by a red dot, is very well captured by the corridor despite the fact that Hurricane Ike drifts sharply to the north east after landfall. This scheme can be implemented on different hurricanes. Figure 8 shows an implementation of the proposed scheme for Hurricane Jimena (2009) in the western Pacific basin. This is shown for longitude and latitude versus time as well as in a latitude versus longitude plot. Again, the corridor proposed includes the landfall location. The cones shown use the mean value of t_c extracted from the statistical analysis shown above for each basin (i.e. North Atlantic for Ike and North Eastern Pacific for Jimena). In fact, such a scheme, and if the TC has been tracked for a long enough time, can also use the t_c calculated from the past trajectory of the cyclone itself. If the considered TC has less or more deviations from the calculated mean, the predicted cone using the actual data from the trajectory of the specific cyclone considered will take this into account and provide a more realistic estimate for the forecast cone. This is illustrated for the two hurricanes in figures 7 and 8 where the cones shown use three different values, the mean characteristic time for the basin considered, the characteristic times calculated from the past trajectory, as well as the values given by the NHC cone for the relevant basin. We believe that both schemes (the use of a mean characteristic time, or the use of the characteristic time extracted from the MSD of the past trajectory of the cyclone itself) can be implemented. This latter procedure would therefore take into account the inherent variability from cyclone to cyclone and provide a means to make TC-specific forecast cones. In the case where the TC is nearing landfall, the use of the parameters given by the past trajectory of the cyclone itself would be feasible since a sufficient number of locations would already be at hand. This procedure, which has the advantage of being cheap and fast to implement, could complement other TC-specific forecast cones such as those obtained from ensemble schemes^{20,21} which are better at including the variability in initial conditions.

Since forecast agencies use a fixed probability (67th percentile for the NHC for example) to determine the forecast cones while our scheme proposes a different method, namely a measure of the deviation from a supposed mean trajectory, a question arises as to how these two schemes compare with each other. To answer this question we tracked the probability that the TC remains within the cone for up to 5 days in the North Atlantic basin. The cones used are those for longitude and latitude versus time. It turns out that for the case where a linear mean track is assumed, the probability that the track remains within the cone is roughly constant and around 63%. If on the other hand, the velocity of the TC is determined using only the last 2 known positions before the prediction, the probability for 12 h, 24 h, and 36 h can be much better with 91, 81, and 71% respectively. In both cases, the use of the characteristic time is that of the TC itself so the cone is cyclone-specific. This scheme can therefore be very

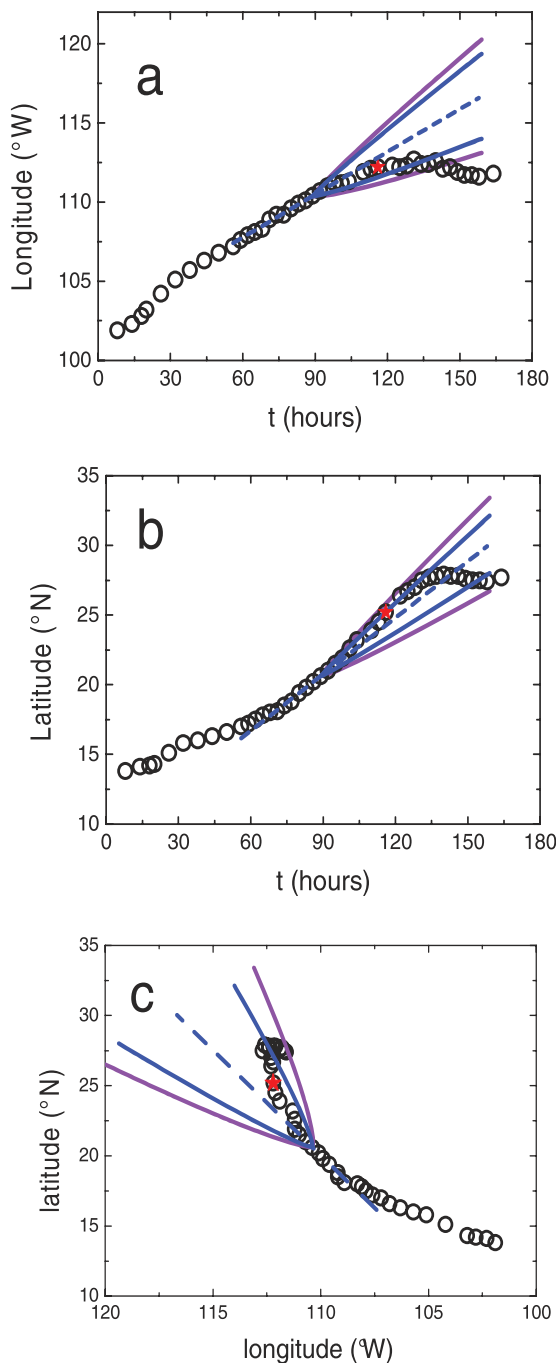


Figure 8 | Implementation of the proposed scheme for predicting hurricane forecast cones for hurricane Jimena (2009). Panel a and b with symbols as defined in the caption of figure 7, illustrate the cone for longitude (a) and latitude (b) versus time. Panel c shows a similar plot as 7c for hurricane Jimena (2009) which made landfall in Baja California in Mexico (the mean characteristic time is for the North eastern pacific basin). Note that the landfall position (red dot) is well captured by the cone started 27 hours before landfall.

useful near landfall and up to at least 36 h since the parameters characterizing the TC would be known from the previous trajectory. A further improvement of this probability can be obtained by taking into account the fluctuations in speed of the TC, which can be estimated from the previous trajectory before the prediction starts. If one uses the mean velocity determined from say the previous 5 known

best track positions, and instead of V_X , we use $V_X \pm V_{rms}$, to take the fluctuations of speed into account (V_{rms} is the root mean square of the velocity averaged over 5 positions and obtained using the known trajectory before the prediction starts), the probabilities are better than 80% for up to 5 days.

The suggested scheme therefore uses the statistical properties of the deviations in hurricane motion from a mean track to delimit the departure from a predicted trajectory. The cones proposed here shed new light on available track forecast cones, to which they compare very well, by linking them directly to the statistics of these deviations. In fact, the track forecast cones used by the National Hurricane Center also follow the power law found here suggesting that deviations from predicted tracks are captured by the behavior of the MSD very well. Our analysis of over 500 TC trajectories allows us to validate our proposal. The procedure suggested here also allows to make TC-specific forecast cones especially near landfall through a cheap, quick, and simple calculation of the MSD of the known part of the trajectory.

Methods

For the experiments using the soap bubble, the experimental techniques were described in⁹ and¹⁷. For all the trajectory data, the analysis of the fluctuations and the calculations of the MSDs were carried out using home made software.

1. 'Global Perspectives on Tropical Cyclones' Edited by Chan, J. C. L. & Kepert, J. D. World Scientific Publishing Co. (2010).
2. Emanuel, K. Tropical Cyclones. *Annu. Rev. Earth and Planet. Sci.* **31**, 75–104 (2003).
3. Fraedrich, K., Morison, R. & Leslie, L. M. Improved tropical cyclone track predictions using error recycling. *Meteorol. Atmos. Phys.* **74**, 51–56 (2000).
4. Brettschnieder, B. Climatological Hurricane landfall probability for the United States. *J. Appl. Meteorology and Climatology* **47**, 704–716 (2008).
5. Leslie, L. M. Abbey Jr. R. F. & Holland, G. J. Tropical cyclone predictability. *Meteorol. Atmos. Phys.* **65**, 223–231 (1998).
6. Leslie, L. M. & Abbey, Jr. R. F. Hurricane predictability: are there simple linear invariants within these complex nonlinear dynamical systems? *Meteorol. Atmos. Phys.* **74**, 57–62 (2000).
7. Hall, T. & Jewson, S. Statistical modeling of North Atlantic tropical cyclone tracks. *Tellus* **59A**, 486–498 (2007).
8. Camargo, S. J., Robertson, A. W., Gaffney, S. J., Smyth, P. & Ghil, M. Cluster analysis of Typhoon tracks. Part I: General properties. *J. Climate* **20**, 3635–3653 (2007).
9. Seychelles, F., Amarouchene, Y., Bessafi, M. & Kellay, H. Thermal convection and emergence of isolated vortices in soap bubbles. *Phys. Rev. Lett.* **100**, 144501 (2008).
10. Kawahara, R. & Nakanishi, H. Slow relaxation in two-dimensional electron plasma under strong magnetic field. *Journal of the Physical Society of Japan* **76**, 074001 (2007).
11. Yoshida, T. Universal dependence of the mean square displacement in equilibrium point vortex systems without boundary conditions. *Journal of the Physical Society of Japan* **78**, 024004 (2009).
12. 'Levy Flights and Related Topics in Physics', edited by Shlesinger, M. F., Zaslavsky, G. M. & Frisch, U. Lecture Notes in Physics (Springer-Verlag, Berlin, 1995).
13. Bouchaud, J. P. & George, A. Anomalous diffusion in disordered media: statistical mechanics, models and physical applications. *Physics Reports* **195**, 127–293 (1990).
14. Wu, X. L. & Libchaber, A. Particle diffusion in a quasi-two-dimensional bath. *Phys. Rev. Lett.* **84**, 3017–3020 (2000).
15. Solomon, T. H., Weeks, E. R. & Swinney, H. L. Observation of anomalous diffusion and Lévy flights in a two dimensional rotating flow. *Phys. Rev. Lett.* **71**, 3975–3978 (1993).
16. Schecter, D. A. & Dubin, D. H. E. Vortex motion driven by a background vorticity gradient. *Phys. Rev. Lett.* **83**, 2191–2194 (1999).
17. Sechelles, F., Ingremau, F., Pradere, J. C. & Kellay, H. From intermittent to nonintermittent behavior in two dimensional thermal convection in a soap bubble. *Phys. Rev. Lett.* **105**, 264502 (2010).
18. Data for Southern hemisphere, North Indian Ocean, North West Pacific are obtained from JTWC (Joint Typhoon Warning Center), http://www.usno.navy.mil/NOOC/nmfcph/RSS/jtwc/best_tracks/, website last accessed in December 2011). Data for North Atlantic and North Eastern Pacific are obtained from the NHC web site last accessed in December 2011.
19. <http://www.nhc.noaa.gov/aboutcone.shtml>. Website last accessed on the 18th of April 2012.
20. Yamaguchi, M., Sakai, R., Kyoda, M., Komori, T. & Kadowaki, T. Typhoon ensemble prediction system developed at Japan Meteorological Agency. *Monthly Weather Review* **137**, 2592–2604 (2009).



21. Dupont, T., Plu, M., Caroff, P. & Faure, G. Verification of ensemble based uncertainty circles around tropical cyclone track forecasts. *Weather and Forecasting* **26**, 664–676 (2011).

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Author contributions

All Authors contributed to data analysis. H. K. wrote the paper.

Additional information

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