Extended Abstract:
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Large ensemble tropical cyclone forecasting

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1. Introduction

Tropical cyclones (TCs) are inherently difficult to predict. Despite substantial recent improvements in track and to a lesser extent in intensity forecasts, there still remain many challenges. Correctly predicting TC intensity is particularly difficult, due to small–scale processes that range from fluctuations in intensity due to eyewall replacement cycles, to fluctuations due to storm–scale processes that greatly depend on the track, and interactions with the large scale environment. These interdependencies cause TC forecasts to be probabilistic by nature.

The benefit of using ensembles requires that a large number of model runs be realized for any given situation, so that the potential spectrum of possible outcomes can be extracted. One of the difficulties with this approach is the need to effectively communicate the spread of results from hundreds (or more) ensemble members in a manner that is easy to understand and to use in decision–making.

We present here some visualization approaches for large ensemble TC forecasting. The focus will be on providing information on the range of potential outcomes, both spatially and temporally. This can only be a static presentation, but in an interactive setting the display system should allow the user to easily modify, subdivide, set parameters for, and animate these plots. Section two provides a brief overview of the data and methodology used, section three discusses the results and a brief summary concludes the paper.

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2. Data and Methodology

This study uses deterministic and ensemble forecasts from the European Centre for Medium–Range Forecasts (ECMWF), issued twice per day at 0000 and 1200 UTC. The ensemble forecasts consist of 51 ensemble members. ECMWF provides track data for each ensemble member. The data used here is on a 2° latitude/longitude grid, with 17 vertical levels from the deterministic forecast, and with 850 and 250 hPa winds from the ensemble forecasts.

Emanuel's downscaling technique (Emanuel et al., 2006) is applied to data that are derived from deterministic and ECMWF ensemble forecasts. The method employed includes the generation and analysis of a large number of potential tropical storms that can be supported by the large–scale environment provided in the ensemble data. The derivation of the large–scale environment is accomplished by surgically removing the ECMWF storms from each ensemble member using a vorticity filter (see Fig. 1). A large number of TC tracks are generated using the

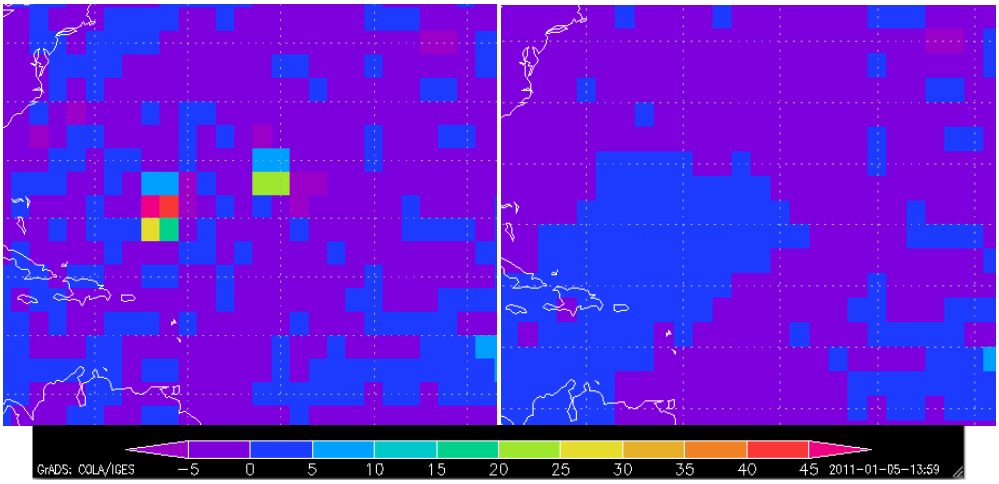

Figure 1: Example of vorticity filter at 850 hPa, for Igor on 1200 UTC 18 Sep 2010. The unfiltered relative vorticity field (10^{-5} ms^{-2}, left panel) shows the positions of Igor (westernmost vorticity maximum) and Juliette (vorticity maximum to the northeast of Igor). The filtered vorticity field (right panel) shows that the TCs have been effectively removed.

method of Emanuel et al. (2008), with the covariances derived from both the ECMWF storm tracks and the large-scale environmental winds. The Coupled Hurricane Intensity Prediction System (CHIPS, Emanuel et al. 2004 and Emanuel 2006) is then used to predict storm intensities along each of the generated tracks, as shown in Figure 2. In the final step, the simulated tracks and intensities are used to generate a large ensemble of wind fields, which in turn can be further used for post–processing and visualization. Some examples of visualizing the results are shown in the next section.

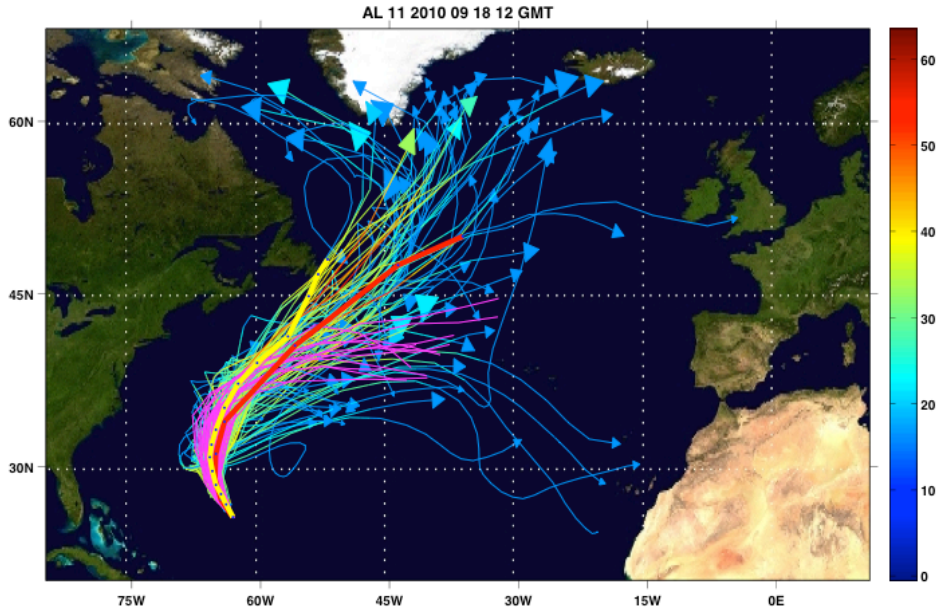

Figure 2: An example of generated track forecasts for Igor on 1200 UTC 18 Sep 2010. The wind speeds are colored according to colorbar (in knots) to the right, and the arrows at the end of the tracks indicate the translation speed of the tracks. Also shown are the 51 ECMWF ensemble tracks (purple), the official NHC forecast (bold red line), as well as the observed track (bold yellow line with blue dots every 12 hours).

3. Results

The map presented in Fig. 2 shows an example of the spatial distribution of the generated ensembles for a particular forecast. An understanding of the temporal evolution, in turn, can be obtained by visualizing the distribution along a timeline, as shown in Figure 3. Here, the maximum wind speeds, in knots, of 100 individual ensemble members are shown as a function of time (days since initialization). The range of the daily track intensities is further summarized in the overlaid boxplot, which in this case is based on the full ensemble set of 1000 generated tracks. The boxes encompass the 25th and 75th percentiles, and the whiskers extend to encompass all points that are not considered outliers. Outliers are plotted as red plus signs outside of the distribution. The red thin line in the interior of the box represents the median of the distribution. The intensities for the contemporaneous official forecast from NHC (red line) and the final best track (yellow line) are also shown. As can be as time increases, some simulated storms die out and the number of tracks decreases. For example, the boxplot for day 1 represents the distribution statistics for 1000 ensemble members, whereas at day 4 the number of tracks represented in the boxplot is reduced to 562, and at day 9 the number of tracks remaining is 16.

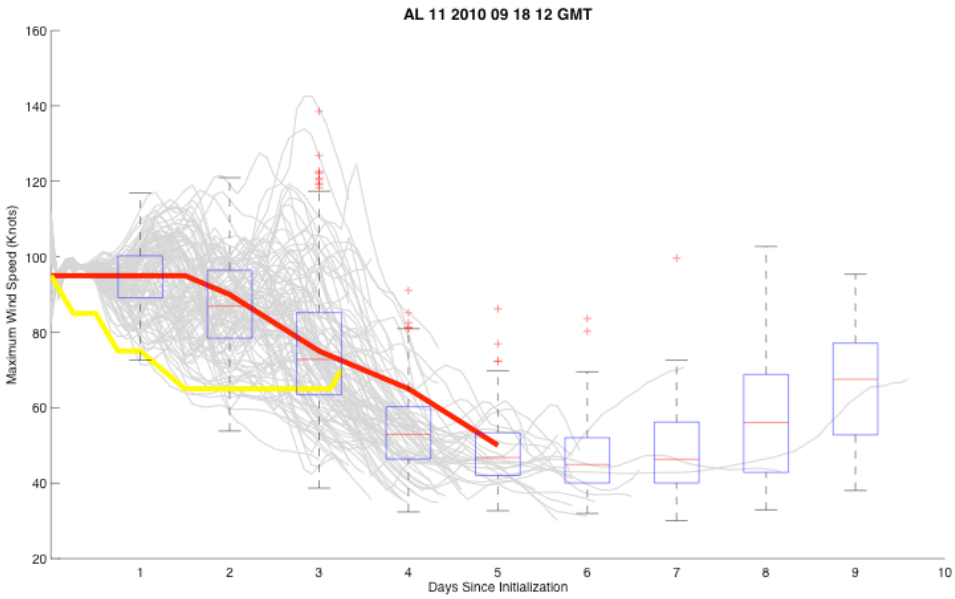

Figure 3: Intensities for 100 ensemble tracks (gray lines), overlaid with boxplots based on the 1000–member ensemble. The intensities for the contemporanous official forecast from NHC (red line) and the final best track (yellow line) are also shown.

By separating tracks according to some user–defined attribute, such as track position in latitude and longitude, more information can be extracted, as shown in Figure 4. A *k*–mean clustering technique has been applied to the storm tracks, which identifies three separate path regions as indicated by the red, blue and green colored paths (left panel), and a time series of intensity has been prepared using the same cluster identifiers (right hand panel). This information can be used to help identify features from the storm environment that affect the storm, such as intensity and timing. From a real–time forecasting perspective, this can be valuable information, as this approach allows one to refine a forecast according to how the observed track of the storm matches one of the suggested clusters. In this case, if the real storm translates along the red cluster, i.e. moves further west and then recurves sharply, then it would more likely weaken faster than if it had followed a path in the blue cluster).

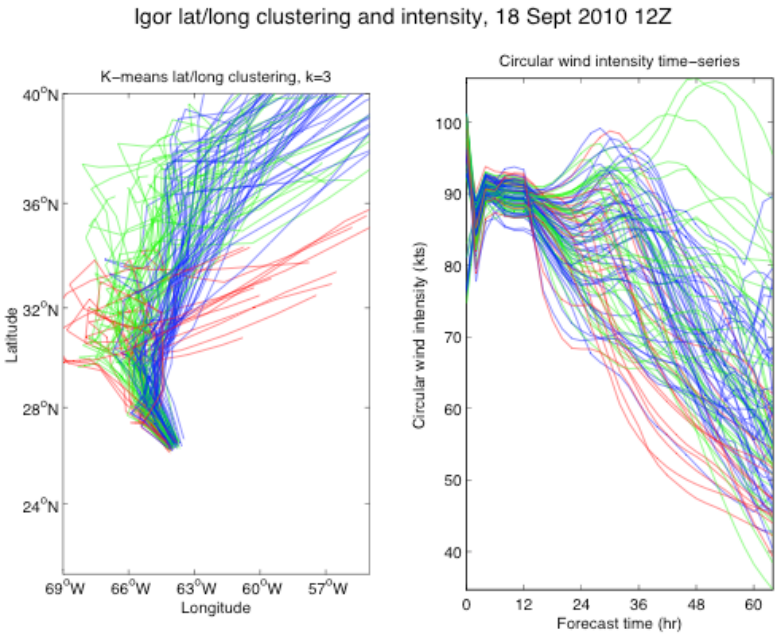

Figure 4: Results of k–mean clustering of latitude/longitude for the first 66 hours for the 100–member ensemble initialized on 1200 UTC 18 Sep 2010. The number of clusters was set to 3 in this analysis. The clusters minimize the sum of the point to cluster–centroid distances. The right hand panel shows the circular winds, i.e., translation speeds are not considered.

An example of an individual ensemble member's wind speed field is shown in Figure 5. The map shows the wind speeds for winds > 20 knots (colored contours in knots) 36 hours into the forecast (valid time is 0000 UTC 20 Sep 2010). The particular track shown passes west of Bermuda, with maximum forecast winds at Bermuda of about 60 knots. The black line shows the past positions for this track, the red line shows the contemporaneous forecast track from the NHC, and the yellow line shows the best track for Igor.

It is not convenient, however, to inspect hundreds or thousands of maps in order to assess the probable wind speed distribution for some particular location, such as Bermuda. This information is more easily conveyed by using a probability distribution of wind speed, as shown with the exceedance probabilities in Figure 6. The histogram was constructed by computing the wind speed at a given latitude and longitude for all 1000 generated storm tracks. It shows that at the target location roughly 50% of the storms are associated with wind speeds in excess of 60 knots, while only about 10% of the storms are forecast to produce 100 knot winds or more at Bermuda's airport.

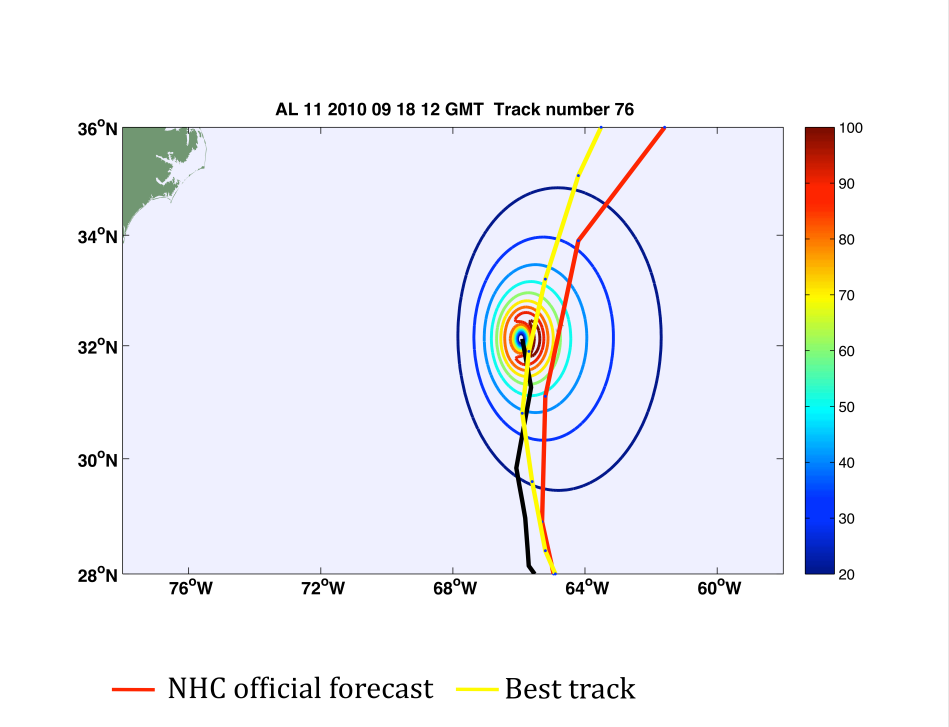

Figure 5: The 36–hour forecast wind (valid at 0000 UTC 20 Sep 2010) is contoured for winds in 20 knots or greater. The black line is the past track for this ensemble member. Also shown are the best track (yellow), and the official NHC forecast track (red).

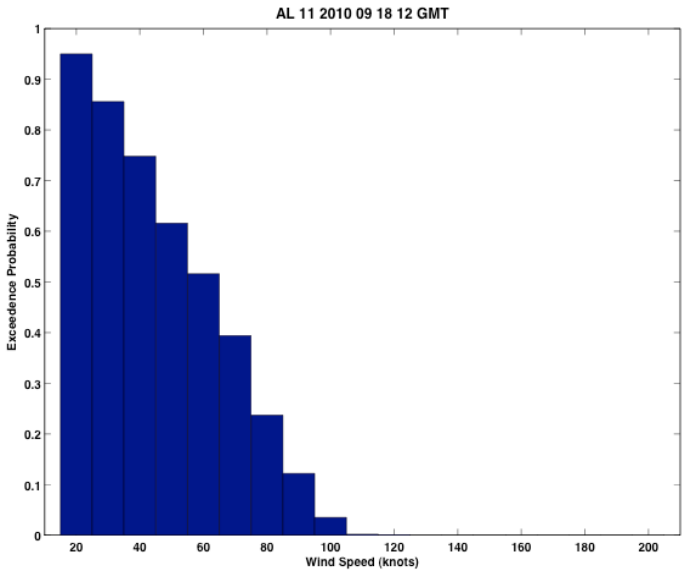

Figure 6: Exceedance probability distribution of 36–hour forecast wind speed at Bermuda airport (TXLF) using 1000 tracks.

Alternatively, a user might be interested in the spatial extent of the probability distribution. To provide this, exceedance distributions are computed for all points in the region of interest, from which exceedance probability maps can be generated. An example of this is given in Figure 7, showing the probabilities of winds exceeding the contoured wind speeds with a 50% probability (left panel) and a 90% probability (right panel) level, respectively.

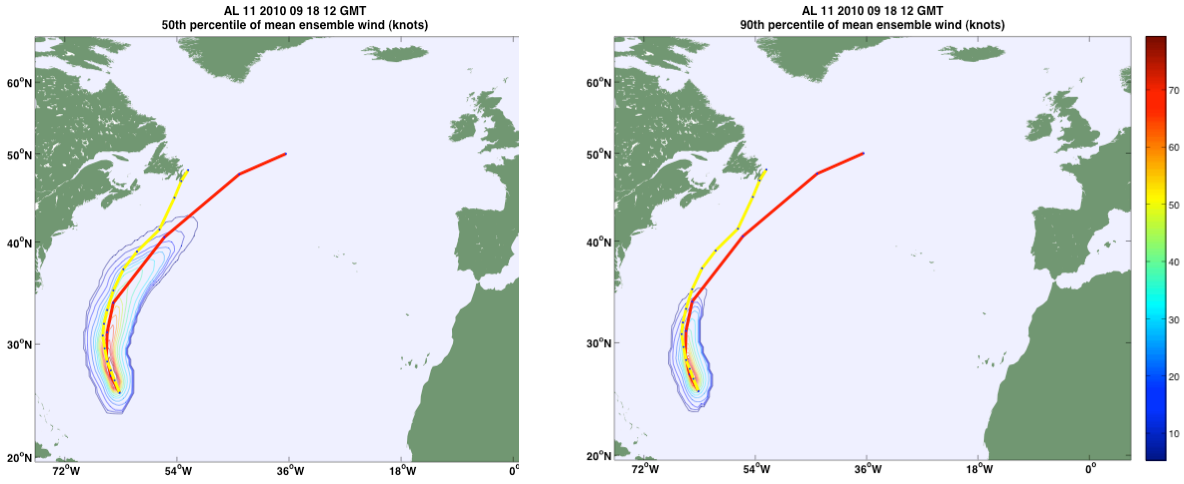

Figure 7: Wind speeds (in knots) associated with a 50% peak wind exceedance probability (left panel), and a 90% exceedance probability (right panel). The official NHC forecast (bold red line), as well as the best track (bold yellow line) are overlaid.

Another alternative for visualizing the information contained in the large ensemble is provided in Figure 8. Here, the ensemble mean wind for the 36-hour forecast (c.f. Fig. 5, which showed the wind field for one ensemble member for that same forecast hour) is shown in contours, and the variance around the mean wind speed that is contained in all generated ensemble tracks is shown in the shaded background. At this time the two lobes of wind speed uncertainty are, to a large extent, the result of the TCs in different ensemble members moving at different speeds.

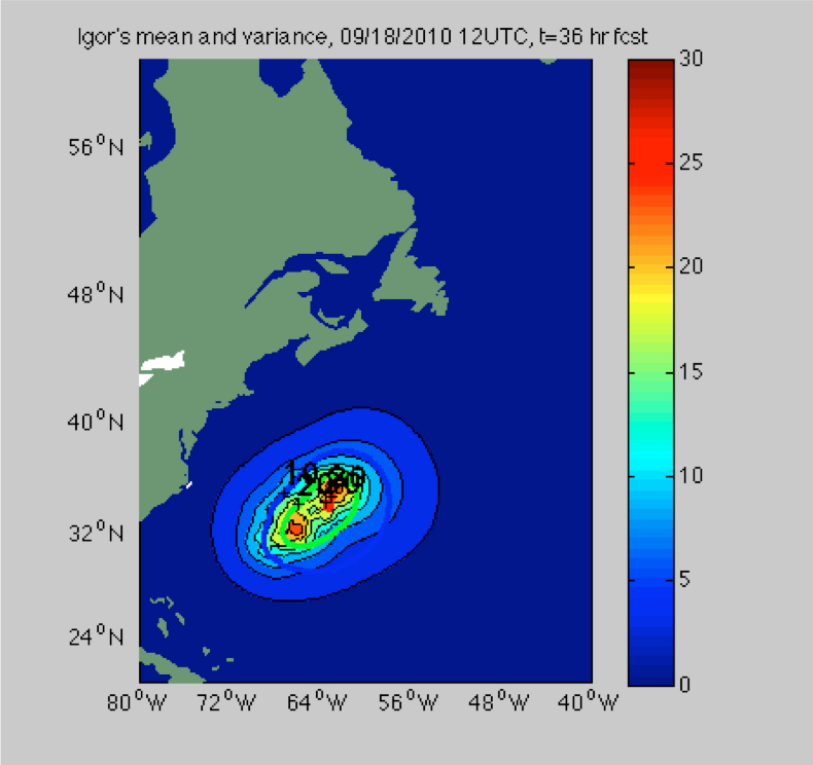

Figure 8: Variance of wind speed (shaded, in knots) and ensemble mean wind speed [contoured in 10 kts increments], for a 36-hour forecast of Igor, issued on 1200 UTC 18 Sep 2010 (i.e., valid time is 0000 UTC 20 Sep 2010).

4. Summary

We developed the capability to generate hundreds or thousands of TC forecasts for individual storms using Emanuel's downscaling technique and applying it to derived fields from ECMWF deterministic and ensemble forecasts. As with all ensemble forecasts, efficient methods to communicate the results need to be developed. The paper provides some experimental approaches that are intended to easily communicate the results, and which might be useful in decision–making processes. One of the challenges is to appropriately define the problem of communicating uncertainty in many dimensions—from communicating the intrinsic information contained in probabilistic forecasts, to finding different skill metrics that are suitable for evaluating these forecasts. There are obviously many potential approaches.

The work presented here provides some initial suggestions of how the data contained in large ensemble data sets can be visualized. The methods shown will be further refined in the near future.

References

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