Year-ahead Prediction of Hurricane Season Sea Surface Temperature in the Tropical Atlantic

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Abstract

One possible method for the year-ahead prediction of hurricane numbers would be to make a year-ahead prediction of sea surface temperature (SST), and then to apply relationships that link SST to hurricane numbers. As a first step towards setting up such a system this article compares three simple statistical methods for the year-ahead prediction of the relevant SSTs.

1 Introduction

Hurricanes expose the insurance industry to a large amount of risk. This risk varies in space and time in complex ways, and in order to set insurance premiums at reasonable levels, it is important to estimate the magnitude and dependencies of this risk as accurately as possible. One important part of making such an estimate involves predicting the distribution of possible hurricane behaviour in the future. Since most insurance contracts are a year in length, and are renewed annually, one of the principal timescales over which hurricane behaviour needs to be predicted is the annual timescale. This corresponds to what we call ‘year-ahead prediction’ of hurricanes: predicting the distribution of properties for next year’s hurricanes, based on all the information we have at the end of this year’s hurricane season. One particular aspect of the distribution of properties of next year’s hurricanes is the distribution of the number of hurricanes, and developing methods for year-ahead predictions of the number of hurricanes is the topic of this article.

There are a number of methods that one might consider using to try and predict the number of hurricanes a year in advance. One set of methods involves searching for statistical predictors of hurricane numbers, and using regression-type methods to use such predictors to make predictions. This is the method followed by Klotzbach and Gray (2004) and Saunders and Lea (2005). Another set of methods is to take the time series of the number of hurricanes per year, study its properties, and try and make a statistical prediction on that basis. We have investigated two versions of this approach in recent articles: first, in Khare and Jewson (2005a) and Khare and Jewson (2005b), we have performed back-testing analyses of simple prediction schemes for the hurricane number time series, and second, in Jewson et al. (2005), we have used shrinkage to combine forecasts based on long and short baselines. All of these time-series methods derive their prediction skill (if any) from the trends and long-term variability in the hurricane number time series.

A third set of methods would be to consider the underlying causes of any long-term fluctuations in hurricane numbers, and predict those causes first. For instance, there is general consensus that much of the variability in hurricane numbers on long time-scales is related to changes in the ocean, and, in particular, to changes in the sea surface temperature (SST). And it is claimed that SST is affected both by long-term cycles (sometimes known as the Atlantic Multidecadal Oscillation, or AMO: see Sutton and Hodson (2003)) and by climate change, both of which might make it predictable to some extent. This raises the possibility that one might be able to predict year-ahead hurricane numbers by first predicting year-ahead sea surface temperatures, and then relating the sea-surface temperatures to the hurricane numbers. Testing out such a system is our goal. In this article we will address the question of how to make year-ahead predictions of SST, while in subsequent articles we intend to address the second half of the problem, which is to relate the SST to the numbers of hurricanes.

There are many ways that one might consider trying to predict SST. A major division is between empirical or statistical methods, on the one hand, and physically-based methods on the other. Empirical methods try to derive statistical relations from the observed historical data. Physically-based methods attempt to apply the laws of dynamics and thermodynamics using differential equations. As a first step,

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we will take a very simple and straightforward empirical approach. From a methodological point of view, this seems to be the most appropriate way to start addressing this question. The results from our simple approach can then be used as a benchmark against which other more complex methods can be judged.

In order to set up an empirical scheme for predicting SST, one has to make some assumptions about the nature of the variability of SST. This is inevitable: it is not possible to create a prediction scheme that doesn’t make at least one assumption. One could, for instance, assume that the trend in SST is linear, or that the AMO has a fixed period, and one could derive an optimal prediction scheme for SST, given these assumptions. However, these particular assumptions are rather restrictive. We will, as an alternative, make the assumption that the characteristics of predictability of SST are the same now as they have been in the past. In other words, we assume that whatever methods would have worked well for the prediction of SST in the past will work well in the future. We then proceed to test and compare a number of simple statistical prediction schemes on past data, and we conclude that whichever works the best on the past data is the best scheme to use for our next prediction. Is this a reasonable approach? In a changing climate, any assumption that the future will be like the past is rather dangerous. However, as we will see below, the recent behaviour of SST does look rather similar to that of the past. For the whole of the historical SST record, SST is apparently affected by a trend, by long term variations, and by interannual noise, and there is no strong indication in the SST data that this has changed recently. Of course if it has, then our method will be misled. In that case, one has to resort to making assumptions about how the processes affecting SST have changed, which is rather difficult.

We note that we do not consider potential predictability of Atlantic SST due to the effects of ENSO. It is well understood that ENSO affects SST in the tropical Atlantic, and one could imagine that by including information about the current or predicted state of ENSO one might be able to improve the predictions that we describe here. We, however, are currently focussing on the much longer timescale processes of AMO and trend. We plan to include ENSO-related predictors at a later date.

Given our interest in hurricane numbers, we start by considering the year-ahead predictability of SST averaged over the hurricane season, from June to November. We then also briefly investigate shorter periods, for comparison, and to assess whether results derived for long periods are likely to apply to shorter periods.

2 Data

The data we use for our SST prediction study is a gridded data set known as HadISST [Rayner et al., 2002]. This data gives estimates of monthly mean SSTs from 1870 to 2005. In figure 1 we show global SSTs averaged over the whole HadISST data set. The most striking pattern in this figure is that the SST in the tropics is much warmer than the SST in the extratropics and near the poles, as one might expect. There are also other large-scale variations in SST, such as colder SSTs off the west coasts of major continents. We are interested in SSTs in the tropical Atlantic, and to that end have defined two regions of particular interest, shown by boxes in the figure. The first box is the Gulf of Mexico, and the second is the so-called Main Development Region for hurricanes (the MDR), which lies between West Africa and the Caribbean. We now investigate SST variability in these two regions.

2.1 Gulf SST

Figure 2 shows the hurricane season mean SST for the period 1870 to 2005 for our Gulf region. Typical SSTs in this region are around 28°C, with a large-scale gradient from the warmest SSTs in the South East of the region, to the coolest SSTs in the North West. Figure 3 shows the standard deviation of hurricane season SST in this region from year to year. Typical variations for most of the region are around a quarter of a degree, with slightly more variability along the North West boundary of the region.

In order to render our SST prediction question slightly more tractable, and as a first step, we average the SSTs in our Gulf region into a single index, with one value per year, based on the months of the hurricane season. A time series of this index is shown in figure 4. This time series shows an overall warming trend, multidecadal variability, and interannual variability. In recent years we see a strong warming trend, but this trend is not unique: it is very similar to the warming trend present during the 1920s and 1930s. Does this index really represent the variability within the whole of the Gulf, or does it throw away much of the detail? To investigate this question, figure 5 shows the linear correlation coefficient between this index and the local SST values. We see that in the central part of the basin, there is a high correlation with the index, of around 0.8. In this region, we conclude that SSTs fluctuate in a fashion that is reasonably well coordinated with our index. In the boundaries of our Gulf region, however, the correlation is somewhat lower, dropping to slightly over 0.6. This suggests that our single index is
less useful for describing SST variability in these regions, and that there are significant variations in SST along the boundaries that are independent of the basin average. We feel that, overall, this correlation structure is sufficient to justify the use of a single spatially averaged index as a first step, but does suggest that at a later stage we may need to consider a more detailed analysis. Figure 6 shows these correlations in more detail using scatter plots. In each plot the horizontal axis shows our SST index, while the vertical axes show SST at 4 points selected from the Gulf region (the exact locations are given in the labelling on the vertical axis of each panel). Again, we see that SSTs in the centre of the region are most highly correlated with the index.

2.2 MDR SST

Figure 7 shows the hurricane season mean SST for our MDR region. There is a considerable variation in mean SST across this region, from waters as cold as 25°C in the North East to waters warmer than 28°C in the West. The year to year variability is illustrated in figure 8; the highest variability is in the East, while temperatures in the West are more constant. Comparison with figure 5 shows that the variability in SST in this region is higher than that in the Gulf. As for the Gulf, we now define an index as the hurricane season average temperature over this region. This index is shown in figure 9. Again, the index shows a long term warming trend, interdecadal and interannual variability. The MDR and Gulf indices are somewhat similar in terms of the shape of the long-term variability: for instance, both show warming in the 1920s and 1930s, and cooling in the 1960s. When we correlate the MDR index with the local temperatures, we find higher correlations than in the Gulf: almost the entire region shows correlations above 0.8, and much of it above 0.9. We conclude that the SST in this region to a great extent moves as one. This is good justification for the use of a single index to summarise the year to year variability. Figure 10 confirms this by showing correlations between the index and individual points: 3 out of 4 of the points chosen show very high correlation with the MDR index. Only the point in the extreme North East of the domain is not highly correlated.

3 Method

As discussed in the introduction, our plan is to test a number of simple statistical methods for predicting SST. We have now reduced the problem to predicting two SST indices that are representative of the SST variability in the two regions we are considering. Whichever prediction methods do best, we will use to make SST predictions for the future. We will compare 3 methods, which we call flat-line, linear trend, and damped linear trend (the use of these three methods is taken from a similar problem that arises in the pricing of weather derivatives: see Jewson and Penzer (2004)). Each of these methods uses the \( n \) years of data from year \( i - n \) to year \( i - 1 \) to predict year \( i \). We will vary \( n \) for each of the methods, to find which values of \( n \) would have given the best results.

We now describe the 3 methods in more detail:

3.0.1 Flat-line

What we call the flat-line (FL) method is the obvious use of a trailing moving average to predict the next year. As a statistical prediction scheme it has the advantage that there is only a single parameter that needs to be estimated, and so the effects of estimation error on the accuracy of the final prediction are likely to be relatively small. The FL method can capture trends and cycles by using a small value of \( n \). However, a small value of \( n \) increases the estimation error.

3.0.2 Linear trend

Perhaps the most obvious extension of the flat-line method is to a best-fit linear trend (LT), extrapolated one year forward to give a prediction. Compared to FL, LT has the disadvantage that there are now two parameters that must be estimated, and this will add extra error in the final prediction because of this overfitting uncertainty. One can say that linear-trends are always more over-fitted than flat-lines. On the other hand, with data like the SST data we are looking at, one might hope that use of a LT model might capture the gradual increasing trend in SST, and so might work well.

3.0.3 Damped linear trend (DLT)

As discussed above, the linear trend is more over-fitted than flat-line. In fact, the best-fit LT model is not even an optimal predictor if the real trend is linear, because of this overfitting; it is only a 'best-fit'
in an in-sample sense, not in an out-of-sample or predictive sense. This raises the question of whether one should ever use best-fit linear trends for prediction, and whether there is something in-between FL and LT that might have some of the benefits of the linear trend model, but is less overfitted. The answer to this question is to use something that we will call a ‘damped linear trend’ (DLT), which we take from Jewson and Penzer (2004). The DLT model is the optimal combination of the FL and LT models, and is the best way to predict a real linear trend (in terms of minimising the root mean square error of the prediction). DLT can also be interpreted and explained in a number of other ways (Jewson and Penzer, 2003).

The one potential shortcoming of the DLT model is that the damping parameter, that determines the proportions of flat-line and linear trend that the method uses, has to be estimated. Given a perfect estimate, damped linear trends are always better than both flat-line and linear trends. Given an imperfect estimate, they may not be.

4 Results

We now show some results from our 3 prediction schemes. In each case we show the root-mean-square error (RMSE), the bias and the error standard deviation (SD). Our goal is to make predictions with low RMSE. The bias and error SD, which are the two components of the RMSE, can help us understand what is driving the RMSE scores from the different models.

4.1 Gulf SST June-November

Figure 12 shows the MSE scores from the 3 models, versus numbers of years of data used in each, when used to predict our June-November Gulf SST index. The blue line shows results from the FL model. We see that the most effective hindcasts from the FL model are for a window length of 12 years. As the window length increases beyond 12 years the FL forecasts become progressively worse, with the RMSE increasing more or less linearly. This is presumably because the FL model ignores the upward trend in the SST index. The pink line shows the results for the LT model. This model gives very poor forecasts for 15 year windows or less, presumably because the two parameters of the model are very poorly estimated when such a small amount of data is used. The LT model performs best at 26 years, but doesn’t do quite as well as the FL model at 12 years. If using less than 22 years of data, the FL model beats LT, while if using more than 21 years of data LT beats FL. The green line shows the results for the DLT model. This model performs best with 27 years of data, and achieves a minimum which is slightly lower than that achieved by the LT model, but slightly higher than that achieved by the FL model. The bias and SD results for the 3 models show that the RMSE is dominated by the SD, except in the FL model for large n, where the bias is also large enough to contribute materially to the RMSE.

If using more than 16 years of data the DLT is the best of the three models. For fewer years of data it is beaten by the FL model. Which, then, is the best of the models? It seems that the worst model of the three is the LT. We say this because the LT model performs the worst of the three numerically and only competes at all with the best of the other two methods for larger numbers of years of data. In general, methods that do well for fewer years of data are more useful because they are more likely to be able to adapt to recent signals, such as an increased rate of climate change, that were not present in the earlier data. Choosing between FL and DLT is harder. The best performance of the two is not materially different. DLT is perhaps slightly better, because the minimum in RMSE is broader, and hence DLT will give good results over a range of window lengths (and so is less sensitive to the wrong choice of window length).

The upper panel of figure 13 shows hindcasts made from the 3 methods using the best window lengths from each. We see that the three predictions are not vastly different, and the FL and DLT predictions are the closest pair. The errors from the 3 different methods (shown in the lower panel of figure 13) are very similar, and are driven by interannual variability, including the effects of ENSO, that is not captured by any of the schemes. The errors do not show any significant trend, decadal or multidecadal variability.

4.2 MDR SST June-November

Figure 14 shows the results for predictions of MDR SSTs. The first thing we notice is that the predictions for MDR SST are worse than those for Gulf SST. For the Gulf SSTs, the best predictions all had MSE values less than 0.21°C. For the MDR region the best predictions have errors that are roughly 50% higher: this is presumably related to the higher level of interannual variability in this region noted earlier.
The FL model does its best with a short window of 11 years, and deteriorates rapidly for longer windows. The LT model does its best for a 24 year window, and does roughly as well as the FL model. The DLT model gives the best results of the three, with the optimal predictions coming from window lengths of 20 years, and again we see that the sensitivity to window width around the point of minimum RMSE is the lowest. For less than 13 years of data the FL model does best. For 13-22 years of data the DLT model does best, while for longer than 22 years of data DLT and LT models are roughly the same.

### 4.3 Gulf SST August-September

Although our principle focus is on the June-November period, we now briefly show results for August-September (in figures 20 to 23) to get some idea whether the results for June-November are likely to hold for shorter time periods. In fact, the results are rather different. The FL model performs the best, the DLT is close behind, and the LT model performs badly. The errors are larger than those for June-November.

### 4.4 MDR SST August-September

In this case (see figures 24 to 27) the results are not too dissimilar from the June-November results, with the DLT model performing best.

### 5 Discussion

We are interested in the prediction of tropical Atlantic SSTs a year in advance, and have tested a number of simple statistical prediction schemes on past SSTs to see which would have given the best predictions. We have considered four SST indices: Gulf and MDR for June-November, and Gulf and MDR for August-September.

For FL models, the best results come from using either 11 or 12 years of data in all four cases. For the LT model, the best results come from using between 15 and 26 years of data. For the DLT model, the best results come from using between 15 and 27 years of data. When only short periods of data are used (less than 10 years) the FL model always does the best. When more than 15 years of data are used, the DLT model usually does best. The best results from the FL and DLT models are typically quite close, and are typically a little better than the best results from the LT model.

What, then, should we use if we want to predict SSTs for next year? There is not a great deal to choose between the models. If one wanted to use the same number of years in all regions, then one might (fairly arbitrarily) choose predictions based on FL with 12 years or DLT with 15 or 20 years. The DLT method might be preferred since good performance is less sensitive on the exact number of years chosen than for LT. Are there any other considerations that should come into play other than the raw backtesting results? One shortcoming of the whole principle of backtesting is that it only tells us what might have worked well in the past, and doesn’t tell us what will work well in the future. If the dynamics of SST variability is different now than it was in the past, then backtesting could mislead us. For this reason, it seems reasonable to choose those methods that rely on less data, since recent data is presumably more relevant if new processes are occurring. This is another reason to avoid using the LT model, and might lead us to prefer FL over DLT. Alternatively one might argue that the recent SST variability may be showing a stronger trend than on average over the backtesting period. This might then lead one to choose DLT, which takes the trend into account and so is likely to do well during periods of strong trends.

Overall, we conclude that this study shows that LT should not be used, and that DLT is probably marginally more useful than FL because of the low sensitivity to the number of years, and the good performance during periods of strong trends, such as we are now experiencing.

There are a number of areas for future work, apart from the obvious next step of trying to relate SST to hurricane numbers. One would be to consider statistical methods for combining these different forecasts. Such combinations may do better than any individual forecasts. Another would be to incorporate the effects of ENSO, especially on predictions for the MDR region.

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Figure 1: Global mean SST from HadISST.
Figure 2: Gulf of Mexico SST for June-November, averaged from 1870 to 2005.

Figure 3: Gulf of Mexico SST for June-November, standard deviation from 1870 to 2005.
Figure 4: June-November average Gulf of Mexico SST by year from 1870 to 2005.

Figure 5: Correlation between the index shown in figure 4 and the local June-November SST.

Figure 6: Scatter plots showing the SST index from figure 4 (horizontal axis) against local SST.
Figure 7: MDR SST for June-November, averaged from 1870 to 2005.

Figure 8: MDR SST for June-November, standard deviation for 1870 to 2005.
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Figure 10: Correlation between the index shown in figure 9 and the local June-November SST.

Figure 11: Scatter plots showing the SST index from figure 10 (horizontal axis) against local SST.
Figure 12: RMSE for year-ahead predictions of the Gulf of Mexico June-November SST index shown in figure 4 for three simple statistical prediction models: flat-line (blue), best fit linear trend (red) and damped linear trend (green).

Figure 13: Bias for the three predictions described above.

Figure 14: SD of errors for the three predictions described above.
Figure 15: The top panel shows hindcasts for the SST index shown in figure 4 from the flat-line (blue), best fit linear trend (red) and damped linear trend (green) models, along with actual values for the index. The lower panel shows the errors from each of the three predictions.
Figure 16: RMSE for year-ahead predictions of the MDR June-November SST index shown in figure 9 for three simple statistical prediction models: flat-line (blue), best fit linear trend (red) and damped linear trend (green).

Figure 17: Bias for the three predictions described above.

Figure 18: SD of errors for the three predictions described above.
Figure 19: The top panel shows hindcasts for the SST index shown in figure 9 from the flat-line (blue), best fit linear trend (red) and damped linear trend (green) models, along with actual values for the index. The lower panel shows the errors from each of the three predictions.
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Figure 21: Bias for the three predictions described above.

Figure 22: SD of errors for the three predictions described above.
Figure 23: The top panel shows hindcasts for the August-September Gulf SST index, from the flat-line (blue), best fit linear trend (red) and damped linear trend (green) models, along with actual values for the index. The lower panel shows the errors from each of the three predictions.
Figure 24: RMSE for year-ahead predictions of an MDR August-September SST index for three simple statistical prediction models: flat-line (blue), best fit linear trend (red) and damped linear trend (green).

Figure 25: Bias for the three predictions described above.

Figure 26: SD of errors for the three predictions described above.
Figure 27: The top panel shows hindcasts for the August-September MDR SST index shown from the flat-line (blue), best fit linear trend (red) and damped linear trend (green) models, along with actual values for the index. The lower panel shows the errors from each of the three predictions.