Predicting basin and landfalling hurricane numbers from sea surface temperature

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Abstract

We are building a hurricane number prediction scheme based on first predicting main development region sea surface temperature (SST), then predicting the number of hurricanes in the Atlantic basin given the SST prediction, and finally predicting the number of US landfalling hurricanes based on the prediction of the number of basin hurricanes. We have described a number of SST prediction methods in previous work. We now investigate the empirical relationship between SST and basin hurricane numbers, and put this together with the SST predictions to make predictions of both basin and landfalling hurricane numbers.

1 Introduction

We are interested in developing practical methods for the prediction of the distribution of the number of hurricanes that might make landfall in the US over the next 5 years. We are investigating a number of ways that one might make such a prediction, such as methods based on a change point analysis of the historical hurricane record (see Binter et al. (2006)), and methods based on predictions of sea surface temperatures (SST). This article contributes to the development of one particular 3 step SST method that works as follows:

1. We predict the distribution of possible SSTs in the main development region (MDR) over the next 5 years
2. We predict the distribution of the number of hurricanes in the Atlantic, given the SST forecast from step 1, using a model for the relationship between MDR SST and Atlantic hurricane numbers
3. We predict the distribution of the number of hurricanes making US landfall, given the prediction for the number in the Atlantic from step 2, and a model for the relationship between Atlantic hurricane numbers and numbers of hurricanes making landfall in the US

The first step, how to predict MDR SST, has been considered in Meagher and Jewson (2006) and Laepple et al. (2007). We now consider steps 2 and 3, and make some predictions. That there is a non-trivial relationship between SST and the number of Atlantic basin hurricanes is both physically intuitive and is supported by a number of studies in the meteorological literature. For instance, Peixoto and Oort (1992) discuss how long-term variability in hurricane activity is ultimately driven by the ocean, with its large thermal and mechanical inertia. Also, ocean SSTs play a direct role in providing energy to developing tropical cyclones (Landsea et al., 1999a; Saunders and Harris, 1997), and higher SSTs decrease the stability of the atmosphere, making tropical cyclones more resistant to windshear (Demaria, 1996). Much of this has been known for a long time: Gray (1968) discusses how warm SSTs promote tropical cyclone development and enhancement. The statistical relationship between Atlantic hurricane activity and SSTs has been studied by a number of authors (e.g. Shapiro (1982); Shapiro and Goldenberg (1989); Saunders and Harris (1997); Goldenberg et al. (2001); Landsea et al. (1999a)) and is a key aspect in a

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number of recent studies concerning the impacts of long-term climate trends on hurricane frequency and intensity (e.g., Emanuel et al. (2005); Kerr (2005); Trenberth (2005); Webster et al. (2005); Klotzbach (2006); Sriver and Huber (2006); Elsner (2006)).

As this is our first attempt to relate SST to hurricane numbers, and our first attempt to build a forecasting system on that basis, we are keen to keep our models as simple as possible. For this reason, we restrict ourselves to representing SST variability using just a single index, and we choose what we think is the simplest possible reasonable index: the average of summer SST in the MDR region of the tropical Atlantic. Based on an analysis of correlation between hurricane numbers and MDR SSTs in different months we define summer to be July to September. In the future it may be appropriate to extend our prediction system to consider more than one SST index, and to derive our index or indices on the basis of some kind of regression or eigenvector analysis.

Given our SST index, our first goal is to test a number of statistical models that relate this index to the observed number of hurricanes. We consider both the total number of hurricanes, and the number of intense hurricanes, where we define intense as falling in categories 3-5. We fit our statistical models to data from both 1900-2005 and 1950-2005, for reasons discussed below.

Having settled on a couple of models for the SST to hurricane number relationship, we then convert SST predictions derived from Laepple et al. (2007) into hurricane number predictions for 2006-2010.

The rest of this article proceeds as follows. In section 2 we briefly discuss the data we use for this study. In section 3 we present the statistical models for the SST-hurricane number relationship that we will test. In section 4 we show the results from these tests, and in section 5 we summarise and discuss those results. Then in sections 6 and 7 we describe how we can use these models to make hurricane number predictions, and in sections 8 and 9 we make some predictions, for all hurricanes and intense hurricanes, respectively. Finally in section 9 we conclude.

2 Data

We use two data sets for this study: one for SST, and the other for hurricane numbers. The SST data we use is HadISST, available from http://www.hadobs.org, and described in Rayner et al. (2002). From this data we create an annual index consisting of the average SST in the region (10°-20°N, 15°-70°W) for the months July to September. This is exactly the same index as was used in our SST prediction study described in Laepple et al. (2007).

The hurricane number data is derived from the standard HURDAT database, available from http://www.aoml.noaa.gov/hrd/hurdat, and described in Jarvinen et al. (1984). In both cases we consider the data to be exact, i.e. without observational errors. This is pragmatic, since neither data-set is delivered with any estimates of the likely error. However, given the (widely discussed) possibility that both data sets may be less accurate earlier in the time period we repeat our analyses for both the periods 1900-2005 and 1950-2005.

3 Statistical models for the SST to hurricane number relationship

The purpose of sections 3, 4 and 5 of this article is to compare the performance of a number of simple statistical models for modelling the relationship between our MDR SST index and observed hurricane numbers. The models we consider are as follows:

3.1 Models

3.1.1 Poisson distribution independent of SST

The simplest model we consider models the number of hurricanes as a poisson distribution independent of SST. We include this model as a baseline that the subsequent models should be able to beat.

We write this model as:

\[ n \sim \text{Po}(\text{rate} = \alpha) \]  

(1)

where \( n \) is the number of hurricanes. We estimate the parameter \( \alpha \) as the mean of the observed hurricane numbers.
3.1.2 Linear normal regression

Our next model is plain-vanilla linear regression, with both the residuals and the response modelled as normal distributions.
We write this model as:
\[ n \sim N(\alpha + \beta s, \sigma^2) \] (2)
where \( s \) is the SST index. We fit the parameters using maximum likelihood, which is equivalent to least squares in this case.
From the point of view of making point predictions of future hurricane numbers this is a perfectly reasonable first model, and the prediction is \( \alpha + \beta s \). From the point of view of making a probabilistic prediction of future hurricane numbers this model is slightly odd, since it models a non-negative integer (the number of hurricanes) using a real number that can be both positive and negative. Nevertheless we include this model for two reasons: (a) as another baseline for comparison, since it is simple and well understood, and there is a closed-form solution for the parameters, and (b) since this model can easily be optimised for predictive purposes (the next model).

3.1.3 Damped linear normal

Our third model is an adaption of linear regression. Standard linear regression, when fitted using in-sample fitting techniques such as maximum likelihood or least squares, is an inherently overfitted model. In other words, these fitting techniques optimise the model’s ability to predict the training data, but not to extrapolate. For large samples and strong signals this doesn’t matter, but for smaller samples and weak signals this means that linear regression does not give good predictions, even when the process being predicted really does consist of a linear trend plus gaussian noise. Adapting linear regression so that it is optimised to make good predictions is, however, difficult, and is not guaranteed to be successful.
Our third model is one such simple adaption, due to Jewson and Penzer (2004), in which the slope of the trend is reduced in order to reduce the overfitting. This model may or may not make better predictions than the unadapted linear regression model because of the difficulty of estimating exactly what this slope reduction should be.
We write this model as:
\[ n \sim N(\alpha + k\beta s, \sigma^2) \] (3)
We fit this model by first fitting the underlying linear regression model, and then calculating the adjustment \( k \) using the expressions in Jewson and Penzer (2004).
As with the linear normal model this model is a reasonable model if used to make point predictions, but is a slightly odd model to use for probabilistic predictions, for the same reasons as given above. We include it in order to see the extent to which overfitting may be an issue.

3.1.4 Linear Poisson

The two normally distributed models given above can be criticized, as probabilistic forecast models, for using a distribution that is clearly not close to being correct. To overcome this criticism we now change the distribution from normal to poisson. We write this model as:
\[ n \sim \text{Po}(\text{rate} = \alpha + \beta s, \sigma^2) \] (4)
We fit this model using iteratively reweighted least squares.
At a mathematical level this model might be criticized because for certain values of the parameters the poisson rate can be negative. However we have found that this is not a problem for the data and parameter ranges that are of interest to us.
The standard fitting procedure we use for this model is an in-sample fitting procedure, and thus leads to inherently overfitted parameter estimates, and sub-optimal predictive properties. It would be possible in principle to fit a ‘damped’ version of this model, in the same way that we have fitted a damped version of linear regression, in order to attempt to overcome this problem. However there appears to be no simple analytic way to do this, and one would have to use more complex methods such as cross-validation. That is beyond the scope of this study, but might be an interesting avenue for future work.
3.1.5 Exponential poisson

The next model that we use is the same as the previous model, but exchanges a linear relationship for the rate of the poisson distribution for an exponential one. This model is common in the statistical literature, where it is known as either ‘poisson regression’ or ‘a generalised linear model for the poisson distribution with a log-linear link function’.

We write this model as:

\[ n \sim \text{Po}(\text{rate} = \exp(\alpha + \beta s)) \] (5)

At a mathematical level this model avoids the potential problem with negative rates described above, since the rates are positive for all parameter values and data sets. This model has previously been used to model the relationship between SST and hurricane numbers by [Elsner and Schmertmann (1993)] and [Solow and Moore (2000)].

Comparing the linear poisson and exponential poisson models, one obvious question is, is there any statistical evidence for the non-linearity included in the exponential poisson model? We will discuss this question when we present our results below.

3.1.6 Exponential negative binomial

Our final model is an adaption of the previous model that allows the distribution around the mean to be negative binomial rather than exponential, and thus has one extra parameter that allows for the variance to be different from the mean.

We write this model as:

\[ n \sim \text{NB}(\text{mean} = \alpha + \beta s, \text{variance} = \gamma) \] (6)

3.2 Model comparison

How are we going to compare the results from these different models? We consider two scores, one of which assesses the ability of the models to make point predictions, and the other of which assesses the ability of the models to make probabilistic predictions. For each of these scores we consider in-sample scores, which are not really what we care about, but are included for interest, and out-of-sample scores, which are the real test. The out-of-sample scores are calculated using leave-one-out cross-validation, a.k.a. the Quenouille-Tukey jack-knife (Quenouille, 1949; Tukey, 1958).

We score the point predictions using the most obvious score available: the root mean square error. We score the probabilistic predictions using (what we consider to be) the most obvious probabilistic score, which is the mean out-of-sample log-likelihood.

4 Comparing the performance of the statistical models

We now present results from our comparisons of the various models. First we consider models for the total number of hurricanes, for the periods 1900-2005 and 1950-2005, and then we consider models for intense hurricane numbers for the same two periods. Correlations between SST and hurricane numbers for these 4 cases are shown in table 1.

In each of the 4 cases we produce a standard set of diagnostics, consisting of four tables and three graphs. The four tables are:

- the scores achieved by the models
- the fitted parameter values, including standard error estimates based on the Fisher information
- the percentage of times each model wins in pairwise comparisons, and corresponding p-values for point predictions
- pairwise comparisons and corresponding p-values for probabilistic predictions

The graphs are:

- a scatter plot showing the data on which the model is based
- the same scatter plot, showing the decade in which each data point occurred
- the same scatter plot showing the fitted curves from the six models
4.1 All hurricanes, 1900-2005

The first results we present are based on all hurricanes, and data from 1900 to 2005. The scatter plot shown in figure 1 shows a clear relationship between the SSTs and the hurricane numbers during this period, with warmer SSTs coinciding with more hurricanes. By eye, the relationship looks more or less linear. The linear correlation was found to be 0.56, while the rank correlation was found to be 0.51, as shown in table 1.

The decade scatter plot is shown in figure 2. Note that the most recent period labelled by ‘A’ gives relatively high SST and basin number count.

Table 2 shows the score comparisons for the six models for this dataset. Considering the RMSE scores we see that all the non-trivial models comfortably beat the trivial flat-line model, as we’d guess would be the case from the scatter plot. Table 4, which shows results for pairwise comparisons in RMSE, shows that the differences between the trivial model and the non-trivial models are statistically significant (at the 5 percent level), with the exception of the exponential binomial model.

The differences between the performance of the 5 non-trivial models are small. The exponential models yield the best out-of-sample RMSEs, but none of the RMSE differences between the five models are statistically significant. Given that the exponential poisson model gives the second lowest out-of-sample RMSE and beats the flat poisson model in a statistically significant way, one might choose the exponential poisson model as the best one. However, since the non-trivial models are not different in a statistically significant way, one shouldn’t be surprised if that result were overturned given more data.

These models all explain around 30% of the variance in the hurricane number time series. Considering the out of sample log-likelihood scores in table 2, we find that the linear and exponential poisson are better than the flat poisson model in a statistically significant way. The linear and damped linear normal are worse than the flat poisson model in a statistically significant way. The exponential negative binomial does yield the best out-of-sample log-likelihood score, but the result is not statistically significant. Based on the log-likelihood scores, one might choose the exponential poisson model once again.

The parameters of all the models are reasonably well estimated: all the parameters given in table 3 are significantly different from zero (judging by the standard error estimates, and assuming normality for the sampling distributions). For instance, the slopes in the linear models are between 4.3 and 4.6, with standard error of roughly 0.7. Each extra degree of SST is therefore related to just over 4 more hurricanes, plus or minus 1.5 hurricanes. The in-sample fits to the data for the various models are displayed in figure 3.

The damping parameter in the damped linear trend model is very close to one. This suggests that the models are not significantly overfitted, and there is no real need to use such damped models in this case. This is because the signal is strong enough that we can estimate it reasonably well.

4.2 All hurricanes, 1950-2005

Given the doubts that one might have about the quality of both the SST and the hurricane number data prior to 1950, it makes sense to repeat the analysis given in the previous section for just the more recent data from 1950 to 2005. The corresponding results and data plots are provided in tables 6, 7, 8 and 9 and figures 4, 5 and 6. For this data set, a linear correlation of 0.62 and rank correlation of 0.56 was found.

There are only small differences in the results relative to the analysis based on 1900-2005 data. Once again, the non-trivial models all beat the trivial constant level model. These results are statistically significant for the linear normal, damped linear normal and linear poisson models. The differences between the non-trivial models are not, once again, statistically significant. Based on these results, one may be inclined to choose the linear poisson model, as it yields the lowest RMSE of the models that beat the flat poisson model in a statistically significant way.

These models all explain around 40% of the variance in the hurricane number time series (a little higher than before).

With regards to the log-likelihood scores, the linear and exponential poisson models and the exponential negative binomial models beat the flat poisson model, whereas the linear normal and damped linear normal do not. The result for the linear poisson model is statistically significant. The linear and damped linear normal are defeated by the flat poisson model in a statistically significant way. Given these results, one might choose the linear poisson model once again. However, it is possible that this conclusion would be overturned by using more data as the differences between the linear poisson, exponential poisson and exponential negative binomial are not statistically significant.
The slope parameters are again significantly different from zero, but the slope of the linear relations is now a bit higher, giving between 5.0 and 5.4 hurricanes per degree, with a slightly larger uncertainty of around 1.0 hurricanes per degree. Given the uncertainties, the slope estimates from the two data sets are entirely consistent.

4.3 Intense hurricanes, 1900-2005

We now consider the relationship between MDR SST and the number of intense hurricanes. Considering the scatter plot in figure 7, and comparing with the scatter plot in figure 1, we see immediately that the relationship is less clear than before. The linear correlation for this data set is 0.52 and the rank correlation is 0.54. This may not be because the underlying relationship is any less strong: simple statistical arguments suggest that the relationship will appear less strongly in the data just because there are fewer events.

We now consider the results in tables 10, 11, 12 and 13. The non-trivial models all beat the trivial constant level model statistically significantly, but are not statistically significantly different from each other in terms of the RMSE scores. The parameters of all models are significantly different from zero, and the linear models give roughly 2.9 extra hurricanes per extra degree of SST, with a standard error of around 0.4. The models explain around 25% of the variability in the number of intense hurricanes.

As far as the log-likelihood scores are concerned, the linear normal and damped linear normal are defeated by the flat poisson model in a statistically significant way. The linear and exponential poisson models and the negative binomial model defeat the flat poisson model in a statistically significant way. The differences between the linear poisson, exponential poisson and exponential negative binomial are not statistically significant.

4.4 Intense hurricanes, 1950-2005

Finally we consider intense hurricane numbers for the more recent data, for which results are shown in tables 14, 15, 16 and 17 and figures 10 through 12. Once again, the non-trivial models defeat the flat poisson model in a statistically significant way. The differences among the non-trivial models in this case are not statistically significant. Once again, the parameter estimates for the models appear to be significantly different from zero. The linear models give a slightly higher number of hurricanes per degree, roughly around 3.4 extra hurricanes per extra degree, with standard error of around 0.7.

With regards to the log-likelihood scores, the linear normal and damped linear normal are defeated by the flat poisson model in a statistically significant way. The linear poisson and exponential negative binomial defeat the flat poisson model in a statistically significant way, whereas the exponential poisson does not. The differences between the linear poisson, exponential poisson and exponential negative binomial are not statistically significant.

5 Summary of statistical model results

In sections 3 and 4 we have considered how to model the relationship between MDR SST and the number of hurricanes in the Atlantic basin. We considered both the total number of hurricanes and the number of intense hurricanes. We now summarise the results of this investigation.

W.r.t. the total number of hurricanes our findings are:

- that there is a clear and statistically significant relationship, such that higher SSTs correspond to higher numbers of hurricanes, with one degree of SST relating to between 4.0 and 5.5 extra hurricanes

- using only more recent data the relationship is slightly stronger, but is less accurately estimated

- that statistical models of this relationship give better point predictions of hurricane numbers than a simple model that ignores this relationship

- w.r.t. point predictions, all the non-trivial models defeat the flat poisson model in a statistically significant way with the exception of the exponential poisson and exponential negative binomial model. The differences between the non-trivial models are, however, not statistically significant. If one had to choose among the models based on the RMSE results, one might choose the linear poisson model as it yields the lowest RMSE of the models that beat the trivial model in statistically significant way.
• that the non-trivial models explain between 29% and 44% of the variability in the number of hurricanes

• w.r.t probabilistic predictions, the linear and damped linear normal models are defeated by the flat poisson model in a statistically significant way. The linear poisson model defeats the flat-line model in a statistically significant way.

That there is a non-trivial relationship between Atlantic MDR SSTs and basin-wide hurricane activity is in general agreement with statistical analyses performed in both Klotzbach (2006) and Landsea et al. (1999).

W.r.t the number of intense hurricanes our findings are the same, with the exception of:

• each extra degree of SST gives between 3.0 and 3.5 extra intense hurricanes

• the non-trivial models explain slightly less of the variability in the numbers of hurricanes: only 25%

• w.r.t. the point predictions, all the non-trivial models defeat the flat-line model in a statistically significant way.

• w.r.t. the probabilistic predictions, the linear poisson and negative binomial models defeat the flat poisson model in a statistically significant way for both data sets.

Our results for intense hurricanes are broadly consistent with an analysis done by Hovos et al. (2006) which suggests that increasing number of category 4-5 hurricanes is directly linked to the trend in tropical SSTs.

Given all of this, what models would we recommend to use to model the SST to hurricane relationship? Firstly, it probably makes sense to use only the recent data, since it is possible to estimate the regression parameters reasonably well using this data, and it avoids doubts about data quality. Assuming we need probabilistic forecasts of hurricane activity, then we have seen that the normal distribution models don’t work well. This leaves 3 reasonable models: linear poisson, exponential poisson, and negative binomial. We could eliminate the negative binomial model on the basis that it is more complex than the other two, but performs no better. This then leaves us with the linear poisson and exponential poisson models. On the basis of our results it is not possible to distinguish between these models, and this is perhaps the most important result of this paper: even though previous authors have, by default, used an exponential poisson model for the SST to hurricane number relationship, the linear poisson model works just as well, and in some forecast applications (especially those that involve applying the modelled SST-hurricane relationships for extreme values of the SST) is likely to give quite different results.

We end this section by mentioning that a number of studies suggest that the strength of the relationship between SST and hurricane frequency is dependent on the region of the north Atlantic being considered (Shapiro and Goldenberg, 1989; Raper, 1993; Goldenberg et al., 2001). Understanding the regional dependence of the statistical relationship between SST and hurricane numbers is therefore an interesting avenue for future work.

6 Making SST based predictions of hurricane numbers

We now have all the pieces we need to make SST-based predictions of hurricane numbers. Firstly, in Laepple et al. (2007), we have derived simple statistical methods for predicting SST. We will take three SST predictions from that article: the flat-line model based on 8 years of data (FL), the linear trend model based on 24 years of data, and a damped linear trend model that is the mean of these two. Secondly, in sections 3 and 4 above, we have analysed the relationship between SST and the number of hurricanes in the Atlantic basin. We were able to find two relatively simple models that were significantly better than the trivial model of no relationship in out-of-sample tests. The first of these models represents the mean number of basin hurricanes as a linear function of SST, and the distribution as a poisson distribution. The second model represents the mean number of basin hurricanes as an exponential function of SST, and the distribution once again as poisson. A more complex model with more parameters (that represents the distribution as negative binomial) was not significantly better, so we ignore it.

Thirdly, using historical hurricane data for the period 1950 to 2005 we can estimate the probability that individual hurricanes make landfall in the US. For cat 1-5 hurricanes the estimate of this probability is 0.254 while for cat 3-5 hurricanes the estimate is 0.240.

Finally, in Jewson (2007), we have derived simple analytic relationships that allow us to put this all together and predict the mean, variance, and standard error of the number of landfalling hurricanes as a
function of the mean, variance and standard error of an SST forecast. In particular, we use the equations given in section 9 of that paper.

Combining our three SST models with two ways of converting SST to basin hurricane numbers gives a total of six different forecast methods. We present results for all of these six different methods, since the SST forecasts capture a range of possible points of view about the possible future behaviour of SST, and the two SST-to-basin relationships are both sensible models, and can’t be distinguished given the observational data, but give clearly different final answers.

7 Predictions for category 1-5 landfalling hurricanes

We now present our various predictions for SST and the number of category 1-5 hurricanes at US landfall. First, in figure 13, we show the three SST predictions. Second, in tables 18 to 22, we show details of the six predictions of basin hurricane numbers that we derive from these SST predictions. Since these are just an intermediate step in the process of predicting landfalling hurricane numbers, we don’t discuss these in detail. We note briefly that the predictions for individual years range from 8.0 to 10.5 hurricanes per year, and the 5 year averages range from 8.9 to 9.9 hurricanes per year.

Thirdly, in tables 23 to 27, we show details of the six predictions of landfalling hurricane numbers that we derive from these predictions of basin hurricane numbers by multiplying by the estimated probabilities that a hurricane will make landfall. These predictions are also illustrated in figures 14 to 19. Model 1 gives a flat prediction of future hurricane numbers by year since it is based on a flat prediction of SST and a linear conversion model. Model 4 gives a very gradual increase in the prediction of the mean number of hurricanes with lead time because of the increasing uncertainty of the SST prediction with lead time, in combination with the non-linearity of the conversion model. Models 3 and 6 give rapidly increasing predictions of hurricane numbers since they are based on rapidly increasing SST predictions. Models 2 and 5 lie somewhere in between these two extremes. Models 4, 5 and 6, based on the exponential poisson model for the relation between SST and hurricane numbers, all give higher predictions of future hurricane numbers than models 1, 2 and 3 that are based on the linear poisson relation.

8 Predictions for category 3-5 landfalling hurricanes

For reference we also include predictions for category 3-5 landfalling hurricanes, in tables 28 to 37.

9 Conclusions

We have described a hurricane number prediction scheme based on three steps. In step 1 we predict MDR SSTs, in step 2 we predict basin hurricane numbers given the MDR SST predictions, and in step 3 we predict landfalling hurricane numbers given the prediction of basin hurricane numbers. We have tested a number of different models for the relationship between SST and hurricane numbers. We have found 2 models that beat the other models tested, but we can’t say which of the two is better based only on the data. We make 6 predictions of landfalling hurricane numbers by combining 3 different SST predictions with these 2 different methods for converting SSTs to basin hurricane numbers. The SST prediction models, which are taken from Laepple et al. (2007), range from a model in which SST remains at a constant level to a model in which the SST increases rather rapidly. Finally we convert the basin number predictions to predictions of numbers of landfalling hurricanes using a constant probability of landfall estimated from 56 years of historical data. Putting this all together, the averages of the predictions for the number of landfalling hurricanes over the next 5 years range from 2.04 to 2.52 hurricanes per year. These predictions are broadly similar to predictions of hurricane numbers from time-series based methods such as those we have described in Binter et al. (2006), but extend to higher numbers of hurricanes for the highest predictions.

Finally we note that there is a large spread between the predictions based on different SST forecasts. Reducing the uncertainty as to how to predict future SSTs would perhaps be the easiest way for us to reduce the uncertainty around our future hurricane number predictions.
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|                          | Linear Correlation | Rank Correlation |
|--------------------------|--------------------|------------------|
| 1900 - 2005 Basin vs SST | 0.56               | 0.51             |
| 1950 - 2005 Basin vs SST | 0.62               | 0.56             |
| 1900 - 2005 Intense Basin vs SST | 0.52 | 0.54             |
| 1950 - 2005 Intense Basin vs SST | 0.53 | 0.56             |
| model | model name                      | RMSE (in) | RMSE (out) | 100-100*RMSE/RMSE_\text{const} | LL (in) | LL (out) |
|-------|--------------------------------|-----------|------------|---------------------------------|---------|----------|
| model 1 | Flat Poisson                  | 2.648     | 2.674      | 0                               | -2.372  | -2.385   |
| model 2 | Linear Normal                | 2.185     | 2.238      | 29.94                           | -2.61   | -2.612   |
| model 3 | Damped Linear Normal         | 2.185     | 2.239      | 29.867                          | -2.169  | -2.189   |
| model 4 | Linear Poisson               | 2.187     | 2.233      | 30.24                           | -2.163  | -2.182   |
| model 5 | Exponential Poisson           | 2.153     | 2.204      | 32.019                          | -2.163  | -2.182   |
| model 6 | Exponential Neg. Bin.         | 2.153     | 2.168      | 34.249                          | -2.163  | -2.171   |

Table 3: Model parameters incl. out of sample RMSE 1900 - 2005 Basin vs SST

| model | ˆα  | s.e. | ˆβ  | s.e. | k   | cov | corr | RMSE (out of sample) |
|-------|-----|------|-----|------|-----|-----|------|----------------------|
| model 1 | 1.664 | 0.042 |     |      |     |     |      | 2.674                |
| model 2 | 5.283 | 0.214 | 4.581 | 0.656 | 0   | 0   | 2.238 |                     |
| model 3 | 5.283 | 0.223 | 4.34  | 0.662 | 0.98 | 0.041| 0.277 | 2.233                |
| model 4 | 1.625 | 0.044 | 0.849 | 0.127 | -0.001| -0.268 | 2.204 |                     |
| model 5 | 1.625 | 0.044 | 0.849 | 0.127 | -0.001| -0.268 | 2.168 |                     |

Table 4: Winning count for particular model 1900 - 2005 Basin vs SST

| model | model 1 | model 2 | model 3 | model 4 | model 5 | model 6 |
|-------|---------|---------|---------|---------|---------|---------|
| model 1 | 0 (1)   | 42 (0.968)| 41 (0.98)| 41 (0.98)| 40 (0.987)| 43 (0.928) |
| model 2 | 58 (0.049)| 0 (1)   | 45 (0.857)| 46 (0.809)| 52 (0.385)| 45 (0.857) |
| model 3 | 59 (0.032)| 55 (0.191)| 0 (1)   | 45 (0.857)| 53 (0.314)| 49 (0.615) |
| model 4 | 59 (0.032)| 54 (0.248)| 55 (0.191)| 0 (1)   | 47 (0.752)| 48 (0.686) |
| model 5 | 60 (0.02) | 48 (0.686)| 47 (0.752)| 53 (0.314)| 0 (1)   | 43 (0.928) |
| model 6 | 57 (0.103)| 55 (0.191)| 51 (0.461)| 52 (0.385)| 57 (0.103)| 0 (1)   |

Table 5: Winning count (LL) for particular model 1900 - 2005 Basin vs SST

| model | model 1 | model 2 | model 3 | model 4 | model 5 | model 6 |
|-------|---------|---------|---------|---------|---------|---------|
| model 1 | 0 (1)   | 77 (0)   | 77 (0)   | 41 (0.98)| 41 (0.98)| 44 (0.897)|
| model 2 | 23 (1)  | 0 (1)    | 45 (0.857)| 12 (1)  | 11 (1)  | 11 (1)  |
| model 3 | 23 (1)  | 55 (0.191)| 0 (1)    | 12 (1)  | 11 (1)  | 11 (1)  |
| model 4 | 59 (0.032)| 88 (0)   | 88 (0)   | 0 (1)   | 47 (0.752)| 48 (0.686)|
| model 5 | 59 (0.032)| 89 (0)   | 89 (0)   | 53 (0.314)| 0 (1)   | 43 (0.928) |
| model 6 | 56 (0.143)| 89 (0)   | 89 (0)   | 52 (0.385)| 57 (0.103)| 0 (1)  |
Figure 1: 1900 - 2005 Basin vs SST

Figure 2: 1900 - 2005 Basin vs SST
Figure 3: Fitted Lines for all Models 1900 - 2005 Basin vs SST
Table 6: RMSE comparison 1950 - 2005 Basin vs SST

| model    | model name          | RMSE (in) | RMSE (out) | 100-100*RMSE/RMSEconst | LL (in) | LL (out) |
|----------|---------------------|-----------|------------|-------------------------|---------|---------|
| model 1  | Flat Poisson        | 2.607     | 2.654      | 0                       | -2.332  | -2.352  |
| model 2  | Linear Normal       | 2.04      | 2.13       | 35.609                  | -2.507  | -2.516  |
| model 3  | Damped Linear Normal| 2.04      | 2.133      | 35.391                  | -2.508  | -2.516  |
| model 4  | Linear Poisson      | 2.042     | 2.122      | 36.063                  | -2.137  | -2.161  |
| model 5  | Exponential Poisson | 1.981     | 2.067      | 39.335                  | -2.126  | -2.149  |
| model 6  | Exponential Neg. Bin.| 1.981 | 2.002      | 43.117                  | -2.126  | -2.136  |

Table 7: Model parameters incl. out of sample RMSE 1950 - 2005 Basin vs SST

| model | $\hat{\alpha}$   | s.e.  | $\hat{\beta}$ | s.e. | $k$  | cov | corr | RMSE (out of sample) |
|-------|------------------|-------|---------------|------|------|-----|------|----------------------|
| model 1 | 1.833           | 0.053 | 2.654         | 0    | 0    |     |      | 2.654                |
| model 2 | 6.25            | 0.278 | 5.38          | 0.92 | 0    | 0   | 0    | 2.13                 |
| model 3 | 6.25            | 0.278 | 5.38          | 0.92 | 0    | 0   | 0    | 2.13                 |
| model 4 | 6.25            | 0.278 | 5.38          | 0.92 | 0    | 0   | 0    | 2.13                 |
| model 5 | 1.8             | 0.055 | 0.832         | 0.172| -0.002| -0.244| 2.067  |
| model 6 | 1.8             | 0.055 | 0.832         | 0.172| -0.002| -0.244| 2.002  |

Table 8: Winning count for particular model 1950 - 2005 Basin vs SST

| model | model 1 | model 2 | model 3 | model 4 | model 5 | model 6 |
|-------|---------|---------|---------|---------|---------|---------|
| model 1 | 0 (1)   | 38 (0.978) | 38 (0.978) | 38 (0.978) | 39 (0.959) | 39 (0.959) |
| model 2 | 62 (0.041) | 0 (1) | 54 (0.344) | 54 (0.344) | 48 (0.656) | 48 (0.656) |
| model 3 | 62 (0.041) | 46 (0.748) | 0 (1) | 52 (0.447) | 52 (0.447) | 48 (0.656) |
| model 4 | 62 (0.041) | 46 (0.748) | 48 (0.656) | 0 (1) | 54 (0.344) | 48 (0.656) |
| model 5 | 61 (0.07) | 52 (0.447) | 48 (0.656) | 46 (0.748) | 0 (1) | 50 (0.553) |
| model 6 | 61 (0.07) | 52 (0.447) | 52 (0.447) | 52 (0.447) | 50 (0.553) | 0 (1) |

Table 9: Winning count (LL) for particular model 1950 - 2005 Basin vs SST

| model | model 1 | model 2 | model 3 | model 4 | model 5 | model 6 |
|-------|---------|---------|---------|---------|---------|---------|
| model 1 | 0 (1) | 77 (0) | 77 (0) | 38 (0.978) | 39 (0.959) | 39 (0.959) |
| model 2 | 23 (1) | 0 (1) | 54 (0.344) | 12 (1) | 12 (1) | 12 (1) |
| model 3 | 23 (1) | 46 (0.748) | 0 (1) | 12 (1) | 12 (1) | 11 (1) |
| model 4 | 62 (0.041) | 88 (0) | 88 (0) | 0 (1) | 54 (0.344) | 48 (0.656) |
| model 5 | 61 (0.07) | 88 (0) | 88 (0) | 46 (0.748) | 0 (1) | 50 (0.553) |
| model 6 | 61 (0.07) | 88 (0) | 89 (0) | 52 (0.447) | 50 (0.553) | 0 (1) |
Figure 4: 1950 - 2005 Basin vs. SST

Figure 5: 1950 - 2005 Basin vs. SST
Figure 6: Fitted Lines for all Models 1950 - 2005 Basin vs SST
### Table 10: RMSE comparison 1900 - 2005 Intense Basin vs SST

| Model    | RMSE (in) | RMSE (out) | 100-100*RMSE/RMSEconst | LL (in) | LL (out) |
|----------|-----------|------------|------------------------|---------|----------|
| Model 1  | 1.861     | 1.878      | 0                      | -1.947  | -1.962   |
| Model 2  | 1.587     | 1.615      | 26.071                 | -2.058  | -2.075   |
| Model 3  | 1.587     | 1.616      | 26.009                 | -2.059  | -2.075   |
| Model 4  | 1.587     | 1.609      | 26.617                 | -1.714  | -1.731   |
| Model 5  | 1.6       | 1.629      | 24.82                  | -1.734  | -1.753   |
| Model 6  | 1.601     | 1.609      | 26.596                 | -1.728  | -1.742   |

### Table 11: Model parameters incl. out of sample RMSE 1900 - 2005 Intense Basin vs SST

| Model     | α       | s.e.    | β       | s.e.    | k      | cov    | corr    | RMSE (out of sample) |
|-----------|---------|---------|---------|---------|--------|--------|---------|----------------------|
| Model 1   | 0.775   | 0.066   | 1.878   |         | 0      | 0      |         | 1.878                |
| Model 2   | 2.17    | 0.156   | 2.976   | 0.476   | 0.975  | 0.028  | 0.612   | 1.615                |
| Model 3   | 2.17    | 0.143   | 2.947   | 0.318   | 1.616  |        |         | 1.609                |
| Model 4   | 2.17    | 0.147   | 2.901   | 0.975   | 0.028  | 0.612  | 1.616   | 1.609                |
| Model 5   | 0.678   | 0.072   | 1.333   | 0.198   | 1.629  |        |         | 1.629                |
| Model 6   | 0.676   | 0.077   | 1.358   | 0.218   | 1.609  |        |         | 1.609                |

### Table 12: Winning count for particular model 1900 - 2005 Intense Basin vs SST

| Model     | model 1 | model 2 | model 3 | model 4 | model 5 | model 6 |
|-----------|---------|---------|---------|---------|---------|---------|
| Model 1   | 0 (1)   | 41 (0.98)| 41 (0.98)| 41 (0.98)| 41 (0.98)| 41 (0.98)|
| Model 2   | 59 (0.032)| 0 (1)   | 53 (0.314)| 47 (0.752)| 48 (0.686)| 46 (0.809)|
| Model 3   | 59 (0.032)| 47 (0.752)| 0 (1)   | 42 (0.951)| 49 (0.615)| 46 (0.809)|
| Model 4   | 59 (0.032)| 53 (0.314)| 58 (0.072)| 0 (1)   | 49 (0.615)| 47 (0.752)|
| Model 5   | 59 (0.032)| 52 (0.385)| 51 (0.461)| 51 (0.461)| 0 (1)   | 46 (0.809)|
| Model 6   | 59 (0.032)| 54 (0.248)| 54 (0.248)| 53 (0.314)| 54 (0.248)| 0 (1)   |

### Table 13: Winning count (LL) for particular model 1900 - 2005 Intense Basin vs SST

| Model     | model 1 | model 2 | model 3 | model 4 | model 5 | model 6 |
|-----------|---------|---------|---------|---------|---------|---------|
| Model 1   | 0 (1)   | 68 (0)  | 68 (0)  | 42 (0.968)| 41 (0.98)| 41 (0.98)|
| Model 2   | 32 (1)  | 0 (1)   | 53 (0.314)| 15 (1)  | 16 (1)  | 14 (1)  |
| Model 3   | 32 (1)  | 47 (0.752)| 0 (1)   | 15 (1)  | 16 (1)  | 15 (1)  |
| Model 4   | 58 (0.049)| 85 (0)  | 85 (0)  | 0 (1)   | 49 (0.615)| 48 (0.686)|
| Model 5   | 59 (0.032)| 84 (0)  | 84 (0)  | 51 (0.461)| 0 (1)   | 48 (0.686)|
| Model 6   | 59 (0.032)| 86 (0)  | 85 (0)  | 52 (0.385)| 52 (0.385)| 0 (1)   |
Figure 7: 1900 - 2005 Intense Basin vs SST

Figure 8: 1900 - 2005 Intense Basin vs SST
Figure 9: Fitted Lines for all Models 1900 - 2005 Intense Basin vs SST
Table 14: RMSE comparison 1950 - 2005 Intense Basin vs SST

| model name                  | RMSE (in) | RMSE (out) | 100-100*RMSE/RMSEconst | LL (in) | LL (out) |
|-----------------------------|-----------|------------|-------------------------|---------|----------|
| model 1 Flat Poisson        | 1.965     | 2.001      | 0                       | -2.018  | -2.044   |
| model 2 Linear Normal       | 1.664     | 1.715      | 26.517                  | -2.154  | -2.184   |
| model 3 Damped Linear Normal| 1.664     | 1.718      | 26.294                  | -2.154  | -2.184   |
| model 4 Linear Poisson      | 1.664     | 1.711      | 26.868                  | -1.811  | -1.847   |
| model 5 Exponential Poisson | 1.668     | 1.717      | 26.307                  | -1.82   | -1.853   |
| model 6 Exponential Neg. Bin.| 1.668   | 1.693      | 28.392                  | -1.82   | -1.837   |

Table 15: Model parameters incl. out of sample RMSE 1950 - 2005 Intense Basin vs SST

|         | ˆα   | s.e. | ˆβ   | s.e. | k   | cov | corr | RMSE (out of sample) |
|---------|------|------|------|------|-----|-----|------|----------------------|
| model 1 | 0.985| 0.082|      |      |     |     |      | 2.001                |
| model 2 | 2.679| 0.226| 3.466| 0.75 | 0   | 0   | 0    | 1.715                |
| model 3 | 2.679| 3.311| 0.955|      |     |     |      | 1.718                |
| model 4 | 2.679| 0.219| 3.435| 0.692| 0.061| 0.405| 1.711|                     |
| model 5 | 0.914| 0.087| 1.235| 0.26 | -0.008| -0.351| 1.717|                     |
| model 6 | 0.913| 0.089| 1.238| 0.266| -0.009| -0.34 | 1.693|                     |

Table 16: Winning count for particular model 1950 - 2005 Intense Basin vs SST

|         | model 1 | model 2 | model 3 | model 4 | model 5 | model 6 |
|---------|---------|---------|---------|---------|---------|---------|
| model 1 | 0 (1)   | 36 (0.989) | 36 (0.989) | 36 (0.989) | 38 (0.978) | 36 (0.989) |
| model 2 | 64 (0.022) | 0 (1)   | 57 (0.175) | 54 (0.344) | 43 (0.886) | 46 (0.748) |
| model 3 | 64 (0.022) | 43 (0.886) | 0 (1)   | 41 (0.93)  | 41 (0.93)  | 43 (0.886) |
| model 4 | 64 (0.022) | 46 (0.748) | 59 (0.114) | 0 (1)   | 43 (0.886) | 45 (0.825) |
| model 5 | 62 (0.041) | 57 (0.175) | 59 (0.114) | 57 (0.175) | 0 (1)   | 45 (0.825) |
| model 6 | 64 (0.022) | 54 (0.344) | 57 (0.175) | 55 (0.252) | 55 (0.252) | 0 (1)   |

Table 17: Winning count (LL) for particular model 1950 - 2005 Intense Basin vs SST

|         | model 1 | model 2 | model 3 | model 4 | model 5 | model 6 |
|---------|---------|---------|---------|---------|---------|---------|
| model 1 | 0 (1)   | 71 (0.001) | 71 (0.001) | 36 (0.989) | 39 (0.959) | 36 (0.989) |
| model 2 | 29 (1)  | 0 (1)   | 57 (0.175) | 12 (1)  | 11 (1)  | 12 (1)  |
| model 3 | 29 (1)  | 43 (0.886) | 0 (1)   | 12 (1)  | 11 (1)  | 12 (1)  |
| model 4 | 64 (0.022) | 88 (0)  | 88 (0)  | 0 (1)   | 43 (0.886) | 45 (0.825) |
| model 5 | 61 (0.07) | 89 (0)  | 89 (0)  | 57 (0.175) | 0 (1)   | 43 (0.886) |
| model 6 | 64 (0.022) | 88 (0)  | 88 (0)  | 55 (0.252) | 57 (0.175) | 0 (1)   |
Figure 10: 1950 - 2005 Intense Basin vs SST

Figure 11: 1950 - 2005 Intense Basin vs SST

| No. | SST Model(Window) | SST2HU Model | 2006 Mean | 2007 Mean | 2008 Mean | 2009 Mean | 2010 Mean | Mean |
|-----|-------------------|--------------|-----------|-----------|-----------|-----------|-----------|------|
| 1   | FL(8)             | Linear Poisson | 8.040     | 8.040     | 8.040     | 8.040     | 8.040     | 8.040|
| 2   | DLT               | Linear Poisson | 8.353     | 8.441     | 8.529     | 8.616     | 8.704     | 8.529|
| 3   | LT(22)            | Linear Poisson | 8.667     | 8.842     | 9.018     | 9.193     | 9.368     | 9.018|
| 4   | FL(8)             | Exp. Poisson | 8.368     | 8.381     | 8.383     | 8.387     | 8.388     | 8.381|
| 5   | DLT               | Exp. Poisson | 8.807     | 8.952     | 9.092     | 9.240     | 9.379     | 9.094|
| 6   | LT(22)            | Exp. Poisson | 9.295     | 9.596     | 9.897     | 10.217    | 10.524    | 9.906|

Table 18: Predictions of mean basin hurricane numbers.
Figure 12: Fitted Lines for all Models 1950 - 2005 Intense Basin vs SST

Table 19: Prediction of the variance of basin hurricane numbers.

| No. | SST Model (Window) | SST2HU Model | 2006 Var | 2007 Var | 2008 Var | 2009 Var | 2010 Var | Mean Var |
|-----|--------------------|--------------|----------|----------|----------|----------|----------|----------|
| 1   | FL(8)             | Linear Poisson | 10.065   | 10.185   | 10.203   | 10.235   | 10.239   | 10.185   |
| 2   | DLT               | Linear Poisson | 10.320   | 10.539   | 10.696   | 10.905   | 11.025   | 10.697   |
| 3   | LT(22)            | Linear Poisson | 10.775   | 11.160   | 11.464   | 11.843   | 12.059   | 11.460   |
| 4   | FL(8)             | Exp. Poisson   | 12.372   | 12.643   | 12.684   | 12.757   | 12.767   | 12.645   |
| 5   | DLT               | Exp. Poisson   | 13.110   | 13.704   | 14.161   | 14.778   | 15.169   | 14.184   |
| 6   | LT(22)            | Exp. Poisson   | 14.442   | 15.646   | 16.701   | 18.094   | 19.017   | 16.780   |

Table 20: Breakdown of the variance in table 19 into variance driven by SST prediction uncertainty and uncertainty in the SST-to-hurricane numbers regression model.

| No. | SST Model (Win) | SST2HU Model | 2006 V/M | 2007 V/M | 2008 V/M | 2009 V/M | 2010 V/M | Mean V/M |
|-----|-----------------|--------------|----------|----------|----------|----------|----------|----------|
| 1   | FL(8)           | Linear Poisson | 1.252    | 1.267    | 1.269    | 1.273    | 1.274    | 1.267    |
| 2   | DLT             | Linear Poisson | 1.235    | 1.249    | 1.254    | 1.266    | 1.267    | 1.254    |
| 3   | LT(22)          | Linear Poisson | 1.243    | 1.262    | 1.271    | 1.288    | 1.287    | 1.271    |
| 4   | FL(8)           | Exp. Poisson   | 1.479    | 1.508    | 1.513    | 1.521    | 1.522    | 1.509    |
| 5   | DLT             | Exp. Poisson   | 1.489    | 1.531    | 1.558    | 1.599    | 1.617    | 1.560    |
| 6   | LT(22)          | Exp. Poisson   | 1.554    | 1.630    | 1.688    | 1.771    | 1.807    | 1.694    |

Table 21: Ratio of the variance to the mean.
| No. | SST Model | S2B   | 2006 RMSE | 2007 RMSE | 2008 RMSE | 2009 RMSE | 2010 RMSE | Mean  |
|-----|-----------|-------|-----------|-----------|-----------|-----------|-----------|-------|
| 1   | FL(8)     | Linear Poisson | 0.764     | 0.774     | 0.776     | 0.778     | 0.779     | 0.774 |
| 2   | DLT       | Linear Poisson | 0.975     | 1.044     | 1.113     | 1.189     | 1.269     | 1.118 |
| 3   | LT(22)    | Linear Poisson | 1.199     | 1.331     | 1.475     | 1.629     | 1.796     | 1.486 |
| 4   | FL(8)     | Exp. Poisson  | 1.247     | 1.266     | 1.268     | 1.273     | 1.274     | 1.266 |
| 5   | DLT       | Exp. Poisson  | 1.612     | 1.744     | 1.878     | 2.029     | 2.187     | 1.890 |
| 6   | LT(22)    | Exp. Poisson  | 2.051     | 2.334     | 2.650     | 3.011     | 3.405     | 2.690 |

Table 22: Standard errors on the predicted means.
| No. | SST Model | S2B Model | B2L Model | 2006 Mean | 2007 Mean | 2008 Mean | 2009 Mean | 2010 Mean | Mean |
|-----|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|------|
| 1   | FL(8)     | LinPois   | PoisConProp | 2.044     | 2.044     | 2.044     | 2.044     | 2.044     | 2.044 |
| 2   | DLT       | LinPois   | PoisConProp | 2.124     | 2.146     | 2.169     | 2.191     | 2.213     | 2.169 |
| 3   | LT(22)    | LinPois   | PoisConProp | 2.204     | 2.248     | 2.293     | 2.338     | 2.382     | 2.293 |
| 4   | FL(8)     | ExpPois   | PoisConProp | 2.128     | 2.131     | 2.132     | 2.132     | 2.132     | 2.132 |
| 5   | DLT       | ExpPois   | PoisConProp | 2.239     | 2.276     | 2.312     | 2.350     | 2.385     | 2.312 |
| 6   | LT(22)    | ExpPois   | PoisConProp | 2.364     | 2.440     | 2.517     | 2.598     | 2.676     | 2.519 |

Table 23: Predictions of mean landfalling hurricane numbers.

| No. | SST Model | S2B Model | B2L Model | 2006 Var | 2007 Var | 2008 Var | 2009 Var | 2010 Var | Mean Var |
|-----|-----------|-----------|-----------|----------|----------|----------|----------|----------|----------|
| 1   | FL(8)     | LinPois   | PoisConProp | 2.695     | 2.703     | 2.704     | 2.706     | 2.706     | 2.703    |
| 2   | DLT       | LinPois   | PoisConProp | 2.791     | 2.828     | 2.860     | 2.896     | 2.926     | 2.860    |
| 3   | LT(22)    | LinPois   | PoisConProp | 2.901     | 2.970     | 3.034     | 3.103     | 3.162     | 3.034    |
| 4   | FL(8)     | ExpPois   | PoisConProp | 2.928     | 2.949     | 2.952     | 2.958     | 2.958     | 2.949    |
| 5   | DLT       | ExpPois   | PoisConProp | 3.087     | 3.162     | 3.228     | 3.305     | 3.366     | 3.230    |
| 6   | LT(22)    | ExpPois   | PoisConProp | 3.297     | 3.452     | 3.597     | 3.768     | 3.906     | 3.604    |

Table 24: Prediction of the variance of landfalling hurricane numbers.

| No. | SST Model | SST2HU Model | 2006(T1,T2) | 2007(T1,T2) | 2008(T1,T2) | 2009(T1,T2) | 2010(T1,T2) |
|-----|-----------|---------------|-------------|-------------|-------------|-------------|-------------|
| 1   | FL(8)     | LinPois       | 24, 76      | 24, 76      | 24, 76      | 24, 76      | 24, 76      |
| 2   | DLT       | LinPois       | 24, 76      | 24, 76      | 24, 76      | 24, 76      | 24, 76      |
| 3   | LT(22)    | LinPois       | 24, 76      | 24, 76      | 24, 76      | 25, 75      | 25, 75      |
| 4   | FL(8)     | ExpPois       | 27, 73      | 28, 72      | 28, 72      | 28, 72      | 28, 72      |
| 5   | DLT       | ExpPois       | 27, 73      | 28, 72      | 28, 72      | 29, 71      | 29, 71      |
| 6   | LT(22)    | ExpPois       | 28, 72      | 29, 71      | 30, 70      | 31, 69      | 31, 69      |

Table 25: Breakdown of the variance in table 24 into variance driven by SST prediction uncertainty and uncertainty in the SST-to-hurricane numbers regression model.

| No. | SST Model | S2B Model | B2L Model | 2006 V/M | 2007 V/M | 2008 V/M | 2009 V/M | 2010 V/M | Mean V/M |
|-----|-----------|-----------|-----------|----------|----------|----------|----------|----------|----------|
| 1   | FL(8)     | LinPois   | PoisConProp | 1.318     | 1.322     | 1.323     | 1.324     | 1.324     | 1.322    |
| 2   | DLT       | LinPois   | PoisConProp | 1.314     | 1.317     | 1.319     | 1.322     | 1.322     | 1.319    |
| 3   | LT(22)    | LinPois   | PoisConProp | 1.316     | 1.321     | 1.323     | 1.328     | 1.327     | 1.323    |
| 4   | FL(8)     | ExpPois   | PoisConProp | 1.376     | 1.384     | 1.385     | 1.387     | 1.387     | 1.384    |
| 5   | DLT       | ExpPois   | PoisConProp | 1.379     | 1.389     | 1.396     | 1.407     | 1.411     | 1.397    |
| 6   | LT(22)    | ExpPois   | PoisConProp | 1.395     | 1.415     | 1.429     | 1.450     | 1.459     | 1.431    |

Table 26: Ratio of the variance to the mean.

| No. | SST Model | S2B | B2L | 2006 RMSE | 2007 RMSE | 2008 RMSE | 2009 RMSE | 2010 RMSE | Mean |
|-----|-----------|----|-----|-----------|-----------|-----------|-----------|-----------|------|
| 1   | FL(8)     | LinPois | PoisConProp | 0.562     | 0.563     | 0.563     | 0.563     | 0.563     | 0.563 |
| 2   | DLT       | LinPois | PoisConProp | 0.601     | 0.614     | 0.627     | 0.641     | 0.656     | 0.628 |
| 3   | LT(22)    | LinPois | PoisConProp | 0.645     | 0.672     | 0.700     | 0.732     | 0.766     | 0.703 |
| 4   | FL(8)     | ExpPois | PoisConProp | 0.634     | 0.637     | 0.638     | 0.638     | 0.639     | 0.637 |
| 5   | DLT       | ExpPois | PoisConProp | 0.708     | 0.736     | 0.764     | 0.796     | 0.829     | 0.767 |
| 6   | LT(22)    | ExpPois | PoisConProp | 0.802     | 0.865     | 0.936     | 1.018     | 1.107     | 0.946 |

Table 27: Standard errors on the predicted means.
| No. | SST Model(Window) | SST2HU Model | 2006 Mean | 2007 Mean | 2008 Mean | 2009 Mean | 2010 Mean | Mean |
|-----|------------------|--------------|-----------|-----------|-----------|-----------|-----------|------|
| 1   | FL(8)            | Linear Poisson | 3.903     | 3.903     | 3.903     | 3.903     | 3.903     | 3.903 |
| 2   | DLT              | Linear Poisson | 4.118     | 4.178     | 4.238     | 4.298     | 4.358     | 4.238 |
| 3   | LT(22)           | Linear Poisson | 4.333     | 4.453     | 4.572     | 4.692     | 4.812     | 4.572 |
| 4   | FL(8)            | Exp. Poisson  | 4.118     | 4.133     | 4.136     | 4.140     | 4.140     | 4.133 |
| 5   | DLT              | Exp. Poisson  | 4.441     | 4.556     | 4.665     | 4.784     | 4.893     | 4.668 |
| 6   | LT(22)           | Exp. Poisson  | 4.818     | 5.062     | 5.306     | 5.574     | 5.826     | 5.317 |

Table 28: Predictions of mean basin intense hurricane numbers.

| No. | SST Model(Window) | SST2HU Model | 2006 Var | 2007 Var | 2008 Var | 2009 Var | 2010 Var | Mean Var |
|-----|------------------|--------------|----------|----------|----------|----------|----------|----------|
| 1   | FL(8)            | Linear Poisson | 4.851    | 4.907    | 4.916    | 4.931    | 4.933    | 4.908    |
| 2   | DLT              | Linear Poisson | 5.038    | 5.160    | 5.252    | 5.369    | 5.444    | 5.253    |
| 3   | LT(22)           | Linear Poisson | 5.319    | 5.537    | 5.717    | 5.932    | 6.072    | 5.716    |
| 4   | FL(8)            | Exp. Poisson  | 6.330    | 6.501    | 6.527    | 6.573    | 6.580    | 6.502    |
| 5   | DLT              | Exp. Poisson  | 6.933    | 7.365    | 7.714    | 8.183    | 8.503    | 7.740    |
| 6   | LT(22)           | Exp. Poisson  | 7.974    | 8.918    | 9.795    | 10.975   | 11.828   | 9.898    |

Table 29: Prediction of the variance of basin intense hurricane numbers.

| No. | SST Model | SST2HU Model | 2006(T1,T2) | 2007(T1,T2) | 2008(T1,T2) | 2009(T1,T2) | 2010(T1,T2) |
|-----|-----------|--------------|-------------|-------------|-------------|-------------|-------------|
| 1   | FL(8)     | Linear Poisson | 20, 80     | 20, 80     | 21, 79     | 21, 79     | 21, 79     |
| 2   | DLT       | Linear Poisson | 18, 82     | 19, 81     | 19, 81     | 20, 80     | 20, 80     |
| 3   | LT(22)    | Linear Poisson | 19, 81     | 20, 80     | 20, 80     | 21, 79     | 21, 79     |
| 4   | FL(8)     | Exp. Poisson  | 35, 65     | 36, 64     | 37, 63     | 37, 63     | 37, 63     |
| 5   | DLT       | Exp. Poisson  | 36, 64     | 38, 62     | 40, 60     | 42, 58     | 42, 58     |
| 6   | LT(22)    | Exp. Poisson  | 40, 60     | 43, 57     | 46, 54     | 49, 51     | 51, 49     |

Table 30: Breakdown of the variance in table 29 into variance driven by SST prediction uncertainty and uncertainty in the SST-to-hurricane numbers regression model.

| No. | SST Model(Win) | SST2HU Model | 2006 V/M | 2007 V/M | 2008 V/M | 2009 V/M | 2010 V/M | Mean V/M |
|-----|----------------|--------------|----------|----------|----------|----------|----------|----------|
| 1   | FL(8)         | Linear Poisson | 1.243    | 1.257    | 1.259    | 1.263    | 1.264    | 1.257    |
| 2   | DLT           | Linear Poisson | 1.224    | 1.235    | 1.239    | 1.249    | 1.249    | 1.239    |
| 3   | LT(22)        | Linear Poisson | 1.228    | 1.244    | 1.250    | 1.264    | 1.262    | 1.250    |
| 4   | FL(8)         | Exp. Poisson  | 1.537    | 1.573    | 1.578    | 1.588    | 1.589    | 1.573    |
| 5   | DLT           | Exp. Poisson  | 1.561    | 1.617    | 1.654    | 1.711    | 1.738    | 1.658    |
| 6   | LT(22)        | Exp. Poisson  | 1.655    | 1.762    | 1.846    | 1.969    | 2.030    | 1.862    |

Table 31: Ratio of the variance to the mean.

| No. | SST Model | S2B  | 2006 RMSE | 2007 RMSE | 2008 RMSE | 2009 RMSE | 2010 RMSE | Mean |
|-----|-----------|------|-----------|-----------|-----------|-----------|-----------|------|
| 1   | FL(8)     | Linear Poisson | 0.520     | 0.527     | 0.528     | 0.530     | 0.530     | 0.527 |
| 2   | DLT       | Linear Poisson | 0.663     | 0.710     | 0.757     | 0.809     | 0.863     | 0.760 |
| 3   | LT(22)    | Linear Poisson | 0.816     | 0.905     | 1.003     | 1.108     | 1.222     | 1.011 |
| 4   | FL(8)     | Exp. Poisson  | 0.859     | 0.872     | 0.874     | 0.878     | 0.878     | 0.872 |
| 5   | DLT       | Exp. Poisson  | 1.097     | 1.188     | 1.280     | 1.386     | 1.496     | 1.289 |
| 6   | LT(22)    | Exp. Poisson  | 1.401     | 1.608     | 1.839     | 2.110     | 2.405     | 1.873 |

Table 32: Standard errors on the predicted means.
Table 33: Predictions of mean landfalling intense hurricane numbers.

| No. | SST Model | S2B Model | B2L Model | 2006 Mean | 2007 Mean | 2008 Mean | 2009 Mean | 2010 Mean | Mean |
|-----|------------|------------|-----------|-----------|-----------|-----------|-----------|-----------|------|
| 1   | FL(8)     | LinPois    | PoisConProp | 0.937     | 0.937     | 0.937     | 0.937     | 0.937     | 0.937 |
| 2   | DLT       | LinPois    | PoisConProp | 0.988     | 1.003     | 1.017     | 1.031     | 1.046     | 1.017 |
| 3   | LT(22)    | LinPois    | PoisConProp | 1.040     | 1.069     | 1.097     | 1.126     | 1.155     | 1.097 |
| 4   | FL(8)     | ExpPois    | PoisConProp | 0.988     | 0.992     | 0.993     | 0.993     | 0.994     | 0.992 |
| 5   | DLT       | ExpPois    | PoisConProp | 1.066     | 1.093     | 1.120     | 1.148     | 1.174     | 1.120 |
| 6   | LT(22)    | ExpPois    | PoisConProp | 1.156     | 1.215     | 1.273     | 1.338     | 1.398     | 1.276 |

Table 34: Prediction of the variance of landfalling intense hurricane numbers.

| No. | SST Model | S2B Model | B2L Model | 2006 Var | 2007 Var | 2008 Var | 2009 Var | 2010 Var | Mean Var |
|-----|------------|------------|-----------|----------|----------|----------|----------|----------|----------|
| 1   | FL(8)     | LinPois    | PoisConProp | 1.216     | 1.219     | 1.220     | 1.221     | 1.221     | 1.219    |
| 2   | DLT       | LinPois    | PoisConProp | 1.280     | 1.301     | 1.320     | 1.338     | 1.356     | 1.319    |
| 3   | LT(22)    | LinPois    | PoisConProp | 1.344     | 1.383     | 1.419     | 1.456     | 1.491     | 1.419    |
| 4   | FL(8)     | ExpPois    | PoisConProp | 1.353     | 1.366     | 1.368     | 1.372     | 1.373     | 1.367    |
| 5   | DLT       | ExpPois    | PoisConProp | 1.465     | 1.518     | 1.564     | 1.620     | 1.664     | 1.566    |
| 6   | LT(22)    | ExpPois    | PoisConProp | 1.616     | 1.729     | 1.838     | 1.970     | 2.080     | 1.846    |

Table 35: Breakdown of the variance in table 34 into variance driven by SST prediction uncertainty and uncertainty in the SST-to-hurricane numbers regression model.

| No. | SST Model | SST2HU Model | B2L Model | 2006(T1,T2) | 2007(T1,T2) | 2008(T1,T2) | 2009(T1,T2) | 2010(T1,T2) | Mean V/M |
|-----|------------|---------------|-----------|-------------|-------------|-------------|-------------|-------------|----------|
| 1   | FL(8)     | LinPois       | PoisConProp | 23, 77      | 23, 77      | 23, 77      | 23, 77      | 23, 77      | 23, 77   |
| 2   | DLT       | LinPois       | PoisConProp | 23, 77      | 23, 77      | 23, 77      | 23, 77      | 23, 77      | 23, 77   |
| 3   | LT(22)    | LinPois       | PoisConProp | 23, 77      | 23, 77      | 23, 77      | 23, 77      | 23, 77      | 23, 77   |
| 4   | FL(8)     | ExpPois       | PoisConProp | 27, 73      | 27, 73      | 27, 73      | 28, 72      | 28, 72      | 28, 72   |
| 5   | DLT       | ExpPois       | PoisConProp | 27, 73      | 28, 72      | 28, 72      | 29, 71      | 29, 71      | 29, 71   |
| 6   | LT(22)    | ExpPois       | PoisConProp | 28, 72      | 30, 70      | 31, 69      | 32, 68      | 33, 67      | 33, 67   |

Table 36: Ratio of the variance to the mean.

| No. | SST Model | S2B Model | B2L Model | 2006 V/M | 2007 V/M | 2008 V/M | 2009 V/M | 2010 V/M | Mean V/M |
|-----|------------|------------|-----------|----------|----------|----------|----------|----------|----------|
| 1   | FL(8)     | LinPois    | PoisConProp | 1.298     | 1.302     | 1.302     | 1.303     | 1.303     | 1.302    |
| 2   | DLT       | LinPois    | PoisConProp | 1.295     | 1.298     | 1.297     | 1.297     | 1.297     | 1.297    |
| 3   | LT(22)    | LinPois    | PoisConProp | 1.293     | 1.294     | 1.293     | 1.293     | 1.291     | 1.293    |
| 4   | FL(8)     | ExpPois    | PoisConProp | 1.369     | 1.377     | 1.379     | 1.381     | 1.381     | 1.378    |
| 5   | DLT       | ExpPois    | PoisConProp | 1.375     | 1.388     | 1.397     | 1.411     | 1.417     | 1.398    |
| 6   | LT(22)    | ExpPois    | PoisConProp | 1.397     | 1.423     | 1.443     | 1.473     | 1.487     | 1.447    |

Table 37: Standard errors on the predicted means.
Figure 13: The three SST predictions we use as input to our hurricane prediction method, along with observed SSTs for the period 1976 to 2005.
Figure 14: Forecasts for the number of basin hurricanes for the years 2006 to 2011 for the 6 models described in the text.
Figure 15: As in figure 14 but also showing observed basin hurricane numbers for the period 1950 to 2005.
Figure 16: Forecasts for the number of landfalling hurricanes for the years 2006 to 2011 for the 6 models described in the text.
Figure 17: As figure [I6] but also showing observed landfalling hurricane numbers for the period 1950 to 2005.
Figure 18: As figure [17] but only showing observed data since 1980, and the forecasts based on a linear conversion from SST to basin hurricane numbers.
Figure 19: As figure 17 but only showing observed data since 1980, and the forecasts based on an exponential conversion from SST to basin hurricane numbers.
S2B2L Models and Uncertainty

LF Cat1–5 Forecasts FL(blue); LT(red); DLT(green)
S2B2L Models and Uncertainty
LF Cat1–5 Forecasts FL(blue); LT(red); DLT(green)