5 Year Prediction of the number of Hurricanes which make U.S. Landfall

Stephen Jewson[1], Enrica Bellone[1,] Shree Khare[1], Thomas Laepple[1,2], Manuel Lonfat[1], Kechi Nzerem[1], Adam O'Shay[1], Jeremy Penzer[1,3], Katie Coughlin[1*]

1. *Risk Management Solutions; London, UK.*
2. *Alfred-Wegener Institut; Bremerhaven, Germany.*
3. *London School of Economics; London, UK.*

[*] Corresponding author e-mail: Katie.Coughlin@RMS.com

ABSTRACT.
The insurance industry is interested in five-year predictions of the number of Atlantic hurricanes which will make landfall in the United States. Here we describe a suite of 20 models developed to make such predictions, along with their predictions for both the 2006-2010 and the 2007-2011 periods. The purpose of developing these models is to represent a broad spectrum of viewpoints as a basis for an expert elicitation.

KEYWORDS
Statistics
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1 Introduction

The question of how to predict the number and intensity of Atlantic hurricanes that make landfall in the United States is of great interest to the insurance and reinsurance industry. There is interest in predictions on time-scales from as short as a few hours to as long as 50 years. The physical processes that determine predictability, and the methods that one might use to make predictions, vary greatly according to the timescale. Here we are concerned with predictions on time-scales of one to five years. For these time-scales both natural variability and anthropogenic influences contribute to the climatic conditions which impact the activity and properties of hurricanes. As a result, 1-5 year hurricane predictability depends on the extent to which decadal fluctuations, stationarity and trends can be estimated in the hurricane numbers and associated climate system. This leads to the use of prediction methodologies that first attempt to define the current state , and then additionally try to capture the variability and/or trends.

Our approach to making predictions of hurricane numbers on these time scales has two steps. First we think of as many possible ways to make skillful predictions of hurricane rates for the next five years and build a large number of forecast models to cover this range of possibilities. Our models are based on inputs such as historical numbers of land-falling Atlantic hurricanes, historical numbers of hurricanes in the Atlantic basin, and historical sea surface temperatures (SSTs) as well as predictions of the future from computer simulations. The methods used are mostly statistical, although there are also some specific uses of dynamical models. Second, we present these models to a panel of experts, who weight the various predictions using their best judgement. This paper focuses on the first step, and presents a set of models that were used for such an expert elicitation process in 2006. The details of the elicitation process are described in another paper (Lonfat et al., 2007).

1.1 Background and Motivation

Insurance and reinsurance rates for property on the gulf and east coasts of the United States are strongly influenced by predictions of the possible number and intensity of future hurricanes making landfall in those regions. The insurance industry is interested in such predictions on a wide range of timescales. In particular, there is interest in predictions of the number of hurricanes in the next one to five years. Such predictions are used for the pricing of insurance and reinsurance contracts, and for the allocation of capital to businesses and business units.

Predictions on this time scale are slightly different from predictions that scientists are usually concerned with, which tend to be on either seasonal or, more recently, climate time scales. Concerning the longer time scales, especially, there is some controversy in the community regarding the physical phenomena that may be influencing these predictions.

Following the high levels of Atlantic basin hurricane activity over the past decade, a considerable amount of research regarding the influences of natural and human-induced variability on various aspects of hurricane behaviour has recently been published. Much of this work is relevant to our question of how to predict hurricane numbers and intensities on 5-year time-scales but there is still quite a bit of controversy regarding the actual mechanisms which are causing these current increases as well as uncertainty regarding future changes. Work by Webster et al. (2005), Elsner (2006), Mann and Emanuel (2006) and Hoyos et al. (2006) suggest that, in the Atlantic, there is an increasing trend in frequency and intensity of hurricanes, in part due to the rise in SSTs brought on by global warming. Trenberth (2005) suggests that increasing SSTs are likely to increase intensity and rainfall from hurricanes, but that the effect on actual hurricane numbers is unclear. Dynamical prediction models have been used to estimate the impact of global warming on hurricane intensity and precipitation (Knutson and Tuleya, 1999, 2004, Vecchi and Soden, 2007) and these models show a CO_2-induced increase in storm intensity and rainfall and a small decrease in storm frequency. Further studies by Klotzbach (2006) and Goldenberg et al. (2001) suggest that long-term Atlantic hurricane variability is more influenced by natural variability, such as the Atlantic Multidecadal Oscillation (AMO), than by anthropogenic changes. A number of other authors have also looked into various aspects of natural and human-induced impacts of hurricane variability (for example: Kerr, (2005), and Bengtsson, 2001). To date, however, there is no clear consensus on what is driving the changes in the number and intensity of hurricanes, and what changes we expect to see in the future. For the development of our predictions, we use a variety of methods that are consistent with a number of different underlying physical mechanisms.

In addition to the internal variability of the Atlantic Multidecadal Oscillation and SST rise due to global warming, other climatic features such as the North Atlantic Oscillation (NAO) (Elsner et al., 2000) and the El Nino Southern Oscillation (ENSO) (Bove et al., 1998; Camargo and Sobel, 2005) are known to influence hurricane activity. Lyons (2004) has shown that ENSO has predictability on annual time scales but for five year time scales there is at present no effective way to predict ENSO, and there very possibly never will be. The lack of predictability of ENSO on 1-5 year timescales means that the prediction methods we describe below are very different from those used in seasonal prediction (see for example Saunders and Lea, 2005 or Vitart and Anderson, 2001). Wind shear has also been shown to be related to hurricane activity (Zehr, 1992; DeMaria et al., 1993; Landsea et al., 1998). However, in the Atlantic, Webster et al. (2005) shows that there is currently no trend in the shear, and so shear would seem not to be a useful predictor over our timescale of interest.

1.2 General Strategy

The first issue we consider in developing our 5-year hurricane number prediction schemes is the problem of estimating the current state. Recent historical data is likely to be more relevant to making such estimates than earlier historical data. The question then arises as to exactly how much of the historical data one should use, and with what weighting. Within our suite of models we answer this question in a variety of ways. The next issue we consider in our model development is how to model potential changes over the next five years. To capture these changes, our methods range from assuming that the future is unchanged from the past to modeling systematic future changes. Some of our methods, attempt to model a trend and extrapolate it into the future. However, even if we assume that there is a trend in the system, the trend in most climate variables is small (relative to interannual variability) and difficult to estimate. As a result, ignoring the trend may be better than extrapolating it incorrectly (this is even the case if we know the trend is linear, as shown in Jewson, 2004). As a result, some of the included methods try to model trends while others do not. We note, however, that *all* of our models incorporate any *past* effects of a trend when they attempt to capture the current level of activity.

To keep things simple, the goal we set for our predictions is to minimize the root mean square error (RMSE) between the predicted and actual numbers of hurricanes. We note, however, that one might eventually want to move beyond RMSE as a metric because RMSE gives equal weight to errors on both sides of the prediction, while the consequences of overpredicting and underpredicting do not have symmetric affects. Furthermore, we note that one might ultimately want to consider making probabilistic forecasts and evaluating them using a probabilistic metric. We have taken this approach in Hall and Jewson, 2006.

We note that most of our analysis uses simple classical statistical methods. Given that the amount of data is rather small, the signals are weak, and the parameter uncertainty is high one might want to use more elements of complex statistical approaches such as shrinkage or Bayesian analysis [Litterman, 1979, 1986] (or, indeed, Bayesian shrinkage analysis [Komaki, 2001; George et al., 2006]). However, such methods can be overly complex and we are not yet convinced that the benefits of using them, in terms of greater scientific accuracy, would outweigh the loss of transparency for the problem at hand. This is partly because one of our goals is to introduce methods that can be widely understood by meteorologists, climate modellers, and insurance industry practitioners. We feel that at this early stage in the development of the ideas presented here it is more important to focus on the discussion of what methods fundamentally make sense, and what assumptions the different methods depend on, rather than taking the level of technical sophistication as far as it could be taken.

In the following sections, we present the methods that we developed for predicting the number of Atlantic hurricanes that will make U.S. landfall in the periods 2006-2010 and 2007-2011. These predictions are made given data up to the end of the hurricane seasons in 2005 and 2006, respectively. We present the predictions for 2006-2010, since those were the actual predictions used in the elicitation process. In section three we describe what we call ‘long baseline methods’. In section four we discuss issues related to the non-stationarity of the hurricane number series. In this section we also describe what we call 'short baseline methods', and introduce the idea of direct and indirect predictions of landfall numbers. In section five we describe what we call 'mixed baseline' methods that mix the long and short baseline methods in an optimal way. In section six we describe methods based on sea-surface temperature. In each case, predictions are made for the expected numbers of category 1-5 and category 3-5 hurricanes hitting the US in these five year periods. Tables of the predictions from all the models are shown, and discussed, in the summary section.

All the methods we present have been described in detail in Risk Management Solutions technical reports, and are available from the Arxiv preprint server at arxiv.org. We cite these reports throughout this article. Relative to those reports, this article summarizes the methods used, explains the connections between them, and presents the results from all the methods side by side for the first time.

2. Data

The hurricane numbers used in our analysis (see figure 1) come from the 2006 version of the HURDAT data-set (Jarvinen et al., 1984) and we use sea surface temperatures from HADISST (Rayner et al., 2002).

The HURDAT data is considered to be reasonably accurate since 1950. Prior to 1950, the numbers of hurricanes in the basin may be less accurate, however, as there were fewer observational opportunities over the ocean at this time. Air-craft reconnaissance, for example, did not begin until 1944. Landfalling hurricane numbers are generally considered accurate since 1900, although the intensities of landfalling storms may be poorly estimated due to the distances between proper meteorological measurements and the probability of missing measurements of the intense inner core. Prior to 1900 both the landfall and basin numbers are suspect because of the sparsity of population along the US coast line. Based on this, we never use data before 1900 and only use data from 1950 to 2005 to build relationships between SSTs, hurricane numbers within the Atlantic basin and hurricane numbers at landfall. Some of the results shown are based partly on basin data from 1900 to 1950, with the understanding that this earlier data may not be realistic. Any conclusions drawn from our analyses need to bear in mind these issues of data quality, since our forecasts can only ever be as good as the data on which they are based.

We use Atlantic SSTs to help predict hurricane numbers and the strength of the relationship between SSTs and hurricane frequency is dependent on the region of the north Atlantic being considered (Shapiro and Goldenberg, 1989; Raper, 1993; Goldenberg et al., 2001). The SSTs which correlate most highly with hurricane activity are the SSTs within the main development region (MDR), 10-20N, 15-70W. MDR SSTs are also highly correlated with each other in space (see figure 10 in Meagher and Jewson, 2006). It therefore makes sense to construct a single index that captures the MDR SST variability. We tested various combinations and came up with an index based on July-September SST variability as having the highest correlation with hurricane activity.

3. Long baseline methods

The simplest method we present for predicting landfalling hurricane numbers is based on taking an average of the number of hurricanes that made landfall in the historical data, using data as far back as is considered accurate. We call this method the 'long baseline' method. As mentioned in section 2, we consider landfalling hurricane number data to be accurate back to 1900, and so our first prediction is the average number of hurricanes per year from 1900 to 2005 (or 1900 to 2006 for the predictions for 2007-2011). The 2006-2010 predictions from this method are given in row 1 of table 2 in the summary section. The 2007-2011 predictions are given in table 2. Since there has been some discussion as to whether the intensities of storms prior to 1950 were really estimated correctly, as mentioned in section 2, we also present results for the alternative long baseline that extends from 1950, in row 2 of both summary tables.

4. Non-stationarity of the hurricane number time-series

As a method for predicting future hurricane numbers, the long baseline method is only appropriate if the landfalling hurricane number record is stationary, or at least close to stationary. A large number of studies have looked at this question. With respect to hurricane numbers in the *basin*, it has been clearly shown that the record is not stationary. For instance, Elsner et al. (2001) detected the presence of statistically significant change-points in the cat 3-5 basin hurricane number series in the years 1942/43, 1964/65 and 1994/95. Using a different methodology and data up to 2001, they [Elsner et al., 2004] showed the presence of statistically significant change-points in the years 1905/06, 1942/43 and 1994/95. In our own change-point analysis, which uses a different methodology again, we detected the existence of statistically significant change-points in the cat 1-5 basin hurricane number series in the years 1931/32, 1947/48, 1969/70 and 1994/95 [Jewson and Penzer, 2006]. In fact, these change-points can be seen rather clearly by eye in the data itself: see figure 2. For the landfalling hurricanes Elsner et al. (2004) repeated their analysis, but did not find any change-points. We also repeated our analysis [Jewson and Penzer, 2006] and did not find any significant change-points. These results suggest that the landfalling series may be stationary. However, in a different kind of analysis, we did find statistically significant evidence of autocorrelation in the landfall time-series (see Khare and Jewson, 2005 a,b), but the signal was rather weak.

Why is it that the basin hurricane number time series shows such significant change-points, while the landfalling time-series does not? There are two obvious limiting-case explanations: (a) the interannual probability[†] of hurricanes making landfall is constant from year to year. This means that the landfalling number time-series inherits all the properties of the basin hurricane number time-series, but that the change-points are obscured by noise for statistical reasons, or (b) the interannual probability of hurricanes making landfall is not constant in time, and either varies predictably on decadal time-scales, meaning that the landfall numbers are actually stationary. Given the importance of this question for the prediction of future numbers of landfalling hurricanes, we have investigated this in some detail. In Nzerem et al. (2006) we asked the question: if the basin series contains real change-points of the same size as the observed 1994/1995 change-point, what is the probability of detecting that change-point in the basin data and in the landfall data? Given an assumption of constant probability of landfall for each storm, it turns out that the change-point would usually be detectable in the basin data, but would usually *not* be detectable in the landfall data. The explanation is purely statistical: in going from basin to landfall, the number of storms reduces by a factor of four. This reduces the signal-to-noise ratio by a factor of two, and makes it twice as hard to detect any change-point. The observed change-points are of a size that this reduction in signal-to-noise is just enough to hide them in the variability of the landfall data. So, based on this result, we should not necessarily be surprised that we can't detect change-points in the landfall series, and the fact that we can not should not lead us to conclude that they are not there. Approaching the same question from a different perspective we looked at the proportion of basin hurricanes that make landfall during the various intervals between change-points [Bellone et al., 2007]. The results are very clear. The proportion of storms making landfall prior to 1948 is different to the proportion making landfall after 1948. This is most likely explained by poor observations of basin storms before that time. However, after 1948, during the period of reliable observations, the proportion of storms making landfall cannot be shown to vary (i.e. we cannot reject the null hypothesis that it is constant). Another way to interpret this result is that if the probability of storms making landfall does vary (and it very likely does at some level) then the size of those variations are too small to detect, and would be too small to estimate effectively, so it seems reasonable to ignore them. Finally, in Hall and Jewson (2007), we studied the historical behaviour of hurricanes in years with warm and cold tropical North Atlantic sea-surface temperatures (SSTs). We find that although the number of hurricanes, their genesis sites and the characteristics of their propagation all depend on SST in statistically significant ways, the overall proportion of Atlantic storms making landfall does not.

We conclude that it makes sense to build hurricane prediction models that use the assumption that the probability of storms making landfall over the next five years is well predicted using the proportion that have made landfall over the last 56 years. We will call this the 'constant landfall probability' model (CLP), although the model does not, strictly speaking, assume landfall probabilities are constant, but just that the probability varies sufficiently little that we cannot properly estimate the variations. Note that the long-baseline model is essentially based on the opposite set of assumptions that the probability of storms making landfall varies in such a way that the number making landfall is approximately constant. We include predictions from both sets of assumptions in our model set, for completeness, although we believe that the data favour the CLP model, as discussed above. The CLP model has various interesting implications, as we discuss below.

5. Short baseline predictions

In the previous section, we justify the CLP model of basin and landfalling hurricane numbers that assumes (a) the mean number of basin storms varies in time and (b) the probability of storms making landfall is constant. A consequence

[†] By 'interannual probability of landfall' we mean the probability of landfall, estimated a year before the beginning of the hurricane season. Such an estimate is unconditional with respect to ENSO, since ENSO is not predictable that far in advance.

of these assumptions is that the mean number of storms making landfall varies in time, following the mean number in the basin.

There are two important implications of this model for the prediction of numbers of landfalling hurricanes. The first is that we can take the change-points that have been identified in the basin hurricane number time-series, and assume that they apply to the landfalling series, even though they cannot be detected in the landfalling series. This leads to a method for predicting the landfalling series, which we call the 'short baseline' method, and which involves making a prediction for future landfalling hurricane numbers which consists of the average number of landfalling hurricanes since the most recent change-point. Based on the CLP model, this is then likely to be a better prediction method than the long baseline method, because of the underlying non-stationarity in the series. Conveniently, the various change-point analyses listed above all give the same point in time for the most recent change-point (1994/1995), and so all lead to the same short baseline prediction. This prediction is given in row 3 of the tables of results.

Based on the estimated levels between the change-points, the CLP model implies that we would expect the long-baseline prediction to be biased. If we assume that the level of hurricane activity over the next 5 years will remain at the same level that it has been at since 1995, then the short baseline prediction will be unbiased. The assumption that the number of hurricanes will remain at the same level clearly ignores decadal oscillations and trends, and the possible occurrence of further change-points in the next five years, but these approximations may be good ones since our forecast horizon is fairly short and the trends are apparently rather weak.

The second implication of the CLP model is that there is an inherent relationship between landfalling hurricane numbers and the number of hurricanes in the basin. Given this, it might make sense to predict landfalling hurricane numbers by first predicting basin hurricane numbers, and then converting the basin prediction to a prediction of landfalling numbers using the probability of landfall estimated from historical data since 1950. We will apply this idea to all subsequent models (thus doubling the number of predictions) and will call such predictions 'indirect' predictions, as opposed to 'direct' predictions which predict landfalls directly from landfall data. We expect such indirect predictions may be better than direct predictions. In Laepple et al. (2007) we find that, if the probability of storms making landfall is constant, then there are situations in which we expect the indirect method to be better. For instance, if we make a short baseline prediction of the number of basin storms using data since 1995, and then convert that to a prediction of landfalling storms using a probability of landfall estimated from the number of basin and landfalling storm numbers since 1950, then we'd expect the resulting prediction to be nearly twice as accurate as the direct short baseline prediction that uses landfalling data alone. The explanation for this statistical effect is that there are more storms in the basin, and so the predictable signal can be estimated more accurately than when only using the landfall data. If the probability of landfall can also be estimated relatively accurately (as it can if we use data since 1950), then this increased accuracy propagates through to the prediction at landfall. Row 6 in the results tables shows this indirect short baseline prediction.

6. Mixed baseline predictions

Up to this point, we have presented averaged baseline prediction methods, with direct and indirect versions of the short baseline scheme. The long baseline prediction method has the advantage that it uses a large amount of historical data, but since, in the CLP model, we believe that the landfalling hurricane number time series is non-stationary, we expect that the long-baseline and medium baseline predictions must be biased. The short-baseline scheme only uses the most recent data, which is more relevant to the current climate, and is likely to reduce the bias, but possibly suffers from the fact that there are simply not many years of data since the last change-point to make an accurate estimate of the mean number of storms. Consideration of the pros and cons of the long and short baseline models motivates the idea that there may be a forecast methodology that lies 'in between' the two, and performs better than both. We have investigated this idea in a series of technical reports [Jewson et al., 2005; Jewson et al., 2006 and Binter et al., 2006]. The methodology we use is to formulate the question as a classical mathematical 'bias-variance trade-off' problem, and we ask what weights we should put on the different intervals of the historical hurricane data in order to minimize the RMSE of our predictions. We call predictions from the resulting method 'mixed-baseline predictions'. Inevitably the mixed baseline predictions must lie between the long baseline predictions and the short baseline predictions. As with the short baseline predictions, we have two versions of each mixed baseline prediction: one direct (i.e. determined by applying weights directly to the historical landfall data) and one indirect (determined by applying weights to the historical basin data, and then converting to a landfall prediction).

To estimate the optimal weights on the levels of activity between change points we use the weights which minimize the RMSE. The lowest RMSE of the current level of category 3-5 storms comes from a straight average of the two most active periods. For the Elsner change points these are 1943-1964 and 1995-2005 and for the RMS change points these are 1932-1947 and 1995-2005. Statistical analysis tells us that this gives a more accurate prediction than just using data from the recent active period because it makes use of more historical data while only introducing a small bias. Interestingly, for the category 1-5 basin storms, the best prediction comes from just using the historical data since the last change point, presumably because there are enough cat 1-5 basin storms since 1995 that it is no longer profitable to introduce the bias error from a similar historical interval.

In order to address the question of how sensitive these predictions are to the change-points identified in the historical hurricane number time-series, we also apply these methods to the change-points from both Elsner et al. (2004) and from Jewson and Penzer (2006) The four combinations: two sets of change-points and direct and indirect methods, lead to the predictions given in rows 4, 5, 7 and 8 of the results tables. Note that the indirect predictions of the category 1-5 hurricane numbers for both the Elsner and RMS change points will be exactly the same as the indirect predictions of the short baseline since the optimal mixed baseline for basin category 1-5 numbers is just the short baseline.

6.1 SST-based predictions

So far we have presented landfalling hurricane-number prediction methods that are based on historically observed hurricane numbers alone. These methods have the advantage that they depend on relatively few assumptions. On the other hand, they have the disadvantages that (a) there seems to be no very satisfactory way to represent possible climate-change related trends in hurricane numbers in these methods, and (b) the signals that we are trying to predict tend to be obscured by noise. In this section we now present a different set of models for predicting future hurricane numbers, based on the idea of first predicting SSTs in the tropical North Atlantic, and then converting such an SST prediction to a prediction of hurricane numbers. The methods we use are described in detail in a series of technical reports [Meagher and Jewson, 2006; Laepple et al., 2007, Jewson, 2007, Binter et al., 2007 a,b]. The rationale for these methods is that (a) the effects of climate trends and climate variability may be more robust, and hence easier to predict, in the SSTs than they are in the hurricane number time-series, and (b) there is a clear correlation between SSTs in the subtropical North Atlantic and Atlantic basin hurricane numbers. The prediction methods assume that this correlation between SST and hurricane numbers will continue into the future. This is an assumption we have to make in order to make these predictions: however, it is not necessarily the case that this assumption is true. For instance, it may be that the historic correlation between SSTs and hurricane numbers will not apply if patterns of SST in the future are different from patterns experienced in the past, and it may be that it is not appropriate to extrapolate the relationship between SST and hurricane numbers to levels of SST that are higher than those experienced in the past.

6.2 SST Predictions

The first part of the development of our SST-based hurricane number prediction schemes is to predict future SSTs. The statistical schemes we use for predicting SST are taken from methods developed for making short-time climate predictions of temperature in the weather derivatives industry. They consist of moving averages, fitted linear trends, and fitted damped linear trends. Damped linear trends are a compromise between moving averages, which don't capture trends, and fitted linear trends, which by construction suffer from being overfitted and are never optimal predictors, even for data with real linear trends (for a discussion of the surprisingly difficult question of how to predict noisy data with linear trends, see Jewson and Penzer, 2004,2006). For moving averages and linear trends, we use backtesting (also known as hindcasting) to determine how many years of data over which to fit the average or the trend. Historically, moving averaged predictions of SST, using an 8 year window, result in the lowest RMSEs. So, for our future flat averaged predictions we also use an 8 year window. For fitting linear trends, the best way to predict SST historically would have been to use a 22 year window, and so again that is what we use for our future predictions. For the damped linear trend, we take the ad-hoc decision to make a 50-50 combination of the prediction from the moving average and the prediction from the fitted linear trend. Due to the relatively large variance in the SSTs, this 50-50 combination is more accurate in hindcast experiments than the trend predictions. These three predictions of future SSTs are given in figure 4.

6.3 SST- hurricane number relationship

The second part of the development of our SST-based hurricane number predictions is to model the relationship between SST and hurricane numbers. To do this, we consider only data from 1950 to the present, because of the data quality issues discussed in section 2. The correlations between SST and basin and landfalling hurricane numbers are shown in table1, and scatter plots of these relations are shown in figure 5. The correlation between SST and basin hurricane numbers is statistically significant. The correlation between SST and landfalling hurricane numbers, however, is marginally significant. Why is there such a difference? Is it that SST really doesn't affect landfalling hurricane numbers, or is the disappearance of the correlation at landfall just a statistical effect, similar to the disappearance of change-points discussed in section 4? We considered this question in detail in Laepple et al., 2007, in which we showed that we would *expect* the correlation between SST and landfalling numbers to disappear, purely on statistical grounds. The argument is indeed very similar to the argument for why change-points disappear in the landfalling series: the signal-to-noise ratio decreases by a factor of two, which is just enough to hide the signal we might want to detect.

year	Index Correlated with MDR SSTs	Linear Correlation	Rank Correlation
1900-2005	Basin Cat 1-5 Numbers	0.56	0.51
1950-2005	Basin Cat 1-5 Numbers	0.62	0.56
1900-2005	Basin Cat 3-5 Numbers	0.52	0.54
1950-2005	Basin Cat 3-5 Numbers	0.53	0.56

Table 1: Linear and Rank Correlations

Based on this result, we believe that it is very possible that there is a dependency between SST and landfalling hurricane numbers, and that it makes sense to develop prediction models based on this assumption. We then have the possibility of using a direct prediction method (regress observed landfalling hurricane numbers directly onto SST) or an indirect prediction method (regress observed basin hurricane numbers onto SST, and then predict landfalling hurricane numbers from basin hurricane numbers). Which is likely to be better? We investigated this question in some detail in Nzerem et al., 2007, and concluded that the indirect method is possibly slightly better, but that the two methods are likely to be very close (in terms of accuracy), and that it is worth considering both.

The next question is what shape of regression curve we should use to model the effects of SST on hurricane numbers. In the academic literature, it is common to use an exponential regression curve (see for example Elsner and Schmertmann, 1993 and Solow and Moore, 2000). This seems to be principally because this is the default option in statistical packages that allow for regression of integer-valued data (such as hurricane numbers). This, in turn, is because using an exponential curve is, mathematically, a neat way to avoid the problem of not wanting to predict negative numbers of hurricanes. Fitting an exponential curve to the SST-hurricane number relation, is, however, rather dangerous, especially since we are going to be predicting SSTs as high or higher than have ever occurred in the past. This could potentially lead to predictions of very large numbers of hurricanes. We performed a laboriously detailed analysis of the observed relationships between SST and hurricane numbers [Binter et al., 2007a,b] and concluded that it is just as reasonable to model this relationship using a piecewise linear function that is a straight line fit in the region of interest.

Our SST model range includes three types of SST predictions; flat, linear and damped, direct and indirect predictions, and linear and exponential curves for the SST-hurricane number relationship, giving a total of 12 SST-based predictions for landfalling hurricane numbers. These predictions are given in rows 9 to 20 of the tables of results.

7. Summary

The problem of predicting the number of Atlantic hurricanes that make landfall in the U.S. is of great interest to the insurance and reinsurance industry. Here we are concerned with predictions on time-scales of one to five years. For these time-scales both natural variability and anthropogenic influences contribute to the climactic conditions which in turn impact the activity of hurricanes. The relative contribution of these two factors, however, is currently unknown.

We have discussed a number of forecast models based on inputs such as historical hurricane numbers in the Atlantic that reach landfall, historical hurricane numbers in the Atlantic basin and historical sea surface temperatures (SSTs). The goal is to produce a broad range of models which a group of hurricane experts can weigh according to their expert opinions.

In developing our 5-year hurricane number prediction schemes we address first address the problem of estimating the current state. For this problem, recent historical data is likely to be more relevant than earlier historical data. The question then arises as to exactly how much of the historical data one should use, and with what weighting. We answer this question in a variety of ways. First we consider the possibility that the rate at which hurricanes are generated and subsequently hit land, is a random stationary process. In that case, it makes sense to use all possible data and we create long-term predictions. However, since the time series of the hurricane numbers is not stationary, we also consider alternative methods to estimate the current state, which involve giving more weight to the more recent years in the data. The next issue we consider in our model development is how to model potential changes from this current state over the next five years. To capture these changes, our methods range from assuming that the future is unchanged to modeling systematic future changes. Some of our methods attempt to model a trend and extrapolate it into the future while others take the stance that there are climate shifts. We note, however, that *all* of our models incorporate any *past* effects of a trend and of the variability of other climate phenomena when they attempt to capture the current level of activity.

To keep things simple, the goal we set for our predictions is to minimize the root mean square error (RMSE) between the predicted and actual numbers of hurricanes. This provides a useful metric of comparison for parameter choices (like window lengths for calibration and extrapolation) as well as for model comparison. We also note that most of our analysis uses simple classical statistical methods which have the benefit of transparency for the problem at hand. This is partly because one of our goals is to introduce methods that can be widely understood by meteorologists, climate modelers, and insurance industry practitioners. This simple suite of models achieves this transparency as well as provides a broad range of predictions representing the various scientific theories that may be involved in predicting annual average hurricane numbers over the next five years. In presenting these models we have emphasized the assumptions, drawbacks and benefits of each model. Finally, we list the models presented in the Risk Management Solution's (RMS) 2006 elicitation and the predictions for 2007-2011 and 2006-2010 (these models and predictions are shown in tables 2 and 3).

Summary Table

	Model	5-year Prediction of Cat 1-5 U.S. Landfall Number	5-year Prediction of Cat 3-5 U.S. Landfall Number
1	Baseline Average 1900-2006	1.70	0.64
2	Baseline Average 1950-2006	1.56	0.63
3	Mixed Baseline Short 1995-2006	2.08	0.83
4	Mixed Baseline Elsner's Change Points	2.00	0.82
5	Mixed Baseline RMS Change Points	2.11	0.86
6	Indirect Mixed Baseline Short 1995-2006	2.05	0.92
7	Indirect Mixed Baseline Elsner Change Points	2.05	0.85
8	Indirect Mixed Baseline RMS Change Points	2.05	0.84
9	Flat-line SST prediction, linear relation to landfalling hurricanes	1.84	0.82
10	Damped SST prediction, linear relation to landfalling hurricanes	1.94	0.88
11	Linear trend SST prediction, linear relation to landfalling hurricanes	2.03	0.95
12	Flat-line SST prediction, exponential relation to landfalling hurricanes	1.92	0.87
13	Damped SST prediction, exponential relation to landfalling hurricanes	2.06	0.96
14	Linear Trend SST prediction, exponential relation to landfalling hurricanes	2.21	1.08
15	Indirect prediction Flat-line SST with linear relation to hurricanes	1.96	0.89
16	Indirect prediction Damped SST with linear relation to hurricanes	2.09	0.98
17	Indirect prediction Linear Trend SST with linear relation to hurricanes	2.23	1.06
18	Indirect prediction Flat-line SST with exponential relation to hurricanes	2.03	0.92
19	Indirect prediction Damped SST with exponential relation to hurricanes	2.21	1.05
20	Indirect prediction Linear Trend SST with exponential relation to hurricanes	2.43	1.21

Table 2. Predictions for the number of Hurricanes hitting US land for the 2007-2011 period.

	Model	5-year Prediction of Cat 1-5 U.S. Landfall Number	5-year Prediction of Cat 3-5 U.S. Landfall Number
1	Baseline Average 1900-2005	1.72	0.65
2	Baseline Average 1950-2005	1.59	0.64
3	Mixed Baseline Short 1995-2005	2.27	0.91
4	Mixed Baseline Elsner's Change Points	2.06	0.85
5	Mixed Baseline RMS Change Points	2.19	0.89
6	Indirect Mixed Baseline 1995-2005	2.12	0.96
7	Indirect Mixed Baseline Elsner Change Points	2.12	0.90
8	Indirec Mixed Baseline RMS Change Points	2.12	0.90
9	Flat-line SST prediction, linear relation to landfalling hurricanes	1.94	0.87
10	Damped SST prediction, linear relation to landfalling hurricanes	2.04	0.93
11	Linear trend SST prediction, linear relation to landfalling hurricanes	2.14	0.99
12	Flat-line SST prediction, exponential relation to landfalling hurricanes	2.05	0.93
13	Damped SST prediction, exponential relation to landfalling hurricanes	2.20	1.04
14	Linear Trend SST prediction, exponential relation to landfalling hurricanes	2.37	1.16
15	Indirect prediction Flat-line SST with linear relation to hurricanes	2.04	0.94
16	Indirect prediction Damped SST with linear relation to hurricanes	2.17	1.02
17	Indirect prediction Linear Trend SST with linear relation to hurricanes	2.29	1.10
18	Indirect prediction Flat-line SST with exponential relation to hurricanes	2.13	0.99
19	Indirect prediction Damped SST with exponential relation to hurricanes	2.31	1.12
20	Indirect prediction Linear Trend SST with exponential relation to hurricanes	2.52	1.28

Table 3. Predictions for the number of Hurricanes hitting US land for the 2006-2010 period.

8. References

Bellone et al. (2007) Statistical testing of the proportion of hurricanes making landfall, in preparation.

Bengtsson (2001) Weather - Hurricane threats, *Science*, **293**, 440-441.

Binter et al. (2006) Year ahead prediction of US landfalling hurricane numbers: the optimal combination of multiple levels of activity since 1900, *http://www.arxiv.org/abs/physics/0611070,* 7 Nov. 2006.

Binter et al. (2007a) Statistical modeling of the relationship between main development region sea surface temperature and Atlantic basin hurricane numbers, *http://www.arxiv.org/abs/physics/0701170,* 29 Jan. 2007.

Binter et al. (2007b) Statistical modeling of the relationship between main development region sea surface temperature and landfalling Atlantic basin hurricane numbers, *http://www.arxiv.org/abs/physics/0701173,* 15 Jan. 2007.

Bove, M.C. et al. (1998) Effect of El Nino on U.S. Landfalling Hurricanes, *Bull. Am. Meteorol. Soc.*, **79**, 2477-2482.

Camargo and Sobel (2005) Western North Pacific Tropical Cyclone Intensity and ENSO, *J. Climate*, **18**, 2996-3006.

DeMaria, M. et al. (1993) Upper-level angular momentum fluxes and tropical cyclone intensity change, *J. Atmos. Sci.*, **50**, 1133-1147.

De Maria, (1996) The effect of vertical shear on tropical cyclone intensity change, *J. Atmos. Sci.*, **53**, 2076-2087.

Elsner, J.B. and C.P. Schmertmann (1993) Improving Extended-Range Seasonal Predications of Intense Atlantic Hurricane Activity, *Weather and Forecasting,* **121**, 345-351.

Elsner, J.B. et al. (1999) Fluctuations in North Atlantic Hurricane Frequency, *J. Climate*, **12**, 427-437.

Elsner, J.B. et al. (2000) Spatial variations in major U.S. hurricane activity: Statistics and a physical mechanism*, J. Climate*, **13**, 2293-2305.

Elsner, J.B. et al. (2001) Changes in the rates of North Atlantic major hurricane activity during the 29th Century, *Geophysical Research Letters,* **27**, 1743-1746.

Elsner, J.B. et al. (2004) Detecting shifts in hurricane rates using a Markov Chain Monte Carlo approach, *J. Climate*, **17**, 2652-2666.

Elsner, J.B. (2006) Evidence in support of the climate change-Atlantic hurricane hypothesis, *Geophysical Research Letters,* v33, L16705, doi:10.1029/2006GL026869, August 2006.

Emanuel K. (2005) Increasing destructiveness of tropical cyclones over the past 30 years, *Nature*, **436**, 686-688.

Epstein, E.S. (1985) Statistical inference and prediction in climatology: a Bayesian approach, *Meteorol. Monographs,* **20**. Am. Meteorol. Soc., p.199.

George, E.I. et al. (2006) Improved minimax prediction under Kullback-Leibler loss, *Annals of Statistics*, **34**, 78-91.

Goldenberg, S.B. and L.J. Shapiro (1996) Physical mechanisms for the association of El Nino and West African rainfall with Atlantic major hurricane activity, *J. Climate*, **9**, 1169-1187.

Goldenberg, S.B. et al. (2001) The recent increase in Atlantic hurricane activity: Causes and Implications, *Science*, **293**, 474-479.

Gray (1968) Global view of the origin of tropical disturbances and storms, *Mon. Wea. Rev.,* **96**, 669-700.

Hall, T. and S. Jewson (2005) Statistical modeling of tropical cyclone tracks: a semi-parametric model for the mean trajectory, http://www.arxiv.org/abs/physics/0503231, 31 Mar. 2005.

Hall, T. and S. Jewson (2006a) Comparing classical and Bayesian methods for predicting hurricane landfall rates, http://arxiv.org/abs/physics/0611006, 01 Nov. 2006.

Hall, T. and S. Jewson (2006b) Predicting hurricane regional landfall rates: comparing local and basin-wide track model approaches, http://arxiv.org/abs/physics/0611103, 10 Nov. 2006.

Hall, T. and S. Jewson (2007) SST and North American tropical cyclone landfall: a statistical modeling study, *J. Climate*, submitted.

Hoyos et al. (2006) Deconvolution of the factors contributing to the increase in global hurricane intensity, *Science,* **312**, 94-97.

Jarvinen et al. (1984) A tropical cyclone data tape for the North Atlantic Basin, 1886-1983: Contents, limitations, and uses. *NOAA Technical Memorandum NWS NHC 22,* Coral Gables, Florida, p.21.

Jewson, S. (2004) The Relative Importance of Trends, Distributions and the Number of Years of Data in the Pricing of Weather Options, *http://ssrn.com/abstract=516503*, 11 March 2004.

Jewson, S. (2004) Probabilistic forecasting of temperature: comments on the Bayesian model averaging approach, *http://www.arxiv.org/abs/physics/0409127*, 24 Sept. 2004.

Jewson, S. and J. Penzer (2004) Weather derivative pricing and the detrending of meteorological data: an empirical evaluation of damped linear detrending, *http://ssrn.com/abstract=623381*, 26 Nov. 2004.

Jewson, S. and J. Penzer (2005) Weather derivative pricing and the detrending of meteorological data: three alternative representations of damped linear detrending, *http://ssrn.com/abstract=653241*, 24 Jan. 2005.

Jewson, S. et al. (2005) Year ahead prediction of US landfalling hurricane numbers: the optimal combination of long and short baselines, *http://www.arxiv.org/abs/physics/0512113*, 13 Dec. 2005.

Jewson, S. and J. Penzer (2006a) An objective change-point analysis of historical Atlantic hurricane numbers, *http://www.arxiv.org/abs/physics/0611071*, 7 Nov. 2006.

Jewson, S. and J. Penzer (2006b) An objective change-point analysis of landfalling historical Atlantic hurricane numbers, *http://www.arxiv.org/abs/physics/0611071*, 7 Nov. 2006.

Jewson, S. and J. Penzer (2006c) Estimating trends in weather series: consequences for pricing derivatives, *Studies in Non-linear Dynamics and Econometrics,* **10**, No. 3, Article 9.

Jewson, S. et al. (2006) Year ahead prediction of US landfalling hurricane numbers: the optimal combination of long and short baselines for intense hurricanes, *http://www.arxiv.org/abs/physics/0606192*, 21 Jun. 2006.

Jewson, S. et al. (2007a) Predicting landfalling hurricane numbers from sea surface temperatures: theoretical comparisons of direct and indirect approaches, *http://arxiv.org/abs/physics/0701176*, 29 Jan 2007.

Jewson, S. et al. (2007b) Predicting hurricane numbers from sea surface temperature: closed-form expressions for the mean, variance and standard error of the number of hurricanes, *http://arxiv.org/abs/physics/0701167*, 15 Jan. 2007.

Jewson, S. et al. (2007c) Predicting landfalling hurricane numbers from basin hurricane numbers: basic statistical analysis, *http://arxiv.org/abs/physics/0701166*, 29 Jan. 2007.

Kerr (2005) Is Katrina a Harbinger of Still More Powerful Hurricanes?, *Science,* **309**, 1807.

Khare and Jewson (2005a) Year ahead prediction of US landfalling hurricane numbers, *http://www.arxiv.org/abs/physics/0507165*, 21 July 2005.

Khare and Jewson (2005b) Year ahead prediction of US landfalling hurricane numbers: intense hurricanes, *http://www.arxiv.org/abs/physics/0512092*, 10 Dec 2005.

Klotzbach (2006) Trends in global tropical cyclone activity over the past twenty years (1986-2005), *Geophys. Res. Letts.,* **35**, L10805, doi: 10.1029/2006GL025881.

Knutson, T.R. and R.E. Tuleya (1999) Increased hurricane intensities with CO2-induced warming as simulated using the GFDL hurricane prediction system, *Climate Dynamics*, **15**, 503-519.

Knutson, T.R. and R.E. Tuleya (2004)Impact of CO2-induced warming on simulated hurricane intensity and precipitation: Sensitivity to the choice of climate model and convective parameterization, *J.Climate,* **17**, 3477-3495.

Komaki, F. (2001) A shrinkage predictive distribution for multivariate normal observables, *Biometrika*, **88**, 859-864.

Laepple, T. et al. (2007a) Correlations between hurricane numbers and sea surface temperature: why does the correlation disappear at landfall?, *http://arxiv.org/abs/physics/0701175*, 15 Jan. 2007.

Laepple, T. et al. (2007b) Five year prediction of sea surface temperature in the tropical Atlantic: a comparison of simple statistical methods, *http://arxiv/org/abs/physics/0701162*, 15 Jan. 2007.

Laepple, T. and S. Jewson (2007) Five year ahead prediction of sea surface temperature in tropical Atlantic: a comparison between IPCC climate models and simple statistical models, *http://arxiv.org/abs/physics/0701165*, 15 Jan. 2007.

Landsea, C.W. (1998) The extremely active 1995 Atlantic hurricane season: environmental conditions and verification of seasonal forecasts, *Mon. Wea. Rev.,* **126**, 1174-1193.

Landsea, C.W. et al. (1999) Atlantic basin hurricanes: Indices of climatic changes, *Climatic Change,* **42**, 89-129.

Lavielle, M. and M. Labarbier (2001) An application of MCMC methods for the multiple change-points problem, *Signal Process*, **81**, 39-53.

Litterman, R.B. (1986) Forecasting with Bayesian vector autoregressions -- 5 years of experience, *The Journal of Business and Economic Statistics*, **4**, 25-38.

Lonfat, M., S. Jewson, and R. Muir-Wood, 2007: Predicting Atlantic Hurricane Activity: A Perspective Based on the Elicitation of Expert Opinions. *Geophys. Res. Lett*., to be submitted.

Lyons, S.W. (2004) U.S. Tropical Cyclone Landfall Variability: 1950-2002, *Weather and Forecasting,* **19**, 473-480.

Mann and Emanuel (2006) Atlantic Hurricane Trends Linked to Climate Change, *EOS Transactions, AGU,* **87**, 233-244.

Meagher, J. and S. Jewson (2006) Year-ahead prediction of hurricane season sea surface temperature, *http://www.arxiv.org/abs/physics/0606185*, 21 June 2006.

Nzerem, K. et al. (2006) Change-point detection in the historical hurricane number time-series: why can't we detect change-points at US landfall?, *http://arxiv.org/abs/physics/0611107*, 10 Nov. 2006.

Peixoto J.P. and A.H. Oort (1992) Physics of Climate, American Institute of Physics, p.520.

Raper, S.C.B. (1993) Observational data on the relationships between climatic change and the frequency and magnitude of severe tropical storms. Climate and Sea Level Change: Observations, Projections and Implications, R.A. Warrick, E.M. Barrow and T.M.L. Wigley, Eds., Cambridge University Press, Cambridge, UK, 192-212.

Rayner et al. (2002) Global analysis of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century, *J. Geophys. Res.,* **108**, D14 4407, doi:10.1029/2002JD002670.

Saunders, M.A. and A.R. Harris (1997) Statistical evidence links exceptional 1995 Atlantic hurricane season to record sea warming, *Geophys. Res. Letts.,* **24**, 1255-1258.

Saunders, M.A. and A.S. Lea (2005) Seasonal prediction of hurricane activity reaching the coast of the United States, *Nature,* **434**, 1005-1008.

Shapiro, L.J. (1982) Hurricane climate fluctuations. Part I: Patterns and cycles, *Mon. Wea. Rev.*, **110**, 1014-1023.

Shapiro, L.J. and Goldenberg, S.B. (1989) Atlantic sea surface temperatures and tropical cyclone formation, *J. Climate*, **11**, 578-590.

Shephard, N. (1993) Distribution of the ML estimator of a MA(1) and a local level model, *Econometric Theory,* **9**, 377-401.

Solow A.R. and L. Moore (2000) Testing for a trend in a partially incomplete hurricane record, *J. Climate,* **13**, 2293-2305.

Sriver R.L. and M. Huber (2006) Low frequency variability in globally integrated tropical cyclone power dissipation, *Geophysical Res. Letts.,* **33**, L11705 doi:10.1029/2006GL026167.

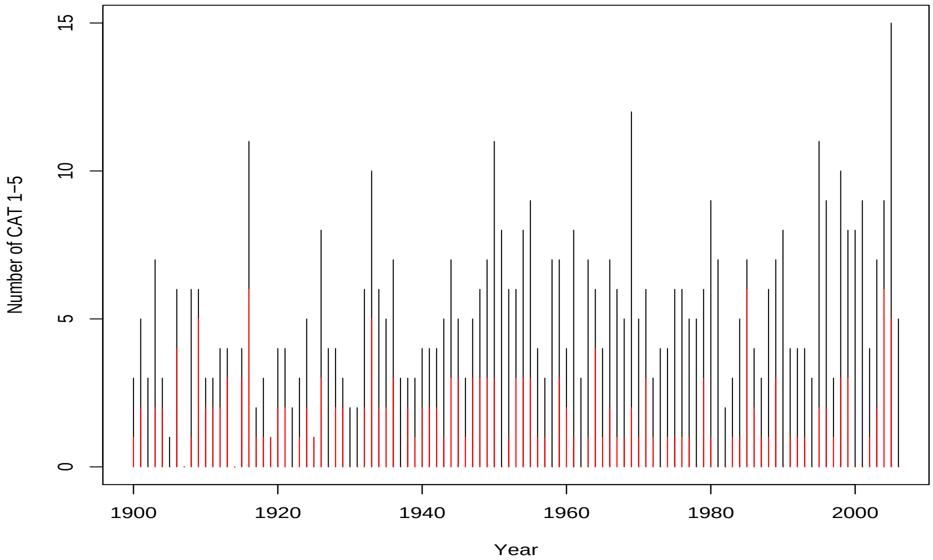
Trenberth, K.; Uncertainty in Hurricanes and Global Warming; *Science,* **17**, 1753-1754, 2005.

Vecchi, G.A. and B.J. Soden (2007) Increased tropical Atlantic wind shear in model projections of global warming, *GRL,* **34**, doi:10.1029/2006GL028905.

Vitart, F. and J.L. Anderson (2001) Sensitivity of Atlantic Tropical Storm Frequency to ENSO and Interdecadal Variability of SSTs in an Ensemble of AGCM Integrations, *J. Climate,* **14**, 533-545.

Webster, P.J. et al. (2005) Changes in Tropical Cyclone Number, Duration and Intensity in a Warming Environment, *Science,* **309**, 1844-1846.

Zehr, R.M. (1992) Tropical cyclogenisis in the Western Pacific, *NOAA Technical Report NESDIS*, **61**, NOAA; Washington D.C., USA.



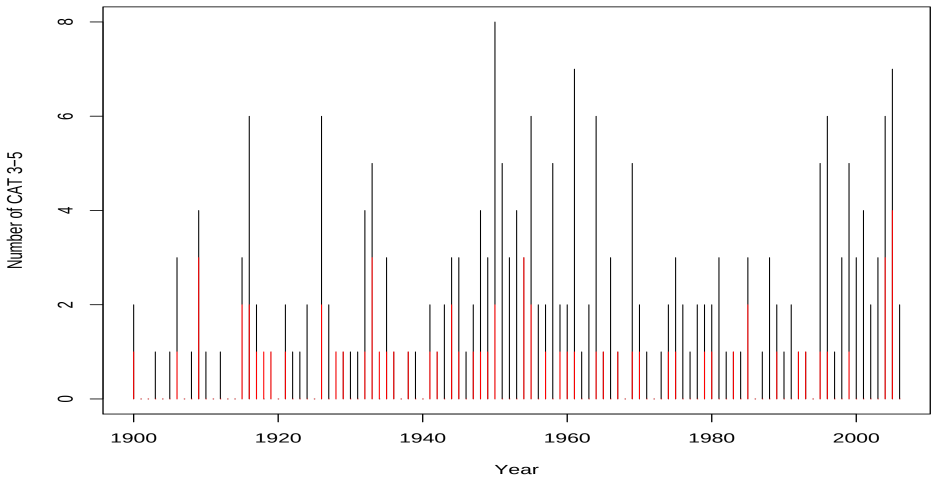


Figure 1. Atlantic Hurricane Numbers since 1900. a) Numbers of Category 1-5 Hurricanes. The red line indicates the number of those that hit the US coastline. b) Number of Category 3-5 Hurricanes. The red line indicates the number hitting the coast.

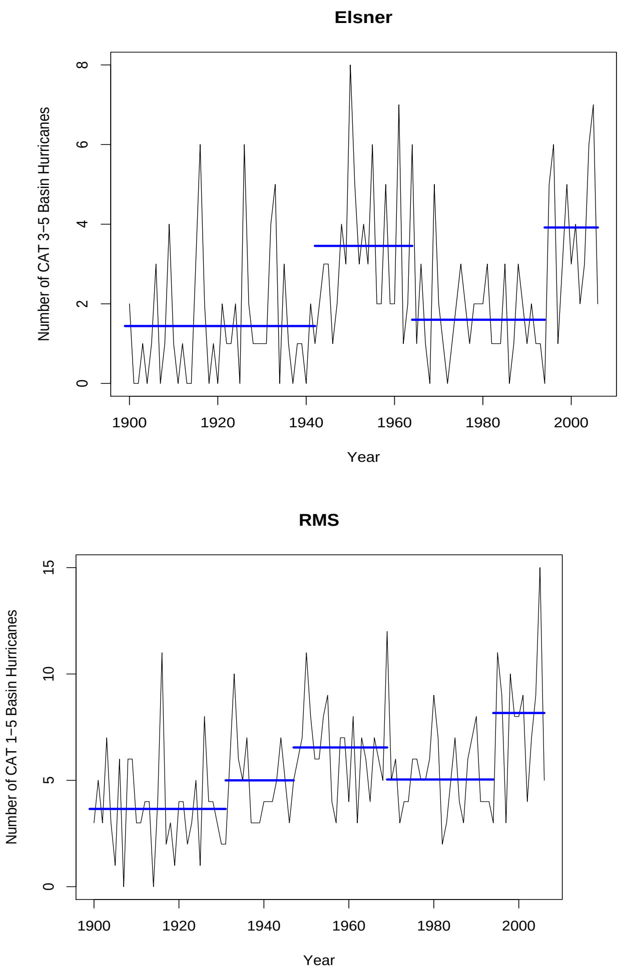


Figure 2. Change points for Elsner for category 3-5 (a) and RMS for category 1-5 (b) overlaid on the Atlantic basin hurricane numbers.

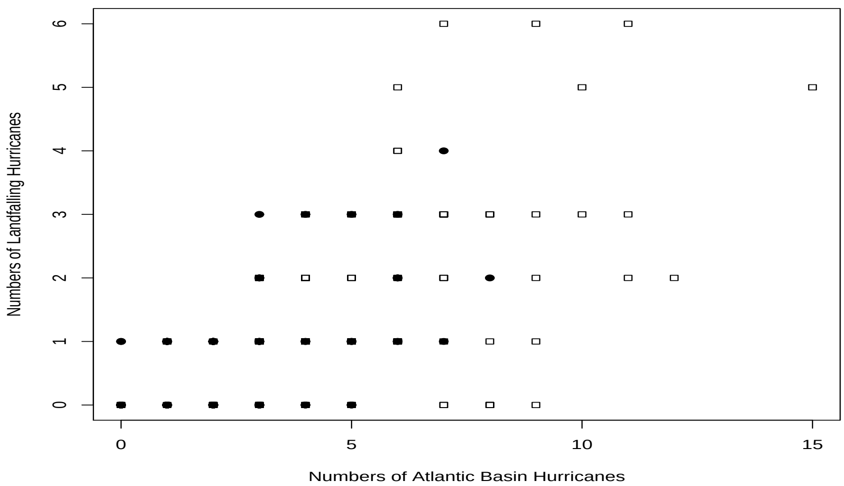


Figure 3. Scatter Plot of the ratio of landfalling hurricanes to total numbers of hurricanes in the Atlantic basin. Numbers of category 1-5 hurricanes are marked with a square for each year and numbers of category 3-5 hurricanes with an solid circle.

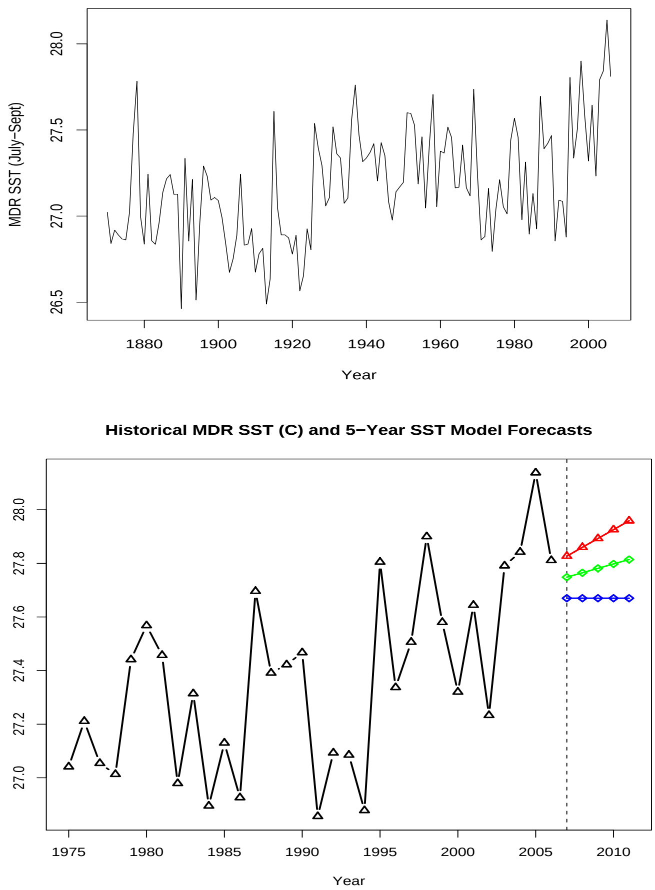
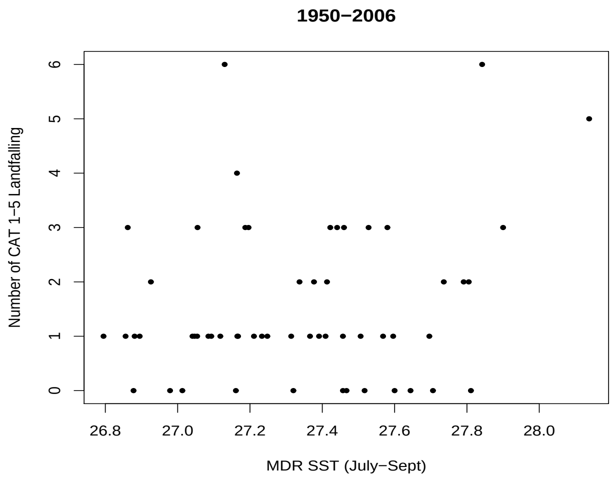


Figure 4. a) The SSTs in the MDR region since 1880. b) Predictions of the 5-year window of MDR SSTs using flat-line (blue), damped trend (green) and linear trend (red) predictions.



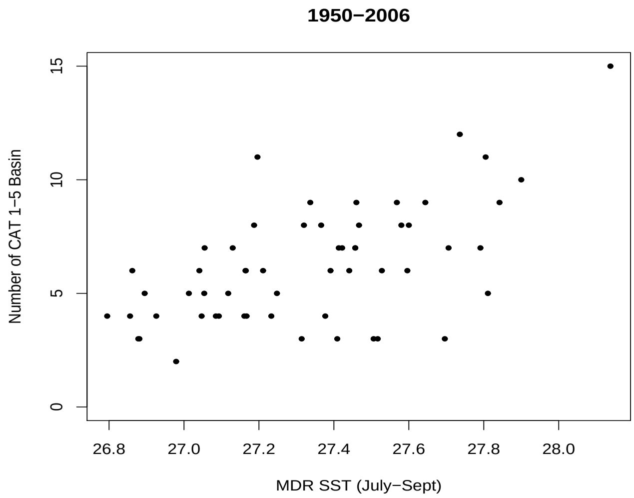


Figure 5. Correlation between Numbers of (a) Landfalling Hurricanes, (b) Basin Hurricanes and the SSTs in the MDR region.