Predicting landfalling hurricane numbers from basin hurricane numbers: statistical analysis and predictions

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Abstract

One possible method for predicting landfalling hurricane numbers is to first predict the number of hurricanes in the basin and then convert that prediction to a prediction of landfalling hurricane numbers using an estimated proportion. Should this work better than just predicting landfalling hurricane numbers directly? We perform a basic statistical analysis of this question in the context of a simple abstract model, and convert some previous predictions of basin numbers into landfalling numbers.

1 Introduction

We are interested in trying to develop and compare methods for the prediction of the distribution of the number of hurricanes that might make landfall in the US in future years. One class of possible methods that one might use involves first predicting the number of hurricanes in the Atlantic basin, and then converting that prediction to a prediction of landfalling numbers using some estimate of the proportion that might make landfall. Is this class of indirect methods likely to work any better than simpler methods based on predicting the number of landfalls directly? On the one hand, the direct methods avoid having to make any estimate of the way that basin hurricanes relate to landfalling hurricanes. On the other, there are more hurricanes in the basin than at landfall and so it might be possible to predict basin numbers more accurately than landfalling numbers (in some sense), and this accuracy might then feed through into the landfall prediction.

In order to try and understand the relationship between these two methods a little better, we investigate some of basic statistical properties of the direct and indirect methods for predicting future hurricane rates.

In section 2 we present some basic statistical ideas that we will use in our analysis. In section 3 we set up the problem and derive expressions for the likely performance of the indirect method in a general context. In section 4 we consider the performance of a set of simple prediction methods for basin hurricane numbers. In section 5 we specialize our analysis to the case where the basin hurricane numbers are poisson distributed. In section 6 we perform some Monte-Carlo simulations to check our approximations. In sections 7 and 8 we apply the indirect method to make predictions of the number of landfalling hurricanes, based on the basin hurricane number predictions of [Binter et al. (2006)]. Finally in section 9 we discuss our results.

2 Background on conditioning

In this section we present some standard statistical results that we will use later.

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2.1 Basic definitions

Consider two random variables $X$ and $Y$ with joint density $f_{X,Y}$ and marginals $f_X$ and $f_Y$. The density of $Y \mid (X = x)$ is defined as

$$f_{Y \mid X}(y \mid x) = \frac{f_{X,Y}(x,y)}{f_X(x)} \quad \text{where } f_X(x) \neq 0$$  (1)

The conditional expectation is defined as $E(Y \mid X) = \psi(X)$ where

$$\psi(x) = E(Y \mid X = x) = \int_R y f_{Y \mid X}(y \mid x) dy.\quad (2)$$

The conditional variance is defined as $\text{var}(Y \mid X) = \nu(X)$ where

$$\nu(x) = \text{var}(Y \mid X = x) = \int_R [y - E(Y \mid X = x)]^2 f_{Y \mid X}(y \mid x) dy.\quad (3)$$

2.2 Disaggregation of the variance

From the definitions given above one can derive a useful expression that disaggregates the variance of $Y$ into conditional expectations and variances.

$$\text{var}(Y \mid X) = E(Y^2 \mid X) - [E(Y \mid X)]^2,\quad (4)$$

and

$$\text{var}(Y) = E[\text{var}(Y \mid X)] + \text{var}[E(Y \mid X)].\quad (5)$$

2.3 Disaggregation of the variance of a product

From equation (5) we can then derive a useful method for disaggregating the variance of a product. First, it is always true that

$$\text{var}(XY) = E[\text{var}(XY \mid X)] + \text{var}[E(XY \mid X)] = E[X^2 \text{var}(Y \mid X)] + \text{var}[XE(Y \mid X)].\quad (6)$$

Now, if $X$ and $Y$ are independent we have $E(Y \mid X) = E(Y)$ and $\text{var}(Y \mid X) = \text{var}(Y)$ so

$$\text{var}(XY) = E(X^2) \text{var}(Y) + E(Y)^2 \text{var}(X) = \text{var}(X) \text{var}(Y) + E(X)^2 \text{var}(Y) + E(Y)^2 \text{var}(X).\quad (7)$$

We will use these expressions below.

3 Basics of the conditional binomial model

We now set up our model. Overall our approach is to start with a very general mathematical framework (e.g. we don’t initially assume that hurricane numbers are poisson distributed), derive what we can with this level of generality, and make additional assumptions on the way through as and when necessary. First, we need random variables for the annual numbers of hurricanes in the basin and at landfall, and their historical totals. We define these as follows:

- Let $\{X_t : t = 1, \ldots, n\}$ be the sequence of annual historical hurricane numbers and let $X = \sum_{t=1}^n X_t$.
- Let $\{Y_t : t = 1, \ldots, n\}$ be the sequence of annual historical landfalling hurricane numbers and let $Y = \sum_{t=1}^n Y_t$.

Now we consider estimating the proportion of hurricanes that make landfall, and the properties of the most obvious estimator of that proportion. To start with, we don’t assume that the number of hurricanes in the basin is poisson, but we do assume that the probability of hurricanes making landfall is constant in time, and is the same for all hurricanes. We write this (unknown) probability as $p$. Then the number of hurricanes that make landfall in a given year, given the number in the basin, is given by a binomial distribution:

$$Y_t \mid X_t \sim \text{binomial}(X_t, p)\quad (8)$$
A useful analogy is that each basin hurricane is a coin toss, with a probability $p$ of giving a head. The number of hurricanes making landfall $Y_t$ is the number of heads in $X_t$ tosses. Extending this to the total number making landfall over $n$ years, we also get a binomial:

$$Y|X_1, \ldots, X_n \sim \text{binomial}(X, p) \quad (9)$$

### 3.1 Estimating the landfall proportion

The most obvious way to try and estimate $p$ from the historical data is using the simple ratio of the total number of historical landfalls to the total number of basin hurricanes:

$$\hat{p} = Y/X \quad (10)$$

What are the properties of this estimator? Is it unbiased, and what is the variance? With bias, first we note that:

$$E(\hat{p}|X_1, \ldots, X_n) = p \quad (11)$$

and that

$$E(\hat{p}) = E(E(\hat{p}|X_1, \ldots, X_n)) = E(p) = p \quad (12)$$

and we see $\hat{p}$ is unbiased.

With variance, a standard result for the binomial distribution is that:

$$\text{var}(\hat{p}|X_1, \ldots, X_n) = p(1-p)/X \quad (15)$$

Using equation [5], we can then decompose var($\hat{p}$) as follows:

$$\text{var}(\hat{p}) = E[\text{var}(\hat{p}|X_1, \ldots, X_n)] + \text{var}[E(\hat{p}|X_1, \ldots, X_n)] \quad (16)$$

That is, the variance of the estimate of the proportion is given only in terms of the proportion itself and $E(1/X)$. The proportion can be estimated using a plug-in estimator, but the $E(1/X)$ factor is slightly harder to deal with, and can only be evaluated once we have settled on a distribution for $X$. We consider this for the poisson distribution in section 5 below.

### 3.2 Landfall predictions

Now we consider making predictions of future landfalling hurricane numbers using the estimated proportion $\hat{p}$, and a prediction of the mean number of basin hurricanes, which we write as $\mu = E(X_{n+1})$. The first question is then how to estimate $\mu$. One fairly general class of methods for estimating $\mu$ is to use the historical data for the basin number of hurricanes in some way. We can write this as $\hat{\mu} = g(X_1, \ldots, X_n)$, where $g$ could be a linear or non-linear function of the historical data.

The most obvious reasonable forecast for the number of hurricanes making landfall is then $\hat{p}\hat{\mu}$. What are the properties of this particular method? We can establish the properties of this predictor as follows.

For the bias:

$$E(\hat{p}\hat{\mu}) = E(E(\hat{p}\hat{\mu}|X_1, \ldots, X_n)) = E(\hat{p}E(\hat{\mu}|X_1, \ldots, X_n)) = pE(\hat{\mu}) \quad (20)$$

Note that if $\hat{\mu}$ is unbiased for $E(X_{n+1})$ then equation [20] implies that $\hat{p}\hat{\mu}$ is unbiased for $E(Y_{n+1})$ (this is a stronger result than asymptotic unbiasedness).

For the variance:

$$\text{var}(\hat{p}\hat{\mu}) = E[\text{var}(\hat{p}\hat{\mu}|X_1, \ldots, X_n)] + \text{var}(E(\hat{p}\hat{\mu}|X_1, \ldots, X_n)) \quad (21)$$

$$= E(\hat{\mu}^2\text{var}(\hat{p}|X_1, \ldots, X_n)) + \text{var}(\hat{\mu}E(\hat{p}|X_1, \ldots, X_n)) \quad (22)$$

$$= E(\hat{\mu}^2p(1-p)/X) + p^2\text{var}(\hat{\mu}) \quad (23)$$

$$= p(1-p)E(\hat{\mu}^2/X) + p^2\text{var}(\hat{\mu}) \quad (24)$$
We consider various approximations to this expression in the next two sections, which will allow us to evaluate it in certain situations.

4 Linear predictors of basin hurricane numbers

We now move on to consider linear predictors of the number of hurricanes in the basin i.e. methods that use a weighted sum of historic values as an estimator of $\mu$.

We write this as:

$$\hat{\mu} = \sum_{i=1}^{n} w_i X_i.$$  \hspace{1cm} (25)

This linear framework includes the mixed baseline models of Jewson et al. (2005), and models that use linear regression of hurricane numbers on sea surface temperature.

To account for climate variability, the weights may be chosen to generate an estimator that uses only recent data. For example:

$$w_i = \begin{cases} 0, & \text{for } i = 1, \ldots, n - m, \\ \frac{1}{m}, & \text{for } i = n - m + 1, \ldots, n. \end{cases}$$  \hspace{1cm} (26)

Under this model it may, in some cases, be reasonable to suppose that $\hat{\mu}$ is generated so that $\text{cov}(\hat{\mu}^2, 1/X)$ is small relative to $E(\hat{\mu}^2 E(1/X))$. Roughly speaking, this occurs if the errors we make when estimating the proportion are not highly correlated with the errors we make when making the basin prediction.

If we can assume that the covariance term is small then we can make some useful simplifications to equation 24, as follows:

$$\text{var}(\hat{p}\hat{\mu}) = \frac{p(1-p)}{n\hat{\mu}} \left[ 1 + \frac{1}{n\hat{\mu}} + 2 \frac{1}{n^2 \hat{\mu}^2} + O\left(\frac{1}{n^3 \hat{\mu}^3}\right) \right] \approx \frac{p(1-p)}{n\hat{\mu}} \left[ 1 + \frac{1}{n\hat{\mu}} + 2 \frac{1}{n^2 \hat{\mu}^2} \right]$$  \hspace{1cm} (27)

$$\Rightarrow E(1/X) = \frac{1}{n\hat{\mu}} \left[ 1 + \frac{1}{n\hat{\mu}} + 2 \frac{1}{n^2 \hat{\mu}^2} + O\left(\frac{1}{n^3 \hat{\mu}^3}\right) \right]$$  \hspace{1cm} (32)

Thus, to first order, $E(1/X) \approx \frac{1}{n\hat{\mu}}$.

If we take this first order approximation and substitute it into equation 17, then we get:

$$\text{var}(\hat{\mu}) \approx \frac{p(1-p)}{n\hat{\mu}}.$$  \hspace{1cm} (33)

5 Poisson model for basin hurricanes

We now specialize our analysis to the case where the number of hurricanes in the basin can be modelled as a poisson distribution, which allows us to approximate the $E(1/X)$ term, and hence evaluate equations 17 and 29.

We start by assuming that the annual counts are poisson distributed, with the same poisson mean in each year:

$$X_t \sim \text{poisson}(\mu) \text{ for all } t.$$  \hspace{1cm} (30)

Then the total number of hurricanes over $n$ years is also poisson distributed:

$$X \sim \text{poisson}(n\mu).$$  \hspace{1cm} (31)

(statisticians usually prove this by inspection of moment generating functions).

At this point we briefly mention a small mathematical problem, which is that we are now going to consider $1/X$, even though $X$, being poisson distributed, can take values of 0. To get around this problem rigorously one can condition on $X > 0$, which would introduce a small adjustment factor to the expressions derived below. We will, however, ignore this. Effectively we are assuming that the probability of $X$ being zero is small, and this should be borne in mind when applying the results we derive. This should be a reasonable assumption if $X$ is the number of Atlantic basin hurricanes, but would not reasonable if $X$ we the number of category 5 Atlantic basin hurricanes, for instance.

Our approximation for $E(1/X)$ is based on a Taylor expansion for the annual numbers:

$$E(1/X_t) = \frac{1}{p} \left[ 1 + \frac{1}{n\mu} + 2 \frac{1}{n^2 \mu^2} + O\left(\frac{1}{n^3 \mu^3}\right) \right]$$  \hspace{1cm} (32)

$$\Rightarrow E(1/X) = \frac{1}{n\mu} \left[ 1 + \frac{1}{n\mu} + 2 \frac{1}{n^2 \mu^2} + O\left(\frac{1}{n^3 \mu^3}\right) \right]$$  \hspace{1cm} (33)

Thus, to first order, $E(1/X) \approx \frac{1}{n\mu}$.

If we take this first order approximation and substitute it into equation 17 then we get:

$$\text{var}(\hat{\mu}) \approx \frac{p(1-p)}{n\mu}.$$  \hspace{1cm} (34)
And if we substitute it into equation \(29\) we get

\[
\text{var}(\hat{p} \hat{\mu}) \approx \frac{p(1 - p)E(\hat{\mu}^2)}{n\mu} + p^2 \text{var}(\hat{\mu}).
\]  

\(35\)

One simple prediction method for the mean number of hurricanes in the basin is to take a straight average of \(m\) years of data. Given this,

\[
\text{var}(\hat{\mu}) = \frac{\mu}{m}
\]  

\(36\)

and

\[
E(\hat{\mu}^2) = \frac{\mu}{m} + \mu^2
\]  

\(37\)

\[
= \frac{\mu(1 + m\mu)}{m}
\]  

\(38\)

In this case we get:

\[
\text{var}(\hat{p} \hat{\mu}) \approx \frac{p(1 - p)(1 + m\mu)}{nm} + p^2 \frac{\mu}{m}.
\]  

\(39\)

How accurate are these results based on the first-order approximations? They will be reasonable if \(n\) is large. Better approximations to \(\text{var}(\hat{p})\) and \(\text{var}(\hat{p} \hat{\mu})\) can easily be generated by using higher order terms in the approximation of \(E(1/X)\).

### 6 Simulation tests

We now test the first order approximation using Monte-Carlo simulations. We consider the following situation:

- We estimate the mean number of hurricanes making landfalling using just the last 11 years of landfalling data. This is one of our predictions.
- We estimate the mean number of basin hurricanes using the same 11 years of data
- We convert the basin estimate to an estimate for landfalling numbers using an estimated proportion, which is based on between 11 and over 50 years of data. 11 of the years of data used to estimate the proportion are the same data that is used to estimate the rates.
- We estimate the variances of all these predictions

Using Monte-Carlo simulations we can compare the variance estimate given by equation \(39\) with the real variance estimates. The results are given in figure [1]. The black-line gives the variance of the landfall prediction based on 11 years of historical landfall data, from equation \(36\). The black-dots give estimates of this variance based on the simulations. The blue-line gives our theoretical approximation to the variance from the indirect method, based on equation \(39\). The coloured dots give estimates of the variance from the indirect method based on the simulations. We see that:

- The theoretical estimate of the variance for the indirect method is in very good agreement with the results from the simulations, even though we’ve only used a first order approximation to derive equation \(39\).
- The variance of the indirect method is lower than the variance of the direct method when the proportion is estimated using more years of data than are being used for the rate estimates. Using 35 or more years of data makes the indirect method more than twice as accurate, in terms of variance.

### 7 Applying the indirect method

We now make some predictions of future numbers of landfalling hurricane numbers by converting the basin hurricane number predictions given in [Binter et al. (2006)] to landfalling predictions.
7.1 Step 1: predicting numbers of basin hurricanes

The predictions of numbers of basin hurricanes that we use are taken from Binter et al. (2006), in which mixed baseline models are used to predict future numbers of hurricanes in the basin. These models are based on an analysis of change-points in the historical time-series of hurricane numbers. The intervals between change-points are taken as periods of levels of constant hurricane activity, and future activity is then predicted on the assumption that the current level of activity will continue. The prediction is given by an optimal combination of the observed activity rates in the historical data, where ‘optimal’ is defined as minimising mean-square-error, and trades off the need to use as much of the historical data as possible (for increased accuracy) against the desire to use only recent data (because it is likely to be the most relevant for the future).

The predictions from Binter et al. (2006) are based on the change-point analysis of Elsner et al. (2000) and Jewson and Penzer (2006). We include predictions based on both of these change-point analyses to get an idea of the level of sensitivity of the results to the details of the methods used to detect the change-points.

7.2 Step 2: relating basin hurricane numbers to landfalling hurricane numbers

The empirical relationships we use to convert the number of basin hurricanes to a number of landfalling hurricanes are simple estimates of the probability that hurricanes will make landfall, based on historical hurricane data for 1950 to 2005. For cat 1-5 hurricanes, we estimate this probability to be 0.254 (with a standard error of 0.058). For cat 3-5 hurricanes, we estimate this probability to be 0.240 (with a standard error of 0.057).

7.3 Step 3: converting basin predictions to landfalling predictions

The predictions used in step 1 above produce estimates for the mean number of basin hurricanes, the variance of the number of basin hurricanes, and the standard error on the mean. The empirical relationships in step 2 tell us how to convert the number of hurricanes in the basin into the number at landfall, given information about the number in the basin. How, then, should we combine this information to tell us about the distribution of the number of hurricanes at landfall? A complete solution for the distribution of the number of hurricanes at landfall would be slightly complicated to derive. The mixed baseline models themselves don’t give a probabilistic prediction, but just the first two moments and the standard error on the mean. Although they are built on the assumption that the number of hurricanes is poisson distributed, the predictions they produce cannot strictly be interpreted as poisson distributions because the mean and variance are not equal. However, deriving expressions for the mean, variance, and standard error on the mean for the number of landfalling hurricanes, which is all we are interested in, is rather simple. These expressions are given in Jewson (2007).

Putting all of this together, we make predictions for:

- The number of landfalling cat 1-5 hurricanes, based on the basin number of cat 1-5 hurricanes
- The number of landfalling cat 3-5 hurricanes, based on the basin number of cat 3-5 hurricanes

In each case we predict the mean number of hurricanes, the variance of the number of hurricanes, and the standard error on the mean (which is based on both the standard error on the prediction of the basin number of hurricanes, and the standard error of the estimate of the proportion making landfall).

8 Predictions from the indirect method

8.1 Predictions based on Elsner change points

The results from our analysis based on the change-points from Elsner et al. (2000) are shown in table 1. The first four rows of this table are for cat 1-5 storms, while the second four rows are for cat 3-5 storms. As an example, consider the first row. From Binter et al. (2006), table 5, we can see that the short baseline model predicts 8.45 hurricanes in the basin, with a standard error of 0.877. Converting that to a prediction of landfalling hurricanes using the estimated probability of landfall of 0.254 gives 2.15 hurricanes, which is the value for the mean shown in the first row of table 1. Similarly the variance of the number of landfalls in this case is 2.74. The standard error, which arises because of (a) the uncertainty
in the prediction of the number of storms in the basin and (b) the uncertainty in how to convert that number to a prediction at landfall, is 0.549.

How do these new predictions for the mean number of landfalling hurricanes compare with the previous results in Binter et al. (2006)? Considering the most complex model in each case (model 4 in table 1), the prediction for cat 1-5 storms changes from 2.09 to 2.08, which is insignificant. For cat 3-5 (model 8 in table 1), however, the prediction changes from 0.82 to 0.92. This is a more significant change (although still well within the standard error estimates). What is driving this increase? It turns out that the percentage increase in the basin number of severe storms that we have seen in the last 11 years is rather larger than the percentage increase in the number of severe storms at landfall (basin severe storms numbers have increased by 88% relative to the long-term baseline, while landfalling severe storms have only increased by 40%). This increase in the basin severe storms leads to a high prediction of the future number of severe storms in the basin, and this in turn leads to a high prediction of the number of severe storms at landfall when using this method of predicting landfall numbers from the predicted basin numbers. As discussed in the introduction, there are good reasons to think this might be a more accurate prediction than the lower prediction based on the landfall data alone, since the landfall data is so sparse.

8.2 Predictions based on RMS change points

The results from our analysis based on the change-points from O’Shay and Jewson (2007) are shown in table 2. Once again, the first four rows of this table are for cat 1-5 storms, while the second four rows are for cat 3-5 storms.

We see a small decrease in the prediction of the number of cat 1-5 storms, and another, although smaller, increase in the number of cat 3-5 storms.

9 Conclusions

One possible way to predict landfalling hurricane numbers is to first predict basin hurricane numbers and then convert the basin numbers to landfall using an estimate of the proportion of the basin hurricanes that make landfall. This method can be compared with the simpler method of just predicting landfall numbers directly. We have performed some statistical analysis of these methods, to try and understand which is likely to be more accurate. In particular we have considered a situation where the direct method consists of estimating the landfall rates using an 11 year average of historical landfalling rates, and the indirect method consists of estimating basin rates using an 11 year average and then converting that to landfall rates using a proportion based on more than 11 years of data. Assuming that the probability of individual hurricanes making landfall is constant in time then we have shown that the indirect method is more accurate, and the more data is used to estimate the proportion, the more accurate it becomes relative to the indirect method. Furthermore we have derived expressions for the variance of the indirect method, and using simulations have shown that a simple analytic expression for the variance of the indirect method works well.

We then apply the indirect method to convert some previous predictions of basin hurricane numbers into predictions of numbers of landfalls. The results for landfalling cat 1-5 storms are not that different between this method and results from predicting landfalling storm numbers directly from historical landfalls. The results for cat 3-5 storms, however, show higher predictions. This is because the number of cat 3-5 storms in the basin has increased more in recent years (proportionately) than the number of cat 3-5 storms at landfall.

Preliminary results (as yet unpublished) suggest that the hypothesis that the probability of storms making landfall doesn’t change in time cannot be rejected. This lends weight to the idea that these higher predictions of future numbers of intense landfalling storms may be more reliable. However, the difference between the two predictions is well within the standard error estimates, and so either prediction could easily have been much higher or lower just due to random effects.

References

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Figure 1: Variances from analytic expressions and Monte Carlo simulations. The black line shows the variance of the direct landfall prediction, based on 11 years of data. The grey line shows an estimate of the variance of the indirect landfall prediction, based on 11 years of basin data, and $N2$ years of basin data, using equation 39. The black circles show simulation-based estimates of the variance of the direct prediction, and the grey circles show simulation-based estimates of the variance of the indirect prediction. The simulations validate the approximations used to derive equation 39.
| 1 | Model Name(No. Yrs) | 2 | Basin Model | LF Model | Mean | Var | Var/Mean | RMSE |
|---|------------------|---|-------------|----------|------|-----|----------|------|
| 1 | SBL (11)         | Basin Cat15 | LF Cat15 | 2.15 | 2.74 | 1.28 | 0.549   |
| 2 | 2 active pds (33)| Basin Cat15 | LF Cat15 | 1.75 | 2.47 | 1.41 | 0.492   |
| 3 | 2 pds, both active opt wi (106) | Basin Cat15 | LF Cat15 | 2.08 | 2.18 | 1.05 | 0.532   |
| 4 | 4 pds (106)      | Basin Cat15 | LF Cat15 | 2.08 | 2.18 | 1.05 | 0.532   |
| 5 | SBL (11)         | Basin Cat35 | LF Cat35 | 0.98 | 1.24 | 1.26 | 0.315   |
| 6 | 2 active pds (33)| Basin Cat35 | LF Cat35 | 0.87 | 1.13 | 1.29 | 0.294   |
| 7 | 2 pds, both active opt wi (106) | Basin Cat35 | LF Cat35 | 0.92 | 0.99 | 1.08 | 0.296   |
| 8 | 4 pds (106)      | Basin Cat35 | LF Cat35 | 0.92 | 0.99 | 1.08 | 0.296   |

Table 1: Predictions for landfalling hurricane numbers, based on the change points from Elsner et al. (2000), and the method described in the text.

| 1 | Model Name(No. Yrs) | 2 | Basin Model | LF Model | Mean | Var | Var/Mean | RMSE |
|---|------------------|---|-------------|----------|------|-----|----------|------|
| 1 | SBL (11)         | Basin Cat15 | LF Cat15 | 2.15 | 2.20 | 1.02 | 0.549   |
| 2 | 2 active pds (33)| Basin Cat15 | LF Cat15 | 1.82 | 1.94 | 1.06 | 0.499   |
| 3 | 2 pds, both active opt wi (106) | Basin Cat15 | LF Cat15 | 2.05 | 2.09 | 1.02 | 0.526   |
| 4 | 5 pds (106)      | Basin Cat15 | LF Cat15 | 2.05 | 2.09 | 1.02 | 0.526   |
| 5 | SBL (11)         | Basin Cat35 | LF Cat35 | 0.98 | 1.00 | 1.02 | 0.315   |
| 6 | 2 active pds (33)| Basin Cat35 | LF Cat35 | 0.87 | 0.89 | 1.02 | 0.294   |
| 7 | 2 pds, both active opt wi (106) | Basin Cat35 | LF Cat35 | 0.91 | 0.93 | 1.02 | 0.295   |
| 8 | 5 pds (106)      | Basin Cat35 | LF Cat35 | 0.91 | 0.93 | 1.02 | 0.295   |

Table 2: Predictions for landfalling hurricane numbers, based on the change points from Binter et al. (2006), and the method described in the text.