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FORECASTING HURRICANE TRACKS USING THE KALMAN FILTER

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SUMMARY

A case study applies state space models and the Kalman filter to forecasting the path of hurricanes. The track of a hurricane is forecast by using its previous motion together with the historical record of storms which follow a similar path. Criteria are described for selecting the predictor storms, which are then incorporated into the measurement equation of the state space model. Linear and quadratic trend structural time series models are used in the transition equation of the state space model and forecasts are produced using the Kalman filter. Forecasts are obtained for hurricanes Andrew (1992), Bob (1991), Hugo (1989) and Gilbert (1988). The Kalman filter approach compares very favourably with the HURRAN and CLIPER benchmark models used by the National Hurricane Center.

KEY WORDS Hurricane Kalman filter State space model Time series

1. INTRODUCTION

Forecasting the path of a hurricane is both an art and a science. Scientists combine meteorological variables, past motion of the storm, and the historical record of similar storms, together with their professional experience to formulate a forecast. Pike[1] and Neumann[2] give overviews of hurricane modelling. The erratic movement of many storms makes it difficult to develop long term forecasts.

In this paper, hurricane movement will be forecast using previous storm positions and the historical record of similar storms. Our method is comparable to the HURRAN and CLIPER models used by National Hurricane Center, which are discussed in Hope and Neumann[3] and Neumann,[4] respectively. The state space approach will be used to model the data and forecasts will be obtained using the Kalman filter. The method will be applied to several celebrated hurricanes of the past five years.

2. SELECTION OF PREDICTOR STORMS

Our method of selecting predictor storms is similar to that of the HURRAN model used by the National Hurricane Center. The database is the 'best' tracks of all North Atlantic tropical cyclones since 1886 that were obtained from the National Climatic Data Center. The position of the eye of each storm is recorded at six hour intervals giving the latitude, longitude, pressure and maximum wind speed. The National Hurricane Center assimilates data from satellite, aircraft, ship, marine buoy, and land observations to determine the best track of a tropical cyclone. Satellite imagery was first available in 1964, and thus track accuracy since this time should be

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near optimum. Aircraft reconnaissance has been used since 1944. In the early years scientists depended on ship and land reports and tracks were often extrapolated from fragmentary information. However, it is felt that those tracks which crossed populated areas are reasonably accurate and that most storms making landfall along the United States coastline were probably detected. There is no way to assess the reliability of a particular storm track, except to say that there has been a gradual increase in data quality over the years.

A target storm to be forecast and a time point from which to begin forecasts is first determined. Five variables are calculated at the forecast origin of the target storm: (1) location; (2) storm speed; (3) storm heading; (4) wind speed, and (5) date. These five criteria are then used to decide whether or not to include a storm as a predictor in the forecast model. Table I summarizes the selection criteria and the acceptable range of values. A storm must be within the acceptable range for all five variables to be included as a predictor. To qualify as a predictor a storm must first be located within 100 nautical miles of the forecast origin. Then at its nearest point to the forecast origin the predictor storm's speed must also be within 10 knots, and its heading must be within 10 degrees, and its wind speed must be within 30 knots, and its date must be within 30 days of the corresponding settings of the target storm at the forecast origin. The ranges were determined by experimentation and more research could be done to tune these settings. The number of selected predictor storms will increase as the ranges are expanded. The last column of Table I gives the ranges used by HURRAN.

After a predictor storm is selected, its nearest point is translated to the forecast origin of the target storm. Thus all predictor storms are adjusted by a linear interpolation to begin at the forecast point. The HURRAN model also performs this translation and further adjusts the initial heading of the predictors to coincide with the initial heading of the target storm. We did not adjust the heading and instead used a small range of 10 degrees for the heading selection variable as opposed to HURRAN's value of 22·5 degrees. We chose to model this 'persistence' factor in the transition equation of the state space model which is described below.

3. STATE SPACE MODELS AND THE KALMAN FILTER

State space methodology has been used in the aerospace industry and it is natural to apply it to other types of tracking problems. The state space model is defined by the measurement or observation equation:

$$\mathbf{Y}_t = \mathbf{A}_t\mathbf{x}_t + \mathbf{v}_t \tag{1}$$

Table I. Selection criteria for predictor storms

Criteria	Acceptable range Kalman filter approach	Acceptable range HURRAN
Distance from forecast origin	100 nautical miles	2·5 degree radius of latitude (about 150 nautical miles)
Storm speed	±10 knots	±10 knots if storm speed >20 knots ±50% to 150% of storm speed if speed is from 10 to 20 knots, ±5 knots if storm speed <10 knots
Heading	±10 degrees	±22·5 degrees
Wind speed	±30 knots	not used
Date in Julian days	±30 days	±15 days

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and the transition or state equation:

$$\mathbf{x}_t = \mathbf{\Phi}\mathbf{x}_{t-1} + \mathbf{w}_t \tag{2}$$

for $t = 1, 2, \ldots, T$. $\mathbf{Y}_t$ is the $r \times 1$ vector of observed data at time t, $\mathbf{x}_t$ is the $p \times 1$ unobserved state vector at time t, $\mathbf{A}_t$ is the $r \times p$ known design matrix at time t, and $\mathbf{\Phi}$ is the $p \times p$ transition matrix. $\mathbf{v}_t$ is an $r \times 1$ white noise process with covariance matrix $\mathbf{R}$ and $\mathbf{w}_t$ is a $p \times 1$ white noise process with covariance matrix $\mathbf{Q}$, assumed to be independent of $\mathbf{v}_t$.

The Kalman filter recursions are used to obtain estimates of the state vector $\mathbf{x}_t$ and its standard error. The matrices $\mathbf{\Phi}$, $\mathbf{R}$ and $\mathbf{Q}$ in the above recursions may depend on unknown parameters. Under the assumption that $\mathbf{x}_t$, $\mathbf{v}_t$ and $\mathbf{w}_t$ have independent multivariate normal distributions, the unknown parameters can be estimated by the method of maximum likelihood. There are several approaches to maximizing the likelihood, many of which are discussed in Harvey.[5] The EM algorithm was used for estimation in this application and details can be found in Shumway[6] and Shumway and Stoffer.[7] Estimation will be discussed further in the next section.

4. APPLICATION OF STATE SPACE MODELS TO HURRICANE FORECASTING

The goal of the analysis is to forecast future latitude and longitude values of a hurricane from some point of origin. The duration of a tropical cyclone is typically one or two weeks and data is only available every six hours, yielding a sample size of 20 to 50 observations for each storm. This is a relatively small sample size for time series modelling. This small sample size discourages modelling latitude and longitude jointly in a bivariate time series model. A bivariate model was tried for a few storms, and it was found that the forecasts from the bivariate model were no better and often worse than the forecasts from separate univariate models for latitude and longitude. Moore[8] found that univariate ARIMA models and univariate exponential smoothing were very competitive with bivariate ARIMA models for predicting iceberg trajectories. The latitudinal and longitudinal motion of a hurricane are certainly linked, though this does not imply they should both follow the same time series model. For Gulf of Mexico hurricanes such as Gilbert, the predominant motion is from east to west. Eastern seaboard storms, such as Bob, have a stronger south to north displacement and in addition recurve in the later stages, changing heading from the northwest to the northeast. Eastern seaboard hurricanes often accelerate in the later stages, suggesting that the parameterization of a bivariate model might not be simple. Our incorporation of predictor storms into the model would lead to an even more complex parameterization. Thus for reasons of parsimony and forecast performance it was decided to model latitude and longitude in separate univariate models.

We now return to state space model defined by equations (1) and (2). Assume that $r-1$ predictor storms were selected for the model by satisfying the criteria of Section 2. Let t index time as measured in six hour intervals, where $t = t_{\mathrm{f}}$ is the time of the forecast origin, and k forecasts are to be made beyond this point, so $t = 1, 2, \ldots, t_f, \ldots, t_{\mathrm{f}} + k$. The $\mathbf{Y}_t$ term in equation (1) will be an $r \times 1$ vector where the first row corresponds to the observed value of the target storm at time t, and the remaining $r-1$ rows refer to the translated values of the $r-1$ predictor storms at time t. Note that the data vectors $\mathbf{Y}_{t_{\mathrm{f}}+1}, \ldots, \mathbf{Y}_{t_{\mathrm{f}}+k}$ will all have a first row equal to zero, since these are the 'unknown' values of the target storm to be forecast. Rows 2 to r of the vectors $\mathbf{Y}_{t_{\mathrm{f}}+1}, \ldots, \mathbf{Y}_{t_{\mathrm{f}}+k}$ will be non-zero and form the basis of the forecasts.

Two models are used for the transition equation (2), both belonging to the class of structural time series models as discussed in Harvey.[5]

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1. Local linear trend model: let

$$\mathbf{\Phi}^{2\times 2} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}^{2\times 2}, \quad \mathbf{x}_t^{2\times 1} = \begin{bmatrix} \mu_t \\ \beta_t \end{bmatrix}^{2\times 1},$$

and the transition equations are

$$\mu_t = \mu_{t-1} + \beta_{t-1} + w_{1t} \tag{3}$$

$$\beta_t = \beta_{t-1} + w_{2t}. \tag{4}$$

2. Quadratic trend model: let

$$\mathbf{\Phi}^{3\times 3} = \begin{bmatrix} 1 & 1 & 0{\cdot}5 \\ 0 & 1 & 1 \\ 0 & 0 & 1 \end{bmatrix}^{3\times 3}, \quad \mathbf{x}_t^{3\times 1} = \begin{bmatrix} \mu_t \\ \beta_t \\ \gamma_t \end{bmatrix}^{3\times 1},$$

and the transition equations are

$$\mu_t = \mu_{t-1} + \beta_{t-1} + 0{\cdot}5\gamma_{t-1} + w_{1t} \tag{5}$$

$$\beta_t = \beta_{t-1} + \gamma_{t-1} + w_{2t} \tag{6}$$

$$\gamma_t = \gamma_{t-1} + w_{3t} \tag{7}$$

Continuing the state space specification, $\mathbf{A}_t$ will be an $r \times p$ matrix, where p corresponds to the number of rows of the state vector. Elements in columns 2 to p of $\mathbf{A}_t$ are all set to 0. If the elements of $\mathbf{Y}_t$ are all non-zero, then the first column of $\mathbf{A}_t$ will all be 1's. If the ith row of $\mathbf{Y}_t$ is 0, then the element in the ith row and 1st column of $\mathbf{A}_t$ is changed from 1 to 0.

Structural time series models were used because of their simplicity and ease of interpretation. The transition equation for the local linear trend model describes a stochastic linear trend with dynamically changing level μ_t and slope β_t. This is a natural model for hurricanes passing through the Gulf of Mexico which generally travel in a northwesterly direction with latitude and longitude changing roughly linearly over time. The quadratic trend model is often appropriate for eastern seaboard storms which tend to accelerate in their later stages as they dissipate and recurve to the northeast. The small sample sizes would have been Box–Jenkins ARIMA modelling difficult and this is another reason structural time series models were employed. The local linear and quadratic trend models can be expressed as constrained ARIMA(0,2,2) and ARIMA(0,3,3) models, respectively. Details are given in Harvey.[5]

The transition matrix, $\mathbf{\Phi}$, is fixed in the above models and need not be estimated. The covariance matrices $\mathbf{R}$ and $\mathbf{Q}$ do need to be estimated, where $\mathrm{var}(\mathbf{v}_t) = \mathbf{R}$ and $\mathrm{var}(\mathbf{w}_t) = \mathbf{Q}$. The row(s) of the transition equation are assumed to be independent so that the off diagonal elements of $\mathbf{Q}$ are zero:

$$\mathbf{Q}^{p\times p} = \begin{bmatrix} q_{11} & 0 & 0 & \dots & 0 \\ 0 & q_{22} & 0 & \dots & 0 \\ 0 & 0 & q_{33} & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \dots & q_{pp} \end{bmatrix}^{p\times p}. \tag{8}$$

It will be assumed that the measurement errors in the target and predictor storms are all

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mutually independent and that the $r-1$ predictor storms have equal measurement error variance. The measurement error variance of the target storm will be set to 0, yielding an **R** matrix of the form:

$$\mathbf{R} = \left[\begin{array}{c|c} 0^{1\times 1} & \mathbf{0}^{1\times(r-1)} \\ \hline \mathbf{0}^{(r-1)\times 1} & r_{11}\mathbf{I}_{r-1} \end{array}\right]^{r\times r} \tag{9}$$

where, $\mathbf{0}$ is a matrix of 0's and $\mathbf{I}_{r-1}$ is an $(r-1)\times(r-1)$ identity matrix. Setting the measurement error variance for the target storm to 0 causes the element in the 1st row of $\mathbf{Y}_t$ to be equal to μ_t, for $t \leq t_f$. This is reasonable, because for times less than or equal to the forecast origin, the μ_t element of the state vector is set to the known observed position of the target storm at time t. For $t > t_f$, when the time is later than the forecast origin, the target storm values are 'not available' and the predictor storms determine the value of the state vector element μ_t.

The elements of the **R** and **Q** matrices can be estimated by maximum likelihood. Four parameters (r_{11}, q_{11}, q_{22} and q_{33}) are estimated under the quadratic trend model and only three under the local linear model. Initially, the log-likelihood function was maximized by a non-linear quasi-Newton optimization routine. The procedure did not always converge and was very sensitive to starting values. The parameters also had to be transformed to insure non-negative estimates. The multivariate nature of the data compounded the problem as the observed data $\mathbf{Y}_t$ is a vector. Thus the EM algorithm was used, though convergence is sometimes rather slow in the later stages. It automatically constructs positive estimates of the variance parameters. Engle and Watson[9] and Shumway and Stoffer[10] recommend running the EM algorithm first to move the estimates to the neighbourhood of the maximum and then finishing with a non-linear optimization routine to pinpoint the maximum. We achieved satisfactory results with the EM algorithm alone. Since the focus of this paper is on forecasting, we are primarily interested in the estimate of the μ_t element of the state vector and its standard error. These values changed negligibly in the closing iterations of the EM algorithm.

Another advantage of the EM algorithm is that it computes filtered as well as smoothed estimates of the state vector. The aim of filtering is to estimate $E(\mathbf{x}_t \mid \mathbf{Y}_t)$, that is, to estimate the state vector based only on information to and including time t. The aim of smoothing is to estimate $E(\mathbf{x}_t \mid \mathbf{Y}_T)$, where $T \geq t$, that is, to estimate the state vector at time t based on data available after time t. Smoothing is a reasonable approach here because we want to forecast hurricanes at time t and data is available on the predictor storms for times greater than t.

Shumway's text[6] includes a disk with computer code for the EM algorithm written in BASIC. That algorithm was slightly modified for structural time series models and rewritten in the language GAUSS and in FORTRAN for use with S-PLUS.

5. FORECASTS

Our primary interest is in forecasting, and hence we focus on the estimate of the μ_t element of the state vector and its standard error estimate as output by the Kalman filter. Several different forecast methods will be compared in the examples. The first method, KF, is the technique outlined in Section 4 which uses the predictor storms in a Kalman filter time series model. This method uses the previous path of the target storm together with the selected predictor storms to fashion a forecast. The second method, HURRAN, is documented in Hope and Neumann[3]. Its forecasts are based only on the means of the predictor storms and no time series model is formed. HURRAN uses slightly different selection criteria for the predictor storms as was presented in

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Table I. HURRAN rotates the initial heading of the predictor storms to agree with the target storm. Thus HURRAN takes account of the 'persistence' of the target storm by tilting the heading of the predictors and our KF method models this persistence in the transition equation of the state space model. The third method, CLIPER, is described in Neumann.[4] It was originally developed by the National Hurricane Center as a backup to HURRAN when insufficient predictor storms were available. CLIPER uses essentially the same inputs as HURRAN, but adds wind speed. The CLIPER method is different in that instead of calculating means, a multiple linear regression model is developed and forecasts are obtained as dependent variables from that model. The final method, NHC, is the 'official' forecast issued by the National Hurricane Center. It is based on extensive current meteorological variables such as wind and pressure gradients, not to mention the knowledge and experience of the staff at the National Hurricane Center. The HURRAN, CLIPER and KF methods do not use wind and pressure gradients and their forecasts would not be expected to perform as well as the NHC method. The National Hurricane Center finds that HURRAN and CLIPER are still useful benchmarks against which to compare its more sophisticated forecasting models.

Forecasts will be obtained for hurricanes Gilbert (1988), Bob (1991), Hugo (1989) and Andrew (1992). The linear trend state space model was used for Gilbert and Andrew since they travelled through the Gulf of Mexico. The quadratic trend model was used for Bob and Hugo, since they

Table II. Forecasts

	12 hour		24 hour		36 hour		48 hour	
	Latitude	Longitude	Latitude	Longitude	Latitude	Longitude	Latitude	Longitude
Gilbert								
True Path	21·9	91·7	22·5	93·8	23·7	95·9	24·4	98·2
NHC	22·2	91·9	23·0	94·5	25·2	96·6	27·4	98·2
CLIPER	22·4	91·9	23·3	94·0	24·3	95·9	25·4	97·5
KF	21·9	91·9	22·4	94·1	22·9	96·1	23·5	98·2
S.E. (KF)	0·16	0·25	0·18	0·41	0·18	0·59	0·27	0·85
Bob								
True Path	34·6	75·3	38·9	73·0	43·8	69·6	47·0	65·5
NHC	34·0	76·0	37·0	74·0	40·6	71·5	44·9	66·9
HURRAN	33·7	75·8	36·1	74·1	38·8	71·0	41·8	66·6
KF	34·2	75·3	37·6	73·0	41·1	69·8	44·5	65·7
S.E. (KF)	0·19	0·20	0·47	0·38	0·71	0·61	1·37	1·09
Hugo								
True Path	26·3	72·2	28·0	74·9	30·2	77·5	33·5	80·3
NHC	26·0	71·4	27·8	72·9	29·2	74·8	30·5	78·0
CLIPER	26·1	71·2	28·0	71·8	29·9	71·9	31·9	71·5
KF	26·3	71·0	28·1	71·6	30·0	71·9	31·9	72·0
S.E. (KF)	0·16	0·22	0·23	0·36	0·30	0·55	0·49	0·85
Andrew								
True Path	26·2	85·0	27·2	88·2	28·5	90·5	30·1	91·7
KF	26·1	85·0	26·7	88·7	27·3	92·4	27·9	96·1
S.E. (KF)	0·29	0·38	0·68	0·92	1·17	1·60	1·75	2·39

True path is the actual storm position
NHC is the official forecast of the National Hurricane Center
CLIPER is the forecast from the CLIPER model
HURRAN is the forecast from the HURRAN model
KF is the forecast from the Kalman filter model
S.E. (KF) is the standard error for the KF forecast

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Table III. Forecast errors in nautical miles

	12 hour forecast error	24 hour forecast error	36 hour forecast error	48 hour forecast error
Gilbert				
NHC	21	49	98	180
CLIPER	32	49	36	71
KF	11	18	49	54
Bob				
NHC	50	123	210	139
HURRAN	59	176	307	316
KF	24	78	162	150
Hugo				
NHC	47	107	153	215
CLIPER	55	164	291	454
KF	65	175	291	430
Andrew				
KF	6	40	124	266

NHC is the official forecast of the National Hurricane Center
CLIPER is the CLIPER model
HURRAN is the HURRAN model
KF is the Kalman filter model

were eastern seaboard storms. The HURRAN, CLIPER and NHC forecasts were provided courtesy of the National Hurricane Center and were not available for all storms. The forecast origin for each storm was chosen to be approximately 48 hours from landfall and 12, 24, 36 and 48 hour forecasts will be reported. Table II summarizes the forecasts and gives the standard errors for the Kalman filter forecasts. Standard errors were not available for HURRAN,

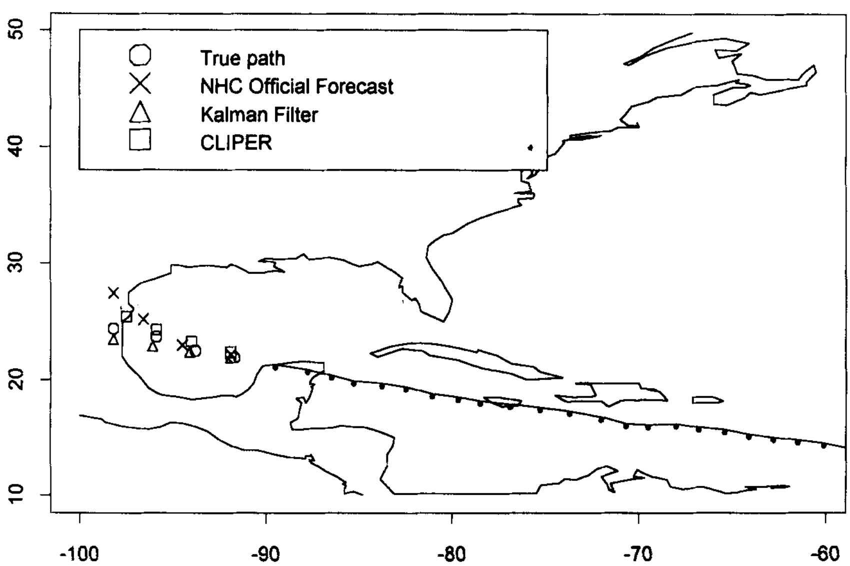

Figure 1. Gilbert (1988) 12 hour forecasts

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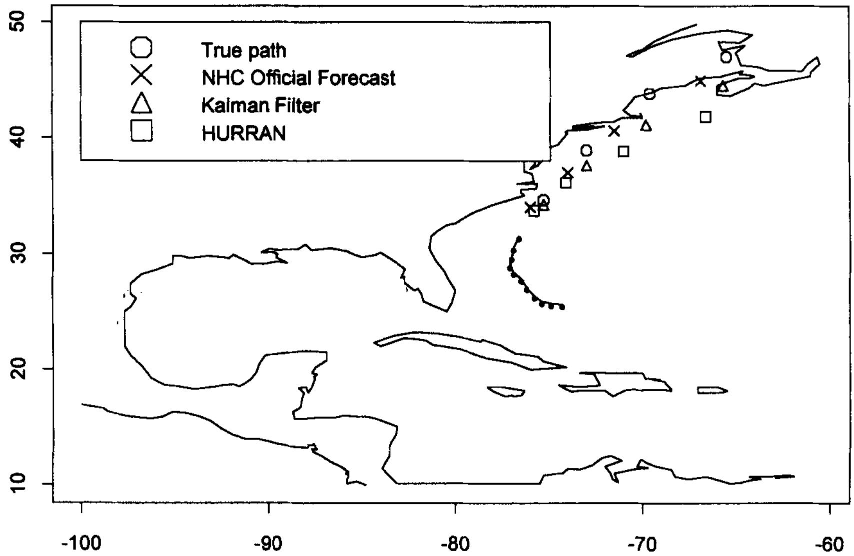

Figure 2. Bob (1991) 12 hour forecasts

CLIPER and NHC. Table III gives the forecasts errors in nautical miles from the true storm positions. Figures 1 to 4 display maps of the true paths and forecasts.

6. DISCUSSION

From Table III and Figures 1 to 4 it can be seen that our Kalman filter approach, KF, is very competitive with the HURRAN and CLIPER methods. KF yields forecast errors as small as CLIPER for the 12, 24 and 48 hour forecasts for Gilbert and the 36 and 48 hour forecasts for Hugo. KF is superior to HURRAN for all the forecasts for Bob. We would not expect KF to be

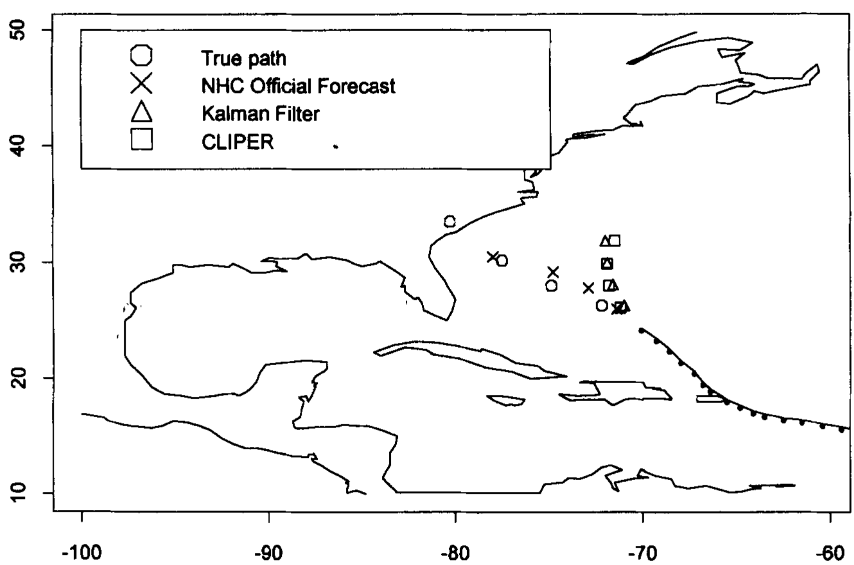

Figure 3. Hugo (1989) 12 hour forecasts

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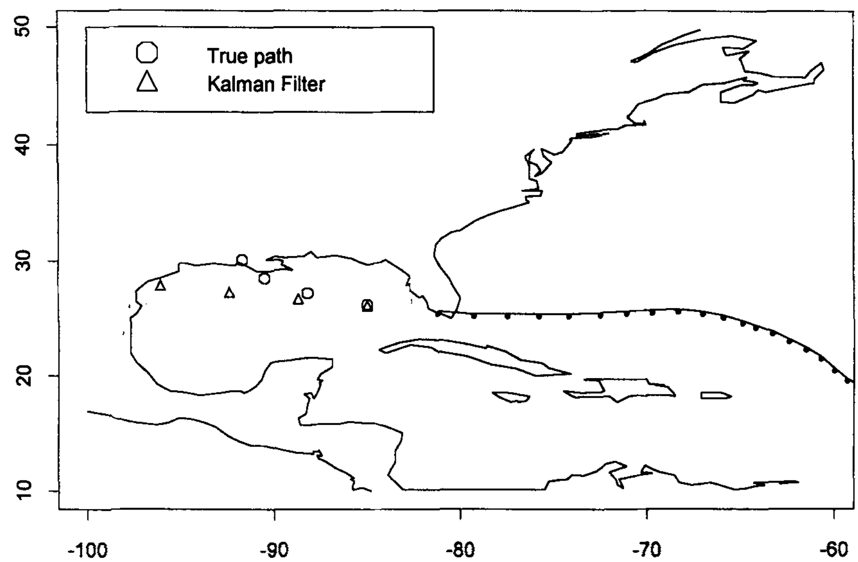

Figure 4. Andrew (1992) 12 hour forecasts

consistently better than NHC, the official National Hurricane Center forecast, since NHC uses extensive meteorological data as input to its forecasts. Yet KF does produce smaller forecasts errors than NHC for the 12, 24, and 36 forecasts for Bob and for all the forecasts for Gilbert.

The limitations of the CLIPER and KF forecasts can be seen for Hugo and Andrew, though the NHC forecast errors for Hugo are also somewhat large. HURRAN, CLIPER and KF will yield poor forecasts for an erratically moving hurricane with few similar storms in the historical record. The quality of the HURRAN, CLIPER, and KF forecasts depends on how close the predictor storms are to the target storm. HURRAN requires that at least five predictor storms are selected and will not produce forecasts if there are fewer than five. KF makes no such restriction, and fewer than five storms were selected for both Bob and Andrew. The predictor storms used by KF are listed in Table IV.

The poor performance of KF for Andrew can be partially explained by the fact that only one predictor storm was selected. There was also little if any south to north motion in Andrew during the 48 hours previous to the forecast origin and in fact Andrew was moving slightly south for a time. The KF method was unable to predict the sudden northward movement.

The large forecast errors for Hugo were perhaps due to a upper-level low pressure system over Georgia which the NHC method accounted for, but KF and CLIPER did not. During the 30 hours prior to landfall Hugo intensified from a category 2 to a category 4 hurricane on the Saffir/

Table IV. Predictor storms

Gilbert 1988	Bob 1991	Hugo 1989	Andrew 1992
Beulah 1967	#6 1934	Gloria 1985	Betsy 1965
Charlie 1951	#3 1893	Edna 1953	
#3 1938	#3 1889	#5 1940	
#15 1933		#2 1924	
#5 1912		#4 1899	
#5 1909		#7 1898	

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Simpson Scale which surprised the scientists at the National Hurricane Center. The KF forecasts are worse than CLIPER at 12 and 24 hours, equal at 36 hours, and better at 48 hours.

HURRAN and CLIPER are useful standard models against which to gauge the performance of NHC. They are not meant to replace the official forecast. KF should likewise be viewed as a benchmark model that gives insight into hurricane behaviour. As a benchmark model, KF is very competitive with HURRAN and CLIPER. To be competitive with NHC, KF would need to incorporate further meterorological variables such as wind and pressure height gradients. An advantage of the state space approach is that it can accommodate additional independent variables. This is a direction for further research and model improvement.

Scientists are still working to completely understand hurricane motion. Some meteorologists would claim that the quality of the data has not kept pace with the sophistication of the models. As usual in statistical applications, there is no substitute for good scientific knowledge of the system.

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