# A Statistical Hurricane Intensity Prediction Scheme (SHIPS) for the Atlantic Basin

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ABSTRACT

A statistical model for predicting intensity changes of Atlantic tropical cyclones at 12, 24, 36, 48, and 72 h is described. The model was developed using a standard multiple regression technique with climatological, persistence, and synoptic predictors. The model developmental sample includes all of the named Atlantic tropical cyclones from 1989 to 1992, with a few additional cases from 1982 to 1988. The sample includes only the times when the storms were over the ocean. The four primary predictors are 1) the difference between the current storm intensity and an estimate of the maximum possible intensity determined from the sea surface temperature, 2) the vertical shear of the horizontal wind, 3) persistence, and 4) the flux convergence of eddy angular momentum evaluated at 200 mb. The sea surface temperature and vertical shear variables are averaged along the track of the storm during the forecast period. The sea surface temperatures along the storm track are determined from monthly climatological analyses linearly interpolated to the position and date of the storm. The vertical shear values along the track of the storm are estimated using the synoptic analysis at the beginning of the forecast period. All other predictors are evaluated at the beginning of the forecast period.

The model is tested using a jackknife procedure where the regression coefficients for a particular tropical cyclone are determined with all of the forecasts for that storm removed from the sample. Operational estimates of the storm track and initial storm intensity are used in place of best track information in the jackknife procedure. Results show that the average intensity errors are 10%–15% smaller than the errors from a model that uses only climatology and persistence (SHIFOR), and the error differences at 24, 36, and 48 h are statistically significant at the 99% level.

## 1. Introduction

According to Sheets (1990), the skill of intensity forecasts of Atlantic tropical cyclones is "sorely lacking." In contrast, the skill of operational track forecasts has improved steadily in recent years (e.g., McAdie and Lawrence 1993). Numerous objective guidance models, ranging in complexity from simple statistical models (Neumann 1972) to three-dimensional dynamical models (Mathur 1991), are available for the prediction of tropical cyclone tracks. However, the only operational intensity prediction model for the Atlantic basin is SHIFOR (Jarvinen and Neumann 1979). The SHIFOR model uses statistical relationships between climatological and persistence factors to predict intensity changes out to 72 h for storms that remain over the ocean.

Pike (1985) used geopotential heights and thicknesses as predictors in an attempt to include synoptic information in a statistical intensity prediction model for oceanic tropical cyclones. In that study, the synoptic information resulted in only a marginal improvement over climatology and persistence. Merrill (1987) considered a wider range of synoptic predictors in an intensity prediction model but again failed to provide a significant improvement over climatology and persistence. However, in the study by Merrill (1987), the prediction model was developed for tropical cyclones over land as well as over the ocean. It is likely that the statistical properties of storms that decay over land are quite different from the properties of storms over the ocean.

Results of intensification studies from other ocean basins are less pessimistic than the results for the Atlantic basin. Elsberry et al. (1988) demonstrated that the use of synoptic information in a statistical prediction model for the western Pacific basin leads to improved predictions, provided that the sample is stratified by initial storm intensity. Leslie and Holland (1991) have shown that an intensity prediction model that uses a Markov chain technique can improve upon climatology and persistence in short-term (6–24 h) forecasts for Australian tropical cyclones.

In this study, results from a Statistical Hurricane Intensity Prediction Scheme (SHIPS) are presented. SHIPS is similar to the model described by Merrill (1987) in that sea surface temperature (SST) and synoptic information are combined with climatology and persistence to produce intensity forecasts for the Atlantic basin. However, in the current study, the sample

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is restricted to storms over the ocean, and some additional synoptic predictors not considered by Merrill (1987) are included. Also, special objective analyses that use the spline-fitting technique described by Lord and Franklin (1987) are used to determine the synoptic predictors. The developmental sample and the spline objective analyses are described in section 2. In section 3, the selection of the predictors and the regression analysis are discussed. In section 4, the SHIPS forecasts are compared with the forecasts from the climatological and persistence model SHIFOR.

## 2. Data sample for SHIPS

Since the beginning of the 1989 season, synoptic data for Atlantic tropical cyclone cases have been collected and analyzed in near real time to test the VICBAR track prediction model (DeMaria et al. 1992). Although VICBAR is a barotropic model, synoptic analyses are produced at the mandatory pressure levels from 850 to 200 mb and then vertically averaged to give the model initial condition. These synoptic analyses are used to develop the SHIPS model.

The objective analyses were produced using the spline-fitting technique described by Ooyama (1987) and Lord and Franklin (1987). Cubic B splines with a derivative constraint are fitted to wind and geopotential height observations, where the constraint acts as a low-pass filter. The derivative constraint of the spline analysis was chosen so that the half-amplitude wavelength of the spatial filter is 4° lat. The data used in the analyses include rawinsondes, satellite cloud-track winds, and aircraft observations from both U.S. Air Force reconnaissance and National Oceanic and Atmospheric Administration research missions. The winds and heights from the National Meteorological Center (NMC) global analysis are also included as a low-weight background field. In regions of poor data coverage, the spline analyses reproduce the NMC analyses. In regions of relatively good coverage, smaller horizontal scales are included in the spline analyses than in the NMC background fields. The analyses are stored on a 50° lat × 50° long area centered on each storm.

The spline analyses are available at 0000 and 1200 UTC for nearly all of the named tropical cyclone cases in the Atlantic basin (including the depression stage) for the period 1989–1992. The synoptic data were not saved on a regular basis prior to 1989, although a few cases were available for the period 1982–1988. The total sample includes 510 analyses (435 from 1989 to 1992 and 75 from 1982 to 1988) of 49 tropical cyclones (38 from 1989 to 1992 and 11 from 1982 to 1988). This sample includes only cases where the storm was over the ocean. The SHIPS model provides intensity forecasts at 12, 24, . . . 72 h. The sample size at 72 h is reduced to 300 because in some cases the storm dissipated or moved over land during the forecast interval.

When a statistical model is developed, it is desirable to use a sample that is homogeneous. It should be pointed out that the sample used here is not completely homogenous, because the NMC background fields have undergone many changes during the period from 1982 to 1992. Also, not all of the storm cases were included prior to 1989, so the sample from this period might not be completely representative of a larger sample of Atlantic tropical cyclones. However, most of the cases prior to 1989 (47 of 75) were from the 1987 season, where some synoptic data was available for every storm during that year. The other 28 cases prior to 1989 were from Hurricanes Gilbert (5 cases) and Joan (16 cases) from the 1988 season, and for storms where special omega dropwindsonde experiments (Franklin and DeMaria 1992) were performed (7 cases).

In this study, the storm intensity is measured by the maximum 1-min sustained surface wind. The intensity estimates and storm positions at 6-h intervals were obtained from the "best track" data (Jarvinen et al. 1984) prepared by the National Hurricane Center (NHC). Note that the best track includes intensity and track information. In about half of the cases, aircraft reconnaissance data were available for the wind and position estimates. For the cases without aircraft data, most of the surface wind speeds and positions were estimated using satellite techniques. The surface winds are forecast in knots, rounded to the nearest 5. For this reason, knots will be used here rather than the more standard meters per second.

If the SHIPS model were run operationally, the best track data would not be available in real time. In section 4, results from tests of SHIPS using operational positions and initial intensities will be presented. On average, the operational intensity estimates differ from the best track estimates by about 5 kt, although the differences can be as large as 30 kt. The operational intensity estimates were obtained from the NHC and were not available prior to 1989. Therefore, in some of the tests of SHIPS presented in section 4, the cases prior to 1989 were omitted. As will be described later, the SHIPS model requires a 72-h track forecast. The model will be developed using the best track positions but will be tested using track forecasts from the VICBAR model.

The SHIPS model uses SST information in the intensity prediction. In all cases, the SST fields were obtained from the climatological analysis described by Levitus (1982). Monthly mean values of SST are available on a 1° lat–long grid. These values are linearly interpolated in space and time to the position and date of each storm.

## 3. Regression analysis

The goal of this study is to develop a statistical model for relating various meteorological parameters to tropical cyclone intensity changes. Perhaps the most common method for developing statistical models is multiple linear regression, although this method is not always optimal. For example, Elsner and Schmertmann (1993) used a nonlinear statistical model for the extended-range prediction of intense Atlantic hurricane activity. Their results show that the use of a Poisson model provides an increase in the "hindcast" skill relative to a linear statistical model. In their case, the use of the Poisson model was motivated by the distribution of the dependent variable (the number of major hurricanes per year), which is a small but positive integer. For the intensity prediction model developed in this study, the dependent variable is the intensity change over some time interval (12, 24, . . . 72 h). The distribution of the intensity changes for a fixed time interval is approximately normal, with a mean close to zero. Therefore, standard multiple regression is a reasonable choice for the development of the intensity prediction model.

One of the most important steps in the development of a regression model is the choice of independent variables. The synoptic analyses described in section 2 could be used to determine an extremely large number of predictors (independent variables) for the model. However, as described by Neumann et al. (1977), the indiscriminate use of regression methods can lead to models that perform well on developmental data but perform poorly in an operational environment. To avoid this problem, our strategy is to select a relatively small number of predictors from physical considerations and then use standard statistical significance tests to select the final independent variables.

As described above, standard multiple regression techniques were used to develop the SHIPS model. The independent variables are climatological, persistence, and synoptic predictors, and the dependent variable is the intensity change. Separate regressions were performed at each forecast interval (12, 24, . . . 72 h). A predictor was considered significant if the probability that the regression coefficient was different from zero exceeded 95%. The significance level of each regression coefficient was determined using a standard F statistic. For consistency of the prediction, the same predictors are used at all forecast intervals, even if the coefficients are not significantly different from zero at all intervals. In general, when a predictor is not significant for a particular forecast interval, the regression coefficient becomes fairly small. A simple backward-stepping procedure was used to select the predictors. All of the predictors are included on the first step, and the coefficient that was the least significant at any forecast interval is determined. The variable associated with this predictor is then removed and the regression is repeated. This process continues until all of the predictors are significant at a minimum of one forecast interval.

The first step in the development of the model is to determine how much of the variability of the observed intensity changes can be accounted for by climatology and persistence. For this purpose, the multiple regression was performed with the predictors listed in Table 1. The first seven predictors are the same as those in the SHIFOR model except that the Julian date for SHIFOR is used without subtracting 253 and taking the absolute value. The Julian date is used in the form shown in Table 1, because the peak of the Atlantic hurricane season in terms of the probability that a storm exists anywhere in the Atlantic basin is a maximum on 10 September (Julian date 253) (Neumann et al. 1987). The effect of leap years is neglected in the Julian date variable. Predictor 8 in Table 1 was included because the speed of motion might be related to intensity change, independent of the direction of storm motion.

All of the predictors listed in Table 1 were significant at a minimum of one forecast interval. Table 2 lists the regression coefficients for each variable, where the variables are ordered by the average magnitude (the average over each forecast interval) of the regression coefficients. Prior to each regression, the dependent and independent variables were normalized by subtracting the mean and dividing by the standard deviation. This normalization allows the comparison of the regression coefficients for different variables and different forecast intervals (e.g., Steel and Torrie 1980). For example, a regression coefficient of 0.5 indicates that if that particular variable is one standard deviation larger than the mean and all other variables are equal to their means, the intensity change for that particular forecast interval will be one-half of a standard deviation larger than the mean.

Table 2 shows that for each variable (except CSM) the sign of the regression coefficient is the same at all forecast intervals, and in most cases, the sign is consistent with physical reasoning. Intensification is negatively correlated with the initial storm intensity (VMX) because strong storms are closer to their maximum possible intensity (determined from the sea surface temperature, as discussed herein) and thus have less potential for further intensification. Storms that have intensified in the past 12 h (positive DVMX) are likely to continue intensifying. Longitude is positively correlated with intensity change, probably because the SST generally increases toward the west in the Atlantic basin. Similarly, latitude is negatively correlated with intensity change. The coefficient for the Julian date

TABLE 1. Climatological and persistence predictors.

| | |
|---|---|
| 1) Absolute value of Julian date - 253. | (JDATE) |
| 2) Initial storm intensity. | (VMX) |
| 3) Intensity change during previous 12 h. | (DVMX) |
| 4) Initial storm latitude (°N). | (LAT) |
| 5) Initial storm longitude (°W). | (LONG) |
| 6) Eastward component of storm motion vector. | (USM) |
| 7) Northward component of storm motion vector. | (VSM) |
| 8) Magnitude of storm motion vector. | (CSM) |

TABLE 2. Normalized regression coefficients for the climatological and persistence predictors. The coefficients that are significant at the 95% level are underlined; $r^2$ is the percent of the total variance explained by the regression.

| | Forecast interval | | | | | |
|---|---|---|---|---|---|---|
| Variable | 12 | 24 | 36 | 48 | 60 | 72 |
| 1) VMX | −0.24 | −0.36 | −0.44 | −0.51 | −0.57 | −0.61 |
| 2) DVMX | +0.46 | +0.34 | +0.25 | +0.22 | +0.23 | +0.20 |
| 3) LONG | +0.19 | +0.27 | +0.27 | +0.26 | +0.24 | +0.24 |
| 4) JDATE | −0.12 | −0.18 | −0.20 | −0.23 | −0.24 | −0.24 |
| 5) LAT | −0.08 | −0.11 | −0.14 | −0.18 | −0.16 | −0.13 |
| 6) VSM | −0.04 | −0.07 | −0.11 | −0.11 | −0.14 | −0.14 |
| 7) CSM | −0.03 | +0.00 | +0.05 | +0.06 | +0.12 | +0.18 |
| 8) USM | −0.09 | −0.11 | −0.09 | −0.05 | −0.04 | −0.05 |
| $r^2$ (%) | 29.8 | 28.6 | 30.2 | 33.6 | 38.4 | 41.3 |

predictor (JDATE) is negative as should be expected since this variable measures the number of days from the peak of the hurricane season. Although the correlations are weaker for the storm motion variables, it seems reasonable that intensification is less likely for storms moving north or east. The correlation with storm speed is somewhat more difficult to explain, since the positive coefficient indicates that fast-moving storms intensify more than slow-moving storms. This is perhaps an indication of the effect of upwelling of cool ocean water. For slow-moving storms, the region of upwelling occurs close to the storm center, while for faster-moving storms, the upwelling tends to occur in a wake behind the storm (e.g., Geisler 1970).

Table 2 shows that the percent of variance explained is larger for the longer forecast intervals. This increase might be a result of the discretization of the intensity values. As will be described later, the sample average of the magnitude of the intensity change at 12 h is only about 5 kt but increases to about 23 kt at 72 h. The intensity values from the best track are rounded to the nearest 5 kt, which is close to the average 12-h intensity change. Thus, some noise is probably introduced into the regressions for the shorter forecast intervals.

Table 2 shows that the climatological and persistence variables explain 30%–40% of the variance of the intensity changes. To increase the variance explained, a number of additional variables were included as predictors. Table 3 lists the additional variables that are loosely referred to as synoptic predictors.

TABLE 3. Synoptic predictors.

| | |
|---|---|
| 1) Maximum possible intensity–initial intensity. | (POT) |
| 2) Magnitude of 850–200-mb vertical shear. | (SHR) |
| 3) Time tendency of vertical shear magnitude. | (DSHR) |
| 4) The 200-mb relative eddy angular momentum flux convergence. | (REFC) |
| 5) The 200-mb planetary eddy angular momentum flux convergence. | (PEFC) |
| 6) The 850-mb relative angular momentum. | (SIZE) |
| 7) Distance to nearest major landmass. | (DTL) |

The first synoptic predictor (intensification potential, POT) was included to take into account the effect of the SST. As described by Merrill (1987), the SST alone does not provide a good indication of whether a given storm will intensify. However, the SST appears to provide an upper bound on the intensity of the storm. The theoretical results of Emanuel (1988) also indicate that the SST provides a limit on the maximum possible intensity (MPI) of the storm. The predictor POT is the difference between the MPI (estimated from the SST at the location of the storm) and the current storm intensity.

The MPI (kt) was determined from an empirical relationship developed by DeMaria and Kaplan (1994) and is given by

$$\mathrm{MPI} = A + B\exp[C(\mathrm{SST} - \mathrm{SST}_0)], \quad (1)$$

where $A = 66.5$ kt, $B = 108.5$ kt, $C = 0.1813°\mathrm{C}^{-1}$, $\mathrm{SST}_0 = 30.0°\mathrm{C}$, and SST is the sea surface temperature (°C). Equation (1) was developed from a 31-year sample of Atlantic tropical cyclones. In the study by DeMaria and Kaplan (1993), the storm translational speed was subtracted from the intensity. The parameter $A$ in (1) was adjusted to account for the average translation speed (12 kt) of the storms in the 31-year sample. The SST in (1) was determined from the monthly mean SST analyses described in section 2. The MPI used in the prediction is averaged over the track of the storm during the forecast interval to account for SST variations along the storm track. For example, for the 24-h forecast, the SST and MPI are determined at the initial 12- and 24-h positions of the storm. The initial storm intensity is subtracted from the average of the three MPI values to give the predictor POT. The best track positions are used to determine the storm positions during the forecast period. If the model were run operationally, forecast track positions would be required. In section 4, the error that results from using forecast rather than best track positions is discussed.

Numerous studies have shown that the vertical shear of the horizontal wind has a negative influence on tropical cyclone intensification (e.g., Gray 1968; Merrill 1988). The vertical shear predictor (SHR) is the magnitude of the difference between the 850- and 200-mb wind vectors. These two levels were used to evaluate the shear because most of the satellite cloud track wind estimates were assigned to these levels. The horizontal wind components from the spline analyses were averaged over a circular area with a radius of 600 km, centered on the storm. The area over which the shear is determined is large relative to the inner-convective area of the storm, and in some cases, small-scale features that affect the storm are not well represented. However, sensitivity studies showed that a smaller fraction of the variance of the intensity changes was explained by the regression when the winds were averaged over smaller horizontal areas.

To help account for the time variation of the vertical shear, the magnitude of the shear was evaluated along the track of the storm, similar to the MPI variable described above. However, only the analysis at the beginning of the forecast period was used to evaluate the shear at the future storm positions. The analyses at the forecast times could have been used to develop the model but these analyses would not be available operationally. The azimuthally averaged radial and tangential winds relative to the initial storm position were subtracted from the analyses before the shear was evaluated along the track of the storm. This subtraction is necessary so that the symmetric part of the storm circulation does not contribute to the vertical shear at the future storm positions. The final value of SHR is the average of the magnitude of the shear at each 12-h storm position from the initial time to the end of the forecast period.

In reality, the 200- and 850-mb flow evolves during the forecast period, but this effect is not taken into account. Sensitivity tests showed that using the magnitude of the shear through the 36-h position of the storm increased the amount of variance explained. If the values past 36 h were included, the explained variance remained approximately constant or decreased slightly. For this reason, the SHR variable does not include contributions from beyond the 36-h storm position. Thus, the 36-, 48-, and 72-h forecasts use the same value of the SHR predictor.

The values of the shear along the track of the storm were also used to evaluate the time tendency of the shear (DSHR). The tendency was calculated from the shear at the 24-h storm position and the initial storm position. If the forecast did not have a 24-h verification in the best track, the shear at 12 h was used for the tendency calculation.

The momentum flux predictors (REFC and PEFC) are included to account for positive interactions between the tropical cyclone and synoptic-scale systems. The theoretical results of Holland and Merrill (1984) and the observational results of Molinari and Vollaro (1989) suggest that when a storm interacts with the large-scale flow in a way that makes the upper-level flow more cyclonic, the intensification rate of the storm may be increased. The eddy flux convergences REFC and PEFC provide a measure of whether the large-scale flow is acting to increase or decrease the azimuthally averaged tangential wind of the storm. REFC and PEFC play a role that is analogous to relative and planetary vorticity advection in quasigeostropic theory (e.g., Holton 1992). The theoretical results of Holland and Merrill (1984) suggest that the interaction of the storm with the environment is more likely to occur in the upper levels. At lower levels, the large inertial stability due to the rapid rotation of the storm circulation limits the interaction with the environment. For this reason, REFC and PEFC are evaluated at 200 mb using

$$\mathrm{REFC} = -r^{-2}\partial/\partial r(r^2\overline{U'_L V'_L}) \tag{2}$$

$$\mathrm{PEFC} = -\overline{f'U'}, \tag{3}$$

where $r$ is the radius from the storm center, $U$ is the radial wind, $V$ is the tangential wind, $f$ is the Coriolis parameter, the overbar denotes an azimuthal average, the prime represents a deviation from the azimuthal average, and the subscript $L$ indicates that these quantities ($U$ or $V$) are evaluated in a coordinate system moving with the storm. Qualitatively, REFC tends to be large when a storm is moving toward an upper-level trough. PEFC tends to be large when the 200-mb flow over the storm is primarily from north to south. REFC and PEFC were determined at 100-km radial intervals from 100 to 1500 km using the 200-mb spline analyses. The storm motion was subtracted from the horizontal wind components to determine the storm relative winds required in (2). Regression tests showed that averaging REFC from 100 to 900 km and PEFC from 700 to 1500 km provided the best predictors of intensity change. Because the eddy fluxes are relatively complicated functions of the wind field, no attempt was made to account for the time variation of the variables during the forecast period. A more complete explanation of the effects of the momentum fluxes on intensity change is given by DeMaria et al. (1993).

The integrated relative angular momentum (SIZE) is included as a measure of the extent of the outer circulation of the tropical cyclone. This variable is defined by

$$\mathrm{SIZE} = \int_{r_1}^{r_2} (rV) r dr, \tag{4}$$

where $V$ is the 850-mb tangential wind, $r_1$ = 400 km, and $r_2$ = 800 km. Although there is usually not enough data to define the circulation near the storm center, there are usually enough satellite cloud track winds at 850 mb to represent the outer circulation of the storm.

The last synoptic predictor in Table 3 is the distance to the nearest landmass (DTL). Although all landfalling cases were eliminated from the sample, the proximity to land might still have a modifying influence on the storm intensity. The DTL was calculated using the method described by Merrill (1987). Only major landmasses are included in the DTL calculation. (Trinidad is the smallest island in the Atlantic basin that is considered.) The storm location at the forecast time is used to evaluate the DTL.

In summary, seven synoptic variables are considered as predictors. REFC, PEFC, and SIZE are evaluated at the initial forecast time. POT is averaged along the storm track through 72 h, SHR is averaged along the storm track through 36 h, and DTL is evaluated at the forecast time. The time tendency of the shear (DSHR) is determined from the shear at the initial time and at the 24-h position of the storm.

The synoptic predictors listed in Table 3 were added to the climatological and persistence predictors, and the regression procedure was repeated. Table 4 shows the normalized regression coefficients for the 10 variables that were retained by the backward-stepping procedure. When the synoptic predictors were added, only three of the climatological and persistence predictors were retained in the stepwise regression. These predictors (DVMX, LONG, and JDATE) include three of the four most important climatological and persistence predictors listed in Table 2. The first predictor in Table 2 (VMX) is not included in Table 4, because it is highly correlated with POT.

Similar to Table 2, the predictors in Table 4 are ordered by the average magnitude of regression coefficients. The three most important predictors are the SST variable (POT), the vertical shear, and persistence (previous 12-h intensity change). These three predictors are significant at all forecast intervals, and the signs of the coefficients are consistent with the physical reasoning used in selecting the predictors. As expected, the persistence variable (DVMX) is more important for the short-term forecasts. The SST variable becomes more important for the longer forecast times. This result is probably because POT is the only variable that contains new information out to 72 h (POT is the only predictor that is different at each forecast interval.) The coefficient for the vertical shear predictor (SHR) has its largest magnitude for the 48-h forecast. The decrease after 48 h is probably due to the fact that the shear along the storm track is evaluated using only the initial analysis as described previously.

The momentum flux predictors (REFC and PEFC) in Table 4 were significant at most forecast periods and all of the coefficients for these predictors were positive. Equations (2) and (3) are defined so that REFC and PEFC are positive when the fluxes are acting to make the upper-level flow more cyclonic. Thus, positive regression coefficients should be expected. The coefficient for the relative momentum flux (REFC) has its largest magnitude for the 48-h forecast, even though this variable is evaluated only at the beginning of the forecast interval. This result suggests that there is a time lag between the momentum fluxes and the response of the tropical cyclone.

The remaining predictors in Table 4 are significant only at some forecast intervals, and the signs of the coefficients are somewhat reasonable. At the times when the coefficients are significant, the Julian date and longitude coefficients have the same sign as in Table 2 but smaller magnitudes. The distance to land coefficient is positive for the short forecast periods, indicating that storms intensify more when they are farther from land. Similarly, storms with a larger outer circulation intensify more than smaller storms. The coefficient for the tendency of the shear (DSHR) is positive at 36 h but negative at 72 h. The negative coefficient at 72 h is reasonable since the storm should decay when the shear increases. The positive coefficient at 36 h is perhaps an indication that the storm is interacting with larger-scale features in a positive way that is not accounted for by the momentum flux predictors.

A comparison of Tables 2 and 4 shows that the addition of the synoptic predictors increases the explained variance by a minimum of 6% at 12 h and by a max-

TABLE 4. Normalized regression coefficients for the combined climatological, persistence, and synoptic predictors. The coefficients that are significant at the 95% level are underlined; $r^2$ is the percent of the total variance explained by the regression.

| | Forecast interval | | | | | |
|---|---|---|---|---|---|---|
| Variable | 12 | 24 | 36 | 48 | 60 | 72 |
| 1) POT | <u>+0.32</u> | <u>+0.46</u> | <u>+0.56</u> | <u>+0.63</u> | <u>+0.68</u> | <u>+0.70</u> |
| 2) SHR | <u>−0.20</u> | <u>−0.26</u> | <u>−0.31</u> | <u>−0.36</u> | <u>−0.31</u> | <u>−0.25</u> |
| 3) DVMX | <u>+0.40</u> | <u>+0.28</u> | <u>+0.18</u> | <u>+0.16</u> | <u>+0.18</u> | <u>+0.16</u> |
| 4) REFC | +0.03 | <u>+0.08</u> | <u>+0.16</u> | <u>+0.22</u> | <u>+0.19</u> | <u>+0.17</u> |
| 5) PEFC | +0.08 | <u>+0.12</u> | <u>+0.12</u> | <u>+0.10</u> | <u>+0.10</u> | +0.10 |
| 6) JDATE | −0.04 | −0.06 | −0.07 | −0.09 | <u>−0.12</u> | <u>−0.13</u> |
| 7) LONG | <u>+0.14</u> | <u>+0.14</u> | +0.08 | +0.03 | −0.02 | −0.09 |
| 8) DTL | <u>+0.12</u> | <u>+0.12</u> | +0.09 | +0.05 | +0.00 | −0.09 |
| 9) SIZE | <u>+0.11</u> | <u>+0.11</u> | <u>+0.09</u> | +0.05 | +0.05 | +0.03 |
| 10) DSHR | −0.01 | +0.06 | <u>+0.13</u> | +0.07 | −0.03 | <u>−0.11</u> |
| $r^2$ (%) | 35.7 | 39.4 | 44.4 | 50.4 | 52.0 | 53.6 |

imum of 17% at 48 h. It might be possible to further increase the explained variance by including nonlinear combinations of the predictors in Table 4. If all of the quadratic combinations of the variables in Table 4 were included, 55 new predictors would be used in the regression. The use of this many predictors is probably not justified since the sample size is only 300 at 72 h and the physical justification for some of the combinations of variables is not obvious. Also, when a large enough set of predictors is tested, some correlations can be found even if the predictors are random variables (e.g., Neumann et al. 1977). For these reasons, the quadratic combinations of only the first three variables in Table 4 (six new variables) were included as potential predictors in the stepwise regression. Also, the regression coefficient was required to be significantly different than zero at the 99% level in order for a quadratic variable to be retained. Using this criterion, the square of the POT variable was the only quadratic predictor that was retained. With the inclusion of this new predictor, the variance explained by the regression increased by 1%–2% relative to the values in Table 4. Thus, the final version of the SHIPS model contains the 10 linear predictors shown in Table 4 and one quadratic predictor.

## 4. Evaluation of the SHIPS intensity forecasts

In this section, the intensity forecasts from the SHIPS model are discussed. The model was tested using the best track and operational intensity and position estimates. Because the operational information prior to 1989 was not readily accessible, the results in this section are restricted to the cases from 1989 to 1992. As described previously, only about 15% of the cases are from the period prior to 1989. The SHIPS model will be compared with the operational prediction model SHIFOR and the official intensity forecast issued by NHC. The operational forecasts do not include a 60-h prediction, so this forecast interval is not used in the comparisons.

Figure 1 shows the average intensity errors from the SHIPS and SHIFOR models, and the average errors from a forecast that assumes the intensity will remain constant during the forecast period (No Change, referred to as NC). The NC forecast errors provide a measure of the average magnitude of the observed intensity changes. The SHIFOR and SHIPS forecasts included in Fig. 1 were made with the best track intensity and position estimates. In all of the results presented in this section, the forecasts are verified using the best track intensities. Figure 1 shows that the SHIFOR and SHIPS forecast errors are smaller than the NC errors. Also, the SHIPS errors are 10%–20% smaller than the SHIFOR errors, suggesting that the synoptic information is improving upon climatology and persistence.

The SHIPS forecast errors discussed above represent a dependent verification of the model since all of the

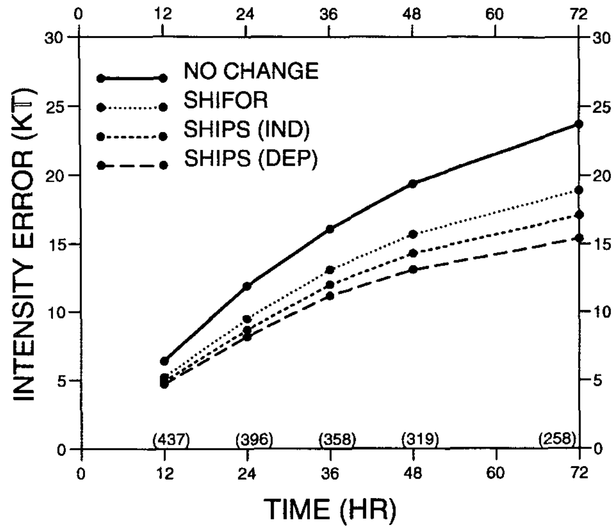


FIG. 1. The average intensity errors for the NC forecast, the SHIFOR model, the SHIPS model with independent coefficients (IND), and the SHIPS model with dependent coefficients (DEP). The sample sizes are indicated along the bottom of the diagram.

cases were used to develop the model. Unfortunately, there are not enough cases to provide an independent sample for verification. To provide some idea of how SHIPS would perform under operational conditions, a jackknife procedure was applied. For this purpose, all of the forecast cases for a given storm were removed from the sample and the regression coefficients were rederived. The rederived coefficients were then used to make forecasts for the storm that was removed from the sample. All of the forecasts for each storm were removed at once rather than on a case by case basis, because the intensity forecasts separated by less than about 30 h are serially correlated (Neumann et al. 1977). Figure 1 shows that when the independent coefficients are used in the prediction, the average forecast errors increase. At 12 h, the errors increase by only 0.2 kt, but at 72 h they increase by 1.7 kt. However, the average errors are still smaller than the NC forecast and the SHIFOR errors.

As described previously, the SHIPS predictions require the storm positions during the forecast period. In real-time forecasts, these positions must be obtained from a track forecast model. To determine the effect of the track errors on the intensity prediction, the best track positions were replaced with the track forecasts from the VICBAR model (DeMaria et al. 1992) in the SHIPS model with the jackknife coefficients. The average intensity errors from this version of the SHIPS model were nearly identical to those where the best track positions were used. The largest difference between the average intensity errors was 0.3 kt at 48 h (the model with the VICBAR tracks had the smaller intensity errors). This result indicates that the use of forecast tracks does not degrade the SHIPS intensity

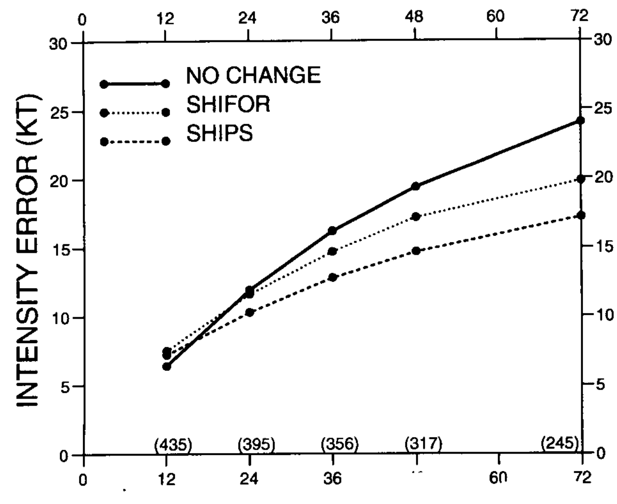


FIG. 2. The average intensity errors for the NC forecast, the SHIFOR model, and the SHIPS model. The SHIFOR and SHIPS models were run using the input that would be available in real time. The sample sizes are indicated along the bottom of the diagram.

forecasts. This result was somewhat surprising, since large track errors should lead to errors in the estimates of the SST and, to some extent, to errors in the vertical shear. However, the SST variable and the shear values are averaged along the track of the storm, which may help to reduce the impact of the large track forecast errors at the longer forecast periods. Also, the average track errors of the VICBAR model increase by just under 100 km every 12 h. However, the average storm speed is about 12 kt, so the storm is moving about 260 km every 12 h. Thus, since the track errors are less than half of the distance the storm moves, the general trends in the SST and shear during the forecast period are probably still reasonable in most cases.

In all of the forecasts discussed so far, the best track intensities were used. In real-time there is some uncertainty in the storm intensity that affects the starting point of the forecast and the persistence estimate (previous 12-h intensity change). All of the SHIFOR and SHIPS forecasts were repeated using the operational intensity estimates. For this comparison, the SHIPS model was run with the VICBAR tracks and the independent (jackknife) coefficients. This version of SHIPS simulates real-time forecasts and will be used in all of the remaining comparisons in this section. Figure 2 shows that the average SHIPS forecast errors are smaller than those from the SHIFOR model. Thus, the SHIPS forecasts can be considered skillful since they improve upon climatology and persistence. The most improvement occurs at 48 h, where the SHIPS forecast errors are about 15% smaller than the SHIFOR errors. A paired $t$ test (e.g., Larsen and Marx 1981) was used to determined whether the differences between the SHIPS and SHIFOR model were significant. The sample size in the test was adjusted to account for the serial correlation between the forecasts. This test showed that the differences between the SHIPS and SHIFOR model at 24, 36, and 48 h were significant at the 99% level. At 12 and 72 h, the differences were significant at the 95% level. Thus, the skill of the SHIPS model is statistically significant for this sample.

A comparison of Figs. 1 and 2 shows that the use of operational intensities degrades both the SHIFOR and SHIPS forecasts, especially at the earlier forecast periods. The average SHIPS errors (with the jackknife coefficients and VICBAR tracks) increased by 2.3 kt at 12 h but only by 0.2 kt at 72 h when the best track intensity estimates were replaced by the operational intensity estimates. The increases in the errors for the SHIFOR model were similar to those for the SHIPS model. These results indicate that some improvement in the short-term intensity forecasts could be obtained by improving the initial intensity estimates.

Figure 3 shows the variance explained by the (simulated) real-time version of the SHIPS and SHIFOR forecasts. The SHIPS model explains much more of the variance than the SHIFOR model, with the maximum improvement in $r^2$ occuring at 48 h ($r^2 = 29.1\%$ for SHIFOR and $r^2 = 48.0\%$ for SHIPS).

Figure 2 shows the SHIPS errors for the 1989–1992 sample. These errors can be normalized to give the relative error **RE** defined as

$$\mathbf{RE} = \frac{100(E_{\mathrm{SHIPS}} - E_{\mathrm{SHIFOR}})}{E_{\mathrm{SHIFOR}}}, \qquad (5)$$

where $E$ is average error from SHIPS or SHIFOR at a given forecast interval. When **RE** is negative, SHIPS has forecast skill because the SHIPS errors are smaller than those from the SHIFOR model. Figure 4 shows the relative error for the 1989–1992 sample and for

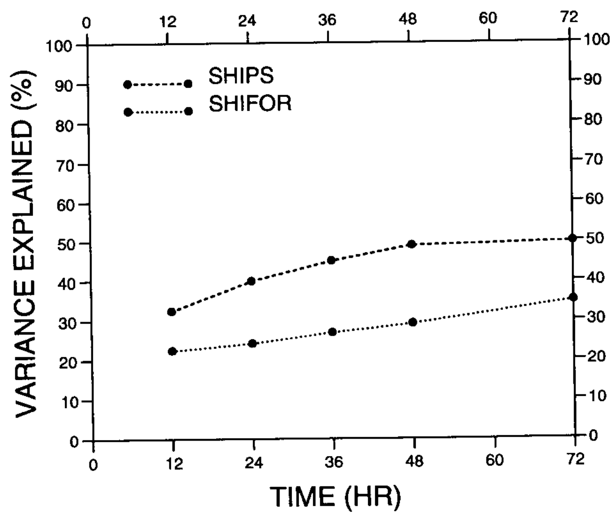


FIG. 3. The variance explained by the SHIPS and SHIFOR models for the 1989–1992 sample.

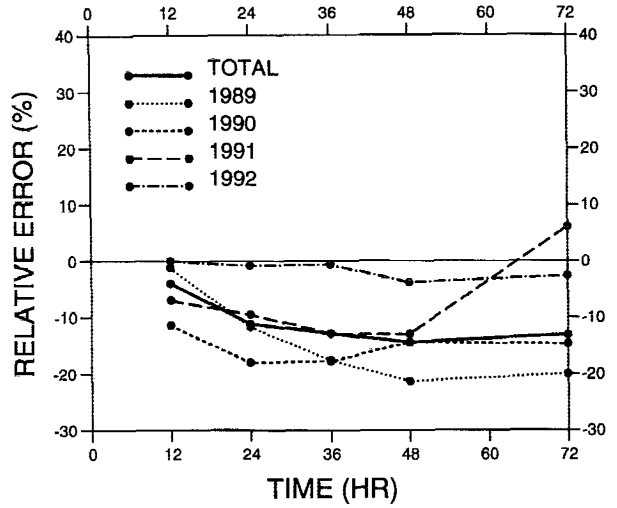


FIG. 4. The error of the SHIPS model normalized by the SHIFOR errors (relative error) for the total sample and for the cases from 1989, 1990, 1991, and 1992. A negative relative error indicates that the SHIPS model has skill relative to SHIFOR (climatology and persistence).

each year. SHIPS had skill at all forecast times for all years except at 72 h for 1991 and at 12 h for 1992. The SHIPS forecasts generally had more skill for 1989–1990 than for 1991–1992. During 1989–1990, many of the tropical cyclones formed from tropical waves and were located in low latitudes for at least part of their lifetime. During 1991–1992, many storms formed from baroclinic systems and spent a larger fraction of their lifetime in higher latitudes. This result suggests that the SHIPS model does not perform as well for storms with baroclinic origins.

To get a better idea of the variability of the intensity predictions, the average errors at 48 h for each storm in the 1989–1992 sample were calculated. The 48-h forecasts were chosen because at this time period the SHIPS forecasts had the most skill. Five of the 38 storms did not have any 48-h verifications, because the storms moved over land or dissipated within two days. The average SHIPS errors were smaller than the SHIFOR errors for 24 of the remaining 33 storms. Table 5 lists the nine storms for which SHIPS did not have forecast skill. Four of these nine storms were in highly baroclinic environments (Bertha and Klaus in 1990 and Earl and Frances in 1992), which may have contributed to the lack of forecast skill. For Bertha and Frances, SHIPS did not predict enough intensification. For Earl and Klaus, SHIPS predicted too much intensification. Three other cases in Table 3 were relatively short-lived tropical storms (Cesar and Fran in 1990 and Danny in 1991). In these three cases, SHIPS tended to forecast too much intensification. It is possible that these systems never became sufficiently organized to respond to the large-scale forcing used in the SHIPS prediction. The remaining two storms in

TABLE 5. Storms for which SHIPS did not have forecast skill at 48 h.

| Storm | Year | No. forecasts | Maximum intensity (kt) |
|---|---|---|---|
| Erin | 1989 | 14 | 90 |
| Gabrielle | 1989 | 24 | 125 |
| Bertha | 1990 | 7 | 70 |
| Cesar | 1990 | 8 | 45 |
| Fran | 1990 | 2 | 35 |
| Klaus | 1990 | 9 | 70 |
| Danny | 1991 | 6 | 45 |
| Earl | 1992 | 10 | 55 |
| Frances | 1992 | 4 | 75 |

Table 5 (Erin and Gabrielle in 1989) were long-lasting storms that formed from easterly waves and eventually moved to high latitudes. SHIPS tended to underforecast the intensity of these two storms. A closer inspection of these forecasts showed that the estimates of the vertical shear were too large because the 850-mb vortex in the spline analyses was displaced by up to 500 km from the actual storm location. Thus, the vortex circulation was contributing to the vertical shear. This problem of a displaced vortex in the analyses is due to the lack of observations and also introduces errors in track prediction models (e.g., McAdie 1991). In summary, it appears that the SHIPS forecasts are less skillful for storms in baroclinic environments, but other factors can also affect the forecast skill.

To help illustrate the utility and the limitations of the intensity predictions, Figs. 5–6 show all of the 0000 UTC forecasts for Hurricane Hugo 1989. Figure 5

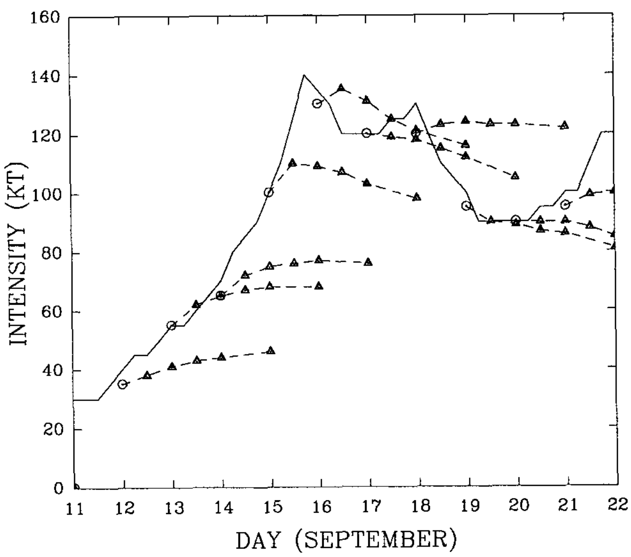


FIG. 5. The observed intensity (solid) and the 0000 UTC intensity forecasts from the SHIFOR model for Hurricane Hugo 1989. The initial intensity estimate is indicated by the circles, and the intensities at 12, 24, 36, 48, and 72 h are indicated by the triangles.

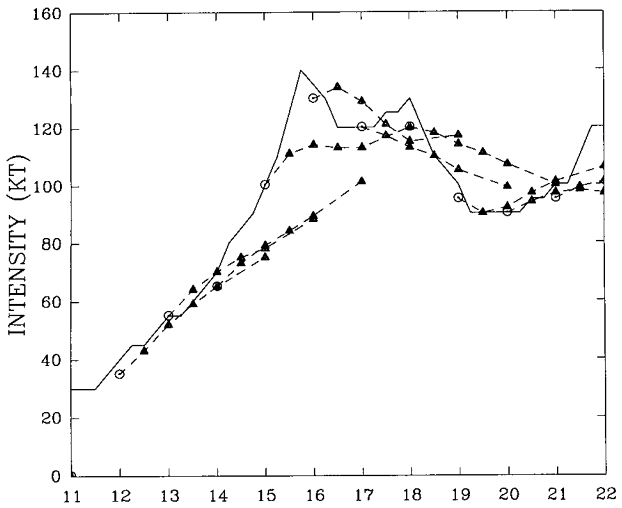


FIG. 6. Same as Fig. 5 for the SHIPS model.

shows that the SHIFOR model did not perform well during the rapid development phase of Hugo. This is not surprising, since Hugo developed much more rapidly than most Atlantic tropical cyclones. The SHIFOR forecasts were a little better after Hugo reached its maximum intensity, although the model did not predict the second intensification that began on 20 September as the storm headed toward the South Carolina coast. Figure 6 shows that the SHIPS forecasts performed better than the SHIFOR model when Hugo was rapidly intensifying. Hugo was in an environment with very low vertical shear and the SST was warm enough for rapid intensification. However, SHIPS still underestimated the intensification rate. This underestimation was also seen in SHIPS forecasts of other rapidly intensifying storms and is probably a limitation of the statistical prediction method. The SHIPS forecasts were somewhat reasonable after the storm reached its maximum intensity, although there are some short-time scale intensity variations that were not forecast. The SHIPS forecasts did, however, capture some of the second intensification that began on 20 September.

Hugo is an example of a storm that intensified rapidly. To get a better idea of how SHIPS performs for rapidly intensifying storms, the cases were stratified by the 48-h intensity change. The average 48-h intensity increase of the 32 most rapidly intensifying cases (top 10%) is 50 kt. This sample includes forecasts from 13 different storms. For these cases, SHIPS predicted an average 48-h intensity increase of 24 kt, compared with a predicted increase of only 12 kt for SHIFOR. Neglecting errors in the operational estimates of the initial intensity, the average 48-h SHIPS error for this sample is 26 kt, compared with 38 kt for SHIFOR. Thus, the average SHIPS errors are 33% smaller than the SHIFOR errors for the rapidly intensifying cases. As shown in Table 7, the average SHIPS and SHIFOR errors for the total sample at 48 h are 14.7 and 17.2 kt, respectively. Thus, for the total sample, the SHIPS errors are 15% smaller than the SHIFOR errors. These results show that the average SHIPS and SHIFOR errors for the rapidly intensifying cases are larger than for the total sample. However, SHIPS has greater skill for the rapidly intensifying cases than for the total sample, as indicated by the greater improvement relative to SHIFOR.

Table 6 shows the average value of each predictor for the 48-h forecasts of the rapidly intensifying cases. The variables are ordered by the magnitude of the predictors. The number of cases (out of 32) that were greater than the total sample mean is also shown for each predictor. Assuming the predictors are normally distributed about their means, there is a 99% probability that the number of cases greater than the mean would range from 9 to 23, if the cases were chosen randomly. Therefore, if less than 9 or more than 23 cases were greater than the mean, the average value of the predictor is considered significantly different from zero. Table 6 shows that for the rapidly intensifying cases, the planetary momentum flux term (PEFC), the SST variable (POT), and the persistence variable (DVMX) were larger than average, and the vertical shear (SHR) and the size variable were smaller than average. The remaining variables were close to average. The relationships for PEFC, POT, SHR, and DVMX are not surprising since PEFC, SHR, and DVMX are positively correlated and SHR is negatively correlated with intensification. However, SIZE is positively correlated with intensification, but the average value of SIZE for the rapidly intensifying cases is less than the average for the total sample. Nearly all of the rapidly intensifying cases were early in the life cycle of the storms. This result suggests that the rapid intensification occurs before the outer wind circulation (measured by the SIZE parameter) increases. This time lag between the intensity increase and size increase is consistent with observations of west Pacific tropical cyclones (Weath-

TABLE 6. The average value of the normalized SHIPS predictors for the 32 cases with the largest 48-h intensity increases. The value of the predictor is underlined if it is significantly different from zero at the 99% level.

| Predictor | Average value | No. of cases greater than the sample mean |
|---|---|---|
| 1) PEFC | <u>+0.82</u> | 25 |
| 2) POT | <u>+0.77</u> | 29 |
| 3) SHR | <u>−0.64</u> | 6 |
| 4) DVMX | <u>+0.43</u> | 24 |
| 5) SIZE | <u>−0.42</u> | 8 |
| 6) DTL | −0.24 | 10 |
| 7) JDATE | −0.23 | 9 |
| 8) REFC | −0.11 | 14 |
| 9) DSHR | −0.10 | 11 |
| 10) RLON | −0.01 | 17 |

erford and Gray 1988) and numerical model results (e.g., Ooyama 1969).

As described previously, the SHIPS errors are considerably smaller than the SHIFOR errors for the rapidly intensifying cases. This difference is probably due to the fact that only one (DVMX) of the top four predictors in Table 6 is directly included in the SHIFOR model. The effect of the SST variable is probably included indirectly through the variables VMX, LAT, LONG, and JDATE (see Table 1), but SHR and PEFC are not included in SHIFOR. It is this additional synoptic information that leads to the smaller SHIPS forecast errors.

Because the NHC produces a forecast every 6 h, a method was developed to run the SHIPS model at intermediate synoptic times (0600 and 1800 UTC). For this purpose, the synoptic analysis from the primary synoptic time (0000 or 1200 UTC) is combined with the updated storm intensity estimate and track forecast. (The VICBAR model is also run at the intermediate synoptic times.) The synoptic variables in Table 3 that depend on the extraction of the symmetric vortex (REFC, PEFC, SIZE, and the initial value of SHR) are determined using the storm position at the time that the spline analysis is valid. All other variables are determined from the updated storm positions.

Table 7 shows that the 0600 and 1800 UTC intensity errors for SHIPS are nearly the same as the errors for the 0000 and 1200 UTC forecasts. The SHIFOR errors are also similar for the two samples. Thus, the SHIPS forecasts at the intermediate synoptic times have about the same skill as the forecasts at the primary synoptic times, and the model can be used to provide intensity predictions four times per day.

Table 7 shows that SHIPS has skill relative to SHIFOR for both the primary and intermediate synoptic time samples. To give a better idea of the utility of SHIPS for operational intensity prediction, Fig. 7 shows the average intensity errors for a homogeneous sample that includes the official NHC intensity predictions. This sample includes all available forecasts from 1989 to 1992 at the primary and intermediate synoptic times. This figure shows that the official forecast errors are smaller than those of SHIFOR (except at 72 h) but are larger than the SHIPS errors at all forecast intervals. The differences between the average SHIPS and official forecast errors at 48 and 72 h are significant at the 95% level. These results suggest that the SHIPS model has the potential to improve operational prediction of tropical cyclone intensity change.

TABLE 7. Average intensity forecast errors (kt) for the 0000/1200 and 0600/1800 UTC samples.

| | Forecast interval | | | | |
|---|---|---|---|---|---|
| Model | 12 | 24 | 36 | 48 | 72 |
| 0000/1200 UTC SHIPS | 7.2 | 10.3 | 12.8 | 14.7 | 17.2 |
| 0600/1800 UTC SHIPS | 7.2 | 10.3 | 12.9 | 14.8 | 17.4 |
| 0000/1200 UTC SHIFOR | 7.5 | 11.6 | 14.7 | 17.2 | 19.8 |
| 0600/1800 UTC SHIFOR | 7.6 | 11.3 | 14.6 | 17.2 | 19.6 |

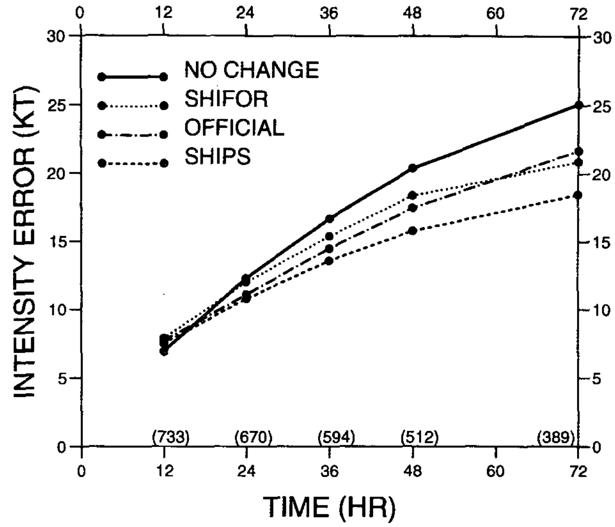


FIG. 7. The average intensity errors for the NC forecast, the SHIFOR model, the official NHC intensity forecast, and the SHIPS model. The SHIFOR and SHIPS models were run using the input that would be available in real time. The sample sizes are indicated along the bottom of the diagram.

## 5. Concluding remarks

A Statistical Hurricane Intensity Prediction Scheme (SHIPS) for the Atlantic basin was described. The model was developed using a standard multiple regression technique with climatological, persistence, and synoptic predictors. The model sample includes all of the named Atlantic tropical cyclones from 1989 to 1992, with a few additional cases from 1982 to 1988. All landfalling cases were excluded from the sample. The four primary predictors are 1) the difference between the current storm intensity and an estimate of the maximum possible intensity determined from the sea surface temperature, 2) the vertical shear of the horizontal wind, 3) persistence, and 4) the flux convergence of eddy angular momentum evaluated at 200 mb. The sea surface temperature and vertical shear variables are averaged along the track of the storm during the forecast period. All of the other primary predictors are evaluated at the beginning of the forecast period.

The model was tested using a jackknife procedure where the regression coefficients are determined with all of the forecasts for each storm removed from the sample. Operational estimates of the initial storm intensity and position were used in place of best track information in the jackknife procedure. The position estimates during the forecast period were obtained from the VICBAR track forecast model. The jackknife procedure simulates real-time conditions. Results showed that the average SHIPS intensity errors are 10%–15% smaller than the errors from a model that uses only climatology and persistence (SHIFOR), and the error differences at 24, 36, and 48 h are statistically significant at the 99% level. The differences at 12 and 72 h are significant at the 95% level. These results indicate that the SHIPS model has skill in the prediction of tropical cyclone intensity change.

Although the SHIPS model improves upon climatology and persistence, the forecasts still explain only about 50% of the variability of the observed intensity changes. Part of the observed variability is due to storm-scale processes such as the formation and evolution of concentric eyewalls (Willoughby 1990). It is unlikely that a statistical model with large-scale predictors will ever be able to adequately include these types of effects. It should be possible, however, to improve the estimates of the large-scale predictors during the forecast period. In the current version of SHIPS, the vertical shear and momentum fluxes are evaluated from synoptic analyses. If a numerical model such as the NMC Aviation model could be used to determine the time evolution of the synoptic parameters, the skill of SHIPS should increase. The skill of SHIPS might also increase if the climatological SST analyses were replaced with real-time SST analyses. These possibilities are currently being investigated.

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