MARINE

AN OPERATIONAL TECHNIQUE FOR PREDICTING TROPICAL STORM FORMATION IN THE WESTERN NORTH PACIFIC OCEAN

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ABSTRACT

Further work is described on statistical forecasting experiments to evaluate the capability of predictors derived from observational data (analysis) fields at 950, 500, and 200 mb to forecast tropical storm formation. In this study, we first describe the redefinition of the projections to make them more meaningful for forecasting purposes and to make forecasts using the statistical algorithms more consistent among the projections. Using the redefined projections, the statistical predictors were re-screened using Rao's technique, and a single set of predictors was selected for all projections. Results in terms of accepted statistical methods are presented for independent data based on the refined tropical storm formation prediction technique in categorical form, and comparisons are made with an earlier form of the forecast technique. A graphical representation of the probabilities of tropical storm formation (and location of the storm at forecast time of formation) is described. An evaluation is made against operational "formation alerts" made by the Joint Typhoon Warning Center for the 1980 tropical storm season. All results confirm the skill of the statistical tropical storm forecasting technique in both categorical and probabilistic form.

1. INTRODUCTION

Since the latter part of World War II, prediction of tropical cyclones has been of concern to U.S. military operations in the western North Pacific and South China Sea. Such tropical phenomena also pose a threat to civilian maritime shipping operating in these regions. Following World War II, the Joint Typhoon Warning Center (JTWC), which is a joint U.S. Navy-U.S. Air Force facility, was established to provide needed tracking and prediction services. It is generally agreed that the main problem that continues to face JTWC forecasters is the prediction of tropical storm movement. However, another vexing problem facing forecasters at this facility has been the accurate, reliable prediction of tropical storm formation. Reasonable success has been achieved in producing physical models for the prediction of tropical cyclone motion but success using physical models to predict tropical storm formation has been elusive. The motivation for this study is to provide objective guidance for use by JTWC in predicting tropical storm formation. This paper discusses a statistical technique to do so.

Perrone and Lowe (3) reported on a successful statistical technique for predicting tropical storm formation. In that study we addressed the forecast problem of predicting the development of a cloud cluster into a tropical storm within 0–24 hr, within 24–48 hr, and within 48–72 hr. We used predictors originally suggested by Gray and collaborators/associates (e.g., (4), (5), (6), and (7); see also (8).) The statistical methodology we used was discriminant analysis. The best-known use of this methodology in weather forecasting research is by Miller (9).

Section 2 of this paper briefly describes the data, methodology, and results of our previous work. Section 3 describes the critical re-examination and re-formulation of our previous work into a form better suited for an operational forecast technique, while Section 4 describes the operational forecast technique. Section 5 presents results of an evaluation of the operational technique. Section 6 presents our conclusion. Appendix A describes the statistical techniques we used, Appendix B describes a regression-derived technique to forecast tropical storm location 24 hr hence, and Appendix C defines the statistical scores used in this study.

2. A SUMMARY OF PREVIOUS WORK

The data used in our previous work were derived from three sources: the National Oceanic and Atmospheric Administration (NOAA) tropical Mosaic visible satellite images for 1974 through 1977; the 12-hourly standard meteorological data fields produced and archived by Fleet Numerical Oceanography Center (FNOC) in Monterey, California; and the post-season ("Best Track") Storm Analyses prepared by JTWC. Area coverage for the work was from the Equator to 30°N latitude and from 180° longitude westward to the Asian mainland (area includes South China and Philippine Seas).

Our objective is to develop a forecast technique capable of predicting tropical storm formation up to 72 hr in advance by using the statistical methodology of discriminant analysis operating on predictors formed from data contained in FNOC observational data (analysis) fields. We defined tropical storm formation as the event in which a cloud cluster grows to a tropical storm. A tropical storm is defined as a closed tropical circulation with maximum sustained surface wind that equals or exceeds 17 m/s (34 kt). To build a database suitable for applying the statistical methodolocy and to identify geographical locations at which to extract predictor data from the FNOC fields, we used satellite imagery. The visible satellite images together with the JTWC best-track analyses were used to identify cloud clusters that later developed into tropical storms. These are called GO cases. The same satellite images from which the GO cases were selected were also used to identify cases of cloud clusters that did not subsequently develop into tropical storms, called NO GO cases.

The GO cases were selected first, as far back as 72 hr from the time of tropical storm formation, if the JTWC analyses allowed us to trace a cloud cluster's location 72 hr back in time. If not, the case was traced as far back as the analysis supported (i.e., 48 or 24 hr, as appropriate). For each GO case selected (for 24, 48, and 72 hr prior to tropical storm formation), the satellite mosaic corresponding to the GO case for a particular time period (24, 48, and 72 hr) was scrutinized for other cloud clusters that met a minimum 1° latitude diameter selection criterion. These clusters were picked as NO GO cases for that time period.

We desired broad geographical coverage for the NO GO cases, because our goal is to develop an objective prediction scheme usable over a broad region of the western North Pacific Ocean. If a tropical storm rarely developed in some portion of the region, we wanted the statistical prediction scheme to be able to account for this. Accordingly, we needed a geographically representative sample of NO GO clusters, so that the differences in the means of the tropical storm predictors for each group (GO and NO GO) would be large enough to allow discriminant analysis to properly distinguish GO cases from NO GOs.

For each of the GO and NO GO cases, the FNOC analysis fields were accessed for the time and location of the cases and a variety of basic environmental quantities were extracted. These quantities were extracted by using the time and position of the cluster locations, as determined from the satellite images and post-season best-track analyses. Bessel interpolation was employed to determine the values of the quantities associated with the cloud cluster positions lying between the FNOC operational grid points. Among the basic quantities extracted from the FNOC analysis fields were the surface pressure, the north-south and east-west component of the winds at 950 and 200 mb, sea surface temperature, and moisture at 950, 700, and 500 mb.

From this basic set of quantities, the candidate predictors for discriminant analysis (Table 1) were formed by applying finite-difference formulae used in numerical modeling. All computations were made on a 2.5° latitude grid, except where noted for the low level (950 mb) and upper level (200 mb) vorticities. The Coriolls parameter was computed and added to the list of candidate predictors. The moist layer stability parameter is the difference between the equivalent potential temperature (θ_e) at 950 mb and 500 mb. For more details on the case selection procedure and the candidate predictors, see (3).

Two further comments on our methodology may facilitate understanding of it: First it should be emphasized that no predictor data was derived from the satellite imagery; all predictors are derived from the FNOC analysis fields. Satellite imagery was used only to help identify GO and NO GO cases, and to select the latitude and longitude of the cases, providing the locations on the analysis fields where predictor information would be accessed.

Second, the tropical depression (TD) stage of tropical cyclone developed was not explicitly addressed in the development of our technique. We reasoned that that it is more important to address forecasting the onset of the tropical storm stage (i.e., closed circulation with maximum wind speed equal to or greater than 17 m/s (34 kt)) so we chose not to complicate our forecast problem or dilute the power of the statistical methodology by trying to separately account for cloud cluster to tropical depression development and/or tropical depression to tropical storm development. Nonetheless, even though our technique does not explicitly address tropical depression to tropical storm development, we decided to test its ability to forecast such situations. Successful results for the 1980 tropical storm season are reported in Section 5 with particular emphasis on the capability to predict the transition from tropical depression stage to tropical storm stage. In view of our case selection procedure described above, our dependent GO case sample may include some tropical depressions (if they developed into tropical storms within 24, 48, or 72 hr from the time they appeared on a given satellite image). Similarly, our dependent NO GO case sample may include some tropical depressions (if they did not develop into tropical storms within 24, 48, or 72 hr from the time they appeared on a given satellite image).

In (3) we applied the BMDP7M stepwise discriminant analysis program (10) to a dependent sample for each of three forecast projections: τ_{24}, defined as 0–24 hr; τ_{48}, 24–48 hr; τ_{72}, 48–72 hr. BMDP7M uses forward stepwise screening to select among candidate predictors (See Appendix A, Section A.1 for details), and selected five predictors for the 0–24 projection, four predictors for the 24–48 hr projection, and one for the 48–72 hr projection. The selected variables are indicated in Table 1, while Table 2 shows scores for the forecasts produced. For more details consult (3).

Table 1. List of candidate and selected predictors.
Column 1 lists initial discriminant function predictors selected for $\tau = 24$.
Column 2 lists initial discriminant function predictors selected for $\tau = 48$.
Column 3 lists initial discriminant function predictors selected for $\tau = 72$.
Column 4 lists final discriminant function predictors selected for $\tau' = 24$, 48, and 72. All τ s expressed in hr. All predictors measured on a 2.5° latitude gride except predictors C and I, which use a 5.0° grid. Low level = 950 mb. Upper level = 200 mb. See text for description of difference in meaning of τ and τ'.

	Candidate Predictors	1	2	3	4
A	Low-level vorticity (2.5°)	x	x	x	x
B	Low-level divergence		x		x
C	Low-level vorticity (5.0°)	x			x
D	Advection of low-level vorticity				
E	Product of A and B	x			x
F	Vertical wind shear				
G	Upper-level vorticity (2.5°)				
H	Upper-level divergence				
I	Upper-level vorticity (5.0°)				
J	Advection of upper-level vorticity	x			
K	Product of G and H				
L	Sea-surface temperature				
M	Relative humidity (700 mb)				
N	Equivalent potential temperature (θ_e) (700 mb)				
O	Relative humidity (500 mb)				
P	Equivalent potential temperature (θ_e) (500 mb)		x		x
Q	Moist-layer stability		x		
COR	Coriolis parameter	x			

Table 2. Scores from original experimental results (after Perrone and Lowe (3), using predictors indicated in Table 1, columns 1–3, on independent data. Scores are defined in Appendix C.

Score	Projection (hr) (τ)		
	0–24	24–48	48–72
Percent Correct	92.9	86.4	85.4
Power of Detection (GO)	0.857	0.875	0.750
False Alarm Rate (GO)	0.038	0.031	0.065
Threat Score	0.706	0.538	0.500
Brier Score	0.090	0.240	0.280

3. NEW RESULTS, FOLLOWING A CRITICAL RE-EXAMINATION OF PREVIOUS WORK

Although pleased with our previous results, summarized in Section 2, we felt that further analysis of the data might yield an improved prediction process. Somewhat troubling was the fact that different predictors were chosen for each projection (See the initial predictor lists in columns 1–3 of Table 1). Although the predictors selected are optimum for each projection, we faced the undesirable prospect that the resulting predictions might not be consistent with projection to projection.

Consequently, we redefined the forecast projections this way:

τ'_{24} designates tropical storm formation *within* 24 hr.

τ'_{48} designates formation *within* 48 hr.
(i.e. anytime between = 0 to = 48)

τ'_{72} designates formation *within* 72 hr.

The redefinition of the projections accomplishes three objectives: (i) it is logical and amenable to interpretation operationally; (ii) it enlarges, in effect, the data samples for the 48- and 72-hr forecasts; (iii) it promotes consistency of forecasts from projection-to-projection. Under the new definition, τ'_{24} is unchanged from τ_{24}. The new τ'_{48} data sample is a combination of the old τ_{24} and τ_{48} data samples and the new τ'_{72} sample combines the old τ_{24}, τ_{48}, and τ_{72} samples.

Two assumptions that underlie discriminant analysis are:

a. both sub-populations (GO and NO GO cases) possess multivariate normal distributions for the predictors.
b. both sub-populations possess identical covariance matrices.

Even if the multivariate normality assumption (a) is not perfectly satisfied, linear discriminant analysis remains quite robust (See (11)). An inordinately large departure from normality, though, will degrade results. Linear discriminant analysis is, however, very sensitive to the satisfaction of the equality of covariance assumption (b); if it is not well satisfied, results will definitely be degraded.

Having as a goal the rescreening of the candidate predictors to perform a better discriminant analysis, we scrutinized our database carefully in light of assumptions (a) and (b). A number of the candidate predictors listed in Table 1 were discarded because they either were highly non-normally distributed (related to assumption (a)) or did not possess equal variances for both GO and NO GO sub-populations (assumption (b)), or both.

For rescreening the candidate predictors, we did not use the BMDP7M program. Of the candidate predictors that remained after scrutiny to determine satisfaction of assumptions (a) and (b), those that did not exhibit significant differences between means for the GO and NO GO samples were removed from further consideration. Doing so acts as a gross filter in the process of selecting a more parisomonious (efficient) set of predictors, by eliminating candidate predictors that do not contribute significantly to the predictive power of the technique. In the next step, which acts as a finer filter in the selection process, the candidate predictors that remained were screened using a procedure developed by Rao (12). See Appendix A, Section A2, for a description of Rao's statistic and its use in the screening process. The coefficients and constants for the resulting discriminant function are given in Table 3. The predictors are also listed in column 4 of Table 1 for comparison with the predictors selected in our previous work.

In our previous work (3) we used equal *a priori* probabilities with discriminant analysis to produce categorical forecasts. Equal *a priori* probabilities imply that there is a 50% chance that a given tropical cloud cluster will grow into a tropical storm, which is a somewhat unrealistic assumption. Because consistent, reliable unconditional probabilities of tropical storm formation derived from climatology were not available for the western North Pacific region, we estimated such probabilities for each month by questioning a number of scientists with either experience in forecasting tropical storms or general tropical meteorology expertise. Estimating *a priori* probabilities through expert consensus has long been advocated by Bayesian statisticians such as Lindley (13) as a valid way to obtain such probabilities when historical frequency of occurrence information (i.e. climatology) is either unavailable or unreliable. The consensus is shown in Table 4 for 24 hr. To obtain *a priori* probabilities for 48 (72) hr, we doubled (tripled) the probabilities for 24 hr. In the absence of any other reasonable basis, we assumed that the probability of a tropical storm formation can be reasonably be expected to increase linearly with the time period involved, particularly for the small probability values we used.

Table 3. Coefficient and constants for the discriminant function produced through rescreening by Rao's method using the redefined projections. The same predictors were selected for each of the redefined projections. These coefficients and constants are for results described in Section 3 of the text. The grid size used to measure each predictor appears in parentheses after the predictor's name.

Rescreened Predictors	Redefined Projections (hr) (τ')		
	0–24	0–48	0–72
Low-level vorticity (2.5°)	−0.35	−0.31	−0.27
Low-level divergence (2.5°)	−0.17	−0.13	−0.10
Low-level vorticity (5.0°)	−0.08	−0.08	−0.08
Product of low level vorticity and divergence (2.5°)	−0.17	−0.11	−0.06
Equivalent potential temperature (500 mb) (5.0°)	−0.26	−0.19	−0.12
Constant	95.0	70.0	43.0

We experimented by varying somewhat the *a priori* probability values about those given in Table 4. We observed as a consequence of these informal sensitivity studies that the use of the *a priori* probabilities acts as a "brake" on the forecast process by tending to reduce false alarm forecasts. The false alarm rates reported in Table 5 (less than 11%) seem acceptable for operational forecasting, thereby justifying our choice and use of the *a priori* probabilities.

To make categorical forecasts, we used the Probability of Error Decision Criterion (See Appendix A, Section A3 for details of the criterion), and produced results on independent data, displayed in Table 5. The same five predictors were used for each projection, as listed in Table 3 and in column 4 of Table 1.

Comparison of the revised with the original results (Table 5 with Table 2) is not easy because of the change in definition of two of the three projections. Only the 24-hr projection is defined the same way in both tables. For the 24-hr projection, all scores except the Brier Score are less favorable in Table 5 than in Table 2. Speaking of the Brier Score, although direct comparison between the two tables of the other two projections is not possible, one is struck nonetheless by the low (favorable) Brier Scores throughout Table 5. This perception motivated the probabilistic refinement which follows in Section 4.

Table 4. Estimated *a priori* probabilities, by month, for tropical storm formation within 24 hr, for the western North Pacific Ocean and South China Sea.

Month	Region	
	Western North Pacific Ocean	South China Sea
January	0.0005	0.0005
February	0.0005	0.0005
March	0.001	0.001
April	0.005	0.005
May	0.01	0.01
June	0.05	0.05
July	0.10	0.03
August	0.10	0.03
September	0.07	0.05
October	0.05	0.05
November	0.01	0.01
December	0.005	0.001

Table 5. Scores for new results described in Section 3 of the text, using predictors indicated in Table 1, column 4, on independent data. Scores are defined in Appendix C. The discriminant function was produced through rescreening by Rao's method using the redefined projections. The same predictors were selected for each of the redefined projections.

Score	Redefined Projection (hours) (τ')		
	0–24	0–48	0–72
Percent Correct	84.0	82.2	87.2
Power of Detection (GO)	0.692	0.667	0.750
False Alarm Rate (GO)	0.108	0.104	0.067
Threat Score	0.529	0.467	0.545
Brier Score	0.090	0.120	0.080

4. OPERATIONAL FORECAST TECHNIQUE USING PROBABILITY FORECASTS

Although the categorical (GO and NO GO) results produced using discriminant analysis as described in Sections 2 and 3 showed considerable skill, discussions with many Navy operational forecasters with tropical storm forecasting experience indicated that they had some preference for probability rather than categorical forecasts. Production of probability forecasts from statistical techniques also finds vigorous support from commentators such as Murphy (14), who argue

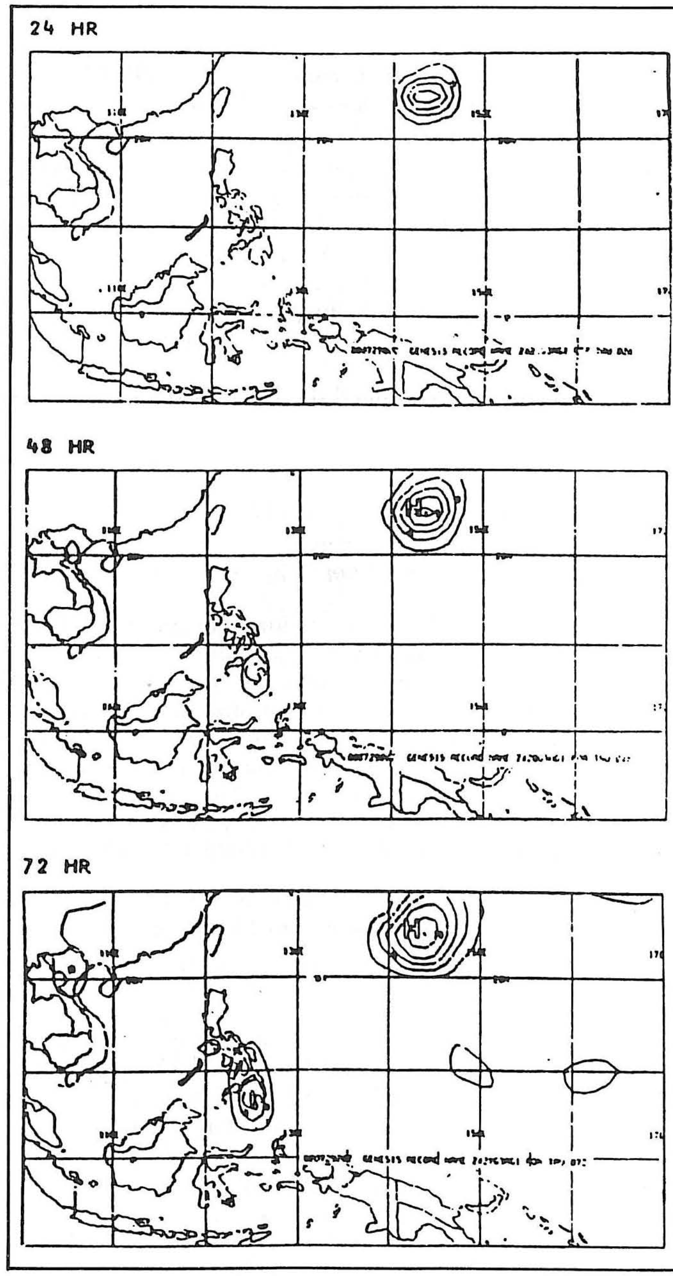

Fig. 1. Sample of the graphical output produced by the computer program described in Section 4 of the text. The charts were produced from FNOC data for the western North Pacific Ocean on 29 July 1980 at 0000 GMT. The labeled panels contain contoured probabilities of tropical storm formation, one for each forecast period as redefined in Section 3 of the text: τ'_{24} (within 24 hours); τ'_{48} (within 48 hours); and τ'_{72} (within 72 hours).

that probability forecast guidance communicates more information to the operational forecaster than categorical forecasts do.

The low Brier Scores achieved by our reworked discriminant analysis technique (See Table 5) indicate considerable probability forecasting skill. We wished to capitalize on this strength in developing an operational technique. To make probability forecasts using our technique, one uses the *a posteriori* probabilities of tropical storm development and non-development. These *a posteriori* probability forecasts are produced using Bayes' theorem with the discriminant function. Bayes' formulation for these probabilities is described in Appendix A, Section A4.

A computer program has been designed and test-implemented to produce a chart of contours of equal probability of tropical storm formation in the western North Pacific and South China Sea. The program calculates the predictor quantities listed in Table 4, column 4 for each of the standard FNOC grid points (spaced 2.5° of latitude apart) in the western North Pacific Ocean and South China Sea. The program then operates on these quantities using the Rao discriminant function described in Appendix A, Section A2. Probabilities of tropical storm formation are calculated at each grid point using the method of Bayes' theorem for calculating *a posteriori* probabilities described in Appendix A, Section A4. Standard contouring techniques are then used to produce charts of contoured probabilities. The computer program is designed to run twice daily (0000 UTC and 1200 UTC) on data available at FNOC.

Figure 1 is a sample of the graphical output of the program and is for 29 July 1980 at 0000 UTC. Three of the panels contain contoured probabilities of tropical storm formation, one for each redefined forecast period τ'_{24} (within 24 hr); τ'_{48} (within 48 hr); and τ'_{72} (within 72 hr). These three panels address the probability of the occurrence of the event of tropical storm formation, but do not directly indicate the tropical storm's location at the time it is forecast to become a tropical storm. To remedy this, we propose a fourth panel, whose concept was developed after the computer program to produce the other three panels was written. This proposed fourth panel (not included in Fig. 1) would contain an indication of the probability of a tropical storm's *location* within 24 hr, given that a storm had been forecast to form. The proposed fourth panel would consist of a series of contoured, concentric ellipses, with each ellipse representing (at a specified probability level) the most likely location for tropical storm formation within 24 hr. See Appendix B for a discussion of a statistical regression experiment (which used data from our study's database) from which these probability ellipses could be derived. If some other short-range movement prediction technique is shown to have more skill than the technique described in Appendix B, it could be incorporated instead into the operational computer program.

In any event, the proposed fourth panel would be produced only if the maximum probability calculated for the first panel (of tropical storm formation within 24 hr) exceeds a defined threshold. Our experience with the data suggests that a threshold of 0.80 is appropriate. We observe that cases of

Table 6. Partial evaluation results for our objective forecast technique compared with JTWC formation alerts; shown in this table are results for tropical depressions (TDs). The full evaluation was performed on independent data for 9 months of the tropical storm season for 1980 (see text). Lead time expressed in hours. Formation of Tropical Storm "DINAH" was a complete miss for both JTWC and our objective forecast technique. FALSE ALARMs are incorrect forecasts of the development of a tropical storm by our objective technique.

Month	TD#	Tropical Storm	JTWC Formation Alert Lead Time	Objective Technique Lead Time	Objective Technique Probability at Lead Time
MAY	3	"DOM"	12	72	.95
	4	"ELLEN"	12	36	.99
	5	"FORREST"	24	72	.92
	6	"GLORIA"	24	72	.90
JUNE	7	"HERBERT"	24	48	.85
JULY	8	"IDA"	24	72	.90
	9	"JAKE"	36	72	.95
	10	------------	------------ FALSE ALARM	------------	------------
	11	"KIM"	24	72	.97
	12	"LEX"	20	36	.90
AUGUST	13	"MARGE"	12	36	.95
	14	------------	------------ FALSE ALARM	------------	------------
	15	"NORRIS"	24	72	.99
SEPTEMBER	16	------------	------------ FALSE ALARM	------------	------------
	17	"ORCHID"	24	72	.99
	18	"RUTH"	27	72	.95
	19	"PERCY"	6	72	.95
	20	"SPERRY"	6	48	.90
	21	"THELMA"	24	36	.95
	22	"VERNON"	24	60	.95
OCTOBER	23	"WYNNE"	24	36	.95
	24	"ALEX"	30	72	.95
	25	"BETTY"	24	36	.90
	26	"CARY"	12	72	.95
NOVEMBER	27	"DINAH"	------------ COMPLETE MISS	------------	------------

non-development into tropical storms have probabilities well below 0.50, while cases which did develop into tropical storms possessed probabilities generally well above 0.80, and usually above 0.90.

5. A TEST OF THE OPERATIONAL FORECAST TECHNIQUE ON INDEPENDENT DATA

The operational probability forecast technique described in Section 4 was evaluated for every day of 9 months of the 1980 Typhoon season (December 1980, January 1981, and February 1981 were excluded). Although our technique was not explicitly developed to forecast the transition from the tropical depression to tropical storm stages, we felt that a demonstration of the technique emphasizing tropical depressions would show whatever skill our technique might have to forecast this stage transition. A tropical depression (TD) is a tropical system with a degree of circulation organization greater than that of a cloud cluster, but whose observed sustained maximum wind speed has not yet reached the tropical storm threshold (17 m/s (34 kt)). Our technique was run on FNOC fields (at 0000 and 1200 UTC) for each day of the period described above.

The results of applying our forecasting technique in 1980 for TDs is presented in Table 6. Indicated are the operational lead time achieved by JTWC in issuing tropical storm formation alerts, our technique's lead time using a threshold probability of formation of 0.80, and the probability indicated by our technique at the lead time. A "formation alert" is issued when the JTWC forecaster determines, though his judgment and use of JTWC rules and empirical forecasting techniques, that tropical storm formation is reasonably likely within the limited area defined in the alert.

Our technique had lead times ranging from 36 to 72 hr, compared with JTWC operational "formation alert" lead times ranging from 6 to 36 hr. Of the 25 tropical depressions that occurred during the 9-month period covered by the study, 21 were correctly forecast by our technique to develop into tropical storms. Three false alarms were TDs incorrectly forecast by our technique to develop into tropical storms. In fact, these false alarms were the only ones our forecast technique produced for the 9-months of the 1980 tropical storm season data used in this study. The formation of tropical storm "DINAH" was apparently completely misseed because of the sparseness of surface data in the mid-Pacific where the storm formed. This inadequacy of surface data was probably reflected in the low-level predictors used by our forecast technique. From a Navy operational viewpoint, the impact of this type of complete miss is minimal, as most naval activities are carried out farther westward, where surface data are more plentiful and our forecast technique performs well.

6. CONCLUSION

All evaluations we have performed indicate that the statistical tropical storm formation forecast techniques developed in this and our previous work demonstrate considerable skill.

APPENDIX A

STATISTICAL TECHNIQUES AND PROCEDURES USED

A1. BMDP7M STEP-WISE DISCRIMINANT ANALYSIS

Our previous work (3) applied the BMDP7M step-wide discriminant analysis program (10) to dependent samples for each of three forecast projections: τ_{24}, τ_{48}, and τ_{72} (i.e., for 0–24 hr, 24–48 hr, and from 48–72 hr, respectively).

The BMDP7M program proceeds in a step-wide manner. At each step, the predictor with the highest F value (i.e., the one that adds most to the separation, statistically, of occurrence from non-occurrence of tropical storm formation) is entered into the analysis. Stepping continues until a minimum F value-to-enter is reached. For tropical storm formation algorithm development, a minimum value of 4.0 was used, the default value of the BMDP7M program.

When the screening procedure is complete, the BMDP7M program produces discriminant functions composed of the predictors that have been selected as the best discriminators. For tropical storm formation algorithm development, two classification functions were produced, one for each of the two categories (GO (tropical storm formation) and NO GO (non-formation)), for each of the three forecast projections described above.

The forward step-wise screening of the candidate predictors resulted in selecting five predictors for the τ_{24} projection, four predictors for the τ_{48} projection, and one for the τ_{72} projection. The selected predictors are indicated in Table 1 of the main text, in columns 1, 2, and 3.

The discriminant functions produced for each forecast projection have this form:

$$CL_x = C_{x,\Phi} + C_{x,1}Z_1 + \ldots + C_{x,n}Z_n \qquad (A1.1)$$

$$CL_y = C_{y,\Phi} + C_{y,1}Z_1 + \ldots + C_{y,n}Z_n \qquad (A1.2)$$

CL_x and CL_y are discriminant functions for GO and NO GO samples respectively; $C_{x,\Phi}$ and $C_{y,\Phi}$ are constant terms for the two samples, and $C_{x,i}$ and $C_{y,i}$ are the coefficients for the ith discriminator predictor Z_i for the two samples.

For categorical forecasting (i.e., classification as GO or NO GO) the discriminant functions are used this way: if CL_x is less than CL_y, the prediction of tropical storm formation (GO) is made; otherwise prediction is for non-formation (NO GO). In other words, a low value of CL_x relative to CL_y is associated with a high tendency for tropical storm formation.

For probability forecasting (i.e., to determine the probability of GO and NO GO), Bayes' theorem is used to produce estimates of the probabilities, when the *a priori* (i.e., unconditional) probabilities of GO and NO GO are unknown or are assumed to be equal:

$$P\,(GO/Z) = 1/(1 + \exp(CL_y - CL_x)) \qquad (A1.3)$$

$$P\,(NO\;GO/Z) = 1 - P\,(GO/Z) \qquad (A1.4)$$

The "/Z" in these two equations means "given that a probability forecast has been made using discriminant analysis."

A2. DISCRIMINANT ANALYSIS USING RAO'S METHOD

Rao's method (12) screens candidate predictors this way: first the Mahalanobis distance[1] is calculated using the available candidate predictors. Then, one predictor is removed from consideration and the Mahalanobis distance is recomputed. The statistic F (defined below) is computed and used to test whether or not the difference $D^2_k - D^2_{k-1}$ is significant. If the difference is significant, the predictor is retained; if not, it is discarded. The procedure is repeated until only significant predictors remain; these resulting predictors are those reported in Column 4 of Table 1.

Rao's statistic has this form:

$$(A2.1)\quad F = (n_x + n_y - k - 1)C(D^2_k - D^2_{k-1})(k - k_1)^{-1}(1 + CD^2_{k-1})^{-1},$$

where:

D^2_k and D^2_{k-1} are the Mahalanobis distances computed using k predictors and k − 1 predictors respectively,

k = number of predictors under consideration,

n_x, n_y are the samples sizes of the GO and NO GO samples respectively,

$C = n_x n_y/((n_x + n_y)(n_x + n_y - 2)$, and

$k - k_1 = 1$ for our application.

Once the predictors are screened, a single discriminant function is derived from then, having the form:

$D_s(Z) = C_0 + C_1Z_1 + \ldots + C_kZ_k$,

where C_0 *(a constant)* $= \frac{1}{2}(\bar{Y} - \bar{X})S^{-1}$

and $C_i = S^{-1}_{ij}(\bar{Y}_j - \bar{X}_j)$;

$\bar{X}, \bar{Y}$ are the mean vectors for the GO and NO GO samples, respectively,

Z_i is the value of the ith candidate predictor,

S^{-1}_{ij} is the ijth element of the inverse of the covariance matrix S, and

k = the number of predictors chosen.

Note that $D_s(Z)$, as a consequence of being a linear combination of predictors having normal distributions, is also normally distributed. Our pre-screening of candidate predictors, limiting consideration only to those possessing normal distributions, assured this result.

A3. CATEGORICAL FORECASTING—GO OR NO GO—USING THE PROBABILITY OF ERROR DECISION CRITERION

The Probability of Error Decision Criterion[2] establishes a threshold for categorical forecasting so as to minimize the total probability of error. Categorical forecasts are made in the following manner. Forecast tropical storm formation (GO) if the discriminant function $D_s(Z)$ is less then:

$\frac{1}{2}\,|(\bar{X} + \bar{Y})| + 2\ln(P(GO)/P(NO\;GO)(Z_y - Z_x)^{-1}$.

Conversely, forecast non-formation (NO GO) is $D^s(Z)$ is more than the quantity above. P(GO) and P(NO GO) are the *'a priori* (i.e. unconditional) probabilities of tropical storm formation and non-formation, respectively.

[1]Mahalanobis' distance is a measure of the separation between two statistical populations. It is the "distance" between the means normalized by the common variance of the populations. For further discussion of Mahalanobis' distance see (11).

[2]Full development and discussion of this decision rule may be found in (15)

The results from applying the forecast rule described above on independent data are presented in Table 5.

A4. CALCULATION OF A POSTERIORI PROBABILITIES

A posteriori probabilities are those determined as a consequence of the forecast process (i.e., "given" that a forecast has been made). The formula for the *a posteriori* probability of tropical storm formation (GO), derivable from an application of Bayes' theorem, is:

$$P(GO/D_s(Z)) = 1/(1 + C\ exp\ (D_s(Z))) \qquad \text{(A4.1)},$$

where C = P(GO)/P(NO GO), the ratio of the *a priori* (i.e., unconditional) probability of tropical storm non-formation (NO GO) to the *a priori* probability of tropical storm formation (GO). The notation "$/D_s(Z)$)" in A4.1 means "given that a forecast has been made using discriminant analysis."

If the *a priori* probabilities of GO and NO GO are unknown or assumed to be equal, then in A4.1, C = 1, and A4.1 reduces to A1.3. It can be shown that $D_s(Z)$ in A4.1 is an alternative formation of ($CL_y - CL_x$) in A1.3.

For the results reported in Table 5, the *a priori* GO probabilities were used that had been estimated for month and location (presented in Table 4). These estimated probabilities were used rather than assuming that the *a priori* probabilities of GO and NO GO are equal, as was true for the results presented in Table 2.

APPENDIX B

FORECASTING TROPICAL STORM LOCATION 24 HR HENCE

A proposed fourth probability panel for the graphical presentation of results from our forecast technique would consist of a series of contoured, concentric probability ellipses. These ellipses would be used to provide prediction guidance for the *location* of a tropical storm within 24 hr, given that a tropical storm has been forecast to form within the next 24 hr.

Using the BMDP2R forward step-wise regression program (16), we developed separate equations for latitude and longitude to predict the position, 24 hr later, of a tropical storm that developed from a cloud cluster. We used the following information in our database: as independent variables, the latitude (longitude) of the GO cluster at the time the forecast is made, together with certain meteorological predictors whose values were measured at the GO cluster's initial position. The dependent variable is the latitude (longitude) of the tropical storm when it develops 24 hr later. Table B1 shows the predictors used in the regression, as well as their coefficients and intercepts.

The standard of error of prediction for the latitude is 1.70° with a residual variance of 2.86 degrees. The standard error in predicting the longitude is 3.05° with a residual variance of 9.31°. For a discussion of the concept of standard error of prediction, see (17). We preformed statistical significance tests on the means of our prediction of latitude and longitude, and found no significant difference between actual and predicted values. We conclude, therefore, that there is no basis in the prediction.

Next we performed the Lillifors test for normality (18) separately on our distributions of predicted latitudes and longitudes. The test results indicate that both the latitude and longitude are normally distributed. Confirmation of the normal distribution of the predicted latitudes (longitudes) is necessary for the validity of the next step: the construction of concentric ellipses of constant probability for selected probability levels. We used this formula:

$$k = ((\lambda - \lambda_p)^2/9.31 + (\phi - \phi_p)^2/2.86) \qquad \text{(B.1)}$$

where λ is the observed longitude,
λ_p is the predicted longitude,
ϕ is the observed latitude,
ϕ_p is the predicted latitude, and
k is a function of the probability level desired.

The resultant concentric probability ellipses can be used as guidance by a forecaster in specifying the region in his "formation alert" where a tropical storm is highly likely to form within the 24 hr following issuance of the alert.

Table B1. Summary of values associated with the prediction, by regression, of the latitude and longitude of a tropical storm's location when it forms. Included are independent variable names and coefficient(s), intercept values, and R square values. All meteorological predictors are measured on a 2.5° grid, except low-level vorticity, which is measured on a 5.0° grid. Upper level = 200 mb. Low level = 950 mb.

Regression Prediction			
Latitude		Longitude	
Independent variable	Coefficient	Independent variables	Coefficient
Observed latitude	1.070403	Observed longitude	1.03198
		Low-level vorticity	−.20728
		Upper-level divergence	−.09733
		Sea-level pressure	−.61743
Intercept	0.46655	Intercept	618.57691
R-square	0.898	R-square	0.947

APPENDIX C

SCORE DEFINITIONS

The power of detection = A/C, the false alarm rate = 1 − A/B, the threat score = A/(B + C − A), where A is the number of correct forecasts of an event, B is the total number of forecasts, and C is the number of observations of the event.

$$\text{Brier score} = 1/N \sum_{i=1}^{N} \sum_{j=1}^{2} (p_{ij} - o_{i})^2,$$

where p_{ij} is the probability estimate from category j for case i (for this study, $p_{i1} = P(GO/D_s(Z))$, and $p_{i2} = 1 - p_{i1}$);

$$o_{ij} = \begin{cases} 1, \text{ when category } j \text{ actually occurs for case } i, \\ 0, \text{ otherwise;} \end{cases}$$

and N is the number of cases in the sample.

Also, percent correct = (N + 2A − B − C)/N.

NOTES AND REFERENCES

1. Paul R. Lowe recently retired as the Senior Scientist at the U. S. Naval Environmental Prediction Research Facility. He performed research there since 1971 (and at its predecessor, the Naval Weather Research Facility since 1960) in statistical meteorology, cloud physics, cloud modeling, and numerical weather prediction. His most recent major research interest has been in pattern recognition techniques. He holds a BS and an MS in Meteorology from New York University and an MS in Education from St. Lawrence University.

2. Thomas J. Perrone has been a Weather Officer in the U. S. Air Force and in the Air National Guard (in California, New Jersey, and Virginia). He has worked as a Marine Meteorologist (with IMCOS Marine Ltd., Allen Weather Corp., and Oceanroutes, Inc.), and as a Research Meteorologist (wih the U.S. Naval Environmental Prediction Research Facility and with Techniques Development Laboratory (NWS)). Since 1984 he has been Senior Computer Systems Analyst with Logicon, Inc. He holds a BS in Economics, Politics, and Engineering from MIT, a BS in Meteorology from Pennsylvania State University, and JD from Lincoln University.

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