

Seasonal Forecasting of Tropical Cyclone Activity over the Western North Pacific and the South China Sea

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ABSTRACT

This paper presents the development of operational statistical forecasts of seasonal tropical cyclone (TC) activity over the western North Pacific (WNP) and the South China Sea (SCS) based on 30 yr of data (1965–94). Predictors include monthly values of indices representing (a) the El Niño–Southern Oscillation phenomenon, and (b) the environmental conditions over East Asia and the WNP for the months from April of the previous year to March of the current year. Trends and short-term oscillations of the TC activity are also incorporated.

The prediction equations are derived from the predictors of individual parameters using the Projection Pursuit Regression technique, which is a statistical method that reduces high-dimensional data to a lower-dimensional subspace before the regression is performed. This technique is found to provide explanations of certain nonlinear variations of the predictands. The predictions from individual parameters are then tested using the jackknife technique. Those predictions that have correlations (with the observed) significant at the 95% level or higher are retained. The values of the correlation coefficients are then used as weights in combining the predictions to form a single forecast of each predictand. The forecasts obtained this way are found to be superior to those from individual parameters.

The combined forecast equations are then used to predict the TC activity over the WNP and the SCS for 1997. The prediction is for a slightly above-normal activity for the entire WNP but slightly below normal for the SCS. The former is found to be correct and the latter has the right trend although the activity over the SCS was far below normal, probably as a result of the El Niño of 1997.

1. Introduction

Tropical cyclone (TC) activity over the western North Pacific (WNP) has been found to possess variations on timescales of a few years (Chan 1985, 1995a) to decades (Chan and Shi 1996). Because these variations have certain identifiable periods, it should be possible to de-

velop a statistical forecasting tool to predict the TC activity for a particular year. Such predictions have been made with considerable success for Atlantic hurricanes since 1989 (e.g., Gray et al. 1992, 1993, 1994; Elsner and Schmertmann 1993; Hess et al. 1995) and for TCs in the Australian region (Nicholls 1992). However, no operational scheme yet exists for TCs over the WNP. This paper presents the results of development of such a scheme and the forecasts for the 1997 season.

In developing an operational scheme, two major issues have to be considered: (a) the types of data to be used and whether the data can be available in near-real time so that a prediction can be made in time, and (b) the methodology to be adopted in selecting the predictors. The first issue will be discussed in section 2, where the selection process will be described.

In many statistical predictions, a stepwise multiple regression is performed between the predictand (here the number of TCs) and the potential predictors to

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choose the ones that have the largest correlation based on the least squares deviation (LSD) concept (see Waterson 1996). Recently, Mielke et al. (1996) have shown that the LSD regression models are generally inferior to the least absolute deviation (LAD) idea, especially for small data samples and in the presence of nonrepresentative data. In most of the LSD and LAD models, the regression equation is generally linear. While linearity is a good approximation in many applications, some variations of the predictand can be nonlinear. However, performing nonlinear regression in the traditional way is generally quite complicated. This is especially so when a large number of potential predictors needs to be considered, although Elsner and Schmertmann (1993) did have some success in predicting Atlantic hurricane activity using a nonlinear Poisson regression.

A new technique, the projection pursuit (PP) method, is therefore adopted. First proposed by Friedman and Tukey (1974), this technique aims to project high-dimensional data onto a lower-dimensional (one to two dimensions) subspace such that the configuration of the data in the projected subspace can reflect the main structure and features of the original high-dimensional data [see Huber (1985) for a detailed description of the concepts involved]. They coined the name "projection pursuit" because the technique automatically pursues the most "interesting" projections. A close analogy of this technique is the empirical orthogonal function analysis, which also has a similar objective.

The most important character of PP techniques is robustness, which enables the removal of the interference of variates irrelevant to the structure and features of the data. Chan and Shi (1997) recently demonstrated the robustness of the PP principal component analysis (PCA) technique when compared with the traditional PCA method in representing sea surface temperature and rainfall in the presence of outliers. The PP methods can also surmount the serious difficulty caused by any sparseness of the high-dimensional data. In addition, although the technique is based on linear projections of the data, it attempts to identify the nonlinear structures within the projections. Therefore, to a certain extent, the PP technique is capable of handling nonlinear problems (Friedman 1985).

Because of these advantages, the PP regression (PPR) technique is adopted in this study. A brief description of the technique is described in section 3. It should be pointed out that linear regression using the LAD approach had actually been tested but no significant predictors could be identified. This is another reason for adopting the PPR technique, which is applied in section 4 to derive the prediction equations for the TC activity over the WNP and the South China Sea (SCS). All equations are tested for their accuracy using the jackknife method. These equations are then employed to predict the number of TCs in 1997, the results of which

are shown in section 5 together with the verifications. The paper is then summarized in section 6.

2. Predictands and predictors

a. Predictands

The monthly numbers of TCs over the WNP (including the SCS) as reported in the annual reports of the Joint Typhoon Warning Center (JTWC) for the years 1965–94 form the basic dataset for the study. The sample is further grouped into the following three predictands:

- annual number of TCs (TCA), "A" meaning annual;
- annual number of tropical storms and typhoons (TSYA); and
- annual number of typhoons (TYA).

Because TC activity over the WNP is mainly concentrated in the months of May through December, and considering that some of the predictors may be parameters in the preceding winter season, three more predictands are defined for the months of May to December:

- number of TCs (TC8), "8" meaning eight months (May to December);
- number of tropical storms and typhoons (TSY8); and
- number of typhoons (TY8).

Since TCs over the SCS have slightly different interannual variability than the entire WNP (see, e.g., Chan 1995b), two other predictands are chosen:

- annual number of TCs (TCS), "S" meaning SCS;
- annual number of tropical storms and typhoons (TSYS).

Note that the annual number of typhoons over the SCS is not a predictand because of its relatively small value. Here the South China Sea covers the area from 0° to 23°N and 100° to 120°E. The numbers for the last two predictands are found by going through the plotted tracks for each individual year. For the years 1965–85, the tracks are from the publication of the Shanghai Typhoon Institute (1990) and the rest from the JTWC reports.

Thus, a total of eight predictands will be considered in this study. For each predictand, a set of potential predictors will be examined in applying the PPR technique.

b. Predictors

In choosing the potential predictors, two factors are considered. First, the predictor should have a physical link with the development and/or movement of TCs (the latter being important for TCs in the SCS). Second, since the forecast should be made early in the season (at the latest by April for the May to December predictions to

be useful), any predictor chosen must be available and easily accessible no later than April. Based on these two considerations, three sets of predictors are selected, which are described as follows.

1) PARAMETERS RELATED TO THE EL NIÑO PHENOMENON

Many studies in the past have linked the El Niño–Southern Oscillation (ENSO) phenomenon to TC activity (Gray 1984; Nicholls 1984; Chan 1985, 1995b; Hastings 1990; Solow and Nicholls 1990; Gray and Shaeffer 1991). Indices that can be used as proxies of ENSO and are easily accessible are those from the Climate Analysis Center (CAC). They include monthly values from April of the previous year to March of the current year of the Southern Oscillation index (SOI), sea surface temperature (SST) anomalies in various equatorial Pacific regions (NINO1+2, NINO3, NINO4, and NINO3+4), and the west Pacific pattern (WP) index. Thus, a total of 72 (12 values of each parameter \times six parameters) potential predictors is available.

2) PARAMETERS RELATED TO THE LARGE-SCALE CIRCULATION

Since environmental influences are crucial for the genesis, intensification, and movement of TCs (e.g., Chan and Gray 1982; Gray 1988), parameters describing the environment associated with TCs may be considered. However, these parameters are occurring simultaneously with the TCs and therefore cannot be used as predictors. Instead, indices that represent the conditions in the wintertime prior to the TC season are used. This is based on the assumption that changes in these conditions are related to subsequent changes during the TC season so that the indices can be proxies of the summertime environment. The indices considered include strength of the subtropical high over the SCS, westward extension of the 500-hPa subtropical ridge, 500-hPa height over the Tibetan Plateau, 500-hPa height over South Asia (representing the strength of the India–Burma trough), frequency of cold surges over China, and areal extent of the polar vortex in the Pacific sector. All these indices are monthly values from April of the previous year to March of the current year. They are all available from the National Climate Center of China (NCC) and should be accessible by April of the current year. See also Table 2 (section 4) for a more detailed description of the predictors.

3) CLIMATOLOGY–PERSISTENCE PREDICTORS

Chan and Shi (1996) have shown that annual TC activity over the WNP has both a long-term trend and short-term fluctuations with periods of 2 and 7 yr. These variations can therefore be used as climatology and per-

sistence (CLIPER) predictors for the activity in the coming year.

For each predictand in a given year, 12 predictors of each parameter (except CLIPER) are available (from April of the previous year to March of the current year). The total number of potential predictors is therefore quite substantial. Because only 30 yr of data are available, it is not appropriate to include too many predictors in the prediction equation. This is another reason why the PPR technique has to be employed to reduce the dimensionality of the problem.

3. The PP regression technique

Regression is a method for modeling a set of response variables y_i ($1 \leq i \leq q$) as functions of a set of predictor variables x_j ($1 \leq j \leq p$) based on a set of training data. Often, $q = 1$ (i.e., a single response variable). The classic linear model expresses the \hat{y}_i as linear functions of the predictor variables

$$\hat{y}_i(x_1, \dots, x_p) = \alpha_{i0} + \sum_{j=1}^p \alpha_{ij}x_j, \quad (1)$$

where the values of the α_{ij} are estimated by least squares.

Friedman and Stuetzle (1981) suggested an extension to this basic linear model and termed the resulting technique projection pursuit regression, or PPR. It has the form

$$\hat{y}_i(x_1, \dots, x_p) = \sum_{m=1}^{M_i} f_{im}(\alpha_{im}^T \mathbf{x}), \quad (2)$$

where \mathbf{x} is the column vector of the predictor variables (x_1, x_2, \dots, x_p) and α_{im}^T is the row vector of the coefficients $\alpha_{im}^{(j)}, j = 1, 2, \dots, p$, for the i th response variable. That is,

$$\alpha_{im}^T \mathbf{x} = \sum_{j=1}^p \alpha_{im}^{(j)} x_j \quad (3)$$

and f_{im} are single-valued (ridge) functions of a single variable, with M_i being the number of such functions (i.e., the number of projections). Therefore, instead of modeling each response as a linear combination of the predictor variables (as in linear regression), PPR models each one as a sum of functions of linear combinations of the predictor variables. The parameters of the linear combinations α_{im}^T as well as the functions f_{im} are estimated by least squares.

In this study, we generalize the PPR model to make it more appropriate for multiple-response regression. This generalization, termed Smooth Multiple Additive Regression Technique (SMART) by Friedman (1985), takes the form

$$E[y_i | x_1, x_2, \dots, x_p] = \bar{y}_i + \sum_{m=1}^{M_i} \beta_{im} f_{im}(\alpha_{im}^T \mathbf{x}) \quad (4)$$

with $\bar{y}_i = E[y_i]$, $E[f_{im}] = 0$, $E[f_{im}^2] = 1$ and $\sum_{j=1}^p [\alpha_{im}^{(j)}]^2$

= 1. The coefficients β_{im} , α_{im}^T , and the functions f_{im} are parameters of the model and are estimated by least squares. The SMART model in (4) contains the PPR model in (2) as a special case (Friedman 1985). The criterion

$$L_2 = \sum_{i=1}^q W_i E \left[y_i - \bar{y}_i - \sum_{m=1}^M \beta_{im} f_{im}(\alpha_m^T \mathbf{x}) \right]^2 \quad (5)$$

is minimized with respect to the parameters β_{im} , α_m^T , and the functions f_{im} . The response weights W_i are specified by the user. The expected values are computed from the data as

$$E[z] = \left(\sum_{k=1}^N w_k z_k \right) / \sum_{k=1}^N w_k, \quad (6)$$

where z is considered to be a random variable and z_k ($1 \leq k \leq N$) are its realized values in the data. The observation weights w_k ($1 \leq k \leq N$), specified by the user, can be employed to assign different weightings to different observations. They can also be used to implement iterative reweighting schemes for “robustification” or approximate maximum likelihood fitting.

It should be pointed out that the criterion in (5) is sensitive to the relative scale of the response variables y_i , as is true for any distance measure. The influence of each y_i will be proportional to its variance $\text{var}(y_i)$. If it is desired that each response variable has the same effect on the criterion, one can set $W_i = 1/\text{var}(y_i)$ or rescale the responses to have the same variance.

In this study, q is taken as 1, $N = 30$ (for 30 yr of data but becomes 29 in jackknife testing—see section 4), and M is set to 2 (representing two projections, the maximum being 12, which is the number of potential predictors for each parameter except for the CLIPER parameter). Initially, $p = 12$ (12 predictors for each parameter) or 3 (for CLIPER predictors). However, after the first iteration (see section 4), this number will decrease depending on the amount of variance of the predictand that each of the predictors can explain. Because only 30 yr of data are available, the most number of predictors selected (i.e., p) is set to 5.

4. Development of the prediction equations

a. Derivation of the basic regression equations

For each of the eight predictands, the PPR technique is applied using the 12 predictors of each parameter listed in section 2, except for the CLIPER parameter in which only three predictors are available. Those predictors that can explain the largest amounts of the variance of the predictand are retained. The prediction equation is then rederived. The following example illustrates how this procedure is carried out for the prediction of TSY8 using the NINO4 parameter.

Applying the PPR technique, it is found that the SST anomalies within the NINO4 area for the months of

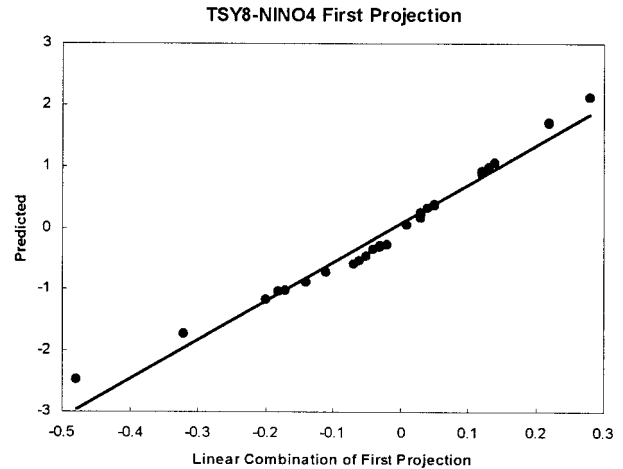


FIG. 1. Plot of the linear combinations of the first projection of the NINO4 predictors against the predicted values for the TSY8 predictand. The straight line is the least squares fit.

June, July, November, December of the previous year and January of the current year are significantly correlated with TSY8. Then, using only these five predictors, the PPR technique is applied again to search for two projections. The relationship between the first projected predictor ($z_1 = \alpha_1^T \mathbf{x}$) and TSY8 is found to be basically linear (Fig. 1). However, after the variance of TSY8 explained by z_1 is removed, the residual, $\gamma(\mathbf{x}) = y - g_1(\alpha_1^T \mathbf{x})$, correlates with the second projected predictor $z_2 = \alpha_2^T \mathbf{x}$ in a nonlinear way (Fig. 2). This example illustrates that, if the predictand varies nonlinearly with some of the predictors, such variations may be accounted for by projecting the predictors onto a subspace using the PPR technique. Although such a procedure is not necessarily the optimal way of selecting the predictors, it is relatively efficient and capable of identifying some nonlinear relationships.

This procedure is repeated for all the eight predictands using each of the potential parameters. That is, each predictand will have a number of prediction equations, each containing up to five values (predictors) of a single parameter. The next step is then to determine which and how many of these prediction equations should be retained. This is accomplished through the jackknife technique.

b. Selection of prediction equations using the jackknife technique

The jackknife technique is a tool to test the usefulness of a prediction equation when the sample size is not large enough to permit a separation of the sample into dependent and independent cases. In this study, the sample of 30 yr of data is obviously not large. Therefore, the jackknife technique is applied to each of the prediction equations derived in the previous subsection. See Miller (1974) for a review of the technique and Elsner

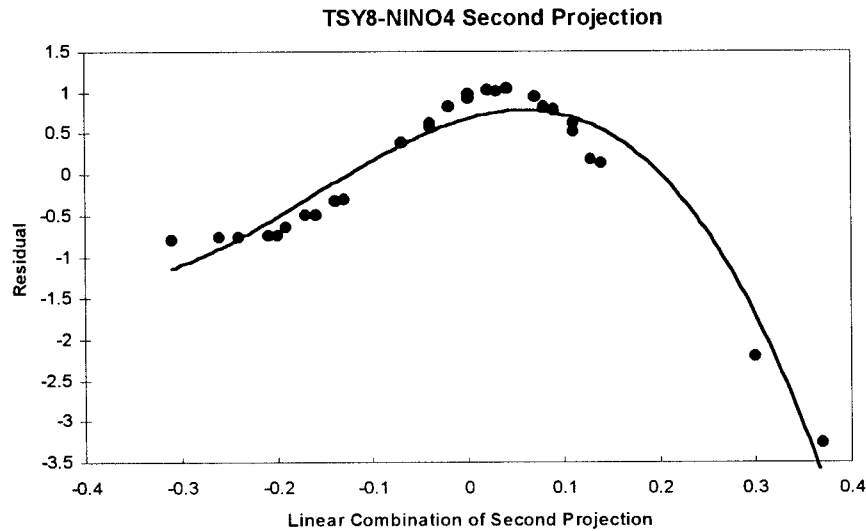


FIG. 2. Plot of the linear combinations of the second projection of the NINO4 predictors against the residual from the first solution for the TSY8 predictand. The curved line is the least squares fit.

and Schmertmann (1994) and Chan (1995b) for applications of this technique in developing prediction equations. The basic method is also outlined in the appendix for reference.

Using the prediction of TSY8 with NINO4 predictors again as an example, this technique produces 30 “independent” predictions that have a correlation of 0.7 with the observed numbers in the TSY8 dataset (see the scatterplot in Fig. 3). With 30 yr of data and five predictors, the limiting values of significant correlations

are 0.46 and 0.36, respectively, at the 99% and 95% level. Thus, this prediction equation should be retained.

This procedure is repeated for all the prediction equations. Only those with significant correlations (at the 95% level or above) between the predicted (from the jackknife technique) and the observed are retained. It turns out that many of the parameters are common to the prediction equations, as can be seen from Table 1 (detailed descriptions of the parameters are listed in Table 2). Notice that the number of parameters that survive the jackknife test tends to be smaller for the predictands that have smaller numbers, probably because of the large variability.

c. The final prediction equations

The results from the last section suggest that for each predictand, a number of prediction equations can be

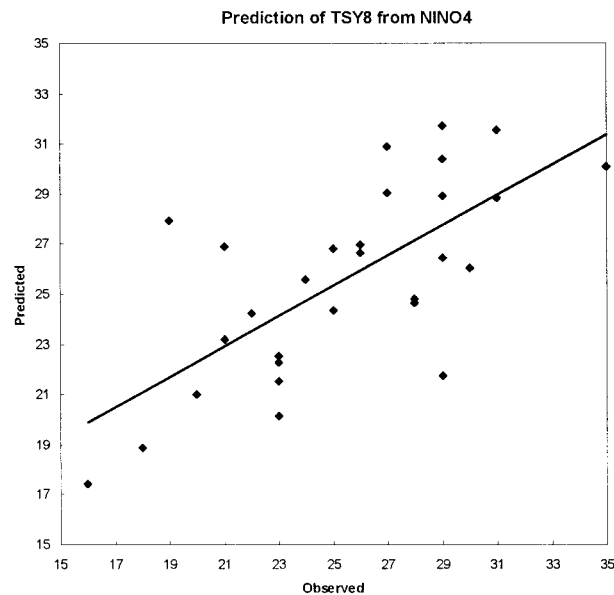


FIG. 3. Observed vs predicted (using the jackknife technique) number of tropical storms and typhoons during May to December over the western North Pacific (TSY8) using the projected NINO4 predictors.

TABLE 1. Parameters that are found to be significantly correlated with each of the eight predictands (** = correlation significant at the 99% level, * = correlation significant at the 95% level). See text for the description of the predictands. Detailed definitions of the parameters are given in Table 2.

Predictors	Predictand							
	TCA	TSYA	TYA	TC8	TSY8	TY8	TCS	TSYS
SOI								**
NINO4	**	**		**	**			**
WP	*	*		*			*	*
HSCS	**	**				*		
HWNP	**	*	*	*	*			
HPV	*	**		**	**	*		
HTP	**	**	**	**	**	**	**	*
HIB	**	**	**	**	**	*	*	
HC	**	*		*				
CLIPER		*		*			**	**

TABLE 2. Definitions of the parameters listed in Table 1. All values are monthly means.

Predictor	Description	Source
SOI	Standardized Southern Oscillation index	NOAA/CAC ^a
NINO4	SST anomalies in the NINO4 region	NOAA/CAC
WP	West Pacific pattern index	NOAA/CAC
HSCS	Index of the northern extent of the subtropical high over the South China Sea (100°–120°E)	NCC ^b
HWNP	Index of the westward extent of the 5880-m contour of the 500-hPa subtropical high over the western North Pacific	NCC
HPV	Index of the area of the polar vortex in the Pacific sector (150°E–120°W)	NCC
HTP	Index of the strength of the 500-hPa subtropical high over Tibet (25°–35°N, 80°–100°E)	NCC
HIB	Index of the strength of the India–Burma trough (15°–20°N, 80°–100°E) at 500 hPa	NCC
HC	Index of the frequency of cold-air intrusion into China during September–December and January–May	NCC
CLIPER	Trend and 2- and 7-yr variations, derived from data of the predictand	

^a NOAA/CAC = National Oceanic and Atmospheric Administration/Climate Analysis Center (now the Climate Prediction Center of the National Centers for Environmental Prediction).

^b National Climate Center, China

used. The obvious way to combine the predictions is through a weighted average. The weights to be used must reflect the ability of the individual equations to predict what is observed. Therefore, the absolute value of the correlation coefficient determined in the last subsection is chosen as the weight. That is,

$$Y = \frac{\sum_{k=1}^K \gamma_k y_k}{\sum_{k=1}^K \gamma_k},$$

where Y is the final predicted number, γ_k the correlation coefficient between the predicted (from the jackknife technique) and the observed for the k th parameter, and y_k the number predicted from the prediction equation of the k th parameter derived from the entire 30 yr of data. For the prediction of TCA, TSYA, and TC8 (with which more than five parameters are found to have significant correlations), only the largest five γ_k 's are used.

The results of the final predictions show that the correlations between the predicted and observed are very high (Table 3), ranging from a low of 0.72 (explaining 52% of the variance) to a high of 0.89 (explaining 79% of the variance). These values are larger than those from the individual parameters (which generally range between 0.4 and 0.7). Both the absolute and the root-mean-square errors are also quite small. Therefore, the skill of these forecasts should be quite high.

TABLE 3. Correlations, absolute and rms errors, and the measure of agreement ρ of the final predictions (compared with the observed) for the 30-yr sample.

Predictand	Correlation	Absolute error	Rms error	Measure of agreement (ρ)
TCA	0.89	2.3	2.9	0.5620
TSYA	0.86	2.3	2.6	0.4892
TYA	0.75	2.0	2.5	0.4378
TC8	0.80	2.6	3.2	0.4668
TSY8	0.86	1.9	2.4	0.5375
TY8	0.72	2.1	2.6	0.3646
TCS	0.77	2.4	2.7	0.3402
TSYS	0.75	1.4	1.9	0.3860

Following Mielke et al. (1996), another measure of agreement, ρ , is used to test the usefulness of the final predictions. This measure is defined as

$$\rho = 1 - \frac{\delta}{\mu_\delta},$$

where

$$\delta = \frac{1}{n} \sum_{i=1}^n |y_i - \tilde{y}_i|$$

and

$$\mu_\delta = \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n |y_i - \tilde{y}_j|.$$

The higher the values of ρ , the better is the agreement between the observed and the predicted quantity. Note that to have a fair comparison between the LAD and LSD regressions, the exponent of $|y_i - \tilde{y}_i|$ and $|y_i - \tilde{y}_j|$ in the above equations is set to 1 instead of 2 as stated in Mielke et al. (1996). It can be seen from Table 3 that the value of this measure is, in general, consistent with the corresponding value of the correlation, with the highest being around 0.56 and the lowest 0.34. These values are comparable to those obtained from LAD regressions (e.g., Mielke et al. 1996, 1997). Thus, both measures indicate the prediction equations should be able to produce reasonable forecasts.

5. Forecasts and verifications for 1997

Based on the results in the previous section, the final eight prediction equations are applied to make the predictions for 1997. The predictions (Table 4) suggest that the 1997 season is close to normal with slightly above-normal number of TCs over the entire WNP but slightly below-normal numbers within the SCS.

The verifications shown in Table 4 are based on the warnings issued by the Joint Typhoon Warning Center in Guam, which indicate that the prediction for an above-normal activity for the entire WNP is verified, with the number of tropical storms and typhoons being even higher than predicted. However, although the predicted trend for a below-normal activity over the SCS

TABLE 4. Forecasts and verifications for 1997. The climatology (1965–94) is also included for comparison.

Predictand	Predicted no.	Observed no.	Climatology
TCA	33	33	31
TSYA	30	31	27
TYA	19	21	17
TC8	30	30	28
TSY8	27	30	25
TY8	17	20	16
TCS	12	7	13
TSYS	9	7	11

is correct, the observed numbers are even lower. Throughout 1997, no TC crossed the Philippines into the SCS, which is very unusual (see the climatology in Xue and Neumann 1984). Because the number of TCs in the SCS is the sum of those that developed within the basin and those entering the SCS from east of the Philippines, the absence of the latter resulted in the far-below-normal activity. While a detailed study has yet to be taken, preliminary analyses suggest that such an absence is probably related to the strong El Niño of 1997. Because the latest predictors used are those in March, when this warm event was not yet apparent, the predictions were not able to identify this signal. Nevertheless, the overall prediction for 1997 should be considered to be rather successful.

6. Summary and discussion

a. Summary of results

This paper has presented a methodology to develop a set of prediction equations for TC activity over the western North Pacific and the South China Sea and to use these equations to predict such activity for 1997. The technique, called the projection pursuit regression (PPR) technique, projects a set of high-dimensional data (in this case, the predictors) onto a lower-dimensional subspace and then uses the projected data to develop the prediction equations. It has been demonstrated that such a technique is capable of identifying some nonlinear variations of TC activity with some of the predictors. This appears to lead to better predictions compared with the traditional linear regression techniques. In fact, some preliminary comparisons have been made between various techniques and PPR has been found to be superior. These results will be reported in a separate paper.

Various parameters that should be related to TC development and/or movement and available prior to the main TC season are identified. Individual monthly values of these parameters are then correlated with the number of TCs, tropical storms, and typhoons using the PPR technique. Those that have the highest correlations for each parameter are then used to develop the prediction equations. For a given predictand, the predictions from various predictors are combined using a weighted-average method. The weights are determined

by the correlations of the observed numbers with individual predictions made from the jackknife technique. The combined forecast is found to have a much higher correlation with the observed than the individual predictions.

Based on the equations derived from the weighted-average method, the number of TCs over the WNP for 1997 is predicted to be slightly above normal while that over the SCS should be slightly below normal. The former prediction is found to be correct but the latter, although giving the correct trend, predicted more than what was observed. This overprediction may be a result of the El Niño of 1997 when no TC crossed the Philippines into the SCS.

b. Discussion

This study represents the first attempt to make an operational prediction of TC activity over the western North Pacific and the South China Sea. While some predictors have also been used for predictions in the Atlantic and Australian regions (e.g., SST anomalies over the equatorial Pacific region representing ENSO), many factors are included for the first time. These include environmental conditions in the wintertime as well as the climatology and persistence components. Except for the latter two, all other factors are monthly values that can be from April of the previous year to March of the current year. Although the results suggest that many of them correlate significantly with TC activity, the physical reasoning remains unclear. The next step of the study will attempt to explain why these predictors give such significant correlations. This type of understanding is crucial in establishing confidence in the forecasts that they are not due to random chance but causality actually exists. Further, evaluations of the forecasts will also be easier, which should lead to better forecasts in the future.

The PPR technique adopted in this study has been demonstrated to be a viable, and probably superior, method of deriving prediction equations from a large set of independent variables. Proof of its superiority over other linear regression techniques will be the focus of a future paper.

To summarize, this study has, for the first time, developed an operational forecast for TC activity over the WNP and the SCS and made a prediction for the activity in 1997. The verifications suggest that perhaps a later update to take into account events that occur after March of the current year may be necessary, as is done by Gray et al. (1993) for the prediction of Atlantic hurricanes.

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APPENDIX

The Jackknife Method

To test the usefulness of a prediction equation derived from a sample of limited size, the “jackknife method” is often used to simulate an independent sample. While various versions of this method have been used, the simplest procedure as described below is adopted in this study.

- 1) Derive the prediction equation based on all except one data point (say, in this paper, the number of TCs in year 1).
- 2) Use the derived equation to predict the number of TCs of year 1 and calculate the error.
- 3) Repeat (1) and (2) but now include year 1 and exclude year 2.
- 4) Repeat (3) until all the years have been excluded once.

With this procedure, each of the predictions can be considered to be independent. If the prediction errors using this sample are reasonable, it may be concluded that the prediction equation using the dependent sample is useful and can be used for future predictions.

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