交通部中央氣象局委託研究計畫期末報告

發展西北太平洋年颱風頻率機率預報方法

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執行期間：98 年 2 月 23 日至 98 年 12 月 31 日

計畫主持人：朱寶信

執行單位：Climate Systems Enterprise

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98 年度政府部門科技計畫期末摘要報告

計畫名稱： 發展西北太平洋年颱風頻率機率預報方法

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主管機關：	交通部中央氣象局	執行單位：	Climate Systems Enterprise
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執行情形：

1.執行進度：

	預定（%）	實際（%）	比較（%）
當年	100	100	0
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2.經費支用：

	預定	實際	支用率（%）
當年	735,000	735,000	100
全程	735,000	735,000	100

3.主要執行成果：

(1) 以貝式方法應用在 Poisson regression model 上成功的發展出預報西北太平洋颱風頻率的機率預報。

(2) 完成 2009 年西北太平洋颱風個數機率預測及校驗。

(3) 完成以西北太平洋主要颱風路徑類型發展具有區域特性的颱風個數機率預測方法。

4.計畫變更說明：

無

5.落後原因：

無

6.主管機關之因應對策（檢討與建議)：

Development of Probabilistic Forecast Models for Seasonal Typhoon Frequency over the Western North Pacific

(MOTC-CWB-98-3M-01)

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Honolulu, Hawaii

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November 27, 2009

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1. Introduction

Our current effort is to develop a Poisson or probit regression model to forecast seasonal typhoon frequency at every 5° latitude-longitude resolution over the Western North Pacific (WNP) and the South China Sea. Dr. Johnny Chan of Hong Kong and others (e.g., U.K.) have successfully performed seasonal forecasts of tropical cyclone (TC) activity over the WNP and posted their forecasts in an operational setting. However, their forecasts are based on a set of single numbers representing the entire WNP. Given the fact that the WNP is a huge basin and typhoons tend to have different tracks, it is desirable to have more detailed knowledge so that one can determine which region within the WNP has higher or lower TC predictability. To the best of our knowledge, this is the first time that an attempt has been made to systematically forecast seasonal typhoon frequency at every grid points over the WNP and the South China Sea.

For this study, the peak typhoon season (July to October) is used and the preseason (May and June) predictors encompass large-scale environmental parameters. The typhoon frequency (counts) is expressed by a Poisson distribution whose intensity is governed by environmental parameters over the ocean basin including sea surface temperatures, precipitable water, low-level relative vorticity, sea-level pressure, and vertical wind shear. Critical regions are determined on the basis of lagged correlations between each of these parameters and tropical cyclone counts at every 5° grid at the 95% confidence level.

Two different experimental forecasts are conducted here. The first one uses the observed TC counts at every grid as the predictand. The second approach is more complicated. We begin by categorizing historical TC tracks by an objective clustering method; in our case eight different track types are identified. For each 5° grid, we count how many track types have passed through every year. For some types, the number of passages is relatively high but for other types, there is no or at most one passage each year. For the former, a Poisson regression model is used while for the latter a probit regression is employed. For a fixed grid, forecasts are made first to each type using a Poisson regression or probit regression model and the summation of each individual forecasts is the overall forecasts. A comparison is made to show which experimental forecasting methods produce better results. In testing prediction skill, a leave-one-out cross-validation method is employed. Cross-validation is a technique of repeatedly omitting one or more observations from the data, reconstructing the model, and then making estimates for the omitted cases. We use correlation coefficients between observations and hindcasts as a measure of forecast skills (Chu et al., 2007). Because probabilistic forecasts are applied, the Brier skill score is also used.

2. Methodology

a. A Clustering method for TC tracks

Our TC track clustering method is based on the mixture Gaussian model. A key feature of the mixture Gaussian model is its ability to model multimodal densities while adopting a small set of basic component densities. Finite mixture models have been widely used for clustering data in a variety of areas such as the large-scale atmospheric circulation (Camargo et al., 2007). In this study, we assume that there are a few distinct path track types characterizing TC tracks in the WNP and the South China Sea. For each TC track path, we model it as a second order polynomial function of the existing time of this TC. The basic assumption we impose here is that, for each specific track type, the set of coefficient of this polynomial function is jointly Gaussian distributed. Each TC track type has its unique distribution parameter. Therefore, the space spanned by the parameters of this track type model is a convex linear combination of a set of Gaussian distribution, or a mixture Gaussian distribution model.

In mathematical notations, let's assume there are n observed track records at 6-h intervals for a given TC. For each record, there will be three features reported, the latitude, the longitude and the time. Let's denote the path record of a TC by:

$$\mathbf{z} = [\mathbf{z}_{lat}, \mathbf{z}_{long}] = \begin{bmatrix} z_{1,lat} & z_{1,long} \\ \dots & \dots \\ z_{n,lat} & z_{n,long} \end{bmatrix} \qquad (1a)$$

where $z_{i,lat}$ and $z_{i,long}$ for $i = 1,..,n$ represent the i-th latitude and longitude record, respectively. And then we denote the relative observed time vector for the second order polynomial function by

$$\mathbf{T}=\begin{bmatrix}1 & t_1 & t_1^2\\ \dots & \dots & \dots\\ 1 & t_n & t_n^2\end{bmatrix} \tag{1b}$$

where t_i for $i=1,..,n$ represents the time for the i-th records of this TC relative to the first record. We further assume that there are K distinct TC track types in the WNP and the South China Sea, where K is assumed to be a constant throughout this study. With the definition (1a) and (1b), provided that this TC is categorized as Type k, $1 \le k \le K$, the linkage between the passage and the relative time is governed by the following formula:

$$\mathbf{z}=\mathbf{T}\boldsymbol{\beta}^{\mathbf{k}}+\boldsymbol{\varepsilon}\text{, where } \boldsymbol{\beta}^{\mathbf{k}}=\begin{bmatrix}\beta_{0,lat}^{k} & \beta_{0,long}^{k}\\ \beta_{1,lat}^{k} & \beta_{1,long}^{k}\\ \beta_{2,lat}^{k} & \beta_{2,long}^{k}\end{bmatrix} \text{ and } \boldsymbol{\varepsilon}\sim N(\mathbf{0},\boldsymbol{\Sigma}^{\mathbf{k}}) \tag{1c}$$

In (1c), the parameter set $\boldsymbol{\beta}^{\mathbf{k}}$ is distinct from other TC types. With model given in (1), for type k, intuitively we can see that, the zero-order coefficient dual provides the mean genesis location of this type; the first-order term features the characteristic direction of this path type; and the second-order type will determine the recursive shape of the typical path of this type; the covariance matrix (Σ) in (1c) determines the spread of a particular type.

Given a set of a total N TC records, $\{\mathbf{z}_i,\mathbf{T}_i \mid i=1,...,N\}$, to get the maximum likelihood estimation of all model parameters and class type, we resort to the Expectation-Maximization (EM) algorithm. In detail, in the E-step, we calculate the membership probability of each type for each TC. In formula, it is:

$$w_{i,k}=\frac{\alpha_k f(\mathbf{z}_i \mid \mathbf{T}_i\boldsymbol{\beta}^{\mathbf{k}},\boldsymbol{\Sigma}^{\mathbf{k}})}{\sum_{j=1}^{K}\alpha_j f(\mathbf{z}_i \mid \mathbf{T}_i\boldsymbol{\beta}^{\mathbf{j}},\boldsymbol{\Sigma}^{\mathbf{j}})},\quad i=1,...,N \tag{2}$$

where α_k = *f*(k) is the prior probability of type *k*. Apparently, the membership probability of a TC in (2) is virtually the posterior probability of each track type given all model parameter sets. Let $\mathbf{w}_{i,k} = w_{i,k}\mathbf{1}_{n_i}$, where n_i denote the record length of the i-th TC and $\mathbf{1}_{n_i}$ represents the n_i vector of ones, we define a new diagonal matrix $\mathbf{W^k} = [w_{1,k}, w_{2,k},..., w_{N,k}]$ for each track type k. In the M-step, we then calculate the following estimation for the model parameter set of each type:

$$\hat{\boldsymbol{\beta}}^{\mathbf{k}} = (\mathbf{T}'\mathbf{W^k T})^{-1}\mathbf{T}'\mathbf{W^k T Z} \tag{3a}$$

$$\hat{\alpha}_k = \frac{1}{N}\sum_{i=1}^{N} w_{i,k} \tag{3b}$$

$$\boldsymbol{\Sigma}^{\mathbf{k}} = \frac{1}{N}\frac{(\mathbf{Z}-\mathbf{T}\boldsymbol{\beta}^{\mathbf{k}})'\mathbf{W^k}(\mathbf{Z}-\mathbf{T}\boldsymbol{\beta}^{\mathbf{k}})}{\hat{\alpha}_k} \tag{3c}$$

In (3), $\mathbf{Z}' = [\mathbf{z}_1, \mathbf{z}_2,..., \mathbf{z}_N]'$, $\mathbf{T}' = [\mathbf{T}_1, \mathbf{T}_2,..., \mathbf{T}_N]'$, where $\mathbf{z}$, $\mathbf{T}$ are defined in (1) and the subscript represents the index of a TC.

Given an initial setting of the model parameters and with multiple iterations of (2) and (3), the proposed EM algorithm will converge to a fixed set of parameter estimation. These convergence values are not necessarily the global best estimation and are determined by the initial starting values. Therefore, we apply multiple different initial values and choose the set of estimation with the maximum likelihood.

b. Poisson regression model

The method of fitting a Poisson regression model is to use the Poisson formula to derive a maximum likelihood function. For a given regression coefficient, Poisson intensity is calculated for each set of predictors, and the likelihood of the observed number of tropical cyclones is estimated using the Poisson distribution. The regression coefficients that maximize the product of probabilities over time are then used to forecast (or hindcast) typhoon counts. To solve the maximum likelihood equations, one resorts to an iterative procedure. Here we use iteratively weighted least squares.

Poisson distribution is a proper probability model for describing independent (memory-less), rare event counts. Given the Poisson intensity parameter λ, the probability mass function (PMF) of h counts occurring in a unit of observation time, say one season, is

$$P(h \mid \lambda) = \exp(-\lambda)\frac{\lambda^h}{h!}, \text{ where } h = 0,1,2,... \text{ and } \lambda > 0 \tag{4}$$

The Poisson mean is simply λ, so is its variance. In many applications, Poisson rate λ, is usually treated as a random variable.

Through a regression model, the relationship between the target response variable, seasonal typhoon counts, and the selected predictors can be mathematically built. In this study, we adopt the Poisson linear regression model. Assume there are N observations that are conditional on K predictors. We define a latent random N-vector $\mathbf{Z}$, such that for each observation h_i, $i = 1,2,..., N$, $Z_i = \log \lambda_i$, where λ_i is the Poisson rate for the i-th observation. The link function between the latent variable and its associated predictors is expressed as $Z_i = \mathbf{X}_i \boldsymbol{\beta} + \varepsilon_i$, where $\boldsymbol{\beta} = [\beta_0, \beta_1, \beta_2, ..., \beta_K]'$ is a random vector; noise ε_i is assumed to be identical and independent distributed (IID) and normally distributed with zero mean and σ^2 variance; $\mathbf{X}_i = [1, X_{i1}, X_{i2}, ..., X_{iK}]$ denotes the predictor vector. In vector form, the general Poisson linear regression model is formulated as below:

$$P(\mathbf{h} \mid \mathbf{Z}) = \prod_{i=1}^{N} P(h_i \mid Z_i), \text{ where } h_i \mid Z_i \sim Poisson(h_i \mid e^{Z_i})$$

$$\mathbf{Z} \mid \boldsymbol{\beta}, \sigma^2, \mathbf{X} \sim Normal(\mathbf{Z} \mid \mathbf{X}\boldsymbol{\beta}, \sigma^2 \mathbf{I}_N), \text{ where, specifically}$$

$\mathbf{X}' = [\mathbf{X}_1', \mathbf{X}_2', ..., \mathbf{X}_N']$, $\mathbf{I}_N$ is the $N \times N$ identity matrix, and

$\mathbf{X}_i = [1, X_{i1}, X_{i2}, ..., X_{iK}]$ is the predictor vector for h_i, $i = 1,2,..., N$

$\boldsymbol{\beta} = [\beta_0, \beta_1, \beta_2, ..., \beta_K]'$.

(5)

Here, *Normal* and *Poisson* stand for the normal distribution and the Poisson distribution, respectively. In model (5), β_0 is referred to as intercept.

It is worth noting that Poisson rate λ is a real value while the TC counts h is only an integer. Accordingly, λ contains more information relative to h. Furthermore, because h is conditional on λ, λ is subject to less variations than h is. Taken together, λ should be preferred as the forecast quantity of the TC activity than h for decision making.

c. Probit Regression Model for a Binary Classification Problem

The Poisson regression model detailed in the previous subsection has been approved very effective for most rare event count series. However, if the underlying rate is significantly below 1, this model may introduce significant bias. In this study, for a given typhoon type, if there is no historical record showing more than one observation in any given season, we shall instead adopt a binary classification model. That is, the response variable here is a binary class label, which is termed by "Y". For each observation period, we define a class "Y = 1" if a typhoon is observed and "Y = 0" otherwise.

As below we formulate the probit regression model (Albert and Chib 1993, Zhao and Cheung 2007). Again, assume there are N observations conditional on K selected predictors. We define a latent random N-vector $\mathbf{Z}$, such that for each observation y_i, $i = 1,2,...,N$, $y_i = 1$ if $Z_i \geq 0$ and $y_i = 0$ otherwise. The link function between the latent variable $\mathbf{Z}$ and its associated predictors is also linear, $Z_i = \mathbf{X}_i\boldsymbol{\beta} + \varepsilon_i$, where $\boldsymbol{\beta} = [\beta_0, \beta_1, \beta_2, ..., \beta_K]'$ is a random vector; noise ε_i is assumed to be identical and independent distributed (IID) and normally distributed with zero mean and σ^2 variance; $\mathbf{X}_i = [1, X_{i1}, X_{i2}, ..., X_{iK}]$ denotes the predictor vector. In vector form, the probit regression model is described by:

$$P(\mathbf{y} \mid \mathbf{Z}) = \prod_{i=1}^{N} P(y_i \mid Z_i), \text{ where } y_i = \begin{cases} 1 & if\ Z_i \geq 0 \\ 0 & if\ Z_i < 0 \end{cases} \text{ and}$$

$\mathbf{Z} \mid \boldsymbol{\beta}, \sigma^2, \mathbf{X} \sim Normal(\mathbf{Z} \mid \mathbf{X}\boldsymbol{\beta}, \sigma^2 \mathbf{I}_N)$, where, specifically

$\mathbf{X}' = [\mathbf{X}_1^{'}, \mathbf{X}_2^{'}, ..., \mathbf{X}_N^{'}]$, $\mathbf{I}_N$ is the $N \times N$ identity matrix, and

$\mathbf{X}_i = [1, X_{i1}, X_{i2}, ..., X_{iK}]$ is the predictor vector for h_i, $i = 1,2,...,N$

$\boldsymbol{\beta} = [\beta_0, \beta_1, \beta_2, ..., \beta_K]'$.

(6)

Classification model (6) is very similar to the Poisson regression model (5). Actually the probability of class "Y = 1" can be viewed as the rate of the typhoon counts.

3. Data

The tropical cyclone data over the WNP and the South China Sea come from the U.S. Joint Typhoon Warning Center in Honolulu. The data cover the period 1970 to 2007. The data sets contain measurements of TC center location in latitude, longitude, one-minute sustained maximum wind speed, and central pressure at 6-h intervals for all TCs in the WNP. Here TP refers to tropical storms and typhoons. Tropical storms are defined as the maximum sustained surface wind speeds between 17.5 and 33 m s^{-1}, and typhoons are defined as wind speeds at least 33 m s^{-1}.

4. Predictor selection procedure

In the Poisson regression and probit regression models we assume the predictors are given a priori. In a real application, however, choosing the appropriate environmental parameters that are physically related to the formation and typhoon tracks is crucial for the success of the final forecast scheme. In Chu and Zhao (2007) and Chu et al. (2007), environmental parameters such as sea surface temperatures, sea level pressures, low-level relative vorticity, vertical wind shear (VWS), and precipitable water were chosen.

Generally speaking, sea surface temperatures are important for TC formation and intensification. Warmer SSTs are expected to fuel the overlying atmosphere with additional warmth and moisture, thereby reducing atmospheric stability and increasing the likelihood of deep tropical convection. A typhoon is characterized by a synoptic-scale low pressure (SLP) system with organized convection and strong cyclonic surface wind circulation (>33 m s^{-1}) over the tropical WNP. Usually lower SLP implies decreased subsidence, which would result in weaker trade wind inversion (Knaff, 1997). Because the trade wind inversion acts as a lid to atmospheric convection, weaker inversion would promote deeper convection. The occurrence of deep convection is important for typhoon formation because it provides a vertical coupling between the upper level outflow and lower tropospheric inflow circulations. Strong VWS disrupts the organized deep convection (the so-called ventilation effect) that inhibits intensification of typhoons. Adequate moisture in the atmosphere provides a fundamental ingredient for deep convection. Conversely, drier atmosphere tends to suppress deep convection and inhibits TC activity. Most TCs in the WNP form in the monsoon trough marked by westerlies on its equatorward side and easterlies on its poleward side. The monsoon trough can be approximately represented by the maximum in the relative vorticity at the 850 hPa level. Local concentration of cyclonic vorticity in the trough enhances the spin-up process by strengthening boundary layer moisture convergence, increasing the likelihood of the formation of TCs. We also examined the lagged correlations between the circulation index (e.g., NAO, AO) and the TC counts for each of eight clusters. However, none of those correlations are statistically significant at the 5% level. For this reason circulation indices are not chosen as predictors.

In this study, we apply the same procedure suggested in Chu and Zhao (2007) and Chu et al. (2007) to determine the critical region for each candidate environmental parameter. We calculate the Pearson correlation between the count series of each type of typhoon track and the preseason environmental parameters. For any tested grid point, if the Pearson correlation between the predictor and the target count series is statistically significant, this point is marked as critical. Based on the linear regression theory, for a sample size of 38, the critical value for a correlation coefficient with two tails is 0.356 at the 95% confidence level (Bevington and Robinson, 2002). Hence, a correlation coefficient with its absolute value greater than 0.356 at a grid point is deemed locally significant and this point is then selected as a critical region. To avoid the large dimensionality of the predictor matrix, which would easily lead to overfitting the model, a simple average over the critical regions is chosen to serve as a final predictor.

5. Results

Figure one shows that there are eight major track patterns over the WNP, with three straight movers (Types A, B, and C), four recurved ones (Types D. E. F, and G), and one mixed pattern of both straight moving and recurved (Type H). Types A and B clusters are similar in nature in that they both move more or less straight across Philippines to South China Sea and/or Hong Kong, Hainan, and Vietnam. The major difference is that Type B storms tend to form farther eastward and southward than

Type A storms. As a result, the mean track for Type B storms is longer than Type A storms. Type C cyclones form in the South China Sea and are landlocked by Indochina peninsula and southern China's coast, with very short path. Just like Types A and B storms, Type D and E systems also form in the Philippine Sea but storms from the latter two types turn north- or northwestward and many of them made landfall on Taiwan, eastern China coast, Japan, and Korea. Type F storms tend to form in low-latitude and away from Asia. Type G storms also form far away from the Asian continent but at higher latitudes (~15°N). They move northwestward and then northward to the east of Japan over the open ocean. Storms associated with Type H are generally formed near the equator and to the east of 165°E. They have a long trajectory over the water. In terms of the frequency of occurrence, Type D has the highest occurrence (316 out of a total of 1261 cases). This is followed by Type C and E. Type H has the least number of occurrence (84) among eight types.

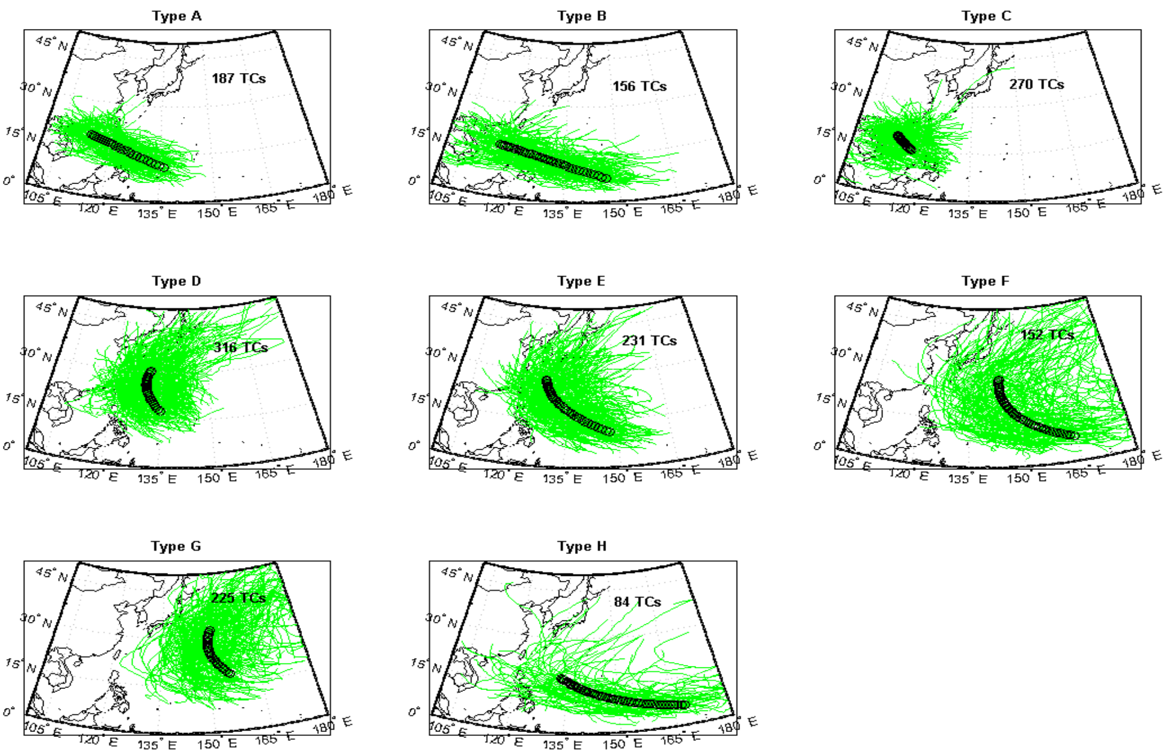

Fig. 1. Eight TC track types identified by the mixture Gaussian model. The number in each panel indicates the number of cases in each type. Black circles denote the mean track for each type.

Figure 2 shows the climatological mean distribution of seasonal TC passage frequency at 5° grid over the WNP and the South China Sea. The maximum is found in an area to the east of Taiwan and the northern Philippines with a value of 3.5 per season. There are three distinct major paths: the first moves westward through the northern Philippines to the South China Sea; the second turns slightly northwestward through Taiwan toward the southern China coast; and the third heads northward towards Japan.

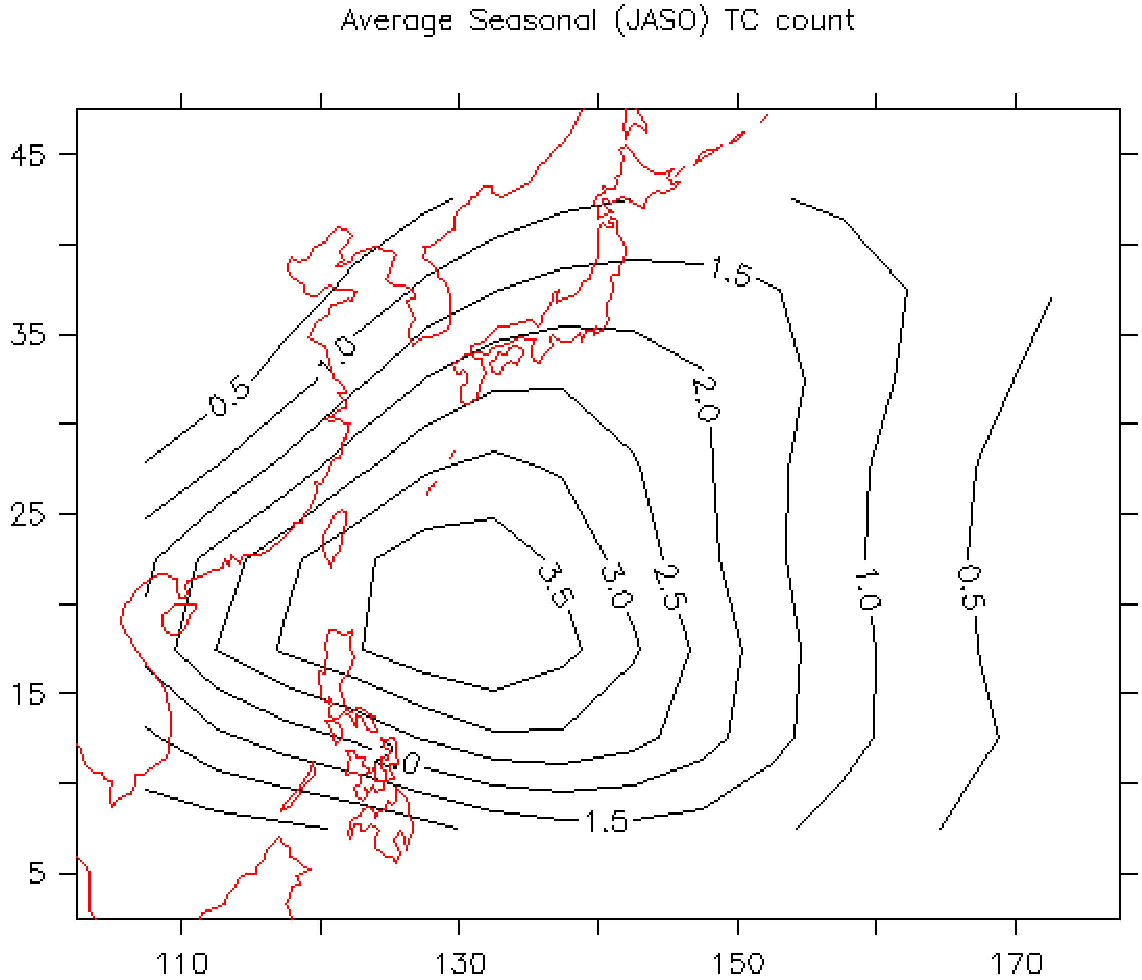

Fig. 2. Geographical distribution of the peak season (July to October) tropical cyclone passage frequency on 5° x 5° grids.

Figure 3 displays the Pearson's correlation for predicting seasonal TC frequency using the Poisson or probit regression model, which is based on the categorized TC tracks. The leave-one-out cross-validation method is used to assess the predictive skill. Overall, the correlation coefficient reaches approximately 0.6 over the WNP and the South China Sea with higher values near Japan and Korea (~0.70) and to the east of 150°E. The predictive skill is slightly lower in a band stretching from south of Japan, through Taiwan, and the northern South China Sea.

Similar to Fig. 3, Fig. 4 displays the Pearson's correlation coefficient between hindcasts and observations without categorizing TC tracks. Results presented in Fig. 4 are similar to those in Fig. 3, showing an overall skill of 0.6 in the core of the study domain and higher correlation in the area to the east of 150°E.

Figures 3 and 4 exhibit similar but also somewhat different skills in forecasting seasonal TC at every 5° resolution from two approaches. To appreciate the subtle difference, Fig. 5 shows the difference in forecast correlation skills between the track based and non track based results. Positive values indicate that the non track based approach has higher skills and vice versa. Two areas of negative difference are found; one covers Taiwan and the South China Sea and the other is in the middle of the WNP near 150°E. Positive areas are found elsewhere, with a relatively large difference in the Yellow Sea, Korea, and Japan. Judging from these results, the track based approach should be used as a method for predicting seasonal TC frequency in midlatitude East Asia while the non track based approach is preferable for lower latitudes near the East Asian marginal Sea. At present, it is unknown what causes this difference.

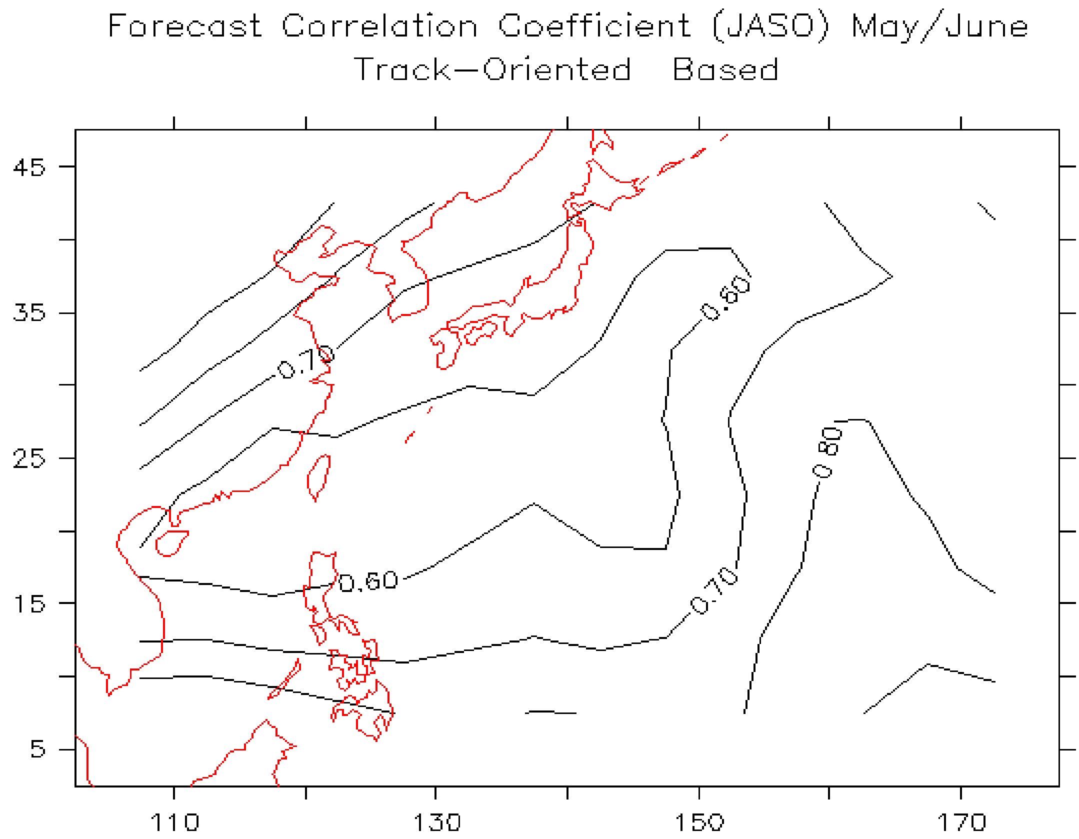

Fig. 3. Leave-one-out cross-validation correlation coefficient between hindcasts and observations of seasonal (July through October) tropical cyclone frequency at 5° grid when forecasts are based on track patterns. The predictors are based on the pre-season conditions of May/June.

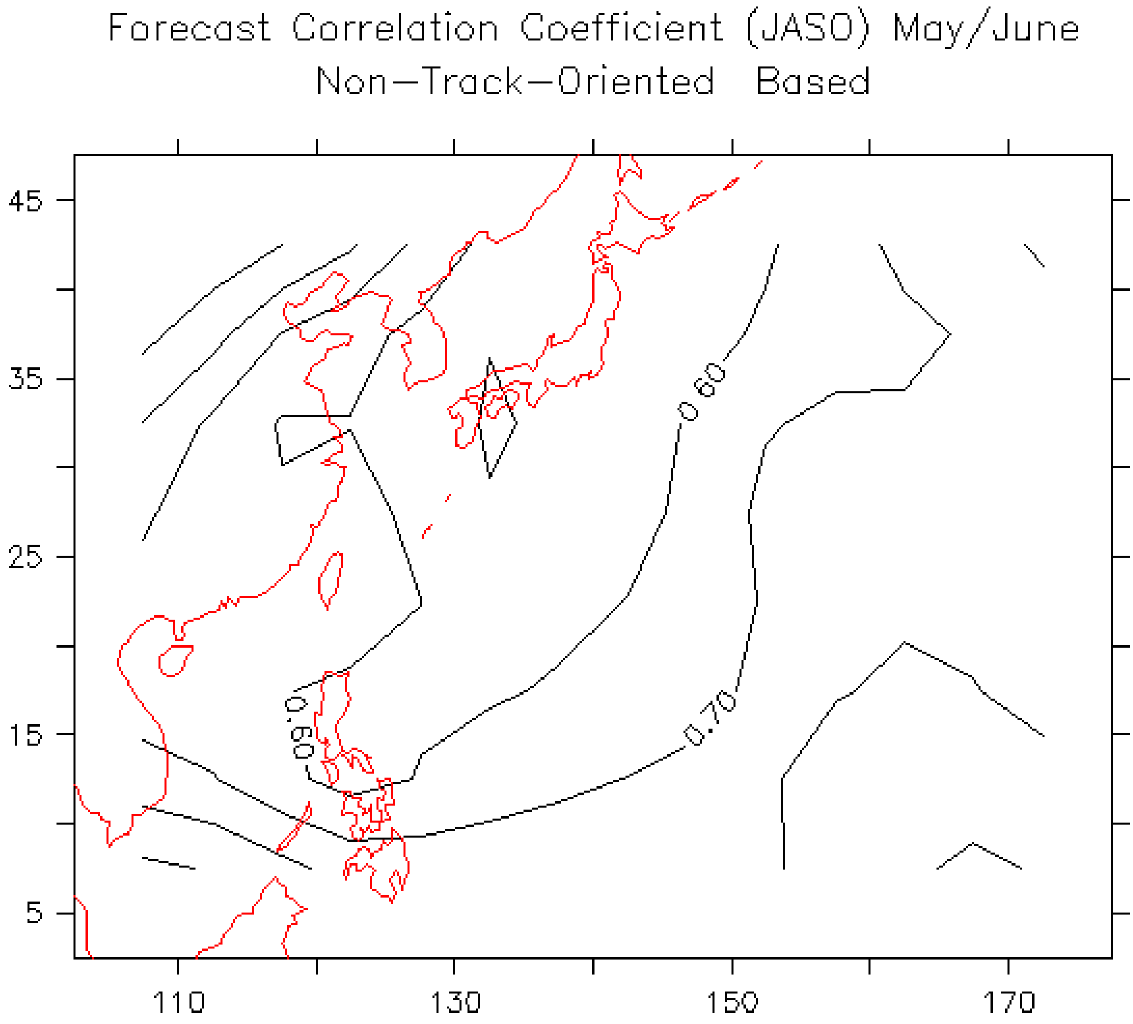

Fig. 4. Same as Fig. 3 but forecasts are not based on track patterns.

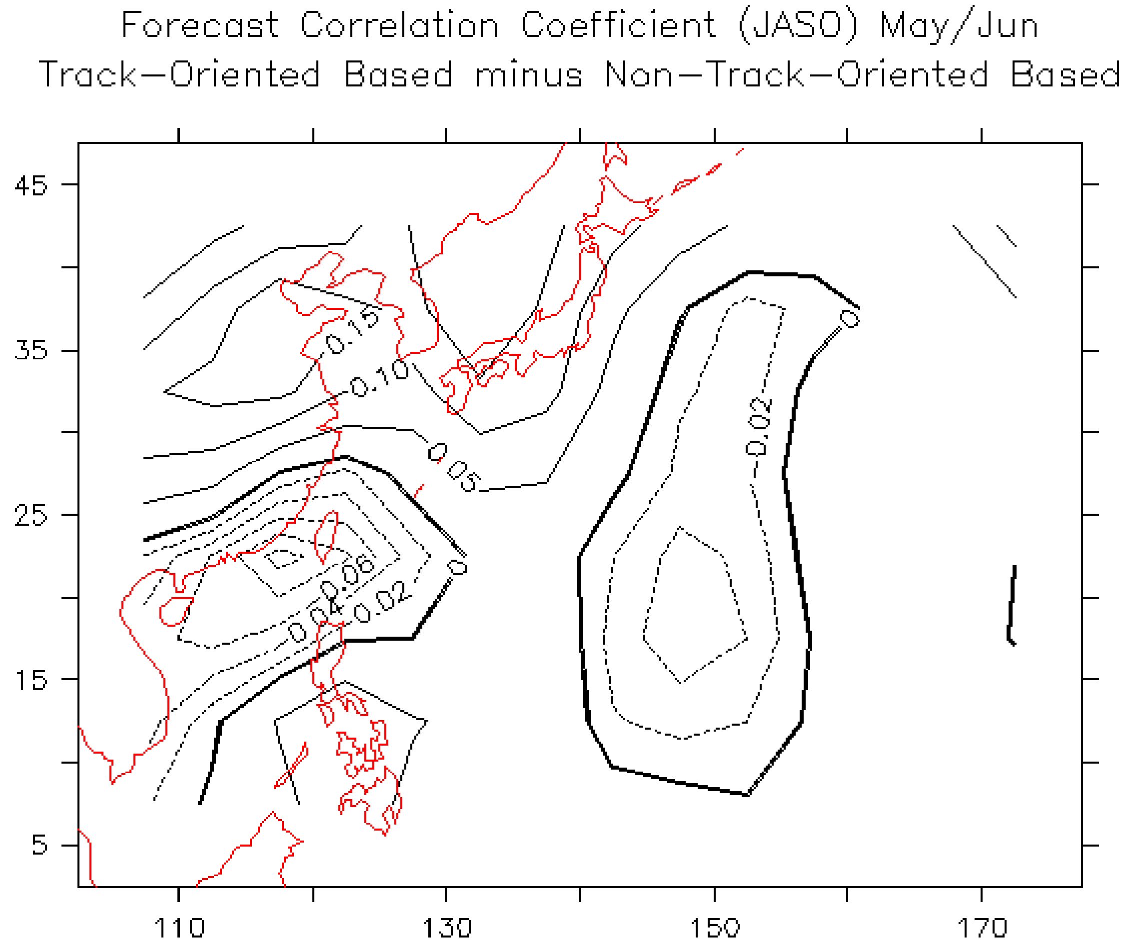

Fig. 5. Difference map in the correlation coefficients between track-based and non track-based forecasting methods.

Because the Poisson or probit regression model provides probability forecasts, it is also of interest to evaluate the model performance using the Brier Skill Score (BSS). The BSS can be viewed as the percentage improvement of model forecasts over climatology with zero indicating no skill relative to the climatological forecast and one for perfect score. Figure 6 displays the BSS when the track patterns were categorized first. For a large region including most of Japan, Taiwan, the northern Philippines, southeast China coast and Hainan, the BSS is approximately 0.3, indicating a 30% improvement over the climatology. The skill is higher elsewhere. If typhoons are directly forecasted at every 5° grid without going through the clustering procedure (Fig. 7), the pattern of the BSS is similar to that shown in Fig. 6, and the difference map between Figs. 6 and 7 reveals that the forecast skill is lower near Taiwan and the South China Sea when the track pattern approach is employed (Fig. 8). Again, these results are qualitatively consistent with those shown in Fig. 5.

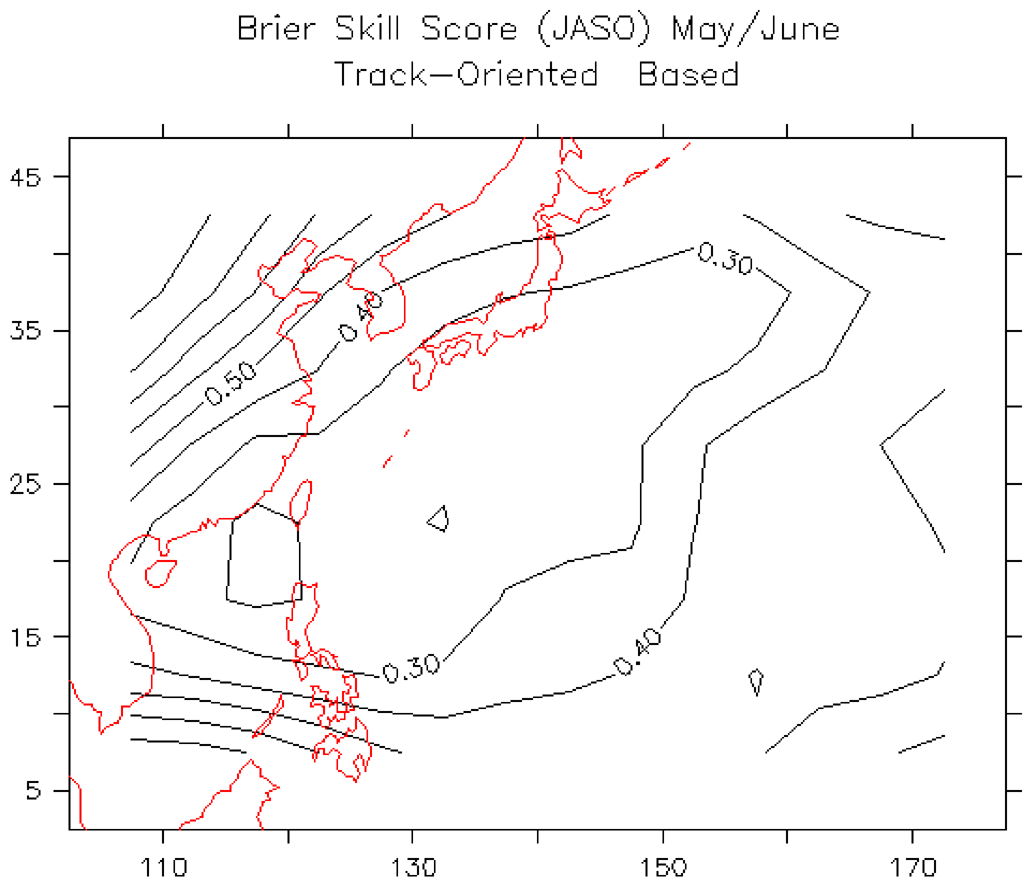

Fig. 6. The Brier Skill Score for the seasonal forecast of tropical cyclone frequency at 5° grid when forecasts are based on track patterns.

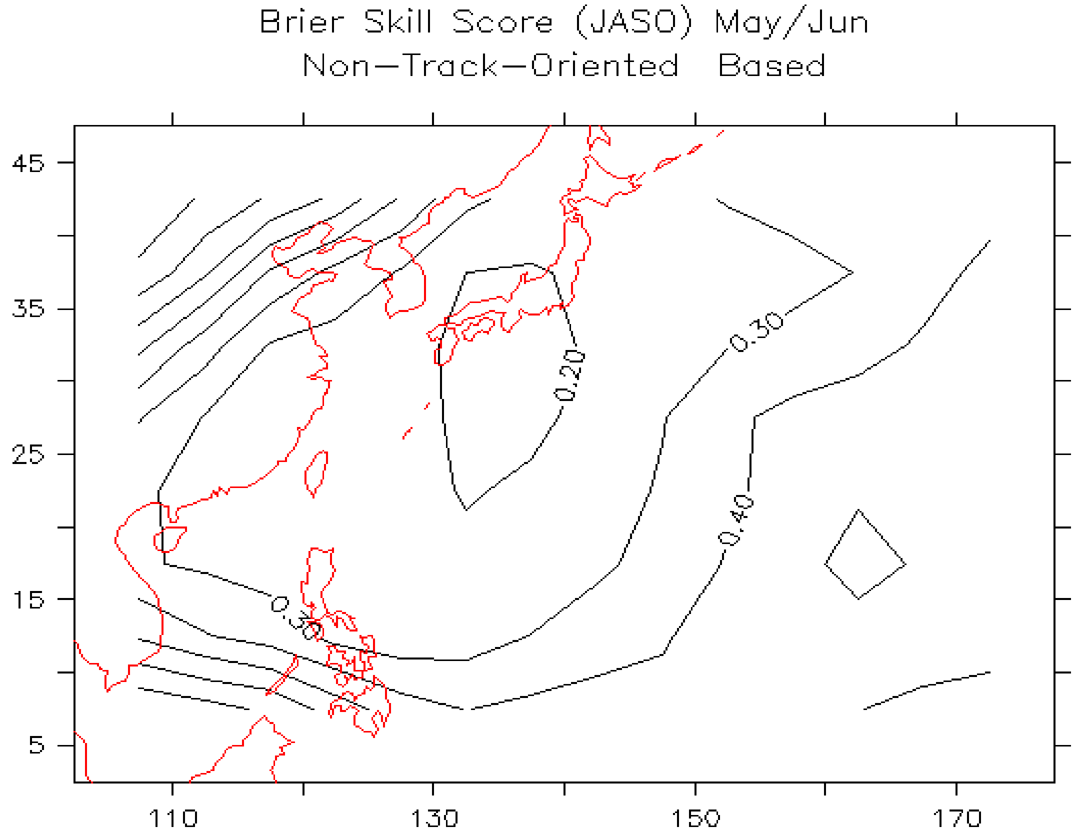

Fig. 7. Same as Fig. 6 but forecasts are not based on track types.

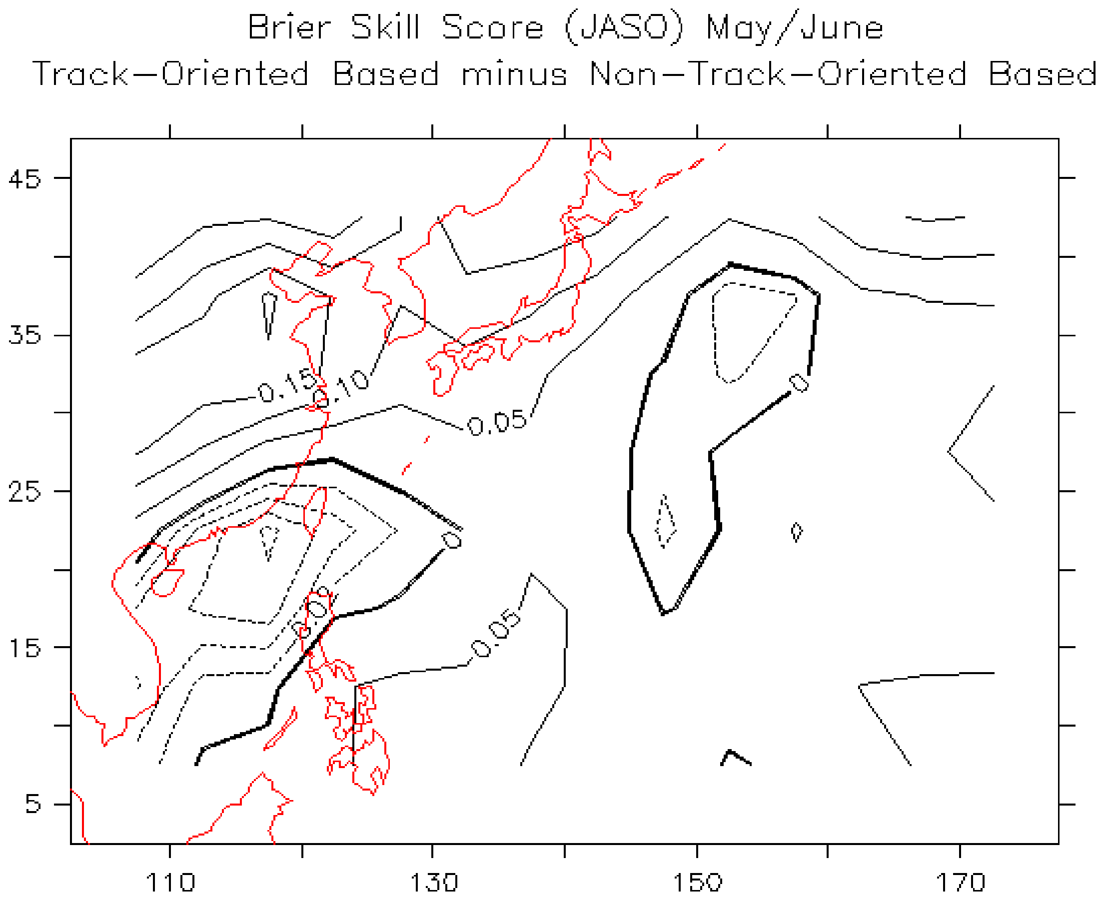

Fig. 8. Difference map in the Brier Sill Score between the track-based and non track-based forecasting system.

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