Construction and Application of an Index for Monthly Typhoon Activity Frequency During Active Seasons

Authors: Chen Xuan, Chen Xuan

Date: 2020-01-30T00:00:00+00:00

Abstract

The frequency of typhoon activity constitutes one of the important agenda items in annual flood season consultations. Current methodologies are predominantly model-based yet incapable of quantitative analysis. To address this limitation, NCEP monthly mean geopotential height data were employed. Based on anomaly information derived from these data and utilizing the cost function from data assimilation, several indices were constructed to represent the number of typhoon activities on the monthly scale from May to October over the western North Pacific. These indices were subsequently used to develop a monthly typhoon frequency index model for the active period. Analysis results indicate that the correlation between the index sequence and the typhoon frequency sequence can reach 0.7, and the index model effectively characterizes the monthly frequency information during the typhoon active season, which can provide a reference for monthly-scale typhoon activity frequency prediction.

Full Text

Construction and Application of a Monthly Typhoon Activity Frequency Index During the Active Season

CHEN Xuan
(The 75839 Army of the PLA, Guangzhou 510510, China)

Abstract

Typhoon activity frequency represents a critical component of annual flood season meteorological consultations. Current operational forecasting schemes rely primarily on numerical simulation outputs and lack quantitative analytical capability. This study employs NCEP monthly mean height field data and utilizes deviation information from data assimilation model cost functions to construct indices that characterize monthly-scale typhoon activity frequency in the Western North Pacific during May–October. An index model for monthly typhoon activity frequency during the active season is subsequently established. Analysis results demonstrate that the correlation coefficient between the index series and typhoon frequency series reaches 0.7, and the index model effectively represents monthly frequency information during the typhoon active season, providing a valuable reference for monthly-scale typhoon activity frequency prediction.

Keywords: deviation; index; typhoon frequency; Western North Pacific

Introduction

The Western North Pacific represents the most active region for tropical cyclone activity globally, with the South China Sea serving as a key waterway along the "Maritime Silk Road" and being particularly vulnerable to tropical cyclone impacts. Typhoon activity significantly influences marine development and construction initiatives. Statistical analyses indicate that tropical cyclones in the Western North Pacific account for approximately 30% to 33% of the global total, with tropical cyclone formation possible year-round. Approximately two-thirds of these generated tropical cyclones develop into typhoons, with about 26% making landfall in China. Chinese scholars have long focused on typhoon research, with Chen Qiushi et al. analyzing 15 typhoon cases to identify three favorable flow patterns in the 200 hPa height field for typhoon formation. Li Chongyin elucidated the physical mechanisms through which strengthened equatorial westerlies or southwest monsoons and moderate cold air influence favor typhoon genesis. Li Xiaoya et al. suggested that tropical cyclone genesis locations may relate to Rossby wave energy dispersion from monsoon gyres. Wang Yunkuan et al. emphasized the role of cold air in typhoon development, while Chen Xiaochen et al. examined the influence of Australian cold air activity on typhoon formation. Ding Yihui et al. systematically compared large-scale circulation differences between active and inactive typhoon seasons, and Wu Guoxiong analyzed sea surface temperature effects on typhoon formation. With deepening understanding of ocean-atmosphere systems, subsequent research has revealed relationships between typhoon activity and climatic factors including tropical intraseasonal oscillations, El Niño-Southern Oscillation (ENSO), Antarctic Oscillation, and North Pacific Oscillation.

The period from May to October constitutes the active season for typhoon activity in the Western North Pacific, coinciding with China' s summer heavy rainfall season. Typhoon frequency serves as a key element in annual flood season meteorological consultations. Current mainstream forecasting approaches rely primarily on numerical weather prediction interpretation, with methods referencing historical statistical results including ENSO indices, Western North Pacific subtropical high indices, and North Pacific Oscillation indices. However, these indices exhibit relatively low correlation with typhoon activity frequency. During the typhoon active season, the correlation coefficient between the Antarctic Oscillation and annual typhoon frequency reaches -0.48 (significant at the 99% level), while the North Pacific Oscillation shows a correlation of 0.37 (significant at the 95% level). The correlation between North Pacific sea ice (North Pacific sea ice area index) and annual typhoon genesis frequency is 0.4 (significant at the 99% level).

In operational applications, beyond predicting annual typhoon frequency, monthly-scale typhoon activity frequency forecasting is also required, yet few studies provide practical methodologies. The aforementioned literature primarily addresses annual typhoon activity frequency. For instance, Fan Ke et al. analyzed the influence of North Pacific sea ice indices from the previous December to May of the current year on annual typhoon activity frequency, while Wang Huijun et al. constructed analysis models using North Pacific Oscillation indices from June to September. These indices lack clear lead-lag relationships and appear to represent truncated causal relationships temporally. Consequently, developing a practical monthly typhoon frequency forecasting model holds significant operational value. Such models should incorporate factors demonstrating strong lead or concurrent correlations with typhoon frequency and possess the following characteristics: (1) the constructed indices should exhibit favorable global properties; (2) for monthly-scale data, typhoons should manifest as perturbations or deviations within corresponding datasets (e.g., monthly mean height fields); (3) from an algorithmic perspective, index construction should function analogously to pooling operations in image processing, accumulating critical information while eliminating redundancy; and (4) compared to black-box characteristics of neural networks and other intelligent algorithms, the constructed indices should possess explicit statistical meaning.

Accordingly, this study utilizes NCEP reanalysis height field data to construct a suite of indices and establishes a monthly typhoon frequency model based on these indices. Section 1 describes the index construction methodology, while Section 2 presents validation results for the monthly typhoon frequency model.

1.1 Index Construction

Constructing indices capable of characterizing monthly typhoon frequency during the active season requires synthesizing elements influencing typhoon activity and associated regions. Based on previous analyses and research findings, this study selects two primary regions for index construction: a large domain (0°–360°E, 90°S–90°N) and a small domain (low-latitude Western Pacific: 120°–170°E, 0°–25°N). The selection of these two domains stems from characteristics of Western North Pacific typhoon activity: (1) Western North Pacific typhoon activity is relatively frequent, accounting for approximately one-third of global tropical cyclones and representing a globally active element; (2) multiple weather/climate phenomena demonstrate relationships with typhoons; (3) algorithmic requirements for global characteristics necessitate inclusion of the large domain; (4) the small domain encompasses primary typhoon activity regions and the Western Pacific warm pool area that significantly influences typhoon activity, generally reflecting source region characteristics that may be obscured in the large domain; (5) during initial typhoon activity stages, typhoon influences may not manifest prominently throughout the entire atmospheric column, meaning small domain indices may not exhibit high correlation with typhoon frequency, yet these influences should be incorporated; (6) based on considerations of cross-equatorial flow influences on typhoons, this study extends the small domain to near-equatorial regions; and (7) focusing on monthly typhoon frequency, selected domains should maintain relatively close associations with typhoon activity regions, as other regions may not influence typhoon activity as directly as the small domain.

In summary, the division into large and small domains reflects the need for algorithms to characterize both overall features and source region characteristics. Primary elements selected for index construction include 200 hPa, 500 hPa, and 850 hPa height fields. The 500 hPa and 850 hPa levels are selected due to their common usage in operational forecasting. Only height fields are employed rather than other element fields because velocity-related elements (moisture flux, divergence, vorticity) and moisture distributions are reflected in height fields. Height fields can characterize large-scale flow patterns, and over oceans, monthly mean moisture distributions coordinate closely with height fields, particularly in 500 hPa subtropical high activity regions and low-level convergence/divergence zones. Furthermore, diagnostic quantities such as divergence, vorticity, and vertical velocity involve calculation errors and deviations that are difficult to control in magnitude and feature extraction, thus they are excluded from consideration.

During index construction, global characteristics must be incorporated. Therefore, this study selects the cost function from three-dimensional variational data assimilation for index construction, with all errors in the cost function replaced by deviations (since gridded reanalysis data are employed, the constructed index cost function excludes observation components): (1) Calculate the deviation H_{bias} of element field H (with dimensions $m \times n$), where H_{mean} represents the climatological mean state of element field H, replaceable by multi-year averages of H. Based on this deviation field sequence, construct deviation covariance matrices H_1 ($m \times m$) and H_2 ($n \times n$). (2) Utilize the cost function calculation method provided by Chen [22] to construct index I_h, where $Trace$ denotes the matrix trace operator and superscript T indicates matrix transpose operations.

$$I_h = Trace(H_{bias}^T H_1 H_{bias}) + Trace(H_{bias} H_2$$

1.2 Data, Model, and Validation Methods

This study constructs relevant indices using NCEP reanalysis monthly mean height field data (http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.html) with a spatial resolution of 2.5°×2.5° and temporal resolution of one month.

Typhoon data are obtained from the CMA Best Track Dataset provided by the China Meteorological Administration Tropical Cyclone Data Center (http://tcdata.typhoon.org.cn/zjljsjj_sm.html) covering January 1979 to June 2016. Monthly typhoon frequencies are shown in Figure 1 [Figure 1: see original paper] (if a typhoon spans multiple months, it is counted once in each month).

This study employs stepwise regression models [25] as the primary application framework. Section 2 validates whether selected factors are representative: first, six random years are generated to construct a comparison database (random comparison test: PART_R), with remaining data used to select index factors; subsequently, in cross-validation tests (divided into PART1, PART2, and PART3), identical factors are used for modeling and comparative validation to verify reliability of selected index factors.

2.1 Index Indicative Performance

This study constructs six indices related to monthly typhoon activity frequency. Correlation analyses between these indices and typhoon frequency series are presented in Table 1 , where "lead" indicates the index leads by one month (i.e., April–September index series correspond to May–October typhoon series). Pearson correlation coefficients are employed.

Among the six indices, those with favorable concurrent indicative performance (correlation coefficient absolute value exceeding 0.3) include the 850 hPa small domain index, while the three large domain indices demonstrate lead indicative performance. Among the three indices with favorable lead performance, the 200 hPa and 500 hPa large domain indices substantially outperform North Pacific sea ice, Antarctic Oscillation, and ENSO indices, with correlation coefficients exceeding 0.7, essentially capable of representing monthly typhoon frequency during May–October and demonstrating clear practical value (lead correlation).

2.2 Index Model Performance Validation

Through stepwise regression screening, selected factors include the 200 hPa large domain index (lead), 500 hPa small domain index (concurrent and lead), and 850 hPa small domain index (concurrent). The monthly typhoon frequency model takes the form of Equation (3):

$$p = a_1 \times I_{500\_s\_b} + a_2 + a_3 \times I_{500\_s\_m} + a_4 \times I_{850\_s\_m} + a_5 \times I_{200\_g\_b} \quad (3)$$

where p represents monthly typhoon activity frequency, a_i denotes weight coefficients, and I represents corresponding indices. Subscripts indicate: g for global, s for small domain, m for concurrent, and b for lead. In subsequent applications, concurrent indices can be replaced with numerical forecast outputs while employing stepwise regression models to calibrate selected parameters to achieve forecasting effectiveness.

This study primarily employs correlation coefficient (CC), mean error (ME), mean absolute error (MAE), root mean square error (RMSE), proportion of model outputs completely consistent with observed typhoon monthly frequency (P100%), proportion of absolute errors less than or equal to one (P1), proportion less than or equal to two (P2), and proportion less than or equal to three (P3) to comprehensively evaluate model reliability and predictive performance. In random comparison tests, six years are randomly generated as comparison years (1986, 1999, 2002, 2008, 2011, and 2016), with remaining years used to construct regression equation coefficients. Cross-validation consists of three segments: Sequence 1 uses September 1990–June 2016 for model construction and January 1979–August 1990 for validation (predicted-observed difference distribution shown in Figure 3 [Figure 3: see original paper]); Sequence 2 uses September 1990–June 2002 for validation (Figure 4 [Figure 4: see original paper]), with remaining data for model construction; Sequence 3 uses July 2002–June 2016 for validation (Figure 5 [Figure 5: see original paper]), with remaining data for model construction. Model coefficients for each comparison segment are presented in Table 2 .

Coefficients in Table 2 remain relatively stable within specific ranges, where 500 hPa small domain indices correlate negatively with typhoon frequency (a_1 and a_3), while 850 hPa small domain indices (concurrent) and 200 hPa global indices (lead) (a_4 and a_5) correlate positively, with global indices contributing substantially more than small domain indices. This indicates that trend variations in the 200 hPa global index substantially influence typhoon frequency trend variations (from least squares methodology: if a signal can be linearly superimposed from other signals, the signal' s trend variation equals the sum of each component signal' s trend variation multiplied by superposition weights).

Random comparison test results are presented in Table 3 and Figure 2 [Figure 2: see original paper]; cross-validation results are shown in Table 4 and Figures 3-5, where "observation" refers to monthly typhoon activity frequency statistics derived from the CMA Best Track Dataset.

Validation results indicate that predicted and observed trends generally align: correlations between model outputs and observations remain approximately 0.8 (random test results may vary due to sample database changes with random number generation). Output errors within two units are controlled at approximately 80% of the comparison sample, within one unit at approximately 60%, and exact matches account for about 20% (Tables 3 and 4). Both random and cross-validation tests include normal and ENSO years, demonstrating that model results possess reference value. During monthly forecasting operations within the typhoon active season, forecasters must predict typhoon counts for the subsequent month (e.g., 6–8 typhoons). Under this forecasting framework, the index model presented herein can be directly applied.

Conclusions

1) During the Western North Pacific typhoon active season, selected indices constructed in this study demonstrate favorable correlations with monthly typhoon frequency: low-level small domain indices correlate concurrently with typhoon activity frequency (correlation coefficient 0.4211), while two large domain indices (200 hPa and 500 hPa) exhibit excellent lead correlations exceeding 0.7 (200 hPa large domain index: 0.7436; 500 hPa large domain index: 0.7247). These three indices provide valuable references for monthly typhoon frequency prediction and analysis.

2) Model (3) outputs maintain correlations of approximately 0.8 with typhoon activity frequency. Absolute errors between model outputs and observations are within two units for approximately 80% of comparison samples, within one unit for approximately 60%, and exact matches occur in about 20% of cases (Tables 3 and 4). During the Western North Pacific typhoon active season, models constructed based on these indices demonstrate practical application value for monthly typhoon frequency prediction.

References

[1] World Meteorological Organization. Global guide to tropical cyclone forecasting [R]. GENEVA: WMO,

[2] Chen Lianshou, Duan Yihong, Song Lili, et al. Typhoon Forecasting and Its Disasters [M]. Beijing: China Meteorological Press, 2012: 1-4.

[3] Chen Yulin, Zhou Jun, Ma Fenhua. Overview of research on typhoons making landfall in China [J]. Journal of the Meteorological Sciences, 2005, 25(3): 319-329.

[4] Chen Qiushi, Sang Jianguo. Synoptic analysis of large-scale motion effects on typhoon formation [J]. Acta Meteorologica Sinica, 1965, 37(4): 486-497.

[5] Li Chongyin. Influence of environmental flow on typhoon genesis and development [J]. Acta Meteorologica Sinica, 1983, 41(3): 275-284.

[6] Li Xiaoya, Wu Liguang, Zong Huijun. Preliminary analysis of monsoon gyre effects on typhoon genesis in the Western North Pacific [J]. Transactions of Atmospheric Sciences, 2014, 37(5): 653-664.

[7] Wang Yunkuan, Liu Junqing, Huang Zhonghua. Simulation experiments on cold air effects in typhoon formation [J]. Chinese Journal of Atmospheric Sciences, 1988, 12(4): 374-

[8] Chen Xiaochen, Zhi Xiefei, Zhao Huan, et al. Influence of Australian cold air activity on tropical cyclone genesis in the Western North Pacific [J]. Transactions of Atmospheric Sciences, 2017, 40(1): 61-70.

[9] Ding Yihui, E R Wright. Large-scale circulation conditions affecting Western Pacific typhoon formation [J]. Acta Oceanologica Sinica, 1983, 5(5): 561-574.

[10] Wu Guoxiong. Influence of sea surface temperature anomalies on typhoon formation [J]. Chinese Journal of Atmospheric Sciences, 1992, 16(3): 322-332.

[11] Li Weijing. Modern Climate Operations [M]. Beijing: China Meteorological Press, 2002: 160-163.
[12] Pan Jing, Li Chongyin, Song Jie. Modulation of MJO activity on Western North Pacific typhoons [J]. Chinese Journal of Atmospheric Sciences, 2010, 34(6): 1059-
[13] Zhou Weican, Shen Haibo, Zhao Haikun. Influence of tropical intraseasonal oscillation on large-scale environments for Western North Pacific typhoon genesis [J]. Transactions of Atmospheric Sciences, 2015, 38(6): 731-741.
[14] Zhang Hongjie, Wu Liang, Huang Ronghui. Possible impacts of two types of El Niño on Western North Pacific monsoon trough and tropical cyclone genesis [J]. Climatic and Environmental Research, 2018, 23(2): 150-160.
[15] Wang Huijun, Fan Ke. Relationship between Western North Pacific typhoon genesis frequency and Antarctic Oscillation [J]. Chinese Science Bulletin, 2006, 51(24): 2910-
[16] Wang Huijun, Sun Jianqi, Fan Ke. Relationship between North Pacific Oscillation and typhoon/hurricane frequency [J]. Science in China (Series D), 2007, 37(7): 966-973.
[17] Shou Shaowen. Introduction to Chinese Weather [M]. Beijing: China Meteorological Press, 2012: 345-347.
[18] Fan Ke. North Pacific sea ice: A predictor for Western North Pacific typhoon genesis frequency? [J]. Science China: Earth Sciences, 2007, 37(6): 851-856.
[19] Fan Ke. New predictor and prediction model for Western North Pacific typhoon genesis frequency [J]. Science China: Earth Sciences, 2007, 37(9): 1260-1266.
[20] Li Kerang, Zhou Chunping, Sha Wanying. Basic characteristics of the Western Pacific warm pool and its climate impacts [J]. Acta Geographica Sinica, 1998, 53(6):
[21] Chen Xuan, Zheng Chongwei, Zhang Weitao, et al. A more generalized linear regression model and its meteorological applications [J]. Journal of PLA University of Science and Technology (Natural Science Edition), 2017, 18(2): 144-149.
[22] Chen Xuan, You Xiaobao, Zheng Chongwei, et al. A new linear regression model and application examples [J]. Chinese Journal of Atmospheric Sciences, 2019, 43(2):
[23] Chen Xuan. A preliminary study on dimension-reduction algorithm for variational methods in three dimensions [OL]. [2019-09-28]. https://www.preprints.org/manuscript/201801.0293/v1.
[24] Ying Ming, Zhang Wei, Yu Hui, et al. An overview of the China Meteorological Administration tropical cyclone database [J]. Journal of Atmospheric and Oceanic Technology, 2014, 31: 287-301.
[25] Huang Jiayou. Meteorological Statistical Analysis and Forecasting Methods [M]. Beijing: China Meteorological Press, 2004: 81-100.

Note: Figure translations are in progress. See original paper for figures.