Exploring the Study of Tropical Cyclone Track Prediction based on Remote Sensing Technology

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Abstract. A typhoon is a meteorological disaster that causes significant harm to human society, and the frequent occurrence of typhoons in recent years has caused significant impacts and damage to the lives of residents in coastal areas. Against this background, this paper addresses the shortcomings of traditional typhoon monitoring methods and proposes three main observation tools: Multisource data fusion, Cyclone Global Navigation Satellite system (CYGNSS) monitoring of sea surface fragmentation, and the MFDLNet deep learning method that combines satellite microwave data. These methods are able to continuously and stably observe the surface climate and reduce the influence of weather on their observation by continuous monitoring and utilizing the advantages of remote sensing technology, thus making up for the shortcomings of traditional observation methods and improving the accuracy of ropical cyclone track prediction. This paper provides an outlook on the future development of typhoon path prediction technology, aiming to reduce the harm of typhoon disasters to human beings, and reduce casualties and economic losses.

Keywords: Ropical cyclone track prediction, Synthetic Aperture Radar (SAR), Cyclone Global Navigation Satellite System (CYGNSS).

1. Introduction

With the intensification of global climate change, the frequency of extreme typhoons is increasing, causing great impacts and damage to human production and life along the coasts and even inland areas. According to statistics from relevant organizations, tropical cyclones worldwide cause an average of 20,000 deaths and more than $10 billion in economic losses each year. ropical cyclone track prediction, as a key to disaster prevention and mitigation, is an important means of mitigating the harm caused by typhoons to human society, reducing financial losses and minimizing casualties.

Traditional methods of predicting typhoon tracks mainly rely on data from ground meteorological stations, ship reports, and sounding balloons, with limited coverage, especially in the ocean area where there are observation gaps, such as the lack of dense observation stations in the typhoon-generating area of the northwestern Pacific Ocean, resulting in a lack of data in the initial field, which affects the accuracy of numerical modeling. In addition, under the influence of global warming and other extreme climates, there are many strong tropical cyclones year by year, and the external factors affecting cyclones are becoming more and more complicated, which also increases the difficulty of trajectory prediction. Satellite remote sensing technology can make up for the shortcomings of traditional measurement methods and statistical data, and it can also play a good role in complex weather conditions such as clouds and fog. It is characterized by continuous observation and is capable of all-weather observation without the influence of cloud cover.

Up to now, there have been several methods to improve the accuracy of ropical cyclone track prediction based on remote sensing technology. For example, synthetic aperture radar (SAR) and Gaofen-3 satellite (GF-3), by combining SAR and GF-3 satellite data, the wind speed and wave information on the ocean surface can be extracted and the wave propagation model can be improved, and this combination of multi-source data can improve the accuracy of ropical cyclone track prediction [1]. Cyclone Global Navigation Satellite System (CYGNSS) satellite mission, CYGNSS satellite mission is able to penetrate extreme precipitation rates by deploying eight low-orbiting satellites and using low-frequency GPS signals for dual-polarized radar observations, which provide sufficient temporal resolution to address short-time processes such as rapid intensification phases of typhoons [2]. As well as based on satellite microwave data and deep learning methods, the proposed MFDLNet is able to realize accurate estimation of typhoon wind speed. This method can be further applied to ropical cyclone track prediction to improve data accuracy [3].

The purpose of this paper is to compare and analyze the use of three techniques for typhoon path prediction, namely, analyzing typhoon paths through multivariate data combination method, observing sea surface fragmentation by CYGNSS satellite mission, and predicting typhoon paths using satellite microwave data combined with MFDLNet deep learning method, as well as the future outlook of typhoon path prediction methods.

2. Wind Speed Retrieval by combining data from multiple sources

2.1. Technical Introduction

The development of synthetic aperture radar (SAR) technology has made it possible to acquire high-resolution ocean surface wind speed data. For example, China's Gaofen-3 (GF-3) satellite [4] and Germany's TerraSAR-X satellite provide high-resolution SAR images that can be used to invert ocean surface wind speed and wave information. The related study combines SAR data from China's Gaofen-3 (GF-3) C-band and Germany's TerraSAR-X (TS-X) X-band for inversion of ocean surface wind speed (SSW) and wave information. The data consist of 140 GF-3 QPS mode images and 50 TS-X strip (SM) mode images, some of which cover the NDBC buoy area to assist in the validation of wind speed and wave parameters [5,6]. The hindcast data are obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis data (ERA-5) for surface winds, HYbrid Coordinate Ocean Model (HYCOM) for surface currents, and measurements from the National Data Buoy Center (NDBC) buoys. derived wind and wave parameters, providing highly accurate in situ observations. The WAVEWATCH-III (WW3) model simulates ocean waves [7], providing significant wave height (SWH) and whitecap coverage with a spatial resolution of 1 km and a 30-minute time interval. The HYCOM model provides sea surface current data with a spatial resolution of 0.08° and a time interval of 3 hours. By combining SAR image data, numerical model data and in situ observation data, more comprehensive information on the marine environment is provided and the accuracy of ropical cyclone track prediction is improved. The section on combining data from multiple sources mainly involves integrating data from different sources to improve the accuracy of wave inversion and to improve the wave propagation model. The Bragg resonance roughness was calculated by a theoretical backscatter model using SAR-derived wind speeds, wave parameters simulated by the WW3 model and HYCOM current data. Subsequently, the polarisation ratios between the VV-polarised and HH-polarised Bragg backscatter resonance components were calculated. Finally, the NP component of the NRCS was estimated using the SAR-measured NRCS and polarisation ratio.

2.2. Limitations

There are still many limitations of the technique. For example, challenges in data fusion, the sum of Bragg and NP components in the NRCS was compared with the NRCS of SAR measurements, and the RMSE was less than 3 dB at low to moderate wind speeds (<15 m/s); however, the accuracy was reduced to 6 dB at wind speeds of about 20 m/s. As well as the effect of wave breakup, SAR images under high wind speed conditions are susceptible to wave breakup and the changes in sea surface roughness, resulting in a decrease in data quality, so the effect of wave breaking should be taken into account, in this case, to optimise the data accuracy at high wind speeds. Future research needs to further improve the algorithms to increase the accuracy of data processing and inversion, and at the same time reduce the cost and technical complexity in order to expand the application and dissemination of the technology.

3. CYGNSS Satellite missions

3.1. Technical Introduction

The satellite system of the Cyclone Global Navigation Satellite System (CYGNSS) [8,9] consists of eight small satellites uniformly distributed in a common orbital plane at an altitude of 510 km and an inclination of 35° [10] Each observation satellite contains a Delayed Doppler Mapping Instrument (DDMI) consisting of a multi-channel GNSS-R receiver, a low-gain zenith antenna for the reception of direct signals and two surface-scattered signals, and two high-gain zenith antennas. The roughness of the ocean surface is closely related to the wind speed. The higher the wind speed, the rougher the ocean surface is, and the intensity and distribution of the scattered GPS signals change By analysing the distribution of the signal intensity in the DDM (delayed Doppler map), the roughness of the ocean surface can be deduced, and thus the wind speed can be estimated [8]. Specifically, there is an empirical relationship between the signal intensity distribution in the DDM and the wind speed, and the measurements in the DDM can be converted to wind speed utilizing an empirically derived geophysical model function. The integration time of a single DDM lasts 1 second, and the wind speed is derived from measurements in a 25 × 25 km area centred on the mirror point. This results in a total of 32 wind speed measurements per second over the entire constellation. The spatial sampling of CYGNSS consists of 32 simultaneous single-pixel 'strips', each 25 km wide and typically hundreds of kilometres in length.CYGNSS uses a two-station radar method [11] to predict wind speeds, which differs from the single-station method used by conventional scatterometers, allowing the transmitter and receiver to be located at the same location. The CYGNSS wind retrieval algorithm, where wind speeds are estimated based on an empirically derived geophysical model function that measures the wind speed at a DDM-estimated 10 m reference height over a 25*25 km area centred on the mirror reflection point. The algorithm is able to handle signals under different wind speed conditions by training on simulated and real data. The performance of the algorithm is verified by simulating the DDM under different wind speed conditions. Then by matching with real data including numerical model output parameters, GPS put sonde, other satellite data (e.g., Advanced Scattering (ASCAT), Oceanic Satellite (Oceansat)-2 Scatterometer (OSCAT), WindSat, Advanced Microwave Scanning Radiometer-2 (AMSR2)), and aircraft measurements through Statistical analysis to assess the accuracy of the algorithm

3.2. Limitations

Although the revisit time of CYGNSS is significantly better than that of conventional scatterometers, its temporal resolution is still limited. Under rapidly changing weather conditions, such as the rapid intensification phase of a tropical cyclone, it may not be able to capture all the critical dynamical changes. [12] and although they are uniformly distributed over a common orbital plane at an altitude of 510 km and an inclination of 35°, there are still gaps in the spatial coverage area [10]. Facing the problem of insufficient spatial coverage and temporal resolution, increasing the number of satellites or adjusting the satellite orbits can be considered to improve the spatial coverage and spatial coverage uniformity of this satellite system, and other satellite data can also be considered to be called to make up for the shortcomings. In addition, other satellite data (such as SCAT wind field data or numerical weather prediction data) can be fused to make up for the observation gap of CYGNSS.

4. ATMS microwave bright temperature data combined with MFDLNet deep learning

4.1. Technical Introduction

The traditional methods of typhoon wind speed measurements have defects such as large cost and high-risk factor, whereas the use of satellite microwave radiation can penetrate the cloud layer and can record the complete type of data on the 3D thermonuclear structure of the typhoon. So microwave bright temperature data from the Advanced Technology Microwave Sounder (ATMS) on board the US polar-orbiting satellite (SNPP) were used. The data below cover 964 typhoon events that occurred in the North Atlantic (NA) and North Pacific (NP) from 2012 to 2019. Table 1 indicates the estimated number of typhoons in the NA and NP regions from 2012 to 2019

Table 1 The estimated number of typhoons in the NA and NP regions from 2012 to 2019

Typhoon category(air velocity, m/s)	North Atlantic(NA)		North Pacific(NP)		Total
		west (WNP)	Central(CNP)	east(ENP)	
TD(<17)	56	126	15	93	297
TS(18~32)	97	177	10	130	417
1(33~42)	24	22	3	28	77
2(43~49)	11	16	3	12	42
3(50~58)	7	12	0	11	30
4(59~70)	9	33	1	31	74
5(>70)	4	30	1	5	40
Total	205	416	33	310	964

Where TD stands for Tropical Depression Cyclone and Tropical Storm.

Using the cloud-water path algorithm, the ATMS data are divided into cloudy and cloud-free (background field) data [13], in the paper [14], only three typhoons in the North Atlantic in 2017 are calculated at the beginning, and no cloud-free temperature data within ±10◦ latitude and longitude are found, and the iterative expansion of the background field algorithm [15] is applied to solve the problem of the lack of cloud-free data in the range of ±10° from the centre of the typhoon, and the cloud-free data within the ±10° of the typhoon centre are found by expanding the search range to find effective background field data. The problem of displaying non-thermokinetic high temperatures at the typhoon edge is solved by the non-thermokinetic high-temperature suppression algorithm to obtain accurate typhoon thermokinetic data and to reduce the interference of the non-thermokinetic data at the typhoon edge on the structure of the actual thermokinetic data. The thermonuclear cross-section sampling algorithm is used to sample the typhoon ATMS highlighted data in three directions: along the satellite scan line direction, the vertical scan line (along the FOV) direction, and the barometric pressure direction for the typhoon thermonuclear dataset. It consists of the 2D cross-section data of the typhoon heat kernel from above, and the cross-section data are taken in the scanline direction, vertical scanning direction, and barometric pressure direction for the temperature anomaly data. Each sample contains 63 300 × 300-pixel image data to construct the 2D dataset.

A deep learning approach is used. The Multiscale Feature Distribution Learning Network (MFDLNet) uses the improved VGG16 as the backbone network for multiscale feature extraction from typhoon temperature anomalies. Multi-task federation of wind speed single-value regression and wind speed probability distribution learning is achieved using multi-scale feature extraction and distribution learning. A fused loss function including MeanVariance (MV) [14], Cross Entropy (CE) and Mean Square Error (MSE) is proposed. The fusion loss function improves the accuracy of the estimation, makes the estimated maximum typhoon wind speed closer to the actual wind speed, solves the problem of the difficulty in extracting the heat kernel features of typhoons of different intensities, and makes effective use of the probability distribution of wind speed values. [3]

4.2. Limitations

The ATMS microwave brightness temperature data combined with MFDLNet deep learning technology still has some limitations, which need to be improved continuously.When a typhoon strikes, timely and accurate access to wind speed information can help relevant departments to prepare for disaster prevention and mitigation in advance, evacuate residents and deploy rescue resources in a timely manner, and minimise casualties and property losses.However, the deep learning architecture of MFDLNet is relatively complex, containing multiple neural network layers and a large number of parameters, which may require a long inference time when performing wind speed estimation.This may not be ideal for disaster warning scenarios that require fast response.When the typhoon's path is about to affect the coastal areas, failure to provide timely and up-to-date wind speed estimation data may lead to a lag in emergency response measures and affect the effectiveness of disaster prevention.Future research can further optimise the MFDLNet model to improve its accuracy and real-time performance in typhoon wind speed estimation.Meanwhile, in order to improve the performance of the model, it needs to be trained using a large amount of data, which requires the size and diversity of the data.In the future, attempts can be made to integrate data from multiple data sources, including different satellite sensors, ground-based observatories, sea buoys, etc., in order to enrich the scale and diversity of the data and provide more adequate support for model training..

5. Conclusion

This paper mainly explores three methods and studies about remote sensing technology in the direction of typhoon tracking. This paper concludes that satellite remote sensing data plays a significant role in the direction of ropical cyclone track prediction, and compared with the traditional methods of using ground weather station monitoring, ship reports, and sounding balloons, it can reduce the influence of weather conditions, increase the data coverage, and has significant advantages and application prospects. The combination of SAR and GF-3, TX-X data can provide detailed information on ocean surface wind speeds and waves, improve the wave propagation model, and invert typhoon wind speeds through ocean surface wave breaking; CYGNSS satellite data, with their combination, can provide detailed information on ocean surface wind speeds and wave breakup, and improve the wave propagation model. The combination of SAR and GF-3, TX-X data can provide detailed ocean surface wind speed and wave information, improve the wave propagation model, and invert the typhoon wind speed through the wave breaking on the ocean surface; the CYGNSS satellite data, with its high temporal and spatial resolution and accurate wind speed measurement capability, provides strong support for the typhoon path prediction in the short-term process; and the MFDLNet, which is based on the ATMS microwave bright temperature data and the deep learning method, can dig deeper into the internal thermodynamic and kinetic characteristics of the typhoon and further improve the accuracy of wind speed estimation and path prediction. Wind speed estimation and path prediction accuracy.

All of the above are solutions for tracking typhoon paths by using remote sensing satellite data in various ways, but there are still many shortcomings, such as satellites will still be affected by weather conditions, satellite data in many extreme conditions will produce greater errors, and the accuracy of the information will be affected, and deep learning requires a large amount of highly accurate training data, which are still deficiencies at present. In the future, research should be directed towards solving these problems, such as improving the performance of satellite sensors to obtain clearer and more accurate information with higher resolution for more accurate typhoon path prediction; optimising algorithmic models, etc., to put forward better scientific solutions for typhoon path prediction and coastal disaster prevention and mitigation work.

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