ESCAP/WMO
Typhoon Committee

THIRD ASSESSMENT REPORT ON IMPACTS OF CLIMATE CHANGE ON TROPICAL CYCLONES IN THE TYPHOON COMMITTEE REGION

DECEMBER 2019

UNITED NATIONS ESCAP
Economic and Social Commission for Asia and the Pacific

WMO

TC/TD-No. 0018

COVER PHOTO:
TYPHOON NORU FROM SPACE
NASA astronaut Randy Bresnik photographed Super Typhoon Noru in the Northwestern Pacific Ocean on August 1, 2017, as the International Space Station passed overhead. NASA

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ESCAP/WMO Typhoon Committee

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TC/TD-No 0018

ISBN 978-99965-779-7-0

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Published in December 2019

Printed in Macao, China by Unique Network Printing Fty, Ltd. - December, 2019

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FOREWORD

The United Nations Economic and Social Commission for Asia (ESCAP)/ World Meteorological Organization (WMO) Typhoon Committee (TC) has been working to reduce the damages caused by tropical cyclone disasters to the lives and property of people in the Asia-Pacific region through its efforts in four areas: meteorology, hydrology, disaster prevention and mitigation, and education and training, helping achieve the goals set in such global agendas as the Sendai Framework for Disaster Risk Reduction 2015-2030 and the 2030 Agenda for Sustainable Development.

The impact of climate change on typhoons is receiving increasing attention from scientific community, public, and policy makers. The projection by the Intergovernmental Panel on Climate Change (IPCC) for the 21st century suggests that global tropical cyclones are likely to decrease or remain the same in frequency but increase in average wind speed and precipitation rate. The Typhoon Committee, a regional intergovernmental organization for typhoon prevention and mitigation in Asia-Pacific, attaches great importance to the issue of typhoon in a changing climate. TC began to develop the Assessment Reports on Typhoon in a Changing Climate in the Asia-Pacific Region in 2008, with two outputs (TC-AR1, TC-AR2) released in 2010 and 2012 respectively, which have attracted widespread attention from the international community. Their main findings or conclusions were cited in the Fifth Assessment Report of IPCC (IPCC-AR5, released in 2013).

Based on the two previous assessment reports, the Typhoon Committee has continued to devote great research efforts to such areas as the homogenization of typhoon observations, typhoon positioning and intensity estimation techniques, the relationship between typhoon climate and global change, and numerical simulation of future trends, with significant progress made. It is our great pleasure to release the Third Assessment Report (TC-AR3).

TC-AR3, an update of the previous two reports, includes observational facts about typhoon frequency, intensity, track, precipitation and storm surge in the region, trends in the context of global warming, possible impact on Members of the Typhoon Committee, uncertainty analysis of the results, and recommendations for related follow-up research. Thus this is a product that will contribute to our understanding of typhoon in a changing climate and the continuous improvement of the long-term typhoon resilience strategy.

On the occasion of its release, I would like to express, on behalf of the UNESCAP/WMO Typhoon Committee, my sincere gratitude and respect to all the members in the assessment expert team for their outstanding, hard and voluntary work. At the same time, my appreciation goes to ESCAP, WMO, Secretariat of the Typhoon Committee and its Members for their strong support!

UNESCAP/WMO Typhoon Committee
Chair: Mr. Yu Wong
December 2019

PREFACE

In recent years, the occurrence of tropical cyclone anomalies around the world has triggered a constant concern about the climate characteristics of tropical cyclones and their relationship to global warming. As the official organization in the Asia-Pacific region for international collaboration for disaster prevention and reduction, the ESCAP/WMO Typhoon Committee attaches great importance to typhoon climate change, and the Working Group on Meteorology has taken it as one of its key projects since 2008. The Working Group on Meteorology started the compilation and editing of the assessment report (series) on climate change on Asia-Pacific typhoons. Two Assessment Reports (TC-AR1, TC-AR2) were published in 2010 and 2012, respectively and received wide attention from the international community. The main conclusion was quoted in the Fifth Assessment Report published by IPCC in 2013 (IPCC-AR5).

The detection and prediction of tropical cyclone climate change in Northwest Pacific is challenging with uncertainty due to the lack of long-sequence observations, limitations on tropical cyclone intensity analysis, and the heterogeneity of best-track datasets in the region. On basis of TC-AR2 and IPCC-AR5, a lot of research work has been carried out by international and Asia-Pacific typhoon researchers on the long-term sequence of tropical cyclones, the homogeneity of different best-track datasets, the relationship between global warming and tropical cyclone climate characteristics and future trends of numerical simulation. Significant progress has been achieved.

In view of this, the ESCAP/WMO Typhoon Committee initiated the research and writing of the Third Assessment Report (TC-AR3) in 2014 (the 46th session in Thailand) and served as the annual key project of the Working Group on Meteorology. A team of experts from China, Japan, Republic of Korea, Hong Kong and United States of America was set up, with experts from the Macau Meteorological Bureau served as project coordinator. After several years of systematic and careful analysis and evaluation based on the latest research results of global warming on tropical cyclones in the Asia-Pacific region, the expert term completed the first draft of TC-AR3 and an expert group meeting was held in 2018. The TC-AR3 was finalized and published in 2019.

TC-AR3 is an update of the previous two reports. It contains detailed observations on the frequency of tropical cyclones, intensity, movement, precipitation and storm surge in the region, trends under the background of global change, and possible impacts to the ESCAP/WMO Typhoon Committee Members. In addition, discussion of the uncertainty of the evaluation results and the follow-up related research work recommendations is also included. It is believed that the report will promote understanding in typhoon climate change and improvement in long-term strategies for typhoon disaster reduction.

On this occasion and on behalf of the ESCAP/WMO Typhoon Committee Working Group on Meteorology, I would like to express my gratitude to all the experts in the expert team for their excellent, hard and unpaid work, and ESCAP, WMO, Typhoon Committee and the Secretariat and all Members for the strong support!

Working Group on Meteorology
ESCAP/WMO Typhoon Committee
Chair: Dr. Xiaotu Lei
Shanghai Typhoon Institute of CMA
December 2019

EXECUTIVE SUMMARY

The report assesses the current state of the science on the relationship between climate change and tropical cyclone (TC) activity in the western North Pacific (WNP) basin.

Two central questions that are addressed through the report are the following:

- Is there a detectable human influence on any TC metric in the Typhoon Committee region?
- What changes in TC activity are expected in the region over the 21st century as a consequence of a 2°C global climate warming scenario?

Past changes

(a) Summary of trends in WNP TC activity

With data updated to 2017, four best track datasets continue to show significant interdecadal variations in basin wide TC frequency and intensity in the WNP. While most of the best track datasets depict a decreasing trend in basin wide TC frequency, the observed trend and its statistical significance are still highly dependent on the best track dataset used, the analysis period chosen, and other analysis details.

For TC intensity, there was encouraging research progress in improving the consensus between best track datasets and increasing use of a homogenized intensity dataset (ADT-HURSAT) to investigate intensity trends. Increases in the number and intensification rate for intense TCs, such as Cat. 4-5s, in the WNP since mid-1980s, were reported by a number of studies using various statistical methods to reduce the uncertainty in intensity assessment among best track datasets. However, comparison of ADT-HURSAT and best track datasets intensity trends suggests there may be remaining homogeneity issues in the best track datasets. Moreover, spatial and cluster analysis of TC intensity depicted substantially different trends in various sub-regions of the WNP.

A statistically significant northwestward shift in TC tracks and poleward shift in the average latitude where TCs reach their peak intensity in the WNP since the 1980s have also been reported. The prevailing track changes also resulted in an increase in the exposure to TC occurrence and landfall in some regions, including East China, Japan, and the Korean Peninsula in recent decades. Moreover, a statistically significant decreasing trend of TC translation speed in the WNP from 1949-2016 was reported. Poleward-shifting trends of storm surges in the WNP after the 1980s were also reported in a study using observations and model simulated storm surge data. Global reanalysis of storm surges and extreme sea levels also suggested that China, Japan and Vietnam in the WNP are among the 10 most-exposed countries to a 1 in 100-year coastal flood. It is also noted that one study indicated no statistically significant trend in 50-year return period TC-induced storm surges in the WNP.

TC rainfall rate trends are significantly influenced by changes in TC frequency, rainfall rate, translation speed and prevailing track and may vary from one region to another. Some available studies on observed TC rainfall in the region reported increasing trends in TC rainfall intensity in several regions, including southeastern China, Japan, the Philippines and central Vietnam.

Frequencies of landfalling and affecting TCs show no statistically significant trend for China, the vicinity of Hong Kong, China and Macao, China, Japan (TC or above), the Philippines, and the Korean Peninsula. Landfalling TC intensities over Japan and east China, have a statistically significantly increase, but those for south China, the Philippines and Vietnam have not changed significantly.

(b) Detection and attribution of TC changes

Progresses have been made in the detection and attribution aspects based on the assessment approach detailed in Knutson et al. (2019a). We first used the conventional perspective of avoiding Type I error (i.e., avoiding overstating anthropogenic influence). Using this approach, the strongest case for a detectable change in TC activity in the WNP is the observed poleward migration of the latitude of lifetime maximum intensity (LLMI). There is *low-to-medium confidence* that the observed poleward migration of LLMI is detectable compared with expected the significant natural variability of TC activity in this basin. However, there is only *low confidence* that anthropogenic forcing contributed to this poleward shift. There is *low confidence* that any other observed TC change in the WNP is either detectable or attributable to anthropogenic forcing.

Alternatively, from the perspective of reducing Type II errors (i.e., avoiding understating anthropogenic influence), some additional tentative TC detection and/or attribution statements can be made. We caution that these may have potential for being false alarms (i.e., overstating anthropogenic influence), but they nonetheless may be useful indicators of evolving risk. With this caveat, the balance of evidence suggests i) a detectable anthropogenic contribution to the observed poleward migration of the latitude of maximum intensity in the WNP; and ii) an anthropogenic influence (but without detection) on the unusually active TC season in the WNP in 2015.

While we are not aware that any TC climate change signal has been convincingly detected to date in sea level extremes data in the WNP basin, a widespread worsening of storm surge levels is believed to be occurring due to sea level rise associated with anthropogenic warming, assuming all other factors equal.

There are a number of reasons for the relatively low confidence in detection and attribution of TC changes in the basin. These include data homogeneity concerns (observation limitations), the small signal to noise ratio for expected anthropogenic changes, and uncertainties in estimating both the background natural variability levels and the response of TC activity to historical forcing agents.

Future projections of TC activity

The results of this assessment on the projections of TC activity in the WNP are generally consistent with those published in TCAR 2012 and the global assessment conducted by the WMO Task Team on Tropical Cyclones and Climate Change (Knutson et al. 2019b).

For projections of TC genesis/frequency, recent studies using higher resolution dynamical models mostly suggested a reduction of TC numbers, but an increase in the proportion of very intense TCs (Cat. 4-5) over the WNP in the future. However, there are still individual studies projecting an increase in TC frequency. Most TC intensity projection studies agree on an increase in intensity of WNP TCs in response to a 2^{o}C global anthropogenic warming scenario. All available projections for TC related precipitation also indicate an increase in TC related precipitation rate in a warmer climate. Anthropogenic warming may lead to potential changes in TC prevailing tracks, although details vary among studies. Climate models continue to predict future increases in sea level and, together with the projected increase in TC intensity, this will likely contribute towards increased storm surge and coastal inundation risk. Some studies also suggested a possible decrease in storm numbers in the WNP in the future, which could contribute toward decreasing surge risk, assuming all other factors equal. The most confident aspect of change in storm inundation risk comes from the highly confident expectation of further sea level rise, which would exacerbate storm inundation risk, assuming all other factors equal.

This assessment also attempts to quantitatively estimate the projected changes of key TC metrics (TC frequency, intensity, frequency of very intense TCs, proportion of very intense TCs and precipitation rates) expected under a 2^{o}C anthropogenic global warming scenario for the WNP by utilizing the approach and relevant data from the assessment of Knutson et al. (2019b) and other study findings for this region. The quantitative estimation of the projected change of these five metrics for the WNP are summarized as follows :

(a) TC Frequency
The median projected change of TC frequency is about – 10% with a 10th – 90th percentile range of -26 % to +11%.

(b) TC Intensity

The median projected change of TC intensity is about +5%, with a 10th – 90th percentile range of +2% to +9%, and with a large majority of models projecting an increase in the TC intensity.

(c) Frequency and proportion of very intense TCs (Cat. 4-5)

While the median projected change of about 0 % and a rather large 10th – 90th percentile range of -24% to +50% indicate no clear tendency of change in very intense TC frequency, the proportion of very intense TCs shows a clear tendency for an increase, with a median projected change of about + 10%.

(d) TC precipitation

All projections are positive, indicating a clear tendency for an increase in TC precipitation rates, with a median change of about + 17%, and a 10th – 90th percentile range of +6 % to +24%.

CHAPTER 1

Introduction

Tropical cyclones (TCs) rank among of the most destructive natural disasters on Earth. The western North Pacific (WNP) is the most active TC basin in the world, with an average of about 26 named TCs affecting the region each year. Among the notably destructive TCs occurring in the ESCAP/WMO Typhoon Committee region[1] in recent years were Washi in 2011, Haiyan in 2013, Rammasun in 2014, Soudelor in 2015, Nepartak and Meranti in 2016, Hato in 2017 and Jebi and Mangkhut in 2018. Against the background of global climate change, possible changes in TC activity and the associated impacts are topics of concern (Landsea *et al*., 2006; IPCC, 2013; Walsh et al., 2016). For the WNP, the Second Assessment Report (SAR) on the influence of climate change on tropical cyclones in the Typhoon Committee region (Ying *et al.,* 2012), concluded that while detection of any long term trends in TC activity in the WNP is still rather uncertain due to large inter-annual and inter-decadal variations and inter-agency inconsistency in the best track dataset, most of the available modeling studies projected an increase in TC intensity and precipitation rates in the WNP basin over the 21st century.

Since the publication of the SAR of Typhoon Committee in 2012, Members of Typhoon Committee and various research groups around the world have continued to investigate the connections between climate change and TCs, including homogenization of best track datasets, attribution and detection studies, model projections, and impact assessments as recommended by the Typhoon Committee expert team in 2012 (Ying *et al.*, 2012). In 2014, the Typhoon Committee at its 46th Session in Bangkok, Thailand commissioned an expert team to update the SAR with the present assessment--a third assessment report (TAR)--for the Typhoon Committee Members' reference.

The TAR reviews the latest scientific publications since 2012 and provides an updated assessment of the current state of the science on the relationship between climate change and TC activity in the WNP basin. Similar to the SAR, the focus will be on reviewing studies of past trends and future projections of TC activity in the WNP in order to identify possible influences of anthropogenic climate change on TC activity and impacts in the region, including storm surge risk.

In the WNP, four TC best track datasets are available, prepared respectively by China Meteorological Administration (CMA), Hong Kong Observatory (HKO), Joint Typhoon Warning Centre (JTWC) and RSMC-Tokyo and Regional Specialized Meteorological Centre Tokyo (RSMC-Tokyo). These four datasets are commonly used by various research groups in TC analysis. In addition to these four datasets, Kossin *et al.* (2007, 2013) re-analyzed satellite imagery and constructed the Advanced Dvorak Technique–Hurricane Satellite dataset (ADT-HURSAT) for the purpose of having a more homogeneous satellite-based estimation of TC intensity for climate change analysis in all ocean basins. The ADT-HURSAT data, covering TCs from 1978 to 2009, was also used by some research groups for comparison studies to conventional best track data.

Different averaging periods for maximum sustained wind and TC classification schemes are adopted by the above four agencies in the WNP. Moreover, some researchers also made use, in the WNP basin, of the five Category (1-5) hurricane intensity categorization used in the eastern North Pacific and North Atlantic basins in studying the TC activity in the WNP. For reference, Annex I provides the comparison of the TC classifications used by CMA, RSMC-Tokyo, HKO, and JTWC as well as the Hurricane Categories 1-5 system.

1 The ESCAP/WMO Typhoon Committee is an intergovernmental body established in 1968 under the auspices of the United Nations Economic and Social Commission for Asia and the Pacific (ESCAP) and the World Meteorological Organization (WMO). The Committee's purpose is to promote and coordinate planning and implementation measures required for minimizing the loss of life and material damage caused by typhoons. It is currently composed of 14 Members: Cambodia; China; Democratic People's Republic of Korea; Hong Kong, China; Japan; Lao People's Democratic Republic; Macao, China; Malaysia; the Philippines; Republic of Korea; Singapore; Thailand; United States of America; and Viet Nam.

In this report Chapter 2 will provide an updated assessment of past observed changes in TC activities and characteristics (including frequency, intensity metrics, prevailing tracks, rainfall, and storm surge). Chapter 3 will examine the latest findings on detection and attribution of changes of TC activities. Chapter 4 will focus on the TC impacts and present the results collected from the survey of the observed trend behavior of TC activity and related impacts among Typhoon Committee Members. Chapter 5 will update the 21st century TC activity projections. Uncertainties will be discussed in Chapter 6, and recommendations for future work will be given in Chapter 7.

While this report does not provide an exhaustive literature review of all studies on these topics, we have attempted to include and discuss at least the key references on which our assessments have been based.

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CHAPTER 2

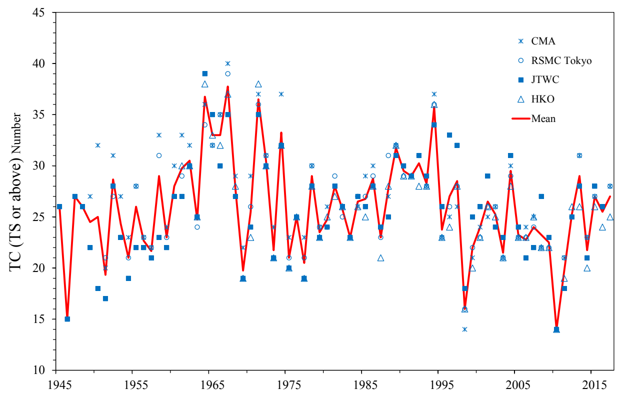
Observed Tropical Cyclone Activity and Characteristics

2.1 Tropical Cyclone Frequency

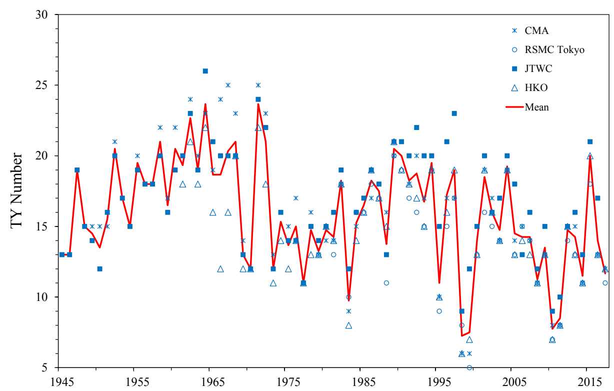
Studies of the variability and trends in tropical cyclone frequency in the WNP basin are reviewed in this section. The analysis of long-term TC frequency variations depicted in the previous assessment reports and based on the four datasets (RSMC-Tokyo, CMA, HKO, and JTWC), are also updated for readers' reference (Lee et al., 2010; Ying et al., 2012).

Similar to results from the first and second assessment reports, there is a statistically significant decreasing trend in annual counts of storms of at least tropical storm intensity or at least typhoon intensity, according to the CMA (1949–2017) and HKO (1961–2017) data sets. However, no statistically significant trends are found for the JTWC (1945–2016) or RSMC-Tokyo (1951–2017) data sets (Table 2.1). Table 2.2 shows that, using a common period across the data sets (1977–2017), all datasets show a decline in tropical storm/typhoon (and above) counts, although the trend is not statistically significant at the 5% level for most of the datasets.

Regarding decadal changes, Choi et al. (2015) studied the interdecadal variations in typhoons (categories 1-3) frequency over the WNP during the period of 1979-2011 based on the datasets of HKO, JTWC, RSMC-Tokyo, CMA and IBTrACS. They noted that the typhoon frequency has decreased since mid-1990s. Over the South China Sea, by using the JTWC data from 1979-2010, Li and Zhou (2014) concluded that there were two inactive periods (1979-1993 and 2003-2010) in the summertime (June-August) TC frequency in that region. Analyzing the IBTrACS dataset, Hu et al. (2018) reported that there was a step-by-step interdecadal decrease in TC genesis frequency in the WNP from 1960 to 2014 in accordance with the phase of the Interdecadal Pacific Oscillation (IPO). They also reported that vertical wind shear (especially the zonal wind shear) has been the most important environmental parameter responsible for the interdecadal TC changes, and that the interdecadal change of vertical wind shear has been caused by SST and associated rainfall pattern changes across the Indo-Pacific Ocean.



(a) storms of tropical storm intensity and above



(b) storms of typhoon intensity

Figure 2.1 Annual storm counts in western North Pacific from 1945-2017 based on the categories assigned according to reported maximum sustained winds converted into 10-min means.

Datasets	Data Period	Original intensity	
		All TC (tropical storm or above)	Typhoons
CMA	1949-2017	**-0.75/ decade**	**-0.97/ decade**
JTWC	1945-2017	+0.16/ decade	-0.28/ decade
RSMC-Tokyo	1951-2017	-0.44/ decade	-0.76/ decade**
HKO	1961-2017	**-1.33/ decade**	**-0.71/ decade**

Datasets	Data Period	Adjusted Intensity (10-min mean)	
		All TC (tropical storm or above)	Typhoons
CMA	1949-2017	**-1.07/ decade**	**-1.15/ decade**
JTWC	1945-2017	-0.16/ decade	**-0.42/ decade**
RSMC-Tokyo	1951-2017	-0.44/ decade	-0.76/ decade**
HKO	1961-2017	**-1.33/ decade**	**-0.71/ decade**

*** The annual numbers from 1951 to 1976 are according to RSMC-Tokyo's assignment of TS category although the MSW data are not available.**

**** Period from 1977 to 2017 as MSW data in RSMC-Tokyo dataset only available since 1977.**

Table 2.1 Trends in annual numbers of TCs in WNP based on different datasets for all available data up to 2017. The trends are estimated by linear least square regression. Results in bold indicate trends that are statistically significant at the 5 % level.

Datasets	Data Period	Original intensity	
		All TC (tropical storm or above)	Typhoons
CMA	1977-2017	-0.86/ decade	-0.59/ decade
JTWC	1977-2017	-0.63/ decade	-0.42/ decade
RSMC-Tokyo	1977-2017	-0.81/ decade	-0.76/ decade
HKO	1977-2017	-0.91/ decade	-0.60/ decade

Datasets	Data Period	Adjusted intensity (10-min mean)	
		All TC (tropical storm or above)	Typhoons
CMA	1977-2017	**-1.54/ decade**	-0.86/ decade
JTWC	1977-2017	-1.03/ decade	-0.41/ decade
RSMC-Tokyo	1977-2017	-0.81/ decade	-0.76/ decade
HKO	1977-2017	-0.91/ decade	-0.60/ decade

Table 2.2 Trends in annual numbers of TCs in WNP based on different datasets from 1977 to 2017. The trends are estimated by linear least square regression. Results in bold indicate trends that are statistically significant at the 5 % level.

2.2 Tropical Cyclone Intensity and Integrated Storm Activity Metrics

Various research groups have adopted different approaches to reduce the uncertainty in TC intensity trend analysis due to wind speed conversion and intensity assessment methods. Kang and Elsner (2012) used a quantile method to identify a consensus trend of TC activity for the RSMC-Tokyo and JTWC datasets from 1977 to 2010. By using the upper (strongest) 45% of the TCs as a threshold, they found an improved consensus between JTWC and RSMC-Tokyo dataset results when compared to traditional methods. The most reliable consensus is considered to be between 1984 and 2010, during which statistically significant decreasing trend in the frequency and increasing trend in intensity are seen, implying fewer but stronger TCs in the WNP during the study period. Moreover, Zhao and Wu (2014) examined the JTWC dataset and applied a downward adjustment to the maximum TC intensities prior to 1973. Then, by using a Bayesian change-point analysis, they detected a statistically significant shift in the frequency of Cat.4-5 TCs in the WNP in 1987 with the average number of Cat. 4-5 TCs increasing from 5.1 per year during their first epoch (1965-1986) to 7.2 per year during their second epoch (1987-2010). Zhao et al. (2014) simulated Cat. 4-5 TC frequency in a TC intensity model by allowing all of the observed TCs in the JTWC dataset to move along the observed TC tracks for 1948-2010. Their numerical simulation suggested there has been statistically significant decadal (12-18 years) variability of Cat. 4-5 TCs in the WNP and that changing TC tracks is the most important factor for decadal variations. The active phase of Cat. 4-5 TC occurrence is closely associated with an eastward shift in TC formation locations, which allows TCs to follow a longer sea track, favoring the development of Cat. 4-5 TCs.

Using the best track dataset (IBTrACS) and the ADT-HURSAT dataset over 1982-2009, Kossin et al. (2013) applied the quantile regression method to examine trends in the quantiles of lifetime maximum intensity (LMI), considering only storms whose LMI was 65 knots or above. They reported that, for the best track data in the WNP, significant positive trends are found in the mean LMI and in a range of quantiles. However, this result is not supported by the ADT-HURSAT data which shows the highest quantile exhibiting a marginally significant negative trend. As pointed out in their study, the 28-year length of the homogenized record of ADT-HURSAT places strong constraints on the interpretation of the observed trends.

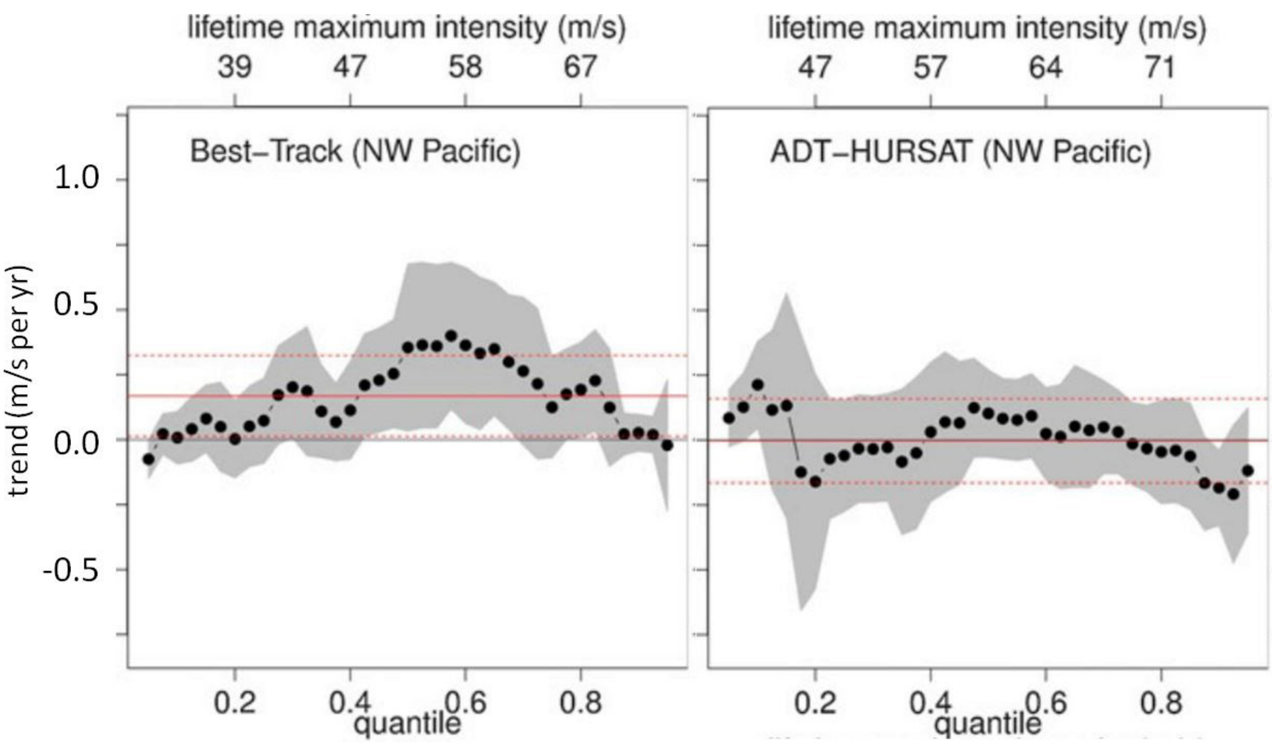


Figure 2.2 Trends in the quantiles of LMI in WNP, limited to storms that achieve typhoon strength (LMI >= 33 m s^{-1}) over the period 1982-2009 based on ADT-HURSAT (top) and Best-Track (bottom) records (Figure 10 of Kossin et al. (2013) © American Meteorological Society. Used with permission).

Kishtawal et al. (2012) used the IBTrACS (v03r03) dataset to assess the trends of TC intensification rate for TCs with peak intensity exceeding 80 knots (10-minute mean) in different basins during the satellite era (1986-2010). Their results suggested that, in the WNP, there is a statistically significant positive trend for the intensification rate from tropical storm to typhoon stage, while the nominally positive trend from typhoon intensity to peak intensity is not statistically significant.

Using an "Anthropogenic Climate Change Index (ACCI)" defined by the difference between global surface temperatures from climate model ensemble simulations with and without anthropogenic climate forcing agents included, Holland and Bruyère (2014) reported substantial relationships between ACCI and the observed proportion of very intense TCs (Saffir-Simpson categories 4 and 5) in the IBTrACS data from 1975 to 2010. While no change in global cyclone frequency or average intensity was found, they concluded there has been a substantial increase in the proportion of hurricanes/typhoons reaching category 4-5 levels, both globally and individually in all basins except for the eastern North Pacific. They also confirmed that an increase in proportion of category 4-5 storms is seen using the homogenized satellite-derived intensity data of Kossin et al. (2013), which begins in 1982.

Concerning spatial variations, Park et al. (2013) investigated the spatial distribution of trends in TC intensity using five TC datasets (RSMC-Tokyo, HKO, CMA, JTWC and the ADT-HURSAT), generally over 1977-2010, and using an overlapping latitude-longitude gridding method. All TC datasets depicted a spatially inhomogenous trend with weakening over ocean areas east of the Philippines (TP) and strengthening in the southern Japan and its southeastern ocean (SJ) regions. More in-depth analysis also suggested that the increasing intensification rate around the center of the WNP could mostly account for the increasing intensity over the SJ, while both the intensification rate and local genesis frequency affect the intensity trend in TP. Cha et al. (2014) reported that while there is a decrease in the overall number of TCs that passed within the vicinity of Republic of Korea from 2001-2010, a statistically significant increase in the number of strong typhoons (maximum wind speed of 44 ms^{-1} or above) has been found. Park et al. (2014) analyzed five TC datasets from 1977-2010 and revealed that there has been a statistically significant shift in the maximum intensity of TCs (maximum sustained wind speed over 17ms^{-1}) close to East Asian coastlines during July-November, resulting in an increase in the intensity of TCs making landfall over East China, Japan and the Korean Peninsula.

Mei and Xie (2016) applied cluster analysis to examine the intensification of landfalling typhoons (1-minute maximum sustained wind of 33 ms^{-1} or above) over the WNP from 1977-2013 using the JTWC and RSMC-Tokyo datasets. In this study, the RSMC-Tokyo dataset was adjusted for the difference in averaging period and changes in conversion methods during the study period. The adjustment greatly improved the consistency and correlation between the two datasets. The study stratified the typhoon tracks into four distinct clusters of which Clusters 1 and 2 contribute to about 85% of the landfalling rate in the basin. Cluster 1 typhoons form east of the Philippines, track north to northwestwards and affect East Asia. Cluster 2 typhoons form slightly to the west of Cluster 1 and over the South China Sea, track west to northwest and affect Southeast Asia and southern China. The analysis of Cluster 1 storms suggested that the annual mean values of lifetime peak intensity has increased by about 15% during 1977-2013 with a factor of four increase in the number Cat. 4-5 typhoons. For Cluster 2 typhoons, the average intensity increased about 12% and the number of Cat.4-5 typhoons doubled over the 37-year period. The study attributed the observed intensification of landfalling typhoons since late 1970s mainly to the strengthening of intensification rates which they inferred was due in turn to enhanced SST warming in a band off the coast of East and Southeast Asia.

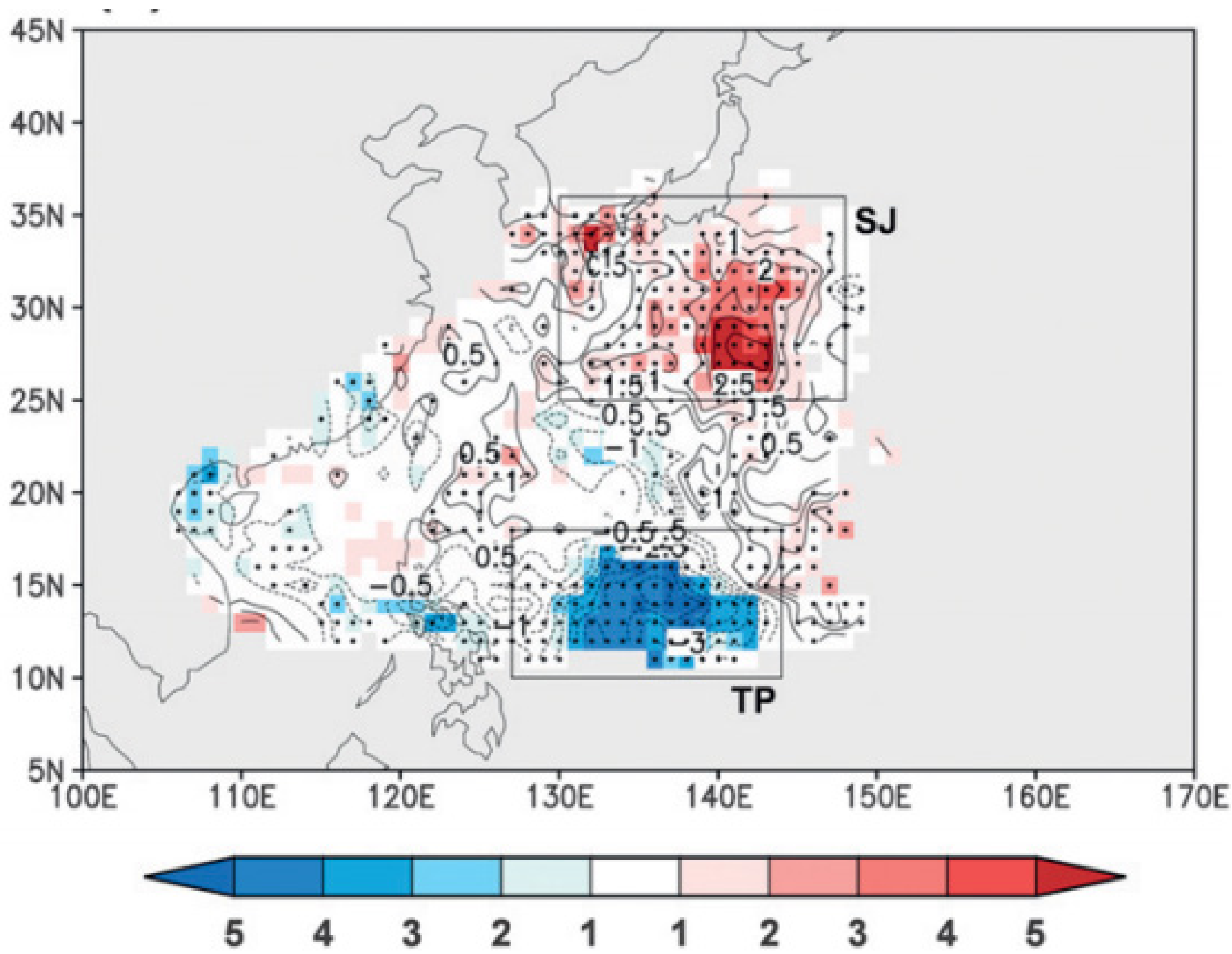


Figure 2.3 Linear trends (m s^{-1} per decade) of TC intensity during the period 1977-2010. Contours indicate the average of five TC datasets; red and blue colors indicate the number of TC datasets for which changes are significant with positive and negative signs at the 90% confidence level; dots indicate regions where all five TC datasets show the same sign (Figure 1 of Park et al. (2013) © American Meteorological Society. Used with permission).

Analyzing rapid intensification, Zhao et al. (2018) reported a statistically significant increase in the proportion of tropical cyclones undergoing rapid intensification at least once during their lifetime (RITCs) over the WNP during 1998-2015 compared to the period 1979-1997. The observed change is composed of the combined effect of a significant decrease in TC counts and unchanged RITC frequency since 1998.

Lin and Chen (2015) analyzed trends in a Power Dissipation Index (PDI) for the WNP over the period 1992-2012 using the JTWC dataset. They reported that the three main PDI contributing factors (frequency, duration and intensity) had made variable-signed contributions to the observed PDI. Decreases in TC frequency and duration outweighed the positive contribution from increasing TC intensity, resulting in a decreasing trend in PDI during the study period. Li et al. (2017) investigated changes in the destructiveness of landfalling TCs over China during 1975–2014 using the TC datasets of the four agencies. They found that TCs making landfall over East China have tended to be more destructive in recent decades, with a statistically significant increase in PDI after landfall. Further analysis also revealed that such an increase in the PDI of TCs landfalling over East China is associated with concomitant enhancements in landfall frequency and intensity over East China. In contrast, changes in the PDI of TCs making landfall over South China are less apparent. Composite analysis suggested that the reduction in TC occurrence over South China tends to offset the positive influence of the intensity and the nonlinear term.

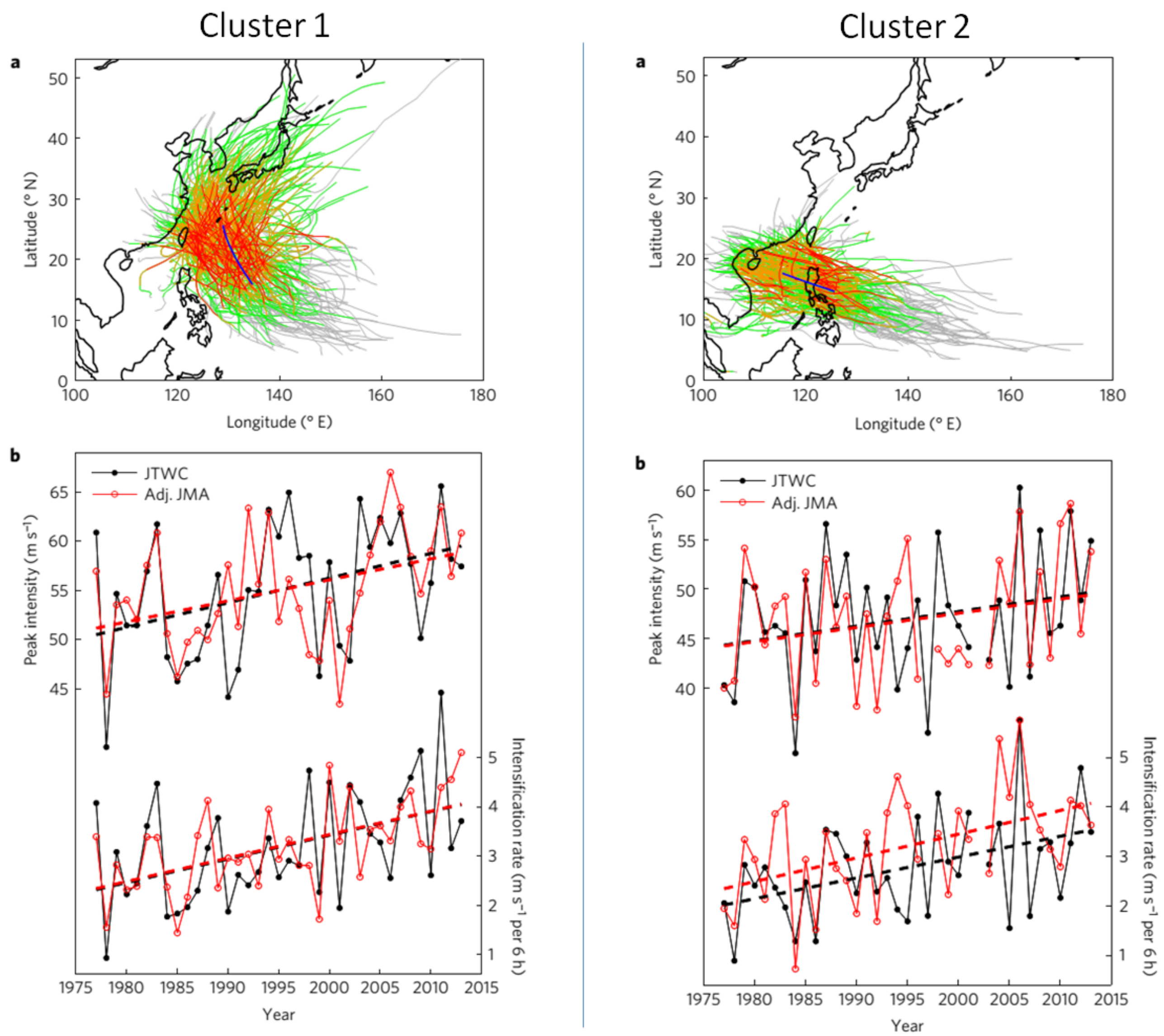


Figure 2.4 Tracks and intensity evolution of typhoons in Clusters 1 (left) and 2 (right). a, Tracks of typhoons from the JTWC data (JMA data show similar results). The colors indicate intensity levels of tropical depression (grey), tropical storm (green), categories 1 and 2 (orange), and categories 3 to 5 (red). b, Annual mean typhoon lifetime peak intensity and annual mean typhoon intensification rate as a function of year from the JTWC (black curve) and adjusted JMA (red curve) data. Thick dashed lines show linear trends during 1977–2013. (Reprinted with permission from Springer Nature: Mei, W. and S.P. Xie, 2016 : Intensification of landfalling typhoons over the northwest Pacific since the late 1970s, ***Nature Geoscience*****, 9, 753–757, Copyright (2016))**

2.3 Prevailing Track and Tropical Cyclone Exposure

Zhao and Wu (2014) investigated the changes in the three climatological prevailing TC track patterns between the first epoch (1965-1986) and second epoch in (1987-2010), referred to as ID1 and ID2, respectively. They reported a pronounced northwestward shift in TC tracks over the WNP during ID2 compared to ID1. This shift in the prevailing tracks from ID1 to ID2 led to a statistically significant decrease in TC occurrence over the South China Sea and a statistically significant increase from the Philippine Sea to the eastern coast of China and in the western part of the WNP. They suggested that while the observed inter-decadal shift in prevailing tracks mainly resulted from the combined effects of changes in large-scale steering flows and TC formation locations, they inferred that changes in steering flows plays a more important role than formation locations. The spatial distribution of intensity trends shown by Park et al. (2014) also indicates that the TC occurrence has a statistically significant decrease over the South China Sea and the eastern subtropical area of the WNP, whereas it has a statistically increase significant changes over sea areas around Taiwan and marginally near the east coast of Japan.

Kossin et al. (2016) analyzed TC exposure in the WNP using the four TC datasets (HKO, RSMC-Tokyo, CMA and JTWC) for 1980-2013. They found a poleward shift in the average latitude where TCs reach their peak intensity in the WNP. The poleward migration in the basin has accompanied with a decrease in TC exposure in the region of the Philippines and South China Sea, including the Marianas, Philippines, Viet Nam and southern China, while TC exposure has increased in the East China Sea region, including Japan and Ryukyu Islands, Republic of Korea, and parts of East China. Further analysis by Zhan and Wang (2017) suggested that this poleward migration over the WNP consists mainly of TCs with maximum sustained surface wind speed less than 33 ms^{-1} which they inferred was linked to the greater SST warming at higher latitudes associated with global warming and its associated changes in the large-scale circulation, which favors more TCs formation in the northern WNP and fewer but stronger TCs in the southern WNP over the past 30 years. Knapp et al. (2018) also found that the region prone to experiencing storms with discernible eyes expanded poleward globally from 1982 to 2015. Song and Klotzbach (2018) found that the poleward migration trends of Latitude of lifetime maximum intensity(LLMI) over the WNP vary on decadal timescales, with statistically nonsignificant and significant trends before and after 1980 respectively. Interdecadal fluctuations of TC genesis latitude as well as increases in latitudinal distance between genesis position and LLMI location are both responsible for the observed LLMI latitude trends. The former is linked to the Interdecadal Pacific Oscillation (IPO), which favors TCs forming in the northwestern (southeastern) quadrant of the WNP during negative (positive) IPO phases. The latter primarily results from a multidecadal warming of WNP sea surface temperature, which has increased the maximum potential intensity and apparently extended the region favorable for TC development to higher latitudes. Liu and Chan (2019) also investigated the variations in the location of TC LLMI over the WNP and the possible implications for TC landfall intensities in various regions of East Asia. They found that while the annual mean latitude of LMI of TCs (considering storms of at least tropical storm intensity) shows a statistically significant increasing trend during 1960–2016, but for intense typhoons (category 4–5) there is no significant trend but rather a pronounced interdecadal variation. A comparison of the spatial patterns of LMI during the periods 1970–1990 and 1991–2011 shows that the LMI location migrates from the southern to the northern part of East Asia from the first to the second period, with the frequency of intense typhoon landfalls and the average landfall intensities of the landfalling TCs increasing in Japan, the Korean Peninsula and

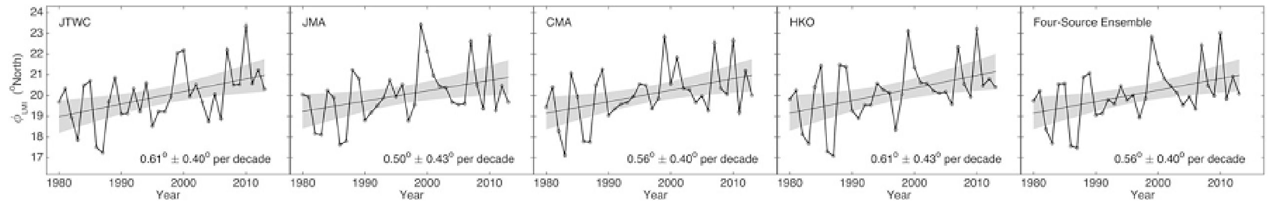


Figure 2.5 Time series (°lat decade^{-1}) of annually averaged (Φ_{LMI}) using best-track data from four WNP sources— JTWC, JMA, CMA, and HKO—and an ensemble of the four sources. Shading shows 95% confidence bounds. (Figure 2 of Kossin et al. (2016) © American Meteorological Society. Used with permission)

east China but decreasing in southern China.

Wu et al. (2015) analyzed the JTWC and ADT-HURSAT datasets from 1979-2009 and inferred that the annual mean TC genesis location is generally controlled by the tropical upper tropospheric trough (TUTT) in the North Pacific. There has been a pronounced westward shift the TUTT since 1979 which suppressed TC genesis in the eastern portion (east of 145°E) of the WNP, resulting in a significant westward shift in the average TC genesis location during the study period.

Kossin (2018) analyzed the annual mean global and regional translation speeds of tropical cyclones based on the IBTrACS, NHC and JTWC data as well as 2-minute Gridded Relief Data. The study reported a statistically significant (about 10% or 0.03 km hr^{-1} yr^{-1}) slowdown of tropical cyclone translation speed globally over 1949-2016. Over the WNP, the study also reported a statistically significant decreasing trend in the TC translation speed, both for basin wide (about -20% or -0.07 km hr^{-1} yr^{-1}) and over land (about -30% or -0.12 km hr^{-1} yr^{-1}). Moreover, a similar significant slowdown trend in translation speed is also observed for TCs at latitudes above 25°N. Chu et al. (2012) also reported that translation speeds of TCs as well as steering flows show a weakening trend over last 50 years in both the western portion of the WNP and northern South China Sea. Similar reductions in mean translation speeds for landfalling TCs in East China during 1975 - 2014 was also reported by Li et al. (2017). However, the robustness of the global decreasing trends in translation speed has been questioned by Moon et al. (2019) and Lanzante (2019), who suggest that the observed global trend reported by Kossin (2018) may be influenced by changes in observing capabilities over time as well as natural variability.

Cinco et al. (2016) reviewed the trends and impacts of TCs in the Philippines from 1951 to 2013 and reported a decrease in the number of TCs landfalling in the Philippines, in particular in the last two decades of the study period. However, the number of extreme TCs (with 150 km hr^{-1} maximum sustained winds or above) shows a slight (nonsignificant) increasing trend. Analyzing the JTWC dataset from 1945 to 2013, Takagi and Esteban (2016) reported a statistically significant increase in TC landfalling frequency in recent decades in the Leyte Island region of the Philippines (in the latitude zone between 10°N and 12°N).

Regarding TC activity around Japan, Grossman et al. (2015) employed a GIS software to investigate the spatial and temporal variations of storm tracks around Japan based on RSMC-Tokyo dataset in 1951-2011. The study reported that the number of years with greater number of TCs (wind speed greater than 17ms^{-1}) affecting the Japan Sea side and Pacific Coast side of Japan has increased since 1980.

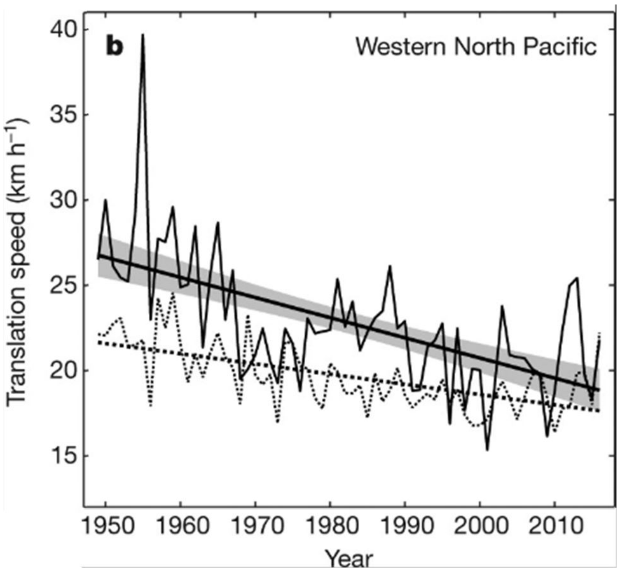


Figure 2.6 Time series of annual mean TC translation speed and their linear trends over land (solid line) and water (dotted line) for the WNP (Reprinted with permission from Springer Nature : Kossin, J.P., 2018 : A global slowdown of tropical cyclone translation speed, *Nature*, 558, 104-107, Copyright (1986)).

2.4 Tropical cyclone related rainfall

Using daily precipitation observations at 514 meteorological stations during 1965 - 2009, Zhang et al. (2013) analyzed the trend and characteristics of TC rainfall in China. The study revealed that the average rainfall per TC has significantly increased in Southeast China during the study period, in particular south of the Yangtze River east of 110°E from July to September. They suggested that this is in agreement with the reported shifts in prevailing TC tracks and increased survival time of landfalling TCs. Chang et al. (2012) reported decreasing TC rainfall frequency and increasing TC rainfall intensity trends to the south of the China monsoon region from 1958 to 2010. Li and Zhou (2015) suggested that the frequency and intensity of TC rainfall over southeast China have undergone significant interdecadal changes during 1960 - 2009. Li et al. (2015) pointed out that rainfall variability in Hong Kong is considerably affected by the TC rainfall which has a decreasing trend in both frequency and intensity in recent decades.

Bagtasa (2017) investigated TC-induced rainfall in the Philippines using RSMC-Tokyo TC dataset and a blended 64-year precipitation dataset which combines ground and satellite observations. Four climate clusters were defined in this study and increasing trends in TC rain and TC percentage contribution were observed in all clusters since 2000.

Nguyen-Thi et al. (2012) investigated long-term trends in rainfall occurring during TCs in Vietnam from 1961-2008 using the JTWC dataset and 58 meteorological stations. They reported significant increasing trends of TC rainfall and TC heavy rain days at most stations along the central coastline. Wang et al. (2015) analyzed autumnal (October and November) precipitation in Vietnam and reported an intensification of precipitation over Central Vietnam since late 1990s. They also inferred that such a change is linked to increased SST and a local increase in TC frequency over the adjacent sea.

2.5 Storm Surge

Needham and Keim (2015) reviewed TC-generated storm surge data sources, observations, and impacts in various TC basins. They reported that observations for the WNP indicate the highest rate of low-magnitude surges, with the coast of China averaging 54 surges (≥1 m) per decade, and rates were likely higher in the Philippines.

By forcing the Global Tide and Surge Model with wind speed and atmospheric pressure from ERA global atmospheric reanalysis, Muis et al. (2015) developed the global reanalysis of storm surges and extreme sea levels (Global Tide and Surge Reanalysis (GTSR) data set). GTSR covers the entire world's coastline and consists of time series of tides and surges, and estimates of extreme sea levels. They estimated that 1.3% of the global population is exposed to a 1 in 100-year flood. In the WNP, China, Japan and Vietnam are among the 10 most exposed countries reported in the study.

By analyzing 64 years (1950–2013) of observations and storm surge model simulations, Oey and Chou (2016) reported a statistically significant rise in the intensity and a poleward-shifting of location of TC induced storm surges in the WNP after the 1980s. They suggested that the rising and poleward-shifting trends of storm surges are mainly attributed to a slowdown of TC translation speed and the tendency for TC tracks to more readily recurve in recent decades which are in turn closely related to the weakening of easterly steering flows over the tropical and subtropical WNP.

2.6 Summary

Using data updated to 2017, four best track datasets continue to show significant interdecadal variations in basin wide TC frequency and intensity in the WNP. While most of the best track datasets depict a decreasing trend in basin wide TC frequency, the observed trend and its statistical significance are still highly dependent on the best track dataset used, the analysis period chosen, and other analysis details.

For TC intensity analysis, there has been encouraging research progress in improving the consensus between best track datasets and increasing use of the homogenized ADT-HURSAT dataset to investigate intensity trends. Increases in the number and intensification rate for intense TCs, such as Cat. 4-5s, in the WNP since mid-1980s was reported by a number of studies using various statistical methods to reduce the uncertainty in intensity assessment among best track datasets. But comparison of ADT-HURSAT and best track datasets intensity trends suggests there may be remaining homogeneity issues in the best track datasets. Moreover, spatial and cluster analysis of TC intensity depicts inhomogenous trends in different subregions of the WNP.

A significant northwestward shift in TC tracks and a poleward shift in the average latitude where TCs reach their peak intensity in the WNP have also been reported based on data since the 1980s. The prevailing track changes have also resulted in an increase in TC occurrence, including TC landfalls, in some regions, including East China, Japan, and the Korean Peninsula in recent decades. Moreover, a significant decreasing trend of average TC translation speeds in the WNP from 1949-2016 has been reported. Poleward-shifting trends of storm surges in the WNP after 1980s were also reported in a study using observations and model simulated storm surge data. A global reanalysis of storm surges and extreme sea levels also suggested that, China, Japan and Vietnam in the WNP are among the 10 most-exposed countries to a 1 in 100-year flood in terms of exposed population. Another study finds no significant trend in 50-year return period TC-induced storm surges in the western North Pacific.

TC rainfall trends can be significantly influenced by changes in TC frequency and prevailing tracks and may vary between regions. Some studies on TC rainfall trends in the region report increasing trends in TC rainfall intensity in southeastern China, central Vietnam, and the Philippines.

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CHAPTER 3

Detection and Attribution of Tropical Cyclone Changes

3.1 Introduction

This chapter addresses the question of whether there are detectable changes in TC activity in the Typhoon Committee Region and whether any changes in TC activity in the region can be attributable to human-induced climate change. Much of the material and conclusions are similar to those in a recently published WMO Task Team report on this topic at the global scale (Knutson et al., 2019), though here we focus only on those changes occurring in the Typhoon Committee Region. Walsh et al. (2016) present a recent literature review of tropical cyclones and climate change that is relevant to this chapter.

A "detectable change" in this report refers to a change in TC activity that is highly unlikely to be due to natural variability alone. Natural variability can either refer to internal variability within the climate system (like El Nino events) or to changes caused by natural forcings on the climate system (like changes in solar radiation or volcanic activity). Different methods can be used to assess whether a TC activity change is detectable, including trend analysis (with careful consideration of the possibility that a trend was produced by natural processes) and comparison of observed TC changes with changes obtained from model simulations of natural or internal variability.

A "detectable anthropogenic change" here refers to a change that is both detectable and where the sign of an anthropogenic influence can be established with some degree of confidence. "Attribution" in this report refers to evaluating the relative contributions of different causal factors to an observed change, including an assessment of statistical confidence (Hegerl et al. 2010). Attribution can be made either for changes that have been established as "detectable" or for changes which have not been shown to be detectable. In the latter case, the attribution claim is of a type known as "attribution without detection", which typically have relatively low confidence, although there may be useful for early identification of changes that may later emerge as detectable changes. The anthropogenic component of change is normally estimated using a climate model historical forcing run. Future projections from climate models can give some sense of the nature of expected historical influence, but should be used with great caution, if at all, for this purpose, since historical climate forcings will differ substantially from expected future climate forcings (mix of aerosols vs. greenhouse gas forcing, etc.)

Changes in TC activity which we assess can include long-term changes such a trend over many decades, or in some cases a particular event (storm case or unusually active season) where a particular "event attribution" study has been published, which makes claims about whether anthropogenic climate change either changed the probability of occurrence of an event over some threshold level or whether it altered the intensity of the event in a given direction. This recognizes recent developments in the field of event attribution (e.g., NAS, 2016). Again a model simulation with historical forcing is normally used in constructing the "counterfactual" case that attempts to represent the world in a pre-industrial state where there was presumably much less human influence on climate than in the industrial era.

In assessing whether a TC change is detectable or whether anthropogenic forcing contributed in a certain direction to the change, different types of errors can be considered. Following Lloyd and Oreskes (2018) if we conclude that a change is detectable or that anthropogenic forcing contributed, and this turns out not to be the case, we have made a Type I error (overstating of anthropogenic influence). On the other hand, if we do not conclude these are the case when in fact anthropogenic forcing had contributed, we are making a Type II error (understating anthropogenic influence).

Previous TC/climate change assessments typically have focused on avoiding Type I errors. Here we will separately consider two complementary viewpoints: emphasis on avoiding Type I error and emphasis on reducing the occurrence of Type II error. (Type II error can be trivially avoided by concluding that *all* TC changes or events had anthropogenic contributions, but we seek a more useful and meaningful assessment by instead trying to reduce occurrence of such errors through, for example, a lowering of the requirements used to conclude that an anthropogenic contribution is present. We will nonetheless require *substantial evidence* and require that at least the *balance of evidence* supports the conclusion of detectable change or anthropogenic influence. We recognize in advance that this approach will result in more speculate statements with a higher expected occurrence rate for Type I errors (e.g., false alarms for detectability or anthropogenic influence), and so any statements arising out of the goal of "Type II-error reduction" will be stated separately from typical Type I error avoidance statements in our conclusion, in order to clearly distinguish the different types of statements.

Before commencing with the assessment of detectable/attributable changes in TCs, we note that there is published evidence of detectable and attributable climate change for some climate variables in the WNP basin. One example of this is Gillett et al. (2008) who found evidence for attributable anthropogenic warming of SSTs in the tropical cyclogenesis region in the basin using detection/attribution fingerprinting techniques. A second example is the regional surface temperature trends analysis of Knutson et al. (2013) who present maps (their Fig. 10 e,f) indicating a number of areas in the basin where a century-scale detectable warming trend is observed, with a contribution from anthropogenic forcing, according to their grid-point based assessment using SST observations and CMIP3/CMIP5 models.

3.2 TC-Climate Change Case Studies

In this section, we consider several published cases where a conclusion about detectable change or about anthropogenic influence on past TC activity has been made.

a) Case Study: Poleward migration of latitude of maximum intensity (western North Pacific)

In the WNP, the latitude of lifetime-maximum intensity (LLMI) of TCs has moved northward since the 1940s (Kossin et al. 2014; 2016; 2018b). A poleward migration has also been identified globally and in both hemispheres, though in not all individual basins, but appears to be statistically most robust in the WNP basin. It is thought to be related to the global poleward expansion of the tropics in general (Sharmila and Walsh 2018). Lucas et al. 2014 review the topic of tropical expansion. Studholme and Gluev (2018) and Tennille and Ellis (2018) reported relatively small poleward migration of LLMI in the basin, but both used much shorter analysis period. Song and Klotzbach (2018) infer that both the Interdecadal Pacific Oscillation and basin SST warming and related potential intensity increase are factors affecting the poleward migration in the WNP, by influencing the genesis latitude (Daloz and Camargo 2018) and the latitudinal distance from genesis to the LMI, respectively.

Liang et al. (2017) provide independent supporting evidence for a poleward shift in TC tracks in the region, and evidence for a slowing of TC propagation speeds near Taiwan in recent decades, based on an analysis of 64 years of TC-induced rainfall trends around Taiwan. Altman et al. (2018) used analysis of tree-rings in the basin to infer that TC-induced damage to forests has increased in the more poleward regions, comparing pre- and post-1920 periods. This supports the notion of a long-term poleward shift of TC activity in the region and lends support to the notion that the observed changes are unusual compared to natural variability.

The LLMI changes in the basin may be related to shifts in TC occurrence of tracks from the South China Sea toward the East China Sea in recent decades and shown in a number of studies (Kossin et al. 2016). In addition, the location of maximum intensity has moved closer to East Asia during 1977–2010 (Park et al. 2014), leading to increased TC landfall intensity over east China, Korea and

Japan. Choi et al. (2016) interpret the poleward movement of the LLMI in the region as due to changes in steering flows producing changes in TC tracks and genesis location. Zhan and Wang (2017) note that the poleward movement of LLMI in the region is most pronounced for weaker TCs, and that environmental conditions over the past 30 years have tended toward favoring genesis in the northwestern part of the basin where there is less available time for a TC to become very intense. The observed decadal shifts in TC activity in the region will be further discussed in a separate case study below.

Exploring the potential causes of the LLMI trends, Kossin et al. (2016) performed linear trend analysis on the poleward shift of LLMI in the WNP since the mid-1940s. While the trend through 2016 is only marginally statistically significant in the full time series, they found that when they removed (via linear regression) the influence of key modes of multidecadal variability in the region (i.e., El Nino/Southern Oscillation and the Pacific Decadal Oscillation), the trend in the residual series became even more statistically significant than in the original series. The statistically significant of the trend is also robust to the statistical removal of the Atlantic Multidecadal Oscillation (which Zhang et al. 2018 showed could be related to WNP TC activity), or the Interdecadal Pacific Oscillation rather than the PDO (J. Kossin, personal communication 2018). The statistically significant of the trend in the residuals is also robust when different TC datasets are used (Kossin et al. 2016a), or with the use of either annually or seasonally (July-November) averaged climate indices (J. Kossin, personal communication 2018).

Modeled trends in WNP LLMI were analyzed based on CMIP5 historical runs and 21st century projections (Kossin et al. 2016a). TC simulations of CMIP5 models have a number of limitations in the basin, with some models simulating 20% or less of the climatological frequency of TCs there. The CMIP5 historical run ensemble mean shows a nominally positive, but not statistically significant, trend in LLMI over 1980-2005, while there is a statistically significant poleward trend in the Representative Concentration Pathway 8.5 (RCP8.5) scenario for the CMIP5 models analyzed by Kossin et al. (2016). The pattern of track density changes in the CMIP5 historical simulations is qualitatively similar to that in the observations, which supports the notion of some anthropogenic influence on the observed track density changes.

In another modeling study, Oey and Chou (2016) explored multidecadal changes of historical storm surge events for the region by simulating surge events, driving an ocean model with observed estimated wind forcing from TCs in the WNP basin. They infer an increase in the intensity of simulated surges since 1950 and a poleward shift of the latitude of intense surge events since about 1980. However, the linkage of these changes to anthropogenic forcing was done only in relatively general terms, and they did not estimate this effect through direct climate forcing experiment nor demonstrate that the changes were outside the range of natural variability.

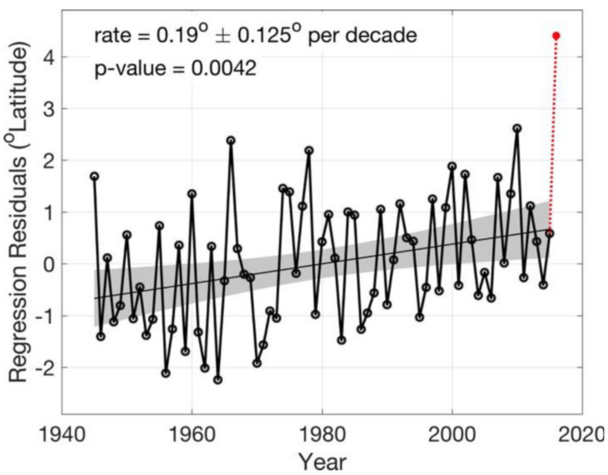

Figure 3.1 Average (July-November) latitude of tropical cyclones in the WNP at the time of their maximum intensity based on surface winds. Shown is the residual time series obtained after regressing the original time series onto the Pacific Decadal Oscillation and El Nino/Southern Oscillation indices and then removing those components from the time series. The trend statistics in the panel include the rate of poleward migration (degrees latitude per decade) and two-sided 95% confidence intervals for the trend. The p-value indicates the statistical significance of the trend based on a calculation that does not include the large positive outlier for 2016 (red) which would make the trend more significant. From Kossin (2018b), licensed under CC BY 4.0

We conclude that from a Type I error perspective, that there is *low-to-medium confidence* that the observed poleward migration of the WNP basin

LLMI is detectable compared with the significant natural variability of TC activity in this basin. However, because the simulated change in the CMIP5 historical runs is not statistically significant, we have only *low confidence* that the observed change has a positive anthropogenic contribution.

Alternatively, from a Type II error perspective, where we are attempting to reduce cases of overlooked detection or anthropogenic influence, we find that the balance of evidence suggests that the observed poleward migration of latitude of maximum TC intensity in the WNP basin is both detectable and that it has a positive contribution from anthropogenic forcing.

b) Case Study: Landfalling TC trends

A relatively long record of landfalling TC activity is the century-scale time series of TC landfalls for Japan, extending back to 1901 (Fig. 2 from Kumazawa et al. 2016). This time series shows no prominent trend since 1901. Similarly the (shorter) available landfalling time series from a number of other subregions of the Typhoon Committee region generally do not show consistent pronounced increasing trends but a mixture of different changes (e.g., Lee et al. 2012). For example, there is a statistically significant increase for the Korean peninsula, but most of the other regional TC landfalling series in Lee et al. (2012) show no change or decreasing trends. To date no study has made a clear demonstration that any observed landfalling TC trends in the region are unusual compared to natural variability. Given this lack of detectable trends and the finding from Kossin et al. (2016) of a lack of statistically significant poleward displacement of TCs in the basin in the CMIP5 historical runs, we conclude there is no strong evidence to indicate a detectable anthropogenic influence on landfalling TC frequency to date in the Typhoon Committee region.

c) Case Study: Event attribution for supertyphoon Haiyan (2013)

Event attribution studies can examine individual TC events for evidence of anthropogenic influence—either on the probability of occurrence of an event beyond some threshold value or on the intensity of an observed event. As discussed in a U.S. National Academy of Sciences (NAS) 2016 report, one approach is to use an “ingredients-based” methodology, re-simulating an event using a model (e.g., a TC forecast model), but altering the large-scale environmental conditions (e.g., sea surface temperatures and atmospheric temperatures) based on an estimate of pre-industrial-to-current anthropogenic climate change.

Takayabu et al. (2015) used this approach to re-simulate supertyphoon Haiyan’s (Philippines, 2013) intensity, using an estimated anthropogenic SST change signal characterized by relatively strong SST warming near the Philippines, with atmospheric boundary conditions from a lower resolution global model, and using a very high resolution (~2 km grid) nested regional model. They found that the imposed anthropogenic changes to the environment strengthened the present-day storm compared to the pre-industrial version of the storm. On the other hand, Wehner et al. (2018) simulated a decreasing anthropogenic influence on Haiyan’s intensity. They used a lower resolution model—a global domain, with grid spacing locally as fine as 8 km in the WNP. They also used a different method of estimating the anthropogenic changes to the environment (climate model simulation with historical forcing vs. the Takayabu approach of using a linear trend obtained from the HadISST reconstructed historical SST data). These ingredients-based studies assume the existence of a particular storm and synoptic situation and thus do not address whether anthropogenic forcing altered the storm’s probability of occurrence. The Takayabu et al. study does not incorporate possible anthropogenic influence on circulation features that could affect the storm’s track (steering flow) or intensity changes (via environmental wind shear), whereas these circulation change influences are included in the Wehner et al. approach.

These event attribution studies do not attempt to provide evidence for an observed change in TC activity being detectable (i.e., an observed climate change signal TC intensity in the region that is highly unusual compared to natural variability alone). Therefore, in the above studies, any cases of inferred anthropogenic attribution are examples of attribution without detection.

From the perspective of avoiding Type II errors, we conclude that the evidence from available studies is divided on whether anthropogenic forcing contributed to the intensity of supertyphoon Haiyan in the WNP.

d) Case Study: Event attribution for recent anomalous TC seasonal activity

Event attribution studies can examine groups of events (e.g., individual TC seasons or even groups of seasons) for evidence of anthropogenic influence—either on the probability of occurrence of a number of events beyond some threshold value or on the total number of events in the season. Model simulations of pre-industrial-to-current anthropogenic climate change can be used to re-simulate entire seasons or multiple seasons of activity under pre-industrial vs. modern day conditions.

Analyzing the causes of the unusually active WNP TC season of 2015 using model simulations, Zhang et al. (2016) infer an anthropogenic contribution to high Accumulated Cyclone Energy (ACE) in the basin in that season. Using a purely statistical approach, Yang et al. (2018) infer a contribution of global warming to record-setting (1984-2015) TC intensity in the WNP in 2015.

The above studies are examples of event attribution studies. Neither of these studies provides convincing evidence that an observed change in TC activity in the WNP is detectable (i.e., an observed climate change signal that is highly unusual compared to natural variability alone). Therefore, in the above studies, any cases of inferred anthropogenic attribution are examples of attribution without detection. The Yang et al. study uses global temperature as a statistical predictor, rather than estimating an anthropogenic contribution from climate model simulation.

From the perspective of avoiding Type II errors, we conclude that the balance of evidence suggests an anthropogenic contribution to the highly active 2015 WNP TC season. We do not conclude that the observed changes are detectable, or unusual compared to natural variability, based on the balance of available evidence.

e) Case Study: Increase in proportion of Category 4-5 TCs

Holland and Bruyère (2014) analyzed changes in TC frequency for various storm categories, assessing IBTrACS/JTWC intensity data and a shorter homogenized satellite-based intensity data (Kossin et al. 2013). From the satellite-based data, they conclude that the global proportion of hurricanes reaching Category 4 or 5 intensity has increased by 25-30% per degree Celsius of global warming in recent decades. They found a similar those weaker trend signal using Kossin's (2013) shorter--but homogenized--global satellite TC intensity record.

Their globally focused analysis contains some information on the WNP basin. Using the JTWC data without correction other than a conversion to 10-minute mean windspeeds, they find a statistically significant positive trend in category 4-5 proportion for the WNP using data from 1975 to 2010. However, they did not report results for the WNP using the shorter, homogenized ADT-HURSAT (Kossin 2013) satellite-based record. For landfalling TCs globally, they find a statistically significant increase in category 4-5 proportions based on the data of Weinkle et al. (2012), but they reported only a weak, negative trend in this metric for the WNP, which they attributed to a shift in recent decades of the main genesis location in the basin toward the equator and eastward.

The potential importance of data homogeneity for this problem was noted by Klotzbach and Landsea (2015). Their trend analysis of category 4-5 percentages used JTWC data for the years 1970-2014. Their results for the WNP indicate statistically significant increasing trend for 1970-2014, but not for 1970-2004 or for 1990-2014. They recommend that global trend studies begin around 1990 owing to data homogeneity concerns (which presumably refers to the JTWC data, but not necessarily to the satellite-based data of Kossin (2013).

These analysis did not compare the observed trends to expected internal climate variability on various multi-decadal timescales from climate model control runs. Holland and Bruyere's linkage to anthropogenic forcing as a mechanism is statistical in nature as there is no explicit comparison between observed storm metrics and those derived from simulations using historical forcings. They inferred that the observed increase may be reaching a saturation point soon and may not continue increasing over the coming century, which would hinder its detectability, although they noted that this saturation point may be higher for the WNP basin than other basins.

Considering this evidence from a WNP focus and from a Type I error perspective, we conclude that there is only low confidence in detection of any anthropogenic climate change signal in historical proportion of category 4-5 TCs in the WNP. Alternatively, from the perspective of reducing Type II errors (where we require less convincing levels of evidence), the studies of Holland and Bruyère (2014) and Klotzbach and Landsea (2015) provide conflicting interpretations for the WNP, and neither study presented clear evidence of a detectable trend there using the shorter, homogenized satellite-based intensity record of Kossin (2013). Therefore, we do not conclude that the balance of evidence supports the notion of a detectable increase in the proportion of Category 4-5 storms in the WNP, nor of an anthropogenic forcing influence on this proportion.

f) Case Study: Slowdown of TC translation speeds

Kossin (2018a) found a statistically significant decreasing trend in TC translation speed over the WNP over 1949-2016—a change seen in a number of other basins, but which was especially pronounced over land regions near the WNP (21% decrease). However, follow-on analyses by Moon et al. (2019), Lanzante (2019) suggest that the observed global trend reported by Kossin (2018a) may be influenced by changes in observing capabilities over time, casting some doubt on the robustness of the reported global trends, which we infer likely applies in the case of reported trends in the WNP since 1949 as well. A previous study by Chu et al. (2012) had also found a statistically significant decline in TC translation speeds (1958-2009) in the WNP and South China Sea regions, accompanied by a decrease in steering flows. Based on the available studies we assess the confidence in a decreasing trend in observed TC translation speed in the WNP as low. There are very few modeling studies of anthropogenic influence on TC propagation speeds in the WNP (e.g., Kim et al. 2014), and none in historical simulation mode, and so we conclude that it is premature to ascribe these observed changes to anthropogenic influence.

Altman et al. (2013) reported very strong century-scale increases in typhoon-related rainfall rates over Korea during 1904-2008, although their study does not present enough methodology details for a careful assessment. Kim et al. (2006) had previously reported large increases in TC-related rainfall rates in Korea beginning around 1980, based on a shorter record extending back to 1954. These changes in TC rainfall could be related to the observed changes in TC propagation speed, since slower-moving TCs would drop more precipitation on given locations.

In summary, from a Type I error avoidance perspective, we have *low confidence* that there has been a detectable decrease in WNP TC translation speeds since 1949 or that anthropogenic forcing has contributed to the observed decrease. Alternatively, from the perspective of reducing Type II errors, the balance of evidence is inconclusive on whether there has been a detectable decrease in TC translation speeds over land regions near the WNP since 1949, nor is there a balance of evidence that anthropogenic forcing contributed to such an observed decrease.

g) Case Study: TC frequency changes

Analyses of time series of TC frequency in the WNP were presented in Ch. 2 for both tropical storms and storms of typhoon intensity. These analyses show some evidence for statistically significant decreasing trends, but the results are dependent on the dataset used and the period examined. The longest records examined (from JTWC, extending back to 1945) show no statistically significant trends in either tropical storms or typhoons. Zhao et al. (2018a) conclude that internal variability (the Interdecadal Pacific Oscillation) contributed to the lower TC frequency observed in the WNP basin after 1998.

We conclude that there is no substantial evidence for a detectable anthropogenic influence on tropical storm or typhoon frequency in the WNP.

h) Case Study: TC intensity changes

The question of whether there has been any detectable anthropogenic influence TC intensities in the basin can be characterized in terms of two issues: whether the data are reliable enough for trend analysis, and if a trend is found, whether the trend can distinguished from natural variability and can any changes be causally attributed to anthropogenic forcing.

Trend analyses of past change in TC intensity in the WNP (Ch. 2) have produced conflicting results. Some studies have reported increasing trends of intensity and related metrics: including increased TC intensity since 1984 (Kang and Elsner 2012), increased intensity and intensification rates since the 1970s (Mei et al. 2015), increased number of very intense (category 4 and 5) typhoons since 1965, with a change-point in 1987, based on adjusted TC data (Zhao and Wu 2014), and increased intensification rates from tropical storm to typhoon stage during 1986-2010 (Kishtawal et al. 2012). These studies were based on use of the conventional best track intensity data, in some cases with adjustments for homogeneity issues. Significant problems with historical records of TC intensity in the basin were noted by Knapp et al. (2013), based on analysis of central pressure data, and they particularly noted low confidence with wind-based estimates in older parts of the best track data. To address the data homogeneity problems using objective intensity estimation from satellite data, Kossin et al. (2013) analyzed intensities using both best track data (IBTrACS) and the ADT-HURSAT satellite-based record over 1982 -2009. Statistically significant increases were found for some quantiles of the data in the best track data, but these were not supported in the ADT-HURSAT data, which had some negative trends at higher quantiles.

Clearly there are data quality issues to be addressed with intensity data in the basin, and trend results will depend on the nature and quality of adjustments made to the data to attempt to correct for time-dependent biases which can introduce spurious trends. In addition to these data concerns, while a number of the above studies link intensity changes to surface temperature metrics, there are not clear demonstrations in the published studies that observed trends in TC behavior are outside the range of expected natural variability in the basin, or that the observed changes have been caused by anthropogenic forcing. For example, changes in the proportion of TCs in the basin undergoing rapid intensification was observed to increase, beginning in 1998, but this change was linked to decadal changes in large-scale atmosphere-ocean conditions, and was not linked to anthropogenic forcings (Zhao et al. 2018c).

Concerning landfalling TC intensity, Mei and Xie (2016) found increased intensity and intensification rates of landfalling typhoons since the 1970s. They estimate that landfalling typhoons that strike East and Southeast Asia have intensified by 12–15% over the past 37 years, which they attributed to locally enhanced surface warming. While data quality issues for landfalling TCs are presumably not as severe as for the basin-wide data, their study links the intensity changes to surface warming but does not claim to have detected an anthropogenic climate change signal.
In summary, we conclude that there is not a balance of evidence to support the notion of a detectable anthropogenic influence on TC intensities in the basin.

i) Case Study: Spatial variations in TC activity within the WNP basin

In addition to the poleward shift of the latitude of maximum intensity discussed above, other examples of spatially varying trends in TC activity have been documented for the WNP basin. These are discussed in Ch. 2. Among these changes are a spatially varying pattern of TC intensity trend (Park et al. 2013) with weakening over an oceanic region east of the Philippines an increases further north (Figure 2.5); TC occurrence changes with a northwestward shift of TC occurrence after the mid-1990s (Fig. 2.8, adapted from Kossin et al. 2016); and a northwestward shift in TC tracks over the period 1977-2013 (e.g. Zhao and Wu 2014; and Figs. 2.6 and 2.7, adapted from Mie and Xie 2016). The changes have produced a decreased TC exposure in the Philippines and South China Sea, including the Marianas, Philippines, Viet Nam, southern China; and increased TC exposure in the East China Sea, including Japan, Republic or Korea, and parts of East China (see also He et al. 2015; Li et al. 2017, Zhao et al. 2018b).

There is not yet compelling evidence linking such changes to anthropogenic forcing nor a demonstration that the observed changes are unusual compared to expected natural variability. The analysis of Kossin et al. (2016) provides some evidence of climate change detection and weak evidence of anthropogenic influence, but their analysis focused mainly on the poleward migration of the latitude of maximum intensity. Oey and Chou (2016) attribute the shift in TC occurrence in the basin in recent decades to a weakening of easterly steering flows, while Liang et al. (2017) attribute it to a weakening and eastward shift of the subtropical high. However, these circulation changes were not shown to be distinct from natural variability or to be caused by anthropogenic forcing. In one modeling study of potential anthropogenic influence on decadal TC variations in the basin, Takahashi et al. (2017) inferred that changes in sulfate aerosol emissions caused more than half of the observed decline in TC frequency in the southeastern part of the WNP during 1992-2011. However, given the high degree of uncertainty in modeling aerosol influence on climate (e.g., Malavelle et al. 2017), more studies of this phenomena are needed, including an exploration of the model dependence of results, before firmer conclusions can be made.

We conclude that for the examples of spatial variation of TC activity discussed above and in Chapter 2, there is not sufficient evidence to conclude that the changes are either unusual compared to natural variability or that they contain a substantial anthropogenic contribution.

j) Case Study: TC rainfall changes

Observational studies of TC rainfall changes in the WNP are reviewed in Section 2.5. Some examples of statistically significant trends in some TC rainfall-related metrics are given. However, some of the observed changes are relatively regional in scale (e.g., Tu and Chou 2013; Li et al. 2015; Nguyen-Thi et al. 2012) and appear related to such factors as tropical cyclone frequency (i.e., more/fewer TCs in a region leading to more/less TC-related rainfall (Zhang et al. 2013)), or regional slowing of TC propagation speeds (Tu and Chou 2013), and in some cases TC rainfall intensity (Li and Zhou 2015). Lau and Zhou (2012) reported a reduction in rainfall energy per storm over the WNP for 1998-2007 compared to 1988-1997 using Tropical Rainfall Measurement Mission (TRMM) and Global Precipitation Climatology Project (GPCP) datasets, but noted that the relatively short data record length and other limitations of the rainfall data prevented their making any definitive conclusions about long-term changes in TC rain rates.

The influence of multiple factors on TC precipitation can confuse the interpretation or attribution of such changes in a climate change context (Chang et al. 2012). Trends over relatively short periods may well have predominant natural variability components that need to be distinguished from any anthropogenic influence (e.g., Bagtasa 2017). While some statistically significant trends were noted in the above studies, none of the observational studies of TC rainfall reviewed in Section 2.5 provide clear evidence for observed changes (e.g., long-term trends) in TC-precipitation metrics that are detectable, or highly unusual compared to expected levels of natural variability. Possible influence of decadal to multidecadal variability of likely natural origin (e.g., the Pacific Decadal Oscillation, or Interdecadal Pacific Oscillation) on the observed trends has not been explicitly addressed.

Additionally, most studies show mixtures of results across stations, and it remains unclear whether the fraction of stations passing certain significance thresholds exceeds the fraction expected by chance (i.e., field significance). Wang et al. (2015b) suggest that anthropogenic warming has probably contributed to increased precipitation and TC activity over central Vietnam since 1970, but this was not an attribution conclusion based on quantitative (modeling) analysis.

In addition to limitations of linear trend analysis and available datasets, another complication with detection and attribution with regard to TC rainfall changes is that such changes can be influenced by a large number of factors, including: changes in track or frequency of occurrence of TCs altering total TC rainfall in a region; changes in size or propagation speed of TCs affecting accumulated rainfall in given locations; changes in storm duration affecting storm-total precipitation; and changes in the average rainfall rate out of a TC, which considers the flux of precipitation, averaged over some region, in a coordinate system that moves along with the storm. We note that it is the latter type of change (TC rainfall rate in the storm-relative context) that climate models and downscaling studies are projecting will likely increase with global warming (e.g., Knutson et al. 2010; Knutson et al. 2015) since there are changes in this Lagrangian precipitation rate that are most closely related to the higher water vapor content of air in a warmer climate.

Concerning modeling studies, Wang et al. (2015a) examined the water budget of two landfalling typhoons on Taiwan using cloud-resolving model simulation case studies. They artificially modified the large-scale environment to reflect the long-time-scale change in the region between 1950–69 and 1990-2009, based on reanalysis data. They showed that in the slightly cooler and drier conditions of the 1950-1969, the TC precipitation rates were slower, due mainly to reduced atmospheric moisture content. This study quantitatively demonstrated the importance of the increased water vapor content for producing enhanced precipitation rates in typhoons under warmer climate conditions. However, since the changes between the two time periods they studied must be considered as some combination of anthropogenic and natural changes, their study does not constitute an anthropogenic forcing attribution study.

We conclude that for TC rainfall rates in the basin, there is not sufficient evidence or a balance of evidence to conclude that any observed changes or trends are either unusual compared to natural variability or that they contain a substantial anthropogenic contribution.

3.3 Summary

In summary, using the conventional perspective of avoiding Type I error (i.e., avoiding overstating anthropogenic influence), the strongest case for a detectable change in TC activity in the WNP is the observed poleward migration of the latitude of lifetime maximum intensity (LLMI). There is *low-to-medium confidence* that the observed poleward migration of the WNP basin LLMI is detectable compared with the significant natural variability of TC activity in this basin. However, there is only *low confidence* that anthropogenic forcing had contributed to this poleward shift. There is *low confidence* that any other observed TC change in the WNP is either detectable or attributable to anthropogenic forcing.

From the perspective of reducing Type II errors (i.e., avoiding understating anthropogenic influence), a number of further tentative TC detection and/or attribution statements can be made. We caution that these may have potential for being false alarms (i.e., overstating anthropogenic influence), but they nonetheless may be useful indicators of evolving risk. With this caveat, the balance of evidence suggests: i) detectable anthropogenic contributions to the poleward migration of the latitude of maximum intensity in the WNP; and ii) an anthropogenic influence (but without detection) on the unusually active TC season in the WNP in 2015

While we are not aware that any TC climate change signal has been convincingly detected to date in sea level extremes data in the WNP basin, a widespread worsening of storm surge levels is believed to be occurring due to sea level rise associated with anthropogenic warming, assuming all other factors equal.

There are a number of reasons for the relatively low confidence in detection and attribution of TC changes in the basin. These include data homogeneity concerns (observation limitations), the small signal to noise ratio for expected anthropogenic changes, and uncertainties in estimating background natural variability levels and the response of TC activity to historical forcing agents, including greenhouse gases and aerosols. Concerning the forced response, it is possible that past aerosol forcing has offset much of the influence of greenhouse gas warming on TC intensities to date, yet aerosol forcing is not be likely to continue to offset this influence during the coming century (e.g., Sobel et al. 2016). We strongly recommend continued monitoring of various TC metrics in the basin for signs of emerging anthropogenic influence.

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CHAPTER 4

Tropical cyclone impacts in the Typhoon Committee region

4.1 Climatological mean features of tropical cyclones (TCs)

The typhoon committee region is composed of the 14 member nations encompassing a variety of climates. Therefore, features of TC impact vary between member nations. For the present report, our expert team conducted a survey in 2016 to 2018 to obtain observed information about regional features of TCs and their impacts from each member nation and/or region. This chapter will summarize the survey and list the survey data in Tables A1 – A3 of the Appendix. In addition to the survey, this chapter reviews new findings on TC impacts in the literature since the Team's second assessment report. The term "tropical cyclone" (TC) can be used to refer to storms of different intensity ranges in different contexts/literature, and the definition can include tropical depressions, tropical storms, severe tropical storms, and typhoons. In this chapter, we generally use TC to refer to cyclones originating over tropical ocean regions including all intensity classes (i.e., including tropical depressions). However, elsewhere in the report, TC will refer to TCs of at least tropical storm (TS) intensity. Definitions of TC different from these conventions will be explicitly noted.

4.2 Frequency and intensity of landfalling and affecting tropical cyclones

4.2.1 Climatology of landfalling/affecting TCs

The climatological mean annual frequency of TC genesis in the WNP for the period of 1971 to 2010 is 25.6, while that of previous three decades is 26.7. Although the 14 member nations share this value, the number of landfalling/affecting TCs varies by nation. The climatological mean numbers of TCs/typhoons landfalling in and affecting each member nation of the Typhoon Committee are summarized in Table A1. The definitions of landfalling and affecting are also listed in Table A2.

China climatologically experiences 9 landfalling TCs each year, the most by any of the 14 Members. The Philippines follows China as the second highest with about 7 to 8 per year (Table A1). TCs with TS intensity or above make landfall in Japan 2.7 times per year. There was about 0.8 landfalling TCs (maximum winds of 17.2 ms^{-1} or above) in Republic of Korea per year. There are about 6.2 TCs and 2.3 typhoons annually affecting within 500 km for Hong Kong, China. There are about 1.0 TCs annually with TS or above intensity necessitating the issue of TC Signal No.8 in Macao (see Table A2) and 0.6 landfalling typhoons. TCs make landfall in Thailand 3 times per year. Singapore does not experience direct effects of TCs but can experience indirect effects, depending on the location of the cyclone such as TS Vami in 2001. According to the second assessment (Lee et al., 2012), there are about 1 to 2 landfalling TCs in Vietnam annually. There are about 18 to 20 TCs annually affecting the area of responsibility of Guam (Eq.−25˚N, 130˚E−180˚E).

4.2.2 Frequency and intensity of landfalling/affecting TCs

This subsection focuses on the frequency and intensity of landfalling/affecting TCs. Recent literature and the results from our survey of member nations are described.

China

Trends in the numbers of TCs and typhoons landfalling in China are not statistically significant (Fig. 4.1), although a nominal decreasing trend in the number of landfalling TCs is observed (Yang et al. 2009).

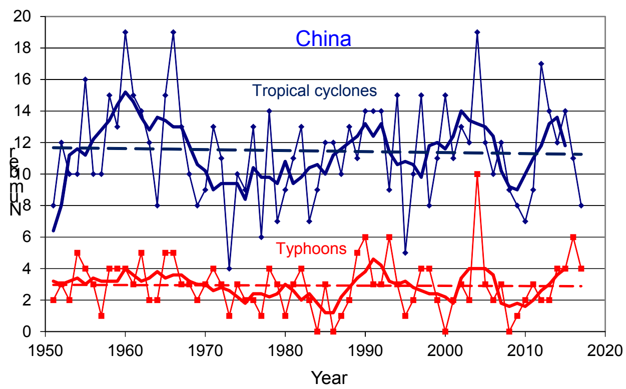


Figure 4.1 Annual number of TCs (blue) and typhoons (red) landfalling in China (1949-2017). The solid, thick and dashed lines represent the annual number, 5-year running mean and linear trend, respectively. (Courtesy of CMA).

Park et al. (2013) reported that geographical distribution of TCs moved to East Asian coastlines from Vietnam to Japan in recent decades, and the TC landfall intensity over east China, Korea, and Japan has significantly increased. In contrast, insignificant trends are observed across south China, Taiwan, and Vietnam (see Figure 2.3).

Kossin et al. (2014) identify a pronounced poleward migration in the average latitude at which TCs achieved their lifetime-maximum intensity (LMI) over the past 30 years (see Figure 2.2). This past poleward migration of the latitude of peak TC intensity in the WNP has coincided with decreased TC exposure in the region of the South China Seas and southern China, and increased exposure in the region of the East China Sea and parts of eastern China. Such a migration, if it continues, is expected to cause systematic changes, both increases and decreases, in regional hazard exposure and risk (Kossin et al. 2016; see Fig. 2.5).

Mei and Xie (2016) divided WNP typhoons into 4 cluster groups. Typhoons in the dominant cluster constituted around 34% of the WNP; these travel northwestwards-to-northwards, and roughly 75% of them make landfall over East Asia (north of ~22˚N; including eastern mainland China, Taiwan, Korean Peninsula and Japan) after forming east of the Philippines (see Figure 2.4). According to the best track data, the annual mean values of their lifetime peak intensity have risen by ~8ms^{-1} (~15%) during 1977-2013, the largest increase among the four groups.

Li et al. (2017) found that TCs making landfall over east China have intensified in recent decades, and the power dissipation index (PD) of the TCs after landfall has significantly increased. The increase in the PDI of landfalling TCs over East China is associated with a concomitant increase in landfall frequency as well as increased landfall intensity over east China.

Hong Kong, China and Macau, China

The time-series of the number of TCs and typhoons within a 500-km radius of Hong Kong both show a decreasing but not statistically significant trend during 1961-2018 (Figure 4.2), and there is no statistically significant trend for TCs coming within 300-km range of Hong Kong, China. There are also no statistically significant trends in the number of TCs (TS or above) affecting Macao, China (Figure 4.3).

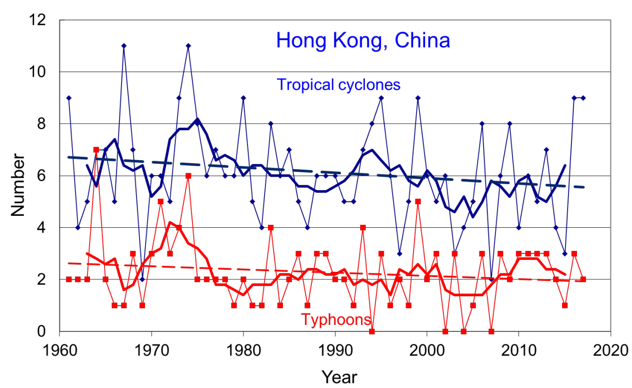


Figure 4.2 Annual number of TCs (blue) and typhoons (red) come within 500 km range of Hong Kong, China (1961-2018). The solid, thick and dashed lines represent the annual number, 5-year running mean and linear trend, respectively. (Courtesy of HKO)

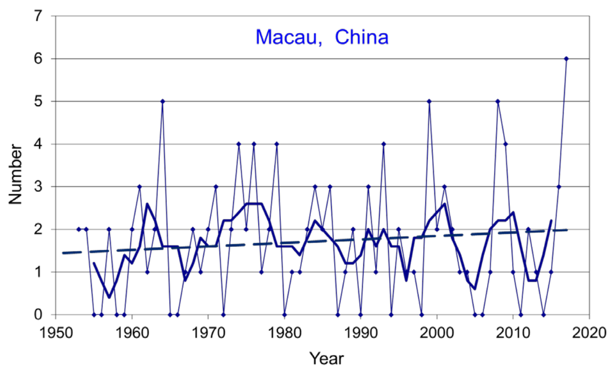


Figure 4.3 Annual number of TCs (blue) (TS or above) necessitating the issuance of Tropical Cyclone No.8 in Macau, China (1953-2017). The solid, thick and dashed lines represent the annual number, 5-year running mean and linear trend respectively. (Courtesy of SMG)

Japan

There is no statistically significant trend in the time series of TCs that approaching with 300 km of Japan or make landfall (Figure 4.4), although decadal and multi-decadal variations are seen. Longer-term analysis also shows no apparent trend over 115 years from 1900 to 2014 (Kumazawa et al. 2016). The record-breaking number of TC landfalls (10) in 2004 is more than three times the climatological mean annual number of 2.7 (JMA 2018). One possible cause of that anomalous number in 2004 was the persistence of favorable conditions related to three active phases of the Madden and Julian Oscillation during June-October that year (Nakazawa 2006).

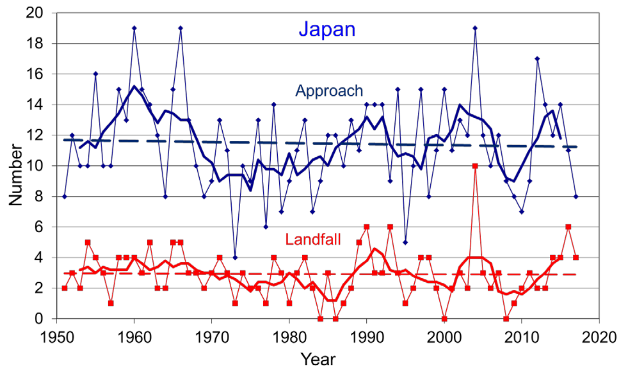


Figure 4.4 The number of TCs with maximum winds of 17.2 m s^{-1} or above that approached Japan (blue) and those making landfall in Japan (red) from 1951 to 2017. The solid, thick and dashed lines represent the annual number, 5-yr running mean and linear trend respectively. (Courtesy of JMA)

Grossman et al. (2015) demonstrated that fewer typhoons approached the area around the four main islands of Japan during 1951-2011 when the North Pacific subtropical high was extended to the west. In contrast, more typhoons approach Japan when it extends to the northwest. The winds around the North Pacific subtropical high modulate the recurvature of the typhoons, affecting storm tracks near Japan.

Republic of Korea

The numbers of TCs with maximum winds of 17.2 ms^{-1} or above affecting and landfalling in Republic of Korea have no long-term trends over 42 years from 1977 to 2018 (Fig. 4.5). While there were no very high impact landfalling or affecting typhoons from 2013 to 2017. The year 2018 was a highly active year, with five typhoons affecting Republic of Korea and two landfalling typhoons.

The number of strong typhoons with maximum speeds of greater than 44 m s^{-1} was significantly increased for the 10-year period from 2001 to 2010, although the total number of TCs existing near Republic of Korea was insignificantly reduced (Cha et al. 2014). Three major factors for the changes include the following. First, the mean genesis region of TCs influencing Republic of Korea was displaced eastward. Second, the North Pacific subtropical high and Asia Monsoon trough were extended to the northwest and southeast. Third, the TCs do not make a landfall until they approach the Korean Peninsula. The reported increased number of strong typhoons occurs only for this period, and the number has returned to the climatological value over the 42 year period for the most recent eight years (Cha and Shin, 2019).

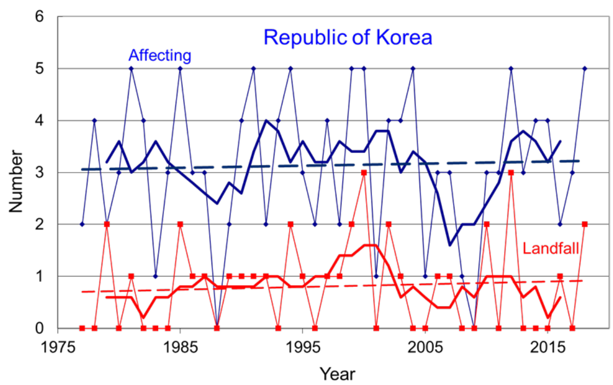


Figure 4.5 The number of TCs with maximum winds of 17 ms^{-1} or above that approached Republic of Korea (blue) and those making landfall in Republic of Korea (red) from 1977 to 2018. The solid, thick and dashed lines represent the annual number, 5-yr running mean and linear trend respectively. (Courtesy of KMA)

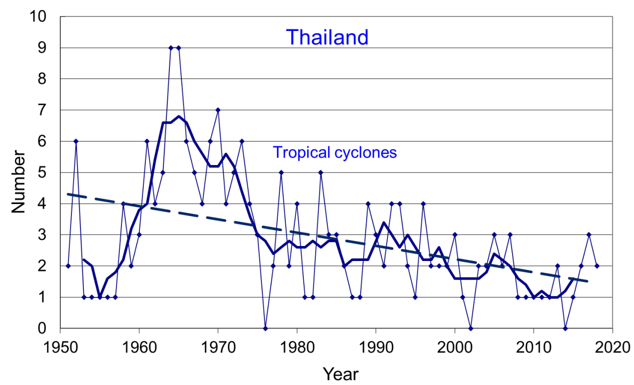


Figure 4.6 The number of TCs (including TDs) making landfall in Thailand (blue) from 1951 to 2017. The solid, thick and dashed lines represent the annual number, 5-yr running mean and linear trend respectively. (Courtesy of TMD)

On a decadal time scale, there was a significant difference in TC behavior in the region, comparing 1965-1983 and 1983-2004. More TCs migrated toward the west for the latter period (1984-2004), recurved in the southwest, and affected Republic of Korea, compared to the former period of 1965-1983 (Choi and Cha 2015). This stronger intensity of TCs affecting Korea for the latter period was related to the more southwestward genesis due to the southwestward expansion of the Subtropical western Pacific high. Weaker environmental vertical wind shear during the latter period was more favorable for TCs affecting Korea to maintain a strong intensity in the mid-latitudes of East Asia. The increased number of strong typhoons in the 2000s (Cha et al. 2014) mentioned above may be an instance of internal decadal variability but has not yet been investigated.

Thailand

The frequency of TCs (most of which are tropical depressions) entering Thailand westward through Vietnam has statistically significant decreased after the mid-1960 (Fig. 4.6). However, the high frequency of TCs during 1960 to 1975 is considered to be a decadal variation. In contrast, the annual number of TCs of tropical storm intensity or above has a slight increase (Ying et al. 2012).

The Philippines and Vietnam

The reported frequency of TCs landfalling in/crossing the Philippines shows no significant trend for the period 1948-2010. The reported number of typhoons landfalling in/crossing the Philippines shows a significant decrease since 1948, although a decadal variation of the number is seen. Cinco et al. (2016) also reported no significant trend in TC frequency and intensity in Area of Responsibility of the Philippines, and in landfalling TCs. A significant increase in TC landfall is identified only in the latitude range of 10˚N–12˚N among the 2-degree ranges of the east coast of the Philippines encompassing Leyte Island, suggesting that TC landfalling frequency may have increased at least in this area (Takagi and Esteban 2016).

An increase in TC genesis frequency over the northern part of the South China Sea leads to a reduction in the maximum TC intensity before landfall, because of their short lifetime; thus, there are no clear tendencies in the landfall intensity across Vietnam, south China and Taiwan (Park et al. 2014). Decreased exposure is observed in Vietnam as well as the Marianas, the Philippines, and southern China (Kossin et al. 2016).

An overview of observed TC activity and trends in the Typhoon Committee Region is given in Chapter 2, and the question of whether any changes in TC activity or characteristics are detectable and/or attributable to human-induced climate change is discussed in Chapter 3 for a series of WNP case studies.

4.3 Tropical cyclone induced precipitation

Zhao and Wang (2012) investigated the decadal variations of extreme TCs influencing China during 1949-2009 and demonstrated that the decade when the maximum daily TC-induced precipitation occurred varies with areas and eras. The duration of TC-induced precipitation varies with era. The dominant empirical mode of TC rainfall in southeast China during 1960-2009 consisted of a dipole pattern over southern southeast China and eastern southeast China, and the associated principal component time series exhibits interdecadal variations, with two potential change points being identified in the late 1970s and early 1990s (Li et al., 2015). These interdecadal shifts in TC rainfall are also found to be synchronous with two regime shifts in total rainfall, and they can account for more than 40% of the total rainfall anomalies over the coastal regions of southeast China. The average rainfall per TC has a statistically significant increase in Southeast China during 1965−2009. In the peak season (July−September), all significant changes are upward trends occurring south of the Yangtze River and east of 110°E (Zhang et al. 2013). The increasing rainfall per TC was found not to coincide with the enhanced TC intensity. In addition, no significant trend was found in the translation speed of TCs that affected China during 1965−2009, suggesting that the increasing TC rainfall per TC in China was not due to the slowdown of TC movement. Taiwan experienced a dramatic increase in typhoon-related rainfall in the beginning of the twenty-first century. Major factors include the occurrence of slow-moving TCs and their track locations relative to the meso-a-scale terrain (Chang et al. 2013). The typhoon rainfall shows a statistically significant increase for all intensities, while the non-typhoon rainfall exhibits a decreasing trend, particularly for lighter rain (Tu and Chou 2013). In rainfall intensity, both typhoon and non-typhoon rainfall extremes become more intense, with an increased rate much greater than the Clausius–Clapeyron thermal scaling.

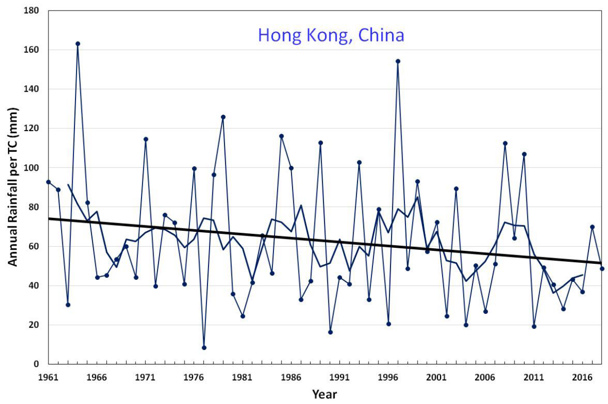


Figure 4.7 Annual rainfall per TC associated with TCs entering within a 500 km range of Hong Kong, China from 1961 to 2018. Thin line represents the year by year statistics, bold line represents its five year running mean, and the straight line represents its linear fit. The trend is not significant at the 5% level.

Li et al. (2015) investigated the influence of TC-induced rainfall on long-term rainfall variations in Hong Kong. Evaluations of the observed trends of different rainfall indices suggest that rainfall variability in Hong Kong is considerably affected by TC rainfall, which has a decreasing trend in frequency and intensity in recent decades. Removing the TC rainfall from the total rainfall reveals that there is an increasing trend in daily rainfall frequency and intensity for non-TC rainfall in Hong Kong. Moreover, time-dependent generalized extreme value analysis of non-TC rainfall also shows an increase in the return values of the maximum daily rainfall in Hong Kong. The annual rainfall per TC and annual maximum hourly rainfall entering within a 500 km range of Hong Kong from 1961 to 2017 has a slight decrease but without statistical significance at the 5% level (Fig. 4.7, Lee et al. 2012). In Macao, there is also no statistically significant trend in annual maximum precipitation per TC nor in mean total precipitation per TC (Fig. 4.8).

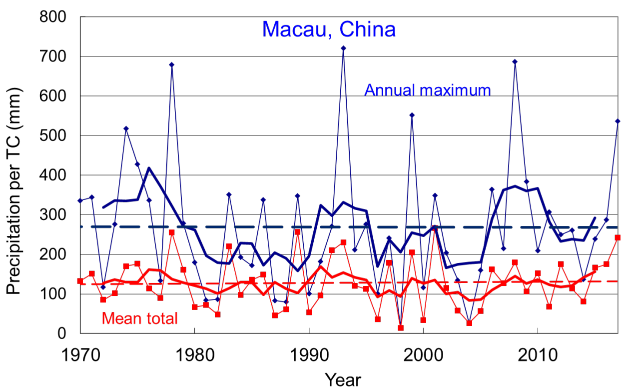


Figure 4.8 Annual maximum precipitation per TC (blue) and mean total rainfall (red) per TC in Macau, China from 1970 to 2017. Thin line represents the year by year values, bold line represents its five year running mean, and the straight line represents its linear fit. The trend is not significant at the 5% level. (Courtesy of SMG)

TC-induced one-day maximum precipitation shows a statistically significant increase in the Pacific Ocean east of Japan although it does not show a significant increase averaged over the entire Japanese region (Sato et al. 2012).

Four climatic subtypes in the Philippines, based on climatological monthly precipitation variation, have significant increasing trends in TC-induced annual precipitation-- 16.9%–19.3% decade^{-1} in TC rain percentage contribution during the recent 15 years (Bagtasa 2017). This trend is probably due to changes in TC steering mechanism and thermodynamic properties since 2000. One-day maximum precipitation shows a significant decrease in Philippines probably because TC-induced precipitation does so with insignificant change in tracks of TCs (Sato et al. 2012).

The interannual variation in precipitation over Indochina over a 33-yr period from 1979–2011 is analyzed from the view point of the role of westward-propagating TCs over the Asian monsoon region (Takahashi et al. 2015). Above-normal precipitation over Indochina occurred when enhanced cyclonic circulation with more westward-propagating TCs along the monsoon trough occurred.

Statistically significant increasing trends in TC rainfall amount (TCRA) and number of days with TC daily rainfall ≥50 mm (TC_R50) were observed at most stations along the central coastline of Vietnam during 1961-2008 (Nguyen-Thi et al. 2012). For a regional perspective, no statistically significant trends were identified in the region north of 20˚N, the region 17˚-20˚N, and south of 12˚N, while the significant increasing trend was found in the region 12˚-17˚N for both of TCRA and TC_R50. The results suggest that cause of the increasing trend in 12˚-17˚N region can be explained partly by TC rainfall, while the decreasing trend in the region north of 20˚N is due to Non-TC rainfall. A significant increase of TC rainfall was revealed during the 1990s in the 12˚-17˚N region.

A case study of the detection and attribution of TC-rainfall changes mentioned above is discussed in Subsection 3.2 j).

4.4 High winds

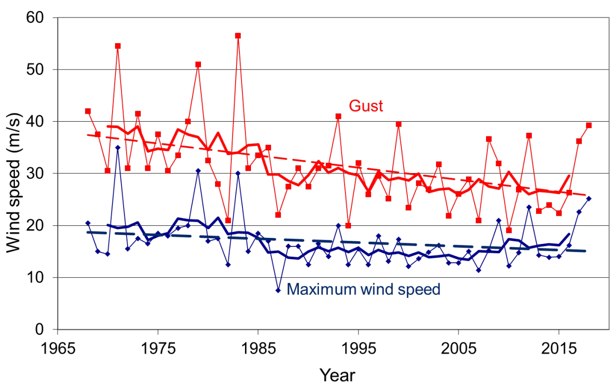
For mainland China, both the TC high wind with windspeeds ≥ 10.8 m s^{-1} (TCHW) frequency (intensity) and HW frequency (intensity) shows a statistically significant downward (weakening) trends after the 1980s. The proportion of HW events accounted for by TCHW decreased, although the trend was not statistically significant (Ni et al 2015). The extreme maximum wind in China had the highest frequency in the 2000s during the period of 1949−2009 (Zhao and Wang 2012).

In Hong Kong, China, TC-induced annual maximum 10-minute mean wind and maximum 1-sec gust as recorded at Waglan Island, an offshore island about 20 km southeast of Hong Kong Observatory Headquarters, have a slight decreasing trend which is not statistically significant (Fig. 4.9b). However, the maximum 10-minute wind at Kai Tak (an urban station) has a statistically significant decreasing trend from 1968 to 2018 (Fig. 4.9a). Based on computational fluid dynamics simulations, this decrease is likely attributed to continuous urban development and elevation in building heights (Peng et al. 2018) over the past few decades. Data from Macao, China show periodic changes on a decadal time scale but no statistically significant trends in either the annual maximum gust or hourly average maximum wind speed (Fig. 4.10).

Figure 4.11 illustrates a time series of the annual average of maximum wind speed of all TCs occurring in the emergency zone (EZ; 28-40°N, 120-132°E) from 1977 to 2018. The largest maximum speeds were seen in 1983, resulting from Typhoon Forrest. The typhoon intensities over the EZ vary by year and a distinct trend is not seen from a long-term perspective (Cha and Shin, 2019). However, Cha et al. (2014) found that the number of strong typhoons in Republic of Korea with maximum wind speeds exceeding 44 m s^{-1}, has a statistically significantly increased over the period 2001 to 2010. Park et al. (2014) reported an increase in landfall intensity over east China, Korea and Japan as well. Poleward migration of latitude of maximum intensity in the WNP is discussed in Subsection 3.2.a) as a case study.

Extreme TCs with high wind speeds in the Philippines have become slightly more frequent for the period of 1971–2013 (Cinco et al. 2016).

(a)



(b)

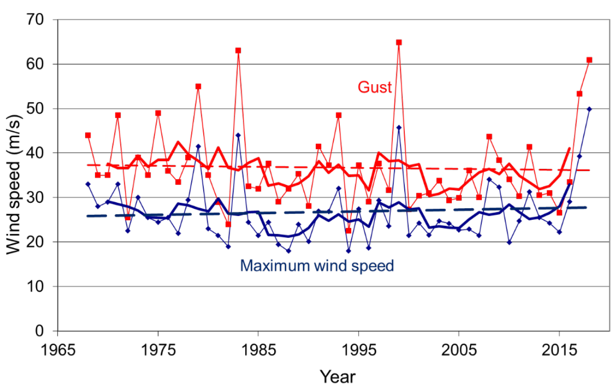


Figure 4.9 Annual maximum 10 minute mean wind speed and gust at (a) Kai Tak and (b) Waglan Island associated with TCs entering within a 500 km range of Hong Kong, China from 1961 to 2018. Thin lines represent the year by year statistics, bold lines represent five-year running means, and the straight lines represent linear fits. (Courtesy of HKO).

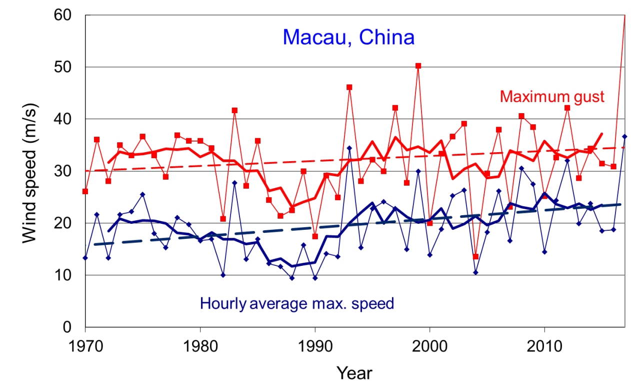


Figure 4.10 Annual maximum gust and hourly average maximum wind speed by TCs in Macao, China from 1970 to 2017. (Courtesy of SMG)

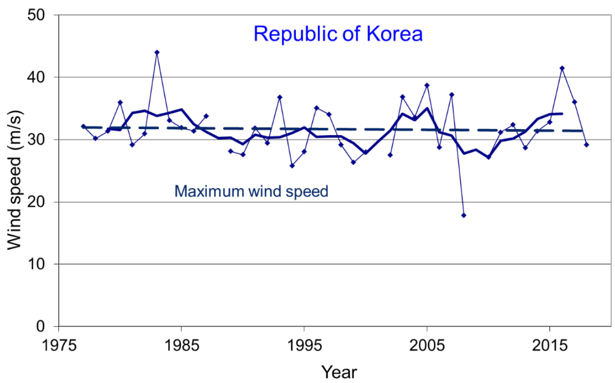


Figure 4.11 Maximum wind speeds during the lifetime of influential TCs over the emergency area (28-40˚N, 120-132˚E) during the 1977-2018 period. Only TCs with 10-min average maximum wind speed of 17 m/s or above at 6-h intervals (00, 06, 12, and 18 UTC) were extracted. The years of 1988 and 2009 were not affected by any TCs. Thus, they were left blank. (Courtesy of KMA).

4.5 Storm surge and extreme sea levels

Needham et al. (2015) comprehensively compiled global storm surge data sources, observations, and impacts, which are archived in the database SURGEDAT. The WNP observes the highest rate of low-magnitude surges, as the coast of China averages 54 surges (≥1 m) per decade, and rates are likely higher in the Philippines.

Muis et al. (2016) developed a global reanalysis of storm surges and extreme sea levels and showed the absolute and relative exposed population to a flood with 100-year return period for the 10 most exposed countries. Three out of the 14 Members of the Typhoon Committee are listed among the 10 most-exposed countries: China, Vietnam, and Japan. China alone accounts for half of the global total exposure.

TC-induced storm surges with 50-year return period (H_{50}) were developed from an 80-year dataset covering 1934 to 2013 (Hatada and Shirakami 2016). H_{50} estimated from the 30-year moving window shows no remarkable trend in the WNP including most of Japan.

4.6 Casualties and economic losses

Climatological annual mean damages due to tropical cyclones in China include 505 fatalities and 5.6 billion USD accounting for 0.4% of annual GDP. Although there was little change in the overall landfall frequency, landfall intensity and overland time, the annual total direct economic loss increased significantly presumably due to the rapid economic development over the past 25 years (Zhang et al. 2011). Chen et al. (2013) analyzed TC-induced damages for mainland China, including the deaths and missing, affected crop area, destroyed houses, and rate of direct economic loss. No clear trend in damage from individual TCs is found. The annual frequency of TCs causing heavy and catastrophic damage shows a clear decrease from 1984 to 2008 with no trend in the total number of damaging TCs.

In Hong Kong, China, with continuous investment and strengthening of infrastructure and disaster risk reduction measures in the city over the past 50 years, the casualties due to TCs have decreased distinctly since 1960s (Figure 4.12).

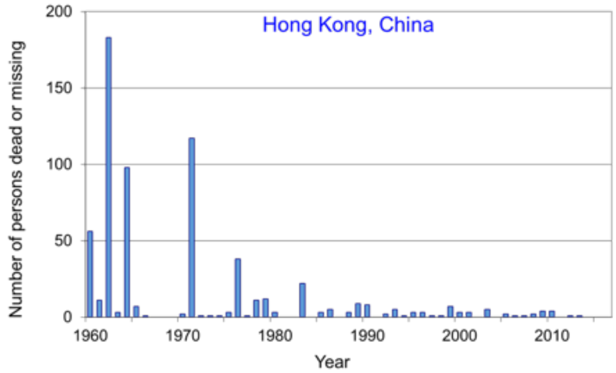


Figure 4.12 Number of dead or missing due to tropical cyclones in Hong Kong, China over the period 1960 to 2018. (Courtesy of HKO)

In Japan, the number of casualties due to TCs has a statistically significantly decrease over 90 years (Figure 4.13) as infrastructure countermeasures have been developed, especially since 1961. Ushiyama (2017) analyzed casualties caused by storms and floods including TCs in Japan for the period of 1968 to 2014. A statistically significant decrease in casualties was identified for the period. The trend remains the same even after 1980s, although the damage to houses caused by other influences besides storms and floods do not show a statistically significant decrease.

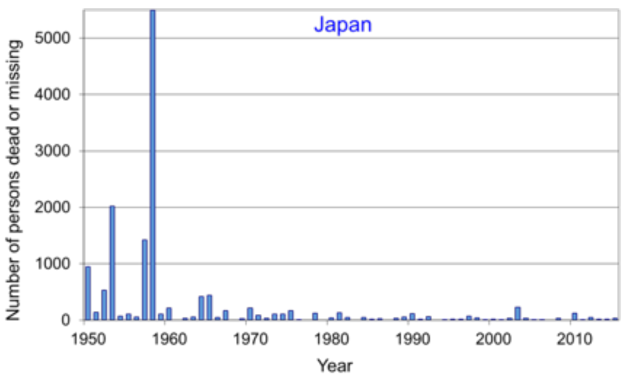


Figure 4.13 Number of dead or missing due to tropical cyclones in Japan from 1951 to 2017. (Data source: "White Paper on Disaster Management" published by the Cabinet Office of the Japanese Government)

In the Republic of Korea, Typhoon Thelma in 1987 caused 345 casualties, and Typhoon Rusa in 2002 caused record-breaking property damage for the period since 1900. However, there is a decreasing trend in typhoon-induced damage, including casualties and economic loss, since 2000 (Cha and Shin 2019).

Normalized cost of damages caused by TCs has increased in the Philippines since 1971 while there were no statistically significant trends reported in the frequency, intensity and landfall of TCs, (Cinco et al. 2016). Therefore, this increasing trend in the costs is presumably due to socio-economic factors such as land use practices, living standards and policy responses. Typhoon Haiyan in 2013 caused historic record-breaking damages with socio-economical cost of 2 billion USD due to a devastating storm surge (Lagmay et al. 2015), with the cost of damages reaching twice the level of the second largest damage event in the historical record. A large number of TC fatalities occur in neglected low income regions such as those destroyed by Super Typhoon Haiyan, as inferred from an examination of 40-years of Australian tropical cyclone reports (Seo 2014).

4.7 Summary

4.7.1 Frequency and intensity of landfalling and affecting tropical cyclones

Frequencies of both landfalling and affecting TCs show no significant trends for China, the vicinity of Hong Kong, China and Macau, China, Japan (TC or above), the Philippines, and the Korean Peninsula.

The intensities of TCs landfalling over east China and Japan have significantly increased, but those for Vietnam, south China, Taiwan, and the Philippines, have not changed significantly. This regional contrast is consistent with the pronounced poleward migration in the average latitude where the TCs have reached their lifetime maximum intensity.

4.7.2 Tropical cyclone induced precipitation

Significant increases in TC-induced precipitation vary with time-scale and area, but include: annual maximum daily precipitation in Japan, annual precipitation in the Philippines and the central coastline of Vietnam, and the annual number of days with TC-induced daily precipitation ≥50 mm in the central coastline of Vietnam.

Annual TC-induced precipitation varies by region in China and on a decadal time scale. Average precipitation per TC has significantly increased in southeast China, but apparently not because of a slowdown of TC movement. Annual TC-induced precipitation in Hong Kong, China affects the total precipitation amount and interannual variability, and non-TC-induced daily precipitation has an increasing trend.

4.7.3 High winds

A significant weakening trend in high winds is observed in mainland China. The impact of typhoon intensities over Republic of Korea varies by year, but with no significant long-term trend over the period examined.

4.7.4 Storm surge and extreme sea levels

The highest climatological rates of low-magnitude surges are experienced in China and the Philippines. Three countries out of the 14 Members of the Typhoon Committee (China, Vietnam, and Japan) are listed among the 10 with the most exposure to a 100-year return period flood when the absolute and relative exposed population to a 100-year return period flood is estimated. One study suggested that TC-induced storm surges with a 50-year return period have no significant trend in the WNP.

4.7.5 Casualties and economic losses

TC-induced annual total direct economic losses have significantly increased in China and the Philippines due to rapid economic development. By using a comprehensive assessment index, one study reviewed that the averaged damages per TC in China (including the dead and missing, affected crop area, destroyed houses, and rate of direct economic loss) does not show a clear trend. In Japan and Hong Kong, China , there is significant reduction in TC-related casualties in the past few decades, mainly attributed to improvements in infrastructure and disaster prevention measures.

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CHAPTER 5

Future Projections

5.1 Introduction

Future changes of TC activity with climate change is a big concern due to the large influences of TC on coastal communities around the world, especially in the Asia Pacific region. A number of studies investigating the potential changes in TC activity based on dynamical models and diagnostic approaches have been carried out, in particular focusing on the potential influence of anthropogenic greenhouse gas-induced global warming on TC genesis, intensity, and rainfall. In recent years, many higher resolution dynamical modeling studies have explored future changes in TCs activity and confidence of these findings is enhanced by comparison with other higher resolution model experiments.

This chapter summarizes the key findings in the literature review, mainly for studies published since the previous assessment in 2012. We focus on the late 21st century projections of TCs activity over the WNP, including TC frequency, intensity, precipitation rate, shift in track pattern and storm surge risk. To adjust results from multiple studies to a common future climate change scenario for our figures, we have rescaled model results to a global surface temperature change of 2 degrees Celsius before inclusion in the figures, following Knutson et al. (2019).

5.2 Frequency

Recent studies published since 2012 on the projections of TC genesis/frequency using higher resolution dynamical models have mostly suggested a reduction of TC numbers, but an increase in intense TC numbers over the WNP in the future. However, there are still individual studies that projected an increase in TC frequency or a decrease in intense TC numbers. Specific results of model experiments are summarized below.

Ogata et al. (2016) found that changes of intense TC frequency are not robust to ocean model treatment. By comparing a coupled atmosphere-ocean general circulation model (AOGCM) and atmosphere-only model (AGCM) they found that future climate TC projections are not robust in the region bounded by 120−160°E and 25−40°N because of its large internal variability. However, both models showed a significant decrease in TC frequency and increase in intense TC frequency in the region bounded by 120−160°E and 10−25°N. Sugi et al. (2016) reported that the projected changes in the frequency of very intense (Category (Cat.) 4−5, $V_{max} \geq 59ms^{-1}$) TCs are not uniform over the globe. The frequency is projected to increase in most regions but decrease in the southwestern part of the WNP. Tang and Camargo (2014) used a ventilation index as a metric to assess possible changes in TC frequency in the Climate Model Intercomparison Project Phase 5 (CMIP5) models. They suggested that by the end of the 21st century there will be an increase in the seasonal ventilation index, implying less favorable conditions for TC genesis or rapid intensification in the majority of the TC basins. Murakami et al. (2012a) investigated uncertainties in projected future changes in TC activity using future (2075−2099) ensemble global warming projections under the Intergovernmental Panel on Climate Change (IPCC) A1B scenario. Their ensemble experiments were performed using three different cumulus convection schemes and four different assumptions for prescribed future SST patterns. All experiments consistently projected reductions in global and WNP TC frequency. But TC frequency of occurrence (TCF) and TC genesis frequency (TGF) increased in the central Pacific. These results implied that differences in SST spatial patterns can cause substantial variations and uncertainties in projected future changes of TGF and TC numbers at ocean-basin scales (Murakami et al. 2012).

Christensen et al. (2013) provided a synthesis of global and regional projections of future TC climatology by 2081-2100 relative to 2000-2019. Globally, their consensus projection is for decreases in TC numbers by approximately

5-30%, and increases in the frequency of categories 4 and 5 storms by 0-25%. An update of these projections based on more recent studies is given in Knutson et al. (2019).

Camargo et al. (2014) concluded that many genesis indices developed for the present climatology are not able to capture the reduction of global TC activity in a warmer climate, at least within the context of the Geophysical Fluid Dynamics Laboratory (GFDL) HiRAM (High Resolution Atmospheric Model). They tried to gain further insights into the reasons for the global mean decrease in TC number in the model under SST changes derived from greenhouse gas−forced warming scenarios. Their results suggested a reduction in global TC frequency in warmer climates simulated by GFDL HiRAM is attributable to the increasing saturation deficit, as temperature increases while relative humidity stays close to constant. This effect is partially offset by increases in potential intensity (PI), which reduces the magnitude of the decrease in TC frequency.

With a view to studying the impact of model resolution on high-impact climate features such as TCs, Roberts et al. (2015) simulated 27 years of global TC activity for both the present climate and an end-of-century future climate, at resolutions (grid-spacing) of N96 (130 km), N216 (60 km), and N512 (25 km). In the future climate ensemble, there is a slight decrease in the frequency of TCs in the Northern Hemisphere and a shift in the Pacific with peak intensities becoming more common in the Central Pacific. There is also a change in TC intensities, with the future climate having fewer weak storms and proportionally more stronger storms. Manganello et al. (2014) investigated future changes in the WNP TC activity projected by the multidecadal simulations with the European Centre for Medium-Range Weather Forecasts (ECMWF) Integrated Forecast System (IFS) at 16-km and 125-km grid spacing. They found that, for the simulations by the higher-resolution version of the IFS there is a significant increase in the frequency of typhoons and very intense (Cat. 3-5) typhoons which is accompanied by a corresponding reduction in the frequency of weaker storms.

Knutson et al. (2015) adopted a regional nested dynamical downscaling approach to investigate the response of TCs to a climate change scenario obtained from a multi-model ensemble of CMIP5 models (the Representative Concentration Pathway 4.5 (RCP4.5) scenario) in all basins. The features of the late-twenty-first-century projected changes include a substantial reduction in global TC frequency (−16%), but an increase in the frequency of the most intense storms (+24% for cat 4−5 and +59% for TC with maximum winds exceeding 65m s^{-1}) in the WNP. Murakami et al. (2014) examined 25-yr present-day simulations and future projections for the last quarter of twenty-first century obtained from 10 Meteorological Research Institute (MRI) AGCMs under the A1B scenario and 11 CMIP5 models under the RCP4.5 and RCP8.5 scenarios using in each case a pair of simulations (a present day simulation (1979–2003) and a global-warmed future projection (2075–99)). Overall, the models projected statistically significant decreases in basin-total frequency of occurrence of TCs and TC genesis frequencies globally (by 15%–29% for A1B; by 6%–23% for RCP4.5; and by 13%–40% for RCP8.5). Tsou et al. (2016) simulated tropical storm (TS) activity using a HiRAM at 20-km resolution over the WNP and Taiwan/East Coast of China (TWCN) at the present time (1979 – 2003) and future climate (2075 – 2099) under the RCP 8.5 scenario. During 2075 - 2099, both TS genesis numbers and TS frequency over the WNP and TWCN are projected to decrease consistent with the IPCC 5th Assessment Report (AR5). However, the rate of decrease (49%) is much greater than that projected in IPCC AR5.

Tory et al. (2013a) examined changes in TC frequency under anthropogenic climate change using an Okubo−Weiss−Zeta parameter (OWZP) TC-detection method with a selection of CIMP3 models. They reported a global reduction of TCs between about 6% and 20%, with a much larger spread of results (about +20% to −50%) in individual basins. Further study by Tory et al. (2013b) using CIMP5 models reported that the eight models with a reasonable TC climatology all projected decreases in global TC frequency varying between 7% and 28%.

Wu et al. (2014) simulated present-day (1980-2008) and projected (late twenty-first century; CMIP3 A1B scenario) TC activity in the WNP using an 18-km-grid GFDL regional atmospheric model. The model simulations suggested a weak tendency for decreases (7%) in the number of WNP TCs and for increases in the more intense TCs. Regionally, the simulations projected an increase in TC activity north of Taiwan, which would imply an increase in TCs making landfall in northern China, the Korean Peninsula, and Japan.

Yamada et al. (2017) simulated TCs under present-day and warmer climate condition using a version of NICAM (Nonhydrostatic Icosahedral Atmospheric Model). Future changes in TC activity and structure were investigated using the output of a 14-km mesh climate simulation. The model projected that a decrease in the global frequency of TCs by 22.7% (a decrease of 11.2% in the WNP) under warmer climate conditions. Satoh et al. (2015) further investigated the mechanisms for the reduction in the global frequency of TCs under global warming. Simulation results obtained by using the 14 km mesh global non-hydrostatic model (NICAM) showed that the reduction in the global frequency of TCs is much larger than that of the total tropical convective mass flux. This study suggested the importance of the changes in the intensities of TCs to constrain the future changes of TC frequency.

Mori et al. (2013) performed ensemble numerical experiments of near-future projections in the WNP targeted for the period of 2016 - 2035 by using three versions of the coupled atmosphere-ocean global climate model, the Model for Interdisciplinary Research on Climate (MIROC). Near-future projections (2016 - 2035) indicated significant reductions (approximately 14%) in TC number, especially over the western part of the WNP, even under scenarios with less prominent global warming than that at the end of this century. Zhang and Wang (2017) studied the late twenty-first-century changes of tropical cyclone activity over the WNP under global warming conditions using WRF-ARW with an improved cumulus parameterization scheme. Future projections under the RCP4.5 and RCP8.5 scenarios suggested an overall reduction of TC genesis frequency over the western part of the WNP. Similar changes are found for the frequency of TC occurrence and the accumulated cyclone energy (ACE).

In contrast to other studies which generally project a reduction in TC frequency in WNP, by applying a statistical/dynamical tropical cyclone downscaling technique to six CMIP5 global climate models running under historical conditions and under RCP8.5 scenario, Emanuel (2013) projected a large increase in global TC activity, most evident in the North Pacific region. But this result for CMIP5 models contrasts with that of applying the same downscaling technique to CMIP3 models which generally predicted a small decrease of global TC frequency.

Moreover, Park et al. (2017) showed that an ensemble mean of CMIP5 models projects an increase in TC activity in the WNP under RCP8.5 scenario, which is due to enhanced subtropical deep convection and favorable dynamic conditions therein in conjunction with the expansion of the tropics. Zhang et al. (2017) also found that, under global warming, the TC-track density and PDI both exhibited robust and significant increasing trends over the North Pacific basin, especially over the central subtropical Pacific, and the positive trends are more significant in the RCP8.5 experiments than in the RCP4.5 experiments. The increase in North Pacific TCs is primarily manifest as increases in both the intense and the relatively weak TCs, whereas there is only a slight increase in the number of moderate TCs.

5.3 Intensity

Most TC intensity projections using relatively high resolution models (60 km grid or finer) agree on an increase in the intensity of strong TCs by the late 21st century in response to projected 21st century warming. Tsuboki et al. (2015) addressed the problem of to what extent the intensity of super typhoons will change in the globally warmed climate of the late 21st century by re-simulating a series of historical cases using altered environmental conditions. High resolution downscale experiments using the 20 km mesh MRI-AGCM for the twelve super typhoons revealed that the super typhoons for the present climate simulation attained an average central pressure of 877 hPa and an average maximum surface wind speed of 74 ms^{-1}. The super typhoons under warmer climate conditions attained average wind speeds of 88 ms^{-1} and minimum central pressures of 857 hPa.

Mei et al. (2015) provided a statistical projection using an observation-based regression model that considers both the effects of SST and subsurface stratification and found that upper ocean temperatures in the low-latitude northwestern Pacific (LLNWP) and SSTs in the central equatorial Pacific control the seasonal average lifetime peak intensity by setting the rate and duration of typhoon intensification, respectively. Continued LLNWP upper-ocean warming as predicted under a moderate (RCP4.5 scenario) is expected to further increase the average typhoon intensity by an additional 14% by 2100. Knutson et al. (2015) examined the CMIP5 multimodel ensemble (RCP4.5 scenario) using a combination of atmosphere-only global models regional dynamical downscaling of individual storms for present-day and warm climate conditions. Their simulations projected an increase in average TC intensity and in the number and occurrence days of very intense category 4 and 5 storms, both globally and in the WNP. Tsou et al. (2016) adopted a High Resolution Atmospheric Model (HiRAM) to 20-km grid-spacing and simulated TCs in a future climate projection (2075–2099) under the RCP8.5 scenario. Their simulations projected that TS intensity will increase under global warming scenario in 2075–2099.

Christensen et al. (2013) provided a synthesis of then-available global and regional projections of future TC climatology by 2081–2100 relative to 2000–2019, for a mid-range A1B-like scenario. Globally, the consensus projection was for increases in the frequency of categories 4 and 5 storms by 0–25%, and an increase of a few percent in typical lifetime maximum intensity. Wu et al. (2014) simulated present-day (1980-2008) and projected (late twenty-first century; CMIP3 A1B scenario) WNP TC activity using an 18-km-grid GFDL regional atmospheric model. The model's TC activity showed a weak tendency for increases in the more intense WNP TCs. Averaged ACE of individual events is expected to increase 5.6%, and the model projected enhancements of the mean TC intensity for both lifetime-mean maximum wind speeds (1.4% increase) and lifetime-maximum wind speed (2.6% increase).

Yamada et al. (2017) simulated TCs under present-day and warmer climate condition using a version of NICAM. Future changes in TC activity and structure from a 14-km mesh climate simulation projected that the ratio of intense TCs increases by 6.6% (increases by 17.8% in the WNP) under warmer climate conditions. The study conducted by Manganello et al. (2014) suggested that, for the higher-resolution version of the IFS model simulations, the frequency of typhoons and very intense (Cat. 3-5) typhoons increases significantly in the future climate scenario and this change is accompanied by a reduction in the frequency of weaker storms.

Using Super Typhoon Haiyan (2013) as a case study, Nakamura et al. (2016) explored potential future typhoon intensity and storm surges around the islands of Samar and Leyte in the Philippines, taking into account monthly mean sea surface temperatures (SST), atmospheric air temperature (AAT), and relative humidity (RH) from MIROC5 according to four RCP scenarios proposed by IPCC AR5. The numerical simulations indicated that, if climate change is considered to only increase SST, typhoon intensity and storm surge will be larger than under the present climate. The minimum sea-level pressure (MSLP) of the future typhoon under scenario RCP 8.5 SST change would be about 21 hPa lower and the storm surge 2.7 m higher than in the present climate. However, if SST, AAT, and RH are all taken into account, which is a more physically plausible scenario, then the increase in typhoon intensity will not be as marked as for the SST change alone, with the MSLP under RCP 8.5 decreasing by 13 hPa and the storm surge increasing by 0.7 m. The results of this study confirmed earlier studies that, while increases in SSTs can contribute to the intensification of future typhoons, when other associated environmental changes (increases in

AAT and RH) are included, the intensification of TCs is moderated compared to the case of SST warming in isolation.

5.4 Precipitation Rates

Kanada et al. (2013) studied composite patterns of hourly TC-related precipitation projected by 20 km mesh MRI-AGCM and 2 km mesh Non-Hydrostatic Model NHM2 in the present-day and future climate. The radii of azimuthally averaged maximum precipitation is smaller in the future climate than in the present-day climate, and the hourly precipitation exceeding 50mm h^{-1} is concentrated in a narrow region within a radius of 60km in the future climate. In addition, their simulations included spirally elongated precipitation patterns exceeding 10mm h^{-1} south of the TC center in the future climate. As projected by a CMIP5 13-model ensemble under the RCP4.5 scenario, Knutson et al. (2015) reported a pronounced increase in TC precipitation rates in the warmer climate. A physical mechanism suggested by the results is that enhanced tropospheric water vapor in the warmer climate enhances moisture convergence and thus rainfall rates. Villarini el al. (2014) simulated an increase in TC rainfall rates on the order of 10-20% globally in response to a uniform increase of 2K in SST (both alone and in combination with CO_2 doubling) using a set of idealized high-resolution atmospheric model experiments.

Tsou et al. (2016) performed experiments with a 20-km grid version of the HiRAM model for the present climate (1979−2003) and future climate (2075−2099) under the RCP8.5 scenario. The mean precipitation rate within 200km of the storm center at LMI time (LMI; the maximum intensity achieved during a storm's lifetime) over the WNP at the end of the 21st century is projected to increase by 22%. The projected change around Taiwan and East Coast of China is even larger, with a projected increase of 54%. Yamada et al. (2017) projected changes in TC activity and structure under present-day versus warmer climate condition using a 14-km mesh climate simulation of the NICAM. The precipitation rate within 100km of the TC center increased by 11.8% under warmer climate conditions.

Utsumi et al (2016) analyzed the relative contributions of different weather systems (i.e., TCs, extratropical cyclones including fronts, and others) to changes in annual mean and extreme precipitation in the late 21st century using multimodel projections of CMIP5. According to the models, total precipitation from TCs decreases (increases) in the tropics (subtropics). An increase in rainfall rates associated with TCs is a common response of numerical models under greenhouse warming (Knutson et al., 2013; Kim et al., 2014; Villarini et al., 2014). Projected increases in TC rainfall typically range from 5 to 20%, although results can vary somewhat between different TC basins (Knutson et al. 2015). In addition, the quantitative changes will also depend on the details of the TC precipitation metric chosen and on the particular future emission scenario assumed.

5.5 Shifts in Activity/Track Pattern and Landfalling

Using a high-resolution global climate model for a suite of future warming experiments (2075–2099), Murakami et al. (2013) projected an increase in future TC occurrence around the Hawaiian Islands. They concluded that the substantial increase in the likelihood of TC frequency is primarily associated with a northwestward shift of TC tracks over the ocean southeast of the islands.

Wu et al. (2014) simulated present-day (1980-2008) and projected (late twenty-first century; CMIP3 A1B scenario) WNP TC activity using an 18-km-grid regional atmospheric model and reported a weak (80% significance level) tendency for projected WNP TC activity to shift poleward under global warming. Lok and Chan (2017) simulated the number of TCs making landfall in South China using a nested regional climate/ mesoscale modelling system and projected a northward migration of TC activity in the WNP throughout the twenty-first century. Their study also projected fewer but more intense landfalling

TCs in South China for the late twenty-first century. Projections of WNP TCs simulated by, and downscaled from, an ensemble of numerical models from CMIP5 by Kossin et al., (2016) showed a continuing poleward migration over the twenty-first century following the projections under RCP8.5. The projected migration causes a shift in regional TC exposure that is very similar in pattern and relative amplitude to the past observed shift which is robust in the WNP Ocean.

Colbert et al. (2015) explored the impact of natural and anthropogenic climate change on TC tracks in the WNP using a beta and advection model (BAM). The BAM captured many of the observed changes in TC tracks due to El Niño–Southern Oscillation (ENSO). Potential changes in TC tracks over the WNP due to anthropogenic climate change were also assessed for 17 CMIP3 models and 26 CMIP5 models. Statistically significant decreases (by 4 - 6% in westward moving TCs) and increases (5 - 7% in re-curving ocean TCs) were found. Manganello et al. (2014) investigated future changes in the WNP TC activity projected by the multidecadal simulations with the ECMWF IFS at 16-km and 125-km grid spacing. The high-resolution version of the IFS projected that in a future climate scenario, a southward (southwestward) shift of the main genesis regions takes place in the T1279 (T159) IFS, with a smaller and less significant increase in the genesis density over the South China Sea. These changes are consistent with a small change in the basinwide seasonal mean TC frequency in both models.

Wang and Wu (2015) assessed the future track and intensity changes of TCs based on the projected large-scale environment in the 21st century from a selection of nine CMIP5 climate models under RCP4.5 scenario. The projected changes in mean steering flows suggested a decrease in the occurrence of TCs over the South China Sea area with an increase in the number of TCs taking a northwestward track. There are also considerable inter-model variability in depicting the changes in prevailing tracks and their contribution to basin-wide intensity change. Nakamura et al. (2017) analyzed the WNP TC model tracks in two large multimodel ensembles and identified two potential changes in track types in a warming climate. The first is a statistically significant increase in the north-south expansion, which can also be viewed as a poleward shift, as TC tracks are prevented from expanding equatorward due to the weak Coriolis force near the equator. The second change is an eastward shift in the storm tracks that occurs near the central Pacific, indicating a possible increase in the occurrence of storms near Hawaii in a warming climate.

5.6 Sea Level Rise and Storm Surge

Sea level rise and TC induced storm surge can cause extreme economic damage and loss of life. Mase et al. (2013) and Yasuda et al. (2014) explored future storm surge risk in East Asia using the results of MRI-AGCM to directly force a storm surge simulation model. The simulation suggested that there will be slight change in the location of severe storm surges in the Yellow Sea, moving from Bohai Bay to the Shandong Peninsula. The East China Sea will remain as a vulnerable area because quite a number of intense TCs pass through it in the future climate. Neumann et al. (2015) assessed future population change in the low-elevation coastal zone and trends in exposure to 100-year coastal floods based on four different sea-level and socio-economic scenarios and showed that the number of people living in the low-elevation coastal zone, as well as the number of people exposed to flooding from 1-in-100 year storm surge events, is highest in Asia. China, India, Bangladesh, Indonesia and Viet Nam were estimated to have the highest total coastal population exposure in the baseline year and this ranking was expected to remain largely unchanged in the future. Hoshino et al. (2016) explored inundation risk in different areas of Japan due to the impacts of future sea level rise and increase in the intensity of TCs and found that the level of defenses around many areas of Tokyo Bay could be inadequate by the end of the 21st century.

Vitousek et al. (2017) used extreme value theory to combine sea-level projections with wave, tide, and storm surge models to estimate increases in coastal flooding on a continuous global scale.

They found that regions with limited water-level variability, i.e., short-tailed flood-level distributions, located mainly in the Tropics, will experience the largest increases in flooding frequency. They concluded that the 10 to 20 cm of sea-level rise expected no later than 2050 will more than double the frequency of extreme water-level events in the Tropics, impairing the developing economies of equatorial coastal cities and the habitability of low-lying Pacific island nations. The review by Woodruff et al. (2013) also highlighted that, although sea level rise rates, storm intensification, and time periods differ among previous studies, the general consensus is for an increase in future extreme flood elevations. They concluded that increasing rates of sea level rise will cause increased flooding by TCs, and that future storm damage will be greatest not where TC activity is the highest, but rather where rapidly evolving coastlines and increasing coastal populations greatly enhance storm impacts.

Lloyd et al. (2016) explored the influences of climate change-associated sea-level rise and socioeconomic development on future storm surge mortality using a statistical global-level storm surge mortality risk model under the A1B scenario. They suggested that climate change is expected to increase storm surge mortality, with the impacts concentrated in regions such as South and South-East Asia. However, given the lack of model validation and the unreliability of the mortality estimates, they pointed out that the projections are best interpreted qualitatively. Moreover, the plausible increase in TC induced extreme wind waves due to the projected increase in TC intensity may further aggravate the impacts of storm surge and sea level rise on coastal structures (Timmermans et al., 2017, 2018).

5.7 Casualties and Economic Losses

Ranson et al. (2014) assessed existing studies of future tropical and extratropical cyclone damages under climate change, where they considered monetary damages and unmonetized “loss potential” damages, but excluded mortality. They formed an ensemble of 478 estimates of temperature-damage relationships from existing studies, and estimated a probability distribution for depended of future storm damages on atmospheric temperatures. Their framework suggested that a 2.5°C increase in global surface air temperature would lead to a 28% increase in TC damages in the WNP. Gettelman et al. (2017) projected future TC damage with a high resolution global climate model (CLIMADA) in the different regions (America, East Asia and Indian). The East Asia region is expected to see a large increase in storm damage with future storms.

5.8 Assessment for the WNP by a WMO Task Team on TCs and Climate Change

A WMO Task Team on Tropical Cyclones and Climate Change (WMO Task Team) has recently conducted an assessment of tropical cyclones and climate change similar to our assessment for the WNP, but from a global perspective (Knutson et al., 2019). However, in conducting their global assessment, the WMO Task Team also prepared some regional TC/climate change assessment statements and summaries for the WNP basin. For TC projections, in addition to attempting to establish the sign of future change compared to present-day, the WMO Task Team also presented quantitative ranges of projected changes. For this product, they rescaled the raw projections from studies that used different climate change scenarios (e.g., IPCC A1B, RCP4.5, RCP8.5) to be roughly compatible with a 2°C anthropogenic global warming scenario. For context, they noted that CMIP5 models on average project a global mean surface temperature warming, relative to the 1986-2005 mean, of 2°C by around year 2055 under the RCP8.5 scenario, while IPCC AR5 concludes with medium confidence that 21st century global warming will remain below 2°C for the RCP2.6 scenario (IPCC, 2013).

Overall, they concluded that a 2°C anthropogenic global warming is projected to impact TC activity at the global level as follows:

i) The most confident TC-related projection is that sea level rise accompanying the warming will lead to higher storm inundation levels, assuming all other factors are unchanged.

ii) For TC precipitation rates, there is at least medium-to-high confidence in an increase globally, with a median projected increase of 14% (range 6-22%).

iii) For TC intensity, there is at least medium-to-high confidence that the global average will increase. The median projected increase in lifetime maximum surface wind speeds is about 5% (range 1-10%).

iv) For the global proportion of TCs that reach very intense (Cat. 4–5) levels, there is at least medium-to-high confidence in an increase, with a median projected change of +13%.

Confidence level is relatively lower for the following three projections:

v) a further poleward expansion of the latitude of maximum TC intensity in the WNP;

vi) a decrease of global TC frequency, although this is projected in most current studies; and

vii) a global increase in very intense TC frequency (Cat. 4–5), as is seen most prominently in higher resolution models.

In our current assessment for the WNP, the Typhoon Committee Expert Team also estimated the projected changes of several key TC metrics in the WNP basin under a 2^{o}C anthropogenic global warming scenario. For this purpose, we used the approach and relevant data from the assessment of Knutson et al (2019) as well as a few additional relevant studies for the WNP region. Our quantitative estimates of the projected changes for TC frequency, TC intensity, frequency/ proportion of very intense (Cat.4-5) TCs, and TC precipitation rates for the WNP are summarized in Tables 5.1 to 5.5 and Figure 5.1.

The projections of these metrics for WNP are generally quite consistent with the corresponding assessment for the WNP contained in the WMO Task Team report (Knutson et al. 2019). Further details of the projections based on the 2^{o}C warming assessment for WNP are summarized below :

(a) TC Frequency
Among the 140 estimates for the WNP, the median change of TC frequency is about – 10% with a 10th – 90th percentile range of -26 % to +11%.

(b) TC Intensity
The median change of TC intensity across the 26 estimates for the WNP is about +5% with a 10th – 90th percentile range of +2% to +9% with a large majority of models projecting an increase in the TC intensity.

(c) Frequency and proportion of very intense TCs (Cat.4-5)
The median change in Cat. 4-5 TC frequency across the 37 estimates in the WNP is about 0 % with a rather large 10th – 90th percentile range of -24% to +50%. This suggests no clear tendency of change in very intense TC frequency when compared with the overall TC frequency in (a). As pointed out by Knutson et al (2019), most of the decreased very intense TC frequency projections are from relatively coarse resolution models. We also examined the change in proportion of very intense TCs, which removes the influence of the overall decrease in TC frequency. Available model projections across 37 estimates suggest that there is a clear tendency of increase with a median change of about + 10%, and a 10th to 90th percentile range of -2 to +29%. This generally agrees with the global findings for this metric by the WMO Task Team (global projected change of about +13%), but with slightly more uncertainty regarding the sign of change.

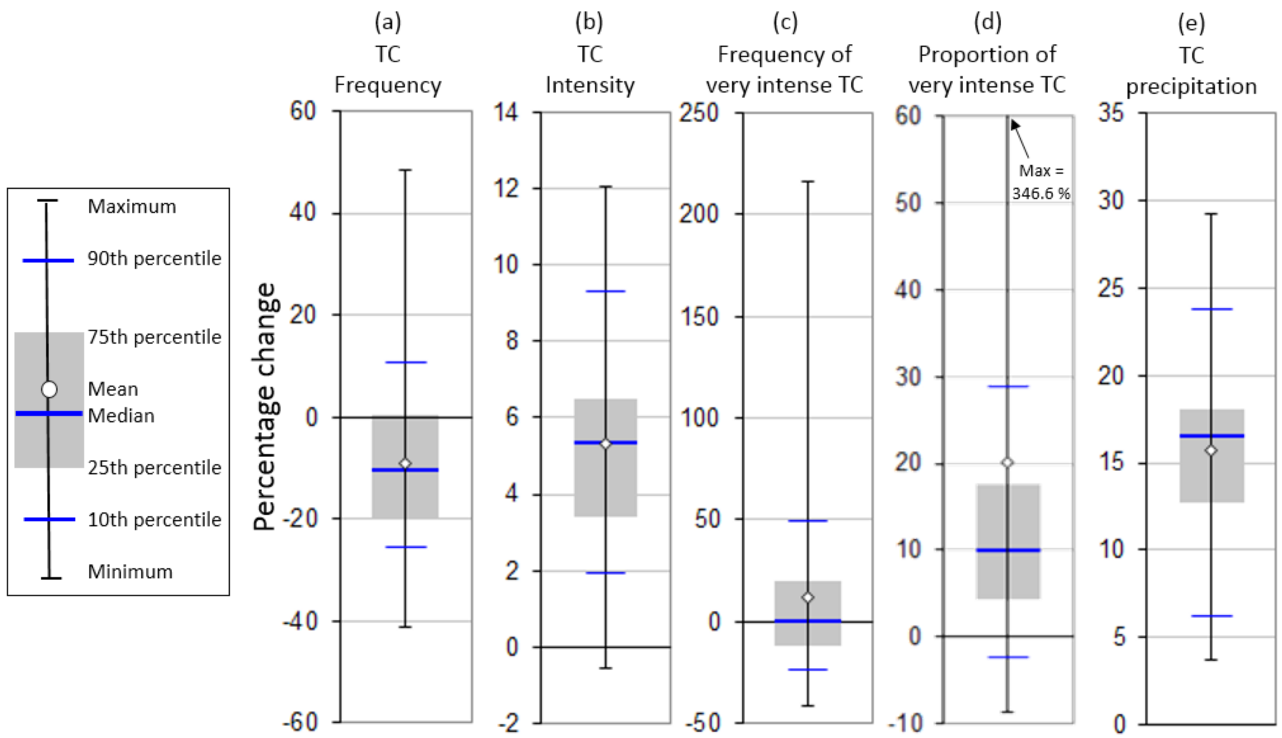
(d) TC precipitation
Among the 16 estimates for the WNP, the median change is about + 17% with a 10th – 90th percentile range of +6 % to +24%. All estimates are positive, indicating a robust tendency for an increase in TC precipitation rates.

5.9 Conclusions

This chapter summarizes the findings of the projected changes in TC activity under global warming scenarios based on numerical model and statistical studies. Most of the results of this report are generally consistent with those published in

TCAR 2012 and the latest global assessment conducted by the WMO Task Team. In particular, this assessment estimated the projected changes of key TC metrics (TC frequency, intensity, frequency of very intense TCs, proportion of very intense TCs and precipitation rates) for a 2^{o}C anthropogenic global warming scenario for the WNP using the approach and relevant data from the assessment of the WMO Expert Team and other study findings for this region.

For projections of TC genesis/frequency, recent studies using higher resolution dynamical models mostly suggest a reduction of TC numbers, but an increase in the proportion of very intense TCs over the WNP in the future. However, some individual studies project an increase in WNP TC frequency. Most studies agree on a projected increase of WNP TC intensity over the 21st century in response to projected 21st century anthropogenic warming. All available projections for TC related precipitation in the WNP indicate an increase in TC related precipitation rate in a climate warmed by anthropogenic forcings. Anthropogenic warming may also lead to changes in TC prevailing tracks. Climate models continue to predict future increases in sea level rise which will contribute toward increased coastal inundation levels, all other factors assumed equal. A further increase in storm surge risk may result from increases in TC intensity. However, some studies suggest a decrease in TC frequency in the WNP over the twenty-first century, which could contribute toward decreasing surge risk, assuming all other factors equal. The most confident aspect of change in storm inundation risk comes from the highly confident expectation of further sea level rise, which would exacerbate storm inundation risk, assuming all other factors equal.



	(a)	(b)	(c)	(d)	(e)
Maximum	48.3	12.1	216.2	346.6	29.2
90th percentile	10.6	9.3	49.6	28.8	23.8
75th percentile	0.4	6.6	20.0	17.7	18.3
Median (Mean)	-10.3 (-8.9)	5.3 (5.3)	0.0 (12.3)	10.0 (20.2)	16.5 (15.7)
25th percentile	-20.0	3.2	-12.1	3.9	12.1
10th percentile	-25.5	1.9	-23.5	-2.3	6.3
Minimum	-41.3	-0.5	-41.1	-8.8	3.7
No. of estimates	140	26	37	38	16

Figure 5.1. Summary distributions for the WNP of projected changes in (a) TC frequency, (b) TC intensity, (c) frequency of very intense TCs (Cat. 4-5), (d) Proportion of very intense TCs (Cat. 4-5) and (e) TC precipitation. The table below the diagrams gives the values of the box and whisker plots.

Table 5.1 Summary of projected changes in WNP TC frequency (based on storms of Tropical Storm or greater intensity). All projections have been rescaled to be consistent with a global mean temperature change of +2°C. Type of ocean coupling for the study is indicated by the following Model/Type: [1] no ocean coupling (e.g., specified sea surface temperatures or statistical downscaling of tropical cyclones; [2] fully coupled ocean experiment; or [3] hybrid type, with uncoupled atmospheric model for storm genesis, but with ocean coupling for the dynamical or statistical/dynamical downscaling step. The frequency projections from Emanuel et al. (2008) have been computed slightly differently from those shown in Fig. 8 of the original paper in order to facilitate intercomparison with projection results from other studies.

Study reference	Model/Type	Resolution	Experiment	WNP (Global) [%]
Sugi et al. (2002)	JMA Timeslice [1]	T106 L21 (~120km)	10y 1xCO2, 2xCO2	-41.25 (-21.25)
McDonald et al. (2005)	HadAM3 Timeslice [1]	N144 L30 (~100km)	15y IS95a 1979-1994 2082-2097	-20 (-4)
Hasegawa and Emori (2005)	CCSR/NIES/FRCAGCM timeslice [1]	T106 L56 (~120km)	5x20y at 1xCO2, 7x20y at 2xCO2	-2.5
Oouchi et al. (2006)	MRI/JMA Timeslice [1]	TL959 L60 (~20km)	10y A1B, 1982-1993, 2080-2099	-28.68 (-22.64)
Stowasser et al. (2007)	IPRC Regional [1]		Downscale NCAR CCSM2, 6xCO2	8.44
Bengtsson et al. (2007)	ECHAM5 timeslice [1]	T213 (~60 km)	2071-2100, A1B	-15.09
Bengtsson et al. (2007)	ECHAM5 timeslice [1]	T319 (~40 km)	2071-2100, A1B	-21.13
Emanuel et al. (2008)	Statistical-deterministic [3]	---	Downscale 7 CMIP3 mods.: A1B, 2180-2200	3.57 (-4.17)
Gualdi et al. (2008)	SINTEX-G coupled model [2]	T106 (~120 km)	30 yr, 1xCO2, 2xCO2,	-12.5 (-10)
Zhao et al. (2009)	GFDL HIRAM timeslice [1]	50 km	Downscale A1B:	
			CMIP3 n=18 ens.	-21.89 (-15.09)
			GFDL CM2.1	-3.77 (-15.09)
			HadCM3	-9.06 (-8.3)
			ECHAM5	-39.25 (-15.09)

<table>
<tr><th>Study reference</th><th>Model/Type</th><th>Resolution</th><th>Experiment</th><th>WNP (Global) [%]</th></tr>
<tr><td rowspan="10">Sugi et al. (2009)</td><td rowspan="10">JMA/MRI global AGCM timeslice [1]</td><td></td><td>Downscale A1B:</td><td></td></tr>
<tr><td rowspan="4">20 km</td><td>MRI CGCM2.3</td><td>-27.17 (-21.89)</td></tr>
<tr><td>MRI CGCM2.3</td><td>-21.89 (-18.87)</td></tr>
<tr><td>MIROC-H</td><td>21.13 (-20.38)</td></tr>
<tr><td>CMIP3 n=18 ens.</td><td>-19.62 (-15.09)</td></tr>
<tr><td rowspan="4">60 km</td><td>MRI CGCM2.3</td><td>-27.17 (-15.09)</td></tr>
<tr><td>MIROC-H</td><td>48.3 (-4.53)</td></tr>
<tr><td>CMIP3 n=18 ens.</td><td>-10.57 (-15.85)</td></tr>
<tr><td>CSIRO</td><td>9.81 (-16.6)</td></tr>
<tr><td>Yokoi and Takayabu (2009)</td><td>CMIP3 ensemble [2]</td><td>various</td><td>A1B (2081-2100)</td><td>-0.75</td></tr>
<tr><td>Yamada et al. (2010)</td><td>NICAM timeslice [1]</td><td>14 km</td><td>Timeslice using CMIP3 A1B SST change, 1990-2090</td><td>0</td></tr>
<tr><td>Li et al. (2010)</td><td>ECHAM5 Timeslice [1]</td><td>40 km</td><td>A1B change (2080-2009)</td><td>-23.4</td></tr>
<tr><td rowspan="5">Murakami and Sugi. (2010)</td><td rowspan="5">JMA/MRI global AGCM timeslice [1]</td><td>V3.1</td><td rowspan="5">Downscale A1B: CMIP3 n=18 ens</td><td></td></tr>
<tr><td>20 km</td><td>-20.38 (-12.08)</td></tr>
<tr><td>60 km</td><td>-9.06 (-14.34)</td></tr>
<tr><td>120 km</td><td>-19.62 (-21.89)</td></tr>
<tr><td>180 km</td><td>-14.34 (-0.91)</td></tr>
<tr><td>Murakami et al. (2011)</td><td>JMA/MRI global AGCM timeslice [1]</td><td>V3.1 20 km</td><td>Downscale A1B: CMIP3 n=18 ens.</td><td>-17.36</td></tr>
</table>

Study reference	Model/Type	Resolution	Experiment	WNP (Global) [%]
Murakami et al. (2012a)	JMA/MRI global AGCM timeslice [1]	V3.2 60 km	Downscale A1B:	
			YS, CMIP3 ens.	-24.91 (-20.38)
			YS, Cluster 1	-24.15 (-18.87)
			YS, Cluster 2	-31.7 (-21.13)
			YS, Cluster 3	-1.51 (-10.57)
			KF, CMIP3 ens.	-21.13 (-15.09)
			KF, Cluster 1	-24.91 (-15.09)
			KF, Cluster 2	-33.21 (-15.85)
			KF, Cluster 3	-6.04 (-10.57)
			AS, CMIP3 ens.	-14.34 (-15.09)
			AS, Cluster 1	-14.34 (-16.6)
			AS, Cluster 2	-24.15 (-9.81)
			AS, Cluster 3	6.04 (-10.57)
Yokoi et al. (2012)	CMIP5 ensemble [2]	Various	RCP4.5 (2061-2100):	
			CNRM-CM5	-5.56
			CSIRO-Mk3.6.0	21.11
			HadGEM2-CC	11.11
			INM-CM4	16.67
			MIROC5	-25.56
			MPI-ESM-LR	7.78
			MRI-CGCM3	4.44

Study reference	Model/Type	Resolution	Experiment	WNP (Global) [%]
Murakami et al. (2012b)	JMA/MRI global AGCM timeslice [1]	V3.1 20 km	Downscale CMIP3 multi-model ens. A1B change (2075-2099 minus control)	-20.38 (-17.36)
		V3.2 20 km		-17.36 (-11.32)
		V3.1 60 km		-15.09 (-17.36)
		V3.2 60 km		-21.13 (-18.11)
Emanuel (2013)	Statistical-dynamical downscaling [3]	---	RCP8.5 CMIP5	
			CCSM4	7.57 (5.95)
			GFDL CM3	23.78 (22.16)
			HADGEM2	18.92 (11.89)
			MPI-ESM-MR	13.51 (15.68)
			MIROC5	17.84 (20.54)
			MRI-CGCM3	12.43 (7.03)
			Periods: 1981-2000, 2081-2100	
Tory et al. (2013b)	Alternative detection method for climate model TCs [1]	---	CMIP5/RCP8.5 Periods: (1970-2000 vs. 2070-2100)	
			CNRM-CM5	-8.11 (-4.81)
			CCSR4	0 (-4.54)
			CSIRO-Mk3.6.0	-0.38 (-5.95)
			GFDL-CM3	-16.22 (-15.14)
			GFDL-ESM2M	2 (-3.68)
			GFDL-ESM2G	-9.19 (-5.03)
			BCC-CSM1.1	-2.49 (-6.49)
			MIROC5	-16.76 (-12.43)

Study reference	Model/Type	Resolution	Experiment	WNP (Global) [%]
Murakami et al. (2014)	Model: MRI		Timeslice using CMIP3 A1B multi model ens. mean SST change (2075-2099 minus 1979-2003)	
	AGCM3.1(AS)	20x20km		-20.38 (-12.08)
	AGCM3.1(AS)	60x60km		-9.06 (-14.34)
	AGCM3.1(AS)	120x120km		-19.62 (-21.89)
	AGCM3.1(AS)	200x200km		-14.34 (-0.75)
	AGCM3.2(YS)	20x20km		-14.34 (-12.83)
	AGCM3.2(YS)	60x60km		-22.64 (-18.87)
	AGCM3.2(YS)	200x200km		-17.36 (-17.36)
	AGCM3.2(KF)	60x60km		-18.11 (-13.58)
	AGCM3.2(AS)	60x60km		-9.81 (-12.83)
	AGCM3.3(YS)	60x60km		6.04 (0)
	Type: global (AGCM) [1]			
	Model:		CMIP5 RCP4.5	
	CCSM4	130x100km		10 (-7.78)
	CMCC-CM	80x80km		-1.11 (-5.56)
	CNRM-CM5	150x150km		-12.22 (-11.11)
	CSIRO Mk3.6.0	200x200km		4.44 (-17.78)
	HadGEM2-CC	200x130km		-2.22 (-17.78)
	HadGEM2-ES	200x130km		-16.67 (-17.78)
	MIROC5	150x150km		-36.67 (-25.56)

Study reference	Model/Type	Resolution	Experiment	WNP (Global) [%]
	MPI-ESM-LR	200x200km		-5.56 (-7.78)
	MPI-ESM-MR	200x200km		-2.22 (-3.33)
	MRI-CGCM3	120x120km		7.78 (-2.22)
	BCC_CSN1.1	120x120km		2.22 (-1.11)
	Type: global (CGCM) [2]			
	Model:		CMIP5 RCP8.5	
	CCSM4	130x100km		6.49 (4.32)
	CMCC-CM	80x80km		16.22 (18.38)
	CNRM-CM5	150x150km		-14.05 (-10.81)
Murakami et al. (2014)	CSIRO Mk3.6.0	200x200km		-2.7 (-11.89)
	HadGEM2-CC	200x130km		-10.27 (-19.46)
	HadGEM2-ES	200x130km		-14.05 (-21.62)
	MIROC5	150x150km		-25.41 (-17.3)
	MPI-ESM-LR	200x200km		-6.49 (-8.11)
	MPI-ESM-MR	200x200km		-8.65 (-7.03)
	MRI-CGCM3	120x120km		1.08 (-1.08)
	BCC_CSN1.1	120x120km		5.95 (3.24)
	Type: global (CGCM) [2]		Periods: 1979-2003, 2075-2099	
Manganello et al. (2014)	Model: IFS Type: global (AGCM) [1]	T1279(16km)	Timeslice using CMIP3 A1B CCSM3.0 ens. mean SST change (2065-2075 minus 1965-1975) Periods:1960-2007, 2070-2117	-3.02
		T159(125km)		1.51

Study reference	Model/Type	Resolution	Experiment	WNP (Global) [%]
Kim et al. (2014)	Model: GFDL CM2.5 Type: global coupled climate model [2]	50 km (atm.); 25 km (ocean)	2xCO2 vs. control (fully coupled) 50-year periods	-10 (-11.88)
Wu et al. (2014)	Model: Zetac Type: regional [1]	18km	Downscale CMIP3 A1B multi model ens. Periods: 1980-2006, 2080-2099	-5.13
Knutson et al. (2015)	Model: GFDL HiRAM (global AGCM) [1]	50 km	Timeslice using CMIP5 RCP4.5 Late 21st century vs. 1982-2005 climatological SST	-38.89 (-17.78)
Roberts et al. (2015)	Model: HadGEM3 Type: global (AGCM) [1]	N96: 130 km	Timeslice using CMIP5 RCP8.5 HadGEM2-ES SST change (2090-2110 minus 1990-2010) Periods: 1985-2011, 2100s	-10.81 (-15.68)
		N216: 60 km		-10.27 (-12.97)
		N512: 25 km		-5.35 (-11.35)
Sugi et al. (2016)	JMA/MRI global AGCM3 CMIP3 Timeslice 25 years [1]		Control (1979-2003) vs. A1B (2075-2099)	
		60km, AGCM3.1	AS-convection CMIP3 ens SST	-15.09 (-18.11)
			AS-convection CSIRO SST	5.28 (-19.62)
			AS-convection MIROC hi SST	43.02 (-10.57)
			AS-convection MRI SST	-23.4 (-15.85)
		60km, AGCM3.2	YS- convection	
			CMIP3 ens. SST	-20.38 (-18.11)
			YS-convection	
			CMIP3, cluster 1	-18.87 (-17.36)
			CMIP3, cluster 2	-25.66 (-18.87)
			CMIP3, cluster 3	0.75 (-9.06)
			KF-convection	
			CMIP3 ens. SST	-18.87 (-15.09)

Study reference	Model/Type	Resolution	Experiment	WNP (Global) [%]
Sugi et al. (2016)	JMA/MRI global AGCM3 CMIP3 Timeslice 25 years [1]	60km, AGCM3.2	CMIP3, cluster 1	-22.64 (-15.09)
			CMIP3, cluster 2	-27.17 (-15.85)
			CMIP3, cluster 3	-3.02 (-9.81)
			AS-convection	
			CMIP3 ens. SST	-7.55 (-12.83)
			CMIP3, cluster 1	-9.06 (-15.09)
			CMIP3, cluster 2	-15.85 (-8.3)
			CMIP3, cluster 3	8.3 (-9.06)
		20 km, AGCM3.1	AS-convection CMIP3 ens SST	-18.11 (-16.6)
		20 km, AGCM3.2	YS-convection CMIP3 ens SST	-15.85 (-11.32)
Kossin et al. (2016)	Model: Emanuel type: statistical-dynamical downscaling [3]		CMIP5 RCP8.5 (2006-2035 versus 2070-2099)	11.89
Ogata et al. (2016)	Atm. Model: MRI-AGCM3.2H Ocean:Model: MRI. COM3 [2]	60 km grid Atm. Model	CMIP5 RCP8.5 (2075-2099 vs. 1979-2003) Coupled: [2]	-22.97 (-17.84)
Tsou et al. (2016)	Atm. Model: HiRAM Type: global AGCM [1]	20 km	CMIP5 RCP8.5 (2075-2099 vs. 1979-2003)	-29.19
Park et al. (2017)	Statistical downscale of CMIP5 models [1]	--	22 CMIP5 models Mean (and quartiles) RCP8.5 (late 21st century)	15.14
Yamada et al. (2017)	NICAM Type: global (AGCM) [1]	14km	Timeslice using CMIP3 A1B multi model ens. mean SST change (2075-2099 minus	-8.3 (-17.36)
Yoshida et al. (2017)	JMA/MRI global AGCM Timeslice 60years Ensemble 90members Statistical downscale for TC intensity [1]	V3.2 60 km	RCP8.5 late 21st century	
			CCSM4	-20 (-17.84)
			GFDL-CM3	-20 (-16.76)
			HadGEM2-AO	-16.76 (-17.3)

Study reference	Model/Type	Resolution	Experiment	WNP (Global) [%]
Yoshida et al. (2017)	JMA/MRI global AGCM Timeslice 60years Ensemble 90members Statistical downscale for TC intensity [1]	V3.2 60 km	MIROC5	-40 (-22.16)
			MPI-ESM-MR	-23.24 (-16.76)
			MRI-CGCM3	-16.22 (-17.3)
Zhang and Wang (2017)	Model: Modified WRF Type: regional climate model (RCM) [1]	20km	RCP4.5 (2080-2099 minus 1989-2010)	0
			RCP8.5 (2080-2099 minus 1979-2010)	-8.65
Lok and Chan (2017)	Downscale of HadGEM2-ES into RegCM3 [1]	RegCM3: 50 km	RCP 8.5 (2090s vs. 2000)	-12.43
Wehner et al. (2018)	Model: CAM5.3 Type: global (AGCM) [1]	28km	+2K global warming; RCP2.6 Forcing changes 60 simulated yrs	-6 (-10)
Bhatia et al. (2018)	Model: HiFLOR Type: global (CGCM) [2]	25km	RCP4.5 (2081-2100) vs.(1986-2005)	6.67 (10)

Table 5.2. Summary of TC intensity change projections in the WNP (percent change in maximum wind speed or central pressure fall, except as noted in the table). All changes have been rescaled to be consistent with a global mean temperature change of +2°C. Type of ocean coupling for the study is indicated by the following Model/Type: [1] no ocean coupling (e.g., specified sea surface temperatures or statistical downscaling of tropical cyclones; [2] fully coupled ocean experiment; or [3] hybrid type, with uncoupled atmospheric model for storm genesis, but with ocean coupling for the dynamical or statistical/ dynamical downscaling step.

Study reference	Model/Type	Resolution/ Metric type (high to low resolution)	Climate Change scenario	WNP (Global) [%]
Emanuel et al. (2008)	Stat./Dyn. Model [3]	Max Wind speed (%)	CMIP3 7-model, A1B (2181-2200 minus 1981-2000)	2.44 (1.01)
Tsuboki et al. (2015)	CReSS regional model downscale of 30 strongest typhoons in MRI-AGCM3.1 present and warm climates [3]	2 km; Average max wind speed (%)	CMIP3 18-model ens. A1B (2074-2087 minus 1979-1993)	11.4

Study reference	Model/Type	Resolution/ Metric type (high to low resolution)	Climate Change scenario	WNP (Global) [%]
Patricola and Wehner (2018)	WRF regional model v. 3.8.1 nested in CAM5.1 atm. Model forced with CMIP5 ens. boundary conditions [1]	4.5 km grid	RCPx 1980-2000 vs. 2081-2100. 10-member ensembles of 1 to 9 cases per basin	
			RCP4.5	6.44
			RCP6.0	4.18
			RCP8.5	6.49
Kanada et al. (2017)	Four Non-hydrostatic regional models [1]	5 km grids % change in Sq Root of central pressure fall. Assume envir pressv = 1013.26 mb	CMIP5 ens. RCP8.5 (1979-2003 vs. 2075-2099)	
			CReSS	5.95
			JMANJM	5.41
			MM5	8.65
			WRF v. 3.3.1	5.95
			WRF with Bogus	2.11
Knutson et al. (2015)	Model: GFDL HiRAM (global AGCM) downscaled into GFDL Hurricane model with ocean coupling [3]	6 km; Max Wind speed change (%) of hurricanes	Timeslice using CMIP5 RCP4.5 Late 21st century vs. 1982-2005 climatological SST	6.11 (4.56)
Knutson and Tuleya (2004)	GFDL Hurricane Model [1]	9 km grid inner nest; Max Wind speed (%)	CMIP2+ +1%/yr CO2 80-yr trend	5.25
Yamada et al. (2017)	NICAM Type: global (AGCM) [1]	14km Lifetime Max: sqrt of pressure fall. +/- indicate increase/decrease in intensity.	Timeslice using CMIP3 A1B multi model ens. mean SST change (2075-2099 minus 1979-2003) Periods: 1979-2008, 2075-2104	2.42 (2.11) Note: based on % change in sqrt of pressure fall
Manganello et al. (2014)	IFS Type: global (AGCM) [1]	T1279 (~16km) Max wind	Timeslice using CMIP3 A1B CCSM3.0 ens. mean SST change (2065-2075 minus 1965-1975) Periods:1960-2007, 2070-2117	9.06
Wu et al. (2014)	Model: Zetac Type: regional [1]	18km	Downscale CMIP3 A1B multi model ens. Periods: 1980-2006, 2080-2099	2

Study reference	Model/Type	Resolution/ Metric type (high to low resolution)	Climate Change scenario	WNP (Global) [%]
Tsou et al. (2016)	Atm. Model: HiRAM Type: global AGCM [1]	20 km	CMIP5 RCP8.5 (2075-2099 vs. 1979-2003)	7.57
Murakami et al. (2012b)	JMA/MRI global AGCM timeslice [1]	V3.1 20 km	Downscale CMIP3 multi-model ens. A1B change (2075-2099 minus control)	12.08 (9.81)
		V3.2 20 km		4.53 (2.26)
		Avg. lifetime max winds		
Oouchi et al. (2006)	MRI/JMA Timeslice [1]	TL959 L60 (~20km) Avg. lifetime max windspeed	10y A1B 1982-1993 2080-2099	3.17 (8.3)
Kim et al. (2014)	Model: GFDL CM2.5 Type: global coupled climate model [2]	50 km (atm.); 25 km (ocean)	2xCO2 vs. control (fully coupled) 50-year periods	1.56 (1.69)
Yoshida et al. (2017)	J JMA/MRI global AGCM Timeslice 60years Ensemble 90members Statistical downscale for TC intensity [1]	V3.2 60 km Max Wind	RCP8.5 late 21st century	
			CCSM4	4.32 (3.78)
			GFDL-CM3	5.41 (4.86)
			HadGEM2-AO	4.32 (4.32)
			MIROC5	-0.54 (4.86)
			MPI-ESM-MR	4.86 (4.86)
			MRI-CGCM3	7.03 (6.49)
Hasegawa and Emori, (2005)	CCSR/NIES/ FRCAGCM timeslice [1]	T106 L56 (~120km) Max winds	5x20y at 1xCO2 7x20y at 2xCO2	De-crease

Table 5.3 Summary of frequency of very intense TCs (i.e., Cat. 4-5) projections in the WNP. The rows of reported results are ordered from top to bottom generally in order of decreasing model horizontal resolution. All changes have been rescaled to be consistent with a global mean temperature change of +2^{o}C. Type of ocean coupling for the study is indicated by the following Model/Type: [1] no ocean coupling (e.g., specified sea surface temperatures or statistical downscaling of tropical cyclones; [2] fully coupled ocean experiment; or [3] hybrid type, with uncoupled atmospheric model for storm genesis, but with ocean coupling for the dynamical or statistical/dynamical downscaling step.

Reference	Model/Type	Resolution: high to low	Experiment	WNP (Global) [%]
Emanuel (2013)	Statistical-dynamical downscaling [3]	---	Downscale RCP8.5 CMIP5:	
			CCSM4	10.81 (7.03)
			GFDL CM3	32.43 (42.16)
			HADGEM2	32.43 (17.84)
			MPI-ESM-MR	17.84 (27.57)
			MIROC5	36.76 (52.97)
			MRI-CGCM3	21.08 (16.76)
			Periods: 1981-2000, 2081-2100	
Knutson et al. (2015)	Model: GFDL HiRAM (global AGCM) downscaled into GFDL Hurricane model w/ ocean coupling [3]	6 km	Timeslice using CMIP5 RCP4.5 Late 21st century vs. 1982-2005 climatological SST	-7.78 (31.11)
Murakami et al. (2012b)	JMA/MRI global AGCM timeslice [1]	V3.2 20 km	Downscale CMIP3 multi-model ens. A1B change (2075-2099 minus control)	-3.02 (3.02)
Tsou et al. (2016)	Atm. Model: HiRAM Type: global AGCM [1]	20 km	CMIP5 RCP8.5 (2075-2099 vs. 1979-2003)	216.22
Bhatia et al. (2018)	Model: HiFLOR Type: global (CGCM) [2]	25km	RCP4.5 (2081-2100) vs.(1986-2005)	1.11 (31.11)
Sugi et al. (2016)	JMA/MRI global AGCM3 CMIP3 Timeslice 25 years [1]	60km, AGCM3.1	Control (1979-2003) vs. A1B (2075-2099)	
		60km, AGCM3.2	AS-convection CMIP3 ens SST	0 (-1.51)
			AS-convection CSIRO SST	6.04 (-18.87)
			AS-convection MIROC hi SST	86.79 (33.21)
			AS-convection MRI SST	-12.83 (-3.02)
			YS- convection CMIP3 ens. SST	-22.64 (-19.62)
			YS-convection	
			CMIP3, cluster 1	-21.89 (-12.08)
			CMIP3, cluster 2	-23.4 (-3.77)
			CMIP3, cluster 3	22.64 (7.55)
			KF-convection	

Reference	Model/Type	Resolution: high to low	Experiment	WNP (Global) [%]
Sugi et al. (2016)	JMA/MRI global AGCM3 CMIP3 Timeslice 25 years [1]	60km, AGCM3.2	CMIP3 ens. SST	-14.34 (-4.53)
			CMIP3, cluster 1	-29.43 (-17.36)
			CMIP3, cluster 2	-27.17 (-3.77)
			CMIP3, cluster 3	9.81 (7.55)
			AS-convection	
			CMIP3 ens. SST	0.75 (-3.02)
			CMIP3, cluster 1	-3.02 (-12.08)
Sugi et al. (2016)	JMA/MRI global AGCM3 CMIP3 Timeslice 25 years [1]	60km, AGCM3.2	CMIP3, cluster 2	-7.55 (0.75)
			CMIP3, cluster 3	19.62 (3.02)
		20 km, AGCM3.1	AS-convection CMIP3 ens SST	-10.57 (9.81)
		20 km, AGCM3.2	YS-convection CMIP3 ens SST	-9.81 (-3.77)
Bacmeister et al. (2016)	Model: CAM5 Type: global [1]	28km	Bias-corrected CAM5 coupled model SSTs: RCP8.5 (2070-2090 vs 1985-2005)	152.43 (108.11)
Wehner et al. (2018)	Model: CAM5.3 Type: global (AGCM) [1]	28km	+2K global warming; RCP2.6 Forcing changes 60 simulated yrs	17 (27)
Yoshida et al. (2017)	JMA/MRI global AGCM Timeslice 60years Ensemble 90members Statistical downscale for TC intensity [1]	V3.2 60 km	RCP8.5 late 21st century:	
			CCSM4	-11.89 (-9.73)
			GFDL-CM3	-10.81 (-5.41)
			HadGEM2-AO	-7.03 (-6.49)
			MIROC5	-41.08 (-12.43)
			MPI-ESM-MR	-16.22 (-7.03)
			MRI-CGCM3	1.08 (-1.08)
Wang and Wu. (2012)	CMIP5 downscaling; statistical/dynamical model [1]	---	A1B (2065-2099 minus 1965-1999)	49.81

Table 5.4 Summary of projected changes in the proportion of very intense TCs (Cat.4-5) in the WNP. The rows of reported results are ordered from top to bottom generally in order of decreasing model horizontal resolution. All changes have been rescaled to be consistent with a global mean temperature change of +2°C. Type of ocean coupling for the study is indicated by the following Model/Type: [1] no ocean coupling (e.g., specified sea surface temperatures or statistical downscaling of tropical cyclones; [2] fully coupled ocean experiment; or [3] hybrid type, with uncoupled atmospheric model for storm genesis, but with ocean coupling for the dynamical or statistical/dynamical downscaling step.

Reference	Model/Type	Resolution: high to low	Experiment	WNP (Global) [%]
Emanuel (2013)	Statistical-dynamical downscaling [3]	---	Downscale RCP8.5 CMIP5:	
			CCSM4	3.02 (1.02)
			GFDL CM3	6.99 (16.37)
			HADGEM2	11.36 (5.31)
			MPI-ESM-MR	3.81 (10.28)
			MIROC5	16.06 (26.91)
			MRI-CGCM3	7.69 (9.09)
			Periods: 1981-2000, 2081-2100	
Knutson et al. (2015)	Model: GFDL HiRAM (global AGCM) downscaled into GFDL Hurricane model w/ ocean coupling [3]	6 km	Timeslice using CMIP5 RCP4.5 Late 21st century vs. 1982-2005 climatological SST	50.91 (59.46)
Yamada et al. (2017)	Model: NICAM Type: global (AGCM) [1]	14km	Timeslice using CMIP3 A1B multi model ens. mean SST change (2075-2099 minus 1979-2003) Periods: 1979-2008, 2075-2104	23.87 (27.40)
Murakami et al. (2012b)	JMA/MRI global AGCM timeslice [1]	V3.2 20 km	Downscale CMIP3 multi-model ens. A1B change (2075-2099 minus control)	17.35 (16.17)
Tsou et al. (2016)	Atm. Model: HiRAM Type: global AGCM [1]	20 km	CMIP5 RCP8.5 (2075-2099 vs. 1979-2003)	346.56
Bhatia et al. (2018)	Model: HiFLOR Type: global (CGCM) [2]	25km	RCP4.5 (2081-2100) vs.(1986-2005)	-2.62 (9.79)
Wehner et al. (2018)	Model: CAM5.3 Type: global (AGCM) [1]	28km	+2K global warming; RCP2.6 Forcing changes 60 simulated yrs	24.47 (41.11)
Sugi et al. (2016)	JMA/MRI global AGCM3 CMIP3 Timeslice 25 years [1]		Control (1979-2003) vs. A1B (2075-2099)	
		20 km, AGCM3.1	AS-convection CMIP3 ens SST	9.22 (31.67)
		20 km, AGCM3.2	YS-convection CMIP3 ens SST	7.17 (8.51)
		60km, AGCM3.1	AS-convection CMIP3 ens SST	17.78 (20.28)
			AS-convection CSIRO SST	0.72 (0.94)
			AS-convection MIROC hi SST	30.61 (48.95)
			AS-convection MRI SST	13.79 (15.25)

Reference	Model/Type	Resolution: high to low	Experiment	WNP (Global) [%]
Sugi et al. (2016)	JMA/MRI global AGCM3 CMIP3 Timeslice 25 years [1]	60km, AGCM3.2	YS- convection CMIP3 ens. SST	-2.84 (-1.84)
			YS-convection	
			CMIP3, cluster 1	-3.72 (6.39)
			CMIP3, cluster 2	3.05 (18.60)
			CMIP3, cluster 3	21.72 (18.26)
			KF-convection	
			CMIP3 ens. SST	5.58 (12.44)
			CMIP3, cluster 1	-8.78 (-2.67)
			CMIP3, cluster 2	0.00 (14.35)
			CMIP3, cluster 3	13.23 (19.25)
			AS-convection	
			CMIP3 ens. SST	8.98 (11.26)
			CMIP3, cluster 1	6.64 (3.56)
			CMIP3, cluster 2	9.87 (9.88)
			CMIP3, cluster 3	10.45 (13.28)
Yoshida et al. (2017)	JMA/MRI global AGCM Timeslice 60years Ensemble 90members Statistical downscale for TC intensity [1]	V3.2 60 km	RCP8.5 late 21st century:	
			CCSM4 (n=15)	10.14 (9.87)
			GFDL-CM3 (n=15)	11.49 (13.64)
			HadGEM2-AO (n=15)	11.69 (13.07)
			MIROC5 (n=15 min/max)	-1.80 (12.50)
			MPI-ESM-MR (n=15 min/max)	9.15 (11.69)
			MRI-CGCM3 (n=15 min/max)	20.65 (19.61)
Ogata et al. (2016)	Atm. Model: MRI-AGCM3.2H Ocean Model: MRI. COM3 [1] vs. [2]	60 km grid Atm. Model ~55 to 110 km grid Ocean model	CMIP5 RCP8.5 (2075-2099 vs. 1979-2003)	
			Coupled mod.[2]	36.39 (34.87)
			Atm. Only [1]	17.73 (5.96)

Table 5.5 TC-related precipitation projected changes (%) for the late 21st century (relative to present day) in the WNP. R refers to the averaging radius around the storm center used for the precipitation calculation. All changes have been rescaled to be consistent with a global mean temperature change of +2°C. Type of ocean coupling for the study is indicated by the following Model/Type: [1] no ocean coupling (e.g., specified sea surface temperatures or statistical downscaling of tropical cyclones; [2] fully coupled ocean experiment; or [3] hybrid type, with uncoupled atmospheric model for storm genesis, but with ocean coupling for the dynamical or statistical/dynamical downscaling step.

Reference	Model/Type	Resolution/ averaging radius (R)	Experiment	WNP (Global) [%]
Hasagawa and Emori (2005)	CCSR/NIES/ FRCAGCM timeslice [1]	T106 L56 (~120km)/ R=1000 km	5x20y at 1xCO2 7x20y at 2xCO2	5.25
Villarini et al. (2014)	Models:			
	GFDL HiRAM	50 km	20 yrs	17 (12)
	CMCC	75 km	10 yrs	15 (13)
	CAM5	25 km	9 yrs	3.7 (17)
	AGCMs with specified SSTs and CO2 levels [1]	Avg, rain rate within 5 deg radius, 10% rainiest storms	2xCO2 and +2K SST increase combined	
Tsuboki et al. (2015)	CReSS regional model downscale of 30 strongest typhoons in MRI-AGCM3.1 present and warm climates [3]	2 km;Average rain rate with 100 km radius	CMIP3 18-model ens. A1B (2074-2087 minus 1979-1993)	18.87
Knutson et al. (2015)	Model: GFDL HiRAM (global AGCM) downscaled into GFDL Hurricane model with ocean coupling [3]	6 km; Radius around storm center (R) = 100 km	Timeslice using CMIP5 RCP4.5 Late 21st century vs. 1982-2005 climatological SST	17.78 (14.44)
Tsou et al. (2016)	Atm. Model: HiRAM Type: global AGCM [1]	20 km; Max precip within 200km of center at max TC intensity	CMIP5 RCP8.5 (2075-2099 vs. 1979-2003)	29.19
Yoshida et al. (2017)	JMA/MRI global AGCM Timeslice 60years Ensemble 90 members [1]	V3.2 60 km Radius around storm center: 200km	RCP8.5 late 21st century	
			CCSM4	15.68 (16.22)

Reference	Model/Type	Resolution/ averaging radius (R)	Experiment	WNP (Global) [%]
Yoshida et al. (2017)	JMA/MRI global AGCM Timeslice 60years Ensemble 90 members [1]	V3.2 60 km Radius around storm center: 200km	GFDL-CM3	20.54 (17.3)
			HadGEM2-AO	16.22 (15.14)
			MIROC5	10.27 (7.03)
			MPI-ESM-MR	16.76 (14.59)
			MRI-CGCM3	23.78 (21.62)
Patricola and Wehner (2018)	WRF regional model v. 3.8.1 nested in CAM5.1 atm. Model forced with CMIP5 ens. boundary conditions [1]	4.5 km grid Precip rate change (%)	RCPx 1980-2000 vs. 2081-2100. 10-member ensembles of 1 to 9 cases per basin.	
			RCP4.5	13.33
			RCP6.0	10.91
			RCP8.5	16.76

Table 5.6 Summary of projections of storm surge in the WNP for approximately the late 21st century.

Study reference	Model details	Scenario	Time-slice	Notes
Hoshino et al. (2016)	-Two-level storm surge model (Yamashita and Tsuchiya (1984) -AGCM T959L60(20km resolution)	-UK Met Office Hadley Center (present climate) -CMIP3 multi-model projections of SRES A1b(future climate)	-1979-2004(present climate) -2015-2031(near future climate) -2075-2100(future climate)	Sea level rise is expected to increase the risk of higher storm surges around Tokyo or Kawasaki.
Nakamura et al. (2016)	MIROC5 FVCOM	RCP 2.6 RCP 4.5 RCP 6.0 RCP 8.5	- 2011-2020 (near future) - 2091-2100 (future)	(Philippines, RCP 8.5) 2.5m higher considering only increases in SST Increase of 12% considering increases in SST and AAT Increase of 12.9% considering increases in SST, AAT and RH

Study reference	Model details	Scenario	Time-slice	Notes
Lloyd et al. (2016)	Mortality risk model (statistically-based)	Dynamic interactive vulnerability assessment	Future time-slice -2026-2030 -2046-2050 -2076-2080	Climate change is expected to increase storm surge mortality. However, given the lack of model validation and the unreliability of the mortality estimates, they also pointed out that the projections are best interpreted qualitatively.

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CHAPTER 6

Uncertainties

6.1 Introduction

After assessing the impacts of climate change on tropical cyclones in previous chapters, we will now discuss the sources of uncertainty to further objectively interpret the assessment results demonstrated in previous chapters.

Studies assessing climate change impacts on TCs can be divided into two branches. One is to examine trends of historical TC data, including the TC best track and deduced metrics, traditional weather observations and remote sensing data associated with TCs, and miscellaneous observed data or geologic proxy data related to TCs and their societal or ecological impacts. The other is to project the future TC activity and associated impacts on human society in the context of a range of future climate scenarios using climate models.

6.2 Historical trend assessment

Three issues, including data, methodology and physical understanding, may potentially impact the uncertainties of the first group of studies. The physical understanding potentially affects all parts of the climate change assessment and here we refer to those aspects of physical understanding associated with specific problems of data and methodology.

6.2.1 Data Completeness and Homogeneity

The data issue refers to the completeness and homogeneity of historical data (Landsea 2007, Walsh *et al.* 2016, Ying *et al.* 2014). The completeness of data is an important issue because the TC activity is an important component of the global energy and moisture cycles (e.g., Jiang and Zipser 2010, Rodgers *et al.* 2000, 2001; Jullien *et al.* 2012, Ying *et al.* 2012). The completeness of data, which is closely tied with temporal and spatial inhomogeneities, is highly dependent on developments of the global observation system and data analysis techniques. Temporal and spatial inhomogeneities can be present in various historical TC datasets (e.g., Landsea and Franklin 2013). They can make it very difficult to distinguish long-term trends due to climate change, or multidecadal internal variability, from spurious changes associated with changes in observing methods. To improve the data homogeneity, it may be imperative to reanalyze the historical TCs using consistent techniques and sufficient data, although there may exist various practical problems (Emanuel *et al.* 2018) with achieving the goal of data homogeneity.

Despite some efforts at homogenization, the four best-track data in the Typhoon Committee region show disagreements in details, even also in the long-term trend, as indicated in previous chapters. For example, the Typhoon Committee sponsored a Best-track Consolidation Meeting and found it was difficult to verify the maximum surface wind speeds due to differences inherent in observations and wind-averaging periods. The Typhoon Committee then designed an annual operating plan (AOP) entitled “Harmonization of Tropical Cyclone Intensity Analysis” to compare the current intensity (CI) number which is a basic parameter to derive TC intensity. It was found that the major causes of large discrepancies may associated with specific details in the analysis process (Koide 2016), such as analysis during rapid intensification, interpretation of parameters based on cloud patterns, and CI-intensity rules. Similar causes were also mentioned in Barcikowska *et al.* (2012). Therefore, an objective and standardized analysis system may avoid some of these problems, and improvements in the general rules used in analysis procedures as well as physical understanding on special problems (e.g. rapid intensification, wind-pressure relationship, etc.) may also help to improve the data analysis techniques.

6.2.2 Methodologies for Homogenization and Trend Detection

The methodology issue concerns mainly the appropriateness of homogenization methods, trend detection techniques, and the methods used to attribute changes to natural and anthropogenic changes.

Unlike other atmospheric metrics such as temperature, it is difficult to find appropriate statistical homogenization approaches for TC best track data due to the very complex conditions of the data (e.g. Koide 2016; Ying *et al.* 2011a; Ying *et al.* 2014). An alternative choice is to reconstruct a new and homogenized dataset specifically for trend analysis based on existing observations such as satellite data (Kossin *et al.* 2013). Another approach is to simulate the historical TC intensity using dynamical downscaling methods (Wu and Zhao 2012). Using the TC best tracks, SST and vertical wind shear as driving parameters, they derived TC intensities using a simple air-sea coupled model with an axisymmetric atmospheric component and one-dimensional oceanic component. They implicitly assumed that the data quality of these driving parameters was high enough to introducing minimum inhomogeneities into the results, and that the dynamical downscaling framework has the capability to accurately reproduce the intensity variability from the input data. The latter assumption is closely associated with our knowledge not only of natural and anthropogenic variability but also on the strengths and limitation of various dynamical model components. Further discussion on dynamics will be presented in next subsection. Their approach is based on identifying inhomogeneities in historical data by comparison with homogeneous samples of variables as derived from models, under the assumption of perfect models and homogeneous environmental inputs.

Regarding trend detection, uncertainty may be introduced by approaches that do not robustly identify climate changes. In a statistical sense, climate change is defined as distinct change of the characteristics of probability distribution function (PDF), such as parameters of scale, shape and location (IPCC 2001; Meehl *et al.* 2000). This suggests the importance of assumed distribution of samples. Since TCs are extreme events with non-normally distributed metrics such as wind (i.e., intensity) and precipitation, important changes may occur in central values (median, mean) or tails of the PDF. Methods that assume a normal distribution should be used with caution since the unbiased estimates of PDF parameters highly depend on the prior assumption of the distribution form. For example, it may not be appropriate to apply normal distribution-assuming methods on samples from only the tails of a PDF to examine the change of extreme events. A better choice may be non-parametric methods, which are independent of the distribution. For example, quantile regression (Koenker 2005; Koenker and Hallock 2001) can used to assess trends in various quantiles (i.e., all parts of PDF) and has been used to assess climate trends (Elsner *et al.* 2008; Haugen *et al.* 2018; Murnane and Elsner 2012; Ying *et al.* 2011b; Ying *et al.* 2011c). However, both parametric and non-parametric methods typically require the samples to be independent. For TCs, interannual and decadal variabilities were identified in some metrics (e.g., He *et al.* 2015; Klotzbach and Gray 2008; Zhang *et al.* 2018; Zhao *et al.* 2018). Such fluctuations suggest that the data are serially correlated, which will introduce uncertainties into tests of significance of long-term trends (e.g., Douglas *et al.* 2000; Hamed 2008; Kam and Sheffield 2016). To address this issue, the influence of the sample's autocorrelation needs to be considered (Douglas *et al.* 2000; Hamed 2008; Kam and Sheffield 2016). In this sense, investigations that consider quasi-periodic variations of in the climate system (e.g., the Interdecadal Pacific Oscillation or Pacific Decadal Oscillation) and their role in TC variability, either using statistical regression (e.g., Kossin et al. 2016) or control model simulations (Bhatia et al. 2019) can help distinguish TC internal variability from long-term forced TC climate trends, with associated confidence levels.

For attribution of observed changes, historical climate model simulations with observed historical forcing agents can be used, although these techniques have been used relatively rarely in the

WNP basin (see Chapter 3). The reliability of such methods depends on the reliability of the climate models and the historical forcings, including the ability of the models to simulate the TC metric in question and the historical changes in a variety of TC-relevant environmental parameters (e.g., SSTs, wind shear, atmospheric circulation, moisture, atmospheric and oceanic vertical temperature profiles).

6.3 Future trend projection

One way to anticipate future trends in TC activity due to climate change is to identify and detect emerging climate-induced trends in the historical TC observational data. Alternatively, model simulations and projections provide a means to quantify potential future TC changes under certain assumptions about future climate forcing and climate change. Such simulations or projections are typically based on numerical models. Due to difficulties in directly solving complex systems of dynamical equations and limitation in understanding of various physical processes of the climate system, numerical models will include various hypotheses and parameterization schemes. These simplifications, in turn, cause discrepancies between "model climate" and the real climate, especially those related to dynamical and moisture processes (e.g. Shepherd 2014).

For TCs, the presently known uncertainty sources include model resolution, parameterization schemes for convection, future SST pattern uncertainty, and a variety of other related environmental climate parameters (e.g. global temperature sensitivity, lapse rate changes, changes in the vertical temperature gradient in the upper ocean, atmospheric circulation changes, etc.), as well as TC detection schemes applied to model data (Horn *et al.* 2014; Murakami *et al.* 2012a; Murakami *et al.* 2012b; Walsh *et al.* 2016; Wehner *et al.* 2015). Due to differences among models and post-processing approaches, biases relative to TC observations may be found in metrics such as annual TC numbers, tracks, intensities, duration, size, precipitation rates, and other metrics (Camargo and Wing 2016; Gettelman *et al.* 2017; Walsh *et al.* 2016). The fidelity of the relationship between simulated TCs and the simulated environments is another source of uncertainty (Camargo *et al.* 2007; Wehner *et al.* 2015). This implies that an evaluation of confidence in simulated or projected TC activity should consider not only a model's performance in reproducing the large-scale air-sea system, but also to what extent the model climate simulates or includes the important physical processes that operate in the real climate. Both are highly dependent on our understanding of the physics of natural and anthropogenic climate change.

Moreover, as Wehner *et al.* (2015) suggested, "projections of future tropical cyclogenesis obtained from metrics of model behavior that are based solely on changes in long-term climatological fields and tuned to historical records must also be interpreted with caution". In other words, empirical TC genesis potential indices based on historical observations should be applied to the projection of numerical models with caution, since the simulated relationship between TCs and various environmental factors was reported to be different from one model to the next (Camargo *et al.* 2007). One approach may be to apply a unified technique to compare historical and future climate aspects produced by a given model (e.g. Emanuel 2013; Knutson *et al.* 2008; Villarini and Vecchi 2012; Zhang *et al.* 2017). However, one should carefully examine and evaluate the reasonableness of any assumptions of particular technique, because such assumptions may introduce uncertainties (e.g., Walsh *et al.* 2016; Tory *et al.* 2014).

As compared with results for global TC activity, researchers found even larger divergence of results between model projections for some metrics for individual basins (Camargo 2013; Tory *et al.* 2013a; Tory *et al.* 2013b). Bacmeister *et al.* (2018) suggested that the large uncertainties of projected basin-scale TC activity, which were as large as the effects of using an RCP8.5 vs. RCP4.5 emission scenario (van Vuuren *et al.* 2011), can be attributed to uncertainties in future SSTs. Nakamura *et al.* (2017) suggested that projected changes in future TC track patterns were model- and scenario-dependent, and they emphasize the importance of multi-model ensembles for more robust future projections.

6.4 TC risk assessment

TC risk is among the fascinating issues of adaption to climate change. Destructiveness of TCs is closely related to TC-structure and accompanying phenomena. In particular, destructive wind, storm surge and waves are closely associated with the near-surface TC wind field; flooding and landslides are mainly associated with torrential rain; and squall lines and tornadoes are associated with deep convection. Therefore, the translational and structural characteristics of TCs (i.e., tracks, intensities, and distribution of destructive wind and torrential rain) are essential for TC risk models. Evaluation focusing on these TC characteristics will help to improve risk models, and consequentially will be a benefit to disaster mitigation and the evaluation of economic impacts. In this section, we will focus mainly on the uncertainties in TC wind field, rainfall, and storm surge

6.4.1 Wind field

TC risk (loss) models usually use empirical TC wind models, although recently more physical models are being used (e.g., Emanuel *et al.* 2006; Loridan *et al.* 2017; Tan and Fang 2018; Vickery *et al.* 2000; Vickery *et al.* 2009; Watson Jr. and Johnson 2004). In fact, TC wind field models are a statistical or dynamical downscaling for the TC wind field. As summarized by Vickery *et al.* (2009), the typical wind field model includes three components: gradient wind modeling, topographical adjustment of the wind field, and gust factor model for final application. Therefore, the first source of uncertainties may come from the gradient wind model, which contains simplified physical representations, empirical parameters (Holland 1980), and some elements that are difficult to measure (e.g., the density of air). Second, the uncertainties may also be attributed to topographical adjustment schemes, using either an atmospheric boundary layer model or a gust factor, which is a roughness-associated wind speed reduction factor between surface wind (10m above water or ground) and gradient wind (at gradient height). The TC boundary layer model remains one of the largest challenges due to the unique features under TC conditions, and numerical models usually have limited resolution to resolve the boundary layer (Gopalakrishnan *et al.* 2016). For the TC gust factor, although many studies demonstrated that the gust factors associated with TC are not different from those extra-tropical storm conditions, the small-scale strong winds due to additional turbulence sources (e.g. rolls, wind swirls, etc.) may be much larger than expected (Vickery *et al.* 2009).

Physical numerical models include more explicit physics processes than empirical models, and a number of high resolution dynamical models can simulate TC intensity (MSW or MCP) and changes response to climate changes. These changes can be used as input to the wind risk models used for damage assessment as discussed above. As suggested in chapter 5, many models currently project an increase in TC intensity in the future in response to the greenhouse warming climate; therefore, the risk of TC wind damage will likely increase as well.

6.4.2 Rainfall

Advances were reported in reducing precipitation uncertainties in CMIP5 models as compared to CMIP3 models (Woldemeskel *et al.* 2016). However, Woldemeskel *et al.* (2016) also found large uncertainties in heavy rain regions, as well as mountainous and coastal areas. Despite this, as chapter 5 indicates, there is a strong consensus among available TC projection studies that TC-induced rainfall rates will increase in a greenhouse warmed climate. The potential uncertainty sources for TC rainfall include the contribution of uncertainties in SST patterns, locations of convection and convergence associated with SST pattern and land-sea thermal contrast (Endo *et al.* 2017; Kent *et al.* 2015). For example, Knutson et al. (2015) reported no significant change in projected TC precipitation rates in the southwest

Pacific basin, which they noted was the basin with the smallest projected SST increase of any TC basin. This suggests the potential importance of SST pattern changes for TC rainfall rate response. Recently, Kendon *et al.* (2017) suggested that the changes in rainfall intensity, as well as in daily and hourly rainfall extremes, show remarkable differences in summertime projections between coarse- and high-resolution models, in which cumulus convection was treated differently.

6.4.3 Storm surge

As discussed in Chapter 5, climate models continue to predict future increases in global and WNP regional sea level rise and this will contribute toward increased coastal flooding and inundation risk during extreme events, assuming all other factors equal.

Storm surge and ocean models are usually driven by atmospheric wind, pressure fields and so forth. One of the challenging issues is the accurate driving force under TC condition, which introduces the first aspect of uncertainties in storm surge evaluation (e.g. Yang *et al.* 2016; Yasuda *et al.* 2014). When remote effects are considered, the storm surge is also highly dependent on TC tracks and intensities, and the distances relative to coasts (Wada *et al.* 2018). Storm surge risk may also be affected by long-term changes of TC activity and sea-level rise (Resio and Irish 2015). In addition to the atmospheric component of driving forces, the ocean or wave models play the essential roles in projecting storm surge. Ocean or wave models, as examples of numerical models, exhibit the same general kinds of uncertainties as atmospheric models but for different essential physical processes and boundary conditions.

6.5 Summary

This chapter outlined some of the uncertainty sources introduced by data, methodology, numerical models, and empirical models. Understanding and considering these uncertainty sources is important for climate change assessment. First, this can improve the quality of each component covered by assessment. Second, this can help to evaluate existing studies more comprehensively and appropriately. We emphasize that discussion of the uncertainties in climate change does not imply that climate change research are of little value for decision making. In that regard, Lewandowsky et al. (2014a,b) conclude that uncertainty in climate science leads to greater, rather than less, concern about unabated warming, and a stronger argument for mitigating climate change than would be the case if there were no uncertainty.

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CHAPTER 7

Recommendations for Future Progress

The following are our recommendations for future research and observation activities that we believe will lead to future progress in the field of TCs and climate change in the WNP basin.

7.1 TC Observed Data and Trend Analysis

Continue to further develop and improve homogenous climate-quality TC datasets. The Typhoon Committee should encourage and continue to coordinate efforts by Members and the research community for the above efforts. Examples include:

(i) Sharing of observations/data between meteorological services and warning centers as well as IBTrACS;
(ii) Analysis of new TC related metrics (LLMI and global TC translation speed are examples of metrics since last report);
(iii) Assessing impact of changes in observing capabilities over time (e.g., satellite vs. pre-satellite; ship tracks; aircraft reconnaissance vs. no aircraft reconnaissance);
(iv) Conducting further research on observed trends in TC-induced high winds, heavy rain and storm surge; and
(v) Enhancing collaboration and coordination of aircraft reconnaissance in the basin.

7.2 Detection and Attribution

Members and research community are encouraged to conduct further research to:
Expand the use of detection and attribution techniques in studies of past TC variations to improve understanding of the causes of past changes and confidence in future projections;
Develop better estimates of expected levels of internal decadal to centennial scale natural variability of TC activity for use in climate change detection and attribution studies; and
Develop better estimates of expected forced responses to historical climate forcing agents such as increases in greenhouse gases and changes in aerosol forcing

7.3 Model projections

Members and the research community are encouraged to conduct further research to:
Investigate TC extreme events under climate change scenarios in support of vulnerability assessments;
Continue to evaluate the sensitivity of TC projections to the details of climate and/or TC downscaling models;
Enhance the use of statistical significance testing, evaluation of present-day simulations (including interannual variations), and multi-model ensemble experiments to better quantify uncertainty in future projections;
Evaluate present-day simulations and future projections for the full life cycle of the TCs and their related impacts, including winds, precipitation, and storm surge;
Reduce or quantify uncertainties to the extent possible in the 21st century projections of regional SST patterns and the vertical structure of the atmospheric (temperature, winds, moisture) and oceanic changes as these differences can lead to large differences in regional TC projections; and
Continue research to better understand the basic physical mechanisms that cause the observed or modeled changes in TC activity (including TC track / genesis position changes) in the basin.

7.4 Impact assessments

The Typhoon Committee may consider coordinating efforts by Members to:

(i) Encourage more cross-cutting research on long-term trends of TC impacts in the region.

ACKNOWLEDGEMENTS

We sincerely thank Members of ESCAP/WMO for kindly providing materials for Chapter 4 and thank other experts from Members of Typhoon Committee for their valuable comments. This work was sponsored by the ESCAP/WMO Typhoon Committee Annual Operating Project. We also wish to thank Dr. Xiaotu Lei and Mr. Kelvin, Kuok-Hou HO for coordinating various affairs during implementation of the project. Sincerely thanks are also given to all staff of the Typhoon Committee Secretariat for their assistance during the project and arranging the expert team working meeting, to SMG for hosting the working meeting of the expert team in Macao, China in 2018 and to STI/CMA for providing a web-based information exchange platform. Moreover, we thank the author team of the WMO Task Team on Tropical Cyclones and Climate Change for their sharing of relevant estimates of changes in TC metrics under 2^{o}C warming which served as a basis for much of the assessment contained in Chapter 5 for the WNP basin, and Dr M C Wu and Mr C W Choy of HKO for their efforts in analyzing the projection data and compiling Tables 5.1 to 5.5 and Figure 5.1.

APPENDIX I - SUMMARY OF SURVEY RESULTS

Table A1: Climatological mean of landfalling / affecting tropical cyclones

Note : Definitions of landfalling TCs and affecting TCs adopted by Members are summarized in Table A2

	Tropical Cyclones		Typhoons		Data Period
	Landfalling	Affecting	Landfalling	Affecting	
China	9 (7*)	14	3	NA	1949 – 2017
Hong Kong, China	2.5#	6.2	1.4#	2.3	1961 – 2018
Japan	2.7	NA	1.4	NA	1981 – 2010
Macao, China	1.0	NA	0.6	NA	1990 – 2016
Republic of Korea	NA	NA	0.8^	3.1^	1977 – 2018
Singapore	0	0	0	0.01**	NA
Thailand	3	NA	0.005	NA	1951 – 2018

*** TS or above**
**** Only TS Vami in 2001 in historical record**
 # Landfalling within 300 km of Hong Kong, China (the number of landfalling tropical cyclones and typhoons with the center passing over Hong Kong, China are 0.3 and 0.2 respectively).
^TCs with maximum winds of 17 ms^{-1} or above
"NA" means Information not available from the survey results.

Table A2 : Definitions of landfalling and affecting tropical cyclones/typhoons

Member	Definitions	
	Landfalling	Affecting
China	Landfalling TS is defined as TC with intensity of TS and above when it makes landfall in China. TC affecting China is defined as a TC that generates severe wind and precipitation in China (Ying et al., 2011) http://tcdata.typhoon.org.cn/en/dlrdqx_zl.html	A TC that induces wind or precipitation in China, with the following having been observed at least one station: (1) either sustained wind at least 13.9 m s^{-1} (Beaufort Scale 7) or wind gusts of at least 17.2 m s^{-1} (Beaufort Scale 8), or (2) storm precipitation greater than 50 mm, or (3) the storm precipitation greater than 30mm with either sustained wind at least 10.8 m s^{-1} (Beaufort Scale 6) or a wind gust of at least 13.9 m s^{-1} (Beaufort Scale 7).
Hong Kong, China	The centre of a TC passing over any part of the territory of Hong Kong Since the number of TCs passing over Hong Kong is small, the number of tropical cyclones making landfall within 300 km of Hong Kong (a TC that crosses the coast within 300 km of Hong Kong, including those coming within 300 km of Hong Kong over land after crossing the coast at more than 300 km) is also adopted in some studies to reflect the impact of landfalling TCs on Hong Kong.	i) A TC affecting Hong Kong means it comes within 500 km of Hong Kong. ii) A typhoon affecting Hong Kong means a TC with typhoon intensity or above comes within 500 km of Hong Kong.
Japan	i) Landfalling TC: one whose center reached the coast of at least one of the four major islands in Japan ii) Same as in i) but for typhoon	NA
Macao, China	i) Landfalling TCs are the tropical cyclones whose nearest distance from Macao are less than 100 km. ii) The landfalling typhoons are the typhoons whose nearest distance from Macao are less than 100 km.	NA
Republic of Korea	Landfalling typhoon: the center of a typhoon lands over Republic of Korea.	Affecting typhoon causing a typhoon advisory to be issued across Republic of Korea.
Singapore	Singapore has not been directly affected by TCs.	
Thailand	Landfalling is defined as the center of circulation of the TC located over land of Thailand	NA

Table A3-1: Changes in tropical cyclone landfalling/affecting frequency, intensity and locations

Member	Frequency and intensity of landfalling/affecting tropical cyclones	Landfalling locations
China	(i) an increasing trend in the peak intensity and frequency of intense typhoons, mainly because of the combined effect of changes in SST and vertical wind shear. Wu and Zhao (2012) (ii) no long-term trend is observed in either the frequency or intensities of TCs making landfall at the Guangdong province (Zhang et al. 2011)	NA
Hong Kong, China	(i) a decrease in the TC frequency in the vicinity of Hong Kong but with statistically insignificance at 5% level (ii) The large differences in the available datasets do not allow for a reliable detection of the long-term trend of the TC intensity in the SCS (Lee et al., 2012)	NA
Japan	No significant change in the TC frequency in Japan is identified. (Kumazawa et al. 2016)	NA
Republic of Korea	(i) The number of strong typhoon with maximum speeds of greater than 44 m/s has significantly increased for a 10-year period from 2001 to 2010; the number of TCs existing near Republic of Korea is insignificantly reduced (Cha et al., 2014) (ii) The numbers of typhoons affecting and landfalling in Republic of Korea have no long-term trend over 42 years from 1977 to 2018 (Cha and Shin, 2019)	NA

Table A3-2: Changes in intensity of high winds and heavy precipitation, and casualties and economic loss

Member	Intensity of high winds and heavy precipitation	Casualties and economic loss
China	Only few stations in southern and eastern China showed significantly decreasing TCR. Meanwhile, significantly increasing TCR is observed in few stations in southwestern China. (Zhang et al. 2018) the average rainfall per TC has significantly increased in Southeast China during 1965-2009. (Zhang et al. 2013)	(i) The annual total direct economic loss increased significantly due to the rapid economic development over the past 25 years although there was little change in the overall landfall frequency, landfall intensity and overland time. (ii) Under the background of global warming, the intensity of tropical cyclones that made landfall on Hainan decreased, but the overland time and frequency of tropical cyclones that made landfall on Fujian and Zhejiang increased, respectively, over the same period of time. (iii) The percentage of direct economic losses of GDP and deaths at the national and provincial levels caused by landfall tropical cyclones decreased due to the effectiveness of disaster prevention and reduction in China. (Zhang et al. 2011)
Hong Kong, China	(i) TCs making landfall over east China have tended to be more destructive in recent decades, with a significant increase in the power dissipation index (PDI) after landfall (1975-2014); in contrast, changes in the PDI of TCs making landfall over south China are less apparent. (Li et al., 2017) (ii) TC rainfall has a decreasing trend in frequency and intensity in recent decades and affecting the observed trends of the rainfall variability in Hong Kong. (Li et al., 2015) (iii) No significant trend on the TC-induced extreme rainfall in Hong Kong. (iv) The extreme high winds associated with TCs within 500 km range of Hong Kong have no significant trend at Waglan Island (offshore island) while those of the urban station at Kai Tak have a significant decreasing trend. (Lee et al., 2017)	NA

Member	Intensity of high winds and heavy precipitation	Casualties and economic loss
Japan	i) A cause of the increasing trend in heavy rainfall in Okinawa was increased rainfall amounts per typhoon rather than a rising number of strong typhoons approaching the island. In particular, typhoons which approached the island within 100 km, during the peak typhoon month of September showed a statistically significant increase in total rainfall of 6.5 mm y^{-1} during 1982 - 2005.(Ikema and et al. 2010) ii) intensity of precipitation with 5-yr return period significantly increases by 0.28%/yr in the Pacific Ocean coast in Japan for 1951 – 2010 but not so for 10-yr one or longer (0.28%/yr)	NA
Macao, China	NA	No casualty occurs during 2007 to 2016 Note: This is a table in a report (Meteorological and Geophysical Bureau, 2016).
Republic of Korea	No long-term trend in high wind is observed in Republic of Korea (Cha and Shin, 2019)	A decrease trend of typhoon- induced damage including casualties and economic loss since 2000 (Ministry of the Interior and Safety, 2017).

ANNEX I

Comparison of the Tropical Cyclone Classification

Maximum Sustained Wind Speed near the centre of the tropical cyclone			western North Pacific				North Atlantic, central/eastern North Pacific
kt	km/h	m/s	Hong Kong, China (10-minute average) HKO	China (2-minute average) CMA	Japan (10-minute average) RSMC, Tokyo	United States (1-minute average) JTWC	United States (1-minute average) CPHC, NHC
< 34	< 63	< 17.1	Tropical Depression (TD)				
34 – 47	63 – 87	17.2 – 24.4	Tropical Storm (TS)			Tropical Storm	
48 – 63	88 – 117	24.5 – 32.6	Severe Tropical Storm (STS)				
64 – 80	118 – 149	32.7 – 41.4	Typhoon (T)		Typhoon 64 – 84 kts		Hurricane categories 1: 64 – 82 kts
81 – 99	150 – 184	41.5 – 50.9	Severe Typhoon (ST)		Very Strong Typhoon 85 – 104 kts	Typhoon 64 – 129 kts	2: 83 – 95 kts 3: 96 – 112 kts
≥ 100	≥ 185	≥ 51.0	Super Typhoon (SuperT)		Violent Typhoon ≥ 105 kts	Super Typhoon ≥ 130 kts	4: 113 – 136 kts 5: ≥ 137 kts

Note : the conversion between kt to km/h and kt to m/s may vary slightly subject to rounding practices and conversion factor decimal places.

Acronym: HKO: Hong Kong Observatory; CMA: China Meteorological Administration; RSMC: Regional Specialized Meteorological Centre, Tokyo; JTWC: Joint Typhoon Warning Center; CPHC: Central Pacific Hurricane Center, Hawaii; NHC: National Hurricane Center, Miami

References:

-WMO Tropical Cyclone Program Operational Plan / Manual (http://www.wmo.int/pages/prog/www/tcp/operational-plans.html);
Typhoon Committee Operational Manual - Meteorological Component, Appendix 1-A
Regional Association IV (North America, Central America and the Caribbean) Hurricane Operational Plan
-WMO Severe Weather Information Centre (http://severe.worldweather.org/);
-Hong Kong Observatory, Classification of Tropical Cyclones (http://www.hko.gov.hk/informtc/class.htm)

Printed in Macao, China December 2019

ISBN ISBN 978-99965-779-7-0

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ISBN 978-99965-779-7-0

ESCAP/WMO TC/TD-No. 0018