

Long Term Projection of Ocean Wave Climate
and Its Climatic Factors

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Abstract

Climate change impacts are a great concern to social sustainable development. Long-term changes in ocean surface waves elicit a variety of impacts on a coastal environment. The quantitative projection of future wave climate, including the likely range expected, is information that would be very useful to assess coastal impacts and how coastal communities will need to adapt.

This study conducted future projections of global ocean wave climate in the end of 21st century under greenhouse gas emission scenario. These future projections were performed with Global Climate Model (GCM) and dynamical wave model. The wave climate projections consist of two types of experiment; (1) Ensemble experiments with single GCM, (2) Multi-GCM ensemble experiments. The experiments of (1) are for identifying the factors which can contribute to the wave climate changes. Those of (2) are for estimating the variation of wave climate change. This study also made clear the historical wave climate variability and its relation with large-scale atmospheric circulation, and the relation was applied in interpretation of the future changes in wave climate.

This study showed the mean and extreme wave height changes; future changes in global annual mean wave height are about ± 0.3 m depending on the region, future changes in annual maximum wave height are about 1 m. Previous studies of wave climate projection just showed the wave property changes such as wave heights, direction and period with little discussion of the factors causing the future changes. This study provided the insight into the factors behind the wave climate changes. The followings were made clear.

- The future changes in wave climate over the Western North Pacific are highly sensitive to Sea Surface Temperature (SST) conditions.
- The future changes in extreme wave climate strongly depend on model performance of tropical cyclones.
- Extreme wave climate changes over the Western North Pacific can be caused by an eastward shift of tropical cyclone track.
- The future changes in winter atmospheric and wave climate are well associated with inherent large-scale pattern of variability (teleconnection pattern).

It can be considered that this study presents a maturing of the wave climate projection literature.

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Chapter 1

Introduction

Climate change impacts are a great concern to social sustainable development. The number of studies assessing the impact of long-term change in oceanographic phenomena (especially the impact of sea level rise) related to climate change has been increasing (e.g., Hallegatte et al., 2013). Changes in ocean surface gravity waves (denoted as waves hereafter) produce impacts for a variety of disciplines. Ocean waves are one of the key components of beach morphology (Short, 1999), and wave energy may be a promising renewable energy source (Cruz, 2008). Changes in long term wave climate have been observed by voluntary observing ships (Gulev and Grigorieva, 2004), reanalysis data (e.g. Wang and Swail, 2001; Semedo et al., 2011), satellite imagery (Hemer et al., 2010, Young et al., 2011) and buoy data (e.g. Menéndez et al., 2008). Impacts of long term wave climate variability and change have been also reported. Kuriyama et al. (2012) found that, for a span of 22 years, the inter-annual shoreline variation at the Japanese coast has been induced by the fluctuation of the deep water wave energy flux. Sasaki (2012) estimated climatological annual mean wave energy around Japan based on 30 years of observations and found an increasing trend caused by more frequent swells. Furthermore, wave inundation has occurred across the western tropical Pacific, and recent accelerated sea level rise contributed to the severity of the impact (Hoeke et al., 2013).

A few studies have assessed impacts of future changes in wave climate using future wave climate projections under greenhouse gas emission scenarios before IPCC-AR5 (2013). For example, Suh et al. (2012) examined the impact of climate change on a caisson type breakwater, including the effect of changes in wave height at the end of this century. Charles et al. (2012) has projected future wave climate for the Bay of Biscay in France and concluded that changes in wave conditions are leading to a decrease in the annual net longshore drift. The quantitative projection of future wave climate, including the likely range expected, is information that would be very useful to assess coastal impacts and how coastal communities will need to adapt.

To assess the future changes in wave climate, several future projections of global wave climate have been conducted using different forcing mechanisms and wave models (Mori et al., 2010; Dobrynin et al., 2012; Hemer et al., 2013b; Fan et al., 2013; Semedo et al., 2013) and statistical models (Wang and Swail, 2006; Mori et al., 2013). Consequently, multi-model ensemble projections of global wave climate have been carried out in the Coordinated Ocean Wave Climate Project (so-called COWCLIP; Hemer et al., 2012; 2013a; IPCC-AR5, 2013). Chapter 13 of the IPCC WGI AR5 (IPCC-AR5, 2013) has summarized current understandings on “mean” future wave climate projections under greenhouse gas emission scenarios, which showed common features of global wave

climate changes such as increased mean wave heights in the Southern Ocean associated with enhanced surface wind speeds in the future. However, there is little discussion about the cause of changes in future wave climate and the differences between projections. Confidence with the projection is greatest if we understand the relationship between external forcing and the physical processes (Knutti et al., 2013). Furthermore, although the impacts of global climate change on “mean” wave climate are being unveiled as described above (IPCC-AR5, 2013), the “extreme” wave climate effects are less understood than the mean ones.

Therefore, a series of future wave climate projection is conducted, and the analyses toward following main objectives are carried out.

- (1) To make clear the relationship between “mean” wave climate change and external forcing, specifically looking at spatial Sea Surface Temperature (SST).
- (2) To project future “extreme” wave climate and investigate the contributions attributable to tropical cyclone changes separately from non-tropical cyclone changes.

This wave climate projection is based on SST ensemble and Perturbed Physics (PP) ensemble experiments of the Global Climate Model which were developed by the Japanese Meteorological Research Institute, denoted as MRI-AGCM3.2H (Mizuta et al., 2012). The results of analysis on mean wave climate is described in **Chapter 2** and those on extreme wave climate is in **Chapter 3**.

Ensemble experiments with single GCM as described above are powerful method to identify the factors which can contribute to the wave climate changes and the variation. However, variation of future change signal is limited by single GCM projection. Ensemble experiments with various GCM can give wider variation of wave climate changes. Therefore, wave climate projection by multi-model ensemble is described in **Chapter 4**.

The global climate has preferred patterns of variability (mode of variability), which are called large-scale circulation patterns or teleconnection patterns. Many studies indicated that climate system responses to external forcing are associated with the inherent mode of variability (e.g. Branstator and Selten, 2009). Thus, mode of variability of wave climate is analyzed in **Chapter 5**. Furthermore, the relationship between future wave climate change and the mode of variability is also discussed in **Chapter 5**.

Finally, the major findings are concluded in **Chapter 6**.

Chapter 2

Future Projection of Mean Ocean Wave Climate Based on Single Model GCM Experiments

2.1 Introduction

To assess the future changes in wave climate, several future projections of global wave climate have been conducted using different forcing mechanisms and wave models (Mori et al., 2010; Dobrynin et al., 2012; Hemer et al., 2013b; Fan et al., 2013; Semedo et al., 2013) and statistical models (Wang and Swail, 2006; Mori et al., 2013). Consequently, multi-model ensemble projections of global wave climate have been carried out in the Coordinated Ocean Wave Climate Project (COWCLIP, Hemer et al., 2012; 2013a; IPCC-AR5, 2013). The results of five independent studies (Wang and Swail, 2006; Mori et al., 2010; Hemer et al., 2013b; Fan et al., 2013; Semedo et al., 2013) showed a consistent future changes in mean wave climate among models: future increases in wave height over the Southern Ocean, and decreases in wave height in the subtropics (Hemer et al., 2013a). However, there is little discussion about the cause of changes in future wave climate and the differences between models. Confidence with the projection is greatest if we understand the relationship between external forcing and the physical processes (Knutti et al., 2013).

A dynamical approach of global wave projection has been developed over the last few years (Mori et al., 2010; Hemer et al., 2013b; Fan et al., 2013; Semedo et al., 2013), and this approach is employed by this study. A framework of the approach can be described as follows.

- (1) Global climate simulation by an Atmosphere-Ocean Coupled Global Climate Model (AOGCM) under an emission scenario.
- (2) Global atmospheric climate simulation by an Atmospheric GCM (AGCM) using Sea Surface Temperature (SST) data from the AOGCM as a boundary condition.
- (3) Global wave simulation by a wave model forced with the sea surface winds of the AGCM.

The procedure in item (2) is sometimes skipped (Dobrynin et al., 2012), but the climate projection with an AGCM is useful for impact assessments because the AGCM has a finer spatial resolution over the AOGCM, with lengths in the range of 20 to 100 km, generally.

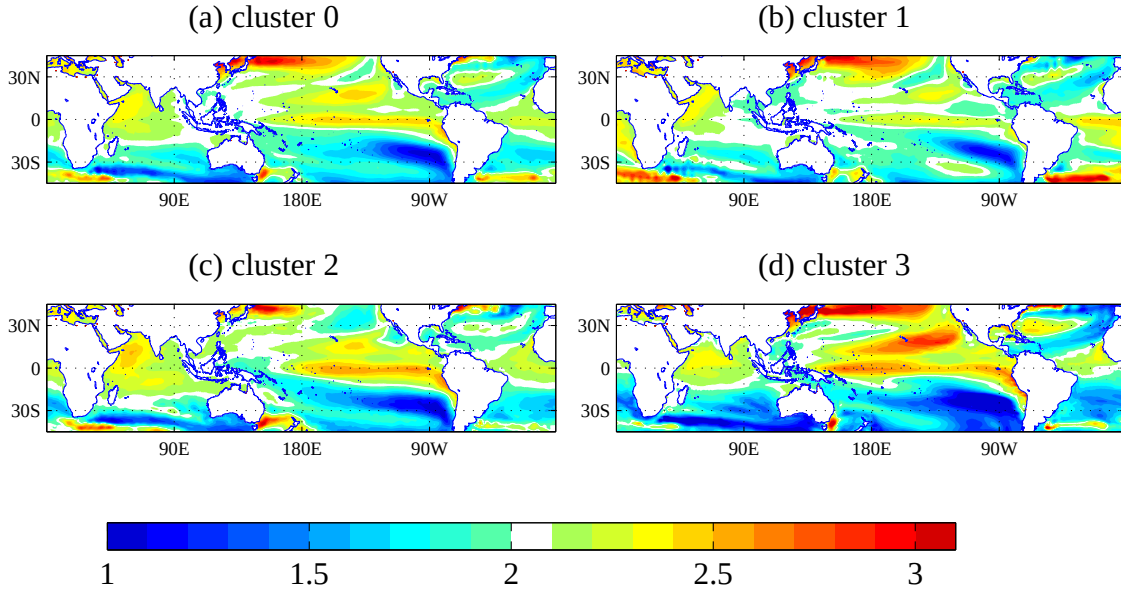


Figure 2.1: Future changes in annual mean SST for the case of (a) cluster 0, (b) cluster 1, (c) cluster 2 and (d) cluster 3 (unit:°C)

The choice of SST is arbitrary for the AGCM; ensemble mean SST of several AOGCMs is sometimes used for a simulation. SST, however, can lead to a fundamental variation in the general circulation and yield significant impacts on the wave climate projection through the sea surface wind. Therefore, it is important to estimate the sensitivity of a wave climate projection to projected SST. It is difficult to understand the mechanisms of future wave change with an arbitrary choice of GCM because there are many different factors behind future projections beside SST, such as cloud physics, advection scheme, radiation scheme, and grid resolution, etc. The analysis of SST ensemble experiments is useful to understand the role of SST while neglecting other factors (e.g. numerical scheme and so on).

The objective of this study is to estimate the response and the sensitivity of mean wave climate to projected SST and to understand the mechanism behind climate forcing by specifically looking at spatial SST variation in the future climate. A series of wave climate projections using the same AGCM are conducted based on SST ensemble experiments. First, this study shows the response and the sensitivity of mean wave height to projected SST conditions, indicating that future summer wave height in the Western North Pacific (WNP) is sensitive to SST conditions. Second, climatological causes behind future wave climate changes in the WNP are discussed in detail with future SST warming and typhoons. In order to generalize the results, we consider the perturbed physics (PP) ensemble experiments and the multi-model ensemble study (COWCLIP) in addition to SST ensemble experiments.

2.2 Methodology

The framework of wave climate projection of this study is same as that described in **Section 2.1**. The methodology of atmospheric climate projection by AGCM using SST projected by AOGCM as the boundary condition, is described in **Section 2.2.1**. The methodology of wave climate projection

Table 2.1: Eighteen CMIP3 models used for cluster analysis and the SST cluster number (Murakami et al., 2012)

Model name	SST cluster number	Letters for Figure 2.14
BCCR-BCM2.0	1	A
CGCM3.1 T47	2	B
CGCM3.1 T63	2	C
CNRM CM3	1	D
CSIRO Mk3.0	3	E
GFDL CM2.0	3	F
GFDL CM2.1	3	G
GISS AOM	1	H
INM CM3.0	1	I
IPSL CM4	1	J
MIROC3.2 hires	2	K
MIROC3.2 medres	2	L
MIUB ECHO-G	1	M
MPI ECHAM5	2	N
MRI CGCM2.3	2	O
NCAR CCSM3.0	1	P
UKMO HadCM3	3	Q
UKMO HadGEM1	3	R

by wave model forced by sea surface wind of AGCM, is described in **Section 2.2.2**.

2.2.1 Atmospheric climate projection

The AGCM used in this study was developed by the Japanese Meteorological Research Institute, the so-called MRI-AGCM version 3.2 (denoted as MRI-AGCM3.2, Mizuta et al., 2012) for IPCC-AR5 (2013). The SST and perturbed physics ensemble experiments were carried out with the 60 km horizontal spatial resolution model of MRI-AGCM3.2 (MRI-AGCM3.2H). The forcing to AGCM is SST, sea ice at the bottom boundary and green house gases in the atmosphere.

The time slice experiments were conducted using 1979 to 2009 for the present climate and 2075 to 2099 for the future climate, respectively. Lower boundary conditions of MRI-AGCM3.2H in the present climate were monthly mean observed sea ice concentration and SST from the Hadley Centre Global Sea Ice and Sea Surface Temperature dataset (HadISST1; Rayner et al. 2003). The boundary conditions for the future climate consisted of four different statistically analyzed SSTs (Murakami et al., 2012). The four future SST conditions as boundary conditions of MRI-AGCM3.2H were defined based on SST projected by eighteen models of the Coupled Model Intercomparison Project Phase 3 (CMIP3, Meehl et al., 2007). The first SST condition is the ensemble mean SST projected by eighteen models of CMIP3 under A1B scenario of the Special Report on Emission Scenarios (SRES). The other three SST conditions are differently classified future SST patterns derived by cluster analysis of the future change pattern of SST from eighteen CMIP3 models under the A1B emission scenario. The detail of the clustering analysis of future SST conditions was described in Murakami et al. (2012). Interannual variations of the future climate SST are given by detrended interannual variations of present climate SST (1979-2003), based on the assumption that the interannual variations of SST in the future climate are similar to those of the present climate.

The four different SSTs are denoted as cluster 0 to 3, where cluster 0 indicates the mean of the eighteen CMIP3 models. **Figure 2.1** shows future changes in SST for clusters 0 to 3. All the SST patterns show that SST in the future climate increases over most of the entire ocean, with

increases up to about 3 °C. The North Pacific, especially, shows a greater increase in temperature than any other region. The different clusters of SST show different spatial characteristics. Cluster 3 shows the warmest SST and cluster 1 shows the lowest SST in the tropical Pacific. Cluster 2 shows the warmest SST in the tropical Indian Ocean. The spatial standard deviations of temperature rise in the tropics (30°S to 30°N) are 0.24, 0.21, 0.27, 0.38 °C for cluster 0 to 3, respectively. The SST cluster numbers for eighteen CMIP3 models are described in **Table 2.1**. Fan et al. (2013) and Hemer et al. (2013b) also conducted global wave climate projections based on several SSTs. SSTs in Fan et al. (2013) and Hemer et al. (2013b) were derived from arbitrary CMIP3 models. On the other hand, four SSTs in this study can objectively express the representative SSTs of eighteen CMIP3 models because of the cluster analysis.

The PP ensemble experiments were conducted with three different cumulus convection schemes: Yoshimura (YS), prognostic Arakawa-Schubert (AS) and the Kain-Fritsch (KF) scheme (see detail in Murakami et al., 2012). The target of PP ensemble experiments was sensitivity of cumulus convection scheme to tropical cyclone projection. It will be discussed in **Section 2.5.3**.

2.2.2 Wave climate projection

Global wave climate projection was carried out by WAVEWATCH III version 3.14 (Tolman, 2009) forced by sea surface wind from MRI-AGCM3.2H. WAVEWATCH III has been used for hindcast, nowcast and future global wave projection studies (Hemer et al., 2013b; Fan et al., 2013). The global domain was set for the latitudinal range of 90°S-67°N over all longitudes with $1^\circ \times 1^\circ$ spatial grids. Directional resolution is 15° , and the frequency space is 0.04 to 0.5 Hz, which is discretized in 25 increments logarithmically as a conventional setup. The Tolman and Chalikov (1996) source term package was used as a set for wind input and dissipation. WAVEWATCH III can represent unresolved islands (Tolman, 2009). The nesting in the WNP (11°N-50°N and 121°E-160°E) was performed with 0.5° spatial resolution and 10° directional resolution. Sea ice was not considered in this wave climate simulation.

Ensemble experiments of wave climate projection were organized as three present climate experiments based on the three PP ensemble experiments and twelve future climate experiments based on three PP ensemble experiments and four SST ensemble experiments. However, in **Section 2.4**, **Section 2.5.1** and **Section 2.5.2**, the results of the SST ensemble experiments with only YS cumulus convection schemes are shown in order to focus on the effect of SST differences. In **Section 2.5.3**, the results of PP ensemble experiments are shown in order to estimate the effect of SST differences relative to perturbed physics. The climate simulation for the present climate condition is denoted as HPA and those for future climate conditions with SST clusters 0 to 3 are denoted HFAc0, HFAc1, HFAc2, HFAc3, respectively for simplicity.

2.3 Validation

To clearly illustrate the accuracy of the simulated wind and wave fields, namely the sea surface wind speed at 10 m height (U_{10}) and significant wave height (H_s), the HPA was validated against reanalysis dataset. There are several reanalysis dataset for this validation. For example, ERA-Interim of the European Centre for Medium-Range Weather Forecasts' Reanalysis (Dee et al., 2011) and Climate Forecast System Reanalysis (CFSR) of the National Centers for Environmental Predictions (NCEP)

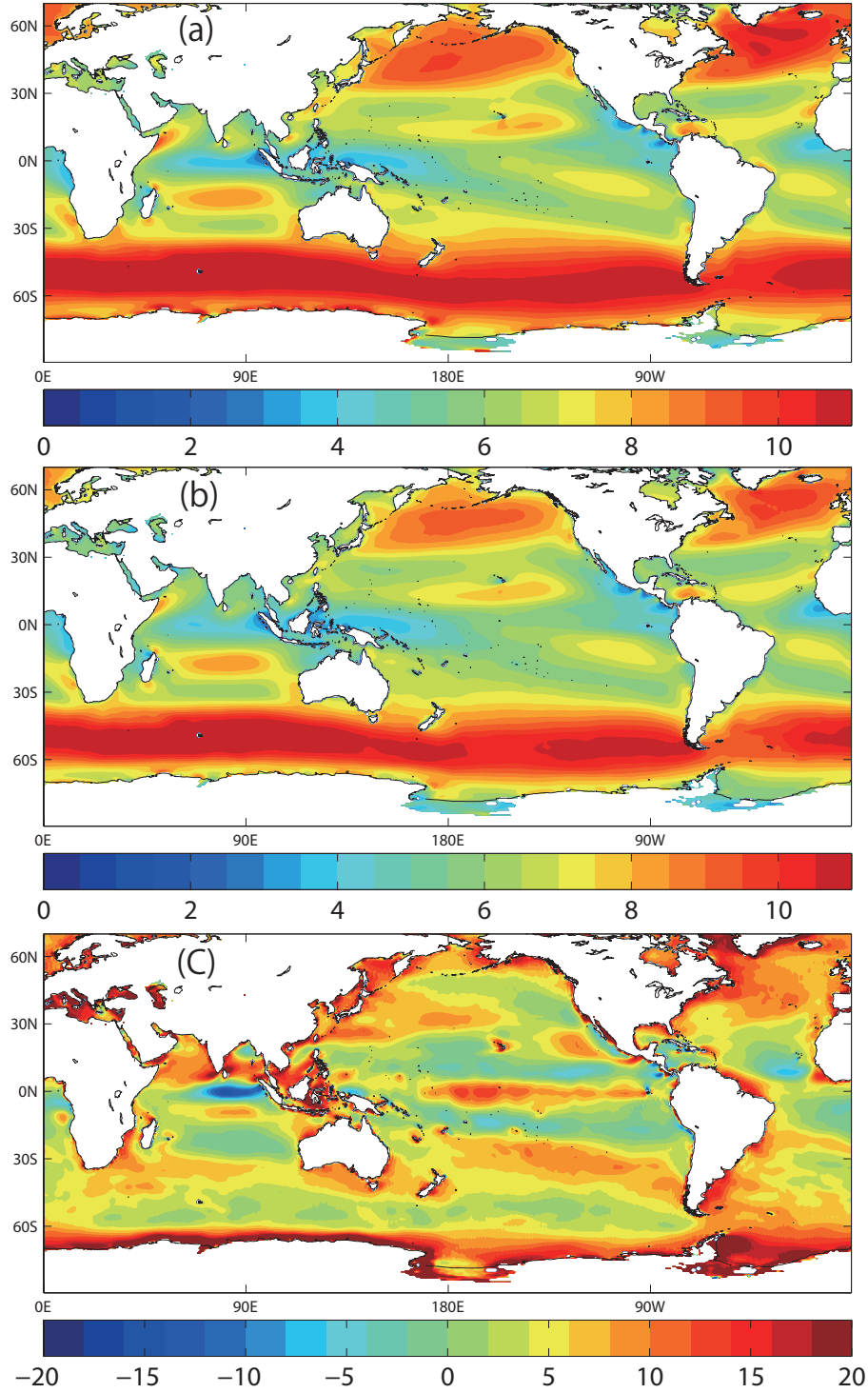


Figure 2.2: $\overline{U}_{10}$ over the period 1979-2009. (a)HPA (unit: ms^{-1}), (b)ERA-Interim (unit: ms^{-1}), (c)Difference of HPA and ERA-Interim (Standardized by ERA-Interim value, unit:%)

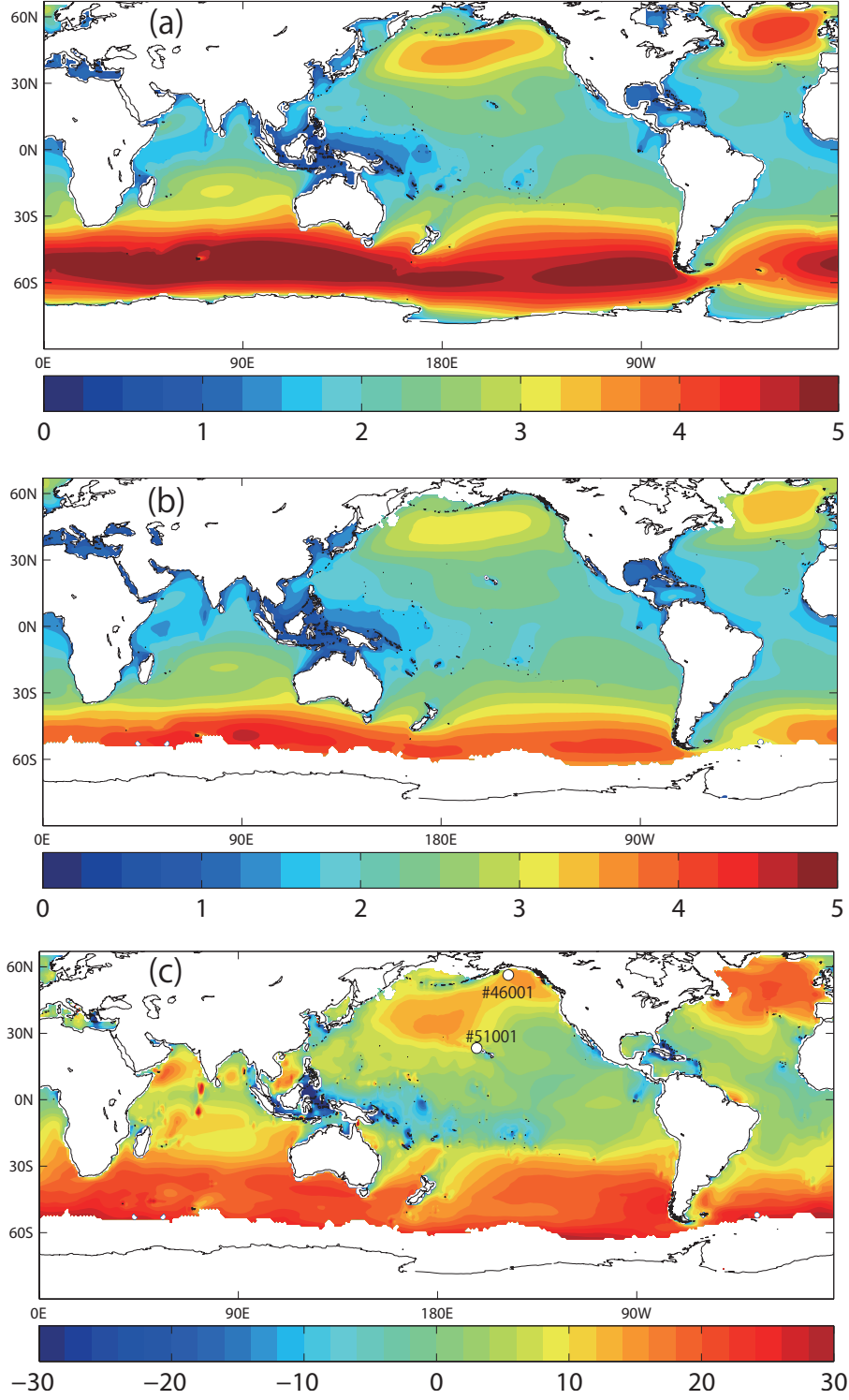


Figure 2.3: $\overline{H_s}$ over the period 1979-2009. (a)HPA (unit:m), (b)ERA-Interim (unit:m), (c)Difference of HPA and ERA-Interim (Standardized by ERA-Interim value, unit:%). The white circles with #46001 and #51001 in (c) are buoy locations for **Figure 2.4**.

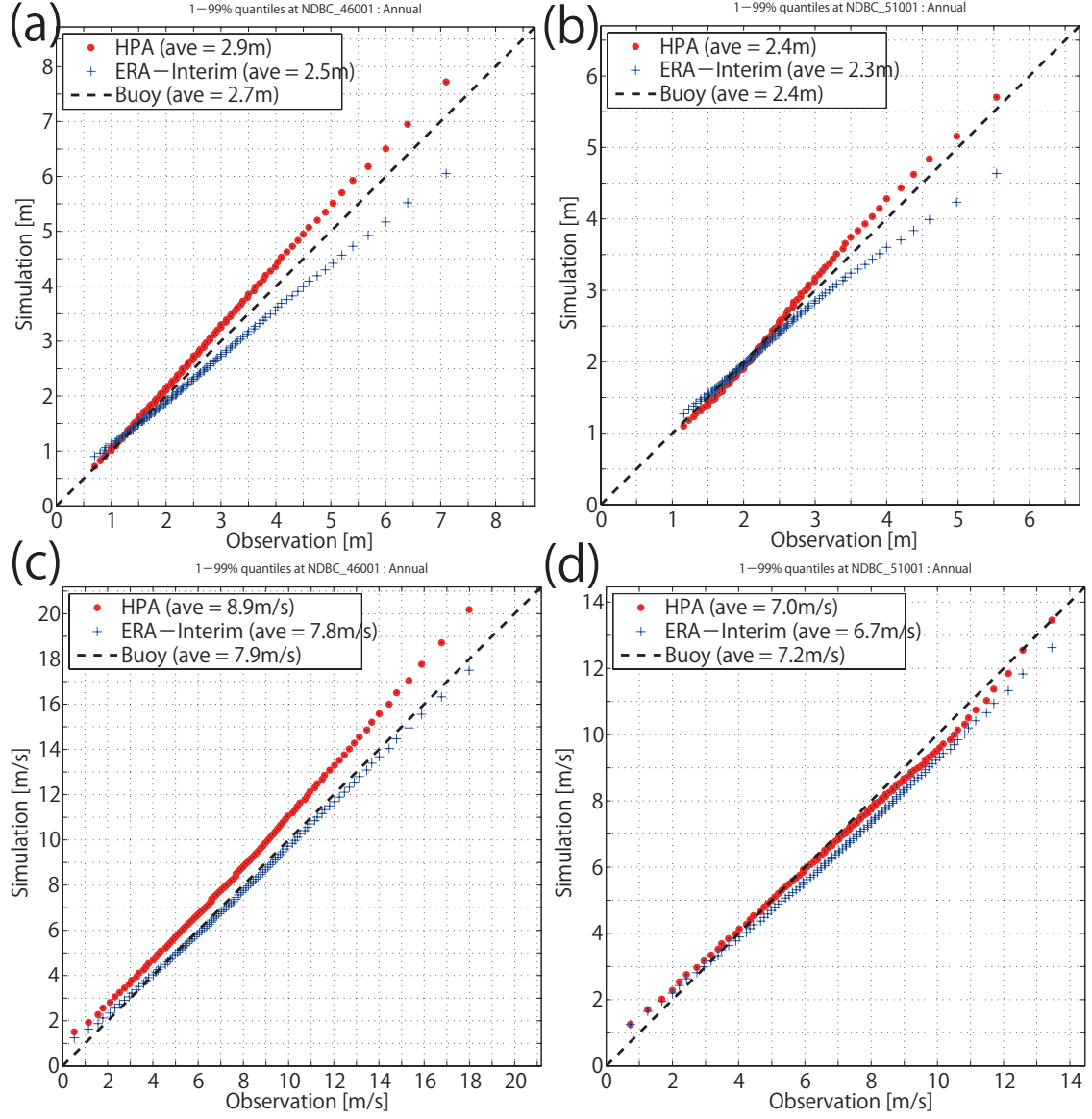


Figure 2.4: Quantile-Quantile plot (1,2 $\cdots$ 99 %) for H_s derived from HPA (red circle), ERA-Interim (blue cross) and buoy data (dashed line) at (a)#46001 (56.3°N, 147.9°W) and (b)#51001 (23.4°N, 162.3°N), and for U_{10} at (c)#46001 and (d)#51001. The locations of comparison site are plotted on **Figure 2.3(c)** by white circle.

Table 2.2: Comparison of H_s between buoy observation, HPA and ERA-Interim; The comparison is based on average, 50, 90 and 99% quantiles of H_s (unit:m)

Buoy ID	Longitude, Latitude	Source	Ave	50%	90%	99%
#21004	135.0°E , 29.0°N	Buoy	1.8	1.6	3.1	5.8
		HPA	1.9	1.7	3.2	5.4
		ERA-Interim	1.8	1.6	2.8	4.7
#22001	126.2°E , 28.1°N	Buoy	1.7	1.4	2.9	5.3
		HPA	1.6	1.4	2.9	4.9
		ERA-Interim	1.7	1.4	2.8	4.6
#41010	78.5°W , 28.9°N	Buoy	1.6	1.4	2.6	4.4
		HPA	1.4	1.2	2.5	3.8
		ERA-Interim	1.4	1.3	2.3	3.7
#44004	70.4°W , 38.5°N	Buoy	2.1	1.7	3.8	6.3
		HPA	2.0	1.7	3.6	5.9
		ERA-Interim	1.9	1.6	3.4	5.3
#44011	66.6°W , 41.1°N	Buoy	2.0	1.7	3.6	6.1
		HPA	2.0	1.7	3.7	6.1
		ERA-Interim	2.0	1.7	3.5	5.5
#46001	148.0°W , 56.3°N	Buoy	2.7	2.4	4.6	7.1
		HPA	2.9	2.6	5.1	7.7
		ERA-Interim	2.5	2.2	4.1	6.1
#46003	155.8°W , 51.8°N	Buoy	3.0	2.7	5.1	7.7
		HPA	3.4	3.1	5.7	8.7
		ERA-Interim	3.0	2.7	4.8	7.1
#46006	137.5°W , 40.9°N	Buoy	2.8	2.4	4.8	7.5
		HPA	3.0	2.6	5.2	7.7
		ERA-Interim	2.8	2.5	4.6	6.8
#46035	177.7°W , 57.1°N	Buoy	2.6	2.3	4.8	7.7
		HPA	2.7	2.3	5.1	7.8
		ERA-Interim	2.5	2.2	4.3	6.6
#51001	162.3°W , 23.4°N	Buoy	2.4	2.2	3.6	5.5
		HPA	2.4	2.2	3.8	5.7
		ERA-Interim	2.3	2.2	3.3	4.6
#51003	160.6°W , 19.0°N	Buoy	2.2	2.1	3.1	4.3
		HPA	2.1	1.9	3.1	4.5
		ERA-Interim	2.1	2.0	2.9	3.8
#51002	157.8°W , 17.1°N	Buoy	2.4	2.3	3.2	4.3
		HPA	2.2	2.1	3.0	4.0
		ERA-Interim	2.2	2.2	2.9	3.7
#51004	152.4°W , 17.5°N	Buoy	2.4	2.3	3.2	4.3
		HPA	2.3	2.2	3.0	4.1
		ERA-Interim	2.3	2.2	2.9	3.7

(Saha et al., 2010). Wave hindcast on CFSR was conducted by Chawla et al. (2013). In this study, we used ERA-Interim for this validation because the performance of multi-model global wave climate simulations (Wang and Swail, 2006; Mori et al., 2010; Hemer et al., 2013b; Fan et al., 2013; Semedo et al., 2013) were compared with ERA-Interim by Hemer et al. (2013a).

Figure 2.2(a) and **(b)** show the mean U_{10} ($\overline{U_{10}}$) for the HPA and the ERA-Interim dataset for the years 1979-2009. The spatial distribution of $\overline{U_{10}}$ of the HPA shows good qualitative agreement with that for the ERA-Interim data. The HPA can represent spatial characteristics in the historical global wind climate, such as strong winds in the Southern Ocean, relatively strong trade winds, and so on (**Figure 2.2(a)(b)**). **Figure 2.2(c)** shows the $\overline{U_{10}}$ differences between the HPA and ERA-Interim dataset. Compared with the ERA-Interim data, the $\overline{U_{10}}$ for the HPA has positive biases over almost the entire ocean (92% of the whole domain). The differences between $\overline{U_{10}}$ for the HPA and ERA-Interim are up to about 1 ms^{-1} .

Figure 2.3(a) and **(b)** show the mean H_s ($\overline{H_s}$) for the HPA and ERA-Interim dataset during the years 1979-2009. Similar to $\overline{U_{10}}$, $\overline{H_s}$ for the HPA can represent historical global wave climate qualitatively. However, $\overline{H_s}$ for the HPA is larger than for ERA-Interim in almost the entire ocean (87% of the whole domain, **Figure 2.3(c)**). These positive biases are remarkable in higher latitudes above 30° in both hemispheres. The positive biases are up to 0.4 m in the North Pacific, 0.7 m in the North Atlantic, and 1 m in the Southern Ocean. A result of the seasonal analysis (not shown), shows increased bias in the winter when wave heights are larger, indicating that the HPA overestimates high waves more than the ERA-Interim dataset.

In addition to the ERA-Interim, H_s and U_{10} for the HPA were compared with long-term observations by moored buoys (of the Japanese Meteorological Agency and the US National Oceanographic Data Center) in the Northern Hemisphere. The present climate results were compared with the data from thirteen buoys, and two representative results of the comparisons are shown in **Figure 2.4**. **Figure 2.4** are Quantile-Quantile plots (1, 2 ... 98, 99 %) of H_s and U_{10} derived from the HPA, ERA-Interim and the relevant buoy at mid-latitude (56.3°N , 147.9°W ; #46001) and the subtropics (23.4°N , 162.3°N ; #51001). The observed $\overline{H_s}$ at #46001 is 2.7 m, but the HPA and ERA-Interim give 2.9 m and 2.5 m. Overall, simulated H_s from the HPA is larger than that from the buoy data, although H_s from ERA-Interim is smaller than buoy. The overestimation of H_s by HPA and underestimation by ERA-Interim are remarkable at higher quantile values, generally. On the other hand, $\overline{H_s}$ from the HPA shows good agreement with the buoy data at lower latitude locations (#51001). Large waves can be simulated well by the HPA when compared with the ERA-Interim. Comparing the HPA and ERA-Interim data with other buoy observations in the Northern Hemisphere shows similar results as described above, such as relatively large positive biases with higher wave heights in mid-latitudes and better agreement with average and high wave heights at lower latitudes. The comparison of H_s between buoy, HPA and ERA-Interim is summarized in **Table 2.2**. Although the overestimation of higher latitudes' H_s by HPA can be partially attributed to the overestimation of U_{10} by HPA (**Figure 2.4(c)**), but other causes can be considered as follows because the spatial distribution of $\overline{H_s}$ bias by HPA compared with ERA-Interim is different to that of $\overline{U_{10}}$ (**Figure 2.2(c)** and **Figure 2.3(c)**).

The overestimation of the wave height by HPA compared to ERA-Interim can be partially attributed to the Tolman and Chalikov (1996) source term package in WAVEWATCH III. A preliminary test of wave climate simulation was conducted by WAVEWATCH III ver.4.18 with other wind

input and dissipation source term packages. In case of ECWAM source term package parameterized by Bidlot (2012) which is basically same parameterization as ERA-Interim, the $\overline{H_s}$ is smaller than that by Tolman and Chalikov (1996) all over the globe. Therefore, the overestimation by HPA compared to ERA-Interim can be partially attributed to the Tolman and Chalikov (1996) source term package. In case of Ardhuin et al. (2010) source term package, the $\overline{H_s}$ over low latitudes is smaller than that by Tolman and Chalikov (1996) and the $\overline{H_s}$ over mid to high latitudes is close to that by Tolman and Chalikov (1996). The major difference in low latitudes is due to new swell dissipation term of Ardhuin et al. (2010). Moreover, beside the wind input and dissipation source term parameterizations, the wave-wave interactions, spatial and directional spectrum resolutions can influence on the accuracy of wave climate projection. However, extra argument of wave modeling is beyond this study.

There is additional reason why HPA overestimates wave height compared to ERA-Interim at high latitudes, especially over the Southern Ocean, which can be due to sea ice effects. Due to lack of sea-ice information for HPA wave simulation, broader open ocean without sea ice has longer fetch, which leads to larger waves. These waves can propagate to tropics. Ardhuin et al. (2011) indicated that wave blocking by even icebergs significantly reduces wave model errors in the region south of 45°S. Furthermore, future changes in sea ice have significant impacts on those in wave climate. Semedo et al. (2013) showed that the future sea ice retraction would lead to increase in wave height over ice retreating area in the future climate. On the other hand, increase in sea ice (Eisenman et al., 2014) can lead to decrease in wave height. IPCC-AR5 (2013) stated that a decrease in sea ice extent and volume is expected in the Antarctic, but with low confidence. Therefore, discussion of wave climate projection around sea ice region and even tropics where swells from the sea ice region in the Southern Ocean might be significant, needs caution. Thus, global wave climate is discussed simply in **Section 2.4**, and WNP wave climate which is unlikely to be affected by the lack of sea ice, is discussed in detail in **Section 2.5**.

2.4 Future changes in global wind and wave climate

This section simply looks at future changes in $\overline{U_{10}}$ and $\overline{H_s}$ on the global scale and the sensitivity to SST conditions. **Figure 2.5** show the ensemble mean and maximum differences of future changes in $\overline{U_{10}}$ and $\overline{H_s}$. Ensemble mean and maximum differences are represented as $\sum_{i=0}^3 (\text{HFAc}i - \text{HPA})/4$ and $\max_{i=0,1,2,3} (\text{HFAc}i - \text{HPA}) - \min_{i=0,1,2,3} (\text{HFAc}i - \text{HPA})$. In the figure, the black contoured regions with dots indicate the regions where future changes of HFAc0 through HFAc3 show the same signs (positive or negative) for reliability of projections. In regions where future changes of HFAc0 through HFAc3 show both different signs and larger differences, these areas have large uncertainty in the projected wave height, which is related to the uncertainty in SST condition.

The spatial distribution of future changes in $\overline{U_{10}}$ and $\overline{H_s}$ are similar, which can be characterized by the changes depending on latitudes such as increases over tropics and higher latitudes and decrease over sub-tropics (**Figure 2.5(a)** and **(c)**). However, that of $\overline{U_{10}}$ depends on latitude more clearly than that of $\overline{H_s}$. This is due to increased swell height from higher latitudes which can cancel out the decrease in wind-wave height over subtropics. Furthermore, decreases in $\overline{U_{10}}$ and $\overline{H_s}$ are remarkable in the North Atlantic. The spatial distribution of future changes in $\overline{H_s}$ is consistent with previous

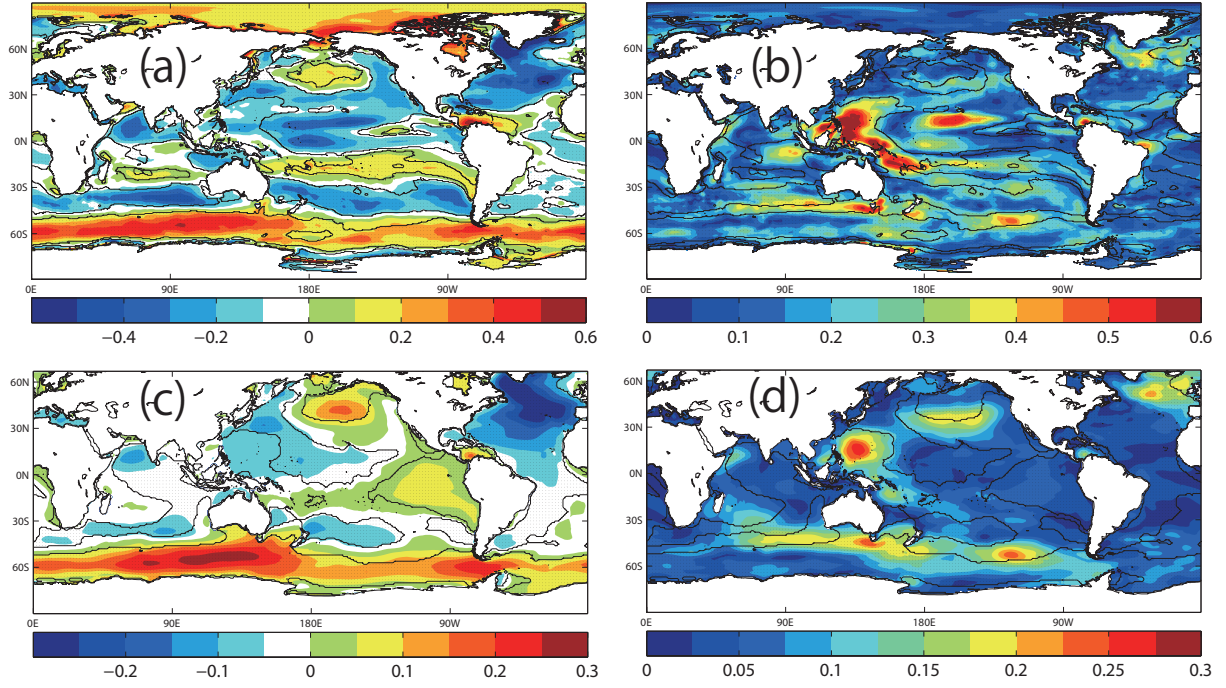


Figure 2.5: Future changes in annual $\overline{U_{10}}$ and $\overline{H_s}$. (a) Ensemble mean of future changes in $\overline{U_{10}}$ (unit: ms^{-1}), (b) Maximum differences of future changes in $\overline{U_{10}}$ (unit: ms^{-1}), (c) Ensemble mean of future changes in $\overline{H_s}$ (unit: m) and (d) Maximum differences of future changes in $\overline{H_s}$ (unit: m). Regions with black dots indicate areas where the four future projections of HFAc0 to HFAc3 show the same sign.

studies (Hemer et al., 2013a) except for increases over the North Pacific. Although the magnitudes need caution because of lack of sea ice described in **Section 2.3**, future changes in $\overline{U_{10}}$ and $\overline{H_s}$ are about $\pm 0.6 \text{ ms}^{-1}$ and $\pm 0.3 \text{ m}$ depending on the region, and the maximum differences are up to about 0.6 ms^{-1} and 0.3 m . Therefore, the uncertainty of the $\overline{U_{10}}$ and $\overline{H_s}$ projection has the same magnitude as its future change.

The spatial distribution of maximum differences in $\overline{H_s}$ future change doesn't correspond to that of $\overline{U_{10}}$ in lower latitudes (**Figure 2.5(b)** and (d)). Wave height is roughly proportional to squared wind speed and wind speed is relatively low in lower latitudes. Therefore, relatively larger maximum differences of future changes in $\overline{U_{10}}$ over lower latitudes (**Figure 2.5 (b)**) cannot contribute to those of $\overline{H_s}$ (**Figure 2.5 (d)**). The regions where the four future changes in $\overline{U_{10}}$ and $\overline{H_s}$ of HFAc0 through HFAc3 show the same sign comprise 49.5% and 42.5% of whole domain. The regions where the future changes of HFAc0 through HFAc3 show different signs and larger differences for both $\overline{U_{10}}$ and $\overline{H_s}$ are the lower latitudes of the WNP and the mid-latitudes of the South Pacific (**Figure 2.5(b)(d)**). The large uncertain region in the lower latitudes of the WNP is discussed in the next section.

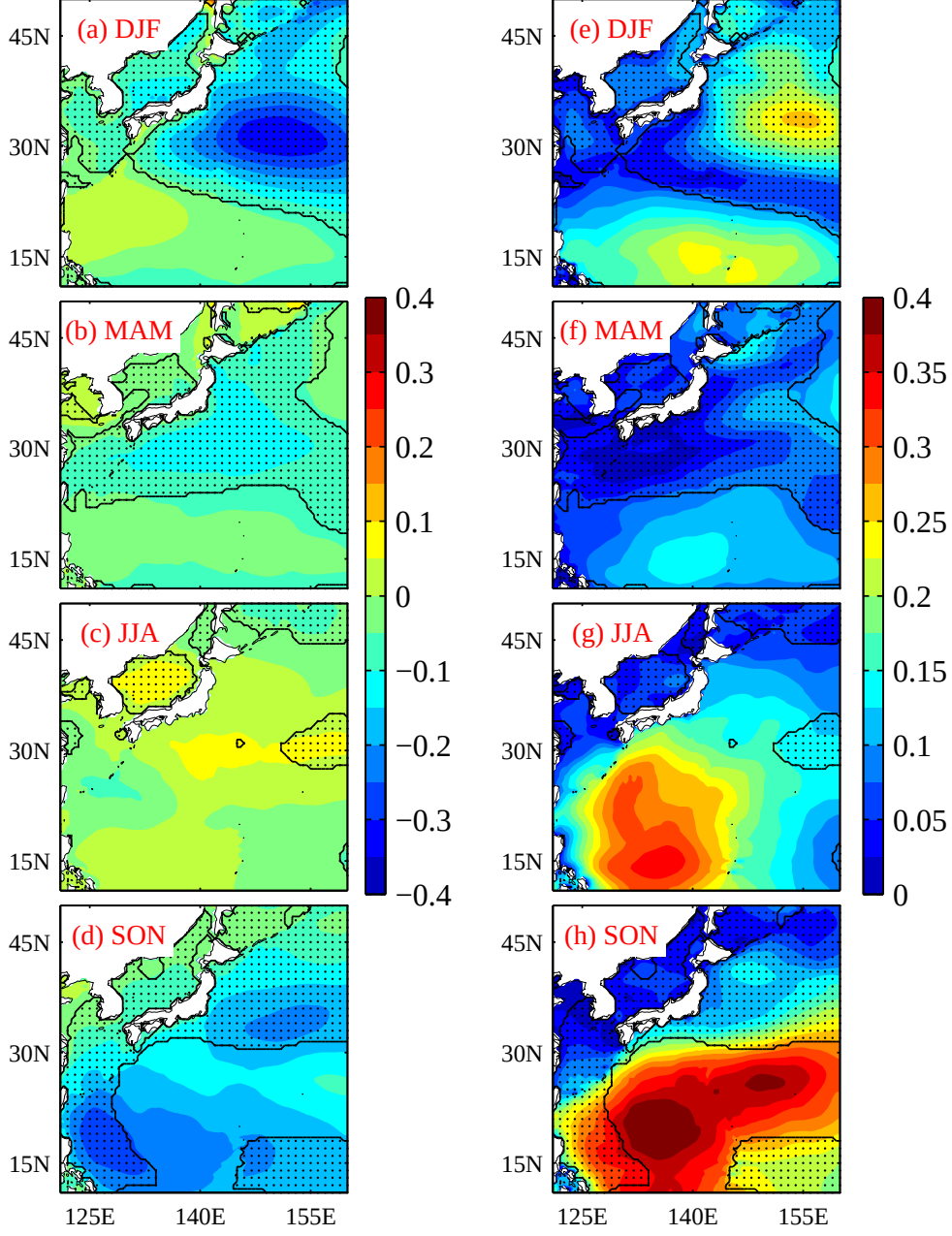


Figure 2.6: Future changes in $\overline{H_s}$ for the WNP during (a) DJF, (b) MAM, (c) JJA and (d) SON, and the maximum differences in future changes during (e) DJF, (f) MAM, (g) JJA and (h) SON (unit:m). Regions with black dots indicate areas where the four future projections show the same sign.

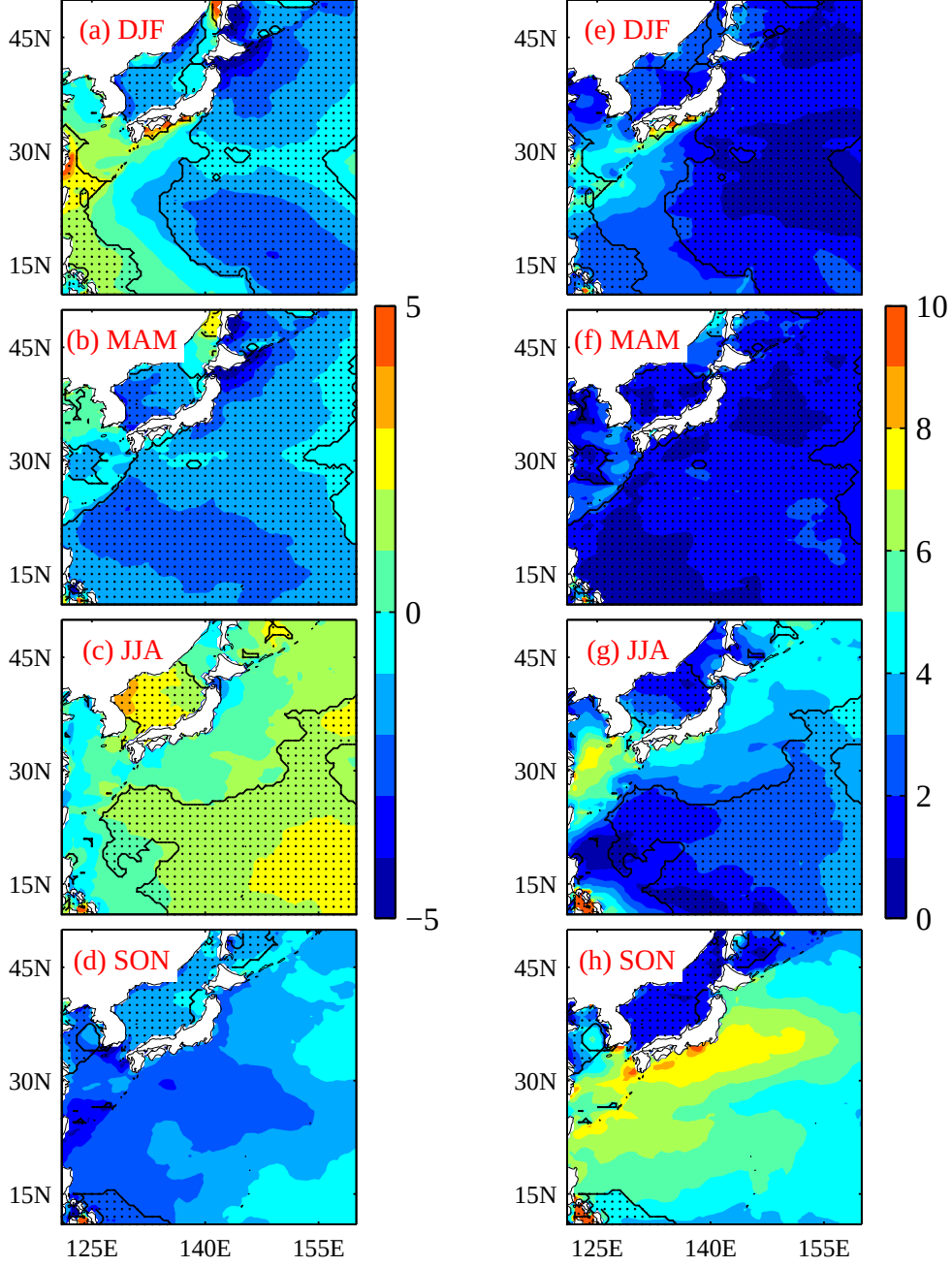


Figure 2.7: Future changes in $\overline{T_p}$ (normalized by HPA value) for the WNP during (a) DJF, (b) MAM, (c) JJA and (d) SON, and the maximum differences in future changes during (e) DJF, (f) MAM, (g) JJA and (h) SON (unit:%). Regions with black dots indicate areas where the four future projections show the same sign.

2.5 Future changes in wave climate over the Western North Pacific

2.5.1 Future changes in wave climate by SST ensemble

To discuss wave climate changes over the WNP in detail, the projected future changes in wave climate over the WNP which were calculated by a nested 0.5° spatial resolution, are shown in this section. **Figure 2.6** shows the future changes in seasonal $\overline{H_s}$ and the maximum differences in the ensembles over the WNP. The four seasons are classified as December to February (DJF), March to May (MAM), June to August (JJA) and September to November (SON). The biggest changes in the future wave climate can be seen around 30°N and 150°E during DJF, where the $\overline{H_s}$ decrease is 0.3 m (**Figure 2.6(a)**). However, there are no significant changes of H_s during MAM and JJA (**Figure 2.6(b)(c)**). The future changes for HFAc0 to HFAc3 around the Japan coast show the same sign during all seasons except for JJA. During MAM, the values of the maximum differences in future change are the smallest. The uncertainty in the lower latitudes of 30°N during JJA and SON is larger. For example, the future changes in $\overline{H_s}$ at 20°N - 30°N and 130°E - 150°E during SON are -0.24, -0.24, -0.23 and +0.07 m for HFAc0 to HFAc3, respectively. Although the results for HFAc0 to c2 are consistent each other, the future changes of only HFAc3 are different. In addition to wave height (**Figure 2.6**), **Figure 2.7** shows the future changes in seasonal mean wave period (peak period : T_p) and the maximum differences in the ensembles. Note that the future changes shown in **Figure 2.7** are normalized by HPA values. Same as wave height, the maximum differences of $\overline{T_p}$ future changes are larger in JJA and SON, especially in SON. $\overline{T_p}$ future changes by HFAc0 to c2 are negative over the WNP, and those by HFAc3 are positive. The seasons JJA and SON in the WNP are active typhoon seasons. Therefore, future changes in wave climate and the large uncertainty in these seasons (JJA and SON) are discussed in relation to typhoon characteristics below.

2.5.2 Relationship between future changes in wave height and typhoon characteristics

The most active area of tropical cyclone over the globe is the WNP. We are going to focus on the analysis for JJA and SON jointly (JJASON) in the WNP to discuss typhoon effects hereafter. The typhoon detection method adopted in the present study employed five criteria of relative vorticity at 850 hPa, temperature anomaly in the warm core region, maximum wind velocity at 850 hPa, maximum wind velocity at 300 hPa and cyclone duration, to identify typhoons (Murakami et al., 2012). Total number of typhoon genesis was controlled by changing threshold of the criteria. The typhoon data detected by Murakami et al. (2012) was used in this study. In this subsection, data from 1979-2003 (and not 1979-2009) were used as the HPA. **Figure 2.8** shows the averaged frequencies of typhoon passing from the HPA and the best track data during 1979-2003 provided by Japan Meteorological Agency (2014). The frequency was smoothed over a $6^\circ \times 6^\circ$ grid. The typhoon passes frequently through the region 10°N - 30°N and 110°E - 140°E compared with other regions. The results of the HPA show good agreement with the best track in this region. However, the HPA underestimates typhoon frequency in higher latitudes of 30°N .

Figure 2.9 displays the future changes in typhoon frequency for HFAc0 to HFAc3. The results for HFAc0, HFAc1 and HFAc2 show less typhoon frequency in the active typhoon region. On the other hand, the reduction in typhoon frequency for HFAc3 is moderate compared with the other three experiments. As indicated in **Section 2.5.1**, the tendency of future $\overline{H_s}$ changes for

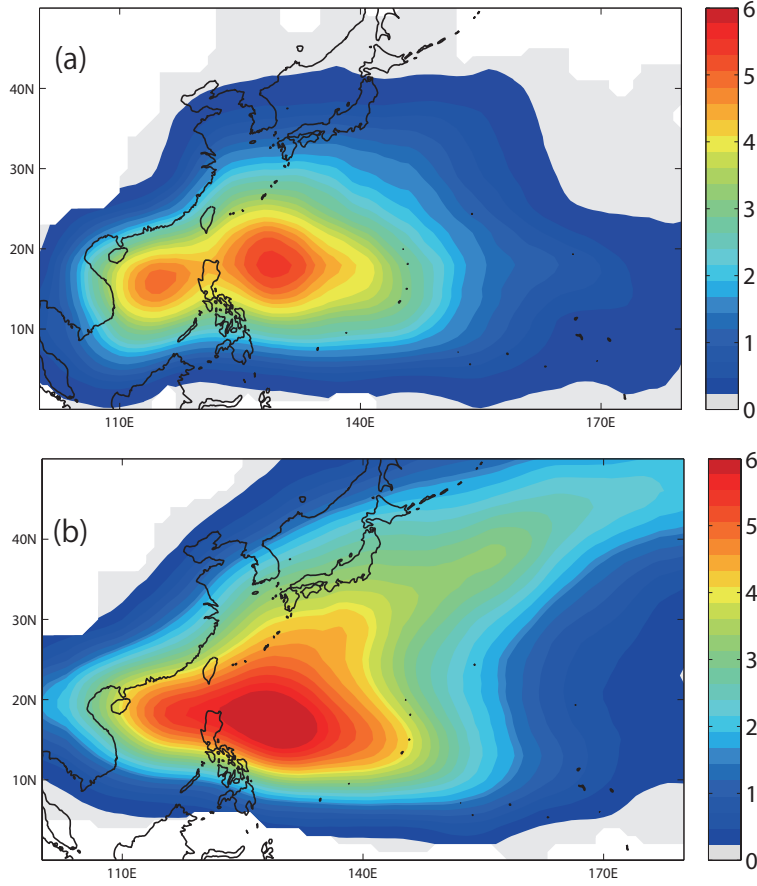


Figure 2.8: Averaged frequency of typhoon passing smoothed over $6^\circ \times 6^\circ$ grid in JJASON. (a) HPA, (b) Best Track. (unit: number per one season)

HFAc3 is different to that of the other experiments. It can be considered that these differences of $\overline{H_s}$ changes between HFAc3 and the other experiments are caused by the differences in future changes of typhoon frequency between the ensembles as shown by **Figure 2.9**. However the contributions of typhoon changes to $\overline{H_s}$ changes are not quantitatively clear. Therefore, how changes in typhoon characteristics affect the $\overline{H_s}$ was estimated quantitatively as follows. The total $\overline{H_s}$ is represented as a combination of both typhoon and non-typhoon events.

$$\overline{H_s} = \overline{H_{tc}} \cdot r_{tc} + \overline{H_{no}} \cdot (1 - r_{tc}) \quad (2.1)$$

where $\overline{H_{tc}}$ is the $\overline{H_s}$ under a typhoon condition (in other words, typhoon wave intensity), $\overline{H_{no}}$ is the $\overline{H_s}$ under a non-typhoon condition (in other words, non-typhoon wave intensity) and r_{tc} is the ratio for the period of timeframe under a typhoon condition to the entire timeframe (in other words, typhoon frequency). Eq. (2.1) can be rewritten for the future change in $\overline{H_s}$ ($\Delta \overline{H_s}$) as

$$\begin{aligned} \Delta \overline{H_s} &= (\overline{H_{tc}} - \overline{H_{no}}) \cdot \Delta r_{tc} + \Delta \overline{H_{tc}} \cdot r_{tc} \\ &+ \Delta \overline{H_{no}} \cdot (1 - r_{tc}) + (\Delta \overline{H_{tc}} - \Delta \overline{H_{no}}) \cdot \Delta r_{tc} \\ &= C_r + C_{Htc} + C_{Hno} + C_\Delta \end{aligned} \quad (2.2)$$

where Δ means future change, and C_r , C_{Htc} , C_{Hno} and C_Δ are contributions of Δr_{tc} (in other words, typhoon frequency change), $\Delta \overline{H_{tc}}$ (typhoon wave intensity change), $\Delta \overline{H_{no}}$ (non-typhoon wave

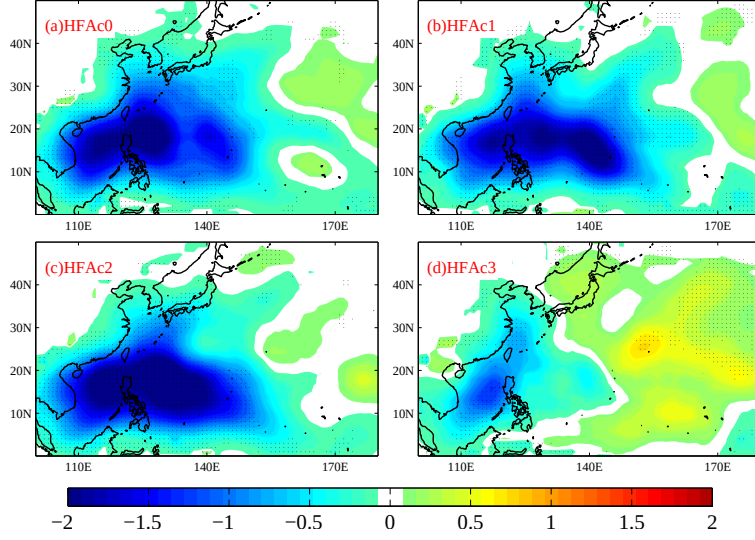


Figure 2.9: Future changes in the frequency of typhoon passing in JJASON for (a)HFAc0, (b)HFAc1, (c)HFAc2 and (d)HFAc3. Regions with black dots indicate significant changes with 5% significance level tested by Mann-Whitney U test. (unit: number per one season)

Table 2.3: Model description of the present study and COWCLIP (Hemer et al., 2013a)

	This study	HE13(1)	HE13(2)	FA13(1)	FA13(2)	MO10	SE13
Reference	-	Hemer et al. (2013b)		Fan et al. (2013)		Mori et al. (2010)	Semedo et al. (2013)
Scenario	A1B	A2		A1B		A1B	A1B
SST	4 clusters	MPI's ECHAM5	CSIRO's MK3.5	GFDL's CM2.1	CMIP3 mean	CMIP3 mean	MPI's ECHAM5
AGCM	MRI-AGCM3.2H	CSIRO's CCAM		GFDL's HiRAM + WW3 coupled		MRI-AGCM3.1S	ECHAM5's AGCM
Wave model	WW3	WW3				SWAN	WAM
SST cluster	0 to 3	(2)	(1)	3	0	0	2

intensity change) and the residual to $\Delta \overline{H}_s$. **Figure 2.10** shows $\Delta \overline{H}_s$, C_r , C_{Htc} , and C_{Hno} for HFAc0 to HFAc3. The figure clearly shows that $\Delta \overline{H}_s$ for HFAc3 are different from the other experiments (**Figure 2.10(a) to (d)**) as described above. The $\Delta \overline{H}_s$ for HFAc0 to HFAc2 show decreases in wave height by 0.3 m, but for HFAc3 show increase by 0.1 m. The values of C_r at lower latitudes are negative for all experiments due to a reduction in typhoon frequency in the future projection, but C_r for HFAc3 are relatively moderate compared to the others (**Figure 2.10(e) to (h)**), which follows the result of **Figure 2.9**. Furthermore, C_{Htc} for HFAc3 are larger than for the other experiments (**Figure 2.10(i) to (l)**). As a result, the differences in typhoon frequency (C_r) and typhoon wave intensity changes (C_{Htc}) between HFAc3 and HFAc0 to HFAc2 yield the differences in $\overline{H}_s$ future changes. Note that in the mid to higher latitudes in **Figure 2.10**, the influence of changes in typhoon characteristics on $\Delta \overline{H}_s$ is less accurate because the HPA underestimates typhoon frequency in this region. Despite this, the general relationship behind the changes is clear.

2.5.3 Comparison with multi-model ensemble

The projections for $\overline{H}_s$ by SST ensemble clearly illustrate the influence of tropical cyclones. The SST ensemble can perform the sensitivity analysis for a projection of SST but the variation for future

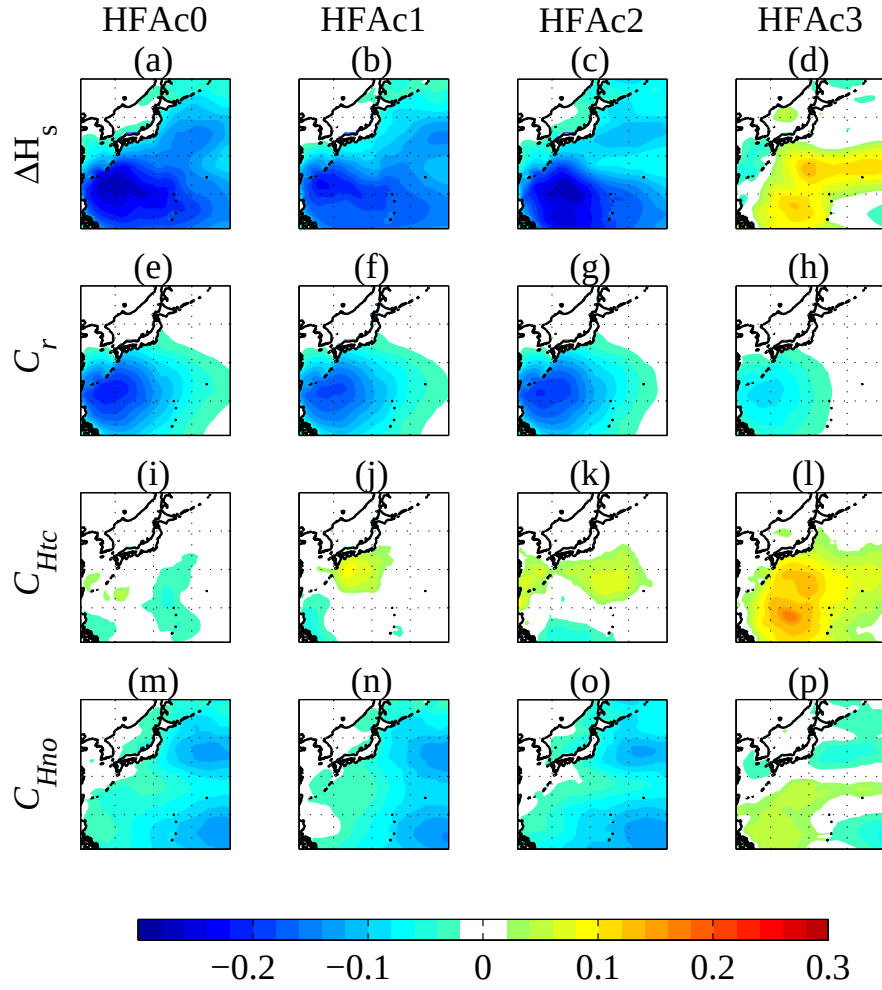


Figure 2.10: Future changes in $\overline{H_s}$ for the WNP and the contributions of typhoon characteristics changes (unit:m). Rows 1 through 4 show future changes in $\overline{H_s}$ ($\Delta\overline{H_s}$), contributions of typhoon frequency change (C_r), contributions of typhoon wave intensity change (C_{Htc}) and contributions of non-typhoon wave intensity change (C_{Hno}), from top to bottom. Columns 1 through 4 show results by SST ensemble for clusters 0 through 3, from left to right.

change is limited; while the multi-model ensemble gives wider variation, it is difficult to understand the reason behind the difference. Therefore, it is important to compare different types of ensembles to understand the origin of this difference and the uncertainty with forcing the projection. The multi-model ensemble experiment (COWCLIP; Hemer et al., 2012, Hemer et al., 2013a) will help to add a general understanding about contributing factors to the projections discussed above. In addition to SST ensemble projections, PP ensemble projections were conducted with three different cumulus convection schemes (YS, AS and KF). Note that the results shown in the above section are based on the YS scheme as described in **Section 2.2**.

Figure 2.11 shows the future changes in $\overline{H_s}$ using SST and PP ensemble projections during the months JJASON. The $\overline{H_s}$ changes for HFAC0 to HFAC2 (**Figure 2.11** except for (j)(k)(l)) are negative in lower latitudes of the WNP, while those for HFAC3 (**Figure 2.11** (j)(k)(l)) are positive. This result confirms that, in lower latitudes of the WNP, future $\overline{H_s}$ changes during summer for

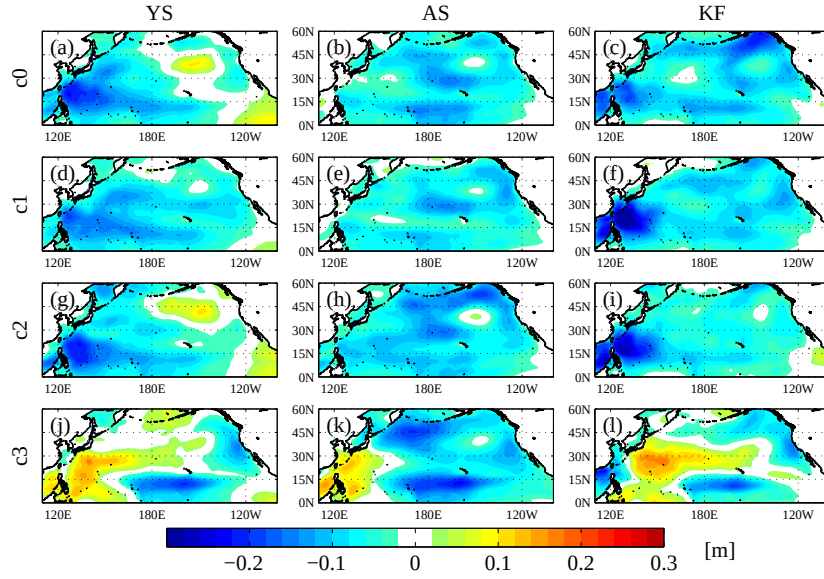


Figure 2.11: Future changes in $\overline{H_s}$ during JJASON (unit:m). Rows 1 through 4 show results based on SST ensemble for clusters 0 through 3, from top to bottom. Columns 1 through 3 show perturbed physics ensemble results for YS, AS and KF schemes, from left to right.

HFAc3 are opposite in sign to those for HFAc0 to HFAc2, and this does not depend on the cumulus convection scheme. **Figure 2.12(a)** shows the maximum differences in $\overline{H_s}$ changes over the twelve ensemble members, indicating that the variation of $\overline{H_s}$ changes over lower latitudes of the WNP are greatest in the North Pacific.

This result is compared with the multi-model ensemble wave climate projection data (COWCLIP) which consists of works by Mori et al. (2010), Hemer et al. (2013b), Fan et al. (2013) and Semedo et al. (2013) (hereafter MO10, HE13, FA13 and SE13; The data were obtained at the COWCLIP's Wiki ; <https://wiki.csiro.au/display/sealevel/COWCLIP+Contributions>). Although the COWCLIP includes both dynamical and statistical wave climate projection data, the dynamical wave climate projection data was used in this comparison. The first reason is that the seasonal $\overline{H_s}$ was calculated by the statistical wave model with seasonal mean SLP (Wang and Swail, 2006). Therefore the statistical wave model could not resolve typhoon generated waves. Second, the statistical wave climate projection was forced by Sea Level Pressure (SLP) of AOGCM. Therefore, SST was not used as boundary condition in comparison with the dynamical projections.

HE13 and FA13 provided two members from each study, because of two different SST conditions respectively, which are denoted as HE13(1), HE13(2), FA13(1), and FA13(2), hereafter. When those members are counted with MO10 and SE13, they total six COWCLIP projections. The COWCLIP projections were conducted based on the dynamical approach which is described in the Introduction section (**Section 2.1**) and same framework as this study, however, the components of the framework are different each other. The main components are future emission scenario, SST conditions for AGCM and wave model. The description of the wave climate projections for COWCLIP is shown in **Table 2.3** focusing on the components and SST cluster number. The six wave projections for COWCLIP are quite different from each other in that they use different SST conditions for AGCM, SRES scenarios, AGCMs and wave models (**Table 2.3**). Although they are different, the

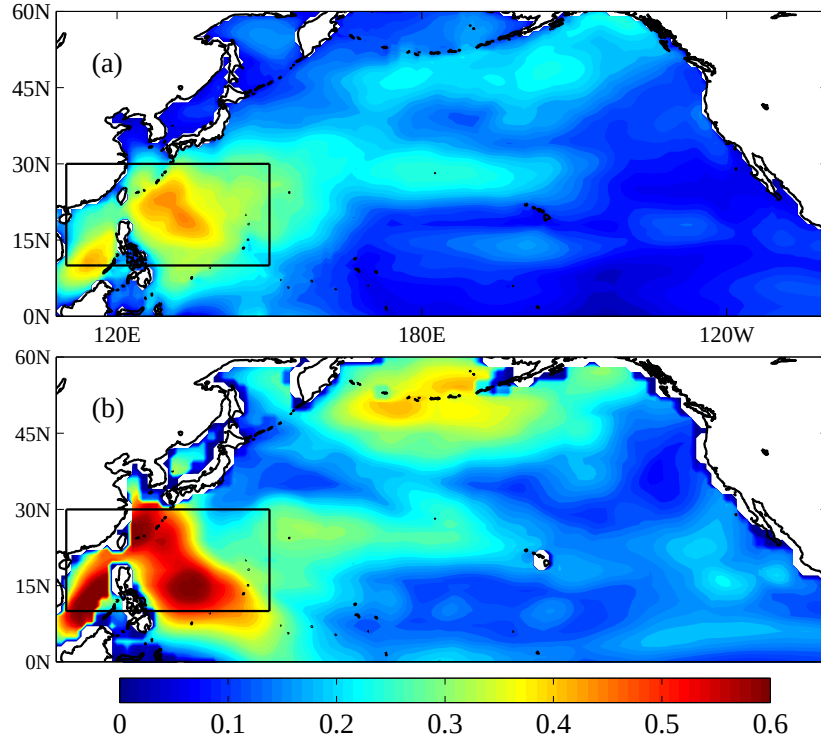


Figure 2.12: Maximum differences in future changes of $\overline{H_s}$ during JJASON over ensemble members. (a) Twelve members of SST and PP ensemble projections. (b) Six members from COWCLIP analyses. (unit:m)

maximum differences in future changes of $\overline{H_s}$ across the COWCLIP projections shown in **Figure 2.12(b)** give a similar spatial distribution to that for this study in **Figure 2.12(a)**. Although the magnitude is different, the spatial distributions are characterized by a greater maximum difference in the lower latitudes of the WNP. This indicates that the COWCLIP projections also have a large uncertainty with the changes in the future wave climate, likely related with typhoon changes.

Future changes in $\overline{H_s}$ for the SST, PP ensemble, and COWCLIP projections for the region demarcated in **Figure 2.12** (10-30°N, 110-150°E) are shown in **Figure 2.13**. It is clear that future changes under SST cluster 3 of this present study have a different tendency when compared to those under clusters 0, 1 and 2; and, future changes under FA13(1) are also different from the other COWCLIP projections. Wave climate projection from FA13(1) is based on SST projected by GFDL's CM2.1 under the A1B scenario, which is classified into SST cluster 3 by clustering analysis (**Table 2.1**, **Table 2.3**). FA13(2) and MO10 are based on CMIP3 ensemble SST under A1B, which can be classified into cluster 0; SE13 is based on SST from MPI's ECHAM5 under A1B which can be classified into cluster 2 (**Table 2.1**, **Table 2.3**). HE13(1) and HE13(2) are based on SST of ECHAM5 and CSIRO's MK3.5 under the A2 scenario (**Table 2.3**) and have not been clustered by Murakami et al. (2012) because the analysis of Murakami et al. (2012) was for the A1B scenario; but, the SST patterns of HE13(1) and (2) correlate relatively well with clusters 2 and 1, respectively, when compared with the other SST clusters.

Therefore, the SST ensemble results show that in the lower latitudes of the WNP future $\overline{H_s}$ changes forced by SST cluster 3 condition are positive and those forced under the other SST

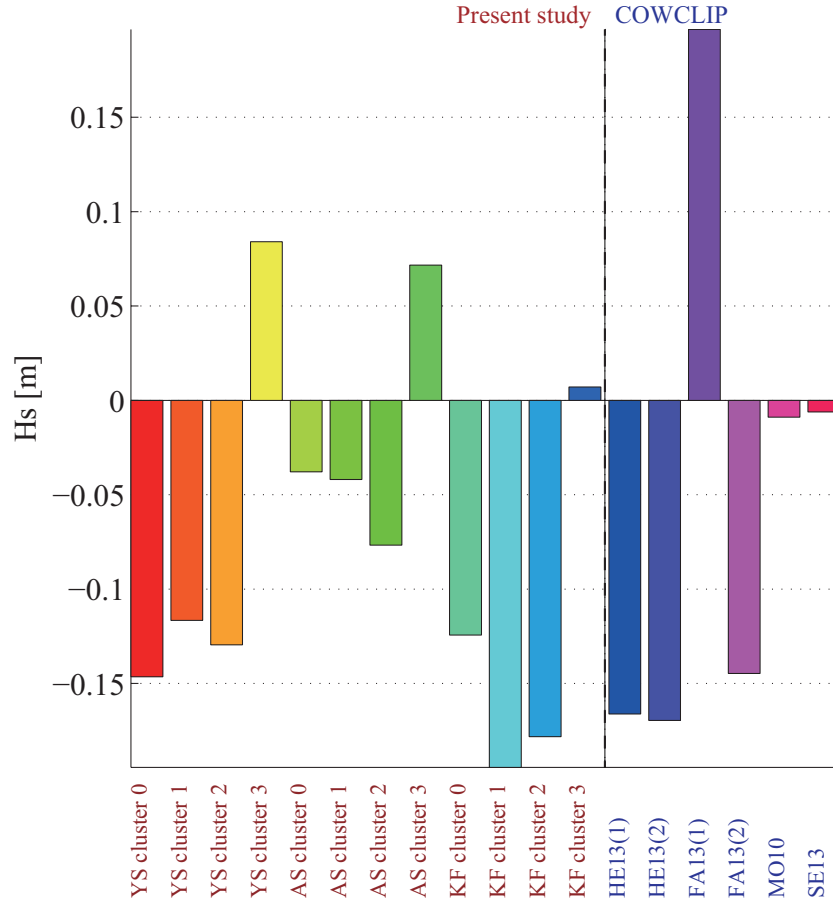


Figure 2.13: Future changes in $\overline{H_s}$ for the present study and COWCLIP analysis for the region outlined in **Figure 2.12** (10-30° N, 110-150° E). The first twelve bars from the left are for the present study and the remaining bars are for COWCLIP models

cluster conditions are negative, results that are consistent with COWCLIP projections. In addition to FA13(1) and (2), Fan et al. (2013) has conducted additional wave climate projections forced by SSTs projected by ECHAM5 and UKMO's HadCM3 under an A1B scenario (which are clusters 2 and 3, **Table 2.1**), indicating that in the west Pacific during the summer months, future changes in $\overline{H_s}$ under the SST cluster 3 condition (UKMO's HadCM3 and GFDL's CM2.1) are larger than those for clusters 0 and 2 (CMIP3 ensemble mean and ECHAM5), a result due to a variation in the future change in typhoon frequency. This results of Fan et al. (2013) are also consistent with this study. In spite of the differences in the GCMs themselves and the other forcing factors, the present study's ensemble experiments yield variation in future $\overline{H_s}$ changes which are consistent variation to COWCLIP ensemble. These similar deviations suggest that the major factor behind mean wave climate changes in the WNP is SST changes and the associated typhoon activity in the future climate.

As discussed above, SST as a boundary condition for AGCM has significant impact on wave climate projection. Although clustering by SST has been defined with future change patterns for the entire tropical domain, SST clusters can be characterized by the magnitudes of warming in the equatorial and subtropical Pacific as seen in **Figure 2.1**. Therefore, SST clusters are described simply by the relationship between the future changes in SST for two identified regions as follows.

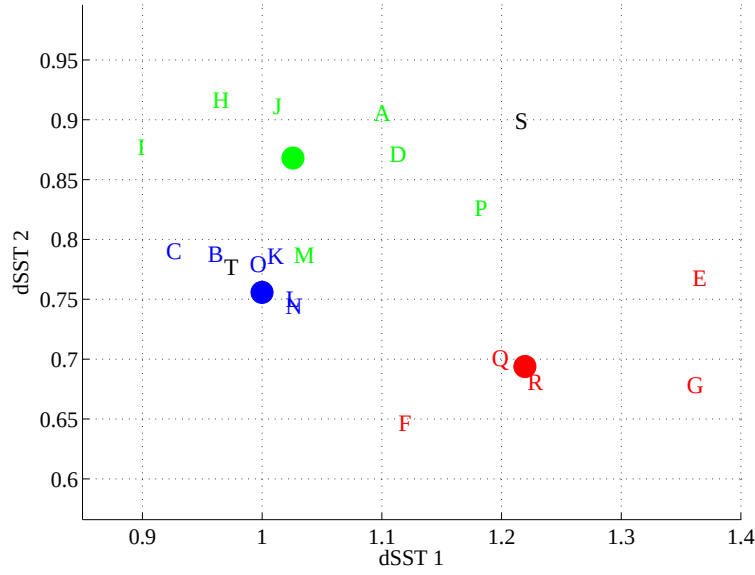


Figure 2.14: The relationship between the future changes in SST for the western equatorial Pacific (5°S - 5°N and 140 - 180°E ; dSST1) and the subtropical South Pacific (5 - 30°S and 90 - 180°W ; dSST2). The future changes in SST are normalized by the mean future change for the whole tropic region. Letters (A to R) denote the individual model run of CMIP3 described in **Table 2.1**. Green indicates that the model SST is cluster 1, blue is cluster 2, and red is cluster 3. Letters S and T denote MPI's ECHAM5 under A2, and CSIRO's MK3.5 under A2 used by HE13.

One of the regions is the western equatorial Pacific (5°S - 5°N , 140 - 180°E ; denoted as dSST1), the other is the subtropical South Pacific (15 - 30°S , 150°E - 90°W ; denoted as dSST2). Normalized future changes in SST within the two regions for CMIP3 models and clusters 1 to 3 are shown in **Figure 2.14**. Normalized future change means that the future change in SST from each model is divided by the mean future change of the whole tropical region (30°S to 30°N). It is clear that SST cluster 3 can be characterized as more relative warming over the western equatorial Pacific and less relative warming over the subtropical South Pacific than other SST clusters. The physical mechanism behind the relationship between these SST characteristics and wave climates has not been addressed in this study in detail. A possible mechanism can be found in the study on the relationship between inter-hemispheric SST gradients and typhoons. Zhan et al. (2013) indicated that warmer SST in the western Pacific warmpool (WWP: 0 - 16°N , 125 - 165°E) and cooler SST in the southwestern Pacific Ocean (SWP: 20 - 40°S , 160°E - 170°W) during MAM induces favorable conditions for typhoon genesis and intensity. Future changes in SST differences between WWP and SWP (SST in WWP - SST in SWP) under clusters 0 to 3 are $+0.07$, -0.05 , $+0.03$ and $+0.48$ $^{\circ}\text{C}$. Therefore, the condition under SST cluster 3 is favorable for typhoons following the result by Zhan et al. (2013) yielding high waves when compared with the other SST clusters.

2.6 Summary

Future projections of global and WNP wave climate were conducted using the atmospheric global climate model (MRI-AGCM3.2H) and the wave model (WAVEWATCH III). In order to analyze the

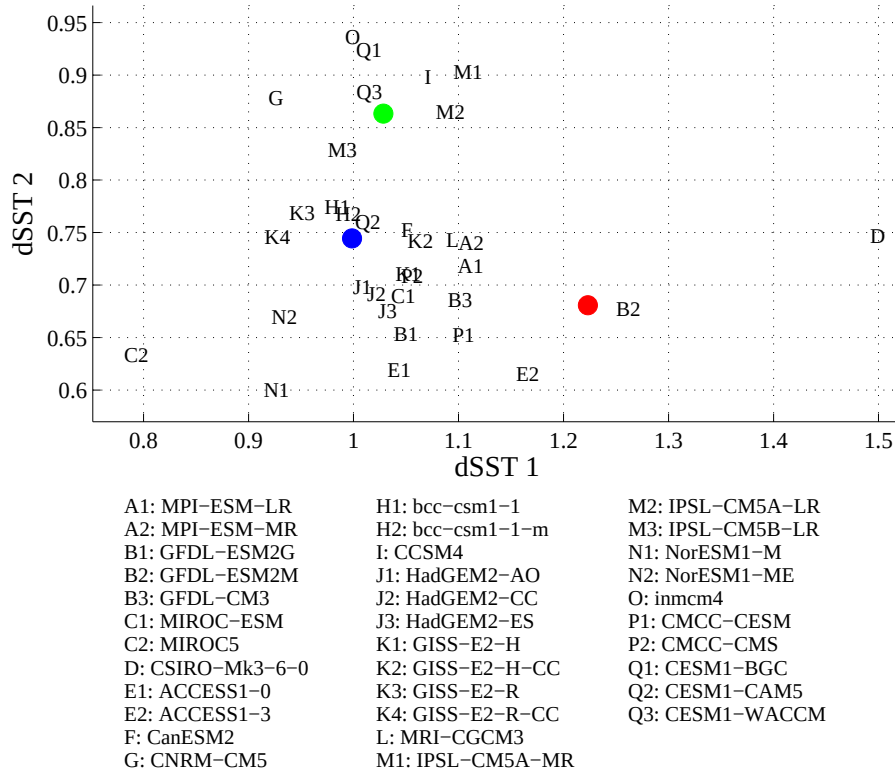


Figure 2.15: Same as **Figure 2.14**, but plotted for thirty-four models of CMIP5

sensitivity of the projected wave climate to SST conditions, SST ensemble experiments were conducted. Four different future SST conditions (SST cluster 0 to 3) were used as boundary conditions for MRI-AGCM3.2H. The four SST conditions were defined based on SST projected by eighteen models of the Coupled Model Intercomparison Project Phase 3 (CMIP3). One of the SST conditions is the ensemble mean SST of eighteen CMIP3 models, and the other three are representative SST conditions derived from eighteen CMIP3 models by applying cluster analysis to the future change patterns of SST.

Future changes in global annual $\overline{H_s}$ are about ± 0.3 m depending on the region. The regions where four future changes under four different SST conditions show the same sign covers 43% of the global domain. Although some future changes are consistent with those from previous studies, such as increases in wave height over the Southern Ocean and reductions over the North Atlantic, some particular regions show either positive or negative future change depending on SST conditions, a result indicates that the uncertainty in future projections are large. The future changes in wave height in the WNP during the summer, where variation in future changes is large, were analyzed in detail. Future changes in $\overline{H_s}$ for the lower latitudes of the WNP during the summer under SST cluster 3 are opposite in sign to those under the cluster 0 to cluster 2 conditions. Future changes under the SST cluster 3 condition are positive. The SST cluster 3 condition is characterized with higher warming in the equatorial Pacific (**Figure 2.1**).

The direct cause of these changes in future wave height is future changes in the frequency and intensity of typhoons. This means that the variation in future changes of SST influences future changes in typhoon characteristics, and then that leads to differences in wave height in the WNP. Furthermore, it is clear that variation of SST is also a major source of uncertainty for the

summertime wave climate in the WNP based on the results by Perturbed Physics (PP) ensemble experiments in this study and multi-model ensemble projections from previous studies (COWCLIP). The PP ensemble experiments and the COWCLIP results confirmed the relationship between the pattern for future change in SST and the wave climate in the WNP during the summer, such as the increases in the mean wave height under relatively warmer SST in the equatorial Pacific, namely the cluster 3 condition. Delcanbre et al. (2013) indicated that uncertainties in SST changes are a major source of uncertainties in the Northern Hemisphere jet stream changes, suggesting that a reduction of uncertainty in the tropical Pacific SST response to global warming will significantly reduce uncertainty in the Northern Hemisphere zonal wind response to climate change. The same holds true for wave climate, especially in the WNP during the summer.

The projected SST conditions used in this study are based on the CMIP3 dataset. The latest data set, CMIP5 (Taylor et al., 2012), has been available for projection and impact assessments. **Figure 2.15** shows the SST changes same as **Figure 2.14**, but **Figure 2.15** uses the CMIP5 SSTs under the RCP8.5 scenario. Future SST changes using CMIP5 have a similar variation to those using CMIP3 data (**Figure 2.15** and **Figure 2.14**). Therefore, wave climate projections based on CMIP5 can still have the uncertainty related with SST uncertainty, such as the uncertainty of future changes in mean wave height over the WNP which significantly depends on future changes in SST as shown through this paper.

Although the details of the physical mechanism behind the relationship have not been addressed in this study, insight into what causes variations in wave projections can provide better understanding of ocean climate change. In this study, the cause behind variations in wave projections across SST conditions has been revealed, especially in the WNP.

Chapter 3

Future Projection of Extreme Ocean Wave Climate Based on Single Model GCM Experiments

3.1 Introduction

Changes in the ocean wave climate, especially extreme climates, have significant impacts on many industries. The extreme wave climate is changing at a faster rate than the mean climate has in the past (Ruggiero et al., 2010; Young et al., 2011; 2012). Extreme wave climate variability and trends can be determined by extratropical and tropical storm activity, generally. The positive trends of extreme wave heights over the past 50 years are due to changes in extratropical storm characteristics, such as intensification and/or track shifts; these trends have been reported for the North Pacific (Bromirski et al., 2013; Menéndez et al., 2008; Graham and Diaz, 2001), the northeastern North Atlantic (Wang et al., 2009; Wang and Swail, 2001) and the Southern Ocean (Hemer, 2010; Sterl and Caires, 2005). Emanuel (2005) showed that, since the mid-1970s, tropical cyclones have become increasingly destructive due to longer storm durations and greater intensities. As a result, extreme waves generated by tropical cyclones have intensified. Sasaki et al. (2005) and Yong et al. (2008) indicated that summertime extreme wave heights have increased in the Western North Pacific during recent years due to intense tropical cyclones. Furthermore, extreme hurricane-generated waves in the Western North Atlantic have also increased (Komar and Allan, 2008; Bromirski and Kossin, 2008), and Moore et al. (2013) concluded that coastline changes to the U.S. east coast were attributed to changes in hurricane-generated waves. Slott et al. (2006) indicated that coastline changes resulting from storm pattern and wave climate changes can be comparable to the effects of sea level rise.

Dynamic wave projections of future wave climates have been studied under greenhouse gas emission scenarios since 2010 (e.g. Mori et al., 2010; Hemer et al., 2013a). Chapter 13 of the IPCC WGI AR5 (IPCC-AR5, 2013) has summarized current understandings on “mean” future wave climate projections under greenhouse gas emission scenarios, which showed common features of global wave climate changes such as increased mean wave heights in the Southern Ocean associated with enhanced surface wind speeds in the future. However, in general, wave climate projections have uncertainty associated with them. Shimura et al. (2015) analyzed the uncertainty in the projected future changes of mean wave heights in the Western North Pacific and concluded that the

uncertainty strongly depends on the future equatorial Sea Surface Temperatures (SST) and typhoon characteristics (described in **Chapter 2**). Although the impacts of global climate change on mean wave climate are being unveiled, the extreme wave climate effects are less understood than the mean ones. Therefore, this study examines extreme wave climate change.

Fan et al. (2013) and Wang et al. (2014) showed that future changes in extreme wave heights which are represented with the 99% non-exceedance probability wave heights (Fan et al., 2013) and 10 year return level wave heights (and annual maximum) (Wang et al., 2014). Fan et al. (2013) concluded that changes in extreme wave heights are mainly dominated by the changes in tropical cyclones, and those changes have large uncertainties. However, Wang et al. (2014) did not mention the effects of tropical cyclones and the future changes in extreme wave heights due to tropical cyclones; these effects and changes are clearly seen in Fan et al. (2013) and cannot be detected explicitly from the results of Wang et al. (2014).

Prior work of Wang and Swail (2006) indicated that projected changes in extreme wave heights were consistent with changes in extratropical cyclones. The differences between Fan et al. (2013) and Wang et al. (2014) can be attributed to model simulations of tropical cyclones; the simulations of Fan et al. (2013) used a high resolution Atmospheric Global Climate Model (AGCM) that can produce tropical cyclone climatology relatively well. On the other hand Wang et al. (2014) used a relatively low resolution Global Climate Model (GCM) that cannot simulate strong tropical cyclones. Therefore, it is not reasonable to compare extreme wave climate change results between models with low- and high-resolution simulations of tropical cyclones, because the dominant causes of extreme wave climate changes are different between them. To compare results with various previous models, we will analyze the extreme climate change by separating the wave contributions into two groups: tropical cyclone generated waves and non-tropical cyclone (especially extratropical cyclone) generated waves. This separation will improve our understanding of the mechanisms contributing to future wave climate changes.

The objectives of this study are to project extreme wave climates and investigate the contributions attributable to tropical cyclone changes separately from non-tropical cyclone changes. We will focus on tropical cyclones in the Western North Pacific (WNP), which is the most active tropical cyclone (TC) region, and on non-tropical cyclones (Non-TC) over the entire global domain.

3.2 Methodology

Wave climate projection data used in this chapter were the same as those in **Chapter 2**. The present climate was defined as 1979 - 2003, and the future climate is defined as 2075 - 2099. The three present climate experiments with three cumulus convection schemes are denoted as HPA_YS, HPA_AS and HPA_KF hereafter. The twelve future climate experiments with three cumulus convection schemes and four future SST conditions are denoted as HFA_{cumulus convection scheme}_{SST condition}, for example, HFA_YS_c0. The methodology of extreme wave analysis is shown below.

Extreme waves generated by TC and Non-TC events were separated; this separation requires TC track data. Murakami et al. (2012) detected TCs in MRI-AGCM3.2H simulations using an objective TC detection method. The TC detection method employed five criteria: relative vorticity at 850 hPa, temperature anomaly in the warm core region, maximum wind velocity at 850 hPa, maximum wind velocity at 300 hPa and cyclone duration. The total number of cyclones, TC

genesis, was controlled by changing the criteria thresholds. The TC data described by Murakami et al. (2012) were used in this study.

3.2.1 Non-TC waves

To identify Non-TC waves, waves in a $20^\circ \times 20^\circ$ box surrounding the TC center were eliminated from the original wave data. To increase the number of extreme event samples, a regional frequency analysis was conducted. A homogeneous region of wave climate characteristics surrounding the target grid point was defined and all the wave data in the homogeneous region were used as data for the target grid point. The definition of a homogeneous region is as follows.

- (1) A region within G km of the target point in longitude - latitude geophysical space. $G = 500$ km in this study, based on the synoptic scale.
- (2) A region within C units of the target point in wave height - wave period climatological space (Cooley et al., 2007). **Figure 3.1(a)** shows the relationship between climatological value (mean value in 25 years) of significant wave height and peak wave period at each grid point over the global domain. (The values were normalized by standard deviation.) **Figure 3.1(b)** shows the global map with colors corresponding to the relationship color-coded in **Figure 3.1(a)**. The relationship from **Figure 3.1** can identify the characteristics of each region such as semi-closed

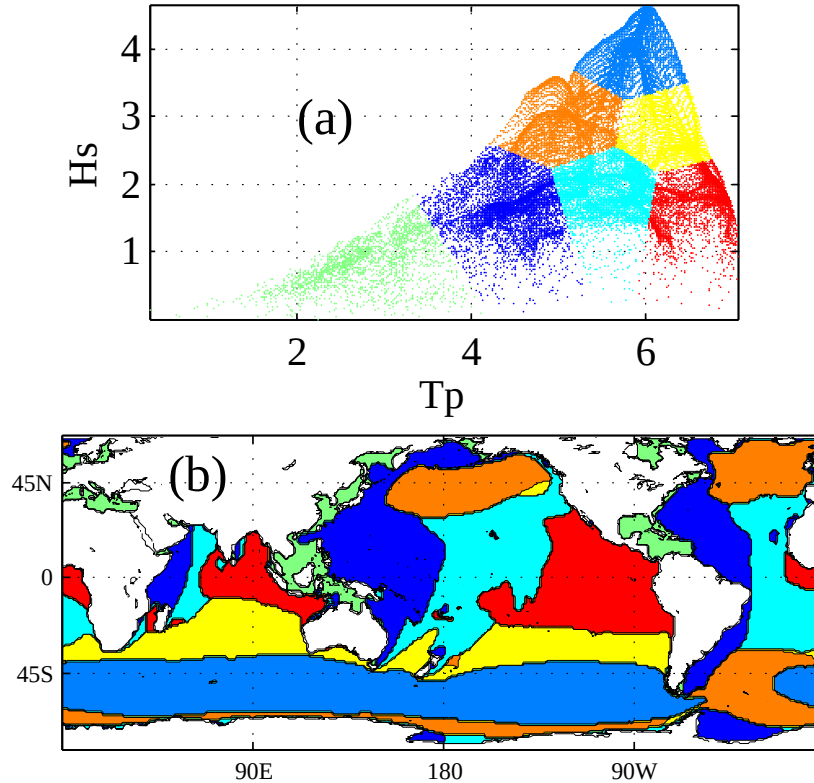


Figure 3.1: Classification of mean wave climate. (a) Relationship between mean significant wave height and period at each grid point. All values are normalized by the standard deviation, (b) Spatial distribution of mean significant wave height and period (a). The colors in (b) correspond to regions (a).

ocean, wind-wave or swell dominated ocean, swell sheltered ocean and so on. This relationship is a useful criterion to define a homogeneous region. The criterion that the distance on **Figure 3.1(a)** is less than 0.5 ($C \leq 0.5$) is used in this study. We confirmed that this criterion ($C \leq 0.5$) is effective at correctly classifying ocean regions across land masses and ocean areas apart from land.

- (3) The discordancy measure (D) is less than 3 (Hosking and Wallis, 1997). D was calculated with the frequency distribution of annual maxima of wave heights.

A region satisfying these three criteria was defined as a homogeneous region. The mean of annual maxima of wave heights (H_{ann}) was analyzed as an extreme value of Non-TC waves.

3.2.2 TC waves in the WNP

TC waves were defined as waves within 500 km of the TC center. For this part of the analysis, a homogeneous region was defined with items (1) and (2) since only TC waves are of interest. The climatological values in item (2) were defined for the Summer and Autumn seasons (Jun through Nov) and normalized by the standard deviation of the WNP domain. The R year return wave height (H_R) was analyzed as an extreme value for TC waves. The duration of sampling was considered to be 25 years $\times$ the number of grid points in the homogeneous region. H_R was calculated by interpolation of the frequency distribution.

3.3 Validation

Section 2.3 validated the use of the same GCM and wave model combination to project mean wave climates. Here, we validate the GCM and wave model combination for extreme wave climates. Simulated extreme wave climate data is estimated and compared with other reanalysis data sets and in-situ buoy data. Although the reanalysis data sets provide a relative comparison, they yield spatial characteristics of bias with the analysis; the buoy data gives quantitative differences of the extreme wave climates.

Since a certain reanalysis data set has specific bias (Stopa and Cheung, 2014), two different reanalysis data sets were used for this comparison. One is the ERA-Interim reanalysis data set developed by the European Centre for Medium-Range Weather Forecasts (Dee et al., 2011), which is widely applied to wave climate study (e.g. Hemer et al., 2013a). The other is JRA-55, developed by the Japanese Meteorological Institute (Kobayashi et al., 2015) and released in 2013; this dataset is the main source for this study (CFSR data are also relevant, but the wave analysis data were not available at the time of this study due to server problems). The one of major facet of JRA-55 is extreme weather, especially tropical cyclones in the Western North Pacific. The JRA-55 includes tropical cyclones with a typhoon bogus model using observational data (airborne data is used before satellite periods).

Murakami (2014) summarized the use of tropical cyclone characteristics in state-of-the-art reanalysis data sets, and concluded that the JRA-55 is the best of the reanalysis data sets. The ERA-Interim used a coupled atmospheric and wave model but the JRA-55 dataset does not include wave data. Therefore, a long-term wave climate was calculated with the wave model WAVEWATCH III version 4.18 (Tolman, 2014) using sea surface wind and sea ice data of JRA-55. Source term

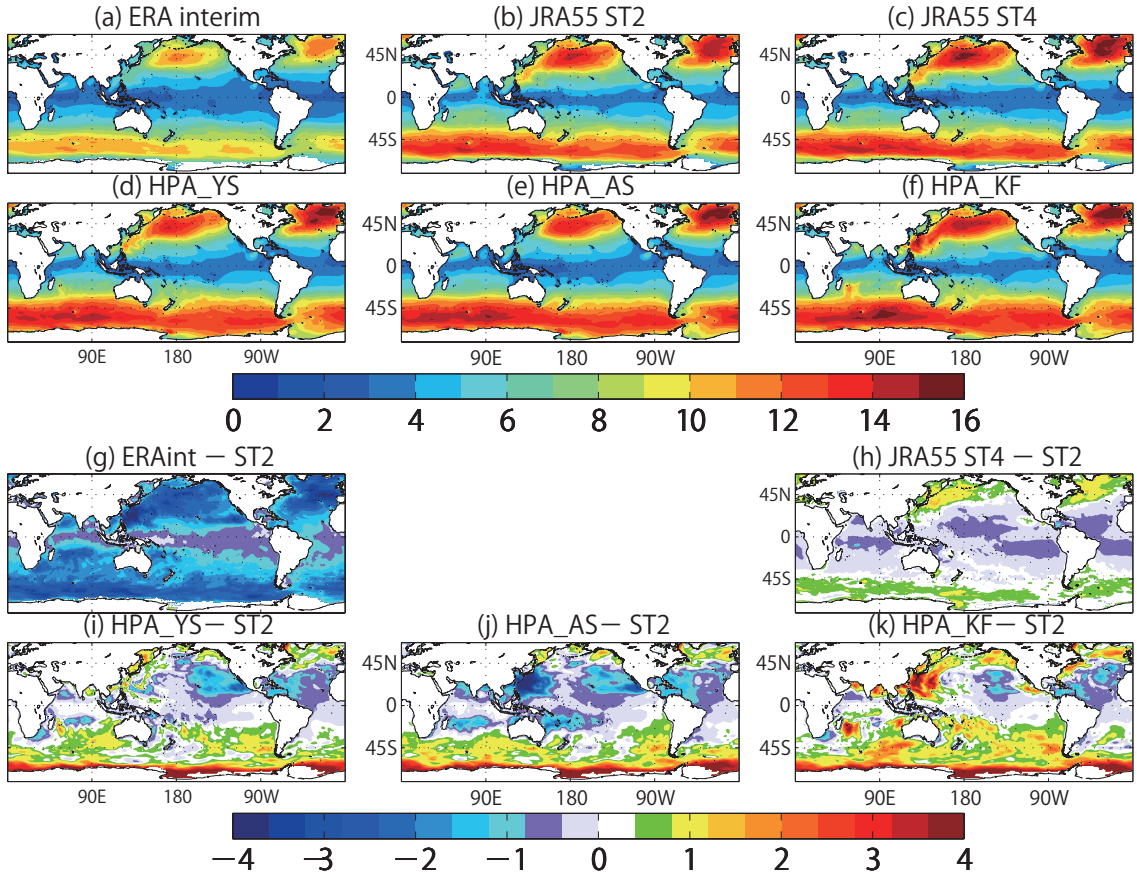


Figure 3.2: Mean annual maximum wave height H_{ann} . (a) ERA interim, (b) JRA-55 ST2, (c) JRA-55 ST4, (d) HPA_YS, (e) HPA_AS, (f) HPA_KF, (g) ERA interim - JRA-55 ST2, (h) JRA-55 ST4 - JRA-55 ST2, (i) HPA_YS - JRA-55 ST2, (j) HPA_AS - JRA-55 ST2, and (k) HPA_KF - JRA-55 ST2

modeling of wave models has improved in recent years, and new source term packages are available (e.g. Ardhuin et al., 2010). Therefore, the wave climate simulation for this study was conducted by different source term packages of WAVEWATCH III. We picked up the Tolman and Chalikov (1996) source term package (so-called ST2) and the Ardhuin et al. (2010) source term package (so-called ST4) to estimate how the extreme wave climate depends on source terms.

Figure 3.2 shows the mean annual maximum wave height (H_{ann}) during the period 1979-2003 for (a) ERA-Interim, (b) JRA-55 with Tolman and Chalikov (1996) source term package (denoted as JRA-55 ST2), (c) JRA-55 with Ardhuin et al. (2010) source term package (denoted as JRA-55 ST4), (d) HPA_YS, (e) HPA_AS and (f) HPA_KF. The differences between the results for (a) through (f) and JRA-55 ST2 are illustrated in **Figure 3.2** (g) through (k), respectively.

It is clear that H_{ann} for ERA-Interim is smaller than for the others by 2-3 m over the mid- to high latitudes and by 4 m over the typhoon region in the WNP. The ERA-Interim underestimated extreme wave heights; this is consistent with other studies (e.g. Stopa and Cheung, 2014). The differences due to wave modeling, that is between JRA-55 ST2 and ST4, are about 1 m. The differences have specific spatial tendencies, namely that extreme waves of ST4 are larger than ST2 extreme waves over the wind wave dominated regions (mid- to high latitudes) and smaller over swell

dominated regions (low latitudes). This result is expected since the Ardhuin et al. (2010) source term package (ST4) has an improved swell dissipation term. The differences between the reanalysis and HPA series are significant over the high latitudes of the Antarctic Ocean and TC passing regions. The differences in the Antarctic Ocean are mainly due to the absence of sea ice simulations in the HPA series.

The spatial distributions of the differences of Non-TC H_{ann} between the HPA series and JRA-55 ST2 (not shown) can be characterized by larger waves (by about 1 m) for the HPA series over the higher latitudes (south of 30°S in the Southern Hemisphere and north of 45°N in the Northern Hemisphere) and with smaller waves (by about 1.5 m) over the Northern Hemisphere in the mid latitudes (30°N - 40°N). As shown above, the extreme wave climate projected with the HPA series is similar to that for JRA-55 compared with ERA-Interim; however, there are systematic differences spatially and significant differences in the TC waves. We will compare the model results with buoy observations quantitatively and estimate how TC generated waves contribute to the extreme wave climate in the following section.

3.3.1 Comparison with buoy observations

Long-term observations (longer than 19 years) from moored buoys in the North Pacific (from the Japanese Meteorological Agency and the US National Oceanographic Data Center) were used for extreme wave climate validation. QQ plots between observed buoy data and simulated series data were used to compare simulated results as follows. Five buoys along the Pacific rim were selected: #46035 (1985 - 2011), #21004 (1982 - 2000), #51001 (1981 - 2009), #46006 (1977 - 2011) and #46003 (1976 - 1999). The buoy notation follows the World Meteorological Organization (WMO) buoy ID numbers. **Figure 3.3** shows the QQ plots for each buoy, and a map of the North Pacific illustrating each buoy location.

The QQ plots are shown by 50, 90, 99, 99.9, 99.99, and 100 (period maximum) % quantities. In the **Figure 3.3** legends, the value following a series name indicates H_{ann} (H_{ann} is not calculated for each buoy since they are not operated year-round); H_{ann} roughly corresponds to the 99.9 % quantiles. For the HPA and JRA-55 series, the quantiles greater than 90 % are larger than those for ERA-Interim, except for HPA_AS at #21004 which is a TC passing region in the WNP. Furthermore, the extreme waves of HPA_KF are much larger than buoy observations at #21004. The model performance of TC waves is discussed in detail in the next subsection. The extreme waves of the HPA series are similar across the HPA series and roughly comparable with buoy observations except for #21004 and the period maximum values. The differences due to wave modeling as shown by JRA-55 ST2 and ST4 are smaller than the differences among the HPA series and between the HPA, JRA-55 and ERA-Interim.

3.3.2 TC characteristics in the WNP

Following the above discussion, the TC characteristics and TC generated waves in the WNP are discussed here. For this part of the analysis, we used observed TC data from the International Best Track Archive for Climate Stewardship (IBTrACS; <http://www.ncdc.noaa.gov/ibtracs/>) data provided by the Japan Meteorological Institute. The IBTrACS data from 1979 to 2003 was selected following the analysis data period. Frequency distributions were calculated to compare between the

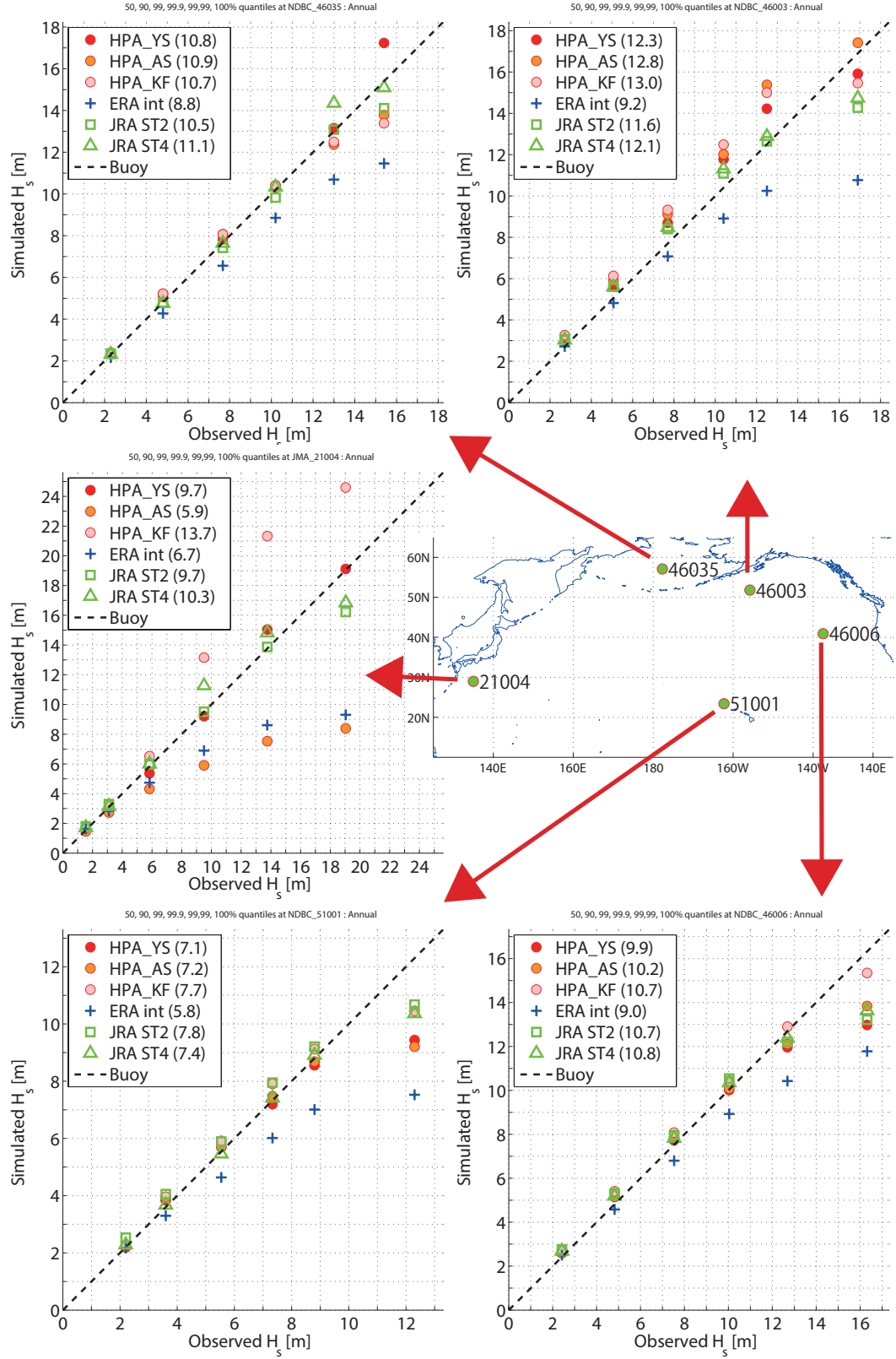


Figure 3.3: Comparison of analysis results and buoy data by Q-Q plot (50, 90, 99, 99.9, 99.99 100 % quantiles). The values in the legend indicate H_{ann} . (unit:m)

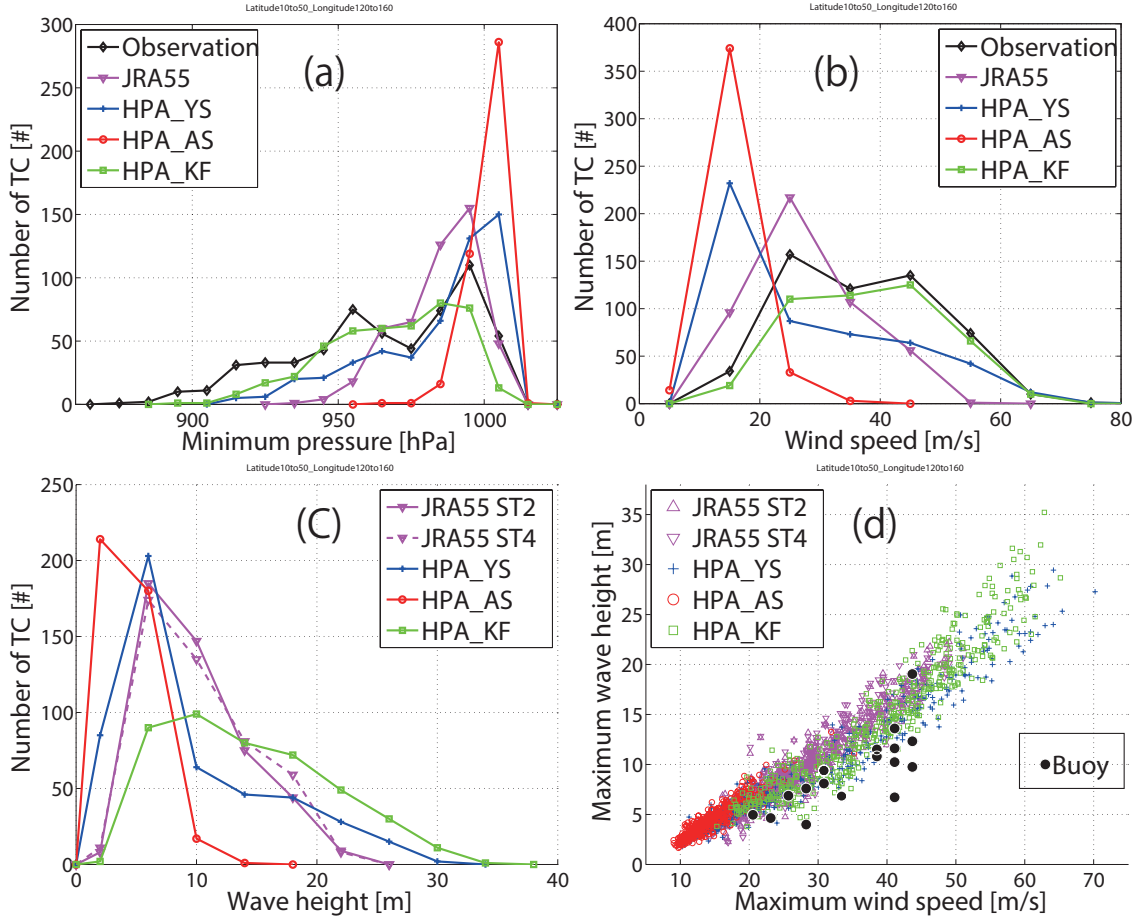


Figure 3.4: Frequency distributions of TC characteristics in the WNP from 1979-2003. (a) minimum central pressure, (b) maximum of wind speed, (c) maximum wave height, (d) relationship between maximum wind speed and wave height (black circles in panel (d) indicate observed relationship by moored buoys (#21004 and #22001) when the waves were observed within 100 km on the right-side of TC travelling direction)

HPA, JRA-55 and observation data; (**Figure 3.4 (a)(b)**) shows frequency distributions of minimum central pressure and maximum wind speed in the TC life-time for the WNP.

When compared with observations, all the HPA experiments underestimate the frequency of intense TCs, especially HPA_AS did not reproduce intense TCs with minimum pressure less than 970 hPa (**Figure 3.4(a)**). The number of TCs with pressures less than 960 hPa simulated by JRA-55, HPA_YS, AS and KF are 10, 36, 0 and 64 % of observation, respectively. The wind speeds from HPA_YS and KF show better agreement with observations (**Figure 3.4(b)**) than did their comparisons of minimum pressure. This is because wind speeds corresponding to minimum pressures are overestimated in HPA experiments. Wind speed is a major factor behind extreme waves. The numbers of TCs with winds stronger than 40 m/s for JRA-55, HPA_YS, AS and KF are 26, 54, 0 and 91 % of observation, respectively. The ability to simulate TC related extreme winds strongly depends on the cumulus physics.

Figure 3.4(c) is a frequency distribution of the maximum wave height for TCs in the WNP. This distribution (**Figure 3.4(c)**) corresponds well with the maximum wind speed distribution (**Figure 3.4(b)**) since the relationship between maximum wind speed and wave height during TC life-time

is shown in **Figure 3.4(d)**. Regarding the simulation of intense TCs, HPA_KF performs best when compared with observations (**Figure 3.4 (a)(b)**). However, **Figure 3.3** shows that HPA_KF overestimates extreme waves over the WNP (#21004) and HPA_YS and JRA-55 show better agreement with buoy observation. This seeming contradiction is because buoys, or in-situ observations, cannot observe the peaks of TC waves.

To illustrate this, the model results and data for the moored buoys in the WNP (#21004 and also #22001:28.1°N,126.2°E) are plotted in **Figure 3.4(d)**. To approximate the TC maximum wave heights, we conditionally collected buoy observation data when waves were observed within 100 km and on the right-side of the TC travelling direction. The maximum wind speeds in the plot were obtained from the TC best track data and corresponded with the time when the buoys observed the approximate maximum wave heights. In **Figure 3.4(d)**, the HPA series show reasonable results. Although HPAs tend to overestimate maximum wave heights from corresponding wind speeds when compared with observations, the HPA overestimation of wave height is reasonable because observed maximum wave heights culled from buoy data are smaller than actual maximum wave heights. The buoys cannot observe intense TC waves when the maximum wind speed is more than 45 m/s (**Figure 3.4(d)**). For this reason, HPA_KF overestimates extreme waves and the less accurate models, HPA_YS and JRA-55, show good agreement with buoy observations (**Figure 3.3 #21004**).

HPA_YS and HPA_KF have reasonable simulations of TC metrics, and JRA-55 has the best TC comparisons with observed data when using state-of-the-art reanalysis data sets (Murakami, 2014). An additional revelation is that HPA_AS does not adequately simulate TC extreme waves. Thus, HPA_AS is excluded for the analysis of TC extreme waves in the following sections.

3.4 Future changes in extreme waves

Future changes in extreme waves are discussed in this section. **Figure 3.5** shows the future changes in H_{ann} for twelve experiments. The changes due to TC and Non-TC effects can be seen clearly in the series of YS and KF experiments. Note that changes due to TC effects are not as pronounced in the AS experiment series because the AS series simulations do not accurately simulate TCs as described in the previous section. It is clear that future changes in extreme wave height strongly depends on model performance and cumulus convection scheme, which was indicated in the difference between Wang et al. (2014) and Fan et al. (2013). Therefore, future changes in TC and Non-TC waves have different causes, and they are discussed separately in the following sections.

3.4.1 Non-TC extreme waves

Figure 3.6 shows future changes in H_{ann} for Non-TC waves for each experiment. **Figure 3.6** also shows the ensemble mean value of future changes in H_{ann} among each SST and PP ensemble experiment (**Figure 3.6(d)(h)(l)(p)** and **(q)(r)(s)**), and all the experiments (**Figure 3.6(t)**). The spatial distribution of the future changes of each experiment is qualitatively similar to the overall mean (**Figure 3.6(t)**). The spatial distribution of future H_{ann} change can be characterized by increases in wave heights over the mid- to high latitudes in the Southern and central North Pacific Oceans by up to 1 m, and decreases over mid-latitudes and the North Atlantic by up to -1 m. This spatial distribution is similar to that of future changes in mean wave heights and wintertime H_{ann} values.

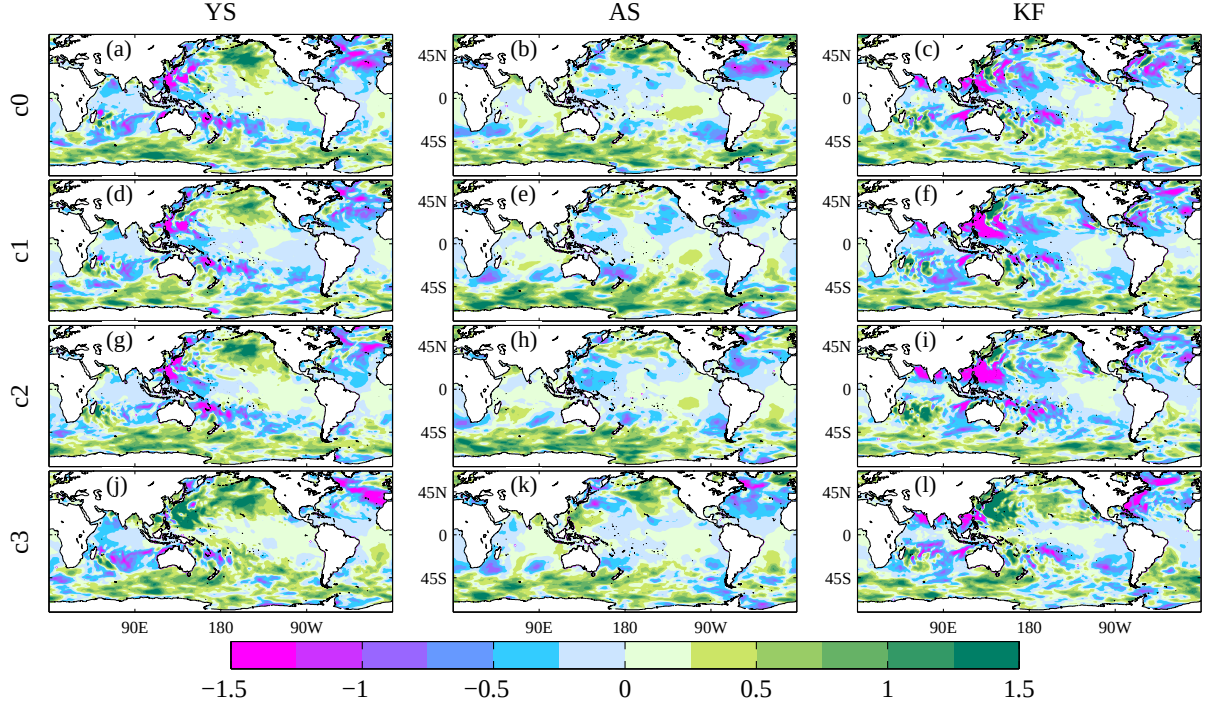


Figure 3.5: Future changes in H_{ann} (unit:m); (contour: future climate minus present climate; columns are grouped by mean perturbed physics (PP) ensemble (YS, AS and KF from left to right); rows are grouped by mean SST ensemble (c0, c1, c2 and c3 from top to bottom))

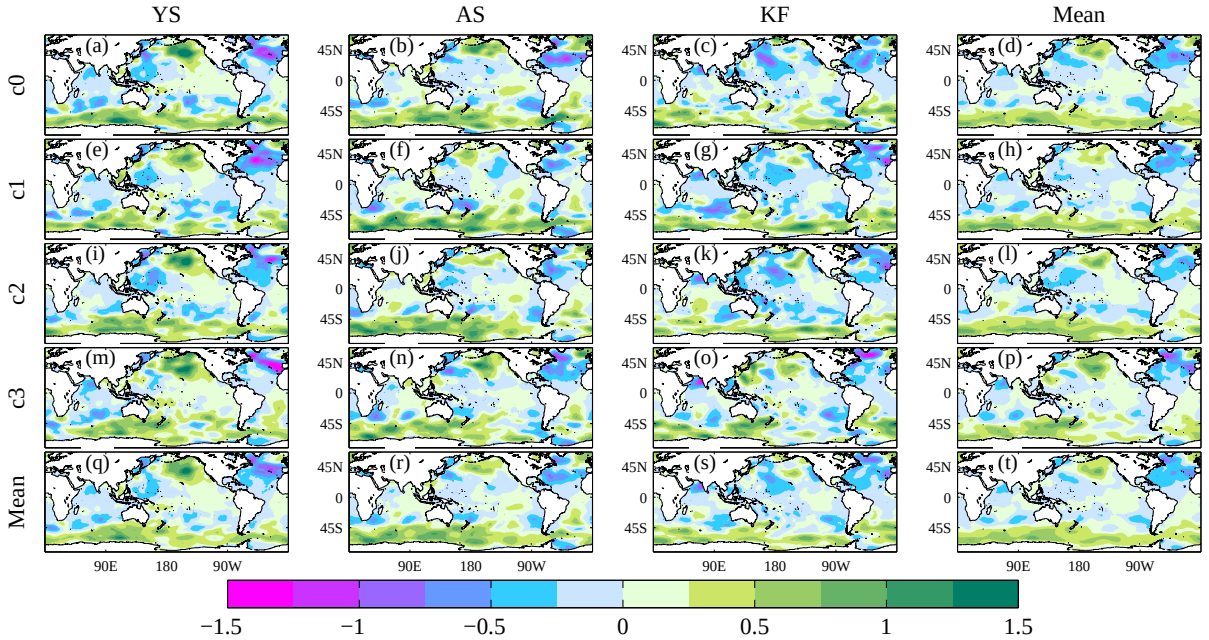


Figure 3.6: Future changes in H_{ann} for Non-TC waves (unit:m); (contour: future climate minus present climate; columns are grouped by mean perturbed physics (PP) ensemble (YS, AS and KF from left to right); rows are grouped by SST ensemble (c0, c1, c2 and c3 from top to bottom))

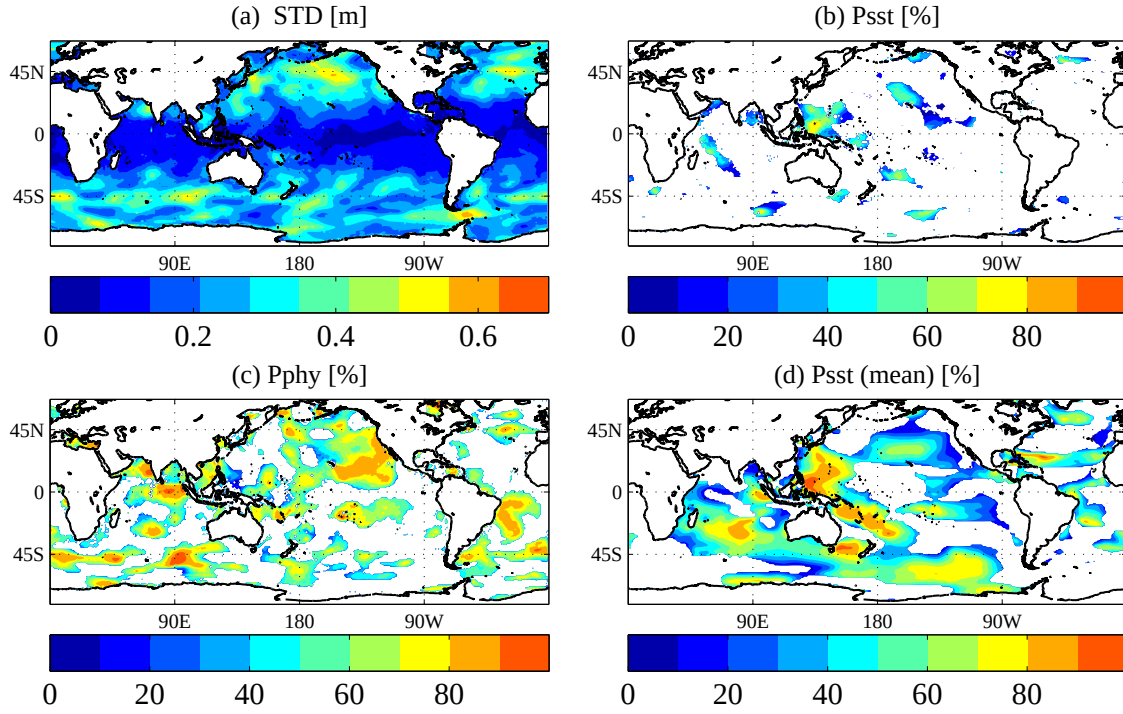


Figure 3.7: Analysis of variance on future changes in H_{ann} ; (a) standard deviation, (b) P_{SST} , (c) P_{phy} , (d) P_{SST} of future changes in mean wave height. The values with 5% statistically significance level are colored in (b), (c) and (d).

Furthermore, this spatial distribution is similar to the future changes in mean wave heights shown in IPCC-AR5 (2013), which is a summary of previous studies. Therefore, future changes in wintertime extratropical storms determine future changes in mean and Non-TC extreme wave characteristics. Additionally, **Figure 3.6(t)** is quite similar to changes in H_{ann} published by Wang et al. (2014) (their Figure 2b), although H_{ann} was derived from all the wave data whereas **Figure 3.6** shows only Non-TC wave data. An explanation for this similarity is that changes in H_{ann} by Wang et al. (2014) are dominated by Non-TC effects since the model and scheme used has a lower TC performance for extreme events. Therefore, the future changes in Non-TC extreme waves above are consistent with another independent study.

The SST and PP ensemble results can be used to analyze the source of uncertainty with the projection. The variance of the future changes in H_{ann} among ensemble experiments was estimated quantitatively. **Figure 3.7(a)** shows the standard deviation of future changes in H_{ann} among ensemble experiments at each grid. The standard deviation is large (up to 0.7 m) in the mid- to high latitudes. To estimate how differences in SST condition and physics contribute to the standard deviation, an analysis of variance (ANOVA, Storch and Zwiers, 1999) was performed. A two way ANOVA without interaction (Storch and Zwiers, 1999) expresses the total sum of squares with three components, which are the sum of squares due to SST difference, physics difference and the residual. In **Figure 3.7**, (b) and (c) show the proportion of sum of squares due to SST difference and physics difference (P_{SST} and P_{phy}).

Although P_{SST} over the low latitudes of the WNP is about 70%, P_{SST} over most of the ocean (90% of entire ocean) is not statistically significant by the 5% significance level. This result

is opposite to P_{SST} of future changes in mean wave heights (**Figure 3.7(d)**), where values are significant over 50% of the entire ocean, and the values are greater than 50% over 27% of the entire ocean. Furthermore, the variance of future changes in mean wave heights depends foremost on the SST difference over the region where the standard deviation of the future changes is relatively larger. On the other hand, P_{phy} of future changes in H_{ann} is significant over 47% of the entire ocean and greater than 50% over 36% of the entire ocean (**Figure 3.7(c)**). And, although not included here, P_{phy} of future changes in mean wave heights (not shown) are significant over 63% of the entire ocean.

Future changes in Non-TC waves can be summarized as follows. The spatial distribution of future changes in Non-TC extreme waves is similar to that of future changes in mean waves. However, the characteristics of variance of future changes in extreme and mean waves are quite different. Although the variance of future changes in mean waves significantly depends on the SST difference, the variance of future changes in extreme waves mainly depends on the cumulus convection scheme.

3.4.2 TC extreme waves in the WNP

To focus on the impact of TCs on extreme waves, the WNP was chosen since it is the basin with the most frequent TCs. To represent extreme waves, R year return wave height (H_R) is analyzed. **Figure 3.8** shows future changes in 10 year return wave heights of TC waves (denoted ΔH_{10}). H_{10} values change within a range of 5 m depending on the region. Although ΔH_{10} varies widely among ensemble experiments, each individual spatial distribution of ΔH_{10} is similar to the overall mean values shown in **Figure 3.8(o)** and **Figure 3.9(a)**, qualitatively. This spatial distribution of ΔH_{10} can be characterized by minus-plus alternating patterns such as decrease, increase, decrease and increase clock-wise from the south-western part of the WNP to the south-eastern part. The variation of ΔH_{10} is quite large, which is comparable in magnitude to the future change value itself. The overall mean of ΔH_{10} for all the experiments is ± 4 m (**Figure 3.9(a)**) and the standard deviation is up to 3 m (**Figure 3.9(b)**). Note that the variation is especially large along the south coast of Japan.

Future change in H_R can be classified into TC wave intensity change and TC wave frequency change as follows. The future change of H_R (ΔH_R) is represented with H_R for the present and future climate (H_R^p, H_R^f) as

$$\Delta H_R = H_R^f - H_R^p$$

H_R is represented by an inverse non-exceedance probability function (F) and mean yearly occurrence of TC waves (λ),

$$\begin{aligned} &= F^f \left(\frac{1}{R\lambda^f} \right) - F^p \left(\frac{1}{R\lambda^p} \right) \\ &= F^f \left(\frac{1}{R\lambda^p} - \frac{\Delta\lambda}{R\lambda^p(1 + \Delta\lambda)} \right) - F^p \left(\frac{1}{R\lambda^p} \right) \end{aligned}$$

where $\lambda^f = \lambda^p(1 + \Delta\lambda)$. Rewritten by the Taylor series expansion,

$$= \left\{ F^f \left(\frac{1}{R\lambda^p} \right) - F^p \left(\frac{1}{R\lambda^p} \right) \right\} - \dot{F}^f \left(\frac{1}{R\lambda^p} \right) \cdot \frac{1}{R\lambda^p} \cdot \frac{\Delta\lambda}{1 + \Delta\lambda} + E_1$$

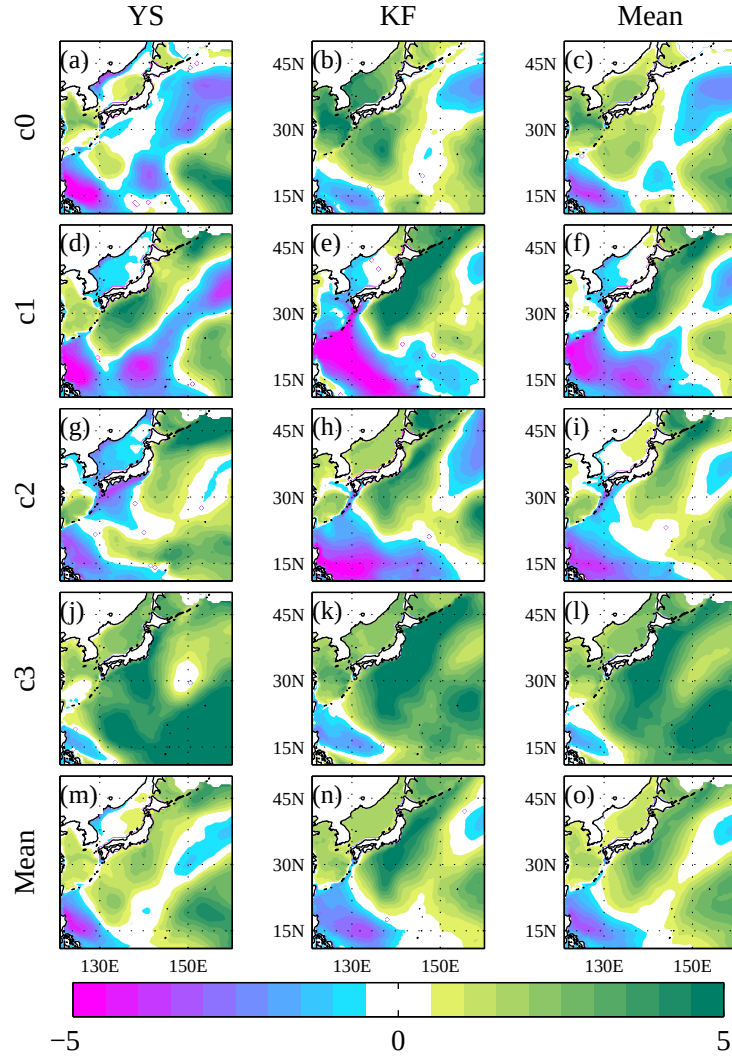


Figure 3.8: Future change of 10 year return wave height ΔH_{10} for TC waves (unit:m). (contour: future climate minus present climate; columns are grouped by perturbed physics (PP) ensemble (YS and KF from left to right), rows are grouped by SST ensemble (c0, c1, c2 and c3 from top to bottom), Colored regions indicate $\lambda \geq 0.1$ #/yr)

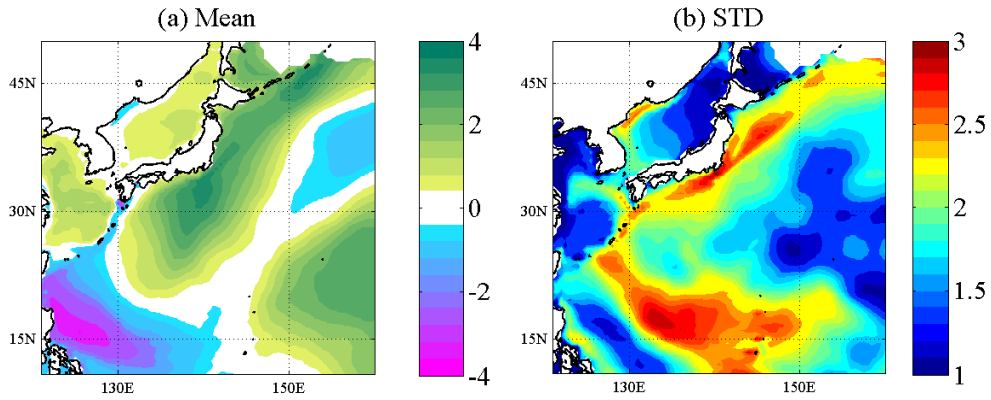


Figure 3.9: Ensemble results of future change of 10 year return wave height ΔH_{10} of TC waves (unit:m). (a) Overall mean across eight experiments (same as **Figure 3.8(o)**), (b) Standard deviation of eight experiments.

where E_1 includes higher order terms of the Taylor series expansion. $\dot{F}^f$ is replaced by $\dot{F}^p$ and the residual is represented by E_2 :

$$= \left\{ F^f \left(\frac{1}{R\lambda^p} \right) - F^p \left(\frac{1}{R\lambda^p} \right) \right\} + \left\{ -\dot{F}^p \left(\frac{1}{R\lambda^p} \right) \cdot \frac{1}{R\lambda^p} \cdot \frac{\Delta\lambda}{1 + \Delta\lambda} \right\} + \{E_1 + E_2\}$$

The first term is represented by the difference in F with the probability of present climate ($\frac{1}{R\lambda^p}$), and this term can be considered a factor of TC wave intensity change (C_i). The second term is represented by F of present climate and frequency change ($\Delta\lambda$), and this term can be considered a factor of TC wave frequency change (C_f). The third term is a residual and nonlinear interaction factor.

Furthermore, the term C_i can be regarded as representing the change between the entire WNP TC wave intensity and the local one. $F(1/R\lambda) = \alpha(1/R\lambda) \cdot F_{wnp}(1/R\lambda)$, where F_{wnp} is F derived from all the TC wave data in the WNP and α is a local factor. F_{wnp} is identical over the WNP and α depends on the location (grid point). Here,

$$\begin{aligned} C_i &= (\alpha^p + \Delta\alpha)F_{wnp}^f - \alpha^p F_{wnp}^p \\ &= \alpha^p \Delta F_{wnp} + \Delta\alpha F_{wnp}^p + \Delta\alpha \Delta F_{wnp} \end{aligned}$$

where $\Delta F_{wnp} = F_{wnp}^f - F_{wnp}^p$ and $\Delta\alpha = \alpha^f - \alpha^p$. The first term includes the difference of F_{wnp} with the present climate local factor, and thus this term can be considered a factor of the change of basin-wide TC wave intensity ($C_{i(wnp)}$). The second term is represented by the difference of α and F_{wnp} for the present climate, and thus this term can be considered a factor of local TC wave intensity ($C_{i(local)}$). The third term is an interaction factor (E_3). Finally, ΔH_R is represented as

$$\Delta H_R = C_{i(wnp)} + C_{i(local)} + C_f + C_e. \quad (3.1)$$

where $C_e = E_1 + E_2 + E_3$. Using the above mentioned component analysis, **Equation 3.1** was applied to ΔH_{10} .

Figure 3.10 shows ΔH_{10} for the HFA_KF series and the $C_{i(local)}$, $C_{i(wnp)}$, C_f and C_e . C_e is small relative to the other factors. It is clear that ΔH_{10} (**Figure 3.10(a)(b)(c)(d)**) is dominated by $C_{i(local)}$ (**Figure 3.10(e)(f)(g)(h)**). $C_{i(wnp)}$ has a positive contribution on ΔH_{10} over the entire the domain, and C_f contributes a secondary effect when compared with $C_{i(local)}$. C_f for c0, c1, and c2 yields a negative contribution on ΔH_{10} over almost the entire domain. But C_f for c3 is not a broadly negative contribution.

In **Figure 3.11**, C_f is the primary effect on ΔH_1 . ΔH_1 for c0, c1, and c2 is negative over a vast area of the WNP, mainly due to C_f . However, ΔH_1 for c3 is positive because C_f is not negative. The difference in TC wave frequency between c0 through c2 and c3 is discussed in detail by Shimura et al. (2015). And, the component analysis results for the KF scheme hold true for the YS scheme.

The spatial distribution of ΔH_{10} can be explained by future changes in TC tracks. Only intense TCs with minimum pressures less than 950hPa are shown hereafter. The threshold value of 950hPa is an arbitrary value but the results are not significantly changed with values of 940 hPa or 960hPa.

Figure 3.12 shows the frequency ratio of TC passing by contour lines and the future change by color variations. Prevailing tracks in the present climate can be represented with three tracks

(illustrated as black arrows in **Figure 3.12**). One track is directed westward from the generation area in the low latitudes, and the other tracks are directed north and northeast to the mid latitudes. These prevailing TC tracks have been reproduced with observation data (Wu and Wang, 2004).

Note that the relative frequency of TCs decreases over the low latitudes in the future climate. For the other two northward prevailing tracks, the relative frequency of TCs also decreases in the future climate. The red arrows on **Figure 3.12** illustrate an eastward shift of TC tracks and an increase in TC frequency in those areas. Also, the spatial distribution of ΔH_{10} (**Figure 3.9(a)**) corresponds to a TC track shift (**Figure 3.12**). In the discussion on ΔH_{10} , it was noted that ΔH_{10} is dominated by factor $C_{i(local)}$. $C_{i(local)}$ can be considered a result of the eastward shift of TC tracks.

To summarize the above discussion, $C_{i(local)}$ is positive in regions where TCs are projected to pass closer, resulting in an increase in TC waves in the future climate. Likewise, negative values of $C_{i(local)}$ indicate regions where TCs are projected to pass farther away, resulting in a decrease in TC waves in the future climate.

Figure 3.13 illustrates the eastward shift of TC waves. **Figure 3.13** shows the H_{10} maxima of the meridional cross section. The values are normalized by the maximum for whole domain for each experiment, respectively. The peaks for the present climate (HPA_YS and HPA_KF) are located at 122°E and 128°E. The peaks for future climates tend to shift eastward up to 139 °E (HFA_KF_c1). And the values for future climates are smaller than present climate values over the western part of 128°E, a result of an eastward shift in TCs.

3.5 Summary

We projected the future ocean wave climate based on a series of ensemble experiments with the single atmospheric global climate model (MRI-AGCM3.2H). The ensemble experiments of MRI-AGCM3.2H consist of four future SST ensemble experiments and three perturbed physics (PP) ensemble experiments. The present (1979-2003) and future (2075-2099) wave climates were projected by WAVEWATCH III using sea surface wind of MRI-AGCM3.2H ensemble experiments. The model performance was validated, and then the future changes in extreme wave heights and the variance among ensemble experiments were analyzed in detail. Regional frequency analysis was applied to increase the number of extreme event samples considering a homogeneous region of target points. The future changes in extreme wave heights strongly depend on model performance of tropical cyclones (TCs) and TC changes.

Future changes in Non-TC waves on a global scale were estimated focusing on annual maxima. The ensemble mean of the future changes and standard deviation are up to about ± 1 m and 0.7 m, respectively. The spatial distribution of future changes in extreme wave heights is similar to that of mean wave heights by our model, previous studies (IPCC-AR5, 2013) and other extreme wave height changes (Wang et al., 2014). This spatial distribution of extreme waves can be characterized as increasing over the mid to high-latitudes in the Southern Ocean and the central North Pacific, and decreasing over mid-latitudes and the North Atlantic. From an analysis of variance on future changes, we found that the variance mainly depends on differences in physics among the PP ensemble experiments. The results depend significantly on the physics scheme of the climate model when future changes in extreme wave heights are quantitatively projected. This is the opposite for the case of mean wave changes, which depend significantly on SST difference (Shimura et al., 2015).

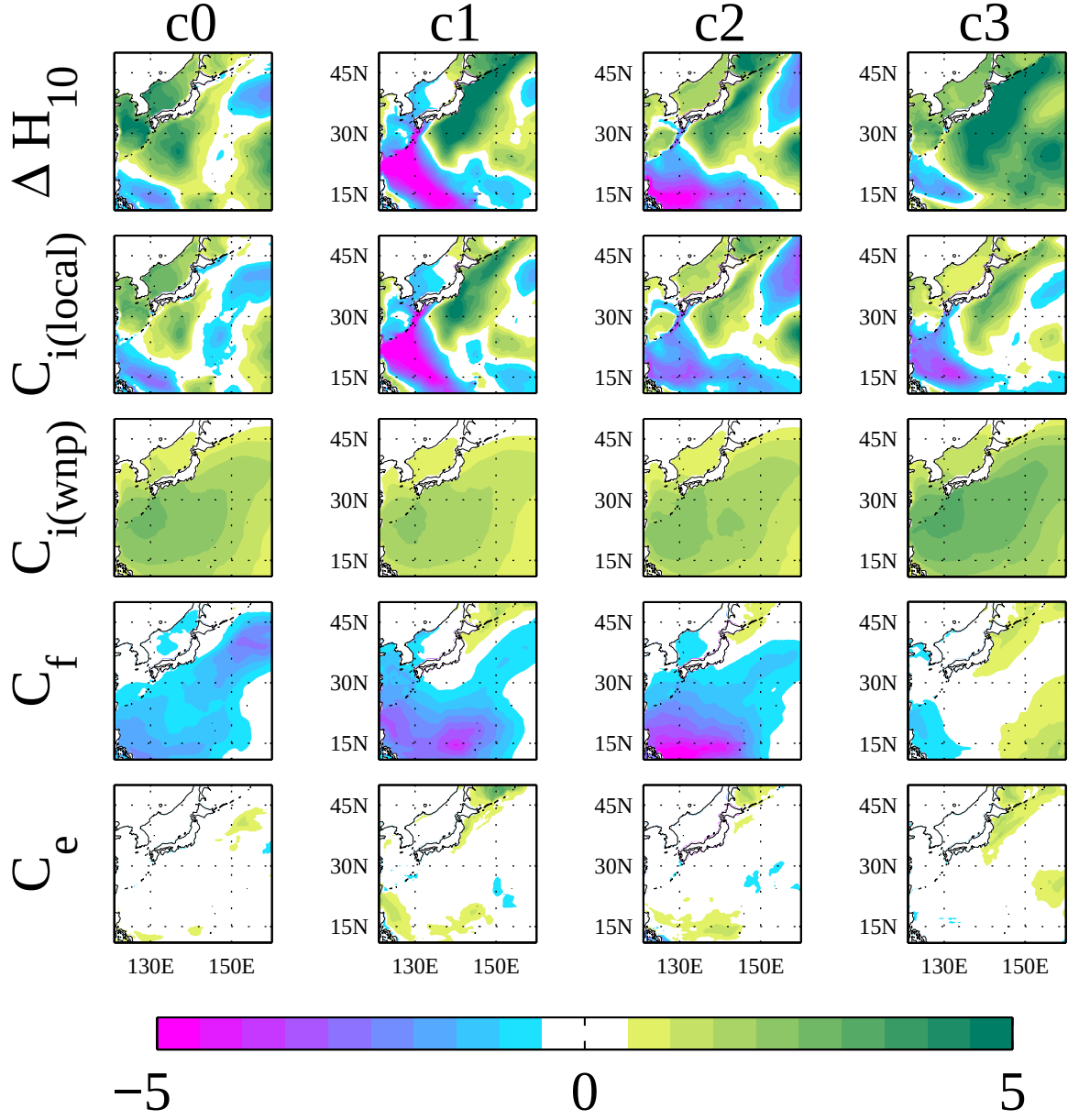


Figure 3.10: Contributions of TC characteristics change to future change in 10 year return wave height ΔH_{10} in HFA_KF (unit:m). The values of ΔH_{10} , $C_{i(local)}$, $C_{i(wnp)}$, C_f and C_e are grouped by row, and the SST conditions are grouped by column.

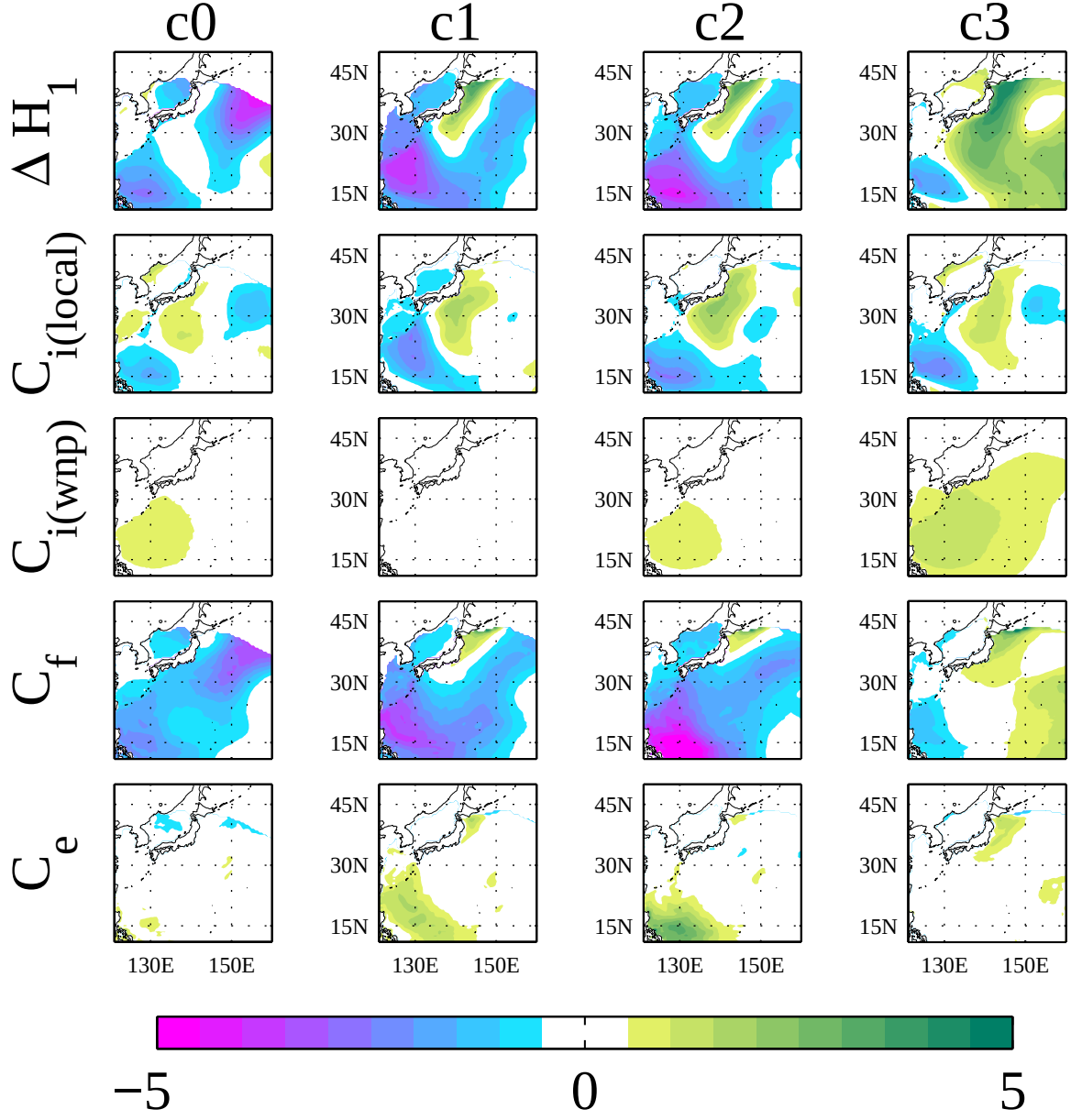


Figure 3.11: Contributions of TC characteristics change to future change in 1 year return wave height ΔH_1 in HFA_KF (unit:m). Descriptions of panels are same as **Figure 3.10**. Colored regions indicate $\lambda \geq 1$ #/yr.

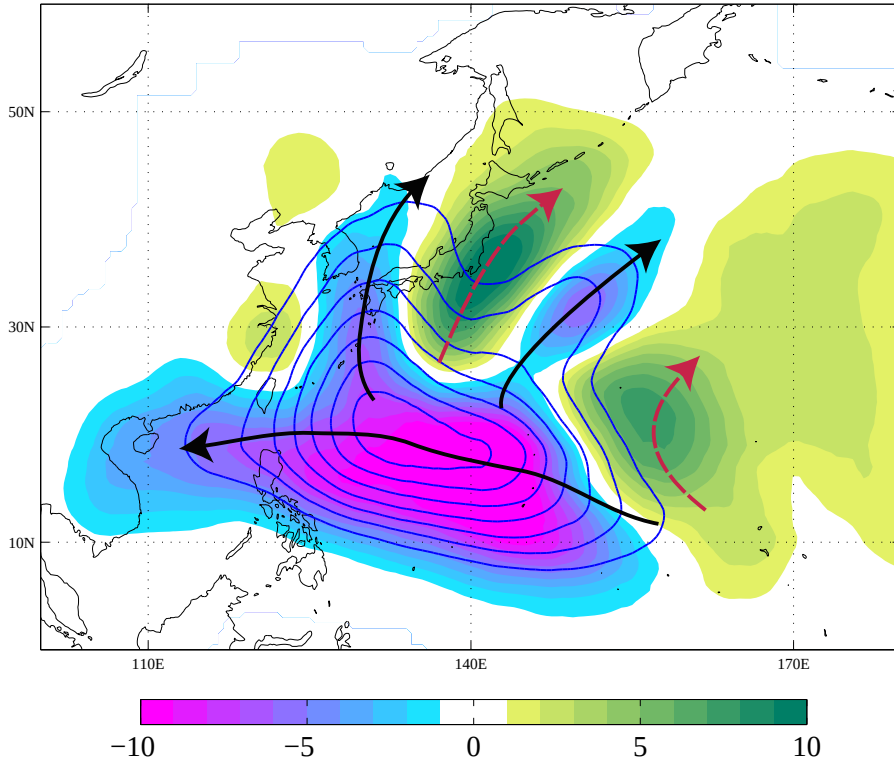


Figure 3.12: Frequency ratio of number of TC passing and its future change. Contour lines indicate the frequency ratio in the present climate (from 10% to 40% by 5% step). Color gradations indicate the future changes (unit: %point). Arrows are prevailing tracks of TCs (black arrows are those in the present climate and red arrows are increased tracks in the future climate).

Future changes in TC waves over the WNP were estimated focusing on 10 year return wave heights. Ensemble means of the future changes and standard deviations are up to about ± 4 m and 3 m, respectively. The spatial distribution of future changes in extreme wave heights can be qualitatively characterized by a minus-plus alternating pattern such as decrease, increase, decrease and increase clock-wise from the southwestern part of the WNP to the southeastern region (**Figure 3.9(a)**). This pattern was found to result from an eastward shift in the TC track. Following the results of this study, estimating the TC track shift is an important component of impact assessments, because a track shift can be the primary factor behind extreme wave change.

In terms of Non-TC waves, future changes in mean wave heights of Non-TC waves (**Figure 3.14(a)**) are almost the same as those of mean wave heights (including TC and Non-TC waves). The spatial distribution of future changes for mean, H_{ann} and $H_{1,10}$ can be characterized with the same features, such as increasing over mid- to high latitudes and decreasing over low to mid latitudes (**Figure 3.14(a)(b)(c)(d)**). However, the magnitude of future change of extreme wave height is larger than for the mean wave height. In the North Pacific (30°N - 45°N , 140°W - 180°W), the future changes in mean wave height, H_{ann} , H_1 and H_{10} are +0.02 m, +0.49 m, +0.38 m and +0.65 m respectively. In the North Atlantic (30°N - 45°N , 10°W - 60°W), the future changes in mean wave height, H_{ann} , H_1 and H_{10} are -0.20 m, -0.44 m, -0.45 m and -0.23 m respectively. And, over the Southern Ocean (45°S - 60°S), the future changes in mean wave height, H_{ann} , H_1 and H_{10} are +0.12 m, +0.35 m, +0.33 m and +0.40 m respectively.

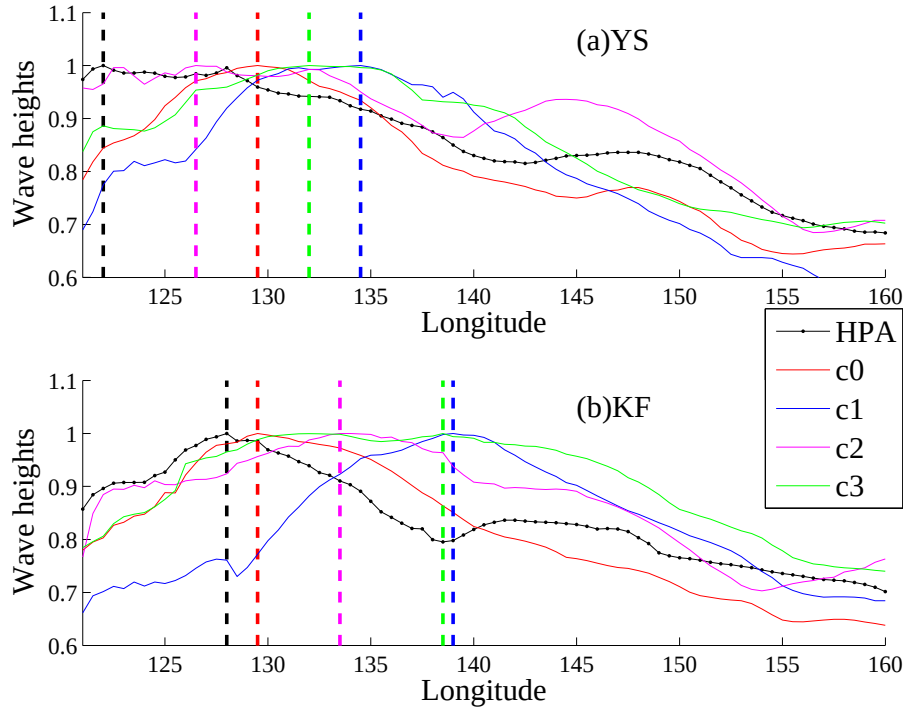


Figure 3.13: Spatial distribution of 10 year return wave height H_{10} in meridional cross section. The values are normalized by the maximum value of each experiment. Dashed vertical lines indicate maximum values.

Global TC waves tend to decrease over the lower latitudes and increase over the higher-latitudes regions (**Figure 3.14(e)(f)**). The future change in H_1 (**Figure 3.14(e)**) is dominated by the effect of TC wave frequency change (C_f) as discussed in **Section 3.4.2**. H_{10} in the North Atlantic decreases over the southwestern regions and increases over northeastern regions, which is similar to the result in the WNP when an eastward shift of TC (and TC waves) occurs. H_{10} in the South Indian Ocean can be characterized as increasing over the region southeast of Madagascar and decreasing over lower latitudes and the eastern part of the ocean basin. H_{10} in the South Pacific shows a reduction over nearly the entire region. Fan et al. (2013) also showed robust strong decreases of extreme wave heights in the South Pacific, which is attributed to a decrease in TC frequency.

Finally, we want to emphasize the following as important points when analyzing extreme wave climate change.

- The GCM model performance needs to be validated with consideration toward the dominant extreme phenomena that cause extreme waves. A simple GCM ensemble is not adequate for the projection of extreme wave heights.
- Extreme wave changes are determined by mixed effects that occur from changes in several characteristics of extreme phenomena such as location shift, intensification (or weakening), increase (or decrease) in frequency, etc.
- And, the ratio of contributing factors behind extreme waves will change and vary depending on the target time frame or design context, for example, whether the return period for wave heights is 1 year and 10 years.

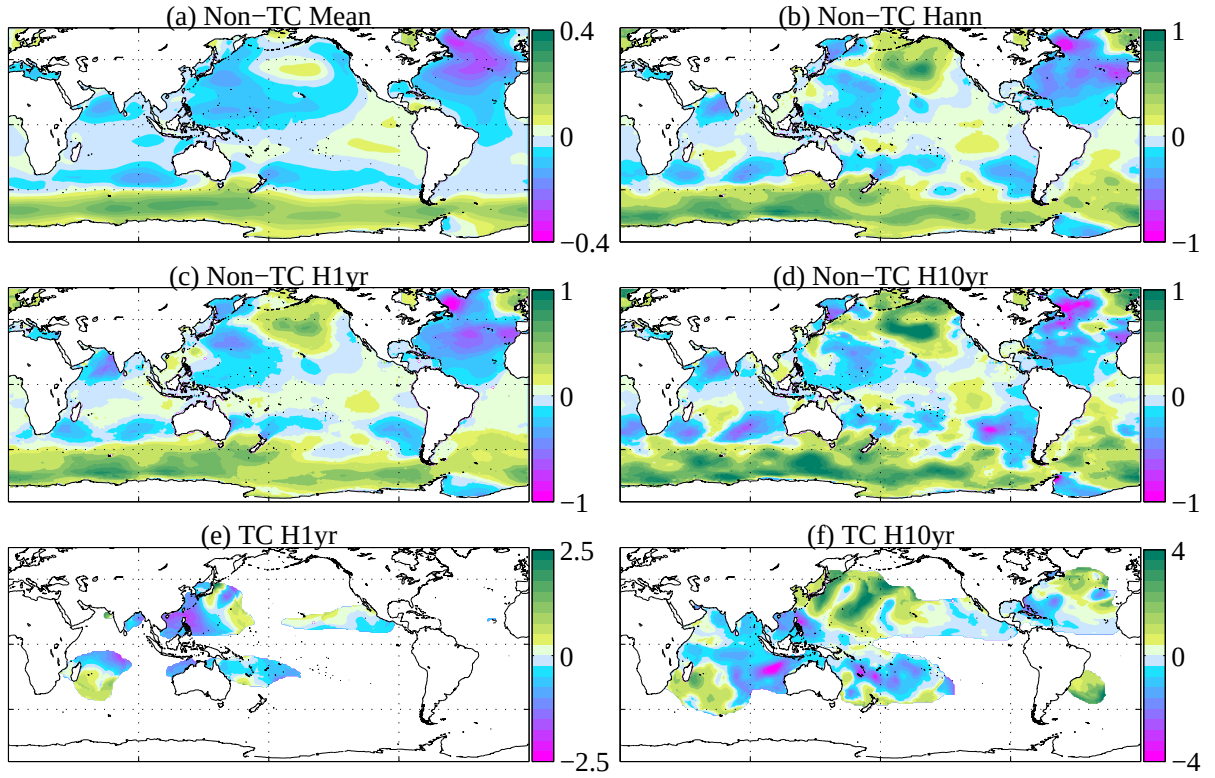


Figure 3.14: Future changes in global Non-TC and TC wave heights for different selections and periods (unit:m). (a) Mean wave heights of Non-TC waves, (b) H_{ann} of Non-TC waves, (c) H_1 of Non-TC waves, (d) H_{10} of Non-TC waves, (e) H_1 of TC waves, (f) H_{10} of TC waves.

Chapter 4

Future Projection of Ocean Wave Climate Based on Multi-Model Ensemble Experiments

4.1 Introduction

Chapters 2 and 3 showed the future changes in ocean wave climate based on ensemble experiments of single global climate model (MRI-AGCM3.2H). The ensemble experiments of single GCM are powerful method to identify the factors which can significantly contribute to the wave climate changes as shown in **Chapters 2 and 3**. However, the variation for future change sign is limited by single model. Ensemble experiments with various GCMs can give wider variation of wave climate changes. Therefore, wave climate projection by multi-model ensemble is conducted in this chapter.

Results of future climate projection from multi-model ensemble including various types of models has been summarized as equally weighted ensemble mean of future change and the deviation generally. For example, IPCC-AR5 (IPCC-AR5, 2013), based on CMIP5 multi-models (Taylor et al., 2012), stated that global mean surface temperatures for 2081-2100, relative to 1986-2005 will likely be in the 5 to 95% range of the CMIP5 models; 0.3 °C to 1.7 °C by RCP2.6 scenario and 2.6 °C to 4.8 °C by RCP8.5. For global mean sea level, those are 0.26 to 0.55 m by RCP2.6 and 0.45 to 0.82 m by RCP8.5. Hemer et al. (2013a) carried out the multi-model projection of wave climate based on five independent studies (Wang and Swail, 2006; Mori et al., 2010; Hemer et al., 2013b; Fan et al., 2013; Semedo et al., 2013), and showed ensemble mean future changes in significant wave height, mean wave period and mean wave direction.

Some studies indicated the relationship between model performance and climate response to external forcing (Fasullo and Trenberth, 2012), between model performance and the reliability of future projection (**Chapter 3**), and between experimental configuration (e.g. boundary condition) and the future change (**Chapter 2**). Multi-model ensemble with understanding of the relationship described above can give more reliable information of climate change than simple ensemble mean. We, in this chapter, show wave climate change (mean and extreme wave height) by multi-model ensemble and the relationship between Tropical Cyclone (TC) model performance and the extreme wave height change in same manner as **Chapter 3**.

Table 4.1: Description of eight CMIP5 models with the approximated atmospheric spatial resolution, the run ID for Historical and RCP run and the name of institution.

Model name	Spatial Res. (lat. x lon. [deg])	Run ID (Historical/RCP)	Institution
ACCESS1.0	1.25 x 1.875	r1i1p1/r1i1p1	Commonwealth Scientific and Industrial Research Organisation Australia
BCC-CSM1.1	2.8 x 2.8	r1i1p1/r1i1p1	Beijing Climate Center, China Meteorological Administration China
CNRM-CM5	1.4 x 1.4	r1i1p1/r1i1p1	Centre National de Recherches Meteorologiques, Meteo-France France
GFDL-CM3	2 x 2.5	r1i1p1/r1i1p1	Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration America
HadGEM2-ES	1.25 x 1.875	r2i1p1/r1i1p1	Met Office Hadley Centre UK
INMCM4	1.5 x 2	r1i1p1/r1i1p1	Institute for Numerical Mathematics Russia
MIROC5	1.4 x 1.4	r1i1p1/r1i1p1	Atmosphere and Ocean Research Institute, The University of Tokyo Japan
MRI-CGCM3	1.125 x 1.125	r1i1p1/r1i1p1	Meteorological Research Institute Japan

4.2 Methodology

The multi-model ensemble for future wave climate projection is based on the results by Hemer and Trenham (2014). Wave model was forced by sea surface wind and sea ice from Atmosphere-Ocean coupled GCMs (AOGCMs) or Earth System Models (ESMs) of the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012). This wave climate projections were based on outputs from AOGCM/ESM, directly. Therefore, the framework of methodology, especially spatial resolution of forcing, is different to that of **Chapters 2 and 3** which were based on high resolution AGCM. The CMIP5 models used in this wave climate projections are described in **Section 4.2.1** and TC detection method is described in **Section 4.2.2**, respectively.

4.2.1 Outline of CMIP5 models

The CMIP5 model results have contributed to the climate change assessment by IPCC-AR5 (IPCC-AR5, 2013). Historical climate simulation were carried out under observed forcing (e.g. greenhouse gas, solar forcing, volcanic influence) and future climate under greenhouse gas concentration scenario. Future simulations under the scenario of Representative Concentration Pathways 8.5 (RCP8.5) were used. RCP8.5 is the highest greenhouse gas concentration scenario in RCP scenarios; radiation forcing will be increased up to 8.5 W/m² at 2100. Eight CMIP5 models were selected for the wave climate projections. The eight CMIP5 models are shown in **Table 4.1** with the approximated atmospheric spatial resolution, the simulation run ID for Historical and RCP run and the name of institution.

Global wave climate projection was carried out by WAVEWATCH III version 3.14 (Tolman, 2009) forced by sea surface wind and sea ice from CMIP5 models. The global domain was set for the latitudinal range of 80°S-80°N over all longitudes with 1° × 1° spatial grids. The directional resolution is 15°, and the frequency space is set to 0.04 to 0.5 Hz, which is discretized in 25 increments logarithmically. The WAM4 source term parameterized by Bidlot et al. (2007) was used as a set for

wind input and dissipation. The time slice experiments were conducted using 1979 to 2005 for the present climate under CMIP5 historical runs and 2081 to 2100 for the future climate under RCP8.5 runs, respectively.

4.2.2 TC detection method

In order to detect the TC in each CMIP5 model, objective TC detection method was used. We employed simple TC detection method based on only atmospheric surface data, mean sea level pressure (MSLP) and surface wind speed (U_{surf}). This simple TC detection method is denoted as SimpleDM hereafter. The SimpleDM consists of two procedures to detect TCs. First one is to obtain the candidate TCs on each time-step (6 hourly time-step). Second one is to obtain TC tracks connecting candidate TCs. The criteria for selecting candidate TC are itemized as follows.

- (1) Local minimum value of MSLP is deeper than environmental averaged MSLP (400 km in radius) by ΔP hPa.
- (2) Maximum U_{surf} is greater than U_{limit} .
- (3) The analysis area is within 45°S to 45°N.

ΔP and U_{limit} are arbitrarily decided. The criteria for TC tracks are as follows.

- (1) A candidate TC on a certain time step and the nearest candidate TC on the next time-step (6 hour later) are connected as same TC system if the distance within 600 km.
- (2) Each TC duration is longer than 36 hours.
- (3) The genesis location is within 25°S to 25°N.

The SimpleDM is validated compared with the well-applied TC detection method used by Murakami (2014). The detection method by Murakami (2014) is denoted as M14 hereafter. M14 employed five criteria for TC detection;

- (1) Relative vorticity at 850 hPa is greater than ζ_{850} .
- (2) Temperature anomaly at 300, 500 and 700 hPa from environmental averaged temperature (10 degree box) is greater than t_a .
- (3) Maximum wind speed at 850 hPa is greater than maximum speed velocity at 300 hPa,
- (4) Maximum surface wind speed is greater than U_{limit} .
- (5) TC duration is greater than Dur .

ζ_{850} , t_a , U_{limit} and Dur are arbitrarily decided.

The performance of SimpleDM is compared with M14 based on JRA-55 reanalysis data set (Kobayashi et al., 2015). 3-D wind fields surrounding TCs created from TC observations are embedded in JRA-55 wind field. Thus, the TCs in JRA-55 are well reproduced compared with observations (Murakami, 2014). SimpleDM and M14 were applied to JRA-55 data set for detecting TCs. The analyzed period was 1979 to 2009. The arbitrary values were decided as follows so as to match the

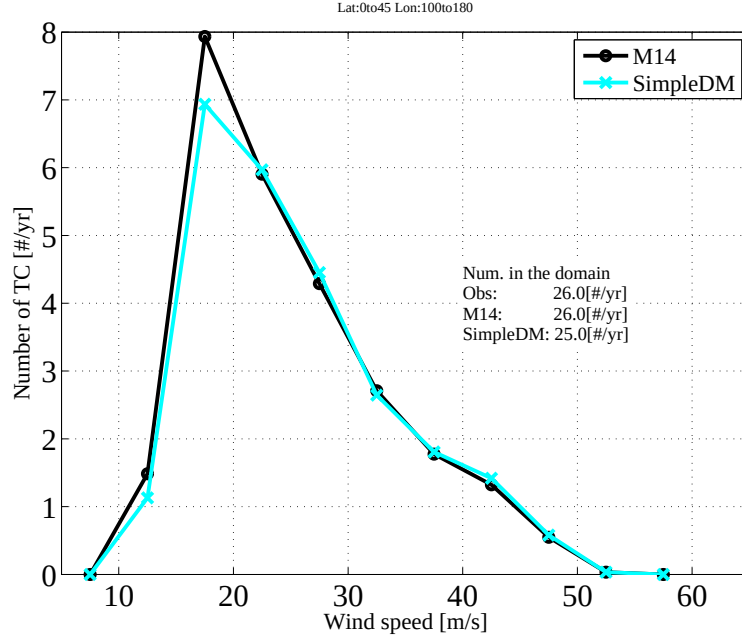


Figure 4.1: Frequency distribution of extracted TC maximum wind speed in the Western North Pacific from JRA-55 by M14 and SimpleDM

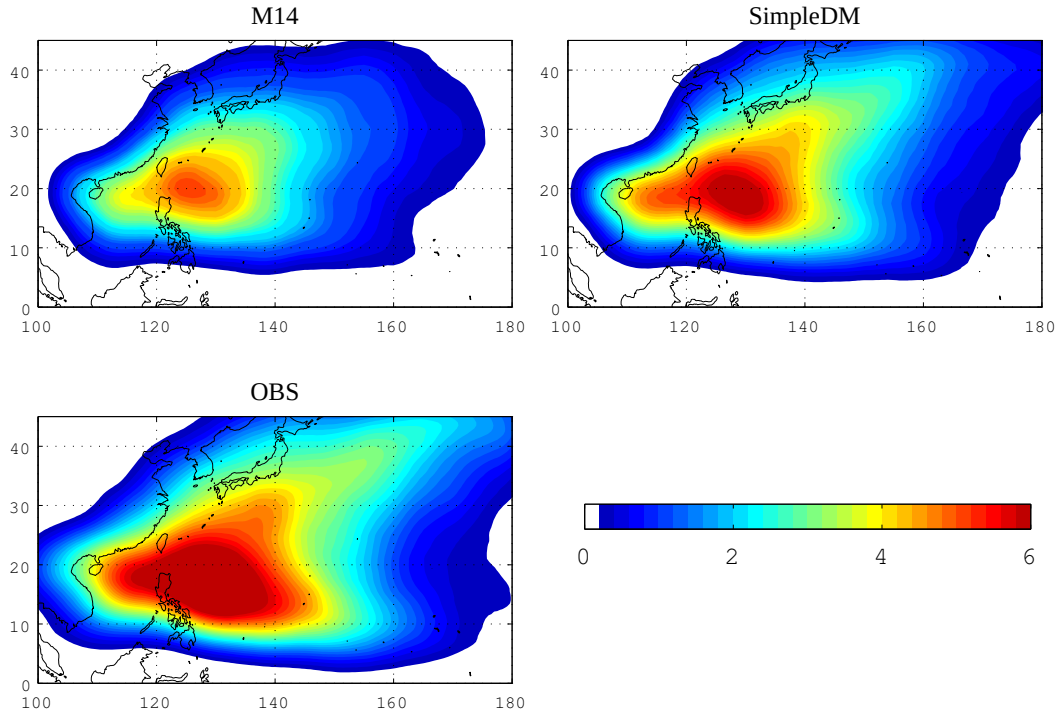


Figure 4.2: TC passing frequency smoothed over $6^\circ \times 6^\circ$ in the Western North Pacific for M14 (upper left), SimpleDM (upper right) and observation (lower left) (unit: #/year).

detected TC number to observed TC number. For SimpleDM, ΔP is 2 hPa and U_{limit} is 11 ms^{-1} . For M14, ζ_{850} is $1 \times 10^{-5} \text{ s}^{-1}$, t_a is 0.8 K, U_{limit} is 11 ms^{-1} and Dur is 36 hours.

Figure 4.1 shows the frequency distribution of TC maximum wind speed in the Western North Pacific (0 to 45°N latitude and 100 to 180°E longitude). It is clear that the performance of SimpleDM is comparable to M14 in terms of maximum wind speed frequency in the Western North Pacific. **Figure 4.2** shows the TC passing frequency for M14, SimpleDM and observation (RSMC Tokyo data in IBTrACKS: <https://www.ncdc.noaa.gov/ibtracs/>). It is remarkable that SimpleDM can capture the feature of spatial distribution of observation better than M14. Therefore, it is confirmed that SimpleDM has adequate performance for detecting TCs, at least for TCs in the Western North Pacific.

4.3 Validation

The model performances for mean and extreme wave heights in the present climate are estimated in this section. Simulated mean and extreme wave heights of the present climate (1979 - 2005) are compared with reanalysis data sets (ERA-interim (Dee et al., 2011) and JRA-55 ST4 (**Chapter 3**)), MRI-AGCM3.2H experiments (**Chapter 2** and **Chapter 3**) and buoy data in the same manner as **Section 2.3** and **Section 3.3**.

Figure 4.3 shows the mean significant wave height ($\overline{H_s}$) during 1979 to 2005. **Figure 4.4** is same as **Figure 4.3** but for the mean annual maximum wave height (H_{ann}). **Figure 4.3** and **Figure 4.4** also show the bias from ERA-Interim. The biases of $\overline{H_s}$ and H_{ann} from ERA-Interim are about $\pm 30\%$ and 60% of ERA-Interim's value. There is a wide variety of bias spatial distribution among CMIP5 models (**Figure 4.3** and **Figure 4.4**). $\overline{H_s}$ is overestimated by MIROC5 and MRI-CGCM3 over almost all the global domain. On the other hand, $\overline{H_s}$ is underestimated by CNRM-CM5 over almost all the global domain. Other models locally underestimate $\overline{H_s}$, for example, lower to mid latitudes in the Atlantic Ocean for BCC-CSM1.1, and the Western Pacific and the Western Atlantic for INMCM4. It can be considered that the local biases are due to lack of model performance for specific local phenomena, although the phenomena are not identified here. As for H_{ann} , it is remarkable that BCC-CSM1.1, CNRM-CM5, MIROC5 and MRI-CGCM3 overestimate H_{ann} over TC passing regions compared with ERA-Interim. The model performance for TC of ERA-Interim is low (Murakami, 2014). Therefore, it can be expected that those models can produce TCs relatively well.

Figure 4.5 shows the comparison with buoy data by $\overline{H_s}$ and 99.9 % quantile value of H_s (which roughly correspond to H_{ann}). The biases for $\overline{H_s}$ from buoy observations are about $\pm 0.5 \text{ m}$, and those for 99.9 % quantile values are about $\pm 4 \text{ m}$ at #21004 point which are in TC passing region and $\pm 2 \text{ m}$ at other points. Although all of eight CMIP5 models underestimate 99.9 % quantile values at #21004, BCC-CSM1.1, MIROC5 and MRI-CGCM3 show better agreement with buoy data. The large difference at #21004 among MRI-AGCM3.2H experiments is due to model performance of TC, which is discussed in **Chapter 3**.

It is clear that model performance of TC is a major contribution to model performance of extreme waves in the mid-latitudes. TCs in each model over the Western North Pacific are estimated. TCs were detected by SimpleDM (**Section 4.2**). **Figure 4.6** shows the TC passing frequency in the Western North Pacific for eight CMIP5 models and observed data (IBTrACS). Only TCs whose

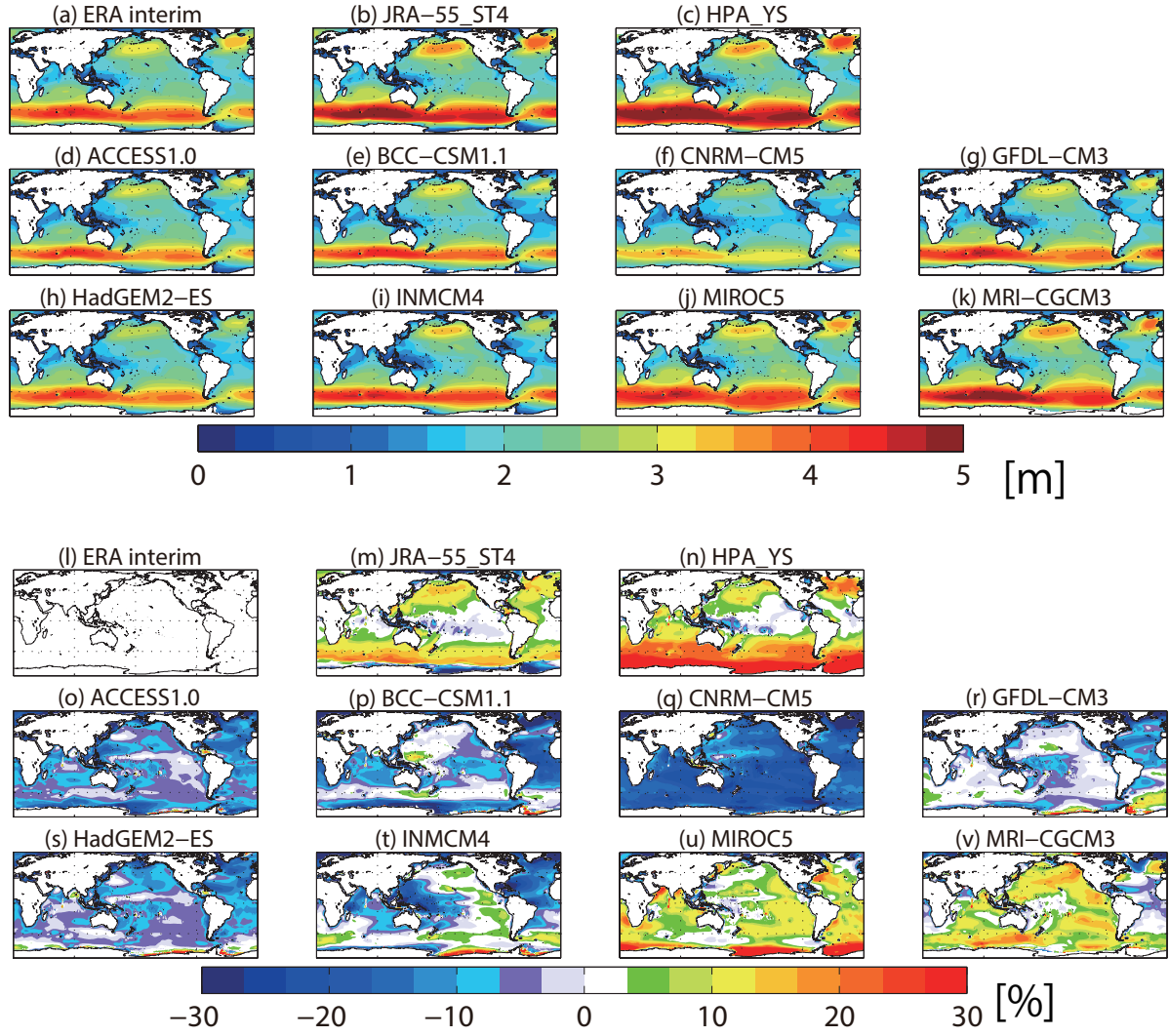


Figure 4.3: $\overline{H_s}$ during 1979 to 2005 for (a) ERA-Interim, (b) JRA-55 ST4, (c) HPA_YS and (d)-(k) eight CMIP5 models. $\overline{H_s}$ differences from ERA-Interim for (l) ERA-Interim, (m) JRA-55 ST4, (n) HPA_YS and (o)-(v) eight CMIP5 models

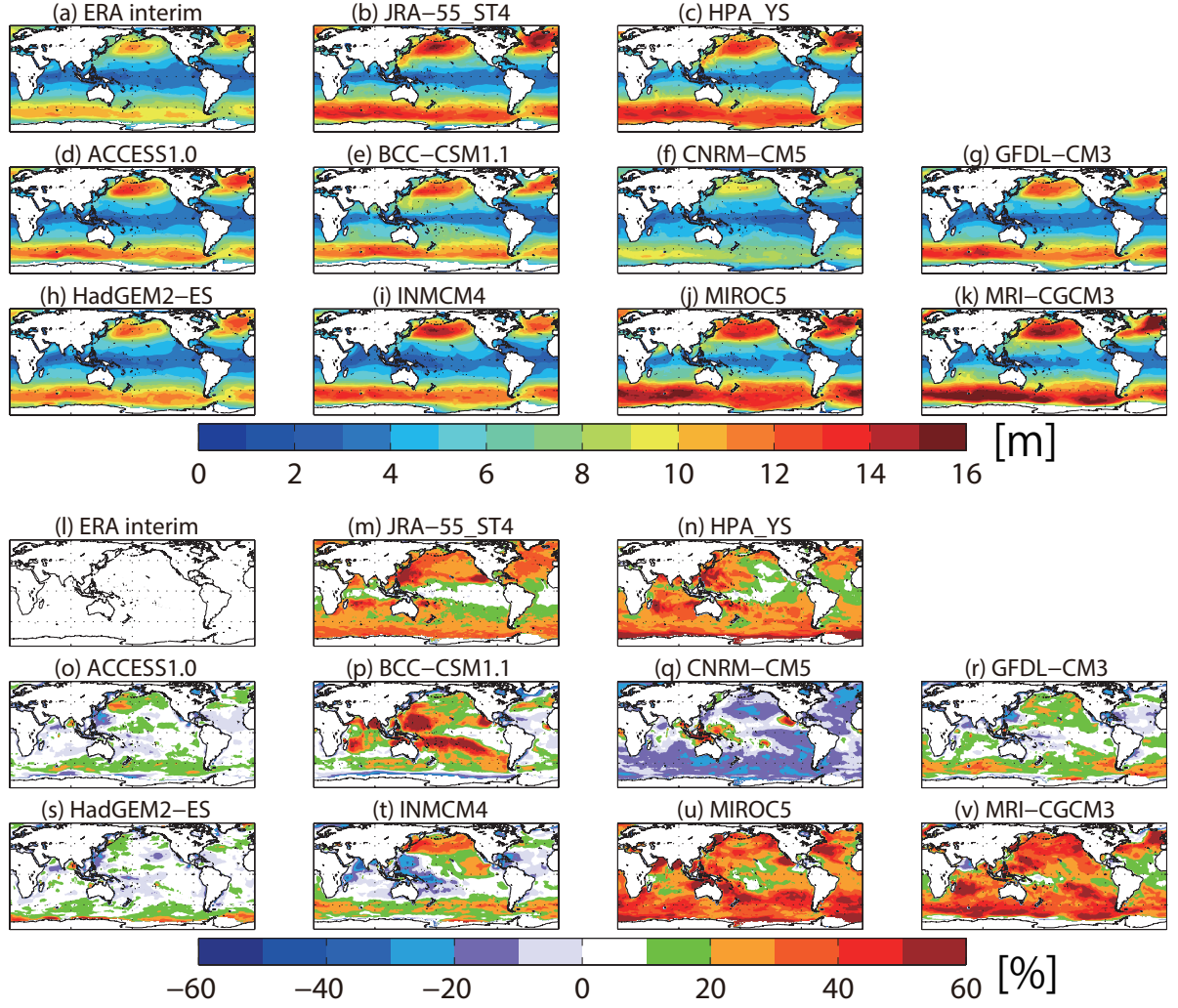


Figure 4.4: H_{ann} during 1979 to 2005 for (a) ERA-Interim, (b) JRA-55 ST4, (c) HPA_Y5 and (d)-(k) eight CMIP5 models. H_{ann} differences from ERA-Interim for (l) ERA-Interim, (m) JRA-55 ST4, (n) HPA_Y5 and (o)-(v) eight CMIP5 models

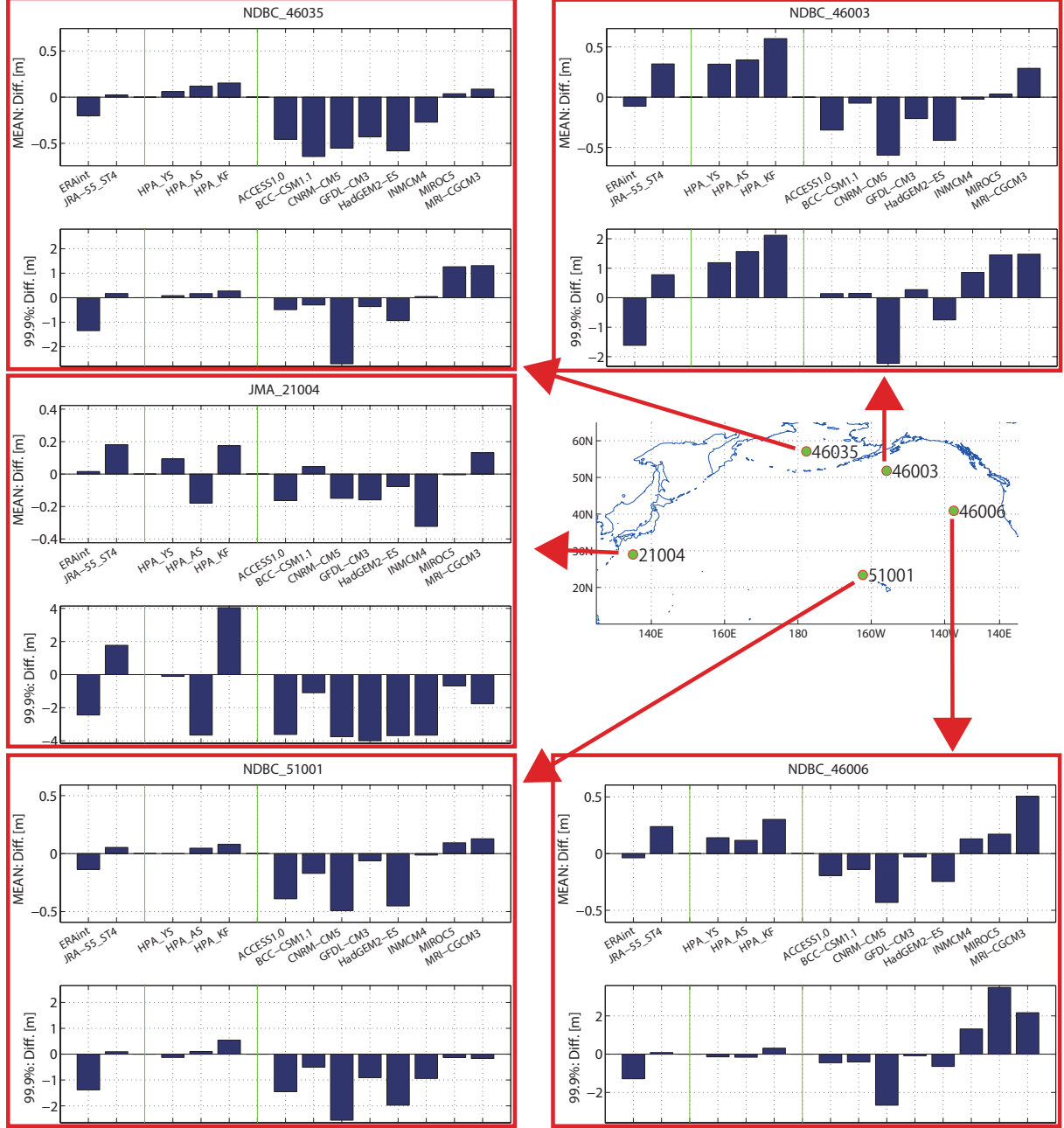


Figure 4.5: Comparison with buoy by $\overline{H}_s$ (upper panel in each point) and 99.9 % quantile value (lower panel). Bars indicate differences from buoy values for ERA-Interim, JRA-55 ST4, HPA_YS, HPA_AS, HPA_KF, and eight CMIP5 models from left to right.

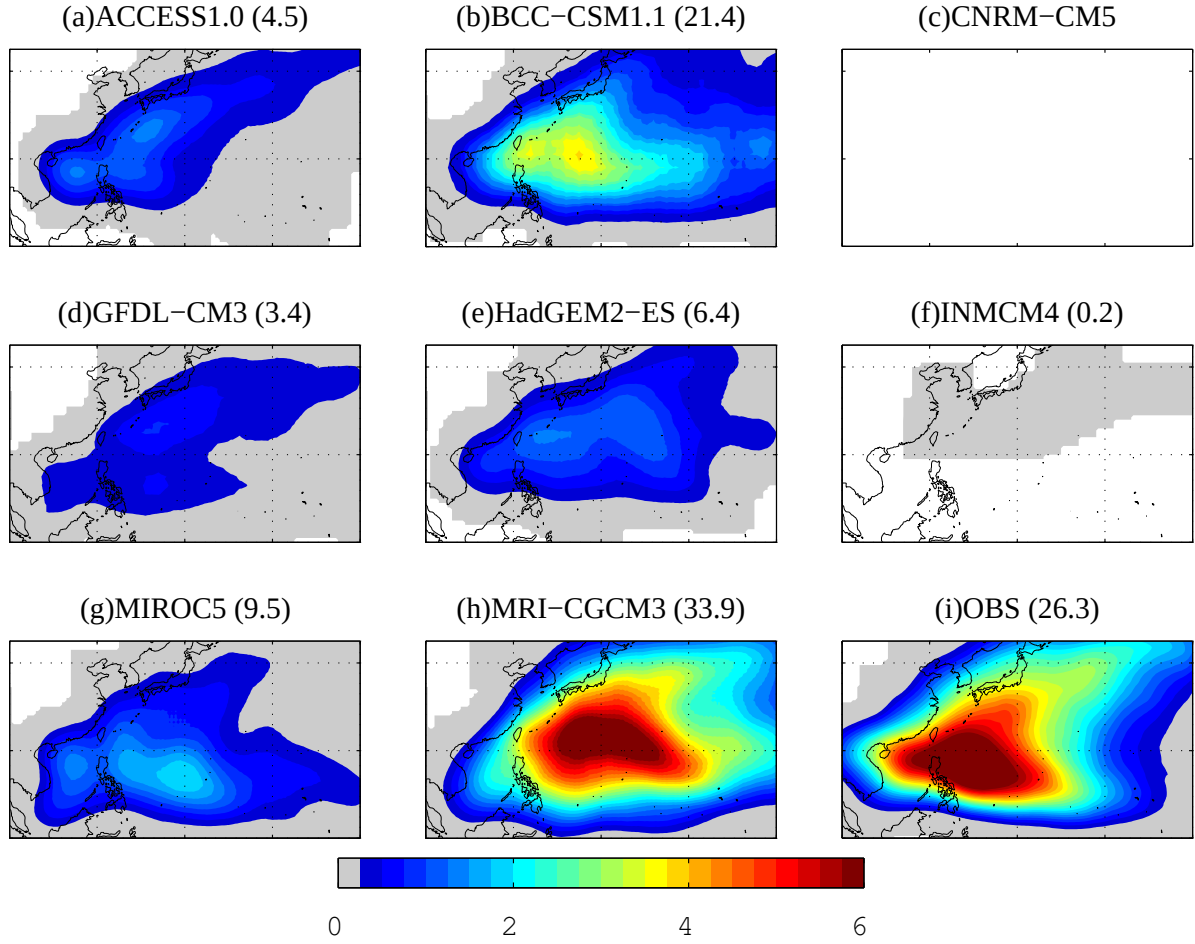


Figure 4.6: TC passing frequency (unit: #/year) smoothed over $6^\circ \times 6^\circ$ in the Western North Pacific for (a)-(h) eight CMIP5 models and (i) observation (Maximum wind speed in TC life-time is greater than 17 ms^{-1}). Value in parenthesis means total TC number in the domain (unit: #/year). TC detection for CNRM-CM5 can't be conducted due to data problem.

maximum wind speed in the life time is greater than 17 ms^{-1} , are shown in **Figure 4.6**. TC detection for CNRM-CM5 can't be conducted due to data supply problem, unfortunately. As the expectation above, BCC-CSM1.1 and MRI-CGCM3 can produce TCs better than other models. MIROC5 has moderate model performance of TC in the Western North Pacific. Moreover, 99.9 % quantile values of BCC-CSM1.1, MIROC5 and MRI-CGCM3 show relatively better agreement with buoy data (**Figure 4.5**). This is because their better model performance of TC (**Figure 4.6**).

Summary of validation of the present climate is as follows. 1) Each CMIP5 model has specific mean wave height bias due to lack of model performance for specific phenomena. 2) Model performances of TC among CMIP5 models are totally different with each other, and the differences significantly contribute to model performance of extreme waves.

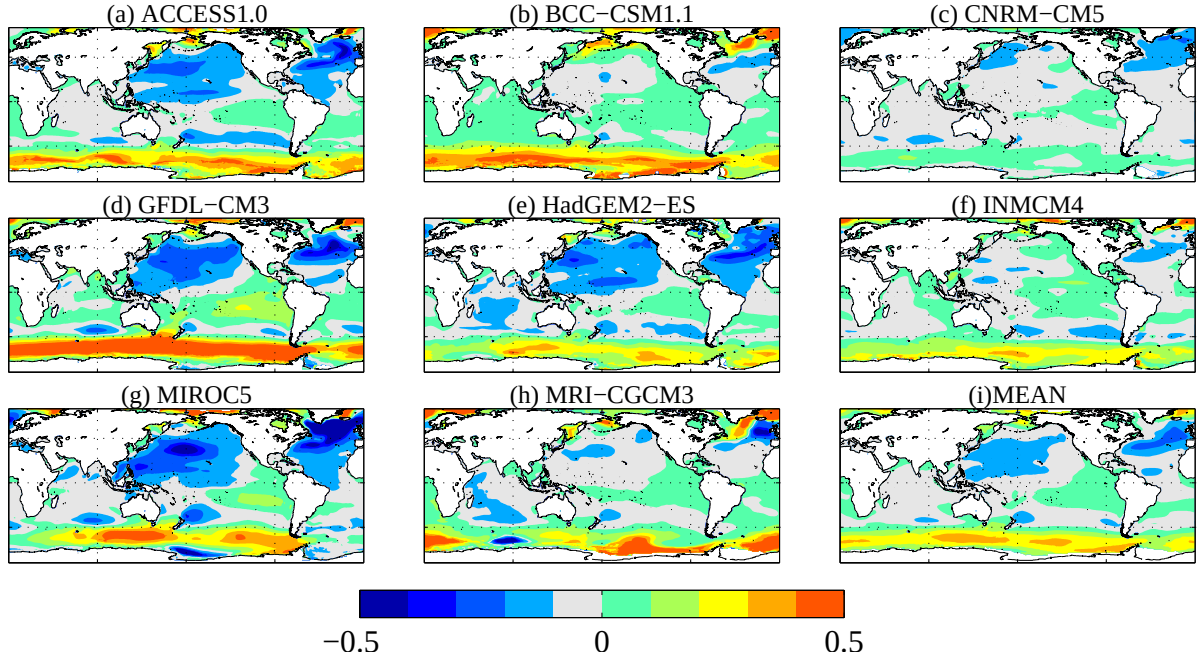


Figure 4.7: Future changes in $\overline{H_s}$ for (a)-(h) eight CMIP5 models and (i) ensemble mean. (unit: m)

4.4 Future changes in wave height

Future changes in mean and extreme wave heights ($\overline{H_s}$ and H_{ann}) by eight CMIP5 models are analyzed in this section. **Figure 4.7** shows the future changes in $\overline{H_s}$ forced by eight CMIP5 models. The future changes in $\overline{H_s}$ are about ± 0.5 m. The spatial distributions of future change in wave height can be roughly characterized as the increase over the Southern Ocean and the decrease over the Northern Hemisphere. An increase in wave height over the Southern Ocean with enhanced wind speed is consistent with previous studies (IPCC-AR5, 2013). The larger variations of future change can be seen around sea ice area such as around the Greenland and higher latitudes of the Southern Ocean, which is due to the larger variation of sea ice representation and the future change. The wider open ocean without sea ice leads to larger waves because of longer fetch but future changes in sea ice are highly uncertain.

Figure 4.8 shows the future changes in H_{ann} . There are large variation in future changes. The future changes in H_{ann} are rather local changes compared with $\overline{H_s}$. **Figure 4.9** shows the ensemble mean of future change by eight models (same as **Figure 4.8(i)**) with indication of significance of the future change. Regions with black dots indicate areas where the seven models out of eight show the same sign of future change signal (**Figure 4.9**). The increase in extreme wave heights over the Southern Ocean is identical feature among the models. Moreover, the decreases over mid-latitudes in the South Pacific, the Western North Pacific and the North Atlantic are relatively consistent among models.

The target of analysis is focused on the Western North Pacific. **Figure 4.10** shows the future changes in H_{ann} over the Western North Pacific (0° to 60° N and 100° E to 180° E). Future changes by ACCESS1.0, GFDL-CM3, HadGEM2-ES and INMCM4 can be characterized as decrease in wave heights over 30° N and increase over the Okhotsk Sea. The cause of the increase in wave height over the Okhotsk Sea is future decrease of sea ice in this region. The TC changes' effects can be seen in the

future changes by BCC-CSM1.1, CNRM-CM5, MIROC5 and MRI-CGCM3. **Section 4.3** showed that those models have relatively better model performance for TC, although TCs in CNRM-CM5 couldn't be shown due to data problem. The future changes in H_{ann} by BCC-CSM1.1, CNRM-CM5, MIROC5 and MRI-CGCM3 are results from changes of TC generated waves (TC waves) and the other waves (Non-TC waves). On the other hand, the future changes by ACCESS1.0, GFDL-CM3, HadGEM2-ES and INMCM4 are mainly result from changes of Non-TC waves. Therefore, results between models with better and lower performance for TC cannot be compared with each other because the causes of the future change are different each other.

In order to compare the models reasonably, Non-TC wave data was derived using TC tracks detected by SimpleDM described as **Section 4.2**. The method of deriving Non-TC waves is denoted in **Chapter 3**. **Figure 4.11** shows future changes in H_{ann} of Non-TC waves. The future changes have the identical feature which is the decrease in wave height over 30°N latitudes, which can be seen in ensemble mean (**Figure 4.11(i)**). The decrease in wave height over 30°N in the Western North Pacific can be seen in MRI-AGCM3.2H experiments (**Chapter 2, Chapter 3**) and previous studies (Hemer et al., 2013a; IPCC-AR5, 2013). Therefore, this Non-TC wave change is robust future change signal. The cause of the future change will be discussed in **Chapter 5**.

Future changes in extreme TC waves have larger variation as seen in the differences among the future changes by BCC-CSM1.1, CNRM-CM5, MIROC5 and MRI-CGCM3 (**Figure 4.10**). Furthermore, future changes in TC characteristics also have larger variation among the models. For example, future changes in TC passing frequency are shown in **Figure 4.12**. It is hard to detect the identical feature of the future changes among the models (**Figure 4.12**). However, four models, ACCESS1.0, HadGEM2-ES, MIROC5 and MRI-CGCM3, show the decrease of TC frequency in large area of the Western North Pacific, but, three models, BCC-CSM1.1, GFDL-CM3 and INMCM4, show rather insignificant changes.

4.5 Summary

Wave climate projections were carried out based on eight CMIP5 models. Spatial distribution of model biases in mean and extreme wave height totally different among eight models. Model performances of the present climate simulation of eight models were estimated in comparison with reanalysis data sets and observations. Some models overestimate (underestimate) wave height globally and some models overestimate (underestimate) wave height locally. It can be assumed that the local biases are due to lack of model performance for specific local phenomena. For example, it was shown that models with low performance of Tropical Cyclone (TC) significantly underestimate extreme wave height and models with the high performance show better agreement of wave height with observations.

The future changes in mean wave height can be roughly characterized as the increase in wave height over the Southern Ocean and the decrease over the Northern Hemisphere. The larger variations of future change can be seen around sea ice area due to uncertain sea ice changes. The future changes in extreme wave height depend on model performance of TC. The future changes in extreme wave height by models with better performance of TC are dominated by TC waves changes, and the future changes by models with lower performance are dominated by Non-TC waves changes. However, the future changes in Non-TC extreme wave in the Western North Pacific are highly

consistent among models and also consistent with previous studies. The Non-TC extreme waves will likely decrease around 30 °N in the Western North Pacific. The projection of TC is highly uncertain, which can significantly contribute to uncertainty of total extreme wave height change including TC and Non-TC waves. Therefore, it is important to consider the extreme wave climate changes taking into account model performance of TC, Non-TC wave changes and TC wave changes.

The results mean that equally weighted ensemble mean of future change among models is not reasonable because each model has specific tendency of climate change response depending on the model performance. Only relation between model performance of TC and the future change in extreme wave height in the Western North Pacific was analyzed, and thus, other relations between model performance and wave climate change will be studied in the future work.

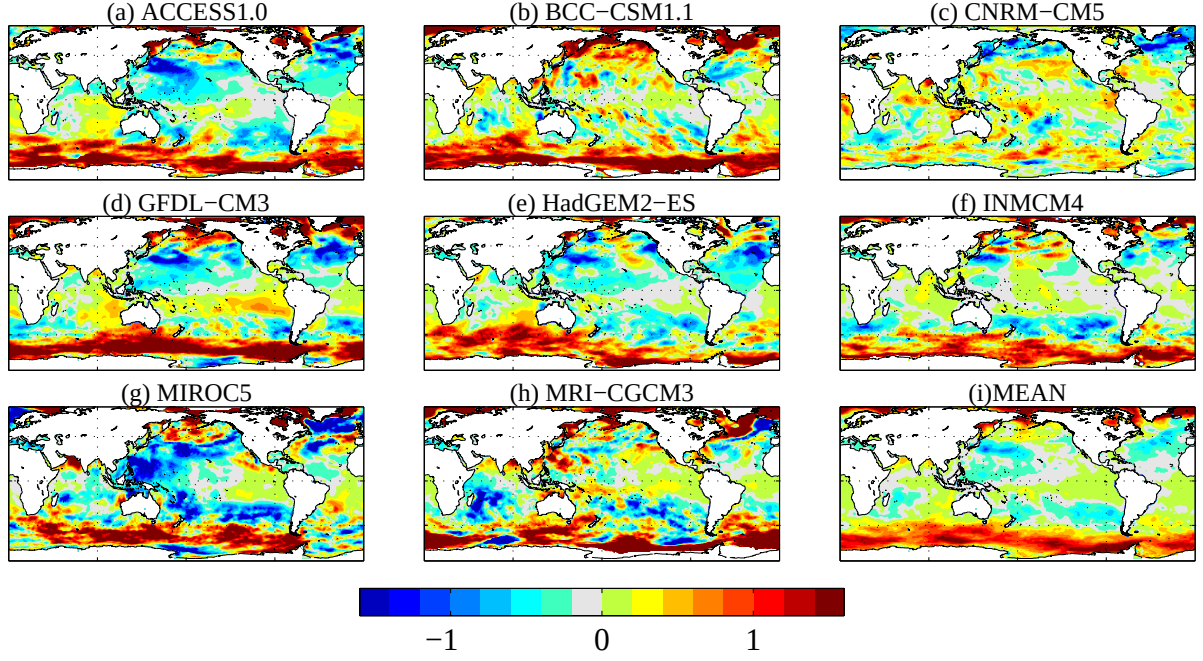


Figure 4.8: Future changes in H_{ann} for (a)-(h) eight CMIP5 models and (i) ensemble mean. (unit: m)

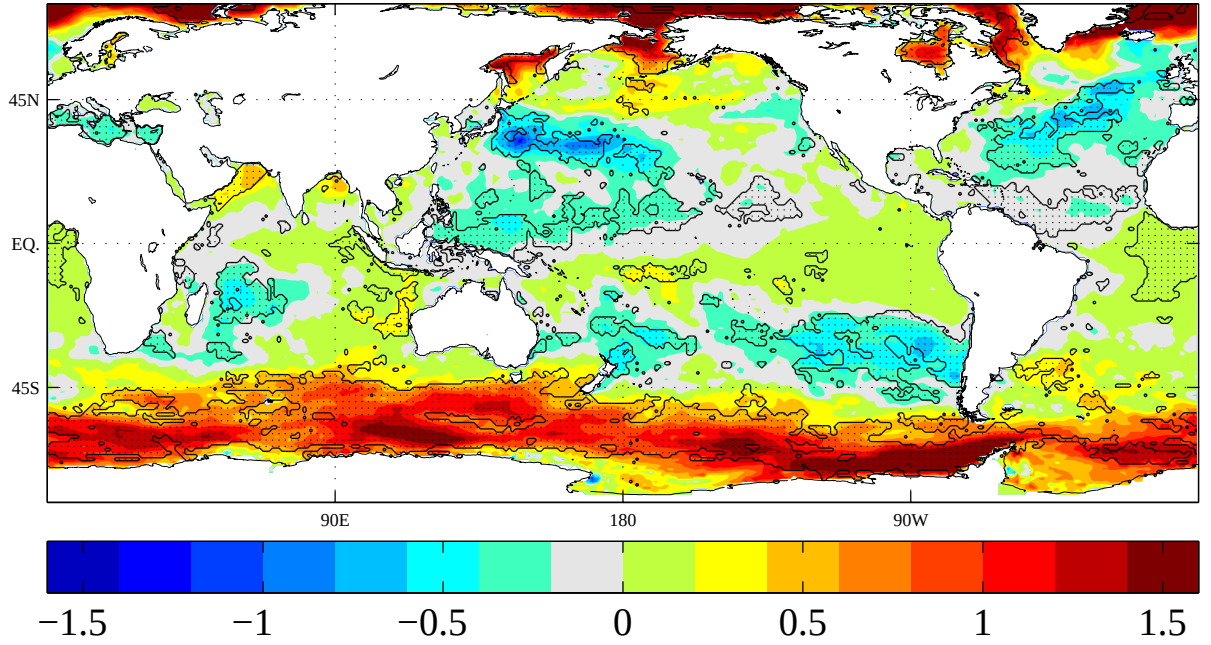


Figure 4.9: Same as **Figure 4.8(i)**, but with indication of significance of the future change. Regions with black dots indicate areas where the seven models out of eight show the same sign of future change signal.

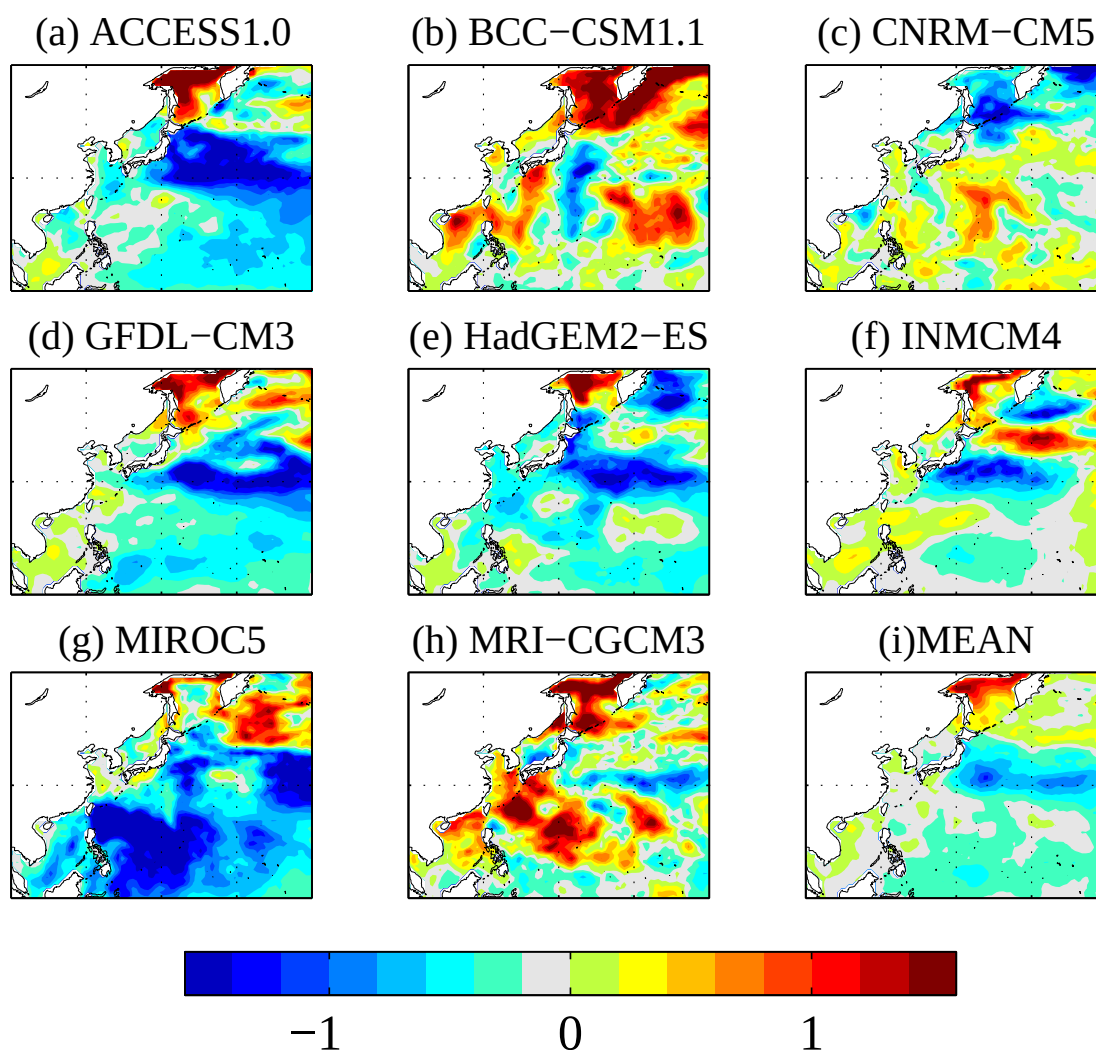


Figure 4.10: Same as **Figure 4.8** but for the Western North Pacific.

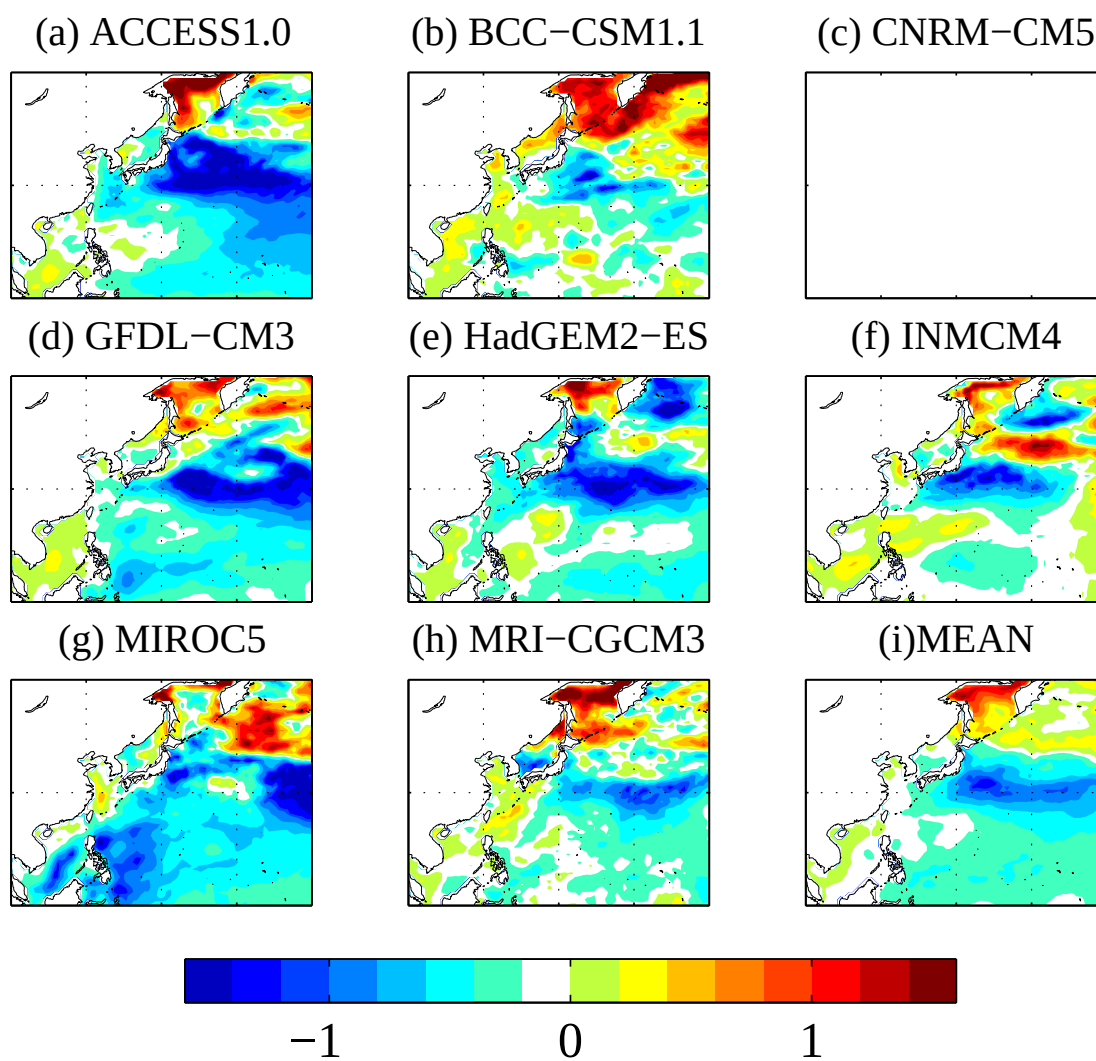


Figure 4.11: Same as **Figure 4.10** but for Non-TC waves over the Western North Pacific.

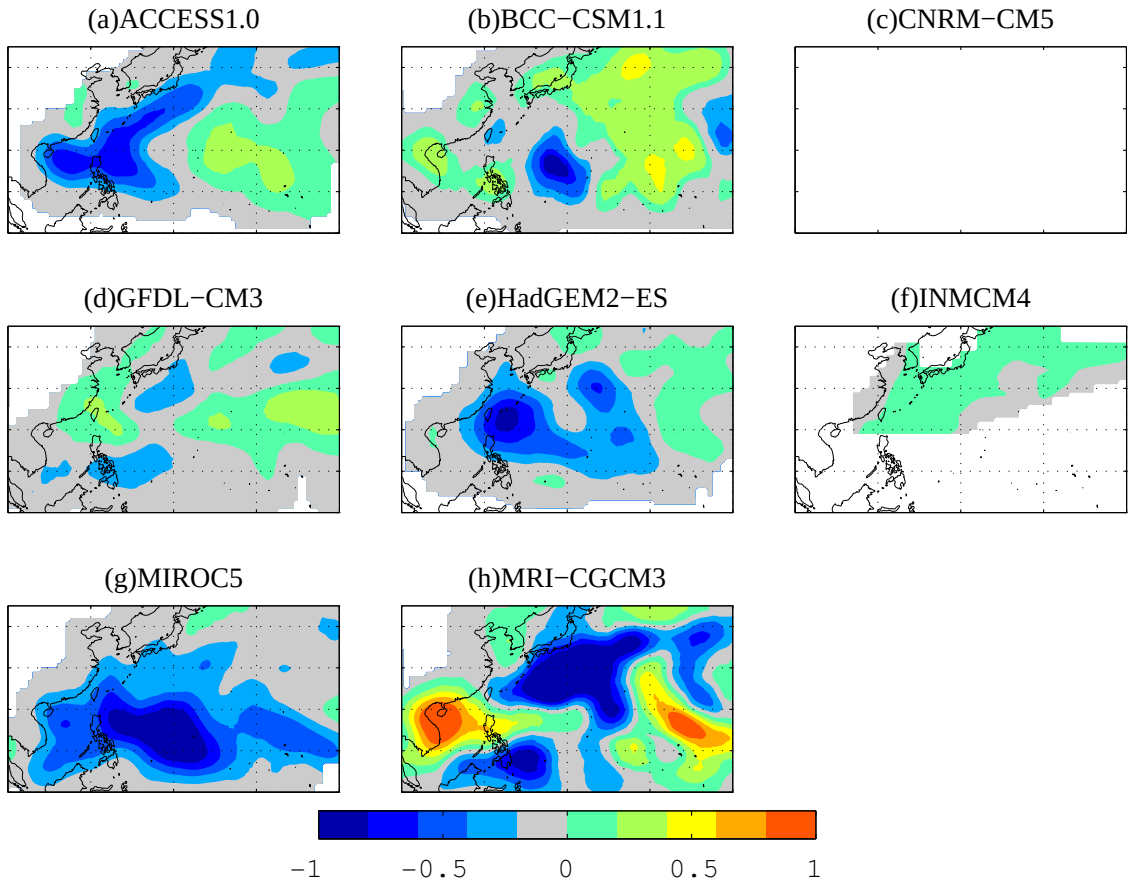


Figure 4.12: Future changes in TC passing frequency (unit: $\#/\text{year}$).

Chapter 5

Ocean Waves and Teleconnection Patterns in the Northern Hemisphere

5.1 Introduction

The global climate has preferred patterns of monthly to decadal variability, which are called teleconnection patterns or large-scale atmospheric circulation patterns. Basically, a teleconnection is made up of a fixed spatial pattern with an associated index time series showing the evolution of its amplitude and phase (Trenberth and Coauthors, 2007), which is defined by monthly Sea Surface Temperature (SST), 500 hPa geo-potential height (Z500), and so on. The teleconnection patterns, such as the El Niño Southern Oscillation (ENSO), the North Atlantic Oscillation (NAO), and the Arctic Oscillation (AO), are widely considered to be associated with typical climate variability (Trenberth et al., 2002; Hurrell et al., 2003; Thompson and Wallace, 1998). It is well known that ENSO has a periodic fluctuation of 2-7 years (McPhaden et al., 2006) and a profound world-wide effect on the annual climate.

Although teleconnection patterns indicate simultaneous fluctuations of climate values at widely separated points and spatial patterns, originally and literally (Walker and Bliss, 1932; Wallace and Gutzler, 1981), the discussion about the relationships between the occurrence trends of teleconnection patterns and multi-decadal change in the climate state started in the 1990s (e.g., Trenberth, 1990, Trenberth and Hurrell, 1994, Hurrell, 1996, Thompson and Wallace, 1998). For instance, local increases in surface temperature were explained by teleconnection patterns. Hurrell (1996) reported that increasing trends in surface temperatures in Europe and decreasing trends in the North East Atlantic from the 1970s correspond to a positive trend of the NAO. Similarly, an increasing trend in surface temperatures in Alaska and a decreasing trend in the North Pacific correspond to a positive trend of the Pacific/North America pattern (PNA). Trenberth et al. (2002) explained that a 0.06°C increase in global-averaged atmospheric surface temperature from 1950-1998 was related to a change in the ENSO. The teleconnection pattern indices are useful for climate study as macroscopic indicators of climate variability and furthermore multi-decadal change in the climate state, rather than the phenomena of teleconnection itself. As pointed out by several studies (Deser et al., 2012; Hawkins and Sutton, 2009; Tebaldi et al., 2011), a major source of uncertainty accompanied with climate projections is the internal natural variability such as decadal or multi-decadal oscillations in the system. Therefore, it is important to understand the natural variability, expressed

as a teleconnection pattern.

In coastal and ocean engineering, the relationship between wave climate (wave height) variability and teleconnection patterns has been discussed. From the global point of view, Semedo et al. (2011) analyzed the connection between wave and teleconnection pattern indices (denoted by large-scale atmospheric circulation indices in their work) based on the ERA-40 dataset. They obtained main patterns of the interannual variability of the swell fields by empirical orthogonal function analysis, and reported a strong relationship between swells and teleconnection patterns. Fan et al. (2012) computed past wave climate using the wave model WAVEWATCH3 coupled with atmospheric model and showed that wave climate exhibits clear relations to the NAO in the North Atlantic and the Southern Oscillation Index (SOI) in the Pacific Ocean, respectively. In addition, wave climate and teleconnection pattern in the Southern Hemisphere has been analyzed. Hemer et al. (2010) showed a strong positive correlation between wave climate and the Southern Annular Mode (SAM) in the Southern Hemisphere.

Regarding regional wave climate, the wave climate of the North Atlantic has been more studied than that in the North Pacific. It is well known that the long-term variability of wave heights in the North Atlantic has a strong connection to the NAO (Bauer, 2001; Wang and Swail, 2001; Woolf et al., 2002; Gulev and Grigorieva, 2006; Izaguirre et al., 2010). There are also several studies analyzing the relationship between wave climate in the North Atlantic and teleconnection patterns such as the East Atlantic pattern (EA) (Woolf et al., 2002; Izaguirre et al., 2010), the East Atlantic/Western Russia pattern (EAWR) and the Scandinavia pattern (SCA) (Izaguirre et al., 2010). On the other hand, wave climate in the North Pacific is likely to be associated with the Aleutian low and southern phenomena (e.g., ENSO) (Graham and Diaz, 2001; Wang and Swail, 2001; Semedo et al., 2011; Izaguirre et al., 2011). The Aleutian low shows a high correlation with the PNA. Thus, the PNA can be a proxy of the wave climate in the North Pacific. The correlation coefficient between the North Pacific Index (NPI) and the PNA Index is -0.91 in the winter season when the Aleutian low is the deepest (Trenberth and Hurrell, 1994). The NPI indicates the magnitude of the Aleutian low. The decadal upward trend of both averaged and extreme wave heights is detected in the mid-latitudes of the North Pacific (Graham and Diaz, 2001; Wang and Swail, 2001; Gulev and Grigorieva, 2006; Izaguirre et al., 2011; Semedo et al., 2011), which corresponds to the change due to the climatology of the Aleutian low (Wang and Swail, 2001). Menéndez et al. (2008) showed that the PNA Index denotes a rather serious impact on extreme wave climate in the Eastern North Pacific based on long-term buoy observations. The significant correlations of wave heights in the North East Pacific with El Niño (Menéndez et al., 2008; Seymour, 2011) and the Pacific Decadal Oscillation (PDO) (Seymour, 2011) were reported.

Teleconnection patterns are useful indicators of how climate change can give impacts on wave climate variability, and evaluating climate natural variability, which can be expressed as teleconnection patterns, is important for climate projections. This study makes clear the relationship between regional wave climate variability and teleconnection patterns so that wave climate will be addressed in context of natural variability and climate change through teleconnection pattern. Most of the previous studies mentioned so far focused on how wave climate variability observed at certain locations can be explained by teleconnection patterns, or on how spatial patterns of wave climate variability derived from satellites, hindcasts or reanalysis data correlate with teleconnection patterns. In other words, previous studies focused on how given wave climate variability can be explained by limited

teleconnection patterns without climatic consideration. Therefore, spatial scopes of influences by teleconnection pattern and how the influences overlap spatially are not well known, especially in the North Pacific. In this study, we start with known general teleconnection patterns to see how they affects wave climate variability in the Northern Hemisphere. The spatial distributions of wave climate variability influenced by teleconnection patterns are addressed. We use not only teleconnection patterns that are known to be related with wave climate but also teleconnection patterns that have been rarely used in wave climate study. This analysis will also examine whether wave climate variability can be estimated from teleconnection patterns using a linear multiple regression model without the use of a dynamic model. In addition, the winter wave climate in the North Pacific and the North Atlantic is statistically analyzed in detail by using an Empirical Orthogonal Function analysis. Deeper analysis is conducted with the winter wave climate in the North Pacific since there is less analysis and evidence.

This chapter is organized as follows. In **Section 5.2**, outline of data sets and procedures for making teleconnection pattern indices are described. Results of analysis are shown in **Section 5.3**, which consists of five subsections: (1) Seasonal differences, (2) Spatial characteristics of teleconnection pattern influences on winter wave climate variability, (3) Wave height predictability by index, (4) Relationship between main spatial patterns of wave climate variability and teleconnection patterns, and (5) Detailed analysis of winter wave climate variability in the North Pacific. Finally, future changes in wave height projected by MRI-AGCM3.2H experiments are discussed in context of the relationship between wave climate and teleconnection pattern in **Section 5.4**. This chapter is summarized in **Section 5.5**.

5.2 Data Sets and Teleconnection Pattern Indices

5.2.1 Data sets

Two different analytical data sets were used in this study. One is the NCEP/NCAR reanalysis data set (Kalnay et al., 1996) provided by the National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR). The spatial resolution is 2.5° in latitude and longitude direction. Monthly averaged data from 1950 - 2000 were used: 500hPa geo potential height (Z500), Sea Level Pressure (SLP), and Sea Surface Temperature (SST). In **Section 5.3.5** only, Z500 data to 2009 were used for the analysis. The NCEP/NCAR reanalysis data set was used to develop ‘reference’ teleconnection patterns following the method of the Climate Prediction Center (CPC) of the National Oceanic and Atmospheric Administration (NOAA), which is described at **Section 5.2.2** in detail.

The other data set is the ERA-40 reanalysis data (Uppala et al., 2005) supplied by the European Center for Medium-Range Weather Forecast (ECMWF). Spatial resolution is 2.5° in latitude and longitude direction. Monthly averaged data of Z500, SLP, SST and Significant Wave Height (SWH) covering 1960 - 1990 were used for the analysis. In **Section 5.3.5** only, monthly averaged data for Z500 and 6 hourly SLP up to 2001 were used. The reason the period 1960 - 1990 was adopted in this analysis is that, although ERA-40 reanalysis is provided to August 2002, the SWH data of ERA-40 is inhomogeneous before and after the assimilation of altimeter wave height data in the 1990s (Sterl and Caires, 2005). Sterl and Caires (2005) showed that the monthly mean wave fields compare well with observations, although ERA-40 underestimates wave heights, particularly

the high wave heights. Z500, SLP and SST data were used to make teleconnection pattern indices in ERA-40 based on ‘reference’ teleconnection patterns derived from the NCEP/NCAR reanalysis, which is described in **Section 5.2.2** in detail. The relationships between the indices and the monthly averaged SWH were analyzed.

We used coarser version of ERA-40 (2.5° resolution) for the analysis but spatial resolution of original ERA-40 is 1.5° . Furthermore, Sterl and Caires (2005) has produced the corrected ERA-40 wave data, showing the clear improvement of the quality as well as the removal of the inhomogeneities that are due to changes in altimeter wave height assimilation. Therefore, the use of coarser version of ERA-40 during 1960-1990 is not considered as an optimal way. However, we conducted same analysis using ERA-40 original version during 1960-1990, corrected ERA-40 data (Sterl and Caires, 2005) during 1960-1990 and 1958-2001, and we got almost same results as those of coarser version of ERA-40 during 1960-1990.

5.2.2 Teleconnection pattern indices

We selected nine teleconnection patterns defined by the Z500 data for analysis: 1) North Atlantic Oscillation (NAO), 2) East Atlantic pattern (EA), 3) East Atlantic/Western Russia pattern (EAWR), 4) Scandinavia pattern (SCA), 5) Polar/Eurasia pattern (POL), 6) West Pacific pattern (WP), 7) East Pacific-North Pacific pattern (EPNP), 8) Pacific/North American pattern (PNA), and 9) Tropical/Northern Hemisphere pattern (TNH). These patterns are well reviewed in Panagiotopoulos et al. (2002), and have been monitored by CPC/NOAA (<http://www.cpc.ncep.noaa.gov/data/teledoc/telecontents.shtml>).

As described in the introduction section, the NAO and PNA are considered to be well associated with wave climate variability in many previous studies (Wang and Swail, 2001; Woolf et al., 2002; Gulev and Grigorieva, 2006; Izaguirre et al., 2010). There are no universally accepted criteria and procedures to define the NAO, PNA and other teleconnection patterns (Panagiotopoulos et al., 2002). CPC/NOAA monitors the behavior of teleconnection patterns and defines these patterns based on the method of Barnston and Livezey (1987), applying one of the Empirical Orthogonal Function analyses, Rotated Empirical Orthogonal Function (REOF) analysis, to Z500 data. As a result of REOF analysis, 9 components of Z500 variability are defined simultaneously as teleconnection patterns mentioned above, including the NAO and the PNA.

The relationship between the spatial patterns of the wave climate and teleconnection patterns are not well understood at present. Therefore it is not reasonable to use only limited teleconnection patterns such as PNA and NAO for a wave climate study despite the fact that the other patterns mentioned above can be defined as components of Z500 variability, in the same way that NAO and PNA can be defined by REOF analysis. In this study, all of the teleconnection patterns that are introduced as prominent teleconnection patterns over the Northern Hemisphere on the CPC/NOAA web site are considered. However, the Pacific Transient pattern (PT) was eliminated because the PT covers August to September, and the analysis in this paper mainly focuses on the winter season.

The numerical procedures to define teleconnection patterns are described as follows. The ‘reference’ teleconnection patterns were derived from the NCEP/NCAR reanalysis following the method of CPC/NOAA, before teleconnection pattern indices were made from the ERA-40 reanalysis. First, the NCEP/NCAR reanalysis monthly averaged Z500 values for the Northern Hemisphere (northward from 20°N) for years 1950 to 2000 were normalized using the corresponding monthly

average values and their standard deviations. Second, the spatial differences in latitudes (ϕ) were considered. On the equator, where ϕ equals zero, the number of grid points per distance is $n/(2\pi R)$, where R is the earth radius and n is the number of grid points in longitude. On a given latitude ϕ , the number of points is $n/(2\pi R \cos \phi)$. To equalize the contribution of each grid point with the total variance in the whole domain, data at each grid point are multiplied by $\sqrt{\cos \phi}$. This procedure is described as ‘the latitudinal correction’ hereafter. Finally, REOF analysis (Von Storch and Zwiers, 2002) was applied to the covariance matrix ($\mathbf{V}$) of the normalized and latitudinal corrected Z500 data. The eigen value equation for $\mathbf{V}$ can be expressed as $\mathbf{V}\mathbf{z}_i = \lambda_i\mathbf{z}_i$ with the i th largest eigen value λ_i and the associated i th eigen vector $\mathbf{z}_i$. Here, $|\mathbf{z}_i| = 1$. Then, the REOF modes matrix ($\mathbf{Q}$) can be expressed as $\mathbf{Q} = (\mathbf{q}_1 \dots \mathbf{q}_k) = \mathbf{Z}\mathbf{R}$ where $\mathbf{q}_i$ is the i th REOF mode, $\mathbf{Z}$ consists of k eigen vectors ($\mathbf{z}_1 \dots \mathbf{z}_k$) and $\mathbf{R}$ is an orthonormal rotation matrix defined by the varimax method (Kaiser, 1958). In this case, $k = 10$ is used for the analysis. These nine REOF modes out of ten were defined as teleconnection patterns mentioned above by comparing the spatial distributions of the REOF modes with teleconnection patterns shown in CPC/NOAA. These nine REOF modes were stored as ‘reference’ teleconnection patterns. The time coefficient a_t of REOF mode ($\mathbf{q}_i$) at a given time (t) was calculated by projecting the normalized and latitudinally corrected Z500 data at t ($\mathbf{w}_t$) onto $\mathbf{q}_i$, such as $a_t = \mathbf{w}_t\mathbf{q}_i$. The coefficient a_t for the ERA-40 reanalysis was calculated by projecting the ERA-40 Z500 data onto the ‘reference’ teleconnection patterns. The value of a_t was defined as a teleconnection pattern index. The time series of indices derived from ERA-40 is, in hindsight, almost the same as that from the NCEP/NCAR reanalysis (**Table 5.1**).

The procedures to calculate teleconnection pattern indices described above can invite the questions, “Why use two reanalyses? Why not apply the REOF analysis directly to the ERA-40 data?” The remarks are addressed below.

1. The NCEP/NCAR reanalysis covers a longer period than the ERA-40.
2. The definition of teleconnection patterns is based on that of CPC/NOAA using NCEP/NCAR reanalysis.
3. It is useful to store ‘reference’ teleconnection patterns when we want to obtain teleconnection pattern indices from a Global Climate Model (GCM); we can get the index easily and consistently by projecting the GCM Z500 data onto the ‘reference’ teleconnection pattern instead of applying REOF analysis. ‘Consistently’ means that indices derived from GCMs are associated with an identical spatial pattern, a ‘reference’ pattern. If the REOF analysis is applied to certain GCM data, it can not be guaranteed to derive an identical pattern in reanalysis. We will examine the relationship between wave climate variability and teleconnection patterns derived from a GCM (**Section 5.4**).

In addition to nine teleconnection patterns, two other teleconnection patterns that are widely associated with climate variability were used for the analysis. One is the Arctic Oscillation (AO) which is the first mode of the Empirical Orthogonal Function (EOF) for SLP in the Northern Hemisphere north of 20°N (Thompson and Wallace, 1998). Indices of the AO in the ERA-40 data were calculated by projecting the ERA-40 SLP data onto the reference pattern derived from the NCEP/NCAR reanalysis. The second is El Niño index, which is defined as the anomalies of SST in the Niño 3.4 region from 5°N to 5°S and from 170°W to 120°W. This index is denoted by NINO3.4.

Table 5.1: Correlation coefficients between indices derived from ERA-40 and NCEP/NCAR reanalysis. Period is 1960 to 1990. TNH is only for winter.

	NAO	EA	WP	EPNP	PNA	EAWR	SCA	TNH	POL	NINO3.4	AO
Winter (DJF)	0.995	0.982	0.992	0.993	0.996	0.993	0.995	0.998	0.986	0.990	0.996
Spring (MAM)	0.995	0.962	0.995	0.996	0.996	0.971	0.974	/	0.984	0.980	0.988
Summer (JJA)	0.990	0.935	0.990	0.992	0.908	0.957	0.965	/	0.993	0.986	0.954
Autumn (SON)	0.994	0.983	0.989	0.996	0.996	0.932	0.995	/	0.994	0.991	0.958

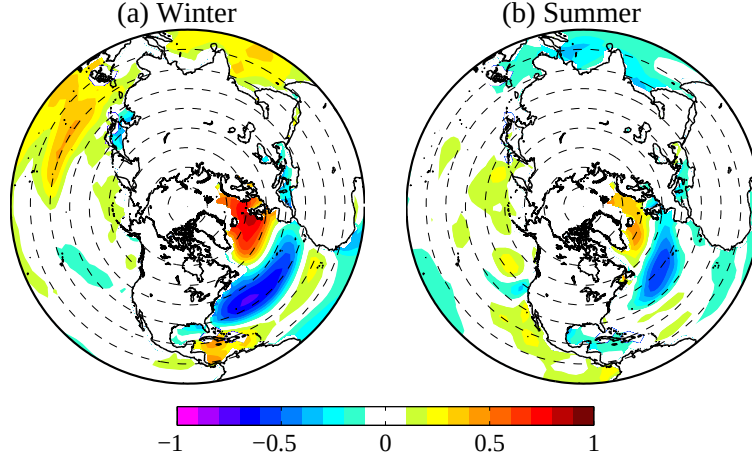


Figure 5.1: Spatial distributions of the correlation coefficients between the NAO index and monthly averaged SWH

5.3 Relation between wave climate and teleconnection patterns

5.3.1 Seasonal differences of wave climate and teleconnection patterns

It is well known that wave climate has seasonal variations depending on the hemisphere. Both the wave climate and teleconnection patterns are sensitive to the season, which is discussed first. Here, winter is defined as the months of December, January and February (DJF). Following the same manner spring, summer and autumn are defined as the months of March, April and May (MAM); June, July and August (JJA); and September, October and November (SON), respectively. As an example, the spatial distributions of the correlation coefficients between the NAO index and the monthly averaged SWH in winter and summer are shown in **Figure 5.1**. Although these two distributions from different seasons in the North Atlantic are similar to each other, the absolute

Table 5.2: Percent variances of teleconnection patterns [%]. The values for AO are based on variance in SLP and others are based on Z500. Those for NINO3.4 cannot be derived. The TNH variance is only for winter.

	NAO	EA	WP	EPNP	PNA	EAWR	SCA	TNH	POL	NINO3.4	AO
Winter (DJF)	9.1	6.1	9.0	6.4	7.7	6.8	5.3	6.4	7.2	/	17.9
Spring (MAM)	6.9	4.3	6.3	4.9	5.0	5.5	5.6	/	8.1	/	15.1
Summer (JJA)	6.6	5.4	4.6	5.1	8.1	4.1	4.7	/	4.5	/	12.3
Autumn (SON)	6.3	4.8	5.2	5.5	6.4	4.9	6.8	/	7.1	/	12.0

values of the correlation coefficients in winter are generally greater than in summer (**Figure 5.1**). We examined similar analyses for other teleconnection patterns. The absolute values of the correlation coefficients in the Northern Hemisphere during the winter are the highest, and those during the summer become the lowest with some exceptions in a few regions and a few indices.

The reason why teleconnection patterns are related to wave climate variability in the winter season is addressed below. Atmospheric pressure in the Northern Hemisphere varies more during the winter compared with other seasons, generally. The normalized total variances of monthly averaged Z500 in the Northern Hemisphere (pole-ward from 20°N) from the ERA-40 data from 1960 - 1990 for the months January through December are 1.00, 1.00, 0.79, 0.52, 0.37, 0.31, 0.25, 0.28, 0.37, 0.48, 0.65 and 0.85, respectively. Here, latitudinal correction is applied, and the values are normalized with the January value. For SLP, the normalized total variances of monthly averaged value are 1.00, 0.75, 0.42, 0.24, 0.19, 0.16, 0.21, 0.27, 0.39, 0.55 and 0.73. Furthermore, for winter, teleconnection patterns can explain the variance to a greater extent than for the other seasons. The percent variances for all seasons are shown in **Table 5.2**. The total percent variances among all of the teleconnection patterns derived from Z500, except for TNH, are 57.6, 46.6, 43.1 and 47.0 % from winter to autumn respectively. As the result of correlation analysis between the monthly averaged SLP and Z500 (not shown), it was found that the way SLP varies in winter corresponds more to how Z500 varies over the ocean on a monthly basis than other seasons. Wang and Swail (2006) showed that SWH variations are closely associated with contemporaneous SLP variations. As described above, in winter, when atmospheric variations such as Z500 and SLP are the greatest, teleconnection patterns dominate the atmospheric variations, and Z500, SLP and SWH are associated well. Therefore, it is not surprising that the correlation coefficients between teleconnection pattern indices and SWH in the Northern Hemisphere during winter are the largest during the year. In this point of view, EL Niño which, despite being defined by SST, is also similar, because the SST variation is the highest during the winter, which when accompanied by a fluctuation in atmospheric pressure, leads to a fluctuation in wave heights.

Although Semedo et al. (2011) reported a strong connection between main patterns of the interannual variability of the swell fields and teleconnection patterns, but coexistence of swells and wind waves complicates the relationship between wave height and teleconnection pattern because wind waves and swells have different sources of wave generation geographically. In addition, it can be easily expected that wind waves are related to teleconnection patterns rather than swell because teleconnection patterns affect winds in advance of ocean waves. Swells dominate ocean waves more in the summer as compared to the stormy winter season. This is one of the reasons why teleconnection patterns are less related with wave climate variability in summer.

Thus we will focus on the stormy winter season when wave climate variability has a stronger relation to teleconnection patterns as shown above.

5.3.2 Spatial characteristics of teleconnection pattern influences on winter wave climate variability

First, significance is defined. The total number of months of data for the analysis is 93 (31 years times 3 months) for each grid point. If the data are independent and the correlation coefficient is larger than 0.2, a null hypothesis indicating no correlation is rejected by the 5% significance level. However, the series of monthly data in a certain year can not be assumed to be independent. Therefore, the

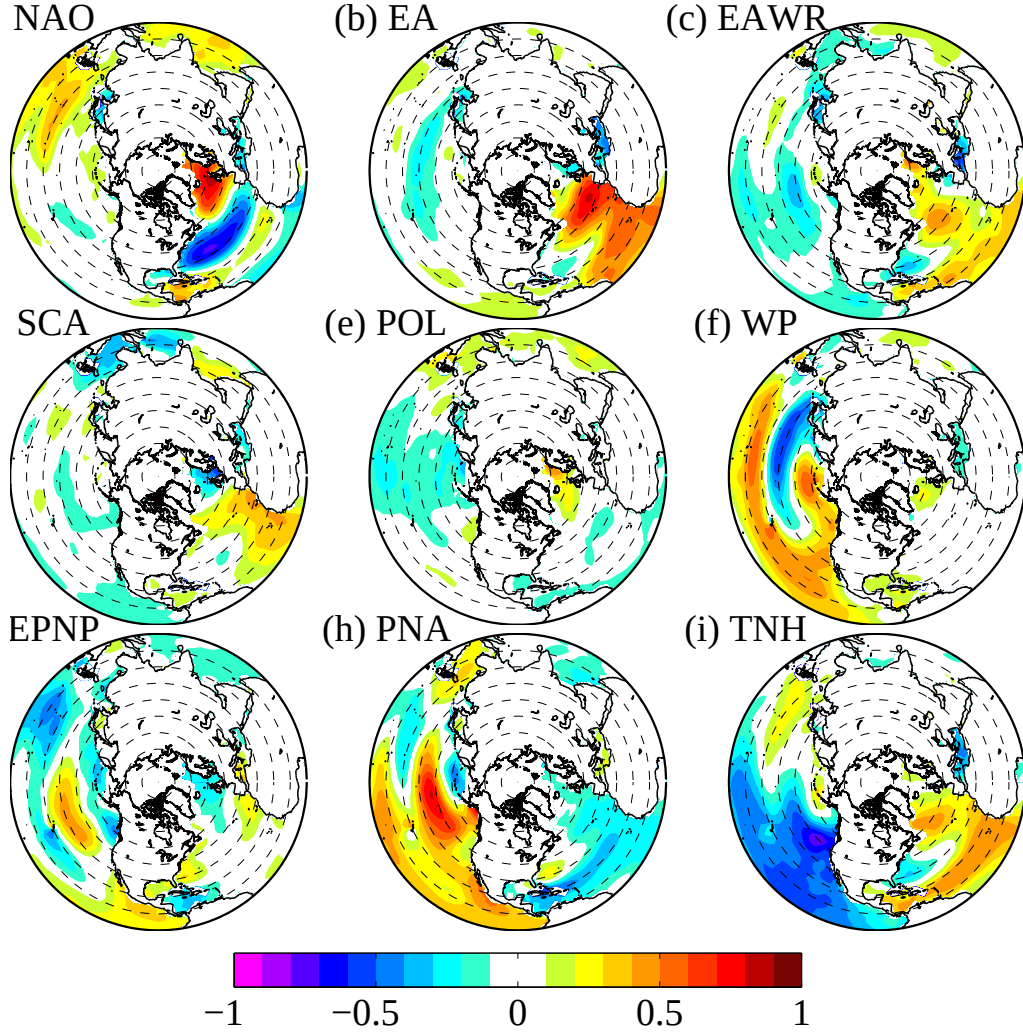


Figure 5.2: Spatial distributions of correlation coefficients from Z500 based teleconnection pattern indices and monthly averaged SWH in winter

three-month dataset for winter is regarded as one unit and the number of independent datasets is assumed to be 31, corresponding to the number of years. Following standard statistical analysis, when the correlation coefficient is larger than 0.36, the correlation is considered to be significant by the 5% significance level.

The distributions of correlation coefficients between all the teleconnection patterns derived from Z500 and monthly averaged SWH were computed and shown in **Figure 5.2**. In addition, the regions which indicate statistically significant correlation with teleconnection pattern indices are all shown in one **Figure 5.3**. In some areas, influences of several teleconnection patterns overlap, illustrating how the complex relationship between wave climate and teleconnection patterns depends on the geographical location. In addition, **Figure 5.4** shows maps of correlation coefficients for the AO and NINO3.4 that are widely associated with climate variability.

The spatial distributions of correlation coefficients with respect to each teleconnection pattern

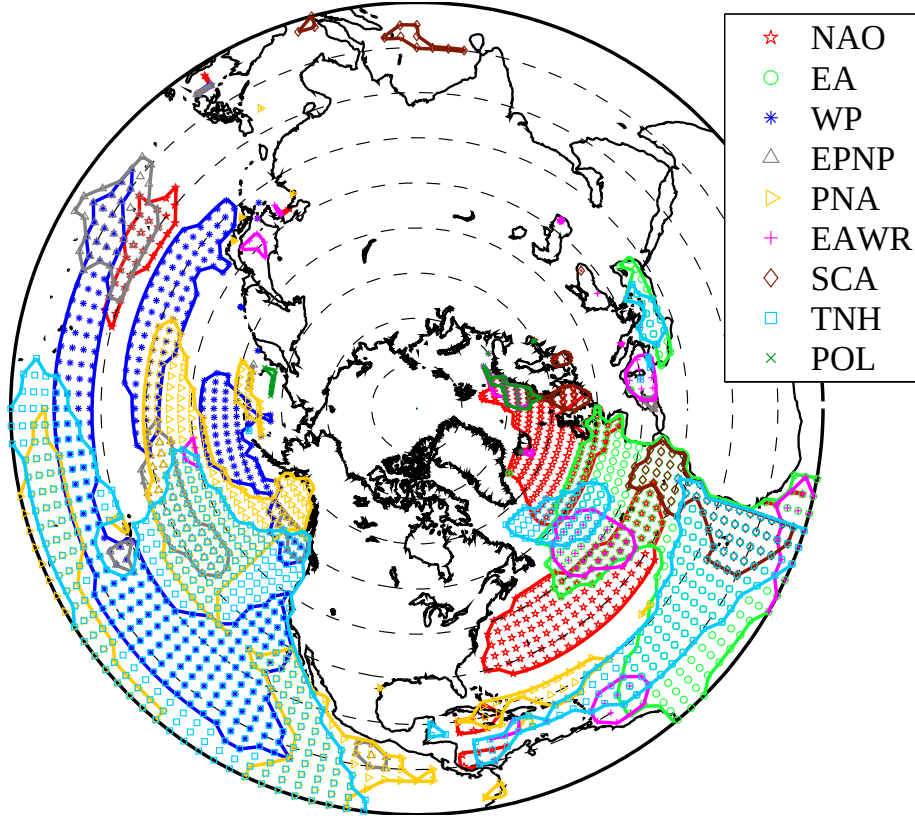


Figure 5.3: Areas of significant correlation in 5% level between teleconnection pattern indices based Z500 and monthly averaged SWH in winter

has a physical meaning such as a winter storm, tropical cyclone, etc. Therefore, the large scale relationship between wave climate and teleconnection patterns can help illustrate the local scale relationship both statistically and physically. Both the North Pacific and the North Atlantic, regions that have significant correlation, are larger in the eastern regions than in the western parts (**Figure 5.3**). This is caused by the smaller spatial fluctuations in the atmosphere that are dominant over the land-sea interface where westerly winds move eastward from the continent. The western parts of the SLP or U10 are strongly influenced by land, and it disturbs the smooth relationship between the local wind and wave fields (e.g., Tokinaga and Xie, 2011). Wang and Swail (2006) and Graham et al. (2012) developed statistical wave models to predict seasonal wave height statistics (average and extreme) using SLP as predictors. They show the model performances in their respective papers: Figure 2(a) (Wang and Swail, 2006) and Figure 10(a) (Graham et al., 2012). Their models' performances at predicting wave heights are relatively low in western regions rather than eastern regions, which indicates that it is not easy to express wave height variability in the western regions by atmospheric values such as SLP. This supports the spatial distribution in **Figure 5.3**, which shows larger areas of significant correlation in eastern areas.

The spatial distributions of the SWH climate variability corresponding to teleconnection patterns derived from reanalysis can be compared with the observed data (spatially limited) as follows. In the North Atlantic, both the NAO and EA indices impact wave climate variability strongly. The spatial distribution of correlation coefficients between winter monthly averaged SWH and the NAO

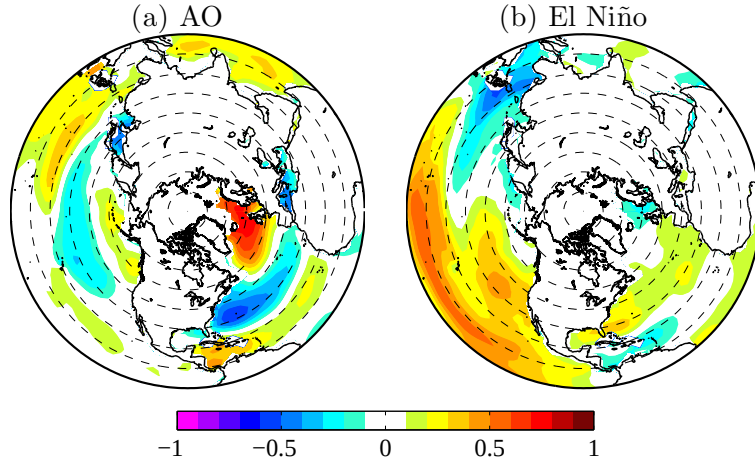


Figure 5.4: Same as **Figure 5.2** but for AO and El Niño

index is characterized by negative values over the region from 30°N - 40°N and positive values northward of 50°N (**Figure 5.2(a)**). This result is consistent with that of satellite observations (Woollf et al., 2002; Izaguirre et al., 2010).

The spatial distribution of correlation coefficients related to the NAO index is similar to that of the AO index (**Figure 5.2(a)**, **Figure 5.4(a)**), because the NAO and AO indices are correlated with each other (the correlation coefficients are 0.80, 0.58, 0.60 and 0.73 from winter to autumn).

The EA index correlates positively with respect to the SWH in the Eastern North Atlantic and negatively in the Mediterranean (**Figure 5.2(b)**). Although ERA-40 wave data is too coarse to allow conclusions on regional enclosed seas like the Mediterranean Sea, ERA-40 wind speeds over the Mediterranean Sea correlate negatively with the EA index. Regarding extreme wave climate, the extreme distribution function model of wave height around the North Atlantic was discussed by Izaguirre et al. (2010). The location parameter expressed as a function of the EA index has a spatial pattern similar to the one for this study (Izaguirre et al., 2010). Also, the results for the EAWR and SCA in Izaguirre et al. (2010) are consistent with this study (**Figure 5.2(c),(d)**).

On the other hand, the PNA, TNH and WP have greater impact on wave climate variability in the North Pacific. The PNA index correlates positively with the SWH in the eastern half, and is especially strong in the center of the North Pacific area (**Figure 5.2(h)**). Menéndez et al. (2008) show that the PNA influences the extreme wave height in the Eastern North Pacific. The TNH also produces strong influences over the Eastern North Pacific (**Figure 5.2(i)**). The TNH has greater impact on more eastern regions when compared with the PNA. Therefore, the TNH is the major index for the winter wave climate along the west coast of the US, rather than the PNA.

Regarding the Western North Pacific, Mase et al. (2010) analyzed field observed SWH data along the coast of the Sea of Japan and showed the correlation coefficients between the AO index and the annual maxima of SWH are about -0.1 to -0.4. Our analysis shows that the correlation coefficients between winter monthly averaged SWH and the AO (or NAO) index are about -0.4 to -0.3 in the Sea of Japan. The spatial pattern of correlation coefficients between the WP index and the SWH is band-shaped (**Figure 5.2(f)**), indicating positive, negative, and positive values in low, middle and high latitudes in the Western North Pacific, respectively. The relation of the TNH and

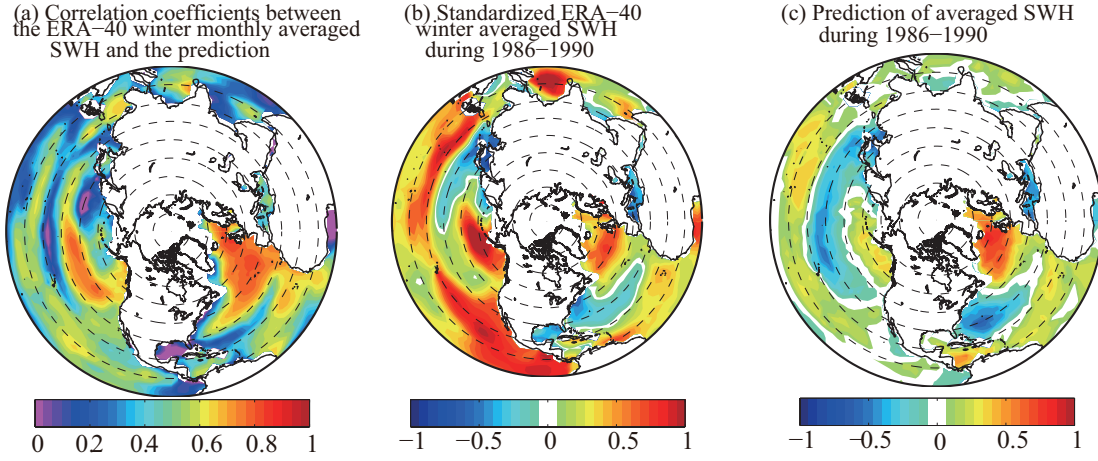


Figure 5.5: Prediction performances for monthly averaged SWH in winter based on teleconnection pattern indices

WP with wave climate has not been discussed in previous studies.

For NINO3.4, the distribution of correlation coefficients with the SWH can be characterized by negative values in the Western North Pacific and positive values in the eastern regions. The correlation coefficients are about ± 0.5 in the lower latitudes, and higher values are not observed northward of 20°N (**Figure 5.4(b)**). Menéndez et al. (2008) indicate that the relationship between extreme wave height in the Eastern North Pacific and El Niño is weak but that a positive correlation is significant.

The spatial characteristics of how teleconnection patterns impact wave climate are consistent with the observations of previous studies referred to in this subsection.

5.3.3 Prediction of wave climate pattern based on teleconnection pattern index

The predictability of winter averaged SWH from a combination of teleconnection pattern indices is discussed in this section. Teleconnection indices derived from Z500 data, for the 9 indices, were used as predictors because the 9 indices are nearly uncorrelated from each other. The prediction was examined by linear multi-variable regression analysis. A linear regression model was developed for each grid point. The linear regression model is expressed as

$$y = b + \sum_{i=1}^k a_i x_i \quad (5.1)$$

where a_i and b are constants determined by the least squares method, y is the SWH given as output, and x_i is the index as predictor. The number (k) and the combination of indices as predictors for each grid point were determined based on the Akaike Information Criterion (Akaike, 1973). Predictable skills were determined by cross-validation.

A total of 93 months (3 months $\times$ 31 years) were split into 78 months (26 years) as the training period and 15 months (5 years) as the prediction period. The start year for the prediction period was changed in 5 year intervals from 1961 to 1986 (1961, 1966, ..., 1986) and the period of training was designated as the rest of the period from 1960 - 1990. Training and prediction were

Table 5.3: Correlation coefficients between EOFs for winter monthly averaged SWH and teleconnection pattern indices. Values in Bold typeface indicate that the correlation is statistically significant with 5% level.

	NAO	EA	WP	EPNP	PNA	EAWR	SCA	TNH	POL	NINO3.4	AO
North Pacific											
1st	0.01	-0.03	0.35	0.06	0.46	-0.17	-0.08	-0.55	-0.06	0.44	-0.00
2nd	0.31	-0.01	0.12	-0.41	-0.20	0.01	0.10	0.17	-0.18	-0.03	0.21
3rd	-0.08	-0.26	-0.80	0.37	0.40	-0.18	-0.09	0.03	-0.09	-0.11	-0.37
North Atlantic											
1st	-0.18	0.62	0.01	0.04	-0.29	0.34	0.29	0.41	-0.08	0.14	0.00
2nd	-0.86	-0.23	-0.08	0.24	0.17	-0.20	-0.03	-0.34	-0.16	0.19	-0.75
3rd	-0.23	0.35	-0.08	0.26	0.29	-0.19	0.26	-0.15	-0.01	0.18	-0.23

conducted for each corresponding prediction period. Therefore, 90 prediction values (3 months $\times$ 5 years $\times$ 6 predictions) for each grid point were produced.

Figure 5.5(a) shows the correlation coefficients between the ERA-40 winter monthly averaged SWH and the prediction. The correlation coefficients are higher in the eastern part of the ocean basin, especially in the regions where the NAO, EA and PNA correlate strongly with the SWH (**Figure 5.5(a)** compared with **Figure 5.2**). In the areas around 20°N and 40°N in the western part of the North Pacific and 20°N in the western part of the North Atlantic, the prediction skills are low, and some of these areas show negative correlation values. As an example for the prediction, **Figure 5.5(b)** and **Figure 5.5(c)** show ERA-40 winter averaged SWH during the period 1986-1990 and the prediction. The values in **Figure 5.5(b)** and **(c)** are standardized by the mean and standard deviations of the training period 1960-1985.

Tendencies of the prediction (**Figure 5.5(c)**) show some agreement with those of ERA-40 SWH (**Figure 5.5(b)**) qualitatively, such as increases in SWH along 15°N, decreases along 30°N, and increases along 55°N in the North Pacific, and NAO-like changes in the North Atlantic. However, quantitatively the predicted values do not agree with ERA-40 SWH values well, especially in the North Pacific. It is possible to improve the accuracy of the prediction by using advanced analysis like a nonlinear regression instead of a linear one. However, we would like to emphasize that the monthly averaged SWH can be estimated roughly from a combination of climate indices depending on the location. This can provide some applications for wave climate research to predict wave heights roughly with less computational cost than using dynamic projection based on physical wave model.

5.3.4 Spatial patterns of wave climate variability and teleconnection patterns

The SWH at each grid point contains various components of fluctuation. Several main components of spatial fluctuation were derived and associated with teleconnection patterns as follows. The EOF analysis was applied to winter monthly averaged SWH in both the North Pacific and the North Atlantic, and the dominant spatial patterns of fluctuation were derived. We defined the North Pacific as the areas of 0°N-60°N and 100°W-100°E, and the North Atlantic as the areas of 0°N-70°N and 90°E-20°W, respectively. EOF analysis was applied to 93 serial datasets, 31 years times 3 months, during the period 1960-1990 for the North Pacific and the North Atlantic separately. Procedures of standardization and latitudinal correction were conducted in the same way as in **Section 5.2.2** before EOF analysis.

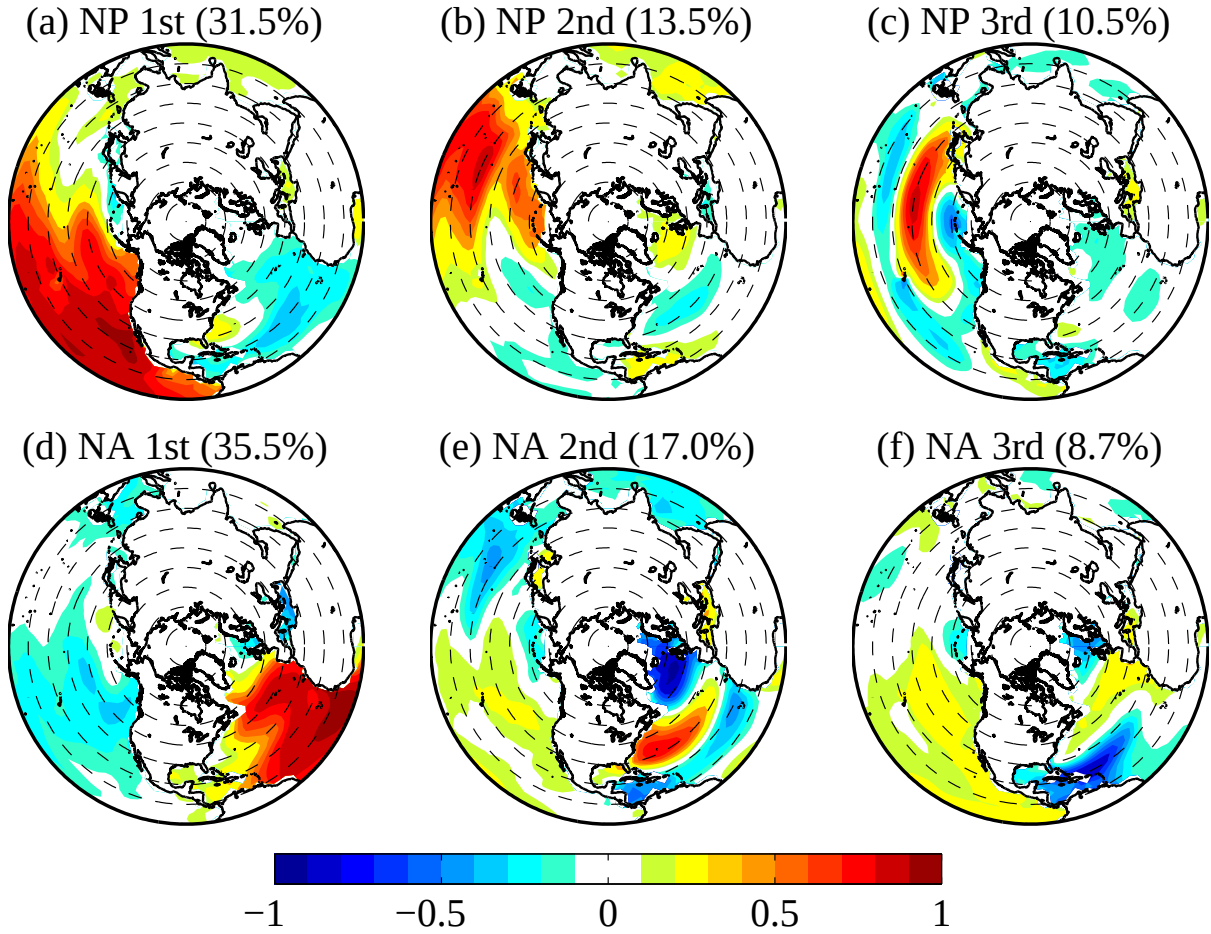


Figure 5.6: Spatial distributions of EOFs of winter monthly averaged SWH in the North Pacific (NP) and the North Atlantic (NA). The percentage in parentheses indicates percent variance.

Figure 5.6 shows spatial patterns derived by EOF analysis. The spatial patterns shown are the patterns of the correlation coefficients between the temporal coefficient of the EOF and the monthly averaged SWH. The reason why the representations in **Figure 5.6** are the patterns of the correlation coefficients instead of the original EOF patterns, is because the former representation can visualize the relationship between the North Pacific and the North Atlantic but the latter expresses only the patterns in the North Pacific or the North Atlantic. The first modes in both the North Pacific and the North Atlantic are distributed widely, covering the eastern parts and lower latitudes of each ocean basin. The percent variances relative to the total are greater than 30 %, respectively. The second mode in the North Pacific expresses a fluctuation at mainly southwestern regions, and the third mode is band-shaped depending on latitude. On the other hand, the second mode in the North Atlantic has a band-shape depending on the latitude, and the third mode is distributed in the southwestern and northeastern regions of the North Atlantic.

As shown in the figures, the three dominant modes in both oceans show three characteristic distributions, such as: 1) the eastern part of the basin, 2) the south-western part of the basin and 3) the band-shaped regions. The total percentage of variance in the three dominant modes is 55-60%; these modes can be regarded as the major modes by EOF analysis.

The relation between the three dominant modes of the SWH and teleconnection patterns is

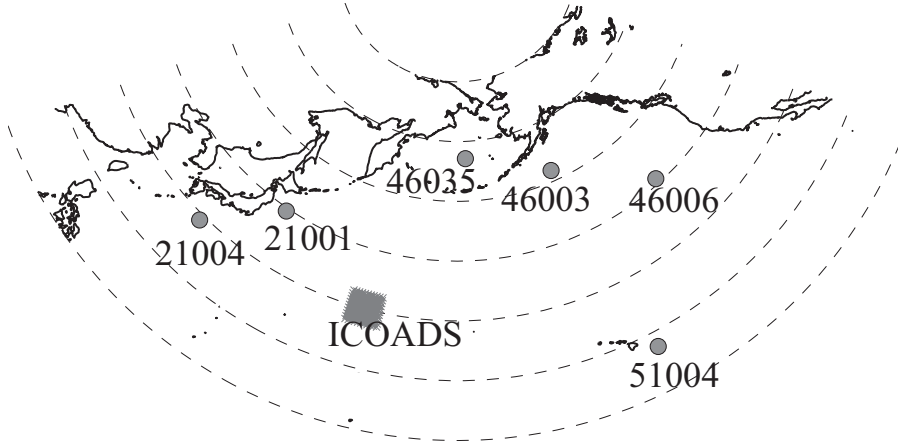


Figure 5.7: Locations of observation in the North Pacific.

discussed. **Table 5.3** shows the correlation coefficients between the temporal coefficients of the three modes and the teleconnection pattern indices. For the North Pacific, the temporal coefficient of the first mode correlates significantly with the PNA, TNH and NINO3.4 indices. The first mode in the North Pacific indicates that SWH fluctuations are forced by fluctuations in the following: trade winds at lower latitudes, westerly winds at mid-latitudes, and southward winds in the eastern North Pacific. NINO3.4 impacts the trade winds. The PNA impacts the westerly winds, and the remaining TNH influences the southward winds in the eastern part of the North Pacific. The linearly-combined index of three indices mentioned above is correlated well with the first mode, and the correlation coefficient is about 0.7.

On the other hand, the second mode has a significant correlation with the EPNP. The third mode is highly related to the WP, and the correlation coefficient is -0.8; this value is the highest among all the indices. This relationship between the third mode and the WP is discussed in detail in the next subsection.

The EOF results for the North Atlantic can be summarized as follows. The first mode, which includes fluctuation in the eastern part of the North Atlantic, is associated with the EA. The second mode shows band-shaped fluctuations that exhibit high correlation with the NAO; the correlation coefficient is -0.86.

The above discussion of the EOF and teleconnection pattern indices in the North Pacific and North Atlantic clearly indicates that the winter-averaged SWH values have similar spatial patterns of fluctuation in both ocean basins. Also, the spatial patterns of fluctuation, especially the band-shaped ones, correspond well to teleconnection patterns.

5.3.5 Winter wave climate variability in the North Pacific

The main spatial patterns (EOFs) of wave climate variability in the North Atlantic have been associated with NAO (Wang and Swail, 2001; Woolf et al., 2002; Gulev and Grigorieva, 2006; Semedo et al., 2011) and EA (Woolf et al., 2002), and those in the North Pacific have been associated with NPI (Gulev and Grigorieva, 2006; Semedo et al., 2011) which is related with PNA as described in the introduction, and SOI (Semedo et al., 2011) which is related with El Niño. In addition, TNH, EPNP and WP have been significantly associated with the main spatial patterns of wave climate

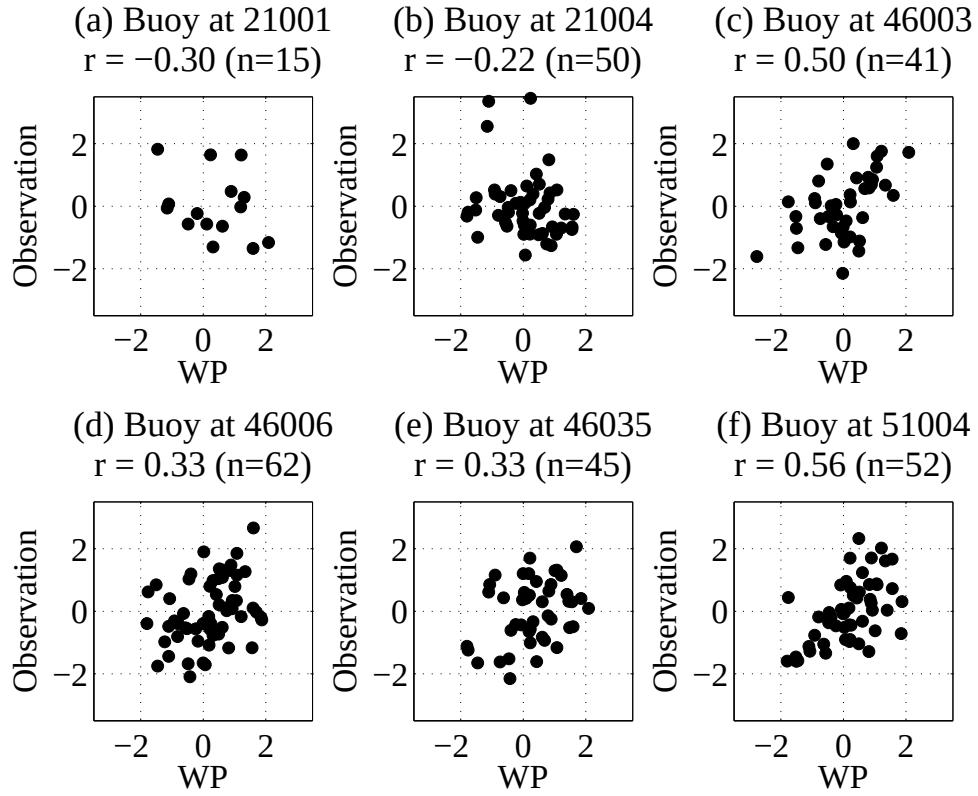


Figure 5.8: Relation between WP index and winter monthly averaged SWH derived from buoy observation data

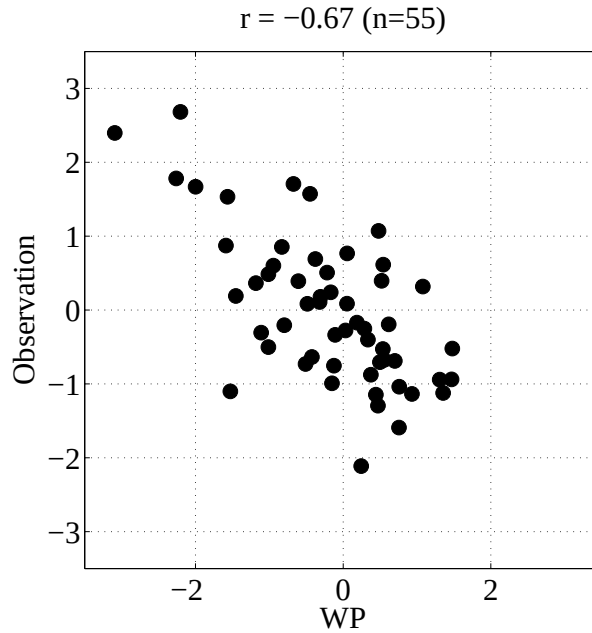


Figure 5.9: Relation between WP index and winter monthly averaged SWH derived from ICOADS observation data

variability in previous subsection. Especially, the band-shaped fluctuation of the SWH in the North Pacific, which is the third EOF mode, showed a strong connection to the WP. This relationship has not been discussed in previous studies. Therefore, the characteristics of the band-shaped fluctuation in the North Pacific are analyzed in detail and compared with observations. The third EOF mode of the SWH in the North Pacific is simply denoted as NP3 in this section. The percent variance of NP3 is only 10.5% (**Figure 5.6**) over the North Pacific, and thus someone can consider NP3 is negligible as wave climate variability. However, the contribution of NP3 becomes 42% in the limited region such as the region 20°N-40°N and 140°E-150°W.

For validation, we selected observed winter wave data by buoy and ship for analysis. The above discussion roughly covers an area of length-scale 5,000-10,000 km; therefore, data should be spread to a similar spatial scale for comparison. We selected 6 offshore buoys around the North Pacific as shown in **Figure 5.7**. Two buoys (World Meteorological Organization (WMO) number 21001 and 21004) are maintained by the Japan Meteorological Agency (available at http://www.data.kishou.go.jp/kaiyou/db/vessel_obs/data-report/html/buoy/buoy_NoS2.e.html). The rest of the four buoys (WMO numbers : 46003, 46006, 46035, and 51004) are maintained by the US National Oceanographic Data Center (available at <http://www.ndbc.noaa.gov/hmd.shtml>). The periods of observation at #21001, #21004, #46003, #46006, #46035 and #51004 are 1978-1989, 1982-2000, 1976-1998, 1977-2009, 1985-2009 and 1984-2008, respectively. In addition, ship observations by the International Comprehensive Ocean - Atmospheric Data Set (ICOADS) (Woodruff et al., 2010) were added to the analysis. The ICOADS covers the region defined as 27.5°N-32.5°N and 162.5°E-167.5°E over the period 1958 to 2009. The monthly averaged SWH observations used for the analysis and the locations of the three different sources are shown in **Figure 5.7**.

The locations of #21001 and #21004 are in the region where the NP3 shows positive values, and the rest of the station locations are in the region with negative values (see **Figure 5.6(c)**, **Figure 5.7**). The location of the ICOADS is in the region where the NP3 shows strong positive values amongst all the locations (**Figure 5.6(c)** and **Figure 5.7**). The monthly averaged values cannot be calculated easily due to missing data in the observations. Therefore, only the monthly averages for those months when the ratio of missing data is less than 10% were used for analysis. Additionally, the ICOADS observations are reported irregularly. Therefore, only the monthly averages for those months when the ratio of missing data is less than the average were used for analysis. As a result, the total numbers of valid observations of monthly averaged SWH at #21001, #21004, #46003, #46006, #46035, #51004 and ICOADS are 15, 50, 41, 62, 45, 52 and 55, respectively. The monthly averages were standardized by each calendar month value. The observations of monthly averaged SWH values by buoy or ICOADS are plotted against the WP index in **Figure 5.8** and **Figure 5.9**. Here, this WP index was derived from NCEP/NCAR reanalysis because observations cover a period longer than the ERA-40 period. The correlation coefficients at #21001, #21004, #46003, #46006, #46035 and #51004 are -0.30, -0.22, 0.50, 0.33, 0.33 and 0.56, respectively.

The highest correlation coefficient of the ICOADS is -0.66. The locations where the correlation coefficients are positive are regions where the NP3 shows negative values, and vice versa. In addition, the magnitude of the correlation coefficient agrees with the magnitude of **Figure 5.6(c)** at each location. This means that the NP3 is solidly related with the WP.

The relationship between the WP and the NP3 can also be discussed from a physical point of view. It is possible to explain the simultaneous fluctuations of the westerly and trade winds

by Wallace et al. (1990) to some extent. Averaged winter SLP climatology in the North Pacific is characterized by higher values along the 20°N to 30°N line. Westerly winds are caused by pressure gradients between areas north of the line and the trade wind in the south. When the WP index is positive, the SLP becomes larger around the 20°N to 40°N region. Then the pressure gradient in this region becomes large, which causes the trade wind and westerly winds to be stronger at the same time. The opposite case is also possible. A strengthened (weakened) trade and westerly winds strengthen (weaken) waves zonally. As a result, the NP3 becomes band-shaped distribution shown in **Figure 5.6(c)**.

However, it is hard to explain the fluctuations of the SWH along 30°N by SLP climatology with the trade wind and westerly wind relationship. Therefore, we analyzed the relationship between extra-tropical cyclones and the NP3 along 30°N .

The extra-tropical cyclone data was culled from the winter SLP data in the ERA-40 reanalysis dataset from 1958 to 2001 based on the method of Geng and Sugi (2001). The definition of an extra-tropical cyclone is described as follows.

1. Atmospheric pressure is less than 1010 hPa.
2. Pressure is less than that of the surrounding 8 grid points.
3. The averaged difference with the surrounding grid points is greater than 0.3 hPa.
4. Data on land is not used.
5. In cases where an extra-tropical cyclone satisfies the conditions listed above at a location 600 km or less from a grid point where an extra-tropical cyclone existed 1 time step (6 hour) before, the two are defined as the same cyclone.

Figure 5.10 shows extra-tropical cyclone tracks (denoted storm tracks hereafter) in a representative month when the WP index is a positive or negative maximum. In cases where the WP index is positive, the storm track shifts northward. On the other hand, in cases where the WP index is negative, the storm track shifts southward and the area extends to a more easterly direction. The months when the WP index is more than 0.5 and less than -0.5 are divided into separate groups, and the monthly averaged number of storm tracks was counted. **Figure 5.11** shows the difference between the positive and negative WP conditions (smoothed by $4^{\circ} \times 4^{\circ}$). Storm tracks shift either north or south depending on the WP index. When the WP index is positive, the storm does not have an effect on the region along 30°N , and vice versa. Therefore, fluctuation in the SWH along 30°N occurs depending on the extra-tropical cyclone activity, which depends on the sign of the WP.

Storm detection based on unfiltered SLP has bias because unfiltered SLP is strongly influenced by large spatial scales, such as the Icelandic Low, and strong background flow (Hoskins and Hodges, 2002). On the other hand, the vorticity field is less influenced by background flow. Therefore, storm detection based on relative vorticity at 850 hPa was also conducted. As a result, the relation between the WP and storm tracks is almost consistent with the results derived from storm detection based on unfiltered SLP, such as storm track shifting either north or south depending on the WP index.

Lastly, another surface climate variability associated with the WP is discussed briefly. As an example, the increase in sea surface temperature south of Japan should be selected for discussion. As shown above, trade winds are strengthened when the WP index is positive. In addition, the

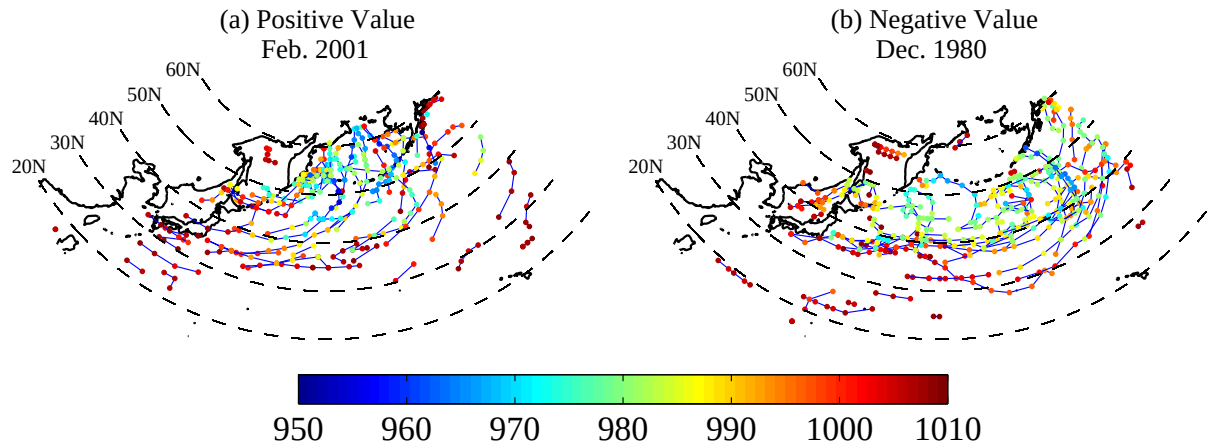


Figure 5.10: Storm tracks in a representative month when the WP index showed positive or negative value (color coding indicates the atmospheric pressure in hPa)

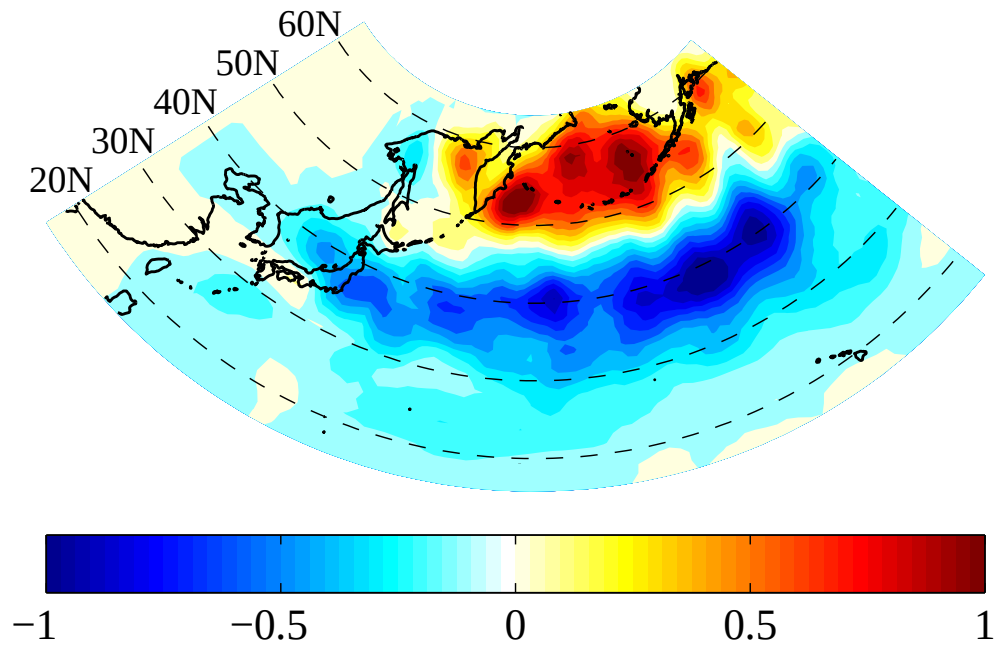


Figure 5.11: The difference in the number of extra-tropical cyclones (winter storm) passing as classified by the WP Index : $(WP > 0.5) - (WP < -0.5)$

southerly wind in the west reaches of the trade wind in the North Pacific is strengthened. As a result, heat is transported from south to north, and SST is increased in the South China Sea and along 30°N in the West North Pacific (Ose, 2000; Wallace et al., 1990). Winter monthly averaged SST values in the regions 25°N - 30°N and 130°E - 160°E correlate well with WP indices in the ERA-40, and the correlation coefficient is 0.59. In this way, several climate variabilities can be associated with each other through teleconnection patterns.

5.4 Discussion: Future changes in wave climate over the North Pacific and teleconnection patterns

We provide insights into the relation between future changes in wave climate and teleconnection patterns based on the analysis in **Section 5.3** and the data of wave climate projection by MRI-AGCM3.2H experiments (**Chapter 2** and **Chapter 3**). The future changes in winter (DJF) mean wave height over the North Pacific are analyzed here. **Figure 5.12** shows the future changes in winter wave height over the North Pacific. The future changes can be characterized as negative values over the western part of the North Pacific Ocean, especially around 30°N , and positive values over the eastern part. This spatial pattern is a common feature of winter wave height change over the North Pacific, which can be seen in many different wave climate projections such as CMIP3 models by Hemer et al. (2013a) and CMIP5 models by Wang et al. (2014). This also can be seen in the results of CMIP5 multi model ensemble described in **Chapter 4** (**Figure 5.13**).

The corresponding atmospheric changes (Z500 changes) of MRI-AGCM3.2H experiments are shown in **Figure 5.14**. Z500 changes consist of atmospheric circulation change and thermodynamics change (Shepherd, 2014). Future Z500 will be higher globally than present climate because of increase in temperature. The thermodynamics change doesn't directly contribute to wave climate change, therefore only circulation change of Z500 is analyzed. In **Figure 5.14**, the Northern Hemispheric (north of 20°N) mean change in Z500 is subtracted as thermodynamics change. The spatial pattern shows anomalous atmospheric ridge over the Western North Pacific mid-latitudes, anomalous trough over the North Pacific and anomalous ridge over the North-Western of the North America. The ridge over the Western North Pacific is associated with decrease in wave height around 30°N and the trough is associated with increase in wave height over the central to eastern North Pacific.

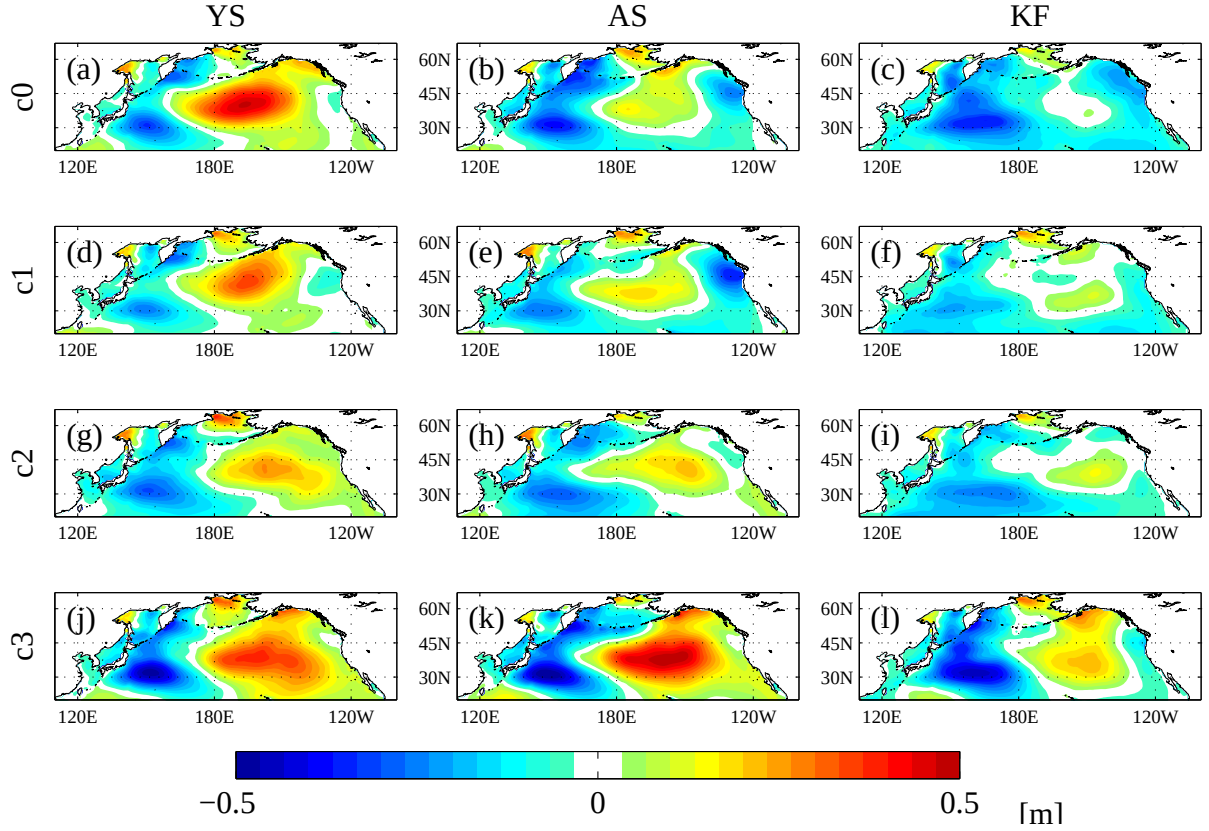


Figure 5.12: Future changes in mean SWH over the North Pacific during winter (DJF) for twelve experiments of MRI-AGCM3.2H (see, **Chapter 2** and **Chapter 3**).

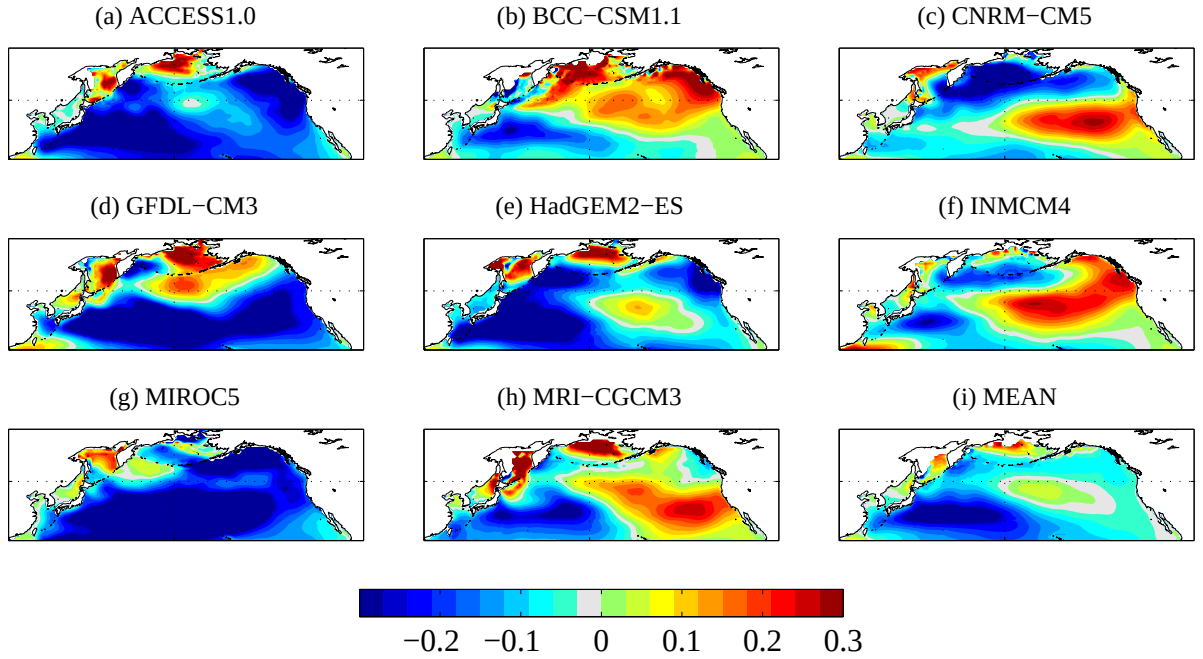


Figure 5.13: Future changes in mean SWH over the North Pacific during winter (DJF) for eight CMIP5 models and ensemble mean (see, **Chapter 4**).

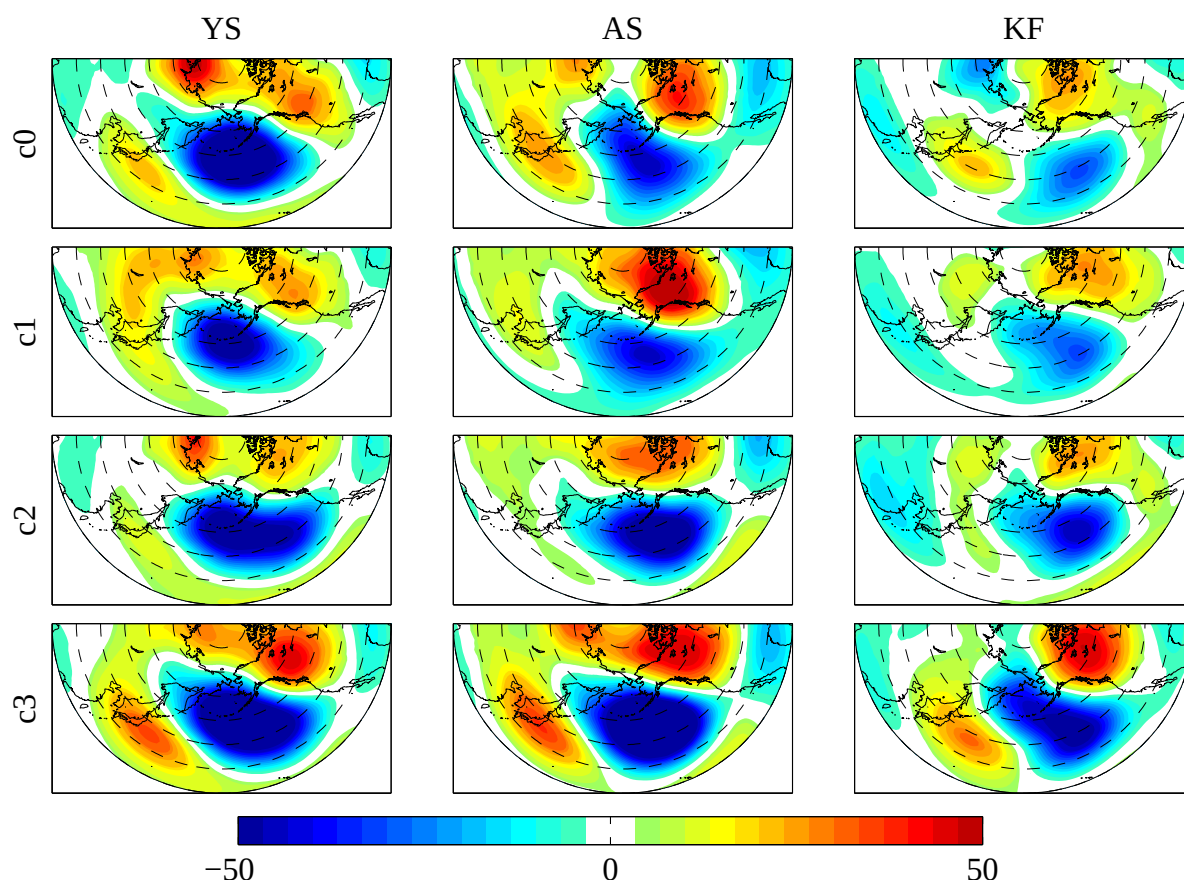


Figure 5.14: Future changes in Z500 over $20^{\circ}\text{N} - 90^{\circ}\text{N}$ and $90^{\circ}\text{E} - 90^{\circ}\text{W}$ during winter (DJF) for twelve experiments of MRI-AGCM3.2H (unit: m).

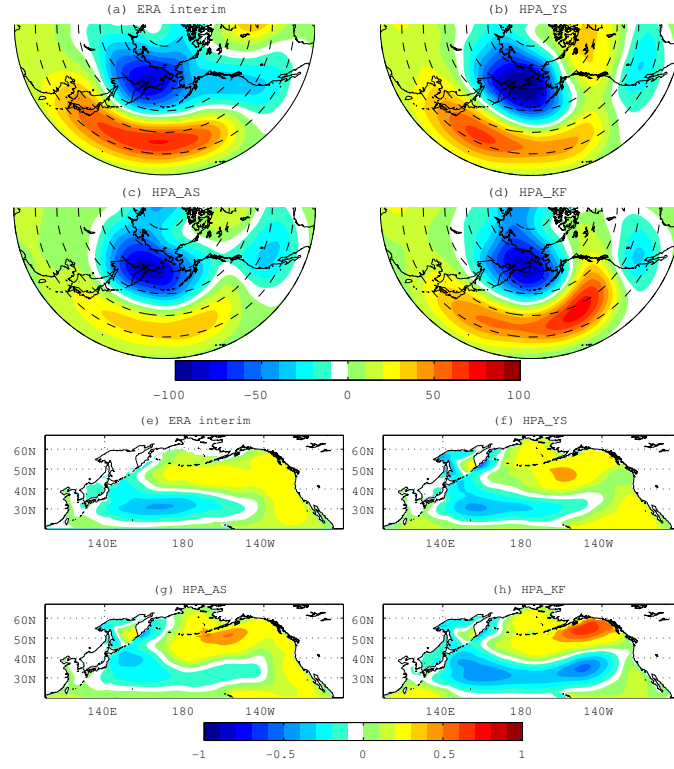


Figure 5.15: Z500 (upper four panels) and SWH (lower four panels) differences between composite among positive and negative value of WP index for ERA-interim and three MRI-AGCM3.2H experiments (unit:m).

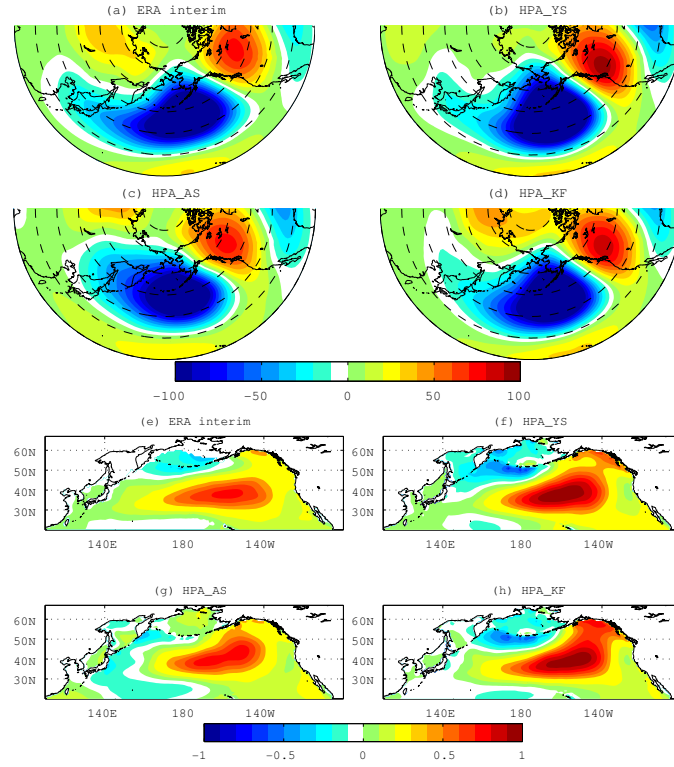


Figure 5.16: Same as **Figure 5.15** but for PNA.

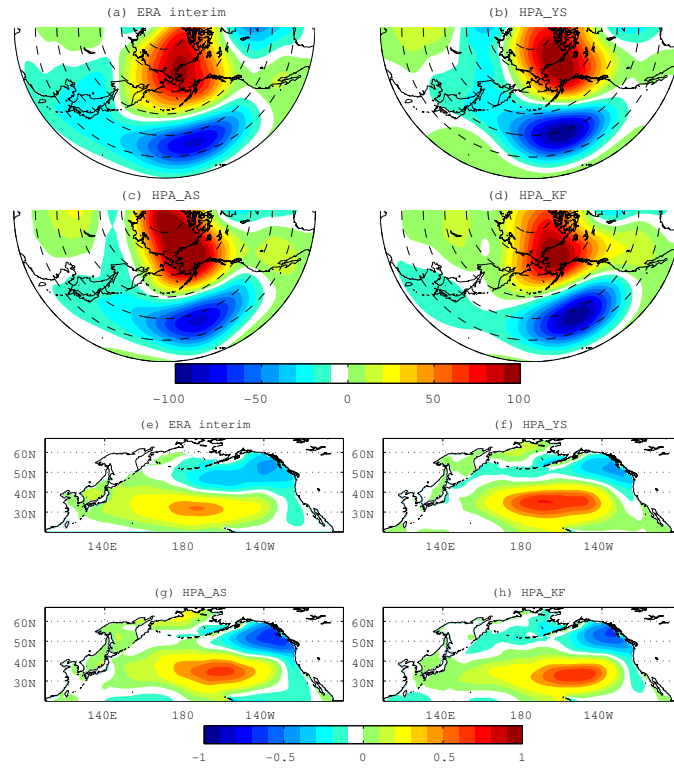


Figure 5.17: Same as **Figure 5.15** but for EPNP.

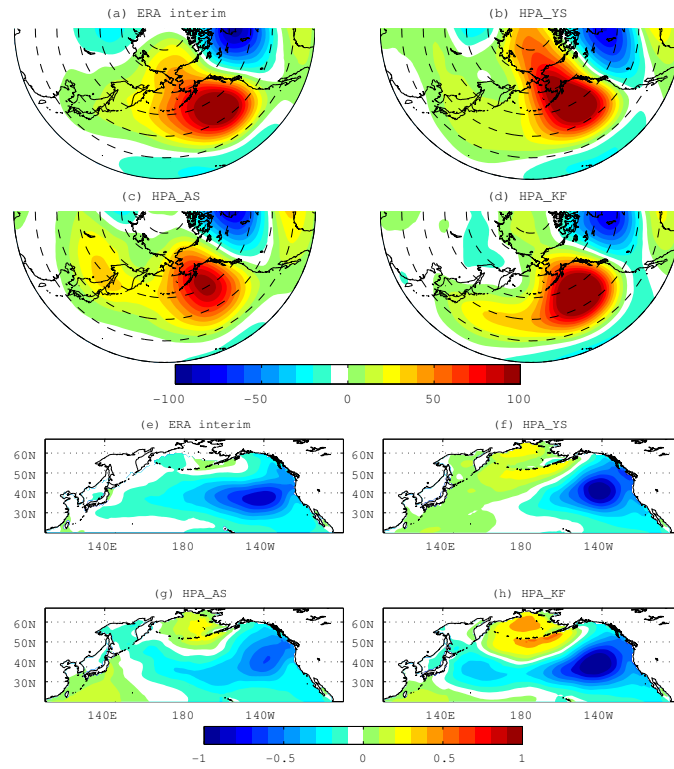


Figure 5.18: Same as **Figure 5.15** but for TNH.

The atmospheric and the related wave climate changes are explained with teleconnection patterns as follows. **Section 5.3** in this chapter showed that WP, PNA, EPNP and TNH have significant impacts on wave climate variability in the North Pacific. At first, the representations of those teleconnection patterns (WP, PNA, EPNP and TNH) in the present climate simulations (1979 - 2009) of MRI-AGCM3.2H (HPA_YS, HPA_AS and HPA_KF), are investigated. Teleconnection pattern indices were calculated by the method described in **Section 5.2.2**. Z500 and SWH differences between composite among positive and negative phases of each teleconnection pattern are shown in **Figure 5.15**, **5.16**, **5.17** and **5.18**. The results of ERA-interim are also shown as reference. The present run of MRI-AGCM3.2H can qualitatively represent the atmospheric and wave field related with teleconnection patterns compared with ERA-interim. The anomalous trough over the central to eastern North Pacific and ridge over the North-Western of the North America tend to appear at the positive phase of PNA and EPNA and the negative phase of TNH. At the same phase, positive anomaly of wave height tend to appear over the central to eastern North Pacific. Furthermore, the anomalous ridge over the Western North Pacific mid-latitudes appears at the positive phase of WP. The negative anomaly of wave height tend to appear over the Western North Pacific at the same phase .

These mixed features of the positive phase of WP, PNA and EPNP and the negative phase of TNH can be seen in the future changes of Z500 and wave height (**Figure 5.14** and **Figure 5.12**), such as anomalous atmospheric ridge over the Western North Pacific mid-latitudes, anomalous trough over the North Pacific and anomalous ridge over the North-Western of the North America. Therefore, the future changes can be expected as the results of positive phase shifts of WP, PNA and EPNP and negative phase shift of TNH. **Figure 5.19** shows the Z500 and SWH differences between composite among the positive phase (index greater than the standard deviation) of any one of WP, PNA and EPNP and negative phase (index less than the minus standard deviation). The spatial distributions are qualitatively similar to the corresponding future changes (**Figure 5.12** and **Figure 5.14**). This also indicates that future changes can be the results of positive phase shifts of WP, PNA and EPNP. The different combination of teleconnection patterns for the composite are shown for combination of WP, PNA and inversed TNH (**Figure 5.20**) and combination of WP and PNA (**Figure 5.21**). The general spatial distribution, such as negative anomaly of wave height on western part of the Ocean and positive on eastern part, is identical among the different combinations (**Figure 5.19**, **5.20** and **5.21**).

Bell and Janowiak (1995) stated that the positive phases of WP, EPNP and PNA and the negative phase of TNH are somewhat distinct, but all of them are preferred flow configurations of ENSO event (El Niño), which are associated with an amplified trough over the North Pacific. Extratropical atmospheric response to El Niño is sometimes positive phase of WP or PNA or EPNP or negative phase of TNH. The similarity between the spatial distributions of future change and those of the positive phase of the teleconnection patterns (WP, PNA, EPNP and inversed TNH), indicates that future change of the North Pacific climate can be partially attributed to El Niño-like response of extratropical atmosphere in the future. The averaged El Niño event response of extratropical atmosphere is shown in **Figure 5.22**. Actually, El Niño event response (**Figure 5.22**), the positive phases of the teleconnection patterns (WP, PNA, EPNP and inversed TNH; **Figure 5.19**, **5.20** and **5.21**) and the future changes (**Figure 5.14**), are similar each other.

It was described that future changes in wave height by the CMIP5 multi-model ensemble

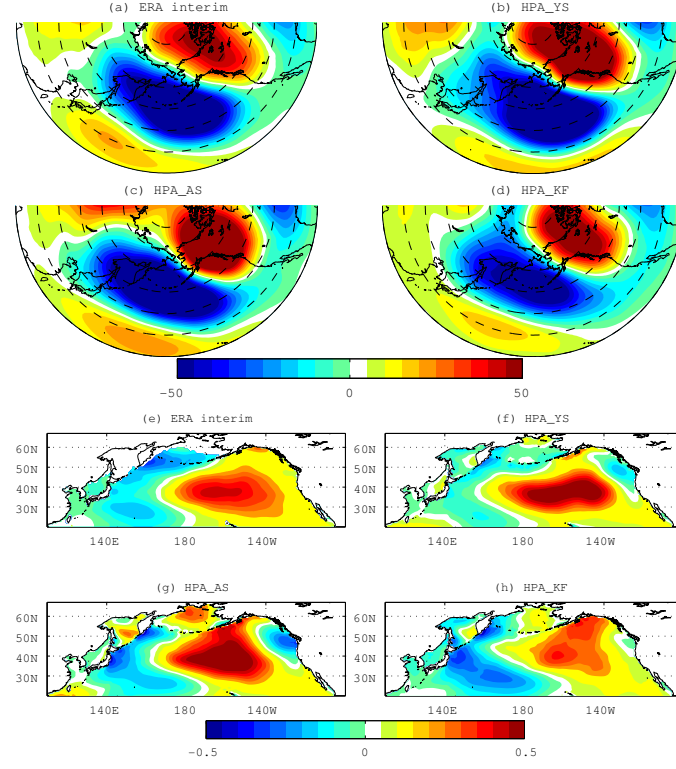


Figure 5.19: Z500 (upper four panels) and SWH (lower four panels) differences between composite among the positive phase (index is greater than 1) of any one of WP, PNA and EPNP and negative phase (unit:m).

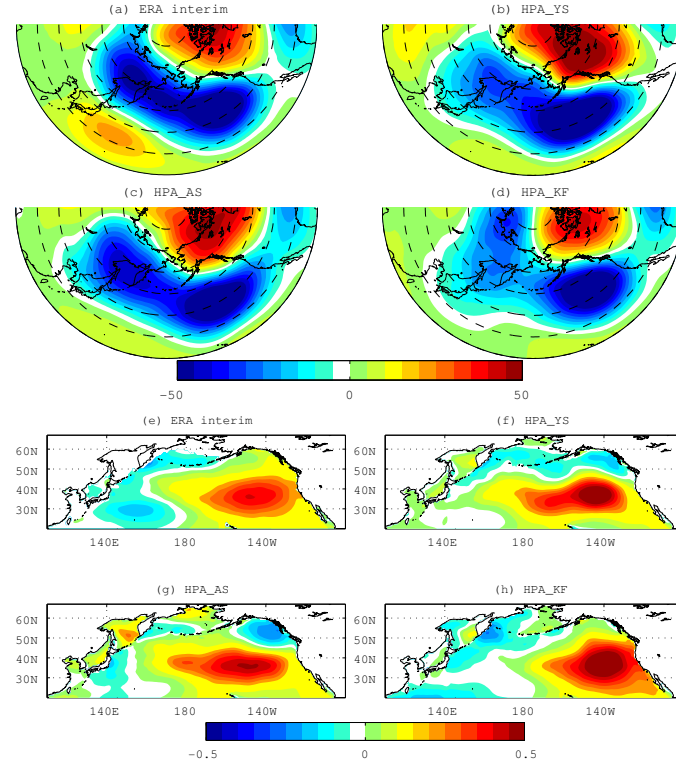


Figure 5.20: Same as **Figure 5.19** but for WP, inversed TNH and EPNP

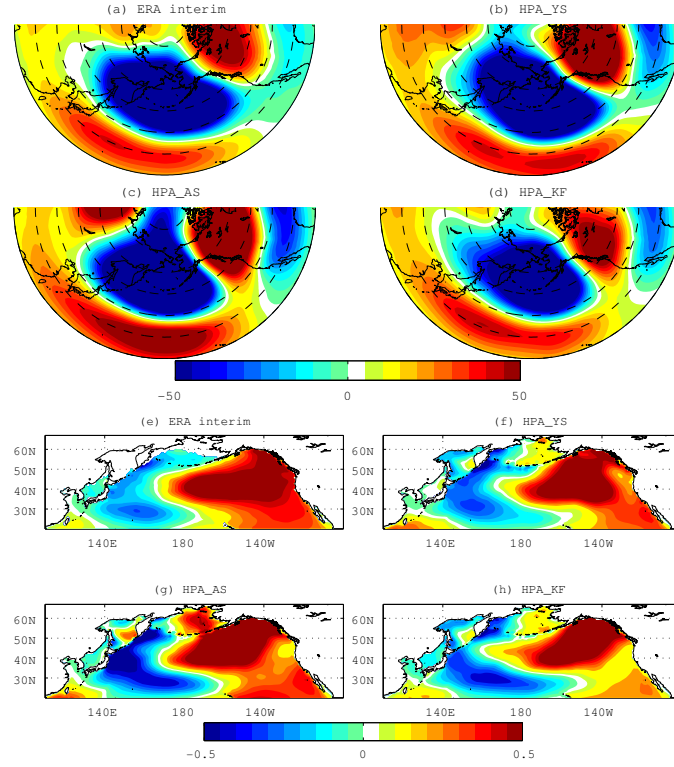


Figure 5.21: Same as **Figure 5.19** but for WP and PNA

have common spatial feature same as those of MRI-AGCM3.2H experiments (**Figure 5.13** and **Figure 5.12**) such as negative values over the western part of the Ocean, especially around 30°N, and positive values over the eastern part. However, the future change by each model has specific spatial pattern which is dominated by specific teleconnection pattern response. For example, future change by GFDL-CM3 are similar to WP response, those by ACCESS1.0 and HadGEM2-ES are similar to WP and EPNP responses, that by CNRM-CM5 is TNH response, that of INMCM4 is WP and PNA responses, and that of MRI-CGCM3 is WP and TNH responses, respectively. Each model among MRI-AGCM3.2H also has tendency of future change pattern depending on cumulus physics schemes (YS, AS and KF; **Figure 5.12**). Therefore, each model has preferred response of climate change related with specific teleconnection patterns.

The prediction of future changes in wave height by linear regression model was carried out. The explanatory variables are teleconnection pattern indices and the linear regression model was developed by least square method using data of present climate simulations. The result of prediction is shown in **Figure 5.23**. This prediction was conducted using WP, PNA and EPNP indices. Compared between the original future change (**Figure 5.12**) and the prediction (**Figure 5.23**), the spatial patterns are qualitatively similar. However, the decrease in wave height around 30°N of the Western North Pacific is strongly underestimated by the prediction. **Figure 5.24** shows the relation between WP index and monthly wave height over the Western North Pacific (25°N to 35°N and 140°E to 160°E) for HPA_YS and HFA_YS.c0 as an example. The wave heights of HFA_YS.c0 are clearly smaller than HPA_YS on the same WP index values. The causes of the underestimation can be attributed in part to the way to calculate the teleconnection pattern indices in the future climate. In this study, the Northern Hemispheric mean change in Z500 was subtracted as thermodynamics

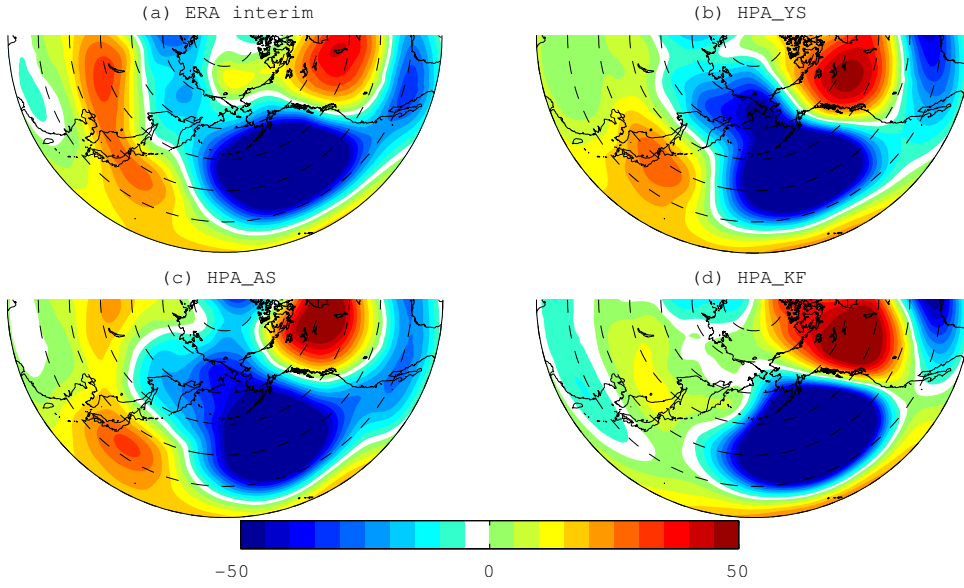


Figure 5.22: Z500 differences between composite among El Niño event and La Niña (unit: m). El Niño years are 1983, 1987, 1988, 1992, 1995, 1998, 2003, 2005 and 2007. La Niña years are 1984, 1985, 1989, 1996, 1999, 2000, 2001, 2006, 2008 and 2009. December is included into next year.

change when calculating the indices. It is not clear that the procedure is optimal for this purpose.

Therefore, the other way to calculate WP index is proposed as follows. Future change in SLP has less thermodynamics change than Z500. Spatial distribution of SLP variability related with WP pattern is a meridional dipole pattern over the North Pacific (Linkin and Nigam, 2008). Linkin and Nigam (2008) considered that SLP representation of WP pattern correspond to the teleconnection pattern known as the North Pacific Oscillation (NPO, Rogers, 1981). SLP gradient anomaly over the North Pacific is positive at the positive phase of WP, and vice versa. Thus, SLP-based WP (SLP-WP) index is calculated by the averaged SLP difference between the mid-latitudes region ($140^{\circ}\text{E} - 160^{\circ}\text{W}$, $30^{\circ}\text{N} - 45^{\circ}\text{N}$) and the higher latitudes ($120^{\circ}\text{E} - 150^{\circ}\text{W}$, $45^{\circ}\text{N} - 70^{\circ}\text{N}$) representing SLP gradient over the North Pacific. SLP-WP index was normalized by mean and standard deviation values of each calendar month. SLP-WP indices during DJF 1979-2009 were derived from NCEP/NCAR reanalysis and ERA-Interim. The correlation coefficients between those indices and CPC/NOAA's WP index are 0.86 and 0.86 for NCEP/NCAR and ERA-Interim, respectively. The SLP-WP index can be substitute for Z500-based WP index because of the good correspondence.

Figure 5.25 shows the SLP-WP index and mean wave height around 30°N of the Western North Pacific, which are derived from ERA-Interim data set. The values in **Figure 5.25** are detrended and sign of mean wave height is inversed. It is no surprising that the variability of mean wave height around 30°N of the Western North Pacific well corresponds to SLP-WP index. Wave height over the Western North Pacific and SLP-WP index show the synchronized decadal oscillation clearly (**Figure 5.25**).

Figure 5.26 is same as **Figure 5.24**, but for SLP-WP index. **Figure 5.24** shows that the wave heights of HFA_YS.c0 are smaller than HPA_YS on the same WP index values. But, the tendency, in **Figure 5.26**, becomes less clear than **Figure 5.24**. Future changes in WP index (SLP-WP index) of

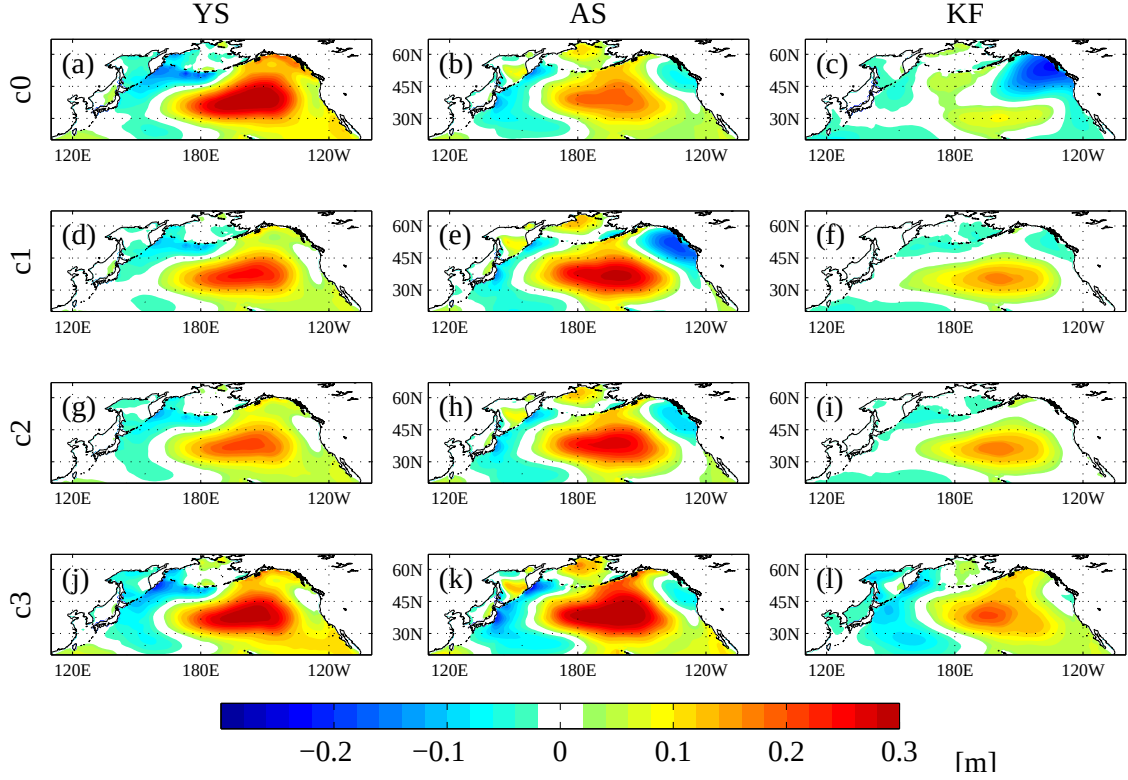


Figure 5.23: Predicted future changes in mean wave height by linear regression model (unit: m). The explanatory variables are WP, PNA and EPNP indices.

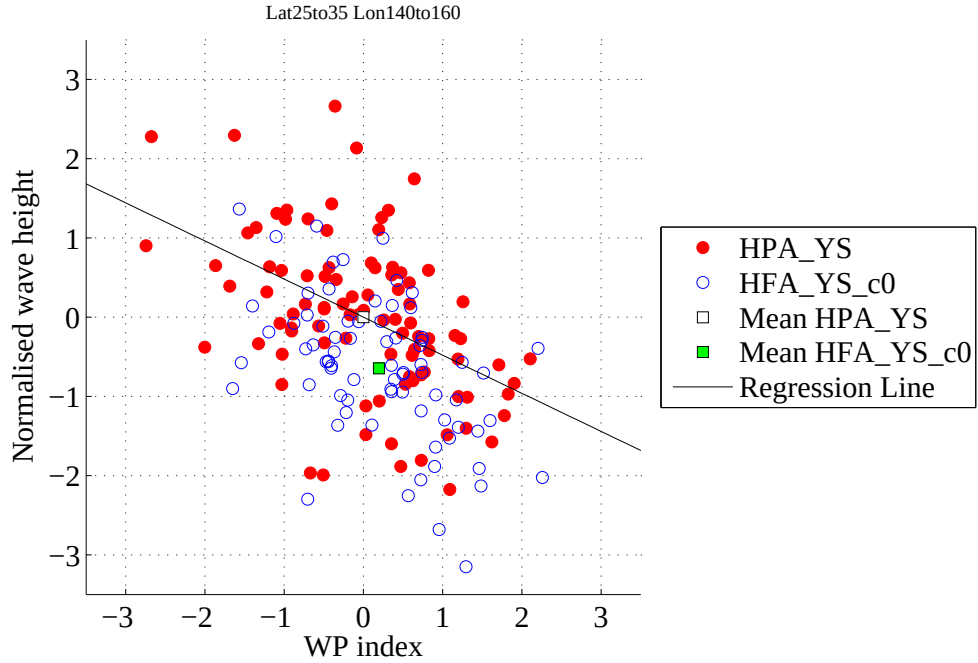


Figure 5.24: The relation between WP index and monthly wave height over the Western North Pacific (25°N to 35°N and 140°E to 160°E) for HPA_YS and HFA_YS_c0.

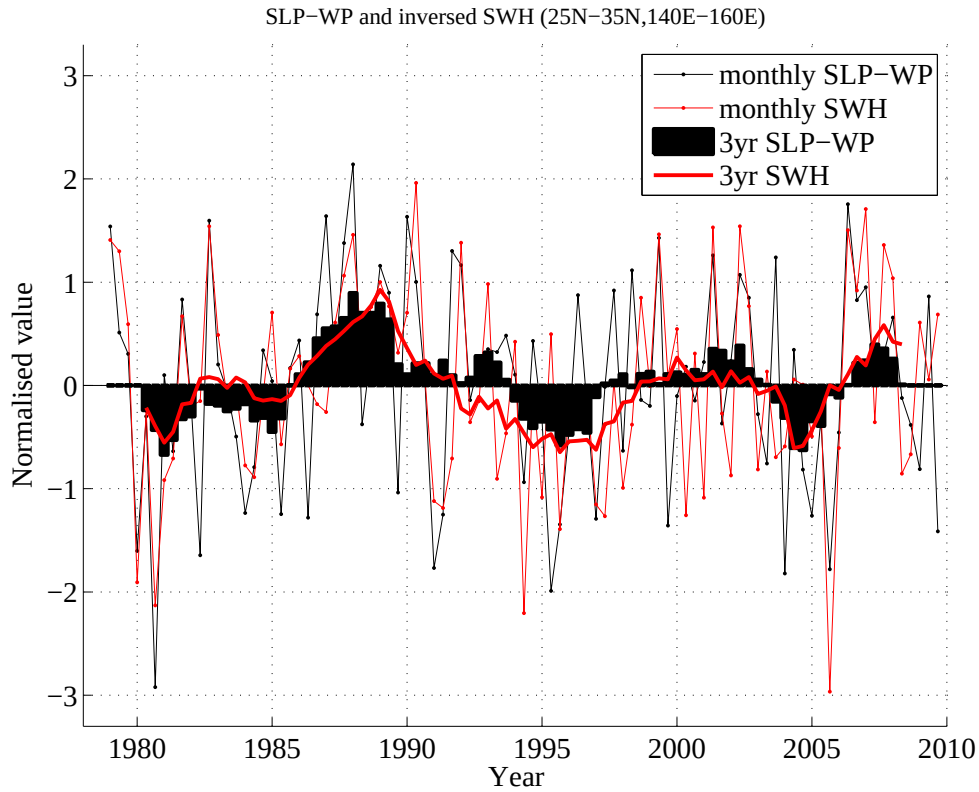


Figure 5.25: SLP-WP index and mean wave height around 30°N of the Western North Pacific (25°N - 35°N and 140°E - 160°E .), which are derived from ERA-Interim data set. The values are detrended and sign of mean wave height is inversed.

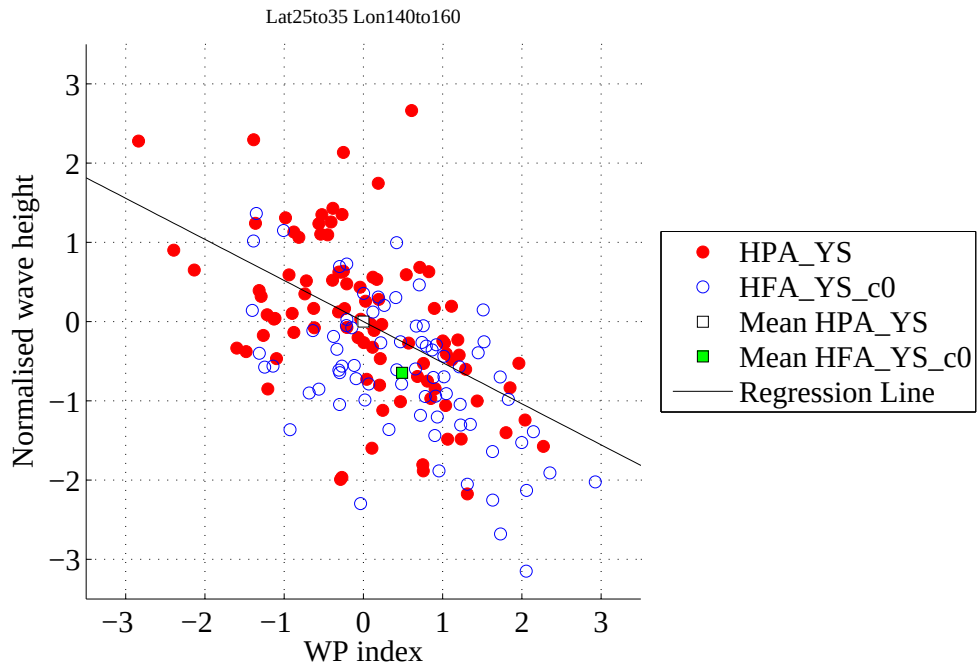


Figure 5.26: Same as **Figure 5.24**, but for SLP-WP index.

HFA_YS.c0, c1, c2 and c3 are 0.20 (0.49), 0.11 (0.48), 0.18 (0.50) and 0.35 (0.66). Therefore, future changes in SLP-WP index can explain wave height changes more than WP index quantitatively. It is confirmed that the decreases in wave height around 30°N of the Western North Pacific can be the result of positive phase shift of WP pattern.

Although the wave height changes were explained by phase shift of teleconnection pattern above, there are, of course, other causes of changes. Furthermore, not only future change in magnitude of variability of teleconnection pattern but also location shift of teleconnection pattern can be expected (Bayr and Dommenget, 2014). These require further analysis but it is left for future work.

5.5 Summary

The preferred pattern of large scale climate variability is called a teleconnection pattern. Understanding the nature of teleconnection patterns and changes in their behaviors is central to understanding regional climate variability and climate change (Trenberth and Coauthors, 2007). This study provides comprehensive insight into the relationship between wave climate variability and teleconnection patterns, which has been studied before in a spatially limited way. The large scale spatial patterns of wave heights on a monthly scale corresponding to teleconnection patterns in the Northern Hemisphere were discussed using reanalysis data.

Analysis was focused on the winter season, because that season exhibits the strongest connection between wave height variability and teleconnection patterns as shown in **Section 5.3.1**. At first, the spatial distributions of wave height variability as influenced by several teleconnection patterns were identified by correlation analysis between monthly mean wave height and teleconnection pattern indices (**Figure 5.2**, **Figure 5.4**). The wave response to teleconnection patterns makes sense in the eastern part of the ocean in the Northern Hemisphere due to a smooth relationship with atmospheric variations in this area. The relationship between wave climate variability and teleconnection patterns strongly depends on the location (**Figure 5.3**).

Second, the predictability of winter averaged SWH from a combination of teleconnection pattern indices was considered. As the result, the winter averaged SWH in some areas in the eastern part of the ocean can be estimated from a combination of teleconnection pattern indices. However, in areas such as those along 20 and 40°N in the western part of the North Pacific and 20 °N in the western part of the North Atlantic, the winter averaged SWH cannot be evaluated well.

Third, the main spatial patterns of wave climate variability were analyzed by adapting EOF analysis to winter averaged SWH in the North Pacific and the North Atlantic respectively. The winter averaged SWH values have similar spatial patterns of fluctuation across both oceans. The spatial patterns of fluctuation, especially the band-shaped pattern, exhibit a strong relation to the teleconnection pattern. The characteristics of the band-shaped pattern of the SWH in the North Pacific was investigated in detail and found to be related to the WP pattern. The tracks of extra-tropical cyclones are related to the WP pattern. The fluctuation of the SWH along 30°N occurs depending on the extra-tropical cyclone activity, which depends on the phase of the WP pattern.

Semedo et al. (2011) investigated the leading modes of variability of wind sea and swell based on the ERA-40 dataset, and swell plays an important role in the Northern Hemisphere. We did not separate wind sea from swell in this study, and swell has different spatial distributions compared to wind seas. We will examine swell data in a similar fashion in the near future.

Finally, the future changes in winter mean wave height over the North Pacific projected by MRI-AGCM3.2H (**Chapter 2**) were analyzed through the relation of wave climate and teleconnection patterns. The spatial distributions of future changes in atmospheric and wave climate are somewhat similar to teleconnection pattern like response. The responses of future wave height change are positive phase shifts of WP, EPNP and PNA, and negative phase shift of TNH. These responses are the preferred conditions of El Niño event. However, each model has preferred responses of climate change which are similar to the specific teleconnection pattern responses.

Chapter 6

Conclusions

Climate change impacts are a great concern to social sustainable development. Changes in ocean surface gravity waves give large impacts for a variety of disciplines, such as beach morphology, coastal structures, renewable energy resources and so on. The quantitative projection of future wave climate, including the likely range expected, is information that would be very useful to assess coastal impacts and how coastal communities will need to adapt in the future.

This study conducted future projections of global ocean wave climate under greenhouse gas emission scenario. These future projections were performed with several Global Climate Models (GCMs) and dynamical spectral wave model. The future projections with ensemble experiments of Japanese Meteorological Research Institute's GCM (MRI-AGCM3.2H) were analyzed toward following objectives. (1) To make clear the relation between “mean” wave climate change and spatial feature of Sea Surface Temperature (SST) change. (2) To project future “extreme” wave climate and investigate the contributions of tropical cyclone.

Future changes in global annual “mean” wave height are about ± 0.3 m depending on the region. The future changes in wave climate over the Western North Pacific are highly sensitive to SST conditions. The variation of future changes in SST influences that of future changes in typhoon characteristics, and consequently that causes the variation in future wave climate over the Western North Pacific. A specific SST condition, higher warming in the equatorial Pacific, leads to typhoon intensification, and leads to increase in wave height over the Western North Pacific. Some SST conditions lead to typhoon frequency reduction, and then lead to decrease in wave height. It is clear that variation of SST is a major source of uncertainty for the summer time wave climate projection in the Western North Pacific.

The future changes in “extreme” wave climate strongly depend on model performance of tropical cyclones (TCs) and TC changes. We analyzed the extreme wave climate change by separating the wave contributions into two groups: TC generated waves and non-TC (especially extratropical cyclone) generated waves. Future changes in non-TC waves on a global scale were estimated focusing on annual maxima. The ensemble mean of the future changes and standard deviation are up to about ± 1 m and 0.7 m, respectively. The results depend significantly on the cumulus physics scheme of the climate model when future changes in extreme wave heights are quantitatively projected. This is the opposite for the case of mean wave changes, which depend on future SST difference significantly. The spatial distribution of future changes in TC extreme wave heights over the Western North Pacific can be characterized by a minus-plus alternating pattern such as decrease, increase, decrease

and increase clock-wise from the southwestern part of the Western North Pacific to the southeastern region. This pattern was found to result from an eastward shift in the TC track. Estimating the TC track shift is an important component for impact assessments, because a track shift can be the primary factor behind extreme wave change.

In addition of wave climate projection by single GCM (MRI-AGCM3.2H), wave climate projection from multi-GCM ensemble experiments were carried out. Results of climate projection from multi-model ensemble including various types of models, has been previously summarized as equally weighted ensemble mean of future change and the deviation as the reports of Intergovernmental Panel on Climate Change (IPCC). However, this study indicated that equally weighted ensemble mean of future change among models is not reasonable because each model has specific tendency of climate change response depending on the model performance.

The global climate has preferred patterns of variability (mode of variability), which are called teleconnection patterns. Many studies indicated that climate system responses to external forcing (e.g. global warming) are associated with the inherent mode of variability (teleconnection patterns). The relation between historical wave climate variability and teleconnection patterns in the Northern Hemisphere was made clear. This study provides the comprehensive insight into the wave climate-teleconnection pattern relationship, which has been studied by spatially limited ways in previous studies. The dominant spatial patterns of wave height variability over the North Pacific and North Atlantic in winter were obtained. It is remarkable that one of the dominant patterns, a band-shaped pattern in longitudinal direction, exhibits a strong relation to the teleconnection pattern in each ocean. The band-shaped pattern for the North Pacific in winter was found to be related to the West Pacific (WP) pattern significantly.

Furthermore, this study discussed the relation between wave climate and teleconnection patterns in context of climate change using wave climate projection of MRI-AGCM3.2H. The winter wave climate changes over the North Pacific and the related atmospheric changes were analyzed. The spatial distributions of future changes in atmospheric and wave climate are similar to the teleconnection pattern like responses. The responses can be characterized by positive phase shifts of West Pacific (WP), East Pacific-North Pacific (EPNP) and Pacific/North America (PNA) patterns, and negative phase shift of Tropical/Northern Hemisphere (TNH) pattern. These responses are the preferred conditions of El Niño event.

This study presented a maturing of the wave climate projections literature. Previous studies of wave climate projection just showed the wave property changes such as wave heights, direction and period with little discussion of the factors causing the future changes. This study provided the comprehensive insight into the relation between wave climate changes and the atmospheric phenomena changes such as tropical cyclone and large-scale atmospheric circulation pattern (teleconnection pattern), and the relation with model configuration such as sea surface temperature as boundary condition, and the relation with model performance. The understanding of the factors causing the future changes would improve the reliability of wave climate projection.

Although climate change impacts on wave climate were studied in this study, but some studies indicated that ocean waves have significant impacts on global climate through atmosphere-ocean interaction processes. Therefore the atmosphere-ocean interaction processes depending on ocean waves and the impacts on global climate will be studied in the future.

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