EL NIÑO-SOUTHERN OSCILLATION: ASYMMETRY, NONLINEAR ATMOSPHERIC RESPONSE AND THE ROLE OF MEAN CLIMATE

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Abstract

The differences between the warm and cold phases of the El Niño-Southern Oscillation have profound implications on their potential socio-economical impacts and predictability; and understanding them provides insights into the fundamental dynamics of the coupled climate system. In this dissertation, these differences are systematically quantified in terms of their amplitude, duration and sequencing preferences. The role of atmospheric nonlinearities in causing these differences is investigated using a hierarchy of models. It is found that the equatorial surface zonal wind response being stronger during El Niño than during La Niña can lead to the observed ENSO asymmetry in a consistent manner.

The nonlinearity in the zonal wind response strength has not been previously explained. With the use of a linear shallow water model, it is demonstrated that the nonlinear surface zonal wind response is related to the nonlinearity in the precipitation response. By decomposing the precipitation anomalies into components attributable to adjustments of the Walker circulation (zonal redistribution) and the local Hadley cell (meridional redistribution) respectively, it is shown that during La Niña, the meridional adjustment acts to reduce the climatological precipitation available for the zonal adjustment to take place, therefore weakens the La Niña surface zonal wind response and enhances the zonal wind response nonlinearity.

As the equatorial climatological precipitation is found to be linearly correlated with the surface zonal wind response during El Niño and La Niña, it follows that the mean state climatological may have a strong control on ENSO characteristics. This hypothesis is tested by flux adjusting a state-of-the-art coupled climate model to different ocean surface climatological states. Some, but not all of the ENSO statistics and feedbacks are shown to depend systematically on the the mean climate state. Several hypotheses on the causal relationships between ENSO and the mean climate are also tested. The extent to which ENSO depends on the mean climate state is quantified and discussed.
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Contents

Abstract ........................................ iii
Acknowledgments ................................ iv
List of Tables ........................................ x
List of Figures ........................................ xii

1 Introduction ........................................ 1

2 ENSO Asymmetry ........................................ 4
   2.1 Preliminaries ........................................ 4
   2.2 Data ........................................ 6
      2.2.1 Observational datasets ......................... 6
      2.2.2 CMIP5 coupled climate models .................. 7
   2.3 Definitions of metrics ............................... 8
      2.3.1 El Niño, La Niña and amplitude asymmetry ....... 8
      2.3.2 Duration ....................................... 8
      2.3.3 Transition ..................................... 9
   2.4 Asymmetries in observations and coupled climate models ...... 10
      2.4.1 Amplitude asymmetry ............................ 10
      2.4.2 Duration asymmetry ............................ 11
      2.4.3 Transition asymmetry ......................... 11
   2.5 Chapter summary ................................. 13
3 Nonlinear atmospheric wind response and ENSO asymmetry

3.1 Abstract ........................................................................................................ 15
3.2 Literature Reviews ....................................................................................... 16
  3.2.1 Theoretical understanding and conceptual models ...................... 16
  3.2.2 Asymmetry in Intermediate models ............................................. 18
  3.2.3 Oceanic nonlinearities ................................................................. 19
  3.2.4 Atmospheric nonlinearities ......................................................... 21
3.3 Data ............................................................................................................. 23
  3.3.1 Observational SST data ................................................................. 23
  3.3.2 Surface wind stress estimates ....................................................... 23
  3.3.3 Coupled GCMs ............................................................................ 24
3.4 Nonlinear zonal surface wind response to SST anomalies ................. 26
3.5 The conceptual ENSO model ................................................................. 26
3.6 Results ......................................................................................................... 34
  3.6.1 Asymmetry in amplitude ............................................................. 36
  3.6.2 Asymmetry in duration ............................................................... 37
  3.6.3 Asymmetry in transition ............................................................. 41
3.7 Chapter summary and discussion .......................................................... 41

4 Nonlinear precipitation response in relation to the surface zonal wind response

4.1 Introduction ................................................................................................. 48
4.2 Methods ....................................................................................................... 50
  4.2.1 Data ............................................................................................... 50
  4.2.2 Shallow water model on a sphere ............................................. 51
  4.2.3 Decomposing the precipitation anomalies ............................. 54
  4.2.4 Defining nonlinearity ................................................................. 58
4.3 Results ......................................................................................................... 59
4.3.1 Nonlinear zonal wind response in models and observations 59
4.3.2 Nonlinear zonal wind response explained by each precipitation anomaly component 64
4.3.3 Contributions from the biases in the climatological precipitation 69
4.4 Chapter summary 75

5 Role of the mean state climate in simulating ENSO

5.1 Introduction 78
5.2 Methods 81
  5.2.1 GFDL CM2.1 81
  5.2.2 Target CMIP5 Models 82
  5.2.3 Flux adjustments 83
5.3 Mean state climate 86
  5.3.1 Surface temperature 87
  5.3.2 Precipitation 92
  5.3.3 Subsurface temperature and surface wind stress 92
5.4 ENSO 95
  5.4.1 SST anomaly standard deviations 98
  5.4.2 Seasonal phase locking 99
  5.4.3 Atmospheric feedbacks 102
  5.4.4 Oceanic feedbacks 108
  5.4.5 Relationships between ENSO characteristics and the mean climate 113
  5.4.6 Nonlinear zonal wind response and asymmetry 120
5.5 Chapter summary and discussion 123

6 Conclusions

6.1 ENSO asymmetry and nonlinear atmospheric response 131
6.2 The sources of the nonlinear atmospheric response 132

viii
6.3 Relationship between the mean state climate and ENSO 133
6.4 Contributions 134

A Uniqueness of the decomposition solution 136

B Resampling surface heat flux anomalies 140
List of Tables

3.1 Values of $r$ estimated from linear regression analysis between wind stress anomalies and Niño-3.4 SST anomaly index. The column shows the data sources for the Niño-3.4 SST anomaly index used in regressions. The row shows the data sources for the zonal wind stress anomalies. ........................................ 30

3.2 Parameters that produce the best simulations of observed, CM2.1 and CM2.5 asymmetry statistics. $b$ is fixed at 0.24/month. $r$ are also fixed at values based on the zonal wind stress analysis. Std = Standard deviation of the temperature anomaly (in Kelvin); Skewness = Skewness of the temperature anomaly; LenDiff = Termination time of cold events minus that of warm events (in months); Pdiff = Probability of warm-to-cold transitions minus that of cold-to-warm transitions. The row(s) below “Best Fit” correspond to the asymmetry statistics derived from the Niño-3.4 SSTA index. Parenthesized values show statistics computed from the first and second halves of the Niño-3.4 SSTA index time series. .................................................. 35

4.1 CMIP5 models and modeling groups. Two models are marked excluded from the composite analysis due to the lack of warm events with the required strength and seasonal locking. CM2.5 FLOR models are also included in this table. The right-most column shows the number associated with each model in ascending order of the nonlinear equatorial zonal wind response. . . . 52
4.2 Magnitudes of the maximum zonal wind anomalies in the shallow water model for different precipitation anomalies either from a single model or by redistributing another model’s climatological precipitation ($P_c$) to one model’s total precipitation pattern ($P_{total}$, or $P_t$) during ENSO. $\Delta r_c$ denotes the change in the nonlinearity from changing the climatological precipitation. $\Delta r_t$ denotes the change in the nonlinearity from changing the total precipitation pattern. Changes are with reference to the free-run (CM2.5-FLOR, i.e top row).

5.1 Relative differences of the CMIP5 models pre-industrial control experiments compared to CM2.1 in terms of their annual mean sea surface temperature and precipitation over the Tropical Pacific (20S-20N, 100E-100W). The differences are measured as the root-mean-square-error normalized by the standard deviation of the corresponding quantity in CM2.1 control. The models are sorted in ascending order of the sum of the root-mean-square errors in SST and rainfall. The lengths of the experiments are also shown.

5.2 Model components of the eight target GCMs to which CM2.1 is flux adjusted. Also listed are numbers used for annotating scatter diagrams in this chapter.

5.3 Modeling groups and references for the eight target GCMs to which CM2.1 is flux adjusted.
List of Figures

2.1 A sample SST anomaly time series, filtered by 5-month running mean, illustrates how terminations, durations and transitions are defined. Filled circles indicate event peaks that are followed by an event of the opposite sign. Crosses indicate event peaks that are not followed by an event. .................................. 10

2.2 ENSO (a) amplitude, (b) duration and (c) transition asymmetries in the observational datasets and CMIP5 pre-industrial control experiments. The amplitude asymmetry is computed by the skewness of the Niño-3.4 SST anomalies. The duration asymmetry is the mean duration of cold events minus that of warm events. The transition asymmetry presented here is the conditional probability of warm-to-cold transition minus that of cold-to-cold transition. Block bootstrapped 50-year records are used to estimate uncertainties in the skewness. Same number of warm and cold events are randomly sampled for estimating the uncertainties in the duration and transition asymmetries. See Sec.2.3 for the definitions of metrics. ............................... 12

2.3 Empirical cumulative distribution of event termination time using HadISST, ERSST Niño-3.4 SSTA anomalies ................................................. 13

2.4 Conditional Probability of transitions for warm and cold events using HadISST, ERSST Niño-3.4 SSTA anomalies ................................. 14
3.1 Regression coefficient of FSU zonal wind stress anomalies onto the HadISST Niño-3.4 index, for Niño-3.4 greater than 0.5K (top) and less than -0.5K (bottom). Regions with confidence level exceeding 60% are hatched.

3.2 Regression coefficient of the area averaged zonal wind stress anomalies onto the Niño-3.4 index, for Niño-3.4 greater than 0.5K (top) or less than -0.5K (bottom). The HadISST Niño-3.4 index is used for the FSU and ERA-40 regression analysis. Reanalysis wind stress anomalies are regressed onto the reanalysis Niño–3.4 indices, for MERRA and NCEP-1 respectively. Model wind stress anomalies are regressed onto the model Niño–3.4 index. Area averages of the wind stress are computed within the 40-degree longitude box spanning from 5°S to 5°N where the regression coefficient is the largest across the equatorial Pacific domain.

3.3 Stability characteristics of the conceptual model in the $c$-$d$ parameter space, with $b = 0.24$/mon and $r = 0$ (top left), $r = 20\%$ (top right), $r = 60\%$ (bottom). Region 1: the system is linearly stable and sustained by normally distributed stochastic forcing ($\sigma > 0, \epsilon = 0$). Region 2: the system is linearly unstable but is limited by additional damping ($\epsilon > 0$); there is no stochastic forcing ($\sigma = 0$). Region 3: unstable, non-oscillatory and is not considered in the current study.

3.4 Sample time series of temperature anomalies. Locations in the parameter space are shown in Fig. 3.7. (a) is an example of self-sustained oscillations free of stochastic forcings. (b) and (c) are examples of stochastically driven oscillations in a stable system.

3.5 Skewness of the simulated SST anomalies for the conceptual model with $r = 60\%$.
3.6 Empirical cumulative distribution of event termination time for the conceptual model with values of \( r = 0, 40\%, 60\% \) for \( b = 0.24/\text{mon} \), \( c = 0.33/\text{mon} \) and \( d = 0.26/\text{mon} \) (region 1). ................................. 38

3.7 Mean termination time (in month) for cold events minus that for warm events in the conceptual model, with \( r = 60\% \) and \( b = 0.24/\text{mon} \). The thick lines separate regions of different stability as in Fig. 3.3. Grey line is the zero skewness contour from Fig. 3.5. Star markers refer to sample temperature anomaly time series in Fig. 3.4. ................................. 39

3.8 Termination time for (a) warm and (b) cold events averaged across region 2, as a function of stochastic forcing amplitude with \( r = 0.6 \). Solid line represents the mean. Dashed lines represent the 95-th and 5-th percentiles of the termination time. ................................. 40

3.9 Conditional probability of warm-to-cold transition minus that of cold-to-warm transitions, for \( r = 60\% \), across the \( c\)-\( d \) parameter space. ................................. 42

3.10 Changes in transition probabilities with increasing stochastic forcing intensity and fixed \( r = 60\% \) for region 2 (self-sustained oscillations). Results are averaged within the region that have Probability(Warm-to-cold) = Probability(Cold-to-warm) = 1 when stochastic forcing is absent. ................................. 43

3.11 Regions in the parameter space where the skewness (magenta, solid lines), warm-to-cold transition probability minus cold-to-warm transition probability (cyan, dotted line) and differences in termination time (yellow, dashed lines) are closest to the required values given by observations (\( r=20\% \)), CM2.1 (\( r=40\% \)) and CM2.5 (\( r=20\% \)); see Table 3.2. Lighter regions correspond to errors less than 50% of the targeted statistics. Darker regions correspond to errors less than 15%. ................................. 45
4.1 Normalized frequency distribution of the maximum composite zonal wind anomaly at 10 meter height [m/s] (averaged from 2S to 2N, after 40-longitude-degree running mean within 100E-100W) during El Niño (light gray) and La Niña (dark gray) in the CMIP5 models, compared to MERRA. (b) Scatter plot of the maximum zonal wind anomaly during El Niño and La Niña. Contour lines (interval: 0.2) show the nonlinearity using Eq. 4.6. The squared point denotes MERRA.

4.2 Spatial correlation (within 100E-100W, 20S-20N) between the zonal wind anomalies simulated by the shallow water model and the CMIP5 models. Circles (crosses) denote the correlations for warm (cold) events. Numbers below bars correspond to those in Figs. 4.1 and 4.4.

4.3 Scatter plot for the equatorial Pacific zonal wind response during ENSO in the coupled models and in the shallow water model with the coupled model precipitation anomalies prescribed as heating (a). The straight line presents the reference for an 1-to-1 mapping. In (b), the La Niña surface zonal wind response in the shallow water model is scaled to match the corresponding coupled model. The same scaling factor is then applied to the surface zonal wind response to El Niño. Such scaling is not applied elsewhere in the paper and does not matter in the nonlinear wind response which is nondimensional (Sec. 4.2.4). See Sec. 4.2.2 for a description on the scaling factor.

4.4 Coupled models nonlinear wind response to ENSO events compared to the nonlinear wind response in the shallow water model with the corresponding precipitation anomalies prescribed as heating. The straight line presents the reference for a 1-to-1 mapping. Points are sorted according to the nonlinear zonal wind response in the coupled models and so the numbered markers are the same as those in Fig. 4.1.
4.5 (a) November-February precipitation anomaly [mm/day] (left) decomposed into zonal (center) and meridional (right) redistributions for El Niño (top) and La Niña (bottom) in MERRA. The contour interval is 4mm/day. (b) Total precipitation for the climatology (left), during El Niño (center) and La Niña (right) in MERRA. An eastward (westward) and equatorward (poleward) movement of the ITCZ and SPCZ during El Niño (La Niña) is apparent.

4.6 Regression coefficients (dimensionless) with the total precipitation anomalies over the tropical Pacific (100E-100W,20S-20N), for the zonal redistribution of the climatological precipitation (yellow), the meridional redistribution of the climatological precipitation (green) and the residual (purple). Models are sorted by the zonal redistribution contribution during El Niño.

4.7 Precipitation anomaly [mm/day] response (upper panels) to ENSO and the corresponding zonal wind anomalies response to the heating anomalies in the shallow water model (lower panels). Precipitation anomalies are averaged from 15S to 15N while wind anomalies are averaged from 2S to 2N. The left panels correspond to the meridional redistribution precipitation anomaly. The center panels correspond to the zonal redistribution precipitation anomaly. The right panels correspond to the pure zonal redistribution anomalies computed when the meridional redistribution anomalies are absent. Solid lines refer to results for the CMIP5 models and the dashed lines refer to that for the observations. Shading shows the standard deviations among the CMIP5 models.

4.8 The nonlinear wind response in the shallow water model forced by zonal redistribution precipitation anomalies with and without concurrent meridional redistribution anomalies. The straight line presents the reference for an 1-to-1 mapping. Points above this line indicate models whose nonlinear response is enhanced by the concurrent meridional redistribution of climatological precipitation. The numbered markers are the same as those in Fig. 4.1.
4.9 Comparison of the Tropical Pacific climatological precipitation (20S-20N, 100E-100W, ocean-only, November-February averaged) for CMIP5 models, MERRA and GPCP. (a) Taylor diagrams with reference to MERRA. Notice that the numbers associated with GPCP and the models are sorted by their distances from MERRA on the Taylor diagram. (b) Meridional average from 5S to 5N. (c) Zonal average from 120E to 100W. Grey dashed lines show the profiles for each model.

4.10 Precipitation anomalies [mm/day] averaged from November to February during El Niño (a,d) and La Niña (b,e) for the CM2.5-FLOR (top row) and CM2.5-FLOR-FA (middle row). The right panels show the climatological precipitation for CM2.5-FLOR (c) and CM2.5-FLOR-FA (f). On the bottom row (g,h,i) shows differences [mm/day] between the top and middle rows. Contour intervals are 4 and 2 [mm/day] in (a-f), and (g-i), respectively.

4.11 Relationship between the equatorial zonal wind anomalies and the November-February climatological precipitation across the CMIP5 models. The differences of the El Niño and La Niña maximum zonal wind response for the CMIP5 models are correlated with the models’ (a) climatological SST (with the tropical Pacific mean for each model removed) and (b) climatological precipitation at every grid point. Regions with statistics significance above 95% are shaded. Scatter diagrams of (c) the maximum (minimum) equatorial zonal wind anomalies during El Niño (La Niña) and (d) the zonal wind response nonlinearity (Eq. 4.6), with the climatological precipitation averaged within 5S-5N, 160E-160W for the CMIP5 model and MERRA. The numbered markers are the same as those in Fig. 4.1.
5.1 Fractional change in the annual-mean climatological surface temperature (a) root mean square error, (b) spatial correlation deviation from one; for experiments flux adjusting towards the climatologies of different target models, as indicated in the horizontal axis. The changes are normalized by the errors between the CM2.1 control and the target model control experiment. Blue, yellow, red and grey bars correspond to areas over the entire globe, over land, over ocean and within the tropical Pacific Ocean (20S-20N, 120E-80W) respectively. Error bars show 25% and 75% percentiles of results from the block bootstrapped 30-year samples. The bars show the median of these samples. Negative values indicate improved representations of the surface temperature in the flux adjusted experiment towards the target model control experiment. Negative 1 indicates a perfect correction.

5.2 Annual-mean of the surface temperature (degree Celsius) from the target control experiment minus that of the FA3 experiment. Values in the brackets show the global averages in degree Celsius. Positive values indicate that the global mean in the FA3 experiments are cooler than the corresponding target models.

5.3 Annual-mean of the surface temperature (degree Celsius) from the target control experiments minus that of the CM2.1 control experiment. Similar to Fig. 5.2.

5.4 Climatology of the zonal surface temperature gradient near the equator measured by the temperature difference between the SST averaged in the equatorial western Pacific (5S-5N, 150E-150W) and that averaged in the equatorial eastern Pacific (5S-5N, 150W-90W). The climatology is computed over periods of time when the NINO3 SST anomalies are within -0.5K and 0.5K, i.e. when ENSO is weak. Results using all time periods are virtually indistinguishable. No filter or running average is applied otherwise.
5.5 Fractional change in the annual-mean climatological precipitation (a) root mean square error, (b) spatial correlation deviation from one; for experiments flux adjusting towards the climatologies of different target models, as indicated in the horizontal axis. Similar to Fig. 5.1.

5.6 Zonal mean of the climatological maritime precipitation [mm/day] over the Tropical Pacific (120E-80W) for the FA3 experiments (color shading) and the target control experiments (contours). Values in the brackets are showing the fractional change in the RMSE with reference to the target control. Negative values mean improvements towards the target control. Negative one represents a perfect adjustment.

5.7 Fractional change in the root mean square for the annual-mean climatological subsurface temperature within the region of 160E-100W, 0-200 meter deep, averaged from 5S to 5N (blue); mean surface zonal wind stress averaged from 5S to 5N, 120E-80W (red); mean depths of the 20-degree-Celsius isotherm for the Tropical Pacific Ocean over the region of 20S-20N, 120E-80W (yellow); curl of the surface wind stress within the same Tropical region (cyan); mean surface zonal wind stress for the same Tropical region (grey); mean surface meridional wind stress for the same Tropical region (purple); equatorial zonal current averaged from 5S to 5N, 120E-80W (white). Negative values indicate improved representations of the surface temperature in the flux adjusted experiment towards the target model control experiment.
5.8 Changes in the equatorial thermocline and the surface zonal wind stress in the control and flux experiments. (a) Annual-mean slope (unit: meter per degree longitude eastward) and (b) the annual-mean depth (unit: meter) of the equatorial 20-degree-C isotherm (5S-5N, 160E-90W); (c) annual-mean depth (unit: meter) of the 20-degree-C isotherm over the NINO3 region (5S-5N, 150W-90W); (d) difference between the annual-mean NINO3 SST and the potential temperature at 50m depth (unit: degree C); (e) maximum annual-mean vertical temperature gradient within the top 300 meter in the NINO3 region; (f) annual-mean zonal wind stress (5S-5N, 160E-90W; unit: Pa).

5.9 Fractional change in the temporal standard deviation of SST anomalies (a) mean square error, (b) spatial correlation deviation from one; between the CM2.1-1860 control and the target model after flux adjustment. The changes are computed for the tropical Pacific region (20S-20N, 120E-110W). Negative values indicate improved representation of the sst anomaly standard deviation.

5.10 Comparisons of the FA experiments and the target control experiments in terms of (a) the maximum SST anomaly temporal standard deviation, averaged between 5S to 5N, over a 40-degree-longitude region on the equator and (b) the longitude of the max SST anomaly temporal standard deviation.
5.11 Seasonal locking quantified by the monthly NINO3 SST anomalies standard deviation for each calendar month, normalized by its annual mean. Black solid line shows the seasonal locking in the target model control experiments. Black dashed line corresponds to the CM2.1 control experiment. Red (Blue) line represents the results from the corresponding FA2 (FA3) experiments. The values in red/blue/black at the corners of each of the subplots show the month when the seasonal dependence peaks for the FA2/FA3/target control experiment, respectively. The light grey shading shows the 5% and 95% percentiles for the free-running CM2.1 control experiment computed from a set of 50-year block bootstrapped samples.

5.12 Surface zonal wind stress anomalies averaged over 5S-5N, 120E-80W (land masked) regressed to NINO3 SST anomalies for each calendar month, filtered using a 6-month moving box car to remove low frequency variability. The filtering is justified by the time scale of Tropical Pacific Oceanic processes that are relevant to ENSO feedbacks.
5.13 Fractional change in the errors in the surface temperature, precipitation, surface zonal wind stress and surface zonal wind anomalies linearly regression with NINO3 SST anomaly indices in the flux adjusted experiments compared to the target models. Red bars correspond to one-sided regressions between the said anomalies with positive NINO SST anomaly indices, and thus the response during El Niño conditions. Blue bars correspond to one-sided regressions when NINO3 SST anomaly indices are negative, i.e. response during La Niña conditions. Yellow bars correspond to regressions at all times. These three regressions are computed over the Tropical Pacific (20S-20N, 120E-80W) with land areas masked. The grey bars are similar to the yellow bars except that only the equatorial region (5S-5N) is considered. The error bars show the 25% and 75% percentiles for a set of 30-year block bootstrapped samples. The bars show the medians of these samples. Results for MIROC-ESM, however, suffer from nonlinearities not captured by linear regression analysis.

5.14 Net surface heat flux anomalies (upward positive) regressed to SST anomalies within the NINO3 region, (unit: W/m²/s/K) in the control and flux experiments. Blue (red) scatter points show the comparisons between FA2 (FA3) experiments and the target control experiments.
5.15 Differences in the surface heat flux anomalies regressed to SST anomalies within the NINO3 region (unit: W/m²/s/K) and the differences in the annual mean fraction convective precipitation in the region (in black; unit: percentage). Solid bars show the differences between the target model control and the CM2.1 control. The hatched bars show the difference between the FA experiments and the CM2.1 control. Changes in the convective precipitation are only shown for FA3 experiments as the data for the target control is not available. Heat flux regressions are always positive upward, i.e. surface damping for positive values. Convective activity is quantified by the percentage of convective precipitation as part of the total annual-mean precipitation. The mean precipitation is computed over periods when NINO3 SST anomalies are between -0.5 and 0.5K, in order to reduce rectification.

5.16 Comparisons of oceanic feedbacks in the control and flux adjusted experiments. (a) Maximum 40-longitude-degree averaged anomalous zonal advection of mean temperature gradients (5S-5N, 120E-80W) regressed with NINO3 SST anomalies (unit: per month); (b) maximum 40-longitude-degree averaged mean zonal advection of anomalous temperature gradients (5S-5N, 120E-80W) regressed with NINO3 SST anomalies (unit: per month); (c) SST anomaly regressed to thermocline depth anomalies in the NINO3 region (unit: K/m); (d) same as Fig. 5.8(c)

5.17 Maximum equatorial zonal wind anomalies within the region of 2S-2N, 100E-100W, versus annual-mean precipitation averaged over 5S-5N, 160E-160W. The maximum equatorial zonal wind response is computed from a 40-longitude-degree running mean of the zonal wind anomalies composited for El Niño and La Niña conditions. The composites are based on events with NINO3.4 SST anomalies peaking between 1.5-2.5K. Missing points for MIROC-ESM are due to nonexisting events at this magnitude range.
5.18 Correlation between the annual-mean precipitation and the maximum zonal wind response to (a) El Niño and (b) La Niña across the FA3 experiments. Shading indicates statistical significance exceeding 95%.

5.19 Relationship between NINO3 SST anomalies (5S-5N, 150W-90W; unit: K) and the mean equatorial zonal wind stress (in Pa) over the NINO4 region (5S-5N, 170W-120W). In (c), the native zonal wind stress are shown in blue and the flux corrected zonal wind stress (experienced by the ocean only) is shown in red.

5.20 Schematics for the possible relationships between the surface temperature, mean climatological zonal wind stress $\tau_{nino4}$ over the NINO4 region (5S-5N, 160E-150W) and the ENSO amplitude measured by the standard deviation of the NINO3 SST anomalies ($\sigma_{nino4}$). These relationships may explain the differences between the FA2 and FA3 experiments in Fig. 5.19. See text in Sec. 5.4.5.

5.21 Relationship between NINO3 SST anomalies (5S-5N, 150W-90W) and the mean precipitation (mm/day) over the same region. Blue points represent the annual-mean precipitation over the NINO3 reconstructed using the method in Watanabe and Wittenberg (2012) and Watanabe et al (2012). Green points represent the annual-mean precipitation averaged over the time when NINO3 SST anomalies is within -0.5K and 0.5K.
5.22 Relationship between NINO3 SST anomalies (5S-5N, 150W-90W) and the mean equatorial zonal wind stress over the NINO4 region (5S-5N, 170W-120W) for each 30-year block bootstrap sample in the control experiments. Blue points represent the annual-mean precipitation over the NINO3 reconstructed using the method in Watanabe and Wittenberg (2012) and Watanabe et al (2012). Green points represent the annual-mean precipitation averaged over the time when NINO3 SST anomalies is within -0.5K and 0.5K. Bracketed number in the bottom right corner of each subplot follows the legend in the previous figures (0: CM2.1-1860, 1: ACCESS1-0...).

5.23 Relationship between NINO3 SST anomalies (5S-5N, 150W-90W) and the mean equatorial zonal wind stress over the NINO4 region (5S-5N, 170W-120W) for each 30-year block bootstrap sample in the flux adjust (FA3) experiments. Blue points represent the annual-mean precipitation over the NINO3 reconstructed using the method in Watanabe and Wittenberg (2012) and Watanabe et al (2012). Green points represent the annual-mean precipitation averaged over the time when NINO3 SST anomalies is within -0.5K and 0.5K. Bracketed number in the bottom right corner of each subplot follows the legend in the previous figures (0: CM2.1-1860, 1: ACCESS1-0...).

5.24 Nonlinearity in the maximum equatorial zonal wind response to SST anomalies in NINO3 region for the control, FA2 and FA3 experiments. The nonlinearity is computed following Eq. 4 of Choi et al. (2013).

5.25 Amplitude, duration and transition asymmetries of ENSO, comparing the flux adjust and the control experiments. The asymmetries are computed using the NINO3 SST anomalies following the procedures described in Choi et al. (2013).

A.1 Two-dimensional quadrapole structures.
A.2 Decomposition of the anomalies resulted from moving some scalar quantities from the bottom right corner to the top left corner. Zonal redistribution anomaly (a) is assumed to take place before the meridional redistribution anomaly (b). In (c) and (d), the meridional redistribution anomaly (c) happens before the zonal redistribution anomaly (d). (e) is the averaged of (a) and (d). (f) is the averaged of (b) and (c). The iterative method described in the text gives the same answers as (e) and (f), exact to the order at which the algorithm is designed to converge.
Chapter 1

Introduction

The El Niño-Southern Oscillation (ENSO) is a major mode of interannual climate variability that has substantial global climatic, ecological and socio-economical impact. During the warm phase of ENSO, the prevailing easterly winds over the central Pacific weaken; these westerly wind anomalies advect warm surface water toward the east, reduce the zonal slope of the thermocline and inhibit the upwelling of cold water in the eastern Pacific, which feeds back positively on the warming of surface water in the eastern Pacific and allows small perturbations to growth. To first approximation, La Niña (the cold phase) anomalies are roughly the opposite of those of El Niño. Linear techniques that are widely used for studying ENSO also tend to treat El Niño and La Niña as simple mirror images of each other and therefore treat ENSO as if it was a symmetry oscillation about a basic climate state. However, considerable differences between El Niño and La Niña do exist (Larkin and Harrison, 2002). The goal of this study is to understand the physical mechanisms that support these differences - the "ENSO asymmetries".

In the past literature, the most noted difference between El Niño and La Niña is in their amplitudes, namely that El Niño tends to be stronger than La Niña (Burgers and Stephenson, 1999). Secondly, there are also differences in the spatial patterns of the sea surface temperature (SST) anomalies and the evolution cycles of El Niño and La Niña, which
have important implications on global teleconnection patterns, regional climatic responses and the predictability of ENSO (Hoerling et al. 1997; Larkin and Harrison 2002; Kessler 2002; Ohba and Ueda 2009; Okumura and Deser 2010; Dommeng et al. 2013). These different facets of the ENSO asymmetries, however, are seldom analyzed together. Understanding the mechanism of these asymmetries is crucial for improving the prediction of ENSO behavior in the current and future climate. A first step is to compute the statistics of these asymmetries. In Chapter 2, we will present a set of metrics for quantifying and comparing the asymmetries in the observations and climate models. The existence of these asymmetries, the disagreements and agreements among models and observations, set the stage for this thesis work.

Previous studies have suggested that either oceanic or atmospheric nonlinear processes may lead to these ENSO asymmetries. Many of these studies focus on the amplitude asymmetry of ENSO. But more recent studies on the duration and the transition preferences of ENSO have highlighted the importance of the nonlinearity in the atmospheric response. In Chapter 3, we will review studies on these oceanic and atmospheric nonlinearities. Then we focus on the nonlinear atmospheric feedbacks and investigate their roles in the ENSO asymmetries. In particular, we quantify the observed nonlinear relationship between the zonal surface wind response and the surface temperature anomalies during ENSO. Using a conceptual model that encapsulates the main processes of ENSO, we show how such a nonlinearity may lead to the amplitude, duration and transition asymmetries of ENSO in a consistent manner. Most results in Chapters 2 and 3 have been presented in Choi et al. (2013).

The nonlinear surface zonal wind response is a robust feature among many observational datasets and coupled climate model experiments. However, there is still a lack of understanding of how such nonlinearity arises. In Chapter 4, we attempt to address this issue with the use of a linear shallow-water atmosphere model and the analysis of observations and climate models. The nonlinearity in the surface zonal wind response is traced back to the nonlinear precipitation response to surface temperature changes. We present a new
method to linearly decompose the Tropical Pacific precipitation anomalies into components that are attributable to the Walker Circulation and local Hadley cell adjustment respectively. By doing so, we show that the local Hadley cell adjustment acts to limit the amplitude of the precipitation anomalies and weaken the surface zonal wind anomalies during La Niña conditions, causing or amplifying the zonal wind response nonlinearity. The work in this chapter has been described in Choi et al. (2015).

Among the coupled models, there is a noticeable correlation between the climatological precipitation over the equatorial central Pacific and the linear surface zonal wind response to SST anomalies. But no relationship is found for the nonlinear zonal wind response. The question arises that whether there is a causal relationship between the climatological precipitation and the linear zonal wind response. To test this hypothesis, we perform a suite of flux adjust experiments with a state-of-the-art coupled climate model and examine how the ENSO dynamics is dependent on the mean ocean surface climatology in the Tropical Pacific (Chapter 5). As the model physical parameterization remains unchanged, these experiments isolate the impact of the mean climate state on the simulated ENSO in coupled climate models. Results from this section would not only challenge, but also complement, previous understanding of the relationship between ENSO and the mean climate.
Chapter 2

ENSO Asymmetry

2.1 Preliminaries

The strong 1982-83 and 1997-98 El Niño events have drawn scientific attention to the amplitude asymmetry of ENSO. Interannual SST anomalies near the coast of Peru were shown to be positively skewed (Deser and Wallace, 1987) during 1925-1986. Similarly, Burgers and Stephenson (1999) showed a statistically significant, positive skewness for the SST anomalies over the eastern Pacific Niño 3 region (150-90W, 5S-5N) during 1950-97. Not only did they falsify the hypothesis that the coupled Pacific ocean-atmosphere system was a linear system forced by Gaussian noise, they also hypothesized that the SST anomalies associated with El Niño are more likely to be stronger than those with La Niña, leading to further studies on the mechanisms that would support the asymmetry.

Apart from the amplitude asymmetry, there are also studies on the different transition preferences of El Niño and La Niña. Following the recharge/discharge theory of ENSO (Jin, 1997), Kessler (2002) examined the quadrature relationship between the sea surface temperature and the equatorial warm water volume that are responsible for the cyclic nature of ENSO. Kessler (2002) found that while the quadrature relationship is steady and persistent during the onset and peak phases of El Niño, such persistence is not seen in the discharge
phase of La Niña and there is almost no connection between the decay phase of La Niña and the next recharge or onset of El Niño. In other words, there were breaks in the ENSO cycle preceding the onset of a warm event while the transition from a warm event to a cold event is more predictable. Larkin and Harrison (2002) took a different approach and studied the time lapses between like events (warm-to-warm, cold-to-cold) and between opposite type events (warm-to-cold, cold-to-warm). They found that most of the direct warm-to-warm transitions occur within a longer time window (4-6 years) than direct cold-to-cold transitions (1 year) and nearly all of the warm-to-cold transitions occurred within a year while cold-to-warm transitions had a larger spread (1-3 years). These findings together with those of Kessler (2002) indicate that El Niño events are more likely to be followed by a La Niña event in the next year than vice versa.

Okumura and Deser (2010) interpreted the preference for warm-to-cold and cold-to-cold transition as a duration asymmetry of ENSO. They analyzed and showed that La Niña tend to persist longer while El Niño tends to terminate rapidly, in agreement with Kessler (2002). They further noted that this asymmetry may contribute to the observed positive skewness of SST anomalies due to the fact that ENSO is defined relative to the time mean. While this hypothesis was not accordingly tested, it suggests that amplitude, duration and transition asymmetries of ENSO should be considered in tandem.

With that, the ENSO asymmetries that motivate this study are categorized into three aspects: (1) amplitude: strong warm events are more probable than strong cold events; (2) duration: cold events are more persistent than warm events and (3) transition: warm events are more likely to be followed by cold events in the next year than vice versa. In this chapter, we will define and present the metric used for quantifying the said asymmetries in the observations and coupled climate models.
2.2 Data

To compare the observations, CGCMs and conceptual model results, consistent definitions of ENSO events, peaks and durations are needed. Despite the richness of the ENSO phenomenon, the monthly sea surface temperature (SST) in the central/eastern Pacific Ocean Niño-3.4 region (5S-5N, 170W-120W) is used as a proxy to illustrate the asymmetries of ENSO in observations and GCMs. The Niño-3.4 SST anomalies, i.e. departure from the seasonally varying climatology, are smoothed using a running 5-month boxcar average before the analysis.

2.2.1 Observational datasets

There are uncertainties in past reconstructions of the tropical Pacific SST (Vecchi et al., 2008) and for illustrating how the asymmetry metrics may be sensitive to these uncertainties, two SST datasets are explored: HadISST and ERSST version 3b. The warming trends in these products are included in the analysis in Sec.2.4. The sensitivity of results to detrending is discussed. Results using different periods of the records are also compared.

1. HadISST

The Hadley Centre sea ice and sea surface temperature dataset for 1880-2012 (HadISST; Rayner et al. 2003) is used for computing the Niño-3.4 SST anomaly index. The historical record is examined entirely as well as in segments. Monthly climatologies and anomalies are computed over the period of time series sampled. The HadISST Niño-3.4 SST has increased by 0.2 degrees from 1880 to 2012.
2. ERSST v3b

The Extended Reconstructed Sea Surface Temperature (ERSST) Version 3b (Smith et al., 2008) provided by NOAA is used as another long-term SST observational record to compare with HadISST. The dataset spans from 1854 to present. In the current study, the time series from 1880 to 2012 is used since the strength of the signal becomes more consistent after 1880. This version of SST analysis uses in situ SST data and improved statistical methods. Unlike the version 3, satellite data that causes a small cold bias is not used in version 3b. From 1880 to 2012, ERSST Niño-3.4 SST has increased by 0.6 degree.

2.2.2 CMIP5 coupled climate models

The Coupled Models Intercomparison Project (CMIP) is organized to coordinate international climate research effort for advancing our knowledge of climate variability and climate change (Meehl et al. 2007; Taylor et al. 2012). The project includes a suite of experiments, each of which has a specific climate model forcing, such as doubling the atmospheric carbon dioxide concentration. Climate modeling groups interested in contributing to the project would perform simulations with their models under the same forcing for the particular experiment.

Coupled model analysis in this thesis makes use of the multi-century pre-industrial simulations in the fifth phase of the CMIP (CMIP5; Taylor et al. 2012), which has played a prominent role in the fifth IPCC assessment report (AR5). These simulations are generally run for 300-500 years, which is required to establish statistical robustness for the analysis of ENSO (Wittenberg 2009; Stevenson et al. 2010).

The ENSO main characteristics in the CMIP5 models are compared to the earlier phase of CMIP (CMIP3) by Bellenger et al. (2014). While some of the biases in the mean Tropical Pacific climate are improved in CMIP5 and more models simulated ENSO amplitudes within 25% of the observed values, several discrepancies in the ENSO representation persist across
model generations. Nevertheless, the intermodel comparison coordinated by CMIP allow scientists to assess the mechanisms and physical processes responsible for the intermodel differences in the mean state climate and the ENSO characteristics as well as their relationships in the real world.

2.3 Definitions of metrics

2.3.1 El Niño, La Niña and amplitude asymmetry

El Niño (La Niña) is defined such that the 5-month running mean of the Niño-3.4 SST anomaly index exceeds (is below) its 90-th (10-th) percentile of the time series, for at least 5 consecutive months. The qualitative results in this chapter are not sensitive to the choice of percentiles ranging from 75-th to 90-th percentile.

The amplitude of an event is defined by the Niño-3.4 SST anomaly index at the event peak. Following the treatment by Deser and Wallace (1987), Burgers and Stephenson (1999) and Zhang and Sun (2014), the amplitude asymmetry of ENSO is measured by the skewness of the SST anomaly index. However, while many previous studies focused mostly on the Niño-3 region (Deser and Wallace 1987 looked at in-situ data located near 80W), the following results are computed using Niño-3.4 region. If the Niño-3 SSTA index is used instead, the observed amplitude and duration asymmetries would be even stronger than discussed here. Nevertheless, the qualitative results are not affected by the choice of Niño-3 or Niño-3.4 region.

2.3.2 Duration

The duration of an event is calculated by the time lapse from the event peak to the time when the Niño-3.4 index first comes within 25% of the standard deviation from the time mean. If an event persists and reintensifies into another event of the same sign such that
both events terminate at the same time, the preceding event is not considered in the duration analysis to avoid double counting.

Reducing the difference in the duration distributions to a single metric is advantageous for comparing the asymmetry among observations and coupled models. Since duration is a positive definite quantity, the tail on the right side of the distribution is of interest. Furthermore, a quantity with a time unit is also physically more meaningful. In this chapter the duration asymmetry is defined by the difference between the mean durations for warm and cold events.

2.3.3 Transition

The asymmetry in transition is examined by calculating the sample conditional probabilities of different types of transitions. This analysis is more uncertain for the observations largely due to the ambiguity of how one identifies a transition type and the relatively small number of events. To be consistent across observational datasets and GCM outputs, we adopt the following procedures when calculating the event transition probability:

1. Identify the El Niño and La Niña events using the percentiles and persistence criteria

2. For each warm or cold event, for example, a warm event:

   - identify when the event terminates

   - if the next event is a cold (warm) event and occurs within 12 months after the termination, this is identified as a warm-to-cold (warm-to-warm) transition

Following these procedures, transition probabilities are calculated such that

\[
P_{\text{warm-to-warm}} + P_{\text{warm-to-cold}} + P_{\text{warm-to-else}} = 1
\]

\[
P_{\text{cold-to-cold}} + P_{\text{cold-to-warm}} + P_{\text{cold-to-else}} = 1
\]
To describe the transition asymmetry, one may focus on the opposite-sign transition probability or the same-sign transition probability (i.e. reintensification). Under the hypothesis that warm events are more likely to be followed by a cold event while a cold event may reintensify after decay, the transition asymmetry would be quantified by $P_{\text{warm-to-cold}} - P_{\text{cold-to-warm}}$ for the former, $P_{\text{cold-to-cold}} - P_{\text{warm-to-warm}}$ for the latter.

Since an event may not be followed by another event (same sign or not) at all, the two measures are neither mutually exclusive nor complementary.

To aid understanding, the above definitions of metrics are also illustrated in Fig.2.1.

![Figure 2.1: A sample SST anomaly time series, filtered by 5-month running mean, illustrates how terminations, durations and transitions are defined. Filled circles indicate event peaks that are followed by an event of the opposite sign. Crosses indicate event peaks that are not followed by an event.](image)

**2.4 Asymmetries in observations and coupled climate models**

**2.4.1 Amplitude asymmetry**

The skewness of HadISST and ERSST v3b monthly Niño-3.4 SSTA indices are 0.27 and 0.37 respectively. To examine the sensitivity of the result to a few particularly strong or weak events in the record, one may consider the earlier-half (year 1880-1946) and the later-half (year 1947-2012) of the records separately: HadISST (ERSST v3b) Niño-3.4 SSTA index
has skewnesses of 0.22 (0.35) and 0.31 (0.33), corresponding to the earlier and latter time intervals respectively. The skewness changes very slightly (+/- 0.02) upon removing a linear warming trend. In short, from the observations, strong El Niño is more probable than strong La Niña.

Coupled models in the CMIP5, however, show a wide range of amplitude asymmetries. Most underestimate the skewness of the Niño-3.4 SST anomalies. Some show a negative skewness in the SST anomalies while some show a positive skewness (Fig.2.2). This result agrees with Zhang and Sun (2014) who used SST anomalies within the Niño-3 region (5S-5N, 90W-150W), over shorter (50-year) records and from fewer coupled models that were available at the time.

2.4.2 Duration asymmetry

Consistent with Larkin and Harrison (2002) and Okumura and Deser (2010), more warm events terminate within a year after peaks than cold events do, as shown by the distributions of the event termination time (Fig.2.3). If the Niño-3.4 SSTA time series is detrended, cold events last longer for ERSST v3b, increasing the duration asymmetry to 4 months.

Although CMIP5 models show very different skewnesses of SST anomalies, the duration asymmetry is fairly robust across the models that La Niña in the models also tends to last longer than El Niño does (Fig.2.2). Uncertainties in the estimates of the duration asymmetries are estimated via randomly sampling warm and cold events without replacement.

2.4.3 Transition asymmetry

Following the procedures described in Sec. 2.3 for calculating the conditional probabilities for different transition types, it is found that there is a higher likelihood to have warm events be followed by cold events than vice versa (Fig.2.4). Cold-to-cold transitions are also more frequent than warm-to-warm transitions. This qualitative conclusion holds with a different choice of Niño-3.4 SSTA threshold or with the linear trend removed from the
Figure 2.2: ENSO (a) amplitude, (b) duration and (c) transition asymmetries in the observational datasets and CMIP5 pre-industrial control experiments. The amplitude asymmetry is computed by the skewness of the Niño-3.4 SST anomalies. The duration asymmetry is the mean duration of cold events minus that of warm events. The transition asymmetry presented here is the conditional probability of warm-to-cold transition minus that of cold-to-cold transition. Block bootstrapped 50-year records are used to estimate uncertainties in the skewness. Same number of warm and cold events are randomly sampled for estimating the uncertainties in the duration and transition asymmetries. See Sec.2.3 for the definitions of metrics.
Figure 2.3: Empirical cumulative distribution of event termination time using HadISST, ERSST Niño-3.4 SSTA anomalies

Niño-3.4 SST index, although the numbers of observed warm and cold events are so small that the statistical significance varies. This transition asymmetry is also fairly robust across the CMIP5 models (Fig.2.2).

2.5 Chapter summary

Previous studies have shown that in the past ENSO has demonstrated asymmetries in terms of its amplitude, duration and transition characteristics. But prior to this work, these asymmetries had not been systematically analyzed for the observations and the coupled models. In this chapter, metrics are defined for quantifying these asymmetries. These metrics are crucial for diagnosing numerical models of varying complexities and for comparing the models to each other and to the observations.

The duration and transition asymmetries are fairly robust across the CMIP5 model control experiments: La Niña tend to last longer than El Niño does and La Niña tends to follow El Niño more readily than vice versa. However, few coupled models agree with the observed positive skewness in the equatorial eastern Pacific, i.e. El Niño tends to be stronger, or
strong El Niño is more probable than strong La Niña. Most models produce ENSOs with little amplitude asymmetry, and some even show a negative asymmetry. The findings that coupled models underestimate the amplitude asymmetry of ENSO are in agreement with Zhang and Sun (2014).

In the next chapter, we derive a nonlinear conceptual model for the understanding of ENSO asymmetry. The results will shed light on why the amplitude asymmetries can be so widely different across models while the duration and transition asymmetries are more robust.
Chapter 3

Nonlinear atmospheric wind response
and ENSO asymmetry

3.1 Abstract

In this chapter, we attempt to use a new nonlinear conceptual model to understand the ENSO amplitude, duration and transition asymmetries in a consistent fashion. In the next section, theoretical understandings of the fundamental mechanism of ENSO are reviewed. These theories are the cornerstones of the conceptual model. Oceanic and atmospheric nonlinearities that have been proposed to be relevant to the ENSO asymmetry are also discussed. Among these proposed nonlinearities, we have focused our attention on the nonlinear zonal surface wind stress response to SST anomalies (Section 3.4). In Section 3.5, we will describe the formulation of the conceptual ENSO model and how this single nonlinearity is incorporated into the model. The effect of this nonlinearity on the amplitude, duration and the transition (predictability) asymmetries of ENSO are examined in Section 3.6. In Section 3.7, a conclusion is offered for this chapter.
3.2 Literature Reviews

3.2.1 Theoretical understanding and conceptual models

It has been widely accepted that El Niño (and La Niña) grows due to the positive feedback between the Walker circulation and the ocean surface temperature changes (Bjerknes, 1969). At the time there was no mechanism provided for explaining the termination and the transition between the warm and cold states of ENSO. In fact, the two states were viewed as stable equilibrium states by Bjerknes (1969) and McCreary and Anderson (1984).

Wyrtki (1975, 1985a,b) observed that the sea level in the equatorial western Pacific rises (is below normal) and there is a buildup (loss) of equatorial warm water volume prior to (after) an El Niño event. This led to a modified hypothesis for El Niño to be initiated by the Kelvin and Rossby waves adjustments that move the excess equatorial warm water from the western Pacific to the eastern Pacific. After the event, the thermocline is left to be abnormally shallow, the equatorial warm water is low and the surface temperature is cold, known as the La Niña phase. Then the equatorial warm water is slowly being replenished for the next event. Under this framework, oceanic dynamics is the key mechanism of the ENSO cycle. This laid the foundation of the set of theories that view ENSO as a self-sustained oscillatory mode governed by deterministic processes.

Several simple coupled conceptual models are proposed in order to explain how the equatorial warm water is built up/dissipated and how an event is terminated. In general, a delayed negative feedback is required to oppose the growth of a warm/cold event, terminate it and eventually turn the phase around. The negative feedback may have multiple sources: (1) oceanic wave reflection in the western boundary of the basin, also known as the delayed oscillator theory (Battisti, 1988; Battisti and Hirst, 1989; Suarez and Schopf, 1988; Battisti and Hirst, 1989), (2) recharge and discharge of equatorial warm water due to Sverdrup balance, known as the recharge-discharge oscillator (Jin, 1997), (3) western Pacific wind-forced Kelvin waves, known as the western Pacific oscillator (Weisberg and Wang 1997; Wang et al.
1999), (4) anomalous zonal temperature advection by ocean currents (Picaut et al., 1997). Wang (2001) proposed a unified oscillator model that includes all the above oscillator models.

The idea that the oceanic dynamic adjustment is the dominating deterministic process for ENSO was challenged. Neelin (1991) suggested that oceanic dynamic adjustment may be of secondary importance compared to local coupled processes related to the SST tendency. By taking asymptotic limits in a modified shallow water ocean model, they demonstrated that if the equatorial oceanic waves adjustments are slow compared to the time scales of SST evolution determined by thermodynamic and coupled processes, ENSO would be dominated by oceanic dynamic adjustments whose time scale provides the "memory" necessary for the oscillation, i.e. the above oscillator theories apply. In the limit when the equatorial wave dynamics adjustment is fast compared to the time scale of the coupling processes associated with the time derivative of the SST equation, an alternative interannual oscillatory mode, termed the SST mode, exists for the coupled system. Jin and Neelin (1993) suggest that ENSO realistically should be a hybrid of these two regimes, namely the fast-SST limit and the fast-wave SST modes. In their model, the two modes are connected in a unified parameter space where most of the coupled modes are best understood as mixtures of the two modes.

The above theoretical models provide a useful framework for studying the coupled system stability and its sensitivity to the rich parameter space (Neelin et al., 1998). Within parameter regimes where the system is unstable and damped, the oscillation is self-sustained. In parameter regimes where the system is stable, however, irregular oscillation maybe obtained by imposing stochastic external forcing. This connects to the class of ENSO theories which suggest that ENSO is driven by stochastic external forcings on an otherwise stable state (McWilliams and Gent, 1978; Lau, 1985; Penland and Sardeshmukh, 1995; Blanke et al., 1997; Thompson and Battisti, 2000, 2001; Dijkstra and Burgers, 2002; Kleeman, 2008). These studies offer an explanation for the aperiodicity and irregularity of the observed ENSO. Other proposed explanations for the irregularity of ENSO involve chaotic dynamics due to nonlinear interactions between the seasonal cycle and the atmosphere-ocean coupled system,
or interaction between ENSO and other non-ENSO mode of variabilities (Imada and Kimoto, 2009). Chaotic dynamics is also proposed as a mechanism for the ENSO amplitude asymmetry (Timmermann et al., 2003). Stochastic and chaotic theories are compatible with each other but the current observation records are insufficient to distinguish which of these frameworks is more relevant to the real world (Penland, 1996; Newman et al., 2011).

Despite the fact that ENSO is not a regular cyclic oscillation (hence this dissertation), several parameters derived from the conceptual frameworks are still informative for understanding and diagnosing the observed and modeled ENSO behavior. These parameters include: (1) air-sea coupling strength via the surface wind response to sea surface temperature changes; (2) time scale for the oceanic adjustment, which is set by the zonal domain size of the Pacific Ocean but is also dependent on the zonal location and the meridional extent of the surface wind response; (3) oceanic mixed layer dynamics, such as the advection feedback by surface currents; (4) depth of the mixed layer, which determines the sensitivity of the surface temperature to changes in the subsurface temperature; (5) surface damping, such as surface radiative and turbulent heat fluxes. The air-sea coupling strength is the main theme of this dissertation. However, the other parameters are also discussed.

### 3.2.2 Asymmetry in Intermediate models

One of the earliest intermediate atmosphere-ocean coupled models for ENSO is the Cane-Zebiak or the Zebiak-Cane model (Cane and Zebiak 1985; Zebiak and Cane 1987). The ENSO simulated in their model have several realistic features compared to observed. Most importantly, the ENSO simulated in their model is aperiodic, with periods of active ENSO and periods of inactive ENSO; and the time scale of oscillation is similar to that of the observations. Therefore they concluded that ENSO aperiodicity can arise from deterministic processes without any external forcing. More insightful description of the model and the experiment results can be found in their report. But it is worth pointing out here that,
judging from the figures, the simulated ENSO in their model shows an amplitude asymmetry that favors stronger SST anomalies during El Niño than during La Niña. However, there is no apparent transition and duration asymmetry. Nevertheless, there are several nonlinearities incorporated in their model; so that one or many of them may be responsible for the amplitude asymmetry.

Their coupled model has nonlinearity in both the oceanic and atmospheric components. Nonlinearities in the ocean include (1) the anomalous zonal advection of the anomalous zonal temperature gradient; (2) the fact that the anomalous vertical temperature gradient would only affect the surface temperature when there is upwelling; and lastly (3) the nonlinear dependence of the subsurface temperature on the mean depth of the thermocline. On the other hand, the atmosphere component is nonlinear because of a parameterized atmospheric convective feedback that is dependent on the mean atmospheric circulation: atmospheric heating (cooling) in the region of mean surface wind convergence leads to a stronger (weaker) positive feedback, and atmospheric cooling in the region of mean surface wind divergence causes no positive feedback (Zebiak, 1986). As the full complexity of the model is required for simulating the mean features of the observed ENSO, it is not clear which piece or pieces of these nonlinearities is/are responsible for the apparent asymmetry simulated.

3.2.3 Oceanic nonlinearities

Although this thesis focuses on the nonlinear atmospheric response, the role of the ocean nonlinearity in ENSO asymmetry is not to be understated. When Meinen and McPhaden (2000) tested the recharge-discharge oscillator theory using the observed subsurface temperature dataset, not only did they confirmed that there is a direct relationship between the equatorial warm water volume (WWV) and the ENSO SST anomalies, but they also found that the SST anomalies of El Niño are larger than that of La Niña for a given change in the equatorial WWV. Therefore they suggest that the oceanic processes controlling the SST maybe of different importance during El Niño and La Niña events.
Later, several oceanic nonlinear processes have been suggested to be responsible for the amplitude asymmetry of ENSO. For example, tropical instability waves in the eastern equatorial Pacific are more active (less active) during La Niña (El Niño), and therefore it may preferentially damp La Niña SST anomalies (Wang and McPhaden, 2000; Vialard et al., 2001; Yu and Liu, 2003). On the other hand, the advection of anomalous temperature by the anomalous subsurface current, known as the nonlinear dynamic heating (Jin et al., 2003; An and Jin, 2004; An, 2009), is shown to have amplified the SST anomalies during the 1997/98 El Niño but weakened those for the La Niña in the following year.

As the nonlinear dynamic heating term depends on the relative phase between the surface current and subsurface temperature changes, it may also be linked to the asymmetry in the zonal phase propagation of SST anomalies (McPhaden and Zhang, 2009) such that an event with SST anomalies propagating eastward would experience a larger nonlinear dynamic heating term than an event with westward propagating SST anomalies (Jin et al., 2003). This implies that a system that resembles more closely to the fast-wave limit of ENSO oscillatory mode (Neelin and Jin, 1993; Neelin et al., 1998) would likely have a stronger ENSO amplitude asymmetry.

Additionally, the nonlinear dynamic heating term during the transition to the 1998/99 La Niña may also be associated with the unusually strong 1997/98 El Niño event through atmospheric processes. In particular, the cooling effect of the nonlinear dynamics heating during the transition to La Niña relied on the westerly surface wind anomalies over the eastern equatorial Pacific that had persisted after the peak of the previous El Niño, whose SST anomalies were so strong that the equatorial ITCZ was established and the easterlies were shut off (Vecchi and Harrison 2006; Vecchi 2006). Because of these westerly anomalies and the associated reduced upwelling in the eastern equatorial Pacific, the growth of the 1998/99 La Niña was damped by the anomalous vertical advection of the anomalous vertical temperature gradient. It seems that in this particular case study, the oceanic nonlinearity is closely related to the nonlinear atmospheric response to SST anomalies as well.
3.2.4 Atmospheric nonlinearities

The atmosphere in the Tropical Pacific has a rich source of nonlinearities, all of which involve how atmospheric convection and atmospheric boundary layer processes respond to changes in the ocean surface boundary condition.

First of all, the equatorial surface zonal wind stress anomalies corresponding to El Niño SST anomalies tend to be about 10 degree east of those during La Niña (Hoerling et al., 1997). This nonlinearity is shown to be an intrinsic property of the atmosphere due to the thermodynamic control on deep convection. Using a hybrid coupled model, Kang and Kug (2002) demonstrate that this difference in the zonal location of zonal wind stress anomalies is responsible for the weaker SST anomalies of La Niña compared to El Niño, i.e. the amplitude asymmetry of ENSO. The physical basis for this argument is that the westward shifted zonal wind stress anomalies leads to a shorter oceanic adjustment time for the delayed negative feedback. Consequently, La Niña terminates sooner and achieves a weaker peak amplitude. However, the La Niña events in their model also last for a shorter time compared to El Niño, which is opposite to the observed duration asymmetry.

Studies have also focused on the statistical distribution of the wind stress anomalies. For example, westerly wind burst events (Harrison and Vecchi, 1997; Vecchi and Harrison, 2000) may have been more frequent than normal prior to a warm condition, thus favor the onset of extreme El Niño events and contribute to the amplitude asymmetry (Lengaigne et al., 2003; Eisenman et al., 2005; Gebbie et al., 2007). Westerly wind burst events and Madden–Julian oscillations can be collectively considered as the "state-dependent" or "multiplicative" noise that could alter ENSO stability and predictability. By preferentially increasing the variance of the stochastic forcing during the warm phase (i.e. "state-dependent noise") in the recharge-discharge oscillator model, Levine and Jin (2010) show that there is a higher probability for a noise-induced instability to occur during warm conditions. Consequently, El Niño events are more likely to be stronger than La Niña.
Adopting a similar approach of Hoerling et al. (1997) and Kang and Kug (2002), Ohba and Ueda (2009) force an idealized atmospheric model with a pair of SST anomaly patterns that have equal magnitudes but opposite signs to examine the nonlinear atmospheric response and its impact on the ENSO duration/transition asymmetry. In addition to the zonal shift of wind stress anomalies simulated by Hoerling et al. (1997) and Kang and Kug (2002), Ohba and Ueda (2009)’s model was able to simulate the end-of-year meridional shift of the wind anomalies for the warm SST anomalies, as the seasonality in the climatological SST boundary condition was included in the model (Vecchi, 2006). In contrast, there was no meridional wind shift simulated for the La Niña condition and the equatorial easterlies persist (but also weaken) into the next season. By imposing this asymmetric surface wind response onto an intermediate atmosphere-ocean coupled model in which the ocean is linear, they show that El Niño tends to terminate faster than La Niña does; the warm-to-cold transition is facilitated by the nonlinear wind response while the cold-to-warm transition is not; and there is a redevelopment of the La Niña event. All of these features are consistent with the observed duration and transition asymmetries of ENSO. Following Ohba and Ueda (2009)’s argument on the persisted equatorial easterlies after the peak of a La Niña, Okumura et al. (2011) suggested that the cooling of SST over the eastern Indian Ocean may also help sustain the easterlies in the western Pacific and therefore allow La Niña to last longer or to reintensify in the next year.

McGregor et al. (2012, 2013) employ a similar approach by Ohba and Ueda (2009) but they focus on the meridional wind shift which has been shown to play a prominent role in the termination of Eastern Pacific El Niño events (Larkin and Harrison, 2002; Vecchi and Harrison, 2003, 2006; Vecchi, 2006; Lengaigne and Vecchi, 2009). First they found that there is also a meridional wind shift for the La Niña event, but the extent of the meridional shift during La Niña, regardless of the event amplitude, is not as large as that of the El Niño events (McGregor et al., 2013). The lesser extent of the meridional shift during La Niña may also be projected onto the equator as persistent easterlies, as in Ohba and Ueda (2009).
McGregor et al. (2013) then use a linear ocean shallow water model and show that the smaller meridional shift during La Niña is linearly related to a weaker recharge/discharge of the equatorial heat content, which leads to a slower termination compared to the El Niño situation.

The above studies suggest that nonlinear atmospheric responses to ENSO may play an important role in all of the amplitude, duration and transition asymmetries of ENSO. However, one feature of the nonlinear atmospheric response seems to have gone largely unexplained: In Fig.6 of Ohba and Ueda (2009), the zonal wind stress response to El Niño not only terminates more abruptly but it is also stronger at its peak compared to that during La Niña. Therefore, it is unclear whether all of the transition and duration asymmetries derived from their model come from the persistence of the wind response. It is possible that the difference in the wind strength also plays a role, be it complementing or opposing. In this Chapter, we will use a conceptual ENSO model and include this asymmetric strength of zonal wind stress response as the only nonlinearity, to investigate its probable contribution to the ENSO asymmetry.

3.3 Data

3.3.1 Observational SST data

The observational datasets for the tropical Pacific SST analyzed in this chapter are described in Sec. 2.2.1.

3.3.2 Surface wind stress estimates

There are also large uncertainties in reconstructions of the wind stress over the Pacific (Wittenberg, 2004), so we use multiple wind stress estimates in our analysis. Observational datasets used here for the wind stress response analysis are: the COAPS third-generation Florida State University objectively Gridded Pacific monthly mean in-situ flux products

3.3.3 Coupled GCMs

In addition to observational record, we have also examined the ENSO asymmetry in two of the GFDL coupled climate models, CM2.1 and CM2.5. CM2.1 is chosen because it has a very strong nonlinearity in the atmospheric zonal wind response, in additional to the fact that its multicentury control experiment has provided a long record for establishing a robust statistics; CM2.5 is chosen because it has demonstrated an ENSO skewness that is of the opposite sign.

1. GFDL CM2.1

CM2.1 is a Geophysical Fluid Dynamics Laboratory (GFDL) global coupled atmosphere-ocean-land-ice GCM. The detailed formulations and the setup of the control experiments are described by Delworth et al. (2006) (and references therein). Wittenberg et al. (2006) describes the behavior of ENSO in this model. The CM2.1 has taken part in the Third and Fifth Coupled Model Intercomparison Project (CMIP3 and CMIP5) and the Fourth Assessment of the Intergovernmental Panel on Climate Change (IPCC). In this chapter, we use the monthly mean output of the pre-industrial control experiment integrated for 4000 years with fixed 1860 estimates of solar irradiance, land cover, and atmospheric composition. The long run provides more than
300 El Niño and 300 La Niña events, and thus allows statistically significant analysis of the behavior of simulated ENSO. The description of the interdecadal variability of ENSO for the first 2200-years of this experiment is described in Wittenberg (2009).

2. GFDL CM2.5

CM2.5 is a newer, higher resolution (atmosphere/land horizontal resolution is 0.5 degree instead of 2 degree; ocean/sea ice resolution is about 0.25 degree instead of 1 degree), global coupled GCM based on CM2.1. The two models are initialized and forced in a similar fashion. The resolutions of the atmosphere and ocean components in CM2.5 are increased. A smaller viscosity is used in CM2.5. Parametrized eddy mixing is excluded in the CM2.5 ocean, while it is included in CM2.1. Further details on CM2.5 and comparisons with CM2.1 are documented in Delworth et al. (2012). The data used in this study is based on a 260-year control experiment using fixed 1990 estimates of solar irradiance, land cover and atmospheric composition. 37 El Niño and 34 La Niña events are identified in this experiment.

3. Comparison of the simulated ENSO in CM2.5 and CM2.1 with observations

Delworth et al. (2012) describe how the simulated ENSO in CM2.5 compares to CM2.1 and observations. More detailed descriptions of the CM2.1 ENSO behavior can be found in Wittenberg et al. (2006). Here we summarize some of their results.

ENSO amplitude in CM2.5 is weaker and is closer to observations, while CM2.1 tends to simulate ENSO events that are too strong. While both models have equatorial Pacific SST anomalies that extend too far to the west, this bias is reduced in CM2.5. Both models have problems simulating the seasonal phase locking of ENSO. The CM2.1 ENSO shows almost no seasonal phase locking, except that the Niño-3.4 index has a slight tendency to peak between October and February and strong events tend to lock better to the seasonal cycle. CM2.5 Niño-3.4 index has better phase locking compared to CM2.1, but is still weaker and later than observations by about a month.
At interannual time scales, the spectrum of tropical Pacific SSTs in CM2.5 is too concentrated at about 2.5 years. CM2.1 shows a broader and more realistic spectrum, but is stronger than the observations at interannual time scales. Accordingly, the ENSO in CM2.5 is noticeably more regular than CM2.1 and the observed. However, the lengths of observational records are short, so the spectra in this frequency band are uncertain (Wittenberg 2009; Vecchi and Wittenberg 2010).

3.4 Nonlinear zonal surface wind response to SST anomalies

Various observational datasets of Pacific surface wind stress support the hypothesis that during ENSO, the wind stress response to the SST anomalies is weaker in the cold phase than in the warm phase. Fig. 3.1 shows regression coefficients of zonal wind stress anomalies onto the Niño-3.4 SSTA index (area average of SST anomalies at 5° S - 5° N, 170° W - 120° W) during warm and cold conditions, for the FSU observational wind product. The asymmetry in the sensitivity is also evident in other estimates of wind stress. Fig. 3.2 shows scatter plots of the zonal wind stress anomalies averaged over a 40° longitude by 10° latitude region where the regression coefficients are largest versus the observed Niño-3.4 SSTA index, from 2 months before an event peak to 2 months after the peak. The averaging area is also shifted zonally according to where the regression coefficients are the largest for a particular ENSO phase. It is clear that wind stress responds more sensitively to sea surface temperature anomalies during warm conditions.

3.5 The conceptual ENSO model

Following the delayed-oscillator model proposed by Battisti and Hirst (1989) (hereafter BH1989), which is closely related to the models studied by Suarez and Schopf (1988) and
Figure 3.1: Regression coefficient of FSU zonal wind stress anomalies onto the HadISST Niño-3.4 index, for Niño-3.4 greater than 0.5K (top) and less than -0.5K (bottom). Regions with confidence level exceeding 60% are hatched.
Figure 3.2: Regression coefficient of the area averaged zonal wind stress anomalies onto the Niño-3.4 index, for Niño-3.4 greater than 0.5K (top) or less than -0.5K (bottom). The HadISST Niño-3.4 index is used for the FSU and ERA-40 regression analysis. Reanalysis wind stress anomalies are regressed onto the reanalysis Niño–3.4 indices, for MERRA and NCEP-1 respectively. Model wind stress anomalies are regressed onto the model Niño–3.4 index. Area averages of the wind stress are computed within the 40-degree longitude box spanning from 5°S to 5°N where the regression coefficient is the largest across the equatorial Pacific domain.
Zebiak and Cane (1987), we model ENSO as arriving from two essential drivers. First, the Bjerknes positive feedback that leads to instability; second, a delayed negative feedback that results in oscillations. We thereby use a conceptual model of ENSO based on the BH1989 model:

$$\frac{\partial T}{\partial t} = -bT + c'\tau^x (t - t_1) - d'\tau^x (t - t_2) - \epsilon T^3$$  (3.1)

where $T$ is the Niño–3.4 SST anomaly. $\tau^x$ is the wind stress anomaly at the central equatorial Pacific near the date line. $t_1$ is the time required for wind stress response to positively feedback to surface temperature $T$. $t_2$ is the time required for the negative feedback to enact. $t_1$ is smaller than $t_2$. $b$, $c'$ and $d'$ are positive scalar parameters. $\epsilon$ is non-zero when the system is unstable otherwise. The current settings for $t_1$ and $t_2$ are 1 and 6 months, which are roughly the time required for the first/second baroclinic Kelvin wave to propagate eastward from the date line to the American coasts and the time required for Rossby waves to propagate westward, and reflect back as Kelvin waves to the eastern Pacific (Harrison and Giese 1988; Harrison and Vecchi 1999). The qualitative conclusion is unchanged if different values of $t_1$ and $t_2$ are used as long as $t_2 > t_1$. If $t_1 = 0$, one recovers the BH1989 formulation.

The first term on the right-hand side of Eq. 3.1 is a qualitative representation of local dampings of $T$ due to air-sea fluxes, the mean zonal advection of the anomalous zonal temperature gradient and the mean vertical advection of the anomalous temperature gradient that depends on $T$. Guided by BH1989 and regression analysis on these processes at the eastern Pacific, the value of $b$ is kept fixed at 0.24/mon throughout the entire study.

The second and the third terms are the positive and the delayed-negative feedbacks. Each of these two terms incorporates the anomalous zonal advection of the mean zonal temperature gradient, (part of the) mean vertical advection of the anomalous vertical temperature gradient and the anomalous vertical advection of the mean vertical temperature gradient.

By construction, Eq. 3.1 gives a symmetric oscillator in which warm and cold maxima have equal persistence, frequencies and amplitudes. To break the symmetry, we write $\tau^x =$
$\tau^x(T)$ such that the wind stress anomalies respond more sensitively to warm SST anomalies than to cold SST anomalies. For simplicity, we write $\tau^x$ as a piecewise linear function of $T$, i.e.:

$$\tau^x = \gamma (T + r|T|)$$  \hspace{1cm} (3.2)

where $\gamma$ (unit: Pa/K) and $r$ (nondimensional) are both scalar parameters. For $r$ positive and less than 1, wind stress anomalies are stronger for the same degree of positive $T$ than negative $T$.

From the regression analysis of wind stress response to SST anomalies (Fig. 3.1), we can estimate $r$ from the difference in the regression slopes:

$$r = \frac{s_w - s_c}{s_w + s_c}$$  \hspace{1cm} (3.3)

where $s_w$, $s_c$ are the slopes for warm and cold events respectively.

Table 3.1 summarizes the value of $r$ estimated from different datasets. Most datasets produce an $r$ of about 20% with the exception of NCEP–1. This agrees with the suggestion made by Wittenberg (2004) that FSU is recommended over NCEP–1 for extended studies of ENSO since the former dataset agrees better with other observations and updated analysis. Why the NCEP–1 does not show the nonlinear relationship between the zonal wind stress and SST during ENSO, as is seen in other datasets, is unclear.

Table 3.1: Values of $r$ estimated from linear regression analysis between wind stress anomalies and Niño-3.4 SST anomaly index. The column shows the data sources for the Niño-3.4 SST anomaly index used in regressions. The row shows the data sources for the zonal wind stress anomalies.

<table>
<thead>
<tr>
<th>$\tau_x$ anomaly dataset</th>
<th>ERA-40</th>
<th>ERA-Interim</th>
<th>FSU</th>
<th>MERRA</th>
<th>NCEP</th>
</tr>
</thead>
<tbody>
<tr>
<td>HadISST</td>
<td>0.21</td>
<td>0.12</td>
<td>0.21</td>
<td>0.19</td>
<td>-0.09</td>
</tr>
<tr>
<td>NCEP</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.00</td>
</tr>
<tr>
<td>MERRA</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.24</td>
<td>-</td>
</tr>
<tr>
<td>ERA-Interim</td>
<td>-</td>
<td>0.23</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>ERA40</td>
<td>0.24</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
In addition to the asymmetry in the intensity of the wind response, it is likely that the zonal shift in the wind stress patterns (Fig 3.1) between El Niño and La Niña may also be an important feature of ENSO (Kang and Kug, 2002). However, we forgo investigation of pattern-change effects in the present study, in order to focus more intensely on the effects of the wind stress strength anomaly.

Further regression analysis of the wind stress response shows that CM2.1 has a large estimated value of $r$ about 46%, much higher than the observed. Conversely, CM2.5 has a smaller value of $r (= 15\%)$.

As in BH1989, there are two key regions in the parameter space, one being a stable region in which the oscillator is damped, another being an unstable region in which small perturbations in the oscillator grow indefinitely. The unstable regime can be further divided into the an oscillatory and a non-oscillatory regime. To sustain an oscillation for the stable region, a stochastic wind forcing is superimposed on $\tau^x$. The stochastic forcing has an amplitude that is normally distributed with mean zero and a standard deviation $\sigma$ (unit: Pa), and has a decorrelation time of 0.2 months. For the unstable region, no stochastic forcing is added, but $\epsilon$ in Eq. 3.1 would be non-zero to stabilize the oscillation (BH1989). The stability characteristics across the parameter space are shown in Fig. 3.3. A few examples of the parameter regimes 1 and 2 are shown in Fig. 3.4. Region 1 is the linearly stable, damped region with $\epsilon = 0$. Region 2 is the linearly unstable region but is nonlinearly stable using $\epsilon > 0$. Region 3 is unstable when $\epsilon = 0$; with $\epsilon > 0$, the oscillation dies quickly and converges to a constant non-zero value, which is far from the observed behavior. Regime 3 is not considered in the rest of this study.

With stochastic forcing, Eq. 3.2 becomes

$$\tau^x = \gamma (T + r |T|) + N(t)$$

(3.4)
Figure 3.3: Stability characteristics of the conceptual model in the $c$-$d$ parameter space, with $b = 0.24$/mon and $r = 0$ (top left), $r = 20\%$ (top right), $r = 60\%$ (bottom), Region 1: the system is linearly stable and sustained by normally distributed stochastic forcing ($\sigma > 0$, $\epsilon = 0$). Region 2: the system is linearly unstable but is limited by additional damping ($\epsilon > 0$); there is no stochastic forcing ($\sigma = 0$). Region 3: unstable, non-oscillatory and is not considered in the current study.
Figure 3.4: Sample time series of temperature anomalies. Locations in the parameter space are shown in Fig. 3.7. (a) is an example of self-sustained oscillations free of stochastic forcings. (b) and (c) are examples of stochastically driven oscillations in a stable system.
where $N$ is Gaussian white noise with zero mean and standard deviation $\sigma$. Eq. 3.1 can be written more compactly as

$$\frac{\partial T}{\partial t} = -bT + c [T(t - t_1) + r |T(t - t_1)|] - d [T(t - t_2) + r |T(t - t_2)|]$$

$$+ c' N(t - t_1) - d' N(t - t_2) - \epsilon T^3$$

(3.5)

where $c = \gamma c'$ and $d = \gamma d'$ now have units of 1/month. $\sigma$ is non-zero only in region 1 unless otherwise specified. $\epsilon$ ($\epsilon > 0$) is non-zero only in regions 2 and 3. The values of $\sigma$ and $\epsilon$ are tuned so that the simulated $T$ has a standard deviation of roughly 0.8K, in order to be compared with the observations. The values of $\sigma$ and $\epsilon$ do not alter qualitative conclusions of this paper regarding the asymmetry of the simulated ENSO.

Since the stochastic forcing is independent of $T$ and the additional damping is an odd function of $T$, neither of these two functions should introduce asymmetries. Any asymmetry in this model will be attributable entirely to $\tau_x$ as a piecewise function of $T$. This permits a focused look at the impacts of this particular nonlinearity, as a foundation for future inclusion of other nonlinearities.

### 3.6 Results

We have analyzed results using different values of $r$ ($r > 0$). Table 3.2 summarizes the asymmetries that the conceptual model is capable of producing at $r = 20\%$ and $r = 40\%$. Since more points in the c-d parameter space (i.e. fixing $b$) would show significant asymmetries with larger values of $r$. Figures in this section present results using $r = 60\%$ for illustrative purposes. We have also explored other intermediate values of $r$ and showed some results using $r = 20\%$ and $r = 40\%$. All the qualitative results hold true for other positive values of $r$. 

34
Table 3.2: Parameters that produce the best simulations of observed, CM2.1 and CM2.5 asymmetry statistics. \( b \) is fixed at 0.24/month. \( r \) are also fixed at values based on the zonal wind stress analysis. Std = Standard deviation of the temperature anomaly (in Kelvin); Skewness= Skewness of the temperature anomaly; LenDiff = Termination time of cold events minus that of warm events (in months); Pdiff = Probability of warm-to-cold transitions minus that of cold-to-warm transitions. The row(s) below “Best Fit” correspond to the asymmetry statistics derived from the Niño-3.4 SSTA index. Parenthesized values show statistics computed from the first and second halves of the Niño-3.4 SSTA index time series.

<table>
<thead>
<tr>
<th>Observations</th>
<th>( r )</th>
<th>Std</th>
<th>Skewness</th>
<th>LenDiff</th>
<th>Pdiff</th>
<th>( b )</th>
<th>( c )</th>
<th>( d )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Best Fit</td>
<td>0.2</td>
<td>0.7</td>
<td>0.26</td>
<td>0.52</td>
<td>0.43</td>
<td>0.24</td>
<td>0.37</td>
<td>0.24</td>
</tr>
<tr>
<td>HadISST</td>
<td></td>
<td>(0.68,0.75)</td>
<td>(0.26,0.43)</td>
<td>(-0.4,2.9)</td>
<td>(0.15,0.2)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERSST</td>
<td></td>
<td>(0.72,0.79)</td>
<td>(0.35,0.38)</td>
<td>(-1.1,4.0)</td>
<td>(0.11,-0.1,0.3)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Niño3.4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Best Fit</td>
<td>0.4</td>
<td>1.0</td>
<td>0.28</td>
<td>1.9</td>
<td>0.6</td>
<td>0.24</td>
<td>0.36</td>
<td>0.25</td>
</tr>
<tr>
<td>CM2.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Niño3.4</td>
<td></td>
<td>1.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Best Fit</td>
<td>0.2</td>
<td>1.1</td>
<td>-0.13</td>
<td>0.4</td>
<td>0.05</td>
<td>0.24</td>
<td>0.28</td>
<td>0.31</td>
</tr>
<tr>
<td>CM2.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Niño3.4</td>
<td></td>
<td>1.1</td>
<td>(-0.16,-0.06)</td>
<td>(2.2,2.8)</td>
<td>(0.11,0.08,0.12)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
3.6.1 Asymmetry in amplitude

The skewness can be positive or negative depending on the relative strength of the positive and negative feedback (Fig. 3.5), i.e. the ratio of $c$ and $d$. If $c/d$ is large, extreme SST anomalies depend more on the instability brought by the positive feedback, i.e. had the damping term been smaller, the system would be non-oscillatory and grow to infinity due to the strong positive feedback. In this case, positive feedback is enhanced with a larger coupling efficiency during warm events. Therefore, warm events are able to grow to larger amplitudes while cold events become relatively weak, resulting in a positive skewness. The magnitude of the skewness also increases with increasing values of $r$.

Figure 3.5: Skewness of the simulated SST anomalies for the conceptual model with $r = 60\%$
Instead, if $d/c$ is large, extreme SST anomalies depend more on the strong overshooting of the preceding events of the opposite sign, i.e. the system would be oscillatory unstable if the damping term was not strong enough. Therefore cold events can grow to larger amplitudes due to the stronger delayed cooling of the preceding warm events, while warm event peaks cannot grow as much since the delayed warming due to the preceding cold events is diminished. In short, if the coupling efficiency is larger during warm events, skewness becomes positive in the parameter region where positive feedback strength is large, or negative where negative feedback strength is large. Notice that the cutoff does not lie along $c = d$ because $b$ is non-zero.

3.6.2 Asymmetry in duration

As $r$ increases, cold events terminate at a later time than warm events do. This difference in termination times resembles the behavior found in the observations and GCMs. Fig. 3.6 shows how the distributions of event termination time change with the value of $r$. The effect of $r > 0$ on the termination time across the parameter space is shown in Fig. 3.7.

Since the delayed negative feedback is strengthened for warm events, warm events tend to terminate faster than cold events do. In addition, as a cold event decays more slowly, the temperature anomaly that precedes the eventual turnaround of the cold event is not as large as it would have been had the event decayed more rapidly. Therefore, the slower termination of cold events weakens the delayed warming and makes the termination even slower.

In addition, part of the longer termination time for cold events can be explained by the fact that the time mean state of the system is warmer than the equilibrium state when the temperature anomaly is strongly positively skewed. Taking the warmer time mean state as the reference neutral state, as is done with the observational datasets, inevitably increases the termination time of cold events. Nevertheless, following the contour of zero skewness in Fig. 3.5, it is clear in Fig. 3.7 that cold events tend to last longer than warm events in the conceptual model even when there is little amplitude asymmetry.
Figure 3.6: Empirical cumulative distribution of event termination time for the conceptual model with values of $r = 0, 40\%, 60\%$ for $b = 0.24/\text{mon}$, $c = 0.33/\text{mon}$ and $d = 0.26/\text{mon}$ (region 1)
Figure 3.7: Mean termination time (in month) for cold events minus that for warm events in the conceptual model, with $r = 60\%$ and $b = 0.24/\text{mon}$. The thick lines separate regions of different stability as in Fig. 3.3. Grey line is the zero skewness contour from Fig. 3.5. Star markers refer to sample temperature anomaly time series in Fig. 3.4.
If stochastic forcing is also added to self-sustained oscillations in region 2 (Fig. 3.8), the spread of the termination time distribution for cold events increases more than that for warm events. When the stochastic forcing intensity is moderate, high percentiles (e.g. 95-th) of the cold event termination time extend more to longer durations than those of the warm events do. As stochastic forcing continues to amplify, the entire distribution of the termination time moves to shorter time scales because the signal begins to be dominated by stochastic forcing which has higher frequencies than the ENSO. This result clearly illustrates the susceptibility of cold events to external forcing.

![Figure 3.8: Termination time for (a) warm and (b) cold events averaged across region 2, as a function of stochastic forcing amplitude with $r = 0.6$. Solid line represents the mean. Dashed lines represent the 95-th and 5-th percentiles of the termination time.](image)
3.6.3 Asymmetry in transition

The conceptual model also shows a higher tendency for warm-to-cold transitions than cold-to-warm transitions with \( r > 0 \). As shown in Fig. 3.9, the probability of warm-to-cold transitions minus that of cold-to-warm transitions are positive everywhere in the stable and stochastically driven region (region 1). In the region 2, the oscillation is self-sustained and is very regular. The positive difference in the transition probabilities in region 2, as shown in Fig. 3.9, is due to the fact that some of the warm events peak later than 12 months after the preceding cold event termination and do not fulfill the transition criterion (see Sec. 2.3.3).

If stochastic forcing is added to the region 2, the probabilities of warm-to-warm and cold-to-cold transitions increase, and the latter increases more than the former, albeit to a slight extent (Fig. 3.10).

With the delayed negative feedback being stronger following warm events, and weaker following cold events, warm events are more likely to be plunge into cold events than vice versa – since the cooling following warm events is strong enough to overshoot, and is more resilient to disruptive stochastic forcing. In contrast, the weakened delayed warming during the termination of a cold event lowers the probability of a cold-to-warm transition. This explains why a stable, stochastically driven parameter region is necessary for the asymmetry in sequencing to be revealed in this conceptual model.

3.7 Chapter summary and discussion

The central equatorial Pacific wind stress anomalies exhibit an asymmetric response to sea surface temperature anomalies in models and observations. Using the well-known delayed-oscillator conceptual model, we parameterize the impact of the zonal wind stress asymmetric response, and we demonstrate that this can lead to the above-mentioned asymmetries in a consistent way. The duration asymmetry is ubiquitous across the parameter space we have explored. The sequencing asymmetry can be obtained as long as there is stochastic external
Figure 3.9: Conditional probability of warm-to-cold transition minus that of cold-to-warm transitions, for $r = 60\%$, across the $c$-$d$ parameter space.
Figure 3.10: Changes in transition probabilities with increasing stochastic forcing intensity and fixed $r = 60\%$ for region 2 (self-sustained oscillations). Results are averaged within the region that have $\text{Probability(Warm-to-cold)} = \text{Probability(Cold-to-warm)} = 1$ when stochastic forcing is absent.
forcing. The amplitude asymmetry has the same sign as that observed when the positive feedback is strong compared to the delayed negative feedback.

The asymmetries due to the additional nonlinearity to the ENSO conceptual model can be understood as follows: warm events are able to grow to larger amplitude with the strengthened positive feedback. When they decay, the strengthened delayed negative feedback causes warm events to terminate faster and increases the chance of a following cold event. The initial growth of the cold events comes from the preceding warm event but the cooling subsides soon after onset. If the overshooting is not too strong, the weakened positive feedback of cold events causes the cold events to mature at weaker amplitude. When cold events terminate, the delayed negative feedback is weaker. The slower neutralization and the warmer long-term mean state are responsible for the longer durations of the cold events. Cold events are also more prone to be disrupted by external forcing and are less likely to be followed by a warm event. As a result, when there is a warm event, the predictability of a following cold event is higher. What follows a cold event is more uncertain. This result is consistent with Dommeng et al. (2013) that El Niño is mostly triggered by wind, less predictable, while La Niña is more predictable.

The conceptual model simplifies the system into a few feedback terms and provides a potential guide for investigations when a climate model simulates ENSO asymmetries that are too strong or too weak. Fig. 3.11 shows the parameter space regions where the conceptual model resembles the asymmetry statistics of the observations, CM2.1 and CM2.5. Table 3.2 summarizes the best solutions and the corresponding asymmetries. We may conclude that the best solutions for the observations and CM2.1 are very close to each other. The fact that CM2.1 shows a stronger ENSO asymmetry may be explained by the larger $r$ diagnosed for CM2.1. The negative skewness in CM2.5, on the contrary, can be explained by the stronger delayed negative feedback parameter relative to that of the positive feedback. We speculate that the meridional extent of the wind stress anomaly may be the cause. Capotondi et al. (2006) show that the CMIP3 coupled GCMs exhibited a pervasive bias in which their patterns
of wind stress anomalies were too far west and too narrow meridionally. They argued that by amplifying the delayed negative feedback, this shortened the simulated ENSO period. The coupled models’ narrow and westward-shifted wind stress response patterns could also help explain their tendency toward overly-symmetric ENSO evolution. CM2.5, for example, has a particularly narrow wind stress anomaly pattern, a strong diagnosed delayed negative feedback, and highly symmetric ENSO behavior.

Figure 3.11: Regions in the parameter space where the skewness (magenta, solid lines), warm-to-cold transition probability minus cold-to-warm transition probability (cyan, dotted line) and differences in termination time (yellow, dashed lines) are closest to the required values given by observations (r=20%), CM2.1 (r=40%) and CM2.5 (r=20%); see Table 3.2. Lighter regions correspond to errors less than 50% of the targeted statistics. Darker regions correspond to errors less than 15%.
In the conceptual model, the difference in the wind stress response during warm and cold conditions also leads to a time mean state that is warmer than the equilibrium state. Since the equilibrium state of nature is unknown, computing anomalies from the climatology has been a conventional approach in analyzing ENSO strength and duration in observations and models. The time mean state, however, cannot be acquired a priori. Therefore, for applications in which the mean climate state is a necessary reference for analysis (e.g. in defining the onset or termination of an event), we suggest that the impact of changes in variability on the mean state be considered.

We also note that the seasonal cycle is not formally included in the current conceptual model. However, the nonlinear wind stress response to SST anomaly is diagnosed from observations and coupled climate models control experiments in which the seasonal cycle is included. Therefore the current results have not excluded, entirely, the contributions of the seasonal cycle on the asymmetry of ENSO.

The coupling efficiency dependence on the polarity of ENSO could have several causes. For example, observations indicate that Westerly Wind Burst (WWB) occurrence depends on the state of ENSO (Harrison and Vecchi 1997; Vecchi and Harrison 2000). The state dependence of WWBs, their skewness, and their more frequent/strong occurrence at the onset of warm events, would potentially be one of the processes that leads to a positive $r$, for example, through the low frequency component of the WWBs. GCM experiments also indicate that the frequency and intensity of WWB can be promoted during El Niño due to shifted location of the warmest water (Lengaigne et al., 2003). Eisenman et al. (2005) suggest that this state dependence may be equivalent to an increase in the air-sea coupling strength during El Niño events and Gebbie et al. (2007) show that adding a state-dependent WWB parameterization to a hybrid coupled GCM increases the instability, irregularity, and asymmetry of its ENSO simulation.

The observational data for the wind stress responses suggests $r = 20\%$ for the conceptual model. While the model at $r = 20\%$ is capable of producing realistic asymmetries in am-
plitude and transition probability, the duration asymmetry is weaker than observed. This suggests that other sources of nonlinearities, such as the meridional wind shift during El Niño (i.e. relative persistence of the La Niña easterly wind anomalies) would be important in the duration asymmetry as well.

The current study raises a number of questions: why is the wind stress response sensitivity stronger during warm events? Nonlinearities in atmospheric convection are a likely source. How important are atmospheric nonlinearities compared to oceanic nonlinearities? What are the roles of seasonality, ocean adjustment times and the spatio-temporal patterns of wind stress coupling in the conceptual framework described here? How will future climate changes affect ENSO asymmetries?

In the next chapter, we will tackle the question why the wind stress response is stronger during warm events than during cold events. The other questions are left for the future.
Chapter 4

Nonlinear precipitation response in relation to the surface zonal wind response

4.1 Introduction

In the previous chapter, the nonlinear zonal wind stress response to SST anomalies is taken as given. In this chapter, we seek to explain why the zonal wind response should be stronger during El Niño, weaker during La Niña. The focus is shifted from zonal wind stress anomalies to zonal wind anomalies, as the distinction between the two is inconsequential regarding the existence of the nonlinearity. The work presented in this chapter is also presented in Choi et al. (2015).

There are two main sources for the pressure gradient anomalies that support the surface wind anomalies in the Tropical Pacific: (1) elevated heating by deep convection (Gill, 1980) and (2) changes in the boundary layer driven by surface temperature (Lindzen and Nigam, 1987). Chiang et al. (2001) showed that the zonal wind anomalies are largely explained by the elevated heating anomalies, which are associated with the precipitation anomalies.

On
the other hand, the eastward (westward) shift of the zonal wind anomalies during El Niño (La Niña) are also understood as being caused by the equatorial rainfall anomalies on an asymmetric climatological SST: the SST warming in the eastern equatorial Pacific causes equatorial rainfall to occur over the climatological cold tongue, whereas the SST cooling over the eastern equatorial Pacific displaces the rainfall onto the climatological warm pool (Hoerling et al., 1997). We hypothesize that the nonlinear precipitation response to the SST anomalies during ENSO is a crucial element in understanding the nonlinear zonal wind response. In this study we will examine if the nonlinear precipitation response to the SST anomalies is sufficient to explain the nonlinear zonal wind response.

While the zonal shift of equatorial convective regions during El Niño and La Niña is associated with the zonal movement of the upward branch of the Walker circulation, it is not obvious why the zonal wind anomaly during El Niño would necessarily be stronger than that during La Niña, if indeed the nonlinearity in the zonal wind response comes mainly from the nonlinearity in the precipitation anomalies. In addition, the precipitation response to ENSO is not just about the zonal movement of convection; there is also an equatorward (poleward) movement of the Intertropical Convergence Zone (ITCZ) and South Pacific Convergence Zone (SPCZ) during El Niño (La Niña) (Trenberth 1976; Folland et al. 2002; Chung et al. 2013; Chung and Power 2014). Trenberth (1976) also noted the possible coupling between the SPCZ movement and the Walker circulation during ENSO. If one models the ITCZ and SPCZ as two gaussian-shape, off-equatorial rain bands, an equatorward movement would lead to stronger precipitation anomalies over the equator than would a poleward movement. This study analyzes how much of the equatorial precipitation anomalies can be associated with this meridional movement and examines if the precipitation anomalies associated with the meridional movement of the ITCZ and SPCZ could be linked to the nonlinear zonal wind response to ENSO.

This Chapter is structured as follows. Section 4.2 describes the data being used and the methods of the analysis including how the precipitation anomalies are decomposed into
zonal and meridional redistribution of the climatological precipitation. Section 4.3 shows
the components of the precipitation anomalies, the nonlinear zonal wind response to each
of these precipitation components, as well as the effect of the biases in the climatological
precipitation and the total precipitation response pattern. Finally, we summarize and discuss
our results in Section 4.4.

4.2 Methods

The nonlinear precipitation and equatorial zonal wind responses to ENSO are examined
using a reanalysis of observations and coupled global climate model control experiments. A
procedure to decompose the precipitation response into zonal, meridional redistribution and
intensification components is designed and applied to models and observational estimates.
After separating the precipitation anomalies into these three components, their individual
impacts on the zonal wind response are explored by prescribing each as a heating anomaly
in a shallow water model. In this section, we describe the data being used, how the ENSO
composites and precipitation decomposition are computed, the shallow water model and how
the nonlinearity of wind response is quantified.

4.2.1 Data

In this study we focused on three physical quantities pertaining to ENSO: sea surface tem-
perature in the Tropical Pacific (20S-20N, 100E-100W), its area average within the Niño3.4
region (5S-5N, 170W-120W), surface zonal wind on the equator (2S-2N, 100E-100W), and
the precipitation in the Tropical Pacific basin (20S-20N,100E-100W). Observational reanaly-
sis datasets are appropriate for this study as a consistent reconstruction of the three physical
fields is required. Among the many reanalysis datasets, we used the Modern Era Retrospec-
tive Analysis for Research and Applications (MERRA; Rienecker et al. 2011) as a reference
for the observations. We also use the Global Precipitation Climatology Project Version 2.2
(GPCP; Adler et al. 2003) dataset for estimating the uncertainty in MERRA precipitation product. Other reanalysis datasets may be included in this study but the differences among them are much smaller than those among the coupled models.

For the model data we used the pre-industrial control experiments in the Couple Model Inter-comparison Project Phase 5 (CMIP5; Taylor et al. 2012). We have also utilized the free-run and flux-adjusted experiments of the Geophysical Fluid Dynamics Laboratory (GFDL) CM2.5 forecast-oriented low ocean resolution version (CM2.5-FLOR; Vecchi et al. 2014; Jia et al. 2014) for understanding the impact of the climatological precipitation on the zonal wind response. The CM2.5-FLOR model is built by coupling the atmosphere and land components of the GFDL Coupled Model version 2.5 (CM2.5; Delworth et al. 2012) to the ocean component of the low-resolution GFDL Coupled Model version 2.1 (Delworth et al., 2006). The atmosphere and land components have a horizontal resolution of about 50km, while the ocean component has a horizontal resolution of 10-25km.

Since the ENSO amplitude and the seasonal locking performance vary among models, we only include in our composite analysis the ENSO events whose Nino-3.4 SST anomalies peak between 1.5K and 2.5K, from November to February. Among the models that have provided the required fields, two of them do not have both El Niño and La Niña simulated at the magnitude required, and are therefore excluded from the composite analysis (Table 4.1).

4.2.2 Shallow water model on a sphere

The shallow water model has been used in many different contexts of meteorology and oceanography. With the beta-plane approximation, it can be utilized as an anomaly model for understanding atmospheric and oceanic dynamics in the tropical regions (Matsuno, 1966; Gill and Clarke, 1974; Gill, 1980). In this study, we follow the approach of Gill (1980).

The one-and-a-half layer, linear shallow water version of the GFDL spectral atmospheric dynamical core (Balaji, 1998) is used to simulate the surface zonal wind anomalies corre-
Table 4.1: CMIP5 models and modeling groups. Two models are marked excluded from the composite analysis due to the lack of warm events with the required strength and seasonal locking. CM2.5 FLOR models are also included in this table. The right-most column shows the number associated with each model in ascending order of the nonlinear equatorial zonal wind response.

<table>
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sponding to a given field of precipitation anomalies. In this configuration, the atmosphere is modeled by two layers of fluid of different densities. The thicknesses of the layers are assumed to be small compared to the characteristic horizontal scale of the motion, for the hydrostatic balance assumption to hold. The top layer is assumed to be at a fixed height, i.e. a rigid lid approximation. The bottom layer is assumed to be stationary, i.e the bottom pressure vanishes. The momentum equations are the same as in Matsumo (1966) but in spherical coordinates. And following Gill (1980), a heating anomaly term $Q$ is added to the model’s thickness equation:

$$\frac{DH}{Dt} = -H \nabla \cdot u - \epsilon H + Q$$

where $H$ is the layer thickness, $u$ is the horizontal velocity in the layer, $\epsilon$ is the damping rate. The intuitive understanding is that a positive heating anomaly would cause the upper layer to thicken, pushes the interface between the two layers downward, leads to a lower pressure and drives wind convergence at the surface. The heating anomaly represents the latent heat anomaly caused by changes in the atmospheric convections. The wind response to a localized heating anomaly in the tropical regions resembles the results in Gill (1980).

This linear anomaly model is sometimes referred to as the "Gill model", and it assumes that latent heating forcings drive low-level flows. This can be compared to the model by Lindzen and Nigam (1987), in which low-level flows are driven by boundary layer pressure gradients due to SST gradients and turbulent mixings. Nevertheless, the two models are formally analogous to each other, as shown by Neelin (1989) that the heating forcing in the thickness equation in the Gill model can be formulated as forcings in the momentum equations similar to those in the Lindzen and Nigam model. In addition, with the use of a more realistic model parameterization, Chiang et al. (2001) found that the elevated thermal heating anomalies are responsible for most of the zonal wind anomalies during El Niño condition, while the surface temperature gradient contributes mostly to the meridional wind response. As our focus here is on the zonal wind response to ENSO, their results justify the Gill model approach in this context.
In this study the shallow-water model is driven by precipitation anomalies and the resulting lower tropospheric/surface zonal wind response is the zonal wind anomalies we are interested in. But there are two more unknown parameters in setting up the shallow water model experiments. First of all, the heating forcings need to be converted from the precipitation anomalies. This is effectively asking for the vertical projection of the atmospheric heating anomalies onto the idealized profile assumed in the Gill model. Different models, including the real world atmospheric heatings, would have a different projection. Therefore there is an unknown scaling factor in the heating anomalies for each model, and the scaling factor could also be different in El Niño and La Niña conditions. As the model is linear, this scaling factor in the heating anomalies would be linearly reflected in the simulated surface wind anomalies. Under the assumption that the vertical projections of the atmospheric deep convections are (nearly) the same for the El Niño and La Niña conditions within one model, the results shown here comparing the relative difference between the wind response to El Niño and La Niña (see Sec. 4.2.4) should not be affected by the unknown scaling factor.

Another unknown parameter is the ratio between the Rayleigh damping (i.e. damping in the momentum equation) and the Newtonian cooling (i.e. damping in the thermodynamics/thickness equation) parameters. The meridional extent of the simulated surface wind anomalies depends on the ratio of these two parameters (Wu et al., 2001). We have checked that our results are insensitive to the ratios of the Rayleigh damping and Newtonian cooling rates ranging from 0.01 to 100.

Since the model is linear, the wind response of the precipitation anomaly components can be added directly to recover the total wind response to the total precipitation anomalies.

### 4.2.3 Decomposing the precipitation anomalies

The total precipitation anomaly is decomposed into 3 components, each of which is attributable to: (1) zonal redistribution of the climatological precipitation; (2) meridional re-
distribution of the climatological precipitation; and (3) intensity change. These components can be added linearly to recover the total precipitation anomaly exactly.

This decomposition is motivated from the observation that during ENSO the total change in the tropical Pacific (20S-20N,100E-100W) mean precipitation is about two orders of magnitude smaller than the anomaly local maxima, indicating most of the anomaly is due to the redistribution of the climatological precipitation. And since the zonal wind response is the primary interest in this study, the zonal and meridional directions are the most relevant choice of axes for the decomposition of precipitation redistribution. Since the atmospheric response occurs fairly quickly relative to the monthly time scale, we assume that the redistribution in the two directions occurs concurrently.

To compute the anomaly corresponding to the zonal redistribution, the total precipitation during ENSO is divided by its zonal mean at each latitude, then multiplied by the zonal mean precipitation in the climatology. In other words, the climatological precipitation is redistributed zonally to recover the zonal profile of the total precipitation. The anomaly $P'_x$ is then calculated by subtracting the climatological precipitation from the normalized total precipitation.

$$P'_x = f_x(P_{total}, P_{clim}) = \overline{P_{clim}}x \overline{P_{total}}x - P_{clim} \quad (4.1)$$

where $P_{total}$ is the total precipitation field and $P_{clim}$ is the climatological precipitation from MERRA or models. The overbar represents taking the mean along a particular axis denoted in the superscript. Similarly, the anomaly $P'_y$ associated with the meridional redistribution of precipitation is computed by normalizing the total precipitation using the meridional mean at different longitude, that is,

$$P'_y = f_y(P_{total}, P_{clim}) = \overline{P_{clim}}y \overline{P_{total}}y - P_{clim} \quad (4.2)$$

Both $\overline{P_{total}}x$ and $\overline{P_{total}}y$ are assumed to be positive definite (i.e. also non-zero).
When only one of the two directional redistributions is computed, the remaining precipitation anomalies not associated with that redistribution are large and also resemble the pattern of the other redistribution direction. This indicates that the redistribution of precipitation is significant in both directions, not just zonal or just meridional. On the other hand, when the zonal and meridional redistribution are performed sequentially, the corresponding anomalies depend on the order of operations. This highlights the fact that the zonal and meridional redistribution interact with each other by changing the mean along the other direction, i.e. the operations do not commute.

However, since we are assuming the redistributions in the two directions occur concurrently, the decomposition should not depend on the relative sequence of the redistribution operations. To address this issue, the zonal and meridional operators (i.e. the $f_x$ and $f_y$ in Eq. 4.1 and Eq. 4.2 respectively) are applied alternately and incrementally, so that at each incremental step a fraction of the diagnosed redistribution anomaly is added to the total precipitation before the normalization on the another axis is applied. This iteration stops when the last anomaly increment is smaller than 1% of the accumulated anomaly. The anomaly increments are then aggregated into the zonal and meridional redistribution anomalies respectively. The algorithm then becomes:
\[ P'_{x,1} = f_x(P_{total}, P_{clim}) \]
\[ P'_{y,1} = f_y(P_{total}, P_{clim} + \frac{1}{2n} P'_{x,1}) \]
\[ P'_{x,2} = f_x(P_{total}, P_{clim} + \frac{1}{2n} P'_{x,1} + \frac{1}{n} P'_{y,1}) \]
\[ P'_{y,2} = f_y(P_{total}, P_{clim} + \frac{1}{2n} P'_{x,1} + \frac{1}{n} P'_{y,1} + \frac{1}{n} P'_{x,2}) \]
\[ \vdots = \vdots \]
\[ P'_{x,i} = f_x(P_{total}, P_{clim} + \frac{1}{2n} P'_{x,1} + \sum_{j=2}^{i-1} \frac{1}{n} P'_{x,j} + \sum_{j=1}^{i-1} \frac{1}{n} P'_{y,j}) \]
\[ P'_{y,i} = f_y(P_{total}, P_{clim} + \frac{1}{2n} P'_{x,1} + \sum_{j=2}^{i} \frac{1}{n} P'_{x,j} + \sum_{j=1}^{i-1} \frac{1}{n} P'_{y,j}) \]

where \( P'_{x,i} (P'_{y,i}) \) is the zonal (meridional) redistribution anomaly computed at the \( i \)-th iteration. The concurrent zonal \( P'_x \) and meridional \( P'_y \) redistribution anomalies are redefined as

\[ P'_{x} = \sum_{i=1}^{k} \frac{1}{n} P'_{x,i} \]  \hspace{1cm} (4.3)
\[ P'_{y} = \sum_{i=1}^{k} \frac{1}{n} P'_{y,i} \]  \hspace{1cm} (4.4)

The iteration stops at the \( k \)-th iteration, when both \( P'_{x,k} \) and \( P'_{y,k} \) are smaller than 1% of \( P'_{x,k-1} \) and \( P'_{y,k-1} \), respectively. The residual component is then \( P_{total} - P_{clim} - P'_{x} - P'_{y} \).

For the datasets used in this study, \( n \) has to be larger than 4 in order for the results to be independent of the relative order of the zonal and meridional redistribution. And the results are insensitive to the choice of \( n \) once \( n \) is larger than 4. In this study, we used \( n = 50 \). And \( n \) and \( k \) are not necessarily the same: the former is chosen such that the decomposition is independent of the order of the zonal and meridional redistributions; the latter is not prescribed but simply dependent on the level of convergence. An alternative method that does not require iterations is presented in Appendix A. The results presented
in this manuscript applied the iterative method, but the alternative method would give the same answers.

The advantage of this decomposition is that \( P'_x (P'_y) \) has zero zonal (meridional) mean and zero area mean over the tropical Pacific. The solution of the decomposition is unique due to the assumption that there is no preferred order of the zonal and meridional redistributions, i.e. the two redistributions occur simultaneously. A proof of the uniqueness is presented in Appendix A.

When investigating the indirect role of the meridional redistribution of precipitation on the nonlinear wind response, the meridional redistribution anomalies are discarded and the resulting zonal redistribution precipitation anomaly is termed the "nonconcurrent zonal redistribution anomaly". In other words,

\[
\text{nonconcurrent } P'_x = f_x (P_{\text{total}}, P_{\text{clim}})
\]  

(4.5)

as defined in Eq. 4.1, which does not involve iterations.

### 4.2.4 Defining nonlinearity

The nonlinearity in the zonal wind response is quantified by the relative difference in the response between El Niño and La Niña, as in (Choi et al., 2013):

\[
\text{nonlinearity} = \frac{\text{El Niño} + \text{La Niña}}{\text{El Niño} - \text{La Niña}}
\]  

(4.6)

When the nonlinearity of equatorial Pacific zonal wind response is sought after, the magnitude of the response refers to the maximum anomaly within 2S-2N, 100E-100W, after a 40-degree-longitude running mean. We use the maximum anomaly in order to account for the fact that the zonal wind anomaly is shifted eastward (westward) during El Niño (La Niña).
4.3 Results

4.3.1 Nonlinear zonal wind response in models and observations

The nonlinearity in the zonal wind response to ENSO in the observations and the CMIP5 models are shown in Fig. 4.1. MERRA shows a stronger equatorial zonal wind response to El Niño than La Niña. The CMIP5 models generally agree with this positive nonlinearity (Eq. 4.6). While models’ response to La Niña tends to cluster around the observed, El Niño zonal wind response tends to be underestimated so that the overall nonlinearity is weaker than observed. This agrees with Zhang and Sun (2014), who found a common underestimate of the ENSO asymmetry and a weaker precipitation response to El Niño in the eastern equatorial Pacific in the CMIP5 models. Here we refine their findings by keeping the amplitudes of the El Niño and La Niña SST anomalies fixed across observation and model composites, therefore eliminating the possible bias due to an increasing nonlinearity with the amplitude of ENSO events.

We test the hypothesis that the nonlinearity in the precipitation anomalies determines the nonlinearity in the zonal wind response. The models’ precipitation anomalies are used to drive the shallow water model as heating anomalies. It is found that the spatial structures (Fig. 4.2) and the inter-model spread in the strength of the coupled models’ zonal wind response (Fig. 4.3) are fairly similar to those simulated in the shallow water model. Furthermore, the coupled models’ nonlinear wind response is also reproduced with a correlation coefficient of about 0.7 (confidence level above 99.9%, Fig. 4.4). As the shallow water model is linear, this result supports the idea that the nonlinearity in the zonal wind response is largely due to the nonlinearity in the precipitation response, although the coupled models generally show less nonlinearity than expected from the linear shallow water response to the observed precipitation anomalies.

Outliers in Fig. 4.4 may be due to the fact that the zonal wind response in these few coupled models are not represented well by the shallow water model for both or either of the
Figure 4.1: (a) Normalized frequency distribution of the maximum composite zonal wind anomaly at 10 meter height [m/s] (averaged from 2S to 2N, after 40-longitude-degree running mean within 100E-100W) during El Niño (light gray) and La Niña (dark gray) in the CMIP5 models, compared to MERRA. (b) Scatter plot of the maximum zonal wind anomaly during El Niño and La Niña. Contour lines (interval: 0.2) show the nonlinearity using Eq. 4.6. The squared point denotes MERRA.
Spatial correlation between the zonal wind anomalies in the coupled models and in the shallow water models

Figure 4.2: Spatial correlation (within 100E-100W, 20S-20N) between the zonal wind anomalies simulated by the shallow water model and the CMIP5 models. Circles (crosses) denote the correlations for warm (cold) events. Numbers below bars correspond to those in Figs. 4.1 and 4.4.
Figure 4.3: Scatter plot for the equatorial Pacific zonal wind response during ENSO in the coupled models and in the shallow water model with the coupled model precipitation anomalies prescribed as heating (a). The straight line presents the reference for an 1-to-1 mapping. In (b), the La Niña surface zonal wind response in the shallow water model is scaled to match the corresponding coupled model. The same scaling factor is then applied to the surface zonal wind response to El Niño. Such scaling is not applied elsewhere in the paper and does not matter in the nonlinear wind response which is nondimensional (Sec. 4.2.4). See Sec. 4.2.2 for a description on the scaling factor.
Figure 4.4: Coupled models nonlinear wind response to ENSO events compared to the nonlinear wind response in the shallow water model with the corresponding precipitation anomalies prescribed as heating. The straight line presents the reference for a 1-to-1 mapping. Points are sorted according to the nonlinear zonal wind response in the coupled models and so the numbered markers are the same as those in Fig. 4.1.
El Niño and La Niña situations (Fig. 4.2). In addition, the shallow water model experiments that show negative nonlinear wind response for CMCC-CM, HadGEM2-CC and bcc-csm1-1, disagree with the coupled model response. This discrepancy is likely due to the small number of events in the composites and the small nonlinearity in these models, thus a small signal-to-noise ratio. In fact, when the composites were computed for weaker events (absolute Niño3.4 index being 0.5-1.5K, not shown) in these models, the number of events increases significantly and the corresponding nonlinear wind response to the precipitation anomalies becomes positive. As the strength of the nonlinearity increases with the strength of ENSO events (Hoerling et al. 2001; Chung et al. 2013) and most CMIP5 models underestimate the observed nonlinearity, there is a trade-off between the signal-to-noise ratio and the number of events while choosing whether to use weaker events (weaker nonlinearity, more events) or stronger events (stronger nonlinearity, fewer events) for the composites. This is also true for observational datasets.

4.3.2 Nonlinear zonal wind response explained by each precipitation anomaly component

Since the nonlinearity in the zonal wind response is mainly due to the nonlinearity in the precipitation anomalies, we investigate how the precipitation anomalies achieve such a nonlinear zonal wind response and, in particular, the roles of the zonal and meridional redistribution of the precipitation anomalies in causing the nonlinearity. Before diagnosing the zonal wind response to each of these precipitation anomaly components, we analyze their spatial features and quantitative contributions to the total precipitation anomalies.

The meridional redistribution of precipitation is characterized by an equatorward (poleward) movement of the ITCZ/SPCZ during El Niño (La Niña), while the zonal redistribution represents the eastward (westward) shift of precipitation during El Niño (La Niña) (Fig. 4.5). Both components have comparable amplitudes but very different spatial structures, though they are not entirely orthogonal (spatial correlations are about 0.0-0.4). They are also simi-
lar to the leading components diagnosed from the principal component analysis which have strictly zero spatial correlation but nonzero zonal and meridional means (not shown; similar analysis using a satellite dataset can be found in Haddad et al. 2004). The sum of the zonal and meridional redistributions recover almost all of the total precipitation anomalies; the residual precipitation anomalies not associated with these redistributions are about two orders of magnitude smaller (Fig. 4.6) and are therefore neglected for most of the following analysis.

Figure 4.5: (a) November-February precipitation anomaly [mm/day] (left) decomposed into zonal (center) and meridional (right) redistributions for El Niño (top) and La Niña (bottom) in MERRA. The contour interval is 4mm/day. (b) Total precipitation for the climatology (left), during El Niño (center) and La Niña (right) in MERRA. An eastward (westward) and equatorward (poleward) movement of the ITCZ and SPCZ during El Niño (La Niña) is apparent.

The relative contribution of each of these components to the nonlinear wind response was examined by forcing the shallow water model with the corresponding heating anomalies. We found that although the zonal and meridional redistribution anomalies have comparable contribution to the overall precipitation anomalies, the zonal wind response estimated from
Figure 4.6: Regression coefficients (dimensionless) with the total precipitation anomalies over the tropical Pacific (100E-100W,20S-20N), for the zonal redistribution of the climatological precipitation (yellow), the meridional redistribution of the climatological precipitation (green) and the residual (purple). Models are sorted by the zonal redistribution contribution during El Niño.

It is informative to compare the zonal redistribution anomalies with and without concurrent meridional redistribution of precipitation, which show that the meridional redistribution plays an important role of limiting the zonal redistribution anomalies during La Niña (Fig. 4.7). The zonal redistribution anomalies without concurrent meridional redistribution were calculated using Eq. 4.5. This nonconcurrent zonal redistribution anomalies can also be understood as the adjustment of the Walker circulation without any concurrent adjustment of the local Hadley cell. Under the situation when meridional redistribution is absent during La Niña (Fig. 4.7, right), there is more precipitation to be displaced zonally and therefore the zonal redistribution anomalies have a much stronger zonal dipole structure along the equator. Consequently the wind response to La Niña strengthens and the overall nonlinearity of the zonal wind response is reduced when meridional redistribution of precipitation is
Figure 4.7: Precipitation anomaly [mm/day] response (upper panels) to ENSO and the corresponding zonal wind anomalies response to the heating anomalies in the shallow water model (lower panels). Precipitation anomalies are averaged from 15S to 15N while wind anomalies are averaged from 2S to 2N. The left panels correspond to the meridional redistribution precipitation anomaly. The center panels correspond to the zonal redistribution precipitation anomaly. The right panels correspond to the pure zonal redistribution anomalies computed when the meridional redistribution anomalies are absent. Solid lines refer to results for the CMIP5 models and the dashed lines refer to that for the observations. Shading shows the standard deviations among the CMIP5 models.
absent. Fig. 4.8 shows that when the meridional redistribution component is absent, the nonlinearity in the zonal wind response to the zonal redistribution precipitation anomalies reduces significantly (the median reduction of all models is 65%). In other words, the meridional redistribution of precipitation, though not directly driving a large equatorial zonal wind response, indirectly contributes to a significant amount of the nonlinearity of the zonal wind response by limiting the possible zonal redistribution of precipitation during La Niña.

Figure 4.8: The nonlinear wind response in the shallow water model forced by zonal redistribution precipitation anomalies with and without concurrent meridional redistribution anomalies. The straight line presents the reference for an 1-to-1 mapping. Points above this line indicate models whose nonlinear response is enhanced by the concurrent meridional redistribution of climatological precipitation. The numbered markers are the same as those in Fig. 4.1.
4.3.3 Contributions from the biases in the climatological precipitation

In the previous subsection it was shown that the meridional redistribution of precipitation limits the equatorial zonal wind response during La Niña, by exhausting the climatological precipitation on the equator. This suggests that the climatological precipitation may provide a simplifying framework from which to interpret intermodel spread in the nonlinear zonal wind response. In this section we study the extent to which biases in the climatological precipitation can help us understand biases in the zonal wind response nonlinearity in the models.

CM2.5-FLOR Free-run vs flux-adjusted

The impact of climatological biases can be isolated by comparing the GFDL CM2.5-FLOR free run simulation (FLOR) to another simulation where the surface ocean biases are corrected toward observations through flux adjustment (FLOR-FA; Vecchi et al. 2014; Jia et al. 2014). Since the two experiments have the same physics but only differ in their surface climatologies, and climatological precipitation is strongly sensitive to climatological SST, they provide us an opportunity to investigate the influence of climatological precipitation on the nonlinear zonal wind response to ENSO.

Both experiments simulate a Tropical Pacific (20°S-20°N, 100°E-100°W) climatological precipitation (November-February averaged) with spatial correlations above 0.9 relative to MERRA and GPCP (Fig. 4.9). The climatological precipitation over most of the equatorial central and eastern Pacific is drier in FLOR-FA than in FLOR (Fig. 4.10). As a result, FLOR-FA is closer to MERRA and GPCP in terms of the area mean precipitation. On the other hand, the SPCZ in FLOR-FA is more diagonal than that in FLOR. Yet this change in the spatial pattern is comparable to the difference between MERRA and GPCP as MERRA also has a more diagonal SPCZ compared to GPCP.
Figure 4.9: Comparison of the Tropical Pacific climatological precipitation (20S-20N, 100E-100W, ocean-only, November-February averaged) for CMIP5 models, MERRA and GPCP. (a) Taylor diagrams with reference to MERRA. Notice that the numbers associated with GPCP and the models are sorted by their distances from MERRA on the Taylor diagram. (b) Meridional average from 5S to 5N. (c) Zonal average from 120E to 100W. Grey dashed lines show the profiles for each model.
Figure 4.10: Precipitation anomalies [mm/day] averaged from November to February during El Niño (a,d) and La Niña (b,e) for the CM2.5-FLOR (top row) and CM2.5-FLOR-FA (middle row). The right panels show the climatological precipitation for CM2.5-FLOR (c) and CM2.5-FLOR-FA (f). On the bottom row (g,h,i) shows differences [mm/day] between the top and middle rows. Contour intervals are 4 and 2 [mm/day] in (a-f), and (g-i), respectively.
With reference to MERRA, FLOR-FA is more similar in its linear equatorial zonal wind response to El Niño than FLOR, while the errors in the zonal wind response to La Niña in FLOR-FA and FLOR are comparable (Fig. 4.1). The overall nonlinearity of zonal wind response in FLOR-FA is stronger than FLOR, and is also closer to MERRA.

If the climatological precipitation from FLOR-FA is redistributed according to the spatial patterns of the FLOR’s total precipitation during ENSO (i.e. swap the FLOR’s $P_{\text{clim}}$ with that of FLOR-FA’s in Eqs. 4.1-4.4), the resulting equatorial precipitation and the corresponding surface zonal wind anomalies simulated in the shallow water model (Sec. 4.2.2) would be weaker (stronger) during La Niña (El Niño) compared to FLOR (Table 4.2). This is consistent with the previous section, since a drier climatological precipitation further limits the negative precipitation anomalies during La Niña. Consequently the nonlinearity in the zonal wind response is stronger when the climatological precipitation is taken from FLOR-FA.

Table 4.2: Magnitudes of the maximum zonal wind anomalies in the shallow water model for different precipitation anomalies either from a single model or by redistributing another model’s climatological precipitation ($P_c$) to one model’s total precipitation pattern ($P_{\text{total}}$, or $P_t$) during ENSO. $\Delta r_c$ denotes the change in the nonlinearity from changing the climatological precipitation. $\Delta r_t$ denotes the change in the nonlinearity from changing the total precipitation pattern. Changes are with reference to the free-run (CM2.5-FLOR, i.e top row).

<table>
<thead>
<tr>
<th>Climatology</th>
<th>$P_{\text{total}}$</th>
<th>El Niño [m/s]</th>
<th>La Niña [m/s]</th>
<th>$\Delta r_c$</th>
<th>$\Delta r_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CM2.5-FLOR</td>
<td>CM2.5-FLOR</td>
<td>4.64</td>
<td>-3.54</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CM2.5-FLOR</td>
<td>CM2.5-FLOR-FA</td>
<td>3.47</td>
<td>-4.97</td>
<td>-0.31</td>
<td></td>
</tr>
<tr>
<td>CM2.5-FLOR-FA</td>
<td>CM2.5-FLOR</td>
<td>7.14</td>
<td>-1.32</td>
<td>0.55</td>
<td></td>
</tr>
<tr>
<td>CM2.5-FLOR-FA</td>
<td>CM2.5-FLOR-FA</td>
<td>5.97</td>
<td>-2.70</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MERRA</td>
<td>MERRA</td>
<td>5.58</td>
<td>-2.93</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

However, if the FLOR wetter climatological precipitation is redistributed according to the FLOR-FA total precipitation spatial patterns, the equatorial zonal wind response becomes stronger (weaker) during La Niña (El Niño) compared to FLOR. In other words, when the surface climatology is flux adjusted (FLOR-FA), the precipitation response to ENSO is changed so as to make the nonlinearity weaker. Nevertheless, the enhancement of the
nonlinearity due to the drier FLOR-FA climatological precipitation is stronger (Table.4.2). As a result, by flux adjusting the ocean surface climatology toward the observations, the nonlinearity of the equatorial zonal wind response simulated by the FLOR is increased and becomes closer to observed.

**CMIP5 models VS observations**

FLOR-FA shows an improvement in the linear and nonlinear zonal wind response to ENSO relative to FLOR; which arises, directly or indirectly, from improvements in climatological SST and rainfall. Here, we explore how the CMIP5 intermodel spread in the equatorial zonal wind response is associated with biases in their Tropical Pacific climatologies, and in particular, their climatological precipitation fields.

Most CMIP5 models have a tropical Pacific mean climatological precipitation wetter than observed, with a spatial correlation ranging between 0.6-0.9 (Fig. 4.9). This wet bias is mostly due to the excess precipitation over the ITCZ, SPCZ and the West Pacific Warm Pool regions. The multimodel mean precipitation has a weak dry bias near the equator and the bias is comparable to the difference between GPCP and MERRA. However, the intermodel spread, especially over the dry cold tongue regions, is as large as 50% of the multimodel mean. As shown by Li and Xie (2013), when the precipitation field is normalized by the area mean for each model, the multimodel zonal mean precipitation would align better in the ITCZ and SPCZ regions but nearly all models would have a normalized precipitation (i.e. spatial pattern only) that is too dry on the equator.

Models that have a cooler SST relative to the tropical Pacific mean and drier precipitation in the equatorial central Pacific climatologies tend to have a weaker equatorial zonal wind response during ENSO (Fig. 4.11(a,b,c)). This shows that the climatological cold tongue bias and the location of the warm pool edge are important for the linear atmosphere-ocean coupling strength over the equatorial Pacific during ENSO.
Figure 4.11: Relationship between the equatorial zonal wind anomalies and the November-February climatological precipitation across the CMIP5 models. The differences of the El Niño and La Niña maximum zonal wind response for the CMIP5 models are correlated with the models’ (a) climatological SST (with the tropical Pacific mean for each model removed) and (b) climatological precipitation at every grid point. Regions with statistics significance above 95% are shaded. Scatter diagrams of (c) the maximum (minimum) equatorial zonal wind anomalies during El Niño (La Niña) and (d) the zonal wind response nonlinearity (Eq. 4.6), with the climatological precipitation averaged within 5S-5N, 160E-160W for the CMIP5 model and MERRA. The numbered markers are the same as those in Fig. 4.1.
The correlation between the climatological precipitation and the equatorial zonal wind response to ENSO described here is insensitive to whether or not the tropical Pacific mean precipitation of each model is removed or used to normalize the precipitation field (not shown). This insensitivity is likely because the intermodel spread in the tropical Pacific mean precipitation is relatively small compared to local differences.

In contrast, the correlation between the tropical climatological SST and the zonal wind response is smaller when the tropical Pacific mean SST is included (not shown). This is consistent with Sobel et al. (2002), Johnson and Xie (2010) and Xie et al. (2010) that the tropical deep convection is controlled not only by the local SST but also the difference between the local SST and the tropical mean SST, as well as the meridional temperature gradient.

The nonlinearity in the zonal wind response has virtually no linear correlation with the bias in the climatological precipitation in the equatorial central Pacific (Fig. 4.11(d)). This is because, while a dry bias in the equatorial central Pacific (associated with the erroneous zonal extent of the cold tongue in some of the models, Brown et al. 2013) causes a weaker La Niña wind response by limiting the negative precipitation anomalies possible, the El Niño zonal wind response is also often weakened in the dry models. Therefore, although there is a strong linear relationship between the linear zonal wind response and the climatological precipitation biases, the bias in the nonlinearity cannot be determined directly from the bias in the climatological precipitation.

4.4 Chapter summary

Observations and the CMIP5 models have shown stronger equatorial zonal wind response to El Niño than to La Niña. The observed nonlinearity in the zonal wind response can be reproduced fairly well by driving an atmospheric shallow water model with the observed precipitation anomalies as the heating source. The varying degree of the wind nonlinearity
in the CMIP5 models is also reproduced using the models’ precipitation anomalies in the shallow water model. We therefore conclude that the nonlinearity in the zonal wind response is largely driven by the nonlinear response of the precipitation, which is a positive definite quantity.

More than 90% of the precipitation anomalies during ENSO are due to the redistribution of the Tropical Pacific climatological precipitation, with little change to the overall mean precipitation. We derived a routine to decompose the precipitation anomalies into three components: zonal redistribution, meridional redistribution, and a residual component which tends to be small. These components are computed such that the zonal (meridional) redistribution component has zero zonal (meridional) mean at all latitudes (longitudes) within the Tropical Pacific region (Figs. 4.5, 4.6).

Based on experiments with a shallow water model, we conclude that although the zonal and meridional redistribution components contribute comparably to the equatorial precipitation anomalies, the zonal redistribution component is responsible for most of the equatorial zonal wind response (Fig. 4.7). However, the meridional redistribution component during La Niña, associated with the poleward shift of the ITCZ/SPCZ (Trenberth 1976; Folland et al. 2002), enhances the nonlinearity in the zonal wind response substantially by reducing the climatological precipitation on the equator, thereby reducing the zonal redistribution and the zonal wind response to La Niña (Sec. 4.3.2). This result highlights the role of climatological precipitation in limiting the zonal wind response to La Niña. On the other hand, the meridional shift during El Niño has little effect on the precipitation and the wind response.

By comparing the free-run and the flux adjusted experiments of the GFDL CM2.5-FLOR model, we found that both the linear and the nonlinear zonal wind response to ENSO are improved by flux correcting the surface ocean climatologies toward the observed. And among the CMIP5 models, the equatorial zonal wind response to ENSO is also shown to be associated with the equatorial central Pacific climatological precipitation and SST (Fig. 4.11).
Previous studies analyzing the CMIP3 models have also indicated relationships between the models' biases in their climatological precipitation and equatorial zonal wind response to ENSO (Capotondi et al., 2006; Lengaigne and Vecchi, 2009; Ohba and Ueda, 2009). Together, these findings imply that the equatorial atmosphere-ocean coupling strength may change under a different climate scenario if there are changes in the climatological SST and precipitation near the edge of the cold tongue.

For the CMIP5 pre-industrial control experiments, while the linear zonal wind response to ENSO has a significant linear dependence on the equatorial central Pacific climatological precipitation and SST (i.e. near the edge of cold tongue), little linear dependence of the nonlinear zonal wind response on the climatological precipitation is found. Therefore we speculate that the intermodel differences in the nonlinear atmospheric response to ENSO are likely due to the different representations of the atmospheric processes, rather than the different ocean surface climatologies in the models. But it may be possible to improve model representations of the linear wind response to ENSO by correcting ocean surface biases.
Chapter 5

Role of the mean state climate in simulating ENSO

5.1 Introduction

After decades of research, scientists have developed a good understanding of the physical processes involved in ENSO. Coupled models’ parameterizations and representation of the atmosphere, ocean, land and carbon cycle also become more comprehensive. ENSO is now an emergent property in most coupled global circulation models in the third and fifth Coupled Models Intercomparison Project (CMIP3 and CMIP5 respectively). More models are now able to simulate an ENSO variability maximum at the 2- to 7-year time scale as observed (AchutaRao and Sperber 2002, 2006; Flato et al. 2014); the intermodel spread in the amplitude of ENSO has reduced (Kim and Yu 2012; Bellenger et al. 2014); there are also improvements in the seasonal phase locking of ENSO (Bellenger et al., 2014).

Despite this progress, simulating ENSO with coupled climate models remains to be challenging due to the interwined coupled feedbacks between the atmosphere and the ocean, the ENSO’s interaction with the mean state climate and the seasonal cycle, as well as the limited length of the historical observational data (Guilyardi et al. 2009; Wittenberg 2009; Li et al.
Several systematic errors in the simulated mean climate and the ENSO variability persist in the CMIP5 models. The main shortcoming in simulating the mean state climate is that models tend to have an equatorial cold tongue extending too far west and the tropical precipitation exhibiting the unrealistic, "double ITCZ" feature. As for ENSO variability, models underestimate (1) the precipitation variability over the eastern equatorial Pacific, (2) the atmospheric Bjerknes feedback, (3) the surface heat flux feedback and (4) the shortwave feedback over the eastern equatorial Pacific (Bellenger et al., 2014). Apart from simulating ENSO in the past climate, models also project the ENSO amplitude in the future climate to weaken, strengthen, or have little to no change (van Oldenborgh et al. 2005; Guilyardi et al. 2009; Collins et al. 2010; Stevenson et al. 2012; Watanabe et al. 2012). An important question to ask is why and how models disagree with the observations and with each other.

Early studies have identified the Tropical Pacific mean climate state as parameters that determine the strength of positive and negative feedbacks of ENSO (Zebiak 1982; McCreary and Anderson 1984; Battisti 1988; Battisti and Hirst 1989; Tziperman et al. 1997; Neelin et al. 1998; Fedorov and Philander 2001). For instance, the horizontal and vertical advection by the mean current in the eastern equatorial Pacific Ocean act to damp ENSO activity. If the equatorial trade wind is weaker, say due to global warming (Knutson and Manabe, 1995; Vecchi and Soden, 2007), the mean advection would also be weaker and ENSO amplitude would strengthen. Consistent with this theoretical understanding, Guilyardi (2006) analyzed the CMIP3 models and identified an inverse relationship between the ENSO amplitude and the strength of the mean equatorial zonal wind stress, although the relationship is more apparent within one model than across different models. On the other hand, the positive correlation found between the mean equatorial central Pacific precipitation and the zonal wind stress response to the SST anomalies of ENSO in the CMIP5 models suggests that the atmospheric positive feedback of ENSO may be stronger when the mean equatorial central Pacific is wetter (previous chapter).
Studies have explored the connections between ENSO characteristics and the mean state climate for understanding intermodel differences, model discrepancies from the observations, models’ projection of ENSO in the future climate as well as changes in the observed ENSO characteristics in the past climate (Wang and An 2002; Guilyardi 2006; Imada and Kimoto 2006; Vecchi and Wittenberg 2010). Following these arguments, it is natural to make the converse hypothesis that the main characteristics of ENSO in the models should improve and the intermodel spread should reduce, if the mean state climate in the Tropical Pacific is better simulated in the models.

The hypothesis to be tested is that correcting the background climate state, at least in the Tropical Pacific, would improve the representation of ENSO main characteristics in the models. If the hypothesis holds, we ask to what extent the intermodel differences in the representation of ENSO is due to differences in the models’ mean state climate. And we address the question of whether the linear correlation between the climatological equatorial central Pacific precipitation and the linear zonal wind response found in Chapter 4 implies any causal relationship. In this quest, we flux adjust the CM2.1 ocean surface climatology to the ocean surface climatologies of a few CMIP5 models and investigate how the ENSO characteristics change accordingly. We will focus on the pre-industrial control experiments of the CMIP5 models. This approach has the following advantages: (1) multiple tests with reasonably different climate states can be performed; (2) specific intermodel differences can be addressed; (3) the long integration of the control experiments improve the robustness of the ENSO characteristics statistics.

Our study is complementary to Philip et al. (2010). To test the influence of different parts of the ENSO feedback loop, they flux adjusted an intermediate complexity model to the observed climate and perturbed several key atmospheric and ocean processes fitted to different reference GCMs. Here, instead of keeping the mean state climate fixed to the first order, we vary the mean state climate according to different GCMs and keep the physics of the model fixed. As the mean state climate and the physics representation are both different
among the GCMs, the results of Philip et al. (2010) and our study together should provide a more complete descriptions of the interwined effects of the mean state and the model physics.

In the next section we describe the model used, how a number of reference GCMs are selected and the methods for setting up the flux adjust experiments. In Section 5.3, we present the changes in the mean state climate achieved by flux adjustments. In Section 5.4, we describe the ENSO characteristics and the main feedbacks simulated in the flux adjust experiments, compared to the reference models. We also examine a few proposed relationship between the mean state climate and the ENSO characteristics. In Section 5.5, we conclude the main results.

5.2 Methods

5.2.1 GFDL CM2.1

The Geophysical Fluid Dynamics Laboratory (GFDL) CM2.1 global coupled atmosphere-ocean-land GCM (Delworth et al., 2006) is used in this study to replicate other models’ mean state climate through flux adjustments. The free running, non-flux-adjusted CM2.1 has contributed to the CMIP3 and the Fourth Assessment of the Intergovernmental Panel on Climate Change (IPCC).

The model formulations and simulation characteristics are described by Delworth et al. (2006), Gnanadesikan et al. (2006) and Griffies et al. (2005). The ocean component of CM2.1 is based on the Modular Ocean Model code (MOM4; Griffies et al. 2004, Griffies et al. 2005). It applies free surface methods of z-coordinate models, contains 50 vertical levels with a constant spacing of 10m in the top 220m and gradually increasing spacing up to a maximum of 370m in the deepest part of the ocean at 5500m. The ocean grid has a horizontal resolution of 1° up to 1/3° meridionally at the equator. A tripolar grid is used such that the grid is a familiar spherical latitude-longitude grid south of 65° N and the grid switches to a bipolar grid with singularities over land masses in Siberia and Canada. The
atmosphere and land components of CM2.1 is the GFDL Atmospheric Model, Version 2.1 (AM2.1; GFDL Global Atmospheric Model Development Team 2004) and the Land Model version 2 (Milly and Shmakin, 2002). The model has a horizontal resolution of 2° latitude × 2.5° longitude and it has 24 vertical levels.

The Tropical Pacific climate and ENSO simulation in CM2.1 have been highly rated among the CMIP3 models (van Oldenborgh et al. 2005; Wittenberg et al. 2006; Guilyardi 2006; Capotondi et al. 2006). The period of ENSO is irregular, ranging from 2 to 5 years. The SST anomalies has a positively skewed distribution. The evolution of the temperature and current anomalies are quite realistic. CM2.1 also simulates a wide diversity of ENSO spatial and temporal structures, sometimes termed ”ENSO flavors” (Kug et al., 2010). However, the amplitude of the SST anomalies are too strong compared to observed. The climatological equatorial cold tongue has extended too far west. The seasonal phase locking of ENSO is not represented well. Despite these shortcomings, the ENSO simulated in CM2.1 has been realistic enough that much is still being learned from the model. For example, the multi-millennium control simulation with CM2.1, under fixed 1860 atmospheric forcing and land conditions, has shown little climate drift and a large decadal-to-centennial modulation of ENSO variability, raising questions about the decadal predictability of ENSO (Wittenberg 2009; Wittenberg et al. 2014).

5.2.2 Target CMIP5 Models

Due to limitations of computing, human resources and time, eight instead of all of the CMIP5 models (Table 4.1) are selected as the target models for flux adjustment. Four of these models (MIROC-ESM, MRI-CGCM, GISS-E2-H, CMCC-CM) are selected based on the fact that their annual mean Tropical Pacific climatologies are most different from the CM2.1 and that the lengths of their control experiments are reasonably long, up to about 500 years. The four other models (ACCESS1-0, GFDL-ESM2G, GFDL-ESM2M, GFDL-CM3) are selected because they share one or more of the atmosphere/ocean/land components with CM2.1.
While GFDL-ESM2M, GFDL-ESM2G and GFDL-CM3 are relatively similar to CM2.1 in terms of their annual mean SST and precipitation in the tropical Pacific, ACCESS1-0 has a substantially different mean rainfall compared to CM2.1 to the extent that ACCESS1-0 is more different from CM2.1 than CMCC-CM is. These differences in the mean state climate are computed based on the root-mean-square-error in the Tropical Pacific mean sea surface temperature and precipitation fields (Table 5.1). The approach and the main results are similar to Masson and Knutti (2011) and Knutti et al. (2013). Model components and literature references are summarized in Tables 5.2 and 5.3.

5.2.3 Flux adjustments

Two sets of flux adjusted experiments are carried out. In the first set of experiments, flux adjustments to sea surface temperature (SST) and salinity (SSS) are achieved by adding enthalpy and freshwater fluxes on the ocean topmost (i.e. surface) grid cells. We will refer to this configuration as "FA2", which indicates that there are two flux corrected physical quantities. In the second set, flux adjustments are also made to the downward momentum flux on the ocean surface, in addition to enthalpy and freshwater fluxes. The latter configuration is referred to as "FA3", indicating that three physical quantities are flux corrected. The procedures for computing the flux adjustments are similar to that of Magnusson et al. (2013) and Vecchi et al. (2014):

- All experiments are initialized by the end of a 101-year control simulation with CM2.1, prescribed with the radiative forcing and land use condition representative of 1860
- For each target model, the CM2.1’s SST and SSS are restored to the full SST and SSS of the target model’s control run using a 5-day restoring time scale. These nudging experiments are referred to as "NUDGE2" and they are integrated for at least 40 years. The monthly climatological SST and SSS restoring fluxes are computed from the NUDGE2 runs after the first 10 years. Then the global mean of these fluxes are
Table 5.1: Relative differences of the CMIP5 models pre-industrial control experiments compared to CM2.1 in terms of their annual mean sea surface temperature and precipitation over the Tropical Pacific (20S-20N, 100E-100W). The differences are measured as the root-mean-square-error normalized by the standard deviation of the corresponding quantity in CM2.1 control. The models are sorted in ascending order of the sum of the root-mean-square errors in SST and rainfall. The lengths of the experiments are also shown.

<table>
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<tr>
<th>Model</th>
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<th>Rainfall</th>
<th>Sum</th>
<th>Length(yr)</th>
</tr>
</thead>
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<tr>
<td>IPSL-CM5A-MR</td>
<td>0.35</td>
<td>0.49</td>
<td>0.84</td>
<td>300</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>0.35</td>
<td>0.49</td>
<td>0.84</td>
<td>1000</td>
</tr>
<tr>
<td>MIROC5</td>
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<td>0.62</td>
<td>1.00</td>
<td>670</td>
</tr>
<tr>
<td>GFDL-ESM2M</td>
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<td>0.59</td>
<td>1.00</td>
<td>500</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
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<td>0.65</td>
<td>1.01</td>
<td>1000</td>
</tr>
<tr>
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<td>0.65</td>
<td>1.01</td>
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</tr>
<tr>
<td>MPI-ESM-MR</td>
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<td>0.64</td>
<td>1.01</td>
<td>1000</td>
</tr>
<tr>
<td>NorESM1-ME</td>
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<td>252</td>
</tr>
<tr>
<td>NorESM1-M</td>
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<td>501</td>
</tr>
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<td>CMCC-CMS</td>
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<td>inmcm4</td>
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<td>CanESM2</td>
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<td>GFDL-CM3</td>
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<tr>
<td>IPSL-CM5B-LR</td>
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<td>bcc-csm1-1</td>
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<tr>
<td>GISS-E2-R-CC</td>
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<td>1.70</td>
<td>500</td>
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<td>GISS-E2-R</td>
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<td>1.70</td>
<td>531</td>
</tr>
<tr>
<td>GISS-E2-H</td>
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<td>0.97</td>
<td>1.71</td>
<td>531</td>
</tr>
<tr>
<td>CMCC-CM</td>
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<td>1.22</td>
<td>1.77</td>
<td>330</td>
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<tr>
<td>GISS-E2-H-CC</td>
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<td>251</td>
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<td>2.69</td>
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Table 5.2: Model components of the eight target GCMs to which CM2.1 is flux adjusted. Also listed are numbers used for annotating scatter diagrams in this chapter.

<table>
<thead>
<tr>
<th>No.</th>
<th>Model Name</th>
<th>Ocean</th>
<th>Atmosphere</th>
<th>Land</th>
</tr>
</thead>
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<td>0</td>
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<td>GFDL AM2.1</td>
<td>GFDL LM2.1</td>
</tr>
<tr>
<td>1</td>
<td>ACCESS1-0</td>
<td>GFDL MOM4p1</td>
<td>MetOffice HadGEM2</td>
<td>MOSES v2.2</td>
</tr>
<tr>
<td>2</td>
<td>GFDL-ESM2G</td>
<td>GFDL GOLD</td>
<td>GFDL AM2.1</td>
<td>GFDL LM3.0</td>
</tr>
<tr>
<td>3</td>
<td>GFDL-ESM2M</td>
<td>GFDL MOM4p1</td>
<td>GFDL AM2.1</td>
<td>GFDL LM3.0</td>
</tr>
<tr>
<td>4</td>
<td>GFDL-CM3</td>
<td>GFDL MOM4p1</td>
<td>GFDL AM3</td>
<td>GFDL LM3.0</td>
</tr>
<tr>
<td>5</td>
<td>MIROC-ESM</td>
<td>CCSR COCO 3.4</td>
<td>MIROC AGCM</td>
<td>MATSIRO</td>
</tr>
<tr>
<td>6</td>
<td>GISS-E2-H</td>
<td>HYCOM</td>
<td>GISS ModelE2</td>
<td>GISS ModelE2</td>
</tr>
<tr>
<td>7</td>
<td>CMCC-CM</td>
<td>OPA8.2/ORCA2</td>
<td>MPI ECHAM5</td>
<td>MPI ECHAM5</td>
</tr>
<tr>
<td>8</td>
<td>MRI-CGCM3</td>
<td>MRI COM3</td>
<td>MRI AGCM3</td>
<td>MRI HAL</td>
</tr>
</tbody>
</table>

Table 5.3: Modeling groups and references for the eight target GCMs to which CM2.1 is flux adjusted.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Modeling group</th>
<th>References</th>
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<tbody>
<tr>
<td>CM2.1</td>
<td>GFDL</td>
<td>Delworth et al. (2006)</td>
</tr>
<tr>
<td>ACCESS1-0</td>
<td>CSIRO-BOM</td>
<td>Bi et al. (2013)</td>
</tr>
<tr>
<td>GFDL-ESM2G</td>
<td>GFDL</td>
<td>Dunne et al. (2012)</td>
</tr>
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<td>GFDL-ESM2M</td>
<td>GFDL</td>
<td>Dunne et al. (2012)</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>GFDL</td>
<td>Donner et al. (2011); Milly et al. (2014)</td>
</tr>
<tr>
<td>MIROC-ESM</td>
<td>MIROC</td>
<td>Watanabe et al. (2011)</td>
</tr>
<tr>
<td>GISS-E2-H</td>
<td>GISS</td>
<td>Schmidt et al. (2014)</td>
</tr>
<tr>
<td>CMCC-CM</td>
<td>CMCC</td>
<td>Scoccimarro et al. (2011)</td>
</tr>
<tr>
<td>MRI-CGCM3</td>
<td>MRI</td>
<td>Yukimoto et al. (2012)</td>
</tr>
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</table>
removed. These two climatological fluxes are added to CM2.1 for the flux adjusted experiments to which we refer as "FA2".

- The climatological monthly surface wind stress in the NUDGE2 runs (the 11-th year onwards) are compared to that of the target model’s control experiment. The difference of the climatologies are computed and used as the downward momentum flux corrections. Then the nudging experiment restoring the SST and SSS to the target control experiment is integrated again, with the momentum flux corrected added. These experiments are referred to as "NUDGE3".

- The monthly climatological SST and SSS restoring fluxes are computed from the NUDGE3 experiments for the 11-th year onwards and the global means are removed. Finally these flux corrections together with the downward momentum flux corrections are added to CM2.1 for the "FA3" experiments.

The FA2 and FA3 experiments are run for 400 years. In the following analysis, the first 30 years of the FA experiments are ignored to allow for some adjustment. We refer to an FA2 experiment flux adjusted towards a model as FA2-MODEL, similarly for FA3 experiments. FA-MODEL (without the number) refers to both FA2 and FA3 experiments flux adjusted towards the said model. For example, an FA2 experiment flux adjusted to the climatology of ACCESS1-0 would be called FA2-ACCESS1-0.

### 5.3 Mean state climate

Although the main focus of this study is on the representation of ENSO characteristics, we will first establish the extent to which the flux adjusted CM2.1 is capable of reproducing the mean state climate of the target CMIP5 models chosen (Sec. 5.2.2).
5.3.1 Surface temperature

The absolute Tropical Pacific SST is improved towards the target models for six out of the eight sets of flux adjust (FA2 or FA3) experiments, and the spatial structure of SST over the Tropical Pacific region is improved substantially for all of the experiments (Fig. 5.1). FA3 experiments generally outperform FA2 slightly. While the changes are most pronounced in the Tropical Pacific SST, there are also improvements in the overall ocean and land surface temperature towards most of the target models (Fig. 5.1a).

Despite the fact that the total mean square errors in the absolute surface temperature are maintained or increased for FA-CMCC-CM and FA-GFDL-CM3, the spatial pattern of the SST over the Tropical Pacific Ocean is significantly improved (Fig. 5.1b). This suggests that the discrepancies are mainly due to differences in the global means. Indeed, the flux adjusted experiments for CMCC-CM and GFDL-CM3 show a global cooling relative to the corresponding target control experiments and those for ACCESS1-0 also show a mild cooling over the oceans (Fig. 5.2).

In some areas, usually near oceanic boundary currents and in the mid latitudes, the surface temperature in the flux adjusted experiments are made worse compared to the target control (Figs. 5.2 and 5.3). Therefore, caution should be taken if the current study is to be extended for studying other regional climatic phenomena. As the main goal of this study is about the main ENSO characteristics, substantial improvements of the SST over the Tropical Pacific Ocean serves as a prerequisite.

The seasonality of the equatorial SST zonal gradient is also represented well for most target models except for FA-GISS-E2-H (Fig. 5.4). The equatorial SST zonal gradient is relevant for the atmospheric positive feedback and the growth rate of ENSO. And therefore its seasonality would be relevant for the seasonal phase locking of ENSO that we will explore in Sec. 5.4.2.
Figure 5.1: Fractional change in the annual-mean climatological surface temperature (a) root mean square error, (b) spatial correlation deviation from one; for experiments flux adjusting towards the climatologies of different target models, as indicated in the horizontal axis. The changes are normalized by the errors between the CM2.1 control and the target model control experiment. Blue, yellow, red and grey bars correspond to areas over the entire globe, over land, over ocean and within the tropical Pacific Ocean (20S-20N, 120E-80W) respectively. Error bars show 25% and 75% percentiles of results from the block bootstrapped 30-year samples. The bars show the median of these samples. Negative values indicate improved representations of the surface temperature in the flux adjusted experiment towards the target model control experiment. Negative 1 indicates a perfect correction.
Figure 5.2: Annual-mean of the surface temperature (degree Celsius) from the target control experiment minus that of the FA3 experiment. Values in the brackets show the global averages in degree Celsius. Positive values indicate that the global mean in the FA3 experiments are cooler than the corresponding target models.
Figure 5.3: Annual-mean of the surface temperature (degree Celsius) from the target control experiments minus that of the CM2.1 control experiment. Similar to Fig. 5.2.
Figure 5.4: Climatology of the zonal surface temperature gradient near the equator measured by the temperature difference between the SST averaged in the equatorial western Pacific (5S-5N, 150E-150W) and that averaged in the equatorial eastern Pacific (5S-5N, 150W-90W). The climatology is computed over periods of time when the NINO3 SST anomalies are within -0.5K and 0.5K, i.e. when ENSO is weak. Results using all time periods are virtually indistinguishable. No filter or running average is applied otherwise.
5.3.2 Precipitation

Upon flux adjustment, the global climatological precipitation field is generally improved towards the target models (Fig. 5.5) by 10-50% in absolute values and 25-85% in spatial correlation. The seasonal meridional migration of the ITCZ and SPCZ are also improved for all of the target models except for GISS-E2-H (Fig. 5.6). Most of the corrections in the absolute precipitation fields come from the corrections in the spatial structure of rainfall, which indicates a spatial reorganization of atmospheric convection.

Although FA3-GISS-E2-H shows little overall improvement in the seasonal meridional migration of the ITCZ/SPCZ, the FA3-GISS-E2-H precipitation is in fact significantly improved during the austral winter and these improvements are compensated by errors introduced in the boreal winter (Fig. 5.6). In both the GISS-E2-H and the FA3-GISS-E2-H, the simulated SPCZ during the austral winter is stronger and more zonal compared to the CM2.1 control. During the boreal winter, however, the FA-GISS-E2-H simulated ITCZ and the SPCZ that are too strong compared to the GISS-E2-H control.

Furthermore, the improvements for the simulated precipitation over the Tropical Pacific Ocean are in agreement with the changes in the spatial structures rather than the absolute values of the surface temperature (Fig. 5.1). All in all these are consistent with the previous understanding that the tropical deep convection is dependent not only on the local SST but also the relative difference between the local SST and the tropical mean SST (Sobel et al. 2002; Johnson and Xie 2010; Xie et al. 2010).

5.3.3 Subsurface temperature and surface wind stress

The annual-mean equatorial subsurface temperature, basin-wide 20° C isotherm depths, equatorial thermocline slopes, basin-wide meridional surface wind stress, basin-wide surface wind stress curl as well as the equatorial surface zonal currents are improved in the flux adjusted experiments for most of the target models with few exceptions (Figs. 5.7,5.8). Again, FA3 experiments generally outperform FA2 experiments in these measures.
Figure 5.5: Fractional change in the annual-mean climatological precipitation (a) root mean square error, (b) spatial correlation deviation from one; for experiments flux adjusting towards the climatologies of different target models, as indicated in the horizontal axis. Similar to Fig. 5.1.

However, despite improvements in the ocean surface temperature, the mean equatorial zonal wind stress may be improved, worsen or unchanged in the FA2 experiments (Fig. 5.7). For the FA2 experiments that simulate a worsen surface wind stress (FA2-ACCESS1-0, FA2-MIROC-ESM), the discrepancies highlight the impact of differences in the atmosphere models among CM2.1 and the target models. In addition, most FA3 experiments require an eastward downward momentum flux adjustment on the ocean surface, which is consistent with the flattening of the mean equatorial thermocline slopes comparing FA3 to FA2 experiments (Fig. 5.8a,c).

Furthermore, the flattening of the mean equatorial thermocline is consistent with the decrease in the mean stratification in the ocean mixed layer in the NINO3 region (Fig. 5.8d). However, the maximum vertical gradients of the subsurface temperature fields in the NINO3 region are virtually insensitive to flux adjustments except for FA-GISS-E2-H (Fig. 5.8d). The fact that models sharing the same ocean component (CM2.1, ACCESS1-0,
Figure 5.6: Zonal mean of the climatological maritime precipitation [mm/day] over the Tropical Pacific (120E-80W) for the FA3 experiments (color shading) and the target control experiments (contours). Values in the brackets are showing the fractional change in the RMSE with reference to the target control. Negative values mean improvements towards the target control. Negative one represents a perfect adjustment.
ESM2M, CM3) cluster together relative to the other models suggests that the intermodel spread in the maximum vertical temperature gradient is more dependent on the formulation of the ocean models (e.g. parameterization of diapycnal mixing) than on the climatologies of surface boundary conditions.

The 20° C isotherm depths are improved by a consistently larger amount in FA3 experiments (30-60%) relative to FA2 (10-40%). A simple spatial correlation analysis (not shown) shows that the relative changes in the 20C isotherm depths between FA2 and FA3 are due to either (1) the corresponding changes in the surface temperature (GFDL-ESM2G, GFDL-ESM2M, GFDL-CM3); or (2) changes in the surface wind stress curl (GISS-E2-H); or (3) both (ACCESS1-0, MIROC-ESM, CMCC-CM, MRI-CGCM3). Therefore some of the improvements seen in the mean surface temperature and precipitation comparing FA3 to FA2 are consistent with an improved simulation of the thermocline depths.

Differences and similarities in the formulations of models are also highlighted by the FA-GFDL-ESM2G experiments. Through flux adjusting the surface temperature and salinity (FA2) towards the target model (GFDL-ESM2G), the equatorial zonal wind stress is enhanced and improved (Figs. 5.7a, 5.8c). Consequently the thermocline is made steeper, deeper and even further away from the target (Fig. 5.8a,b). Further adjusting the downward momentum flux (FA3) worsens the subsurface temperature field even though the surface temperature and precipitation fields are improved relative to FA2 (Fig. 5.7). These discrepancies are attributable to the differences in the treatment of the ocean surface mixed layer and the use of different vertical coordinate systems, which are the major differences between ESM2G and CM2.1 or ESM2M.

5.4 ENSO

We shall begin by reviewing whether and how the flux adjusted experiments simulate the target models’ ENSO in terms of the Tropical Pacific sea surface temperature, followed by
Figure 5.7: Fractional change in the root mean square for the annual-mean climatological subsurface temperature within the region of 160E-100W, 0-200 meter deep, averaged from 5S to 5N (blue); mean surface zonal wind stress averaged from 5S to 5N, 120E-80W (red); mean depths of the 20-degree-Celsius isotherm for the Tropical Pacific Ocean over the region of 20S-20N, 120E-80W (yellow); curl of the surface wind stress within the same Tropical region (cyan); mean surface zonal wind stress for the same Tropical region (grey); mean surface meridional wind stress for the same Tropical region (purple); equatorial zonal current averaged from 5S to 5N, 120E-80W (white). Negative values indicate improved representations of the surface temperature in the flux adjusted experiment towards the target model control experiment.
Figure 5.8: Changes in the equatorial thermocline and the surface zonal wind stress in the control and flux experiments. (a) Annual-mean slope (unit: meter per degree longitude eastward) and (b) the annual-mean depth (unit: meter) of the equatorial 20-degree-C isotherm (5S-5N, 160E-90W); (c) annual-mean depth (unit: meter) of the 20-degree-C isotherm over the NINO3 region (5S-5N, 150W-90W); (d) difference between the annual-mean NINO3 SST and the potential temperature at 50m depth (unit: degree C); (e) maximum annual-mean vertical temperature gradient within the top 300 meter in the NINO3 region; (f) annual-mean zonal wind stress (5S-5N, 160E-90W; unit: Pa).
the changes in the atmospheric and oceanic feedbacks. A few of the proposed relationships between ENSO and mean state are also tested: (1) surface zonal wind stress response to SST increases with the mean rainfall over the equatorial central Pacific; (2) amplitude of SST anomalies increases with decreasing mean equatorial zonal wind stress and (3) NINO3 SST anomaly standard deviation increases with the climatological precipitation over the same region.

5.4.1 SST anomaly standard deviations

Upon flux adjustment, five out of the eight FA3 experiments show improvements towards the target models in their local temporal standard deviations of tropical Pacific SST anomaly (Fig. 5.9). For these five models, 20-96% of the differences in the NINO3 SST anomaly standard deviations are reproduced (Fig. 5.10a). The reasons why the other three FA3 experiments fail to improve the simulation of the amplitude of NINO3 SST anomalies will be explored. In addition, it is worth noting that the CM2.1 control has the strongest ENSO amplitude among the target models in this study. Therefore any reduction in the ENSO amplitude in the flux adjusted experiments may be considered as an improvement towards the target model.

For the other three sets of FA experiments that show degradation in the ENSO amplitude, two of the target control experiments (GFDL-ESM2M, FA-GFDL-CM3) are already close to CM2.1’s. This can be explained by the fact that these models are structurally very similar (Table 5.2), so are their mean state climate and the simulations of ENSO in the pre-industrial control situation. Consequently, the internal decadal variability of the ENSO amplitudes in the target control and flux adjusted experiments are just as large as the differences between the mean ENSO statistics for these models (Fig. 5.10a). However, the failure in recovering the GFDL-CM3’s mean ocean surface temperature in the FA experiments may also be a contributing factor (Fig. 5.1).
The flux adjusted experiments for CMCC-CM, however, have a significantly degraded ENSO amplitude. This could be due to the fact that the FA-CMCC-CM experiments have simulated a much more different mean climatological Tropical Pacific sea surface temperature state compared to the target model (Figs. 5.1 and 5.9). This suggests that an improved simulation of the climatological tropical Pacific sea surface temperature is crucial, and perhaps necessary, to the improved simulation of the SST variability in the area.

Among the four target models (GFDL-ESM2G, CMCC-CM, MIROC-ESM, ACCESS1-0) whose longitudes of the maximum SST anomalies are significantly different from CM2.1’s, the FA3 experiments were able to simulate the longitudes for two of them (GFDL-ESM2G and CMCC-CM; Fig. 5.10b). The zonal location of the maximum SST anomalies in FA-ACCESS1-0 shows either no change or a degradation from CM2.1, which can be traced back to the worsen SST anomalies pattern during La Niña conditions. The zonal location of the maximum SST anomalies in FA-MIROC-ESM is difficult to detect given its weak ENSO. Indeed, the CM2.1 NINO3 SST variability is reduced by more than 50% to be in close agreement with the MIROC-ESM control (Fig. 5.10a). This is the most notable change among the flux adjusted experiments and it accounts for a large fraction of the intermodel spread.

5.4.2 Seasonal phase locking

Six out of the eight sets of flux adjusted experiments (i.e. except FA-GFDL-ESM2M and FA-GISS-E2-H) have shown improved seasonal phase locking either by shifting the peak months closer to the target models’ or by improving the magnitude of the seasonal variance, or both (Fig. 5.11). However, FA-CMCC-CM shows a very weak seasonal locking, as in its target control, and therefore the improved seasonal locking may not be statistically significant.

The changes in the seasonal locking are generally consistent with the low-pass filtered seasonal dependence of the zonal wind stress feedbacks in the FA3 experiments. ENSO tends to peak near the months when the surface zonal wind stress response to SST anomalies is
Figure 5.9: Fractional change in the temporal standard deviation of SST anomalies (a) mean square error, (b) spatial correlation deviation from one; between the CM2.1-1860 control and the target model after flux adjustment. The changes are computed for the tropical Pacific region (20S-20N, 120E-110W). Negative values indicate improved representation of the sst anomaly standard deviation.
Figure 5.10: Comparisons of the FA experiments and the target control experiments in terms of (a) the maximum SST anomaly temporal standard deviation, averaged between 5S to 5N, over a 40-degree-longitude region on the equator and (b) the longitude of the max SST anomaly temporal standard deviation.
weakest (Fig. 5.12), in agreement with Tziperman et al. (1995, 1997); Galanti and Tziperman (2000). The phasing of the seasonal zonal wind stress response is improved for all FA3 experiments except for FA-GISS-E2-H, which explains the corresponding failure in simulating an improved seasonal phase locking.

For FA-GFDL-ESM2M, the seasonal locking is made almost equally different from the target as the free running CM2.1 is. On the one hand, the change in the seasonal phase locking may arise from randomness as the seasonal phase locking is weak in both CM2.1 and ESM2M (i.e. the month when ENSO should peak appears to be random). On the other hand, the fact that the seasonal locking in FA-GFDL-ESM2M is similar to that in FA3-CM2.1 and that the change in the seasonal locking is (narrowly) significant suggest that this may also be an error introduced by flux adjustments.

5.4.3 Atmospheric feedbacks

Tropical Pacific precipitation, surface zonal wind and wind stress response to NINO3 SST anomalies are consistently improved in six of the eight target models (FA2-ACCESS1-0, FA-GFDL-ESM2G, FA-GFDL-ESM2M, FA-GISS-E2-H, FA-CMCC-CM and FA-MRI-CGCM3; Fig. 5.13). The results show that about 10%-50% of the intermodel differences in the Tropical Pacific atmospheric responses can be explained by their ocean surface climatologies. In addition, 70% of the target intermodel spread in the surface heat flux feedback over the NINO3 region is reproduced by the flux adjusted experiments, suggesting that the feedback has a strong dependence on the surface climatology (Fig. 5.14).

Positive feedbacks (Bjerknes feedbacks)

Most flux adjusted experiments show consistent improvements in the SST, precipitation, surface zonal wind and wind stress anomalies during ENSO (Fig. 5.13). But by comparing the inconsistencies among them in FA-GISS-E2-H and FA-CMCC-CM, we may conclude that the improved precipitation, surface zonal wind and wind stress responses are due to
Figure 5.11: Seasonal locking quantified by the monthly NINO3 SST anomalies standard deviation for each calendar month, normalized by its annual mean. Black solid line shows the seasonal locking in the target model control experiments. Black dashed line corresponds to the CM2.1 control experiment. Red (Blue) line represents the results from the corresponding FA2 (FA3) experiments. The values in red/blue/black at the corners of each of the subplots show the month when the seasonal dependence peaks for the FA2/FA3/target control experiment, respectively. The light grey shading shows the 5% and 95% percentiles for the free-running CM2.1 control experiment computed from a set of 50-year block bootstrapped samples.
Figure 5.12: Surface zonal wind stress anomalies averaged over 5S-5N, 120E-80W (land masked) regressed to NINO3 SST anomalies for each calendar month, filtered using a 6-month moving box car to remove low frequency variability. The filtering is justified by the time scale of Tropical Pacific Oceanic processes that are relevant to ENSO feedbacks.
improvement in the spatial pattern of the climatological tropical Pacific SST and precipitation, regardless of its tropical mean (Figs. 5.1b, 5.5a,b). However, FA-GFDL-CM3 seem to disagree.

Even though both the GFDL-CM3 and GFDL-ESM2M control experiments have similar ENSO amplitudes as CM2.1 and that the internal decadal variability of ENSO in CM2.1 has rendered it difficult to detect significant changes between the FA and control experiments for these models, FA-GFDL-ESM2M experiments have shown significant improvement in the atmospheric response while FA-GFDL-CM3 have not (Fig. 5.13). One may speculate that the explanation should lie in the differences between the atmosphere-land components of the models. The atmosphere-land component in CM3 is different (Table 5.2): CM3 has a different deep and shallow convection parameterization scheme. It also simulates aerosol-cloud interaction, interactive chemistry and coupling between the troposphere and stratosphere (Donner et al., 2011), which are not included in the ESM2M and CM2.1. Therefore the results here suggest that the different atmospheric response between GFDL-CM3 and GFDL-CM2.1 (which are in fact small compared to other non-GFDL target models) are due to the different representations of atmospheric processes.

Instead of computing the one-sided regression, warm and cold composite (events peak between 0.5K-1.5K) show qualitatively similar results except for FA-MIROC-ESM and FA-CMCC-CM (not shown). For FA-MIROC-ESM, the atmospheric response to SST anomalies are in fact improved when the warm and cold composites are used instead of the regression analysis. As the magnitudes of the NINO3 SST anomalies in FA-MIROC-ESM are reduced by more than 50% compared to the CM2.1 control, it is not surprising that the nonlinearity in the atmospheric response becomes important and linear regression analysis is no longer appropriate. These nonlinearities are also reflected by the differences between the one-sided regression using warm NINO3 SST anomalies and that using cold NINO3 SST anomalies (Fig. 5.13).
As for FA-CMCC-CM, the ENSO is so unrealistically strong that very few events have an amplitude (0.5-1.5K) close to the target model’s control. Therefore the composites for FA-CMCC-CM under these criteria may not have averaged out the anomalies unrelated to ENSO.

Negative feedbacks

Comparisons among different surface heat flux components reveal that the significant improvement in the surface heat flux damping is mainly due to changes in the downward shortwave radiation (Fig. 5.15). These changes are consistent with changes in the annual-mean atmospheric convective activity in the NINO3 region, measured by the fraction of convective precipitation relative to the total precipitation in the region. We also found that only 20% of the intermodel spread in the surface flux feedback can be explained by the nonlinear rectification effect due to changes in the ENSO SST amplitudes (see Appendix B). The results suggest that (1) a large portion of the intermodel spread in the surface heat flux feedback is originated from differences in the ocean surface climatology; (2) differences in the atmospheric parameterization that do not significantly alter the surface climatology through coupled atmosphere-ocean feedback processes likely play a secondary role. This is consistent with the findings by Lloyd et al. (2012) that the relative changes in the dynamical mean state between coupled and atmosphere-only (AMIP) simulations are directly related to the atmospheric dynamical response to SST, which dominates the biases in the shortwave heat flux feedback.

The results can be understood as follows: As the surface temperature in the FA experiments is adjusted and the mean atmospheric convective activity distribution reorganizes accordingly, more area of the NINO3 region has an increased fraction of mean atmospheric convection and nearby areas also become closer to establishing atmospheric convection. Consequently, the regional cloudiness becomes more sensitive to anomalous surface warming. For example, the ITCZ and SPCZ in FA-ACCESS1-0 are closer to the equator than in the
CM2.1 control, consistent with the mean precipitation spatial distribution in ACCESS1-0 control and the increase in the mean fractional convective precipitation computed for the FA-ACCESS1-0 NINO3 region. As a result, as the NINO3 SST increases during El Niño, more convection is drawn to the regions, leading to more clouds and less downward shortwave flux. The latter is also associated with an opposing but smaller change in the downward longwave heat flux, as is expected with the change in cloudiness.

The downward shortwave flux feedback is also highly nonlinear (Lloyd et al., 2012). In the FA experiments, the downward shortwave flux decreases with the surface cooling during La Niña. In other words, the downward shortwave flux feedback changes sign, going from being a negative feedback during El Niño to being a positive feedback during La Niña. The latter is consistent with the response in a subsidence regime, where surface cooling (warming) enhances (reduces) the static stability of the atmospheric boundary layer, allows (breaks up) the formation of stratiform clouds that block incoming sunlight (Klein and Hartmann, 1993). This behavior in the FA experiments follows that of the CM2.1 control, and therefore is likely an intrinsic property of the model.

A closer look at the scatter diagram (not shown) between the downward shortwave flux anomalies and the SST anomalies also reveals that the sign change of the shortwave feedback does not occur at zero SST anomaly but at some nonzero value that is different for different models. Based on a visual analysis, the SST anomaly at which the sign change occurs is modified in the FA experiments. We speculate that this change is consistent with the target model control experiments. However, more rigorous analysis is needed to verify this statement.

Lastly, the surface heat flux feedback is found to be worsen in the FA3-MIROC-ESM experiment, in contrast to the slight improvement found in the FA2-MIROC-ESM experiment (Fig. 5.14). There are two competing factors that affect the surface heat flux feedback for the FA-MIROC-ESM experiments. First of all, the ENSO amplitude in these experiments are significantly reduced compared to the CM2.1 control and is in agreement with the target
control experiment (Fig. 5.9). Due to the nonlinear relationship between the surface heat flux anomalies and SST anomalies, this reduction in the range of the ENSO amplitude reduces the linear damping term and explained one-third of the difference between MIROC-ESM and CM2.1 control (likewise for MRI-CGCM3 and GFDL-ESM2G; see Appendix B for the method). Secondly, the mean fractional convective precipitation in the NINO3 region increases for both the FA2-MIROC-ESM and FA3-MIROC-ESM experiments by about the same amount. As explained above, this should lead to a stronger damping from the shortwave radiative feedback and pull the FA-MIROC-ESM further away from the target control. We speculate that the competition of these two factors leads to the different behaviors of FA2-MIROC-ESM and FA3-MIROC-ESM. But it may or may not explain their discrepancies from the target control experiment.

5.4.4 Oceanic feedbacks

Upon flux adjusting the downward momentum flux and thereby correcting the surface currents and subsurface temperature structures (FA3 experiments), the sensitivity of the NINO3 SST anomalies to the change in the thermocline depth is improved for all the target models; the anomalous zonal advection of the mean ocean temperature gradients is also improved for all target models except for GISS-E2-H and MIROC-ESM (Fig. 5.16), which is consistent with the fact that the surface zonal current is worsen in their FA3 experiments (Fig. 5.7). However, the mean zonal advection of anomalous ocean temperature gradient is made substantially worse for all models.

These changes in the oceanic feedbacks are not evident for the FA2 experiments in which only the surface temperature and fresh water flux are flux adjusted, indicating that the ocean feedbacks to ENSO depends strongly on the climatologies of surface currents.
Figure 5.13: Fractional change in the errors in the surface temperature, precipitation, surface zonal wind stress and surface zonal wind anomalies linearly regression with NINO3 SST anomaly indices in the flux adjusted experiments compared to the target models. Red bars correspond to one-sided regressions between the said anomalies with positive NINO SST anomaly indices, and thus the response during El Niño conditions. Blue bars correspond to one-sided regressions when NINO3 SST anomaly indices are negative, i.e. response during La Niña conditions. Yellow bars correspond to regressions at all times. These three regressions are computed over the Tropical Pacific (20S-20N, 120E-80W) with land areas masked. The grey bars are similar to the yellow bars except that only the equatorial region (5S-5N) is considered. The error bars show the 25% and 75% percentiles for a set of 30-year block bootstrapped samples. The bars show the medians of these samples. Results for MIROC-ESM, however, suffer from nonlinearities not captured by linear regression analysis.
Figure 5.14: Net surface heat flux anomalies (upward positive) regressed to SST anomalies within the NINO3 region, (unit: W/m²/s/K) in the control and flux experiments. Blue (red) scatter points show the comparisons between FA2 (FA3) experiments and the target control experiments.
Figure 5.15: Differences in the surface heat flux anomalies regressed to SST anomalies within the NINO3 region (unit: W/m²/s/K) and the differences in the annual mean fraction convective precipitation in the region (in black; unit: percentage). Solid bars show the differences between the target model control and the CM2.1 control. The hatched bars show the difference between the FA experiments and the CM2.1 control. Changes in the convective precipitation are only shown for FA3 experiments as the data for the target control is not available. Heat flux regressions are always positive upward, i.e. surface damping for positive values. Convective activity is quantified by the percentage of convective precipitation as part of the total annual-mean precipitation. The mean precipitation is computed over periods when NINO3 SST anomalies are between -0.5 and 0.5K, in order to reduce rectification.
Figure 5.16: Comparisons of oceanic feedbacks in the control and flux adjusted experiments. (a) Maximum 40-longitude-degree averaged anomalous zonal advection of mean temperature gradients (5S-5N, 120E-80W) regressed with NINO3 SST anomalies (unit: per month); (b) maximum 40-longitude-degree averaged mean zonal advection of anomalous temperature gradients (5S-5N, 120E-80W) regressed with NINO3 SST anomalies (unit: per month); (c) SST anomaly regressed to thermocline depth anomalies in the NINO3 region (unit: K/m); (d) same as Fig. 5.8(c)
5.4.5 Relationships between ENSO characteristics and the mean climate

Equatorial zonal wind response and the climatological precipitation

In the previous chapter, a positive correlation between the composited equatorial zonal wind anomalies and the climatological precipitation over the equatorial central Pacific was found among the CMIP5 models. As correlation does not necessarily imply causality, this section aims to test whether there is a causal relationship between the intermodel spread in the mean precipitation over the equatorial central Pacific and the intermodel spread in the maximum equatorial zonal wind response to SST anomalies. Fig. 5.17 shows that such causality is not supported by the flux adjusted experiments, in which the climatological rainfall over the equatorial central Pacific is altered to represent the intermodel spread through flux correcting the ocean surface climatology.

The lack of impact may be in part due to the particular model sample used, as the eight target CMIP5 models in the current study are the ones whose control experiments do not support the positive correlation between the equatorial zonal wind anomalies and the mean equatorial precipitation during the warm phase (Fig. 5.17a), but do support that during the cold phase (Fig. 5.17b). Nevertheless, considering FA2 experiments or FA3 experiments alone, the relationship does not exist or is even reversed in the warm phase; the maximum equatorial zonal wind response during the cold phase also appears to be insensitive to the mean equatorial central Pacific rainfall.

However, the results regarding the cold phase are not as conclusive as those regarding the warm phase. As shown in Fig. 5.17b, the change in the maximum equatorial zonal wind response between the FA-CM2.1 experiments and the CM2.1 control is almost as large as half of the intermodel spread, which is enough to tilt a correlation. In contrast, such discrepancy between FA-CM2.1 experiments and CM2.1 control is small for the warm phase. Therefore, the causal link between the maximum zonal wind response to SST anomalies and the mean
equatorial central Pacific rainfall is refuted for El Niño condition; for the La Niña condition, although such causality is not supported, the experiments are not sensitive enough to reject the hypothesis.

We may speculate the reasons why the correlation was found in the control experiments but not in the FA experiments. First of all, flux adjustment is not very effective at correcting the dry bias in the CM2.1, despite improvements in the sea surface temperature. Although the overall spatial patterns of the mean Tropical Pacific precipitation in the FA3 experiments are significantly improved towards the target models (Fig. 5.5), a lot of the improvements come from changes in the zonal extent and the meridional location of the ITCZ and SPCZ; the equatorial central Pacific still remains relatively dry compared to some of the wetter target models (Fig. 5.17). Consequently, the strongest correlation between the zonal wind response to La Niña and the mean precipitation is confined within an area that is further west (Fig. 5.18), outside of the equatorial central Pacific region (5S-5N, 160E-160W) that was previously used for the correlation analysis.

This search for correlations suggests a revised hypothesis: the linear zonal wind response to La Niña is constrained by the mean equatorial precipitation, but only near the region where the zonal gradient of the mean precipitation is greatest, i.e. near the edge where the rainfall retreats as La Niña occurs. This "edge" may also be described as the dynamic warm pool edge (DWPE), defined by the longitude of the maximum zonal gradient of ocean salinity (Brown et al., 2013), as precipitation in the Tropical Pacific is strongly correlated with the surface salinity.

Nowhere could a linear correlation between the mean precipitation and the linear zonal wind response to El Niño be found (Fig. 5.18). The alternative hypothesis would be that the linear zonal wind response to El Niño may depend on the mean precipitation over the equatorial central Pacific but only when there is mean convective precipitation in the equatorial central Pacific. Otherwise, the atmospheric convection would not be sensitive to warming in the equatorial eastern Pacific. If this hypothesis is true, the fact that flux adjustment fails
to correct the dry bias in the CM2.1 in the equatorial central Pacific eliminates the linear correlation. This dry bias also highlights the importance of the physical parameterization in the atmosphere model in correctly simulating the dynamic warm pool edge.

Figure 5.17: Maximum equatorial zonal wind anomalies within the region of 2S-2N, 100E-100W, versus annual-mean precipitation averaged over 5S-5N, 160E-160W. The maximum equatorial zonal wind response is computed from a 40-longitude-degree running mean of the zonal wind anomalies composited for El Niño and La Niña conditions. The composites are based on events with NINO3.4 SST anomalies peaking between 1.5-2.5K. Missing points for MIROC-ESM are due to nonexisting events at this magnitude range.

SST anomaly amplitude and the mean equatorial surface wind stress

A linear correlation is found between the NINO3 SST anomaly standard deviations ($\sigma_{\text{nino3}}$) and the mean surface zonal wind stress over the NINO4 region ($\bar{\tau}_{\text{nino4}}$: 5S-5N, 160E-150W)
Figure 5.18: Correlation between the annual-mean precipitation and the maximum zonal wind response to (a) El Niño and (b) La Niña across the FA3 experiments. Shading indicates statistical significance exceeding 95%.
in the FA2 experiments, but not in the FA3 experiments (Fig. 5.19). The linear relationship in the FA2 experiments are consistent with the global warming response studied by Guilyardi et al. (2009). However, the lack of correlation in the FA3 experiments suggests that the mean equatorial zonal wind stress may not be the primary control of the ENSO amplitude. Despite the imposed flux correction on the ocean surface zonal momentum flux, most of the FA3 experiments have a similar amplitude of ENSO as their FA2 counterparts, except for FA3-MRI-CGCM3 where the subsurface structure is significantly altered (see Sec. 5.4.1 and Fig. 5.10a).

The results here do not seem to support a causal relationship between $\bar{\tau}^{x_{\text{nino}4}}$ and the magnitude of $\sigma_{\text{nino}3}$. We speculate three possible explanations for the linear correlation found in the FA2 experiments and the lack thereof in others (Fig. 5.20). First of all, the correlation reflects the fact that both the ENSO amplitude and the equatorial zonal wind stress are dependent on the ocean surface temperature climatology. Changing the surface wind stress without changing the surface temperature climatology does not lead to changes in the ENSO amplitude. Besides, across different models, the relationship between the mean surface zonal wind stress and the surface temperature climatology may be so different that an intermodel correlation would be masked.

Secondly, as the zonal wind stress response to the NINO3 SST anomalies is nonlinear (Choi et al. 2013; Sec. 5.4.6), the linear correlation between $\sigma_{\text{nino}3}$ and $\bar{\tau}^{x_{\text{nino}4}}$ may be caused by rectification effects. In other words, even if the NINO3 SST anomaly is not skewed, the fact that the westerly wind stress anomalies during El Niño tend to be stronger than the easterly wind stress anomalies during La Niña would lead to an overall weaker zonal wind stress in the mean state. A positively skewed ENSO would amplify the rectification even more. However, we have not proceeded with quantitatively analyzing the rectification effect on this correlation.

Thirdly, it is possible that the causality relationship between $\bar{\tau}^{x_{\text{nino}4}}$ and $\sigma_{\text{nino}3}$ is established via atmospheric processes and the flux correction approach is not sufficient to test
the hypothesis. For the FA3 experiments, the flux correction for the surface wind stress are only imposed on the ocean surface momentum flux while the surface wind stress in the atmosphere is not adjusted. In other words, the surface wind stress in the atmosphere is primarily determined by the surface temperature, which are very similar comparing the FA3 experiments with their FA2 counterparts.

Figure 5.19: Relationship between NINO3 SST anomalies (5S-5N, 150W-90W; unit: K) and the mean equatorial zonal wind stress (in Pa) over the NINO4 region (5S-5N, 170W-120W). In (c), the native zonal wind stress are shown in blue and the flux corrected zonal wind stress (experienced by the ocean only) is shown in red.

**Relationship between ENSO SST anomaly amplitude and mean precipitation climatology**

The methodology of Watanabe et al. (2012) is applied on the single-ensemble-member flux adjusted experiments to test whether the positive relationship between the NINO3 SST anomalies standard deviation $\sigma_{\text{nino3}}$ and the annual-mean precipitation climatology over the same region $\bar{P}_{\text{nino3}}$ holds, when the mean state climate is explicitly perturbed without changing the model’s physics. Such a relationship among the single-ensemble-member experiments is not found or is unclear (Fig. 5.21).

Despite the fact that the control experiments studied here are pre-industrial simulations versus historical runs explored by Watanabe et al. (2012), the $\sigma_{\text{nino3}}-\bar{P}_{\text{nino3}}$ dependence in
(a) **no direct causality**

\[
\sigma_{\text{nino3}} \quad \tau_{x_{\text{nino4}}} \quad \text{SST}
\]

(b) **rectification**

\[
\sigma_{\text{nino3}} \rightarrow \tau_{x_{\text{nino4}}} \quad \text{SST}
\]

(c) **atmospheric processes only**

\[
\sigma_{\text{nino3}} \quad \tau_{x_{\text{nino4}}} \quad \text{SST}
\]

Figure 5.20: Schematics for the possible relationships between the surface temperature, mean climatological zonal wind stress \(\tau_{x_{\text{nino4}}}\) over the NINO4 region (5S-5N,160E-150W) and the ENSO amplitude measured by the standard deviation of the NINO3 SST anomalies (\(\sigma_{\text{nino4}}\)). These relationships may explain the differences between the FA2 and FA3 experiments in Fig. 5.19. See text in Sec. 5.4.5.

Fig. 5.21a (blue points) is similar to Fig. 3b in Watanabe et al. (2012): models with \(\bar{P}_{\text{nino3}}\) drier than about 2.5mm/day conform to the positive relationship but the wetter models do not. However, the relationship is clearly absent for the FA2 experiments (Fig. 5.21b) and is very weak only for half of the FA3 experiments clustered near the CM2.1 control on the dry side (Fig. 5.21c).

Thirty-year records are randomly selected (block bootstrapping) from the single-ensemble-member run to mimic the result of multi-ensemble-member runs. The \(\sigma_{\text{nino3}}-\bar{P}_{\text{nino3}}\) relationship becomes apparent again for the control (Fig. 5.22), FA2 (not shown) and FA3 experiments (Fig. 5.23). The experiments that do not show a clear relationship tend to be those that have weaker ENSO. Furthermore, for the control experiments of CM2.1, ESM2M, CMCC-CM, the dependence does not take off until the ENSO amplitude reaches a certain magnitude (Fig. 5.22). Therefore, questions arise over whether the reconstructed mean precipitation still suffers from ENSO rectification.
By computing the mean NINO3 precipitation during the time when NINO3 SST anomaly is within the range of -0.5K and 0.5K, i.e. close to neutral conditions or when ENSO is weak, it is found the ENSO amplitude has virtually no dependence (or vice versa) on the mean precipitation during neutral conditions (Figs. 5.21, 5.22 and 5.23). This suggests that the magnitude of $\sigma_{\text{nino3}}$ may not be predicted from $\bar{P}_{\text{nino3}}$ in the basic state.

Figure 5.21: Relationship between NINO3 SST anomalies (5S-5N, 150W-90W) and the mean precipitation (mm/day) over the same region. Blue points represent the annual-mean precipitation over the NINO3 reconstructed using the method in Watanabe and Wittenberg (2012) and Watanabe et al (2012). Green points represent the annual-mean precipitation averaged over the time when NINO3 SST anomalies is within -0.5K and 0.5K.

5.4.6 Nonlinear zonal wind response and asymmetry

In the previous chapter, no direct correlation is found between the nonlinear zonal wind response and the mean precipitation climatologies. Here it is confirmed once again that flux adjusting the ocean surface climatology does not influence the nonlinearity in the zonal wind response (Fig. 5.24). All except one (FA3-GISS-E2-H) of the FA experiments exhibit a nonlinearity near the CM2.1 control’s. This suggests that the nonlinearity is largely determined by the representation of atmospheric processes within the model, rather than the model mean state.
Figure 5.22: Relationship between NINO3 SST anomalies (5S-5N, 150W-90W) and the mean equatorial zonal wind stress over the NINO4 region (5S-5N, 170W-120W) for each 30-year block bootstrap sample in the control experiments. Blue points represent the annual-mean precipitation over the NINO3 reconstructed using the method in Watanabe and Wittenberg (2012) and Watanabe et al (2012). Green points represent the annual-mean precipitation averaged over the time when NINO3 SST anomalies is within -0.5K and 0.5K. Bracketed number in the bottom right corner of each subplot follows the legend in the previous figures (0: CM2.1-1860, 1: ACCESS1-0...).
Figure 5.23: Relationship between NINO3 SST anomalies (5S-5N, 150W-90W) and the mean equatorial zonal wind stress over the NINO4 region (5S-5N, 170W-120W) for each 30-year block bootstrap sample in the flux adjust (FA3) experiments. Blue points represent the annual-mean precipitation over the NINO3 reconstructed using the method in Watanabe and Wittenberg (2012) and Watanabe et al (2012). Green points represent the annual-mean precipitation averaged over the time when NINO3 SST anomalies is within -0.5K and 0.5K. Bracketed number in the bottom right corner of each subplot follows the legend in the previous figures (0: CM2.1-1860, 1: ACCESS1-0... )
Despite the small change in the nonlinear zonal wind response, the flux adjusted experiments have shown improvements in the skewness of the NINO3 SST anomalies for all of target models except for GFDL-ESM2M; as much as 80-90% of the skewness is corrected for four of the target models (Fig. 5.25). Since the ENSO in CM2.1 is the most skewed of all the coupled models in this study, any reduction in the skewness is an improvement. Nevertheless, it is worth noting that a coupled model as skewed as CM2.1 is capable of generating a much less skewed ENSO upon flux adjustment, indicating that the mean state climate can have a strong influence on the skewness. Application of the results by Choi et al. (2013) suggests that this change in the skewness would be achieved by changes in the relative strengths of the positive and negative feedbacks. For instance, the meridional extent of the zonal wind stress response to the SST anomalies can alter the relative strength of the delayed negative feedback (Kirtman, 1997; An and Wang, 2000; Capotondi et al., 2006). If the meridional extent of the surface wind stress response is narrower, in the recharge/discharge oscillation paradigm, there would be less warm water involved in the recharge/discharge process; likewise in the oceanic-wave-reflection paradigm, fewer higher-order off-equatorial Rossby wave modes would be excited and the negative feedback associated with the equatorial Rossby waves would be strengthened. Further investigation would be needed to verify these statements.

The changes in the duration and transition asymmetries in the flux adjustments are indistinguishable from the internal decadal variability (Fig. 5.25). Therefore no conclusive statement can be made about the duration and transition asymmetries.

5.5 Chapter summary and discussion

The hypothesis that the model simulated ENSO should improve with a better mean state climate holds for quite a few, but not all, of the aspects of ENSO. And the extent to which ENSO characteristics and feedbacks depend on the mean state climate is quantified. By
Figure 5.24: Nonlinearity in the maximum equatorial zonal wind response to SST anomalies in NINO3 region for the control, FA2 and FA3 experiments. The nonlinearity is computed following Eq. 4 of Choi et al. (2013).
Figure 5.25: Amplitude, duration and transition asymmetries of ENSO, comparing the flux adjust and the control experiments. The asymmetries are computed using the NINO3 SST anomalies following the procedures described in Choi et al. (2013).

flux adjusting the ocean surface temperature, fresh water flux and downward momentum flux in the GFDL CM2.1 to the climatologies of eight other CMIP5 pre-industrial control simulations, 20-70% (10-50%) of the intermodel differences in the mean Tropical Pacific sea surface temperature and precipitation are removed except for two target models (Figs. 5.1, 5.5). Substantial improvements in the subsurface temperature structures and surface zonal currents are also noted (Figs. 5.7, 5.8). Among the six target models whose ocean surface climatologies are represented in the flux adjusted experiments to some extent, these changes in the mean state explain:

- 20-96% of the differences in the ENSO amplitudes, except for GFDL-ESM2M which is very similar to CM2.1 (Fig. 5.10);

- 10-50% of the models’ differences in Tropical Pacific precipitation, surface zonal wind and wind stress response to NINO3 SST anomalies (Fig. 5.13);

- 70% of the intermodel spread in the surface heat flux feedback over the NINO3 region, mainly due to changes in the downward shortwave surface fluxes associated with the changes in the percentage of the mean convective precipitation (Figs. 5.14, 5.15);
• 40-80% of the differences in the NINO3 SST anomalies response to thermocline depth (Fig. 5.16c);

• 20-90% of the differences in the anomalous zonal advection of the mean ocean surface temperature gradients, only as long as the mean surface zonal currents are improved (Fig. 5.16);

• 25-94% of the differences in the NINO3 SST anomalies skewness except for GFDL-ESM2M which is, again, similar to CM2.1 (Fig. 5.25a).

The seasonal locking is also notably improved through flux adjustment (Fig. 5.11), except for GISS-E2-H. This is consistent with the improvement, and the lack thereof, in the seasonal meridional migration of the climatological ITCZ/SPCZ in the flux adjusted experiments (Fig. 5.6).

However, flux adjusting the CM2.1 towards another model’s ocean surface climatology:

• does not improve the mean zonal advection of the anomalous ocean temperature gradients (Fig. 5.16);

• does not improve the nonlinearity in the surface zonal wind response to ENSO SST anomalies (Fig. 5.24), consistent with the hypothesis in the previous chapter;

• appears to be inconsequential for the maximum vertical temperature gradients in the eastern equatorial Pacific Ocean (Fig. 5.8).

The insensitivity of the maximum vertical subsurface temperature in the eastern equatorial Pacific Ocean suggests that differences in the physical representations of the ocean mixed layer, such as diapycnal mixings, are of more fundamental control in the sharpness of the thermocline in the region. Nevertheless, the intermodel spread in the maximum vertical temperature gradient may be less crucial to the ENSO growth rate, as much of the NINO3 SST anomalies response to the thermocline depth anomalies is nevertheless substantially improved in the flux adjusted experiments (Fig. 5.16c). The latter is consistent with changes
in the vertical temperature gradient in the mixed layer, as the thermocline mean depths and slopes are modified via flux adjustments.

The above results indicate that a lot of the feedbacks and features of ENSO are closely linked to ocean surface climatologies and therefore, linked to each other. The implication is that these feedback parameters cannot be viewed as independent metrics for evaluating how well a model simulates ENSO. In addition, as a model’s representation of the ocean surface climatology improves with the advancement of model parameterizations, complexity and resolutions, we should also expect consistent improvements from the feedbacks that respond positively to flux adjustments.

On the other hand, processes that are insensitive to flux adjustments provide information in addition to the ocean surface climatology, and can be utilized while evaluating model performance. For example, the thermocline sharpness is one candidate for evaluating ocean model parameterizations relatively independent of the SST simulation. The nonlinearity in the zonal wind response to ENSO SST anomalies may be another candidate for evaluating the atmosphere model, as the lack of change in the nonlinearity in the flux adjusted experiments (Fig. 5.24) suggests that the nonlinearity should be controlled by the physical parameterizations of CM2.1, rather than the imposed ocean surface climatology.

However, a caveat remains that the quantitative and qualitative versions of these results maybe dependent on the choice of the coupled model used for the flux adjusted experiments. Replacing the CM2.1 with another model and performing flux adjusted experiments with the same set of target models may yield different results. Therefore, for the purpose of aiding model development, it would be best to perform a similar set of flux adjusted experiments using the particular model of interest. For the more general purpose of relating the mean state climate and ENSO, repeating the flux adjustment exercise using a different coupled model, especially one that is more distant from CM2.1 in terms of model genealogy (Knutti et al., 2013), would be helpful for gauging the robustness of the results presented here.
Results for the ENSO amplitude, skewness, NINO3 thermocline feedback and the non-linear zonal wind response should also be subject to greater scrutiny. As these quantities in the CM2.1 control are the strongest among other target models, any reduction of these quantities in the flux adjusted experiments is considered as an improvement. In other words, the sensitivity tests on these quantities are essentially one-sided due to our choice of models. On the contrary, the sensitivity test on the surface heat flux feedbacks, for example, is two-sided and therefore the results bear a higher confidence.

A few relationships between the mean state (of quantities not directly adjusted) and ENSO characteristics are also tested. First, it is found that the equatorial zonal wind response to SST anomalies does not directly depend on the mean precipitation over the equatorial central Pacific, in contrast to what was suggested by the intermodel correlation of the control experiments (the previous chapter). However, the CM2.1 dry bias over the equatorial central Pacific has persisted in the flux adjusted experiments and this may render the test insufficient.

Secondly, the relationship between ENSO amplitude and the mean equatorial zonal wind stress over the NINO4 region (Guilyardi, 2006) is a robust, internal feature of CM2.1 when the surface wind stress is not flux adjusted. The relationship is weakened when the surface wind stress is corrected. This raises the question of whether the mean equatorial zonal wind stress is a controlling factor of the ENSO amplitude, or that the two are, in fact, independent products of the sea surface temperature climatology.

Thirdly, the relationship between ENSO amplitude and the mean precipitation over the NINO3 region (Watanabe et al., 2012) is not apparent among the flux adjusted experiments. Besides, it is possible that the analysis still suffers from the rectification effect of the nonlinear precipitation response to ENSO, that a strong El Niño increases precipitation in the region while La Niña does little influence.

It is demonstrated that flux adjustment is a useful tool for quantitatively diagnosing the impact of the mean state climate without sacrificing the atmosphere-ocean coupling. Alter-
natively, flux adjustment may also be applied with projected climatic forcings to quantify the extent to which the models’ projections of ENSO in the future may be dependent on the simulated control mean state climate. Similar experiments using an energy balance model in the context of climate sensitivity to increased CO$_2$ scenarios have shown reinforcing and counteracting contributions from perturbing the mean state climate and physical parameters (Dommenget, 2015). Similarly, these experiments may also be used to study other climatic variability. However, caution should be taken as the mean ocean climate in other regions of interest may not be corrected via flux adjustments as easily as the Tropical Pacific Ocean is.
Chapter 6

Conclusions

The initial goal of this dissertation is to understand how ENSO asymmetry is supported. The question is partly motivated by pure curiosity, but is also motivated by the societal need to better understand and predict the ENSO characteristics in the present and future climate. In this quest, a number of questions are raised:

- Can atmospheric nonlinearities contribute to the observed ENSO asymmetries? If so, how?

- What does the nonlinear atmospheric feedback depend on?

- Is there a causal relationship between the mean state climate and the atmospheric feedbacks?

- Can intermodel differences in the simulated ENSO characteristics be attributed to the intermodel differences in the mean state climate?
6.1 ENSO asymmetry and nonlinear atmospheric response

To answer these questions, we begin by systematically quantifying the different facets of ENSO asymmetries in the observations and state-of-the-art coupled climate models. The three aspects of asymmetries we have explored are referred to as (1) amplitude asymmetry: warm events are stronger than cold events; (2) duration asymmetry: cold events are more persistent than warm events; and (3) transition asymmetry: strong warm events are more likely to be followed by cold events than vice versa. We found that most coupled GCM simulations underestimate the amplitude asymmetries. There is also a wide diversity of duration and transition asymmetries, although the qualitative results for these two asymmetries are more robust across models.

To shed light on these asymmetries, we use a widely-used delayed-oscillator conceptual model for ENSO, and modify it so that wind stress anomalies depend more strongly on SST anomalies during warm conditions - as is observed. The new nonlinear conceptual model shows that with the nonlinearity entering both the positive and delayed negative feedbacks, the correct signs of the duration and transition asymmetries are found everywhere in the parameter space, and they can coexist with a positive or negative amplitude asymmetry, depending on the relative strengths of the positive and delayed negative feedbacks in the model. If the positive feedbacks are stronger (weaker) than the negative feedbacks, then the simulated ENSO is positively (negatively) skewed, i.e. El Niño (La Niña) tends to be stronger.

We then apply the modified oscillator to observational records, and to control simulations from two global coupled ocean-atmosphere-land-ice models (GFDL-CM2.1 and GFDL-CM2.5), to elucidate the causes of their differing asymmetries. We found that the fact that CM2.1 has a stronger ENSO asymmetry than observed may be explained by the excessive nonlinearity in the model’s surface zonal wind response. On the other hand, the negative
skewness in the CM2.5’s ENSO may be due to the stronger delayed negative feedback parameter relative to that of the positive feedback.

6.2 The sources of the nonlinear atmospheric response

Next, we try to understand what drives the nonlinearity in the surface zonal wind response to ENSO. First, we found that most global coupled climate models in CMIP5 exhibit such nonlinearity, yet weaker than observed. The fact that the nonlinearity already exists in the coupled models allow us to perform intermodel comparisons. We found that the wind response nonlinearity can be reproduced by driving a linear atmosphere shallow-water model with a coupled model’s or the observed precipitation anomalies, which can be decomposed into two main components: the zonal and meridional redistribution of the climatological precipitation. Both redistributions contribute comparably to the total rainfall anomalies while the zonal redistribution plays the dominant role in the zonal wind response.

The meridional redistribution component plays an indirect role in the nonlinear wind response by limiting the zonal redistribution during La Niña and thus enhancing the nonlinearity in the wind response significantly. During La Niña, the poleward movement of the ITCZ/SPCZ reduces the equatorial zonal mean precipitation available for the zonal redistribution and its resulting zonal wind response. Conversely, during El Niño, the equatorward movement of the ITCZ and SPCZ do not limit the zonal redistribution of precipitation.

The linear equatorial zonal wind response to ENSO is found to have a significant linear correlation with the equatorial central Pacific climatological precipitation and SST among the CMIP5 models control experiments. However, no linear correlation is found between the nonlinear equatorial zonal wind response and the climatological precipitation.
6.3 Relationship between the mean state climate and ENSO

In Chapter 5, we directly test the hypothesis that the intermodel differences in the simulated ENSO statistics and feedbacks are due to the intermodel differences in their ocean surface climatology. By flux adjusting the CM2.1 ocean surface climatology to those in a number of other CMIP5 coupled models, we found that the hypothesis holds for some but not all aspects of ENSO. The extent to which the intermodel differences in the mean state climate can affect ENSO feedbacks are quantified.

The following ENSO characteristics and feedbacks respond positively to corrections in the mean ocean surface climatologies:

- ENSO amplitude measured by the SST anomalies in the eastern equatorial Pacific;
- Seasonal phase locking of ENSO;
- Precipitation, surface zonal wind and wind stress response to the SST anomalies in the eastern equatorial Pacific;
- Surface heat flux feedback over the equatorial eastern Pacific, largely due to changes in the downward shortwave flux feedback;
- Thermocline feedback, i.e. equatorial eastern Pacific surface temperature sensitivity to the changes in thermocline depth;
- Anomalous zonal advection of the mean zonal gradient of the surface temperature;
- Skewness of ENSO.

The feedbacks and characteristics of ENSO that are not sensitive to the changes in the ocean surface climatology include the following:

- Mean zonal advection of the anomalous ocean temperature gradient;
• Nonlinearity in the zonal wind response to SST anomalies;

The motivation of performing these flux adjust experiments was to verify the results from Chapter 4 that (1) the linear zonal wind response has a dependence on the climatological precipitation on the equatorial central Pacific, while (2) the nonlinearity in the zonal wind response does not have such a direct relationship. For the former, the relationship is not supported by the flux adjust experiments. However, the dry bias that has persisted in the CM2.1 makes the test results questionable. For the latter, indeed there is virtually no change in the nonlinearity upon changing the ocean surface climatology.

6.4 Contributions

There are several novelties in the above studies. First of all, earlier conceptual frameworks of ENSO tend to focus on oceanic processes and the amplitude asymmetry only. The nonlinear conceptual model presented here is one of the first to incorporate the atmospheric nonlinearities in a conceptual model and view the different aspects of ENSO asymmetries together. Dommenget et al. (2013) have independently developed a similar model using the recharge/discharge oscillator framework to understand the transition asymmetry. Our results very much agree with theirs: the predictability of an ENSO event following a La Niña event is weaker than following an El Niño event. In addition, the results from the nonlinear conceptual ENSO model offer an explanation for the negatively skewed ENSO simulated in a number of coupled climate models.

Secondly, we have presented here a new method to linearly decompose the Tropical Pacific precipitation anomalies associated with ENSO. The method is proved to be insightful for understanding the zonal wind response nonlinearity that had not been explained. We have also demonstrated the importance of the climatological precipitation on constraining the zonal wind response during La Niña, which is a new result that has not been shown before.
Lastly, flux adjusting a climate model to the climatologies of other climate models, as a method to test the ENSO dependence on the mean state climate, was not attempted before. Previous studies that used flux adjustments aimed at correcting the mean state climate towards the observations in order to investigate how different model physics parameterizations may affect ENSO. Our approach in this study is therefore complementary to others’. While it is a triumph that nowadays most coupled climate models do not require flux adjustments to simulate a reasonable mean state climate and climatic variabilities, the results presented here prove that flux adjustment is still a valuable tool for sensitivity testing, aiding model developments and assessments.
Appendix A

Uniqueness of the decomposition solution

This appendix proves the uniqueness of the solution given by the decomposition method described in Sec. 4.2.3.

The solution is unique because of the requirement that the solution should not depend on the order of the zonal and meridional redistribution, i.e. the two redistributions occur simultaneously. Unless there is a reason to believe that the Walker circulation adjusts before the local Hadley cell does (or vice versa), the simultaneity is the best assumption that one could make. We will show how the simultaneity leads to a unique solution.

As the residual component can be uniquely defined by the difference between the total precipitation field during El Niño (or La Niña) and the same field normalized by the tropical mean climatological precipitation, for now we may ignore the residual component, i.e. any basin-wide intensification or reduction of precipitation, and focus on the pure spatial (two-dimensional) redistribution of precipitation in the Tropical Pacific.

With that, we let

\[ P' = P'_x + P'_y \]

where \( P' \) is the total precipitation anomalies with zero area mean; \( P'_x \) is the precipitation anomaly due to the zonal redistribution; \( P'_y \) is the precipitation anomaly due to the meridional redistribution. By definition, the zonal mean of \( P'_x \) is zero; the meridional mean of
\( P'_y \) is zero. We shall prove that this is a unique decomposition under the aforementioned assumptions.

An alternative solution for the decomposition would be

\[
\begin{align*}
P'_{x,1} &= P'_x + P_1 \\
P'_{y,1} &= P'_y - P_1
\end{align*}
\]

So that \( P' = P'_{x,1} + P'_{y,1} \).

To satisfy all the above statements, \( P_1 \) has zero zonal mean and zero meridional mean. Therefore \( P_1 \) is either zero everywhere or has a structure of a quadrupole or higher order multipoles. We will continue the proof with the quadrapole solutions, which can be easily generalized to higher order multipoles. There are two quadrupole solutions for \( P_1 \), as shown in Fig.A.1.

Figure A.1: Two-dimensional quadrapole structures.
Without loss of generality, let $P_1$ take the structure of Fig.A.1(a). That is to add Fig.A.1(a) to $P_x'$ and add an equal magnitude of Fig.A.1(b) to $P_y'$. This forms a proposed alternative solution. But this solution violates our assumption that the zonal and meridional redistribution occur simultaneously.

What the additional $P_1$ implies is a counterclockwise movement of a block of precipitation that eventually moves back to where it was and causes no overall anomaly anywhere. This also implies a preferred order of redistribution. In other words, when there is no preference for the zonal redistribution to occur prior to the meridional redistribution, another choice of $P_1$, i.e. a clockwise movement, should exist if the counterclockwise solution existed. These two choices of $P_1$ cancel each other. Therefore there is no alternative solution to $P' = P_x' + P_y'$.

Q.E.D.

In the current implementation, $P_1$ is eliminated by small-step iterations between the zonal redistribution and the meridional redistribution operations. An alternative implementation would be to average two pairs of redistribution anomalies: the first set assumes that all of the zonal redistribution takes place before the meridional redistribution; the second set assumes the opposite. Then the average of the two sets of $(P_x', P_y')$ would have no preference for the order of redistribution (i.e. the clockwise and counterclockwise movements are averaged out). This implementation is illustrated in Fig.A.2.

The iterative method (used in the main body of this manuscript) and the averaging method give answers that are the same, exact to the order at which the first method is designed to converge (1% of the anomalies for the experiments presented). In retrospect, the second method may be better because there is no need for an iteration and a choice when the iteration converges. But the first method gives intermediate steps for animating how the redistribution occurs progressively.
Figure A.2: Decomposition of the anomalies resulted from moving some scalar quantities from the bottom right corner to the top left corner. Zonal redistribution anomaly (a) is assumed to take place before the meridional redistribution anomaly (b). In (c) and (d), the meridional redistribution anomaly (c) happens before the zonal redistribution anomaly (d). (e) is the averaged of (a) and (d). (f) is the averaged of (b) and (c). The iterative method described in the text gives the same answers as (e) and (f), exact to the order at which the algorithm is designed to converge.
Appendix B

Resampling surface heat flux anomalies

In Sec. 5.4.3, the surface heat flux feedbacks are analyzed by regressing the surface heat flux anomalies with the SST anomalies in the NINO3 region. As there is a large nonlinearity in the shortwave surface flux feedback (Lloyd et al., 2012), changes in the linear regression coefficients may arise due to (1) changes in the relationship between the shortwave flux anomalies and the SST, and/or (2) mere changes in the range of the SST anomalies. These two causes are distinguished by reconstructing a time series of surface heat flux anomalies for the given time series of NINO3 SST anomalies under the assumption that the relationship between the flux anomalies and the SST anomalies remains the same as that in the CM2.1 control experiment. The procedures for the reconstruction are as follows:

- The area averaged surface heat flux anomalies and the SST anomalies over the NINO3 region are computed for the CM2.1 control experiment. The NINO3 SST anomalies are binned to 50 bins $T_i$ (or any other number of bins that could result in a histogram that is well-resolved but is also reasonably populated at the tails);

- For each NINO3 SST anomaly from another experiment that is being compared to CM2.1,
  - identify the bin $T_i$ where this SST anomaly should fall; if the bin is out of range, this SST anomaly is rejected;
– compute the cumulative distribution function of the CM2.1 surface heat flux anomalies within this bin;

– pseudo-randomly generate a number based on a uniform distribution, invert the random number onto a surface heat flux anomaly using the cumulative distribution function.

This method is made applicable by the fact that CM2.1 has a very strong ENSO, i.e. a wide range of bins $T_i$, and the length of the experiment is long enough to establish a large enough sample size at each bin.
Bibliography


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