The Influence of Cloud Feedbacks on Climate Variability and Change

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THE INFLUENCE OF CLOUD FEEDBACKS ON CLIMATE VARIABILITY AND CHANGE

By
Katinka Bellomo

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Doctor of Philosophy

THE INFLUENCE OF CLOUD FEEDBACKS ON CLIMATE VARIABILITY AND
CHANGE

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One of the greatest challenges in projections of future climate change is narrowing the uncertainty in the magnitude and sign of cloud feedback. The main limitations are that cloud processes need to be parameterized in climate models, and long-term observations of cloud cover are limited. In this dissertation we address this problem by studying the interplay of cloud feedbacks with atmospheric circulation and Sea Surface Temperature (SST). We first investigate the response of clouds to external radiative forcing by examining changes in cloud cover and their radiative impact in multiple and independent surface and satellite cloud cover datasets. Observed changes in cloud cover and estimated cloud amount feedback from 1954 to 2008 over the Indo-Pacific Ocean are found to be consistent in sign but significantly smaller in amplitude than changes simulated by an ensemble of historical simulations in the Coupled Model Intercomparison Project Phase 5 (CMIP5) archive over the same period of time. However, climate models are capable of simulating changes in cloud cover of the same strength and pattern as observed, when they are forced with a greater increase in SST. This suggests that observed changes in cloud cover are at least in part forced by anthropogenic emissions. It remains unclear whether observations exhibit unrealistically large trends in cloud cover, or clouds are not sensitive enough to changes in surface temperature in climate models. However, climate models underestimate changes in cloud
cover also on shorter and better constrained timescales. The implications of underestimating the strength of a positive cloud feedback is explored using idealized model experiments in the context of internal climate variability. It is found that a positive feedback among cloud cover, SST, and large-scale atmospheric circulation over the subtropical stratocumulus regions affects basin-wide pattern and persistence of SST anomalies in both the Atlantic and Pacific Oceans. Collectively, these findings suggest that climate models underestimate the impacts of cloud feedbacks on the persistence of regional and global SST anomalies, thus potentially underestimating climate sensitivity to future climate change.
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Contents

List of Figures ................................................................................................................................. vi

List of Tables ................................................................................................................................. xi

Chapter 1: Introduction ...................................................................................................................... 1
  1.1 Motivation ................................................................................................................................. 1
  1.2 Approach .................................................................................................................................. 4
    1.2.1 Observational datasets ................................................................................................. 4
    1.2.2 CMIP5 models ............................................................................................................... 6
    1.2.3 Idealized model experiments ....................................................................................... 7
  1.3 Outline ...................................................................................................................................... 8

Chapter 2: Observational and Model Estimates of Cloud Amount Feedback over the Indian and Pacific Oceans ........................................................................................................... 11
  2.1 Background ............................................................................................................................. 11
  2.2 Data ......................................................................................................................................... 14
  2.3 Methods .................................................................................................................................... 16
  2.4 Results ....................................................................................................................................... 21
    2.4.1 Cloud amount change .................................................................................................. 21
    2.4.2 Cloud amount feedback ............................................................................................. 26
  2.5 Discussion ................................................................................................................................. 33
  2.6 Conclusions ............................................................................................................................. 38

Chapter 3: Evidence for Weakening of Tropical Atmospheric Circulation from Cloud Observations ................................................................................................................................. 40
  3.1 Background ............................................................................................................................... 40
  3.2 Data and methods ..................................................................................................................... 42
    3.2.1 Observations .................................................................................................................. 42
    3.2.2 Models ............................................................................................................................ 43
  3.3 Results ....................................................................................................................................... 44
  3.4 Discussion and conclusions ....................................................................................................... 53

Chapter 4: Simulating the Role of Subtropical Stratocumulus Clouds in Driving Pacific Climate Variability ............................................................................................................................ 56
List of Figures

Figure 1.1: (Shaded) SST forcing used for AMIP-Future simulations, (contours) SST climatology. Here SST is computed as the multi-model mean change in SST between AMIP-Future and AMIP, but the SST forcing is the same for all models.................................................................6

Figure 1.2: Enhanced positive cloud feedback function from equation (1.1).....................8

Figure 2.1: Total cloud amount change (1954-2005): (a) EECRA, (b) CMIP5 multi-model mean. Contours represent cloud amount climatology (long-term mean), while stippling indicates where the changes are robust. In (a) changes are considered robust if they pass a two tailed Student's t test at the 90% level where the degrees of freedom for the test correspond to the number of observations in each grid box, and are adjusted to take into account autocorrelation at lag1 where the autocorrelation is significant at the 90% level of a Pearson's R test. In (b) stippling indicates where at least 31 models out of 42 (74%) agree on sign. The boxed regions highlight where observed cloud changes are robust ..........................22

Figure 2.2: Regional time series of total cloud amount inter-annual anomalies in the four boxed regions of fig. 1. Blue refers to EECRA (1954-2008), red to ISCCP (1984-2007), and green to PATMOS-X (1984-2007). The blue dashed line is the linear trend fitted to EECRA .................................................................23

Figure 2.3: Cloud amount radiative kernel computed as mean Cloud Radiative Effect (CRE) divided by mean cloud cover. (a) Observational estimate: CRE is from CERES and mean cloud cover is from EECRA, (b) CMIP5 multi-model mean......26

Figure 2.4: Cloud amount feedback: (a) Observational estimate computed multiplying cloud amount radiative kernel (fig. 2.3a) by EECRA cloud amount changes (fig. 2.1a) and then dividing by tropical mean change in SST from HadISST (0.46 °C). Contours represent total cloud amount climatology from EECRA. Stippling indicates where cloud amount feedback is robust and is computed as in fig. 1. (b) CMIP5 multi-model mean. Contours represent the multi-model mean cloud amount climatology. Stippling indicates where at least 31 models out 42 (~74%) agree on sign. Boxes indicate the regions where cloud changes in fig. 1a are statistically significant.................................................................28

Figure 2.5: Cloud amount feedback averaged over the first two boxed regions of fig. 2.4: (a) western Indian, (b) western Pacific. The numbers indicate the model name (see legend in Table 2.4). Horizontal lines represent the estimated range of observational errors, which are computed using the propagation of uncertainty formula assuming that the error in the estimate of cloud amount change is much larger than the errors in the estimates of tropical mean SST change and cloud amount radiative kernel. The observational error on cloud amount feedback
(CAF) can therefore be written as: $\sigma_{CAF}/CAF = \sigma_{\Delta c}/\Delta C$. From eq. (2.4): $CAF = \frac{k\Delta c}{\Delta T_s}$, therefore: $\sigma_{CAF} = \sigma_{\Delta c} (k/\Delta T_s)$ where $k$ is averaged over the boxed region and $\Delta T_s$ is the tropical mean SST change (0.46 °C). $\sigma_{\Delta c}$ represents the 90% confidence range, and is computed as the standard error on the estimate of the cloud amount trend multiplied by the t-value at the 90% probability level of a two-tailed Student's t test with degrees of freedom equal to the number of observations adjusted to account for the autocorrelation at lag 1........................31

Figure 2.6: Same as fig. 2.5 but for cloud amount feedback averaged over the other two boxes regions of fig. 2.4: (a) NE Pacific, (b) central Pacific..........................32

Figure 3.1: (Shaded) High-level cloud cover and (contours) $\omega_{500}$. Stippling indicates where at least 5 out of 7 models agree in sign: (a) AMIP climatological multi-model mean. Contours range from -100 hPa day$^{-1}$ to 100 hPa day$^{-1}$ with intervals of 5 hPa day$^{-1}$. (b) AMIP-Future minus AMIP multi-model mean and (c) AMIP-4K minus AMIP multi-model mean: Contours range from -30 hPa day$^{-1}$ to 30 hPa day$^{-1}$ with intervals of 2 hPa day$^{-1}$ ..........................................................45

Figure 3.2: Scatterplots of mean High-Cloud Cover (HCC) against mean $\omega_{500}$ from which the regression coefficients in the middle column of Table 3.1 are computed: (a) Observations: HCC is from ISCCP, $\omega_{500}$ is from the NCEP-NCAR reanalysis; (b) AMIP (ISCCP simulator) multi-model mean; (c) AMIP multi-model mean............46

Figure 3.3: Scatterplots of change in High-Cloud Cover (HCC) against change in $\omega_{500}$ from which the regression coefficients in the right column of Table 3.1 are computed: (a) AMIP-Future minus AMIP (ISCCP simulator) multi-model mean; (b) AMIP-4K minus AMIP (ISCCP simulator) multi-model mean; (c) AMIP-Future minus AMIP multi-model mean; (d) AMIP-4K minus AMIP multi-model mean ..........................................................47

Figure 3.4: (Shaded) Change in total cloud cover, (contours) climatological mean total cloud cover: (a) EECRA 1954-2008. Stippling indicates where the linear trend is statistically significant at the 90% level of a Student's t-test (autocorrelation is accounted for determining the degrees of freedom), (b) ICOADS 1920-2010...........49

Figure 3.5: (Shaded) Change in $\omega_{500}$, (contours) climatological mean $\omega_{500}$: (a) observational estimate from EECRA (1954-2008), (b) multi-model estimate from AMIP-Future, (c) AMIP-Future multi-model mean simulated change. Contours range from -100 hPa day$^{-1}$ to 100 hPa day$^{-1}$ with intervals of 5 hPa day$^{-1}$. Stippling indicates where at least 5 out of 7 models agree in sign. For this figure, all the datasets are regridded to a common 2.5º x 2.5º grid ......................................................51

Figure 4.1: (a) Cloud feedback in the control simulation (estimated as regression of CRE at the surface on SST, units of W m$^{-2}$ K$^{-1}$). (b,c,d) Difference in the strength of cloud feedback between the three experiments and the control run. Overlaid is cloud cover climatology from the control run. (b) NE+SE Pacific minus control,
(c) SE Pacific minus control, and (d) NE Pacific minus control. Black boxes indicate where low-cloud feedback is enhanced ..................................................64

Figure 4.2: (a) Variance of SST in the control simulation. (b,c,d) Difference in variance of SST between the three experiments and the control: (b) NE+SE Pacific minus control, (c) SE Pacific minus control, and (d) NE Pacific minus control .......................66

Figure 4.3: (a) e-folding timescale in the control simulation (units of months). (b,c,d) Difference in e-folding timescale between the three experiments and the control: (b) NE+SE Pacific minus control, (c) SE Pacific minus control, and (d) NE Pacific minus control.................................................................67

Figure 4.4: Climatology in the control simulation: (shaded) SST, (contours) SLP ranging from 990 hPa to 1040 hPa, 2 hPa intervals, (vectors) surface winds in m/s ..........69

Figure 4.5: Regression of (shaded) SST, (vectors) surface winds, and (contours) SLP on the PCs of the (a) North Pacific mode and (b) South Pacific mode in the control simulation. The PCs are normalized by their standard deviation. Negative SLP contours are dashed, positive SLP contours are solid, and the zero SLP contour is thick solid. Contour range is from -2 hPa to 2 hPa, 0.2 hPa interval .........................70

Figure 4.6: Power spectra of the Nino3 index in the (black) control, (red) NE+SE Pacific, (blue) SE Pacific, and (green) NE Pacific simulation. Markers indicate where the variance is statistically different from the variance in the control simulation at the 95% level of a Fisher's F test. Gray lines indicate the error range estimated with the chi-square distribution (see text for details). Units are years for period (top label) and month^{-1} for frequency (bottom label) .................................................73

Figure 4.7: Composites of SST and surface heat fluxes during Nino3 index warm events in the southeastern Pacific (5°S-20°S, 70°W-100°W): (a) Control, (b) SE Pacific. Black is SST, blue is latent heat flux, green is sensible heat flux, red is cloud radiative effect, and orange is clear-sky radiation. All time series are smoothed with a 6-month running average..........................................................77

Figure 5.1: Masking used in the model experiments with enhanced positive cloud feedback. Red box: Namib experiment; black boxes 1-9: regional experiments in the South Atlantic.................................................................88

Figure 5.2: Regression of observed (shaded) SST, (contours) SLP, (vectors) surface winds on the Atl3 SST index (black box) for the years 1960-2010. Contours are from -2.0 hPa to 2.0 hPa with interval of 0.2 hPa. Solid lines refer to positive SLP anomalies, dashed lines to negative SLP anomalies, while the thick solid line is the zero-level contour. Stippling indicates where the correlation between local SSTs and the Atl3 SST index is statistically significant at the 95% level of the Pearson's R-test for correlations. All data are de-trended .................................................90
Figure 5.3: Regressions on the Atl3 index (black box) of (shaded) cloud amount feedback, units of W m$^2$ K$^{-1}$; (contours) cloud cover, units of % K$^{-1}$. Contour levels range from -10% to +10%, with 1% interval. Solid lines indicate positive values, dashed lines indicate negative values, while solid thick lines indicate the zero-level. (a) Cloud cover is from ISCCP (years 1984-2007); (b) Cloud cover is from EECRA (years 1954-2008). In this plot we use inter-annual anomalies differently from all the other plots because the temporal resolution of EECRA is of seasonal monthly means.

Figure 5.4: (a) Difference in local cloud feedback between Namib and the control simulation. Cloud feedback is computed as regression of local CRE at the surface on SST (units of W m$^2$ K$^{-1}$). Contours represent mean cloud cover climatology in the control simulation. Black box represents the Namib region; (b) Cloud feedback in the control simulation.

Figure 5.5: (a) Variance of SST in the control simulation; (b) Ratio of variance of SST in the Namib experiment to the control simulation; (c) Variance of SLP in the control simulation; (d) Ratio of variance of SLP in the Namib experiment to the control simulation. Stippling indicates where the difference in variance between the Namib and the control simulations is significant at the 95% level of a Fisher's F-test. The black box indicates the Namib region.

Figure 5.6: (a) e-folding timescale in the control simulation; (b) difference in e-folding timescale between the Namib and the control simulations. The black box indicates the Namib region.

Figure 5.7: Power spectra of SST averaged over the Atl3 region (5°S-5°N, 20°W-0°E) in the (red) Namib experiment and (black) control simulation. A 24-month smoothing has been applied to the periodogram estimates. Black dots indicate where the variance of the Namib curve is significantly different from the variance of the control simulation at the 95% level of a Fisher's F-test.

Figure 5.8: Difference in cloud feedback between enhanced cloud feedback experiments and the control simulation. Cloud feedback is estimated as regression of local CRE at the surface on SST, units of W m$^2$ K$^{-1}$ (as in fig. 5.4). The black-boxed regions in each plot indicate where positive cloud feedback is enhanced.

Figure 5.9: Ratio of variance of SST in the nine enhanced cloud feedback experiments to the control simulation. Stippling indicates where the difference in variance between the enhanced cloud feedback experiments and the control simulation is significant at the 85% level of a Fisher's F-test.

Figure 5.10: Values of difference in cloud feedback from Fig. 5.8 (green) and ratios of SST variance from Fig. 5.9 (orange) averaged over the nine boxes in each corresponding experiment. Units are W m$^2$ K$^{-1}$ for the differences in cloud feedback, while the ratios of SST variance are unitless.
Figure 5.11: Difference in e-folding timescale between the nine enhanced cloud feedback experiments and the control simulation.................................................................104

Figure 5.12: Power spectra of SST averaged over the Atl3 region (5°S-5°N, 20°W-0°E) in the (black) control simulation and (colors) enhanced cloud feedback experiments (see legend). A 24-month smoothing has been applied to the periodogram estimates. The power spectra are computed on timeseries of 80 years with the exception of the lines with markers (see legend) .................................................................105

Figure 5.13: Mean climatology in the control simulation: (shaded) SST in °C, (contours) SLP in hPa, (vectors) surface winds in m s\(^{-1}\) .................................................................107

Figure 5.14: Lagged composites of warm Atl3 index events in the Namib experiment: (shaded) SST, units of °C, (contours) SLP, units of hPa, ranging from -2 hPa to 2 hPa with intervals of 0.2 hPa, (vectors) surface winds, units of m s\(^{-1}\). (a) Lag -18 months from the peak of the event; (b) Lag -12; (c) Lag -6; (d) Lag 0. The white box highlights the Namib region, while the black box highlights the Atl3 region .108

Figure 5.15: (a) Variance of the sum of the net surface fluxes (long-wave + short-wave + latent + sensible); (b) Damping rate of net surface fluxes computed as in Park et al. (2005); (c) Variance of net surface fluxes divided by their damping rate; (d) Variance of SST in the control simulation (same as in Fig. 5.5a). Superimposed are (red) box of the Namib experiment and the (black) box of the Box 6 experiment ..................................................................................................................112
List of Tables

Table 2.1: 42 ocean-atmosphere coupled climate models that provided the first ensemble member (r1i1p1) for the historical experiment in the CMIP5 archive
                      .................................................................17

Table 2.2: Linear correlation coefficient between the time series shown in fig. 2.2. Bolded values indicate where correlations are significant at the 95% level of a Pearson's R test
                      ........................................................................24

Table 2.3: Observed minus multi-model mean fractional changes of cloud amount radiative kernel $k$ (left column), cloud cover change $\Delta C$ (central column), and tropical mean SST change $\Delta T_s$ (right column), in the four boxed regions of fig. 2.4. The denominators are mean cloud amount radiative kernel, cloud cover change, and tropical mean SST change from observations. The numbers shown are the absolute values
                      ..................................................................................30

Table 2.4: Legend of model numbers for figures 2.5 and 2.6
                      .................................................................32

Table 3.1: Spatial regression coefficients of (middle column) climatological mean HCC on $\omega_{500}$ and (right column) change in HCC on change in $\omega_{500}$ averaged over 30°S-30°N, 30°E-80°W. The standard errors on the regression coefficients (not shown) are one order magnitude smaller
                      ..................................................................................45

Table 3.2: Spatial regressions of HCC on $\omega_{500}$ for individual models (as in Table 3.1). Values in parentheses are for the ISCCP simulator output, "(-)" indicates no data
                      ..........................................................................................47

Table 4.1: Cloud feedback averaged over the NE and SE Pacific boxed regions in each simulation. Units are W m$^{-2}$ K$^{-1}$
                      ..........................................................................................65

Table 4.2: Variance explained by the North Pacific and South Pacific modes in each simulation
                      ..........................................................................................71
Chapter 1: Introduction

1.1 Motivation

Greenhouse gases have negligible effect on incoming solar radiation, while they absorb outgoing terrestrial radiation. Their net effect is to increase temperature in the lowest part of the atmosphere. Therefore, with increasing concentration of greenhouse gases due to anthropogenic emissions, global mean surface temperature is expected to increase.

The temperature response to greenhouse gases is commonly referred to as *climate sensitivity* and is defined as the global mean surface temperature change following a doubling of atmospheric CO₂ concentration. Climate models currently project a spread in climate sensitivity ranging from 1.5 °C to 4.5 °C (IPCC 2013). This inter-model spread is primarily caused by climate feedbacks, i.e., processes that either amplify (positive feedback) or reduce (negative feedback) the temperature increase. To gain more confidence in projections of future climate change, the uncertainty in the sign and magnitude of climate feedbacks must be narrowed.

Since the earliest assessments of climate change, the response of clouds to greenhouse forcing has represented the largest uncertainty among the climate feedbacks (Cess et al. 1990). Clouds both cool the planet due to their reflectivity (albedo effect) and warm it because they absorb outgoing terrestrial radiation (greenhouse effect). If it is their cooling effect to dominate, cloud feedbacks will reduce climate change; instead, if it is their warming, they will further amplify climate change. Inter-model disagreement in cloud feedback arises because clouds are involved in processes occurring on a vast range of time and spatial scales, including scales that cannot be resolved and need
to be parameterized. Although recent advances have led to a better understanding of the causes of inter-model spread in cloud cover changes (Zelinka et al. 2012a; Zelinka et al. 2012b; Qu et al. 2014), cloud feedbacks still represent the greatest challenge in projections of future climate change (Soden and Held 2006; Dufresne and Bony 2008; Trenberth and Fasullo 2009).

In response to greenhouse gases, climate models from the Coupled Model Intercomparison Project phase 3 (CMIP3) and phase 5 (CMIP5) archives simulate a robust positive high-level cloud feedback (Zelinka et Hartmann 2010). High clouds rise higher in the atmosphere as they conserve cloud top temperature (fixed-anvil-temperature hypothesis), which results in a positive high cloud feedback (Hartmann and Larson 2002). Instead, the response of low-level clouds in regions of large-scale atmospheric subsidence is the most uncertain (Bony et al. 2005; Soden and Vecchi 2011). While the increase in Sea Surface Temperature (SST) on its own would decrease low-level cloudiness leading to a positive feedback (Brient and Bony 2013), the projected increase in Lower Tropospheric Stability (LTS) favors more low-level clouds, opposing the effects of SST (Miller 1997; Medeiros et al. 2008). The sign and magnitude of low cloud feedback in each model depends on how low clouds respond to these environmental changes.

Several hypotheses have been proposed to explain a reduction in low-level clouds and positive feedback, including ideas that: warming induces changes in the energy budget of the boundary layer that demand a reduction in low clouds (Bretherton et al. 2013; Brient and Bony 2012; Sherwood et al. 2014); surface evaporation does not increase as much as dry entrainment reducing the supply of moisture to sustain the
formation of low clouds (Rieck et al. 2012; Webb and Lock 2013); greenhouse gases reduce radiative cooling, hence low clouds (Caldwell and Bretherton 2009; Stevens and Brenguier 2009). In contrast, there is no consensus on a mechanism that would explain an increase in low-level clouds and negative feedback (IPCC 2013). In addition to these thermodynamic considerations, low-level clouds are also dynamically coupled and respond to changes in large-scale overturning circulations and SST, although these interactions have not been extensively investigated (Bony et al. 2004; Fasullo and Trenberth 2012).

To narrow the uncertainty in the magnitude and sign of low-level cloud feedback over the ocean, models must be constrained with observations. However, constraining model simulations of clouds with observations is problematic because available cloud datasets are affected by observational biases and instrumental artifacts (Norris 1999; Eastman et al. 2011; Norris and Evan 2015). Observational cloud datasets that are long enough to be suitable for climate studies comprise surface-based observations from volunteer observing ships and satellite-based retrievals, although satellites cover only the last thirty years and are strongly influenced by decadal climate variability (Clement et al. 2009). The main goal of this dissertation is to examine these observational datasets and constrain the response of clouds in climate model simulations. A better understanding of how and why clouds change in response to internal climate variability and forced climate change will help narrow the uncertainty in future projections of climate change.

Key research questions are:
1. Can long-term changes in cloud cover from ship-based observations be used to constrain climate models?

2. Do climate models simulate changes in cloud cover that are consistent with observations?

3. Are observed long-term changes in cloud cover consistent with other signals of tropical climate change and attributable to anthropogenic greenhouse gas forcing?

4. How do observed cloud feedbacks affect surface temperature anomalies and their spatial pattern?

The following sections in this chapter contain (1.2) our approach and (1.3) an outline for the rest of this dissertation.

1.2 Approach

To address the questions raised above we analyze cloud cover and cloud radiative effects in multiple and independent observational datasets, climate models in the CMIP5 archive, and perform idealized model experiments. These observational and model datasets are reviewed here.

1.2.1 Observational datasets

Observations of cloud cover over the ocean are obtained from ship-based and satellite-based archives. Ship-based archives include the International Ocean-Atmosphere Data Set (ICOADS) covering the years 1900 to present (Woodruff et al. 2005) and the
Extended Edited Cloud Report Archive (EECRA) covering the years 1954 to 2008 (Hahn and Warren 2009; Eastman et al. 2011). These observations are a collection of synoptic weather reports taken aboard volunteer observing ships. Satellite-based archives include the International Satellite Cloud Climatology Project (ISCCP) (Rossow and Schiffer 1999) and the AVHRR Pathfinder Atmosphere-Extended (PATMOS-X) (Pavolonis et al. 2005) both covering the years 1984-2007.

Cloud information in EECRA is post-processed and quality controlled from ICOADS. EECRA also contains information regarding the number of observations and cloud type. We find, however, that information on cloud type is generally inconsistent with satellite retrievals. Ship-based observers cannot see high-level clouds when there are low-level clouds, while satellite-based retrievals cannot detect low-level clouds when they are obscured by high-level clouds and must use overlapping assumptions. Because of these inconsistencies we limit our analysis to total cloud cover (Bellomo et al. 2014a).

Both ship-based and satellite-based observations are affected by observational biases. Cloud observations in ICOADS and EECRA exhibit a spurious and steady global mean increase. The origins of this trend are unknown, but the trend is deemed spurious because it is largely inconsistent with radiation anomalies at the top-of-atmosphere and the observed global mean increase in surface temperature (Norris 1999, 2005; Deser et al. 2010b). We correct this trend by removing the global mean annual mean total cloud cover from each grid point at each time step. Similar corrections were applied in previous studies (Deser et al. 2004; Clement et al. 2009). Cloud observations in ISCCP and PATMOS-X were corrected for artifacts introduced by orbital drifts and failures in the instruments. Remaining unknown artifacts were corrected by removing long-term and
global scale trends from each grid box (Norris and Evan 2015). Therefore, all observational data are relative to the global mean.

1.2.2 CMIP5 models

We compare changes in cloud cover and associated radiative effects with general circulation model experiments from the CMIP5 archive. Observed changes are compared first with historical experiments (chapter 2) and then with AMIP simulations (chapter 3). Historical simulations are forced by observational estimates of atmospheric composition over the industrial period, from 1850 to 2005. We examine only one ensemble member (r1i1p1) of 42 models for the years 1954-2008 that are common to the ship-based (EECRA) observations. AMIP experiments are atmospheric-only simulations forced with historical SST over the years 1979-2008 (AMIP), uniform 4K SST increase (AMIP-4K), and patterned SST increase (AMIP-Future). The patterned SST forcing is plotted in fig. 1.1.

![SST forcing (AMIP-Future)](image)

Figure 1.1: (Shaded) SST forcing used for AMIP-Future simulations, (contours) SST climatology. Here SST is computed as the multi-model mean change in SST between AMIP-Future and AMIP, but the SST forcing is the same for all models.
The prescribed SST increase in AMIP-4K and AMIP-Future is with respect to the observed SST climatology (1979-2008) in AMIP. Because they are forced with SST, AMIP simulations isolate the effect of externally forced warming from changes due to internal variability, while historical simulations are affected both by the historical forcing and internal variability.

1.2.3 Idealized model experiments

Observations show anti-correlation between total cloud cover and SST anomalies over the subtropical stratocumulus regions, which suggests a positive low-level cloud feedback on inter-annual timescales. Climate models underestimate the strength of this correlation (Bony et al. 2005; Clement et al. 2009). However, from observations alone it is not possible to quantify and separate the role of low cloud feedbacks from other processes. To investigate the influence of cloud feedbacks on the spatial pattern and persistence of SST anomalies we perform idealized climate model experiments.

The experimental setup consists of a state of the art atmospheric general circulation model (ECHAM6) coupled to a slab-ocean model (Stevens et al. 2013). The model has a horizontal resolution of 3.75° x 3.75° and 31 vertical levels. Because the ocean is motionless, internal variability is solely driven by atmospheric heat fluxes at the surface. Monthly mean ocean heat fluxes are prescribed and do not change from year to year. The influence of cloud feedback is studied by enhancing the sensitivity of cloud liquid water to SST in the radiation module of ECHAM6. Cloud liquid water is multiplied at each time step by a function \( y \) of underlying SST anomalies (\( SST' \)):

\[
y = 1 - \arctan(SST') \cdot \frac{2}{\pi}
\]  

(1.1)
At each time step SST anomalies \((SST')\) are computed as the difference between SST in the current run minus the climatological monthly mean SST from a control run. Equation (1.1) increases the strength of positive cloud feedback (fig. 1.2) because when \(SST'\) is positive (negative) cloud liquid water is multiplied by a number \(y < 1\) (\(y > 1\)), decreasing (increasing) cloud radiative cooling at the surface. The advantage of this model setup is that it isolates the effects of cloud feedbacks from other processes and can be prescribed over selected regions of interest.

Figure 1.2: Enhanced positive cloud feedback function from equation (1.1)

1.3 Outline

In chapter 2 (Bellomo et al. 2014a) we examine cloud cover in multiple observational datasets. We correct cloud datasets for observational biases and devise a method to estimate cloud amount feedback over the years 1954-2008 from trends in ship-based observations. We then compare observed cloud amount feedback in historical simulations
from the CMIP5 archive for the same period of time and find that models simulate a similar pattern of cloud amount feedback but of significantly smaller magnitude.

In chapter 3 (Bellomo et al. submitted) we question whether observed cloud trends are consistent with other signals of tropical climate change and if they are externally forced. We compare observed trends in cloud cover with atmospheric-only (AMIP) simulations of future climate change forced with warmer SST, which isolate the SST forced response from internal variability. We find that although observed cloud cover change is certainly influenced by internal variability, its pattern and strength is consistent with the externally forced response in the AMIP simulations. We show that trends in cloud cover are associated with mid-tropospheric vertical velocity and we assert that observed trends in cloud cover suggest an externally forced weakening of tropical overturning circulation from the beginning of the 20th century.

In chapter 4 and 5 (Bellomo et al. 2014b; Bellomo et al. 2015) we examine the implications of underestimating cloud feedbacks in climate models in the context of internal climate variability. We perform idealized model experiments in which we increase the strength of cloud feedback over selected regions as described in section 1.2. We find that increasing the strength of cloud feedback over the subtropical stratocumulus regions in a way that is more similar to observations leads to an increase in the persistence of basin-wide SST anomalies. The implications are that models may underestimate the persistence of SST anomalies on timescales ranging from internal climate variability to global climate change thereby reducing the predictive skill of near-term forecasts and the accuracy of future climate change projections.
In chapter 6 we summarize the main conclusions, while in chapter 7 we discuss the caveats of this work and a few ideas to consolidate the results of this dissertation.
Chapter 2: Observational and Model Estimates of Cloud Amount Feedback over the Indian and Pacific Oceans

2.1 Background

Cloud feedback represents the largest uncertainty of future climate change in Coupled Model Intercomparison Project phase 3 (CMIP3) climate models used for the Intergovernmental Panel of Climate Change Fourth Assessment Report (IPCC-AR4) (Solomon et al. 2007, Soden and Held 2006, Ringer et al. 2006, Dufresne and Bony 2008, Trenberth and Fasullo 2009, Stephens 2005). Inter-model disagreement in cloud feedback has been attributed to differences in cloud parameterization schemes, and is largest for tropical low-level clouds (Bony et al. 2006, Webb et al. 2006), which are ubiquitous over the oceans (Norris 1998). Some components of cloud feedback, however, show inter-model agreement. For example, there is model agreement on the change in the altitude of tropical high-level cloud cover, which results in positive high cloud altitude feedback (Zelinka and Hartmann 2010). Hartmann and Larson (2002) proposed the fixed-anvil-temperature (FAT) mechanism to explain positive cloud altitude feedback. According to the FAT mechanism, high clouds in the tropics tend to rise as the climate warms in order to conserve their cloud top temperature. This mechanism appears to be robust across climate models, and is consistent with the response of high clouds to El-Niño events (Zelinka and Hartmann 2011).

Bony and Dufresne (2005) and Soden and Vecchi (2011) showed that the largest source of inter-model disagreement in tropical cloud feedback arises from the response of
clouds in regions of large-scale subsidence over the tropical oceans. The subtropical stratocumulus regions at the eastern side of the ocean basins are among the regions of largest inter-model spread in cloud feedback among the CMIP3 models (Soden and Vecchi 2011). These regions are mainly covered by stratus and stratocumulus cloud types, which form over oceans with relatively cold sea surface temperature (SST), and to the east of the subtropical highs. Klein and Hartmann (1993) and subsequent studies have identified five major subtropical stratocumulus regions located off the coasts of Australia (SE Indian), California (NE Pacific), Peru (SE Pacific), Canaries (NE Atlantic), and Namibia (SE Atlantic). In these regions, marine boundary layers are often well mixed and capped by strong temperature inversions. Increased cloud cover is associated with relatively cold SST, high lower tropospheric stability (LTS), large-scale atmospheric subsidence, and surface wind divergence (Klein and Hartmann 1993, Wood and Bretherton 2006, Klein et al. 1995, Muñoz et al. 2011). While strong subsidence generally coincides with strong LTS on seasonal to inter-annual timescales, individually these two quantities can have opposing effects on clouds. For example, Myers and Norris (2013) show that strong subsidence favors reduced cloud cover for the same LTS while stronger LTS promotes greater cloudiness for the same subsidence rate.

Given this complexity, simulating cloud variability in climate models is challenging. While observations show clear relationships between environmental variables and cloud fraction, the simulated relationships are highly model-dependent (Clement et al. 2009). Moreover, in response to greenhouse gas forcing models project an increase in SST, which on its own would decrease low-level clouds (Brient and Bony 2012, Sandu and Stevens 2011), an increase in lower tropospheric stability (LTS), which
would increase low-level clouds (Miller 1997, Medeiros et al. 2008), and weaker mid-
tropospheric large-scale subsidence (Vecchi and Soden 2007a, Vecchi and Soden 2007b),
which could either decrease low-level clouds (Sandu and Stevens 2011, Mauger and
Norris 2010, Stevens et al. 2007), or increase them (Myers and Norris 2013). An
observational perspective on long-term cloud changes could therefore provide an
important constraint on cloud feedback simulated by the models and on mechanisms of
cloud change.

Long-term cloud observations from synoptic ship reports are the longest source of
cloud information and could potentially narrow the uncertainties in climate models.
However, only a few studies have looked at long-term changes in observations, mainly
because of the artifacts that affect the available cloud datasets (Norris 1999, Eastman et
al. 2011). Clement et al. (2009) examined cloud variability in the NE Pacific subtropical
stratocumulus region in multiple satellite and surface data sets. They found that cloud
cover, SST, and large-scale atmospheric circulation co-varied on decadal timescales,
suggesting a positive feedback among stratocumulus clouds and large-scale Pacific
climate variability. Eastman et al. (2011) examined low-level cloud cover changes in
observations from ships over the years 1954-2008 in the subtropical stratocumulus
regions. They found that decreased stratocumulus cloud cover was partially compensated
by increased cumulus cloud cover, which suggests a long-term Stratocumulus-to-
Cumulus transition and positive low-cloud feedback (Albrecht et al. 1995, Bretherton and
examined long-term trends in cloud cover from 1900 to present and found an eastward
shift in cloud cover in the Western Pacific that is consistent with a weakening of the
Walker Circulation. Norris (2005) investigated upper-level cloud trends in ship-based observations from 1954 to 1997. He found an increase in high clouds over the central equatorial South Pacific, and decrease over the adjacent subtropics, the western Pacific, and the equatorial Indian Ocean.

Despite the uncertainties in ship-based observational data sets, all the studies mentioned above showed that cloud changes were consistent with changes in precipitation, surface wind divergence, SST, SLP, total-sky radiation flux anomalies, and satellite-based cloud observations in the overlapping period. In this study we will address the following questions: are ship-based cloud observations reliable enough to constrain cloud feedback simulated by climate models? What is the radiative impact of the observed cloud changes? Can models reproduce the observed cloud change and cloud feedback? To address these questions we compare cloud cover changes in three observational ship- and satellite-based cloud data sets (EECRA, ISCCP, and PATMOS-X) in the overlapping years of coverage. We estimate cloud amount feedback from long-term ship-based observations where they agree with satellites, and then compare these estimates with historical simulations from the CMIP5 archive.

2.2 Data

We examine total cloud amount over the ocean in ship-based (EECRA) and satellite-based (ISCCP and PATMOS-X) cloud data sets. The Extended Edited Cloud Reports Archive (EECRA) is a collection of synoptic weather reports taken aboard volunteer observing ships (Hahn and Warren 1999, 2009). Reports of cloud cover are archived in the International Comprehensive Ocean-Atmosphere Data Set (ICOADS) (Woodruff et
al. 2005, 2011), and then further processed to form EECRA, which currently provides cloud amount, cloud type, and frequency of occurrence, in 10° x 10° grid boxes over the global oceans for the years 1954-2008 (Eastman et al. 2011). EECRA represents the longest source of cloud information, but is affected by observational artifacts that introduce spurious trends in the global mean long-term variability (Norris 1999, Norris 2005, Eastman et al. 2011).

To evaluate possible errors in EECRA, we supplement ship observations with two satellite-based cloud data sets: the International Satellite Cloud Climatology Project (ISCCP) (Rossow and Schiffer 1999) and the Advanced Very High Resolution Radiometer Pathfinder Atmosphere - Extended (AVHRR - PATMOS-X) (Jacobowitz et al. 2003, Pavolonis et al. 2005). These data sets were corrected for artifacts introduced by the replacement of instruments and orbital drifts over time (Clement et al. 2009, Evan et al. 2007). Unknown remaining artifacts were corrected by subtracting global scale long-term variability from each grid box (Evan et al. 2013). ISCCP and PATMOS-X provide monthly means of total cloud amount in 2.5° x 2.5° grid boxes from June 1983 to July 2008.

To compute cloud amount feedback we use total cloud cover from EECRA along with radiation fluxes at the top-of-atmosphere (TOA) and SST. Radiation fluxes at TOA are from the Clouds and Earth's Radiant Energy System (CERES) Energy Balanced and Filled (EBAF_Ed2.6r) data set. This product is provided by the NASA Langley Research Center and is available for the years 2001-2010 in 1° x 1° grid boxes (Loeb et al. 2009). For SST, we use the Hadley Centre Sea Ice and Sea Surface Temperature (HadISST)
reanalysis, which is provided in $1^\circ \times 1^\circ$ grid boxes and is available from 1870 to today (Rayner et al. 2003).

We compare observational estimates of cloud change and cloud amount feedback with historical simulations of 42 coupled ocean-atmosphere climate models in the Coupled Model Intercomparison Project phase 5 (CMIP5) archive (Taylor et al. 2012). The historical simulations are forced by observed atmospheric composition changes and cover most of the industrial period from 1850 to 2005. We analyze one ensemble member (r1i1p1) for each model and examine the same years (1954-2005) covered by ship observations. A list of the models used is provided in Table 2.1.

Total cloud fraction from observations, which is retrieved from visually or remotely measured optical depth, is not the same as total cloud fraction from models, which is computed from the model equations (e.g., Marchand et al. 2010). To provide a more accurate evaluation of model performance, cloud simulators have been developed (Klein et al. 2013, Pincus et al. 2012). Unfortunately there are not simulators of human observers (i.e., ship-based data sets), but we will show that inter-model spread in the sign of cloud changes is larger than errors that could arise from the different definitions of cloud cover in models and ship observations.

2.3 Methods

In this study, we focus on cloud changes over the tropical and subtropical Indian and Pacific basins. To correct long-term spurious variability in EECRA, we subtract the tropical annual mean from all years and all grid boxes.
<table>
<thead>
<tr>
<th>Institution</th>
<th>Model name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM) (Australia)</td>
<td>ACCESS1.0</td>
</tr>
<tr>
<td></td>
<td>ACCESS1.3</td>
</tr>
<tr>
<td>Beijing Climate Center, China Meteorological Administration (China)</td>
<td>BCC-CSM1.1</td>
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<tr>
<td></td>
<td>BCC-CSM1.1(m)</td>
</tr>
<tr>
<td>College of Global Change and Earth System Science, Beijing Normal University (China)</td>
<td>BNU-ESM</td>
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<tr>
<td>Canadian Centre for Climate Modelling and Analysis (Canada)</td>
<td>CanESM2</td>
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<tr>
<td>National Center for Atmospheric Research (U.S.)</td>
<td>CCSM4</td>
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<tr>
<td>Community Earth System Model Contributors (U.S.)</td>
<td>CESM1(BGC)</td>
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<td>CESM1(CAM5)</td>
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<td>CESM1(FASTCHEM)</td>
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<td></td>
<td>CESM1(WACC)</td>
</tr>
<tr>
<td>Centre National de Recherches Meteorologiques / Centre European de Recherche et Formation Avancees en Calcul Scientifique (France)</td>
<td>CNRM-CM5</td>
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<td>Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence (Australia)</td>
<td>CSIRO-Mk3-6-0</td>
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<td>LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua (China)</td>
<td>FGOALS-g2</td>
</tr>
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<td>The First Institute of Oceanography, SOA (China)</td>
<td>FIO-ESM</td>
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<td>NOAA Geophysical Fluid Dynamics Laboratory (U.S.)</td>
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<td>GFDL-ESM2G</td>
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<td></td>
<td>GFDL-ESM2M</td>
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<td></td>
<td>GISS-E2-R-CC</td>
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<td>National Institute of Meteorological Research/Korea Meteorological Administration (Korea)</td>
<td>HadGEM2-AO</td>
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<td>Met Office Hadley Centre (U.K.)</td>
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<tr>
<td></td>
<td>HadGEM2-CC</td>
</tr>
<tr>
<td></td>
<td>HadGEM2-ES</td>
</tr>
<tr>
<td>Institute for Numerical Mathematics (Russia)</td>
<td>INM-CM4</td>
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<tr>
<td>Institut Pierre-Simon Laplace (France)</td>
<td>IPSL-CM5A-LR</td>
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<td>IPSL-CM5B-LR</td>
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<td>Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology (Japan)</td>
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<td>Max Planck Institute for Meteorology (Germany)</td>
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<td>MPI-ESM-P</td>
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<tr>
<td>Meteorological Research Institute (Japan)</td>
<td>MRI-CGCM3</td>
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<tr>
<td></td>
<td>MRI-ESM1</td>
</tr>
<tr>
<td>Norwegian Climate Centre (Norway)</td>
<td>NorESM1-M</td>
</tr>
<tr>
<td></td>
<td>NorESM1-ME</td>
</tr>
</tbody>
</table>

Table 2.1: 42 ocean-atmosphere coupled climate models that provided the first ensemble member (r1i1p1) for the historical experiment in the CMIP5 archive.
A similar approach was taken by Deser et al. (2010b) to correct the ICOADS cloud data set, which is affected by the same observational errors as EECRA since cloud observations in EECRA are processed from ICOADS. For consistency, we subtract the tropical annual mean from cloud observations in the corrected ISCCP and PATMOS-X data sets, and in the 42 CMIP5 historical simulations. Therefore, all results shown in this study should be interpreted as relative to the tropical mean. In the observational data sets, we also mask out poorly sampled regions by requiring an average of at least 25 observations per season in each grid box (c.f. Eastman et al. 2011).

We form inter-annual anomalies by removing the seasonal cycle from all model and observational data, and then calculate long-term changes in cloud amount and SST as the linear trend in each grid box multiplied by the number of years. Estimates of cloud amount feedback are calculated as follows. Net (i.e., short-wave plus long-wave) radiation flux at TOA ($R_{tot}$) can be expressed as the sum of overcast sky radiation ($R_{cld}$) with area c and clear sky radiation ($R_{clr}$) with area ($1-c$), where c is the fraction of sky covered by clouds, and $R_{tot}$ is positive for downwelling fluxes:

$$R_{tot} = cR_{cld} + (1-c)R_{clr}$$  \hspace{1cm} (2.1)

The change in $R_{tot}$ between two climate states can therefore be written as:

$$\Delta R_{tot} = \Delta R_{cld} + \Delta c(R_{cld} - R_{clr}) + c(\Delta R_{cld} - \Delta R_{clr}) + \epsilon$$  \hspace{1cm} (2.2)

The first term on the RHS of (2.2) represents the change in clear-sky flux. The second term represents the contribution from changes in cloud cover ($\Delta c$) with all the other properties affecting radiation held fixed, while the third term represents the effect of changes in radiation fluxes weighted by the mean cloud cover. The last term ($\epsilon$) accounts for the covariance among the fields.
In previous studies observational estimates of cloud feedback have often been computed as the change in Cloud Radiative Effect (CRE) at TOA divided by change in global mean SST ($\Delta T_s$). The change in CRE can be written rearranging equation (2.2) as:

$$\Delta CRE = \Delta R_{tot} - \Delta R_{ctr} = \Delta c(R_{ctd} - R_{ctr}) + c(\Delta R_{ctd} - \Delta R_{ctr})$$  \hspace{1cm} (2.3)

where the covariance term is much smaller than the other terms and can be omitted (c.f. Taylor et al., 2007). This method has been criticized because the third term on the RHS of (2.3) may include changes in clear-sky fluxes due to non-cloud feedbacks (see discussion in Soden et al., 2008). These changes can cause a change in CRE that is not caused by a change in cloud cover.

In this study, we use only the second term on the RHS of (2.3) to define cloud feedback, thus our definition is not contaminated by changes in clear-sky radiation. When this term, i.e., $\Delta c(R_{ctd} - R_{ctr})$, is divided by change in SST ($\Delta T_s$) it represents cloud feedback. We note that we cannot evaluate cloud feedback due to changes in cloud vertical and optical properties because long-term ship-based observations only provide information about cloud amount. Therefore, $\Delta c$ in our study corresponds to changes in cloud amount and we can only estimate the cloud amount component of cloud feedback.

Since CRE is defined as $CRE = R_{tot} - R_{ctr}$, we can write $R_{ctd} - R_{ctr}$ using (1) as:

$$k = \frac{CRE}{\bar{c}}$$  \hspace{1cm} (2.4)

where $k$ represents the sensitivity of $R_{tot}$ to changes in cloud amount, and is calculated as mean Cloud Radiative Effect ($\overline{CRE} = \overline{R_{tot}} - \overline{R_{ctr}}$) at TOA from CERES divided by mean cloud amount ($\overline{c}$) from EECRA. We will refer to $k$ as "cloud amount radiative kernel" in the reminder of this text in analogy to cloud radiative kernels developed by
Zelinka et al. (2012a). In previous studies, \( k \) has been evaluated using a radiative transfer model that calculates cloud radiative kernels directly (Zelinka et al. 2012a, Zhou et al. 2013) or as a residual from radiative kernels of all the other non-cloud feedback variables (Soden et al. 2008). Other methods have also been developed (e.g., the "approximate partial radiative perturbation method" of Taylor et al. 2007). Soden et al. (2008) provides a good overview of these different techniques. In addition to changes in cloud amount, these methods generally take into account the sensitivity to perturbations in cloud vertical and optical properties.

Cloud Amount Feedback (units of \( \text{W/m}^2/\text{K} \)) can then be finally written as:

\[
 CAF = \frac{k \Delta c}{\Delta T_s} 
\]  

(2.5)

The sign convention is that positive values indicate positive cloud amount feedback, which means an amplification of climate change, and negative values indicate negative cloud amount feedback, which means a reduction of climate change. We note that since we do not consider vertical changes in cloud cover and cloud properties, our computation of cloud amount feedback is not the same as cloud feedback, which can be written as the sum of cloud amount, cloud altitude, cloud optical feedbacks, and a residual term (Zelinka et al. 2012b).

We estimate cloud amount feedback in models as in observations using equation (5). We compute model estimates for the first ensemble member (r1i1p1) of the 42 models considered, and then obtain the multi-model mean by averaging all estimates. Averaging across multiple models ensures better separation of long-term forced climate trends from internal climate variability. Since we subtracted tropical mean cloud amount from cloud fields, both model and observational estimates of cloud amount feedback are
relative to the tropical mean. Hence, positive local feedback means more positive than the tropical mean, and negative local feedback more negative than the tropical mean. We note that the tropical multi-model mean cloud change is -0.25%, therefore the absolute and relative estimates of local cloud amount feedback in the multi-model mean are not much different from one another, and exhibit the same sign. We cannot evaluate the difference between absolute and relative estimates of local cloud amount feedback in observations because of the observational biases discussed above.

2.4 Results

2.4.1 Cloud amount change

Fig. 2.1 shows total cloud amount changes from 1954 to 2005 in (a) observations (EECRA) and (b) CMIP5 multi-model mean. Contours represent cloud climatology, while stippling indicates where the change is robust. For observations, the change is considered robust where it is significant at the 90% level of a two-tailed Student's t test. The degrees of freedom in each grid box correspond to the number of observations, and are adjusted to take into account autocorrelation at lag 1 where the autocorrelation is significant at the 90% level of a Pearson's R test. For models, stippling indicates where at least 31 out of 42 (~74%) models agree on the sign of cloud change. Fig. 2.1 shows that the tropical pattern of the multi-model mean cloud amount change shares many large-scale features with observations, although changes are smaller (note the different color scales).
Figure 2.1: Total cloud amount change (1954-2005): (a) EECRA, (b) CMIP5 multi-model mean. Contours represent cloud amount climatology (long-term mean), while stippling indicates where the changes are robust. In (a) changes are considered robust if they pass a two tailed Student's t test at the 90% level where the degrees of freedom for the test correspond to the number of observations in each grid box, and are adjusted to take into account autocorrelation at lag1 where the autocorrelation is significant at the 90% level of a Pearson's R test. In (b) stippling indicates where at least 31 models out of 42 (74%) agree on sign. The boxed regions highlight where observed cloud changes are robust.

Observations (fig. 2.1a) display robust cloud changes in the four regions contoured by black boxes: cloud cover is found to decrease over the NE Pacific and equatorial western Pacific, and to increase over the southern central Pacific and western Indian Ocean. Over these regions, the multi-model mean exhibits cloud changes of the same sign as observations but smaller in magnitude (fig. 2.1b). In addition, models simulate robust cloud increase over the subtropical SE Pacific ($80^\circ$W:$120^\circ$W - $5^\circ$S:$20^\circ$S), which is the only region where there is good inter-model agreement. While there are not enough observations in EECRA to constrain cloud cover changes over this region, the multi-
model mean is consistent with observed positive cloud trends from 1900 to present in the SE Pacific found in the ICOADS observations by Deser et al. (2010b).

To corroborate these long-term cloud changes, we compare cloud anomalies in EECRA with ISCCP and PATMOS-X. Fig. 2.2 shows inter-annual cloud cover anomalies in the four boxed regions of fig. 2.1 where cloud changes in EECRA are statistically significant. EECRA anomalies are plotted in blue, ISCCP in red, and PATMOS-X in green. Dashed blue lines represent the linear trend fit to EECRA anomalies.

Figure 2.2: Regional time series of total cloud amount inter-annual anomalies in the four boxed regions of fig. 2.1. Blue refers to EECRA (1954-2008), red to ISCCP (1984-2007), and green to PATMOS-X (1984-2007). The blue dashed line is the linear trend fitted to EECRA.

Cloud anomalies in EECRA show less inter-annual variance than satellite observations, however, inter-annual fluctuations and trends are consistent in the three data sets in the
overlapping years of coverage (1984-2007). For example, inter-annual peaks during ENSO events in the western and central Pacific boxes are evident in all three data sets, and decadal fluctuations in cloud cover over the NE Pacific due to shifts in the Pacific Decadal Oscillation (Deser et al. 2004) are also captured by all data sets. In table 2.2 we compute correlation coefficients between the time series shown in fig. 2.2. All correlations are significant at the 95% level of a two-tailed Pearson's R test with the exception of the western Indian box where surface observations do not show statically significant correlation with satellites. We note that there is less agreement also between the two satellites in this region.

<table>
<thead>
<tr>
<th>Correlation coefficient</th>
<th>EECRA-ISCCP</th>
<th>EECRA-PATMOSX</th>
<th>ISCCP-PATMOSX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Western Indian</td>
<td>0.24</td>
<td>0.20</td>
<td>0.64</td>
</tr>
<tr>
<td>Western Pacific</td>
<td><strong>0.81</strong></td>
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<tr>
<td>NE Pacific</td>
<td><strong>0.83</strong></td>
<td>0.77</td>
<td>0.82</td>
</tr>
<tr>
<td>Central Pacific</td>
<td><strong>0.75</strong></td>
<td>0.78</td>
<td>0.86</td>
</tr>
</tbody>
</table>

Table 2.2: Linear correlation coefficient between the time series shown in fig. 2. Bolded values indicate where correlations are significant at the 95% level of a Pearson's R test.

As discussed above, EECRA observations suffer from global spurious variability, which makes the interpretation of long-term trends problematic. However, consistency with satellite data sets where cloud changes are statistically significant (fig. 2) gives increased confidence in the credibility of cloud changes in EECRA. The western Indian Ocean is a region where there is less agreement with satellites, and this needs to be taken into account in the interpretation of long-term cloud changes. We note, however, that models simulate consistent sign of cloud change with observations over this region and similar large-scale patterns in all the Indo-Pacific Ocean (fig. 2.1), which suggests that there
could be robust physical mechanisms in models to explain the observed cloud cover changes.

We quantify the radiative impact associated with these long-term cloud trends by computing cloud amount feedback, and then compare observational estimates of cloud amount feedback with those derived in climate models. While satellite products may seem a more reliable data set to estimate cloud feedbacks, their short-term coverage (less than thirty years) limits their applicability for climate change studies. In fact, trends in atmospheric variables on time scales of thirty years or shorter tend to reflect internal climate variability, in particular over regions characterized by high variability on decadal time scales, such as the North Pacific (Deser et al. 2012) and North Atlantic (Ting et al. 2009). For example, cloud signals in the NE Pacific exhibit significant decadal fluctuations, which are linked to shifts in the Pacific Decadal Oscillation (PDO) occurred in the 1976-77 and late 1990s. The time series in fig. 2.2c show that all data sets exhibit reduced cloud cover from the mid-70s to the late 90s when SST in the eastern Pacific was warmer due to the positive phase of the PDO, and then increased cloud cover from the late 1990s when SST was colder due to the negative phase of the PDO. Therefore, the slightly positive trend in cloud cover from 1984 to 2007 in the NE Pacific reflects decadal variability and is not representative of the long-term trend in EECRA (blue dashed line in fig. 2.2c). This suggests that satellite cloud products are not suitable for climate change studies in regions where decadal variability is important. For this reason, we choose to estimate long-term cloud amount feedback from ship-based observations, which cover more than five decades and are less sensitive to decadal fluctuations.
2.4.2 Cloud amount feedback

To obtain the cloud amount feedback, we multiply cloud amount radiative kernel by cloud cover change and then divide by tropical mean change in SST, as defined in equation (2.5). We first obtain the observational estimate of cloud amount radiative kernel (fig. 2.3a), which is computed as the mean Cloud Radiative Effect (CRE) from CERES divided by the mean cloud cover from EECRA, after re-gridding CERES to the grid-box size of EECRA. The model estimates of cloud amount radiative kernel are computed as in observations for each of the 42 models. The multi-model mean (fig. 2.3b) is then obtained by averaging all model estimates. Fig. 2.3a (observations) and 2.3b (models) show good agreement in sign. Negative values indicate where clouds have a net (i.e., short-wave plus long-wave) cooling effect, while positive values indicate where clouds have a net warming effect.

![Cloud amount radiative kernel](image)

Figure 2.3: Cloud amount radiative kernel computed as mean Cloud Radiative Effect (CRE) divided by mean cloud cover. (a) Observational estimate: CRE is from CERES and mean cloud cover is from EECRA, (b) CMIP5 multi-model mean.
Cloud amount radiative kernels are negative almost everywhere in both observations and models, which means that clouds have a net cooling effect. Models display even larger values than observations, suggesting that the radiation budget in the models is more sensitive to changes in cloud cover. This is consistent with the fact that models simulate too few and too bright clouds (Nam et al. 2012), so that the numerator of the cloud amount radiative kernel (i.e., CRE) is too large (negative) while the denominator (i.e., cloud amount) is too small, making the cloud amount radiative kernel larger and more negative in models than in observations. The largest discrepancies between the multi-model mean and observational estimates occur over the central and western tropical Pacific and southern Indian Ocean, where clouds in observations have a smaller cooling effect than in models (fig. 2.3).

We note that the observational estimate shown in fig. 2.3a is sensitive to cloud climatology. For instance, if we use ISCCP or PATMOS-X instead of EECRA, the cloud amount radiative kernel looks slightly different, although we still get less negative values than the multi-model mean especially in the western Pacific. These slight differences do not influence our conclusions because we use cloud amount radiative kernel not to evaluate model performance, but rather to weigh the radiative impact of cloud cover changes in relation to the mean cloud cover. For example, if in a particular location of the world cloud cover is larger in ISCCP (e.g., 80%) than in EECRA (e.g., 60%) for the same value of CRE, then a 5% change in cloud cover will have relatively larger impact on cloud amount feedback computed from EECRA than from ISCCP, because the fraction of cloud change to mean cloud cover is larger in EECRA (5%/60%) than ISCCP (5%/80%). The same applies to inter-model differences, although models simulate
different cloud climatology due to different model parameterizations rather than different retrieval methods.

After obtaining the cloud amount radiative kernel, we compute model and observational estimates of cloud amount feedback, which are shown in fig. 2.4. Fig. 2.4 is calculated multiplying long-term trends in cloud cover by cloud amount radiative kernel, and then dividing by tropical mean SST change. Model estimates of cloud amount feedback are computed for each model, and then the multi-model mean is obtained by averaging all model estimates. Contours in fig. 2.4 represent total cloud cover climatology, while stippling indicates where the changes are statistically significant.

Figure 2.4: Cloud amount feedback: (a) Observational estimate computed multiplying cloud amount radiative kernel (fig. 2.3a) by EECRA cloud changes (fig. 2.1a) and then dividing by tropical mean change in SST from HadISST (0.46 °C). Contours represent total cloud amount climatology from EECRA. Stippling indicates where cloud amount feedback is robust and is computed as in fig. 1. (b) CMIP5 multi-model mean. Contours represent multi-model mean cloud amount climatology. Stippling indicates where at least 31 models out 42 (~74%) agree on sign. Boxes indicate the regions where cloud changes in fig. 1a are statistically significant.
Observational cloud amount feedback is statistically significant where cloud trends shown in fig. 2.1a are, that is, over the NE Pacific and western Pacific where cloud amount feedback is positive, and central Pacific and western Indian where cloud amount feedback is negative. Model cloud amount feedback is only significant over the SE Pacific where there is inter-model agreement in cloud trends. The multi-model mean cloud amount feedback (fig. 2.4b) is less than half the observational values (fig. 2.4a), nevertheless the sign of the feedback is consistent with observations over most of the Indian and Pacific Oceans.

Cloud amount feedback (eq. 2.4) can be split into contributions from $1/\Delta T_s$, $\Delta C$, and $k$. To roughly estimate which of these terms contribute the most to weaker model cloud amount feedback, we compute the fractional change in cloud amount feedback (CAF) in the four boxed regions of fig. 2.4. The fractional change in CAF can be written as: \[ \frac{\delta \text{CAF}}{\text{CAF}} = \frac{\delta k}{k} + \frac{\delta \Delta C}{\Delta C} - \frac{\delta \Delta T_s}{\Delta T_s}, \] where $\delta$ represents the differences between observed and multi-model mean values. We do not expect the LHS of this equation to be equal to the difference between the computed multi-model mean and observations because this equation is a valid approximation only for small perturbations. Nonetheless, this approximation indicates which terms contribute the most to the differences between models and observations. The fractional changes of the RHS terms of the equation are reported in Table 2.3, and shows that the largest contribution to weaker model cloud amount feedback comes from smaller model simulated cloud cover changes than observed.
Table 2.3: Observed minus multi-model mean fractional changes of cloud amount radiative kernel $k$ (left column), cloud cover change $\Delta C$ (central column), and tropical mean SST change $\Delta T_s$ (right column), in the four boxed regions of fig. 2.4. The denominators are mean cloud amount radiative kernel, cloud cover change, and tropical mean SST change from observations. The numbers shown are the absolute values.

<table>
<thead>
<tr>
<th>Differences between observations and the multi-model mean</th>
<th>$\delta k / k$</th>
<th>$\delta \Delta C / \Delta C$</th>
<th>$\delta \Delta T_s / \Delta T_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Western Indian</td>
<td>0.70</td>
<td>0.89</td>
<td>0.24</td>
</tr>
<tr>
<td>Western Pacific</td>
<td>0.41</td>
<td>1.00</td>
<td>&quot;</td>
</tr>
<tr>
<td>NE Pacific</td>
<td>0.16</td>
<td>0.96</td>
<td>&quot;</td>
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<tr>
<td>Central Pacific</td>
<td>0.72</td>
<td>0.91</td>
<td>&quot;</td>
</tr>
</tbody>
</table>

Figures 2.5 and 2.6 show the estimates of cloud amount feedback in the four boxed regions of fig. 2.4 in each model (numbered bars), multi-model mean (denoted by "M"), and observations ("OBS"). Numbered bars correspond to individual model estimates according to the legend in Table 2.4. Fig. 2.5 shows the estimates in the (a) western Indian and (b) western Pacific, while fig. 2.6 shows the (a) NE Pacific and (b) central Pacific. Also plotted in fig. 2.5 and 2.6 are estimates of observational errors (horizontal lines), which represent the error on the estimates of cloud trends (see the caption of fig. 2.5). While generally the multi-model mean is significantly smaller than observations, models individually can simulate cloud amount feedback of the same strength if not larger than observations. In the western Indian (fig 2.5a), 30 models out of 42 (~71%) agree in sign with observations. Of these, 10 fall within the error range of observations, and 2 exceed the upper extent of the error range. In the western Pacific (fig. 2.5b), 24 models (~57%) agree in sign with observations, 8 fall within the error range, and one exceeds the upper extent of the error range. In the NE Pacific (fig. 2.6a), 21 models (50%) agree in sign with observations, and only one falls within the error range.
In the central Pacific (fig. 2.6b), 25 models (~59%) agree with observations, 3 fall within the error range, and one exceeds the upper extent of the error range. The region of largest uncertainty is therefore the NE Pacific, which is a region predominantly covered by low-level marine stratocumulus clouds. It is also noteworthy that the observational estimate in the NE Pacific is larger than that simulated by any models, while this is not the case for the other regions, where some of the model estimates can exceed the observed changes.

Figure 2.5: Cloud amount feedback averaged over the first two boxed regions of fig. 2.4: (a) western Indian, (b) western Pacific. The numbers indicate the model name (see legend in Table 2.4). Horizontal lines represent the estimated range of observational errors, which are computed using the propagation of uncertainty formula assuming that the error in the estimate of cloud amount change is much larger than the errors in the estimates of SST change and cloud amount radiative kernel. The observational error on cloud amount feedback (CAF) can therefore be written as: $\sigma_{CAF}/CAF = \sigma_{\Delta c}/\Delta c$. From eq. (2.4): $CAF = \frac{k_{\Delta c}}{\Delta T_s}$, therefore: $\sigma_{CAF} = \sigma_{\Delta c}(k/\Delta T_s)$ where k is averaged over the boxed region and $\Delta T_s$ is the tropical mean SST change (0.46 °C). $\sigma_{\Delta c}$ represents the 90% confidence range, and is computed as the standard error on the estimate of the cloud amount trend multiplied by the t-value at the 90% probability level of a two-tailed Student's t test with degrees of freedom equal to the number of observations adjusted to account for the autocorrelation at lag 1.
1. ACCESS1-0  15. GFDL-CM3  29. MIROC-ESM-CHEM
2. ACCESS1-3  16. GFDL-ESM2G  30. MIROC-ESM
3. BNU-ESM   17. GFDL-ESM2M  31. MIROC4h
4. CCSM4      18. GISS-E2-H-CC  32. MIROC5
5. CESM1-BGC  19. GISS-E2-H    33. MPI-ESM-LR
6. CESM1-CAM5 20. GISS-E2-R-CC  34. MPI-ESM-MR
7. CESM1-FASTCHEM 21. GISS-E2-R  35. MPI-ESM-P
8. CESM1-WACCM 22. HadCM3       36. MRI-CGCM3
9. CNRM-CM5-2 23. HadGEM2-AO   37. MRI-ESM1
10. CNRM-CM5  24. HadGEM2-CC   38. NorESM1-ME
11. CSIRO-Mk3-6-0 25. HadGEM2-ES 39. NorESM1-M
13. FGOALS-g2 27. IPSL-CM5A-MR  41. BCC-CSM1-1
14. FIO-ESM   28. IPSL-CM5B-LR  42. INMCM4

Table 2.4: Legend of model numbers for figures 2.5 and 2.6.

Figure 2.6: Same as fig. 2.5 but for cloud amount feedback averaged over the other two boxes regions of fig. 2.4: (a) NE Pacific, (b) central Pacific.

We computed similar bar charts for changes in cloud cover in these four regions. No model simulated cloud cover changes larger than the observed in any of the regions.
(not shown). Therefore, some models are able to simulate similar magnitude cloud amount feedback as observations (fig. 2.5 and 2.6) not because they reproduce the same cloud amount changes but because they overestimate the radiative effect of clouds (fig. 2.3). We do not find any particular model that performs better than the others in the simulation of cloud cover changes or cloud amount feedback in all four regions.

We mentioned that total cloud fraction computed in the models is not the same as observed total cloud fraction, which introduces uncertainty in the estimates of cloud amount feedback. However, the uncertainty in the estimation of cloud amount feedback due to the different definitions of total cloud fraction in models and observations (Marchand et al., 2010) seems to be much smaller than the uncertainty that arises from the large inter-model spread in the simulation of cloud cover changes and cloud amount feedback (fig. 2.5 and 2.6).

2.5 Discussion

The pattern of observed cloud cover changes over the tropical Pacific Ocean (fig. 2.1) for the years 1954-2005 is similar to century time scales cloud cover changes (1900 to present) computed from ICOADS (Deser et al. 2010b). Those authors argued that the pattern in fig. 2.1a is reminiscent of El Niño because there is decrease in cloud cover over the western Pacific and increase over the central Pacific. They found that this El Niño-like cloud change pattern in the western Pacific was consistent with an observed eastward shift in precipitation in the tropical Pacific and weakening of the Walker Circulation over the last century (Vecchi et al. 2006). Furthermore, Tokinaga et al. (2012) ran AGCM experiments with prescribed SST patterns from observations and showed that the models
were able to reproduce cloud cover changes consistent with fig. 2.1a, along with an
eastward shift in convection and weakening of the Walker Circulation. Thus, the east-
west dipole pattern of cloud change and feedback in the central and western Pacific may
be explained by El Niño-like mechanisms occurring on long time scales.

On the other hand, cloud increase in the SE Pacific subtropical stratocumulus and
trade-cumulus regions shown by both fig. 2.1b of this study and Deser et al. (2010b) does
not resemble cloud changes during El Niño events, because during El Niño events cloud
cover decreases over both the SE and NE Pacific stratocumulus regions (Deser et al.,
2004). This suggests that, in contrast to the western and central Pacific, mechanisms of
climate change in the eastern Pacific might not be explained by El Niño-like mechanisms
(c.f. DiNezio et al. 2009).

The decrease in cloud amount and the resulting positive cloud amount feedback
over the NE Pacific stratocumulus region is instead consistent with a stratocumulus-to-
cumulus (Sc-to-Cu) transition hypothesis (Bretherton and Wyant, 1997). Eastman et al.
(2011) used the same data set (EECRA) used in the present study to look at changes in
low-level cloud types over the years 1954-2008. They found an increase in the frequency
of occurrence in cumulus and a decrease in stratocumulus in the NE Pacific and other
subtropical stratocumulus regions, which suggests a long-term Sc-to-Cu transition.
Cumulus cloud cover is more scattered than stratocumulus, therefore cloud fraction
decreases during the transition resulting in positive cloud amount feedback.

The only region where there is inter-model agreement in cloud amount changes is
the SE Pacific, where cloud amount increases in the historical simulations. The
subtropical SE Pacific is a region where models robustly simulate a minimum in SST
warming in response to climate change (Xie et al. 2010, DiNezio et al. 2011). This minimum warming has usually been explained as arising from a strengthening of the trade winds (Falvey and Garreaud 2009). Our results suggest that negative cloud amount feedback in the SE Pacific could contribute as well to enhance this minimum warming.

The observed and simulated changes in cloud amount feedback are consistent with some of the mechanisms explaining climate change cloud feedbacks in doubled-CO$_2$ (Zelinka et al. 2012b) and abrupt CO$_2$ quadrupling GCM experiments (Zelinka et al. 2013). Zelinka et al. (2012b) split cloud feedback into contributions from cloud amount, cloud altitude, and cloud optical depth feedbacks. As in our study, they found a negative cloud amount feedback over the central Pacific due to an increase in cloud amount. This negative cloud amount feedback, however, was largely compensated by a positive cloud altitude feedback, resulting in net positive cloud feedback over the central Pacific. Their results were consistent with the hypothesis of fixed-anvil-temperature (FAT) of Hartmann and Larson (2002), according to which high-level clouds in the tropics tend to rise as the climate warms to conserve their cloud top temperature. Our findings support the cloud amount feedback part of this mechanism. Over the NE Pacific, Zelinka et al. (2012b) found positive cloud amount feedback as in our study. They also found positive cloud altitude feedback, which along with positive cloud amount feedback is consistent with the Sc-to-Cu transition hypothesis and deepening of the marine boundary layer in response to warmer SST.

The complexity of the mechanisms involved in cloud changes, which is reflected by the observed north-south and east-west asymmetries suggest that regional differences in mechanisms of cloud change need to be taken into account. Since observed cloud-
environment relationships are similar in all subtropical stratocumulus regions on inter-
annual timescales (e.g., Klein and Hartmann 1993), some studies have suggested using
composites of cloud cover changes to explore mechanisms of cloud change in regions
characterized by the same large-scale subsidence rates such as the NE and SE subtropical
stratocumulus regions (Bony et al. 2004). While this technique has improved our
understanding of the relative roles of the thermodynamic and dynamic components of
cloud changes under idealized climate change scenarios (e.g., Bony et al. 2004, Brient
and Bony 2012), our results suggest that mechanisms of cloud changes need to be studied
regionally. In fact, environmental conditions (e.g., SST, SLP, large-scale subsidence,
precipitation) can respond differently to climate change in regions characterized by the
same large-scale subsidence regime (e.g., Vecchi and Soden, 2007a). Regional
differences can be therefore very large, even within the same dynamic regime.

Soden and Vecchi (2011) showed that the subtropical stratocumulus regions are
among the regions of largest inter-model disagreement in cloud feedback. Three of the
subtropical stratocumulus regions identified by Klein and Hartmann (1993) are located in
the Indo-Pacific Ocean (NE and SE Pacific, and SE Indian). In this study we provide
observational support for positive cloud amount feedback relative to the tropical mean
over the NE Pacific from the second half of the 20th century. We find positive but not
statistically significant cloud amount feedback over the SE Indian. Over the SE Pacific,
instead, cloud cover is found to increase in both observations (Deser et al. 2010b) and
climate models (fig 2.1b) suggesting negative cloud amount feedback, but there are not
sufficient data in EECRA to estimate cloud amount feedback in this region.
We finally note that cloud feedback has been historically defined as the cloud-induced change in TOA radiation per unit change in SST, all else being equal. To diagnose cloud feedback, idealized model experiments in which the only variable that is changing is SST (e.g., perturbed SST experiments) or the CO\textsubscript{2} concentration (e.g., abrupt 4xCO\textsubscript{2} experiments) are commonly used. In our study, however, we examine historical simulations and observations. In these experiments and in the real world cloud cover is also responding to changing in other variables in addition to planetary warming. For example, changes in anthropogenic aerosols, which have direct and indirect effects on clouds (c.f. Booth et al. 2012, Allen et al. 2012), and the ozone hole (Grise et al. 2013), which along with changes in aerosols have affected the large-scale atmospheric circulation and therefore cloud patterns in ways that differ from the response to an increase in SST alone. Moreover, trends may be influenced by the timing of ENSO or other sources of internal climate variability, thereby giving a single estimate of cloud feedback that is valid, but possibly biased on one direction or another relative to the "true" value.

We are unable to separate the temperature-mediated cloud changes (those that feedback on the warming) from those cloud changes that arise due to other forcing agents included in the historical runs and observations. Nevertheless, some large-scale features such as and east-west asymmetry in the western Pacific, positive cloud amount feedback in the NE Pacific, and the robust negative cloud amount feedback in the SE Pacific, are also simulated by idealized climate change experiments (Zelinka et al. 2012b, Soden and Vecchi 2011), which suggests that some of the mechanisms explaining cloud
changes in idealized increasing CO₂ experiments may be already evident in the available observations.

2.6 Conclusions

In this study we have examined the problem of constraining cloud feedback in climate models by taking a long-term perspective from cloud observations. Synoptic reports of cloud cover from ships contained in the EECRA data set are the longest record of cloud information over the ocean, and could potentially be used to constrain cloud feedback in climate models. In order to remove spurious variability in this data set, we subtracted the annual tropical mean from each grid box. Then, we compared the corrected inter-annual cloud cover anomalies with two satellite products (ISCCP and PATMOS-X), from which the tropical mean was also removed. During the overlapping years of coverage, EECRA and the two satellites showed good degree of agreement over most part of the Indian and Pacific Oceans, although reduced degree of agreement was found in the western Indian Ocean among all data sets.

We showed that long-term cloud changes relative to the tropical mean in EECRA were similar to the multi-model mean of 42 CMIP5 historical simulations over the years 1954-2005 but smaller in magnitude. Models and observations displayed a north-south asymmetry in cloud change in the eastern Pacific, with decreases in cloud cover over the NE Pacific and increases over the central and SE Pacific, and an east-west dipole, with decreases in cloud cover over the equatorial western Pacific, and increases over the central Pacific. The east-west dipole in the western Pacific is reminiscent of cloud cover
changes during El Niño events, and consistent with eastward shift in precipitation and reduced strength of the Walker Circulation observed over the last century.

We estimated cloud amount feedback relative to the tropical mean associated with these cloud changes. Observational estimates showed statistically significant cloud amount feedback over four regions: cloud amount feedback was found to be positive over the NE Pacific subtropical stratocumulus region and equatorial western Pacific, and negative over the southern central Pacific and western Indian. Compared to observations, the multi-model mean displayed consistent but weaker cloud amount feedback over these regions and similar large-scale features. Although the multi-model mean was found to be significantly smaller than in observations, some models simulated cloud amount feedback of the same strength if not stronger than in observations.

We proposed a method to estimate cloud amount feedback that can be easily used to compare models with observations. As more years of data from satellite-based cloud observations become available, this method can be used to corroborate the observational estimates of cloud amount feedback provided here. Finally, since climate models and observations showed similar large-scale patterns of cloud changes, we suggest that mechanisms responsible for cloud changes in models could help explain the observed changes.
Chapter 3: Evidence for Weakening of Tropical Atmospheric Circulation from Cloud Observations

3.1 Background

In response to increasing concentrations of greenhouse gases, models simulate a weakening of tropical atmospheric overturning circulation (Held and Soden 2006; Gastineau et al. 2008, 2009; Chou and Chen 2010; Bony et al. 2013). The weakening is in very good agreement across models and is projected to manifest primarily as a change in the Walker Circulation (Vecchi and Soden 2007a; Chadwick et al. 2013; He et al. 2014).

Held and Soden (2006) propose that a weakening of overturning circulation is expected because global mean precipitation increases at a slower rate than atmospheric water vapor. This mechanism has been verified in coupled climate models (Vecchi and Soden 2007a). Other hypotheses have been proposed to explain a weakening of tropical circulation in climate models, including ideas that: dry static stability increases at a faster rate than the radiative cooling of the troposphere inducing a weakening of the subsidence rate (Knutson and Manabe 1995); mean vertical advection of increased low-level moisture stratification in regions of ascent weakens convective mass flux (Ma et al. 2012); convective outflow height rises stabilizing the atmosphere and weakening convection (Chou et al. 2009; Chou and Chen 2010). In addition, Ma and Xie (2013) show that also the pattern of Sea Surface Temperature (SST) warming affects the response of the overturning circulations.
Constraining simulated changes in atmospheric overturning circulation with observations is difficult because there are no direct measurements of overturning circulation strength. Circulation strength can be inferred from trends in zonal and meridional gradients of Sea Level Pressure (SLP), however previous studies show long-term trends of inconsistent sign in different datasets. Some studies show that trends in the observed SLP datasets are consistent with a weakening of the Pacific Walker circulation (Vecchi et al. 2006; Deser et al. 2010b; Tokinaga et al. 2012; Di Nezio et al. 2013), while others suggest a strengthening of the Pacific Walker circulation (e.g., Luo et al. 2012; Meng et al. 2012; Wang et al. 2012; L'Heureux et al. 2013), Deser et al. (2010b) show that changes in SLP from the beginning of the 20th century are consistent with observed changes in SST, precipitation, and cloud cover, which together suggest an El Niño-like weakening of the Pacific Walker circulation. In contrast, L'Heureux et al. (2013) show that trends in SLP from the 1950s are consistent with a strengthening of the Pacific Walker circulation. Reanalysis products generally suggest that both the Walker and Hadley cells have strengthened from the beginning of the 20th century, but this increase might be an artifact of the assimilation techniques (Mitas and Clement 2005; Sandeep et al. 2014).

In this study we take a different approach and exploit the strong linear relationship between cloud cover and mid-tropospheric velocity ($\omega_{500}$) to estimate changes in overturning circulation from observed trends in cloud cover.
3.2 Data and methods

3.2.1 Observations

We use ship-based observations of cloud cover archived in the ICOADS release 2.5 (Woodruff et al. 2011) for the years 1920-2010, which is on a 2º x 2º grid with units of
okta; and in the Extended Edited Cloud Reports Archive (EECRA) for the years 1954-
2008, which is on a 10º x 10º grid with units of % (Hahn and Warren 2009; Eastman et
al. 2011). Cloud cover data in both these datasets are affected by a spurious and steady
positive trend of unknown origin, which we correct by subtracting the global mean cloud
cover at each time step (cf. Deser et al. 2010b; Eastman et al. 2011; Bellomo et al.
2014a). We supplement these datasets with total and high-level cloud cover obtained
from the International Satellite Cloud Climatology Project (ISCCP) satellite dataset for
the years 1984-2007, which is on a 2.5º x 2.5º grid with units of % (Rossow and Schiffer
1999). Cloud cover in the ISCCP database is corrected for errors introduced by
instrumentation failures and orbital drifts. Remaining errors are corrected by regressing
out global mean long-term trends as described in Norris and Evan (2015). Therefore, all
cloud datasets contain information of cloud cover relative to the global mean.

We calculate changes in cloud cover in these datasets as the linear trend multiplied
by the number of years in each grid box. We require each grid box to have a minimum of
25 observations per season as recommended by Eastman et al. (2011) and mask regions
where data are insufficient. Bellomo et al. (2014a) shows that when both ship-based and
satellite-based cloud observations are corrected, they exhibit consistent inter-annual
anomalies and long-term changes. Our analysis is limited to the Indo-Pacific Ocean
because there are inconsistencies over the tropical Atlantic among these datasets.
(Bellomo et al. 2014a). Climatological values of mid-tropospheric pressure velocity ($\omega_{500}$) are from the NCEP-NCAR reanalysis (Kalnay et al. 1996) on a 2.5º x 2.5º grid with units of hPa day$^{-1}$.

3.2.2 Models

We analyze atmospheric model simulations submitted for the Coupled Model Intercomparison Project phase 5 (CMIP5) forced with historical SST over the years 1979-2008 (AMIP), uniform 4K SST increase (AMIP-4K), and patterned SST increase (AMIP-Future). The patterned SST forcing used for AMIP-Future simulations is plotted in Fig. 1.1. The prescribed SST increase is with respect to the observed SST climatology (1979-2008) for both AMIP-4K and AMIP-Future and is the same in each model (Taylor et al. 2012). Because we compare cloud cover output with satellite observations we present results for 7 models that made available the ISCCP simulator output (Bodas-Salcedo et al. 2011; Klein et al. 2013) for both the AMIP-4K and AMIP-Future simulations. These models are: CanAM4, CNRM-CM5, HadGEM2-A, IPSL-CM5A-LR, IPSL-CM5B-LR, MIROC5, MRI-CGCM3.

We use the ISCCP simulator output of total cloud and high-level cloud cover. We compute high-cloud cover as the sum of the three highest bins of cloud top pressure (above 440hPa) and all cloud thicknesses. Results are qualitatively consistent if we use the standard model output of cloud cover instead of the ISCCP simulator, or include additional models that did not make available the ISCCP simulator output (not shown).

We compute changes in cloud cover and $\omega_{500}$ as the difference between the climatological mean in the forced (AMIP-4K and AMIP-Future) and historical (AMIP)
simulations. Differences are computed for each model separately, and then averaged together to produce the multi-model mean. Because they are forced with SST, these simulations isolate the effect of externally forced warming from changes due to internal climate variability.

3.3 Results

Fig. 3.1a shows the climatological multi-model mean (shaded) High Cloud Cover (hereafter, HCC) and (contours) mid-tropospheric pressure velocity ($\omega_{500}$) of the AMIP simulations. Similar patterns are found in observations. Pattern correlations of simulated mean HCC and $\omega_{500}$ with the respective observed variables are of ~0.9 (using ISCCP for high-cloud cover and the NCEP-NCAR reanalysis for $\omega_{500}$).

Regions of deep-convection coincide with larger amounts of HCC, while regions of mean subsidence with smaller amounts of HCC. HCC scales linearly with $\omega_{500}$: the spatial regression slope of mean HCC on mean $\omega_{500}$ of the AMIP multi-model mean and observations are reported in Table 3.1 (middle column). All regressions shown on Table 3.1 are statistically significant at the 99% level of a Student's t-test and the standard error on the regression coefficients are one order magnitude smaller (not shown). The scatterplots of HCC against $\omega_{500}$ are plotted in fig. 3.2 and 3.2.

The slope of AMIP multi-model mean HCC on mean $\omega_{500}$ is -0.58 (units of % / hPa day$^{-1}$), while the slope computed from observations is -0.56. The multi-model mean slope for the standard output (i.e., run without the ISCCP simulator) is smaller (-0.43) and less consistent with the ISCCP observations.
Figure 3.1: (Shaded) High-level cloud cover and (contours) $\omega_{500}$. Stippling indicates where at least 5 out of 7 models agree in sign: (a) AMIP climatological multi-model mean. Contours range from -100 hPa day$^{-1}$ to 100 hPa day$^{-1}$ with intervals of 5 hPa day$^{-1}$. (b) AMIP-Future minus AMIP multi-model mean and (c) AMIP-4K minus AMIP multi-model mean: Contours range from -30 hPa day$^{-1}$ to 30 hPa day$^{-1}$ with intervals of 2 hPa day$^{-1}$.

<table>
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<th>Dataset</th>
<th>HCC/$\omega_{500}$</th>
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<tr>
<td>ISCCP (Obs.)</td>
<td>-0.56</td>
<td>-</td>
</tr>
<tr>
<td>AMIP (ISCCP simulator)</td>
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<td>-</td>
</tr>
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<td>AMIP-4K</td>
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</tr>
</tbody>
</table>

Table 3.1: Spatial regression coefficients of (middle column) climatological mean HCC on $\omega_{500}$ and (right column) change in HCC on change in $\omega_{500}$ averaged over 30°S-30°N, 30°E-80°W. The standard errors on the regression coefficients (not shown) are one order magnitude smaller.
We note that for Table 3.1 we used 6 models instead than 7 because HadGEM2-A was not available for the non-ISCCP simulations. Results are not much different if we instead use all available models for each experiment. Individual model slopes are reported in Table 3.2.

Figure 3.2: Scatterplots of mean High-Cloud Cover (HCC) against mean $\omega_{500}$ from which the regression coefficients in the middle column of Table 3.1 are computed: (a) Observations: HCC is from ISCCP, $\omega_{500}$ is from the NCEP-NCAR reanalysis; (b) AMIP (ISCCP simulator) multi-model mean; (c) AMIP multi-model mean.
Figure 3.3: Scatterplots of change in High-Cloud Cover (HCC) against change in $\omega_{500}$ from which the regression coefficients in the right column of Table 3.1 are computed: (a) AMIP-Future minus AMIP (ISCCP simulator) multi-model mean; (b) AMIP-4K minus AMIP (ISCCP simulator) multi-model mean; (c) AMIP-Future minus AMIP multi-model mean; (d) AMIP-4K minus AMIP multi-model mean.

<table>
<thead>
<tr>
<th>Model</th>
<th>HCC/$\omega_{500}$</th>
<th>$\Delta$HCC/$\Delta \omega_{500}$ AMIP-4K</th>
<th>$\Delta$HCC/$\Delta \omega_{500}$ AMIP-Future</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCC-CSM1-1</td>
<td>-0.36 (-)</td>
<td>-0.21 (-)</td>
<td>-0.22 (-)</td>
</tr>
<tr>
<td>CanAM4</td>
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<td>-0.20 (-0.20)</td>
<td>-0.33 (-0.40)</td>
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<tr>
<td>CCSM4</td>
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<td>-0.18 (-)</td>
<td>-0.24 (-)</td>
</tr>
<tr>
<td>CNRM-CM5</td>
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<td>-0.17 (-0.19)</td>
<td>-0.23 (-0.20)</td>
</tr>
<tr>
<td>HadGEM2-A</td>
<td>(-) (-0.45)</td>
<td>(-) (-)</td>
<td>(-) (-0.28)</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
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<td>-0.22 (-0.23)</td>
<td>-0.29 (-0.34)</td>
</tr>
<tr>
<td>IPSL-CM5B-LR</td>
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<tr>
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<td>-0.13 (-0.27)</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
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<td>-0.30 (-0.32)</td>
<td>-0.34 (-)</td>
</tr>
<tr>
<td>MPI-ESM-MR</td>
<td>-0.39 (-)</td>
<td>-0.26 (-)</td>
<td>-0.34 (-)</td>
</tr>
<tr>
<td>MRI-CGCM3</td>
<td>-0.36 (-0.51)</td>
<td>-0.15 (-0.27)</td>
<td>-0.26 (-0.37)</td>
</tr>
</tbody>
</table>

Table 3.2: Spatial regressions of HCC on $\omega_{500}$ for individual models (as in Table 3.1). Values in parentheses are for the ISCCP simulator output, "(-)" indicates no data.
In response to externally forced SST change, the linear relationship between HCC and $\omega_{500}$ remains robust. Fig. 3.1b and 3.1c show the multi-model change in (shaded) HCC and (contours) $\omega_{500}$ in AMIP-4K and AMIP-Future, respectively. In both scenarios, where $\omega_{500}$ decreases (less subsidence) HCC increases, while where $\omega_{500}$ increases (more subsidence) HCC decreases. Table 3.1 reports the spatial regression slope of multi-model mean change in HCC on change in $\omega_{500}$ (right column). The spatial regression of HCC with $\omega_{500}$ is still linear although smaller than in the mean climate. Moreover, the regressions slopes are steeper for the patterned SST (AMIP-Future) than for the uniform (AMIP-4K) simulations.

The strong linear relationship between HCC and $\omega_{500}$ suggests that changes in $\omega_{500}$ may be predicted from changes in cloud cover. Since changes in $\omega_{500}$ are not directly measured and trends in SLP are of inconsistent sign in different datasets (L'Heureux et al. 2013) we estimate changes in $\omega_{500}$ from observed trends in cloud cover.

Fig. 3.4a and 3.4b shows (shaded) changes in Total Cloud Cover (hereafter, TCC) in EECRA (years 1954-2008) and ICOADS (years 1920-2010). A through discussion of trends and time series of cloud cover anomalies in these different datasets can be found in previous studies (Clement et al. 2009; Deser et al. 2010b; Bellomo et al. 2014a). Observations of HCC are not available from surface-based archives. In EECRA there is a classification of cloud cover in cloud types, but these do not coincide with the cloud top height classification of ISCCP. Moreover, Eastman et al. (2011) discuss how reports of middle and high cloud types are less reliable than those of low clouds and that the frequency of occurrence of clouds at upper levels is taken only in a subset of
observations in which their level is observable. The number of observations is also smaller for individual cloud types than for TCC.

![Image of Figure 3.4: (Shaded) Change in total cloud cover, (contours) climatological mean total cloud cover: (a) EECRA 1954-2008. Stippling indicates where the linear trend is statistically significant at the 90% level of a Student's t-test (autocorrelation is accounted for determining the degrees of freedom), (b) ICOADS 1920-2010.](image)

Changes in TCC are similar in the two datasets, despite that they cover a different period of time (fig. 3.4). This indicates that changes in the EECRA dataset are qualitatively a good representation of changes observed from the early 20th century to today, with the exception of the increase in cloud cover over the western Indian Ocean, which is not seen in fig. 3.4b. The observed trends are also remarkably similar to multi-model mean simulations in fig. 3.1, suggesting that at least part of the observed trends is externally forced. The uniform warming simulations (AMIP-4K) capture most of the changes in cloud cover, however the robust increase over the central Pacific and western
Indian is only seen in the patterned simulations (AMIP-Future), when the atmosphere is forced with an enhanced El Niño-like equatorial warming (fig. 1.1). These differences between AMIP-4K and AMIP-Future may reflect the influence of dynamic processes on regional cloud trends as suggested Bony et al. (2004). In fact, those authors show that the thermodynamic processes, which could be thought as the response to a uniform warming, explain most of tropical mean cloud cover change. However, regional cloud cover changes, which could be thought as the response to regional patterns of SST warming, are dominated by changes in local atmospheric circulations.

Although there are not observations for HCC, an estimate of change in $\omega_{500}$ can be obtained from changes in TCC. Trends in TCC are a good representation of trends in HCC in regions where HCC is predominant. Instead, over the subtropical stratocumulus regions at the eastern side of the Indian and Pacific Oceans, namely the Californian, Peruvian, and Australian stratocumulus decks (Klein and Hartmann 1993), simulated changes in TCC are dominated by (not shown) changes in low-cloud cover (hereafter, LCC) in all AMIP experiments.

To obtain estimates of changes in $\omega_{500}$ given changes in TCC we multiply the spatial regression slope of observed mean $\omega_{500}$ on mean HCC (-1.29 hPa day$^{-1}$ %$^{-1}$) by the change in TCC, for both ship-based observations and AMIP-Future multi-model mean. We remind the reader that we cannot use a regression slope of change in $\omega_{500}$ on change in HCC because we do not have observational values to estimate a change in HCC.

Fig. 3.5a and 3.5b show (shaded) estimates of changes in $\omega_{500}$ from TCC in the ship-based EECRA observations for the years 1954-2008 and the AMIP-Future multi-model mean, respectively. Fig. 3.5c shows the actual multi-model mean AMIP-Future
change in $\omega_{500}$. Superimposed in contours is the climatological mean $\omega_{500}$. Blanked out in Fig. 3.5a and 3.5b are regions where either there is not sufficient data (cf. fig. 3.4) or the inter-annual anomaly correlation of TCC with HCC from ISCCP observations is not statically significant at the 95% level of a Pearson's r-test. This way, regions where LCC is predominant do not affect estimates of changes in $\omega_{500}$ from HCC.

![Figure 3.5](image)

Figure 3.5: (Shaded) Change in $\omega_{500}$, (contours) climatological mean $\omega_{500}$: (a) observational estimate from EECRA (1954-2008), (b) multi-model estimate from AMIP-Future, (c) AMIP-Future multi-model mean simulated change. Contours range from -100 hPa day$^{-1}$ to 100 hPa day$^{-1}$ with intervals of 5 hPa day$^{-1}$. Stippling indicates where at least 5 out of 7 models agree in sign. For this figure, all the datasets are regridded to a common 2.5° x 2.5° grid.

The patterns and magnitude of observational (fig. 3.5a) and model estimates (fig. 3.5b) of changes in $\omega_{500}$ are remarkably similar to one another and to the actual simulated values (fig. 3.5c). The observational estimates of $\omega_{500}$ show that there is an overall
decrease in subsidence (convection) in regions of mean descent (ascent), which is consistent with a weakening of the tropical overturning circulation over the years 1954-2008. Given the similarity of cloud changes in fig. 3.4, our estimates suggest a weakening of tropical overturning circulation also from the beginning of the 20th century.

We note that since the regression slope of mean $\omega_{500}$ on HCC is bigger than it would be for climate change values (cf. Table 3.1), the model estimates (fig. 3.5b) are smaller than the simulated values (fig. 3.5c) and this might also be the case for the observational estimates. At this point, we do not have sufficient data and enough confidence from ship-based observations to provide an exact, quantitative estimate of the change in $\omega_{500}$, although model results suggest that this calculation might underestimate the true values.

Held and Soden (2006) propose that precipitation increases at a slower rate than atmospheric water vapor because convective fluxes weaken in response to increasing concentrations of CO$_2$. Simplistically, precipitation ($P$) can be thought of as convective mass flux ($M$) multiplied by atmospheric water vapor ($q$). To the first order, change in convective mass flux can be therefore written as:

$$\frac{\delta M}{M} = \frac{\delta P}{P} - \frac{\delta q}{q}$$

(3.1)

Since $q$ scales with the Clausius-Clayperon relation at a rate of $7\% \, K^{-1}$, but $P$ (in climate models) increases at the slower rate of $\sim 2\% \, K^{-1}$, $M$ is expected to decrease at a rate of $\sim -5\% K^{-1}$. This relation holds in coupled climate model simulations forced with increased concentrations CO$_2$ in the CMIP3 and CMIP5 archives (Vecchi and Soden 2007a; Chadwick et al. 2013). Convective mass flux output is not currently available, but we
estimate the fractional change in $\frac{\delta \omega_{500}}{\omega_{500}}$, which is a good approximation for $\frac{\delta M}{M}$ (Vecchi and Soden 2007a) to compare our observational estimates with the theoretical values predicted by Held and Soden (2006). We divide the observational estimate of $\delta \omega_{500}$ obtained from cloud cover change (shaded in fig. 3.5a) by the climatological mean of $\omega_{500}$ (contoured in fig. 3.5a), and then divide by 0.5 K, which is roughly the increase in global surface temperature observed since the beginning of the twentieth century (cf. Deser et al. 2010b). In regions of convection, we find values of $\frac{\delta \omega_{500}}{\omega_{500}}$ ranging from -3% K$^{-1}$ in regions of climatological mean $\omega_{500} \leq -5$ hPa day$^{-1}$ to -5% K$^{-1}$ in regions of $\omega_{500} \leq -30$ hPa day$^{-1}$. These values are in agreement with the expected values of Held and Soden (2006), and within the inter-model range (Vecchi and Soden 2007a).

3.4 Discussion and conclusions

Previous modeling studies show that in response to global climate change, models robustly simulate a weakening of tropical atmospheric overturning circulation. However, observations show inconsistent trends in SLP across datasets or for different time periods. Instead of looking at only changes in SLP, Deser et al., (2010) compare changes in SST, SLP, precipitation, and cloud cover from the beginning of the 20$^{th}$ century to present day. Together, changes in these different variables suggest a weakening of the Pacific Walker Circulation along with an El Niño-like change in precipitation and HCC. Here we estimate the change in mid-tropospheric pressure velocity ($\omega_{500}$) from observed changes in cloud cover over the Indo-Pacific Ocean. Observed cloud cover is not a direct measure of circulation strength, but it is highly correlated with $\omega_{500}$ and is consistent with other
observed changes in the tropical climate (Deser et al. 2010b). The estimated change in $\omega_{500}$ from cloud cover suggests a weakening of tropical overturning circulation since the beginning of the 20th century. This weakening is quantitatively within the theoretical predictions of Held and Soden (2006).

In addition, we compare observed changes in cloud cover with changes simulated by atmospheric model simulations forced with uniform and patterned SST forcing (AMIP-4K and AMIP-Future). AMIP-4K simulations capture part of the observed changes, but the enhanced equatorial warming forcing (AMIP-Future) is needed to fully capture the observed changes over the equatorial Pacific and Indian Ocean. Although we limit our analysis to atmosphere-only simulations, cloud cover change simulated by AMIP simulations is consistent in magnitude and sign with fully coupled model simulations forced with increasing concentrations of CO₂ (Zelinka et al. 2012b; IPCC 2013). This suggests that observed cloud cover change and the estimated weakening of tropical overturning circulation must be at least in part externally forced.

Ship-based observations should be compared with reanalysis products and historical simulations in the CMIP5 archive over the same years of coverage. Reanalysis products show either no change or strengthening of the overturning circulation (e.g., Sandeep et al. 2014), which are generally accompanied by consistent and opposite sign local changes in cloud cover (not shown). However, changes in cloud cover exhibit different patterns and signs in the different reanalysis products, and are inconsistent with the observed changes in both ship and satellite datasets. Bellomo et al. (2014a) compare cloud cover change in the EECRA dataset over the years 1954-2008 with historical model simulations in the CMIP5 archive over the same period of time.
They find that the multi-model mean pattern of climate change is consistent with observed cloud cover change, but the amplitude is much smaller than observed. Their results suggest that internal variability is larger than external forcing in driving changes in cloud cover in the historical simulations and that observations are instead consistent with an externally forced response.

Based on these results, either the historical simulations underestimate observed trends, or the observations are affected by artifacts that introduce unrealistically large trends. Di Nezio et al. (2013) compare observed SLP trends with CMIP5 historical simulations and also find that observed SLP trends are underestimated by most of the historical simulations and the multi-model mean. There is no obvious reason why two independent datasets like the SLP in Di Nezio et al. (2013) and cloud cover in the present study should both exhibit a spurious trend in the same direction. However, further research and continued observations are needed to provide better and more quantitative observational estimates of tropical atmospheric circulation change.
Chapter 4: Simulating the Role of Subtropical Stratocumulus Clouds in Driving Pacific Climate Variability

4.1 Background

Several studies have documented low-frequency fluctuations in Pacific Ocean Sea Surface Temperature (SST) associated with basin-wide changes in climate. These fluctuations are characterized by a triangular pattern of SST anomalies over the eastern side of the Pacific Ocean, surrounded by anomalies of the opposite sign to the west, and over the central North and South Pacific. This pattern is usually referred to as Pacific Decadal Variability (PDV), and represents the primary mode of Pacific climate variability on time scales longer than inter-annual (Chen et al. 2008).

Over the 20th century, a shift from cold to warm PDV occurred in 1924-25, followed by a shift from warm to cold in 1946-47, and from cold to warm in 1976-77. The latest shift to a cold phase seems to have occurred after the major El Niño event of the 1997-98, and still persists (among others, Nitta and Yamada 1989, Trenberth and Hurrell 1994, Mantua et al. 1997, Zhang et al. 1997, Deser et al. 2004, Alexander 2010, Deser et al. 2010a, Wang et al. 2014). The shifts in PDV were accompanied by changes in large-scale atmospheric circulation, Sea Level Pressure (SLP) over the Aleutian low, air temperature and rainfall over North America (e.g., Mantua et al. 1997, Minobe 1997, Hare and Mantua 2000, McCabe et al. 2004, Deser et al. 2004), and had far reaching consequences on marine ecosystems and fish production (e.g., Mantua and Hare 2002, Peterson and Schwing 2003, Di Lorenzo et al. 2008).
In the tropical Pacific, the low-frequency SST fluctuations of PDV resemble interannual anomalies associated with El Niño Southern Oscillation (ENSO), and are similarly accompanied by changes in the Walker Circulation and precipitation. These low-frequency fluctuations in the tropical Pacific are often referred to as ENSO-like decadal variability (e.g., Wang and Ropelewski 1995, Zhang et al. 1997, Clement et al. 2011) and are linked to persistent rainfall anomalies over land such as the dustbowl drought of the 1930s (Barlow et al. 2001, Hoerling et al. 2001, Schubert et al. 2004a, Schubert et al. 2004b, Seager et al. 2005). Given the substantial economic and societal impacts of PDV, understanding the processes responsible for the persistence of SST anomalies in the tropical Pacific is of primary importance because a better understanding of these processes improves predictability of decadal changes in SST, which is currently limited (Kim et al. 2012, Smith et al., 2012).

The mechanisms underlying PDV are under debate (Alexander, 2010). Given the similarity between SST patterns associated with PDV and ENSO, most studies have suggested mechanisms for PDV that presume a fundamental role for coupled ocean-atmosphere dynamics and ocean waves (e.g., Latif and Barnett 1994, Gu and Philander 1997, Timmerman and Jin 2002, Karspeck et al. 2004, Yeh and Kirtman 2006, Kwon and Deser 2007). More recently, a few studies challenged this notion, and showed that atmospheric dynamics and air-sea interactions can alone explain ENSO-like variability on both interannual (Dommenget 2010) and longer timescales (Dommenget and Latif 2008, Clement et al. 2011, Okumura, 2013). These studies examined AGCMs coupled to a motionless slab ocean model (AGCM-slab simulations) in which the atmospheric model is thermodynamically but not dynamically coupled to the ocean model. Clement et
al. (2011) showed that ENSO-like low-frequency variability simulated by an ensemble of AGCM-slab models from the Coupled Model Intercomparison Project phase 3 (CMIP3) archive shares several features with observations, including precipitation, SLP, and atmospheric circulation patterns. Those authors found that the persistence of ENSO-like SST anomalies in the AGCM-slab models is consistent with an integration of atmospheric white noise by the oceanic mixed-layer (i.e., as in the theoretical model of Frankignoul and Hasselmann, 1977) In this context, the duration of the SST anomalies is regulated by weakly damped atmospheric feedbacks involving the interaction among SST, winds, and cloud cover. Clement et al. (2011) also showed that the persistence of SST anomalies in the tropical Pacific is model dependent and suggested that cloud feedbacks could explain these differences. Zhang et al. (2014a) showed that inter-model spread in variance of tropical Pacific SST in AGCM-slab models is correlated with the strength of cloud feedback.

Low-level clouds over the subtropical eastern Pacific exert a strong radiative cooling and increase the persistence of local SST anomalies in the NE and SE Pacific subtropical stratocumulus regions (Klein and Hartmann 1993, Park et al. 2005, Clement et al. 2009, Bellomo et al. 2014a). Ma et al. (1996) increased the amount of stratocumulus cloud cover over the SE Pacific off the coasts of Peru in a coupled climate model. They found that greater cloud cover reduces the warm SST bias in the SE Pacific and results in a better simulation of precipitation and trade winds across the tropical Pacific. Several other studies have then suggested that there is a positive feedback among subtropical low-level clouds, SST, and large-scale atmospheric circulation in the tropical Pacific (Philander et al. 1996, Nigam 1997, Norris 2005, Clement et al. 2009). The SST
anomalies propagate from the subtropical NE and SE Pacific regions to the equatorial Pacific via the atmospheric wind-evaporation-SST (WES) feedback (Zhou and Carton, 1998) and influence ENSO and the tropical Pacific climate (Chang et al. 2007, Matei et al. 2008, Okumura 2013, Zhang et al. 2014). Cloud feedback in the subtropical stratocumulus regions could therefore lead to decadal anomalies in SST throughout the Pacific basin (cf. Clement et al., 2009).

In this study we examine the hypothesis that low-level cloud feedback influences the persistence of tropical Pacific climate variability patterns. We increase the strength of positive low-cloud feedback over the NE and SE Pacific subtropical stratocumulus regions in a AGCM-slab model, and evaluate the influence of these regions on the modes of Pacific climate variability simulated by the model. This investigation gives important insights on the role of low-level clouds on the persistence of SST anomalies, and indicates that a better representation of clouds could increase the predictive skill of decadal climate variability in the Pacific Ocean.

4.2 Data and methods

4.2.1 Experimental design

We perform experiments with the ECHAM6 (v6.1.04) atmospheric general circulation model (AGCM) coupled to a slab-ocean model for the open ocean and a thermodynamical sea ice model. The details of ECHAM6 are given in Stevens et al. (2013). We use a variant of the coarse-resolution model (ECHAM6-CR) with T31 horizontal grid (3.75° x 3.75°) and 31 vertical levels instead of 47. The coarse-resolution unlike the other versions of ECHAM6 does not include a representation of the
stratosphere. The mixed-layer depth of the slab-ocean model is fixed to 50 m everywhere and does not vary seasonally. When the AGCM is coupled to slab-ocean, the atmosphere and the ocean are thermodynamically but not dynamically coupled. We choose this configuration because AGCM-slab models simulate realistic low-frequency Pacific climate variability even in the absence of ocean dynamics (Clement et al. 2011), and it is easier to interpret the effects due to atmospheric feedbacks without the complications of dynamical coupling with an interactive ocean.

We perform a simulation in pre-industrial control conditions (i.e., constant greenhouse gas forcing), which we will refer to as the "control" run. In AGCM-slab ocean simulations, SST is determined at each time step by atmospheric heat fluxes in the current run and prescribed monthly mean ocean heat fluxes—commonly referred to as the "q-flux"—which represent the effects of the mean ocean heat transport but do not drive internal variability. We compute q-fluxes from a run of the AGCM forced with fixed climatological monthly mean SST.

We compare the control run with simulations in which we enhance the strength of positive low-cloud feedback, where positive means an amplification of a local SST anomaly. To increase the strength of positive low-cloud feedback we multiply cloud liquid water in the radiation code of ECHAM6 by an amplification factor "y" at each time step of the model run. The factor y is a function of underlying SST and ranges between 0 and 2 as follows:

\[ y = 1 - \arctan(SST) \times \frac{2}{\pi} \]  

(4.1)

where SST is the monthly mean SST anomaly calculated as the SST in the current run minus the climatological monthly mean SST computed from the last 50 years of the
control run. In other words, at each time step and grid point the model checks which month it is, calculates the monthly mean SST anomaly with respect to the control simulation, and computes "y". Then, the cloud liquid water is multiplied by "y" and becomes a function of the underlying SST monthly anomaly.

By changing the radiative effect of cloud liquid water seen by the radiation module with eq. (4.1), we modify the cloud radiative effect (CRE). In this study we only show the CRE at the surface, which is defined as total-sky minus clear-sky net (i.e., short- plus long-wave) radiative flux at the surface and is positive for downward fluxes. Our conclusions do not change when we examine the CRE at the top-of-atmosphere. Eq. (4.1) shows that when SST is positive the net cloud radiative effect (CRE) decreases (warming effect) because cloud liquid water is multiplied by $y < 1$, while when SST is negative net CRE increases (cooling effect) because cloud liquid water is multiplied by $y > 1$. Therefore, eq. (4.1) increases the strength of positive cloud feedback in the model.

We increase the strength of positive cloud feedback over the NE and SE Pacific, which we define as the subtropical regions (i.e., outside 15°N-15°S) where the mean subsidence at 500 hPa is greater than 10 hPa/day, and the lower tropospheric stability (LTS) is greater than 17.5 K (LTS is defined as the difference in potential temperature at 700 hPa and 1000 hPa). This definition is somewhat arbitrary, but it allows us to target regions and atmospheric conditions in which subtropical stratocumulus clouds are predominant in the climatological mean of the model (cf. Medeiros and Stevens, 2011). The regions that we choose are contoured by black boxes in fig. 1. We verify that in these regions cloud liquid water in the model is present only in clouds below 700 hPa in the climatological mean so that we enhance the strength of cloud feedback at low-level. We
note that we only modify the radiative effect of cloud liquid water in the radiation module, thus we do not change cloud liquid water in the atmospheric water budget.

We perform three experiments with enhanced low-cloud feedback. The first experiment is one in which we increase the strength of positive low-cloud feedback in both the NE and SE Pacific subtropical stratocumulus regions. This experiment will be referred to as the "NE+SE Pacific" simulation. The second experiment is one in which we enhance positive low-cloud feedback only in the SE Pacific ("SE Pacific") while in the third experiment we enhance positive low-cloud feedback only in the NE Pacific ("NE Pacific"). All simulations, including the control run, are integrated for 200 years, but the first 50 years are discarded from the analysis to allow the model to spin up. We form monthly mean anomalies by subtracting the climatological monthly mean from each month. Each experiment is run with prescribed ocean heat fluxes calculated from AGCM simulations with fixed SST.

The difference in the long-term global mean SST between the three experiments with enhanced low-cloud feedback and the control run is less than 0.4 K. We verified that this increase in mean SST does not affect our conclusions by running another experiment in which we modified the q-flux so that the mean SST change was nearly zero (0.07 K). In this simulation (not shown) we find consistent results with the ones shown in the rest of this paper. This means that changes in the mean climate do not affect the changes in internal climate variability due to enhanced cloud feedbacks. We also note that the enhanced cloud feedback does not influence the simulation of the seasonal cycle of SST (not shown).
4.2.2 Observations

We compare the model simulation of cloud feedback with observations. CRE is obtained from the Clouds and Earth's Radiant Energy System (CERES) Energy Balanced and Filled (EBAF) dataset (EBAF_Ed2.6r; Loeb et al. 2009). SST is from the Extended Reconstructed SST version 3b (ERSSTv3b) dataset of the National Oceanic and Atmospheric Administration (NOAA) Earth System Research Laboratory (Smith et al. 2008). We form monthly mean anomalies by subtracting the climatological monthly mean from each month using the years 2001-2009 for which the two datasets are both available.

4.3 Results

4.3.1 Enhanced strength of cloud feedback

We estimate the strength of cloud feedback as the regression of local CRE (defined at surface throughout this study) on SST. Fig. 4.1 shows cloud feedback in the control simulation (fig. 4.1a) as well as the differences between the three enhanced cloud feedback experiments and the control run (fig. 4.1b, 4.1c, and 4.1d). Contours represent cloud cover climatology in the control run, while the black boxes indicate the regions where we increased the strength of cloud feedback applying eq. (1).

Fig. 4.1a shows that the model simulates positive cloud feedback over the eastern Pacific and negative cloud feedback over the equatorial western Pacific. Therefore, the model simulates cloud feedback of the same sign as it is seen in observations over the tropical Pacific (Bellomo et al., 2014a), but overestimates the strength of positive cloud
feedback over some regions (e.g., the cold tongue) and underestimates it over the subtropical stratocumulus regions.

Figure 4.1: (a) Cloud feedback in the control simulation (estimated as regression of CRE at the surface on SST, units of W m\(^{-2}\) K\(^{-1}\)). (b,c,d) Difference in the strength of cloud feedback between the three experiments and the control run. Overlain is cloud cover climatology from the control run. (b) NE+SE Pacific minus control, (c) SE Pacific minus control, and (d) NE Pacific minus control. Black boxes indicate where low-cloud feedback is enhanced.

In fact, the observational estimates of cloud feedback defined as the regression of CRE at the surface from CERES on SST from ERSST are 5.5 W m\(^{-2}\) K\(^{-1}\) over the NE Pacific and 4.2 W m\(^{-2}\) K\(^{-1}\) over the SE Pacific, while in the control simulation they are 1.6 W m\(^{-2}\) K\(^{-1}\) and 2.7 W m\(^{-2}\) K\(^{-1}\), respectively. Although we increase the strength of cloud feedback in the subtropical stratocumulus regions, in this study we perform sensitivity tests to qualitatively explore the role of cloud feedbacks on Pacific climate variability, but we are not in a position yet to assess their actual magnitude. Therefore, we will compare the
enhanced cloud feedback experiments with the control simulation but not with observations. Other estimates of strength of cloud feedback over the Pacific subtropical stratocumulus regions and the deficiency of models in simulating strong enough cloud feedback can be found in previous studies (e.g., Bony and Dufresne 2005, Cronin et al. 2006, Clement et al. 2009, Lauer et al. 2010, de Szoeke et al. 2012).

Fig. 4.1b shows that the NE+SE Pacific simulation exhibits stronger cloud feedback over both the NE and SE Pacific than in the control simulation, as intended. Fig. 4.1c and 4.1d similarly show that cloud feedback gets stronger mainly over the SE Pacific and NE Pacific in the other two experiments, with smaller effects outside of these regions. Although some regions exhibit less positive cloud feedback (e.g., over the cold tongue), the sign of cloud feedback in the three experiments is of the same sign as in the control simulation (fig. 4.1a) everywhere. Therefore, the sign of cloud feedback is consistent with observations in all simulations. The average cloud feedback over the NE and SE Pacific is reported in Table 4.1 for each experiment.

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>NE+SE Pacific</th>
<th>SE Pacific</th>
<th>NE Pacific</th>
</tr>
</thead>
<tbody>
<tr>
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<td>5.7</td>
<td>1.5</td>
<td>5.7</td>
</tr>
<tr>
<td>SE Pacific</td>
<td>2.7</td>
<td>7.2</td>
<td>7.3</td>
<td>2.4</td>
</tr>
</tbody>
</table>

Table 1. Cloud feedback averaged over the NE and SE Pacific boxed regions in each simulation. Units are W m$^{-2}$ K$^{-1}$.

4.3.2 Effects of cloud feedback on internal climate variability

The stronger low-cloud feedbacks over the subtropical stratocumulus regions increase the magnitude of monthly mean SST anomalies over the eastern Pacific. Fig. 4.2a shows the
The variance of SST increases in the eastern Pacific, mostly where cloud feedbacks are enhanced, but also outside of these regions. In particular, there is an increase over the eastern equatorial Pacific and the cold tongue, which originates from the SE Pacific region. Compared to observations, we note that the model underestimates the variance of SST over the equatorial Pacific in the control simulation (fig. 4.2a).
This is due to the absence of ocean dynamics and of ENSO (Clement et al., 2011). We note that there is not much increase in variance in the lower left corner of the SE Pacific box. This is related to the fact that the increase in strength of cloud feedback is less pronounced there due to less cloud cover in the climatological mean (fig. 4.1b).

Cloud feedbacks also have a considerable impact on the persistence of SST monthly mean anomalies, as is shown in fig. 4.3 by the difference between the $e$-folding timescale in the three experiments and the control run.

![Figure 4.3](image)

Figure 4.3: (a) $e$-folding timescale in the control simulation (units of months). (b,c,d) Difference in $e$-folding timescale between the three experiments and the control: (b) NE+SE Pacific minus control, (c) SE Pacific minus control, and (d) NE Pacific minus control.

The $e$-folding timescale is defined as the month at which the autocorrelation of SST reduces by a factor of $1/e$ and is a measure of the persistence of SST anomalies. For reference, we plot the $e$-folding timescale in the control simulation in fig. 4.3a. In the
control simulation (fig. 4.3a), the e-folding timescale exhibits the largest values along the equatorial Pacific and the cold tongue, and over the subtropical eastern Pacific off the coasts of California and Peru. The NE+SE Pacific experiment (fig. 4.3b) exhibits the largest change from the control run, that is, an increase in e-folding time scale by ~7 months, which occurs over the Niño3.4 region (5°S-5°N, 120°W-170°W) and almost doubles the e-folding timescale of the control run in this region (fig. 4.3a). Fig. 4.3c and 4.3d show similar results, in particular that the SE Pacific has a larger effect on SST in the equatorial ENSO region than the NE Pacific.

These results indicate that cloud feedbacks influence the magnitude of SST anomalies and their persistence. To understand what is the effect of cloud feedback on the modes of climate variability simulated by the model, and to better characterize the relative influences from the NE and SE Pacific regions, we compare the mean climate state (fig. 4.4) with an Empirical Orthogonal Function (EOF) analysis of the leading modes of variability (fig. 4.5).

Fig. 4.4 shows the climatology of (shaded) SST, (contours) SLP, and (vectors) surface winds in the control simulation. As in observations, the subtropical stratocumulus regions (boxed) are characterized by relatively cold SST and are located equatorward and westward of the subtropical high-pressure systems (Norris, 1998). To obtain the leading modes of climate variability in the tropical Pacific Ocean, we compute EOFs of tropical Pacific SST (140°E-70°W, 30°S-30°N), and then use the Kaiser row normalization and the varimax rotation to obtain the first two rotated EOFs in each model simulation. After the rotation, the EOFs are orthogonal but the principal components (PCs) are not. The PCs of the first two rotated EOFs are then normalized by their standard deviation.
Figure 4.4: Climatology in the control simulation: (shaded) SST, (contours) SLP ranging from 990 hPa to 1040 hPa, 2 hPa intervals, (vectors) surface winds in m/s.

Figure 4.5 shows the regression of SST, surface winds, and SLP on the PCs of the first two rotated EOFs in the control run. These regressions represent the anomalies associated with the sign of SST (shaded) shown in the plots. When these modes shift to the opposite phase with reversed SST sign, the anomalies associated with the opposite phase have the same pattern as those shown in the plots in fig. 4.5 but reversed sign.

The first EOF explains 10% of the variance and the regression on its PC (fig. 4.5a) shows a pattern of variability that resembles the Pacific Decadal Oscillation (PDO), which is the North Pacific signature of PDV (Mantua et al. 1997). During the positive phase of PDO, the Aleutian low and the cyclonic wind circulation around the low are enhanced, and SST anomalies over the central North Pacific and eastern Pacific Ocean are of opposite sign. These features are all captured by the first EOF of the control run (fig. 4.5a). We will refer to this pattern as the "North Pacific" mode.
Figure 4.5: Regression of (shaded) SST, (vectors) surface winds, and (contours) SLP on the PCs of the (a) North Pacific mode and (b) South Pacific mode in the control simulation. The PCs are normalized by their standard deviation. Negative SLP contours are dashed, positive SLP contours are solid, and the zero SLP contour is thick solid. Contour range is from -2 hPa to 2 hPa, 0.2 hPa interval.

The second EOF explains similar variance (9.8%) and the regression on its PC (fig. 4.5b) is reminiscent of ENSO although the largest variance occurs over the southeast Pacific rather than on the equator because of the absence of ocean dynamics in the slab-ocean model configuration. This mode resembles the thermally coupled Walker (TCW)
mode of Clement et al. (2011). Those authors showed that the TCW mode is associated with interannual to decadal timescale fluctuations in the Southern Oscillation index, and arises even in the absence of ocean dynamics. Similarly to Clement et al. (2011), we find that the warm phase of this mode (fig. 4.5b) is characterized by warm SST and westerly wind anomalies along the equatorial Pacific, a low and cyclonic wind circulation over the SE Pacific, and weaker Walker Circulation. We will refer to this second regression as the "South Pacific" mode.

The North and South Pacific modes are the two dominant modes of Pacific climate variability simulated by the model, and explain similar variances. Linear cross-correlations of the principal components associated with the two modes reveal that they are weakly correlated at lag 0 but this correlation (0.16) is small and not significant (at the 85% level confidence of a Pearson's R test for correlation). Thus, even after the rotation of the EOFs, these two modes exist as separate patterns of variability in the model.

The experiments with enhanced positive low-cloud feedback over the subtropical stratocumulus regions simulate the same two dominant modes of variability, but the variance explained by the two modes is larger. Table 4.2 shows the variance explained by the two modes in each experiment.

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>NE+SE Pacific</th>
<th>SE Pacific</th>
<th>NE Pacific</th>
</tr>
</thead>
<tbody>
<tr>
<td>North Pacific mode</td>
<td>10.0%</td>
<td>13.4%</td>
<td>11.0%</td>
<td>12.8%</td>
</tr>
<tr>
<td>South Pacific mode</td>
<td>9.8%</td>
<td>13.5%</td>
<td>15.3%</td>
<td>10.2%</td>
</tr>
</tbody>
</table>

Table 4.2: Variance explained by the North Pacific and South Pacific modes in each simulation.
In the NE+SE Pacific experiment the variance of the two modes increases by about the same amount. Instead, the other two experiments show that the SE Pacific increases mainly the variance of the South Pacific mode, whereas the NE Pacific increases mainly the variance of the North Pacific mode. It is noteworthy that the North Pacific mode (fig. 4.5a) remains confined to the northern hemisphere, while the South Pacific mode (fig. 4.5b) reaches the equatorial ENSO region, which is consistent with previous studies. In fact, Okumura (2013) and Zhang et al. (2014b) suggested that the mean location of the Inter-Tropical Convergence Zone (ITCZ) in the northern hemisphere prevents the wind-induced anomalies from the northern hemisphere to reach the equator, and our findings support this idea (cf. wind patterns in fig. 4.5a and 4.5b with wind climatology in fig. 4.4).

We note that the third EOFs in all experiments explain variances ranging from 6.3% to 7.0%. Since these remain similar in all experiments whereas the first two EOFs increase in variance when low-cloud feedback is stronger, this means that the there is a shift of variability from smaller spatial scales to the large-scale leading modes. To test whether the values of variances explained by each EOF reported in Table 4.2 are robust, we perform a Monte Carlo test taking three intervals of 50 years each in the 150 years of the model simulations. We compute the EOFs for each interval, and find that the values reported in Table 4.2 are consistent in magnitude and within the range of the variances explained by the EOFs in each 50-year interval.

The EOF analysis therefore shows that low-cloud feedbacks in the subtropical stratocumulus regions increase the variability of basin-wide climate variability patterns. In particular, cloud feedback in the SE Pacific seems to play a fundamental role in
modulating equatorial Pacific variability. To understand the influence of cloud feedback on equatorial climate variability as a function of timescale, we compute power spectra of the Niño3 SST index (fig. 4.6). The Niño3 region (90°W-150°W, 5°S-5°N) is located in the eastern equatorial Pacific and is a commonly used index to detect ENSO variability. Although we choose to show the Niño3 region, we find consistent results for other indices in the equatorial Pacific and the Niño3.4 index. The power spectrum of the Niño3 index in the control run is plotted in black (fig. 4.6), while colored curves represent the power spectrum in the three experiments. In the calculation of the spectra we taper 10% of the data and apply a 15-month smoothing to the periodogram estimates.

![Power spectra of the Niño3 index](image)

**Figure 4.6:** Power spectra of the Niño3 index in the (black) control, (red) NE+SE Pacific, (blue) SE Pacific, and (green) NE Pacific simulation. Markers indicate where the variance is statistically different from the variance in the control simulation at the 95% level of a Fischer's F test. Gray lines indicate the error range estimated with the chi-square distribution (see text for details). Units are years for period (top label) and month$^{-1}$ for frequency (bottom label).
The combined effects of the NE and SE Pacific feedbacks (red curve) increase the variance of the Nino3 index at timescales longer than 10 years. Variance at timescales longer than 10 years is also enhanced by the SE Pacific (blue) and NE Pacific (green), although the influence of the NE Pacific at the equator is small. The SE Pacific (blue) increases interannual (2-7 years) time scale variability, which suggests that SE Pacific cloud feedbacks could modulate ENSO amplitude on interannual time scales (Dommenget 2010).

The thin grey curves in fig. 4.6 represent an estimate of the error range in the control run. The error range is obtained from the inverse chi-square distribution function at the 95% probability level by calculating the upper integration of the non-central chi-square distribution from the degrees of freedom. The curves representing the NE+SE Pacific (red) and SE Pacific (blue) experiments lie well outside the error range, while the curve of the NE Pacific experiment is not statistically different from the control simulation. We also apply the Fischer's F-test for variances to show where the variances are statistically different from the control run. The black markers on the colored curves indicate at which frequencies the difference in the variance from the control simulation is significant at the 95% level of the F-test. The Fischer's test shows that the enhanced variability at decadal and longer timescales in the NE+SE Pacific and SE Pacific experiments, and at interannual timescales in the SE Pacific, are statistically significant, in agreement with the estimated error range from the chi-square distribution.

We also compute power spectra of SST indices in the NE and SE Pacific boxes and in the regions where the variance of SST increases by most in the subtropical eastern Pacific (not shown). We find an increase in the variance of SST at decadal and longer
timescales, and in the SE Pacific also at interannual timescales, consistent with the power spectra shown for the Niño3 index in fig. 4.6.

Interestingly, when the NE and SE Pacific feedbacks are both enhanced (red curve), they interfere constructively at decadal and longer timescales enhancing the variance of the Niño3 index spectrum, but they interfere destructively at interannual timescales where the red curve (NE+SE Pacific) exhibits less variance than the blue curve (SE Pacific only). It is not clear what processes could lead to these different behaviors at interannual and decadal timescales, but additional analysis of composites of Nino3 warm events in the NE+SE Pacific and control simulations (not shown) seems to suggest that a Pacific Meridional Mode characterized by SST anomalies of one sign in the northern tropical Pacific and of opposite sign over the cold tongue (Chiang and Vimont 2004) is predominant at interannual timescales, while an ENSO-like pattern (e.g., Deser et al. 2010a) is predominant at longer timescales. This is also confirmed by lead/lag correlations of SST composites in the North and South Pacific with the Niño3 index during warm/cold events of the Nino3 index (not shown). In fact, these correlations reveal that prior to Niño3 warm/cold events the SST in the North and South Pacific are anti-correlated at interannual timescales, but correlated at decadal timescales. This hypothesis needs further verification with a multi-model analysis and longer simulations to rule out the possibility that this behavior is model or time dependent.

4.3.3 Mechanisms of SST propagation and persistence

Since we are examining AGCM-slab simulations, the processes that contribute to the development, propagation, and persistence of SST variability are driven solely by surface
heat fluxes (i.e., short-wave, long-wave, latent, and sensible). We find that the mechanisms of ENSO-like variability in our runs are consistent with previous findings (cf. Dommengen 2010, Zhang et al. 2014). Composites of ENSO-like events reveal that an initial SST anomaly develops in the SE Pacific several months prior to the peak of the event. This anomaly propagates northward and westward via the wind-evaporation-SST (WES) feedback. The WES feedback takes place when a weakening of the climatological north-south and east-west tropical SST gradients along with a weakening of the trade winds (fig. 4.4) favors the migration of SST anomalies from the SE Pacific to the eastern equatorial Pacific. Latent heat flux due to weaker northeastward trade winds initially favors the warming in the SE Pacific, but then damps SST anomalies after the event reaches its peak because of the strong dependence of latent heat release on specific humidity (Wang 2010). In contrast, CRE contributes to the warming of SST throughout the event reducing the damping effect of latent heat flux. In the western Pacific CRE has opposite sign and tends to damp SST, thereby preventing the anomaly to reach further west.

To visualize the relative roles of the surface heat fluxes in driving ENSO-like anomalies, we composite surface heat fluxes and SST in the south-eastern Pacific (5°S-20°S, 70°W-100°W) prior and after the peak of Nino3 index warm events (fig. 4.7). Fig. 4.7 displays the processes that contribute to the growth and decay of warm SST in the SE Pacific associated with warm Nino3 events. The Nino3 warm events are chosen as the months at which SST is larger than one standard deviation of the Niño3 index that are also local maxima in the time series. Fig. 4.7a shows the composites in the control simulation, while fig. 4.7b shows the composites in the SE Pacific experiment.
Figure 4.7: Composites of SST and surface heat fluxes during Nino3 index warm events in the southeastern Pacific (5°S-20°S, 70°W-100°W): (a) Control, (b) SE Pacific. Black is SST, blue is latent heat flux, green is sensible heat flux, red is cloud radiative effect, and orange is clear-sky radiation. All time series are smoothed with a 6-month running average.

SST (black curve) in the SE Pacific leads the peak of Niño3 events by few months, which is consistent with a WES feedback and northwestward propagation from the subtropical stratocumulus SE Pacific region. We note that in the SE Pacific experiment (fig. 4.7b) there is a larger contribution to SST warming from CRE, which explains larger-amplitude and more persistent SST anomalies than the control run (fig. 4.7a). Instead, latent heat fluxes damp SST anomalies in both simulations throughout the event. Clear-sky and sensible heat fluxes have much smaller effects. These results do not change when we apply low-pass filters to remove high-frequency variability indicating that these mechanisms explain both inter-annual and low-frequency SST fluctuations in the model. The composites are not sensitive to the exact location of the box that we choose in the southeast Pacific, and compositing cold instead of warm Nino3 events leads to similar results.
4.4 Discussion and conclusions

In this study we examine the role of the NE and SE Pacific subtropical stratocumulus regions in driving Pacific climate variability in an AGCM (ECHAM6) coupled to a slab-ocean. We enhance the strength of positive low-cloud feedback over the NE and SE Pacific by increasing the radiative effect of cloud liquid water in response to SST anomalies. We find that low-cloud feedbacks over the subtropical stratocumulus regions increase the variance and persistence of SST in the eastern Pacific Ocean, and enhance the variability of the two dominant modes of Pacific climate variability. The two dominant modes of variability correspond to a mode resembling the Pacific Decadal Oscillation (PDO) in the North Pacific, and a mode resembling El Niño Southern Oscillation (ENSO) in the equatorial eastern Pacific. We name these modes "North Pacific" and "South Pacific", respectively.

We perform two additional experiments in which we increase the strength of positive low-cloud feedback only in one of the two subtropical stratocumulus regions at the time. We find that the NE Pacific enhances the North Pacific mode but has little influence at the equator. Instead, the SE Pacific enhances the South Pacific mode increasing the variance of the Nino3 index on both interannual (2-7 years) and decadal (>10 years) timescales.

To understand the mechanisms contributing to the persistence of ENSO-like events, we composite heat fluxes in the southeastern Pacific during warm events of the Nino3 index. We find that CRE at the surface is largely responsible for the persistence of SST anomalies in the southeastern Pacific, contrasting the damping effect of latent heat fluxes. In addition to what is in the literature, we show a primary role for clouds in
increasing the persistence of basin-wide climate variability patterns, in particular at
decadal and longer timescales.

We assert that the results of these model experiments are relevant to understanding
observed decadal climate variability. In fact, decreases and increases in low-cloud in the
eastern subtropical Pacific cover have been observed over the last century in response to
warm and cold phases of PDO, respectively (Deser et al. 2004, Clement et al. 2009). Changes
in the amount of cloud cover have a strong impact on the radiative budget
(Bellomo et al. 2014a) and could influence SST on long timescales. Based on our results
and the observational evidence for decadal shifts in cloud cover, we propose one
mechanism for Pacific decadal climate variability that involves a positive feedback
among cloud cover in the subtropical stratocumulus regions, SST, and large-scale
atmospheric circulation. This mechanism can briefly summarized as follows.

SST anomalies in the subtropical stratocumulus regions influence the strength of the
trade wind and latent heat fluxes (namely, the WES feedback). The WES feedback favors
a propagation of SST from the subtropical stratocumulus regions to the equator along the
mean track of the trade winds. If cloud feedbacks are enhanced in the subtropical
stratocumulus regions the variance of SST anomalies increases at longer than interannual
timescales especially at timescales longer than 10 years. These SST anomalies in the
subtropical stratocumulus regions increase the persistence of basin-wide SST anomalies
via the WES feedback mechanism. Hence, decadal climate variability can be explained
by thermally coupled heat fluxes at the ocean surface (Clement et al. 2011), but cloud
feedbacks in the subtropical stratocumulus regions play an important role in
setting the duration of these climate shifts. This mechanism does not presume a primary role for ocean dynamics.

In the present study we did not address the role of ocean dynamics, which remains an open question. Okumura (2013) examined the mechanisms of tropical Pacific Decadal Variability in both the fully-coupled and slab-ocean version of Community Climate System Model, version 4 (CCSM4; Gent et al. 2011). They suggested that ocean dynamics increase the coherency of the North and the South Pacific modes by enhancing equatorial SST variability and associated atmospheric teleconnections. Ma et al. (1996) also looked at the role of ocean dynamics and showed that advection by ocean dynamics (Humboldt current) was important in the equatorward propagation of SST. These two studies both support the idea that ocean dynamics increase the variance of Pacific climate variability, but Clement et al. (2011) examined an ensemble of CMIP3 slab-ocean models and showed that this effect is model-dependent and generally small at timescales longer than interannual.

Finally, we note that the role of clouds in modulating climate variability is receiving increasing attention. A number of studies showed that atmospheric feedbacks including the cloud feedback over the cold tongue can drive ENSO events and modulate ENSO characteristics in coupled climate models, and also in observations if the cold tongue is sufficiently strong (Dommengen 2010, Bellenger et al. 2013, Dommengen et al. 2014). Some recent studies showed that subtropical stratocumulus clouds influence climate variability patterns in the Atlantic Ocean. Among others, Evan et al. (2013) showed that positive stratocumulus cloud feedbacks in the NE and SE Atlantic Ocean reduce the damping rate of SSTs associated with the Atlantic Meridional Mode, while
Trzaska et al. (2007) suggested an important role for positive cloud feedbacks off the coasts of Namibia in propagating SST anomalies from the South Atlantic to the equatorial Atlantic.

Given the important role of cloud feedbacks in modulating climate variability in different ocean basins, we suggest that a better representation of cloud-environment relationships would potentially improve near-term predictions of interannual and decadal time scales SST anomalies. Incorporating cloud radiative effects from satellite products in statistical prediction models such as the Linear Inverse Model of Newman et al. (2003) or in GCMs could give insights on the predictive skill gained by including information of clouds and radiation fluxes in near-term forecasts.
Chapter 5: The Influence of Cloud Feedbacks on Equatorial Atlantic Variability

5.1 Background

Equatorial Atlantic climate variability is dominated by a zonal mode of Sea Surface Temperature (SST) anomalies occurring primarily during boreal summer (June-July-August) over the Atlantic cold tongue region (6ºS-2ºN, 20ºW-5ºE). SST anomalies over the cold tongue are accompanied by changes in atmospheric and oceanic circulations that resemble those associated with El Niño Southern Oscillation (ENSO) in the Pacific Ocean, and have therefore been referred to as "Atlantic Niño" events (Merle 1980; Hisard 1980; Xie and Carton 2004). Atlantic Niños are characterized by warm anomalies along the equator and the eastern side of the South Atlantic Ocean (Ruiz-Barradas et al. 2000), weakening of equatorial trade winds west of 20ºW, and weakening of meridional winds associated with the North African summer monsoon to the east of 20ºW (Horel et al. 1986; Zebiak 1993; Xie and Carton 2004). During warm Atlantic Niños, equatorial deep convection shifts southward (Wagner and da Silva 1994; Carton et al. 1996; Mitchell and Wallace 1992; Biasutti et al. 2003) and precipitation increases over the Gulf of Guinea (Hirst and Hastenrath 1983). Like their Pacific counterparts, Atlantic Niños have impacts on sea level, precipitation over surrounding continents, and fisheries (Brundrit 1995; Hagen et al. 2001; Boyer et al. 2001). For these reasons, understanding the origin, dynamics, and the physical mechanisms of SST variability over the equatorial Atlantic is of primary importance to improve the predictability of Atlantic Niños and their impacts.
In addition to Atlantic Niño, previous studies have shown that equatorial Atlantic variability is affected by another dominant mode of variability: the decadal timescale Atlantic Meridional Mode, which is characterized by asymmetric SST anomalies about the equator within the tropical Atlantic (among others: Servain 1991; Servain et al. 1999; Nobre and Shukla 1996; Chang et al. 1997; Penland and Matrosova 1998; Tanimoto and Xie 2002; Chiang and Vimont 2004). However, because of possible statistical artifacts in the detection and interpretation of these modes of variability, it is still unclear whether the North Atlantic is correlated with Atlantic Niños and South Atlantic variability through the inter-hemispheric Atlantic Meridional Mode and on which timescales that mechanism operates (Mehta 1998; Enfield et al. 1999; Dommenget and Latif 2000). A number of studies suggest that the Atlantic Meridional Mode does not arise as a mode of variability after the rotation of the first leading Empirical Orthogonal Functions (EOFs). In fact, the first two leading rotated EOFs are each confined to one hemisphere with little projection on the other hemisphere (Houghton and Tourre 1992; Dommenget and Latif 2000; Trzaska et al. 2007).

The Atlantic cold tongue is more influenced by the South Atlantic because of the geometry of the African continent and because the climatological position of the ITCZ in the northern hemisphere predominantly drives surface cross-equatorial flow from the south to the north, which means that perturbations in the trade winds in the northern hemisphere have relatively little influence on equatorial SSTs (cf. Okumura 2013; Zhang et al. 2014b; Bellomo et al. 2014b). For these reasons, it is argued that Atlantic equatorial variability is more strongly influenced by South Atlantic rather than North Atlantic SST variability (Dommenget and Latif 2000; Trzaska et al. 2007).
Several studies have shown connections between the subtropical and extra-tropical South Atlantic and equatorial Atlantic variability (Venegas et al. 1996; Robertson et al. 2003, Barreiro et al. 2004). These can be divided into studies that argue for a fundamental role for oceanic processes and ocean waves (among others, Zebiak 1993; Carton et al. 1996; Delecluse et al. 1994; Servain et al. 1999; Sutton et al. 2000; Florenchie et al. 2003; Florenchie et al. 2004), and studies that contend that thermodynamic feedbacks involving the interaction of atmospheric circulation, latent heat flux, and cloud cover can alone explain tropical Atlantic variability and to the first order, Atlantic Niño (among others, Dommenget and Latif 2000; Tanimoto and Xie 2002; Haarsma et al. 2003; Sterl and Hazeleger 2003; Chaves and Nobre 2004; Trzaska et al. 2007, Evan et al. 2013).

Dommenget and Latif (2000) used a hierarchy of models to show that a positive feedback among SST, wind stress, and latent heat flux at the surface is more important than ocean dynamics in driving upper ocean tropical Atlantic variability. In addition, a number of studies, including Tanimoto and Xie (2002), Park et al. (20005), Trzaska et al. (2007), and Evan et al. (2013), have shown the importance of positive cloud feedbacks in increasing the persistence of SST anomalies over low-level cloud regions located off the coasts of Namibia. For example, Evan et al. (2013) estimated the influence of low-level cloud feedback from observations, and then showed with an idealized coupled linear model that cloud feedbacks are necessary for the SST anomalies associated with the simulated Atlantic Meridional Mode to persist as long as it is observed.

Using observations, idealized climate models, and theoretical frameworks, these previous studies provide evidence that local coupling between SSTs and cloudiness can
influence equatorial Atlantic variability. However, those studies do not evaluate the impacts of cloud feedbacks relative to other atmospheric or oceanic processes, or the influence of cloud feedbacks from different regions over the South Atlantic basin. To address these questions, we use an atmospheric general circulation model (ECHAM6) coupled to a slab-ocean in which we artificially increase the strength of positive cloud feedback over selected regions. First, we investigate the role of cloud feedbacks over the Namibian stratocumulus region in modulating the persistence of local and equatorial SST variability, and then we evaluate the influence of cloud feedbacks from other regions in the South Atlantic on equatorial SST variability.

5.2 Data and methods

5.2.1 Observations

We use monthly mean values of Sea Surface Temperature (SST) from the Extended Reconstructed SST reanalysis (ERSSTv3b; Smith et al. 2008) along with surface winds and Sea Level Pressure (SLP) from the NCEP/NCAR reanalysis (Kalnay et al. 1996). Observed cloud feedback is estimated using cloud cover and Cloud Radiative Effect (CRE). We use monthly mean values of cloud cover from the International Satellite Cloud Climatology Project (ISCCP; Rossow and Schiffer 1999) for the years 1984-2007, and seasonal mean values of cloud cover from the Extended Edited Cloud Reports Archive (EECRA; Hahn and Warren 1999, 2009) for the years 1954-2008. Monthly mean values of CRE are from the Clouds and Earth's Radiant Energy System (CERES) Energy Balanced and Filled (EBAF_Ed2.7) data set for the years 2001-2010 (Loeb et al. 2009), and from ISCCP for the years 1984-2007.
We de-trend all observational data by removing the least squares regression line, and compute monthly mean anomalies by subtracting the long-term monthly mean from each calendar month. For cloud data from EECRA we compute seasonal mean anomalies subtracting the long-term seasonal mean from each season.

Observational datasets are affected by observational errors. In satellite data, errors are mostly caused by replacement of instruments and orbital drifts over time. Instead, in ship-based data errors arise due to unknown observational artifacts that introduce a spurious trend in the tropical mean long-term variability. This trend is inconsistent with the observed increase in tropical mean surface temperatures and satellite cloud datasets (Norris 2005; Eastman et al. 2011; Clement et al. 2009). For these reasons, all cloud datasets were corrected for presumed spurious artifacts by removing tropical mean variability (cf. Bellomo et al. 2014a). We note that these artifacts mostly affect estimates of long-term trends in cloud cover, while we are interested in de-trended interannual to decadal timescale climate variability.

5.2.2 Model experiments
To test the role of positive cloud feedbacks on Atlantic climate variability, we perform model experiments using a state-of-the-art AGCM (ECHAM6, v. 6.1.04) coupled to slab-ocean for the open ocean and a thermodynamical sea ice model (Stevens et al. 2013). We use the coarse-resolution (ECHAM6-CR) with T31 horizontal grid (3.75° x 3.75°) and 31 vertical levels. The mixed-layer depth of the slab-ocean model is fixed to 50 m everywhere and does not vary seasonally.
In the slab-ocean configuration, interactive ocean dynamics are absent and internal climate variability is driven solely by the thermal coupling between the ocean and the atmosphere (i.e., short- and long-wave radiation plus latent and sensible heat fluxes). The monthly climatology of ocean heat transport (commonly referred to as "q-flux") is prescribed to maintain the SST climatological mean, but does not vary from year to year. For all experiments, the q-flux is obtained from a control simulation using the AGCM with fixed climatological monthly mean SSTs computed from observations.

We perform a control simulation using the prescription of Coupled Model Intercomparison Project phase 5 (CMIP5) pre-industrial control experiments (Taylor et al. 2012), which we compare with model experiments in which we increase the strength of local positive cloud feedbacks. To increase the strength of positive cloud feedback, we use the experimental design of Bellomo et al. (2014b). Following their methods, we multiply cloud liquid water in the radiation module by an amplifying factor \(y\), which is a function of underlying SST anomalies:

\[
y = 1 - \arctan(SST) \times \frac{2}{\pi}
\]  \hspace{1cm} (5.1)

In the equation above, SST indicates local SST anomalies computed as SST in the current run minus SST monthly mean climatology computed from a control simulation. Eq. (5.1) is applied at each time step of the model simulation and at each grid point where we increase the strength of local positive cloud feedback. In this study positive feedback means a reduction (increase) in cloud radiative effect when the underlying SST anomaly is warm (cold). Further details of the model setup are provided Bellomo et al. (2014b).

We perform a first experiment in which cloud feedback is enhanced in the subtropical South Atlantic where the mean subsidence at 500 hPa is greater than 10 hPa
day$^{-1}$ and the mean Lower Tropospheric Stability (LTS) is greater than 16.5 K (LTS is defined as the difference in potential temperature at 700 hPa and the surface). These criteria are chosen to target regions in which subtropical stratocumulus clouds predominate in the model (Medeiros and Stevens 2011). The box in which these constraints are met in the model is highlighted in red in Fig. 5.1 and corresponds to the Namibian stratocumulus region (Klein and Hartmann, 1993). Hereafter, we will refer to the experiment that enhances cloud feedbacks in this region as the "Namib" simulation. Both the Control and the Namib simulations are run for 200 years.

![Figure 5.1](image)

Figure 5.1: Masking used in the model experiments with enhanced positive cloud feedback. Red box: Namib experiment; black boxes 1-9: regional experiments in the South Atlantic.

To investigate the role of cloud feedbacks over other South Atlantic regions, we perform a series of sensitivity experiments in which we enhance the strength of positive cloud feedback in nine regions located within 5°N-30°S, 40°W-10°E. These experiments are named according to the number in the black boxes in Fig. 5.1 (e.g., "Box 1", "Box 2", etc.), where we note that Box 6 is a subset of the Namib experiment. We run all sensitivity experiments for a period of 100 years. The length of these simulations is
constrained by computational resources but is deemed sufficient because an analysis of 80 years instead of 180 years in the control and Namib experiments leads to qualitatively similar results. The analysis of the nine experiments in the boxes motivated longer simulations for Box 3 and Box 6, which were run for an additional 50 years (i.e., a total of 150 years of simulation time). We use these longer experiments to further characterize the influence of these regions on low-frequency equatorial variability.

For all experiments, we discard the first 20 years of spin-up time from the analysis to remove the possible influence of the initial conditions, and we compute monthly mean anomalies by removing the simulated annual cycle from each month. For all slab-ocean experiments shown in this paper we find that the global mean change in SST from the control simulation is negligible (order of ~0.01 K). Moreover, Bellomo et al. (2014b) showed that changes in the mean climate do not affect the changes in internal climate variability caused by enhanced cloud feedbacks or the simulation of the seasonal cycle of SST.

5.3 Results

5.3.1 Observations

Figure 5.2 shows the regressions of observed local (shaded) SST anomalies, (contours) SLP, and (vectors) surface winds on an equatorial Atlantic index (Atl3) for the years 1960-2010. The Atl3 index (5°S-5°N, 20°W-0°E), which is highlighted by the black box in Fig. 5.2, is commonly used to measure Atlantic Niño activity. Stippling in Fig. 5.2 indicates where the linear correlation of SST with the Atl3 index is statistically significant at the 95% level of a Pearson's R test for correlations.
Figure 5.2: Regression of observed (shaded) SST, (contours) SLP, (vectors) surface winds on the Atl3 SST index (black box) for the years 1960-2010. Contours are from -2.0 hPa to 2.0 hPa with interval of 0.2 hPa. Solid lines refer to positive SLP anomalies, dashed lines to negative SLP anomalies, while the thick solid line is the zero-level contour. Stippling indicates where the correlation between local SSTs and the Atl3 SST index is statistically significant at the 95% level of the Pearson's R-test for correlations. All data are de-trended.

The regression in Fig. 5.2 displays a zonal mode along the equator – the Atlantic Niño. Atlantic Niño is accompanied by large anomalies in the strength of trade winds along the equator and northerly wind anomalies crossing the equator (Fig. 5.2). A weakening of SLP and wind circulation around the subtropical high is evident in the South Atlantic. Atlantic Niño is correlated with SST anomalies of the same sign in the southeastern part of the South Atlantic Ocean, and with SST of opposite sign in the southwest. It is noteworthy that Atlantic Niño SST anomalies are significantly correlated with SSTs in the South Atlantic Ocean (stippling in Fig. 5.2), but not correlated with
North Atlantic SSTs, suggesting that Atlantic Niños are influenced by South Atlantic SSTs but not by North Atlantic SSTs and the Atlantic Meridional Mode (see discussion in Marshall et al. 2001).

Atlantic Niño is also accompanied by changes in cloud cover, which influence the radiation budget at the surface. To calculate the anomalies in the net radiation budget at the surface due to changes in cloud cover, we estimate cloud amount feedback as defined in Bellomo et al. (2014a) from observations. To estimate cloud amount feedback, we first divide climatological mean net (i.e., long-wave plus short-wave) Cloud Radiative Effect (CRE) by climatological mean total cloud amount, where CRE is computed as the difference between total-sky and clear-sky radiation fluxes at the surface. This ratio is called "cloud amount radiative kernel" \((k)\) as in Bellomo et al. (2014a), and represents the sensitivity of CRE to changes in mean cloud amount (units of W m\(^{-2}\) %\(^{-1}\)):

\[
k = \frac{\text{CRE}}{c}
\]  

(5.2)

Cloud amount radiative kernel is computed using radiative fluxes from CERES using the years 2001-2009 and all years available for cloud data in the two cloud datasets. Then, we multiply the cloud amount radiative kernel (eq. 5.2) by the regression of total cloud amount on the Atl3 SST index anomalies to obtain the regression of cloud amount feedback on the Atl3 SST index (units of W m\(^{-2}\) K\(^{-1}\)). As discussed in Bellomo et al. (2014a), cloud amount feedback as estimated here does not take into account perturbations in cloud vertical and optical properties and should be interpreted as the cloud amount component of the total cloud feedback, which can be written as the sum of cloud amount, cloud altitude, cloud optical feedbacks, and a residual term (Zelinka et al. 2012b). We note that this cloud amount feedback includes all cloud types.
The regressions of cloud amount feedback on Atl3 SST index are shown in Fig. 5.3. Fig. 5.3a is obtained using cloud data from ISCCP for the years 1984-2007, while Fig. 5.3b is obtained using cloud data from EECRA for the years 1954-2008. These regressions represent the net radiation anomaly at the surface that is due to changes in cloud cover associated with Atlantic Niño SST fluctuations.

Figure 5.3: Regressions on the Atl3 index (black box) of (shaded) cloud amount feedback, units of W m\(^{-2}\) K\(^{-1}\); (contours) cloud cover, units of % K\(^{-1}\). Contour levels range from -10% to +10%, with 1% interval. Solid lines indicate positive values, dashed lines indicate negative values, while solid thick lines indicate the zero-level. (a) Cloud cover is from ISCCP (years 1984-2007); (b) Cloud cover is from EECRA (years 1954-2008). In this plot we use inter-annual anomalies differently from all the other plots because the temporal resolution of EECRA is of seasonal monthly means.

Changes in cloud cover (contours) display a decrease in the eastern part of the South Atlantic, which is mostly covered by low-level stratocumulus clouds, and an increase in cloud cover in the western equatorial Atlantic, where deep-convective clouds predominate (Norris 1998). The decrease in low-level clouds in the eastern part of the basin associated with warm SST anomalies in the Atl3 region is interpreted as a positive cloud amount feedback (shaded) that further amplifies SST anomalies (cf. Evan et al. 2013). In contrast, the increase in deep-convective clouds in the western equatorial Atlantic is interpreted as a negative cloud amount feedback, which damps underlying
warm SST anomalies (Fig. 5.2). Therefore, a positive cloud feedback associated with low-level clouds in the eastern part of the basin promote the persistence of SST anomalies associated with the Atl3 region (Fig. 5.2), whereas negative cloud feedback due to deep-convective clouds in the western equatorial Atlantic damps SST anomalies.

The negative values of the regression of cloud amount feedback on Atl3 SST index found over the southwestern part of the basin (Fig. 5.3) also represent a positive cloud feedback because SST anomalies are negative in this region when Atl3 anomalies are positive (cf. Fig. 5.2). That is, cooler SSTs over the southwestern South Atlantic are associated with more cloud cover (contours), and hence less radiation into the surface. Observations from ships (Fig. 5.3b) are coarser and sparser but also resemble the large-spatial pattern seen from satellites (Fig. 5.3a). Most importantly, they show that these changes in cloud cover are not particular to the satellite era, suggesting that they are not related to spurious trends or biases in the ISCCP dataset (Bellomo et al. 2014a).

Observations over the last six decades show that clouds co-vary with SST in the Atl3 region and with atmospheric large-scale circulation in a way that would amplify SST anomalies over the Namibian stratocumulus deck and the eastern equatorial basin – how does this cloud radiative forcing influence the variability of Atlantic Niño?

5.3.2 Role of cloud feedbacks over the Namibian region

To investigate the role of cloud feedbacks on Atlantic Niño and large-scale modes of climate variability, we run model experiments in which we enhance positive cloud feedback over the Namibian region, as outlined in Section 5.2.2. Differently from observations, cloud feedback is estimated in model simulations as the regression of net
CRE at the surface on local SST anomalies. This definition is different from the cloud amount feedback estimate shown for observations in Fig. 5.3 for two reasons. First, local cloud feedback is used now to highlight the response of the model to the imposed cloud liquid water-SST relationship (eq. 1), whereas the observed regressions in Fig. 5.3 show cloud radiative effect associated with anomalies in the Atl3 SST index to understand the variability associated with Atlantic Niño. Second, in the model we compute cloud feedback using radiative fluxes instead of cloud amount. We cannot use cloud amount as we do for observations because in this particular experimental design we do not change the coupling between cloud amount and SST, but rather between CRE and SST. Nevertheless, changing CRE in response to SST anomalies has the same effects as changing cloud amount. In fact, the regression of CRE on the Atl3 SST index using CRE from the short CERES dataset (2001-2009) and from ISCCP (1984-2007) gives qualitatively similar results to those shown in Fig. 5.3 (not shown).

Figure 5.4a shows the difference in cloud feedback between the Namib experiment, in which we enhance positive cloud feedback over the Namibian stratocumulus region, and the control run. For comparison, Fig. 5.4b shows cloud feedback in the control run. As intended, the model simulates stronger positive cloud feedback over the stratocumulus deck off the coasts of Namibia (Fig. 5.4a) where we enhance it (black box), and a decrease in the strength of cloud feedback in the equatorial regions due to dynamical adjustments in the model. The equatorial response in local cloud feedback to this remote forcing is not trivial. There is a strengthening of the negative feedback in the west, and a weakening of the positive feedback in the east. Either way, the overall effect of the imposed enhanced local feedback in the Namib region to increase the local cloud
radiative damping of SST (i.e., more negative cloud feedback) in the equatorial region.

Figure 5.4: (a) Difference in local cloud feedback between Namib and the control simulation. Cloud feedback is computed as regression of local CRE at the surface on SST (units of W m$^{-2}$ K$^{-1}$). Contours represent mean cloud cover climatology in the control simulation. Black box represents the Namib region; (b) Cloud feedback in the control simulation.

The imposed relationship of cloud liquid water to SST (eq. 5.1) in the Namib experiment makes the model simulation of cloud feedback more similar to observations. In the control simulation (Fig. 5.4b) cloud feedback is underestimated over the Namibian region and overestimated over the equator, where observations show cloud feedback of negative sign while in the model the sign is positive (cf. Evan et al. 2013 and references therein). In the Namib experiment, cloud feedback over the Namib region shows values of cloud feedback that are stronger and more similar to observations, while over the equator it shows smaller but still positive cloud feedback. Although there are still differences between the simulations and observations especially along the equator, the simulation of cloud feedback in the Namib experiment is closer to observations and helps us interpret the role of cloud feedbacks in regulating SSTs. Moreover, since we only
enhance cloud feedback, these experiments are helpful to separate the role of cloud feedbacks on the simulated internal climate variability from other processes.

The effect of increasing the strength of the positive cloud feedback over the Namibian region (Fig. 5.4a) is an overall increase in the variance of SST and SLP (Fig. 5.5), both locally where the feedback is enhanced, and remotely in the equatorial regions. Figures 5.5a and 5.5c show the climatological mean SST and SLP variance, respectively. Compared to the climatological mean, the Namib experiment displays enhanced variance of both SST and SLP as shown by the ratio of variance of SST and SLP in the Namib experiment to the control run in Fig. 5.5b and 5.5d, respectively.

Figure 5.5: (a) Variance of SST in the control simulation; (b) Ratio of variance of SST in the Namib experiment to the control simulation; (c) Variance of SLP in the control simulation; (d) Ratio of variance of SLP in the Namib experiment to the control simulation. Stippling indicates where the difference in variance between the Namib and the control simulations is significant at the 95% level of a Fisher's F-test. The black box indicates the Namib region.
In the control simulation the variance of SLP (Fig. 5.5c) resembles observations (not shown) but is smaller than observations over the Namibian region, while the variance of SST (Fig. 5.5a) is smaller than observations (not shown) both over the Namibian region and the equatorial Atlantic due to the absence of ocean dynamics in the slab-ocean configuration (Clement et al. 2011). It is noteworthy that the increase in the strength of cloud feedback over the Namibian region alone can more than double equatorial variability, and makes the variance of SST and SLP more similar to what is observed. This happens despite the increased local cloud radiative damping of SST anomalies (Fig. 5.4a).

Another important effect of enhanced cloud feedback over the Namibian region is an increase in the persistence of SST anomalies as measured by the $e$-folding timescale, which is defined as the month at which the autocorrelation of local SST anomalies drops below a value equal to or smaller than $1/e$ at each grid point. Figure 5.6 shows the $e$-folding timescale in the control simulation (Fig. 5.6a) and the difference in $e$-folding timescale between the Namib experiment and the control simulation (Fig. 5.6b).

Figure 5.6: (a) $e$-folding timescale in the control simulation; (b) difference in $e$-folding timescale between the Namib and the control simulations. The black box indicates the Namib region.
In the control simulation the largest e-folding time is found off the coasts of Namibia (Fig. 5.6a), while in the Namib experiment the largest increase occurs at about 5ºS in the eastern part of the basin (Fig. 5.6b). Interestingly, the variance of SST and SLP, and the e-folding time, are all enhanced in near-equatorial regions far away from where cloud feedback is increased.

The remote influence of cloud feedbacks in the subtropics on equatorial SST indicates that regional cloud feedbacks are connected to large-scale atmospheric circulation and climate variability patterns. In particular, cloud fluctuations and their influence on local SST in the Namibian region are connected to equatorial climate variability. To understand this influence as a function of timescale, we compute power spectra of SST anomalies averaged over the Atl3 region in the (black) control simulation and (red) Namib experiment in Fig. 5.7.

Figure 5.7: Power spectra of SST averaged over the Atl3 region (5ºS-5ºN, 20ºW-0ºE) in the (red) Namib experiment and (black) control simulation. A 24-month smoothing has been applied to the periodogram estimates. Black dots indicate where the variance of the Namib curve is significantly different from the variance of the control simulation at the 95% level of a Fisher's F-test.
Black markers on the red curve (Namib experiment) indicate where the difference in variance from the control run is statistically significant at the 95% level of a Fisher's F-test for variances. Figure 5.7 shows that positive cloud feedback over the Namibian stratocumulus deck significantly increases the variance of equatorial SST anomalies at inter-annual to decadal timescales.

To quantify the contribution of the imposed cloud feedbacks to modes of variability, we perform an Empirical Orthogonal Function (EOF) analysis on South Atlantic SST anomalies (40°S-10°N, 50°W-20°E) in the control and Namib simulations (not shown). The first EOF exhibits a mode of variability as the one seen from observations (Fig. 5.2) and explains 16.4% of the variance. This mode of variability is referred to the South Atlantic Dipole in the literature (e.g., Trzaska et al. 2007) and explains ~20% of SST variance in observations (not shown). The first EOF in the Namib experiment also exhibits the same mode, but explains a larger variance (23.3 %) at the equator due to the enhancement of Atlantic Niño variability (Fig. 5.5b).

These results collectively indicate that cloud feedbacks from the eastern subtropical Atlantic can play an important role in setting the timescale and amplitude of equatorial modes of variability especially at low-frequency timescales. In the following sections we will: explore whether equatorial SSTs are influenced by other regions in the South Atlantic (section 5.3.3); examine the mechanisms connecting the Namib region to the equator (section 5.3.4); and provide a heat flux framework to interpret these mechanisms (section 5.3.5).
5.3.3 Role of cloud feedbacks over other regions in the South Atlantic

To test the possible role of other regions in the South Atlantic, we perform nine experiments in which we increase the strength of positive cloud feedback over the nine boxes shown in Fig. 5.1. We note that while in the Namib region cloud liquid water is mostly present at lower levels in the atmosphere (below 700hPa), in the other regions over the South Atlantic it can be present also at upper levels, especially where deep convection is more common, for instance along the equator in the South Atlantic Convergence Zone. This means that in these nine experiments we are not enhancing only low-level cloud feedbacks. Moreover, differently from observations, cloud feedback over the deep-convective regions in the model has a net positive sign like over the Namibian region (Fig. 5.4b). However, despite these differences from observations, these experiments will reveal the regions over the tropical South Atlantic where the positive feedback between cloud cover and SST can trigger a response over the equatorial Atlantic.

Figure 5.8 shows the difference in cloud feedback between the nine enhanced cloud feedback experiments and the control simulation. Cloud feedback is estimated as in Fig. 5.4 as the regression of local CRE at the surface on local SST. Although we enhance positive cloud feedback in the same manner in all regions, we see from Fig. 5.8 that regions where low-clouds are more common over the eastern Atlantic (e.g., Box 6 over the Namibian region) display a more enhanced positive cloud feedback. This is because the total cloud cover is larger where low-level clouds predominate.

The response to enhanced feedbacks, however, is not trivially proportional to the change in cloud feedback strength shown in Fig. 5.8. Figure 5.9 shows the ratio of SST
variance in the nine cloud feedback experiments to the control simulation and there is not linear relationship between enhanced cloud feedback (Fig. 5.8) and SST variance (Fig. 5.9).

Figure 5.8: Difference in cloud feedback between enhanced cloud feedback experiments and the control simulation. Cloud feedback is estimated as regression of local CRE at the surface on SST, units of W m$^{-2}$ K$^{-1}$ (as in Fig. 5.4). The black-boxed regions in each plot indicate where positive cloud feedback is enhanced.

This is even more evident in Fig. 5.10, which shows the difference in cloud feedback from Fig. 5.8 (green bars) versus the ratio of SST variance (orange bars) averaged over the nine boxes in each corresponding experiments (i.e., the bars for "Box 1" represent the averages over the coordinates of Box 1 in the Box 1 experiment, etc.). For example, the variance of SST over Box 2 increases as much as over Box 1, but the increase in cloud feedback over Box 2 is much bigger than over Box 1. This suggests that the change in SST variance must be explained by other terms in the surface heat budget.
Figure 5.9: Ratio of variance of SST in the nine enhanced cloud feedback experiments to the control simulation. Stippling indicates where the difference in variance between the enhanced cloud feedback experiments and the control simulation is significant at the 85% level of a Fisher's F-test.

Figure 5.10: Values of difference in cloud feedback from Fig. 5.8 (green) and ratios of SST variance from Fig. 5.9 (orange) averaged over the nine boxes in each corresponding experiment. Units are W m$^{-2}$ K$^{-1}$ for the differences in cloud feedback, while the ratios of SST variance are unitless.
In general, we find that the effects of enhanced cloud feedbacks in the western Atlantic (Boxes 1, 4, and 7) and central equatorial Atlantic (Box 2) are small, whereas the central South Atlantic (Boxes 5 and 8) and the eastern Atlantic (Boxes 3, 6, and 9) have more noticeable impacts (see Fig. 5.9). Box 6, which sits on the Namibian stratocumulus deck, has the largest impact on the variance of local and equatorial SST. The effectiveness of the cloud-SST coupling in this region highlights the importance of Namibian stratocumulus clouds in tropical Atlantic variability and is consistent with the results of the Namib experiment. Box 3, which is located at the eastern side of the equatorial Atlantic, also shows some influence on equatorial SST variance.

Cloud feedbacks over Boxes 5 and 8, which are located over the central part of the basin, enhance local SST variance, but they do not impact equatorial variability. Instead, cloud feedbacks over Box 2 and Box 3, which are located over the equatorial Atlantic, not only increase SST variance along the equator, but also over the central southern Atlantic (Fig. 5.9) in contrast with the effects of cloud feedback over Box 8, which shows no remote influence on SST variance along the equator.

In regards to the effects of these regional cloud feedbacks on the persistence of SST anomalies, the difference in $e$-folding timescale between the nine experiments and the control simulation in Fig. 5.11 shows very little influence of cloud feedbacks from all regions with the exception of Box 6 (Namibian region) and possibly Box 3 (eastern equatorial Atlantic). We note that positive cloud feedbacks over some regions on the western side of the Atlantic actually tend to reduce the persistence of SST anomalies along the eastern equatorial Atlantic (Boxes 1, 2, and 7 in Fig. 10), but these effects are small.
Figure 5.11: Difference in e-folding timescale between the nine enhanced cloud feedback experiments and the control simulation.

The more decisive role of positive cloud feedbacks over the Namibian region (Box 6) compared to the equatorial eastern Atlantic (Box 3) is most clearly seen from power spectra of SST anomalies of the Atl3 index computed for the nine regional experiments (Fig. 5.12). Compared to the control simulation (black), the only box that clearly enhances the variance of SST at inter-annual and longer timescales is Box 6 (magenta). Since the difference in e-folding timescale shown in Fig. 5.11 indicates that also Box 3 over the eastern equatorial Atlantic exerts an influence on the persistence of SST anomalies, we ran Box 3 and Box 6 for additional 50 years to ensure that the effects of cloud feedback over Box 6 are not due to the length of the simulation. These longer simulations are represented by lines with dot markers in Fig. 5.12. The longer timeseries show no effects on Atl3 SST anomalies from Box 3 (dotted orange line), while the effects
from Box 6 (dotted magenta line) become even more evident with a longer simulation, especially at low-frequency timescales.

Figure 5.12: Power spectra of SST averaged over the Atl3 region (5°S-5°N, 20°W-0°E) in the (black) control simulation and (colors) enhanced cloud feedback experiments (see legend). A 24-month smoothing has been applied to the periodogram estimates. The power spectra are computed on timeseries of 80 years with the exception of the lines with markers (see legend).

For reference, we plot the power spectra for the Namib experiment for 80 years of simulation (solid gray line) and the full simulation (180 years; dotted gray line). The Namib experiment increases the variance of equatorial SST anomalies by even more than
Box 6. Consistently with the values of $e$-folding timescale in Fig. 5.11, the boxes over the western Atlantic reduce the variance of the Atl3 index.

To verify that Box 6 has not the largest impact on SST variance just because enhanced cloud feedback is larger than over the other boxes (Fig. 5.8 and 5.10), an additional experiment has been performed in which we make cloud feedback over Box 6 less sensitive to SST (referred to as "Box 6b"). In this experiment, we change the relationship between cloud liquid water and SST anomaly in eq. (1) to:

$$y = 1 - 0.7 \times \arctan(0.7 \times \text{SST}) \times 2/\pi \quad (5.3)$$

Although the overall increase in variance is less than that shown by Box 6 (see corresponding bars in Fig. 5.10), Box 6b still exhibits a large response at the equator especially at lower frequencies, which is different from all the other boxes (see the Box 6b curve in the power spectra of Fig. 5.12).

In separate experiments, we enhanced the strength of cloud feedback according to eq. (5.1) in the entire North Atlantic basin and over the North Atlantic subtropical stratocumulus region (Canaries). These experiments show that enhanced cloud feedbacks over the North Atlantic influence SST variability in the North Atlantic basin, but have no effects on equatorial Atlantic variability.

In conclusion, both an analysis of observational data and our modeling results suggest that the Namibian region plays a fundamental role on local and equatorial SST variability. Because we also verify that the central role of the Namibian region on equatorial SSTs is not trivially related to (i) the fact that the enhancement of cloud feedback is most effective over the Namibian region (Fig. 5.8) or (ii) the length of the
simulation (Fig. 5.12), we now investigate in further detail the mechanisms of Atlantic Niño variability in our slab-ocean simulations and the role of the Namibian region.

5.3.4 The relationship between the Namibian region and equatorial Atlantic variability

To understand why low-level cloud feedbacks over the Namibian region have a remote influence along the equator, we compare the mean state of (shaded) SST, (contours) SLP, and (vectors) winds in the control run (Fig. 5.13) with lagged composites of these same variables during warm events of the Atl3 SST index in the Namib experiment (Fig. 5.14). Warm events are chosen as the months at which SST anomalies averaged over the Atl3 region exceed one standard deviation of the Atl3 index timeseries. We show the Namib experiment because anomalies are larger, but results are consistent if we use the control simulation. We obtain qualitatively similar results if we increase the threshold for warm events from 1.0 to 1.5 standard deviations or we look at cold instead of warm events.

Figure 5.13: Mean climatology in the control simulation: (shaded) SST in °C, (contours) SLP in hPa, (vectors) surface winds in m s⁻¹.
In the mean state, the South Atlantic climate (Fig. 13) is characterized by east-west and north-south gradients of SST with relatively colder SSTs where Namibian stratocumulus clouds are located. Mean surface winds are southeasterly over the Namibian region and easterly along the equator, and there is a counter-clockwise circulation at 30ºS associated with the subtropical high.

Figure 5.14: Lagged composites of warm Atl3 index events in the Namib experiment: (shaded) SST, units of ºC, (contours) SLP, units of hPa, ranging from -2 hPa to 2 hPa with intervals of 0.2 hPa, (vectors) surface winds, units of m s⁻¹. (a) Lag -18 months from the peak of the event; (b) Lag -12; (c) Lag -6; (d) Lag 0. The white box highlights the Namib region, while the black box highlights the Atl3 region.

Lagged composites of Atl3 index warm events (Fig. 5.14) show that anomalously warm SSTs develop over the southeast Atlantic at approximately 20ºS at lag -18 months from the peak of the warm events along with a weakening of the atmospheric circulation in the central part of the basin (Fig. 5.14a). SSTs remain anomalously warm over the southeast Atlantic throughout the development of the event, while weaker trade winds
favor the progressive warming of SSTs over the northeastern part of the basin through the Wind-Evaporation-SST (WES) feedback (Zhou and Carton, 1998), until the Atl3 region (black box) reaches its warm peak. The WES feedback can be briefly explained as follow: a local warm (cool) SST anomaly favors weakening (strengthening) of winds, which affect winds and latent heat fluxes downwind the anomaly, thereby promoting a downwind expansion of the anomaly. Signals propagate via the WES feedback both zonally and meridionally depending on the mean climate (Wang 2010). Differently from the other eight regions, the Namib region has mean southeasterly trades, and along with its location upstream of the Atl3 region, this makes the Namib region uniquely suited for influencing eastern equatorial Atlantic (cf. Klein et al. 1995).

The southwestern part of the basin, characterized by an opposite sign, cold SST anomaly, is driven by different but complementary mechanisms. If we compare this region with the mean climate in Fig. 5.13, we see a strengthening rather than a weakening of the surface winds. The strengthening of the surface winds through latent heat fluxes, and the advection of cold air from the southern mid-latitudes, promote colder SSTs in the southwest part of the basin.

The analysis of composites of the control simulation shows qualitatively similar results to those shown in Fig. 5.14 for the Namib experiment. The differences between the two simulations are in the persistence of the events (cf. Fig. 5.6), with the control simulation showing the first SST anomalies over the southeast Atlantic at lag -12 instead of lag -18, and the magnitude of the events, with the control simulation exhibiting weaker SST anomalies.
It is reassuring that the mechanisms of the simulated Atlantic Niño in the slab-ocean simulations appear similar to observations. The composites of SST and atmospheric circulation on the Atl3 index at lag 0 (Fig. 5.14d) resemble the observed anomalies associated with Atlantic Niño (Fig. 5.2) although ocean dynamics are absent in our simulations (cf. Trzaska et al. 2007). Moreover, composites of the same fields in observations give similar results as in Fig. 5.14 (not shown). Therefore, understanding the dynamics of slab-ocean Atlantic Niño and the role of cloud feedbacks is relevant to understand the processes driving Atlantic Niño and its persistence in the real world (cf. Dommengen et al. 2014).

5.3.5 Analysis of surface flux damping rates

The variability of SST anomalies associated with Atlantic Niño can be explored using the Frankignoul and Hasselmann (1977) framework, according to which the persistence of SST anomalies is tied to the damping rate \( \lambda \) of SST:

\[
\rho C_p H \frac{dT}{dt} = -\lambda T + N \tag{5.4}
\]

where \( T \) is the temperature of the mixed layer (i.e., SST), \( H \) is the depth of the mixed layer, \( \rho \) is the density of seawater, and \( C_p \) is the specific heat capacity of seawater at constant pressure. The term \( N \) is interpreted as stochastic noise from atmospheric dynamics that is integrated by the oceanic mixed layer. According to eq. (5.4), the persistence of SST is largest where the damping rate \( \lambda \) is weakest and the depth of the mixed layer \( H \) is greatest. In our experiments \( H \) does not change, therefore it does not influence the persistence of SST.
The damping rates can be linearly decomposed into contributions from each surface flux terms. Positive damping rates reduce the persistence of SST anomalies, while negative damping rates increase their persistence (cf. eq. 5.4). We calculate the damping rates as in Park et al. (2005):

\[
\lambda_i = \frac{\text{cov}[Q_i(-L),\text{SST}(0)]}{\text{cov}[\text{SST}(-L),\text{SST}(0)]}
\]  

(5.5)

where \(\lambda_i\) is the damping rate of each of the four surface fluxes \(Q_i\) (clear-sky radiation, CRE, latent heat, sensible heat), while "-L" indicates negative lags. In the equation, "cov" stands for covariance. Each \(\lambda_i\) is computed as the average of the first three negative lags (-1, -2, and -3 months).

Figure 5.15b shows that the sum of damping rates of the four surface fluxes is positive, that is, the fluxes tend to restore SST anomalies to their climatological mean. Of the four surface fluxes, the largest contribution to positive values comes from the latent heat flux (contours in Fig. 5.15b), while the damping rate due to CRE is negative because cloud feedbacks tend to increase the persistence of SST anomalies over the eastern part of the basin (not shown). The damping rates associated with sensible heat and clear-sky radiation are one order of magnitude smaller.

The sign of the surface flux damping rates in the model is consistent with the observational estimates of Park et al. (2005), while the meridional structure of the damping rate is similar to the one estimated by Evan et al. (2013) (their Fig. 5). The spatial pattern of the damping rate in Fig. 5.15b is also consistent with the equatorial expansion of SST anomalies seen from the lagged composites (Fig. 5.14). In fact, damping rates are weakest along the eastern part of the basin, hence with large-scale
weakening of the trade winds, SST anomalies are the same sign and maximum in amplitude over the Namibian and eastern equatorial regions.

Instead, the stronger damping rates over Box 1, 2, 4, and 7 explain why the variance of SST (Fig. 5.9) does not increase as a function of cloud feedbacks as much as it does in the eastern part of the basin.

It is important to note that the SST anomalies associated with Atlantic Niño develop at lag -18 months where the variance of SST is largest (Fig. 5.14), which occurs over the
Namibian region (Fig. 5.15d), and not at the equator, even though we composite by Atl3 SST anomalies. Also in the control simulation the peak of the composites (lag 0) occurs where the variance is largest in the control simulation, and not in the Atl3 region. In the slab-ocean experiments the variance of SST (Fig 5.15d) can be explained to the first order as the variance of total surface fluxes (Fig. 5.15a) scaled by the sum of the damping rates of these fluxes (Fig. 5.15b). In fact, fig. 5.15c shows the variance of total fluxes divided by their total damping rate, which exhibits a spatial pattern that largely resembles the variance of SST (Fig. 5.15d). When we enhance cloud feedback over Box 6 (black box) or the Namibian region (red box), we introduce a positive feedback that increases the variance of total surface flux and decreases its damping rate (not shown), and therefore increases the variance of SST. Box 6 has a smaller effect than the Namib experiment on equatorial SST spectra (Fig. 5.12) because the Namib experiment encompasses a bigger region than Box 6 (see boxes in Fig. 5.15d) where SST variance is large and damping rate is small.

In summary, SST anomalies prior to warming in Atlantic Niños develop where the variance of SST is largest and the damping rate of SST is weakest, that is, over the Namibian region. This region has mean winds that are favorable for propagation into the eastern equatorial Atlantic. Thus both positive cloud feedback and its geographical position explain why the Namibian subtropical stratocumulus area is the most important region in affecting equatorial climate variability and the slab-ocean Atlantic Niño.
5.4 Summary

Previous studies have shown the importance of stratocumulus clouds over the Namibian region in enhancing meridional modes of variability both in observations and theoretical models (e.g.; Tanimoto and Xie 2002; Evan et al. 2013). For example, Evan et al. (2013) showed that in the absence of cloud feedbacks over the stratocumulus regions the magnitude of the WES feedback associated with meridionally propagating modes would not be sufficient to overcome the damping rates of SST anomalies. Klein et al. (1995) also showed in observations that stratocumulus clouds respond to upstream SST anomalies enhancing the WES feedback and the propagation of SST anomalies. Here we build on these previous studies by examining the role of cloud feedbacks in a full AGCM coupled to slab-ocean, and focusing on the role of cloud feedbacks on equatorial Atlantic variability.

We examine observations of cloud radiative effect and show that Atlantic Niño SST anomalies co-vary with positive cloud feedback over the Namibian stratocumulus region. Changes in cloud cover seen in observations over this region can influence the persistence of SST anomalies (e.g.; Park et al. 2005), but from observations alone it is not possible to distinguish the role of regional cloud feedbacks on large-scale climate variability from other processes.

To address this issue, we perform sensitivity experiments using the atmospheric component (ECHAM6) of an earth system model coupled to a slab-ocean, in which we artificially increase the strength of positive cloud feedback over selected regions using the experimental design of Bellomo et al. (2014b). We show that low-level cloud feedback over the Namibian stratocumulus region influences the variance and persistence
of large-scale SST variability. In particular, low-level cloud feedback over the Namibian region enhances the simulated Atlantic Niño in the model. Together, model and observations suggest that cloud feedbacks can modify the characteristics and persistence of Atlantic Niño events.

We perform additional experiments to investigate the influence of cloud feedback in nine regions spanning the tropical South Atlantic (5°N-30°S, 40°W-10°E). The purpose of these experiments is to determine whether other regions influence local or remote SST variability. We find that: regions over the central and eastern South Atlantic south of 20°S increase only local SST variability; regions over the eastern South Atlantic north of 20°S increase both local and equatorial SST variability; while regions over the western South Atlantic do not influence local SST variability but they reduce equatorial SST variability, although their effects are small compared to the eastern regions. Of all the regions, the Namibian stratocumulus region has the strongest influence on the variance and persistence of equatorial Atlantic SSTs at inter-annual and longer timescale.

We investigate the mechanisms associated with the development of Atlantic Niño events using composites and regression analysis. We find that SST anomalies originating over the Namibian region are amplified by positive cloud feedbacks. These anomalies eventually favor anomalies of the same sign over the equatorial eastern Atlantic because they influence the strength of surface winds and associated latent heat fluxes through the WES feedback. The Namibian region has the largest impact of all the South Atlantic regions on the persistence of equatorial SST anomalies because it is located where Atlantic Niño events develop, that is, where the variance of SST is largest and the damping rate of SST is weakest.
Our approach is helpful to evaluate the effects of regional cloud-SST feedbacks on large-scale modes of variability. However, we note that the variability of cloud cover and its effects on SSTs is certainly influenced by other processes, including: inversion strength, subsidence rate, radiative cooling above the boundary layer, and moisture above the inversion (e.g., Wood 2012), which we have not examined here. Moreover, in our experiments we keep the mixed layer depth fixed at 50 m. The effects of including a seasonal mixed layer depth should be tested with a different experimental design, but since we are interested in annual mean climate fluctuations, a fixed mixed layer depth is justified. Terray (2011) argues that a shallower mixed layer during summer can lead to larger changes in SST which may provide a rectified annual mean change and could even amplify the effects of cloud feedbacks.

We also have not addressed the role of ocean dynamics here since our results are based on observations and experiments with an AGCM coupled to slab-ocean. Power spectra of Atl3 index in CMIP3 models coupled to slab-ocean and full-ocean models reveal that ocean dynamics enhance interannual variability with negligible effects at longer timescales (not shown), consistently with the results of Clement et al. (2011) for Pacific El Niño variability. Another study by Zhang et al. (2010) suggests that cloud feedbacks amplify the large-scale effects induced by changes in the Atlantic Meridional Overturning Circulation (AMOC). Hence, the interaction of cloud feedbacks with ocean dynamics remains an interesting yet unresolved question.

Although we did not focus in this study on predictive skill, we note that predictability increases if a timeseries of SSTs is strongly autocorrelated (i.e, if to predict the SST of next month we assume that it will be the same as the present month scaled by
the autocorrelation function of SST). Because increasing the strength of positive cloud feedback results in a more autocorrelated SST timeseries (as measured by the \( e \)-folding time), we expect that improving the simulation of cloud processes and the coupling between clouds, SST, and circulations (Evan et al. 2013; Stevens and Bony 2013) would lead to improved predictability of internal climate variability.
Chapter 6: Conclusions

The greatest challenge in projections of future climate change is narrowing the uncertainty on the sign and strength of cloud feedback. Constraining inter-model spread in cloud feedback with observations is problematic because available cloud datasets are affected by spurious behavior in long-term variability. In this dissertation we address this problem by examining multiple cloud datasets and model simulations.

The main finding of this work as a whole is that climate models underestimate observed cloud cover variability and change. It is shown that subtropical stratocumulus regions at the eastern side of ocean basins affect basin-wide SSTs through their coupling with surface winds. Imposing more realistic cloud cover anomalies in idealized climate model simulations show an increase in the persistence of SST anomalies. The implications are that models may underestimate the persistence of large-scale SST anomalies thereby reducing the predictive skill of near-term forecasts, and might underestimate climate sensitivity in future climate change projections. More detailed conclusions for each chapter are provided below.

Chapter 2 examines cloud cover changes in long-term ship-based archives covering the years 1954-2008 and satellite-based archives covering the years 1984-2007 over the Indo-Pacific Ocean. After correcting these datasets for observational artifacts, we show that ship-based observations are in agreement with satellite-based retrievals and inter-annual climate variability. We compare observed cloud changes in ship-based observations with cloud changes simulated by historical simulations in the CMIP5 archive for the years 1954-2008. We find that climate models simulate patterns of cloud cover change that are in agreement but smaller in magnitude than the observed ones.
These results open two fundamental questions that are explored in the following chapters:
1) Are observed long-term changes in cloud cover consistent with other signals of tropical climate change and attributable to anthropogenic greenhouse gas forcing? 2) How do observed cloud feedbacks affect surface temperature anomalies and their spatial patterns? Chapter 3 addresses the first question, while chapters 4 and 5 address the second one.

Chapter 3 examines changes in cloud cover in the context of tropical climate change. We examine atmospheric-only simulations (AMIP) forced with a uniform increase in SST (AMIP-4K) and a pattern of SST change (AMIP-Future). These simulations isolate the externally forced response from internal climate variability. We show that simulated changes in cloud cover are consistent in sign, pattern, and magnitude with observed cloud cover changes from 1954 to 2008. Therefore, we assert that changes in observed cloud cover are at least in part externally forced. We show that high-level cloud cover co-varies with mid-tropospheric velocity, and that the observed pattern of cloud cover change is consistent with an externally forced weakening of tropical atmospheric overturning circulation from the early 1900s.

Chapter 4 and 5 focus on the implications of underestimating cloud feedbacks in climate models as found from chapter 2, in the context of internal climate variability. With the aid of an idealized model configuration, we investigate the influence of cloud feedbacks on spatial pattern and persistence of SST anomalies. Chapter 4 examines the influence of the NE and SE Pacific stratocumulus regions on Pacific climate variability. Both regions increase the variance and persistence of the leading modes of climate variability, but the NE Pacific increases only the variance of SST in the North Pacific,
while the SE Pacific influences ENSO-like variability along the equator. Chapter 4 explores in more detail the physical mechanisms relating cloud feedbacks with large-scale modes of variability in the Atlantic Ocean. We find that only cloud feedbacks in the stratocumulus regions and only in the southern hemisphere affect equatorial variability. Stratocumulus regions, differently from others, are located upstream of trade winds. Because of their location, SST anomalies are easily propagated to the equator via a progressive weakening of latent heat fluxes, namely the Wind-Evaporation-SST (WES) feedback. In contrast, stratocumulus clouds in the northern hemisphere do not affect equatorial variability because the Intertropical Convergence Zone (ITCZ) converges northerly winds before they reach the equator.

These results have limitations. Because of the corrections in the cloud datasets, we cannot quantify with enough confidence the magnitude of cloud cover change. Although ship-based observations are in agreement with satellite-based retrievals over the last thirty years of data (Bellomo et al. 2014a), the uncertainties in both datasets prevent from taking a decisive conclusion. Continued monitoring of cloud cover changes will help resolving this issue.

However, it must be noted that climate models underestimate cloud feedback also on inter-annual timescales, which are better constrained with observations (Bony et al. 2005; Nam et al. 2012). Therefore, the small changes seen in the historical simulations might be due the fact that cloud cover is not sensitive enough to changes in SST. In fact, models are capable of producing trends of the same strength as observations when they are forced with SST ≥ 4K as we show in chapter 3.
The outstanding question therefore is: How much cloud cover change is expected in response to the ~0.5K SST increase observed over the last century?

In the next and final chapter we propose some analysis to address this question, and discuss some more caveats and next steps to consolidate the results of this dissertation.
Chapter 7: Future Work

In the following sections we discuss some caveats of this dissertation and future work. The discussion is articulated around the following main points:

1. Models underestimate the observed strength of cloud cover change but are capable of simulating it when forced with warmer SST ($\geq 4K$) forcing. How much cloud cover change is expected in response to the $\sim 0.5K$ SST increase observed over the last century?

2. The observed cloud cover change is consistent in pattern, sign, and magnitude with simulations of anthropogenically forced future climate change. However, observed cloud trends are also influenced by internal climate variability. How much does internal variability influence the sign and strength of the observed patterns of cloud cover change?

3. In idealized model simulations with an AGCM coupled to a mixed-layer ocean we show that cloud feedbacks increase the persistence of SST anomalies in the context of internal climate variability. How do ocean dynamics influence the coupling of clouds with atmospheric circulation and SST? What is the impact of enhanced cloud feedbacks in simulations forced with doubling of CO$_2$?

7.1 Sensitivity of cloud cover to change in SST

In chapter 2 we show that cloud trends in historical simulations are consistent in sign and pattern with observed cloud trends but significantly smaller in magnitude. Is this because observed trends are too large, or because clouds in climate models are not as sensitive to
SST change as they are in the real world? Addressing this question is difficult because there is only one long observational record of cloud cover, while climate models are deficient in the representation of clouds. However, we propose further observational analysis that can shed some light on this matter.

Further analysis is needed to ensure that cloud cover trends in EECRA are not too large. Because the earlier period in the dataset has scarcer observations, we should test whether the number of observations affects the trends. One way to do this is to subsample the more recent records in order to have the same number of observations as in the earlier period. Would a subsampling affect the trends? Fig. 2.2 also shows that in some regions the variance of cloud anomalies appears to be bigger in the more recent years, which could potentially affect the magnitude of the estimated trends. Further analysis needs to show whether these more recent inter-annual anomalies in cloud cover are explained by bigger inter-annual SST anomalies or whether the earlier records are affected from having fewer observations.

Moreover, trends in cloud cover in the ship-based archives should be compared with trends in other correlated variables to see if the magnitude of their changes is consistent. Further analysis needs to show whether the correlation of clouds with other environmental variables (e.g., SST, SLP, subsidence, and surface wind divergence) is the same on inter-annual and longer timescales, focusing especially on the subtropical stratocumulus regions, in which changes in cloud amount are most critical for determining the sign of cloud feedback. This could be achieved by examining changes in cloud cover from satellite datasets and computing correlations with changes in the other environmental variables from other datasets and reanalyses as a function of timescale. If
the correlations remain robust also on longer timescales, then changes in other environmental variables could be used to estimate trends in cloud cover and compare with the observations in EECRA.

### 7.2 The role of internal variability on cloud trends

Observed trends in cloud cover from 1954-2008 are consistent with the SST forced AMIP simulations but are also certainly affected by internal climate variability. Because these trends are consistent with an El Niño-like change in SST gradient and overturning circulation, we linearly removed the regression of cloud cover on the Niño 3.4 index from cloud data. Removing the Niño 3.4 variability had an almost null effect on the magnitude and pattern of cloud trends. Perhaps linearly regressing out the pattern associated with ENSO is not the best way, however there is no other efficient way of removing the influence of internal variability from observed trends.

The issue of separating internal variability from forced trends can be addressed using idealized model experiments. The National Center for Atmospheric Research (NCAR) community provides a large ensemble of CESM-CAM5 model simulations (Kay et al. in press) forced with historical forcing (1920-2005) and RCP8.5 projected emissions (2005-2080). Each simulation in the ensemble is run using the same coupled model but is integrated from different initial atmospheric conditions. Therefore, the differences from one simulation to another are solely due to internal variability.

Although the historical simulations do not exhibit cloud trends of the same strength as observations, we could examine the role of internal variability in the 21st century projections. Computing and comparing patterns of cloud cover trends in each
simulation would be helpful to estimate the magnitude of the forced response and compare with internally driven climate variability (Deser et al. 2012). This ensemble could also be used to address a more general question: How big is the inter-model spread in cloud cover trends due to inter-model differences in the CMIP5 archive compared to the spread just due to internal variability?

7.3 Influence of ocean dynamics on the persistence of SST anomalies

The limitation of the idealized model experiments in chapter 4 and 5 are that the AGCM is coupled to a slab ocean model where ocean dynamics are absent. The oceans dynamics could act to further increase, decrease, or not change the effects of cloud feedbacks on the persistence of SST anomalies.

Previous studies suggest that ocean dynamics either enhance decadal variability or have small effects at timescales longer than inter-annual. Okumura (2013) show that in the Community Climate System Model version 4 (CCSM4) ocean dynamics enhance equatorial SST variability in the Pacific Ocean, but Clement et al. (2011) show that this happens at inter-annual timescales whereas the effects of ocean dynamics at longer timescales are small and may even damp decadal variability. Coupling the experimental design of chapter 4 and 5 with a full OGCM is a bit technical but certainly feasible, and we plan to implement this change to consolidate the results of this dissertation and examine more generally the role of ocean dynamics on decadal climate variability.
7.4 Enhancing the strength of subtropical stratocumulus feedback in 2xCO$_2$ simulations

The experiments described in chapter 4 and 5 showed the influence of the subtropical stratocumulus regions in the context of internal climate variability. It would be interesting to see the effects of an enhanced cloud feedback when the simulations are forced with a doubling of CO$_2$. In particular, there are three aspects that emerged from previous chapters that are worth examining.

First, climate models simulate a minimum warming in the SE Pacific (fig. 1.1), which is accompanied by observed and simulated increase in cloud cover over the Peruvian stratocumulus region (chapter 3). If we impose a positive stratocumulus clouds feedback, would we still see an increase in cloud cover there? If the increase in cloud cover is associated with changes in atmospheric overturning circulation, as suggested by chapter 3, then we expect to still see an increase in cloud cover dominated by an increase in high-level clouds. In this scenario, imposing an enhanced positive feedback in the SE Pacific would favor an accelerated equatorial warming and an El Niño-like change in the circulation. These ideas are worth testing and would shed some light on the coupling of clouds, SST, and atmospheric circulation in the context of future climate change.

Second, how would an increase in the strength of cloud feedback over all the subtropical stratocumulus regions affect global climate sensitivity? This question is not trivial because in chapter 4 and 5 we showed that regional cloud feedbacks are connected and impact large-scale modes of variability and the persistence of SST anomalies.

Third, in chapter 5 we show that the effects of cloud feedbacks are not simply proportional to the spatial extent or magnitude of enhanced cloud feedback.
It is therefore of interest to perform an idealized modeling study that addresses the following question: at which spatial scale and magnitude, do cloud feedbacks start to have a significant impact on global climate sensitivity? This question can be addressed by performing a set of sensitivity experiments in which the climate response to cloud feedbacks is analyzed in relation to incremental increases in spatial scale and magnitude of imposed cloud feedbacks in the different stratocumulus regions.
Bibliography


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