Cloud-Radiative Feedback and Ocean-Atmosphere Feedback
In the Southeast Pacific Ocean Simulated by IPCC AR4 GCMs

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ABSTRACT

Representation of clouds in global climate models (GCMs) offers a key source of uncertainty in current climate projections. More specifically, low level cloud cover, such as marine stratocumulus (MSc), is often resolved with bias in these GCMs. MSc cloud layers are the vast “climate refrigerators” of the Tropics and subtropics, which they cool by reflecting sunlight back to space that could otherwise warm the ocean surface. This albedo effect is quite powerful as a theorized 4% increase in low level clouds could offset the warming of doubling CO₂ in GCM projections. The formation of MSc favors the eastern subtropical oceans, and involves the interactions among many processes such as radiation, boundary layer turbulence, subtropical high, ocean upwelling, and cold currents, making it a highly coupled system that is difficult to model. No previous study has provided a comprehensive evaluation of MSc and the associated atmosphere and oceanic feedbacks in the GCMs, especially the model ensemble participating in the most recent Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) released in 2007, which often serves as the basis for climate change projection and policy.

This study aims to provide the first systematic evaluation of the Peruvian MSc clouds located in the southeast Pacific (SEP) and the associated feedbacks in the 24 AR4 GCMs. Comparisons with long-term observational datasets are produced to assess the representation of mean state and climate feedbacks in the models. Three feedbacks are
specifically discussed: the cloud-radiative feedback, the SST-upwelling feedback, and the SST-latent heat feedback. Horizontal plots are produced to assess spatial representation of atmospheric variables while cross spectrum analyses yield statistical and quantitative information on the robustness of the air-sea interactions and cloud-radiative feedback of the SEP region. Extension of the cloud-radiation feedback analysis into the whole Tropics is provided with additional cross-spectrum analyses.

Most GCMs generate a persistent warm sea surface temperature (SST) bias of approximately 2 K capable of destabilizing the marine boundary layer. Since MSc evolve in regions associated with high lower-troposphere stability this destabilization process leads to the deterioration of the cloud deck. Almost all models simulate quite well the subtropical high and the weakening of trade winds associated with warm SST anomaly, which plays a key role in SST-upwelling feedback in SEP. Most models have significant difficulty in simulating the amount, location and land-sea contrast of stratocumulus clouds, which may stem from a deeper problem that they cannot reproduce the observed inverse relationship between stratocumulus clouds and SST. Six of the 24 GCMs cannot produce the albedo effect of stratocumulus clouds. Most models produce overly weak or even wrong sign of the SST-LHF feedback in SEP. A preliminary analysis of cloud-radiation feedback for the whole tropics reveals that almost all GCMs fail to capture the observed increase of cloud amount associated with tropical warming.
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CHAPTER 1: INTRODUCTION

The challenge of modeling climate change on both a regional and global scale is daunting. In contemporary methods, global climate models (GCMs) have been created and utilized to offer a tool to assess projected future climate change based on the ability to emulate past climates from observations. However, the observational datasets currently available to scientists are abridged as early observational records were documented by in situ means (e.g., ship, weather stations). These records may be subject to biases in measurements, through instrumentation, or gaps in coverage and, thus, the reliability of the GCM is questioned. It was not until the advent of the satellite era in the 1960s that remote sensing of atmospheric phenomenon became possible and allowed the production of more comprehensive and sophisticated datasets.

The climate change phenomenon has taken on a higher level of significance in society today as more of the world’s population becomes conscious of the magnitude of such this event. Furthermore, climate change has transcended the realm of pure science and has permeated into political, societal, and economical venues. Different government entities from federal to local levels are taking steps to mitigate climate change by “becoming green” or “reducing their carbon footprint”. Through this contentious reduction of heat capturing greenhouse gases that are linked to global climate change, climate change may be slowed or mitigated.
While it is generally agreed that global climate change is currently underway (Meehl, 2007; Trenberth, 2007), the debate centering around the driver largely revolves around whether climate change is anthropogenically based (McCarthy, 2001; National Academy of Sciences, 2001), involved in a natural cycle of variability (Corti, 1999), or a combination of the two (Hulme, 1999). The current understanding of global climate change is assessed by the United Nations’ Intergovernmental Panel on Climate Change (IPCC). It consists of the world’s leading scientific researchers and scholars who synthesize scientific research into a single climate assessment that addresses climate change. The most recent climate assessment, the 4th Assessment Report (AR4), was released in 2007. The AR4 addressed a wide range of climate problems but specifically mentioned that atmospheric moisture and clouds as the most difficult variables to quantify and account for in GCMs (Bony and Dufresne, 2005; Clement et al., 2009).

Further complicating the representation of atmospheric moisture and clouds are the resulting feedbacks generated in the climate system that enhance warming scenarios (Colman, 2003; Webb et al., 2006; Clement et al., 2009; Dessler, 2010). One cloud type of particular interest is the low-level marine stratocumulus (MSc). MSc have been called “climate refrigerators” (Bretherton et al., 2004) because they reflect incoming solar radiation to space based on their high albedo (Twomey et al., 1984; Bretherton et al., 2007), cooling surface temperatures. Modeling these clouds has proven to be difficult as GCMs must account for the numerous air-sea interactions that occur on subgrid scales and, therefore, must be parameterized. A delicate balance of moisture, entrainment, energy fluxes, and aerosol concentrations must be achieved to accurately represent MSc. As climate feedbacks affect both ocean and atmosphere, coupled
GCMs are under further demand to produce increasingly accurate projections of the future climate without either the comprehensive understanding of cloud microphysics necessary (Cess et al., 1989; Stephens, 2005; Cheng and Xu, 2009) or the current computational power to perform superparameterizations (Arakawa, 2004).

This dissertation will largely address the MSc cloud amount as well as climate feedbacks in GCMs found in the IPCC AR4. The current hypothesis is that global climate models are unable to properly assess future climate projections based on current levels of scientific knowledge and computational limitations. This study will pose the following questions: (1) Are GCMs representing MSc appropriately? (2) How are different GCMs vulnerable to climate feedbacks? (3) What are the individual strengths and weaknesses of each GCM? (4) What are different methods that can improve GCM climate projections in terms of the cloud-radiative feedback and air-sea interactions? As the main goals of this study are to assess MSc representation and quantification of air-sea interactions on global, regional, and microphysical scales, these proposed questions will be addressed in detail.
CHAPTER 2: LITERATURE REVIEW

Assessing the cloud component of global climate models (GCMs) can promote broad and complex issues when interpreting climate projections. Each cloud type has distinct radiative and physical properties which become difficult to account for in the atmospheric environment. The International Satellite Cloud Climatology Project (ISCCP) organized by NASA aims to utilize satellites to gather data in order to improve the understanding and modeling of clouds in the climate system (ISCCP; http://isccp.giss.nasa.gov/index.html). Information gathered from the ISCCP is used to analyze cloud variables such as cloud optical thickness and cloud top pressure allowing for the classification of different cloud types based on thickness and height. Table 1 displays the ISCCP cloud types based on height and thickness.

Cloud types are classified by height into low, mid, and high level clouds (Fig. 1). When discussing the southeast Pacific Ocean (SEP) low-cloud types are most prevalent, and impact the regional climate significantly. Low-level clouds, characterized as cumulus, stratocumulus, and stratus, are composed primarily of liquid water droplets and possess a relatively high albedo allowing for the reflection of incoming solar radiation. As insolation is reflected rather than penetrating the cloud deck and reaching the surface, surface temperatures decrease (Albrecht et al., 1988; Cahalan et al., 1994; Bretherton et al., 2004; George and Wood, 2010). These low-level clouds inhibit the greenhouse effect a deficit in shortwave energy results as planetary
cooling occurs. As low-level clouds effectively reflect shortwave energy away from the planet, these clouds have been termed the “climate refrigerators” (Bretherton et al., 2004).

Conversely, high-level clouds act to warm the planet by capturing longwave energy from the earth (Fleming and Cox, 1974; Reynolds et al., 1975; Chen et al., 2000; Comstock et al., 2002). Cirrus, cirrostratus, and deep convection characterize high-level clouds and are composed of ice although ice is limited to cloud tops in deep convection. Other high clouds, such as anthropogenically produced jet contrails, have been documented to behave in a similar radiative manner (Travis et al., 2002). Therefore, high-level cloud abundance will yield a scenario closely linked to enhanced
Fig. 1 A map of the location of the southeast Pacific Ocean (SEP) is provided. The SEP is defined as the region enclosed between 0°-40°S latitude and 60°-120° W longitude. Map courtesy of VOCALS-REx.
greenhouse effect as longwave energy is retained in the atmosphere. In this respect, high-level clouds behave similarly to greenhouse gases and their presence in climate projections would exacerbate global warming. Even with the suite of modeling techniques and methods employed today, the ability to model complex atmospheric features (e.g., atmospheric moisture) accurately is still out of reach (Kerr, 1997). In order to attempt to address global climate change, international entities have partnered together to provide a better synthesis of the possible ramifications of climate change.

The dominant cloud type discussed in this dissertation will primarily be low-level clouds as these clouds are often most difficult to model (Teixeira and Hogan, 2002) and provide a significant impact on the radiation budget of the planet (Klein and Hartmann, 1993; Dessler, 2010). Specifically, marine stratocumulus (MSc) possess the physical characteristics typical to low-level clouds necessary for cooling the planet. These MSc have fostered numerous regional field experiments and analytical literature to improve the current inadequate understanding of the cloud microphysical interactions that govern the formation, evolution, and dissipation of this climatologically important cloud type.

A modest increase of 4% in MSc cloud cover could potentially offset the warming projected in GCMs from a doubling of CO₂ (Randall et al. 1984). This inherent ability to cool surface temperatures has garnered additional interest from the climate and modeling communities as surface temperatures are predicted to increase over the next century. Efforts to geoengineer low-level marine stratocumulus have been discussed and implemented with encouraging results (Latham, 1990, 2002; Bower et al. 2006, Latham et al. 2008, Rasch et al. 2009).
Despite grasping how MSc affect the planetary radiative equilibrium, the air-sea interactions involved are poorly comprehended (Chlond and Wolkau, 2000; Wang et al. 2003; Richter and Mechoso, 2006). This lack of understanding is compounded within GCMs as key atmospheric and oceanic exchanges involved in MSc evolution must be parameterized using a variety of cloud schemes (Bretherton et al. 2004; Caldwell et al. 2005; Eitzen et al., 2008). The ability to accurately model physical subgrid scale processes that produce MSc and other low-level clouds and the subsequent surface cooling in GCM simulations poses a current challenge to the climate modeling community.

The physical structure along with critical environmental factors and energy transfer processes in the marine boundary layer (MBL) are illustrated in Fig. 2. MSc source regions are located offshore of the western coasts of subtropical continents where sea surface temperatures (SSTs) are modified by oceanic upwelling. Reinforcing the upwelling, ocean circulation patterns advect additional cold water from high latitudes toward the equator. This combination of upwelling and advection contribute to the oceanic component of lower tropospheric stability (LTS) necessary for low-level clouds to flourish. Overlying these subtropical locations is warm, subsiding air associated with the subtropical high position identified as the descending branch of the Hadley cell circulation (Siebesma et al., 2004; Caldwell et al., 2005) establishing an inversion above the MBL. The stratified arrangement of a cool oceanic layer maintained by deep, oceanic upwelling and cold, polar water advection superimposed by a warm, dry atmospheric inversion creates strong LTS and allows for low-level cloud development. The stratocumulus topped boundary layer structure and the
interactions and energy transfers within were first described by Lilly (1968) and has become a highly influential study to the modeling of MSc. Past studies pertaining to the affects of a stable inversion layer and the evolution of MSc have been extensively documented (Klein and Hartmann, 1993; Gordon et al., 2000; Ciesielski et al., 2001). Once the MSc cloud deck is established, the inversion layer promotes high LTS. As MSc, along with other low-level clouds, are characterized by a high albedo, incoming solar radiation is reflected back to space (Bretherton et al.,

Fig. 2 A schematic to illustrate a profile of a stable boundary layer conducive to marine stratocumulus evolution. Lower tropospheric stability is generated by the elevated inversion layer along with the cool subcloud layer. Cloud regulating mechanisms such as entrainment and drizzle occur at cloud level. Reflected shortwave and longwave cooling energy transfers are illustrated at both cloud and ocean level. Subcloud layer transport of latent heat and sensible heat fluxes via turbulent eddies supply energy and moisture to the cloud deck.
2004) and longwave radiative cooling from the cloud top occurs (Duynkerke and Hignett, 1993; Bretherton and Wyant, 1997; Comstock et al., 2005). However, the energy radiated to space must be replaced from the subcloud layer (SCL). Maintenance of the cool and moist SCL is due to combined efforts of cool SSTs, MSc shielding from shortwave energy, and evaporative cooling at the ocean surface and evaporation of drizzle precipitating from the cloud (Bretherton et al., 1995; van Zanten et al., 2005a; Wood, 2005). Moisture in the SCL is transported to the boundary layer top by turbulent eddies where it condenses releasing latent energy and expands horizontally (Duynkerke and Hignett, 1993; Ackerman and Toon, 1996; Bretherton et al., 2004). The SEP stratocumulus cloud field, or the Peruvian MSc, peaks around October when annual static stability is at the greatest levels and SSTs are the coldest (Yu and Mechoso, 1999; Wood et al., 2011).

Several key research cruises have been completed with objectives centering on understanding the physical processes involved in MSc source regions. The first of these field projects was the First ISCCP Regional Experiment (FIRE) that occurred in July 1987 near San Nicolas Island (Californian stratus), to assess satellite retrieval of cloud parameters using aircraft, surface based remote sensing systems, and tethered balloons (Cox et al., 1987; Albrecht et al., 1988; Minnis et al., 1992). FIRE gathered foundational scientific observations of low-level marine clouds such as identifying diurnal variations in cloud height, cloud thickness, cloud liquid water content, and effective droplet radius. The succeeding major cruise was the Atlantic Stratocumulus Transition Experiment (ASTEX) near the Azores Islands in June of 1992 (Albrecht et al., 1995; Bretherton et al, 1995; Gerber, 1996). This project aimed to assess the
transition from MSc to trade wind cumulus resulting from changes in droplet radius (Gerber, 1996) and droplet concentration (Platnick and Twomey, 1994; Taylor and McHaffie, 1994), and thus influencing the albedo and composition of the cloud deck. The Eastern Pacific Investigation of Climate (EPIC) during October 2001 focused on air-sea interactions of the coupled environment in the eastern Pacific Ocean (Bretherton et al., 2004; Raymond et al., 2004; Comstock et al., 2005). Excellent weather for the study yielded an ideal boundary layer supporting MSc and, consequently, exceptional results were gathered. Most recently in 2008, the Variability of American Monsoon Oscillation System (VAMOS) Ocean-Cloud-Atmosphere-Land Study – Regional Experiment (VOCALS-REx) was conducted in the SEP. Ship, aircraft, and buoy observations were made to assess the SEP interactions between clouds, aerosols, marine boundary layer (MBL) processes, upper ocean dynamics and thermodynamics, coastal currents and upwelling, large-scale subsidence, and regional diurnal circulations, to the west of the Andes mountain range (VOCALS-Rex; http://www.atmos.washington.edu/~robwood/VOCALS/vocals_uw.html) with the goal of gathering information necessary for improve model simulations of the SEP and more widespread applications throughout the tropics and subtropics.

MSc are highly affected by diurnal cycles that have been documented extensively in past literature (Kraus, 1963; Rozendaal et al., 1995; Ciesielski et al., 2001; Garreaud and Munoz, 2004; Caldwell and Bretherton, 2008). These effects manifest in stability of the MBL primarily through changes in heating by insolation leading to buoyancy and turbulent mixing as well as the transition between a coupled and decoupled MBL.
These daily fluctuations of MBL processes are relatively constant but the MSc coverage is dependent upon the period of the diurnal cycle.

During the daytime, longwave cooling continues to be the primary driving mechanism in the MSc evolution but the warming at cloud level through absorption of shortwave energy decreases the cloud-top cooling effect, causing the MSc deck to thin (Cess et al., 1995; Stephens, 1996; Bretherton and Wyant, 1997; Comstock et al., 2005) suppressing turbulent mixing. This thinning of the cloud deck allows the incoming solar radiation to penetrate below causing enhanced evaporation rates from the ocean surface (Lilly, 1968). Moreover, if the MSc is precipitating, the drizzle and associated absorption of latent energy in the SCL results in cooling temperatures and moisture content retention. The warming that occurs as shortwave energy is absorbed at the cloud base, triggering a negative buoyancy flux, and condensation within the cloud releases latent heat. As the above cloud inversion warms due to subsiding air from the inversion and latent energy is released by condensation at cloud level, the MBL remains cool through evaporation, absorbing latent energy, and from cool SSTs. These temperature differences cause the cloud and ocean layers to act independently (Bretherton and Wyant, 1997), resulting in MBL decoupling during daytime hours usually peaking around local noon to shortly before sunset (Nicholls, 1984; Duynkerke and Hignett, 1993).

With the loss of shortwave energy during the nocturnal hours, longwave cooling from the top of the cloud layer dominates (Duynkerke and Hignett, 1993; Comstock et al., 2005). With the longwave radiation of energy to space, turbulent eddies in the SCL transport moisture and energy vertically to the top of the MBL. As the exchange of
energy and moisture occurs at cloud level, the boundary layer is described as coupled 
(Bretherton and Wyant, 1997; Comstock et al., 2005), as the ocean and cloud layers 
share moisture and temperature characteristics. As a result, diabatic processes drive the 
MSc cloud deck thickening, peaking during the late night or early morning (Bretherton 
et al., 2004). With cloud thickness increasing during the nocturnal hours and turbulent 
eddies transporting moisture to the top of the MBL, light precipitation in the form of 
drizzle is more likely during the nocturnal and early morning hours (Bretherton et al., 
2004). The cycle then repeats each morning as solar absorption initiates decoupling but 
the MBL may be stabilized by precipitation (Caldwell et al., 2005).

In the presence of significant topography, such as the Andes Mountains, 
interactions with topography may affect the formation and evolution of the MSc deck. 
However, conclusive evidence to explain the role, if any, orography has on MSc has not 
yet been attained. Several 21st century studies have examined the effects of terrestrial 
modeled the global circulation with the removal of orography. In terms of the SEP 
region, SSTs were reduced with the retention of orography due to the increases in 
evaporation rates, stronger trade winds, and additional low-level cloud amount. 
Following this study, it was theorized that descending leeward winds on the western 
side of the Andes reinforced the inversion layer enhancing LTS (Richter and Mechoso, 
2006). However, when utilizing an atmospheric GCM, no significant differences were 
found between the smoothed and unsmoothed orography, leading to the conclusion that 
orography representation would not yield any significant improvement in AGCMs. A 
recent contemporary study conducted by George and Wood (2010) suggests orography
affects cloud macrophysical properties as well as aerosol transport within approximately 10° of the coastline. The implications of this most recent study suggest that orographic influence on low-level clouds is largely localized and not as significant when assessing the global or regional scale.

The cloud-radiative feedback within the SEP is central to the discussion of this study. Since low clouds, such as MSc, have a high albedo, energy can be reflected back to space and result in a cooling of surface temperatures (Slingo, 1990; Weare, 1994; Albrecht et al., 1995; Chlond and Wolkau, 2000; Bennhold and Sherwood, 2008). The reflective characteristic of the low-level clouds allows for less shortwave energy to reach the surface and, consequently, a deficit in the amount of available energy for surface heat fluxes or heat storage (Leach and Raman, 1995). The amount of MSc potentially adds a strong negative feedback to stabilize climate system (Bennhold and Sherwood, 2008) but accurately modeling the MBL in this environment is challenging due to the complex microphysical processes that must be parameterized in the GCMs (Caldwell and Bretherton, 2009). The parameterization process, however, can produce erroneous measurements of climate variables (Zhu et al., 2005), resulting in the observed biases afflicting the AR4 ensemble. The spatial extent and location of MSc can affect the amount of incoming shortwave energy reaching the ocean surface and contribute to the enhanced positive feedback of increased SSTs in the SEP consequently resulting in destabilization of the MBL and a loss of MSc cloud amount. Therefore, the cloud-radiative feedback is an important component of the radiative budget and regulation of surface temperatures of the SEP.
The importance of the cloud-radiative feedback is critical to the understanding of the SEP climate. Due to the lack of understanding of cloud microphysical interactions involved in this region, representation of low-level clouds in GCMs are insufficient. If MSc are not accurately depicted, the generally agreed upon global warming scenario discussed in the IPCC AR4 (Meehl et al., 2007) may be overestimated in GCM output. Further complicating this situation are positive biases in SSTs (Lin, 2007). In a region such as the subtropics that have ramifications on global regulation of temperature, these positive biases may have teleconnections that manifest in additional positive biases outside of the tropics. The cloud-radiative feedback in the SEP serves a main topic of discussion within this paper along with the interactions between air and sea, identifying the quantitative properties of these relationships, and subsequent feedbacks that manifest in GCMs.

Introduction of aerosols and other particulate matter, such as sea salt or dust, into the atmosphere act as cloud condensation nuclei (CCN), providing additional surfaces for water vapor to condense upon. This promotes the development of smaller water droplets that are better suited to reflect incoming solar radiation, thus, increasing cloud albedo (Ackerman et al., 2004). In addition to natural sources of CCN, anthropogenic sources have been observed. Pollution, likely originating with copper smelting industries of northern Chile, is transported seaward by the prevailing easterly trade winds (Huneeus et al., 2006). Additionally, plumes from shipping activity have also been noted to produce this effect (Coakley Jr. and Walsh, et al., 2002; Christensen et al., 2009). This process of anthropogenic based aerosol introduction has been identified
as the Twomey effect (Twomey, 1959; Twomey and Warner, 1967) and is a strong factor in SEP cloud microphysical interactions.

The Twomey effect has been studied extensively in the past literature (Ackerman et al., 2004; Lu and Seinfeld, 2005; Caldwell and Bretherton, 2009) and two associated indirect aerosol effects induced by this process have been examined. The first indirect effect pertains to the radiative effect of low-level clouds when cloud droplet radii decrease from increased aerosol introduction (Twomey, 1977). Observational retrieval conducted by ship, aircraft, and satellite platforms has illustrated this effect. The second indirect effect relates to decreasing precipitation efficiency, resulting in increased cloud liquid water content and albedo (Albrecht, 1989; Phillips et al., 2002). Observational evidence of precipitation suppression exists from sources such as biomass burning (Rosenfeld, 1999; Rosenfeld et al., 2002) and industrial activity (Rosenfeld, 2000). Quantifying the second direct effect is often more difficult as local properties can vary greatly in terms of available liquid water and energy (Grabowski, 2006). Modeling these indirect effects pose a challenge in the climate modeling community (Houghton et al., 2001). While the key cloud properties are generally agreed upon (e.g., radiative transfer, surface processes), modeling the cloud dynamics and microphysical interactions are less defined (Grabowski, 2006). Unfortunately, the uncertainty presented by the Twomey effect will likely persist until improved understanding of vital microphysical interactions is gained.

Evolution of MSc depends on a balance of temperature, moisture, and stability. Water vapor content within the MBL and liquid water at cloud level affect the physical properties of MSc. Two processes have been identified to potentially regulate MSc
development, although the most effective method remains unclear. Precipitation, in the form of drizzle, depletes liquid water from the cloud, thus lowering the water content of the MBL. On the other hand, entrainment introduces dry air from the elevated inversion layer into the MBL. Calculating entrainment rates is highly uncertain (Caldwell et al., 2005), so it is proving difficult to quantify the effect of this process on cloud regulation.

Precipitating MSc can decrease the amount of available moisture in the STBL but in order to precipitate, cloud droplets must be of sufficient size. Smaller water droplets, produced by increased CCN concentrations, increase the liquid water amount and albedo but decrease precipitation rates (Pincus and Baker, 1994; Ackerman et al., 2004; Lebsock et al., 2011). Precipitation clouds have a large impact on cloud albedo, as non-precipitating MSc albedo is approximately 75% but may be reduced to as low as 35% when drizzle is occurring (Savic-Jovic and Stevens, 2008). With a strong diurnal cycle associated with MSc, nocturnal thickening promotes increased droplet sizes and increased precipitation rates during the late night or early morning hours (Reynolds et al., 1975; Bretherton et al., 2004; Comstock et al., 2005; van Zanten et al., 2005a). Moisture maintained in the MBL as drizzle is evaporated, reinforcing the cool SCL (Wood, 2005; Bretherton et al., 2007) while turbulent eddies return moisture back to cloud level (Bretherton et al., 2004). Removal of this diurnal cycle proved to have little effect on liquid water path but changes in droplet concentration resulted in large nocturnal liquid water path differences (Caldwell and Bretherton, 2009). Therefore, droplet concentration appears to be the largest determining factor of precipitating or non-precipitating MSc.
Differences in precipitation rates, as well as aerosol introduction, can create “pockets of open cells”, or POCs (Stevens et al., 2005; van Zanten et al., 2005b; Feingold et al., 2010). POCs can be about 100 km² in area, persist for up to 2 h and are replenished by MBL moisture (Comstock et al., 2005; Stevens et al., 2005). These structures have been discussed in previous literature but the physical mechanisms governing the development of POCs are poorly understood (Feingold et al., 2010). POCs create a honeycomb-like structure within the cloud deck resulting in increased precipitation rates near the boundary between open and closed cell structures (van Zanten et al., 2005b; Comstock et al., 2007; Wood et al., 2011). These structures are largely nocturnal features, coincide with precipitation maximum, are not independent on solar absorption and have low aerosol concentrations (Wood et al., 2008). The persistence of POCs has been theorized to be generated by atmospheric oscillations based on differences in stability. Precipitation involved with POCs produce downdrafts and outward motion where surface divergence occurs. The collisions with neighboring outflows create surface convergence and new POCs, with the new generation precipitation and outflows displacing the older generation (Xue et al., 2008; Feingold et al., 2010).

Entrainment of dry air from the inversion layer above the STBL regulates the MSc physical properties. Measuring entrainment rates are quite complicated as entrainment greatly varies on small spatial scales (Faloona et al., 2005), making the exact magnitude difficult to calculate. Determining cloud entrainment rates has largely utilized vertical motion using large eddy simulations (LES) (Bretherton et al., 1995; Kogan et al., 1995; Moeng, 2000; Dawe and Austin, 2011). Unfortunately,
overestimation of the entrainment rate compared with LES is common (Duynkerke et al., 1999; Pelly and Belcher, 2001). LES overestimation may result from inadequate domain size or resolution as the area time averaging procedure for the second-order moments produce only a low degree of statistical reliability (Chlond and Wolkau, 2000). When warm, dry air is entrained from the inversion layer into the wet, cool cloud, evaporative cooling can cause the air mixture to become denser than the surrounding air, producing negatively buoyant air, a process termed “buoyancy reversal” (Siems et al., 1990). This buoyancy reversal process is pivotal in cloud-top entrainment instability (CTEI) first proposed by Lilly (1968). However, the importance of CTEI on MSc regulation has been debated. In the late 20th century, CTEI was deemed an unnecessary or insufficient condition for stratocumulus dissipation (Stage and Businger, 1981; Albrecht et al., 1985). Recently, the CTEI has been rejuvenated in LES as the positive feedback between cloud-top entrainment and turbulence during a buoyancy reversal is capable of destroying the cloud deck within several hours (Richter and Mechoso, 2006; Yamaguchi and Randall, 2008).

Similar to precipitation, droplet concentration determines entrainment rates through droplet sedimentation feedbacks rather than drizzle (Caldwell et al., 2009). Sedimentation, referring to the fall rate of liquid water droplets, decreases entrainment rates while increasing liquid water path. The origin of cloud sedimentation is disagreed upon. One hypothesis is that the reduction in MBL turbulence is largely responsible (Ackerman et al., 2004), while others argue that the removal of liquid water from the entrainment zone is largely the reason (Bretherton et al., 2007; Caldwell and Bretherton, 2009). During the important EPIC study of 2001, entrainment was deemed
to be the primary regulator of MSc, with precipitation indirectly inhibiting and changing the turbulent structure of the MBL (Bretherton et al., 2004). Entrainment rates in the SEP, like precipitation, appear to have a diurnal cycle, as nocturnal rates of entrainment were found to be the strongest at approximately 4 mm s\(^{-1}\) while very little entrainment occurs around local noon (Caldwell et al., 2005).

When analyzing the cloud cover, it is important to also consider high clouds that capture longwave energy and behave like greenhouse gases. Field studies pertaining to high-level clouds have confirmed this result (Chen et al., 2000; McFarquhar et al., 2000; Comstock et al., 2002; Del Genio et al., 2005). Cirrus clouds, characterized as high altitude and optically thin, are best at retaining longwave radiation, as top of atmosphere (TOA) fluxes have revealed the shortwave component to be significantly decreased (Fleming and Cox, 1974). Deep convective anvils are optically thick and high-level clouds that retain longwave energy effectively (Chen et al., 2000), but have high liquid water paths. Since cloud tops are high with deep convection, deep convection is classified as retaining longwave retention and behaves similarly to other high-level clouds, such as cirrus. In subtropical regions (e.g. SEP), high altitude clouds are unlikely to occur, as strong subsidence and dry free atmosphere generally dominate. When examining tropical cloud development associated with the Intertropical Convergence Zone (ITCZ), cirrus and deep convection amount are critical to modeling the cloud scheme.

Climate feedbacks act to exacerbate or hinder the climate representational performance of GCMs. As clouds and atmospheric moisture have been identified as a major source of uncertainty in climate projections (Soden et al., 2004; Clement et al.,
2009; Dessler, 2010), the ability to resolve feedbacks associated with cloud coverage becomes critical. Since cloud amount in the climate system is heterogeneous, cloud type can affect radiative properties (Bergman and Salby, 1997; Chen et al., 2000; Ringer and Allan, 2004) and the albedo (Cahalan et al., 1994) of clouds, altering the radiative budget and microphysical interactions within a GCM and leading to enhancement or suppression of climate features. Climate feedbacks are not limited exclusively to the atmosphere; marine influences may factor into feedbacks involved in coupled GCMs (Gordon et al., 2000; Santoso et al., 2011) and, as such, are equally important. Three common climate feedbacks associated with GCMs in the SEP are discussed in detail below.

The cloud-radiative feedback, illustrated in Fig. 3, is critical to the climate system as cloud type regulates the amount of energy reaching the surface resulting in cooling or warming. In the SEP, it is generally expected that low-level clouds and high LTS dominate the cooling of the climate due to high cloud albedo and low liquid water content (Bretherton et al., 2004; Gerber et al., 2005). As clouds are classified by optical thickness and cloud top pressure, cumulus, MSc, and stratus are classified as low-level clouds, with stratus being thickest (Chen et al., 2000). When expanding to equatorial regions, the cloud-radiative feedback acts as an enhanced greenhouse effect, as high-level clouds from cirrus, cirrostratus and deep convective anvils trap outgoing longwave radiation (tropical cloud-radiative feedback addressed extensively in chapter 7). Since low clouds, such as MSc, possess a high albedo, insolation can be returned to space, cooling surface temperatures (Slingo, 1990; Weare, 1994; Albrecht et al., 1995; Chlond and Wolkau, 2000; Bennhold and Sherwood, 2008).
The amount of MSc potentially adds a strong negative feedback to stabilize the climate system (Bennhold and Sherwood, 2008). However, should insolation reach the surface through cloud dissipation, aerosol introduction, or absorption of shortwave energy at cloud level, enhanced SSTs would destabilize the MBL, leading to increased surface temperatures. Enhanced SSTs are prevalent in GCMs as noted by the persistent 2 K SST bias within the AR4 ensemble (Lin, 2007). The increase in SSTs would result in destabilization of the MBL and dissipation of MSc, likely transitioning them to trade wind cumulus (Albrecht et al., 1995; Bretherton and Pincus, 1995; Bajuk and Leovy, 1998), which are less expansive and less reflective than MSc (Medeiros et al., 2008).

Fig. 3 A schematic detailing the interactions involved in the cloud-albedo feedback of the SEP. As SSTs increase, the amount of MSc decreases as the stable boundary layer is lost. As a result of the decreased cloud amount, increased shortwave energy penetrates the cloud deck and enhances SST warming in a positive feedback loop.
This modeling problem manifests in GCMs, as complex microphysical interactions that must be parameterized in the GCMs (Caldwell and Bretherton, 2009). The parameterization process produces differences in feedback variables (Zhu et al., 2005), resulting in biased projections in GCMs. Misrepresentations of climatologically significant low-level cloud amount is a major source of error in modeling and one that model developers aim to remedy. Despite the complexity, progress on rectifying these climate biases in the next decade is likely (Stephens, 2005).

Enhancement of SSTs can have oceanic origins, as illustrated in the SST-upwelling feedback in Fig. 4. In the SEP, oceanic upwelling transported deep ocean water pools at the surface, moderating SSTs near the Arican Bight. Upwelling can become cut off, as increasing SSTs warm the air temperatures resulting in decreasing sea level pressure (SLP) as described by Lindzen and Nigam (1987). Consequently, the pressure gradient decreases and wind speed in the zonal and meridional directions weakens, preventing the zonal transference of upwelled water seaward. Interaction between surface winds and local SSTs resulting in a positive climate feedback was documented in Chang and Philander (1994). Atmosphere-ocean interactions within the equatorial cold tongue and ITCZ region are shown to destabilize the coupled systems consistent with the uplift and convergence described in Lindzen and Nigam (Chang and Philander, 1994). With less meridional wind stress in the SEP, the transport of water from coastline to sea decreases, causing warmer SSTs and effectively capping the oceanic upwelling and the subsequent partitioning of the surface and deep ocean layer. This wind transported upwelling mechanism has been discussed in both Li and Philander (1996) and Yu and Mechoso (1999). Temporal properties of
this feedback suggest there is a specific periodicity, as both studies agreed with Chang and Philander (1994) that the dynamical effect of the wind induced upwelling was most significant to the annual cycle of SSTs in the SEP (Li and Philander, 1996; Yu and Mechoso, 1999).

Increased latent heat with enhanced SSTs constitutes the SST-latent heat feedback of the SEP presented schematically in Fig. 5. Through enhancement of SSTs, VAS decreases as the pressure gradient is lessened and, consequently, LHTF decreases. Moreover, SSTs act to increase $q_{\text{surface}}$, which represent the humidity at the ocean.
Increasing SSTs surface heating in the tropics (Gudgel et al., 2001; Lebsock et al., 2010). Another study performed by Lin (2007) approached the latent heat-SST feedback in the tropics by analyzing GCMs in response to the double ITCZ problem. As incoming solar radiation reaches the ocean surface, evaporation occurs increasing the latent heat flux. As MSc precipitate, the drizzle is evaporated adding to the moisture content of the SCL and reinforcing the stability. Evaporative cooling of both
oceanic and atmospheric sources simultaneously occurs in the SCL contributing to increased LHTF rates.

Consistent with upwelling-SST feedback, weakening of the subtropical high subsequently loosens the pressure gradient disrupting the ambience of the SEP as surface winds increase. Strengthening winds promote increased evaporation rates and, subsequently, the amount of latent heat flux will increase (Wang et al., 2005) leading to signify an increase in $q_{\text{surface}}$ yielding an enhanced LHTF. Previous literature has addressed this feedback in two terms: first, cloud effects on horizontal and vertical latent heat release (Chen et al., 2000; de Roode et al., 2004) and, second, through abundant moisture in the SCL and greater stability rates by fortifying the inversion layer. Release of this latent energy through condensation at the top of the STBL promotes cloud development. Increasing cloud cover and atmospheric moisture may induce increased precipitation rates in the tropics. This could potentially cause an excessive LHTF-SST feedback (Lin, 2007). Overestimation of surface wind speeds, leading to an increase in surface evaporation rates are considered as the origin of this bias. The importance of this energy flux has been documented in past literature to affect atmospheric eddy circulation (O’Gorman, 2011) and determining the energy budget and surface heating (Yamaguchi and Randall, 2008; Winter and Eltahir, 2010).

The diagnosis of GCMs vulnerability to climate feedbacks of both atmospheric and oceanic origins has an extensive history (Cess et al., 1990; Cess et al., 1996; Colman, 2003; Lin, 2007; Clement et al., 2009). Identifying the sources of bias in climate models is essential to the continued improvement of GCM representation. With the unique framework of individual GCMs, inherent differences in model output will
continue to persist; however, establishing quantitative relationships between atmospheric and oceanic interactions are an important process in bridging to improved climate modeling. Efforts to progress climate modeling have been conducted (Baker, 1997; Stephens, 2005; Beare et al., 2006).

Accurately modeling the future climate has been a goal of science for generations (Edwards, 2011). GCMs are highly complex and are susceptible to miscalculations, potentially rendering the model inaccurate. With limitations on current microphysical knowledge and computational power, parameterization schemes are prone to introducing biases (Duynkerke et al., 1999; Cheng et al., 2009; Zhu et al., 2010). Despite the seemingly herculean effort necessary from the climate modeling community, progress have been made in recent history which raises the optimism of significant climate modeling advancement.

The climate is one that is not rigid or constant, as variations in the climate system are introduced on varying temporal scales ranging from the short term of seasonal to annual or the long term of multi-decadal to millennial. The climate system is capable of fluctuating based on both terrestrial and extraterrestrial stimuli. Society has become increasingly aware of the potential impacts of the climate and conducted scientific studies in order to better understand the complex nature behind this planetary system. In order to understand the vast scope of climate modeling, a foundation on the past and current climate modeling methods must be discussed. While climate modeling has increased in sophistication over the inception of the earliest modern climate models, there remains space for increased advances in the accuracy and resolution of GCMs.
Conceptual models can be traced to applications in assessing climate variability in various ways. In 1862, John Tyndall had proposed that heat-trapping gases, a precursor for greenhouse gases, could be the source of strong shifts in the climate. This proposal was addressed further by geologist Thomas Chamberlin by examining geological records for volcanism and proposing carbon dioxide gas (CO₂) as a primary driver of global climate change (Chamberlin, 1897; Chamberlin, 1898). The theory of high and low periods of volcanic activity and the increase and decrease on global temperatures, respectively, was one that was widely believed until the 20th century, when water vapor replaced CO₂ as the greatest perceived modifier of temperature (Russell, 1941; Brooks, 1951).

Energy balance models (EBMs) became increasingly common, as modeling the climate took a simplified approach: to measure the amount of incoming solar radiation with the amount of outgoing energy, or what is known as terrestrial longwave energy. As EBMs were being discussed, the study of the interactions with the source of energy (i.e., the sun) and the planet was increased. Changes in the solar output and the orbital path of the Earth began to emerge in the 1920s by Milutin Milanković. In his work, Milanković described that shifts in climate from astronomical processes were cyclical based on the eccentricity of the orbit, the precession of the planet, and the tilt of the planetary axis (Muller and McDonald, 2000). These cycles were determined to alter the insolation at given latitudes by 20-30% affecting the albedo at these latitudes. Changes in the poles, for example, could alter the amount of snow and ice cover, generating a higher reflectivity.
Different methods were employed to exploit the EBMs by calculating the radiative budget of the planet based on climate variables and whether absorption (insolation) or reflectance (albedo) occurred with each variable. One such method was a zero-dimension EBM which treated the planet as a point and calculated the energy budget based on the planet (North, 1990). The energy balance could also be derived from one-dimensional EBMs by utilizing latitudinal bands (Arrhenius, 1896) or from two-dimensional EBMs which incorporated meridional and zonal radiation components (North and Stevens, 1998). A second method is termed a radiative-convective model and enables energy to travel vertically in the atmosphere (MacKay and Khalil, 1998). Modelers can choose whether to emulate the profile of the atmosphere, usually divided into various layers, in either a one-dimensional or two-dimensional approach. The third approach represents a statistical and dynamically based two-dimensional model. The purpose of such modeling methodology is primarily for the analysis of circulation in both the meridional and vertical directions (Schneider and Dickinson, 1974; McGuffey and Henderson-Sellers, 2005).

It was not until the onset of World War II when modeling the atmosphere above the surface began to occur. As aircraft allowed for measurements of the mid and upper level atmosphere, the necessity for higher detailed atmospheric models was realized. In addition, the equations involved in climate modeling were becoming increasingly complex, which required a new piece of technology: the computer. As a result, global climate models (GCMs) first started being produced.

The groundwork of GCMs can be traced to the early 20th century when Vilhelm Bjerknes used Newton’s “primitive equations” of motion to explain the transport of
momentum, energy, mass, and moisture throughout the atmosphere (Bjerknes, 1906; 
Bjerknes et al., 1910). While the Bjerknes model was able to describe this transfer and 
motion of the atmosphere, the equations required computational methods that were not 
possible using the technology available at the time. Lewis Richardson attempted to 
modify Bjerknes’s work using a finite-difference grid (Richardson, 1922; Lynch 2006) 
but found large computational errors in the solutions to the equations. The dawn of the 
computer age, allowed for improved calculations and a sophisticated version of 
Bjerknes and Richardson could be constructed.

The WWII period witnessed the production of weather modeling in both the 
military and forecasting sector (Harper, 2008). These weather models were produced 
using both horizontal and vertical energy transfers on a Cartesian grid. After the war 
ended, meteorologists began to attempt to forecast longer time intervals rather than the 
shorter time intervals previously generated. During this time, GCMs developed in order 
to provide the tools for conducting climate research. The first successful GCM run was 
produced by Norman Phillips by modeling a 2-layer, hemispheric, quasi-geostrophic 
model in 1955 (Phillips, 1956; Lewis, 1998). With the success of Phillips’s model and 
the belief that better GCMs could be produced, the event triggered the inception of the 
scientific modeling community. Modeling the climate involves creating a grid based on 
latitude and longitude which define the resolution of the model. However, the more 
fine the resolution the more computations are required to resolve the model. GCMs 
take climatological data from a source and run the dataset using Newton’s primitive 
equations of motion, called the dynamics core, to simulate atmospheric processes. 
Using this method, it was realized that certain climate variables would occur at scales
below the model resolution and, thus, parameterization methods were developed to account for these subgrid scale processes. A Cartesian system yielded a source of difficulty: the grid spacing would be heterogeneously distributed as the resolution near the tropics would be increased while the level of resolution near the poles decreased. To combat this, spectral models were developed to model the atmospheric motion on a sphere (Silberman, 1954; Platzman 1960). Employing Fourier transformations, for example, allowed for the conversion of data from a Cartesian system to a wave-based system without the loss of data. These spectral models were developed in the 1950s, but by the 1970s they had became more common and efficient than Cartesian models, as the involved calculations became less rigorous (Orszag 1970; Bourke et al., 1977).

The establishment of atmospheric GCMs as a climate analysis tool was a great scientific and computer breakthrough. However, the demand for improved climate modeling resulted in the coupling of the atmospheric GCMs to different earth systems, such as the oceans or land, during the 1980s. The interactions at their interface could yield a plethora of climate knowledge. Coupled GCMs were originally designed for specific purposes usually by the parent institution, but later evolved into greater applicability to climate analysis. After the turn of the century, the need for coupled GCMs expanded and modeling institutions began to offer a ‘mix and match’ service, allowing different layers from different agencies to be coupled in a climate model (Hill et al., 2004; Edwards, 2011). The compatibility of these datasets and models indicates the future trend of coupled GCMs to incorporate a broad base of resources as well as a potential ‘open source’ for climate data analysis.
Coupled GCMs are relevant to the research here, as atmosphere, ocean, and cloud components are utilized. The ability of these physical and energetic interactions between each layer to affect others is critical to climate understanding and potentially provide invaluable results, as clouds and atmospheric moisture are observed in an atmosphere and ocean coupled model. The trade off is these require more extensive computations and, thus, are more difficult to accurately model. Flux adjustments are occasionally employed by GCMs, for example the CC63 and CCCM, but risk affecting climate sensitivity (Gordon et al., 2000; Gudgel et al., 2001; Bony and Dufresne, 2005).

The magnitude of climate change is of great concern to many individuals. The ramifications of climate change will likely be felt throughout the world and to varying degrees of severity. With many nations likely to suffer major shifts in climate that may permeate into social and economical channels of their culture, the United Nations Environment Programme (UNEP) and the World Meteorological Organization (WMO) formed the Intergovernmental Panel on Climate Change (IPCC) in 1988 to address this pressing global issue. The IPCC is composed of climate scientists and researchers who seek to “provide the world with a clear scientific view on the current state of knowledge in climate change and its potential environmental and socio-economic impacts” (IPCC; http://www.ipcc.ch/organization/organization.shtml). This entity does not perform any individual scientific research nor play a role in monitoring climate data, but rather assesses the recent climate literature, research, and socio-economical data to provide an overview to the current state of the climate.

In order for the climate to be assessed by the IPCC, understanding the past, present, and future climate is necessary. As the IPCC is concerned with global climate
change, the availability of reliable data globally is limited prior to the advent of the satellite era. Even with satellite data, the collection of atmospheric variables that factor into climate change may have biases embedded in the data, whether generated by climate feedbacks or inaccurate readings or measurements. Climate data collection methods, either by remote sensing and in situ observations, have improved in quantity and quality since satellites were launched but the observational record is not of the sufficient length that climatologists desire. Proxy records, such as ice cores, provide an excellent sample of the climate, but are restricted to the specific area and do not provide as broad a swath of climate coverage as climatologists seek in the paleoclimate record. Ideally scientists would have global coverage of the climate fully utilizing remote sensing and in situ observations, however the funding and logistics of collecting and transporting data and equipment is simply not feasible at the current time. Furthermore, agreement on a homogeneous dataset of climate variables has yet to be achieved, allowing the collection of climate datasets to produce potentially radical differences in past climate. These problems need to be considered when discussion of past climate is considered.

The water vapor variable is not the only sub-grid scale feature that affects the climate system, as numerous other key climate variables factor into the climate projections. Perhaps the most influential sub-grid scale interaction, in terms of this dissertation, is the introduction of aerosols. The involvement of aerosols on the SEP is one that has been studied extensively, as their presence effects cloud droplet size (Coakley and Walsh, 2002; Ackerman et al., 2004), cloud droplet concentration (Ackerman et al., 2004; George and Wood, 2010), and precipitation amount (Savic-
Jovic and Stevens, 2008; Xue et al., 2008). The source of these aerosols comes primarily offshore from copper smelters and other heavy industry that populate northern Chile. As the easterly trade winds come offshore, they transport these pollutants out to sea where they act as CCN. Since these aerosols remain confined to the boundary layer, atmospheric liquid water attaches to these CCN, increasing the number of water droplets in the region. However, the atmospheric moisture remains constant, resulting in smaller sized droplets that can condense to form clouds. With smaller droplet sizes, the incoming solar radiation is more readily reflected due to the increased water droplet concentration. GCM representation of this indirect effect (i.e., Twomey effect) makes atmospheric moisture difficult to account for in GCM output (Houghton, 2001).

The IPCC aims to synthesize the current climate research and generate an overall assessment addressing the current scientifically understood state of the climate. This assessment is significant on the global level as climate legislation designed to address climate changed is based upon this document. GCMs form the foundation of the climate outlook based on numerous different conditions of greenhouse gases production and climate mitigation strategies.

In the most recent IPCC AR4, it was identified that a source of uncertainty in climate change projection revolved around the atmospheric moisture and cloud coverage contained within GCMs. The amount of energy that can be captured by water vapor is similar to that of the more widely known greenhouse gas, carbon dioxide. Furthermore, water vapor is a highly variable gas which can be difficult to quantify in the modeling process (Larson et al., 1995; Cess et al., 2005). These issues add to the complexity of climate models, as inaccurate modeling of these features may lead to
biases in temperature and other atmospheric processes, enhancing the warming that is
projected in the next century. Atmospheric processes such as turbulent mixing,
entrainment, evaporation, and moisture advection all lead to changes in moisture levels
in the atmosphere and some of these processes occur on the sub-grid scale of GCMs,
indicating that parameterization methods must be employed to analyze the contributions
to climate change.
CHAPTER 3: METHODOLOGY

The SEP region is defined as the region within 0° to 40° S and 60° W to 120° W and was chosen since the climatological MSc maximum is generally located near 20° S, 80° W, near the center of this region. Since the study area has a larger zonal component, the maximum concentration of MSc is not centered in the SEP. The dimensions of the study area were established in order to maximize the potential oceanic and atmosphere interactions that factor into MSc evolution, as a majority of the SEP surface is oceanic and characterized by cool SSTs that are essential to increased lower tropospheric stability (LTS), which is linked to an environment suitable for MSc formation and evolution.

Utilized observational climate datasets are obtained from numerous institutions and are highlighted in Table 2. The observational data serves as a benchmark for the assessment of each individual GCM to reproduce the climate. Analysis of the accuracy regarding GCM output is based primarily on two criteria. The first criterion is the ability of climate projections to emulate the maximum and minimum values consistent with observations. Achieving correct magnitude minimizes climatic biases and supports the effective resolution of the air-sea interactions and the cloud-radiative feedback in GCMs. Consistency in resolving the spatial pattern of GCMs with observations forms the basis of the second criterion. Accurate reproduction of the
spatial parameters of involved interactions are essential to the projection put forth by GCMs. Discrepancies in spatial dimensions would likely induce climate feedbacks discussed in this dissertation.

GCM from the 24 IPCC AR4 were obtained from their parent agencies. Specifics on the modeling resolution and parameterization schemes employed by each GCM are presented in Table 3. Parameterization schemes aim to resolve subgrid scale processes involving oceanic, atmospheric, and cloud components. Representation of interactions between air and sea are accounted for by use of a coupler. This coupler provides a link between the different “layers” of the climate system to simulate the air-sea transferences of mass and energy that take place in a GCM. The ensemble of GCMs utilized in the IPCC AR4 have different and unique parameterization schemes, offering

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**Table 2.** Climate variables analyzed in this thesis, their abbreviations and the agency that provided the observational data. Data are in the form of monthly averages.

<table>
<thead>
<tr>
<th>Name</th>
<th>Variable Code</th>
<th>Corresponding Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sea surface temperature</td>
<td>SST</td>
<td>NOAA ERSST</td>
</tr>
<tr>
<td>Sea level pressure</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Meridional wind speed (north)</td>
<td>SLP</td>
<td>National Centers of Environmental Prediction (NCEP) reanalysis</td>
</tr>
<tr>
<td>Meridional wind stress (north)</td>
<td>VAS,</td>
<td></td>
</tr>
<tr>
<td></td>
<td>TAUV</td>
<td></td>
</tr>
<tr>
<td>Surface upward latent heat flux</td>
<td>LHTF</td>
<td>Surface Oceanic Analyzed Air-Sea Fluxes (OAFlux) for Global Oceans</td>
</tr>
<tr>
<td>Surface downwelling shortwave flux</td>
<td>DSW</td>
<td></td>
</tr>
<tr>
<td>Cloud amount</td>
<td>CA</td>
<td>International Satellite Cloud Climatology Project (ISCCP)</td>
</tr>
<tr>
<td>Shortwave cloud radiative forcing</td>
<td>SCRF</td>
<td>Earth Radiation Budget Experiment (ERBE)</td>
</tr>
<tr>
<td>Longwave cloud radiative forcing</td>
<td>LCRF</td>
<td></td>
</tr>
<tr>
<td>Total cloud radiative forcing</td>
<td>CRF</td>
<td></td>
</tr>
</tbody>
</table>
Table 3. The selected 24 Intergovernmental Panel on Climate Change (IPCC) 4th Annual Assessment (AR4) global climate models features used for this study. Listed below are the vintage years indicating the first publication on results for the model, the sponsoring institution, pressure at the top of the atmospheric model, horizontal and vertical resolution of the atmospheric and ocean layers, cloud scheme employed, and whether adjustments were applied in regards to surface momentum, heat or freshwater fluxes in coupling of the atmosphere, ocean and cloud components.

<table>
<thead>
<tr>
<th>Model Name, Vintage</th>
<th>Sponsor, Country</th>
<th>Atmosphere Resolution Top Resolution</th>
<th>Ocean Resolution Resolution, Z Cord.</th>
<th>Coupling Flux adjustments</th>
<th>Cloud Scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCCR, 2005</td>
<td>Bjerknes Center for Climate Research, Norway</td>
<td>Top = 25 hPa</td>
<td>0.5°-1.5° x 1.5° L35 Density, free surface</td>
<td>No adjustments</td>
<td>Statistical cloud scheme</td>
</tr>
<tr>
<td></td>
<td></td>
<td>T63 (1.9° x 1.9°) L16</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CC63, 2005</td>
<td>Canadian Centre for Climate Modeling and Analysis, Canada</td>
<td>Top = 1 hPa</td>
<td>0.9° x 1.4° L29 Depth, rigid lid</td>
<td>Heat, freshwater</td>
<td>Statistical cloud scheme</td>
</tr>
<tr>
<td></td>
<td></td>
<td>T63 (≈1.9° x ≈1.9°) L31</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCCM, 2005</td>
<td>National Center for Atmospheric Research, USA</td>
<td>Top = 1 hPa</td>
<td>1.9° x 1.9° L29 Depth, rigid lid</td>
<td>Heat, freshwater</td>
<td>Statistical cloud scheme</td>
</tr>
<tr>
<td></td>
<td></td>
<td>T47 (≈2.8° x ≈2.8°) L31</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCSM, 2005</td>
<td>Météo France / Centre National de Recherches Météorologiques, France</td>
<td>Top = 2.2 hPa</td>
<td>0.3°-1.0° x 1.0° L40 Depth, free surface</td>
<td>No adjustments</td>
<td>Prognostic</td>
</tr>
<tr>
<td></td>
<td></td>
<td>T85 (1.4° x 1.4°) L26</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNRM, 2004</td>
<td>Commonwealth Scientific and Industrial Research Organisation (CSIRO) Atmospheric Research, Australia</td>
<td>Top = 0.05 hPa</td>
<td>0.5°-2.0° x 2.0° L31 Depth, rigid lid</td>
<td>No adjustments</td>
<td>Statistical cloud scheme</td>
</tr>
<tr>
<td></td>
<td></td>
<td>T63 (≈1.9° x 1.9°) L45</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CSIR, 2001</td>
<td>Commonwealth Scientific and Industrial Research Organisation (CSIRO) Atmospheric Research, Australia</td>
<td>Top = 4.5 hPa</td>
<td>0.8° x 1.9° L31 Depth, rigid lid</td>
<td>No adjustments</td>
<td>Stratiform cloud scheme</td>
</tr>
<tr>
<td></td>
<td></td>
<td>T63 (≈1.9° x 1.9°) L18</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CSI2, 2006</td>
<td>Commonwealth Scientific and Industrial Research Organisation (CSIRO) Atmospheric Research, Australia</td>
<td>Top = 4.5 hPa</td>
<td>0.8° x 1.9° L18 Depth, rigid lid</td>
<td>No adjustments</td>
<td>Stratiform cloud scheme</td>
</tr>
<tr>
<td></td>
<td></td>
<td>T63 (≈1.9° x 1.9°) L18</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### Table 3. (continued)

<table>
<thead>
<tr>
<th>Model Name, Vintage</th>
<th>Sponsor, Country</th>
<th>Atmosphere Resolution Top Resolution</th>
<th>Ocean Resolution Resolution, Z Cord.</th>
<th>Coupling Flux adjustments</th>
<th>Cloud Scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>GFDL 2.0, 2005</td>
<td>U.S. Department of Commerce / National Oceanic and Atmospheric Administration (NOAA) / Geophysical Fluid Dynamics Laboratory, USA</td>
<td>Top = 3 hPa 2.0° x 2.5° L24</td>
<td>0.3°-1.0° x 1.0° Depth, free surface</td>
<td>No adjustments</td>
<td>Microphysics and macrophysics</td>
</tr>
<tr>
<td>GFDL 2.1, 2005</td>
<td>National Aeronautics and Space Administration (NASA) / Goddard Institute for Space Studies (GISS), USA</td>
<td>Top = 3 hPa 2.0° x 2.5° L24 with semi-Langrangian transports</td>
<td>0.3°-1.0° x 1.0° Depth free surface</td>
<td>No adjustments</td>
<td>Microphysics and macrophysics</td>
</tr>
<tr>
<td>GISA, 2004</td>
<td>NASA/GISS, USA</td>
<td>Top = 0.1 hPa 4.0° x 5.0° L20</td>
<td>2.0° x 2.0° L16 Density, free surface</td>
<td>No adjustments</td>
<td>Prognostic</td>
</tr>
<tr>
<td>GISH, 2004</td>
<td>National Key Laboratory of Atmospheric Sciences and Geophysical Fluid Dynamics (LASG)/Institute of Atmospheric Physics, China</td>
<td>Top = 0.1 hPa 4.0° x 5.0° L20</td>
<td>4.0° x 5.0° L13 Mass/area, free surface</td>
<td>No adjustments</td>
<td>Prognostic</td>
</tr>
<tr>
<td>INMC, 2004</td>
<td>Institute for Numerical Mathematics, Russia</td>
<td>Top = 10 hPa 4.0° x 5.0° L21</td>
<td>2.0° x 2.5° L33 Sigma, rigid lid</td>
<td>Regional freshwater</td>
<td>Diagnostic</td>
</tr>
<tr>
<td>IAPC, 2004</td>
<td>Istituto Nazionale di Geofisica e Vulcanologia, Italy</td>
<td>Top = 10 hPa T106 (~1.1° x 1.1°) L19</td>
<td>2.0° x 2.0° L31 Sigma, free surface</td>
<td>No adjustments</td>
<td>Prognostic</td>
</tr>
<tr>
<td>INGV, 2005</td>
<td>Istituto Nazionale di Geofisica e Vulcanologia, Italy</td>
<td>Top = 10 hPa T106 (~1.1° x 1.1°) L19</td>
<td>2.0° x 2.0° L31 Sigma, free surface</td>
<td>No adjustments</td>
<td>Prognostic</td>
</tr>
</tbody>
</table>

(continued)
<table>
<thead>
<tr>
<th>Model Name, Vintage</th>
<th>Sponsor, Country</th>
<th>Atmosphere Resolution Top Resolution</th>
<th>Ocean Resolution, Z Cord.</th>
<th>Coupling Flux adjustments</th>
<th>Cloud Scheme</th>
</tr>
</thead>
<tbody>
<tr>
<td>IPSL, 2005</td>
<td>Institut Pierre Simon Laplace, France</td>
<td>Top = 4 hPa 2.5° x 3.75° L19</td>
<td>2.0° x 2.0° L31 Depth, free surface</td>
<td>No adjustments</td>
<td>Diagnostic</td>
</tr>
<tr>
<td>MIRH, 2004</td>
<td>Center for Climate Systems Research (University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change (JAMSTEC), Japan</td>
<td>Top = 40 km T106 (=1.1° x 1.1°) L56</td>
<td>0.2° x 0.3° L47 Sigma/depth, free surface</td>
<td>No adjustments</td>
<td>Prognostic</td>
</tr>
<tr>
<td>MIRM, 2004</td>
<td>Meteorological Institute of the University of Bonn, Meteorological Research Institute of the Korea Meteorological Administration (KMA), and Model and Data Group, Germany/Korea</td>
<td>Top = 30 km T42 (=2.8° x 2.8°) L20</td>
<td>0.5°-1.4° x 1.4° L43 Sigma/depth, free surface</td>
<td>No adjustments</td>
<td>Prognostic</td>
</tr>
<tr>
<td>MIUB, 1999</td>
<td>Max Planck Institute for Meteorology, Germany</td>
<td>Top = 10 hPa T30 (=3.9° x 3.9°) L19</td>
<td>0.5°-2.8° x 2.8° L20 Depth, free surface</td>
<td>Heat, freshwater</td>
<td>Prognostic</td>
</tr>
<tr>
<td>MPIC, 2005</td>
<td>Meteorological Research Institute, Japan</td>
<td>Top = 10 hPa T63 (=1.9° x 1.9°) L31</td>
<td>1.5° x 1.5° L40 Depth, free surface</td>
<td>No adjustments</td>
<td>Prognostic</td>
</tr>
<tr>
<td>MRIC, 2003</td>
<td>National Center of Atmospheric Research, USA</td>
<td>Top = 4.0 hPa T42 (=2.8° x 2.8°) L30</td>
<td>0.5°-2.0° x 2.5° L23 Depth, rigid lid</td>
<td>Heat, freshwater, momentum (12 S–12 N)</td>
<td>Diagnostic</td>
</tr>
<tr>
<td>PCIM1, 1998</td>
<td>Hadley Centre for Climate Prediction and Research/Met Office, UK</td>
<td>Top = 2.2 hPa T42 (=2.8° x 2.8°) L26</td>
<td>0.5°-0.7° x 1.1° L40 Depth, free surface</td>
<td>No adjustments</td>
<td>Prognostic</td>
</tr>
<tr>
<td>UKGM, 2004</td>
<td>UK</td>
<td>Top = 39.2 km ≈1.3° x 1.9° L38</td>
<td>0.3°-1.0° x 1.0° L40 Depth, free surface</td>
<td>No adjustments</td>
<td>Diagnostic</td>
</tr>
</tbody>
</table>
a range of possible future climate scenarios.

Statistical correlation performed on the NOAA and the Hadley Center monthly SST datasets provided strong correlation in recorded SSTs (not shown) indicating similar values in the datasets. The NOAA ERSST dataset is selected due to the additional 204 months, or 17 years, of data when compared to the Hadley Center SST observations. The NOAA ERSST dataset extends from 1854 and end in 2007, providing 1836 months of SST observations. NASA Goddard Space Flight Center provided monthly satellite retrieved cloud data pertaining to cloud amount, cloud top pressure, and cloud optical thickness from the ISCCP over June 1983 to December 2007. Cloud amount describes the percentage of total cloud amount. In other words, all ISCCP cloud types factor into the analysis of cloud amount. Since significant attention is given to the SEP, low-level cloud amount is most likely to form in this region based on assessing the synoptic environment of this region. In terms of the cloud radiative feedback central to this study, low-level cloud amount is of importance to the energy budget of the SEP and will be discussed in detail. Monthly mean surface heat fluxes and shortwave downwelling are given by the NOAA OAFlux dataset from 1958-2008. The resulting downwelled shortwave flux may be dependent on differences in MSc amount. The inverse relationship between surface downwelled shortwave energy and concentration of MSc has been documented in past literature (Klein and Hartmann, 1993; Gordon et al., 2000). The surface warming that is rendered by increased shortwave energy at the surface acts to destabilize the boundary layer and contribute to the positive feedback loop of SSTs in the SEP.
Radiative forcing data were collected from the Earth Radiation Budget Experiment (ERBE) sponsored by NASA Goddard Space Flight Center. This experiment commenced in 1984 and provided two years of data detailing the longwave and shortwave radiation forcings. Total cloud forcing can be obtained through these parameters and is calculated from the total sky minus clear sky radiative forcings. Unfortunately, the length of ERBE hinders the analysis of long term temporal scales. Therefore, emphasis on short time periods are provided in the form of seasonal (0.25 – 0.8 year), annual (0.8-1.2 years), and biennial (1.2-3.0 years). GCM output will generate a feedback for extensive temporal intervals, but since no adequate comparison to an observational value can be made with confidence, these quantitative relationships will be presented yet largely ignored. Further division of the longwave and shortwave radiation fluxes occurred by processing both cloud cover and clear sky conditions. This technique allowed net longwave and shortwave radiation fluxes to be presented in this paper after calculating the respective fluxes with clear sky conditions subtracted from the cloud cover. Shortwave fluxes are surface based measurements while longwave fluxes are derived from TOA measurements. Analyses of these net radiative fluxes provides insight to the interactions between tropical cloud and ocean involved in the cloud feedback and how these interactions are represented by GCMs.

By encompassing the entire AR4 ensemble, the uniqueness of this study is the scale of this analysis. Such a collection of GCM projections in a single study has never been conducted. Horizontal plots were constructed using IDL computer programming code for the SEP region. Utilization of horizontal plots allows the spatial properties of studied climate variables affecting the MSc evolution to be analyzed. With the
mathematical assumptions raised through parameterization schemes in coupled GCMs, assessment of the air-sea interactions affect the SEP and how the spatial properties of such interactions project versus the observational data are essential to this study. GCMs are coupled using both the atmospheric and oceanic layers in their climate simulations and output. If the climate variable is unavailable, the GCM projection with the missing data may be ignored. While one AR4 model, the BCCR (not shown), produced output in the SEP, the sporadic nature of essential climate variables that factor into modeled feedbacks forced the removal from the AR4 ensemble. Therefore, 23 of the 24 models in the AR4 are presented. Despite the reduction of AR4 size, the original motivation for this research remains and a thorough analysis can be assembled. Other GCMs yielded unavailable data but these cases were sporadic and ultimately were retained. Instances where this removal was applicable are noted in Table 4. Examination of the ensemble can continue using projections from other available GCMs. For each atmospheric and oceanic variable in this analysis, 24 horizontal plots are produced using 23 coupled GCMs and 1 observational panel. These figures provide the opportunity to assess which variables are best represented spatially and parameterized effectively in order to gain further understanding of the air-sea interactions that factor into the atmospheric and oceanic feedbacks in the SEP. Through this method of spatial analysis, biases in climate variables can be identified and origins to these differences can be speculated. Biases, in this sense, refer to any departure from observational values that are produced in the GCM ensemble output regarding any individual climate variable.
Table 4. GCMs unavailable for analysis. The climate variables include of downwelled shortwave (DSW), meridional wind speed (VAS), latent heat flux (LHTF), shortwave cloud radiative forcing (SCRF), longwave cloud radiative forcing (LCRF) and total cloud radiative forcing (CRF).

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Missing GCMs</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSW</td>
<td>INGV</td>
</tr>
<tr>
<td>VAS</td>
<td>CCSM, CSIR, INGV, PCM1</td>
</tr>
<tr>
<td>LHTF</td>
<td>GFDL 2.1, MIRM</td>
</tr>
<tr>
<td>SCRF</td>
<td>CCSM, CSI2, GISA, INGV</td>
</tr>
<tr>
<td>LCRF</td>
<td>GISA, INGV</td>
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<tr>
<td>CRF</td>
<td>CCSM, CSI2, GISA, INGV</td>
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Extension of the SEP region to the tropics is conducted in Chapter 7 and focuses specifically on cloud-radiative feedback susceptibility in GCMs. The tropics region is defined as a latitudinal belt between 30° N to 30° S latitude encompassing the entire spectrum of longitudinal coordinates. The radiative energy received by the planet is critical as this energy is ultimately redistributed poleward. The tropics and subtropics are subject to different dynamical processes that impact the radiative balance, cloud type and amount, and shortwave, longwave, and total cloud radiative forcings at TOA. One major source of cloud development is surface convergence associated with the ITCZ. Atmospheric uplift generated by this surface convergence drives cloud development in the vertical, creating high cloud types such as deep convective anvils and cirrus clouds. General circulation of the tropics is governed by the Hadley cell,
which is comprised of uplift generated by the ITCZ and subsidence in the form of subtropical high pressures at approximately 30° N and 30° S. Regions of atmospheric subsidence, such as the SEP, are characterized by low clouds that possess a high albedo, such as MSc and stratus. As a result, a wide range of cloud types from low and high altitudes along with high and low radiative properties, respectively, are expected. Consequently, discerning cloud amount and type in the tropics poses a challenging modeling task when assessing the cloud-radiative feedback in the tropics contained in coupled GCMs.

As discussed previously, LTS is critical to MSc development (Klein and Hartmann, 1993; Klein et al., 1995). Cool SSTs play a pivotal role in the formation and maintenance of the stable MBL that fosters an environment conducive to the evolution of low-level clouds, which, in turn, reflect insolation and further stabilize the MBL. In order to quantify the relationship between SSTs and atmospheric climate variables in the SEP, cross spectrum analyses evaluate statistical and temporal properties of the AR4 GCMs. This statistical procedure was selected due to the potential robust data in covariability and phase relationships of SST and climate variables over time. In other words, the procedure aims to find a frequency in which SST and the climate variables are “in sync. The time intervals in the cross spectrum analysis range constitute long-term (multidecadal, decadal), intermediate (interannual, biannual), and short-term (annual, seasonal) intervals. Employing this specific statistical method provides the best tool for gathering significant data on the magnitude and general behavior of atmosphere and ocean variables in climate models that have never been previously undertaken.
Cross spectrum analyses are produced to illustrate the relationship between two variables at different time scales. It provides an excellent source of statistical information, such as coherence squared ($\text{coh}^2$), phase, and statistical significance that can potentially identify the vulnerability of GCMs to climate feedbacks. Additionally, the linear regressions between the two variables at different time scales are produced to assess the quantitative relationship between them. In these analyses SSTs are referenced per 1°C warming. Atmospheric variables (e.g., CA, SLP) are studied against this projected warming and behavior of the variable is observed. In other words, with enhanced SSTs, the influence on atmospheric components is examined using this cross spectrum analysis. Temporal relationships are derived on long-term, intermediate, and short-term scales and linear regressions produced by this analysis provide statistical information of the frequency of this atmosphere-ocean relationship. Climate variable averages of the SEP are performed from 10° S -30° S latitude and from 70° W - 90° W longitude. Oceanic surfaces are most crucial to this study so a filter was applied to GCM grid spacing involving surface composition. If land covered 50% or more of the surface of each grid square, then that grid was determined to be land and removed from the area average. Therefore, regions associated with greater than 50% ocean are strictly considered in the cross-spectrum analysis. In order to establish a quantitative relationship of climate variables based on rising SSTs, the cross spectrum analysis provides the tools necessary to assess the magnitude of these relationships as well as statistical significance, $\text{coh}^2$, and phase. Comparisons between the variables are conducted with respect to increasing SSTs in the hopes of identifying the source(s) of the climate feedbacks.
Relationship strength between the climate variables and SST are given in the upper panel of each figure. A sample cross spectrum analysis output between cloud amount and SST is provided in Fig. 6. A dashed line is present in this panel representing statistical significance at the 95% confidence level. The observed line graph plots the coherence squared ($\text{coh}^2$) values over the time series, providing information on the atmosphere and ocean interaction strength over time. It is emphasized that $\text{coh}^2$ is different from correlation ($r^2$) term in that $r^2$ is the relationship over a specific time period (e.g. decadal, interannual) and is used to address whether a relationship is robust over a fixed temporal scale. The $\text{coh}^2$ analyzes the correlation over the entire time series. In other words, the collection of each temporal interval is factored into determining the magnitude of the air-sea interaction. Correlation of the relationship is provided in assessing the phase value. A phase value that ranges between -0.25 to +0.25 results in the relationship being in quarterature and, subsequently, positively correlated. A positive (negative) phase value is given, and the studied variable leads (lags) the reference variable by a quarter cycle in time. Phase values between ±0.25 and ±0.5 indicate the relationship is negatively correlated. A phase of zero indicates that both variables are in phase. If the phase is -0.5 or +0.5, the variables are out of phase. Linear regressions, presented in the lower panel of the cross-spectrum figures, indicate the magnitude of the feedback with respect to SST. Linear regression units correspond to the amount of change within the studied variable, in the respective units, relative to a 1°C SST increase. This is a particularly useful analysis method in determining the sensitivity of the studied variable in a positive feedback loop that would result in warmer SSTs. The methodology of this paper closely follows the
work of Madden and Julian (1971; 1972) by attempting to determine the spatial scale of an oscillation associated with the different characteristics in a temporal series.

The utilization of cross spectrum analysis has been used in previous works with tropical regions. Salby and Hendon (1994) used this method in analysis of spatial and temporal differences in outgoing longwave radiation, temperature, and atmospheric
motion within the tropics in association with the Madden-Julian Oscillation.

Additionally, Zhang (1996) performed cross-spectrum analysis in the examination of interseasonal variability of climate variables within the western tropical Pacific Ocean. This study continues the application of cross-spectrum analyses in the tropical environment by assessing the cloud microphysical interactions and feedback vulnerability of GCMs on a regional scale.
CHAPTER 4: CLOUD – RADIATIVE FEEDBACK

MSc cloud amount (CA) in the SEP is critical in determining the magnitude of the cloud-radiative feedback. However, due to poorly understood cloud microphysical processes (i.e., entrainment, aerosols, cloud liquid water content), modeling CA properly within GCMs poses great difficulty in the climate modeling community. CA biases produced in both spatial and quantitative properties are capable of affecting the magnitude and distribution of downwelled shortwave (DSW) energy. Erosion of low-level CA, through such mechanisms as development of POCs, precipitation, aerosol introduction, and increased entrainment of air, can potentially allow for increased rates of DSW and subsequent SST enhancement. This section discusses, in terms of spatial, temporal, and quantitative characteristics, the ability of coupled GCMs to resolve the cloud-radiative feedback in the SEP.

Assessment of the SEP cloud-radiative feedback begins with examination of SSTs (Figs. 7-9). Cool SSTs promote increased LTS of the MBL leading to the evolution and maintenance of low-level clouds, such as MSc. Disruption of LTS through SST enhancement destabilizes the MBL as low-level CA transitions to a more convective cloud scheme. Identified by Lin (2007), the tendency of GCMs to produce a persistent warm SST bias is confirmed in the SEP as 10 GCMs project a +2 K bias in SST. Those GCMs prone to this warm SST bias are identified as the CNRM, GISA, GISH, GISR,
Fig. 7 Sea surface temperature (SST) of the southeast Pacific (SEP) region with (a) NOAA ERSST observations and the coupled GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CSI2, (g) CSIR, and (h) GFDL 2.0.
Fig. 8 Same as Fig. 7 but with GCMs (a) GFDL 2.1, (b) GISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL
Fig. 9 Same as Fig. 7 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM
IAPC, INGV, INMC, IPSL, MPIC, and PCM1. With enhanced SSTs projected in these models, the likelihood of a climate feedback within these GCMs is high.

The prevalent SST bias does not manifest in the entire GCM ensemble. Maximum SST values are reproduced consistent with NOAA ERSST values in 12 GCMs that include: CC63, CCCM, CCSM, CSI2, CSIR, GFDL 2.0, GFDL 2.1, MIRH, MIRM, MIUB, MRIC, and UKCM. Despite a consistent SST maximum magnitude, the spatial properties of SSTs within these 12 GCMs vary with observations. The observations represent a spatial configuration zonally oriented warm SST tongue of 298 K approaching 280° E at approximately 10° S. 8 GCMs (CCCM, CCSM, CSI2, GFDL 2.0, GFDL 2.1, MIRH, MRIC, and UKCM) further extend this warm tongue to the South American coastline typically near the Peru – Ecuador border. This overextension of SST in the northern SEP suggests the possible contamination of SSTs from warm equatorial waters resulting in extension to the continent rather than increased absorption of SW energy. The CC63, CSIR, MIRM, and MIUB possess consistent maximum 298 K contour to the ERSST data indicating SSTs are properly represented and SST enhancement is minimal. An intriguing case develops regarding the UKGM as maximum SST is 2 K cooler than observational values. Furthermore, this cool SST bias extends to the South American coastline. An explanation of the cool maximum is uncertain at this time and may be improperly resolved in ocean resolution but provides a potentially cooling SST case.

Minimum SSTs, approximately 288 K, are reproduced with a fair amount of consistency by the GCM ensemble. The 288 K SST contour traces 40° S latitude before turning northward under the influence of the SEP ocean gyre resulting in polar
water advection. Several GCMs, specifically the CSIR, GISA, IPSL, MIRM, and UKGM, produce a 286 K contour near 40° S but are unable to penetrate deeply into the SEP, indicating a likely minimal effect on SST regulation. Oceanic upwelling contributes to SEP SST regulation, but division between the respective upwelling and polar advection influence on SSTs is difficult to deduce at the current time. Based on the number of GCMs impacted by a minimum SST bias and limited spatial properties compared with those yielding a warm SST bias, it appears the maximum SST bias is more significant in affecting SSTs and, thus, impacts model output more readily.

As stated previously, cool SSTs promote LTS that are necessary for the evolution of MSc and low cloud types and subsequently cloud type is linked with differences in SST and any potential climate feedbacks in the SEP. Specifically, MSc have a comparatively high albedo to the underlying dark ocean surface, resulting in the return of DSW to space, and induce surface cooling. With erosion of low-level clouds, however, the potential for absorption of shortwave energy by the ocean increases. The enhanced warming of SSTs causes the continued reduction of CA and further DSW energy absorption by the ocean surface. CA in the SEP (Figs. 10-12) reaches a climatological maximum off the Peruvian coast and northern Chile at approximately 20° S, 240° E with 80% CA. This locale is favored for MSc development as coastal upwelling maintains a cool subcloud layer (SCL), reinforcing local LTS. In addition to oceanic stability, atmospheric stability is generated by the subtropical high, allowing warm, dry subsiding air to form an inversion above the MBL, limiting vertical development in the SEP.
Fig. 10 Cloud amount (CA) of the SEP with (a) ISCCP observations and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CSi2, (g) CSIR, and (h) GFDL 2.0
Fig. 11 Same as Fig. 10 but with GCMs (a) GFDL 2.1, (b) GISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL.
Fig. 12 Same as Fig. 10 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM
As cloud microphysical processes must be parameterized, GCM representation of SEP CA is poor. Two major issues emerge from analysis of CA and are discussed in detail. First, placement of the maximum CA varies between GCMs, making achievement of a consensus difficult to attain. Based on ISCCP observations, CA maximum is located approximately at 20° S, 280° E. One relocation tendency is northwest migration of CA maximum to approximately 15° S, 270° E within CC63, CCCM, CSI2, GFDL 2.0, GFDL 2.1, and INMC where LTS is likely maintained. CA maximum varies within these GCMs as the CSI2, GFDL 2.0, and GFDL 2.1 produce 10% less CA. Contrary to this trend, the INMC increases CA maximum by 10%, suggesting projected increased LTS conducive for MSc development despite the presence of the prevalent warm SST bias. The CC63 and CCM CA maxima remain consistent with ISCCP observations, even with the northwest migration.

A second migration tendency places CA maximum eastward in the GCM ensemble, as displayed in the CNRM, GISH, GISR, IAPC, IPSL, MIRH, MIRM, MIUB, MPIC, MRIC, PCM1, UKCM and UKGM. Eastward displacement of maximum CA encroaches on the South American continent, thereby relinquishing their marine characteristics. However, the large orographic component of western South American continent, namely the Andes Mountains, poses an unlikely environment for low-level cloud development. The CNRM, MPIC, PCM1, UKCM and UKGM have an approximate 10% less bias in CA similar to the departure in CSI2, GFDL 2.0, and GFDL 2.1 GCMs found in the northwest migrated CA maximum. Elevated rates of CA dissipation are depicted in 6 eastward migrating GCMs (GISH, GISR, IPSL, MIRM, MIUB, and MRIC) as CA maximum decreases 20%, a condition exclusive to the
eastward migration of GCMs. The 20% decrease is likely the result of differential heating of the South American continent, allowing for rapid destabilization and increased convective potential as opposed to the marine environment to the northwest, which takes a longer period to destabilize. Furthermore, uncertainty regarding the eastward placement of CA maximum exists as placement over a highly topographic landscape, one capable of deteriorating CA more readily than the northwest migration, appears unlikely.

Other location differences are identified in maximum CA projections but are isolated to specific models. The CCSM produces a dipole with CA maximum but with a 10% less bias in each maximum. The location is fairly well placed with respect to the climatological center, suggesting spatial characteristics are adequately resolved. The CA maximum in the CSIR and GISA each produce a 20% less CA bias, but spatial properties vary from a concentrated CA maximum in the GISA to a broad SEP-extensive bias in the CSIR. In an extreme case, reversal in CA is shown with the INGV as a minimum of 40% total CA at the observed climatological maximum location.

The second issue pertains to spatial properties of CA as determined by large scale features. This issue is evident in GCMs with maximum CA placement over the South American continent, such as eastward migrating CA maximum, as contours appear to trace the coastline. GCMs producing CA maximum over the open ocean, such as northwest CA maximum do not display this coastal interaction tendency suggesting the influence of the land-sea contrast. This tendency suggests that GCMs appear to resolve cloud spatial properties coarsely as coastline interactions likely increase and become
subject to orographic influences. The exceptions to this issue appear to be CSIR, GFDL 2.0, GFDL 2.1, INMC, and MIUB, which do not appear to follow coastal topography.

With differences in cloud fraction that have been discussed, likely differences in the DSW (Figs. 13-15) will be evident. As GCMs have different methods of cloud parameterization schemes the changes in CA can affect the DSW flux. The DSW amount should exhibit an inverse relationship with CA, as the reflective MSc diminish DSW reaching the surface. When comparing the observed MSc amount and DSW, this pattern is apparent. Minimum DSW of approximately 200 W/m² occurs approximately at 20° S, 280° E, analogous with the maximum in MSc. Conversely, the minimum in MSc at approximately 5° S, 300° E corresponds to the maximum of DSW. A decrease of approximately 40 W/m² of DSW energy is observed from the change from maximum to minimum observed MSc amount of 40% coverage. Changes in DSW compared with CA reflectivity appear to generally agree with the rate established in the TOA energy budgets (Albrecht et al., 2005; Chlond and Wolkau, 2005; Yuan et al., 2008).

Similar to the projected CA by the AR4 ensemble, DSW estimates agree on the minimum of DSW converge throughout the model ensemble of approximately 200 W/m². In regards to maximum DSW, exclusive focus is given to the oceanic portions of the SEP analyzing the cloud-radiative feedback. Large positive DSW differences develop over land surfaces, the DSW maximum approaching 300 W/m². As the observational horizontal plot was constructed with masking of land surfaces, land based DSW biases are removed from this study. GCMs are found to follow one of three general patterns in terms of marine-centric DSW. The first pattern involves a maximum DSW flux of 260 W/m², consistent with the observations. These included the CCSM,
Fig. 13 Downwelled shortwave (DSW) energy of the SEP with (a) OAFlux observations and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CSI2, (g) CSIR, and (h) GFDL 2.0.
Fig. 14 Same as Fig. 13 but with GCMs (a) GFDL 2.1, (b) GISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV (unavailable), (g) INMC, and (h) IPSL.
Fig. 15 Same as Fig. 13 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM
GISA, GISH, IAPC, INMC, and PCM1. Throughout the SEP ocean surface the range of DSW values were similar in strength to that found in observations. Spatial patterns of the DSW in the CCSM, GISA, GISH, and IAPC have a high zonal characteristic to their respective projections. The INMC and PCM1 are generally zonal but possess a slight meridional orientation to the contours further seaward.

The second pattern contains GCMs similar to the first configuration but have an intrusion of positive DSW bias of +20.0 W/m². However, the 280 W/m² contour fails to penetrate deeply into the SEP and remains largely a coastal feature. The CNRM, CSI2, CSIR, GFDL 2.0, GFDL 2.1, MIRM, MIUB, MPIC, MRIC, UKCM, and UKGM resolve this coastal intrusion. Origins of this pattern may stem from the dry conditions from the Atacama Desert or the adiabatically compressed trade winds that descend the leeward side of the Andes that can dry the atmosphere and allow for increased warming. Since the 280 W/m² contour remains in proximity to the coastline, these origins would appear plausible. Other GCMs such as the CC63, CCCM, GISR, IPSL, and MIRH have a similar 280 W/m² DSW contour but comprise a third pattern of having a completely oceanic +20.0 W/m² bias. This bias is likely associated with employed cloud parameterization methods, due to air and sea interactions occurring in the SEP with limited influence from the South American continent. Production of positive DSW anomalies in addition to the presence of warm SSTs in the GISR and IPSL projections indicate the likely emergence of the cloud-radiative feedback.

The spatial properties of CA and DSW outputs are of qualitative concern as the established radiative relationship between CA and DSW is lost in certain models. With identification of locations of high (low) CA and low (high) DSW, the ability to model
this relationship should be fundamental to GCMs. However, the interaction between CA and DSW continues to be poorly represented. GCMs such as the GISA, GISH, GISR, IAPC, IPSL, and PCM1 do not display this relationship clearly and result in the production of the prevalent warm SST bias. Within these GCMs areas of higher CA correspond to areas of high DSW which contradicts the albedo effect of the MSc. These models likely have difficulties in cloud parameterization methods and handle the cloud-radiative feedback poorly. The remaining 17 GCMs appear to model this feedback reasonably well by displaying the inverse relationship between cloud amount and DSW energy.

Overall, the MSc amount was best represented by the CC63, CCCM, CSI2, GFDL 2.0, GFDL 2.1, and INMC GCMs. However, these coupled GCMs display a trend to place maximum CA northwest of the observed maximum CA. The magnitude of the CA is generally reasonable within the models with a ±10% bias. The most challenging aspect of modeling the CA appears to be spatial representation of clouds. Local features such as orography may induce changes in CA as contours appeared to trace the Andes Mountains and the South American coastline. The DSW behaved similarly to the MSc amount in the respect that models can generally agree on the magnitude of the relationship but perform poorly on the spatial representation. Although GCMs universally agreed on SEP minimum DSW energy, maximum DSW favors a +20 W/m² energy bias. Three patterns were established in regards to the marine influence of DSW, with GCMs producing (1) an observationally consistent DSW maximum of approximately 260 W/m² over the SEP, (2) a coastal intrusion DSW bias of +20 W/m², and (3) a +20 W/m² DSW bias that is entirely oceanic based. Certain GCMs, GISA,
GISH, GISR, IAPC, IPSL, and PCM1, were discovered to be unable to clearly represent the inverse relationship between CA and DSW and, thus, showed an increase in DSW associated with a high concentration of MSc. In addition to this misrepresentation of the CA and DSW relationship, the persistence of warm SST biases within these GCMs support the manifestation of the cloud-radiative feedback in the SEP.

Additionally, cross spectrum analysis can be utilized to assess temporal characteristics of climatological relationships. With the positive cloud-radiative feedback generating enhanced SSTs and GCMs susceptible to warm biases in SSTs, the interactions between CA and DSW are discussed in terms of warming SSTs, in other words, analysis on the effect of increasing SSTs on atmospheric variables that factor into the cloud-radiative feedback of the SEP. Due to the multidecadal component of the cross spectrum analysis being unavailable in observational data, it is ignored in the GCMs.

It has been established that MSc prefer a stable MBL where cool SSTs are prevalent. Warming of SSTs, possibly due to a positive cloud-radiative feedback, would destabilize the MBL and, thus, dissipate MSc in the SEP. The CA cross spectrum (Figs. 16-18) agrees with the described interactions in a positive cloud-radiative feedback. The observed CA decreases with an increase in SSTs over the time series. The strongest decrease in CA is apparent during the decadal (7-20 years) period where an approximate 2% loss in low-level CA for each 1° C of warming in SST is projected in observations. Furthermore, SST and CA are a half cycle out of phase, indicative of negative correlation. Statistical significance at the 95% confidence level is achieved as well. This negative relationship translates to the interannual (3-7
Fig. 16 Cross-spectrum analyses between CA and SST with (a) ISCCP observational cloud amount and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CSI2, (g) CSIR, and (h) GFDL 2.0.
Fig. 17 Same as Fig. 16 but with GCMs (a) GFDL 2.1, (b) GISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL. Fig. 16c and Fig. 16d uses a regression range from [-5,12].
Fig. 18 Same as Fig. 16 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM. Fig. 17e uses a regression range from [-6,6].
years) and biennial (1-3 years) time periods. Negative correlations and a negative linear regression persist but the quantitative properties of this cloud loss with increasing SSTs are less than the decadal. Interannual CA loss is lowest at approximately 1% statistical significance. During the biennial period, greater statistical significance is generated compared to the interannual along with a stronger CA-SST relationship with an approximate 2% decrease in CA. Annual and seasonal feedbacks have a similar decrease of 2% in CA per 1°C warming with the strongest statistical significance occurring in the annual. In addition, the phase shortens during the annual as CA and SST are in quarterature indicating that the SST maximum leads the CA maximum by 3 months. This observed negative correlation between SST and low-level CA agrees with that found by Klein and Hartmann (1993; hereafter KH93), in particular the negative relationship during the interannual.

Despite the observations yielding similar results to that found in KH93, the AR4 GCMs widely vary in their cross spectrum analyses. Two findings of significance were discovered in this analysis. The first key finding is the difficulty of representing the correct sign of the relationship while a secondary point is the differences in the GCM linear regression magnitude. While it has been established that increasing SST will decrease the CA based on observations and KH93, approximately half of the GCMs invert this relationship. A positive relationship between CA and SSTs results in the CC63, CCCM, CSI2, CSIR, GFDL 2.0, GFDL 2.1, GISH, GISR, IAPC, IPSL, MPIC, and PCM1 GCMs. However, within these models the CSIR, GFDL 2.0, GFDL 2.1, IAPC, MPIC, and PCM1 have a similar magnitude compared to observations but yield an inverse relationship. It is possible that GCMs are getting the appropriate value of the
linear regression but struggle to achieve the correct sign of the feedback. Other GCMs (CNRM, INGV, INMC, MIRH, MIRM, and UKCM) display a reversal in regression sign over the time series. With the exception of the INGV that reverses during the decadal-interannual transition, the other GCMs reverse on shorter temporal periods. Moreover, the reversal is from a negative to positive regime with the exception of the UKCM. This reversal in linear regression sign that occurs frequently at the interannual suggests the potential link with, and misrepresentation of, the periodicity of ENSO. The possibility that the GCMs are favoring a CA change associated with the onset of an El Nino is plausible. The reversal in linear regressions within GCMs is not uniform throughout the analysis. The CCSM, GISA, MIUB, MRIC, and UKGM depict a negative relationship similar to the observational relationship, although differences in regression strength exist. Enhanced loss of CA is suggested in the GISA and UKGM, while a weak signal is found in the MIUB. The CCSM and MRIC both perform adequately at emulating the correct sign and magnitude of the CA and SST relationship, although a weakened decadal and interannual period emerges in the CCSM.

The second key finding arises in statistical significance during the interannual consistent with observational data and from KH93. A majority of the GCMs (CNRM, CSI2, CSIR, GFDL 2.0, GFDL 2.1, GISA, GISH, GISR, IAPC, INGV, IPSL, MIRH, MIRM, MRIC, PCM1, UKCM, and UKGM) yield statistical significance during the interannual and agreed with observations and KH93. Of the GCMs that did not achieve statistical significance during the interannual, the tendency to favor short temporal intervals is evident in CCSM, MIUB, and MPIC during the biennial and annual period in the CC63. The CCSM and MIUB both obtain a consistent sign to observations while
the CC63, GISH, and MPIC produce a positive relationship between CA and SST. The cause of the differences in statistical significance, however, is unclear at this time.

In association with the negative correlation between CA and SST observations, the DSW and SST depict a positive relationship in Fig. 19-21. As SSTs are enhanced by the cloud-radiative feedback, the MBL will destabilize and a lower CA ensues allowing for the increased penetration of DSW further enhancing SSTs. The cross spectrum analysis yields a positive correlation throughout the time series, although statistical significance is achieved outside the interannual period. The decadal time is significant but skips the interannual before regaining significance during the biennial. This appears to weaken the argument that the CA is potentially linked with El Nino Southern Oscillation (ENSO) based on the lack of statistical significance to compliment the significant negative CA. Statistically significant time periods, such as the biennial, annual, and seasonal, are closely related with an approximate 15 W/m² increase in DSW corresponding to a 1° C SST increase. The largest change in DSW occurs during the decadal period with an approximate +20.0 W/m² increase, similar to the largest change in CA during the decadal and generated from horizontal plots of DSW.

In general, GCMs correctly identify a positive relationship between DSW and SST. GCMs resolve a positive relationship throughout the entire time series with the exception of three models, the CC63, CCCM, and MIUB, which transition from a positive interannual to a negative biennial. The CC63 and CCCM had a positive relationship with CA and, thus, the decrease in DSW seems to agree based on increased cloud component of the GCM. The MIUB reversal of the relatively weak CA-SST linear regression suggests a subtle shift in cloud scheme during this transition.
Fig. 19 Cross-spectrum analyses downwelling shortwave energy and SST with (a) OAFlux observational data and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CSI2, (g) CSIR, and (h) GFDL 2.0.
Fig. 20 Same as Fig. 19 but with GCMs (a) GFDL 2.1, (b) GISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL.
Fig. 21 Same as Fig. 19 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
When assessing the cloud-radiative feedback and air-sea interactions, the impact of one variable on another is significant. The capability for a GCM to resolve a certain variable, such as DSW, depends largely on the CA within the atmospheric layer, as it dictates energy reaching the surface. GCMs have difficulty resolving the CA and DSW flux relationship, as apparent with 12 GCMs, the CSI2, CSIR, GFDL 2.0, GFDL 2.1, GISH, GISR, IAPC, INGV, INMC, IPSL, MPIC, and PCM1, depicting an increase in CA which yields a positive DSW flux. With an increase in CA, the likelihood of increased DSW energy is remote. Consequently, the capability of these GCMs to handle the cloud-radiative feedback is lacking. In terms of SST bias, the CSI2, CSIR, GFDL 2.0, GFDL 2.1, and the INMC are free from the persistent SST warm bias. Therefore, this increased DSW may not enhance SST as effectively and are likely influenced by the cloud-radiative feedback.

The CC63 and CCCM increase CA and decrease in DSW with respect to increasing SST. A possible explanation to this relationship could be a high emphasis on CA linear regression values compared with DSW. The increase in reflective low-level MSc then contributes to the decrease in DSW as a result. Three GCMs, the CNRM, MIRH, and UKCM, produce a reversal in regression sign of the CA yet the DSW remains unaffected. This reversal occurs after the interannual period in all three models, with the CNRM and MIRM transitioning from a negative to positive CA regime and vice versa with the UKCM. The DSW remains positive, indicating that changes in CA do not factor into the CA and DSW relationship as much as the observed.
The cloud-radiative feedback is least pronounced in the CCSM, GISA, MIRM, MIUB, MRIC, and UKGM based on the link between decreasing CA with increasing DSW. A majority of these specific models have no significant warm SST biases, the exception being the GISA. It is possible that these GCMs can handle this feedback loop with some accuracy in global climate simulations.

In summary, the relationship between SSTs and CA is poorly resolved in GCMs with both increasing and decreasing CA with warming of SSTs. The CCSM, GISA, MIUB, MRIC, and UKGM display a negative relationship between SST and CA throughout the time series, although differences in magnitude emerge. The remaining GCMs either posses positive CA-SST relationships or had a reversal in linear regression sign during the time series. Statistical significance was found during the interannual time consistent with observations and KH93. The temporal aspect of the data can be adequately resolved but the sign of the relationship orientation fluctuates throughout the ensemble. In regards to DSW, the GCMs generally performed well in resolving the DSW flux increase, though statistical significance is achieved during the decadal and biennial and skipping the interannual, the period found most significant in CA-SST. Using cross-spectrum analysis, 12 GCMs had a tendency to favor an increase in CA that coincided with an increase in DSW energy. This relationship is opposite of the cloud-radiative feedback loop, yet enhanced warming of SSTs was found in 5 GCMs. The CCSM, GISA, MIRM, MIUB, MRIC, and UKGM each produced a relationship between CA and DSW, suggesting invulnerability to cloud-radiative feedback based on the representation of a decrease in CA and an increase in DSW. Only the GISA had a
warm SST bias indicating that the cloud-radiative feedback does not frequently appear in these GCMs.
CHAPTER 5: SEP SST-UPWELLING FEEDBACK

The interactions between ocean and atmosphere are critical to understanding coupled climate model feedbacks discussed in previous literature (Chang and Philander, 1994; Lin, 2007). This section describes the spatial, temporal, and quantitative properties and interpretation of the GCM output of SLP, meridional wind speed (VAS), and meridional wind stress (TAUV) that are involved in the SST-upwelling feedback.

Oceanic upwelling entails the transport of deep ocean water to the surface moderating SSTs. In the SEP, the ocean surface is subject to surface winds, primarily in the meridional direction, which affect translational advection of cool coastal water by distributing the cool SST pool across the SEP basin. As this cool oceanic mass is transported westward, additional cold water is upwelled to replenish the loss of departed cool surface SSTs. However, oceanic upwelling may be disrupted by changes in subtropical high strength and subsequent alteration of regional circulation, particularly the VAS and TAUV. As SSTs increase, the subtropical high weakens consistent with that described in Lindzen and Nigam (1987; hereafter LN87), resulting in an increase of VAS as the pressure gradient loosens. On the other hand, TAUV would have an inverse relationship with respect to the atmosphere. This relationship between VAS and TAUV appears counterintuitive, as an increase of VAS increases TAUV at the surface (i.e. ocean). In terms of the atmosphere, energy is transferred to the surface, resulting in negative TAUV when referenced to the atmosphere. With less
TAUV to affect the ocean surface, the mechanism for the westward transport of cool surface SSTs is diminished, preventing further deep water upwelling. Consequently, SSTs are enhanced, as minimal moderation of SSTs occurs. The SST-upwelling feedback loop is illustrated in Fig. 4. This feedback primarily addresses the ocean impact on the projected warming of the SST in GCMs. As found in Chapter 4, the warm SST bias is evident in 10 GCMs; the CNRM, GISA, GISH, GISR, IAPC, INGV, INMC, IPSL, MPIC, and PCM1.

A major force in SEP upwelling is the transport of cold SSTs by atmosphere and ocean circulation patterns. Atmospheric circulation is driven by wind and influences the upwelling process. As wind speed is related to atmospheric pressure, the SLP horizontal plots (Figs. 22-24) provide insight on the spatial and quantitative properties of the subtropical high identification of the prevailing wind flow. Described in LN87, the enhancement of SSTs weakens the subtropical high. The NCEP reanalysis SLP observation depicts the subtropical high centered approximately at 30° S, 265° E. In general, the GCM ensemble places the location of the subtropical high with accuracy. 15 GCMs, including the CC63, CCCM, CCSM, CSIR, GFDL 2.0, GFDL 2.1, GISA, GISH, IAPC, INGV, MIRH, MIUB, MRIC, UKCM, and UKGM, have an observationally consistent placement of the subtropical high. Remaining GCMs transplant the subtropical high with zonal biases from climatological location. When analyzing the CNRM, INMC, IPSL, MPIC, and PCM1, an eastward placed subtropical high center is resolved. This scenario would likely be affected by the South American land-sea contrast provided in this region. Westward extension of the subtropical high
Fig. 22 Sea level pressure (PSL) of the SEP region with (a) NCEP reanalysis data and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CSII2, (g) CSIR, and (h) GFDL 2.0.
Fig. 23 Same as Fig. 22 but with GCMs (a) GFDL 2.1, (b) GISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL.
Fig. 24 Same as Fig. 22 but with models (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
is evident in CSI2, GISR, and MIRM, as the area of influence in the SEP broadens due to the vast expanse of ocean.

The strength of subtropical high within the AR4 ensemble is less robust compared to the consensus displayed by SLP spatial properties. 14 GCMs generally agree with the observed SLP 1020 mb maximum. This consistent trend in SLP strength appears in the CC63, CCCM, CCSM, CNRM, CSI2, CSIR, GFDL 2.1, GISA, IAPC, INGV, IPSL, MIRM, MPIC, and UKCM. However, of these select GCMs, half project inaccurate minimum SLP. The NCEP reanalysis observed minimum SLP is determined to be 1012 mb in the SEP, but the research finding of -2 mb SLP minimum is produced in the CCCM, GFDL 2.1, GISA, INGV, IPSL, and UKCM. With half of the GCMs displaying an extended subtropical high range, the SLP decreases are consistent with LN87, suggesting the emergence of an SST-upwelling feedback in these GCMs. The prevalent warm SST bias manifests exclusively in the CNRM, GISA, INGV, and IPSL, potentially explaining the enhanced SSTs and initiation of the SST-upwelling feedback. However, the SST bias is absent in the CCCM, GFDL 2.1, and UKCM, suggesting the feedback may be resolved despite yielding consistent SSTs.

Differences in maximum SLP were noted in GCMs, as both positive and negative SLP biases were resolved. Weakened subtropical highs were projected in the GFDL 2.0, GISH, GISR, MIUB, MRIC, and PCM1, as a -2.0 mb bias subtropical high is represented. The GISH resolved an extreme -8 mb SLP bias, but this bias appears overestimated based on the extreme magnitude depicted in resolving the atmospheric component of the coupled GCM. Warm SST biases existed in the GISH, GISR, and PCM1, providing additional GCM candidates subject to SST enhancement and
weakened SLP consistent with the SST-upwelling feedback. Strengthened SLP were projected in INMC, MIRH, and UKGM, yet only the INMC projects a warm SST bias. Given the inverse relationship between increasing SSTs and decreasing SLP, the likelihood of a strengthened subtropical high in conjunction with an enhanced SST warm pool linked to the SST-upwelling feedback is unlikely.

Examination of the NCEP reanalysis of the observational VAS in the SEP, (Figs. 25-27) depicts the maximum of VAS of 7 m/s centered at approximately 10° S, 280° E. Maximum VAS appears to correspond to the sharp northward spur of the 294 K SST contour near the Peruvian coastline as seen in Fig. 7-9. This location is significant as the advection of cool SSTs along with upwelled water interacts with the warm equatorial SSTs to the north. The mixing of these two oceanic masses induces an SST gradient, creating localized pressure differences affecting VAS distribution in the SEP. SEP VAS are generally southerly and are likely dependent on both strength and location of the subtropical high. The spatial properties of the VAS field appear to mimic the coastline remarkably well and generally agree in the GCM ensemble. The land-sea contrast of the South American continent is likely the source of configuring the VAS and manifestation of the SST-upwelling feedback.

GCMs have difficulty replicating the maximum VAS value in the SEP. GCMs generally underestimate the magnitude of VAS in the SEP from -1.0 m/s to -3 m/s. The CCSM, CSIR, INGV, and PCM1 VAS data was unavailable; hence, these GCMs are ignored and 19 GCMs are utilized in VAS assessment. Within the remaining 19 GCMs, stark differences in VAS magnitude develop and three groups generally explain
Fig. 25 VAS of the SEP region with (a) NCEP reanalysis data and IPCC AR4 GCMs (b) CC63, (c) CCCM (unavailable), (d) CCSM, (e) CNRM, (f) CSI2, (g) CSIR (unavailable), and (h) GFDL 2.0.
Fig. 26 Same as Fig. 25 but with GCMs (a) GFDL 2.1, (b) GIISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV (unavailable), (g) INMC, and (h) IPSL.
Fig. 27 Same as Fig. 25 but with models (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1 (unavailable), (g) UKCM, and (h) UKGM.
modeled quantitative VAS properties: GCMs that yield a weakened VAS maximum, a strengthened VAS maximum, and an observational consistent VAS.

11 GCMs yield negative VAS biases on the order of -1.0 m/s (GFDL 2.0, GISR, IAPC, and MIRM), -2 m/s (IPSL, MIUB, MRIC, UKCM, and UKGM), and -3.0 m/s (CNRM and GISH). The magnitude of this weakened VAS in the GCM ensemble is concerning as 7 GCMs generate a -2.0 m/s or greater VAS bias in their respective climate projections. The possible origin of this underestimation of VAS stems from the misrepresentation of weakened subtropical high strength, as resolved in the GFDL 2.0, GISH, GISR, MIUB, and MRIC. However, this would explain only half of the instances and, therefore, not inclusively to GCMs generating negative VAS biases. Instances where the prevalent warm SSTs bias occurred were the CNRM, GISH, GISR, IAPC, and IPSL. The GISH and the GISR share warm SST and weakened subtropical high biases consistent with SST-upwelling feedback. The MIRM, UKCM, and UKGM are unaccounted, as biases of either a weakened SLP or enhanced SSTs are noted in the GCMs. Although the VAS is weakened in the MIRM, UKCM, and UKGM consistent with an SST-upwelling feedback, the support of SST and SLP is lacking, suggesting that modeled VAS representation is inadequate.

Conversely, stronger maximum VAS is evident in horizontal plots. The CCCM and INMC overestimate VAS by approximately +1.0 m/s, significantly fewer when compared to the weakened VAS GCMs. This positive VAS bias is not as extensive with the spatial extent of weakened VAS but remains an important finding. The CCCM produces a SST and SLP consistent with the observations yet produces a stronger VAS, while the INMC yields a warm SST bias and a positive SLP bias. Therefore, the
likelihood of the CCCM and INMC generating the SST-upwelling feedback appears remote as neither GCM reproduces atmospheric and oceanic features in the described feedback. The amount of consistency in the CCCM representation of SST and SLP dispels the theory of feedback in increased VAS. In regards to the INMC, the SST criteria is met for SST-upwelling feedback but given the SLP strengthening, feedback into increased VAS is unlikely.

When examining the observational VAS within the GCMs (i.e., maximum of 7.0 m/s), the CC63, CSI2, GFDL 2.1, GISA, MIRH, and MPIC resolved the VAS magnitude consistent with the observations. The magnitude of maximum VAS is correctly projected by these GCM but spatial properties of the VAS field are represented insufficiently. The GCMs favored a southeast migration of maximum VAS along the South American coast at approximately 25° S, 285° E. Relocation of the maximum VAS near the northern Chilean coast corresponds to the approximate location where the cool water introduced into the SEP by upwelling and polar advection is drawn from shore and warm equatorial water interacts with cool water. With proximity to the South American continent, localized circulation affecting wind speed is likely to incur. Despite described differences in spatial placement of VAS maximum, the CC63, CSI2, and GFDL 2.1 were consistent in resolving the magnitude of SSTs, SLP, and VAS without biases. With no quantitative biases in these variables, the prospect of SST-upwelling feedback developing in these GCMs is improbable. The level of agreement displayed between air and sea variables within these GCMs may be suited for analysis of climate change in the SEP.
TAUV (Figs. 28-30) serves a potential transport mechanism of surface ocean water seaward. The sign of TAUV is emphasized with respect to the atmosphere, as negative TAUV values signify transference of kinetic wind energy to the ocean surface. In other words, atmospheric wind energy is lost while increasing the force on the ocean. The general atmospheric circulation in SEP is linked with the subtropical high and emerges from TAUV observations. A broad swath of positive TAUV values extends approximately from 35° S, 285° E northwestward tracing the South America coastline. The observed TAUV configuration is likely driven by atmospheric circulation around the subtropical high and deflection of wind direction consistent with the Coriolis force.

Spatial characteristics of TAUV generally agree with observed values. Observationally consistent spatial TAUV properties are represented in the CC63, CCCM, CCSM, CS12, CSIR, GFDL 2.0, GFDL 2.1, IPSL, and MIRH. Excluding these select GCMs TAUV spatial properties, the ensemble is prone to subtle spatial differences and exaggerated strength of TAUV. Frequent modeled tendencies were the production of a sharp west protrusion or placement of the minimum TAUV further west. The zonally oriented west protrusion at 10° S is evident in the CSIR, GISA, GISR, and UKGM and extends past the 265° E longitude consistent with the observations. Although the CSIR VAS data was unavailable and the GISA appear similar to observations, weak VAS biases identified previously were present in the GISR and UKGM, offering a possible vulnerability within the CSIR, GISA, GISR, and UKGM resolution of TAUV. SLP were generally consistent with the observed values, despite a slight broadening of subtropical high in the GISR. SLP appears more unlikely to induce a TAUV bias than VAS, suggesting that the relationship between TAUV and
Fig. 28 Meridional wind stress (TAUV) of the SEP region with (a) NCEP reanalysis data and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CSI2, (g) CSIR, and (h) GFDL 2.0.
Fig. 29 Same as Fig. 28 but with GCMs (a) GFDL 2.1, (b) GISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL.
Fig. 30 Same as Fig. 28 but with models (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
VAS is more robust than the TAUUV and SLP pairing. The westward shift associated with positive TAUUV is generated within the GISH, INMC, MIRM, MIUB, MRIC, and PCM1. This western shift suggests an association with the weakened subtropical high resolved by the GISH, MIUB, MRIC, and PCM1. However, this situation is not applicable throughout the identified GCMs, as the INMC produced a stronger subtropical high while the MIRM generates a broader pressure gradient. The confidence of VAS affecting TAUUV is present in the selected GCMs as positive biases were prevalent. The PCM1 VAS was unavailable but widespread and appreciable strength negative VAS biases suggest a greater impact than SLP on the westward shift in TAUUV, reinforcing the evidence presented in the westward protrusion.

Magnitude differences are prevalent in GCMs such as the CCCM, CCSM, CSI2, CSIR, GISA, GISR, INGV, IPSL, MIRH, MPIC, and UKCM where a +.05 N/m² bias is produced within the +0.05 N/m² contour. The spatial extent of the identified positive TAUUV bias is confined primarily to an area 25° S, 280° E with possible enhancement from orographic or oceanic sources. With approximately half the ensemble favoring strengthened positive biases in TAUUV, the quantitative properties of TAUUV prediction lacks a concise degree of accuracy. Considering the previously discussed linkage between TAUUV and VAS spatial properties, translation of VAS magnitude affecting TAUUV magnitude is less defined. GCM performance is improved on projecting the TAUUV magnitude, as the CSI2, GISA, MIRH, and MPIC depict observationally consistent VAS magnitude while the CCSM, CSIR, and INGV remain inconclusive based on unavailable data. Although the positive CCCM and the negative IPSL and UKCM biases in VAS appear in the SEP, it may prove problematic associating VAS
magnitude to the strength of TAUV. SLP magnitude and location are relatively consistent throughout the ensemble, reinforcing the theory suggesting the observationally consistent subtropical high is not affecting VAS to the more likely extent of TAUV. Furthermore, the prevalent SST bias generates mixed results, but increased TAUV appears to subtly favor unbiased SSTs. The presence of orography is not overshadowed, as affecting the TAUV magnitude is supported by the enhanced wind stress off the Chilean coast. However, the role of the oceanic upwelling and polar water advection may exacerbate the land-sea contribution on TAUV creating an intensified sea breeze. Given that isolated areas of increased TAUV appear near the coastline, the likelihood of localized enhancement of VAS remains high.

In summary, the SST-upwelling feedback is based largely on enhancement of SSTs and the described affects on SLP, VAS, and TAUV. GCMs generating a weakened SLP and prevalent SST bias were determined to be the GISA, INGV, and IPSL. The warm SSTs appear to possess a minimal effect on dictating the location of the subtropical high, but yield an increased range of SLPs that favored weakened SLP, consistent with the feedback. GCMs tend to expand the domain of influence of the subtropical high in the SEP, yet the overall magnitude of the climate system was preserved if expansion of SLP influence occurred. In terms of the VAS, the spatial pattern contoured the South American coastline suggesting a strong orographic influence. Underestimation of VAS was widespread, as 11 GCMs yield negative anomalies with 7 GCMs yielding a 2.0 m/s bias or greater. Spatially, maximum VAS was located in close proximity to the undulation in 294 K SST contour near the Arican Bight, where the cool upwelled or polar advected water is transported seaward. TAUV
spatial properties were similar to observations but experienced a slight westward shift in GCMs that projected weakened subtropical high strength. GCMs tend to overestimate VAS and TAUV values near shore, suggesting the influences of localized coastal circulation (e.g., sea breezes) in this enhancement.

In order to assess the statistical and temporal properties of SST-upwelling feedback within the SEP climate system, a series of cross spectrum analyses are performed. Using a standard reference variable, such as SSTs, the interaction between a studied variable (e.g., SLP, VAS) and the reference variable can be analyzed. This approach can allow for a comprehensive understanding in regards to the air-sea interactions that govern the SEP. Statistical information, such as the significance at the 95% confidence level, the coh², the phase of the variables, and the linear regressions are provided within the cross-spectrum analysis. The results can assist in determining the vulnerability of GCMs to the air-sea interactions biases and consequent climate feedback.

Consistent with LN87, the cross spectrum between observed SLP and SST values (Figs. 31-33) yield a negative correlation, as increasing SSTs lead to SLP decreases and MBL destabilization. Since the NCEP reanalysis of the SLP dataset does not encompass the extent of years contained within the ERSST dataset, the multidecadal period is ignored. A negative correlation between SLP and SST occurs during the entire time series. Statistical significance of this relationship is first achieved during the decadal and interannual period. The decrease in SLP coupled with increase of SST during the interannual could possibly be associated with ENSO cycle. Decreasing SLP in the SEP is characterized by the warm phase of ENSO, thus, the
Fig. 31 Cross-spectrum analyses between sea level pressure and SST with (a) NCEP reanalysis data and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CSI2, (g) CSIR, and (h) GFDL 2.0.
Fig. 32 Same as Fig. 31 but with GCMs (a) GFDL 2.1, (b) GISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL.
Fig. 33 Same as Fig. 31 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
periodicity of ENSO may affect the SST-SLP relationship in the interannual. Moreover, the possibility exists of ENSO and the SST-upwelling feedback working in tandem to create the observed interannual correlation. SLP-SST relationship tend to be strongest on the interannual time scale, reinforcing the possibly link in the Walker Circulation during an ENSO event and affecting the variability observed in the SEP. The trend of SLP is adequately rendered in the ensemble yet the strength of the relationship varies. During the time series, SLP and SST are out of phase by approximately half of one cycle indicating that the SLP maximum leads the SST maximum by half a cycle. Therefore, in the interannual period, constituting 3-7 years time, the SLP maximum would be predicted to occur at 1.5 years and 3.5 years before the SST maximum at 3 years and at 7 years, respectively. Statistical significance is maintained throughout the time series until the seasonal, where fluctuations in significance occur. These fluctuations are expected, however, given the brief duration and high variability of the seasonal scale.

When cross spectrum analysis is performed on the GCM ensemble, there is a remarkable agreement on the negative correlation between SLP and SST. All 23 models depict a negative correlation throughout the time series, indicating that changes in SLP with increased SSTs are exceptionally reproduced within the GCMs.

Analyzing the GCM ensemble, 4 GCMs, including the CSI2, CSIR, GISH, and GISR, provided a lengthy negative phase often during the interannual phase. As the shift from a positive to negative phase occurred, statistical significance remained high and the negative linear regression was maintained. This shift in polarity of phase implies the reversal of the lead variable, as the SST maximum leads the SLP maximum.
Since this occurrence is most prevalent during the interannual period, the possibility of ENSO manipulating this phase shift is likely. The CC63, CCCM, CCSM, GFDL 2.1, INGV, IAPC, INMC, IPSL, MIRH, MPIC, PCM1 and UKGM are predominantly positive in phase and emulate the observational phase with the greatest degree of accuracy. The CCCM, IAPC, and IPSL display a negative phase in multidecadal and decadal but reverse phase during the decadal period and remain positive for the analysis. A brief reversal in phase is present during the annual interval of the observations and the INGV, PCM1 and UKGM yield a similar reversal in phase. The significance of this phase reversal may be minimal, as INGV, PCM1, and UKGM produce either a model consistent, weaker, or stronger subtropical high strength, respectively, in the horizontal figure (Figs. 22-24). The remaining GCMs, the CNRM, GFDL 2.0, GISA, MIRM, MIUB, and MRIC display this brief reversal in phase polarity at the interannual and biennial transition, remain statistically significant, and retain a negative relationship between SLP and SST for the duration of the time series.

The magnitude of the SLP decrease for 1°C warming of SST ranges from an approximate 1.0 mb during the interannual to an approximate 0.5 mb on the annual. This range of a 0.5-1 mb loss for 1°C SST rise is generally agreed throughout the GCM ensemble. Interactions between SLP and SST were strengthened in the CC63, CCCM, GFDL 2.1, GISH, GISR, MIRH, and MIRM. These GCMS that yield this amplification of the SLP-SST interaction is concerning as the CC63, CCCM, GFDL 2.1, and MIRM produced consistent SLP and SST values in the horizontal figures, appearing to contradict this finding. This discrepancy reinforces the need for improved modeling.
techniques and understanding of subgrid scale processes involved in GCM air-sea interactions.

Temporal properties of these GCMs were consistent with the observed and are considered conditionally accurate. In other words, the GCMs depict a general consensus of the regression magnitude, but since the multidecadal scale cannot be referenced, consensus on the multidecadal scale remains inconclusive. Two GCMs, the CSI2 and MPIC, offer an enhanced SLP-SST relationship during interannual period than shown in the observational value yet maintain a similar observational trend in linear regression throughout the time series. GCMs deemed consistent throughout the time series and simulate the SLP-SST relationship most effectively included CSIR, GISA, INMC, MIUB, and UKGM. It is likely that these five GCMs are capable of resolving this SST-upwelling relationship realistically.

With decreasing SLP and increasing SST confirmed by the GCMs, the cross spectrum analysis of observed VAS produces a near-neutral linear regression (Figs. 34-36). Extensive time intervals, such as the decadal and interannual, display a slight negative regression as SST leads the VAS maximum as the two variables are in quarterature during the statistically significant interannual. Maximum significance paired with maximum linear regression during the interannual adds credence to the potential link with ENSO variability. Further support is illustrated by the negative SLP-SST relationship during the same temporal interval. Short temporal intervals maintain and weaken these negative linear regressions as the phase shifts from positive to negative correlation. Statistical significance is not achieved until the interannual, suggesting minimal correlation between SST and VAS permeates the confidence level.
Fig. 34 Cross-spectrum analyses between VAS and SST with (a) NCEP reanalysis data and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM (unavailable), (e) CNRM, (f) CSI2, (g) CSIR (unavailable), and (h) GFDL 2.0.
Fig. 35 Same as Fig. 34 but with GCMs (a) GFDL 2.1, (b) GISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV (unavailable), (g) INMC, and (h) IPSL.
Fig. 36 Same as Fig. 34 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1 (unavailable), (g) UKCM, and (h) UKGM.
Furthermore, the weak VAS-SST relationship is likely affected by changes in SLP rather than changes in SST. With the relatively low statistical confidence on extended temporal periods combined with suppressed a short-term SST-VAS relationship, the VAS lacks robustness compared to the SLP-SST cross spectrum. In addition, the increase in VAS described in the SST-upwelling feedback does not appear to manifest quantitatively in the SEP as strongly as anticipated.

The relationship between VAS and SST, as generated by the GCM ensemble generally emulates observational sign but with increased negative magnitude. Several GCMs, including the CCSM, CSIR, INGV, and PCM1, are unavailable to provide statistical information and were subsequently ignored. With the emergence of quantitative discrepancies in calculating VAS statistical properties and several GCMs unavailable for analysis, the scope of VAS is somewhat limited in widespread applicability, proving challenging to achieve a comprehensive synthesis. Analyzing the remaining 19 GCM ensemble, VAS on short term intervals are relatively similar to the observations, while the long-term intervals display weakening of the VAS-SST relationship. The negative regression in the biennial, annual, and seasonal is reasonably simulated in the CCCM, CSI2, GFDL 2.0, GFDL 2.1, GISR, IAPC, IPSL, MIRM, MIUB, MPIC, and UKGM. Distribution of the weakened VAS-SST relationship appeared split into short-term and long-term variability. The CNRM and MIRH favor strengthened VAS response to SST warming over long term periods, while a short term diminished VAS emerges in CCCM, GFDL 2.0, GISA, IAPC, MIRH, MIRM, and MRIC. CC63, GISH, and INMC increase VAS magnitude over the entire time series. Weakened linear regressions are generated by GISA and IPSL during short
intervals, while UKCM suppresses the entire time series. CNRM and MIUB GCMs reverse the negative regression trend during the decadal period, although only the CNRM relationship is significant. This finding illustrates the tendency of GCMs to underestimate VAS on short temporal periods, but extrapolation of VAS into long-term trends increases the number and magnitude of GCMs prone to the prescribed VAS-SST relationship.

Further investigation into the VAS-SST relationship provides two key points on the statistical properties of the GCMs. First, GCMs possess a tendency for elevated statistical significance. GCMs display greater amount of significance, indicating the VAS-SST relationship is modeled with increased robustness than the observational VAS with the exception of the GFDL 2.1. Second, the phase of the VAS-SST relationship remains generally positive during the time series within the ensemble, but observational phase lacks the longevity possessed by GCMs. Positive phase trend is observed in the CC63, CCCM, CNRM, CS12, GFDL 2.0, GISA, GISR, INMC, IPSL, MIRH, MIRM, MIUB, MPIC, MRIC, UKCM, and UKGM. Negative phase values are resolved in the GCM ensemble during the annual period. Reversal indicates that VAS maximum leads SST maximum by nearly 6 months in GCMs, altering the SST leading the VAS maximum in other temporal periods. Origins of this observed role reversal in the VAS-SST relationship during the annual is uncertain at the current time.

In conjunction with VAS, the cross spectrum analysis regarding TAUV (Figs. 37-39) is performed. Adhering to sign convention established previously, TAUV is analyzed with respect to the atmosphere. Consistent with the discovered linear regression contained in VAS, TAUV exhibits a slight negative relationship during the
Fig. 37 Cross-spectrum analyses between TAUV and SST with (a) NCEP reanalysis data and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CS12, (g) CSIR, and (h) GFDL 2.0.
Fig. 38 Same as Fig. 37 but with GCMs (a) GFDL 2.1, (b) GISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL.
Fig. 39 Same as Fig. 37 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
time series. Decadal and biennial periods exhibit the strongest linear regression values ignoring the interannual period. This finding proves intriguing as the VAS-SST relationship was determined to be strongest during the interannual. Interannual relationship of TAUV-SST based on magnitude established a period of weakened relationship signal. Based on this recent finding, explanation of this gap may be provided by TAUV relinquishing influence to VAS on the interannual period. Transition from TAUV to VAS during the interannual period supports ENSO impacting the SEP circulation. Statistical significance is limited to the biennial period in the TAUV-SST cross spectrum analysis, suggesting that the influence TAUV variability on the decadal may be uncertain from GCMs.

The GCM ensemble magnifies the strength of the TAUV-SST relationship over the time series apparent in the CC63, GFDL 2.0, GISA, GISH, GISR, INMC, and MIRH. Enhancement may be generalized to specific temporal intervals, as the CCCM, CCSM, CSIR, MIRM, and MPIC increase the long-term periods while CSI2 and INGV favor short-term intervals. Generation of wide ranges of TAUV-SST relationships are produced, illustrating inaccuracies of circulation features in GCMs. Despite the production of TAUV biases in terms of relationship with SST, representation of maximized biennial and decadal relationships is evident. Consensus with observational values depicting temporal periods when the TAUV-SST relationship is most influential appear to be resolved adequately. Decadal maximums, CC63, CCSM, CSIR, GFDL 2.0, GISA, GISR, IAPC, IPSL, MIRH, MIRM, MPIC, UKCM, and UKGM, and biennial maximums, CNRM, CSI2, GFDL 2.1, GISH, and INGV, encompass a majority of the GCM ensemble. Cross spectrum analysis yields the CCCM, INMC, MIUB,
MRIC, and PCM1 as an interannual maximum between TAUV-SST, although these GCMs rendered a maximum negative VAS relationship during this period as well, implying greater influence likely from VAS than TAUV. The annual negative phase shift present emerges in the TAUV-SST relationship as well, indicating that SEP atmospheric circulation is altered on the annual scale, triggering a reversal in lead variables throughout the AR ensemble.

In summary, cross spectrum analysis yields negative trend in regressions when assessing the SLP-SST, relationship with a maximum -1.0 mb per 1° C warming during the interannual. While this decrease in SLP characterizes the SST-upwelling feedback, the susceptibility to ENSO influences is speculated. VAS appears better suited to describe short term trends rather than long term based on GCM emulation. Sharp decreases in interannual VAS compliments the decrease in SLP, adding credence to the modeled SST-upwelling feedback and ENSO influences in the SEP. TAUV is maximized during the decadal and biennial period, while appearing to relinquish influence to VAS during the interannual period. Negative phase shifts occur in all GCMs during the annual period of both TAUV and VAS, indicating a shift in lead variable from SST to VAS. Origins of this phase shift in the ensemble are uncertain at the current time.
CHAPTER 6: SST-LATENT HEAT FEEDBACK

The latent heat flux serves a significant component of the earth’s radiative budget. The impact of the latent heat flux (LHTF) on the evolution of MSc is twofold. First, the evaporation of drizzle within the SCL requires latent heat absorption. Energy lost from the atmosphere through evaporative cooling allows greater LTS in the MBL and, thus, promotes the evolution of MSc. Second, as cloud top longwave cooling drives the evolution of MSc in the SEP, the energy radiated to space at cloud level is replaced by latent and sensible energy fluxes transported through the SCL by turbulent eddies. These turbulent eddies provide the moisture necessary to maintain the cloud deck through condensation at the lifted condensation level and the associated release of latent energy reinforces the inversion above the cloud deck.

The amount of the LHTF projected by the IPCC AR4 models is presented in Fig. 40-42. Observed maximum values of +120.0 W/m² regarding the LHTF in the SEP is centered at 15° S, 250° E, near the warmest SSTs and lowest CA. Strong LHTF along with warmer SSTs indicates the LHTF feedback manifests in GCMs that possess a warm SST bias. Minimum LHTF are confined near the equator and midlatitudes where cooler SSTs prevail from the equatorial cold tongue in the north and polar water advection in the south. Additional minima are resolved near coastal areas but likely result from localized land-sea interactions and are less emphasized than
Fig. 40 Latent heat flux of the SEP region with (a) OAFlux observations and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CS12, (g) CSIR, and (h) GFDL 2.0.
Fig. 41 Same as Fig. 40 but with GCMs (a) GFDL 2.1 (unavailable), (b) GiSA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL.
Fig. 42 Same as Fig. 40 but with models (a) MIRH, (b) MIRM (unavailable), (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
oceanic-based minima. However, the presence of LHTF minima is considered in determining the factors of the latent heat feedback in the SEP.

In the LHTF analysis, the GFDL 2.1 and MIRM data are unavailable and ignored for this feedback. In the remaining 21 GCMs, there is a widespread +20.0 to +40.0 W/m² latent energy bias that emerges within the GCM ensemble. With the exception to this being the CSI2, CSIR, and MRIC, all GCMs yield a positive bias. Despite an energetic bias the spatial properties of the LHTF are generally agreed by the GCMs. Maximum LHTF is approximately +120 W/m² in the SEP and protrudes from the western edge. Positive LHTF biases approach, but rarely extend, eastward of 270° E and southward of 20° S consistent with observations. Positive biases in LHTF occasionally decrease minimum values, expanding the gradient range by approximately 20 W/m². GCMs that produced this tendency include the CCSM, GFDL 2.0, INGV, MPIC, UKCM, and UKGM, with lower LHTF rates 10-20° further west in equatorial zones than depicted in the observations. Additionally, these contours elongate in observations, suggesting a broader spatial influence. The nature of both maximum and minimum LHTF being affected is an intriguing case, as the range of LHTF values expands in extremes rather than being unilaterally increased.

GISA, GISH, IAPC, INMC, IPSL, and MIUB produce +20.0 W/m² bias with all GCMs, but the MIUB develops the warm SST bias. Further positive enhancement of the latent heat feedback is depicted, as GCMs produce greater positive biases. +40.0 W/m² biases occur in the CC63, CCSM, GISR, INGV, MIRH, PCM1, UKCM and UKGM. This positive LHTF anomaly may be explained with the development of the persistent SST warm bias in the GISR, INGV, and PCM1. Additionally, +60.0 W/m²
bias is given by the CNRM and MPIC, with both displaying the warm SST bias. However, citing warm SSTs as the cause to positively enhanced LHTF proves troublesome. Warm SSTs may play a large role in generating these strong biases, but other climate variables likely factor into this extreme case. Regardless, the poor resolution of the latent heat feedback in GCMs is quite apparent.

Contrary to the widespread positive biases in LHTF, the CSI2, CSIR, and MRIC produced maximum similar to the observed values. Maximum LHTF +120.0 W/m² contour extends eastward of 260° E in the CSI2 and CSIR. In the case of the MRIC, the +120 W/m² is confined primarily to the western edge of the SEP. Minimum LHTF are generated west of the observed values in the CSI2 and CSIR, but are generally consistent with the MRIC. While the spatial pattern and magnitude of the LHTF generally agree with the observations, the reasons may be largely unknown due to the complexity of the SEP region. Therefore, it proves difficult to identify the specific causes that allow for the accurate spatial representation of LHTF. The statistical analysis conducted in the following section may provide further insight into the nature of these biases, how these biases are formed, and the spatial pattern followed.

With good spatial agreement from GCMs on VAS in the analysis of the SST-upwelling feedback in the AR4 GCMs, the degree of spatial consensus displayed in the LHTF is less encouraging. Based on spatial properties of the LHTF, it is evident that the LHTF feedback is poorly resolved and, as a result, large positive biases manifest in GCMs. This behavior is multilateral, as minimum LHTF values decrease within several GCMs, causing a broader range of values instead of generating a more concise
projection into LHTF. However, with GCMs prone to warm SST biases, the likelihood
that SST and LHTF feedback appears in model outputs is likely.

LHTF is referenced with SSTs to assess the vulnerability of latent heat feedback
in the SEP over different time periods as well as testing for a significant relationship
between the variables. As temperatures in GCMs are predicted to increase, the warmer
environment likely evaporates moisture more readily, increasing the amount of latent
energy in the SEP. VAS may factor into evaporation rates and are considered when
discussing possible sources of bias within regression trends.

Analysis of the OAFlux latent heat flux cross spectrum analysis with SST (Figs.
43-45) reveals a positive regression throughout the time series, with values ranging
from approximately +5.0 - 8.0 W/m². Maximum linear regression signal occurs during
the decadal period which is statistically significant. Other time periods, with the
exception of multidecadal, yield a generally homogeneous value of approximately +5.0
W/m² although the interannual is slightly stronger in magnitude. The tendency for the
strongest relationships designated to long term intervals indicates fluctuations in LHTF
occur over extensive temporal periods, while short intervals are generally consistent in
relationship strength. Enhanced signal during the decadal and interannual emerged in
the VAS-SST relationship, suggesting that an increase in VAS likely would enhance
evaporation rates over oceanic surfaces and explain the enhanced LHTF during this
period.

The IPCC AR4 ensemble reproduces the latent feedback well, as positive
relationship values are obtained consistent with observations. While the LHTF sign is
reproduced correctly, no link with VAS emerges as cross spectrum analysis yielded a
Fig. 43 Cross-spectrum analyses between latent heat flux and SST with (a) observational and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CSI2, (g) CSIR, and (h) GFDL 2.0
Fig. 44 Same as Fig. 43 but with GCMs (a) GFDL 2.1 (unavailable), (b) GiSA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL.
Fig. 45 Same as Fig. 43 but with GCMs (a) MIRH, (b) MIRM (unavailable), (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
negative regression with respect to enhanced SSTs. GCMs diminish the contribution of VAS to the LHTF, resulting in a positive correlation. SST-latent heat relationship magnitudes are generally suppressed from their observational value, especially during the biennial and shorter frequencies. VAS may influence the LHTF, as on short temporal periods the reduction in the LHTF-SST relationship may be minimized due to decreased wind speed. The GCM underestimation of latent heat results allows for the weakened LHTF over short temporal intervals in the SEP found in the CC63, CCCM, CNRM, CS12, GFDL 2.0, GISA, GISH, GISR, IAPC, INGV, INMC, IPSL, MIRH, MIUB, PCM1, and UKCM. Out of these identified GCMs that generate a weakened signal, several GCMs minimize the single to near neutral (GISH, IAPC, INMC, MIRH, PCM1, and UKCM), while others reverse the sign such as those of GISH and IAPC. GCMs that produce a weakened signature are not entirely inaccurate, as the observationally consistent linear regression during the biennial, annual, and seasonal periods exist in the CC63, CCCM, CNRM, CSIR, CSIR, GFDL 2.0, INGV, IPSL, and MIUB. Regression values of approximately +2.0 - 3.0 W/m² indicate a quantitatively weakened signature, but temporal characteristics of the GCM are maintained. GCM consistency during these intervals appears to emulate that observed in the OAFlux, suggesting an adequate representation of LHTF on short intervals.

Examining the LHTF-SST relationship on long-term periods, complication arises attempting to reach a model consensus. Diminished signals during the decadal period highlight the volatility within this period in modeling the LHTF-SST relationship. GCMs identified as the CC63, CCCM, CCSM, CS12, CSIR, GFDL 2.0, GISA, INGV, INMC, IPSL, MPIC, MRIC, PCM1, and UKGM produce an approximate -3.0 W/m²
bias compared to observations exclusively during this period. Suppression of regression values persist into the interannual, but are generally more realistic to observational than decadal values. Observational consistent LHTF-SST linear regression values within the CNRM, IAPC, and MIUB indicate that representation of this long-term relationship is possible at the current time, but an overestimated annual period within the CNRM and IAPC cast doubt on the reliability of such GCMs long-term modeling schemes. In the case of MIUB, which employs a relatively coarse vertical atmospheric and oceanic resolution, the heat and freshwater flux adjustments that are absent in the CNRM and IAPC may be the origin of annual overestimation. Negative values for the LHTF-SST relationship are yielded by GISH, GISR, and MIRH, implying that a decrease in LTHF is likely when an increase in SSTs would increase the atmospheric moisture and LTHF of the climate. This discrepancy manifests in the decadal period, possibly offering difficulties in representing the long term frequency embedded in climate models leading to these apparent miscalculations.

Decadal and interannual LHTF-SST linear regressions are typically the highest magnitude of the time series agreeing with the ensemble consensus. This described tendency is illustrated in CC63, CNRM, CSI2, GISA, IAPC, INGV, INMC, MIUB, MPIC, and PCM1, suggesting the capability to identify the decadal and interannual as periods of great volatility is an achievement.

In summary, LHTF is generally overestimated with 18 GCMs yielding a positive bias ranging from +20.0 to +60.0 W/m². GCMs that projected LHTF appropriately were the CSI2, CSIR, and MRIC. Minimum LHTF values decrease by 20 W/m² suggesting that both maximum and minimum projected LHTF values are prone to bias
generation. Cross spectrum analysis illustrates better representation of LHTF on short
intervals and becomes weakened. Negative VAS anomalies may suppress magnitude of
LHTF and offer a possible explanation to the observed weakening. Success in
extrapolating a LHTF-SST relationship to long term has yielded similar observational
values in CNRM, IAPC, and MIUB, but an overestimated annual period raises doubt on
the validity of this representation.
CHAPTER 7: TROPICAL CLOUD - RADIATIVE FEEDBACK

As previously discussed, CA within the tropics affects the radiative balance. Moreover, differences in cloud type and cloud optical thickness further dictate whether energy is either reflected or captured in the atmosphere. Sadly, the microphysical understanding of clouds is quite limited, allowing biases to manifest. Establishment of radiative properties of tropical clouds is essential to modeling the tropical cloud-radiative feedback. With a broad range of cloud types typically found in tropical regions, a fundamental understanding of the radiative properties ranging from shallow boundary layer clouds to deep convective clouds and anvils prove essential in assessing the earth’s radiation budget. These two specific types of clouds form the foundation of this chapter by garnering an advanced grasp on cloud physical properties, such as cloud height, optical thickness, and amount. Assessment that addresses the cloud-radiative feedback must undoubtedly account for these variables.

GCM representation of clouds can be divided into two classifications: low-level clouds that generate surface cooling rendering a negative feedback and high-level clouds capturing longwave radiation enhancing the global warming scenario in the tropics. Assessing tropical CA with radiational values acquired from the TOA can provide further insight on characteristics of the resolved cloud scheme and potential biases induced by varying cloud types from individual components of the radiation flux.
Application of this information can deduce the tendency of GCMs to favor climate warming (cooling) by high (low) clouds.

Observational CA reinforces several generally accepted cloud patterns in the tropics based on established atmospheric circulation. Synoptic scale features such as subtropical highs typically associate with areas of diminished cloud cover such as the Hawaiian High and the Bermuda-Azores High. This case links regional scales with warm SSTs and large scale subsidence. Subtropical highs cannot be linked exclusively with minimal CA due to sustainability of low-level clouds in stable boundary layers regulated by the cool waters of oceanic upwelling along western coastlines (i.e., Peruvian MSc).

Diminished CA prevails in areas associated with aridity which lack moisture necessary for condensation and cloud development. The Middle East and the Australian Outback illustrate this tendency as CA is less ubiquitous in dry regions. Therefore, decreased CA appears to be linked primarily to regions with large scale subsidence and arid conditions. Conversely, maximum CA is associated with prevalent equatorial surface convergence (i.e., the ITCZ). Additional maximum CA is generated in regions of dense vegetation and high rates of evapotranspiration such as the tropical rainforests of the Amazon and central Africa. In regions where perpetual warm SSTs dominate and atmospheric uplift occurs, global scale circulation patterns such as the Walker Circulation may be depicted in observational analysis. Increased CA in proximity to Indonesia as well as reduced cloud amount in the south-central Pacific and upper level subsidence necessary for low-level cloud evolution in the southeast Pacific
suggests the presence of this climate feature and the potential impacts on the ENSO cycle.

Tropical CA representation in GCMs (Figs. 46-48) varies between models, emphasizing the difficulty when modeling climate features that rely heavily on subgrid scale microphysics on a large area such as the tropics. Several recurring instances were found in the GCM ensemble. CA maximum generally is located in proximity to Indonesia. Due to perpetual warm SSTs and surface convergence, the representation of clouds in the region appears appropriate. GCMs produce a CA magnitude that is consistent with the ISCCP observations of approximately 80%. Composition of this cloud maximum likely includes deep convective anvils that are best suited for heat retention and result in atmospheric warming. Additionally, outgoing long wave radiation at TOA would be diminished as a prelude to an enhanced greenhouse effect. The entire GCM ensemble agrees on the existence of maximum CA near Indonesia but variations regarding magnitude are represented.

The development of a subtropical Pacific cloud minimum dipole is observed over the south central Pacific Ocean and Hawaii. Strong subsidence associated with the climatology of these regions likely affect the evolution of this dipole evident in the CC63, CCCM, CCSM, CNRM, CSI2, GFDL 2.0, GFDL 2.1, INGV, IPSL, MIRH, MIRM, MIUB, MRIC, UKCM, and UKGM. The source of subsidence, however, may not be mutual. Minimal cloud coverage in the northern Pacific and Hawaii are likely associated with the Hawaiian High’s presence. On the other hand, the south central Pacific is subject to the descending arms of both the Hadley cell and Walker Circulation. With two subsidence mechanisms acting in tandem, the probability that
Fig. 46 Cloud amount (CA) of the tropics from 30° N to 30° S with (a) ISCCP observation data and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CSI2, (g) CSIR, and (h) GFDL 2.0.
Fig. 47 Same as Fig. 46 but with GCMs (a) GFDL 2.1, (b) GiSA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL.
Fig. 48 Same as Fig. 46 but with GCMs (a) MIRH, (b) MIRM (unavailable), (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
this region would exhibit less cloud cover supports the observed CA. GCMs appear to have difficulty in resolving this feature, as a wide range of projections are generated. The GFDL 2.0, INGV, IPSL, and MIRH depict an equal CA in the dipole. The CC63, CCCM, CCSM, CNRM, CSi2, GFDL 2.1, MIM, MIUB, MRIC, UKCM, and UKGM minimize the Southern Hemisphere dipole CA consistent with observations, while the CCSM and GFDL 2.1 further agree on magnitude differences. Building consensus in the ensemble remains difficult, as biases of both the positive and negative nature contaminate subtropical regions of the Atlantic and Pacific Ocean basins. GCMs such as the CNRM, IAPC, and INMC substantially increase CA in subtropical regions by nearly 30%. Conversely, the CC63, GFDL 2.1, UKCM, and UKGM decrease cloud coverage by approximately 10-20%. Extreme cases in subtropical cloud coverage provide a climate view shrouded in uncertainty and the confidence of GCM capabilities to resolve climate feedbacks induced by clouds is questioned. The accuracy of CA in subtropical regions appears to improve when assessing the Atlantic. Magnitudes and spatial extent of subtropical clearing produce more observationally consistent properties. The broad range observed in the Pacific attenuates in the Atlantic to approximately ±10% in CA indicating a potentially better handling of the climate dynamics. The CCSM, CSIR, GFDL 2.0, GFDL 2.1, GISA, GISH, GISR, INGV, INMC, and MIUB adequately resolve the CA magnitude and general spatial properties in the Atlantic basin. Causes behind the origin of the possible improvement are attributable to land-sea interactions, as aerosols and particulate matter from the nearby continents may impact cloud coverage more readily than areas previously identified in the central Pacific. Subtropical clouds are characterized by low-level clouds due to
areas of subsidence suppressing vertical development, as the Azores and African MSc evolve in this ocean basin. Proper representation of these clouds is critical to the energy balance of the planet. With this theory of improved representation of CA in the Atlantic, it would appear plausible to assume that the Atlantic basin yields radiational fluxes with greater accuracy than the Pacific.

MBL clouds, such as stratocumulus and trade wind cumulus characterized by subtropical environments, appear less prevalent in GCM representations. Regions classified as source regions for low-level, highly reflective clouds off western coasts of continents generate minimal CA percentages, indicating a tendency to underestimate low-level cloudiness such as the CSIR, GISA, GISH, GISR, INGV, IPSL, MIRM, MIUB, and UKCM. CA in subtropical regions serving as source regions for MSc are decreased in these GCMs, indicating the likely minimizing of low-level clouds in the tropics. Minimizing the CA in subtropical regions emphasizes the complexity of atmospheric moisture and CA in climate simulations and the uncertainties surrounding climate change. Difficulty in assessing low-level clouds arises from discerning whether subtropical clouds are melded into the overestimated tropical CA or subject to continentally based interactions as low-level clouds encroach on subtropical continental landmasses. Overestimation of tropical CA emerges in GCMs such as the CNRM, IAPC, and INMC as equatorial regions yield high cloud percentages, some on the order of 90%. This bias in cloud coverage envelops a majority of the oceanic regions in the tropics and surrounds low-level clouds in subtropical regions where strong subsidence and cool SSTs promote LTS. It remains difficult to determine whether low-level clouds become incorporated into this “runaway cloud scheme” or maintain their individual
radiative properties and promote surface cooling through the reflection of shortwave energy.

Terrestrial influences on subtropical CA are examined as critical placement of low-level cloud decks can disturb the equilibrium of the stable boundary layer and promote convection and anvils, thus altering radiative capabilities of these decks. Placement of low-level clouds over continental landmasses rather than ocean surfaces results in highly different requirements for heating and radiative fluxes in the tropics. Stratiform cloud source regions may be transplanted to coastal or land-based environments, fostering greater vertical development resulting in increased cloud optical thickness and an enhanced greenhouse effect. Migration to regions with high land influence is illustrated in coastal regions depicted in GISH, GISR, MIRH, UKCM, and UKGM or entirely over continents in IAPC, IPSL, and MPIC, in which case, longwave radiation is reduced while enhancing the global warming scenario. A secondary, but likely significant, arrangement is the cloud field possessing an extension that reaches the continent. This feature may be the result of continental cloud remnants that blow off and reform over the ocean. GCMs including the CC63, CCCM, CSI2, GFDL 2.0, GISA, GISH, INGV, INMC, MIRM, MIUB, MRIC, UKCM, and UKGM illustrate this possible cloud reformation over oceanic regions. In the case of subtropical low-level cloud decks associated with South America and Africa, dense vegetation and the related high rates of evapotranspiration would possess the capability to produce ample cloud coverage, likely in the form of deep convective anvils. The atmospheric moisture from these rainforests and jungles potentially could be transported into these low-level cloud source regions by the easterly trade winds further
enhancing the cloud decks. Whether clouds are associated with land based convection or a component of the ITCZ poses a significant challenge in tropical CA assessment. Therefore, identification of the source of atmospheric moisture is difficult to discern. GCMs reproduce the deep convective CA in these regions consistent with that of the ISCCP and, thus, the described transport of moisture is plausible.

Arid regions appear to be subjugated to biases in GCM output based likely on the lack of available moisture. Two areas that epitomize this relationship are the Saharan-Middle East region and the Australian Outback. While projecting a minimum in CA over these dry regions, the cloud gradient and broad areas of clear sky embellishes the observational values. The SME region appears with greater volatility than the Australian Outback as 21 of the 23 GCMs, the exceptions being GFDL 2.1 and MPIC, produce cloud amounts less than 20%. Minimal CA expands from the observational northern Egypt to encompass the Middle East and northern Africa. Cloud representation paired with the Australian Outback is resolved more effectively than the Saharan-Middle East region. GCMs produce an approximate 40% of Australian interior or a 10% decrease bias in CA. Others, such as the CCCM, GISA, GISH, GISR, IPSL, MIRH, MIUB, MRIC, UKCM, and UKGM generate minimal CA over the Australian continent, with the GISA, IPSL, and MRIC exhibiting the strongest cloud deficiency. Given the surrounding environment of high CA and proximity to ocean moisture, the ability to model the Outback with greater efficiency than the Saharan-Middle East region is expected. This highlights the vulnerability of GCMs to model in transitional zones from wet to dry conditions, resulting in a general underestimation of atmospheric moisture and CA. Consequently, with little cloud cover and highly reflective surfaces,
the amount of escaping radiation would likely lead to a negative net radiative flux and a likely decrease in the climate change magnitude.

CA modeled in the tropics has been analyzed from the AR4 ensemble for spatial properties. Since coupling an atmospheric model with an oceanic model introduces further complexity into the model, temporal characteristics of cloud amount associated with increasing SSTs are presented. SSTs departures are essential to the assessment of cloud type, as low-level clouds favor cool SSTs which provide lower tropospheric stability necessary for their development and evolution. Increasing SSTs destabilize the atmosphere in a positive cloud radiation feedback conducive for vertical development of cloud types, contributing to enhanced greenhouse effect.

ISCCP observation CA data yields an increasing tendency in cloud amount with increasing SSTs (Figs. 49-51). This result suggests that deep convection is likely, as SSTs are enhanced by increased insolation rates at the surface. Increased cloud development in terms of cloud top height and optical thickness possess a high probability of elevating atmospheric temperatures and enhancing the greenhouse effect.

The strongest regression values in the CA-SST relationship are observed during the decadal and annual period, with an approximately 5% increase for 1°C warming of SST. The value reported here has never been reported until the present work. However, Gordon et al. (2000) performed a study which found a similar rate of approximately +5.0 to +6.0% per 1°C warming, but was limited specifically to low-level clouds. Furthermore, the rate previously reported by Gordon et al. was negative, contrary to the present finding. Failure to achieve statistical significance during the maximum +5.0% decadal signal of CA-SST raises doubt pertaining to the relevance of
Fig. 49 Cross-spectrum analyses between tropical CA and SST with (a) observational and IPCC AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM, (e) CNRM, (f) CS12, (g) CSIR, and (h) GFDL 2.0.
Fig. 50 Same as Fig. 49 but with GCMs (a) GFDL 2.1, (b) GISA, (c) GISH, (d) GISR, (e) IAPC, (f) INGV, (g) INMC, and (h) IPSL.
Fig. 51 Same as Fig. 49 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
this finding. Statistical significance does not occur until the annual period, indicating short term applications of this relationship and the challenges of extending this trend across longer temporal intervals. If the value determined from Gordon et al. pertains to low-level clouds, the increase in CA over the tropics likely results from the addition to deep convection, spurring a possible 10% increase over the reported Gordon et al. rate.

Reproducing this observed positive trend in cloud radiation feedback in the tropics to the GCM ensemble is troublesome. AR4 GCMs project a general negative trend in this feedback throughout most time scales, offering little agreement with ISCCP observational data. GCMs that produce a positive CA-SST relationship in the time series are CC63, CCCM, CCSM, GFDL 2.0, GFDL 2.1, GISA, IAPC, INGV, MIUB, MPIC, and PCM1. The IAPC and INGV produce positive linear regressions throughout the time series similar to the observations. The difficulties faced by GCMs to appropriately handle atmospheric moisture are reinforced by this tendency. Several key points become evident when analyzing the ensemble. First, analysis from the spatial properties of CA appeared to underestimate the amount of low-level clouds in a majority of the GCMs. If such a trend is justified, the feedback signal should be increased to levels consistent with the observational data. The weakened or negative nature of the CA-SST relationship may indicate cloud schemes with increased concentrations of low-level clouds consistent with prescribed relationship orientation. General weakened CA-SST relationships are observed in the CCCM, CCSM, CSIR, GFDL 2.0, GISR, INGV, and IPSL. Since these relationships are predominately negative, such as the CCCM, CCSM, CSIR, GISR, and IPSL, resolving the correct sign of the feedback is more critical at this juncture.

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Second, while the difficulties in producing the correct relationship sign are abundantly clear, the annual period is generally large enough to be consistent with the ISCCP data. Negative relationships produced by the CC63, CNRM, GFDL 2.1, INMC, MIRH, MIRM, MIUB, MRIC, UKCM, and UKGM are closely related to the observational data in magnitude, indicating the representation of the CA impacts is adequate. Accurate representation of the feedback sign is questionable, but the comparable magnitude of modeled linear regressions and observational values suggest success in resolving the strength of the tropical CA-SST relationship. The amount of statistical significance within the GCM ensemble, however, is extraordinarily high suggesting the GCM tendency to overestimate the robustness of the data. The strength of the regressions induced by the relationship between CA and SST are doubtful, compared to the abundance of significance in the GCMs when compared to ISCCP data.

Third, although the general trend is negative in GCMs, the signal in several appears suppressed, suggesting uncertainty within the model of whether to produce a positive or negative feedback tendency. Suppressed nature of feedbacks constitutes a maximum value of less than approximately 2%, which is found in CCCM, CCSM, CSIR, GFDL 2.0, GISA, GISR, INGV, IPSL, MPIC, and PCM1. These identified GCMs may produce a mix of cloud types of both low-level and high-level clouds, allowing for a near-neutral state in feedback structure.

Observational shortwave cloud radiative forcing (SCRF) values indicate a positive correlation when paired with increasing SSTs during the time series. Enhanced SSTs foster an unstable atmosphere conducive for vertical development from surface
based convection in addition to low-level convergence in association with general atmospheric circulation of the tropics. Towering cumulus and cumulonimbus generated by atmospheric uplift possess a high albedo due to abundant liquid water content but limited zonally allowing for additional incoming shortwave radiation to penetrate the cloud deck and reach the surface. In addition, the erosion of low-level clouds that rely on a stable lower troposphere would decrease the tropical albedo, as the comparatively dark ocean or land surface is exposed, absorbing shortwave energy and creating an enhanced greenhouse effect. Analysis of SCRF can provide information of preferred cloud types in GCMs, as increased SCRF indicates the capturing of shortwave energy in the greenhouse effect by high cirrus clouds and deep convection. GCMs that produce a positive bias in SCRF likely generate convective cloud schemes and enhanced greenhouse effect, ultimately projecting warming in the climate.

The annual period displays the strongest relationship of SCRF and increasing SSTs (Figs. 52-54) coinciding with the maximum in linear regression values of the net radiation of an approximate +8.0 W/m² flux over a 1°C SST increase. Statistical significance is achieved during the annual as well, indicating a robust relationship. Furthermore, the phase correlation suggests that SCRF and SST are in phase during the annual. With this robust relationship in phase variables, the annual period likely influences the SCRF-SST feedback strongly. The positive relationships produced during the biennial and seasonal have limited significance but only during the seasonal. Despite a significant relationship in the seasonal, the magnitude of the biennial period is slightly greater by approximately approximate +1.0 W/m². With a non-significant, yet relatively large, biennial SCRF-SST feedback, impacts from coupled oscillations such
Fig. 52 Cross-spectrum analyses between tropical SCRF and SST with (a) ERBE observational and AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM (unavailable), (e) CNRM, (f) CSI2 (unavailable), (g) CSIR, and (h) GFDL 2.0.
Fig. 53 Same as Fig. 52 but with GCMs (a) GFDL 2.1, (b) GISA (unavailable), (c) GISH, (d) GISR, (e) IAPC, (f) INGV (unavailable), (g) INMC, and (h) IPSL.
Fig. 54 Same as Fig. 52 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
as ENSO and MJO possibly manifest during this temporal period. While ENSO is generally classified as an interannual oscillation, extension into the biennial is plausible. Brief significance occurs during the transition between interannual and biennial but given the limited exposure of ERBE and the lack of interannual analysis, establishing residence of significance is ambiguous. The seasonal SST-SCRF relationship produces statistical significance but, like the biennial, is brief. However, the level of significance is comparable to the sustained significance of the annual, suggesting a seasonal component to the relationship. Seasonality of SCRF appears to factor in regulation of cloud and radiation variations in GCMs but the exact magnitude of each component remains unclear.

GCMs commonly lack clarity in emulating the observational relationship between SCRF and SST, yet the ensemble does reproduce several key features. First, a positive relationship emerges, indicating the interactions between SCRF and SST are resolved in a realistic, observationally consistent manner. GCMs that show this widespread consensus (CC63, CCCM, CNRM, GFDL 2.0, GFDL 2.1, GISH, INMC, IPSL, MIRH, MIRM, MPIC, MRIC, UKCM, and UKGM) of a positive relationship are encouraging to efforts to remedy this source of bias in shortwave energy, but the agreement is not absolute. Second, annual statistical significance and regression magnitude are consistent with observational values. Tendencies for GCMs to produce a strong annual relationship are reinforced by observations in the ERBE data suggesting the likelihood of enhancement during this period is high. Strong linear regression relationships are gathered from the CC63, CNRM, GFDL 2.0, GFDL 2.1, INMC, IPSL, and UKCM. Statistical significance is achieved during this period, indicating the robust relationship
between SCRF and SST. Third, the seasonality depicted in observations is supported by the ensemble. Strong seasonal SCRF-SST relationships are evident yet slightly overdone in terms of magnitude. Certain GCMs, such as the CCCM, MIRH, MIRM, MIUB, MPIC, and MRIC, generate regressions more intense than the annual feedback indicated by observations and the general ensemble. Emphasis on the seasonality of SCRF with increasing SSTs remains an elusive issue when assessing the magnitude of the cloud-radiation feedback of the tropics.

With the numerous successes noted in SCRF, shortcomings within the AR4 GCMs emerge. The overestimation of the SST – SCRF relationship poses a common hindrance of shortwave radiation, notably during biennial and seasonal time scales. Biennial enhancement is depicted in the CC63, CCCM, CNRM, GFDL 2.0, GFDL 2.1, INMC, IPSL, MIRH, MIRM, and UKCM. The more frequent occurring seasonal enhancement of SCRF-SST relationship manifests in the CC63, CCCM, CNRM, GFDL 2.0, GFDL 2.1, INMC, IPSL, MIRH, MIRM, MIUB, MPIC, MRIC, UKCM, and UKGM. Higher incidence rates during the seasonal suggest that seasonality of GCMs is an important factor in radiative forcing at TOA. Biases produced during these periods enhance the feedback to a comparable strength of the observational maximum annual. Therefore, GCMs appear to generate scenarios depicting the biennial, annual, and seasonal having comparable magnitudes to observational linear regressions, approximately +5.0 W/m², and increased statistical significance. With these time periods lacking the variation in feedback strength illustrated by ERBE, the likelihood for enhancement of SCRF within coupled GCMs is high, resulting in an accelerated greenhouse effect. Conversely, several GCMs produce negative feedbacks apparent in
the CSIR, GISR, IAPC, MIUB, and PCM1. With the exception of IAPC, a strong reversal in sign occurs as the annual transitions to seasonal. Occurrence of this reversal reinforces the theory of a seasonal component regulating the feedback in the tropics. The strong seasonal reversal and the enhancement of seasonal SCRF-SST relationship from GCMs that yield accurate orientation suggest the volatility and importance of accounting for SCRF on short temporal periods that GCMs have difficulty representing.

Radiation emitted from the planetary surface and cloud tops constitute the longwave cloud radiative forcing (LCRF). Quantifying the amount of longwave energy escaping to space can establish the vulnerability of a GCM to enhanced greenhouse effect, or lack thereof, and cloud classification. Inherent longwave cooling at cloud top and through planetary radiation contribute to this LCRF observed at TOA. As a result of this transference of energy away from the planet, surface cooling is expected, leading to a weakened greenhouse effect and diminished warming in climate simulations. Examination of LCRF can determine prevailing cloud type in the climate system. GCMs yielding increased rates of LCRF develop a low-level cloud scheme conducive for longwave radiational cooling. As GCMs produce higher incidences of LCRF at TOA, CA characterized by stratus and MSc are expected.

Compared with SCRF, the weaker LCRF – SST relationship in cross spectrum analysis (Figs. 55-57) indicates that the contribution to the radiative equilibrium of the tropics lacks robustness. Although the magnitude of the LCRF is abated, the temporal pattern exhibited by the feedback bears similarity to that established in SCRF in linear regression. Annual LCRF-SST relationship yields the strongest component of approximately +2.5 W/m² and is statistically significant. This robust feature is similar
Fig. 55 Cross-spectrum analyses between tropical LCRF and SST with (a) ERBE observational and AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM (unavailable), (e) CNRM, (f) CSI2, (g) CSIR, and (h) GFDL 2.0.
Fig. 56 Same as Fig. 55 but with GCMs (a) GFDL 2.1, (b) GISA (unavailable), (c) GISH, (d) GISR, (e) IAPC, (f) INGV (unavailable), (g) INMC, and (h) IPSL.
Fig. 57 Same as Fig. 55 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
to both SCRF and LCRF, implying the importance of the radiative equilibrium of the tropics during this period. As SCRF and LCRF have strong annual components, it suggests that an annual feature affects both radiative forcings equally. Such a forcing could be from the amount of energy received and radiated by the planet over the course of a year, although cloud variability and persistence of synoptic to global scale systems could alter the energy budget. Secondary maximum in feedback intensity is achieved during the biennial period but lacks statistical significance. The seasonal produces a modest magnitude of the regression compared to the biennial, but is significant. During the time series, increasing LCRF results in enhanced cooling as energy is drawn away from the planet. However, the magnitude observed is weaker than the SCRF signature, indicating the cooling mechanism is insufficient to offset the more energetic SCRF on these temporal intervals. Since observational trends of both radiative forcings offer similarities in terms of pattern of feedback and relative intensity, the origins of this symmetry are likely mutual. The LCRF and SST relationship observed during the annual period may stem from consistency during orbital cycles, resulting in homogenous sun angles and energy. Annual periods are subject to variability on a year to year basis and may be largely impacted by persistent synoptic scale features or changes in moisture availability. Biennial departures remain difficult to address due to the availability of ERBE data or the potential remnant effects of oscillations such as ENSO impacting this period. Despite the uncertainty surrounding the sources of bias, the trend in which enhancement of LCRF is depicted has clarity.

GCM capabilities to reproduce the observed relationship between LCRF and SST are limited, as sign and magnitude differences emerge. Linear regression sign varies
widely in the ensemble as positive and negative regression values are generated. GCM maximum LCRF values range from approximately +3.0 \( \text{W/m}^2 \) (CC63, CNRM, IPSL, PCM1) to -4.0 \( \text{W/m}^2 \) (GISH, GISR, INMC, MIUB), emphasizing the disparity inherent with model output that assesses LCRF behavior in the tropics. Furthermore, the relationship appears vulnerable during the seasonal, as intensities fluctuate sharply, shifting towards more frequent and robust seasonal differences. This occurrence agrees with SCRF representation on the seasonal, adding further credence to the volatility of GCM LCRF representation during the seasonal. While both radiative forcings exhibit enhanced seasonal signals, the tendency of the seasonal relationship to surpass the annual maximum is exclusive to LCRF as evident in CC63, CCCM, CCSM, CNRM, IAPC, IPSL, MPIC, and PCM1. In assessing SCRF, this pattern is less common, suggesting GCM misrepresentation lies primarily with longwave energy rather than shortwave energy. 14 GCMs combined produce a seasonal magnitude greater than the annual and, as such, are subject to differences in longwave energy escaping to space or captured in accordance with the greenhouse effect.

The suppressed magnitude, characterized by the maximum modeled linear regression being lower than the minimum observational linear regression, of the LCRF-SST relationship emerging from the CCCM, CCSM, CSI2, CSIR, GFDL 2.0, GFDL 2.1, MIRH, and UKGM suggests that GCMs are better suited for projecting shortwave energy than longwave energy. Moreover, increasing the energetic shortwave energy in the earth’s climate system would undoubtedly raise global temperature, increasing the likelihood of producing an enhanced greenhouse effect. With decreased amounts of longwave energy reaching the TOA, that energy is likely retained within the
atmosphere contributing to global temperature rises. Examination of long term LCRF reveals a general weakened regression trend, suggesting LCRF is less effectively resolved on long-term temporal scales while impactful on short-term scales. As noted, the seasonal LCRF- SST interaction projected in GCMs displays enhancement over the observational, potentially magnifying short term climate change. As seasons change and the ITCZ migrates, variations in CA and available moisture would act to regulate energy that is either captured by or escapes the atmosphere. Tropical regions associated with wet and dry seasons are potentially the most vulnerable to these described changes, as significant changes in CA can affect the radiative budget, further exacerbating the global climate change issue. Evidence to support the theory of LCRF having a significant short term warming mechanism is substantial, but more extensive in-depth analyses are required.

Seasonal values of modeled LCRF-SST relationships appear subject to a wide range of solutions. With the approximate 7.0 W/m² difference in extreme cases, this range of variability is not observed in the SCRF-SST cross spectrum. Therefore, if LCRF varies significantly during short temporal intervals, the inability for current GCMs to account for LCRF is highlighted. While discrepancies in SCRF-SST relationship magnitude persist, the departures from the observational value, along with the correct sign, were generally reasonable on seasonal periods. This finding reinforces GCMs difficulty accounting for LCRF in climate simulations. Ramifications of this arrangement are noted in cloud composition, as GCMs generating a negative feedback would enhance the natural greenhouse effect and increase high clouds with heat capturing capabilities preventing longwave energy from escaping the atmosphere.
GCMs identified as the CSI2, CSIR, GFDL 2.0, GFDL 2.1, GISH, GISR, INMC, MIRH, MIUB, UKCM, and UKGM illustrate this situation, as negative seasonal LCRF-SST interactions are coupled with negative CA-SST relationships.

Statistical significance during the annual and seasonal reveals the robust nature of the LCRF-SST relationship exclusively on short temporal intervals. GCMs generate statistically significant relationships during extended periods, such as the interannual and decadal characterized within CNRM, CSI2, CSIR, GFDL 2.0, GFDL 2.1, GISH, IAPC, INMC, IPSL, MIRM, MRIC, PCM1, UKCM, and UKGM. Discerning the validity of this modeled feedback is uncertain, as the lack of extensive temporal coverage of ERBE is inadequate to properly perform long term analysis. An intriguing case develops in CC63, CCCM, CCSM, CNRM, INMC, MIRH, MIRM, MIUB, and UKCM as a period of minimal significance during these extended periods is encountered.

Cross spectrum analyses to quantify the relationship between cloud radiative forcing (CRF) and increasing SSTs (Figs. 58-60) yield a general positive feedback in the tropics. As increased insolation strikes the surface, the availability for additional energy to be transferred to the surface is enhanced, translating to increases in surface temperatures. When addressing the CRF, short frequencies in particular are prone to observed enhancement, suggesting the impacts are short-lived and are recurrent. The strongest observational signal manifests during the annual period with statistical significance above the 95% confidence level, with a regression of approximately +6.5 W/m². This amount of increase in energy is critical for atmospheric stability or enhanced energy fluxes. Similar regression signatures are produced during the seasonal
Fig. 58 Cross-spectrum analyses between tropical CRF and SST with (a) ERBE observational and AR4 GCMs (b) CC63, (c) CCCM, (d) CCSM (unavailable), (e) CNRM, (f) CSI2 (unavailable), (g) CSIR, and (h) GFDL 2.0.
Fig. 59 Same as Fig. 58 but with GCMs (a) GFDL 2.1, (b) GiSA (unavailable), (c) GISH, (d) GISR, (e) IAPC, (f) INGV (unavailable), (g) INMC, and (h) IPSL.
Fig. 60 Same as Fig. 58 but with GCMs (a) MIRH, (b) MIRM, (c) MIUB, (d) MPIC, (e) MRIC, (f) PCM1, (g) UKCM, and (h) UKGM.
and biennial scales but with magnitudes of approximately 2.0 and 3.0 W/m², respectively.

Seasonal variations of net radiation flux appear statistically significant, suggesting seasonality affects insolation, possibly contingent on tropical CA which has been noted to incur within a seasonal cycle (Gupta et al., 1993; Bajuk and Leovy, 1998). While trends in the CA and net radiation form mutual consensus, the sources driving this pattern have less certainty. Gupta et al. attributed this relationship to the annual cycle of cloud coverage, cloud height and water vapor content, while Bajuk and Leovy propose seasonal variations from mid-tropospheric heating and convective available potential energy (CAPE). However, Bajuk and Leovy’s theory pertains to the Pacific Ocean basin in terms of governing cumulonimbus convection and lack widespread applicability in the tropics. While the observational CRF favors a strong annual regression, the annual cycle of heating differences from the land-ocean contrast and the moisture availability through evaporative processes and through seasonal variations of cloud coverage, the relationship appears to agree with Gupta et al. rather than changes of seasonal atmospheric stability proposed by Bajuk and Leovy.

GCMs generally overestimate the CRF especially in the biennial and earlier frequencies. This overestimation tendency appears widespread within the ensemble, as CC63, CCCM, CNRM, INMC, IPSL, MIRH, MIRM, MPIC, and UKCM depict an enhanced interaction during the seasonal scale. While the seasonal scale is statistically significant in the observational ERBE data, the regression resolved by the CC63, CCCM, CNRM, IPSL, MIRH, MIRM, and MPIC generate an approximate +8.0 W/m² relationship, four times the observed value. Since CRF is derived from the sum of both
radiative forcings and SCRF produces the more robust response, SCRF appears to be subjugated to a wide variety of atmospheric influences resulting in modeling uncertainty. This source of uncertainty agrees with recent literature (Dessler, 2010) and becomes an inherited source of bias in CRF calculations. The fluctuations in short term magnitude further emphasizes annual and seasonal scale events impacting the cloud-radiation feedback of the tropics suggested by both SCRF and LCRF. The energy bias of that caliber would likely have extensive ramifications in model resolution, spurring the evolution of additional errors in the modeled global climate system.

Despite the overestimation of CRF with respect to increasing SST during the biennial and seasonal, the annual period is surprisingly consistent with the observed approximate +6.0 W/m² value. Consensus is found within 11 GCMs identified as CC63, CCCM, CNRM, GFDL 2.0, INMC, IPSL, MIRH, MIRM, MPIC, MRIC, and UKGM. While several models are comparable to the observationally prescribed strength of feedback, vulnerability to an amplified signal such as GFDL 2.1 and UKCM or diminished state evident in the MIUB are projected. Regression values from the biased 3 GCMs generally depicted an approximate 4.0 W/m² offset, suggesting a somewhat striking symmetric signal in annual interaction of those GCMs with correct sign. With annual representation of CRF and SST adequately portrayed and the presence of large biases produced during biennial and seasonal, the origins behind accurate annual representation and not neighboring temporal intervals is intriguing. Cyclical patterns in radiation during the course of the year are suspected, as solar angles remain consistent on an annual basis and offer a sense of homogeneity. On the other hand, seasonal variations are subject to variability in atmospheric moisture, general
circulation, and synoptic scale features on a year-to-year basis. Atmospheric oscillations ENSO and Madden-Julian Oscillation (MJO) can affect moisture availability for cloud development, thus indirectly regulating the radiative energy in the tropics. However, linking such oscillations to CRF during the biennial may prove difficult. Coupled features, in particular ENSO, often occur less frequently and are associated with interannual events. Given the limitations of observational data from ERBE, assessing the contribution from these oscillations is hindered.

Unfortunately while GCMs have a general tendency to produce positive CRF feedbacks, certain GCMs reverse the sign. Negative linear regressions in the CSIR, GISR, and during the biennial and annual scale of the PCM1 manifest within the ensemble. Based on the consensus of GCMs, the CRF-SST relationship appears misconstrued and consequently prone to likely deficiencies in radiational values. Despite this shortcoming within GCMs, achieving a reasonable quantitative magnitude of the relationship between CRF and SST based off observations can be obtained. The CSIR and GISR generate a biennial and annual relationship consistent to observational data, suggesting the capabilities of assessing the magnitude of the feedback, albeit with opposite sign. On the other hand, the seasonal feedbacks in the two identified GCMs are diminished, potentially refuting the validity of the output. With both SCRF and LCRF components exhibiting robust seasonal signals, this period should be more pronounced. Reversal in regression sign during the annual to seasonal transition found in PCM1 suggests a strong seasonal component, consistent with other GCMs, inducing a switch in regime.
Examination of the individual radiative forcings of CSIR and GISR indicates LCRF is stronger than SCRF on short-term temporal intervals resulting in negative feedback and potential dampening of modeled energy budget. PCM1 produces a large seasonal LCRF regression contributing to the positive seasonal trend in the model. The SCRF-SST relationship is appreciably smaller in magnitude and likely less influential on the seasonality of the interaction. The preceding biennial and annual periods depict the SCRF as the dominate forcing, inferring that a change in radiative forcing occurs between the transition of the annual and seasonal. This described reversal suggests that low-level clouds that cool the planet via longwave radiational cooling may be short-lived and impact climate on a seasonal basis, with more convective anvils and energy capturing clouds in long term climate projected by PCM1.

The tendency of coupled GCMs to increase the magnitude of seasonal CRF-SST regressions in a positive manner and enhance of the short-term relationships in both SCRF and LCRF supports the significance of seasonal variations in radiative forcings as well as an indirect influence from CA. Therefore, it appears plausible that coupled GCMs display an accelerated feedback during the seasonal period, suggesting a heightened sense of modeling volatility within climate projections. Identifying a seasonal component of cloud coverage, particularly low-level clouds, has been discussed previously by KH93 and documented as governed by a complex chain of interactions between the general circulation of the atmosphere and the ocean. Bajuk and Leovy (1998) found deep convective clouds produce a near linear relationship between cloud amount and outgoing longwave radiation (OLR) during the seasonal time. GCMs that exhibit increased LCRF and enhanced tropical CA identified from the
CNRM, IAPC, and PCMI likely result from deep convective cloud scheme described in Bajuk and Leovy. On the other hand, GCMs such as CC63, CCCM, MIRM, and MPIC that depict additional seasonal LCRF resolve cloud minima in the tropics in association with the equatorial cold tongue. Despite the minimum CA in equatorial regions, a general enhanced deep convective scheme is likely especially in areas associated with deep convective anvils such as Indonesia and central Africa.

In conclusion, spatial distribution of CA reinforces several key cloud patterns based on global circulation: diminished CA generally occurs with areas associated with large scale subsidence, CA is minimized over arid regions, and CA is maximized over warm SSTs of Indonesia and dense vegetation such as equatorial rainforests. Development of a Pacific Ocean dipole emerges in the Pacific, with the CCSM and GFDL 2.1 best simulating this feature. The Atlantic basin and subtropical CA are generally represented adequately by 10 GCMs, suggesting the modeling of the Atlantic being realistic. Low-level CA is generally less prevalent in GCM representation, likely favoring more convective cloud schemes. Terrestrial transport of moisture from rainforests and jungles may affect CA, as coastal regions tend to increase CA in GCM output, but discerning from ITCZ deep convection is difficult at the present time. Cross spectrum analysis yield increasing CA over the time series by as much as 5%, consistent with a regionalized study performed by Gordon et al (2000). GCMs struggle to achieve the correct sign and magnitude of the CA-SST relationship by favoring a negative trend, but reach a consensus during the annual period of maximum CA-SST relationship. SCRF produces the strongest relationship with SST during the annual period of approximately +8.0 W/m², with large biennial and seasonal linear regressions.
GCMs typically increase SCRF consistent with observations as well as a strong maximum seasonal relationship, yet the seasonal period yields a strong, significant relationship. LCRF-SST cross spectrum generates a positive maximum relationship during the annual period of approximately +2.5 W/m², but GCMs weaken this relationship. Development of a broad range of values during the seasonal period highlights the poor understanding of cloud variability in the tropics. However, the wide range of modeled relationship values between LCRF and SST suggests GCMs have greater difficulty resolving longwave energy than shortwave energy. Total CRF is characterized by a maximum +6.5 W/m² annual value. GCMs generally overestimate this value by increasing the seasonal relationship to a greater magnitude than the observed annual. GCMs are able to resolve the positive sign of the CRF-SST relationship with regularity. LCRF may act to suppress the signal on short temporal intervals consistent with an increase in low-level clouds and their prescribed radiative properties.
CHAPTER 8: MODEL ASSESSMENT

A summary of the performance of GCMs is provided to assess the overall strengths and weaknesses. Assessing GCM performance is based closely on emulating the observational data in terms of spatial and quantitative measurements and vulnerability of GCMs to climate feedbacks. Classification of GCMs into clusters with similar characters is created to assess which GCMs show accurate representation of the SEP climate system and which require further improvement. The GCMs will be classified into clusters or groups of similar output characteristics in each of the three described climate feedbacks.

Assessment of the cloud-radiative feedback yielded a response that was anticipated: atmospheric moisture and CA are poorly resolved in GCMs. Results of the assessment for cloud cover are presented in Table 5. Many GCM cloud parameterization schemes yield lower CA in the SEP which likely induces an increase in DSW. The described relationship is observed in cluster 1 with CNRM, CSI2, CSIR, GFDL 2.0, GFDL 2.1, GISR, IPSL, MIRH, MIRM, MIUB, MPIC, MRIC, UKCM, and UKGM. The prevalent warm SST bias was generated in the CNRM, GISR, IPSL, and MPIC suggesting the high vulnerability for the cloud-radiative feedback. These four GCMs have a mutual eastward migration of maximum CA toward the South American continent. Continental influences from South American orography and differential
Table 5. GCM assessments on key physical and statistical properties associated with the cloud-radiative feedback in the SEP. Indication of a bias is denoted with Y followed by the magnitude of bias in respective units. Indications on variable relationships to SST are given in terms of the temporal period that corresponds to maximum intensity. Blank grid cells represent an observationally consistent variable or relationship.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>SST bias and strength</th>
<th>CA bias and strength</th>
<th>CA maximum migration</th>
<th>DSW bias maximum placement</th>
<th>CA-DSW spatial relationship</th>
<th>CA-SST relationship</th>
<th>CA-SST maximum feedback</th>
<th>DSW-SST maximum feedback</th>
<th>CA-DSW relationship</th>
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<td>CA↑, DSW ↑</td>
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<td>positive</td>
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<td>Y (20 W/m², ocean)</td>
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<td>CA reverse, DSW same</td>
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<td>Y (-10%) E</td>
<td>Y (20 W/m², coastal)</td>
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<td>both positive</td>
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<tr>
<td>MRC</td>
<td>Y (-20%) E</td>
<td>Y (20 W/m², coastal)</td>
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<tr>
<td>PCM1</td>
<td>Y (2 K) Y (-10%) E</td>
<td>positive</td>
<td>positive</td>
<td>both positive</td>
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<td>UKCM</td>
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<tr>
<td>UKGM</td>
<td>Y (-2 K) Y (-10%) E</td>
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</table>
heating induced by land-sea contrast near the coast likely influences decreasing CA with additional DSW energy enhancing SSTs and further destabilizing the MBL. With the exception of the CNRM producing a near neutral linear regression with a slight positive regression during the seasonal, the GISR, IPSL, and MPIC possess a positive CA-SST relationship indicating increasing SSTs and the resulting increase of CA, likely in the form of medium to high-level clouds. Increased DSW along with elevated CA was resolved in IPSL after horizontal analysis yielded similar results. A similar relationship was determined to be present in the MPIC after the cross spectrum analysis. The GISR yielded positive relationships after each analysis raising the confidence of a cloud-radiative feedback. Enhanced SST and DSW suggest the energy balance in the GISR, IPSL, MPIC are likely disrupted, triggering this feedback with increase in CA attributed to the transition to an elevated cloud scheme capable of enhancing the greenhouse effect. The CNRM case offers a weakened cloud-radiative feedback, as analytical evidence suggests CNRM is vulnerable yet the cross spectrum analysis tempers such confidence. CA transitions to a positive regime during the seasonal; DSW remains constant during this period. Furthermore, the DSW magnitude is insufficient in strength to warrant consideration for a strong feedback. The dynamics within the cloud-radiative feedback appear lacking, but the thermal properties (i.e., warm SSTs) suggest a possible weakened cloud-radiative feedback.

GCMs with the prevalent warm SST bias, including the GISH, IAPC, INMC, and PCM1, are grouped together as similar properties are apparent in cluster 2. In addition to the warm SST bias, decreased CA by approximately 20% in most of these GCMs is represented. The exceptions to this would be the INMC, yielding a positive 10% bias,
and the PCM1 with a minimal 10% less CA bias. Prevailing tendencies for CA maximum were migration toward the east (GISH, IAPC, and PCM1) in addition to a positive relationship between CA and DSW. Similar to Cluster 1, overestimation of DSW and decreased CA suggests disruption in the SEP energy budget conducive to enhanced warming. Therefore, the GISH, IAPC, and PCM1 are classified as generating a “moderate” cloud-radiative feedback.

The Canadian CC63 and CCCM constitute cluster 3 and appear to resolve the cloud-radiative feedback remarkably well. Northwest migration of maximum CA occurs, but CA magnitude remains consistent with ISCCP observations. Moreover, the prevalent warm SST bias is absent from the GCMs. Based on cross spectrum analysis, CA increases with warming SST, indicating a positive relationship between the CA and SST variables. The CC63 and CCCM undergo a reversal in linear regression sign in the transition to the biennial period during the DSW-SST cross spectrum analysis. This reversal in sign maintains negative orientation on short temporal intervals, suggesting an increase in CA is associated with decreasing DSW, which describe the condition devoid of the cloud-radiative feedback. Despite positive DSW biases near the continent and northwest displacement of maximum CA, the CC63 and CCCM appear to represent this cloud-radiative feedback sufficiently compared with other clusters. These GCMs are described as producing “weak” feedbacks.

Cluster 4 contains the GISA and INGV models and yields a “conditional” cloud-radiative feedback. Minimal CA near the climatological source region of MSc resolved in the INGV signifies the potential for a strong feedback but uncertainty arises. Cross spectrum analysis on CA yields a general negative trend in linear regression, with the
exception of the positive interannual transition indicating that SEP low-level CA is increasing. This arrangement is difficult to prove, however, in INGV as DSW data is unavailable. Horizontal analysis yields an appreciable decrease in CA in the tropics, but conclusive evidence to support the presence of a cloud-radiative feedback is not provided. Therefore, the INGV is experiencing a “conditional” feedback that requires further analysis. Assessment of the GISA reveals that while CA is represented spatially adequate, formation of a negative 10% CA bias emerges. The modeled SEP energy balance appears disrupted, as CA and DSW increase in tandem. Cross spectrum analysis reveals strong negative regression trend in CA, suggesting an environment conducive to low-level cloud development. A positive DSW feedback in the SEP questions this finding after cross spectrum analysis is performed. As increasing low-level CA and positive DSW relationship appear incompatible, this result is somewhat surprising. Other Goddard GCMs were classified as possessing strong feedbacks. The evidence supporting GISA cloud-radiative feedback classification is not prominent, given the strong negative CA-SST cross spectrum analysis. Therefore, classification to “conditional” feedback is appropriate. The INMC appears similar to the CNRM in Cluster 1 as a cloud-radiative feedback reversal in regression occurs, but the suppressed nature of positive DSW-SST regression likely indicates a weakened cloud-radiative feedback as the energy is insufficient for the onset of a strong feedback.

Cluster 5 is comprised of Australian (CSI2 and CSIR) and American (GFDL 2.0 and GFDL 2.1) GCMs, as migration of CA maximum to the NW transpires and decrease CA maximum by 10-20%. DSW maximum intrudes on the South American coastline with an approximate +20.0 W/m² bias. Reduction in CA along with a positive
DSW bias signifies the vulnerability of the CSI2, CSIR, GFDL 2.0, and GFDL 2.1 to cloud-radiative feedback in the SEP. Similarities to Cluster 1 emerge after the cross-spectrum analysis results in positive CA-SST relationships, implying low-level CA dissipation with increasing SST in addition to a positive DSW flux of approximately +5-10 W/m² bias. The differences between Cluster 5 and Cluster 1 are the direction of maximum CA migration, in addition to absence of the prevalent warm SST bias. The components of the cloud-radiative feedback are evident with a decrease in CA, increase in DSW, and a misrepresentation of the energy relationship between low-level cloud and shortwave energy. Absence of enhanced SSTs, however, challenges the described feedback criteria, leading to debate whether a feedback actually manifests. The question is raised: Can a climate feedback without SST enhancement emerge and maintain the feedback loop? Enhanced SSTs are indicative of atmosphere and ocean based climate feedbacks, but dynamical structure of the feedback is apparent. With the critical SST element lacking from the SEP in these models and absence of a triggering mechanism, the answer appears to be no. However, this issue demands further study before a conclusive answer can be provided. The CSI2, CSIR, GFDL 2.0, and GFDL 2.1 are classified as “inconclusive” cloud-radiative feedbacks.

MIRH, MIRM, MIUB, MRIC, and UKCM compose cluster 6, as they possess mutual thermal, spatial, and radiative properties. The prevalent warm SST bias does not manifest; therefore, enhancement of SSTs is not projected. CA maximum migrates to the east and, like similar eastward propagating GCMs, increasing DSW and decreasing CA are shown. DSW maximum largely remain a coastal feature with the exception of MIRH that expands enhanced DSW to the open ocean. CA maximum
generally decreases approximately 20% in most Cluster 6 GCMs, with diminished effect in the UKCM with a minimal 10% decrease. Cross spectrum analysis yields a reversal in CA-SST regression sign in the MIRH, MIRM, and UKCM, as the positive transition to interannual occurs with the more frequent UKCM during the biennial period. Regression reversal is unrealized in the MIUB or MRIC, but a regression reversal is depicted in the MIUB DSW-SST relationship. Reversals in CA appear to have minimal effect on cloud radiative feedback representation, as DSW remains positive with the exception of MIUB. Therefore, increased DSW is indicated to be somewhat inconsequential to CA in GCM simulations. The absence of enhanced SSTs in an environment with decreasing CA and increasing DSW suggest that the cloud-radiative feedback is minimal in these GCMs. The MIRH, MIRM, MIUB, MRIC, and UKCM are deemed “nominal” cloud-radiative feedback models.

Cluster 7 contains the CCSM and UKGM GCMs. These GCMs depict minimal influence of a cloud radiative feedback. SSTs are observationally consistent or, in the case of UKGM, cooler than observations. Migration of CA eastward occurs in UKGM, but it splits to form a dipole in CCSM. Decrease in CA is minimal, as a 10% bias emerges from these models. Positive +20 W/m² DSW bias remains a coastal feature in the UKCM. The ramifications of increased DSW may be offset by the cooler SSTs in the UKCM. The CCSM does not resolve any energy bias in the SEP, indicating good representation of the radiative budget. With limited biases affecting the CCSM (separation of CA maximum) and UKGM (coastal DSW bias) in addition to a mutual 10% decrease in CA, these GCMs are identified as “best” in resolving the cloud-radiative feedback with respect to the AR4 ensemble.
Assessing the SST-upwelling feedback involving SLP, VAS, and TAUV reveals that while SLP is generally represented well in GCMs, VAS and TAUV are depicted with less accuracy. The main source of error in representation of the SST-upwelling feedback appears to be weakened VAS evident from horizontal and cross spectrum analysis. Since VAS can vary over a region with domain size of the SEP, representation of atmospheric circulation constitutes a significant component in the construction of GCMs devoid of this SST-upwelling feedback. Table 6 provides the results of the SST-upwelling assessment.

Strong negative VAS values characterize cluster 1 of the GCMs CNRM, MIUB, and MRIC. In addition to underestimation of VAS, the CNRM projects the prevalent warm SST bias. Subtropical high strength is consistent with observational data with the lone exception of MIUB, which decreases SLP. The weakness of these 3 GCMs appears to be the lack of confidence in generating a VAS consensus. A reversal in VAS-SST linear regression sign emerges, as a positive to negative regime shift occurs in the CNRM and MIUB during the decadal to interannual transition. The MRIC switches orientation and accelerates to the interannual and biennial transition. VAS appears to weaken in Cluster 1 based on cross spectrum analysis. Similar trends emerge in the TAUV-SST relationship, as a positive to negative reversal in linear regression orientation occurs during the interannual to biennial in the CNRM while lagging in the MIUB to the decadal and interannual transition. GCM depiction of VAS and TAUV appears widely scattered, resulting in questionable strength of the wind transport mechanism. With weakened VAS and warm SST bias emerging in Cluster 1,
### Table 6. GCM assessments on key physical and statistical properties associated with the SST-upwelling feedback in the SEP. Indication of a bias is denoted with Y followed by the magnitude of bias in respective units. Indications on variable relationships to SST are given in terms of the temporal period that corresponds to maximum intensity. Additional information on whether a reversal or opposite in the regression trend is provided. Blank grid cells represent an observationally consistent variable or relationship.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>SST bias and strength</th>
<th>SLP location bias</th>
<th>SLP magnitude bias</th>
<th>VAS magnitude bias</th>
<th>TAUV magnitude bias</th>
<th>SLP-SST maximum feedback</th>
<th>VAS-SST maximum feedback</th>
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<td>Y (west)</td>
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<td>Y (west)</td>
<td>Y (-2.0 m/s)</td>
<td></td>
<td></td>
<td></td>
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</tr>
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</table>
the SST-upwelling feedback appears involved in these GCMs and classification as “strong” feedbacks is appropriate.

Cluster 2 is composed of GCMs (INGV, MPIC, and PCM1) primarily prone to the prevalent warm SST bias along with an observationally consistent VAS. Despite the observational consistent VAS values, TAUUV displays a positive bias in the SEP. TAUUV-SST relationships appear strongest during the interannual in the PCM1 but the INGV and MPIC are consistent with observations. The subtropical high strength remains generally consistent with NCEP reanalysis data with the exception of PCM1, which weakens SLP. Variations of subtropical high influence may act to broaden westward as shown in the MPIC, but remain relatively stationary in INGV and PCM1. With the SLP generally consistent and VAS agreeing with observations, the likelihood of positive TAUUV values illustrated in the horizontal plots of INGV, MPIC, and PCM1 compensating for warm SSTs appears high. With enhanced SSTs in the SEP and the insufficient VAS to transport water westward, the oceanic-upwelling feedback is likely present. TAUUV acts to push ocean water, but without the complimentary VAS, TAUUV solely acting as the transport mechanism seems unlikely. Therefore, these GCMs are classified as “moderate” feedback.

The GCMs identified as CC63, CCCM, CCSM, GISA, GISH, GISR, INMC, IPSL, and MIRH compose the largest group of similar SST-upwelling feedback in cluster 3. While approximately half these GCMs (GISA, GISH, GISR, INMC, and IPSL) have the prevalent warm SST bias, VAS is somewhat consistent with observational SLP, data but anomalies persist. GCMs of Cluster 3 are closely related to the observation, with the exception of two strengthened subtropical highs (INMC and
MIRH) and one weakened subtropical high (GISR). A domain of VAS values are obtained ranging from +1.0 m/s VAS anomalies (CCCM and INMC), consistent VAS (CC63, CCSM, GISA, and MIRH), -1.0 m/s VAS anomalies (GISR), -2.0 m/s VAS anomalies (IPSL), and -3.0/s VAS anomalies (GISH). With GISH SLP being 8 mb weaker, a decreased wind maximum of that magnitude appears unlikely; therefore, GISH is determined to behave similar to a statistical outlier in this assessment. With CCCM and INMC producing overestimated VAS values and several GCMs with consistent to near consistent VAS values, wind transport of the cool SST pool seems plausible. TAUV exhibits increased magnitude in the horizontal plots of CCCM, CCSM, GISA, GISR, IPSL, and MIRM, suggesting that TAUV acts as a strong transportation mechanism of surface ocean water. Temporal properties are remarkably consistent in Cluster 3, with maximum linear regression values unanimously agreeing on the decadal period for SLP-SST relationship, 3 GCMs for decadal frequency of VAS-SST (CC63, GISA, and IPSL), and 6 GCMs for decadal maximum of TAUV-SST (CC63, CCSM, GISA, GISR, IPSL, and MIRH). Wind transport of warm SSTs appears likely, allowing cool upwelled water to reach the surface. However, the diminished number of GCMs with prevalent warm SST bias suggests this arrangement may pertain only to half of Cluster 3. The support of the strong wind variables alleviates most worries involved, possibly enough to prevent this SST-upwelling feedback from developing. These GCMs are deemed to be “weak” at representing the SST-upwelling feedback.

Cluster 4 constitutes the GCMs GFDL 2.0, IAPC, MIRM, UKCM, and UKGM. Shared properties include minimal SST bias, a weakened VAS, and a decadal maximum
feedback in the VAS-SST relationship. The prevalent warm SST bias is confined solely to the IAPC, with the UKGM providing a cool SST bias. SLP is generally consistent with observations, with the exceptions of a strengthened high (UKGM) and a weakened high (GFDL 2.0) by 2.0 mb. VAS values are underestimated by GCMs as –1.0 m/s anomalies are generated by GFDL 2.0, IAPC, and MIRM while the British models of UKCM and UKGM produce weaker anomalies of –2.0 m/s. Agreement on a maximum VAS-SST feedback temporal scale is attained during the decadal period. The GFDL 2.0, IAPC, MIRM, and UKGM illustrate this agreement, while the UKCM resolves lags more frequently during the annual period for maximum VAS-SST feedback. As there are few warm SST biases, the likelihood of the SST-upwelling feedback permeating these GCMs appears unlikely. Additionally, weakened VAS anomalies are relatively close to NCEP reanalysis data, indicating a minimal effect on SST-upwelling feedback. The group consensus on periodicity is rather remarkable, as decadal feedback of VAS-SST prevails. Elevated TAUV values are isolated to the UKCM, suggesting that TAUV is fairly consistent with observational values in Cluster 4. Development of SST-upwelling feedback appears unlikely so classification of “unlikely” is designated to these 5 GCMs.

Cluster 5 consists of CSI2, CSIR and GFDL 2.1 as these GCMs appear to resolve the SST-upwelling feedback well. No prevalent warm SST bias affects SST representation of the SEP. SLP is broadened to the west in the CSI2, but consensus is reached with SLP strength and VAS properties. The Australian GCMs increase SEP TAUV values implying additional force on the ocean surface. VAS-SST linear regression experiences a reversal in orientation during the interannual to biennial
progression in the GFDL 2.1, but the CSI2 is consistent with observations. CSIR cross spectrum VAS-SST data is unavailable, but possibly bears similarities to the CSI2. CSI2 maximum VAS-SST relationship occurs during the interannual period consistent with observations, although the GFDL 2.1 resolves more frequent occurrence as the annual period projects greatest linear regression magnitude. Despite these differences in wind parameters, there is general consensus in magnitude with observational values. Furthermore, without the warm SST bias coupled with consistent VAS values, the CSI2, CSIR, and GFDL 2.1 constitute the “best” GCMs at mitigating the SST-upwelling feedback.

Few components to the LHTF-SST feedback suggest diagnosing feedback can be produced swiftly and effectively. In this assessment, emphasis is given on the magnitude of LHTF maximum and minimum values as well as the presence of the prevalent warm SST bias. Results from this analysis are presented in Table 7. Consideration to VAS properties are provided, but assessment of LHTF-SST feedback depends largely on the LHTF modeled in the SEP.

Cluster 1 exclusively caters to GCMs that produce a +20 W/m² bias in maximum LHTF. The GISA, GISH, IAPC, IPSL, INMC, and MIUB are included in this collection, as maximum LHTF flux within SEP horizontal plots is increased. High prevalence of warm SSTs reveal biases in this cluster, as GISA, GSIH, GISR, INMC, and IPSL indicate widespread enhanced SSTs. GCM consensus dictates weakened LHTF-SST relationships as all GCMs display this trend. The GISH negative linear regression values suggest that increasing SST promotes decreasing LHTF, an unlikely scenario. Weakened states are evident during the short-term intervals, as illustrated by
IAPC and MIUB. Temporal properties indicate a tendency of maximum LHTF-SST relationship to occur during the decadal as in the GISH (although negative), INMC, and MIUB, or the interannual, as displayed by GISA, IAPC, and IPSL cross spectrum.

Given high instances of warm SSTs and increased LHF values, these GCMs likely are subject to “very strong” LHTF-SST feedbacks.

CC63, CCCM, GISR, MIRH, and PCM1 comprise cluster 2 and are characterized by a +40 W/m² bias in maximum LHTF. Enhanced SSTs prevail in GISR and PCM1, indicating the vulnerability to the LHTF-SST feedback. GCMs yield weakened LHTF-SST relationships compared with observations with GISR, producing a negative oriented trend in linear regressions. Consensus on Cluster 2 temporal properties is
scattered. Decadal periods are stressed by CC63, GISR, and PCM1, while the interannual and seasonal periods are emphasized in the MIRH and CCCM, respectively. The vulnerability to LH-SST feedbacks appears high based on the strong positive LHF anomalies and presence of warm SST. As a result, LHTF-SST feedback prevalence in these GCMs is “strong”.

GCMs that yield a decrease in LHTF minimum or generate a maximum LHTF bias constitute cluster 3. These GCMs include the CCSM, CNRM, GFDL 2.0, INGV, MPIC, UKCM, and UKGM. The exception to this case is CNRM, which fails to yield a decreased minimum LHTF but is classified in Group 1, as mutual radiative properties are observed with MPIC, which decreases the LHTF minimum. In addition to the decreased 20 W/m² LHTF minimum, increased maximum LHTF anomalies are generated. Values of maximum LHTF anomalies range from as +20 W/m² (GFDL 2.0, UKCM, and UKGM), +40 W/m² (CCSM and INGV), to +60 W/m² (CNRM and MPIC) biases. Manifestation of the prevalent warm SST bias is illustrated in the CNRM, INGV, and MPIC, with the UKGM producing the anomalous cool SST. Approximately half of Cluster 3 (CNRM, GFDL 2.0, INGV, and UKCM) generate weakened LHTF-SST relationship, particularly over short temporal intervals as illustrated in CNRM, INGV, and UKCM. All GCMs favor maximum LHTF-SST relationship during the interannual period, as observational values suggest maximum magnitude occurring later during the decadal. With increased maximum LHTF and the decreasing of minimum LHTF, the range of LHTF values increases accordingly. Expansion of this range indicates uncertainty in handling changes in atmospheric moisture and the phase changes associated with this flux. The prevalence of warm SSTs in the cluster add to
the likelihood of the described feedback emerging. Therefore, these GCMs are considered “moderate” LHTF-SST feedback.

Best cases for LHTF-SST feedback compose Cluster 4, which includes CSI2, CSIR, and MRIC. The absence of enhanced SSTs indicates that the LHTF-SST feedback fails to manifest appreciably in these GCMs. Moreover, no maximum LHTF biases are depicted, indicating the range of modeled LHTF values is consistent with the observations. Weakened cases of the LHTF-SST relationship are confined to the Australian models, with CSIR favoring suppressed feedback intensity over the long term temporal intervals. Recurrence of the LHTF-SST is strongest on shorter temporal periods projected during the interannual (CSI2 and CSIR) and biennial (MRIC) displayed in cross-spectrum analyses. With the CSI2, CSIR, and MRIC devoid of warm SST biases or LHTF anomalies, these GCMs serve as the “best” cases for resolving the LHTF-SST feedback.

Examination of the tropics covers a large area of the globe and, with increased area, an increased risk for spatial and quantitative bias is introduced. Analysis of tropical cloud-radiative feedback, similar to the SEP, is conducted in an effort to determine GCMs capable of modeling the critical tropical radiative budget. Information on tropical cloud radiative feedback physical processes is available in Table 8.

Cluster 1 of GCMs yield a reversal in CA-SST regression orientation during the cross spectrum analysis, as the observational CA-SST interaction remains strictly positive. Cluster 1 is categorized by the CC63, CCCM, CCSM, GFDL 2.0, GFDL 2.1, GISA, MPIC, and PCM1. Differences in the temporal transition of feedback
Table 8. Model assessment on key physical and statistical properties associated with the tropical cloud-radiative feedback. Indication of a bias is denoted with Y followed by the magnitude of bias in respective units. Information on the relationship strength is given with respect to observational data. The temporal period producing the maximum feedback magnitude is provided. Blank grid cells represent an observationally consistent variable or relationship.

<table>
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<tr>
<th>Model Name</th>
<th>CA-SST relationship</th>
<th>CA-SST maximum feedback</th>
<th>SCRF-SST relationship</th>
<th>SCRF-SST maximum feedback</th>
<th>LCRF-SST relationship</th>
<th>LCRF-SST maximum feedback</th>
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orientation and direction of transition emerge. Orientation shifts primarily during the transition to the biennial or seasonal period, with biennial favoring shift observed in CCSM, GFDL 2.0, GFDL 2.1, GISA, and PCM1 with no distinct tendency in orientation preference. CCSM, GFDL 2.0, and GFDL 2.1 illustrate a positive to negative regime shift, while the GISA and PCM1 reverse this shift. The seasonal shift occurring in CC63, CCCM, and MPIC is exclusively negative to positive regime. With the exception of GISA, all GCMs are coupled with a reversal in LCRF-SST regression, indicating widespread uncertainty in resolving this energy balance component. SCRF is represented with greater certainty, but the GFDL 2.1 and PCM1 reverse the regression orientation. The total CRF, however, is represented well as reversals in radiative relationships are absent. This cluster is susceptible to differences in LCRF, but appears to resolve the SCRF and CRF adequately. Representation of atmospheric moisture proves to challenge the GCMs, as radiative energy is increased in the tropics, resulting in “strong” tropical cloud-radiative feedbacks.

Cluster 2 yields a negative CA-SST relationship in addition to reversing the CRF-SST relationship. GCMs that behave in this manner are identified as CSIR, GISH, IAPC, MIRH, and MIUB. With negative regression trends in tropical CA-SST suggesting increase in low clouds, a negative trend in radiative forcings with SST are likely. Only the CSIR and IAPC switch from a positive to negative regime during the biennial and annual periods, respectively. The CSIR remains negative after this switch, while the IAPC returns to the original positive state in the seasonal transition. The GISH, MIRH, and MIUB switch from negative to positive regime and retain that orientation for the entirety of the cross spectrum analysis. This reversal manifests in the
biennial transition (GISH and MIUB) or the interannual (MIRH), indicating long
temporal periods are vulnerable to positive CRF-SST relationships while short term
intervals are vulnerable to negative CRF-SST relationships. Furthermore, the CSIR,
MIRH, and MIUB reverse trends in the SCRF and LCRF suggesting that energy
balance components are resolved with uncertainty. The IAPC uncertainty is limited to
the SCRF, while uncertain radiative forcings remain unrealized within the GISH. The
likelihood of a cloud-radiative feedback in the tropics within these models is
“moderate”, as radiative forcing provides a wide range of representations indicating
uncertainty in the impact on the tropical radiative budget.

The CNRM, CSI2, INMC, UKCM, and UKGM compose cluster 3 with
characteristics of a negative CA-SST relationship and a reversal in LCRF-SST
feedback. This LCRF reversal tends to manifest during the interannual transition
period, as illustrated by the CSI2 and INMC positive to negative orientation shift, while
the UKGM produces opposite orientation. CNRM depicts a positive shift during the
biennial period and the UKCM displays a frequent seasonal shift to a negative regime.
Despite the shortcomings in Cluster 3, the SCRF and CRF are resolved with some
adequacy, suggesting LCRF and CA as sources of inaccurate GCMs. The likelihood of
the cloud-radiative feedback afflicting the tropics is “weak” due to biases in LCRF
representation and increased CA.

Two GCMs, GISR and MIRM, produce a negative CA-SST regression trend in
addition to the maximum seasonal SCRF-SST relationship describe cluster 4. Seasonal
variations in SCRF are maximized in both GCMs, although the MIRM displays
maximum feedback intensity of the CA-SST during the seasonal. GISR reverses the
SCRF-SST relationship, as the transition to a positive regime occurs during the seasonal period. The emergence of a “weak” cloud radiative feedback is generated primarily through complications in resolving the SCRF of the tropics.

Cluster 5 comprises INGV and IPSL, with only a negative CA-SST relationship mutual to both GCMs. The CRF-SST feedback is maximized during the seasonal period in the IPSL, suggesting seasonality could be a factor in the tropical cloud-radiative feedback. Unfortunately, SCRF data was unavailable in the INGV rendering that portion of the feedback uncertain. After assessment of limited radiative information, it appears that inaccurate cloud amount is the main source of error in the climate representation based on the CA-SST linear regression orientation. However, more information is necessary to designate a conclusive trend in the INGV and IPSL; therefore, these GCMs are labeled “inconclusive” in regard to the tropical cloud-radiative feedback.

Cluster descriptions with constituent GCMs are provided in Table 9. Assessment of GCMs based on similar characteristics is performed and individual strengths and weaknesses of GCM groups have been discussed. The GISA, GISH, IAPC, IPSL, MPIC, and PCM1 are prone to the SEP cloud-radiative feedback, due to the prevalent warm SST bias coupled with eastward propagation of maximum CA, which causes decreased CA likely from the land-sea contrast. These identified GCMs modeled a positive CA and DSW relationship which indicates potential warming and convective cloud scheme. Three GCMs, the CNRM, MIUB, and MRIC, projected the strongest SEP SST-upwelling feedback in the ensemble. Habitual underestimation of VAS
Table 9. Description and classification of atmospheric and oceanic feedbacks, in terms of similar spatial, temporal, and/or quantitative properties, in both the SEP and tropics in the AR4. The potential vulnerability of the respective feedbacks is given by cluster name. Constituent GCMs of each cluster are provided.

<table>
<thead>
<tr>
<th>SEP Cloud-Radiative Feedback</th>
<th>SEP SST-upwelling Feedback</th>
<th>SEP LHTF-SST Feedback</th>
<th>Tropics Cloud-Radiative Feedback</th>
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</thead>
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<td>GCMs</td>
<td>GCMs</td>
<td>GCMs</td>
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<td>Strong CNRM, MIUB, MRIC</td>
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<td>Weak CC63, CCCM, GISS, GISA, GISH, IPSL, INMC</td>
<td>Moderate CCM, CNRM, GFDL 2.0, INGV, MPIC, UKCM, UKGM</td>
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<td>Nominal GFDL 2.0, IAPC, MIRM, UKCM, UKGM</td>
<td>Best CSI2, CSIR, MRIC</td>
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<td>Best CSI2, CSIR, GFDL 2.1</td>
<td>5 Inconclusive INGV, IPSL</td>
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<td>Nominal MIRH, MIRM, MIUB, MRIC, UKCM</td>
<td>6 Nominal MIRH, MIRM, MIUB, MRIC, UKCM</td>
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<td>Best CCSM, UKGM</td>
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</table>
signifies the difficulty with dispersing the cool water upwelled in the SEP leading to enhanced SSTs. The LHTF-SST feedback was strongly evident in the GISA, GISH, IAPC, IPSL, INMC, and MIUB. Warm SST biases were generated in the SEP indicating widespread misrepresentation of the ocean component of the coupled climate model. Consequently, positive biases in LHTF energy suggest increased evaporation rates and atmospheric moisture in these GCMs. The cloud-radiative feedback in the tropics is poorly resolved in the CC63, CCCM, CCSM, GFDL 2.0, GFDL 2.1, GISA, MPIC, and PCM1. Inability to accurately resolve the LCRF and SCRF components of the CRF indicate the radiative budget of the tropics is prone to bias resulting in increased warming.

Classification of GCMs representing the climate exceptionally with minimal impact from climate feedbacks are identified and briefly discussed. The CCSM and UKGCM resolve the cloud-radiative feedback appropriately from the AR4 ensemble. The absence of the warm SST bias indicates high LTS conducive for MSc development. Minimal cloud loss of 10% was resolved and relatively no migration of CA maximum is observed. SEP SST-upwelling feedback is minimized in CSI2, CSIR, and GFDL 2.1. Observationally consistent SLP and VAS values coupled with no warm SST bias likely indicate minimal vulnerability to this climate feedback. The CSI2, CSIR, and MRIC produce no warm SST anomalies. Furthermore, no positive LHTF biases are generated, indicating the LHTF-SST feedback in the SEP does not manifest in these GCMs. The tropical cloud-radiative feedback may be minimal in the INGV and IPSL. However, with minimal radiative forcing data available, it remains difficult to conclusively label the INGV and IPSL best at resolving this feedback.
GCM improvement is likely to be garnered by improving on several key points that become evident after assessing model performance to atmosphere and ocean interactions and climate feedbacks. Establishing a better understanding to cloud radiative properties is essential. Instances in which cloud amount is not reflected in the radiative balance of the SEP and tropics emerge as this relationship is often mistreated. In some cases, it appears as though cloud amount has minimal impact on the radiative energy received or lost in GCMs resulting in errors in computing the energy balance. This misrepresentation of cloud radiative properties may result in the GCM difficulty resolving the CA-SST relationship in the tropics. Remedying the warm SST bias in GCMs remains a top priority as the sensitivity of clouds to warm SSTs are a source of error. This may stem from the radiative properties of cloud amount being misrepresented in GCMs leading to increased energy for surface absorption.

Improved cloud representation and microphysical parameterization methods are essential to overcoming this obstacle. Sadly, improvement to resolving CA may largely depend on computational power, which has not yet reached the level necessary for adequate analysis. In the event that improved climate representation is delayed, efforts must be made in preventing cloud migration in GCM to regions that are not climatologically conducive to specific cloud types. This point is emphasized by low-level CA placement over the South American continent. The highly orographic nature of the Andes likely dissipates the low-level MSc, as interaction with local climate features and terrain perturb MSc evolution and maintenance.

More accurate wind representation is necessary in future climate models. Negative wind biases present in the SST-upwelling feedback illustrate the need to
understand the global circulation and transfer of energy. This arises with the handling of the land-sea contrast especially in coastal regions where the localized wind patterns, such as the sea breeze, are strong contributors to the distribution of energy and the SST-upwelling feedback. Applications extend farther than mitigation of feedbacks, as improved wind representation can improve GCM performance of atmospheric circulation and better define local features, such as coastal offshore winds that affect the SEP MSc deck.
CHAPTER 9: DISCUSSION AND CONCLUSION

Analysis of MSc and atmospheric and oceanic feedbacks in GCMs has been discussed in great detail regarding the cloud-radiative feedback and the air-sea interactions that govern MSc formation. Accurate representation of clouds in the climate system is necessary in order to understand the potential ramifications of climate change both regionally and globally. This systematic approach to the spatial and temporal properties of atmospheric and oceanic components of coupled climate models has yielded new insight into the field of climate modeling.

The cloud-radiative feedback in the SEP is poorly represented in the ensemble, likely stemming from the inability to resolve the correct relationship between CA and SST. 10 GCMs in the ensemble produce a warm SST bias of 2 K in the SEP. Through this warm SST bias, the destabilization of the MBL and deterioration of MSc are likely. CA maximum tends to relocate in two manners: to the northwest, where stability is maintained, or eastward closer to the South American continent where land-sea contrast and localized coastal phenomenon (i.e., sea breezes) impact cloud amount. Increased DSW is resolved in 13 of the GCMs with eastward propagating CA most vulnerable to the DSW increase. Cross-spectrum analysis illustrates the difficulty resolving the sign of the CA-SST relationship, with 5 GCMs yielding a negative trend, consistent with observational ISCCP, while 12 other GCMs resolve a positive relationship.
Representation of the SST-upwelling feedback in the SEP is poorly resolved. The subtropical high is projected generally well in the AR4 ensemble, but differences in strength emerge as 6 GCMs weaken SLP while 3 GCMs increase SLP. Cross spectrum analysis yields a negative relationship between SLP and SST consistent with LN87. Strong underestimation of VAS indicates wind speed as a source for significant bias, as 11 GCMs weaken VAS in the SEP. Maximum VAS migrated southeastward toward the African Bight, where greater influence from the land-sea contrast manifest. Furthermore, this area is linked to the 294 K SST contour that appears to separate the cold upwelling water from intruding warm equatorial water, creating a sharp SST gradient. Similar to VAS, TAUV is underestimated in the SEP. TAUV contours to the western South American coastline suggesting likely influence of the land-sea contrast. Diminished wind properties imply that transport of cool SSTs through this mechanism is unlikely, leading to the development of the SST-upwelling feedback.

LHTF is overestimated by approximately 20-60 W/m$^2$ in 18 of the GCMs. Additionally 6 GCMs decrease the projected minimum in LHTF in the SEP, indicating that direction of LHTF bias extends both in the positive and negative direction. Increased LHTF is reinforced from cross spectrum analyses, as 14 GCMs produce a positive LHTF-SST trend. However, the relationship is weakened during short temporal intervals, suggesting a decrease in VAS may impact this relationship on the short-term.

The tropical cloud-radiative feedback is represented poorly in the AR4 ensemble. While certain regions associated with maximum CA (e.g., Indonesia, tropical rainforests) and minimum CA (e.g., subtropics, arid regions) are depicted adequately in
the tropics, the general cloud scheme is inadequate. 12 GCMs reverse the observed relationship between CA and SST, while 6 GCMs reverse the relationship during the time series. Preliminary results indicate representation of CA in the Atlantic basin appears spatially and quantitatively better than the Pacific basin, but further detailed analysis is necessary. Biases in radiative forcings emerge in the AR4 ensemble, as difficulty arises in simulating both SRF and LRF. Improvement is required on both components of the CRF in order to alleviate the cloud-radiative feedback in the tropics.

The results from this systematic assessment of the IPCC AR4 GCMs have generated new insight into MSc evolution and important atmospheric and oceanic variables that affect climate feedbacks. The quantitative relationship between SST and atmospheric variables, both spatially and temporally, will provide a powerful tool for climate developers in alleviating warm SST biases and climate feedbacks from coupled GCMs. This dissertation proves to be a significant step in the progression toward improved projections of coupled GCMs.
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### APPENDIX A: ACRONYM LIST

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR4</td>
<td>Intergovernmental Panel on Climate Changes 4th Assessment Report</td>
</tr>
<tr>
<td>ASTEX</td>
<td>Atlantic Stratocumulus Transition Experiment</td>
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<tr>
<td>CA</td>
<td>Cloud amount</td>
</tr>
<tr>
<td>CAPE</td>
<td>Convective available potential energy</td>
</tr>
<tr>
<td>CCN</td>
<td>Cloud condensation nuclei</td>
</tr>
<tr>
<td>CRF</td>
<td>Cloud radiative forcing</td>
</tr>
<tr>
<td>CTEI</td>
<td>Cloud top entrainment index</td>
</tr>
<tr>
<td>DSW</td>
<td>Downwelled shortwave</td>
</tr>
<tr>
<td>EBM</td>
<td>Energy balance model</td>
</tr>
<tr>
<td>ENSO</td>
<td>El Nino Southern Oscillation</td>
</tr>
<tr>
<td>EPIC</td>
<td>Eastern Pacific Investigation of Climate</td>
</tr>
<tr>
<td>ERBE</td>
<td>Earth Radiation Budget Experiment</td>
</tr>
<tr>
<td>FIRE</td>
<td>First ISCCP Regional Experiment</td>
</tr>
<tr>
<td>GCM</td>
<td>Global climate model</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>ISCCP</td>
<td>International Satellite Cloud Climatology Project</td>
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<tr>
<td>ITCZ</td>
<td>Intertropical Convergence Zone</td>
</tr>
<tr>
<td>LCRF</td>
<td>Longwave cloud radiative forcing</td>
</tr>
</tbody>
</table>
LES  Large eddy simulation
LHTF  Latent heat flux
LTS  Lower tropospheric stability
MBL  Marine boundary layer
MJO  Madden-Julian Oscillation
MSc  Marine stratocumulus
NCEP  National Center of Environmental Prediction
OAFlux  Surface Oceanic Analyzed Air-Sea Fluxes
PGF  Pressure gradient force
POC  Pockets of open cells
SCL  Subcloud layer
SCRF  Shortwave cloud radiative forcing
SEP  Southeast Pacific Ocean
SLP  Sea level pressure
SST  Sea surface temperature
TAUV  Meridional wind stress
TOA  Top of atmosphere
UNEP  United Nations Environmental Programme
VAMOS  Variability of the American Monsoon Oscillation System
VAS  Meridional wind at surface
VOCALS-REx  VAMOS Ocean-Cloud-Atmosphere-Land Study – Regional Experiment
WMO  World Meteorological Organization