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Modeling, Understanding and Possible Anthropogenic Changes of Marine Stratocumulus Clouds

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Modeling, Understanding and Possible Anthropogenic Changes of Marine Stratocumulus Clouds

A dissertation submitted in partial satisfaction of the requirements for the degree of Doctor of Philosophy in Atmospheric and Oceanic Sciences

by Alexandre Jousse

2015
ABSTRACT OF THE DISSERTATION

Modeling, Understanding and Possible Anthropogenic Changes of
Marine Stratocumulus Clouds

by
Alexandre Jousse

Doctor of Philosophy in Atmospheric and Oceanic Sciences
University of California, Los Angeles, 2015
Professor Alexander Dean Hall, Chair

Marine Stratocumulus clouds are prevalent over the eastern boundary of the subtropical oceans (e.g. northeast and southeast Pacific). Due to their shortwave properties, these low clouds significantly impact the regional and global climate. However marine stratocumulus clouds are subject to modeling approximations as well as, numerous uncertainties on the factors contributing to their radiative properties, variability and possible future changes. In this dissertation, we present three regional modeling studies that intend to provide some more understanding to these issues. We first analyze the sensitivity of marine stratocumulus to parameterizations in the Weather Research and Forecasting (WRF) model. We use the southeast Pacific as a testbed region and compare the simulated surface energy fluxes to those measured during VOCALS-REx. Our results show that errors in shortwave fluxes are traceable to errors in liquid water path (LWP). Two mechanisms controlling the LWP in our simulations are diagnosed. The first mechanism involves boundary layer and shallow cumulus schemes, which control moisture available for cloud by regulating boundary layer height. The second mechanism involves microphysics schemes, which control LWP through the production of drizzle. This
study demonstrates that when parameterizations are appropriately chosen, the stratocumulus deck and the related surface energy fluxes are reasonably well represented in WRF. In a second study, we take advantage of these advancements to evaluate the importance of aerosol indirect effects on clouds shortwave properties in the northeast Pacific. Satellite retrievals (e.g. MODIS) show that the cloud droplet number concentration is generally high along the U.S. west coast (~300 cm$^{-3}$), while it drops to smaller values further offshore (~50 cm$^{-3}$). Our results highlight the importance of representing accurately this aerosol spatial variability and the associated indirect effects on LWP for realistic shortwave fluxes simulations in the northeast Pacific. Finally, we analyze the marine stratocumulus variability and their possible anthropogenic changes using a suite of dynamically downscaled experiments in the California region. In particular, we develop a methodology that enables a clear identification of the factors contributing to low cloud cover anthropogenic changes. Our results show a systematic reduction in low cloud cover, which is mostly imputable to a reduction of the coupling between boundary layer top and surface. Our analysis suggests that the enhanced decoupling conditions might be at least partially driven by the drying of the free troposphere in comparison to the boundary layer in future climate.
The dissertation of Alexandre Jousse is approved.

Carlos R. Mechoso
David Neelin
Joao Teixeira

Alexander Dean Hall, Committee Chair

University of California, Los Angeles

2015
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Vita

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General Introduction

A stratocumulus is a low cloud made of an ensemble of convective elements that form together a layer. This cloud type is very common over oceans. In fact, stratocumulus clouds cover more than 20% of the ocean surface (e.g. Hahn and Warren 2007). In particular, marine stratocumulus clouds (MSc) are very persistent over the eastern boundaries of the subtropical oceans, where the stability of the lower troposphere favors their formation (e.g. Wood and Bretherton, 2006). Stratocumuli strongly reflect incoming solar radiation, while their low altitude prevents them from having a significant greenhouse effect. Thus, as a result of both their abundance and radiative properties, MSc have a significant negative effect on the Earth’s energy budget (e.g. Hartmann et al., 1992).

Despite their climatic importance, radiative properties in MSc regions are generally poorly simulated in climate models (e.g. Wyant et al., 2010). Inaccurate representations of turbulent and microphysical processes are likely contributing to these errors. In fact, these cloud-controlling processes happen on such small scale that they require parameterizations, which are by definition approximate. The importance of cloud-aerosol interactions is also uncertain. In fact, it is unclear whether their approximate representations are significant contributors to model errors in MSc simulations (e.g. Stevens et al., 2009). Finally, possible misrepresentations in the meteorological conditions that favor MSc may also contribute to the simulated errors. However, at this stage the relative importance of all these potential sources of errors is not clearly established.
Climate models are the only practical way in which experiments on the climate system can be performed. Thus, these models are essential to evaluate the response of MSc to anthropogenic forcings. However, MSc future changes are very uncertain. In fact, global circulation models show both an increase and a decrease of MSc coverage in future climate (Qu et al., 2014). Clarifying the MSc response to anthropogenic forcings is particularly important, since only small changes in MSc coverage are required to produce a radiative effect comparable to those associated with the anthropogenic increase in greenhouse gases (e.g. Randall et al. 1984).

In this dissertation, we intend to provide some new understanding to these scientific questions. We use the Weather Research and Forecasting (WRF) regional model to carry out our analyses. Using this regional model offers multiple advantages. First, numerous parameterizations are available in this model. Thus, it enables a systematic evaluation of the various parameterizations that are currently available. Second, WRF can be run with higher horizontal resolution than the typical global circulation models generally used for climate studies (few km vs. 50-100km). Thus, WRF may be more suited to represent the mesoscale specificities that affect MSc (e.g. Koracin and Dorman, 2001). This model also enables to carry out climate change experiments. Thus, it is a valuable tool to downscale anthropogenic signals on the regional scale.

The purpose of this dissertation is threefold: (1) to evaluate whether WRF can be used to simulate accurately MSc; (2) to evaluate the processes important for realistic MSc simulations. In particular, we aim to assess the importance of aerosol indirect effects; (3) to use an optimized version of WRF to analyze the changes in MSc associated with anthropogenic signals.
To respond to these objectives, we present in this dissertation three regional modeling studies. In the first chapter, we analyze the sensitivity of marine stratocumulus to parameterizations in WRF. In particular, we demonstrate the capability of WRF to simulate marine stratocumulus clouds. In chapter 2, we take advantage of these advancements to evaluate the importance of aerosol indirect effects on clouds shortwave properties in the northeast Pacific. Finally, in chapter 3, we analyze the marine stratocumulus variability and their possible anthropogenic changes using a suite of dynamically downscaled experiments in the California region. Note that the three chapters in this dissertation are written as independent manuscripts. Each chapter contains its own introduction, literature review, description of methodology, presentation of results, discussion, and conclusion. Also note that chapter 1 corresponds to previously published material (Jousse, A., A. Hall, F. Sun, and J. Teixeira, 2015: Causes of WRF surface energy fluxes biases in a stratocumulus region, Climate Dynamics, doi: 10.1007/s00382-015-2599-9), which will be referred as Jousse et al. (2015) in chapters 2 and 3.
1 Causes of WRF Surface Energy Fluxes Biases in a Stratocumulus Region

1.1 Introduction

Climatological conditions over the eastern boundary of the subtropical oceans favor the formation of persistent stratocumulus decks (Klein and Hartmann, 1993). Large-scale subsidence promotes dry and stable conditions in the lower troposphere, and helps maintain a surface anticyclone and associated alongshore equatorward winds. These winds induce coastal upwelling, reducing ocean surface temperature. As a result of these relatively low sea surface temperatures and warm air aloft, the boundary layer is shallow and moist, and is often topped with a layer of stratocumulus (e.g. Garreaud and Munoz, 2005). In return, these low clouds have a significant impact on the global and regional climate, due to their radiative properties. Despite their importance, stratocumulus properties are generally poorly represented in climate models (e.g. Wyant et al, 2010; Nam et al., 2012). The physical processes that drive the stratocumulus dynamics have much smaller length scale than the typical grid spacing of a regional or global model (e.g. boundary layer turbulence and cloud droplet coalescence). To represent these sub-grid scale processes, climate models use parameterizations. Microphysics (MP), boundary layer (BL), and cumulus (CU) schemes are the main parameterizations affecting low cloud dynamics. However, these parameterizations lack by definition an explicit treatment of low cloud dynamics and are often sources of errors in low cloud simulations.

In this study, we evaluate the ability of the Weather Research and Forecasting (WRF) model to simulate stratocumuli. WRF is a community regional scale model that offers an array
of MP, BL and CU schemes. WRF performance in simulating low clouds has already been evaluated in a single column model framework (e.g. Huang et al., 2013). However, only few studies have been dedicated to an inter-comparison of the various schemes in a 3D framework (e.g. Zhang et al., 2011). Moreover, the main focus in these previous studies was on low cloud properties. Here instead, our primary focus is on surface energy fluxes, essential elements of the regional climate system. Stratocumuli affect them in multiple ways (e.g. through their radiative and turbulent properties). The various processes parameterized by MP, BL and CU schemes are all potential contributors to these fluxes. However, we are not aware of any study that quantifies their relative contributions. In this work, we aim to provide that missing information. Our objectives are: 1) to examine WRF performance in representing the various components of the surface energy fluxes in a stratocumulus regime, 2) to attribute errors in surface fluxes to the respective errors in cloud properties and 3), to relate these errors to physical processes. Thus, this work is intended to be relevant to both the model user and the model developer. We aim to inform the model user whether or not WRF can realistically represent the surface fluxes in a stratocumulus region, and provide guidance as to which parameterizations to use. We aim to inform the model developer which physical processes and parameterizations are limiting model performance and to what degree.

The testbed for this investigation is the southeast Pacific in October and November 2008. This region off the coast of Peru and northern Chile is covered with the world’s largest and most persistent stratocumulus deck. A major field campaign, the VAMOS Ocean-Cloud-Atmosphere-Land Regional Experiment (VOCALS-REx; Wood et al., 2010; Mechoso et al. 2014), took place during this study-period. Thus we have access to numerous in-situ measurements for model evaluation purposes. In section 1.2, we present the model set up and
the parameterizations. In section 1.3, we describe the observational data-set and the model evaluation methodology. In section 1.4, we analyze the radiative components of the surface energy fluxes while in section 1.5, we focus on sensible and latent heat fluxes. In section 1.6, we focus on the net effect and we diagnose the most important mechanisms contributing to the simulated spread. Finally, in the last two sections we conclude and discuss our main findings.

1.2 Model setup

In this study, we use WRF model version 3.3.1 (Skamarock et al., 2008). Our model domain covers the tropical and subtropical southeast Pacific and a portion of the South American continent with two nested domains. The outer and inner domains have horizontal resolution of 45 and 15 km, respectively. In this paper, we only present results from the innermost domain, shown in Fig. 1.1. (The results for the outer-most domain are quantitatively consistent with those for innermost domain.) There are 43 sigma-levels in the vertical, with enhanced resolution near the lower boundary (30 sigma-levels below 700 hPa). The model is initialized on 2 October 2008, and run continuously for 60 days. The initial and lateral boundary conditions for the WRF model simulations are derived from the National Centers for Environmental Prediction’s final analysis field (FNL) at 1° × 1° horizontal resolution every 6 hours. The sea surface temperature prescribed at the lower boundary is provided by continuous daily-varying optimum interpolation sea surface temperature analysis (Reynolds and Smith, 1994). The model output is stored every 3 hours. To ensure smooth solutions, the domain grid cells closer than 5 cells from the boundary are relaxed towards the FNL solution.

WRF provides numerous parameterization options apart from MP, BL and CU schemes. In this study, our choices are: Rapid Radiative Transfer Model (RRTM) longwave
radiation (Mlawer et al., 1997); Dudhia shortwave radiation schemes (Dudhia, 1989); and the NOAH Land Surface Model (Chen and Dudhia, 2001) for land surface processes including vegetation, soil, snowpack and land atmosphere energy, momentum and moisture exchange.

The physical processes governing low cloud dynamics are primarily parameterized in WRF with BL, MP and CU schemes. In this study, we test the sensitivity to these schemes by performing a total of 18 runs. (See Table 1.1 for a list of the tested schemes with references and the appendix 1 for more details.) Three MP (Lin, WSM6, Thompson) and five BL (YSU, ACM2, MYJ, MYNN, QNSE) schemes are cross-tested while using the KF cumulus scheme (no shallow cumulus parameterization). One additional run is performed using the MYNN BL scheme, with the droplet concentration tuned to 100 cm$^{-3}$ instead of 300 cm$^{-3}$ in WSM6. (These two values correspond to the observed range during VOCALS-REx; e.g. Bretherton el al. 2010). To study the effect of a cumulus scheme that includes a shallow cumulus parameterization, we perform two additional experiments with Tiedtke and the BL schemes MYNN and YSU while using WSM6 as the MP scheme. (See Table 1.2 for our matrix of experiments.) The schemes tested use a variety of methodologies and formulations and thus, our suite of experiments can be considered broadly representative of WRF performance.
Boundary Layer (BL) schemes

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>YSU (Y)</td>
<td>The Yonsei University scheme is a first order closure (Hong et al., 2006). YSU explicitly represents non-local mixing and entrainment.</td>
</tr>
<tr>
<td>ACM2 (A)</td>
<td>The Asymmetric Convective Model version 2 is a first order closure (Pleim, 2007). ACM2 has a representation for non-local mixing.</td>
</tr>
<tr>
<td>MYNN (N)</td>
<td>The Mellor Yamada Nakanishi and Niino scheme is turbulent kinetic energy based (Nakanishi and Niino, 2004).</td>
</tr>
<tr>
<td>QNSE (Q)</td>
<td>The Quasi-normal scale elimination scheme is turbulent kinetic energy based (Sukoriansky et al., 2005).</td>
</tr>
</tbody>
</table>

Microphysics (MP) schemes

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lin (•)</td>
<td>The Lin scheme is a single moment 6-class scheme (Lin et al, 1983).</td>
</tr>
<tr>
<td>WSM6 (•)</td>
<td>WSM6 is the WRF Single Moment 6-class scheme (Hong et al., 2003). It has a tunable critical droplet number concentration (set by default to 300 cm$^{-3}$).</td>
</tr>
<tr>
<td>Thompson (•)</td>
<td>Thompson is a double moment scheme (Thompson et al., 2008). It has a tunable critical droplet number concentration (set by default to 100 cm$^{-3}$).</td>
</tr>
</tbody>
</table>

Cumulus (CU) schemes

<table>
<thead>
<tr>
<th>Scheme</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>KF</td>
<td>The Kain and Fritsch scheme only parameterizes deep convection (Kain and Fritsch, 1990).</td>
</tr>
<tr>
<td>Tiedtke (t)</td>
<td>The Tiedtke scheme parameterizes both shallow and deep convective plumes (Zhang et al., 2011).</td>
</tr>
</tbody>
</table>

Table 1.1: List of BL, MP and CU schemes tested in this study. (See appendix 1 for details)

<table>
<thead>
<tr>
<th>ACM2 KF</th>
<th>MYJ KF</th>
<th>MYNN KF</th>
<th>QNSE KF</th>
<th>YSU KF</th>
<th>MYNN Tiedtke</th>
<th>YSU Tiedtke</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lin</td>
<td>A</td>
<td>J</td>
<td>N</td>
<td>Q</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Thompson</td>
<td>A</td>
<td>J</td>
<td>N</td>
<td>Q</td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>$N_c=100$ cm$^{-3}$</td>
<td>WSM6, $N_c=300$ cm$^{-3}$</td>
<td>WSM6, $N_c=100$ cm$^{-3}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1.2: Matrix of experiments with MP schemes on the left and BL and CU schemes on the top.

Note that we did some additional tests using the CU scheme Tiedtke with the shallow cumulus parameterization switched off (i.e. only deep convection on). The results are very similar to those with KF. Thus, the differences between KF and Tiedtke (when the shallow CS
is on) can be attributed to the shallow cumulus parameterization in Tiedtke. To avoid redundant information we will only show the experiments that use Tiedtke with the shallow CU switched on.

Surface heat and moisture fluxes are handled by the surface layer scheme. We use the Monin-Obukhov scheme (Beljaars, 1994) for the runs using the BL schemes YSU, MYNN and ACM2. QNSE and MYJ are not compatible with the Monin-Obukhov scheme so we use instead the QNSE surface layer scheme for QNSE and the Monin-Obukhov Janjic Eta scheme (Janjic, 1994) for MYJ. MYNN is also compatible with the Monin-Obukhov Janjic Eta scheme and the MYNN surface layer scheme, and we did some additional tests using those. However, the effects of these various surface layer schemes on our results are negligible. Therefore, in our analysis differences between simulations will not be attributed to the surface layer schemes.

1.3 Observations and data processing

1.3.1 VOCALS-REx dataset

In this work we use the VOCALS-REx data collected on the Ronald Brown vessel from October 25 to November 29 2008 (N.B., no data are available from November 3 to 10) along the 20°S transect between 86°W and 72°W (de Szoeke et al. 2010). We take advantage of the various surface data (e.g. latent and sensible heat fluxes), vertical profiles (e.g. temperature and specific humidity), as well as cloud related variables (e.g. cloud top height and liquid water path) measured during that campaign to evaluate the model’s performance.
3.2 Remote sensing dataset

We also use cloud cover (CC) and liquid water path (LWP) measured by the Moderate-resolution Imaging Spectrometer (MODIS, Platnick et al., 2003; Platnick and King, 2007). MODIS is deployed on 2 polar-orbiting satellites, Aqua and Terra, which pass over the equator twice a day at 1:30 am/pm and 10:30 am/pm local time, respectively. (LWP data are only available during daytime at 10:30 am and 1:30pm.) MODIS data allow a comparison over the entire southeast Pacific, as MODIS scans cover 90% of this region, on average. In this study, we correct MODIS LWP data according to the adiabatic liquid water profile assumption, as it is the most realistic in the Southeast Pacific (i.e. we multiply MODIS LWP data by 0.83; e.g. Borg and Bennartz, 2007). Our comparison with in situ measurements reveals that MODIS LWP data overestimate in situ measurements in the southeast Pacific by about 15% (not shown; similar results are seen in Painemal and Zuidema, 2011). However, these uncertainties do not affect our conclusions, as the model spread is much greater than observational uncertainties.

1.3.3 Data processing

To ensure the comparison between model data and observations is well posed, we process them both. When compared to MODIS, we select the same phase of the observed diurnal cycle in simulations by linearly interpolating WRF 3-hourly outputs onto the satellite measurements times. When compared to VOCALS-REx measurements, we select the model grid points nearest to the locations measured during this field campaign. VOCALS-REx observations are taken every 10 minutes, and to select the same phase of simulated diurnal cycle, we average the 6 measurements closest in time to each 3-hourly snapshot in the model
output. As CC was greater than 85% during VOCALS-REx, this data set is well suited to evaluate the representation of the stratocumulus regime in WRF. Moreover, for the quantities examined, averages over the nearest grid points measured during VOCALS-REx are well correlated (r>0.9) to averages over the grid cells along the 20°S transect between 86°W and 72°W during October and November 2008. Therefore, the general conclusions we reach are not dependent on the limited sample of measurements.

The resolution mismatch between model and in situ measurements is potentially an issue as we compare 15-km grid cells to point measurements. However, we compare a given model grid cell with the average across 6 point-measurements that sample sub-grid variability, suppressing such biases. We also include error bars that represent observational standard deviations to account for potential biases due to the scale mismatch in the comparison.

There is no CC parameterization in WRF, so we define simulated CC to be 100% if a grid cell has a LWP greater than 5 g m\(^{-2}\). (CC is set to 0 otherwise.) Although simple, this definition is appropriate as 5 g m\(^{-2}\) roughly corresponds to the minimum LWP that satellite instruments can detect (e.g. MODIS). Since it is not well posed to compare CC using this binary definition computed on a 15-km model grid to point measurements, we use MODIS CC as the observational data set. To account for the resolution mismatch between the model and MODIS (15-km vs. 1~5-km), we interpolate MODIS level 2 data (i.e. orbital swath) to the same grid as WRF. Then, to match our definition of CC in the model as well as possible, we set interpolated MODIS 15-km pixels with CC greater than zero as 100% cloudy. We call this variable the upper bound for MODIS 15-km CC. We also define a lower bound for MODIS 15-km CC. In this case, only the MODIS 15-km pixels with CC greater than 50% are defined as
100% cloudy, while others are set as non-cloudy. Simulated CC is considered realistic if it falls within these two extremes.

In this study, we use two distinct variables for LWP: (1) the cloud LWP ($LWP_{cld}$) corresponding to the average LWP over grid cells or point measurements considered cloudy (i.e. those with $LWP>5g \text{m}^{-2}$), and (2) the total LWP ($LWP_{tot}$), which does not discriminate between cloudy and non-cloudy grid cells. This distinction allows to differentiate contributions due to the integrated liquid water in clouds from those related to cloud frequency (i.e. cloud cover). However, the resolution mismatch between point measurements and WRF necessarily produces systematic overestimates in measurements of $LWP_{cld}$ on a 15-km grid. We estimate a correction factor of 5% by using MODIS level 2 CC data. This correction factor is relatively small compared to LWP uncertainties already included in our errorbars. Therefore its impact on our analysis is minimal.

For model and observations, grid points with cloud top temperature lower than 270K are set to zero CC to ensure we are examining only low cloud. This is a reasonable threshold for low clouds in the southeast Pacific. Since MODIS cloud top pressures are not accurate for low clouds (Marchand et al., 2010), we use this temperature threshold instead. In any case, higher clouds with cloud top temperature below 270K represent less than 5% of the cloudy events in both model and observations during our study period. Thus, the chosen criteria for low cloud has a negligible impact on our results, no matter how arbitrary it may be.

### 1.3.4 Satellite-based model evaluation

Cloud cover (CC) and liquid water path (LWP) are two natural variables to characterize a cloud field. We show in Fig. 1.1a unprocessed MODIS mean cloud cover (colors) as well as
MODIS mean LWP$_{cld}$ (contours; LWP$_{cld}$ referring to cloudy pixels only; see 1.3.3 for details) during October and November 2008 over the Southeast Pacific. This figure confirms the existence of a stratocumulus deck that covers 80% of the region on average, and peaks about 500km offshore. LWP$_{cld}$ increases away from the coast, in accordance with the observed deepening of the boundary layer (e.g. Rahn and Garreaud, 2010). MODIS unprocessed CC in Fig. 1.1a is very similar to what we define as the lower bound for MODIS 15-km CC (not shown; see 1.3.3 for details on MODIS 15-km CC). In Fig. 1.1b, we show the corresponding upper bound for MODIS 15-km CC. It is much more homogeneous than MODIS unprocessed CC, with values greater than 90% over most of the domain. In the remaining panels of Fig. 1.1, we plot the simulated CC and LWP$_{cld}$ for a representative sample of our simulations. A stratocumulus deck can clearly be identified in all experiments. Overall, the simulated CC falls within the observational range or is slightly lower than the lower bound. Our simulations also capture the offshore increase of LWP$_{cld}$. 
Fig. 1.1: (a) MODIS low cloud cover (shaded, %), and MODIS $LWP_{cld}$ (low cloud events only, contour, g m$^{-2}$); (b) upper bound for MODIS 15-km low CC (%, see text for details); WRF 15-km low cloud cover (shaded, %) and $LWP_{cld}$ (low cloud events only, contour, g m$^{-2}$) using the MP scheme WSM6, the CU scheme KF, and the BL scheme YSU (c), MYJ (d), ACM2 (e), QNSE (f), MYNN (g); (h) As in (g) but using the MP Lin; (i) As in (g) but using the MP Thompson; (j) As in (g) but using WSM6 with a droplet concentration of 100 cm$^{-3}$; (k) As in (g) but using the CU scheme Tiedtke; (k) As in (c) but using the CU scheme Tiedtke. The corresponding data are averaged over October/November 2008. Cloud cover data are averaged between Aqua and Terra overpasses (1:30 am/pm and 10:30 am/pm LT). $LWP_{cld}$ data are averaged between Aqua and Terra daytime overpasses (1:30 pm and 10:30 am LT). Capital letters on the upper right of each figure correspond to the representation used for the respective experiments in the remaining figures of this paper.
1.4 Surface radiation fluxes

We now discuss the relationships between cloud properties and surface radiation fluxes. To discuss the differences across our experiments more quantitatively, we focus on domain averages over the nearest grid cells measured during VOCALS-REx (see 1.3.3 for details).

The scatterplot in Fig. 1.2a illustrates the positive correlation between CC and downward longwave radiation flux at surface (LW; r=0.81). The relationship between CC and LW arises from the fact that CC is the primary means by which clouds influence the greenhouse effect. Observations stand very close to the regression line relating these two variables. This gives confidence that if the model were to simulate the correct CC, it would produce realistic LW. In other words, model errors in LW are probably not attributable to problems with the radiative transfer subroutine.

During VOCALS-REx, the CC range across our experiments is relatively small, between 80% and 90%. The MODIS 15-km lower bound for the corresponding grid points is 88%, so that the model generally slightly underestimates CC, consistent with Fig. 1.1. Fig. 1.2a also shows that BL scheme is the primary control on CC. In fact, the CC range associated with the various MP schemes is less than 3%, while it is more than 10% for the BL schemes. The CU scheme also contributes to the spread in CC. In fact, when the CU scheme Tiedtke is used instead of KF, CC is reduced by about 7% in the test with MYYN. However, this reduction is not systematic as there is no significant change when Tiedtke is combined with YSU. The best results for CC are realized when the CU scheme KF (which has no shallow cumulus parameterization) is combined with MYNN or QNSE. In that case simulated LW (~375 W m$^{-2}$) is within observational error. In the least realistic simulation (with MYJ), the lower observational bound for LW (~373 W m$^{-2}$) is underestimated by about 5 W m$^{-2}$. This is much
smaller than other surface energy biases discussed below. Thus, CC errors may not be that consequential for LW, and our simulations can be considered fairly realistic for this component of the surface energy flux.

Turning to the downward shortwave flux at surface (SW), Fig. 1.2b reveals a strong anti-correlation between SW and the total liquid water path (LWP$_{\text{tot}}$) in the model ($r=$-0.86). This relationship is the result of the fact that LWP$_{\text{tot}}$ controls optical depth in stratocumuli (e.g. Borg and Bennartz, 2007). For VOCALS-REx grid cells, the relationship between SW and the cloud liquid water path (LWP$_{\text{cld}}$) is as strong as the one with LWP$_{\text{tot}}$ ($r=$-0.84; Fig. 1.2c). Apparently CC variations do not contribute strongly to variations in SW. This may be because the simulated spread in CC is relatively small (Fig. 1.2a). To focus on the most important processes for SW, we center our discussion on LWP$_{\text{cld}}$.

As with CC and LW, observations stand very close to the regression line that relates SW and LWP$_{\text{cld}}$ in the simulations. This gives confidence that if the model were to simulate the correct LWP$_{\text{cld}}$, it would produce realistic SW fluxes. As with LW, this also implies model errors in SW are probably not attributable to problems with the radiative transfer subroutine. Simulated LWP$_{\text{cld}}$ generally overestimates observations and as a result, most experiments underestimate SW. The simulated range goes from 160 to 220 W m$^{-2}$ for SW and from 60 to 180 g m$^{-2}$ for LWP, while observations stand close to 218 W m$^{-2}$ (± 15 W m$^{-2}$) and 91 g m$^{-2}$ (± 15 g m$^{-2}$).
Fig. 1.2: (a) Downward surface longwave flux (W m$^{-2}$) as a function of CC; (b) downward surface shortwave flux (W m$^{-2}$) as a function of LWP$_{tot}$ (g m$^{-2}$); (c) downward surface shortwave flux (W m$^{-2}$) as a function of LWP$_{clad}$ (g m$^{-2}$). Data are averaged over grid cells measured during VOCALS-REx from October 25 to November 29 along the 20°S transect. The black diamond corresponds to VOCALS-REx measurements on the Ron Brown vessel (except for CC in panel a, which corresponds to MODIS data). Error bars that account for potential biases due to the comparison methodology are also included (see section 1.3.3). The dashed lines represent the least squares regression between simulated variables.
MP, BL and CU schemes all contribute to the spread in LWP_{cld} and SW. However, the MP contributions are the greatest. Experiments using Thompson and Lin systematically underestimate the observed lower bound for SW by 5 to 45 W m\(^{-2}\) and overestimate the LWP_{cld} upper bound by 20 to 70 g m\(^{-2}\). The biases are reduced to less than 15 W m\(^{-2}\) for SW and 10 g m\(^{-2}\) when WSM6 is used instead. For a given MP scheme, and when the CU scheme is fixed to KF, results are best when the BL scheme MYNN is used. When both MYNN and WSM6 are employed with N_e=300 cm\(^{-3}\), simulated SW and LWP are within the uncertainty range. When the CU scheme KF is replaced by Tiedtke in the tests that use the BL schemes YSU and MYNN with the MP scheme WSM6, LWP_{cld} is reduced by about 25 g m\(^{-2}\) and SW is very close or within the observed uncertainty range. Thus, MP, BL and CU schemes all contribute in multiple ways to SW and LWP_{cld}. The mechanisms that control LWP_{cld} will be analyzed in 1.6.

### 1.5 Sensible and latent heat fluxes

In this section, we focus on sensible heat (SH) and latent heat (LH) fluxes. It turns out that the boundary layer variable most tightly linked to both is BL height. To determine BL height, we follow the same methodology as Rahn and Garreaud (2010b). (Note that average BL height matches cloud top height almost perfectly in both model and observations. Thus, we can use these two terms interchangeably without ambiguity.)

In Figs. 1.3a and 1.3b, we show that SH and LH are significantly correlated to BL height (r=-0.94 and r=0.87, respectively). To diagnose the potential contributors to these relationships, we scatter BL height against average BL liquid potential temperature (⟨Θ⟩; Fig. 1.3c) and average BL total specific humidity (⟨q⟩; Fig. 1.3d). These figures show that
simulations with greater BL heights have systematically greater \(<\Theta_l>\) (r=0.95) and smaller \(<q_i>\) (r=-0.81). Such relationships are consistent with the fact that higher boundary layers entrain warmer and drier air into the BL, which controls \(<\Theta_l>\) and \(<q_i>\) from the BL top. Apparently, this mechanism controls temperature and specific humidity all the way to the surface, as surface air temperature and surface specific humidity exhibit nearly identical relationships with BL height (not shown). In our experiments, SH and LH decrease with surface air temperature (r=-0.94; not shown) and surface specific humidity (r=-0.70; not shown), respectively. (Note that since sea surface temperature is forced in our experiments, it does not contribute to the spread in SH and LH.) Thus, this suggests that BL height likely contributes to SH and LH in our simulations. However, feedback processes are also likely, since SH and LH are potential drivers of the BL deepening. As a result, the relationships exhibited in Figs. 1.3a and 1.3b are most likely the result of interconnections between SH, LH and BL height. Observational values are fairly close to the regression lines that relate simulated BL heights to SH, LH, \(<\Theta_l>\) and \(<q_i>\). Although observational departures from the regression lines are not negligible (see below), this once again gives confidence that if the model were to produce realistic BL height, SH and LH would also be fairly realistic.
Fig. 1.3: (a) Surface sensible heat flux (W m$^{-2}$); (b) surface latent heat flux (W m$^{-2}$); (c) average BL liquid potential temperature (K); and (d) average BL total specific humidity as a function of BL height (m). Data are averaged over grid cells measured during VOCALS-REx from October 25 to November 29 along the 20°S transect. The black diamond corresponds to VOCALS-REx measurements on the Ron Brown vessel. Error bars that account for potential biases due to the comparison methodology are also included (see section 1.3.3). The dashed lines represent the least squares regression between variables.
The average BL height observed during VOCALS-REx is 1380m, while it ranges from 900 to almost 1600m in our simulations. (Note that the observed offshore increase in BL height is well captured in all the simulations; not shown.) BL and CU schemes are the main contributors to the BL height spread across our experiments, although MP contributions are not negligible (±150m for a given BL scheme). When the CU scheme KF is used (i.e. no shallow CU parameterization), the simulated BL is systematically underestimated. The most realistic BL heights are simulated with MYNN. In that case, BL heights are underestimated by less than 150m when combined with WSM6, and by less than 50m when combined with Lin or Thompson. The shallow cumulus parameterization in Tiedtke promotes the deepening of the BL. However, this deepening is too pronounced as BL height is overestimated by more than 150m in our two tests. Thus, none of our simulations matches the observed BL height precisely, though some come close.

As a result of the BL height underestimation for the experiments using the cumulus scheme KF, temperature in the BL is generally colder than observed (between 288 and 289.5K instead of 290.5K; Fig. 1.3c), and SH is often overestimated (between 22 and 9 W m⁻² instead of 2 W m⁻²; Fig. 1.3a). MYNN behaves the best with a cold bias of about 1K and an overestimation of SH by almost 10 W m⁻². When the CU Tiedtke is combined with MYNN, the BL temperature has a warm bias of about 1K and SH is underestimated by almost 10 W m⁻². When Tiedtke is combined with YSU, simulated \( \langle \Theta_i \rangle \) and SH are very close to observations, although BL heights are overestimated by about 150m. Similarly, BL specific humidity is moister than observed when KF is used (between 8.5 and 7.8 g kg⁻¹ instead of 7.7 g kg⁻¹), with MYNN being the closest. When the cumulus scheme Tiedtke is used instead of KF, the BL is too dry, with low biases of 0.2 and 0.4 g kg⁻¹ in the cases of YSU and MYNN, respectively.
For LH, all the simulations that use ACM2, YSU and MYNN (with KF) are within the observed uncertainty range (92±6 W m\(^{-2}\)), while those that use QNSE and MYJ underestimate LH by almost 10 W m\(^{-2}\). LH is overestimated by about 10 W m\(^{-2}\) in the two simulations that use the CU scheme Tiedtke.

None of our experiments perfectly represents both SH and LH. There are also systematic compensations between SH and LH in the model. In fact, their rates of change with BL height have similar amplitudes (~0.03 W m\(^{-2}\) per meter) but opposite signs. As a result, the total cooling contribution to the surface energy budget from LH and SH is nearly constant. It is close to 107 W m\(^{-2}\) in all our simulations (see Fig. 1.4). As the observed upper bound is close to 98 W m\(^{-2}\), the model systematically overestimates the total cooling of the surface from LH and SH by about 10 W m\(^{-2}\). However, there does not appear to be a single physical reason for this.
Fig. 1.4: As in Fig. 1.3, but with the sum of LH and SH on the y-axis (W m$^{-2}$).

1.6 Net surface flux

To underline the implications of cloud biases for surface energy balance, we now focus on the net surface energy flux. We first look at its radiation component in Fig. 1.5a. Downwelling SW and LW both contribute positively to the net radiation surface flux, while the outgoing longwave radiation contributes negatively to it. (Note that we account of a sea surface albedo of 0.05 to compute the net shortwave flux at surface in both model and observations.) As the sea surface temperatures prescribed in our experiments agree well with observed values during the Ron Brown field measurement, the simulated outgoing longwave radiation at the surface matches observations, with an average value of 397 W m$^{-2}$ during VOCALS-REx. The net radiation flux at surface is highly correlated ($r=-0.86$) to LWP$_{cld}$. This is consistent with results shown in Fig. 1.2. Thus SW, primarily controlled by LWP$_{cld}$, dominates the spread in
the radiation component of the energy flux. As with SW and LW, the regression line is within observational uncertainties. This once again gives confidence that if the model were to produce realistic LWP\textsubscript{cld}, it would produce a realistic net surface radiation flux.

Fig. 1.5: (a) Net surface radiation flux (W m\(^{-2}\)), and (b) net surface total energy flux (W m\(^{-2}\)) as a function of LWP\textsubscript{cld} (g m\(^{-2}\)). Data are averaged over grid cells measured during VOCALS-REx from October 25 to November 29 along the 20°S transect. The black diamond corresponds to VOCALS-REx measurements on the Ron Brown vessel. Error bars that account for potential biases due to the comparison methodology are also included (see section 1.3.3). The dashed lines represent the least squares regression between variables.
In Fig. 1.5b, we turn to the net surface energy flux. To compute this flux, latent and sensible heat fluxes are subtracted from the net radiation flux. The relationship between LWP\textsubscript{cld} and the net energy flux (r=−0.86) is very similar to the relationship between LWP\textsubscript{cld} and the net radiation flux. The variations in the net radiation flux seem to control the variations in the net energy flux. As shown in Fig. 1.4, the sum of LH and SH is roughly constant in our experiments. Thus, it does not contribute to the spread of the net surface energy flux. However, the sum of LH and SH is systematically overestimated by about 10 W m\textsuperscript{−2}. This explains why the few simulations with realistic LWP\textsubscript{cld} underestimate the lower bound of the net surface flux by about 10 W m\textsuperscript{−2}. (e.g. in the experiment that combined MYNN, KF and WSM6).

Removing the approximate 10 W m\textsuperscript{−2} bias in the sum of LH and SH still leaves an underestimation of the observed net surface flux (93 ± 15 W m\textsuperscript{−2}) in many of the simulations. This is due to an overestimation of LWP\textsubscript{cld}, and too little incoming solar radiation (Fig. 1.2b). To investigate the reasons for this, we scatter LWP\textsubscript{cld} against average BL specific humidity in Fig. 1.6. This figure shows that for a given MP scheme, LWP\textsubscript{cld} increases at a rate close to 40 g m\textsuperscript{−2} per g kg\textsuperscript{−1} of <q_t> as BL schemes are swapped out. The case of WSM6, where 7 experiments have been carried out, is a good support for the robustness of this relationship (r=0.97). Fig. 1.5b also shows that, for any BL scheme, LWP\textsubscript{cld} changes by roughly a constant value from one MP scheme to another, while <q_t> remains almost unchanged. For example, when Thompson replaces WSM6, LWP\textsubscript{cld} increases by about 40 g m\textsuperscript{−2}. Note that Lin behaves slightly differently as LWP\textsubscript{cld} increases with a greater rate of <q_t> than the other two MP schemes (65 vs. 40 g m\textsuperscript{−2} per g kg\textsuperscript{−1} of <q_t>). Nevertheless, the behavior of Lin remains similar and does not undermine our argumentation.
Fig. 1.6: LWP\(_{\text{cld}}\) (g m\(^{-2}\)) as a function of the average BL total specific humidity \(<q_t>\) (g kg\(^{-1}\)).

The dashed lines represent the least squares regression between variables for a given MP scheme (blue for WSM6, red for Thompson, and black for Lin). Data are averaged over grid cells measured during VOCALS-REx from October 25 to November 29 along the 20°S transect. The black diamond corresponds to VOCALS-REx measurements on the Ron Brown vessel. Error bars that account for potential biases due to the comparison methodology are also included (see section 1.3.3).
The data in Fig. 1.6 indicate that two mechanisms are potentially controlling LWP\textsubscript{cld}. The first involves BL and CU schemes. These schemes determine BL depth and BL specific humidity (see section 1.4). The BL specific humidity, in turn, limits the liquid water supply to the cloud, and thus LWP\textsubscript{cld}. The second mechanism involves MP schemes, which systematically change LWP\textsubscript{cld} independently of \(<q_i>\). MP schemes simulating higher LWP\textsubscript{cld} consistently produce less precipitation (not shown). Thus, MP schemes contribute to LWP\textsubscript{cld} through the formation of raindrops. Note that BL and MP contributions to LWP\textsubscript{cld} cannot clearly be identified when each simulation is analyzed individually. Thus, our multisimulations approach enables the identification of processes contributing to LWP\textsubscript{cld} that were otherwise not straightforward to untangle. According to Fig. 1.6, microphysical and specific humidity contributions to LWP\textsubscript{cld} are most realistic when WSM6 is combined with MYNN and KF, as well as with YSU and Tiedtke. However, the representation of the specific humidity contribution remains slightly unrealistic as \(<q_i>\) is overestimated and underestimated by about 1g kg\(^{-1}\) and 2g kg\(^{-1}\), respectively. As mentioned in section 1.4, \(<q_i>\) biases are related to biases in BL heights.

The two experiments that use WSM6 with different droplet concentration numbers highlight that the cloud droplet auto-conversion into raindrops participates in the MP contribution to LWP\textsubscript{cld}. In fact, LWP\textsubscript{cld} is lower in the case that favors rain formation through auto-conversion (i.e. smaller \(N_c\)). (Note that since the simulated spread in precipitation during VOCALS-REx (~0.1 mm d\(^{-1}\)) is within observed uncertainties, precipitation measurements cannot be used to determine which simulation is most realistic.) Fig. 1.6 also suggests that a droplet concentration number of 300 cm\(^{-3}\) in WSM6 represents the microphysical contribution to LWP\textsubscript{cld} better than 100 cm\(^{-3}\). In fact, the observed lower bound for LWP is underestimated.
by about 6 g m$^{-2}$ in the test that uses MYNN, KF and WSM6 with $N_c=100$ cm$^{-3}$, while average LWP is realistic when $N_c=300$ cm$^{-3}$. However, a closer look at the spatial pattern for LWP$_{cld}$ in these two simulations (Figs. 1.1g and 1.1j) gives a more nuanced view. In fact, experiments with $N_c=300$ cm$^{-3}$ only matches observations in coastal regions, while the one using $N_c=100$ cm$^{-3}$ agrees with observations further offshore. This is consistent with the observed spatial variability for $N_c$, which generally reaches 300 cm$^{-3}$ close to the coast and drops below 100 cm$^{-3}$ 1000 km offshore (Bretherton et al., 2010). Thus, LWP$_{cld}$ matches observations (Fig. 1.1a, contours) in regions where the imposed value for $N_c$ is reasonable, providing evidence for the realism of the auto-conversion scheme in WSM6. However, due to the large spatial variability of $N_c$, a constant value in the model is not sufficient to represent LWP$_{cld}$ over the entire domain. Nevertheless, for the VOCALS-REx grid points, $N_c$ is not as critical as other factors mentioned, as differences in the net flux are less than 10 W m$^{-2}$ (Fig. 1.5b) when it varies from 300 to 100 cm$^{-3}$ in WSM6.

1.7 Conclusions

In this study, we use VOCALS-REx data and a process-based model evaluation to analyze the ability of WRF to represent surface energy fluxes in the southeast Pacific stratocumulus region. Five BL (YSU, ACM2, MYJ, MYNN, QNSE) and three MP (Lin, WSM6, Thompson) schemes are cross-tested with the CU scheme fixed to Kain-Fritsch (no shallow CU parameterization). Three additional tests with the BL scheme MYNN and the MP scheme WSM6 are also carried out: one where the droplet concentration number is tuned from 300 cm$^{-3}$ to 100 cm$^{-3}$ in WSM6, and two using the CU scheme Tiedtke, which has a shallow CU parameterization. In this last section, we summarize our main findings.
Model errors in LW and SW are not attributable to the radiative transfer subroutine. Instead, they are related to misrepresentations of cloud properties. In the case of LW, errors are primarily controlled by errors in CC. However, the average amount of low clouds is fairly realistic in all our experiments and LW errors are negligible. For SW, biases are primarily controlled by biases in LWP\textsubscript{cld}. Most simulations significantly overestimate LWP\textsubscript{cld} leading to underestimation of SW (60 W m\textsuperscript{-2} in the worst case).

Model errors in SH and LH correlate with errors in BL height. Our results suggest that the level of entrainment likely regulates SH and LH by controlling temperature and humidity at the surface. Nevertheless, feedback processes are also likely, as SH and LH are potential contributors to BL depth. Some experiments exhibit significant biases in BL height, which are associated with SH and LH biases. However, there are systematic compensating effects between these fluxes. In fact, the total surface cooling from SH and LH is close to constant in all our experiments and overestimates observations by roughly 10 W m\textsuperscript{-2}. There does not appear to be a single physical reason for this. However, this bias is not the primary source of errors for the net surface flux as it is negligible in comparison to the SW underestimation in most simulations. Thus, errors in net surface energy fluxes are mostly traceable to errors in LWP\textsubscript{cld}, which control SW.

Given the importance of LWP\textsubscript{cld} for the net surface flux, we diagnose two mechanisms that control the variability in LWP\textsubscript{cld} across our experiments. One involves MP schemes, which contribute to LWP\textsubscript{cld} through the production of raindrops. The second mechanism involves BL and CU schemes, which control moisture available for cloud through regulation of BL depth. By evaluating the representation of these two processes in our experiments, we attribute errors
in LWP$_{cld}$ to the schemes involved. By using a process-based evaluation, we also ensure that realistic simulation of LWP$_{cld}$ does not take place through a compensation of errors.

According to our set of experiments, the microphysical contribution to LWP$_{cld}$ is most accurate when the MP scheme WSM6 is used, while it is overestimated in Lin and Thompson. Our study also suggests that there is a better agreement between observed and simulated LWP$_{cld}$ when the cloud droplet concentration number ($N_c$) is tuned to a realistic value in WSM6. This highlights the importance of the cloud droplet auto-conversion into raindrops for the accurate representation of LWP$_{cld}$. However, since the observed spatial variability for $N_c$ is high over the region, the single value for $N_c$ currently prescribed in the model is not appropriate to represent the spatial variability in LWP. This will be further analyzed in a future study.

According to our pool of experiments, the specific humidity contribution to LWP$_{cld}$ is most accurate when MYNN and KF, or YSU and Tiedtke are combined. This can be attributed to a better representation of BL depth in these two cases. However, BL heights remain slightly biased even in our two most accurate simulations. In fact, BL heights is underestimated by about 150m when WSM6, MYNN and KF are combined, while it is overestimated by roughly the same amount in the case of WSM6, YSU and Tiedtke. These relatively small errors in BL height do not lead to noticeable biases for LWP$_{cld}$ in these cases. Thus, the remaining net surface flux biases ($\sim$10W m$^{-2}$) are primarily related to the systematic overestimation of the total cooling from LH and SH. Nevertheless, a more accurate representation of BL height would certainly help the model to gain further realism. In particular, our study suggests that BL temperature and specific humidity biases would be reduced if the BL height representation were more realistic.
1.8 Discussion

Our results suggest that inaccurate representation of BL height is an important factor limiting further gains in the realism of WRF. Our study suggests some possible pathways that could be investigated to improve the representation of BL height. In the following paragraphs, we discuss a few of them.

Our results show that, when no shallow cumulus parameterization is employed, WRF underestimates BL height during VOCALS-REx. Nevertheless, the behavior of MYNN is very close to reality. This could suggest that only minor modifications to MYNN might be sufficient to approach observations further. For instance, the differences between MYNN and MYJ highlight the impact of the mixing length formulation in turbulent kinetic energy (TKE) eddy-diffusivity (ED) schemes. In fact, while MYNN and MYJ have similar TKE formulations and differ only with their mixing length expressions, the BL deepening produced in these two schemes are significantly different. (BL heights are about 300m lower in the case of MYJ.) Thus, one potential pathway for BL height improvement would be to develop a mixing length formulation that promotes slightly further deepening than MYNN. The key role of the mixing length has already been recognized (e.g. Mellor and Yamada, 1982) and new mixing length formulations that lead to deeper boundary layers have been proposed (e.g. Teixeira and Cheinet, 2004).

On the other hand some processes not explicitly represented in TKE ED schemes could be the reason for the lack of BL deepening in these schemes. For instance, non-local mixing is a potential contributor to BL deepening and is not represented explicitly in TKE ED schemes. First order ED schemes such as YSU and ACM2 have a representation for non-local mixing
(with counter-gradient terms). However, these schemes are not as successful as MYNN since they reduce BL height by about 100m in our experiments. Siebesma et al. (2007) have shown that ED schemes that use a counter-gradient term to represent non-local mixing, significantly reduce entrainment (and BL growth) because of the way they are formulated. To overcome this issue, a physically based way of representing non-local mixing in the boundary layer has been proposed where ED and the mass-flux (MF) approximations are combined in an optimal manner. In this Eddy-Diffusivity/Mass-Flux (EDMF) approach, the ED component represents small-scale turbulence, while the larger plumes responsible for the non-local transport are represented by the MF term. This approach was originally formulated by Siebesma and Teixeira (2000). EDMF has been implemented in WRF by Angevine et al. (2010) and was shown to perform well for various cloudy boundary layer regimes in the single column model framework (Huang et al., 2013). However, our preliminary tests in the 3D framework have not been particularly successful in reproducing the stratocumulus deck during VOCALS-REx.

The use of a shallow cumulus parameterization is another possible pathway as such parameterizations are meant to represent BL non-local moist mixing. Our tests using the CU Tiedtke parameterization confirm that the shallow cumulus mixing promotes BL deepening, though the deepening is too pronounced during VOCALS-REx. The BL height overestimation remains relatively close to observations when Tiedtke is combined with YSU, and this contributes to the realism of this simulation. When MYNN and Tiedtke are combined, the BL height is much greater than observed by about 200m, contributing to a significant drying of the BL. As a result, the model seems to deviate towards a slightly different regime, with fewer clouds and a peak cloud region moving further offshore than observations (Fig. 1.1k). This highlights that the blending of the boundary layer parameterization with the cumulus
parameterization is a key problem in cloudy boundary layer model development. In this context, the EDMF parameterization provides an optimal solution since it is a unified approach that combines the boundary layer and cumulus parameterizations into one single scheme (e.g. Soares et al 2004; Suselj et al 2013). Other methods, such as the assumed probability density function method of Golaz et al. (2002), have also been recently attempted to unify the parameterizations of boundary layer and shallow convection mixing.

Finally, another potential missing piece in all our experiments may be an explicit representation of the turbulent mixing generated by a thin layer of radiative cooling at the cloud top (e.g. Bretherton and Park, 2009). (Note that this term may be particularly important for configurations with lower vertical resolution than ours.) The BL scheme developed by Bretherton and Park (2009) that includes this additional term has recently been implemented in WRF. However, our preliminary tests using this scheme have not been very successful in reproducing the stratocumulus deck in the southeast Pacific.
Appendix 1: MP, BL and CU parameterizations

MP schemes handle phase changes of water. In this study, we test 3 MP schemes that predict the concentrations of 6 water species: water vapor, cloud liquid water, rain, snow, ice, and graupel. Two of the MP schemes, Lin (Lin et al, 1983) and WSM6 (Hong and Lim, 2006), are single moment schemes. The third one, the Thompson MP (Thompson et al., 2008), is a double-moment scheme. There are many differences between these three schemes. As stratocumuli are liquid clouds, we focus here on one difference involving the liquid phase. In Lin and WSM6, the autoconversion rate from cloud liquid water to rain can be expressed as:

\[ P_{\text{aut}} = \beta h(q_c - q_{co}) \]  \hspace{1cm} (1.A1)

where \( h \) is the Heaviside unit step function, \( q_c \) is the cloud liquid water content, \( q_{co} \) a critical water content threshold, and \( \beta \) the conversion rate efficiency. While \( \beta \) and \( q_{co} \) are kept constant in Lin, these parameters are predicted with a physically-based formula in WSM6 (Hong et al., 2003). To compute them, a critical droplet number concentration \( N_c \) is introduced, representing the concentration when cloud droplets start to coalesce in raindrops. In Thompson, the autoconversion scheme is more elaborated, but a critical droplet number concentration also plays an essential role. \( N_c \) is set to a default value of 300 cm\(^{-3}\) in WSM6 and 100 cm\(^{-3}\) in Thompson. We keep these default values in most experiments. To study the sensitivity to \( N_c \), we also perform one additional experiment with \( N_c \) tuned to 100 cm\(^{-3}\) in WSM6.

Five different BL schemes are tested in this study. These schemes parameterize subgrid-scale turbulent vertical fluxes from prognostic grid-scale variables with an eddy-diffusivity (ED) model:
Here, \( a \) represents the variable being considered (\( u, v, \theta \) or \( q \)) and \( K_a \) the eddy-diffusivity. Two different approaches are used to compute the eddy diffusivity in the tested schemes. The first involves a first order closure and is used by YSU (Hong et al., 2006) and ACM2 (Pleim, 2007). In these schemes, **BL height is first diagnosed using critical Richardson theory and the eddy-diffusivity profile in the BL is then deduced.** In addition to the eddy-diffusivity model, YSU and ACM2 also represent non-local mixing. There is also a representation of entrainment in YSU, which is computed as a function of surface fluxes. In the second approach, turbulent kinetic energy (TKE) closures are involved. This approach is used by MYJ (Janjic, 1990), MYNN (Nakanishi and Niino, 2004), and QNSE (Sukoriansky et al., 2005). In these schemes, prognostic equations are implemented to compute the TKE in any grid cell, and then the eddy diffusivity is deduced locally from mixing length theory:

\[
K_a = l_m \sqrt{TKE} S_a \quad (1. A3)
\]

Here \( l_m \) is the mixing length, and \( S_a \) is a dimensionless stability function. MYNN and MYJ employ the same equations to compute TKE. However they differ in their mixing length formulation. QNSE uses different formulations for both TKE and mixing length, and is especially designed for stable stratification regimes. Non-local mixing is not represented in TKE schemes and entrainment is only implicit.

CU schemes estimate the redistribution of heat, moisture and momentum in the vertical due to convective processes. In this work, we mostly use the Kain and Fritsch (KF, 1990) scheme. This scheme only parameterizes deep convection (i.e. updrafts deeper than 2 km), and therefore does not affect boundary layer mixing. Some CU schemes also have a shallow
cumulus parameterization to represent non-local transport in the boundary layer (i.e. updrafts below 2 km). To study the effect of such schemes, we present in this work a few tests with the Tiedtke scheme (Zhang et al., 2011) that includes a shallow cumulus parameterization.
2 Climatic Importance of Aerosol Indirect Effects in the Northeast Pacific

2.1 Introduction

Aerosols are thought to contribute to cloud reflective properties through two main pathways. First, aerosol concentration regulates the number and size of cloud droplets, which modifies the cloud albedo (i.e. first aerosol indirect effect; Twomey, 1977). Secondly, by increasing the cloud droplet concentration, aerosols reduce the cloud precipitation efficiency. This alters cloud macro-physical structure and thus modifies cloud reflectivity (i.e. second aerosol indirect effect; Albrecht, 1989). However, attempts to statistically quantify these aerosol indirect effects in observations are not definitive due to covariances between aerosols, clouds and meteorological conditions (e.g. George and Wood, 2010). As a result, the climatic importance of the aerosol indirect effects remains controversial (e.g. Stevens et al., 2009).

Climate models could potentially help to improve our understanding of cloud-aerosol interactions. However, their realism remains questionable. For instance, cloud shortwave properties are generally poorly represented in climate models (e.g. Nam et al., 2012). Although there are many other potential sources of error, these biases call into question the validity of the simulated aerosol indirect effects. To evaluate whether cloud-aerosol interactions are accurately represented in climate models, some studies attempt to use observational constraints (Wang et al., 2012; Ban-Weiss et al., 2014). However, these evaluations remain subject to uncertainties due to the observational limitations noted above.
Thus, cloud-aerosol interactions are subject to numerous questions. For instance, aerosol concentrations vary significantly over the oceans. In fact, coastal areas are usually more concentrated in aerosols than remote oceanic regions (e.g. Bennartz, 2007). However, it is not well established whether these spatially varying aerosol conditions are significant contributors to variations in cloud shortwave properties. As a result, it is also unclear whether approximate representations in average aerosol distributions are significant sources of errors in model representations of shortwave flux.

In this study, we aim to provide some new insights to these uncertainties. In particular, we focus on the northeast Pacific. The spatial variability in aerosol conditions is particularly pronounced in this region (e.g Bennartz, 2007). Moreover, the northeast Pacific is predominantly covered with low clouds (e.g. Lin et al., 2009), which are important contributors to the global energy budget (e.g. Randall et al., 1984). Thus, this region represents an ideal test-bed to study the climatic importance of aerosol indirect effects. To perform our analysis, we carry out a suite of sensitivity experiments using the Weather Research and Forecasting (WRF) model. We first discuss our methodology in section 2.2. We then present our results in section 2.3 and discuss them in section 2.4.
2.2 Methodology

In this study, we use the Weather Research and Forecasting (WRF) model version 3.6 (Skamarock et al., 2008). Model representations of cloud are particularly sensitive to microphysics, boundary layer, and cumulus parameterizations. Here we use a set of schemes that was demonstrated to be optimal for low cloud simulations in WRF (Jousse et al, 2015): the WRF Single Moment 6-class microphysics scheme (WSM6; Hong and Lim, 2006), the Mellor Yamada Nakanishi and Niino boundary layer scheme (MYNN; Nakanishi and Niino, 2004), and the Tiedtke cumulus scheme (Zhang et al., 2011). (Note that as recommended in Jousse et al., we turn off the shallow cumulus parameterization in Tiedtke.) To parameterize shortwave radiative processes, we use the new Goddard scheme (Chou et al., 1999). According to our tests (not shown), this parameterization is more accurate in our region of interest than the Dudhia shortwave scheme (Dudhia, 1989) used in Jousse et al. (2015).

The WRF configuration we use does not allow for prognostic simulations of aerosol concentrations. Nevertheless, there are model parameters that represent aerosol conditions and their potential effect on cloud properties. The first parameter of interest is the cloud droplet number concentration \( N_d \), an element of the microphysics scheme WSM6. This parameter aims to represent the effect of cloud-active aerosol concentration on cloud droplet autoconversion. (See Appendix 2.1 for details). Thus, we will consider the sensitivity to \( N_d \) as a quantification of the second aerosol indirect effect in the model.

The second parameter of interest is the cloud effective radius \( r_e \), an element of the new Goddard shortwave radiation scheme. This parameter is involved in the computation of the cloud optical depth. It aims to represent the effect of the droplet size on cloud reflectivity.
Since other processes can potentially affect cloud droplet size, the effective radius parameter may not only reflect aerosol conditions. Nevertheless, the sensitivity to that parameter will be considered a quantification of the first aerosol indirect effect in the model. Note that there is potentially a lack of consistency between the mean droplet size computed in the microphysics scheme and the effective radius parameter used in the radiation scheme. In fact, the microphysics scheme does not provide droplet sizes to the radiation scheme in the model. (The microphysics scheme only provides water elements mixing ratios to the radiation scheme.) However, this is not an issue for the purpose of our study, as we evaluate the sensitivity to microphysical and radiative processes separately.

According to satellite data, both $N_d$ and $r_e$ are varying spatially over the northeast Pacific. In Figs. 2.1a and 2.1b, we show the summer season (JJA) climatology for $N_d$ and $r_e$. $N_d$ is retrieved from the Moderate-resolution Imaging Spectrometer (MODIS; Platnick et al., 2003; see Appendix 2.2 for details), while $r_e$ is retrieved from the Clouds and the Earth’s Radiant Energy System (CERES; Wielicki et al., 1998). This figure reveals that $N_d$ and $r_e$ are spatially anti-correlated. While $N_d$ is greatest in the southern California coastal region (~250 cm$^{-3}$) and lowest in the offshore regions (~50 cm$^{-3}$), it is the other way around for $r_e$ (with a range going from 9.5 µm to 11 µm). This spatial anti-correlation is consistent with the first aerosol indirect effect (i.e. greater aerosol concentrations lead to smaller cloud droplets). There are many potential drivers to these observed distributions. For instance, the presence of continental dust and/or pollutants in coastal areas, wind patterns and potential feedbacks with cloud processes are all likely players. However, the purpose of this study is not to evaluate the driving mechanisms. Instead, we aim to quantify the potential effects of such distributions on shortwave fluxes.
By default, both $N_d$ and $r_e$ are set to constant values in WRF. Thus, the model effectively assumes aerosol conditions are not varying spatially. To establish the model sensitivity to spatially varying conditions, we implemented spatial distributions for both $N_d$ and $r_e$ in WRF. Three simulations are carried out for the summer of 2005. In the first one, model default values for both $N_d$ and $r_e$ are used (i.e. $N_d=300$ cm$^{-3}$ and $r_e=10$ µm). To establish the model sensitivity to the second aerosol indirect effect, $N_d$ is tuned to the observed climatology (i.e. Fig. 2.1a) in our second experiment. Finally, to evaluate the model sensitivity to the first indirect effect, both $N_d$ and $r_e$ are tuned to their respective climatologies in our third experiment (i.e. $r_e$ is tuned to the climatology depicted in Fig. 2.1b).

For each experiment, the model is initialized on 1 June 2005, and run continuously for 3 months. The horizontal resolution is 18km. There are 39 sigma-levels in the vertical, with
enhanced resolution near the lower boundary (24 sigma-levels below 700 hPa). The initial and lateral boundary conditions are derived from the Climate Forecast System Reanalysis (CFSR; Saha et al., 2010) at 40 km horizontal resolution every 6 hours. The sea surface temperature prescribed at the lower boundary is provided by the daily Operational Sea Surface Temperature and Sea Ice Analysis at 7 km horizontal resolution (OSTIA; Donlon et al., 2011).

Remote sensing data are used for validation proposes. Surface shortwave fluxes are compared to those from the Common Ocean Reference Experiment (CORE; Yeager et al., 2008). For cloud cover (CC), MODIS level 2 data are used. To account for the resolution mismatch between the model and MODIS (18 km vs. ~5 km), we create a MODIS data set that matches WRF resolution as well as possible (hereafter MODIS 18-km; see section 3.3 in Jousse et al. for details). Finally, we use the Advanced Microwave Scanning Radiometer-EOS (AMSR-E) data (Wentz and Meissner, 2000) to retrieve observed all sky liquid water path (LWP). Note that in the cases of CC and LWP, we linearly interpolate WRF 3-hourly outputs to the satellites’ measurement time.

2.3 Results

We now present the results of our simulations. We first focus on cloud cover. In Fig. 2.2a, we show MODIS total CC (shaded) and MODIS low CC (i.e. cloud top pressure greater than 650 hPa; contours) during the JJA season of 2005. This confirms that clouds are very common over the northeast Pacific (77% mean total coverage). This figure also shows that low clouds are the most prevalent type, and they peak in the southeastern part of the domain. In Fig. 2.2b, we show the corresponding fields for MODIS 18-km. Both total and low CC
increase in comparison to the unprocessed MODIS data (91% mean total coverage). Spatial
distributions are also homogenized. However, the same general features can be observed. CC
differences are negligible across our 3 WRF simulations. As a result, in Fig. 2.2c, we only
depict CC fields corresponding to the ensemble mean among our 3 WRF experiments. Both
total and low CC simulations are very similar to those from MODIS-18km. Thus, simulated
average CC and the partitioning between low and high cloud can be considered fairly realistic.

Fig. 2.2: (a) Mean total cloud cover (%; shaded) and total low cloud cover (i.e. cloud top
pressure smaller than 650hPa; contours) during summer 2005 retrieved from MODIS level 2
data (both Aqua and Terra satellites are used); (b) same as (a), but for MODIS level 2 data
interpolated on WRF 18km grid and c), WRF ensemble mean total cloud cover (shaded) and
low cloud cover (contours) during JJA 2005 (WRF outputs are interpolated to satellites'
measurements times; Note that the mean value m is shown on each figure.)

Unlike CC, there are significant differences in net surface shortwave fluxes (SW)
among our simulations. In Fig. 2.3, we show SW retrieved from CORE (Fig. 2.3a), as well as
the simulated values (Figs. 2.3b, 2.3c and 2.3d; shaded) and their biases (i.e. WRF-CORE;
contours). This figure reveals that the default experiment (i.e. N_d=300 cm^-3 and r_c=10 µm; Fig.
2.3b) underestimates observed SW by an average of 33 W m^-2, while mean biases are reduced
to less than 9 W m^-2 in the two experiments with varying N_d (Figs. 2.3c and 2.3d). However,
the magnitude of the biases is not uniform. For instance, in the default experiment, biases are
pronounced offshore (e.g. -60 W m$^{-2}$ in the northern part of the domain), while they remain relatively small in the southeastern part of the domain (~ 10 W m$^{-2}$, which may be considered within observational uncertainties). In the two experiments with varying $N_d$, offshore biases in SW are significantly reduced (~ -20 W m$^{-2}$), while positive biases increase slightly in the southeastern region (~ 20 W m$^{-2}$). Thus, apart from the southeastern region, SW simulations are significantly improved with the implementation of spatially varying climatological $N_d$ in the northeast Pacific. Implementation of spatially varying climatological $r_e$, further reduces biases with observed SW in the north and offshore regions. However, the effects remain relatively small in our simulations. Differences between Figs. 2.3c and 2.3d are not larger than 5 W m$^{-2}$.

To relate the SW biases to the simulated cloud macro-physical structure, we now turn to LWP (Fig. 2.4). (Note that we do not show the simulation with varying $r_e$ in Fig. 2.4 since there are only negligible differences with the one that uses the default value.) As with SW, average LWP biases dramatically decrease in the simulation where the varying $N_d$ is implemented (6 g m$^{-2}$ instead of 35 g m$^{-2}$). The spatial variability in LWP biases is also very similar to the spatial pattern of the SW biases. In the default experiment, LWP biases are pronounced offshore and reach 60 g m$^{-2}$ in the northern part of the domain. In the simulation with spatially varying climatological $N_d$, biases are negligible over most of the northeast Pacific and the even the largest values (~20 g m$^{-2}$) seen elsewhere can be considered to be within observational uncertainties (e.g. Seethala and Horvath, 2010).
Fig. 2.3: (a) Mean net surface shortwave fluxes (SW; W m$^{-2}$) retrieved from CORE during summer 2005; (b) Mean net surface shortwave fluxes (W m$^{-2}$) during summer 2005 in the default WRF experiment (i.e. $N_d$=300 cm$^{-3}$ and $r_e$=10$\mu$m; shaded) and mean biases with CORE (i.e. WRF-CORE; contours; note that negative contours are depicted with dashed lines); (c) same as (b) but with $N_d$ tuned to the climatology and (d), same as (b) but with both $N_d$ and $r_e$ tuned to the climatology. (Note that the mean value $m$ is shown on each figure)
The comparison between Figs. 2.3 and 2.4 suggests that the SW biases arise from biases in LWP. Here we aim to evaluate this relationship more precisely. To account for spatial differences in the top of atmosphere incoming shortwave radiation (SW$_0$), we use the albedo (i.e. SW/SW$_0$) and plot it as a function of LWP in Fig. 2.5. Averaged values over three representative areas are shown in this figure (the entire domain, a coastal/southeast sub-domain and an offshore/north sub-domain; see Fig. 2.1 for the boundaries of the sub-domains). The results are consistent with LWP being the primary contributor to albedo differences among our various experiments. The albedo spatial variability also exhibits the same strong relationship with LWP ($r=-0.94$ overall). Since SW$_0$ is essentially based on observed values and does not vary across our experiments, Fig. 2.5 corroborates that LWP is the primary contributor to SW in our simulations. This figure confirms the negligible impact of $r_e$ tuning.

**Fig. 2.4:** (a) Mean liquid water path (LWP; g m$^{-2}$) retrieved from AMSR-E during summer 2005; (b) Mean LWP (g m$^{-2}$) during summer 2005 in the default WRF experiment (i.e. N$_d$=300 cm$^{-3}$ and $r_e$=10µm; shaded) and mean biases with AMSR-E (i.e. WRF-AMSR-E; contours; note that negative contours are depicted with dashed lines); (c) same as (b) but with N$_d$ tuned to the climatology. (Note that the experiment with varying $r_e$ is not depicted here, as it is almost similar to the results for Fig. 2.4c; Note that the mean value m is shown on each figure)

Observed values are relatively close to the simulated regression line in Fig. 2.5. However, there are some noticeable departures. For instance, in the southeastern sub-domain, the experiment with spatially varying climatological N$_d$ accurately represents the averaged
LWP measured by AMSR-E (~ 60 g m$^{-2}$), while simulated and observed SW have noticeable differences (205 W m$^{-2}$ vs. 194 W m$^{-2}$). Model error may contribute to these differences. However, they may also be attributable to observational uncertainties in LWP and SW. Thus, attributing the causes to these observational departures from the simulated regression line in Fig. 2.5 is not straightforward. However, this issue is not central to the purpose of this study, and will not be investigated further here.

To evaluate the sensitivity of our results to N$_d$ uncertainties, in Fig. 2.5 we show an additional experiment where we use a shape parameter k of 0.5 instead of 0.7 to retrieve N$_d$ in the southeast Pacific (i.e. observational upper range; see Appendix 2.2 for details). By using this assumption, averaged N$_d$ increases from 165 cm$^{-3}$ to 225 cm$^{-3}$ in this domain. This reduces

Fig. 2.5: Average albedo (SW/SW$_0$) as a function of LWP (g m$^{-2}$) during JJA 2005. Southeast and North domains correspond to those highlighted in Fig. 2.1. The dashed lines represent the least squares regression between the simulated variables (r=−0.94).
SW biases to less than 5 W m$^{-2}$, while LWP are now overestimated by less than 10 g m$^{-2}$, well within observed uncertainties. Thus, the tuning of $N_d$ to its observational upper range eliminates most SW biases in the southeast coastal region.

The relatively small biases remaining in the north and western sides of our domain (~20 W m$^{-2}$) do not seem to be fully correctable with further tuning of $N_d$ or $r_e$. In fact, $N_d$ is already relatively small in these regions (~50 cm$^3$). The observational lower range (i.e. k=0.5) is only 15 cm$^3$ smaller. Tuning to that value does not impact significantly SW simulations (not shown). Similarly, the elimination of all errors through an additional tuning of $r_e$ would require unrealistic $r_e$ values. Therefore, the remaining biases may be related to other factors. The relatively coarse resolution we are using (18km) may be one factor. In fact, the fine structures of clouds that take place in the western regions are not well represented at 18km (see Fig. 2.2). To attempt to solve this issue, we tested the effect of using a cloud cover parameterization in the model (Xu and Randall, 1996). However, the impact of such an addition in SW is relatively negligible (less than 5 W m$^{-2}$; not shown). This may due to the fact that the tested parameterization (as with all the others currently available) was developed for models with much coarser resolutions (~100km). As a result, it may not parameterize well the fine scale structures relative to the resolution we are using in this study. Fortunately these remaining biases do not undermine the bottom line of our study.

2.4 Discussion

In this study, we evaluate the importance of the spatial variability in aerosol conditions for shortwave fluxes simulations in the northeast Pacific. To carry out our analysis, we use a
suite of sensitivity experiments in WRF. Our results show that the prescription of cloud droplet number concentration ($N_d$) to spatially varying climatological values in the microphysics scheme WSM6 enables significant LWP biases corrections. This reduces most SW errors over the northeast Pacific. The tuning of the effective radius ($r_e$) in the new Goddard shortwave radiation scheme also lowers SW biases. However, $r_e$ effects are comparatively negligible. Thus, our results highlight the importance of representing accurately aerosol spatial variability and the associated indirect effects on LWP for realistic shortwave fluxes simulations in the northeast Pacific.

Our results may be affected by model approximations. In particular, aircraft measurements suggest that rain production by auto-conversion is too pronounced in the scheme we use (Wood, 2005). Thus, while total precipitation rates are within observational uncertainties (not shown), the simulated partitioning between auto-conversion and accretion processes differs from measurements. In fact, auto-conversion dominates over accretion in our simulations, while aircraft observations suggest the other way around. These approximations may affect the realism of the simulated LWP sensitivity to $N_d$.

To evaluate this possibility, we expose here the simulated sensitivity to $N_d$. In Fig. 2.6a, we show the mean LWP differences between the varying $N_d$ experiment and the default one ($\Delta$LWP) binned as a function of $N_d$ differences ($\Delta N_d$) for grid cells in the southeast subdomain (see Fig. 2.1). This figure highlights the linear relationship between these two variables ($r=0.92$) in a region where low clouds are prevalent. To exhibit the underlying mechanism that contributes to LWP decreases when $N_d$ decreases, we show in Fig. 2.6b the mean differences in rain production rate ($\Delta r_{pr}$) binned as a function of $\Delta N_d$ (again only grid cells in the southeast subdomain are selected). (Note that although auto-conversion is generally greater than
accretion rate in our simulations, we account for both in the calculation of \( \Delta rpr \). This figure highlights the linear relationship between\( \Delta rpr \) and \( \Delta N_d \) (\( r=-0.71 \)). Similar relationships can be established over the entire domain if only low clouds are selected (not shown). However, high clouds behave differently. For instance, \( \Delta rpr \) does not exhibit a clear relationship with \( \Delta N_d \) when high clouds are included. Therefore, differences between our experiments are mostly driven by the sensitivity to \( N_d \) in low clouds.

Fig. 2.6: (a) Average JJA 2005 LWP differences (g/m\(^2\)) between the climatological \( N_d \) and default experiment (i.e. \( N_d=300 \) cm\(^{-3}\)) binned as a function of \( N_d \) differences (cm\(^{-3}\)) between the two experiments. Only grid cells in the southeast domain are selected (see Fig. 2.1). Error bars show the standard deviation for each bin, while the dashed line represents the least squares regression between the two variables (\( r=0.92 \)); (b), same as (a), except that the y-axis shows the difference in rain production rate (mg/m\(^2\)/s) between the two simulations (\( r=-0.71 \)).

Due to co-varying factors in observations (e.g. George and Wood, 2010), the \( N_d \) sensitivity of LWP and rain production rate cannot clearly be established. As a result, observational constraints on the simulated \( N_d \) sensitivity of Fig. 2.6 are not available. Thus, while there is certainly more work ahead to confirm the realism of our findings, the model
skillfulness that was demonstrated in this study, as well as in some previous work (Jousse et. al., 2015), certainly supports their robustness.
Appendix 2.1: Auto-conversion in WSM6

To parameterize the auto-conversion of cloud droplet into rain, the microphysics WSM6 follows the methodology described in Tripoli and Cotton (1980):

\[
P_{\text{aut}} = \alpha \frac{\rho_{w}^{5/3} q_{c}^{7/3}}{N_{d}^{1/3}} H(q_{c} - q_{co}) \quad (2. A1)
\]

where \( P_{\text{aut}} \) is the auto-conversion rate, \( H \) is the Heaviside unit step function, \( q_{c} \) the cloud liquid water content, \( q_{co} \) a critical mixing ratio, \( \rho \) the air density, and \( \alpha \) a constant (see Hong and Lim (2006) for details).

Note that \( q_{co} \) is also a function of \( N_{d} \):

\[
q_{co} = 4/3 \rho_{w} r_{c}^{3} N_{d}/\rho \quad (2. A2)
\]

Here, \( r_{c} \) is the critical radius number (\( r_{c}=8 \mu m \)), and \( \rho_{w} \) the density of water.

Appendix 2.2: Cloud droplet number concentration (\( N_{d} \)) retrieval

To retrieve \( N_{d} \), we follow the methodology exposed in Bennartz (2007):

\[
N_{d} = \frac{2^{-5/2}}{k} \left[ \frac{3 \pi Q}{5} \right]^{3/2} \left[ \frac{3}{4 \pi \rho_{l}} \right]^{2} c_{w}^{1/2} \tau^{1/2} r_{e}^{-5/2} \quad (2. A3)
\]

where \( r_{e} \) is the effective radius derived from the Moderate-resolution Imaging Spectrometer (MODIS, Platnick et al., 2003), \( \tau \) the optical depth derived from MODIS, \( Q \) the scattering efficiency (Here we use \( Q=2 \)), \( \rho_{l} \) the density of liquid water, \( c_{w} \) the adiabatic condensation rate,
and k the ratio between the volume mean radius and the effective radius (i.e. shape parameter). To establish the \( N_d \) climatology, we use MODIS level 3 data from 2005 to 2012 measured by instruments deployed on both satellites Terra and Aqua.

The methodology from Bennartz (2007) is only valid for stratocumulus clouds. As a result, we only select MODIS grid cells with cloud fraction greater than 80% and cloud top temperature greater than 273K for the retrieval of \( N_d \). Due to these specific conditions needed for the validity of the methodology, \( N_d \) retrievals are relatively infrequent in areas where stratocumuli are not prominent (e.g. in the northern part of the domain). Thus, the day-to-day variability in \( N_d \) is not well defined in observations. As a result, a temporally varying \( N_d \) could not be used to force the model. However, this is not an issue for the purpose of our study. Also note that we made the choice to force the model with the retrieved climatology and not the field retrieved for the specific year where the model is run (i.e. 2005). However, the interannual variability is negligible in comparison to other sources of uncertainties. Therefore, this decision does not affect our results.

The shape parameter k is the greatest source of uncertainty in the calculation of \( N_d \) (0.5<k<0.9). The climatology we use in this study employs the median value of k=0.7. The sensitivity to this assumption is discussed in Fig. 2.5.
3 Low Cloud Cover Variability and Anthropogenic Changes over the California Ocean

3.1 Introduction

Marine stratocumulus clouds (MSc) are important elements of the Earth’s system. In fact, due to both their abundance and net cooling effect, these low clouds significantly contribute to the Earth’s energy balance (e.g. Klein and Hartmann, 1993). MSc are particularly persistent over the eastern boundaries of the subtropical oceans. Thus, MSc have exacerbated effects in these regions. In particular, they are important regulators to the productivity of the eastern boundary upwelling systems (e.g. Huyer, 1983). MSc also impact the climate of the near coastal regions (i.e. subtropical western coasts). In fact, these regions generally encounter hot and dry weather and the eventual presence of MSc significantly mitigates their temperature (Iacobellis and Cayan, 2013). As a result, MSc have important consequences for human populations living on the subtropical western coasts (e.g. public health, energy production and consumption….). MSc are also essential to the vegetation in these regions. In fact, many species depend on the shading and water deposition related to the presence of MSc (Dawson, 1998; Williams et al., 2008; Baguskas et al., 2014).

Despite these important aspects, climate predictions for MSc remain uncertain. In particular, it is not well established how MSc will react to anthropogenic climate change in the coming decades. In fact, the global climate models (GCMs) commonly used for climate projections display a wide range of low cloud response to anthropogenic forcings (e.g. Qu et al., 2014). Moreover, MSc are generally poorly simulated in these models (e.g. Nam et al., 2012). This renders the GCMs capability to predict changes in MSc highly questionable.
Some recent modeling efforts have demonstrated the capability to simulate realistic MSc in regional climate models (Wang et al., 2011; O’Brien et al, 2013; Jousse et. a, 2015). Moreover, due to their relatively higher resolutions, these models are more suited than GCMs to represent the mesoscale specificities that may affect MSc along the subtropical western coasts (e.g. Koracin and Dorman, 2001; Renault et al., 2015). Thus, regional models seem to be valuable tools to study and evaluate possible changes in MSc.

In this work, we carry out a regional model study of MSc over the California region. MSc are very common in this region (e.g. Lin et al., 2009), and their possible changes are especially concerning for the highly populated U.S. west coast. To carry out our simulations, we use the Weather Research and Forecasting (WRF) model. We perform both a historical reconstruction and a dynamical downscaling of future climate projections from four GCMs. To characterize changes in MSc, we will only focus here on the low cloud cover (LCC) metric. In particular, we aim to provide a comprehensive analysis that enables the identification of factors contributing to LCC variability and changes in our simulations.

We first describe the model set up in section 3.2, followed by a validation of the LCC mean state in section 3.3. We then expose our methodology of analysis in section 3.4. Finally, the simulated results for the current LCC interannual variability and future climate changes are exposed in section 3.6 and 3.7, respectively.

### 3.2 Model Setup

#### 3.2.1 Baseline simulation

In this study, we perform a regional climate simulation over the California region with the Weather Research and Forecasting (WRF) model version 3.5 (Skamarock et al. 2008). Our
baseline simulation spans the year 1991-1999. Two one-way nested domains with horizontal resolutions of 27 and 9 km from outermost to innermost are used. The model is forced along the outermost boundary with 6-hourly North America Regional Reanalysis (NARR, Mesinger et al. 2006). The innermost domain (i.e. 9 km resolution) covers the California west coast region and the adjacent ocean (see Fig. 3.1). This domain will be our focus of interest in this study.

We use the package of physical parameterizations recommended in Jousse et al. (2015) for MSc simulations in the southeast Pacific. According to short-term sensitivity experiments, this set of parameterization also happens to be optimal over the California region (not shown). To reduce potential model drifts, we employ spectral nudging of temperature, winds and geopotential height above 850 hPa in the outermost domain.

3.2.2 Climate change simulations

Using the same model configuration, we perform four experiments to simulate future 2091–2099 climate using four global circulation models (GCMs) associated with the phase 5 of the Coupled Model Intercomparison Project (CMIP5): CNRM-CM5, GFDL-CM3, INMCM4, and IPSL-CM5A-LR. This suite of GCMs was selected to bracket the ranges of end-of-21st century changes (2081 – 2100 minus 1981 – 2000) in sea surface temperature (SST) and estimated inversion strength (EIS; Wood and Bretherton, 2006) from all available GCMs. SST and EIS are two important variables dominating low cloud cover (LCC) changes in CMIP5 (Qu et al. 2014). Thus, our selection of GCMs is meant to evaluate the effect of the full range of GCMs projections in SST and EIS for MSc simulations in WRF.

While RCP8.5 is the most aggressive emissions scenario used in the CMIP5 experiments, it may in fact also be the most realistic given that current emission levels already
exceed those projected in RCP8.5 (Peters et al., 2013). In this simulation, CO₂ levels are increased in WRF to match the changes in CO₂-equivalent radiative forcing in the RCP8.5 scenario averaged over the end-of-century period compared to the baseline.

To produce future climate boundary conditions for the WRF simulations, we first quantify the differences in GCM monthly climatology changes (2081–2100 average minus 1981–2000 average) using GCM output from the historical and Representative Concentration Pathway (RCP) 8.5 experiments (available at http://pcmdi9.llnl.gov/esgf-web-fe/). We average across multiple realizations when available for a given GCM. Monthly differences are calculated for three-dimensional variables, including temperature, humidity, winds, and geopotential height, and two-dimensional surface variables, including surface temperature, humidity, winds, and pressure. Then for each of the four downscaled GCMs, we add these climate change signals to the baseline 6-hourly NARR reanalysis data. Thus, we perturb the NARR baseline boundary conditions with monthly-averaged climate change signals given by each GCM and use this perturbed NARR to force WRF and generate future climate. This approach allows us to quantify how the climate change signals simulated in GCMs are expressed at the regional scale without the future simulation being subject to the very large biases in mean state often found in GCMs. However, note that a caveat to this technique is that it does not downscale the potential changes in GCM variability. In fact, it assumes that the weather and transient signals (e.g., frequency and intensity) applied on the model domain’s boundaries remain structurally the same as the baseline in future simulation. Thus, the technique we employ is meant only to downscale the effects of mean climate change.
3.3 Model Validation

The purpose of this study is not to provide an exhaustive validation of the clouds simulated in WRF. Nevertheless, to support the realism of our baseline simulation, we present here some comparisons with measurements from the Moderate-resolution Imaging Spectrometer (MODIS; Platnick et al., 2003). We use MODIS Terra level 2 data interpolated on the same grid as WRF 9km. MODIS measurements only started in year 2000. As a result, the time period we use for comparison (2000-2008) does not correspond to the WRF baseline simulation (1991-1999). However, since we only examine here climatological values, the comparison can be considered as fair.

Fig. 3.1: (a) MODIS Terra low cloud cover summer (JJA) climatology (2000-2008) and (b), WRF baseline simulation low cloud cover summer (JJA) climatology (1991-1999). Note that for a proper comparison, WRF outputs are interpolated to satellites measurements times (i.e. 10:30 am/pm)
In Fig. 3.1, MODIS summer season (JJA) low cloud cover (LCC) climatology (2000-2008) is compared to the one simulated in WRF (1991-1999). (Please refer to Jousse et al. (2015) for details on the methodology we use to define cloud cover in WRF. Also note that we use a threshold of 650 hPa for cloud top pressure to define LCC in both MODIS and WRF.) This figure shows that WRF represent relatively well the JJA LCC climatology over the California oceanic region (similar results for other seasons; not shown). However, WRF exhibits low biases (~20%) within the first few grid cells offshore the coasts of northern and central California. As we only focus on domain averages in this study, these biases are acceptable. Note that the reasons to the simulated coastal biases will be investigated in future work.

**Fig. 3.2**: MODIS Terra (2000-2008) and WRF baseline (1991-1999) LCC seasonal cycle in the northern (a) and southern California (b) domains. WRF outputs are interpolated to satellites measurements times (i.e. 10:30 am/pm)
In Fig. 3.2, we compare the seasonal cycle for LCC mean value over the northern and southern California domains (see Fig. 3.1 for the domains’ limitations). This figure shows that WRF fairly represents the seasonal cycle in both domains. In fact, both phasing and amplitude of the seasonal cycle are well represented. In particular, this figure shows that LCC peaks in the summer season in both WRF and MODIS with average values close to 60%. This highlights the preponderance of MSc during JJA over the California Ocean.

Finally, in Fig. 3.3, we compare the seasonal cycle for LCC daily standard deviation average over the north and south domain. The fair agreement between WRF and MODIS in this case supports the realism of the LCC day-to-day internal variability in the model. Thus, all these results support the realism of our baseline simulation.

*Fig. 3.3: MODIS Terra (2000-2008) and WRF baseline (1991-1999) seasonal cycle of daily LCC standard deviation (%) in the northern (a) and southern California (b) domains. WRF outputs are interpolated to satellites measurements times (i.e. 10:30 am/pm)*
3.4 Methodology

We now present the methodology we developed to analyze the contributors to LCC variability in our simulations. To characterize a boundary layer (BL) where MSc are taking place, it is appropriate to use two moist-conserved variables: the total water mixing ratio

\[ q_t = q_v + q_l \quad (3.1) \]

and the liquid potential temperature, which can be approximated as

\[ \theta_l \approx \theta - \frac{L}{C_p} q_l \quad (3.2) \]

Here \( q_v \) is the water vapor mixing ratio, \( q_l \) the liquid water mixing ratio, \( \theta \) the potential temperature, \( L \) the latent heat of vaporization, and \( C_p \) the specific heat of dry air. In stratocumulus regions, while boundary layers are often close to well mixed (i.e. \( q_t \) and \( \theta_l \) are close to constant in the boundary layer), there is a sudden jump right above the top of BL (i.e. sharp decrease and increase of \( q_t \) and \( \theta_l \), respectively). During the summer season (JJA), the boundary layer is well defined in our simulations. In fact, more than 95% of the oceanic grid cells have an inflexion point for \( \theta_l \) in the first 3km. Thus, we use the height of the most significant inflexion point as a measure of the BL height in the model. When low clouds are present, their tops almost correspond to the BL height top retrieval based on with \( \theta_l \) (not shown). Moreover differences are negligible if \( q_t \) is used instead of \( \theta_l \) as a criterion for BL height. This confirms the robustness of our retrieval methodology for BL height.

Cloud generation is essentially driven by relative humidity (RH). In fact, clouds form when RH reaches saturation (i.e. RH=100%) and dissipate when RH decreases. Due to the decrease in temperature with altitude, RH generally increases with altitude in well-mixed BLs. As a result, the relative humidity at the top of the BL (RH\(_{zi}\)) may be a legitimate criterion for
cloudiness in the California coastal region. To establish its relevance in our simulations, we plot JJA daily domain average LCC as a function of RH\textsubscript{zi} in Fig. 3.4a. This figure highlights the tight relationship between the two variables (r=0.89). (Note that an exponential fit may suit the data set more precisely. However, this will not be investigated here.)

Thus, the predicting value of RH\textsubscript{zi} on LCC is significant. However, RH depends on variables that are not conserved through moist processes (i.e. q\textsubscript{v} and the temperature T). As a result, RH\textsubscript{zi} may not be straightforward to analyze. To bypass this issue, we use moist-conserved variables to define a RH-related variable we call the potential relative humidity (RH\textsubscript{POT}). We define it as

\[ RH_{POT} = \frac{q_t}{q_s(P,T_l)} \quad (3.3) \]

Here q\textsubscript{v}(P,T\textsubscript{l}) is the saturated mixing ratio at atmospheric pressure P, and at the liquid water temperature T\textsubscript{l}, which we define as

\[ T_l = \theta_l \left( \frac{P}{P_0} \right)^K \quad (3.4) \]

Here K is the ratio of the gas constant of dry air R and the specific heat of dry air C\textsubscript{p}. Thus, RH\textsubscript{POT} represents the relative humidity the air would have if no condensation of water vapor occurred (i.e. no cloud formation). In Fig. 3.4b, we plot JJA daily domain average LCC as a function of the potential relative humidity at the top of the BL (RH\textsubscript{POT,zi}). This figure shows that the linear fit represents very accurately the relationship between the two variables (r=0.97). Thus, RH\textsubscript{POT,zi} happens to be more tightly correlated to LCC than RH\textsubscript{zi} (94% vs. 79% of the LCC variability explained by a linear fit). This improvement seems coherent since, unlike RH, RH\textsubscript{POT} does not saturate at 100%. Thus, RH\textsubscript{POT} is more qualified than RH to quantify differences in cloud favorable conditions.

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As a result, \( RH_{\text{POT,zi}} \) seems the most appropriate variable to use for an analysis of LCC variability. We now present the methodology we developed to evaluate the factors that contribute to its variability. \( RH_{\text{POT,zi}} \) is a function of total water mixing ratio and liquid potential temperature at BL top (i.e. \( q_{t,zi} \) and \( \theta_{l,zi} \)). To derive the change in \( RH_{\text{POT,zi}} \) (i.e. \( dRH_{\text{POT,zi}} \)), we differentiate equation (3.3):

\[
\frac{dRH_{\text{POT,zi}}}{RH_{\text{POT,zi}}} = \frac{dq_{t,zi}}{q_{t,zi}} - \frac{dq_s(T_{l,zi}, P_{zi})}{q_s(T_{l,zi}, P_{zi})}
\]  

(3.5)

To simplify our analysis, we aim to quantify \( q_{t,zi} \) and \( \theta_{l,zi} \) with surface variables (i.e. \( q_{t,sfc} \) and \( \theta_{l,sfc} \)) and the BL height (i.e. \( zi \)). For that matter, we define \( \alpha_q \) and \( \alpha_q \) such that:

\[
y = 5x - 417 \quad r = 0.89
\]

\[
y = 2.5x - 200 \quad r = 0.97
\]

Fig. 3.4: (a) WRF low cloud cover (LCC, %) binned as a function of the boundary layer top relative humidity (\( RH_{zi}, \% \)). Daily averages over the entire domain (ocean grid cells only) during the seasons (JJA) of 1991 to 1999 are used in this figure; (b) same as (a), except that LCC is binned as a function of the boundary layer top potential relative humidity (\( RH_{\text{POT,zi}}, \% \)). (See text for details). Error bars represent the LCC standard deviation for each bin.
\( q_{t,zi} = q_{t,sfc} + \alpha_q zi \) (3.6)

\( \theta_{l,zi} = \theta_{l,sfc} + \alpha_\theta zi \) (3.7)

Note that \( \alpha_q=0 \) and \( \alpha_\theta=0 \) if the BL is well mixed. However, \( \alpha_q \) is generally negative, while \( \alpha_\theta \) is positive. Thus, a decrease of \( \alpha_q \) towards negative value and an increase of \( \theta_l \) towards positive value characterize a reduction of the coupling of the BL top with the surface. As a result, we will consider \( \alpha_q \) and \( \alpha_\theta \) as parameters representing the coupling of the BL in total water mixing ratio and liquid potential temperature.

By using the Clausius–Clapeyron equation, we can then derive the following (see Appendix 3 for details):

\[
\frac{dR_{H_{POT,zi}}}{R_{H_{POT,zi}}} = \gamma_{qt}dq_{t,sfc} + \gamma_{\theta l}d\theta_{l,sfc} + \gamma_{\rho}dP_{sfc} + \gamma_{\alpha_q}d\alpha_q + \gamma_{\alpha_\theta}d\alpha_\theta + \gamma_{zi}dz_i
\] (3.8)

The integration of this equation leads to:

\[
R_{H_{POT,zi}}(t') = R_{H_{POT,zi}}(t)\exp\left(\gamma_{qt}\Delta q_{t,sfc} + \gamma_{\theta l}\Delta\theta_{l,sfc} + \gamma_{\rho}\Delta P_{sfc} + \gamma_{\alpha_q}\Delta\alpha_q + \gamma_{\alpha_\theta}\Delta\alpha_\theta + \gamma_{zi}\Delta zi\right)
\] (3.9)

Here \( \Delta \) represent the difference between the time steps \( t' \) and \( t \). Thus, equation (3.9) enables the prediction of \( R_{H_{POT,zi}} \) with surface variables (\( q_{t,sfc}, \theta_{l,zi} \) and the surface pressure \( P_{sfc} \)), decoupling variables (\( \alpha_q \) and \( \alpha_\theta \)), and boundary layer height (\( zi \)). (See Appendix 3 for the full expressions of the \( \gamma \) coefficients.)

We now use equation (3.9) to retrieve an estimation of \( R_{H_{POT,zi}} \). To perform the computation of daily values, we use daily domain average differences for the \( \Delta \) terms in equation (3.9). Then to compute the estimated \( R_{H_{POT,zi}} \) at a given time step, we use the value
from the previous time step (i.e. WRF RH\textsubscript{POT,zi} is only use for initialization at the first time step). We show the results in figure 3.5, where JJA daily domain average RH\textsubscript{POT,zi} are plotted as a function of the estimated value. The linear fit gives a correlation coefficient of 0.97 and a slope of 0.86. Moreover, a fit that enforces an intercept of 0 gives a slope of exactly 1. This confirms the robustness of our prediction methodology for RH\textsubscript{POT,zi}. Thus, we created a framework that use relatively simple physical factors (i.e. surface variables, BL height and decoupling parameters) to estimate RH\textsubscript{POT,zi}. Since LCC happens to be very tightly correlated with RH\textsubscript{POT,zi} in our simulations, we are now in a position where we can quantify the factors contributing to LCC variability in our simulations.

![Graph showing the relationship between estimated RH\textsubscript{POT,zi} and RH\textsubscript{POT,zi} with a linear fit and correlation coefficient](image)

**Fig. 3.5:** WRF Potential relative humidity at BL top (RH\textsubscript{POT,zi}, %) binned as a function of the estimated one from equation (3.9) (%). Daily averages over the entire domain (ocean grid cells only) during the seasons (JJA) of 1991 to 1999 are used in this figure. Error bars represent the LCC standard deviation for each bin.
3.5 LCC interannual variability

In this section, we take advantage of the methodology developed previously to analyze the factors contributing to summer season LCC interannual variability in our baseline simulation. Here, we first demonstrate the capability of this methodology to estimate the JJA interannual variability for RH_{POT,zi}. For each year, to retrieve the estimated value, we use WRF climatological value for RH_{POT,zi} (i.e. 1991 to 1999 average), as well as the domain averaged climatological anomalies for the various Δ terms on the right hand side of equation (3.9). In Fig. 3.6, we show WRF JJA year averages LCC as a function of the estimated RH_{POT,zi} for the south domain (Fig. 3.6a), the north domain (Fig. 3.6b), and the entire domain average (Fig. 3.6c). For each domain of interest, LCC and the estimated RH_{POT,zi} are tightly correlated (r=0.98, r=0.81, and r=0.96 for south, north, and entire domain average, respectively). Moreover, slopes are relatively close to the one computed on daily time scale (e.g 1.94 vs. 2.5 for the domain average). This confirms that the framework of study we developed is also relevant to use on interannual time scales. Nevertheless, we can note that LCC and the estimated RH_{POT,zi} are slightly less significantly correlated in the north domain (r=0.81 vs. r>0.95 in other cases). This is related to errors in our estimation of RH_{POT,zi} in this domain. In fact, WRF “true” year average RH_{POT,zi} remains very tightly correlated with LCC in the north domain (r=0.96, not shown). However, these approximations on the estimation of RH_{POT,zi} are relatively small and the reasons to them will not be investigated here.

To evaluate the factors driving the interannual variability in estimated RH_{POT,zi}, we show in Fig. 3.8 the relative contributions due to surface conditions (i.e \(\gamma_q \Delta q_{t,sfc} + \gamma_{\theta_t} \Delta \theta_{t,sfc} + \gamma_P \Delta P_{sfc}\)), decoupling in total water mixing ratio (i.e. \(\gamma_{\alpha_q} \Delta \alpha_q\)), decoupling in
liquid potential temperature (i.e. $\gamma_{\alpha g} \Delta \alpha_g$), and BL height (i.e. $\gamma_{zi} \Delta zi$). This figure shows that all factors contribute to the interannual variability in RH$_{POT,zi}$. Similarities between north and south domains can be observed some years (e.g. 1996 and 1999), but not always (e.g. 1991, 1992, 1993). Some years exhibit a strong influence by a given factor (e.g. 1994 and 1996 by surface conditions, 1999 by decoupling in water mixing ratio), while some others are more evenly influenced by all factors (e.g. 1998). There are also some years where RH$_{POT,zi}$ are very close, but the conditions leading to them are different (e.g. 1995 and 1996). Thus, figure 3.8 reveals and enables the quantification of the variety of factors that contribute to interannual variability in RH$_{POT,zi}$.

![Graph](image)

*Fig. 3.6: (a) WRF JJA year averages LCC (%) as a function of estimated RH$_{POT,zi}$ (%) in the southern California domain (See Fig. 1); (b) same as (a) but for the northern California domain and (c), same as (a) but for the entire domain average. Only ocean grid points are selected for the spatial averages.*
Due to the tight relationship between LCC and RH\textsubscript{POT,zi}, these results provide some advancements in our comprehension of LCC interannual variability. In fact, the results of Fig. 3.7 enables to relate interannual changes in LCC to those in surface conditions, decoupling and BL height. However, cloud feedback with these variables may also come into play. Thus, there is certainly more work ahead to comprehend LCC interannual variability. In particular, it would be valuable to relate the variability of the contributors highlighted in Fig. 3.7 to large-scale conditions. Such investigations will be subject to future work.

![Graph showing contributors to JJA interannual anomalies in estimated RH\textsubscript{POT,zi} average over the southern California domain (a), northern California domain (b), and all domain (c). In the legend, sfc refers to the terms $\gamma_q \Delta q_{lsfc} + \gamma_{\theta_l} \Delta \theta_{lsfc} + \gamma_p \Delta P_{sfc}$, $\alpha_q$ to $\gamma_{\alpha_q} \Delta \alpha_q$, $\alpha_T$ to $\gamma_{\alpha_p} \Delta \alpha_p$, and $zi$ to $\gamma_{zi} \Delta zi$. Please refer to equation (3.9) and text for details.]

Fig. 3.7: Contributors to JJA interannual anomalies in estimated RH\textsubscript{POT,zi} average over the southern California domain (a), northern California domain (b), and all domain (c). In the legend, sfc refers to the terms $\gamma_q \Delta q_{lsfc} + \gamma_{\theta_l} \Delta \theta_{lsfc} + \gamma_p \Delta P_{sfc}$, $\alpha_q$ to $\gamma_{\alpha_q} \Delta \alpha_q$, $\alpha_T$ to $\gamma_{\alpha_p} \Delta \alpha_p$, and $zi$ to $\gamma_{zi} \Delta zi$. Please refer to equation (3.9) and text for details.
3.6 LCC anthropogenic changes

3.6.1 Simulated LCC changes and anthropogenic forcings

We now evaluate LCC changes in our WRF dynamically downscaled climate change simulations. (Please refer to section 3.2.2 for details on the technique employed.) We will only focus here on the changes during the JJA seasons, which corresponds to the time of the year where low clouds are the most prominent.

Previous studies have identified sea surface temperature (SST) and the estimated inversion strength (EIS; Wood and Bretherton; 2006) as important control on low cloud cover changes (e.g. Qu et al, 2014). Both EIS and SST will increase with anthropogenic climate change (e.g. Soden and Held, 2006; Qu et al. 2015). However the amplitude of their changes and their relative contributions to LCC is subject to uncertainties. Here we use histograms in figs. 3.8a and 3.8b to show the mean JJA changes in SST and inversion strength ($\Delta$SST and $\Delta$IS) between the 4 dynamically downscaled climate change simulations (i.e. CNRM, IPSL, GFDL and INMC) and the baseline simulation average over the south, north and entire domain (i.e. mean JJA differences between 2091-2099 and 1991-1999). (Note that we plot here the “true” WRF inversion strength (IS) and not the GCMs estimated version (i.e. EIS) from Wood and Bretherton (2006). However, the inversion strength computed in WRF matches very well with the estimation from the parent GCM (not shown). Therefore, Fig. 3.8b reflect GCMs forcings in EIS.) Due to the choice of GCMs we made to cover the full ranges of changes, SST and inversion strength vary to different degrees in our simulations. In fact, Figs. 3.8a and 3.8b show that the simulations forced with CNRM and INMCM have relatively mild SST warming (2-3K) but different degree of IS increase (~0.5K in CNRM and ~2K in INMCM), while those forced with IPSL and GFDL have stronger SST warming (~5K) but again different degree of
inversion strength increase (~0.5K in IPSL and ~2K in GFDL).

Fig. 3.8: (a) Histogram showing JJA sea surface temperature change ($\Delta$SST, K) between the four WRF dynamically downscaled climate change simulations and the baseline simulation. We show domain averages over south, north and entire domain (ocean grid cells only); (b) Same as (a), but for inversion strength change ($\Delta$IS, K); (c) Same as (a), but for low cloud cover change ($\Delta$LCC, %). Only ocean grid points are selected for the spatial averages. Note that unlike other variables shown here, $\Delta$SST is not computed in WRF and reflect only the forcing at the lower boundary. However, as mentioned in the text, WRF computed inversion strength is also mainly driven by the boundary forcings.

Despite this variety of SST and EIS forcings, Fig. 3.8c reveal that WRF dynamically downscale climate change experiments exhibit a systematic decrease in LCC over the California oceanic region (also see Fig. 3.9 for maps). However, the amplitude of the signal differs between experiments, as well as spatially. In fact, LCC decreases are most pronounced
in the cases where IPSL and GFDL models are used in the boundary forcing ($\Delta$LCC $\sim$ -20%). In the case of CNRM, LCC decrease by about 10%, while in the case of INMCM the reduction is roughly 5%. Histograms in Fig. 3.9a also show that LCC reductions are less pronounced by 5 to 10% in the northern part of the domain in comparison to the southern part.

Thus, the results of Fig. 3.8 reveal that LCC decrease scales very well with the SST increase (r=-0.9; not shown), while EIS does not exhibit any clear contribution. These results agree with previous studies establishing the likeliness of a positive low cloud feedback (e.g. Bretherton et al., 2013; Clement et al., 2009).

![Fig. 3.9: (a) Mean JJA LCC change ($\Delta$LCC, %) between the WRF dynamically downscaled climate change simulation forced with CNRM and the baseline simulation (i.e. 2091/2099-1991/1999); (b) same as (a), but with the IPSL model used in the forcing; (c) same as (a), but with the GFDL model used in the forcing; (d) same as (a), but with the INMCM model used in the forcing](image)
3.6.2 Contributing factors

To analyze further the factors that may contribute to summer season LCC changes in WRF climate change simulations, we apply here the methodology developed in section 3.3.4. We first demonstrate the capability of this methodology to estimate JJA anthropogenic changes in $\text{RH}_{\text{POT,zi}}$. For each year, to retrieve the estimated value of $\text{RH}_{\text{POT,zi}}$ in WRF climate change experiments, we use WRF baseline value for $\text{RH}_{\text{POT,zi}}$, as well as the domain average differences between climate change experiments and baseline experiment for the various $\Delta$ terms on the right hand side of equation (3.9). In Fig. 3.10, we show WRF JJA year averages LCC differences between climate change and baseline experiments as a function of the estimated difference in $\text{RH}_{\text{POT,zi}}$ (i.e difference between the estimated value for climate change from equation (3.9) and the WRF value in the baseline). For each domain of interest, changes in LCC and estimated $\text{RH}_{\text{POT,zi}}$ are tightly correlated ($r=0.90$, $r=0.91$, and $r=0.96$ for south, north, and entire domain average, respectively). The slopes of the simulated relationships are also fairly close to those simulated on daily and interannual times scales (see Figs. 3.4b and 3.6). This confirms that the methodology we developed in section 3.4 is relevant for an analysis of WRF climate change experiments.
Fig. 3.10: (a) WRF JJA average LCC change between the four WRF dynamically downscaled climate change simulations and the baseline simulation ($\Delta$LCC, %) as a function of the corresponding change in estimated RH$_{POT,z_{i}}$ (%) in the south domain (See Fig. 1); (b) same as (a) but for the north domain and (c), same as (a) but for the entire domain average. Only ocean grid points are selected for the spatial averages. The dashed lines represent the least squares regression between the simulated variables.

We now evaluate the factors driving the differences in estimated RH$_{POT,z_{i}}$ in WRF climate change simulations. In Fig. 3.11, we show the contributions due to surface conditions (i.e. $\gamma_{q_{t}}\Delta q_{t,sfc} + \gamma_{\theta_{l}}\Delta \theta_{l,sfc} + \gamma_{P}\Delta P_{sfc}$), decoupling in total water mixing ratio (i.e. $\gamma_{\alpha_{q}}\Delta \alpha_{q}$), decoupling in liquid potential temperature (i.e. $\gamma_{\alpha_{\theta}}\Delta \alpha_{\theta}$), and BL height (i.e. $\gamma_{z_{i}}\Delta z_{i}$). For each variable, histograms show the contributions to the mean change between 2091/2099 and
1991/1999, while errors bars show the values for the year with the greatest and lowest contributions. Thus, Fig. 3.11 highlights some systematic features. For instance, surface contributions are consistently positive, while decoupling and BL height contributions are negative. The relative importance of each contributor is also consistent throughout each experiment and domain. For instance, the contribution due to BL height is negligible in most case, while the positive surface component is small but not negligible. The contributions due to changes in decoupling are the most prominent ones. Therefore, the decrease in estimated RH_{POT,zi} is mostly driven by a reduction of the coupling between BL top and surface. (Note that due to the signs of the decoupling coefficients ($\gamma_{a_q} > 0; \gamma_{a_\theta} < 0$; see appendix 3 for details), reductions of $\gamma_{a_q}\Delta a_q$ and $\gamma_{a_\theta}\Delta a_\theta$ correspond to a decrease in $a_q$ and an increase in $a_\theta$. According to the discussion related to equations (3.6) and (3.7), this is consistent with a reduction of the coupling between BL top and surface.)
Fig. 3.11: Contributors to JJA estimated changes in RH_{POT,zl} between the four WRF dynamically downscaled climate change simulations and the baseline simulation average over the southern California domain (a), northern California domain (b), and all domain (c). In the legend, sfc refers to the terms $\gamma_{qz} \Delta q_{t,sfc} + \gamma_{\theta l} \Delta \theta_{l,sfc} + \gamma_{\rho} \Delta P_{sfc}$, $\alpha_q$ to $\gamma_{q} \Delta \alpha_q$, $\alpha_{\theta}$ to $\gamma_{\theta} \Delta \alpha_{\theta}$, and $zl$ to $\gamma_{zl} \Delta zl$. Please refer to equation (3.9) and text for details. In each subplot, histograms show the contributions of each term to the mean state change (i.e. mean change between 2091/2099 and 1991/1999). Error bars show for each term the values of the year with the greatest and lowest contributions. The dashed lines represent the least squares regression between the simulated variables.
3.6.3 Potential physical drivers

Due to the tight relationship between LCC and RH\textsubscript{POT,zi}, the results of section 3.6.2 provide some important advancements in our comprehension of LCC changes in WRF climate change experiments. In fact, the results in Fig. 3.11 establish that LCC changes are mostly attributable to enhanced decoupling conditions. However, the mechanisms contributing to these changes remain uncertain. Moreover, cloud feedback contributions may not be negligible. Here we attempt to provide some physical understanding to the results of Fig. 3.11.

3.6.3.1 Surface component

We first examine the surface contributors (i.e. $\gamma_q \Delta q_{t,sfc} + \gamma_\theta_l \Delta \theta_{l,sfc} + \gamma_p \Delta P_{sfc}$). Although this component is smaller than decoupling contributions, it is not negligible. In fact, the surface component is positive in all cases and mitigate to a fair degree the decrease in RH\textsubscript{POT,zi} due to decoupling. The surface pressure term (i.e. $\gamma_p \Delta P_{sfc}$) is negligible in all cases, and will not be analyzed here. Both the mixing ratio term (i.e. $\gamma_q \Delta q_{t,sfc}$) and temperature term (i.e. $\gamma_\theta_l \Delta \theta_{l,sfc}$) have significant amplitudes. However, they have opposite signs ($\gamma_q \Delta q_{t,sfc} > 0$ and $\gamma_\theta_l \Delta \theta_{l,sfc} < 0$) and only their net effect matters for RH\textsubscript{POT,zi}. In fig. 3.12a, we show this net effect (i.e. $\gamma_q \Delta q_{t,sfc} + \gamma_\theta_l \Delta \theta_{l,sfc}$) as a function of changes in surface relative humidity ($\Delta$RH\textsubscript{sfc}). Most simulations show a relatively small increase in RH\textsubscript{sfc} (~1-2%). This increase is positively correlated with $\gamma_q \Delta q_{t,sfc} + \gamma_\theta_l \Delta \theta_{l,sfc}$ (r=0.73). However, this relationship happens to predict more significantly the interannual variability within a climate change experiment than the differences between them. In fact, when each model is treated separately, the correlation is more significant (r~0.9) and the slopes are very similar to each other. However, intercepts are significantly different in each case. To evaluate a potential contributor to these differences, we show in Fig. 3.12b the residuals of the regressed
relationship of Fig. 3.12a as a function of surface temperature. These two variables appear to be significantly correlated (r=0.86). Thus, the results of Fig. 3.12 seem to provide two physical reasons with roughly equal importance to the positive net effect of surface temperature and surface mixing ratio changes on $\text{RH}_{\text{POT,zi}}$ changes. The first contributor is the increase in $\text{RH}_{\text{sfc}}$. However, at this stage, due to the numerous potential contributors, the reasons to these increases in $\text{RH}_{\text{sfc}}$ remain unknown to us. The second contributor is surface temperature. The positive correlation between $\gamma_q \Delta q_{\text{t,sfc}} + \gamma_{\theta_1} \Delta \theta_{\text{t,sfc}}$ and $T_{\text{sfc}}$ may reflect an effect of the Clausius-Clapeyron relationship. In fact, in a BL where the BL decoupling and $\text{RH}_{\text{sfc}}$ remain constant, the BL total water mixing ratio increases with the same rate as the surface saturation mixing ratio. However, due to the Clausius-Clapeyron relationship, if temperature increases uniformly in the BL, the surface saturation mixing ratio increases more at the surface than at the top of the BL (because temperature decreases with increasing altitude). As a result, under all these assumptions, the potential relative humidity at the BL top must increase. Thus, this argument supports that $T_{\text{sfc}}$ drives the relationship highlighted in Fig. 3.12b. As result, the physical reasons to the systemic positive contributions of the surface component to $\text{RH}_{\text{POT,zi}}$ changes are now less obscure.
3.6.3.2 Decoupling component

As mentioned in section 3.6.2, LCC changes are mostly attributable to enhanced decoupling conditions. However, feedbacks between decoupling and LCC are likely. Moreover, there are two components to the decoupling (i.e. total mixing ratio and liquid potential temperature) that also may feedback with each other. Thus, diagnosing the driving mechanisms is not straightforward. The contribution to LCC changes due to decoupling in water mixing ratio is the most prominent one in most cases (see Fig. 3.11). This may suggest that a key contributing mechanism to LCC changes could originate from there. Here we attempt to evaluate the factors that may contribute to changes in the mixing ratio BL decoupling parameter (i.e. $\alpha_q$).
In Fig. 3.13, we plot year average mixing ratio BL decoupling parameter (i.e. $\alpha_q$ from equation (3.6)) in all experiments (i.e. baseline and climate change) as a function of the following variable:

$$\alpha_{q,inv} = \frac{q_{v,700} - q_{v,sfc}}{z_{i_top} - z_i}$$ (3.10)

Here $q_{v,700}$ and $q_{v,sfc}$ are the water vapor mixing ratio at 700 hPa and surface. (Note they are very similar to $q_{t,700}$ and $q_{t,sfc}$ due to the negligible presence of clouds at these altitudes). $z_{i_top}$ is the inversion top height, which we defined in the model as the height where $q_v$ drops to a value that has the same order of magnitude as $q_{v,700}$ (i.e. $z_{i_top}$ could also be named the free troposphere base). Thus, $\alpha_{q,inv}$ essentially represents the mean rate of change of the mixing ratio in the inversion layer. Fig. 3.13 confirms the decrease of $\alpha_q$ in the boundary layer in future climate simulations. This figure also highlights the very significant correlation between $\alpha_q$ and $\alpha_{q,inv}$ ($r>0.91$). Moreover, the slopes are identical in all domains (~0.33). Thus, the rate of change of $q_t$ in the BL (i.e. $\alpha_q$) scales very well with the rate of change in the inversion layer. This significant relationship may reflect the existence of an underlying mechanism. However, at this stage, we have no robust evidence for it.
Fig. 3.13: (a) Rate of change in total water mixing ratio in the BL (i.e. decoupling parameter $\alpha_q$ from equation (3.6)), as a function of the rate of change in the inversion layer (i.e. above BL). Each year of simulation and climatological value for both baseline and climate change experiments are shown (g/kg/km). Average over the entire domain (oceanic grid points only). The dashed lines represent the least squares regression between the simulated variables.

One reasonable possibility may be that mixing processes between the BL and the free troposphere are contributing to the constant scaling between $\alpha_{q,inv}$ and $\alpha_q$. If this happened to be true, this would mean that reduction in $\alpha_q$ is partially driven by decrease in $q_{v,700} - q_{v,sfc}$. The future decrease in $q_{v,700} - q_{v,sfc}$ is relatively well established. In fact, as a result of the Clausius-Clapeyron relationship, and due to the decrease of temperature with increasing altitude, if relative humidity remains close to constant, changes in $q_v$ with increasing
temperature are greater at surface than in the free troposphere (i.e. decrease of $q_{v,700} - q_{v,sfc}$).

This argument seems to be valid in our simulations (see Fig. 3.14; $r=-0.84$ between $q_{v,700} - q_{v,sfc}$ and $T_{sfc}$). Thus, if the relationship in Fig. 3.13 happened to be driven by mixing processes, this would support the idea that $\alpha_q$ decrease (and thus, LCC decrease) in future climate is driven by the mixing of BL air with drier air of the free troposphere. This argument is in agreement with findings established in previous studies (e.g. Bretherton and Blossey, 2014; Sherwood et al., 2014). However, further work will be necessary to establish with certitude the reality of this mechanism in our simulations.

**Fig. 3.14:** Difference between water vapor mixing ratio at 700 hPA and at surface ($q_{700} - q_{sfc}$; g/kg) as a function of surface temperature ($T_{sfc}$; K). Each year of simulation and climatological value for both baseline and climate change experiments are shown. Average over the entire domain (oceanic grid points only). The dashed lines represent the least squares regression between the simulated variables.
3.7 Conclusions

In this study, we use the regional model WRF to perform both a historical reconstruction and a dynamical downscaling of future climate projections from four GCMs over the California region. The California Ocean is extensively covered with marine stratocumulus clouds. Our baseline simulation confirms the results of a previous study (Jousse et al., 2015) that established a fair representation of this low cloud regime in the model configuration we use. In this study, we focus on the JJA season where low clouds are most prevalent. In particular, we analyze the simulated JJA low cloud cover (LCC) interannual variability, as well as the anthropogenic changes. We summarize here our findings.

The primary goal of this study was to provide a comprehensive analysis of LCC variability in our simulations. Thus, our approach was first to establish a criterion for cloudiness. The physical relevance of relative humidity and the convenience of moist conserved variables lead us to define the potential relative humidity. This variable represents the relative humidity the atmosphere would have if no cloud condensation occurred (see equation 3.3). Since RH\textsubscript{POT} decreases with altitude in stratocumulus BLs, its value at BL top (i.e. RH\textsubscript{POT,zi}) is a legitimate criterion to use for cloudiness. The relevance of this criterion is supported in our simulations (94% LCC day-to-day variability explained by a linear fit; Fig. 3.4b).

In a second step, we used the Clausius-Clapeyron to develop an analytical framework that predicts changes in RH\textsubscript{POT,zi} as functions of those in surface quantities (i.e. temperature, water vapor mixing ratio and pressure), boundary layer height (zi) and variables representing the coupling of the BL top with the surface (i.e. \(\alpha_q\) and \(\alpha_\theta\)). Our results show the good predictability of RH\textsubscript{POT,zi} through that methodology (Fig. 3.5). Thus, we developed a
framework that enables a quantification of the contributors to LCC variability in our simulations.

We then took advantage of this methodology to analyze the JJA LCC interannual variability. Our results show that all factors (i.e. surface conditions, decoupling and BL height) are significant contributors (Fig. 3.7). Our methodology enables a clear identification of the factors contributing to LCC interannual changes. This represents an advancement in our comprehension of the LCC interannual variability. However, further investigations will be needed to scale back these changing conditions to large-scale patterns. This will be subject of future studies. The applicability of the methodology to observations will be also investigated in future work.

We then analyzed the LCC response to anthropogenic climate changes during JJA in WRF. Four GCMs representing the full range of CMIP5 projections in SST and EIS were dynamically downscaled. Our results show a systematic decrease in LCC. This decrease scales relatively well with SST increase (~ -3.5 %/K), while EIS increase seems to have negligible effects on LCC in our simulations (Fig. 3.8). To comprehend further the reasons to these changes in our simulations, we applied our methodology of analysis to the climate change experiments. It shows that LCC decrease is associated with some systematic changes in our simulations. In fact, the LCC decrease is mostly imputable to a reduction of the coupling between BL top and surface, while changes in surface conditions partially mitigate the decrease (Fig. 3.10). These systematic changes are clearly different from the interannual case. This suggests the existence of very specific mechanisms contributing to LCC anthropogenic changes in our simulations.
To provide further understanding to these results, some of the possible driving mechanisms have been investigated. We first focused on surface changes. The positive contribution to LCC changes due to surface variables appear to be both driven by the increase in surface relative humidity (RH$_{sfc}$) and an effect of the surface temperature increase (T$_{sfc}$; Fig. 3.12). While the reasons to RH$_{sfc}$ increases remain unknown to us, we argued that the surface temperature contribution is likely an effect of the Clausius-Clapeyron relationship.

We then attempted to provide some preliminary understanding to the changes in decoupling conditions. In particular, we focused on the water mixing ratio decoupling parameter (i.e. $\alpha_q$), whose changes are the most prominent contributors to LCC decrease in almost all cases. Our analysis indicates that $\alpha_q$ is very significantly correlated with the mean rate of change of the mixing ratio in the inversion layer (i.e. $\alpha_{q,inv}$; Fig. 3.13). Here we argued that the constant scaling between $\alpha_q$ and $\alpha_{q,inv}$ may suggest that mixing processes between the free troposphere and the BL contribute to this relationship. If that happened to be true, that would mean that LCC changes are at least partially driven by anthropogenic increase in $q_{v,700} - q_{v,sfc}$. Thus, this would be essentially an effect of the Clausius-Clapeyron relationship (Fig. 3.14). However, at this stage, further investigations are required to establish the veracity of this mechanism.

Finally, our results highlight the potential threat that anthropogenic climate change may be for the California region. In fact, the LCC decrease (~10-20%) our study predicts would significantly impact the California climate, as well as its ecosystems. However, the spread in our results are mostly driven by SST changes. Thus, a better comprehension of the potential changes in the upwelling system along the California coast will be required to reduce the uncertainties associated with these projections. This will be investigated in future work in a
coupled ocean atmosphere framework (i.e. WRF coupled with the Regional Oceanic Modeling System; Shchepetkin and McWilliams, 2009).
Appendix 3: Expression of the $\gamma$ coefficients

To express the saturation mixing ratio as a function of the temperature $T$ we use the Clausius-Clapeyron equation:

$$\frac{dq_s(T, P)}{q_s(T, P)} = \frac{L}{R_v T^2} dT - \frac{dp}{p} \quad (3. A1)$$

According to equation (3.5), this leads to:

$$\frac{dRH_{POT,zi}}{RH_{POT,zi}} = \frac{dq_{t,zi}}{q_{t,zi}} - \frac{L}{R_v T^2_{l,zi}} dT_{l,zi} + \frac{dp_{zi}}{p_{zi}} \quad (3. A2)$$

To express $p_{zi}$ as a function of surface terms, we assume an hydrostatic pressure profile in the boundary layer:

$$p_{zi} = p_{sfc} \exp \left(\frac{-zi}{H}\right) \quad (3. A3)$$

Here $H$ is the scale height. (We use $H=8500m$ in this study, which is the scale height at 290K.)

Thus, $T_{l,zi}$ can be expressed such that:

$$T_{l,zi} = \theta_{l,zi} \sigma_{zi} \quad (3. A4)$$

With $\sigma_{zi}$ defined as:

$$\sigma_{zi} = \exp \left(\frac{-Kzi}{H}\right) \left(\frac{p_{sfc}}{p_0}\right)^K \quad (3. A5)$$

By differentiating equations (3.6) and (3.7), we get:

$$d\theta_{l,zi} = d\theta_{l,sfc} + d\alpha_\theta zi + \alpha_\theta dzi \quad (3. A6)$$
\[
d q_{t,zi} = d q_{t,sfc} + d \alpha q z_i + \alpha q d z_i \quad (3. A7)
\]

Finally, we differentiate (3. A3), (3. A4) and (3. A5) to get:

\[
d P_{zi} = d P_{sfc} \exp \left( \frac{-z_i}{H} \right) - \frac{1}{H} P_{sfc} \exp \left( \frac{-z_i}{H} \right) d z_i \quad (3. A8)
\]

\[
d T_{l,zi} = d \theta_{l,zi} \sigma_{zi} + \theta_{l,zi} d \sigma_{zi} \quad (3. A9)
\]

\[
d \sigma_{zi} = -\frac{K}{H} \exp \left( \frac{-K z_i}{H} \right) \left( \frac{P_{sfc}}{P_0} \right)^K d z_i + \frac{K}{P_0} \exp \left( \frac{-K z_i}{H} \right) \left( \frac{P_{sfc}}{P_0} \right)^{K-1} d P_{sfc} \quad (3. A10)
\]

Then, by replacing (A6), (A7), (A8), (A9), (A9) and (A10) into (A2), we get the following \( \gamma \) coefficients for equation (3.8):

\[
\gamma_{q_t} = \frac{1}{q_{t,zi}} \quad (3. A11)
\]

\[
\gamma_{\alpha q} = \frac{z_i}{q_{t,zi}} \quad (3. A12)
\]

\[
\gamma_{zi} = \frac{\alpha q}{q_{t,zi}} - \frac{L}{R_v T^2_{l,zi}} \left[ \sigma_{zi} \alpha \theta - \theta_{l,zi} \frac{K}{H} \sigma_{zi} \right] + \frac{K}{H} \quad (3. A13)
\]

\[
\gamma_p = -\frac{1}{P_{sfc}} - \frac{L}{R_v T^2_{l,zi}} \left[ K \theta_{l,zi} \frac{\sigma_{zi}}{P_{sfc}} \right] \quad (3. A14)
\]

\[
\gamma_{\theta_l} = -\frac{L}{R_v T^2_{l,zi}} \sigma_{zi} \quad (3. A15)
\]

\[
\gamma_{\alpha \theta} = -\frac{L}{R_v T^2_{l,zi}} \sigma_{zi} \quad (3. A17)
\]
References


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