Physical modeling of stratocumulus cloud mixing processes in numerical weather prediction models

A dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy

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by

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This work is dedicated to my parents for everything they’ve provided for me and to my grandparents for their immeasurable love.
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Stratocumulus (Sc) clouds are vast sheets of convective clouds which are responsible for the colloquial “May Gray” and “June Gloom” in southern California. The most prevalent cloud type by area, Sc possess strong reflective properties which result in a net cooling effect on the Earth’s radiative balance. Accurate prediction of the spatial coverage and lifetime of Sc reduces uncertainty in global climate response due to the associated cloud feedback effect and facilitates the integration of solar power into the electrical grid through predictions of solar energy production. The modeling of Sc in global climate (GCM) and
numerical weather prediction (NWP) models requires parameterization of physics governing Sc which consist of a complex interplay between cloud top- and surface-driven convection, radiative forcings, microphysical processes, and small-scale mixing across a stratified interface. The difficulty in characterizing these processes is compounded by the coarse resolution at which GCMs and NWPs operate. This thesis focuses on the Weather Research and Forecasting (WRF) NWP model and its ability to predict Sc. First, different initialization techniques are compared to characterize the effect of initial cloud cover. Even when augmented with satellite-derived cloud cover, WRF predicts overly thick clouds over ocean and early dissipation times over land. Second, the WRF planetary boundary layer (PBL) scheme, which is responsible for mixing processes in the PBL is investigated in a single-column model. A thick cloud bias was discovered to result from a cold and moist bias. Modifications were made to two PBL schemes to better account for deep mixing due to downdrafts and entrainment mixing at cloud top, leading to more accurate cloud thickness and lifetimes. Finally, a radiatively-driven downdraft mass flux model was developed in order to account for deep mixing in WRF through an eddy diffusivity-mass flux framework using large-eddy simulation, observational data, and turbulence theory. Many WRF PBL schemes neglect downdraft mixing, but turbulent downdrafts help couple the cloud layer with surface moisture and distribute the warm and dry air mixed in from aloft. These processes aid in sustaining the cloud, preventing the early dissipation bias frequently observed in weather predictions.
Chapter 1

Introduction

1.1 Motivation

Stratocumulus (Sc) clouds comprise about 20% of global cloud cover in the annual mean, making them the most common cloud type on the planet (Wood, 2012). Due to their prevalence, stratocumulus has been the focus of many studies over the past few decades, as the prediction of both their spatial coverage as well as lifetime is of interest to climate, weather, and solar forecasters as well as the airport operations, for example.

Currently, the response of Sc to environmental changes leads to major uncertainties in climate models, and the disagreement between models suggests that Sc are not accurately simulated (Bony and Dufresne, 2005; Zelinka et al., 2013). Governed by a complex set of interrelated phenomenon like both surface and top-down (caused by longwave cooling) convection, wind shear, drizzle, and the entrainment of free atmospheric air into the boundary layer (Wood, 2012), Sc are sensitive to small perturbations in environmental
conditions, and their properties and lifetime are difficult to quantify due to the feedbacks caused by the governing physical mechanisms.

To summarize the physics of the stratocumulus-topped boundary layer (STBL), surface heat and moisture fluxes drive ascending updrafts while cloud-top longwave cooling drives descending downdrafts. During daytime, absorption of solar radiation counteracts longwave cooling. Together, these updrafts and downdrafts drive turbulence within the STBL, while the turbulent energy cascade produces smaller scale mixing motions. Turbulence couples the cloud deck at the top of the STBL to the surface, leading to well-mixed (or constant in height) profiles in reversible moist adiabatically conserved temperature and total water mixing ratio. Above cloud top, temperature and moisture profiles make a large jump to those of the warm, dry, subsiding free troposphere caused by synoptic scale conditions. The turbulent eddies in the STBL, radiative forcings, evaporative cooling, and wind shear all contribute to small-scale mixing at the cloud-top interface which entrains the warm, dry air from aloft. Finally, evaporative cooling, latent heating, drizzle, and other microphysical effects all further contribute to the structure of the STBL.

This proposed thesis work is an extension of the work by Ghonima et al. (2016), who found that cloud lifetime mainly depends on cloud-top entrainment flux, the ratio between sensible and latent heat flux at the surface (Bowen ratio), and the advection of cool, moist ocean air. This work focuses on the parameterization of entrainment flux in numerical weather prediction (NWP) models.

The understanding of cloud-top entrainment was initially pioneered by Lilly (1968), and many have followed in an effort to both observe, simulate, and formulate parameteri-
zations for entrainment rates (Tennekes and Driedonks, 1981; Nicholls and Turton, 1986; Bretherton and Blossey, 2014; Albrecht et al., 2015). Efforts to include entrainment effects in NWP models have been undertaken by, for example, Hong (2010), Lock et al. (2000), and Grenier and Bretherton (2001) to varying degrees of success. Recently, direct numerical simulations of the entrainment interface (de Lozar and Mellado, 2013) have also aided in advancing the understanding of the cloud-top entrainment process. However, accuracy in simulating Sc is still lacking, especially in coastal and continental regions, as most of the research effort has been focused on marine Sc due to their prevalence.

Over the Southern California region, for example, NWP forecast insufficient inland coverage of Sc as well as cloud lifetime. Since the terrain height in the region gradually increases inland (see Figure 1.1), the PBL height directly affects the farthest inland penetration, as clouds cannot exist in regions where the terrain height exceeds that of the synoptic subsidence-induced temperature inversion. The entrainment of free atmospheric air into the PBL alters both the thermodynamic properties of the PBL and the inversion height due to the air mass entrained. This work aims to improve the physical modeling of Sc in NWP models—specifically, the Weather Research and Forecasting (WRF) model (Skamarock et al., 2008).

A brief description of WRF will be given in the following section, followed by a description and analysis of improved initialization methods in Chapter 2) based on a publication by the author. However, improved initializations do not result in satisfactory forecast accuracy. Therefore, deficiencies and improvements of WRF model physics are presented in Chapter 3) along with future work.
1.2 The Weather Research and Forecasting Model (WRF)

The Weather Research and Forecasting Model (WRF, Skamarock et al. (2008)) is a numerical weather prediction (NWP) model designed with both the research and operational communities in mind. It is maintained by the National Center for Atmospheric Research (NCAR) as a community model to facilitate transfer of mesoscale weather research to weather forecasting operations. The WRF-ARW v3.7.1 uses the Advanced Research WRF (ARW) dynamics solver, which solves the fully compressible, Euler nonhydrostatic equations in flux form on a terrain-following mass vertical coordinate. The equations are solved for variables which have conservation properties (the three Cartesian velocity components and perturbation potential temperature, geopotential, and surface pressure of dry air). Scalars such as water vapor/liquid/ice mixing ratios and chemical species and tracers may also be included. While horizontal diffusion and advection is handled by the
ARW solver, the vertical sub-grid-scale fluxes are parameterized by a planetary boundary layer parameterization scheme (see Section 4.2). Since computational cost of global runs is prohibitive, initial and boundary conditions need to be provided by other models. Such models are typically run operationally by weather centers. The following chapter discusses sensitivities and corrections to the initial conditions of these models.
Chapter 2

Development and validation of an initial conditions preprocessor for WRF

2.1 Introduction

The accurate prediction of coastal stratocumulus (Sc) in the southern California region is crucial for solar energy forecasting, as Sc is the dominant cloud type in the region, and their presence greatly attenuates the solar resource in the area with the majority of rooftop solar installations. Numerical weather prediction (NWP) models become increasingly important from hours-ahead to days-ahead forecasts, since non-linearities and global coupling in the atmospheric processes make other extrapolation methods less accurate for longer forecast horizons. Furthermore, the mesoscale and global processes which develop
in these forecast horizons can only be modelled by physical models and not statistical models.

Hence, NWP forecasting accuracy has been the subject of many studies. Comparisons between the North American Mesoscale (NAM), Global Forecast System (GFS), and European Centre for Medium-range Weather Forecasts (ECMWF) over the continental United States by Mathiesen and Kleissl (2011) found mean bias error (MBE) and root mean square error (RMSE) of hourly-averaged forecast surface irradiance to exceed 30 W m\(^{-2}\) and 110 W m\(^{-2}\), respectively, over a period of about a year. Similarly, a more comprehensive intercomparison of Global Environmental Multiscale model (GEM), Mesoscale Atmospheric Simulation System (MASS), and Advanced Multiscale Regional Prediction System (ARPS) models by Perez et al. (2013) found predominantly positive MBE over the United States. NWP models thus tend to overpredict expected solar power due to errors in cloud cover, aerosol optical depth, clear sky models, and the lack of consideration of shading effects from the horizon. Since regional or mesoscale NWP models are generally initialized from synoptic or global models, errors in the larger scale model are directly inherited. Additionally, a break in the simulation timeline occurs at the transition point from one model to another (e.g. NAM to WRF) due to the subsequent “spin-up” period, during which model dynamics stabilize. For some models, this discontinuity is further exacerbated by an imperfect transfer of atmospheric state caused by absent model output, such as missing atmospheric liquid water content in NAM.

While previous studies have highlighted the sensitivity of WRF forecasts to physics parameterizations—notably the planetary boundary layer (Hu et al., 2010), microphysics
(Jankov et al., 2011), and cumulus (Jankov et al., 2005) schemes, model initial conditions
also play an important role in forecast accuracy, and improvements are typically obtained
through data assimilation techniques. While the WRF system contains its own data
assimilation system in the form of WRFDA, external data assimilation systems are also
available. For example, the Local Analysis and Prediction System (LAPS) (Albers et al.,
1996) is a data assimilation system designed to incorporate a variety of observations from
surface sites, satellites, Doppler radars, atmospheric profilers, and aircraft into analyzed
grids intended for NWP initialization. Improvement in short-range WRF forecast accuracy
was demonstrated by Etherton and Santos (2008).

Other researchers have developed methods to improve cloud field initialization, such
as the cloud package used within the Gridpoint Statistical Interpolation (GSI) system (Hu
et al., 2007). GSI blends surface, satellite, and radar observations into a 3-dimensional
field describing cloud cover and precipitation, and it is currently implemented in the NAM
and Rapid Refresh (RAP) models.

In this study, the impact of model initial conditions is evaluated by quantifying
forecast errors of WRF 3.6 (with the Advanced Research WRF, or ARW, dynamical core)
simulations with different initialization data sets. To take advantage of NAM’s data as-
simulation system, WRF simulations were initialized at times coinciding with NAM initial-
ization. This study focuses on targeted preprocessing of NAM output in order to facilitate
transfer of cloud cover information and to supplement the cloud field with a high-resolution
satellite cloud assimilation method. Standard initializations using data from the NAM and
RAP are compared against two preprocessing schemes applied to the NAM data.
The first preprocessing scheme, the Well-mixed Preprocessor (WEMPP), was developed to provide an initial guess at liquid water content, which is lacking from NAM data. Since Sc is governed by a complex system of physics with feedbacks, the intent of WEMPP is to retain cloud water content in order to prevent radiative feedbacks caused by a sudden elimination of liquid water path (LWP) at initialization. Additionally, a more accurate initial guess at the cloud water field allows the microphysics scheme to produce a stable nocturnal Sc field in only 1-2 hr. The second preprocessing scheme is the satellite Cloud Data Assimilation (CLDDA) package developed by Mathiesen et al. (2013) (applied here at initialization rather than mid-simulation). A combination of the two preprocessing schemes was also explored. In order to isolate the effects of cloud liquid water initialization from the two preprocessors, additional data assimilation (e.g. through WRFDA, LAPS, or GSI) was not applied. WEMPP and CLDDA provide relatively simple and computationally inexpensive ways to maintain consistency with the parent NAM model and improve liquid water initialization. The implementation of the preprocessing is specific to boundary layer clouds and cannot be easily adapted to other cloud types such as altocumulus or cirrus. However, boundary layer clouds are the predominant cloud type, and due to their generally large optical depth they are of most interest to solar forecast applications. We therefore expect that similar algorithms could be applied elsewhere in North America (the NAM domain) for WEMPP and globally for CLDDA.

In the following sections, the methodology will be explained, beginning with the WRF domain and physics configurations (2.2.1), followed by a description of the two preprocessing schemes used (2.2.2 and 2.2.3). Next, the study setup (time period and in-
tercomparison setup in 2.2.4), validation methods, and data sources are presented (2.2.6). Validation results are presented and discussed in Section 2.3. Section 2.4 provides conclusions.

2.2 Methodology

2.2.1 WRF configuration

Two one-way nested domains at 8.1 km and 2.7 km resolution were initialized at 12Z (0400 PST) in WRF 3.6 with the physics configuration summarized in Table 2.1, which was based on a sensitivity study by López-Coto et al. (2013). Each domain contains 100 grid points in both horizontal directions and 75 vertical levels, with 50 levels below 3 km; their locations are shown in Figure 2.1. Output was recorded at 15-min intervals, and the time stepping interval was 10 s.

![Figure 2.1](image.png)

**Figure 2.1**: Outer and inner domains at 8.1 km (100x100x75 grid points) and 2.7 km (100x100x75) resolution. Satellite image ©2015 Google.
Table 2.1: Summary of WRF physics parameterizations

<table>
<thead>
<tr>
<th>Parameterization type</th>
<th>Namelist setting (outer/inner)</th>
<th>Scheme name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Planetary boundary layer</td>
<td>5/5</td>
<td>MYNN2</td>
</tr>
<tr>
<td>Surface layer</td>
<td>5/5</td>
<td>MYNN</td>
</tr>
<tr>
<td>Land surface</td>
<td>2/2</td>
<td>Noah LSM</td>
</tr>
<tr>
<td>Radiation (LW &amp; SW)</td>
<td>5/5</td>
<td>New Goddard</td>
</tr>
<tr>
<td>Microphysics</td>
<td>10/10</td>
<td>Morrison 2-moment</td>
</tr>
<tr>
<td>Cumulus</td>
<td>14/0</td>
<td>New SAS</td>
</tr>
</tbody>
</table>

2.2.2 Well-mixed Preprocessor (WEMPP)

In a WRF simulation initialized with atmospheric state variables obtained from the North American Mesoscale (NAM) model, temperature and relative humidity (RH) fields are ingested, but atmospheric liquid water is not present in NAM output. This leads to a cloud cover spin-up period of a few hours during which the microphysics scheme produces a cloud field based on temperature and relative humidity fields.

Since stratocumulus cloud decks play an important role in radiative and entrainment fluxes in the planetary boundary layer (PBL) (Wood, 2012), a simple preprocessing scheme was developed in order to preserve cloud cover information between NAM and WRF atmospheric states. In addition to preserving consistency between the NAM parent model and WRF, adding liquid water ab initio contributes to more accurate modelling of land surface fluxes and the Earth’s energy budget by reducing both surface longwave cooling during nighttime (due to longwave emission from low clouds exceeding atmospheric longwave radiation) and shortwave heating during daytime.

The Well-mixed Preprocessor (WEMPP) was developed based on the well-mixed...
stratocumulus-topped boundary layer (STBL) framework developed by Lilly (1968). A key characteristic of the STBL is the presence of a capping temperature inversion: a vertical layer in which temperature increases with height. The abrupt drop in ambient density caused by the strong positive temperature gradient at the inversion base height (IBH) acts as a lid for ascending air parcels, therefore approximately coinciding with the cloud top height. At nighttime, longwave radiative cooling at the cloud top drives turbulence within the boundary layer which strongly mixes the air within, leading to near-constant conserved variables (e.g. total water mixing ratio $q_t$ and equivalent potential temperature $\Theta_e$) (Wood, 2012). The conservation of $q_t$ can be used to predict the amount of liquid water within the boundary layer. Since the goal of WEMPP is only to facilitate the carryover of “missing” liquid water input, the temperature profile is not adjusted. Based on the above, the algorithm developed is as follows:

1. In every model column, the temperature inversion, if present, is detected by searching for adjacent layers in which temperature continuously increases with height. The layer with the largest difference in temperature between the top and base is defined to be the capping inversion, similarly to the method described by Iacobellis et al. (2009). Only inversions with base height $< 3$ km above ground level (AGL) are considered.

2. Cloud top $z_{ctop}$ is then defined as the highest point below the IBH with RH $\geq 95\%$ (although physically cloudy air parcels should be 100% RH, this criterion was chosen to correct observed dry biases in NAM).
3. Assuming a single cloud layer, compute mass-weighted cloud layer means of RH for subsequently lower grid points until layer RH < 95%. Define this point to be cloud base $z_{cbase}$. This computation for the WRF-ARW grid is:

\[
\overline{RH} = \frac{\sum_{k=n}^{k(z_{ctop})} \text{RH}(z_k) \Delta \eta(z_k)}{\sum_{k=n}^{k(z_{ctop})} \Delta \eta(z_k)},
\]

for $n = k(z_{ctop}) - 1, k(z_{ctop}) - 2, \ldots$ until $\overline{RH} < 95\%$, \hspace{1cm} (2.1)

where $\Delta \eta$ is the change in $\eta$ (the vertical coordinate in WRF-ARW) between full model levels.

4. At the cloud base, take the saturation water vapor mixing ratio $q_{sat}$ to be the constant conserved total water mixing ratio $q_t$ within the PBL:

\[
qu(t)(0 \leq z \leq z_{ctop}) \equiv q_{sat}(z_{cbase}).
\] \hspace{1cm} (2.2)

5. Set $q_v$ to $q_{sat}$ in all grid points within the cloud layer, and partition $q_t - q_{sat}$ to liquid water mixing ratio $q_l$:

\[
\begin{cases}
q_v(z) = q_{sat}(z), & \text{for } z_{cbase} \leq z \leq z_{ctop} \\
q_l(z) = q_{t} - q_{sat}(z).
\end{cases}
\] \hspace{1cm} (2.3)

An illustration of the procedure is shown in Figure 2.2. In the left panel, the
detected cloud top and cloud base are overlaid on the original input relative humidity profile. In the right panel are adjusted vertical moisture profiles (see caption for detailed description). The lifting condensation level (LCL) was computed after Stull (2000) from the equation

\[ z_{\text{LCL}} = a(T - T_d), \]  

(2.4)

where \( a = 125 \text{ m K}^{-1} \), \( T \) is temperature, and \( T_d \) is the dew point temperature. Atmospheric state variables were obtained from the first vertical grid point, and the LCL is found to typically agree with the algorithmically-determined cloud base height to within a few tens of meters.

**Figure 2.2:** Left: Original initial temperature (red) and relative humidity (green) profiles above a land grid point at 12Z. Right: Preprocessed moisture profiles at initialization. Original water vapor mixing ratio \( q_v \) in green, preprocessed \( q_v \) as crosses, preprocessed liquid water mixing ratio \( q_l \) in solid blue, and saturated water vapor mixing ratio \( q_{sat} \) in dashed red. Lifting condensation level (LCL) is denoted by black triangles. The LCL does not necessarily equal \( z_{\text{cbase}} \), but supports the cloud base height determined by the algorithm.
2.2.3 Cloud Data Assimilation (CLDDA)

The Cloud Data Assimilation (CLDDA) preprocessor was designed by Mathiesen et al. (2013) to populate liquid cloud fields based on satellite observations. In short, the latitude and longitude positions of low clouds are first obtained from cloud top temperature data in the GOES Sounder cloud product (Li et al., 2001) maintained by CIMSS at the University of Wisconsin-Madison. In observed cloudy regions, cloud tops are defined at the temperature inversion base height or, in the absence of an inversion, at the intersection of the initial vertical temperature profile and satellite-derived cloud top temperature. Cloud base is then estimated from an empirical function of cloud top height (see Mathiesen et al. (2013)). Relative humidity is then set to 110% within all cloud decks. In order to avoid intense latent heating from the resulting condensation, microphysics heating is turned off for 1 hr following application. Lastly, in observed clear regions, RH is adjusted to a maximum of 75% in order to remove falsely predicted clouds. Figure 2.3 depicts the adjusted RH profile at initialization for the same time and grid point as in Figure 2.2, as well as the water vapor $q_v$ and liquid water $q_l$ (condensed by the microphysics scheme) mixing ratios 15 min after initialization. The LCL typically agrees within several tens of meters with the initially detected cloud base, though notable departure is observed after 15 min due to a decrease in the near-surface temperature (common in all NAM-initialized simulations).
Figure 2.3: **Left:** Temperature (red) and CLDDA adjusted relative humidity (green) profiles at initialization. **Right:** Moisture profiles 15 min after initialization. The lifting condensation level is denoted by black triangles.

2.2.4 Setup

Because both preprocessing schemes were designed to target stratocumulus clouds, the period of validation was chosen based on frequency of occurrence of stratocumulus in the San Diego region. Klein and Hartmann (1993) showed that the three-month seasonally-and spatially-averaged (10° x 10°) marine stratus, stratocumulus, and fog amount off of the Californian coast over 30 years peaked in June, July, and August. Recently, Clemesha et al. (2016) showed that the seasonal cycle of coastal low cloudiness peaks in the San Diego region during the month of June (see Figure 4 in Clemesha et al. (2016)). Therefore, the month of June, 2013 was chosen for study, as maximal cloud coverage will coincide with maximal forecast error.

Five model outputs and/or preprocessing schemes were used to initialize WRF:

1. 12Z-cycle **NAM** (0th-hr forecast on 218 AWIPS CONUS grid at 12 km resolution)
2. 00Z-cycle **RAP** (hybrid levels at 13 km resolution)
3. 12Z-cycle NAM with **WEMPP**
4. 12Z-cycle NAM with CLDDA

5. 12Z-cycle NAM with CLDDA and WEMPP (COMBO)

All simulations were initialized at 12Z (0400 PST) and were run past sunset for 17 hr until 05Z (2100 PST). Average sunrise and sunset were at 0442 PST and 1858 PST, respectively. The first two configurations will function as baselines for comparison. The 00Z-cycle RAP was chosen rather than the 12Z-cycle because it is the only cycle in current archives containing liquid water information. It is therefore a reference case for an initialization that mitigates the lack of cloud water in NAM output. Additionally, the two original raw data forecasts (RAW-NAM and RAW-RAP) were included as performance baselines and were interpolated onto the same 8.1 km and 2.7 km WRF grids to facilitate intercomparison.

Configurations 3 and 4 were implemented as described in Sections 2.2.2 and 2.2.3. The COMBO configuration was designed to maximize initial cloud cover, and both preprocessing methods were applied. First, two independent simulations of configurations 3 and 4 were run for 15 min each. After completion, a composite moisture field was created by using the moisture profile from the simulation with the highest liquid water path (LWP) at each column, and the simulation was resumed.

Over the month, the average modification to the outer (inner) domain was 37.7% (45.6%) by WEMPP and 26.8% (52.1%) by CLDDA. Regions of modification in the inner domain for a typical day are shown in Figure 2.4.
2.2.5 Spinup Period

Although cloud water is expected to be accurate at initialization in preprocessed simulations, a spin-up period is still necessary to correctly simulate atmospheric dynamics. Skamarock (2004) quantified the spin-up period of model dynamics by analyzing model kinetic energy spectra. Using the same methods, kinetic energy spectral densities of all five WRF configurations is shown for the inner domain in Figure 2.5 for a day when the discrepancy between initialization and subsequent spectra is most pronounced. The initial spectra, which is lacking in energy at finer scales, becomes fully developed about 1-2 hr into the simulation, which is significantly shorter than that found by Skamarock (2004). We hypothesize that the finer spatial resolution of initialization data (12-13 km vs. 40-80 km) combined with the 10 s timestepping interval significantly reduced the spin-up period from the previously determined 6-12 hr.
Figure 2.5: Spectral density of kinetic energy for various simulation times in the inner domain for June 20, 2013. The $k^{-5/3}$ line shows the theoretical slope for mesoscale motions ($\approx k > 10^{-5}$ rad m$^{-1}$).

### 2.2.6 Validation sites and data

**Ground sites**

Measurments from ground stations maintained by the San Diego Gas & Electric Company (SDGE) were used for validation. Four weather stations with LI-COR LI200 pyranometers were selected along a line from west to east. Station locations are shown in Figure 2.6, and their geographical coordinates, elevation, distance from the coast, averaging interval, and mean observed GHI and clear sky index $k_c$ (see caption) are tabulated in Table 2.2.

All stations recorded averaged global horizontal irradiance (GHI) data at 5-min resolution (sampled every 10 s), with the exception of station 4 which recorded at 10-min resolution (sampled every 3 s). Measurements from all stations were aligned with instantaneous model output (hourly for raw data, 15-min intervals for WRF) for error computation through linear interpolation.
Figure 2.6: Locations of the four ground stations used for validation. The white dashed line marks the border of the coastal marine layer region, defined as the region where land elevation < 375 m MSL and monthly mean observed GHI is < 92% of clear sky GHI. The region contains 972 WRF grid points in the inner domain. Satellite image ©2015 Google.

Table 2.2: Summary of ground stations used for validation. $k_c$ is clear sky index, which is GHI normalized by modelled clear sky GHI. Mean GHI and $k_c$ are monthly values computed from daytime data collected in June, 2013.

<table>
<thead>
<tr>
<th>Station ID</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Latitude [°]</td>
<td>33.12°N</td>
<td>33.14°N</td>
<td>33.13°N</td>
<td>33.16°N</td>
</tr>
<tr>
<td>Longitude [°]</td>
<td>117.29°W</td>
<td>117.24°W</td>
<td>117.20°W</td>
<td>117.03°W</td>
</tr>
<tr>
<td>Elevation [m MSL]</td>
<td>85</td>
<td>143</td>
<td>165</td>
<td>315</td>
</tr>
<tr>
<td>Distance from coast [m]</td>
<td>3,800</td>
<td>9,300</td>
<td>12,200</td>
<td>28,700</td>
</tr>
<tr>
<td>Averaging interval [min]</td>
<td>5</td>
<td>5</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>Mean GHI [W m$^{-2}$]</td>
<td>449</td>
<td>481</td>
<td>509</td>
<td>518</td>
</tr>
<tr>
<td>Mean $k_c$ [-]</td>
<td>0.71</td>
<td>0.76</td>
<td>0.84</td>
<td>0.84</td>
</tr>
</tbody>
</table>

**Satellite solar resource data**

Additional validation was performed against Clean Power Research’s SolarAnywhere® (2013) satellite data at 0.02° spatial and 30-min (hourly averaged) temporal resolution, with the exception of the raw NAM and RAP forecasts which were at 1-hr instantaneous temporal resolution. Jamaly et al. (2012)’s validation against 52 California
Irrigation Management Information System (CIMIS) ground stations at hourly-averaged temporal resolution over the year 2010 showed a previous version of SolarAnywhere to have MBE of 18.8 W m\(^{-2}\), mean absolute error (MAE) of 45.6 W m\(^{-2}\), and RMSE of 65.3 W m\(^{-2}\)—an accuracy which is comparable to that of typical ground stations.

Because the validation region contains the Pacific Ocean, regions affected by sunglint were computed after Gardashov and Eminov (2015), wherein the principal point of sunglint (PPS) could be determined as a function of geostationary satellite longitude and time of year. The PPS migrates farthest to the north and closest to the region of interest during the summer solstice. Computations of the PPS on June 21 show that the PPS resides a minimum of 17° latitude south of the southern edge of the outer WRF domain, thereby eliminating sunglint as a source of error.

**Model output statistics (MOS) correction**

A model output statistics (MOS) correction was applied in order to correct clear-sky bias, similar to that applied in Section 3.4 of Mathiesen and Kleissl (2011), except the MOS correction used in this paper is solely a function of solar zenith angle and was trained only during periods of clear sky. MOS correction functions were created for RAW-NAM, RAW-RAP, WRF-NAM, and WRF-RAP configurations from observations at solar zenith angle < 75° from May 2, 13, 19, 24, and 29, 2013. In validation against ground stations, MOS correction functions were derived at each station. Against satellite observations, the MOS function was derived at the grid point containing ground station 4 and applied to the entire domain. The WRF-NAM MOS function was applied to WRF-WEMPP, WRF-
CLDDA, and WRF-COMBO since they share the same initialization data set and clear
sky biases. The application of MOS is intended to match clear-sky irradiance predictions
between all models to emphasize cloudy conditions in the evaluation of the preprocessing
schemes. Otherwise, since all tested configurations overpredicted clear-sky GHI, a system-
atic underprediction of GHI under cloudy conditions could be offset by the clear-sky bias
and artificially reduce MBE.

The clear-sky irradiance biases are dependent on the physics parameterizations
used, and therefore affect the entire domain. The highest clear-sky bias is observed in
RAW-NAM (using the Geophysical Fluid Dynamics Laboratory (GFDL) radiation scheme
at the time), while RAW-RAP shows almost no clear-sky bias (using the Goddard short-
wave scheme at the time). The clear-sky bias in the WRF simulations has since been
corrected by Zhong and Kleissl (2016) through a modification to the New Goddard short-
wave radiation scheme.

**Error metrics**

The error metrics chosen here for validation are mean absolute error (MAE):

\[
\text{MAE} \equiv \frac{1}{N} \sum_{n=1}^{N} |x_n - x_n^{\text{obs}}|, \tag{2.5}
\]

and mean bias error (MBE):

\[
\text{MBE} \equiv \frac{1}{N} \sum_{n=1}^{N} x_n - x_n^{\text{obs}}, \tag{2.6}
\]
where $x_n$ and $x_{n}^{\text{obs}}$ are respectively the $n^{\text{th}}$ forecast and observed variables over a total of $N$ data points. Errors were computed for GHI for SDGE ground stations, and for clear sky index $k_c$ for SolarAnywhere satellite measurements, where

$$k_c \equiv \frac{\text{GHI}}{\text{GHI}_{\text{clearsky}}},$$

(2.7)

with GHI$_{\text{clearsky}}$ obtained from the Kasten clear sky model as modified by Ineichen and Perez (Ineichen and Perez, 2002; Perez et al., 2002).

The GHI errors will facilitate comparison of these preprocessing schemes against 24-hr persistence forecasts and other forecasting methods in the literature, while $k_c$ errors will allow visualization of the spatial and temporal patterns of coastal stratocumulus in the San Diego region by normalizing out the time of day and locational dependence of solar irradiance. Since marine layer stratocumulus mostly occur during morning periods when the magnitude of GHI is low to medium, $k_c$ errors more clearly show errors in cloud cover patterns than GHI errors, which are weighted towards solar noon. Overall errors over the coastal regions most frequently affected by marine layer cloud cover were computed by spatially averaging over land-only regions with satellite-observed monthly mean $k_c < 0.92$ and at an elevation of $< 375$ m MSL. This region contains 972 WRF grid points in the inner domain.

Monthly averages of errors were computed at the finest available temporal resolution, constrained by either the forecast output interval or measured data availability. The time periods sampled, temporal resolution, number of daily samples, and total samples $N$
are tabulated in Table 2.3 for WRF and raw data (NAM and RAP) forecasts.

**Table 2.3:** Summary of validation data set

<table>
<thead>
<tr>
<th>Type</th>
<th>Time period</th>
<th>Resolution</th>
<th>Daily samples</th>
<th>Total samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground stations</td>
<td>0500 - 1900</td>
<td>15 min / 1 hr</td>
<td>57 / 15</td>
<td>1710 / 450</td>
</tr>
<tr>
<td>Satellite $[k_c]$</td>
<td>0600 - 1700</td>
<td>30 min / 1 hr</td>
<td>23 / 12</td>
<td>690 / 360</td>
</tr>
</tbody>
</table>

To directly compare each preprocessing method, a forecast skill was calculated for each ground station. Kleissl (2013) defined a general forecast skill suitable for forecast result intercomparison as the ratio of forecast model RMSE to persistence model RMSE. Here, MAE was used instead of RMSE due to its linear nature. Forecast skill $FS$ is therefore defined as

$$FS \equiv 1 - \frac{MAE}{MAE_{\text{persistence}}}.$$  \hspace{1cm} (2.8)

Positive values of forecast skill indicate superior performance to persistence forecast, with a maximum value of 1. The persistence forecast here was generated by taking the prior day’s measured irradiance at local times coinciding with WRF output times. Thus, the ground station (satellite) persistence forecast was at 15-min (30-min) resolution with 57 (23) samples per day and 1710 (690) over the month.
2.3 Results and Discussion

2.3.1 Validation against ground station measurements

An example time series at station 2 of pyranometer-measured and forecast GHI from all configurations as well as persistence forecast is shown in Figure 2.7 for June 2, 2013. Also shown is a time series of the WEMPP forecast prior to application of MOS for reference. Note that raw forecasts are at 1-hr resolution while WRF and persistence forecasts are at 15-min resolution.

![Figure 2.7: Time series at ground station 2 of pyranometer-measured (thick solid black) and forecast GHI of all forecast configurations as well as persistence forecast (dot-dashed gray with hexagonal markers) for June 2, 2013. WRF-WEMPP is shown both with and without MOS correction for reference. Note RAW-NAM and RAW-RAP are at 1-hr resolution while observations, WRF, and persistence forecasts are at 15-min resolution.](image)

Figure 2.8 shows monthly-averaged GHI MAE and MBE for all forecast configurations. Between the raw data forecasts, RAW-RAP consistently performs better than RAW-NAM in terms of both MAE and MBE. At all stations except for station 1, cloudier conditions are present in RAW-RAP as indicated by lower MBE. While the raw data forecast MAE’s are not directly comparable to those of the WRF forecasts due to a temporal resolution mismatch (the variability of irradiance increases with temporal resolution, thus increasing MAE), comparison against their children WRF forecasts reveals the importance
of liquid water content at initialization through MBE, which is unaffected by the mismatch. WRF-NAM performs similarly to RAW-NAM, with a slight reduction in MAE and MBE across all stations. WRF-RAP, however, shows slightly increased MAE at all stations and similar MBE at stations 2-4 compared against RAW-RAP, but a significant decrease in MBE at station 1 of nearly 75% due to newly resolved cloud cover.

Also shown in Figure 2.8 are errors from cross-validation of the SolarAnywhere data at the ground station locations. Compared to Jamaly et al. (2012), MAE is higher by 13.4 W m\(^{-2}\), while MBE is lower by 7.1 W m\(^{-2}\), on average.

Figure 2.8: Top: GHI mean absolute error and bottom: GHI mean bias error of ground stations grouped by station ID (1: coastal to 4: inland). Errors of 24 hr persistence forecasts are also shown. Note that RAW forecasts are at 1-hr resolution while all other forecasts are at 15-min resolution. Lastly, errors of the 30-min resolution SolarAnywhere observational data set are shown.

WRF-NAM is more positively biased than WRF-RAP, partly due to the proximity of the WRF-NAM initialization to sunrise as the microphysics scheme acts too slowly to generate a cloud field from zero initial liquid water content. In other words, without a preprocessing scheme it may have been beneficial to initialize WRF-NAM earlier to allow cloud fields to spin up. Indeed, the introduction of liquid water at initialization through
the application of WEMPP lowers errors to similar values as that of the WRF-RAP reference case (about 9% less MAE and 3% greater MBE). Considering all state variables at initialization in WRF-WEMPP are identical to those in WRF-NAM with exception of liquid water, this improvement in error metrics is significant, especially because RAW-NAM was shown to perform worse than RAW-RAP.

Assimilating satellite cloud information through CLDDA further lowers both MAE and MBE as compared with the WRF-RAP and WRF-WEMPP configurations. The additional application of WEMPP in the WRF-COMBO configuration slightly lowers MBE by further increasing liquid water content throughout the simulation domain, but the increase in MAE suggests local overestimation of liquid water content.

For all stations, MAE decreases as the distance from the coast increases, as cloud cover is less frequent in inland regions. Defining clear periods to be times when $k_c$ falls between 0.9 and 1.1 (i.e. approximately cloud-free and without cloud edge enhancement effects), the percentage of observed clear data points was, in order from most coastal (1) to most inland (4): 39.7%, 46.3%, 51.9%, and 61.2%. Because station 4 is just outside of the typical marine layer region and rarely observes much cloud cover except for early mornings, persistence forecast tends to perform very well. Overall, all configurations show only positive bias, indicating a systematic underprediction of cloud cover. At station 1, however, WRF-RAP and the preprocessed configurations occasionally overpredicted the optical thickness of present clouds or predicted cloud cover during clear conditions. Because of this, MBE at station 1 is lower than at stations 2 and 3, but the higher MAE reveals the occurrence of errors is greater.
Forecast skills were computed for each configuration at each ground station, indicating performance against the baseline persistence forecast. Positive values of forecast skill indicate superior performance compared to persistence forecast, and the maximum value is 1. According to Figure 2.9, the best performer is CLDDA with an average skill of -0.15. The remaining configurations rank as COMBO (-0.16), RAW-RAP (-0.18), WEMPP (-0.30), WRF-RAP (-0.35), WRF-NAM (-0.49), and RAW-NAM (-0.71). The main contributor to negative forecast skills is station 4, where the early morning cloud cover is typically not captured by any configuration, indicating a lack of simulated inland Sc penetration. At stations 1-3, CLDDA shows positive skill, as does the COMBO configuration for stations 2-3, and RAW-RAP at station 3.

![Figure 2.9](image.png)

**Figure 2.9:** Forecast skill against ground station GHI persistence forecast for each configuration as a function of station ID. Positive values indicate performance superior to 24-hr persistence forecast.

## 2.3.2 Validation against satellite observations

A time series at the grid point containing station 2 of satellite-derived and forecast clear sky index $k_c$ from all configurations as well as satellite persistence forecast is shown
in Figure 2.10 for June 2, 2013. Also shown is a time series of the WEMPP forecast prior to application of MOS for reference. Note that raw forecasts are at 1-hr resolution while WRF and persistence forecasts are at 30-min resolution.

**Figure 2.10**: Time series at ground station 2 of satellite-derived (thick solid black) and forecast $k_c$ of all forecast configurations as well as persistence forecast (dot-dashed gray with hexagonal markers) for June 2, 2013. WRF-WEMPP is shown both with and without MOS correction for reference. Note RAW-NAM and RAW-RAP are at 1-hr resolution while observations, WRF, and persistence forecasts are at 30-min resolution.

Figure 2.11 spatially depicts monthly-averaged MAE of each configuration alongside the satellite persistence forecast and monthly-average observed $k_c$ (bottom right). Of the raw data forecasts, RAW-NAM shows significant errors everywhere in the domain, and RAW-RAP performs similarly to WRF-RAP, with both showing highest errors over the ocean and near the coastline. The baseline WRF-NAM configuration shows highest MAE of all WRF configurations over the coast, and while WRF-RAP performs better than WRF-NAM, the coastal MAE still exceeds that of the preprocessed configurations. Among the preprocessors, WEMPP is the worst performer, and CLDDA shows the most significant improvement over WRF-NAM, especially farther inland. The COMBO configuration performs similarly to CLDDA in the San Diego region, but performs slightly better in the Los Angeles area, though errors over the ocean near the San Diego coast are highest of all configurations. The errors in the satellite persistence forecast are concentrated in
the regions of lowest observed $k_c$: predominantly over the ocean and the coastline. This is mostly because persistence forecasts are unable to predict day-to-day variations from cloudy to clear conditions (and vice versa).

![Figure 2.11](image)

*Figure 2.11*: Monthly mean absolute $k_c$ errors for each configuration as well as satellite persistence forecast. Monthly-averaged clear sky index $k_c$ is shown in the **bottom right** panel. The boundary of the marine layer region is marked by the black dashed line.

From Figure 2.12, all WRF configurations show a systematic positive bias over the coast and a systematic negative bias over the ocean. Both raw forecasts show positive bias everywhere. In the coastal marine layer region (bounded by the Californian border and black dashed line in Figure 2.12), the positive bias is caused by an underprediction of cloud cover. However, in typically clear regions (i.e. regions of $\approx 1.0$ $k_c$ in Figure 2.12, bottom right), a positive bias of $\approx 0.05$ to $\approx 0.1$ $k_c$ remains in the RAW-NAM despite application of MOS correction. This positive bias is due to the high clear-sky $k_c$ errors at high solar zenith angles in the RAW-NAM which are not corrected by MOS (evident at 0600-0700 PST and at 1700 PST in Figure 2.10).

While all WRF configurations show negative bias over the ocean, all preprocessing schemes further increase this bias, indicating an overprediction of cloud cover. In WEMPP,
the overprediction is caused by the conservative 95% relative humidity criterion. Because slightly subsaturated air parcels are considered cloudy by WEMPP, preprocessed cloud bases are lower than would be in the original NAM data, thus increasing cloud optical thickness. The CLDDA algorithm appears to overestimate cloud thickness over the ocean because it was empirically developed from observations over land. The COMBO configuration shows the highest negative bias since it was designed to maximize liquid water content. The satellite persistence forecast shows near-zero MBE due to the day-to-day offsetting of bias errors.

![Figure 2.12](image)

**Figure 2.12**: Monthly mean bias $k_c$ errors for each configuration as well as satellite persistence forecast. Monthly-averaged clear sky index $k_c$ is shown in the **bottom right** panel. The boundary of the marine layer region is marked by the black dashed line.

Errors averaged over the coastal marine layer region are summarized in Figure 2.13. While the WRF-NAM configuration is the worst performer of all WRF configurations, application of WEMPP to NAM initialization data lowers MAE below that of the WRF-RAP configuration (though MBE remains slightly higher). Application of CLDDA lowers errors further, and the COMBO configuration is the best performer in terms of both MAE and MBE computed from both GHI and $k_c$. Of the raw forecasts, RAW-NAM is the worst.
performer overall, but RAW-RAP performs similarly to WRF-RAP and WRF-WEMPP in MAE (however, RAW-RAP is at hourly resolution which tends to decrease MAE), but with much higher MBE and coarser temporal resolution. Compared with ground station validation, spatially-averaged MBE is lower over the marine layer region due to the increased spatial coverage of Sc.

Shown in Figure 2.14 are forecast skills computed from GHI MAE at ground station locations as well as for the marine layer region. The configurations rank as follows in terms of average skill over the ground stations [marine layer region]: CLDDA (0.07) [0.05], COMBO (0.06) [0.06], WEMPP (-0.01) [-0.01], RAW-RAP (-0.07) [-0.06], WRF-RAP (-0.11) [-0.12], WRF-NAM (-0.14) [-0.16], and RAW-NAM (-0.47) [-0.45]. Forecast skills averaged over all ground stations are in good agreement with those averaged over the marine layer region, suggesting the chosen ground stations are representative of the region. Again, the main contributor to the station-averaged forecast skill is station 4, indicating a lack of simulated inland Sc penetration. CLDDA, WEMPP, and COMBO all show positive skill at stations 1-3. Over the marine layer region, both COMBO and CLDDA exhibit positive skill, with COMBO performing slightly better.

**Figure 2.13**: Monthly mean errors in GHI (left) and clear sky index $k_c$ (right) over the coastal land-only marine layer region (defined in Figure 2.6) computed from satellite data. These errors are spatially averaged over 972 WRF grid points in the inner domain.
The simulated evolution of coastal Sc can be observed by computing the monthly mean of hourly $k_c$ bias errors, as shown in Figure 2.15. The WRF-NAM configuration greatly underpredicts cloud cover over the coast, while WRF-RAP was able to predict some coastal cloud cover in the San Diego region, as well as over the Los Angeles basin. Applying WEMPP to NAM initial conditions slightly improved prediction of cloud cover over most of the coastline, but inland coverage is still lacking. The most significant improvement in spatial Sc coverage was gained by applying CLDDA. Both CLDDA and COMBO configurations show similar cloud cover over land, but all preprocessed configurations overpredicted cloud cover over the ocean, with COMBO showing the most overprediction over ocean. While RAW-NAM is the worst performer overall, RAW-RAP appears to better capture early morning cloud cover than the WRF-RAP configuration and shows similar inland cloud coverage at 0600 PST as simulations preprocessed by CLDDA, though lifetime of coastal clouds is much shorter. Satellite persistence forecast is not shown in Figure 2.15 due to its near-zero MBE.
Figure 2.15: Monthly mean of hourly $k_c$ bias errors, from 0600 to 1000 local time (PST) (sunrise was around 0442 PST) for each configuration (each hourly panel is an average of 30 data points). Magnitudes are in clear sky index $k_c$, with warm (cool) colors representing underprediction (overprediction) of cloud cover.
2.4 Conclusions and future work

In this study, two initial condition preprocessing schemes WEMPP, CLDDA, and their combination were compared against baseline WRF simulations initialized with NAM and RAP data sets. Comparison against ground station measurements showed CLDDA as the best performer, consistently surpassing persistence forecast at 3 out of 4 ground stations, with the COMBO configuration as a close second.

Supplementary validation against satellite ground irradiance data showed CLDDA to offer the most significant improvement in the prediction of both spatial coverage and lifetime of coastal stratocumulus, while WEMPP led to minor improvements. Their combination, however, provided the most improvement overall over the coast, while also causing the most overprediction of cloud cover over the ocean. All preprocessed schemes overpredicted cloud cover over the ocean.

Quantitative comparisons against persistence forecast were determined by the forecast skill metric, where positive (negative) values indicate superior (inferior) performance to persistence forecast. Against ground stations, all configurations showed negative forecast skill on average, mostly due to poor forecast skill at the most inland station, indicating insufficient simulated inland penetration of Sc. Slightly positive skills ranging from 0.01 to 0.08 were demonstrated by CLDDA (at 3 stations), COMBO (2), and RAW-RAP (1). Against satellite observations, positive forecast skills ranging from 0.06 to 0.07 were demonstrated by CLDDA and COMBO when averaged over the ground station locations. CLDDA and COMBO also demonstrated positive forecast skill ranging from 0.05 to 0.06...
when averaged over the coastal marine layer region.

The lack of significant forecast skill indicates that accurate forecasts of marine layer Sc cannot be obtained solely through initial conditions processing and data assimilation, though a large improvement has been made. Pragmatically, however, persistence forecasts for behind-the-meter generation require collocated measurements which is typically not the case for distributed generation. Persistence forecasts also are unable to capture large changes from day to day, while NWP models are designed to predict these changes and (at least with continued improvement of the physics parameterizations) forecast irradiance over large spatial domains. The error magnitudes presented here are representative for days with low cloud cover, which primarily occurs from May through July and intermittently for the rest of the year (Clemesha et al., 2016). Forecast accuracy would be better on other days which are predominantly clear.

Since the amount of liquid water $q_l$ added in CLDDA as 110% RH was “calibrated” using coastal data (Mathiesen et al., 2013), it is not surprising that CLDDA is without bias along the coast. The CLDDA and WEMPP findings point to the need for modification of the addition of water vapor with less water to be added over the ocean and more further inland. The finding of larger WEMPP biases further inland can be explained by Figure 2.4: the NAM parent model clouds’ inland penetration is insufficient and cannot be corrected relying solely on parent model fields. CLDDA, on the other hand, leverages satellite measurements, reducing both MBE and MAE.

Although CLDDA provided the best forecast improvement, its performance depends on the accuracy of the satellite cloud mask. Nighttime low clouds such as stratocumulus
are notoriously difficult to detect as the thermal infrared signature is not significantly
different than that of the underlying ocean or land. Regions wrongly detected as clear
in observed cloud fields (e.g. around $33.5^\circ$N, $117.5^\circ$W in Figure 2.4) sometimes appear
over both land and ocean, nullifying any advantage gained from CLDDA. The additional
application of WEMPP as in the COMBO configuration can correct such errors at least
for ocean and coastal regions, but the increased cloud cover over the ocean is potentially
problematic. If satellite data quality is an issue, the combination of both WEMPP and
CLDDA may be considered; otherwise, only CLDDA should be applied. If satellite data
is unavailable, WEMPP is a computationally cheap method to generate an initial liquid
cloud field provided the initial cloud field is predominantly stratus or stratocumulus. All
schemes complete on order of a few minutes on a 3.4 GHz Intel i7 machine. CLDDA and
COMBO, however, require additional time to retrieve the relevant satellite data which is
dependent on the data source.

From this study, the role of initial conditions on the prediction of coastal stra-
tocumulus is shown to be significant. Although improvements in both spatial coverage
and cloud lifetime were accomplished, validation against satellite observations still show
underprediction of cloud cover, suggesting the need of more accurate parameterization of
physical processes such as entrainment of warm, dry air from the free troposphere, advec-
tion, and surface fluxes (Ghonima et al., 2016). The lack of inland cloud cover also suggests
possible systematic underestimation of inversion base height (IBH): since the IBH physi-
cally constrains Sc cloud tops, clouds cannot be present in regions where the land elevation
exceeds the IBH. Future work will thus focus on improving physical parameterization of
2.5 Acknowledgements

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Chapter 2, in full with slight modifications, is a reprint of the material in the article “Preprocessing WRF initial conditions for coastal stratocumulus forecasting,” published in Solar Energy in 2016 (Yang and Kleissl, 2016). The dissertation/thesis author was the
primary investigator and author of this paper.
Chapter 3

Evaluation of WRF SCM Simulations of Stratocumulus-Topped Marine and Coastal Boundary Layers and Improvements to Turbulence and Entrainment Parameterizations

3.1 Introduction

Stratocumulus clouds are a common occurrence across the globe and have a strong impact on the local boundary layer energy and water budgets as well as the global climate.
Stratocumulus clouds usually form under a sharp inversion that may only be a few meters thick. Because of the large range of spatial scales and turbulent motions associated with stratocumulus clouds and the limited resolution of models, numerical weather prediction (NWP) and global climate models (GCMs) parameterize the turbulence within the boundary layer through planetary boundary layer (PBL) schemes. Of particular importance to stratocumulus is entrainment (mixing) across the inversion, which is driven by turbulence generated in the boundary layer through cloud top longwave and evaporative cooling, thus entrainment plays an integral role in determining the liquid water path (LWP), lifetime, and spatial extent and structure of the clouds (Ghonima et al., 2016; Moeng, 2000). However, the mixing processes occurring near the cloud top between the two-phase fluids at very high Reynolds numbers have proven difficult to address even with the highest resolution models (Stevens, 2010a). As this process is better understood, new parameterization methods are being developed to more accurately represent its impact on the stratocumulus-topped boundary layer (STBL) and its breakup. Efforts to develop physical models of stratocumulus have traditionally been focused on idealized marine cases, with stratocumulus clouds over land receiving less attention; however, stratocumulus clouds impact agriculture, solar installations, and aviation visibility, for example. We therefore extend stratocumulus test cases to land as well as over ocean conditions.

In contrast to NWPs and GCMs, large eddy simulations (LES) have higher resolutions and are able to explicitly represent the energetic larger turbulent eddies within the boundary layer while the smaller eddies are parameterized. Multiple intercompari-
son studies of LES of STBL have found good agreement with measurements from various field campaigns (Ackerman et al., 2009; Stevens et al., 2005). Hence, LES have been utilized as benchmarks to evaluate different PBL schemes. Comparing against LES and measurements from the DYCOMS campaign, Zhu et al. (2005) evaluated the capability of 10 single-column models (SCMs) to model the STBL and found that although all models were capable of maintaining the sharp inversion, liquid water paths (LWP) varied by a factor of 10 between SCMs.

To identify the cause of this discrepancy and improve the representation of STBL in NWPs and GCMs, in this paper we employ the findings of Ghonima et al. (2016), where an improved parameterization for cloud top entrainment mixing in a mixed layer model improved simulations of both coastal and marine stratocumulus. We evaluate several SCM representations of the STBL in the Weather Research and Forecasting (WRF; Skamarock et al. (2008)) model against LES. Due to its importance, a specific focus is the SCM representation of entrainment or mixing across the inversion. We analyze the Yonsei University (YSU) scheme that is a first-order scheme that models flux as a function of the eddy viscosity (Hong et al., 2006). The model includes a correction for counter-gradient mixing and explicitly models the entrainment at the inversion. YSU was recently updated with a top-down mixing model and a revision to the entrainment model to better simulate fog (Wilson, 2015). Second, we investigate the Asymmetric Convective Model version 2 (ACM2) that is also a first-order scheme but uses a transilient matrix that defines mass flux to account for the convective eddies instead of using a counter-gradient correction term (Pleim, 2007). Finally, we examine the Mellor- Yamada-Nakanishi-Niino (MYNN) model,
which is a turbulent kinetic energy (TKE) closure scheme (Nakanishi and Niino, 2004). MYNN uses TKE, which in theory provides a better measure of turbulence in the STBL, to determine the eddy diffusivity. Both the YSU and the ACM2 are less complex, more computationally economical models while the MYNN scheme takes into account more of the physics of the boundary layer at a higher computational cost.

To account for the effects of the microphysics parameterizations, we run each PBL scheme with four different microphysics schemes offered in WRF. In Section 3 we find that (with the exception of the recent Wilson (2015) update to YSU) the above PBL models are unable to account for the turbulence generated by cloud-top longwave cooling and therefore underestimate entrainment flux. We propose a correction to the velocity scale in the YSU PBL parameterization based on the in-cloud buoyancy flux in order to improve the representation of longwave-generated cooling. Simulations of both coastal (under dry and moist land surface conditions) and marine (with two different initial profiles) STBL through an entire 24-hour diurnal cycle resulted in better agreement with the LES (Section 4). In conclusion, Section 5 provides a discussion on the ability of the changes introduced here to address the deficiencies in current PBL schemes and improve the simulation of STBL over coastal lands and ocean.
3.2 Design of numerical experiments

3.2.1 Model setup

For this analysis, we used WRF v3.7.1 in single column mode to evaluate three PBL and four microphysics schemes (refer to Tables 1 and 2 for an overview of the schemes). The vertical domain of the SCM consists of 74 levels up to an altitude of 10,000 m (with 49 levels concentrated below 2 km), and the simulation time step is 20 s. The SCM employs the New Goddard scheme for longwave and shortwave radiation (Chou and Suarez, 1999; Chou et al., 2001), Monin-Obukhov similarity theory for the surface layer parameterization (Paulson, 1970), and the Kessler microphysics scheme Kessler (1969). The radiation scheme is called at every time step. For conciseness, we do not examine the impact of radiative, surface, and land parameterizations (surface fluxes are assumed constant in ocean cases) and instead focus on the fluxes into or out of the boundary layer at the land surface and across the inversion. As reference cases, we utilize the DYCOMS RF01 initial profile in agreement with the intercomparison study conducted by Zhu et al. (2005). Following Zhu et al. (2005), we set the surface sensible heat flux (SHF) to be 15 W m$^{-2}$ and the latent heat flux (LHF) to be 115 W m$^{-2}$ for the DYCOMS RF01 ocean case. Simulations of STBL over wet and dry coastal lands were also conducted using the DYCOMS RF01 initial profiles using a simplified land surface model as described in Ghonima et al. (2016) which was coupled to both the LES and SCM. Unlike in the DYCOMS SCM intercomparison study that evaluated a nocturnal 6-hour simulation, we run a 24-hour simulation in order to study how well the SCM are capable of simulating the STBL over the diurnal
Table 3.1: List of PBL schemes used in this study.

<table>
<thead>
<tr>
<th>PBL scheme</th>
<th>Parameterization type</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yonsei University (YSU)</td>
<td>First-order closure scheme. Turbulence is parameterized using the eddy-diffusivity approach and a gradient adjustment term is added to account for large-scale eddies. Entrainment is explicitly modelled.</td>
<td>Hong et al. (2006)</td>
</tr>
<tr>
<td>Asymmetric convective Model version 2 (ACM2)</td>
<td>First-order nonlocal closure scheme. Turbulence is parameterized as a combination of local eddy diffusion and a non-local transient matrix that defines mass flux between any pair of model layers.</td>
<td>Pleim (2007)</td>
</tr>
<tr>
<td>Mellor-Yamada-Nakanishi-Niino level 2.5 (MYNN)</td>
<td>TKE closure scheme</td>
<td>Nakanishi and Niino (2004, 2009)</td>
</tr>
</tbody>
</table>

cycle that is driven by shortwave radiative absorption in the cloud deck. All simulations are initialized at midnight.

To demonstrate generalizability of the results, additional simulations are run on the CGILS S12 control initial profile, which is a well-mixed STBL that has been used to evaluate both LES and SCM (Zhang et al., 2012; Blossey et al., 2013; Zhang et al., 2013). The SHF and LHF for the CGILS S12 control ocean case were 5 W m-2 and 80 W m-2, which were approximated by first running an LES simulation with modeled surface fluxes and then taking the approximate 24-hr mean values. The LES results shown here were run with the subsequent fixed fluxes. The UCLA-LES model is setup as in the DYCOMS LES intercomparison study (Stevens et al., 2005). The only difference is that we couple the LES to a one-dimensional radiative model with Monte Carlo sampling of
the spectral integration rather than the parameterized radiative scheme employed in the 
DYCOMS LES intercomparison (Stevens et al., 2005; Pincus and Stevens, 2009). We 
find that the one-dimensional radiative model produces fluxes that are closer to the New 
Goddard scheme employed in the WRF SCM. Minimizing this source of discrepancy allows 
a focused validation of the PBL parameterization.

3.2.2 PBL scheme formulation

YSU

**YSU: Model description**

Following Hong et al. (2006), the YSU scheme parameterizes the vertical turbulent 
flux $w'c'$ of any prognostic variable $C$ (where the overbar denotes an ensemble average 
and lowercase with primes denote deviations from the average, and $W$ is the vertical wind 
speed) as

\[
(w'c')_{YSU} = -K_c \left( \frac{\partial c}{\partial z} - \gamma_c \right) + w'c'_{z_{inv}} \left( \frac{z}{z_{inv}} \right)^3.
\]

(3.1)

With the newly added top-down mixing option (Wilson, 2015), YSU expresses the 
eddy diffusivity coefficient $K_c$ in cloud-capped boundary layers as a linear combination of 
surface-driven mixing and top-driven mixing:

\[
K_c = \kappa w_s z (1 - z/z_{inv})^2 + \kappa w_{pbl} \left( \frac{z^2}{z_{inv}} \right) (1 - z/z_{inv}),
\]

(3.2)
where $\kappa$ is the von Karman constant, $z$ is height, and $z_{\text{inv}}$ is the inversion base height. The mixed layer velocity scale is expressed as $w_s = (u^*_s + \phi_{h,m} \kappa w_{sb} z / z_{\text{inv}})^{1/3}$ where $u_s$ is the surface friction velocity, $\phi_{h,m}$ is the wind profile function evaluated at the top of the surface layer, and $w_{sb} = [g / \theta_v (\bar{w} \bar{c})_0 z_{\text{inv}}]^{1/3}$ is the convective velocity scale. The surface-driven profile is zero at the surface and PBL top, with a maximum in the lower third of the boundary layer. The top-down velocity scale $w_{pbl}$ is formulated in the same way as $w_s$ except $w_{pbl}$ is a function of the PBL top flux, so the top-driven profile maintains the same shape as the surface-driven profile but is reversed so the maximum occurs in the top third of the boundary layer.

In Equation 3.1, $\gamma_c$ is the counter-gradient term and incorporates the contributions of large-scale eddies to the total flux and is computed as $\gamma_c = b \frac{(w'c')_0 + (w'c')_z}{w_s z_{\text{inv}}}$, where $(w'c')_0$ represents the surface flux, $(w'c')_z = w_e \Delta C_{\text{inv}}$ represents the PBL top flux, $\Delta C_{z_{\text{inv}}} = C_{z_{\text{inv}}+1} - C_{z_{\text{inv}}}$ represents the jump value of $C$ across the inversion, and $b$ is a coefficient of proportionality. Finally, entrainment $w_e$ is parameterized as

$$w_e = -\frac{\theta_v}{g \Delta \theta_{vi} z_{\text{inv}}} (0.15 w^3_m + A w^3_T),$$

(3.3)

where $A$ is computed following the integral closure method described by Grenier and Bretherton (2001) as $A = a_1 (1 + a_2 E)$ with $a_1 = 0.2$ and $a_2 = 8$. Here, $a_2 E$ describes the evaporative enhancement of entrainment. Typical values of $A$ range from about 0.2 to 0.5 for the cases simulated here. Finally, $\theta_{v0}$ is the reference virtual potential temperature, $\Delta \theta_{vi}$ represents the inversion jump, $w^3_m$ is a velocity scale based on the surface turbulence,
\[ w_m^3 = w_s^3 + 5 \times u_s^3, \]  

(3.4)

where \( w_s = \left[ \frac{g}{\theta_v a} \left( \frac{w'\theta'}{u' \theta'} a \right) z_{inv} \right]^{1/3} \) is the mixed-layer velocity scale for dry air (when \( \theta = \theta_v \)), and \( w_T = \left[ \frac{g}{\theta_v a} \left( \frac{w'\theta'}{u' \theta'} \right) \rho_{rad} z_{inv} \right]^{1/3} \) is a velocity scale based on the net radiative flux divergence at the cloud top \( F_{rad} \) with \( \left( \frac{w'\theta'}{u' \theta'} \right)_{rad} = \frac{F_{rad}}{\rho c_p} \).

**Proposed modifications: YSU-BUOY**

The second term in Equation 3.3 is intended to describe the contribution of cloud-top longwave radiative cooling to turbulence generated in the STBL. These thermals originate at the cloud-top and sink through the STBL, as shown in plots of the third moment of vertical wind speed (Figure 3.1 (c) later). Currently, the top-driven eddy diffusivity profile in the YSU scheme (Equation 3.2) is simply a reversed version of the surface-driven profile without adjusting the shape. However, based on LES results, mixing is more intense near the source of turbulence (i.e. cloud top), so we revise the eddy diffusivity profile following Lock et al. (2000) to capture the skewness in cloud-top driven mixing, as

\[ K_c = \kappa w_s z \left( 1 - \frac{z}{z_{inv}} \right)^2 + \kappa w_{cld} \left( \frac{z}{z_{inv}} \right)^2 \left( 1 - \frac{z}{z_{inv}} \right)^{0.5}, \]  

(3.5)

where \( w_{cld} \) is the cloud velocity scale and is formulated as:

\[ w_{cld} = \frac{g}{\theta_v a} \int_{z_b}^{z_{inv}} \frac{w'\theta'}{u' \theta'} dz, \]  

(3.6)

with the cloud base height \( z_b \) taken as the lowest grid level with liquid water content.
Note that the exponent in the quantity \((1 - \frac{z}{z_{inv}})^p\) differs from Equation 3.2 (where \(p\) is implied to be 1) here in Eq. 5 \((p = 0.5)\), though our tests have indicated negligible differences (not shown). The virtual potential temperature vertical flux is expressed as

\[
\overline{w'}\theta'_v(z) = D_1 \overline{w'}\theta'_l(z) + D_2 \overline{w'}q'_T(z), \quad z_b < z < z_{inv},
\]

where \(D_1 = \frac{1+\frac{\tau_s}{\tau}+\frac{\kappa c_p \theta_c (d\theta_c/\theta_c)}{1+\frac{\tau_s}{\tau}+\frac{\kappa c_p \theta_c (d\theta_c/\theta_c)}{1+\frac{\tau_s}{\tau}+\frac{\kappa c_p \theta_c (d\theta_c/\theta_c)}{1+\frac{\tau_s}{\tau}+\frac{\kappa c_p \theta_c (d\theta_c/\theta_c)}}}} \approx 0.5\) and \(D_2 = \frac{L_v}{c_p} \left( \frac{1+\frac{\tau_s}{\tau}+\frac{\kappa c_p \theta_c (d\theta_c/\theta_c)}{1+\frac{\tau_s}{\tau}+\frac{\kappa c_p \theta_c (d\theta_c/\theta_c)}} - \bar{\theta} \approx 970 \text{ K} \right)\) within the cloud layer (see Stevens (2002) for a more detailed derivation of the constants).

Here, these coefficients are treated as constants for computational efficiency. Instead of formulating the cloud velocity scale as a function of radiative divergence (as in both Wilson (2015) and Lock et al. (2000)), we have chosen the buoyancy flux within the cloud layer, as longwave emission becomes insensitive to LWP changes for thick clouds \((\text{LWP} > 50 \text{ g m}^{-2})\) (Kazil et al., 2015). Thus, by formulating \(w_{cld}\) as function of radiative divergence the parameterization fails to account for additional turbulence generated by latent heat releases in updrafts within in the cloud layer. Additionally, parameterizations dependent on the radiative flux divergence are bound to the frequency at which the radiative scheme is called, which may introduce further sensitivity and errors if the radiative time step is long.

Similarly, the entrainment velocity parameterization was revised to not be a function of radiative divergence. Hence, following Ghonima et al. (2016) we define a new velocity scale for the entrainment parameterization in Equation 3.3 as
\[ w_T^{*3} = 1.25 \frac{g z_{inv}}{\theta_v} \frac{w' \theta'_v}{v_0} + 2.5 \frac{g}{\theta_v} \int_{z_b}^{z_{inv}} \frac{w' \theta'_v}{v_0} dz. \] (3.8)

The convective velocity scale in Equation 3.8 follows Lock et al. [1999], except instead of using the net radiative flux we use the integral of the in-cloud buoyancy flux. For YSU-BUOY we use the original closure constants of Nicholls and Turton (1986) in the computation of \( A \) in Equation 3.3, so that \( a_2 = 60 \); typical values of \( A \) for the YSU-BUOY simulations ranged from about 0.5 to 0.9. Finally, the updated entrainment parameterization uses only the second term in Equation 3.5 during cloudy conditions (the revised definition of \( w_T^{*3} \) already includes surface-based entrainment), and only the first term in clear conditions. These modifications alter the PBL top flux and hence the counter-gradient term \( \gamma_c \), though we, like Wilson (2015), note the effect of this change is miniscule. While the buoyancy flux generated due to longwave radiative cooling rarely exceeds 4 m\(^2\) s\(^{-3}\) for the DYCOMS RF01 ocean case, over land strong thermals generated by the surface flux causes buoyancy fluxes to regularly exceed 10 m\(^2\) s\(^{-3}\) (Figure 3.1 (a, b) later). For the ocean cases, the thermals are not as strong as for the land case and we do not need to enhance the counter-gradient term further to account for them: the boundary layer becomes sufficiently well-mixed upon addition of the cloud-top driven mixing profile. For the remainder of the study we refer to the corrected YSU scheme as YSU-BUOY.

ACM2

ACM2: Model description
Figure 3.1: Horizontally averaged temporal evolutions from LES for the DYCOMS case of vertical profiles of (a, b) buoyancy flux and (c, d) third moment of vertical velocity ($w'^3$). Results are shown for the DYCOMS RF01 ocean case (a, c) and land case with Bowen ratio equal 1.0 (b, d). While the LES domain extends up to 1.6 km, only the lowest 1.2 km is shown to focus on the boundary layer dynamics. Inversion height is indicated by solid black lines, and cloud base by dashed black.

The ACM2 uses a staggered grid where scalar quantities and horizontal momentum components are represented at the grid layer centers designated by $i$, while the vertical fluxes, vertical velocities and eddy diffusivities are located at the layer interface $i + 1/2$. Hence, ACM2 computes flux at the interface as

$$
(w'^3 c'_{i+1/2})_{ACM2} = -(1 - f_{conv})K_{C,z=3/2} \frac{\partial C_i}{\partial z} + f_{conv} \frac{K_{C,z=3/2}(h - z_{i+1/2})}{\Delta z_{z=3/2}} (C_1 - C_i), \quad (3.9)
$$

where $f_{conv}$ is a weighting factor that splits mixing between local and non-local components and is expressed as
\[
 f_{\text{conv}} = \left[1 + \frac{\kappa^{-2/3}}{0.1a} \left(\frac{-h}{L}\right)^{-1/3}\right]^{-1},
 \]  

(3.10)

where \(a\) is a constant set to 7.2, \(h\) is the PBL height and \(L\) is the Obukhov length.

The value of \(f_{\text{conv}}\) for stable and neutral conditions is 0 (local transport only) and increases to a maximum of about 0.5 in strongly convective conditions (splitting mixing between local and non-local components) (Pleim, 2007).

**Proposed modifications: ACM2-BUOY**

ACM2 was designed such that the second term on the right hand side of Equation 3.9 represents mass fluxes due to upward transport in convectively buoyant plumes. The first term on the right hand side of Equation 3.9 represents the local eddy diffusion similar to the first term in Equation 3.1 for the YSU scheme. Thus, to account for longwave cooling at the cloud top we utilize Equation 3.5 and Equation 3.6 to define \(K_{C,z}\) in the same way as in YSU-BUOY. Similar to the YSU parameterization, we do not need to add in Equation 3.9 an analogous term to the counter-gradient term in Equation 3.1 because the longwave cooling-driven downward thermals are not as strong as the upward thermals.

Initial testing revealed that the revised eddy diffusivity did not resolve PBL thermodynamic biases suggesting an underestimation of entrainment. Thus, a supplementary explicit entrainment scheme was implemented only for cloudy conditions in the same way as in YSU-BUOY (Eq. 3), except with \(A = 0.08\). The smaller value of \(A\) here is due to the existing ability of ACM2 to implicitly model entrainment.

The ACM2 modifications proposed here are only intended to test the hypothesis
that entrainment flux is being underestimated—they are not intended for operational use, as the explicit entrainment scheme conflicts with the original design of ACM2. The experimental ACM2 scheme will be referred to as ACM2-BUOY.

**MYNN**

The MYNN scheme determines the eddy diffusion coefficient as a function of turbulent kinetic energy (TKE, $q^2 = u'^2 + v'^2 + w'^2$), stability correction functions for momentum ($S_M$, used for e.g. wind) and heat ($S_H$, used for e.g. heat and moisture), and the master length scale ($L$) as

$$\langle w'c' \rangle_{MYNN} = -qLS_{M,H} \frac{\partial C}{\partial z}. \quad (3.11)$$

The master length scale is a function of the Obukhov length, TKE, and buoyancy flux (Nakanishi and Niino, 2004). However, despite the fact that MYNN uses a more complex TKE closure framework, we find that MYNN is not capable of accurately representing the vigorous vertical mixing throughout the STBL, as well as the heating and drying due to entrainment mixing of dry air aloft. This could be a result of inadequate representation of longwave radiative cooling and/or inadequate modeling of cloud top entrainment. In this regard, the TKE equation currently employed in MYNN is lacking in accounting for STBL-specific processes. Due to the complexity of MYNN, further modification was left for future work. The unmodified MYNN results are provided for reference only.
3.2.3 Corrections to the inversion height determination in the single column model

In WRF v3.7.1, the YSU and ACM2 schemes detect planetary boundary layer height (inversion height) based on the height at which the bulk Richardson number \((R_i)_b\) exceeds 0 for YSU and 0.25 for ACM2. In ACM2, \((R_i)_b\) is computed as a function of virtual potential temperature \(\theta_v\), while the recent addition of the top-down mixing option in YSU (Wilson, 2015) revised the computation of \((R_i)_b\) to a function of ice-liquid potential temperature \(\theta_{li}\). MYNN uses a hybrid method which blends PBL heights determined from 1) the first point at which \(\theta_v\) exceeds the minimum \(\theta_v\) within the PBL by 1.5 K in neutral and convective conditions and 2) where TKE drops below 5% of the maximum TKE near the surface in stable conditions (Benjamin et al., 2016).

As \(\theta_v\) is defined for unsaturated air, \(\theta_v\) is not conserved within the cloud layer (\(\theta_v\) increases with height above the cloud base height). Therefore ACM2, MYNN, (and YSU prior to the top-down mixing option, where the conserved variable \(\theta_{li}\) was introduced) underestimate inversion height (Fig. 2). False assignment of the PBL height to a lower level within the boundary layer could lead to underestimation of thermodynamic jump values and hence entrainment in YSU, YSU-BUOY, and ACM2-BUOY, as well as an underestimation of eddy viscosity near the PBL top in YSU and YSU-BUOY.

Therefore, PBL height diagnostics need to be corrected before the proposed parameterizations can be tested. To this end we substitute \(\theta_v\) in all computations regarding PBL height in ACM2 and MYNN with liquid virtual potential temperature \(\theta_{vl} = \theta_l(1 + 0.608q_t)\)
which is conserved within the STBL (Grenier and Bretherton, 2001).

Theoretically, cloud top height coincides with the inversion base height \( z_{\text{inv}} \); however, even after correcting the inversion height detection this may not always be true. Therefore, in Eqs. 3.6 - 3.8 where the existence of a cloud impacts mathematical terms, the cloud top height \( z_{\text{ctop}} \) is substituted for \( z_{\text{inv}} \), where cloud top height \( z_{\text{ctop}} \) is defined as the highest grid level with liquid water content in the SCM within 1 grid point of \( z_{\text{inv}} \).

LES inversion height is defined at the maximum gradient of liquid potential temperature.

### 3.2.4 Correction of SCM numerical instability

As of WRF v3.7.1, the function which calculates temperature and scalar tendencies in the SCM computes vertical derivatives using a 2-point 2nd-order accurate centered finite difference with uniform spacing centered on the boundary between two grid points. This scheme was found to produce a numerical instability at the inversion layer which acts to unphysically transport moisture from the dry air aloft into the moister air within the PBL, as well as lock adjacent grid cells to the same thermodynamic values, and the effects increased with simulation time. The cause appears to be numerical dispersion caused by the strong temperature and moisture gradients near the inversion. The finite differencing scheme was modified to a 5-point 4th order accurate centered finite difference scheme with uneven spacing (Bowen and Smith, 2005) relative to the grid center (as is customary in NWPs, the simulations in this study were performed with non-uniform grid spacing), and the numerical instability was partially alleviated. Locking no longer occurs except for in 1 to 2 grid points above the inversion for MYNN at the end of the 24 hour simulation,
and the drying of above-PBL $q_t$ is limited to 0.5 g / kg, compared to 0.9 g / kg originally (removing almost all water vapor present). Because the function in question is specific to the SCM, this numerical instability does not affect real-data WRF simulations. In the SCM, this numerical instability does not affect the entrainment velocity, but rather increases the moisture jump value, so that entrainment drying $(w'q_t'_{z_{inv}} = w_e \Delta q_{z_{inv}}$ is overestimated; however, this effect is small.

### 3.3 Evaluation of WRF SCM simulations of the STBL

#### 3.3.1 Baseline DYCOMS RF01 ocean case evaluation

The diurnal cycle of the WRF SCM vertically integrated LWP is shown in Figure 3.3, along with LES results. Both ACM2 and MYNN yield a LWP that is more than twice that in LES, while YSU (with the Wilson (2015) addition of top-down diffusion) matches well with LES. For ACM2 and MYNN, the LWP increases rapidly at initialization at midnight reaching a maximum LWP shortly after sunrise after which LWP decreases during the day due to solar heating and precipitation. Running YSU without the Wilson (2015) correction (not shown) yields similar results to those from ACM2 and MYNN.

Figure 3.3 (b) depicts the boundary layer averaged liquid potential temperature, $\theta_l = \theta - \frac{L_v c_p}{q_l}$, with $\theta$ the potential temperature, $L_v$ the latent heat for condensation of water, $c_p$ the specific heat of dry air at constant pressure and $q_l$ the cloud liquid water mixing ratio. The total water mixing ratio, $q_t = q_v + q_l$, which is the sum of water vapor ($q_v$) and cloud liquid water mixing ratio is plotted in Figure 3.3 (c). Both $\theta_l$ and $q_t$ are conserved.
in adiabatic motions of moist air parcels in a well-mixed STBL (i.e. both variables are constant with height in the STBL); hence, we use the boundary layer averaged quantities as a proxy for the STBL heat and moisture content. All three schemes simulate lower $\theta_l$ and higher $q_t$ values within the boundary layer compared to LES. Hence, the SCM yields a cooler, moister STBL. STBL moisture content simulated by SCMs increases throughout the 24-hour simulation period. Since the surface flux is kept constant for both the LES and the SCMs, the moisture and heat bias of the SCMs compared to LES is indicative of deficiencies in either the microphysics or the PBL parameterizations.

3.3.2 Microphysics scheme evaluation

Table 3.2 outlines the different microphysics schemes employed in the study. For the YSU scheme, there is negligible dependence of LWP on the microphysics scheme (not shown). For the ACM2 and MYNN scheme, we observe a large spread in LWP for the different microphysics schemes, whereby the WSM5 scheme produces the least LWP (Figure 3.4 (a,b)). The spread is mainly due to precipitation (Figure 3.5), whereby the different autoconversion schemes within the microphysics schemes form raindrops due to collision of cloud droplets at different efficiencies. The MYNN in particular experiences a strong growth in LWP initially, resulting in thicker clouds that drizzle more (Figure 3.4). The thick drizzling clouds simulated by the ACM2 and MYNN and different microphysics schemes are not consistent with DYCOMS LES results or the campaign measurements.

All microphysics schemes simulate the sharp increase in LWP at the start of the simulation; hence, the cold, moist bias of the PBL schemes is not a result of deficiencies
Table 3.2: List of microphysics schemes used for the microphysics sensitivity study

<table>
<thead>
<tr>
<th>Microphysics scheme</th>
<th>Hydrometeors</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kessler</td>
<td>water vapor, cloud water, and rain</td>
<td>Kessler (1969)</td>
</tr>
<tr>
<td>Lin</td>
<td>water vapor, cloud water, ice, rain, snow, and graupel</td>
<td>Lin et al. (1983)</td>
</tr>
<tr>
<td>Thompson</td>
<td>water vapor, cloud water, rain, ice, snow, and graupel</td>
<td>Thompson et al. (2008)</td>
</tr>
<tr>
<td>WSM5</td>
<td>water vapor, cloud water, rain, ice, snow</td>
<td>Hong et al. (2004)</td>
</tr>
</tbody>
</table>

in the parameterization of the microphysics schemes. Thus, we hypothesize that the overestimation of cloud liquid water content is the result of incorrect PBL parameterization of entrainment flux.

3.3.3 PBL scheme evaluation

In a one-dimensional PBL and neglecting horizontal advection and non-local terms, the tendency of a variable $C$, where $C$ can represent $\theta_l$ or $q_t$, can be expressed in terms of the convergence of its flux $F_c$ as

$$\frac{\partial C_{BL}}{\partial t} = -\frac{\partial F_c}{\partial z}, \quad (3.12)$$

where $F_c$ can represent vertical turbulent (e.g. $w'c'$) or radiative flux. The boundary layer average $C_{BL}$ is used to facilitate analysis through a mixed layer framework, wherein the vertical gradient of $F_c$ is linear and can be determined solely from the surface and PBL-top fluxes. This formulation is sufficient to describe the tendency of $C_{BL}$, as mixing
is assumed to occur instantaneously throughout the PBL. We use cloud thickness tendency as a proxy for the liquid water path tendency as they are analogues (Ghonima et al., 2015). The tendency is expressed as function of the inversion height $z_{inv}$ and cloud base height $z_b$ tendencies as $\frac{\partial h}{\partial t} = \frac{\partial z_{inv}}{\partial t} - \frac{\partial z_b}{\partial t}$. For a well-mixed STBL, the cloud base height ($z_b$) tendency equation is expressed as

$$\frac{\partial z_b}{\partial t} = B_1 \frac{\partial \theta_{l, BL}}{\partial t} + B_2 \frac{\partial q_{l, BL}}{\partial t} + B_1 \frac{\partial F_R}{\partial z},$$

(3.13)

where $B_1 = \frac{\partial z_b}{\partial \theta_l}$ and $B_2 = \frac{\partial z_b}{\partial q_t}$ (for full derivation, see Ghonima et al. (2015)), and $F_R$ is the sum of longwave and shortwave radiative fluxes. Since the inversion height change over the diurnal cycle is much smaller than that of the cloud base height (Figure 3.2), we will limit our analysis to the cloud base height tendency.

All three schemes produce a negative cloud base height tendency $\frac{\partial z_b}{\partial t}$, ranging from -5 to -15 mm s$^{-1}$ nocturnally that is indicative of a thickening cloud layer (Figure 3.6 (a)); during the day, solar loading causes the cloud to thin and hence $\frac{\partial z_b}{\partial t}$ to turn positive. The LES, on the other hand, simulates a cloud base height tendency that is initially slightly positive (slightly thinning) nocturnally and then near-zero during the day before turning negative after sunset.

Next, we substitute Equation 3.12 into each term in Equation 3.13 to split up the cloud base height tendency contributions integrated over the PBL due to liquid potential temperature vertical flux ($B_1 \frac{\partial \bar{w}'\bar{\theta}_l}{\partial z}$), total water mixing ratio vertical flux ($B_2 \frac{\partial \bar{w}'q_t}{\partial z}$), and radiative flux ($B_1 \frac{\partial F_R}{\partial z}$). Surface sensible heat flux and cloud top entrainment flux
both act to warm the STBL, while surface latent heat flux acts to moisten the STBL and entrainment flux acts to dry the STBL. For the first 6 hours, $B_1 \partial \bar{w} \theta_l' / \partial z$ is underestimated for all three schemes compared to the LES results, particularly for the MYNN (Fig. 6b). During the day, $B_1 \partial \bar{w} \theta_l' / \partial z$ is then overestimated. Noting that the surface flux is held constant for all schemes and assuming the STBL is well-mixed, we conclude that the entrainment flux warming is underestimated in the morning and evening in the three PBL schemes resulting in a cooler STBL with a thicker cloud deck.

Similarly, $B_2 \partial \bar{w} q_t' / \partial z$ is negative for the three PBL schemes, which indicates that there is little entrainment flux drying of the STBL. Therefore the surface latent heat flux moistening of the STBL dominates entrainment drying, thereby decreasing the cloud base height (Figure 3.6 (a)). Thus, for all three schemes we observe a systematic under-prediction of cloud-top entrainment flux in the morning. Since the LES radiative scheme simulates very similar radiative flux divergence to the SCM (Figure 3.6 (d)), radiation does not appear to be the cause of discrepancy.

3.3.4 Modified PBL scheme validation

In this section, we validate the corrected PBL schemes for the DYCOMS RF01 case as well as the CGILS S12 control case. Results from MYNN will no longer be considered, as its complexity causes modification to exceed the scope of this paper. Furthermore, to test different regimes, we simulate STBL occurring over coastal lands where the main source of turbulence shifts from longwave cooling at the cloud top to surface-driven buoyancy flux during the day. Following Ghonima et al. (2016), we initialize the LES with
DYCOMS profiles to a simplified land surface model that computes the surface flux based on prescribed Bowen ratio (defined as the ratio of sensible to latent heat flux) and net radiation at the surface. Root-mean-square errors (RMSE) and mean bias errors (MBE) for all simulations are given in Table 3.3.

**DYCOMS Rf01 over ocean**

Both the corrected YSU scheme (YSU-BUOY) and experimental ACM2 scheme (ACM2-BUOY) simulate a drier warmer STBL that matches well with the LES (Figure 3.7), with ACM2 showing a dramatic improvement while YSU-BUOY performs similarly to YSU. This improvement is a result of increased entrainment flux drying and warming in the STBL in ACM2-BUOY (Figure 3.6). As expected, both schemes then simulate LWP close to the LES and DYCOMS measurements (Figure 3.7, Table 3.3). We do not observe any dependence on the microphysics schemes as the reduced LWP eliminates precipitation in both schemes (not shown). While YSU-BUOY slightly underestimates LWP the diurnal cycle of LWP is accurately captured. Similarly, ACM2-BUOY accurately captures the diurnal cycle of LWP, though LWP is overestimated in the morning and underestimated in the evening.

*Sensitivity to vertical resolution*

Next, we test the effect of resolution on the YSU-BUOY scheme to find that resolution plays an important role (Figure 3.7). Instead of the 74 vertical levels employed for the other simulations, we ran YSU-BUOY with 50 vertical levels in the same configuration as the Rapid Refresh (RAP) mesoscale model and find that the LWP is less accurate,
Table 3.3: Table of LWP errors in [g / m$^2$] for each simulation case and each PBL scheme. Errors were computed over the full 24 h of simulation time.

<table>
<thead>
<tr>
<th></th>
<th>YSU</th>
<th>YSU-BUOY</th>
<th>ACM2</th>
<th>ACM2-BUOY</th>
<th>MYNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>DYCOMS</td>
<td>RMSE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RF01</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ocean</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wet land $\beta = 0.1$</td>
<td>RMSE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>MBE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.6</td>
<td>-4.8</td>
<td>110.5</td>
<td>7.3</td>
<td>176.5</td>
</tr>
<tr>
<td>Dry land $\beta = 1.0$</td>
<td>RMSE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>MBE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>20.2</td>
<td>16.7</td>
<td>68.1</td>
<td>-2.0</td>
<td>101.7</td>
</tr>
<tr>
<td>CGILS S12 Control Ocean</td>
<td>RMSE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>MBE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-3.1</td>
<td>-0.5</td>
<td>8.2</td>
<td>-20.8</td>
<td>67.8</td>
</tr>
</tbody>
</table>

with larger LWP RMSE by 45% on average compared to the 74 vertical level simulation (RMSE and MBE are 11.8 and 14.3 g m$^{-2}$, respectively). The worse performance is mainly attributed to the coarse resolution at the inversion: the grid spacing at the temperature inversion in the RAP configuration is about 200 m, in contrast to about 50 m for the original 74 vertical levels. These increased errors are due not only to the decrease in grid points, but also to the distribution of grid points within the boundary layer: in the original setup, 49 points are concentrated below 2 km, whereas only 14 points are below 2 km in the RAP configuration. The coarse resolution is unable to resolve the sharp gradients present at the temperature inversion, and the explicit entrainment parameterizations used here are sensitive to the thermodynamic jump values across the inversion (e.g. Equation 3.3). Additionally, the entrainment efficiency $A = a_1(1 + a_2E)$ is dependent on the jump...
values through the evaporative enhancement term $E$, and the coefficient of $E$ is $a_1a_2 = 4$ in the original YSU and 12 in YSU-BUOY. In the $N_z = 74$ case, $0.7 < A < 0.9$, while in the $N_z = 50$ case, $0.55 < A < 0.75$, leading to less entrainment and larger LWP in the coarse simulation. Similar sensitivity tests to vertical resolution for the original YSU (not shown) showed that values of $A$ were more stable at about 0.35. Due to this stability, LWP in YSU was more consistent between simulations, with the $N_z = 50$ case (RMSE and MBE of 9.97 and 2 g / m$^{-2}$) showing only 5% less LWP RMSE than the $N_z = 74$ case (RMSE and MBE of 10.46 and -1.12 g / m$^{-2}$). The use of more sophisticated inversion detection algorithms like those of Grenier and Bretherton (2001) may alleviate the dependence of inversion jump values on vertical resolution. Finer grid spacing near the temperature inversion also allows more granular PBL height changes rather than large jumps of several hundred meters at a time which leads to smoother thermodynamic jump timeseries. The improvement in the representation of STBL at the higher resolution could also be due to numerics—for instance, Lenderink et al. (2004) found that convective schemes tend to produce liquid water through a numerical detrainment process at the cloud top.

**Wet land ($\beta = 0.1$)**

To demonstrate performance of the scheme in different conditions following Ghonima et al. (2016) we test YSU-BUOY and ACM-BUOY for STBL occurring over coastal lands with DYCOMS initial profiles. The land differs from the ocean because of the diurnal cycle of surface latent and sensible heat fluxes. The Bowen ratio $\beta$ controls the ratio
of sensible and latent heat fluxes and therefore the rate of heating and moistening of the STBL. We find that for a wet land surface ($\beta = 0.1$) YSU-BUOY is able to simulate LWP similar to LES for the first 12 hours of the simulation capturing the increase in inversion height driven by surface flux during the day (Figure 3.9 (a,b)). However, after 12 hours as surface flux decreases, the convective velocity scale and hence surface-driven mixing also decrease. Additionally, the clouds are not thick enough to produce sufficient longwave-induced turbulent mixing in the boundary layer. Due to the lower simulated turbulent mixing overall, YSU-BUOY underestimates entrainment, leading to cooler, moister STBL with higher LWP compared to the LES. Compared with the unmodified YSU, YSU-BUOY more accurately simulates inversion height, boundary layer temperature, and hence LWP for most of the simulation. For hours 12-17 in the simulation, YSU-BUOY underpredicts boundary layer moisture compared with YSU, indicating excessive entrainment drying, though the reverse is true afterwards.

ACM2-BUOY appears to overestimate entrainment for this case, suggesting the supplemental entrainment was too strong. Furthermore, the cloud unphysically dissipates twice, coinciding with times when the PBL height increases. As the temperature inversion rises, the inversion jump values between adjacent grid cells approaches zero, causing an excessive estimation of the entrainment velocity $w_e$ (recall from Equation 3.5 that $\Delta \theta_v$ appears in the denominator). After 12 hours, ACM2-BUOY also appears to underestimate entrainment.
Dry land ($\beta = 1.0$)

Over a relatively dry land surface ($\beta = 1.0$) YSU-BUOY accurately simulates the cloud dissipation driven by surface sensible heat flux warming. Furthermore, YSU-BUOY is able to capture the sharp increase in inversion height in the dry convective boundary layer regime during the day and the subsequent collapse at night (Figure 3.9 (e-h)). ACM2-BUOY performs similarly well here for both dissipation time and boundary layer heating, but underestimates PBL height and overestimates boundary layer moisture.

CGILS S12 control over ocean

In order to test how well YSU-BUOY and ACM2-BUOY perform under different initial conditions we compare both schemes to LES for the CGILS S12 control case. Both YSU-BUOY and ACM2-BUOY match the results of the LES relatively well, simulating shortwave daytime radiative warming (not shown) and the resulting drop in LWP (Figure 3.9 (i-l)).
Figure 3.2: Inversion heights as detected by the original SCM algorithm ($z_{inv,\text{org}}$) plotted with grey lines and circle markers and inversion heights as detected by the modified SCM algorithm plotted with grey lines and square markers for (a) YSU scheme, (b) ACM2 scheme, and (c) MYNN scheme. LES derived inversion height is plotted with the solid black line. Cloud base heights are also shown for reference.
Figure 3.3: (a) Domain averaged vertically integrated LWP. (b) Boundary layer averaged liquid potential temperature and (c) total water mixing ratio.
Figure 3.4: Domain averaged vertically integrated LWP in the DYCOMS RF01 test case for (a) ACM2 and (b) MYNN with different microphysics schemes (Table 2). Since the YSU showed negligible spread in LWP for all microphysics schemes, YSU is not shown.

Figure 3.5: Precipitation flux at the surface for (a) ACM2, and (b) MYNN with different microphysics schemes. Since precipitation in the YSU scheme was 0 for all microphysics schemes, YSU is not shown.
Figure 3.6: (a) Total cloud base height tendency, (b) $\theta_l$ vertical turbulent flux contribution to cloud base height tendency, (c) $q_t$ vertical turbulent flux contribution to cloud base height tendency, and (d) radiative flux contribution to cloud base height tendency in the DYCOMS RF01 ocean case.
Figure 3.7: DYCOMS RF01 over ocean results for (Top) Domain averaged vertically integrated LWP, (Center) Boundary layer averaged liquid potential temperature and (Bottom) total water mixing ratio. YSU-BUOY is shown in the left column (a-c), while ACM2-BUOY is shown in the right column (d-f). See Fig. 3 for comparison with unmodified schemes.
Figure 3.8: (a) Domain averaged vertically integrated LWP and (b) Inversion height and cloud base height for LES (solid black line), YSU-BUOY with 50 vertical points (grey dashed line), and YSU-BUOY with 74 vertical points (grey solid line).
Figure 3.9: DYCOMS RF01 over ocean results for (Top) Domain averaged vertically integrated LWP, (Center) Boundary layer averaged liquid potential temperature and (Bottom) total water mixing ratio. YSU-BUOY is shown in the left column (a-c), while ACM2-BUOY is shown in the right column (d-f). See Fig. 3 for comparison with unmodified schemes.
3.4 Conclusions

We employed three WRF-SCM simulations with various PBL schemes and benchmarked the results against LES to investigate the capability of the YSU, ACM2, and MYNN PBL schemes in modeling the STBL. We find that ACM2 and MYNN underestimate entrainment flux resulting in a cooler, moister boundary layer with much larger LWP. The ACM2 scheme’s turbulent flux parameterization does not take into account the longwave-cooling-induced turbulence in the boundary layer, thereby leading to entrainment underestimation. The MYNN TKE closure scheme fails in representing the STBL which indicates the inherent difficulty in modeling such regimes and a deficiency in the current TKE equation. Although the YSU scheme performs well for ocean cases, simulations over land showed room for improvement. The choice of microphysics schemes primarily regulates the upper bound of LWP through different amounts of drizzle precipitation, but an unphysical initial sharp rise in LWP is common in all microphysics schemes. This rise in LWP further substantiates that entrainment flux is insufficient to counteract the longwave radiative cooling of the STBL and surface latent heat flux moistening. In order to improve the parameterization of the STBL we propose a revision to the YSU scheme (YSU-BUOY) that accounts for the skewness of top-driven convection and parameterizes entrainment based on the in-cloud buoyancy flux rather than radiative flux divergence as in the Wilson (2015) YSU update. This revision results in a more robust entrainment model since longwave emission becomes insensitive to changes in LWP for thick clouds (Kazil et al., 2015). Similar modifications were made to the ACM2 scheme (ACM2-BUOY) in
order to explore the impact of explicitly modelling these effects.

We tested both YSU-BUOY and ACM2-BUOY against LES for four different test cases and find that more accurate entrainment fluxes result in LWPs that closely match those simulated by the LES. The improvement of YSU-BUOY over the original YSU scheme is predominantly due to the revision of the convective velocity scale. In ACM2-BUOY, the improvement is mostly due to the addition of the explicit entrainment model. However, because the ACM2-BUOY scheme is capable of implicitly modeling some entrainment, the contribution from both entrainment models is difficult to modulate. In addition, ACM2-BUOY currently suffers from discretization issues, preventing immediate implementation.

While Wilson (2015) was interested in simulation of fog, fog and STBL share many similarities. Our original YSU-BUOY model development actually preceded the publication of the Wilson article and was originally published in (Ghonima et al., 2016). We therefore arrived independently at the same conclusion regarding deficiencies in current PBL parameterizations: a lack of accounting for downward mixing originating from the cloud top driven by longwave cooling and inaccurate modelling of entrainment mixing across the cloud-top interface.

Modelling of mixing driven by longwave cooling at the cloud top increases the coupling between the cloud and land/ocean surface, leading to more realistically well-mixed STBL; this enhanced mixing may reduce the occurrence of stratocumulus breakup due to boundary layer decoupling, wherein cool, moist air is unable to mix into the cloud deck. The fluxes of heat and moisture caused by entrainment are more difficult to determine, as
these entrainment fluxes depend not only on the entrainment velocity $w_e$ (which is itself difficult to determine) but also the inversion jump values $\Delta C_i$. While the improvements in STBL simulations shown here under a variety of conditions are encouraging, the remaining biases in boundary layer heat and moisture suggest further research is needed. Hence, entrainment remains the subject of active ongoing research, though this study shows a step towards correctly simulating STBL in WRF. Future work will explore modifications aimed at improving the modeling of STBL processes in MYNN and include extensive testing of these modified schemes in the full 3D WRF, both in idealized and real scenarios. Proper validation will then aid the implementation of these modifications into WRF.

Correctly modelling entrainment under conditions typical to NWPs and GCMs (i.e. coarse discretization of thermodynamic gradients, especially vertically, and limited information available both in time and space) is expected to improve predictions of boundary layer temperature, humidity, and precipitation for the weather forecasting community, ceiling heights for the aviation industry, and cloud cover for the solar energy and climate modelling communities. In this study, the most accurate modelling of cloud-top entrainment was achieved with an explicit entrainment model utilizing a revised convective velocity scale, which is a function of in-cloud buoyancy flux rather than radiative flux divergence, thereby eliminating insensitivity for thick clouds.
3.5 Acknowledgements

All data for this chapter is properly cited and referred to in the reference list. The source code for the LES model used in this study, the UCLA-LES, is freely available at https://github.com/uclales, and initial profiles and forcings are included. The WRF model is also freely available at http://www2.mmm.ucar.edu/wrf/users/downloads.html.

Chapter 3, in full with slight modifications, is a reprint of the material in the article ”Evaluation of WRF SCM Simulations of Stratocumulus-Topped Marine and Coastal Boundary Layers and Improvements to Turbulence and Entrainment Parameterizations,” published in Journal of Advances in Modeling Earth Systems in 2016 (Ghonima et al., 2017). The dissertation/thesis author was the joint primary investigator and joint first author of this paper.
Chapter 4

Development and validation of radiatively-driven downdraft-based eddy-diffusivity mass flux scheme in idealized WRF simulations

4.1 Introduction

The experiments and modifications performed in Chapter 3 revealed that the Asymmetric Convective Model (ACM2) and Mellor-Yamada-Nakanishi-Niino (MYNN) planetary boundary layer (PBL) turbulence models in the Weather Research and Forecasting (WRF) numerical weather prediction model underestimate entrainment flux in simulations of stratocumulus-topped boundary layers (STBL), causing a cold and moist bias in
the boundary layer which results in a much larger liquid water path (LWP) than that observed from large eddy simulations (LES). Furthermore, a low boundary layer height bias was observed, which would result in an underestimation of coastal cloud cover due to topographical effects. This chapter extends upon those findings and proposes a set of modifications to the MYNN scheme in order to address these biases. Due to the complexity of the MYNN scheme, we limit this set of modifications to marine STBL only, and investigate the impact of accounting for the descending downdrafts driven by cloud-top radiative cooling characteristic of the STBL. A general introduction to PBL parameterization schemes is presented in Section 4.2, including a detailed discussion on the MYNN model and proposed modifications. Following, methodology on the derivation of model constants and experimental setup is discussed in Section 4.2.2 and Section 4.3. Finally, validation of proposed changes to MYNN is presented (Section 4.4) with discussion (Section 4.5), and direction for future work towards further improvements for MYNN is outlined (Section 4.6).

4.2 Planetary boundary layer parameterizations

In WRF, the planetary boundary layer (PBL) scheme determines flux profiles within the PBL as well as the overlying air, providing tendencies of temperature, moisture, and horizontal momentum for the entire atmospheric column. Assuming horizontal gradients are much smaller than vertical gradients, these schemes are one-dimensional. The application of a PBL scheme requires the additional assumption that there exists a clear
separation of scales between the sub-grid eddies and grid-scale motions. With the above assumptions, the tendency of a scalar $C$ (e.g. temperature, moisture, chemical species, and horizontal momentum components) due to turbulent mixing can be described by:

$$\frac{\partial C}{\partial t} = -\frac{\partial \overline{w'c'}}{\partial z}.$$  (4.1)

The primary difficulty is in specifying the turbulent flux $\overline{w'c'}$, which arises from the decomposition of the governing equations of motion into mean quantities and turbulent fluctuations. The major difference in PBL parameterizations lies in the modeling of turbulent flux terms. In version 3.9 of WRF-ARW, 12 PBL parameterizations are available with various degrees of complexity and origins of development. The selection of PBL parameterizations include first-order (i.e. relating turbulent fluxes to mean quantities) K-theory schemes such as the Yonsei University (YSU) scheme, to hybrid schemes describing mixing between both adjacent and nonadjacent model levels like the Asymmetric Convective Model 2 (ACM2) scheme, to higher-level prognostic turbulent kinetic energy schemes such as the Mellor-Yamada Nakanishi and Niino (MYNN) scheme. This chapter will focus in particular on the MYNN schemes, with the following sections providing a brief description (4.2.1), proposed modifications (4.2.2), proposed testbed (4.3.2), and validation.

### 4.2.1 The Mellor-Yamada Nakanishi and Niino model (MYNN)

The Mellor-Yamada Nakanishi and Niino (MYNN) model is a modified implementation of the Mellor-Yamada turbulence closure scheme originally developed by Mellor and
Yamada (1982). A full description can be found in Nakanishi and Niino (2009).

In brief, the MYNN model is a local K-theory (eddy diffusivity) scheme. In the Mellor-Yamada framework, additional prognostic equations are added to solve for higher order turbulent moments, with varying levels of complexity denoted by ”levels.” In this work, the focus will be on the ”Level 2.5” closure model, wherein a single prognostic equation is added for the turbulent kinetic energy (TKE). Despite the name, the MYNN Level 2.5 model is a 1.5 order turbulence closure scheme, as only TKE is solved for while the other second order turbulent covariances are parameterized.

Prognostic equations are formulated as before in Equation 4.1. In MYNN, the prognostic variable for heat is liquid water potential temperature \( \theta_l = \theta - \frac{L_v}{c_{pd}} \frac{q_t}{\rho_0} \), where \( L_v \) is the latent heat of vaporization and \( c_{pd} \) the specific heat of dry air at constant pressure. The prognostic variable for water is total water mixing ratio \( q_t = q_v + q_l + q_i \), and the remaining two prognostic variables are the horizontal components of wind \( u \) and \( v \). The additional prognostic equation of the Level 2.5 model solves \( q_t^2 = 2 \cdot \text{TKE} = u'^2 + v'^2 + w'^2 \), and is formulated as:

\[
\frac{\partial q_t^2}{\partial t} = -\frac{\partial}{\partial z} w' (u'^2 + v'^2 + w'^2 + 2p'/\rho_0) \\
-2 \left( u'w' \frac{\partial U}{\partial z} + v'w' \frac{\partial V}{\partial z} \right) + 2 \frac{g}{\theta_0} w' \theta' v - 2\epsilon \quad (4.2)
\]

Equation 4.2 describes the tendency of TKE due to turbulent and pressure transport, shear production, buoyant production, and turbulent dissipation, respectively. The
turbulent and pressure transport term is modeled as

$$w'(u'^2 + v'^2 + w'^2 + 2p'/p_0) = LqS_q \frac{\partial q^2}{\partial z},$$  \hspace{1cm} (4.3)

where $L$ is the master length scale, and $S_q = 3S_m$ is the stability correction function for TKE (see Nakanishi and Niino (2009) for detailed formulations). The master length scale is designed such that the smallest length scale out of 3 different formulations dominates. The first is a surface length scale $L_{sfc}$, which is a function of the stability (i.e. the Obukhov length scale) and is small near the surface but increases rapidly through the PBL. Second, a turbulent length scale $L_{turb}$ is formulated as a function of the integrated TKE within the atmospheric column, and it is independent of height. Finally, a buoyancy length scale $L_{buoy}$ is computed as a function of the local stratification (i.e. $\partial \theta / \partial z$), and it decreases with increasing stratification. The buoyancy length scale is only active in stable conditions. The stability functions for heat and moisture $S_{h,m}$ contain empirical constants, but generally decrease with increasing stability (they are inversely related to the Richardson number; for detailed definitions, please refer to Equations (27-28) in Nakanishi and Niino (2009)).

Second order turbulent moments are modeled according to a K-theory local eddy diffusivity model similar to that of Holtslag and Boville (1993), where the turbulent fluxes are represented by gradient diffusion as:

$$\overline{w'c'} = -K \frac{\partial C}{\partial z},$$  \hspace{1cm} (4.4)

where eddy diffusivity $K$ is parameterized as a function of the TKE, a master length scale.
\[ K_{h,m}(z) = q(z)L(z)S_{h,m}(z) \]  

Finally, the dissipation rate is parameterized as \( \epsilon = \frac{q^3}{B_1 L} \), where \( B_1 \) is a closure constant (\( B_1 = 24 \) in the MYNN scheme).

### 4.2.2 Proposed changes: MYNN with radiative cooling (MYNN-RAD)

In contrast to the non-local framework of the Yonsei University (YSU) scheme, the MYNN Level 2.5 model determines mixing at each vertical level based on gradients in scalars between immediately adjacent vertical levels (Equation 4.4). In scenarios when deep mixing due to large eddies is important such as the STBL, the MYNN scheme has been shown to produce erroneous thermodynamic profiles (Huang et al., 2013). Non-local models such as the YSU and ACM2 schemes account for this deep mixing through the use of a counter-gradient term (Hong et al., 2006) or a transilient mass flux matrix (Pleim, 2007). This section details a set of modifications to the MYNN model in order to explicitly model non-local transport due to downdrafts driven by cloud-top radiative cooling through a mass flux framework; the modified MYNN is henceforth termed ”MYNN-RAD.” Updrafts are not accounted for in MYNN-RAD because an existing option to activate an updraft-based mass flux model is available in WRF 3.9 (Sušelj et al., 2013), henceforth termed ”MYNN-STEM,” and can be used in conjunction with MYNN-RAD.
Siebesma and Cuijpers (1995) showed that the vertical turbulent transport of a scalar $\phi$ can be decomposed into active cloudy updrafts and downdrafts and passive environmental transport as:

$$
\overline{w'\phi'} \approx a_u (w_u - \overline{w})(\phi_u - \overline{\phi}) + a_d (w_d - \overline{w})(\phi_d - \overline{\phi}) + (1 - a_u - a_d) (w_{env} - \overline{w})(\phi_{env} - \overline{\phi}),
$$

(4.6)

where $a$ is the area fraction, $w$ the vertical velocity, with overlines denoting environmental averages and subscripts $u$ and $d$ denoting updraft and downdraft properties, respectively. Teixeira and Siebesma (2000) originally proposed a unified PBL parameterization method in order to describe the small-scale passive environmental "local" mixing through an eddy-diffusion (or gradient diffusion) approach:

$$
\overline{w'\phi'_{env}} = (1 - a_u - a_d) (w_{env} - \overline{w})(\phi_{env} - \overline{\phi}) \approx -K \frac{\partial \phi}{\partial z},
$$

(4.7)

while modeling the active cloudy updraft plumes through a "non-local" mass-flux approach:

$$
\overline{w'\phi'_{u}} = a_u (w_u - \overline{w})(\phi_u - \overline{\phi}) = M_u (\phi_u - \overline{\phi}),
$$

(4.8)

where $M_u \equiv a_u (w_u - \overline{w})$. This "eddy-diffusivity mass-flux" framework, or EDMF, represents the state-of-the-art in PBL parameterization schemes. It is, for example, utilized in the European Centre for Medium-Range Weather Forecasts (ECMWF) model.
Typically, current EDMF schemes only consider updrafts and do not explicitly model downdrafts, and instead include downdrafts implicitly in the eddy-diffusion environmental mixing component (Siebesma et al., 2007; Neggers et al., 2009; Köhler et al., 2011). In clear convective and shallow cumulus boundary layers, downdrafts are typically produced by mass conservation as a consequence of surface heating-driven thermal updrafts. Thus, downdrafts do not descend at a comparable vertical velocity as warm updrafts, so the contribution of downdrafts to the total mixing in the PBL is small and can be well accounted for by eddy diffusion.

In STBL, however, the effects of downdrafts are comparable to the effects of updrafts. Recently, Davini et al. (2017) used octant analysis to track and classify convective structures in the STBL. Davini et al. (2017) show that updrafts and downdrafts dominate over the 6 other convective structures over most of the STBL, with entrainment contributing up to 40% of the number of total convective structures in the top 5% of the STBL.

As demonstrated by Ghonima et al. (2017), the major deficiencies in WRF’s PBL parameterization schemes in simulating STBL arise from poor modeling of cloud-top entrainment and radiatively-cooled downdrafts, as indicated by the consistent cold and moist biases in combination with a low PBL height bias. In this study, we aim to add a mass-flux component to the Mellor-Yamada-Nakanishi-Niino (MYNN) model in order to explicitly account for radiatively-cooled downdrafts that are particularly important to STBL:

\[
\bar{w'}\phi'_d = a_d(w_d - \bar{w})(\phi_d - \bar{\phi}) = M_d(\phi_d - \bar{\phi}),
\] (4.9)

84
where \(M_d \equiv a_d(w_d - \overline{w})\). To quantify the properties \(\phi_d\) of descending downdrafts, we adopt a framework similar to that described by Köhler (2006), in which plumes are initialized with heat and moisture excesses proportional to the fluxes at the plume origin, originally proposed by Troen and Mahrt (1986), which was later utilized by Siebesma et al. (2007) and Sušelj et al. (2013), for example, to produce a scaling similar to Monin-Obukhov scaling for surface fluxes (Stull, 1988). We utilize an analogous scaling with respect to fluxes at the top interface of the STBL. Here, we assume the moisture of the plume is dried solely through mixing with entrained air, so that the downdraft plume moisture excess \(q_{t,\text{exc}}\) can be parameterized as proportional to the entrainment flux of total water mixing ratio \(q_t\):

\[
q_{t,\text{exc}} \equiv q_{t,\text{down}} - \overline{q_t} = -\alpha_{\text{ent}} \frac{w'q_{\text{ent}}'}{w_{*,\text{rad}}}.
\] (4.10)

Here, the convective velocity scale for radiatively driven convection \(w_{*,\text{rad}}\) is formulated after Lock and MacVean (1999) as:

\[
w_{*,\text{rad}} = \left(\frac{g z_{\text{inv}} F_0}{\theta l \rho c_p}\right)^{1/3}.
\] (4.11)

Although longwave radiation emission becomes insensitive to LWP above \(\approx 50\) g m\(^{-2}\) (Kazil et al., 2015), this formulation for \(w_{*,\text{rad}}\) is more reliably obtained internally in WRF for the MYNN scheme as compared with the formulation utilized by Ghonima et al. (2017), where \(w_{*,\text{rad}}\) was formulated as a function of the integral of the in-cloud buoyancy flux. Compared with the first-order K-profile PBL parameterization schemes.
used in Ghonima et al. (2017), the MYNN model does not produce a steady profile of buoyancy flux within the boundary layer; due to the complexity of the MYNN model, large changes in tendencies from timestep to timestep are likely to lead to numerical instability. We therefore formulate $w_{s,rad}$ as a function of radiative cooling as a practical choice and acknowledge that, if obtainable, the integral of the in-cloud buoyancy flux better characterizes radiatively-driven convection characteristic of the STBL.

Next, we assume that the plume is rendered negatively buoyant by a fraction of the total radiative cooling and opposed by heating through mixing of entrained air. The downdraft buoyancy excess is then:

$$b_{exc} \equiv b_{down} - \bar{b} = \alpha_{rad} \frac{B_0}{w_{s,rad}} - \alpha_{ent} \frac{w'\bar{b}_{ent}}{w_{s,rad}}, \quad (4.12)$$

where $B_0$ represents the reference buoyancy flux produced by radiation as formulated by de Lozar and Mellado (2013):

$$B_0 = \frac{F_0 g}{\rho_c c_p \theta_{l,cld}}, \quad (4.13)$$

with $F_0$ the radiative cooling per unit surface of the cloud (i.e. radiative flux divergence $F(z_i) - F(z_{cb})$, $g$ the gravitational acceleration, $\rho_c$ the density of the cloudy air, and $c_p$ the constant pressure heat capacity of the cloudy air. The reference cloud liquid water potential temperature $\theta_{l,cld}$ is used instead of the reference cloud physical temperature $T_c$ used in de Lozar and Mellado (2013) to remain consistent with the definition of buoyancy used in MYNN-RAD.
The buoyancy excess $b_{exc}$ is then converted to liquid water potential temperature $\theta_{l,exc}$:

$$b = g(\theta_l - \overline{\theta}_l)/\theta_l.$$  
(4.14)

The entrainment fluxes $\overline{w^'c^'}_{ent}$ are modeled according to the flux-jump relation

$$\overline{w^'c^'}_{ent} = w_e \Delta C_{z_{inv}}$$ (Lilly, 1968), where $\Delta C_{z_{inv}} = C_{z_{inv}+1} - C_{z_{inv}}$ represents the jump value of the scalar $C$ across the inversion, and is determined by the inversion reconstruction method described by Grenier and Bretherton (2001).

Following Grenier and Bretherton (2001) and Ghonima et al. (2017), we substitute $\theta_v$ in all computations related to the PBL height with the conserved quantity liquid virtual potential temperature $\theta_{vt} = \theta_l(1+0.608q_t)$. Since $\theta_v$ is not conserved in STBL, PBL heights computed based on $\theta_v$ underestimates the height of the STBL. The depth of the PBL height indirectly influences the MYNN model through the determination of the master length scale $L$ (Nakanishi and Niino, 2009). In the MYNN-RAD, the determination of the PBL height and hence inversion base height is imperative, as the jump values must be correctly determined in order to correctly parameterize the downdraft properties. The inversion height $z_{inv}$ is determined within the downdraft model as the highest point with non-zero $q_l$. For the purposes of the controlled testing conducted here on 2 selected STBL cases, this definition of $z_{inv}$ always correctly determines the inversion height. However, in practical situations, where liquid water clouds may exist above the stratocumulus cloud deck, this definition will wrongly determine the inversion height as the top of the highest liquid
cloud layer aloft. In the future, the determination of $z_{inv}$ needs to be refined. Altering the determination of PBL height to depend on liquid water virtual potential temperature $\theta_{vl}$ correctly determines $z_{inv}$ most of the time and is robust to higher cloud layers, though this method occasionally fails, leading to compounding errors and thus cannot be used.

The entrainment velocity $w_e$ is parameterized following Ghonima et al. (2017):

$$w_e = -\frac{\theta_v\theta_{l0}}{g\Delta\theta_{v,inv}z_{inv}}(0.15(w_3^3 + 5u_3^3) + Aw_3^3\sigma_{rad}),$$  \hspace{1cm} (4.15)

where $\theta_{l0}$ is the virtual potential temperature at the first model level, $\Delta\theta_{v,inv}$ the inversion jump in virtual potential temperature, $w_3$ the Deardorff convective velocity scale $w_3 = \left[\frac{g}{T}z_{inv}\theta_0^2\right]^{1/3}$ (Deardorff, 1970), and $u_3$ the surface friction velocity. We select the parameter $A = 0.35$ as the mean of values obtained in Ghonima et al. (2017).

The last component is to obtain the downdraft plume velocity $w_{down}$. Following observations made by Siebesma et al. (2007) that the nondimensional updraft plume velocity $w_{up}/w_*$ scales well with the nondimensional standard deviation of vertical velocity $\sigma_w/w_*$, we hypothesize that the same is true for downdrafts. As the structure of the marine STBL consists of strong descending downdrafts and weak ascending updrafts (Ghonima et al., 2016), as opposed to the convective atmospheric boundary layer (CABL) in which strong rising updrafts dominate over weaker descending downdrafts, a simple starting point is to assume is that the velocity variance has a similar structure in marine STBL as in the CABL, but flipped vertically. We utilize the formulation proposed by Holtslag and Moeng (1991), in the form used by Siebesma et al. (2007), to parameterize $\sigma_w/w_*$, in which the
normalized standard deviation of the vertical velocity in the CABL is parameterized as a function of $u_*$ and Deardorff convective velocity scale $w_*$. Here, we utilize $w_{*,\text{rad}}$ in place of the Deardorff convective velocity scale and modify the formulation in Siebesma et al. (2007) so the vertical coordinate is positive downwards originating at the STBL top:

$$
\frac{w_{\text{down}}(z)}{w_{*,\text{rad}}} \approx -\mu_w \frac{\sigma_w}{w_{*,\text{rad}}} = -1.3\mu_w \left[ \left( \frac{u_*}{w_{*,\text{rad}}} \right)^3 + 0.6 \frac{z_* - z}{z_*} \right]^{1/3} \left( 1 - \frac{z_* - z}{z_*} \right)^{1/2}.
$$

While the surface friction velocity $u_*$ scaling is retained in Equation 4.16, $u_*$ is not a physically meaningful parameter in the characterization of downdraft plume velocity. A more appropriate shear velocity scale would be as defined by Mellado et al. (2014), where the shear velocity scale at the entrainment interface is estimated to be a function of the velocity difference across the inversion, buoyancy reversal parameter, and saturation mixture fraction. However, in the coarse vertical resolutions (50-200 m) characteristic of current WRF simulations, the computation of a shear velocity scale following Mellado et al. (2014) is dubious, and we retain the use of $u_*$ solely to produce a nonzero $w_{\text{down}}$ at cloud top when $z \approx z_*$ and note that the contribution of the $u_*$ scaling term is small outside of this limit.

Finally, the plume is assumed to not interact with the environment (i.e. no lateral entrainment occurs between the plume and its surroundings), so that the plume properties are constant in height. The downdraft plume is assumed to terminate its descent upon reaching a vertical level at which $\theta_{l,\text{exc}} > \bar{\theta}_l(z)$.
Table 4.1: Summary of large eddy simulation setups in UCLA-LES, including uniform horizontal grid spacing $\Delta x, y$, vertical grid spacing at the inversion $\Delta z_{inv}$, horizontal domain size $L_{x,y}$, and divergence of large-scale winds $D$.

<table>
<thead>
<tr>
<th>Case</th>
<th>$\Delta x, y$ [m]</th>
<th>$\Delta z_{inv}$ [m]</th>
<th>$z_{inv}$ [m]</th>
<th>$L_{x,y}$ [m]</th>
<th>$L_z$ [m]</th>
<th>$D$ [s$^{-1}$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>DYCOMS RF01</td>
<td>35</td>
<td>5</td>
<td>837</td>
<td>3,360</td>
<td>1568</td>
<td>$3.75 \times 10^{-6}$</td>
</tr>
<tr>
<td>CGILS S12 Control</td>
<td>25</td>
<td>5</td>
<td>677</td>
<td>2,400</td>
<td>1572</td>
<td>$1.68 \times 10^{-6}$</td>
</tr>
</tbody>
</table>

4.3 Methodology

4.3.1 Large eddy simulation (LES) setup

Large eddy simulations were performed using UCLA-LES (Stevens, 2010b) in order to establish downdraft properties. Two idealized marine Sc cases were chosen as baseline simulations: the DYCOMS RF01 (Stevens et al., 2005) and CGILS S12 Control (Blossey et al., 2013) cases. The LES simulations were setup as in Ghonima et al. (2017): identically to the respective original intercomparison studies, but utilizing a one-dimensional radiative model with Monte Carlo sampling of the spectral integration in the DYCOMS RF01 case. A summary of model setups is provided in Table 4.1.

Determining plume properties

Simulations were run for 24 hours, with the output from hour 3-4 stored at 1-min intervals in order to derive downdraft plume properties. While Siebesma et al. (2007) determined updraft plume properties by isolating the strongest 5% of upward vertical velocities in the domain, this approach does not perform as well for Sc because isolating the strongest 5% of downward vertical velocities may include air which has been radiatively
cooled as well as separate entrainment events. Using this method, points categorized as downdrafts may be warmer than the environment, which invalidates the assumption that radiatively cooled downdrafts sink due to a buoyancy deficit.

In an effort to isolate descending downdrafts forced solely by radiative cooling, quadrant analysis was utilized to separate entrainment events from radiatively cooled downdrafts. We define four quadrants of liquid water potential temperature flux $\overline{w'\theta'}_l$ as follows:

1. $w' > 0, \theta_l > 0'$: Rising updraft
2. $w' > 0, \theta_l < 0'$: Ascending cold shell
3. $w' < 0, \theta_l > 0'$: Entrainment event
4. $w' < 0, \theta_l < 0'$: Descending downdraft

Downdraft plume properties were then derived from points corresponding to the strongest 5% of downward vertical velocities at each vertical level, while only considering points which fall into Quadrant 4. Similarly, updrafts were characterized only considering points which fall into Quadrant 1. This explicitly constrains the area fraction $a = 0.05$. An example vertical $x-z$ cross-section is shown in Figure 4.1.

The resulting downdraft and updraft properties are shown in Figure 4.2 for DYCOMS RF01 and Figure 4.3 for the CGILS S12 Control case. The normalized downdraft velocities $w_{down}/w_{*,rad}$ are shown alongside proposed parameterization $\mu_w \sigma_w/w_{*,rad}$ in Figure 4.4 for DYCOMS RF01 and in Figure 4.5 for CGILS S12 Control. Plume properties
Figure 4.1: Cross section of LES simulation of DYCOMS RF01 case at $y = 420$ m at $t = 3:53$ h. Shaded regions indicate positive (negative) vertical velocities in red (blue). Contours (dashed) of liquid water mixing ratio $q_l$ are overlaid to show cloud boundaries.

Table 4.2: Summary of downdraft plume properties and fit coefficients for MYNN-RAD.

<table>
<thead>
<tr>
<th>Case</th>
<th>$\theta_{l,exc}$ [K]</th>
<th>$q_{l,exc}$ [g/kg]</th>
<th>$\alpha_{ent}$ [-]</th>
<th>$\alpha_{rad}$ [-]</th>
<th>$\mu_w$ [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>DYCOMS RF01</td>
<td>-0.024</td>
<td>-0.011</td>
<td>3.53</td>
<td>2.15</td>
<td>2.10</td>
</tr>
<tr>
<td>CGILS S12</td>
<td>-0.071</td>
<td>-0.005</td>
<td>4.0</td>
<td>3.9</td>
<td>2.16</td>
</tr>
<tr>
<td>Average</td>
<td>-0.048</td>
<td>-0.008</td>
<td>3.77</td>
<td>3.03</td>
<td>2.13</td>
</tr>
</tbody>
</table>

were averaged from $0.1 \leq z/z_{inv} \leq 0.9$ in order to determine $\alpha_{rad}$ and $\alpha_{ent}$; a summary of plume properties and their corresponding fit coefficients obtained using parameters computed in WRF is provided in Table 4.2.

Based on the quadrant analysis, the updrafts are observed to ascend at comparable velocities to downdrafts and terminate at a lower level (as evident in the liquid water mixing ratio $q_l$).
Figure 4.2: Environmental (black), downdraft (blue), and updraft (red) liquid water potential temperature $\theta_l$ (left), total water mixing ratio $q_t$ (center left), liquid water mixing ratio $q_l$ (center right) and vertical velocity (right) obtained from hour 3-4 of the DYCOMS RF01 LES simulation.

4.3.2 3D WRF-Ideal testbed

While WRF provides a single column model test environment, Ghonima et al. (2017) showed that some numerical schemes and hence errors are specific to the single column model, thus test results may not directly transfer into the full 3D WRF. In an effort to test changes to PBL parameterizations in an environment as similar as possible to the full 3D WRF, an 3D idealized WRF test domain was developed and implemented in version 3.9 of the WRF model.

The idealized domain, henceforth termed "WRF-Ideal," consists of $51 \times 51 \times 51$ points, at a horizontal spacing of $\approx 13.5$ km, with vertical levels distributed as in the Rapid Refresh (RAP) model ($\approx 30$ to $100$ m within the PBL) (Benjamin et al., 2016). The domain spans $\approx 690$ km$^2$ and is centered on $33.2^\circ$N, $119^\circ$W in order to match Coriolis forces and shortwave radiation with those of the DYCOMS RF01 (between $31^\circ$ – $32^\circ$N and CGILS S12 Control (35$^\circ$N) cases. Periodic boundary conditions are utilized in the
The surface is a homogeneous ocean, with constant sea surface temperature, set according to observations at initialization. Surface fluxes are dynamically computed by the Rapid Update Cycle land surface model (Smirnova et al., 2016). A summary of physics options used in the WRF-Ideal setup is provided in Table 4.3.

Simulations were initialized in WRF-Ideal by editing real WRF input files *met_em.* with interpolated LES input profiles of temperature $T$, water vapor and liquid water mixing ratios $q_v$ and $q_l$, wind $u, v$, and pressure $P$. Because the DYCOMS RF01 case becomes numerically unstable when using the original homogeneous wind profile, the geostrophic wind is replaced within the boundary layer with a wind power law profile, according to Hsu et al. (1994):

$$u = 6(z/500)^{0.11}, \quad v = -4.25(z/500)^{0.11},$$

where the observed mean wind speeds $u = 6$ m/s and $v = -4.25$ m/s at 500 m were obtained from LES after allowing 1 hr spinup time. The CGILS S12 Control wind profile is unchanged. Following, the input
Figure 4.4: Normalized downdraft vertical velocity $w_{\text{down}} / w_{*,\text{rad}}$ (black) shown alongside proposed parameterization $\mu_w \sigma_w / w_{*,\text{rad}}$ (blue) for the DYCOMS RF01 case, with $\mu_w = 1.53$ (fit with LES parameters).

*met_em.* files are interpolated onto the WRF-Ideal grid via `real.exe`. This data flow is identical to that used in operational real-data WRF runs. All simulations were run for 24 hr to capture one full diurnal cycle, at a fixed timestep of 60 s, as in the operational RAP model.

Five different WRF PBL schemes were used to create an intercomparison data set. A brief description of each is as follows:

1. **YSU**: K-theory PBL scheme with prescribed profile for eddy diffusivity $K$.
   
   A counter-gradient transport term accounts for non-local mixing.

2. **MYNN**: K-theory PBL scheme with $K$ determined by a TKE-closure model.
   
   Non-local mixing is not included in the Level 2.5 implementation used here.

3. **MYNN-RAD**: Same as MYNN, but accounts for non-local mixing through a radiatively-cooled downdraft model.
4. **MYNN-STEM**: Same as MYNN, but accounts for non-local mixing through a stochastic surface-driven updraft model.

5. **MYNN-STEMRAD**: Combination of MYNN-RAD and MYNN-STEM to include non-local mixing through both radiatively-cooled downdrafts and surface-driven updrafts.

Performance of the PBL models will be assessed by standard root-mean-square error (RMSE) and mean bias error (MBE) metrics, computed against values of LWP obtained from LES. Because LWP is an analog for cloud thickness (Ghonima et al., 2015) and is influenced by both temperature and moisture, LWP is a convenient single quantity to use for validation.
Table 4.3: Summary of physics options used in the WRF-Ideal experiments.

<table>
<thead>
<tr>
<th>Parameterization type</th>
<th>Parameterization name</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Planetary Boundary Layer</td>
<td>Yonsei University</td>
<td>(Hong et al., 2006)</td>
</tr>
<tr>
<td></td>
<td>Mellor-Yamada-Nakanishi-Niino Level 2.5</td>
<td>Nakanishi and Niino (2006, 2009)</td>
</tr>
<tr>
<td></td>
<td>RAD radiatively-cooled downdraft EDMF</td>
<td>Section 4.2.2</td>
</tr>
<tr>
<td></td>
<td>STEM stochastic updraft EDMF</td>
<td>Sušelj et al. (2013)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameterization type</th>
<th>Parameterization name</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cumulus</td>
<td>Grell-Freitas</td>
<td>Grell and Freitas (2013)</td>
</tr>
<tr>
<td>Radiation</td>
<td>RRTMG</td>
<td>Iacono et al. (2008)</td>
</tr>
<tr>
<td>Microphysics</td>
<td>Morrison double-moment</td>
<td>Morrison et al. (2009)</td>
</tr>
<tr>
<td>Land surface model</td>
<td>Rapid Update Cycle</td>
<td>Smirnova et al. (2016)</td>
</tr>
</tbody>
</table>

4.4 Evaluation of MYNN-RAD in WRF ideal domain

4.4.1 DYCOMS RF01

For the DYCOMS RF01 simulations, all WRF PBL schemes consistently overestimate LWP compared to LES (Figure 4.6, top left), with the exception of simulations utilizing the MYNN-STEM updraft component, which immediately dissipates the cloud deck, prior to reforming at around 14 h into the simulation, after which all of the MYNN schemes show a sharp rise in LWP. The YSU scheme simulates thickening of the cloud at around 16 h, but thins again near the end of the simulation. The error metrics shown in Table 4.4 indicate that YSU is the best performer, with RMSE and MBE of 108.4 g/m$^2$ and 96.7 g/m$^2$, respectively. MYNN-RAD shows an improvement over the original MYNN in RMSE (MBE) by 5% (16%). Although MYNN-STEM and MYNN-STEMRAD produced lower RMSE and MBE values, the cloud erroneously dissipates. The error values
in the MYNN-STEM and MYNN-STEMRAD simulations are artificially deflated by the 14 h during which LWP = 0 g/m².

Boundary layer heights as determined by the highest vertical level with \( q_l > 0 \) show that all schemes simulate an increase in PBL height by one grid point (Figure 4.6, top right), with the timing varying between schemes. All simulations reached a PBL height in agreement with the LES by the end of the simulation.

Boundary-layer averages of heat (Figure 4.6, center left) and moisture (Figure 4.6, center right) show that the YSU scheme simulates a warmer and drier boundary layer than the MYNN simulations, which leads to a thinner cloud. Compared with the original MYNN, MYNN-RAD produces a warmer and drier boundary layer, though the sharp decrease in \( \theta_l \) near the end of the simulation leads to an overestimation in LWP. When the updraft model is active in MYNN-STEM and MYNN-STEMRAD, the boundary-layer averages are simply values at the first model level when no clouds exist, as the boundary layer height is determined as the first grid point in that case. When the cloud returns after 15 h, MYNN-STEM and MYNN-STEMRAD both simulate a warmer PBL than MYNN and MYNN-RAD, though boundary-layer averaged moisture values are inconclusive. All configurations produced a boundary layer which is too cold and moist.

Based on the vertical profiles of heat at \( t = 5 \) hr (Figure 4.6, bottom left), YSU produces a well-mixed profile, but shows a cold bias compared with LES. MYNN-RAD produces a slightly more well-mixed profile than MYNN, with slight entrainment heating at the PBL top. MYNN-STEM and MYNN-STEMRAD both produce a clear boundary layer. The profiles in total moisture (Figure 4.6, bottom right) show again that YSU
Table 4.4: Table of LWP errors in [g / m²] for each PBL scheme for the DYCOMS RF01 case. Errors were computed over the full 24 h of simulation time.

<table>
<thead>
<tr>
<th>Configuration</th>
<th>RMSE [g / m²]</th>
<th>MBE [g / m²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>YSU</td>
<td>108.4</td>
<td>96.7</td>
</tr>
<tr>
<td>MYNN</td>
<td>158.0</td>
<td>136.2</td>
</tr>
<tr>
<td>MYNN-STEM</td>
<td>125.2</td>
<td>54.8</td>
</tr>
<tr>
<td>MYNN-RAD</td>
<td>150.4</td>
<td>114.9</td>
</tr>
<tr>
<td>MYNN-STEMRAD</td>
<td>113.2</td>
<td>36.0</td>
</tr>
</tbody>
</table>

produces a more well-mixed PBL, in agreement with the LES, but with a moist bias. The profile of $q_t$ in MYNN-RAD is similar to that of MYNN, but with slight entrainment drying at cloud top.

Prior to sunrise ($\approx 6$ h), the YSU scheme maintains a constant, underestimated PBL temperature which increases as the sun rises and shortwave heating increases. As sunset approaches ($\approx 17$ h, actual sunset is at $\approx 20$ h), the temperature ceases to increase. The total moisture $q_t$ follows a similar trend as the LES, but is consistently overestimated during most of the day. Near the end of the simulation, $q_t$ recovers to the LES value, likely due to entrainment drying produced by the explicit entrainment model, which is also responsible for countering the boundary layer cooling due to longwave radiation emission at night. Both MYNN and MYNN-RAD simulate a cooling and moistening tendency during nighttime, suggesting that entrainment mixing is still underestimated.

4.4.2 CGILS S12 Control

Simulations of the CGILS S12 Control case show that all PBL schemes overpredict LWP (Figure 4.7), top left, with all schemes showing an increasing trend in LWP. Contrary
to the DYCOMS RF01 case, YSU simulates one of the highest LWP during the 24 h, with an RMSE (MBE) of 178.4 g/m$^2$ (151.7 g/m$^2$). Compared with the original MYNN, all EDMF versions showed improvement in LWP, with MYNN-RAD improving upon MYNN in RMSE (MBE) by 19% (21%). The largest improvement in LWP was obtained by the MYNN-STEMRAD configuration, in which RMSE (MBE) improved by 21% (33%) over the original MYNN. The MYNN-STEMRAD produced the lowest RMSE (MBE) values of 141.4 g/m$^2$ (99.8 g/m$^2$).

Unlike the DYCOMS RF01 case, the LES boundary layer height of the CGILS S12 Control simulation decreases in time. All configurations erroneously predicted an increase in PBL height by one grid point at around 20 h into the simulation (Figure 4.7, top right).

All PBL schemes again show a warm (Figure 4.7, center left) and dry (Figure 4.7, center right) bias. Compared against MYNN and MYNN-RAD, when the MYNN-STEM updraft model is active, the boundary layer is warmer and drier, leading to a lower LWP. The MYNN-based schemes again show net cooling during nocturnal hours, indicating underestimation of entrainment flux.

The vertical profiles of heat at $t = 5$ hr (Figure 4.7, bottom left) show similar behavior between the different configurations as for the DYCOMS RF01 case: YSU produces a well-mixed profile with a slight cold bias, while MYNN-RAD produces a more well-mixed PBL compared with MYNN in addition to slight entrainment warming at cloud top. The addition of updrafts in the MYNN-STEM configuration warms the boundary layer while producing a more well-mixed PBL than the MYNN-RAD. The inclusion of both updrafts and downdrafts in the MYNN-STEMRAD configuration only differs from
Table 4.5: Table of LWP errors in [g / m$^2$] for each PBL scheme for the CGILS S12 Control case. Errors were computed over the full 24 h of simulation time.

<table>
<thead>
<tr>
<th>Configuration</th>
<th>RMSE [g / m$^2$]</th>
<th>MBE [g / m$^2$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>YSU</td>
<td>178.4</td>
<td>151.7</td>
</tr>
<tr>
<td>MYNN</td>
<td>178.3</td>
<td>148.9</td>
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<tr>
<td>MYNN-STEM</td>
<td>147.8</td>
<td>107.6</td>
</tr>
<tr>
<td>MYNN-RAD</td>
<td>143.8</td>
<td>118.3</td>
</tr>
<tr>
<td>MYNN-STEMRAD</td>
<td>141.4</td>
<td>99.8</td>
</tr>
</tbody>
</table>

the MYNN-STEM in the slight entrainment warming at cloud top. The profiles in total moisture (Figure 4.7, bottom right) show similar trends, with YSU producing the most well-mixed PBL, followed in order by MYNN-STEM, MYNN-STEMRAD, MYNN-RAD, and the original MYNN. Again, the primary difference between MYNN-STEMRAD and MYNN-RAD is evidence of slight entrainment drying at cloud top.

4.5 Conclusions

A mass-flux model which represents deep mixing in STBL due to radiatively-driven downdrafts was proposed as an addition to the eddy-diffusion-based MYNN PBL parameterization available in WRF 3.9, termed "MYNN-RAD." In this eddy-diffusivity mass-flux (EDMF) framework, small-scale eddies (on order of one or few grid cells) are modeled by an eddy-diffusion component and large-scale eddies (on order of the PBL height) are modeled by a mass-flux component.

Tests upon two 3D idealized cases in WRF, the DYCOMS RF01 and CGILS S12 Control cases, showed improvements in the simulation of liquid water path (LWP). All configurations, including the latest YSU scheme with top-driven mixing option overestimated
LWP for both the DYCOMS RF01 and CGILS S12 Control cases. The MYNN-RAD model yielded improvements in LWP RMSE (MBE) of 5% (16%) in the DYCOMS RF01 case and 19% (21%) in the CGILS S12 Control case when compared with LES baseline simulations. The inclusion of updrafts from an existing model, termed ”MYNN-STEM” erroneously dissipated the cloud in the DYCOMS RF01 case, but produced more accurate LWP values in the CGILS S12 case. When both downdrafts and updrafts are active, the ”MYNN-STEMRAD” configuration again erroneously dissipated the cloud in the DYCOMS RF01 case, but yielded the highest improvement over the original MYNN in RMSE (MBE) of 21% (33%).

Although all WRF PBL schemes consistently overpredicted LWP, the addition of mass-flux components to the MYNN model shows promise in correcting the associated cold and moist PBL biases present in WRF. However, net cooling effects during nocturnal hours indicate that entrainment is still underestimated in MYNN even when including the effects of cold downdrafts, warm updrafts, or a combination of both. Further development of eddy-diffusivity mass-flux (EDMF) schemes could lead to a more accurate representation of boundary layer processes by representing deep mixing processes which are not represented by eddy-diffusion alone.

Due to the sensitivity and feedbacks present in the STBL, care must be taken to modulate the strength of updrafts and downdrafts, as an overprediction of mixing due to updrafts may cause early dissipation, as was seen in the DYCOMS RF01 test.
4.6 Direction for future work

This chapter proposed a formulation to include non-local transport in the MYNN model by explicitly modeling contributions from strongly descending downdrafts. While tests on two marine STBL scenarios proved promising, utilizing a larger data set to derive model parameters as well as to perform testing and validation would be beneficial.

Downdraft plume properties could be obtained from LES simulations initialized with radiosonde profiles. A minimum of 30 randomly selected STBL days should be used to establish a sufficiently large data set in order to reduce the spread in model fit parameters.

Since the addition of the downdraft model alone was insufficient to correct the consistent cold and moist bias, the issue of cloud-top entrainment flux must further be addressed. In the nocturnal marine STBL, the sole mechanism which opposes surface moistening and longwave radiative cooling is cloud-top entrainment heating and drying. Explicitly replacing the PBL-top scalar fluxes in MYNN as in the YSU model would cause localized heating and drying of cloud top as gradient diffusion acts slowly to mix downwards, in addition to introducing numerical instability. Modeling of entrainment mixing in MYNN must be performed in conjunction with a mechanism to distribute the resulting cloud-top heating and drying into the remainder of the STBL, as is realistically performed by updrafts and downdrafts. A potential starting point is to implement a two-plume model, in which entrainment plumes are initiated and terminated separately from radiatively-driven downdrafts. Through octant analysis, Davini et al. (2017) showed that
entrainment plumes, downdrafts, and updrafts all contribute to a significant fraction of convective structures within the STBL. The careful characterization of transport by these 3 components is necessary to correctly model STBL in WRF.

Using historical RAP data, the same (and/or additional) days could be used to initialize WRF simulations over coastal lands in Southern California, in comparison with YSU, MYNN, MYNN-RAD, MYNN-STEM, and MYNN-STEMRAD. This would allow a more thorough validation of MYNN-RAD in a real-world scenario, in which performance may be examined over ocean and land surfaces. In such an environment, updrafts will certainly play a non-negligible role in STBL dynamics over the coast and land, and the modulation of contributions from downdrafts and updrafts must be more carefully examined due to the delicate balance and feedbacks present in the STBL system. Additionally, care must be taken to ensure numerical stability, which will be increasingly difficult to satisfy due to topographical effects and potentially strong shear inherent in assimilated wind fields.

In the validation process, SolarAnywhere (SolarAnywhere®, 2013) satellite-derived surface irradiance may be used as a proxy for cloud thickness to indirectly compare forecast surface irradiance (attenuated by cloud cover) against observed surface irradiance, as in Yang and Kleissl (2016).

4.7 Acknowledgements

Chapter 4, in part, is being prepared for publication.
Figure 4.6: For the DYCOMS RF01 WRF-Ideal simulation, **Top left**: Domain-averaged liquid water path. **Top right**: Domain-averaged PBL height as determined by the highest vertical level with $q_t > 0$, **Center left**: Domain-averaged liquid water path. **Center right**: Domain-averaged PBL height as determined by the highest vertical level with $q_t > 0$. **Bottom left**: vertical profile at $t = 5$ hr of liquid water potential temperature $\theta_l$ and **Bottom right**: total water mixing ratio $q_t$. 
Figure 4.7: For the CGILS S12 Control WRF-Ideal simulation, **Top left**: Domain-averaged liquid water path. **Top right**: Domain-averaged PBL height as determined by the highest vertical level with $q_l > 0$, **Center left**: Domain-averaged liquid water path. **Center right**: Domain-averaged PBL height as determined by the highest vertical level with $q_l > 0$. **Bottom left**: vertical profile at $t = 5$ hr of liquid water potential temperature $\theta_l$ and **Bottom right**: total water mixing ratio $q_t$. 
References


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SolarAnywhere®(2013). Web-based service that provides hourly, satellite-derived solar irradiance data forecasted 7 days ahead and archival data back to january 1, 1998.


