The Subtropical Stratocumulus-Topped Planetary Boundary Layer: 
A Climatology and the Lagrangian Evolution

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ABSTRACT

Prior work has shown that deeper planetary boundary layers (PBLs) are associated with cloud breakup and reduced droplet concentration in subtropical stratocumulus cloud decks, motivating a need for a thorough understanding of PBL mechanics. Here, 169 000 boundary layer trajectories are calculated in four eastern subtropical ocean basins following reanalysis winds at 925 mb (1 mb = 1 hPa). These trajectories combined with a twice-daily cloud-top-height-inferred PBL depth product allow for a comprehensive Lagrangian analysis of the stratocumulus (Sc)-topped PBL as the cloud deck transitions from Sc to trade cumulus (Cu). Month-to-month variations of this PBL product are strongly positively correlated with an independent PBL product derived from GPS radio occultation.

A climatology shows the PBL deepening offshore in every region. The yearly cycle of PBL depth varies in opposition to the yearly cycle of lower-tropospheric stability (LTS), but high-frequency variation between LTS and PBL depth is more complex. Observed geographical patterns of Lagrangian PBL deepening rates appear nonuniform between and within study regions, with smaller regions of maximum deepening rates. A Lagrangian analysis suggests that many variables act to alter the PBL: increased sea surface temperature and droplet concentration act to deepen the PBL, while increases in upper-level humidity, LTS, precipitation, upper-level temperature, and subsidence lead to PBL shallowing.

1. Introduction

Subtropical marine stratocumulus (Sc) form low continent-sized cloud decks beneath the trade inversion near the equator. These cloud decks cause significant cooling of the climate system by reflecting incoming solar radiation while emitting upwelling infrared radiation at a temperature near that of the surface. Changes to the extent and structure of these cloud decks will have a significant effect on Earth’s radiation budget (Randall et al. 1984). Eastman and Wood (2016) showed that anomalies in cloud cover, liquid water path (LWP), and droplet concentration \(N_d\) in subtropical Sc decks are as sensitive to the depth of the PBL as they are to the lower-tropospheric stability (LTS). Cloud cover, LWP, and \(N_d\) decline more relative to their climatological evolution when the PBL is deeper or capped by a weaker inversion. While controls on inversion strength are relatively straightforward, controls on the depth of the PBL are more complex and underrepresented in current literature, with very few observational studies done. Here we present a climatology of the PBL depth as well as a study of factors that influence the Lagrangian evolution of the PBL depth.

The Sc-topped marine boundary layer in the eastern subtropical oceans forms in offshore and equatorward flow along the western coasts of the major continents. Warm air at upper levels flows offshore over the cool air mass in contact with the ocean surface. This offshore flow combines with strong subsidence in the middle and lower troposphere to establish a strong temperature inversion near the coast, capping a shallow, cloudy, and persistent marine boundary layer (Wood 2012; Garratt 1990; Angevine et al. 2006). Infrared radiation is emitted from the cloud tops, sharpening the inversion, and driving an overturning circulation as cold air forming at cloud top circulates downward toward the sea surface (Lilly 1968; Nicholls 1989; Paluch and Lenschow 1991; Krueger et al. 1995). Radiatively driven PBL deepening is evident in the diurnal cycle, where the PBL is deeper at night when cloud-top cooling is not partially offset by shortwave heating (Wood 2012; Painemal et al. 2013). The degree to which the circulation from cloud top to sea surface is
completed is defined as the degree of coupling. Wood and Bretherton (2004) state that the degree of coupling is strongly tied to the depth of the PBL, with shallow PBLs showing greater coupling. Krueger et al. (1995) showed that a deeper, well-mixed PBL precedes decoupling. Van der Dussen et al. (2014) show that decoupled PBLs are more prone to cloud breakup at lower values of a stability parameter relative to shallower well-mixed PBLs.

The shallow, overcast PBL deepens as it advects over a warmer sea surface as shown by numerous modeling studies (Albrecht et al. 1979; Betts and Ridgeway 1989; Krueger et al. 1995; Bretherton and Wyant 1997; Sandu and Stevens 2011) and into an environment with less large-scale subsidence. Warmer sea surface temperatures (SSTs) add energy to the PBL through latent and sensible heating, while turbulence at the cloud top drives the entrainment of warm, dry air from the free troposphere into the PBL. As these fluxes continue to deepen the PBL, the degree of coupling declines, separating the circulation within the cloud layer from the sea surface. Deeper PBLs are associated with more precipitation, which simultaneously removes cloud droplets and evaporates below the cloud base, reducing turbulence and possibly slowing PBL growth by stabilizing the subcloud layer (Sandu and Stevens 2011; Stevens et al. 1998). Sufficiently deep and decoupled PBLs have a layer of cumulus (Cu) cloud form at the top of a mixed layer beneath the Sc, which can penetrate into the Sc deck, creating a “cumulus coupled” system. The overlying Sc eventually give way to the cumulus beneath, completing the transition from a shallow, Sc-topped PBL to a deep trade Cu PBL (Krueger et al. 1995; Wyant et al. 1997; Karlsson et al. 2010; Jones et al. 2011; De Roode et al. 2016).

Several observational studies use data from field campaigns or a combination of reanalyses and satellites to study the evolution of the PBL. A Lagrangian PBL study done by Pincus et al. (1997) followed eight samples of Sc in the northeast Pacific and found that increased SST and reduced LTS were strong drivers of PBL deepening. Precipitation was not seen as a significant predictor; however, their sample size was much too small to adequately study the effects of precipitation, while droplet concentration was not tested at all. Sandu et al. (2010) constructed a Lagrangian study and found that breakup of Sc is mostly as a result of decreasing LTS; however, this study does not quantify or test the effects of PBL depth, which Eastman and Wood (2016) showed to have an effect on Sc breakup independent of LTS. Sandu et al. (2010) did not assess the effects of precipitation and $N_d$ on PBL evolution, nor did they quantify the relative importance of different cloud-controlling parameters. Mauger and Norris (2010) also studied the Lagrangian evolution of subtropical Sc and concluded that large-scale divergence, SST, and stability parameters were primarily driving Sc breakup, but they were unable to test the effects of precipitation and $N_d$. Mauger and Norris (2010) go on to suggest that PBL decoupling plays a significant role in Sc breakup and implore future studies to further investigate this using new data sources. Using data from a field campaign in the northeast Pacific, Zhou et al. (2015) determined that entrainment of warm dry air at cloud top is the major driver of PBL decoupling. Painemal et al. (2013) showed that the Sc-topped PBL in the southeastern Pacific has a pronounced diurnal cycle with a deeper PBL at night. They go on to show that waves of enhanced subsidence near the coast cause PBL shallowing to occur on subdiurnal time scales.

Quantifying the depth of the PBL is a challenging endeavor, with several different strategies employed. Zuidema et al. (2009) and Painemal et al. (2013) used the difference between SST and the cloud-top temperature (CTT) in overcast conditions along with a lapse rate based on the SST–CTT difference to estimate cloud-top height. This is a reliable proxy for the depth of the PBL in overcast Sc regimes where cloud tops sit at the inversion base. Zuidema et al. (2009) used cloud-top temperatures from the polar-orbiting Moderate Resolution Imaging Spectroradiometer (MODIS; King et al. 2003), while Painemal et al. (2013) used Geostationary Operational Environmental Satellite-10 (GOES-10) data. Both studies produced comparable results. Other studies do not rely on the presence of boundary layer clouds; GPS radio occultation can be used to detect the hydro lapse, the rapid change in moisture with height, seen between the moist PBL and the dry free troposphere as in Guo et al. (2011), Ao et al. (2009), and Chan and Wood (2013). Von Engeln and Teixeira (2013) use the hydro lapse seen in model profiles contained in ERA-Interim (Dee et al. 2011) to estimate the PBL depth. Luo et al. (2016) use lidar backscatter from the Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO; Vaughan et al. 2004) to ascertain the height of the PBL and the mixed layer beneath, providing a valuable dual measure of PBL depth and coupling. While these studies produce reasonable climatologies, they do not provide a continuously observed, subdaily measure of PBL depth suitable for a large-scale Lagrangian study.

Prior work suggests that the depth of the PBL is as important as the LTS in forcing Sc breakup. However, the depth of the PBL is likely controlled by many factors (Svensson et al. 2000) that are in part independent of LTS, including, but not limited to, subsidence, upper-level humidity, precipitation, and microphysical processes. Previous works fail to compare the effects of
PBL-depth-controlling variables in a single observational framework. Specifically, the effects of precipitation and droplet concentration on PBL evolution are only well sampled in models, with rigorous observational studies lacking. Furthermore, a reliable measure of PBL depth on short time scales is not available in prior work. Here we seek to test the effects of precipitation and droplet concentration alongside many other better-understood PBL-affecting parameters on a measure of PBL depth observed twice every day, allowing for a more direct comparison of each variable’s influence at short time scales. First, we will verify the validity of our new measure of PBL depth by analyzing a detailed climatology, followed by an analysis of how LTS interacts with the PBL on long versus short time scales; then we will employ a Lagrangian analysis to test the effects of the largest set of PBL-controlling variables in any available study to date.

2. Data

Currently, this study uses data solely in stratocumulus regions in the eastern subtropical ocean basins: the northeast (NE) Pacific, southeast (SE) Pacific, southeast (SE) Atlantic, and east (E) Indian Oceans. We choose these regions because of the low prevalence of interfering high clouds and the relative homogeneity of the cloud decks. Explanations detailing the selection of these regions are found in Eastman and Wood (2016). Briefly, these regions are large enough to contain the climatological maximum in stratocumulus coverage as well as the coastal regions where the Sc PBL initially forms and the offshore regions where the Sc transitions to trade Cu (the regions are shown in Fig. 2). We study the years 2007–10.

a. PBL depths from CALIPSO, MODIS, and ERA-Interim

The depth of the boundary layer is estimated from the difference between the SST and CTT using the method detailed in Eastman et al. (2016). To summarize, this method uses the SST–CTT temperature difference along with a parameterized lapse rate (Wood and Bretherton 2004) to estimate the distance from the sea surface to the cloud top in a similar way to Zuidema et al. (2009) and Painemal et al. (2013). SST values come from the surface skin temperature contained in the ERA-Interim dataset (Dee et al. 2011) interpolated to match the spacing of the MODIS 1° × 1° L3 grid and timing of the MODIS Aqua overpass. Daily day and night CTT values come from the MODIS Aqua joint CTT histograms on the 1° × 1° L3 grid (King et al. 2003). These histograms provide a frequency distribution of CTT for subgrid pixels within each L3 grid box. When broken cloud conditions occur, it is likely that some CTT retrievals within the histograms represent the relatively warm cloud edges, underdeveloped clouds, or the sea surface. We counter this issue by selecting representative CTT values increasingly on the “cold” side of the histogram for lower cloud amounts (below 90%). Figures 1–3 in Eastman et al. (2016) describe this process and provide a basis for our assumptions using a subset of overlapping CALIPSO (Vaughan et al. 2004) and MODIS measurements. PBL heights are only estimated when cloud amount is greater than 30%.

This PBL product differs from that in Eastman et al. (2016) in a few ways: We fit a curve to the CTT histograms, allowing us to interpolate the coarse 5-K histograms to every 5/3 K. The new MODIS collection 6 (c6) joint histograms are used rather than collection 5, and now the product is extended for years 2007–10, rather than 2007–08. The joint histograms allow us to filter observations so that all cloud scenes with CTT < 270 K or at pressure levels above the PBL are removed from the analysis, eliminating interfering high clouds. MODIS collection 6 also employs a new gridding process that eliminates overlapping observations taken within a single day. The current 4-yr span represents the years where CloudSat, CALIPSO, and MODIS were all operating continuously and concurrently.

In Eastman et al. (2016), PBL depths were compared between MODIS and CALIPSO in overcast conditions. MODIS PBLs were shown to be ~150 m deeper, which agrees with Zuidema et al. (2009), who also report a high-altitude bias in PBL depths derived from MODIS CTTs. They attribute this discrepancy to a cold bias in the MODIS CTT retrieval (~1.3 K) and apply a standard correction to the CTT but do not offer an explanation. This work uses new c6 MODIS data but still sees a ~155-m high bias at night, though a negligible bias during daytime. We choose to apply a standard altitude correction to all nighttime retrievals, as in Eastman et al. (2016). We do not apply the correction to the CTT as in Zuidema et al. (2009) because the discrepancy may also be due to errors in our lapse-rate parameterization or in the reanalysis skin temperature.

In Fig. 1, we show a comparison between our PBL depth product and an independent product derived from the Constellation Observing System for the Meteorology, Ionosphere and Climate (COSMIC) satellites (Chan and Wood 2013). Briefly, the COSMIC PBL product relies on sensing GPS radio occultation when the path between two satellites encounters a strong temperature or humidity gradient. The altitude of the strongest humidity gradient is assumed to be the height of the boundary layer. We plot the monthly mean PBL depth for each of our regions using both products in Fig. 1. The two time series are not expected to be
identical, owing to diurnal differences in sampling times and spatial irregularities in the products; however, an encouraging degree of agreement is seen in all regions. The time series correlate significantly in all regions, suggesting that the variation seen by one product is usually seen by the other independent product.

b. Cloud, boundary layer, and precipitation products from MODIS, AMSR-E, and CloudSat

Several MODIS products remain unchanged from Eastman and Wood (2016) and Eastman et al. (2016), except that collection 6 has been used rather than 5.1. These include cloud cover from the MODIS cloud mask (Hubanks et al. 2008; Oreopoulos 2005) and droplet concentration $N_d$ using Eq. (1) from Eastman and Wood (2016) now using the 3.7-µm retrievals for cloud droplet effective radius and LWP.

A separate measure of LWP is provided by the Advanced Microwave Scanning Radiometer for EOS (AMSR-E; Wentz and Meissner 2004), also aboard *Aqua*, so observations are always concurrent with MODIS. Liquid water path data are averaged to match the MODIS L3 grid.

Precipitation is measured using the *CloudSat* RAIN PROFILE product (Lebsock and L’Ecuyer 2011). Methods concerning this product are unchanged from Eastman and Wood (2016).

c. Trajectories from boundary layer winds and cloud-controlling variables from ERA-Interim

We use winds from ERA-Interim (Dee et al. 2011) available on a 0.75° × 0.75° latitude–longitude grid at 925 mb (1 mb = 1 hPa) to produce our boundary layer trajectories. We assume little vertical motion relative to the horizontal winds, so only use winds in the $U$ and $V$ directions. Trajectories are calculated as in Bretherton et al. (2010), who showed that ERA-Interim winds were suitable for trajectory analyses in the SE Pacific. Trajectories must begin within the bounds of our four study regions, but subsequent samples along trajectories that advect out of the regions are also included. Trajectories are only included if they are moving from east to west.

ERA-Interim is used to estimate several cloud-controlling variables: LTS is defined as the difference in potential temperature $\theta$ between the surface and 700 mb ($\theta_{700}$). We define the upper-level humidity as the specific humidity at 700 mb ($q_{700}$). SST is inferred from the surface skin temperature of the ocean. Subsidence is measured at 700 mb ($\omega_{700}$). It is calculated as the pressure velocity minus the average 12-h surface pressure tendency at the time of observation. These reanalysis fields have been used extensively for this purpose in prior works [Sandu et al. (2010); Sandu and Stevens (2011); Eastman and Wood (2016); Eastman et al. (2016); and Mauger and Norris (2010) use operational ECMWF fields, though they suggest using ERA-Interim when available].

Several quantities ($\omega_{700}$, $\theta_{700}$, and $q_{700}$) are not directly observed but are instead more akin to model output. We choose to use the ERA-Interim values for these quantities because of that reanalysis’ ability to most accurately reproduce cloud conditions in our regions of study, as shown in Dolinar et al. (2016). To test whether variations in these fields are physically real, we correlate anomalies of these three fields at each trajectory beginning with anomalies of independently measured variables. Results show that LWP anomalies correlate significantly with $\omega_{700}$ and $q_{700}$ ($r = -0.41$ and 0.27, respectively) agreeing with Myers and Norris (2013) and Mauger and Norris (2010), and that PBL anomalies correlate significantly (though very weakly) with $\theta_{700}$ ($r = -0.11$), agreeing with Pincus et al. (1997) and virtually all PBL modeling studies cited in the introduction that the PBL is shallower when the capping inversion is stronger.

FIG. 1. Time series of monthly mean PBL depth (km) in each of our four study regions shown in Fig. 2 from two completely independent PBL products: the product presented here (MODIS; red) and the COSMIC GPS (blue) product presented by Chan and Wood (2013).
d. Trajectory sampling, averaging, anomalies, and zenith angle bias

Boundary layer trajectories begin along the CloudSat/CALIPSO curtain providing a measure of 0-h precipitation. Trajectory beginnings are spaced 200 km apart. Trajectories are run for 48 h and are sampled every 12 h as the A-Train satellite constellation flies overhead at 0130 and 1330 local time. Reanalysis grid samples (available uniformly every 6 h UTC) are interpolated to match the timing of the A-Train overpass. Each sampling point represents a sampling radius of 100 km. Any 1° × 1° L3 grid box center that falls within the sampling radius is included in the sample. All boxes with centers within the sampling radius are then averaged to produce a sample mean. A total of 169,824 trajectories are calculated spanning 2007–10. Changes observed along trajectories reflect the difference between a quantity at the specified hour and 0 h, so a 24-h change in a quantity is the value at 24 h minus the value at 0 h.

In portions of this paper, we use anomalies of our variables in order to remove seasonal-scale variability. To produce an anomaly, we subtract from each daily gridbox value the 100-day running-mean gridbox value centered on that day using data from all 4 years of 2007–10 for day and night separately. Anomalies are denoted in figures either by the word “anomaly,” or by a prime. Past work used anomalies based on traditional seasonal means (DJF, MAM, JJA, and SON), and results were not sensitive to this change.

The MODIS and AMSR-E sensors both sample wide swaths with each pass, meaning many observations are taken at high sensor viewing angles near the edges of the swath. At high viewing angles the sensor sees more cloud edges, and optically thin clouds are seen from a diagonal rather than nadir, producing a longer path through the cloud. These effects combine to produce an overestimation of cloud cover at high angles first shown by Maddux et al. (2010). We use the same techniques as in Eastman and Wood (2016) to minimize zenith angle bias.

3. Methods and results

a. Climatology of the stratocumulus-topped marine PBL

1) GEOGRAPHIC DISTRIBUTION

Figure 2 shows yearly mean PBL depths for our four regions based on all available observations from our
PBL product. Also shown are the yearly mean wind vectors at 925 mb. In each region, the boundary layer is shallow near the coast and deepens offshore. Winds are anticyclonic, blowing equatorward near the coasts, but westward offshore. The PBL in the east Indian Ocean is by far the deepest and shows the least geographic variability, while the other three regions show similar gradients and values, with shallow PBLs (~400 m) deepening offshore (~2 km). The diurnal cycle of PBL depths can currently be computed with only two points daily, so it is not a focus of this study.

2) SEASONAL CYCLE

The phase of the seasonal cycle of PBL depth for each 1° × 1° grid box is represented in Fig. 3. Values shown represent the month of minimum PBL depth. Cycles were approximated for each grid box using a polynomial fit to daily mean data. Polynomials were chosen so that a full wave was seen in every year, but with polynomials the wave is not required to be sinusoidal.

Figure 3 shows that the seasonal cycle of PBL depth is different in every region. In the NE Pacific (Fig. 3a) the minimum PBL depth is observed in Boreal summer, with earlier minima near the coast and later minima toward Hawaii. To the northwest and southeast, the PBL reaches its minimum much earlier, in April and May. In the SE Pacific (Fig. 3b) the PBL minimum occurs around September, with later minima in the extreme upstream and downstream regions, but earlier offshore to the southwest. In the SE Atlantic (Fig. 3c) the minimum in PBL depth near the coast occurs during late austral winter, while offshore the minimum occurs later, during late austral spring. In the east Indian Ocean region (Fig. 3d) the PBL minimum occurs uniformly in late spring/early summer offshore, but in the eastern half of the box it shows a minimum in autumn, trending earlier very near the shore.

The amplitudes of the seasonal cycle of PBL depth for each grid box are shown in Fig. 4. Amplitudes are based on the same polynomials from Fig. 3 but represent the difference between the peak and valley of each wave, or twice the amplitude of a sinusoidal wave. The
geographic patterns in the NE and SE Pacific are similar (Figs. 4a and 4b, respectively), showing areas of low amplitude right near the coast, larger amplitudes farther offshore, then lower amplitudes again in the far-offshore parts. In these two areas, low amplitudes are around 100–300 m, while the larger amplitudes are on the order of 500 m. The SE Atlantic (Fig. 4c) shows a large area of low-amplitude seasonal cycle near the shore on the upwind side of the region. Seasonal amplitudes in the downwind, coastal portion of the SE Atlantic are the highest in any of our regions, on the order of 1 km or more. This is an area with a large amount of offshore smoke and aerosol transport, so these extreme amplitudes may be biased by issues associated with smoke or dust, in addition to possible biases caused by weather systems. In the east Indian Ocean, the largest-amplitude seasonal cycle occurs near the western Australian coast, with an area of low amplitude seen offshore, then moderate amplitude farther offshore.

To further characterize the average seasonal-scale time evolution of the PBL, for each region the seasonal cycles of monthly mean cloud cover, PBL depth, LTS, and SST are shown in Fig. 5. Means were calculated for years 2007–10. In each region the seasonal cycles of cloud cover and SST are 180° out of phase, while PBL depth and LTS also vary 180° out of phase. The mean amplitude of the seasonal cycle in PBL depth is similar between all regions, with values around 300 m. Larger-amplitude yearly cycles in cloud cover are found in the SE Pacific and SE Atlantic regions. In these two regions all four variables vary either in phase or exactly 180° out of phase, possibly contributing to the larger seasonal cycles of cloud cover.

In Figs. 6 and 7, we look at the monthly average Lagrangian behavior for all parameters sampled along our trajectories. Values are averaged every 12 h, creating a mean trajectory for each parameter during each month. This allows for a comparison of the mean daily scale Lagrangian behavior with the seasonal-scale evolution of the PBL. Monthly means and Lagrangian changes are shown for 10 variables by plotting the mean value for each variable at all five observation times from left to right, centered on each month.
Figure 6 shows the Lagrangian change for variables that we consider internal PBL variables, measured by the A-Train satellites, including the PBL depth, cloud cover, LWP, \( N_d \), and 0-h precipitation frequency. The yearly cycle of Lagrangian PBL deepening is different in every region, though there is a slight tendency for more deepening during the warm season and shallowing during the cooler season. More specifically, strong deepening occurs in the NE Pacific during summer, but there is nearly no Lagrangian change in winter. Weak deepening and shallowing occur in the SE Pacific summer and winter, respectively. There is consistent moderate deepening year-round in the SE Atlantic with only a slight tendency for less deepening in winter. Weak deepening occurs in summer, but strong shallowing occurs in winter in the E Indian Ocean. Cloud changes are more consistent, with declines over most of the year in most regions, though regional and temporal inconsistencies are still present. Liquid water path exhibits strong increasing tendencies in the NE Pacific and E Indian Oceans but shows more interesting changes in the SE Pacific and SE Atlantic with a pattern of decrease to strong increase to decrease occurring throughout the year. Droplet concentration usually declines between hours 0 and 24 but shows a rebound at later hours. Precipitation frequency shows a maximum during winter in every region, meaning drizzle is more common when the PBL shows less Lagrangian deepening.

Figure 7 shows the mean Lagrangian evolution of reanalysis variables that are external to the PBL, including SST, LTS, \( \omega_{700} \), \( q_{700} \), and \( \theta_{700} \). These variables tend to show more consistent Lagrangian change, with SST and \( q_{700} \) increasing, LTS and \( \omega_{700} \) decreasing, and \( \theta_{700} \) showing the most variability, with Lagrangian increases only seen during winter.

Figures 6 and 7 illustrate a more complex Lagrangian evolution of internal and external PBL-affecting parameters, measured by satellites (internal) and reanalyses (external). While SST and LTS appear to modulate the seasonal cycles of cloud amount and PBL depth, respectively (Fig. 5), Figs. 6 and 7 show that no single variable appears individually responsible for the seasonal cycles of Lagrangian change. This suggests that several processes both internal and external are acting to alter the PBL at any given time.

b. Tropospheric stability and the PBL

Figures 5–7 show that in all four regions the seasonal cycle of PBL depth is anticorrelated with LTS, as expected. However, the seasonal cycle of Lagrangian PBL deepening shows little relation with the seasonal cycle of LTS or of the Lagrangian evolution of LTS, meaning something else is driving the short-term evolution of PBL depth. To further show this apparent inconsistency, we isolate the high- and low-frequency temporal variation of PBL depth and compare it to LTS variation first in an Eulerian framework.

In Figs. 8a–d, we show the time series for LTS and PBL depth for two different \( 5^\circ \times 5^\circ \) grid boxes for each day from January 2007 through December 2010. Boxes are both located in the SE Atlantic region and are shown in Figs. 9c and 10c. The time series are shown along with a twelfth-degree polynomial fit, which isolates the variation on a seasonal time scale. The smooth time series of seasonal-scale variation show the expected pattern of anticorrelation between LTS and PBL depth. To further show this apparent inconsistency, we isolate the high- and low-frequency temporal variation of PBL depth and compare it to LTS variation first in an Eulerian framework.

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those two boxes, the correlations between residuals of LTS and PBL depth show opposite signs.

To show this on a larger scale we do the same analysis shown in Fig. 8 for each $1^\circ \times 1^\circ$ grid box in all four regions and map the correlation coefficients for both long and short time scales in Figs. 9 and 10, respectively. A pattern emerges: the seasonal-scale variation of PBL depth shows consistent negative correlation with LTS throughout every region, but the residual high-frequency variation is negatively correlated only in the upwind portions of the grid boxes, as determined by the wind vectors in Fig. 2. This suggests that high LTS has a strong influence on maintaining a shallow PBL when the PBL is relatively new or forming, but as the PBL advects downwind the relationship between these variables changes. The following Lagrangian analysis will attempt to establish a framework to find parameters that affect the short-term evolution of the PBL in addition to the LTS.

c. The Lagrangian evolution of the PBL

1) Geographical distribution of PBL deepening

Figures 11 and 12 show the annual-mean deepening rate from all westward-traveling trajectories on a $2^\circ \times 2^\circ$ grid. Deepening rates are assigned to the midpoints between 0 and 24, 12 and 36, and 24 and 48 h. We choose 24-h spans to eliminate any diurnal asymmetries.

Figure 11 shows Lagrangian PBL deepening rates along with annual-mean wind vectors, SST, and $\omega_{700}$. Boundary layer deepening rates are shown by the filled color contour, with blues representing shallowing and reds showing deepening. Regions exhibiting strong
Lagrangian deepening (rates above 3 mm s\(^{-1}\)) are shown in magenta/purple. Sea surface temperatures are shown by the grayscale lines, with darker lines representing cooler SST. Subsidence is shown by the colored lines, with warm (red and yellow) colors representing strong subsidence. PBL deepening rates are not spatially uniform within our regions, with small pockets of intense deepening observed in each region. The NE Pacific shows a large region of Lagrangian PBL deepening to the east of 140°W and a transition to weak deepening or even shallowing to the west. Strong deepening is isolated to a relatively small region between 20° and 25°N and between 120° and 130°W. In the SE Pacific the mean PBL deepening is largely limited to the southern half of the domain with weak deepening/shallowing observed over much of the region except for a region of very strong deepening in the southern coastal area, which shows the strongest mean deepening rate of any of our study regions. The SE Atlantic shows more uniform deepening than the other regions, with a tendency toward stronger deepening in the coastal half of the region, especially between 10° and 20°S. Finally, in the E Indian Ocean the deepening of the PBL is isolated to the eastern quarter of the region with weak deepening or shallowing occurring to the west. In each region the Lagrangian deepening is strongest nearer the coast and where advection across the SST and subsidence gradients is present. However, there are many locations on each plot showing strong advection across gradients of SST or subsidence with little to no corresponding PBL deepening, suggesting that the pattern is not fully explained by these fields.

In Fig. 12, we show the same PBL deepening rates and winds as in Fig. 11 but show fields of LWP and LTS.
Liquid water path is evident in grayscale, with darker lines representing higher LWP. A pattern is shown with higher LWP downwind of the strongest deepening, most prominently in the SE Pacific. Lower-tropospheric stability is indicated by the colored lines, with warm colors representing lower stability. The geographic correspondence between PBL deepening and LTS is not consistent when comparing our regions. While the strongest PBL deepening occurs when the flow moves down the LTS gradient in the NE Pacific and SE Atlantic, the strongest deepening in the SE Pacific is observed where the mean flow is across or even slightly up...
the mean LTS gradient. Taken together, Figs. 11 and 12 show that, on average, the PBL deepens when the flow is oriented up the SST gradient and down the LTS gradient; however, the spatial nonuniformity and regional differences in the PBL deepening pattern show that PBL deepening is not well explained by the LTS and SST alone.

2) MEAN TRAJECTORIES AND REGIONS OF RAPID DEEPENING

Within each study region there are subregions showing more rapid Lagrangian PBL deepening relative to surrounding areas. In this section the mean Lagrangian evolution of our PBL-controlling parameters will be compared between trajectories that pass through these regions and other nearby shallow coastal trajectories. Rapidly deepening regions are shown as white boxes in Fig. 12. Box boundaries were constructed around the magenta/purple bullseyes exhibiting PBL deepening rates greater than 3 mm s\(^{-1}\) in each region.

Figure 13 shows the mean 48-h Lagrangian evolution and 2\(\sigma\) standard error bounds of our 10 parameters for two groups of trajectories. The darker group is composed of trajectories that pass through the white boxes shown in Fig. 12 between 12 and 36 h. The lighter colored group shows trajectories that originated in the eastern 40% of our study regions but did not pass through the rapidly deepening boxes at those times.

Figure 13a shows that trajectories that passed through the rapidly deepening regions start shallower on average, but are deeper by 36 h. Overall, the trajectories that pass through these regions deepen by around 100 m more than surrounding areas. In Fig. 13b cloudiness shows a smaller decline in the rapidly deepening regions. Liquid water path, shown in Fig. 13c, undergoes a strong spike that is exaggerated in the rapidly deepening regions. The evolution of droplet concentration is shown in Fig. 13d, where \(N_d\) stays significantly higher in the deepening regions. A pronounced difference is also seen in precipitation frequency in Fig. 13e, with rapidly deepening trajectories showing significantly less-frequent drizzle at 0 h.

Mean SST in Fig. 13f starts significantly lower but increases much more for trajectories that pass through
the deepening regions, while mean LTS shown in Fig. 13g increases, then remains higher for the deepening trajectory set. Mean subsidence, from Fig. 13h, starts higher for the rapidly deepening trajectories but declines more when compared to the less-deepening set. Mean upper-level humidity is consistently lower for the deepening trajectory set as seen in Fig. 13i. Finally, mean $v_{700}$ starts lower but ends higher for the rapidly deepening set, as seen in Fig. 13j.

The plots in Fig. 13 show almost no overlap between the means of the two sets of trajectories, meaning that all of our PBL variables may play a significant role in the evolution of the boundary layer. The picture is more complicated, however, because many of these variables are highly spatially correlated within our regions of study. This leads to the possibility that one variable, or a select few variables, is actually responsible for the Lagrangian deepening of the PBL, but others may appear responsible just as a result of their similar spatial distributions. In the following section we attempt to overcome this limitation by converting our variables to anomalies and investigating their effects on the PBL while other variables are held constant.

3) ACCOUNTING FOR CROSS CORRELATION BETWEEN VARIABLES, GEOGRAPHY, AND RED NOISE EFFECTS

In this section we attempt to isolate the effect that each PBL-controlling variable has on the Lagrangian evolution of the PBL. Aside from the aforementioned cross correlation, trajectories are not uniform in direction or distance, so longer trajectories or trajectories traversing stronger climatological gradients are likely to show greater changes. This creates the possibility of biases when grouping and comparing trajectories by initial conditions, since different initial conditions of one variable lead to different geographical distributions of the groups and different initial conditions of other variables. To reduce these potential biases we have converted all of our PBL-controlling variables to anomalies (defined in the data section) except for precipitation frequency. Total values of precipitation frequency remain in order to isolate the effects of drizzle versus no drizzle instead of purely looking across a gradient.

Tables 1 and 2 show the correlation coefficients $r$ between each variable for raw values and for anomalies,
respectively. The numbers of correlated variables and the magnitude of the correlations are much larger before converting to anomalies, which indicates that the anomaly framework reduces variable cross correlation.

For variables that are internal to the PBL (Figs. 13a–e), we group trajectories and compare based only on the 0-h values since these variables may be driving the deepening, or they may be being changed by the deepening. For external variables (Figs. 13f–j), we can compare the effects of the variables’ initial values or their Lagrangian change, since the PBL depth is not significantly affecting these variables. Figure 13 suggests that the changes in SST, subsidence, and $u_{700}$ may be more important to the PBL than just their initial values, so we use the observed 24-h Lagrangian change in these variables as our PBL-controlling variables.

In this analysis we will study the effects of a variable by grouping trajectories into bins based on the initial value (or the 0–24-h change) of that variable, then compare the changes seen in PBL depth between the bins of trajectories. A problem arises when comparing change between groups if the groups have different mean PBL depth anomalies at 0 h. Figure 14 shows the 24-h change of PBL depth anomalies as a function of their initial 0-h anomalies for 1 in every 50 trajectories. Also shown are bin means (squares) for eight bins of initial PBL depth. There is a linear relationship (fitted line) between the mean change and the mean initial PBL depth anomaly, indicating that groups of trajectories with deeper-than-average initial anomalies will show shallowing while groups with shallower initial anomalies will show deepening. This Lagrangian linear relationship is not unique to PBL depth and applies to many other PBL-related variables, as detailed in Eastman et al. (2016). That work shows that the average Lagrangian change in PBL depth anomalies as a function of their 0-h anomalies is well modeled as a red noise process, where the lagged autocorrelation $r(T)$ between initial and subsequent anomalies at time $T$ is an exponential function of a specific $e$-folding time $\tau$ as in Eq. (1):
In this work we call the portion of the Lagrangian change of a variable driven by red noise $\Delta RN(t, \text{initial distribution})$, as it is a red noise (RN) process dependent on time $t$ and the initial distribution (dist) of PBL depth. The potential for biases when comparing changes in cloud variables caused by these red noise processes, as well as several ways to reduce these biases, is thoroughly discussed in Eastman and Wood (2016).

Eastman and Wood (2016) show the steps necessary in order to compare changes between groups of trajectories with different initial conditions with minimal bias. Briefly, this method computes and compares a residual change that is independent of the linear red noise relationship described above and is a product of anomalous environmental forcing:

$$\Delta PBL = \Delta RN(t, \text{dist}) + \Delta RES(\text{env}).$$

The residual change driven by anomalous environmental forcing $[\Delta RES(\text{env})]$ is the observed change $\Delta PBL$ minus the change driven by red noise $[\Delta RN(t, \text{dist})]$. In Fig. 14 the linear red noise function is shown as the black line fit to the data using a robust least squares fit.

Frequency distributions of trajectories binned by the 0–24 h $\Delta$Subsidence and 0-h precipitation frequency are shown in Figs. 15a and 15e, respectively. The distributions of trajectories are divided into four standard deviation ($\sigma$) bins for 0–24-h $\Delta$Subsidence and three $\sigma$ bins for 0-h precipitation. For $\Delta$Subsidence the $\sigma$ bins represent $\Delta$Subsidence intervals: $-2 < \sigma \leq -1$, $-1 < \sigma \leq 0$, $0 < \sigma \leq 1$, and $1 < \sigma \leq 2$, while for precipitation frequency the $\sigma$ bins represent the following: precipitation frequency $= 0$, $0 < \sigma \leq 1$, and $1 < \sigma \leq 2$. Grouping trajectories by $\sigma$ bins allows us to compare PBL depth changes for equivalent scales of variability of each PBL-controlling variable. The relative impact of each variable can then be compared to see which variable “drives” the strongest change.
Figures 15b and 15f show the residual \( \Delta \text{PBL} \) depth from hour 0 to hour 24 for each \( \sigma \) bin shown above. Fig. 15b shows a negative relationship between residual \( \Delta \text{PBL} \) depth and 0–24-h \( \Delta \text{Subsidence} \), meaning that decreasing subsidence leads to PBL deepening. Figure 15f shows a negative relationship between 0-h precipitation frequency and residual \( \Delta \text{PBL} \) depth, indicating that more precipitation leads to less deepening of the PBL. For each figure, the slope of \( \Delta \text{PBL} \) (m) per \( \sigma \) bin is shown in the upper right, suggesting that variations of subsidence and precipitation may have nearly equivalent effects on PBL deepening. Slopes are estimated using a robust least squares fit, with error estimates computed as in Warren et al. (2007).

The relationships described above and shown in Figs. 15b and 15f could still be biased by cross correlation between variables. Table 2 shows that 0–24-h \( \Delta \text{Subsidence} \) anomalies are weakly, but positively correlated with precipitation frequency. It is possible, then, that the coinciding precipitation is driving the change in PBL depth and not the changing subsidence. The same possibility exists for Fig. 15f, where positive correlation between precipitation frequency and upper-level humidity anomalies is seen in Table 2, leading to the possibility that the humidity anomalies are actually to blame for the changing PBL depth. To reduce these possibilities, we compare changes for each \( \sigma \) bin shown above within bins of another variable held constant. In Fig. 15c, we show the residual \( \Delta \text{PBL} \) depth for each \( \Delta \text{Subsidence} \) \( \sigma \) bin within bins of constant precipitation frequency. In three of the four constant-precipitation bins, the relationship shown in Fig. 15b remains, though in the higher-precipitation bins the error bars overlap, diminishing the signal. The mean residual \( \Delta \text{PBL} \) depth is shown on the far right of Fig. 15c, which indicates that, on average, greater subsidence still leads to PBL shallowing even with precipitation held constant. The same technique is applied in Fig. 15g, where the precipitation...
Cloud % 0.000 0.104 0.054 0.127 0.251 0.117 0.267
d | LWP | 0.000 0.007 0.001 0.001 0.007 0.001 0.001
Precipitation frequency | q_700 | LTS | Δθ_700 | LWP | Cloud %
Noise | 1 | −0.001 | 0.001 | 0.000 | 0.001 | 0.003 | −0.001 | −0.001 | −0.007 | 0.001
ΔSST | 0.001 | 1 | 0.165 | −0.019 | −0.088 | −0.149 | 0.340 | 0.328 | −0.065 | 0.104
ΔSubsidence | −0.004 | 0.165 | 1 | 0.035 | 0.075 | −0.031 | 0.081 | 0.066 | 0.097 | 0.054
N_d | −0.002 | −0.019 | 0.035 | 1 | −0.183 | 0.167 | 0.147 | −0.037 | −0.129 | 0.127
Precipitation frequency | 0.001 | −0.088 | 0.075 | −0.183 | 1 | 0.096 | −0.142 | 0.001 | 0.736 | 0.251
q_700 | 0.001 | −0.149 | −0.031 | 0.167 | 0.096 | 1 | −0.374 | −0.135 | 0.132 | 0.117
LTS | 0.005 | 0.340 | 0.081 | 0.147 | −0.142 | −0.374 | 1 | −0.129 | −0.038 | 0.267
Δθ_700 | 0.003 | 0.328 | 0.066 | −0.037 | 0.001 | −0.135 | −0.129 | 1 | −0.013 | −0.031
LWP | 0.000 | −0.065 | 0.097 | −0.129 | 0.736 | 0.132 | −0.038 | −0.013 | 1 | 0.507
Cloud % | 0.000 | 0.104 | 0.054 | 0.127 | 0.251 | 0.117 | 0.267 | −0.031 | 0.507 | 1

Table 1. Correlation coefficients r between all predictor variables used in this study. Each point represents a sample at 0 h at the beginning of each trajectory; Δ variables represent change from 0 to 24 h. For ease of use, the table is mirrored between the top right and bottom left.

frequency σ bins are compared within bins of constant 0-h q_700 anomalies. The precipitation signal is obscured at very low humidity anomalies but otherwise persists, again showing that the mean relationship persists even when q_700 is held constant.

In Figs. 15d and 15h, we plot the mean residual ΔPBL depth shown in Figs. 15c and 15g, respectively, against their σ bins. We calculate the slope as in Figs. 15b and 15f to see if the relationship has changed after controlling for a confounding variable. In both cases the relationship remains qualitatively unaffected, indicating that cross correlation between the variables controlled for is not responsible for the relationships shown. Figures 15c and 15g do suggest that there are subtle differences in how one variable affects PBL growth depending on the state of another, as in the reduced effectiveness of precipitation when humidity is anomalously low. These relationships warrant much more attention but may be too numerous to explore at this time.

Figure 16 follows the same format as Fig. 15 but explores the aforementioned ambiguous forcing of LTS anomalies on PBL deepening. Table 2 shows that LTS anomalies are negatively correlated with 0–24-h Δθ_700 and 0-h values of q_700. Figures 16c and 16g show that the effects of 0-h LTS are more apparent when Δθ_700 and 0-h values of q_700 are held constant. In both cases the slope between LTS and residual PBL depth steepens after accounting for the confounding variables, suggesting that anomalies in Δθ_700 and especially q_700 are acting to mask the effects of LTS on PBL deepening.

To compare the effects of all variables on PBL deepening, we perform the same analysis as shown in Figs. 15 and 16 for every variable in our study. Figure 17 shows the results of this analysis with linear fits for the four σ bins of each variable shown as a thin black line. Slopes were also calculated while holding every other variable constant in bins. If these slopes were significantly different from the original (black line) slope, they are plotted as thick colored lines and labeled; otherwise, they are shown in gray. The range of slopes represents the 2σ error bounds for the original fit in addition to any slopes that are significantly different than the original fit.

Figure 17 suggests that the major drivers of PBL deepening are external variables: q_700, ΔSST, ΔSubsidence, and LTS after accounting for q_700. The internal variables of precipitation and droplet concentration are also important, though less so than the external variables. Liquid water path may also have an effect, though the range of slopes suggests many confounding variables may be present. Relationships appear qualitatively as expected, with PBL deepening driven by a dry upper troposphere, a warming sea surface, declining subsidence, reduced stability, and more numerous cloud drops, while precipitation hinders PBL deepening. The 700-mb potential temperature increases are associated with PBL shallowing. The 0-h cloud amount does not show a consistent sign when other variables are controlled for, so it is currently ruled out as a PBL-controlling variable. Also shown in Fig. 17a is this analysis carried out with white noise as a PBL-affecting variable. This is done to compare the analysis’s response to environmental variables to the response to random variables. The absence of any appreciable or consistent slope shows that the results seen in response to our environmental variables are not due to chance.

4. Discussion

a. Mechanisms

While seasonal-scale PBL variability appears driven by LTS, daily scale variability is not. Results of this
Lagrangian analysis show that many independent internal and external variables are acting on the boundary layer at any one time.

Of the variables tested, the strongest driver of PBL deepening appears to be \( q_{700} \). Water vapor above the PBL inhibits deepening for two reasons: Increased water vapor above the inversion leads to increased infrared radiation (IR) being emitted downward toward the cloud deck. This would offset the IR cooling at cloud top, weakening the circulation within the Sc. Additionally, increased \( q_{700} \) can reduce evaporative cooling at the interface between the saturated cloudy layer and the drier air directly above the inversion. Reduced evaporation at this interface could weaken the lapse rate near the cloud top. These combined effects may explain why \( q_{700} \) appears to be such a powerful driver. The impact of humidity above the PBL on deepening/decoupling agrees with the conclusions of Zhou et al. (2015). While \( q_{700} \) does appear to strongly drive short-term variability of PBL depth, the mean Lagrangian behavior of \( q_{700} \) is to increase downwind, opposing the mean deepening of the PBL, so \( q_{700} \) is likely responsible for higher-frequency changes in PBL depth, but not for the mean climatological evolution of the PBL.

The other external drivers of PBL deepening appear to be the changes in SST and subsidence. The effects of SST have long been hypothesized as a primary driver of PBL deepening (Bretherton and Wyant 1997), and this has been shown observationally here and by (Messager and Swart 2016). Increases in SST lead to increases in turbulent fluxes into the atmosphere, which in turn enhance cloud-top entrainment, deepening the PBL. Subsidence is the primary force counteracting the deepening of the PBL (Wood and Bretherton 2004). The deepening of the PBL through entrainment is offset by the downward velocity at and above the inversion. Here we show that, if the downward velocity decreases, the balance between entrainment and subsidence is altered, leading to a deeper PBL. Future work may focus on estimating entrainment rates after subtracting the effects of subsidence.

Lower-tropospheric stability appears most strongly synchronized with the seasonal cycle of PBL depth, and studies (Angevine et al. 2006) have shown that newly formed PBLs deepen less when stability is high, likely owing to the reduced mixing across stronger inversions. These results are challenging to substantiate until

![FIG. 14. Deseasonalized anomalies of 0-h PBL depth (x axis) plotted against the subsequent 24-h Lagrangian changes (y axis) seen for each anomaly; 1 in 50 trajectories is shown to reduce clutter. Dot colors represent individual bins of 0-h PBL depth anomalies, with bin means plotted as squares of the same color. Bin boundaries of 0-h PBL depth anomalies are chosen so each bin contains the same number of observations. A least squares fit to the bin means is shown as a black line.](image-url)
accounting for $q_{700}$ and $\Delta \theta_{700}$. Low 0-h LTS tends to be associated with higher upper-level humidity and significant subsequent increases in $\theta_{700}$, which both act to slow PBL deepening. Only after accounting for these confounding variables can the effects of LTS be shown to agree with prior assumptions. The actual magnitude of the effect of stability is difficult to estimate in this framework because of the number of

Fig. 15. (a),(e) Frequency distributions of trajectories grouped by values of (a) 0–24-h $\Delta$Subsidence anomaly and (e) 0-h precipitation. The distributions are broken into colored standard deviation ($\sigma$) bins for both variables. (b),(f) The mean residual 0–24-h $\Delta$PBL depth anomaly within each $\sigma$ bin and 2$\sigma$ error bounds for the least squares best-fit line. Error bars represent the 2$\sigma$ standard error of the mean. (c),(g) The mean residual 0–24-h $\Delta$PBL depth anomaly within each $\sigma$ bin (solid dots) within bins of constant (c) precipitation frequency and (g) 700-mb $q$ anomalies with the mean across all bins shown to the right of the vertical black line (hollow dots). (d),(h) As in the hollow dots in (c) and (g): the mean across all bins with (d) precipitation effects and (h) upper-level humidity effects removed, but plotted against their $\sigma$ bins.
confounding variables, but this analysis suggests that LTS as defined here is not the strongest driver of PBL deepening.

Internal feedbacks are also taking place within the PBL. Precipitation and droplet concentration show a significant negative correlation with one another, but both appear to have an effect on the PBL independent of one another. Precipitation is correlated with deeper PBLs (Jones et al. 2011) but is shown here to inhibit further deepening of the PBL. This effect agrees with...
Stevens et al. (1998), which attributes this effect to the subcloud cooling and in-cloud heating caused by precipitation, creating a weaker circulation within the Sc. Vogel et al. (2016) also show that precipitation inhibits the deepening of shallow Cu clouds. Increased droplet concentration is shown to deepen the PBL. This works in a few ways, though this work is unable to determine the dominant mechanism: low droplet
concentrations are often indicative of larger cloud drops, which subside from the cloud top faster than smaller drops, reducing the evaporative cooling at the cloud top (Bretherton et al. 2007). Also, abundant small cloud droplets at cloud top can evaporate more readily because of the larger surface area relative to cloud water volume, leading to more cloud-top cooling. Finally, more available cloud condensation nuclei at cloud base leads to more, smaller drops, and possibly faster droplet activation, lower supersaturation, greater latent heat release, and more turbulence within the cloud (Kogan and Martin 1994; Feingold et al. 1999).

b. Limitations

This study presents a method for ranking the effects of several PBL-controlling variables and shows agreement with many prior studies about how the PBL evolves in time. However, we only investigate the PBL in the marine Sc environment, leaving many other environments and regions unaddressed. Further work must focus on expanding these products and methods to other environments in order to better understand the processes discussed.

Because of the relatively wide scope of this work, we are unable to fully investigate each individual variable to address possible nonlinearities and dependencies on initial conditions. Eastman and Wood (2016) show that the effects of drizzle on cloud breakup may be dependent on the state of the PBL and on the rain rate at the surface. Dependencies of this nature are likely prevalent for many variables included here, necessitating further study of each variable in much greater detail. Also, the four-point plots in Fig. 16 show linear fits to points that are not perfectly linear. It is likely that the effects of each variable are not only state dependent but nonlinear across their own spectrum of variability. Finally, detailed results will be made much more robust with additional sources of cloud data and reanalysis data. Further work should address these potential nonlinearities using a more diverse dataset.

5. Conclusions

A climatology of PBL depth is presented for four regions of persistent subtropical Sc. On regional scales and on long time scales, the PBL is shown to behave as previously observed and modeled, with shallow PBLs (∼400 m) near the coast and much deeper PBLs (∼2 km) offshore in each region, though noticeably deeper with less gradient in the east Indian Ocean. The seasonal cycle of PBL depth shows a peak amplitude of ∼400–500 m in each region, and the cycle varies in opposition to the seasonal cycle of LTS. Mapped correlations between Eulerian LTS and PBL depth time series are uniformly negative at seasonal time scales. When seasonal-scale variability is removed, the correlation between LTS and PBL depth is only negative in the upwind portions of our study regions, suggesting greater complexity in the short-term controls on PBL depth.

The seasonal cycle of Lagrangian PBL deepening vaguely follows the seasonal cycle of precipitation frequency, with stronger deepening coinciding with less precipitation during the warm season. Spatial patterns of mean Lagrangian PBL deepening rates show smaller subregions within each study region with enhanced annual-average deepening rates greater than 3 mm s⁻¹. The location of these regions of enhanced deepening is not fully explained just by advection over mean SST and LTS gradients. A comparison is done between trajectories that pass through these regions and those nearby. This comparison shows that the trajectories that pass through the regions of enhanced deepening see greater cloud cover, a stronger spike in LWP, greater droplet concentration, less precipitation, greater increases in SST and θ_700, lower q_700, and a stronger decline in subsidence, while displaying a counterintuitive, small increase in LTS.

Trajectories grouped by initial conditions were compared. Possible biases caused by variable cross correlation and geographic differences between trajectories are discussed. To account for these biases, we converted variables (except precipitation) to anomalies with the diurnal and seasonal-scale variation removed. Comparing the 0–24-h Lagrangian evolution of PBL depth anomalies for different groups of trajectories requires the removal of red noise effects. A residual change in PBL depth anomalies was calculated with the mean red noise effects subtracted from the observed change.

We compared changes in residual PBL depth anomalies for trajectories grouped into standard deviation (σ) bins to keep scales of variability comparable while also holding other variables constant. Results show that reduced q_700, increasing SST, declining subsidence, and reduced LTS all independently resulted in a similar magnitude of PBL deepening. It is shown for the first time observationally that precipitation reduces the deepening of the PBL while higher cloud droplet concentration leads to enhanced PBL deepening, agreeing with many previously published modeling studies. The effects of precipitation and droplet concentration act independently. Future work is needed to address likely nonlinearities and dependencies that go unaddressed here.
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REFERENCES


