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3 **Assessing Free Tropospheric Quasi-Equilibrium for Different GCM**
4 **Resolutions Using a Cloud-Resolving Model Simulation of Tropical**
5 **Convection**

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Abstract

This study examines the free-tropospheric quasi-equilibrium at different global climate model (GCM) resolutions using the simulation of tropical convection by a cloud-resolving model during the Tropical Western Pacific International Cloud Experiment. The simulated dynamic and thermodynamic fields within the model domain are averaged over subdomains of different sizes equivalent to different GCM resolutions. These coarse-grained fields are then used to compute CAPE and its change with time, and their relationships with simulated convection. Results show that CAPE change with time is controlled predominantly by variations of thermodynamic properties in the planetary boundary layer for all subdomain sizes ranging from 64 km to 4 km. Lag correlation analysis shows that CAPE generation by the free-tropospheric dynamical advection ($dCAPE_{ls}$) leads convective precipitation but is in phase with convective mass flux at 600 mb and 500 mb vertical velocity for all subdomain sizes. However, the correlation coefficients and regression slopes decrease as the subdomain size decreases for subdomain sizes smaller than 16 km. This is probably due to increased randomness of convection and more scale-dependence of the relationships when the subdomain size reaches the grey zone. By examining the sensitivity of the relationships of convection with $dCAPE_{ls}$ to temporal scales in different subdomain size, it shows that the quasi-equilibrium between $dCAPE_{ls}$ and convection holds well for timescales of 30 min or longer at all subdomain sizes. These results suggest that the free tropospheric quasi-equilibrium assumption may still be useable even for GCM resolutions in the grey zone.

1. Introduction

Convection occurs on spatial scales from sub-kilometer for shallow cumulus to tens of kilometers or larger for organized mesoscale convective systems. Despite its small scales, the role of deep convective towers in maintaining the atmospheric thermodynamic structure, atmospheric circulation and tropical energy balance was recognized more than half a century ago (Riehl and Malkus 1958; Manabe and Strickler 1964). Global climate models (GCMs) in the past and up till now typically have a horizontal grid spacing of ~ 100 km or larger. Within such a GCM grid box, the collective effect of convection is parameterized. In doing so, various assumptions were made to relate convection to grid-scale fields. Kuo (1965, 1974) proposed a moisture convergence closure, which related convection to column moisture convergence in the atmosphere. This closure was later modified by Tiedtke (1989) to determine cloud base updraft mass flux using moisture convergence in the subcloud layer. However, moisture convergence-based closure has been faulted for causing grid-point storms (Yano et al., 1998) and artificial CISK (conditional instability of the second kind) (Ooyama, 1982). Arakawa and Schubert (1974) proposed a convective quasi-equilibrium, which assumed that the removal of convective instability by a population of convective clouds of different sizes within a GCM grid box equals the generation of convective instability by GCM-resolved processes. The convective quasi-equilibrium is probably the most fundamental assumption among many assumptions involved in convective parameterization schemes. From the tropical circulation point of view, Emanuel et al. (1994) showed that under the convective quasi-equilibrium framework the tropical atmospheric systems such as the Hadley circulation, tropical cyclones and Madden-Julian oscillation (MJO), are much easier to understand. The variation of the thickness of the convecting layer is entirely governed by the surface entropy fluxes into the atmosphere.

Other closures have also been proposed since then, including CAPE (convective available potential energy) relaxation-based closure (Fritsch and Chappell 1980; Kain and Fritsch 1993; Kain 2004; Zhang and McFarlane 1995), boundary layer turbulent kinetic energy (TKE) and convective inhibition (CIN)-based closure (Mapes 2000), boundary layer quasi-equilibrium closure (Raymond 1995), and free tropospheric quasi-equilibrium closure (Zhang 2002). Yano et al. (2013) provides a thorough review of different closure assumptions and their merits. CAPE is an approximation of cloud work function used in the Arakawa-Schubert (1974) convection scheme. It assumes that convective instability in the atmosphere is removed by convection within a relaxation time scale of a few hours. Based on the concept of activation control of convection by Mapes (1997), Mapes (2000) proposed a closure relating convection to boundary layer TKE and CIN. Fletcher and Bretherton (2010) and Hohenegger and Bretherton (2011) further tested it using a cloud-resolving model and single column model.

Zhang (2002) analyzed the observational data from the U.S. DOE Atmospheric Radiation Measurement (ARM) program and found that the net variation of convective instability as measured by CAPE is significant in both convective and non-convective situations. This variation is largely controlled by boundary layer temperature and moisture fluctuations. Further analyses of tropical and midlatitude observational data by Zhang (2003) and Donner and Phillips (2003) reached similar conclusions. This indicates that contributions to the *net* CAPE variation from temperature and moisture changes in the troposphere above the planetary boundary layer are insignificant. Based on this finding, Zhang (2002) proposed a free-tropospheric quasi-equilibrium (FTQE), in which CAPE generation by free-tropospheric large-scale processes is balanced by the removal of CAPE from convective heating. By design, a positive CAPE generation by the free

102 tropospheric large-scale processes was also used as a trigger condition¹ for convection onset. A
103 similar trigger condition was used in Xie et al. (2004, 2019). An evaluation of trigger conditions
104 in many convective parameterization schemes using observational data showed that this trigger
105 condition is among the best performing trigger functions (Suhas and Zhang 2014). The application
106 of the FTQE in the Zhang-McFarlane convection scheme (Zhang and McFarlane 1995) in the
107 National Center for Atmospheric Research Community Atmosphere Model version 3 (NCAR
108 CAM3), Community Climate System Model version 3 (CCSM3) and Community Earth System
109 Model version 1 (CESM1) has shown improved simulations of some features of tropical
110 convection, including MJO and intertropical convergence zone (ITCZ) (Zhang and Mu 2005a, b;
111 Zhang and Wang 2006; Song and Zhang 2009; Zhang and Song 2010; Song and Zhang 2018).
112 Wilcox and Donner (2007) implemented it into the Donner (1993) scheme in the Geophysical
113 Fluid Dynamics Laboratory (GFDL) Atmospheric Model AM2. They showed, among other
114 improvements, that the free tropospheric quasi-equilibrium closure greatly improved the
115 simulation of the frequency of extreme precipitation events in the AM2. Benedict et al. (2013)
116 showed that a version of the GFDL AM3 with the FTQE closure produced a better simulation of
117 MJO than in the standard AM3 model. The FTQE closure was also implemented into the Finite-
118 volume Atmospheric Model of IAP/LASG (FAMIL) GCM (Zhou et al. 2015) and tested in single
119 column models of the NCAR CAM4 and CAM5 (Wang and Zhang 2013). Bechtold et al. (2014)
120 incorporated this free-tropospheric quasi-equilibrium, with modifications to include some non-
121 equilibrium elements from the planetary boundary layer, into the European Centre for Medium-

¹ Here and in the rest of this paper trigger condition means a set of conditions that the atmospheric state or processes must satisfy before the call to convective parameterization is triggered.

range Weather Forecasts (ECMWF) Integrated Forecasting System (IFS) and showed that it improved the forecast of the diurnal variation of convection.

Both observational and GCM evaluations of FTQE are for GCM grid-spacings of ~ 200 km or larger. As GCM resolutions increase, is FTQE still a good assumption? Developing a convection scheme that can adapt to different GCM resolutions, i.e., scale-aware, has been an active research topic in recent years since Arakawa et al. (2011) proposed it (Arakawa and Wu 2013, Grell and Freitas 2014, Kwon et al. 2017). However, all these studies are concerned with how to factor in the fact that convective cloud fraction will no longer be negligible as GCM resolution increases to the grey zone (~ 10 km or less). Not as much has been explored on whether the closures of convective schemes are still useable as the GCM resolution approaches the grey zone. Suhas and Zhang (2015) evaluated several closure assumptions including CAPE-based, moisture convergence-based, and boundary layer turbulent kinetic energy (TKE)-based closures using a cloud-resolving model (CRM) simulation for different GCM resolutions. They found that the moisture convergence closure of Tiedtke (1989) is well correlated to convective precipitation and convective cloud mass flux at the 600 hPa level for a large range of grid spacings from 128 km to 4 km. To what extent is the FTQE assumption still applicable or appropriate for use in convective parameterization at high horizontal resolutions? We will address this issue in the paper.

At this point, it is necessary to clarify a nomenclature. In relating convection to large-scale fields through a closure, the large-scale fields are often referred to as “forcing”, by which it implies a causality, that is, the large-scale forcing causes convection. Since the FTQE involves atmospheric circulation, it can be equally valid to argue that the large-scale circulation is a result of convection. More discussion on this will be presented in Section 3. In the paper, we will refrain

from using the word “forcing” to describe the circulation unless it is specified from observations to drive the CRM, in which case it is indeed used as forcing in the CRM setup.

The paper is organized as follows. In section 2, the CRM simulation data used for the evaluation will be described, along with a brief description of the free-tropospheric quasi-equilibrium and the analysis method. Section 3 will present the results. Section 4 will conclude the paper with a summary and some discussions.

2. Data and analysis method

The use of the cloud-resolving model (CRM) output for evaluating or developing convective parameterization schemes has been explored in the past (Xu et al. 1992; Plant and Craig 2008; Jones and Randall 2011). Although there are deficiencies in simulating the detailed structure of convective systems and the intensity of convective updrafts (Bryan et al. 2003; Varble et al. 2011), the macroscopic behavior of convection under a given large-scale condition is realistically simulated. Therefore, CRM data are still suitable for evaluating convective parameterization schemes.

The data used in this study are the same as those used in Suhas and Zhang (2015). They are from a CRM simulation of convection (Zeng et al. 2011) during the intensive observation period (IOP) of Department of Energy (DOE) Atmospheric Radiation Measurement (ARM) program’s Tropical Warm Pool International Cloud Experiment (TWP-ICE) in Darwin Australia during the northern Australian summer monsoon season of 2006 (May et al. 2008). The model is the three-dimensional Goddard Cumulus Ensemble (GCE) model (Tao and Simpson 1993). It has 41 vertical levels from the surface to 21 km height, with a vertical resolution varying from 42.5 m at the bottom to 1 km at the top, and a horizontal resolution of 1 km. The simulation covers the monsoon break period from 2100 UTC 4 February 2006 to 2100 UTC 10 February 2006. The model domain

covers an area of 256 km $\times$ 256 km over the ARM Darwin site. The model simulation is output at 6-min interval.

To evaluate the free tropospheric quasi-equilibrium assumption for different subdomain sizes equivalent to various GCM resolutions, the raw data is averaged over different spatial and temporal scales. For spatial averaging, subdomain sizes of 64 km, 32 km, 16 km, 8 km and 4 km are used. Within each subdomain, we first identify convective grid points at the native CRM resolution of 1 km. A grid point is considered convective if its vertical velocity is greater than 1 m/s or less than -1 m/s and the sum of the mixing ratios of cloud liquid water and ice water exceeds 1×10^{-5} kg/kg. The GCM-equivalent domain-averaged convective mass flux ($M_c = \sum_i \rho w / N$) is calculated to measure convective activity in each subdomain. Here w is vertical velocity at a CRM grid point, the summation is over all convective grid points within the subdomain, and N is the total number of CRM grid points for the subdomain. For convective precipitation, if a CRM column contains any convective grid point, then the surface precipitation is classified as convective, and the subdomain-mean convective precipitation is given by $P_c = \sum_j P / N$. Here the summation is over all convective columns. For temporal averaging, 1, 2, and 3 hours are chosen.

Before going into the details of methodology of evaluating the free tropospheric quasi-equilibrium, we first define CAPE and its time rate of change resulting from subdomain-scale processes. CAPE is defined by the vertical integral of buoyancy of a parcel lifted from the most unstable level in the planetary boundary layer (PBL) to the level of neutral buoyancy:

$$CAPE = \int_{p_t}^{p_b} R_d (T_{pv} - \bar{T}_v) d \ln p \quad (1)$$

where $T_p(1 + 0.608q_p - q_l)$ and $\bar{T}_v = \bar{T}(1 + 0.608\bar{q})$ are virtual temperatures of the air parcel and the domain average. p_b and p_t are pressure values at the parcel's originating level and the neutral buoyancy level, respectively. R_d is gas constant for dry air and q_l is liquid water condensed

following the reversible moist adiabat of the air parcel. Subscript p stands for parcel's properties and overbar for domain average. Thus, CAPE change with time can be rewritten as:

$$\frac{\partial \text{CAPE}}{\partial t} = \frac{\partial \text{CAPE}_p}{\partial t} + \frac{\partial \text{CAPE}_e}{\partial t} \quad (2)$$

where $\frac{\partial \text{CAPE}_p}{\partial t} = R_d \frac{\partial}{\partial t} \int_{p_t}^{p_b} T_{pv} d \ln p$ and $\frac{\partial \text{CAPE}_e}{\partial t} = -R_d \frac{\partial}{\partial t} \int_{p_t}^{p_b} \bar{T}_v d \ln p$ represent contributions to CAPE change from changes of the parcel's thermodynamic properties and its environment in the free troposphere, respectively. For an undiluted parcel, its virtual temperature is determined by the temperature and moisture at its originating level in the PBL. With simple manipulation it can be shown (Zhang et al. 1998) that $\frac{\partial \text{CAPE}_p}{\partial t}$ is related to surface entropy flux, and $\frac{\partial \text{CAPE}_e}{\partial t}$ is the change of the thickness of the convective layer. Using ARM observations, Zhang (2002, 2003) and Donner and Phillips (2003) found that CAPE variation is largely controlled by boundary layer thermodynamic changes, that is, $\frac{\partial \text{CAPE}}{\partial t} \approx \frac{\partial \text{CAPE}_p}{\partial t}$ and $\frac{\partial \text{CAPE}_e}{\partial t} \approx 0$. Based on this finding, Zhang (2002) further decomposed $\frac{\partial \text{CAPE}_e}{\partial t}$ into contributions from large-scale and convective scale processes,

$$\frac{\partial \text{CAPE}_e}{\partial t} = \left(\frac{\partial \text{CAPE}_e}{\partial t} \right)_c + \left(\frac{\partial \text{CAPE}_e}{\partial t} \right)_{ls} \approx 0. \quad (3)$$

This leads to the free tropospheric quasi-equilibrium assumption, which states that CAPE generation by large-scale advection in the free troposphere is in equilibrium with the CAPE removal by convective heating:

$$\left(\frac{\partial \text{CAPE}_e}{\partial t} \right)_c \approx - \left(\frac{\partial \text{CAPE}_e}{\partial t} \right)_{ls}. \quad (4)$$

This assumption was used to devise a closure to determine convective mass flux at the cloud base (Zhang, 2002; Zhang and Mu, 2005). In fact, the left-hand side of Eq. (4) is proportional to the cloud-based convective mass flux (M_b):

$$\left(\frac{\partial CAPE_e}{\partial t}\right)_c = M_b \int_{p_t}^{p_b} (1 + 0.608q) \left(-\eta \frac{\partial s}{\partial p}\right) + 0.608T \left[-\eta \frac{\partial q}{\partial p} + \delta(q_s - q)\right] d\ln p \quad (5)$$

where η is the net cloud mass flux normalized by the cloud base mass flux, i.e., $\eta = M_c/M_b$. The vertical integral on the rhs of Eq. (5) represents the consumption rate of CAPE per unit cloud-base mass flux [see Eq. (8) of Zhang (2002)]. Thus,

$$M_b = \max\{-(\partial CAPE_e/\partial t)_{ls}, 0\}/F \quad (6)$$

Here F denotes the vertical integration on the rhs of Eq. (5). Note that the diagnostic relationship in Eq. (4) is well-known in large-scale tropical dynamics through scale analysis (e.g. Yano and Bonazzola, 2009) and is the basis of weak temperature gradient approximation of tropical circulation (Sobel et al., 2001). But it was not formally used in the context of convective parameterization until Zhang (2002).

To evaluate the free tropospheric quasi-equilibrium closure for a given subdomain size mimicking a corresponding GCM resolution, the following procedure is taken to calculate CAPE changes due to subdomain-scale advection. First, CAPE is computed using Eq. (1) and subdomain-mean fields, and we call it $CAPE_0$. Second, we compute advective tendencies of temperature ($-\bar{v} \cdot \nabla \bar{s} - \bar{\omega} \frac{\partial \bar{s}}{\partial p}$) and moisture ($-\bar{v} \cdot \nabla \bar{q} - \bar{\omega} \frac{\partial \bar{q}}{\partial p}$) using subdomain-mean temperature, moisture and velocity fields from neighboring subdomains and finite difference as if they were representing GCM grid point variables. Here s is dry static energy normalized by heat capacity of air, $s = T + gz/c_p$. The forcing from observations used to drive the CRM is also added uniformly to each subdomain, as was done in the CRM simulation. These advective tendencies are then used to update the subdomain-mean temperature and moisture fields at all levels *above the parcel's originating level*, so that the parcel's properties are not affected by this update:

$$\bar{T}_1 = \bar{T}_0 + \left(-\bar{v} \cdot \nabla \bar{s} - \bar{\omega} \frac{\partial \bar{s}}{\partial p}\right) \Delta t + F_{adv} \Delta t \quad (7a)$$

$$\bar{q}_1 = \bar{q}_0 + \left(-\bar{v} \cdot \nabla \bar{q} - \bar{\omega} \frac{\partial \bar{q}}{\partial p} \right) \Delta t + F_{advq} \Delta t \quad (7b)$$

where Δt is 6 minutes, the time interval for CRM model output, and $\bar{T}_0$ and $\bar{q}_0$ are temperature and moisture used to compute $CAPE_0$. F_{advT} and F_{advq} are observed forcing of temperature and moisture that is used to drive the CRM. Next, CAPE is recomputed using Eq. (1) with the updated temperature $\bar{T}_1$ and moisture $\bar{q}_1$, and we call it $CAPE_1$. Thus, $CAPE_1$ is equivalent to CAPE in the atmosphere after the dynamics core but before convection parameterization is called in GCMs such as the NCAR CAM5. Finally, we obtain the CAPE change due to subdomain-scale (or GCM grid-scale) advection:

$$\left(\frac{\partial CAPE_e}{\partial t} \right)_{ls} = \frac{CAPE_1 - CAPE_0}{\Delta t} \quad (8)$$

Hereafter we will use the shorthand $dCAPE_{ls}$ for $\left(\frac{\partial CAPE_e}{\partial t} \right)_{ls}$. Note that neither $\left(\frac{\partial CAPE_e}{\partial t} \right)_c$ nor $\left(\frac{\partial CAPE_e}{\partial t} \right)_{ls}$ has contributions from changes of thermodynamic properties at and below the parcel's initiation level in boundary layer. Thus, this closure is decoupled from the surface and boundary layer processes that affect the convective parcel's properties. While this may seem unconventional since it is well known that convection is rooted in the boundary layer, it should be pointed out that heating and moistening, such as those from surface turbulent fluxes, in the boundary layer often do not directly affect deep convection. They first deepen the boundary layer, which subsequently leads to the development of shallow convection. Many previous observational and modeling studies have pointed out that shallow convection can serve to precondition the lower troposphere by moistening it (e.g. Kemball-Cook and Weare, 2001; Wu et al., 2009; Zhang and Klein, 2010) and can produce enhanced low-level mass convergence (Wu, 2003) before deep convection. The diabatic heating from shallow convection generates the grid-scale circulation which would

generate $dCAPE_{ls}$. This $dCAPE_{ls}$ will lead to the development of deep convection if the environmental conditions are favorable for shallow to deep convection transition. In addition, although boundary layer forcing is not considered in the closure, a positive CAPE is required, which is largely controlled by the PBL properties. Therefore, deep convection is indirectly related to PBL properties in this closure.

3. Results

Fig. 1 shows the time series of observed precipitation during the IOP and $dCAPE_{ls}$ due to observed/background large-scale forcing applied to the CRM. Observationally, there is a close correspondence between variations of precipitation and $dCAPE_{ls}$, with a correlation coefficient of 0.90 for points with positive $dCAPE_{ls}$. Fig. 2 shows the time evolution of model precipitation and $dCAPE_{ls}$ for selected subdomain sizes (64 km and 32 km). Also shown are contributions to $dCAPE_{ls}$ from the imposed observed forcing and advection from model generated circulations. For a 64 km subdomain, the total $dCAPE_{ls}$ largely comes from the contribution of model-generated circulations, and the prescribed, observed forcing is relatively small. As a result, the temporal variation of $dCAPE_{ls}$ is largely dominated by that of the contribution from model circulation, with a correlation coefficient of 0.92 between the two, and the correlation between the total $dCAPE_{ls}$ and the observed large-scale contribution is only 0.59. The precipitation variation clearly follows that of the total $dCAPE_{ls}$. In a 32 km subdomain, $dCAPE_{ls}$ variation also predominantly comes from the model-generated contribution, with a correlation coefficient of 0.93. The contribution from the background forcing becomes much less significant, particularly during heavy precipitation events. The time series for other 64 km and 32 km subdomains are similar to those shown in the figure. This clearly demonstrates that the model-generated circulation on subdomain scale becomes more closely related to convection and the local relationship between convection

and circulation is less dependent on the imposed forcing for the CRM as the subdomain size decreases.

Zhang (2002, 2003) and Donner and Phillips (2003) showed using field observational data that on spatial scales of a few hundred kilometers, variability in CAPE is mainly controlled by planetary boundary layer variability in thermodynamic fields. In tropical atmosphere, this is at least partly due to the weak temperature gradients in the free troposphere. To examine if the CAPE variation is still controlled by the PBL properties as the spatial scale decreases, Fig. 3 shows the scatter plots of net CAPE change ($dCAPE$) versus contributions from boundary layer changes ($dCAPE_p$), that is, the left-hand side vs. the first term on the right-hand side of Eq. (2), using 1-hour average data. For all subdomain sizes, there is a strong correlation between $dCAPE$ and $dCAPE_p$, with correlation coefficients greater than 0.97. The slopes show that boundary layer contribution accounts for up to 93% of the total $dCAPE$. Furthermore, the relative contribution from the boundary layer increases as the domain size decreases. For example, at the 64 km subdomain size the regression slope is 0.938; it increases to 0.966 at 4 km subdomain size. These results, together with earlier observational results (Zhang 2002, 2003; Donner and Phillips 2003), indicate that boundary layer control of CAPE applies to all scales from ~ 100 km to grey zone scales of sub-10 km. In other words, Eq. (4) is a very good approximation to relate convection to GCM grid-scale CAPE generation in the free troposphere for all GCM grid spacings down to 4 km.

To verify this, Fig. 4 shows the relationship between $dCAPE_{ls}$ and convective mass flux at 600 mb. The red, cyan and orange lines are median values, first and third quartiles in each $dCAPE_{ls}$ bin, respectively. As in Suhas and Zhang (2015), the 600 mb convective mass flux is used to measure the amount of convection because it is difficult to define cloud base accurately in the

CRM. Convective mass flux increases linearly with $dCAPE_{ls}$ for 64 km, 32 km and 16 km, indicating GCM grid-scale advective CAPE generation, as represented by $dCAPE_{ls}$, is closely related to convective mass flux at these subdomain sizes. The linear relationship between $dCAPE_{ls}$ and mass flux begins to degrade, with the median values plateauing off from the linear regression line, when the subdomain size further decreases to 8 km and 4 km, indicating that a larger amount of CAPE generation is needed to produce a given amount of convection as the GCM grid size decreases. The scatter is also increased. There are two possible explanations for the degeneration of the linear relationship at small subdomain sizes. First, as the subdomain size decreases, for a given grid-scale circulation and thermodynamic state, the stochastic behavior of convection becomes more prominent, thereby making convection in individual subdomains deviate more from the convective quasi-equilibrium. Second, as the subdomain size decreases, some of the convection may become GCM grid-resolved, resulting in less subgrid convective mass flux for given grid-scale state. This scale-aware issue should become more noticeable when the subdomain size becomes smaller.

To further evaluate the accuracy of free tropospheric quasi-equilibrium as GCM grid size decreases, Fig. 5 shows the lag correlation between $dCAPE_{ls}$ and convective precipitation, 600 mb convective mass flux, and 500 hPa vertical velocity, respectively, averaged over different subdomain sizes. The maximum correlation occurs when $dCAPE_{ls}$ leads convective precipitation. The lead time decreases from 18 minutes for 64 km subdomain size to 10 minutes for sub-10 km subdomain size. The maximum correlation coefficient remains about the same from 64 km subdomain sizes to 16 km subdomain sizes but decreases as the subdomain size further decreases. The variation of time lag with subdomain size can be explained by the strength of GCM grid-scale forcing and the time it takes for convection to adjust. Wang and Randall (1996) demonstrated that

it takes longer for convection to adjust under weak large-scale forcing, and vice versa. Fig. 4 shows that when the subdomain size is larger, the forcing is smaller. Thus, it takes longer for convective heating to adjust the atmosphere to an equilibrium state. The maximum correlation between convective mass flux and $dCAPE_{ls}$ occurs at zero lag for all subdomain sizes. This indicates that the development of convective precipitation lags convective updraft mass flux at 600 mb, the larger the subdomain, the longer the time lag. The fact that the highest correlation occurs between convective mass flux and $dCAPE_{ls}$ at zero lag suggests that using $dCAPE_{ls}$ as a closure to determine the amount of convection at a given GCM time step is reasonable. However, this should not be construed as a causal relationship, but rather a diagnostic one. In a balanced state it may be difficult or pointless to identify causality. In the past convection has been considered both as a cause and a result of large-scale circulation, depending on one's viewpoint. In dynamic models of tropical circulation (e.g. Gill 1980), the large-scale circulation is often viewed as a response to convective heating. On the other hand, in cloud-resolving models (e.g., Grabowski 2001) or single-column models (Randall et al. 1996), large-scale forcing is prescribed to drive the models and convection in the models responds to the forcing. In the real world, large-scale circulation and convection interact with each other and neither view provides a complete picture of this interaction. In the context of convective parameterization, the amount of convection determined by a parameterization closure can be viewed as that needed to balance the model-predicted thermodynamic state or process, be it a cause or an effect. Therefore, it is unnecessary to determine whether one is the cause or the effect of the other.

Previous work by Davies et al. (2013) and Kumar et al. (2015) using Doppler radar observations of convection and ECMWF reanalysis data in Darwin, Australia found that convection is highly correlated with 500 mb large-scale vertical velocity. Another study by Qiao

and Liang (2016) used a regional climate model Climate-Weather Research and Forecasting (CWRF) to evaluate the effects of cumulus parameterization closures on summer precipitation simulation over the U.S. east coast and Gulf of Mexico. They showed that vertical velocity and moisture convergence-based closures reproduce the observed precipitation pattern and amount, and capture the frequency of heavy rainfall events better than CAPE-based closures. Since the large-scale generation of CAPE is closely linked to vertical velocity through vertical advection of dry static energy, this indirectly supports the free tropospheric quasi-equilibrium closure. As shown in Fig. 5c, the correlation coefficients reach a maximum at zero lag between $dCAPE_{ls}$ and 500 mb vertical velocity for all subdomain sizes, the same as that between $dCAPE_{ls}$ and convective updraft mass flux at 600 mb, indicating that $dCAPE_{ls}$, 500 mb vertical velocity and convection occur concurrently. This concerted action between convection, adiabatic cooling and upward motion was noticed 30 years ago by Fraedrich and McBride (1989) as a free ride. It is also the basis of the weak temperature gradient approximation (Sobel et al. 2001). In terms of the values of correlation coefficients, $dCAPE_{ls}$ and 500 mb vertical velocity are highly correlated, with coefficients over 0.8 for all subdomain sizes. Nonetheless, it should be noted that $dCAPE_{ls}$ does not necessarily have a one-to-one relationship with the 500 mb vertical velocity since vertical motion at other levels also contributes to $dCAPE_{ls}$.

Fig. 6 shows the lag correlation between $dCAPE_{ls}$ and vertical velocity (color shading) at different levels for different subdomain sizes. At zero lag, there is a broad maximum correlation in the mid-troposphere between 600 and 300 hPa. Also, there is a clear tilted structure, showing a time lag between the lower and upper troposphere for all subdomain sizes, with the lower tropospheric vertical velocity leading $dCAPE_{ls}$ and the upper tropospheric vertical velocity lagging $dCAPE_{ls}$. The vertical velocity below 800 hPa leads $dCAPE_{ls}$ by as much as 2 hours for 64 km

369 subdomain size, reduced to less than half an hour for 4 km subdomain size. This indicates that the
 370 low-level grid-scale circulation acts first to generate $dCAPE_{ls}$. Also shown in Fig. 6 is the time-
 371 lag correlation between convective mass flux and $dCAPE_{ls}$ (contours). Similar to vertical velocity,
 372 convective mass flux in the lower troposphere also leads $dCAPE_{ls}$, although the vertical tilt in the
 373 time lag-height plot is not as much as that for vertical velocity. This suggests that vertical velocity
 374 below 800 hPa develops first, followed immediately by shallow convection, which reenforces the
 375 vertical motion. Then $dCAPE_{ls}$ peaks, accompanied by deep convection in the troposphere. This
 376 is consistent with previous observational and modeling studies that shallow convection often
 377 appears before deep convection (Wu 2003, Zhang and Klein 2010). The lead time decreases with
 378 subdomain size, reflecting that convection responds faster to stronger forcing as the subdomain
 379 size decreases.

380 From Figs. 5 and 6, convective mass flux and grid-scale vertical velocity w are closely related.
 381 Since $\bar{w} = \frac{M_c}{\rho} + (1 - \sigma)\tilde{w}$, where $\bar{w}$ is the subdomain-mean vertical velocity, M_c is convective
 382 mass flux, ρ is the air density, σ is the convective fraction and $\tilde{w}$ is vertical velocity in the
 383 convection-free environment within the subdomain, the difference between $\bar{w}$ and M_c/ρ measures
 384 the compensating subsidence in the convection-free environment. Fig. 7 shows the vertical profiles
 385 of $\bar{w}$ and M_c/ρ for different subdomain sizes. Convective mass flux exceeds $\bar{w}$ at most levels
 386 except in the boundary layer, meaning that there is systematic compensating subsidence in the
 387 convective environment. The strength of the subsidence relative to convective mass flux or
 388 subdomain-mean vertical velocity decreases with subdomain size. In other words, more
 389 compensating subsidence occurs non-locally outside the subdomain where convection occurs as
 390 the subdomain size decrease. This is in agreement with the conceptual model of scale-dependence
 391 of convective effects as envisioned by Arakawa et al. (2011).

Fig. 8 shows the regression slope between 600 mb mass flux and $dCAPE_{ls}$ for different subdomain sizes. Similar to the correlation coefficients, for a given subdomain size the regression slope is the largest at zero lag. For different subdomain sizes, the regression slope first increases from 64 km subdomain sizes to 16 km subdomain sizes, but then decreases as the subdomain size becomes smaller, similar to that of correlation coefficient shown in Fig. 5b. However, the fluctuations are relatively smaller compared to the regression slopes themselves, in the range of 12 to 14 ($kg\ m^{-2}\ day^{-1}$)/($J\ kg^{-1}\ hr^{-1}$). The slight decrease of the slopes for subdomain sizes < 32 km can be explained by the following reasoning. Convection, as measured by precipitation or updraft mass flux, is positive-definite (i.e. the amount of convection cannot be negative) whereas the subdomain-scale $dCAPE_{ls}$ can be either positive or negative. In neighboring subdomains, $dCAPE_{ls}$ can be either positive or negative. In strongly positive $dCAPE_{ls}$ subdomains, it is likely there is active convection and convective precipitation. In negative $dCAPE_{ls}$ subdomains, there is likely no convection. Assume that there is a linear relationship between convection and $dCAPE_{ls}$ in subdomains where $dCAPE_{ls}$ is positive. When averaging over a larger subdomain containing subdomains with both positive and negative $dCAPE_{ls}$, the rate of reduction of convective updraft mass flux will be smaller than the rate of reduction of $dCAPE_{ls}$ because the former contains positive or zero values only while the latter contains both positive and negative values. Thus, the ratio of convective mass flux to $dCAPE_{ls}$ for larger subdomains is larger than that for smaller subdomains, as seen in Fig. 8. A similar GCM-resolution dependence was also recognized by Xiao et al. (2015) and Yun et al. (2017) when examining the scale-awareness of vertical transport in the Zhang-McFarlane convection scheme.

Finally, to examine the sensitivity of the relationships between $dCAPE_{ls}$ and convective mass flux to temporal scales for different subdomain sizes, Fig. 9 shows the variation of correlation

coefficients and regression slopes between $dCAPE_{ls}$ and 600 mb convective mass flux with time averaging intervals from 6 minutes to 3 hours for all subdomain sizes. The correlation coefficients for 32 km to 4 km subdomain sizes have a maximum at 30 min averaging time and then decrease slightly as the averaging intervals increase to 3 hours. For 64 km subdomain size, the correlation coefficient reaches a maximum at 1-hr averaging interval. However, its variation with averaging time intervals is relatively small. For the regression slopes, their variations with averaging time intervals have a similar pattern to that for the correlation coefficients. Therefore, these indicate that free tropospheric quasi-equilibrium between the subdomain scale forcing (i.e. $dCAPE_{ls}$) and convection holds well for timescales of 30 min or longer, implying that for GCM applications with 30-min timestep, the free tropospheric quasi-equilibrium assumption is suitable.

4. Conclusions

This study uses the cloud-resolving model simulation of convection in Darwin, Australia to examine the validity of the free tropospheric quasi-equilibrium assumption for different spatial scales equivalent to GCM grid sizes from 64 km to 4 km. The CRM output is averaged over different subdomains equivalent to different GCM resolutions to investigate the relationships between convection, as measured by convective precipitation and convective mass flux at the 600 mb level, and the generation of convective available potential energy, $dCAPE_{ls}$, by subdomain-scale circulation. Results show that although observed advective forcing is used to drive the CRM simulation of convection, CAPE generation for convection on subdomain scales is dominated by model-generated circulation when subdomain sizes become smaller. It is further shown that the total CAPE variation is controlled by contributions from the boundary layer properties on all spatial scales from 64 km down to 4 km subdomain sizes. The smaller the subdomain size, the larger the contribution from the boundary layer. For 64 km, the boundary layer contributes about

93% to the total CAPE variation. For sub-10 km (8 to 4 km) subdomain sizes, it contributes as much as 96% to the total CAPE variation. This implies that convective removal and large-scale generation of CAPE in the free troposphere are largely in balance, with their sum accounting for about less 7 to 4% of the total CAPE change (Fig. 3).

Convective precipitation, mass flux at 600 mb and vertical velocity at 500 mb all correlate well with $dCAPE_{ls}$ for subdomain sizes from 64 km to 4 km, suggesting that the free tropospheric quasi-equilibrium assumption can be applied to GCMs with resolutions in the grey zone. However, the correlation coefficient decreases as subdomain size decreases for subdomain sizes smaller than 16 km. This is likely due to increased randomness of convection and more noticeable scale-dependence of the relationships when the subdomain size reaches the grey zone. The regression slope also becomes smaller with decreasing subdomain sizes on these scales, although the decrease is relatively small. This can be explained by the fact that convection is positive-definite whereas the free tropospheric forcing can be either positive or negative. Thus, as the subdomain size becomes smaller, the same amount of CAPE generation by the grid-scale circulation will correspond to a smaller amount of convection in the averaging domain. This implies that although free tropospheric quasi-equilibrium can still be useable as the GCM resolution increases, it needs to be modified to account for the decreasing regression slope in order to make it scale-aware. Finally, the sensitivity of relationship between $dCAPE_{ls}$ and convective mass flux at 600 mb to temporal scales for all subdomain sizes is examined. It shows that their correlations remain similar for all subdomain sizes for timescales of 30 min or longer. However, there is a noticeable increase for 8 km and 4 km subdomain sizes from 6 min to 30 min intervals. As for the regression slopes, there is also little change for different averaging intervals for all subdomain sizes, especially timescales longer than 30 min. These results indicate that the free tropospheric quasi-equilibrium

between $dCAPE_{ls}$ and convection holds well for 30 min or longer timescales at all subdomain sizes from 64 km to 4 km.

As the computing power increases, GCMs have begun to increase the horizontal resolution to 25 km or higher. This requires convective schemes to be able to adapt to the higher resolutions. While some schemes have incorporated the fact that convective cloud fraction within a GCM grid box typically increases with the GCM resolution, not much has been done to modify convection parameterization closure. This study provides a diagnostic evaluation on a closure assumption, which can be used to guide future development of a scale-aware closure for convection parameterization in high-resolution GCMs.

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Figure Captions:

Fig. 1: Time series of observed precipitation (mm/hr) and CAPE generation (J/kg/hr) by large-scale advective forcing averaged over the IOP domain during the break monsoon period (February 5 to February 10, 2006) of TWP-ICE IOP.

Fig. 2: Sample time series of cloud-resolving model simulated precipitation (mm/hr) and net CAPE generation (J/kg/hr) in subdomains at size of (a) 64 km and (b) 32 km for 30 min time-averaging intervals. Contributions to net CAPE generation from observed forcing (black) and model-generated forcing (blue) are also shown to demonstrate their relative importance as subdomain size changes. The correlation coefficients between net CAPE generation and contribution from observed/model-generated forcing are given above each frame.

Fig. 3: Scatter plots of total CAPE change ($dCAPE/dt$) versus CAPE change due to thermodynamic changes in the planetary boundary layer ($dCAPE_p/dt$) for different subdomain sizes ranging from 64 km to 4 km. Each point represents a 1-hr average of model output at 6 min interval. The regression lines (black), slopes and correlation coefficients are also provided. For visual clarity, only a portion (chosen randomly) of data points is used in the scatterplots at 16, 8 and 4 km subdomain sizes, but all data are used in the calculation of statistics.

Fig. 4: Scatter plots of convective mass flux at 600 mb and $dCAPE_{ls}$ for different subdomain sizes. The blue line is linear regression, with correlation coefficient and slope shown at the top of each plot. Red solid curves are for median values and green and yellow solid curves are for first and third quartiles, respectively. For plotting the quartile curves, the data are divided into a number of bins and the bin sizes are larger for smaller subdomains. For visual clarity, only a portion (chosen randomly) of data points is used in the scatterplots, but all

data are used in the calculation of statistics. Note that the horizontal and vertical scales are different across the plots.

Fig. 5: Lag correlation (a) between $dCAPE_{ls}$ and convective precipitation, (b) between $dCAPE_{ls}$ and convective mass flux at 600 mb and (c) between $dCAPE_{ls}$ and 500 mb vertical velocity for subdomain sizes ranging from 64 km to 4 km. Positive values in x-axis mean $dCAPE_{ls}$ leads the associated convective fields, and vice versa.

Fig. 6: Lag correlation between vertical velocity and $dCAPE_{ls}$ (color shading), and between convective mass flux and $dCAPE_{ls}$ (contours) at (a) 64 km, (b) 32 km, (c) 16 km, (d) 8 km and e) 4 km. Contour lines start at 0.2 with an interval of 0.2. Negative value in x-axis means $dCAPE_{ls}$ lags vertical velocity and mass flux.

Fig. 7: Vertical profiles of subdomain-mean vertical velocity (W) and convective mass flux (MF) for different subdomain sizes. MF is divided by air density (ρ) at each level to give the same unit as that for W .

Fig. 8: Regression slopes between $dCAPE_{ls}$ and 600 mb convective mass flux at different time lags for different subdomain sizes. Positive value in x-axis means $dCAPE_{ls}$ leads mass flux, and vice versa.

Fig. 9: Lag 0 (a) correlation and (b) slope between $dCAPE_{ls}$ and 600 mb convective mass flux for subdomain sizes ranging from 64 km to 4 km for different time-averaging intervals.

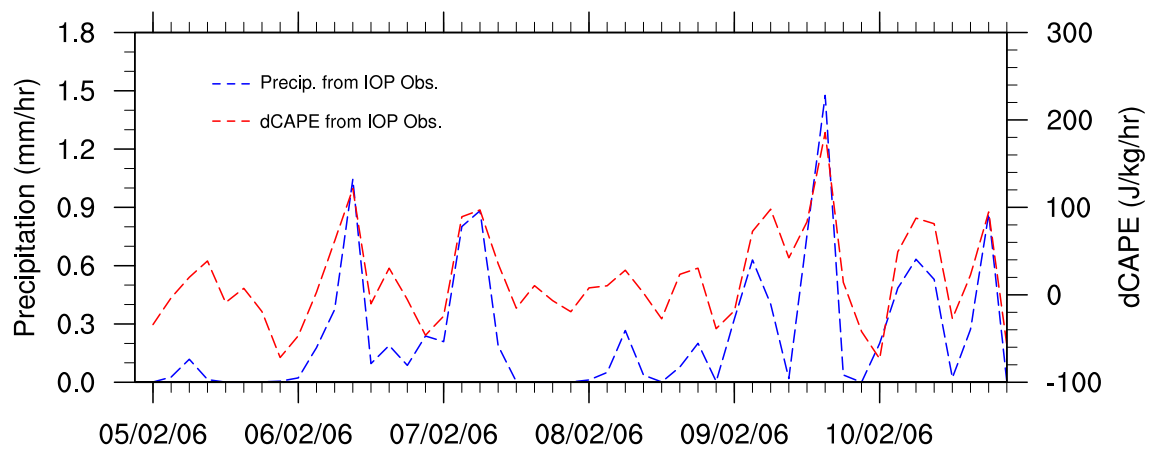


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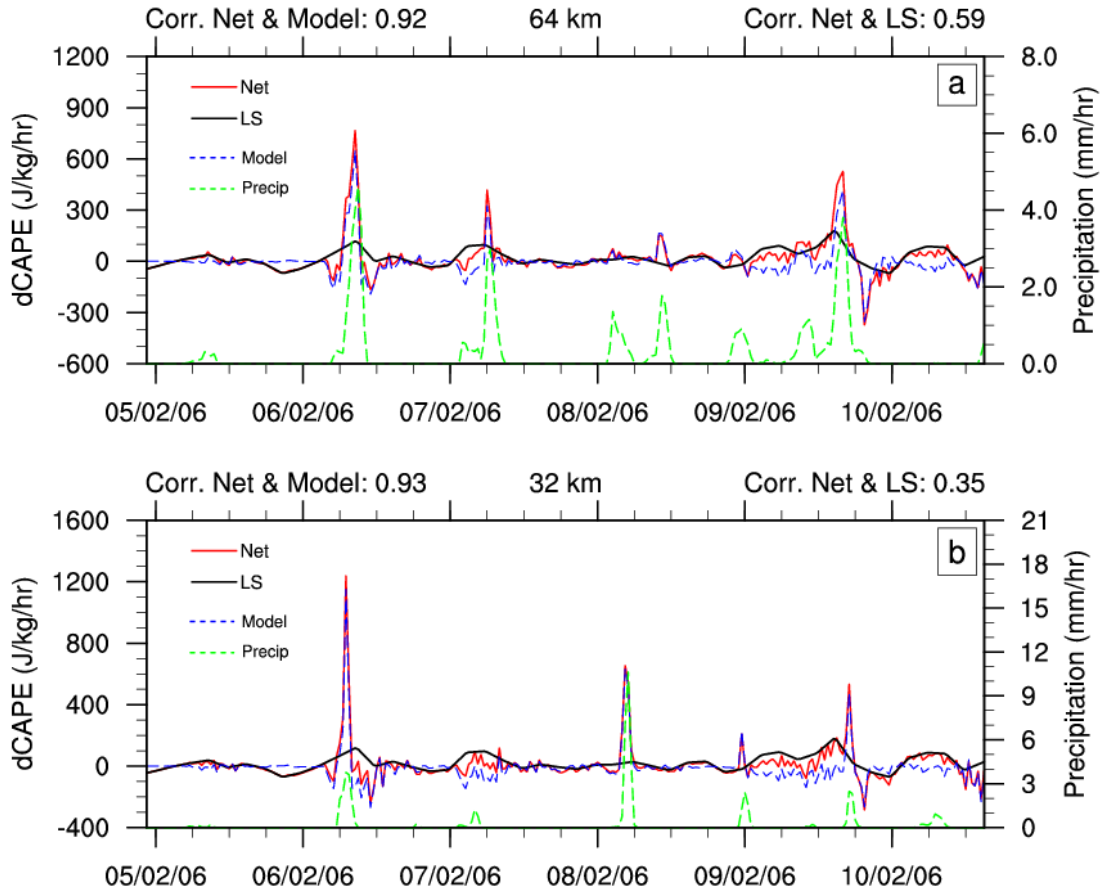
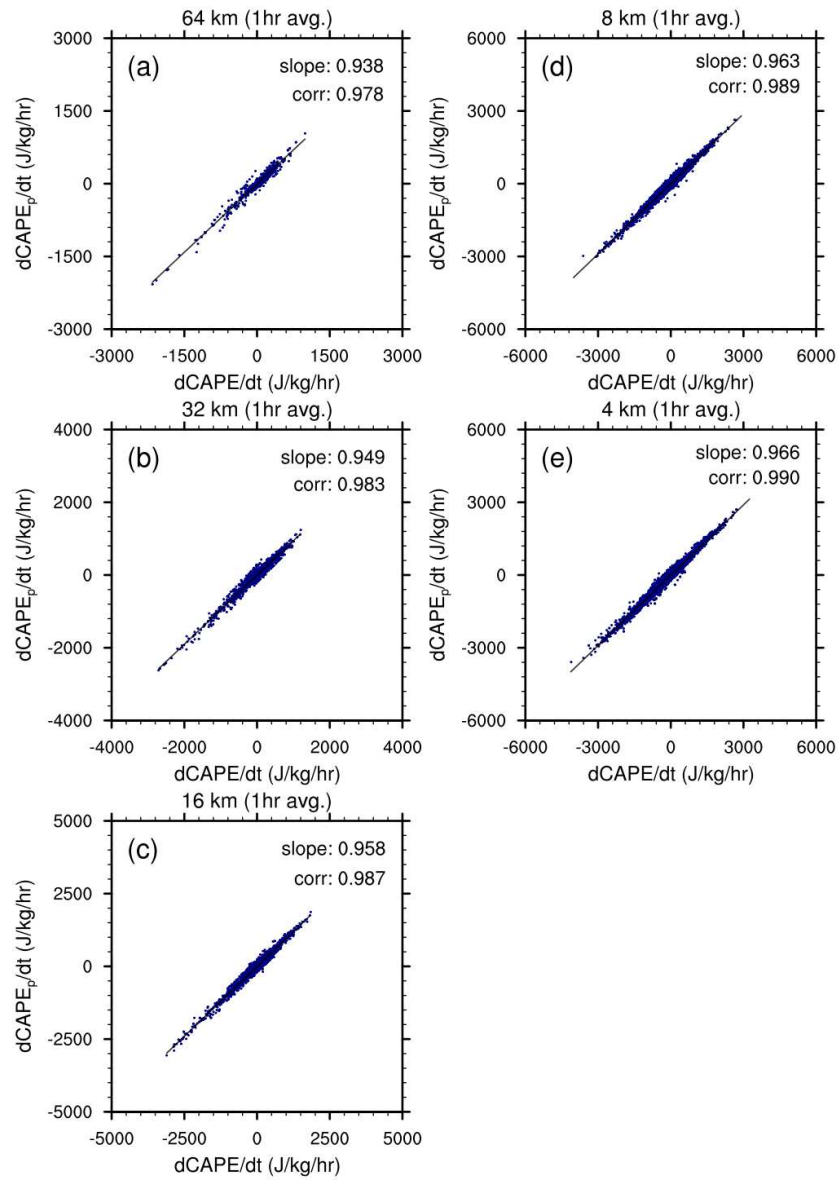


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722 **Fig. 3** Scatter plots of total CAPE change ($dCAPE/dt$) versus CAPE change due to
 723 thermodynamic changes in the planetary boundary layer ($dCAPE_p/dt$) for different subdomain
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 727 and 4 km subdomain sizes, but all data are used in the calculation of statistics.

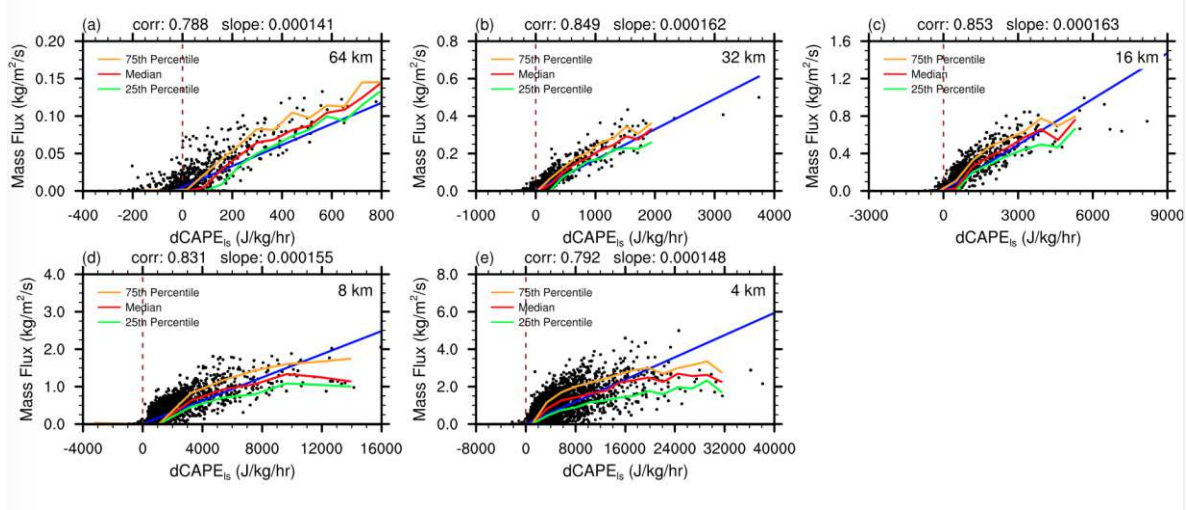
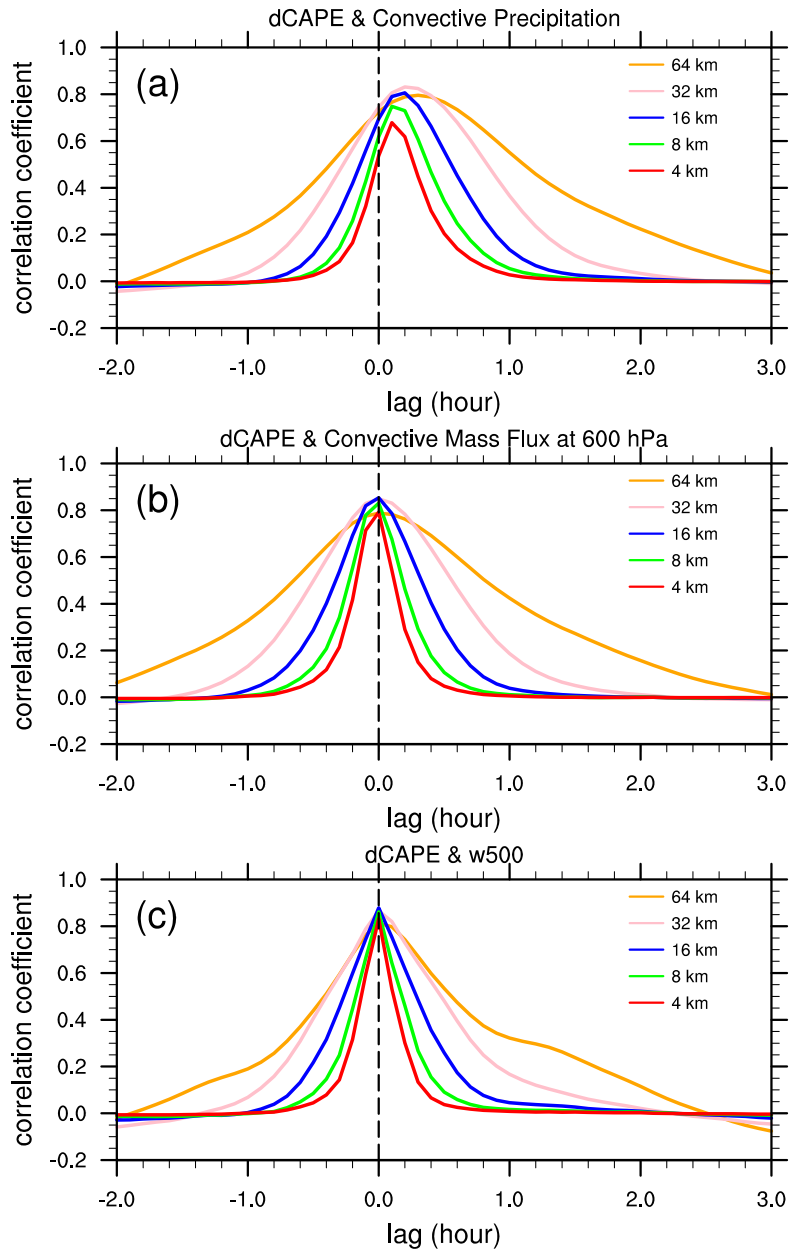


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744 **Fig. 5** Lag correlation (a) between $dCAPE_{ls}$ and convective precipitation, (b) between $dCAPE_{ls}$
 745 and convective mass flux at 600 mb and (c) between $dCAPE_{ls}$ and 500 mb vertical velocity for
 746 subdomain sizes ranging from 64 km to 4 km. Positive values in x-axis mean $dCAPE_{ls}$ leads the
 747 associated convective fields, and vice versa.

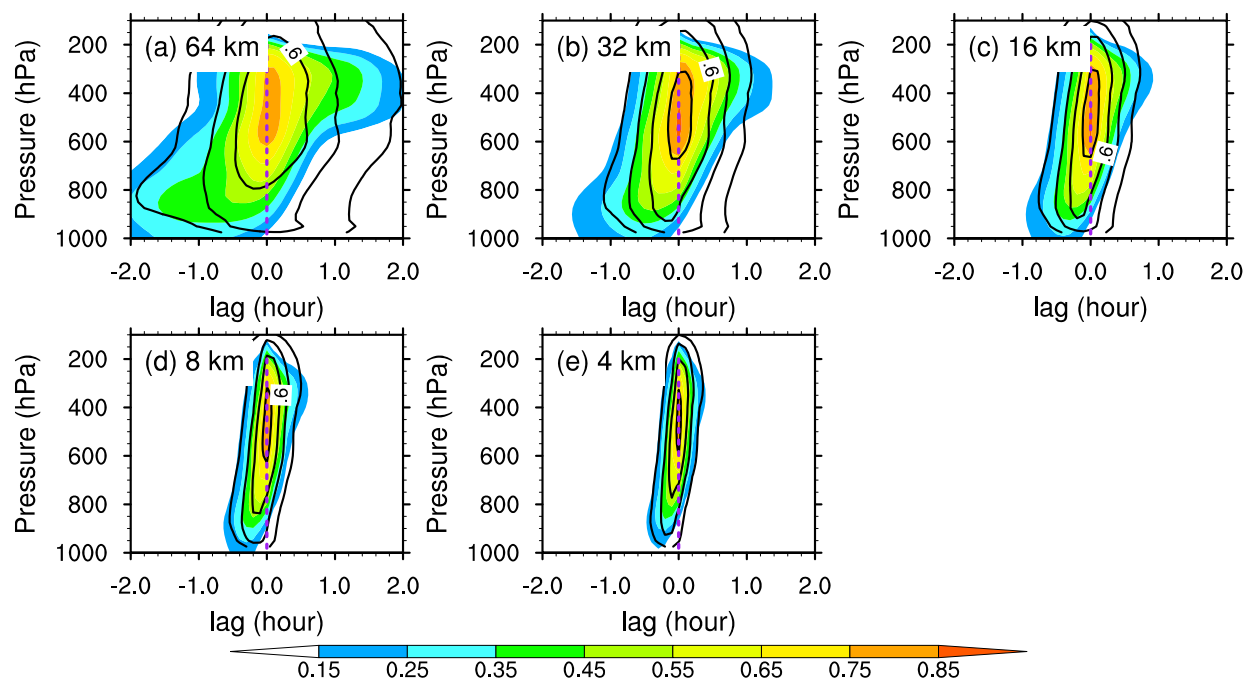


Fig. 6 Lag correlation between vertical velocity and dCAPE_{ls} (color shading), and between convective mass flux and dCAPE_{ls} (contours) at (a) 64 km, (b) 32 km, (c) 16 km, (d) 8 km and (e) 4 km. Contour lines start at 0.2 with an interval of 0.2. Negative value in x-axis means dCAPE_{ls} lags vertical velocity and mass flux.

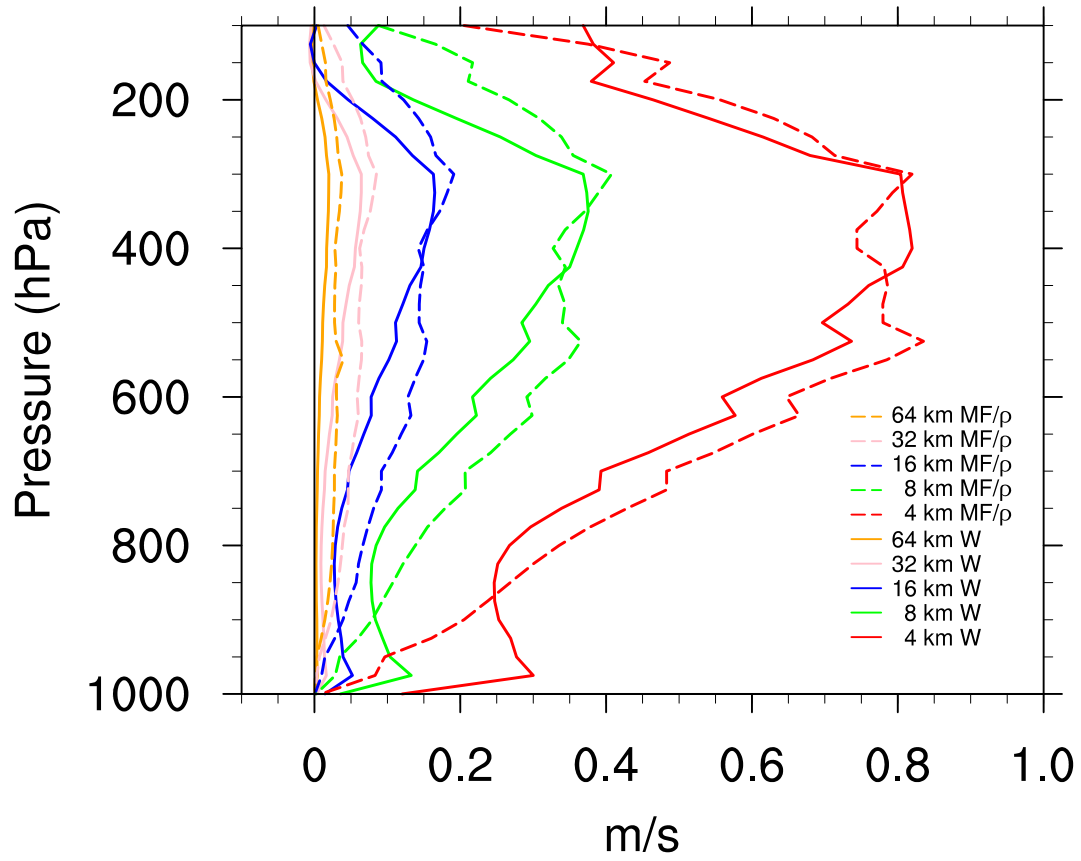


Fig. 7 Vertical profiles of subdomain-mean vertical velocity (W) and convective mass flux (MF) for different subdomain sizes. MF is divided by air density (ρ) at each level to give the same unit as that for W .

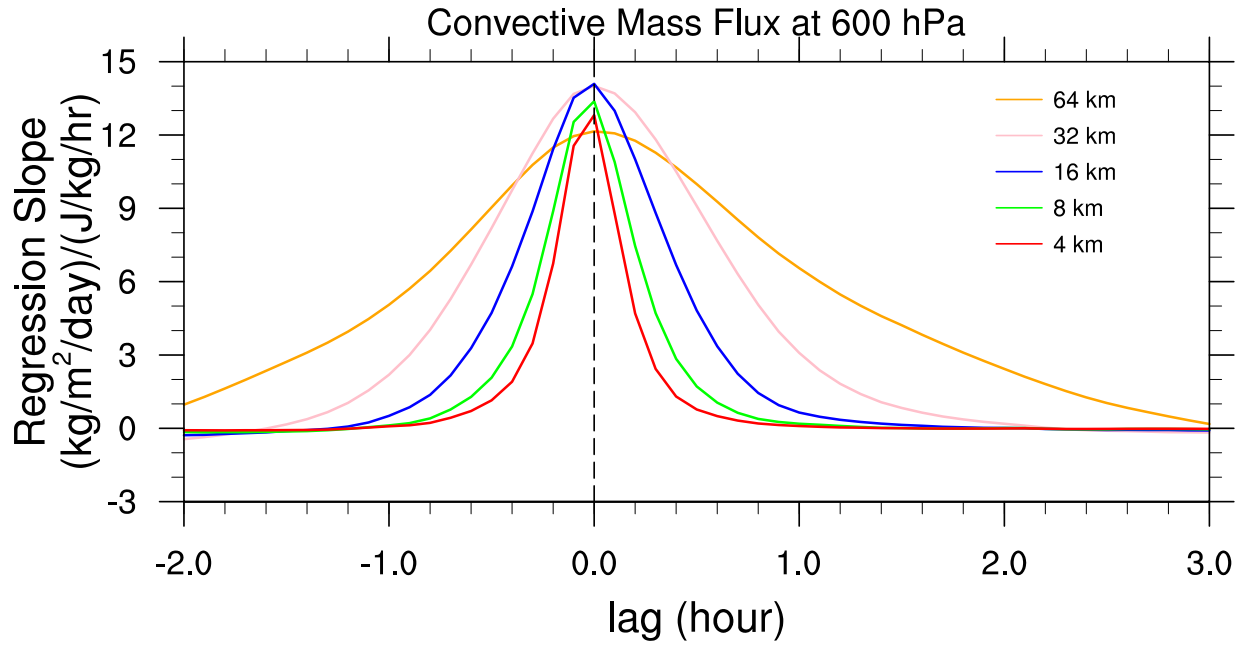


Fig. 8 Regression slopes between dCAPE_{ls} and 600 mb convective mass flux at different time lags for different subdomain sizes. Positive value in x-axis means dCAPE_{ls} leads mass flux, and vice versa.

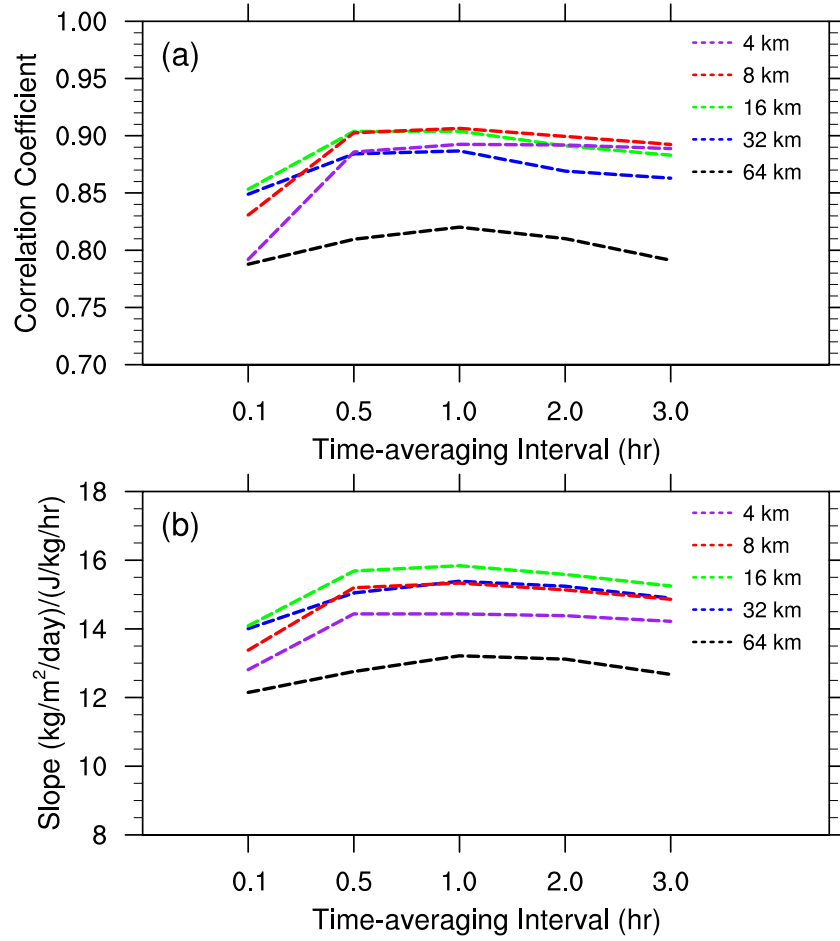


Fig. 9 Lag 0 (a) correlation and (b) slope between $dCAPE_{ls}$ and 600 mb convective mass flux for subdomain sizes ranging from 64 km to 4 km for different time-averaging intervals.