Improving Trigger Functions for Convective Parameterization Schemes Using GOAmazon Observations

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(Manuscript received 19 January 2017, in final form 18 July 2017)

ABSTRACT

Using observations from the Green Ocean Amazon (GOAmazon) field campaign, this study aims to improve trigger functions of convection schemes. Results show that the CAPE generation rate (dCAPE)-type triggers are the first tier and that the Bechtold and heated condensation framework (HCF) triggers are a distant second tier. The composite analysis reveals that the undilute dCAPE trigger underpredicts convection when there is bottom-heavy upward motion but overpredicts convection with low-level downward and upper-level upward motions. The empirical orthogonal function (EOF) analysis on vertical velocity shows that EOF1 (62.65%) exhibits upward motion throughout the troposphere and that EOF2 (28.05%) has lower-level upward motion and upper-level downward motion. Both of them have close relationships with precipitation, indicating the role of vertical velocity in triggering convection. The skill sensitivity analysis shows that the inclusion of 700-hPa upward motion significantly enhances the undilute dCAPE trigger. For the dilute dCAPE trigger, entrainment rate and dCAPE threshold are optimized to improve it. Opposite to dCAPE-type triggers, the Bechtold trigger overemphasizes the low-level vertical velocity and underpredicts the mature and decaying phases of long-lasting convection events. The HCF trigger overemphasizes the near-surface moist static energy and overlooks the vertical velocity. The performance of dCAPE-type triggers on various convective systems over the Amazon region is examined. The eastward-propagating systems are best represented, with only a few underpredictions in their decaying stages. The weak locally occurring systems and marginal phases of westward-propagating systems are easy to underpredict. The revised dCAPE-type triggers perform better on different convection systems and the diurnal cycle of convection.

1. Introduction

A convective parameterization scheme (CPS) is needed to represent the collective effects of subgrid-scale convection in current global climate models (GCMs). The model convection is triggered when some criteria for the possibility of convection are met. Thus, these criteria are commonly referred to as trigger functions in the convective parameterization community. The trigger function largely determines the timing and location of model convection. Hence, it has large impacts on the simulation of many atmospheric phenomena, such as the Madden–Julian oscillation (MJO; Wang and Schlesinger 1999; Zhang and Mu 2005; Lin et al. 2008), intertropical convergence zone (ITCZ; Chao and Chen 2004; Liu et al. 2010), and diurnal cycle of convection (Bechtold et al. 2004; Xie et al. 2004a; Lee et al. 2007, 2008).

Physically, what the trigger function needs to determine is whether (and if so, how) the unstable air at the boundary layer leads to the onset of convection. In different CPSs, this is considered differently. The first issue is to identify the source of the convective air. In some CPSs, the near-surface air is chosen as the source layer of convective air (Donner 1993; Tiedtke 1989; Tawfik and Dirmeyer 2014), while other CPSs choose the layer of maximum moist static energy (Arakawa and Schubert 1974; Zhang and McFarlane 1995). Once the source layer is determined, it needs to know whether this layer of unstable air can develop into convection. It depends on many physical processes and is considered differently in trigger functions. Some consider atmospheric thermodynamic state, such as the atmospheric instability, measured by convective available potential energy (CAPE; Zhang and McFarlane 1995) as important, while others emphasize the role of surface thermodynamic conditions in convection initiation (Tawfik and Dirmeyer 2014). In addition to thermodynamic conditions, dynamical factors are also incorporated in different forms, such as large-scale vertical velocity at the lifting condensation level (LCL; Kain and Fritsch 1990;
Bechtold et al. 2001), boundary layer convergence (Tiedtke 1989), and the CAPE generation rate (dCAPE) from large-scale advective forcing (Xie and Zhang 2000; Zhang 2002). However, it is still uncertain which way is the best to construct a trigger function.

Recently, Suhas and Zhang (2014, hereafter SZ14) systematically evaluated the performance of different trigger functions using long-term single-column model forcing data and intensive observation period (IOP) field data from the Atmospheric Radiation Measurement (ARM) Program. A unique feature of SZ14 is a quantitative comparison of different trigger functions using the high-quality datasets under the same standard. As a follow-up of SZ14, this study will first examine the applicability of the conclusions obtained in SZ14. The CPSs are used globally in the model, but only datasets from two geographic sites (one at the ARM Southern Great Plains site and the other at the ARM Darwin site) were examined in SZ14. Whether the conclusions apply to other sites remains to be seen. More importantly, this study will focus on how to improve the trigger functions. We will also probe the performance of trigger functions on different types of convection systems. Even at the same geographical location, there are different convective systems. How do the trigger functions perform on these different convective systems? Do they have any preference on some types of convective systems over others? Recently, the Green Ocean Amazon (GOAmazon) field campaign was conducted over the central Amazon west of Manaus, Brazil, from January 2014 to December 2015 (Martin et al. 2016). This provides an opportunity for us to answer the above questions by examining the performance of trigger functions in this tropical land region, which is affected by different convection systems (Cifelli et al. 2002; Silva Dias et al. 2002; Williams et al. 2002; Tang et al. 2016).

The rest of the paper is organized as follows: Section 2 describes the trigger functions, GOAmazon dataset, and evaluation method. Main results are presented in section 3, including evaluation of trigger functions, improvement of the first two tiers of trigger functions, performance of dCAPE-type triggers in different convection systems, and evaluation of trigger functions with GOAmazon 2015 data. Section 4 gives a summary.

2. Trigger functions, GOAmazon dataset, and evaluation method

a. Trigger functions

In this study, we follow SZ14 and select the trigger functions of commonly used CPSs, including the Arakawa–Schubert (AS) scheme (Arakawa and Schubert 1974), Bechtold scheme (Bechtold et al. 2001), Donner scheme (Donner 1993), Kain–Fritsch (KF) scheme (Kain 2004), Tiedtke scheme (Tiedtke 1989), and four variants of the Zhang–McFarlane (ZM) scheme (undilute CAPE, dilute CAPE, undilute dCAPE, and dilute dCAPE; Zhang and McFarlane 1995; Zhang 2002; Neale et al. 2008). In addition, we include a recently proposed trigger function, the heated condensation framework (HCF; Tawfik and Dirmeyer 2014). Except the HCF, all other trigger functions have been described in SZ14, so we only briefly describe the HCF trigger function below.

Different from other schemes introduced here, the HCF is not based on parcel concept but defines some new variables to isolate atmospheric boundary state from local surface forcing. The most important one is the buoyant condensation level (BCL), which is defined as the level at which saturation would occur through buoyant mixing alone resulting from sensible heating from the surface. There are four steps to find the BCL: 1) increase the near-surface potential temperature by a small increment, representing the result of surface heating; 2) find the top of the potential mixed layer (PML) where the perturbed near-surface parcel is neutrally buoyant; 3) inside the PML, ensure that the specific humidity is well mixed such that it returns a constant mixed layer specific humidity; and 4) upon mixing, check if saturation occurs at the top of PML by comparing the mixed layer specific humidity with saturation specific humidity there. Repeat these four steps until saturation occurs. This represents the incremental growth of the planetary boundary layer as a result of surface heating. The BCL is the PML at which saturation is reached. When the BCL is obtained, the sum of all potential temperature increments is called temperature deficit $T_{\text{def}}$. The $T_{\text{def}}$ represents the cumulative surface heating needed for convection initiation. When $T_{\text{def}}$ equals to or is smaller than zero ($T_{\text{def}} \leq 0$), it is thought that convection initiates. Refer to Tawfik and Dirmeyer (2014) and Tawfik et al. (2015) for more details. Bombardi et al. (2016) applied this trigger function to the NCEP Climate Forecast System, version 2. They found that it improved the simulation of convection frequency, Indian summer monsoon, and hurricanes owing to the reduction of the false alarm rate.

b. GOAmazon dataset

During this 2-yr field experiment, two 40-day IOPs were also conducted in wet and dry seasons, respectively. The first IOP is from 15 February to 26 March 2014 in the wet season, and the second IOP is from 1 September to 10 October 2014 in the dry season. Here the large-scale forcing for the single-column cloud-resolving model and evaluation dataset of
GOAmazon during the whole year of 2014, the wet season, and the dry season is used first for evaluation and improvement of trigger functions. The data from the second year (year 2015) are then used to independently confirm the improvements on the selected triggers. These datasets represent spatial averages over the analysis domain centered at the System for the Protection of Amazonia (SIPAM) radar station (3.21°S, 60.60°W) with a radius of 110 km (Tang et al. 2016). They are developed based on the European Centre for Medium-Range Weather Forecasts (ECMWF) analyses, which are subsequently constrained with surface and top-of-the-atmosphere observations using the constrained variational analysis approach (Zhang and Lin 1997; Zhang et al. 2001). These constraints improve the quality of large-scale vertical velocity and budgets in operational analysis data and make the datasets suitable for budget analysis and cloud modeling studies (Xie et al. 2004b). There are two versions of the forcing datasets, which are constrained by surface precipitation retrieved from SIPAM radar and the Tropical Rainfall Measuring Mission (TRMM) Precipitation Radar measurements (3B42 dataset), respectively, to address uncertainties in surface rainfall. In this study, we use the forcing datasets constrained by surface precipitation retrieved from SIPAM. There are slight differences between these two datasets, but we find that the main conclusions remain the same when comparing these results from these two datasets. The vertical resolution of the datasets is 25 hPa from 1115 to 15 hPa and the temporal resolution is 3 h. Refer to Tang et al. (2016) for more details about the datasets. We mainly focus on the yearlong dataset during 2014, but the analysis of the datasets during wet and dry seasons are also included throughout the study.

c. Evaluation method

Except for the HCF trigger function, deep convection is determined by cloud depth estimated by the trigger function, consistent with SZ14. Note that not all triggers require a cloud depth of 3 km in their original schemes. Only the Bechtold, KF, and Tiedtke triggers have an explicit cloud depth requirement. Since we focus on deep convection, we apply this requirement to all other trigger functions as well in this study. This is different from how these trigger functions are actually used in their respective cumulus parameterizations. The cloud depth is the thickness between LCL and equilibrium level. When the cloud depth is higher than 3 km, deep convection is thought to have occurred. In the HCF, deep convection occurs when $T_{\text{def}} \leq 0$, regardless of convective cloud depth (Bombardi et al. 2016). We also applied the cloud depth constraint to the HCF trigger using a near-surface parcel, to be consistent with other triggers. The skill score results do not change much (results not shown). In observations, deep convection is identified using precipitation amount as in SZ14, with a threshold of domain average precipitation exceeding 0.5 mm h$^{-1}$ for convection. Note that we do not impose any cloud-top height requirement for observed convection because this information is often not available outside the IOP. Nevertheless, we calculated the cloud-top heights at precipitation rate of 0.5 mm h$^{-1}$ (0.45–0.55 mm h$^{-1}$ bin) during the wet season IOP using the cloud height information in the forcing data and found that the average cloud height is much higher than 3 km (about 4.8 km). Thus, a precipitation rate of 0.5 mm h$^{-1}$ is a reasonable threshold for convection. Based on the predicted and observed convection at each time, the datasets are divided into four categories: correct prediction $a$, overprediction $b$, underprediction $c$, and correct prediction of no convection $d$, which form a 2 × 2 contingency table. To evaluate the trigger function accounting for all of these categories, a skill score (SS) is defined as

$$SS = \frac{A - A_{\text{ref}}}{1 - A_{\text{ref}}},$$

(1)

where $A$ is the percentage of correct prediction (including both $a$ and $d$ in the contingency table), and $A_{\text{ref}}$ is a measure of accuracy of the reference prediction, say, by chance. We adopt the Heidke skill score (HSS) (Schaefer 1990; Hogan et al. 2009), which was also used in SZ14. The HSS is similar to the commonly used equitable treat skill (ETS) but is more equitable according to Doswell et al. (1990) and Hogan et al. (2010). The probability of correct prediction by chance is

$$A_{\text{ref}} = \frac{(a + b)(a + c) + (b + d)(c + d)}{n^2},$$

(2)

where $a$, $b$, $c$, and $d$ are the number of occurrences of correct prediction, overprediction, underprediction of convection, and correct prediction of no-convection cases, and $n$ is the total number of data points ($n = a + b + c + d$). The first term is the correct prediction of convection by chance and the second term is the correct prediction of no convection by chance. Substituting Eq. (2) into Eq. (1) gives the expression for HSS:

$$\text{HSS} = \frac{2(ad - bc)}{(a + c)(c + d) + (a + b)(b + d)}.$$  

(3)

A skill score value of 1 means perfect prediction, 0 means the prediction by chance, and a negative value means that the prediction is worse than that by chance.
3. Results

a. Evaluation of trigger functions

The composites of temperature, moisture, vertical velocity, moisture advection, and dry static energy (DSE) advection in convection and no-convection events in the GOAmazon observation are shown in Fig. 1. The anomalies are relative to the average of the whole year, wet season, and dry season, respectively, for the corresponding periods. When convection occurs, there are cold anomalies in the lower troposphere and warm anomalies in the upper troposphere (Figs. 1a,f,k). Meanwhile, there are also large positive moisture anomalies (Figs. 1b,g,l), upward motion (Figs. 1c,h,m), positive moisture advection (Figs. 1d,i,n), and negative DSE advection (Figs. 1e,j,o) in the entire troposphere.

In terms of seasonal differences, anomalies associated with convection are larger in the dry season than in the wet season. The gray shading indicates the standard error of the mean.
wet season, especially for moisture. The maximum level of large-scale upward motion is higher in the wet season than in the dry season (400 vs 500 hPa). Generally, use of 0.5 mm h\(^{-2}\) as a convection threshold can separate convection from no convection clearly. The results are not very sensitive to other precipitation thresholds (0.3 and 0.7 mm h\(^{-2}\)).

The evaluation results of different trigger functions for the whole year of 2014 and the wet and dry seasons are displayed in Fig. 2. The undilute and dilute dCAPE triggers stand out as the first tier in terms of skill score, with an HSS skill score of 0.70 and 0.64 for the whole year, respectively. The Bechtold and HCF triggers are the distant second tier, with an HSS skill score of only 0.21. All other trigger functions belong to the third tier, with HSS skill score ranging from 0 to 0.12. All trigger functions perform better in the wet season than in the dry season. This may be related to different convection systems in the two seasons, which will be discussed in section 3c. Evaluations of all triggers, except the HCF trigger, which is newly included in this study, are consistent with SZ14, suggesting the robustness of their results. For dilute and undilute dCAPE, the difference is small in the wet season but large in the dry season. This indicates that the impact of entrainment is small when the environment is wet but large when the environment is dry, consistent with Zhang (2009).

To examine if the environmental conditions in the four categories (correct prediction, overprediction, underprediction, and correct prediction of no convection) are distinctly different, Fig. 3 shows the composite of temperature, moisture, vertical velocity, moisture advection, and DSE advection anomalies under each category for the undilute dCAPE trigger. Since dCAPE-type triggers mainly account for the free tropospheric dynamical forcing by large-scale advection, the large-scale vertical velocity, DSE, and moisture advections in the correct prediction and underprediction exhibit remarkable differences (Figs. 3c–e), but temperature and moisture anomalies in the two cases are similar (Figs. 3a and 3b, respectively). In the correct prediction case, upward motion reaches the maximum at 400 hPa. Associated with it are large DSE and moisture advections in the upper levels as well. The underprediction composite shows maximum upward motion between 800 and 600 hPa. Correspondingly, thermodynamic advection features bottom-heavy structure. It is often corresponding to the developing phase of long-lasting convective systems, based on examination of the temporal evolution of precipitation. The overprediction composite exhibits warm and moist anomalies throughout the troposphere below 200 hPa. However, the vertical velocity shows a strong dipole structure, with upward motion above 600 hPa and downward motion below. This structure leads to a warm/dry advection in the lower level and cold/moist advection in the upper level. Although it produces large CAPE as a result of strong upward motion in the middle and upper troposphere, the downward motion in the lower troposphere actually suppresses convection development. The correct prediction of no-convection category shows a similar structure to the no-convection category in Fig. 1. The underprediction and overprediction of convection categories indicate an important role of vertical velocity structure that is not captured well by the undilute dCAPE trigger function. When the lower-level vertical velocity is anomalously upward it underpredicts convection onset, and when the lower-level vertical velocity is anomalously downward it overpredicts convection.

The dCAPE-type triggers implicitly consider the influence of large-scale vertical velocity in CAPE change, since the large-scale advection of DSE and moisture mainly comes from vertical advection. For the Bechtold trigger, it explicitly includes the vertical velocity at the LCL as temperature perturbation. Hence, the vertical velocity may be an important factor for the better
To confirm this, two leading EOF modes of vertical velocity are shown in Fig. 4. The EOF1 features upward motion in the whole troposphere, and EOF2 exhibits upward motion in the lower level and downward motion in the upper level. The EOF1 and EOF2 account for 62.65% and 28.05% of the vertical velocity variance, respectively. Both the first and second principal components (PC1 and PC2) have a good correlation with precipitation, with a correlation coefficient of 0.90 for PC1 and 0.29 for PC2, both significant at the 1% level. The EOF analysis on vertical velocity in the wet and dry seasons exhibits similar characteristics (figure not shown).

To further examine the physical nature of two leading EOF modes, the associated temperature, moisture, apparent heat source $Q_1$, and apparent moisture sink $Q_2$ are also examined (Fig. 5). The EOF1 exhibits large cold anomalies below 800 hPa and warm anomalies above 600 hPa, while the EOF2 shows the cold anomalies from the surface to 350 hPa (Fig. 5a). Both EOF1 and EOF2 have large moisture content in the whole troposphere with maximum at about 700 hPa, but the magnitude in EOF1 is much larger than EOF2 (Fig. 5b). The EOF1 shows deep heating and drying in the whole troposphere (Figs. 5c and 5d, respectively). The heating and drying depth in the EOF2 is much shallower but can also extend to about 400 hPa. Further examination of the cloud fraction associated with EOF1 and EOF2 in the wet and dry seasons shows that EOF1 is associated with more high cloud and EOF2 is associated with more midlevel cloud. The cloud top for EOF1 reaches 11.2 km and cloud thickness is about 6.9 km, whereas they are 7.5 and 3.2 km, respectively, for EOF2. Therefore, both EOF1 and EOF2 belong to deep convection, although the latter is a little shallower. Since dCAPE is measured by the vertical integral of DSE and moisture advection, the

![Fig. 3. The composites of (a) temperature (K), (b) specific humidity (g kg$^{-1}$), (c) vertical velocity (hPa h$^{-1}$), (d) dry static energy advection (K h$^{-1}$), and (e) specific humidity advection (g kg$^{-1}$ h$^{-1}$) for correct prediction of no convection (black line), correct prediction (red line), overprediction (yellow line), and underprediction (blue line) using the undilute dCAPE trigger for the whole year of 2014. The gray shading indicates the standard error of the mean.](image-url)
dominant contribution comes from EOF1. On the other hand, the Bechtold trigger considers the lower-level vertical velocity. Thus, it represents EOF2 well. Since EOF1 accounts for larger variance and has a better relationship with precipitation than EOF2, dCAPE-type triggers perform better than the Bechtold trigger.

b. Improvement of trigger functions

The EOF structure of large-scale vertical velocity, high correlation between their PCs and precipitation, and vertical velocity characteristics of over- and under-prediction of convection indicate that the undilute dCAPE trigger function can be improved by incorporating the structure of vertical velocity. Moreover, a multivariate regression analysis on vertical velocity reveals that the underprediction (Fig. 3c) can be constructed as 0.61 EOF1 + 0.74 EOF2 + 0.09, while the overprediction as 0.60 EOF1 − 0.96 EOF2 − 0.14. In other words, underprediction is associated with positive EOF2 pattern and overprediction is associated with negative EOF2 pattern. This suggests that considering EOF2 of vertical velocity will improve the undilute dCAPE trigger by reducing both the underprediction and overprediction. A direct way to consider EOF2 is to require the lower-level vertical velocity be upward, with the choice of the optimal level to be determined. When this requirement is added, the dCAPE threshold may need to be adjusted as well to achieve the best skill. But first, we examine how the skill score varies with dCAPE threshold without considering vertical velocity. In Fig. 2, the skill score was based on a dCAPE threshold of 65 J kg$^{-1}$ h$^{-1}$, the same as in SZ14, which may or may not be an optimal value for convection in the Amazon region. Furthermore, it is also uncertain what precipitation rate should be used to identify convection in observations. Therefore, we use a range of precipitation and dCAPE thresholds to calculate the skill score for each of the combinations. We vary the dCAPE threshold from 0 to 300 J kg$^{-1}$ h$^{-1}$ with a bin interval of 10 J kg$^{-1}$ h$^{-1}$ and precipitation rate from 0.1 to 2.0 mm h$^{-1}$ varying by 0.1 mm h$^{-1}$. Figure 6a plots the HSS as functions of dCAPE and precipitation thresholds. For a given precipitation threshold that defines convection, the HSS first increases with dCAPE threshold and then decreases after reaching a maximum. The dependence of HSS on precipitation threshold and dCAPE threshold is nearly linear. For a certain skill score, the higher the precipitation threshold, the higher the dCAPE threshold. This is understandable since precipitation is highly correlated with undilute dCAPE (at a correlation coefficient of ~0.90). When the definition for convection is more stringent (e.g., a higher precipitation threshold in the observation and a higher dCAPE threshold in the trigger function), fewer precipitation events will be classified as convection. As such, there will be fewer correct prediction, over-prediction, and under-prediction of convection but more correct prediction of no convection. For a precipitation threshold of 0.5 mm h$^{-1}$ as used in Fig. 2, it corresponds to a broad range of dCAPE threshold from 60 to 110 J kg$^{-1}$ h$^{-1}$ for the best HSS value of 0.70. In Fig. 2a, the dCAPE threshold of 65 J kg$^{-1}$ h$^{-1}$ is within this range. For skill dependence on the dCAPE threshold and upward motion in the troposphere, a similar analysis is performed and the result is shown in Fig. 6b. The best HSS skill of 0.76 is achieved for dCAPE value of 65 J kg$^{-1}$ h$^{-1}$ and upward motion at about 700 hPa. Therefore, we add the following requirement to improve the undilute dCAPE trigger: the vertical velocity at 700 hPa must be upward. This improves the representation of developing phase of long-lasting convection events and reduces false alarm rates of cases.
with low-level dynamical suppression. The comparison of original and revised undilute dCAPE trigger is shown in Table 1. For the whole year of 2014, although the revised trigger slightly decreases the correct prediction (from 342 to 324) and increases the underprediction (from 73 to 91), the overprediction is reduced by about half (from 151 to 74). Wet and dry seasons exhibit similar results. Hence, the improvement of revised undilute dCAPE trigger is mainly from the reduced overprediction cases.

Now we turn our attention to dilute dCAPE trigger. The composites of temperature, moisture, vertical velocity, DSE, and moisture advections in the four prediction categories are shown in Fig. 7. The temperature anomalies in the overprediction are comparable to those in the correct prediction and underprediction, but the moisture anomalies in the overprediction are the largest (Figs. 7a,b). The vertical velocity in the overprediction is similar to that in the undilute dCAPE trigger, with upward motion in the upper level and downward motion in the lower level (Fig. 7c). This also leads to cooling and moistening in the upper level (Figs. 7d,e) and heating and drying in the lower level. However, in the current version of the dilute dCAPE trigger, the number of overpredictions is only 8 (compared to 151 in the undilute dCAPE trigger). The vertical velocity, DSE advection, and moisture advection in the correct prediction and underprediction show similar structures but with much smaller amplitudes for underprediction. This indicates that unlike the undilute dCAPE trigger, the threshold of dilute dCAPE trigger may not be suitable. Note that both undilute and dilute dCAPE triggers use the same dCAPE threshold (65 J kg\(^{-1}\) h\(^{-1}\)). As shown in Fig. 6a, this value works well for the undilute dCAPE trigger. Since entrainment dilution reduces CAPE generation, this threshold value may be high for the dilute dCAPE trigger. Since entrainment dilution reduces CAPE generation, this threshold value may be high for the dilute dCAPE trigger. This is confirmed in Fig. 8a, which shows the sensitivity of HSS to dCAPE and precipitation thresholds. The best dilute dCAPE threshold is found to be about 40 J kg\(^{-1}\) h\(^{-1}\) when precipitation threshold is set as 0.5 mm h\(^{-1}\). To see if including the EOF2 of vertical velocity also improves the dilute dCAPE trigger, we examined the sensitivity of HSS to dCAPE threshold and
upward motion at different levels. Surprisingly, the HSS skill is insensitive to the upward motion, whichever level is included (figure not shown). This may be because entrainment dilution is most effective at the lower levels, and advection there has been weighted more than the levels above. Instead, it is sensitive to entrainment rate, which controls the degree of dilution (Fig. 8b). It is shown that the dCAPE threshold range for high skill score (HSS > 0.6) is between 25 and 40 J kg\(^{-1}\) h\(^{-1}\) when the entrainment rate is larger than 10\(^{-3}\) m\(^{-1}\). But when entrainment rate is reduced, the HSS becomes much larger. The highest skill occurs when the entrainment rate is 0.25 × 10\(^{-3}\) m\(^{-1}\) and dCAPE threshold is 55 J kg\(^{-1}\) h\(^{-1}\). The comparison between the original and revised dilute dCAPE triggers is shown in Table 2.

The performance of Bechtold and HCF triggers follows that of dCAPE-type triggers in the skill score and thus is examined next. The composites of temperature, moisture, and vertical velocity for Bechtold and HCF triggers are shown in Fig. 9. For Bechtold trigger, the boundary layer is cold in both correct prediction and underprediction (Fig. 9a). Both correct prediction and underprediction have large positive moisture anomalies in the whole troposphere, especially for the correct prediction. The overprediction is moist below 650 hPa and dry above. The correct prediction exhibits strong upward motion in the whole troposphere, with a broad maximum from 800 to 400 hPa. The underprediction also exhibits strong upward motion in almost the entire troposphere with a maximum at 400 hPa, except weak downward motion below 800 hPa. Comparing the time series of underprediction events with that of observed precipitation, it is found that the underpredictions often correspond to the mature and decaying phases of long-lasting convection systems, during which convective downdrafts reduce large-scale upward motion in the troposphere.
lower levels. This is consistent with SZ14. It is opposite in the overprediction: the upward motion occurs in the lower troposphere below 650 hPa and downward motion aloft. Since the Bechtold trigger only considers the lower-level vertical velocity, the lower-level vertical velocity is similar between correct prediction and over-prediction (Fig. 9e). In comparison with the undilute dCAPE trigger (Fig. 3c), the vertical structure of vertical velocity in overprediction of the two triggers is almost opposite. Moreover, the correct prediction (under-prediction) in the Bechtold trigger is similar to the underprediction (correct prediction) in the undilute dCAPE trigger. It suggests that in contrast to undilute dCAPE trigger, the information of upper-level vertical velocity should be included in the Bechtold trigger to represent the mature and decaying phases of long-lasting convection systems. This way, it enhances the prediction skill by reducing the number of over- and underpredictions (figure not shown).

For the HCF trigger, the largest difference in temperature and moisture among correct prediction, under-prediction, and over-prediction of convection occurs near the surface (Figs. 9b,d). It is cold and wet in both correct prediction and underprediction but too warm and a little dry in the overprediction (Figs. 9b,d). The too-warm and dry conditions are caused by lower-level downward motion (Fig. 9f). Since the HCF trigger only considers the near-surface temperature and moisture, convection will be predicted when the near-surface moist static energy is high enough. In observations, the correlation between precipitation and near-surface moist static energy is not significant. This trigger can capture some surface heating-induced convection in wet season. But in dry season it misses all the convection events since the near-surface is much drier (about 1 g kg\(^{-1}\) drier than the wet season). This trigger overlooks large-scale vertical velocity, so in the underprediction the upward motion is the largest (Fig. 9f). When vertical velocity is included and temperature deficit is relaxed to consider dynamical forcing more, its skill can be improved to some degree (figure not shown).

The purpose of a trigger function is to invoke the CPS. Strictly speaking, whether convection is finally predicted by the CPS is also constrained by the cloud model and closure assumptions used in the CPS. To determine the
final prediction results, the datasets are further applied to the cloud model and closure assumption from Community Atmospheric Model, version 5 (CAM5; Neale et al. 2010), after passing the dCAPE-type trigger functions. The closure is changed to dCAPE (Zhang 2002) with a threshold value of 65 J kg$^{-1}$ h$^{-1}$ to be consistent with the trigger function. In this application, whether there is deep convection is determined by nonzero cloud base mass flux. Surprisingly, it is found that the final prediction results remain almost unchanged compared to those from the trigger function alone for both the dilute and undilute dCAPE triggers. For the revised dCAPE-type triggers, it shows the same results. This suggests that the dCAPE-type trigger functions largely determine the occurrence of convection in this scheme.

c. Performance of dCAPE-type triggers in different convection systems

Over the Amazon region, there are three different types of convection systems, namely, locally occurring systems (LOS), westward-propagating systems (WPS), and eastward-propagating systems (EPS) (Cifelli et al. 2002; Silva Dias et al. 2002; Williams et al. 2002; Tang et al. 2016). The LOS often occur in the afternoon because of solar heating at the surface and are small in size (area less than 1000 km$^2$), scattered, and short-lived (about several hours). The WPS often start at the northeast coast of Brazil by sea breeze and propagate westward into the Amazon region as squall lines. They are often associated with midlevel easterlies and affect the Amazon region in the morning. The EPS often form in the Amazon basin as mesoscale convection systems, covering areas larger than 1000 km$^2$ and lasting about a day. The performance on these three different convective systems in wet and dry seasons is listed in Table 3 based on radar loop and satellite infrared images (Tang et al. 2016). In the wet season, there are 19 LOS, 38 WPS, and 19 EPS. In the dry season, there are 24 LOS, 12 WPS, and no EPS. Hence, the dominant systems in wet and dry seasons are different: remote WPS dominate in wet season while LOS dominate in dry season.

How do the trigger functions perform in these different convection systems in wet and dry seasons? Here, we select one of the best trigger functions, the dilute dCAPE trigger, as an example to compare the performance of its...
original and revised versions (Table 3). For the original dilute dCAPE trigger, in the wet season, 11 of 19 LOS are correctly predicted, and 8 are underpredicted owing to weak magnitude. For WPS, 21 of 38 are correctly predicted, and 17 are underpredicted when the systems start to enter or leave the domain. The EPS is best predicted, with only 3 underpredicted in the decaying stage of the systems. This may be because EPS are often associated with large-scale dynamical forcing (Williams et al. 2002), which is represented well by the dilute dCAPE trigger. Since EPS only occurs in the wet season, this may be one of the reasons why trigger functions perform better in the wet season shown in Fig. 2. After the revision, the trigger performs better in all three convection systems, especially for EPS and LOS. The LOS are underpredicted only once and no EPS are underpredicted. For WPS, although the correct prediction is increased from 21 to 32, 6 are still underpredicted. In dry season, only 6 of 24 LOS are correctly predicted by the original trigger, and 18 are underpredicted due to weak magnitude. It is similar for WPS: only 4 of 12 are correctly predicted, and 8 are underpredicted in their marginal positions to the domain. After the revision, the correct predictions of LOS and WPS increased to 20 and 8, respectively. There are still 4 underpredictions for each of them. By using GOAmazon dataset, convection is predicted in a domain with radius of 110 km. The horizontal scale of many LOS is much smaller than this domain, and WPS only cover part of this domain when they start to enter or leave the domain. This may be the main reason why there are still some WPS and LOS underpredicted.

Different convection systems occur at different times of a day; for example, LOS often occur in the afternoon because of the solar heating, while WPS and EPS often affect the domain in the morning (Tang et al. 2016). Hence, the representation of different convection systems reflects the ability to reproduce the diurnal cycle of convection. Figure 10 shows the diurnal cycle of...
convection events in both the observation and predictions from dCAPE-type triggers. In observations, convection events peak at 1400 local solar time (LST) of the day in both the whole year and the dry season. In the wet season, convection events have two peaks, one at 0800 LST and the other at 1400 LST. The peak at 1400 LST is due to LOS, and the peak at 0800 LST in the wet season is due to WPS and EPS. The original dilute dCAPE trigger generally captures the peak at 1400 LST in the whole year and dry season but misses the peaks at 0800 and 1400 LST in the wet season. It also underestimates convection events all day long in the whole year and dry season, while it overestimates convection events in wet season. The revised dilute dCAPE predicts convection events more comparably to observation for the whole day in three periods. Moreover, the peak at 1400 LST in the wet season is captured, although the peak at 0800 LST is still missed. The original undilute dCAPE trigger overestimates the convection events at around 1400 LST peak time for three periods, but the revised trigger matches the observation very well.

d. Testing trigger function modifications with GOAmazon 2015 data

The above analysis is based on data from year 2014. Recently, the dataset from year 2015 also became available. This provides an opportunity for us to use it to verify our conclusions independently, especially for the improvement. As shown in Fig. 11a, the evaluation results from 2015 are similar to those from 2014. The dCAPE-type triggers still stand out as the first tier, with the skill of approximately 0.6. The second tier includes KF and dilute CAPE, in addition to the Bechtold and HCF triggers, with the skill of approximately 0.15 (Fig. 11a). The revision of dCAPE-type triggers shown in Tables 1 and 2 is based on the dataset from 2014. Figure 11b shows the prediction skills from the original and revised triggers using data from 2015. It shows that after including 700-hPa upward motion in the undilute dCAPE, the skill is increased from 0.61 to 0.69. This is mainly due to the decreased overprediction. For the dilute dCAPE trigger, the skill is increased from 0.62 to 0.79 using optimized dCAPE threshold and entrainment rate from 2014. This is mainly due to the increased correct prediction. This verification using independent data from 2015 greatly enhances our confidence in the revision.

4. Conclusions

In this study, different trigger functions are evaluated using GOAmazon data. It is found that dCAPE-type triggers belong to the first tier, with skill of approximately 0.60. The second tier includes Bechtold and HCF triggers, with skill of approximately 0.20, and all others belong to the third tier, with skill ranging from 0 to 0.10 (Fig. 2). The composite analysis of four prediction categories in undilute dCAPE trigger shows that the correct prediction exhibits upward motion in the whole troposphere, which produces large CAPE (Fig. 3c). The overprediction shows low-level downward and upper-level upward motion. This structure leads to large negative low-level moisture advection and upper-level DSE advection. While capable of large CAPE generation, it actually suppresses convection development because of dynamical suppression from downward motion in the lower troposphere. The underprediction exhibits bottom-heavy upward motion. Compared to the overprediction, this structure generates less CAPE, but it often corresponds to the developing phase of long-lasting convection events. Hence, the vertical structure of vertical velocity is important for the prediction results. This is also confirmed by EOF analysis of vertical velocity. It shows that EOF1 exhibits upward motion in the whole troposphere and that EOF2 exhibits low-level upward motion and upper-level downward motion (Fig. 4). The EOF1 is a typical deep convection mode and EOF2 is a shallower deep convection mode (Fig. 5). Both EOF1 and EOF2 are closely related to precipitation, with correlation coefficients of 0.90 and 0.29, respectively.

For the undilute dCAPE trigger, when the upward motion at 700 hPa is required in addition to the original dCAPE threshold of 65 J kg$^{-1}$ h$^{-1}$, the HSS can be enhanced from 0.70 to 0.76 for the yearlong data of 2014

<table>
<thead>
<tr>
<th>Time period</th>
<th>Dilute dCAPE</th>
<th>Total</th>
<th>Cor</th>
<th>Und</th>
<th>Total</th>
<th>Cor</th>
<th>Und</th>
<th>Total</th>
<th>Cor</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Wet season</td>
<td>Original</td>
<td>19</td>
<td>11</td>
<td>8</td>
<td>38</td>
<td>21</td>
<td>17</td>
<td>19</td>
<td>16</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Revised</td>
<td>24</td>
<td>6</td>
<td>18</td>
<td>12</td>
<td>4</td>
<td>8</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Dry season</td>
<td>Original</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Revised</td>
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</table>
This improvement is mainly from the reduction of overprediction. It reduces the false alarm rate of cases with low-level dynamical suppression.

In the dilute dCAPE trigger, the composites of correct prediction and underprediction show similar structures, but the magnitude is much weaker in the underprediction category (Fig. 6). It suggests that dCAPE threshold and entrainment rate, which controls the degree of dilution, need to be optimized. The sensitivity of skill score to dCAPE threshold and entrainment rate shows that the highest skill is obtained when the dCAPE threshold is set to $55 \, \text{J} \, \text{kg}^{-1} \, \text{h}^{-1}$ and entrainment rate is reduced from $1 \times 10^{-3}$ to $0.25 \times 10^{-3} \, \text{m}^{-1}$ (Fig. 7 and Table 2). After the revision, the skill of dilute dCAPE increases from 0.64 to 0.82 for the data of 2014.

We also examined two second-tier trigger functions in detail. For Bechtold trigger, the composite analysis shows that it is opposite to undilute dCAPE. The underprediction shows maximum upward motion in the upper level but slight downward motion near the surface, which often corresponds to the mature and decaying phase of long-lasting convection systems. The overprediction exhibits low-level upward motion and upper-level downward motion (Fig. 8e). For the HCF trigger, it does not consider vertical velocity directly but only emphasizes the near-surface temperature and
moisture. Hence, the cases with high near-surface moist static energy but lower-level downward motion are easily overpredicted (Figs. 8b,d,f).

The Amazon region is most influenced by westward-propagating systems in the wet season and locally occurring systems in the dry season (Table 3). One of the best trigger functions, dilute dCAPE, is chosen to examine its performance for different convection systems. The dilute dCAPE trigger performs best for eastward-propagating systems, with only three underpredictions in their decaying phases by the original trigger and no underpredictions by the revised one. The locally occurring systems are often underpredicted owing to weak magnitude. When the westward-propagating systems start to enter or leave the domain, they are often underpredicted. The revised dilute dCAPE trigger improves the prediction of both locally occurring and westward-propagating systems. Different convection systems are closely related to the diurnal cycle of convection (Fig. 10). The observation shows a single peak at 1400 LST in the dry season and whole year data, mainly because of locally occurring systems. The wet season shows a double peak, with a primary peak at 1400 LST and a secondary peak at 0800 LST related to propagating systems. Compared to the original version, the revised dCAPE-type triggers also perform better in the diurnal cycle of convection events.

In this study, based on the GOAmazon field data, it is found that the revised dilute dCAPE trigger (with dCAPE threshold of 55 J kg$^{-1}$ h$^{-1}$ and entrainment rate of 0.25 × 10$^{-3}$ m$^{-1}$) can capture various types of convection systems over the Amazon region and its skill is the highest (0.82 for the whole year of 2014). Hence, this trigger function is recommended for the Amazon region. In this study, we adopt the composite and EOF analyses to find the key physical processes related to convection and conduct skill sensitivity analysis on multiple parameters to optimize the trigger function. Other researchers can adopt similar approaches to improve their preferred triggers. We should point out that the threshold values for trigger function improvement may need to be readjusted for other locations. However, in climate models, one threshold is used globally to identify the possibility of convection. The possible impact of these differences is beyond the scope of this study.

Note that the convection trigger function in this study means that if the conditions in the trigger function are met the convection scheme is invoked. It does not necessarily mean convection is initiated, consistent with SZ14. The initiation of convection is also constrained by cloud model and closure assumption. By using dCAPE-type triggers, we find that cloud model and closure do not impose additional constraints on convection initiation for the revised Zhang–McFarlane scheme. However, since cloud model and closure in different CPSs are different, this conclusion may change for other schemes.

Acknowledgments. This material is based upon work supported by the National Science Foundation Grant AGS-1549259 and the U.S. Department of Energy, Office of Science, Biological and Environmental Research Program (BER), under Award DE-SC0016504. We thank Dr. Shuaiqi Tang of LLNL for providing the GOAmazon dataset. We also thank the anonymous reviewers for their constructive comments, which have helped improve the quality of the manuscript.

REFERENCES


