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Precipitation efficiency and its role in cloud-radiative feedbacks to climate variability

Chung-Hsiung Sui, Masaki Satoh, Kentaroh Suzuki

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Corresponding Author: Chung-Hsiung Sui: Department of Atmospheric Sciences, National Taiwan University, No. 1 Sec. 4, Roosevelt Rd., Taipei 10617, Taiwan, sui@as.ntu.edu.tw

Masaki Satoh: Atmosphere and Ocean Research Institute, The University of Tokyo, 5-1-5 Kashiwanoha, Kashiwa, 277-8564, Japan, satoh@aori.u-tokyo.ac.jp

Kentaroh Suzuki: Atmosphere and Ocean Research Institute, The University of Tokyo, 5-1-5 Kashiwanoha, Kashiwa, 277-8568, Japan, ksuzuki@aori.u-tokyo.ac.jp
Abstract

Precipitation efficiency (PE) is a useful concept for estimating precipitation under a given environmental condition. PE is used in various situations in meteorology: to evaluate severe precipitation associated with a single storm event; as a parameter of cumulus convective parameterization; and to separate clouds and precipitation in climate projection studies. PE has been defined in several ways. In this review, we start with definitions of PE from microscopic and macroscopic perspectives, and provide estimates of PE based on observational and modeling approaches. Then, we review PE in shallow and organized deep convective systems that provide either a conceptual framework or physical constraints on representations of convection in models. Specifically, we focus on the roles of PE in cloud-radiative feedbacks to climate variability. Finally, we argue the usefulness of PE for investigating cloud and precipitation changes in climate projection studies.

Keywords precipitation efficiency; cloud microphysics; hydrological cycle; cumulus parameterization; cloud feedback
1. Introduction

Precipitation is produced by cloud microphysics processes in response to dynamical and thermodynamic forcing at different spatial and temporal scales. The precipitation flux at the surface is the final destination in the atmospheric water cycle from surface evaporation, condensation of water vapor to clouds, and precipitating hydrometeors. The fraction of total condensation in an atmospheric column falling to the surface is a physical measure of precipitation efficiency (PE) that determines the portion of total water vapor influx at the surface as precipitation while the remaining vapor influx can moisten the environmental atmosphere.

Since precipitation processes are at the heart of meteorological research and prediction, the concept of PE is used in various fields of meteorology. For example, PE is explicitly used in the diagnosis of observational and numerical results, and implicitly used as a key parameter for numerical models. PE is used as a measure of the cloud and precipitation separation of condensed vapors in the water cycle. PE also plays a key role in reducing the uncertainties of climate sensitivity associated with cloud simulations in climate models.

Precipitation processes are generally parameterized in atmospheric general circulation models (GCMs) with a grid resolution coarser than several tens of kilometers, while they are treated explicitly in high-resolution non-hydrostatic cloud permitting/resolving models with cloud microphysics. Advances in remote sensing of meteorological variables, numerical models, and computational facilities have enabled improved simulation and prediction of weather and climate system in recent years (e.g. Bechtold et al. 2014). However, cloud and precipitation processes remain challenging to model. Uncertainties in modeling cloud and precipitation processes at different spatial and temporal scales cause difficulties in estimating and predicting quantitative precipitation, errors in forecasting tropical cyclone intensity, and biases in seasonal to
sub-seasonal (S2S) predictions (e.g. Arakawa and Wu 2013; Vitart 2017; Kim et al. 2018). Correctly resolving coupled water cycle-atmospheric circulation in climate models is critical in modeling climate variability and climate change (e.g. Stevens and Bony 2013).

In this review, we introduce several definitions of PE, based on cloud microphysics and the large-scale water cycle, and different evaluations of PE for various storms using observations and numerical models (Section 2). We then briefly discuss the concept of cumulus parameterization in tropical weather and climate to emphasize the usefulness of PE in comparing and understanding cumulus schemes in GCMs and non-hydrostatic models (Section 3). In Sections 4 and 5, we review various scientific issues related to cloud microphysics in shallow and deep clouds, respectively, that are crucial in interactions between cloud, radiation, and large-scale dynamics. In Section 6, we discuss changes in clouds associated with global warming, particularly through simulations by GCMs and higher-resolution global non-hydrostatic models. The robust changes in clouds are attributed to fundamental thermodynamics and cloud microphysics. It appears that the net cloud feedback to warming is crucially affected by changes in PE in the warming climate.

2. Definition and quantification of PE based on models and observations

In the early stage of numerical modeling of convection in the late 1960s, warm-rain was first treated in a bulk water-continuity model (Kessler 1969, 1995). Ice cloud microphysics have been included in numerical models since the 1980s in the form of a bulk scheme as shown in Fig. 1 (e.g. Lin et al. 1983; Tao and Simpson 1993; Rutledge and Hobbs 1983, 1984; Ferrier et al. 1995). To quantify the performance of models in simulated convective systems, PE was introduced to estimate the ratio of surface rain rate to the sum of vapor condensation and deposition rates (e.g. Murray and Koenig...
Sui et al. (2007) define a more complete PE based on vertically integrated budgets of water vapor ($q_v$) and total cloud content ($C$):

\[
\partial_t [q_v] = [\text{CONV}_{q_v}] + E_s - [SI_{q_v}] + [SO_{q_v}],
\]

(1)

\[
\partial_t [C] = [\text{CONV}_C] - P_s + [SI_{q_v}] - [SO_{q_v}],
\]

(2)

where $C$ is the sum of all categories of water substance, which normally consist of non-precipitating hydrometeors (cloud water and ice) and precipitating hydrometeors (rain, snow, graupel/hail). $[\text{CONV}_{q_v}]$ and $[\text{CONV}_C]$ denotes convergence of water vapor and hydrometeors, and $\partial_t [q_v]$ and $\partial_t [C]$ are local tendency change in water vapor and total cloud content. $P_s$ is mass flux of precipitating hydrometeors falling to the surface.

$[SI_{q_v}]$ and $[SO_{q_v}]$ represent the vertically integrated sink and source terms for $q_v$ and $C$ that consist of vapor condensation/deposition rates ($C_{vw}$, $D_{vi}$, $D_{vs}$, $D_{vg}$), evaporation of raindrops ($E_{rv}$, $E_{sv}$, $E_{gv}$), melting of frozen clouds, and so on. See Fig. 1 for details.

A straightforward definition of PE is the fraction of condensed particles that subsequently rain out. This can be expressed based on the total cloud budget (2) as

\[
\text{PE} \approx \frac{P_s}{[SI_{q_v}]},
\]

(3)

which is commonly used in many modeling studies of convection. Such a definition of PE is termed ‘cloud microphysics PE’ (CMPE) because of its microscopic perspective. Among modeling studies of different convective systems, Ferrier et al. (1995) obtained a reasonable estimate of PEs for mid-latitude and tropical squall systems from a sophisticated cloud model. Miltenberger et al. (2018) simulated mixed-phase convective clouds during the COnvective Precipitation Experiment (COPE) field campaign over the southwestern peninsula of the United Kingdom in 2013. They obtained a PE of around 16~24% from different aerosol scenarios in Cloud–AeroSol Interacting Microphysics (CASIM) module. The studies of simulated water budgets for typhoons in the tropics show that an averaged PE per typhoon is $\sim 60\%$ (Sui et al. 2005;

Jiang and Smith (2003) simulated precipitation by upslope lifting over isolated mountains in cold climates. They estimated essential steady-state volume-averaged cloud physics based on single-pathway snow formation models with both linear and nonlinear accretion formulations. The linear model suggests that the precipitation efficiency is determined by three timescales—the advection timescale ($\tau_a$), fallout timescale ($\tau_f$), and a constant timescale for snow generation ($\tau_{cs}$). Snow generation is controlled by the ratio of $\tau_{cs}/\tau_a$ and the fraction of the snow that falls to the ground is controlled by the ratio of $\tau_f/\tau_a$. The utility of the timescale concept is reduced by nonlinear accretion. Huang et al. (2014) analyzed further the impact of orography on the PEs in Typhoon Morakot. They found that the PEs were 60–75% over ocean and more than 95% over the mountain area. Morales et al. (2018) performed a study of orographic precipitation response to microphysical parameter perturbations in atmospheric rivers flowing over bell-shape mountains (an idealized modeling study for the Olympic Mountain Experiment, OLYMPEX; Houze et al. 2017). They analyzed PE based on $P_s = \text{PE} \times$ vertically integrated total condensation rate over sub-regions of limited spatial extent, so that PE is also affected by horizontal advection of condensate. They found that PE ranged from 20% to 200% under various microphysical parameters and mountain locations. PE can be larger than 100% at downwind top of the bell-shaped mountain.

Besides the above-defined PE as the fraction of condensed particles that subsequently rains out, Langhans et al. (2015) defined PE in a Lagrangian particle framework as the probability of a water molecule to reach the surface given that it condensed at least once at an earlier time. Their large-eddy simulations of individual cumulus congestus clouds show that the clouds convert entrained vapor to surface
precipitation with an efficiency of around 10%. About 1/3 of the water that passes through the cloud does so by entering through the cloud base while the other 2/3 enters the cloud by entrainment in the free troposphere above cloud base. The PE associated with the vapor entrained through the cloud base (46-50%) is higher than the PE associated with laterally entrained water (25-30%). The larger efficiency with which that entrained water through the cloud based is converted into surface precipitation results from the larger efficiencies with which it condenses, forms precipitating hydrometeors, and reaches the surface.

In addition to the above modeling studies of PE for various types of convection, how the PE changes in the warming climate is of fundamental importance. Muller (2013) investigated the effect of a warming scenario on precipitation extremes in a cloud-resolving model with explicit cloud microphysics. They found that the amount of the extreme changed with increasing temperature, but PE did not. More studies of changes of PE in climate warming are reviewed in Section 6. A summary of PE in the aforementioned modeling studies is listed in Table 1.

Since it is difficult to observe cloud microphysical quantities, PE may be defined based on the total water budget (1)+(2) for a convective event averaged over its life time and areal extent such that

$$ P_s = -\partial_t[q_v] + [CONV_{qv}] + E_s - \partial_t[C] + [CONV_C], \quad (4) $$

$$ \text{PE} \equiv P_s / (\text{all sources of } P_s) \approx P_s / (H[CONV_{qv}] + E_s), \quad (5) $$

Note that each of the RHS terms in (4) can contribute to $P_s$ when positive and $H$ in (5) denotes Heaviside function. Sui et al. (2007) showed that the PE defined by (5) including all moisture and hydrometeor sources associated with surface rainfall processes are highly correlated with PE defined by (3) in cloud resolving model simulations. The linear correlation coefficient and root-mean-squared difference between the two PEs are insensitive to the spatial scales of averaged data and are
moderately sensitive to the time period of averaged data. The PE defined in (5) was termed ‘large scale PE’ (LSPE) because of its macroscopic perspective (Li et al. 2002; Tao et al. 2004; Sui et al. 2007).

Earlier studies have attempted to determine PE from approximate forms of the water vapor budget based on observations from surface rain gauge networks, radar reflectivity maps, radio sounding, and aircraft flights (e.g. Braham 1952; Auer and Marwitz 1968; Fankhauser 1988; Rauber et al. 1996). These studies estimated PE as the ratio of the surface rainfall rate to the rate of boundary layer moisture supply averaged over the area and period of respective observations. Some of the studies estimated the boundary layer moisture supply using aircraft measurements of upward mass flux and humidity through the cloud base.

There are a few studies estimating PE based on cloud budget using radar-retrieved cloud microphysical parameters along with other observations. Chong and Hauser (1989) estimated PE based on the water budget by retrieved thermodynamic and microphysical quantities (like condensation in updraft, Cc) using radiosonde and Doppler radar data. Recently, Chang et al. (2015) estimated PE, averaged over its life time, using the ratio of total rainfall flux to accumulated moisture flux retrieved from S-band dual-polarization Doppler radar (S-Pol) and three-hourly sounding data at the Ping-Dong station in Taiwan.

The observed events and estimated PEs by the aforementioned studies are summarized in Table 2. Note that these studies had to make crucial assumptions such as the steady state of the boundary layer moisture budget during the observation time. As a result, uncertainties are to be expected in their PE estimates.

PE can also be defined based on a thermodynamic budget, similar to the PE defined by cloud and water budgets in (3) and (5). This is discussed by Shen and Li (2011), who showed that radiative flux convergence is an important source of rainfall. The
Precipitation Radar (PR) on board the Tropical Rainfall Measuring Mission (TRMM) provided measurements of vertical profiles of rainfall reflectivity in the global tropics. These satellite measurements are used with a cloud-resolving model to retrieve net heat release by condensation and cloud re-evaporation. Using this physical quantity along with the TRMM rainfall products, Shige et al. (2004, 2009) estimated the ratio of vertically integrated latent heat to surface precipitation:

$$ R_{\text{conv}} = \frac{C_p}{L_v} \int_{z_0}^{z_t} \frac{\rho L H(z)}{P_c} \, dz $$

(6)

where $LH$ is the retrieved net heat release by condensation and evaporation of water vapor in different precipitation top height ($z_t$) from the TRMM PR, $P_c$ is the surface precipitation at the lowest level, $\rho$ is air density, $C_p$ is the specific heat of air at constant pressure, and $L_v$ is the latent heat of vapor. According to Figure 7 of Shige et al. (2004), PE corresponds to $R_{\text{conv}}^{-1}$ for convective clouds, which is estimated as about $R_{\text{conv}}^{-1} \sim 0.7$ for clouds with precipitation top height between 6 and 14 km. For anvil clouds, $R_{\text{anvil}}^{-1}$ corresponds to PE by using precipitation at the melting level. According to Shige et al. (2004), $R_{\text{anvil}}^{-1} \sim 2.0$, and $R_{\text{anvil}}^{-1}$ is generally larger than PE because of the evaporation of rain drops below the melting level. This is consistent with the fact that anvil clouds are formed by cloud waters detrained from convective clouds in other columns.

Other studies have used different quantities to represent PE indirectly. Lau and Wu (2003) used the residence time of liquid water, defined as the ratio of the liquid water path (LWP) to surface precipitation. Stephens and Ellis (2008) introduced the ratio of global changes in precipitation to global changes in water vapor as a gross indicator of the global PE under global warming. These studies are introduced in Section 6.

3. Ensemble mean cumulus PE in tropical weather and climate

The importance of cumulus convection in large-scale tropical waves was
recognized in pioneering works by Matsuno (1966), Ooyama (1971), Yanai et al. (1973),
and Arakawa and Schubert (1974). In the proposed concept, cumulus convection affects
large-scale environment through:
1. warming and drying via a component of compensating downward motion,
2. cooling and moistening via the re-evaporation of cloud droplets, and
3. moistening via detrainment.
The above concept forms a basis for cumulus parameterization. Many schemes for
cumulus parameterization have been proposed since then (e.g. Arakawa 2004; Emanuel
and Raymond 1993; Bechtold et al. 2014; Plant and Yano 2015 and references therein).
In order to estimate the cumulus effect on large-scale fields of moisture, temperature
and momentum, a cloud model must be constructed to calculate cloud properties like
mass, temperature, cloud content, and precipitation in different large-scale environment.
There are several key processes (variables) in such cumulus schemes. One is the
cumulus mixing (entrainment rate, $\varepsilon$) for convective updraft and downdraft that is
function of cloud radius (or depth), humidity, temperature and wind shear of the
environmental. Another is the microphysical conversion from cloud to precipitation (a
critical condensation rate, $C_0$). $C_0$ separates two states: a precipitating state and a
nonprecipitating state. The two processes largely determine the PE as demonstrated in
Jiang and Smith (2003), Langhans et al. (2015), Morales et al. (2018), and Zhao (2014)
discussed in the previous section. Specifically, Zhao (2014) proposed convective PE as
a simple measure of the aggregated properties of parameterized convection important
to the GCM simulated clouds. He generated eight perturbed-physics models by
increasing and decreasing $\varepsilon$ and $C_0$ to check for the linearity of the cloud response to
each parameter. As the convective PE increases in the perturbed-physics experiments,
both liquid and ice water path decrease, with low and middle cloud fractions
diminishing at a faster rate than high cloud fractions. This asymmetry results in a large
sensitivity of top-of-atmosphere net cloud radiative forcing to changes in convective precipitation efficiency in a limited set of models.

Convection-coupled dynamics is of central importance not only to tropical weather but also to the study of tropical climate. For example, how convection and related processes are treated is critical for modeling climate variability from intra-seasonal oscillations (Lin et al. 2008; Kim et al. 2011; Blackburn et al. 2013; Benedict et al. 2013; Kim and Maloney 2017) to anthropogenic change (Boucher et al. 2013). For example, tropical intra-seasonal variability (TISV) is sensitive to deep convection and tropospheric moisture. A change in entrainment rate or cloud microphysics (such as re-evaporation of rainfall) in climate models often causes large changes in PE and therefore mid-tropospheric humidity and the simulated TISV (Maloney and Hartmann 2001; Lee et al. 2003; Bechtold et al. 2008; Lin et al. 2008; Hannah and Maloney 2011; Kim et al. 2012; Klingaman and Woolnough 2013; Zhu and Hendon 2015). Besides convection-coupled dynamics, cloud-radiative forcing can further enhance the intensity of TISV (e.g. Sobel et al. 2014; Kim et al. 2014; Wolding and Maloney 2015).

Because tropical climate oscillations are multiscale in nature, cumulus convective must be considered explicitly in more updated high-resolution non-hydrostatic models (Fig. 2). In such a new dynamic model, a generalized framework for cumulus parameterization applicable to any horizontal resolution between those typically used in general circulation and cloud-resolving models is required (Arakawa and Wu 2013).

With more parameterized processes involved in simulating multiscale convection in climate variability, the aggregated properties of convection need to be evaluated based on physics and observations. PE can facilitate such an evaluation, because it can be estimated by high-resolution non-hydrostatic cloud-resolving models with CMPE and by analyzing the observed water cycle with LSPE. Bearing in mind that the mutual consistency between CMPE and LSPE still needs to be examined, PE can serve as a
critical physical quantity for understanding a cumulus scheme or for comparing water
cycles simulated by different models, such as GCMs and non-hydrostatic models.

4. Cloud microphysics and PE: Shallow clouds

The macroscopic and large-scale aspects of PE (i.e. LSPE) discussed above is linked
to the microscopic and process-level aspects of PE (i.e. CMPE). This relationship can
be explored in the context of the PE for shallow clouds. The CMPE for shallow clouds
is largely controlled by microphysical processes of warm rain formation. These
processes govern how cloud water suspended in the atmosphere is converted into
(liquid) precipitation, which thus controls how much cloud water remains after the
precipitation occurs. Cloudiness is a fundamental characteristic that determines the
radiative effect and influences our ability for climate projection. The formation of warm
rain is also a pathway through which aerosols affect clouds, referred to as the aerosol
indirect effect or the aerosol-cloud interaction. This is a major uncertainty in climate
projection that is often ‘tuned’ so that models can reproduce historical climate change
(Penner et al. 2010; Golaz et al. 2013). One of the ‘tunable knobs’ arises from a
fundamental uncertainty in representing cloud physics that determines the CMPE and
its modulations due to perturbed aerosols in climate models.

Warm rain formation is typically represented in numerical weather prediction and
climate models by parameterizations for two modes of the water conversion process,
i.e. auto-conversion and accretion, and for the water depletion process, i.e. evaporation.
The former expresses the water conversion rate as a function of the mixing ratio and
the number concentration of cloud and rain water contents, and the latter is represented
by two different time scales of evaporation for cloud and rain waters. The functional
form describing the conversion and depletion rates suffers from large uncertainty, which
also makes the CMPE for shallow clouds uncertain. It is thus critical to better constrain
the fundamental uncertainty in cloud physics modelling.

Recent progress in satellite observation, particularly in measurements from active satellite sensors such as those for CloudSat and CALIPSO within the A-Train constellation (Stephens et al. 2008, 2018; Winker et al. 2010), offers an unprecedented opportunity to study microphysical processes on the global scale. Most notable in the context of the CMPE is the capability of new satellites that measure cloud and precipitation simultaneously, providing critical information to diagnose the cloud-to-rain water conversion process, which is central to the quantification of CMPE. This capability is enabled by combining multiple satellite observations of cloud and precipitation in particular ways to construct conditional statistics that probe key signatures of the water conversion process. Recent studies have devised several methodologies for such analyses by exploiting these new satellite measurement capabilities.

The first example is the analysis of probability of precipitation (POP) as a function of LWP, which were obtained from the CloudSat radar measurements and the Moderate Resolution Imaging Spectroradiometer (MODIS) or Advanced Microwave Scanning Radiometer-EOS (AMSR-E) passive retrievals, respectively (Lebsock et al. 2008; L’Ecuyer et al. 2009). The statistics showed that POP tends to increase monotonically with LWP on the global scale and that this trend varies depending on aerosol conditions. This illustrates how aerosol turbidity influences the conversion of cloud water to precipitation. The aerosol dependency of POP can also be quantified by introducing its susceptibility to perturbed aerosols (denoted by $S_{pop}$), which is defined as (Wang et al. 2012)

$$S_{pop} = - \frac{d \ln(POP)}{d \ln(N_a)},$$

(7)

where $N_a$ is the number of cloud condensation nuclei. The susceptibility is found to correlate well with the magnitude of the aerosol indirect effect, thus serving as an index
for observationally constraining the aerosol indirect effect. According to comparisons of the susceptibility between model and satellite statistics, current climate models tend to overestimate the aerosol indirect effect (Wang et al. 2012).

The second example for process diagnostics of warm rain formation makes maximum use of vertical cloud profiling of CloudSat radar measurements combined with MODIS optical retrievals. The methodology accumulates the vertical profile of radar reflectivity in a form normalized by the cloud optical depth and further classified according to the cloud-top particle size to construct a Contoured Frequency by Optical Depth Diagram (CFODD; Suzuki et al. 2010; Nakajima et al. 2010). The CFODD ‘fingerprints’ the transition of the vertical microphysical structure from non-precipitating to precipitating regimes. It also serves as an observation-based metric that can be compared with corresponding statistics from climate and cloud-resolving models and evaluated in representations of warm rain formation (Suzuki et al. 2011, 2015; Jing et al. 2017). Such comparisons reveal biases towards too-efficient rain formation, which is common among state-of-the-art climate models and can be traced back to the fundamental uncertainty in auto-conversion formulations (Suzuki et al. 2015). These studies propose that the time scale for the cloud-to-precipitation water conversion tends to be shorter in models than in reality, implying that the CMPE might be larger for shallow clouds in models.

Satellite-based metrics could be used to fix model biases by constraining the uncertainty in modelling of cloud physics. Specifically, particular uncertain parameters in the parameterization formulation could be constrained with satellite observations, such as in the form of the POP-LWP relationship and the CFODD statistics, to mitigate the bias towards too-efficient rain formation. However, such a process-based constraint has been found to produce an aerosol indirect effect that is too large (i.e. negative), which overly compensates for the greenhouse-gas-induced global warming (Suzuki et
This exposes a dichotomy between process and energy, or the “P&E dichotomy” as coined by Jing and Suzuki (2018), which is inherent in climate models that largely rely on error compensations. This dichotomy between the microscopic and macroscopic aspects of shallow clouds also implies that climate models are likely to suffer from compensating errors in representing the two different levels of precipitation efficiency, i.e. CMPE and LSPE. This points to a critical need to explore how the two types of PE are linked and how both can be better constrained with observations. To this end, satellite-based microphysical process diagnostics described above need to be somehow linked to CMPE and LSPE in the context of cloud water budget. In particular, emerging methodologies of microphysical process diagnostics need to be integrated in the manner that enables to quantify different components of cloud water budget, including source and sink terms that appear in definitions of CMPE and LSPE. Through such an approach, the two different levels of precipitation efficiency could be put into the common perspective of cloud water budget over multiple scales that would be better constrained by satellite observations.

5. Cloud microphysics and PE: deep clouds

In this section, we examine PE of deep clouds, focusing on cloud clusters and mesoscale convective systems (MCSs) in the tropics that are composed of deep convective clouds and upper stratiform clouds or anvils (Houze 2004). Deep convective clouds have narrower upward cores with horizontal scale of O (km) and are associated with convective precipitation, whereas anvils prevail in wider areas with horizontal scale of O(100 km) with stratiform rain below (Fig. 3). The upper clouds of MCSs have large and complicated impacts on radiation budgets. They reflect shortwave radiation as the umbrella effect, and they absorb upward longwave radiation from below and emit less longwave radiation outward to space, known as the greenhouse effect. To a first
approximation, the negative cloud forcing on the shortwave radiation and the positive cloud forcing on the longwave radiation cancel each other out (Hartmann and Berry 2017); more in detail, as upper clouds become optically thicker, cloud forcing becomes more negative due to enhanced shortwave reflection, whereas as upper clouds become optically thinner, cloud forcing becomes more positive due to the enhanced greenhouse effect (Kubar et al. 2007).

In MCSs, anvils are formed from cloud condensate that is detrained from the portion of a deep convective precipitation area that does not fall as convective precipitation. In the stratiform region of MCSs, condensates are eventually either precipitated or re-evaporated to the atmosphere. If we define PE separatory in each region as the ratio of surface precipitation to total condensation such as in CMPE, there is a clear contrast in PE between convective and stratiform regions as described in Section 2 with the observational result (Shige et al. 2004). Figure 4 schematically shows the vertical profiles of latent heating in convective and stratiform regions (Houze 2004; Schumacher et al. 2004). The total heating profile over an MCS depends on the coverage of stratiform clouds. Since the condensation heating is almost proportional to the condensation of water vapor or evaporation of rain (if we neglect the contributions of ice processes), profiles of latent heating in convective and stratiform regions provide an estimate of PE in each region (Section 2).

Here, convective precipitation and stratiform precipitation in MCSs are denoted by $P_c$ and $P_s$, respectively, and stratiform precipitation at the melting level, by $P_M$ (Fig. 4).

The column-integrated condensation in the convective and stratiform areas is denoted by $CONc$ and $CONs$, respectively, with $CON = CONc + CONs$, which are defined by unit area. According to Fig. 7 of Shige et al. (2004) (and see Eq. (6), the ratio of latent heating to precipitation in the convective and stratiform regions is estimated as $R_{conv} \sim 1.3$ and $R_{anvil} \sim 0.5$, respectively, where $R_{anvil}$ is defined with respect
to \( P_M \). \( P_s \) is smaller than \( P_M \). We define the PE of the convective region and that of the stratiform region respectively, as

\[
PE_c = \frac{P_c}{CON_c}, \quad PE_M = \frac{P_M}{CON_s}
\]  

(8)

Thus, we obtain \( PE_c \sim R_{\text{conv}}^{-1} \sim 0.7 \) and \( PE_M = P_M/CON_s \sim R_{\text{anvil}}^{-1} \sim 2.0 \). By introducing the ratio of stratiform rain to convective rain, \( S = P_s/P_c \), we can express the total PE over MCSs as

\[
PE = \frac{P_c + P_s}{CON} = \frac{1 + S}{1 + S \cdot \frac{P_M \cdot PE_c}{P_s \cdot PE_M}} PE_c.
\]  

(9)

According to Schumacher and Houze (2003), the stratiform rain ratio, defined as stratiform rain to total rain, is estimated as 40%; that is, \( S \sim 0.67 \). If we use \( P_M/P_s \sim 1.5 \) (e.g. Fig. 2 of Shige et al. 2004) and \( PE_c/PE_M \sim 0.35 \), we estimate \( PE \sim 0.86 \), which is larger than \( PE_c \). Equation (9) indicates that, as the portion of stratiform rain \( S \) increases, the total PE over MCSs also increases, because \( \frac{P_M \cdot PE_c}{P_s \cdot PE_M} < 1 \) in general. The stratiform rain ratio is used as a measure of the degree of convective aggregation (Yokoyama and Takayabu 2008). This implies that as convection becomes more aggregated, PE increases.

This simplified framework of MCSs cannot be extended easily to the real atmosphere or numerical results. In particular, the effect of PE on radiation budget is more complicated because of isolated cirrus and the effects of other types of upper clouds in addition to anvil clouds. This is best illustrated by the controversies involving the cirrus-cloud thermostat hypothesis (Ramanathan and Collins 1991), as discussed in Lau et al. (1994) and many other studies. In GCMs, because precipitation is generally accounted for by a cumulus parameterization scheme and a large-scale condensation scheme, it is thought that precipitation associated with MCSs is divided into convective precipitation and stratiform precipitation; convective precipitation is calculated by a cumulus parameterization scheme, and stratiform precipitation is calculated by a large-
scale condensation scheme. Such an application of the simplified MCS framework is
unwarranted due to the highly scale-dependent nature of parameterization schemes and
grid resolutions of GCMs.

As an example of the use of PE in GCMs, the responses to changes in convective
PE in the Geophysical Fluid Dynamics Laboratory (GFDL) GCM are discussed by
Zhao (2014). He showed that for a type of cumulus parameterization, convective PE is
equivalent to the convective detrainment efficiency; raising PE in the model decreased
both liquid and ice water path (IWP), with low and middle cloud fractions diminishing
at a faster rate than high cloud fractions. Such model physics results in top-of-
atmosphere net cloud radiative forcing having high sensitivity to changes in convective
PE.

The second example is found in Lau et al. (2005), who used the NASA Goddard
Earth Observing System (GEOS) GCM to examine changes in the hydrologic cycle by
altering an auto-conversion parameter. In Lau et al. (2005), the residence time of cloud
water is used to determine the sensitivity of PE, defined by Lau and Wu (2003) as the
ratio of cloud liquid water (CLW) to precipitation. An increase in the auto-conversion
rate implies an increase in PE. The authors argue that an increase in PE results in
enhanced deep convection in the convectively active zones near tropical land regions,
more warm rain but less cloud over oceanic regions, and an increased ratio of
convective to stratiform rain over the entire tropics.

To understand the PE of MCSs in terms of cloud microphysics, an idealized
framework of direct numerical calculations of radiative-convective equilibrium (RCE)
is useful (Nakajima and Matsuno 1988; Held et al. 1993; Sui et al. 1994). RCE
numerical experiments are direct calculations of deep convective circulations under a
horizontally uniform sea surface condition to achieve a statistically balanced state.
Satoh and Matsuda (2009) conducted a series of RCE experiments under a small planet
configuration by changing cloud microphysics parameters. One aspect of the relationship between convective clouds and the upper cloud fraction is the ratio of graupel to total ice clouds; this ratio is negatively correlated with cloud fraction. In the simulations by Satoh and Matsuda (2009), more graupel leads to more precipitation in the convective clouds, higher PE, and a smaller fraction of upper cloud.

Cloud microphysics also affect the high cloud coverage. In numerical models, high cloud coverage depends on the fall speed of cloud ice and on the conversion rate from cloud ice to snow (Kodama et al. 2012) and the parameters of these processes are generally used to improve the radiation budget. High clouds are viewed as detrained from deep clouds (or MCSs) (Fig. 3), and this portion of the detrained clouds is also related to PE. Because both optically thin and thick high clouds affect radiation budgets, one area of study is to examine a possible link between characteristics of high clouds and the PE of deep convection. It is suggested that reduced coverage of cirrus clouds over warmer SST is associated with higher PE (Choi et al. 2017; Daloz et al. 2018). This plausible relationship is frequently raised in the context of climate change and is discussed in the next section.

MCSs and associated upper clouds have various horizontal scales and are organized into larger-scale cloud clusters or super-cloud clusters (Nakazawa 1987), and sometimes into the Madden-Julian oscillations (Madden and Julian 1971, 1972). In recent years, characterization of such organizations of convective systems has motivated researchers to develop an idealized concept of convective aggregation, which has been investigated in a simple RCE framework (Bretherton et al. 2005). PE may depend on the horizontal scale of convective systems, which range from $O(10\text{km})$ to $O(1000\text{km})$, and on the degree of aggregation. Based on observations, Stein et al. (2017) found a reduction of the anvil cloud amount in more aggregated situations, suggesting that aggregated convection has a higher PE than does disaggregated convection, which
is consistent with Tobin et al. (2012). However, this relationship between PE and aggregation does not necessarily hold for changes in global warming (Lutsko and Cronin 2018), which we examine in Section 6.

While aerosols affect the PE of shallow clouds as we discussed (Section 4), studies have also examined how aerosols affect precipitation in deep convection; for example, Rosenfeld et al. (2008) proposed the hypothesis of ‘convective invigoration’. This relationship has also been examined in terms of how aerosols affects PE for various types of clouds, including deep convection (Khain et al. 2005, 2008; Khain 2009), with studies suggesting a variety of precipitation responses to perturbed aerosols depending on environmental conditions.

6. Understanding cloud-radiation changes with climate warming in view of PE

Future changes in clouds present some of the largest uncertainties in projections of climate warming. Cloud coverage, thickness, altitude, and microphysical properties collectively contribute to the atmospheric radiative energy budget. These characteristics are potentially related to how PE and its change are determined.

The observed interannual variability of clouds is frequently used to test simulated future changes in clouds in terms of their dependency on SST, although it is not always provable that the interannual dependency should be the same as the projected dependency. Zelinka and Hartmann (2011) analyzed interannual variations of SST and high clouds and found that the observed high clouds rise approximately isothermally in accordance with the fixed anvil temperature (FAT) hypothesis by Hartmann and Larson (2002). The authors also showed an overall decrease in high cloud coverage when the tropics warm, and argued that such cloud changes cause absorbed solar radiation to increase more than OLR, resulting in a positive but statistically insignificant net high cloud feedback. However, more precisely, their results indicate that the upper part of
high clouds above the ~200 hPa level shows an increase in cloud cover, which is not explained by the tropopause rise of the FAT hypothesis. The FAT hypothesis is related not only to the altitude of high cloud top but also to high cloud size. Sensitivity of the applicability of the FAT hypothesis to high cloud size was examined by observationally (Xu et al. 2007) and numerically (Noda et al. 2016), and both studies showed that high cloud size is an important factor for the relation between OLR and the cloud top temperature. Although the altitude of high cloud top may only be indirectly related to PE, the high-cloud size is directly related to PE of individual deep convective clouds. In this sense, the extent to which the FAT hypothesis is validated is related to the characteristics of PE.

To examine projected changes in high clouds simulated by climate models, Zelinka and Hartmann (2010) analyzed global climate models in the Cloud Feedback Model Intercomparison Project (CFMIP) and showed a future decrease in cloud cover if projected changes are compared at the same temperature less than 230K. Zelinka et al. (2012) classified clouds according to categorization by the International Satellite Cloud Climatology Project (ISCCP) – that is, cloud top height and cloud optical depth – so that they could quantify each cloud characteristic, such as cloud amount, altitude, and optical depth, and analyzed the CFMIP results. Note that the ISCCP defines high clouds as clouds between 50 and 440 hPa and the upper part of high clouds as clouds between 50 and 180 hPa. Zelinka et al. (2012) showed a decrease in high cloud coverage below the 180 hPa level and an increase of cloud coverage in the upper part of high clouds.

Future changes in clouds are studied by high-resolution global non-hydrostatic models that explicitly calculate cloud microphysics without cumulus parameterization. These models, known as a global cloud-resolving model, are becoming more popular (Satoh et al. 2019). Among them, the Nonhydrostatic Icosahedral Atmospheric Model
(NICAM; Tomita and Satoh 2004; Satoh et al. 2008, 2014) is used to test future cloud changes with global warming, and results have shown that changes in high clouds in response to a warming climate are different from those in GCMs analyzed by Zelinka et al. (2012). Chen et al. (2016) showed that the high cloud coverage increases in a warmer climate in NICAM and that such an increase is commonly seen in results from models using two types of cloud microphysics schemes. Similar sensitivities were found by Satoh et al. (2012) by analyzing NICAM simulation results; they argued that as PE increases, the upper cloud fraction in the tropics decreases. Chen et al. (2016) showed that high thin clouds in particular increase with warmer climate but that IWP decreases with warmer climate. The cloud changes simulated by NICAM in global warming experiments are summarized by Satoh et al. (2018).

To understand future changes in high clouds, Bony et al. (2016) conducted idealized experiments under RCE and showed that high cloud coverage is systematically reduced in warmer climates across several global climate models under the idealized RCE configuration. Bony et al. (2016) argued that this future decrease in circulation would lead to a shrinkage in high cloud coverage. NICAM has also been used by Ohno and Satoh (2018) to test cloud changes under RCE, The authors showed a consistent increase in high cloud coverage in a warming climate, as in Chen et al. (2016). These contrasting results suggest that future high cloud coverage is not only dynamically constrained but also affected by other physical processes, including cloud microphysics and turbulence (Ohno et al. 2019). Although the above studies did not analyze PE in detail, Bony et al. (2016) suggested the effect of PE on high cloud changes; if PE remains the same, the decrease in the high cloud fraction implies thicker high clouds due to more detrainment of clouds at warmer temperature. If the same argument is applied to the NICAM results, then if PE remains the same, the increase in the high cloud fraction implies a thinning of high clouds.
Lutsko and Cronin (2018) used the RCE framework to investigate the change in PE with warming. They showed that PE generally increases with warming in the case of non-aggregation of convective clouds, because of increases in PE due to cloud condensate converted into precipitation. They also showed that PE decreases as convection becomes more organized. This dependency does not necessarily agree with the observation that PE increases as more aggregated (Tobin et al. 2012; Stein et al. 2017). The different definitions of PE among the literature is one of the sources of the divergent results.

The advantage of RCE is that it is easier to analyze the results and more understandable than the realistic experiments, as long as they show similar responses of clouds to those seen in simulations with a realistic configuration of the corresponding models. However, clouds and their responses to warming are generally different from model to model, even in the simplified framework of RCE. To reduce uncertainty and to understand reasons of the diversity of the model results, a model inter-comparison project of RCE, RCEMIP, was proposed (Wing et al. 2018). The preliminary results of RCEMIP were published in Wing et al. (2018), and more results – including those concerning cloud changes and the changes in PE across the different models used in RCEMIP – will be analyzed in the near future.

Zhao (2014) investigated physical links between parameterized convection and climate changes in the GFDL GCM. He found that a scheme using threshold removal for precipitation and an entrainment rate formulated to be inversely dependent on convective depth produced a notable increase in PE in response to warming. Such a convection scheme also resulted in increased cloud feedback and climate sensitivity.

Projection of cloud changes is complicated, and different types of clouds respond differently to warming. Changes in the water and ice phases of clouds can be used to understand the response of clouds to warming; a projected change in the separation of
cloud phases is affected by a change in PE. Lau and Wu (2003) analyzed the residence times of warm and cold clouds using the TRMM data. They used the residence time (defined as the ratio of CLW to precipitation) to represent PE and found that as the residence time becomes shorter, the PE increases. They found that the PE of light rain from warm clouds increases as SST increases, but that the PE of heavy rain associated with deep convection is independent of SST. Lau et al. (2005) further performed a modeling study in GEOS by changing an auto-conversion rate to investigate the sensitivity of atmospheric hydrologic processes to cloud microphysics due to warm and cold clouds. Noda et al. (2015) analyzed precipitation changes due to warm and cold rains using data from two different horizontal resolutions (7 and 14 km) of NICAM simulations. They explained the different responses of warm and cold rains in terms of residence times of cold and warm clouds respectively, and found no significant changes in PE for cold clouds but higher PE for warm clouds.

Projected changes in LWP and IWP have been analyzed by a series of NICAM experiments. The NICAM experiments generally show a decrease in IWP in tropical areas for warmer climate (Chen et al. 2016). Satoh et al. (2012) used a simple column model to show that the decrease in IWP is caused by the slowdown of the overturning circulation, and suggested an increase in PE. Using the NICAM 7 km and 14km mesh data, Noda et al. (2014) statistically analyzed the dependency of IWP and LWP on the horizontal size of clouds, which is defined as the area of high clouds defined by a threshold value of OLR. A comparison between the control and the warming experiment shows that IWP decreases for all types of cloud size, while LWP increases for clouds whose horizontal size is larger than about 100 km and decreases for clouds whose size is smaller than about 100 km. Yamada and Satoh (2013) analyzed cloud changes in tropical cyclones and showed that both IWP and LWP of the composite structure of tropical cyclones increase with warming. However, the averaged IWP in
the tropics decreases as the climate warms. This apparently contradictory result can be explained by combination of the decrease in number and increase in strength of tropical cyclones under global warming condition (Knutson et al. 2019). These results urge a deeper understanding of how PE changes for different types of clouds.

To show how increased water vapor is converted into precipitation in modeled climate change, Stephens and Ellis (2008) shed light on projected changes in precipitation and water vapor using PE defined as the ratio of global changes in precipitation to global changes in water vapor. What their definition tells us is somewhat different from what we want to know from PE for cloud information. In fact, they introduced an efficiency as the ratio

$$\varepsilon \sim \frac{W \Delta P}{P \Delta W}$$  \hspace{1cm} (10)

where $W$ and $P$ are global mean values of column water vapor and precipitation, respectively, and $\Delta$ is their increase related to global warming. The change in precipitation in response to warming is theoretically constrained by the energy budget and the precipitation heating is almost balanced by the radiative cooling. The future slowdown of large-scale overturning circulation is due to the larger increase in water vapor (in the mixed layer) compared to the increase in precipitation (Satoh and Hayashi 1992; Held and Soden 2006), thus generally $\varepsilon < 1$. The future change in precipitation is affected by the uncertainties in the projection of the radiative fluxes, such as those due to clouds and water vapor.

The issue of the change in high cloud coverage in response to surface warming is invoked by Lindzen et al. (2001) by referring to the adaptive ‘iris effect’. The authors analyzed cloud data for the western Pacific from the Japanese Geostationary Meteorological Satellite-5 and found that the area of cirrus cloud coverage normalized by a measure of the area of cumulus coverage decreases as the surface temperature of
the cloudy region increases. This mechanism would act to control the OLR in response
to changes in surface temperature in a manner similar to the way in which the iris of
the eye opens and closes the pupil in response to changing light levels – hence the iris
effect. Lindzen et al. (2001) argued that the possibility exists that the PE within cumulus
towers can increase significantly with increasing surface temperature, thus reducing
cirrus outflow. Many studies have looked into observations and modeling results to
evaluate the iris effect (e.g. Lin et al. 2002; Hartmann and Michelsen 2002; Rapp et al.
2005; Lindzen and Choi 2009; Trenberth et al. 2010; Lindzen and Choi 2011; Su et al.
2017). In particular, we note here the influence of different types of clouds and water
vapor on radiative feedbacks; e.g., an increase in thin upper clouds leads to more
positive feedback through more long wave forcing (Kubar et al. 2007), while a decrease
in the humid area leads to negative feedback through more OLR. Mauritsen and Stevens
(2015) introduced a parameter that mimics the iris effect in a GCM and suggested that
the iris effect could be important for realistically reproducing the observed climate
sensitivity. This study invoked the importance of the iris effect on constraining climate
sensitivities.

The validity of the iris effect hinges on enhanced PE in deep convection in a warmer
climate. In this context, an increasing PE in a warming climate reduces cirrus clouds
detrained in the upper layers, which leads to smaller coverage of anvils and lower
humidity (although, as described above, this is not the only outcome but just one
possible consequence of larger high cloud cover). If humidity decreases, it would cause
relatively more infrared radiative cooling and the iris effect. Thus, one might argue that
the iris effect could be tested with future changes in PE, or the temperature dependency
of PE. Under a warming climate, precipitation generally increases due to more radiative
cooling. The effect of a change in PE on precipitation is thus through the change in
radiative cooling, which is fundamentally constrained by water vapor in the free
In the context of the future warming climate, aerosol effects on PE are also key issues. There are two pathways for such effects on precipitation. One pathway is through the aerosol direct radiative effect, which perturbs the global energy budget by modulating global precipitation relative to water vapor content. The second pathway is through the indirect effect; the aerosol-cloud interaction that affects the precipitation formation from clouds. The former pathway modulates PE defined by (10) through energy balance controls on global precipitation, typically due to anomalous atmospheric heating induced by absorbing aerosols (e.g. Allen and Ingram 2002; Pendergrass and Hartmann, 2012; Suzuki et al. 2017). With this mechanism, global-mean precipitation tends to decrease substantially with increasing absorbing aerosols although the magnitude of this decrease is subject to large uncertainty in current climate modeling (Myhre et al. 2013). The latter pathway involving the aerosol-cloud interaction is particularly pronounced in low-level clouds. Aerosol-induced modulations of the PE of these clouds also influence their radiative effect. Given this link between PE and radiative effect, research efforts have been devoted to estimating the precipitation susceptibility to aerosols (Sorooshian et al. 2009; Wang et al. 2012) based on numerical modeling and satellite observations. These two pathways for aerosol effects on precipitation jointly contribute to uncertainty in estimates of future climate change in precipitation.

7. Summary

In this review, we summarize our current understanding of the water cycling processes in the earth atmosphere in terms of precipitation efficiency (PE) and the influence of its representation in weather and climate models. We focus on PE because it is a fundamental measure of integrated microphysical changes linking water and energy fields. As a result, PE is a quantity of microphysical nature that can link to some
key macrophysical terms in various weather and climate modeling studies, as is evident from the definition of PE based on cloud budget (CMPE), water vapor budget (LSPE), and thermodynamic budget.

Estimates of CMPE in various modeling studies of different convection systems and the corresponding values of PE are summarized in Table 1. The systems include tropical cumulus (0.2–0.8) and cumulus congestus (0.3–0.5), tropical and mid-latitude squall systems (0.2–0.5), hurricanes/typhoons (0.6–0.75 over ocean, 0.95 over steep mountain), mixed-phase mid-latitude convection (~0.2), and Arctic clouds. Estimates of PE based on observations, which are shown in Table 2, include systems such as thunderstorms in Florida and Ohio (0.1), on the central US high plains (0.2–0.6), and over SE Montana (0.2–0.5); tropical squall line in west Africa (0.45–0.57); trade wind clouds over the north central tropical Pacific Ocean (0.2–0.3); tropical convective and stratiform form convection in TOGA COARE (0.7, 2.0); and prefrontal squall line and MCS in SoWMEX/TiMREX (0.45, 0.53).

The estimated PEs from models and observations provide a consistent set of values for convective systems from tropical to polar zones, although uncertainties exist due to either parameterized cloud microphysics or the inaccuracy of measuring key physical quantities and limited samples in space and time. We can use these PEs to evaluate and improve the role of a cumulus ensemble in simulating multiscale weather-climate oscillations and anthropogenic climate change.

Following the above considerations, we reviewed studies that evaluate model microphysical processes in shallow clouds (auto-conversion, accretion, evaporation) using satellite measurements of precipitation, LWP, aerosol index as a proxy for cloud condensation nuclei, and CFODD by CloudSat radar measurements and MODIS or AMSR-E passive retrievals. These studies suggest that models tend to overestimate the aerosol indirect effect and the rain formation efficiency. A modeling experiment to
mitigate the rain formation biases, however, results in an aerosol indirect effect that is too large, which overly compensates for the greenhouse-gas-induced global warming.

With regard to the evaluation of cloud microphysics and PE in deep convection, we review conceptual frameworks of MCS, self-aggregation, and cirrus-SST feedback, along with relevant analyses based on satellite and ancillary observations and various model experiments.

The PE of deep convection is related to the partition of the condensed water between precipitation and clouds that remain and eventually evaporate in the atmosphere. The upper part of deep convection is generally in the ice phase and undergoes horizontal advection and slow sedimentation, forming stratiform or anvil clouds. High cloud cover and cloud thickness partly depends on characteristics (size or shape) of cloud ice detrained from deep convective clouds. PE also varies according to the environmental conditions that characterize deep convection, such as SST, wind shear, and environmental humidity. However, it is not completely clear how PE depends on these conditions. For example, aerosols affect PE differently for various types of deep convection depending on environmental conditions.

Organized convection like a MCS consists of stratiform and convective clouds and its PE depends on the degree of organization. As the portion of stratiform rain increases, the PE of the total MCS increases. PE is related to the degree of convective aggregation in general, but the relationship depends on how convective aggregation is defined.

Future changes in clouds (for example, their coverage, thickness, altitudes, and microphysical properties) and radiative fluxes are among the most uncertain factors in projections of climate warming. This requires research efforts aiming at a deeper understanding of cloud microphysics and cloud-radiation interaction processes and appropriate ways of resolving and/or parameterizing them in weather and climate models. It is unknown how PE will change in warmer climate. This uncertainty,
however, is a key factor that might lead to changes in the characteristics of high clouds, including high cloud cover and thickness through a linkage of these characteristics with PE of deep convection.

High cloud cover, cloud thickness, and ice water path (IWP) associated with deep convection are important to understanding cloud feedback. Studies aiming to understand how these factors depend on SST or how they change with warming are ongoing. Observations show that high cloud cover (categorized by ISCCP) decreases as SST increases; by contrast, detailed analyses show that high thin cloud cover increases with SST. These changes might be related to change in PE with warming, but they could occur even if PE remained unchanged. In the explicit treatment of cloud microphysics, increasing CMPE reduces upper cloud ice in the tropics. However, the relationship between changes in cloud ice and high cloud cover and its effect on radiation budgets is not straightforward.

In cumulus parameterization, increasing detrainment or the auto-conversion rate can raise convective PE and results in more warm rain but less cloud content with low and middle cloud fractions diminishing at a faster rate than high cloud fractions. Such studies suggest that changes in convective PE lead to a large sensitivity of top-of-atmosphere net cloud radiative forcing. Aerosols affect climate warming directly by scattering or absorbing solar radiation and indirectly by affecting the formation of precipitation from clouds, particularly low-level clouds, and the associated radiative effect. To study the link between the PE and radiative effect, combined numerical modeling and satellite observations have focused on estimates of precipitation susceptibility to aerosols. The two pathways for aerosol effects on precipitation contribute jointly to uncertainty in estimates of future climate change in precipitation.

The studies reviewed here show that reliable estimates of PE for tropical, mid-latitude, and arctic convective systems are an important reference for evaluating the
results of climate models, improving the modeling of water cycling processes, and understanding future changes in clouds. As increasing computational power enables more high-resolution models to perform cloud resolving simulations and predictions, it will become more critical to evaluate and improve cloud microphysics models. We should bear in mind that both the microphysical and macro-physical aspects of PE need to be considered in order to improve understanding and modeling of water and energy cycles.

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Table captions:

**Table 1:** PEs for convection at different scales based on modeling studies.

**Table 2:** PEs for convection at different scales based on observational studies.

Figure captions:

**Figure 1:** Conversions of water substance from one form to another in a bulk water-continuity model in which there are six categories of water substance: vapor (v), cloud water (w), cloud ice (i), rain (r), snow (s), and graupel (g). Lines connecting the six categories indicate various cloud microphysics processes (CMP): accretion (A), condensation (C), deposition (D), evaporation (E), freezing (F), collection (L), melting (M), riming (R), autoconversion (U). The CMP that converts one of the six categories of water substance (i) to another (j) is denoted as $\text{CMP}_{ij}$, e.g. $\text{A}_{ws}$ indicates conversion from cloud water to snow by accretion. The CMP is temperature dependent as shown by color. See Chapter 1 in Li and Gao (2016) for some common parameterizations for $\text{CMP}_{ij}$.

**Figure 2:** Processes considered in implicit cumulus parameterization and explicit parameterization of cloud microphysics (see Fig. 1). A unified representation of deep moist convection needs be considered in the new generation of numerical models as suggested in Arakawa and Wu (2013).

**Figure 3:** Conceptual model of a tropical mesoscale convective system in its mature stage. Convective precipitation and stratiform precipitation at the surface are denoted by $P_C$ and $P_s$, respectively, and stratiform precipitation at the melting level is by $P_M$. Light shading indicates cloud. Vertical lines with medium shading indicate stratiform precipitation. Black box indicates convective precipitation. Straight, solid arrows indicate convective updrafts and downdrafts. Wide, open arrows indicate mesoscale ascent and subsidence in the stratiform region, where vapor deposition and evaporation occur. Modified from Figure 3 of Houze (2004), originally from Figure 2 of Houze (1982).

**Figure 4:** Idealized profiles of net heating in a MCS. (a) Idealized profiles of net heating associated with convective and stratiform precipitation in a MCS. (b) Idealized profiles of net heating by a MCS with different fractions of stratiform precipitation. The horizontal axis is nondimensional until precipitation amounts are...
specified for the convective and stratiform regions. Adapted from Figure 4 of Houze (2004), originally from Figure 3 of Schumacher et al. (2004). (C) American Geophysical Union. Use with permission.
Table 1. PEs for convection at different scales based on modeling studies.

<table>
<thead>
<tr>
<th>Publication</th>
<th>Type of system</th>
<th>Model [ref]</th>
<th>Microphysics</th>
<th>Cloud efficiencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ferrier et al. (1995b)</td>
<td>Mid-latitude and tropical squall systems</td>
<td>2D, GCE [TS93]</td>
<td>4ICE scheme by Ferrier (1994)</td>
<td>20–35% (tilted storms) to 40–50% (erect storms)</td>
</tr>
<tr>
<td>Jiang and Smith (2003)</td>
<td>Orographic precipitation</td>
<td>3D, ARPS</td>
<td>Kessler (1969) and GCE 3ICE scheme (Li et al. 1999)</td>
<td>PE increases from 26% to 83% with the width of mountains.</td>
</tr>
<tr>
<td>Morrison et al. (2005b)</td>
<td>Arctic clouds</td>
<td>1D, ARCSAM [M03]</td>
<td>Morrison et al. (2005a)</td>
<td>Faster contact/immersion freezing rates will increase PE (numbers not shown)</td>
</tr>
<tr>
<td>Sui et al. (2007)</td>
<td>Convections during TOGA COARE</td>
<td>2D, GCE model [TSL]</td>
<td>GCE 3ICE scheme (Li et al. 1999)</td>
<td>LSPE and CMPE (&lt;100%) correlated, less insensitive to spatial than temporal average</td>
</tr>
<tr>
<td>Muller (2013)</td>
<td>Tropical convections in the ideal warming scenario.</td>
<td>3D, SAM [KR03]</td>
<td>[KR03]</td>
<td>70–90% in different time scale and environment settings</td>
</tr>
<tr>
<td>Yang et al. (2011)</td>
<td>Typhoon Nari (2001)</td>
<td>3D, MM5</td>
<td>Reisner et al. (1998)</td>
<td>Averaged with radii &gt; 60 km, CMPE ~ 67 (73%) over ocean (Taiwan island)</td>
</tr>
<tr>
<td>Huang et al. (2014)</td>
<td>Typhoon Morakot (2009), following major convective cells</td>
<td>3D, WRF</td>
<td>WSM6 (Hong and Lim 2006)</td>
<td>60−75 (&gt; 95%) over ocean (over Taiwan Central Mtn.)</td>
</tr>
<tr>
<td>Langhans et al. (2015)</td>
<td>Cumulus congestus clouds</td>
<td>3D, DAM [R08]</td>
<td>Lin et al. (1983); Lord et al. (1984); Krueger et al. (1995)</td>
<td>46–50% (25–30%); vapor entrained through (above) cloud base</td>
</tr>
<tr>
<td>Miltenberger et al. (2018)</td>
<td>Mixed-phase convective clouds during COPE over the south-west peninsula of the UK in 2013</td>
<td>3D, Unified Model</td>
<td>CASIM module (Shipway and Hill 2012)</td>
<td>16–24% from different aerosol scenarios.</td>
</tr>
<tr>
<td>Morales et al. (2018)</td>
<td>Idealized orographic rain events in atmospheric rivers in OLYMPEX</td>
<td>2D, CM1 [BF02]</td>
<td>Morrison et al. (2005a)</td>
<td>20–200%, in various microphysical parameters and locations of bell-shape mountain</td>
</tr>
</tbody>
</table>

Abbreviations: M70 (Murray 1970); KW78 (Klemp and Wilhelmson 1978); M03
<table>
<thead>
<tr>
<th>Publication</th>
<th>Type of systems</th>
<th>Summary of data and method</th>
<th>PE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Braham (1952)</td>
<td>Thunderstorm cells in Florida and Ohio (Thunderstorm Project)</td>
<td>Updraft and downdraft flux estimated by soundings, radar and aircraft data; surface observations (rain, wind).</td>
<td>PE = ( \frac{r_{\text{moisture infow}}}{\text{cloud base}} ) ~ 10%</td>
</tr>
<tr>
<td>Auer and Marwitz (1968)</td>
<td>Thunderstorms on the central US high plains (Colorado, Oklahoma, South Dakota)</td>
<td>Following system movement by radar; rain gauge network; vertical flux at cloud base estimated by aircraft.</td>
<td>PE = ( \frac{R_{\text{sfc}}}{(wq)_{\text{cloud base}}} ) ~ 20–60% (6 cases in CO)</td>
</tr>
<tr>
<td>Fankhauser (1988)</td>
<td>Thunderstorms over south-east Montana (CCOPE)</td>
<td>Radar rainfall; vertical flux at cloud base estimated by aircraft; rawinsondes; surface network stations</td>
<td>PE = ( \frac{R}{(wq)_{\text{cloud base}}} ) ~ 20–47%</td>
</tr>
<tr>
<td>Chong and Hauser (1989)</td>
<td>Tropical squall line in west Africa (COPT)</td>
<td>Estimate of water budget (Gamache and Houze 1983) by retrieved thermodynamic and microphysical quantities (like condensation in updraft, ( C_c )) using radiosonde and Doppler radar data</td>
<td>PE = ( \frac{r_c}{C_c} ) ~ 45–57%</td>
</tr>
<tr>
<td>Rauber et al. (1996)</td>
<td>Trade wind clouds over the north central tropical Pacific Ocean</td>
<td>Radar rainfall; ocean surface latent heat flux (LH) by satellite</td>
<td>PE = ( \frac{\text{radar rain sfc LH}}{\text{LH}} ) &lt; 20–30%</td>
</tr>
<tr>
<td>Shige et al. (2004, 2009)</td>
<td>Tropical convective systems (TOGA COARE)</td>
<td>Rain profile from TRMM PR2A25; estimated LH profiles in a cloud resolving model driven by soundings data.</td>
<td>Convective PE ( PE \sim R_{\text{conv}}^{-1} \sim 70% )</td>
</tr>
<tr>
<td>Chang et al. (2015)</td>
<td>Prefrontal squall line and mesoscale convective systems in SoWMEX/TiMREX</td>
<td>Doppler radar wind and moisture profile from sounding to calculate moisture flux ( Q_{\text{tot}} ); rain at 2 km and ice water content by S-Pol radar</td>
<td>PE = ( \frac{R_{\text{tot}}}{Q_{\text{tot}}} ) squall line: ~ 45% MCS: ~ 53%</td>
</tr>
</tbody>
</table>

Table 2. PEs for convection at different scales based on observational studies.

Abbreviations: CCOPE (Cooperative Convective Precipitation Experiment), COPT (the cooperative experiment 1981), TOGA COARE (Tropical Ocean - Global Atmosphere Coupled Ocean - Atmosphere Response Experiment), SoWMEX/TiMREX (Southwest Monsoon Experiment/Terrain-Influenced Monsoon)
Rainfall Experiment)
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Figure 1: Conversions of water substance from one form to another in a bulk water-continuity model in which there are six categories of water substance: vapor (v), cloud water (w), cloud ice (i), rain (r), snow (s), and graupel (g). Lines connecting the six categories indicate various cloud microphysics processes (CMP): accretion (A), condensation (C), deposition (D), evaporation (E), freezing (F), collection (L), melting (M), riming (R), and autoconversion (U). The CMP that converts one of the six categories of water substance (i) to another (j) is denoted as CMP$_{ij}$, e.g. A$_{ws}$ indicates conversion from cloud water to snow by accretion. The CMP is temperature dependent as shown by color. See Chapter 1 in Li and Gao (2016) for some common parameterizations for CMP$_{ij}$.

**Microphysical processes**
- A: accretion
- C: condensation
- D: deposition
- E: evaporation
- F: freezing
- L: collection
- M: melting
- R: riming
- U: autoconversion

**Temperature threshold**
- No threshold
  - T > 0 °C
  - T < 0 °C
  - 0 °C > T > -35°C
  - T < -35 °C
Figure 2: Processes considered in implicit cumulus parameterization and explicit parameterization of cloud microphysics (see Fig. 1). A unified representation of deep moist convection needs be considered in the new generation of numerical models as suggested in Arakawa and Wu (2013).
Figure 3: Conceptual model of a tropical mesoscale convective system in its mature stage. Convective precipitation and stratiform precipitation at the surface are denoted by $P_c$ and $P_s$, respectively, and stratiform precipitation at the melting level is by $P_M$. Light shading indicates cloud. Vertical lines with medium shading indicate stratiform precipitation. Black box indicates convective precipitation. Straight, solid arrows indicate convective updrafts and downdrafts. Wide, open arrows indicate mesoscale ascent and subsidence in the stratiform region, where vapor deposition and evaporation occur. Modified from Figure 3 of Houze (2004), originally from Figure 2 of Houze (1982).
Figure 4: Idealized profiles of net heating in a MCS. (a) Idealized profiles of net heating associated with convective and stratiform precipitation in a MCS. (b) Idealized profiles of net heating by a MCS with different fractions of stratiform precipitation. The horizontal axis is nondimensional until precipitation amounts are specified for the convective and stratiform regions. Adapted from Figure 4 of Houze (2004), originally from Figure 3 of Schumacher et al. (2004). (C) American Geophysical Union. Use with permission.