Cloud-resolving model simulations of KWAJEX: Model sensitivities and comparisons with satellite and radar observations

Peter N. Blossey*, Christopher S. Bretherton, and Jasmine Cetrone

Department of Atmospheric Sciences,

University of Washington, Seattle, WA

Marat Kharoutdinov

Department of Atmospheric Sciences

Colorado State University, Fort Collins, CO

May 10, 2006

*Corresponding author address: Dr. P. N. Blossey, University of Washington, Atmospheric Sciences, Box 351640, Seattle, WA 98195-1640, USA. Email: bloss@atmos.washington.edu

Abstract

Three-dimensional cloud resolving model simulations of a mesoscale region around Kwajalein Island during the KWAJEX experiment are performed. Using observed winds along with surface and large-scale thermodynamic forcings, the model tracks the observed mean thermodynamic soundings without thermodynamic nudging during 52-day simulations spanning the whole experiment time period, July 24–September 14, 1999. Detailed comparisons of the results with cloud and precipitation observations, including radar reflectivities from the Kwajalein ground validation radar and ISCCP cloud amounts and radiative fluxes, reveal the biases and sensitivities of the model’s simulated clouds. The amount and optical depth of high cloud are underpredicted by the model during less rainy periods, leading to excessive outgoing longwave radiation (OLR) and insufficient albedo. The simulated radar reflectivities tend to be excessive, especially in the upper troposphere, suggesting that simulated high clouds are precipitating large hydrometeors too efficiently. Occasionally, large-scale advective forcing errors also seem to contribute to upper-level cloud and relative humidity biases.

An extensive suite of sensitivity studies to different microphysical and radiative parameterizations is performed, with surprisingly little impact on the results in most cases.

1 Introduction

Cloud-resolving models (CRMs) have seen growing use over the last decade in a number of areas, such as in studies of radiative-convective equilibrium (e.g. Tompkins and Craig (1998)), in evaluations of subgrid parameterizations in climate models (e.g. Liang and Wu (2005)), and in place of subgrid cloud and convective parameterizations in climate model simulations (e.g. Khairoutdinov et al. (2005)).

As part of the Tropical Rainfall Measuring Mission (TRMM) ground validation program (Kummerow and Coauthors 2000), the Kwajalein Experiment (KWAJEX) took place on and around Kwajalein Atoll in the Republic of the Marshall Islands during the time period 23 July–14 September 1999. Data were collected from three aircraft, five upper-air sounding sites, one ship and a collection of remote and *in situ* surface-based sensors, including two scanning Doppler radars (Yuter et al. 2005). This extensive set of measurements provides a detailed view of the state of the atmosphere during KWAJEX. The Kwajalein ground validation (S-band) radar in particular supplies both high quality estimates of area-averaged precipitation rates and information about the three-dimensional structure of precipitation.

The KWAJEX dataset was gathered primarily to validate and improve TRMM satellite rainfall retrieval algorithms. However, its combination of radar and in-situ sensing of cloud microphysics, satellite retrievals of clouds and radiation, and well constrained thermodynamic profiles and surface fluxes presents a valuable new test of CRMs as a tool for improving climate models. Specifically, it tests the ability of a CRM to simultaneously simulate the vertical spectrum of cloud heights, the mean profiles and size distributions of ice and water particles within clouds, and the top-of-atmosphere radiative forcing by tropical

convection over a nearly two-month period spanning a variety of convective regimes.

In 1992-3, the Tropical Ocean Global Atmosphere Coupled Ocean-Atmosphere Response Experiment (TOGA COARE) gathered many of the same types of observations in the heart of the west Pacific warm pool. During KWAJEX, the sea-surface temperature was lower, mean rainfall rates were lower, and the convection was typically less organized than in TOGA COARE (Sobel et al. 2004, Lin and Johnson 1996), providing a useful comparison for future investigations to exploit.

This study presents a detailed comparison of simulations with the System for Atmospheric Modeling, a CRM developed at Colorado State University (Khairoutdinov and Randall 2003), to the full KWAJEX observational dataset from 23 July–15 September 1999. As described by Sobel et al. (2004), a wide variety of meteorological conditions were observed during KWAJEX including three intense precipitation events on July 25, August 11 and September 3. Simulating the conditions during the whole experiment allows the model’s performance to be statistically assessed across this variety of regimes to discern persistent climate-relevant model biases. These biases are also apparent when this CRM is used as a ‘superparameterization’ in a global climate model (Wyant et al. 2006). We hope that this study motivates other CRM developers to similarly compare their model with the KWAJEX dataset.

Section 2 describes the SAM CRM. In section 3, the large-scale meteorological conditions during KWAJEX are discussed along with their use as forcings that provide the large-scale context for the CRM simulations. Section 4 compares the simulations to these thermodynamic observations. Simulated radar reflectivities and cloud amounts are compared to observations by the Kwajalein ground validation radar and the satellite-derived cloud amounts from the International Satellite Cloud Climatology Project (ISCCP) D1 product in sections 5

and 6, respectively. Further microphysical sensitivity studies are included in section 7. Section 8 examines possible sources of significant OLR biases during a few periods. Finally, a summary and discussion of the results is presented in section 9.

2 Model Description

These simulations employ the System for Atmospheric Modeling (SAM, Version 6.3), a CRM developed by Marat Khairoutdinov at Colorado State University and described in detail in Khairoutdinov and Randall (2003). The model uses a single-moment bulk microphysical parameterization and has prognostic equations (numerically implemented with a positive definite advection scheme) for liquid–ice static energy, total non-precipitating water (vapor/cloud) and precipitating water. Liquid–ice static energy is conserved by atmospheric motions and microphysical transformations (but not the sedimentation of hydrometeors) and is defined as $s_{li} = C_p T + gz - L_c q_{liq} - L_s q_{ice}$ where C_p is the specific heat of dry air at constant pressure, T is the absolute temperature (in Kelvin), g is the gravitational constant, q_{liq} is the mass mixing ratio of liquid phase hydrometeors, q_{ice} is the mass mixing ratio of ice phase hydrometeors, and L_c and L_s are the latent heats of condensation and sublimation, respectively. A diagnostic relationship based on temperature is used to distinguish the different phases of non-precipitating hydrometeors (cloud liquid water and cloud ice) and precipitating hydrometeors (rain, snow and graupel). Cloud ice has a non-zero terminal velocity that depends on cloud ice water content and is derived from observations in Heymsfield (2003). A Smagorinsky-Lilly parameterization of subgrid turbulence (Smagorinsky 1963) is employed. No planetary boundary layer scheme, such as those used in global climate or weather models,

is used for vertical diffusion.

The default SAM 6.3 employs the radiation scheme from the National Center for Atmospheric Research (NCAR) Community Climate Model (CCM3) (Kiehl et al. 1998) and the bulk microphysics parameterization described in Khairoutdinov and Randall (2003). To explore the sensitivity of the model to its radiative and microphysical parameterizations, the authors have adapted for use in SAM 6.3 (i) the radiation scheme from the more current NCAR Community Atmosphere Model (CAM3) (Collins et al. 2005), (ii) a microphysical package developed at the University of Utah (UU) by Dr. S. Krueger and collaborators, which is a modified version of the schemes developed by Lin et al. (1983) and Lord et al. (1984), and (iii) an alternate parameterization of effective radii (Luo et al. 2003) (also developed at UU and consistent with the definitions of cloud water, cloud ice and snow in the UU microphysics) which can be used in place of the default CAM3 effective radii assumptions. The sensitivity of the model’s results to different radiation and microphysical schemes and to changes in SAM’s microphysical parameterization is explored in sections 4 and 7, respectively. In the remainder of this section, some of the differences between the radiative, effective radius and microphysical parameterizations are described.

The CAM3 radiation scheme has an updated treatment of the absorption and emission of longwave radiation and the absorption of near-infrared radiation by water vapor relative to the CCM3 radiation scheme, on which it was based (Collins et al. 2005). In addition, the assumptions about the cloud ice effective radii r_{ei} changed substantially, from a range of $10\mu\text{m}$ to $30\mu\text{m}$ in the CCM (with larger r_{ei} at lower pressures characteristic of tropical anvil clouds (Kiehl et al. 1998)), to $6\text{--}250\mu\text{m}$ in the CAM3 (where r_{ei} decreases with temperature to a minimum of $6\mu\text{m}$ at 180K (Kristjansson and Kristiansen 2000)). The radiative effects

of snow, graupel and rain are neglected in both the CCM3 and CAM3 radiation schemes. The Luo et al. (2003) parameterization includes the radiative effects of snow and assumes the effective radii of cloud water, cloud ice and snow are 10, 25 and 75 μm , respectively, independent of temperature and pressure.

The two microphysical packages differ in the number of prognostic water species and in the representation of individual microphysical transformations. While the default SAM microphysics includes prognostic equations for only two water species (total non-precipitating water and precipitating water), the UU microphysical package (see e.g. Krueger et al. (1995)) includes prognostic equations for six water species (water vapor, cloud liquid water, cloud ice, rain, snow and graupel). As an example of the differences in individual parameterizations, the two microphysical schemes differ in their threshold for the autoconversion of cloud liquid water into rain — with a threshold cloud liquid water mixing ratio q_{c0} of 1 g/kg in SAM and 0.5 g/kg in UU — and in the type of autoconversion parameterization — with SAM and UU following the schemes of Kessler (1969) and Orville and Kopp (1977), respectively. Assuming a cloud droplet number concentration $N_c = 70\text{cm}^{-3}$ (the average number concentration observed by Rangno and Hobbs (2005) during KWAJEX) and an air density of 1 kg/m³, the autoconversion thresholds in SAM and UU correspond to homogeneous populations of 30 μm and 24 μm diameter droplets. These values are comparable to the effective radii r_{el} and droplet threshold diameters D_T (the concentration of droplets with diameters greater than D_T is 3 cm⁻³ by definition) observed during KWAJEX by Rangno and Hobbs (2005), who found r_{el} to be 12–15 μm and $D_T \geq 30\mu\text{m}$ when more than 1 km above cloud base.

3 Design of Simulations

The CRM is run using initial soundings and time-dependent forcings (Zhang 2003), based on data and reanalyses for the time period July 24–September 14, 1999 and generated using the multivariate constrained optimization method of Zhang et al. (2001).¹ The mean horizontal velocity profiles in the model are nudged to the observed, time-dependent velocity profiles on a two hour timescale. In addition, three types of thermodynamic forcings are used in the CRM: volumetric forcings (large-scale horizontal advection of sensible energy and moisture), surface forcings (either prescribed surface latent and sensible heat fluxes — here, a combination of NCEP reanalysis and measurements on Meck Island — or a prescribed sea surface temperature along with sea surface pressure) and a mean vertical velocity w_{ls} . The large-scale advective tendencies are computed as:

$$\left(\frac{\partial s_{li}}{\partial t}\right)_{ls} = -\mathbf{u}_{ls} \cdot \nabla \bar{s}_{li} - w_{ls} \frac{\partial s_{li}}{\partial z} \quad (1)$$

$$\left(\frac{\partial q}{\partial t}\right)_{ls} = -\mathbf{u}_{ls} \cdot \nabla \bar{q} - w_{ls} \frac{\partial q}{\partial z} \quad (2)$$

where the large-scale horizontal advection terms $\mathbf{u}_{ls} \cdot \nabla \bar{\cdot}$ (uniform in x and y but varying in z) are specified by the forcings, and the large-scale vertical advection terms $w_{ls} \frac{\partial \cdot}{\partial z}$ depend on the local value of the liquid–ice static energy s_{li} and total non-precipitating water q . Here, overbars indicate horizontally-averaged quantities. Using observations from the Kwajalein Ground Validation radar, Houze et al. (2004) have estimated rainfall and assessed the uncertainties in both the radar observations and estimation technique. Because the time series of area-averaged, radar-estimated rainfall was considered to be comparatively reliable, the

¹The initial soundings have been supplemented with temperature and water vapor mixing ratios from ERA40 above 100 hPa.

forcings were constrained to closely reproduce it. Hence, model simulations will also tend to track the radar-estimated area-mean rainfall closely. Time series of the precipitation, 500 hPa large-scale vertical velocity and column-integrated large-scale horizontal advection are shown in Figure 1. Although the figure shows only a single time series for each quantity, the large-scale vertical velocity and horizontal advection have time-varying profiles in the vertical coordinate z .

While the forcings described above did not include a sea surface temperature (SST), measurements of SST were taken on the NOAA ship *Ronald H. Brown* from 28 July–18 August and 24 August–12 September 1999. These measurements cover a majority of KWAJEX and were averaged into six hour blocks, consistent with the other forcings. Missing data was filled by interpolation (using the NCEP reanalysis ocean skin temperatures from 24 July and 14 September as observations at the beginning and end of KWAJEX) with the addition of an average diurnal cycle computed from the available data. The time series of sea surface temperature constructed using this method is shown in Figure 1b.

A number of simulations were performed using SAM over the whole 52 day period of KWAJEX, from 06Z on 24 July 1999 to 06Z on 14 September 1999. Here the setup of the base simulation (denoted BASE) will be described in detail, and only the differences of the other simulations with the base simulation will be highlighted as each is introduced. Periodic boundary conditions are applied in the horizontal directions, and a rigid lid boundary condition is used at the top of the domain. The base simulation uses 64 vertical levels, with grid spacings that increase smoothly from 75 m at the surface to a nearly uniform spacing of 400 m through the troposphere and then to 1 km in a Newtonian damping region between 19 km and the domain top (at 27 km) that prevents the reflection of upward-propagating

gravity wave disturbances. In the damping region, perturbations of all prognostic variables from their horizontal mean are damped on a timescale that varies from two hours at 19 km to two minutes at the domain top. The mean values of the thermodynamic variables are not nudged to observed values in the damping region. A horizontal grid of 64×64 points is employed with a resolution of 1 km. This domain size compromises our ability to realistically simulate large mesoscale systems, but has little effect on the statistics of the convection, as we will show. The base simulation is forced by the large-scale vertical velocity and horizontal advective tendencies, as well as the sea surface temperature described above, and uses the CAM3 radiation scheme (as do all other runs with one exception mentioned below) with radiative transfer computed in each model grid column approximately every three minutes. Table 1 summarizes the simulations to be presented. These include BASE and a number of sensitivity studies on the effect of domain size, resolution and choice of radiative and microphysical parameterizations. All of these runs are performed without any nudging of the mean thermodynamic profiles.

4 Model Results

4.1 Temperature and moisture biases

Time series of troposphere-averaged (surface to 100 hPa) moist static energy, dry static energy (both expressed as equivalent temperatures by dividing by C_p) and precipitable water from the simulations and observations are shown in Figure 2. Overall, the simulations exhibit remarkably similar and realistic behavior. The simulated dry static energy remains mainly

within 1K of the nearly constant observed value, and the simulated precipitable water tracks the major variations in the observations with only small mean biases. This suggests that the forcings are fairly accurate, and that the model responds appropriately to these forcings. The SST-forced simulations (simulations with a prescribed SST, as opposed to prescribed surface fluxes, see Table 1) show a slight warm and moist bias as seen in Figure 2b–c, resulting in an excess of moist static energy during KWAJEX. The simulation forced by surface energy fluxes (denoted FLX) has a cold bias in dry static energy (fig. 2b) from the fifth day of the simulation onward. While all of the simulations track the tropospheric moist static energy through the first ten days of the simulation with an error of less than 1K, this is accomplished with more variability in the dry static energy and less variability in the moisture than is seen in the observations.

The vertical structure of the time-averaged biases in temperature and relative humidity (with respect to water saturation) can be seen in Figure 3. Note that above 200 hPa, detailed comparison of the observed and modelled relative humidity is unwarranted, because cold temperatures rendered the radiosonde observations of relative humidity less reliable at some KWAJEX sites (e.g. Fig. 7 of Sobel et al. (2004) and Miloshevich et al. (2004)).

All simulations have mean temperature biases of less than 1K up to almost 250 hPa, with the SST-forced simulations showing warm biases and FLX showing a cold bias. Each simulation has a large cold bias at the tropopause. The vertical resolution and horizontal extent of the model do not permit the accurate simulation of the processes that maintain the tropopause (Kuang and Bretherton 2004) and should not be expected to closely reproduce the tropopause temperature in this case.

All of the simulations show a slight dry bias from the surface up to 950 hPa and, ex-

cept for BIG and 2KM, a moist bias above 800 hPa. The relatively small middle- and upper-tropospheric relative humidity bias in BIG suggests that a larger domain may allow sufficient area for more realistic mesoscale organization of convection and humidity, allowing dry patches to form even during convectively active periods (Bretherton et al. 2005). Despite the bias in middle and upper tropospheric relative humidity, the smaller domain ($64\text{ km} \times 64\text{ km}$) does not lead to other significant biases and is computationally affordable for sensitivity studies, so it has been adopted as the default domain size in this paper.

Figure 4 shows simulated time series of latent and sensible heat fluxes along with near-surface wind speeds, while the time series of temperature, water vapor mixture fraction and relative humidity at 1000 hPa are shown in Figure 5. In the SST-forced runs, the model generally reproduces the surface energy fluxes from the forcings (Fig. 4b–c), with the exception of brief periods when sensible heat flux in the model or analysis – but not both – jumps from its time-averaged value by a factor of two to four. These jumps are associated with cold pools driven by rainfall evaporation and convective downdrafts. The observations come in part from point measurements, explaining the more frequent and intense spikes in the observed sensible heat flux. The modeled surface wind speeds generally underpredict the observations and would be expected to produce a low bias in the latent heat fluxes. However, the latent heat fluxes generally exceed those observed (surface energy flux observations were constructed from a combination of NCEP reanalyses and measurements), due (we believe) to the dry bias near the surface (Fig. 5b). The 1000 hPa temperature (Fig. 5a) in the SST-forced runs reproduces the observations, suggesting that the our assumed SST time series is consistent with the near-surface temperature measured by the radiosondes. The run FLX shows greater variability in its 1000 hPa temperature than the observations, as

one would expect. Figure 5b–c shows a dry bias of the models near the surface, also seen in Fig. 3b. However, there is general statistical consistency between the simulated and observed boundary-layer response to convection. In particular, the pronounced cold and dry periods seen on days 223 and 246 in both of the observations and model arise due to cold pools (see e.g. Tompkins (2001)) associated with convective rainfall during those days.

4.2 Precipitation, cloud and radiative biases

Figure 6a shows that the model simulations accurately reproduce the observed precipitation time series reconstructed from the Kwajalein Ground Validation radar. This result is expected, since the large-scale vertical velocity in the forcings was constructed in part using the observed precipitation time series.

Figures 6b–d show comparisons of selected radiation and cloud time series from the model and observations.² The model systematically underpredicts both shaded cloud fraction and the radiative impact of the clouds on top-of-atmosphere (TOA) radiative fluxes through much of KWAJEX, with overestimation of outgoing longwave radiation (OLR) and underestimation of reflected shortwave radiation (RSW) at TOA. Notable exceptions are days 223 and 246 (August 11 and September 3) — two of the most heavily precipitating days during KWAJEX — when the model simulations closely match the observed TOA radiative fluxes as well as the observed complete cloud cover. However, these simulations suggest that the model underestimates cloud cover during weakly precipitating periods characterized by

²The observed time series, extracted from the ISCCP dataset, were supplied by Dr. M. Zhang with the forcings. The shaded cloud fraction is the ISCCP infrared cloud amount, which can be observed during both day and night. Model columns whose cloud optical depth exceeds 0.3 are considered to have cloud.

congestus and isolated deep convection, a common regime during KWAJEX.

In deep convective regions over tropical oceans (as around Kwajalein, which is on the edge of the western Pacific ITCZ), the top-of-atmosphere OLR is closely correlated to precipitation (Xie and Arkin 1998), and the top-of-atmosphere shortwave cloud radiative forcing approximately balances their longwave forcing (Ramanathan et al. 1989), implying a parallel relation between RSW and precipitation. As shown in Figure 7, which includes a representative subset of the model runs, the satellite-observed dependence of daily-averaged OLR and RSW on precipitation is qualitatively reproduced by the simulations, with greater suppression of OLR and an increase in RSW on days with substantial precipitation. However, as seen in the time series in Figure 6, the observations show a much stronger trend toward decreased OLR and increased RSW on days with moderate (less than 20 mm d^{-1}) precipitation. The alternate effective radius parameterization used in EFF shows a smaller but still significant bias on such days. Advected condensate (e.g. in cirrus anvils diverging from the core ITCZ to the South of the Kwajalein region) is not included in the forcings and could explain some of these biases. The exclusion of aerosols from the radiative computations in the model may contribute to the mismatch of RSW in suppressed conditions but explains only a small fraction of the bias. The underlying causes for these discrepancies will be further studied in sections 7 and 8.

In an analysis of satellite and radar observations (including the ground validation radar at Kwajalein), Bretherton et al. (2004) documented an exponential relationship over tropical ocean regions between precipitation and column relative humidity (CRH, defined as the ratio of the water vapor path to that required to saturate the column). Raymond and Zeng (2005) and Bretherton et al. (2005) documented similar relationships in idealized CRM simulations;

we now use this as a statistical test of the CRM simulations of KWAJEX. Figure 8 shows the relationship between daily- and domain-averaged precipitation and CRH for the observations and a representative selection of model runs. The precipitation is shown on a log scale above 1 mm d⁻¹ and a linear one below, so days with both heavy and light precipitation can be seen. An exponential fit to the observations $P = \exp(18(r - 0.74))$, where P is precipitation in mm d⁻¹ and r is column relative humidity, is also shown. The simulations are all in fair agreement with the observational fit and show similar levels of scatter about this fit as are found in the observations.

4.3 Time-averaged microphysical profiles

Time-averaged profiles of horizontal mean hydrometeor mass mixture fractions are shown in Figure 9. In the default (SAM) microphysics scheme, hydrometeor mass mixture fractions are diagnosed based on temperature-dependent partitioning of the condensate and precipitate mass. All the runs using the SAM microphysics behave similarly for the most part, although CCM (which uses the CCM3 radiation scheme) shows smaller levels of ice hydrometeors as well a smaller cloud fraction above the melting level. The larger domain runs (BIG and 2KM) have a slightly smaller peak cloud fraction, corresponding to their lower relative humidity around 300 hPa (Fig. 3). The effect of horizontal resolution can be clearly seen around 900 hPa in cloud water mixing ratio q_c , where the cloud water content increases from 10 to 14 mg kg⁻¹ as the horizontal grid spacing increases from 500 m to 2 km. The finer grid spacing supports smaller cumuli with more vigorous updrafts, requiring less cloud to carry the same area-averaged upward mass flux.

There are clear differences between UU, which uses a single-moment microphysical scheme with prognostic equations for all hydrometeors, and the other runs. The UU run exhibits a sharper transition between liquid and ice phase precipitation near the melting level, more than twice as much graupel and about half as much cloud ice as the SAM microphysics scheme in BASE. Note that UU uses the alternative Luo et al. (2003) effective radius specification and includes snow as radiatively active, so that the relatively smaller amount of cloud ice in this run does not lead to further biases in the TOA radiative fluxes. The SAM and UU microphysical schemes also differ in their specification of cloud ice sedimentation. The UU scheme assumes no cloud ice sedimentation velocity, while the SAM scheme has a fall speed based on ice water content that is derived from Heymsfield (2003). The smaller cloud ice mixing ratios in UU may be attributed in part to effective accretion of cloud water and cloud ice by the substantial graupel amounts just above the melting level.

While the transition between liquid and ice phase cloud condensate in the SAM scheme appears to match that of the UU run, the transition between the liquid and ice phase precipitating hydrometeors is much broader. If the melting layer is defined (roughly) as the region over which the time-averaged precipitating hydrometeors fields are between 20% and 80% liquid water, the SAM microphysics melting layer occurs over 271–280K. The UU scheme melting layer lies between 274 and 277K. Since precipitation phase changes are explicitly simulated in UU, this suggests that the range of temperatures over which mixed phase precipitation exists in the SAM microphysics is too large in this case.

Despite variability between these runs in the ice phase microphysics, many other properties of these runs, even including the top-of-atmosphere radiative fluxes, match closely. This is less surprising than it may seem, as the UU microphysical/radiation schemes were used

to help set some adjustable microphysical parameters in SAM (Marat Khairoutdinov, pers. comm. 2005).

4.4 Profiles of horizontal variances

Time-averaged values of dynamical quantities are shown in Figure 10. The root mean square (rms) fluctuations are computed from the variation of each quantity with respect to the time-varying, rather than the time-averaged, domain-mean profile of that quantity. The rms vertical velocity fluctuations are approximately uniform with height from 2–12 km, and are insensitive to the model configuration. The rms horizontal velocity fluctuations (especially u_{rms}) have a peak near 200 hPa, associated with strong convective detrainment, and also a surface peak associated with cold pools.

The rms fluctuations of total moisture (water vapor/cloud) peak just between 850 and 950 hPa, possibly due to gradient production of moisture fluctuations by convective motions. The fluctuations of liquid–ice static energy, on the other hand, are almost uniform between 200 and 800 hPa, except for UU where the increased variability above the melting level (~ 550 hPa) may result in part from large amounts of graupel.

Domain size dependence is seen in the fluctuations of horizontal velocity, total moisture and liquid–ice static energy, with larger variability throughout the troposphere in BIG and 2KM ($(256 \text{ km})^2$ and $(128 \text{ km})^2$ domains, respectively), while 500M has smaller horizontal velocity variability up to 400 hPa. Convective overshoots induce a peak in the skewness of the vertical velocity at 150 hPa, whose strength grows with the horizontal grid spacing in these runs.

4.5 Energy and moisture budgets

Figure 11 shows time-mean energy and moisture budgets for BASE. In the liquid–ice static energy budget (Fig. 11a), a rough balance exists between latent heating (Lat) and the divergence of eddy energy fluxes (Eddy). Note that Lat is associated with the fall of precipitation through the air, as s_{li} is invariant under changes in phase. The large-scale vertical s_{li} advection (LSVadv) and radiative heating (Rad, roughly constant at -1 K d^{-1} up to 12 km) are smaller sinks at most heights. There is a very slight mean large-scale horizontal warm advection (LSHadv). The latent heating (Lat) is positive in the middle and upper troposphere and negative below 2 km due to rain evaporation, while the convective eddies diverge s_{li} from the upper troposphere and converge it into the boundary layer through high s_{li} convective downdrafts and surface sensible heat fluxes.

The budget for total moisture (vapor + cloud + precipitate) in Figure 11b shows a similar balance in which each term has opposite sign. Here, the divergence of the precipitation flux (Fall), the eddy moisture flux divergence and the large-scale vertical advection can be identified with the latent heating, eddy flux divergence and large-scale vertical advection terms in the s_{li} budget. The eddy flux moves moisture from the 0–2 km layer higher into the troposphere, where it is removed by the precipitation flux and partly recycled by evaporation into the 0–2 km layer. Large-scale horizontal moisture advection noticeably dries the atmosphere just above the boundary layer.

Frozen moist static energy, $h_f = C_p T + gz + L_c q_v - L_f q_{ice} = s_{li} + L_c q_{tot}$, is conserved by adiabatic processes including phase changes and liquid-phase precipitation. Its budget in Figure 11c is an informative complement to the other two budgets, since the large eddy and

precipitation terms in those budgets largely cancel when expressed as sources/sinks of h_f . For example, the latent heating term in the h_f budget can be written $d(L_f P_{ice})/dz$ where P_{ice} is the precipitation flux of ice. This term is much smaller than in the s_i budget, where it involves all precipitating hydrometeors and the latent heats of condensation and sublimation. The column-integrated budget of h_f is particularly simple, reducing to a balance between the surface h_f flux, radiative cooling, and large-scale advection. This has been exploited in numerous theoretical studies (e.g. Neelin and Held (1987), Neelin and Zeng (2000), Bretherton and Sobel (2002)).

Through most of the troposphere, eddies are the main source of h_f , vertically distributing the surface h_f fluxes, and radiation is the leading sink of h_f . Latent heating above the melting level and cooling below are also significant. Vertical advection is an important h_f source at low levels but is nearly canceled by the horizontal advective h_f sink. This balance in large-scale advection is typical of the narrow central Pacific ITCZ and contrasts with the west Pacific warm pool, which exhibits strong column-integrated convergence of moist static energy — mainly associated with vertical advection (Back and Bretherton 2005). Above 14km, in the tropopause transition layer above the peak in convective detrainment and cloud, the balance changes as eddy processes and vertical advection cool the atmosphere, and radiation and ice fallout warm it.

5 Radar Reflectivities

A distinguishing feature of KWAJEX was the presence of a well-calibrated, research-quality radar during the experiment which provides a time-resolved, three-dimensional reflectivity

dataset. As noted above in section 3, the forcings were constrained to reproduce the radar-derived, area-mean precipitation time series. Hence we expect the good agreement between the simulated and observed area-mean rainfall time series seen in Fig. 6.

However, the observed rainfall is derived only from areal averages of the lowest level radar scans. The CRM is not constrained to match the observed vertical structure and horizontal variability of the radar reflectivity field. Hence, these provide discriminating tests of the CRM-simulated storm structure and microphysics which we will exploit in this section. Because radar preferentially detects the largest hydrometeors and radiation responds mostly to small condensate particles, these tests are useful complements to top-of-atmosphere radiation observations.

To compare the model precipitation fields with the radar observations, we derive simulated radar reflectivity from the model-predicted hydrometeor mass mixing ratios using $Z - M$ relationships (see e.g. Battan (1973)) which encode assumptions about the distribution of particle sizes (and habits, in the case of ice) that are built into the model. The $Z - M$ relationship for rain can be computed directly from the model-assumed Marshall-Palmer drop size distribution. Those for snow and graupel are based on Heymsfield et al. (2002) and use the properties of the model’s assumed exponential particle size distribution. (See Khairoutdinov and Randall (2003) for a fuller description of the model’s microphysical parameterization.) This results in the following expression for the equivalent radar reflectivity:

$$Z_e = 2.0 \cdot 10^4 (\rho q_r)^{1.75} + \frac{0.197}{0.93} \left(6.0 \cdot 10^3 (\rho q_s)^{1.72} + 4.9 \cdot 10^3 (\rho q_g)^{1.72} \right) \quad (3)$$

where the air density ρ is expressed in $g\ m^{-3}$, the effective radar reflectivity Z_e in $mm^6\ m^{-3}$,

and the coefficient $0.197/0.93$ accounts for the index of refraction difference between ice and water.

Interesting comparisons could be made by examining the time-space structure of individual radar echoes as in Houze and Cheng (1977) and Cetrone and Houze (2006), but we simply compare the probability density functions of simulated and observed radar reflectivities during KWAJEX. Figure 12 shows the probability distribution of radar reflectivity as a function of altitude from two simulations, BASE and UU, as well as the observations. These are similar to the CFADs introduced by Yuter and Houze (1995), but are scaled differently so that the integral of the probability distribution at any height will give the area fraction of precipitation at that height. Both BASE and UU predict a substantially broader reflectivity distribution at each height than observed. The BASE model run shows area fractions of echoes with high dBZe values (e.g. greater than 50 dBZe at 2 km or 40 dBZe at 5km) that are several times those seen in the observations. The observations, on the other hand, have a strong peak in area fraction between 10 and 20 dBZe and fall off quickly below 10 dBZe due to processing of the radar signal. The model reflectivities below 10 dBZe correspond to weakly precipitating columns, likely on the edges of more strongly precipitating regions. Increased concentrations of simulated graupel in UU result in higher area fractions of significant precipitation above the freezing level than in BASE. The reflectivity distribution from BASE underestimates the area of significant precipitation (as measured by the fraction of 20 dBZe or larger radar reflectivity at 2km elevation) in the observations (2.9% in BASE vs. 5.1% observed), while UU (3.4%) shows a slightly smaller bias. The models correctly predict (to within 10%) the area fraction of echoes with reflectivities greater than 30 dBZe and overestimate the area fraction of echoes with reflectivities above 40 dBZe by a factor of

three. These biases are seen consistently throughout KWAJEX when the reflectivity PDFs are plotted as functions of time as well as height. The excessive occurrence of high reflectivities and underprediction of moderate reflectivities suggest inadequate production of simulated stratiform rainfall. Indeed, the model seems to produce smaller and less extensive regions of radar-reflective anvil than observed, consistent with the tendency seen in Figure 6 to simulate excessive outgoing longwave radiation under all but the most intense forcing.

This reflectivity bias is robust to model resolution, domain size, SAM vs. UU microphysics, and possible radiative feedbacks on the dynamics, and so is a useful target for future model improvements. However, there are also issues of interpretation. The Z-M relationship in (3) depends sensitively on the assumed hydrometeor size distributions and radar scattering properties. For instance, the assumption of a gamma – rather than an exponential – distribution for the precipitating hydrometeors would give a smaller range of simulated reflectivities for a given variation in hydrometeor concentrations and improve to some extent the agreement with observations. In addition, uncertainties in the radar observations described in Houze et al. (2004) could also contribute in small measure to the biases between the observed and modeled reflectivities.

6 ISCCP Cloud Amounts

Global circulation models are tuned to satisfy the top of atmosphere radiation balance and are often able to capture the observed geographical distribution of TOA shortwave and longwave cloud forcing over areas of persistent tropical convection. However, they fail dramatically to reproduce the observed distribution of cloud height and optical depth (Lin and Zhang

2004, Wyant et al. 2005), with far too little cloud with a radiatively-derived top height in the mid-troposphere and too little cloud of moderate optical depth. CRMs provide a more detailed representation of cloud and convective processes that should enable a more faithful reproduction of both individual clouds and the statistics of deep convective cloud populations.

Satellite measurements have been used to generate the climatology of cloud height and optical depth in the ISCCP D1 dataset, which can be directly compared to the model cloud fields using an ISCCP simulator (Klein and Jakob 1999). Given a model cloud field, an ISCCP simulator estimates the distribution of cloud height and optical depth which would be observed from space using a method consistent with that used to produce the ISCCP dataset. In the ISCCP dataset, clouds are binned into 42 categories according to cloud height and optical depth. The cloud fraction comparison in Figure 6 shows a time series of the total cloud fraction, including all cloud heights and optical depths.³ To simplify comparisons here, the ISCCP height/optical depth bins are aggregated into three height categories: low (surface to 680 hPa), middle (680 to 440 hPa) and high (above 440 hPa); and three optical depth bins: thin (0.3 to 3.6), medium (3.6 to 23) and thick (above 23) following Rossow and Schiffer (1999).

As seen in Table 2, the observations show a substantial amount of total high cloud (>45%), predominantly of low optical depth. The ISCCP cloud amount also decreases with decreasing cloud top height, in part from the blocking of low clouds by high clouds when

³The ISCCP simulator adds an additional category for thin clouds with optical depths below 0.3 (the minimum optical depth in the ISCCP D1 dataset), but that category is not included in the results shown in Figure 6 or Table 2.

viewed by satellite. The simulated ISCCP cloud amounts reconstructed from model cloud fields are shown for two simulations in Table 2: BASE and EFF (identical to BASE except for the Luo et al. (2003) specification of effective radius). Both simulations do a good job of estimating the amount of high, thin cloud but somewhat underestimate the amount of other types of high cloud, and considerably underestimate the mid-top and low-top cloud fractions. Compared to BASE, EFF somewhat improves the high cloud amounts through the use of a fixed ($r_{ei} = 25\mu\text{m}$) effective radius for cloud ice and the inclusion of snow ($r_{es} = 75\mu\text{m}$) as a radiatively active hydrometeor. (Snow is not considered radiatively active in the runs that use the default effective radius definitions.) While EFF reduces the biases in OLR and RSW on some days (see Fig. 7), the model continues to overpredict OLR during periods of less intense convection. The same holds true for the other sensitivity studies.

7 Further Microphysical Sensitivity Studies

While the forcing method constrains the simulated area-mean rainfall to nearly match the radar-derived rainfall, the distribution of simulated radar reflectivities differ from observations. The model produces an excessively broad spectrum of radar reflectivities at all heights and excessive convective rainfall. Taken together with simulated ISCCP cloud amounts, which indicate a deficit of medium and high optical depth clouds, this suggests that the model precipitates moisture too efficiently out of a few, highly convective columns, in contrast to observations that indicate more stratiform cloud.

To explore the role of microphysical assumptions in the model’s apparently excessive precipitation efficiency, three microphysical sensitivity studies have been performed. In the

first sensitivity study, the threshold cloud water mixing ratio in the SAM warm cloud autoconversion parameterization (based on Kessler (1969)) has been decreased from a default value of $q_{c0} = 1 \text{ g kg}^{-1}$ to 0.5 g kg^{-1} and 0.2 g kg^{-1} in two separate simulations. These smaller thresholds correspond to homogeneous populations of $24\mu\text{m}$ and $18\mu\text{m}$ droplets with $N_c = 70\text{cm}^{-3}$ (Rangno and Hobbs 2005). The lower thresholds in these simulations lead to a decrease in cloud liquid water but does not significantly change the amount of cloud ice in the simulation or the radiative effect of the clouds. In fact, the decrease in cloud liquid water leads to a decrease in albedo and in reflected shortwave radiation. The second sensitivity study decreased the rates of autoconversion and accretion in both warm and cold clouds by a factor of two, while holding the warm cloud autoconversion threshold fixed. (See the appendix of Khairoutdinov and Randall (2003) for the default values.) The cloud liquid water and cloud ice mixing ratios increase in this case, leading to a slight reduction in the model’s biases in reflected shortwave and outgoing longwave radiation. However, this change does not substantially reduce the model’s radiative biases during periods of moderate precipitation and worsens the model’s moist bias in the mid-troposphere. Halving the cloud ice fall speed in the third sensitivity study reduces the time-averaged biases in OLR, RSW and ISCCP high cloud amount, but does not improve the model’s radiative bias during periods of moderate precipitation. It also leads to a warm bias in the upper troposphere of 3.5K. Our overall experience is that plausible changes to SAM’s microphysical parameters have rather little impact on the large cloud radiative forcing biases during periods of lightly precipitating congestus convection and do not improve the overall quality of the KWAJEX simulation.

8 Transient Model Biases

In this section, we will take a more detailed look at biases in the cloud systems simulated during one two-week subperiod, and the roles of CRM physics errors vs. forcing errors in creating these biases. We use the BIG simulation for this comparison because its large domain size produces much less artificial time variability in domain-averaged cloud statistics than in BASE.

Figure 13 shows a model–observation comparison of time-varying quantities relevant to clouds and radiation for the period from days 212–225 (July 31–August 13, 1999) using the model results from BIG. The OLR (Fig. 13a) is strongly correlated to relative humidity (Fig. 13b–c), which in turn is influenced by its total (horizontal and vertical) large-scale advective forcing (Fig. 13d). This advective forcing is driven mainly by large-scale vertical motion. The figure also includes area-averaged cloud water content (Fig. 13e) from the model and area-averaged radar reflectivities (Fig. 13f–g) from both the model and the Kwajalein radar. The latter are computed as $dB\bar{Z}_e = 10\log_{10}(\bar{Z}_e)$ where $\bar{Z}_e$ is horizontal average of effective radar reflectivity over the domain of the simulation or areal coverage of the radar (which will strongly weight heavily precipitating regions).

As mentioned in section 4.2, the simulated OLR generally matches the observations in the heaviest rainfall events (such as day 224), but tends to overestimate OLR during periods of weak to moderate precipitation (such as days 212–217). We believe this to be a bias of the CRM microphysical parameterizations, since it is so persistent throughout our KWAJEX simulations.

To examine this bias more carefully, we compared simulated ISCCP cloud statistics

(Table 3) and vertical profiles of relative humidity, condensate and radar reflectivity PDF averaged over days 212–217 with available observations (Fig. 14). This period is marked by large-scale upper-tropospheric mean advective drying of about 5% in relative humidity per day, so cirrus clouds are presumably formed mainly from convective detrainment and have lifetimes of at most a few hours. The simulated relative humidity is somewhat too low (Fig. 14a), but it is unclear if this is a cause or an effect of the insufficient cloud. Visual inspection of infrared satellite imagery during this and other weak convection periods in KWAJEX did not suggest that cirrus was systematically advecting horizontally into the study area to create the observed OLR; such an effect would not be included in our model forcings. In fact, the KWAJEX-mean wind at 250 hPa is nearly zero (Sobel et al. 2004).

Thus we investigated possible deficiencies in the simulation of convectively detrained condensate and its radiative characteristics during this period. The simulated ISCCP high and mid-top cloud amounts are only roughly 10% as much as observed (Table 3). This suggests that the cloud amount, rather than the effective radius or cloud optical depth, is probably the biggest contributor to the model OLR bias. Fig. 14b shows that about half of the simulated condensate is precipitating ice, and the radar reflectivity PDFs in Fig. 14c-d suggest that although the simulated cloud depths are realistic, there are excessive highly reflective (hence large and rapidly falling) hydrometeors at all heights during this period, just as we earlier found for KWAJEX as a whole. This suggests that the modelled congestus clouds are precipitating too efficiently and leaving far too few small, long-lived cloud ice particles after they decay. There is a wealth of in-situ aircraft microphysical observations from KWAJEX that could be used in the future to investigate this hypothesis and to improve the CRM microphysical parameterizations.

Sometimes, model bias may be mainly induced by errors in the large-scale forcings, as occurs on days 218–222. This period is one of the few times during KWAJEX when the model OLR is less than that observed. Fig. 15 compares simulated and observed vertical profiles of humidity and cloud averaged over days 219 and 220 in the same format as Fig. 14. The high observed OLR suggests there is little cirrus cloud and the soundings indicate a dry upper troposphere (Fig. 15a). In contrast, the lower simulated OLR is associated with extensive upper tropospheric cirrus, high relative humidity and large-scale upward motion in the upper troposphere. The time-series (Fig. 13) and reflectivity histogram (Fig. 15c) of radar observations show precipitating shallow or congestus convection but no reflectivity above 10km indicative of deep convection. The CRM-simulated radar reflectivity reproduces this behavior, except for one brief deep convective event on day 219 that does not impact the simulated reflectivity histogram (Fig. 15d), and the upper- and lower-tropospheric condensate maxima are well separated (Fig. 15b). Hence, deep convection probably appears not to have a significant impact on upper tropospheric humidity or cloud during this period in either the simulations or the observations. The easiest explanation for the discrepancy between the CRM and the observations is that the prescribed upward motion in the upper troposphere forcing the modelled cirrus is spurious. This is quite plausible, since radar-derived rainfall and other KWAJEX observations did not constrain the detailed upper-tropospheric vertical motion profile used to force the CRM nearly as tightly as they constrain column-integrated heat and moisture divergence.

Another possible forcing bias in Fig. 13 can be seen on day 222, when the simulations lag the observed relative humidity increase by a day. As the observed relative humidity increases before the onset of significant convective rainfall, this model bias may be caused by

errors in the large-scale horizontal advective forcing. The advantage of long simulations like those presented in this paper is that such transient forcing biases may average out to allow a clearer view of systematic model errors such as the inadequate clouds seen here during weakly convective 'congestus' regimes.

9 Summary and Discussion

Three-dimensional cloud resolving model simulations of the whole 52-day KWAJEX period using prescribed time-varying large-scale advective forcings and wind profile nudging, but without thermodynamic nudging, successfully track synoptic variability in precipitable water and reproduce the time-mean thermodynamic profiles without significant bias.

In comparisons of simulated TOA radiative fluxes, ISCCP cloud amounts and radar reflectivity profiles to observations, different microphysical/radiation schemes and different horizontal resolutions and domain sizes had only minor impacts on the results. The amount and optical depth of high cloud are systematically underpredicted by all versions of the model, leading to excessive OLR and insufficient albedo, except during the rainiest periods. Sometimes, cirrus advected from remote convection or errors in the imposed upper-level vertical velocity also help to create model-observation differences.

While the forcing method constrains the simulated area-mean rainfall to nearly match the radar-derived rainfall, the distribution of simulated radar reflectivities differ from observations. The model produces an excessively broad spectrum of radar reflectivities at all heights and excessive convective rainfall. Taken together with simulated ISCCP cloud amounts, which indicate a deficit of medium and high optical depth clouds, this suggests

that the model precipitates moisture too efficiently out of a few, highly convective columns, in contrast to observations that indicate more stratiform cloud. Changes to the microphysics can lead to improved ISCCP cloud amounts and reduce the time-averaged OLR and RSW biases during KWAJEX; however, they do not substantially improve the ability of the simulations to track the observed changes in OLR and RSW during periods of moderate precipitation. The reflectivity, cloud and radiation biases deserve further investigation and suggest that prediction of the number concentration of cloud and precipitation particles may be necessary for the proper representation of the range of meteorological conditions observed during KWAJEX.

The many airborne datasets from KWAJEX (Yuter et al. 2005, Rangno and Hobbs 2005) at altitudes up to 10 km invite comparison with CRM-predicted microphysics as well. Simulations such as those presented here provide an excellent opportunity for bridging between such data and regional or global applications of CRMs for which faithful simulation of radiation and cloud microphysics are of great importance.

Acknowledgments. This research was supported by NASA Tropical Rainfall Measuring Mission (TRMM) under grant NAG5-13564. The authors would like to thank Bob Houze, Sandra Yuter, Zhiming Kuang and Larissa Back for useful discussions, Marc Michelson for help with computations, Matt Wyant for help with ISCCP data obtained from NASA Langley DAAC, Minghua Zhang for providing the forcings, Steve Krueger for the microphysical package and useful discussions regarding microphysical assumptions, and three anonymous reviewers for their suggestions.

References

- Back, L. E. and C. S. Bretherton 2005. The relationship between wind speed and precipitation in the Pacific ITCZ. *J. Climate* **18**, 4317–4328.
- Battan, L. J. 1973. *Radar Observation of the Atmosphere*. Chicago: University of Chicago Press.
- Bretherton, C. S. and A. H. Sobel 2002. A simple model of a convectively coupled walker circulation using the weak temperature gradient approximation. *J. Climate* **15**, 2907–2920.
- Bretherton, C. S., M. E. Peters, and L. E. Back 2004. Relationships between water vapor path and precipitation over the tropical oceans. *J. Climate* **17**, 1517–1528.
- Bretherton, C. S., P. N. Blossey, and M. Khairoutdinov 2005. An energy-balance analysis of deep convective self-aggregation above uniform sst. *J. Atmos. Sci.* **62**, 4273–4292.
- Cetrone, J. and R. A. Houze 2006. Characteristics of tropical convection over the ocean near Kwajalein. *Mon. Wea. Rev.* **134**, 834–853.
- Collins, W. D., P. J. Rasch, B. A. Boville, J. J. Hack, J. R. McCaa, D. L. Williamson, B. P. Briegleb, C. M. Bitz, S.-J. Lin, and M. Zhang 2005. The formulation and atmospheric simulation of the Community Atmosphere Model: CAM3. *J. Climate* . accepted.
- Heymsfield, A. J. 2003. Properties of tropical and midlatitude ice cloud particle ensembles. Part II: Applications for mesoscale and climate models. *J. Atmos. Sci.* **60**, 2592–2611.

- Heymsfield, A. J., A. Bansemer, P. R. Field, S. L. Durden, J. L. Stith, J. E. Dye, W. Hall, and C. A. Grainger 2002. Observations and parameterizations of particle size distributions in deep tropical cirrus and stratiform precipitating clouds: Results from in situ observations in TRMM field campaigns. *J. Atmos. Sci.* **59**, 3457–3491.
- Houze, R. A. and C.-P. Cheng 1977. Radar characteristics of tropical convection observed during GATE: Mean properties and trends over the summer season. *Mon. Wea. Rev.* **105**, 964–980.
- Houze, R. A., S. Brodzik, C. Schumacher, S. E. Yuter, and C. R. Williams 2004. Uncertainties in oceanic radar rain maps at kwajalein and implications for satellite validation. *J. Appl. Meteor.* **43**, 1114–1132.
- Kessler, E. 1969. *On the Distribution and Continuity of Water Substance in Atmospheric Circulation*. Number 32 in ‘Meteorological Monographs’, Amer. Meteor. Soc.
- Khairoutdinov, M. F. and D. A. Randall 2003. Cloud resolving modeling of the ARM Summer 1997 IOP: Model formulation, results, uncertainties, and sensitivities. *J. Atmos. Sci.* **60**, 607–625.
- Khairoutdinov, M. F., D. A. Randall, and C. DeMotte 2005. Simulations of the atmospheric general circulation using a cloud-resolving model as a super-parameterization of physical processes. *J. Atmos. Sci.* **62**, 2136–2154.
- Kiehl, J. T., J. J. Hack, G. B. Bonan, D. L. W. B. A. Boville, and P. J. Rasch 1998. The National Center for Atmospheric Research Community Climate Model: CCM3. *J. Climate* **11**, 1131–1149.

- Klein, S. A. and C. Jakob 1999. Validation and sensitivities of frontal clouds simulated by the ECMWF model. *Mon. Wea. Rev.* **127**, 2514–2531.
- Kristjansson, J. E. and J. Kristiansen 2000. Impact of a new scheme for optical properties of ice crystals on climates of two GCMS. *J. Geophys. Res.* **105**, 10063–10079.
- Krueger, S. K., Q. Fu, K. N. Liou, and H. S. Chin 1995. Improvements of an ice-phase microphysics parameterization for use in numerical simulations of tropical convection. *J. Appl. Meteor.* **34**, 281–287.
- Kuang, Z. and C. S. Bretherton 2004. Convective influence of the heat balance of the tropical tropopause layer: A cloud-resolving model study. *J. Atmos. Sci.* **61**, 2919–2927.
- Kummerow, C. and Coauthors 2000. The status of the Tropical Rainfall Measuring Mission (TRMM) after two years in orbit. *J. Appl. Meteor.* **39**, 1965–1982.
- Liang, X.-Z. and X. Wu 2005. Evaluation of a GCM subgrid cloud-radiation interaction parameterization using cloud-resolving model simulations. *Geophys. Res. Lett.* **32**, L06801.
- Lin, W. Y. and M. H. Zhang 2004. Evaluation of clouds and their radiative effects simulated by the near community atmospheric model against satellite observations. *J. Climate* **17**, 3302–3318.
- Lin, X. and R. H. Johnson 1996. Heating, moistening and rainfall over the western pacific warm pool during TOGA-COARE. *J. Atmos. Sci.* **53**, 3367–3383.

- Lin, Y. L., R. D. Farley, and H. D. Orville 1983. Bulk parameterization of the snow field in a cloud model. *J. Climate Appl. Meteor.* **22**, 1065–1092.
- Lord, S. J., H. E. Willoughby, and J. M. Piotrowicz 1984. Role of a parameterized ice-phase microphysics in an axisymmetric tropical cyclone model. *J. Atmos. Sci.* **41**, 2836–2848.
- Luo, Y., S. K. Krueger, G. G. Mace, and K. Xu 2003. Cirrus cloud properties from a cloud-resolving model simulation compared to cloud radar observations. *J. Atmos. Sci.* **60**, 510–525.
- Miloshevich, L. M., A. Paukkunen, H. Vömel, and S. J. Oltmans 2004. Development and validation of a time-lag correction for vaisala radiosonde humidity measurements. *J. Atmos. Oceanic Technol.* **21**, 1305–1327.
- Neelin, J. D. and I. M. Held 1987. Modeling tropical convergence based on the moist static energy budget. *Mon. Wea. Rev.* **115**, 3–12.
- Neelin, J. D. and N. Zeng 2000. A quasi-equilibrium tropical circulation model – Formulation. *J. Atmos. Sci.* **57**, 1741–1766.
- Orville, H. D. and F. J. Kopp 1977. Numerical simulation of the life history of a hailstorm. *J. Atmos. Sci.* **34**, 1596–1618.
- Ramanathan, V., R. D. Cess, E. F. Harrison, P. Minnis, B. R. Barkstrom, E. Ahmad, and D. Hartmann 1989. Cloud-radiative forcing and climate: Results from the Earth Radiation Budget Experiment. *Science* **243**, (4887) 57–63.

- Rangno, A. L. and P. V. Hobbs 2005. Microstructures and precipitation development in cumulus and small cumulonimbus clouds over the warm pool of the tropical Pacific Ocean. *Quart. J. Roy. Meteor. Soc.* pp. 639–673.
- Raymond, D. J. and X. Zeng 2005. Modeling tropical atmospheric convection in the context of the weak temperature gradient approximation. *Quart. J. Roy. Meteor. Soc.* **131**, 1301–1320.
- Rossow, W. B. and R. A. Schiffer 1999. Advances in understanding clouds from ISCCP. *Bull. Amer. Meteor. Soc.* **80**, 2261–2287.
- Smagorinsky, J. 1963. General circulation experiments with the primitive equations. *Mon. Wea. Rev.* **91**, 99–164.
- Sobel, A. H., S. E. Yuter, C. S. Bretherton, and G. N. Kiladis 2004. Large-scale meteorology and deep convection during TRMM KWAJEX. *Mon. Wea. Rev.* **132**, 422–444.
- Tompkins, A. M. 2001. Organization of tropical convection in low vertical wind shears: The role of cold pools. *J. Atmos. Sci.* **58**, 1650–1672.
- Tompkins, A. M. and G. C. Craig 1998. Radiative-convective equilibrium in a three-dimensional cloud-ensemble model. *Quart. J. Roy. Meteor. Soc.* **124**, 2073–2097.
- Wyant, M. C., C. S. Bretherton, J. T. Bacmeister, J. T. Kiehl, I. M. Held, M. Zhao, S. A. Klein, and B. J. Soden 2005. A comparison of low-latitude cloud properties and responses in AGCMs sorted into regimes using mid-tropospheric vertical velocity. *Clim. Dyn.* . In press.

- Wyant, M. C., M. Khairoutdinov, and C. S. Bretherton 2006. Climate sensitivity and cloud response of a GCM with a superparameterization. *Geophys. Res. Lett.* **33**, L06714.
- Xie, P. and P. A. Arkin 1998. Global monthly precipitation estimates from satellite-observed outgoing longwave radiation. *J. Climate* **11**, 137–164.
- Yuter, S. E. and R. A. Houze 1995. Three-dimensional kinematics and microphysical evolution of Florida cumulonimbus. Part II: Frequency distributions of vertical velocity, reflectivity, and differential reflectivity. *Mon. Wea. Rev.* **123**, 1941–1963.
- Yuter, S. E., R. A. Houze, E. A. Smith, T. T. Wilheit, and E. Zipser 2005. Physical characterization of tropical oceanic convection observed in KWAJEX. *J. Appl. Meteor.* **44**, 385–415.
- Zhang, M. H. 2003. Variational objective analysis of the TRMM KWAJEX IOP data. Version 1, available at <ftp://atmgcm.msfc.suoi.hawaii.edu/pub/trmm/kwjx/>.
- Zhang, M. H., J. L. Lin, R. T. Cederwall, J. J. Yio, and S. C. Xie 2001. Objective analysis of the ARM IOP data: method and sensitivity. *Mon. Wea. Rev.* **129**, 295–311.

List of Tables

1	List of simulations described in this work. The effective radii parameterizations describe the radiative properties of condensate and are $r_{el} = 14\mu m, r_{ei} = 6 - 250\mu m, r_{es} = \infty$ for the maritime CAM3 default, $r_{el} = 10\mu m, r_{ei} = 10 - 30\mu m, r_{es} = \infty$ for the CCM3 default, and $r_{el} = 10\mu m, r_{ei} = 25\mu m, r_{es} = 75\mu m$ in Luo et al (2003). Here, r_{el} , r_{ei} , and r_{es} are the effective radii for cloud liquid water, cloud ice and snow, respectively. The radiative effects of rain and graupel are neglected in all parameterizations used here.	41
2	ISCCP D1 cloud amounts (%) from observations and simulations, averaged over Days 206–257.	42
3	Mean ISCCP D1 cloud amounts (%) from observations and simulations during the weakly convective period of Days 212–217.	43

List of Figures

1	Time series of (a) precipitation, (b) sea surface temperature, (c) large-scale vertical velocity at 500 hPa and (d) column-integrated large-scale horizontal advection of sensible and latent energy.	44
2	Time series of mass-weighted tropospheric (a) moist static energy h/C_p and (b) dry static energy s/C_p , along with a time series of (c) precipitable water.	45
3	Time-averaged profiles of (a) temperature bias (model minus observations) and (b) relative humidity with respect to water saturation.	46
4	Comparisons of (a) lowest grid level wind speed, (b) latent heat flux and (c) sensible heat flux between simulations and observations. The thick solid lines depict NCEP surface wind speeds and observed surface energy fluxes (used to force FLX).	47
5	Comparisons of near-surface (a) temperature, (b) water vapor mixture ratio and (c) relative humidity.	48
6	Time series of horizontally-averaged (a) surface precipitation rate, (b) shaded cloud fraction (fraction of model grid columns with optical depth>0.3), (c) top-of-atmosphere outgoing longwave radiation and (d) daily-averaged top of atmosphere reflected (outgoing) shortwave radiation.	49

7	Scatter plots showing the relationship of daily-averaged top-of-atmosphere (a) outgoing longwave radiation and (b) reflected shortwave radiation to precipitation. The daily-averaged TOA radiative fluxes have been binned by daily-averaged precipitation (bin width=2mm d ⁻¹) and averaged within each bin.	50
8	Scatter plot showing the relationship of daily-averaged precipitation rate to daily-averaged column relative humidity along with an exponential fit to the observations. The precipitation scale is logarithmic above the dashed line at 1 mm d ⁻¹ and linear below.	51
9	Time-averaged mixing ratio profiles of (a) cloud water, (b) cloud ice, (d) rain, (e) graupel and (f) snow along with a time-averaged profile of (c) cloud fraction. Cloud is defined by regions with cloud condensate > 1.3×10^{-3} g m ⁻³ , which gives an optical depth of 0.3 for cloud particles with $r_e = 10\mu\text{m}$ integrated over a 1.4 km layer.	52
10	Time-averaged profiles of rms fluctuations from the domain mean of (a) zonal, (b) meridional and (c) vertical velocity, (d) total water mixing ratio, and (e) liquid-ice static energy, along with (f) vertical velocity skewness.	53
11	Time-averaged (a) liquid-ice static energy, (b) total moisture (vapor + cloud + precipitate) and (c) frozen moist static energy budgets for BASE.	54
12	Vertical profile of the frequency distribution of radar reflectivity (in 5 dBZe bins) for (a) Kwajalein ground validation radar (OBS), (b) BASE and (c) UU. Contour values have been multiplied by 10 ⁴ , so that the contour levels are (2, 8, 14, 20, 30) · 10 ⁻⁴ dBZe ⁻¹	55

- 13 (a) Time series of observed (blue) and BIG (green) outgoing longwave radiation at top of atmosphere and the observed precipitation time series (red). Time-height contour plots in (b)–(g) show (b) observed and (c) BIG relative humidity profiles, (d) large-scale relative humidity forcing, (e) horizontally-averaged BIG cloud water content (includes both liquid and ice), and (f) BIG and (g) observed horizontally-averaged radar reflectivity (expressed in dBZe). The color scales are identical in (b) and (c) as well as (f) and (g). 56
- 14 Averaged from 00Z on day 212 to 00Z on day 217, vertical profiles of (a) relative humidity, (b) non-precipitating (qn) and precipitating (qp) condensate, frequency distribution of radar reflectivity for (c) Kwajalein ground validation radar (OBS), (d) BIG with contour intervals of $(0.2, 0.5, 1, 2, 5, 10, 20) \cdot 10^{-4}$ dBZe⁻¹. Note that smaller contour values are included than in Figure 12. . . 57
- 15 As in Figure 14, except averages are taken over days 219 and 220. 58

Table 1: List of simulations described in this work. The effective radii parameterizations describe the radiative properties of condensate and are $r_{el} = 14\mu m, r_{ei} = 6 - 250\mu m, r_{es} = \infty$ for the maritime CAM3 default, $r_{el} = 10\mu m, r_{ei} = 10 - 30\mu m, r_{es} = \infty$ for the CCM3 default, and $r_{el} = 10\mu m, r_{ei} = 25\mu m, r_{es} = 75\mu m$ in Luo et al (2003). Here, r_{el} , r_{ei} , and r_{es} are the effective radii for cloud liquid water, cloud ice and snow, respectively. The radiative effects of rain and graupel are neglected in all parameterizations used here.

Run	Microphysics	Radiation	Effective Radii	Surface Forcing	L_x, L_y	$\Delta x, \Delta y$
BASE	SAM	CAM3	CAM3 default	SST	$64 \times 64 \text{ km}$	1km
CCM	SAM	CCM3	CCM3 default	SST	$64 \times 64 \text{ km}$	1km
FLX	SAM	CAM3	CAM3 default	LHF, SHF	$64 \times 64 \text{ km}$	1km
UU	UU	CAM3	Luo et al. (2003)	SST	$64 \times 64 \text{ km}$	1km
BIG	SAM	CAM3	CAM3 default	SST	$256 \times 256 \text{ km}$	1km
500M	SAM	CAM3	CAM3 default	SST	$64 \times 64 \text{ km}$	500m
2KM	SAM	CAM3	CAM3 default	SST	$128 \times 128 \text{ km}$	2km
EFF	SAM	CAM3	Luo et al. (2003)	SST	$64 \times 64 \text{ km}$	1km

Table 2: ISCCP D1 cloud amounts (%) from observations and simulations, averaged over Days 206–257.

Case	OBS				BASE				EFF		
	Optical Depth				Optical Depth				Optical Depth		
Height	Thin	Med.	Thick	Height	Thin	Med.	Thick	Height	Thin	Med.	Thick
High	25.3	12.9	8.3	High	25.8	8.2	4.2	High	24.4	10.1	6.7
Mid.	9.2	5.5	0.7	Mid.	0.8	1.7	1.4	Mid.	0.6	1.7	1.7
Low	4.9	2.5	0.2	Low	1.6	1.9	1.0	Low	1.4	2.0	1.1

Table 3: Mean ISCCP D1 cloud amounts (%) from observations and simulations during the weakly convective period of Days 212–217.

Case	OBS				BIG		
	Optical Depth				Optical Depth		
Height	Thin	Med.	Thick	Height	Thin	Med.	Thick
High	30.0	5.6	1.9	High	2.9	0.2	0.2
Mid.	14.4	8.5	0.3	Mid.	0.4	1.2	1.4
Low	6.6	3.4	0.0	Low	3.5	2.8	1.1

Figure 1: Time series of (a) precipitation, (b) sea surface temperature, (c) large-scale vertical velocity at 500 hPa and (d) column-integrated large-scale horizontal advection of sensible and latent energy.

Figure 2: Time series of mass-weighted tropospheric (a) moist static energy h/C_p and (b) dry static energy s/C_p , along with a time series of (c) precipitable water.

Figure 3: Time-averaged profiles of (a) temperature bias (model minus observations) and (b) relative humidity with respect to water saturation.

Figure 4: Comparisons of (a) lowest grid level wind speed, (b) latent heat flux and (c) sensible heat flux between simulations and observations. The thick solid lines depict NCEP surface wind speeds and observed surface energy fluxes (used to force FLX).

Figure 5: Comparisons of near-surface (a) temperature, (b) water vapor mixture ratio and (c) relative humidity.

Figure 6: Time series of horizontally-averaged (a) surface precipitation rate, (b) shaded cloud fraction (fraction of model grid columns with optical depth >0.3), (c) top-of-atmosphere outgoing longwave radiation and (d) daily-averaged top of atmosphere reflected (outgoing) shortwave radiation.

Figure 7: Scatter plots showing the relationship of daily-averaged top-of-atmosphere (a) outgoing longwave radiation and (b) reflected shortwave radiation to precipitation. The daily-averaged TOA radiative fluxes have been binned by daily-averaged precipitation (bin width=2mm d⁻¹) and averaged within each bin.

Figure 8: Scatter plot showing the relationship of daily-averaged precipitation rate to daily-averaged column relative humidity along with an exponential fit to the observations. The precipitation scale is logarithmic above the dashed line at 1 mm d⁻¹ and linear below.

Figure 9: Time-averaged mixing ratio profiles of (a) cloud water, (b) cloud ice, (d) rain, (e) graupel and (f) snow along with a time-averaged profile of (c) cloud fraction. Cloud is defined by regions with cloud condensate $> 1.3 \times 10^{-3} \text{ g m}^{-3}$, which gives an optical depth of 0.3 for cloud particles with $r_e = 10 \mu\text{m}$ integrated over a 1.4 km layer.

Figure 10: Time-averaged profiles of rms fluctuations from the domain mean of (a) zonal, (b) meridional and (c) vertical velocity, (d) total water mixing ratio, and (e) liquid-ice static energy, along with (f) vertical velocity skewness.

Figure 11: Time-averaged (a) liquid-ice static energy, (b) total moisture (vapor + cloud + precipitate) and (c) frozen moist static energy budgets for BASE.

Figure 12: Vertical profile of the frequency distribution of radar reflectivity (in 5 dBZe bins) for (a) Kwajalein ground validation radar (OBS), (b) BASE and (c) UU. Contour values have been multiplied by 10^4 , so that the contour levels are $(2, 8, 14, 20, 30) \cdot 10^{-4} \text{ dBZe}^{-1}$.

Figure 13: (a) Time series of observed (blue) and BIG (green) outgoing longwave radiation at top of atmosphere and the observed precipitation time series (red). Time-height contour plots in (b)–(g) show (b) observed and (c) BIG relative humidity profiles, (d) large-scale relative humidity forcing, (e) horizontally-averaged BIG cloud water content (includes both liquid and ice), and (f) BIG and (g) observed horizontally-averaged radar reflectivity (expressed in dBZe). The color scales are identical in (b) and (c) as well as (f) and (g).

Figure 14: Averaged from 00Z on day 212 to 00Z on day 217, vertical profiles of (a) relative humidity, (b) non-precipitating (qn) and precipitating (qp) condensate, frequency distribution of radar reflectivity for (c) Kwajalein ground validation radar (OBS), (d) BIG with contour intervals of $(0.2, 0.5, 1, 2, 5, 10, 20) \cdot 10^{-4} \text{ dBZe}^{-1}$. Note that smaller contour values are included than in Figure 12.

Figure 15: As in Figure 14, except averages are taken over days 219 and 220.