Does the ECMWF IFS Convection Parameterization with Stochastic Physics Correctly Reproduce Relationships between Convection and the Large-Scale State?

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ABSTRACT

Important questions concerning parameterization of tropical convection are how should subgrid-scale variability be represented and which large-scale variables should be used in the parameterizations? Here the statistics of observational data in Darwin, Australia, are compared with those of short-term forecasts of convection made by the European Centre for Medium-Range Weather Forecasts Integrated Forecast System. The forecasts use multiplicative-noise stochastic physics (MNSP) that has led to many improvements in weather forecast skill. However, doubts have recently been raised about whether MNSP is consistent with observations of tropical convection. It is shown that the model can reproduce the variability of convection intensity for a given large-scale state, both with and without MNSP. Therefore MNSP is not inconsistent with observations, and much of the modeled variability arises from nonlinearity of the deterministic part of the convection scheme. It is also shown that the model can reproduce the lack of correlation between convection intensity and large-scale CAPE and an entraining CAPE, even though the convection parameterization assumes that deep convection is more intense when the vertical temperature profile is more unstable, with entrainment taken into account. Relationships between convection and large-scale convective inhibition and vertical velocity are also correctly captured.

1. Introduction

Representation of atmospheric convection is presently one of the most challenging problems in the development of weather and climate models (e.g., Arakawa 2004; Randall 2013; Yano et al. 2013). Convective processes occur at length scales below the resolutions of the dynamical cores of modern numerical weather prediction (NWP) and climate models and, therefore, need to be parameterized. The relationship between convection and large-scale variables in observations can help to inform how convection parameterizations ought to be structured. However, the complexity of the dynamics means that it is difficult to deduce the best way to parameterize convection based on observations alone. A better indicator of whether a convection scheme is reasonable is a comparison of observations with output from an NWP or climate model using the scheme. Here we test whether the convection scheme of the European Centre for Medium-Range Weather Forecasts (ECMWF) Integrated Forecast System (IFS) produces predictions consistent with a variational analysis (VA; a combination of ECMWF analysis and observations) produced for Darwin, Australia.

We first test whether the IFS is able to reproduce the observed relationships between variability of convection and the large-scale state when its representation of subgrid-scale variability is included. The IFS represents this variability in part using multiplicative-noise stochastic physics, with the total parameterized tendencies at each grid point being multiplied by a random number that has spatial and temporal autocorrelation (Palmer et al. 2009). This approach has been shown to improve the quality of weather forecasts (e.g., Buizza et al. 1999; Palmer et al. 2009; Weisheimer et al. 2011) and has been justified for representing subgrid-scale variability of convection by coarse-graining studies (Shutts and Palmer 2007; Shutts and Pallarès 2014). However, Davies et al. (2013) found in the VA for Darwin that the variability of convection increases less quickly than the mean as large-scale moisture convergence increases. Peters et al. (2013)

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found a similar relationship between variability of convection and large-scale vertical velocity ($\overline{w}$) and relative humidity ($\overline{\mathrm{RH}}$). These authors argued that this behavior is not consistent with the multiplicative-noise stochastic physics used in the IFS. Finding that the stochastic scheme used operationally at ECMWF is incapable of representing convective variability would be highly important. However, as previously stated, owing to the complexity of the dynamics, it is best to evaluate the use of multiplicative noise by comparing observations with the output of forecasts made by a model that includes it, which we present in section 3. These results may also be informative for the development of alternative schemes for representing subgrid-scale variability of convection (e.g., Lin and Neelin 2003; Plant and Craig 2008; Biello et al. 2010).

It is also important to test whether the IFS convection scheme correctly reproduces other relationships between convection and the large-scale state that have been used to inform the development of convection parameterizations—this will also be informative about whether the structure of the scheme is appropriate. The IFS scheme (Bechtold et al. 2014) determines the intensity of deep convection using convective available potential energy (CAPE) with entrainment taken into account, with a triggering condition for the occurrence of convection based on conditions in the lower troposphere (section 2b). Numerous studies have found that CAPE is not strongly related to convective intensity in observations, suggesting that it is not appropriate to use CAPE alone to determine convective intensity (e.g., Thompson et al. 1979; Mapes and Houze 1992; Sherwood 1999; Xie and Zhang 2000; Sobel et al. 2004; Davies et al. 2013; Peters et al. 2013). Convection is generally weak when convective inhibition (CIN) is high (e.g., Chaboureau et al. 2004; Fletcher and Bretherton 2010) and Fletcher and Bretherton (2010) argued that CIN should be used to determine convective intensity rather than CAPE. Tropical convection is also observed to be stronger when there is greater moisture convergence (e.g., Davies et al. 2013; Birch et al. 2014). We test in section 4 whether the IFS correctly reproduces these relationships in the Darwin region of Australia.

2. Data and the IFS

a. IFS forecasts

We use forecasts made by the operational ECMWF Ensemble Prediction System (EPS). These forecasts are produced using the IFS Cy40r1—a spectral general circulation model with parameterization of processes including convection, radiation, gravity wave drag, and boundary layer and land surface physics (with full documentation available at http://www.ecmwf.int/en/research). The forecast model was run at resolution T639. For each start time, the ensemble of forecasts consists of one "control" or "deterministic" forecast, made by the IFS with the best-guess ECMWF analysis initial conditions and no stochastic physics, and 50 "perturbed" or "stochastic" forecasts, for which initial-condition perturbations are applied (Buizza et al. 2008; Isaksen et al. 2010). The model used for the perturbed forecasts includes two stochastic physics schemes: multiplicative noise (Palmer et al. 2009) and the stochastically perturbed backscatter scheme (Berner et al. 2009). Sea surface temperatures are prescribed and persisted from the initial state.

We use forecast data generated during the northern Australian wet season between 23 November 2013, the first full day when the most recent ECMWF convection parameterization was used operationally, and 31 March 2014, which was the latest data available when this study was done. Forecasts were started at 0000 and 1200 UTC each day and we present results for lead times every 3 h between 12 and 24 h. This allows the convection scheme to mostly spin up with the synoptic situation remaining close to that observed (Kallberg 2011). Results for lead time ranges 6–18 and 36–48 h are very similar to what we show here. Precipitation rates at each forecast step were calculated as the mean rate over the period beginning 3 h before and ending 3 h after each step, following Davies et al. (2013). CAPE and CIN are defined as

$$\mathrm{CAPE} = \int_{z_{\mathrm{dep}}}^{z_{\mathrm{top}}} g\frac{\theta_{e,\mathrm{up}} - \overline{\theta}_{e,\mathrm{sat}}}{\overline{\theta}_{e,\mathrm{sat}}}\,dz$$

and

$$\mathrm{CIN} = -\int_{z_{\mathrm{dep}}}^{z_{\mathrm{LFC}}} g\frac{\theta_{e,\mathrm{up}} - \overline{\theta}_{e,\mathrm{sat}}}{\overline{\theta}_{e,\mathrm{sat}}}\,dz\,,$$

where $\theta_{e,\mathrm{up}}$ and $\overline{\theta}_{e,\mathrm{sat}}$ are the updraft and saturated environmental equivalent potential temperatures, respectively, and z_{top} and z_{LFC} are, respectively, the cloud-top height and the level of free convection. The term z_{dep} is the height of the convection departure level when convection is triggered and the height that maximizes CAPE otherwise. Model data were averaged over the Darwin region, as defined for the VA (section 2c). The relationships studied at individual grid points (not shown) are similar and not strongly affected by this averaging.

b. The IFS convection scheme

The IFS Cy40r1 convection parameterization is described in detail by Bechtold et al. (2014) and in part IV of the IFS documentation (http://www.ecmwf.int/en/research).

The scheme first identifies if convection should occur by test ascents of parcels on different levels in the lower troposphere. The parcels are assumed to entrain environmental air, and deep convection is triggered if any parcel's upward velocity would not reach zero before it reaches its lifting condensation level and if the cloud top, where the parcel's vertical velocity vanishes, is at least 200 hPa above this. If a test ascent from the surface gives a cloud with thickness less than 200 hPa, then the grid point is identified as having shallow convection.

If deep convection is identified, the mass flux at cloud base is set to depend linearly on $(\mathrm{PCAPE} - \mathrm{PCAPE}_{\mathrm{BL}})/\tau$:

$$\mathrm{PCAPE} = -\int_{p_{\mathrm{base}}}^{p_{\mathrm{top}}} \frac{T_v^{\mathrm{up}} - \overline{T}_v}{\overline{T}_v}\,dp$$

and is similar to an entraining CAPE but defined as an integral over pressure rather than height. In the above equation, T_v^{up} is the virtual temperature of a parcel lifted with entrainment, $\overline{T}_v$ is the virtual temperature of the environmental air, and p_{base} and p_{top} are the pressures of the cloud base and top, respectively. $\mathrm{PCAPE}_{\mathrm{BL}}$ accounts for surface buoyancy flux and is nonzero only for convection with its root in the boundary layer (Bechtold et al. 2014). The convective adjustment time scale τ depends on the convective cloud depth and the vertically averaged updraft velocity, which is itself dependent upon PCAPE.

If shallow convection is identified, the mass flux at cloud base is set to depend linearly on the tendency of the vertically integrated moist static energy. Midlevel convection is identified where there is strong large-scale ascent of moist air.

c. *Variational analysis*

We compare the data from the IFS with the VA produced for Darwin by combining ECMWF analysis with observational data (Xie et al. 2010), as used by Davies et al. (2013) and Peters et al. (2013). Variables are averaged over 6-h periods and over an approximately 30 000-km^2 pentagonal region. This dataset includes the majority of the wet seasons (September–April) of 2004/05, 2005/06, and 2006/07. Precipitation rates were calculated in the same way as for the forecast data, and CAPE, PCAPE, and CIN were calculated using the IFS convection scheme run offline, with observed temperature and humidity as the input, to give as fair a comparison as possible with the forecast data.

3. Variability of convection and stochastic physics

In this section we compare the mean and variability of precipitation in the VA and IFS forecasts as a function of $\overline{w}$ and $\overline{\mathrm{RH}}$. We focus on the qualitative nature of the relationships, since quantitative differences may arise owing to errors in the VA, model errors in processes besides convection, and differences in the synoptic variability between the datasets, which are difficult to accurately account for.

Figure 1 shows the mean, standard deviation, and the ratio of standard deviation to mean of total precipitation as a function of $\overline{w}$ and $(1-\overline{\mathrm{RH}})$ for the VA, the deterministic EPS ensemble member, and the first stochastic ensemble member. Figures 1a and 1c are comparable to the data shown for Darwin in Fig. 5 of Peters et al. (2013), except we have plotted total precipitation instead of the convective and stratiform rain area fraction because this is available for both the forecast data and in the VA, allowing a fair comparison. Davies et al. (2013) found that total precipitation is well correlated with the convective and stratiform precipitation area in the VA. In the IFS, nearly all the precipitation is due to convection (not shown). Data are shown only for bins that contain at least 10 data points.

Figure 1a shows that the VA mean total precipitation is greater when $\overline{w}$ and $\overline{\mathrm{RH}}$ are greater, indicating that more convection is occurring, in agreement with the results of Peters et al. (2013). Figure 1b shows that the standard deviation of convection within each bin is also larger when $\overline{w}$ and $\overline{\mathrm{RH}}$ are greater, and Fig. 1c shows that the ratio (standard deviation to mean) decreases—also in agreement with Peters et al. (2013).

Figures 1d–f and 1g–i show the same relationships for IFS forecasts from the control deterministic member and the first perturbed member with stochastic physics, respectively. The relationships between the statistics of precipitation and $\overline{w}$ and $\overline{\mathrm{RH}}$ are similar to those in the VA (Figs. 1a–c). Most significantly, the ratio of the standard deviation of precipitation to the mean does decrease in forecasts with stochastic physics as in the VA, showing that including multiplicative-noise stochastic physics in an NWP model is consistent with this behavior.

4. Relationships between convection and large-scale variables

In this section we evaluate whether the IFS forecasts of precipitation have the correct statistical relationships with large-scale variables that are related to convection. We focus on the stochastic forecasts, except when evaluating the relationship between precipitation and PCAPE, since the data required to calculate PCAPE was not archived for the stochastic forecasts—for the other variables, the relationships in the deterministic forecasts are similar to those in the stochastic forecasts

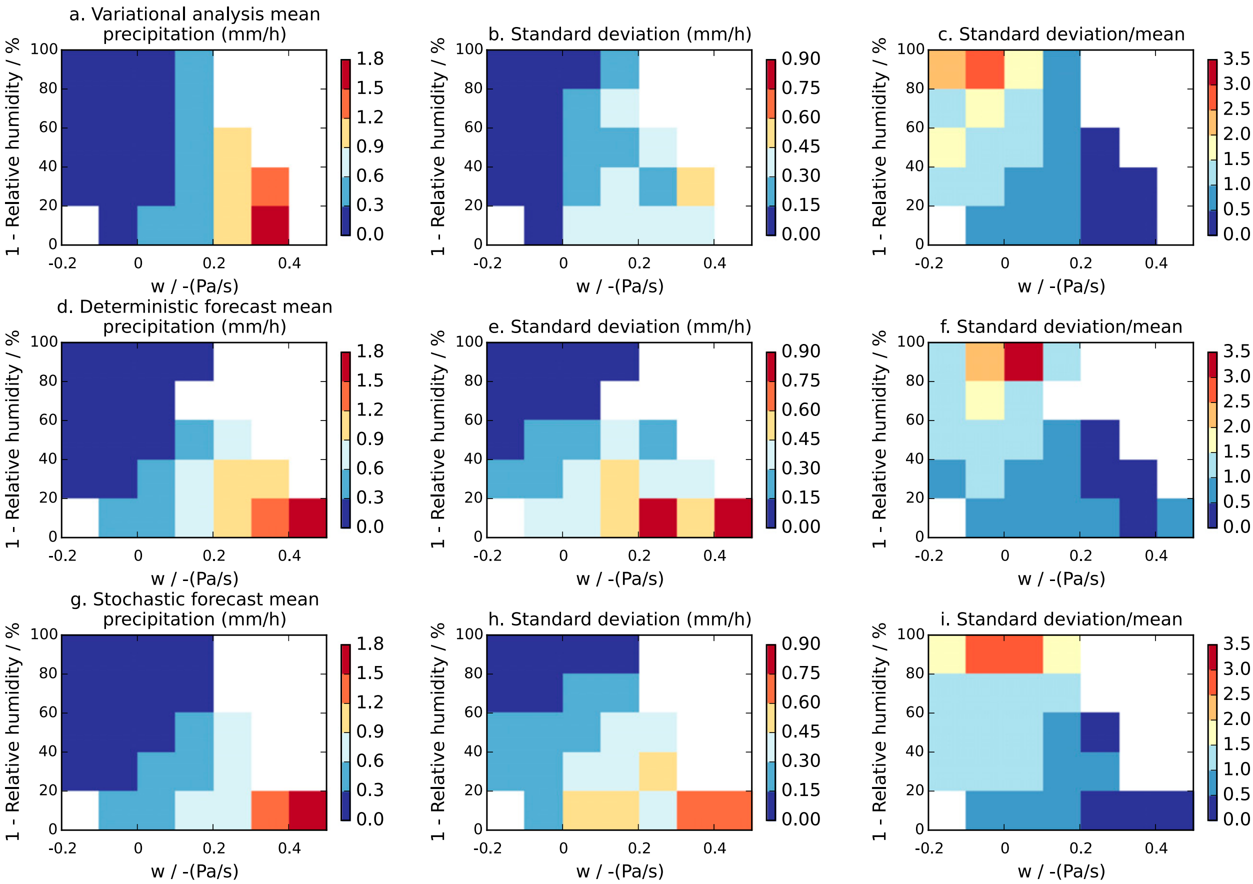

FIG. 1. (a)–(c) The relationship between Darwin-mean total precipitation and $\overline{w}$ and $(1-\overline{\mathrm{RH}})$ in the variational analysis, (d)–(f) the deterministic control IFS forecasts, and (g)–(i) the stochastic perturbed IFS forecasts. For data binned according to $\overline{w}$ and $(1-\overline{\mathrm{RH}})$ (left) the mean precipitation, (center) the standard deviation of precipitation in each bin, and (right) the ratio of the standard deviation to the mean. Data are plotted only for bins with at least 10 data points. Both types of IFS forecast reproduce the observed relationships well.

(not shown), and we expect this to also be the case for the relationship between convection and PCAPE.

Figures 2a and 2b show scatterplots of total precipitation rate against CAPE in the VA and the first member of the stochastic IFS forecasts, respectively. There is little correlation between these variables in either the VA [in agreement with Davies et al. (2013)] or the forecasts, and the IFS captures the relationship qualitatively quite well, though with fewer instances of high precipitation for CAPE values above approximately 2500 J kg^{-1}. Additionally, Figs. 2c and 2d show that there is little correlation between precipitation and PCAPE in either the analysis or the deterministic forecast. Note that in Figs. 2c and 2d, data are only plotted for times when the IFS convection scheme indicates triggering of deep convection, which is when PCAPE is relevant in the scheme. Therefore, even though the IFS convection scheme produces stronger convection when the atmosphere is more vertically unstable and PCAPE is higher, it is able to reproduce the lack of correlations between convection and CAPE and PCAPE. This may be because situations when CAPE is large are also situations when convection is unlikely to be triggered, because $\mathrm{PCAPE_{BL}}$ is also important during deep convection or because convective precipitation is not only a function of the mass flux at cloud base.

Figures 2e and 2f show precipitation against CIN in the VA and in the first stochastic forecast, respectively. In both cases, strong convection only occurs when CIN is small. The IFS may be able to capture this relationship because convective activity is strongly limited by entrainment if the lower troposphere is dry or convectively stable. This shows that it is not necessary for CIN to be used in the calculation of the mass flux at cloud base for a model to reproduce this relationship.

Finally, Figs. 2g and 2h show the relationships between precipitation and $\overline{w}$ in the VA and the forecasts, respectively. In both cases there is a strong positive correlation between the two variables, again in agreement with Davies et al. (2013), though the relationship is

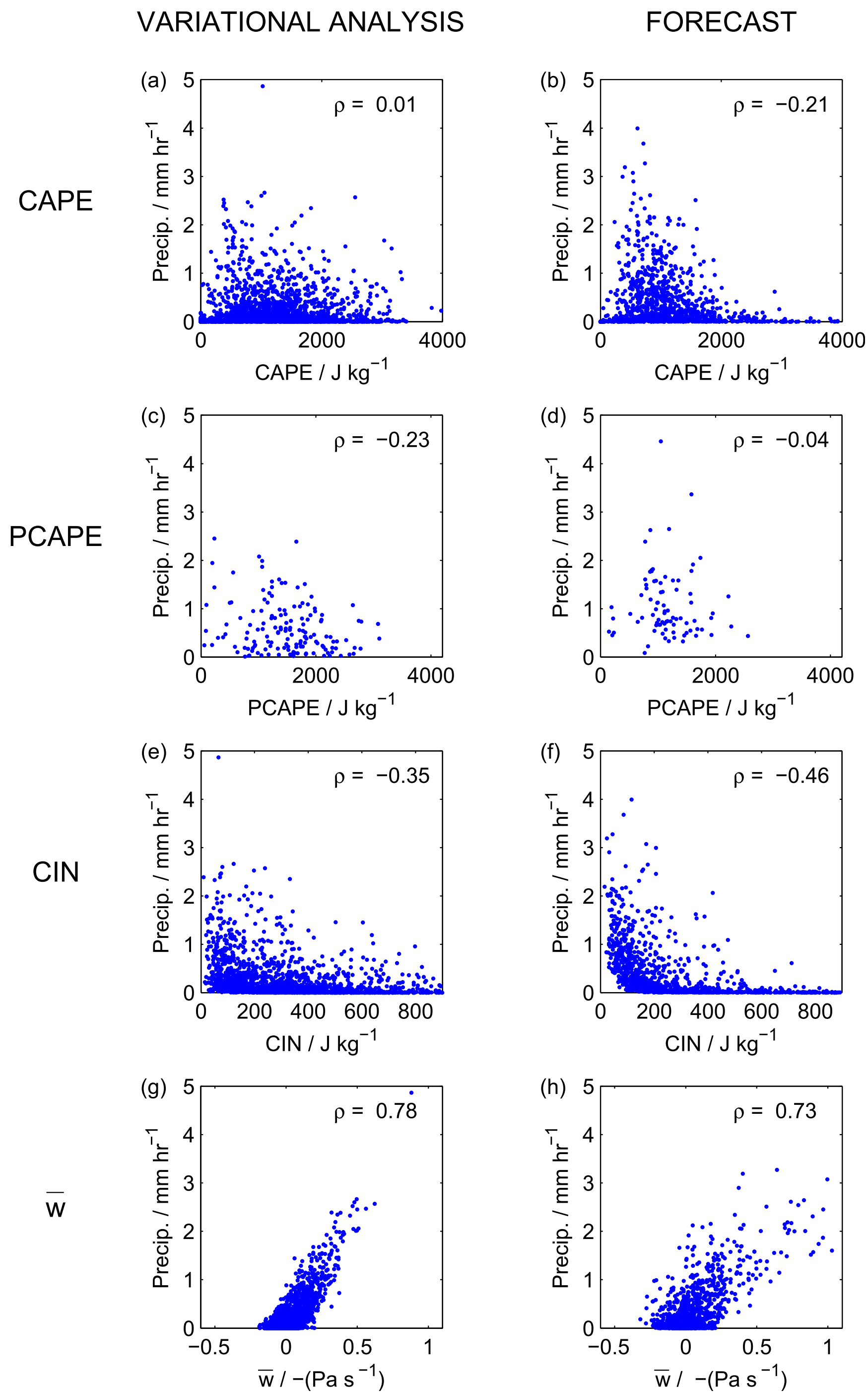

FIG. 2. The relationship between Darwin-mean total precipitation and important large-scale variables (a),(c),(e),(g) in the variational analysis and (b),(d),(f),(h) in the IFS forecasts. The relationship with (a),(b) CAPE in the VA and the first stochastic forecast ensemble member; (c),(d) PCAPE in the VA and the deterministic forecast when deep convection is identified according to the IFS convection scheme; (e),(f) CIN in the VA and the first stochastic forecast ensemble member; and (g),(h) $\overline{w}$ in the VA and first stochastic forecast member. The correlation for each pair of variables ρ is written in the top-right-hand corner of each panel.

slightly less strong in the forecasts. Therefore, the IFS captures this relationship quite well even though $\overline{w}$ is not used for predicting shallow or deep convection, perhaps because convection causes heating that may in turn cause large-scale ascent.

5. Conclusions

We have evaluated the ability of the ECMWF IFS to reproduce observed statistical relationships between precipitation, a proxy for convection, and large-scale variables in Darwin, Australia. The IFS reproduces well all the relationships that we have studied, both when multiplicative-noise stochastic physics is included and when it is not, indicating that its parameterization of convection and representation of subgrid-scale variability are consistent with observations.

Significantly, we have shown that the IFS with multiplicative-noise stochastic physics included can reproduce the behavior identified by Peters et al. (2013)—namely, that the ratio of the standard deviation of convection to its mean decreases as the coincident $\overline{w}$ and $\overline{\mathrm{RH}}$ increase (Figs. 1c and 1i). This is in contrast to the suggestion of Davies et al. (2013) and Peters et al. (2013) and indicates that the stochastic physics used operationally at ECMWF is consistent with observations.

The fact that the deterministic forecast also reproduces the correct variability of convection as a function of large-scale variables (Figs. 1e and 1f) shows that this variability is not wholly due to subgrid-scale variability. Rather, in the IFS it must be due to the strong sensitivity of the convection scheme to changes in large-scale variables, arising for example from the convection trigger. This makes it difficult to infer how stochasticity ought to be introduced into a convection parameterization from the observed behavior alone. Assessing the appropriateness of a given parameterization is likely to require including it in a dynamical model and comparing the output of that model with observations. The deterministic forecast behavior also raises the question of whether the IFS convection scheme is producing variability by the right physical mechanism.

We have also shown that the IFS reproduces the observed lack of correlation between convection and CAPE and PCAPE (an entraining CAPE), even though the IFS convection scheme generally increases the intensity of deep convection as PCAPE increases. Therefore, parameterizing convection in this way can be reasonable despite this lack of correlation. It also illustrates that deducing causal relationships between convection and large-scale variables by correlation analysis is difficult—applying such reasoning to the IFS data could lead to the erroneous conclusion that PCAPE is not causally related to convection in the IFS (Fig. 2d). The IFS also reproduces well the observation that convection does not occur when CIN is large, likely because of strong mixing by entrainment, so that the negative correlation between these variables does not, on its own, provide a strong argument to use CIN to calculate the mass flux at cloud base. The relationship between convection and $\overline{w}$ is also well reproduced.

This does not mean that other convection parameterizations and representations of subgrid variability are unreasonable (e.g., Kuo 1974; Fletcher and Bretherton 2010; Peters et al. 2013) but suggests that deducing the best way of parameterizing convection requires not just examining the observed statistics of convection, but also comparing them with the output of models with different convection parameterizations implemented.

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REFERENCES

Arakawa, A., 2004: The cumulus parameterization problem: Past, present, and future. *J. Climate,* **17,** 2493–2525, doi:10.1175/1520-0442(2004)017<2493:RATCPP>2.0.CO;2.

Bechtold, P., N. Semane, P. Lopez, J.-P. Chaboureau, A. Beljaars, and N. Bormann, 2014: Representing equilibrium and nonequilibrium convection in large-scale models. *J. Atmos. Sci.,* **71,** 734–753, doi:10.1175/JAS-D-13-0163.1.

Berner, J., G. J. Shutts, M. Leutbecher, and T. N. Palmer, 2009: A spectral stochastic kinetic energy backscatter scheme and its impact on flow-dependent predictability in the ECMWF Ensemble Prediction System. *J. Atmos. Sci.,* **66,** 603–626, doi:10.1175/2008JAS2677.1.

Biello, J., B. Khouider, and A. Majda, 2010: A stochastic multicloud model for tropical convection. *Commun. Math. Sci.,* **8,** 187–216, doi:10.4310/CMS.2010.v8.n1.a10.

Birch, C. E., J. H. Marsham, D. J. Parker, and C. M. Taylor, 2014: The scale-dependence and structure of convergence fields preceding the initiation of deep convection. *Geophys. Res. Lett.,* **41,** 4769–4776, doi:10.1002/2014GL060493.

Buizza, R., M. Miller, and T. Palmer, 1999: Stochastic representation of model uncertainties in the ECMWF Ensemble Prediction System. *Quart. J. Roy. Meteor. Soc.,* **125,** 2887–2908, doi:10.1002/qj.49712556006.

——, M. Leutbecher, and L. Isaksen, 2008: Potential use of an ensemble of analyses in the ECMWF Ensemble Prediction System. *Quart. J. Roy. Meteor. Soc.,* **134,** 2051–2066, doi:10.1002/qj.346.

Chaboureau, J.-P., F. Guichard, J.-L. Redelsperger, and J.-P. Lafore, 2004: The role of stability and moisture in the diurnal cycle of convection over land. *Quart. J. Roy. Meteor. Soc.,* **130,** 3105–3117, doi:10.1256/qj.03.132.

Davies, L., C. Jakob, P. May, V. V. Kumar, and S. Xie, 2013: Relationships between the large-scale atmosphere and the small-scale convective state for Darwin, Australia. *J. Geophys. Res.,* **118,** 11 534–11 545, doi:10.1002/jgrd.50645.

Fletcher, J. K., and C. S. Bretherton, 2010: Evaluating boundary layer-based mass flux closures using cloud-resolving model simulations of deep convection. *J. Atmos. Sci.,* **67,** 2212–2225, doi:10.1175/2010JAS3328.1.

Isaksen, L., M. Bonavita, R. Buizza, M. Fisher, J. Haseler, M. Leutbecher, and L. Raynaud, 2010: Ensemble data assimilation at ECMWF. ECMWF Tech. Memo. 636, 41 pp.

Kallberg, P., 2011: Forecast drift in ERA-Interim. ECMWF ERA Rep. Series 10, 9 pp.

Kuo, H. L., 1974: Further studies of the parameterization of the influence of cumulus convection on large-scale flow. *J. Atmos. Sci.,* **31,** 1232–1240, doi:10.1175/1520-0469(1974)031<1232:FSOTPO>2.0.CO;2.

Lin, J. W.-B., and J. Neelin, 2003: Toward stochastic deep convective parameterization in general circulation models. *Geophys. Res. Lett.,* **30,** 1162, doi:10.1029/2002GL016203.

Mapes, B., and R. Houze, 1992: An integrated view of the 1987 Australian monsoon and its mesoscale convective systems. I: Horizontal structure. *Quart. J. Roy. Meteor. Soc.,* **118,** 927–963, doi:10.1002/qj.49711850706.

Palmer, T., R. Buizza, F. Doblas-Reyes, T. Jung, M. Leutbecher, G. Shutts, M. Steinheimer, and A. Weisheimer, 2009: Stochastic parametrization and model uncertainty. ECMWF Tech. Memo. 598, 42 pp.

Peters, K., C. Jakob, L. Davies, B. Khouider, and A. J. Majda, 2013: Stochastic behavior of tropical convection in observations and a multicloud model. *J. Atmos. Sci.,* **70,** 3556–3575, doi:10.1175/JAS-D-13-031.1.

Plant, R. S., and G. C. Craig, 2008: A stochastic parameterization for deep convection based on equilibrium statistics. *J. Atmos. Sci.,* **65,** 87–105, doi:10.1175/2007JAS2263.1.

Randall, D. A., 2013: Beyond deadlock. *Geophys. Res. Lett.,* **40,** 5970–5976, doi:10.1002/2013GL057998.

Sherwood, S., 1999: Convective precursors and predictability in the tropical western Pacific. *Mon. Wea. Rev.,* **127,** 2977–2991, doi:10.1175/1520-0493(1999)127<2977:CPAPIT>2.0.CO;2.

Shutts, G., and T. N. Palmer, 2007: Convective forcing fluctuations in a cloud-resolving model: Relevance to the stochastic parameterization problem. *J. Climate,* **20,** 187–202, doi:10.1175/JCLI3954.1.

——, and A. C. Pallarès, 2014: Assessing parametrization uncertainty associated with horizontal resolution in numerical weather prediction models. *Philos. Trans. Roy. Soc.,* **A372,** 20130284, doi:10.1098/rsta.2013.0284.

Sobel, A., S. Yuter, C. Bretherton, and G. Kiladis, 2004: Large-scale meteorology and deep convection during TRMM KWAJEX. *Mon. Wea. Rev.,* **132,** 422–444, doi:10.1175/1520-0493(2004)132<0422:LMADCD>2.0.CO;2.

Thompson, R., Jr., S. Payne, E. Recker, and R. Reed, 1979: Structure and properties of synoptic-scale wave disturbances in the intertropical convergence zone of the eastern Atlantic. *J. Atmos. Sci.,* **36,** 53–72, doi:10.1175/1520-0469(1979)036<0053:SAPOSS>2.0.CO;2.

Weisheimer, A., T. N. Palmer, and F. J. Doblas-Reyes, 2011: Assessment of representations of model uncertainty in monthly and seasonal forecast ensembles. *Geophys. Res. Lett.,* **38,** L16703, doi:10.1029/2011GL048123.

Xie, S., and M. Zhang, 2000: Impact of the convection triggering function on single-column model simulations. *J. Geophys. Res.,* **105** (D11), 14 983–14 996, doi:10.1029/2000JD900170.

——, T. Hume, C. Jakob, S. A. Klein, R. B. McCoy, and M. Zhang, 2010: Observed large-scale structures and diabatic heating and drying profiles during TWP-ICE. *J. Climate,* **23,** 57–79, doi:10.1175/2009JCLI3071.1.

Yano, J.-I., M. Bister, v. Fuchs, L. Gerard, V. T. J. Phillips, S. Barkidija, and J.-M. Piriou, 2013: Phenomenology of convection-parameterization closure. *Atmos. Chem. Phys.,* **13,** 4111–4131, doi:10.5194/acp-13-4111-2013.