Ensemble single column model simulations of TWP-ICE

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1. Motivation

The TWP-ICE GCSS/ARM single column modelling intercomparison project is using an ensemble technique to supplement the simulation of a best estimate forcing. The ensemble accounts for one source of uncertainty in deriving a best estimate forcing data set - the estimation of rainfall from radar data. We have, therefore, an ensemble of forcing data sets that represent a range of physically plausible atmospheric states. Analysis of the ensemble of model simulations will provide an additional dimension to the standard intercomparison analysis by comparing ensemble mean to the best estimate response and investigating model spread. As with all GCSS/ARM intercomparisons results can also be compared to CRM and NWP inter.comparison project strands.

2. Deriving an ensemble forcing data set

Figure 1

100 precipitation timeseries shown in grey, key percentiles in broken lines and best estimate in solid, dark line.
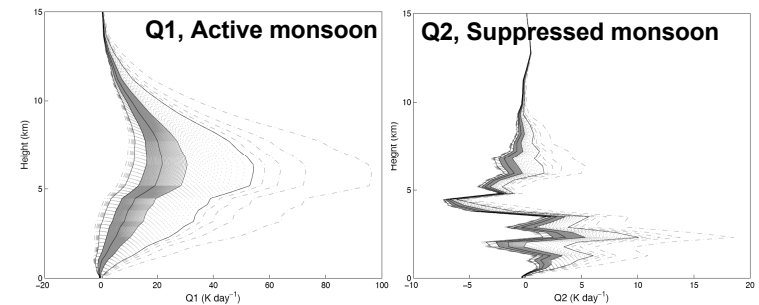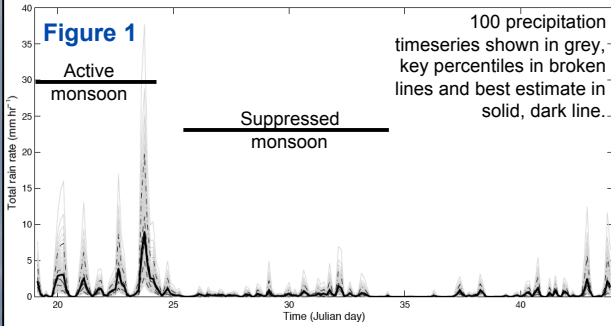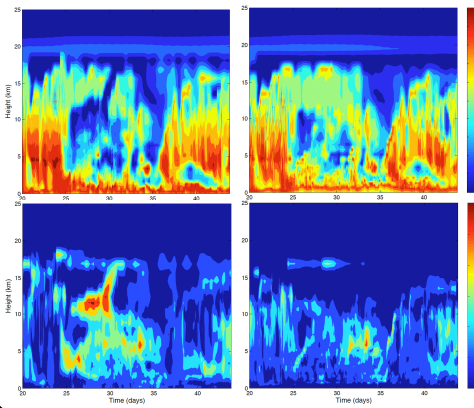

Figure 2 Forcing period-averaged heat and moisture sources, Q1 and Q2, for all ensemble members.

Forcing data derived by variational analysis is sensitive to precipitation input. Radar-derived rainfall measurements can also have large errors. Comparison of radar-derived rainfall and rain gauge rain is used to construct 100 possible rainfall scenarios (Figure 1). 100 possible forcing data sets are derived using each of these rainfall scenarios. Key forcing variables (Figure 2) show large differences between the ensemble members.

3. Additional information from an ensemble compared to best estimate forcing

Using a standard best estimate forcing data set two different models have qualitatively similar behaviour (Figure 3) and both are similar to observations. Ensemble spread, however, shows that different models have very different sensitivities possibly due to different parameterisations? An example is presented for relative humidity (RH) from two similar models.

• Both models have higher RH than observations particularly below 10km during the active monsoon.
• During the transition between active and suppressed monsoon both models dry more in mid-levels than was found in observations.
• The PC scheme RH has large spread in the suppressed monsoon particularly where high cloud may or may not persist.
• The GR scheme has more uniform standard deviation below 10km.

Figure 3 Relative humidity from best-estimate simulation (top panels) and ensemble standard deviation (bottom panels) for UKMO Unified Model with differing convection paramterisations. Left, with Plant-Craig (PC) stochastic scheme. Right, with Gregory-Rowntree (GR) scheme.

4. Comparing model sensitivities

Period-averaged model spread is similar to observations for Q1 but not for Q2 (compare Figure 4 to Figure 1). Time evolution of precipitable water (PW) can be presented as a plume or condensed to box plots (Figure 5). These show the model dependence of PW and PW spread. Further investigation of these characteristics will form part of further work.
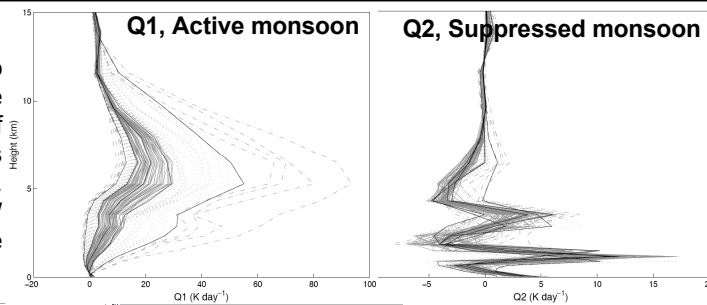

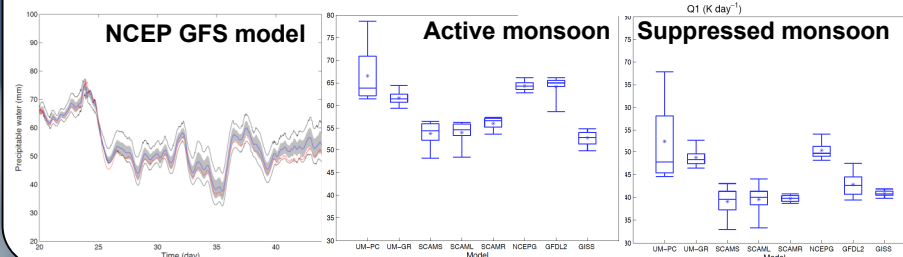**Figure 4** GFDL AM2 model period-averaged heat and moisture sources, Q1 and Q2, for all ensemble members.

Figure 5 Ensemble precipitable water for the NCEP GFS (left panel) showing ±σ (shaded area), 90th and 10th percentiles (black lines), ensemble mean (blue line) and best estimate (red line). Box plots of period-averaged precipitable water for several models for active monsoon (centre panel) and suppressed monsoon (right panel).