

Evaluation of a Cloud Fraction Parameterization Using Observations and Model Data

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Introduction

We examine an empirical cloud fraction parameterization developed by Xu and Randall (XR 1996). The XR parameterization relates the large-scale relative humidity \overline{RH} and the large-scale cloud water mixing ratios \overline{q}_1 to the large-scale cloud fraction $\overline{\sigma}$. By large scale, we refer to space and time scales resolved by a global climate model. We approach the evaluation from two perspectives, the first of which incorporates observations from the Global Atmospheric Research Program's Atlantic Stratocumulus Transition Experiment (ASTEX). The liquid water mixing ratio, retrieved from the liquid water path (LWP) measured by a microwave radiometer and cloud radar reflectivity, and the relative humidity (RH) field obtained from sounding data are used as inputs to the XR cloud parameterization and then compared with the cloud fraction determined from cloud radar measurements. Results indicate that, for the generally small ASTEX liquid water paths, the XR parameterization is more sensitive to the large-scale RH than it is to the large-scale liquid water-mixing ratio (Lazarus et al. 1999). Herein, we examine the sampling limitations of the observations, and the potential impact on the XR parameterization using simulated data obtained from a cloud ensemble model experiment of a stratus-to-cumulus transition. In particular, we sample the model data in an attempt to assess whether the q_1 and RH profiles obtained from retrievals and a single sonde launch is representative of the large-scale \overline{RH} .

Method

In order to test a large-scale cloud fraction parameterization such as XR's, we need time series of the input quantities (in this case, \overline{q}_1 and \overline{RH}) and observations of the output quantity, the cloud fraction, $\overline{\sigma}$. Of these quantities, only RH is routinely measured (i.e., by radiosondes), although in actuality, radiosondes sample only a very small fraction of the volume of a large-scale atmospheric column, and normally do this only once every 12 h. It is not clear under what circumstances such a measurement accurately represents the large-scale relative humidity.

Because of the inherent limitations and problems associated with observations (e.g., data sampling, missing data etc., Lazarus et al. 1999), we apply XR to a CRM data set of a stratus-to-cumulus transition (Krueger et al. 1995). One important issue that is particularly difficult to answer using observations, for example, is determining whether or not the differences between the observational estimates of the large-scale quantities \bar{q}_1 , \overline{RH} , and $\bar{\sigma}$ and their actual values are significant? That is, do they affect our evaluation of XR's parameterization of $\bar{\sigma}$?

We emulate the observations by sampling the model data as if they were a detailed set of observations (taken at 2.5-min intervals). The XR cloud fraction parameterization is given by:

$$\bar{\sigma} = \overline{RH}^p \left[1 - \exp \left(\frac{-\alpha_o \bar{q}_1}{[(1-\overline{RH})q_{vs}]^\gamma} \right) \right], \text{ if } RH < 1$$

$$\bar{\sigma} = 1, \text{ if } \overline{RH} \geq 1$$

The parameters γ , α , and p can be empirically determined from the data (XR 1996). Here they are taken to be the same as XR, namely 0.49, 100, and 0.25, respectively.

The large-scale cloud fraction is obtained from the CRM data using the following:

$$\bar{\sigma} = q_1 / (0.01 \times q_{vs}), \text{ if } q_1 \leq 0.01 \times q_{vs}$$

$$\bar{\sigma} = 1, \text{ if } q_1 > 0.01 \times q_{vs}$$

where the overbar denotes a horizontal average over the CRM domain and a time average of 3-h.

Experiments

We test the large-scale $\bar{\sigma}$ against the XR $\bar{\sigma}$ for varying input parameters (i.e., \bar{q}_1 , \overline{RH} , and q_{vs}). The 72-h CRM simulation yields 24 large-scale soundings, i.e., 24 large-scale profiles of the observed \bar{q}_1 , \overline{RH} , and $\bar{\sigma}$. We conduct the following four experiments in which the XR inputs (q_1 and RH) are varied:

Experiment A:

XR input profiles of RH , q_{vs} , and q_1 at a single model time and point.

Experiment B:

XR input RH is the same as Experiment A and q_1 is averaged over a time window of 40 min.

Experiment C:

XR input RH is horizontally averaged at a single time and q_1 is the same as Experiment B.

Experiment D:

XR inputs RH and q_1 are equal to their large-scale values (i.e., averaged over entire domain and 3-h period).

The sampling method in Experiment A is a more stringent test of XR than that of the observations (over which we time average q_1). For this experiment, the RH values are fairly representative of the large-scale \overline{RH} (Figure 1), but q_1 is not well represented (Figure 2). As a result, there is a significant amount of scatter between the large-scale and parameterized cloud fractions in Figure 3. For Experiment B, we emulate the observational sampling by averaging q_1 over the same time period (40-min window). This reduces the scatter in the q_1 (Figure 4) as well as in the cloud fraction (Figure 5) but there is still a large difference between the parameterized cloud fraction and the large-scale cloud fraction obtained from the CRM. In Experiment C, we use the same time window for q_1 , and average RH over the CRM domain (at a single time). One can view this experiment as the practical equivalent of sending up multiple soundings (at the same time) across a region. Here the RH is nearly the same as that of the large scale (Figure 6) yet the scatter in the cloud fraction is still quite large (Figure 7). This latter finding suggests that much of the remaining scatter can be attributed to q_1 . Indeed, when the XR inputs are the actual large-scale quantities (Experiment D), the scatter in the cloud fraction is greatly reduced (Figure 8).

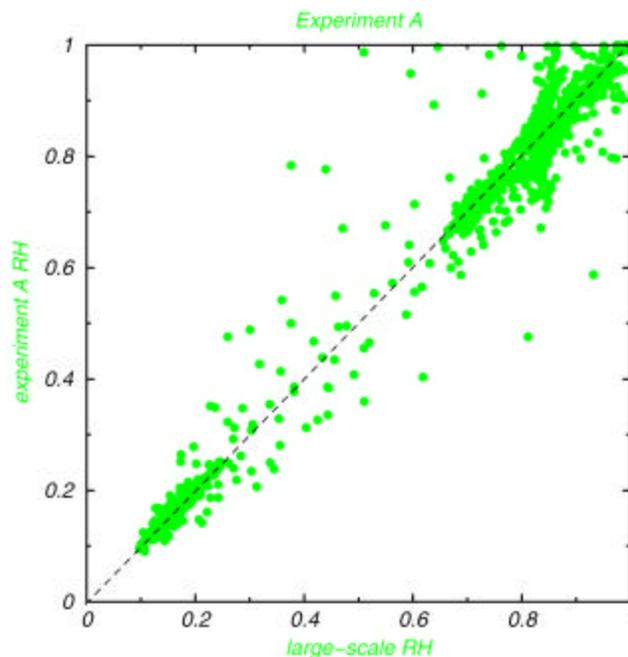


Figure 1. Experiment A RH versus $large\text{-}scale \overline{RH}$. Experiment A RH is obtained from CRM values at a single model time and point. The large-scale values are 3-h averages over the CRM domain.

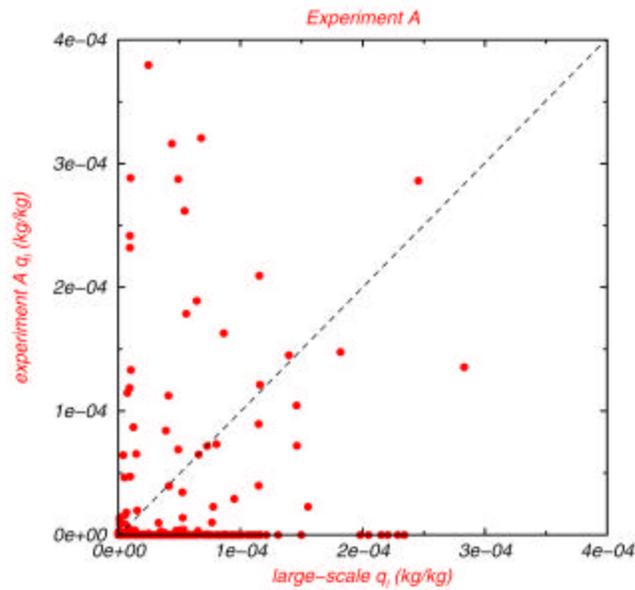


Figure 2. Experiment A q_1 versus $large\text{-}scale \bar{q}_1$. Experiment A q_1 is obtained from CRM values at a single model time and point. The large-scale values are 3-h averages over the CRM domain.

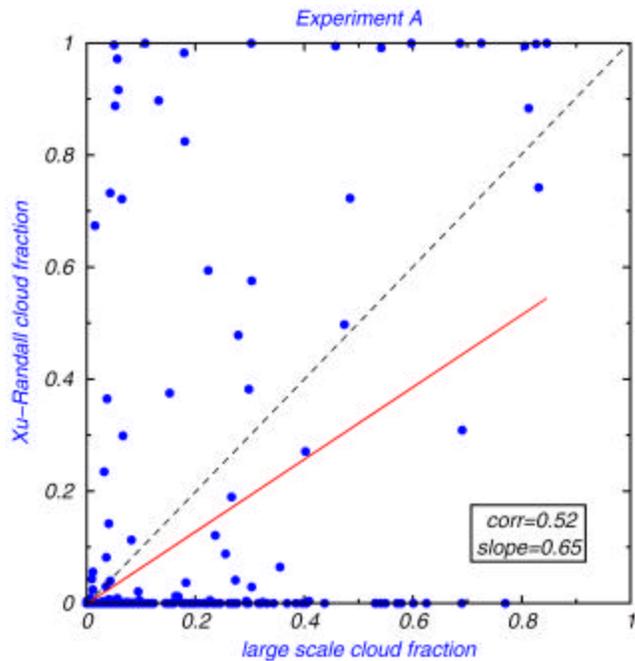


Figure 3. Experiment A σ versus $large\text{-}scale \bar{\sigma}$. Experiment A σ (XR) is obtained using the inputs shown in Figures 1 and 2 (i.e., CRM values of RH and q_1 at a single model time and point). The large-scale cloud fraction is estimated using RH and q_1 values averaged over 3-h and the entire CRM domain.

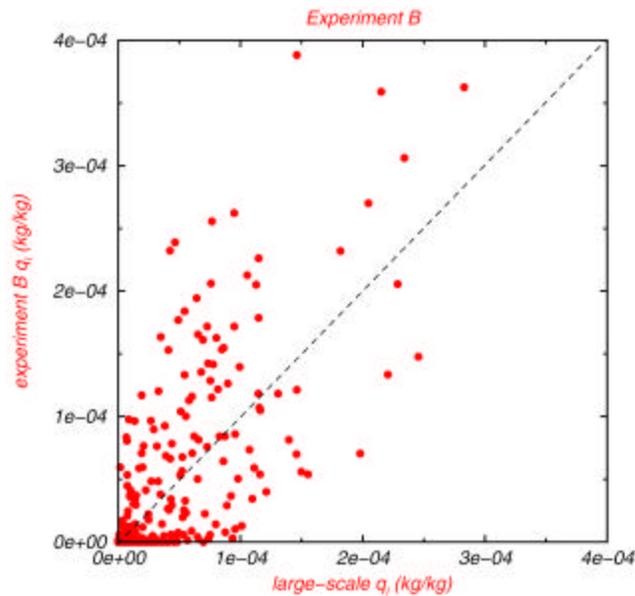


Figure 4. Experiment B q_1 versus *large-scale* \bar{q}_1 . Experiment B q_1 is obtained from CRM values over a 40-min window and a single model point.

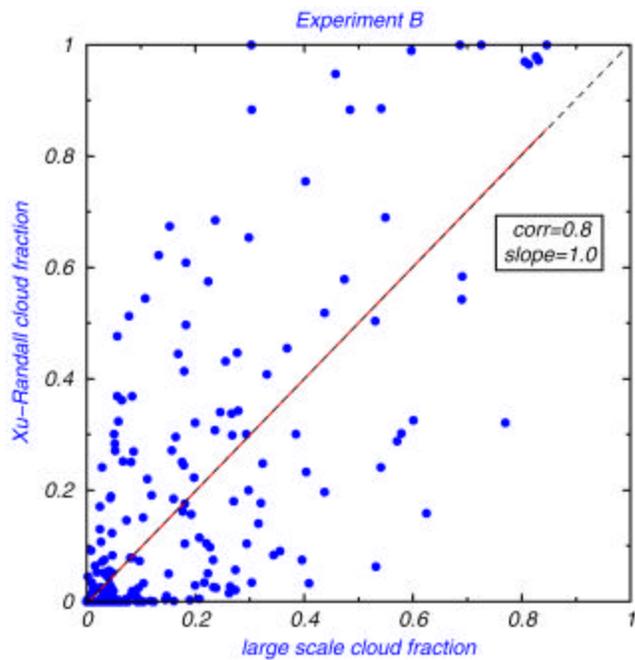


Figure 5. Experiment B σ versus *large-scale* $\bar{\sigma}$. Experiment B σ (XR) is obtained using the inputs shown in Figures 1 and 4 (i.e., CRM values of RH at a single point and q_1 averaged over a 40-min window).

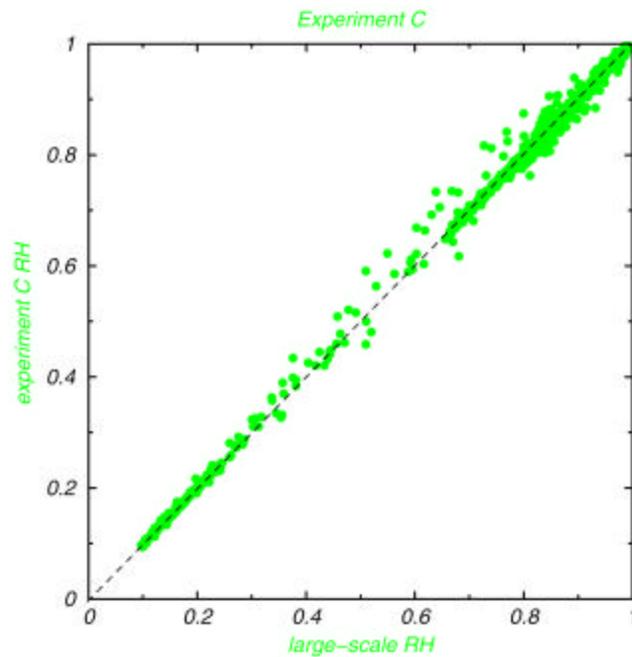


Figure 6. Experiment C RH versus $\overline{\text{large-scale RH}}$. Experiment C RH is obtained by taking a horizontal average of CRM RH values at a single model time.

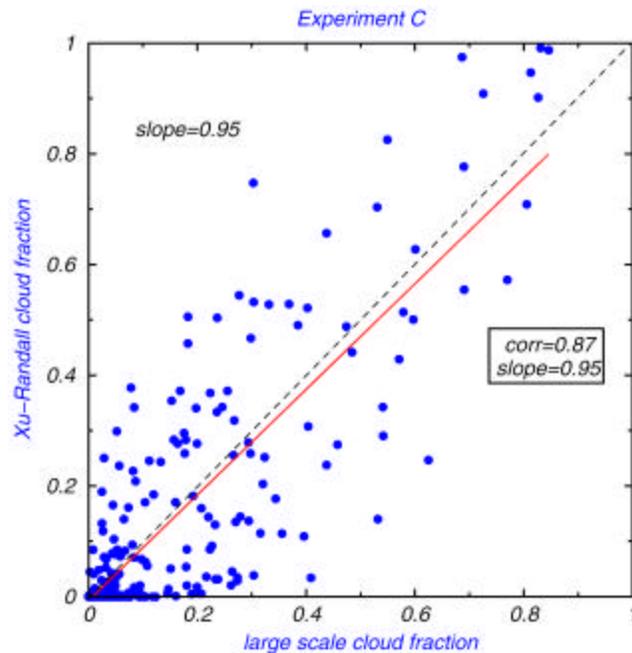


Figure 7. Experiment C σ versus $\overline{\text{large-scale } \sigma}$. Experiment C σ (XR) is obtained using the inputs shown in Figures 4 and 6 (i.e., CRM values of horizontally averaged RH at a single time and q_1 averaged over a 40-min window at a single point).

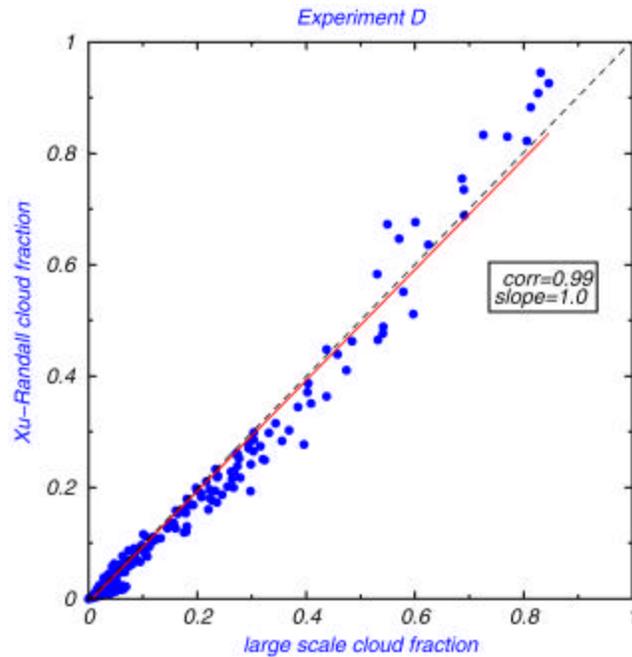


Figure 8. Experiment D σ versus *large-scale* $\bar{\sigma}$. Experiment D σ (XR) is obtained using the large-scale inputs (i.e., CRM values of RH and q_1 averaged horizontally over the entire domain and spatially over a 3-h window).

Discussion

We show that model data can be used as a surrogate for observations when testing a parameterization. This is particularly useful when the observations themselves are limited in a way that precludes a thorough examination of parameterization sensitivities. Here, we show that, for the CRM status-to-cumulus simulation, the mesoscale variability of q_1 is greater than that of the RH. Our results suggest that the 40-min average we applied to the actual observations of q_1 (Lazarus et al. 1999) is not sufficient.

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