Global Predictability of Daily Rainfall





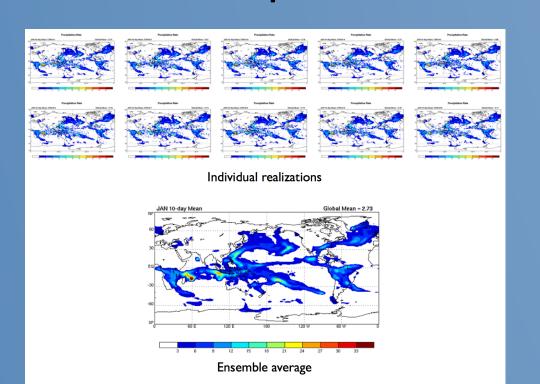
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Introduction

It is widely known that convective precipitation is difficult to forecast and predict, largely due to the chaotic nature of the atmosphere. The purpose of this study is to further understand the factors leading to strong and unpredictable, ie. chaotic, precipitation. Daily precipitation measurements were simulated using the superparameterized Community Atmospheric Model (SP-CAM) with ten embedded cloud-resolving models (CRMs) per grid column. Each CRM runs separately and starts at slightly different initial conditions, while receiving same input from the global circulation model (GCM). Because the solutions produced by the CRM are sensitively depend on initial conditions, if only a single CRM is used, the solution would be chaotic. However, if multiple CRMs are used, the ensemble mean would be expected to be non-chaotic.



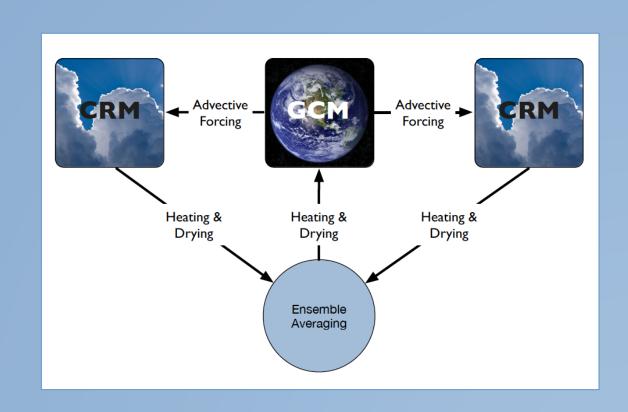
The daily precipitation as simulated by each individual realization of the CRM is shown to the left. In the lower image, the average for all 10 CRMs is shown.

Key Questions

- > How predictable is precipitation?
- Does predictability of rainfall vary with geography or season?
- What determines strong and unpredictable precipitation?
- > Can we detect chaos in any of the hourly time series of precipitation?

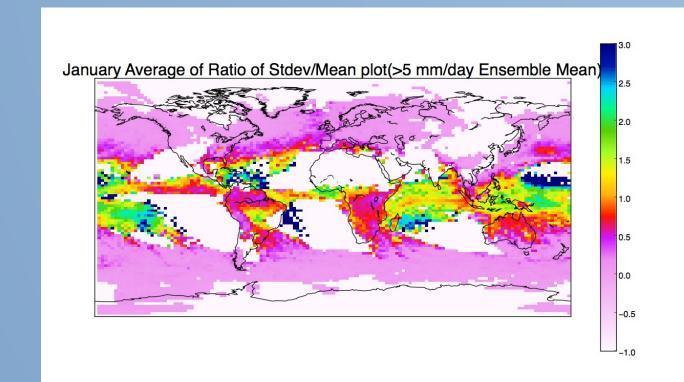
Materials and Methods

The hourly precipitation output produced by the global simulation of the SP-CAM was analyzed for the coefficient of variation (CoV), which is the ratio of the standard deviation to the ensemble mean. The CoV is a measure of predictability; a smaller value would indicate high predictability whereas a higher value would indicate low predictability. The CoV was compared against the CAPE, the vertical shear of the horizontal wind, and the Richardson number. All of the parameters were visually analyzed with global maps and scatterplots.

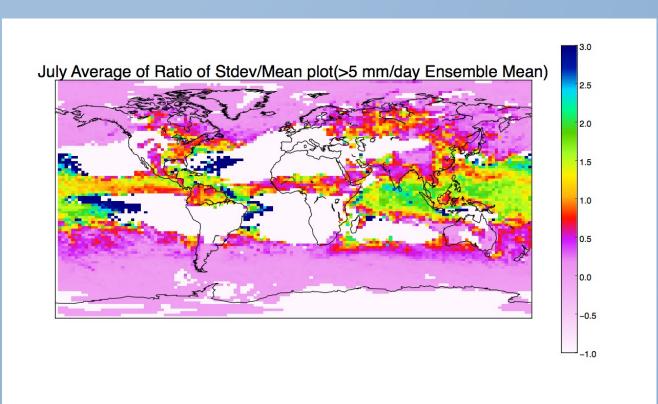


This diagram illustrates 2 CRMs interacting with the GCM (although the results shown below are based on 10 CRMs). With a single CRM, the GCM receives feedback from only a single realization. However, with multiple CRMs, the GCM receives feedback from the ensemble mean.

Results

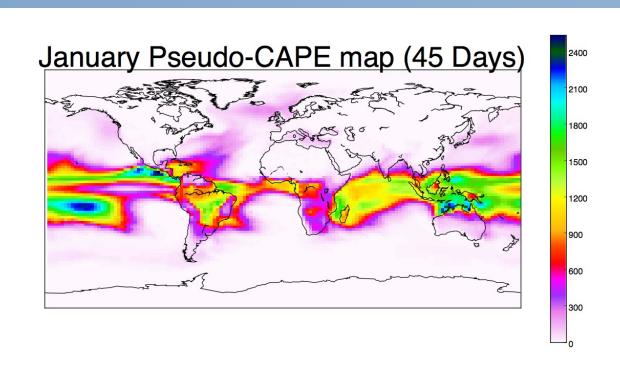


Global map of averaged CoV of daily rainfall for thirty days in January

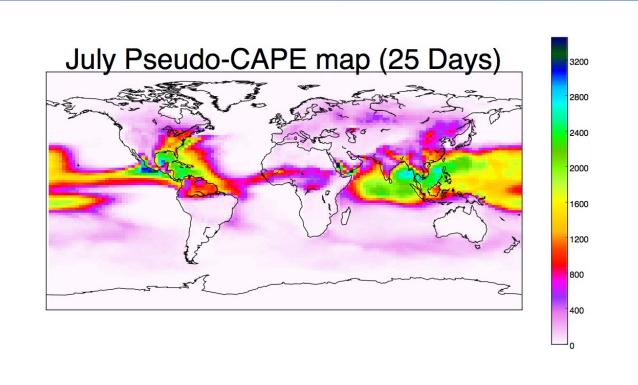


Global map of averaged CoV of daily rainfall for thirty days in

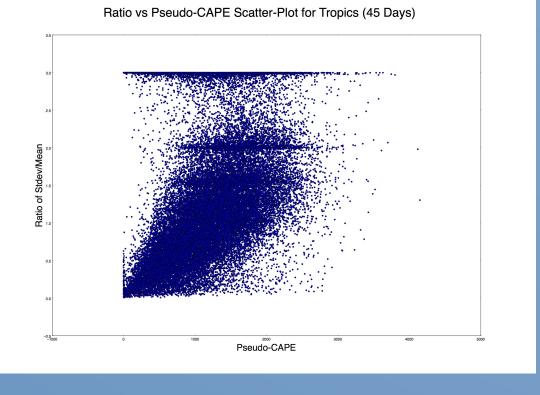
These two graphs are critical because they illustrate the differences in season and geography in rainfall predictability.

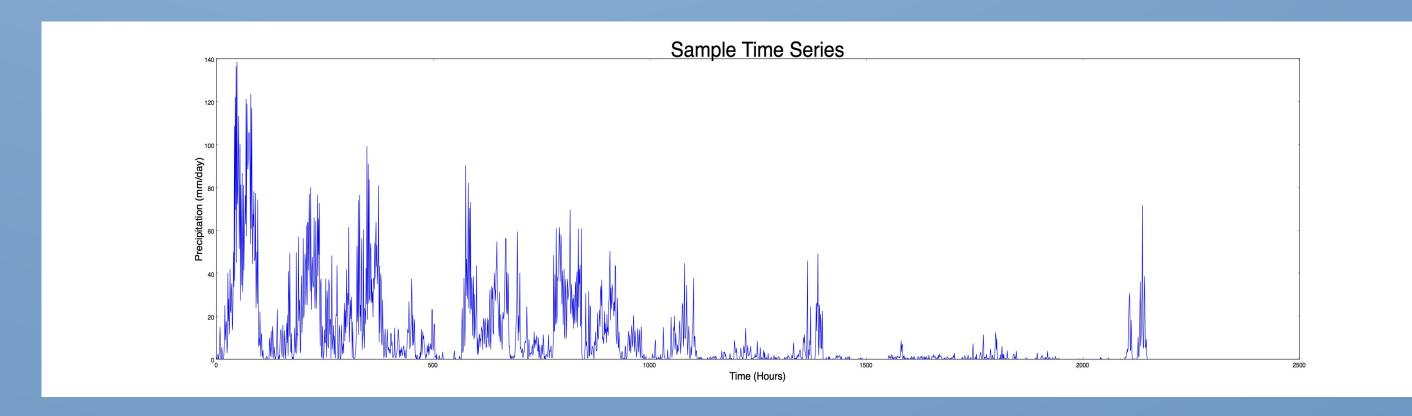


Global map of averaged CAPE for forty-five days in January and **February**



Global map of averaged CAPE for twenty-five days in July





Scatterplot showing the CoV versus the CAPE Example of a time series, showing the precipitation value at a particular location for 10,800 hours in the Tropics for forty-five days in January and February

Conclusion

Geographically, the Tropics is the region where rainfall predictability is lowest, due the highest CoV. In the midlatitude region, the predictability is higher in January than it is in July, whereas the predictability is approximately equal seasonally in the Tropics.

We found a strong correlation between the CAPE and the coefficient of variation. There was a moderate correlation between the Richardson number and the coefficient of variation. All other factors showed little to no correlation. For determining chaos in hourly time series produced by one SP – CAM, the results are inconclusive.

References

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