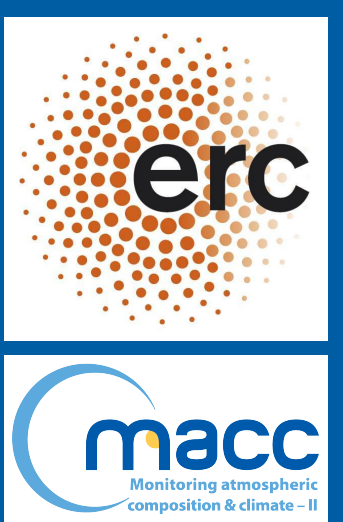


# CBASE: Using CALIOP to estimate the base height of cloud fields

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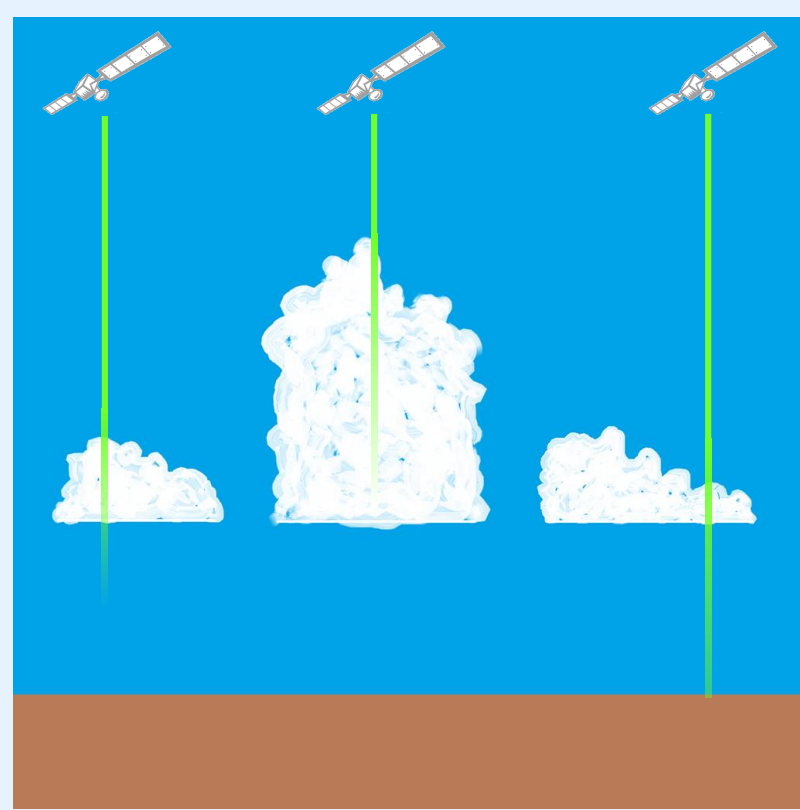
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## Motivation

- ▶ Unlike cloud top, cloud base is difficult to observe from space
- ▶ However, accurate knowledge of the cloud base height (CBH) — and thence cloud geometric thickness — would improve estimates of highly uncertain variables in the climate system, such as **cloud subadiabaticity** and **surface downwelling longwave flux**
- ▶ A CBH measurement on the A-Train would be particularly advantageous because of the possibility of combining CBH with many other retrieved cloud properties
- ▶ In this work, we present the **Cloud Base Altitude Spatial Extrapolator (CBASE)**, CALIOP-based estimate of cloud-field base height

## Method

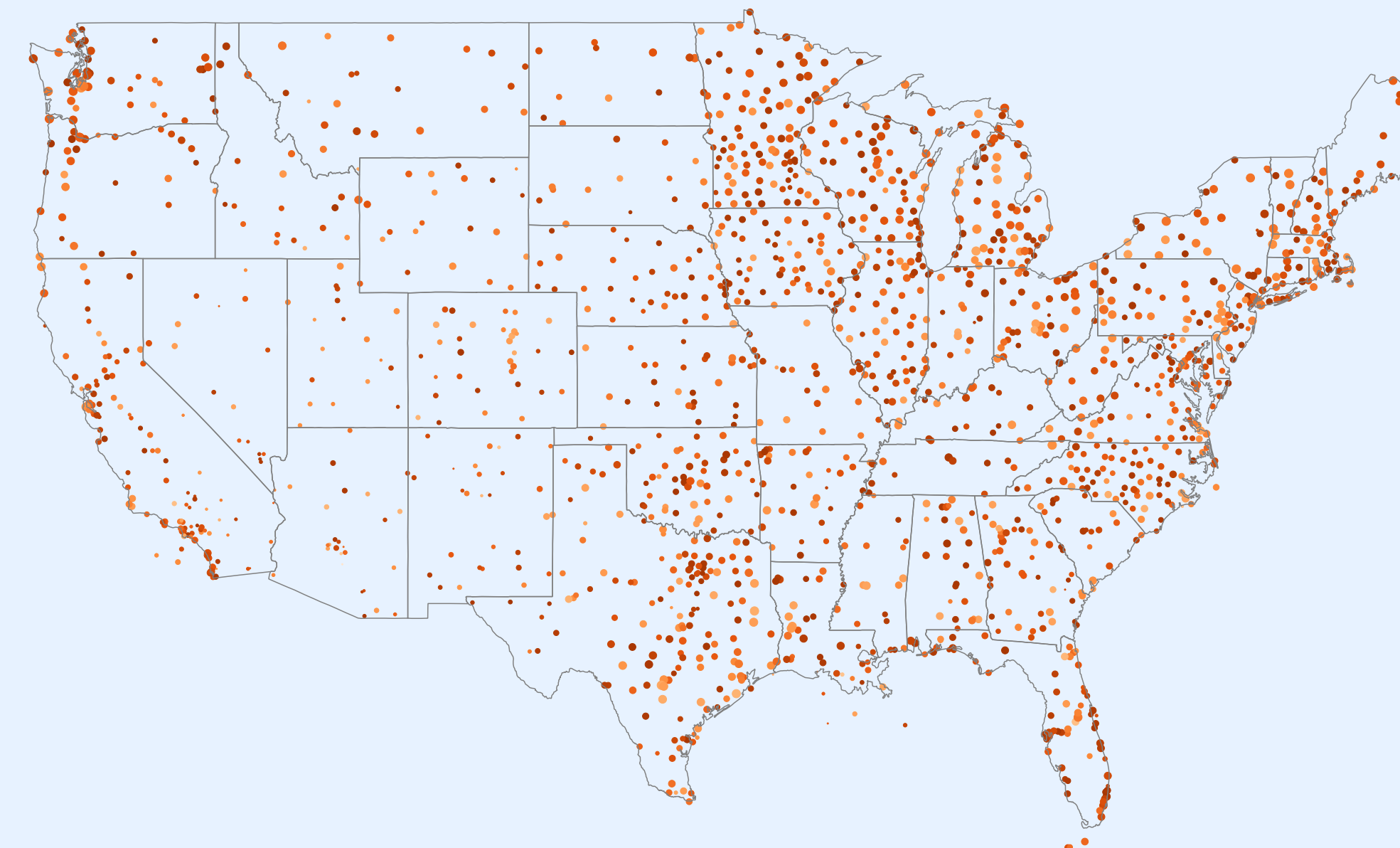


Even though CALIOP attenuates in optically thick ( $\tau \gtrsim 5$ ) clouds, the cloud base height of a homogeneous cloud field can be inferred from thin clouds or cloud edges that CALIOP can penetrate

## CBASE algorithm

1. We determine the CBH from all CALIOP profiles where the surface generates a return, indicating that the lidar is not completely attenuated by cloud. We refer to this as the *local CBH* in the sense that it is local to the CALIOP profile.
2. Using ground-based ceilometer data, we determine quality of cloud base height depending on a number of properties of the CALIOP profile. Assuming those properties suffice to determine the quality of the CBH determination, we can then predict the quality of a cloud base as a function of those factors. The quality metric we use is the root mean square error (RMSE); the category RMSE determined from comparison to ceilometer CBH then serves as the predicted CBH uncertainty. In the language of machine learning, we refer to this step as *training* the algorithm on the ceilometer data to predict CBH and CBH uncertainty.
3. Based on the predicted quality of each local cloud base, we either reject the local cloud base or combine it with other local cloud bases within a distance  $D_{\max}$  of the point of interest (POI) to arrive at an estimate of the CBH and its uncertainty at the POI.
4. Using a **statistically independent validation dataset**, we verify that the predicted CBH and its uncertainty are correct.

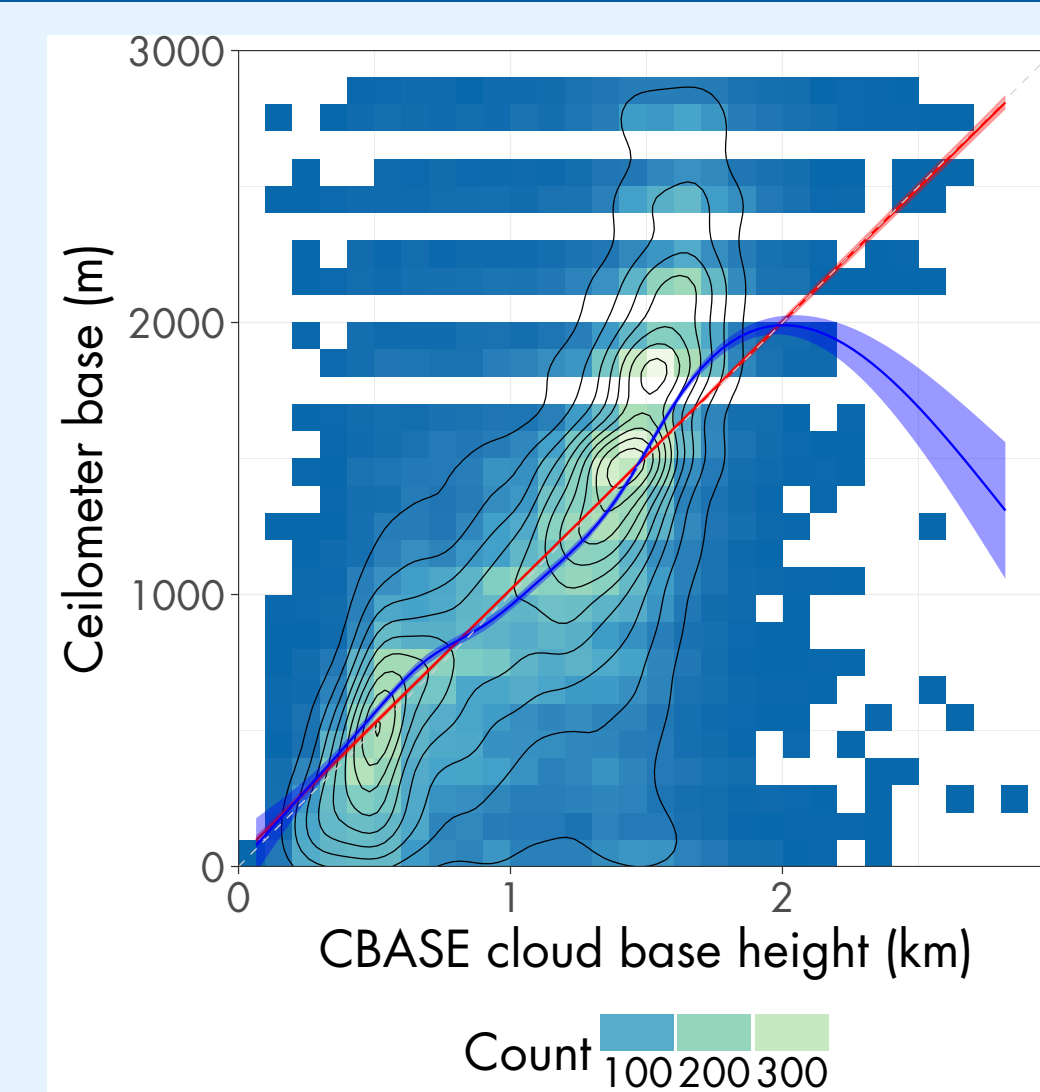
## "Ground truth"



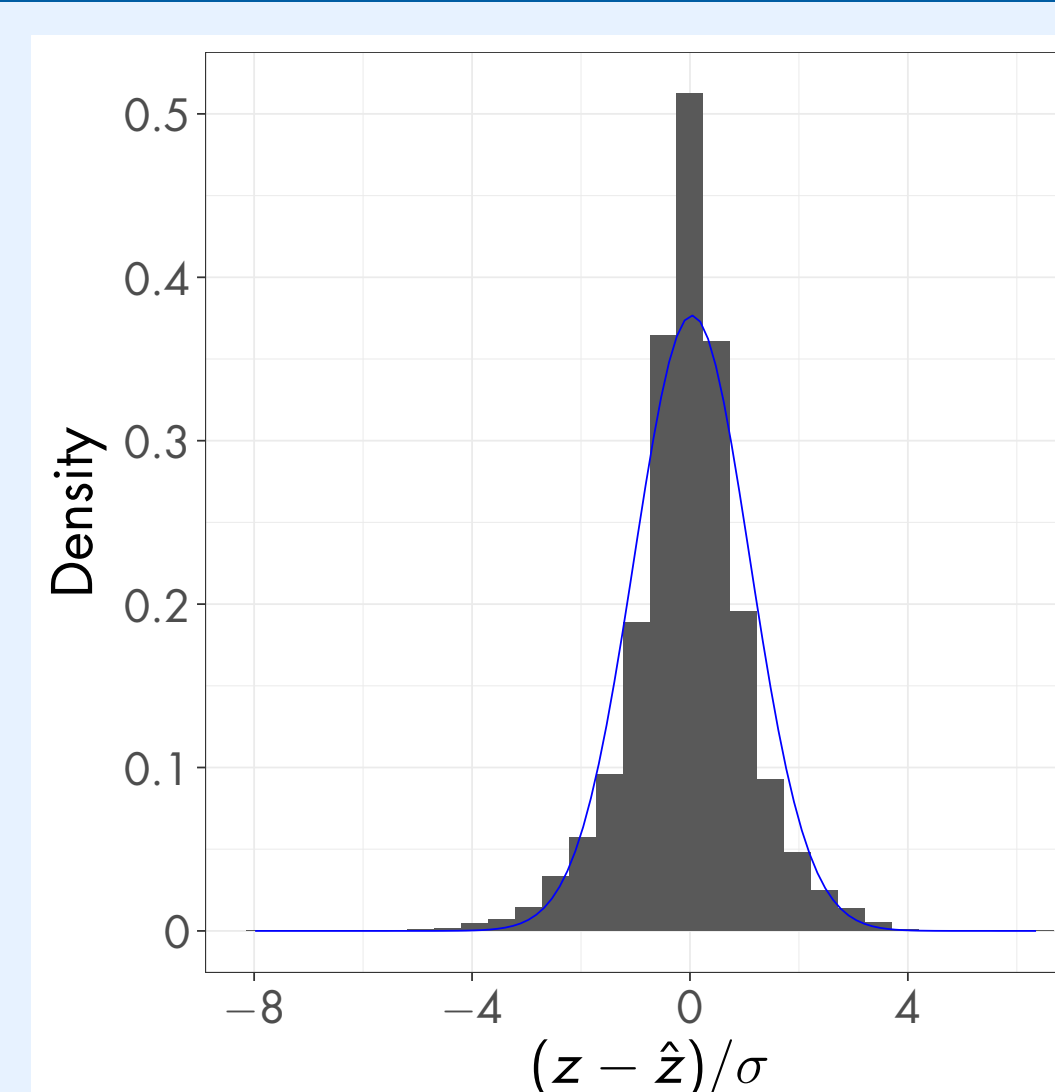
min( $D$ ) (km) 25 50 75  $N \cdot 10 \cdot 20 \cdot 30 \cdot 40$

Automated Surface Observing System (ASOS) ceilometers are used to train (using the year 2008) and validate (using the year 2007) the CBASE algorithm

## Validation: How well do we estimate CBH and CBH uncertainty?



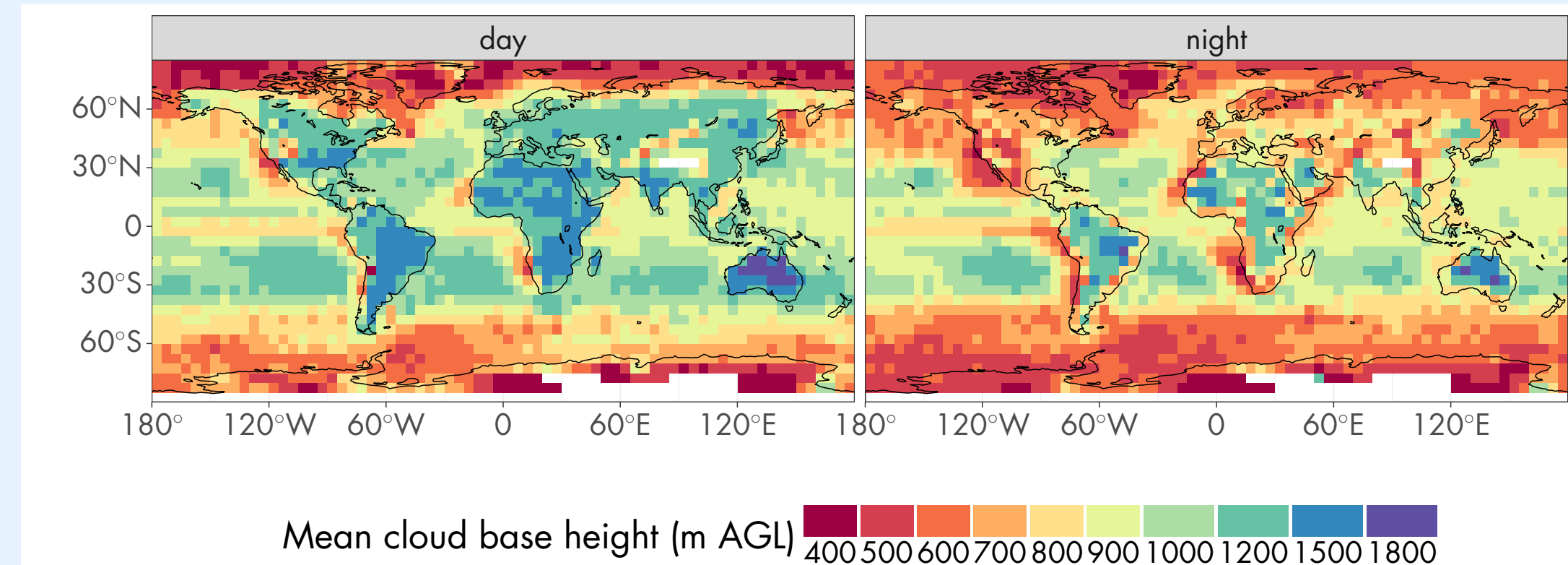
Joint histogram of CBASE and ceilometer CBH; 1:1 line, linear fit, and LOESS fit



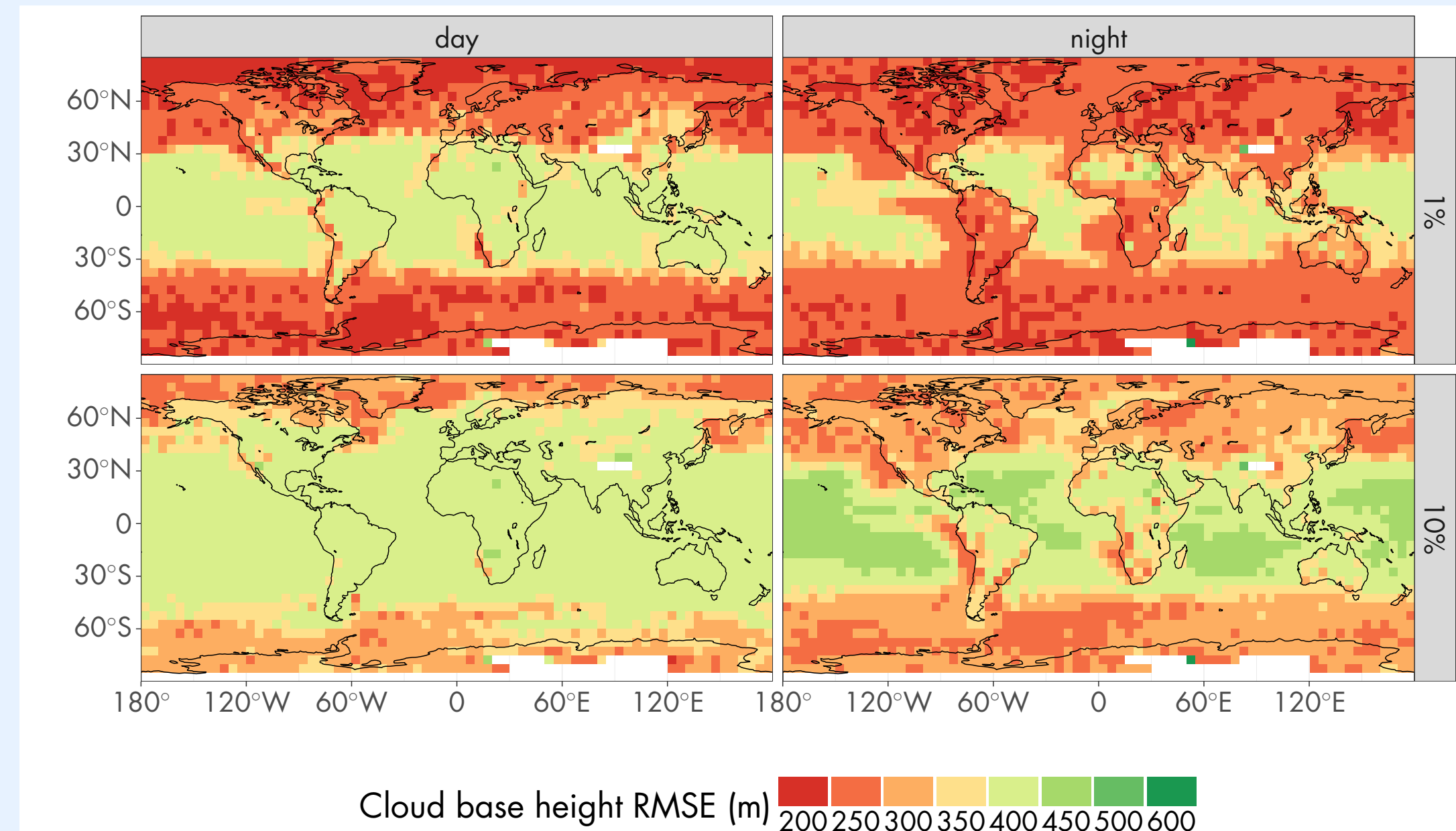
Cloud base error divided by predicted uncertainty

Unbiased CBH and unbiased uncertainty would yield Gaussian with zero mean (actual mean: 0.04) and unit standard deviation (actual SD: 1.06); we find **the CBH and its uncertainty to be unbiased to better than 10%.**

## Daytime and nighttime CBH distributions



## CBH uncertainty



## Conclusions

- ▶ CBASE performance is very close to 2B-GEOPROF-LIDAR (which is reassuring, since the underlying physical measurement is the same)
- ▶ The rigorous CBH uncertainty estimate provided by CBASE makes it possible to select the lowest-uncertainty cloud bases or to weight cloud bases statistically, as appropriate for each analysis
- ▶ By selecting the lowest-uncertainty cloud bases, the CBH uncertainty can be reduced from the 480 m assumed 2B-GEOPROF-LIDAR uncertainty to approximately 250 m in the extratropics and 400 m over tropical oceans
- ▶ CBASE data will be freely available from the World Data Center (Climate) at the German Climate Computing Center

