

Dear Prof. Zhang,

We sincerely thank you and the two referees for the time and effort spent reviewing our manuscript and providing constructive comments. Your feedback is invaluable for improving the quality of our paper. We fully understand and agree with your emphasis on the need for transparency, reproducibility, and uncertainty analysis regarding the cloud-base height (CBH) retrieval method used in this study. We have carefully addressed each of the four points you raised and made corresponding revisions to the manuscript, as detailed below.

Editor Comment 1: Add a Methods + Supplement section that documents the CBH algorithm in sufficient detail for reproduction (data and matchups; predictors/features; model architecture and hyperparameters; training/validation design and leakage controls; metrics by regime; and inference steps).

Response: We have incorporated a description of the CBH algorithm into Section 3 (Methodology) of the manuscript, as suggested. In addition, a detailed documentation of the algorithm has been provided in the Supplement in the form of a PDF file for reproduction. This document includes: Data and Matchups; Predictors/Features; Model Architecture and Hyperparameters; Training/Validation Design and Leakage Controls; Metrics by Regime; and Inference steps.

Detailed modifications are as follows: In the revised Section 3 (Methodology), we have added the following comprehensive description of the cloud base height (CBH) retrieval algorithm:

3.6 Cloud base height retrieval algorithm

The cloud base height (CBH) retrieval algorithm employed in this study is based on a deep neural network trained on Parasol L1 measurements collocated active sensor observations. The training dataset comprises Parasol L1 data—including intensity from 14 viewing angles in the oxygen A-band (763 nm and 765 nm channels), longitude, latitude, elevation, and cloud indicator—along with the corresponding CBH values and cloud detection information obtained from the CloudSat-CALIPSO L2 product 2B-CLDCLASS-LIDAR. Data from March, June, September, and December 2007 are primarily used, with the last seven days of each month reserved for testing and the remaining data used for training. To ensure high-quality training data, only cases where Parasol confidently detected cloudy scenes and CloudSat identified single-layer clouds are retained. Spatial collocation accuracy is constrained to within 0.01° , while temporal discrepancies are negligible due to the near-simultaneous observations from the A-Train satellites. The model utilizes geographic coordinates (longitude, latitude, elevation) and multi-angle oxygen A-band information from Parasol as inputs to predict CBH, with CloudSat-derived heights serving as ground truth. This method enables the CBH retrieval using only passive observations as input. The validation results indicate that the retrieval achieves a mean absolute error (MAE) of 0.78 km, a bias of 0.22 km, and a correlation coefficient (R) of 0.82.

It is important to note that the development, comprehensive validation, and detailed methodological discussion of this algorithm are beyond the scope of this study. A full description of the algorithm has been submitted to a separate journal and is currently under

review. To ensure transparency and reproducibility, we provide a complete documentation of the algorithm in the Supplementary Material of this article. Furthermore, the code and pre-trained model have been made publicly available (see the Data and Code Availability section). We have documented the CBH retrieval algorithm in detail in the Supplement, as follows:

Supplement

S1. Methodology Details for Cloud Base Height Retrieval

This method primarily retrieves cloud bottom height (CBH) by utilizing a deep neural network (DNN) based on multi-angle passive satellite observations—POLDER/Parasol data in the Oxygen A (O-A) band.

1. Data and Matchups

The data used in this study consist of four months (March, June, September, and December) of Parasol L1 products from 2007 and the corresponding CloudSat-CALIPSO 2B-CLDCLASS-LIDAR joint product. Spatial collocation between active and passive sensors maintains an accuracy within 0.01° , and temporal differences are negligible owing to the near-simultaneous measurements provided by the A-Train satellite constellation. During data preprocessing, only pixels that are identified as cloudy in Parasol data and simultaneously classified as single-layer clouds in the CloudSat-CALIPSO product are selected.

2. Predictors/Features

The training data used is shown in the table below.

Table S1. The training data and related parameters

Satellite	Product Name	Parameters	Note
Parasol	L1	longitude	
		latitude	
		elevation	
		cloud indicator	Cloud detection
		I763NP (14 view angles)	OA band
		I765NP (14 view angles)	OA band
CloudSat-CALIPSO	2B-CLDCLASS-LIDAR	Longitude	
		Latitude	
		CloudLayerBase	Cloud base height
		Cloudlayer	

3. Model Architecture and Hyperparameters

This method primarily employs deep neural networks to train the combined active and passive data, with specific parameter settings detailed in the table below.

Table S2. Parameter settings for training the model

Parameter Category	Parameter Name	Value / Setting
Randomness control	random_state	42
	dense_units	[1024, 512, 256, 64]
Network Architecture Parameters	dense_activations	['relu', 'relu', 'relu', 'relu']
	output_activation	'relu'
Training Parameters	batch_size	21000

/ Hyperparameters	epochs	44
	optimizer	'adam'
	loss_function	'mae'
	metrics	['mae']

4. Training/Validation Design and Leakage Controls

For each month, the last seven days of data serve as the test set, while the remaining days form the training set.

5. Metrics by Regime

The validation results of the model for predicting CBH across different cloud phases and various cloud types are as follows.

Table S3. The validation results for different cloud phases.

Cloud phase	Error metric	Value
Water cloud	N	188282
	MAE	0.3831
	Bias	-0.0532
	RMSE	0.9361
	R	0.6295
Ice cloud	N	76507
	MAE	0.6403
	Bias	-0.1291
	RMSE	1.1839
	R	0.6877
Mixed cloud	N	87373
	MAE	1.7632
	Bias	1.1279
	RMSE	3.1291
	R	0.7329

Table S4. The validation results for different cloud types.

Cloud type	Error metric	Value	Cloud type	Error metric	Value
Cirrus	N	36577	Stratus	N	37464
	MAE	2.6885		MAE	1.4915
	Bias	2.1800		Bias	0.5277
	RMSE	4.4079		RMSE	2.0529
	R	0.1909		R	0.6539
Altostratus	N	27637	Stratoculumus	N	9850
	MAE	1.1790		MAE	0.1520
	Bias	0.2194		Bias	0.0006
	RMSE	1.7428		RMSE	0.2630
	R	0.6458		R	0.8246
Altoculumus	N	153395	Culumus	N	47891
	MAE	0.2653		MAE	0.5238
	Bias	0.0051		Bias	-0.3217

RMSE	0.4765	RMSE	1.4175
R	0.7447	R	0.2962

6. Inference Steps

The detailed steps for performing cloud base height prediction using the proposed method are as follows:

Step 1. Read Parasol L1 data.

Step 2. Apply quality control flags to filter cloudy pixels.

Step 3. Extract all predictor variables specified in the "feature list" from the data.

Step 4. Preprocess the extracted features exactly as done during the training stage.

Step 5. Feed the preprocessed feature matrix into the loaded pre-trained DNN model.

Step 6. Perform inference to obtain the estimated CBH for each pixel.

Editor Comment 2: Publicly archive the CBH materials (e.g., a preprint or methods note) and provide a stable citation. This is for transparency; the current paper must still be self-contained.

Response: The paper detailing the CBH retrieval algorithm has been submitted to *Remote Sensing of Environment* (Manuscript ID: RSE-D-25-02483) and is currently under review. Following your suggestion, we have made a preprint version of the manuscript available on Elsevier's Preprints (SSRN) platform to ensure a stable and citable reference. The full citation which has been added to reference of our manuscript is as follows:

Ji, T., Shang, H., Wei, L., Bao, F., Liu, Z., Wang, Y., Bao, S., Yin, S., Shi, C., Wang, H., Liu, Z., and Letu, H.: Retrieval of the base heights and cloud geometric thicknesses of clouds based on the PARASOL measurement, SSRN, <https://ssrn.com/abstract=5515438> or <http://dx.doi.org/10.2139/ssrn.5515438>, 2025.

Editor Comment 3: Release code/model artifacts and a minimal dataset slice under a permanent DOI, and include a clear Data & Code Availability statement.

Response: We have archived the relevant code, pre-trained model, and a minimal input data slice for the CBH retrieval algorithm in a repository on *Zenodo*, which has been assigned a permanent DOI (10.5281/zenodo.17082185). A direct link to this repository has been added to the "Data and Code Availability" section of the manuscript to ensure full access for readers. Additionally, to protect the intellectual property associated with both this study and the CBH study prior to formal publication, the associated code and model resources are currently under restricted access (the right to view but no download) on *Zenodo*. The repository will be transitioned to fully public access immediately upon the formal acceptance of both manuscripts.

Detailed modifications are as follows: The modified "Data and Code Availability" section is as follows:

Data and Code Availability

All datasets used in this work are open-source. The CloudSat datasets are available from the

CloudSat Data Processing Center of the Cooperative Institute for Research in the Atmosphere (<http://www.cloudsat.cira.colostate.edu/>). The Parasol products are available from ICARE Data and Services Center (<https://www.icare.univ-lille.fr/>). The code and pre-trained model for the cloud base height retrieval algorithm, along with a minimal dataset required to reproduce the key results, have been deposited on Zenodo under a permanent DOI: [10.5281/zenodo.17082185].

Editor Comment 4: Provide an ablation/uncertainty analysis quantifying how CBH errors propagate into TP_CER/TP_NCOT and the reconstructed profiles (include a “perfect CBH” benchmark for context).

Response: Thank you very much for your valuable comment. The issue you raised regarding quantifying how CBH uncertainties propagate into the retrieval results is indeed crucial and represents a core aspect of our study. We fully agree with this point and have conducted a detailed ablation/uncertainty analysis accordingly. Below is an overview of our uncertainty analysis method and key findings:

This study quantifies how CBH errors propagate into TP_CER/TP_NCOT and the reconstructed profiles. We use a representative single-layer liquid stratiform cloud profile scene (from the track on March 2, 2007, corresponding to the profile data in Fig.9 of the original manuscript) as the test case. The CloudSat-measured CBH serves as the “perfect CBH” benchmark. We add Gaussian errors with standard deviations of 0.1 km and 0.5 km, along with systematic errors of 0.1 km and 0.5 km, to generate four perturbation experimental groups. These perturbed CBH values then serve as inputs for estimating TP_CER and TP_NCOT. The TP_CER estimation results with added Gaussian errors and systematic errors are shown in Figures R1 and R2, respectively. Similarly, the TP_NCOT estimation results with added Gaussian errors and systematic errors are presented in Figures R3 and R4, respectively. For clarity, we summarize all error evaluation metrics in Table R1.

For TP_CER: As shown in Table 1 and Figures R1-R2, the addition of Gaussian errors of 0.1 km and 0.5 km to CBH increases the RMSE from 1.04 to 1.05 and 1.08, respectively, while R remains unchanged. When a systematic error of 0.1 km is added to CBH, the RMSE shows no change and remains at 1.04. With a systematic error of 0.5 km, the RMSE increases from 1.04 to 1.07. Throughout the addition of systematic errors, R continues to show no change. These results demonstrate that CBH errors within 0.5 km have negligible impact on TP_CER estimation.

For TP_NCOT: As shown in Table 1 and Figures R3-R4, the addition of a 0.5 km Gaussian error to CBH increases the RMSE from 0.08 to 0.09. In contrast, the addition of 0.1 km Gaussian error, 0.1 km systematic error, or 0.5 km systematic error produces no measurable change in RMSE. Furthermore, all variations in R remain within 0.01. We therefore conclude that CBH errors within 0.5 km have negligible impact on TP_NCOT estimation.

In conclusion, these results demonstrate that CBH errors within 0.5 km have negligible impact on the estimation of both TP_CER and TP_NCOT. Consequently, the profile reconstruction is virtually unaffected by these errors. Based on the negligible impact observed in our sensitivity experiments, further analysis of CBH uncertainty effects on profile reconstruction is deemed unnecessary.

Table R1. The assessment results of the influence of cloud base height uncertainty on TP_CER and TP_NCOT

	Group	Specific operation	RMSE	R	Bias	MAE
TP_CER	Control group	No error added to CBH	1.04	0.94	0.05	0.84
	Gaussian error group	CBH with gaussian error (std=0.1km)	1.05	0.94	0.05	0.84
		CBH with gaussian error (std=0.1km)	1.08	0.94	0.03	0.87
	Systematic error group	CBH with systematic error (+0.1km)	1.04	0.94	-0.00	0.84
		CBH with systematic error (+0.5km)	1.07	0.94	-0.22	0.85
	Control group	No error added to CBH	0.08	0.73	-0.00	0.06
	TP_NCOT	Gaussian error group	CBH with gaussian error (std=0.1km)	0.08	0.75	0.00
CBH with gaussian error (std=0.5km)			0.09	0.64	-0.01	0.06
Systematic error group		CBH with systematic error (+0.1km)	0.08	0.76	0.01	0.05
		CBH with systematic error (+0.5km)	0.08	0.75	0.01	0.05

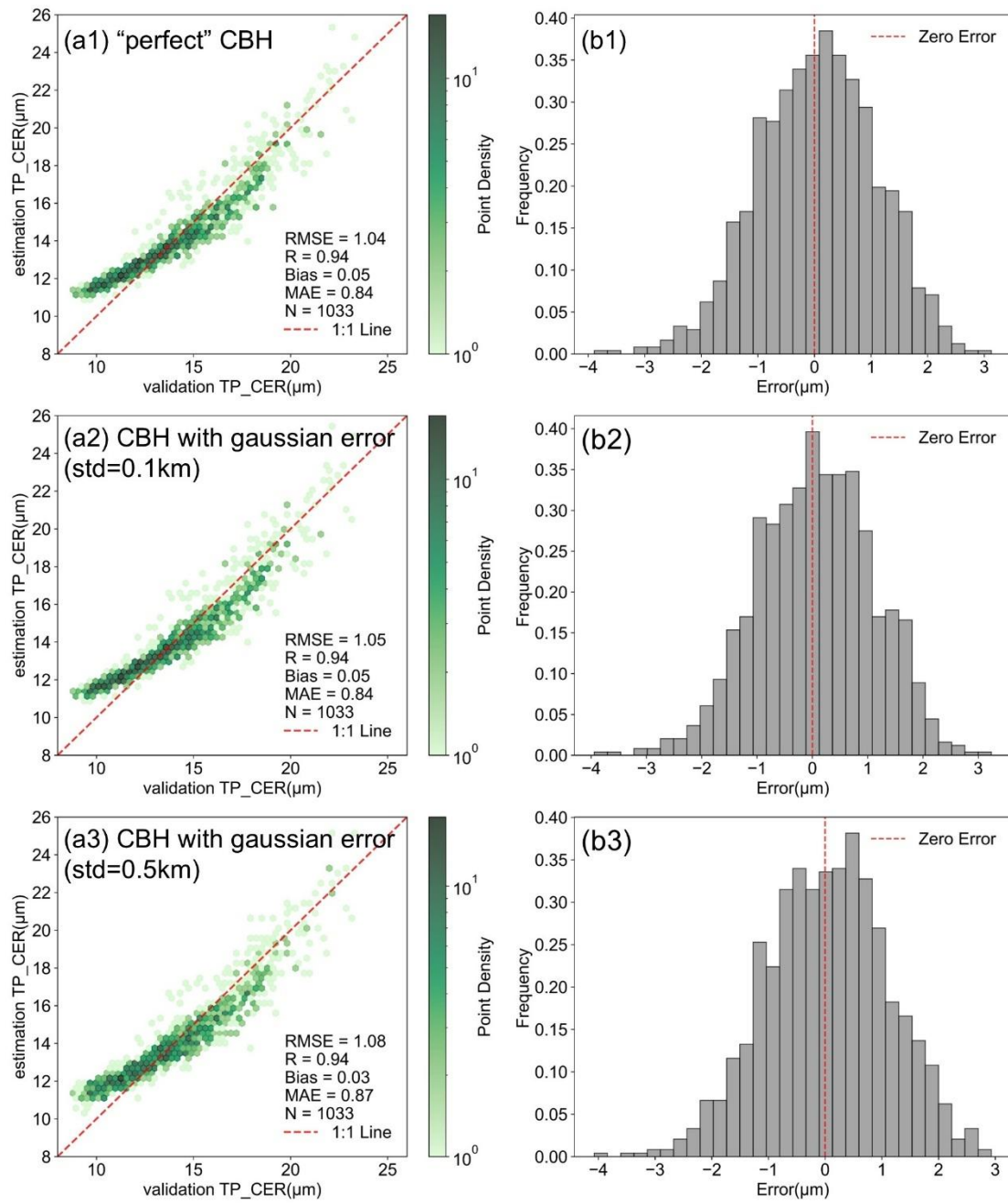


Figure R1. Comparison of TP_CER results between no error added to CBH and Gaussian error added to CBH. (a1) and (b1): no error added to CBH – “perfect” CBH; (a2) and (b2) CBH with gaussian error (std = 0.1km); (a3) and (b3) CBH with gaussian error (std = 0.5km).

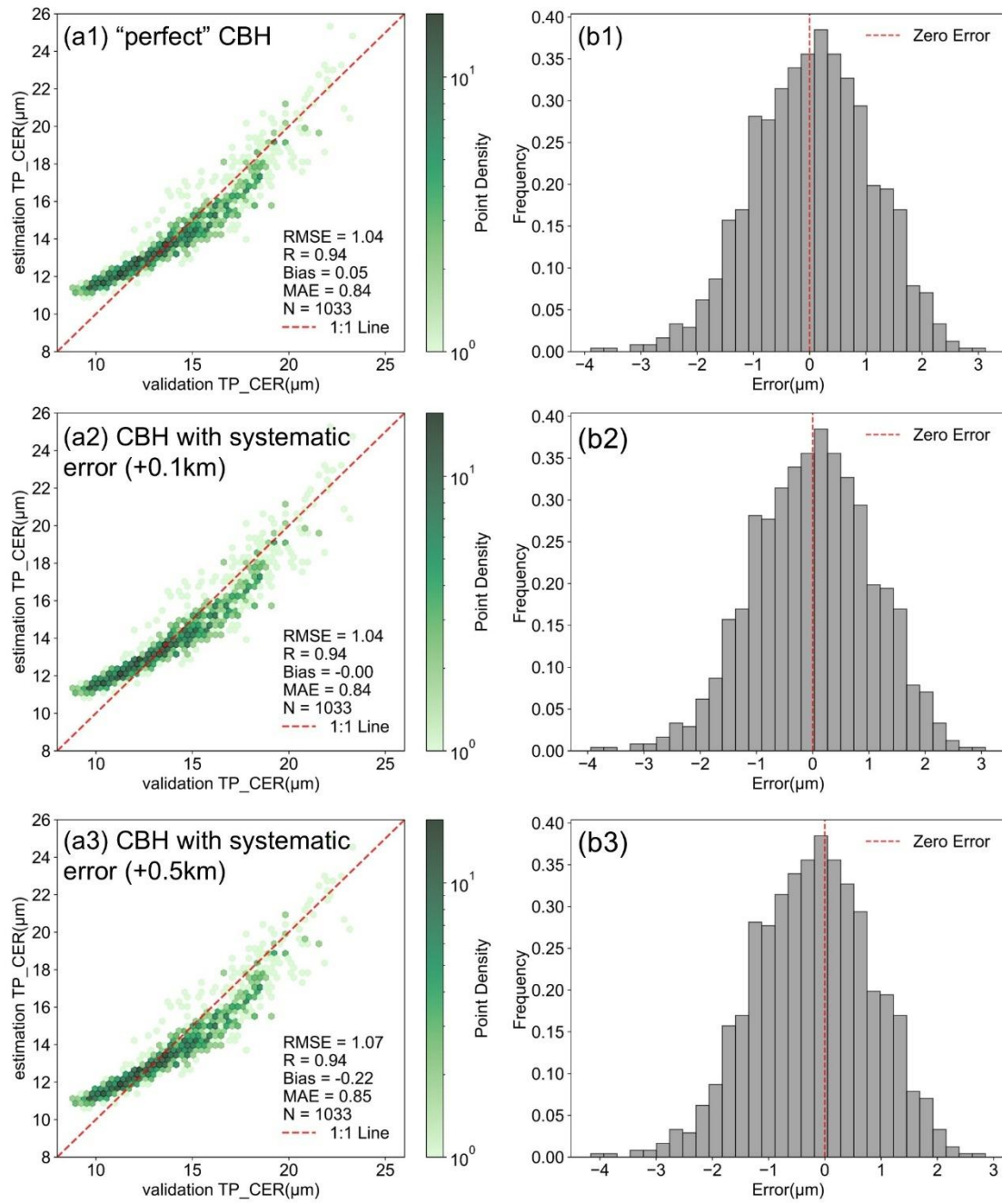


Figure R2. Comparison of TP_CER results between no error added to CBH and system error added to CBH. (a1) and (b1): no error added to CBH – “perfect” CBH; (a2) and (b2) CBH with system error (+0.1km); (a3) and (b3) CBH with system error (+0.5km).

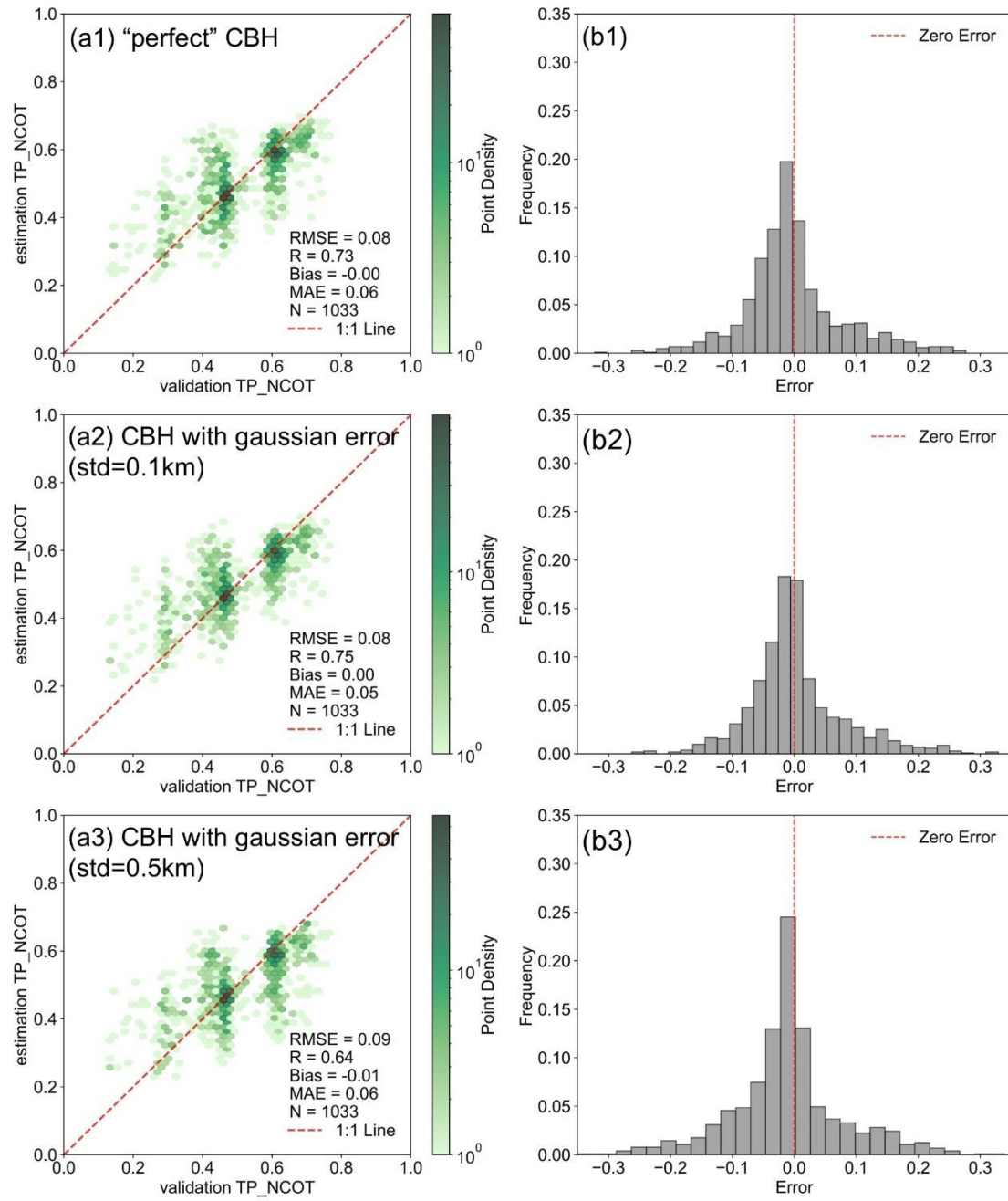


Figure R3. Comparison of TP_NCOT results between no error added to CBH and Gaussian error added to CBH. (a1) and (b1): no error added to CBH – “perfect” CBH; (a2) and (b2) CBH with gaussian error (std = 0.1km); (a3) and (b3) CBH with gaussian error (std = 0.5km).

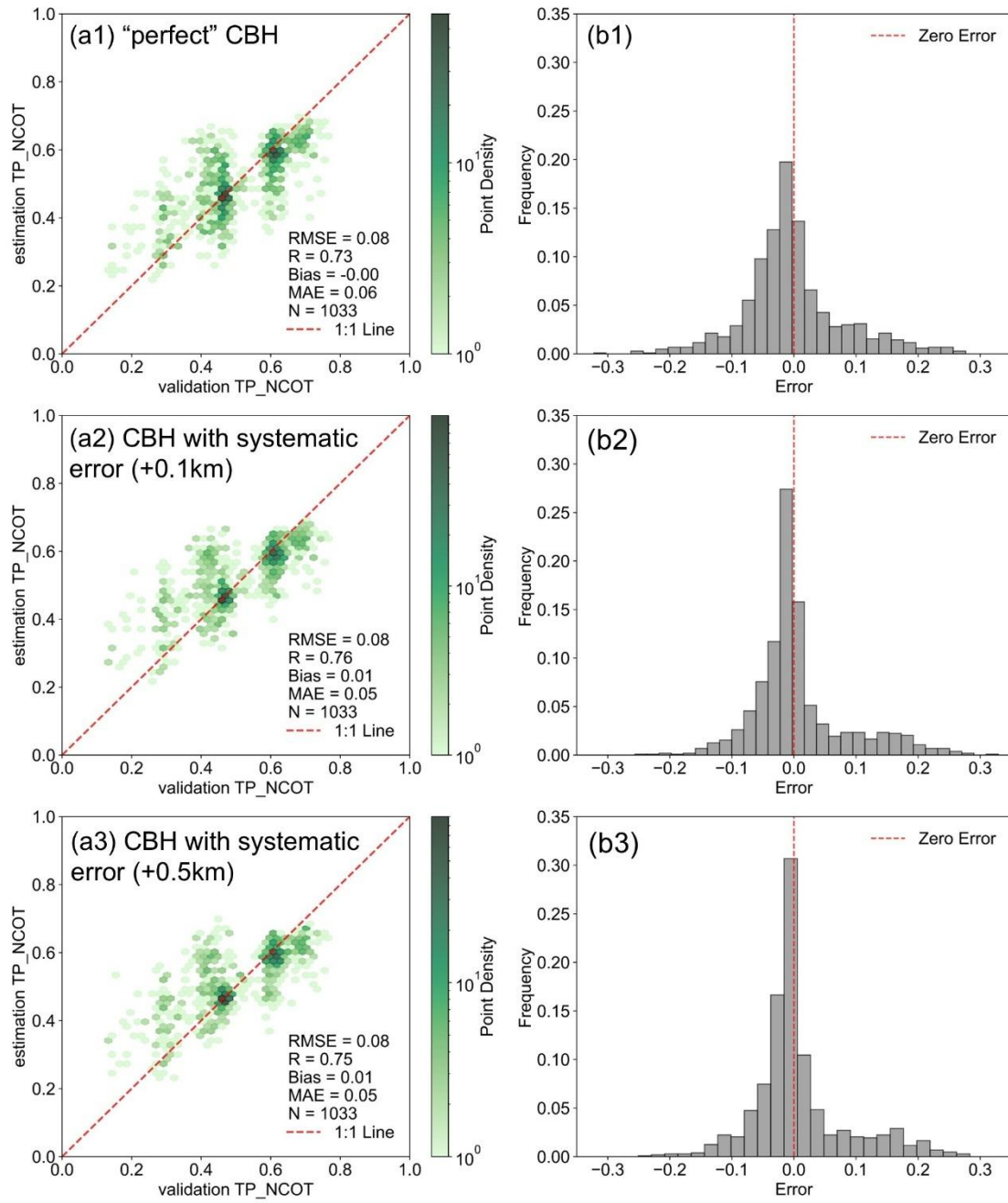


Figure R4. Comparison of TP_NCOT results between no error added to CBH and system error added to CBH. (a1) and (b1): no error added to CBH – “perfect” CBH; (a2) and (b2) CBH with system error (+0.1km); (a3) and (b3) CBH with system error (+0.5km).