Response to Reviewer #2 comments

We thank the reviewers for their time in reviewing the manuscript. Those comments are valuable and helpful to improve the manuscript. We have considered the comments very carefully and made revisions to the manuscript. We hope our revision could satisfy your requirements and meet your approval. Our point-by-point replies to the comments and suggestions are described as below.

The authors proposed a downscaling method based on CDF to obtain hourly 0.05 ° grid precipitation data. This topic is interesting and would be useful for the climate change community. In general, this paper is well-written for most parts. However, a minor revision is needed before it is published in HESS.

Comment 1

Precipitation is more complex to downscaling than temperature. Until now, hundreds of methods have been developed via statistical and dynamical approaches. However, there is none common method for all regions. The authors did not state clearly about statistical and dynamical downscaling methods in the introduction. The presented study is a statistical downscaling which only used the outputs (CMORPH and GEO-IR) to explore a statistical link. From my side, this approach is similar with Quantile-Mapping (QM), which the authors did not mention. What is the difference between QM and DCDF? The reviewer did not figure out from the Equations (1) to (7).

Response:

Thank you for your very valuable advice. It is very significant to improve our paper. CDF matching belongs to quantile mapping. CDF matching relates one variable (Tb in our study) to reference (precipitation in our study) using same cumulative frequency. We used figure and formula to explain the CDF matching.

The matching process is implemented by a one-to-one mapping CDF of variable onto that of the reference (Eq. 5). We added equation 5. Please see line 5~6 in page 5 (red color).

For matching between Tb and CMORPH, all precipitation rate (Tb) are sorted in ascending (descending) order. Then cumulative probability distributions are both obtained. The cumulative probability is defined as critical probability when precipitation rate equals zero. The rain-no-rain threshold is the Tb with cumulative probability same as the critical probability. Then the CDF matching was applied. All pixels in the Tb images (Tb0.05) were divided into two categories, raining ones less than the rain-no-rain threshold and non-raining ones larger than the threshold. Tb-R relationships were applied to these raining pixels. Finally, CMORPH data were downscaled to 1-hour, 0.05°×0.05°.

Two different approaches are currently being pursued. Dynamical downscaling uses regional climate models (RCMs) to translate the large-scale weather evolution from a GCM into a physically consistent evolution at higher resolution. Statistical downscaling is based on empirical relationships between the regional climate and carefully selected large-scale predictor variables. Please see line 19~22 in page 2 (red color).

Thanks again for your valuable advice.

Comment 2

Is it possible that the information is missing in the process of 0.05 degree data aggregated to 0.25degree? Can the built relationship from a coarse resolution represent the similar features for a higher resolution? What method was used in the aggregation, sum or mean? Does it affect the result?

Response:

Thank you for your very valuable comment. 0.05° Tb was aggregated to 0.25° by arithmetic averaging. Then 0.25° Tb (after aggregation) is matched with CMORPH for raining pixels by quantile-mapping the CDF. Because variability of precipitation cloud is small over 0.25° region, we think the values (number=25) of 0.05° Tb within a raining pixel are almost the same. That is, the information is to some extent missing in the process of 0.05° data aggregated to 0.25°, but which has a little effect on the Tb-Rain relationship and DCDF result. That is, the built relationship from a coarse resolution generally can represent the similar features for a higher resolution.

We think what method was used in the aggregation would affect the result. If we use the bi-cubic convolution method or bi-linear method, 0.25° Tb after aggregation will involves the information beyond 0.25° pixel. Then it will have effect on the Tb-Rain relationship and DCDF result, and the built relationship from a coarse resolution generally can not represent the similar features for a higher resolution.

In summary, we think arithmetic averaging method is propably best choice.

Comment 3

The structure may be adjusted. I prefer to introduce the data and study area firstly and then followed by the method. The equations for validate criteria are not necessary since they are common used.

Response:

Thank you for your helpful advice. We have changed the order of chapter 2 and 3. We first introduced study areas and datasets (chapter 2), and then the methodology (chapter 3). We have removed dedcription of well known validation index (correlation coefficient (CC), root mean square error (RMSE) and bias, and tab.1).

Comment 4

The authors claimed that DCDF performs better in the frontal rain systems but worse in mountainous. Is CMORPH the main reason for that? If use the reanalysis (e.g. ERA-Interim) for downscaling, will be better? I suggest more discussions on it.

Response:

Thank you for your very valuable advice. We agreed with you. It is very significant to improve our paper. The table below gives R2 in four seasons. The most average of R2 are higher than 0.90 for six regions in four seasons. This result may infer that the bad performance of the approach is mainly caused by low accuracy of CMORPH. Thus using reanalysis data for downscaling may be better than satellite products. Additionally, the assumption of DCDF method is also applied to reanalysis data. It is expected that the DCDF method also applied to reanalysis precipitation data (e.g. ERA-Interim, 0.75°/6 hourly).

We have discussed this issue in the paper. Please see line 13~17 in page 10 (red color).

Time		SE	CE	NE	CW	NW	TP
SP	Mean	0.91	0.97	0.96	0.98	0.97	0.98
	Max	0.99	0.99	0.99	0.99	0.99	0.99
	Min	**0.64**	0.89	**0.60**	0.83	**0.73**	**0.78**
	Std	0.05	0.02	0.04	0.01	0.02	0.02
SU	Mean	0.92	0.96	0.96	0.97	0.99	0.97
	Max	0.98	0.99	0.99	0.99	0.99	0.99
	Min	0.84	**0.77**	0.85	0.86	0.97	0.86
	Std	0.03	0.03	0.02	0.03	0.00	0.03
FA	Mean	0.97	0.97	0.97	0.97	0.88	0.98
	Max	0.99	0.99	0.99	0.99	0.99	0.99
	Min	0.82	0.89	0.87	0.86	**0.64**	0.94
	Std	0.04	0.03	0.03	0.02	0.11	0.01
WI	Mean	0.92	0.92	0.89	0.95	0.92	0.97
	Max	0.99	0.99	0.99	0.99	0.99	0.99
	Min	**0.65**	**0.51**	**0.60**	**0.71**	**0.58**	**0.69**
	Std	0.07	0.07	0.09	0.04	0.07	0.03

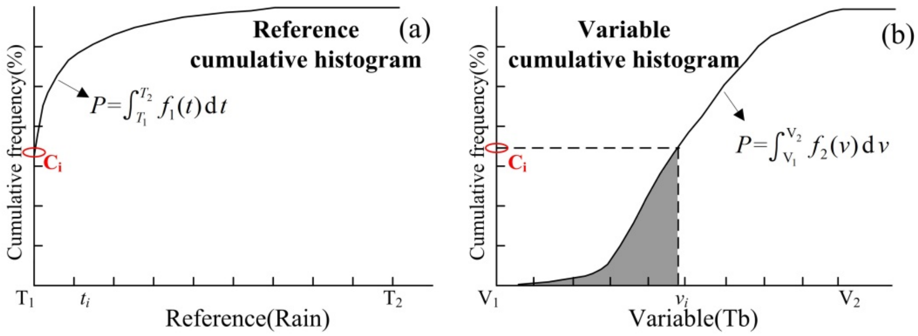
Comment 5

How to define the rain-no-rain threshold?

Response:

As shown in figure below, the rain–no-rain threshold is set at about v_i (fig. b) where the cumulative frequency equals C_i (fig. a and b). Specially, all precipitation rate (Tb) are sorted in ascending (descending) order. Then cumulative probability distributions are both obtained. The cumulative probability is defined as critical probability when precipitation rate equals zero. The rain-no-rain threshold is the Tb with cumulative probability same as the critical probability. As shown in Fig. 2c and 2d (T means precipitation rate; V represents Tb), the rain–no-rain threshold is set at about vi where the cumulative probability equals Ci (critical probability). Please see line 11~15 in page 6 (red color).

Thanks again for your valuable advice.



Comment 6

How the DCDF works for each region in each month, rather than seasonal? Figure 8 is for all regions?

Response:

It is unavailable for hourly gauge data. A disdrometer installed at Xingzi station (29.45°N, 116.05°E) in the Jiangxi province (Fig. 1) provided hourly data in 2014, except June and July when the instrument was subject to a transmission error. Figure 8 is just for a point using this disdrometer data at the hourly scale.

Table below lists the statistics (We only showed CC and Bias) at the daily scale for each region in each month. The results showed that DCDF generally performed at each month same as at each season.

Indexes	Month	Type	SE	CE	NE	CW	NW	TP
B(%)	Jan	CMORPH	-99.27	-34.28	-103.31	1294	205.31	1598
		DCDF	18.28	27.15	22.98	2159	185.94	1628
	Feb	CMORPH	-91.83	-33.94	-90.64	1323	67.24	1767
		DCDF	5.65	15.24	20.38	1642	39.29	2338
	Mar	CMORPH	-22.44	-3.92	-48.56	41.85	170.55	80.27
		DCDF	-10.61	2.72	40.90	50.72	197.69	96.51
	Apr	CMORPH	-20.45	-3.10	-43.72	45.86	153.91	82.25
		DCDF	-10.72	3.26	37.59	44.42	192.35	100.76
	May	CMORPH	-15.93	-3.10	-43.98	47.37	157.57	86.20
		DCDF	-6.61	2.95	30.26	55.19	187.38	104.40

	Jun	CMORPH	-16.83	2.29	5.61	-37.22	162.62	-20.68
		DCDF	-8.92	2.07	5.68	20.91	222.37	19.53
	Jul	CMORPH	-24.42	3.27	5.54	-46.77	153.39	-11.25
		DCDF	-15.57	2.98	5.80	25.62	218.35	16.17
	Aug	CMORPH	-25.25	3.00	7.02	-40.43	117.33	5.17
		DCDF	-14.90	2.63	7.16	29.85	197.94	10.36
	Sept	CMORPH	-68.59	-33.92	-17.58	19.90	120.25	41.33
		DCDF	9.39	30.28	16.68	15.47	118.37	54.45
	Oct	CMORPH	-69.99	-34.74	-19.21	9.18	118.69	45.95
		DCDF	11.57	36.56	12.70	17.37	130.66	58.72
	Nov	CMORPH	-50.36	-27.92	-12.15	11.29	112.30	48.99
		DCDF	0.21	39.88	20.33	9.86	116.71	62.28
	Dec	CMORPH	-95.41	-30.92	-91.95	921	61.25	1770
		DCDF	7.73	22.2	23.51	1623	50.22	1862
CC	Jan	CMORPH	0.30	0.01	0.00	0.06	0.03	0.05
		DCDF	0.45	0.16	0.04	0.01	0.02	0.11
	Feb	CMORPH	0.38	0.05	0.00	0.06	0.04	0.10
		DCDF	0.60	0.18	0.06	0.01	0.04	0.19
	Mar	CMORPH	0.57	0.31	0.36	0.20	0.07	0.00
		DCDF	0.63	0.39	0.35	0.16	0.06	0.01
	Apr	CMORPH	0.61	0.42	0.38	0.17	0.07	0.06
		DCDF	0.64	0.41	0.38	0.19	0.05	0.05
	May	CMORPH	0.67	0.34	0.36	0.17	0.07	0.09
		DCDF	0.71	0.45	0.38	0.17	0.05	0.08
	Jun	CMORPH	0.38	0.26	0.30	0.17	0.41	0.30
		DCDF	0.49	0.28	0.51	0.46	0.44	0.39
	Jul	CMORPH	0.36	0.17	0.24	0.17	0.40	0.22
		DCDF	0.47	0.27	0.44	0.44	0.45	0.35
	Aug	CMORPH	0.35	0.18	0.24	0.17	0.40	0.22
		DCDF	0.47	0.25	0.43	0.44	0.44	0.36
	Sept	CMORPH	0.39	0.48	0.36	0.07	0.31	0.19
		DCDF	0.54	0.50	0.44	0.09	0.20	0.08
	Oct	CMORPH	0.41	0.48	0.36	0.07	0.32	0.10
		DCDF	0.51	0.52	0.50	0.09	0.20	0.08
	Nov	CMORPH	0.42	0.54	0.36	0.07	0.35	0.06
		DCDF	0.52	0.54	0.51	0.14	0.26	0.08
	Dec	CMORPH	0.33	0.02	0.00	0.05	0.02	0.06
		DCDF	0.47	0.16	0.06	0.00	0.02	0.17

Comment 7

Table 3, CDF => DCDF

Response:

Thank you for your useful advice. We have revised them. Please see table 2.

Comment 8

P7 L18: It seem => It seems

Response:

Thank you for your useful advice. We have revised them. Please see line 3 in page 10 (red color).

Comment 9

What is the specific means of a, b, c, and d in equations 11 to 13.

Response:

Thank you for your useful advice. These evaluation metrics in chapter 2.3 and 2.4 are well known, thus they have been deleted. We have removed chapter 2.3 and 2.4 also fig 3 (Schematic of the variogram curve), tab.1 (Contingency table for the definition of the categorical metrics).

Comment 10

Figure 7 is hard to follow. Please revise it in a more readable way.

Response:

Thank you for your useful advice. We have revised it. Please see fig. 5.

Comment 11

Some information is missing or wrong in Fig 9a.

Response:

Thank you for your useful advice. We have revised them. Please see line Fig 7a.