

# **Appendices-Supplementary Materials**

## **Appendix.A: Description of bias correction Methods**

The current study evaluated five different methods for bias correction and downscaling of precipitation projections and three methods for temperature. The work mainly follow the methodology suggested by [1], with an additional method for precipitation, which combine a method suggested by [1] with a post processing frequency scaling step to ascertain that same ratio of wet days as possessed by “raw historical to raw-scenario” prevails in the “observed to correct scenario”. Most of the processing were carried out using the “CMhyd” (Climate Model data for hydrologic modeling) tool, by [2] available at “<https://swat.tamu.edu/software/cmhyd/>”.

A brief overview of these methods is given in the following sections while for detail description of these methods. [1, 2], can be consulted.

### *Appendix A.I: Linear scaling of precipitation and temperature (LS)*

The linear-scaling method is based on work of [3]. It first generate monthly correction values, equal to the differences between observed and historical (present-day) simulated values. The method entails by definition that the corrected GCM/RCM simulations agree perfectly with the observations, in their monthly mean values.

In case of precipitation the correction factor is based on the ratio of long-term monthly mean observed and long-term monthly mean control/historical run data, While in case of temperature, the correction is done with the help of an additive factor based on the difference between the long-term monthly mean observed and long-term monthly mean control/historical simulation run data.

### *Appendix A.II: Local Intensity Scaling (LIS)*

The local intensity and frequency scaling method (LIS) used here is a slightly modified version of the method suggested by [4], for Climate model downscaling. This method corrects adjusts the mean as well as both wet-day frequencies and wet-day intensities of precipitation time series, by effectively matching the climatological wet-day frequency and intensity of the historical/control run with that of the observer data, and then applying the same calibrated RCM precipitation threshold to adjust the future scenario. The LIS method consists of three steps. In the first step, at each point location, a wet-day threshold for the  $m^{\text{th}}$  month “ $WDT_P$ ” is determined from the daily historical model precipitation series, such that the threshold exceedance matches the wet-day frequency at the same location in the observed precipitation series.

In a second step, a scaling factor is calculated from the wet-day intensities for each month by:

$$sf_m = \frac{\mu(P_{m,d}^{obs})}{\mu(P_{m,d}^s \text{ given } P_{m,d}^s \geq WDT_{m,d}^h)} \quad (1)$$

In the third step, this scaling factor for each month is applied to the daily scenario time series (above the threshold) to ensure that the mean of the corrected precipitation match to that of the observed precipitation at these locations.

$$P_{(cor)}^s = \begin{cases} 0, & \text{if } P_{m,d}^s < WDT_{m,d}^h \\ P_{m,d}^s \times sf_m & \text{otherwise} \end{cases} \quad (2)$$

Here  $P_{m,d}^{obs}$  and  $P_{m,d}^s$  are daily precipitation values of the observations and the scenario run for a specific month respectively,  $\mu$  indicate the long term averages,  $WDT_{m,d}^h$  is the wet-days threshold for each month and  $P_{(cor)}^s$  is the corrected scenario precipitation.

The local intensity and frequency scaling could be calibrated on a monthly, seasonal or annual scale. In the current study the precipitation series at the point locations were corrected for wet-day frequencies and intensities on a monthly scale. During this exercise, a total of 24 fitting parameters were determined, including 12  $WDT_{m,d}^h$  and 12  $sf_m$ , (one for each month).

#### Appendix A.III: Power transformation of precipitation (PT)

Power transformation is a step forward from the linear scaling, as it does not only accounts for a bias in the mean but also allow for adjusting differences in the variance. To do this, a non-linear correction in an exponential form, [5], may be used to exactly apply adjustments to the variance statistics of a precipitation time series. In this correction each of the daily precipitation amount  $P$  is converted to a corrected  $P^*$  using:

$$P_{\text{corr}} = a \cdot P^b$$

The parameter  $b$  is determined iteratively, following Brent's method [6] Whereby the CV of the corrected daily historical precipitation ( $P_{\text{corr}}$ ) is matched with the CV of the observed daily precipitation ( $P$ ) for each month  $m$ . This is done with a distribution-free approach on a monthly basis using a interval of 30 days before and after the considered month. The identified  $b$ , is then applied to correct the scenario series. In this way, the CV is only a function of parameter  $b$  according to:

$$CV(P) = \text{function}(b)$$

After correction for variance, the data also subjected to the slandered liner scaling correction (a), explained above in section App-A.II

#### Appendix A.IV: Variance scaling of temperature (VS)

Similar to power transformation, a corresponding stepwise approach to correct both the mean and the variance of temperature time series (without a power function), proposed by [7, 8] is adopted for variance scaling of temperature .

1. In a first step, the means of the historical model simulated time series are adjusted by linear scaling (App-A.I), and standard deviations as well as means are calculated for both;
2. In second step, the mean-corrected historical/control and scenario runs are shifted to a zero mean on a monthly basis;
3. In third step, the standard deviations of the historical/control and scenario runs, with zero means, are scaled based on the ratio of standard deviations of observed and historical/control-run identified in step-1
4. Finally, corrected time series in step-3 are shifted back using the corrected means derived in step-1

By definition, this approach ascertains that the adjusted model historical/control run match with the mean and standard deviation / variance of the observed series.

#### Appendix A.V: Distribution mapping of precipitation and temperature (DM)

The distribution mapping (DM), as mentioned here, correct the distribution function of simulated climate values to agree with the observed distribution function. This is done by generating a transfer function to shift the occurrence distributions of precipitation and temperature [9]. This approach is also called 'probability mapping', 'quantile-quantile mapping' or 'histogram equalization' etc.

For distribution mapping of precipitation we assumed that the precipitation events follow The Gamma distribution [10], while in case of temperature, the Gaussian distribution [11] is assumed to be the best fit.

#### Appendix A.VI: Distribution mapping and Intensity/Frequency scaling of precipitation (DM-IS)

This is a modified version of the distribution mapping (DM) method, in which the magnitudes and frequency of precipitation are adjusted once more after the DM, to ensure that the relation

between raw historical and raw scenario run, in terms of frequency as well as magnitudes, is reflected in the observed and corrected scenario runs.

The intensity and frequency scaling method (IS) used here is different than the one mentioned above (App-A.II). This method adjusts the ratio of the means as well as wet-day frequencies of scenario run to the observed precipitation time series, by effectively matching these ratios in the model simulation from historical to scenario runs (raw). The IS method consists of three steps.

In the first step, the ratio between wet-day frequencies of uncorrected scenario run to the uncorrected historical run ( $wd_{f-raw}$ ), as well as the ratio between wet-day frequencies of scenario run to the observed precipitation ( $wd_{f-corr}$ ) is calculated.

$$wd_{f-raw} = \frac{wd_{m,d}^{sce-raw}}{wd_{m,d}^{his-raw}} \quad (3)$$

$$wd_{f-DM,obs} = \frac{wd_{m,d}^{sce-DM}}{wd_{m,d}^{obs}} \quad (4)$$

In second step, at each point location, a wet-day threshold for the  $m^{th}$  month " $WDT_{m,d}^{DM}$ " is determined from the daily corrected scenario precipitation series, such that the threshold exceedance confirm that ratio of  $wd_{f-DM,obs}$  match with that of  $wd_{f-raw}$ .

In the third step, a scaling factor is calculated from the wet-day intensities for each month by:

$$sf_m = \frac{\mu(P_{m,d}^{obs})}{\mu(P_{m,d}^{s-DM} \text{ given } P_{m,d}^{s-DM} \geq WDT_{m,d}^{DM})} \quad (5)$$

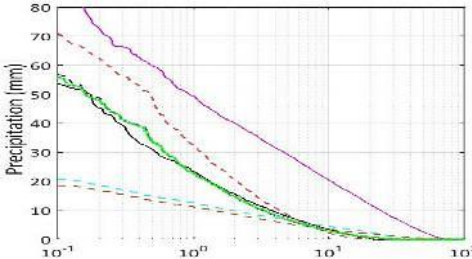
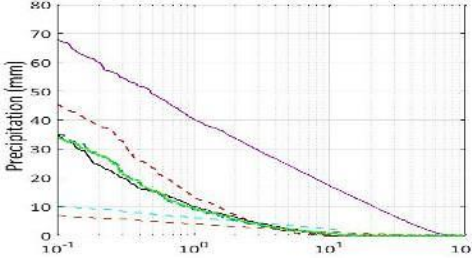
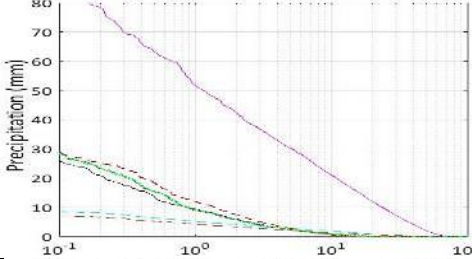
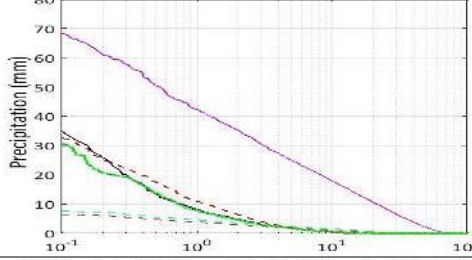
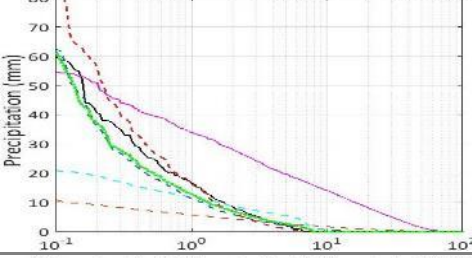
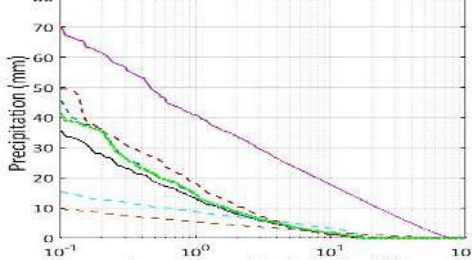
In the third step, this scaling factor for each month is applied to the daily scenario time series (above the threshold) to ensure that the mean of the corrected precipitation match to that of the observed precipitation at these locations.

$$P_{(cor)}^s = \begin{cases} 0, & \text{if } P_{m,d}^{s-DM} < WDT_{m,d}^{DM} \\ P_{m,d}^{s-DM} \times sf_m & \text{otherwise} \end{cases} \quad (6)$$

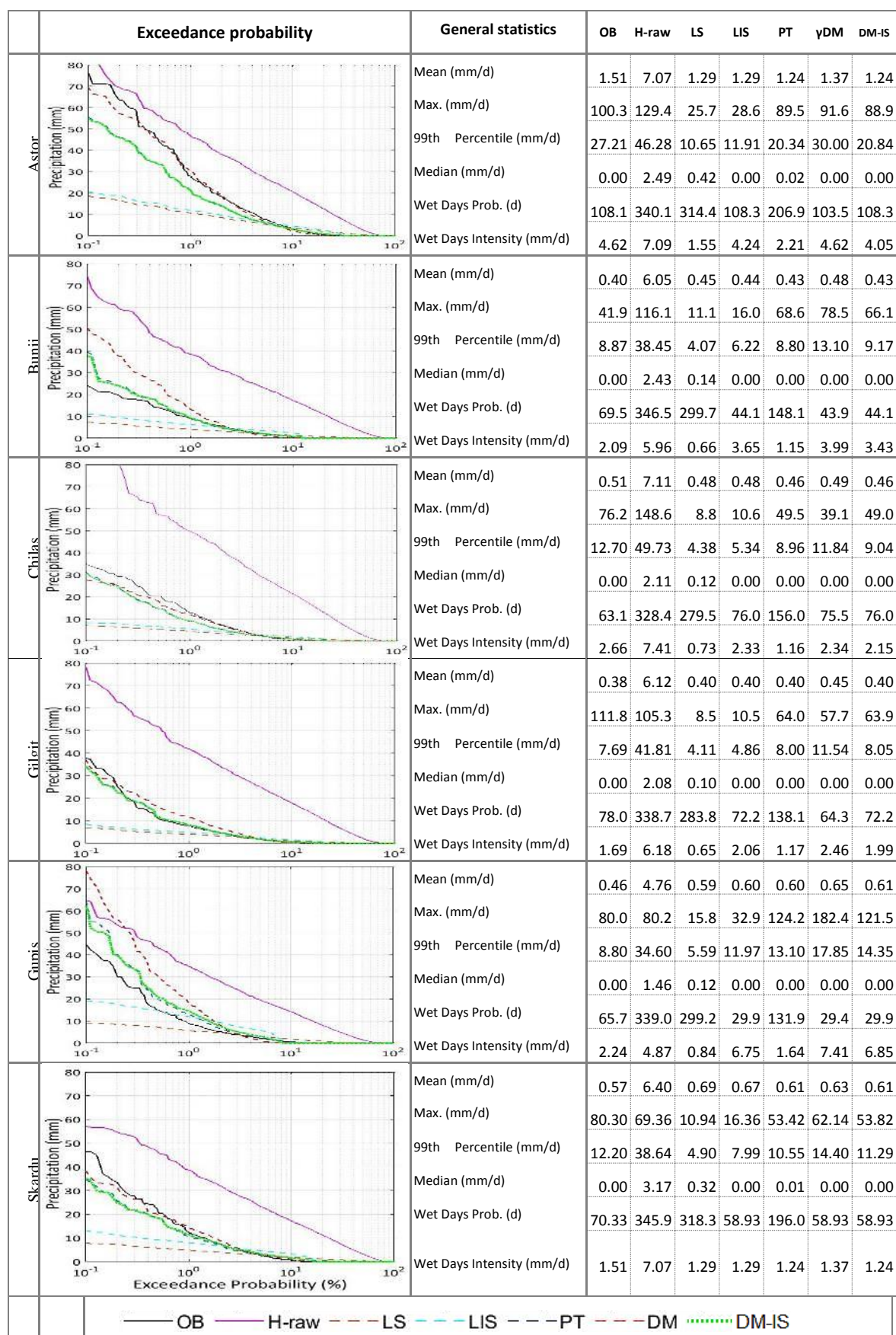
Here  $P_{m,d}^{obs}$  and  $P_{m,d}^{s-DM}$  are daily precipitation values of the observations and the DM-corrected scenario run for a specific month respectively,  $\mu$  indicate the long term averages,  $WDT_{m,d}^{DM}$  is the wet-days threshold for each month and  $P_{(cor)}^s$  is the corrected scenario precipitation.

In the current study the precipitation series were corrected for wet-day frequencies and intensities on a monthly scale. During this exercise, a total of 24 fitting parameters were determined, including 12  $WDT_{m,d}^{DM}$  and 12  $sf_m$  (one for each month).

114 *Appendix B.I: Observed precipitation vs Historical-GCM (IPSL) Calibration Period*

	Exceedance probability	General statistics	OB	H-row	LS	LIS	PT	yDM	DM-IS
Astor		Mean (mm/d)	1.31	7.04	1.27	1.27	1.29	1.47	1.29
		Max. (mm/d)	118.2	113.4	25.1	28.0	94.0	128.5	89.6
		99th Percentile (mm/d)	23.30	49.38	11.11	12.58	22.62	31.95	22.74
		Median (mm/d)	0.00	2.51	0.40	0.00	0.02	0.00	0.00
		Wet Days Prob. (d)	113.1	333.4	309.4	105.3	204.7	100.9	105.3
		Wet Days Intensity (mm/d)	3.94	7.13	1.55	4.27	2.29	4.98	4.2
Bunji		Mean (mm/d)	0.44	6.08	0.44	0.44	0.45	0.50	0.45
		Max. (mm/d)	66.4	82.2	10.3	14.8	74.7	74.6	72.4
		99th Percentile (mm/d)	10.15	40.10	4.08	6.18	8.88	13.18	9.41
		Median (mm/d)	0.00	2.34	0.13	0.00	0.00	0.00	0.00
		Wet Days Prob. (d)	44.83	342.8	296.4	43.73	146.7	43.57	43.73
		Wet Days Intensity (mm/d)	3.41	6.12	0.65	3.71	1.21	4.06	3.56
Chilas		Mean (mm/d)	0.46	7.05	0.47	0.47	0.47	0.52	0.47
		Max. (mm/d)	68.0	107.1	10.2	12.3	58.0	51.2	57.7
		99th Percentile (mm/d)	9.42	51.62	4.17	5.16	9.13	11.96	9.16
		Median (mm/d)	0.00	2.00	0.12	0.00	0.00	0.00	0.00
		Wet Days Prob. (d)	76.83	323.4	276.3	72.93	152.9	72.23	72.93
		Wet Days Intensity (mm/d)	2.13	7.35	0.72	2.36	1.22	2.59	2.31
Gilgit		Mean (mm/d)	0.39	6.10	0.39	0.39	0.39	0.45	0.39
		Max. (mm/d)	54.6	85.3	11.3	13.1	104.4	71.7	104.1
		99th Percentile (mm/d)	8.30	42.35	3.87	4.67	7.57	10.96	7.70
		Median (mm/d)	0.00	2.03	0.10	0.00	0.00	0.00	0.00
		Wet Days Prob. (d)	75.40	334.4	280.3	72.07	136.0	63.27	72.07
		Wet Days Intensity (mm/d)	1.81	6.22	0.63	2.01	1.12	2.52	1.88
Gupis		Mean (mm/d)	0.61	4.70	0.57	0.57	0.57	0.63	0.57
		Max. (mm/d)	147.3	73.6	17.6	36.5	177.9	236.9	169.6
		99th Percentile (mm/d)	16.50	33.90	5.76	11.87	11.41	16.04	12.77
		Median (mm/d)	0.00	1.39	0.11	0.00	0.00	0.00	0.00
		Wet Days Prob. (d)	30.17	334.9	294.6	28.73	128.6	28.47	28.73
		Wet Days Intensity (mm/d)	6.47	4.88	0.82	6.72	1.61	6.95	6.57
Skardu		Mean (mm/d)	0.65	6.47	0.71	0.72	0.75	0.79	0.75
		Max. (mm/d)	82.0	96.9	24.2	34.0	113.7	128.4	109.6
		99th Percentile (mm/d)	13.10	40.87	5.36	8.71	13.88	17.95	14.43
		Median (mm/d)	0.00	3.00	0.29	0.00	0.01	0.00	0.00
		Wet Days Prob. (d)	60.37	342.9	314.1	59.77	189.2	59.77	59.77
		Wet Days Intensity (mm/d)	1.31	7.04	1.27	1.27	1.29	1.47	1.29
		— OB — H-row — LS — LIS — — PT — — DM ..... DM-							

## 115 Appendix B.II: Observed precipitation vs Historical-GCM (IPSL)-Validation period



## 116 Appendix B.III: Observed Temperature (minimum) vs Historical-GCM (IPSL)

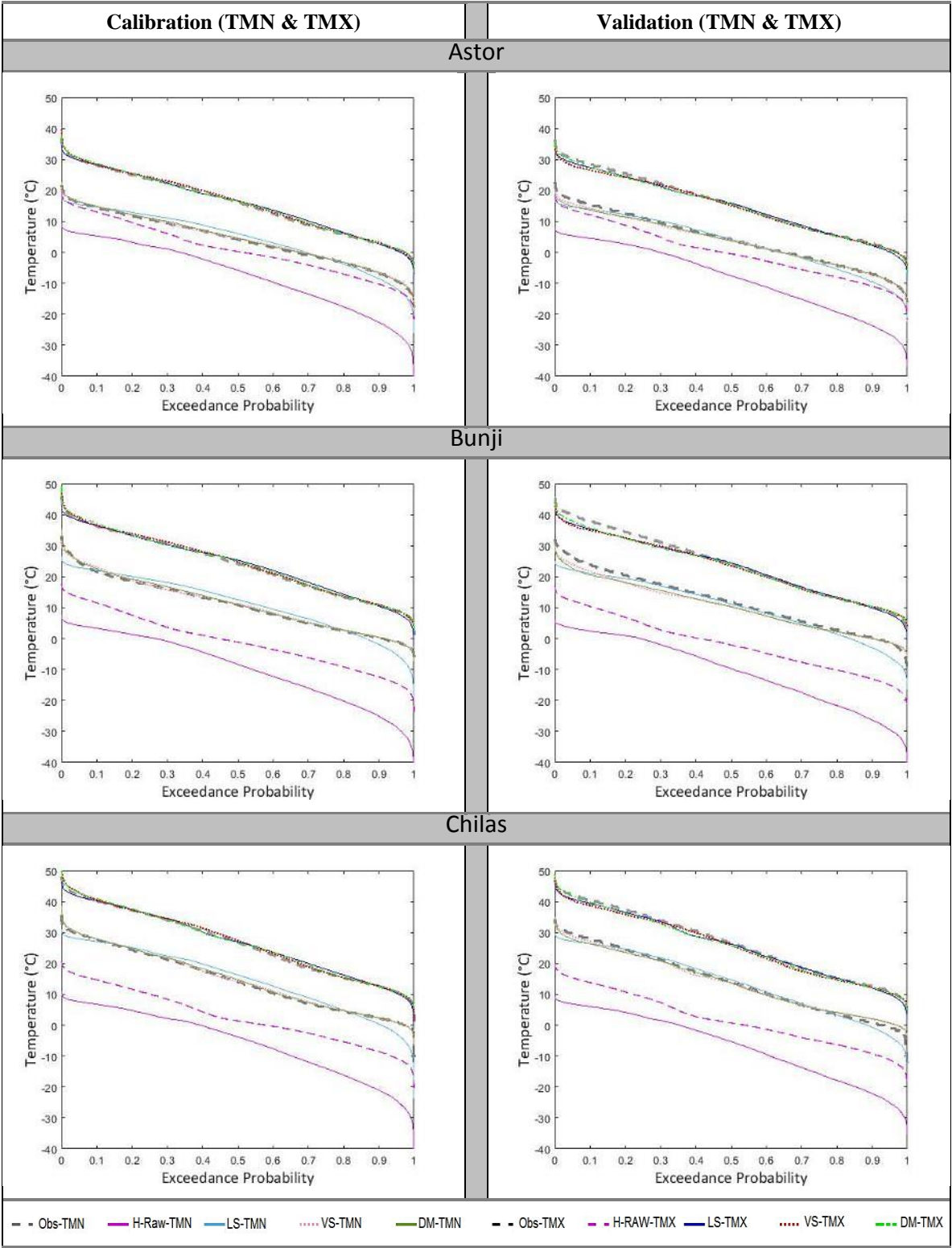
Performance Indices (°C)	Calibration (TMN)						Validation (TMN)				
	OB	H-RAW	LS	VS	DM		OB	H-RAW	LS	VS	DM
	Astor										
Mean	4.1	-7.3	4.5	4.3	4.3		4.0	-8.5	3.3	3.5	3.5
Maximum value	21.7	9.4	18.5	21.3	22.7		22.8	8.1	17.1	20.1	20.0
Minimum value	-17.7	-40.5	-26.2	-19.5	-19.8		-16.1	-36.9	-22.5	-18.9	-17.4
90 <sup>th</sup> Percentile	14.4	5.3	14.6	14.8	14.8		15.6	4.5	14.0	14.2	13.7
10 <sup>th</sup> Percentile	-6.7	-22.6	-8.5	-6.6	-6.4		-7.2	-23.6	-9.5	-7.2	-7.0
Median	4.2	-5.8	6.1	4.5	4.6		3.9	-7.6	4.2	4.0	3.7
Standard Deviation	7.9	10.5	8.8	7.9	8.0		8.4	10.6	8.8	7.9	7.8
	Bunji										
Mean	10.9	-9.2	11.7	11.6	11.6		11.8	-10.7	10.2	10.3	10.3
Maximum value	33.3	7.6	26.5	31.5	35.4		32.2	6.1	25.0	30.7	30.6
Minimum value	-5.0	-42.3	-19.4	-6.9	-6.8		-9.9	-40.8	-16.3	-6.6	-6.1
90 <sup>th</sup> Percentile	21.4	3.8	22.5	23.7	23.8		23.9	2.4	21.1	21.6	20.5
10 <sup>th</sup> Percentile	0.3	-24.5	-1.4	0.6	0.6		0.1	-26.3	-2.9	0.0	0.1
Median	10.8	-7.9	13.0	11.5	11.2		11.7	-9.7	11.2	10.5	10.2
Standard Deviation	8.0	10.7	9.0	8.4	8.6		8.9	10.9	9.0	8.0	7.8
	Chilas										
Mean	14.6	-5.2	15.4	15.2	15.2		14.0	-6.9	13.7	13.9	13.8
Maximum value	33.9	10.9	31.2	35.9	38.8		34.2	9.6	29.9	34.9	35.0
Minimum value	-2.4	-43.6	-23.7	-5.3	-5.8		-12.8	-35.5	-12.4	-4.5	-3.6
90 <sup>th</sup> Percentile	27.8	7.2	27.6	28.6	29.1		27.8	6.0	26.4	27.0	26.3
10 <sup>th</sup> Percentile	2.8	-20.3	1.0	2.6	2.6		0.6	-22.1	-0.7	2.0	2.1
Median	14.0	-3.3	16.8	14.5	15.1		13.9	-5.3	14.7	13.6	13.8
Standard Deviation	9.3	10.4	10.0	9.6	9.8		10.1	10.6	10.2	9.4	9.2
	Gilgit										
Mean	7.2	-8.0	8.4	8.2	8.2		7.8	-9.6	6.8	7.0	6.9
Maximum value	27.2	9.6	22.6	25.5	29.4		29.4	8.0	21.0	24.6	25.4
Minimum value	-11.0	-42.2	-24.5	-12.2	-13.0		-10.0	-39.2	-20.8	-12.0	-11.2
90 <sup>th</sup> Percentile	16.7	5.2	18.4	18.7	19.1		18.3	3.9	17.0	17.3	16.5
10 <sup>th</sup> Percentile	-3.0	-24.1	-4.5	-2.3	-2.6		-3.3	-25.4	-5.6	-3.1	-3.1
Median	7.8	-6.4	10.1	8.6	8.5		8.3	-8.3	8.1	7.4	7.5
Standard Deviation	7.5	11.0	8.6	7.8	8.0		8.2	11.1	8.6	7.6	7.4
	Gupis										
Mean	5.8	-9.9	7.4	7.2	7.1		7.2	-11.5	5.7	5.9	5.9
Maximum value	23.9	8.0	22.1	26.6	29.1		26.1	6.5	20.5	23.7	25.0
Minimum value	-12.3	-46.9	-26.8	-13.1	-14.6		-11.7	-43.6	-21.9	-12.2	-12.2
90 <sup>th</sup> Percentile	16.6	3.8	18.1	18.9	18.9		19.1	2.6	16.7	17.3	16.5
10 <sup>th</sup> Percentile	-5.1	-26.4	-6.5	-4.3	-4.4		-4.4	-27.9	-7.9	-5.0	-4.8
Median	6.0	-8.4	9.1	7.2	7.1		7.2	-10.6	7.0	6.3	5.9
Standard Deviation	8.2	11.5	9.4	8.5	8.7		8.7	11.5	9.4	8.2	8.1
	Skardu										
Mean	4.9	-10.1	5.7	5.8	5.6		5.2	-11.5	4.4	4.4	4.5
Maximum value	26.5	6.1	20.0	23.2	26.1		26.0	5.2	19.2	22.3	22.7
Minimum value	-24.1	-41.5	-25.7	-20.7	-17.8		-22.4	-39.8	-22.5	-19.9	-19.2
90 <sup>th</sup> Percentile	15.9	2.7	16.8	17.9	17.1		16.7	1.8	15.9	15.8	15.5
10 <sup>th</sup> Percentile	-6.7	-24.7	-8.2	-6.2	-6.4		-7.2	-26.0	-9.0	-7.1	-6.9
Median	5.4	-9.4	7.0	6.4	5.8		6.1	-11.2	5.3	5.2	5.0
Standard Deviation	8.8	10.5	9.6	8.8	9.1		9.2	10.5	9.5	8.7	8.6

## 117 Appendix B.IV: Observed Temperature (maximum) vs Historical-GCM (IPSL)

Performance Indices (°C)	Calibration (TMX)						Validation (TMX)				
	OB	H-RAW	LS	VS	DM		OB	H-RAW	LS	VS	DM
	Astor										
Mean	15.6	0.9	16.0	16.0	16.0		15.4	-0.1	15.0	14.8	14.9
Maximum value	37.0	19.6	34.8	39.7	37.5		36.3	18.5	33.6	35.7	35.7
Minimum value	-6.1	-22.0	-9.4	-7.0	-6.8		-6.3	-21.6	-8.8	-5.2	-6.4
90 <sup>th</sup> Percentile	28.1	13.0	28.3	28.3	28.7		28.3	12.1	27.4	26.6	27.6
10 <sup>th</sup> Percentile	2.8	-10.2	2.8	3.2	3.0		2.8	-10.9	2.2	2.6	2.5
Median	16.2	0.3	16.7	16.7	16.5		15.6	-0.5	15.9	15.2	15.6
Standard Deviation	9.4	8.4	9.3	9.5	9.5		9.6	8.4	9.3	9.1	9.3
	Bunji										
Mean	23.7	-0.4	24.6	24.6	24.7		23.9	-1.9	23.2	23.0	23.1
Maximum value	43.3	17.5	43.3	49.3	49.3		45.6	16.9	42.1	44.1	44.2
Minimum value	1.4	-23.9	-1.5	3.5	2.7		1.7	-23.0	0.0	3.5	3.6
90 <sup>th</sup> Percentile	35.8	12.1	37.1	37.6	38.0		37.8	10.4	35.4	35.0	35.8
10 <sup>th</sup> Percentile	11.1	-11.8	10.9	11.1	11.0		10.0	-13.0	9.9	10.4	10.3
Median	23.9	-0.9	25.6	25.0	25.3		24.0	-2.1	24.4	23.5	23.8
Standard Deviation	9.3	8.6	9.5	10.0	9.7		10.3	8.5	9.5	9.3	9.4
	Chilas										
Mean	26.2	3.1	27.2	27.4	27.4		26.4	1.6	25.8	25.5	25.6
Maximum value	47.7	20.8	46.6	53.9	50.2		47.1	20.0	45.5	49.1	49.1
Minimum value	1.2	-20.4	0.4	1.4	3.8		2.8	-19.3	1.8	5.5	4.1
90 <sup>th</sup> Percentile	40.0	15.2	40.7	41.9	41.6		40.6	13.8	39.4	38.8	39.8
10 <sup>th</sup> Percentile	12.5	-8.0	13.1	12.9	13.0		12.8	-9.2	12.0	12.2	12.1
Median	26.4	1.7	27.3	27.9	27.1		26.7	0.7	26.3	25.8	25.9
Standard Deviation	10.4	8.5	10.2	10.8	10.5		10.4	8.5	10.2	10.1	10.3
	Gilgit										
Mean	24.5	0.8	24.9	25.1	25.1		23.4	-0.7	23.5	23.3	23.4
Maximum value	46.3	18.7	44.2	53.9	51.1		45.0	17.9	43.2	47.8	46.6
Minimum value	3.0	-23.0	-2.1	2.1	2.2		1.1	-21.7	-0.4	3.4	3.0
90 <sup>th</sup> Percentile	37.8	13.2	37.8	38.9	39.0		37.8	11.8	36.5	35.8	37.0
10 <sup>th</sup> Percentile	11.0	-10.6	10.9	10.8	10.9		10.0	-11.8	9.9	10.2	10.2
Median	24.7	0.0	25.7	25.4	25.4		23.3	-1.1	24.6	23.6	24.0
Standard Deviation	24.5	0.8	24.9	25.1	25.1		23.4	-0.7	23.5	23.3	23.4
	Gupis										
Mean	18.9	-0.7	19.6	19.7	19.7		18.4	-2.1	18.2	18.0	18.1
Maximum value	41.1	18.4	39.1	48.9	45.1		41.1	16.1	37.2	42.8	40.8
Minimum value	-1.7	-24.2	-7.0	-4.5	-3.1		-5.0	-23.8	-5.8	-2.2	-2.2
90 <sup>th</sup> Percentile	32.7	12.0	33.1	34.1	34.4		32.8	10.4	31.6	31.0	32.1
10 <sup>th</sup> Percentile	5.5	-12.2	5.4	5.4	5.5		4.4	-13.4	4.3	4.9	4.7
Median	18.8	-1.0	20.2	19.9	19.9		18.3	-2.1	19.2	18.2	18.5
Standard Deviation	10.1	8.7	10.1	10.7	10.5		10.4	8.7	10.1	9.9	10.1
	Skardu										
Mean	19.3	-2.2	19.9	19.9	20.0		17.8	-3.7	18.4	18.3	18.3
Maximum value	40.6	15.1	38.8	46.0	42.4		40.0	14.3	37.4	41.5	41.0
Minimum value	-6.6	-25.5	-7.5	-4.3	-6.6		-7.0	-25.9	-6.8	-5.5	-6.0
90 <sup>th</sup> Percentile	33.0	9.8	33.5	33.7	34.8		32.0	7.7	31.5	31.6	31.9
10 <sup>th</sup> Percentile	5.0	-13.4	5.1	4.9	5.1		3.9	-14.7	3.8	4.4	4.0
Median	19.8	-2.3	21.0	20.3	20.7		18.3	-3.6	19.7	18.7	19.2
Standard Deviation	10.4	8.3	10.3	11.0	10.7		10.6	8.3	10.3	10.2	10.4

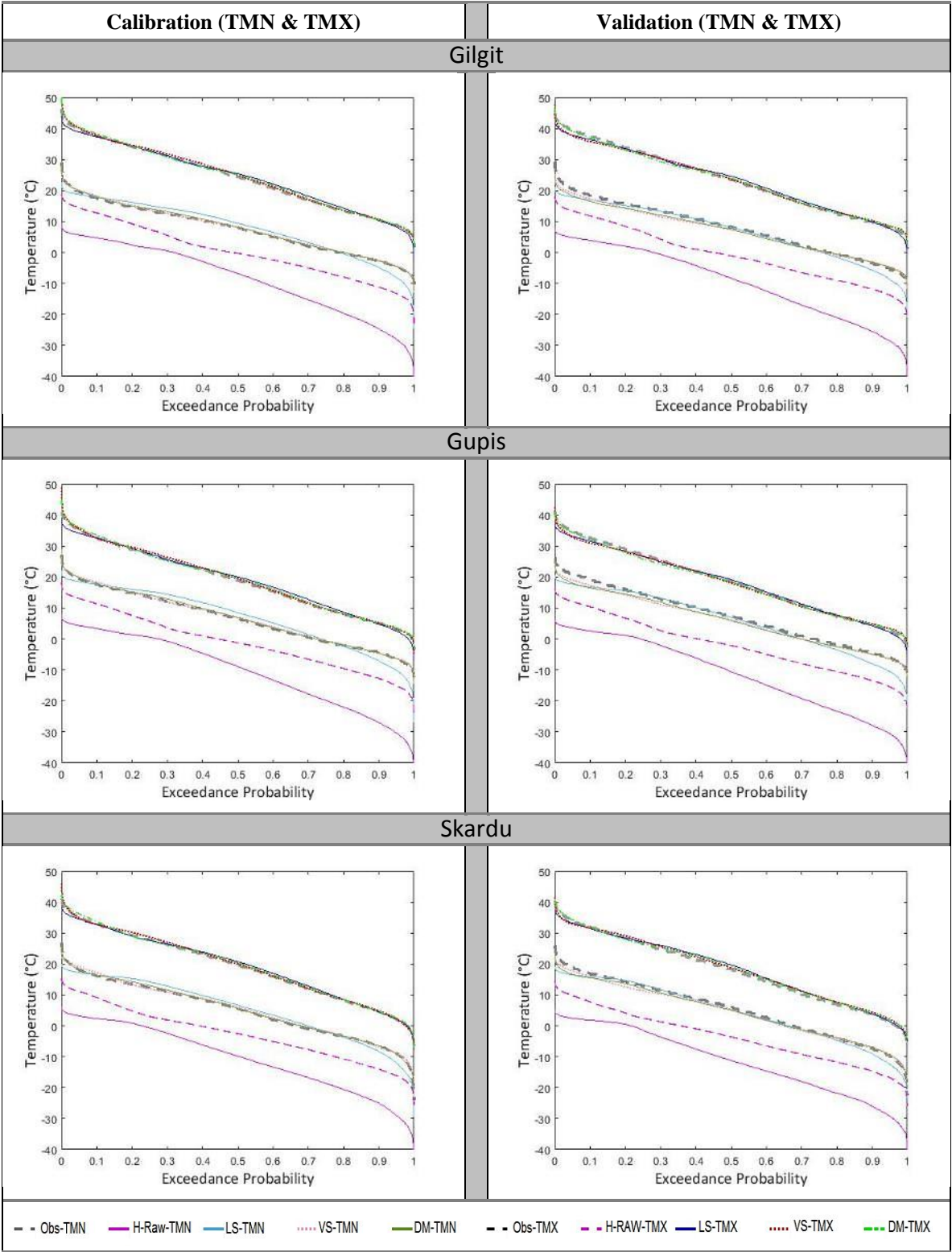


Appendix B.V: Exceedance probability plots of observed Temperature and Historical-GCM (IPSL), uncorrected and bias-corrected/downscaled with three methods (Astor, Bunji & Chilas)





Appendix B.VI: Exceedance probability plots of observed Temperature and Historical-GCM (IPSL), uncorrected and bias-corrected/downscaled with three methods (Gilgit, Gupis & Skardu)



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