

27	Peshawer AP	71.51	33.99	353	1979-2015	PMD	
28	Risalpur	71.98	34.08	308	1979-2015	PMD	
29	Rohri	68.90	27.67	66	1979-2015	PMD	
30	Saidu Sharif	72.35	34.73	961	1979-2015	PMD	
31	Sakardu-PBO	75.68	35.30	2210	1979-2015	PMD	
32	Sargodha	72.67	32.05	187	1979-2015	PMD	
33	Shaheed Banazirabad	68.37	26.25	37	1979-2015	PMD	
34	Sialkot Cant	74.53	32.52	255	1979-2015	PMD	
35	Zhob-PBO	69.47	31.35	1405	1979-2015	PMD	
36	Burzil	75.09	34.91	4030	1999-2015	WAPDA	
37	Deosai	75.60	35.10	3910	1995-2015	WAPDA	
38	Kunjrab	75.40	36.85	4730	1994-2015	WAPDA	
39	Hushey	76.40	35.37	3010	1994-2015	WAPDA	
40	Naltar	74.27	36.22	2810	1995-2015	WAPDA	

Table S2. The seasonal outcome of S-Mode PCA over different predictor fields. PCs are the number of retained principal components and Exp. Var denotes the percentage of total predictor variance, as explained by the retained PCs

Predictors	WS		PMS		MS	
	PCs	Exp.Var	PCs	Exp.Var	PCs	Exp.Var
	(Nos)	(%)	(Nos)	(%)	(Nos)	(%)
zg200	8	89	3	92	4	88
va200	12	90	12	87	15	86
ua200	10	88	9	88	10	89
zg500	8	88	3	82	8	86
va500	10	83	13	83	20	83
ua500	10	85	9	84	11	79
zg700	9	91	6	87	7	84
va700	10	76	14	79	19	79
ua700	11	83	9	79	12	81
hus700	2	85	2	90	5	92
hur700	3	79	4	80	4	77
va850	16	83	15	79	19	80
ua850	11	81	13	80	11	79
ta850	6	86	4	85	7	82
hus1000	3	85	4	90	2	92
hur1000	5	80	3	76	7	77
psl	5	87	7	88	6	87
Average	8	84	8	84	10	84

Table S3. The CMIP5-GCMs offering complete spatial coverage of the temperature ($T_{\max}$ and $T_{\min}$) governing predictors and are used for temperature modeling in our study.

Sr. No.	Model ID	Horizontal Resolution (Lon X Lat) in degrees	Modeling Centre	Key Reference
1	CMCC-CMS	1.875 x 1.875	CMCC	[97]
2	CMCC-CM	0.75 x 0.75	CMCC	[98]
3	CNRM-CM5	1.40625 × 1.40625	CNRM- CERFACS	[99]
4	Can-ESM2	2.8125 × 2.8125	CCCMA	[100]
5	MPI-ESM-LR	1.875 × 1.875	MPI-M	[101]
6	MPI-ESM-MR	1.875 × 1.875	MPI-M	[101]
7	Nor-ESM-ME	2.5 × 1.9	NCC	[92]
8	Nor-ESM-M	2.5 × 1.9	NCC	[92]

Table S4. Same as **Table 2** but for $T_{\min}$ models under the basin-wide regionalization experiment.

WS Models											
Region	Reg. Alt	RR	Mean Obs. $T_{\min}$	Predictors	PCs	RMSE (C°)		MSESS (%)		R ²	
	(m-amsl)		(C°)	(Name)	(Nos)	Cal	Val	Cal	Val	Cal	Val
R1	2223 (1251-3200)	Chilas	4.30	hus1000	2	1.01	1.04	87.95	86.65	0.88	0.90
R3	1173.5 (308-2744)	Kakul	2.79	hus1000	2	0.89	0.91	85.91	84.69	0.86	0.88
R5	3266 (2156-4030)	Gupis	-2.82	hus1000	2	1.50	1.54	77.90	75.90	0.78	0.80
R4	266 (35-1097)	Jacobabad	11.04	hus1000	3	1.25	1.30	87.80	86.39	0.88	0.89
R6	365 (122-1405)	Jehlum	8.26	hus1000	3	0.95	0.99	90.98	89.98	0.91	0.92
Avg. Basin					2	1.12	1.16	86.11	84.72	0.86	0.88
Avg. UIB					2	1.13	1.16	83.92	82.41	0.84	0.86
Avg. Lower Indus					3	1.10	1.15	89.39	88.19	0.90	0.91
PMS Models											
R1	2627 (1251-4030)	Astore	7.63	hus1000	4	0.89	0.95	92.05	90.64	0.92	0.93
R3	1327 (508-2168)	Ghari Duputta	16.22	ua500	7	1.20	1.29	87.98	85.54	0.88	0.89
R5	1281 (353-2591)	Dir	11.41	hus1000	3	1.25	1.31	87.29	85.52	0.87	0.89
R7	961 (961)	Saidu Sharif	16.39	ua850	6	1.00	1.10	92.03	90.12	0.92	0.93
R4	419 (187-1097)	Sialkot	21.81	va700	8	1.03	1.17	91.49	88.76	0.91	0.92
R6	259 (28-1405)	DI Khan	22.56	hus1000	4	1.08	1.16	89.63	87.45	0.90	0.90
Avg. Basin					5	1.08	1.16	90.08	88.01	0.90	0.91
Avg. UIB					5	1.09	1.16	89.84	87.96	0.90	0.91
Avg. Lower Indus					6	1.06	1.17	90.56	88.11	0.91	0.91
MS Models											
R1	2218 (1251-4030)	Sakardu	14.07	ua850	5	0.95	1.03	86.74	84.02	0.87	0.89
R3	746.25 (122-2591)	Jehlum	24.99	va500	13	0.52	0.61	84.74	78.28	0.85	0.87
R4	2868 (1464-3719)	Darosh	20.49	va850	7	1.42	1.52	75.02	70.50	0.75	0.78
R5	961 (961)	Saidu Sharif	20.59	va850	9	1.07	1.15	81.12	77.34	0.81	0.84
R7	2892.5 (2156-4730)	Gupis	15.35	va850	8	1.15	1.26	81.76	77.26	0.82	0.85
R6	659 (172-1425)	Risapur	24.28	va500	10	0.76	0.88	85.64	80.23	0.85	0.87
R2	52 (9-122)	Hyderabad	26.42	hus1000+va500	9	0.53	0.60	78.45	72.07	0.78	0.81
Avg. Basin					9	0.91	1.01	81.92	77.10	0.82	0.84
Avg. UIB					8	1.02	1.11	81.88	77.48	0.82	0.85
Avg. Lower Indus					10	0.65	0.74	82.05	76.15	0.82	0.84

Table S5. Same as Table 4, but shows the GCM and ERA-Interim reanalysis predictor correspondence for the T_{min} .

Seasons	Regions	CMCC-CMS	CMCC-CM	CNRM-CM5	Can-ESM2	MPI-ESM-LR	MPI-ESM-MR	Nor-ESM1-ME	Nor-ESM1-M	Model Ensemble
WS	UIB									
	R1	0.79	0.80	0.82	0.79	0.70	0.71	0.68	0.71	0.75
	R3	0.79	0.80	0.82	0.79	0.70	0.71	0.68	0.71	0.75
	R5	0.76	0.79	0.82	0.78	0.67	0.67	0.66	0.69	0.73
	Avg. over UIB	0.78	0.80	0.82	0.79	0.69	0.70	0.67	0.70	0.74
	UIB Uncertainty (in %)	22.00	20.33	18.00	21.33	31.00	30.33	32.67	29.67	25.67
	Lower Indus									
	R4	0.79	0.8	0.82	0.79	0.70	0.71	0.68	0.71	0.75
	R6	0.67	0.74	0.81	0.69	0.6	0.61	0.59	0.62	0.67
	Avg. over Lower Indus	0.73	0.77	0.82	0.74	0.65	0.66	0.64	0.67	0.71
	Lower Indus Uncertainty (in %)	27	23	18.50	26	35	34	36.50	33.50	29.19
PMS	UIB									
	R1	0.59	0.65	0.72	0.48	0.60	0.59	0.46	0.41	0.56
	R3	0.80	0.71	0.66	0.73	0.69	0.74	0.69	0.68	0.71
	R5	0.60	0.66	0.72	0.50	0.62	0.60	0.47	0.43	0.58
	R7	0.64	0.65	0.67	0.69	0.71	0.67	0.66	0.67	0.67
	Avg. over UIB	0.66	0.67	0.69	0.60	0.66	0.65	0.57	0.55	0.63
	UIB Uncertainty (in %)	34.25	33.25	30.75	40.00	34.50	35.00	43.00	45.25	37.00
	Lower Indus									
	R4	0.62	0.59	0.55	0.52	0.61	0.53	0.57	0.56	0.57
	R6	0.57	0.64	0.72	0.51	0.6	0.56	0.48	0.45	0.57
	Avg. over Lower Indus	0.60	0.62	0.64	0.52	0.61	0.55	0.53	0.51	0.57
	Lower Indus Uncertainty (in %)	40.50	38.50	36.50	48.50	39.50	45.50	47.50	49.50	43.25
MS	UIB									
	R1	0.54	0.64	0.59	0.61	0.60	0.56	0.56	0.60	0.59
	R3	0.43	0.42	0.41	0.39	0.42	0.43	0.39	0.35	0.41
	R4	0.50	0.52	0.49	0.46	0.55	0.48	0.42	0.42	0.48
	R5	0.54	0.54	0.51	0.47	0.58	0.50	0.46	0.43	0.50
	R7	0.49	0.49	0.48	0.42	0.54	0.45	0.44	0.42	0.47
	Avg. over UIB	0.50	0.52	0.50	0.47	0.54	0.48	0.45	0.44	0.49
	UIB Uncertainty (in %)	50	47.80	50.40	53.00	46.20	51.60	54.60	55.60	51.15
	Lower Indus									
	R2	0.42	0.46	0.40	0.18	0.45	0.45	0.39	0.47	0.40
	R6	0.40	0.40	0.41	0.39	0.43	0.41	0.36	0.33	0.39
	Avg. over Lower Indus	0.41	0.43	0.41	0.29	0.44	0.43	0.38	0.40	0.40

	Lower Indus Uncertainty (in %)	59	57	59.5	71.5	56	57	62.5	60	60.31
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Table S6. P-values of the Wilcoxon signed-rank test [86] to estimate the statistical significance of seasonal $T_{\max}$ and $T_{\min}$ changes during 2071-2100 relative to 1976-2005 under both RCP scenarios. Results are statistically significant, where the p-value is less than 0.05.

Seasons	Sub-regions	RCP4.5		RCP8.5	
		Tmax	Tmin	Tmax	Tmin
WS	UIB				
	R1	1.64E-05	7.28E-256	7.34E-05	3.12E-293
	R3	6.06E-09	1.96E-264	0.00012	3.29E-298
	R5	3.63E-120	6.25E-218	2.04E-218	2.07E-268
	Lower Indus				
	R4	9.25E-144	3.22E-258	5.27E-183	3.50E-292
	R6	6.06E-09	3.57E-261	2.30E-268	2.49E-294
PMS	UIB				
	R1	0.07312	2.17E-23	0.006488627	1.61E-55
	R3	2.99E-10	0.41789	1.27E-24	0.76316
	R5	1.66E-05	1.32E-23	2.56E-12	5.03E-56
	R7	5.60E-06	0.01265	3.60E-13	0.0014186
	Lower Indus				
	R4	1.63E-119	0.07357	2.52E-180	0.0541761
	R6	5.37E-11	2.84E-26	2.96E-27	1.34E-64
MS	UIB				
	R1	0.01770	0.00393	2.05E-13	0.0001706
	R3	8.63E-109	0.00122	3.30E-23	2.94E-14
	R4	1.43E-06	0.05359	7.05E-17	5.99E-05
	R5	2.69E-05	0.10281	2.48E-13	0.002231
	R7	0.1134584	0.18033	3.94E-06	0.0674985
	Lower Indus				
	R2	1.65E-174	1.14E-179	8.93E-217	2.59E-232
	R6	4.47E-56	0.00233	2.27E-142	2.80E-13

Appendix S1

GCM Ranking and Model Uncertainty

Following stepwise procedure is adapted to rank the GCMs in terms of their ability to simulate temperature governing circulations (of the ERA-Interim reanalysis) during the overlapping historical period (1979–2005):

- I) Initially, S-mode PCA is performed (Section 3.2) on every governing predictor (Table 1) of the individual GCMs to extract the same number of PCs as from ERA-Interim.
- II) Subsequently, the model PC loadings are compared with corresponding ERA-Interim loadings (separately for each GCM) using Taylor diagrams (Taylor, 2001). A simple performance score (PS) derived by using two of the three summary statistics of the Taylor diagrams is developed to quantify the correspondence. Mathematically, the PS is

$$PS = |CR| - |NSD - 1| \quad (A1)$$

where

PS = performance score. For a perfect predictor agreement, $PS = 1$

CR = pattern correlation between the reference (ERA-Interim) and model (GCM) loadings. For a perfect phase match, $CR = 1$.

NSD = normalized ratio of variance (standard deviation of the reference and model loadings). Ideally, the NSD should also take the value 1.

Under ideal conditions, the PS will attain its maximum value due to the maximization of phase correspondence (i.e., $CR = 1$) and the same magnitude of predictor spread (i.e., the term $NSD - 1$ becomes zero) between the reference and model simulations. Similarly, a smaller PS value will show a weaker predictor correspondence. The magnitude of the PS will also intuitively influence the third summary statistics (i.e., standardized RMSE), where its maximum value ($PS = 1$) will ensure zero error. Conversely, the smaller values ($PS < 1$) will reflect higher errors, though not following a clear linear trend due to the typical relationships among these three summary statistics (see Taylor, 2001). Thus, the PS contains useful information about the strength of correspondence between the reference and model-simulated fields and can be used to identify the best-matching pairs for every governing predictor.

- III) We draw two separate sets of Taylor diagrams for each precipitation region and season. The first set of diagrams uses PS to identify the best PC match between reference and modeled PC s of a given predictor (separately for each GCM). In this context, we evaluate all modeled loadings of a predictor against a reference loading. The reference-model pair, which shows the highest PS , is selected as the best GCM- PC for that particular reference. This process is repeated for all other PC s and predictors that appear in the final regression models used for downscaling. Subsequently, all best-matching (individual) PC s of different predictors are grouped into the second set of Taylor diagrams (separately for each GCM) to assess the ability of the GCMs in representing ERA-Interim precipitation predictors over a region. The summary

statistics of the second Taylor diagram is used to compute the average *PS* for each GCM and is termed as unweighted *PS* due to equal weighting of each *PC* in its computation.

- IV) Given that each *PC* has a different influence in a regression model, we adapted (absolute) regression coefficients of the *PCs* as weights and computed the weighted *PS*. Thus, a model with the highest (lowest) weighted *PS* score can be identified as the best (worst) GCM due to its improved (poor) simulations for more important predictors.
- V) This process (step I to IV) is repeated for all sub-regions to identify the best regional GCM in different seasons.

Finally, we consider GCM performance over multiple regions to identify models that show superior simulations over the whole spatial scales of the UIB and LI, respectively. We prefer a GCM that performs well in multiple regions. This spatial consideration is important since an outlier may strongly influence the *PS* of a model (e.g., very high *PS* just over one sub-region).

Source: Pomee and Hertig (2020).