In the final reduction step, a multi-objective distance-based history matching approach was used to select four RGCM-runs for each RCP based on their ability to simulate the monthly average mean air temperature ($\bar{T}$) and precipitation ($\bar{P}$). The RGCM-run set showed a lower Mean Absolute Error (MAE) for both climatic variables compared to the full set. Specifically, for RCP4.5, the MAE of $\bar{T}$ between the reference and RGCM-runs was 0.45, contrasting with 0.58 for the full set. For RCP8.5, the MAE of $\bar{T}$ was 0.51 compared to 0.75 for the full set. Similarly, for the $\bar{P}$, the MAE between the reference and RGCM-runs was 0.31 for RCP4.5 and 0.25 for RCP8.5, while 0.42 and 0.36 for the full set, respectively. The consistently lower MAE for both climatic variables in the RGCM-run set for RCP4.5 and RCP8.5 indicated that the model's projections in the RGCM-runs are close to the reference values.

After conducting an assessment of a wide range of GCM-runs in the WNA region, the four best-performing RGCM-runs were selected for each RCP, considering past climatic conditions and projected changes in climatic and extreme indices. This subset can aid in developing climate change adaptation and mitigation strategies for the WNA region.

7. Acknowledgements

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8. Conflict of Interest

The authors declare no conflict of interests.

Appendix A. List of GCM-runs

The GCM-runs from CMIP5 based on RCP4.5 and RCP8.5 are collected in this study, as depicted in Table A.1.

Table A.1: Initial pool of CMIP5 GCMs and GCM-runs used in this study, consisting of 77 runs for RCP8.5 and 105 runs for RCP4.5. GCM-runs marked with an asterisk (*) are exclusively available for RCP4.5, while those marked with a dagger (†) are exclusively available for RCP8.5.

GCM	**rip**	**GCM**	**rip**
ACCESS1–0	r1i1p1	GISS-E2-H	r1i1p1, r1i1p2, r1i1p3
ACCESS1.3	r1i1p1	GISS-E2-H	r2i1p1*, r2i1p2*, r2i1p3*, r2i1p1*, r2i1p2*, r2i1p3*, r4i1p1*, r4i1p2*, r4i1p3*, r5i1p1*, r5i1p2*, r5i1p3*
bcc–csm1-1-m	r1i1p1*	GISS-E2-R-CC	r1i1p1*
bcc–csm1-1	r1i1p1	GISS-E2-R	r1i1p1, r1i1p2, r1i1p3, r2i1p1*, r2i1p2*, r2i1p3*, r3i1p1*, r3i1p2*, r3i1p3*, r4i1p1*, r4i1p2*, r4i1p3*, r4i1p1*, r4i1p2*, r4i1p3*, r4i1p1*, r4i1p2*, r4i1p3*
BNU-ESM	r1i1p1	HadGEM2-AO	r1i1p1
CanESM2	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1	HadGEM2-CC	r1i1p1
CCSM4	r1i1p1, r2i1p1, r3i1p1 r4i1p1, r5i1p1, r6i1p1	HadGEM2-ES	r1i1p1, r2i1p1, r3i1p1, r4i1p1
CESM1-BGC	r1i1p1	inmcm4	r1i1p1
CESM1-CAM5	r1i1p1r1i1p1, r2i1p1, r3i1p1*	IPSL-CM5A-LR	r1i1p1, r2i1p1, r3i1p1, r4i1p1
CMCC–CM	r1i1p1	IPSL-CM5A-MR	r1i1p1
CMCC–CMS	r1i1p1	IPSL-CM5B-LR	r1i1p1
CNRM-CM5	r1i1p1, r2i1p1†, r4i1p1†, r6i1p1†, r10i1p1†	MIROC-ESM-CHEM	r1i1p1
CSIRO-Mk3-6–0	r1i1p1, r2i1p1, r3i1p1, r4i1p1, r5i1p1, r6i1p1, r7i1p1, r8i1p1, r9i1p1, r10i1p1	MIROC-ESM	r1i1p1
EC-EARTH	r2i1p1, r8i1p1, r9i1p1, r12i1p1	MIROC5	r1i1p1, r2i1p1, r3i1p1
FGOALS-g2	r1i1p1	MPI-ESM-LR	r1i1p1, r2i1p1, r3i1p1
FIO-ESM	r1i1p1, r2i1p1, r3i1p1	MPI-ESM-MR	r1i1p1, r2i1p1*, r3i1p1*
GFDL-CM3	r1i1p1	MRI-CGCM3	r1i1p1
GFDL-ESM2G	r1i1p1	NorESM1-M	r1i1p1
GFDL-ESM2M	r1i1p1	NorESM1-ME	r1i1p1
GISS-E2-H-CC	r1i1p1		

Appendix B. Changes in ETCCDI indices

The computation of changes in the four ETCCDI indices between 1981-2010 and 2071-2100 involves the selected GCM-runs after the initial screening, with the results presented in Table B.1 and Table B.2. Within these tables, the model-runs highlighted in blue will be utilized in the final phase of reduction.

Table B.1: Percentage change in the ETCCDI indices (R99pTOT, CDD, WSDI, and CSDI) for different corners (Warm-Wet, Warm-Dry, Cold-Wet, and Cold-Dry) in RCP4.5. The GCM-runs with the highest and the second highest averaged rank are selected (blue color).

RCP	**Projection**	**Model**	**ΔR99pTOT (%)**	**ΔCDD (%)**	**ΔWSDI (%)**	**ΔCSDI (%)**	**T index rank**	**P index rank**	**Averaged rank**
RCP4.5	Warm-Dry	ACCESS1-0.r1i1p1	–	5.0	739.6	–	2	4	3
		CSIRO-Mk3-6-0.r10i1p1	–	3.4	1253.7	–	4	3	3.5
		BNU-ESM.r1i1p1	–	2.5	1331.4	–	5	2	3.5
		HadGEM2-CC.r1i1p1	–	2.3	742.1	–	3	1	2
		HadGEM2-ES.r4i1p1	–	8.9	707.1	–	1	5	3
	Warm-Wet	CanESM2.r1i1p1	68.4	–	679.9	–	4	2	3
		CanESM2.r3i1p1	67.7	–	878.8	–	3	3	3
		CanESM2.r4i1p1	63.2	–	603.9	–	2	1	1.5
		CanESM2.r5i1p1	54.2	–	907.7	–	1	4	2.5
		CSIRO-Mk3-6-0.r1i1p1	105.9	–	1202.9	–	5	5	5
	Cold-Wet	CCSM4.r2i1p1	32.8	–	–	-79.4	4	1	2.5
		CCSM4.r4i1p1	51.3	–	–	-80.2	3	5	4
		GISS-E2-R.r6i1p1	40.3	–	–	-74.3	5	2	3.5
		IPSL-CM5B-LR.r1i1p1	48.5	–	–	-81.0	2	4	3
		MRI-CGCM3.r1i1p1	44.0	–	–	-83.0	1	3	2
	Cold-Dry	CCSM4.r3i1p1	–	3.5	–	-71.9	3	3	3
		GFDL-ESM2G.r1i1p1	–	3.4	–	-70.6	2	2	2
		GFDL-ESM2M.r1i1p1	–	3.6	–	-50.2	4	5	4.5
		inmcm4.r1i1p1	–	0.8	–	-65.5	1	4	2.5
		MPI-ESM-MR.r3i1p1	–	6.3	–	-86.5	5	1	3

Table B.2: Percentage change in the ETCCDI indices (R99pTOT, CDD, WSDI, and CSDI) for different corners (Warm-Wet, Warm-Dry, Cold-Wet, and Cold-Dry) in RCP8.5. The GCM-runs with the highest and the second highest averaged rank are selected (blue color).

RCP	Projection	Model	**ΔR99pTOT (%)**	**ΔCDD (%)**	**ΔWSDI (%)**	**ΔCSDI (%)**	T index rank	P index rank	Averaged rank
RCP8.5	Warm-Dry	HadGEM2-AO.r1i1p1	–	15.4	1423.3	–	5	2	3.5
		HadGEM2-ES.r3i1p1	–	16.5	1208.1	–	2	1	1.5
		HadGEM2-ES.r4i1p1	–	14.0	1383.9	–	4	5	4.5
		IPSL-CM5A-LR.r1i1p1	–	25.6	1145.7	–	3	4	3.5
		IPSL-CM5A-MR.r1i1p1	–	29.7	1335.0	–	1	3	2
	Warm-Wet	CanESM2.r1i1p1	148.0	–	982.8	–	2	5	3.5
		CanESM2.r2i1p1	134.2	–	1184.3	–	4	4	4
		CanESM2.r3i1p1	122.9	–	1164.8	–	3	2	2.5
		CanESM2.r4i1p1	130.4	–	894.1	–	1	3	2
		CanESM2.r5i1p1	119.7	–	1475.5	–	5	1	3
	Cold-Wet	CCSM4.r6i1p1	73.4	–	–	-98.3	1	3	2
		CESM1-BGC.r1i1p1	81.7	–	–	-97.8	2	4	3
		CNRM-CM5.r1i1p1	101.9	–	–	-95.6	3	5	4
		IPSL-CM5B-LR.r1i1p1	69.0	–	–	-95.0	4	1	2.5
		MRI-CGCM3.r1i1p1	73.1	–	–	-89.8	5	2	3.5
	Cold-Dry	CCSM4.r1i1p1	–	60.2	–	-96.2	1	4	2.5
		CCSM4.r2i1p1	–	50.8	–	-90.3	4	2	3
		CCSM4.r3i1p1	–	48.7	–	-94.4	2	1	1.5
		GFDL-ESM2M.r1i1p1	–	66.9	–	-87.8	5	5	5
		inmcm4.r1i1p1	–	54.9	–	-93.6	3	3	3

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