GLACIOLAB / RIVE / ECCC CDR seminar presentation

From ORCHIDEE to CLASSIC: improving the simulated snow cover heterogeneity and its impact on the climate

Mickaël Lalande

Postdoc at UQTR / RIVE / GLACIOLAB

ESA CCI Fellowship — 01/10/2023 to 30/09/2025 (2 years)

supervised by Christophe Kinnard and Alexandre Roy

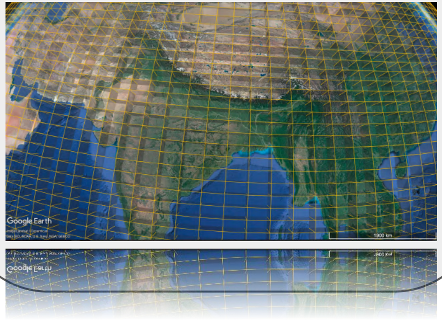
Objectives and presentation outline

1. Study and quantify climate change in HMA using general circulation models (GCMs) and observation datasets

PhD (UGA - Grenoble, France)

(UQTR - Trois-Rivières, Québec) Postdoc

#1 CMIP6 multi-model analysis of climate change in HMA



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2. Improving the representation of snow cover in mountain regions in CMGs (ORCHIDEE/LMDZ)

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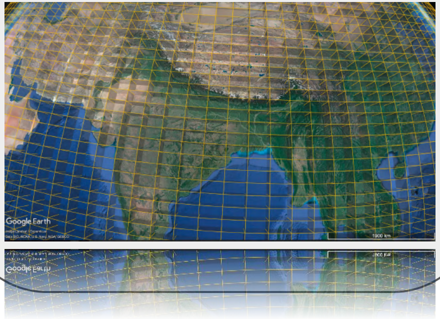

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2. Improving the representation of snow cover in mountain regions in CMGs (ORCHIDEE/LMDZ)
3. Enhancing the snow model in CLASSIC for the Arctic (snow cover, multi-layer, blowing snow sublimation)

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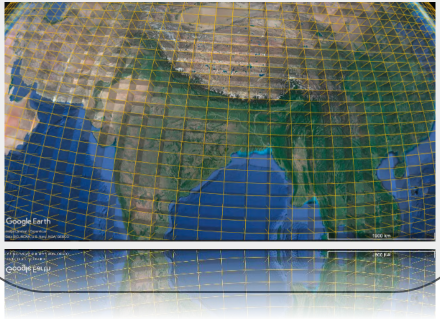

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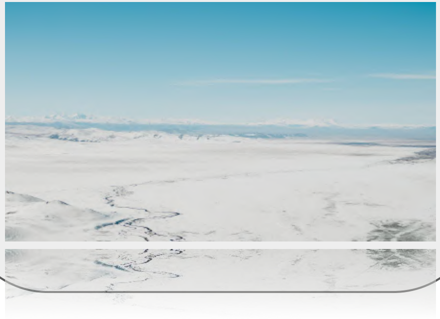
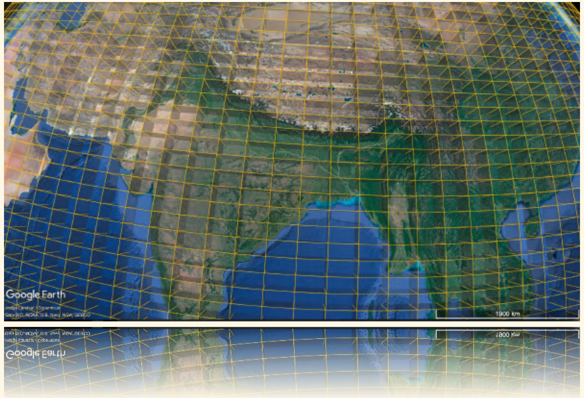
#3 Snow cover heterogeneity in the Arctic (CLASSIC)



Part #1

Climate change in the High Mountain Asia in CMIP6



Mickaël Lalande[1], Martin Ménégoz[1], Gerhard Krinner[1], Kathrin Naegeli[2], and Stefan Wunderle[2]

[1] Univ. Grenoble Alpes, CNRS, IRD, G-INP, IGE, 38000 Grenoble, France
[2] Institute of Geography and Oeschger Center for Climate Change Research, University of Bern, 3012 Bern, Switzerland

Earth Syst. Dynam., 12, 1061–1098, https://doi.org/10.5194/esd-12-1061-2021, 2021

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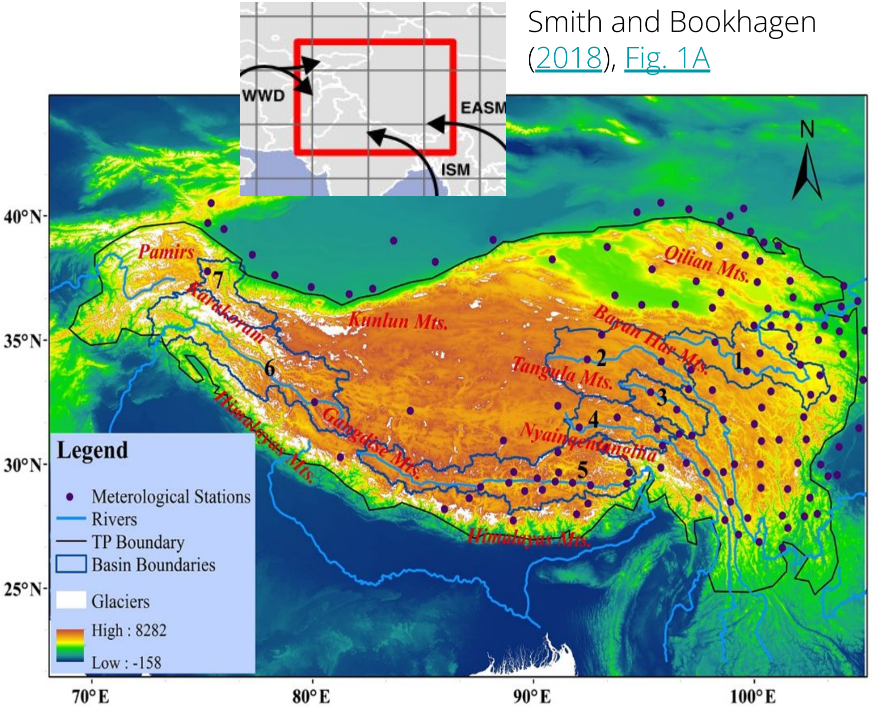
- The Tibetan Plateau (TP): world's highest plateau (average elevation 4000m) ➝ influence on regional and global climate (e.g., Kutzbach et al., 1993)



Smith and Bookhagen (2018), Fig. 1A

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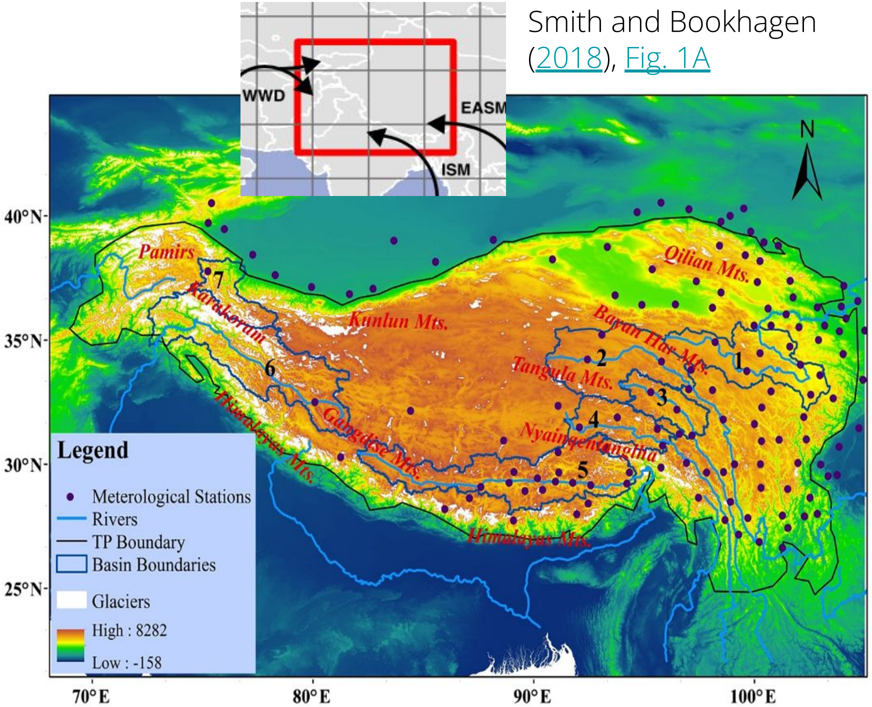

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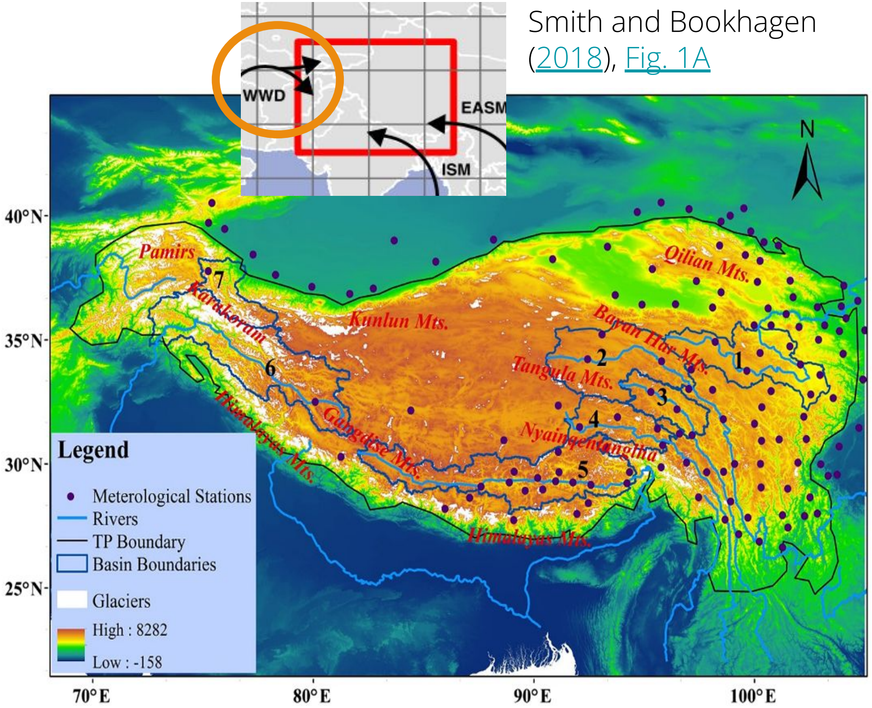

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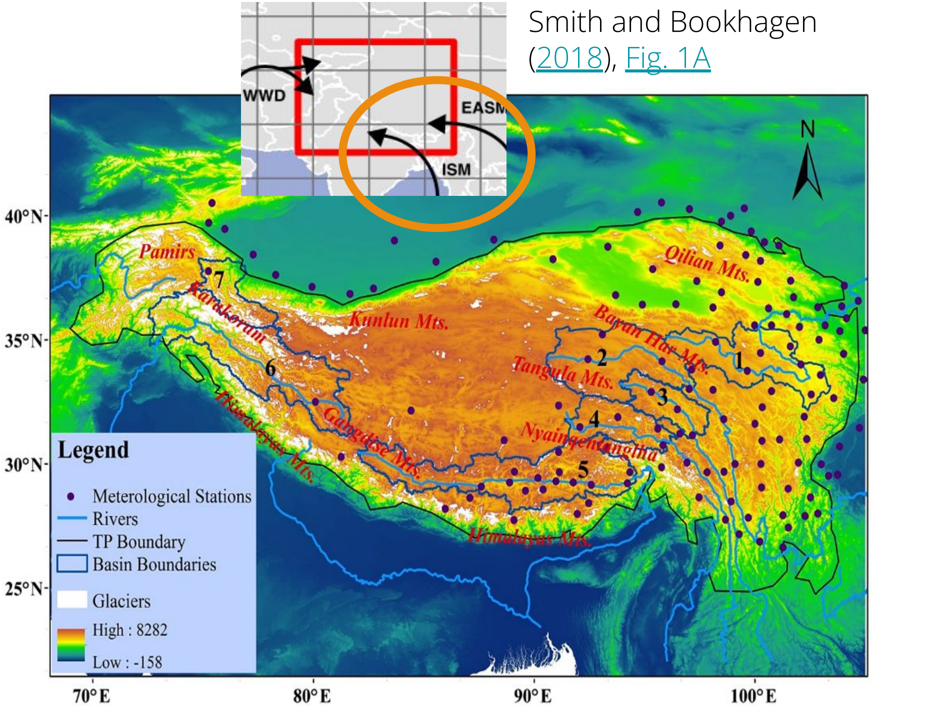

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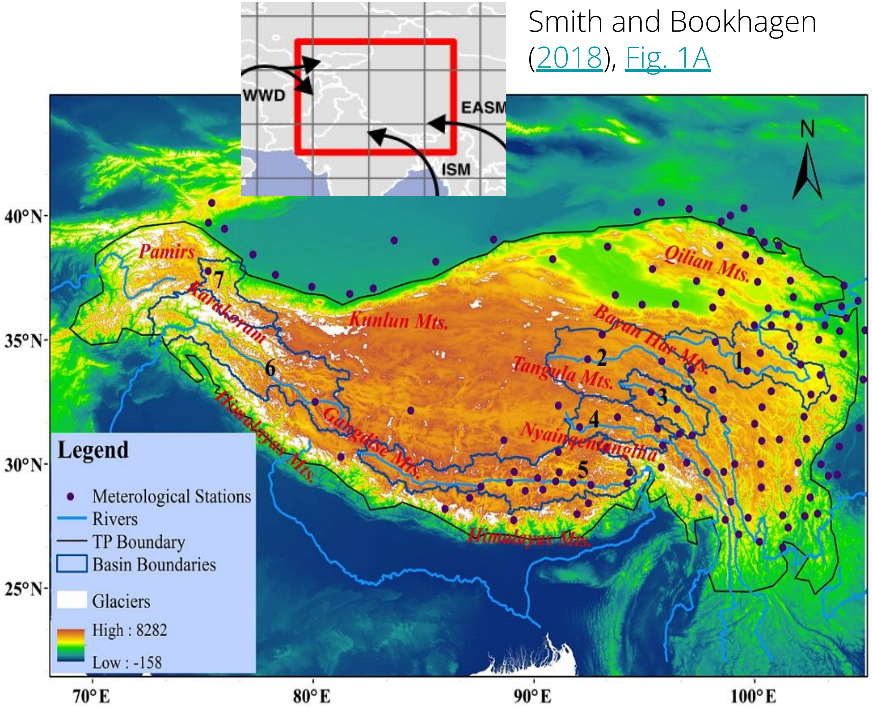

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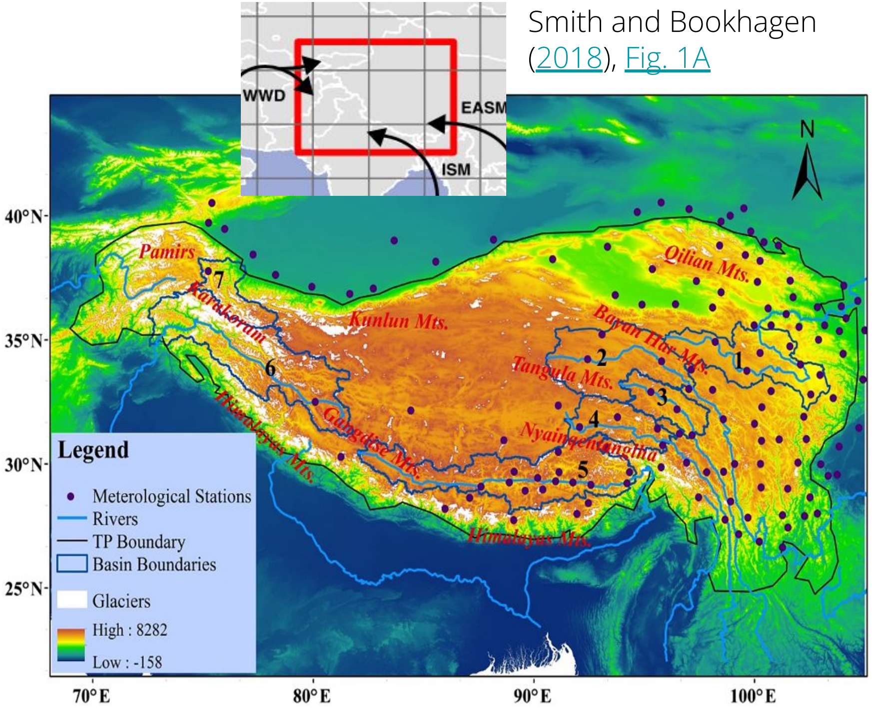

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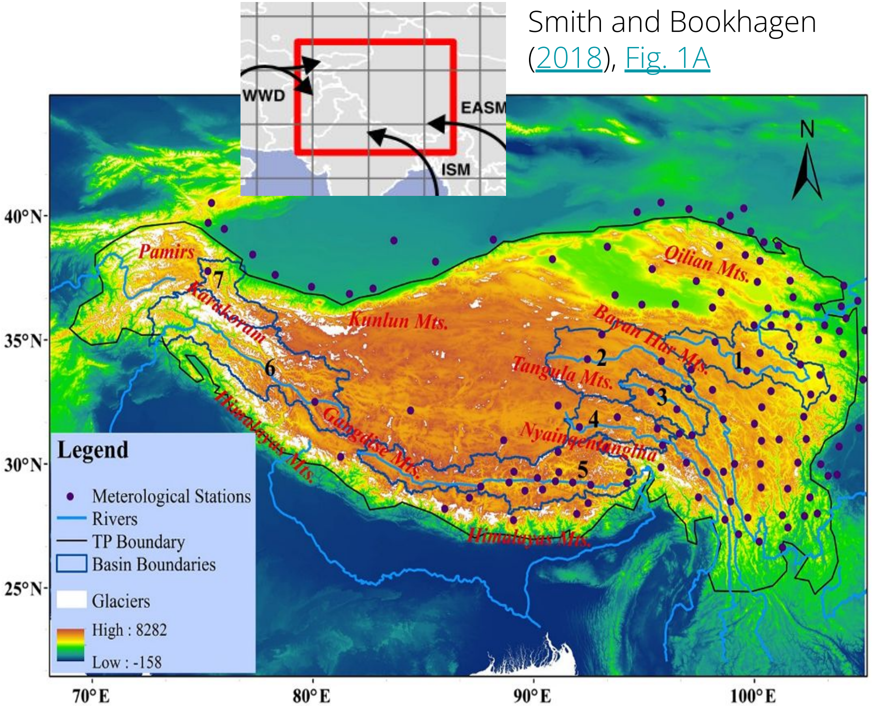

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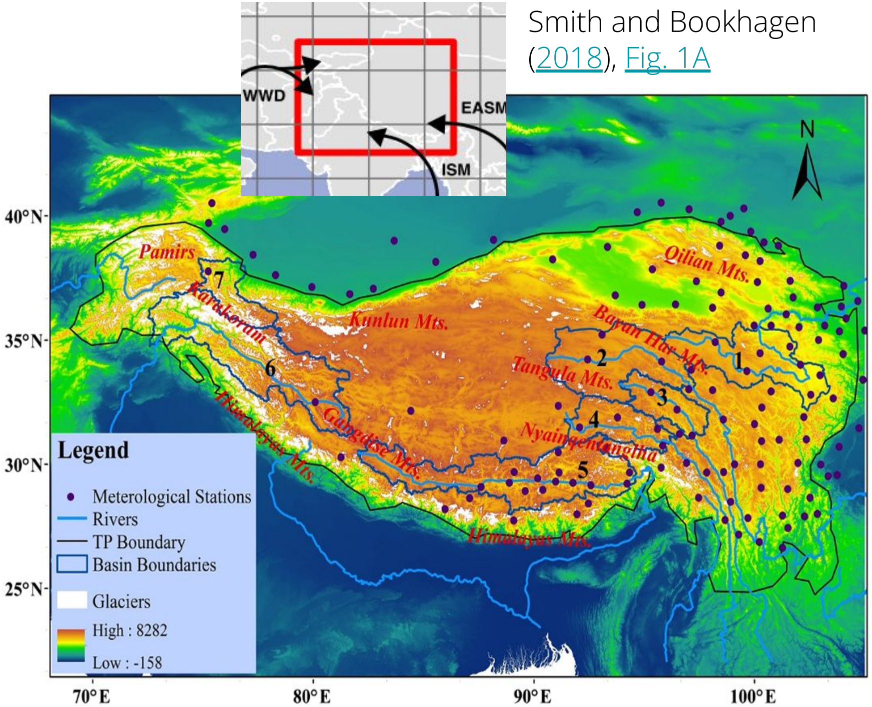

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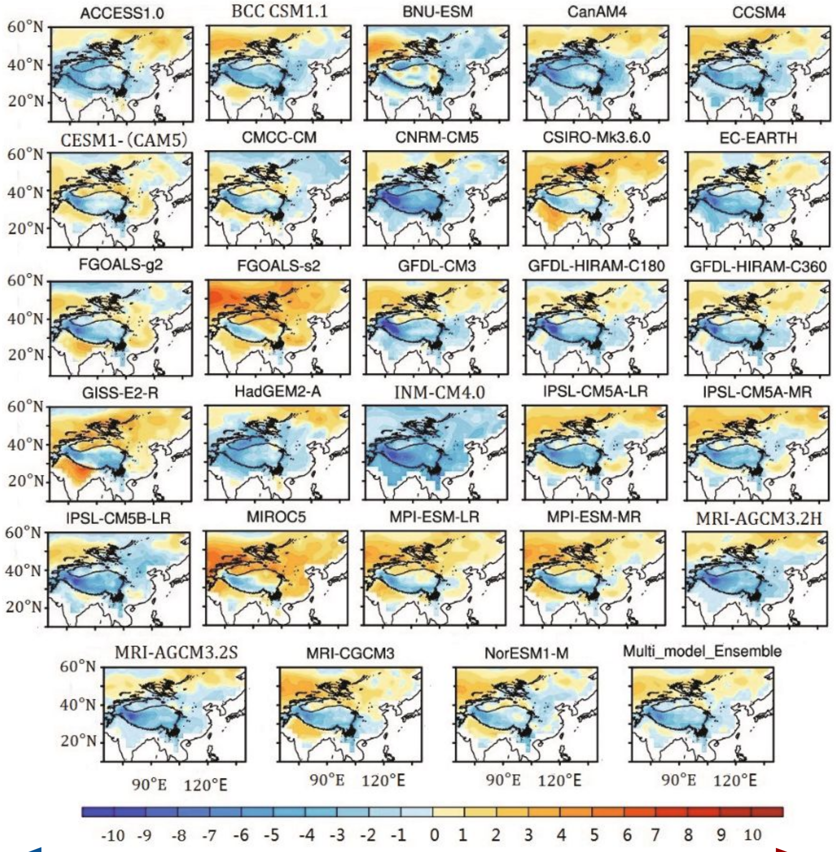
Use of GCMs (even if coarse spatial resolution ~50-300km) provides a coherent picture of the large-scale temporal and spatial patterns of key variables at a regional scale !

"Cold bias" over Tibetan Plateau



CMIP5 cold bias
(Chen et al., 2017; Fig 2)

- Cold biases in models from first AMIP experiments over HMA and TP (Mao and Robock, 1998)
- Possible explanations: excess precipitation (Lee & Suh, 2000), snow–ice albedo issues (Su et al., 2013), cold biases in T500 due to smoothed topography (Boos and Hurley, 2013), snow cover parameterization and boundary layer (Chen et al., 2017), lack of high-elevation observation stations in the CRU (Gu et al., 2012), etc.

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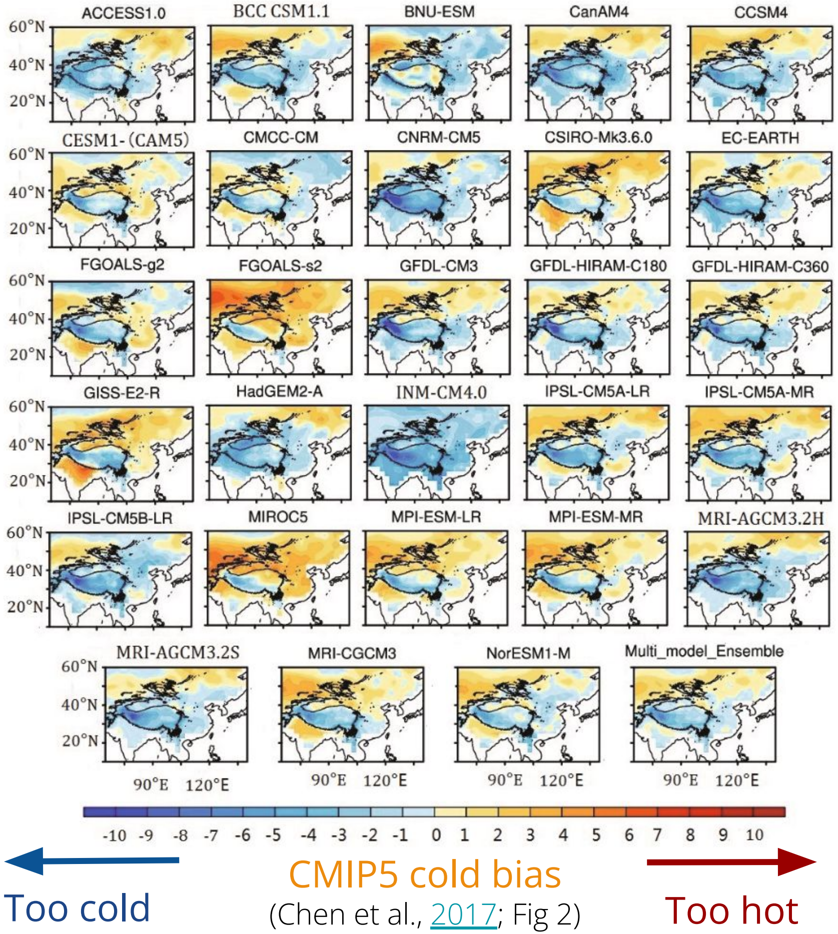

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Our study

1. Biases in CMIP6 for near-surface air temperature, total precipitation and snow cover extent?
2. What are the links between the model biases?
3. Do the model biases impact the trends?
4. Projections over the next century?

Data and methods

- 26 CMIP6 GCMs simulations for historical period 1979-2014
- 10 CMIP6 models for the future projections: SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 (O’Neill et al., 2016)

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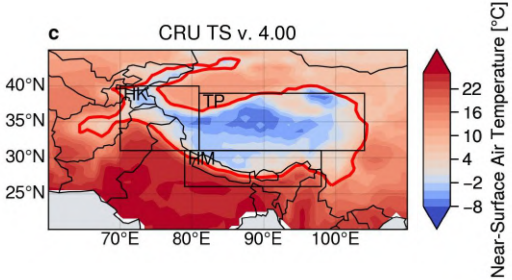

Annual climatologies (1979-2014)

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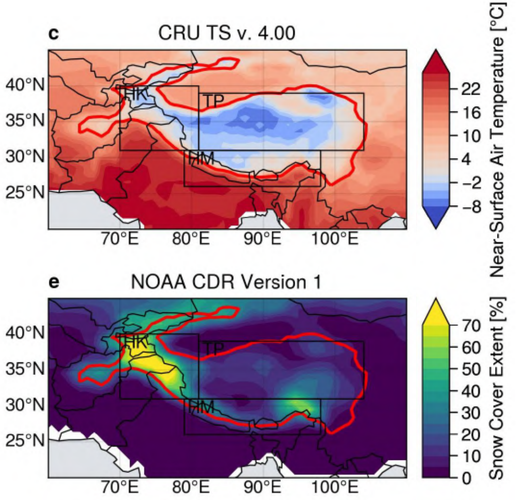

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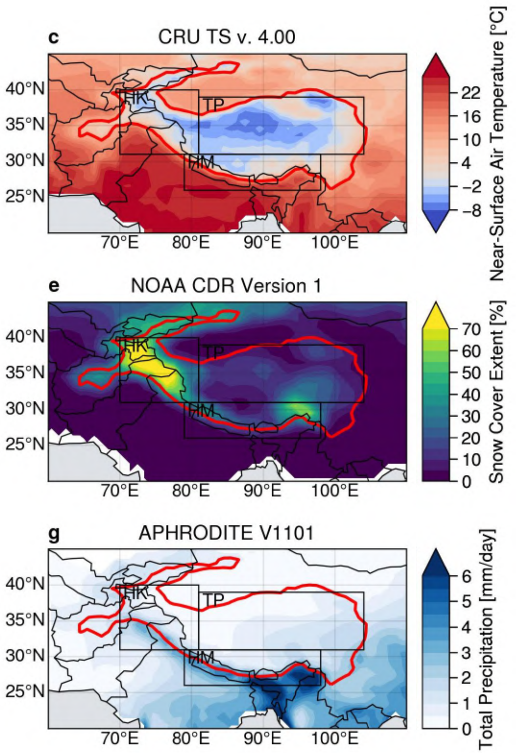

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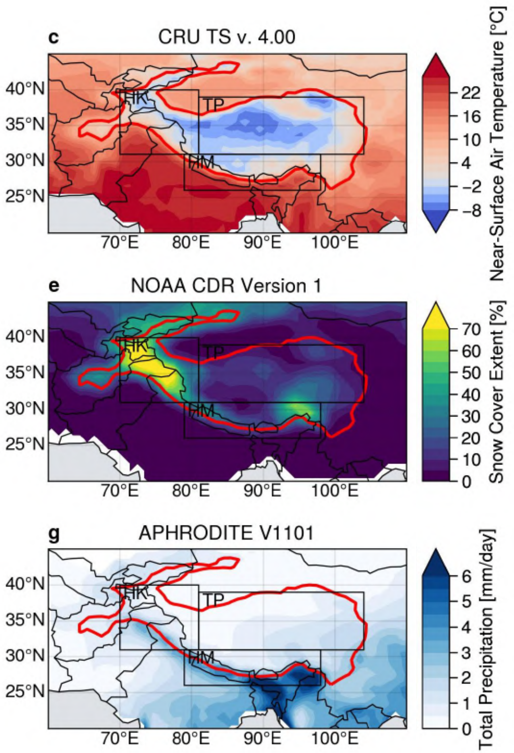

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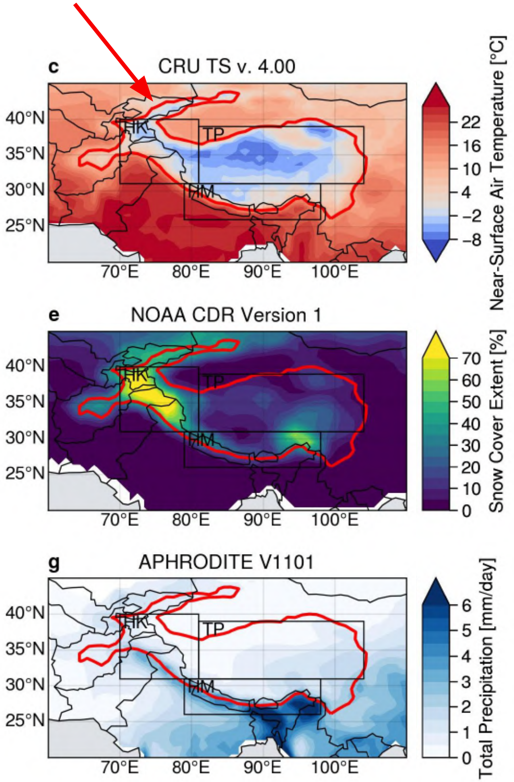
- Domain: High Mountain of Asia (HMA) including the Tibetan Plateau (TP), with elevation higher than 2500 m.asl (red contour)



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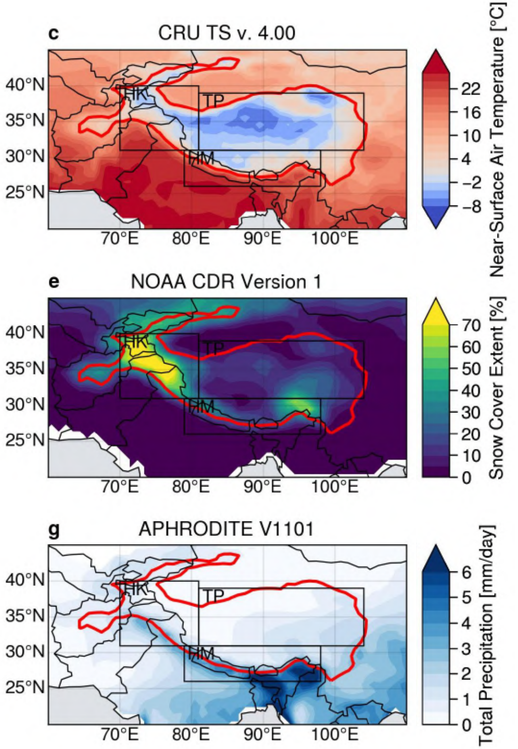
- Seasons: winter DJFMA (WDs) and summer JJAS (Asian summer monsoon)



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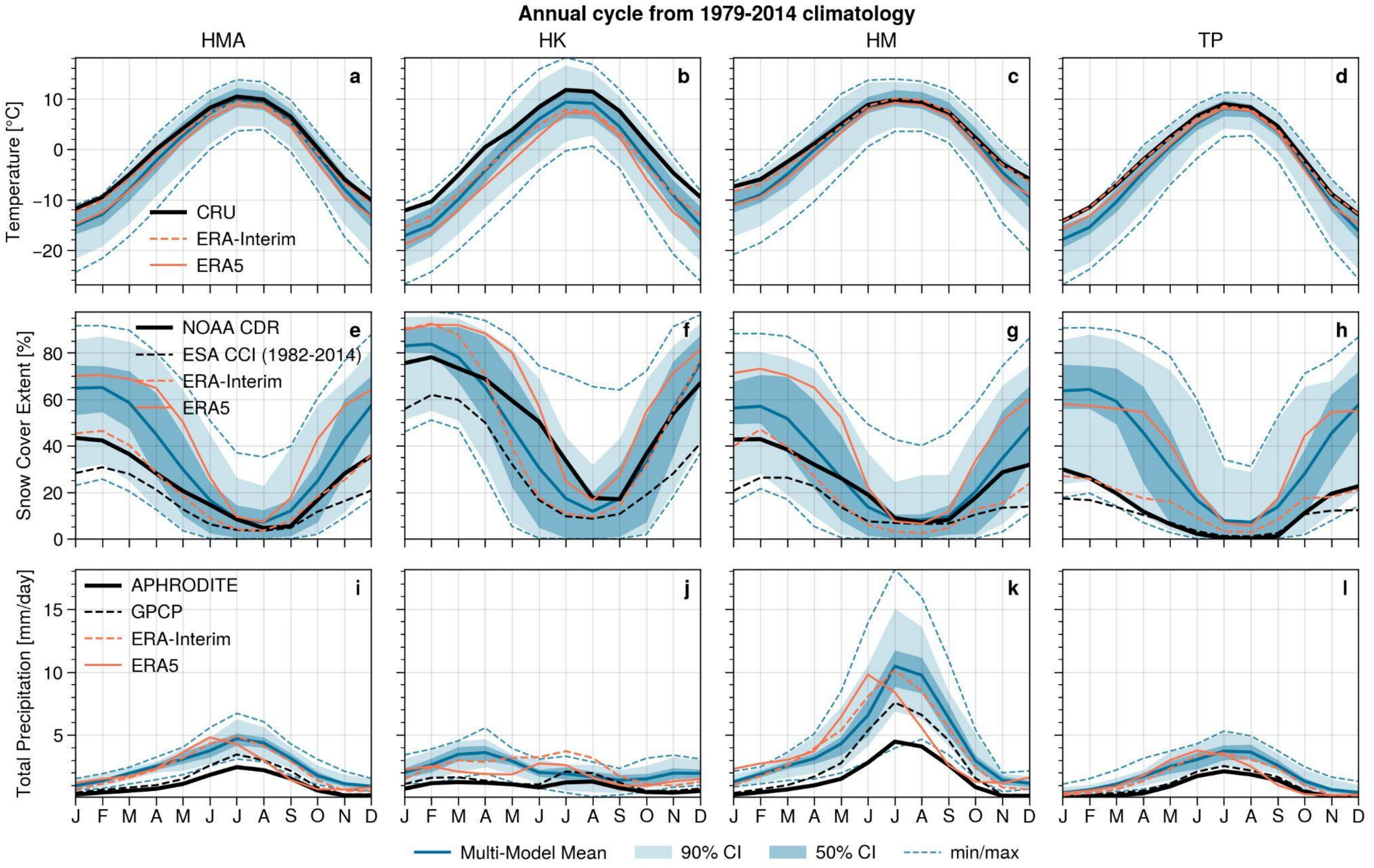

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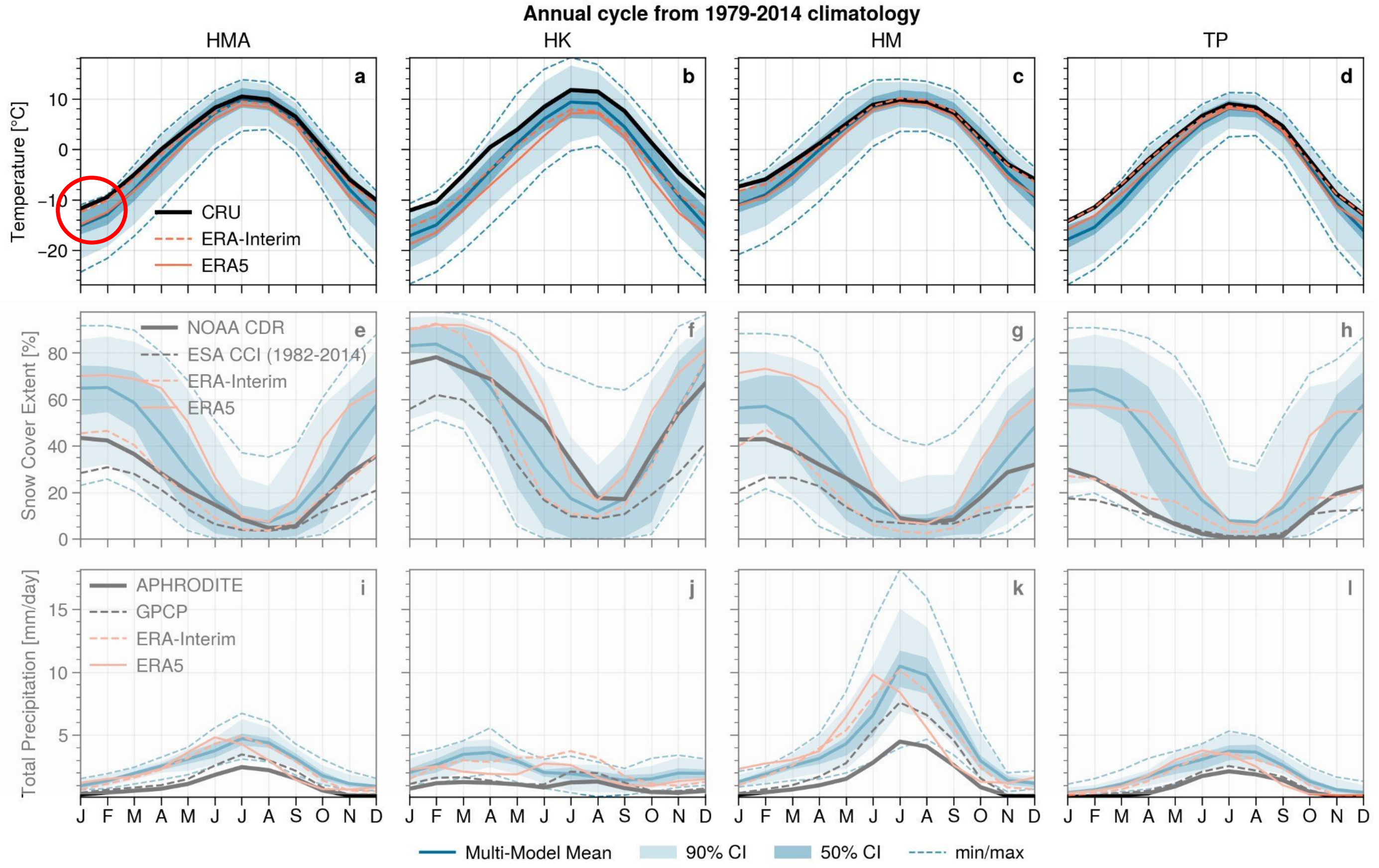

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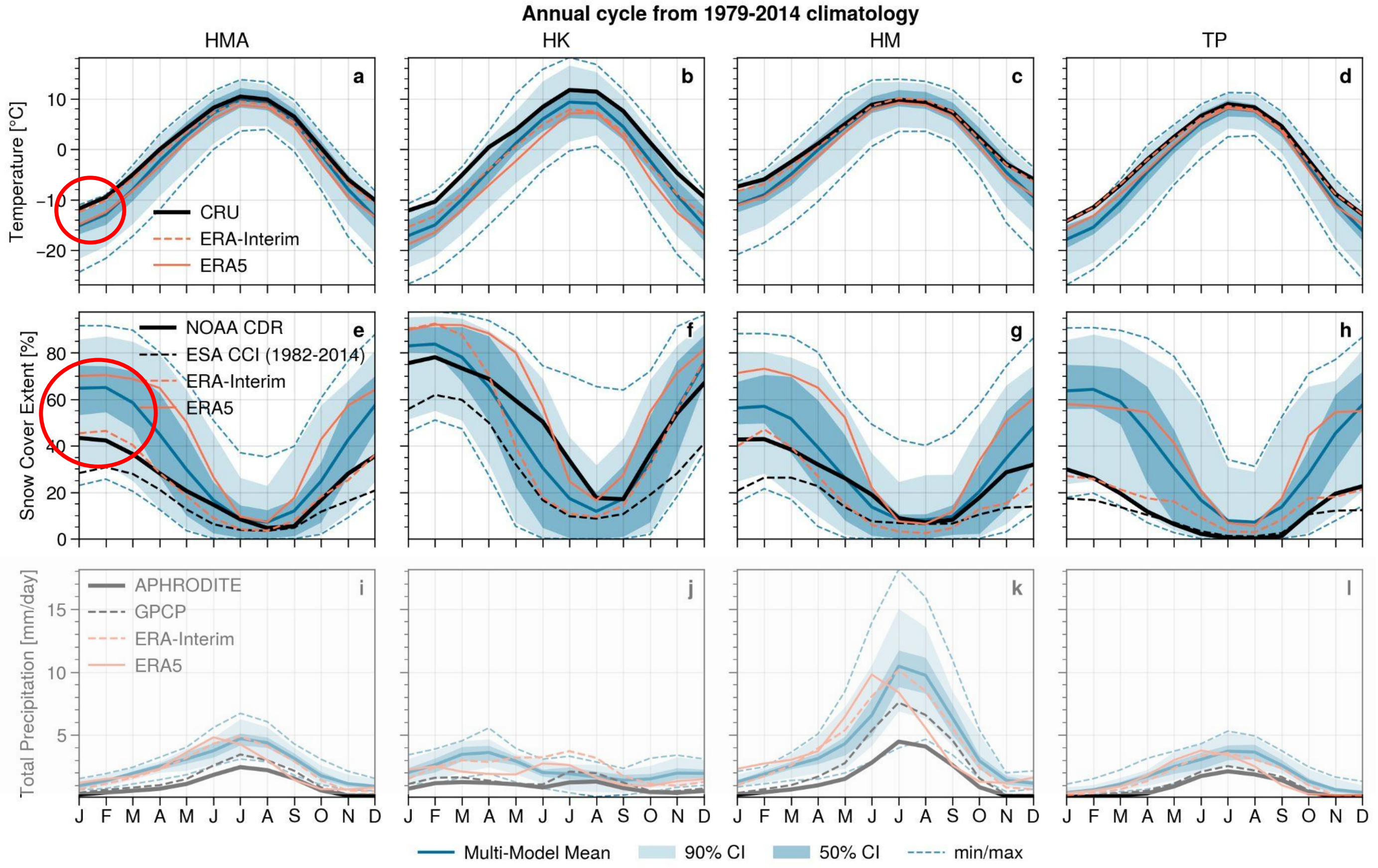

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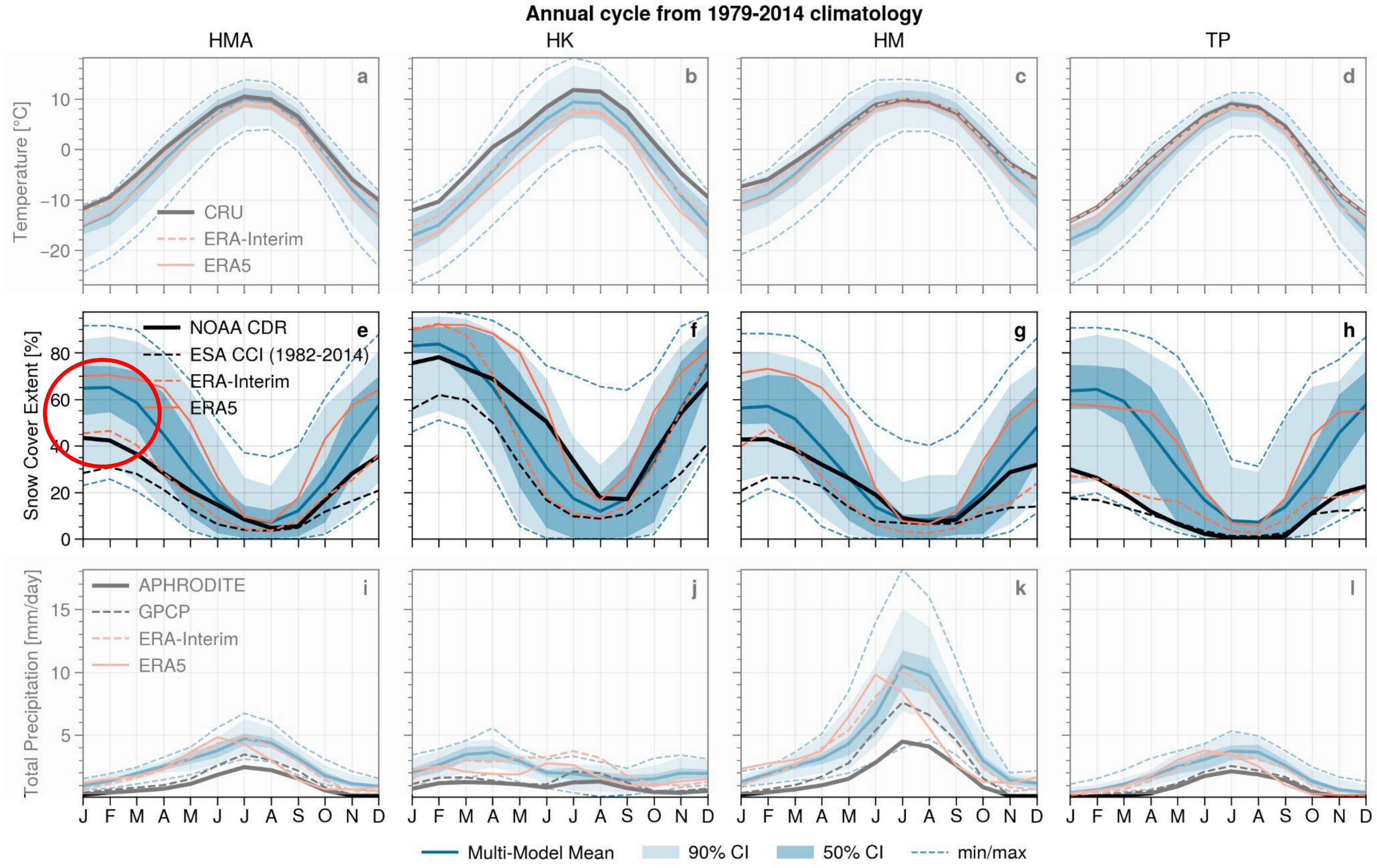

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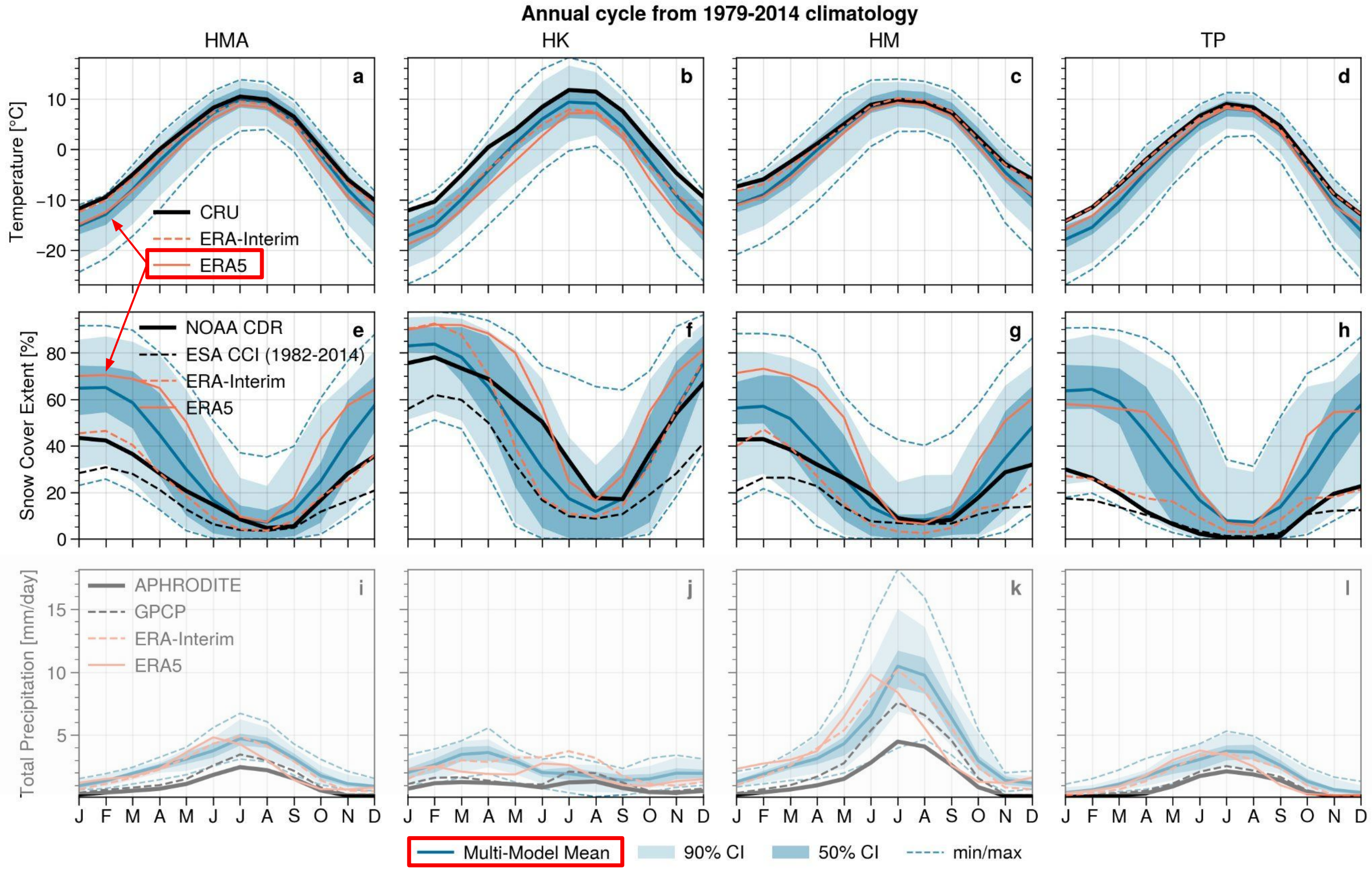

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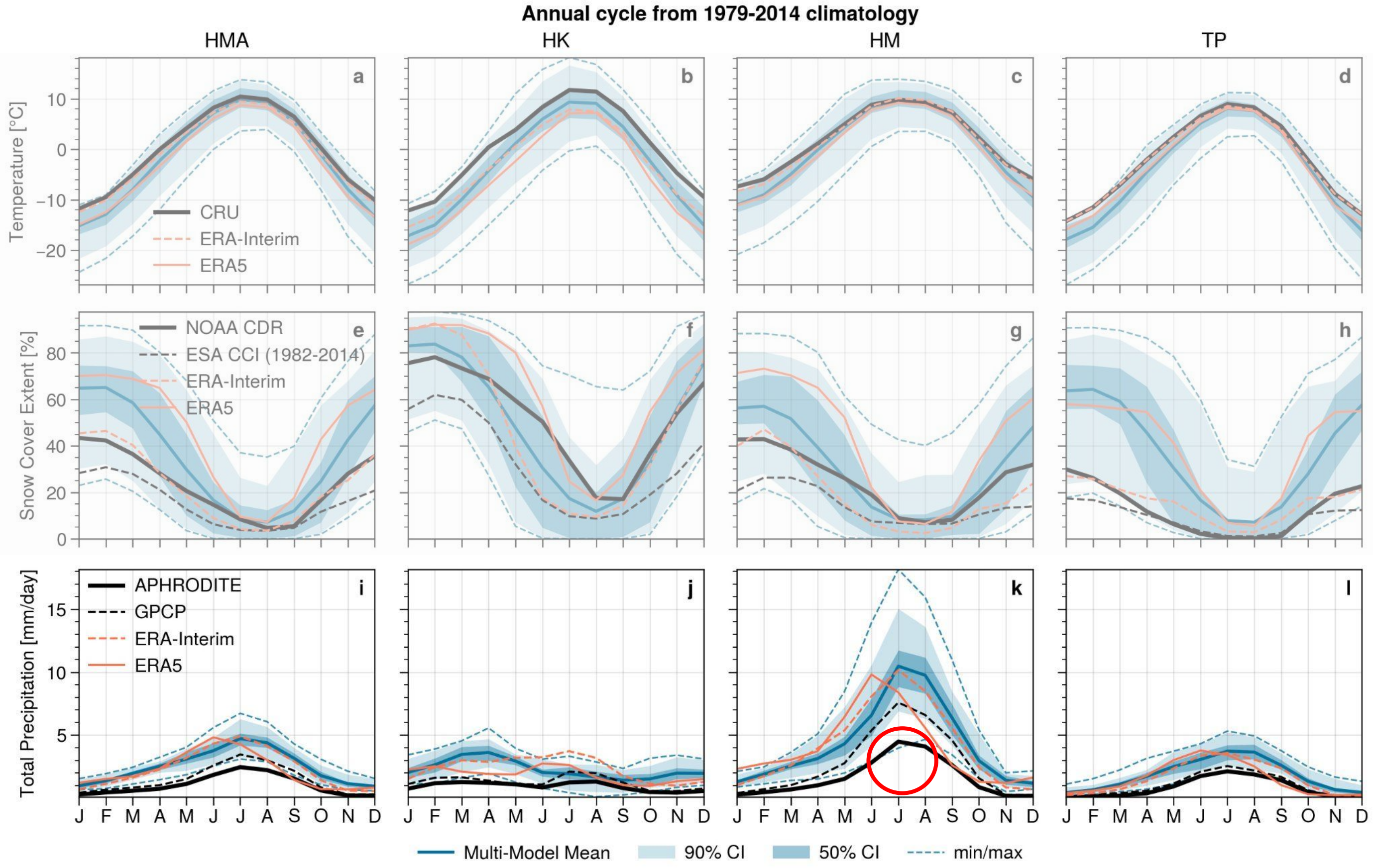
- pr obs lower than models -> snow undercatch issues by rain gauge (e.g. Jimeno-Saez et al., 2020)



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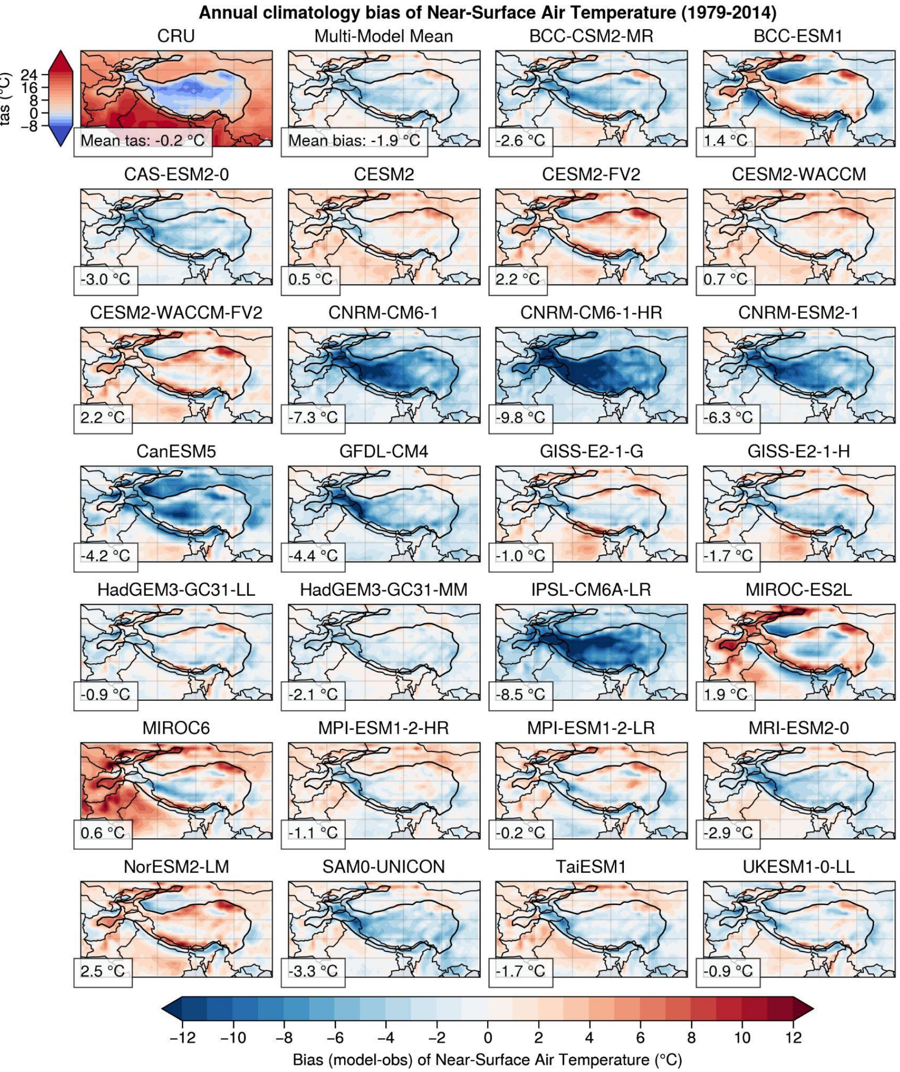

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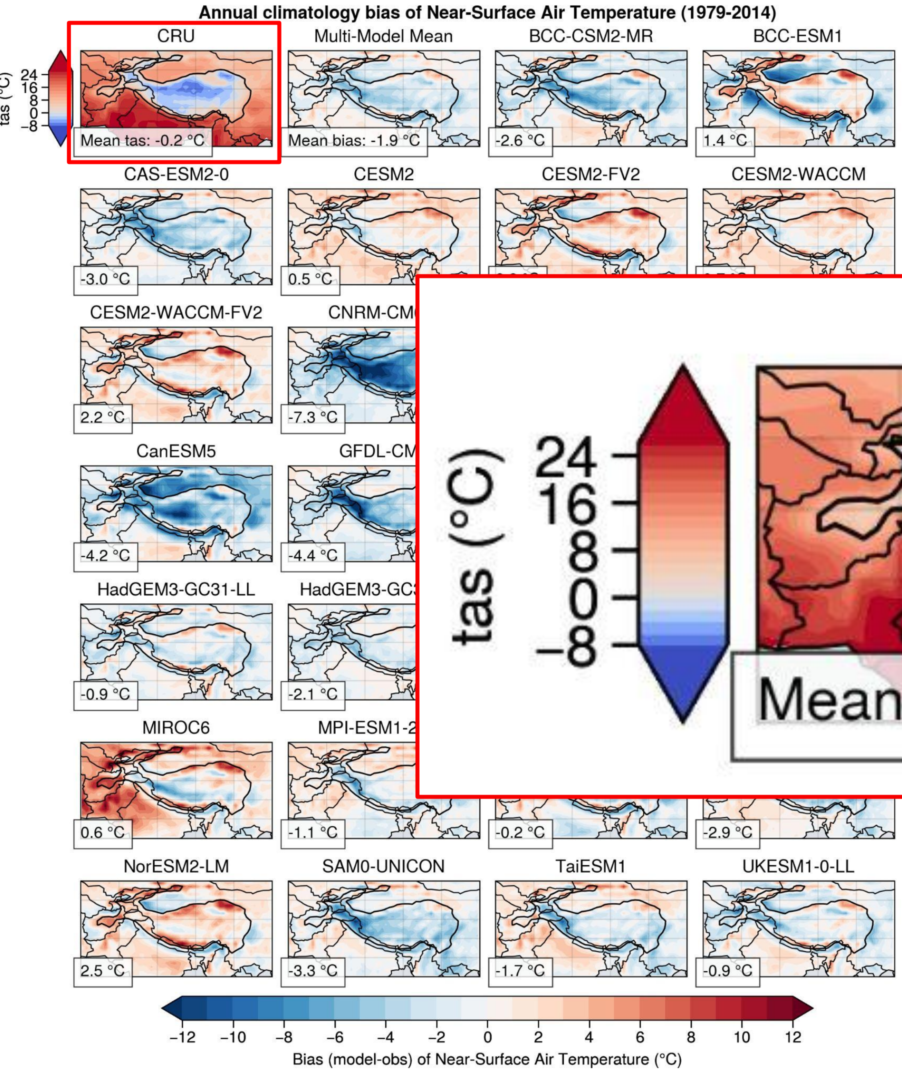

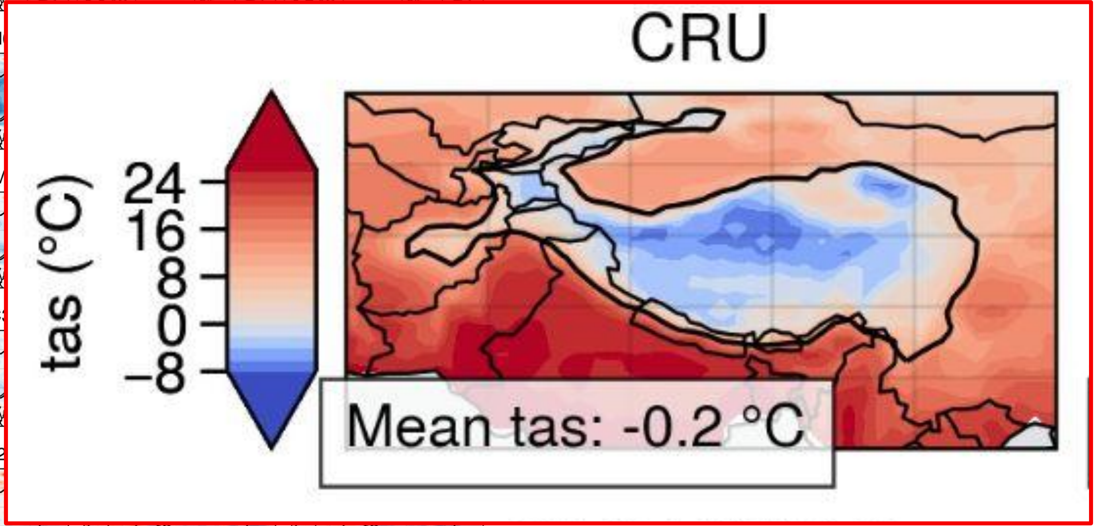

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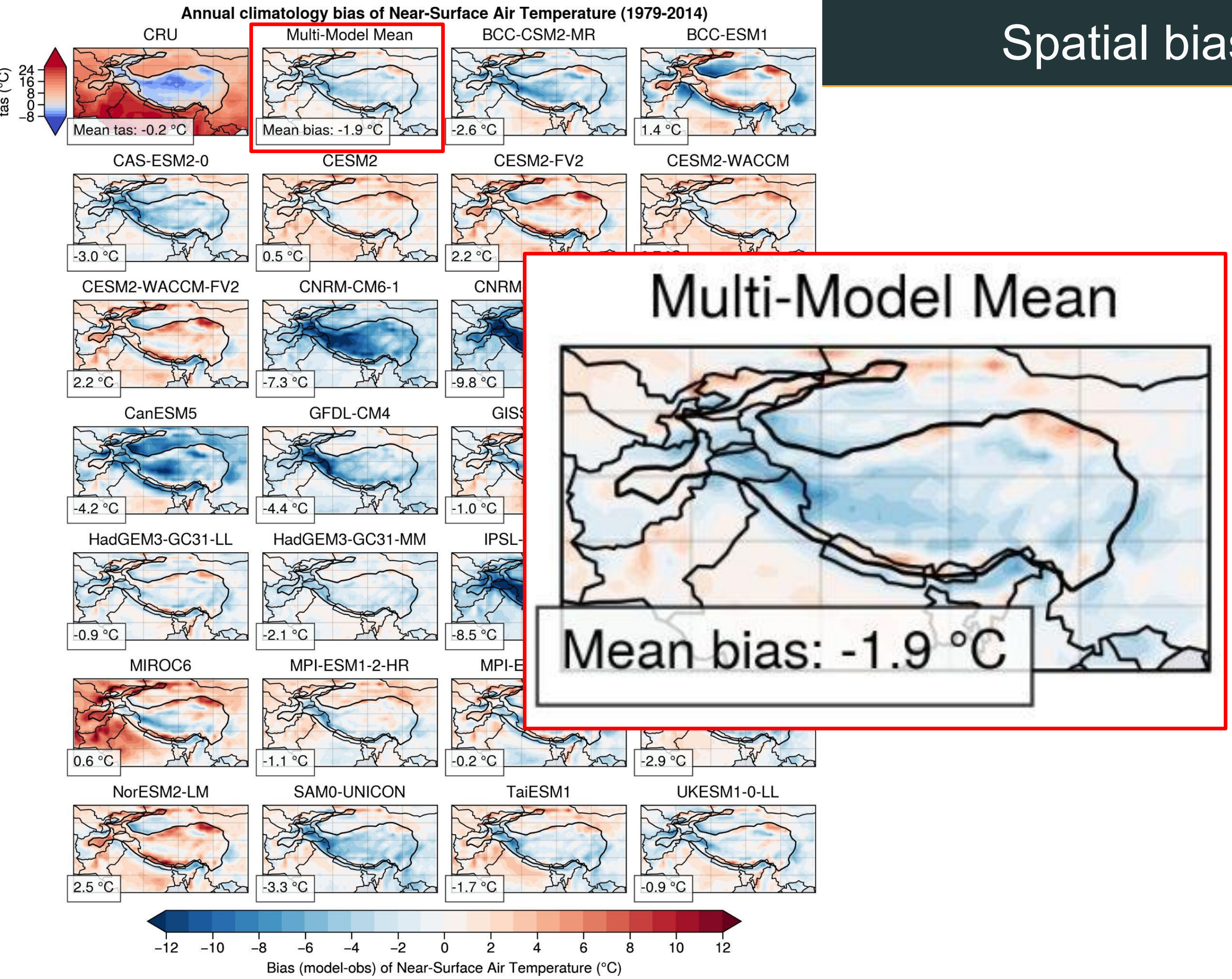

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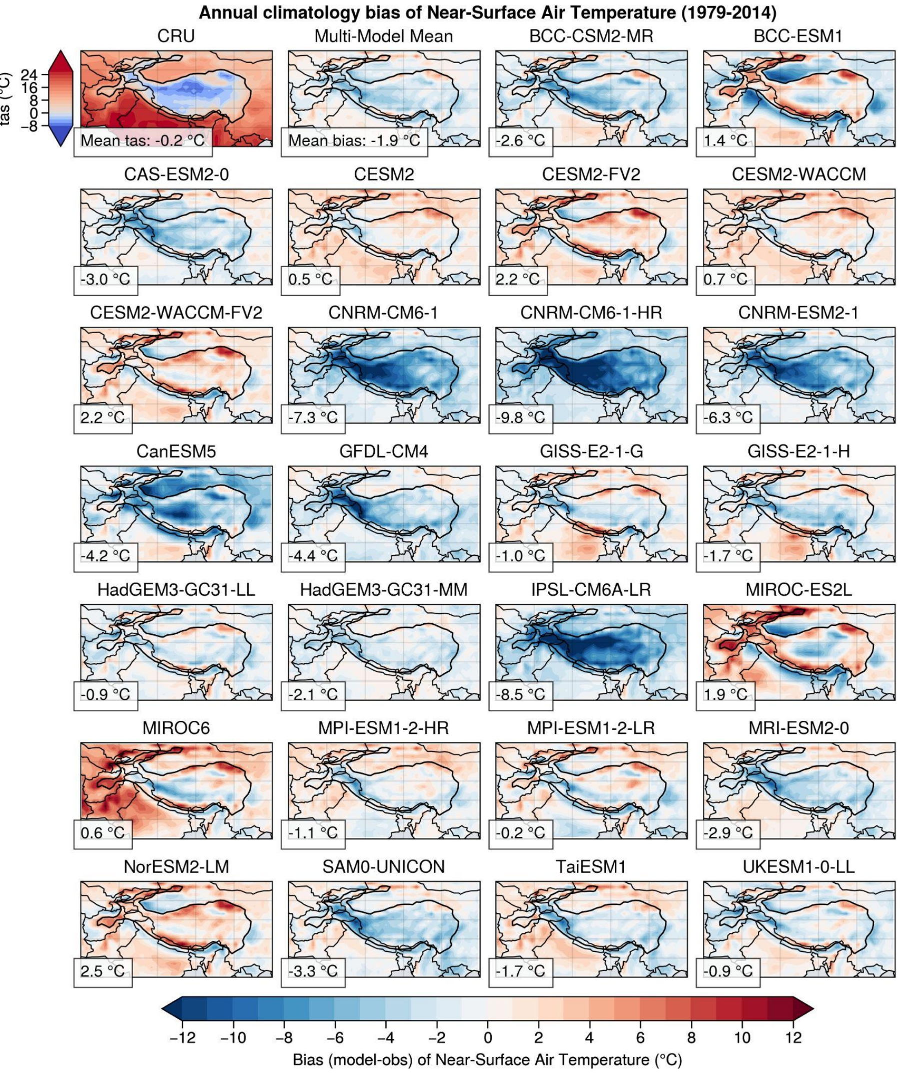

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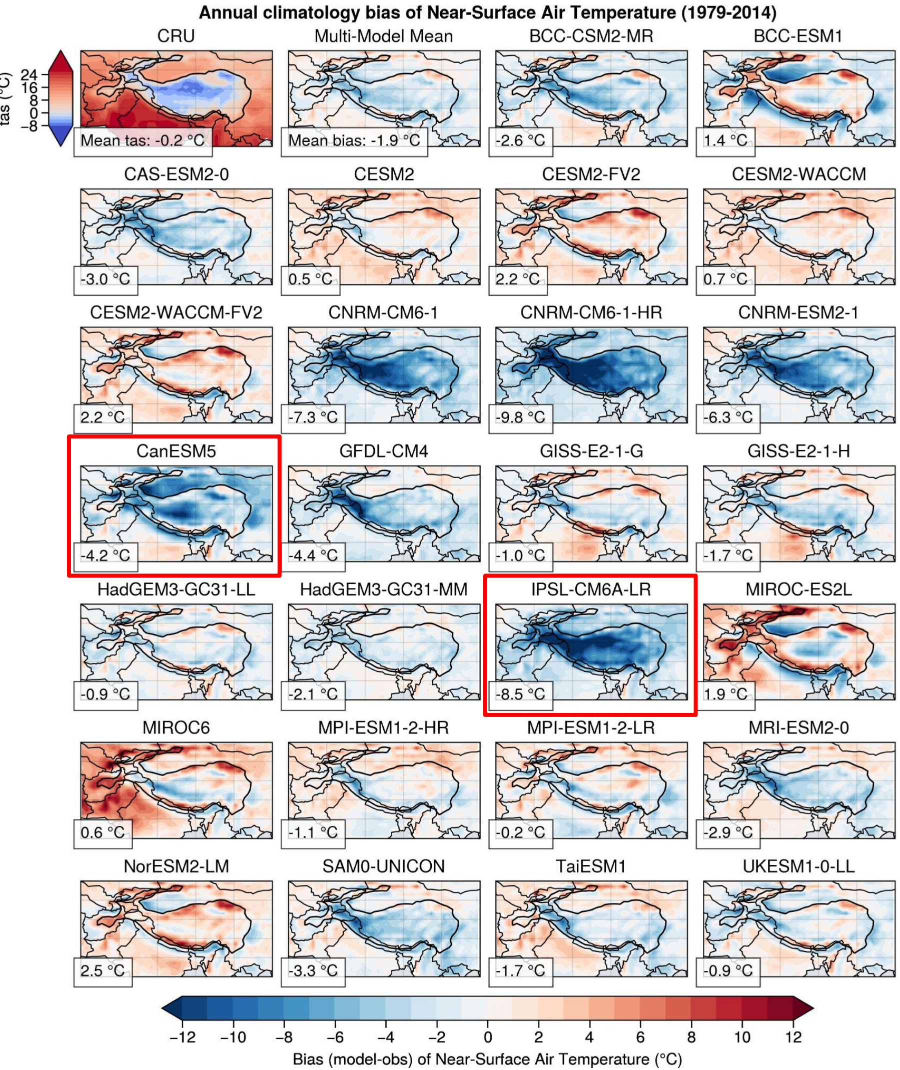

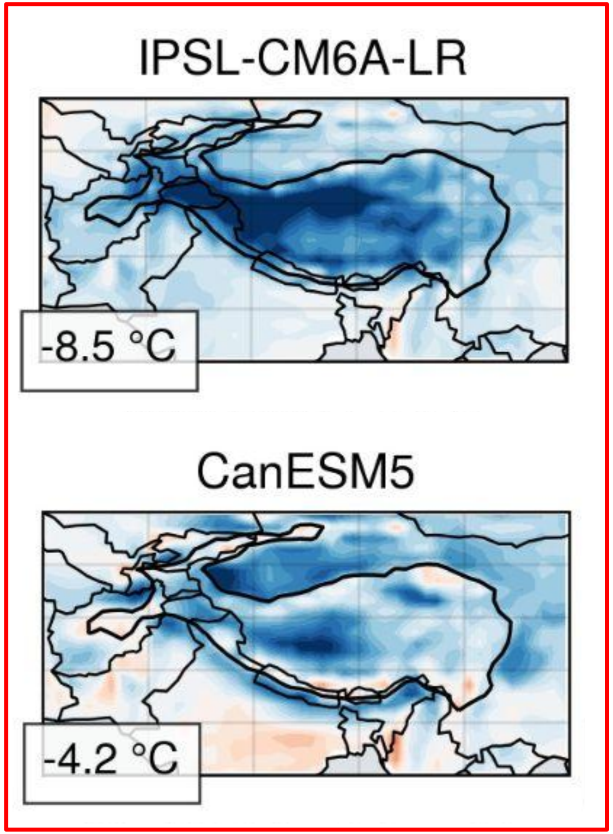

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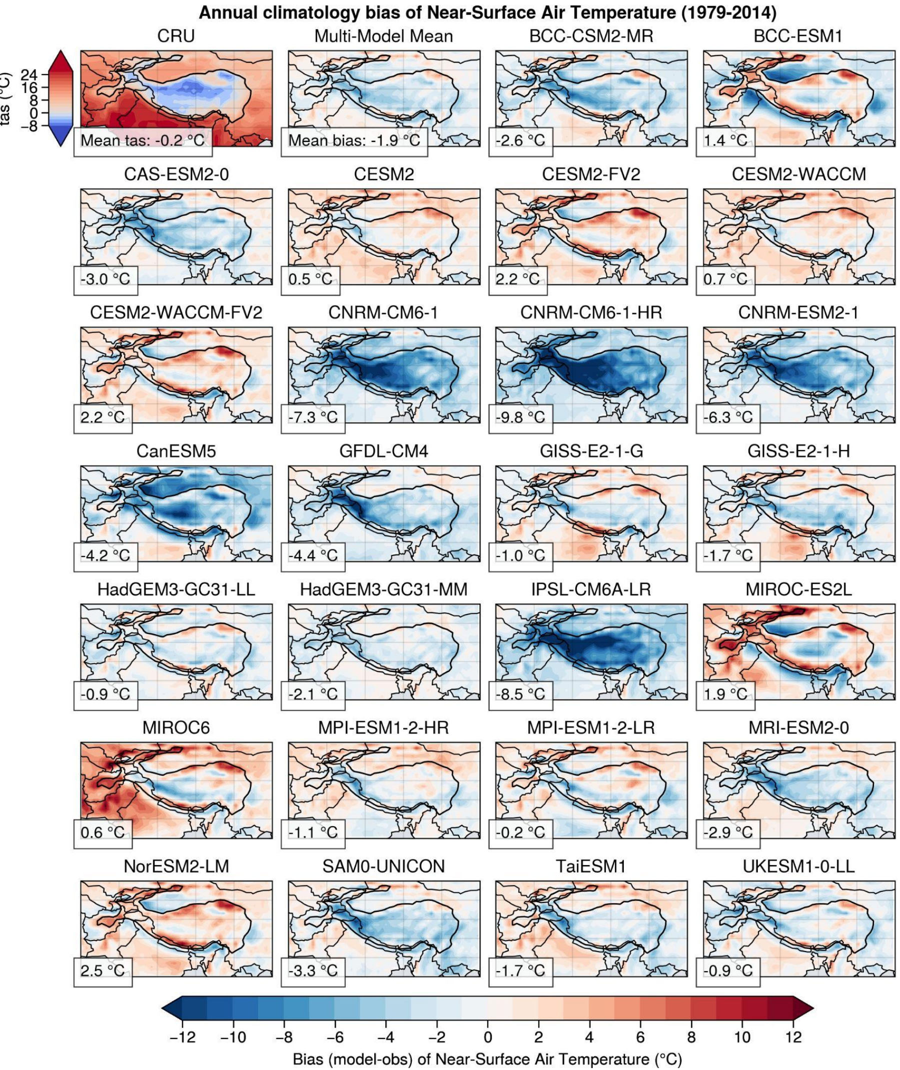

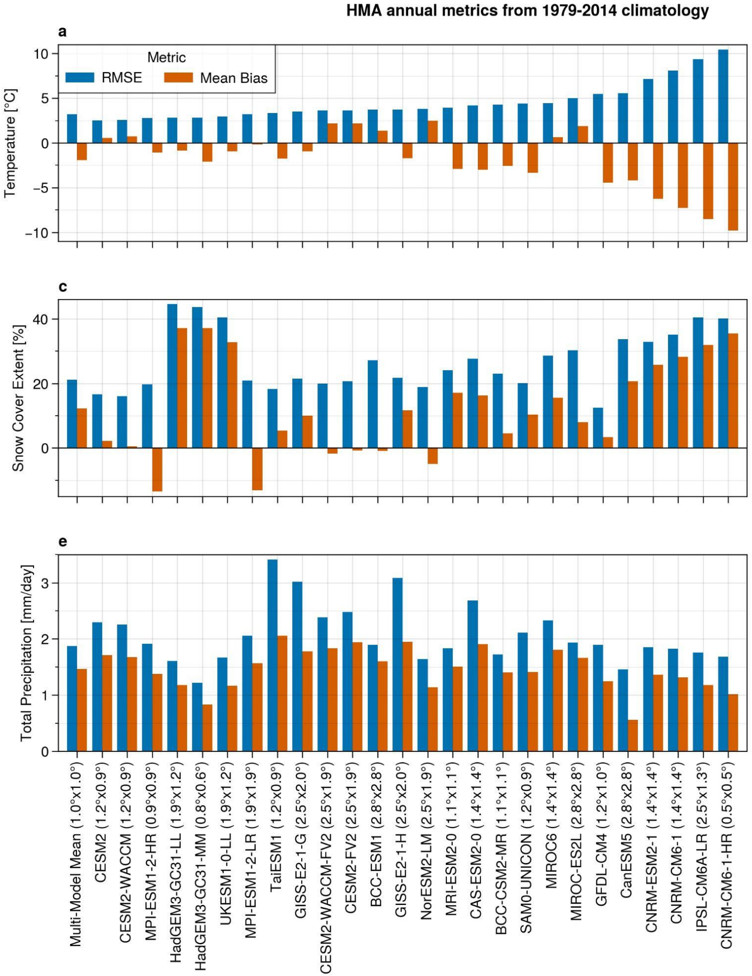

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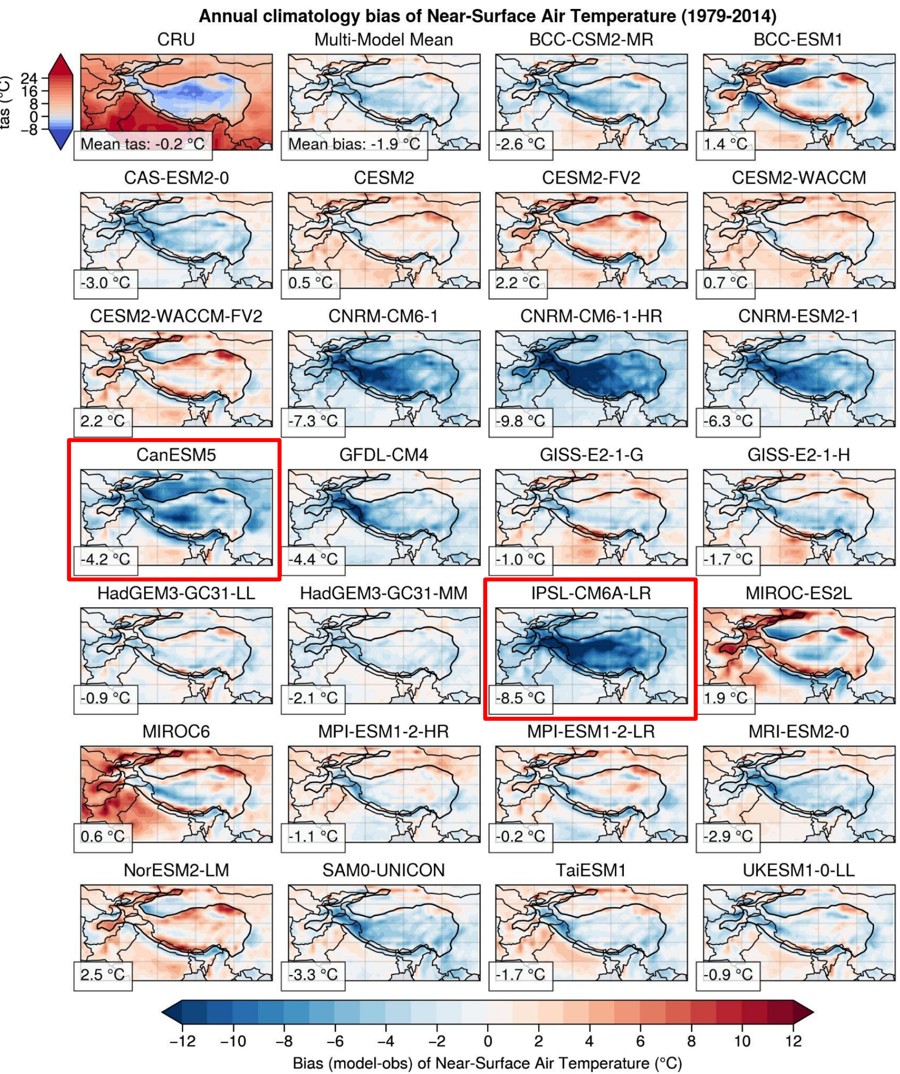

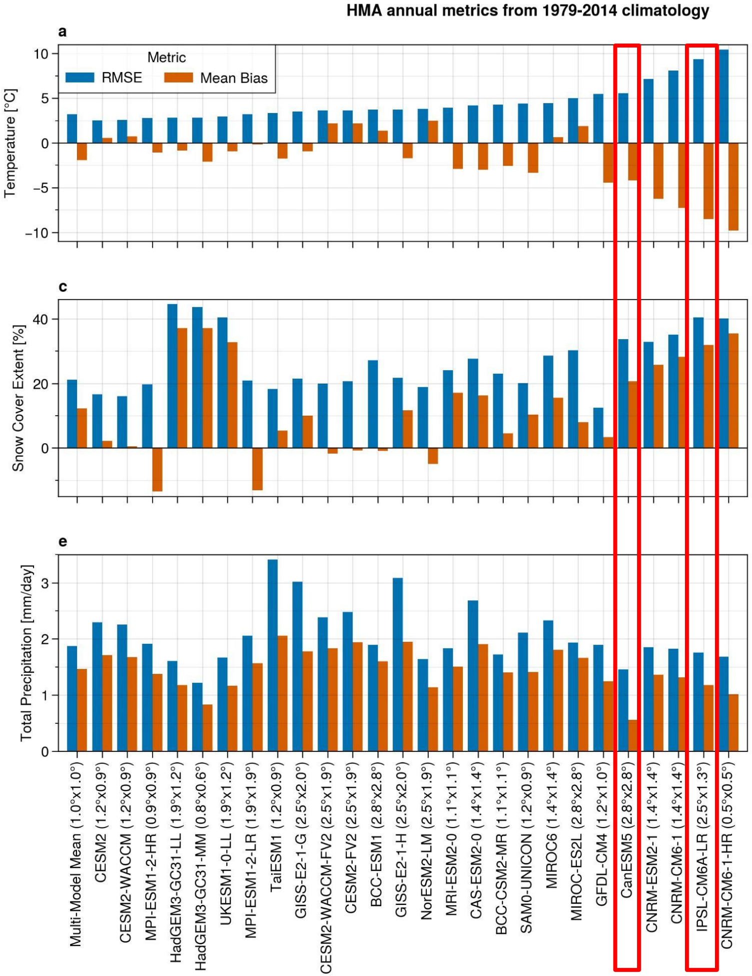

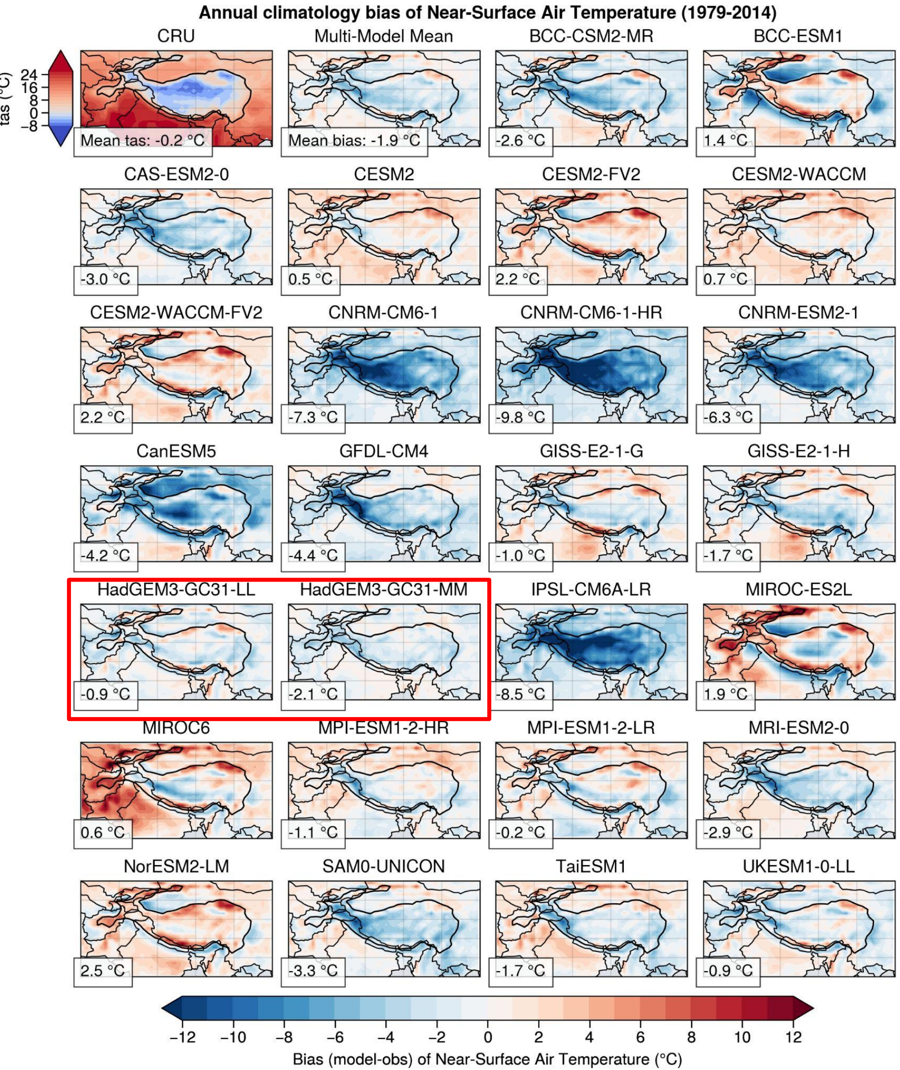

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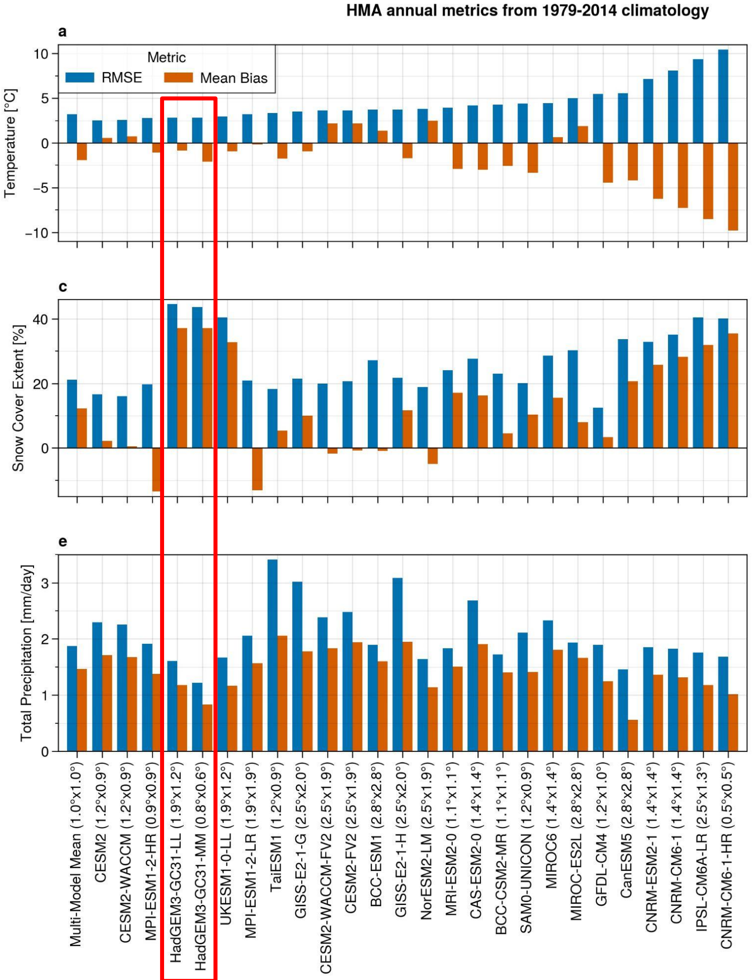
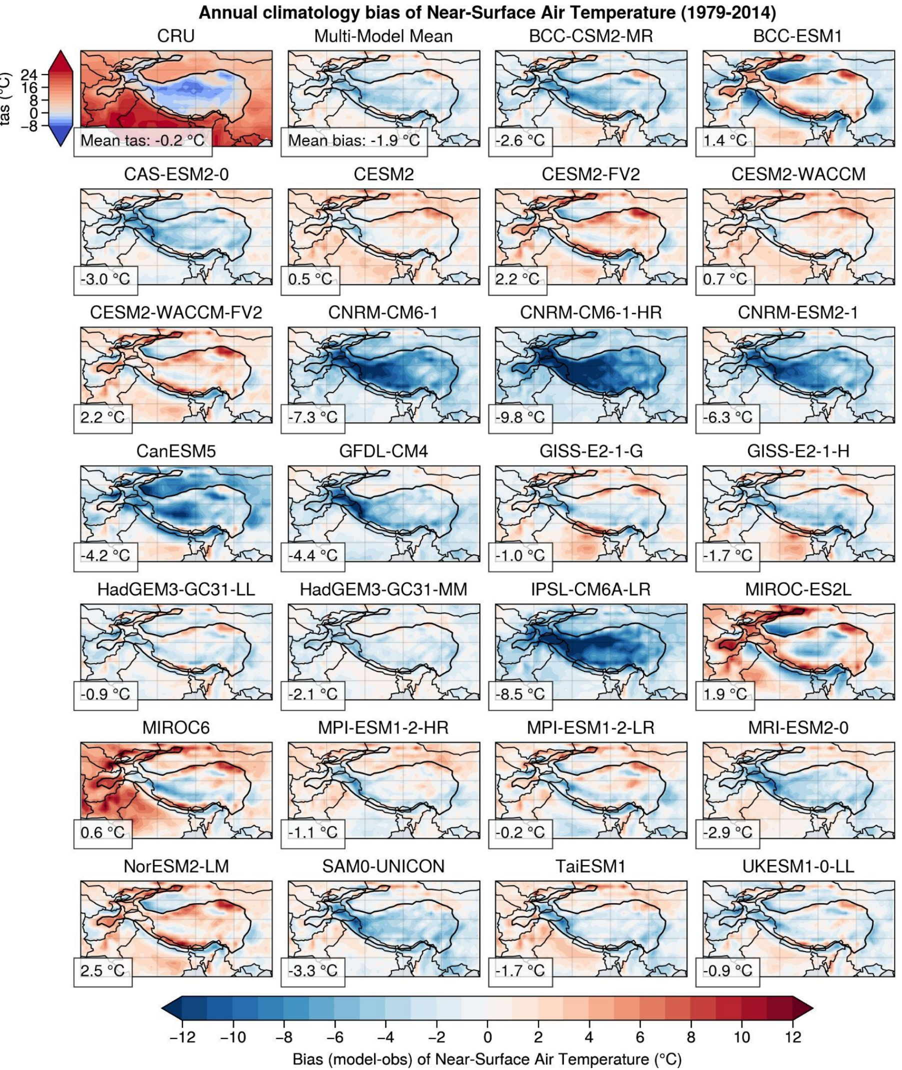
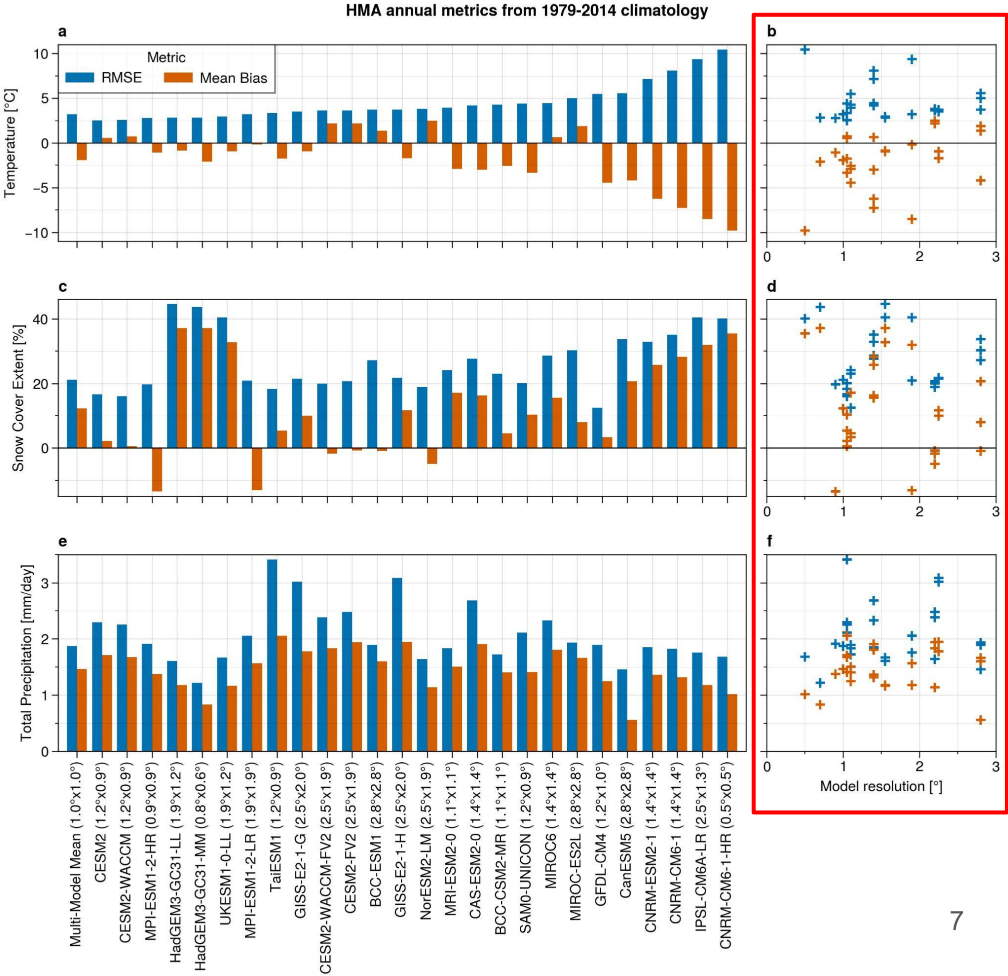
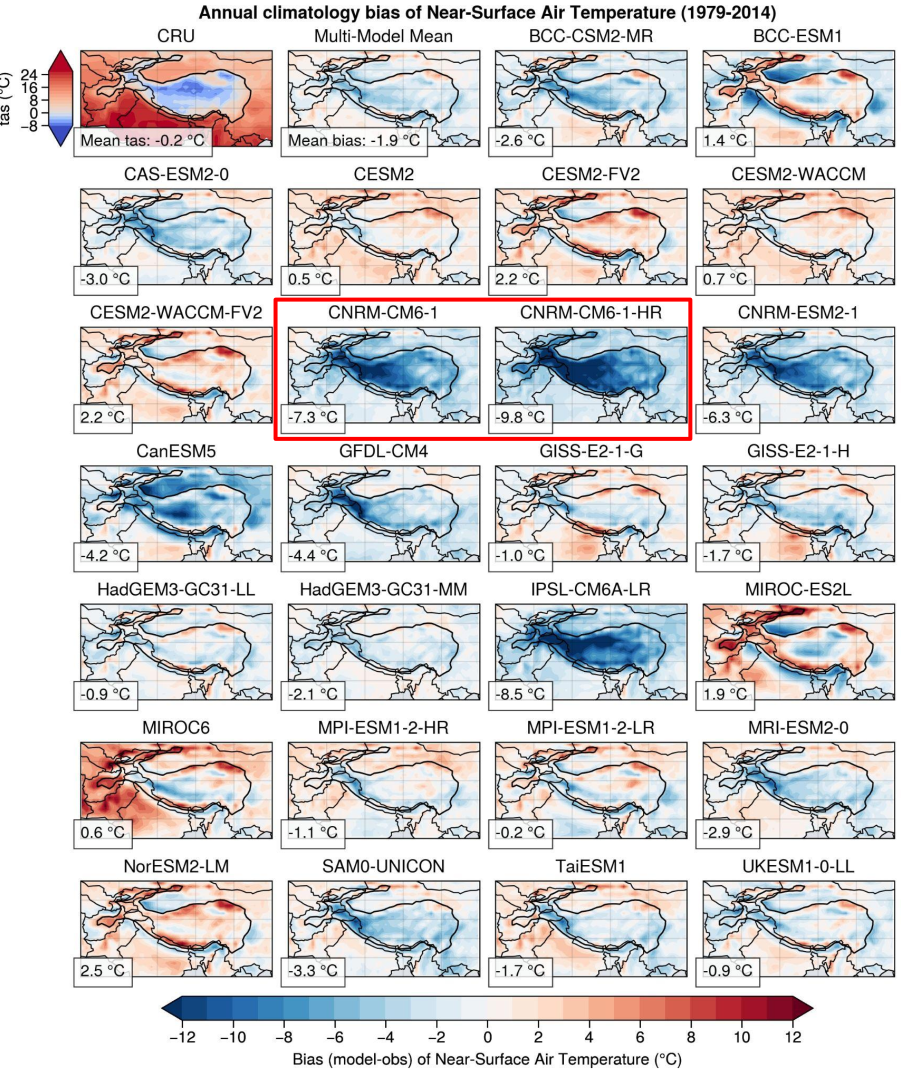


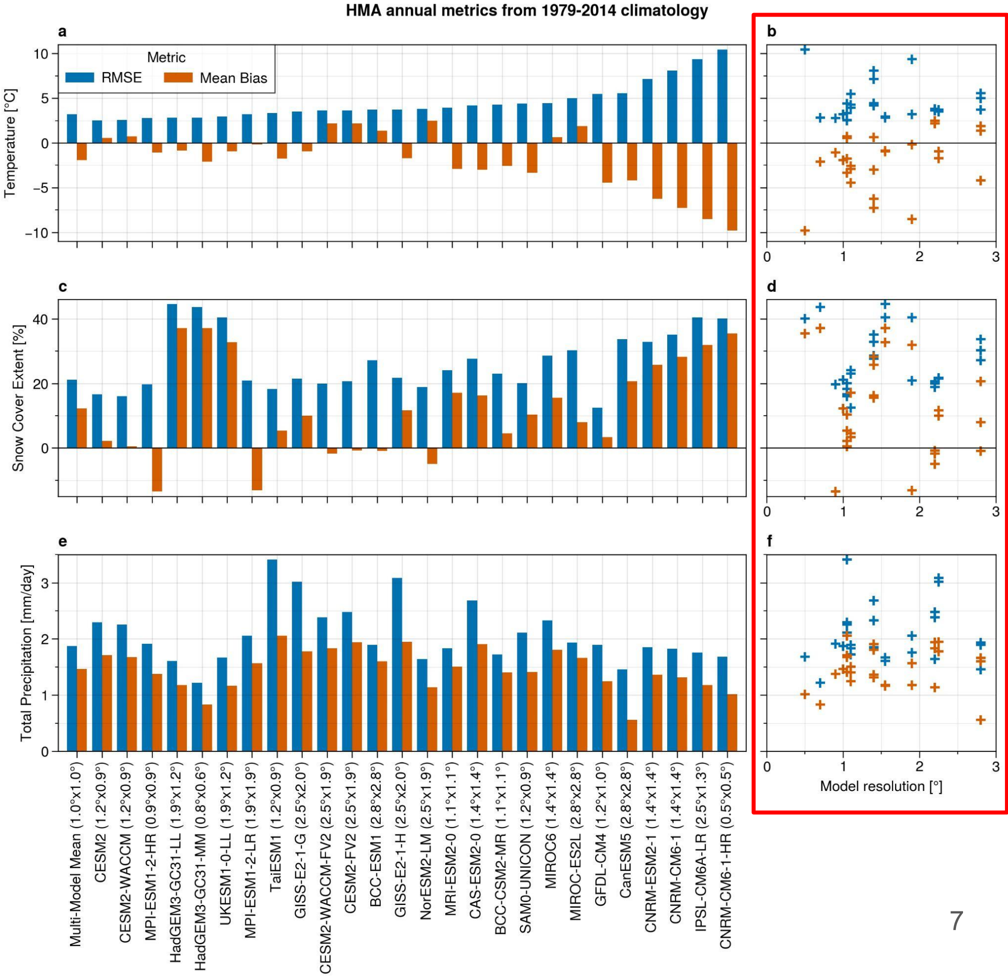
Spatial biases and metrics





Spatial biases and metrics





Bias spatial correlation

Annual spatial correlation of bias over HMA from 1979-2014 climatology

	BCC-CSM2-MR	BCC-ESM1	CAS-ESM2-0	CESM2	CESM2-FV2	CESM2-WACCM	CESM2-WACCM-FV2	CNRM-CM6-1	CNRM-CM6-1-HR	CNRM-ESM2-1	CanESM5	GFDL-CM4	GISS-E2-1-G
tas normalized bias	−0.26	0.14	−0.31	0.06	0.22	0.07	0.22	−0.74	−1	−0.64	−0.43	−0.45	−0.1
tas bias / snc bias	**−0.51**	**−0.45**	**−0.21**	−0.02	**−0.29**	0.01	**−0.29**	**−0.5**	**−0.39**	**−0.47**	**−0.53**	**−0.4**	**−0.36**
tas bias / pr bias	−0.09	**−0.22**	−0.08	**−0.18**	**−0.21**	**−0.19**	**−0.22**	0.02	−0.05	−0.02	**0.16**	**−0.16**	**−0.11**
snc bias / pr bias	**0.18**	**0.48**	**0.41**	**−0.22**	−0.05	**−0.18**	−0.04	**−0.23**	**−0.38**	**−0.23**	−0.06	0.04	−0.02
tas bias / elevation	**−0.41**	−0.04	**−0.36**	**−0.28**	−0.09	**−0.26**	−0.1	**−0.56**	**−0.66**	**−0.55**	**−0.32**	**−0.37**	**−0.34**
snc bias / elevation	**0.63**	**0.5**	**0.5**	**0.53**	**0.46**	**0.51**	**0.44**	**0.54**	**0.67**	**0.53**	**0.5**	**0.45**	**0.46**
pr bias / elevation	**0.18**	**0.43**	**0.12**	**−0.13**	0.07	**−0.12**	0.07	**−0.15**	**−0.31**	**−0.13**	−0.05	−0.08	**−0.19**

	GISS-E2-1-H	HadGEM3-GC31-LL	HadGEM3-GC31-MM	IPSL-CM6A-LR	MIROC-ES2L	MIROC6	MPI-ESM1-2-HR	MPI-ESM1-2-LR	MRI-ESM2-0	NorESM2-LM	SAM0-UNICON	TaiESM1	UKESM1-0-LL
tas normalized bias	−0.18	−0.09	−0.21	−0.87	0.19	0.07	−0.11	−0.02	−0.3	0.25	−0.34	−0.2	−0.1
tas bias / snc bias	**−0.35**	**−0.28**	**0.16**	**−0.62**	**−0.71**	**−0.58**	0.09	**−0.23**	**−0.16**	**−0.25**	**−0.18**	−0.09	**−0.17**
tas bias / pr bias	−0.04	−0.04	−0.07	0.02	−0.07	0.02	**−0.37**	**−0.35**	**−0.24**	**−0.26**	**−0.12**	**−0.14**	−0.02
snc bias / pr bias	0.03	0.05	−0.04	0.06	0.01	**−0.31**	**−0.12**	0.1	**−0.22**	**0.13**	0.1	0.01	−0.03
tas bias / elevation	**−0.43**	**−0.16**	−0.09	**−0.63**	**−0.28**	**−0.52**	**−0.3**	**−0.21**	**−0.42**	−0.05	**−0.45**	**−0.34**	**−0.12**
snc bias / elevation	**0.5**	**0.47**	**0.32**	**0.56**	**0.41**	**0.56**	**0.22**	**0.24**	**0.44**	**0.29**	**0.48**	**0.39**	**0.49**
pr bias / elevation	**−0.18**	0.01	**−0.28**	−0.06	0.03	−0.05	−0.01	**0.15**	0.01	−0.01	−0.03	**−0.12**	0.01

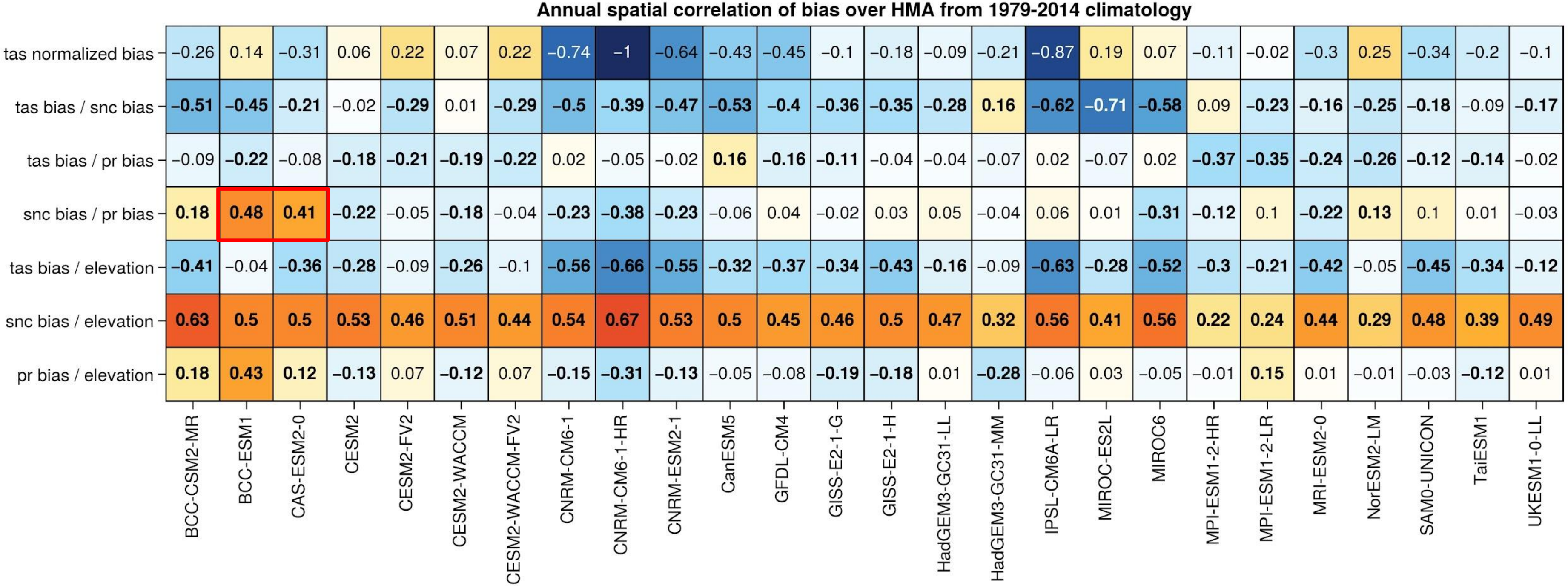
Bias spatial correlation

Annual spatial correlation of bias over HMA from 1979-2014 climatology

	BCC-CSM2-MR	BCC-ESM1	CAS-ESM2-0	CESM2	CESM2-FV2	CESM2-WACCM	CESM2-WACCM-FV2	CNRM-CM6-1	CNRM-CM6-1-HR	CNRM-ESM2-1	CanESM5	GFDL-CM4	GISS-E2-1-G	GISS-E2-1-H	HadGEM3-GC31-LL	HadGEM3-GC31-MM	IPSL-CM6A-LR	MIROC-ES2L	MIROC6	MPI-ESM1-2-HR	MPI-ESM1-2-LR	MRI-ESM2-0	NorESM2-LM	SAM0-UNICON	TaiESM1	UKESM1-0-LL
tas normalized bias	−0.26	0.14	−0.31	0.06	0.22	0.07	0.22	−0.74	−1	−0.64	−0.43	−0.45	−0.1	−0.18	−0.09	−0.21	−0.87	0.19	0.07	−0.11	−0.02	−0.3	0.25	−0.34	−0.2	−0.1
tas bias / snc bias	**−0.51**	**−0.45**	**−0.21**	−0.02	**−0.29**	0.01	**−0.29**	**−0.5**	**−0.39**	**−0.47**	**−0.53**	**−0.4**	**−0.36**	**−0.35**	**−0.28**	**0.16**	**−0.62**	**−0.71**	**−0.58**	0.09	**−0.23**	**−0.16**	**−0.25**	**−0.18**	−0.09	**−0.17**
tas bias / pr bias	−0.09	**−0.22**	−0.08	**−0.18**	**−0.21**	**−0.19**	**−0.22**	0.02	−0.05	−0.02	**0.16**	**−0.16**	**−0.11**	−0.04	−0.04	−0.07	0.02	−0.07	0.02	**−0.37**	**−0.35**	**−0.24**	**−0.26**	**−0.12**	**−0.14**	−0.02
snc bias / pr bias	**0.18**	**0.48**	**0.41**	**−0.22**	−0.05	**−0.18**	−0.04	**−0.23**	**−0.38**	**−0.23**	−0.06	0.04	−0.02	0.03	0.05	−0.04	0.06	0.01	**−0.31**	**−0.12**	0.1	**−0.22**	**0.13**	0.1	0.01	−0.03
tas bias / elevation	**−0.41**	−0.04	**−0.36**	**−0.28**	−0.09	**−0.26**	−0.1	**−0.56**	**−0.66**	**−0.55**	**−0.32**	**−0.37**	**−0.34**	**−0.43**	**−0.16**	−0.09	**−0.63**	**−0.28**	**−0.52**	**−0.3**	**−0.21**	**−0.42**	−0.05	**−0.45**	**−0.34**	**−0.12**
snc bias / elevation	**0.63**	**0.5**	**0.5**	**0.53**	**0.46**	**0.51**	**0.44**	**0.54**	**0.67**	**0.53**	**0.5**	**0.45**	**0.46**	**0.5**	**0.47**	**0.32**	**0.56**	**0.41**	**0.56**	**0.22**	**0.24**	**0.44**	**0.29**	**0.48**	**0.39**	**0.49**
pr bias / elevation	**0.18**	**0.43**	**0.12**	**−0.13**	0.07	**−0.12**	0.07	**−0.15**	**−0.31**	**−0.13**	−0.05	−0.08	**−0.19**	**−0.18**	0.01	**−0.28**	−0.06	0.03	−0.05	−0.01	**0.15**	0.01	−0.01	−0.03	**−0.12**	0.01

- Significant negative correlations between tas and snc biases

Bias spatial correlation



- Significant negative correlations between tas and snc biases
- Less obvious for pr (/!\ APHRODITE underestimate solid precip /!\ -> more negative correlation)

Bias spatial correlation

Annual spatial correlation of bias over HMA from 1979-2014 climatology

	BCC-CSM2-MR	BCC-ESM1	CAS-ESM2-0	CESM2	CESM2-FV2	CESM2-WACCM	CESM2-WACCM-FV2	CNRM-CM6-1	CNRM-CM6-1-HR	CNRM-ESM2-1	CanESM5	GFDL-CM4	GISS-E2-1-G	GISS-E2-1-H	HadGEM3-GC31-LL	HadGEM3-GC31-MM	IPSL-CM6A-LR	MIROC-ES2L	MIROC6	MPI-ESM1-2-HR	MPI-ESM1-2-LR	MRI-ESM2-0	NorESM2-LM	SAM0-UNICON	TaiESM1	UKESM1-0-LL
tas normalized bias	−0.26	0.14	−0.31	0.06	0.22	0.07	0.22	−0.74	−1	−0.64	−0.43	−0.45	−0.1	−0.18	−0.09	−0.21	−0.87	0.19	0.07	−0.11	−0.02	−0.3	0.25	−0.34	−0.2	−0.1
tas bias / snc bias	−0.51	−0.45	−0.21	−0.02	−0.29	0.01	−0.29	−0.5	−0.39	−0.47	−0.53	−0.4	−0.36	−0.35	−0.28	0.16	−0.62	−0.71	−0.58	0.09	−0.23	−0.16	−0.25	−0.18	−0.09	−0.17
tas bias / pr bias	−0.09	−0.22	−0.08	−0.18	−0.21	−0.19	−0.22	0.02	−0.05	−0.02	0.16	−0.16	−0.11	−0.04	−0.04	−0.07	0.02	−0.07	0.02	−0.37	−0.35	−0.24	−0.26	−0.12	−0.14	−0.02
snc bias / pr bias	0.18	0.48	0.41	−0.22	−0.05	−0.18	−0.04	−0.23	−0.38	−0.23	−0.06	0.04	−0.02	0.03	0.05	−0.04	0.06	0.01	−0.31	−0.12	0.1	−0.22	0.13	0.1	0.01	−0.03
tas bias / elevation	−0.41	−0.04	−0.36	−0.28	−0.09	−0.26	−0.1	−0.56	−0.66	−0.55	−0.32	−0.37	−0.34	−0.43	−0.16	−0.09	−0.63	−0.28	−0.52	−0.3	−0.21	−0.42	−0.05	−0.45	−0.34	−0.12
snc bias / elevation	0.63	0.5	0.5	0.53	0.46	0.51	0.44	0.54	0.67	0.53	0.5	0.45	0.46	0.5	0.47	0.32	0.56	0.41	0.56	0.22	0.24	0.44	0.29	0.48	0.39	0.49
pr bias / elevation	0.18	0.43	0.12	−0.13	0.07	−0.12	0.07	−0.15	−0.31	−0.13	−0.05	−0.08	−0.19	−0.18	0.01	−0.28	−0.06	0.03	−0.05	−0.01	0.15	0.01	−0.01	−0.03	−0.12	0.01

- Significant negative correlations between tas and snc biases
- Less obvious for pr (/!\ APHRODITE underestimate solid precip /!\ -> more negative correlation)
- Correlations between tas/snc biases with elevation -> difficulty representing physical processes at high elevation?

Bias spatial correlation

Annual spatial correlation of bias over HMA from 1979-2014 climatology

	BCC-CSM2-MR	BCC-ESM1	CAS-ESM2-0	CESM2	CESM2-FV2	CESM2-WACCM	CESM2-WACCM-FV2	CNRM-CM6-1	CNRM-CM6-1-HR	CNRM-ESM2-1	CanESM5	GFDL-CM4	GISS-E2-1-G
tas normalized bias	-0.26	0.14	-0.31	0.06	0.22	0.07	0.22	-0.74	-1	-0.64	-0.43	-0.45	-0.1
tas bias / snc bias	**-0.51**	**-0.45**	**-0.21**	-0.02	**-0.29**	0.01	**-0.29**	**-0.5**	**-0.39**	**-0.47**	**-0.53**	**-0.4**	**-0.36**
tas bias / pr bias	-0.09	**-0.22**	-0.08	**-0.18**	**-0.21**	**-0.19**	**-0.22**	0.02	-0.05	-0.02	**0.16**	**-0.16**	**-0.11**
snc bias / pr bias	**0.18**	**0.48**	**0.41**	**-0.22**	-0.05	**-0.18**	-0.04	**-0.23**	**-0.38**	**-0.23**	-0.06	0.04	-0.02
tas bias / elevation	**-0.41**	-0.04	**-0.36**	**-0.28**	-0.09	**-0.26**	-0.1	**-0.56**	**-0.66**	**-0.55**	**-0.32**	**-0.37**	**-0.34**
snc bias / elevation	**0.63**	**0.5**	**0.5**	**0.53**	**0.46**	**0.51**	**0.44**	**0.54**	**0.67**	**0.53**	**0.5**	**0.45**	**0.46**
pr bias / elevation	**0.18**	**0.43**	**0.12**	**-0.13**	0.07	**-0.12**	0.07	**-0.15**	**-0.31**	**-0.13**	-0.05	-0.08	**-0.19**

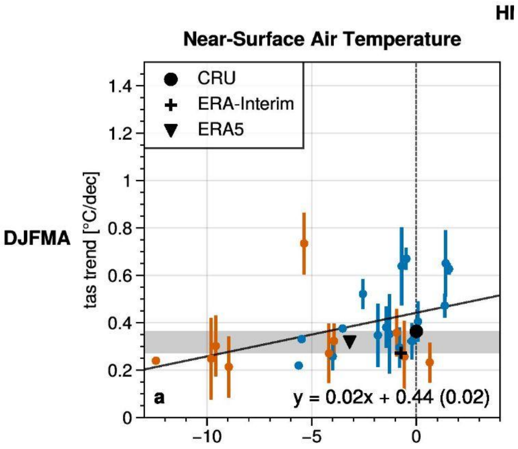
	GISS-E2-1-H	HadGEM3-GC31-LL	HadGEM3-GC31-MM	IPSL-CM6A-LR	MIROC-ES2L	MIROC6	MPI-ESM1-2-HR	MPI-ESM1-2-LR	MRI-ESM2-0	NorESM2-LM	SAM0-UNICON	TaiESM1	UKESM1-0-LL
tas normalized bias	-0.18	-0.09	-0.21	-0.87	0.19	0.07	-0.11	-0.02	-0.3	0.25	-0.34	-0.2	-0.1
tas bias / snc bias	**-0.35**	**-0.28**	**0.16**	**-0.62**	**-0.71**	**-0.58**	0.09	**-0.23**	**-0.16**	**-0.25**	**-0.18**	-0.09	**-0.17**
tas bias / pr bias	-0.04	-0.04	-0.07	0.02	-0.07	0.02	**-0.37**	**-0.35**	**-0.24**	**-0.26**	**-0.12**	**-0.14**	-0.02
snc bias / pr bias	0.03	0.05	-0.04	0.06	0.01	**-0.31**	**-0.12**	0.1	**-0.22**	**0.13**	0.1	0.01	-0.03
tas bias / elevation	**-0.43**	**-0.16**	-0.09	**-0.63**	**-0.28**	**-0.52**	**-0.3**	**-0.21**	**-0.42**	-0.05	**-0.45**	**-0.34**	**-0.12**
snc bias / elevation	**0.5**	**0.47**	**0.32**	**0.56**	**0.41**	**0.56**	**0.22**	**0.24**	**0.44**	**0.29**	**0.48**	**0.39**	**0.49**
pr bias / elevation	**-0.18**	0.01	**-0.28**	-0.06	0.03	-0.05	-0.01	**0.15**	0.01	-0.01	-0.03	**-0.12**	0.01

- Significant negative correlations between tas and snc biases
- Less obvious for pr (/!\ APHRODITE underestimate solid precip /!\ -> more negative correlation)
- Correlations between tas/snc biases with elevation -> difficulty representing physical processes at high elevation?

Are trends impacted by overall biases?

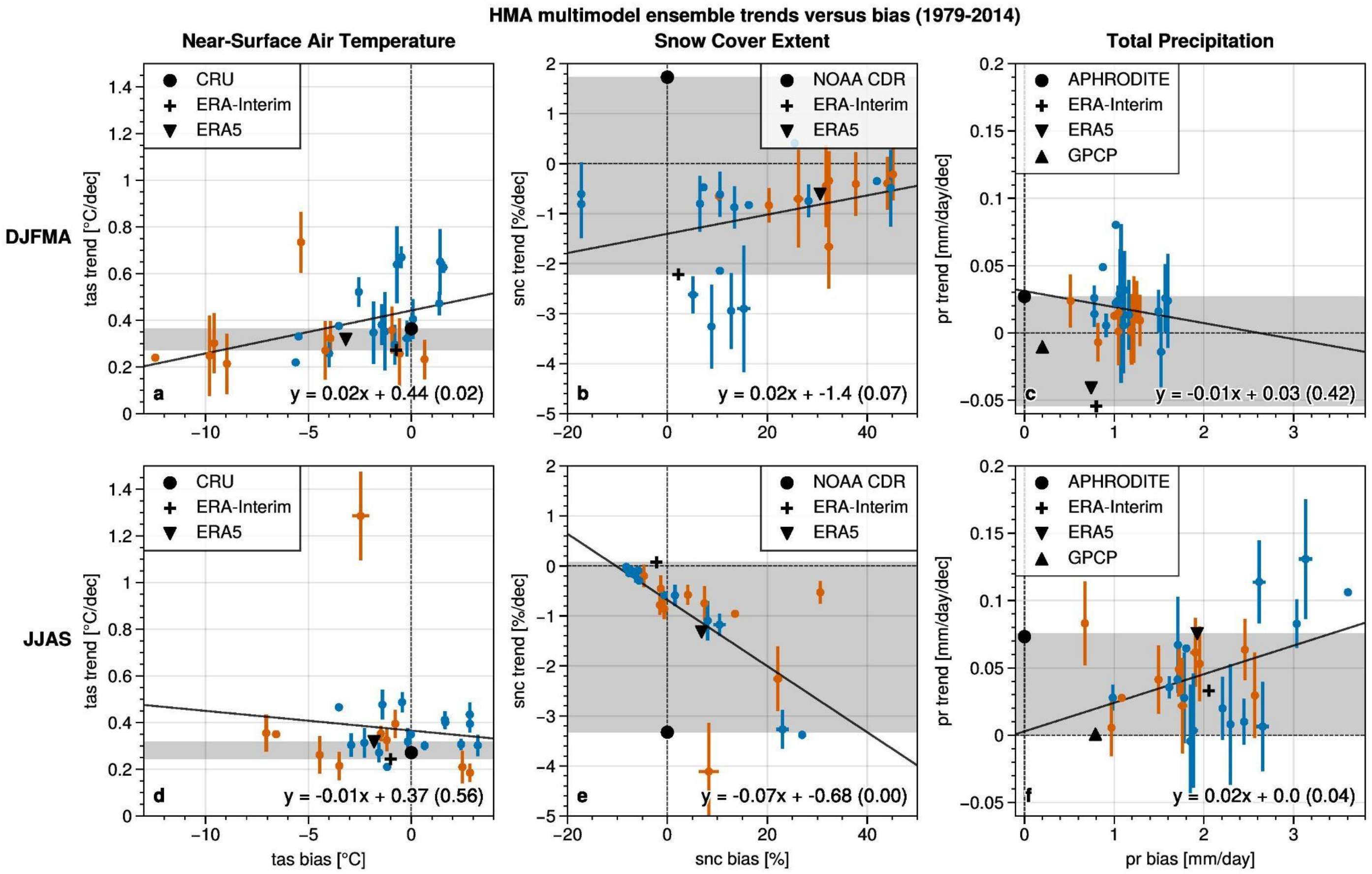
Historical trends analysis

- Available models for projections



Historical trends analysis

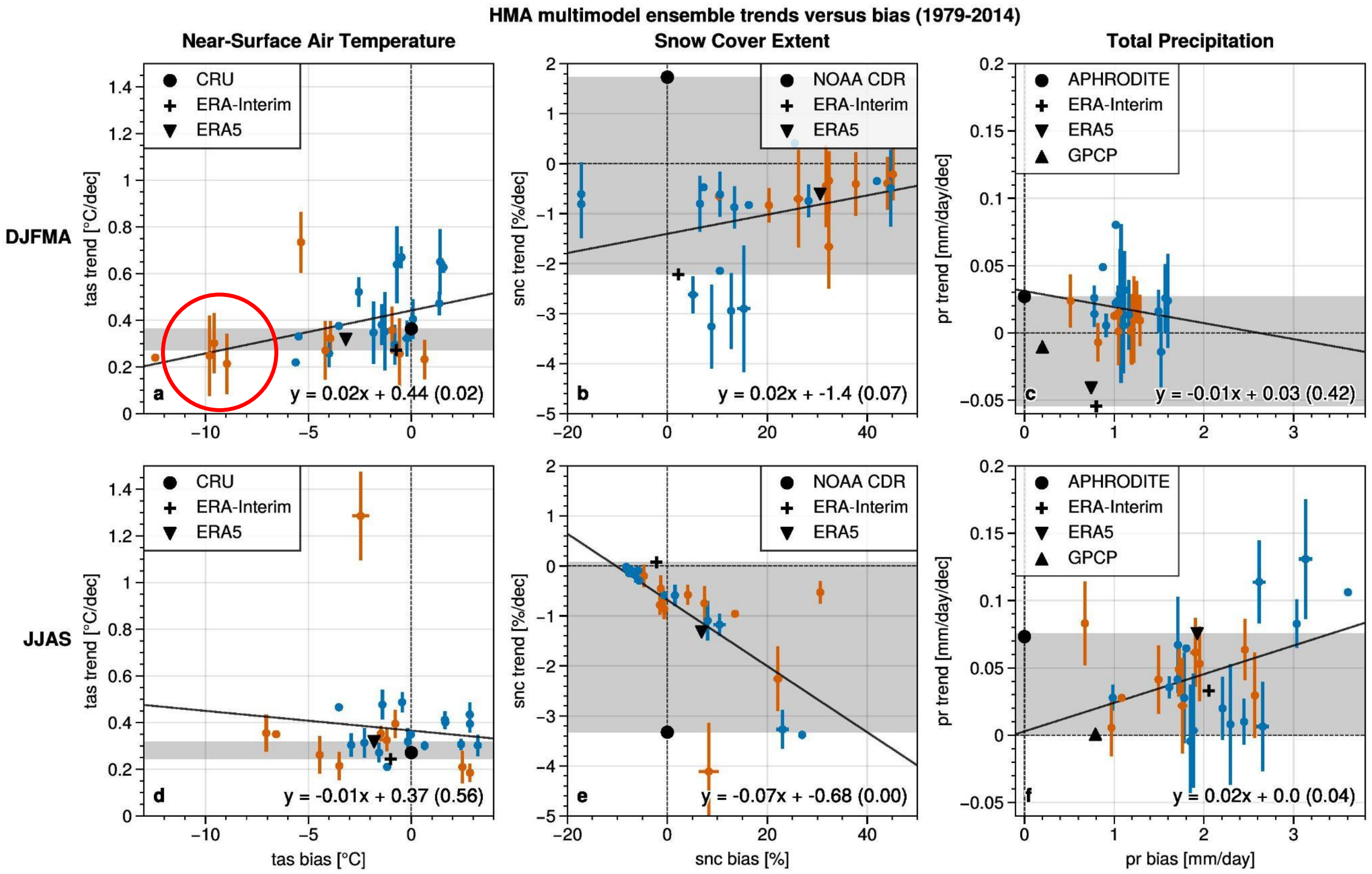
- Available models for projections



- No obvious link between model biases and trends

Historical trends analysis

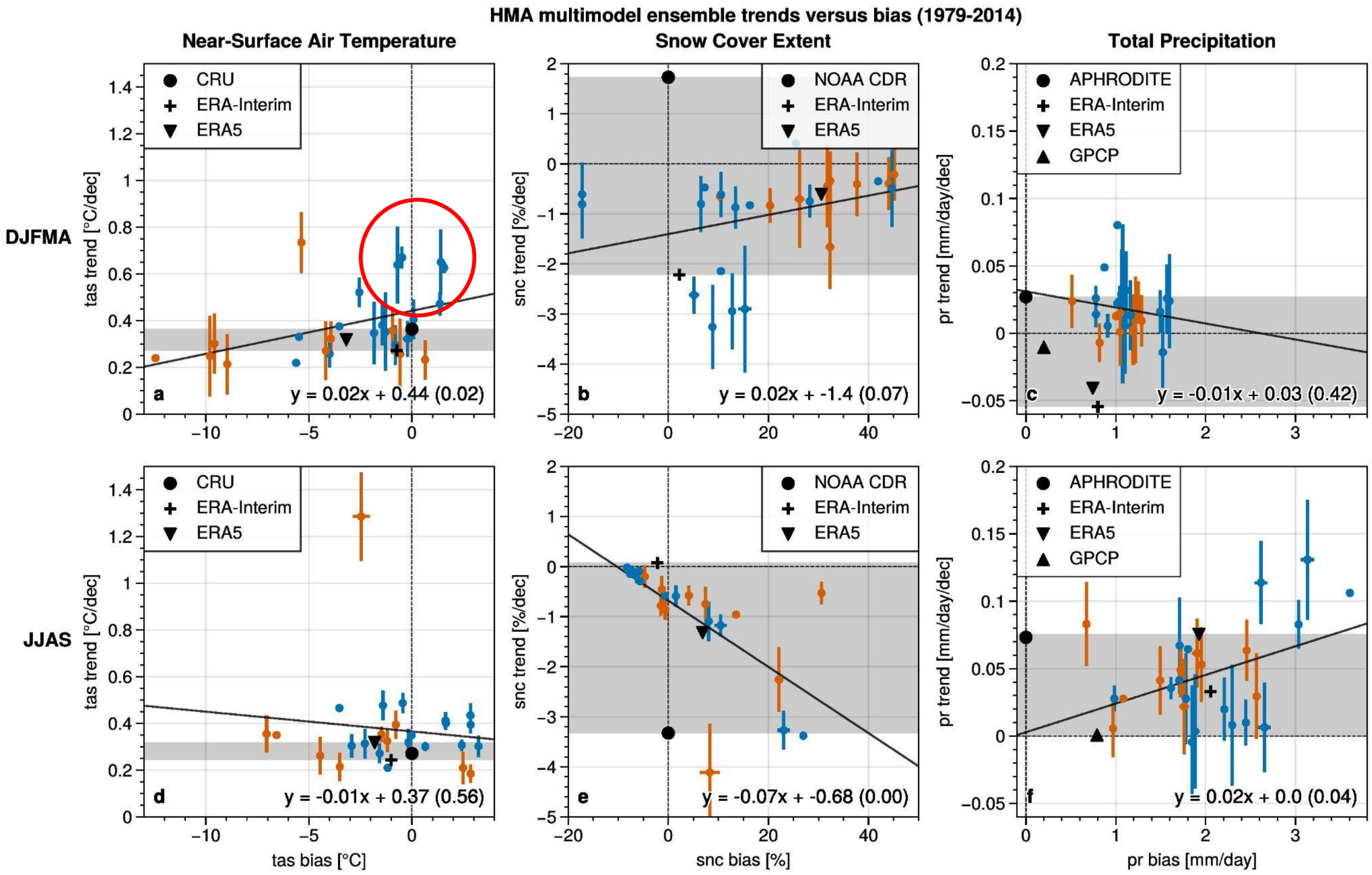
- Available models for projections



- No obvious link between model biases and trends
- Some strongly biased models have trends close to observations

Historical trends analysis

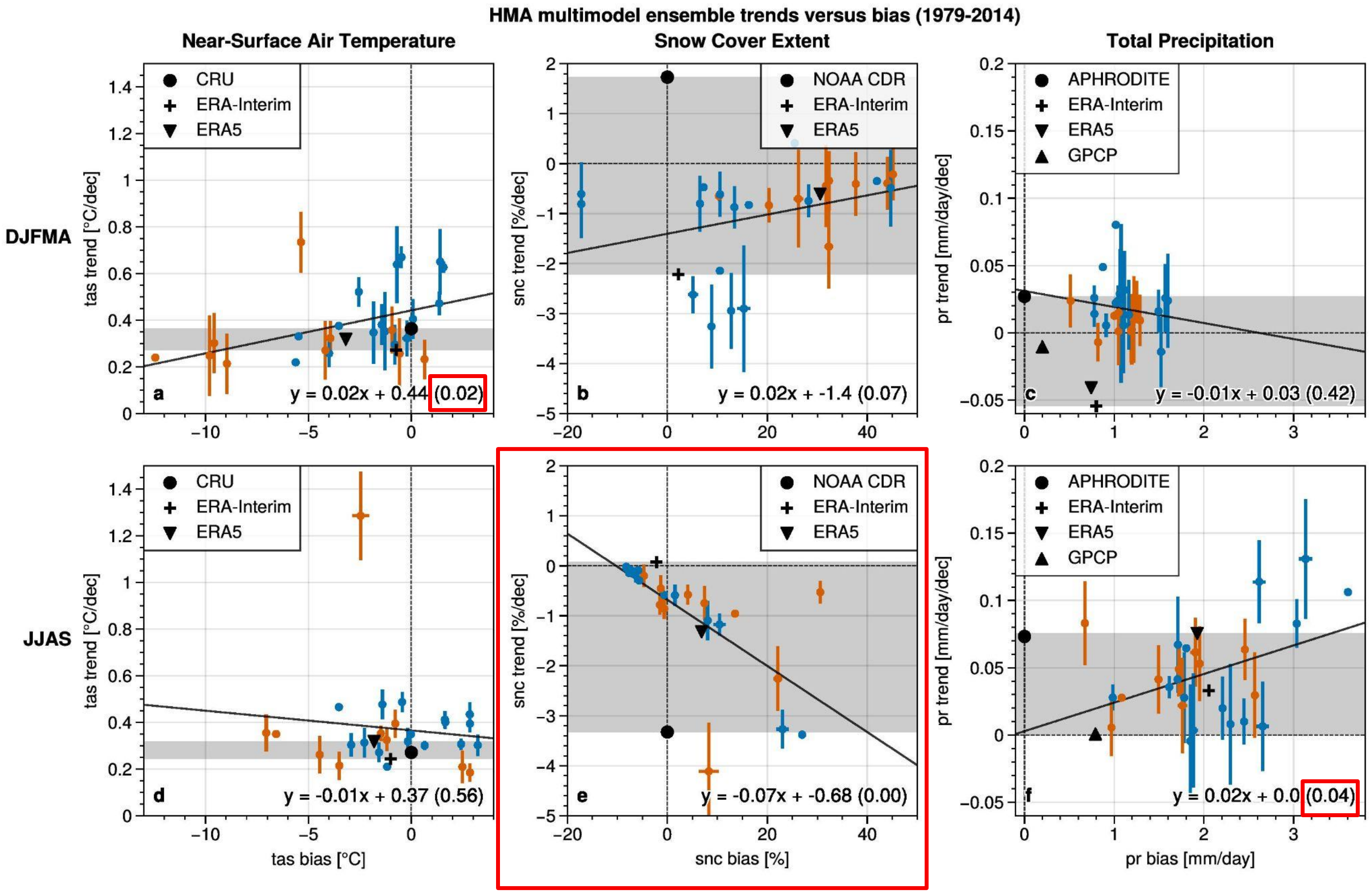
- Available models for projections



- No obvious link between model biases and trends
- Some strongly biased models have trends close to observations
- On the contrary, some models with little bias have very different trends

Historical trends analysis

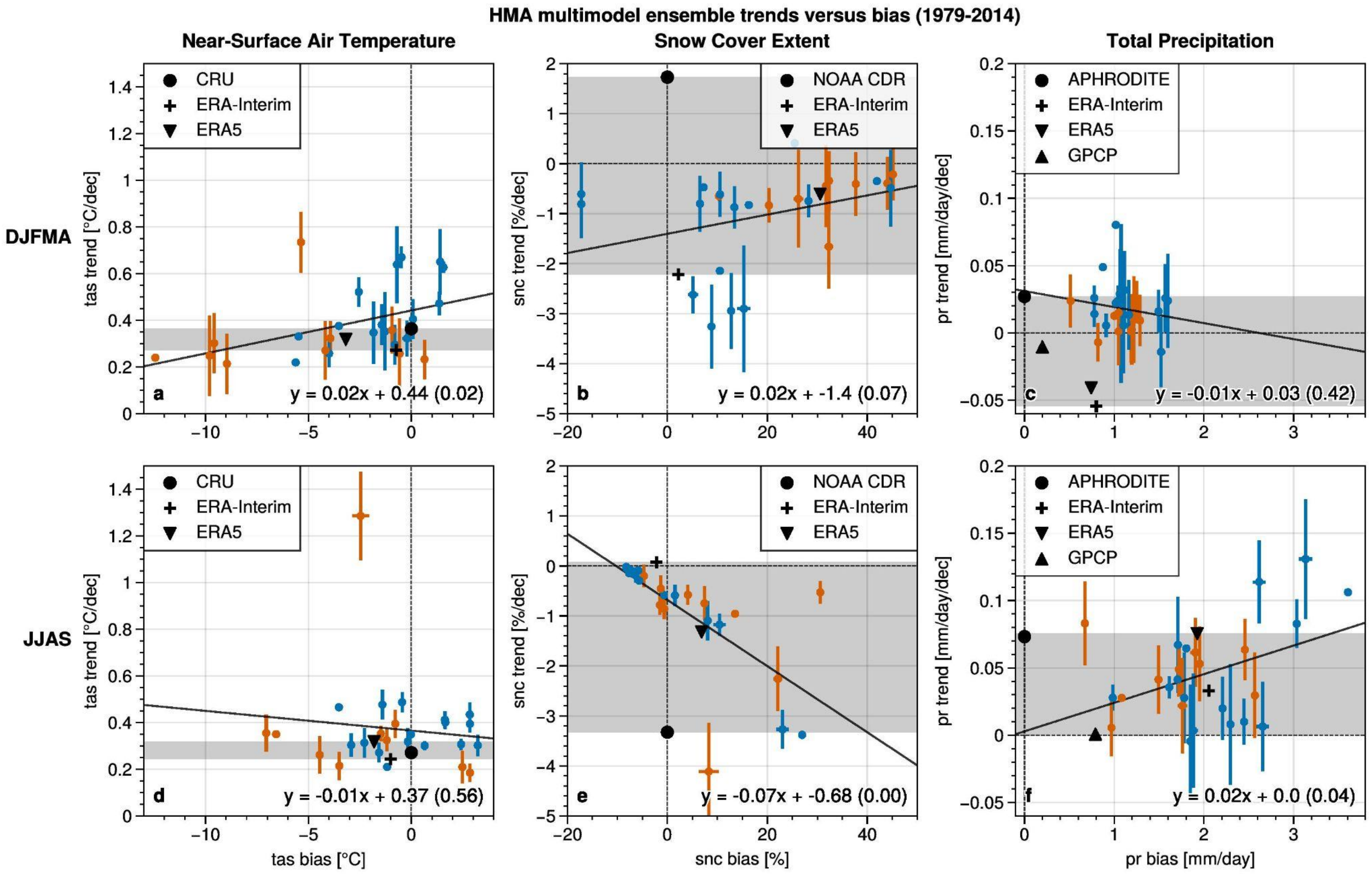
- Available models for projections



- No obvious link between model biases and trends
- Some strongly biased models have trends close to observations
- On the contrary, some models with little bias have very different trends
- Except for snow cover in summer -> very small snow cover

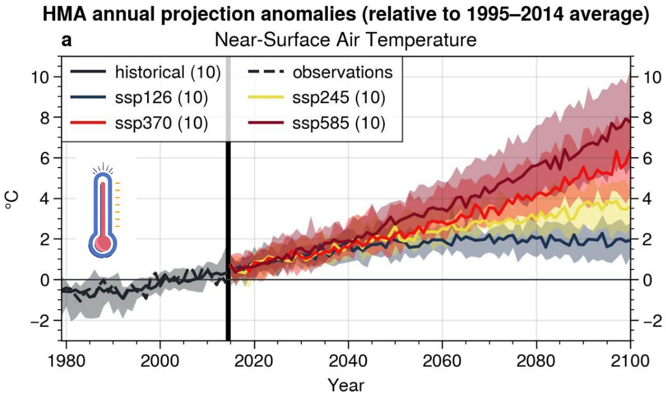
Historical trends analysis

- Available models for projections



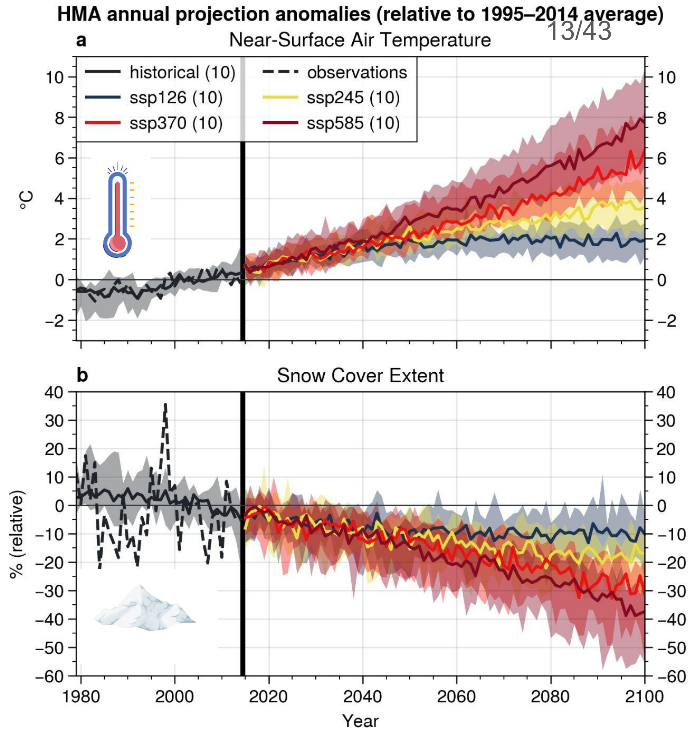
- No obvious link between model biases and trends
- Some strongly biased models have trends close to observations
- On the contrary, some models with little bias have very different trends
- Except for snow cover in summer -> very small snow cover

-> All available models are kept for projections (orange points)



Projections

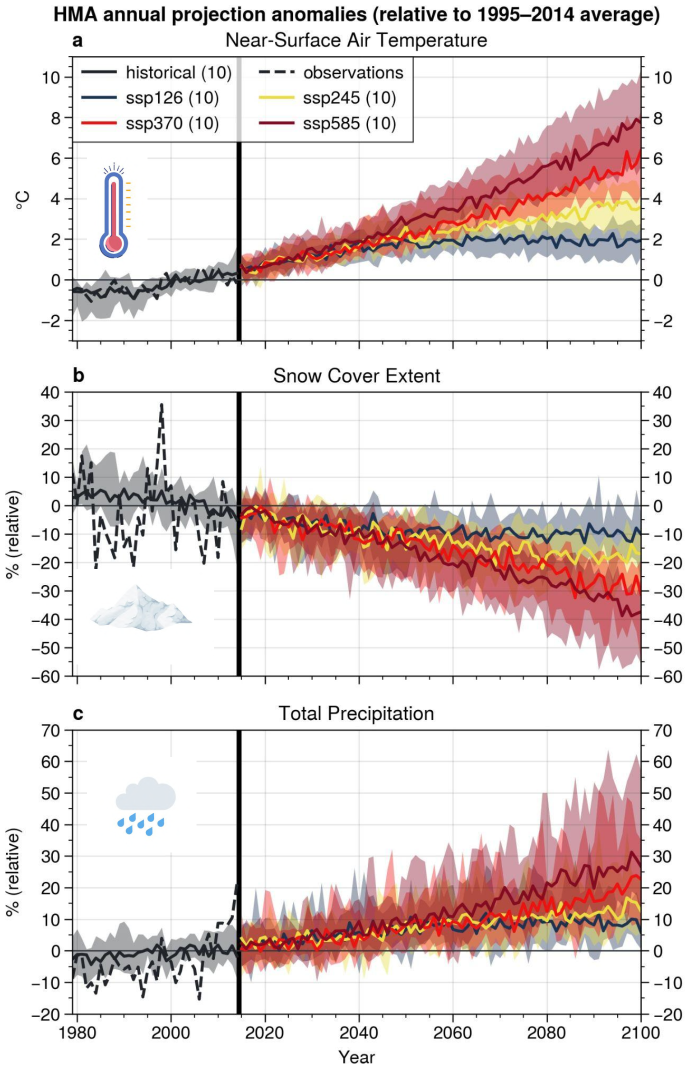
- annual median 2081-2100 with respect to 1995-2014 average:
  - tas: 1.9 [1.2 to 2.7] °C (SSP1-2.6) to 6.5 [4.9 to 9.0] °C (SSP5-8.5)



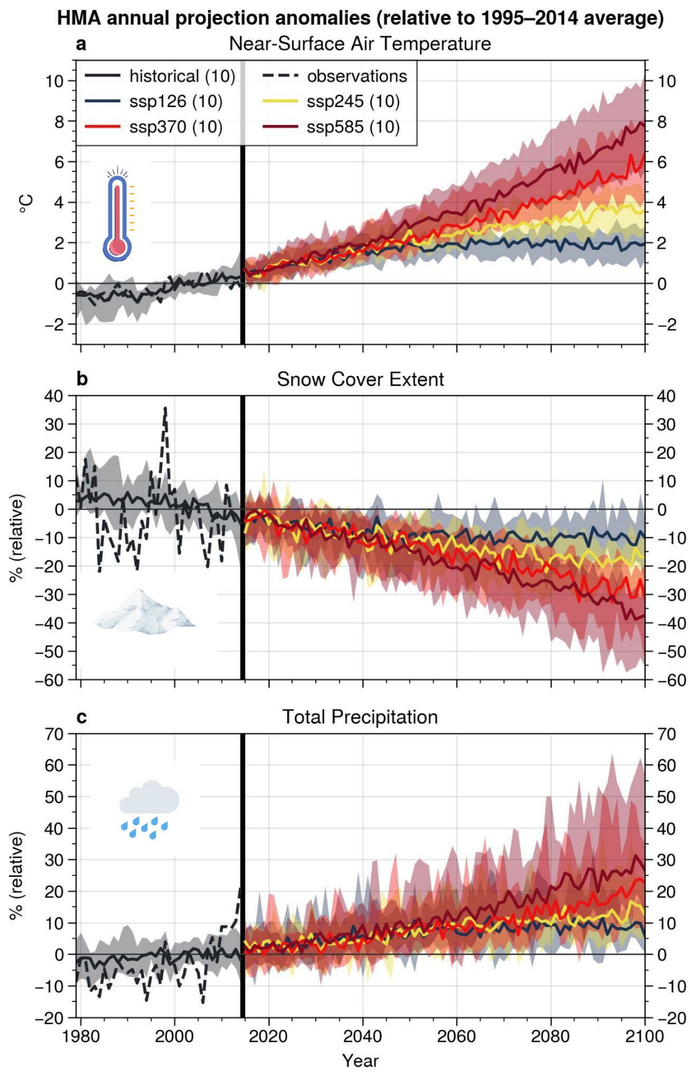
Projections

- annual median 2081-2100 with respect to 1995-2014 average:
  - tas: 1.9 [1.2 to 2.7] °C (SSP1-2.6) to 6.5 [4.9 to 9.0] °C (SSP5-8.5)
  - relative snc: -9.4 [-16.4 to -5.0] % (SSP1-2.6) to -32.2 [-49.1 to -25.0] % (SSP5-8.5)

Projections

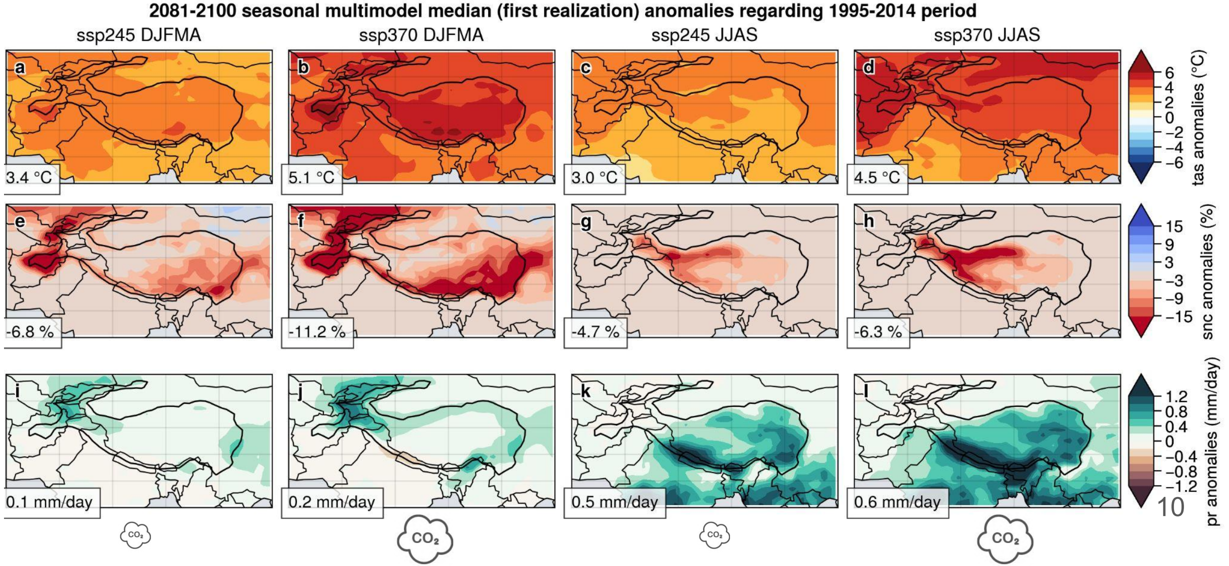


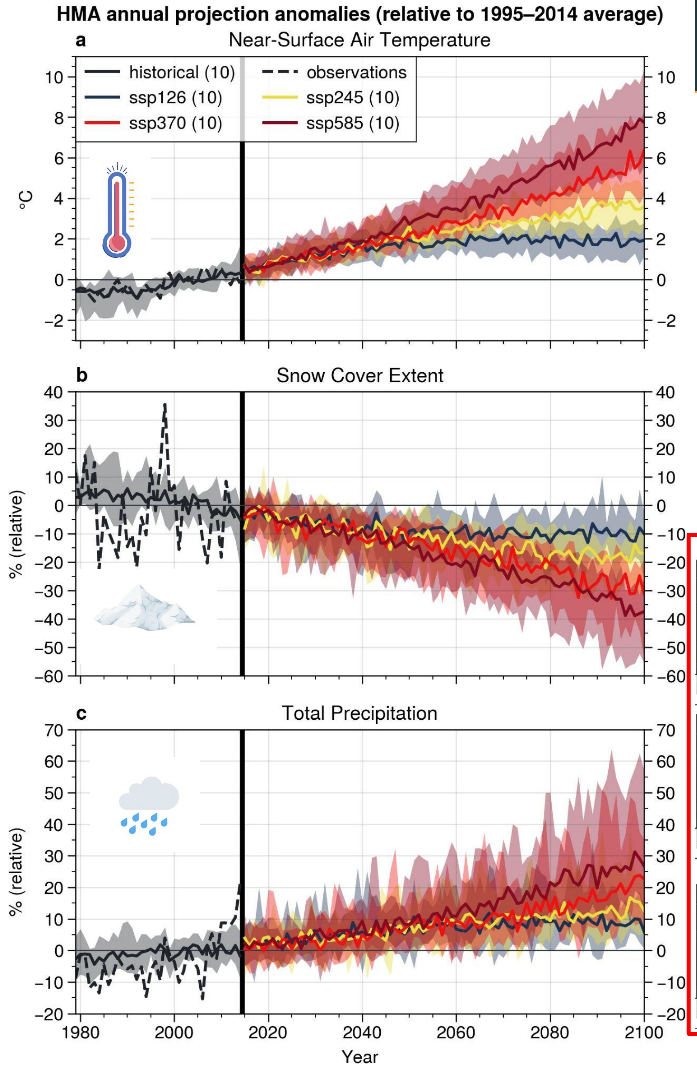
- annual median 2081-2100 with respect to 1995-2014 average:
  - tas: 1.9 [1.2 to 2.7] °C (SSP1-2.6) to 6.5 [4.9 to 9.0] °C (SSP5-8.5)
  - relative snc: -9.4 [-16.4 to -5.0] % (SSP1-2.6) to -32.2 [-49.1 to -25.0] % (SSP5-8.5)
  - relative pr: 8.5 [4.8 to 18.2] % (SSP1-2.6) to 24.9 [14.4 to 48.1] % (SSP5-8.5)



Projections

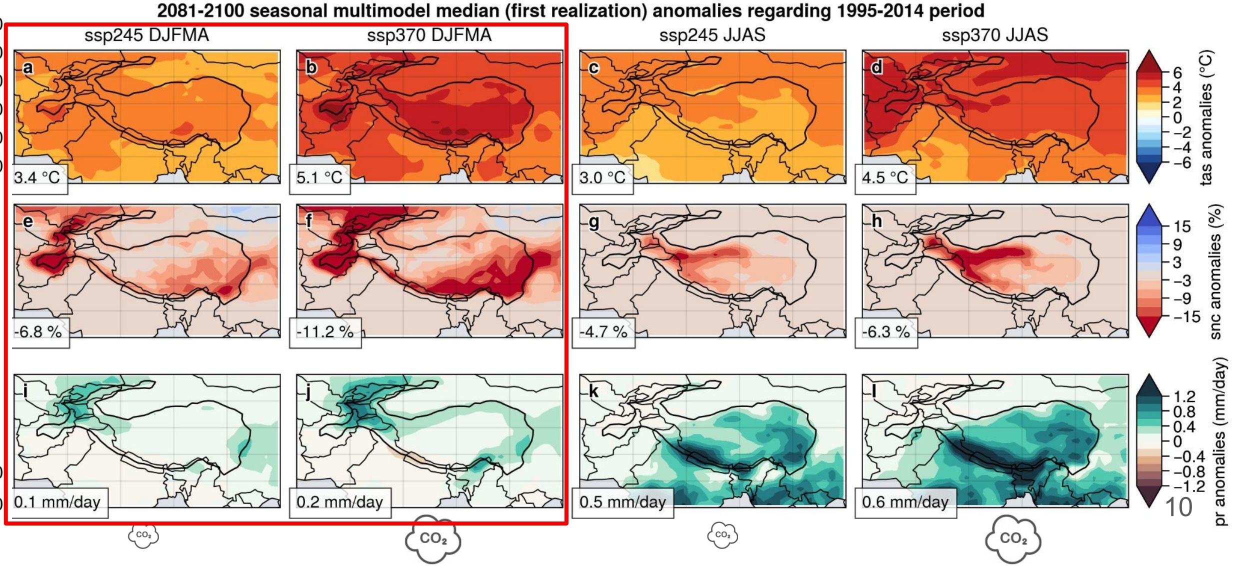
- annual median 2081-2100 with respect to 1995-2014 average:
  - tas: 1.9 [1.2 to 2.7] °C (SSP1-2.6) to 6.5 [4.9 to 9.0] °C (SSP5-8.5)
  - relative snc: -9.4 [-16.4 to -5.0] % (SSP1-2.6) to -32.2 [-49.1 to -25.0] % (SSP5-8.5)
  - relative pr: 8.5 [4.8 to 18.2] % (SSP1-2.6) to 24.9 [14.4 to 48.1] % (SSP5-8.5)

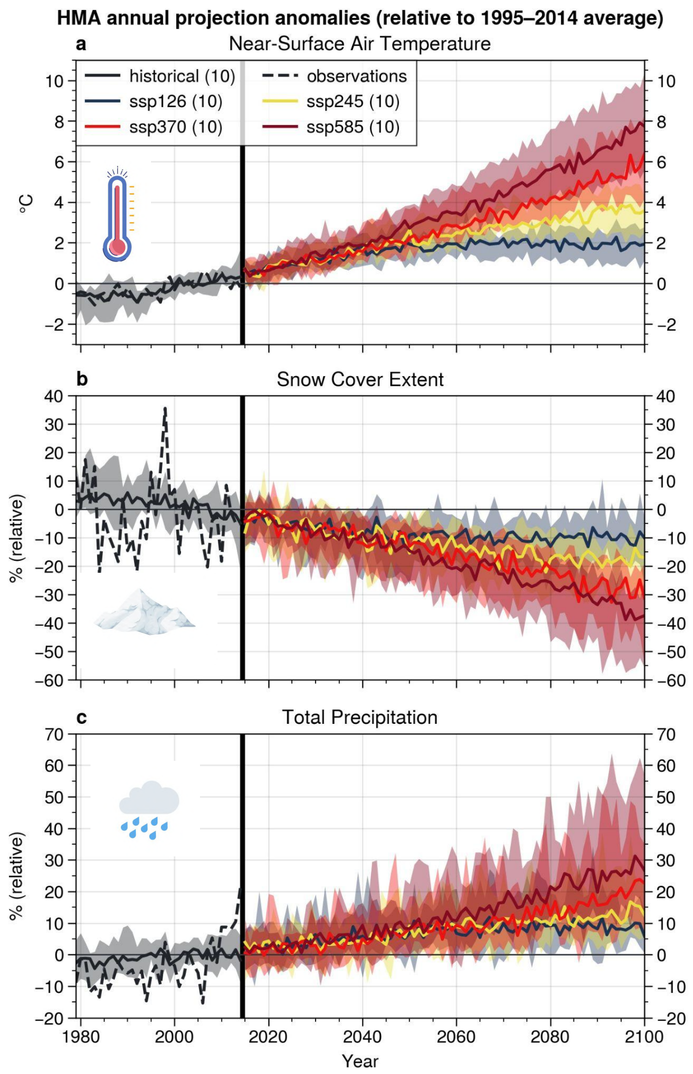




Projections

- annual median 2081-2100 with respect to 1995-2014 average:
  - tas: 1.9 [1.2 to 2.7] °C (SSP1-2.6) to 6.5 [4.9 to 9.0] °C (SSP5-8.5)
  - relative snc: -9.4 [-16.4 to -5.0] % (SSP1-2.6) to -32.2 [-49.1 to -25.0] % (SSP5-8.5)
  - relative pr: 8.5 [4.8 to 18.2] % (SSP1-2.6) to 24.9 [14.4 to 48.1] % (SSP5-8.5)





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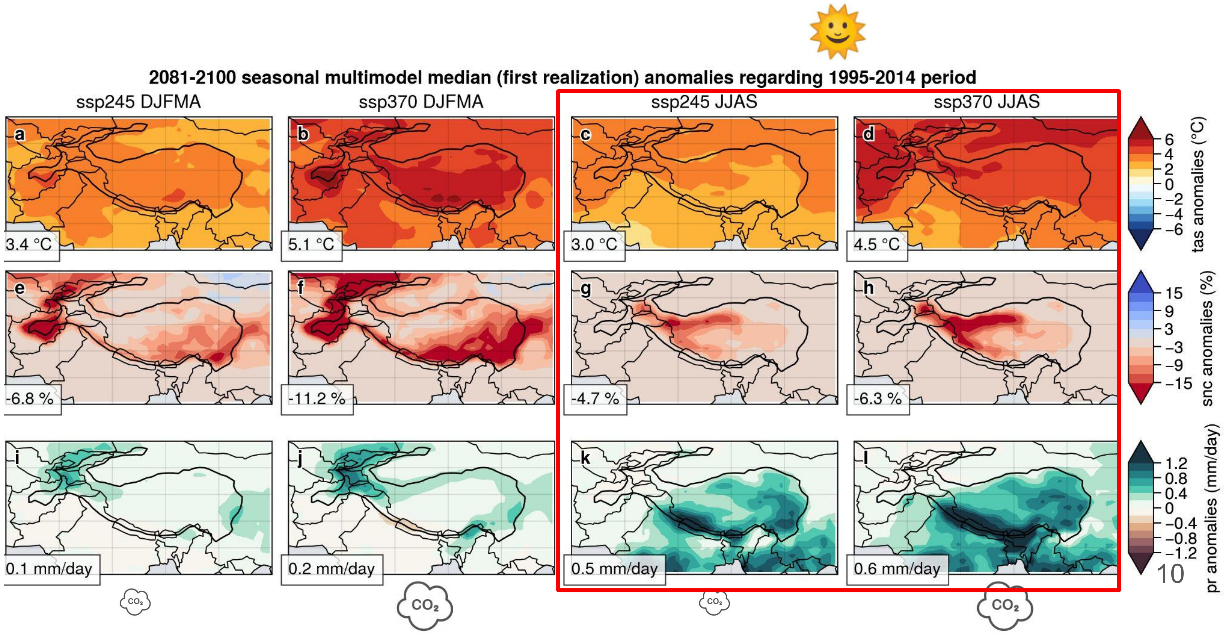

Take-home messages

- Multimodel analysis with 26 CMIP6 GCMs over HMA

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    - snc overestimated 12 [-13 to 43] % (or 52 [-53 to 183] % relative)
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- Annual projections (2081-2100 with respect to 1995-2014 average with 10 GCMs):
  - median warming from 1.9 °C to 6.5 °C
  - relative median snc decrease from -9.4 % to -32.2 %
  - relative median pr increase from 8.5 % to 24.9 %

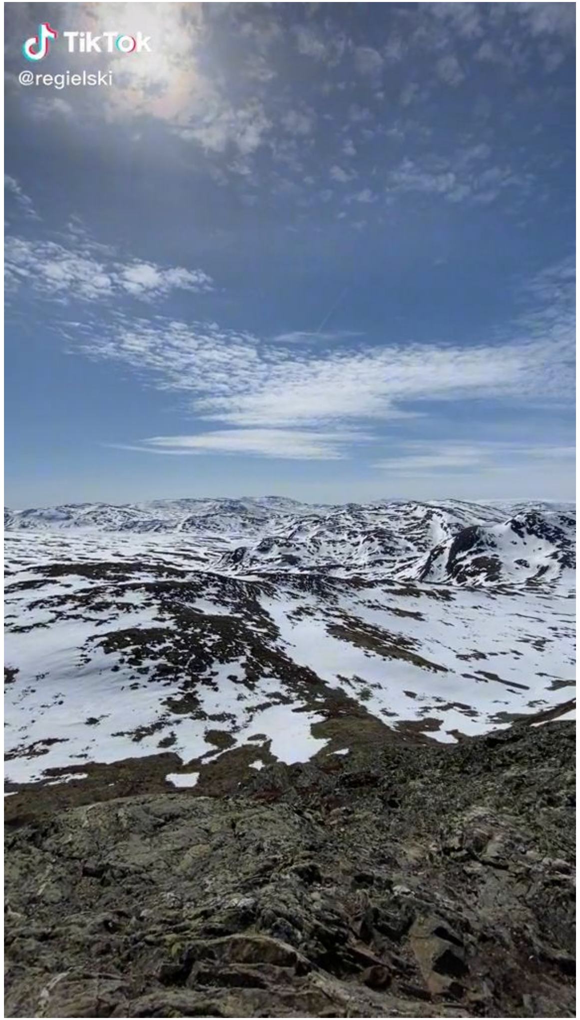
Part #2

Reducing the High Mountain Asia cold bias in GCMs by adapting snow cover parameterization to complex topography areas

Mickaël Lalande[1], Martin Ménégoz[1], Gerhard Krinner[1], Catherine Ottlé[2], and Frédérique Cheruy[3]

[1] Univ. Grenoble Alpes, CNRS, IRD, G-INP, IGE, 38000 Grenoble, France
[2] LSCE-IPSL (CNRS-CEA-UVSQ), Université Paris-Saclay, Gif-sur-Yvette, France
[3] Laboratoire de Météorologie Dynamique (LMD)/IPSL/Sorbonne Université/CNRS, UMR 8539, Paris, France

The Cryosphere Discuss. [preprint], https://doi.org/10.5194/tc-2023-113, in review, 2023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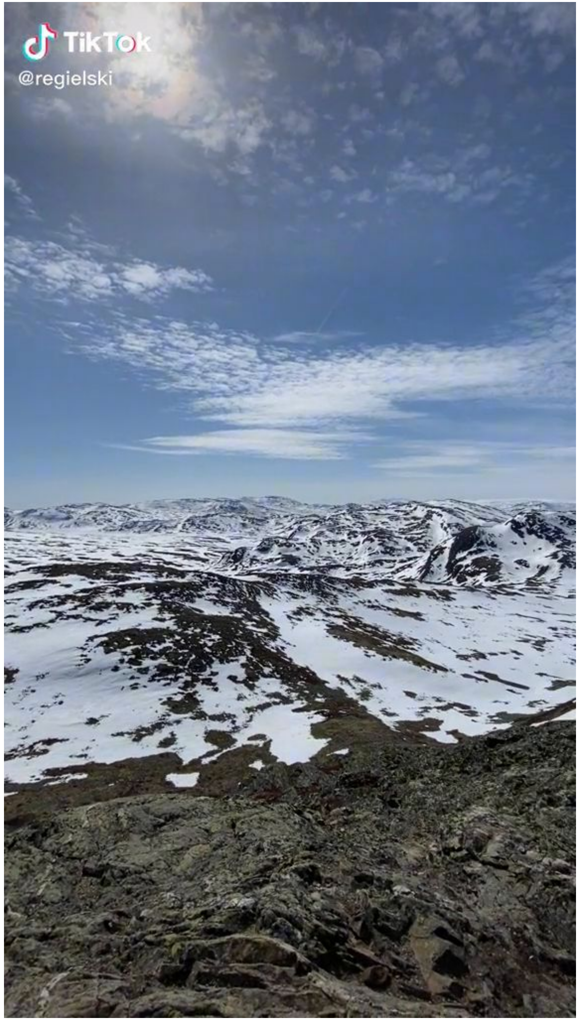
@regielski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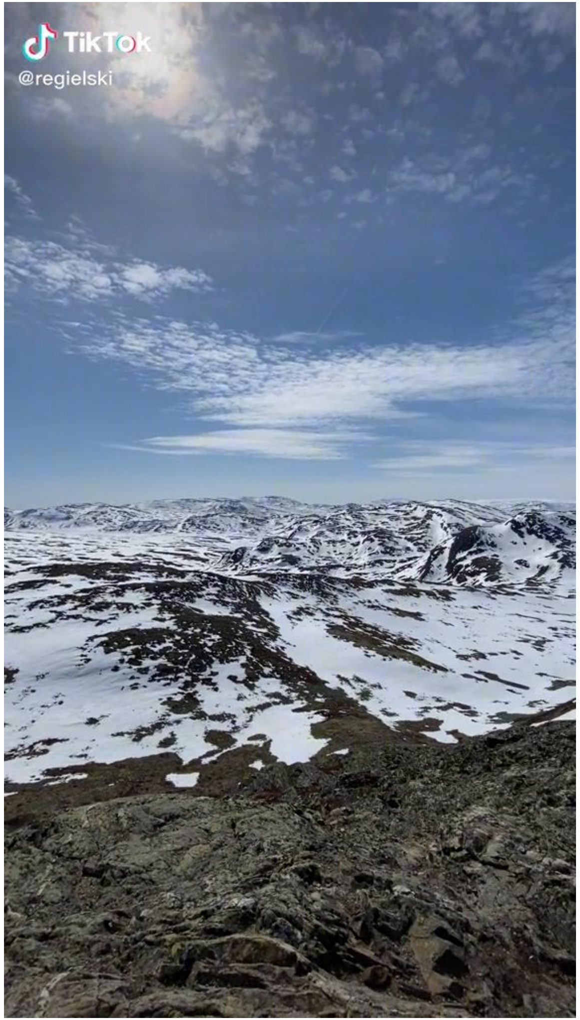
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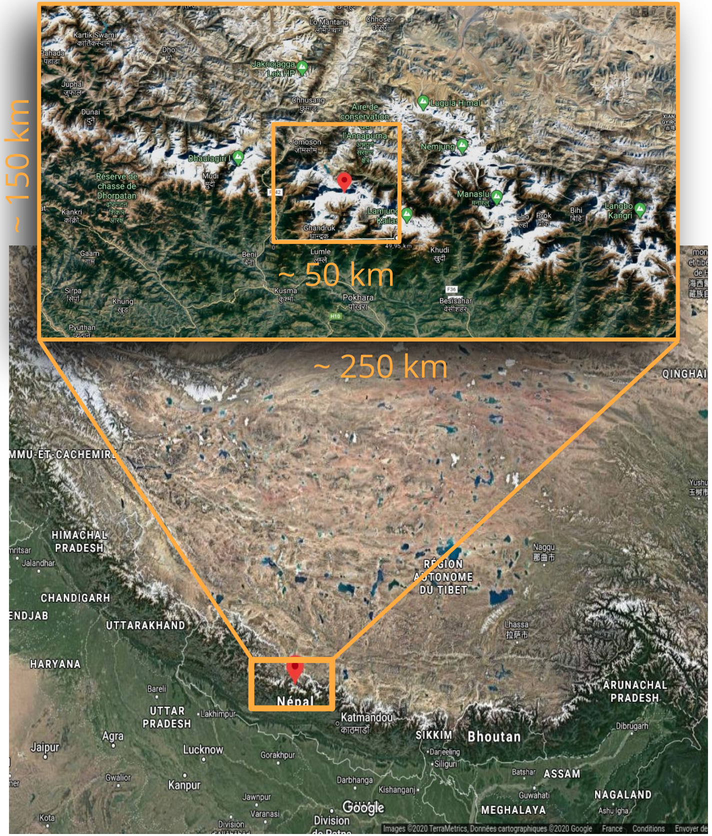
Snow cover over mountainous areas in global climate models



IPSL-CM6A

How do we compute the

snow cover fraction (SCF)

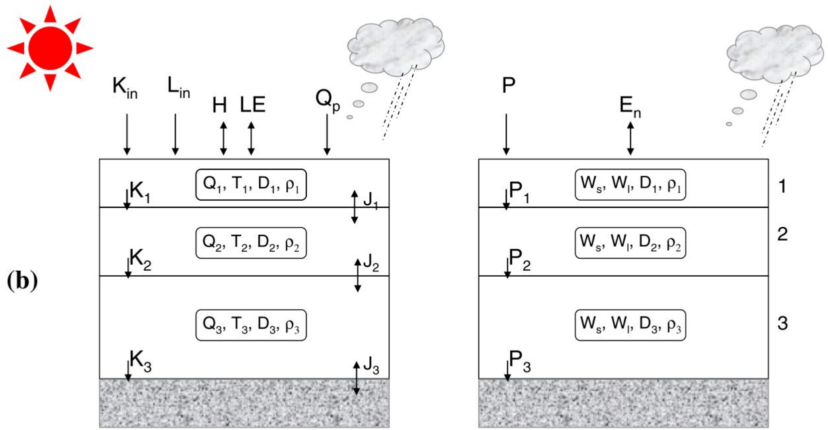
in global climate models?

&

How does the SCF evolves

over mountainous areas?

Snow scheme



$\mathbf{K_{in}}$ (short wave radiation), $\mathbf{L_{in}}$ (longwave radiation), **H** (sensible heat flux), **LE**(latent heat flux), **J** (conduction heat flux), **Q** (snow layer heat content), $\mathbf{Q_p}$(advective heat from rain and snow), **W** (snow layer SWE), $\mathbf{W_l}$ (snow layer liquid water content), **D** (snow layer depth), **ρ** (snow layer density) , **P** (precipitation), $\mathbf{E_n}$ (evaporation)

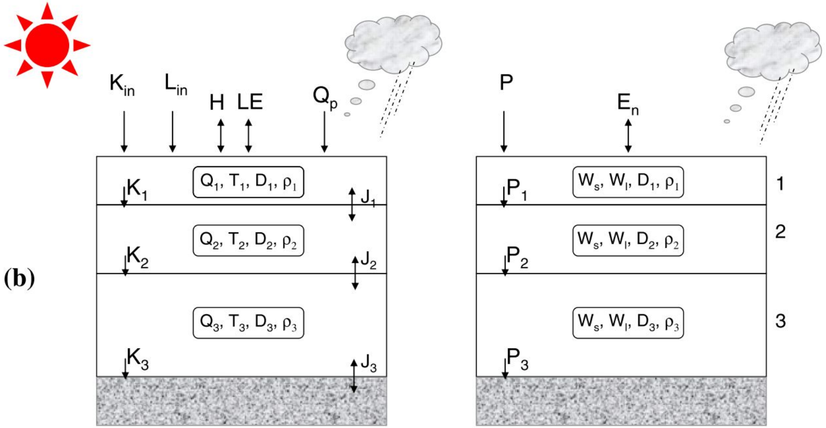
snow scheme in the ORCHIDEE land surface model
(Wang et al., 2013)

Snow Depth

Snow Water Equivalent

Snow Density

Snow scheme



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Snow Cover Fraction

Snow cover parameterizations

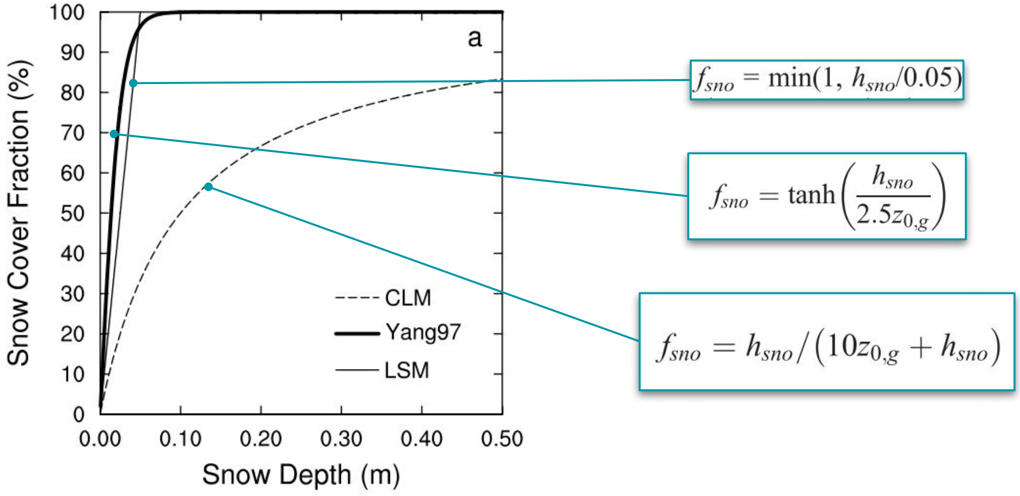


Figure 1. (a) SCF (or f_{sno}) computed from equation (2) (used in the default CLM and BATS), equation (3) of *Yang et al.* [1997], and a formulation used in the NCAR LSM1.0, $f_{sno} = \min(1,\ h_{sno}/0.05)$, where h_{sno} is snow depth (m) and (b) SCF as a function of ground surface roughness, snow depth, and snow density computed from equation (4) with new snow density $\rho_{new} = 100$ kg m^{-3} and $m = 1.6$. The thick line (i.e., $\rho_{sno} = 100$ kg m^{-3}) is equivalent to equation (3).

Niu and Yang (2007)

Snow Cover parameterization: Niu and Yang (2007) - NY07

$$f_{sno} = \tanh\left(\frac{h_{sno}}{2.5 z_{0g} (\rho_{sno}/\rho_{new})^m}\right)$$

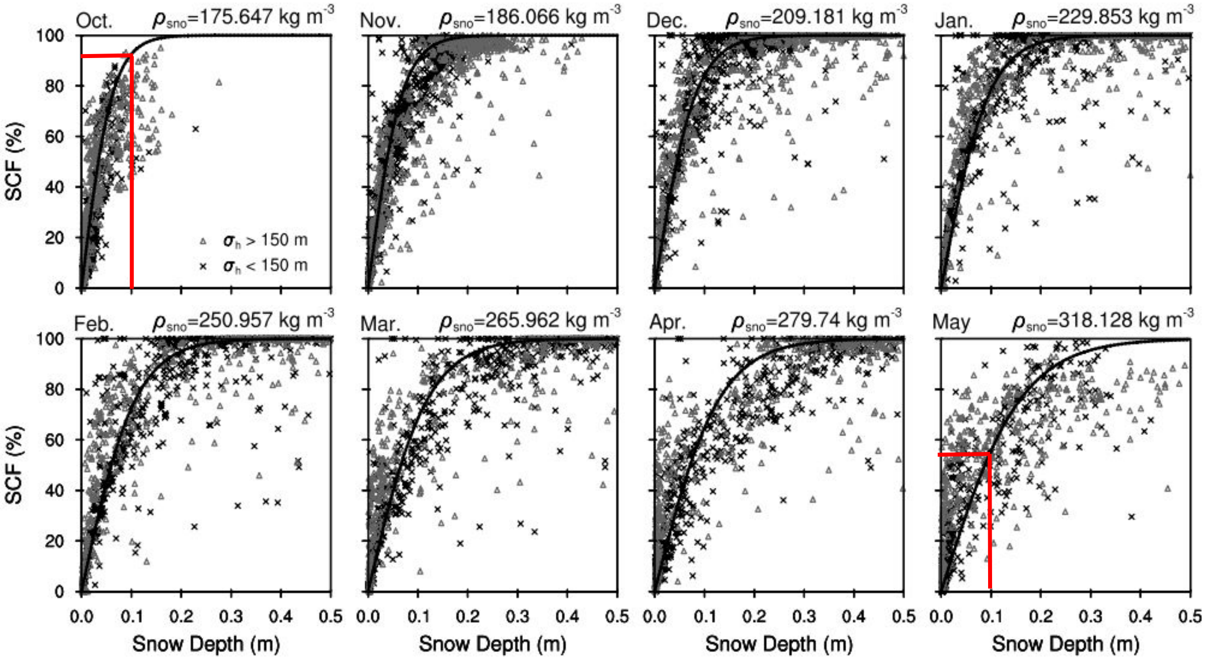


Figure 2. Relationship between AVHRR SCF (%) and CMC snow depth (m) in 1° × 1° grid cells of major NA river basins including the Mackenzie, Yukon, Churchill, Fraser, St. Lawrence, Columbia, Colorado, and Mississippi from October to May. The darker crosses stand for 1° × 1° grid cells where the standard deviation of topography σ_h < 150 m, and the lighter triangles stand for 1° × 1° grid cells where σ_h >150 m. The fitted lines are computed from equation (4) (m = 1.6) with the mean snow densities shown above each frame.

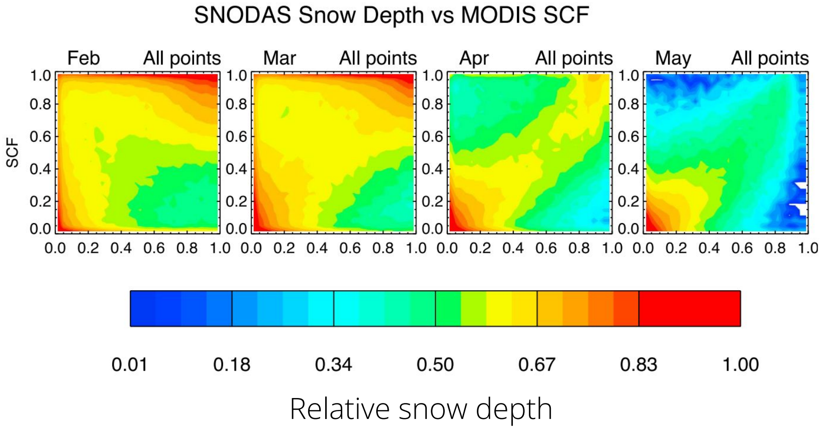
Snow cover micro to macro

Snow cover micro to macro






Snow cover in mountainous area: Swenson & Lawrence (2012) - SL12



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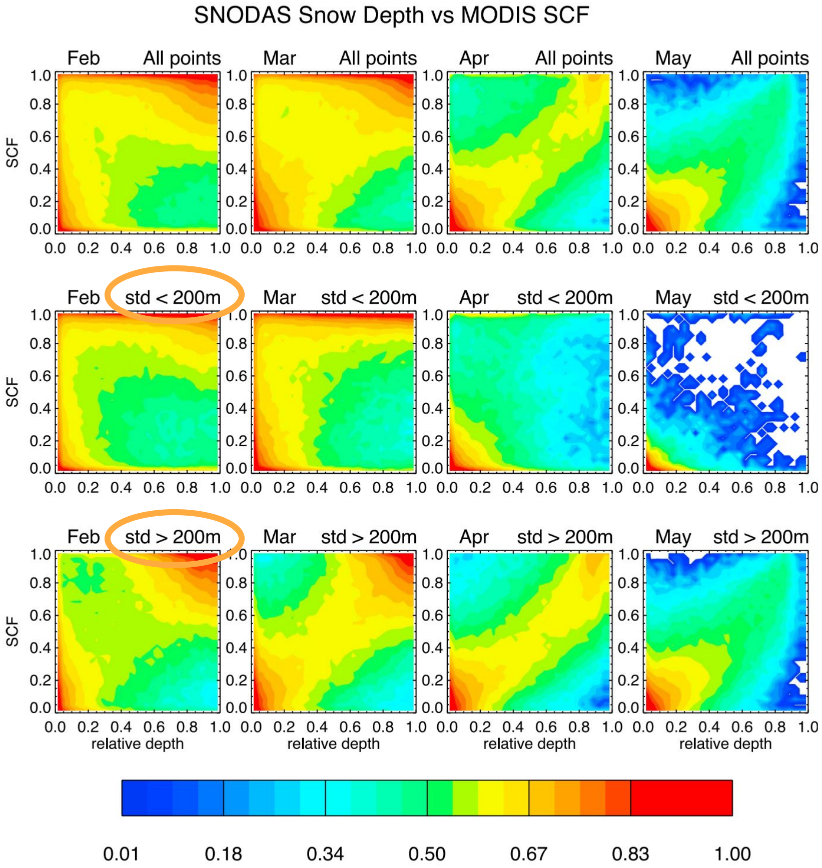

Swenson & Lawrence (2012)

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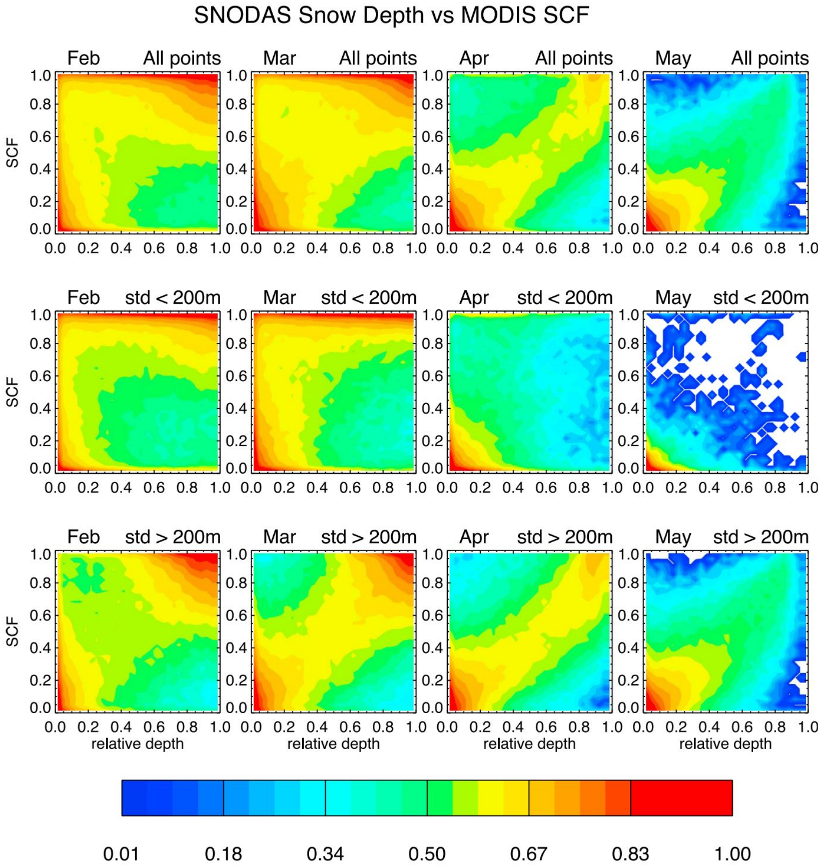


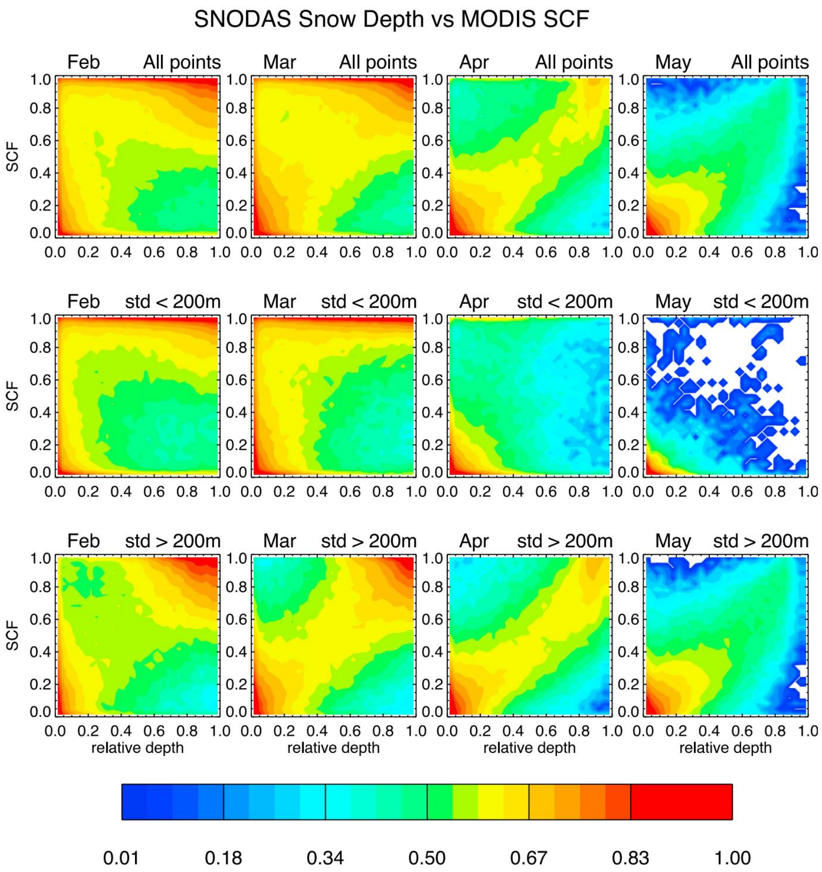
Swenson & Lawrence (2012)

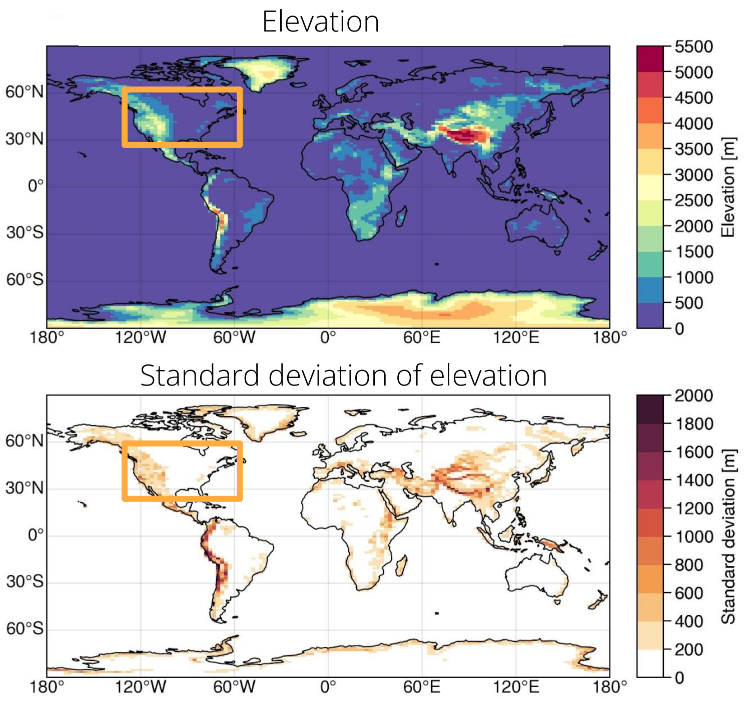
Standard deviation of topography (σ_{topo}) in SCF parameterization first introduced by Douville et al. (1995), then Roesch et al. (2001), etc.

$$\mathrm{SCF} = 1 - \left[\frac{1}{\pi}\mathrm{acos}\left(2\frac{\mathrm{SWE}}{\mathrm{SWE_{max}}} - 1\right)\right]^{N_{\mathrm{melt}}}$$

$$N_{\mathrm{melt}} = \frac{200}{\max(30, \sigma_{\mathrm{topo}})}$$

Snow cover in mountainous area: Swenson & Lawrence (2012) - SL12





Swenson & Lawrence (2012)

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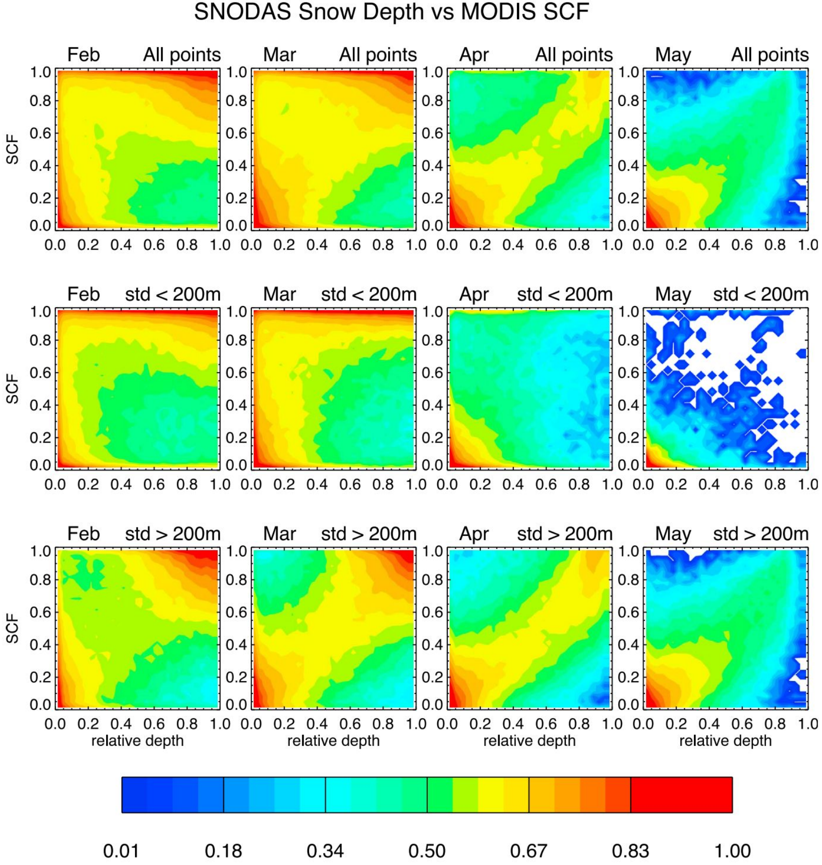
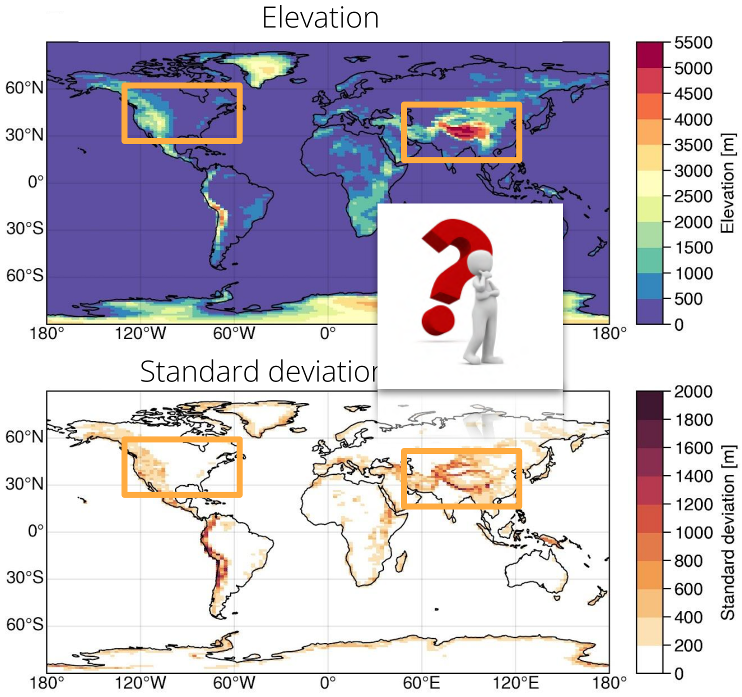


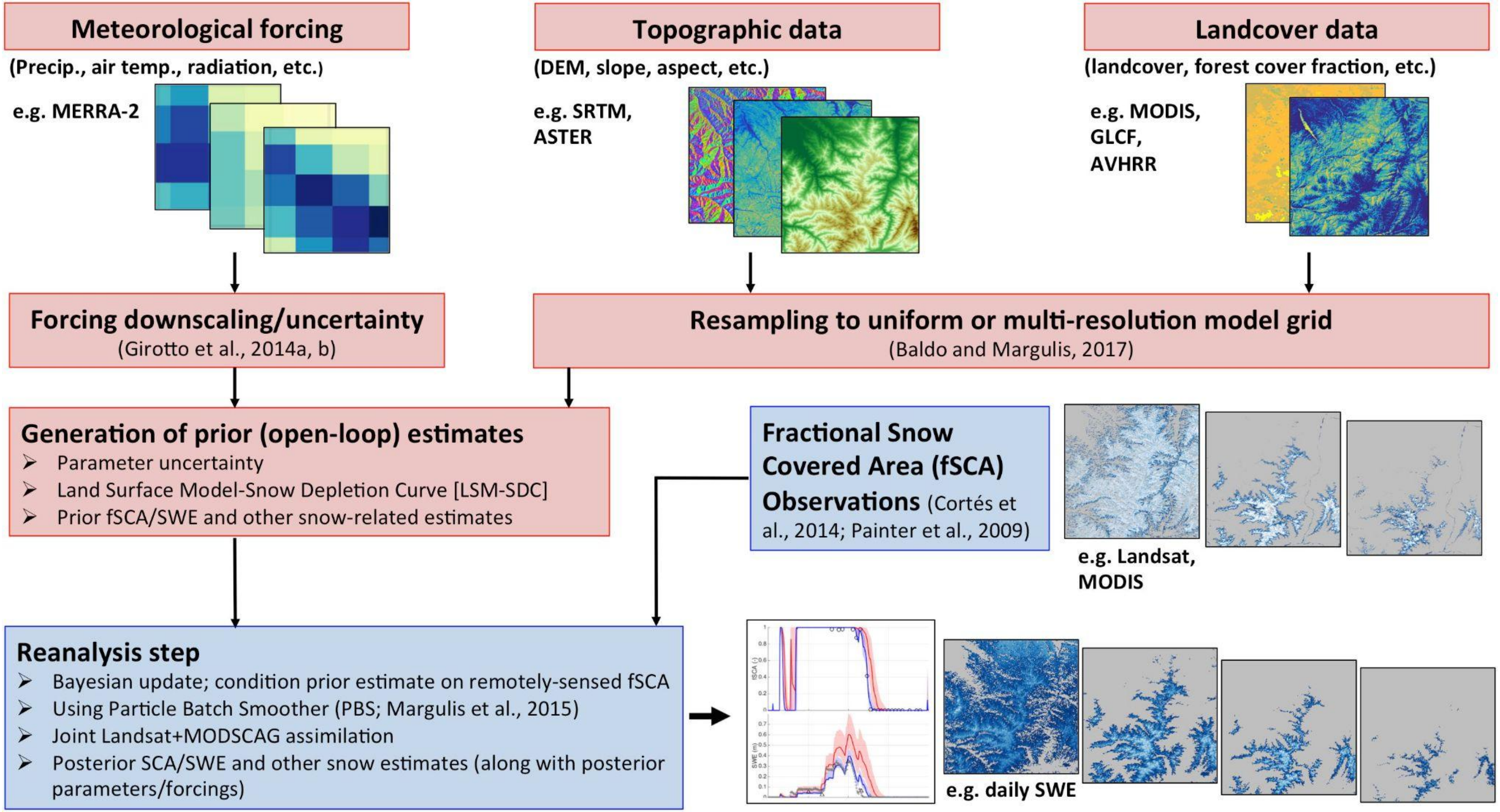


Swenson & Lawrence (2012)

"Estimating the spatial distribution of snow water equivalent (SWE) in mountainous terrain is currently the most important unsolved problem in snow hydrology."

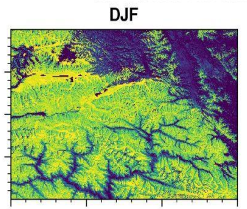
Dozier et al. (2016)

High Mountain Asia UCLA Daily Snow Reanalysis (HMASR)



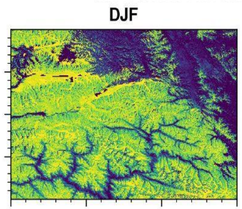
Margulis et al. (2019)

HMASR -> snow cover parameterizations



500 m

HMASR -> snow cover parameterizations



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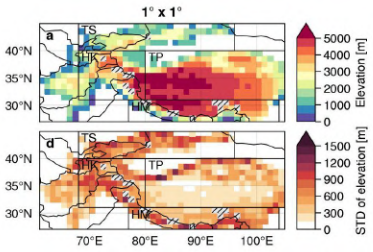

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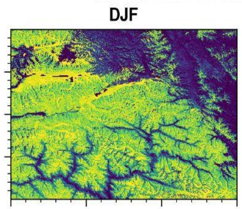

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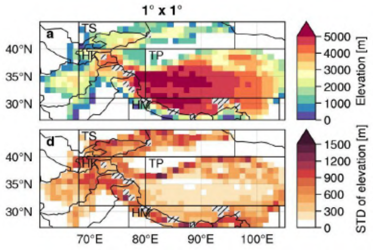
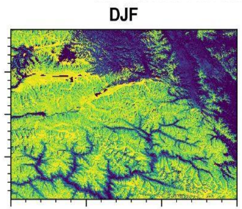
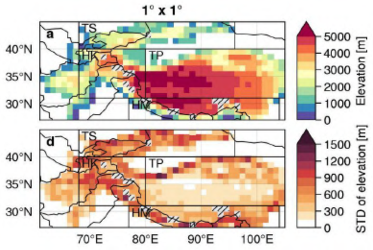


HMASR
SD / SWE / density
+ STD topo
at 1°x1°

SCF

HMASR -> snow cover parameterizations





HMASR
SD / SWE / density
+ STD topo
at 1°x1°

→

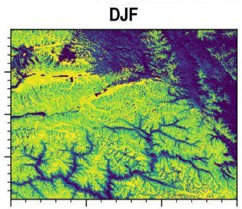
→

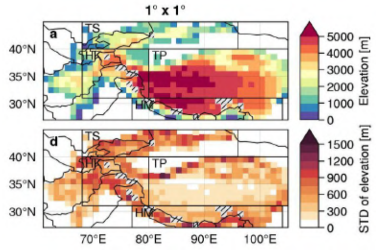
SCF

R01 (Roesch et al., 2001)

$$\mathrm{SCF} = 0.95 \cdot \tanh(100 \cdot \mathrm{SWE})\sqrt{\frac{1000 \cdot \mathrm{SWE}}{1000 \cdot \mathrm{SWE} + \varepsilon + 0.15 \cdot \sigma_z}}$$

HMASR -> snow cover parameterizations





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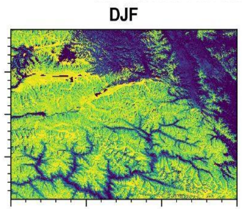
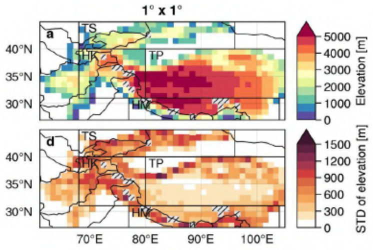
$$\mathrm{SWE}_{max} = \frac{2 \cdot \mathrm{SWE}}{\cos\left[\pi(1 - SCF)^{1/N_{melt}}\right] + 1}$$

HMASR -> snow cover parameterizations





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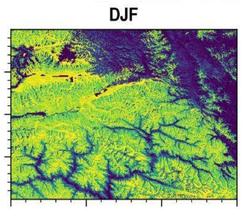
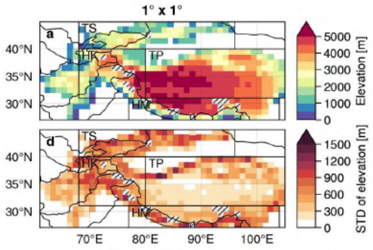
HMASR -> snow cover parameterizations





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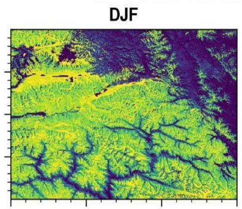
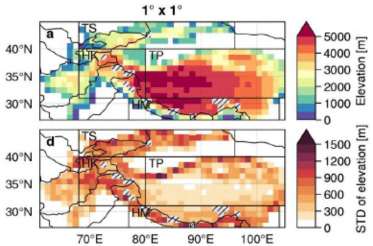
HMASR -> snow cover parameterizations





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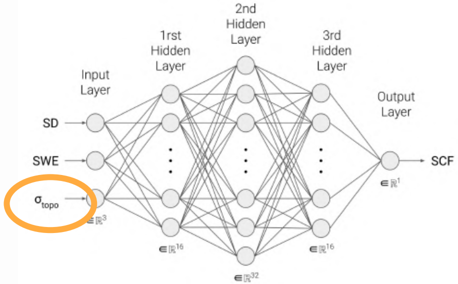
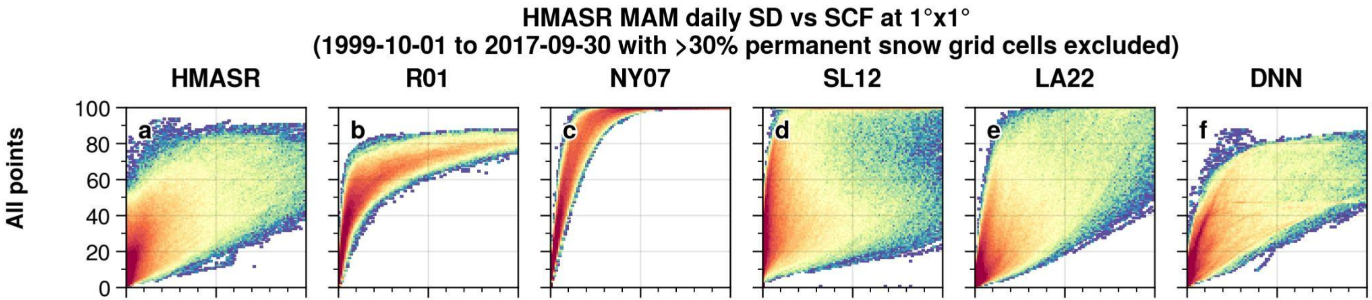
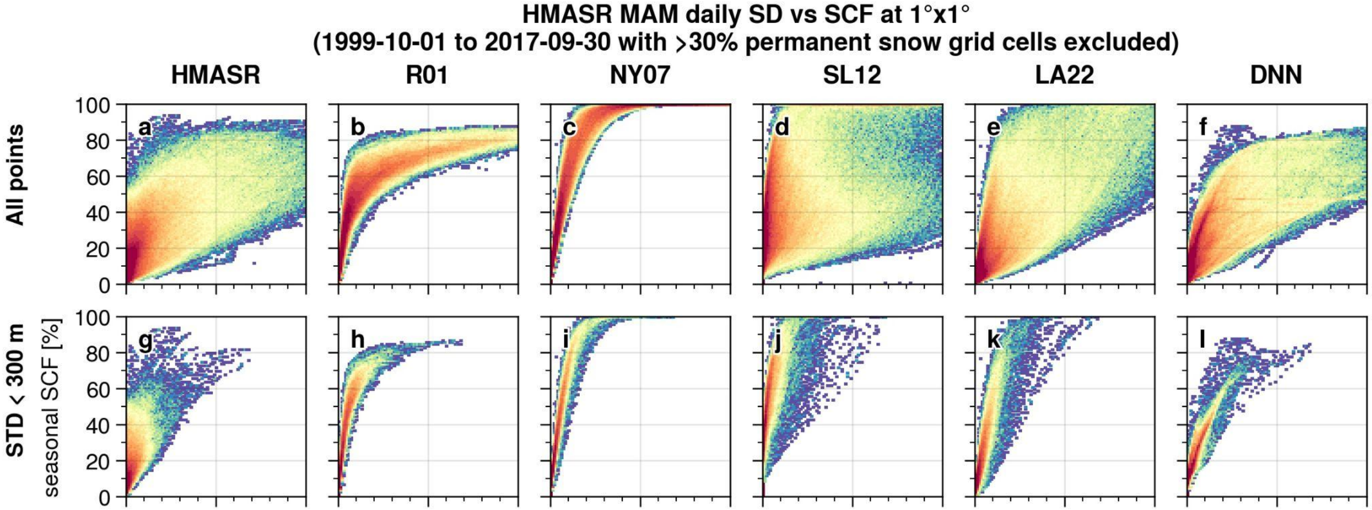
DNN (deep neural network)



Histograms of the daily HMASR seasonal SCF and SD



Histograms of the daily HMASR seasonal SCF and SD



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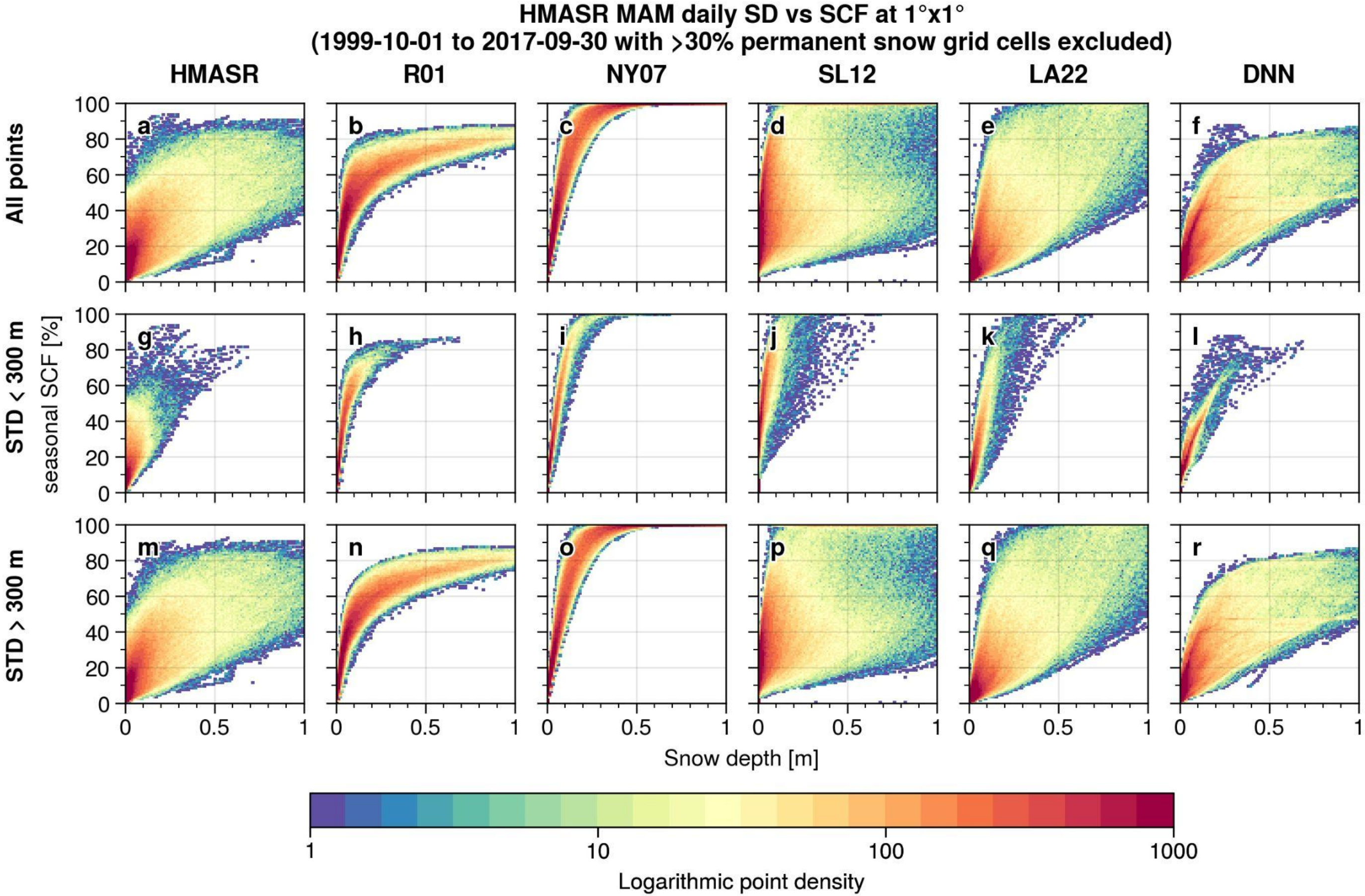

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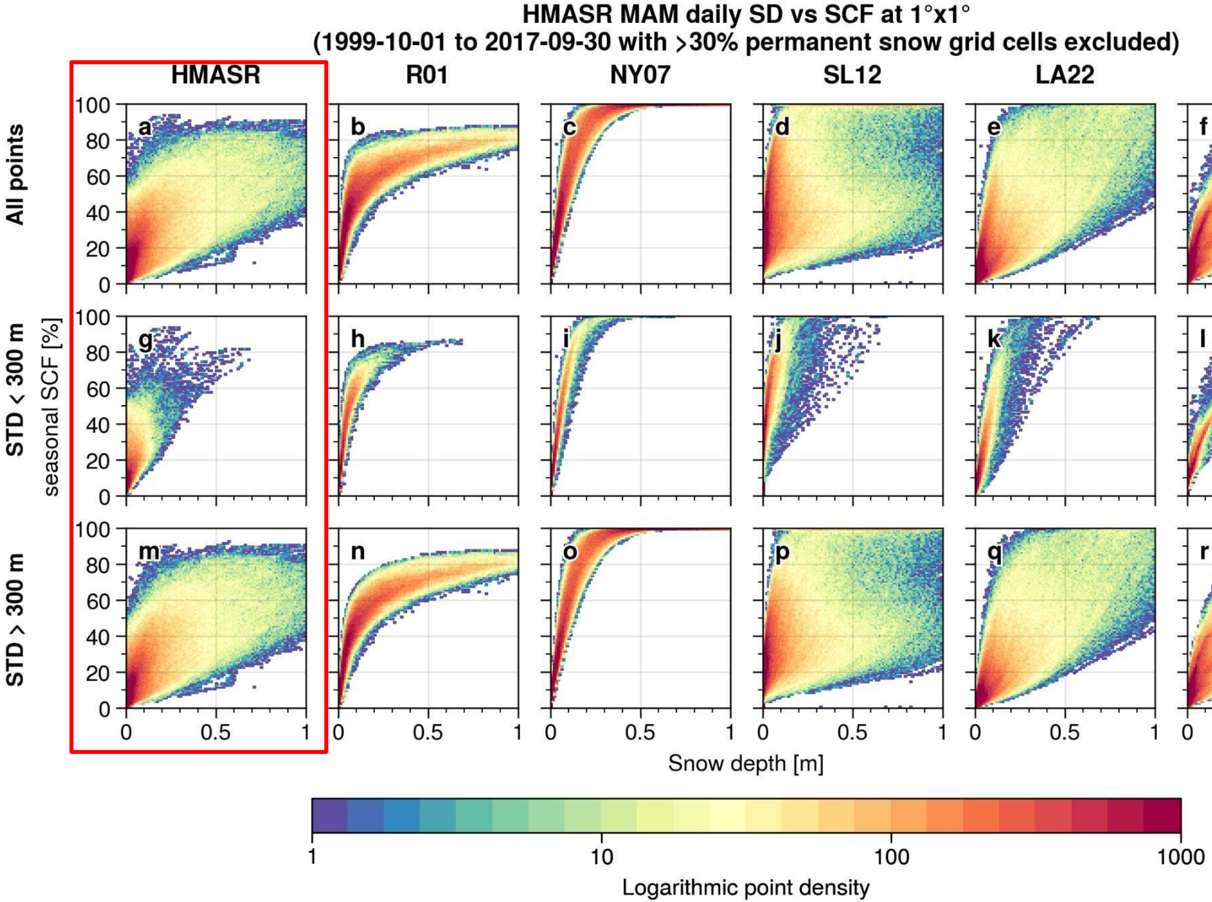

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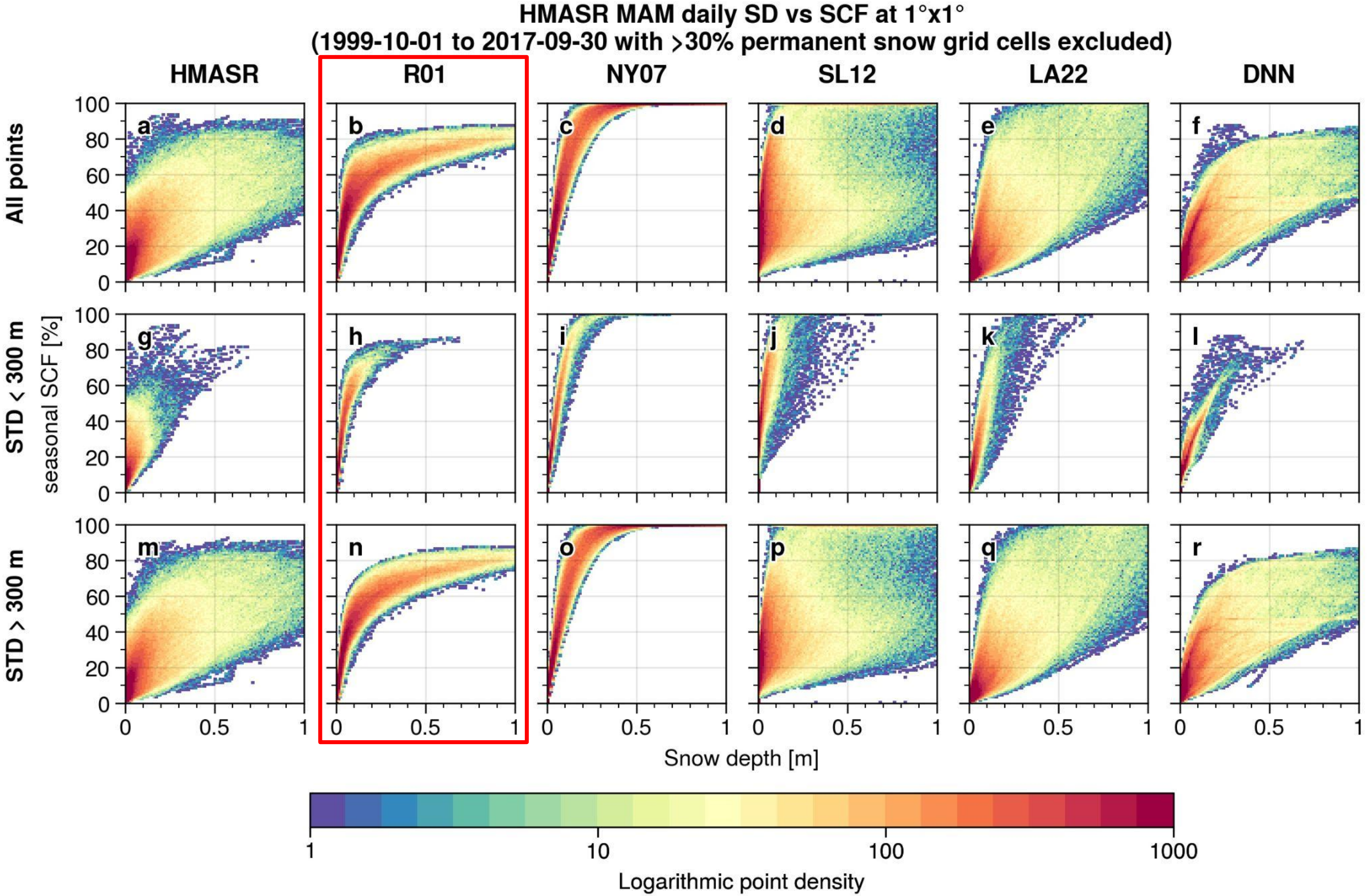
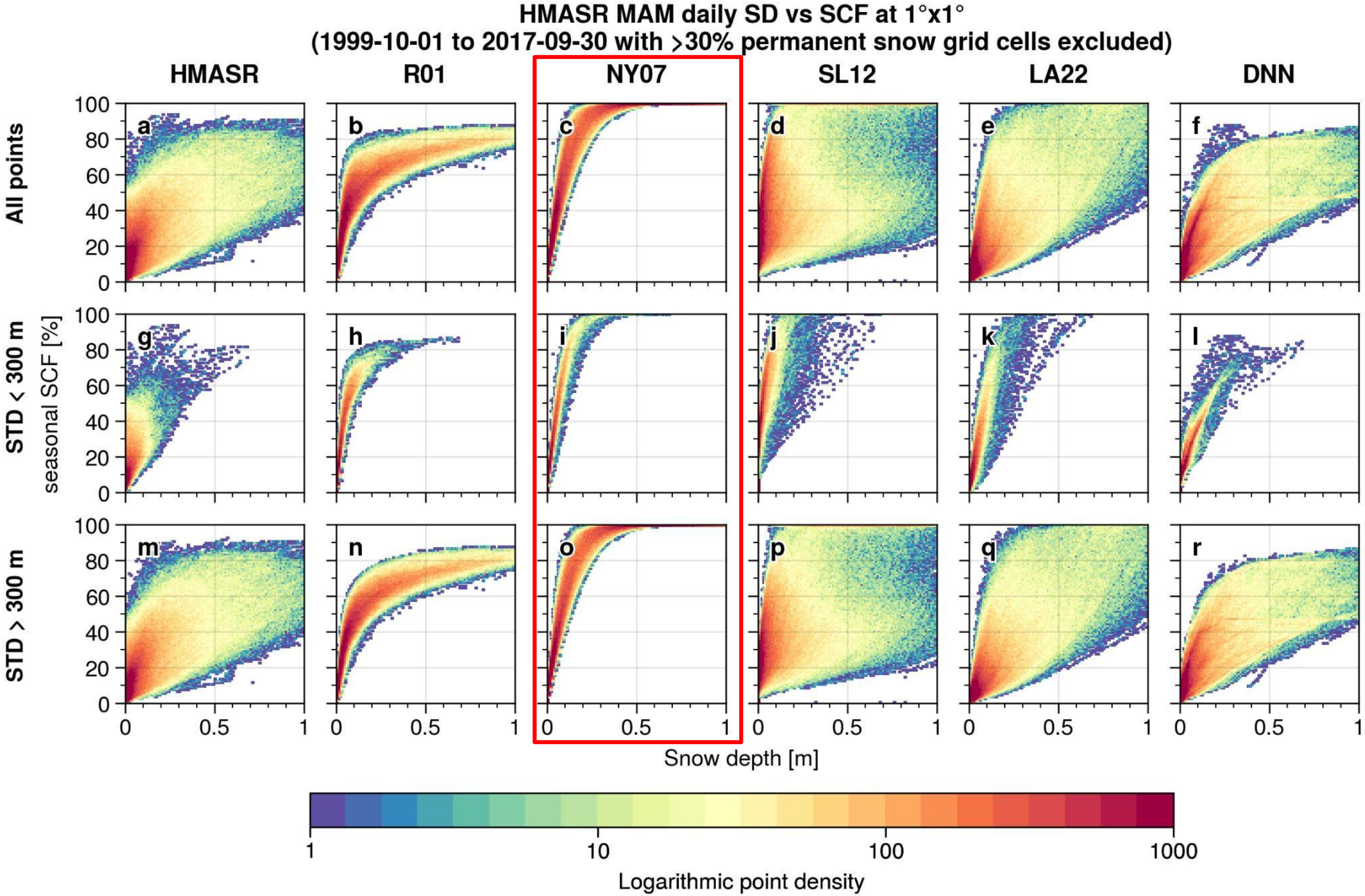


Histograms[#3] of the daily HMASR seasonal SCF and SD



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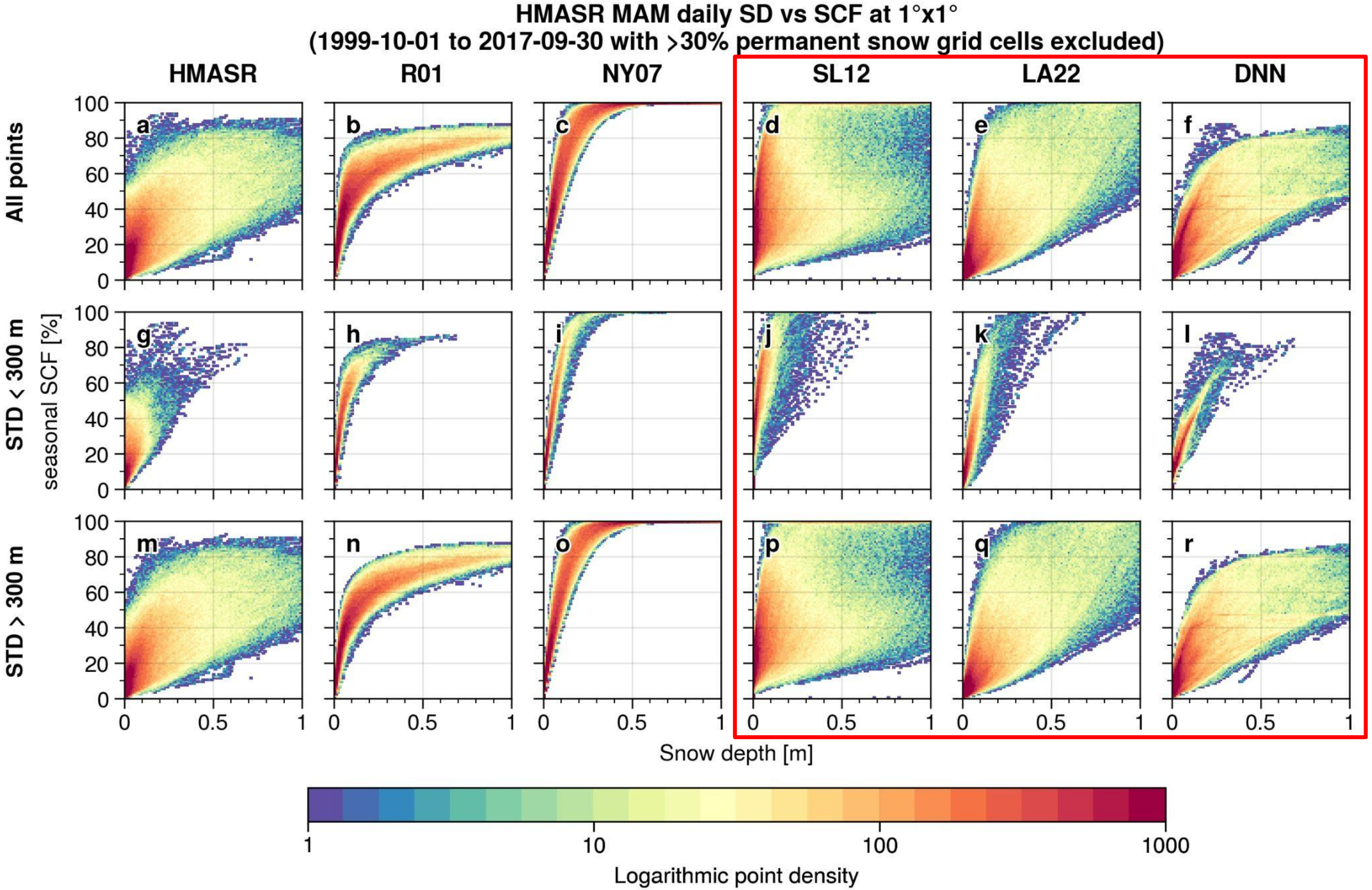
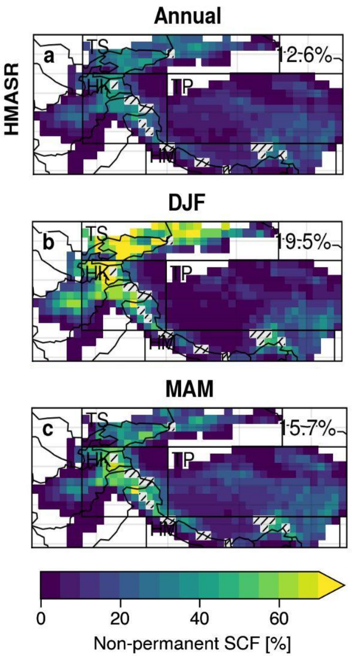
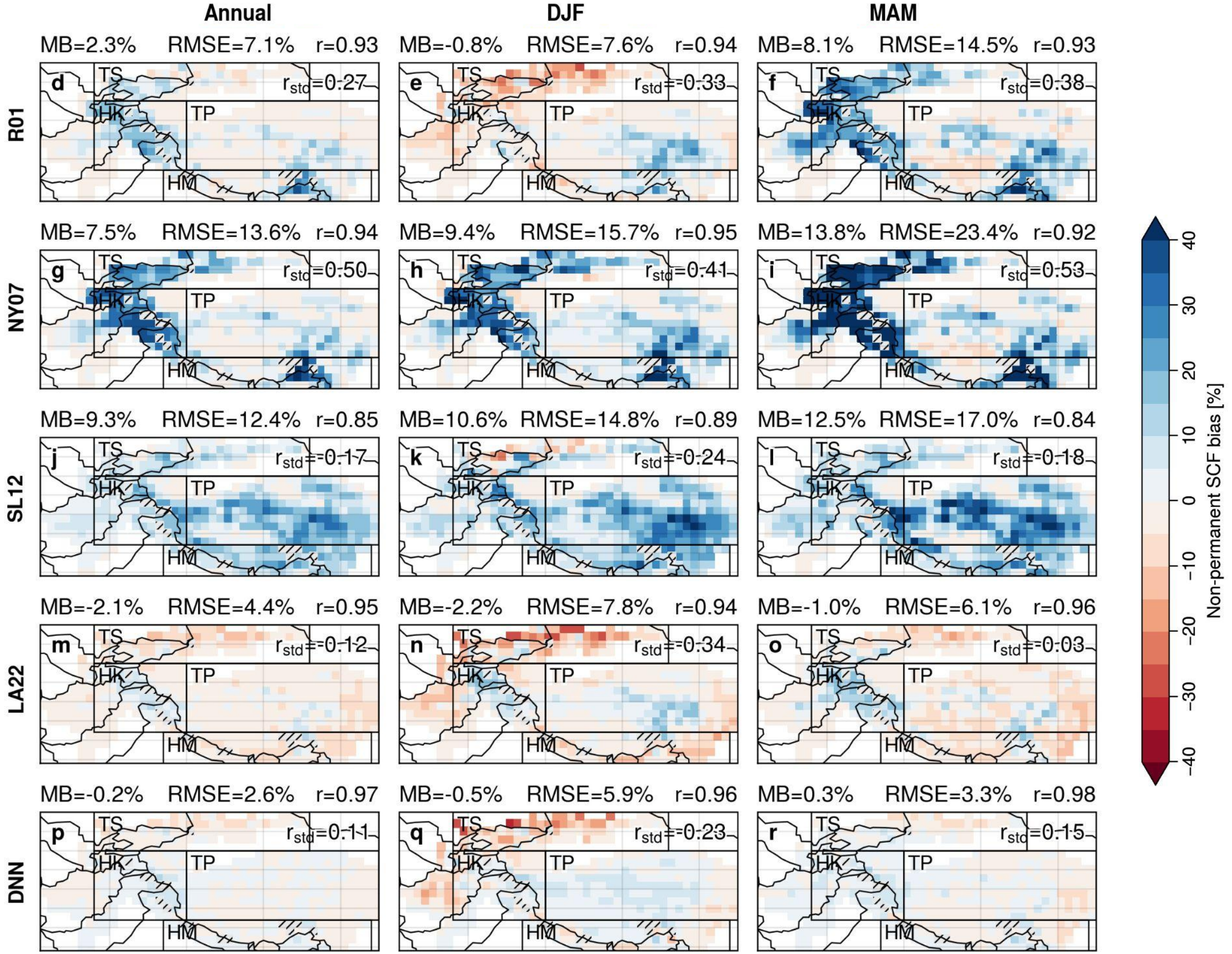


HMASR -> snow cover parameterizations

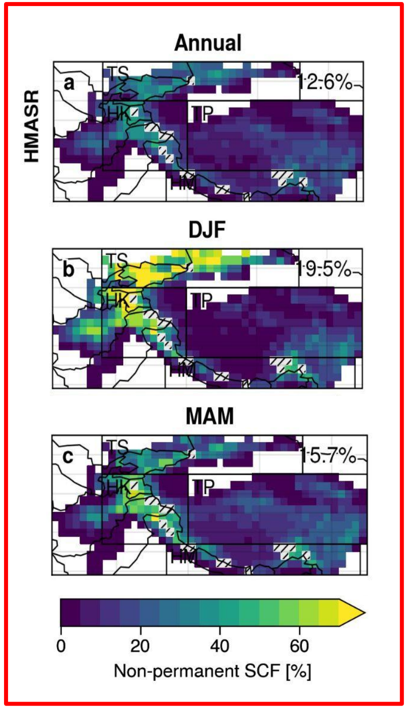


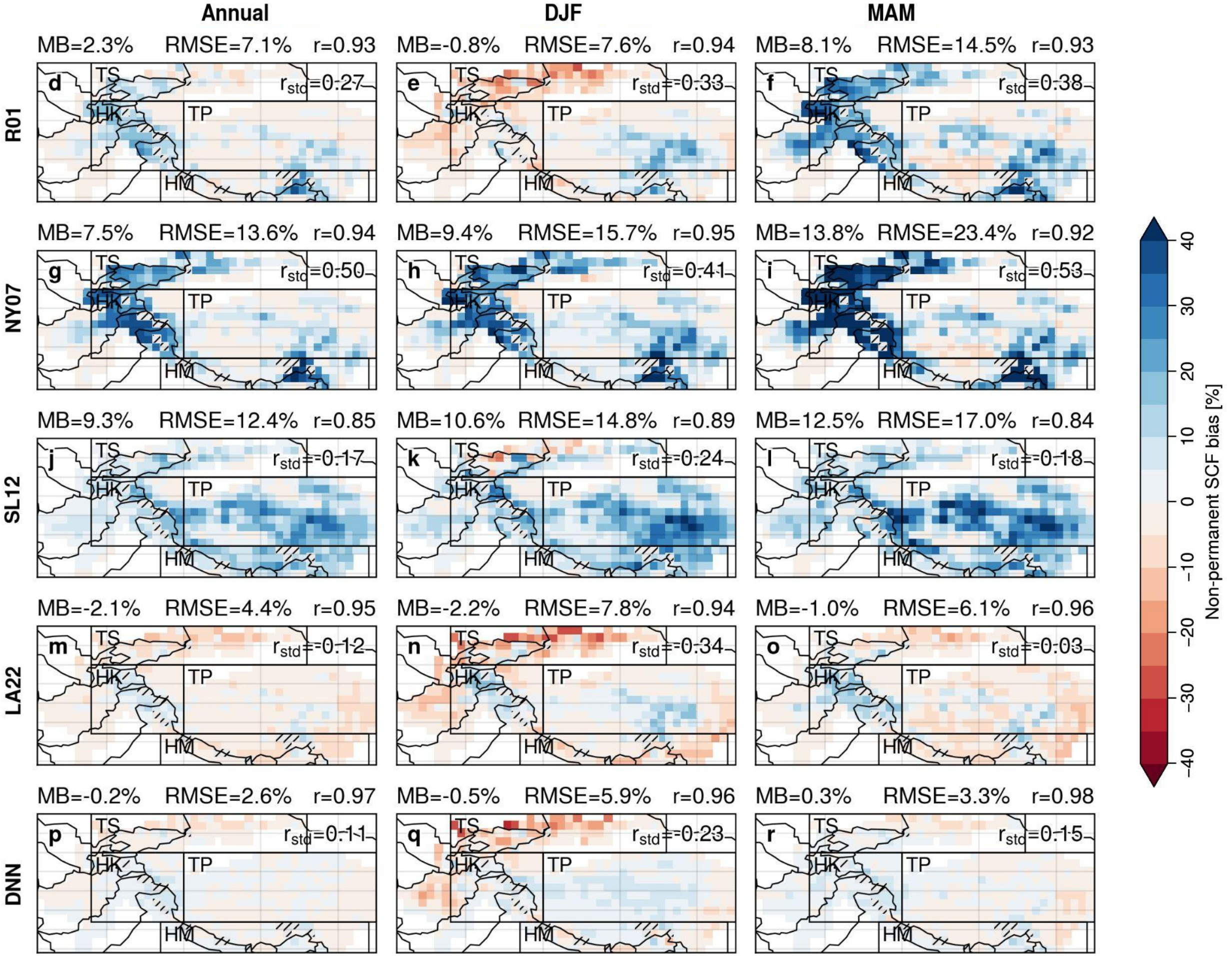


Too much snow

Not enough snow

HMASR -> snow cover parameterizations





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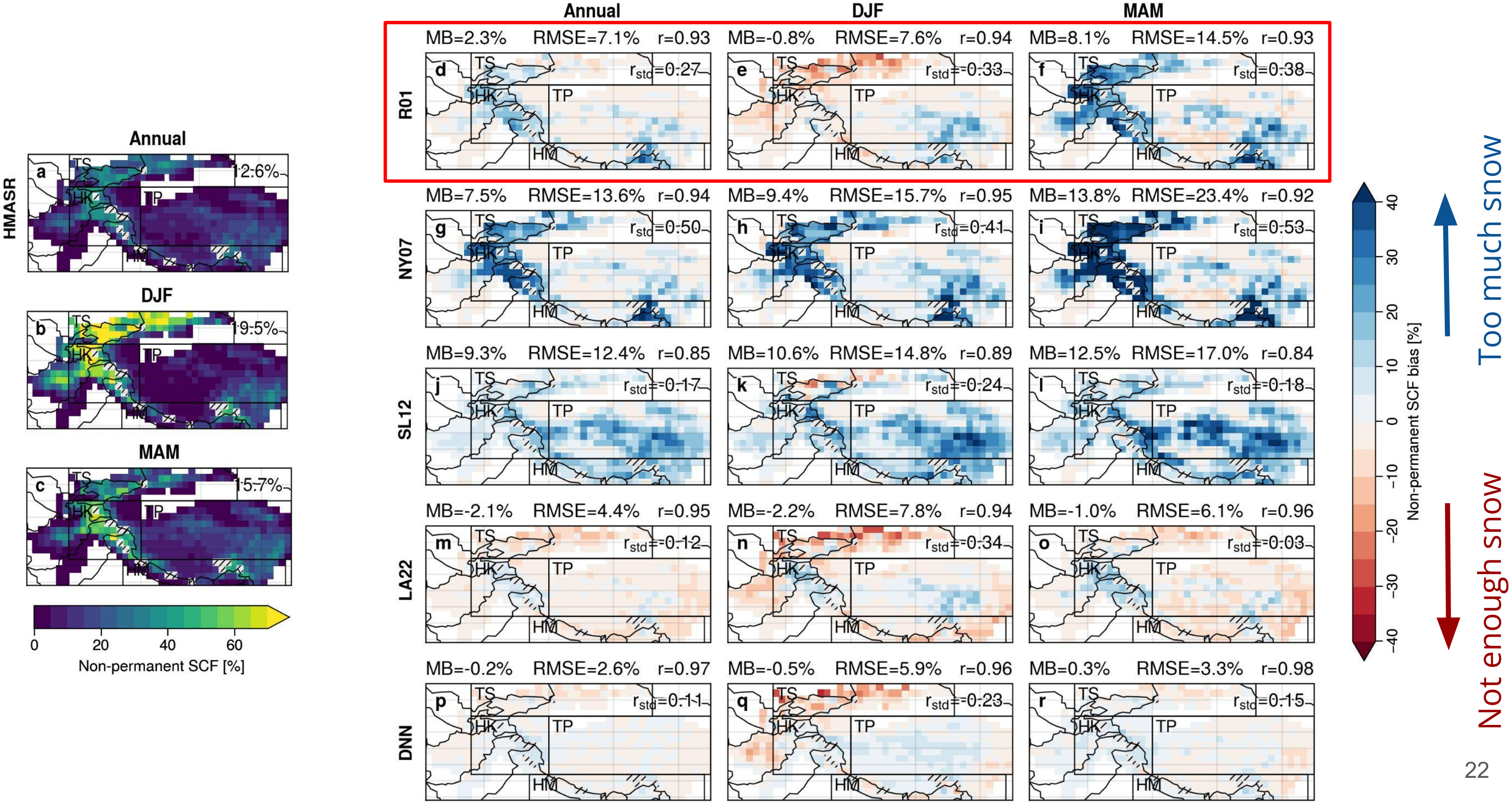

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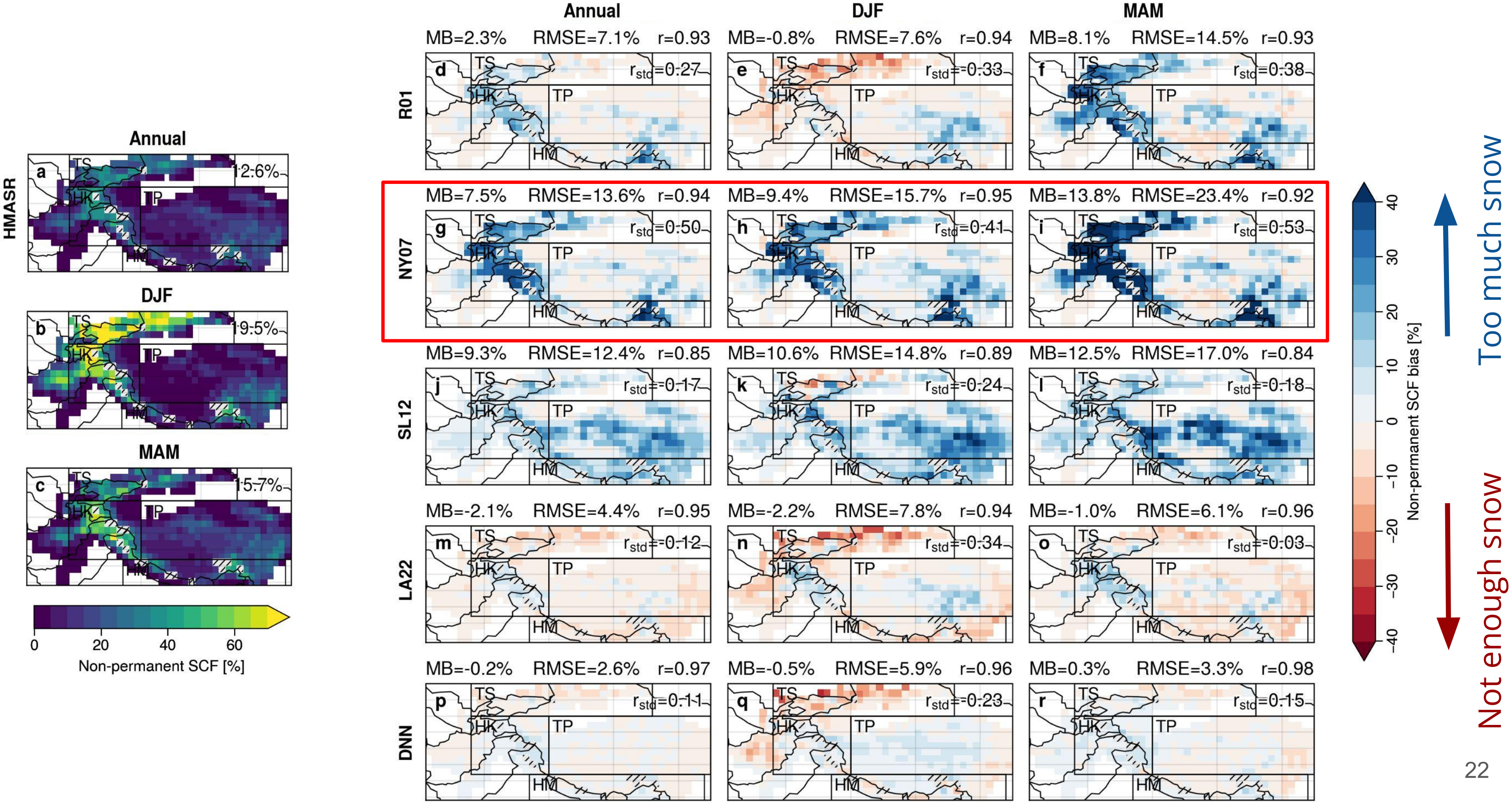

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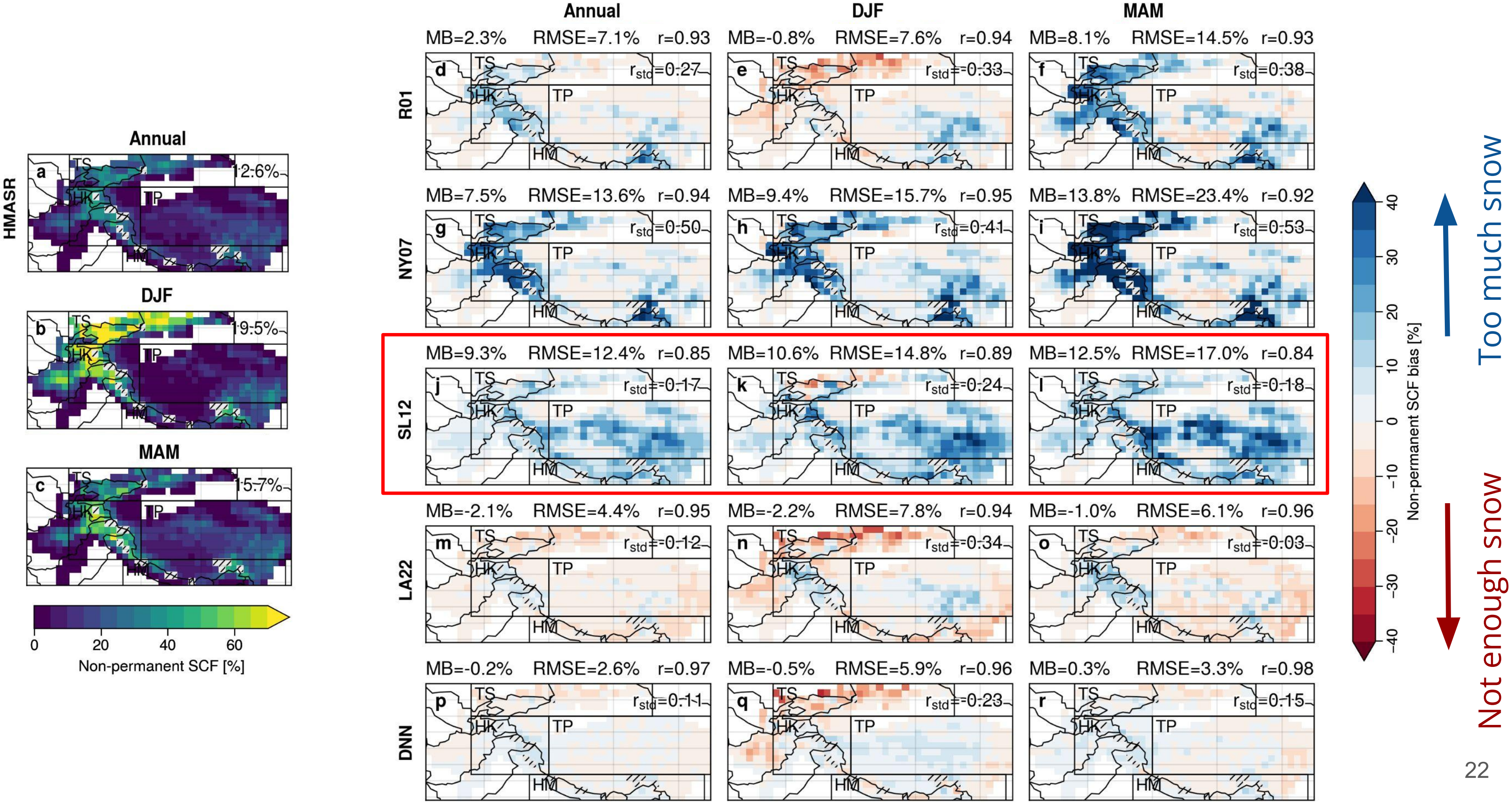

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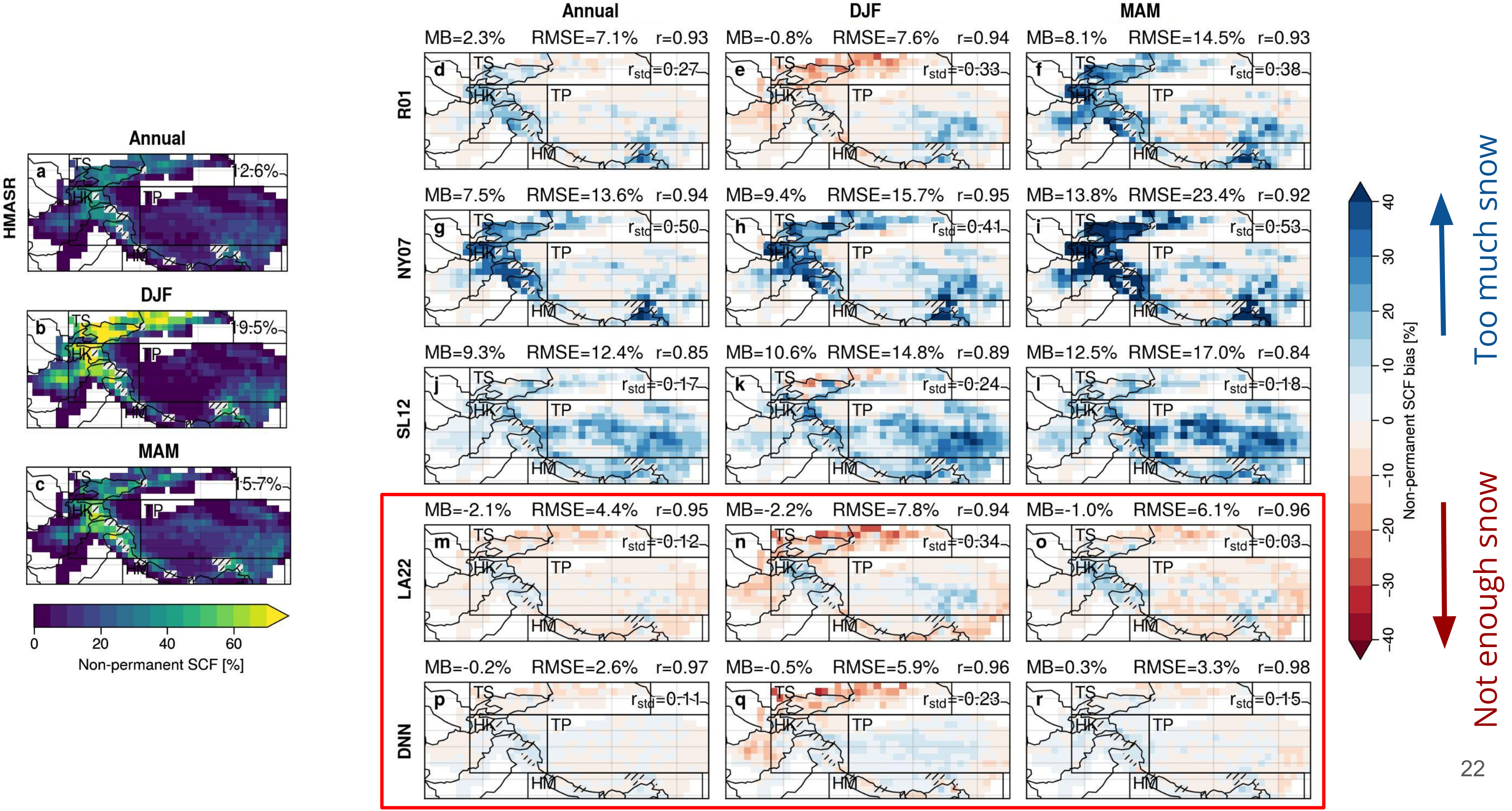
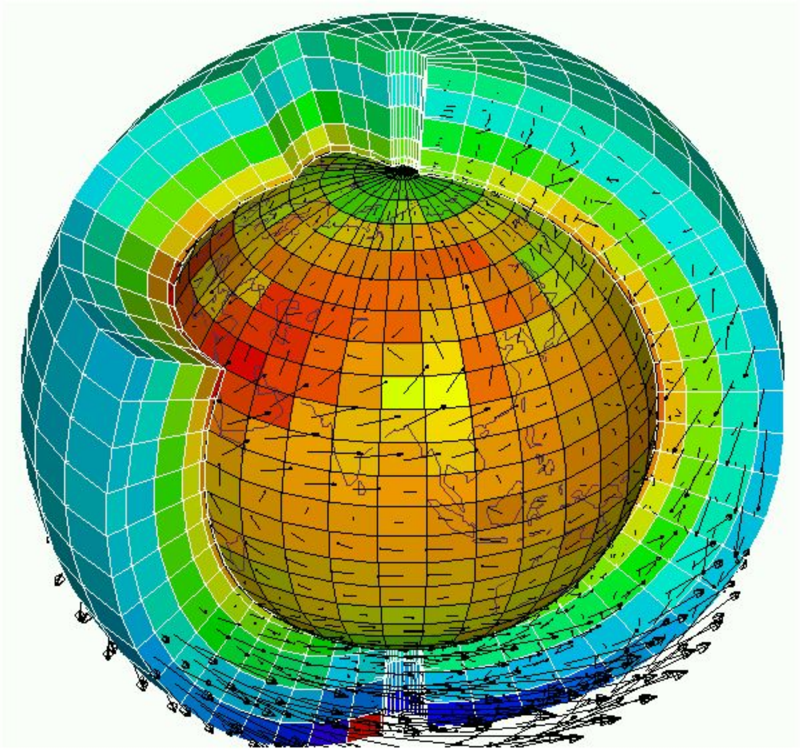


Application in GCM (LMDZ/ORCHIDEE)

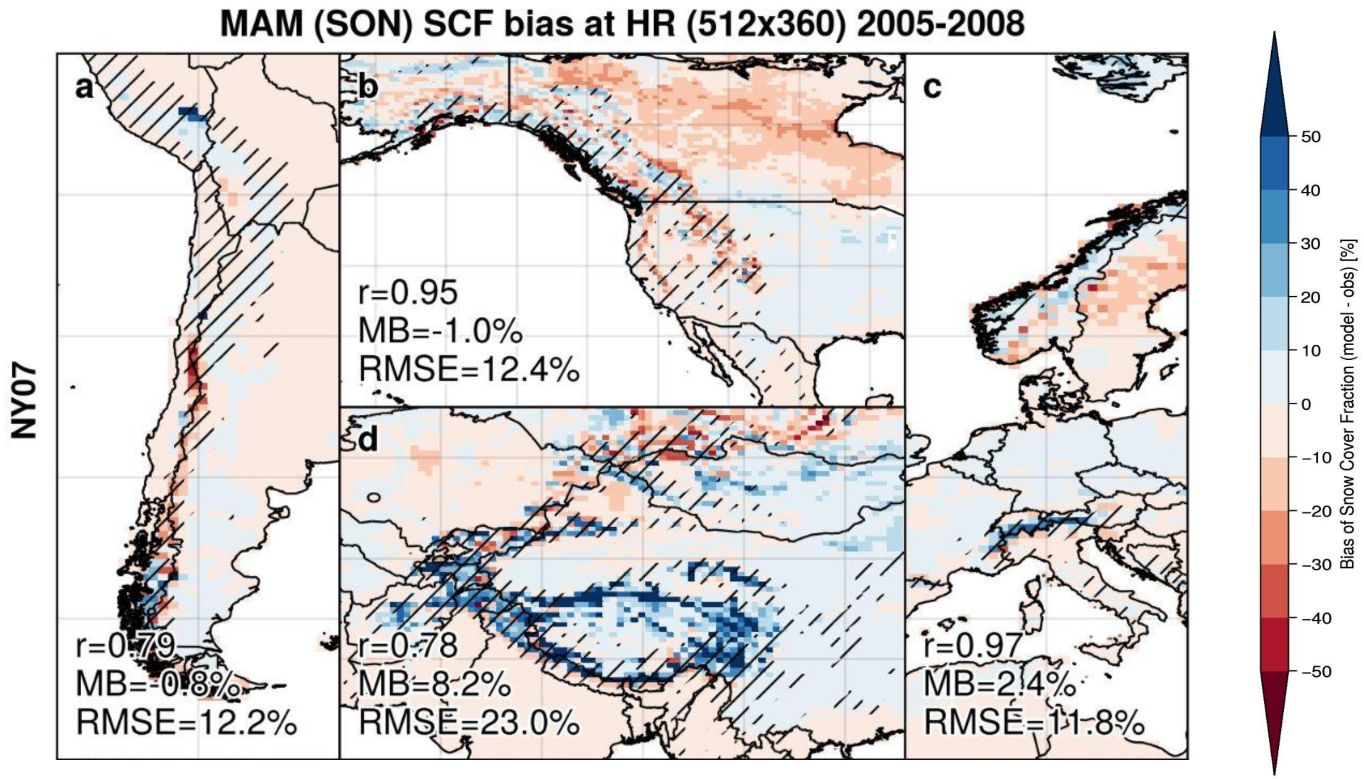


- Nudged land-atmosphere coupled simulations (LMDZ/ORCHIDEE)
- 2 resolutions:
  - LR 144x142 (~100/200 km)
  - HR 512x360 (~50 km)
- 2005-2008 (2004 spin-up)
- NY07, LA23, and SL12 parameterizations
- Snow CCI MODIS observational reference

Application in GCM: HR simulation biases (reference NY07)

Spring snow cover bias

Reference
(Niu and Yang, 2007)



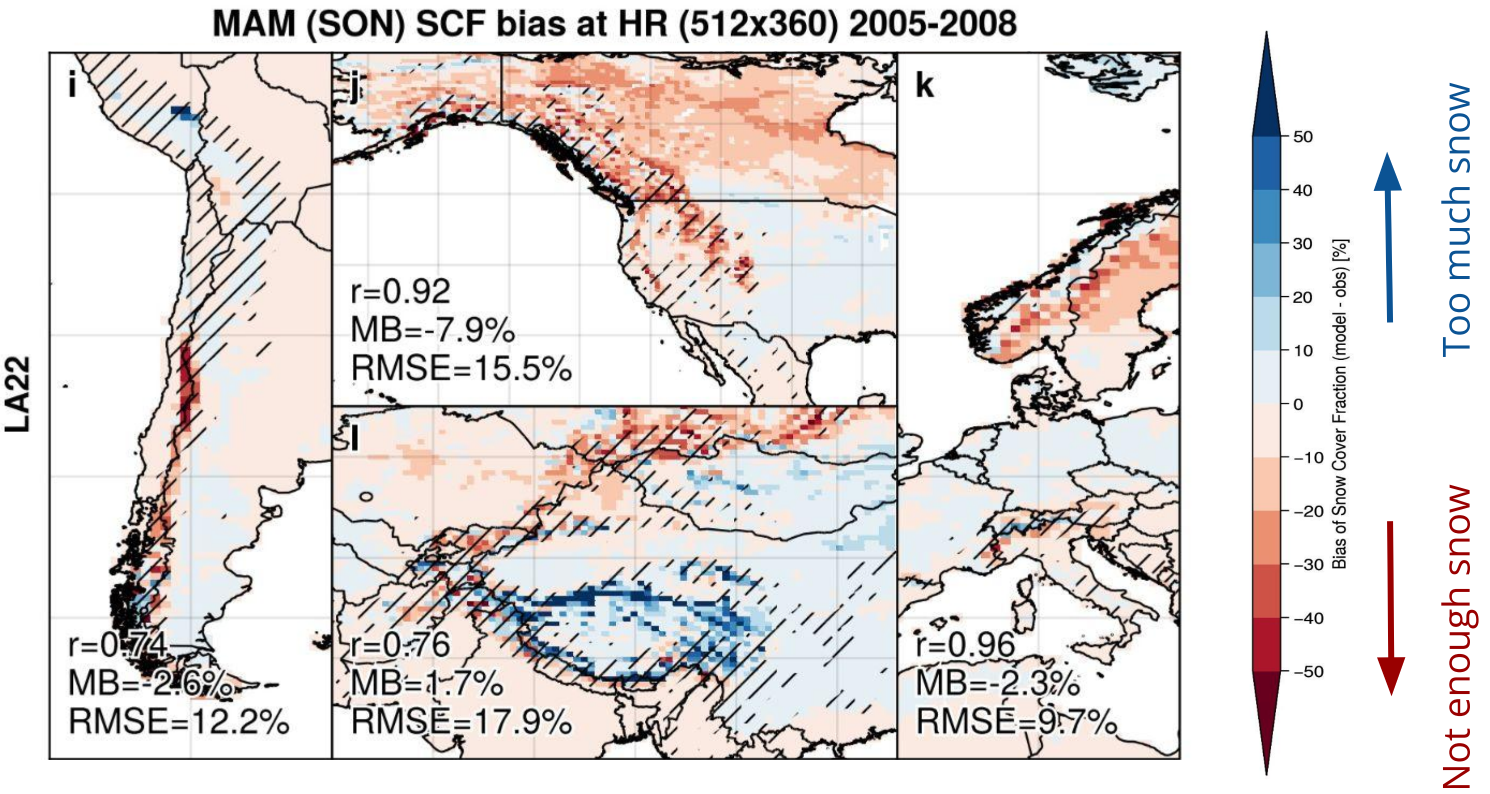
Too much snow

Not enough snow

Application in GCM: HR simulation biases (new LA23)

Spring snow cover bias

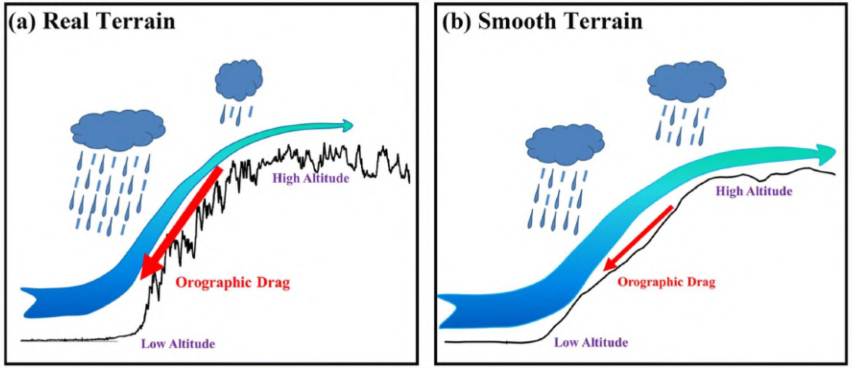
New LA23
(based on NY07)

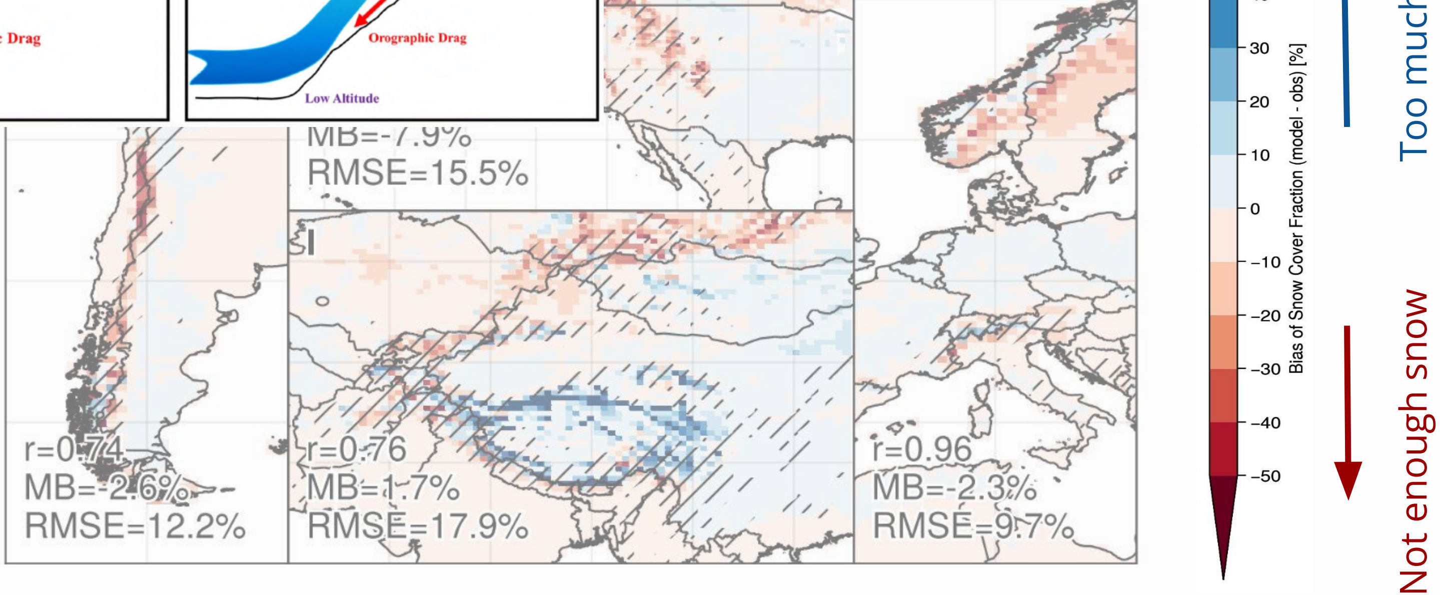


Application in GCM: HR simulation biases (new LA23)

Spring snow cover bias

Fig. 5 Wang et al. (2020)

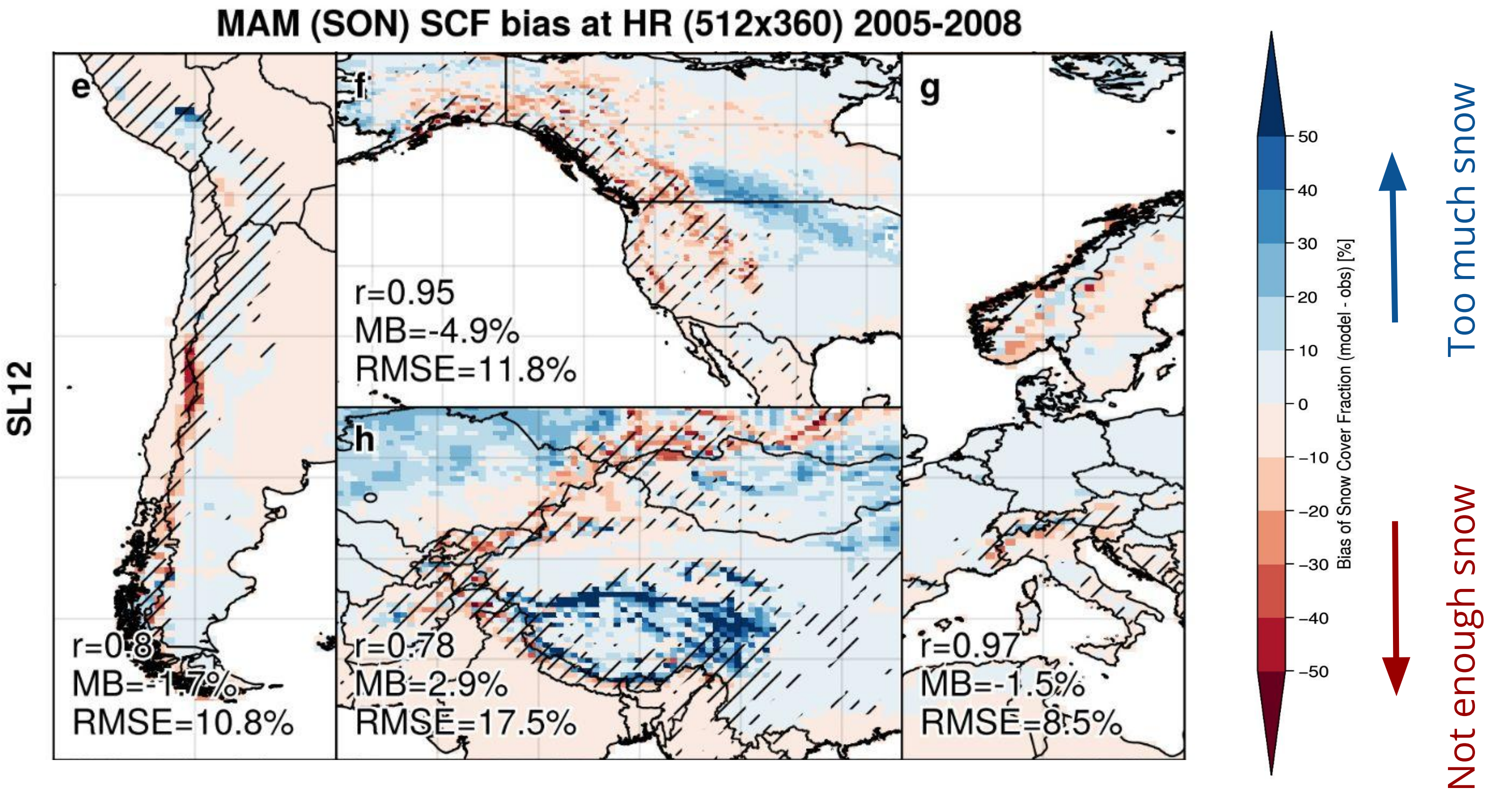




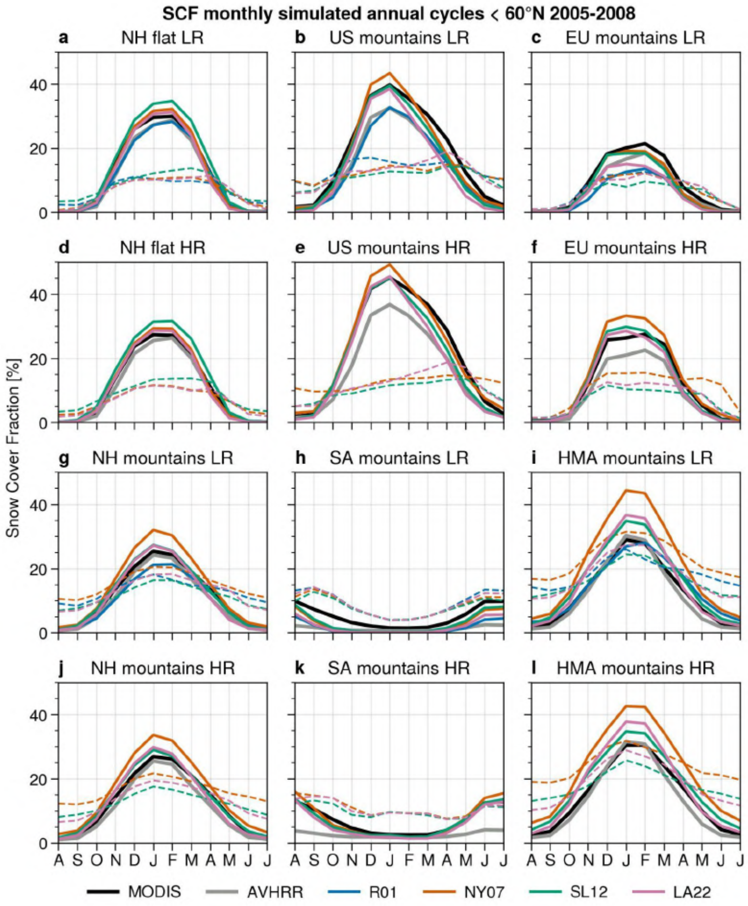
Application in GCM: HR simulation biases (new SL12)

Spring snow cover bias

New SL12
(Swenson and Lawrence, 2012)



Application in GCM: LR/HR comparison



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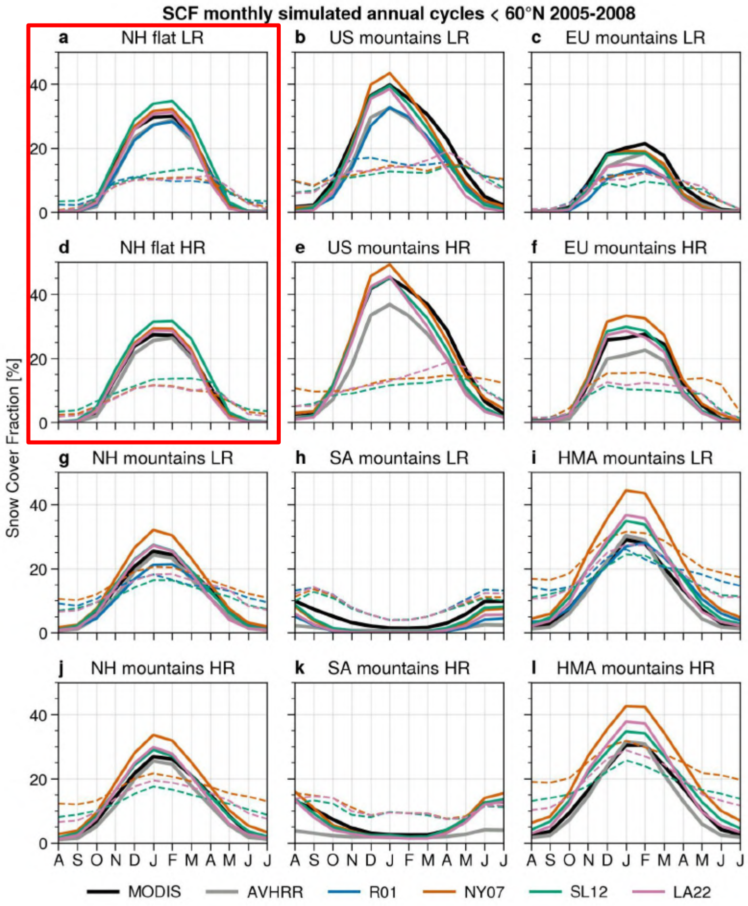

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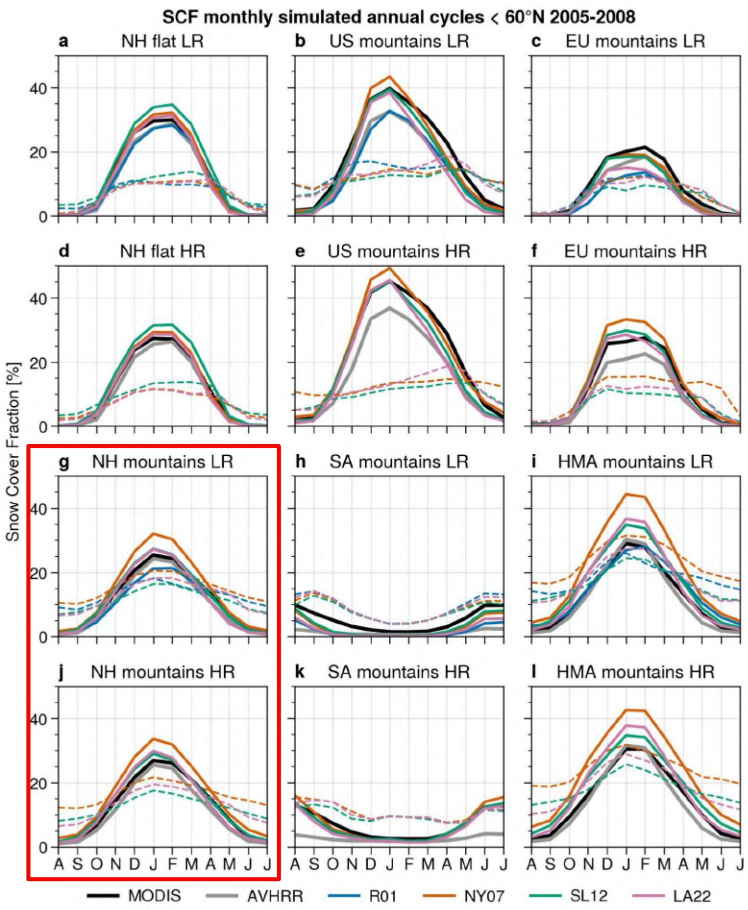

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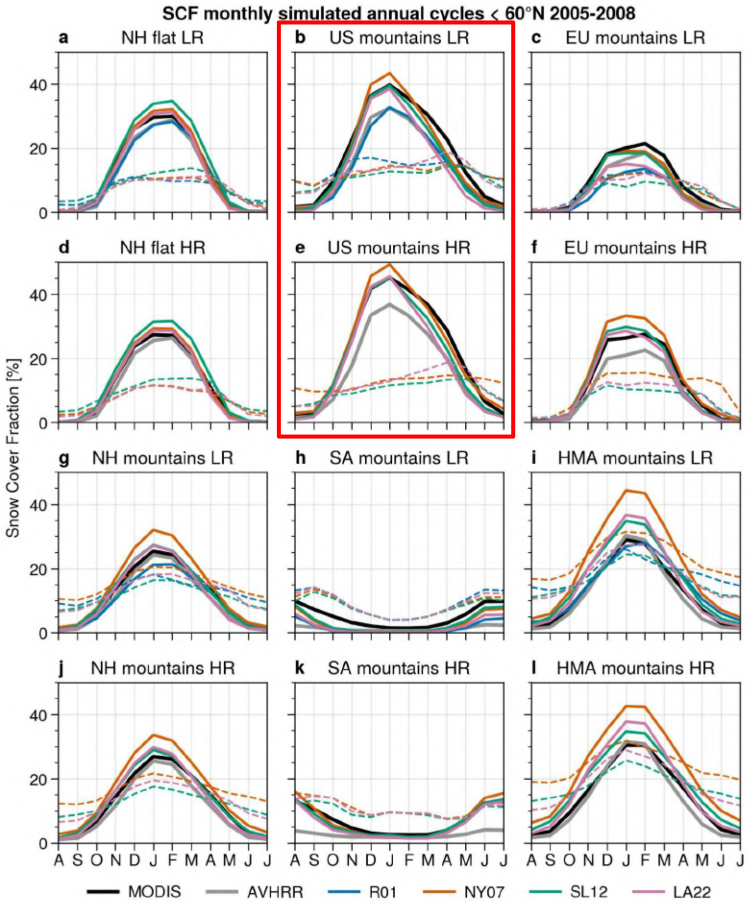

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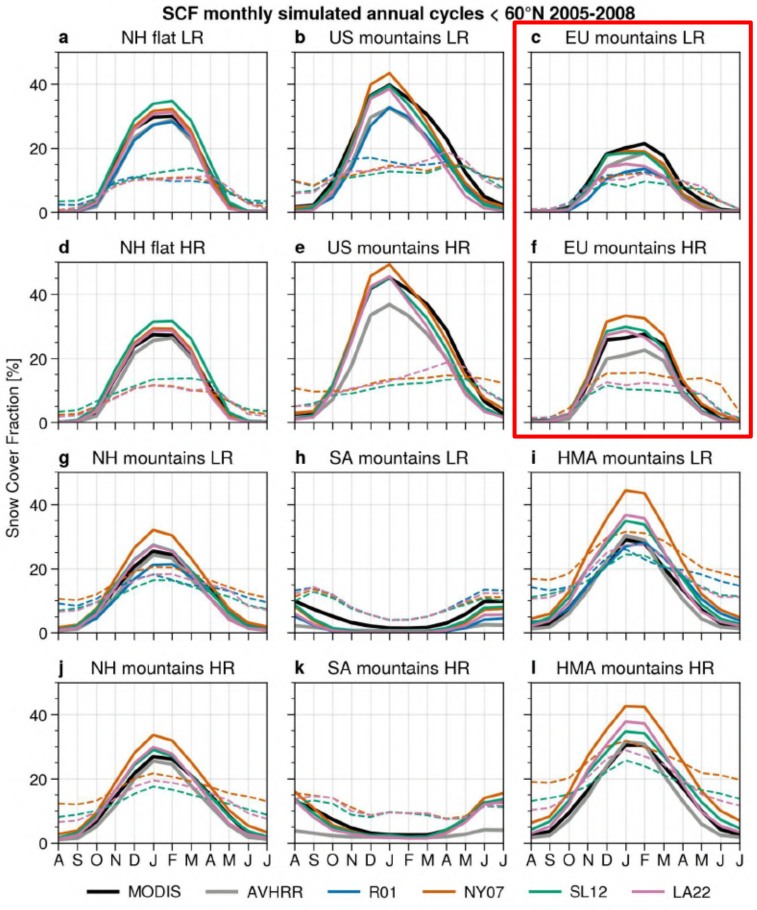

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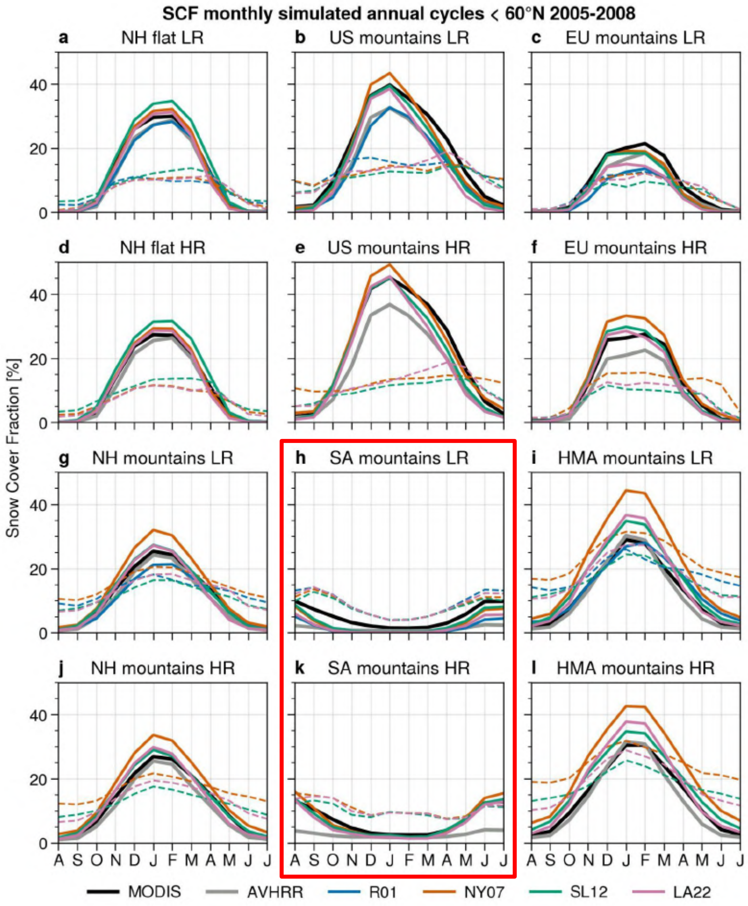

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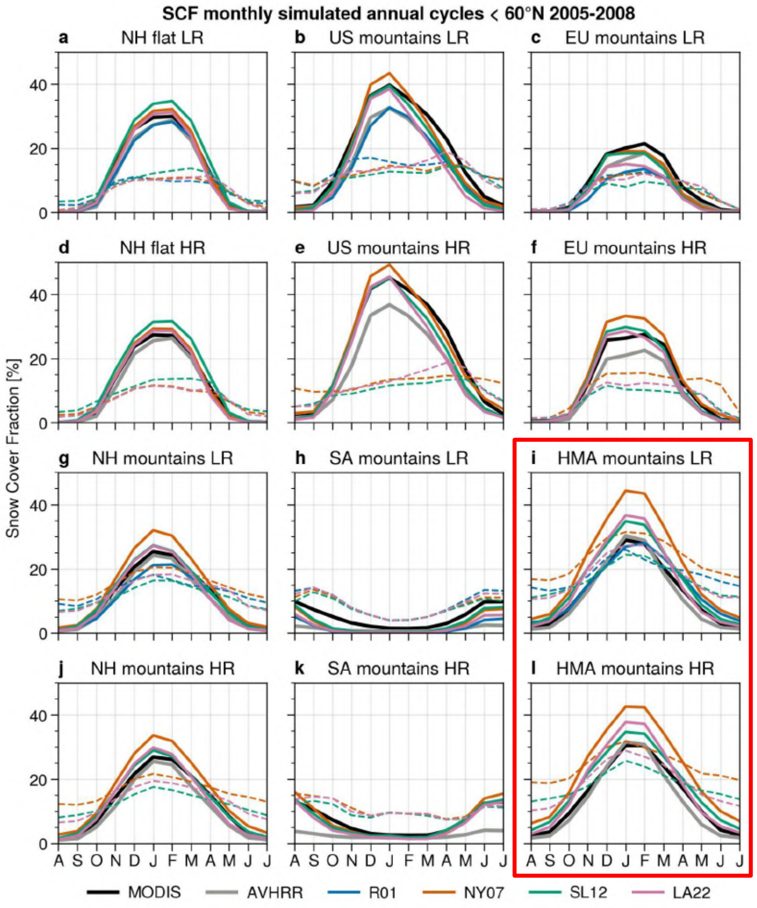

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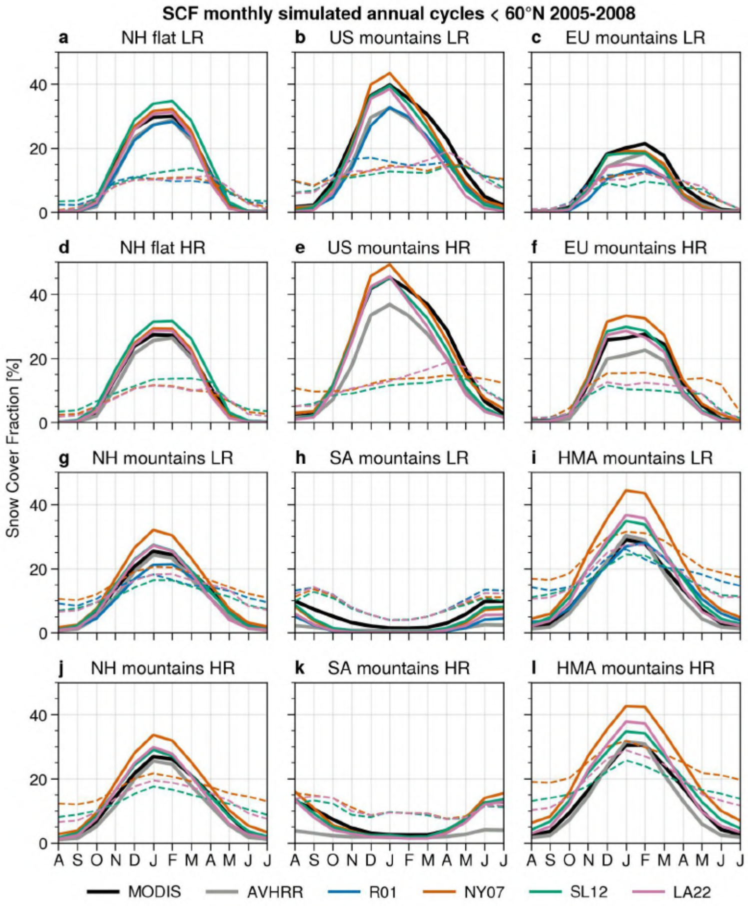

- Contrasting results depending on the location

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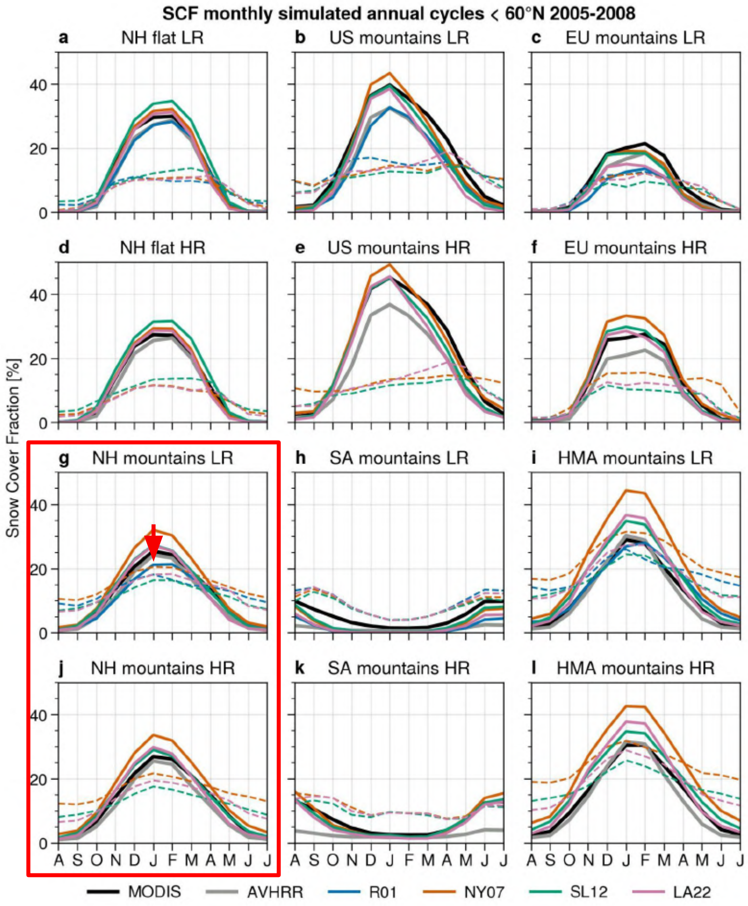

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- Snow cover overestimation in mountain areas is reduced by about 5 to 10 % (when including a dependency on the subgrid topography in the SCF parameterizations)

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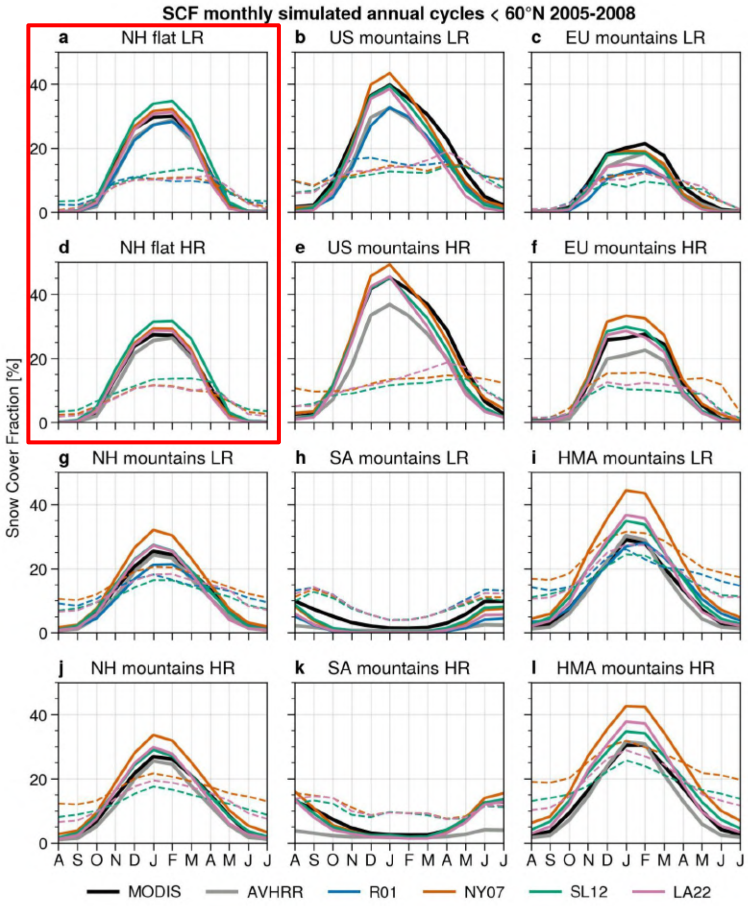

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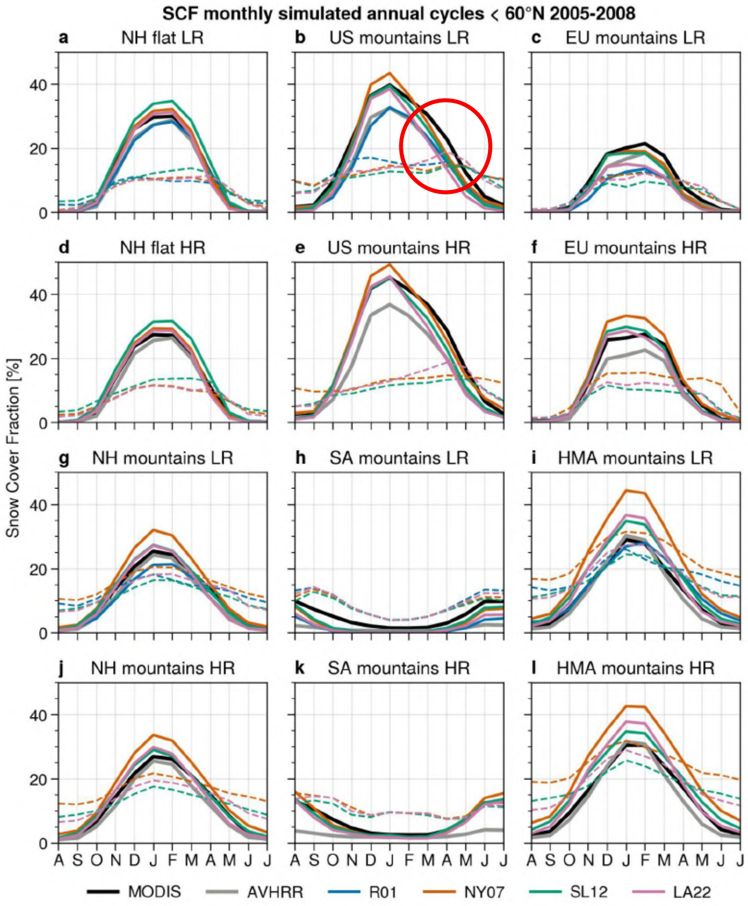

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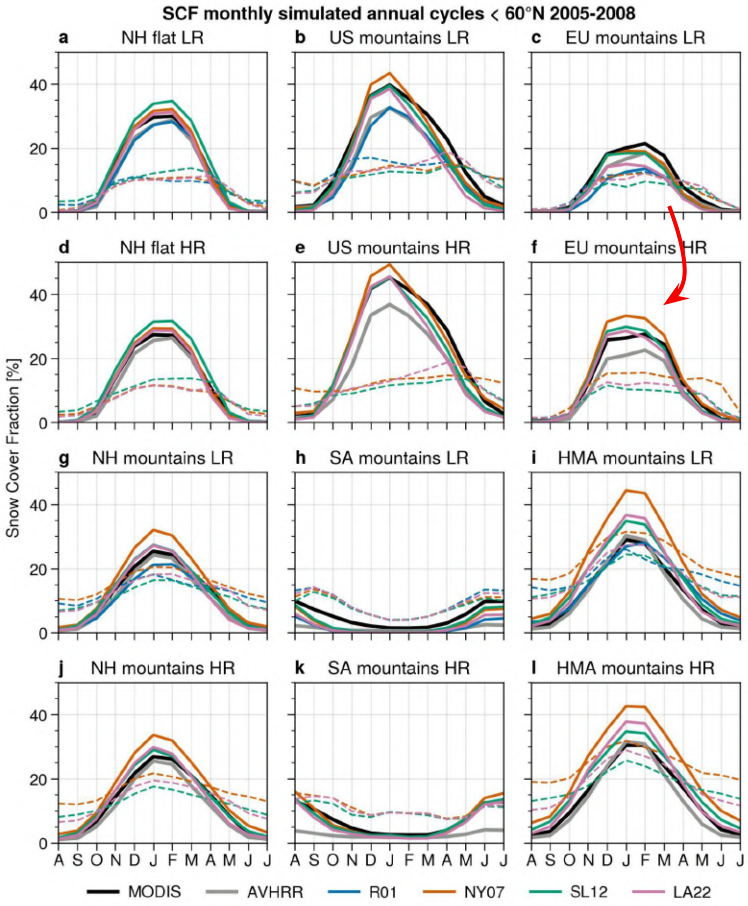
Application in GCM: LR/HR comparison



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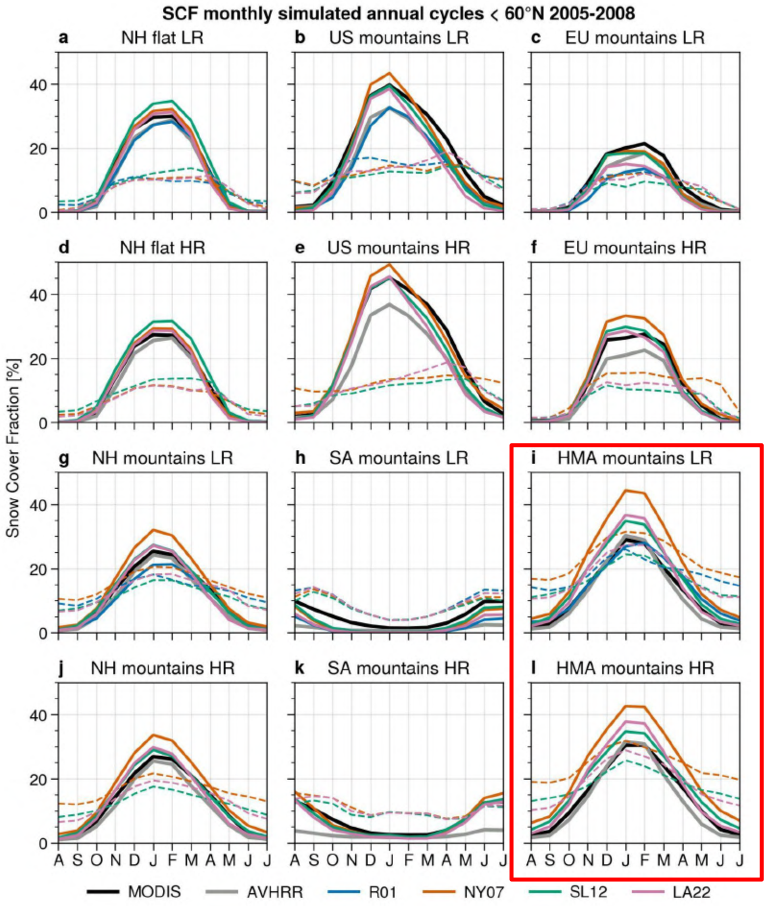

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- Early melting in the US mountainous region
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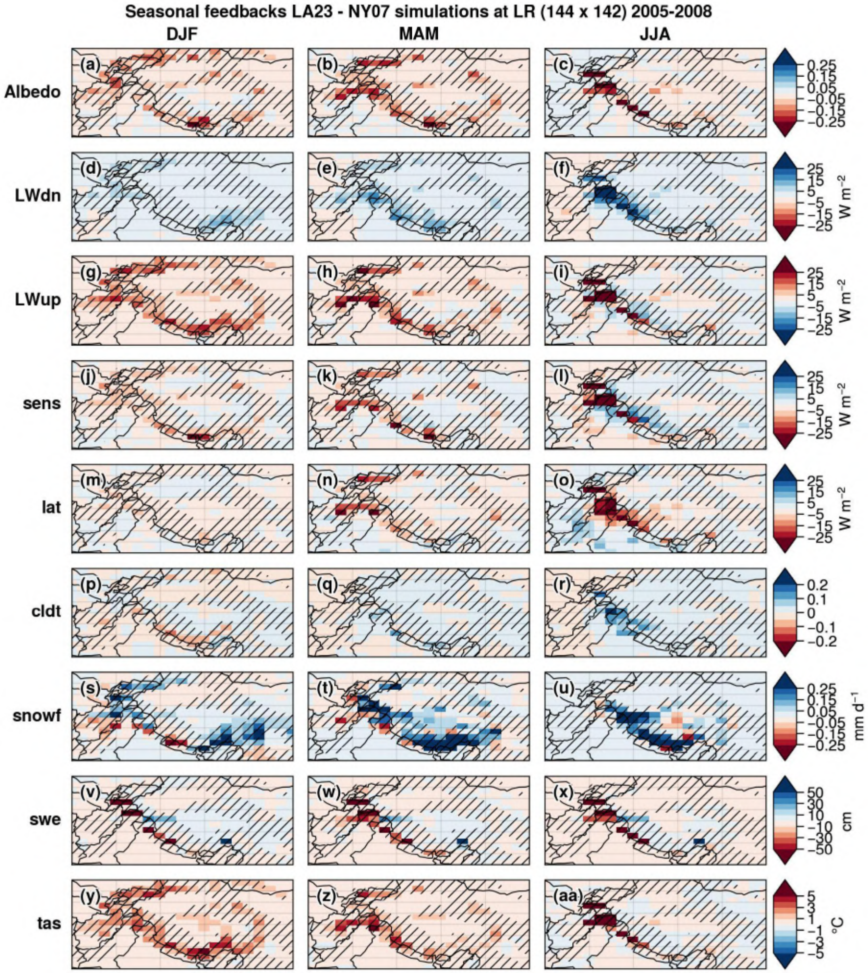
- Persistent snow cover overestimation in HMA mountainous region (tropo bias)

Application in GCM: feedbacks (LA23 - NY07)



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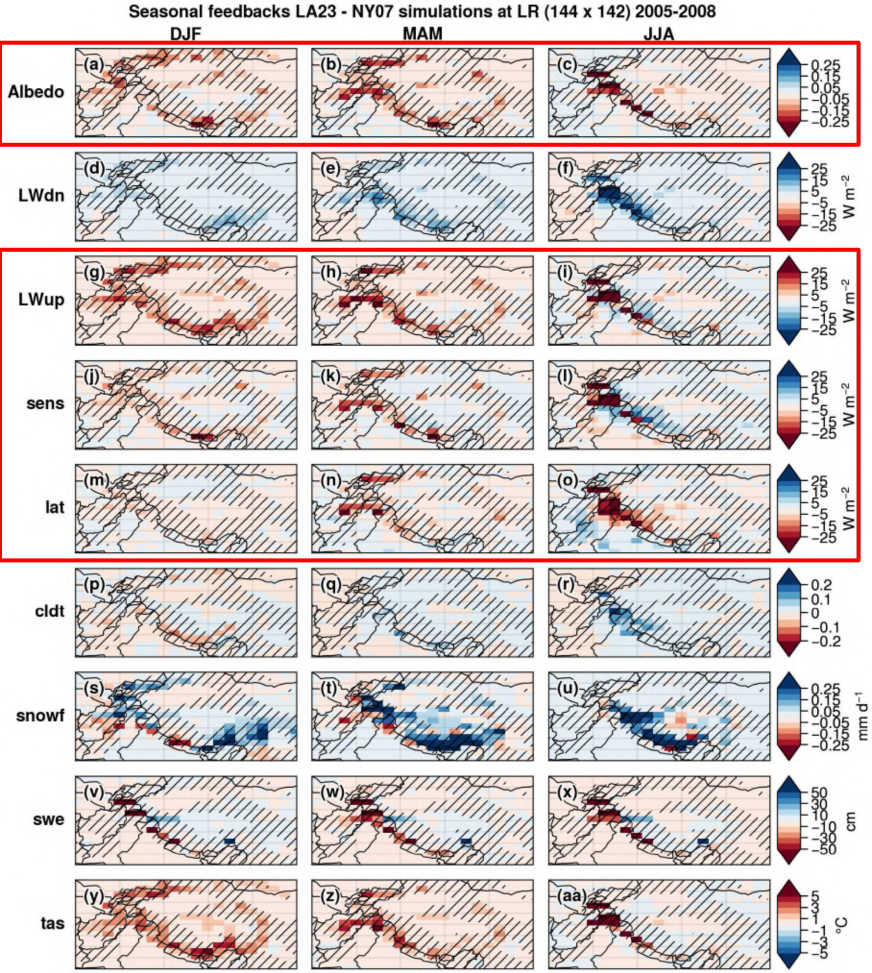

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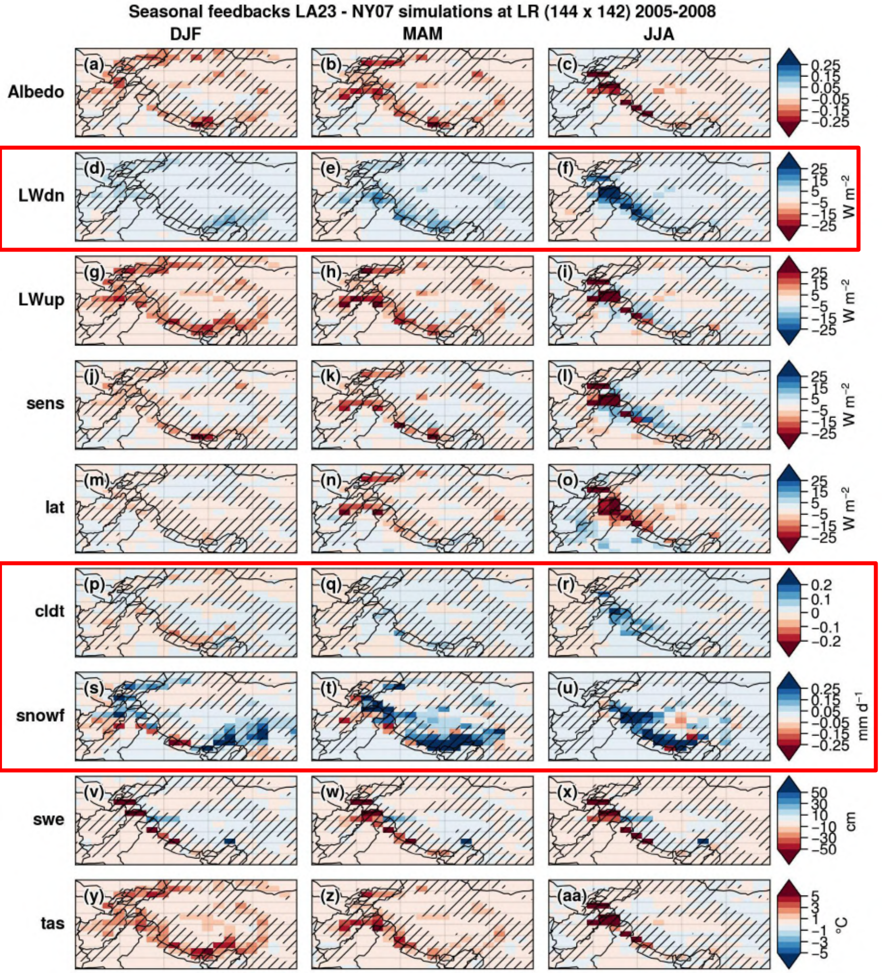

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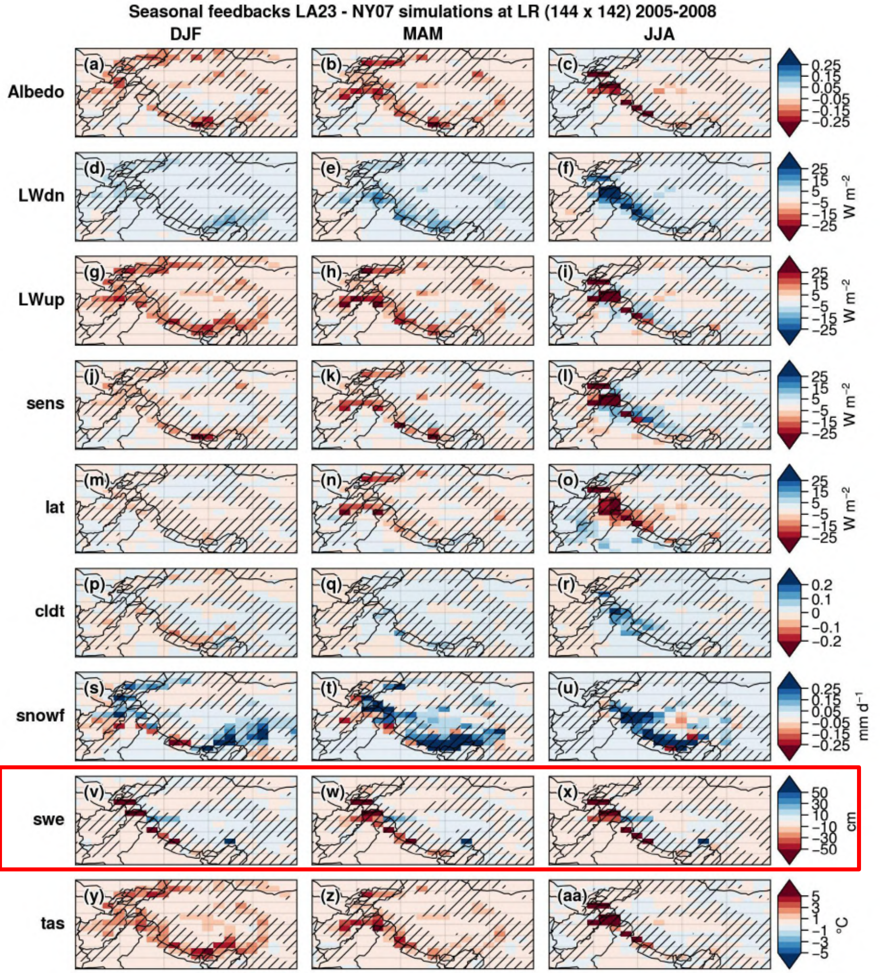

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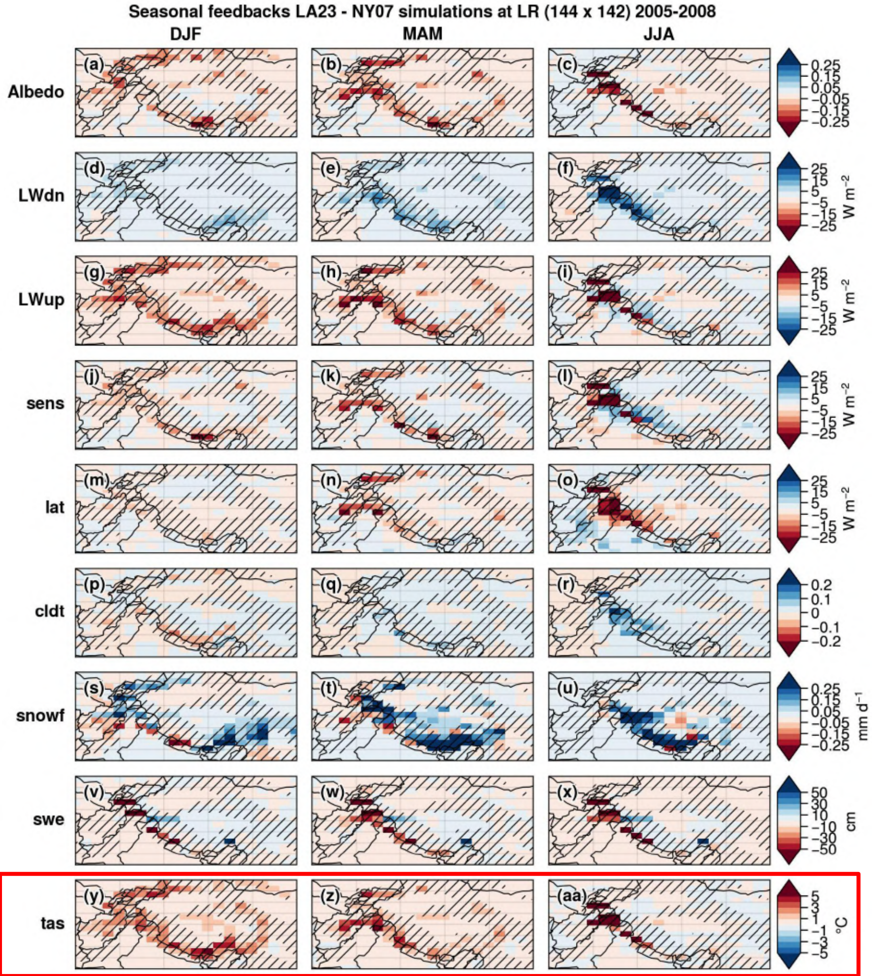

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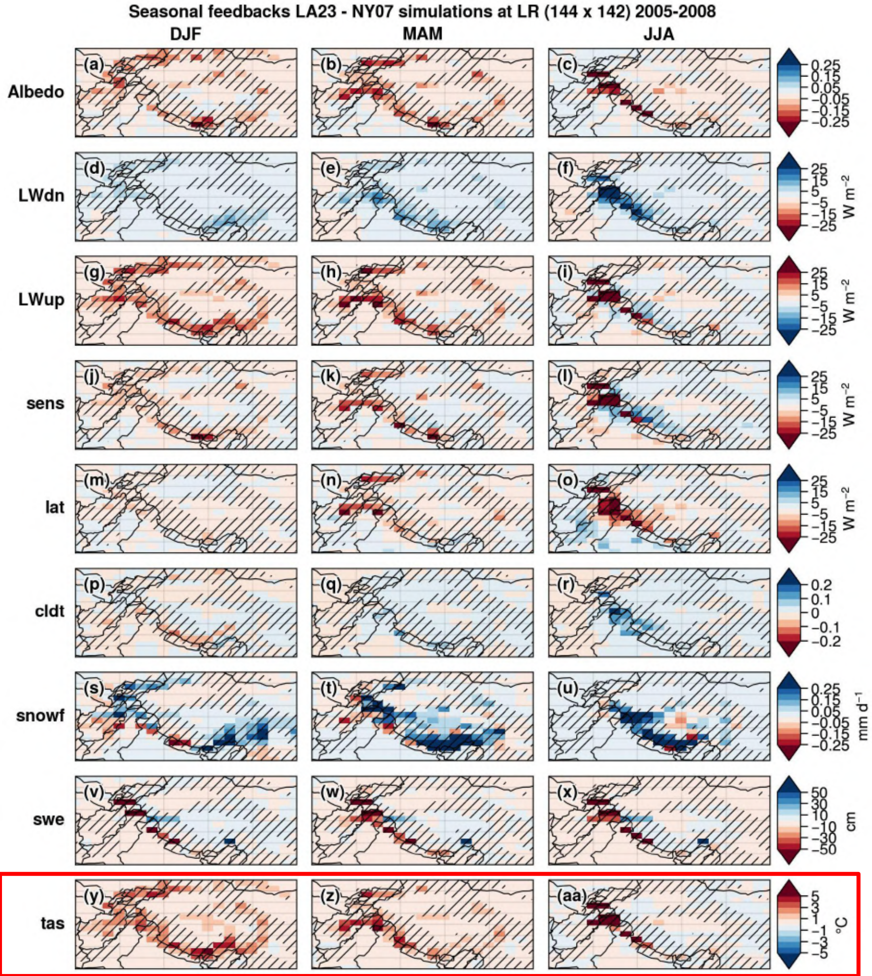

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- Decrease of SWE of more than 50 cm locally
- Increase in near-surface temperature and
- Surface cold bias decrease from −1.8 °C to about −1 °C in the High Mountain Asia (HMA) region

Take home messages

- Taking into account the sub-grid topography in SCF parameterization seems essential over mountainous areas (Swenson and Lawrence, 2012 ; Miao et al., 2022 ; Lalande et al., in review)

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- Further calibration -> other regions / datasets (+ other variables, forested areas?, etc.) +
  ⤷ Crucial need of snowfall, SD/SWE observations over mountainous areas!

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- Other parameterizations not tested, e.g.: Liston (2004), Helbig et al. (2021), etc.
- Deep learning very promising for such parameterizations (+ help to test the influence of other parameters)

Part #3

Annex B: Climate Change Initiative Fellowship Project Proposal

Project (2 years): **Snow cover heterogeneity and its impact on the Climate and Carbon cycle of Arctic regions (SnowC²)**

01/10/2023 - 30/09/2025

Objectives : **Improving snow model in CLASSIC** (SCF, multi-layer snow scheme, blowing snow sublimation) and **assessing these improvements over the Arctic**

Location : **Trois-Rivières, QC, UQTR / GLACIOLAB / RIVES (Canada)**

Supervision : **Christophe Kinnard** (+ Alexandre Roy / ECCC)

GLACIOLAB

Mickaël Lalande

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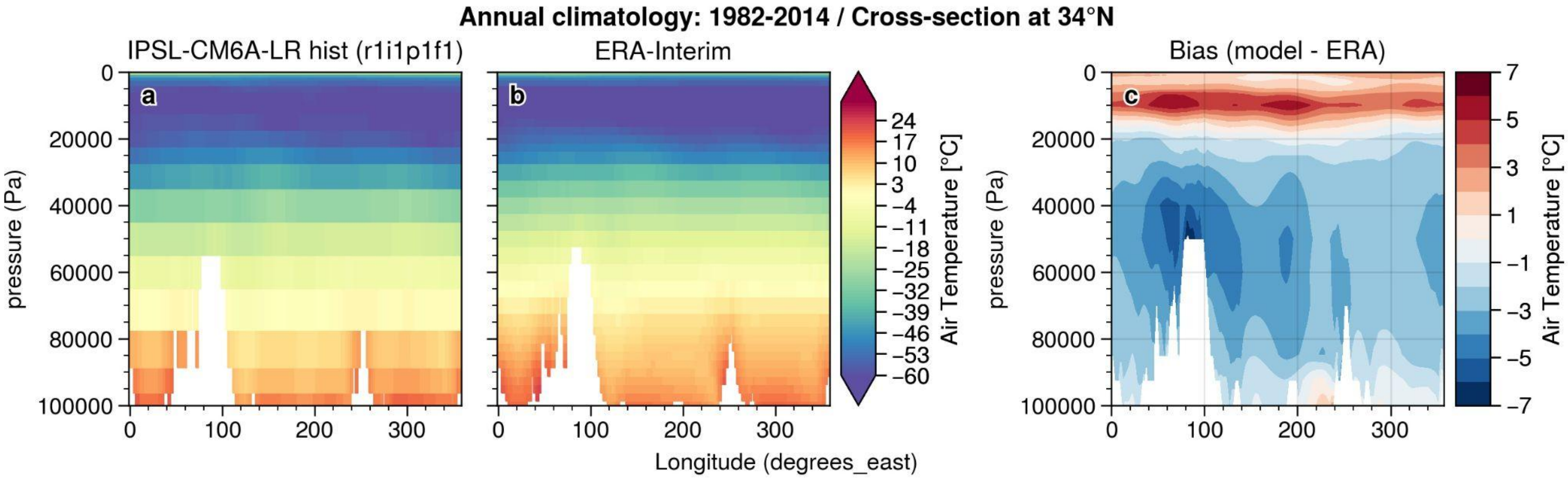
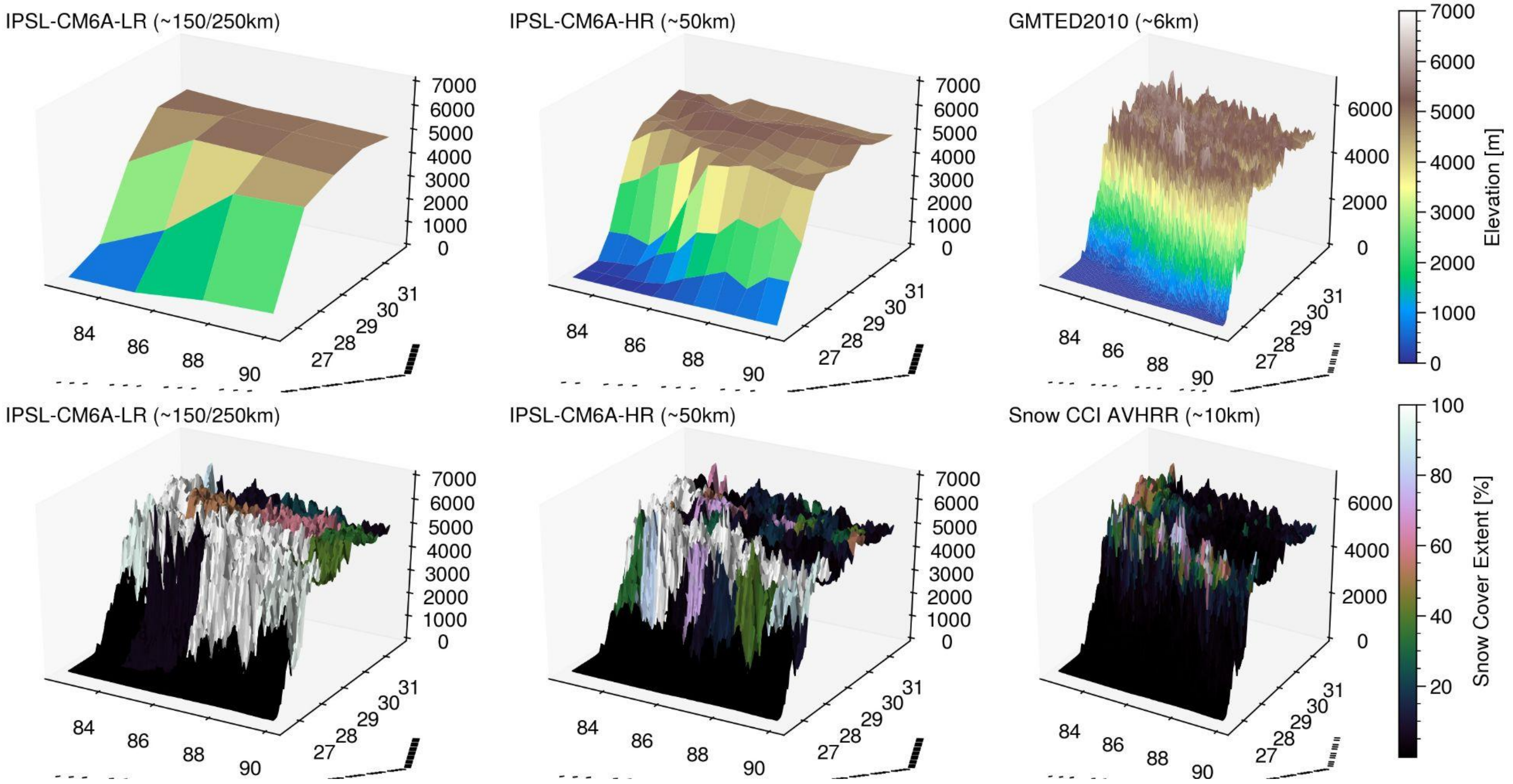
Supplementary materials

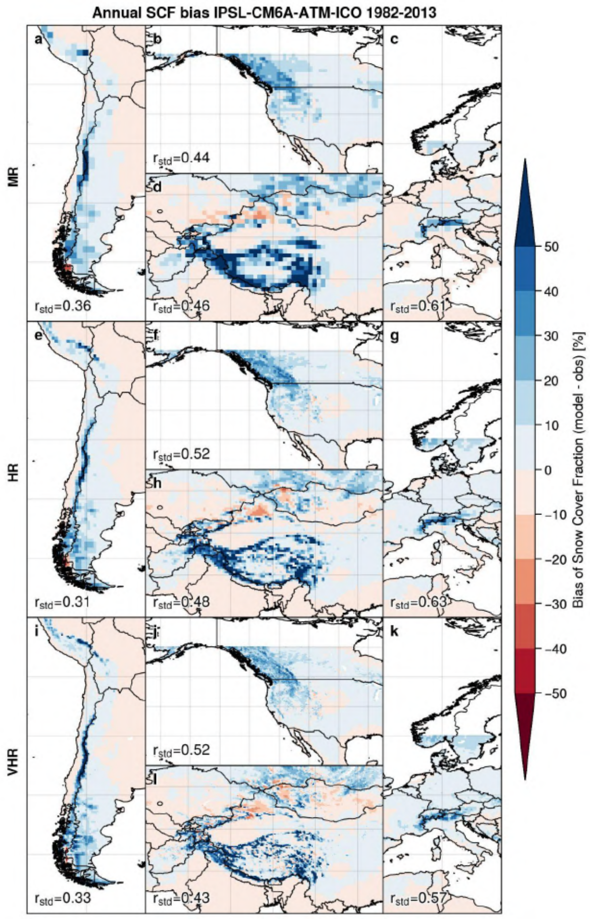
Air Temperature meridional cross-section means bias

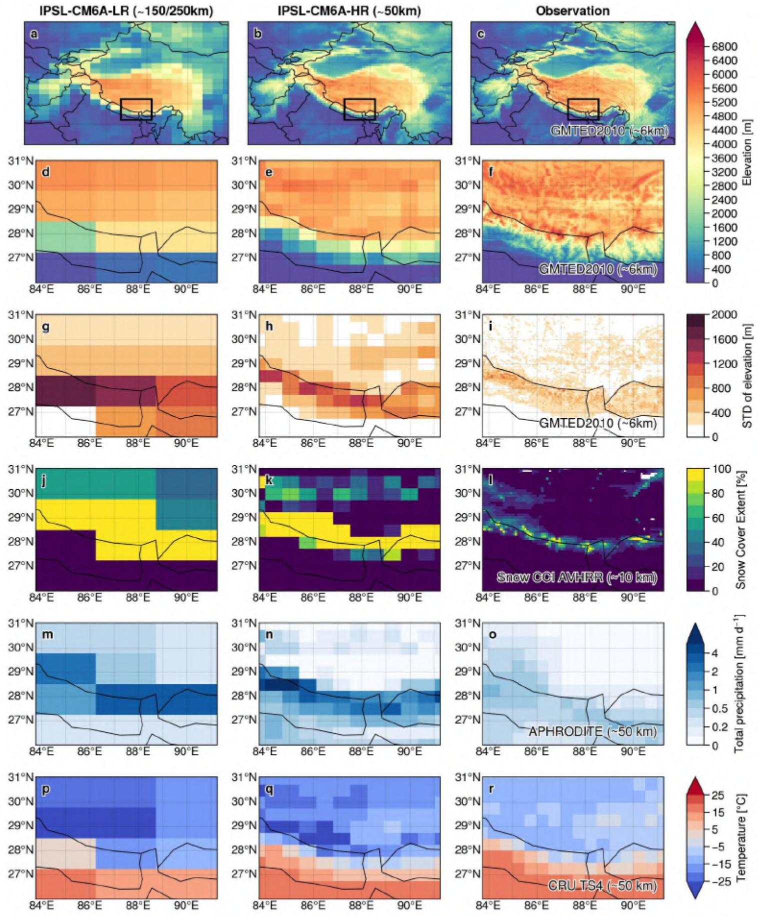


Lien avec la topographie ?

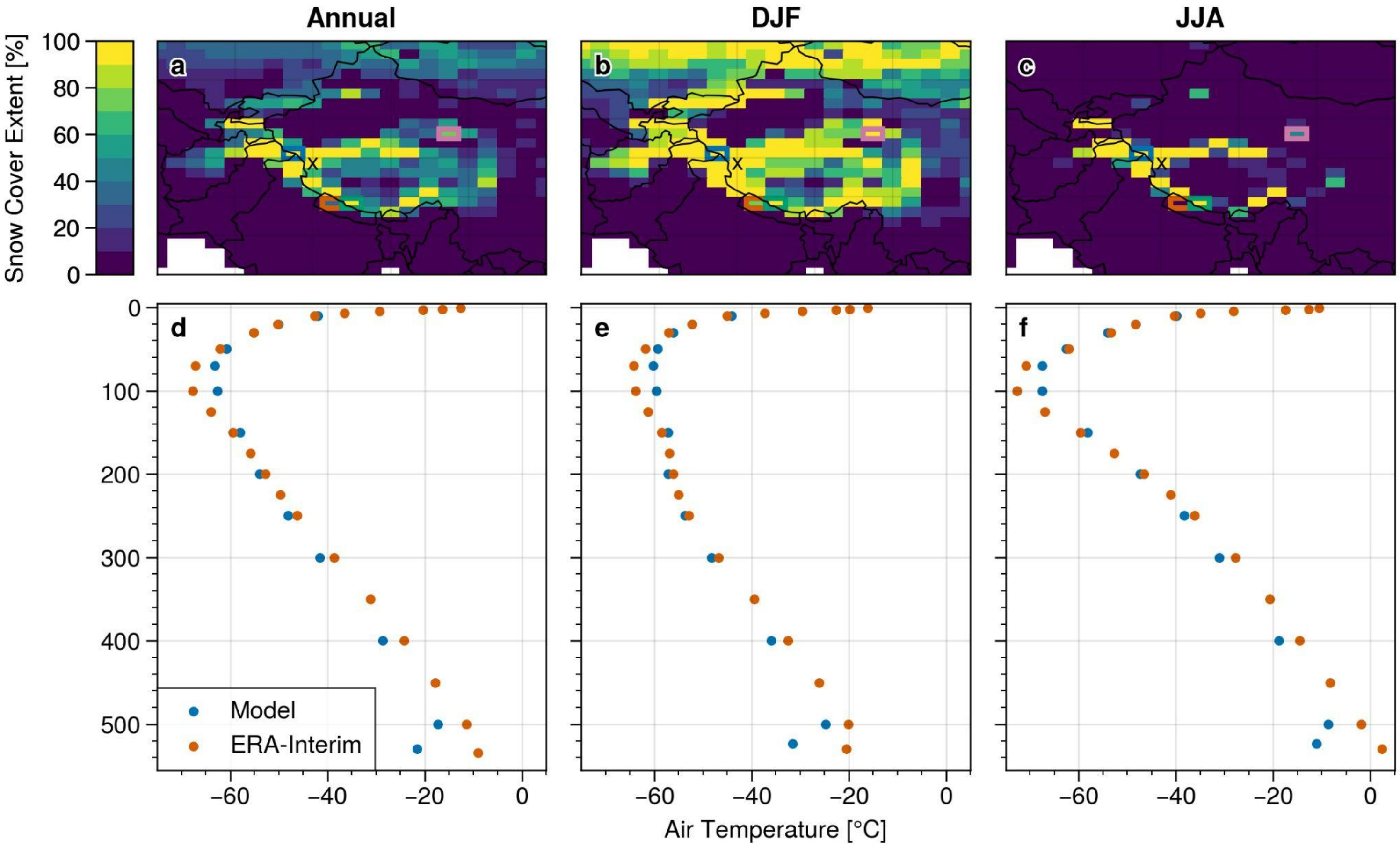


Influence de la résolution

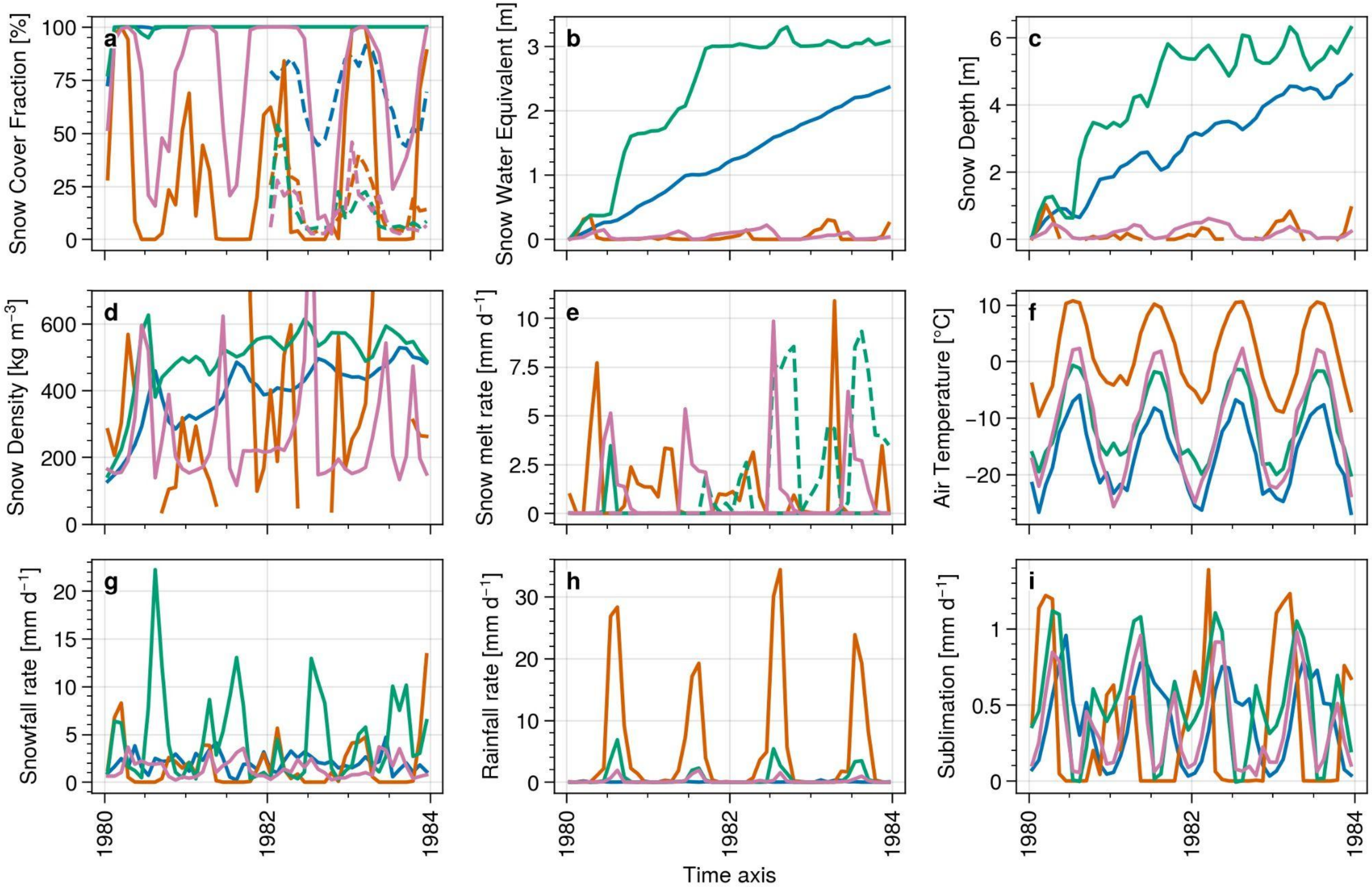




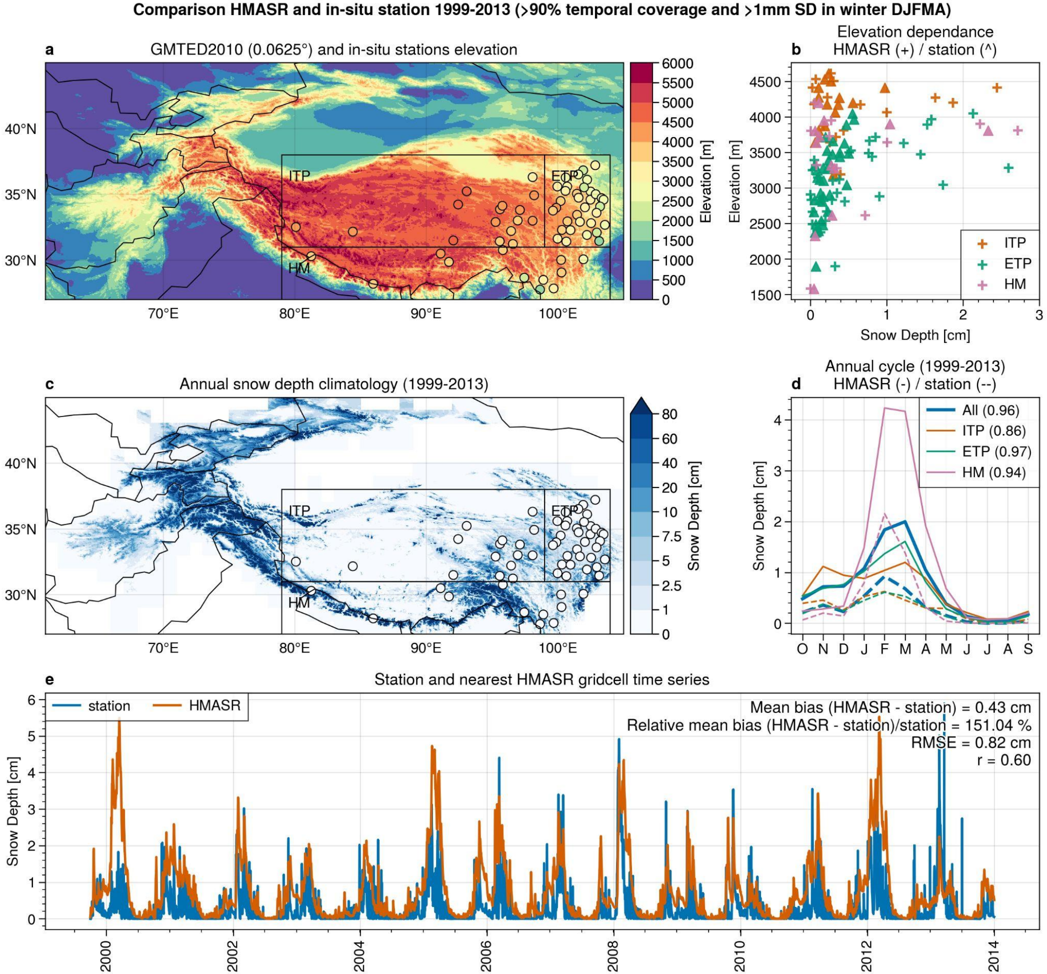
Neige permanente



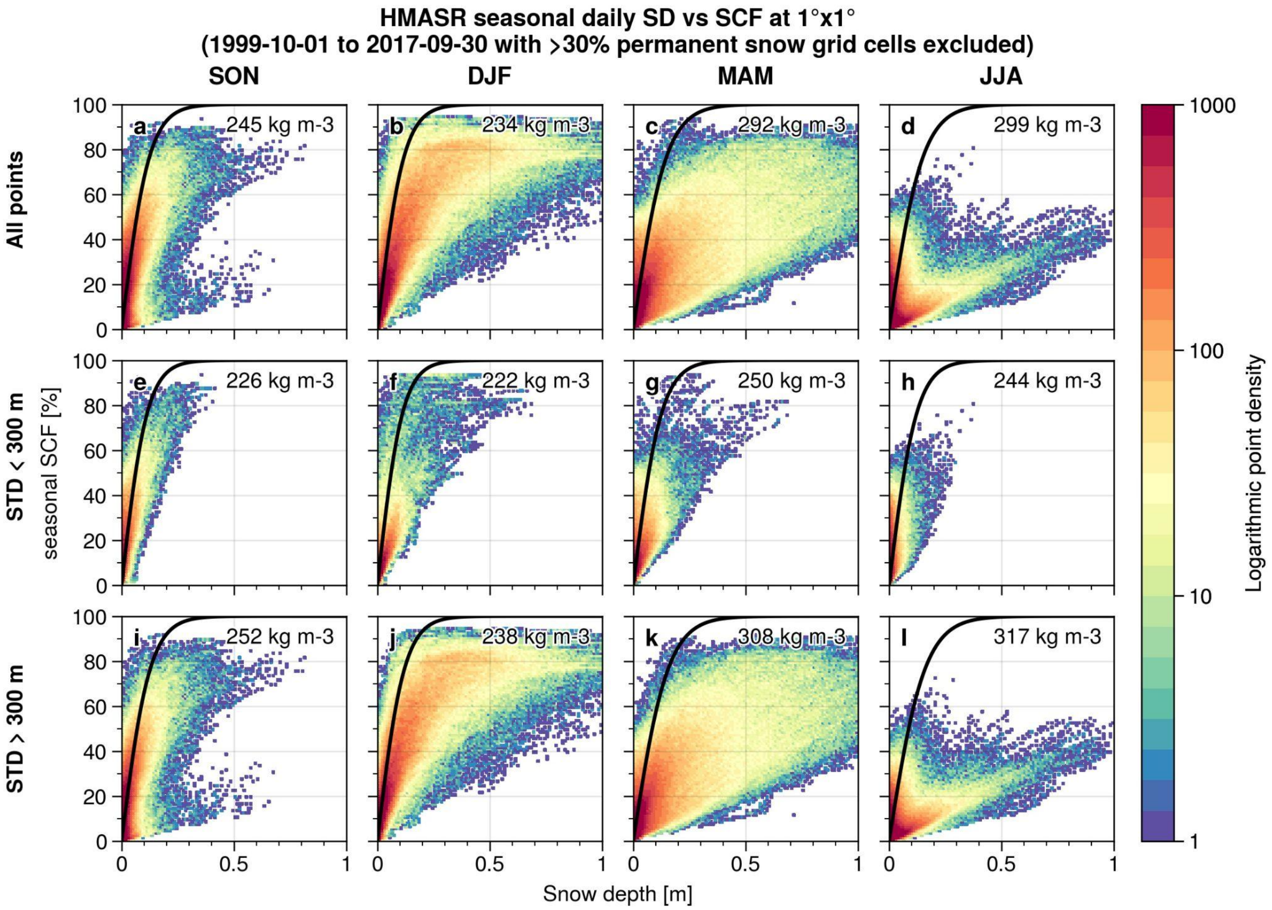
Neige permanente



High Mountain Asia UCLA Daily Snow Reanalysis (HMASR)



High Mountain Asia UCLA Daily Snow Reanalysis

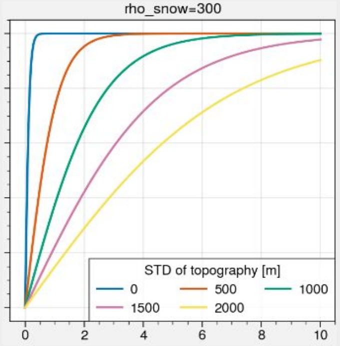


Other snow cover parameterizations

Niu and Yang (2007) custom

$$F = \tanh\left(\frac{d}{2.5 z_{0g} \left(\rho_{snow}/\rho_{new}\right)^m}\right)$$

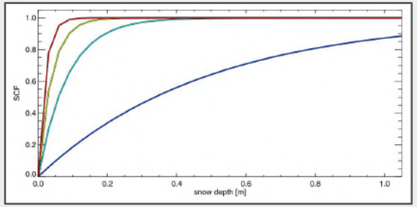
STD
topo



Swenson and Lawrence (2012)

Accumulation

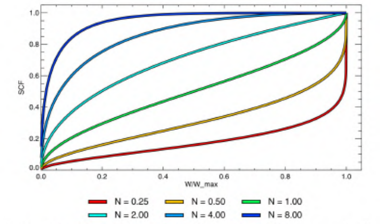
$$F_{N+1} = 1 - (p_{N+1})(p_N) = 1 - (1 - s_{N+1})(1 - F_N)$$



Depletion

$$F = 1 - \left[\frac{1}{\pi} \text{acos}\left(2 \frac{W}{W_{\max}} - 1\right)\right]^{N_{melt}}$$

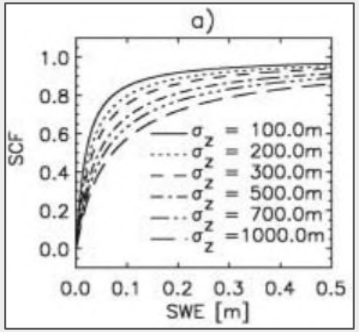
$$N_{melt} = \frac{200}{\sigma_{topo}}$$



Roesch et al. (2001)

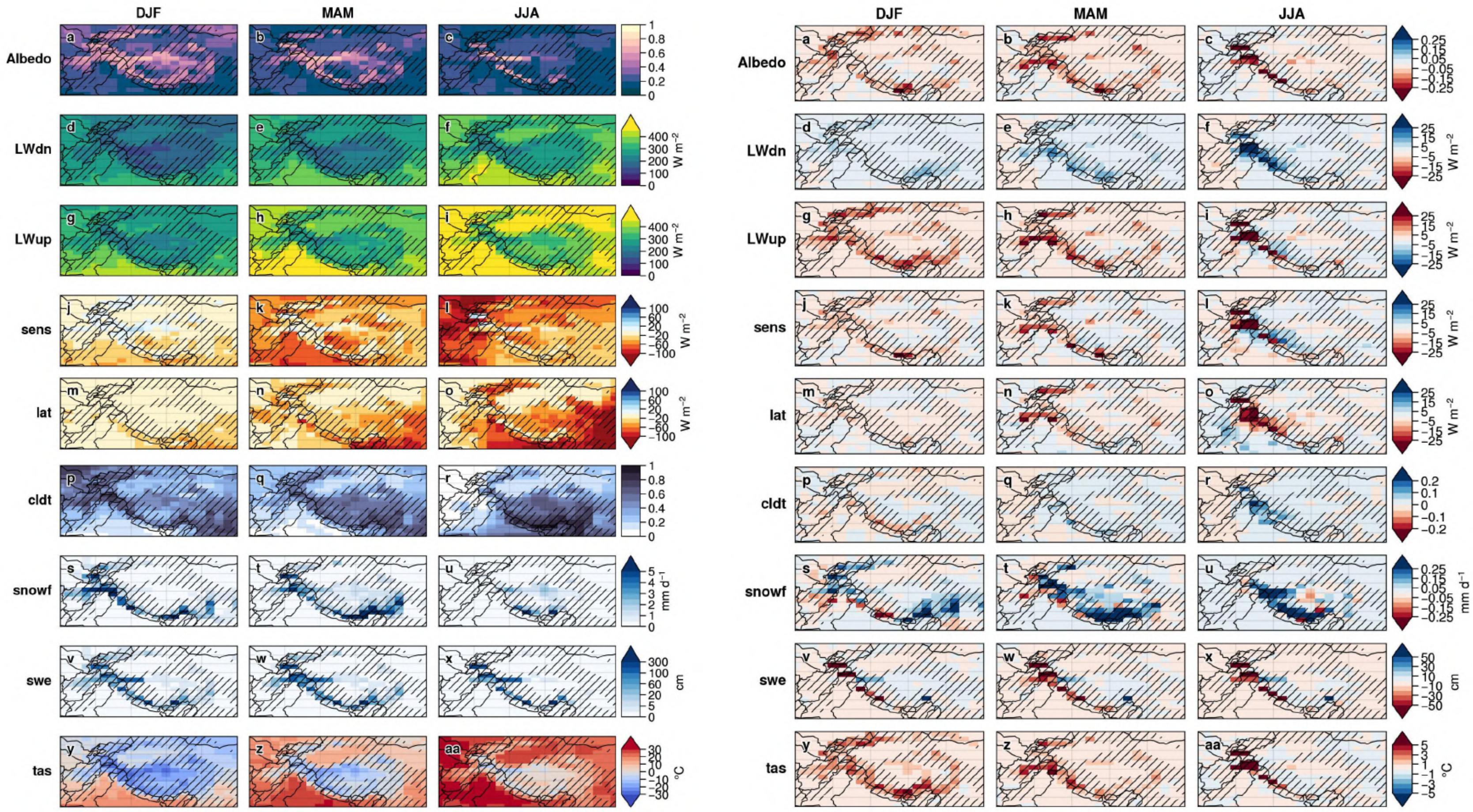
Mountainous areas

$$f_s = 0.95 \cdot tanh(100 \cdot S_n) \sqrt{\frac{1000 \cdot S_n}{1000 \cdot S_n + \epsilon + 0.15\sigma_z}}$$

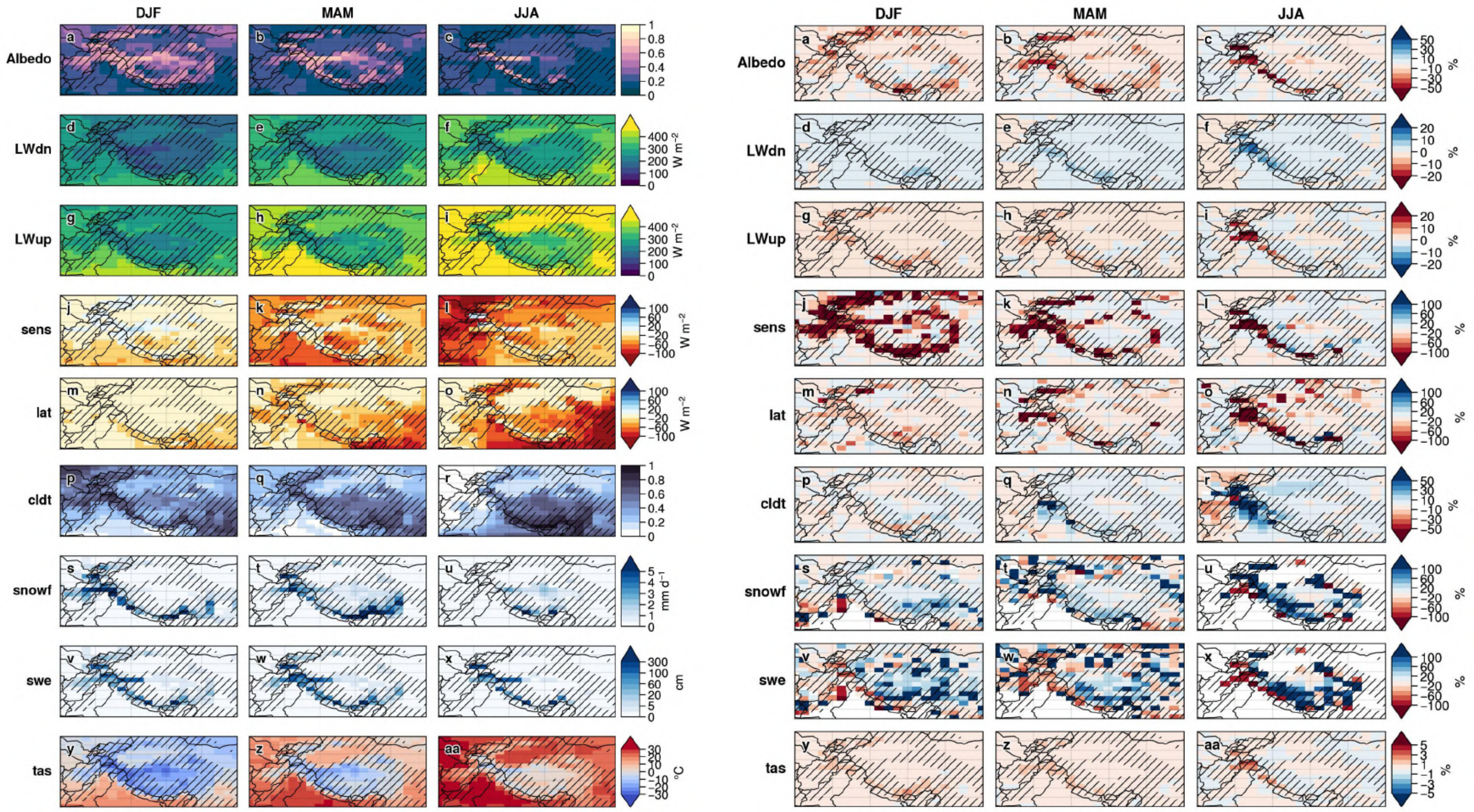


Depends only on SWE so no hysteresis

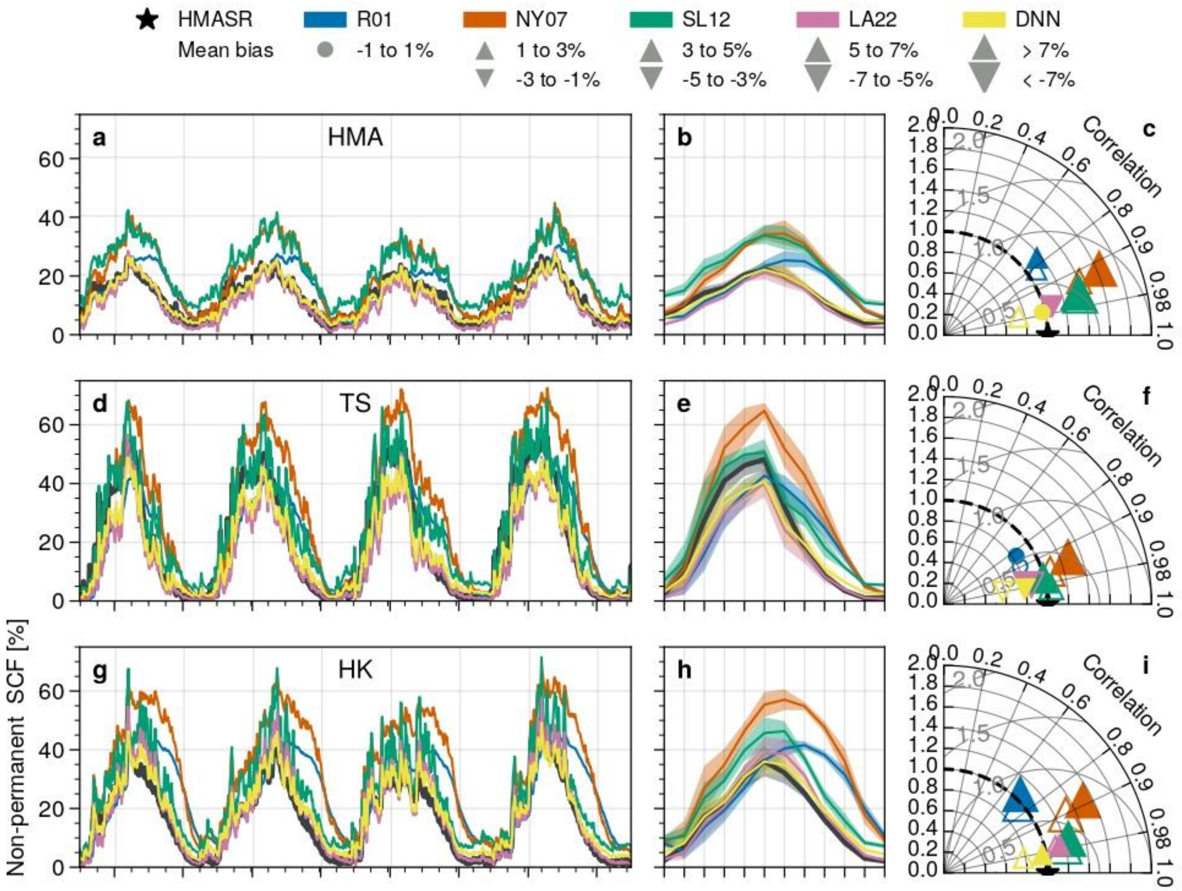
Feedbacks (LA23 - NY07)



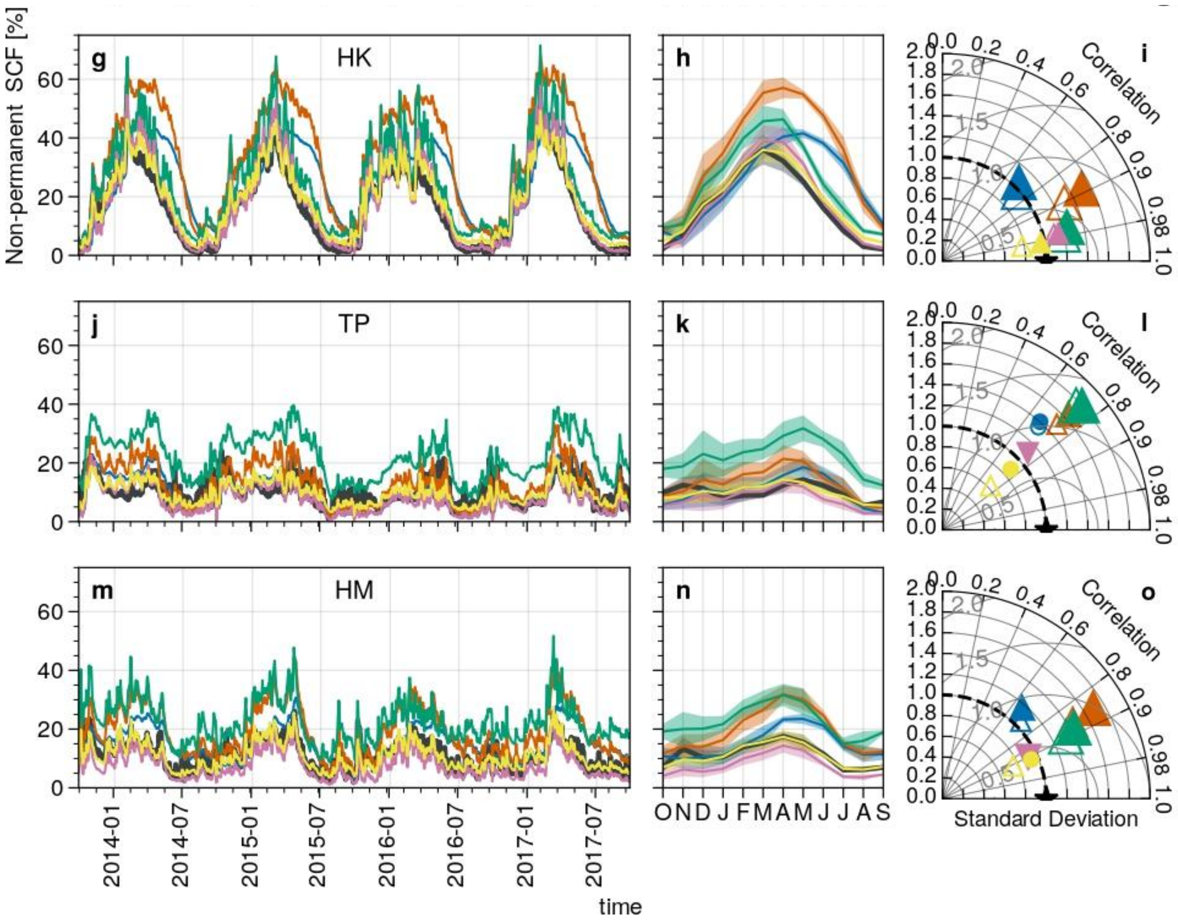
Feedbacks (LA23 - NY07)/NY07



Time series


HMASR
R01
NY07
SL12
LA22
DNN
Mean bias
-1 to 1%
1 to 3%
-3 to -1%
3 to 5%
-5 to -3%
5 to 7%
-7 to -5%
> 7%
< -7%
a
HMA
b
c
Correlation
d
TS
e
f
g
HK
h
i
Non-permanent SCF [%]

Time series

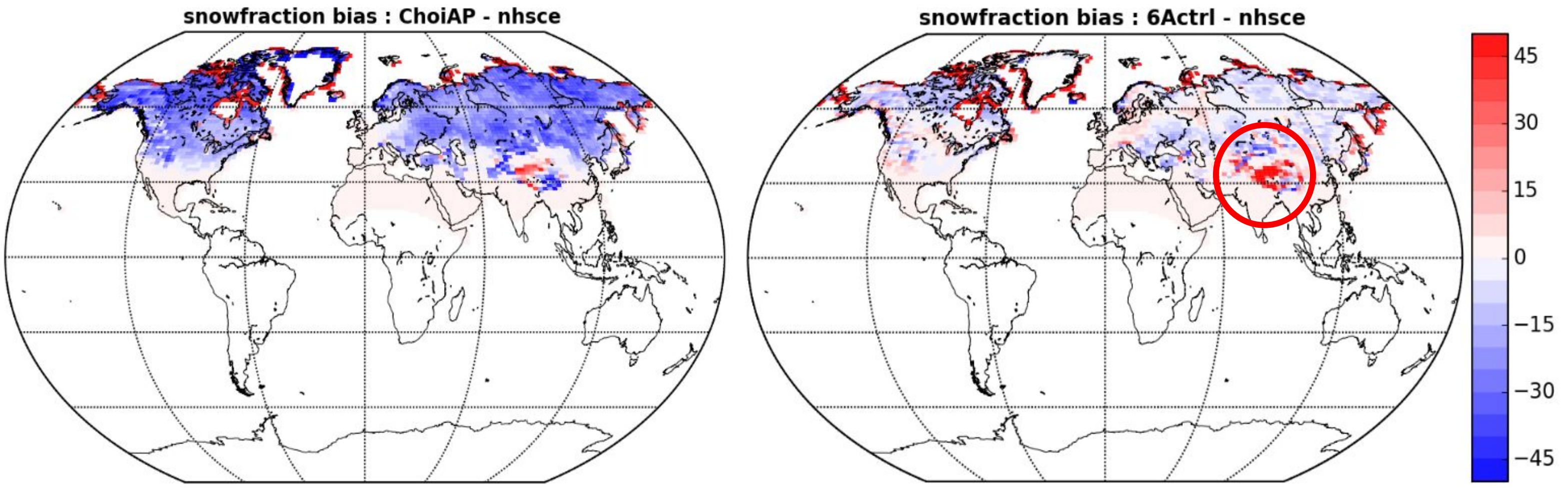


Non-permanent SCF [%]
g
HK
h
i
Correlation
j
TP
k
l
m
HM
n
o
2014-01
2014-07
2015-01
2015-07
2016-01
2016-07
2017-01
2017-07
time
O N D J F M A M J J A S
Standard Deviation

Context: snow bias in IPSL model CMIP5 versus CMIP6

Bias of the snow cover fraction
(i.e., simulated - observed snow fraction)

Old version (CMIP5) | New version (CMIP6)

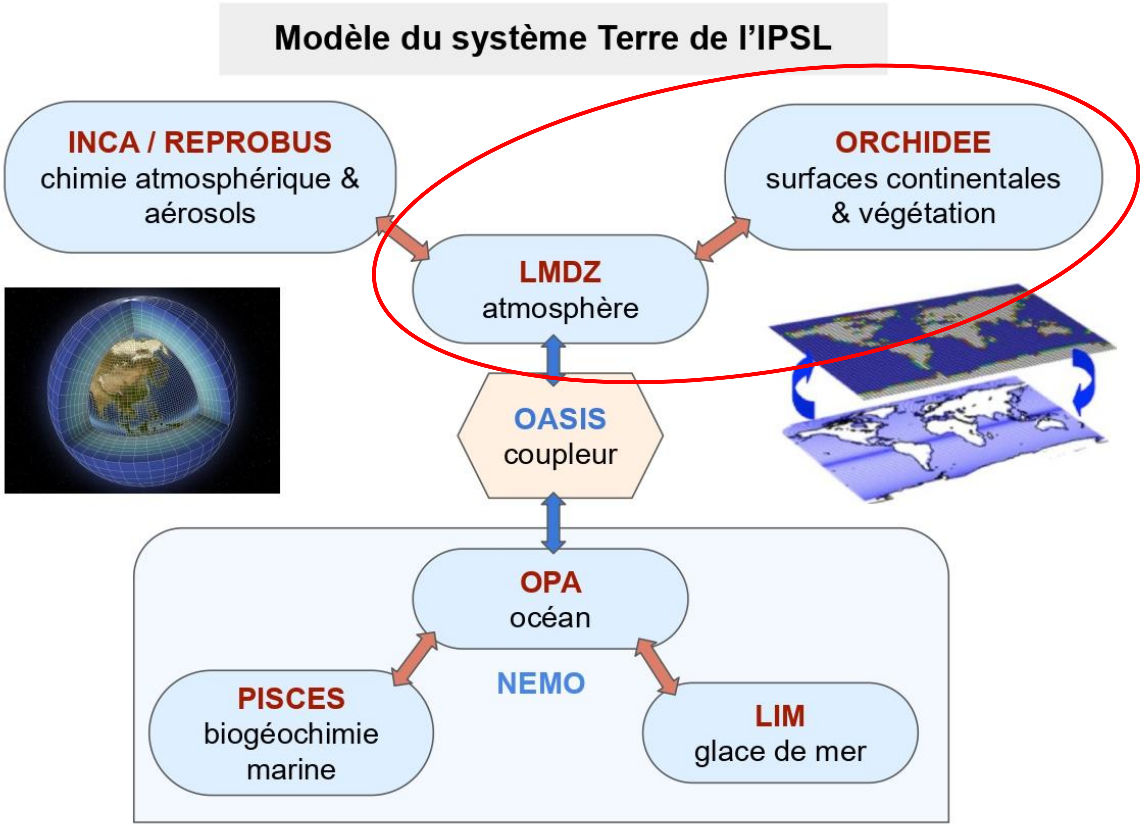


Too much snow

Not enough snow

Fig. 7 Cheruy et al. (2020)

IPSL Earth System Model

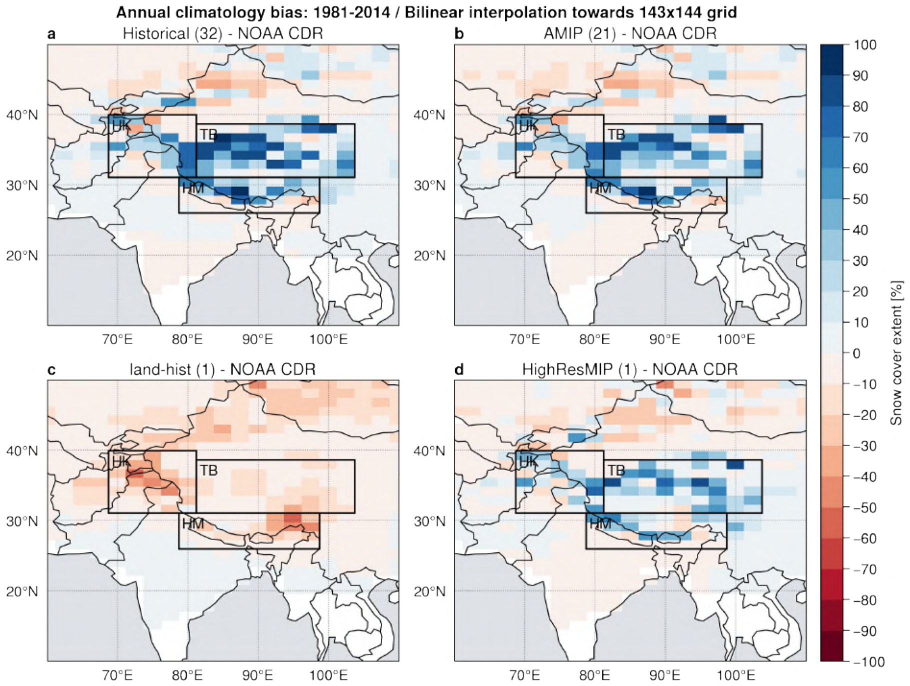


- Version 6A-LR (CMIP6):
  - 144 x 142 (grid points lon / lat)
  - ~ 2,5° x 1,25°
  - 79 vertical layers (up to ~80 km altitude)
  - time step of the physics: 15 min

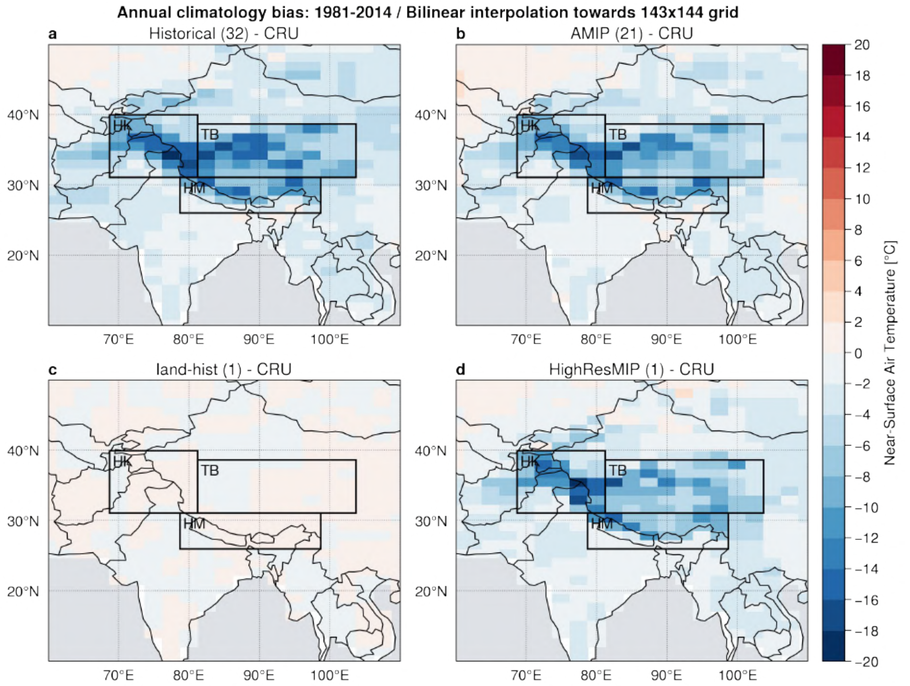
- Version 6A-HR (CMIP6):
  - 360 x 180 (grid points lon / lat)
  - ~ 0,5° x 0,5°
  - time step of the physics: 3,75 min

IPSL-CM6A-LR: Historical, AMIP, land-hist / IPSL-CM6A-ATM-HR bias

Snow cover bias

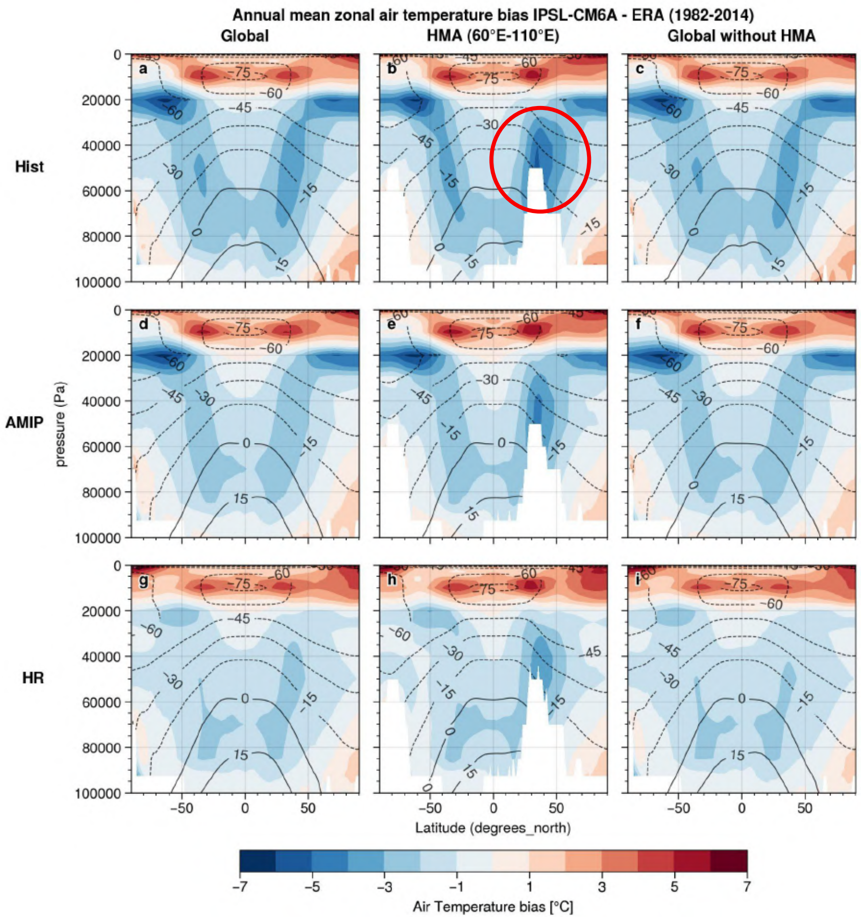


Temperature bias



- Large cold bias (up to -20 °C) and excess of snow cover (> 50 %) mainly located on the Tibetan Plateau
- Historical / AMIP similar and reduced biases in HighResMIP
- land-hist slightly underestimate the snow cover (/!\ poor quality of atmospheric forcing? /!\)

Air Temperature zonal means bias global versus HMA



- Cold bias in troposphere and hot bias in stratosphere
- Cold bias of air temperature not restricted to HMA!
  - HMA seems to amplify this bias
  - The bias is reduced in HighResMIP

Questions

1. Does the surface biases trigger tropospheric biases?
2. Are the tropospheric biases responsible of surface biases?

Experiments

1. Experience without snow
2. Nudged experiments (temperature and wind)

Tropospheric bias reduction: nudged experiments

6h u, v

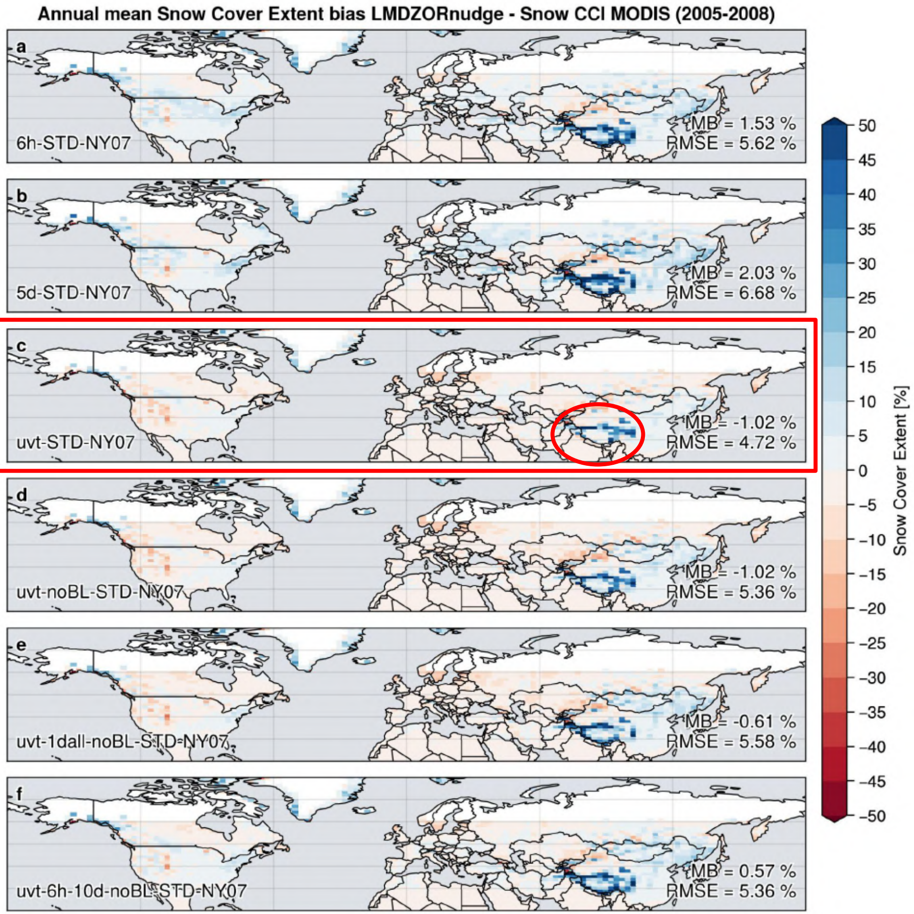
5j u, v

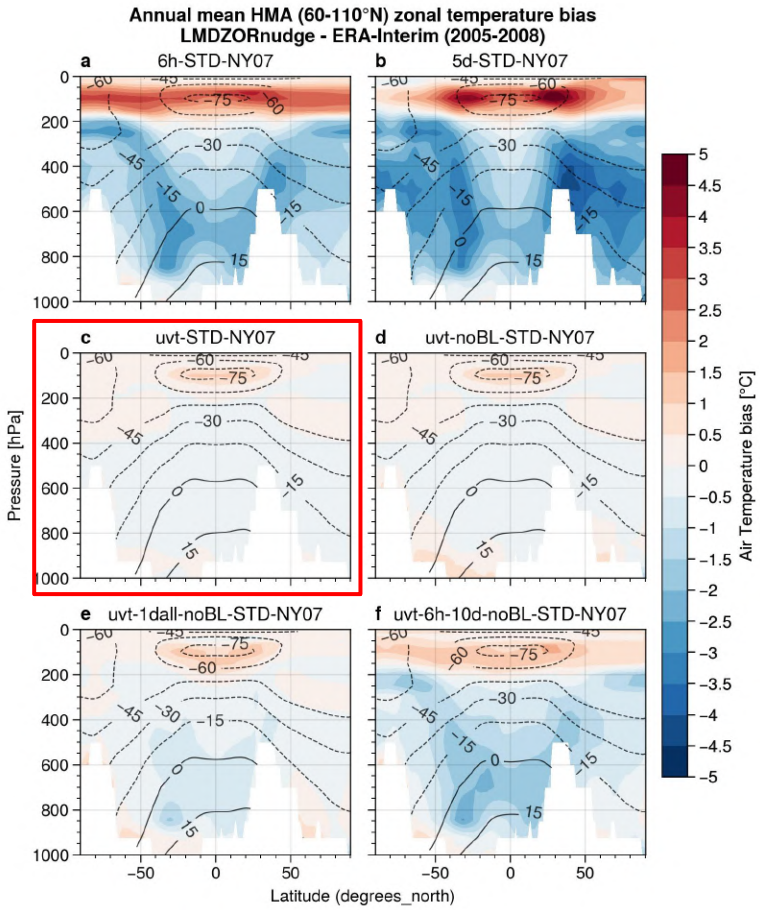
3h u, v, T

3h u, v, T NoBL

1j u, v, T NoBL

6h u, v, 10j T NoBL

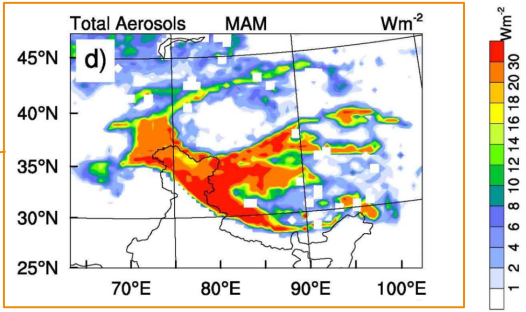




Perspectives: CMIP6 -> CMIP7 LMDZ/ORCHIDEE

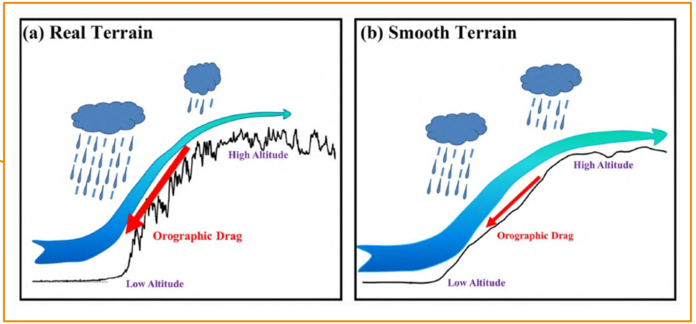
- Improved representation of snow albedo including aerosol deposition (e.g., Warren and Wiscombe, 1980; Kokhanovsky and Zege, 2004; Wang et al., 2020b)

Fig. 7 Usha et al. (2020)



- Small-scale orographic drag

Fig. 5 Wang et al. (2020)



- Improved calculation of surface energy balance

- Elevation bands and snow-ice coupling

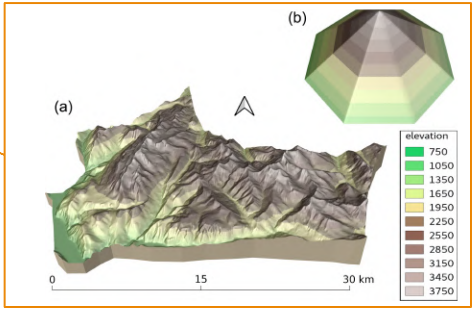
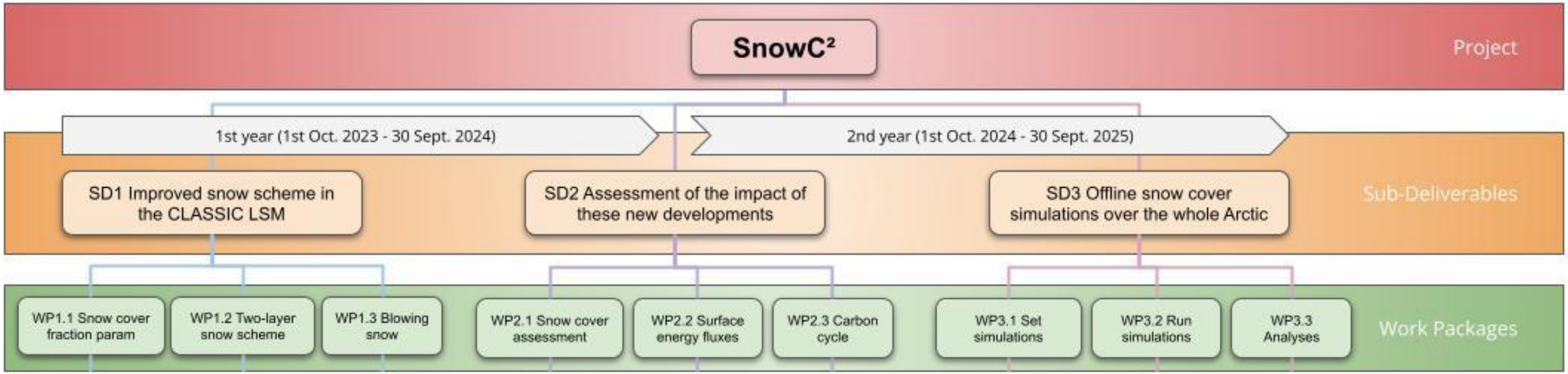


Fig. 3 Vernay et al. (2022)

- Boundary layer in mountain areas (Wekker and Kossmann, 2015; Serafin et al., 2020)

Work Package breakdown: Snow cover heterogeneity and its impact on the Climate and Carbon cycle of Arctic regions

ESA CCI Fellowship - Mickaël Lalande - supervised by Christophe Kinnard at UQTR / RIVES (Canada)



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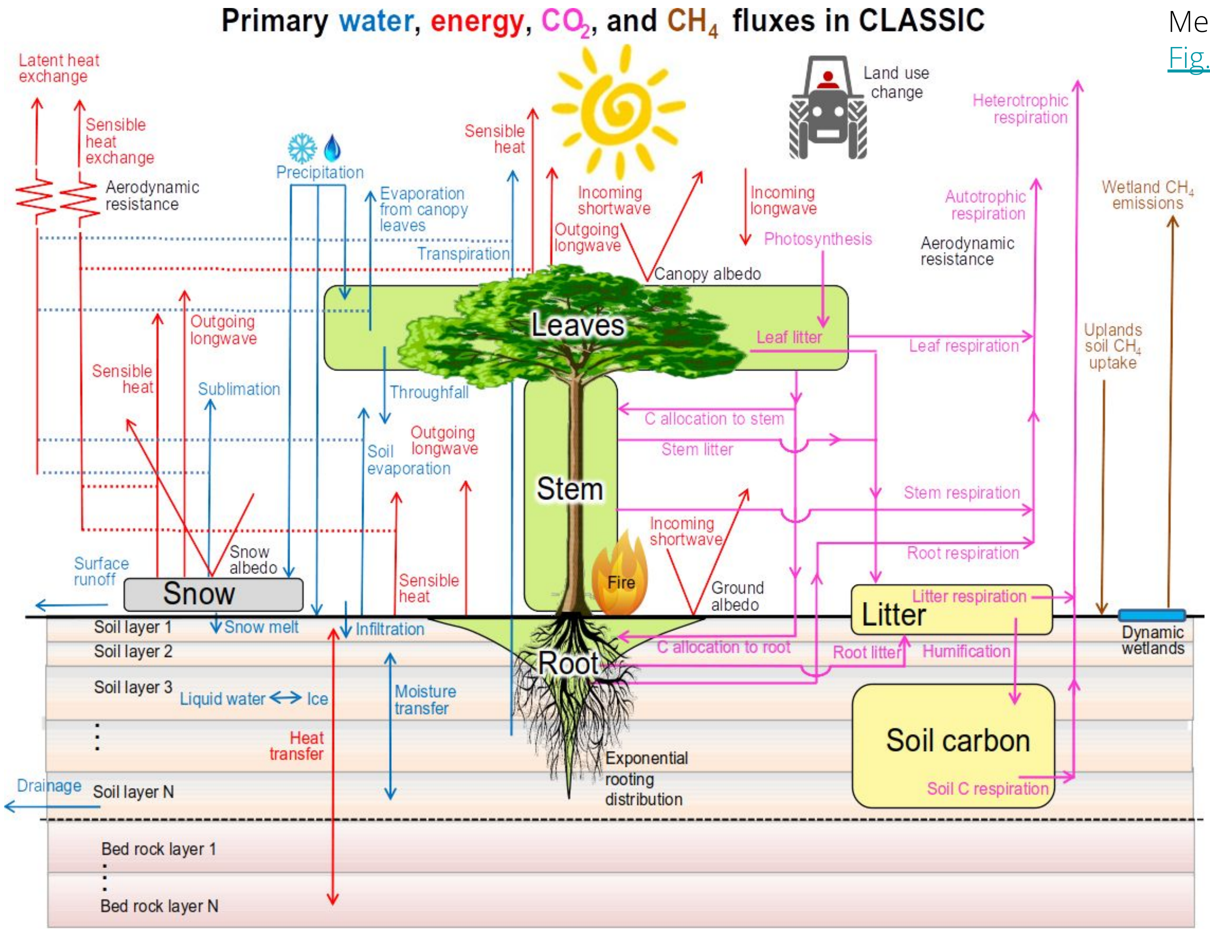
Snow model in CLASSIC: description



Melton et al. (2020), Fig. 1

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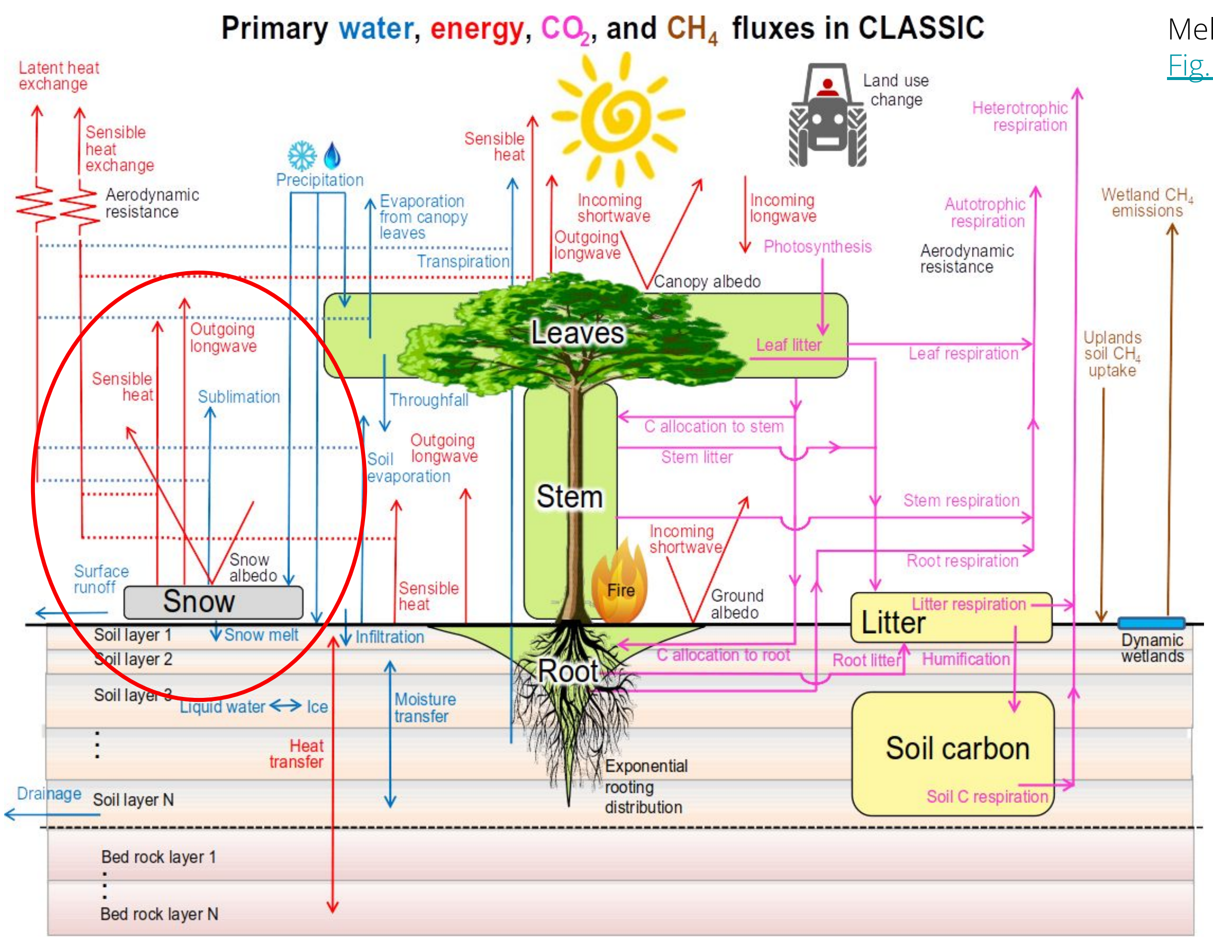

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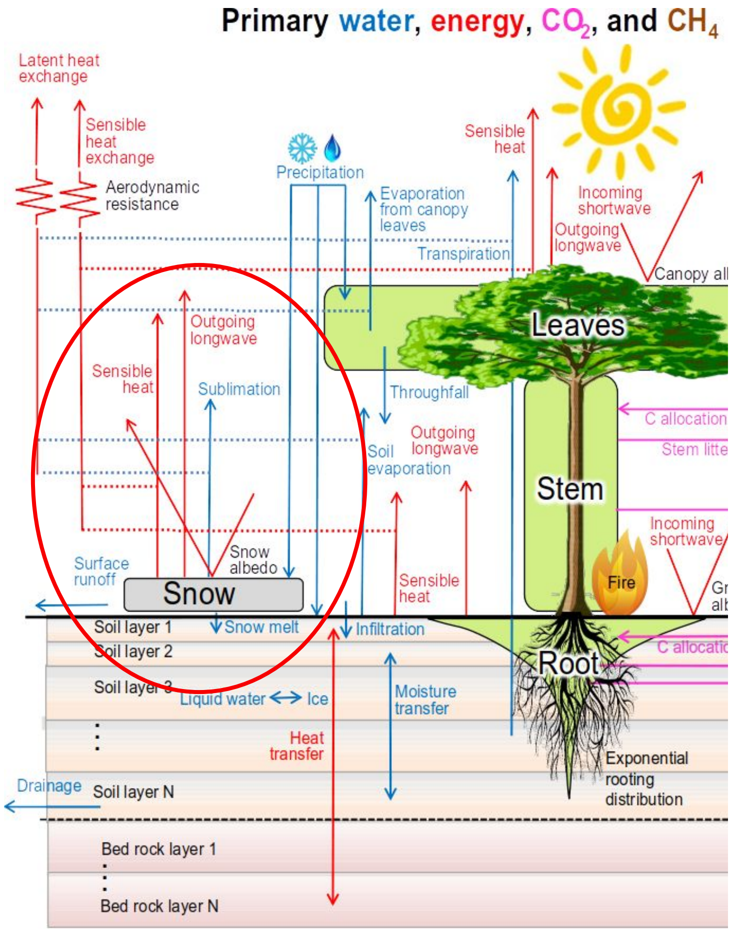
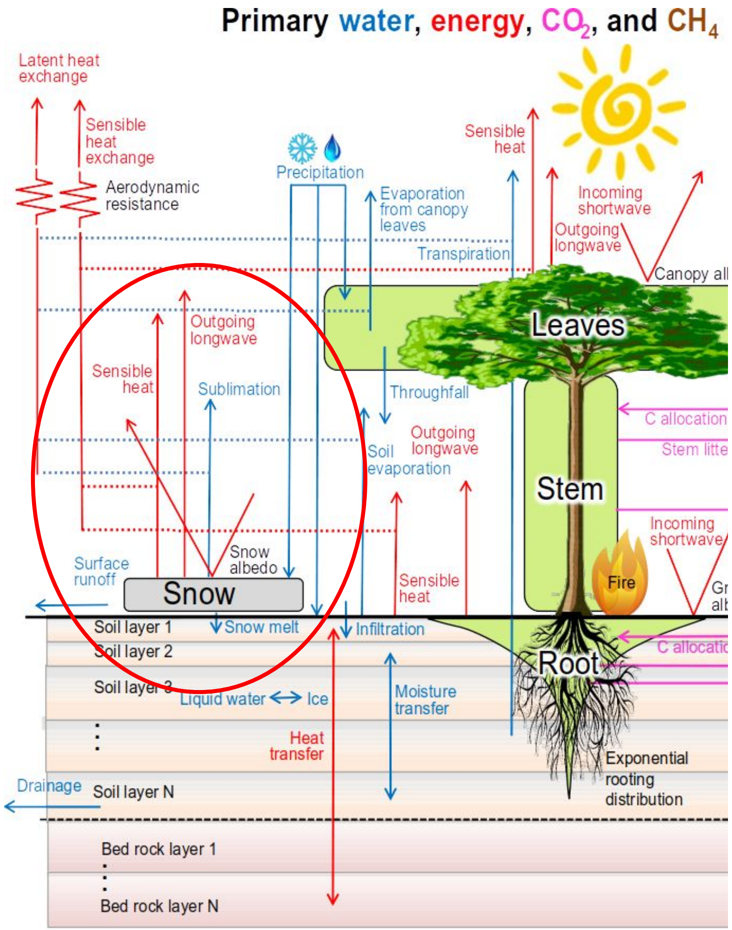


CLASS description and snow model characteristics (Verseghy et al., 2017 - version 2.7 -> 3.6.1):

- Separate energy and water balances for the vegetation canopy, snow, and soil
- Single-layer snow model
- Snow albedo decreases and the snow density increases exponentially with time
- Fresh snow density is determined as a function of the air temperature
- The snow thermal conductivity is derived from the snow density
- Melting of the snow layer can occur either from above or from below (percolation and refreezing taken into account)

Snow model in CLASSIC: description



- Interception of snowfall by vegetation is explicitly modeled
- SCF = 100 % if SD > 10 cm then linear decrease?

Updates version 2.7 -> 3.6.1:

- Revised formulation for vegetation interception of snow
- New parameterization for unloading of snow from vegetation
- Adjustments to the albedo of snow-covered canopies
- Revision of the limiting snow density as a function of depth
- New algorithms for snow thermal conductivity
- Water retention in snow packs has also been incorporated
- Snow albedo refreshment threshold has been updated

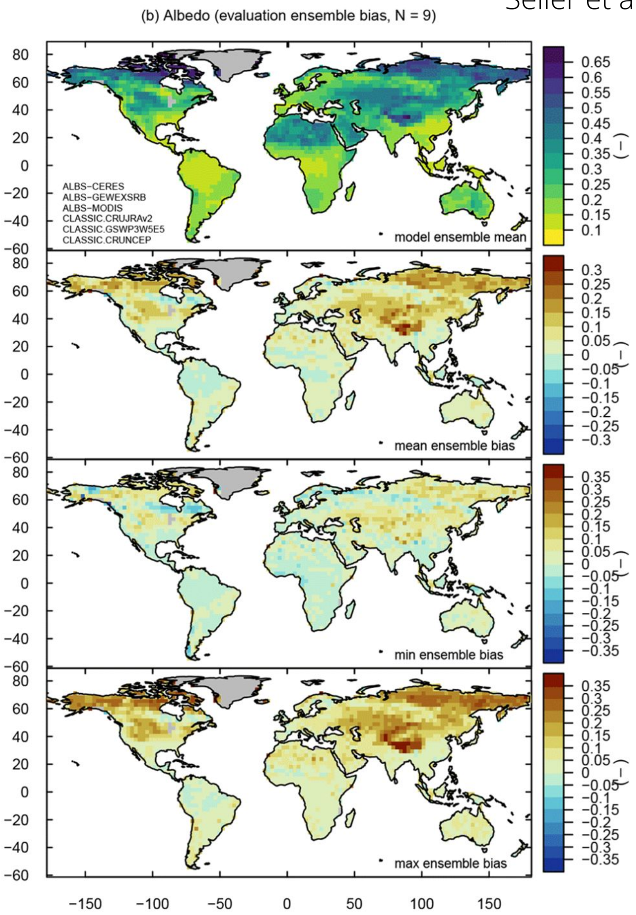
Note: A parameterization of the effect of black carbon on the snow albedo has recently been developed for CLASS (when coupled)

Snow model in CLASSIC: evaluation

Evaluation of CLASS Snow Simulation over Eastern Canada (Verseghy et al., 2017):

- SCF agreed well with the observational estimates.
- Albedo of snow-covered areas showed a bias of up to -0.15 in boreal forest regions (-> neglect of subgrid-scale lakes).
- In June, positive albedo bias in the remaining snow-covered areas (neglect of impurities in the snow?).

Snow model in CLASSIC: evaluation



Seiler et al. (2021), Fig. 7

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CLASSIC v1.0: Global benchmarking (Seiler et al., 2021):

- Albedo biases -> possible relation with snow and/or the large solar zenith angle?

Snow model in CLASSIC: further work (SnowC^2)

SCF

Keep up with what already exists and continue my thesis work

- SL12, LA23,...
- New calibrations / validations?
- Tuning in the model
- Using the Snow CCI datasets
- Vegetation?

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Multi-layer

Pro

- Arctic snowpack -> 2 layers (depth hoar + wind slab)

Cons

- Some single-layer models perform as well as multilayer models (SnowMIP - Etchevers et al., 2004)

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Blowing snow subli loss

Gordon et al. (2006)

- Sublimation of blowing snow developed and implemented in CLASS
- Blowing snow sublimation generally improves the results

6% of all grid points (2.5° × 2.5°) and days throughout the year (Déry and Yau, 1999a) / 25% in north-eastern Canada (Hanesiak and Wang, 2005)