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Modeling the glacio-hydrological response of a Himalayan watershed to climate change using a physically-oriented distributed model: sources of model uncertainty

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1. Introduction

Physically-oriented modeling of glacio-hydrological processes in the Himalaya is affected by uncertainties due to the complexity of the process spatial variations and low data availability. We use the glacio-hydrological model TOPKAPI-ETH to simulate glacier mass balances and runoff from the Hunza River Basin, Karakoram, Northern Areas of Pakistan. Three key sources of model uncertainty in future runoff projections are compared: model parameters, climate projections and natural climate variability. The model performance is discussed by comparing model outputs to recent observations about glacier mass balances in the area

2. Project aims

- Identify the sources of uncertainty that affect the reliability of projections about future water availability in high-mountain Asia.
- Assess how these model uncertainties vary in space and in time.
- Identify individual model parameters and variables that mostly affect uncertainty in simulated streamflow.
- Use these insights to answer question where resources should be allocated for observational network design and how field experiments should be designed, in order to efficiently reduce model uncertainty.

3. Study area

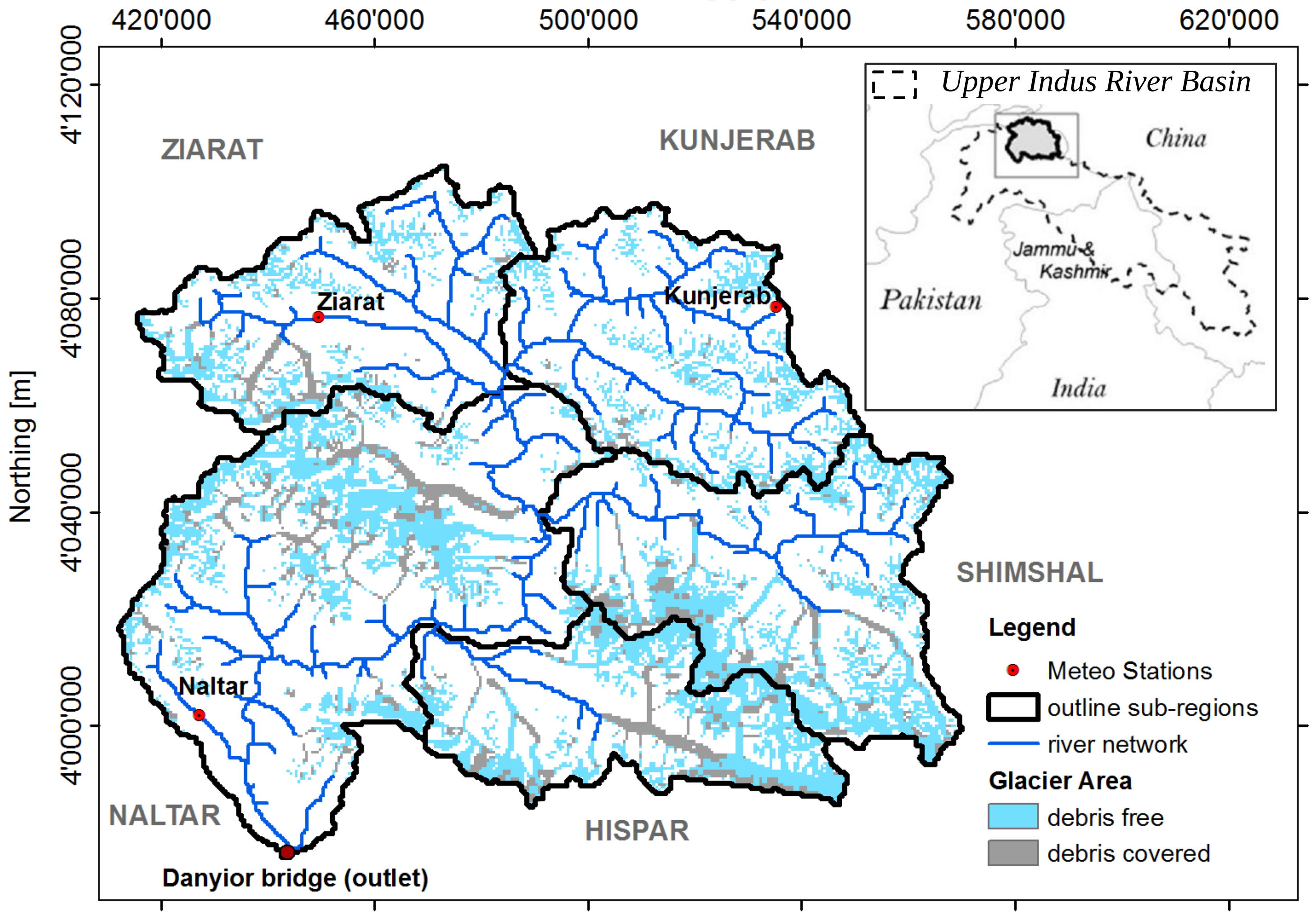

Fig. 1: Map of the Hunza River Basin and the 5 sub-regions, for which model results are evaluated separately. The area of the entire catchment is about 13'715 km^2 while approximately 26% of the basin is covered by glaciers.

4. Model and model calibration

TOPKAPI-ETH is a physically-oriented, distributed glacio-hydrological model. It has been successfully applied to simulate streamflow from high-elevation catchments (e.g. Ragettli & Pellicciotti, 2012).

The 34 parameters of the model are estimated using values given in the literature and derived from scarcely available observed data, using 3 years of measured runoff (**Fig. 2**).

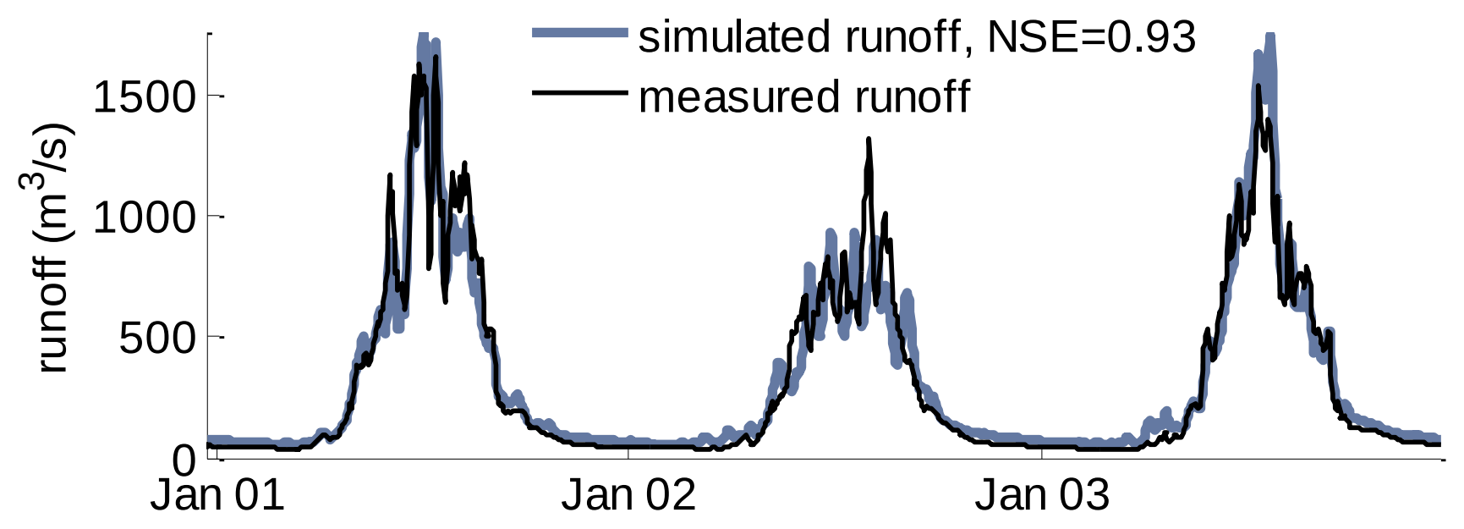

Fig. 2: Simulated and measured runoff of the calibration period.

5.1 Parametric uncertainty

1.) Considering ±10% parameter uncertainty, we generate 1000 random parameter sets using Sobols' quasi-random number generator.

2.) We run TOPKAPI-ETH for 50 years, using the 1000 parameter sets and one time series of stochastically simulated precipitation and temperature.

3.) We explore the capacity of individual parameters to explain the resulting uncertainty in simulated runoff using a regional sensitivity analysis approach (**Fig. 3**). The information content of variables is assessed using the same 1000 model realizations. This allows to analyze how individual model components (and intermediate model outputs) affect overall model uncertainty given the ±10% parameter uncertainty.

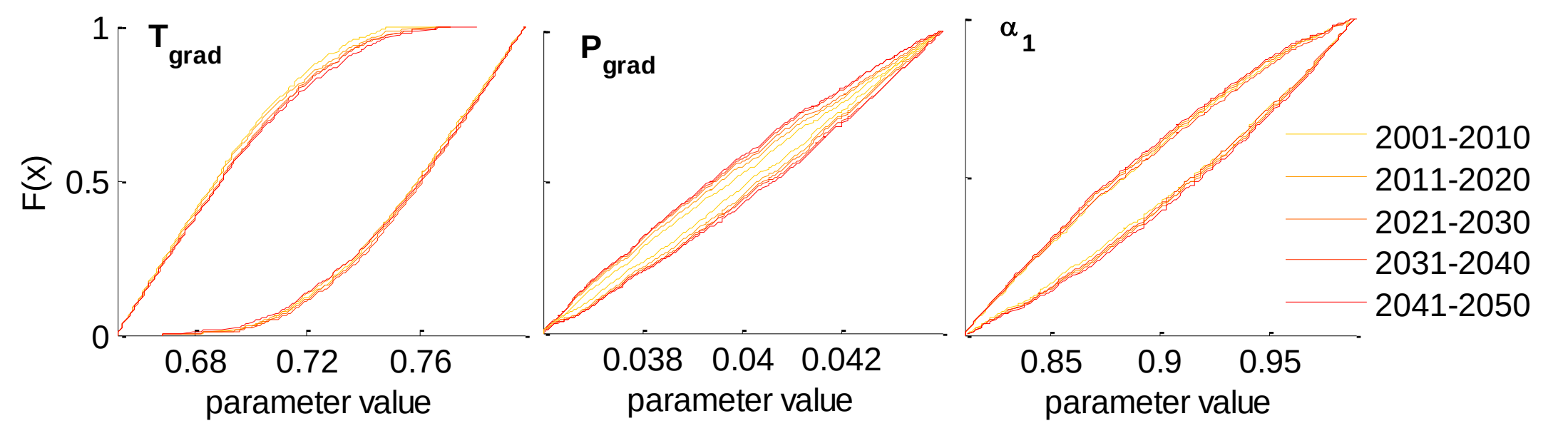

Fig. 3: The maximum difference between pairs of CDFs reflects the information content of a parameter to simulate runoff of a specific period. Each CDF represents parameter sets resulting in higher and lower mean runoff per decade, than the average runoff of all parameter sets together. The figure shows CDFs of selected parameters: precipitation gradient (P_{grad}), temperature gradient (T_{grad}) and albedo of fresh snow ($α_1$).

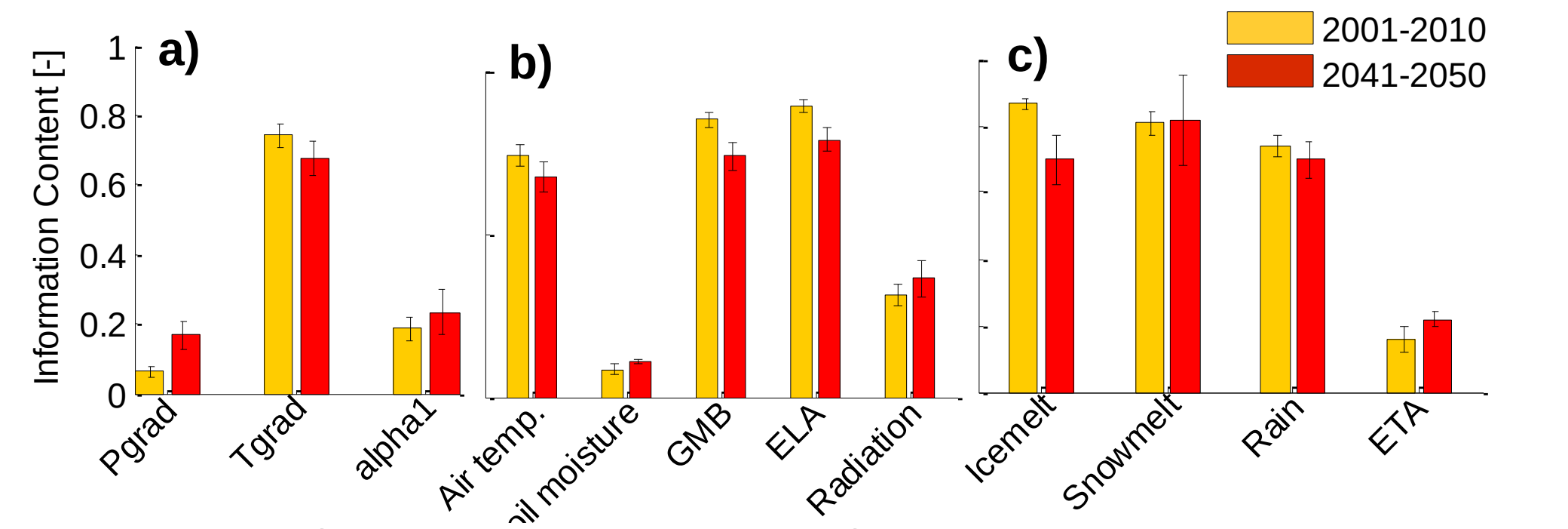

Fig. 4: Information content of selected parameters (a), variables (b) and water balance components (c), for runoff simulated for the present (2001-2010) and future (2041-2050).

5.2 Climate model uncertainty

1.) Three GCMs are used: CGCM3, CM2 and MIROC3, considering the 1AB emission scenario and monthly outputs.

2.) GCM outputs are downscaled to daily temporal resolution at the station locations using a stochastic approach, providing an ensemble of future scenarios.

3.) For each GCM we generate 100 stochastic series of precipitation and temperature data of 10-year length each, for each decade until 2050.

4.) We run TOPKAPI-ETH for 50 years, using each of the 3x100 stochastic series of input data and the calibrated parameter set.

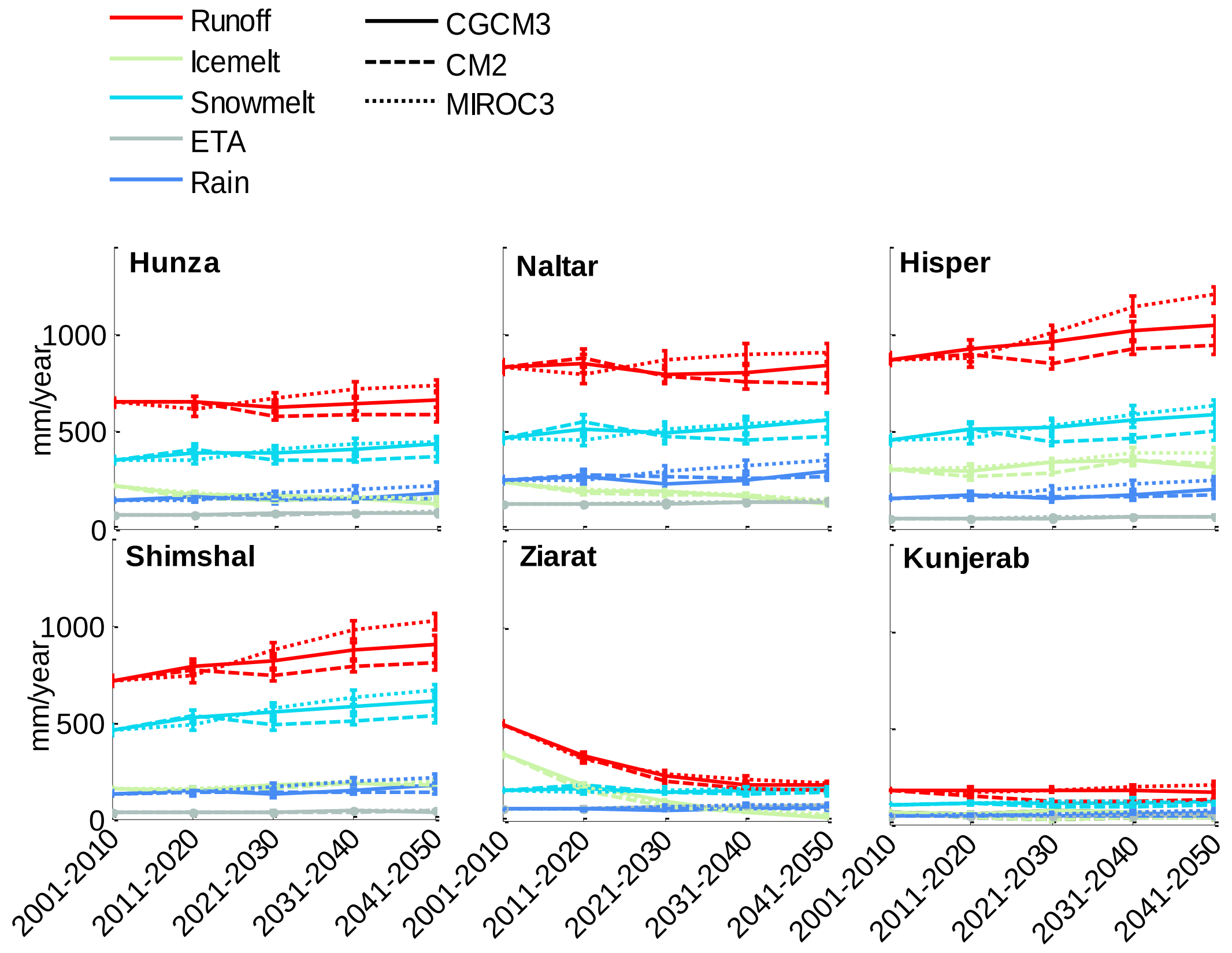

Fig. 5: Future runoff and runoff composition projected by TOPKAPI-ETH simulated using three stochastically downscaled GCMs (CGCM3, CM2 and MIROC3). Error bars represent the standard deviation in mean annual values, reflecting the stochastic nature of the climate input.

5.3 Natural climate variability

The stochastic downscaling approach accounts for the natural variability of climate by preserving the observed statistical properties of precipitation and temperature. In turn, the effect of the stochastic nature of these variables can be taken into account when simulating the hydrological response of a catchment.

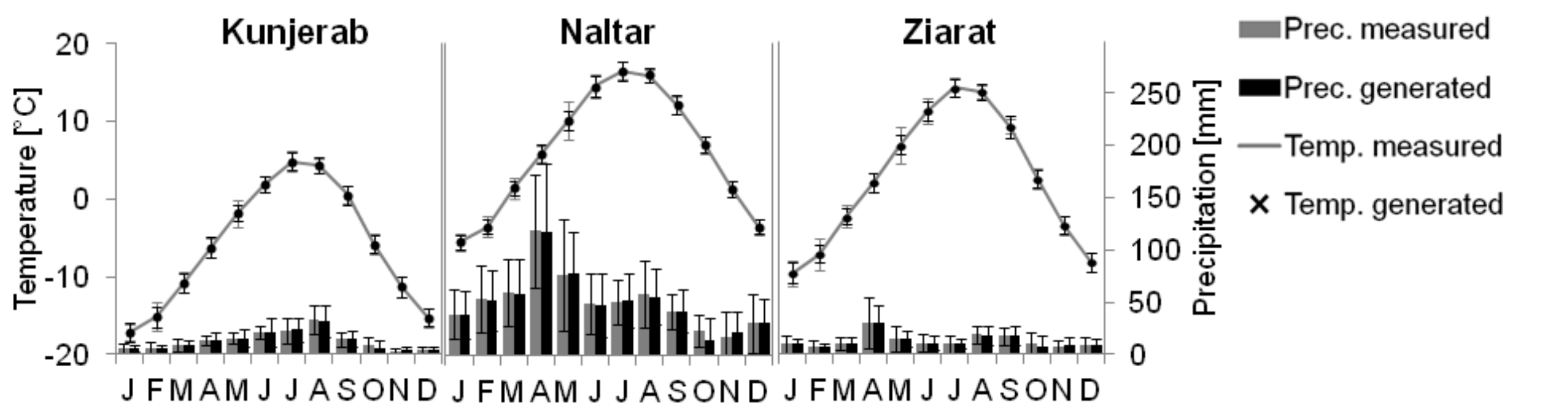

Fig. 6: Annual cycle of monthly precipitation and temperature measured at the three meteorological stations (1996-2009) and generated by the stochastic approach, for the same period. Error bars represent the standard deviation in monthly mean values.

6. Model performance

The model performance is discussed by comparing model outputs to recent observations about glacier evolution in the area by geodetic mass balance observations, satellite images and direct measurement. In order to take into account the uncertainty due to the lack of adequate locally observed climate data, model performance is analyzed for each sub-region (**Fig. 1**) separately.

	Hunza		Ziarat	Kunjerab	Naltar	Hisper	Shimshal
Runoff (mm/y)	**650.9**	**±25.0**	500.8	174.1	835.9	873.9	714.7
Temp. (°C)	**-5.6**	**±0.1**	-4.5	-6.7	-2.9	-7.4	-8.8
Snow (mm/y)	**590.0**	**±39.1**	156.1	121.8	667.4	907.2	987.6
Rain (mm/y)	**147.8**	**±11.8**	58.6	43.8	249.7	158.3	130.8
GMB (m/y)	**-0.07**	**±0.13**	-1.82	-0.31	0.48	0.45	1.12
ELA (m)	**4739**	**±30**	5327	5143	4502	4496	4489

Table 1: Mean values of simulated runoff and selected variables for the Hunza River Basin as well as for 3 sub-regions. Shown are the results of simulations forced with optimal parameters and generated climate data for the control period (2001-2010).

7. Discussion and Conclusions

- The main effects of the three sources of uncertainty (sections 5.1-5.3) on simulated runoff can be compared quantitatively. **Fig. 7** shows that the effect of different sources is subject to strong variability in time and in space:

→ The effect of ±10% parametric uncertainty often exceeds the effect of other sources of uncertainty. Since there is no evidence that parameters are stable in time and in space, parametric uncertainty has to be taken into account in future projections.

→The effect of the climate model uncertainty increases with time. For sound projections of future runoff and glacier response, GCMs outputs should be used in an ensemble manner.

→ The effect of the stochastic uncertainty in meteorological input cannot be neglected and is especially important for sub-regions with an important fraction of total precipitation falling as rain (especially Naltar, see Table 1).

- Total mass of glaciers in the Hunza River Basin is more or less stationary during the control period (Table 1). This is in accordance with recent studies (Hewitt 2005, Scherler et al. 2011, Gardelle et al., 2012; Kääb et al., 2012) and is an indication that the used climatic input might represent adequately the local climate. Likely, precipitation in the Shimshal basin is overestimated.
- The approach does not take into account interactions between sources of uncertainty and thus provides only estimates about the main effects of individual sources.
- In order to reduce most efficiently uncertainty in simulated runoff, the temperature distribution should be monitored in the field (**Fig. 4a**). The analysis of information content (IC) is an efficient tool to screen many-parametered models for model components that are disproportionately affected by parameter uncertainty. The method can also be applied to calculate IC of intermediate model outputs at grid-cell level, and thus to estimate the distribution of IC both in time and in space.

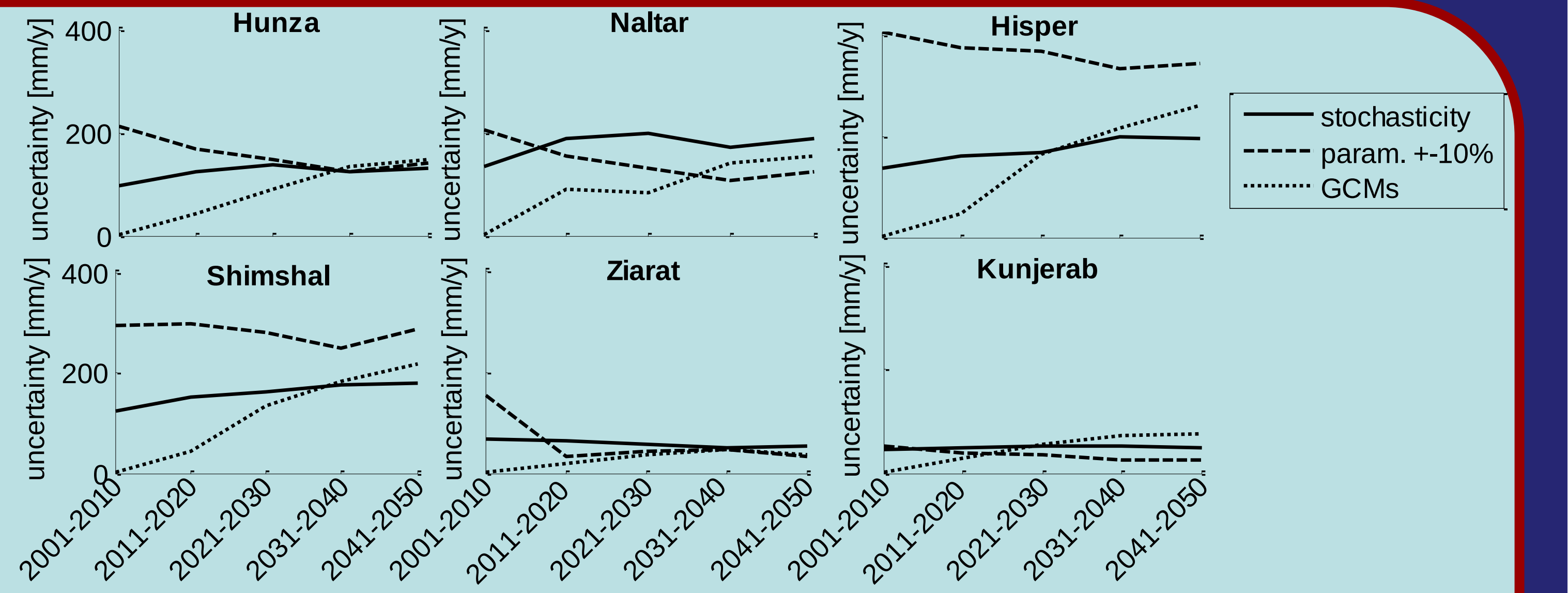

Fig. 7: Uncertainty in simulated runoff: 95% confidence interval in model outputs resulting from ±10% parametric uncertainty, from using stochastic timeseries of precipitation and temperature (reflecting the natural inter-annual climate variability) and the maximum difference in model outputs resulting from the climate model uncertainty (running the model with three downscaled GCMs).

References:

- Gardelle, J. et al., Slight mass gain of Karakoram glaciers in the early twenty-first century, *Nature Geoscience*, 5 (5), 322-325, 2012.
- Hewitt, K., The Karakoram Anomaly? Glacier Expansion and the 'Elevation Effect', Karakoram Himalaya, *Mountain Research and Development*, 25 (4), 332-340, 2005.
- Kääb, A., E. et al., Contrasting patterns of early twenty-first-century glacier mass change in the Himalayas, *Nature*, 488 (7412), 495-498, 2012.
- Ragettli, S., and F. Pellicciotti, Calibration of a physically-based, fully distributed hydrological model in a glacierized basin: on the use of knowledge from glacio-meteorological processes to constrain model parameters, *Water Resources Research*, 48, 1-20, 2012.
- Scherler, D. et al., Spatially variable response of Himalayan glaciers to climate change affected by debris cover, *Nature Geoscience*, 4 (3), 156-159, 2011.