Performance of M&Rfi weather generator at different climates

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Introduction

Stochastic weather generators (WGs) are tools, whose main purpose is to produce arbitrarily long synthetic weather series statistically similar to "learning" data, mostly being observations. By appropriate modification of WG parameters, one may, however, produce also weather data representing **changed climate conditions** or weather series, which **fit the weather forecast**. WGs are usually used to provide input weather series for various weather-dependent models. Coupled with crop growth models, WGs play an important role in assessing **impacts of climate change on crop yields** and in **probabilistic crop yield forecasting**. Applicability of a WG is conditioned on its quality, which may be measured by the WG's ability to reproduce statistical features of real-world data.

This contribution assesses quality of single-site multi-variate stochastic weather generator M&Rfi. **M&Rfi is a new parametric generator**, which is currently being developed as a more flexible follower of Met&Roll generator. M&Rfi may be run with various numbers of variables (precipitation, solar radiation and daily extreme tamperatures are typically involved) and at various time steps (1-day, 3-day, 5-day, 1-week, 10-day, ½-month, 1-month). This contribution brings the first validation tests made with M&Rfi. It focuses on reproduction of monthly variability of daily extreme temperatures and precipitation by M&Rfi run at three time scales: 1-day, 10-day, 1-month.

The **motivation** for the present experiment is the fact, that some impact models are run at longer than 1-day time step (e.g. FAO's water balance model), so we want to examine, what is the effect of the WG's time step on reproducing longer time-step characteristics, e.g. monthly variability (which may affect variability of output from the impact model fed by the synthetic weather series produced by WG).

M&Rfi – model

M&Rfi generator is based on the Met&Roll generator [1,2,3]. Compared to Met&Roll, it is more general, allowing (for example) to model **optional number of variables** at **optional time step**.

Time series are modelled by a the **1st–order multi-variate autoregressive (AR) model**. **Precipitation** is modelled either together with other variables by the AR model, or separately using a combination of **Markov-chain model** for precipitation occurrence and **Gamma distribution** for precipitation amount. In the latter case, parameters of the AR model are optionally conditioned on precipitation occurence. The user may set various degrees of complexity of the underlying model, thus adjusting the number of parameters to be derived from the learning (= observed) weather series.

3 versions of M&Rfi are employed in the test. All of them are **3-variate** generators (variables: *TMAX*, *TMIN*, *PREC*). The three versions differ in **(i)** the time step, **(ii)** a way in which the precipitation is involved.

M&Rfi-daily: daily weather generator. Precipitation occurrence is modelled by Markov chain (1st order), precipitation amount by Gamma distribution. TMAX, TMIN are modelled by bivariate 1st-order Markov chain. This generator is equivalent with Met&Roll except for not emloying solar radiation.

M&Rfi-10day: time step = **10 days**. All three variables (including precipitation) are modelled by the 3-variate 1st-order autoregressive model.

M&Rfi-monthly: time step = **1 month**. All other settings are the same as in M&Rfi-10d.

Experiment

For each station (see Table I for the list):

(i) estimating parameters of M&Rfi-daily, M&Rfi-10day and M&Rfi-monthly from 30-y observed series
(ii) generation of 30× 30-year synthetic series with all three WGs
(iii) analysis of the synthetic series for selected characteristics.

Figures

show variabilities of monthly means of ***TMAX*** (daily temperature maximum), ***TMIN*** (daily temperature minimum) and ***PREC*** (daily precipitation sum) for summer and winter, estimated from 30-year series. Single value is shown for **observed data**. The standard error shown for **synthetic data** are based on 30 realisations of the 30-year series.

The results shown in the figures demonstrate, that the best performance in reproducing monthly variability is obtained by monthly generator.

References

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[3] Dubrovsky M., Buchtele J., Zalud Z., 2004: High-Frequency and Low-Frequency Variability in Stochastic Daily Weather Generator and Its Effect on Agricultural and Hydrologic Modelling. *Climatic Change* **63** (No.1-2), 145-179.

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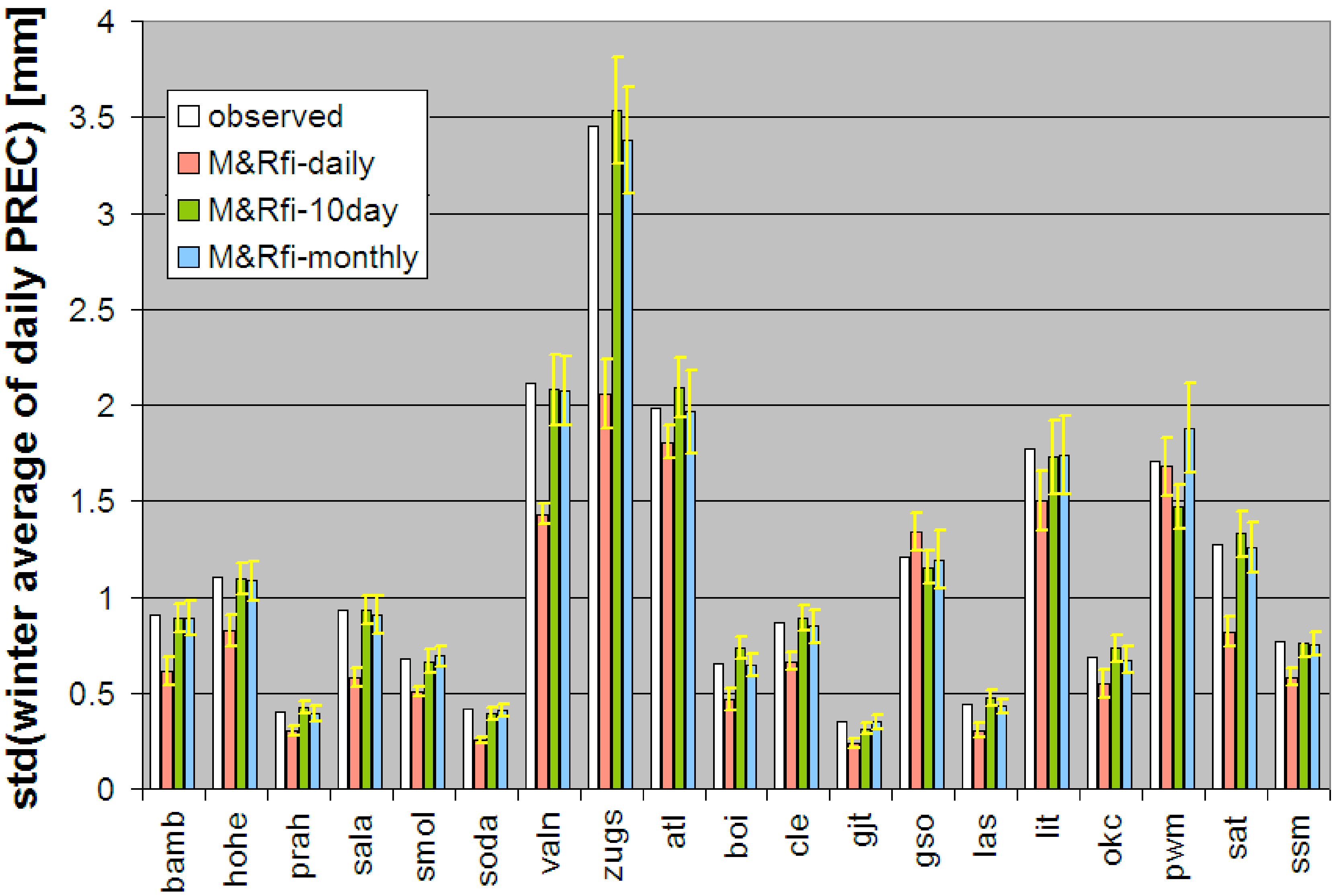
Table I Stations used in the analysis

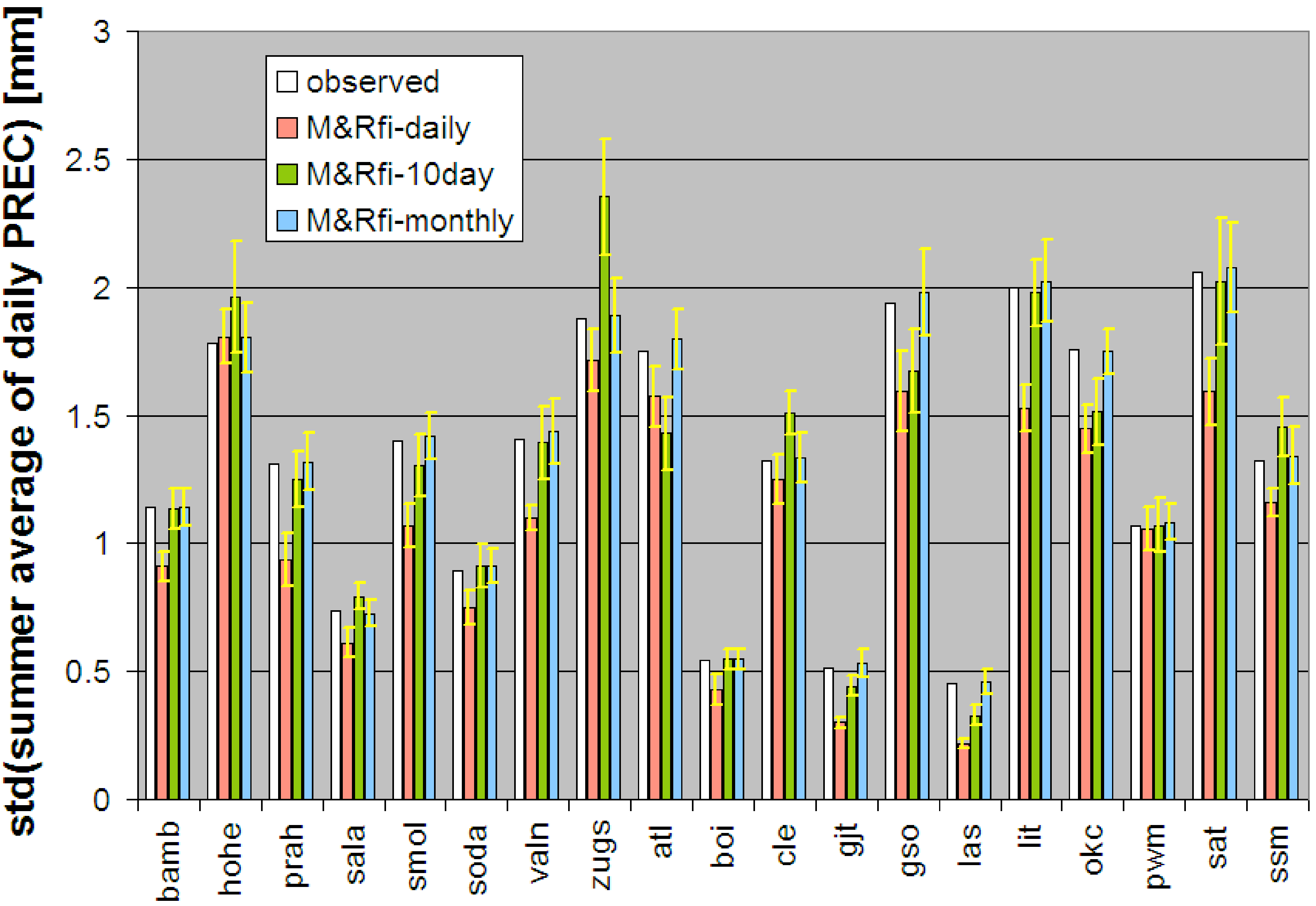
acronym	station	state	LAT	LONG	ALT [m]
Europe					
BAMB	BAMBERG	DE	N 49.88	E 10.88	282
HOHE	Hohenpeissenberg	DE	N 47.80	E 11.02	977
PRAH	Praha	CZ	N 50.09	E 14.42	191
SALA	Salamanca	ES	N 40.95	W 5.47	790
SMOL	Smolensk	RU	N 54.75	E 32.07	239
SODA	Sodankyla	FI	N 67.37	E 26.65	179
VALE	Valencia	ES	N 39.48	W 0.35	11
ZUGS	Zugspitze	DE	N 47.42	E 10.98	2960
USA					
ATL	Atlanta	GA	N 33.72	W 84.38	
BOI	Boise, Idaho	ID	N 43.61	W 116.21	
CLE	Cleveland	OH	N 41.46	W -81.67	
GJT	Grand Junction	CO	N 39.08	W -108.53	
GSO	Greensboro	NC	N 36.05	W -79.84	
LAS	Las Vegas	NV	N 36.11	W -115.07	
LIT	Little Rock	AR	N 34.74	W -92.27	
OKC	Oklahoma City	OK	N 35.47	W -97.53	
PWM	Portland	ME	N 43.67	W -70.34	
SAT	San Antonio	TX	N 29.37	W -98.48	
SSM	Sault Ste. Marie	MI	N 46.46	W -84.34	

European data taken from the “EC&D” project (http://eca.knmi.nl); U.S. data provided by D.Wilks.

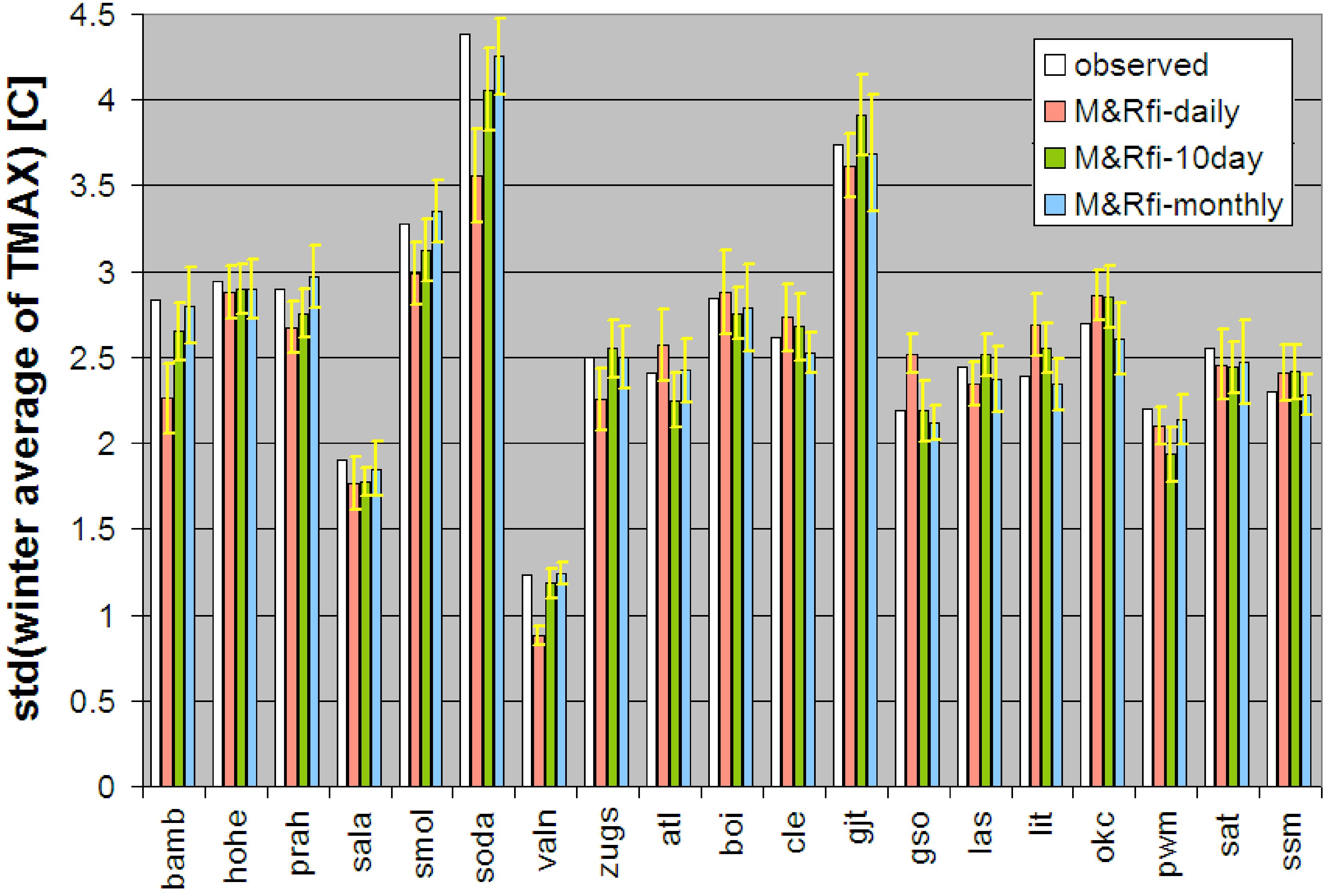
variability of monthly average PREC - winter



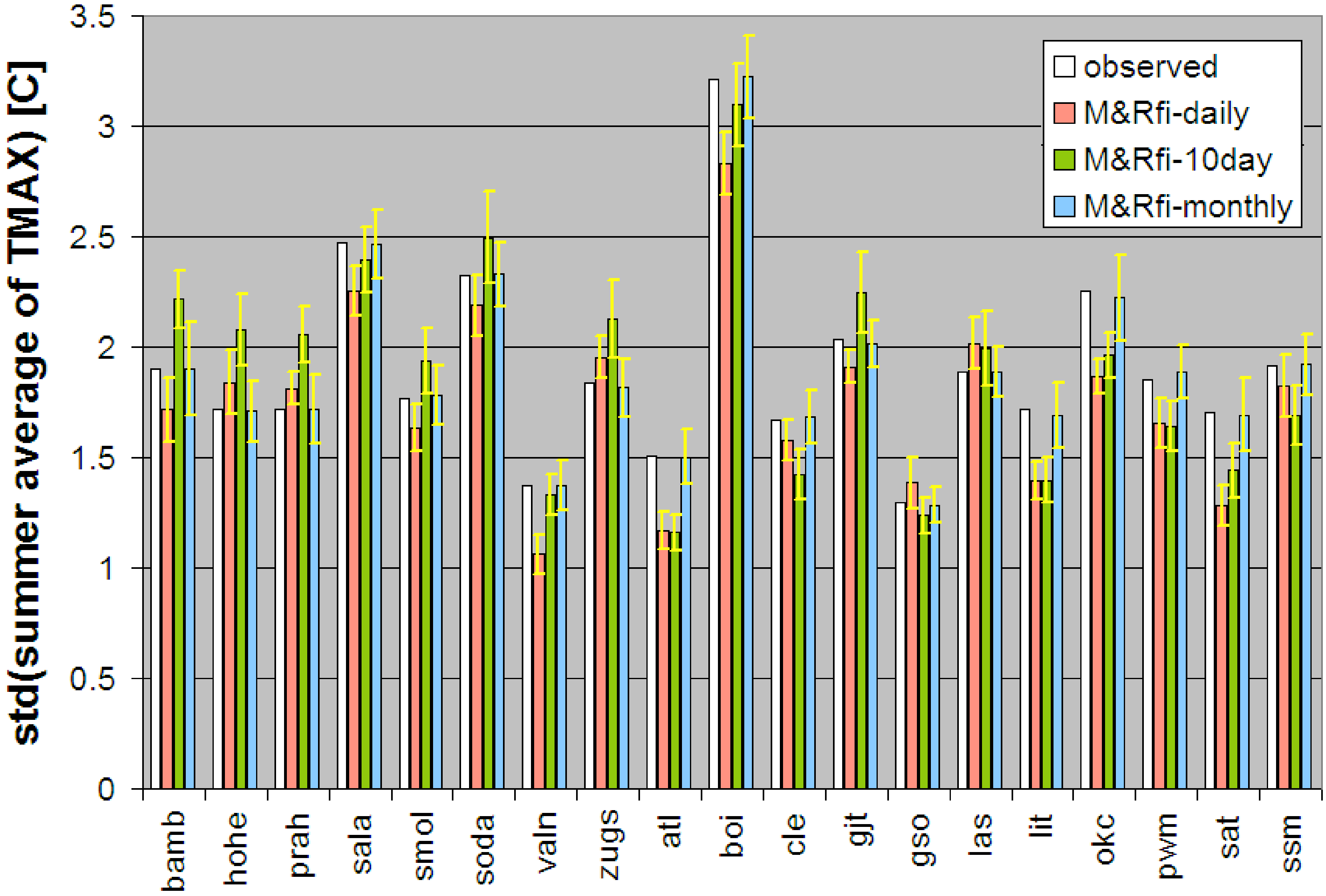
variability of monthly average PREC - summer



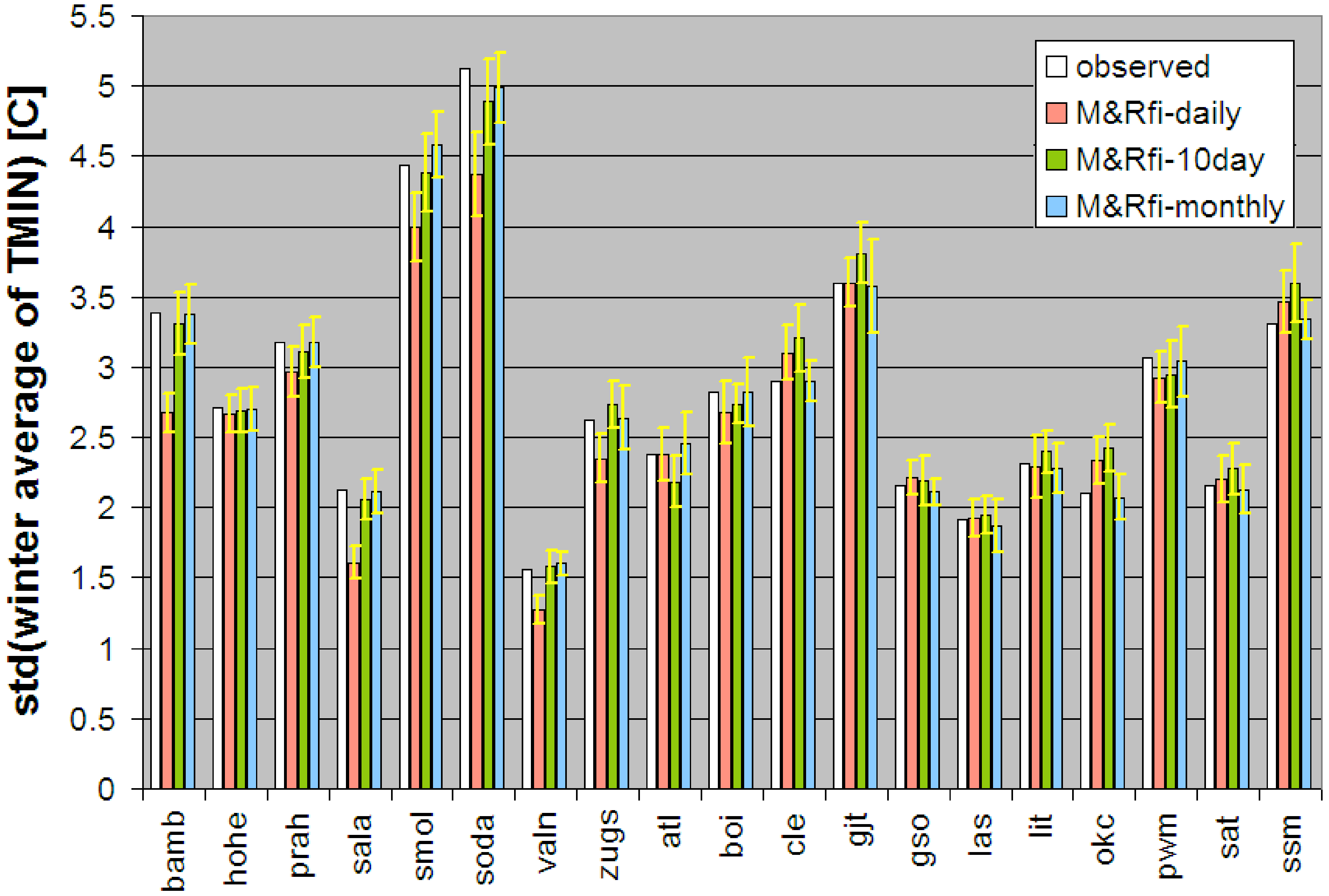
variability of monthly average TMAX - winter



variability of monthly TMAX - summer



variability of monthly TMIN - winter



variability of monthly TMIN - summer