H21A-1018: The role of temporal disaggregation and land surface initial conditions for hydrological forecasting

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1. Introduction

Hydrological extremes like floods and droughts are causing severe socio-economic damages. Hydrological models allow to forecast state variables and fluxes of the hydrological cycle, providing a tool for decision makers to mitigate damages. This study aims to gain a better understanding of how land surface initial conditions and temporal disaggregation of meteorological forcings are impacting hydrological forecasts.

2.1 Stochastic Weather Generator (WG)

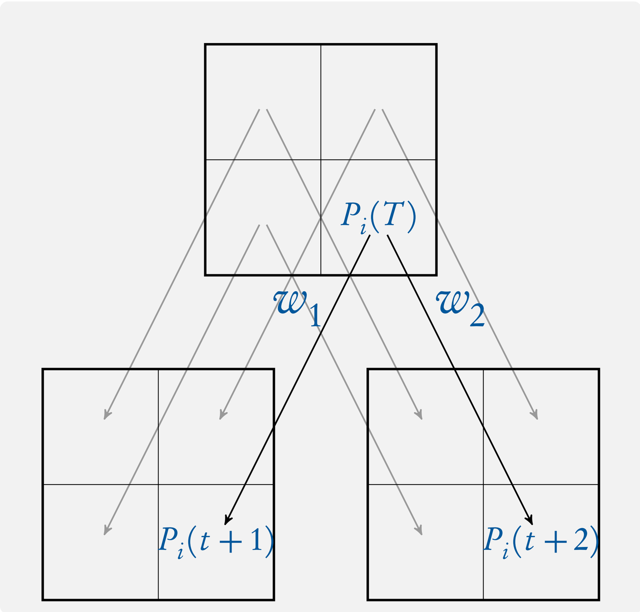

Fig. 1: multiplicative cascade model structure

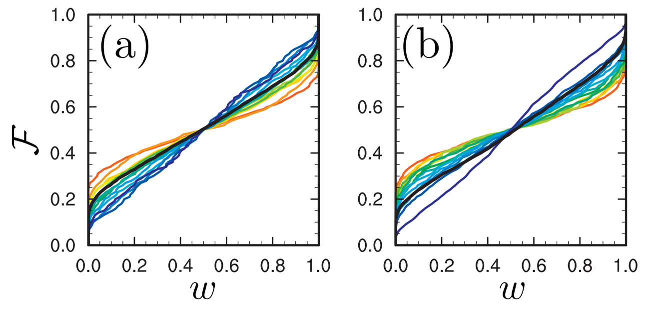

Fig. 2: distribution functions of weights w at two locations (a) Berlin and (b) Feldberg for different precipitation intensities (colored lines)

A multiplicative cascade approach [2] (Fig. 1) is employed to stochastically disaggregate monthly to daily precipitation via

$$P_i^{(k)}(2t) = w_1^{(k)} \cdot P_i^{(2k)}(t),$$
$$1 = w_1^{(k)} + w_2^{(k)},$$
$$w_1^{(k)} = \mathcal{F}_i^{-1}(N(\epsilon)),$$
$$\epsilon(t) \sim N(0, \hat{\mathbf{C}}),$$

where $P^{(k)}$ denotes precipitation at scale k, $\mathcal{F}$ the distribution function of the weights w (Fig. 2), N the standard normal distribution function, and $\hat{C}$ a cross covariance matrix calculated from the observations. This approach generates the weights as random number.

A sequential Gaussian sampling algorithm is used for assuring numerical stability in the calculation of ϵ on spatial grids of any size.

2.2 Historic Rescaling (ESP)

A historic rescaling approach [3] to generate an ensemble of forcings is used. The detailed steps are as follows:

1. Determine historic weights w_h^y via

$$P_d^y(t) = w_h^y(t) \cdot P_m^y, \qquad (1)$$

for a given monthly value P_m^y and the corresponding daily values P_d^y in a given year y.

2. Substitute P_m^y with a monthly observation of another year in eq. 1 to generate a new daily time series P_d^{y*}, keeping the weights w_h^y fixed.

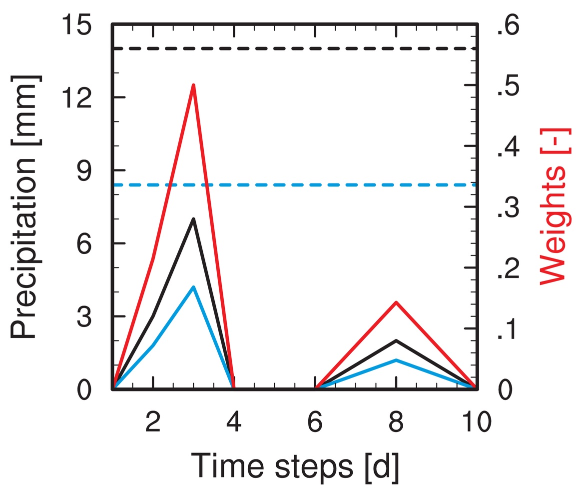

Fig. 3: Exemplary rescaling for 10 day precipitation. The weights (red line) are derived as ratios between given daily precipitation (black line) and its sum (black dashed line). Then the weights are multiplied with a new 10 day precipitation value (blue dashed line) to derive new daily precipitation (blue line).

3. Experimental Design

The hydrological model mHM [1] was used to evaluate monthly discharge forecasts during January and July of the years 1960 to 2010. These months have been selected since they show an opposing behavior with respect to long-term hydrological fluxes (Fig. 5). Two set ups for monthly forecasts were evaluated:

1. different initial conditions x_k (Fig. 4); same observed precipitation forcing
2. same initial condition; 51 different forcings obtained by each disaggregation method (e.g., WG and ESP)

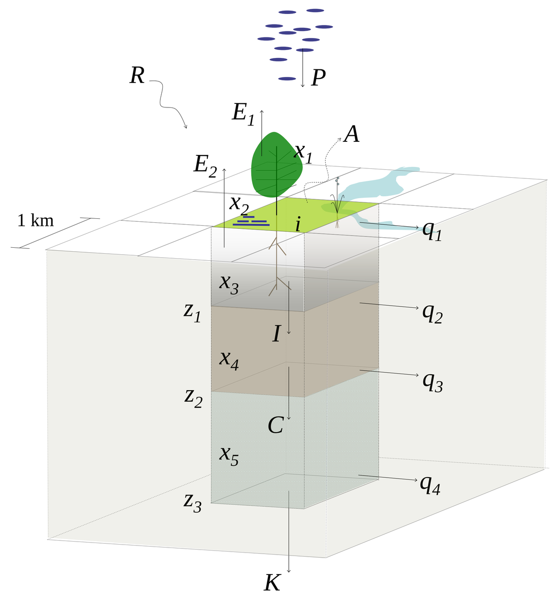

Fig. 4: mesoscale hydrologic model - mHM, State variables (x_k) and fluxes (q_k, E_k) at cell i

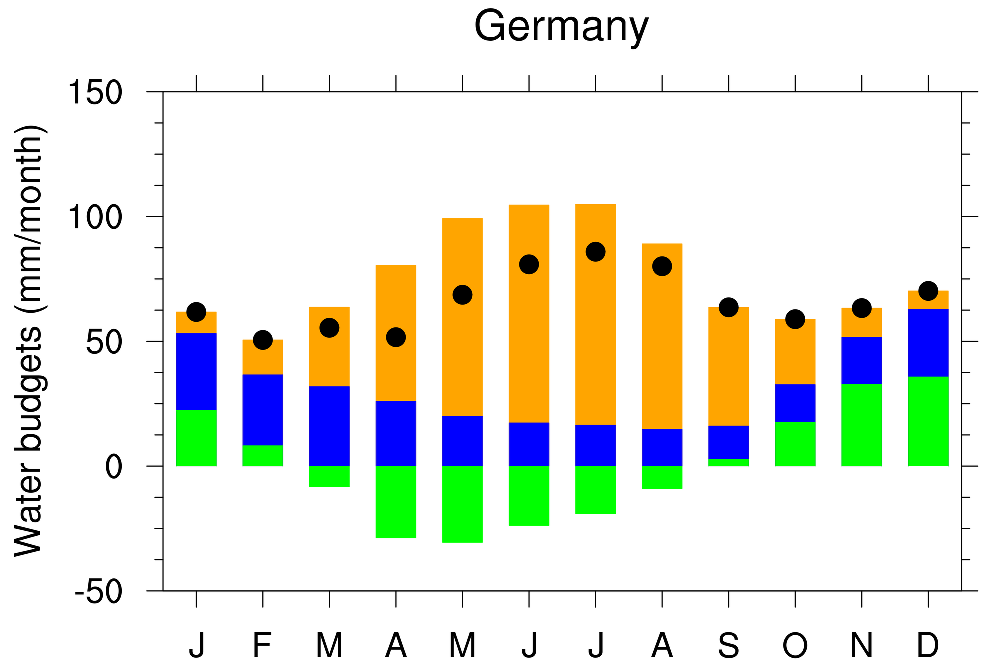

Fig. 5: Longterm monthly water balances over Germany; dot - precipitation, blue - discharge, orange - actual evapotranspiration, green - $\frac{dS}{dt}$

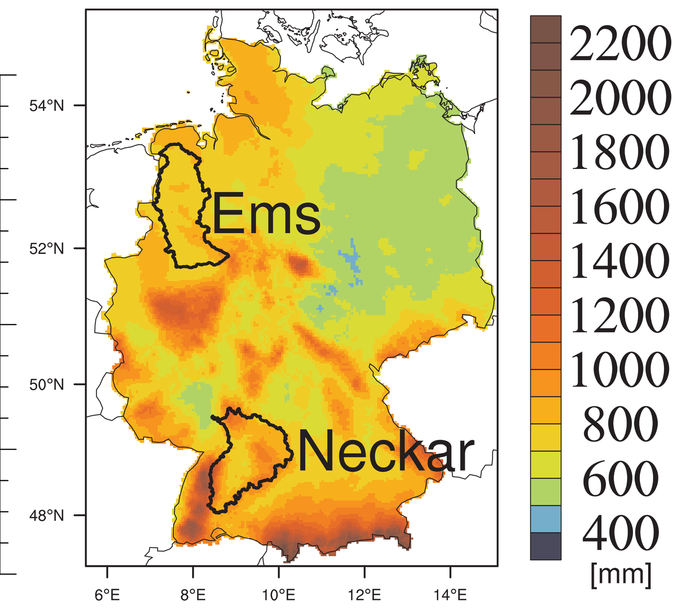

Fig. 6: Long-term annual precipitation over Germany (obtained by DWD measurements) during the period from 1960 to 2010

4. Impact of Initialization

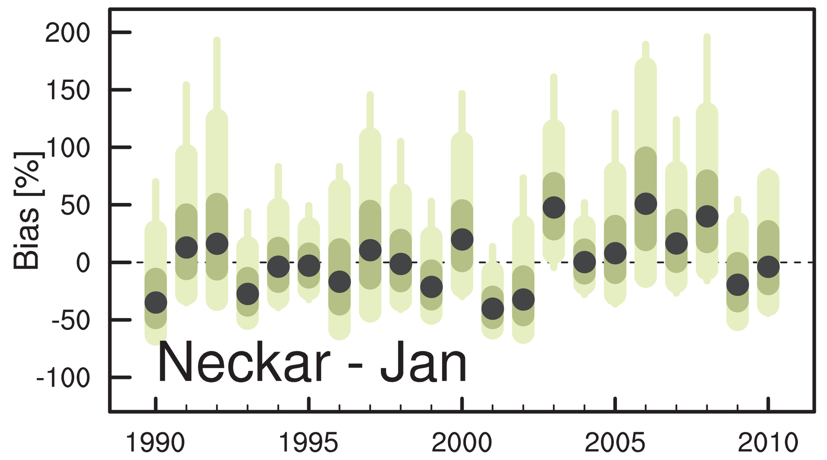

Fig. 7: Long-term median(standard deviations) are **7.7%(34.7%)**

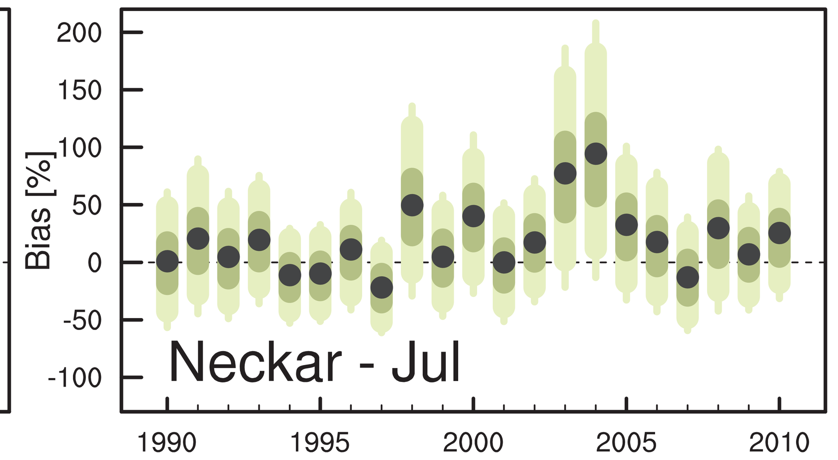

Fig. 8: Long-term median(standard deviations) are **9.5%(25.9%)**

Min to Max — 90% CI — 50% CI — • median

The variability of the monthly discharge forecasts are higher during January (Fig. 7) compared to during July (Fig. 8) in the Neckar basin.

5. Impact of Disaggregation

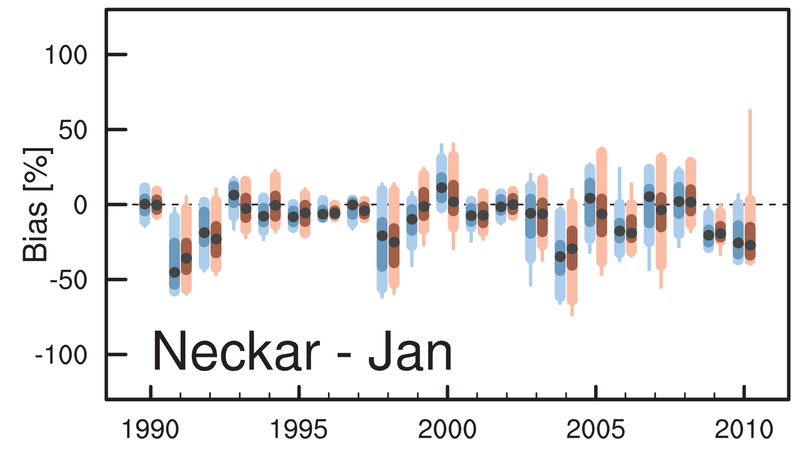

Fig. 9: Long-term median(standard deviation) for WG (blue lines) **-9.9%(10.6%)** and ESP (red lines) **-10.0%(11.8%)**

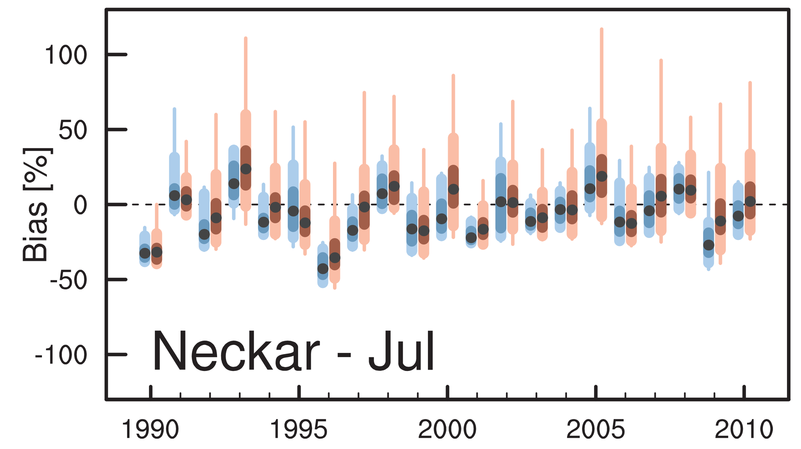

Fig. 10: Long-term median(standard deviation) for WG (blue lines) **-6.0%(10.2%)** and ESP (red lines) **-2.2%(13.8%)**

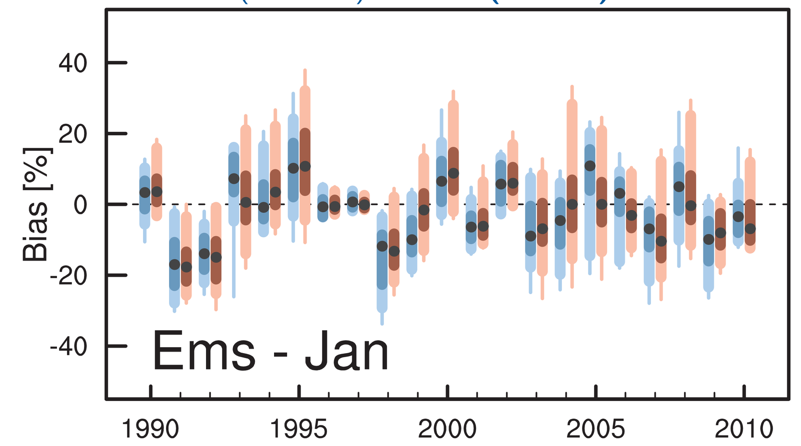

Fig. 11: Long-term median(standard deviation) for WG (blue lines) **-2.6%(6.5%)** and ESP (red lines) **-3.8%(7.3%)**

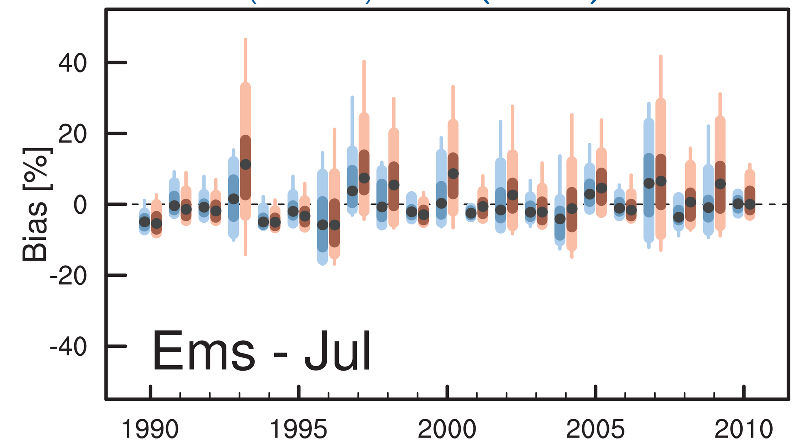

Fig. 12: Long-term median(standard deviation) for WG (blue lines) **-1.6%(4.2%)** and ESP (red lines) **-0.4%(5.7%)**

WG	Min to	90% conf.	50% conf.	median
ESP	Max	interval	interval	

The variability of monthly discharge forecasts are dependent on location, month, and disaggregation method (i.e., WG and ESP).

6. Sources of Uncertainty

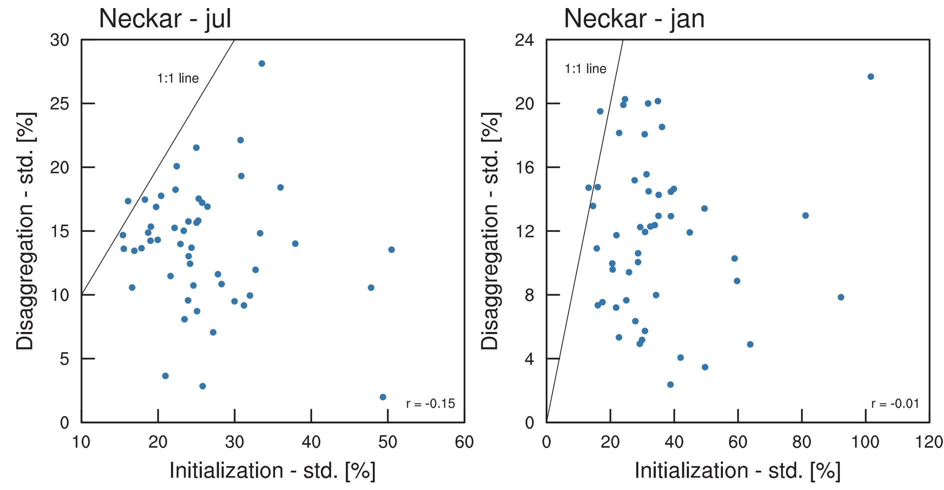

Fig. 13: Scatter plot of standard deviations of monthly discharge induced by varying initial conditions (x-axis) and ESP method (y-axis)

The impact of initialization on monthly discharge variability is two to five times higher as that of temporal disaggregation in the Neckar basin. There is no statistical correlation between initial condition and disaggregation uncertainty.

7. Conclusions

1. Both, initial conditions and temporal disaggregation have an substantial impact on monthly discharge forecasts and are location dependent.
2. Initial conditions have an higher impact on monthly discharge as compared to temporal disaggregation.
3. WG disaggregation induces less variability as compared to ESP.

References

[1] L. Samaniego, R. Kumar, and S. Attinger, "Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale," *Water Resources Research*, vol. 46, no. 5, 2010. [Online]. Available: http://dx.doi.org/10.1029/2008WR007327

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[3] A. W. Wood, E. P. Maurer, A. Kumar, and D. P. Lettenmaier, "Long-range experimental hydrologic forecasting for the eastern United States," *Journal of Geophysical Research: Atmospheres*, vol. 107, no. D20, pp. ACL 6–1–ACL 6–15, 2002. [Online]. Available: http://dx.doi.org/10.1029/2001JD000659

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