Diagnostic efficiency - a diagnostic approach for model evaluation

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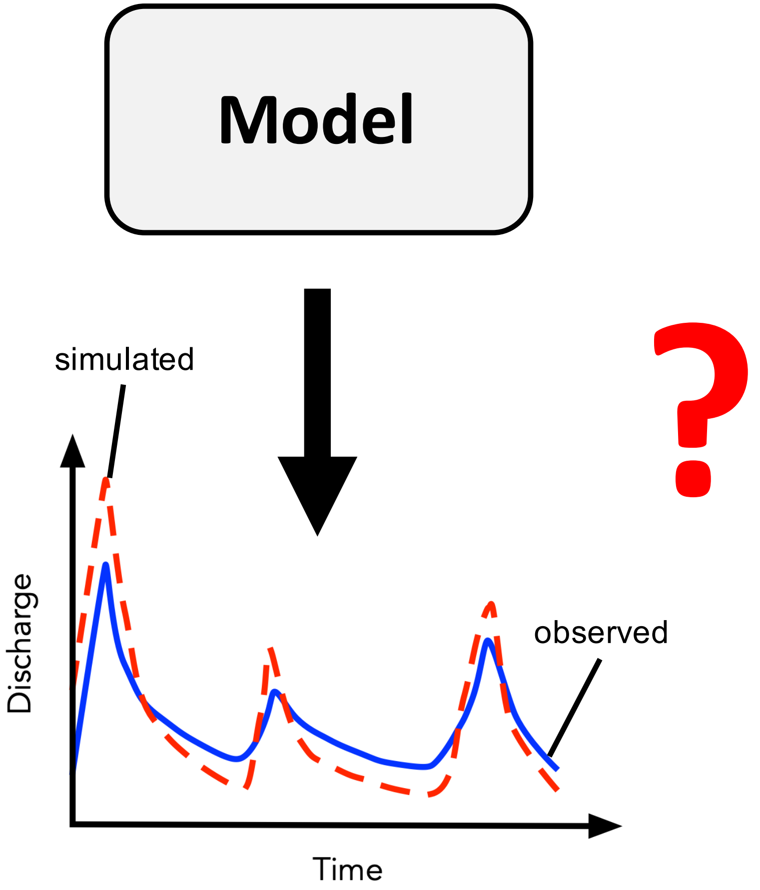
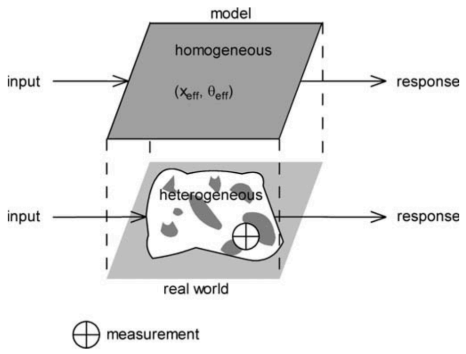
HYDROLOGY

Diagnostic model evaluation



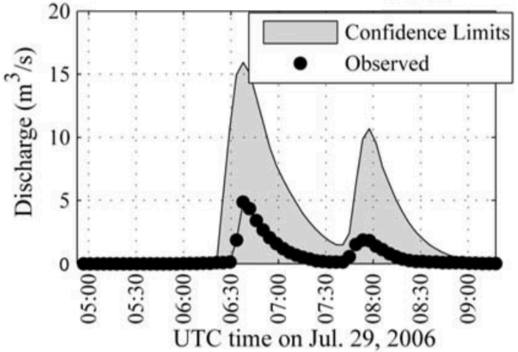
Origin of errors in hydrological simulations

Model parameters



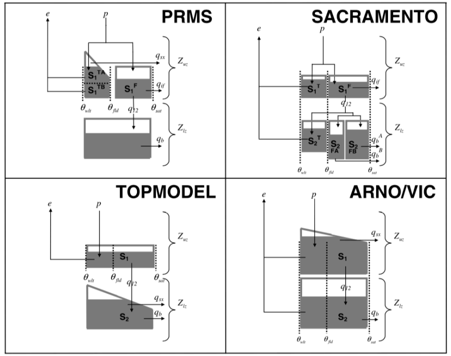
Wagener and Gupta (2005), *SERRA*

Input data



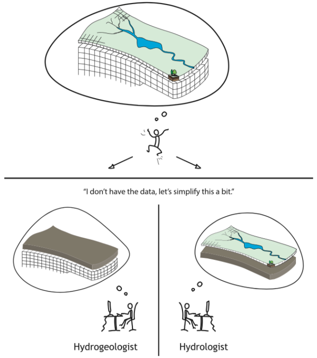
Yatheendras et al. (2008), *WRR*

Model structure



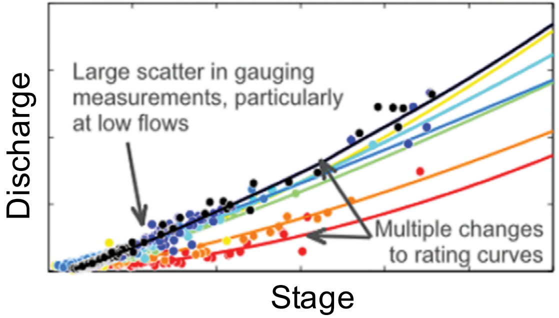
Clark et al. (2008), *WRR*

Initial and boundary conditions



Staudinger et al. (2015), *JoH*

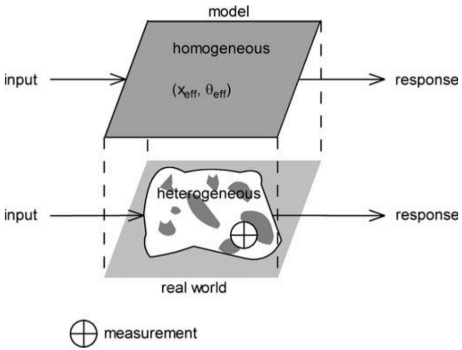
Observations



Coxon et al. (2015), *WRR*

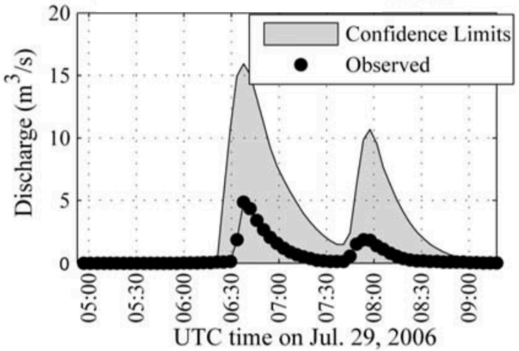
Origin of errors in hydrological simulations

Model parameters



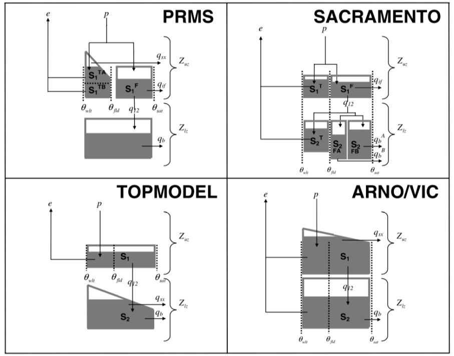
Wagener and Gupta (2005), *SERRA*

Input data



Yatheendras et al. (2008), *WRR*

Model structure



Clark et al. (2008), *WRR*

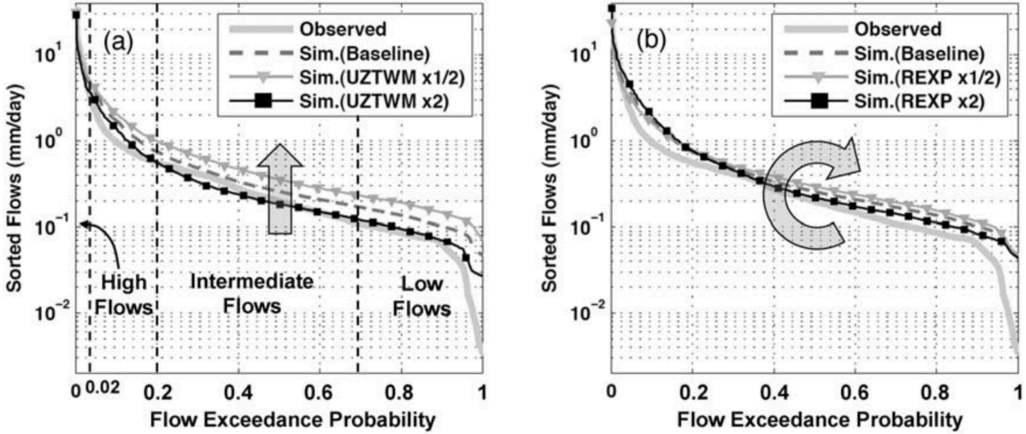
Research gap

- Traditional efficiency measures (e.g. Kling-Gupta Efficiency)

  → diagnostic meaning of a number between **-∞** and **1?**

- Diagnostic signatures (e.g. high flow bias)

  → comprehensive visualization**?**



Yilmaz et al. (2008), *WRR*

Research objectives

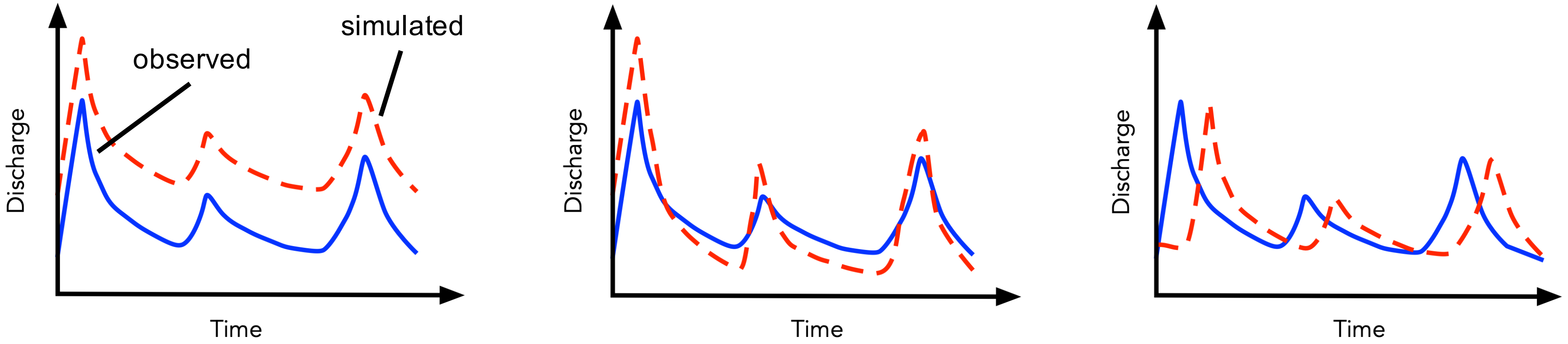
- **Defintion of a diagnostic efficiency measure** based on flow duration curve and correlation which hints to the **origin of errors**
- Visualising **contributions of different model errors**
- Provide an easily extendable **evaluation tool**

diag-eff on GitHub: https://github.com/schwemro/diag-eff

Documentation (including tutorials): https://diag-eff.readthedocs.io/en/latest/

Diagnostic Efficiency (*DE*)

$$DE = 1 - \sqrt{constant\ error + dynamic\ error + timing\ error}$$

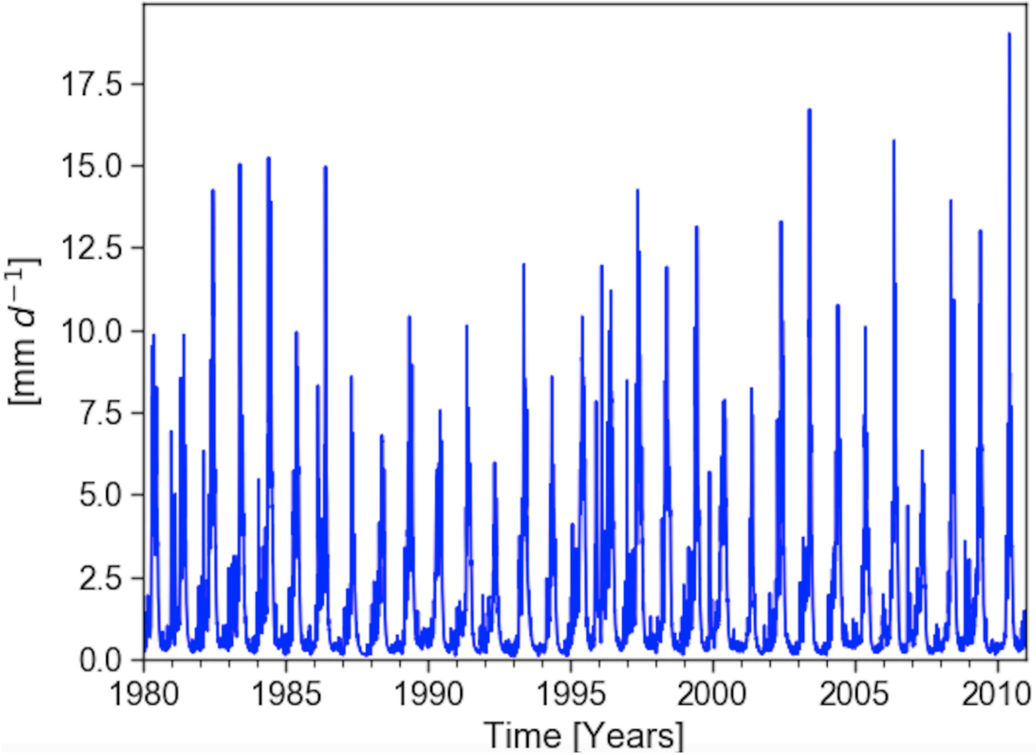


$$DE = 1 - \sqrt{\overline{B_{rel}}^2 + |B_{area}|^2 + (r-1)^2}$$

Schwemmle et al. (2020) in prep., (will be submitted to HESS shortly after EGU2020)

Mimicking errors

gauge_id: 13331500; gauge_name: Minam 160 River near Minam, OR, U.S.



CAMELS dataset; Addor et al. (2017)

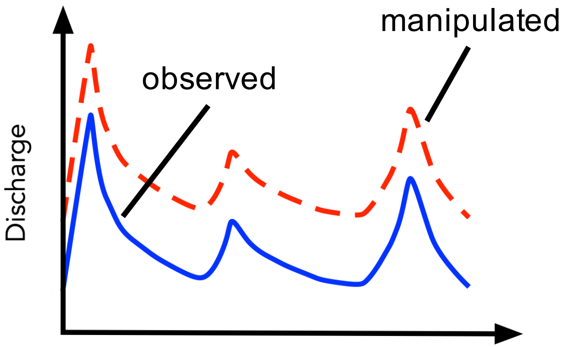
Mimicking errors by **systematic manipulation** of an **observed streamflow time series:**

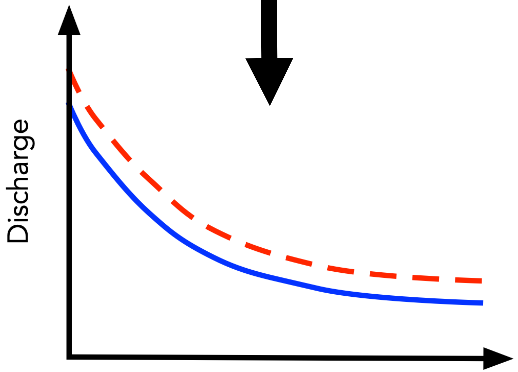
→ constant error (i)

→ dynamic error (ii)

→ timing error (iii)

Mimicking constant error (i)





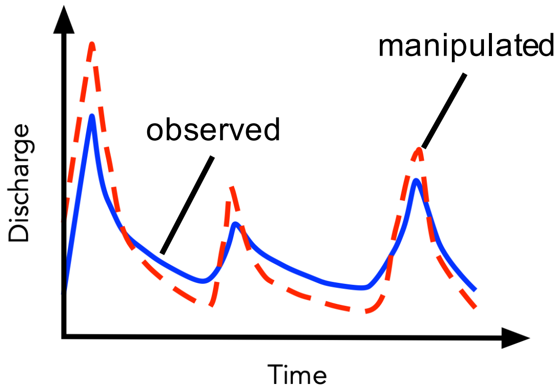
Multiplying the **observed time series** with a **constant >1** to **generate a positive offset**

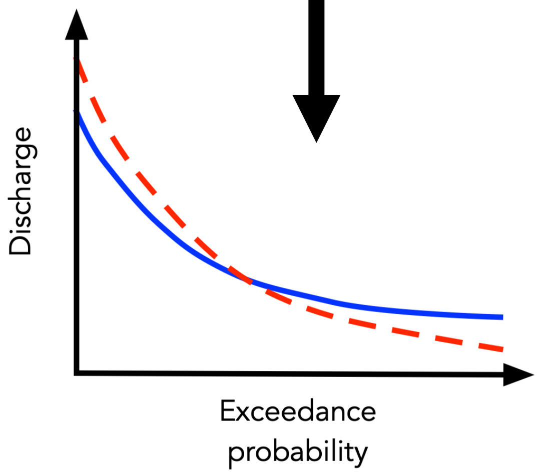
$$DE = 1 - \sqrt{\overline{B_{rel}}^2 + |B_{area}|^2 + (r-1)^2}$$

arithmetic mean of the relative bias

$$\overline{B_{rel}} = \frac{1}{N} \sum_{i=0}^{i=1} B_{rel}(\mathrm{i})$$

Mimicking dynamic error (ii)





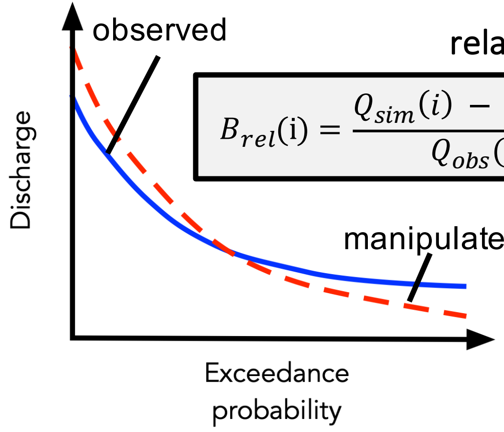
Multiplying the **observed time series** with an **linearly interpolated vector** (1.5, ..., 0.5) to **increase high flows** and **decrease low flows**

$$DE = 1 - \sqrt{\overline{B_{rel}}^2 + |B_{area}|^2 + (r-1)^2}$$

area of the residual bias

$$|B_{area}| = \int_0^1 |B_{res}(i)|\, di$$

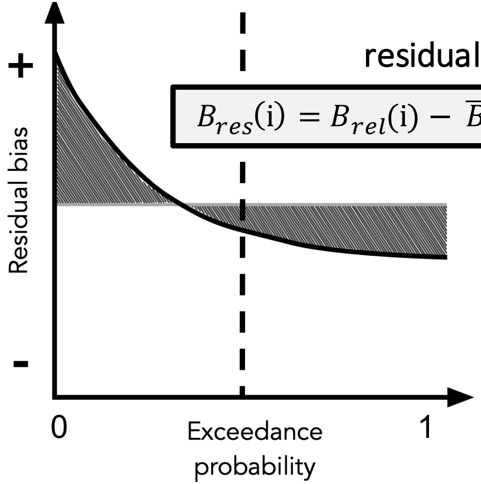
Calculation of the dynamic error term



relative bias **1**

$$B_{rel}(\mathrm{i}) = \frac{Q_{sim}(i) - Q_{obs}(i)}{Q_{obs}(i)}$$

$$DE = 1 - \sqrt{\overline{B_{rel}}^2 + |B_{area}|^2 + (r-1)^2}$$



residual bias **2**

$$B_{res}(\mathrm{i}) = B_{rel}(\mathrm{i}) - \overline{B_{rel}}$$

area of the residual bias **3**

$$|B_{area}| = \int_0^1 |B_{res}(i)|\ di$$

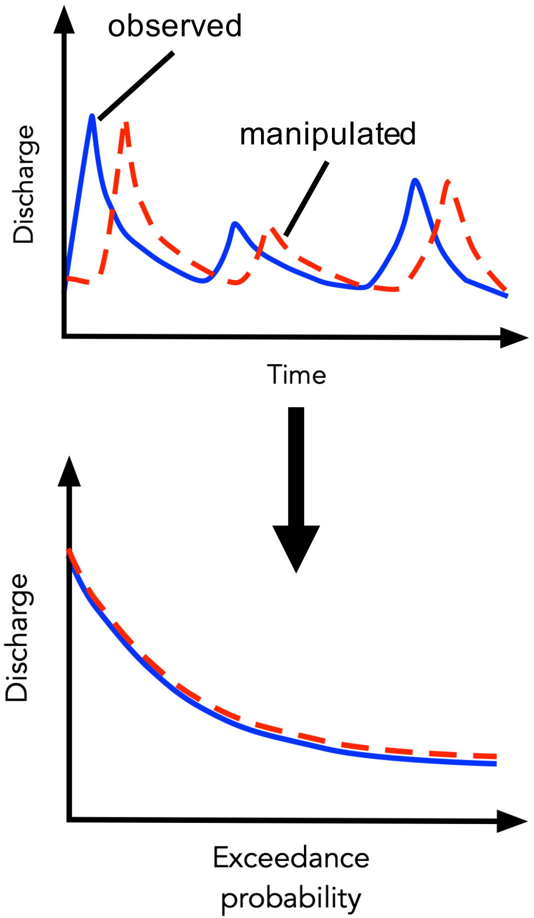
direction of dynamic error **4**

$$B_{dir} = \int_0^{0.5} B_{res}(i)\ di$$

slope of the residual bias **5**

$$B_{slope} = \begin{cases} |B_{area}| \cdot (-1), & B_{dir} > 0 \\ |B_{area}| \quad , & B_{dir} < 0 \\ 0 \quad , & B_{dir} = 0 \end{cases}$$

Mimicking timing error (iii)

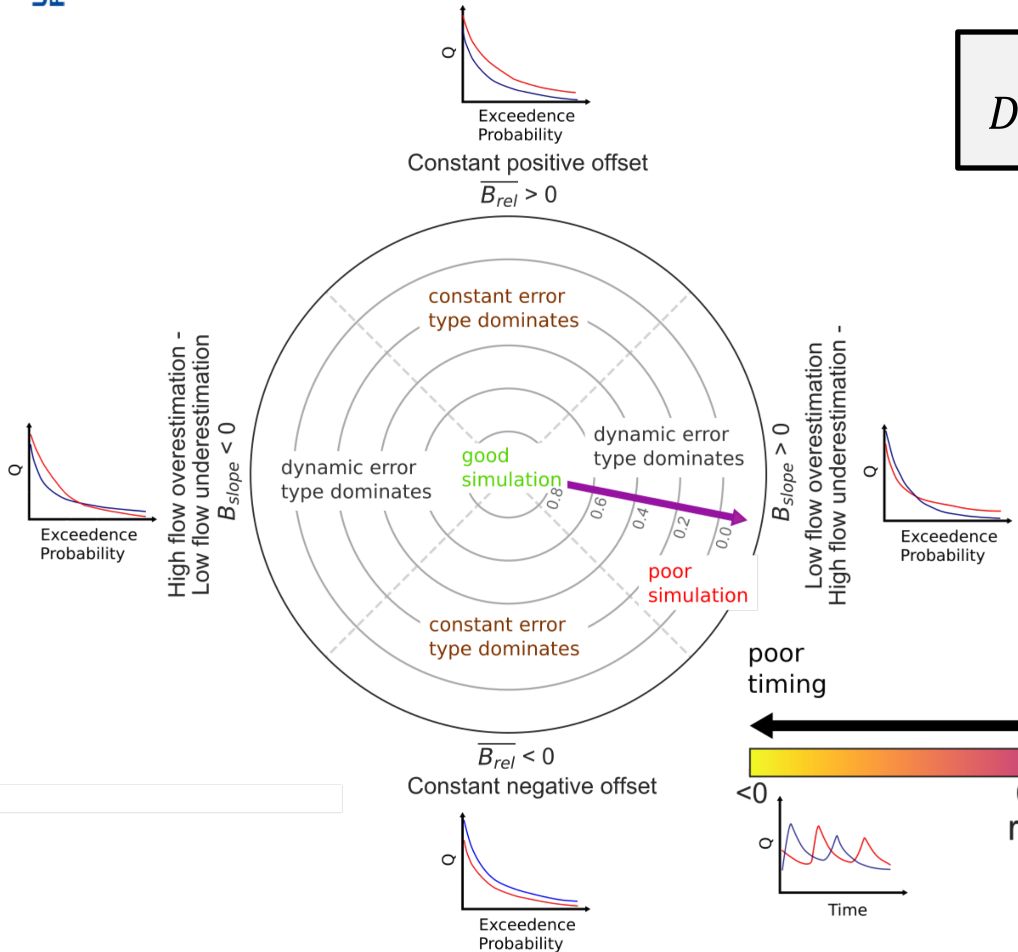


Randomizing the order of the observed time series

$$DE = 1 - \sqrt{\overline{B_{rel}}^2 + |B_{area}|^2 + (r-1)^2}$$

linear correlation between simulations and observations

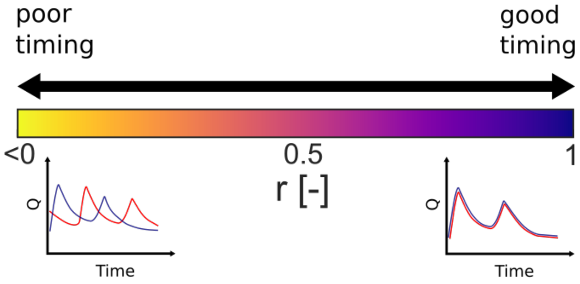
Diagnostic polar plot



$$DE = 1 - \sqrt{\overline{B_{rel}}^2 + |B_{area}|^2 + (r-1)^2}$$

ratio between constant and dynamic error

$$\varphi = arctan2(\overline{B_{rel}}, B_{slope})$$



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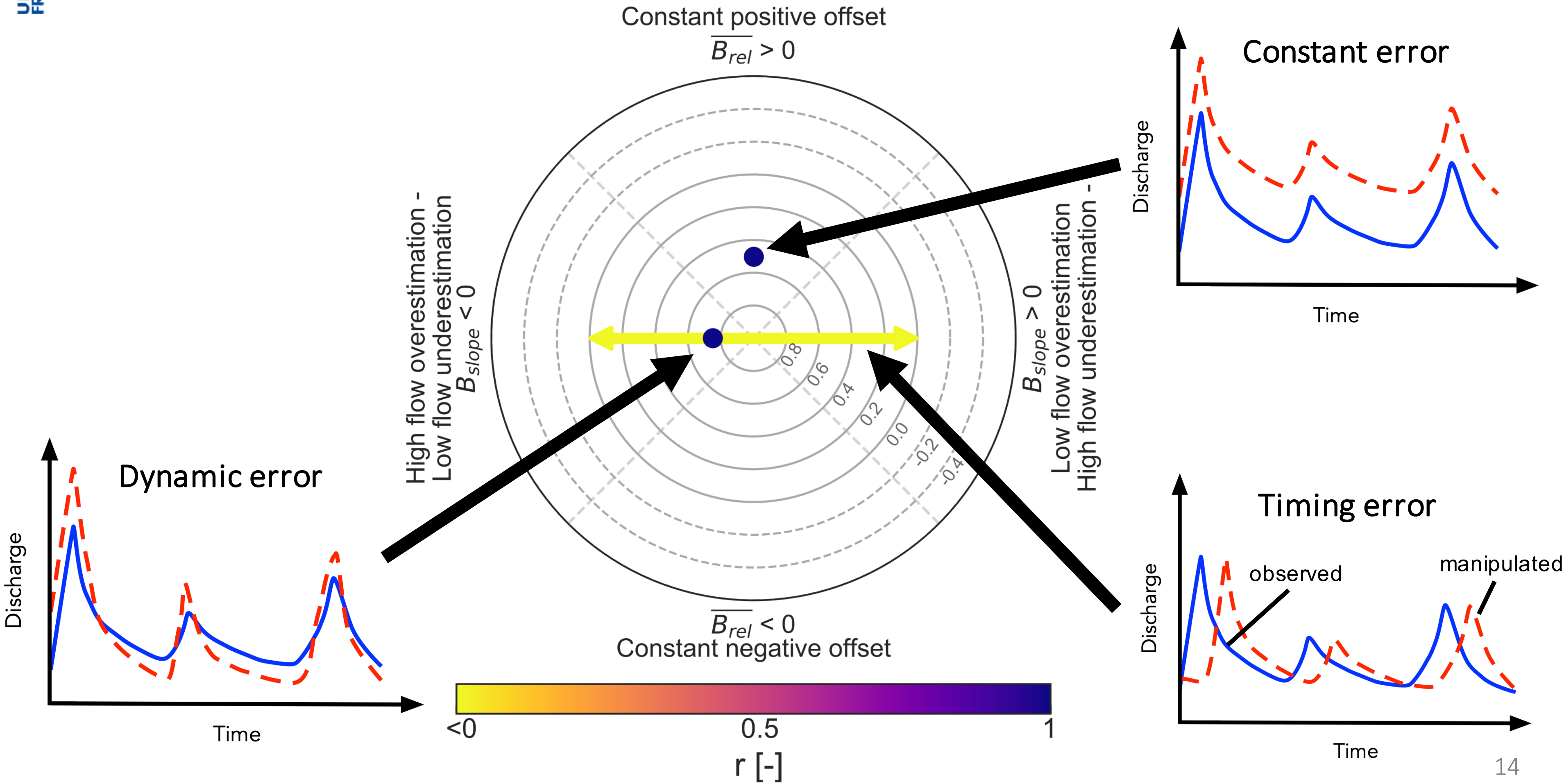
Proof of concept



Comparison to *KGE*

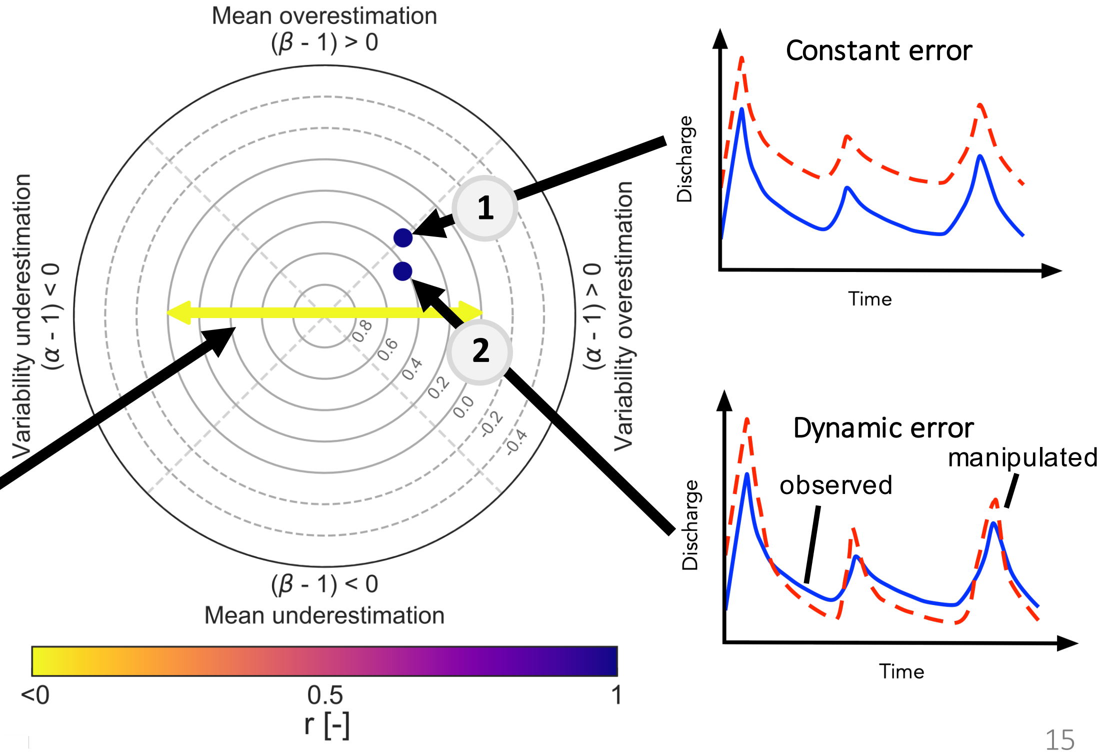
$$KGE = 1 - \sqrt{(\beta - 1)^2 + (\alpha - 1)^2 + (r - 1)^2}$$

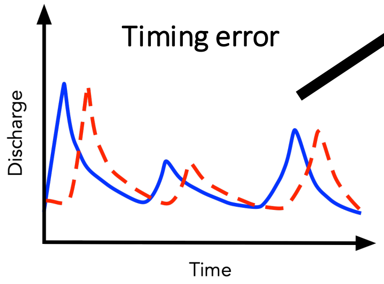
ratio between bias error and flow variability error

$$\varphi = arctan2(\beta - 1, \alpha - 1)$$

1 Polar plot for *KGE* falsely indicate an equal share of bias error and variability error

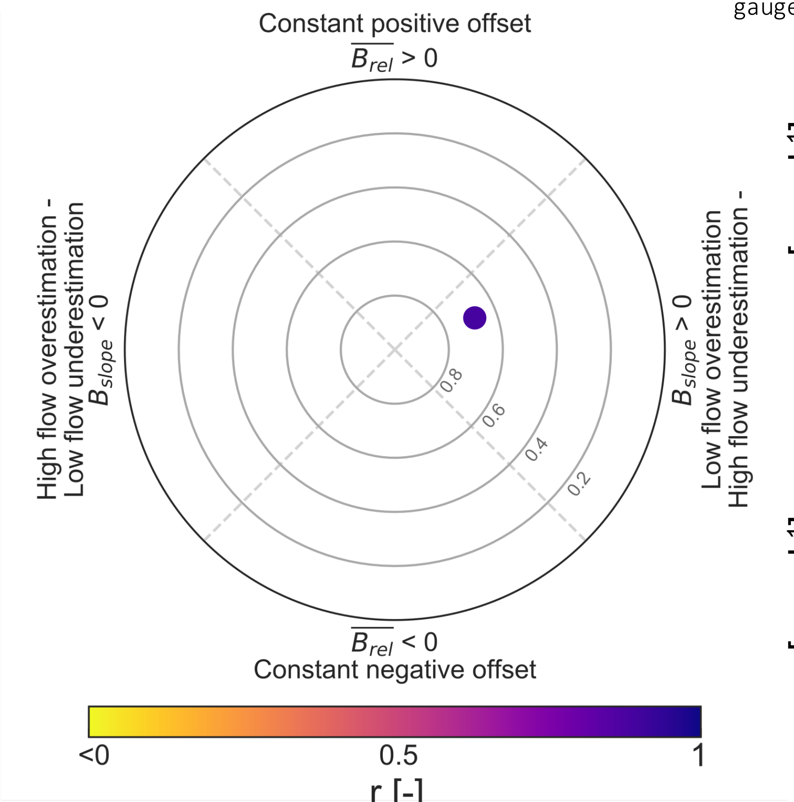
2 Contribution of bias error is falsely displayed

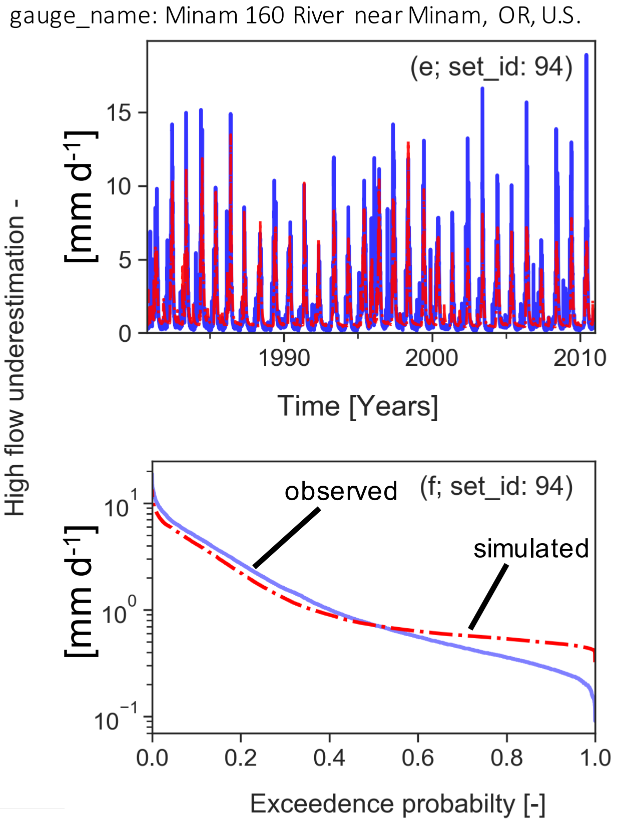




Real case example (Newman et al. (2015))

- positive dynamic error dominates
- slight positive constant error
- lowest share by timing





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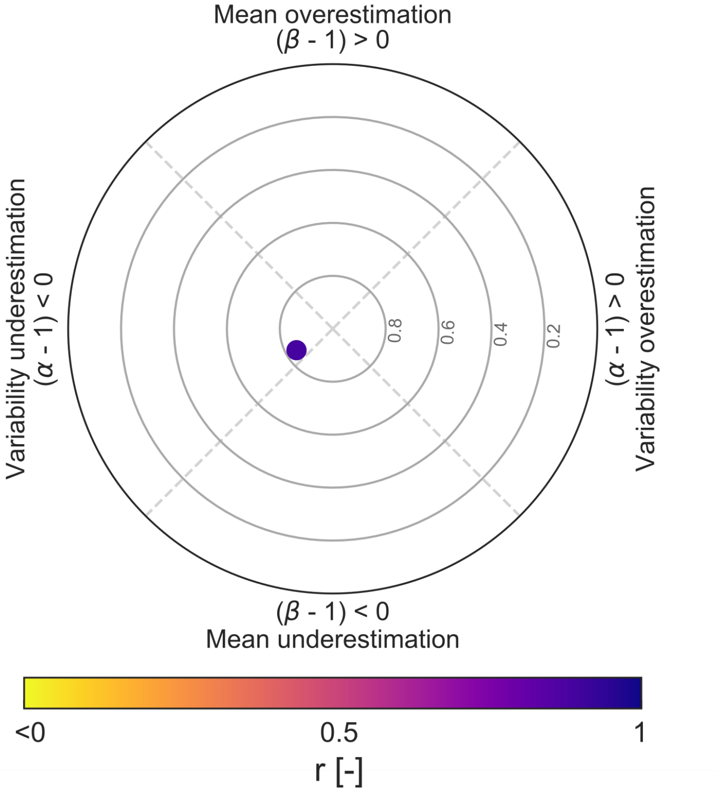
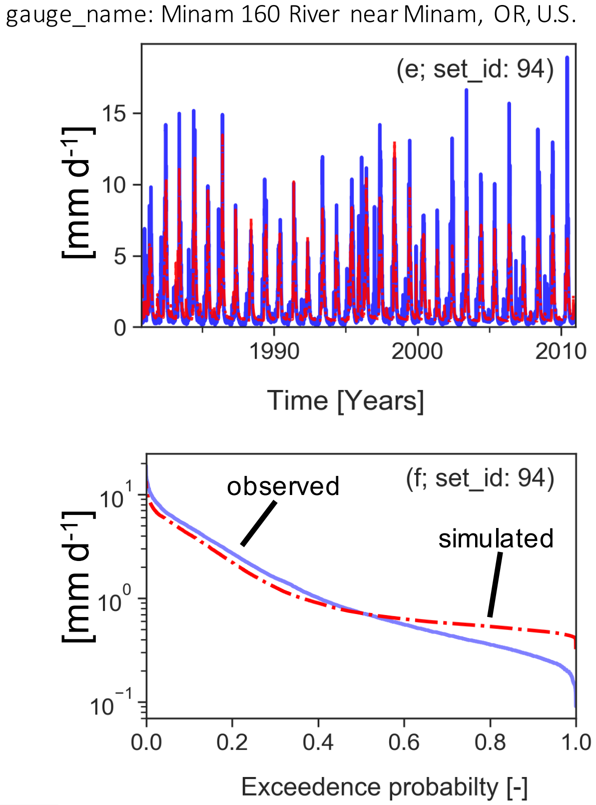
Comparison to *KGE*

Polar plot of *KGE* leads to different error contributions than diagnostic polar plots





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Conclusions

- theoretical proof of concept and real world applicability
- diagnostic polar plots provide hints on the origin of errors
- blueprint for systematic development of other diagnostic efficiency measures

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Documentation (including tutorials): https://diag-eff.readthedocs.io/en/latest/

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