

professional rain gauge networks



often misses small intense events



Opportunistic sensors



Rainfall estimates from opportunistic sensors in Germany across spatio-temporal scales – Geostatistical interpolation framework

can increase network density

$$Z(u_0) = \lambda_{DW D_1} Z(DW D_1) + \sum_{i=1}^2 \alpha_{PWS_i} Z(PWS_i) + \beta_{CML_1} Z(CML_1)$$

$$\lambda_{DW D_1} + \sum_{i=1}^2 \alpha_{PWS_i} + \beta_{CML_1} = 1$$

$$\begin{pmatrix} \gamma(DW D_1, DW D_1) & \gamma(DW D_1, PWS_1) & \gamma(DW D_1, PWS_2) & \gamma(DW D_1, CML_1) & 1 \\ \gamma(PWS_1, DW D_1) & \gamma(PWS_1, PWS_1) + c_{PWS} & \gamma(PWS_1, PWS_2) & \gamma(PWS_1, CML_1) & 1 \\ \gamma(PWS_2, DW D_1) & \gamma(PWS_2, PWS_1) & \gamma(PWS_2, PWS_2) + c_{PWS} & \gamma(PWS_2, CML_1) & 1 \\ \gamma(CML_1, DW D_1) & \gamma(CML_1, PWS_1) & \gamma(CML_1, PWS_2) & \gamma(CML_1, CML_1) + c_{CML} & 1 \\ 1 & 1 & 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} \lambda_{DW D_1} \\ \alpha_{PWS_1} \\ \alpha_{PWS_2} \\ \beta_{CML_1} \\ \mu \end{pmatrix} = \begin{pmatrix} \gamma(u_0, DW D_1) \\ \gamma(u_0, PWS_1) \\ \gamma(u_0, PWS_2) \\ \gamma(u_0, CML_1) \\ 1 \end{pmatrix}$$

$$\gamma(u_i, u_j) = \frac{1}{|u_i| |u_j|} \int_{u_i} \int_{u_j} \gamma(u, u) du dv$$

$$\gamma(DW D_1, CML_1) = \frac{1}{|CML_1|} \int_{CML_1} \gamma(DW D_1, u) du$$

$$\gamma(u_i, u_j) = \frac{1}{|u_i| |u_j|} \int_{u_i} \int_{u_j} \gamma(u, v) du dv$$

$$\gamma(CML_1, CML_1) = \frac{1}{|CML_1| |CML_1|} \int_{CML_1} \int_{CML_1} \gamma(u, v) du dv$$

Micha Eisele¹, Maximilian Graf², Abbas El Hachem¹, Jochen Seidel¹, Christian Chwala^{2,3}, Harald Kunstmann^{2,3}, and András Bárdossy¹

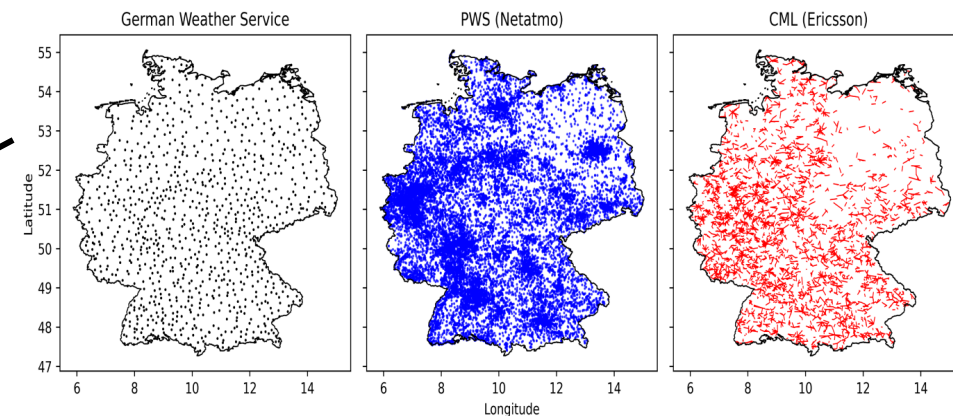
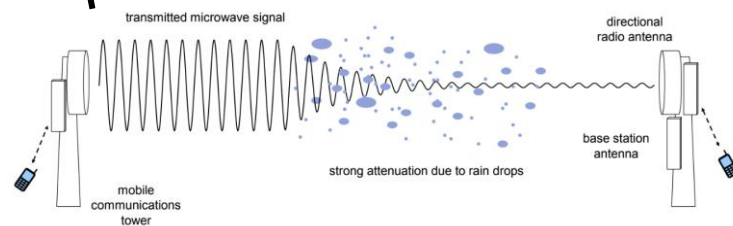
¹Institute for Modelling Hydraulic and Environmental Systems, University of Stuttgart, Stuttgart, Germany (micha.eisele@iws.uni-stuttgart.de)

²Institute of Meteorology and Climate Research, Karlsruhe Institute of Technology - Campus Alpin, Garmisch-Partenkirchen, Germany

³Institute of Geography, University of Augsburg, Augsburg, Germany

combined in a block kriging approach

but come with different geometric properties and measurement uncertainties



Rainfall estimates from opportunistic sensors in Germany across spatio-temporal scales – Geostatistical interpolation framework

Micha Eisele¹, Maximilian Graf², Abbas El Hachem¹, Jochen Seidel¹, Christian Chwala^{2,3}, Harald Kunstmann^{2,3}, and András Bárdossy¹

•¹Institute for Modelling Hydraulic and Environmental Systems, University of Stuttgart, Stuttgart, Germany (micha.eisele@iws.uni-stuttgart.de)

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Motivation

- Especially for modelling and prediction in fast reacting catchments, e.g. in urban areas, a higher space-time resolution than current ground measurement networks offer is needed (Cristiano et al., 2017; Ochoa-Rodriguez et al., 2015).
- Weather radar data and precipitation measurements on the ground show only low correlations, especially at sub-hourly resolution (Bárdossy & Pegram, 2017)

Opportunistic sensors for rainfall monitoring

Definition: Sensors that were not designed to provide high-quality rainfall data or any rainfall data at all.



Commercial Microwave
Link (CML)



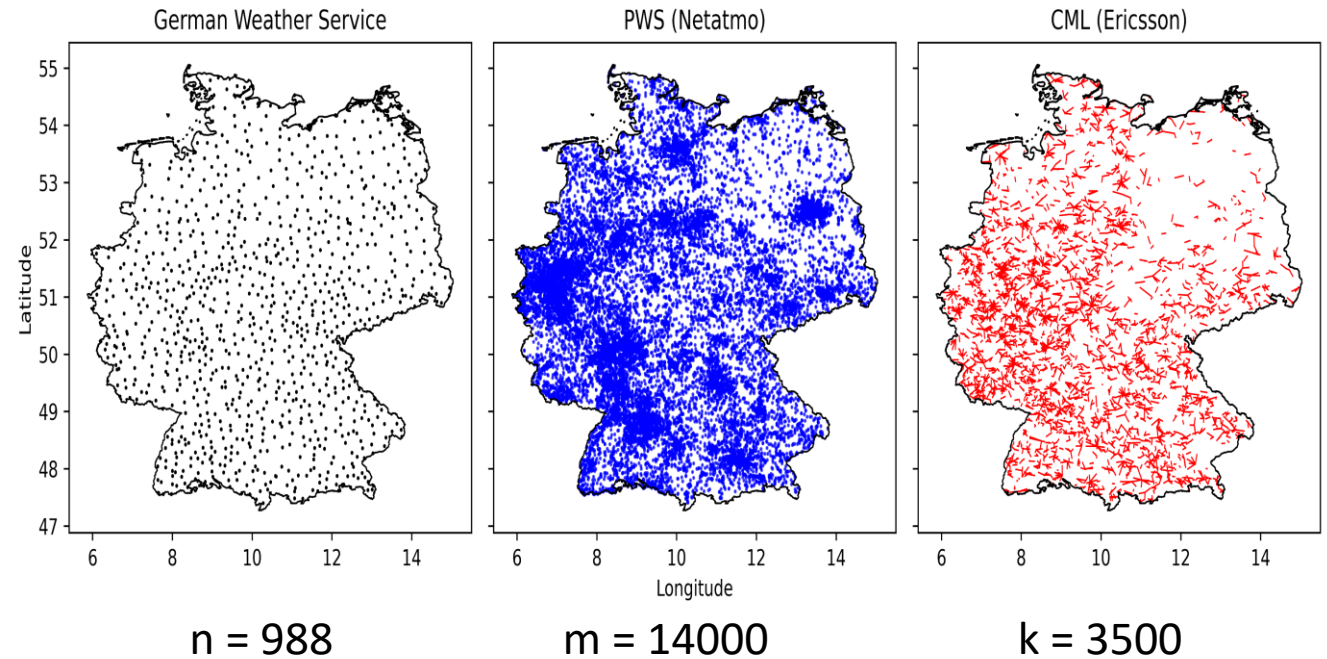
Personal Weather Station
(PWS)



Windshield wipers
(rainfall binary info)

Opportunistic sensors for rainfall monitoring

Pro:
High network density



Contra:
Low data quality → Extensive filtering necessary

Ordinary Kriging - Theory

Estimation at given location x^*

$$Z(x^*) = \sum_{i=1}^n \lambda_i Z(x_i)$$

Condition of unbiasedness

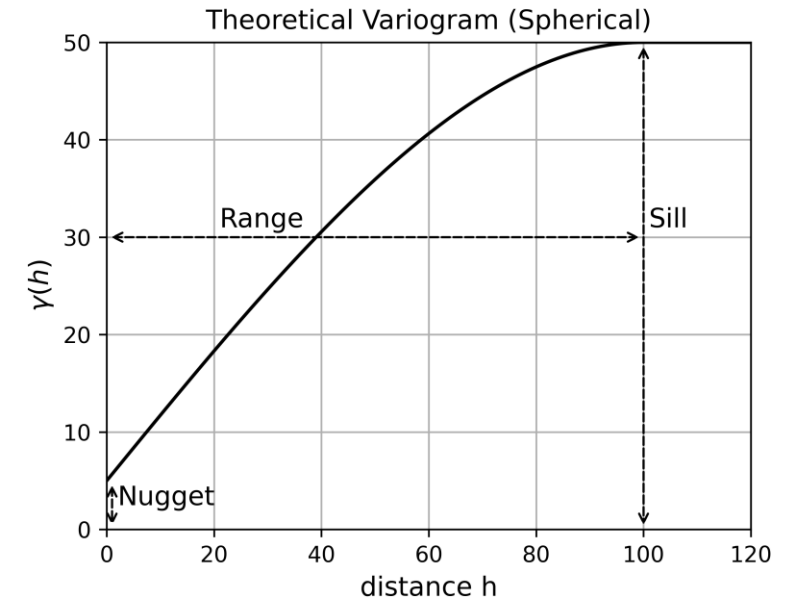
$$\sum_{i=1}^n \lambda_i = 1$$

The weights can be obtained by solving the linear equation.
 μ is the Lagrange multiplier introduced to ensure the fulfilment of the unbiasedness condition.

$$Aw = c$$

$$\begin{pmatrix} \gamma(x_1, x_1) & \cdots & \gamma(x_1, x_n) & 1 \\ \vdots & \ddots & \vdots & \vdots \\ \gamma(x_n, x_1) & \cdots & \gamma(x_n, x_n) & 1 \\ 1 & \cdots & 1 & 0 \end{pmatrix} \begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_n \\ \mu \end{pmatrix} = \begin{pmatrix} \gamma(x^*, x_1) \\ \vdots \\ \gamma(x^*, x_n) \\ 1 \end{pmatrix}$$

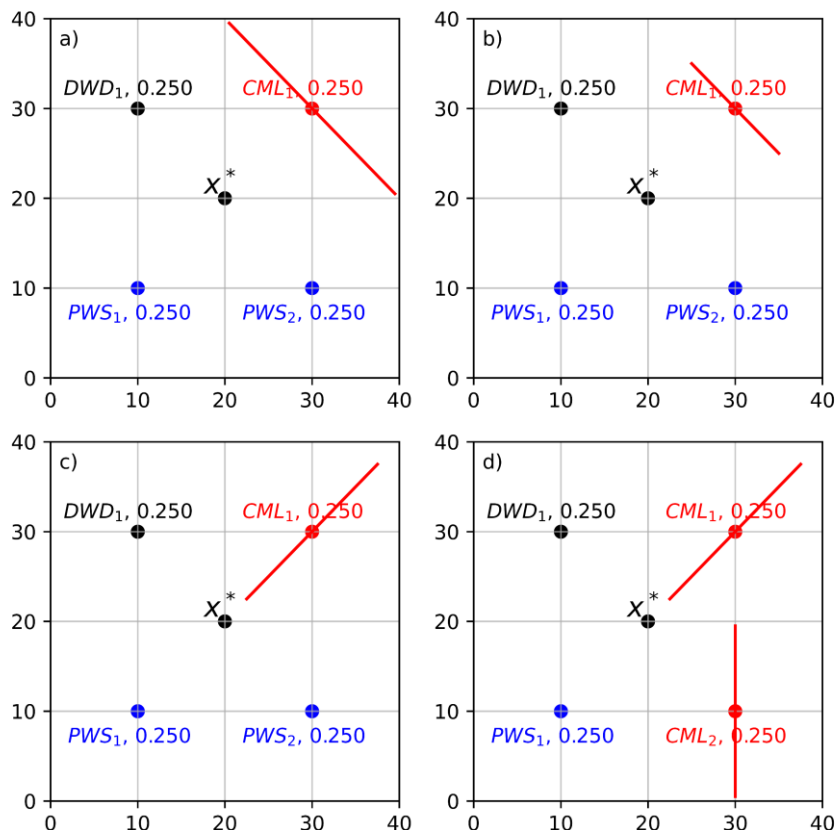
Variogram



For any pair of point, $\gamma(x_i, y_j)$ is the variogram value corresponding the vector $x_i - y_j$

Example

Replacing each line segment (CML) with its central point (as done e.g. in Overeem et al., 2016a)



Equations for examples a) to c)

$$Z(u_0) = \lambda_{DWD_1} Z(DWD_1) + \sum_{i=1}^2 \alpha_{PWS_i} Z(PWS_i) + \beta_{CML_1} Z(CML_1)$$

$$\lambda_{DWD_1} + \sum_{i=1}^2 \alpha_{PWS_i} + \beta_{CML_1} = 1 \quad Aw = c$$

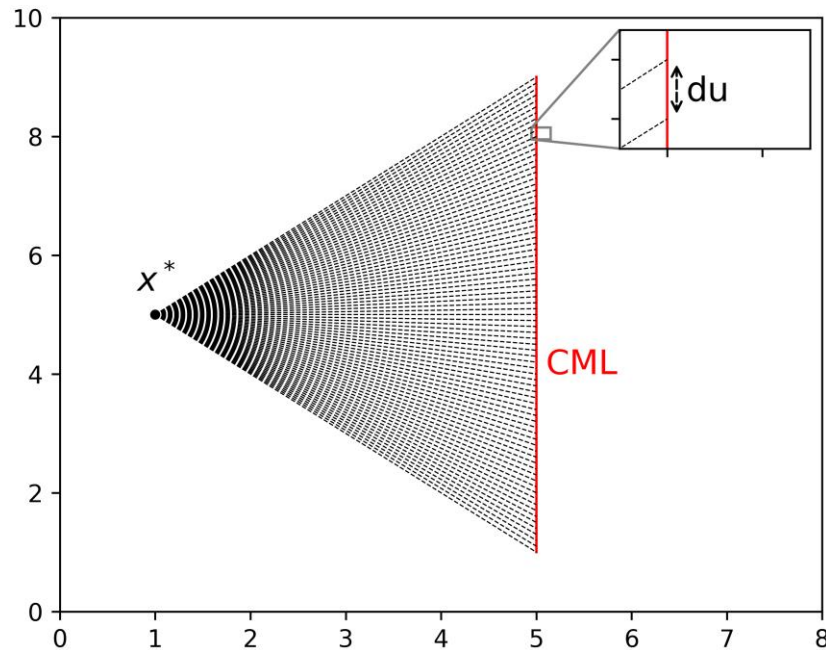
$$A = \begin{pmatrix} \gamma(DWD_1, DWD_1) & \gamma(DWD_1, PWS_1) & \gamma(DWD_1, PWS_2) & \gamma(DWD_1, CML_1) & 1 \\ \gamma(PWS_1, DWD_1) & \gamma(PWS_1, PWS_1) & \gamma(PWS_1, PWS_2) & \gamma(PWS_1, CML_1) & 1 \\ \gamma(PWS_2, DWD_1) & \gamma(PWS_2, PWS_1) & \gamma(PWS_2, PWS_2) & \gamma(PWS_2, CML_1) & 1 \\ \gamma(CML_1, DWD_1) & \gamma(CML_1, PWS_1) & \gamma(CML_1, PWS_2) & \gamma(CML_1, CML_1) & 1 \\ 1 & 1 & 1 & 1 & 0 \end{pmatrix}$$

$$w^T = (\lambda_{DWD_1}, \alpha_{PWS_1}, \alpha_{PWS_2}, \beta_{CML_1}, \mu)$$

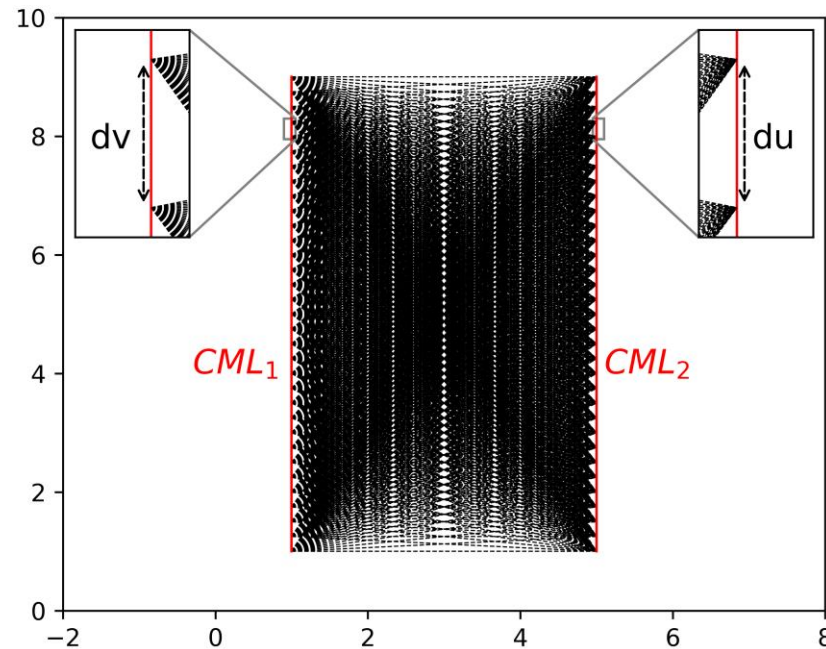
$$c^T = (\gamma(u_0, DWD_1), \gamma(u_0, PWS_1), \gamma(u_0, PWS_2), \gamma(u_0, CML_1), 1)$$

Different sensors - Different geometric properties

Since CML measure an integral over a defined distance, this information should be incorporated in geostatistical interpolation. The combination of a point and line segment/two line segments requires a mean variogram value over the segment(s).



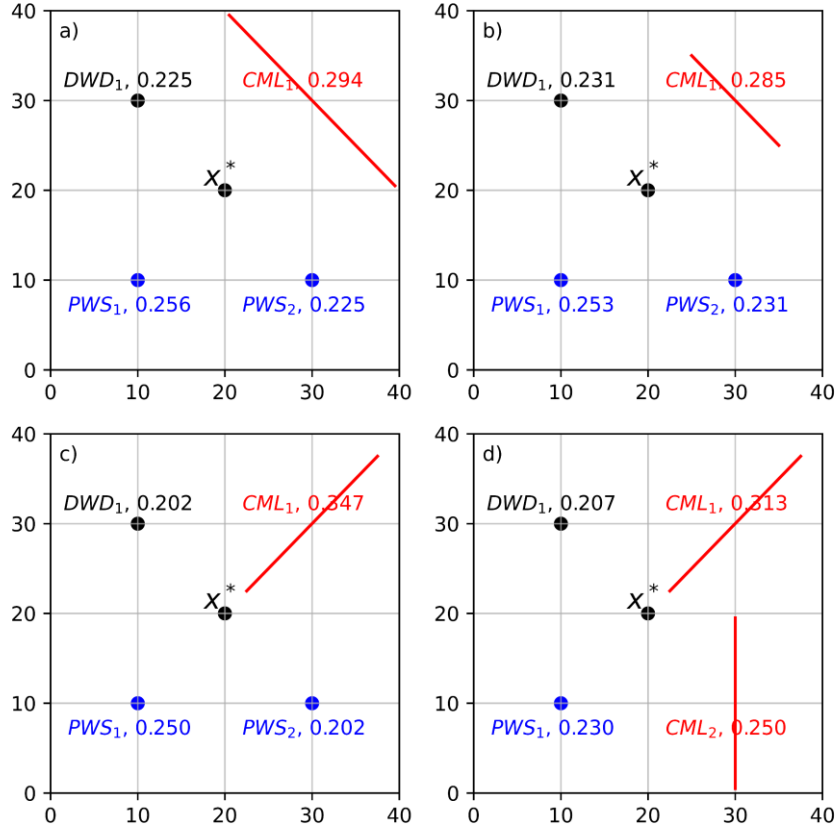
$$\bar{\gamma}(x^*, CML) = \frac{1}{|CML|} \int_{CML} \gamma(x^*, u) du$$



$$\bar{\gamma}(CML_1, CML_2) = \frac{1}{|CML_1||CML_2|} \int_{CML_1} \int_{CML_2} \gamma(u, v) du dv$$

Example

Considering length and orientation of the line segments leads to different weights depending on geometric properties



Equations for example a) to c)

$$Z(u_0) = \lambda_{DWD_1} Z(DWD_1) + \sum_{i=1}^2 \alpha_{PWS_i} Z(PWS_i) + \beta_{CML_1} Z(CML_1)$$

$$\lambda_{DWD_1} + \sum_{i=1}^2 \alpha_{PWS_i} + \beta_{CML_1} = 1$$

$$Aw = c$$

$$A = \begin{pmatrix} \gamma(DWD_1, DWD_1) & \gamma(DWD_1, PWS_1) & \gamma(DWD_1, PWS_2) & \bar{\gamma}(DWD_1, CML_1) & 1 \\ \gamma(PWS_1, DWD_1) & \gamma(PWS_1, PWS_1) & \gamma(PWS_1, PWS_2) & \bar{\gamma}(PWS_1, CML_1) & 1 \\ \gamma(PWS_2, DWD_1) & \gamma(PWS_2, PWS_1) & \gamma(PWS_2, PWS_2) & \bar{\gamma}(PWS_2, CML_1) & 1 \\ \bar{\gamma}(CML_1, DWD_1) & \bar{\gamma}(CML_1, PWS_1) & \bar{\gamma}(CML_1, PWS_2) & \bar{\gamma}(CML_1, CML_1) & 1 \\ 1 & 1 & 1 & 1 & 0 \end{pmatrix}$$

$$w^T = (\lambda_{DWD_1}, \alpha_{PWS_1}, \alpha_{PWS_2}, \beta_{CML_1}, \mu)$$

$$c^T = (\gamma(u_0, DWD_1), \gamma(u_0, PWS_1), \gamma(u_0, PWS_2), \bar{\gamma}(u_0, CML_1), 1)$$

Different sensors – Different uncertainties

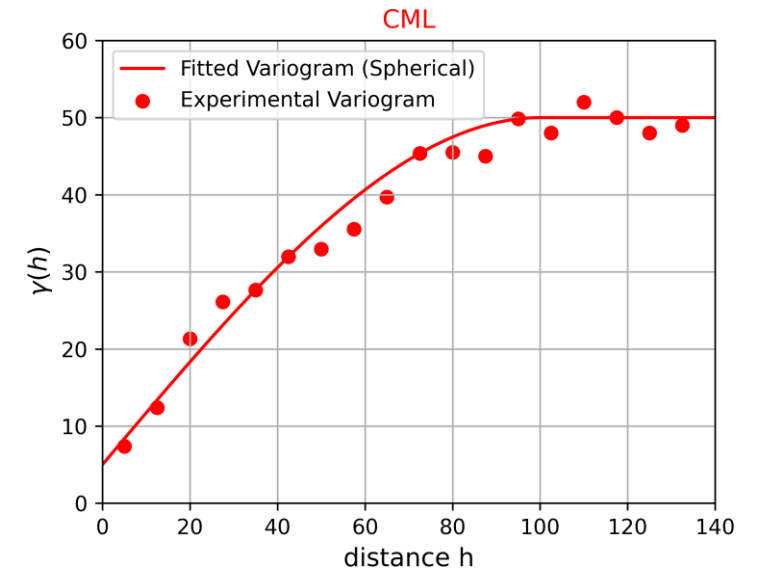
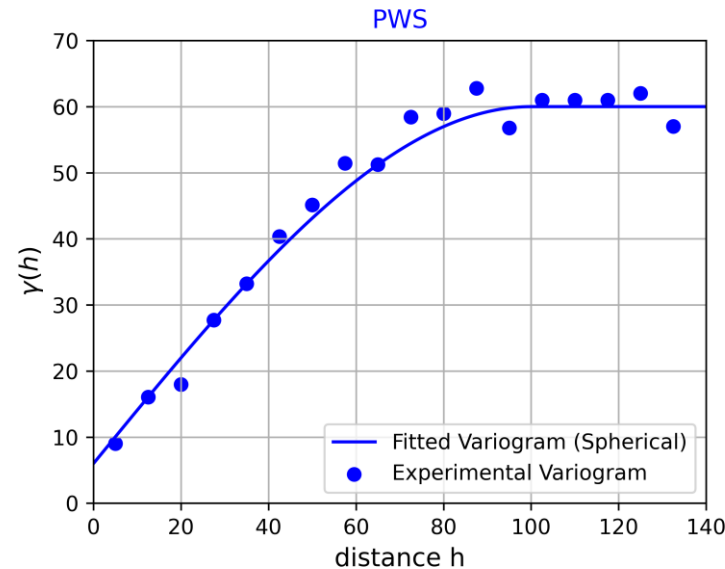
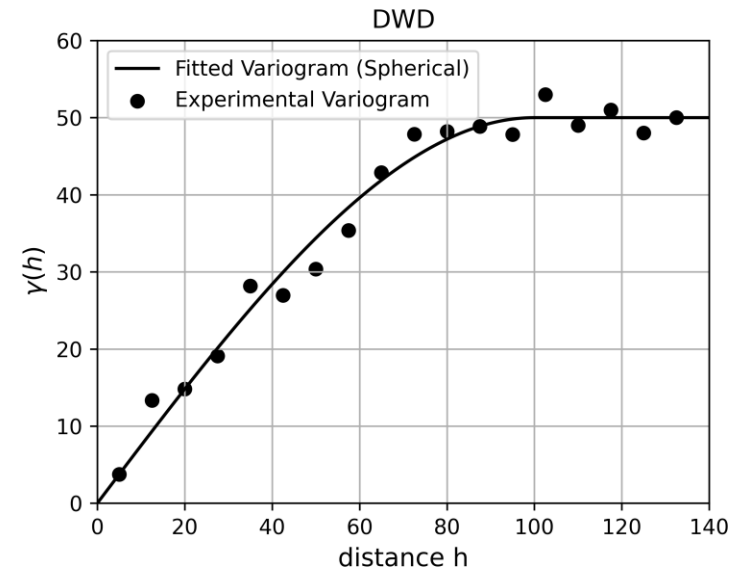
To account for different measurement uncertainties for PWS and CML, the values ε_{PWS} and ε_{CML} are added to the diagonal of the matrix.

$$A = \begin{pmatrix} \gamma(DWD_1, DWD_1) & \cdots & \gamma(DWD_1, DWD_n) & \gamma(DWD_1, PWS_1) & \cdots & \gamma(DWD_1, PWS_m) & \gamma(DWD_1, CML_1) & \cdots & \gamma(DWD_1, CML_k) & 1 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \gamma(DWD_n, DWD_1) & \cdots & \gamma(DWD_n, DWD_n) & \gamma(DWD_n, PWS_1) & \cdots & \gamma(DWD_n, PWS_m) & \gamma(DWD_n, CML_1) & \cdots & \gamma(DWD_n, CML_k) & 1 \\ \gamma(PWS_1, DWD_1) & \cdots & \gamma(PWS_1, DWD_n) & \gamma(PWS_1, PWS_1) + \varepsilon_{PWS} & \cdots & \gamma(PWS_1, PWS_m) & \gamma(PWS_1, CML_1) & \cdots & \gamma(PWS_1, CML_k) & 1 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \gamma(PWS_m, DWD_1) & \cdots & \gamma(PWS_m, DWD_n) & \gamma(PWS_m, PWS_1) & \cdots & \gamma(PWS_m, PWS_m) + \varepsilon_{PWS} & \gamma(PWS_m, CML_1) & \cdots & \gamma(PWS_m, CML_k) & 1 \\ \gamma(CML_1, DWD_1) & \cdots & \gamma(CML_1, DWD_n) & \gamma(CML_1, PWS_1) & \cdots & \gamma(CML_1, PWS_m) & \gamma(CML_1, CML_1) + \varepsilon_{CML} & \cdots & \gamma(CML_1, CML_k) & 1 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ \gamma(CML_k, DWD_1) & \cdots & \gamma(CML_k, DWD_n) & \gamma(CML_k, PWS_1) & \cdots & \gamma(CML_k, PWS_m) & \gamma(CML_k, CML_1) & \cdots & \gamma(CML_k, CML_k) + \varepsilon_{CML} & 1 \\ 1 & \cdots & 1 & 1 & \cdots & 1 & 1 & \cdots & 1 & 0 \end{pmatrix}$$

Different sensors – Different uncertainties

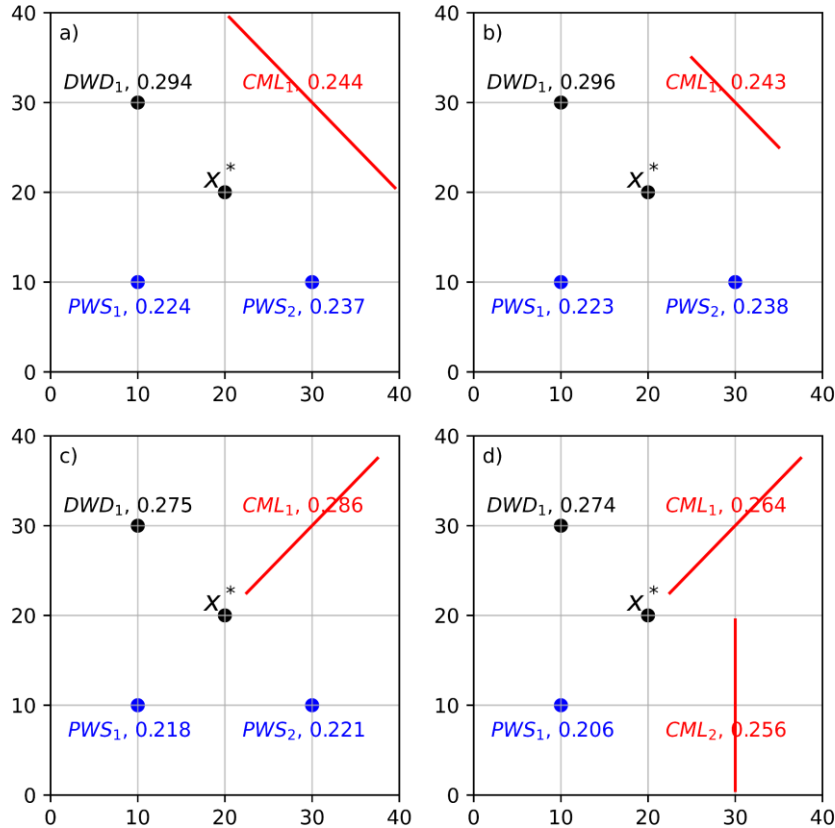
How to select ε_{PWS} and ε_{CML} .

The variograms based on the DWD data showed no nugget effect, while the PWS and CML based variograms had a nugget of about 10 %. This was the reason why the ε was selected as 10 % of the sill.



Example

Considering different measurement uncertainty.



Equations for example a) to c)

$$Z(u_0) = \lambda_{DWD_1} Z(DWD_1) + \sum_{i=1}^2 \alpha_{PWS_i} Z(PWS_i) + \beta_{CML_1} Z(CML_1)$$

$$\lambda_{DWD_1} + \sum_{i=1}^2 \alpha_{PWS_i} + \beta_{CML_1} = 1$$

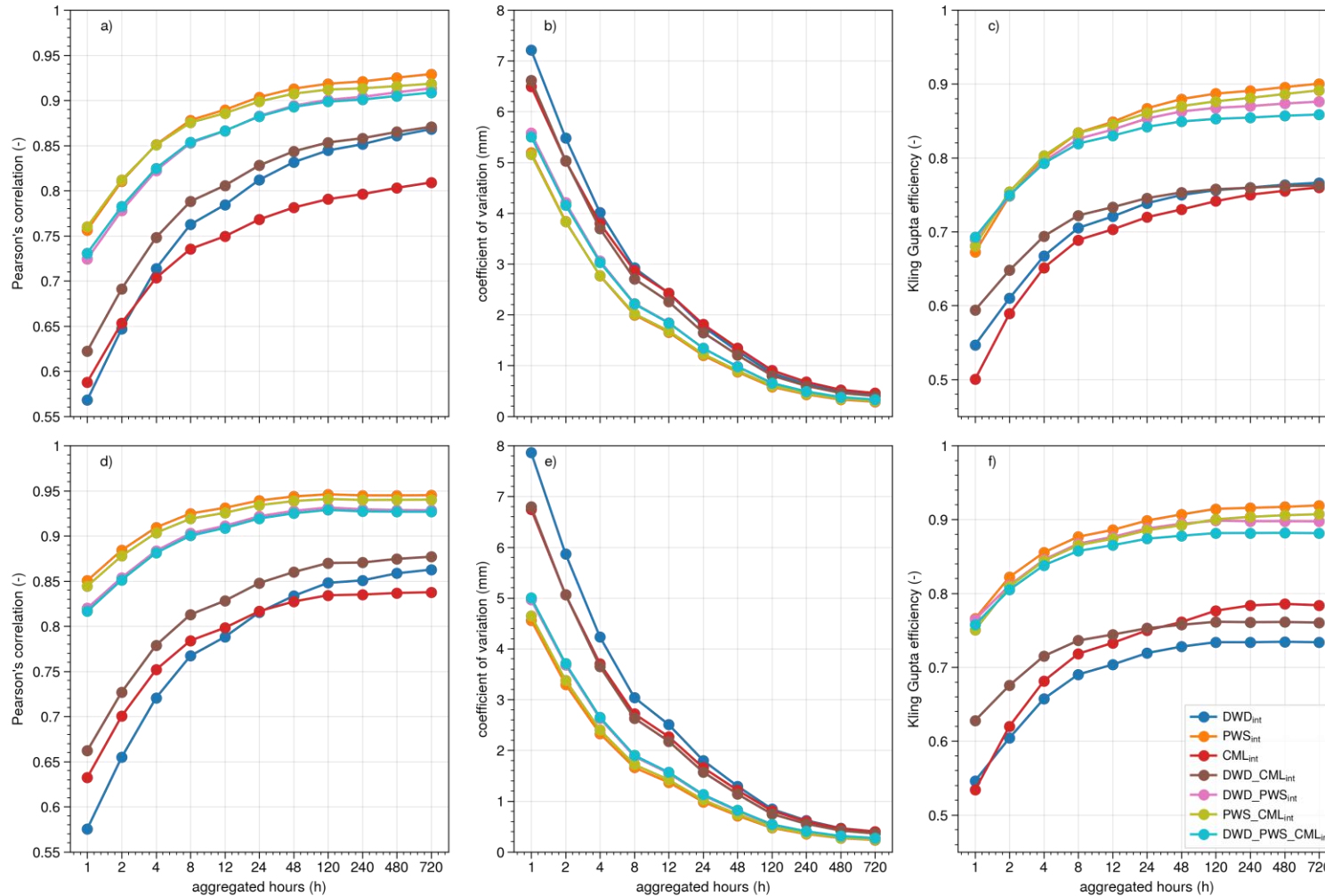
$$Aw = c$$

$$A = \begin{pmatrix} \gamma(DWD_1, DWD_1) & \gamma(DWD_1, PWS_1) & \gamma(DWD_1, PWS_2) & \bar{\gamma}(DWD_1, CML_1) & 1 \\ \gamma(PWS_1, DWD_1) & \gamma(PWS_1, PWS_1) + \varepsilon_{PWS} & \gamma(PWS_1, PWS_2) & \bar{\gamma}(PWS_1, CML_1) & 1 \\ \gamma(PWS_2, DWD_1) & \gamma(PWS_2, PWS_1) & \gamma(PWS_2, PWS_2) + \varepsilon_{PWS} & \bar{\gamma}(PWS_2, CML_1) & 1 \\ \bar{\gamma}(CML_1, DWD_1) & \bar{\gamma}(CML_1, PWS_1) & \bar{\gamma}(CML_1, PWS_2) & \bar{\gamma}(CML_1, CML_1) + \varepsilon_{CML} & 1 \\ 1 & 1 & 1 & 1 & 0 \end{pmatrix}$$

$$w^T = (\lambda_{DWD_1}, \alpha_{PWS_1}, \alpha_{PWS_2}, \beta_{CML_1}, \mu)$$

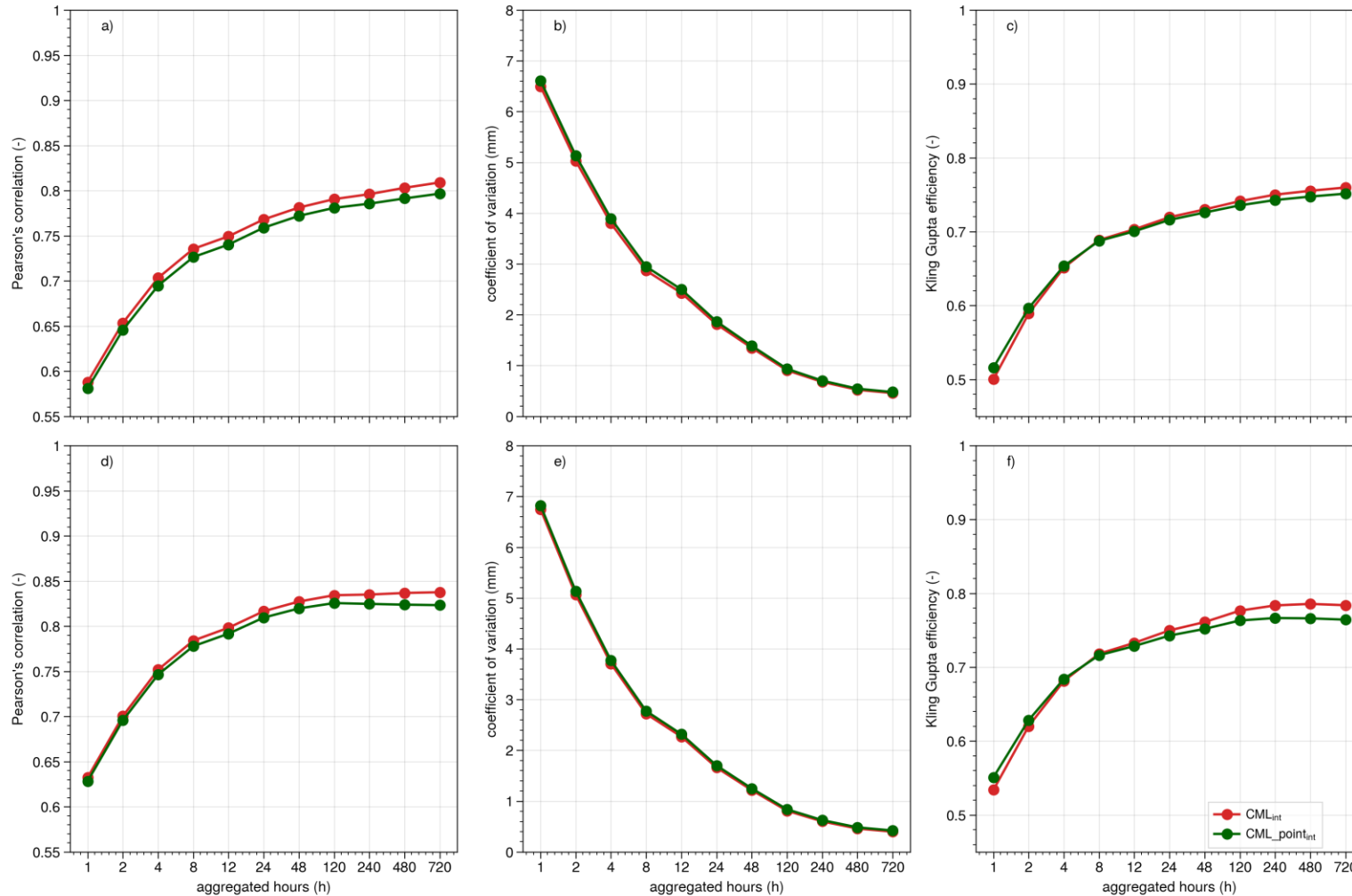
$$c^T = (\gamma(u_0, DWD_1), \gamma(u_0, PWS_1), \gamma(u_0, PWS_2), \bar{\gamma}(u_0, CML_1), 1)$$

Results



Performance measures of the cross validation from the interpolation framework for different temporal aggregations. a) to c) show PCC, CV and KGE for all country-wide DWD_{auto} validation stations and d) to f) show PCC, CV and KGE for validation stations with more than 80 PWS or CMLs in 20 km vicinity. Those are the 10 percent of the validation station which are surrounded by the most opportunistic sensors.

Results



Performance measures of the cross validation results from the interpolation framework for different temporal aggregations. Here CML_{int} and $CML_{point_{int}}$ are shown. For $CML_{point_{int}}$ the points at the center of each CML were used as point information in the interpolation framework. a) to c) show PCC, CV and KGE for country-wide validation stations and d) to f) show PCC, CV and KGE for validation stations with more than 80 PWS or CMLs in 20 km vicinity. Those are the 10 percent of the validation station which are surrounded by the most opportunistic sensors.

More Results

Graf, M., El Hachem, A., Eisele, M., Seidel, J., Chwala, C., Kunstmann, H., and Bárdossy, A.: Combined rainfall estimates from personal weather station and commercial microwave link data in Germany, EGU General Assembly 2021, online, 19–30 Apr 2021, EGU21-12445, <https://doi.org/10.5194/egusphere-egu21-12445>, 2021.

References

- Bárdossy, A., & Pegram, G. (2017). Combination of radar and daily precipitation data to estimate meaningful sub-daily point precipitation extremes. *Journal of Hydrology*, 544, 397–406. doi:10.1016/j.jhydrol.2016.11.039
- Cristiano, E., ten Veldhuis, M.-C., & van de Giesen, N. (2017). Spatial and temporal variability of rainfall and their effects on hydrological response in urban areas – a review. *Hydrology and Earth System Sciences*, 21, 3859–3878. doi:10.5194/hess-21-3859-2017
- Ochoa-Rodriguez, S., Wang, L.-P., Gires, A., Pina, R. D., Reinoso-Rondinel, R., Bruni, G., Ichiba, A., Gaitan, S., Cristiano, E., van Assel, J., Kroll, S., Murl`a-Tuyls, D., Tisserand, B., Schertzer, D., Tchiguirinskaia, I., Onof, C., Willems, P., & ten Veldhuis, M.-C. (2015). Impact of spatial and temporal resolution of rainfall inputs on urban hydrodynamic modelling outputs: A multi-catchment investigation. *Journal of Hydrology*, 531, 389–407. doi:10.1016/j.jhydrol.2015.05.035
- Overeem, A., Leijnse, H., & Uijlenhoet, R. (2016a). Retrieval algorithm for rainfall mapping from microwave links in a cellular communication network. *Atmospheric Measurement Techniques*, 9, 2425–2444. doi:10.5194/amt-9-2425-2016