Improvement of rainfall estimates using opportunistic sensors - the example of the flood in Rhineland-Palatinate in July 2021

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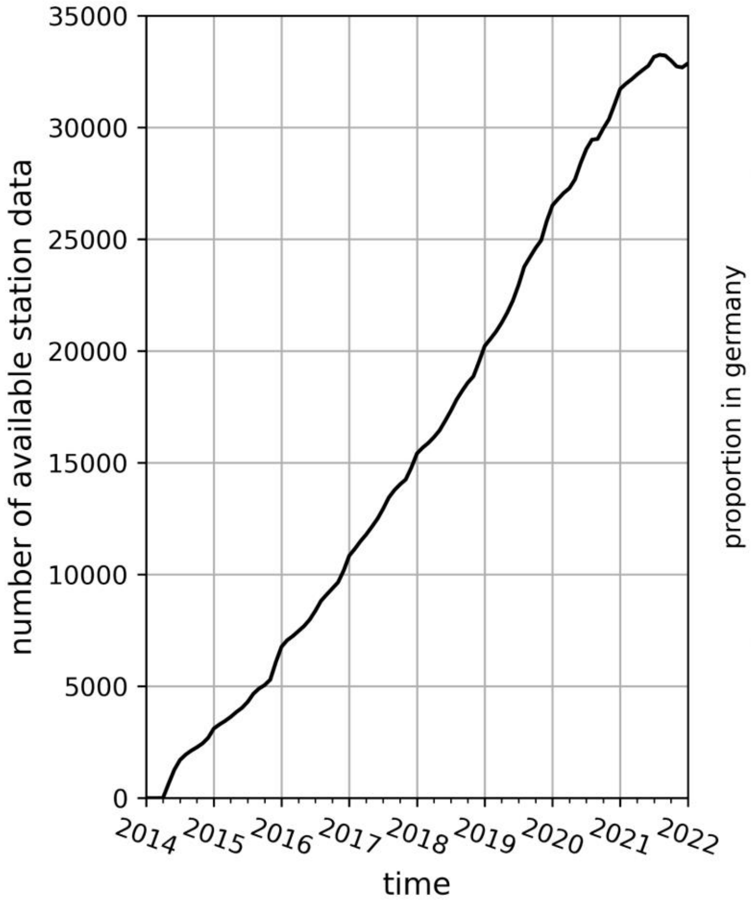
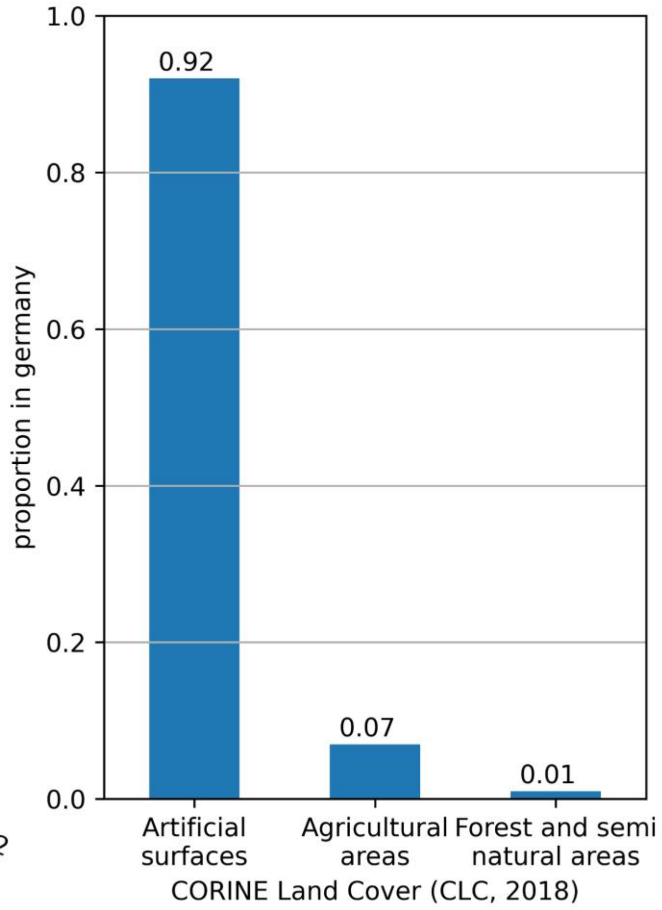
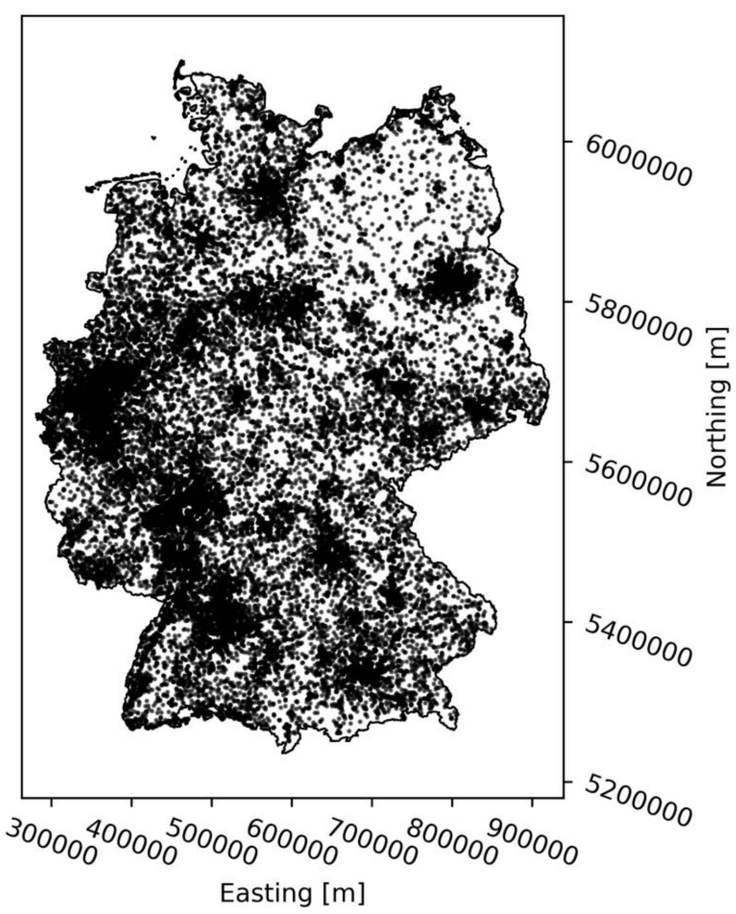
BY

Personal Weather Stations (PWS) - Facts

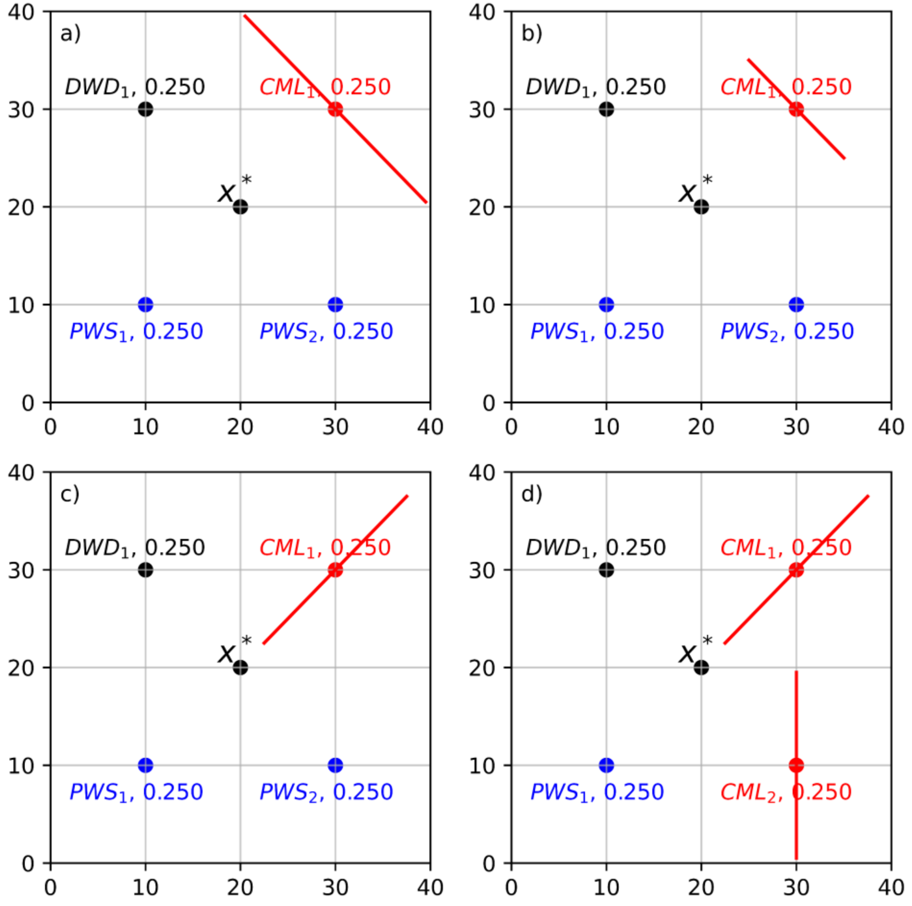






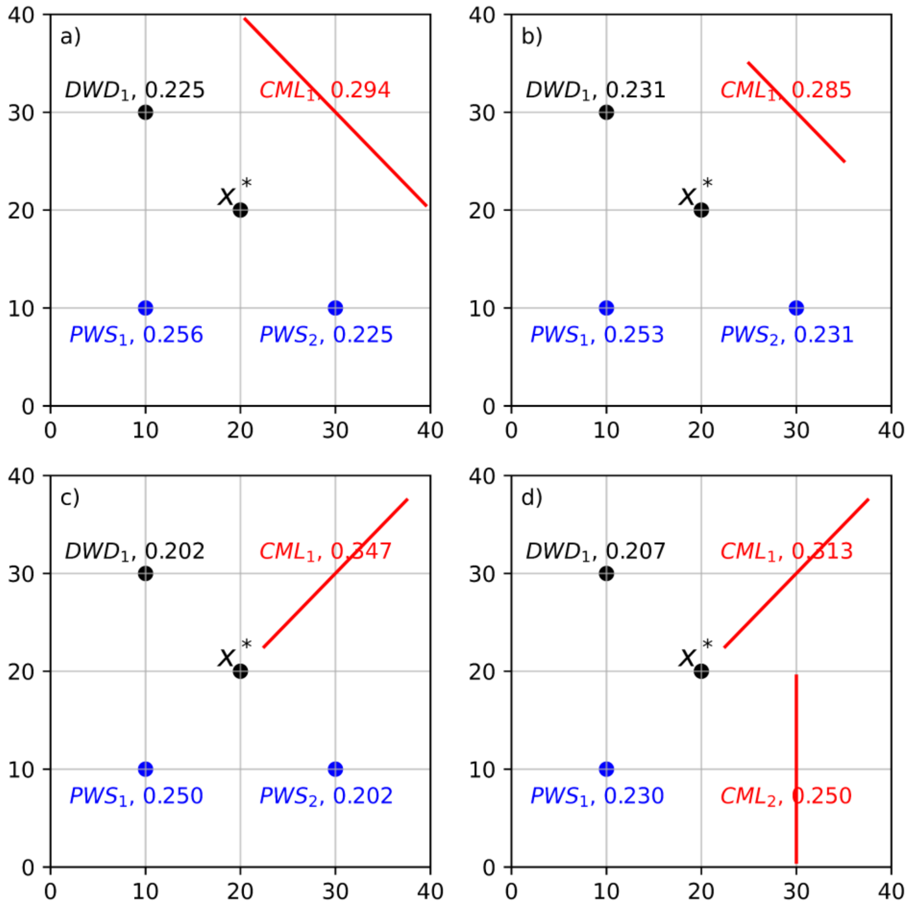
Interpolation Framework

- Replacing each line segment (CML) with its central point as a reference.



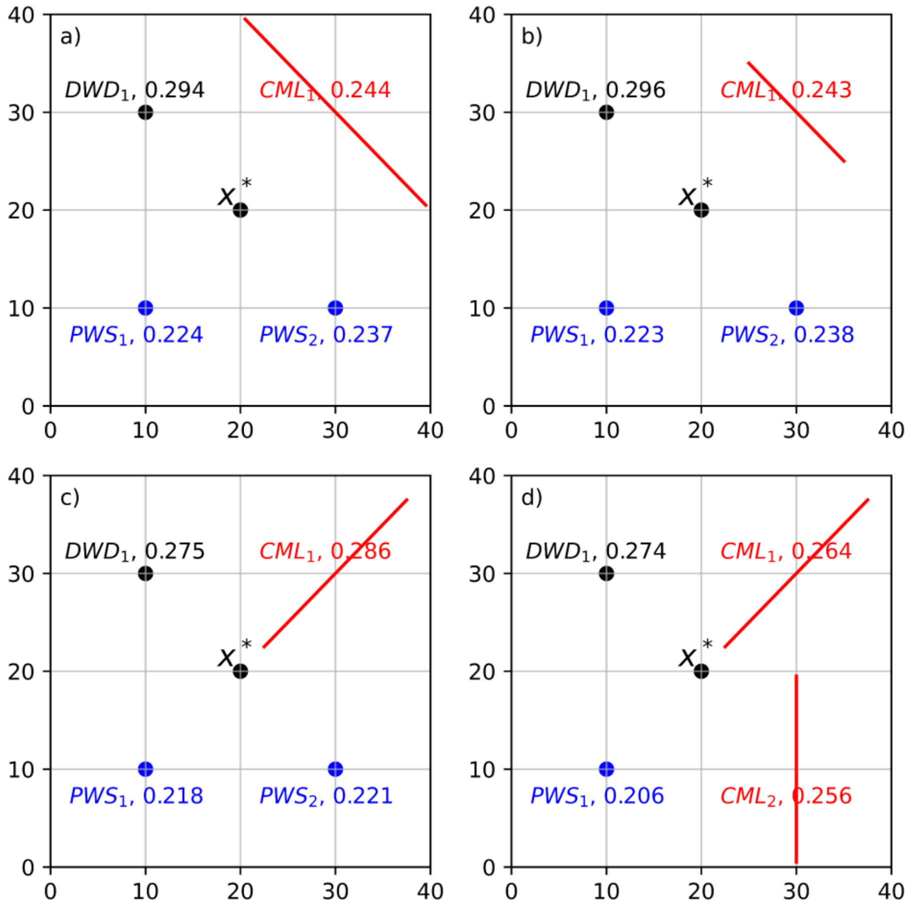
Interpolation Framework

- Replacing each line segment (CML) with its central point as a reference.
- Add Block-Kriging to consider for geometric properties

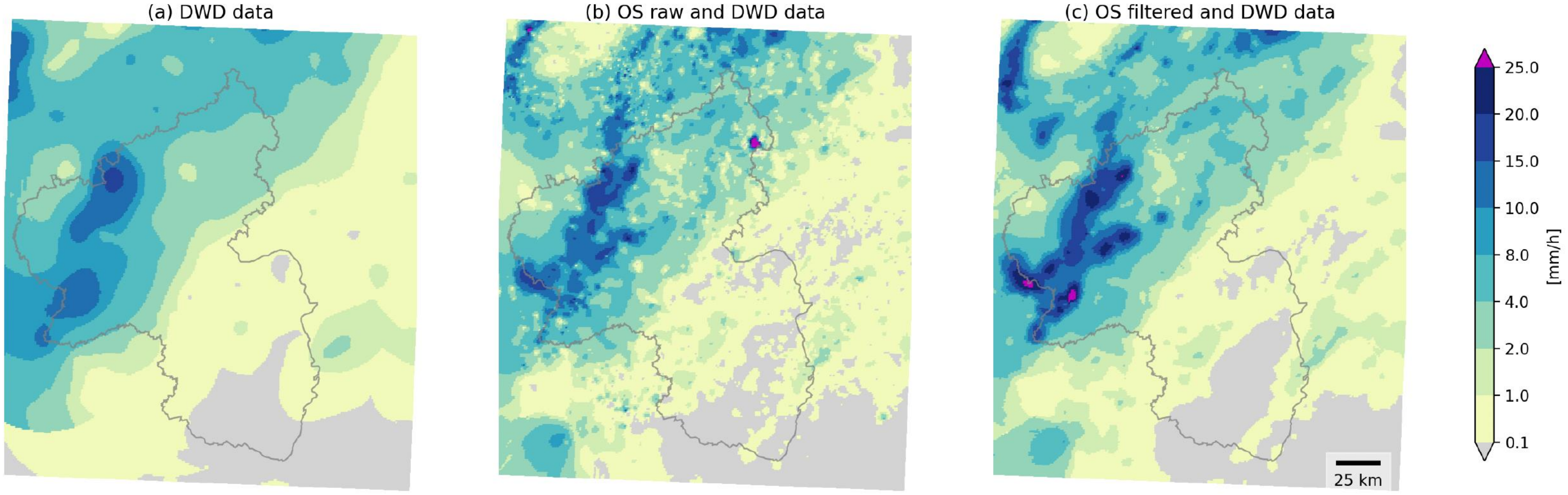


Interpolation Framework

- Replacing each line segment (CML) with its central point as a reference.
- Add Block-Kriging to consider for geometric properties
- Account for varying data uncertainties by adding an error component to the diagonal of the kriging matrix

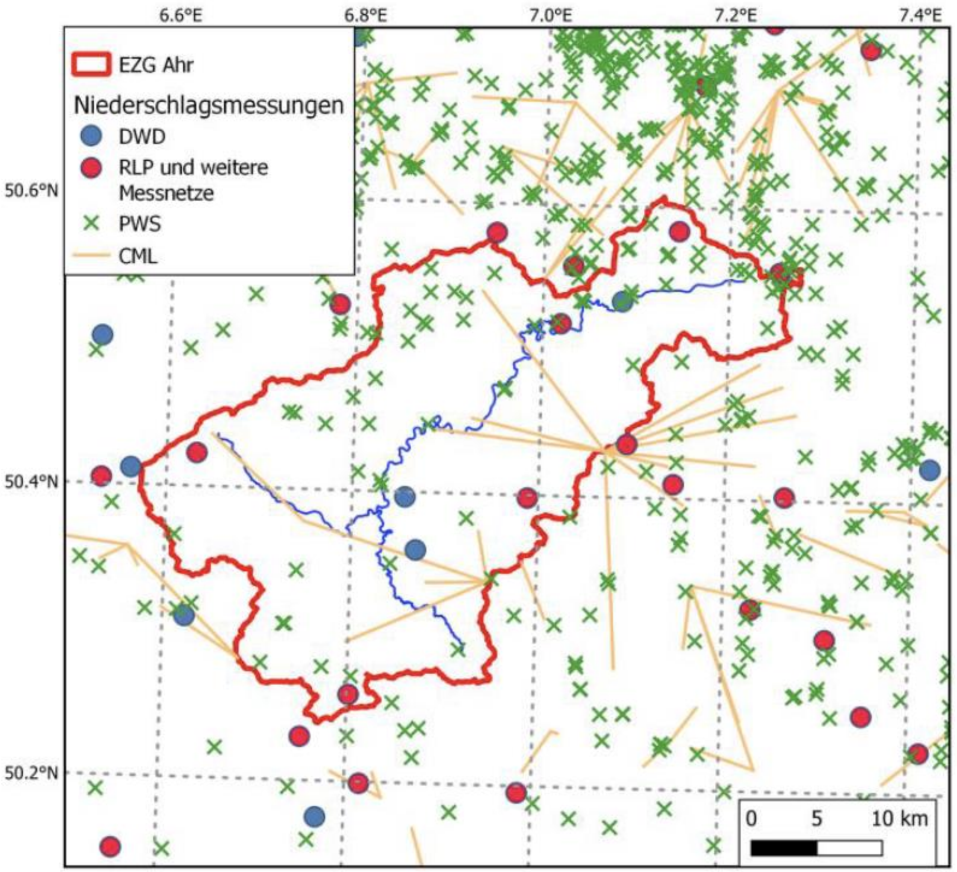


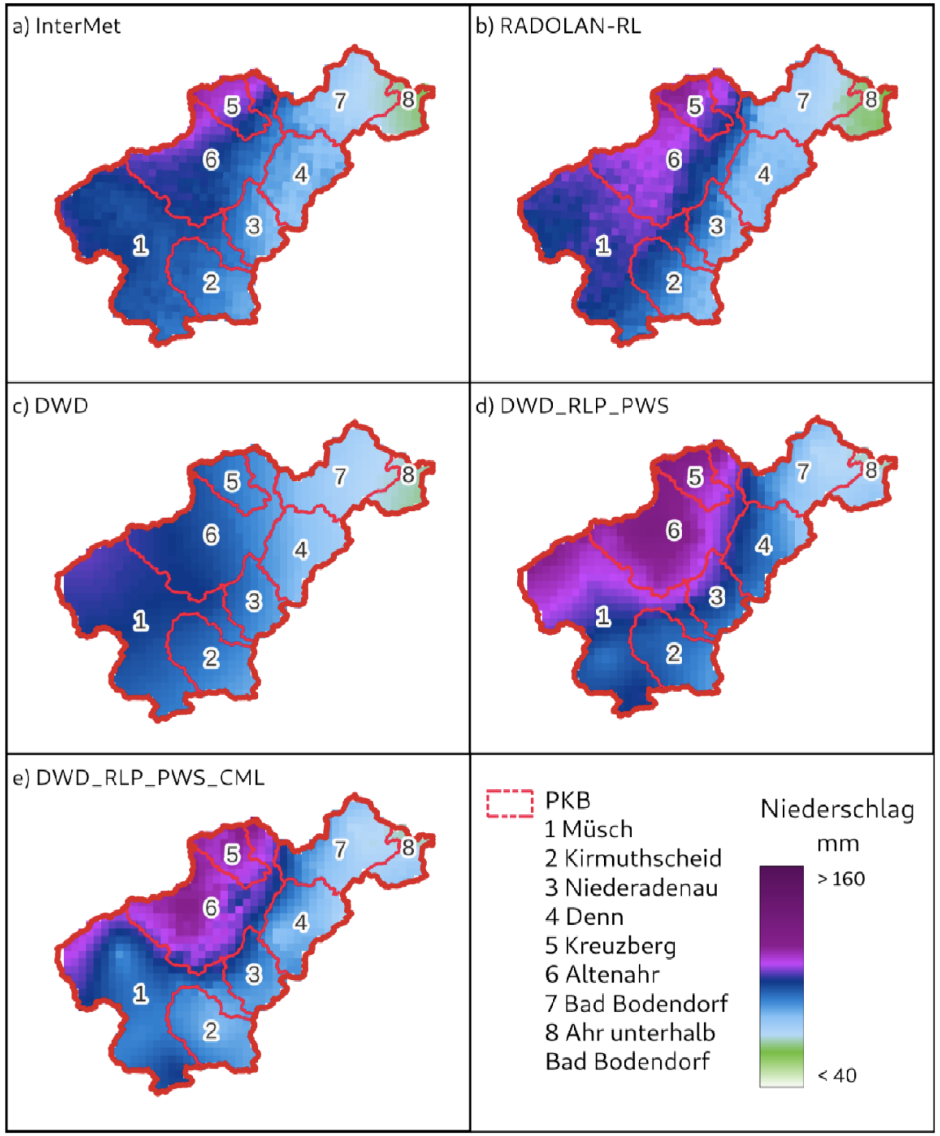
Results



1 hour of interpolated rainfall fields for Rhineland-Palatinate

14. July 2021 - Ahrtal





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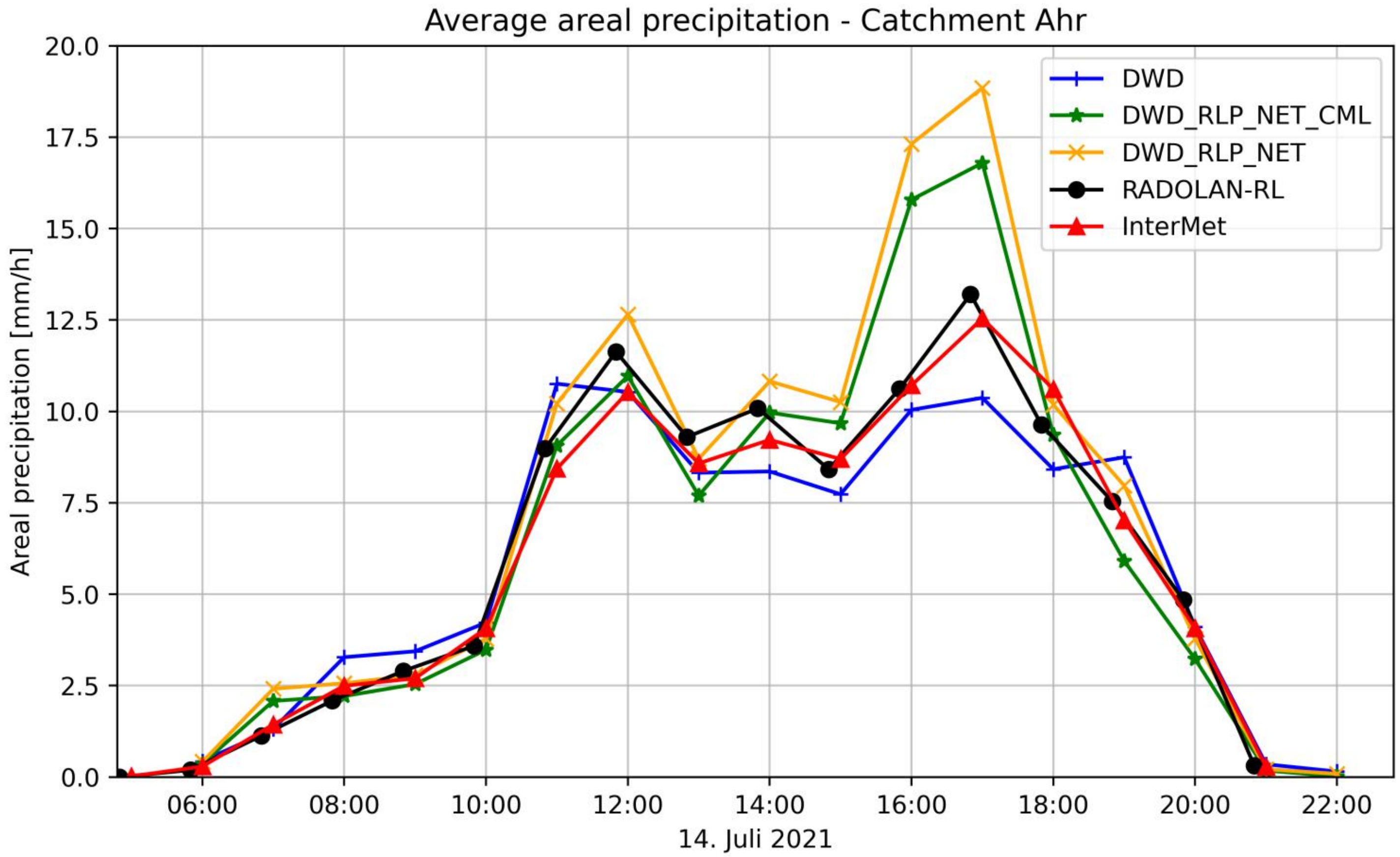


Opportunistic sensors can deliver valuable rainfall information

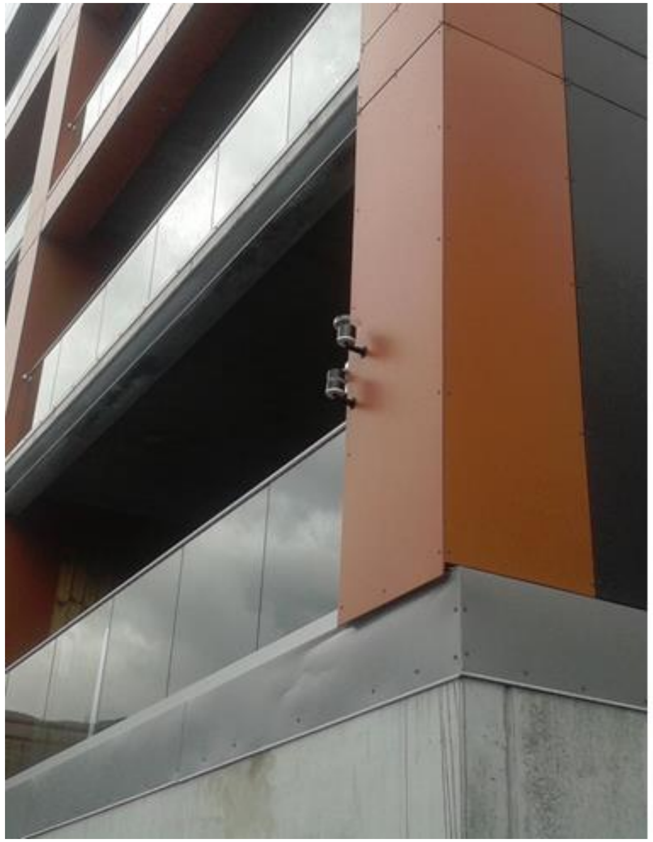
Thank You!

Opportunistic sensors - Definition

- **Opportunistic sensors**, are sensors that were not designed to provide high-quality rainfall data or any rainfall data at all.
- **Commercial microwave links** (CMLs) are part of the mobile communication infrastructure and their attenuation data can be used for rainfall estimation.
- A **personal weather station (PWS)** is a set of **weather** measuring instruments that you can install at your own home or business. Most PWS include instruments to measure **temperature**, **relative humidity**, **pressure**, **rain fall**, and **wind**.

Personal Weather Stations (PWS) - Data

- Installation conditions of PWS are unknown (-> mostly not according WMO standards)

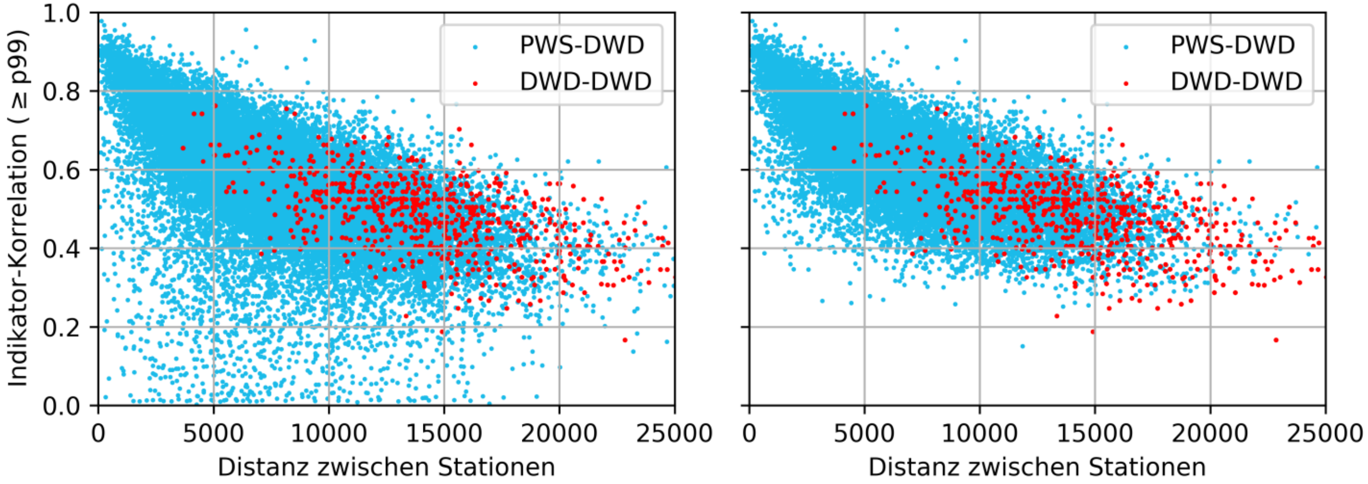


Personal Weather Stations (PWS) - Filter

1. Indicator Correlation Based Filter (IBF)

$$I_{\alpha,\Delta t,Z}\left(x,t\right) = \begin{cases} 1 & \text{if } F_{x,\Delta t}(U_{\Delta t}(x,t)) > \alpha \\ 0 & \text{else} \end{cases}$$

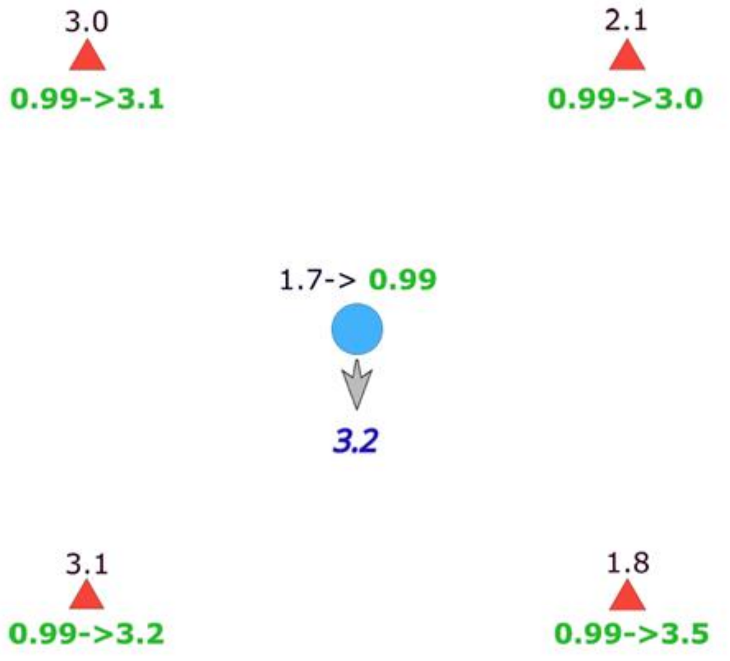
- Indicator Correlation decreases with increasing distance
- Identifies PWS that do not match the spatial pattern of the primary stations



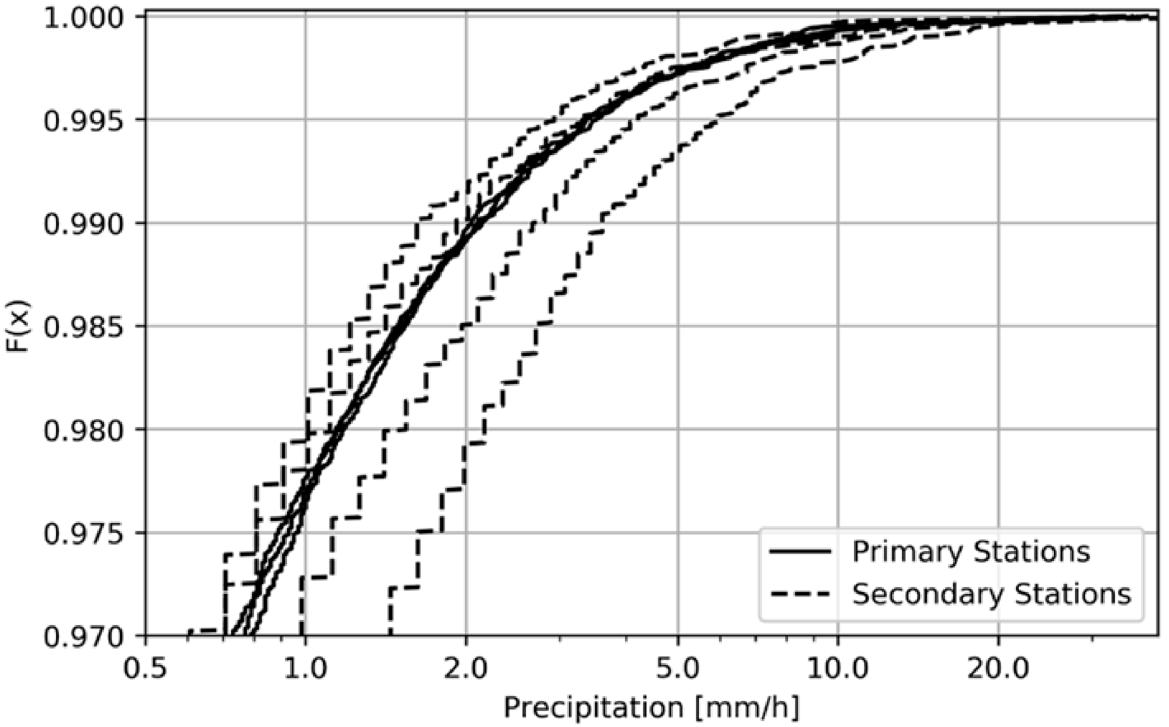
Personal Weather Stations (PWS) - Filter

2. Bias-Correction

Individually for each PWS since there are negative and positive biases



Bárdossy et al. (2021)

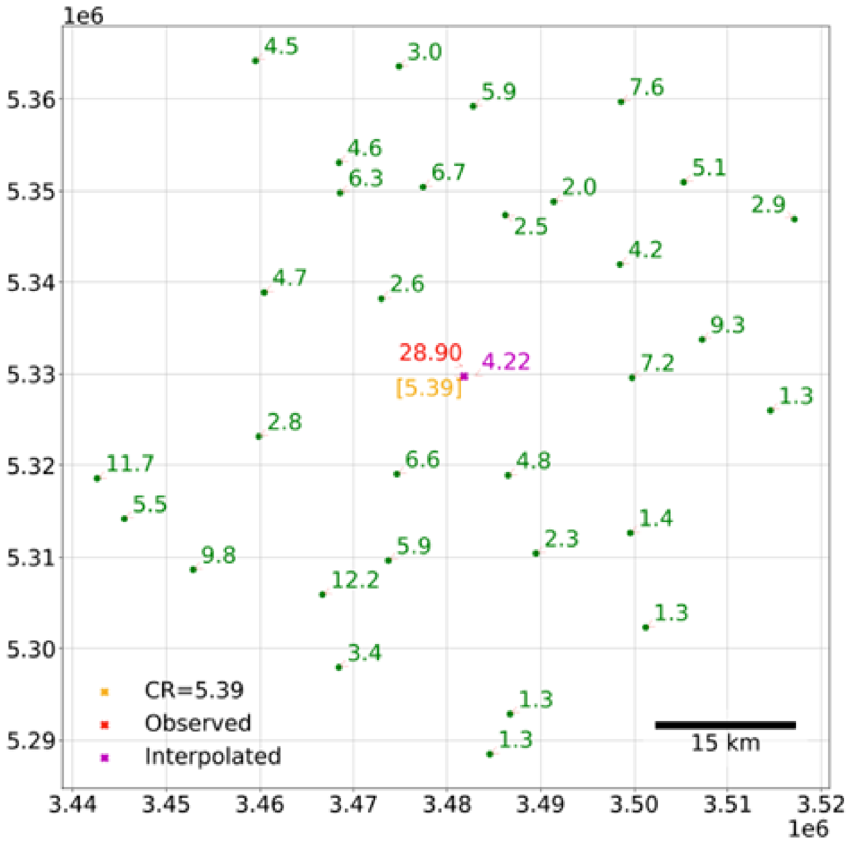


Personal Weather Stations (PWS) - Filter

3. Event-Based Filter (EBF)

Identifies PWS where the measured values do not match the spatial pattern of the event

$$\left|\frac{\boxed{Z^{*}_{\Delta t}(y_j,t)}-\boxed{Z^{o}_{\Delta t}(y_j,t)}}{\sigma_{\Delta t}(y_j,t)}\right|\boxed{>3}$$



More Information

Bárdossy, A., Seidel, J., & El Hachem, A. (2021). The use of personal weather station observations to improve precipitation estimation and interpolation. *Hydrology and Earth System Sciences*, *25*(2), 583–601. https://doi.org/10.5194/hess-25-583-2021

Ordinary Kriging - Theory

Estimation at given location x^*

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

Condition of unbiasedness

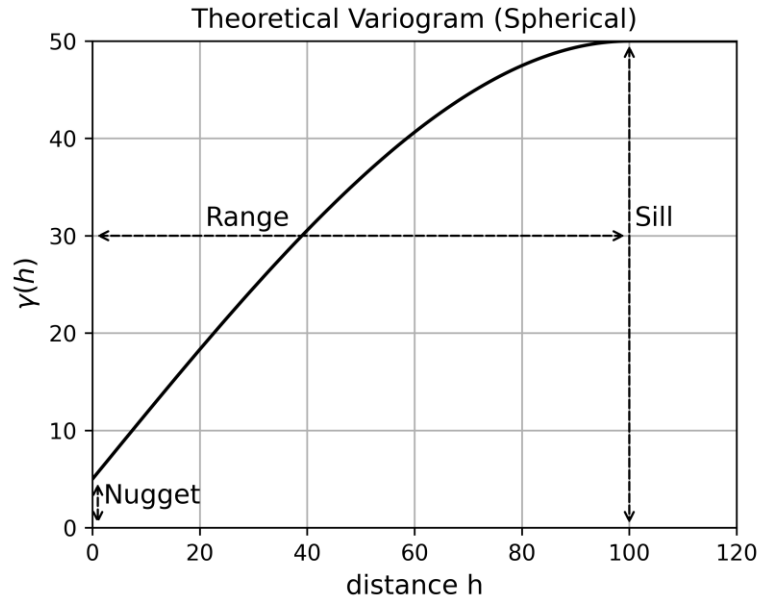
$$\sum_{i=1}^{n} \lambda_i = 1$$

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

$$Aw = c$$

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

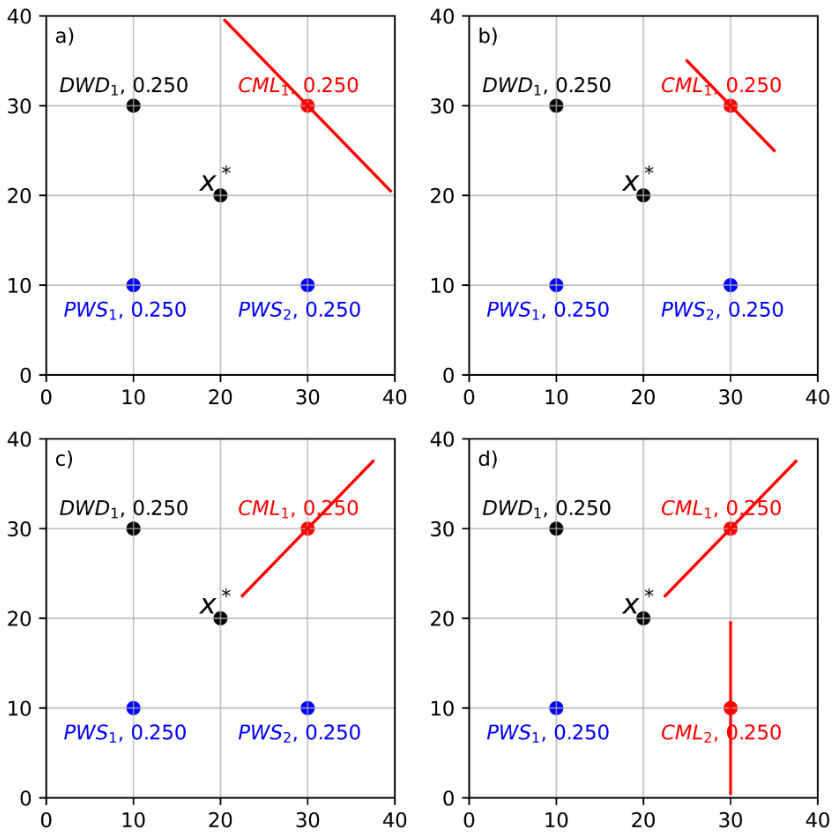
Variogram



For any pair of point, $\gamma\left(x_i, y_j\right)$ 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)

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

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

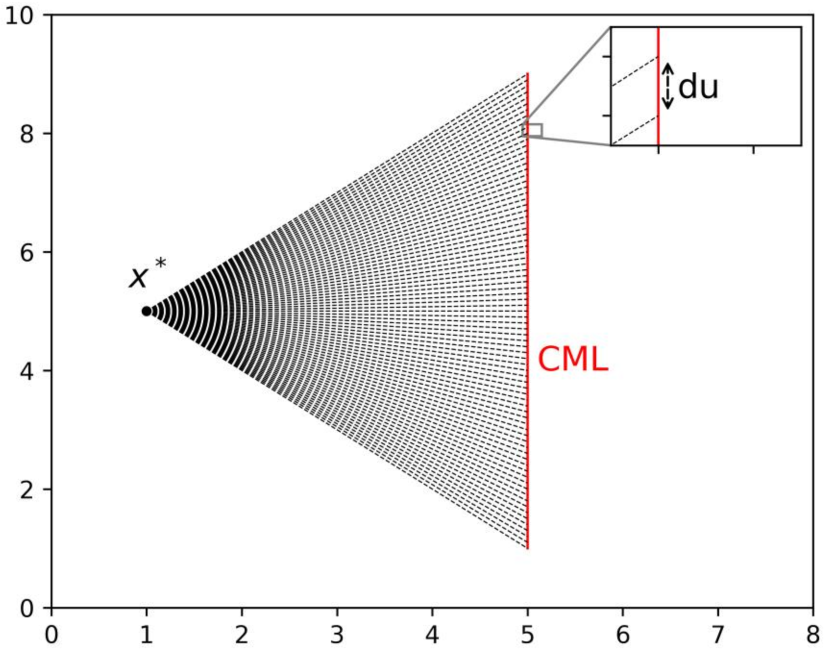
$$A = \begin{pmatrix} \gamma(DWD_1, DWD_1) & \gamma(DWD_1, PWS_1) & \gamma(DWD_1, PWS_2) & \gamma(DWD_1, CML_1) & 1 \\ \gamma(PWS_1, DWD_1) & \gamma(PWS_1, PWS_1) & \gamma(PWS_1, PWS_2) & \gamma(PWS_1, CML_1) & 1 \\ \gamma(PWS_2, DWD_1) & \gamma(PWS_2, PWS_1) & \gamma(PWS_2, PWS_2) & \gamma(PWS_2, CML_1)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

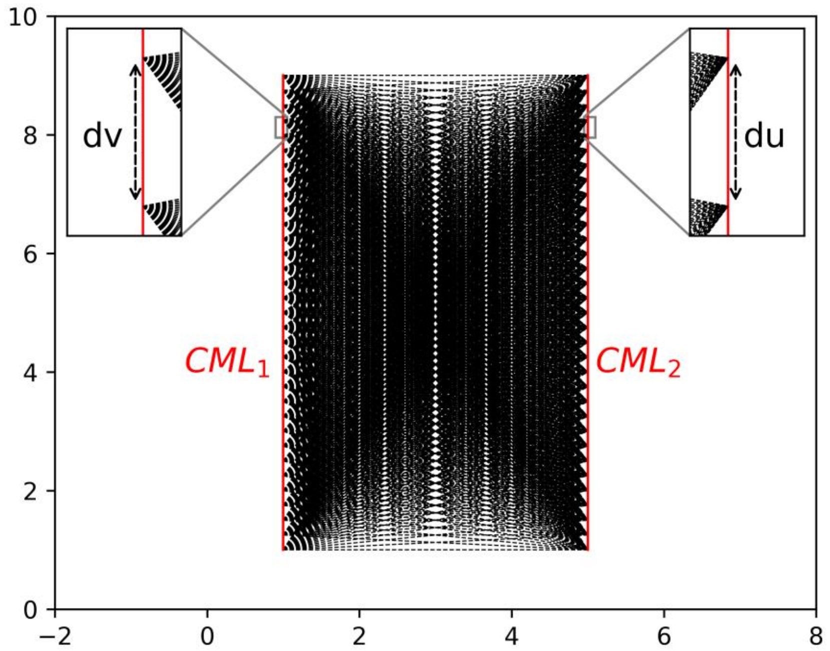
$$w^T = (\lambda_{DWD_1}, \alpha_{PWS_1}, \alpha_{PWS_2}, \beta_{CML_1}, \mu)$$

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

Different sensors - Different geometric properties

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



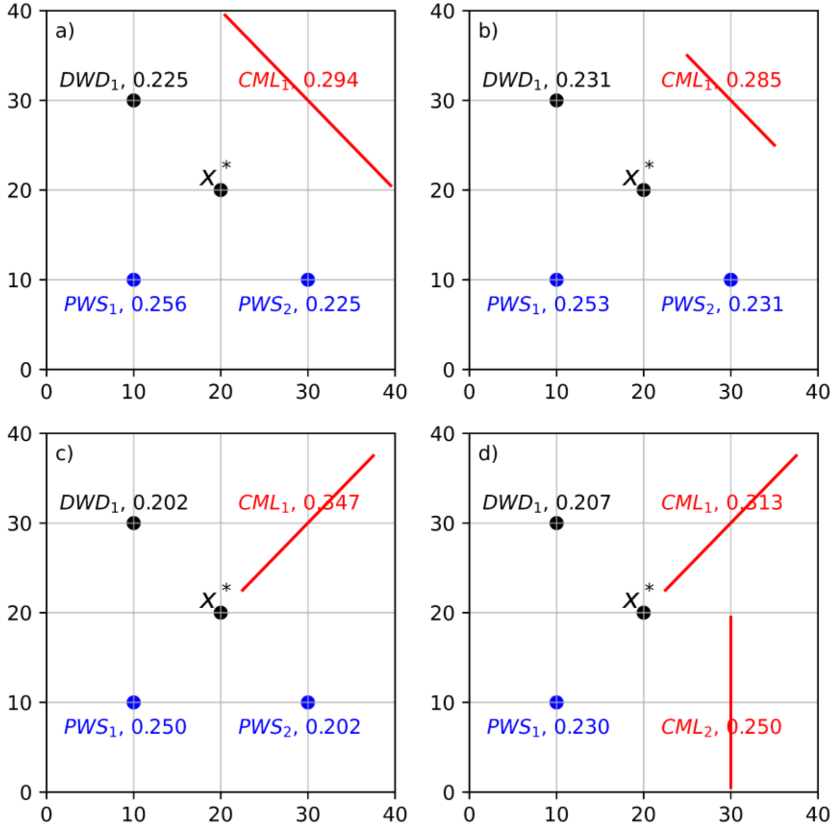


$$\bar{\gamma}(x^*, CML) = \frac{1}{|CML|}\int_{CML}\gamma(x^*, u)du$$

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

Example

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



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

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

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

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

Different sensors – Different uncertainties

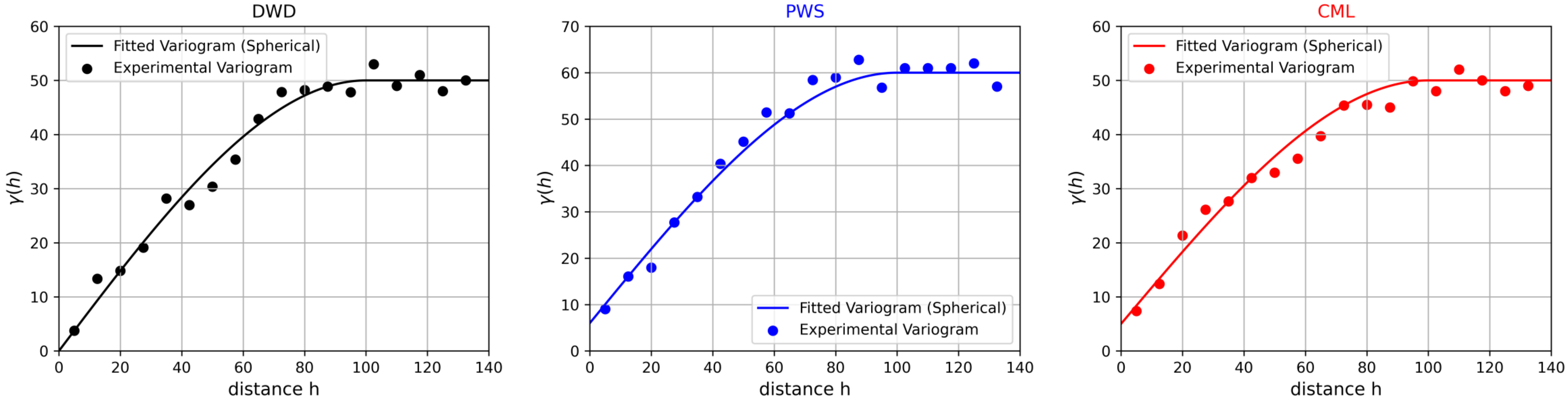
To account for different measurement uncertainties for PWS and CML, the values ε_{PWS} and ε_{CML} are added to the diagonal of the matrix.

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

Different sensors – Different uncertainties

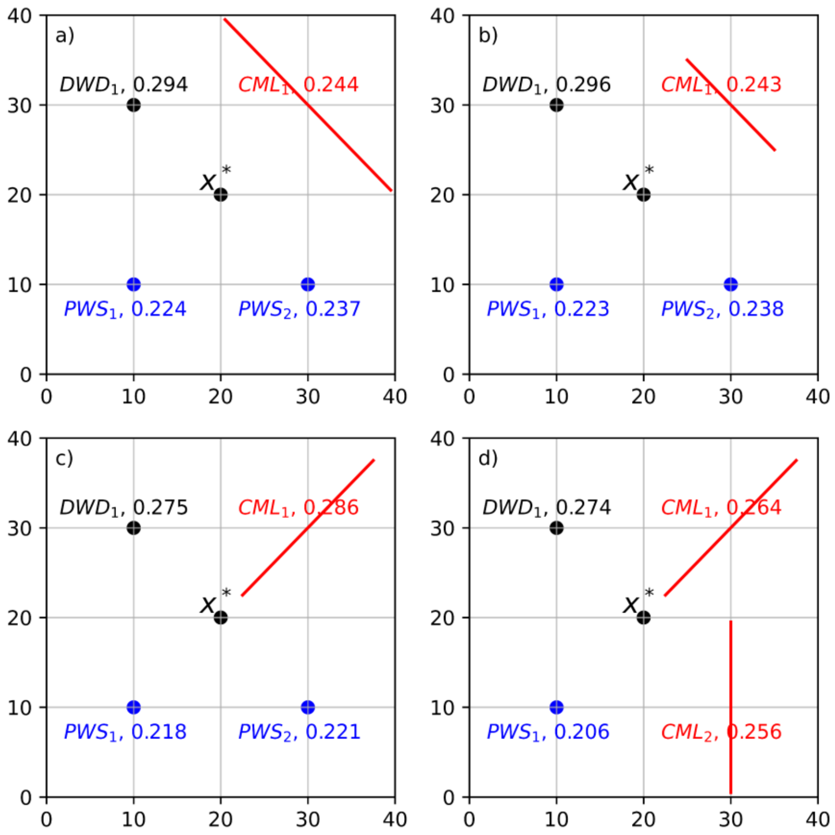
How to select ε_{PWS} and ε_{CML}.

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.



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More Information

Graf, M., El Hachem, A., Eisele, M., Seidel, J., Chwala, C., Kunstmann, H., & Bárdossy, A. (2021). Rainfall estimates from opportunistic sensors in Germany across spatio-temporal scales. *Journal of Hydrology: Regional Studies*, *37*, 100883. https://doi.org/10.1016/j.ejrh.2021.100883