

Geostatistical combination of radar and rain gauges – does data transformation improve uncertainty estimates?

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Motivation

- Enable applications of probabilistic spatial precipitation estimates, e.g. precipitation ensembles for hydrological modeling

Aims

- Apply Trans-Gaussian kriging for geostatistical radar-gauge combination in Switzerland
- Better satisfy theoretical assumptions of geostatistics
- Illustrate effect of data transformation on point estimate and uncertainty
- Evaluate and compare reliability of probabilistic precipitation estimate by different transformation levels

Data

- Operational hourly composite of 3 C-band radars (Germann et al., 2006) (Fig. 1), 1x1km resolution
- Quality checked hourly data of 75 automated gauges (Fig. 1), average inter-gauge distance 25 km

Methods

- Kriging with radar as external drift (KED) (e.g. Haberlandt, 2007)
- Isotropic exponential variogram REML (restricted maximum likelihood)
- Cross-validation
- Box-Cox transformation of radar and gauge values

$$Y^{\lambda} = \begin{cases} \frac{Y^{\lambda} - 1}{\lambda} & \lambda \neq 0 \\ \log(Y) & \lambda = 0 \end{cases}$$

- Comparison of different transformation strengths:
 - $\lambda = 1$ no transformation
 - $\lambda = 0.5$ square root transformation
 - $\lambda = 0.1$ close to log transformation
 - λ by MLE estimated for each hour
- MLE for λ : maximizing likelihood of linear radar-gauge relation with Gaussian errors, beta prior distribution, positive on [0.2, 1.5]

Example case, June 2008

Swiss Radar Composite 10.6.2008 18:00-19:00 UTC

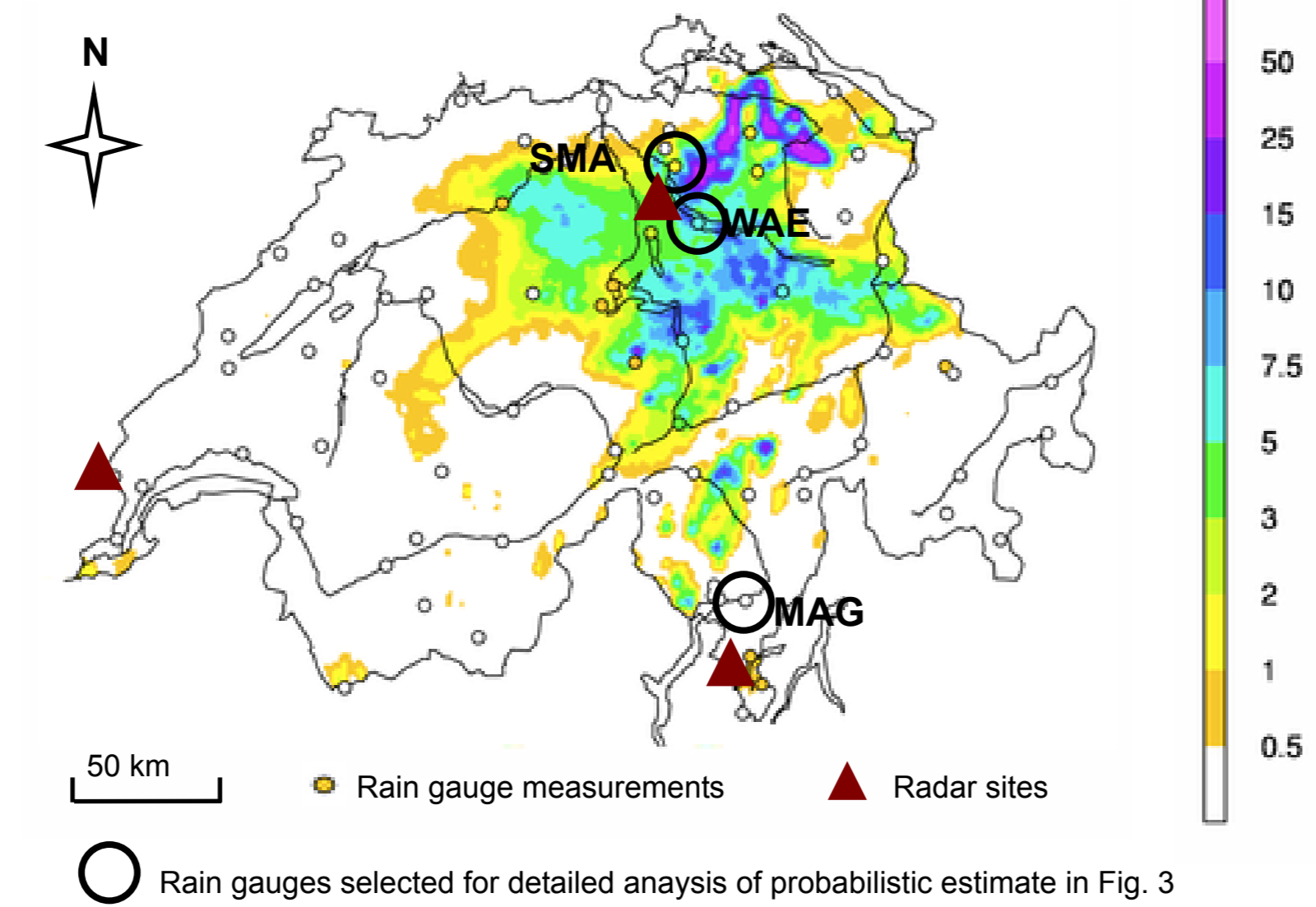
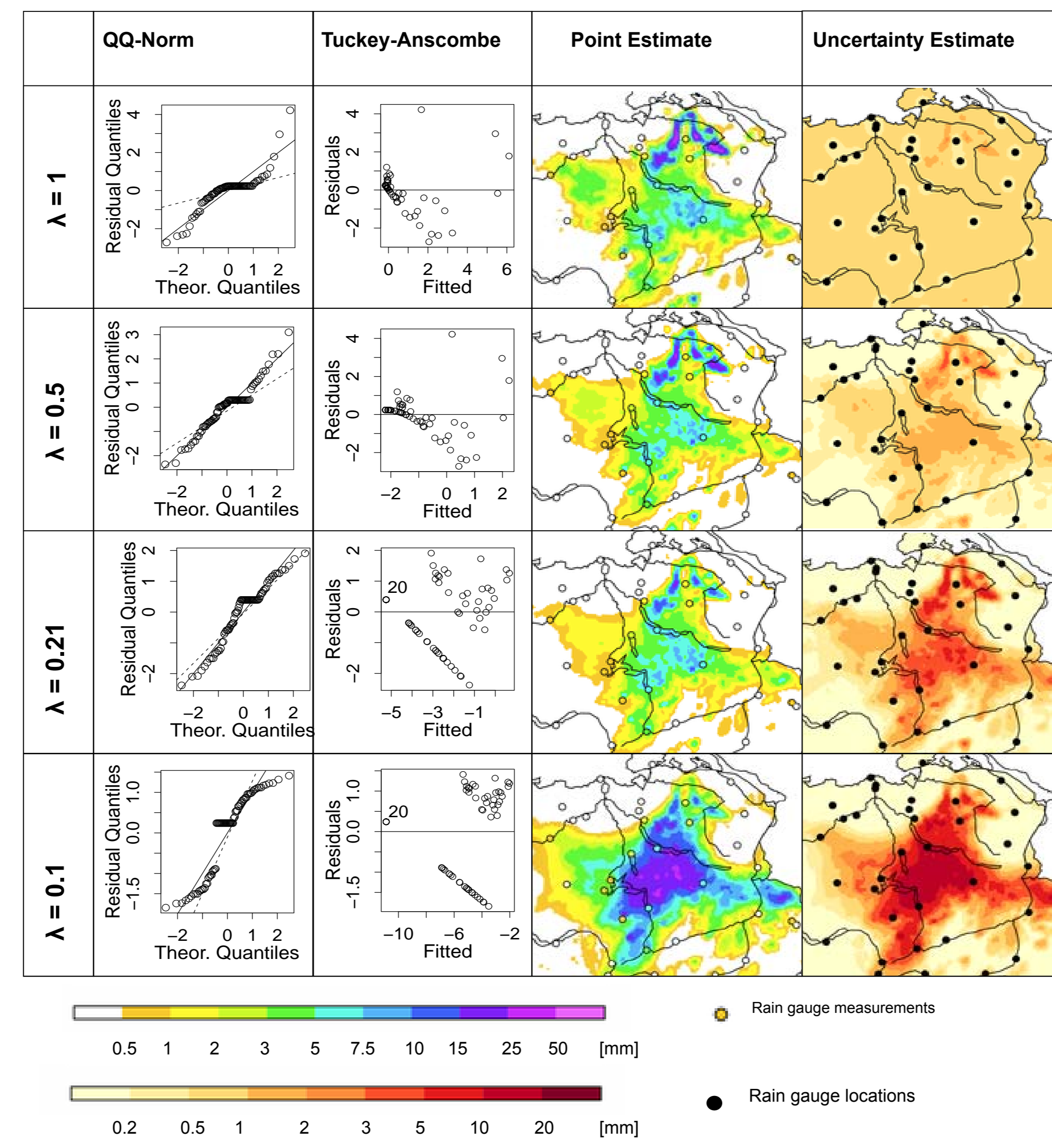


FIG. 1. Map of radar composite and rain gauge measurements showing hourly accumulated precipitation of example case.

Example case, June 2008



Probabilistic estimates at selected gauges

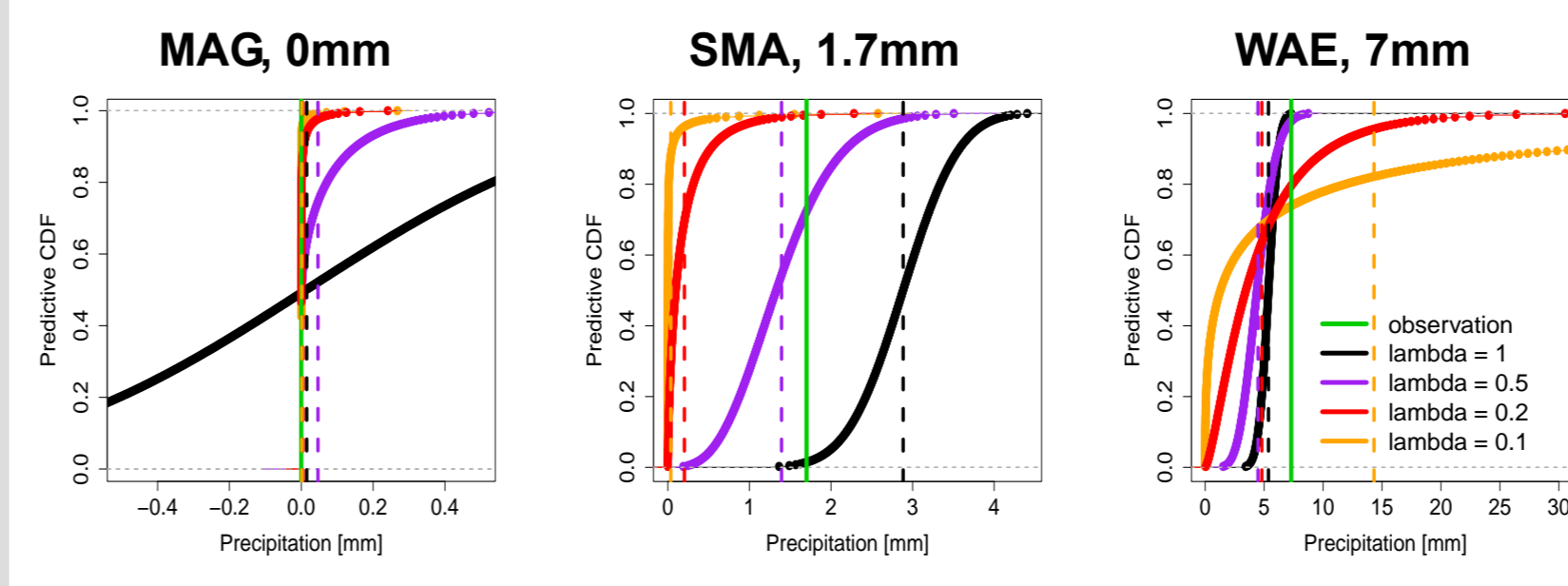


FIG. 3. Cross-validated cumulative probabilistic precipitation estimates by KED for 10.6.2008 18:00-19:00 UTC at selected gauge locations (circled in Fig. 1). Comparison of different transformation levels: no transformation ($\lambda=1$), square root transformation ($\lambda=0.5$), transformation with estimated λ by MLE ($\lambda=0.21$) and close to log transformation ($\lambda=0.1$). Dashed lines indicate point estimates, solid green line and amount in title show observed precipitation.

Results

Suitable Data Transformation (λ by MLE)

- Model assumptions better fulfilled (Fig. 2): heteroscedasticity eliminated, residuals closer to Gaussian distribution
- Precipitation estimate restricted to non-negative values (Fig. 3)
- Uncertainty estimate positively skewed and dependent on precipitation amount (Fig. 2 & Fig. 3)
- Better performance of probabilistic estimate in general (Fig. 4)
- Helps not to miss heavy precipitation (Fig. 4 & Fig. 5)

Exaggerated Data Transformation ($\lambda < 0.2$)

- Separates residuals (wet radar/dry gauge vs. others) (Fig. 2)
- Exaggerated upper quantiles → positive bias in point estimate (Fig. 2 & Fig. 3)

FIG. 2. Example case 10.6.2008 18:00-19:00 UTC. Rows compare different transformation levels for radar and rain gauge data. First two columns: plots to assess fulfillment of model assumptions: QQ-Norm plot of standardized residuals - standardized residuals vs. fitted values (Tuckey-Anscombe) Third column: map sections of point estimates and observed gauge measurements Last column: map sections of $0.5^{(Q_{0.84}-Q_{0.16})}$, a robust measure of uncertainty estimate, and station locations.

Systematic evaluation 2008

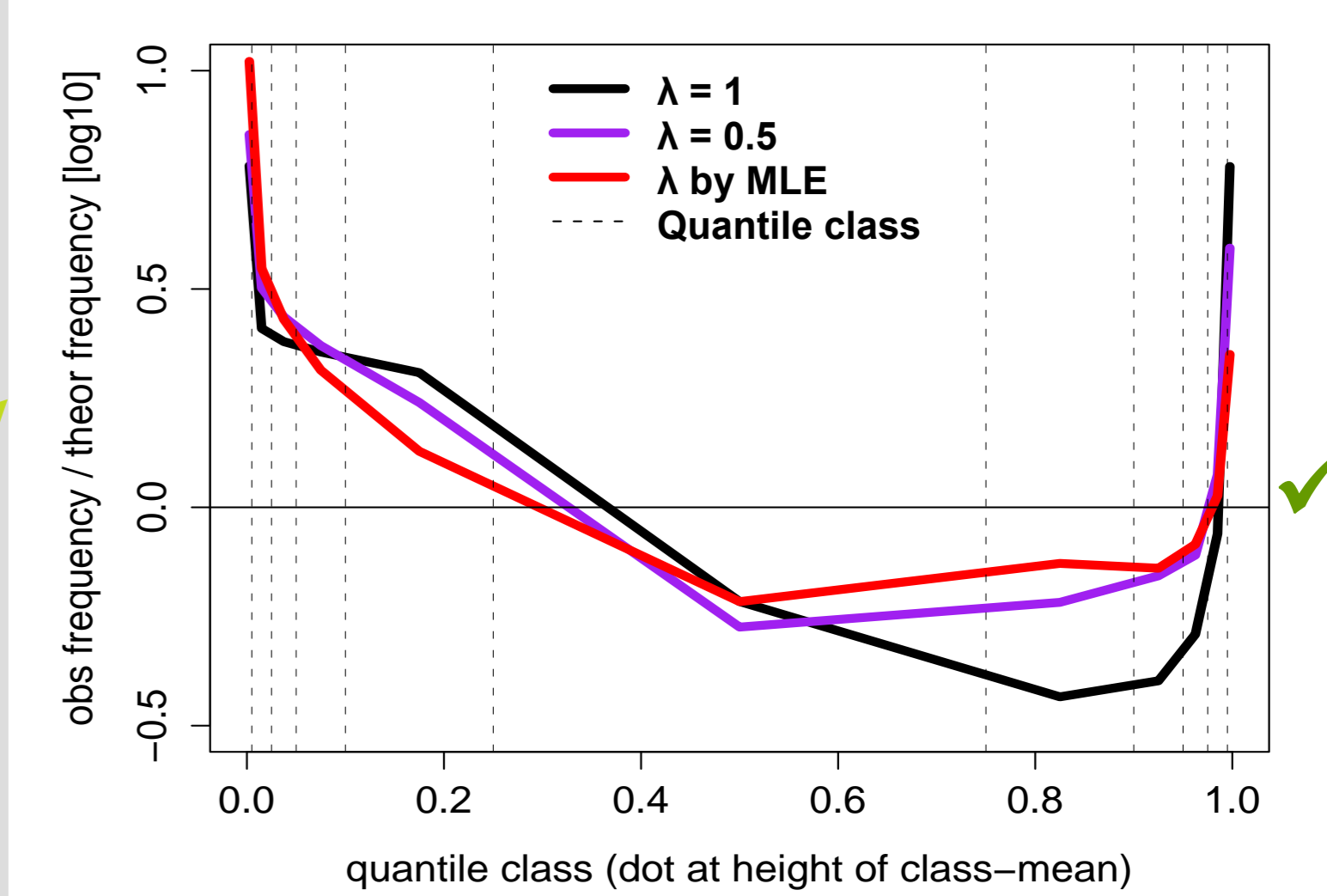


FIG. 4. Systematic evaluation of probabilistic estimate in 2008: 1438 hourly accumulations with minimum of 10 wet gauges (≥ 0.5 mm): $\log(\text{obs.freq}/\text{theor.freq})$ (zero for perfect estimate) in different quantile classes comparing probabilistic precipitation estimate of different transformation strengths.

Systematic evaluation 2008

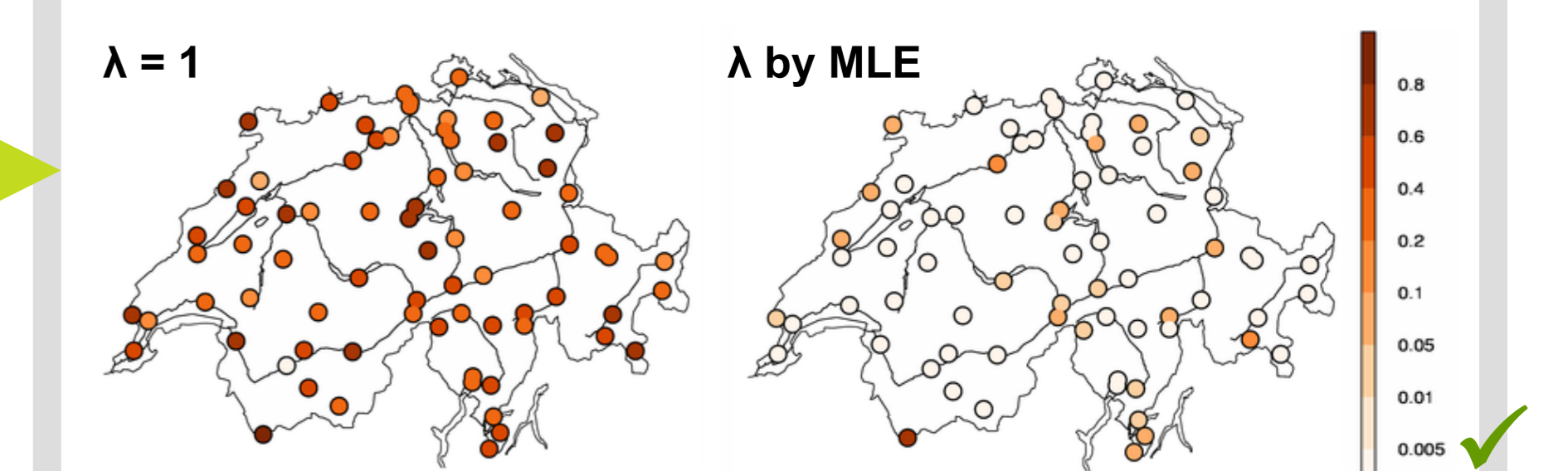


FIG. 5. Fraction of observed heavy precipitation (>5mm) considered as extremely unlikely ($P \leq 0.005$) by cross-validated probabilistic estimate, i.e. $Q_{0.995}$ below observed precipitation amount. Based on the 1672 observations >5mm in the systematic evaluation 2008 for $\lambda=1$ and λ by MLE.

Conclusions

- Box-Cox transformation can improve fulfillment of model assumptions and probabilistic precipitation estimate in geostatistical radar-gauge combination
- Uncertainty estimate becomes increasingly skewed and dependent on precipitation amount with increasing transformation strength
- Box-Cox transformation with suitable λ particularly helpful to improve the inclusion of heavy precipitation in the probabilistic estimate
- Finding a λ that suits the data is crucial → several criteria could be optimized: homoscedasticity, Gaussian distribution, radar-gauge relation → too small values of λ (<0.2) can introduce bias to point estimates → should be avoided

References

- Germann, U., G. Galli, M. Boscazzi, and M. Bolliger, 2006: Radar precipitation measurement in a mountainous region. *Q. J. R. Meteorol. Soc.*, **132**, 1669–1692.
Haberlandt, U., 2007: Geostatistical interpolation of hourly precipitation from rain gauges and radar for a large-scale extreme rainfall event. *Journal of Hydrology*, **332**, 144–157.