

Propagation of precipitation uncertainties in distributed water balance assessments of a data sparse semi arid environment

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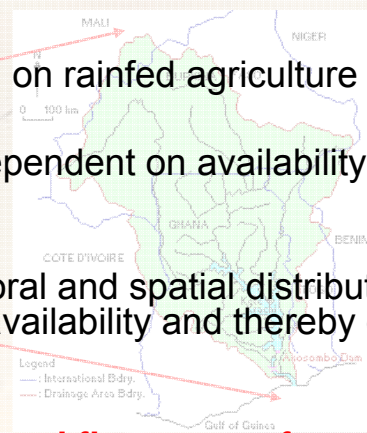
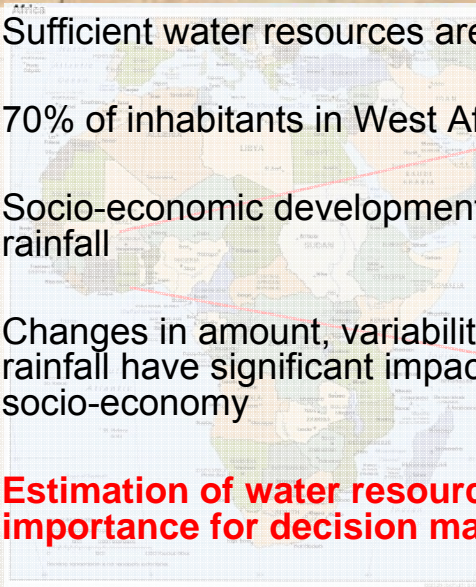
- 1) Karlsruhe Institute of Technology
2) Stuttgart University

Motivation

- Scientifically sound **decisions in sustainable water management**: usually based on hydrological modelling
⇒ can only be accomplished with **meteorological information**.
- Particularly in developing countries where **observation networks are coarse**, spatial interpolation is afflicted with **uncertainties**.
- Spatial variability of **rainfall**: often **major source of uncertainty** for water balance estimations

Challenge West Africa

- Sufficient water resources are life-blood of West African economies
- 70% of inhabitants in West Africa depend on rainfed agriculture
- Socio-economic development strongly dependent on availability of rainfall
- Changes in amount, variability and temporal and spatial distribution of rainfall have significant impact on water availability and thereby on socio-economy
- **Estimation of water resources, stocks and flows, are of crucial importance for decision making**



Volta Basin

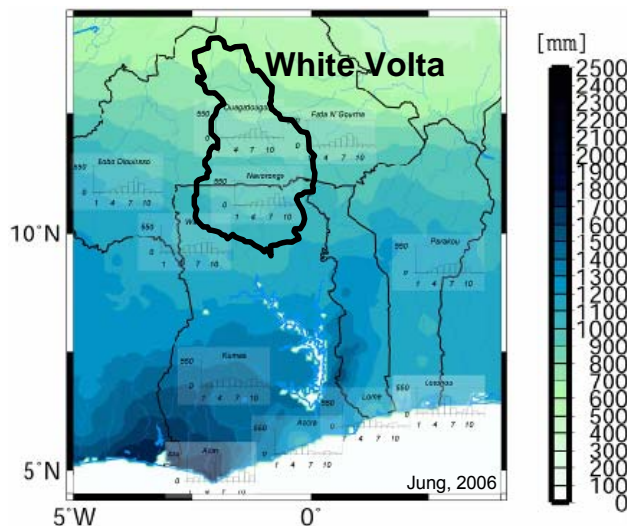
Challenge West Africa



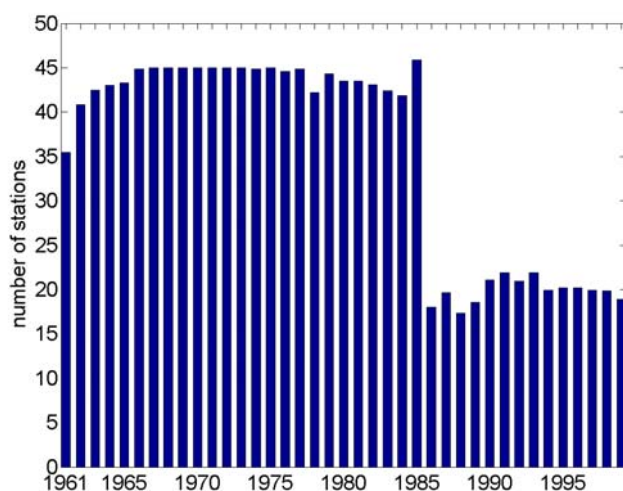
Scientifically sound information
under weak infrastructure

Area of Investigation: White Volta/West Africa

- 94000 km², upstream of Lake Volta
- Flat topography
- Semiarid climate: rainy season May - October
dry season November – April



Data Sparse Environment White Volta



Precipitation:

- 1 station/6,000km² 1961-84
- 1 station/15,000km² 1985-2001

Wind, humidity, pressure

- ≈ 1 station/30,000km²

Discharge:

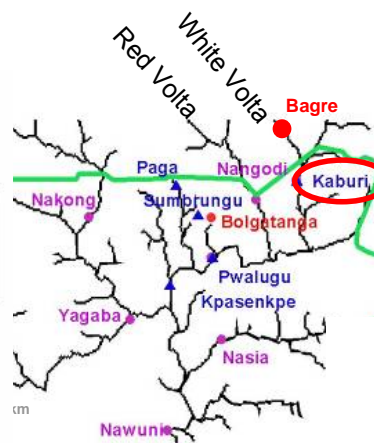
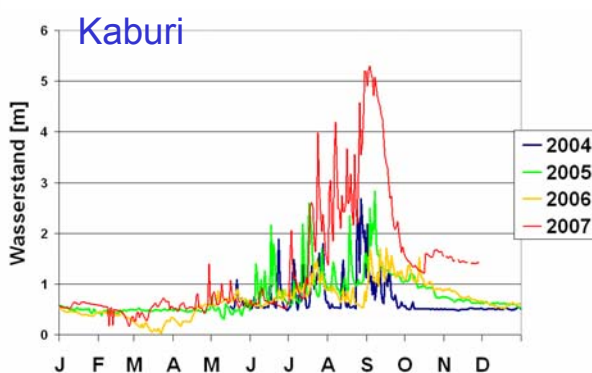
- Only available in Ghana

Development of methods for distributed, model based water balance estimations in data sparse environment

- Application of near real time atmospheric models to provide meteorological fields for hydrological modeling
- Integration of remote sensing data for land surface properties in hydrological models
- **Impact of uncertainties arising from precipitation interpolation on water balance estimates**

Measurement Campaign: Start in May 2004

Hydrometeorological Network



Hydrological Model WaSiM: Concept

Physically based algorithms for vertical water fluxes & groundwater:

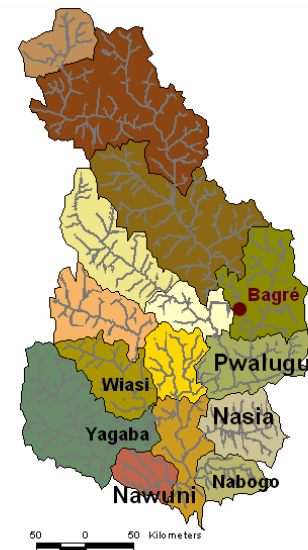
- Evapotranspiration: soil and vegetation specific (Monteith)
- Flow through unsaturated zone (Richards)
- Suction head & hydraulic conductivity (van Genuchten)
- 2-dim groundwater model dynamically coupled to unsaturated zone

Conceptual approaches for lateral runoff aggregation

- Traveltime approach folded with linear storage
- Discharge routing: cinematic wave

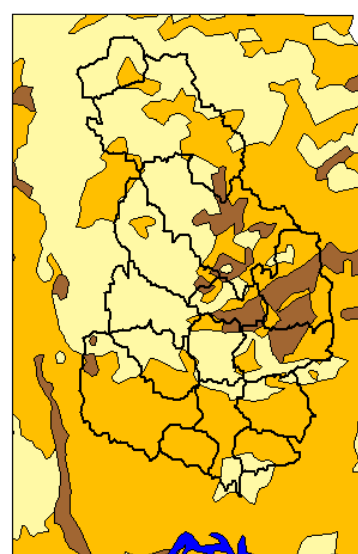
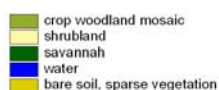
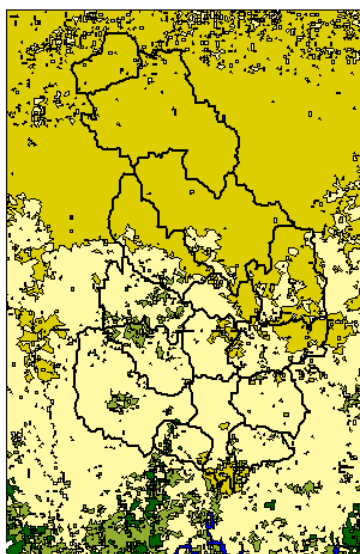
Setup White Volta

- Spatial resolution Δx : 1x1km²
- Temporal resolution Δt : 24h
- Subdivision into 15 sub-catchments



Hydrological Model WaSiM: Setup

Example: Spatial land use and soil information



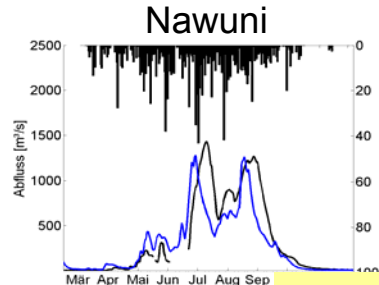
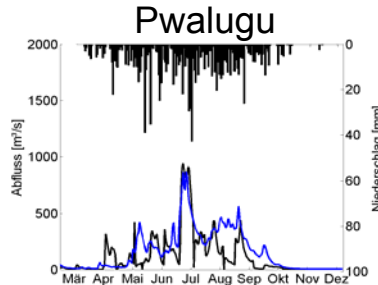
Calibration/Validation

Historical data: 1968 & 1961-1967

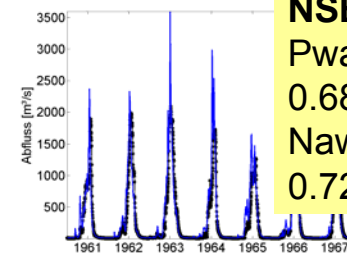
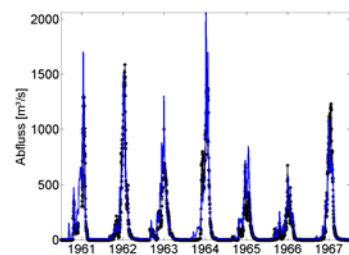
- Data availability: meteorology & runoff for BF & GH
- Small anthropogenic impacts



Calibration:
1968



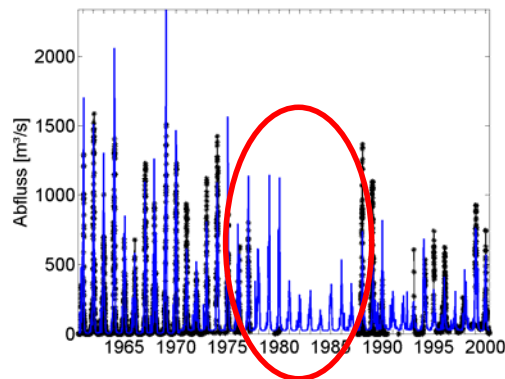
Validation:
1961-1967



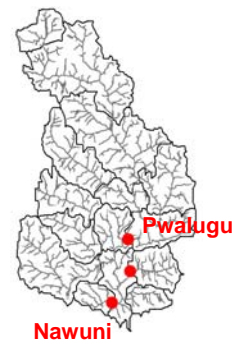
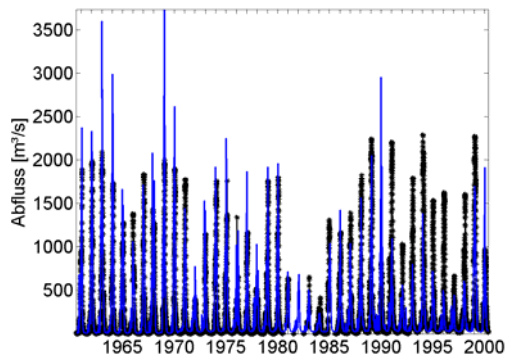
NSE (log):
Pwalugu: 0.47;
0.68
Nawuni:
0.72; 0.81

Long Term Simulations

Pwalugu:



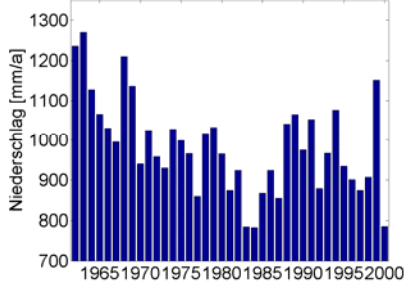
Nawuni:



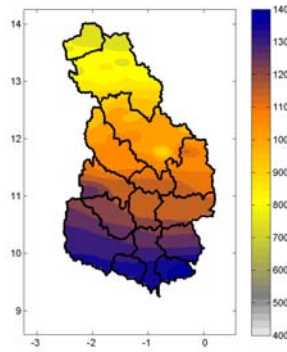
NSE (log):
Pwalugu: 0.55
Nawuni: 0.70

Long Term Simulations

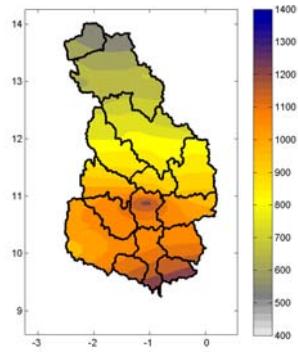
Annual Precipitation [mm]



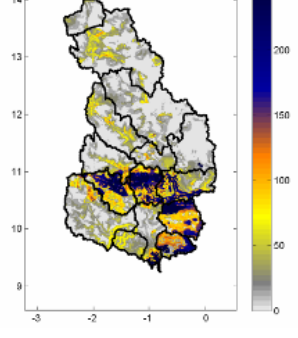
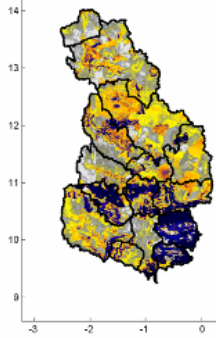
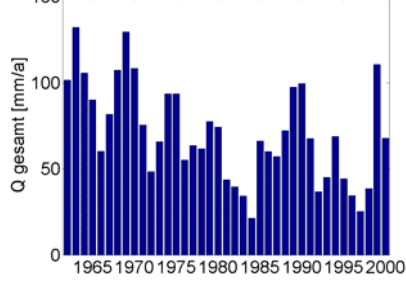
1961-1970



1981-1990



Annual Runoff [mm]



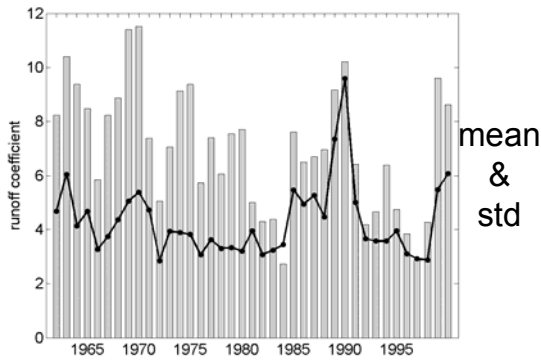
Long Term Simulations

Runoff coefficient:

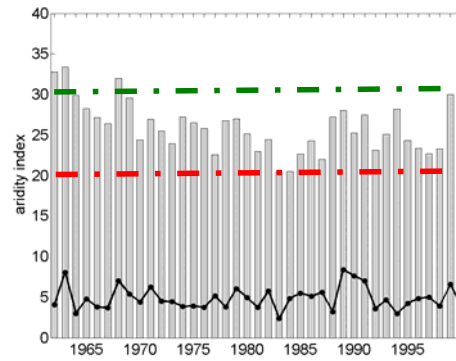
$$RC = 100 * \frac{Q}{P}$$

Aridity index (de Martone):

$$dMI = \frac{P}{T + 10}$$



Overall: RC = 7% (2.7% – 11.5%)

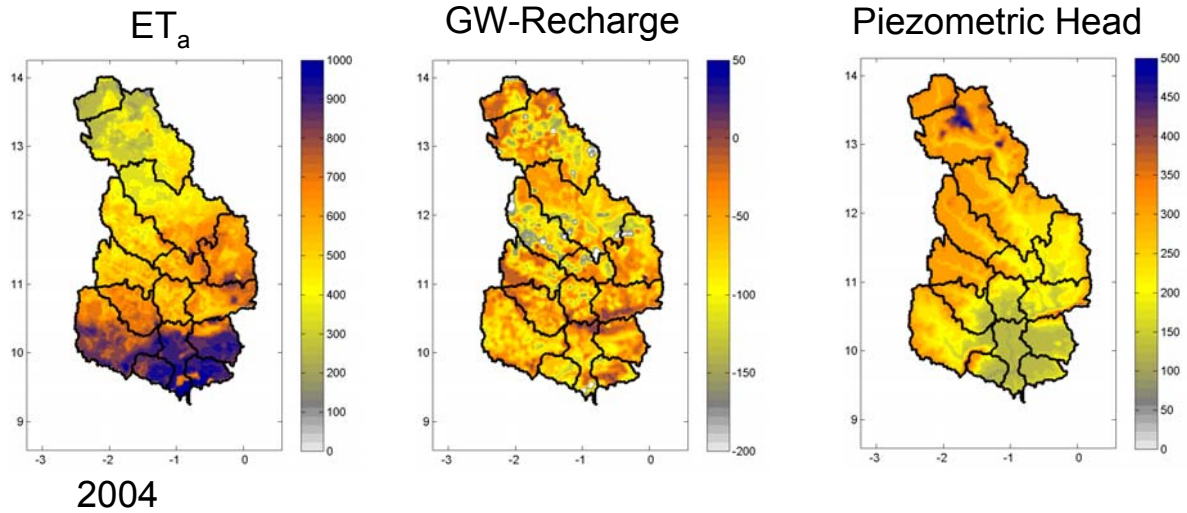


--- 20-30: Irrigation often required

--- < 20: Necessity of irrigation

Hydrometeorological Decision Support – Current Simulations

... through estimates on
temporal and spatial distribution of **current** water balance variables



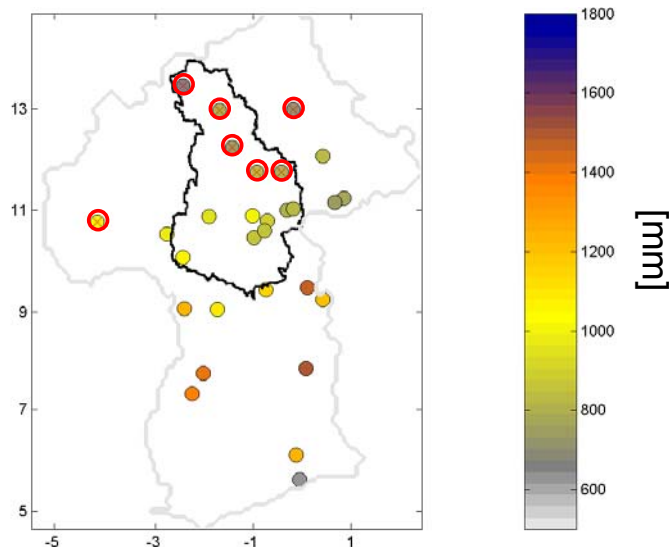
Data Sparse Environment White Volta

Decision Support: Problem of temporal delay till station data are available

2004-2007

No data for
Burkinabé
part of
catchments

⇒ Application
of scaled
TRMM*
information at
Burkinabé
station
locations

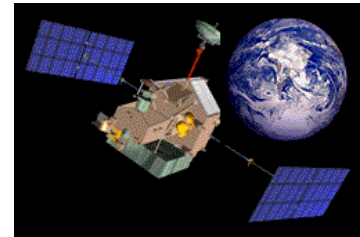


* Tropical rainfall mission product 3B42, $\Delta t=3h$, $\Delta x=0.25^\circ$

TRMM (1 Month Delay)

Tropical Rainfall Measuring Mission

- Sub-, tropical precipitation
- MW and VIR sensors plus precipitation radar
- Mission of NASA and JAXA
- Start 1997, Orbit 400 km



3B-42 Product: TRMM Merged HQ/Infrared Precipitation

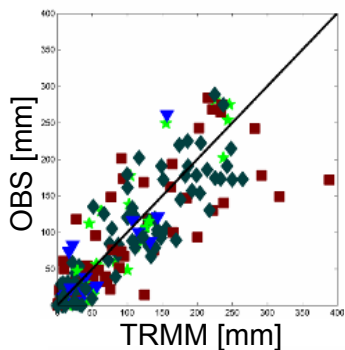
1. Combination of MW and VIR Daten
2. Scaled with observed monthly precipitation (3B-43:GPCC)

0.25°x 0.25°, 3-h, 50°S to 50°N

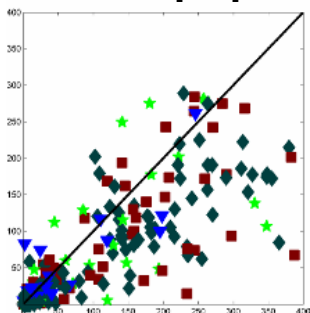
Validation TRMM - 2004

Validation with observations in Ghana

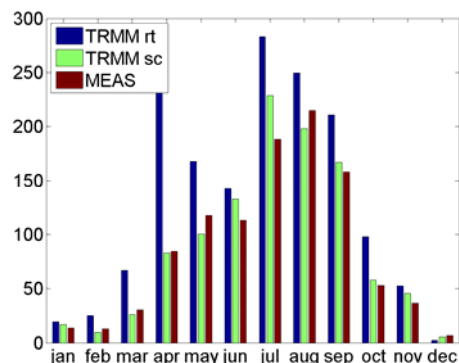
TRMM
scaled:



TRMM
unscaled:

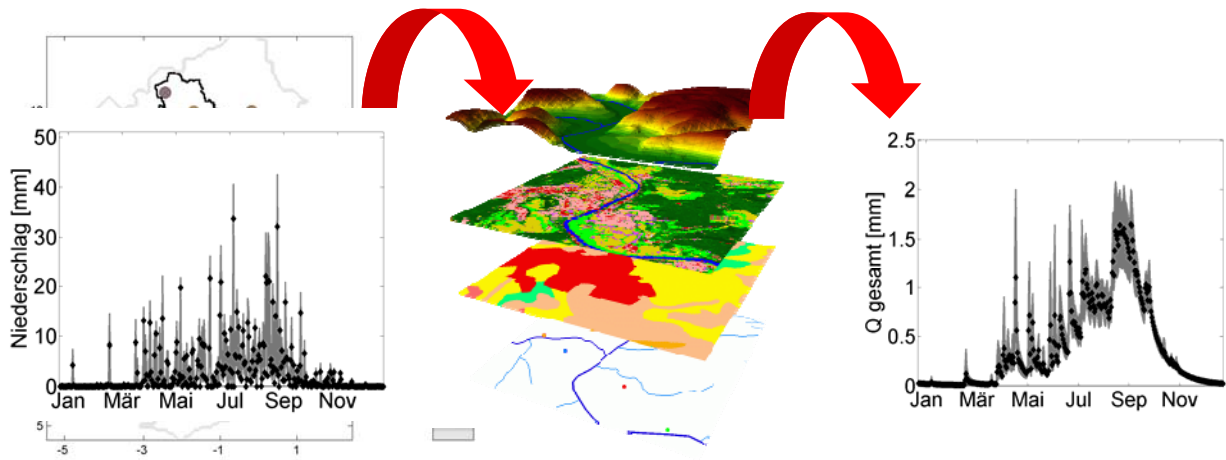


Annual cycle:



Legend: stations along coast,
between latitude 7.5 & 8, 8.5 & 9.5, 10.0 & 11.5

Central Question: Impact of Uncertainties from Precipitation Interpolation on Simulated Water Balances

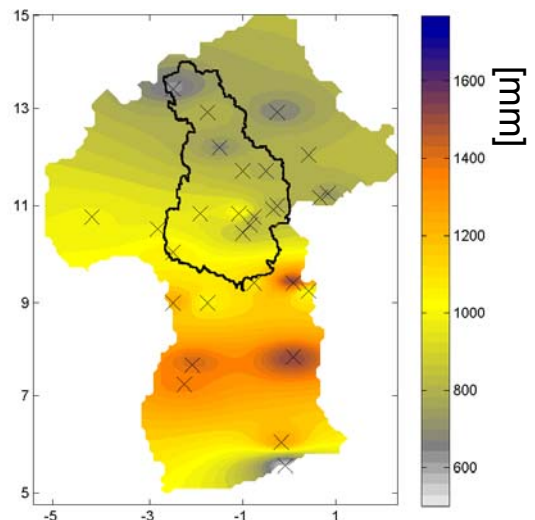
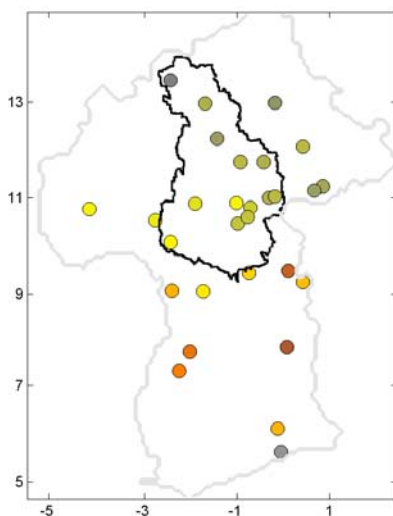


Geostatistical Interpolation Methods

General: Point Information



Spatial Information



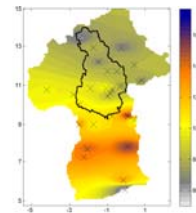
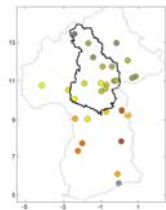
IDW

Geostatistical Interpolation Methods

General: Point Information



Spatial Information



Methodologies

Spatial Interpolations

- IDW, Kriging
- smoothing

⇒ one field

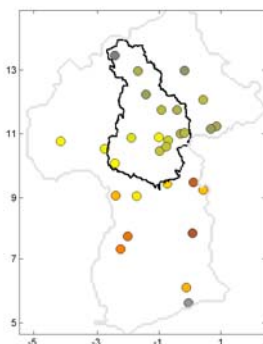
Simulations

- Turning Bands
- Conservation variability of obs.

⇒ many equally probable realisations

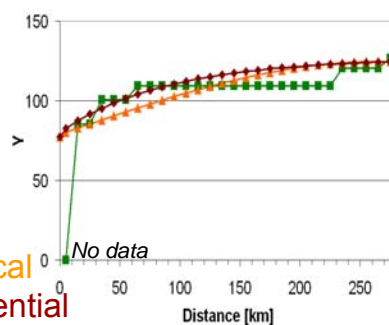
$$\text{Ex. Variogram: } \gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(u_i) - Z(u_i + h)]^2$$

Spatial Interpolation: IDW and Ordinary Kriging



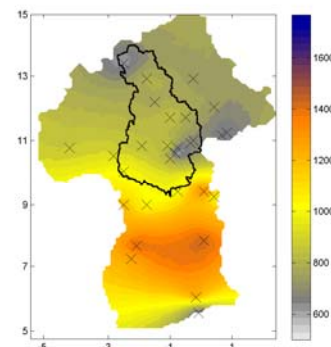
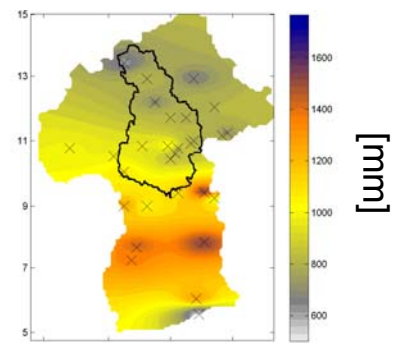
⇒ Inverse Distance weighting (IDW):

⇒ Ordinary Kriging (OK):



Variograms:

- experimental
- nugget & spherical
- nugget & exponential



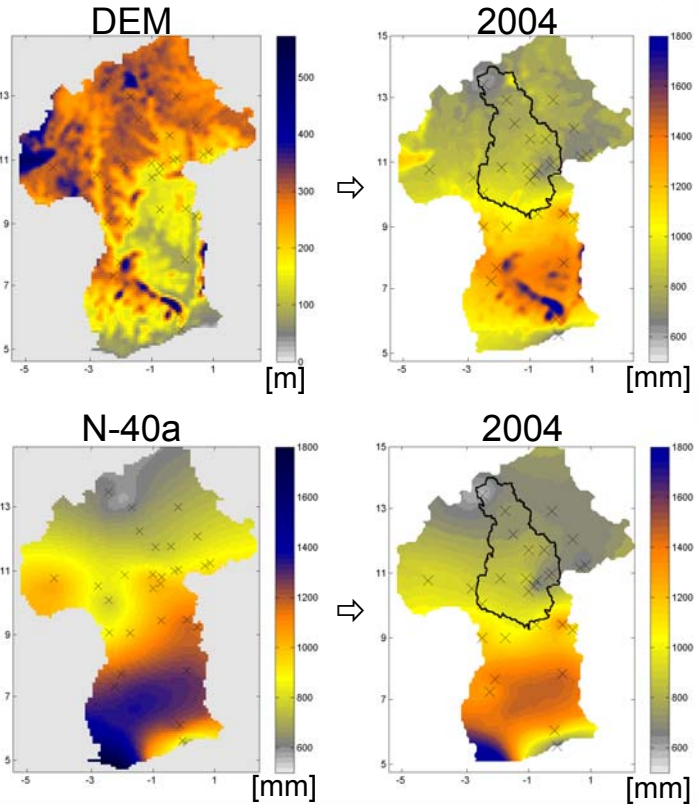
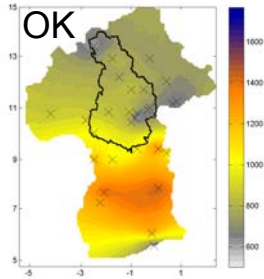
Spatial Interpolation: External Drift Kriging (EDK)

⇒ Suited additional information considered for interpolation

$$\sum_{j=1}^N \lambda_j \gamma(u_i - u_j) + \mu_0 + \mu_1 \cdot Y(u_j) = \gamma(u_i - u_0),$$

Applied External Drifts:

- Digital Elevation Model (DEM)
- Mean annual precipitation (40a)
- Latitudinal dependency
- LAI



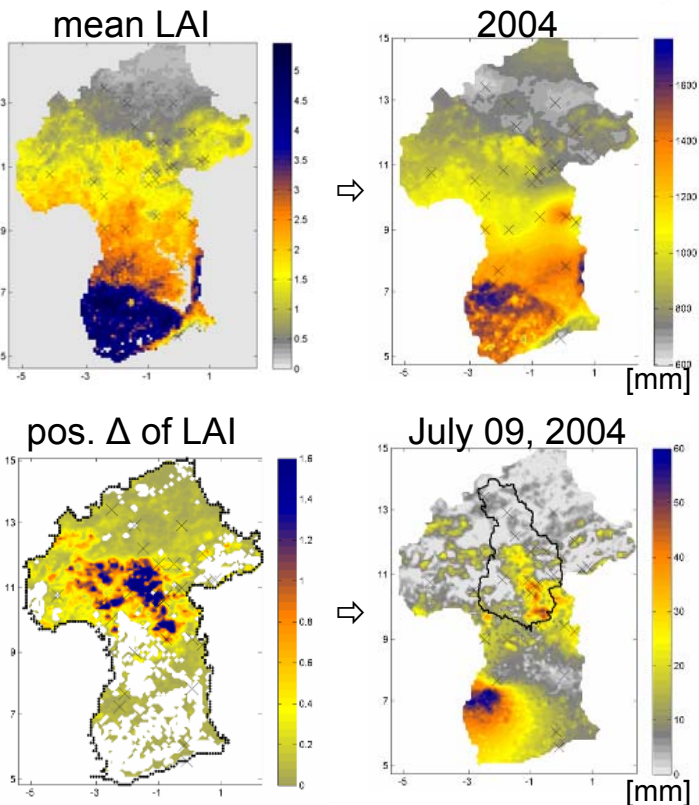
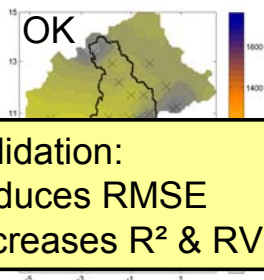
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Applied External Drifts:

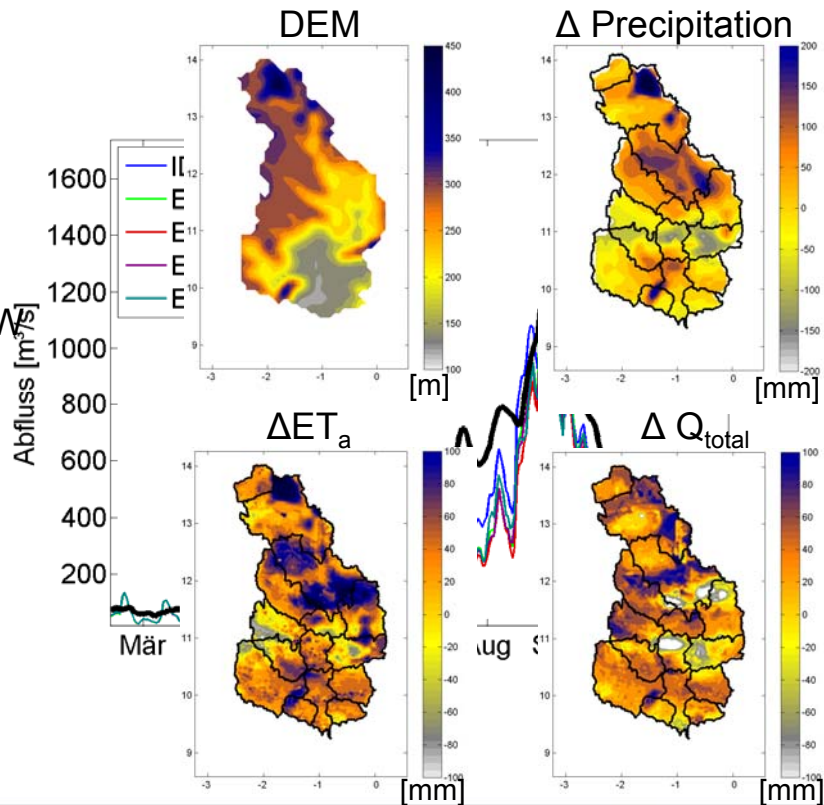
- LAI: MODIS, 8-day composites
 1. mean LAI
 2. positive change of LAI



Cross validation:
• EDK reduces RMSE
• EDK increases R² & RVar

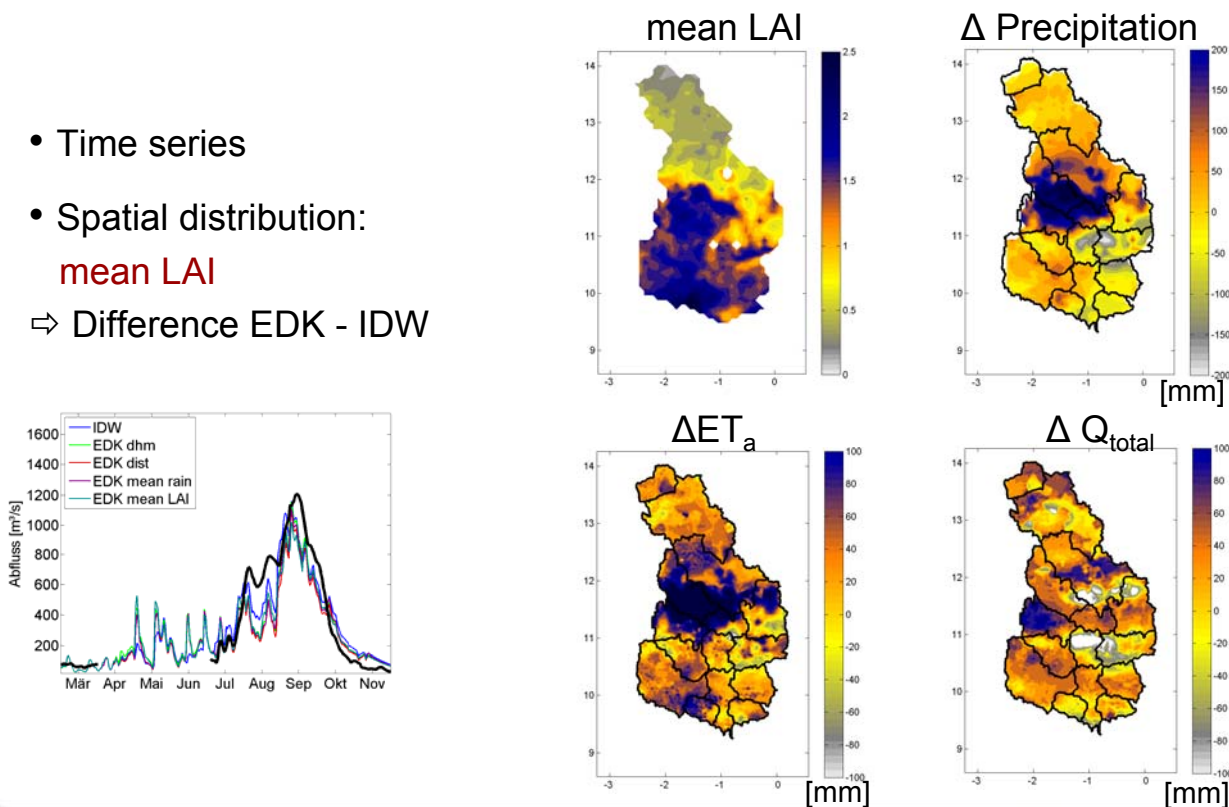
Impact Interpolation on Water Balance Estimates

- Time series
 - Spatial distribution:
DEM
- ⇒ Difference EDK - IDW

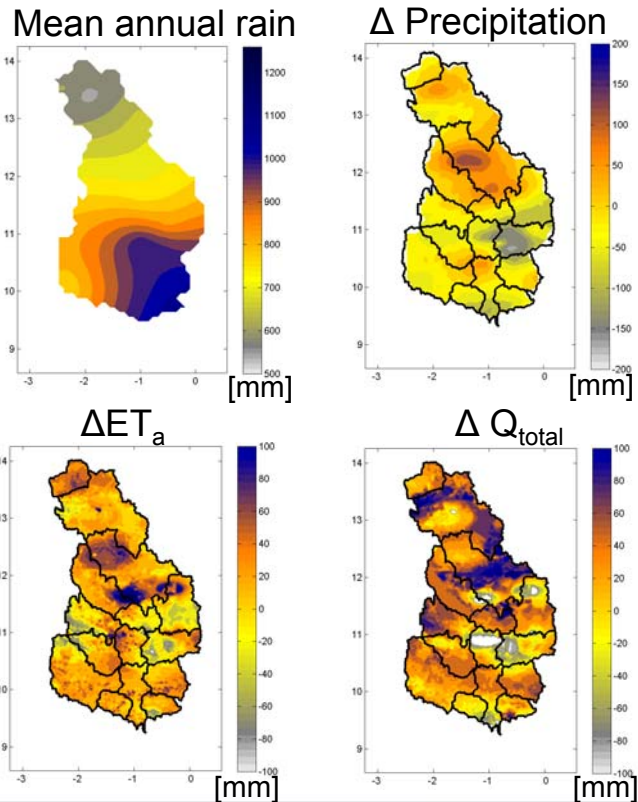
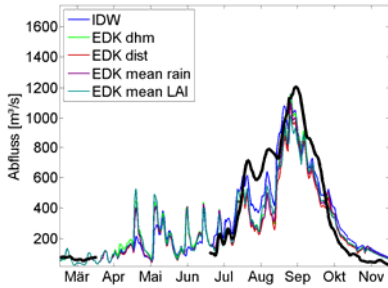


Impact Interpolation on Water Balance Estimates

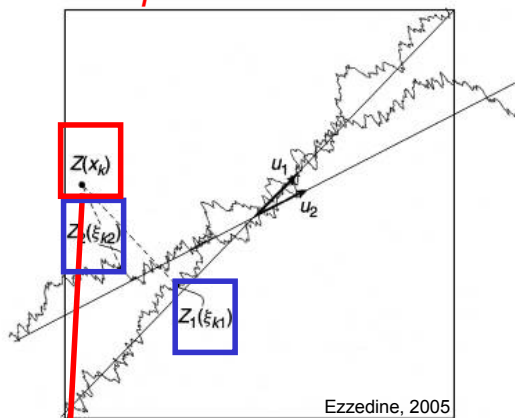
- Time series
 - Spatial distribution:
mean LAI
- ⇒ Difference EDK - IDW



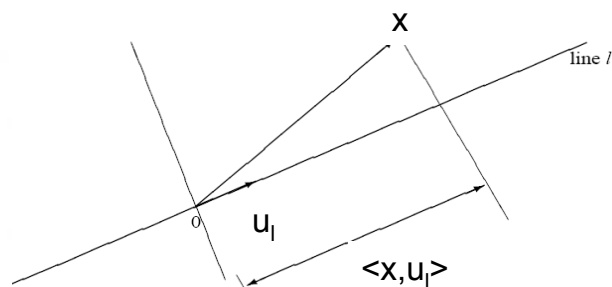
- Time series
- Spatial distribution:
mean annual rain
 ⇒ Difference EDK - IDW



- 1-D simulations ⇒ 2-D fields
- Unconditional
- Prerequisite: standard Gaussian field $Z(x)$



Turning band lines and projections



$$Z(x) = \frac{1}{\sqrt{L}} \sum_{l=1}^L Z_l(\langle x, u_l \rangle)$$

$Z_l(u)$:

Random function with zero mean & $C(r)$ covariance function

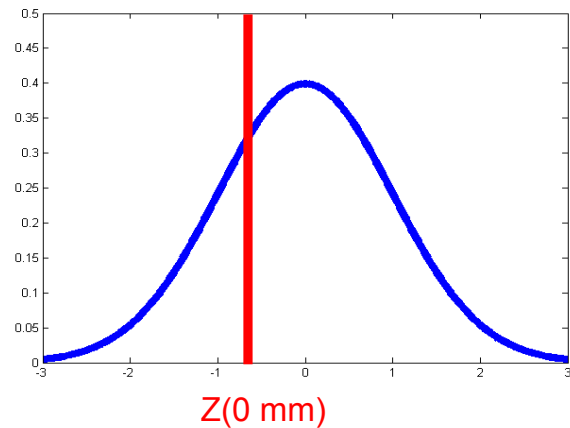
Normal score transformation

- Transform daily precipitation data to Gaussian distribution
- Problem: no negative precipitation exists
- Standard normal distribution: $Z = \frac{X - \mu}{\sigma}$

Using random numbers (normally distributed & $X \leq 0$ mm) for $Z(0 \text{ mm})$:

→ fill the curve left of $Z(0 \text{ mm})$

- Using transformed variable:
 - Calculate variograms
 - Perform turning band simulations
- *Creating conditional fields*
- Results are transformed back to original scale



Conditional Simulations

$$Z_C(x) = Z^*(x) + (Z_S(x) - Z_S^*(x))$$

$Z_C(x)$: Conditionally simulated value at point x

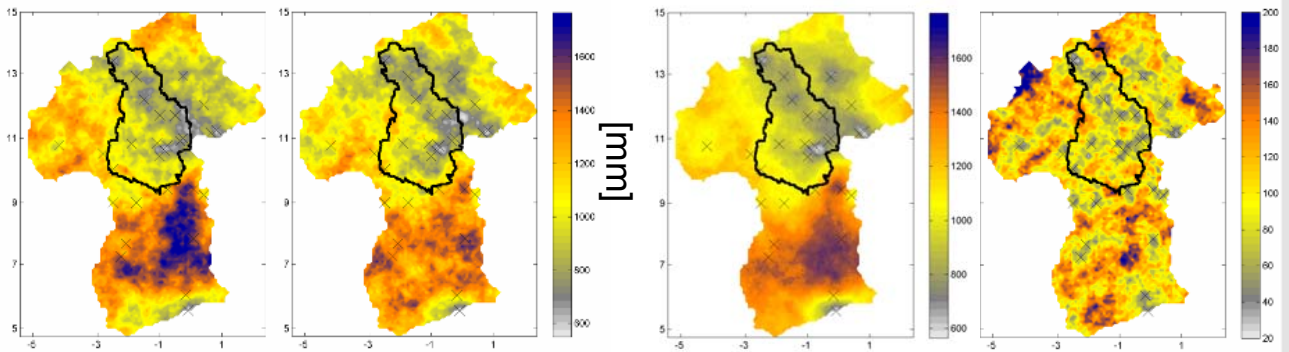
$Z^*(x)$: **Kriging** estimator of Z at x based on measurements

$Z_S(x)$: Unconditionally simulated value at point x (**TB method**)

$Z_S^*(x)$: **Kriging** estimator of Z_S at x based on unconditionally simulated values at measurement points

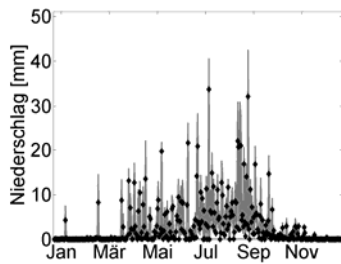
Examples: Turning Band results

Statistics: Mean & standard deviation

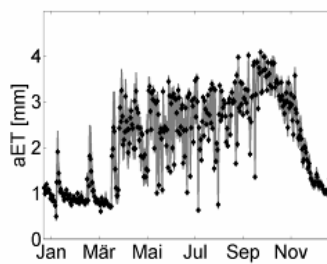


Uncertainties Propagated into Water Balance

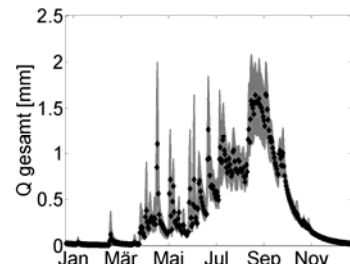
Precipitation Time Series:



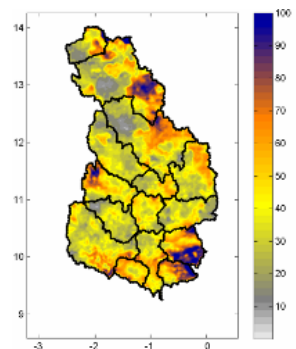
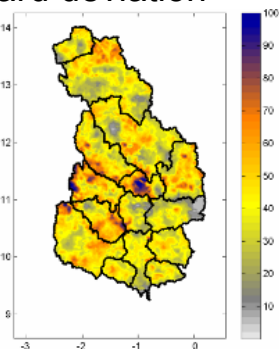
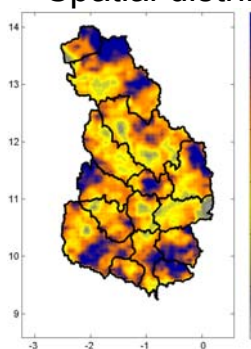
ET_a



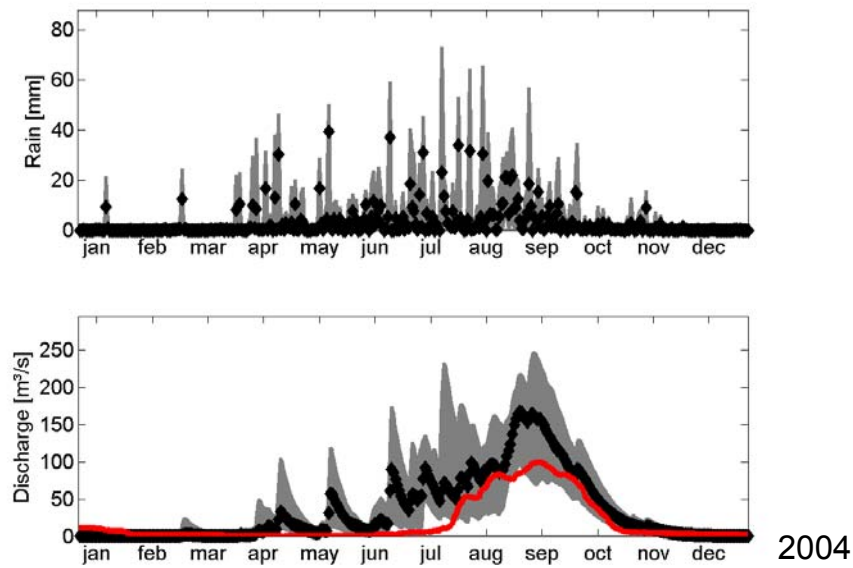
Q_{total}



Spatial distribution: standard deviation

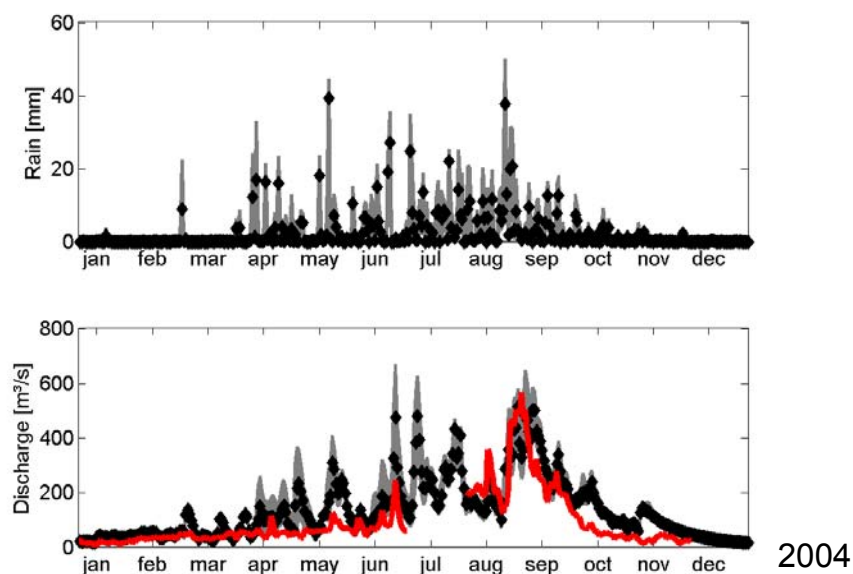


Uncertainties Propagated into Water Balance

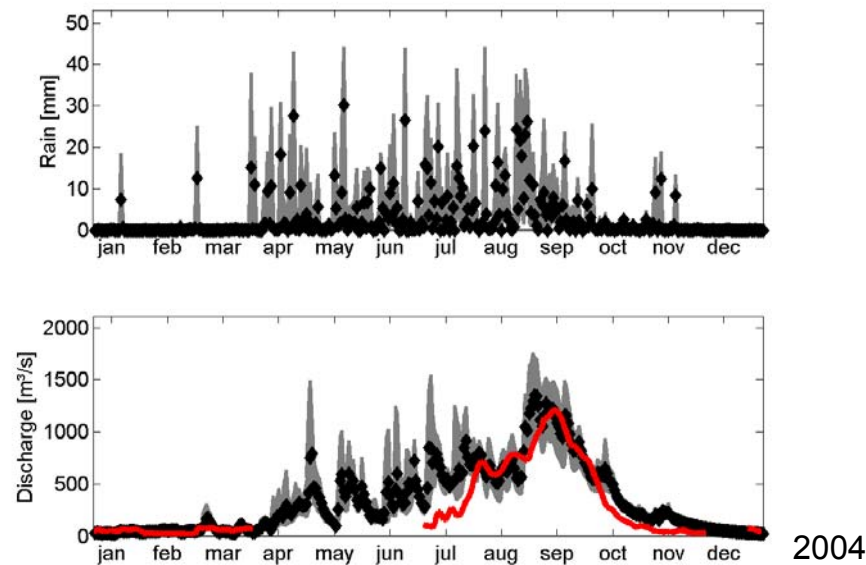


Gauge Nasia

Uncertainties Propagated into Water Balance



Gauge Pwalugu



Gauge Nawuni

Summary

- Kriging methods outperform IDW interpolation (cross validation comparison)
- Use of external drifts increases variance of areal precipitation fields
- **Turning Band simulations:** uncertainty ranges of spatial & temporal distribution of water balance variables due to uncertainties in spatial distribution of precipitation; increase variance further
- Minor impact of spatial precipitation interpolation methods for spatially aggregated variables & corresponding time series.
- Interpolation method significantly affect spatial distribution of water balance variables
- **Turning Band method for precipitation assists in sustainable water management under uncertainties in data sparse environments**



Thank you for your attention