

QPE-QPF Ensemble Prediction System Based on WRF-NOAH-MP Including Polarization Radar Data Assimilation

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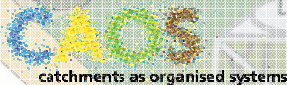
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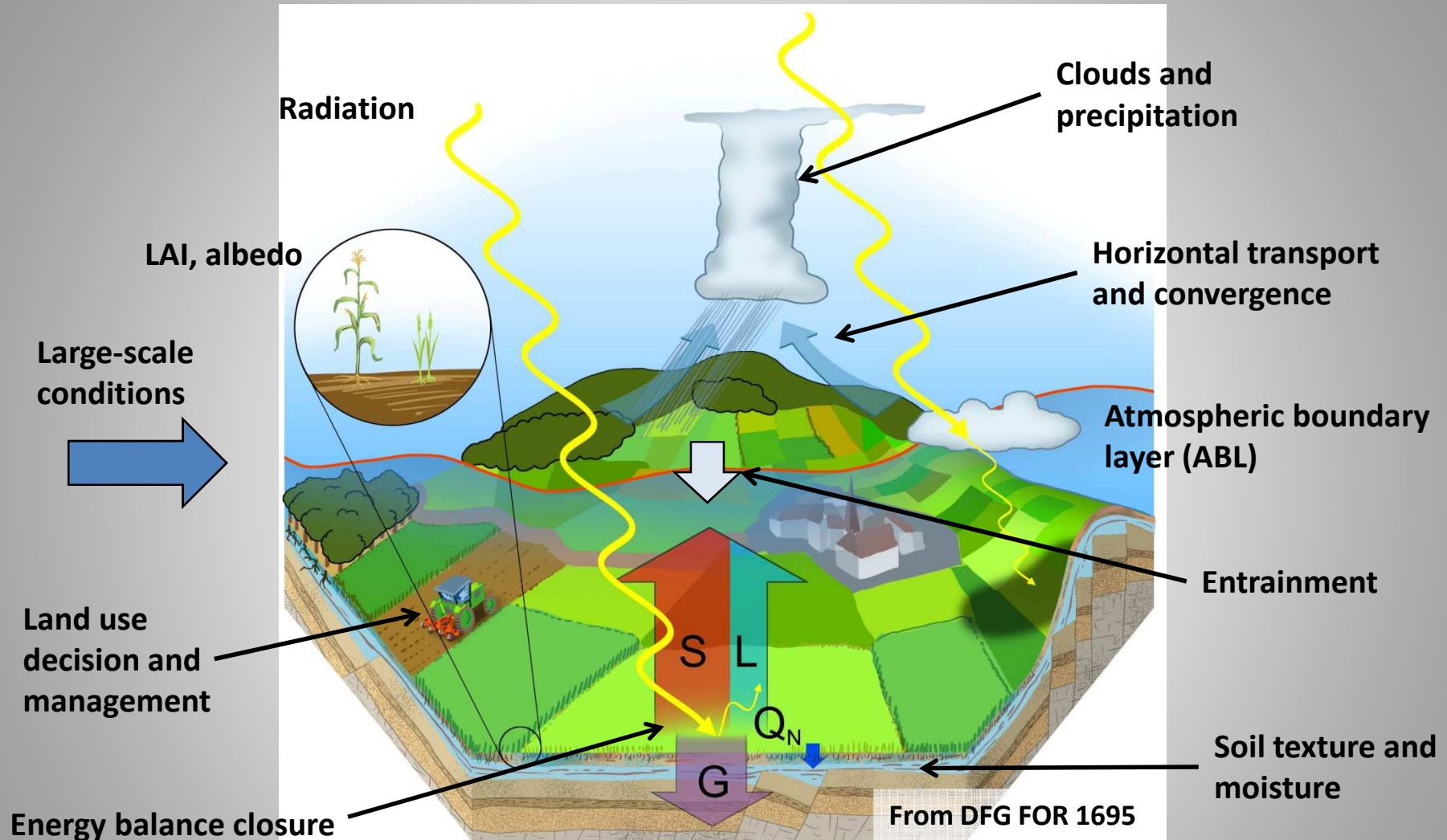
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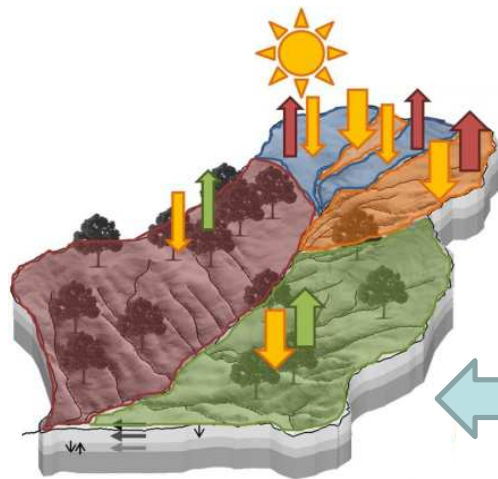


The Land System

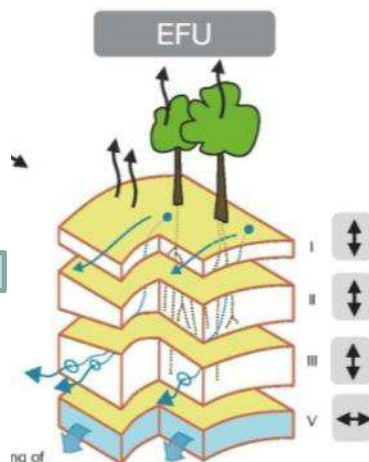
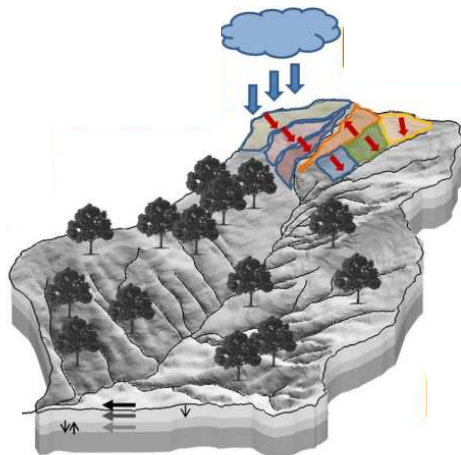


Accurate modeling and prediction of water and matter fluxes requires the simulation of the land system and its feedback processes on all temporal scales (for QPF in complex terrain see WWRP RDP COPS, Wulfmeyer et al. QJRM 2011).

Radiative driven case DFU



Precipitation driven case DFU

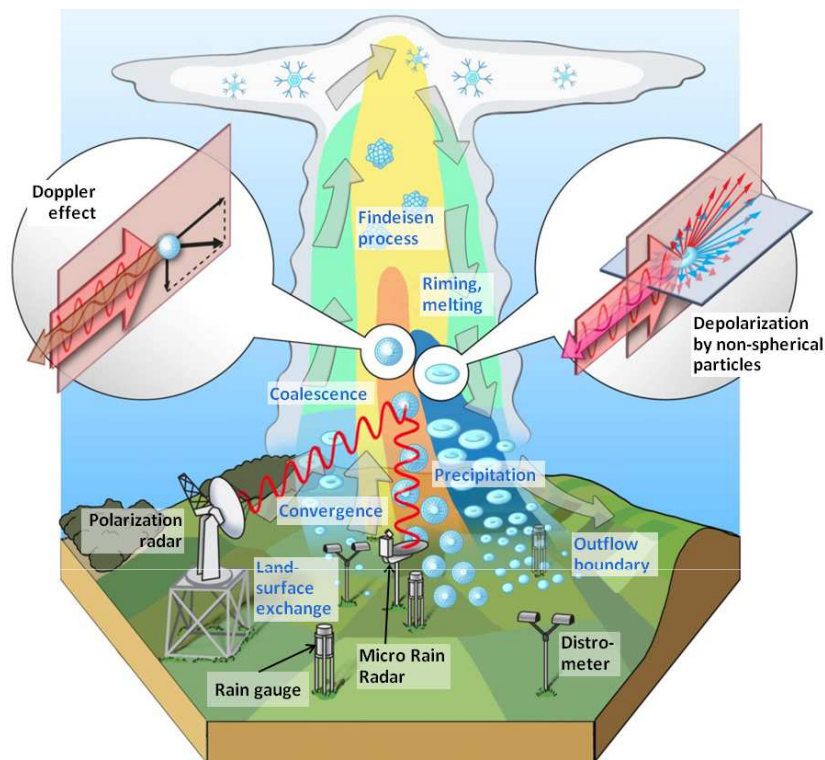


Key topics:

- New hydrological model consisting of *Dynamic Functional Units* (DFUs)
- DFUs are constructed by *Elementary Functional Units* (EFUs)
- Optimal combination of physics and parameterization effort for the modeling of exchange and transport processes

- **Transdisciplinary research** of hydrologists, soil, plant, and atmospheric scientists
- **Budget:** 7 PostDocs, 6 PhDs + field experiment
- Requires very accurate, high-resolution **Quantitative Precipitation Estimation (QPE)** (Zehe and Sivaplan, HESS 2009)

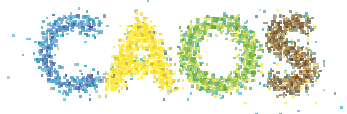
Radar & Model QPE – Objectives and Hypotheses



Objectives:

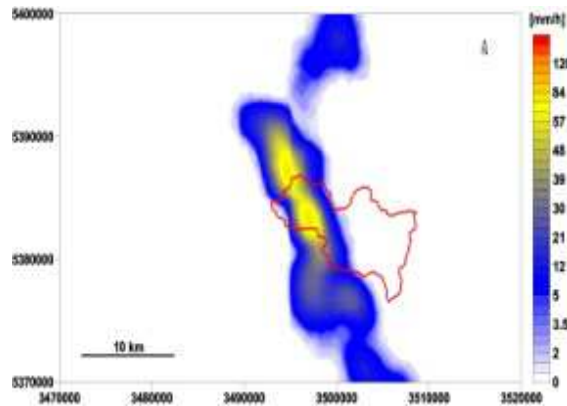
- Provide quantitative precipitation estimation (QPE) fields (incl. error estimates) for meso-scale hydrological modeling (1000 km², 1000 m, < 1 h).
- Exploit new observation techniques & high resolution models of cloud and precipitation microphysics.
- Advanced process understanding of convective and land-surface-cloud-precipitation feedbacks.

- Hypotheses:**
- QPE can be improved by new sensors, such as polarization radar and micro rain radar (MRR).
 - QPE can further be optimized by merging observations and modeling via data assimilation (DA).
 - Improved model-based QPE leads to advanced nowcasting and SRQPF performance.

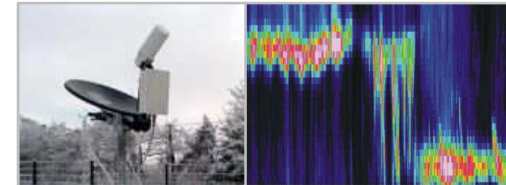


Radar & Model QPE – Approach 1

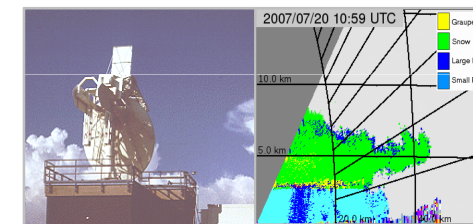
Radar-based QPE



Micro Rain Radar



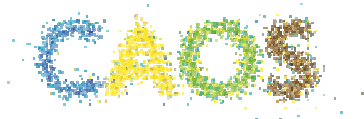
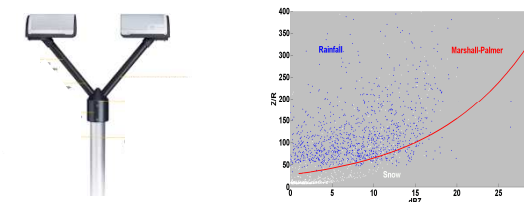
C-Band Polarization Doppler Radar



Observation-Based QPE:

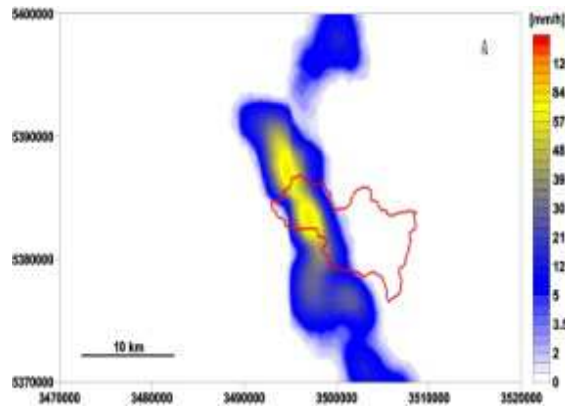
- Radar reflectivity & polarization
- Micro Rain Radar (MRR)
- Distrometers

Distrometer



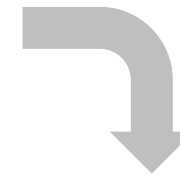
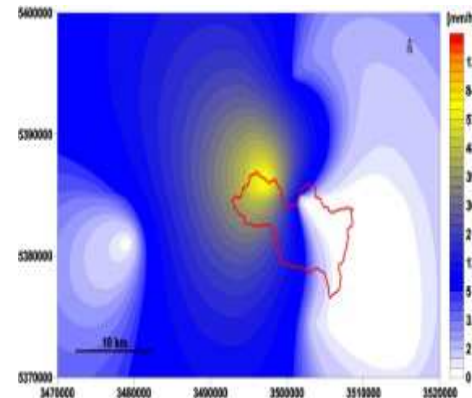
Radar & Model QPE – Approach 1

Radar-based QPE



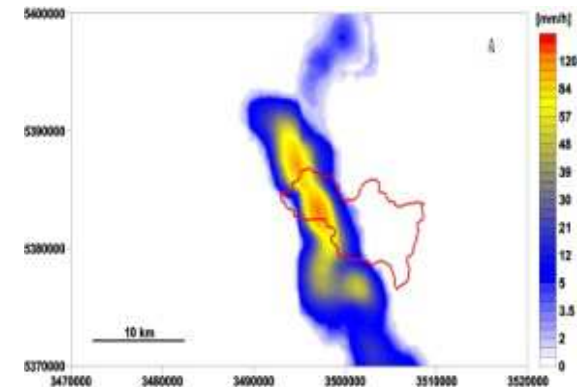
+

Gauged-based interpolation

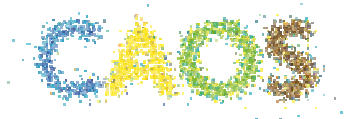


Observation-Based QPE:

- Radar reflectivity & polarization
- Micro Rain Radar (MRR)
- Distrometers
- Rain gauges & geostatistics

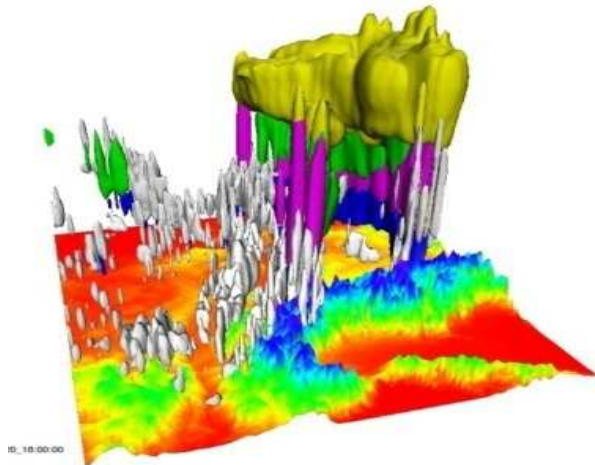


Merging

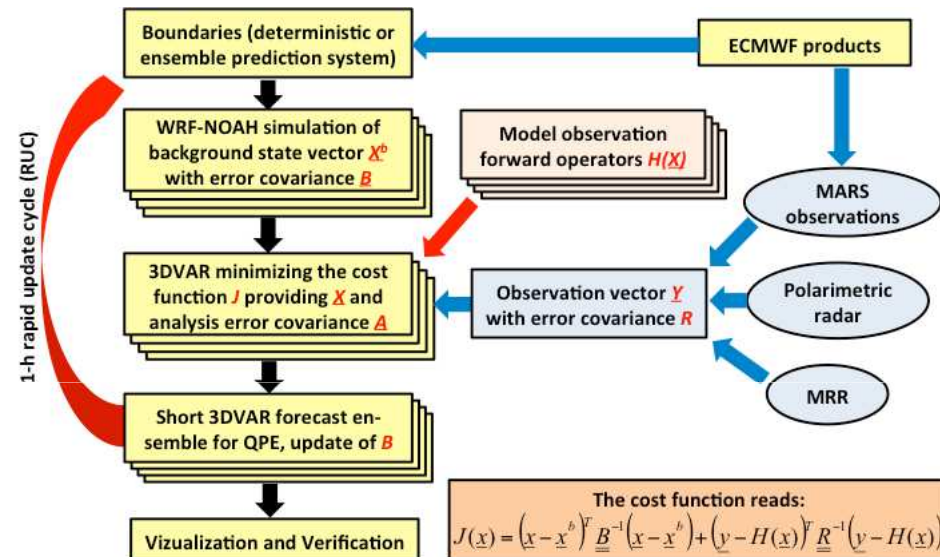


Radar & Model QPE – Approach 2

WRF-NOAH modeling

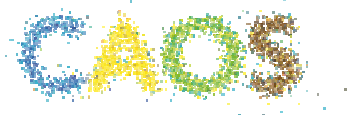


Data assimilation (DA), e.g., ensemble based 3DVAR



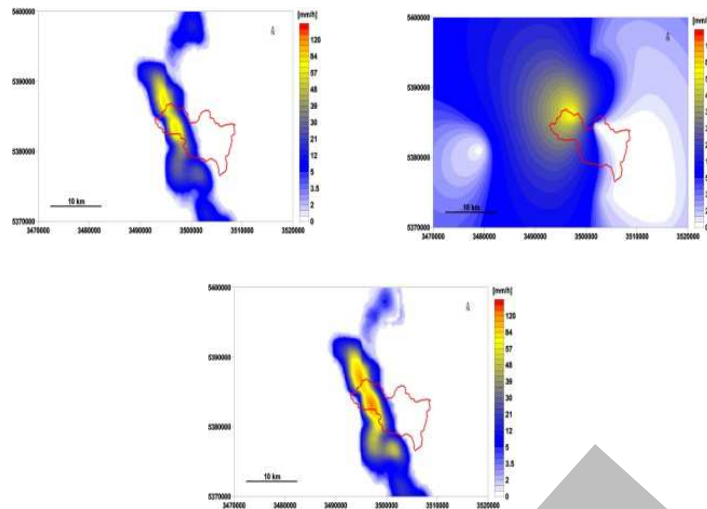
Model-based QPE:

- Convection-permitting modeling (WRF-NOAH) containing sophisticated knowledge on dynamics, thermodynamics, and microphysics
- Assimilation of 3D-observations (radial wind, reflectivity, polarization) leading to an optimal combination of information contents

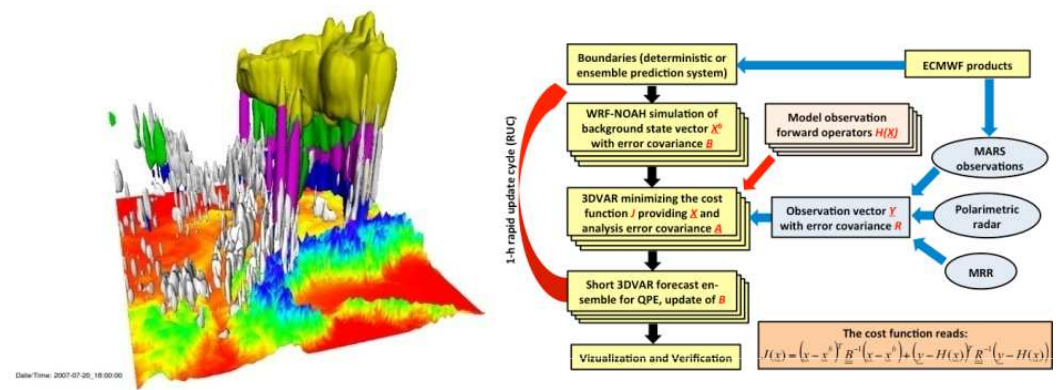


Radar & Model QPE – Approach 3

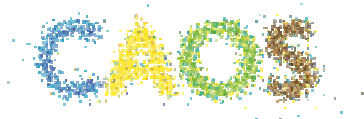
Observation-based QPE



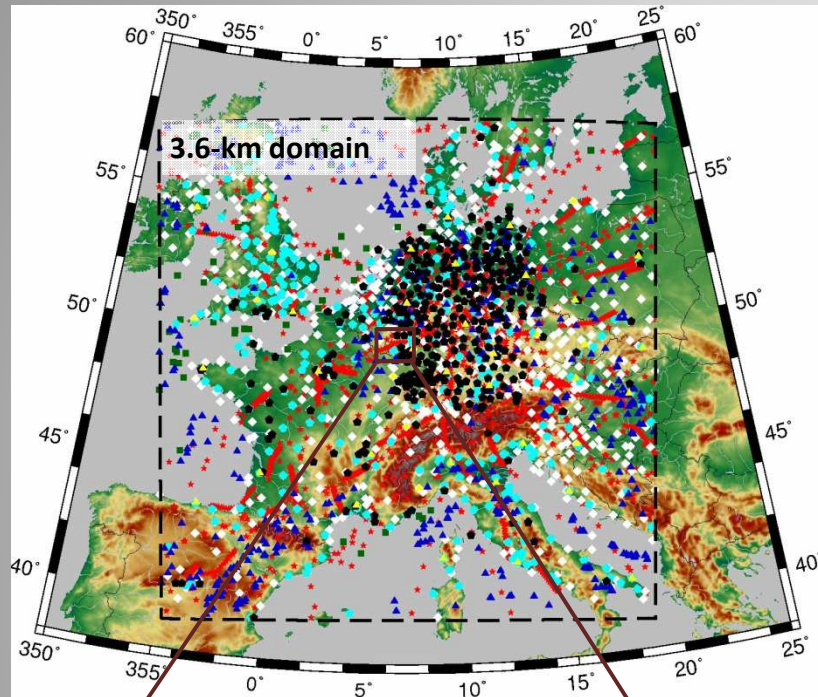
Modeling-based QPE



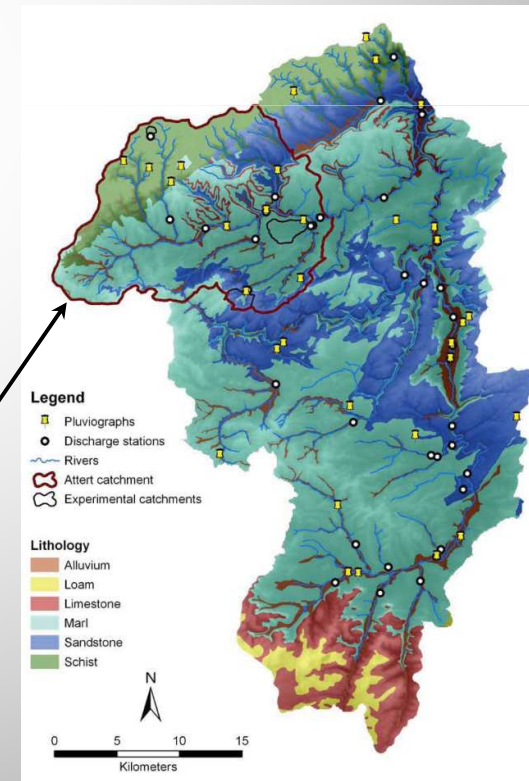
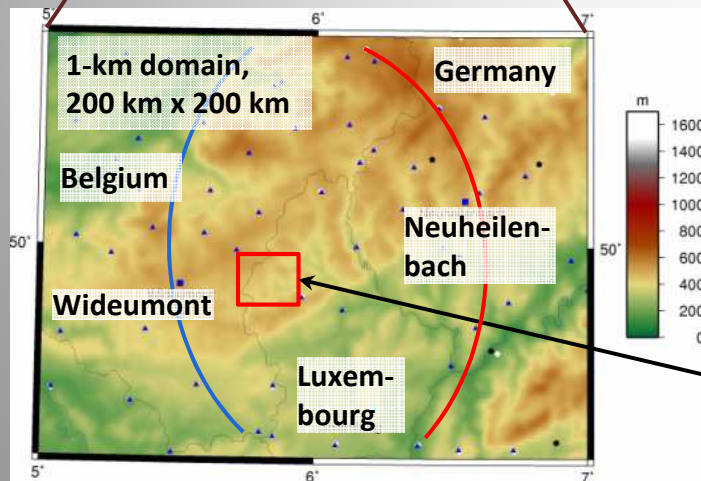
Hybrid combination of model- and observation-based QPE fields



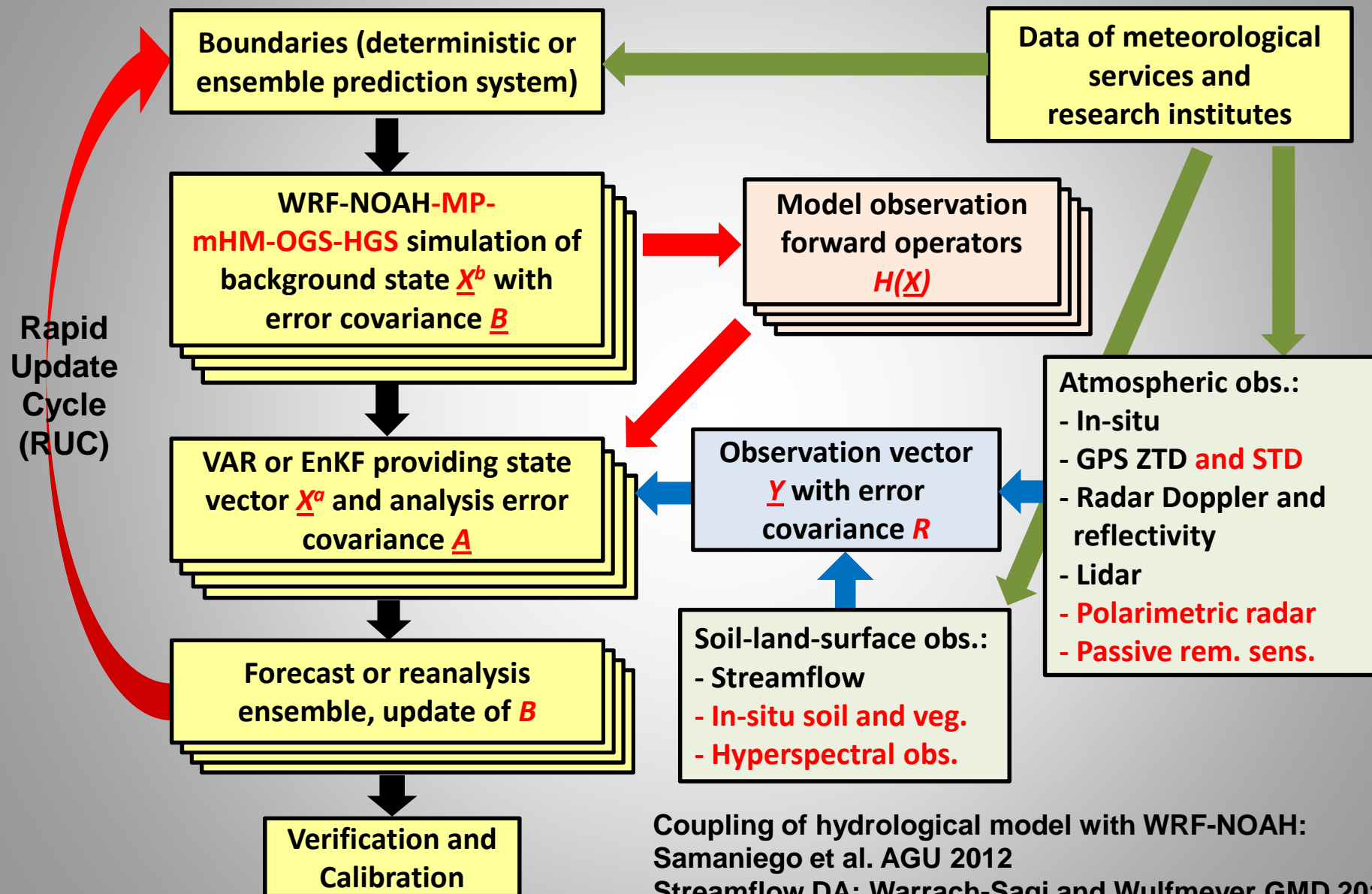
Model Domain and Standard Observations



- Yellow:** Upper air soundings
- Black:** GPS Zenith Total Delay (ZTD)
- Dark blue:** atmospheric motion vectors
- Light Blue:** metar airport
- Green:** Ship reports
- White:** synop
- Red:** aircraft amdar, acars, airep



Integrated Ensemble Simulation Model



Coupling of hydrological model with WRF-NOAH:
 Samaniego et al. AGU 2012
 Streamflow DA: Warrach-Sagi and Wulfmeyer GMD 2012

Some Considerations Concerning B -Matrix

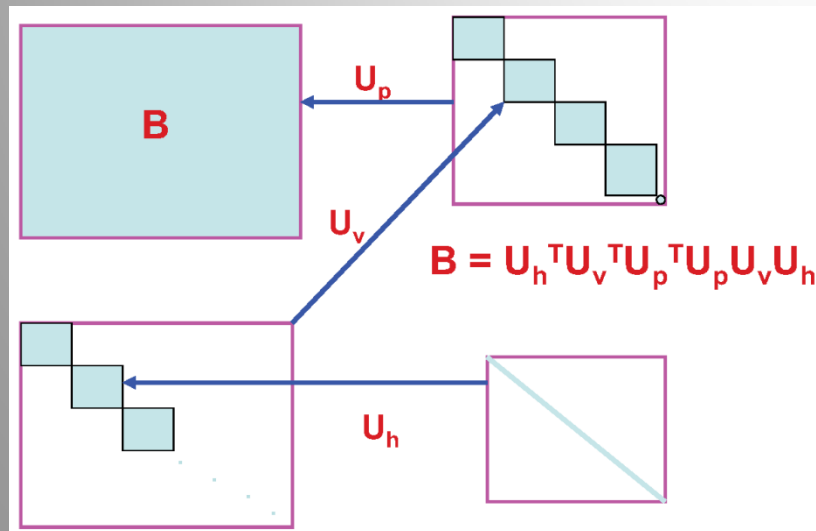
B is the covariance of (forecast - truth): $\underline{\underline{B}} = \left\langle \left(\underline{x} - \underline{x}^t \right), \left(\underline{x} - \underline{x}^t \right)^T \right\rangle$

As truth is not known, B needs to be estimated, e.g., by the NMC method: $\underline{x} - \underline{x}^t \approx \underline{x}_{t1} - \underline{x}_{t2}$ (Forecast differences valid for same time)

More reasonable is the ensemble method with the update step $\underline{x}_{i,t+1}^b = M(\underline{x}_{i,t}^a)$ using the model operator M for i ensemble members:

$$\underline{\bar{x}}^b = \frac{1}{m} \sum_{i=1}^m \underline{x}_i^b, \underline{x}_i^{b'} = \underline{x}_i^b - \underline{\bar{x}}^b, \underline{X}^b = \left(\underline{x}_1^{b'}, \dots, \underline{x}_m^{b'} \right), \text{ e.g., } \underline{\hat{B}} = \frac{1}{m-1} \underline{X}^b \underline{X}^{bT}$$

3DVAR requires the inversion of B thus its degree of freedom ($10^7 \times 10^7$) must be reduced. In the WRF 3DVAR system, this is accomplished by a series of unitary transformations



using the control variables:

Stream function (ψ)

Unbalanced part of velocity potential (χ_u)

Unbalanced part of temperature (T_u)

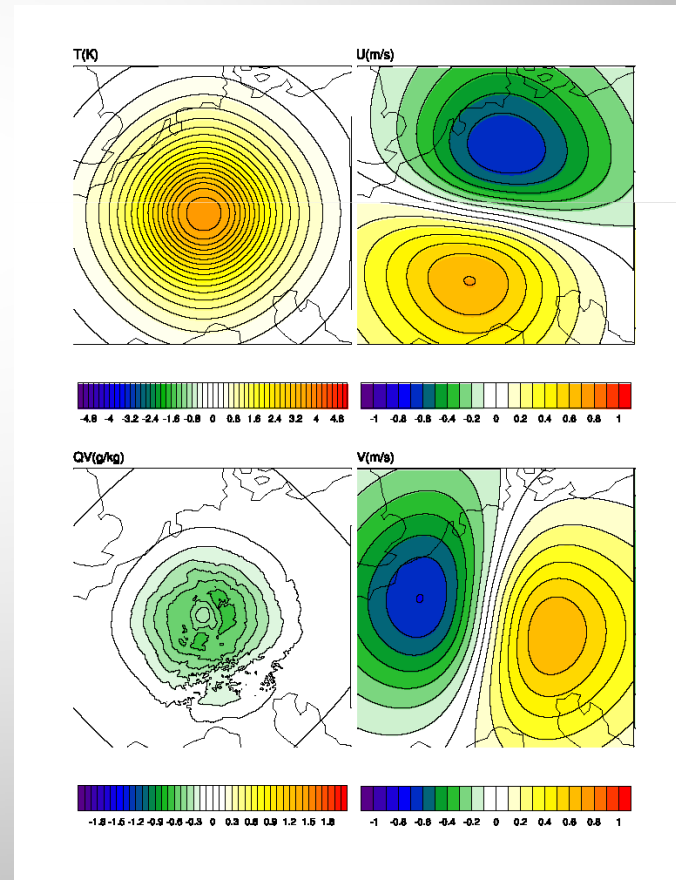
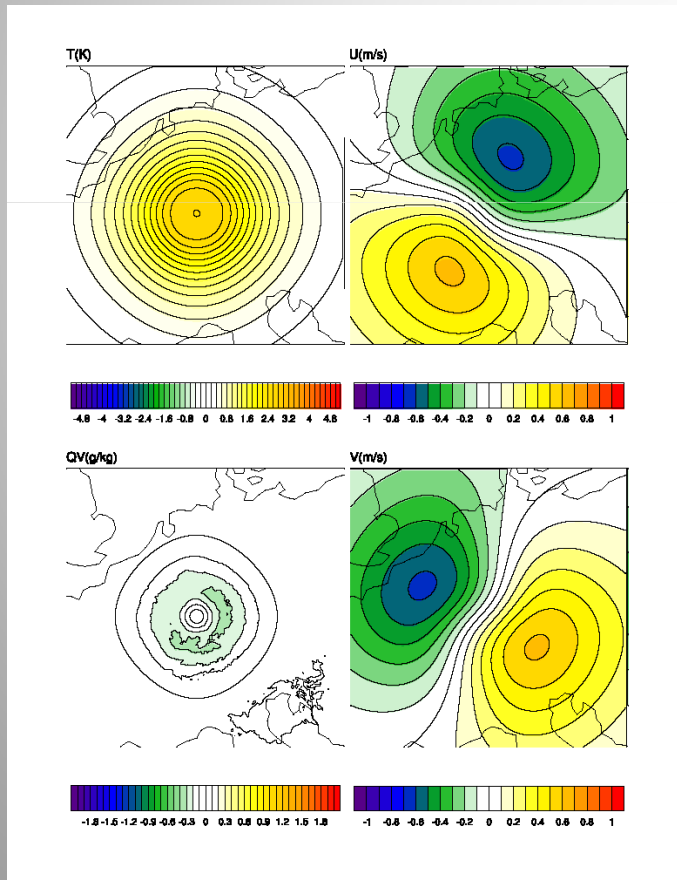
Relative Humidity (q)

Unbalanced part of surface pressure (p_{s_u})

For further details see Rivzi,
WRF Tutorial 2012

Some Considerations Concerning *B*-Matrix

- *B* must spread information both vertically & horizontally with proper weights to observations and first guess.
- Not only an initial (time independent) *B*-matrix but also an update can be constructed. This is the starting point for our En3DVAR.
- Currently, this technique is tested using a series of single observation tests.





WRF RUC and Radar DA during COPS IOP9c



Doppler
wind speed:

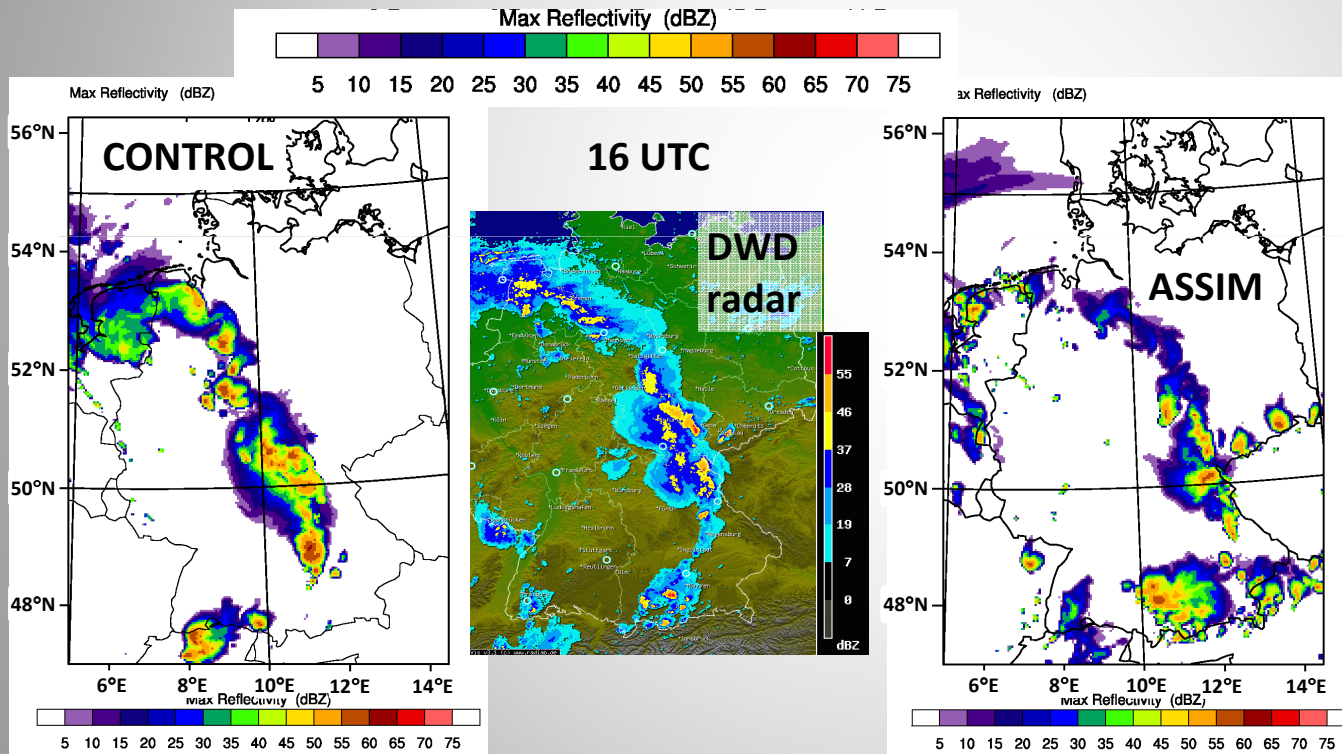
$$V_r = \frac{x - x_{radar}}{R} u + \frac{y - y_{radar}}{R} v + \frac{z - z_{radar}}{R} (w - v_T)$$

$$v_T = 5.4 \frac{m}{s} \left(\frac{p_0}{p} \right)^{0.4} q_r^{0.125}$$

Reflectivity:

$$Z = 43.1 \text{ dBZ} + 17.5 \log \left(\rho q_r \frac{\text{m}^3}{\text{kg}} \right) \text{ dBZ}$$

(Xiao et al. JAM 2005,
Xiao and Sun MWR 2007)



COPS IOP 9c on July 20, 2007 (see Corsmeier et al. QJRMS 2011).
First WRF 3DVAR RUC from 18-24 UTC on July 19, 2007, using DWD radar data.

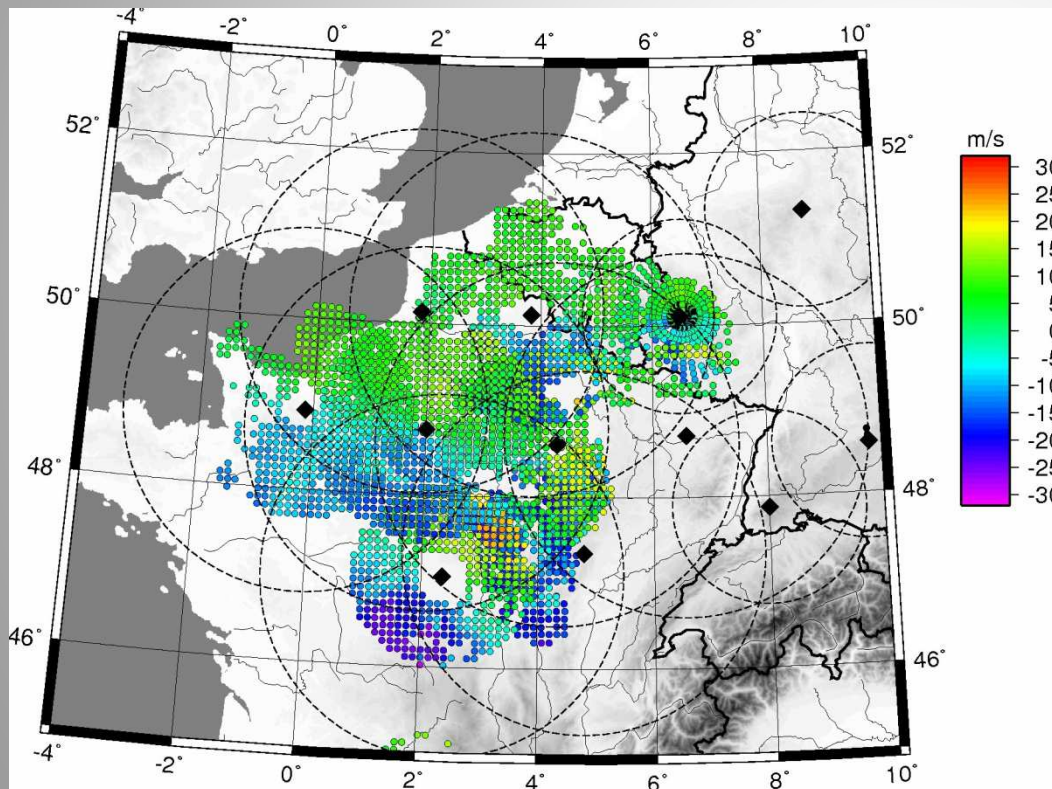
Positive impact on QPF up to 16 h, however, overestimation of precipitation amounts (Schwitalla et al. QJRMS 2011, Schwitalla et al. Meteorol. Z. to be submitted 2012).



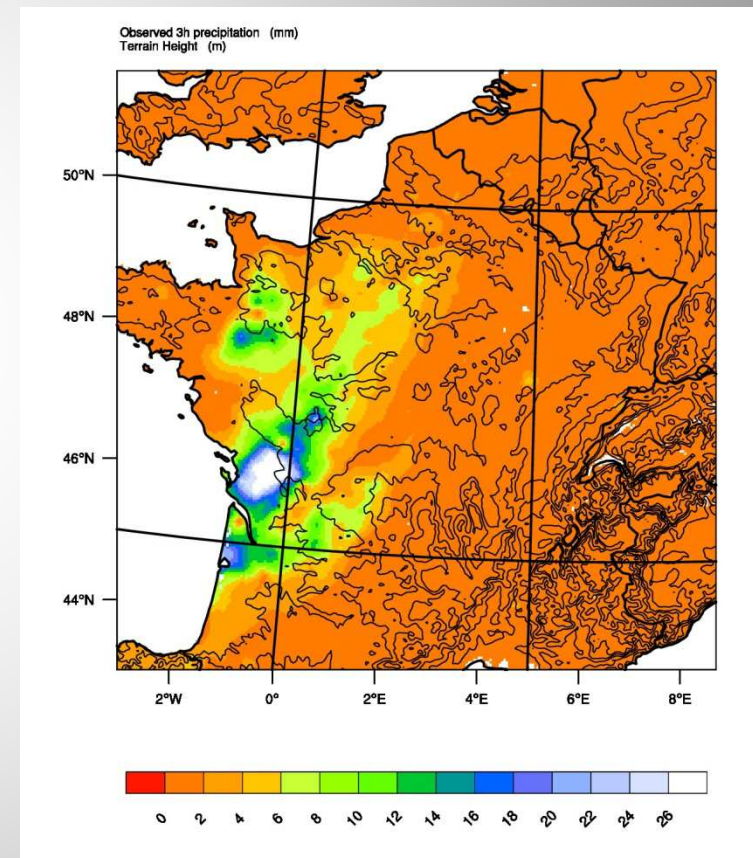
WRF RUC and Radar DA during COPS IOP10



Application of digital filter, update of tendency equations for boundaries after DA, full RUC including Météo-France and DWD radar network from 12 UTC, July 22, to 6 UTC, July 23, 2007.



Radar coverage, Doppler velocity data



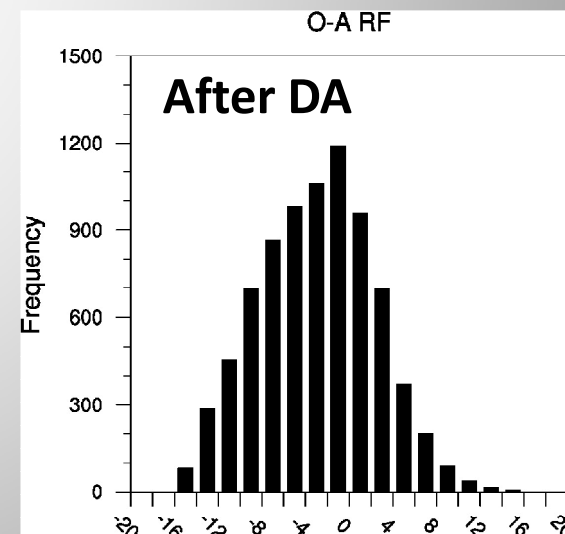
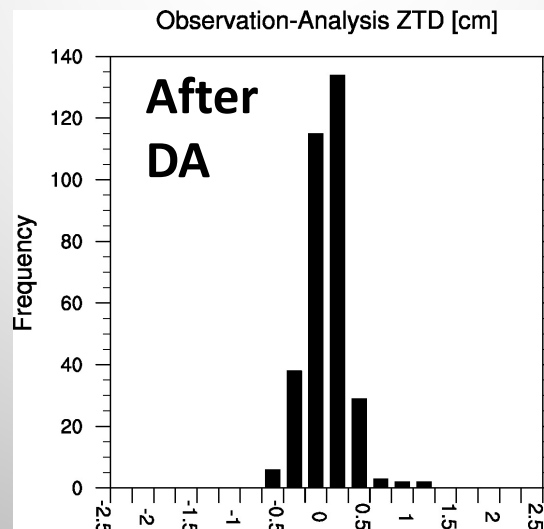
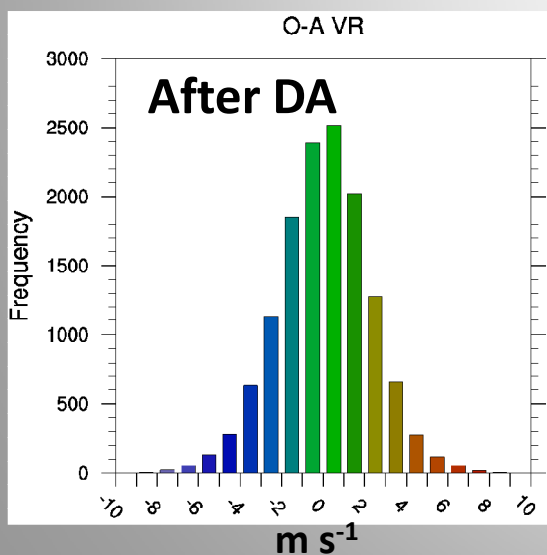
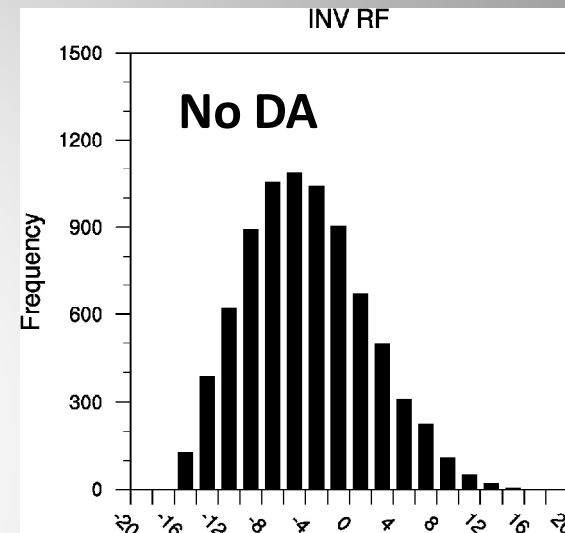
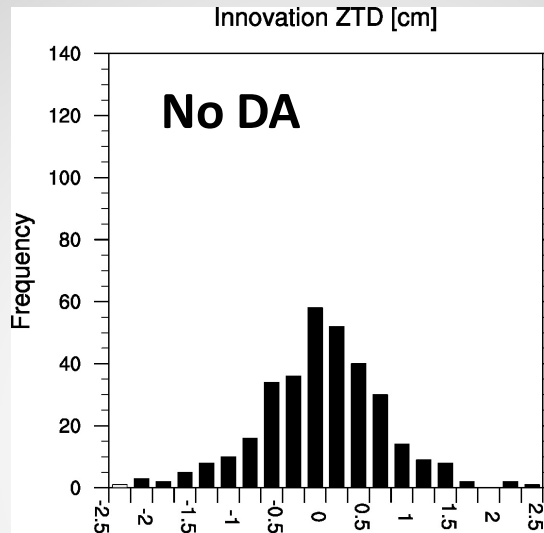
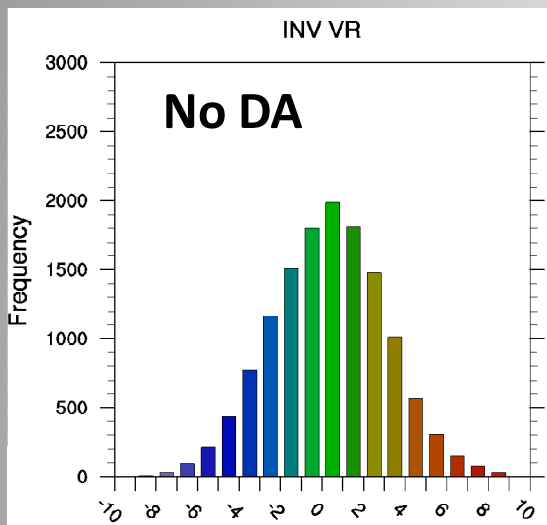
JDC Verification data, 6-9 UTC
(Wulfmeyer et al. QJRM 2011)



WRF RUC and Radar DA during COPS IOP10



Innovation and obs. – analysis statistics for 6 UTC.

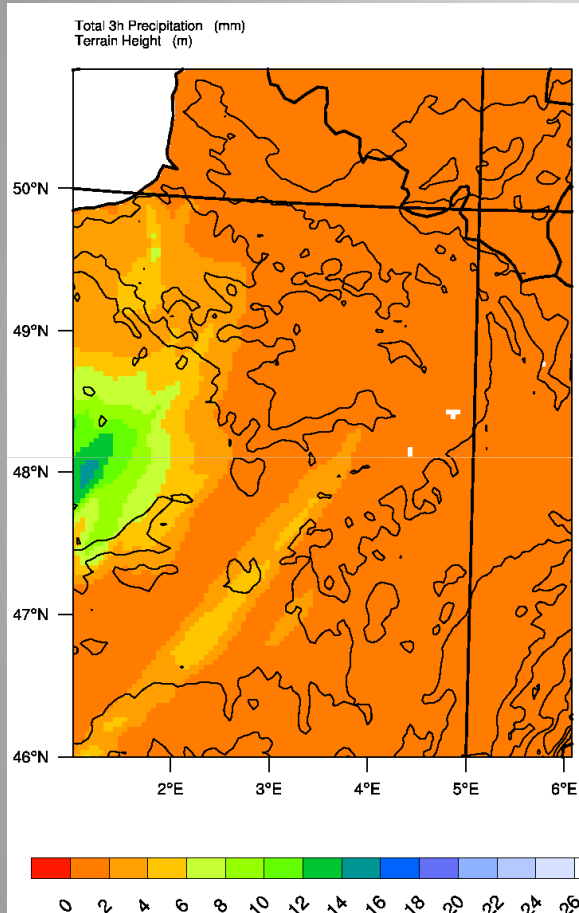




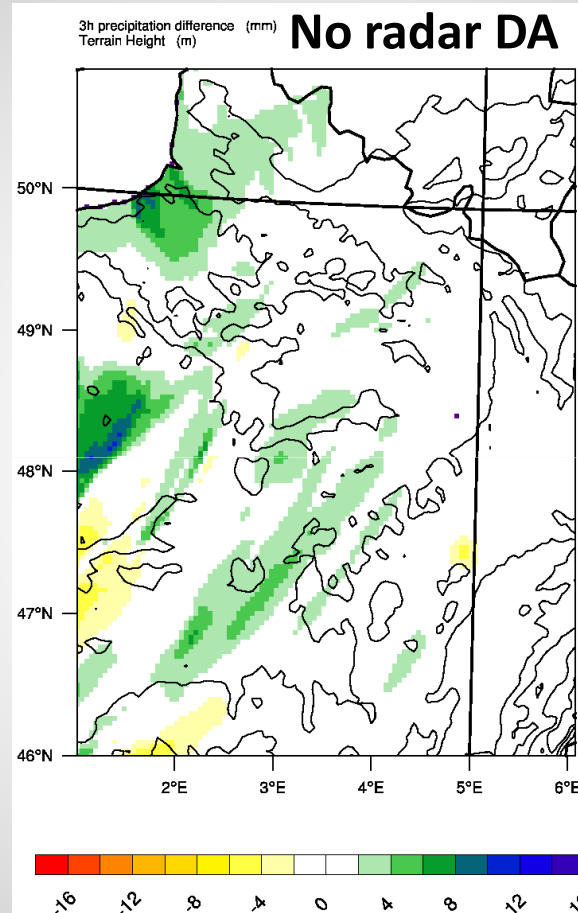
WRF RUC and Radar DA during COPS IOP10



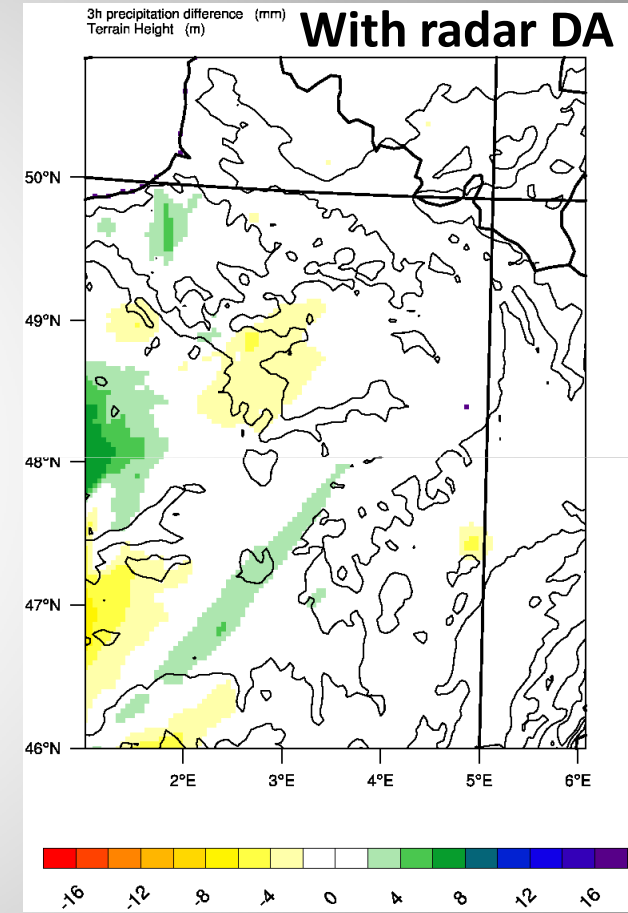
Improvement of precipitation nowcasting after RUC from 6-9 UTC:



Simulation with radar DA



Obs. – no radar

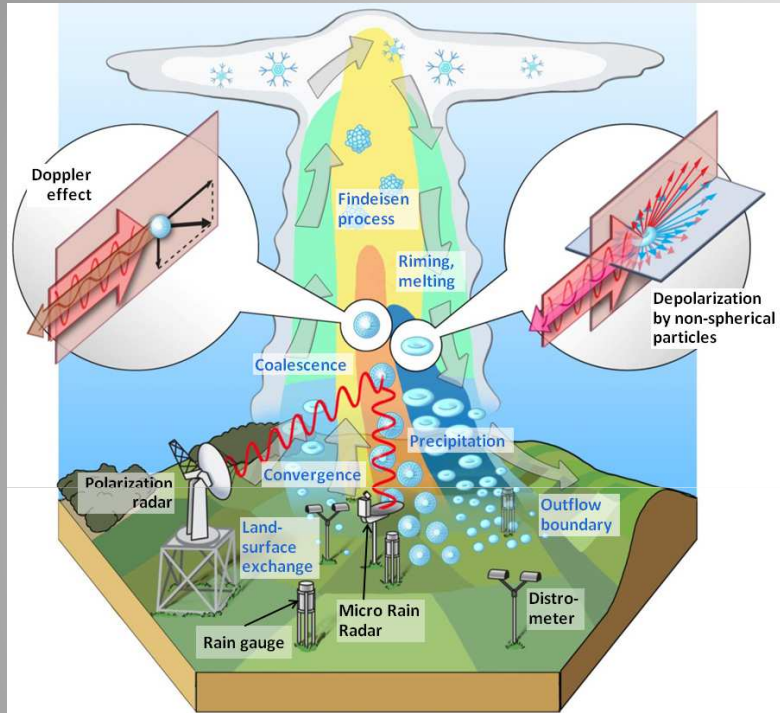


Obs. – radar DA

Promising reduction of precipitation bias by 50 %. Improvement of spatial distribution (Schwitalla et al. to be submitted Meteorol. Z. 2012).

Future Key Clear Air Observations

(see Hardesty et al. NCAR/TN-488+STR 2012)



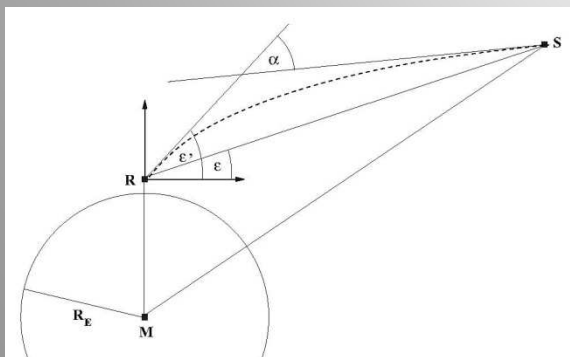
Clear-air dynamics: Doppler lidar but **no network**

Temperature: T-lidar (Radlach et al. ACP 2008), MWR, and FTIR but **neither networks nor observation operators**

Humidity: WV-lidar (Wulfmeyer et al. MWR 2006, Grzeschik et al. JTECH 2008), **no network**

Humidity: GPS ZTD and STD (Zus et al. PhD Diss. IPM 2010, Bauer et al. Tellus 2011), **not implemented in WRF DA system yet**

New IPM GPS STD operator:



$$STD = \int_{z_0}^{TOA} \left(c_1 \frac{p}{T} + c_2 \frac{pm}{(c_3 + m)T^2} \right) ds + STD_0$$

Works down to elevation angles of 5°!

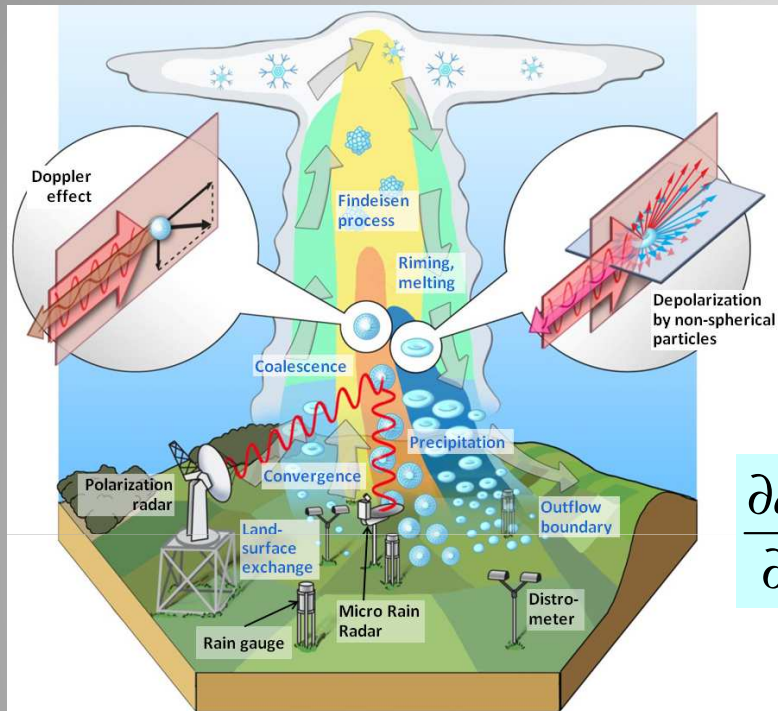
$$L = \int_a^b n(x, y(x), z(x)) \sqrt{1 + y'(x)^2 + z'(x)^2} dx$$

$$\equiv \int_a^b f(x, y, z, y', z') dx = \min.$$

$$\frac{d}{dx} \frac{\partial f}{\partial y'} - \frac{\partial f}{\partial y} = 0$$

$$\frac{d}{dx} \frac{\partial f}{\partial z'} - \frac{\partial f}{\partial z} = 0$$

Modeling and Observations of Microphysics



Two-moment microphysical scheme
(Morrison and Gettleman J. Climate 2008):

$$\phi(D) = N_0 D^\mu e^{-\Lambda D}$$

N_0 Intercept parameter
 Λ Slope parameter
 μ Spectral shape parameter

Prognostic equations for number N and mass concentration q of hydrometeors:

$$\frac{\partial q_r}{\partial t} = \frac{1}{\rho} \frac{\partial (V_{q_r} \rho q_r)}{\partial z} + S_{q_r}$$

$$R = \frac{\pi}{6} \int_0^{D_{\max}} V_T(D) D^3 \phi(D) dD$$



Must be merged by introduction of more control variables for the B-matrix.

$$Z_{h,x} = \frac{4\lambda^4}{\pi^4 |K_w|^2} \int \phi(D) (A|f_a|^2 + B|f_b|^2 + 2C|f_a||f_b|) dD$$

$$Z_{v,x} = \frac{4\lambda^4}{\pi^4 |K_w|^2} \int \phi(D) (B|f_a|^2 + A|f_b|^2 + 2C|f_a||f_b|) dD$$

$$K_{DP,x} = \frac{180\lambda}{\pi} \int E \phi(D) \text{Re}(f_a - f_b) dD$$

A, B, E: Weighting functions
depending on canting angle

x: Hydrometeor type

f_a, f_b : Backscattering amplitudes for polarization along the major (a) and minor (b) axes calculated according to T-matrix algorithm

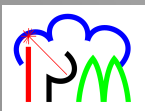
(Pfeifer et al. JAMC 2008, Jung et al. MWR 2008a,b)

Summary

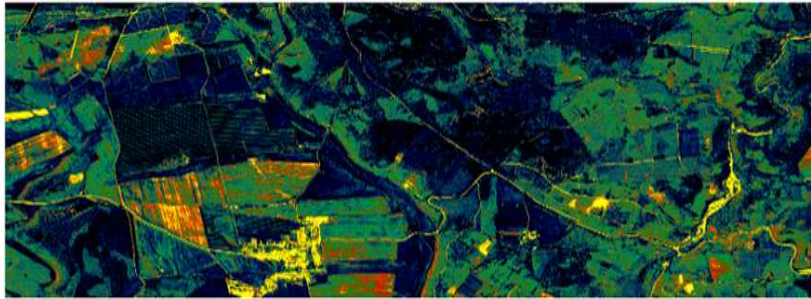
- A new LAM EPS based on WRF-NOAH(-MP) for the simulation of water and matter cycles in the land system under development.
- 3DVAR (and 4DVAR) operating with GPS ZTD as well as radar Doppler and reflectivity.
- New observation operator for GPS STD developed.
- Positive impact of radar reflectivity on nowcasting and SRQPF.

- 1) NWP strongly limited by lack of clear air observations. A strong tasks force fostering the development of networks and technologies is needed.
- 2) A huge potential on merging observations with models is not exploited due to a lack of operators for passive and active remote sensing data.

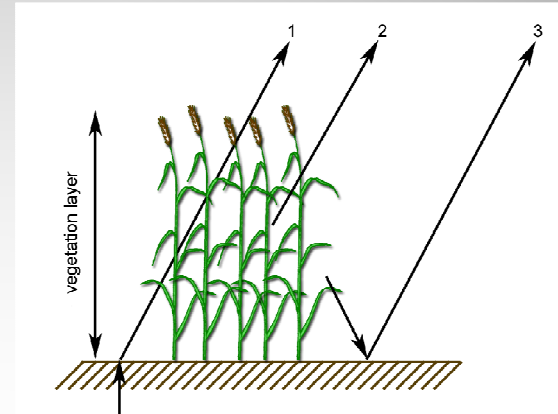
Should be key activities of WWRP WGs on MWFR and Nowcasting.



Hyperspectral Observations of the Land Surface



AISA NDVI achieved on May 26, 2011 over the Schäfertal area.



$$T_{B,p} = e_{r,p} T_s \Gamma_p + (1 - A_p)(1 - \Gamma_p) T_c + (1 - A_p)(1 - \Gamma_p) T_c (1 - e_{r,p}) \Gamma_p$$

$$e_{r,p} = 1 - r_{s,p} \exp(-h_r \cos^2 u)$$

$$r_{s,p} = \left[\frac{|\epsilon| \cos u - \sqrt{|\epsilon| - \sin^2 u}}{|\epsilon| \cos u + \sqrt{|\epsilon| - \sin^2 u}} \right]^2$$

- T_B brightness temperature
- T_s soil surface temperature
- T_c canopy temperature
- Γ canopy transmission
- A single scattering albedo
- e_r rough surface emissivity
- P polarization (horizontal or vertical)

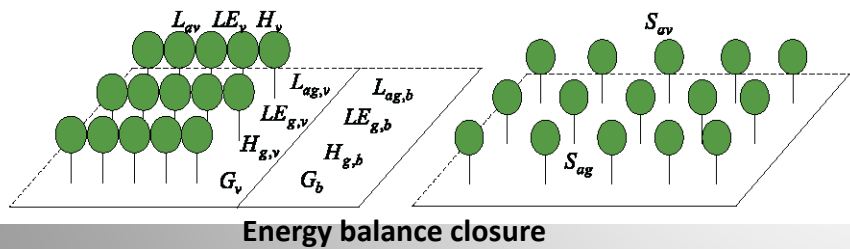
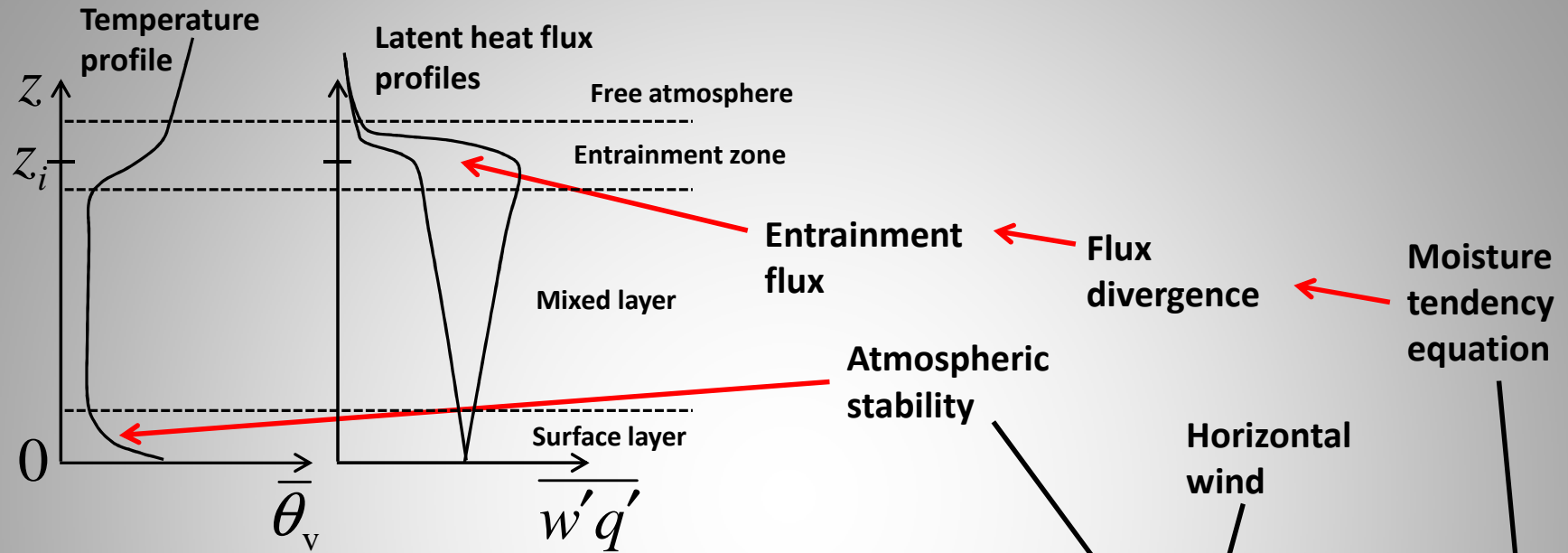
Wang and Schmugge dielectric mixing model (1980), INPUT:

- P porosity of the soil
- W_p water content at wilting point or sand and clay content
- T temperature of soil water
- ν frequency
- W_c soil water content

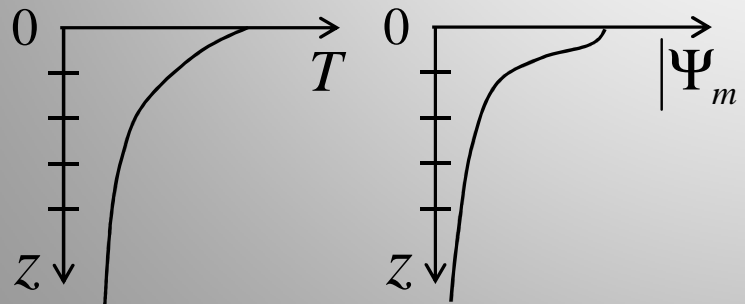
OUTPUT:

ϵ = complex dielectric constant of the soil

Understanding Feedbacks. Example: Latent Heat



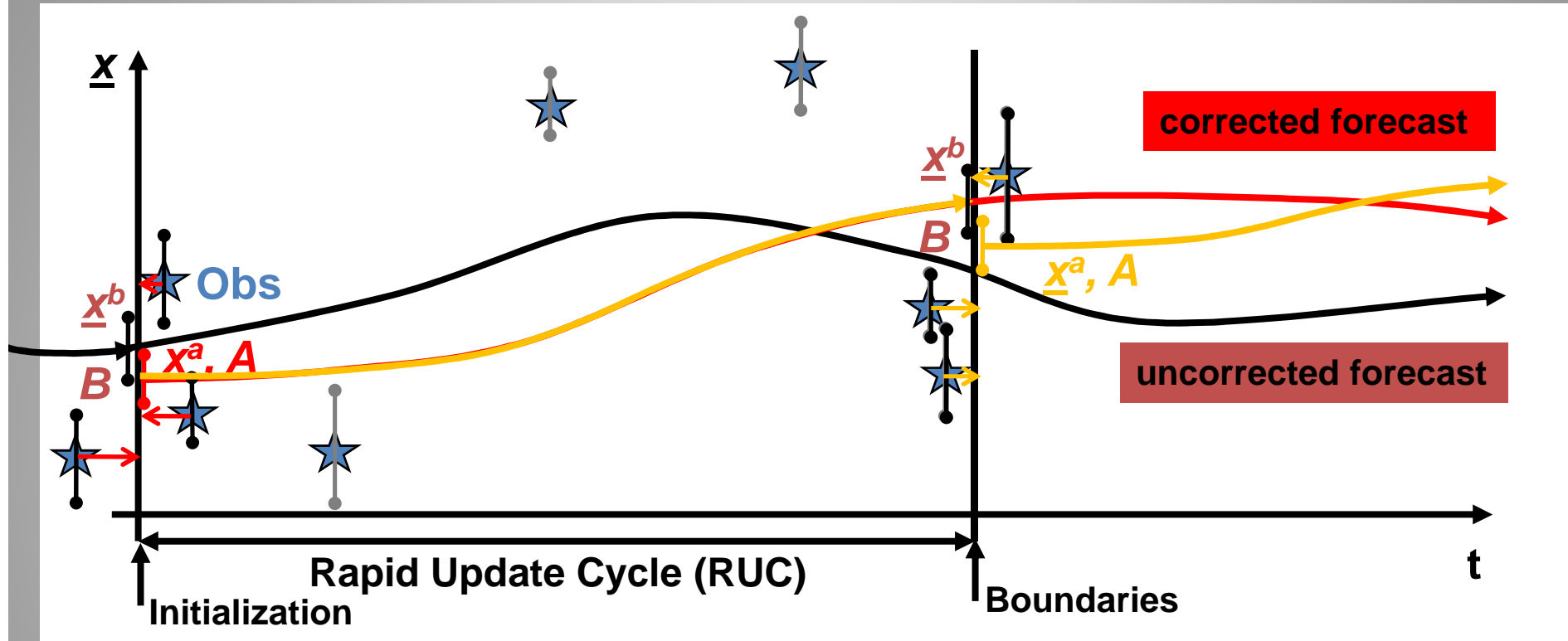
$$\overline{w'q'} \cong -K \frac{\partial q}{\partial z} \cong C_{wv} r^{-1} (e_{sat}^*(T_{b,g,v}) - e_{air})$$



Canopy and aerodyn. resistance, photosynthesis

Soil and canopy water content evolution

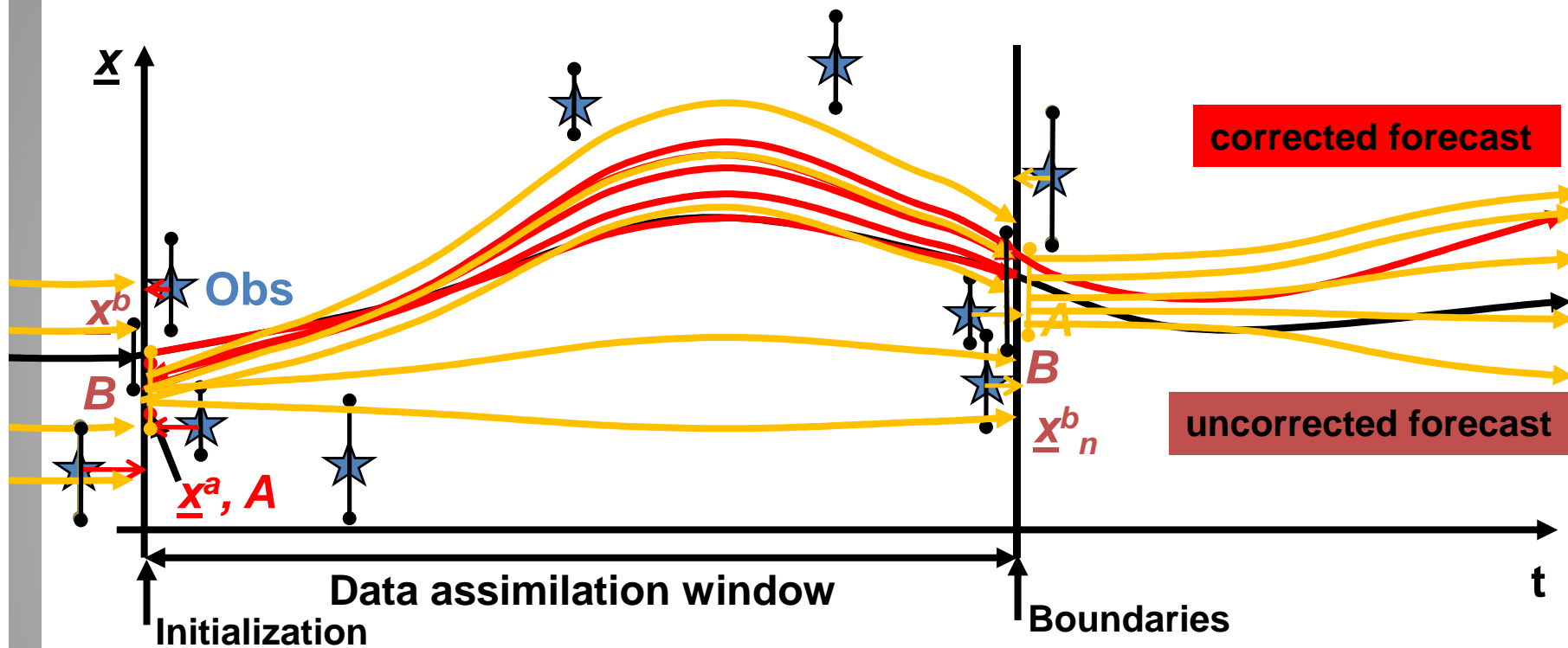
3DVAR Methodology



3DVAR cost function:
$$J(\underline{x}) = (\underline{x} - \underline{x}^b)^T \underline{\underline{B}}^{-1} (\underline{x} - \underline{x}^b) + (\underline{y} - H(\underline{x}))^T \underline{\underline{R}}^{-1} (\underline{y} - H(\underline{x}))$$

In **3DVAR**, the full complex model can be applied but B matrix remains constant and must be estimated. Generally, adjoint of H needed.

4DVAR and EnKF Methodology



4DVAR cost function:
$$J(\underline{x}) = (\underline{x} - \underline{x}^b)^T \underline{\underline{B}}^{-1} (\underline{x} - \underline{x}^b) + \sum_{i=1}^n (\underline{y}_i - H_i(\underline{x}_i))^T \underline{\underline{R}}_i^{-1} (\underline{y}_i - H_i(\underline{x}_i))$$

$\underline{\underline{A}} = \left(\underline{\underline{B}}^{-1} - \underline{\underline{M}}^T \underline{\underline{H}}^T \underline{\underline{R}}^{-1} \underline{\underline{H}} \underline{\underline{M}} \right)^{-1}$ becomes flow dependent.

EnKF: Approximate **EKF** analysis by ensemble of simulations, which provide flow dependent updates of **B** and **A**.

Techniques Based on Gaussian Error Characteristics

$$\bar{x} = \frac{1}{m} \sum_{i=1}^m \underline{x}_i, \underline{x}_i' = \underline{x}_i - \bar{x}, \underline{X} = (\underline{x}_1', \dots, \underline{x}_m'), \text{ e.g., } \hat{\underline{B}} = \frac{1}{m-1} \underline{X}^b \underline{X}^{bT}, \underline{y} = H(\underline{x})$$

Update step: $\underline{x}_{i,t+1}^b = M(\underline{x}_{i,t}^a)$

Deterministic EnKF, here Ensemble Transform KF (ETKF)

$$\underline{x} = \sum_{i=1}^m w_i \underline{x}_i^b = \bar{x}^b + \underline{X}^b \underline{w}$$

$$\tilde{\underline{K}} = \frac{1}{m-1} \underline{Y}^{bT} \left(\underline{R} + \frac{1}{m-1} \underline{Y}^b \underline{Y}^{bT} \right)^{-1}$$

$$\tilde{\underline{A}} = \frac{1}{m-1} (\mathbf{1} - \tilde{\underline{K}} \underline{Y}^b) = \frac{1}{m-1} \underline{W}^a \underline{W}^{aT}$$

$$\underline{\bar{w}}^a = \tilde{\underline{K}} (\underline{y}^{obs} - \bar{y}^b), \underline{X}^a = \underline{X}^b \underline{W}^a$$

Fast algorithm in subspace of weights. But can a linear combination of ensemble members produce a correct ensemble spread on the CP scale?

Stochastic EnKF

$$\underline{x}_i^a = \underline{x}_i^b + \hat{\underline{K}} (\underline{y}_i - H(\underline{x}_i^b))$$

with $\underline{y}_i = \underline{y} + \underline{y}_i'$ and $\sum_i \underline{y}_i' = 0$

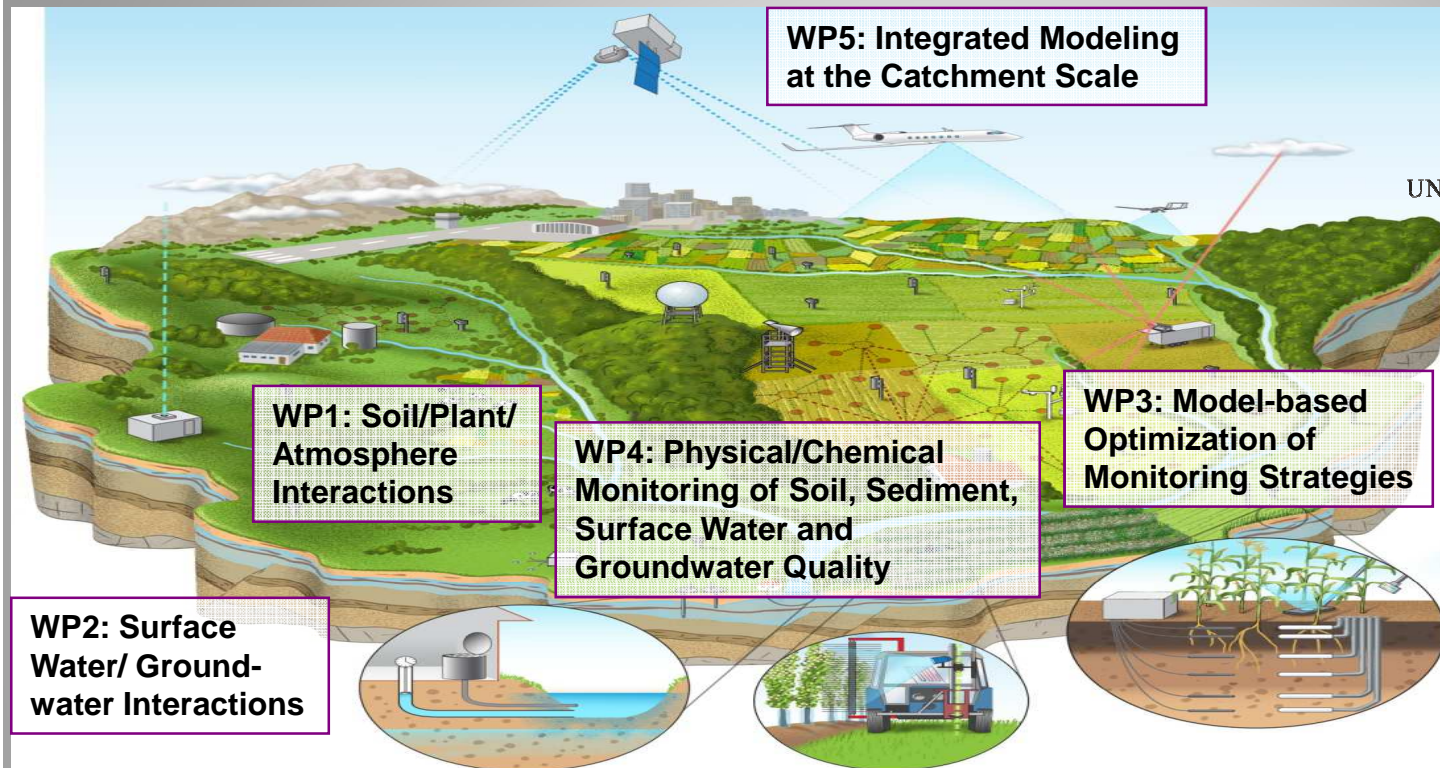
$$\hat{\underline{K}} = \hat{\underline{B}} \underline{H}^T (\underline{H} \hat{\underline{B}} \underline{H}^T + \underline{R})^{-1}$$

Just $\hat{\underline{B}} \underline{H}^T$ and $\underline{H} \hat{\underline{B}} \underline{H}^T$ must be calculated. Furthermore, observations can be assimilated sequentially (Houtekamer and Mitchell 2001) reducing the rank of $\underline{H} \hat{\underline{B}} \underline{H}^T$. Perturbation of physics parameters can also be included.

Stochastic filter more reasonable on CP scale. Problem: Analysis may not be consistent with conservation of quantities.



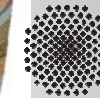
Water and Solute Fluxes at Catchment Scale (www.wess.info)



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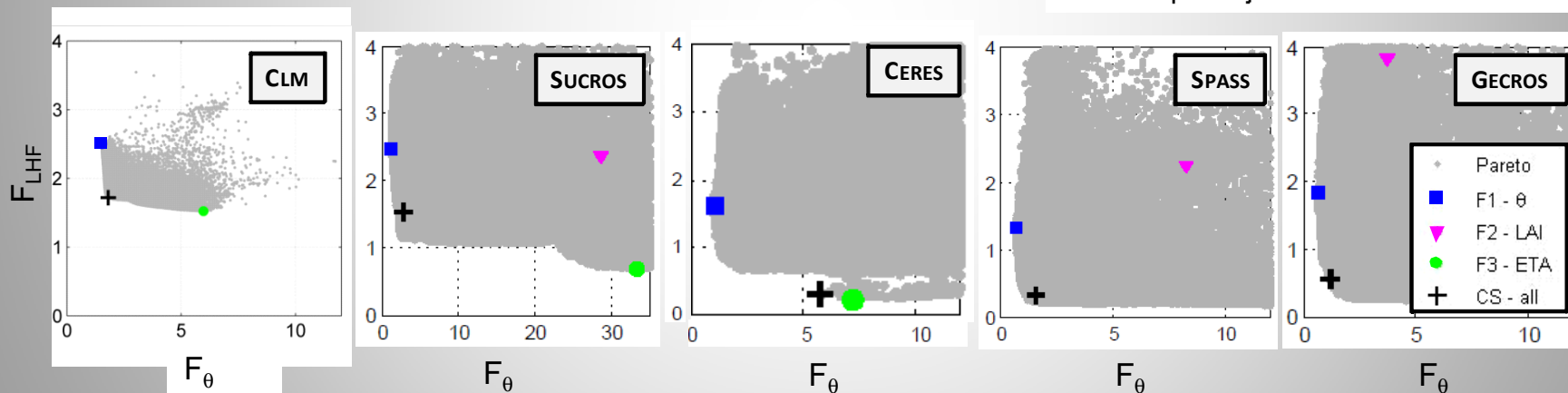
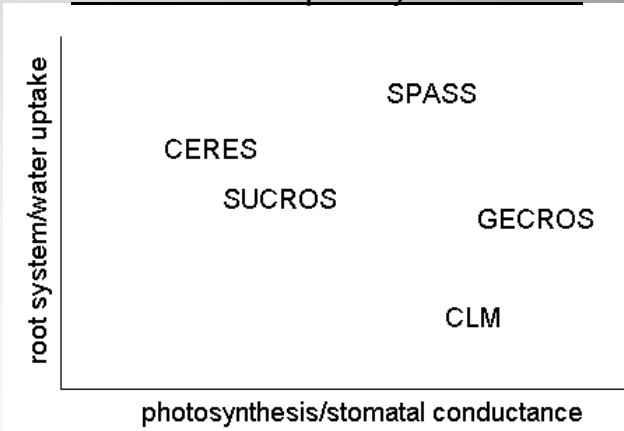
- **Competence Cluster** in Research Field 3 “Understanding Matter Fluxes at Catchment Scale” in **German Water Science Alliance / Helmholtz Water Network**
- **Budget:** 12 PostDocs, Data Manager, 10 PhDs + infrastructure
- **Transdisciplinary research** of hydrologists, soil, plant, and atmospheric scientists
- Requires simulations of **QPE, nowcasting, and SRQPF** as well as **reanalyses** (further details see Grathwohl et al. submitted to Environ. Earth Science, 2012)

Which degree of detail is needed in a land-surface scheme to simulate simultaneously soil moisture (θ) and latent heat flux (LHF) at plot scale?

→ **Multi-objective parameter estimation** using data from EC-stations and TDR-probes:

Comparison of **Pareto-fronts** of the Community-Land-Model (CLM) and 4 crop models with different degrees of structural complexity (variation of the **same number of model parameters**, irrespective of model complexity)

structural complexity of models



More accurate soil hydraulic coefficients and a plant model including root growth dynamics are needed, e.g., SPASS or GECROS
(Gayler et al. EES, submitted 2012; Wöhling et al. IAHS, in press 2012).