Assimilation of four-dimensional soil moisture response to assess the saturated hydraulic conductivity at LEO: a sensor failure analysis

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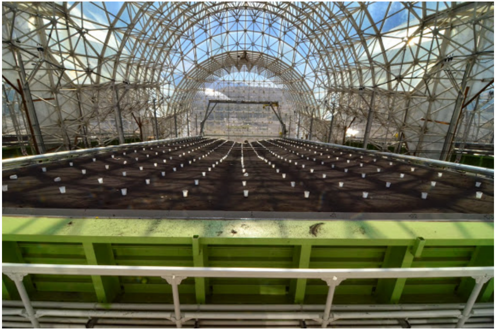
TERENO - University of Bonn - Germany, 2nd October 2014

Outline

1. The Landscape Evolution Observatory (LEO) at Biosphere 2
2. Hydrological Model: CATHY
3. Experiment 1 - LEO
4. DA for parameter estimation and sensor failure analysis
5. Conclusions

Landscape Evolution Observatory (*LEO*)



LEO: three identical convergent landscapes (30 m long, 11 m wide, 10 degrees average slope, 1 m soil) in an environmentally controlled greenhouse facility (Biosphere 2, Oracle, Arizona)

Objective: study the interactions between earth surface processes:

- Hillslope hydrology
- Surface/subsurface water flow paths & connectivity
- Microbial and plant colonization
- Biogeochemical weathering & ecosystem dynamics

Landscape instrumentation:

- rainfall simulator (3-45 mm/h)
- 10 load cells
- 6 tipping buckets and flow meters to measure the seepage face outflow
- 1,835 sensors embedded in the soil (volumetric water content, pore water pressure, temperature, water level)
- water sample collectors
- vertical profiles of air temperatures and humidity

Numerical simulations: CATchment HYdrology (CATHY)

Coupled surface/subsurface model

- Richards equation for variably saturated porous media:

$$S_w(\psi)S_s\frac{\partial\psi}{\partial t}+\phi\frac{\partial S_w(\psi)}{\partial t}=\nabla\cdot\left[K_sK_{rw}(S_w(\psi))\left(\nabla\psi+\eta_z\right)\right]+q_{ss}(h)$$

- 1-D path-based surface routing:

$$\frac{\partial Q}{\partial t}+c_k\frac{\partial Q}{\partial s}=D_h\frac{\partial^2 Q}{\partial s^2}+c_kq_s(h,\psi)$$

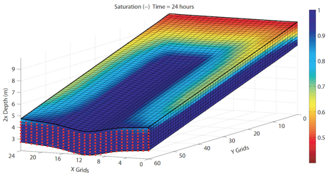
- B-C-switching/forcing terms used to enforce mass balance and pressure continuity at the surface-subsurface interface.

(Camporese et al. 2010, WRR)

First experiment at LEO (18 February 2013)

Experiment setup:

- Unsaturated initial conditions
- Imposed rainfall: $\approx$12 mm/h
- With homogeneous soil, steady state expected after 36 h



Before the experiment

First experiment at LEO (18 February 2013)

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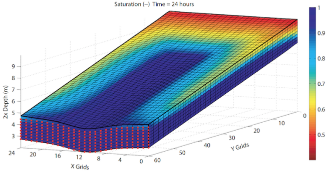
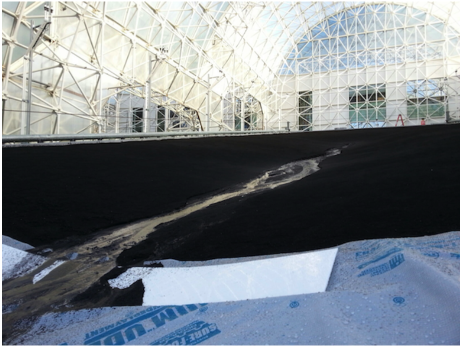
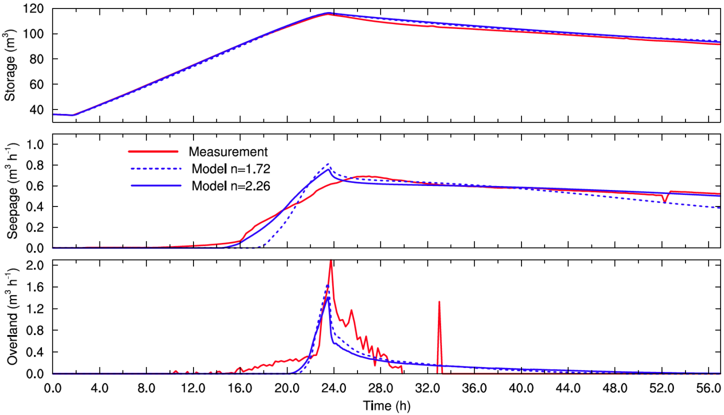




After the experiment: the rainfall was stopped after 22 h due to the occurrence of overland flow.

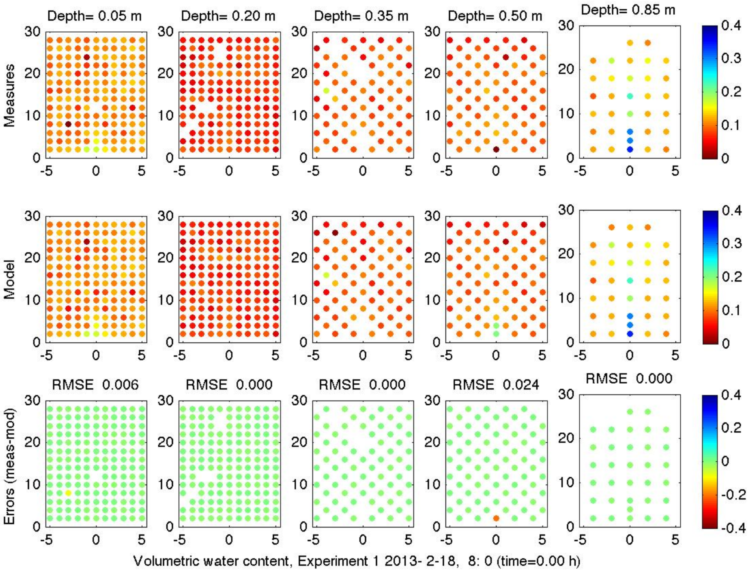
Hydrological response and model results



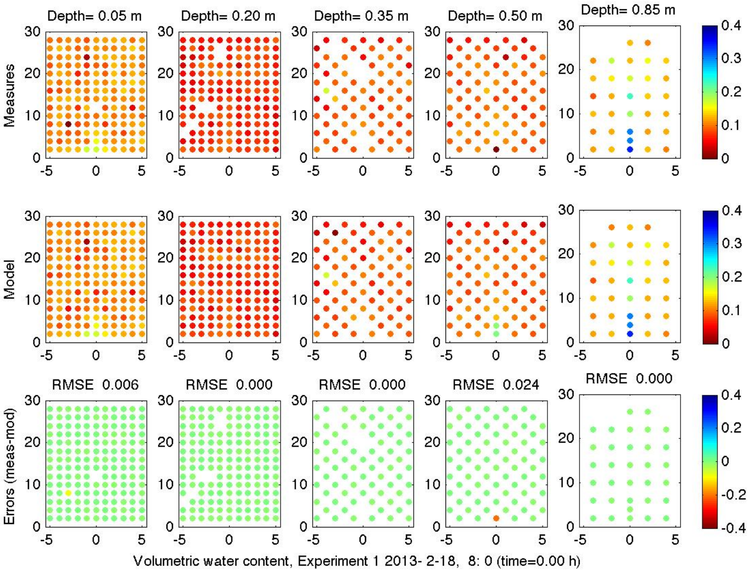
Measurements and model results for two values of the Van Genuchten parameter n. Results with heterogeneous K_S at the seepage face.

(Niu et al. 2014, HESS)

Sensors of volumetric water content



Sensors of volumetric water content



From the first experiment at LEO it is evident that the soil hydraulic properties are heterogeneous along the landscape.

Main questions addressed

- Is it possible to estimate the spatial distribution of the saturated hydraulic conductivity assimilating the volumetric water potential measurements?
- Since the embedded sensors are expected to fail over time and it will not be possible to replace them, how does the observability of the system (and the parameter estimation process) deteriorate in the presence of sensor failure?

Synthetic scenario reproducing Experiment 1 at LEO

Assumption: $Y = log(K_S)$ is a Gaussian random field with exponential covariance function. $E[K_S] = 10^{-4}$ m/s with coefficient of variation 100% ($\mu_Y = -9.56$, $\sigma_Y = 0.83$)

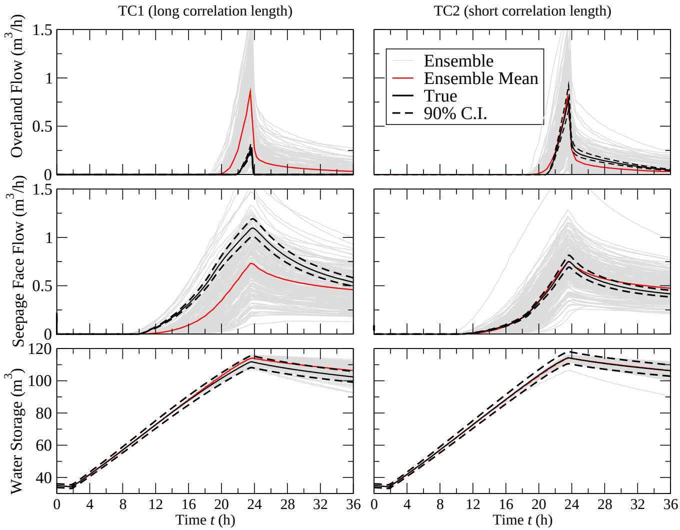
- Test case 1 (TC1): $\lambda_x = \lambda_y = 8$ m; λ_z= 0.5 m
- Test case 2 (TC2): $\lambda_x = \lambda_y = 4$ m; λ_z= 0.25 m

Data Assimilation scheme

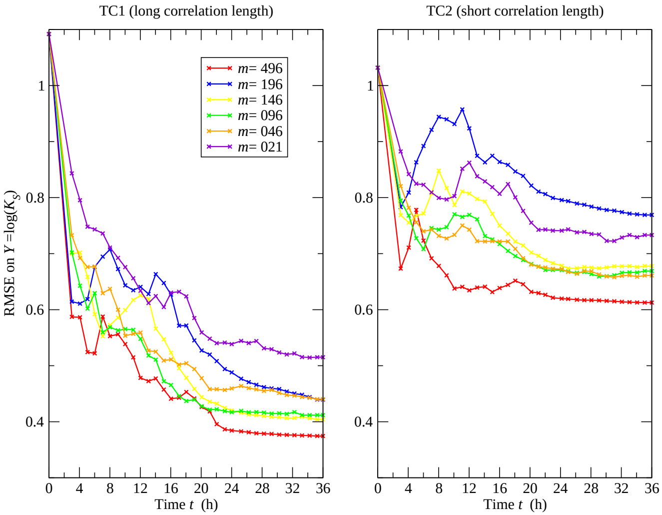
Ensemble Kalman filter with state augmentation

Sensor failure analysis

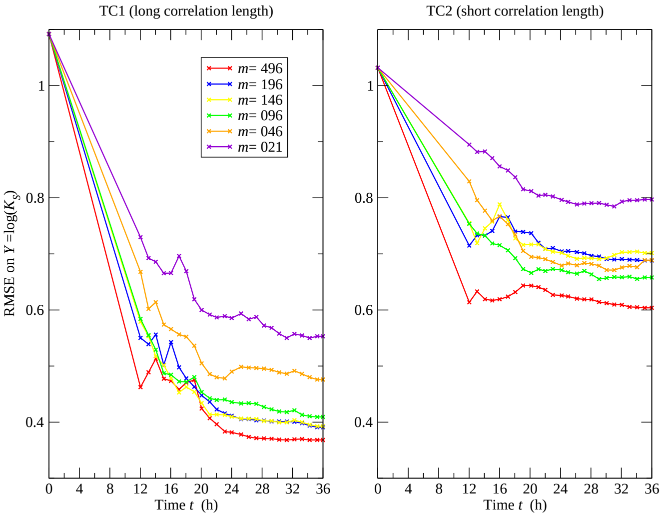
The assimilation is repeated decreasing the number of measurements, from m=496 to m= 21 active sensors.



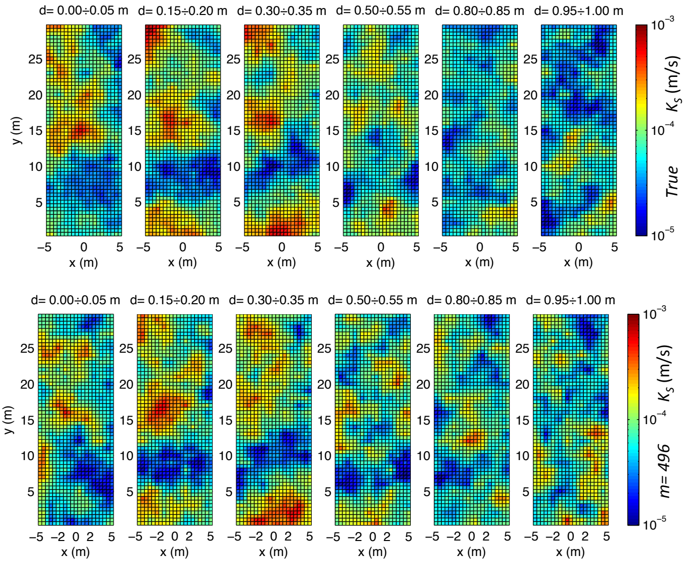
Open loop: model response with 200 random realizations of the prior distribution of $Y = log(K_S)$ without data assimilation.



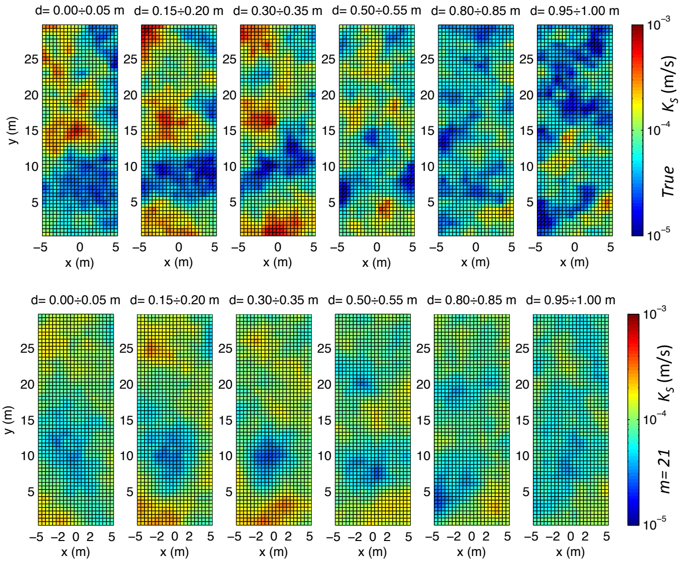
Root mean squared error (RMSE) between the true K_S and the ensemble realizations of K_S. First assimilation is performed at t= 3 h.



Root mean squared error (RMSE) between the true K_S and the ensemble realizations of K_S. First assimilation is performed at t=12 h.



True and estimated spatial distributions of K_S in TC2.



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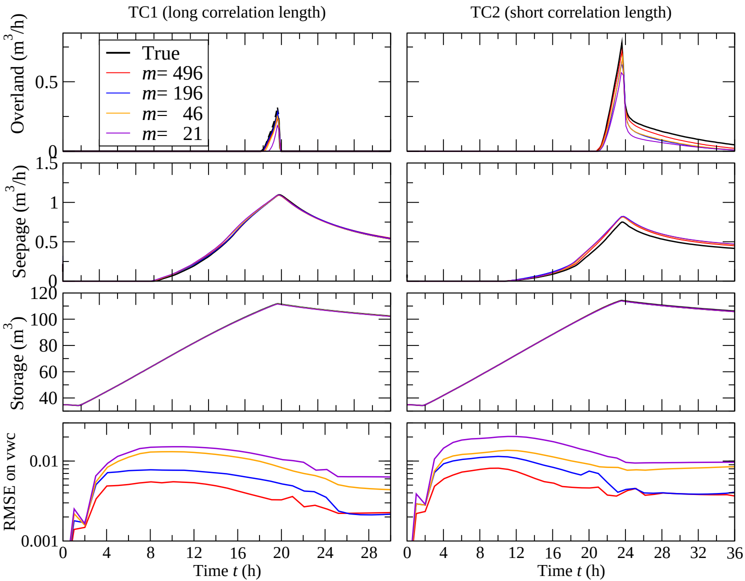
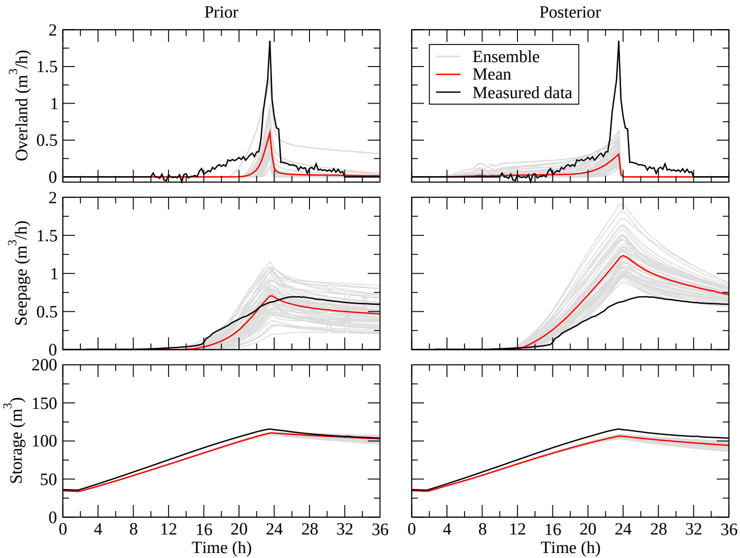


Model response with the calibrated saturated hydraulic conductivity

Conclusions

- Assimilation of volumetric water content from the LEO sensor network seems to successfully reconstruct the main features of the spatial distribution of K_S in the numerical model of LEO.
- The parameter estimation is more accurate for the higher correlation length.
- Differences in reconstruction are apparent according to the degree of sensor failure; nonetheless we are able to reproduce the integrated hydrological response of LEO also with a low number of sensors (m=46).
- The parameter estimation is more accurate when assimilation is activated after all the sensors have responded to the signal.



Assimilation of the real measurements (WORK IN PROGRESS)


Thank you for your attention