



**Royal Netherlands** Meteorological Institute Ministry of Infrastructure and the Environment

Exploring the use of an ensemble Kalman Filter in a continuous SCM evaluation at the ARM sites

Peter Baas **Roel Neggers**  Exploring the use of ensemble Kalman Filtering in a continuous SCM evaluation at the ARM sites







# The SCM approach

#### SCM

- Transparent / flexible
- Cheap

#### What about the forcings?

- Go with uncertainty
- Nudging towards some "true" state
- Alternative: assimilate observations! → enKF

#### Motivation

- Improve the ability to compare SCM results with observations
- Compare different parameterizations
- Compare results of SGP with Cabauw, The Netherlands









# Ensemble Kalman Filter (enKF)

- Weighted average between model and observations
- Based on statistics of ensemble of model realizations
- Model covariances evolve in time



Source: Data Assimilation Research Testbed (NCAR)



# SCM details and enKF implementation

- ECMWF, REF version vs. TKE
- Monthly runs ARMSGP Central Facility with coupled soil/vegetation scheme (here: 1999)
- Assimilated variables (hourly):
  - Surface observations of  $u_1$ ,  $v_2$ , T and  $q_2$
  - Soil moisture and soil temperature of ERAinterim
- Initial profiles drawn from Gaussian distribution with correlations derived from climatology
- → How effective is the enKF in transporting the impact of the assimilated surface observations upwards?



# Localization and large-scale forcings

- A localization function\* constrains the impact of the enKF to the lowest kms
- In the upper part of the domain relaxation to the forcings is applied (τ = 6h):
  - Geostrophic wind and subsidence from ERAinterim
  - Dynamic tendencies from ARM variational analysis



\* 5th order polynomial by Gaspari and Cohn (1999)



#### 1999 results for cloud cover

- Model underestimates cloud cover
- REF better than TKE
- Runs with enKF generate higher cloud cover
- EnKF retains differences between model branches



Example: modeled and observed total cloud cover at the ARM site. Monthly averages for 1999.



# Southern Great Plains versus Cabauw (NL)

- Rms error profiles of temperature and relative humidity for 12 LT
- Atmospheric soundings serve as a reference





### Nocturnal low-level jet (JJA)





Diamonds = ARMSGP radiosondes

Comparison with wind profiler observations



#### EnKF improves mixed layer representation

- EnKF retains differences between model branches
- Cloud cover is underestimated (REF better)
- Nocturnal jet is underestimated (TKE better)
- Comparable results were obtained for Cabauw (NLD)

#### Exploring the use of ensemble Kalman Filtering in a continuous SCM evaluation at the ARM sites

#### Peter Baas\*, Roel Neggers

In single-column modeling (SCM), often relaxation is applied towards a "true" state that can be either observations or model products. Relaxation prevents excessive model drift, while still allowing the physics to develop its own unique state. In this way, a valid comparison of SCM results with observations remains possible. A possible alternative to relaxation is the assimilation of local measurements. As such, in the present study we explore the use of an ensemble Kalman filter (enKF).

small.

2. Results
2.1 Thermodynamic State

2.2 Cloud Cover

Monthly averages over 1999.

averages over 1999):

cloud cover.

cover.

A comparison of three months of SCM

simulations with 1800 LT atmospheric

soundings demonstrates that employing an

Hodeled and observed total cloud cove

Figure B compares modeled total cloud cover to combined observations of a cloud

radar and a micropulse lidar as obtained from the ARM CMBE database (monthly

· The models underestimate cloud

The enKF retains the differences

between the model branches.

2.3 Nocturnal low-level let

· The runs with enKF generate higher

Consequences for the representation of the

summertime nocturnal low-level let are

shown in Figure C. It presents averaged

hodographs at 200 m above the surface. Additionally, Figure D gives rms profiles for

enKF gives a significant improvement of

the representation of temperature and

boundary layer (Figure A). Differences

between the two model branches are

humidity profiles in the convective

#### 1. Method

An enKF uses the statistics of an ensemble of model realizations as a proxy for the model covariance matrix. A weighted average between model and observations provides a most probable estimate of the state of the atmosphere.

We assimilate surface observations of wind (u,v), temperature, and specific humidity obtained from the ARM Central Facility site into the SCM of the ECMWF model. The model is run for a long period of time to build up statistical significance (see poster by Roel Heggers). As large-scale forcing we use a combination of ERAinterim and the ARM variational analysis product.

We compare the REF version of the model, which uses a K-profile method, with an experimental TKE version, which applies a turbulent kinetic energy closure formulation.







0000 LT.

# 

Repare C. Composite hodographs at 200 m above the surface for Jane-August 1999. The distinct fine represents wind profiler observations; numbers indicate local time.

A comparison with observations from the 915 MHz wind profiler shows that: • TKE captures the wind dynamics much better than REF, but differences with observations remain (complexity of

the forcings may play a role).

The impact of the enKF is negligible.



Figure D. Arenage rats error profiles of whot speed over Jane-August 1999 for 6650 LT. Wild profiler observations serve as a reference.

#### 3. Conclusion

Using an ensemble Kalman filter, rms errors were significantly reduced over the depth of the daytime mixed layer in comparison with applying a simple nudging technique.

Replacing the reference 1<sup>st</sup> order diffusion scheme by a TKE scheme yields a much better representation of the nocturnal lowlevel jet. Cloud cover is underestimated by both model branches.

Comparable results were obtained for the Cabauw site (The Netherlands).



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# Initial conditions

- Create perturbed profiles of u, v, T, q,  $T_{skin}$ ,  $q_{skin}$ ,  $T_s$ ,  $q_s$  for each ensemble member with realistic correlations
- Monthly correlations are derived from 3-year driverfile archive





### Initial conditions

- Generate random perturbation matrix with correct correlations (derived from driverfile climatology).
- Specify stdevs:  $\sigma_u = \sigma_v = 1$ m/s,  $\sigma_T = \sigma_{Tskin} = \sigma_{Ts} = 1$ K,  $\sigma_q = 0.5$ g/kg,  $\sigma_{qskin} = \sigma_{qs} = 0.02$ m<sup>3</sup>/m<sup>3</sup>.
- Calculate profiles

1. E.g. for every ensemble member: T(z,ens#) = 3D(z) + RM(T(z),ens#) \* std(T) \* max(0 ; 1-z/4000)





### Motivation

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- Compare different parameterizations
- Improve the ability to compare SCM results with observations
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Southern Great Plains

Cabauw