17th Conference on Mountain Meteorology
27 Jun – 1 Jul 2016
Burlington, VT

Bias estimation and correction for *in situ* observations over complex terrain using an ensemble Kalman filter with the WRF model

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Assimilating near-surface in-situ observations over complex terrain is challenging for several reasons. One is that observation representativeness errors can be fundamentally different, and greater, than those from many other above-surface observing platforms. An example is an anemometer sited on a slope that cannot be properly represented within discretized numerical weather prediction (NWP) model equations, or affected by surrounding features such as buildings or vegetation that a model cannot represent. Observation errors can be both random and systematic. In the data assimilation process, systematic observation representativeness errors can lead to systematic errors in initial conditions for a prediction. To mitigate systematic errors in data assimilation over complex terrain, this work presents a methodology to correct and estimate biases of individual in-situ observations.

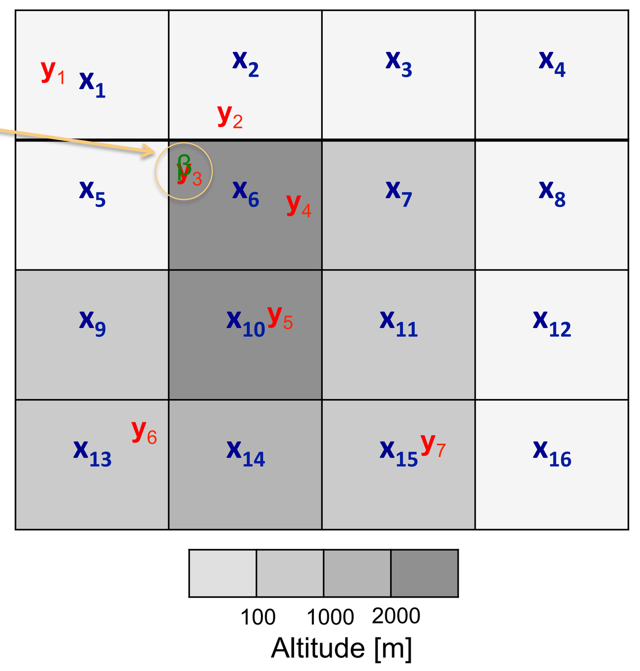
METHODS

Biased observations are modeled as:

$y = h(x) + \varepsilon + \beta$

y_i observations
x_j state variable
β parameter

β parameter that estimates the bias in y_3



ε Gaussian noise with zero mean and standard deviation σ_0^2

h(x) forward operator: linear interpolation considering the nearest grid point

State-vector augmentation is used to estimate β

$$z=[\mathbf{x}, \beta]^T$$

x and **β** are simultaneously updated by applying the Kalman filter equations. The methodology of **Kalman filter** equations is applied to the state space augmentation, then analysis equation are given by:

$$\mathbf{z^a} = \mathbf{z^f} + \mathbf{K}(\mathbf{y^o} - \mathbf{Hz^f})$$

$$\mathbf{K} = \mathbf{P^f H^\top}(\mathbf{HP^fH^\top} + \mathbf{R})^{-1} \quad \text{where} \quad \mathbf{P^{f,a}} = \begin{bmatrix} \mathbf{P^{f,a}_x} & \mathbf{P^{f,a}_{x\beta}} \\ \mathbf{P^{f,a}_{x\beta}} & \mathbf{P^{f,a}_{\beta}} \end{bmatrix}.$$

$$\mathbf{P^a} = (\mathbf{I} - \mathbf{KH})\mathbf{P^f}$$

Matrix of ensemble perturbations $P^{f,a}=Z^{f,a}(Z^{f,a})^T$

Linking the model state variable to the parameters

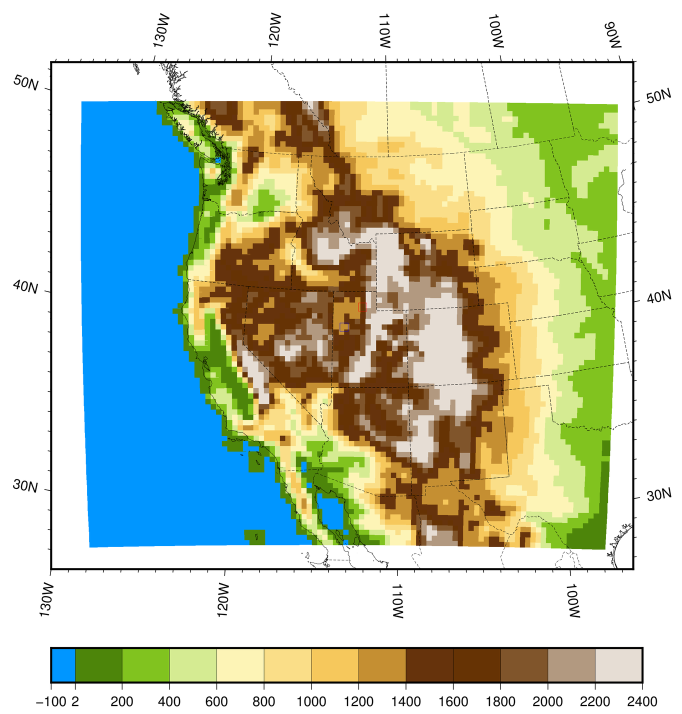
minimum threshold value!

EXPERIMENTS

MODEL CONFIGURATION

Weather Research and Forecasting (**WRF**; Skamarock et al. 2008): Version 3.6.1

- The target region is the western U. S with 30-km horizontal grid spacing
- Full 3-h cycling for 10-day period, starting at 00 UTC on 20 Sep 2012
- The initial and lateral boundary conditions are from GFS



PARAMETERIZATION	NAME
Longwave Radiation	RRTM
Shortwave Radiation	Dudhia
Boundary Layer	YSU
Cumulus	Grell-Freitas
Land Surface	Noah
Surface Layer	MM5 Similarity Theory
Microphysics	Thompson

DATA ASSIMILATION STRATEGIES

WRF is coupled with the Data Assimilation Research Testbed (**DART**; Anderson et al. 2009)

Filter type	EAKF (Anderson, 2001)
Ens. members	80
Assim interval	3h
Inflation	Adaptive and spatially-varying : ini 1.1, std 0.6
Localization	Surf. Obs 0.05 (300 Km) Upper obs 0.12 Parameters 0.00 Adaptive (1000 obs.)

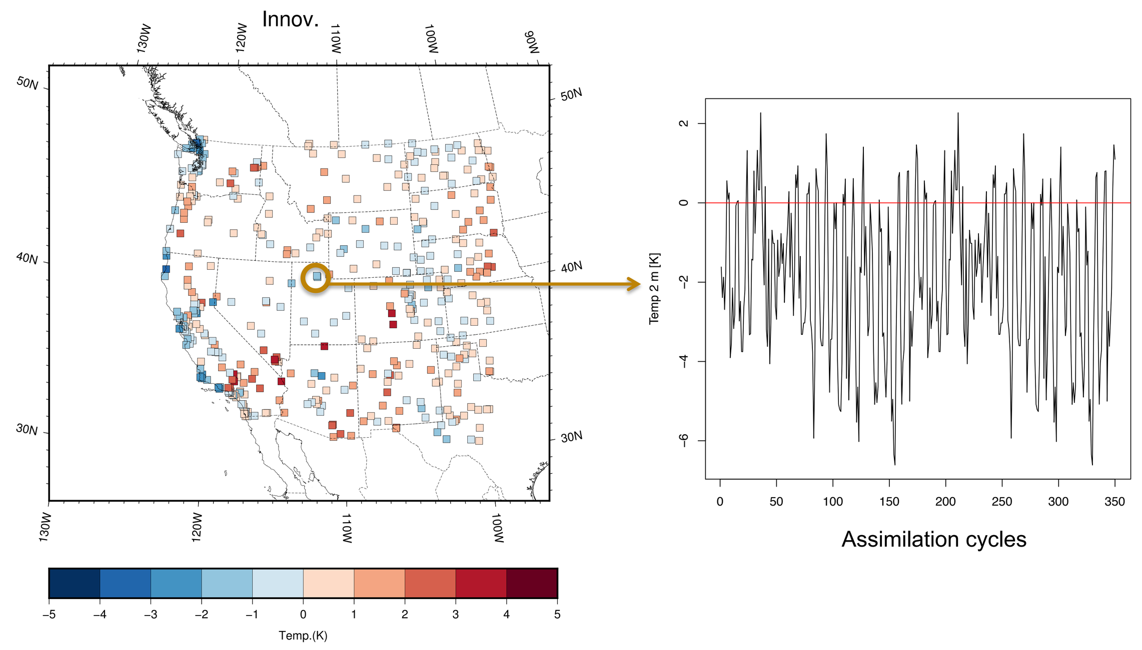
Assimilated Obs.	MADIS and MATERHORN
Estimated	METAR T2 (423)
σ^2_O	6.25 K
Minimum σ^2_β	0.5

- Observations from **MADIS** (NCEP Meteorological Assimilation Data Ingest System) platform are radiosonde, aircraft, ACARS, satellite winds, marine, METAR, and mesonet observations.
- **MATERHORN** field campaigns using tethersondes for wind components, temperature, and specific humidity.

RESULTS

Evidence of systematic representativeness errors

Time mean for the innovation (y-$h(x^f)$) at each METAR ob for 2-m temperature. Most of the larger values are associated to height differences between the model and the observation.



The time evolution of the innovation is analyzed for an observation affected by systematic representativeness error (height difference between the model and the observation larger than 300 m). Negative innovations occurred during most assimilation cycles.

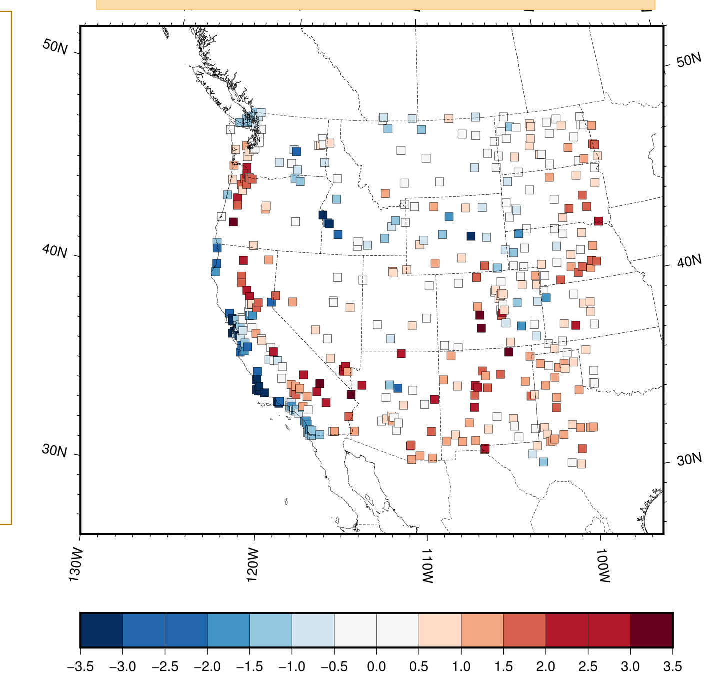
Bias estimation and correction for METARs (T2)

Parameters are included to estimate the bias of 423 METAR obs for 2-m temperature

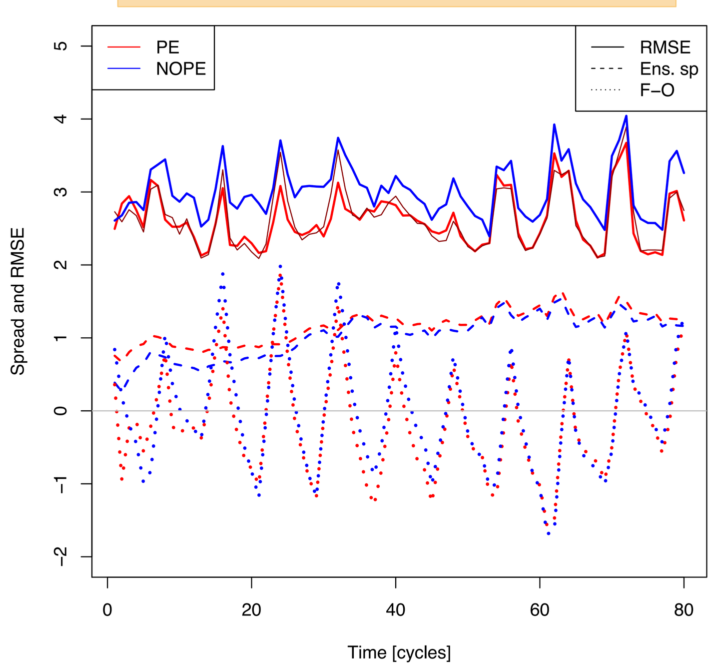
The analysis is performed in the observational space of the METARs

Is the bias estimated?

The spatial distribution of the estimated biases has negative values along the West Coast and positive values in some mountainous regions.



Is the bias corrected?

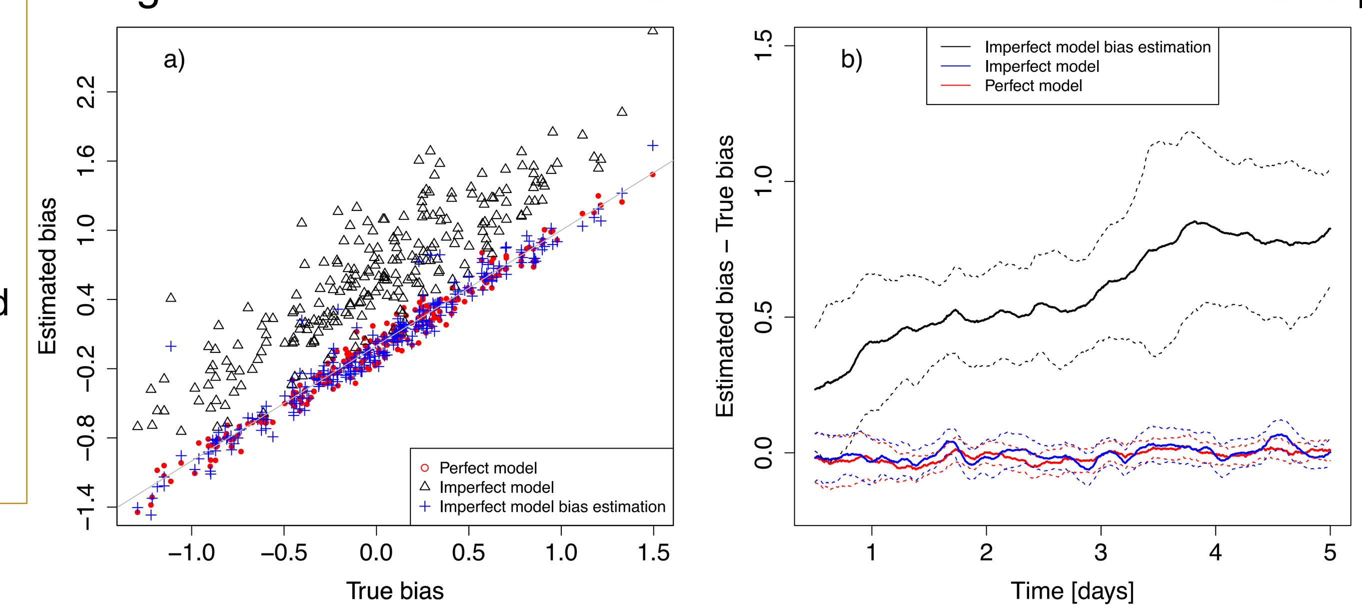


RMSE for parameter estimation (PE) is lower than for no bias estimation (NOPE) experiments. However, there are negligible differences between the two experiments for innovation and ensemble spread.

Performance of the methodology (Lorenz 2005)

A highly chaotic model (Lorenz 2005) is used to test the performance of the bias estimation, Using **960** state variables and **240** unknown observations with **240 β_O**

The bias in the obs follow a Gaussian spatial distribution. Biases are accurately estimated for a perfect model and for imperfect model if also model errors are estimated.



However, bias estimation in a model with unknown errors could be worse than no bias estimation.

Perfect model (F=15) **z=[x, β_O]** Imperfect model (F=13) **z=[x, β_O]** Imperfect model bias estimation **z=[x, β_O, β_M]**

DISCUSSIONS

- The bias can be flow dependent, e.g., surface temperature is underestimated during the day.
- Correlations between biases and observations could introduce noise.
- How to evaluate the methodology? The ideal will be using unbiased observations co-located where the biased observations are.

CONCLUSIONS

- The methodology estimates and corrects the bias in a **low-level perfect model**, but blind-bias methods may be advisable when model errors are significant.
- Conclusions from the **WRF model** are more ambiguous. The estimated bias has a spatial distribution with larger values in areas affected by representativeness errors. Errors are lower when observation biases are estimated.

References

- Anderson, J. L., 2001: An ensemble adjustment Kalman filter for data assimilation. *Mon. Wea. Rev.*, **129**, 2884-2903.
- Skamarock, W. C., and Coauthors: A description of the advanced research WRF version 3. Tech. rep., NCAR Tech. Note TN-475+STR, 113 pp. doi:10.5065/D68S4MVH
- Lorenz, E.N., 2005: Designing chaotic models. *J. Atmos. Sci.*, **62**, 1574–1587. doi: 10.1175/JAS3430.1.

Acknowledgment

This work was funded by the Mountain Terrain Atmospheric Modeling and Observation Program (MATERHORN)