GRoW - GlobeDrought
Characterizing drought risk and impact

Modeled water – vegetation dynamics under revision using GRACE-based data assimilation

Helena Gerdener[1], Jürgen Kusche[1], Kerstin Schulze[1], Gohar Ghazaryan[2,3,4], Olena Dubovyk[2,3]
[1]Institute of Geodesy and Geoinformation, University of Bonn, Bonn, Germany
[2] Remote Sensing Research Group (RSRG), Department of Geography, University of Bonn, Bonn, Germany
[3] Center of Remote Sensing of Land Surfaces, University of Bonn, Bonn, Germany
[4] Leibniz Center for Agricultural Landscape Research, Müncheberg, Germany

This presentation participates in OSPP
Outstanding Student & PhD candidate Presentation contest

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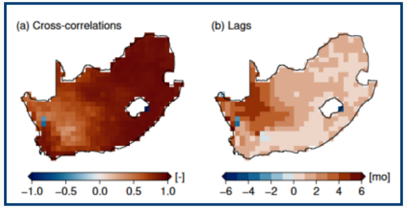
MOTIVATION

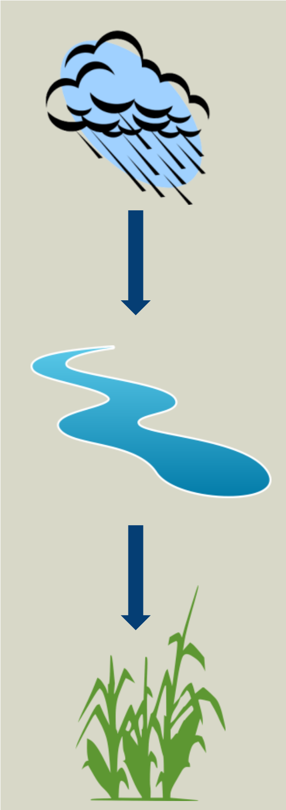
- Water is an essential source for food production and drinking water
- Countries where a large part of the population depends on the agrictultural sector are strongly affected by water shortages, for example South Africa
- Important to build a realistic picture of the response dynamics of fluxes precipitation to water storages and vegetation
- Analysis of surface and subsurface water mostly based on in-situ data or models; GRACE data rarely explored due to resolution issues, does not separate storages

WATER PROPAGATION

Model simulations

- Enable extending the very local scale to a regional or global scale
- Here we use Watergap 2.2d/e Water storage and vegetation measures
- Based on assumptions and forcing data uncertainty
- E.g. there can be unrealistic values of actual evapotranspiration (AET) in some regions compared to observed AET:





Observation-based data

- GRACE assimilation into WGHM
    - Soil mositure
    - Surface water
    - Groundwater
- Vegetation indices from remote sensing
    - MODIS Actual Evapotranspiration
    - MODIS Leaf Area Index

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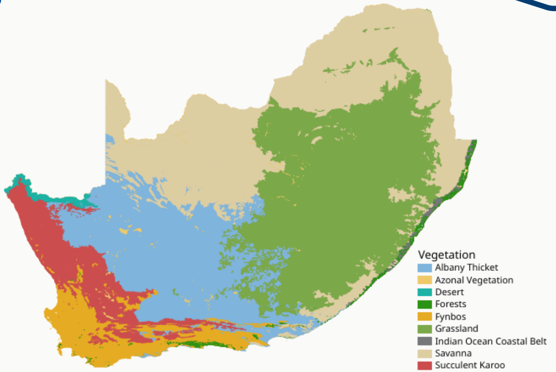
STUDY IN SOUTH AFRICA

In revision JoH
May 2022

Revising precipitation - water storages - vegtation signatures with GRACE-based data assimilation

H. Gerdener, J. Kusche, K. Schulze, G. Ghazaryan, O. Dubovyk

- **AIM:** Assessing modeled water - vegetation dynamics by observation-based data sets



- Methods:

Regression model

- Extract subsignals
- Relate Ampltudes and Phases

$$\phi(j)_{P,GW} = \phi(j)_{GW} - \phi(j)_{P},$$

Process Model

- Relate current water storage to precipitation of the same month and previous month water

$$S_i(t) = c_i \cdot S_i(t-1) + d_i \cdot P_i(t),$$

Principal Component Analysis

- Extract dominant modes
- e.g. Drought or ENSO related

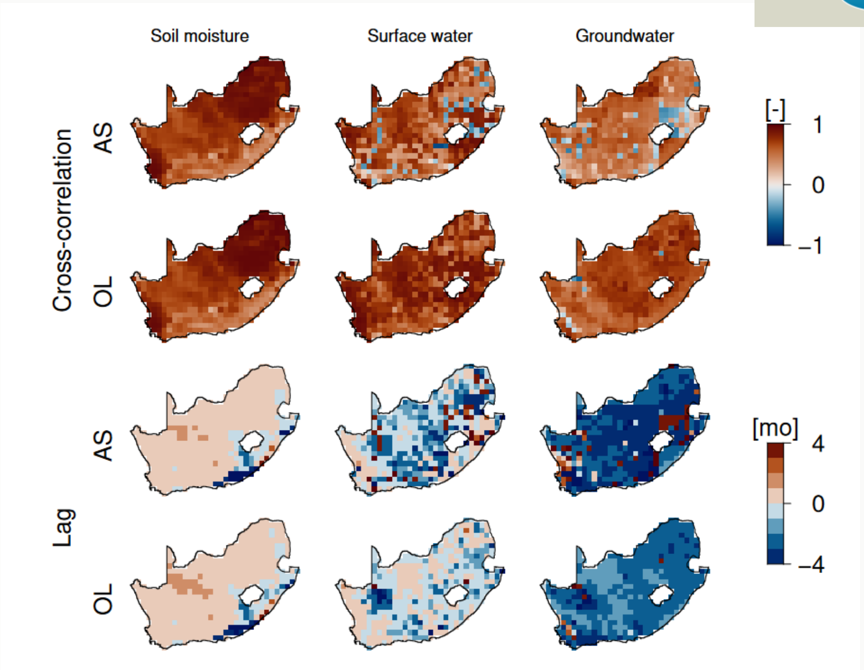
$$\mathbf{X} = \mathbf{P}\mathbf{E}^T, \mathbf{P} = \mathbf{X}\mathbf{E},$$

Correlation Analysis

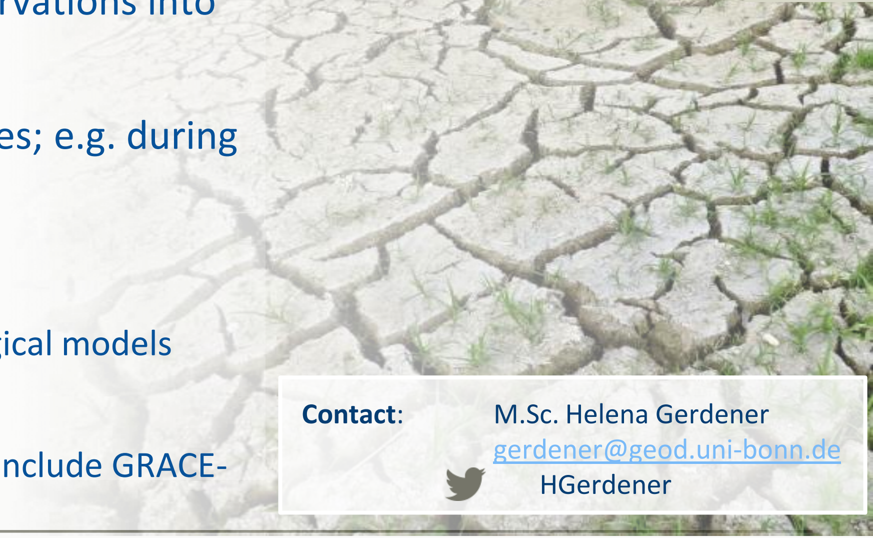
- Extract correlations and lags between data sets

DA STUDY IN SOUTH AFRICA: RESULTS

- Duration for precipitation recharging surface and groundwater storage is shorter modeled than observed
- Model overestimates precipitation amount contributing to water storage (same for water storage amount contributing to vegetation)
- Observed propagation time of vegetation to soil mosture if often shorter than in the model



TAKE HOME



1) Observation-based data sets enable a more realistic picture of water propagation through water cycle as compared to the model

   →emphasize the need for assimilating GRACE observations into the models

2) Insights will help modelers improve model structures; e.g. during climate events

OUTLOOK:

- Compare the water – vegetation dynamics in other hydrological models with our data sets
- Extend the assimilation framework further: Global analysis, include GRACE-FollowOn, simultaneous calibration and data assimilation

Contact: M.Sc. Helena Gerdener
gerdener@geod.uni-bonn.de
HGerdener

LITERATURE

Döll, P., F. Kaspar and B. Lehner (2003).A global hydrological model for derivingwater availability indicators: model tuning and validation. J Hydrol, 207:105–134.doi:10.1016/S0022-1694(02)00283-4.

Eicker, A., Schumacher, M., Kusche, J., Döll, P., & Schmied, H. M. (2014). Calibration/data assimilation approach for integrating GRACE data into the WaterGAP Global Hydrology Model (WGHM) using an ensemble Kalman filter: First results. Surveys in Geophysics, 35(6), 1285-1309.

Evensen, G. (1994). Sequential data assimilation with a nonlinear quasi-geostrophic model using Monte Carlo methods to forecast error statistics. *Journal of Geophysical Research: Oceans*, *99*(C5), 10143-10162.

Gerdener, H., Kusche, J., Schulze, K., Ghazaryan, G., Dubovyk, O. (submitted): Revising precipitation – water storages – vegetation signatures with GRACE-based data assimilation

Mayer-Gürr, T., Behzadpour, S., Ellmer, M. Kvas, A. Klinger, B., Zehentner, N. (2016): ITSG-Grace2016 - Monthly and Daily Gravity Field Solutions from GRACE. GFZ Data Services. http://doi.org/10.5880/icgem.2016.007

Müller Schmied, H., Cáceres, D., Eisner, S., Flörke, M., Herbert, C., Niemann, C., Peiris, T. A., Popat, E., Portmann, F. T., Reinecke, R., Schumacher, M., Shadkam, S., Telteu, C.-E., Trautmann, T., and Döll, P.: The global water resources and use model WaterGAP v2.2d: model description and evaluation, Geosci. Model Dev., 14, 1037–1079, https://doi.org/10.5194/gmd-14-1037-2021, 2021.

Scanlon, B. R., Zhang, Z., Save, H., Sun, A. Y., Schmied, H. M., Van Beek, L. P., ... & Bierkens, M. F. (2018). Global models underestimate large decadal declining and rising water storage trends relative to GRACE satellite data. Proceedings of the National Academy of Sciences, 115(6), E1080-E1089.

BACKUP SLIDES

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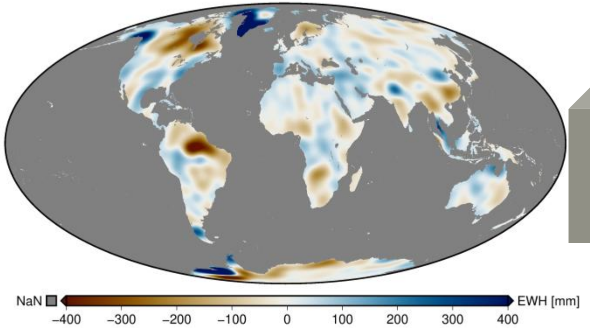
ADDRESS CHALLENGE:

COMBINATION OF REAL OBSERVATIONS WITH MODEL OUTPUT

PDAF
Parallel data assimilation framework
http://pdaf.awi.de

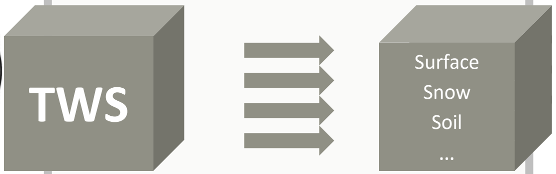
GRACE – Real observation



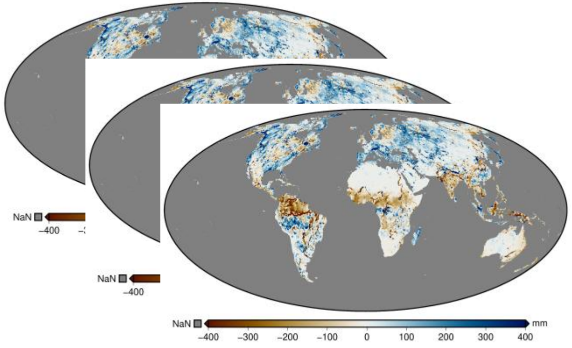
Spatial resolution ca. 300 km
monthly

Data Assimilation

Based on Eicker et al., (2014), Evensen (1994)



WGHM – Hydrological model



Spatial resolution ca. 50 km
daily

By assimilating GRACE into WGHM…
… the model gets closer to reality
… the spatial resolution of GRACE is increased
… the vertical resolution of GRACE is increased

GLWS: Global Land Water Storage data set
available based on GRACE/-FO assimilation

DATA ASSIMILATION CONCEPT

PDAF
Parallel data assimilation framework
http://pdaf.awi.de

AIM:

Improving the realism of model simulations by updating the model prediction with observations

ENSEMBLE KALMAN FILTER:

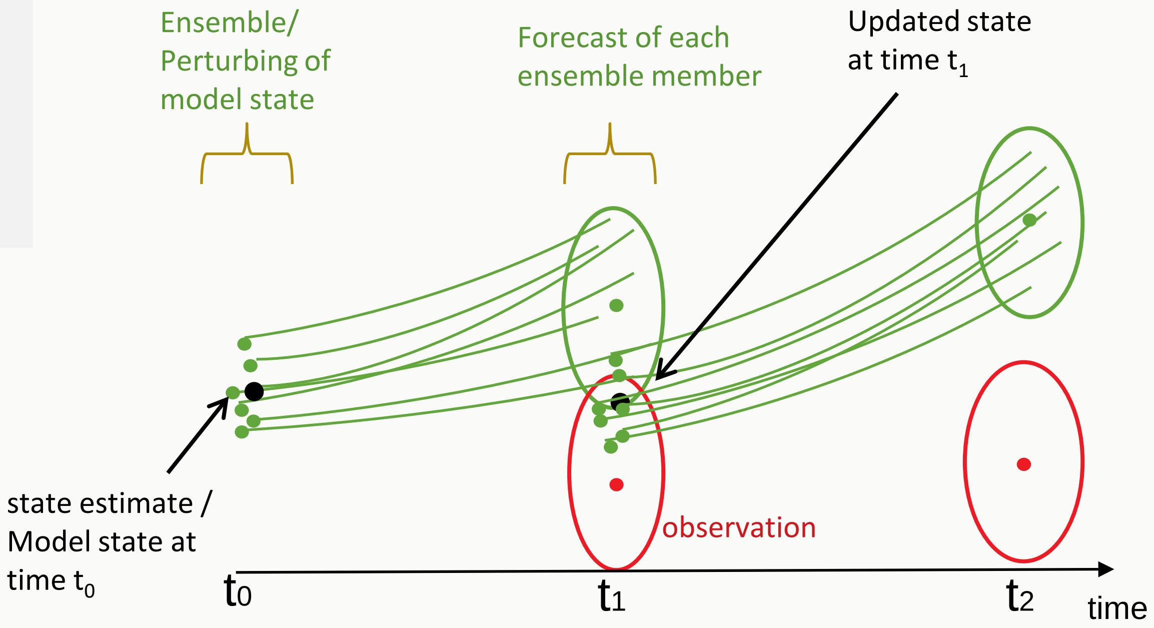
Integrate the observations into the model based on the ensemble spread (Evensen 1994)

PREDICTION:

$$X_k^- = [X_k^{(1)-}, \ldots, X_k^{(N)-}]$$

UPDATE:

$$X_k^+ = X_k^- + K_k(Y_k - AX_k^-)$$



BACKUP: DA STUDY IN SOUTH AFRICA

Multi Linear Regression

Methods:

$$x(j,t) = a_0(j) + a_1(j)(t - t_0) + b_1(j)\cos(\omega t) + b_2(j)\sin(\omega t) + c_1(j)\cos(2\omega t) + c_2(j)\sin(2\omega t)$$

$$A(j)_{annual} = \sqrt{\hat{b}_1(j)^2 + \hat{b}_2(j)^2} \qquad \phi(j)_{annual} = \arctan\left(\frac{\hat{b}_2(j)}{\hat{b}_1(j)}\right)$$

$$A(j)_{P,GW} = \frac{\frac{A(j)_{GW}}{\sigma_{A_{GW}}}}{\frac{A(j)_P}{\sigma_{A_P}}} \qquad \phi(j)_{annual} = \phi(j)_{GW} - \phi(j)_P$$

Principal Component Analysis

$$X = PE^T, P = XE \qquad PC_i = \frac{p_i}{\sigma_{p_i}} \qquad EOF_i = \sigma_{p_i} e_i$$

Process Model

$$S_i(t) = c_i \cdot S_i(t-1) + d_i \cdot P_i(t)$$

$$V_i(t) = e_i \cdot V_i(t-1) + f_i \cdot S_i(t)$$