Using ERS spaceborne soil moisture observations to predict groundwater heads in space and time

Edwin H. Sutanudjaja

Steven M. de Jong, Frans C. van Geer and Marc F. P. Bierkens



ERS Soil Water Index (SWI): → profile soil moisture content (1st meter)

SWI time series are derived from SSM (surface soil moisture ~ 1-5cm)
 SSM time series are derived from backscatter signals.

 \succ An exponential filter is used to convert from SSM to SWI.



Study area: Rhine-Meuse basin



SWI resolution used: half arc-degree and monthly

Study area: Rhine-Meuse basin



> 5000 point-scale groundwater head time series are used.

Correlation SWI & head time series:



In some areas, there are time lags between SWI and head time series.
 Stronger correlations are in shallower groundwater heads.

Histogram of correlation coefficients



 $\stackrel{\scriptstyle \succ}{\scriptstyle \rho}_{(lag=0)}$

- : cross correlation coefficients without lags (lag = 0)
- : highest $\boldsymbol{\rho}$ (from CCF), with lags = lagbest

Maps of correlation coefficients & lags:



$$(lag = 0)$$
 : cross correlation coefficients without lags (lag = 0)

: highest *P* (from CCF), with lags = lagbest

best

Stronger correlations & shorter lags are in shallower groundwater.

Can we use SWI to predict heads? Transfer function noise (TFN) models:

TFN model:

$$h_t = h_t^* + n_t \tag{1}$$

$$h_t^* = \sum_{i=1}^{r} \delta_i h_{t-i}^* + \sum_{j=0}^{s} \omega_j \text{SWI}_{t-j-b}$$
 (2)

$$(n_t - c) = \sum_{k=1}^p \phi_k (n_{t-k} - c) + a_t + \sum_{l=1}^q \theta_l a_{t-l}$$
(3)

Using a simple TFN model:

> deterministic parameters

$$\delta_1$$
 , ω_0 and reference/base level c

> stochastic/noise parameters : ϕ_1 and variance σ_a

Parameter estimation:

- Embedding the TFN model in a Kalman Filter algorithm.
- > Objective function: log-likelihood

Prediction with measurement update:



- Calibration: 1995-2000 ; Validation: 2004-2007 (graphs show time updates)
- > Measurement update intervals: red \rightarrow a month; yellow \rightarrow 3 months; black \rightarrow 4 months
- Good performance is (*partly*?) due to measurement updates.

Prediction without measurement update:



red: without measurement update; black: 95% confidence interval
 In shallow groundwater, SWI is useful for predicting groundwater heads.

Prediction without measurement update:



total stations

= 2761

Performances based on the validation run 2004-2007

Timing agreements (ρ_{TF}) are good.

stats with $\rho_{\text{TF}} > 0.5 = 1730$ (63%) But, some with biases (ME); some due to changing parameters (c)

Prediction without measurement update:



- MAE: mean absolute errors
- If biases are removed, the error (MAE) will be smaller.

Maps of prediction performance without measurement updates:



^{*} From ρ_{TF} (timing agreement), predictions are better for shallower groundwater.

Prediction in unvisited locations:

Previous exercise: forecasting in time.

> What about spatial predictions / interpolations?

Spatio-temporal predictions:

- We used few stations (40) ~ data-poor environments
 → Identifying parameters (from the forecasting exercise)
- 2. TFN parameters are estimated using DEM (30" ~ 1km). Derive the regression models: TFN parameters = f (DEM)
- 3. Using estimated parameters (and SWI) to run TFN.

HAND to predict TFN model parameters



- Simplification
- : groundwater heads follow topography as a subdued replica
- Limitations
- Motivation
- : accuracy of DEM (16 m), not incorporating other variations (e.g. soil types) : prediction in un-gauged basins

Spatio-temporal predictions: (parameters are estimated from DEM)



- Example 1: prediction is reasonably good (MAE is small and ρ_{TF} is high)
- ▶ Example 2: MAE is large, but ρ_{TF} is high (0.83 and 0.72) → to detect data errors / local phenomena
- Example 3: deep groundwater (Please don't expect anything!!)

Spatio-temporal predictions (histograms):



- Based on the period 2004-2007. # stations
- [>] Number of stations with ρ_{TF} > 0.50
- Number of stations with MAE_{ano} < 0.25 m</p>

= 1376 **(47%)** = 1901 **(65%)**

= 2925

Spatio-temporal predictions (maps):



Predictions are generally better in shallower groundwater.

Conclusions:

- There are correlations between ERS SWI and groundwater head time series.
- Correlations are stronger in shallower groundwater.
- SWI time series are useful as the input of TFN models for predicting groundwater heads in space and time.
- Predictions are better for shallower groundwater.

Using ERS spaceborne soil moisture observations to predict groundwater heads in space and time

Edwin H. Sutanudjaja

Steven M. de Jong, Frans C. van Geer and Marc F. P. Bierkens



YES!!!

Edwin H. Sutanudjaja

Steven M. de Jong, Frans C. van Geer and Marc F. P. Bierkens



Using ERS spaceborne soil moisture observations to predict groundwater heads in space and time

Edwin H. Sutanudjaja

Steven M. de Jong, Frans C. van Geer and Marc F. P. Bierkens

