

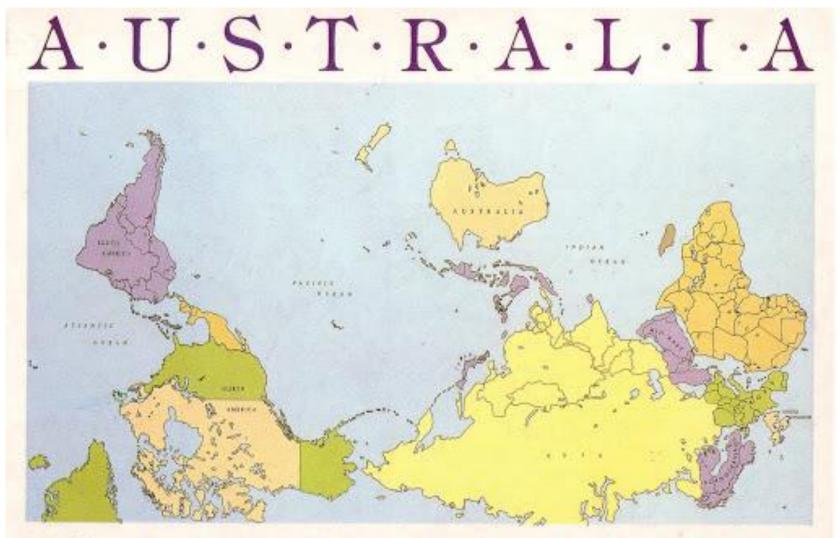


Assimilation of satellite observations into hydrological forecasting An Australian perspective

Albert van Dijk Australian National University, CSIRO Land and Water, Canberra

Thanks to: Luigi Renzullo, Marcela Doubkova, a.o.

H-SAF/HEPEX Workshop on Coupled Hydrology, 3-7 November, Reading



NO LONGER DOWN UNDER

Summary

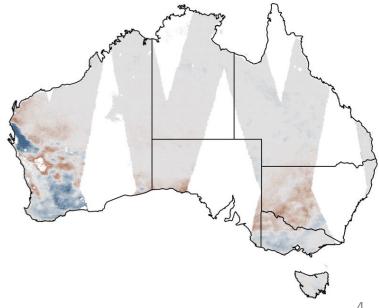
- 1. Assimilating satellite observations of one hydrological variable can demonstrably *improve analysis* of that particular variable.
- 2. However, due to the sometimes loose coupling between variables, those **benefits do not always propagate far** (more so in land surface than atmospheric models).
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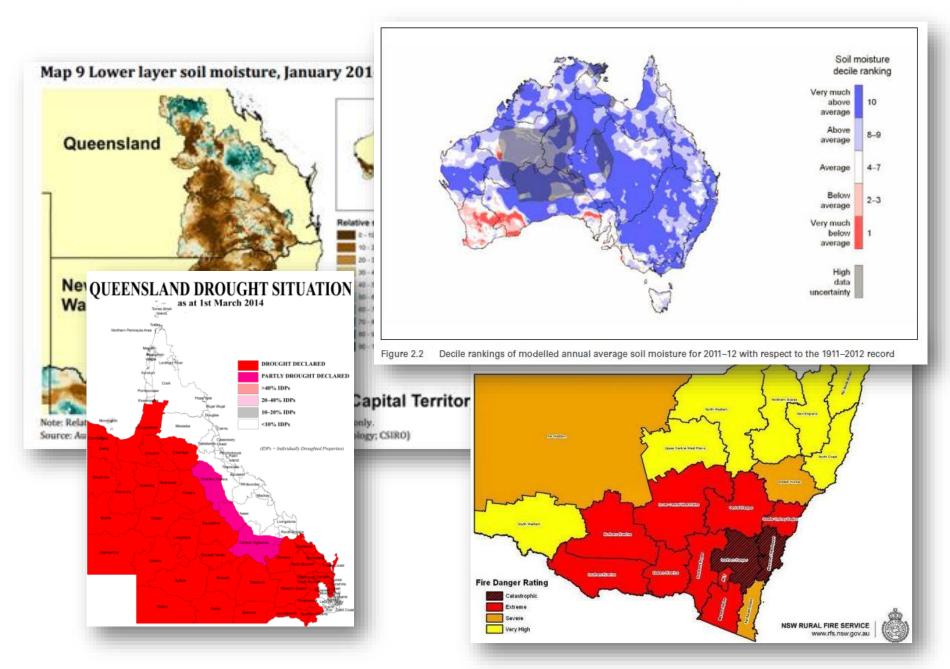
Continental satellite soil moisture data assimilation improves rootzone moisture analysis for water resources assessment

L.J. Renzullo, A.I.J.M. van Dijk, J.-M. Perraud, D. Collins, B. Henderson, H. Jin, A.B. Smith, D.L. McJannet (2014)

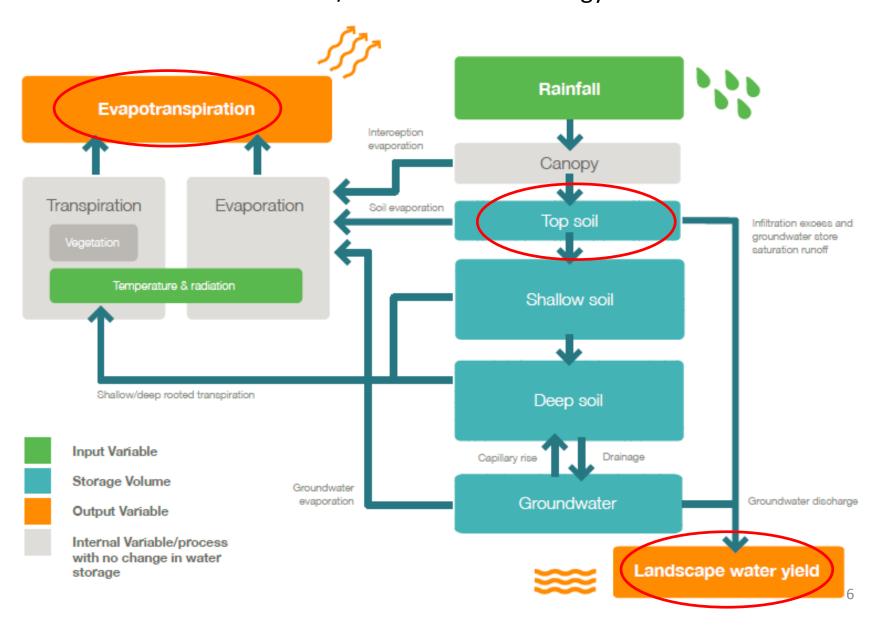
Journal of Hydrology (pre-published, doi: 10.1016/j.jhydrol.2014.08.008)



Soil moisture is of interest in its own right

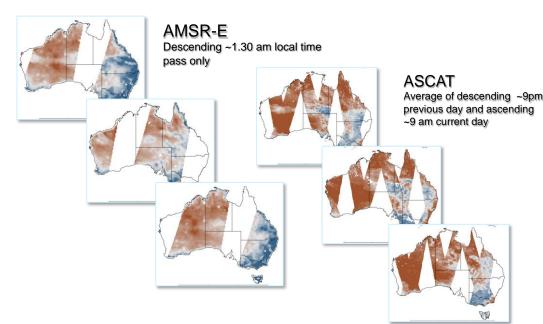


Australian Water Resources Assessment system Landscape (AWRA-L) model CSIRO / Bureau of Meteorology



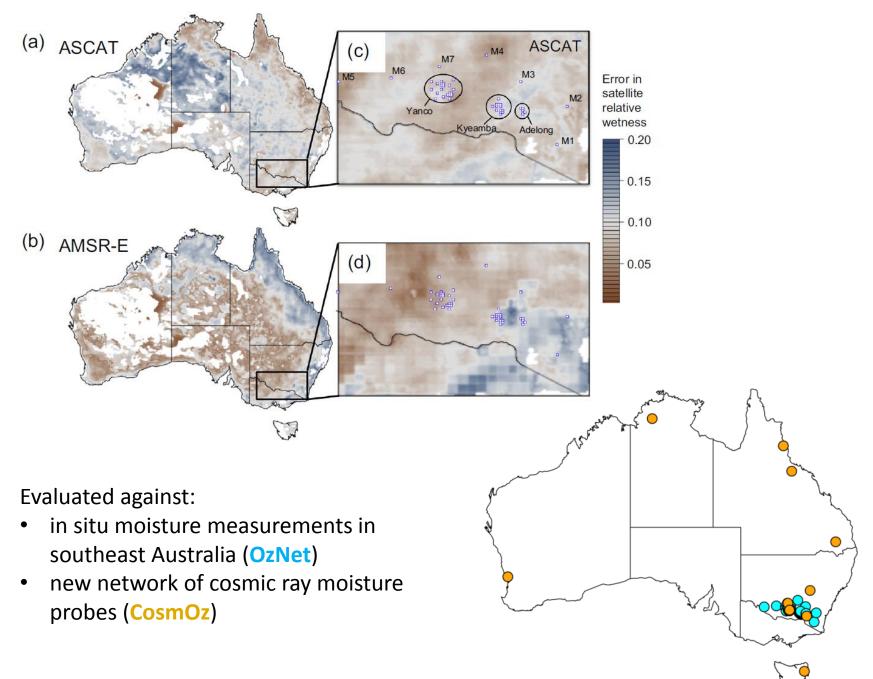
Method

- Perturbed meteorological forcing
- ensemble Kalman filter
- AMSR-E and ASCAT-derived nearsurface soil moisture
- AWRA-L model
- ensembles of daily top-layer and shallow root-zone soil moisture analyses for Australia at 0.05°



Evaluated against:

- in situ moisture measurements in southeast Australia (OzNet)
- new network of cosmic ray moisture probes (CosmOz)



Renzullo J Hyd 2014

AWRA root-zone moisture (open loop; shaded band)

Cosmic-ray probe soil moisture (blue dots)

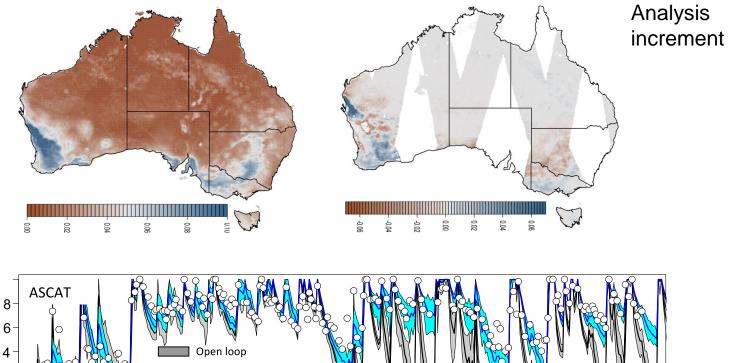
- Already good agreement
- Model misses wet and sometimes dry extremes

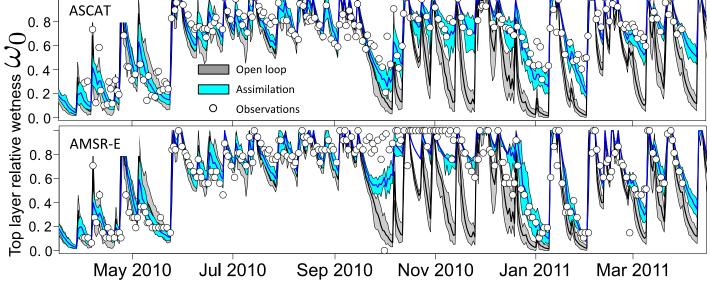
Baldry 4 8 Normalised wetness 3 2 -2 Daly Tullochgorum Yanco 4 Normalised wetness 3 2 0 -1 -2 2011 2012



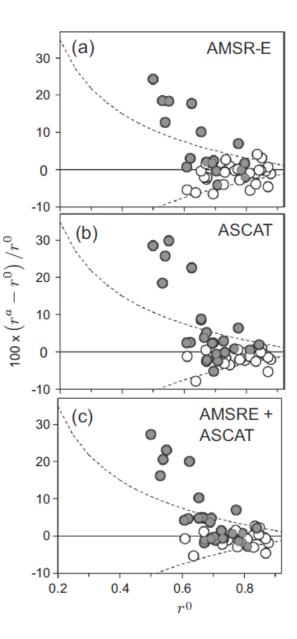
Renzullo J Hyd 2014

Relative wetness for 7 July 2009 (median)





AWRA root-zone moisture estimates correlation against in situ probes increases (r^{α}) as a result of assimilating satellite observations



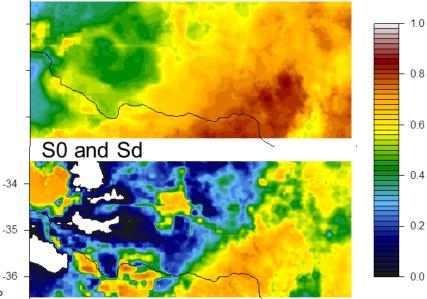
Does the benefit propagate to deeper layers?

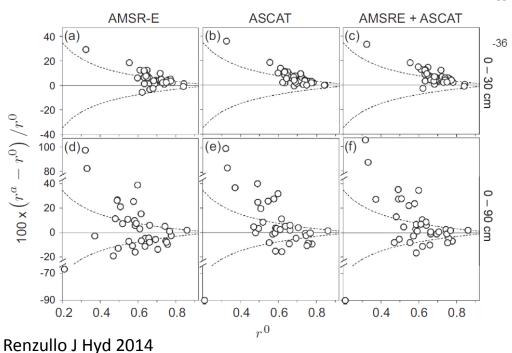
Not really. Partly, that is a lag and temporal averaging issue.

Implications for *temporal* DA scheme design?

Vertical coupling

S0 and Ss





Does assimilating satellite soil moisture (AMSR-E, ASCAT) or satellite ET (CMRS-ET, SLST-ET) improve daily streamflow estimates?

No – they are insufficiently strongly coupled.

0.6

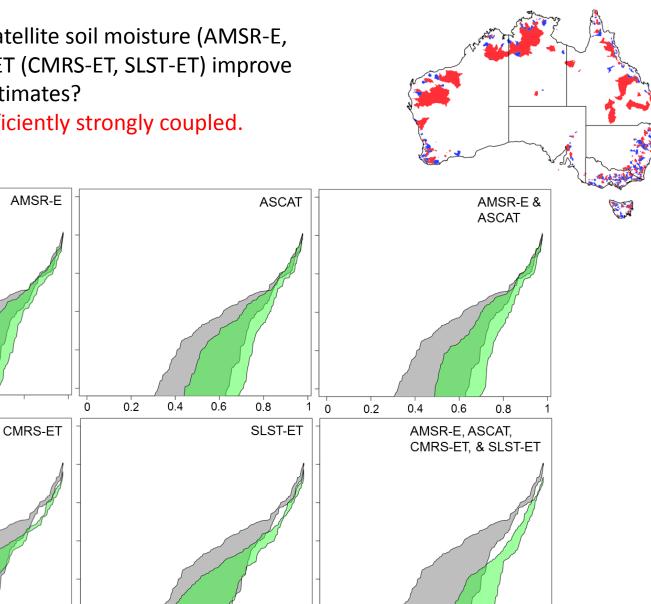
0.8

0

1

0.2

0.4



Percentage of gauged catchments (N=305) with lesser performance

0.4

0.6

0.8

1 0

Nash-Sutcliffe Model Efficiency

1.0

0.8

0.6

0.4

0.2

0.0

1.0

0.8

NSE 0.6

0.4

0.2

0.0

0

0.2

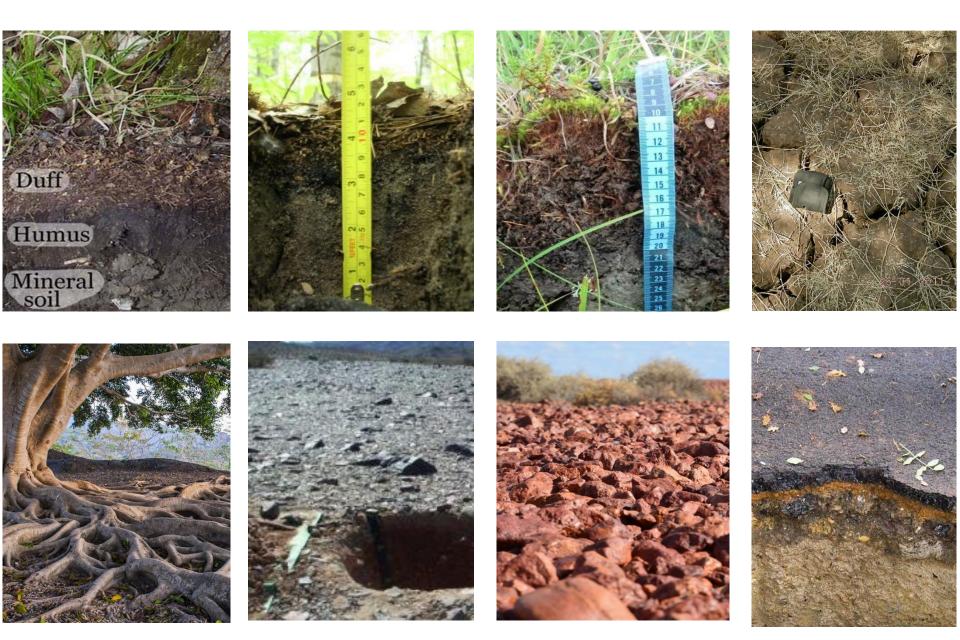
0.6

0.8

0.4

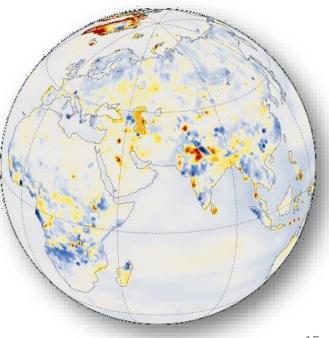
0.2

Some reasons why "absolute" soil moisture is irrelevant

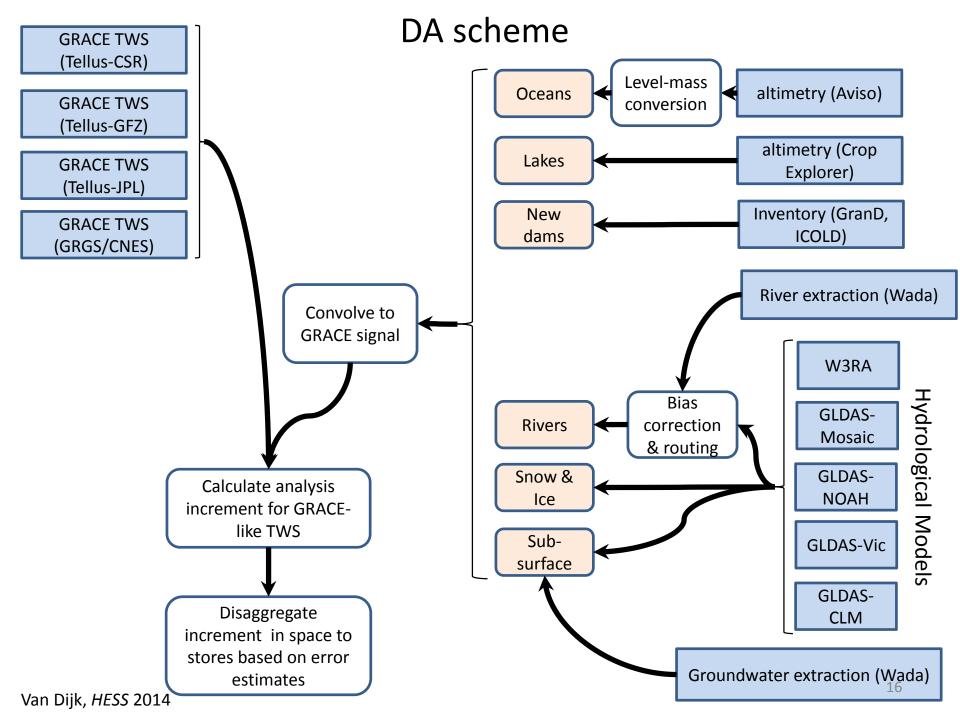


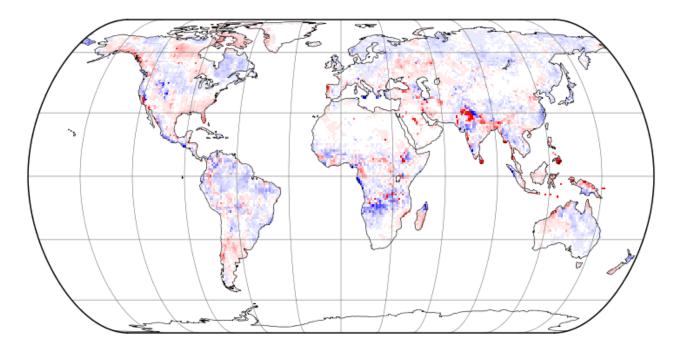


A global water cycle reanalysis (2003–2012) merging satellite gravimetry and altimetry observations with a hydrological multi-model ensemble



A van Dijk, LJ Renzullo, Y Wada, P Tregoning (2014). Hydrology and Earth System Sciences 18 (8), 2955-2973





Trends in seasonal anomalies in subsurface water storage (posterior)

Main change terms in global water budget

Trend 2003-2012 (Gt/y, km3/y)

polar ice caps

mountain glaciers

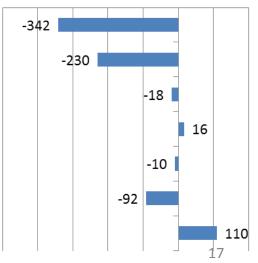
seasonal snow pack

new impoundments

other surface water bodies

subsurface (temperate, monsoon)

groundwater depletion



Van Dijk, HESS 2014

Impact of GRACE data assimilation

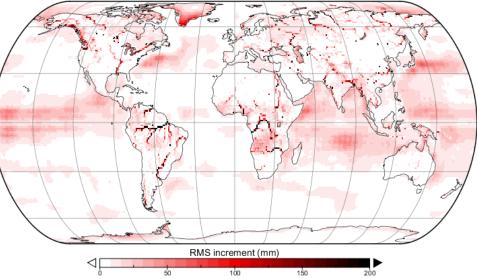
Greatest adjustments:

- large rivers
- ice sheets
- glaciers
- seasonal tropics

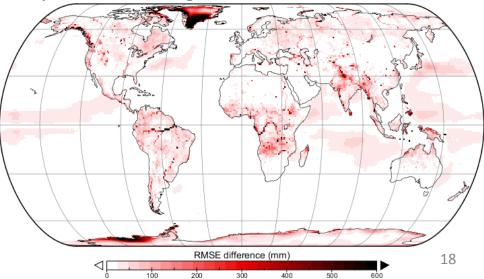
Typically, one water balance term (i.e. the least constrained) 'sucks up' all the innovation.

Indicative of greatest model deficiencies

root mean square (RMS) analysis increment



RMS difference between prior and posterior storage time series.



Van Dijk, HESS 2014

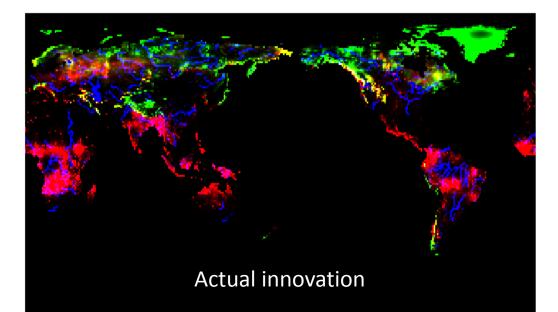
Impact of GRACE data assimilation

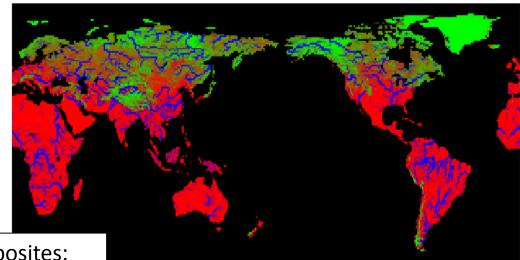
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Indicative of greatest model deficiencies





as a fraction of total innovation

RGB composites: soil & groundwater snow & ice rivers & lakes

Van Dijk, HESS 2014

Summary

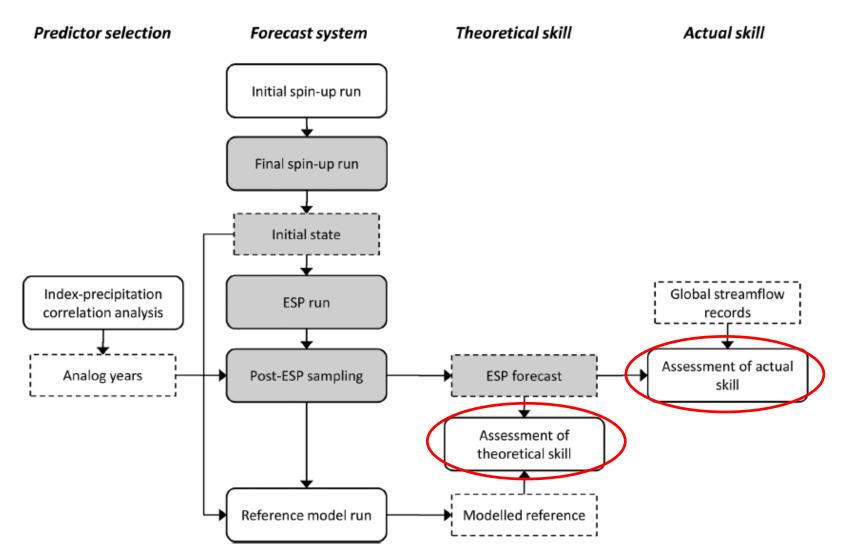
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Global analysis of seasonal streamflow predictability using an ensemble prediction system and observations from 6192 small catchments worldwide

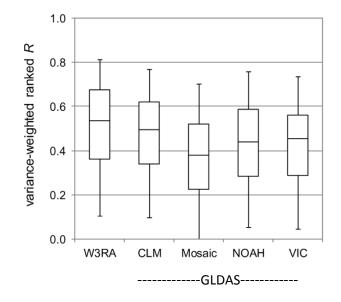
van Dijk, A. I. J. M., J. L. Peña-Arancibia, E. F. Wood, J. Sheffield, and H. E. Beck (2013) *Water Resources Research* 49, 2729–2746, doi:10.1002/wrcr.20251.

Approach: conditional ESP

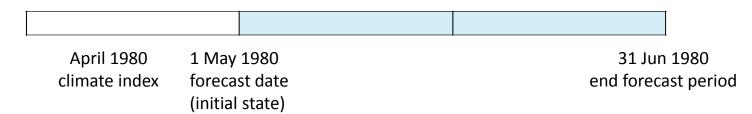


Configuration

- Meteorological forcing: 1° daily, 1948-2008 (Sheffield et al., 2006, *J Clim* 19): precipitation, incoming shortwave radiation, max and min daily temperature
- Hydrological model W3RA v1: fairly simple model based on
 - AWRA v0.5 (Van Dijk & Renzullo, 2011, HESS 15)
 - HBV-96 snow module (Lindström et al., 1997, J Hyd 201)
 - inputs: forest cover, wind speed, albedo climatologies



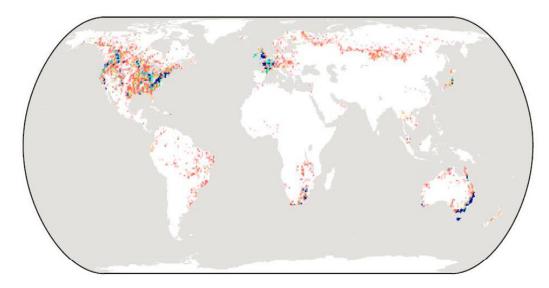
- Climate indices (Nino3.4, SOI, IOD, PDO, PC-NAO, STR, S-NAO, EA, WP, EP/NP, PNA, EA/WR, SCA, TNH, PL, PT, NP, SAM)
- (Re-)forecast configuration
 - o two-month total streamflow
 - o forecast date 1 Jan, Mar, May, Jul, Sep, Nov of years 1979-2008
 - o analogues sampled from preceding 30 years

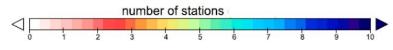


Distribution of stations

Streamflow data

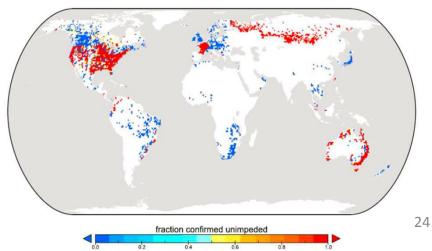
- Source: GRDC, MOPEX, Min. Environment France, WIRADA
- >12 years of data
- <10,000 km²
- 6192 catchments



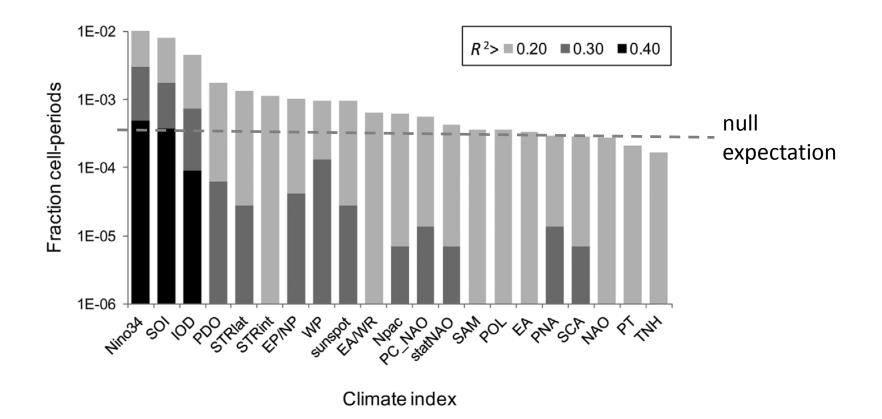


 the usual bias towards OECD countries

Unimpeded vs unknown

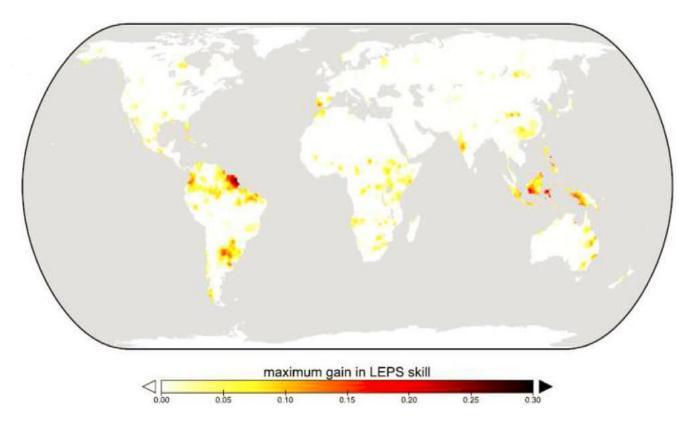


Climate predictor selection



Frequency of exceedance of different r² thresholds for the 21 climate mode indices tested for each grid cell forecast period combination

Climate predictor selection



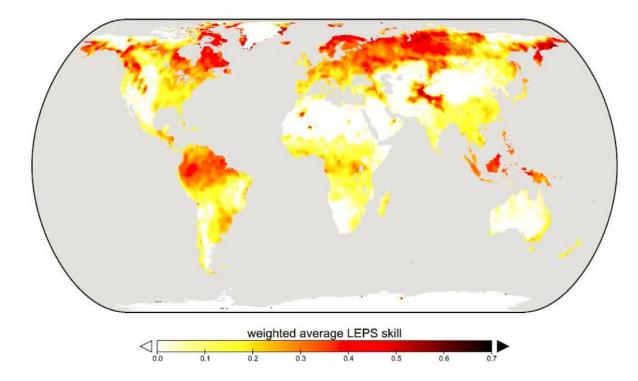
Contribution of climate indices to theoretical skill, calculated as the difference between LEPS skill with and without ensemble sampling based on climate index, resp.

Does that mean we cannot forecast streamflow 2 months out for most of the world?

Theoretical streamflow forecast skill

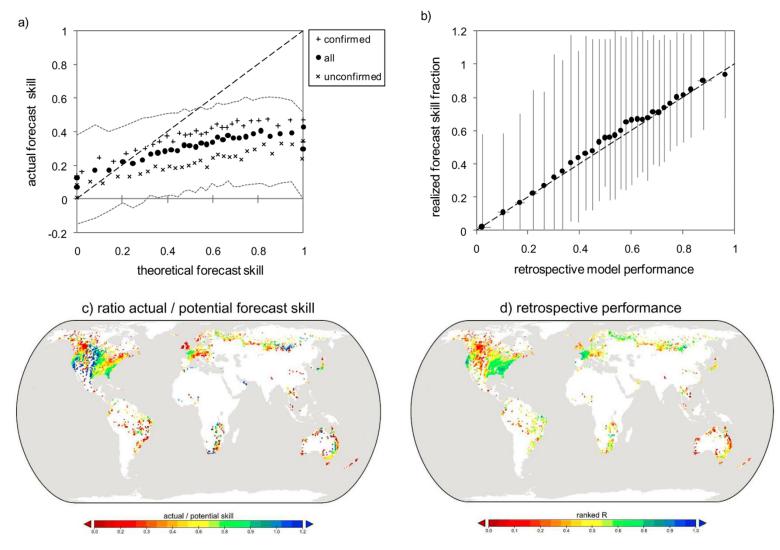
Of course not.

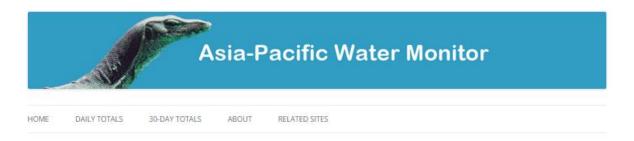
It does mean that hydrological initial state (water storage) typically contributes more to skill than does ESP conditioned by climate index.



Summary metrics of theoretical skill over the six forecast periods calculated as mean LEPS weighted by streamflow variance.

Verification: How much of the theoretical skill can we realise?

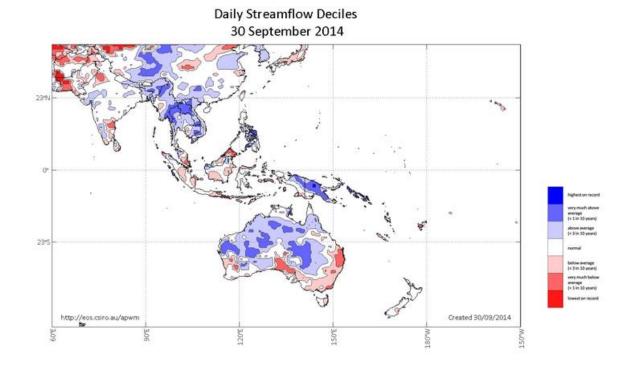




Daily Streamflow Deciles



Back to Daily Totals



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