AOGS 2022

Hydrologic forecasting over long lead times: A wavelet-based variance transformation approach

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UNSW Sydney Australia's Global University

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Asia Oceania Geosciences Society

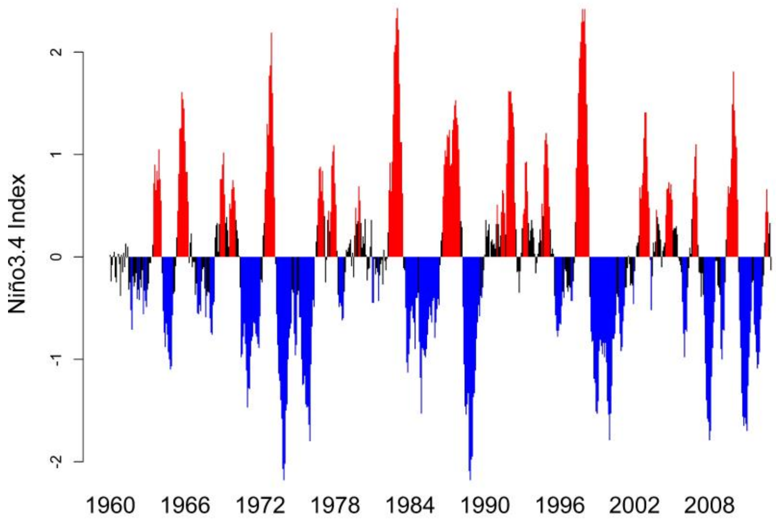
Acknowledgements

Australian Research Council

Department of Planning and Environment

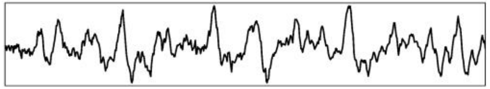
Why do we need spectral transformation?

Time domain



Why do we need spectral transformation?

Niño3.4

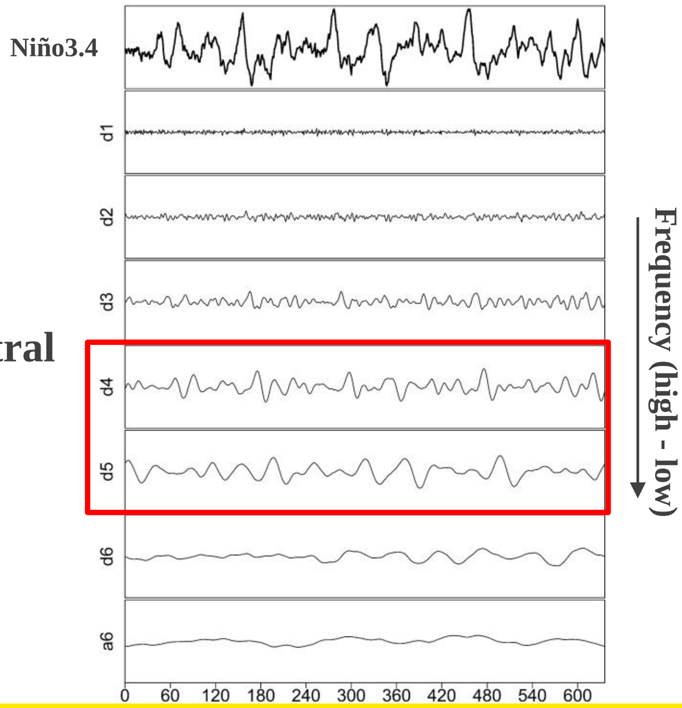


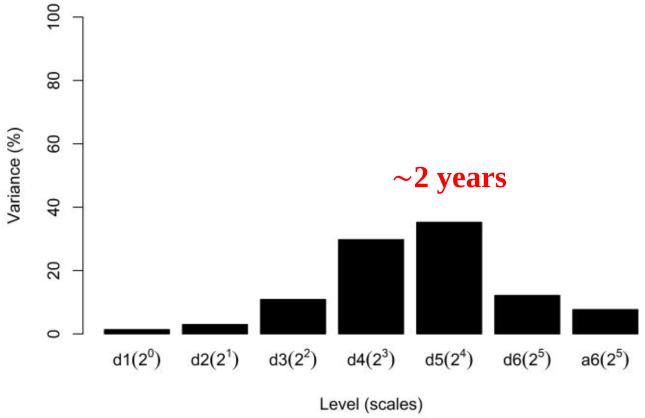
Frequency (high - low)

Frequency/Spectral domain

Why do we need spectral transformation?

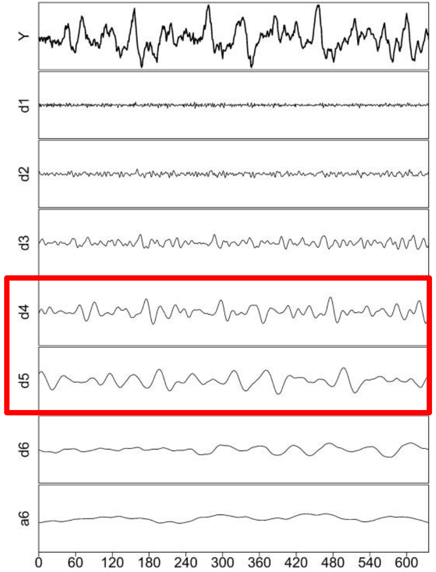
Frequency/Spectral domain



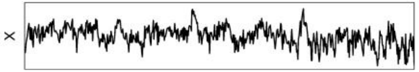


Why do we need spectral transformation?

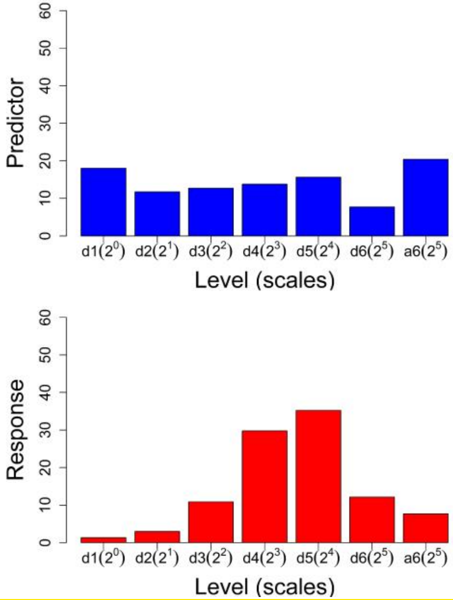
Target Response Y (Niño3.4)



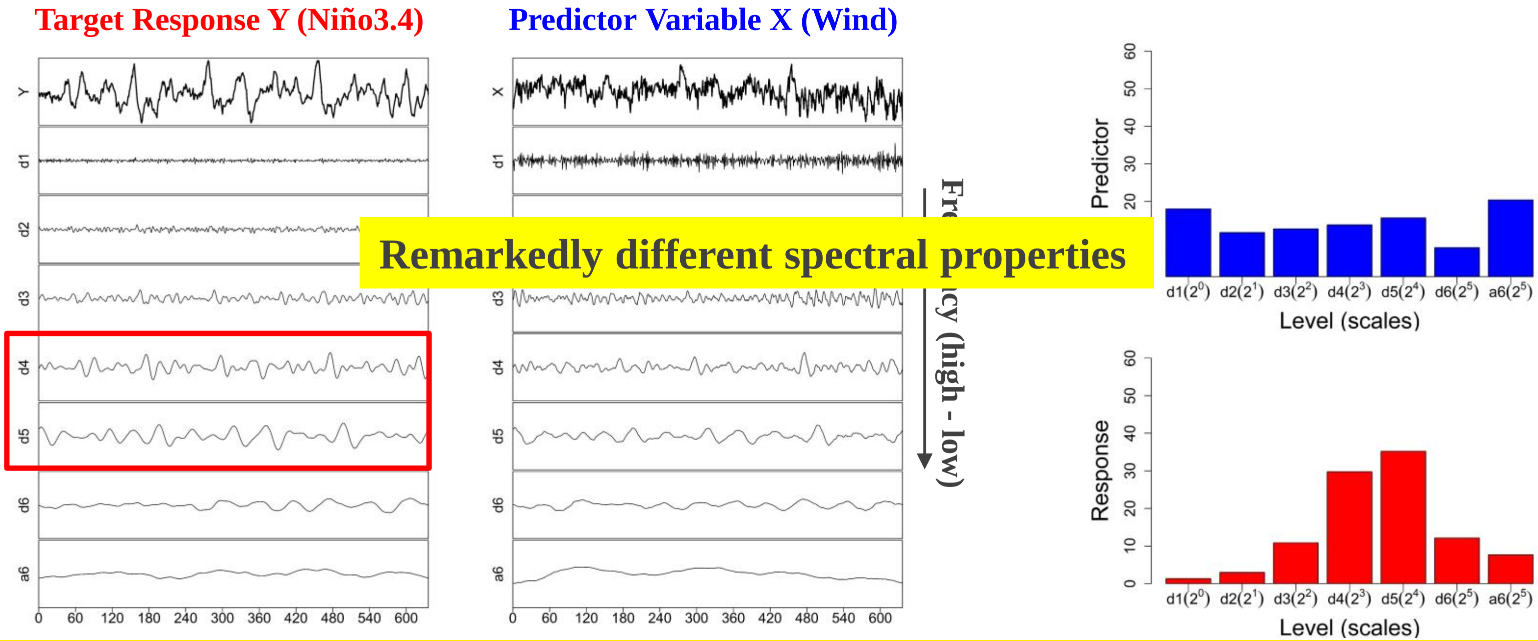
Predictor Variable X (Wind)



Frequency (high - low)



Why do we need spectral transformation?



Why do we need spectral transformation?

The hypothesis:

If the spectrum of the predictor is similar to response, the predictive model exhibits better accuracy than otherwise.

Is there an optimal variance transformation?

Is there an optimal variance transformation?

Change predictor X to X' such that X' has a closer spectral representation to the response Y:

$$X' = \tilde{R}\alpha$$

$$\alpha = \sigma_X \tilde{C}$$

where $\boldsymbol{R}$ is wavelet decompositions of X, and $\tilde{C}$ is the normalized covariance between the variable set $(Y, \tilde{R})$.

$$\boldsymbol{C} = \frac{1}{n-1}\boldsymbol{Y}^T\tilde{\boldsymbol{R}} = \left[S_{Y\tilde{d}_1}, \ldots, S_{Y\tilde{d}_J}, S_{Y\tilde{a}_J} \right]$$

$$RMSE_{\min} = \sqrt{\frac{n-1}{n}(\sigma_Y^2 - \|\boldsymbol{C}\|^2)}$$

Water Resources Research

Technical Reports: Methods

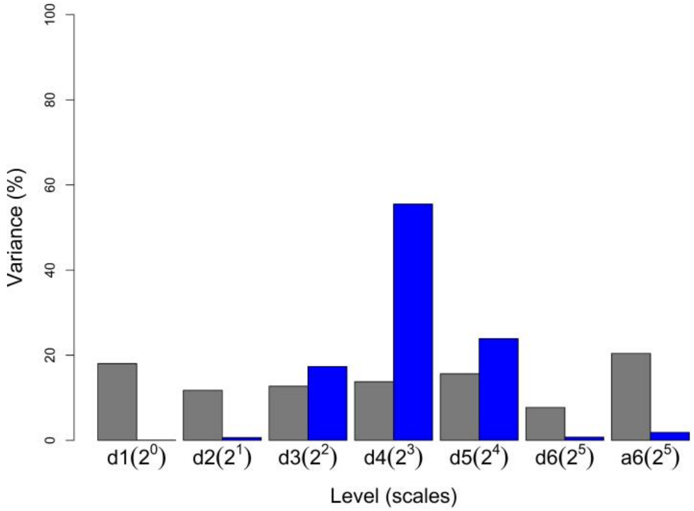
Refining Predictor Spectral Representation Using Wavelet Theory for Improved Natural System Modeling

Ze Jiang, Ashish Sharma, Fiona Johnson

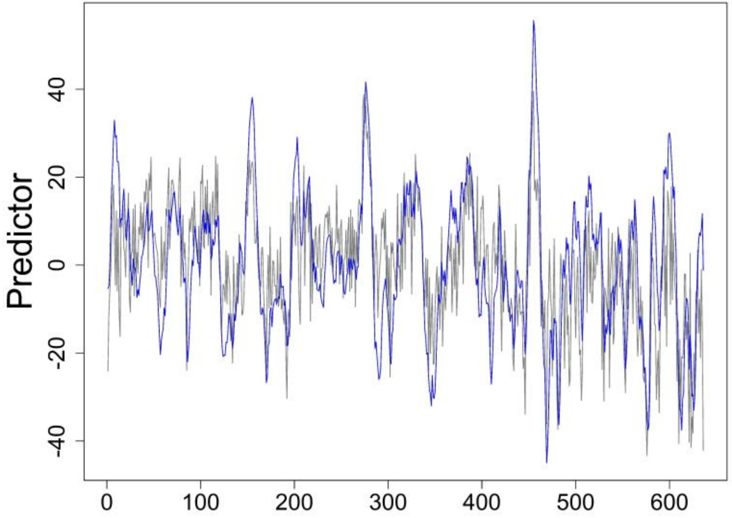
First published: 20 February 2020 | https://doi.org/10.1029/2019WR026962 | Citations: 9

Is there an optimal variance transformation?

Frequency domain



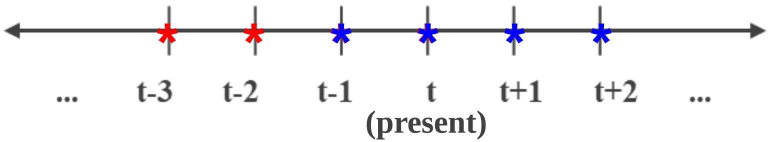
Time domain

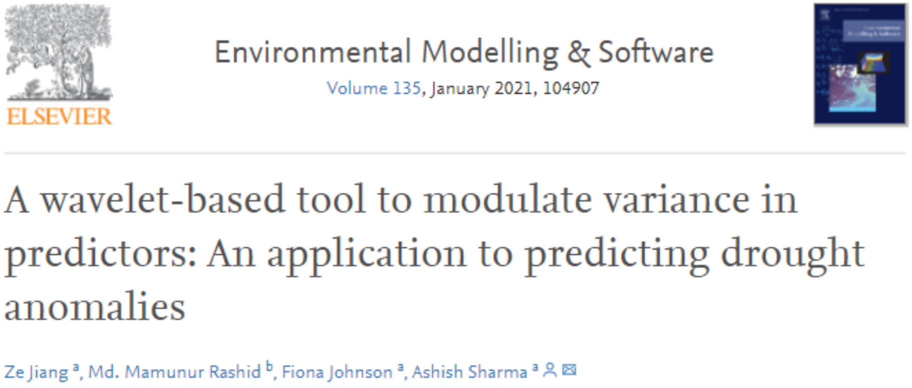


How do we take it to forecasting?

- DWT mathematically requires future information in the decomposition.
- Can we generalise this method to also apply in a forecasting context?

Maximal overlap DWT (MODWT)




ELSEVIER

Environmental Modelling & Software
Volume 135, January 2021, 104907

A wavelet-based tool to modulate variance in predictors: An application to predicting drought anomalies

Ze Jiang [a], Md. Mamunur Rashid [b], Fiona Johnson [a], Ashish Sharma [a]

Wavelet System Prediction (WASP)
http://www.hydrology.unsw.edu.au/software/WASP

How do we consider multiple predictors in the system?

- Variance transformation refines the predictor spectral representation individually.
- Can we generalise this method to account for existing predictors in the system?

$$X'_{VT} = g(X, Y) \qquad X'_{SVT} = g(X|Z, Y|Z)$$

Stepwise VT = Variance transformation + Input variable selection

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Jiang, Z., et al. (2021). "Variable transformations in the spectral domain – Implications for hydrologic forecasting." Journal of Hydrology, 603, 126816.

ENSO forecasting over long lead times

Target response: Niño3.4

Predictors: 30 predictor variables (10 predictors from each region)

Predictor variable	Region I	Region II	Region III	Depth
Zonal wind stress (m^2/s^2)	180–220E, 4S–4N	180–210E, 10S–0	160–200E, 0–10N	Surface
Sea surface temperature (°C)	140–160E, 5S–5N	140–180E, 10S–5N	120–170E, 10S–5N	Surface
Subsurface temperature (°C)	120–140E, 10S–7N	150–200E, 10S–7N	140–210E, 5–10N	50, 100, 150, 200, 250, 300, 400, and 500 m

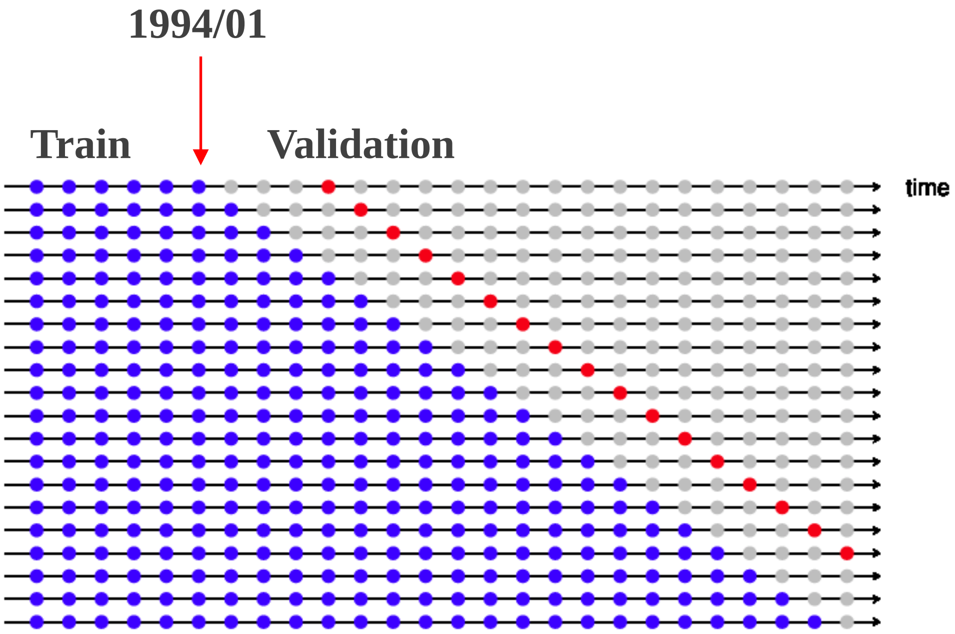
Note: This table is adapted from ***Petrova et al. (2019)***.

ENSO forecasting over long lead times

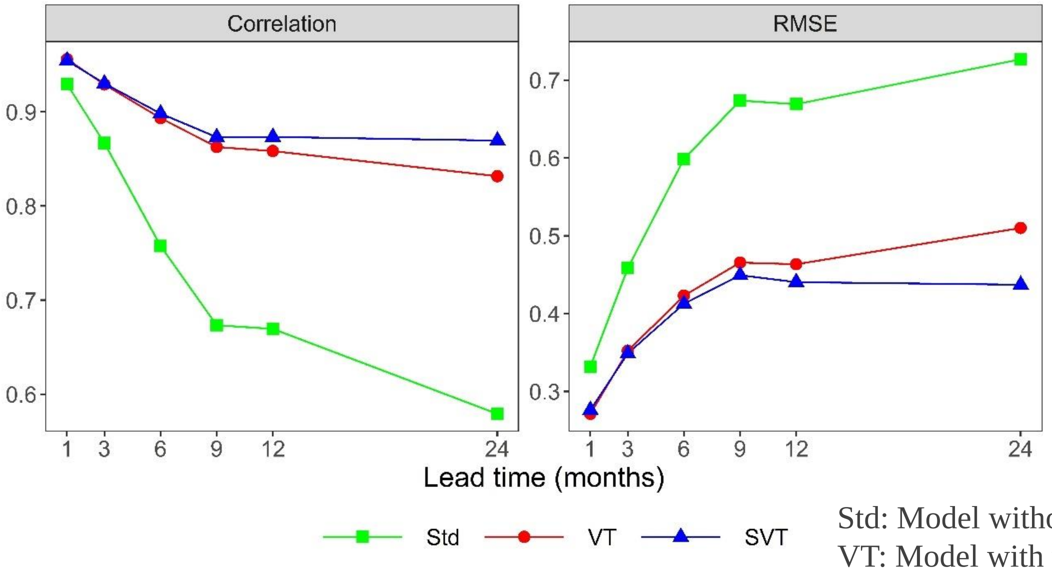
Retrospective experiment:

- Obtain the transformed predictors
- Identify the significant predictors
- Data split: 1960–1993 (train)

  1994–2012 (validation)



ENSO forecasting over long lead times



- VT and SVT are better than Std, and SVT is the best among three models.
- Forecasting skill of VT and SVT model decays more slowly than Std model.

Std: Model without transforming predictors
VT: Model with variance transformation
SVT: Model with stepwise VT

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Conclusions

- A **unique** variance transformation in the frequency domain
- A **generic** method along with open-source tools
- A wide range of applications not limited to hydro-climatology

ELSEVIER
Journal of Hydrology
Volume 603, Part A, December 2021, 126816

Research papers

Variable transformations in the spectral domain – Implications for hydrologic forecasting

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