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Hydro-climatological forecasting: A view from the spectral domain

Ze Jiang¹, Ashish Sharma¹ and Fiona Johnson¹

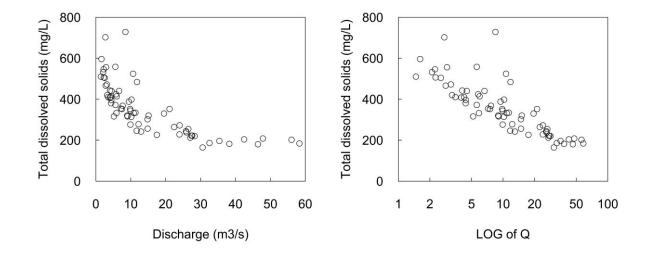
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Do we need transformation in predictor variables?



Helsel, D. R., & Hirsch, R. M. (2002). *Statistical methods in water resources (04-A3)*. *Retrieved from Reston, VA: http://pubs.er.usgs.gov/publication/twri04A3*





Do we need transformation in predictor variables?

Need transformation in the frequency domain?

The hypothesis:

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





Predictor Variable X (EPT)

Background: Wavelet Transform

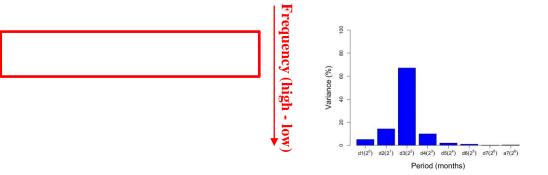
Discrete wavelet transform (DWT) Multiresolution Analysis (MRA)

DWT-MRA:

$$X = \sum_{j=1}^{J} d_j + a_J$$

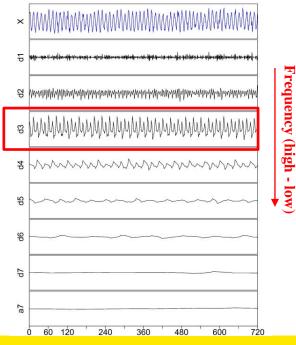
$$\sigma_X^2 = \sum_{j=1}^{J} \sigma_{d_j}^2 + \sigma_{a_j}^2$$



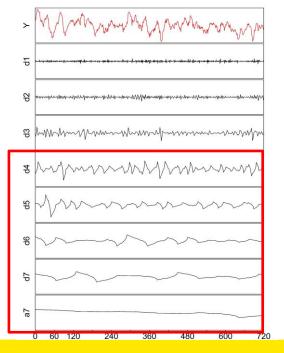


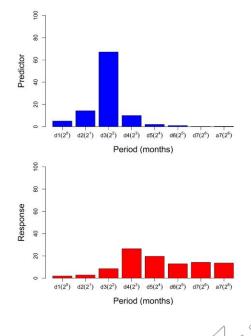


Predictor Variable X (EPT)



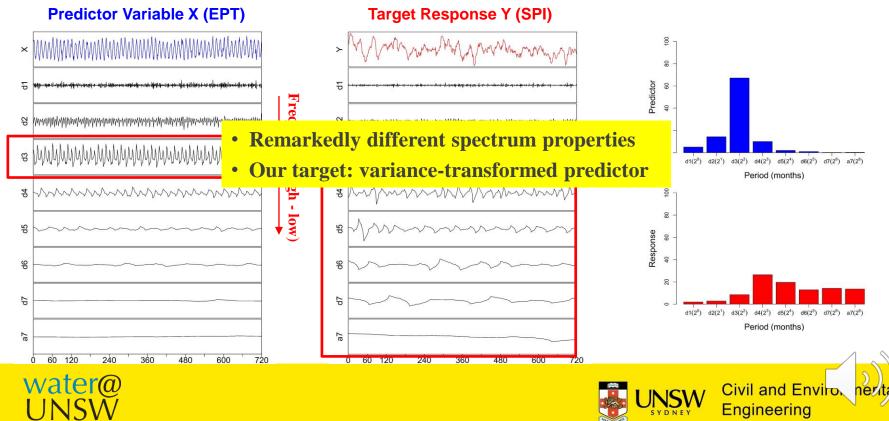
Target Response Y (SPI)





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Related

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

$$\boldsymbol{C} = \frac{1}{n-1} \boldsymbol{Y}^{T} \tilde{\boldsymbol{R}} = \left[\boldsymbol{S}_{\boldsymbol{Y}\tilde{d}_{1}}, \dots, \boldsymbol{S}_{\boldsymbol{Y}\tilde{d}_{J}}, \boldsymbol{S}_{\boldsymbol{Y}\tilde{a}_{J}} \right]$$

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

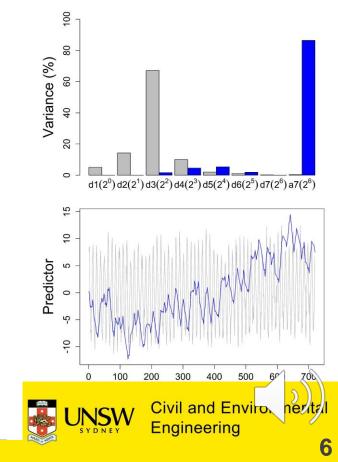
Water Resources Research

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 water research centre



How to apply the method in practice?

Step 1 - identify best possible drivers from large numbers of predictor variables (inputs)

- Step 2 form a predictive model based on the identified drivers, estimate the model parameters that best fit to the data
- Step 3 predict the system response for new inputs.

Wavelets: obtain filtered (variance-transformed) predictor variables

$$X' = g(X, C)$$
$$y = f(X) \rightarrow y = f(X')$$



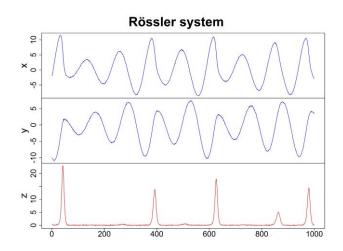


Example 1 – synthetic example

A dynamic example (Rössler system):

 $\dot{x} = -y - z,$ $\dot{y} = x + ay,$ $\dot{z} = b + z(x - c).$

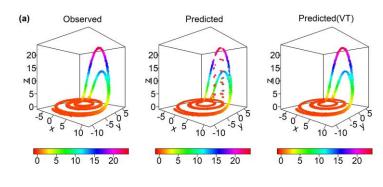
Use x and y to predict z: **Predicted:** predicted z using original x and y **Predicted(VT):** predicted z using variance-transformed x and y







Example 1 – synthetic example



(b) Observed Predicted Predicted(VT) 20 20 20 15 15 15 MO MO MO 5-5 0 10 15 20 10 15 20 5 10 15 20 5 Ó 5 Ó

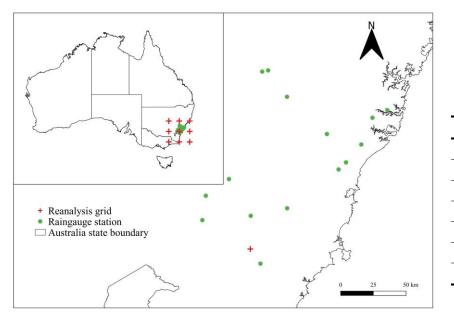
Predicted: predicted z using original x and y Predicted(VT): predicted z using variance-transformed x and y

Model	Predictor	RMSE	Correlation	SD
Calibration (a)	Original	1.274	0.922	3.1
	Transformed	0.118	0.999	3.3
Validation (b)	Original	4.462	0.354	4.5
	Transformed	2.556	0.560	2.3





Example 2 – real case



Target response: Drought Index (SPI12) Study Period: 1950 – 2009 (2-fold cross-validation)

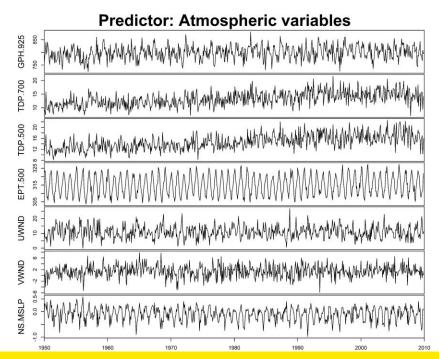
Predictor No.	Predictor Name	
1	Geopotential heights (m) at 925 hPa (GPH@925)	
2	Temperature depression (degree C) at 700 hPa (TDP@700)	
3	Temperature depression (degree C) at 500 hPa (TDP@500)	
4	Equivalent potential temperature (Kelvin K) at 500 hPa (EPT@500)	
5	Zonal Wind (m/s) at 500 hPa (UWND@500)	
6	Meridional Wind (m/s) at 500 hPa (VWND@500)	
7	N-S gradient of mean sea level pressure (NS-MSLP)	

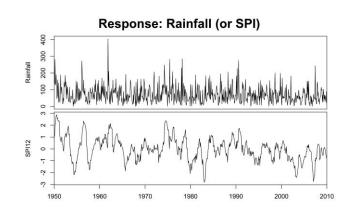




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Example 2 – real case



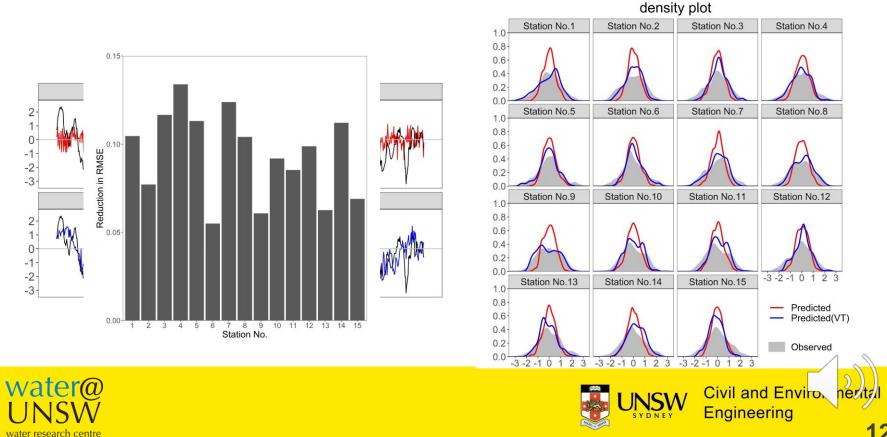






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Example 2 – real case



Conclusions

- A unique variance transformation is identified for each predictor variable that explains maximal information in the corresponding response.
- Results of the synthetic and real case example show clear improvements in predictability compared to the use of untransformed predictors.
- It is a generic method and not limited to hydro-climatological systems.



for Improved Natural System Modeling

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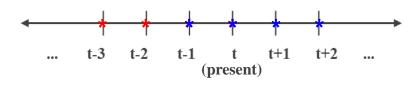


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Extension to broad applications

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





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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 🙁 🖾

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https://doi.org/10.1016/j.envsoft.2020.104907



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Civil and Enviro Engineering The open-source R-package WASP (WAvelet System Prediction) is available for download from the Hydrology@UNSW website: https://www.hydrology.unsw.edu.au/software/WASP

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Data and Code	Home Data and Code WAvelet System Prediction (WASP) - 2020			
WAvelet System Prediction (WASP) - 2020	WAvelet System Prediction (WASP) - 2020 Jiang, Z., Rashid, M. M., Johnson, F., & Sharma, A. (2020). A wavelet-based tool to modulate variance in predictors: An application to predicting drought anomalies. Environmental Modelling & Software, 104907. doi:https://doi.org/10.1016/j.envsoft.2020.104907 Jiang, Z., Sharma, A., & Johnson, F. (2020). Refining Predictor Spectral Representation Using Wavelet Theory for Improved Natural System Modeling. Water Resources Research, 56(3), e2019WR026962. doi:https://doi.org/10.1029/2019WR026962 The R package, namely Wavelet System Prediction (WASP), is based on a discrete wavelet transform (DWT)-based variance transformation method (Jiang et al., 2020). This method refines predictor spectral representation using wavelet theory and improves the prediction accuracy of the associated response. We further introduce the maximal overlap DWT (MODWT)-based variance transformation method (Jiang et al., 2020). This method refines predictor spectral representation using wavelet theory and improves the prediction accuracy of the associated response. We further introduce the maximal overlap DWT (MODWT)-based variance transformation which miligates the well-known issue of edge effects in wavelet transforms. The predictive model in the framework is a <i>k</i> -nearest neighbor (knn) approach. The main functionalities of the software include: (1) transforming the system predictors, (2) identifying significant predictors corresponding to the response, ignore response using the knn. An application to predicting sustained drought anomalies across Australia in the EMS paper shows clear improvements in predictive skill compared to the use of untransformed predictors. The software described in the above mentioned papers can be obtained by clicking here.			
Robust Multivariate Bias Correction (RoMBC) - 2020				
Data for Guo et al. (2019) GeoHealth				
Parameter Optimization and Simulation Toolkit (POST) for Flood Warning - 2018				
Multivariate Bias Correction (MBC) - 2017				
Multisite Rainfall Downscaling (MRD) - 2017				
Dynamic Linear Combination - 2016				
KNN, PIC, PMI and NPRED - 2016				
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Thank you!

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