Forecasting drought revisited – the importance of spectral transformations to dominant atmospheric predictor variables

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Water Resources Research

Technical Reports: Methods

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

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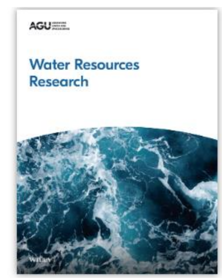

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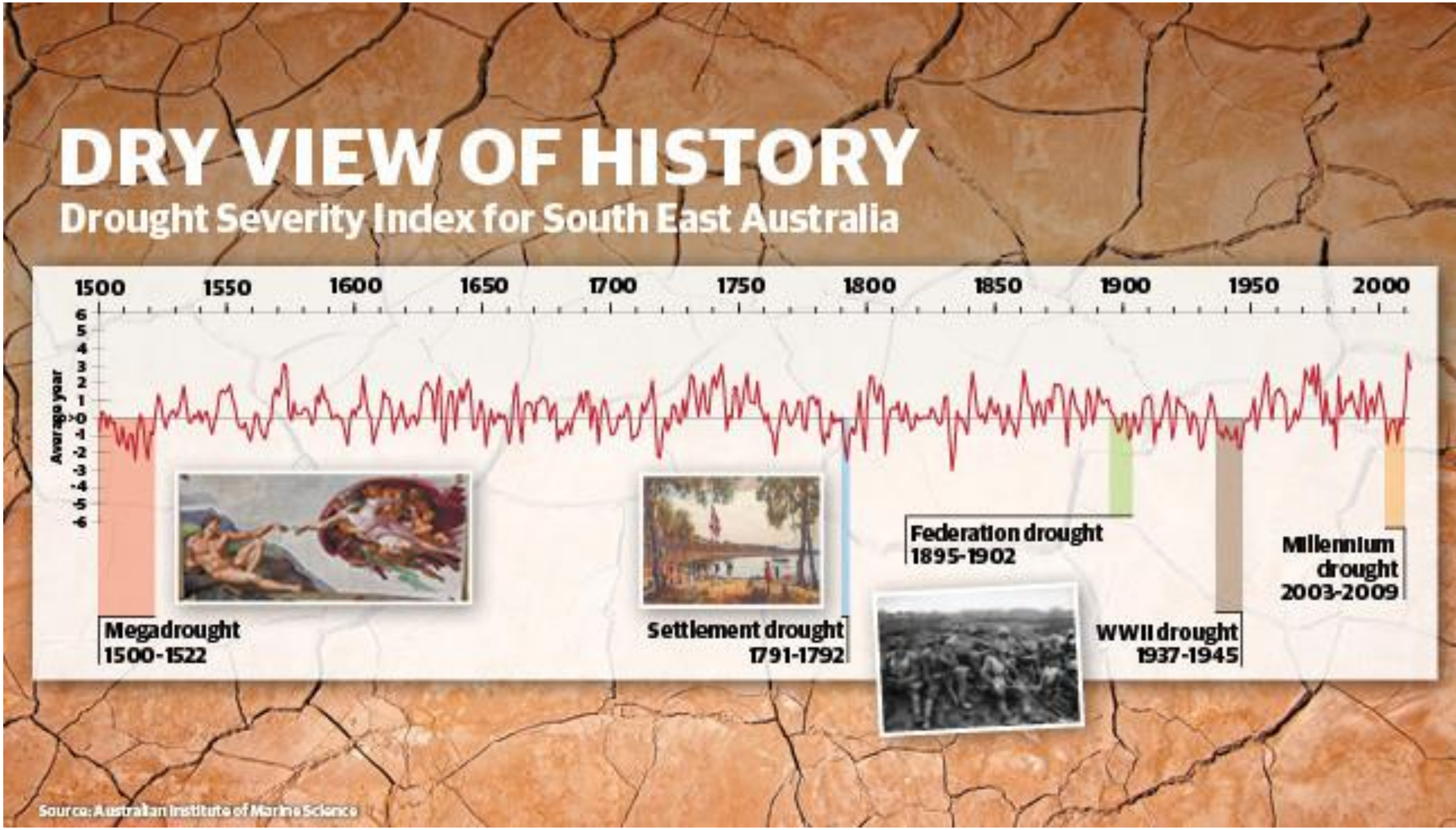

DRY VIEW OF HISTORY
Drought Severity Index for South East Australia
1500
1550
1600
1650
1700
1750
1800
1850
1900
1950
2000
Average year
Megadrought
1500-1522
Settlement drought
1791-1792
Federation drought
1895-1902
WWII drought
1937-1945
Millennium
drought
2003-2009
Source: Australian Institute of Marine Science

Forecasting basics revisited

1. Should predictor variables be transformed to mimic the probability distribution of the response?

ANS – Yes, especially for linear models where log or Box-Cox transforms are often used

2. Should predictor variable be required to exhibit similar spectral attributes as the response?

ANS – Ideally yes, as they will have similar persistence attributes as the response

3. HOW?

ANS – Using a suitable Fourier or Wavelet transformation

PROBLEM – Need to know "future" values of the predictor – only possible when the predictors are being simulated using a model (such as a General Circulation Model)

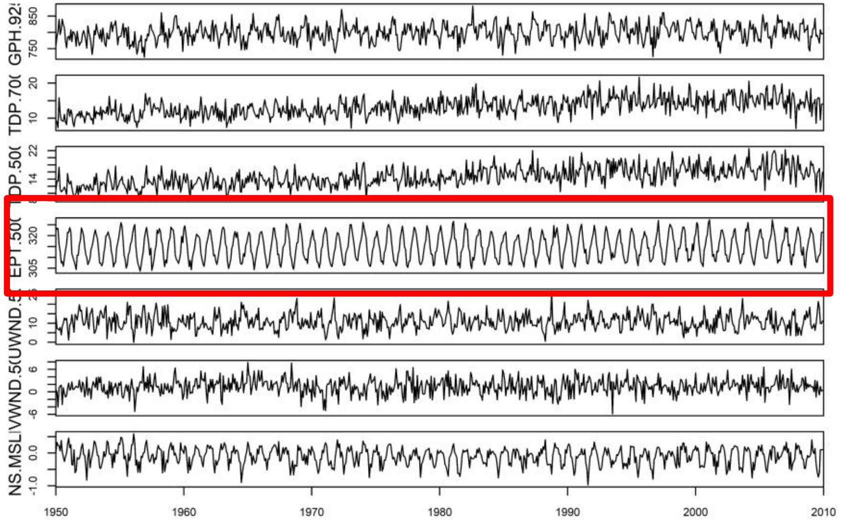
THIS MAY BE OUR BEST OPTION FOR PREDICTING DROUGHT INTO THE FUTURE!

How to refine predictor variable to improve modelling?

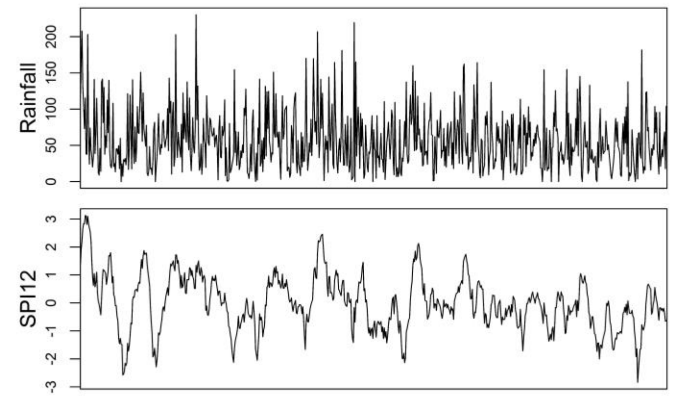
The hypothesis:

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

Predictor: atmospheric variables



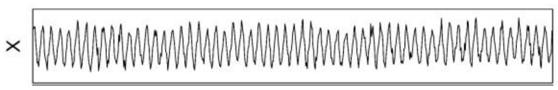
Response: Rainfall (or SPI)



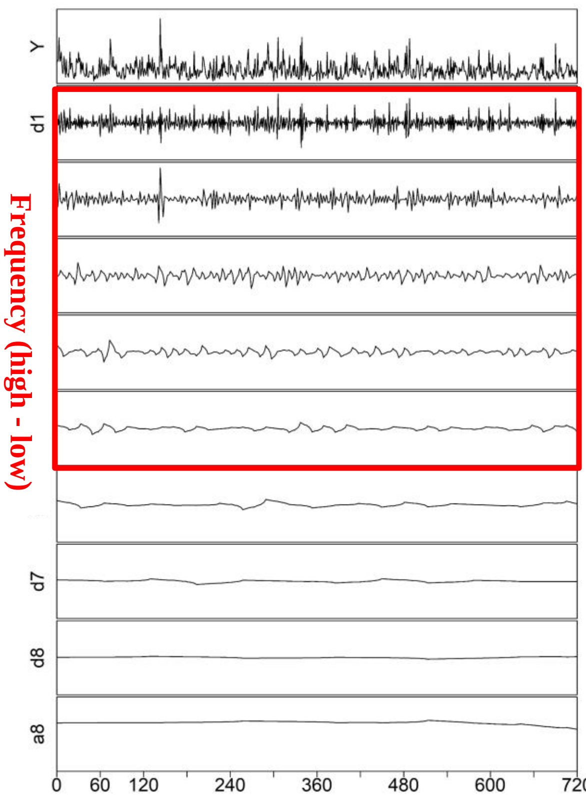
How to modify the spectrum?

Background: Wavelet Transform

Predictor Variable X (EPT)



Target Response Y (Rainfall)



Additive Decomposition:

(Multiresolution Analysis, MRA)

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

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

- **Remarkedly different spectrum properties**
- **Our target: variance-transformed predictor**

How to modify the spectrum to optimise predictability?

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

MRA:

$$\boldsymbol{X} = \sum_{j=1}^{J} \boldsymbol{d}_j + \boldsymbol{a}_J$$

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

Matrix form:

$$\boldsymbol{X} = \tilde{\boldsymbol{R}}\boldsymbol{I}$$

where $\tilde{\boldsymbol{R}}$ is standardized reconstructions matrix.

$$\boldsymbol{R}=[\boldsymbol{d}_1,\ldots,\boldsymbol{d}_J,\boldsymbol{a}_J] \qquad \boldsymbol{I}=[\sigma_{d_1},\ldots,\sigma_{d_J},\sigma_{a_J}]^{\mathrm{T}}$$

What we are looking for:

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

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

where $\tilde{\boldsymbol{C}}$ is the normalized covariance matrix for the variable set $(\boldsymbol{Y}, \tilde{\boldsymbol{R}})$

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

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

Results – Synthetic example

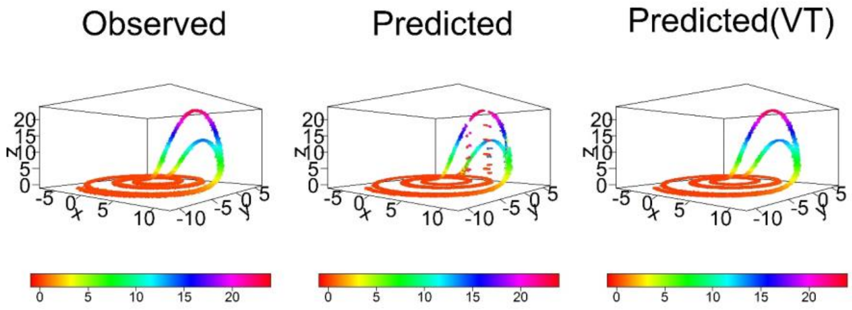
A dynamic example (Rössler system):

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

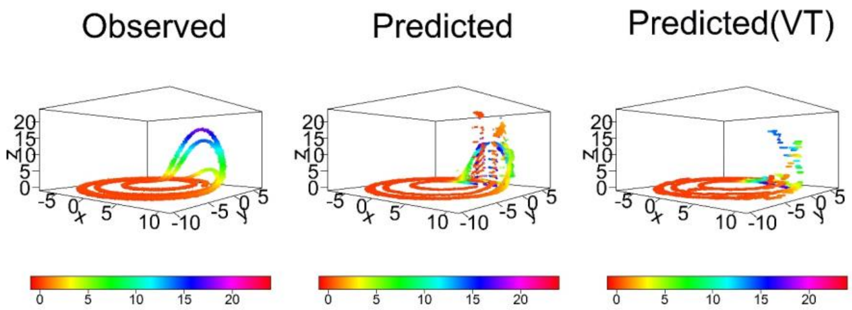
Use x and y to predict z

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

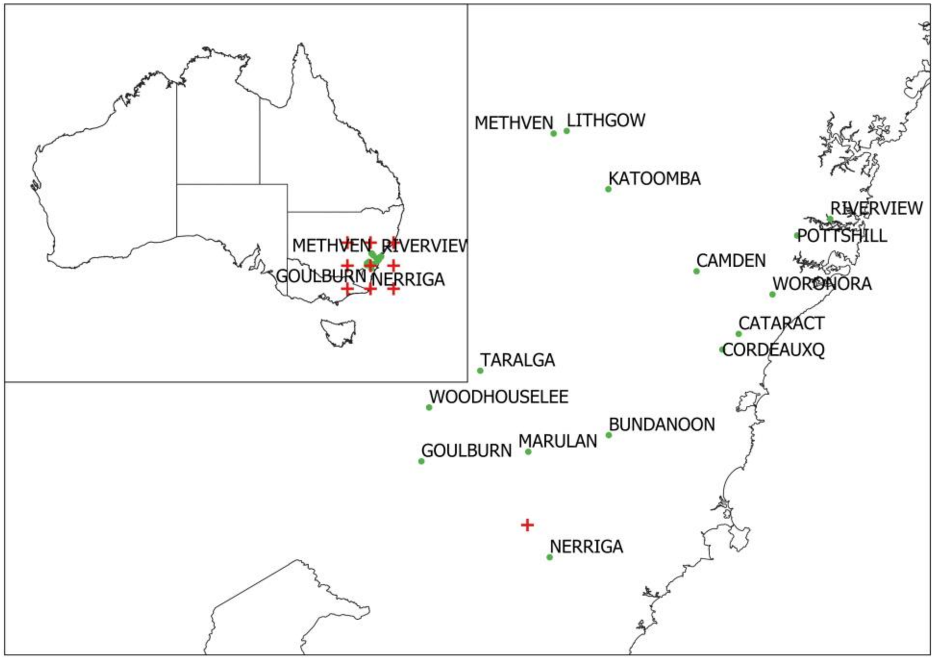
Calibration: RMSE = 0.113 against 1.189



Validation: RMSE = 2.550 against 4.493



Results – Real example



- Sydney Region Rainfall Stations
- NCEP-NCAR Reanalysis Grids

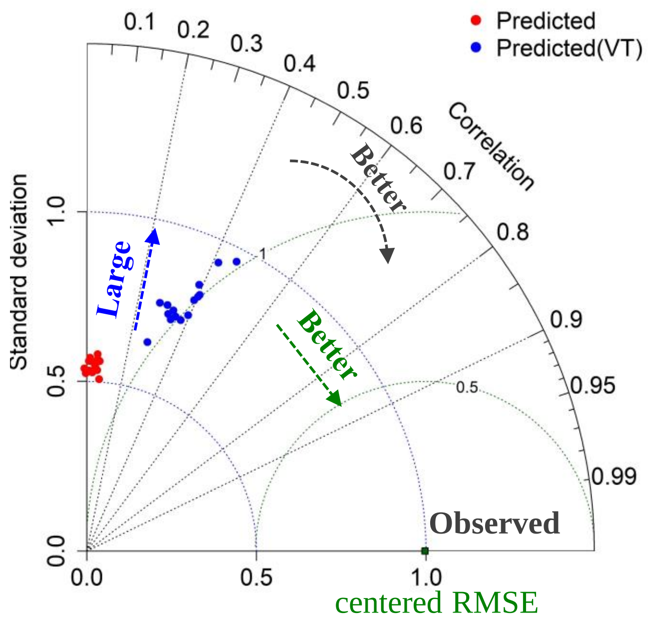
Target response: Drought Index (SPI12, 1950 – 2009)

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)

Results – Real example

Predicted: Original predictors

Predicted (VT): Variance-transformed predictors



Taylor diagram evaluating model performance by the standard deviation, centered RMSE and correlation coefficient.

To wrap up….

- A **unique** variance transformation is identified for each predictor variable that explains **maximal** information in the corresponding response.
- Results of a dynamic example and a real application show **clear improvements in predictability** compared to the use of untransformed predictors.
- It is a **generic** method and not limited to hydro-climatological systems.
- Application to **correct** GCM drought projections using this approach are underway

Future Work:

- **The variance transformation technique for forecast with no dependence on future data**
- **The variance transformation technique for multivariate response characterization**

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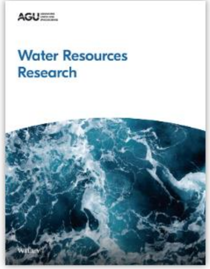

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