Climate influence on Susquehanna River streamflow dynamics

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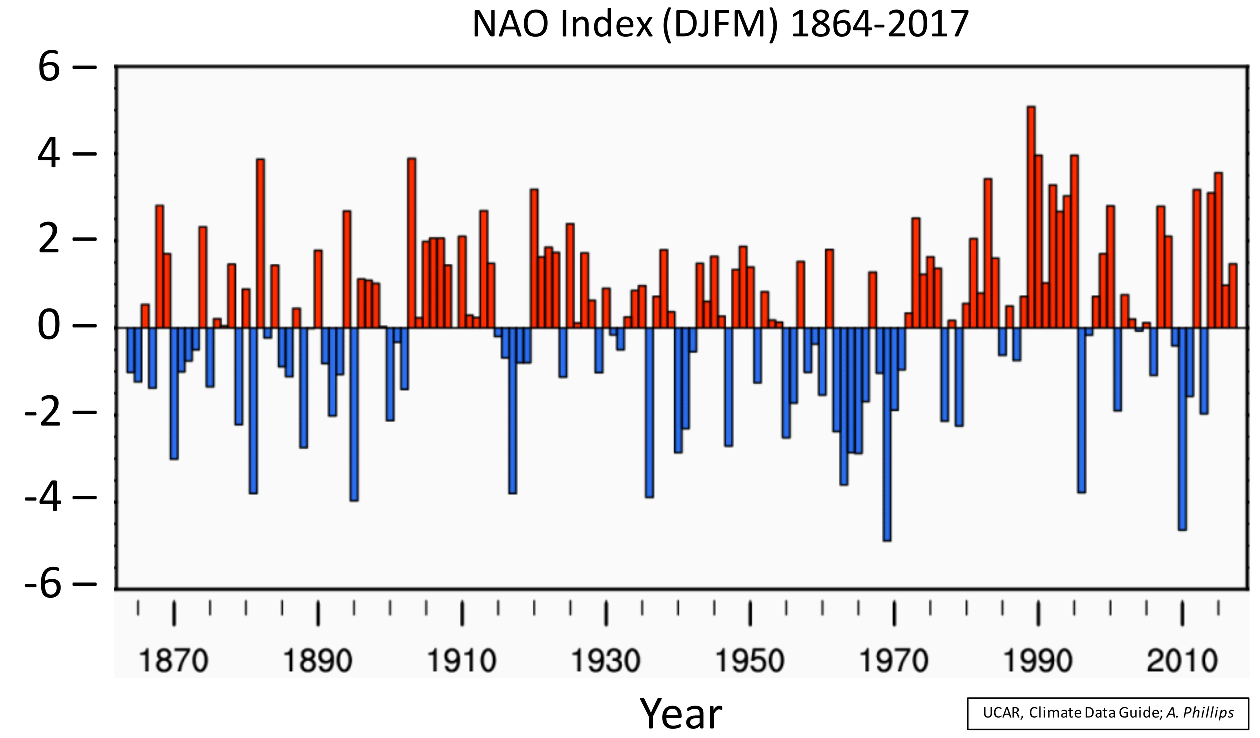
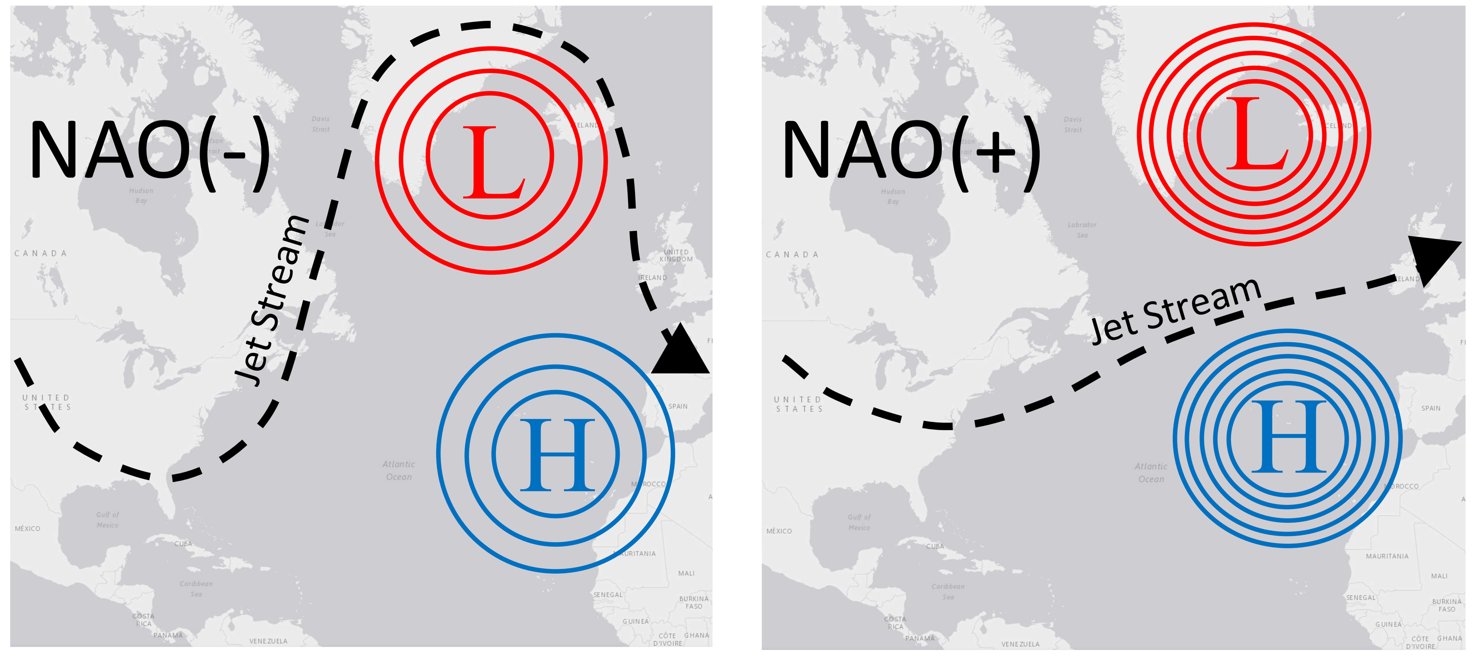
1. North Atlantic Oscillation and Streamflow Variability

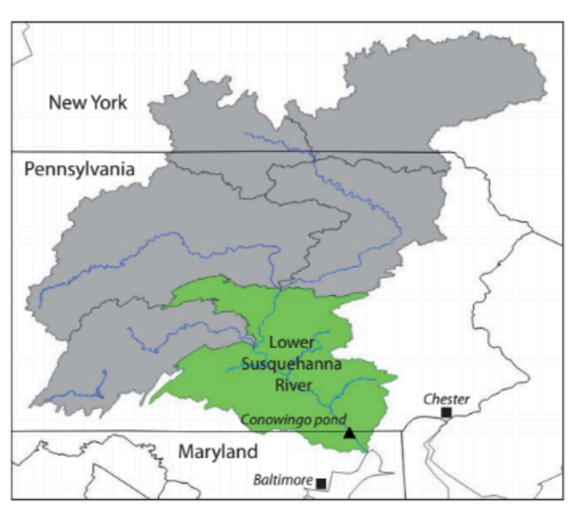
The **North Atlantic Oscillation (NAO)** is the most persistent climate mode, always present in one of its forms day-by-day, either in a neutral, negative, or positive phase. Pressure anomalies to the Subtropical High and Subpolar Low results in different NAO phases. Pressure anomalies with a positive relationship correspond to the positive phase of the NAO and a negative relationship corresponds to the negative phase of the NAO.

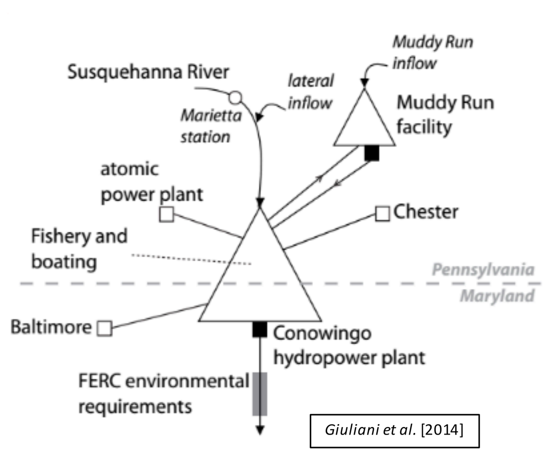
NAO Index (DJFM) 1864-2017

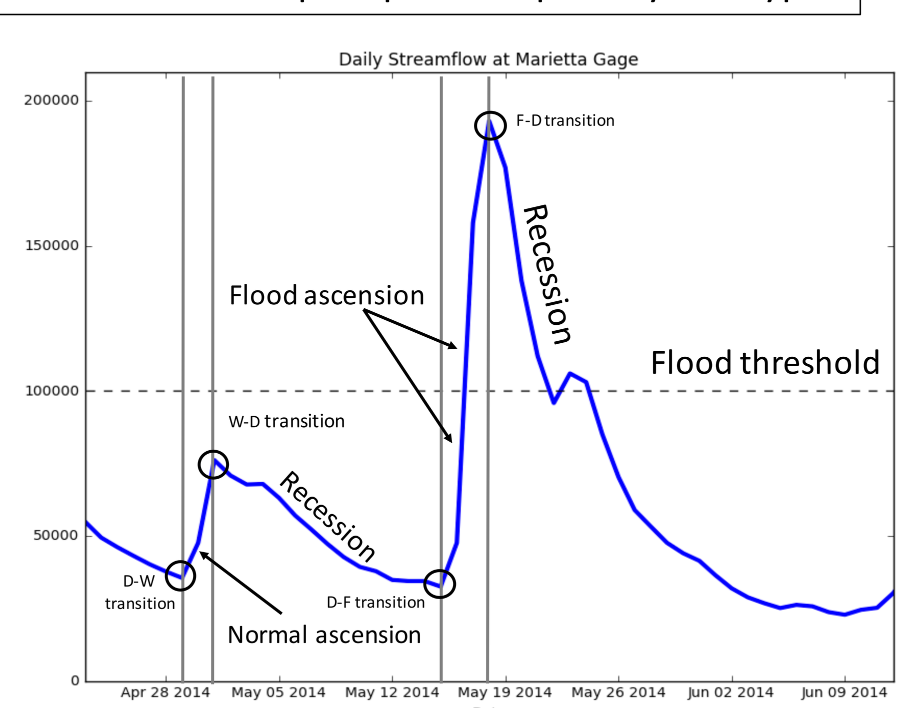




The top time series shows the winter NAO index based on the difference of normalized sea-level pressure between Lisbon, Portugal and Reykjavik, Iceland between 1864 and 2017. Each phase of the NAO results in changes to the flow across the Mid-Atlantic region which results in variations in precipitation quantity and type.







The streamflow record is from Marietta, PA (accessed through the USGS) within the **Susquehanna River Basin** and contains daily, continuous streamflow from 1931-Present. Using a streamflow generator, the Dry-Dry, Dry-Wet, Dry-Flood, and all other **transition probabilities** were calculated. The **Peak over Threshold** was calculated for each independent flood event as well as each annual **flood frequency**.

2. Model Selection and Intercomparison

To determine connections between the NAO index and streamflow transition probabilities, flood frequency, and peak over threshold, annual NAO, DJFM NAO, and one-year lagged NAO indices were selected.

Model Forms

Transition Probabilities – Beta model selected since P(Transition)∈(0,1)

Flood frequency and Peak over Threshold – GPD-Poisson selected since it models these relationships which are dependent on each other

Parameter Estimation

Maximum likelihood estimates for each parameter of the Beta and GPD-Poisson were calculated using the Nelder-Mead simplex algorithm as implemented by the SciPy optimize 'fmin' function. We compare each set of possible parameter combinations using Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) for model selection.

Parameters	Predictors	Predictor Form
Stationary	Annual NAO	Neutral
α	DJFM NAO	Non-neutral
β	Lagged-DJFM NAO	Continuous
$\alpha\beta$		

Beta Model

α, β = Shape parameter

Parameters	Predictors	Predictor Form
Stationary	Annual NAO	Neutral
ν	DJFM NAO	Non-neutral
σ	Lagged-DJFM NAO	Continuous
$\nu\sigma$		
$\sigma\xi$		
$\nu\sigma\xi$		

GPD-Poisson Model

ν = Event rate

σ = Scale parameter

ξ = Shape parameter

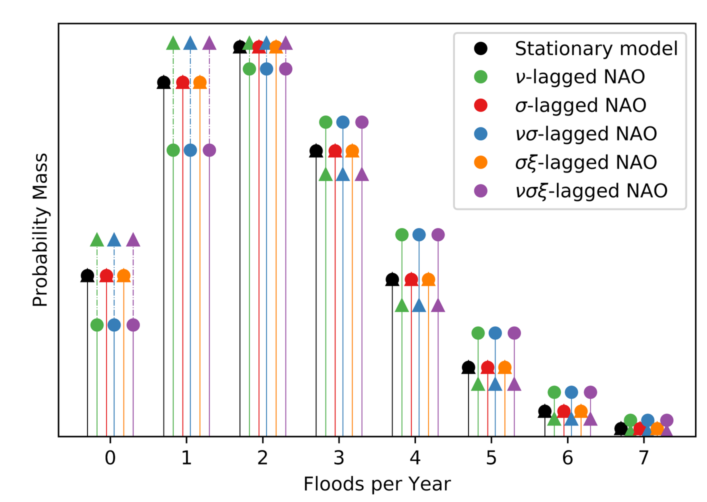
Predictor Forms

Neutral = $x_0 + x_1 \cdot$ NAO(neutral)

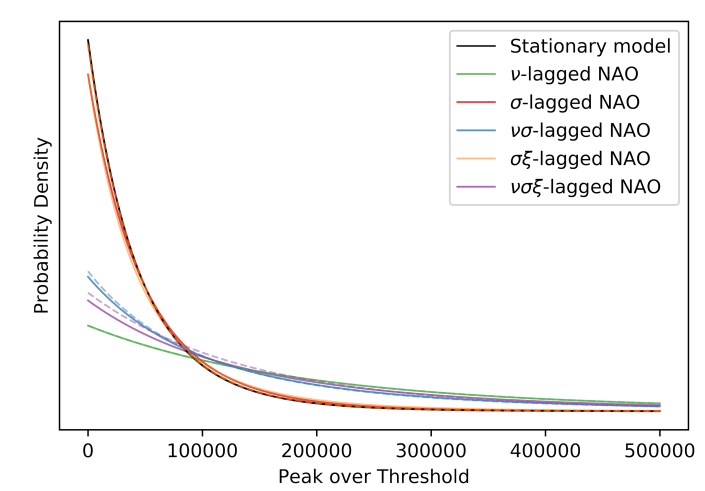
Non-neutral = $x_0 + x_1 \cdot$ NAO(-) $+ x_2 \cdot$ NAO(+)

Continuous = $x_0 + x_1 \cdot$ NAO

Comparing Model Structures - Poisson

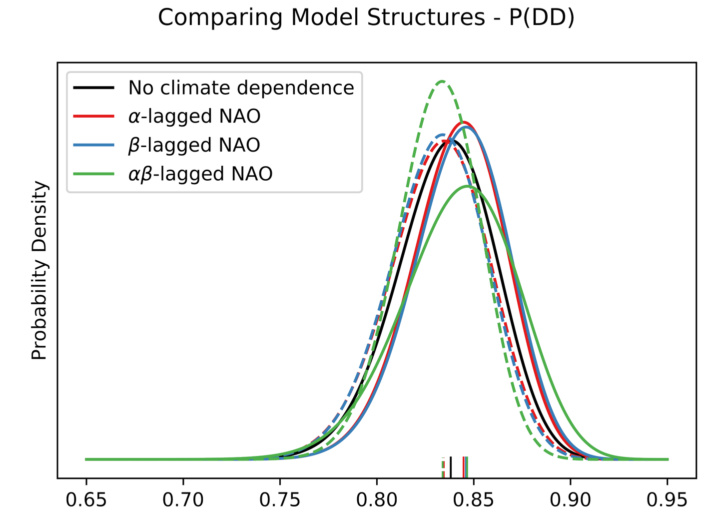


Comparing Model Structures - GPD



Model	GPD-Poisson Stationary*	ν(neutral)-lag-DJFM	σ(neutral)-lag-DJFM	$\nu\sigma$(neutral)-lag-DJFM	$\sigma\xi$(neutral)-lag-DJFM	$\nu\sigma\xi$(neutral)-lag-DJFM
ΔBIC	0.000	7.570	10.343	17.913	20.687	28.256
ΔAIC	0.000	**-0.773**	2.000	1.227	4.000	3.227

Comparing Model Structures - P(DD)

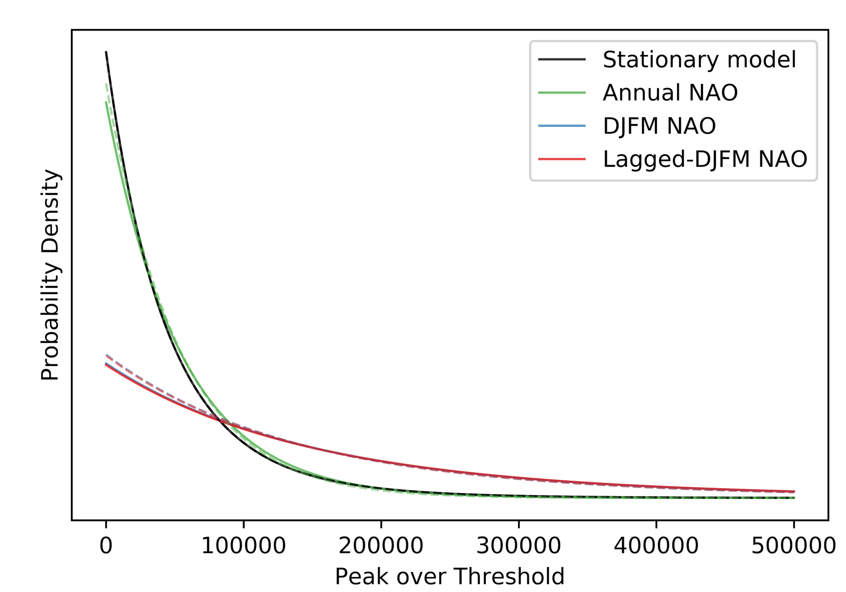


Model	DD-Stationary model*	α(neutral)-lag-DJFM	β(neutral)-lag-DJFM	$\alpha\beta$(neutral)-lag-DJFM
ΔBIC	0	1.243	-0.013	**-0.546**
ΔAIC	0	-1.199	-2.456	**-5.431**

Each of these plots show comparisons between model structures, signifying how different parameter selections contribute to the strength of the model. Solid lines represent one-year lagged neutral NAO predictor and dashed lines represent the same model structure but uses the extreme NAO as the predictor. Each table has the best performing model structure emphasized through a bold ΔBIC or ΔAIC relative to the stationary model.

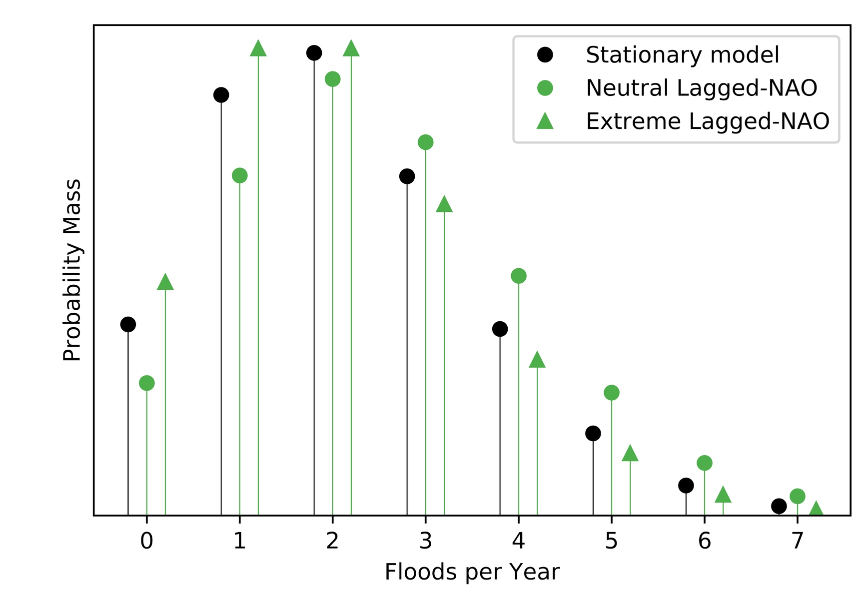
3. Results and Implications

Competitive Model Predictors - GPD



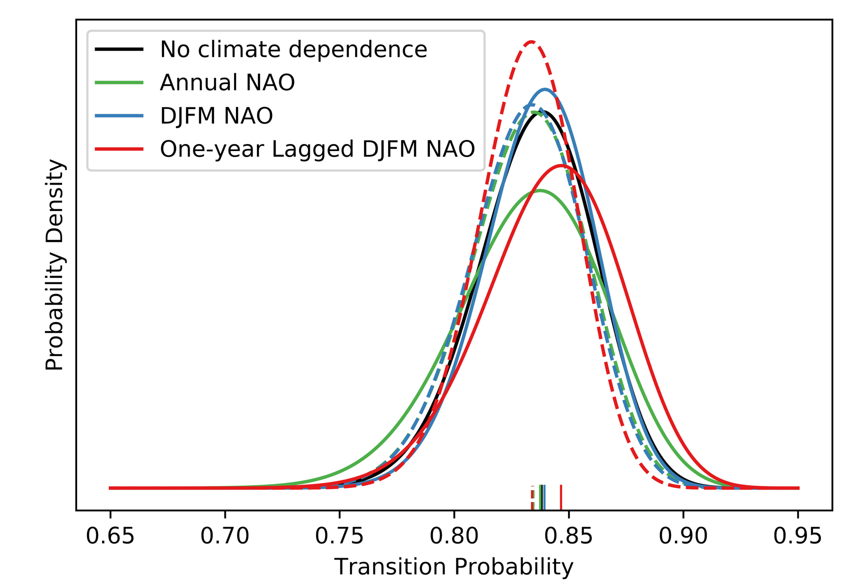
GPD models with non-stationary parameters showed little improvement relative to the stationary model. NAO does not appear to have a strong relationship with the magnitude of floods, but this framework can be used to investigate other teleconnections.

Non-stationary Poisson Model



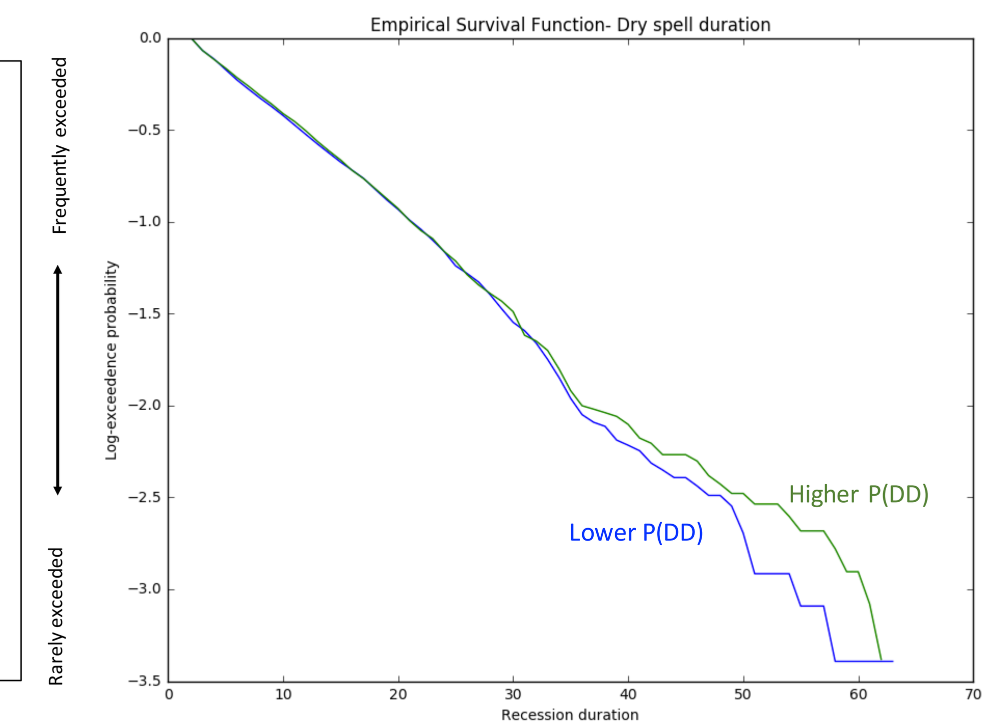
This neutral ν-lagged-DJFM model with a ΔAIC=-0.773 is the most competitive Poisson model. Under neutral NAO non-stationarity, the neutral phase of the NAO results in more floods per year relative to extreme values of the NAO.

Competitive Model Predictors - P(DD)



The difference in dashed and solid lines is the same as in previous plots. This shows that during neutral NAO phases, persistence of dry-dry states is greater than the stationary model, but dry spell persistence is is lower under extreme values of the NAO.

These models show the relationship between NAO and streamflow dynamics. This survival function illustrates the connection between dry-dry transition probabilities and dry spell duration which could affect drought management. This framework can be expanded on to investigate other streamflow teleconnections.



4. Acknowledgements

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