Discriminating anthropogenic climate change from natural climate oscillation signals in dissolved organic matter export from headwater catchments

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London, Ontario, CANADA

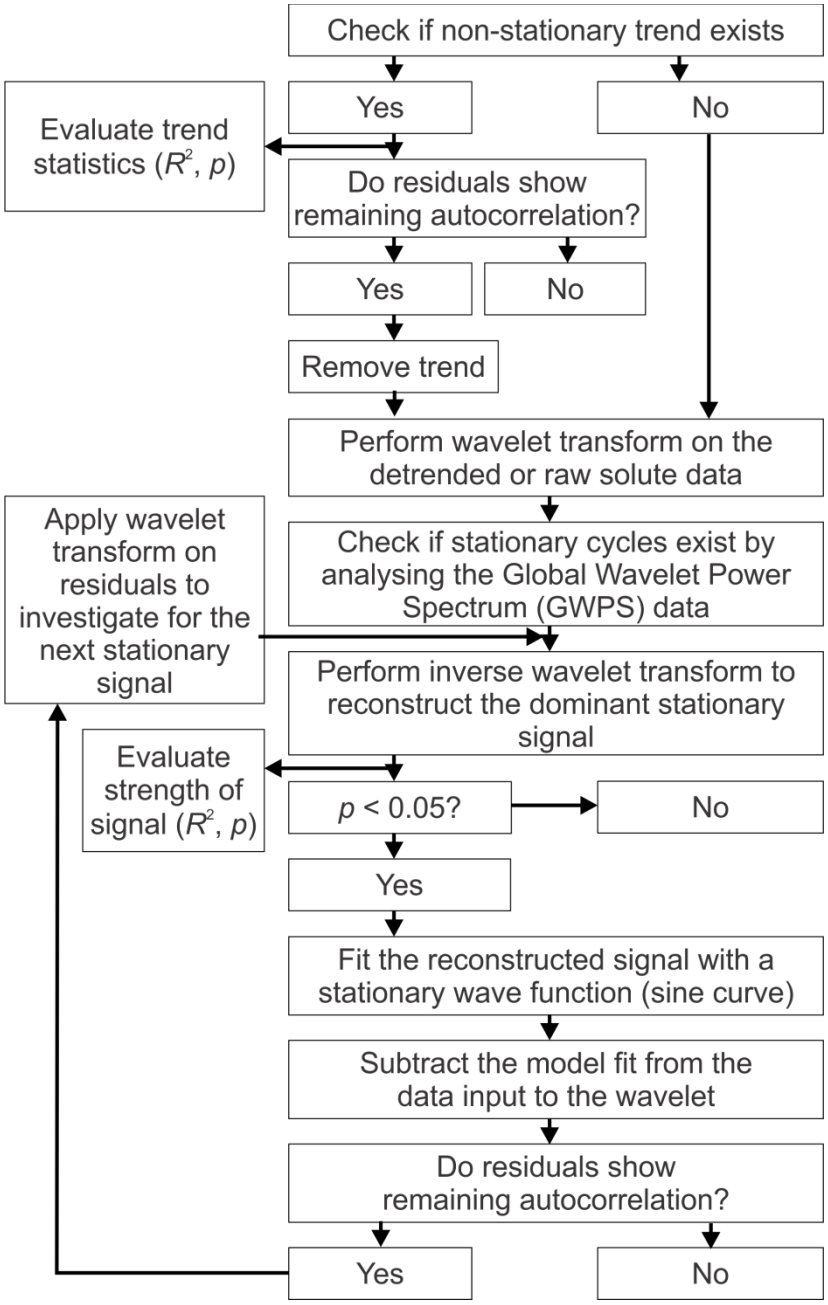
Rationale

- Catchments are influenced by a complex mix of climate drivers:
  - **Non-stationary** (climate trends)
  - **Stationary** (climate cycles)

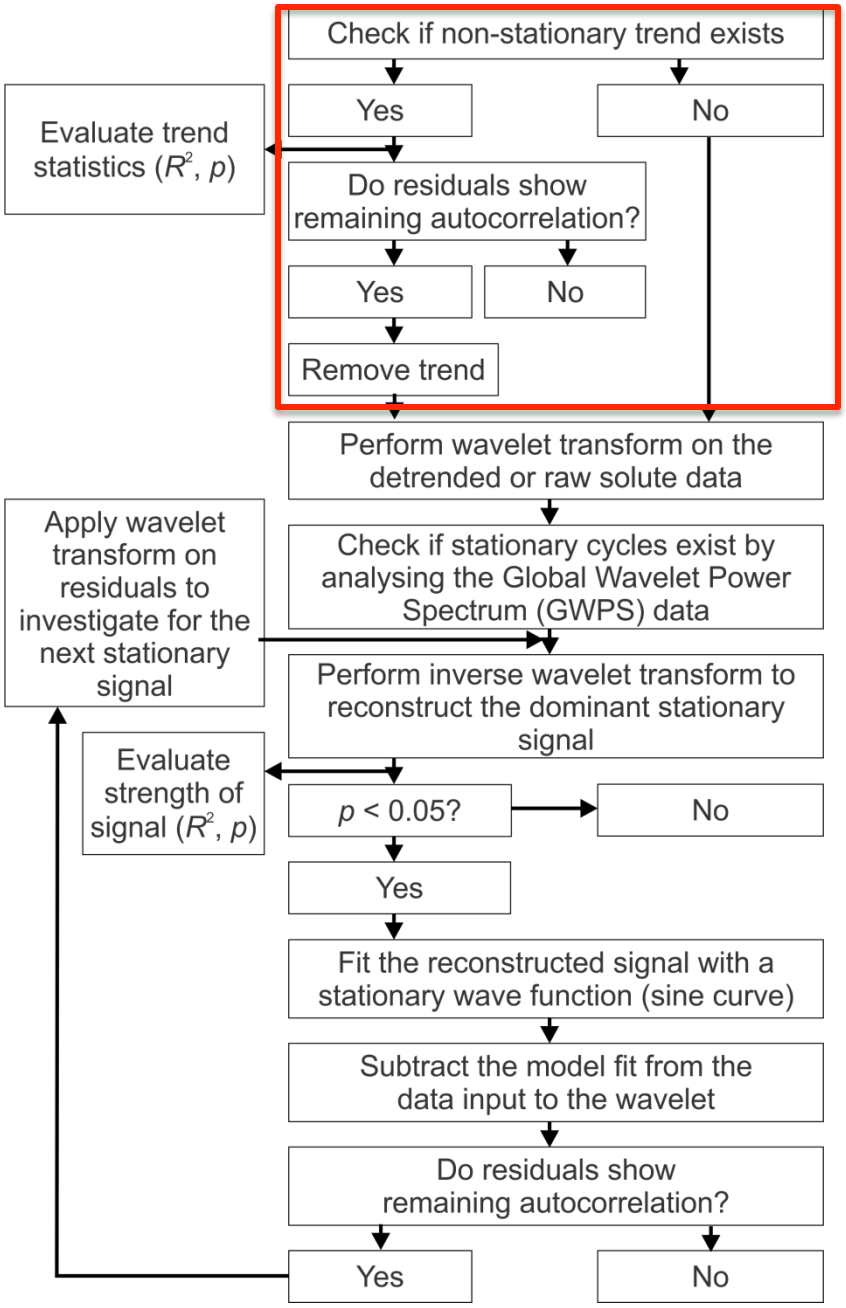
- How do these complex climate drivers affect dissolved organic matter export to rivers?

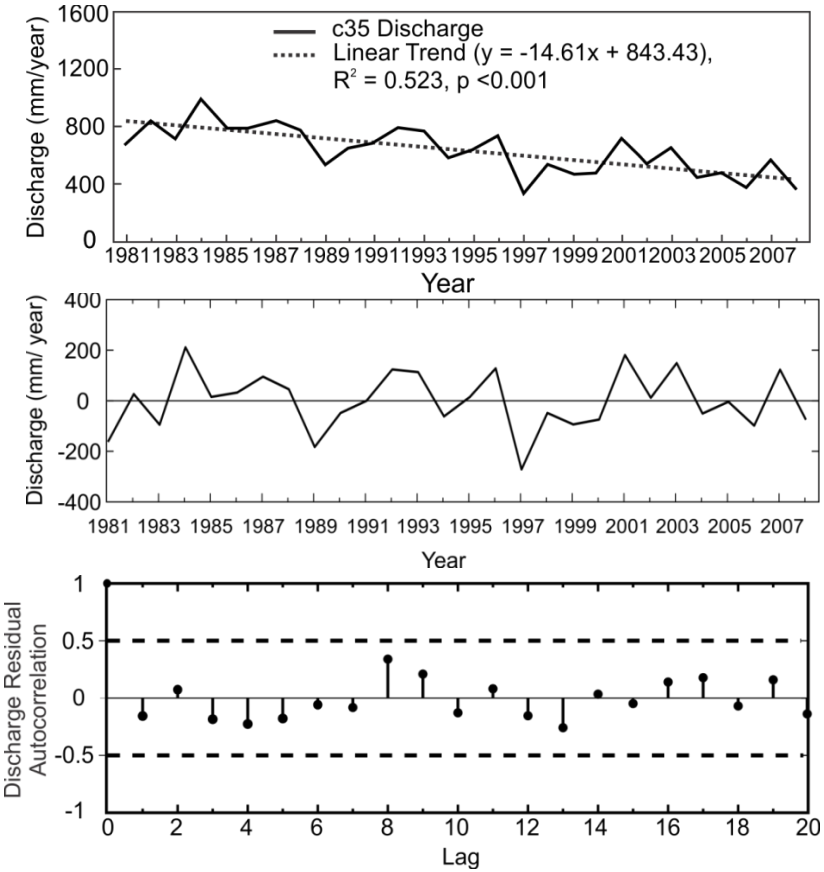
Hypotheses

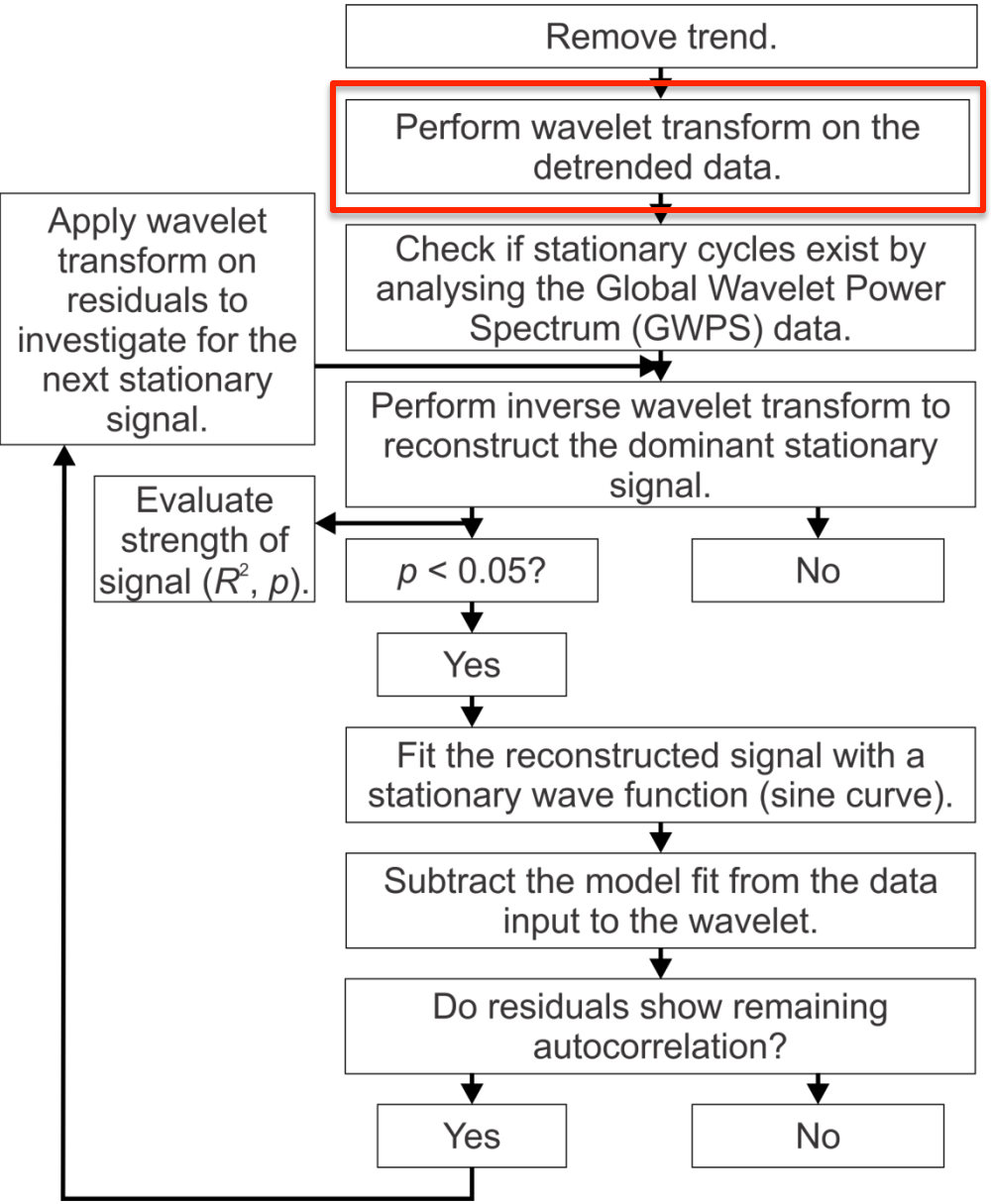
1. Climate trends and cycles explain the majority of **variation**, but trends explain the majority of **magnitude** in DOM export.
2. Catchment properties that influence **water storage** will affect responsivity to these climate signals.
3. DOM constituents that are **metabolically more active** (e.g., DON) will show greater sensitivity to these climate signals.

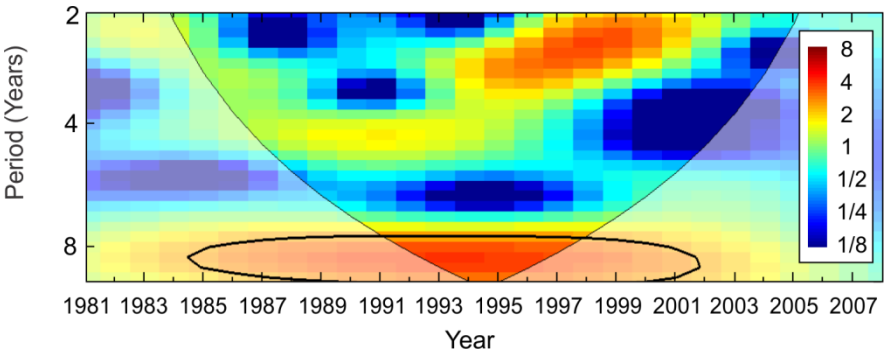


Detection of trends and cycles in **annual** time series

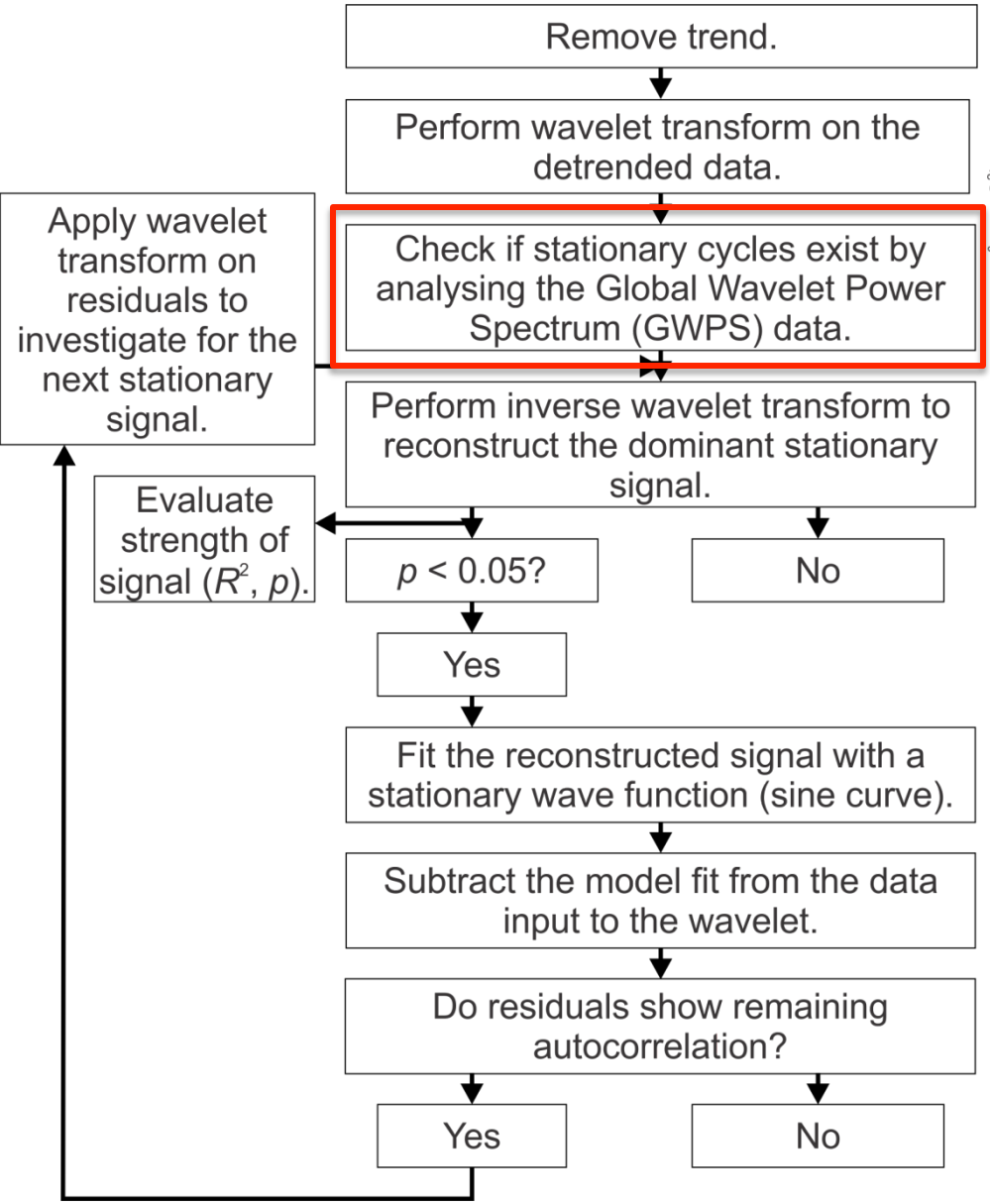

Check if non-stationary trend exists
Yes
No
Evaluate trend statistics (R^2, p)
Do residuals show remaining autocorrelation?
Yes
No
Remove trend
Perform wavelet transform on the detrended or raw solute data
Apply wavelet transform on residuals to investigate for the next stationary signal
Check if stationary cycles exist by analysing the Global Wavelet Power Spectrum (GWPS) data
Perform inverse wavelet transform to reconstruct the dominant stationary signal
Evaluate strength of signal (R^2, p)
p < 0.05?
No
Yes
Fit the reconstructed signal with a stationary wave function (sine curve)
Subtract the model fit from the data input to the wavelet
Do residuals show remaining autocorrelation?
Yes
No


c35 Discharge
Linear Trend (y = -14.61x + 843.43),
R^2 = 0.523, p <0.001
Discharge (mm/year)
Year
Discharge (mm/ year)
Year
Discharge Residual Autocorrelation
Lag





Morlet wavelets best at capturing hydrological patterns.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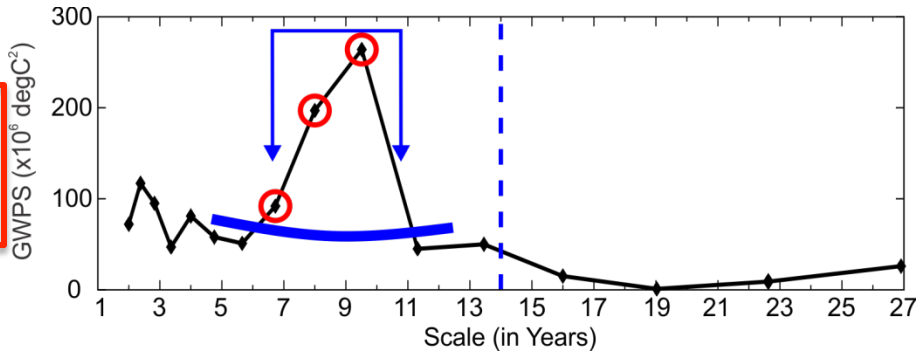
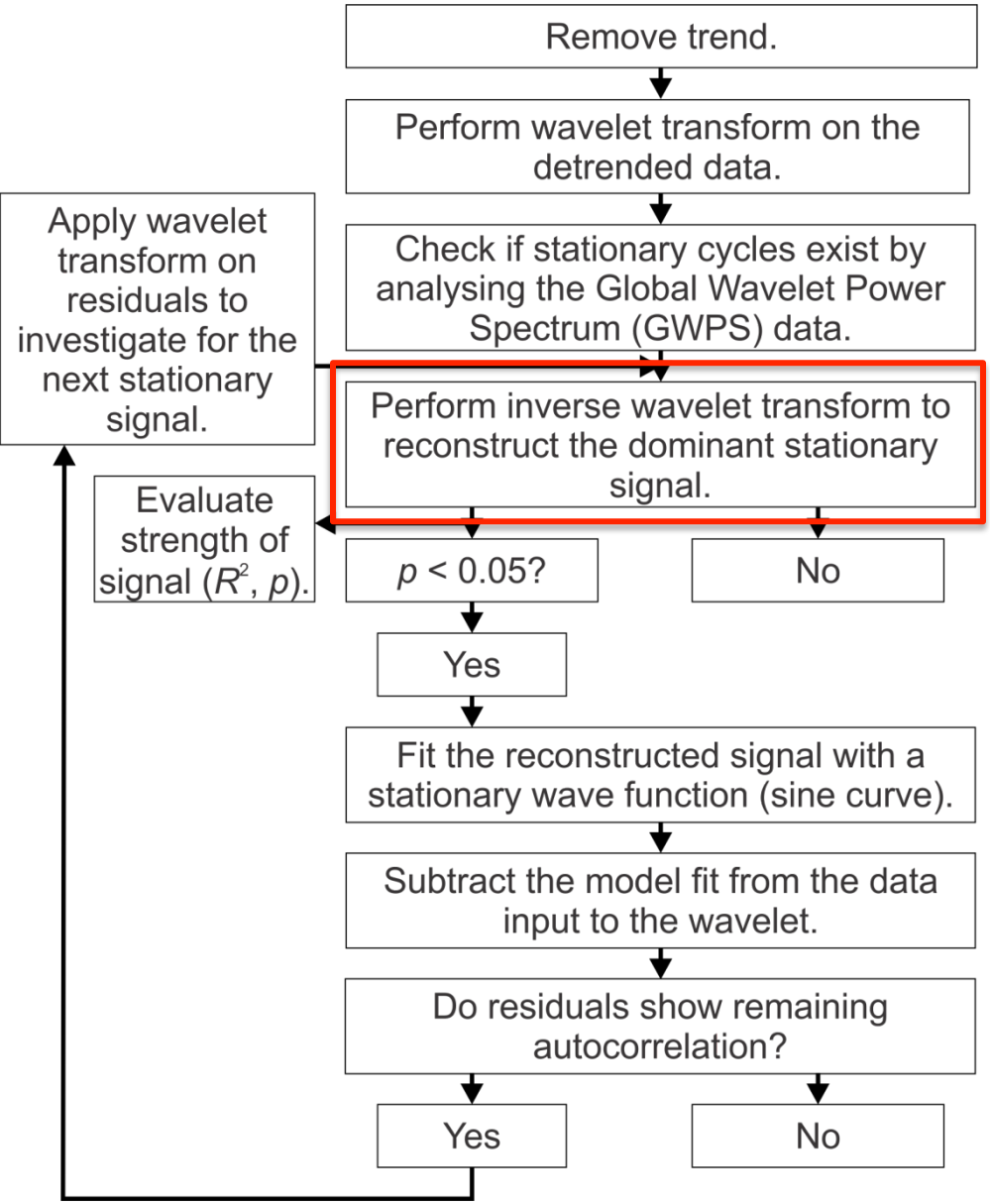

GWPS (x10^6 degC^2)
300
200
100
0
1
3
5
7
9
11
13
15
17
19
21
23
25
27
Scale (in Years)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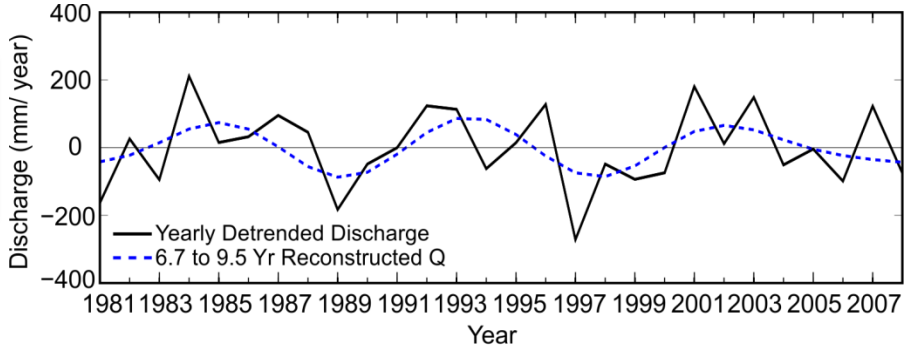
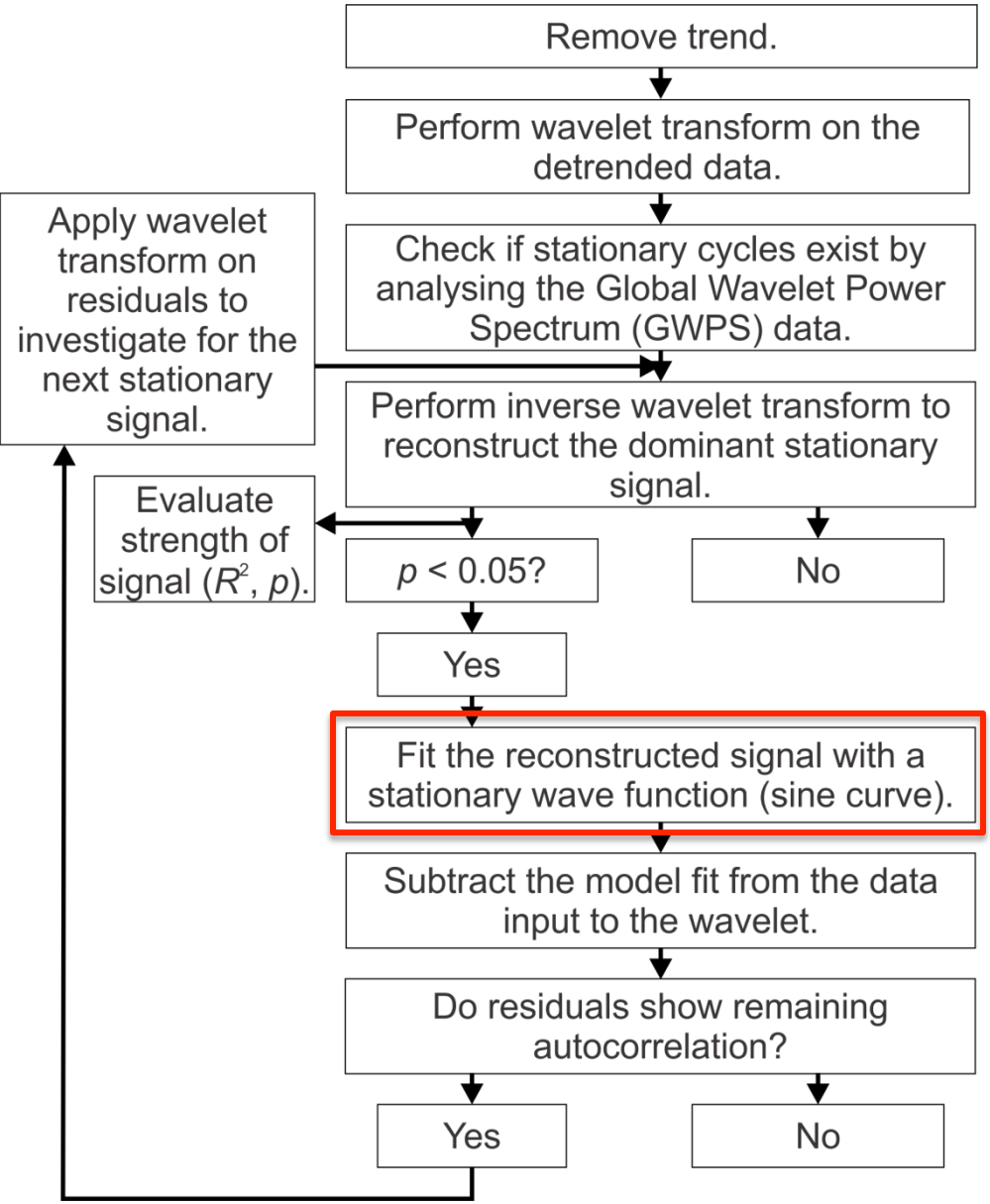

Discharge (mm/ year)
400
200
0
−200
−400
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005 2007
Year
Yearly Detrended Discharge
6.7 to 9.5 Yr Reconstructed Q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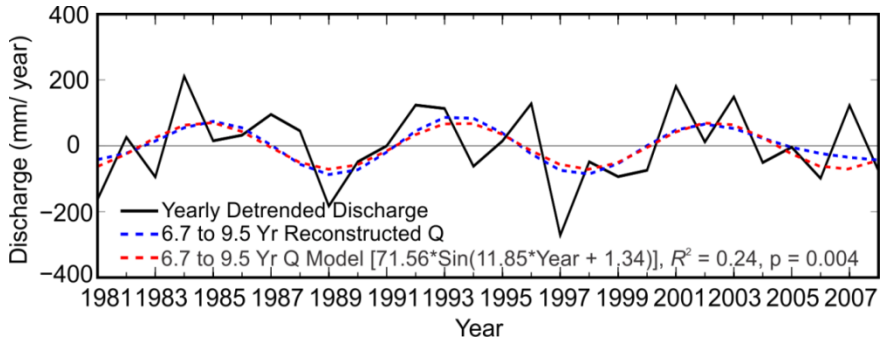
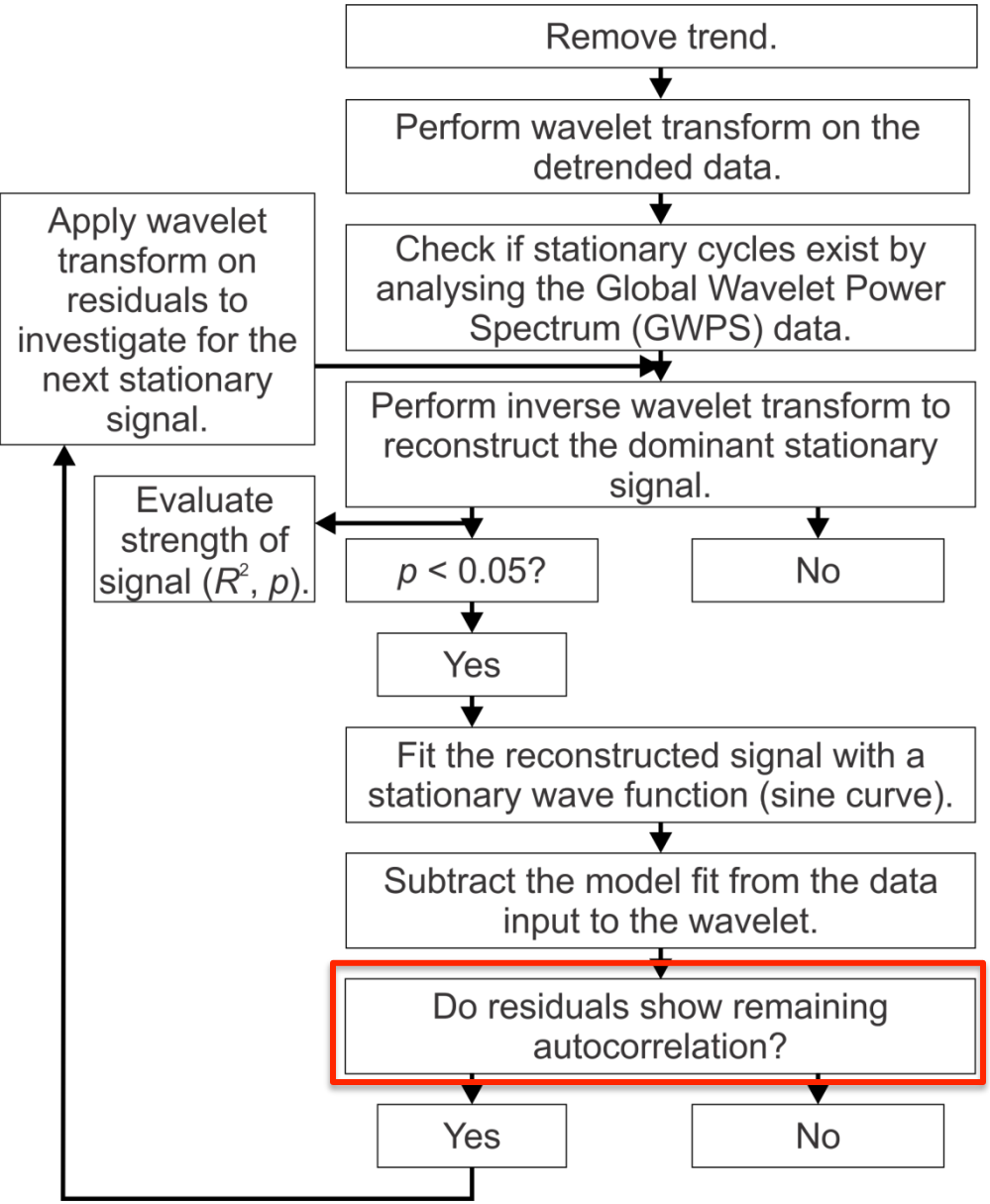

Discharge (mm/ year)
400
200
0
−200
−400
Yearly Detrended Discharge
6.7 to 9.5 Yr Reconstructed Q
6.7 to 9.5 Yr Q Model [71.56*Sin(11.85*Year + 1.34)], R^2 = 0.24, p = 0.004
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005 2007
Year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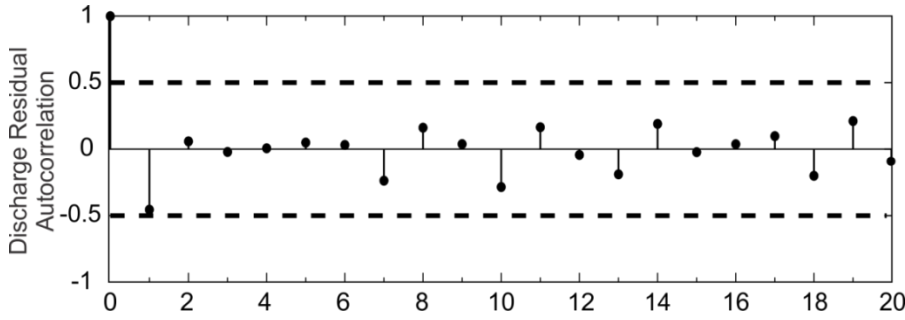
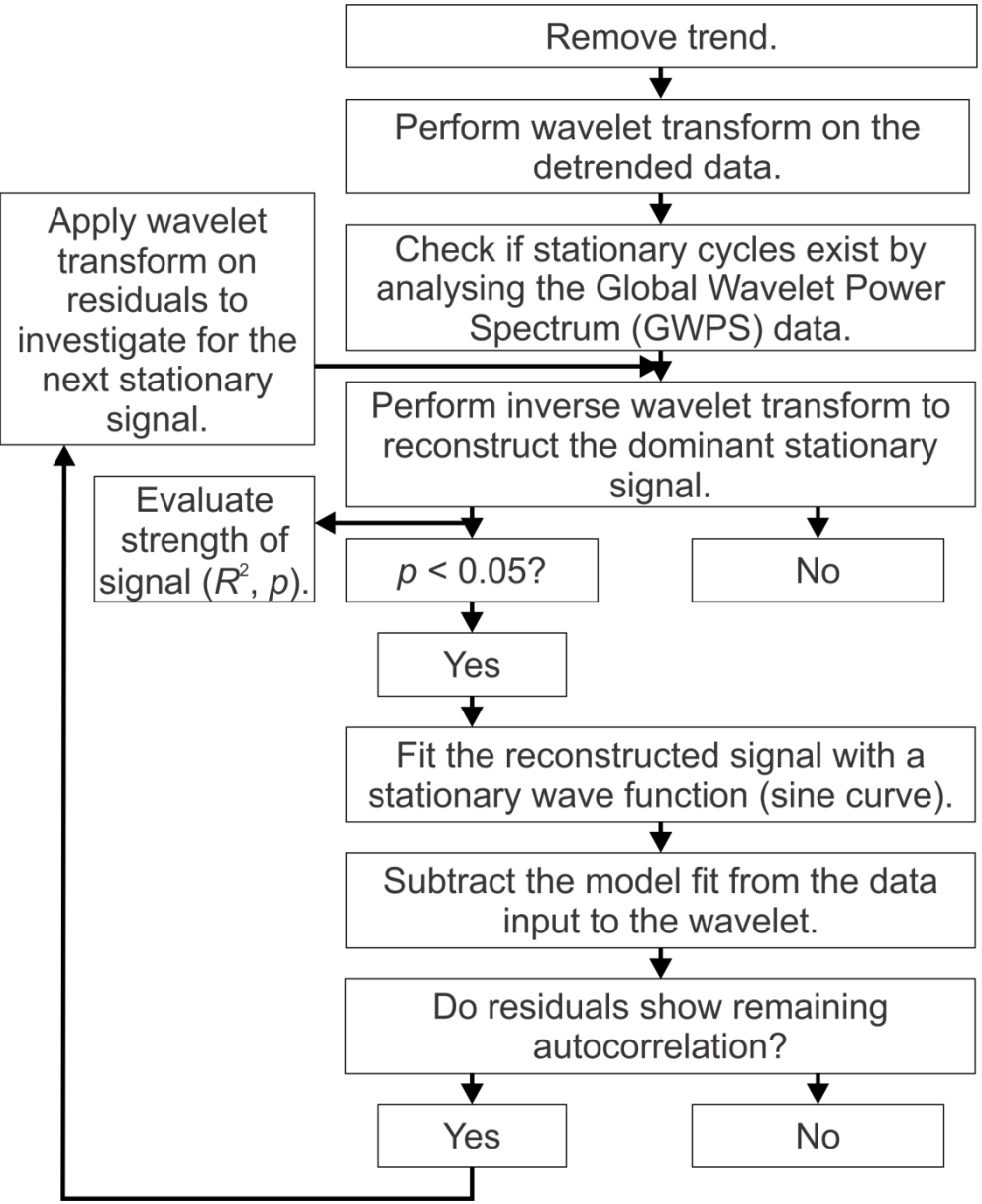

Discharge Residual Autocorrelation
1
0.5
0
-0.5
-1
0
2
4
6
8
10
12
14
16
18
20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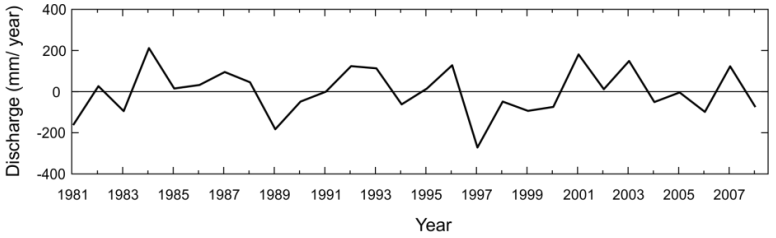
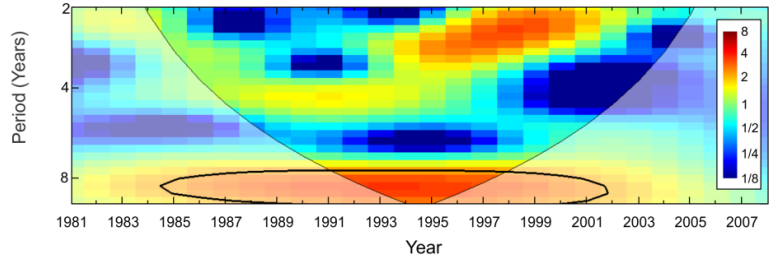
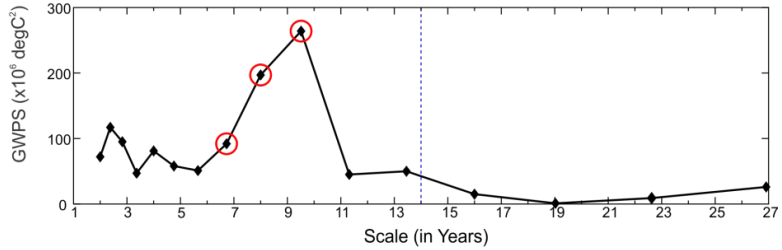
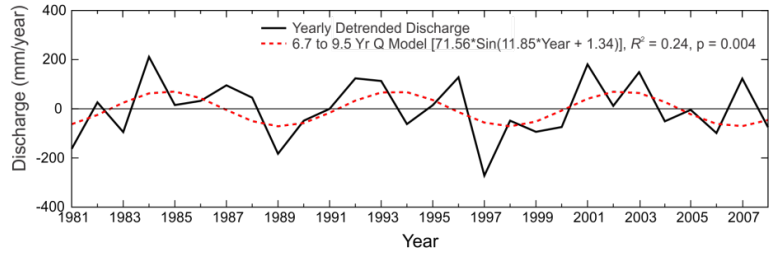

Discharge (mm/ year)
Year


Period (Years)
Year


GWPS (x10⁶ degC²)
Scale (in Years)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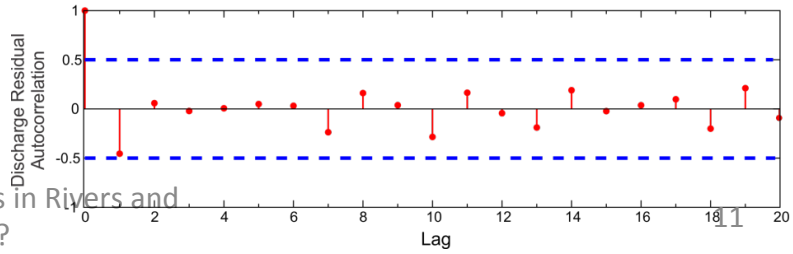
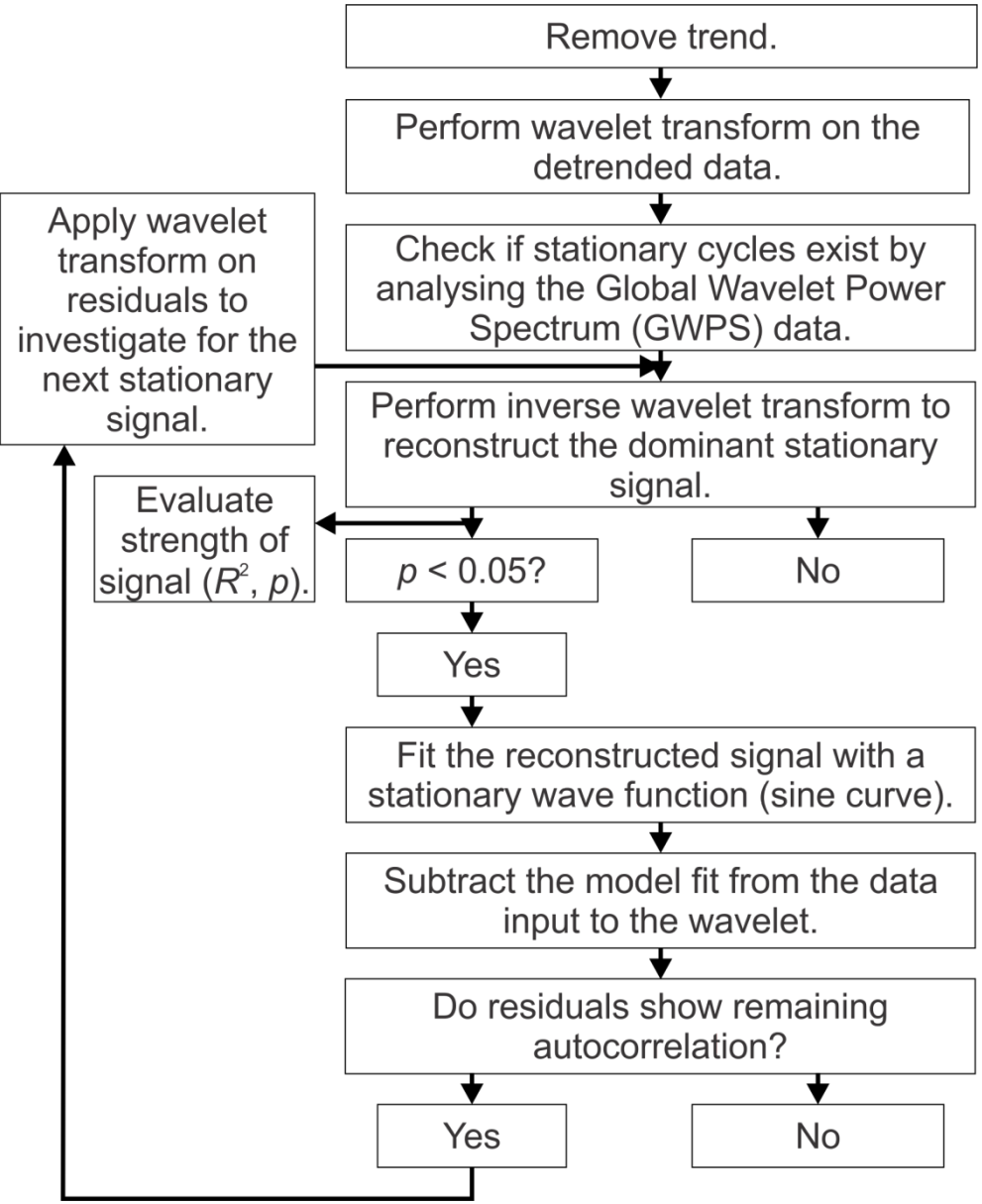
Discharge (mm/year)
Year


Discharge Residual Autocorrelation
Lag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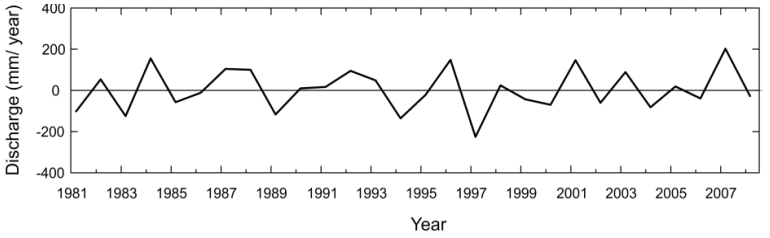
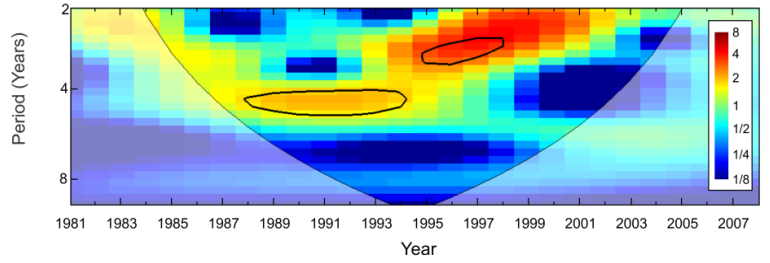
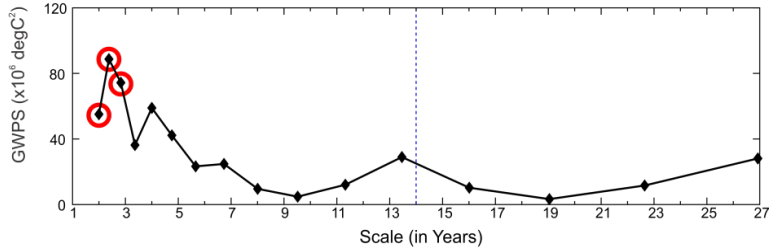
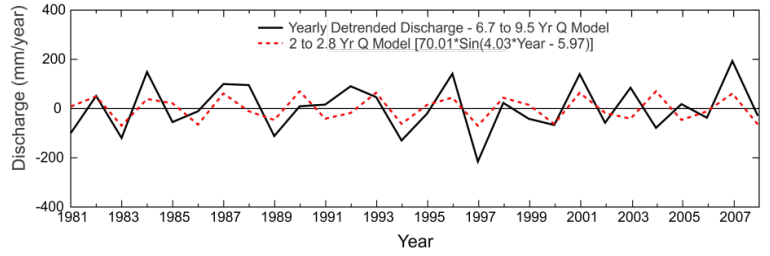
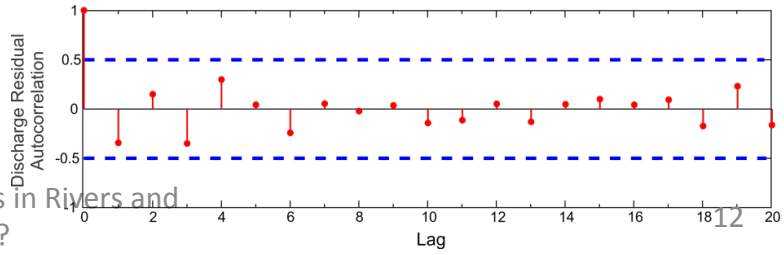

Discharge (mm/ year)
Year


Period (Years)
Year


GWPS (x10⁶ degC²)
Scale (in Years)


Yearly Detrended Discharge - 6.7 to 9.5 Yr Q Model
2 to 2.8 Yr Q Model [70.01*Sin(4.03*Year - 5.97)]
Discharge (mm/year)
Year


Discharge Residual Autocorrelation
Lag

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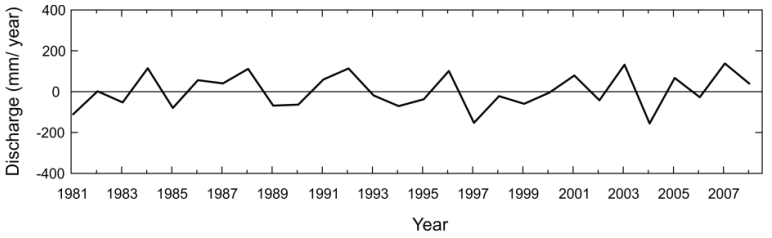
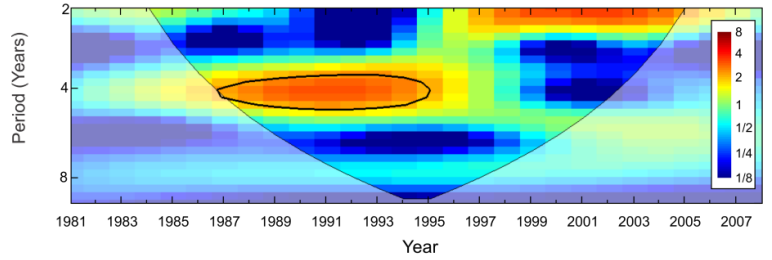
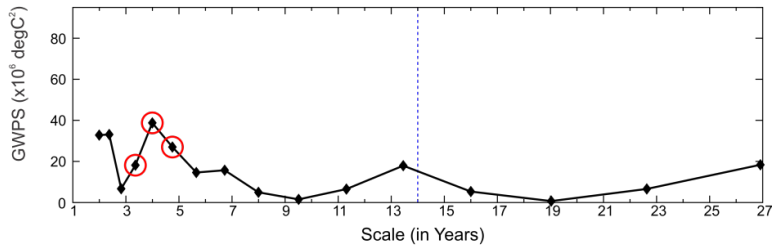
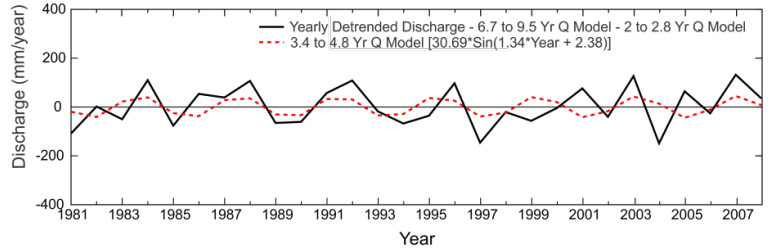
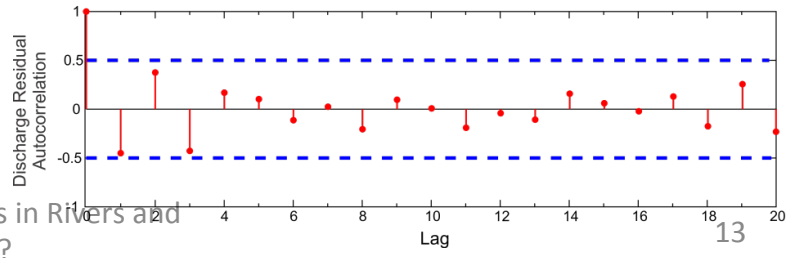






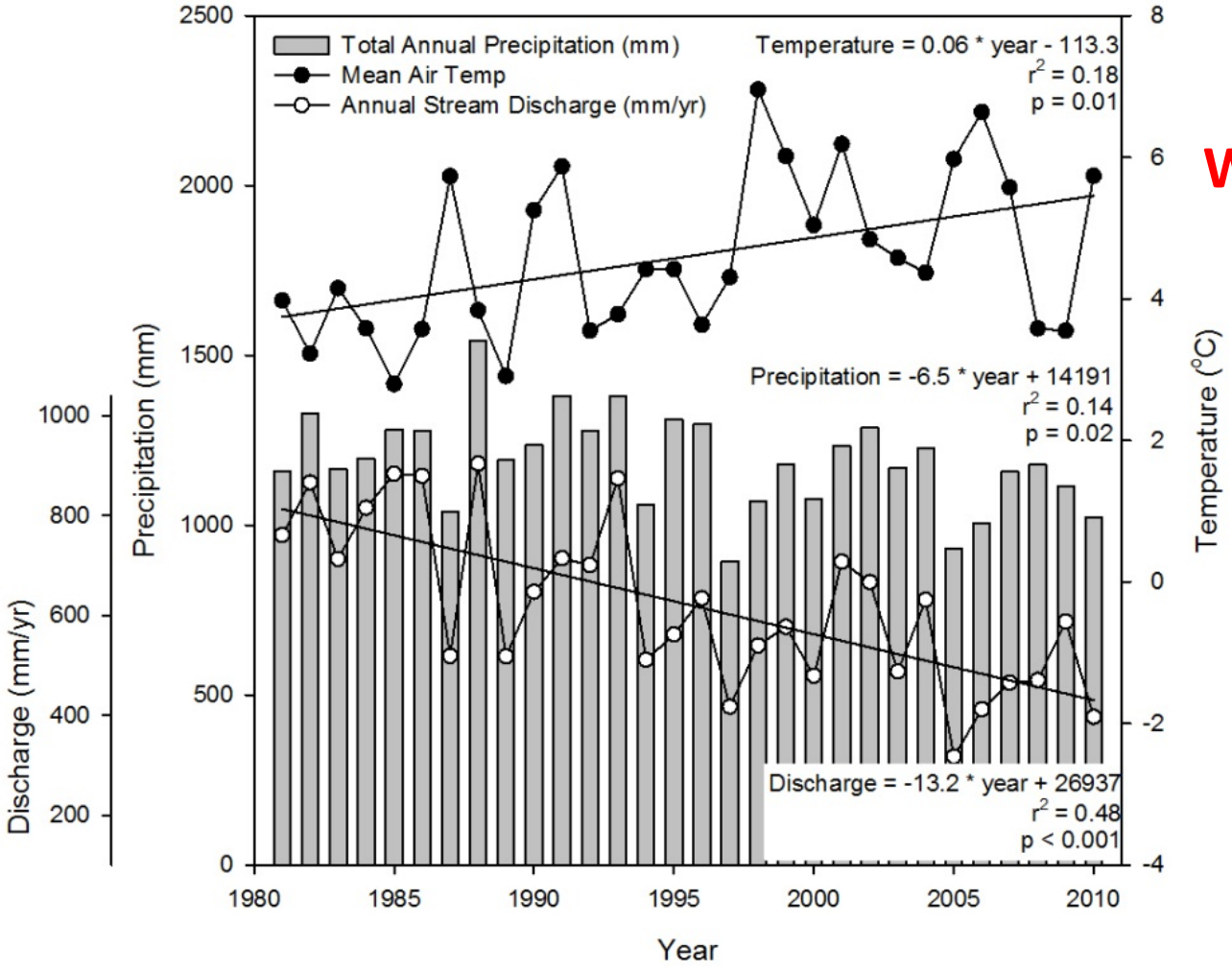




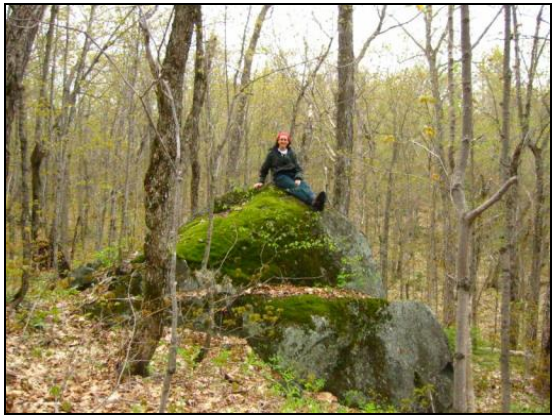
Application to catchments with high rates of climate change

Algoma Highlands is one of the largest areas of pristine forested landscape remaining in the Great Lakes basin

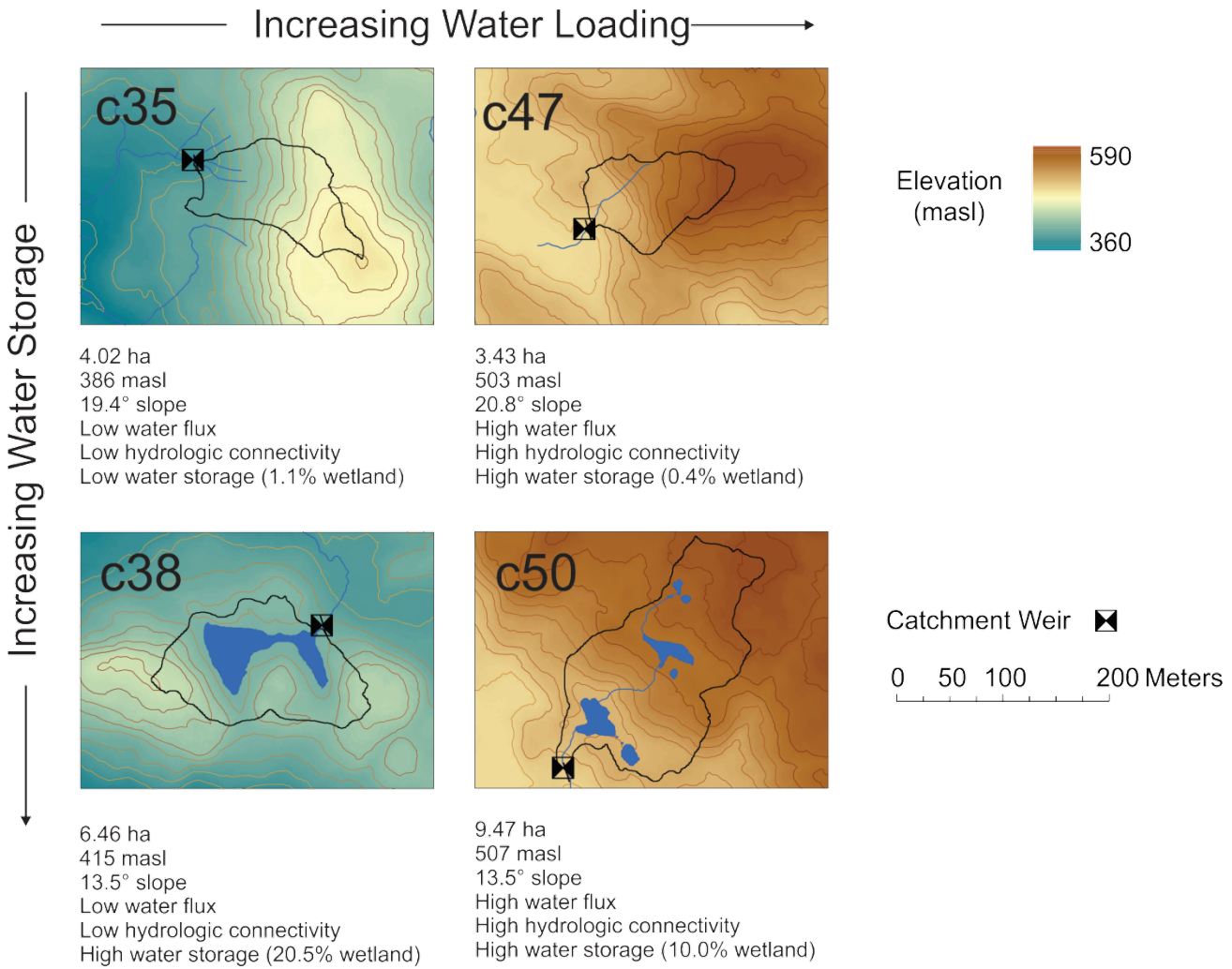
Thirty-year meteorological record in Algoma Highlands

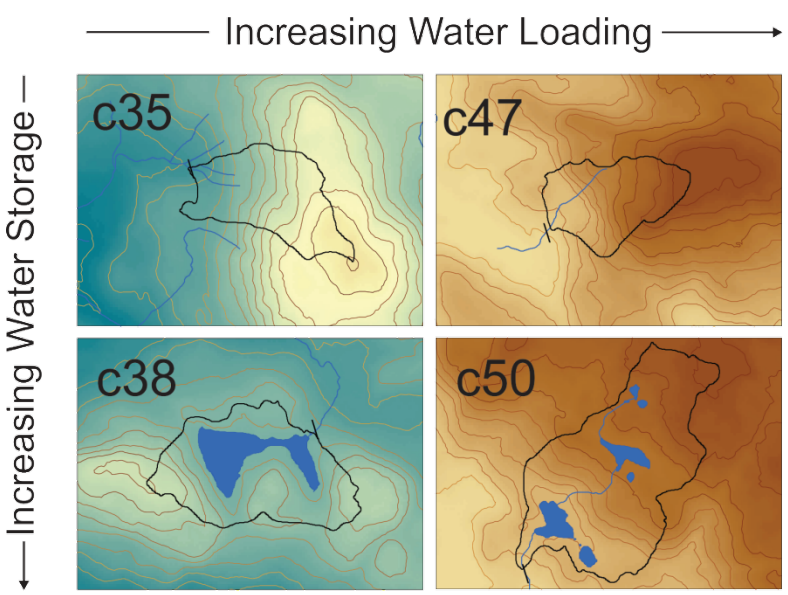


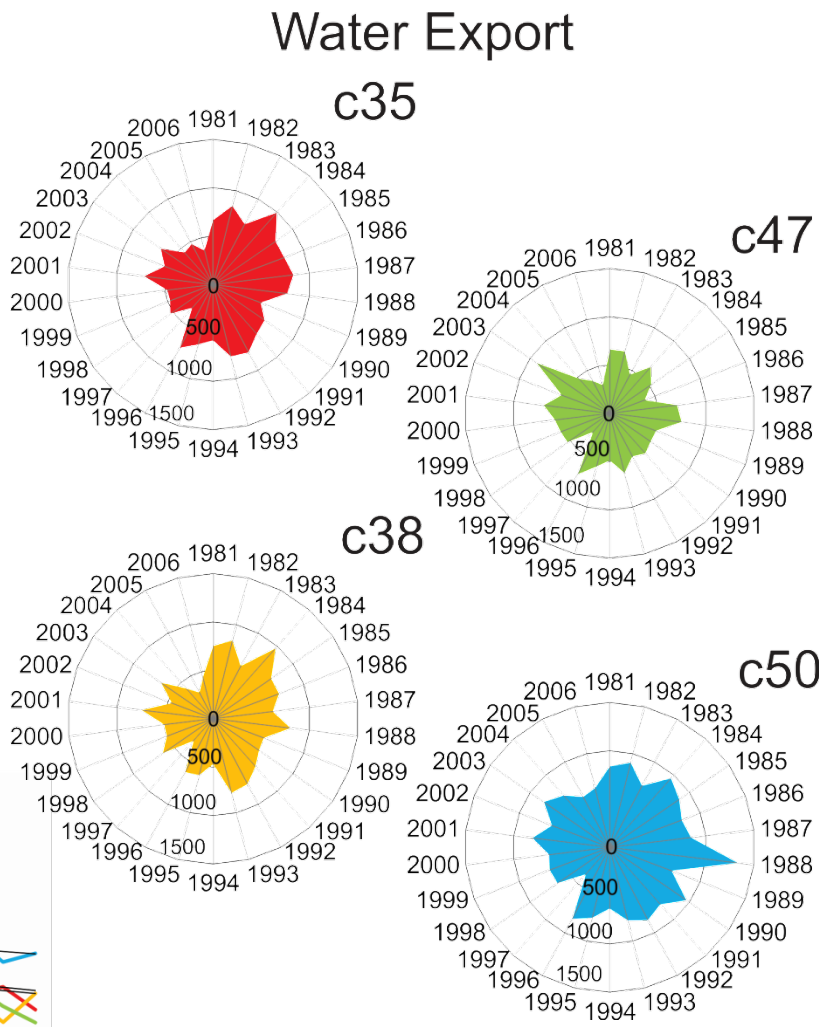
Warming of almost 1°C per decade!

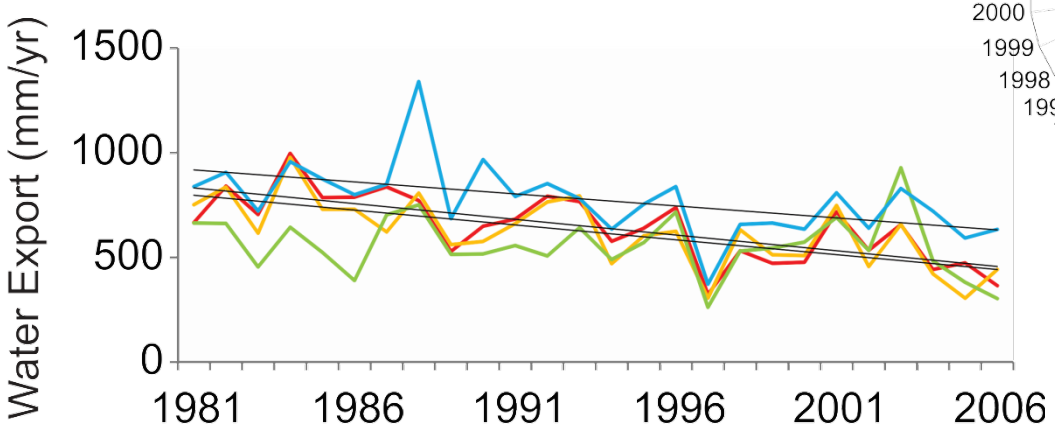


What is the role of catchment properties in mitigating climate signals?









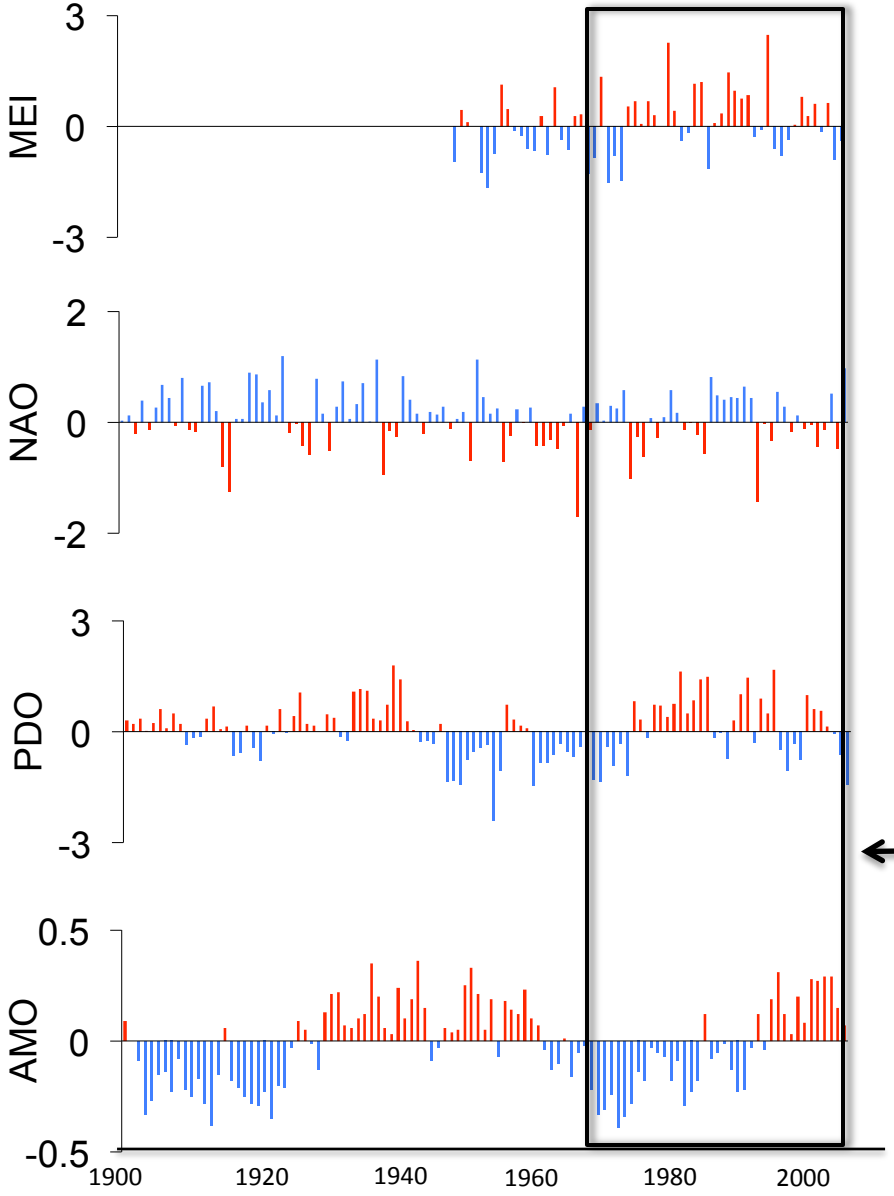
c35, y = -14.6x + 843.4, R^2 = 0.52
c47
c38, y = -13.0x + 801.1, R^2 = 0.44
c50, y = -8.9x + 905.6, R^2 = 0.18

Water Export

	Water Export	C35	C38	C47	C50
VARIATION	**Non-stationary trend (%)**	**52**	**44**	**NS**	**18**
	Trend + Cycle 1	65	59	19	39
	Trend + Cycle 1 + 2	76	68	38	56
	Trend + Cycle 1 + 2 + 3	**81**	**76**	**56**	**63**
	Stationary cycles (%)	**29**	**32**	**56**	**45**
MAGNITUDE	**Trend (slope) (mm/yr)**	**-15**	**-13**	**NS**	**-9**
	Cycles (amplitude) (mm/yr)	**±72**	**±83**	**±79**	**±100**

Catchments with **low water loading** show steeper slopes of decline.
Catchments with **high water storage** show larger amplitudes.

Global climate oscillation indices

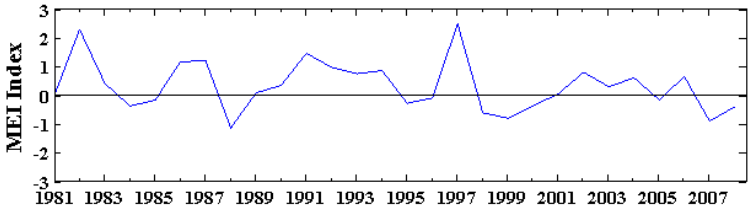


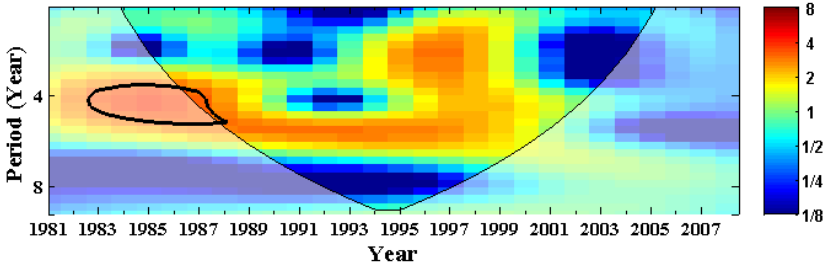
MEI = 2 to 7 years
NAO = 7 to 9 years, 20 years
PDO = 20 to 30 years
AMO = 60 to 90 years

Turkey Lakes Watershed period of record

Wavelet cross-coherence between climate oscillations and water export

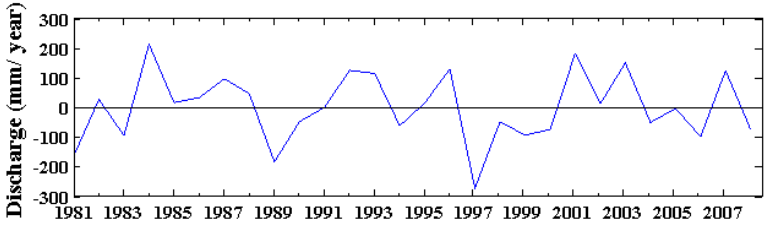
Wavelet power spectrum of MEI Index

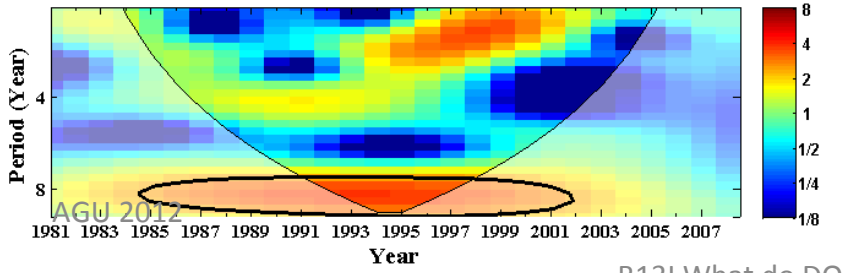




versus

Wavelet power spectrum of c35 discharge





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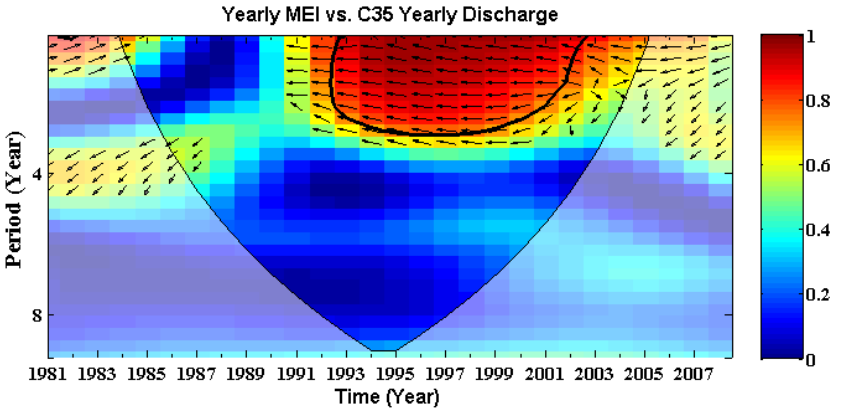
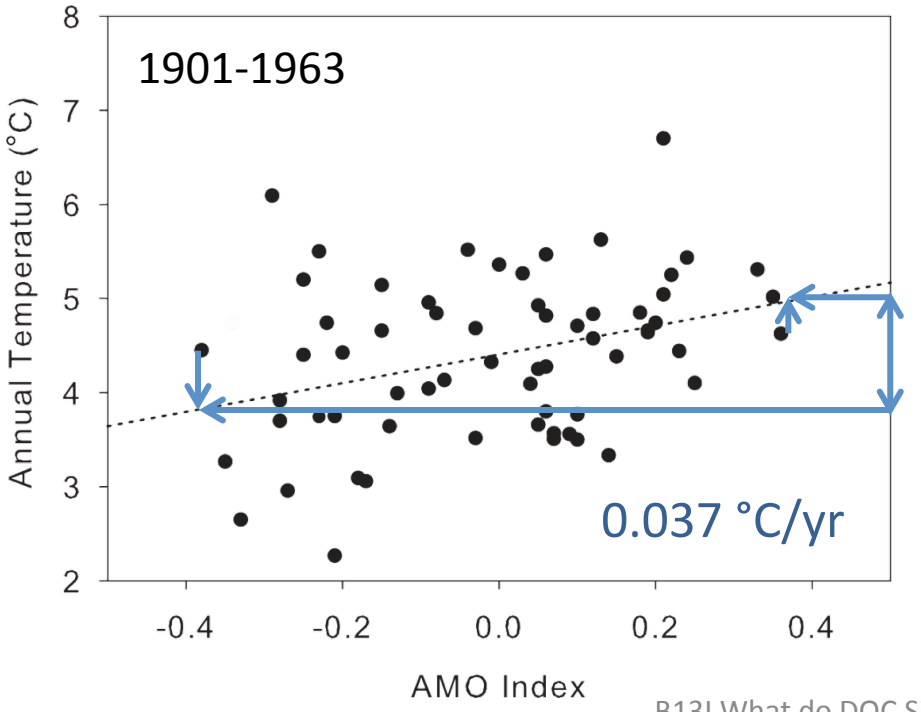


The **thick solid lines** show 95% confidence level.

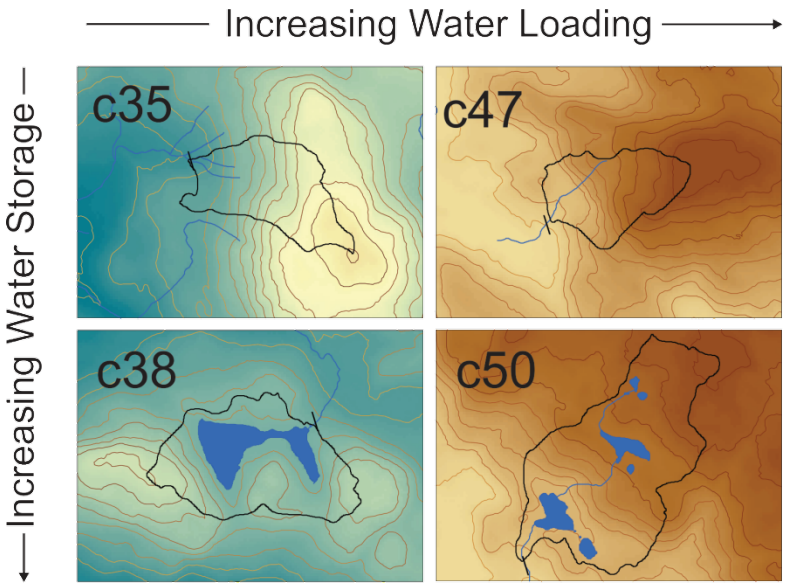
stationary signals *vs.* global climate oscillations

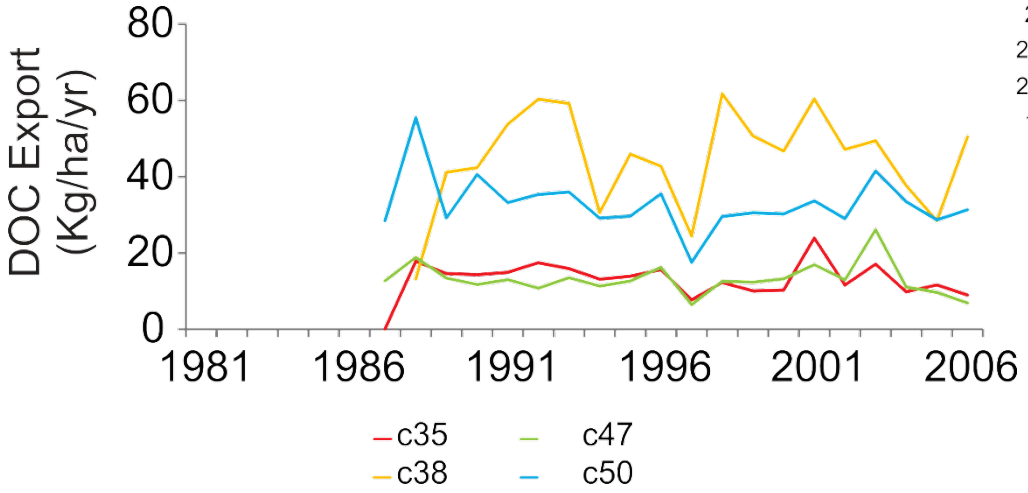
Pearson correlation matrix (* = p<0.05)

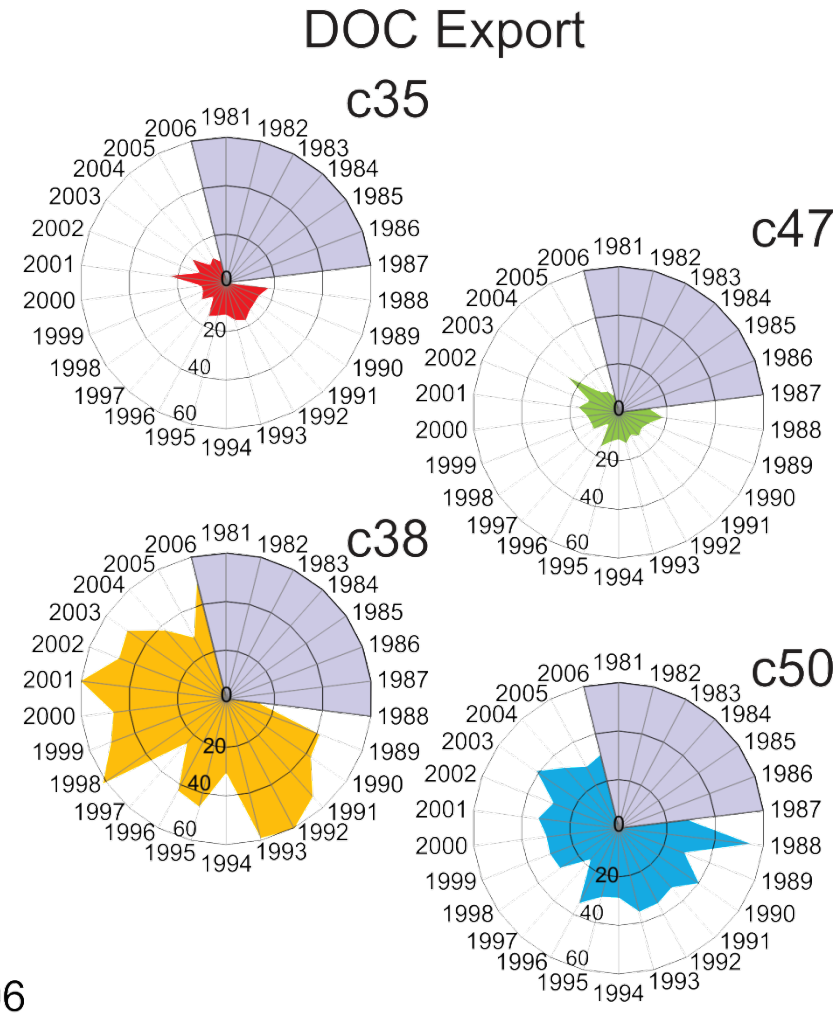
Climate oscillations		C35	C38	C47	C50
MEI		NS	NS	NS	NS
NAO		NS	NS	NS	NS
PDO	**r^2**	0.15*	NS	NS	NS
AMO	**r^2**	**0.49***	**0.46***	NS	**0.19***



AMO explains 55% of the observed 0.067°C/yr warming


Increasing Water Loading
Increasing Water Storage
c35
c47
c38
c50


DOC Export
(Kg/ha/yr)
80
60
40
20
0
1981
1986
1991
1996
2001
2006
c35
c47
c38
c50

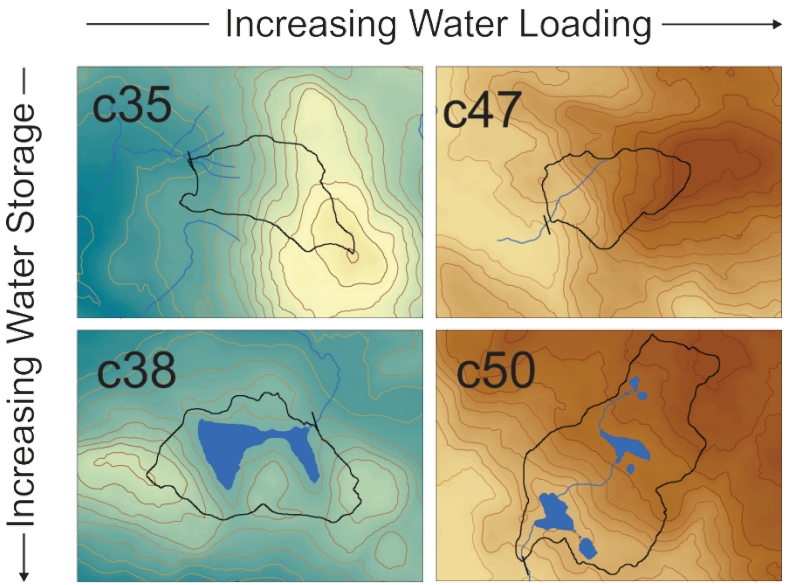

DOC Export
c35
c47
c38
c50

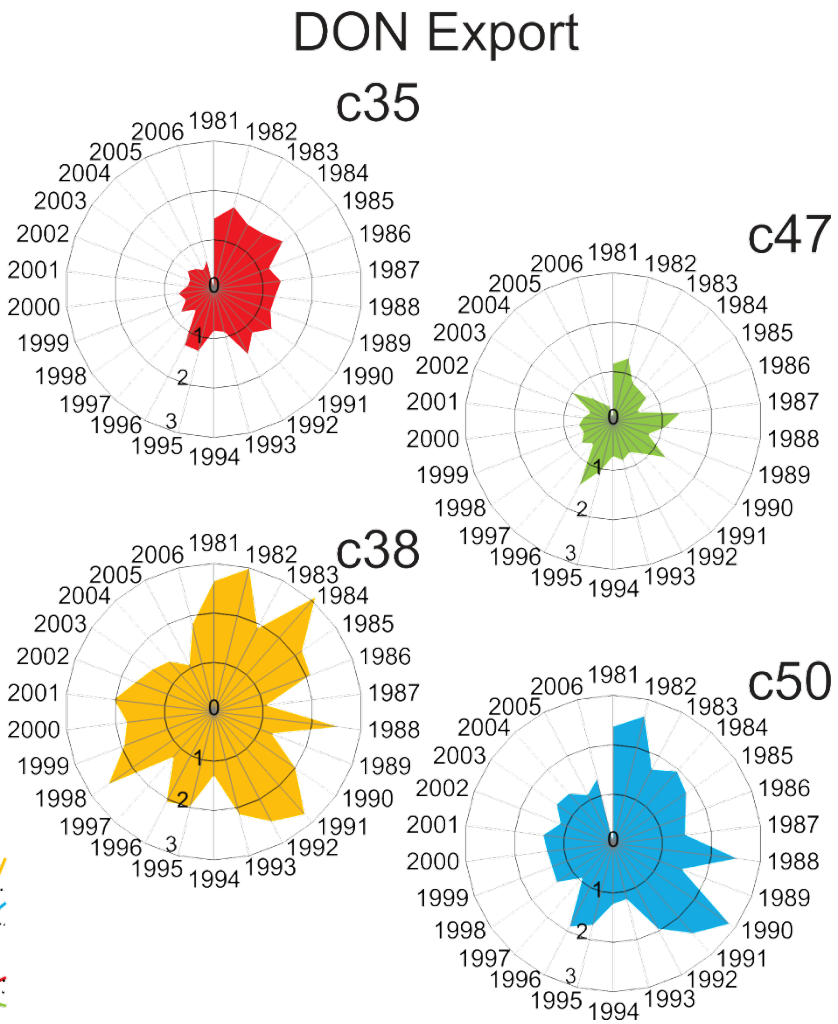
DOC Export

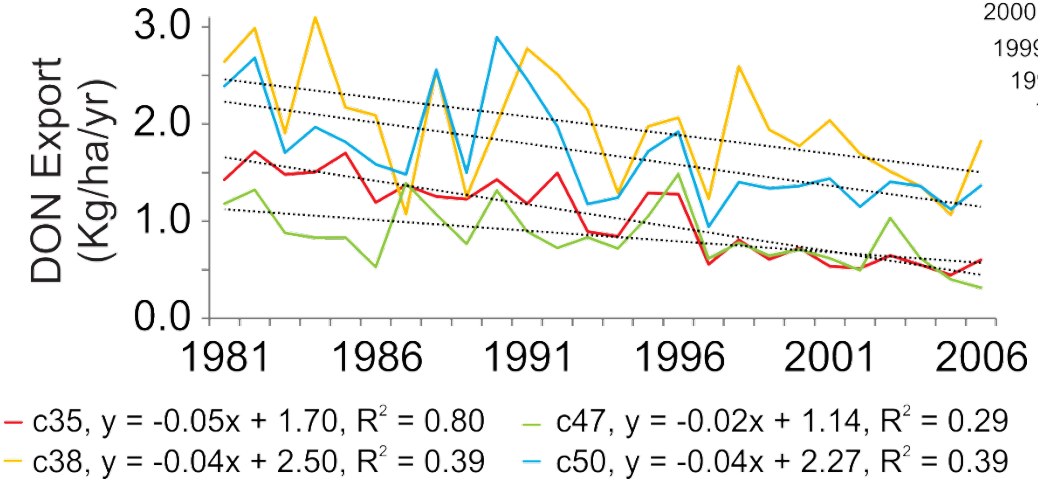
	DOC	C35	C38	C47	C50
VARIATION	**Non-stationary trend (%)**	**NS**	**NS**	**NS**	**NS**
	Trend + Cycle 1	29	34	20	18
	Trend + Cycle 1 + 2	**53**	67	50	**53**
	Trend + Cycle 1 + 2 + 3	-	**88**	**69**	-
	Stationary cycles (%)	**53**	**88**	**69**	**53**
MAGNITUDE	**Trend (slope) (g/ha/yr)**	**NS**	**NS**	**NS**	**NS**
	Cycles (amplitude) (g/ha/yr)	**±2,587**	**±9,121**	**±3,104**	**±4,217**

No trends; significant cycles.

Catchments with **high water storage** show **larger amplitudes** in DOC export.







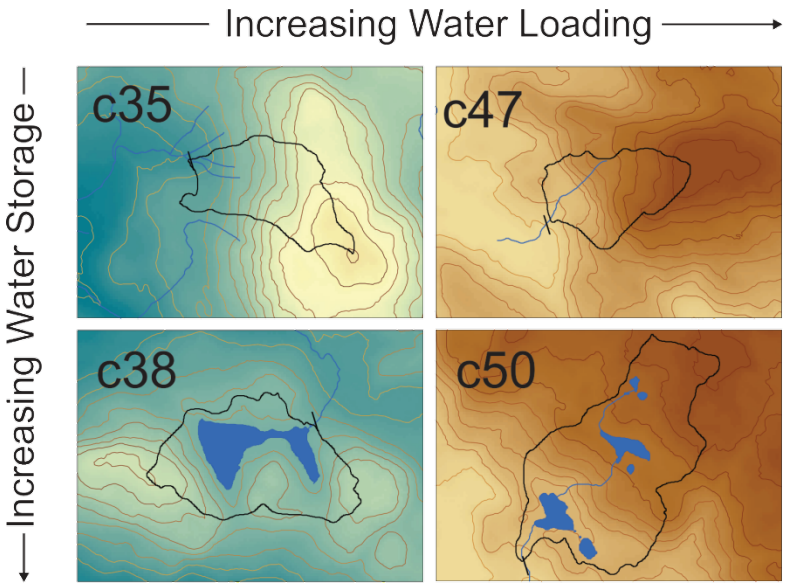
c35, $y = -0.05x + 1.70$, $R^2 = 0.80$ c47, $y = -0.02x + 1.14$, $R^2 = 0.29$

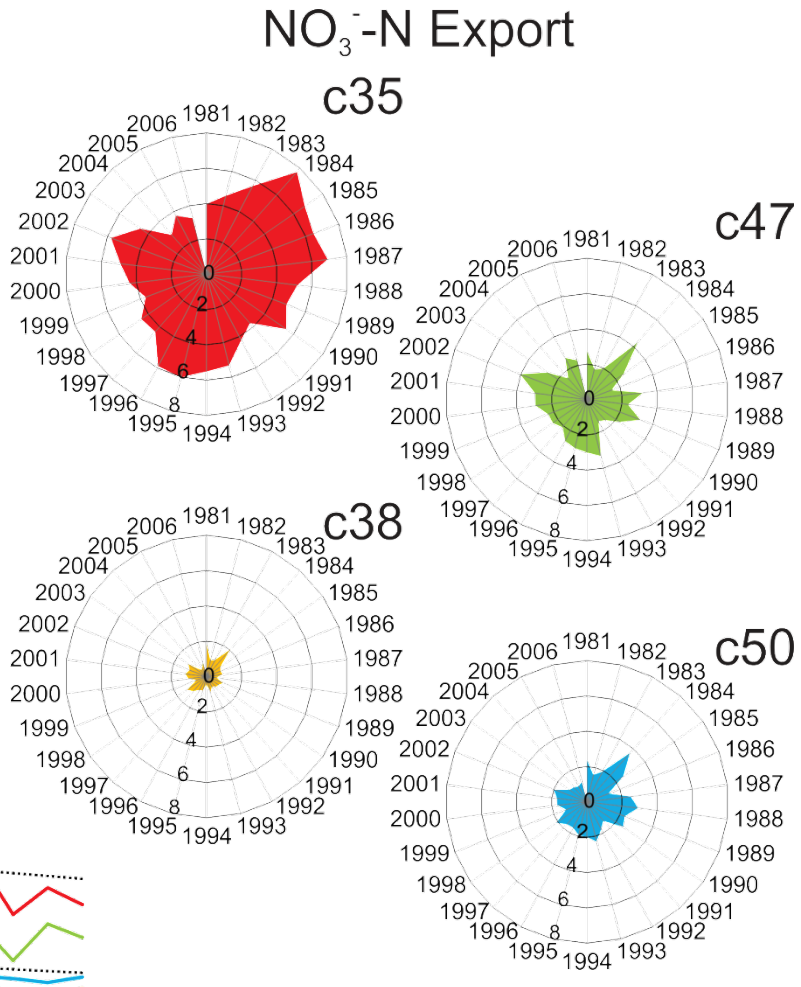
c38, $y = -0.04x + 2.50$, $R^2 = 0.39$ c50, $y = -0.04x + 2.27$, $R^2 = 0.39$

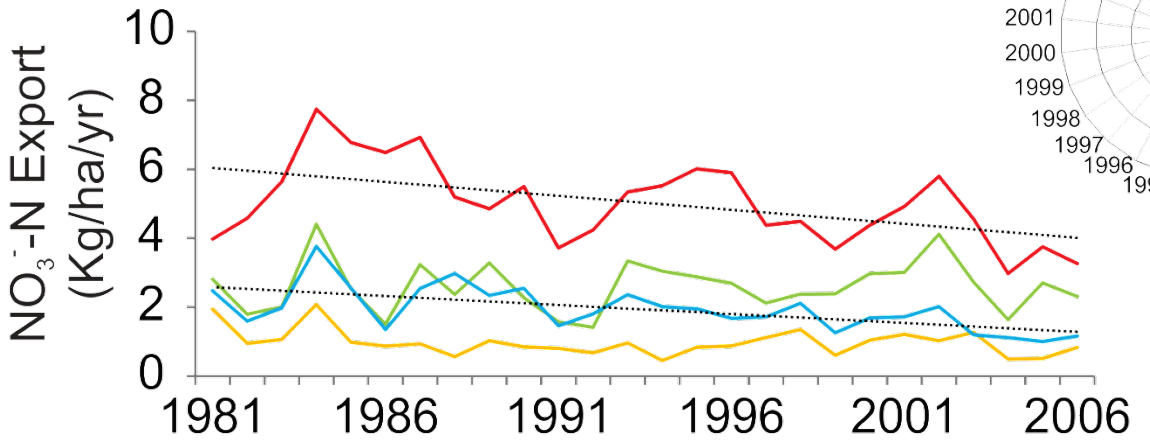
DON Export

	DON	C35	C38	C47	C50
VARIATION	**Non-stationary trend (%)**	**80**	**26**	**29**	**39**
	Trend + Cycle 1	86	43	50	51
	Trend + Cycle 1 + 2	**89**	55	67	59
	Trend + Cycle 1 + 2 + 3	-	**69**	**76**	68
	Trend + Cycle 1 + 2 + 3 + 4	-	-	-	**73**
	Stationary cycles (%)	**9**	**43**	**47**	**34**
MAGNITUDE	**Trend (slope) (g/ha/yr)**	**-48**	**-38**	**-22**	**-43**
	Cycles (amplitude) (g/ha)	**±137**	**<u>±336</u>**	**±163**	**<u>±221</u>**

Catchments with **<u>high water storage</u>** show **<u>larger amplitude</u>** in DON export.







c35, y = -0.08x + 6.12, R^2 = 0.28
c47
c38
c50, y = -0.05x + 2.65, R^2 = 0.39

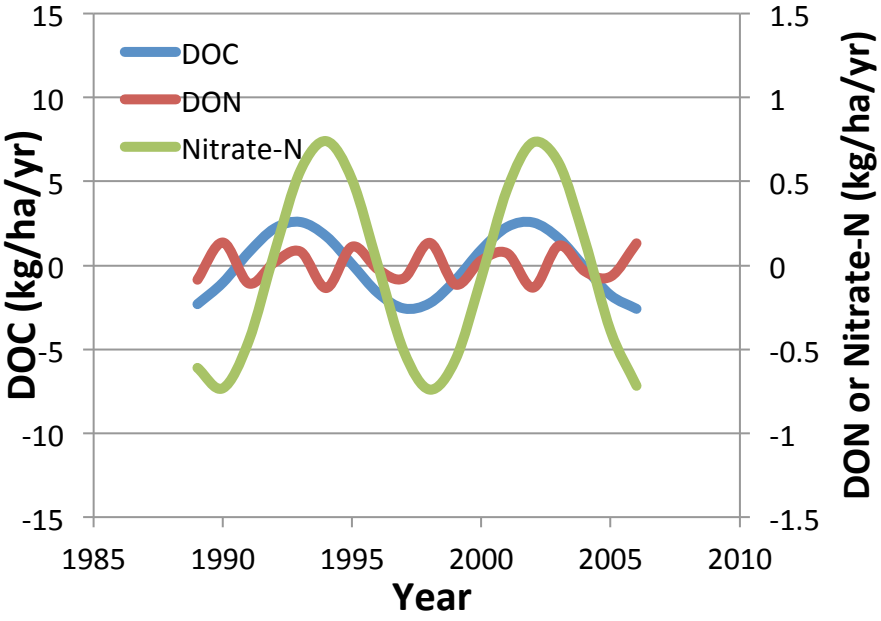
NO_3^--N Export

	NO_3^--N	C35	C38	C47	C50
VARIATION	**Non-stationary trend (%)**	**28**	**NS**	**NS**	**39**
	Trend + Cycle 1	61	31	24	55
	Trend + Cycle 1 + 2	73	42	39	**65**
	Trend + Cycle 1 + 2 + 3	82	**52**	**60**	-
	Trend + Cycle 1 + 2 + 3 + 4	**85**	-	-	-
	Stationary cycles (%)	**57**	**52**	**60**	**26**
MAGNITUDE	**Trend (slope) (g/ha/yr)**	**-81**	**NS**	**NS**	**-52**
	Cycles (amplitude) (g/ha)	**±740**	**±213**	**±521**	**±413**

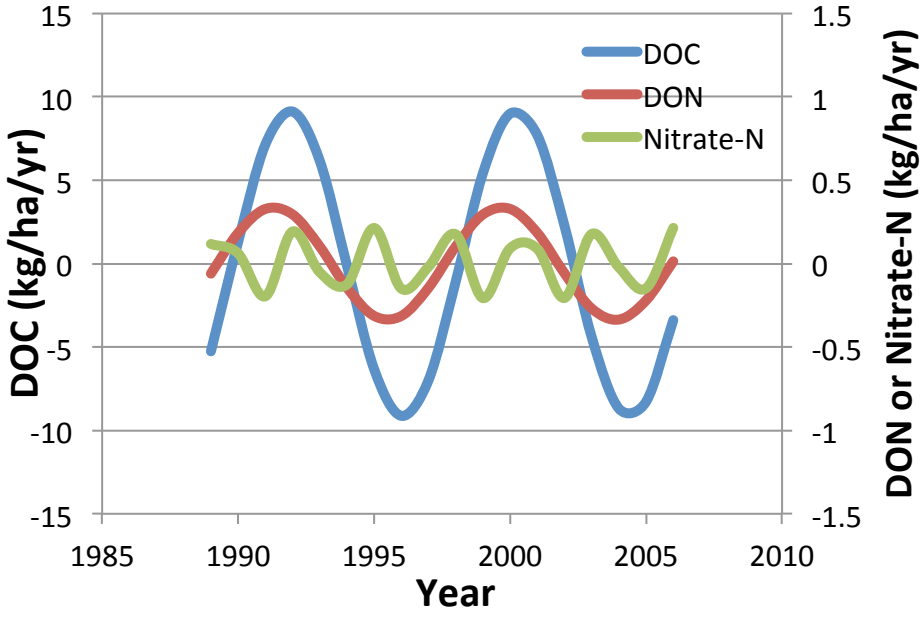
Catchments with **high water storage** show **smaller amplitude** in NO_3^--N export.

Next steps: implication of changes in stoichiometry of nutrient export to rivers?

LOW water storage potential (c35)



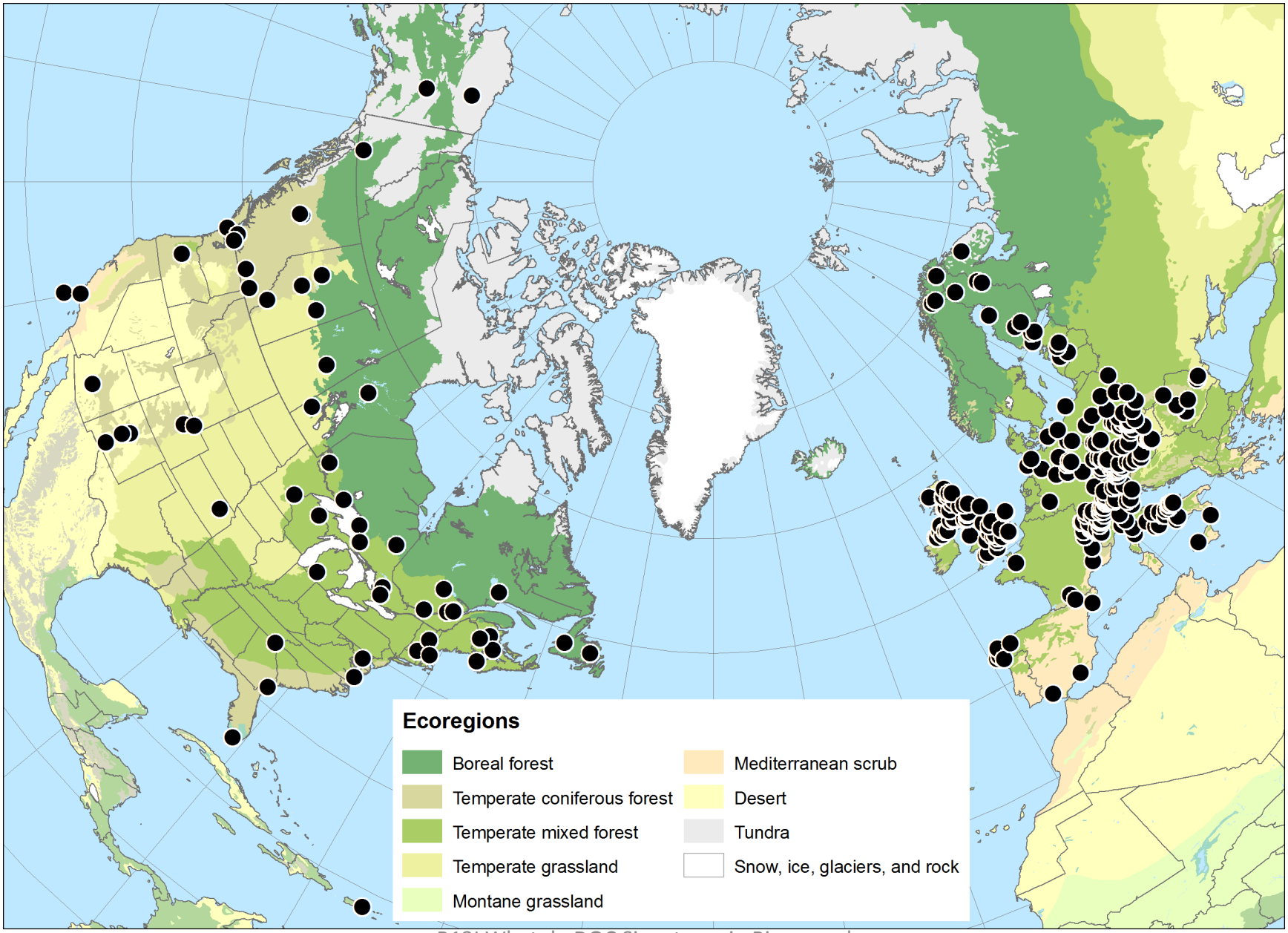
HIGH water storage potential (c38)



Stoichiometry varies over time (with cycles) and over space (with catchments)

Take home messages

- Trends plus cycles explain majority of variation in DOM export.
- No trends in DOC flux, but significant trends in DON and nitrate-N export.
- Significant cycles in DOC, DON and nitrate-N fluxes.
- Cycles can override trends in terms of DOM export, particularly in catchments with high water storage.
- Potential for substantial cycles in stochiometry of DOM export.


Ecoregions
Boreal forest
Temperate coniferous forest
Temperate mixed forest
Temperate grassland
Montane grassland
Mediterranean scrub
Desert
Tundra
Snow, ice, glaciers, and rock