Discriminating between stationary and non-stationary responses in catchment water and nutrient export using wavelet analysis

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Do we have adequate data to distinguish climate warming trends from naturally occurring climate oscillations?

Rationale

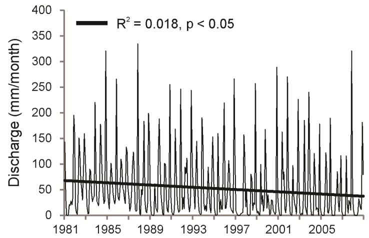
- Headwater catchment export signals contain a complex mix of signals:
  - Non-stationary (climate trends)
    - deterministic responses where the statistical mean and variance change with time, predictably and unpredictably
  - Stationary (climate oscillations)
    - stochastic responses where the statistical mean and variance do not change with time
- In landscapes that are not impacted by human activities, if we are able to discriminate climate trends from climate oscillations, these headwater catchments could serve as sentinels of climate change.

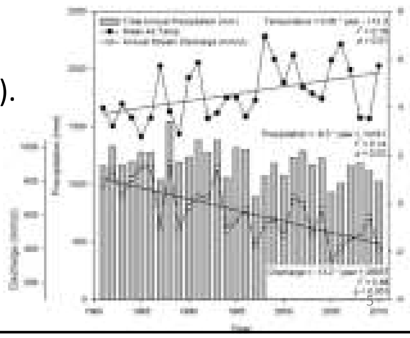
Hypotheses

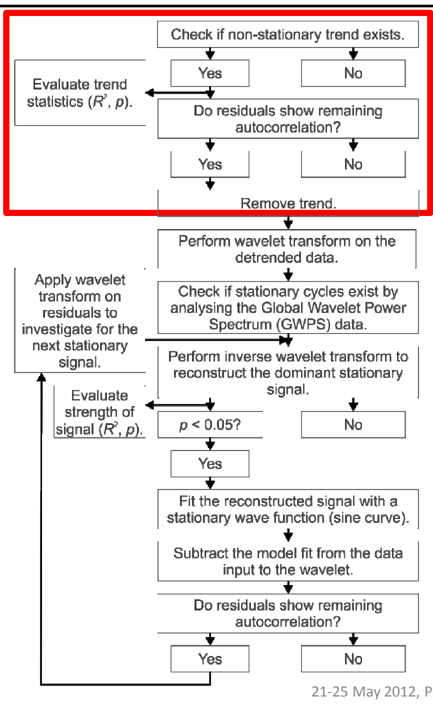
- Non-stationary signal > stationary signal.
- Both signals are greater in catchments that have higher water loading potential and/or with lower water storage capacity.
- Non-stationary signals are related to global warming while stationary signals are related to global climate oscillations at scales that range several years to several decades.

Optimal time scale?

- Climate indices provided at monthly intervals.
- We examined monthly, seasonal and annual (water year) time scales.
- Observed no to minimal non-stationary signals in monthly and seasonal time series (too variable).
- Chose to focus on annual time series.

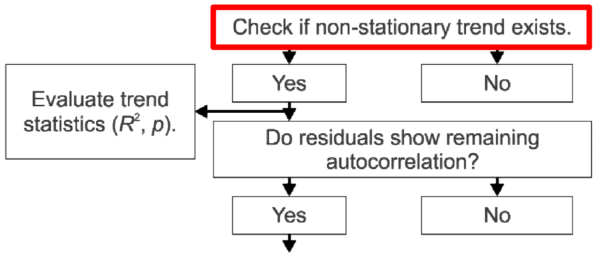


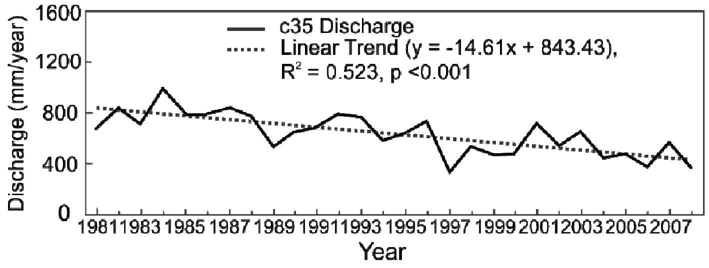




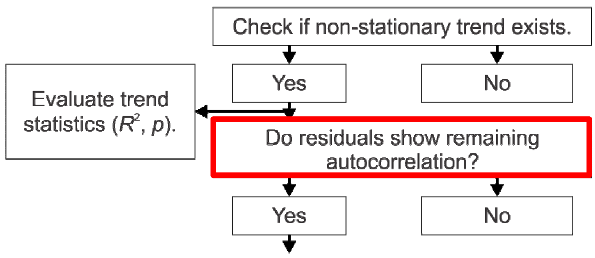
Analytical framework for signal detection

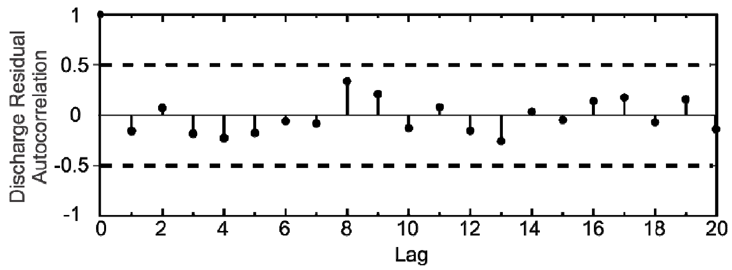
Detecting non-stationary trend

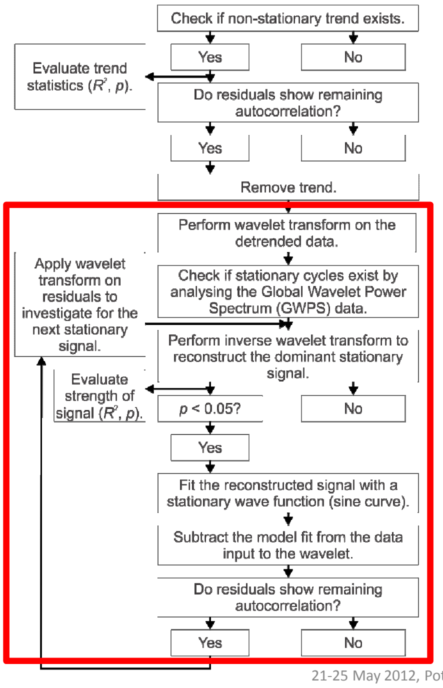




Detecting non-stationary trend

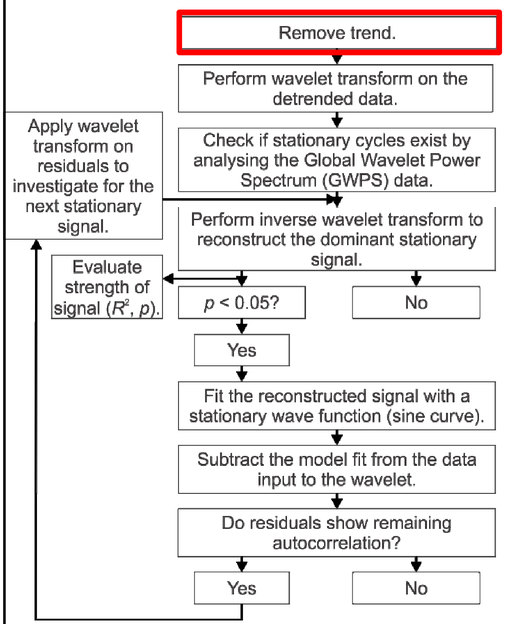


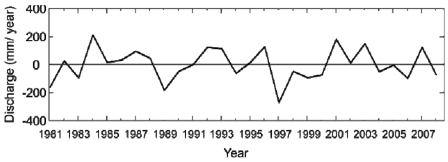


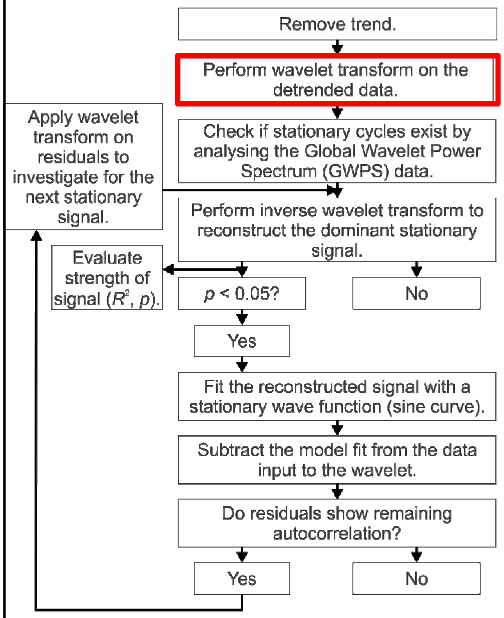


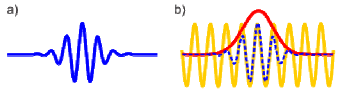
Analytical framework for signal detection

21-25 May 2012, Potsdam, Germany 9

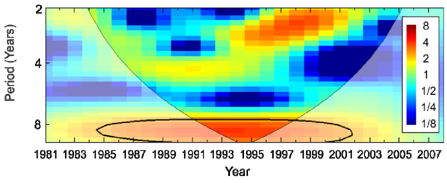






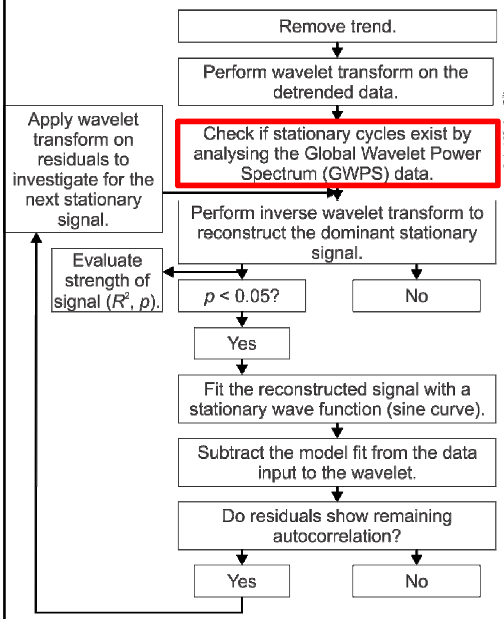


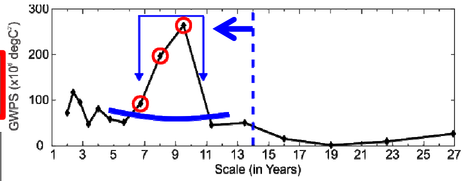
Morlet wavelet is a
sine wave (blue curve) multiplied by a
Gaussian envelope (red curve).



The **thin solid line** (cone of influence),
delimits region not influenced by edge effect.

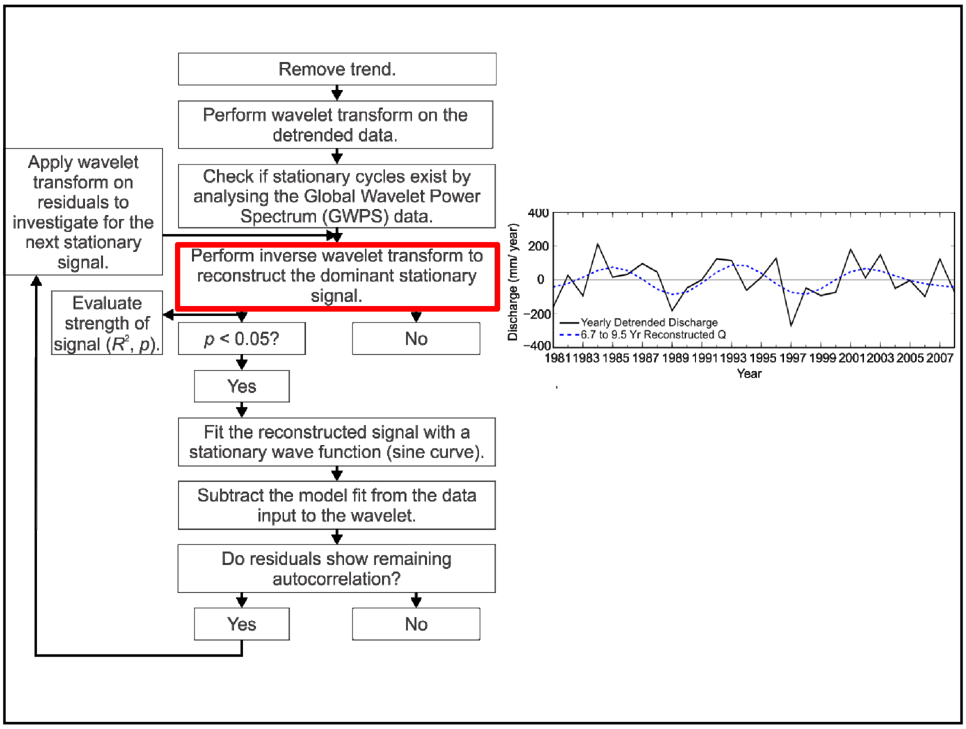
The **thick solid lines** show the
95% confidence level.

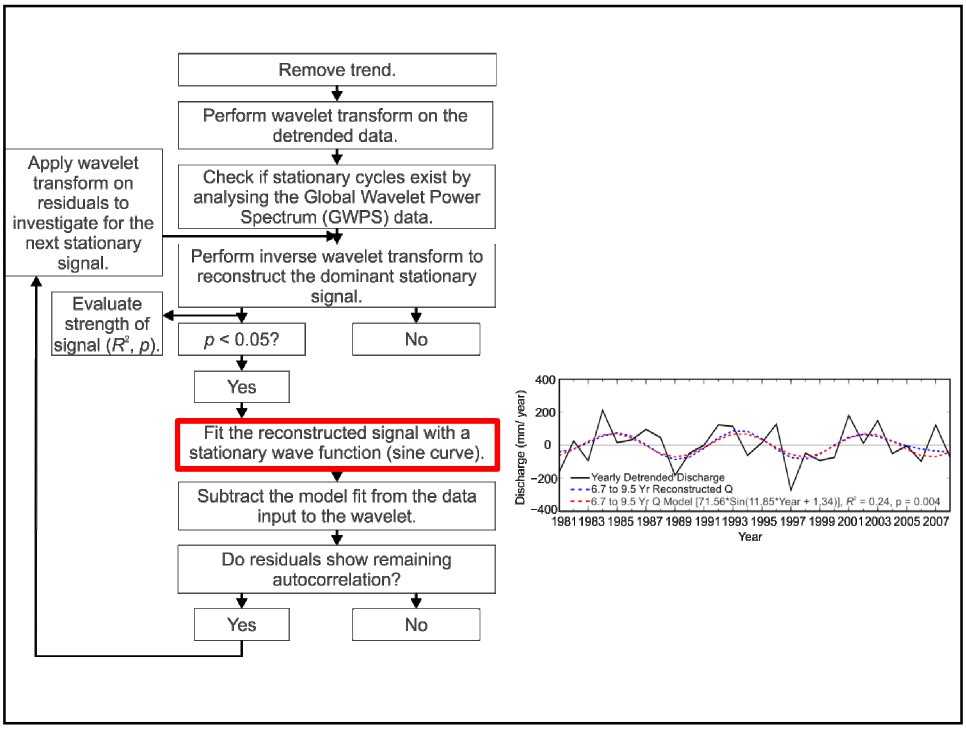




<u>**Rules for signal detection:**</u>

1. Signal must occur twice in record
2. Entire signal must be within half the record
3. Select dominant signal
3. Establish baseline and identify the scales (years) above baseline that form the beak
4. Never select same scales (years) twice


Remove trend.
Perform wavelet transform on the detrended data.
Check if stationary cycles exist by analysing the Global Wavelet Power Spectrum (GWPS) data.
Perform inverse wavelet transform to reconstruct the dominant stationary signal.
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
Apply wavelet transform on residuals to investigate for the next stationary signal.
Evaluate strength of signal (R², p).
Discharge (mm/ year)
400
200
0
−200
−400
Yearly Detrended Discharge
6.7 to 9.5 Yr Reconstructed Q
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005 2007
Year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Discharge (mm/ year)
400
200
0
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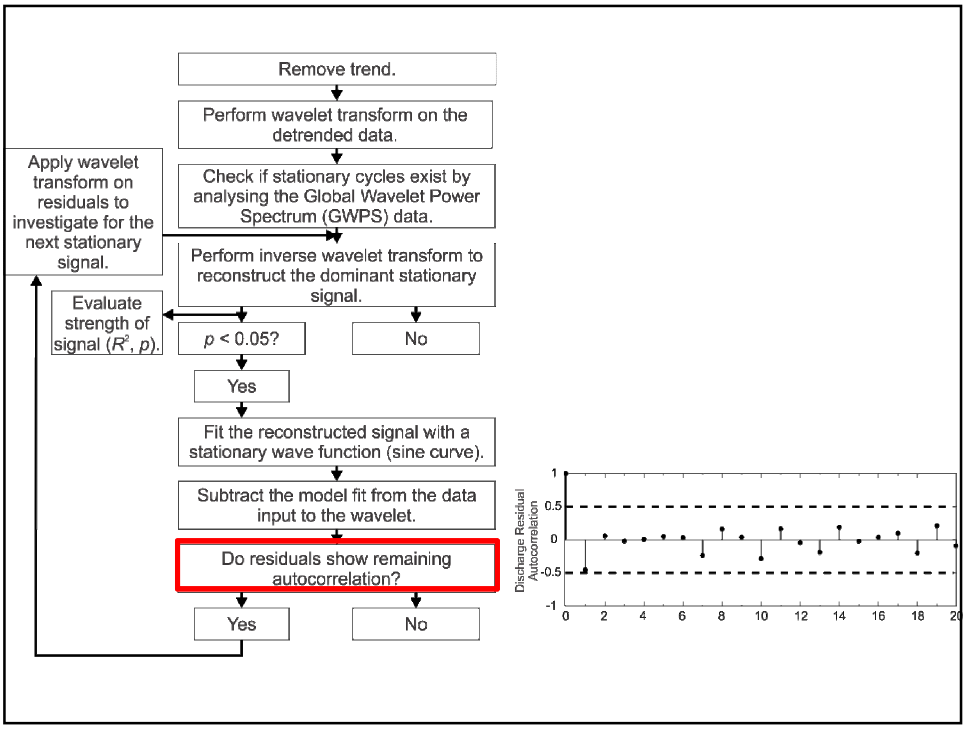
Yearly Detrended Discharge
6.7 to 9.5 Yr Reconstructed Q
6.7 to 9.5 Yr Q Model [71.56*Sin(11.85*Year + 1.34)], R² = 0.24, p = 0.004
1981 1983 1985 1987 1989 1991 1993 1995 1997 1999 2001 2003 2005 2007
Year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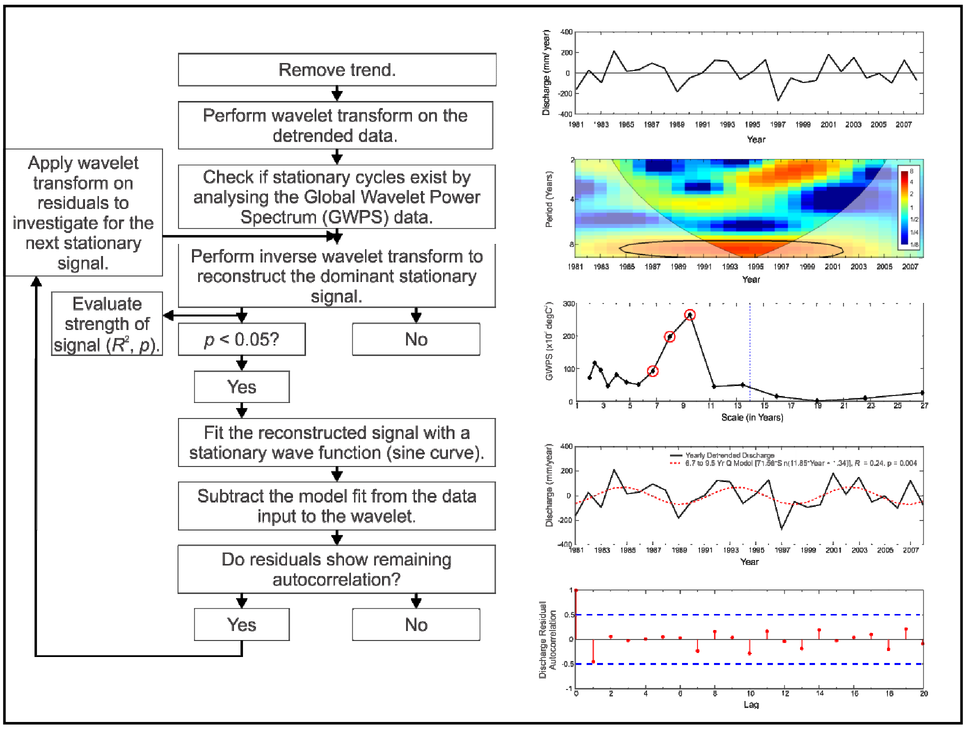
Yes
No
Discharge Residual Autocorrelation
1
0.5
0
-0.5
-1
0 2 4 6 8 10 12 14 16 18 20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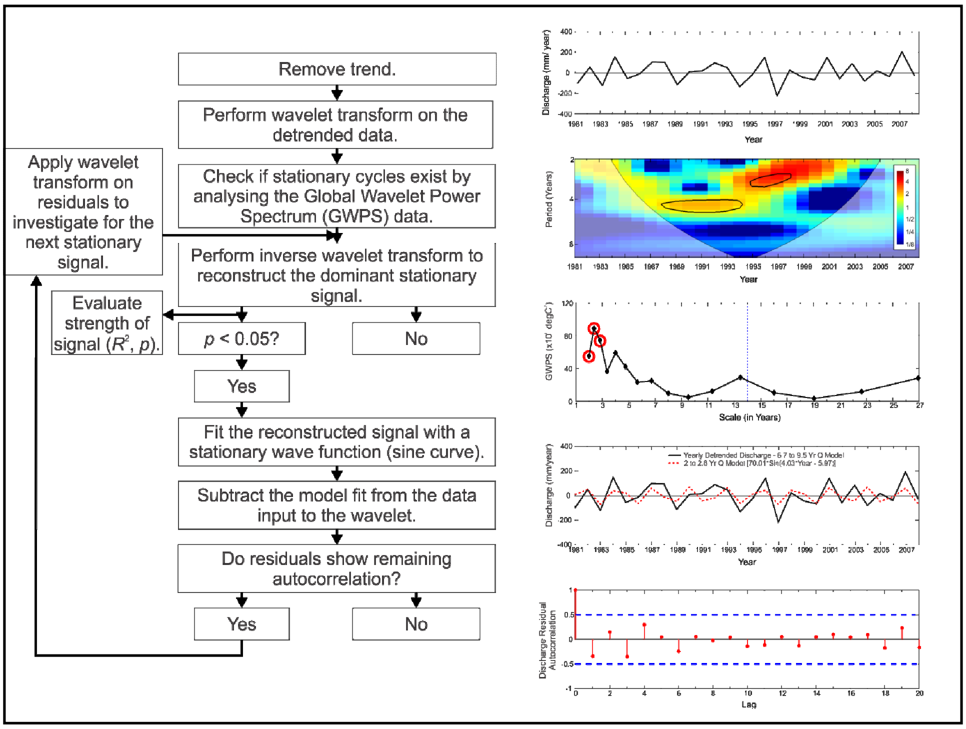
Year
Period (Years)
Year
Scale (in Years)
Year
Discharge Residual Autocorrelation
Lag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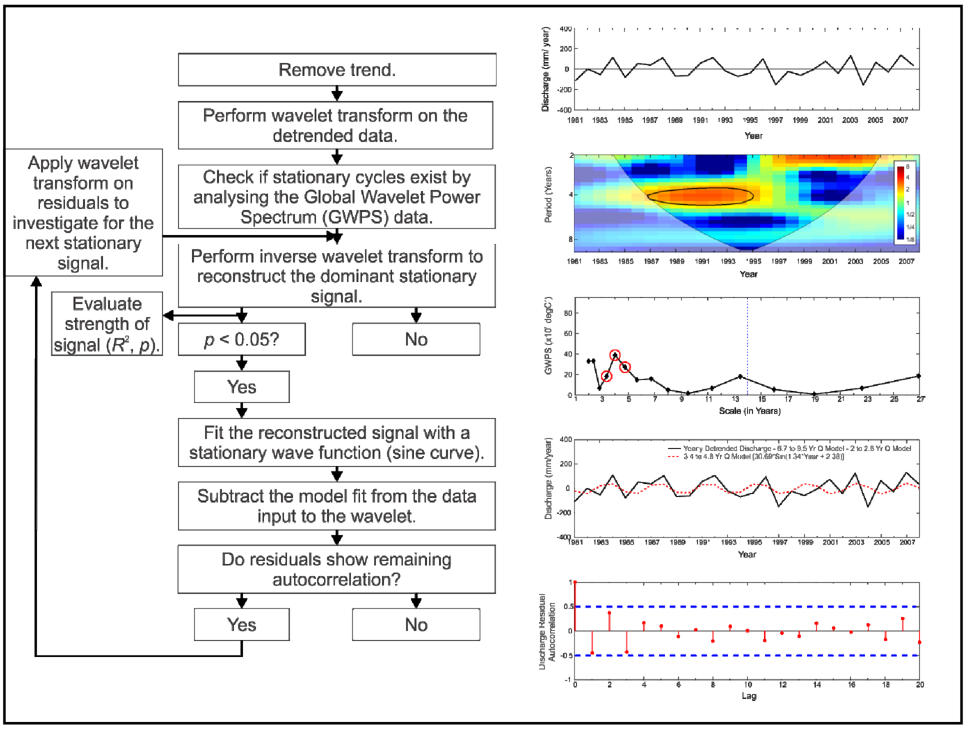
Discharge (mm/ year)
Year
Period (Years)
Year
GWPS (x10' degC')
Scale (in Years)
Discharge (mm/year)
Year
Discharge Residual Autocorrelation
Lag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Year
Period (Years)
Year
GWPS (x10' degC')
Scale (in Years)
Discharge (mm/year)
Year
Discharge Residual Autocorrelation
Lag

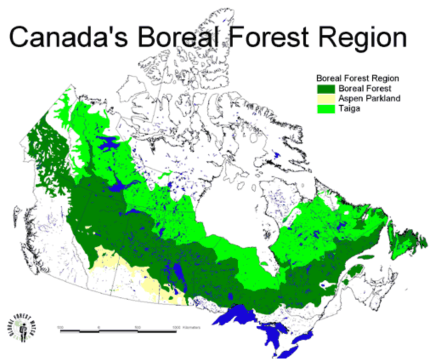
Discriminate non-stationary vs. stationary signals

	R^2
Linear trend vs. Raw Q	
Signal 1 vs. Raw Q – Linear trend	
Signal 2 vs. Raw Q – Linear trend, Signal 1	
Signal 3 vs. Raw Q – Linear trend, Signal 1, 2	
Signal 4 vs. Raw Q – Linear trend, Signal 1, 2, 3	
Linear trend	
Linear trend + Signal 1	
Linear trend + Signal 1 + 2	
Linear trend + Signal 1 + 2 + 3	

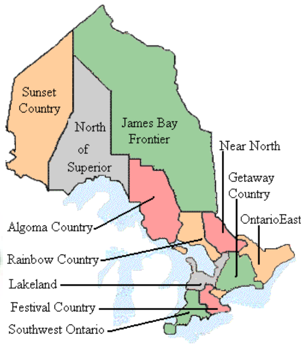
→ Non-stationary

→ Stationary

Application to catchments in Canada's "north"



The old-growth forest of the **Algoma Highlands** is one of the largest areas of **pristine forested landscape** remaining in the Great Lakes basin



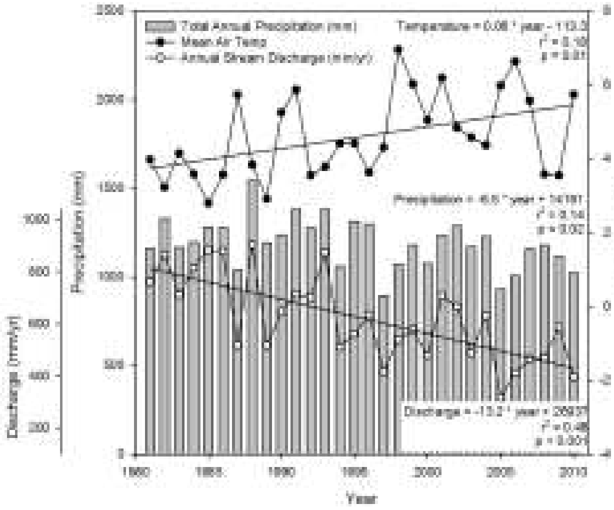
Study Area

Field station in Algoma Highlands

Inter-institutional consortium of researchers

Mobile accommodation and field laboratory

30-year record shows climate is dynamic in Algoma Highlands

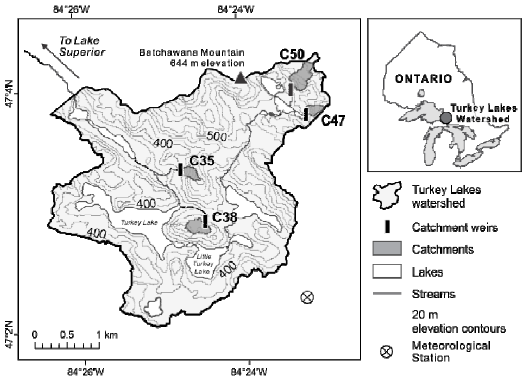


Until 2008, warming of 1 degree Celsius per decade!

Is there similarity in catchment responses to climate dynamics?

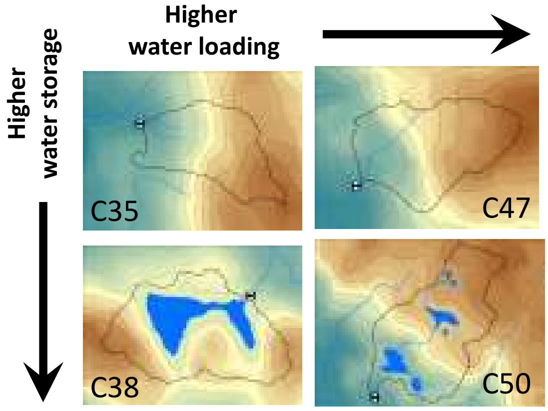
Turkey Lakes Watershed

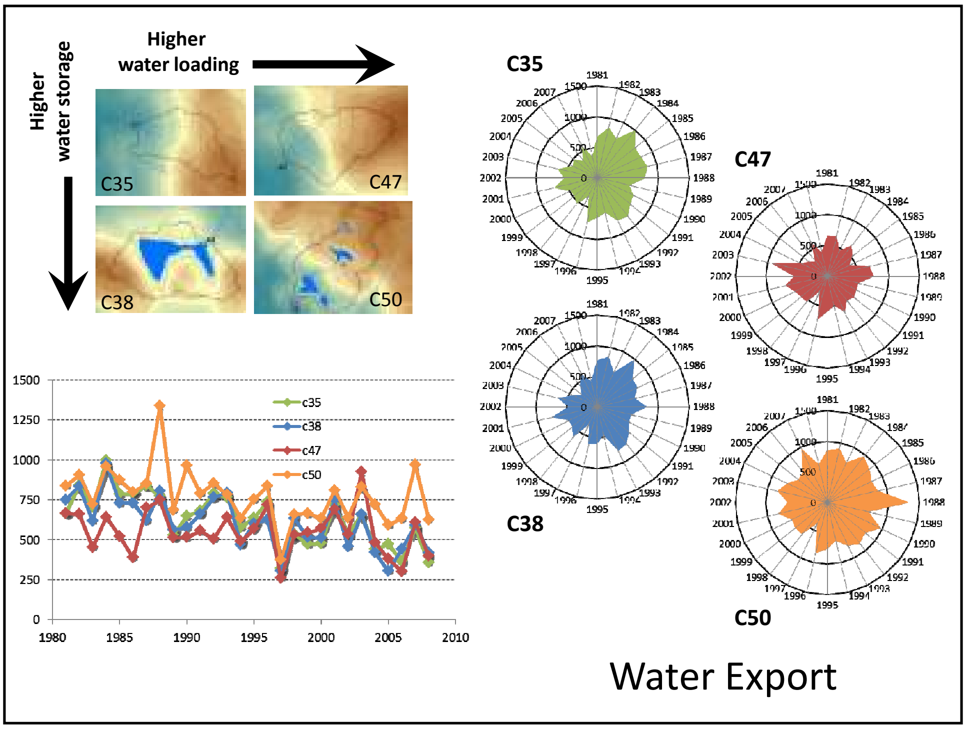
Since 1981, monitoring hydrology and biogeochemistry of 12 headwater catchments, chain of five lakes, and Norberg Creek that drains into Lake Superior



	c35	c38	c47	C50
Size (ha)	4.0	6.5	3.4	9.5
Water loading	Lower	Lower	Higher	Higher
Water storage (% wetland)	1	21	0.3	10

Is there similarity in catchment responses to climate dynamics?





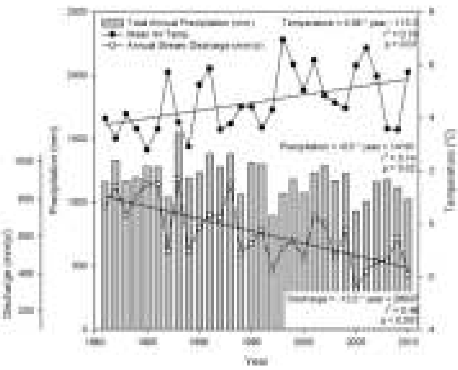
Catchment water export
(r^2)

	C35	C38	C47	C50
Linear trend vs. Raw Q	**0.52**	**0.44**	**NS**	**0.18**
Linear trend (slope)	**-14.8**	**-13.0**	**NS**	**-8.9**
Signal 1 vs. Raw Q – Linear trend	0.27	0.26	0.19	0.26
Signal 2 vs. Raw Q – Linear trend, Signal 1	0.31	0.26	0.23	0.28
Signal 3 vs. Raw Q – Linear trend, Signal 1, 2	0.19	0.26	0.32	0.15
Signal 4 vs. Raw Q – Linear trend, Signal 1, 2, 3	NS	NS	NS	No Signal

Catchment water export (cumulative r^2)

	C35	C38	C47	C50
Non-stationary signal	**0.52**	**0.44**	**NS**	**0.18**
Linear trend + Signal 1	0.65	0.59	0.19	0.39
Linear trend + Signal 1 + 2	0.76	0.68	0.38	0.56
Linear trend + Signal 1 + 2 + 3	0.81	0.76	0.56	0.63
Stationary signals	**0.29**	**0.32**	**0.56**	**0.45**

Non-stationary signals

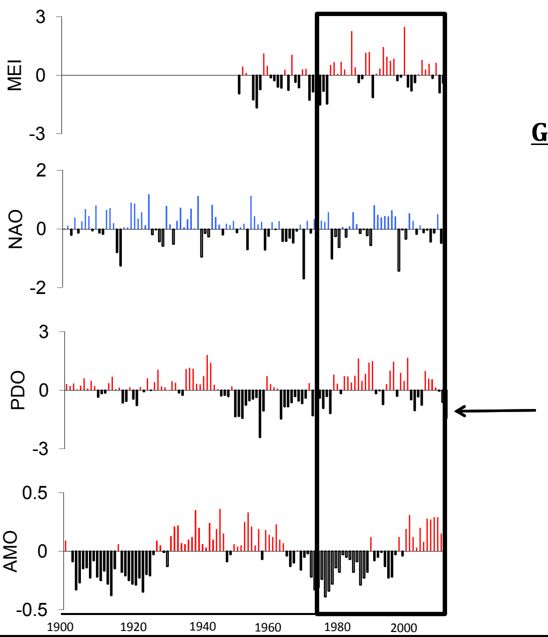


Climate warming	C35	C38	C47	C50
r	-0.53	-0.57	-0.37	-0.43
r^2	**0.28**	**0.33**	**0.13**	**0.19**
p	**< 0.05**	**< 0.05**	**p=0.055**	**< 0.05**

Stationary signals

Indices	Periodicity	Influence
Multivariate El Nino Southern Oscillation Index (MEI)	A periodicity of 2 to 7 years	Positive numbers = warmer winters
Northern Atlantic Oscillation (NAO)	Periodicities of 7 to 9 years and 20 years	Positive numbers = colder winters
Pacific Decadal Oscillation (PDO)	A periodicity of 20 to 30 years	Positive numbers = warmer and drier winters
Atlantic Multidecadal Oscillation (AMO)	A periodicity of 60 to 90 years	Positive numbers = warmer and drier conditions

Stationary signals



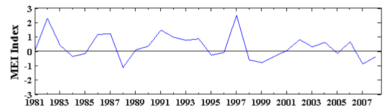
Global Climate Oscillation Indices

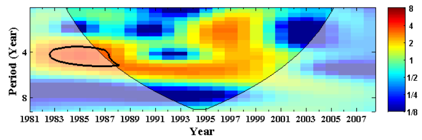
MEI = 2 to 7 years
NAO = 7 to 9 years, 20 years
PDO = 20 to 30 years
AMO = 70 to 90 years

Turkey Lakes Watershed period of record

Wavelet cross-coherence between climate oscillations and water export

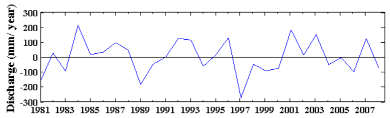
Wavelet power spectrum of MEI Index

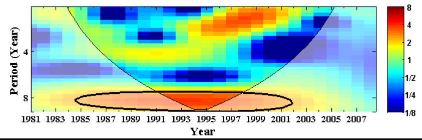




versus

Wavelet power spectrum of c35 water export





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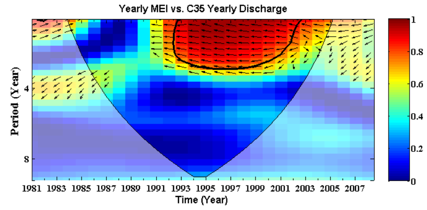
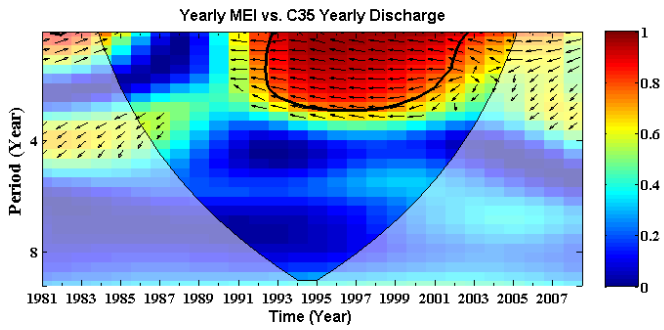


The **thin solid line** (cone of influence), delimits region not influenced by edge effect.

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

Wavelet cross-coherence between climate oscillations and water export



← Negative correlation or precipitation lags behind NO_3^- export

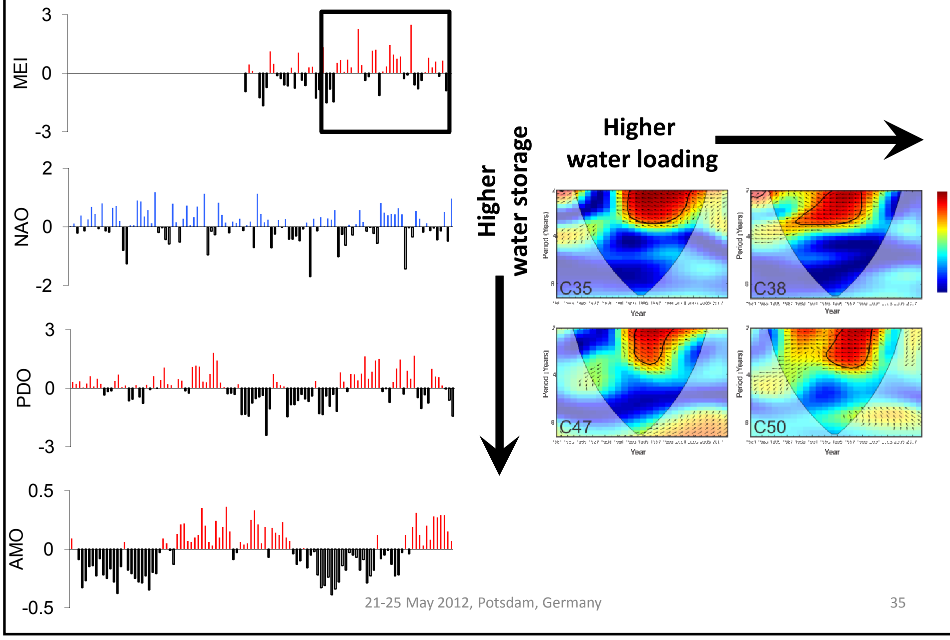
→ Positive correlation or precipitation leads NO_3^- export

Determining Lag/Lead at a Period

phaseangle: (arrow angle * pi) / 180

Lag/Lead = phaseangle*period/(2*pi)

Wavelet cross-coherence between climate oscillations and water export



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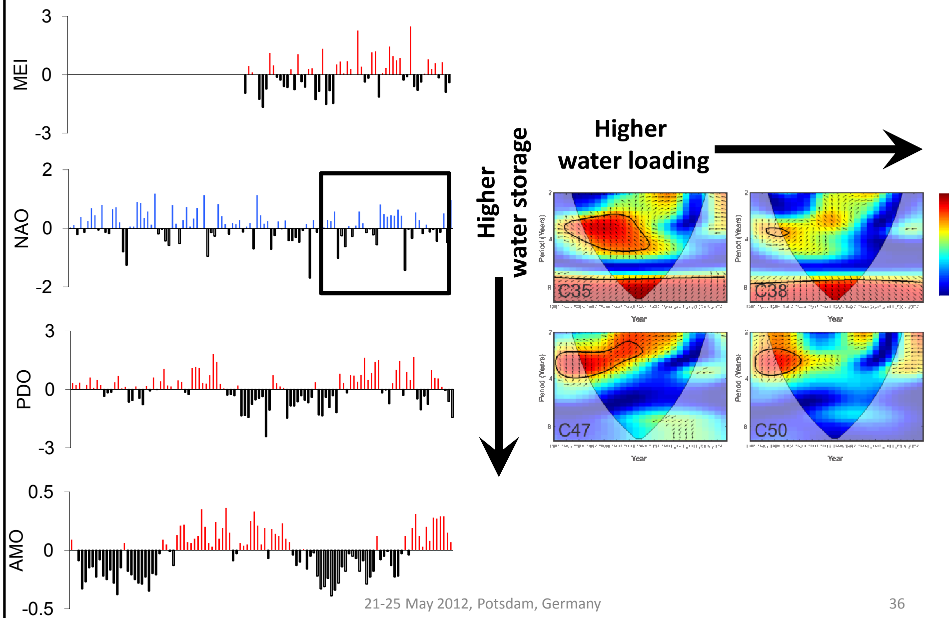

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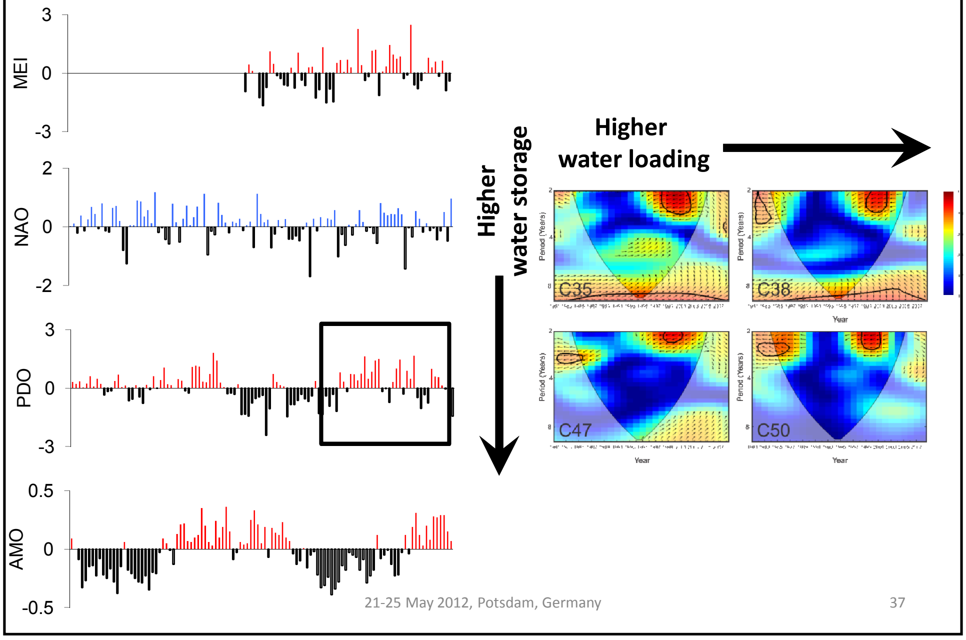

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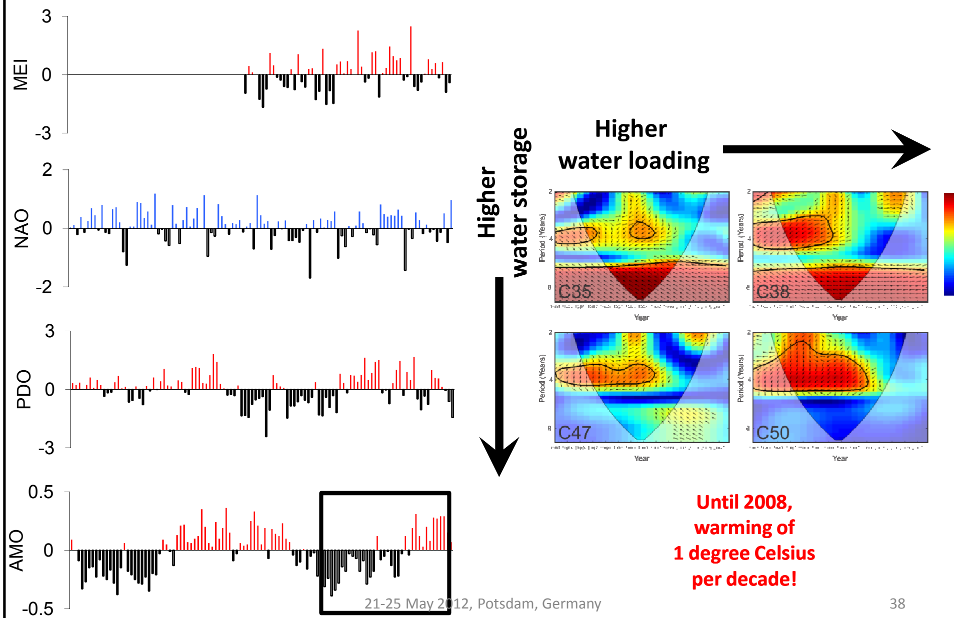


Until 2008, warming of 1 degree Celsius per decade!

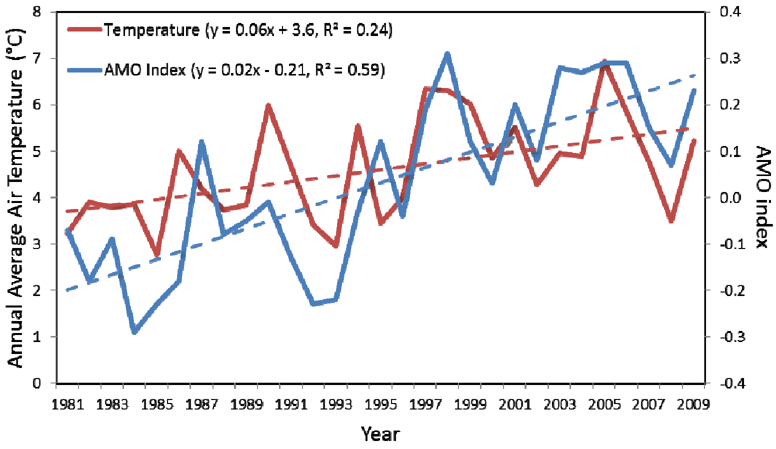
Pearson correlation matrix

	MEI	NAO	PDO	AMO
MEI	-	0.011	0.600***	-0.152
NAO	-	-	-0.387*	-0.257
PDO	-	-	-	-0.314
AMO	-	-	-	-

Stationary signals

Climate oscillations		C35	C38	C47	C50
MEI		NS	NS	NS	NS
NAO		NS	NS	NS	NS
PDO	**r**	**0.38**	-	-	-
	r^2	**0.15**	-	-	-
	p	**< 0.05**	NS	NS	NS
AMO	**r**	**-0.70**	**-0.68**	-	**-0.43**
	r^2	**0.49**	**0.46**	-	**0.19**
	p	**< 0.05**	**< 0.05**	NS	**< 0.05**

AMO: Dominant global climate oscillation driving local temperature patterns



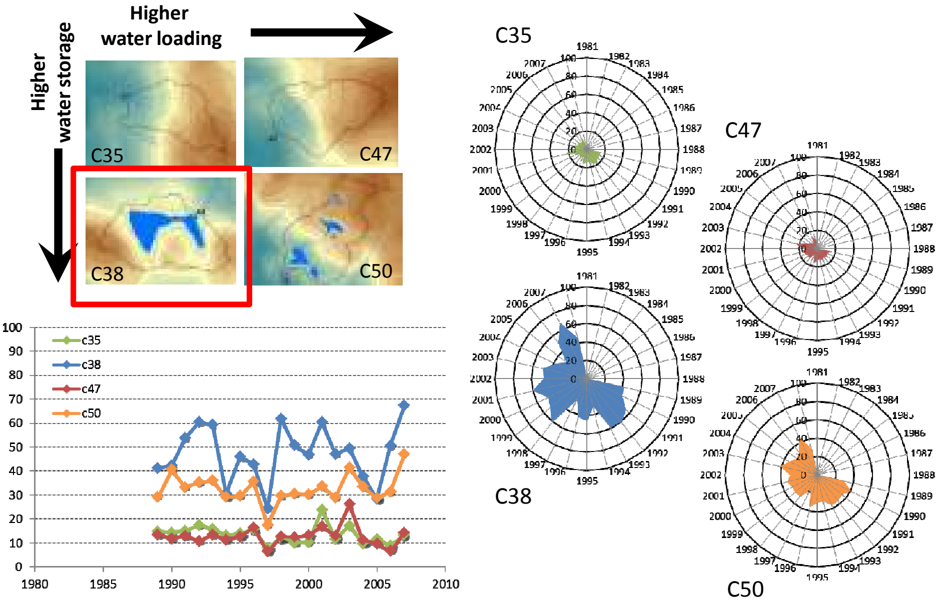
Findings for water export

- **Non-stationary signal > stationary signal.**
  NON-STATIONARY SIGNALS GREATER IN CATCHMENTS WITH LWLP (c35, c38).
  STATIONARY SIGNALS GREATER IN CATCHMENTS WITH HWLP (c47, c50).

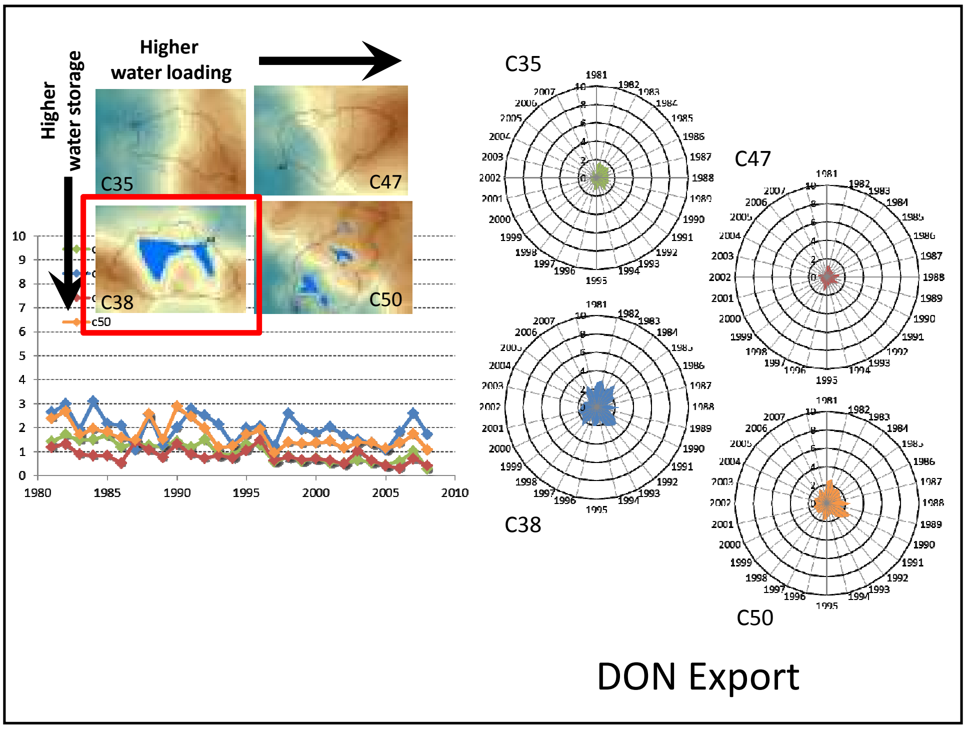
- **Combined signals are greater in catchments that have lower water loading potential and/or with lower potential water storage capacity.**
  COMBINED SIGNALS GREATEST IN CATCHMENT WITH LWLP and LWSC (c35).

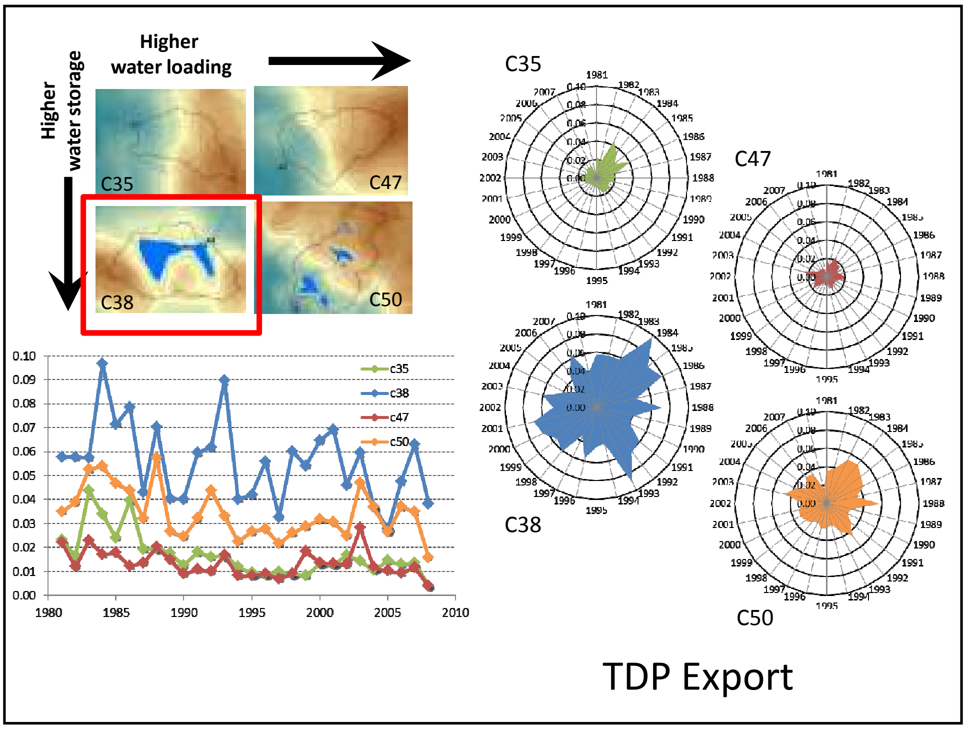
- **Non-stationary signals are related to global warming while stationary signals are related to global climate oscillations at scales that range several years to several decades.**
  SIGNFICANT RELATIONSHIPS BETWEEN CLIMATE WARMING AND CLIMATE OSCILLATIONS AND WATER EXPORT OBSERVED.

Should we expect the same findings for solute export? (DOC, DON, TDP, nitrate export)



DOC Export


Higher
water loading
Higher
water storage
C35
C47
C38
C50
C35
C47
C38
C50
DON Export


Higher
water loading
Higher
water storage
C35
C47
C38
C50
c35
c38
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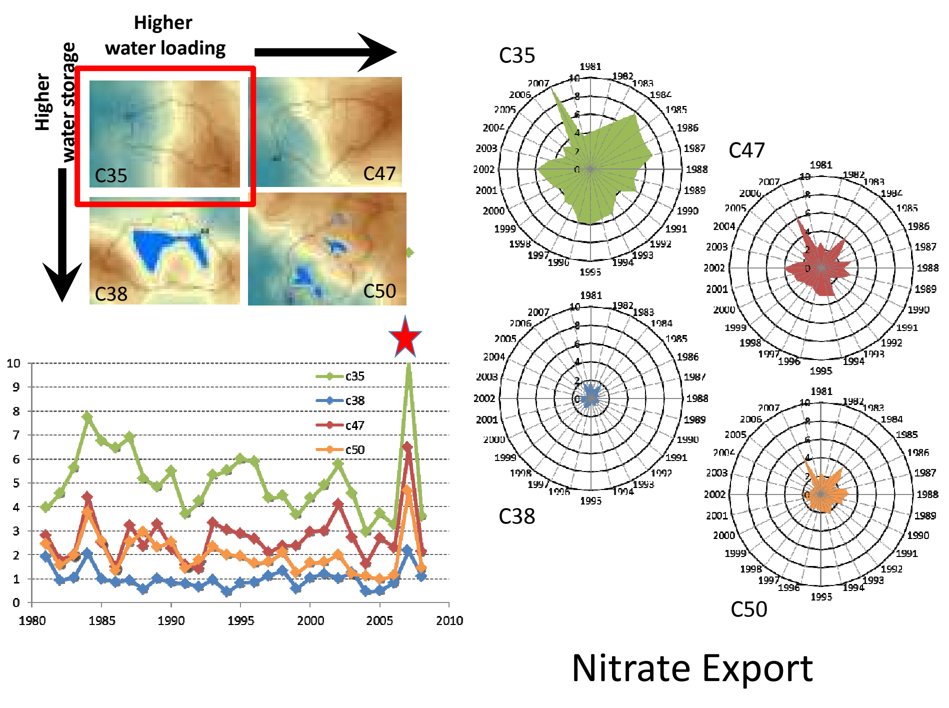
C35
C47
C38
C50
TDP Export



100-year storm event in 2007!

Extreme events buggered wavelet analyses

Cumulative r^2 explained by non-stationary and stationary signals (1981-2006)

	C35		C38		C47		C50	
	Non Stationary	Stationary	Non Stationary	Stationary	Non Stationary	Stationary	Non Stationary	Stationary
Water	0.52	0.29	0.44	0.32	0	0.56	0.18	0.45
DOC	0	0.53	0	0.88	0	0.69	0	0.53
DON	0.80	0.09	0.26	0.43	0.29	0.47	0.39	0.34
TDP	0.42	0.20	0.16	0.61	0	0.32	0.19	0.30
Nitrate	0.28	0.57	0	0.52	0	0.60	0.39	0.26

Findings for solute export

WATER AND SOLUTE EXPORTS HAVE DIFFERENT COMPOSITION OF SIGNALS.

- **Non-stationary signal > stationary signal.**
  C35 (LWLP, LWSC) MOST SENSITIVE TO NON-STATIONARY SIGNALS.
- **Combined signals are greater in catchments that have lower water loading potential and/or with lower potential water storage capacity.**
  COMBINED SIGNALS FOR INORGANIC SPECIES STRONGEST IN C35 (LWLP, LWSC), WHILE FOR ORGANIC SPECIES STRONGEST IN C38 (LWLP, HWSC).

  DOC DIFFERENT FROM DON & TDP IN CATCHMENTS WITH LWSC, BUT SIMILAR IN CATCHMENTS WITH HWSC.
- **Non-stationary signals are related to global warming while stationary signals are related to global climate oscillations at scales that range several years to several decades.**
  TBA.

Take home messages

- Natural climate oscillations have resulted in reduction in water, solute export in past 30 years.
- The rate of reduction accelerated by climate warming trends in some catchments.
- Water and solutes behave differently to these climate drivers.
- Catchments with lowest water loading and lowest water storage most sensitive to both types of signals, suggesting it to be a good sentinel of climate change.

21-25 May 2012, Potsdam, Germany 51

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Left to Right

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21-25 May 2012, Potsdam, Germany 52