Towards an operational model to forecast water supply to water bodies

Guillaume Guénard

Québec 20 Septembre 2016

CONTENT

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WATER SUPPLY

- The net amount of water reaching a waterbody or a stream
- $Supply = Precip - evap \pm storage$[1]
- Value: a head start for decision-making, for instance,
  1. know whether and when to use or store water
  2. foresee public safety issues (flooding risk)

[1] snow pack – meltdown, groundwater

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  2. vegetation cover
  3. ground material and thickness
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OBJECTIVE

Question

Is it possible to estimate the water supply of a given water body in the future using information from different sources (predictors)?

- Predictors may be taken in
  - the past (historical records),
  - the present (automated sampling), and
  - the future (predictable)

Challenge

Find a way to associate information from various sources and their consequence on the future water supply.

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DEFINITIONS

- Autocorrelation: the correlation of a series with a version of itself having an offset
- Cross-correlation: the correlation of two series, with one of them having an offset
- By analogy:
  - autoregression (AR): a model predicting values of a variable from its previous values, and
  - cross-regression: a model prediction values of a variable from values of another variable taken at previous time in the past
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DESCRIPTOR COLLINEARITY

- Hopefully, autoregressive descriptors are collinear as this is a corellary for auto-regression
- Problem: descriptors are numerous and of uneven relevance
  - a single descriptor from the recent past is more relevant that for the more distant past,
  - information from closeby descriptors is redundant
- It would be best to use fewer descriptors for the past than for the present
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SOLUTION

Multi-Resolution Impulse (MRI) Filter

Apply a low-pass filter whose bandwidth shrink as we proceed back in time. Sub-sample the resulting signal in steps of increasing size.

- Initial bandwidth: infinite (no filtering at all)
- Final bandwidth: 0 (only a constant "bias", or mean value)

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IMPLEMENTATION

- Take a record of observations of a given duration (aperture: *width*; most recent first, most ancient last)
- Decompose that record using Discrete Wavelets Transforms (DWT)
- Keep only the first (or first few) Wavelet coefficient for each resolution level
- Reconstruct the MRI-filtered signal with the remaining Wavelet coefficients
- Sample the filtered signal in dyadic (power of two) steps: $2^0, 2^1, 2^2, ..., 2^n$, where $n = \lfloor \log_2 width \rfloor$(the mean can be used as well)

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EXAMPLE OF AN MRI

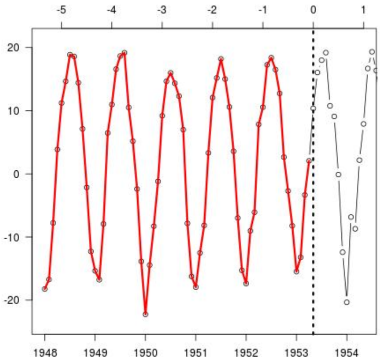

Figure: Time series (temperature in International Falls airport, MN, USA) with unfiltered past record of *width* $= 64$ observations (in red).

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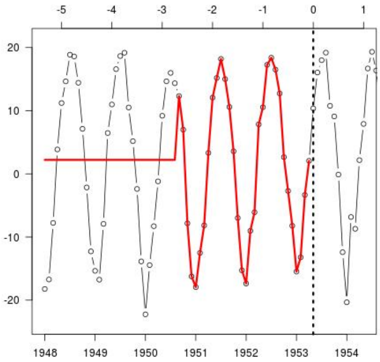

Figure: Filtered time series: half of the (Haar) wavelet coefficients (or at least one) were kept for each level of resolution.

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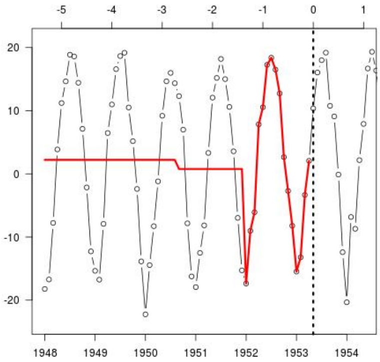

Figure: Filtered time series: a quarter of the wavelet coefficients (or at least one) were kept for each level of resolution.

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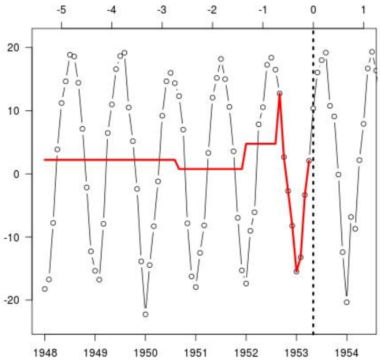

Figure: Filtered time series: an eighth of the wavelet coefficients (or at least one) were kept for each level of resolution.

EXAMPLE OF AN MRI

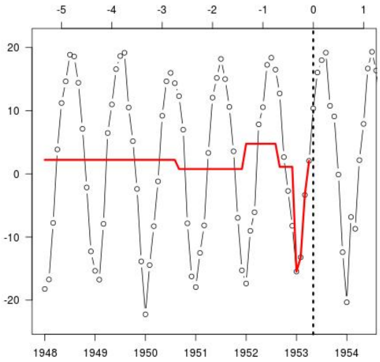

Figure: Filtered time series: an 16^{th} of the wavelet coefficients (or at least one) were kept for each level of resolution.

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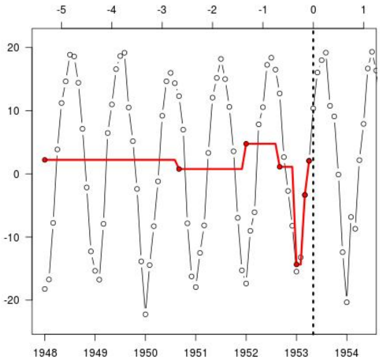

Figure: Filtered time series: a 32^{th} of the wavelet coefficients (or at least one) were kept for each level of resolution.

SEASONAL FORCING

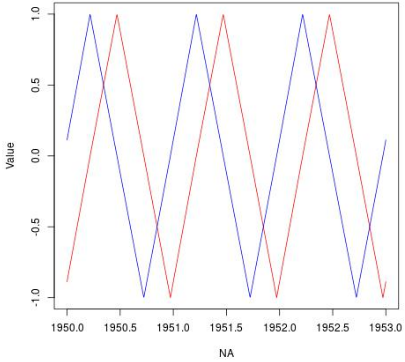

Figure: Models were also given a pair of variables with a one-year period and offset by $0.25\,\mathrm{y}$ to inform them about the time of the year and help them model seasonal variation (it is highly predictable indeed).

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ANN MODELS

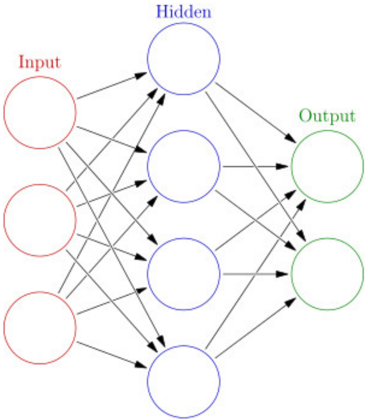

Figure: An ANN model involves a stack of multi-descriptor and multi-response regression models connected together with non-linear transformation functions (the link function) at the hidden layer.

ANN MODELS

- We used a single-hidden-layer perceptron
- Single input, hidden, and output layers
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- The hidden layer has logistic links to the second regression
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  1. median daily air temperature at International Falls airport (IFL, 48.5614, −93.3981; local)
  2. North-Atlantic Oscillation (NAO; global)
- Seasonal forcing
- MRI-filtered AR descriptors from the water supply time series

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THE MODELS

- Different number of hidden nodes were tried:
  1. Air temperature and NAO – from 1 to 10 nodes
  2. Water supply – from 1 to 6 nodes
- A single value of (L_2) regularisation parameters was applied to each type of descriptors
- Optimal number of nodes and values of weight regularisation estimated by Differential Evolution (DE) using 12-month cross-validation sub-samples[2]):
  1. Air temperature and NAO – 20 individuals and 100 generations.
  2. Water supply – 40 individuals and 100 generations

[2] Takes 2 – 3d to compute on a 16 core Intel® Xeon® E5-2650 @ 2GHz machine running parallel code

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  2. MRI-filtered AR descriptors for monthly air temperature time series ($width = 64$; 7 descriptors)

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WATER SUPPLY

- Goal of the present study
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  2. The first four MRI-filtered AR descriptors for air temperature (times 1, 2, 4, 8: from present to 7 months in the past)
  3. The last four MRI-filtered AR descriptors for the NAO (times 8, 16, 32, 64: from 7 months to 5 y and 4 months in the past)
  4. The MRI-filtered AR descriptors for the monthly water supply time series (present to 5 y and 4 months in the past; 7 descriptors)

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- Goal of the present study
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1. Seasonal forcing
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CONTENT

AUXILIARY MODELS

Table: Hyper-parameters of the auxiliary models

series	nodes	S Forcing	AR	RMS Error
Air temp	4	$6.96\,\mathrm{e}-4$	$8.41\,\mathrm{e}+3$	2.63°C
NAO[3]	8	$2.43\,\mathrm{e}+1$	$1.73\,\mathrm{e}+4$	$1.71\,\mathrm{kPa}$

[3] A flat model for all practical purposes

WATER SUPPLY

Table: Hyper-parameters of the water supply models

series	nodes	L_2 regularisation parameters				RMS Error
		S Forcing	Air temp	NAO	AR	$(\mathrm{m}^3\mathrm{s}^{-1})$
Namakan	2	$1.02\mathrm{e}-1$	$6.75\mathrm{e}+1$	$3.00\mathrm{e}+2$	$4.21\mathrm{e}+2$	77.40
Rainy (net)	6	$2.25\mathrm{e}-1$	2.20	$6.96\mathrm{e}+3$	$8.48\mathrm{e}+3$	81.81
Rainy (tot)	2	$2.27\mathrm{e}-4$	$4.27\mathrm{e}-1$	$7.24\mathrm{e}+3$	$3.04\mathrm{e}-2$	151.0

CONTENT

NAMAKAN LAKE

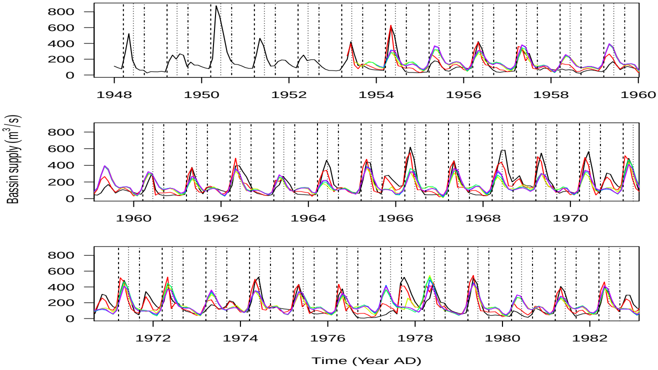

Figure: Observed water supply in Namakan Lake between 1948 and 1982 (black line) with forecasts made from different months in the past (red: 1, yellow: 2, green: 3, blue: 6, and purple: 12). Vertical lines mark the mid-March (dashed), mid-June (dotted), and mid-August (dot-dash).

NAMAKAN LAKE

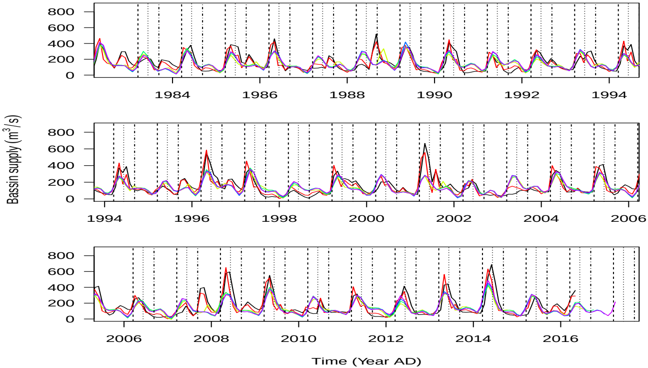

Figure: Observed water supply in Namakan Lake between 1982 and 2016 (black line) with forecasts made from different months in the past (red: 1, yellow: 2, green: 3, blue: 6, and purple: 12). Vertical lines mark the mid-March (dashed), mid-June (dotted), and mid-August (dot-dash).

RAINY LAKE (NET)

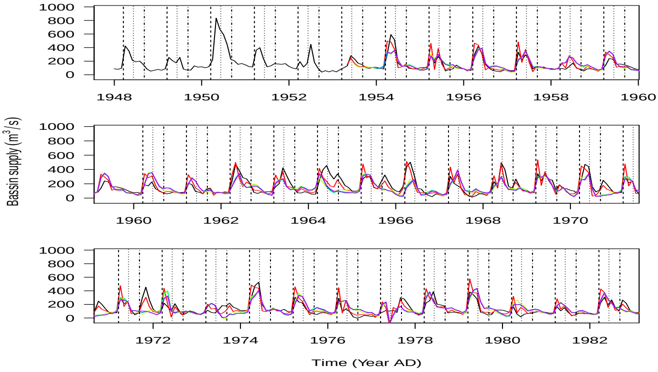

Figure: Observed net water supply in Rainy Lake between 1948 and 1982 (black line) with forecasts made from different months in the past (red: 1, yellow: 2, green: 3, blue: 6, and purple: 12). Vertical lines mark the mid-March (dashed), mid-June (dotted), and mid-August (dot-dash).

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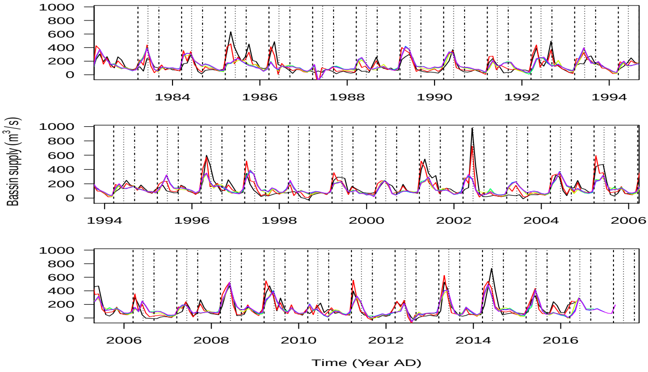

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RAINY LAKE (TOTAL)

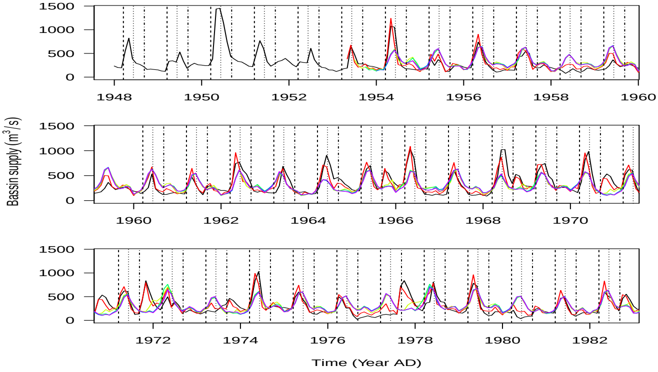

Figure: Observed total water supply in Rainy Lake between 1948 and 1982 (black line) with forecasts made from different months in the past (red: 1, yellow: 2, green: 3, blue: 6, and purple: 12). Vertical lines mark the mid-March (dashed), mid-June (dotted), and mid-August (dot-dash).

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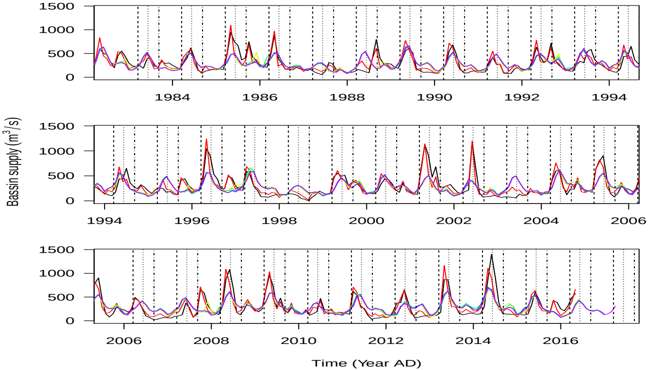

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RAINY + NAMAKAN

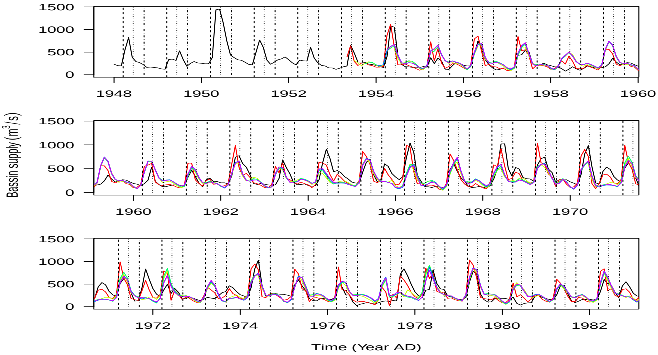

Figure: Observed total water supply in Rainy Lake between 1948 and 1982 (black line) with the sum of the forecasts for the two lakes (Namakan + net Rainy) made from different months in the past (red: 1, yellow: 2, green: 3, blue: 6, and purple: 12). Vertical lines mark the mid-March (dashed), mid-June (dotted), and mid-August (dot-dash).

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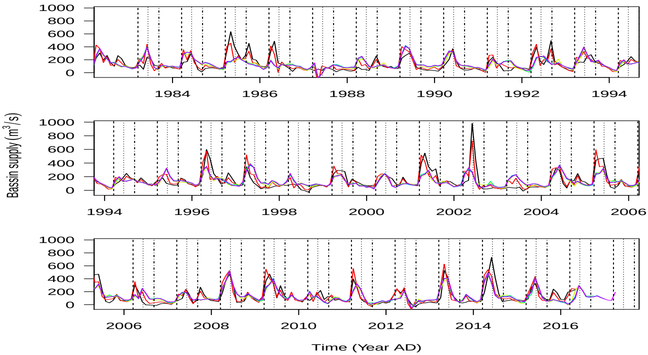

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CONTENT

FORECASTING POWER

Table: Root Mean Square Error and R^2 (in parenthesis) associated with forecasts performed from 1 to 12 months in the future for Namakan Lake and Rainy Lake.

	Namakan	Rainy (net)	Rainy (total)	Rainy+Namakan
1	65 (0.76)	69 (0.70)	100 (0.81)	141 (0.61)
2	82 (0.62)	91 (0.48)	148 (0.57)	158 (0.52)
3	96 (0.48)	94 (0.45)	173 (0.42)	171 (0.44)
4	95 (0.49)	94 (0.44)	175 (0.41)	171 (0.43)
5	94 (0.50)	95 (0.44)	176 (0.41)	171 (0.44)
6	94 (0.50)	95 (0.44)	176 (0.41)	172 (0.43)
7	94 (0.50)	95 (0.44)	175 (0.41)	172 (0.43)
8	94 (0.51)	95 (0.44)	175 (0.41)	172 (0.43)
9	94 (0.51)	95 (0.44)	176 (0.41)	172 (0.43)
10	94 (0.51)	95 (0.44)	175 (0.41)	172 (0.43)
11	94 (0.51)	95 (0.44)	175 (0.41)	172 (0.43)
12	94 (0.51)	95 (0.44)	175 (0.41)	172 (0.44)

SEASONAL PREDICTIONS: SPRING FLOOD

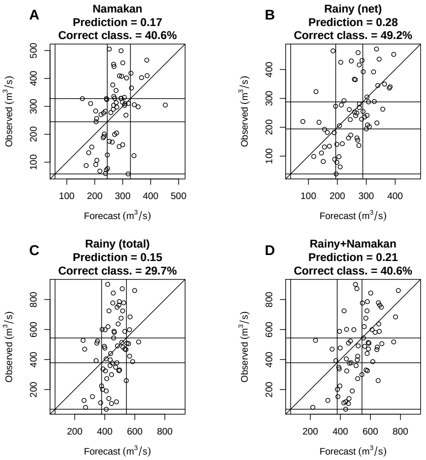

Figure: Average water supply observed and forecast during the spring flood (March–June) with their prediction coefficients.

SEASONAL PREDICTIONS: LOW WATERS

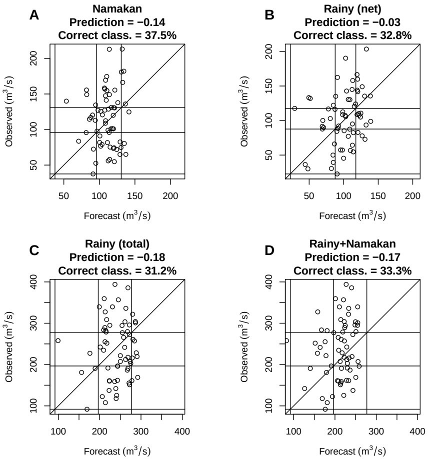

Figure: Average water supply observed and forecast during the low waters (July–February) with their prediction coefficients.

CONCLUSION

Answer

Water supply model can be developed to predict water supply to water bodies

- Forecasting power degrades after 2 months, when the model starts to predict average yearly fluctuations
- Much more capable at predicting the short-terms spring high waters than the low waters
- Way of improvement
  1. Using a deep neural network (one with > 1 hidden layer)
  2. Using El-Niño Southern Oscillation (ENSO) rather than NAO

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