The hunt for deterministic structures in noisy hydrological data

Holger LANGE Forest and Landscape Institute, Ås, Norway



- Properties of river runoff time series
- Properties of *k* noise
- Microintroduction to order statistics
- Definition of entropy and complexity for time series
- The Complexity-Entropy Causality Plane (CECP)
- Results: H_s and MPR-C_{JS}
- Conclusions and Outlook



Properties of river runoff time series

- Available from many stations at daily resolution (from HCDN, GRDC, and other sources)
- Are usually non-stationary
- Are noisy, highly fluctuating (intermittent, volatile, ...)
- Contain trends and cycles, in particular the seasonal cycle
- Exhibit long-range correlations or persistence
 - expressed by the Hurst exponent , $\frac{1}{2} < H < 1$
 - Autocorrelation decays slowly as a power law, correlation length diverges
 - long («infinite») memory
- ...are complicated!
- Are they also complex? How complex?
- How much information do they contain?
- Is it possible to model them (statistically)?





Properties of k noise

Generated from Gaussian noise by tunable distortion of the power spectrum: $P(f) \sim f^{-k} \ (f \to 0), k \ge 0$ Autocorrelation:

$$C(\tau) \sim \tau^{k-3} \ (\tau \gg 1, k < 3)$$

Hurst exponent:

$$H = \frac{k-1}{2} \ (1 < k < 3)$$

- Power law, long-range correlated^{*}
- Diverging correlation length
- Infinite memory



Is this a good description of runoff (deseasonalized time series)?





Approach: quantify information and complexity using order statistics



Order Statistics

Given a sequence / time series $\{x_i\}, i = 1, ..., N$

Define a subsequence ("word") length $D \ll N$

The order pattern of length D of the series at time iis the permutation $\pi_D(i) = (r_0, r_1, ..., r_{D-1})$ of (0, 1, ..., D-1) satisfying $x_{i-r_0} \ge x_{i-r_1} \ge ... \ge x_{i-r_{D-1}} \ge x_{i-r_{D-1}}$

A clever coding of the order patterns (Keller 2008) reveals the order pattern frequency distribution







Information and Complexity of Time Series

1. Information

(first order in randomness)

Zero for constants, max for pure noise

Here: *Time-ordered* Shannon entropy

2. Complexity

(second order in randomness)



Information

Zero for constants, zero for pure hoise

Complexity

(†)

Max for structured data

Here: Jensen-Shannon MPR Complexity:

$$H_{S} = -\sum_{i=1}^{D!} p_{i} \ln p_{i} / \ln D! \qquad C_{JS} = H_{S} Q_{JS} [P, P_{u}]$$
$$Q_{JS} = Q_{0} \{ S[(P + P_{u})/2] - S[P]/2 - S[P_{u}]/2 \}$$

 P_{μ} is the uniform distribution and

$$Q_0 = -2 / \left\{ \left(\frac{D! + 1}{D!} \right) \ln(D! + 1) - 2 \ln(2D!) + \ln D! \right\}$$

Martín, Plastino and Rosso (2006)

The Complexity-Entropy Causality Plane (CECP)







Runoff and *k* noise, D=3











Runoff and tuned k noise (example)











Runoff is time-reversal asymmetric, k noise is not



skog+

landskar

NORWEGIAN FOREST AND LANDSCAPE INSTITUTE

Time asymmetry of runoff and tuned k noise - quantified















Conclusions and Outlook

- Runoff time series *are* complex (in the sense of the CECP)
 - The higher *D*, the more complex
- Runoff is *not* k noise



- Correlation structure is intricate even at *small* lags
- Information and Complexity of runoff is qualitatively different from that of other variables
- Future plans:
 - Relate CECP position to auxiliary variables
 - Use CECP as sensible model evaluation tool
 - Construct a time series generator producing series with a prescribed H_s and C_{JS} how do these compare to the observed runoff?



