

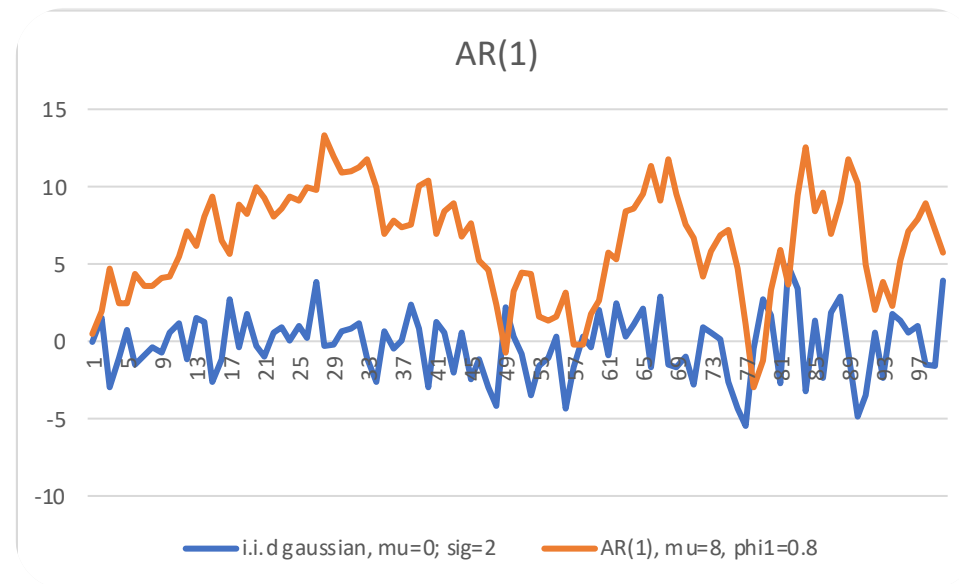
Water Resources Engineering and Management

(CIVIL-466, A.Y. 2024-2025)

5 ETCS, Master course

Prof. P. Perona

Platform of hydraulic constructions



Lecture 7-1: Univariate linear Models, periodic models, Thomas-Fiering model

Models identification

The model identification phase requires determining the orders of the p-autoregressive and the q-moving average components.

• **ACF**

$$\rho_k = \frac{E[x_{t+k}, x_t]}{E[x_t^2]} \quad \text{vs} \quad r_k = \frac{\sum_{t=1}^{N-k} (x_{t+k} - x_t)}{\sum_{t=1}^N x_t^2}$$

$$\rho_m = 0, \quad k > m \quad \text{vs} \quad r_j \approx 0 \quad k > j$$

BECAUSE FOR A MA(q) PROCESS $\rho_k = 0$ FOR $k > q$,
 j CORRESPONDING TO $r_j \approx 0$ INDICATES THE
 max number of moving average components

• **PAF** THE VECTOR OF PARAMETERS, ϕ_i , OF THE AUTOREGRESSIVE COMPONENT DEFINES THE **partial autocorrelation function** ↴

FROM THE YULE-WALKER EQUATION ↴

$$\begin{bmatrix} \phi_1 \\ \vdots \\ \phi_k \end{bmatrix} = \begin{bmatrix} 1 & \rho_1 & \dots & \rho_{k-1} \\ \vdots & & & \vdots \\ \vdots & & & \vdots \\ \rho_{k-1} & \dots & \dots & 1 \end{bmatrix} \begin{bmatrix} \phi_1 \\ \vdots \\ \vdots \\ \phi_k \end{bmatrix}$$

BY SUBSTITUTING SAMPLE ACF, r_1, \dots, r_k ONE CAN ESTIMATE THE EMPIRICAL PAF AND COMPARE IT WITH PAF OF MODELS.

FOR AR(p) $\phi_k = 0 \quad \forall k > p$

$\hat{\phi}_j \approx 0 \Rightarrow j = \max p$

Summary table

Given a time series, compute and plot the sample autocorrelation function and check if

- Exp decrease \rightarrow AR(1)
- Mixed damping from lag 1 asymptotically to zero \rightarrow AR(p)
- ACF lag 1 < 0.5 and then drops to zero then MA(1)
- ACF becomes zero after lag q , then MA(q)

Table 4.1 Identification of Box-Jenkins models using autocorrelation and partial autocorrelation functions

<i>Model type</i>	<i>Autocorrelation function</i>	<i>Partial autocorrelation function</i>
AR(1), first-order autoregressive (Markov)	Exponential decrease	$\phi_{1,1} \neq 0$ $\phi_{i,i} = 0$ for $i = 2, 3, 4, \dots$
AR(p), p th-order autoregressive	Mixed type of damping from lag 1	$\phi_{i,i} \neq 0$ for $i \leq p$ $\phi_{i,i} = 0$ for $i > p$
MA(1), first-order moving-average	$\rho_1 \neq 0$ $\rho_i = 0$ for $i = 2, 3, 4, \dots$	Exponential decrease
MA(q), q th-order moving-average	$\rho_i = 0$ for $i > q$ $\rho_i \neq 0$ for $i \leq q$	Mixed type of damping from lag 1
ARMA(1, 1), autoregressive moving-average	Exponential decrease after lag 1	Exponential decrease after lag 1
ARMA(p, q), autoregressive moving-average	Mixed type of damping after lag $q + 1$	Mixed type of damping after lag $p - q$

Model estimators based on the method of moments

AR(1) model

$$\begin{aligned}\hat{\mu} &= \bar{y} \\ \hat{\sigma}_\varepsilon^2 &= s^2 (1 - r_1^2) \\ \hat{\phi}_1 &= r_1\end{aligned}$$

MA(1) model

Obvious given the type of ACF and the mean

ARMA(1,1) model

$$\begin{aligned}\hat{\sigma}_\varepsilon^2 &= \frac{s^2 (1 - \hat{\phi}_1^2)}{(1 - 2 \hat{\phi}_1 \hat{\theta}_1 + \hat{\theta}_1^2)} \\ \hat{\phi}_1 &= \frac{r_2}{r_1} \\ \hat{\theta}_1 &= \frac{-b \pm \sqrt{b^2 - 4 (r_1 - \hat{\phi}_1)^2}}{2 (r_1 - \hat{\phi}_1)}\end{aligned}$$

Model testing and diagnostic

After model estimate, then :

- 1) Check if model correctly represent process statistics (obviously yes if calibration was done with method of the moment;
- 2) Use the model to decompose noise from the observed time series.
Revert the equation, e.g., for an AR(2)

$$\varepsilon_t = y_t - \mu - \phi_1(y_{t-1} - \mu) - \phi_2(y_{t-2} - \mu) \quad \text{Here now } y \text{ is the data}$$

Reconstruct the series of the noise ε_t , and check if its serial correlation is zero

YES, serial correlation of reconstructed noise is zero for all lags



FINISHED, model good to be used

NO, serial correlation of reconstructed noise is non zero for all lags

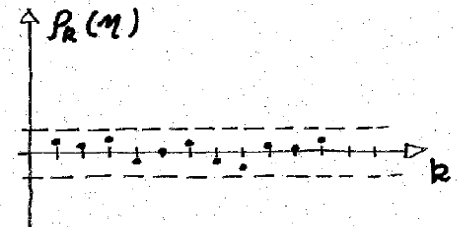


Model is not able to remove all serial correlation → change model

$$\rho_k(m) \approx 0 \quad \forall k > 0$$

VISUAL CHECK!

↓
TESTS!



Always use models with as lowest order as possible (parsimoniousness)

Modeling of univariate periodic time series

Periodic Autoregressive Models

PAR(p) & PARMA(p,q)

$$x_{v,\tau} = \mu_\tau + \sum_{j=1}^p \phi_{j,\tau} (x_{v,\tau-j} - \mu_{\tau-j}) + \varepsilon_{v,\tau}$$

seasonal hydrologic series

$v = \text{year}$

$\tau = \text{season } \tau = 1, \dots, \omega$

MODEL PARAMETERS

$\varepsilon_{v,\tau} = \text{NORMAL VARIABLE, UNCORRELATED, ZERO MEAN, } \sigma_\tau^2(\varepsilon)$

PAR(1)

$$x_{v,\tau} = \mu_\tau + \phi_{1,\tau} (x_{v,\tau-1} - \mu_{\tau-1}) + \varepsilon_{v,\tau}$$

e.g. THOMAS-FIERING MODEL

PARMA (1,1)

$$x_{v,t} = \mu_t + \phi_{1,t}(x_{v,t-1} - \mu_{t-1}) + \varepsilon_{v,t} - \theta_1 \varepsilon_{v,t-1}$$

↳ PRESERVATION OF BOTH SEASONAL
& ANNUAL STATISTICS

PARAMETER ESTIMATION



see SALAS, J. in

Handbook of Hydrology, Ch-19, McGraw-Hill, 19..

Identification of time series models

BASED ON AUTOCORRELOGRAM ANALYSIS

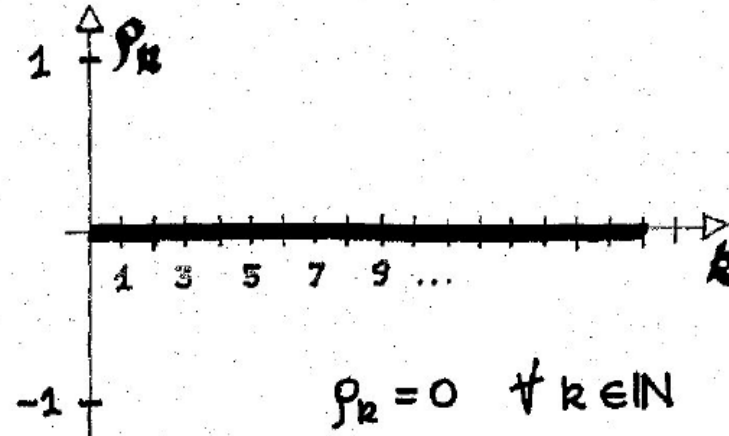
COMPARISON BETWEEN

r_k PLOT and ρ_k PLOT



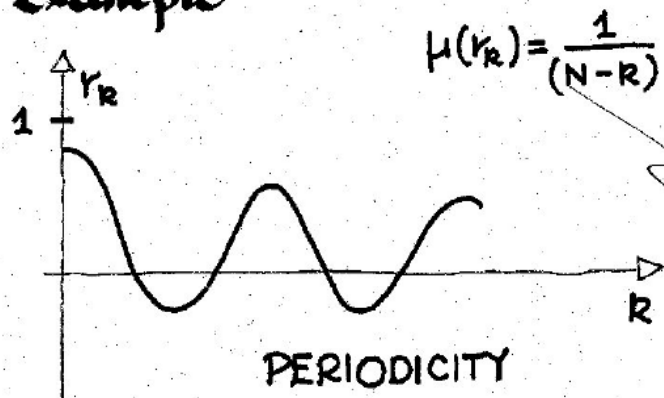
The analysis of the correlogram should allow to identify the deterministic component that must be considered to obtain a STATIONARY and INDEPENDENT time series

STATIONARY and INDEPENDENT
STOCHASTIC PROCESS



2

example

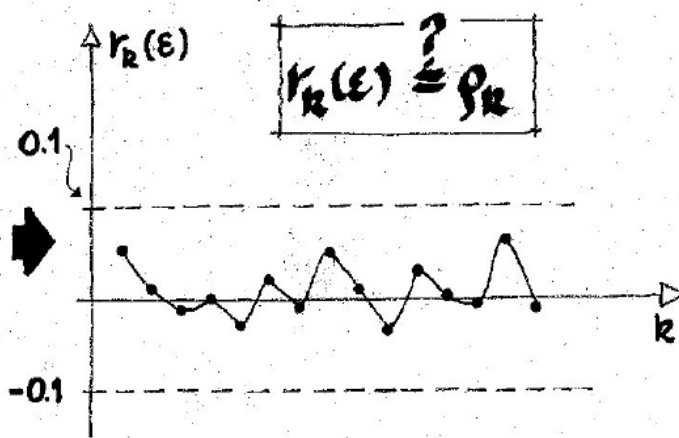
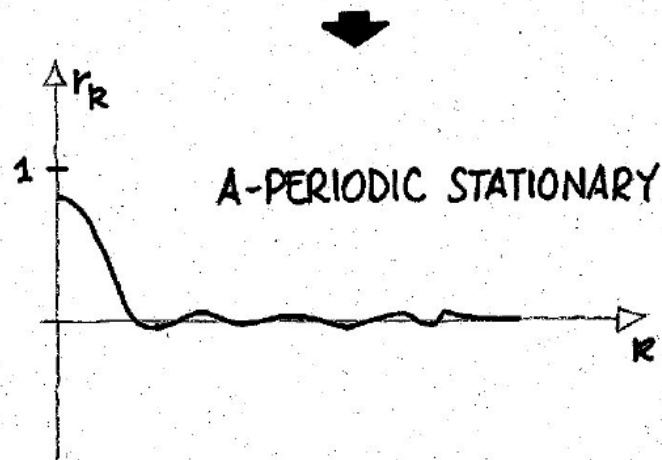


$$\mu(r_k) = \frac{1}{(N-k)}$$

FOR THE A-PERIODIC, TREND-FREE
TIME SERIES ONE CAN DEFINE
A CONFIDENCE INTERVAL, BASED
ON THE ASSUMPTION THAT THE
RESIDUALS ARE STATIONARY, INDE-
PENDENT AND NORMALLY DISTR.

$$\mu(r_k) \pm K \sigma(r_k) \quad \sigma^2(r_k) = \frac{N-k-1}{N-k}$$

$$Pr = 0.90 \rightarrow K = 1.645$$



Model of univariate periodic time series

NON STATIONARITY INDUCED BY *seasonality*

e.g. river flows \rightarrow monthly persistence

$$AR(p) \Rightarrow \boxed{x_t = \sum_{i=1}^p \phi_i x_{t-i} + \eta_t}$$

BEING x_t A STATIONARY VARIABLE

$$x_t = \frac{y_t - \mu}{\sigma}$$

PERIODIC AR(p)

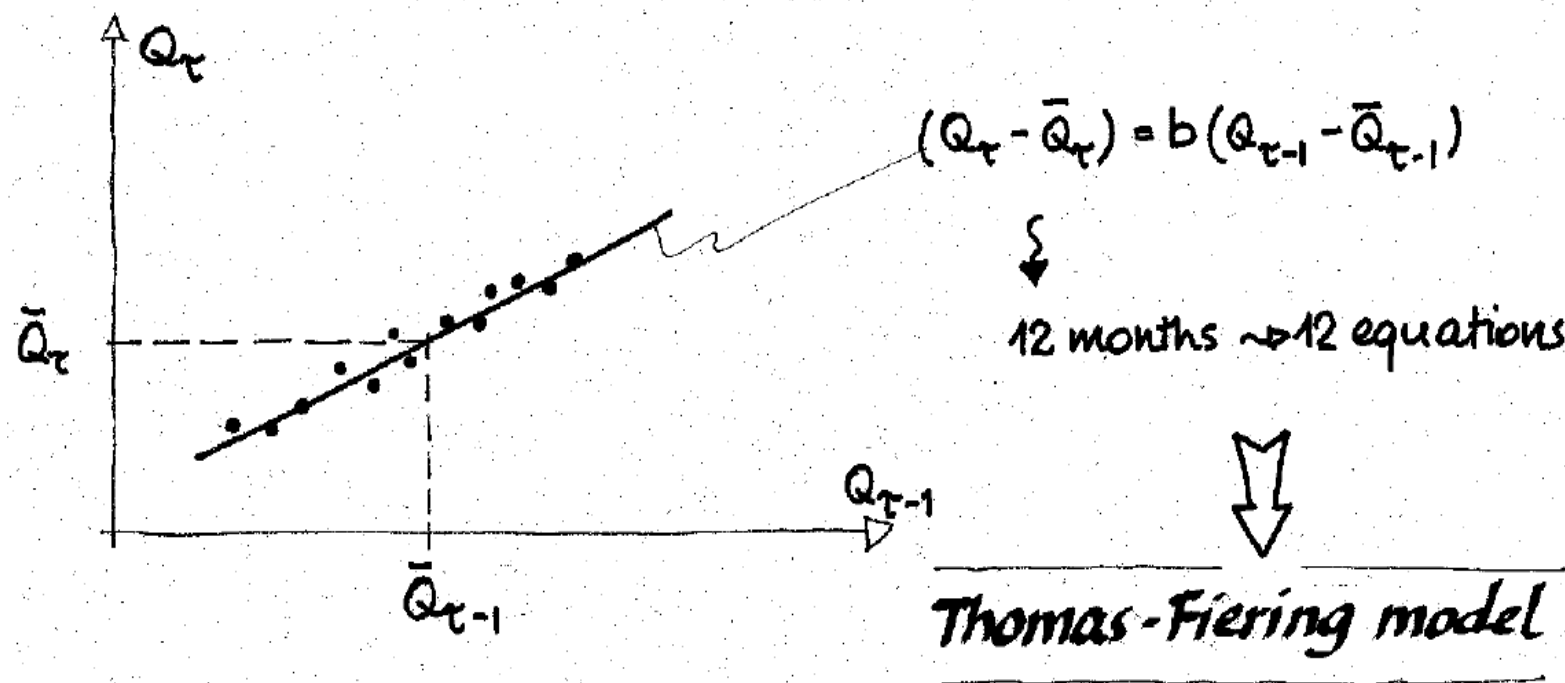
MEAN and STANDARD DEVIATION
FOR "SEASON" τ

$$\boxed{y_{t,\tau} = \mu_\tau + \sigma_\tau \sum_{i=1}^p \phi_i (y_{t-i,\tau} - \mu_{\tau-i}) / \sigma_{\tau-i} + \sigma_\tau \eta_{t,\tau}}$$

$E[\eta_t] = 0$ $\text{Var}[\eta_t] = \sigma_\eta^2$
uncorrelated
normal variable

example of MONTHLY PERSISTENCE

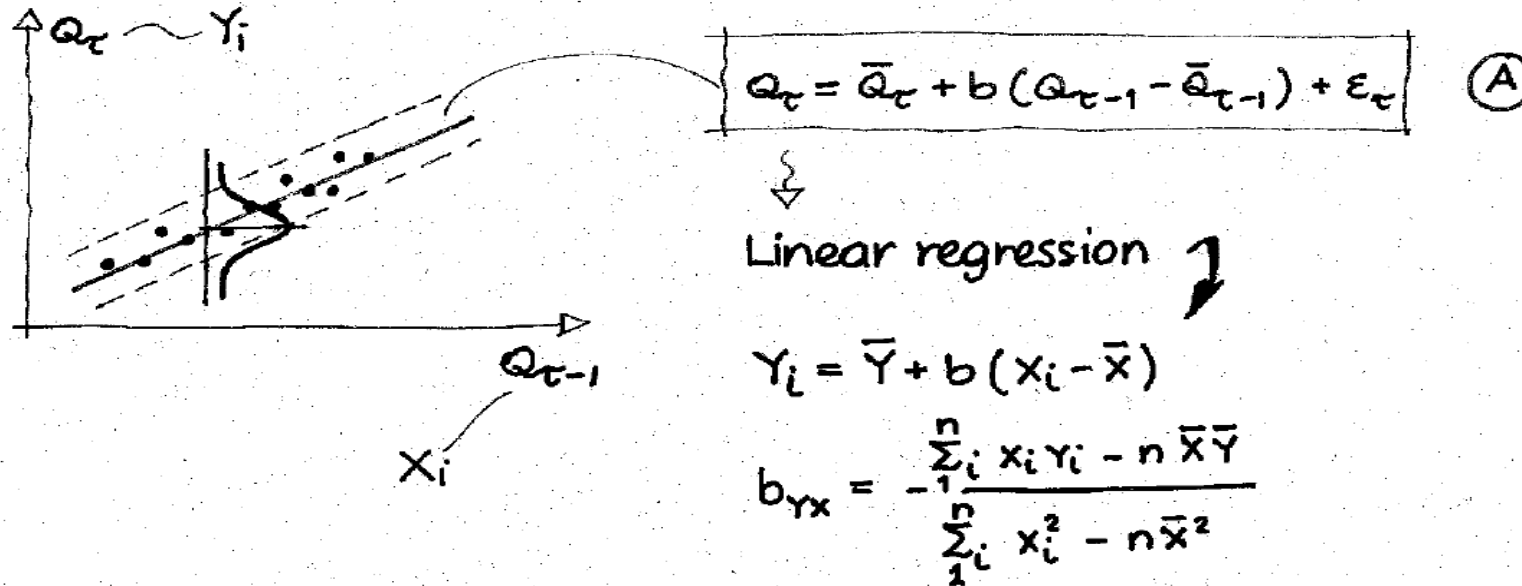
river flows (effects of storage and subsurface flow)



Build this plot by comparing, for example, mean or total Q in February vs same Q in January for all available years

Repeat for all month pairs

Thomas-Fiering model



STANDARD ERROR OF ESTIMATE

$\sigma_Y \sqrt{1-r^2}$ (B)

VARIANCE

$\sigma^2 = \sigma^2 r^2 + \sigma^2 (1-r^2)$

$$r = \frac{\sum_{i=1}^n x_i y_i - n \bar{X} \bar{Y}}{\sqrt{(\sum_{i=1}^n x_i^2 - n \bar{X}^2)(\sum_{i=1}^n y_i^2 - n \bar{Y}^2)}}$$

$$b_{yx} = r \frac{\sigma_y}{\sigma_x}$$

(A) (B)

$$(*) \Rightarrow Q_\tau = \bar{Q}_\tau + r_\tau \frac{\sigma_\tau}{\sigma_{\tau-1}} (Q_{\tau-1} - \bar{Q}_{\tau-1}) + \eta_\tau \sigma_\tau \sqrt{1 - r_\tau^2}$$

$p=1$

$$Y_{t,\tau} = \mu_\tau + \frac{\sigma_\tau}{\sigma_{\tau-1}} \phi_1(Y_{t-1,\tau-1} - \mu_{\tau-1}) + \sigma_\tau \eta_\tau$$

AR(1) $\rightarrow \rho_1!$ (B)

\bar{Q}_τ AVERAGE FLOW FOR τ -th MONTH

$\bar{Q}_{\tau-1}$ " " FOR $(\tau-1)$ th MONTH

r_τ AUTOCORR. COEFF. τ -th \rightarrow $(\tau-1)$ th MONTH

η_τ GAUSSIAN RANDOM VARIATE

σ_τ VARIANCE OF FLOW FOR τ -th MONTH

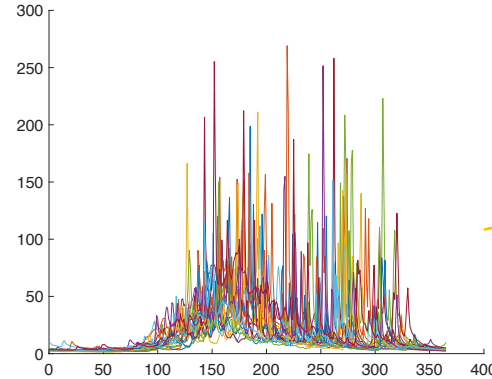
36 parameters!

$12 \bar{Q}_\tau, 12 \sigma_\tau, 12 r_\tau$

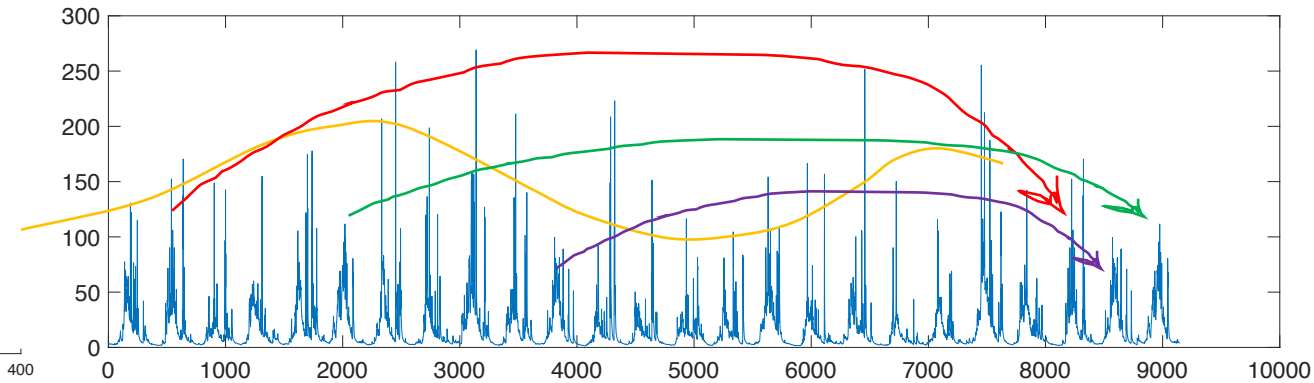
Other techniques

- **Reshuffling by swapping data conditions:**

no lower frequency trends,
long enough time series
preserve serial correlation
swap cycles



Check this **cycle**, then **swap years**



- **Use time series from neighborhood gauging stations**

conditions:

Catchments must have similar
dynamics

Size can be rescaled, but try
maintain variance

