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HS6 Impacts of climate change on hydrological response and on water resources management

Climatic change certainty versus climatic uncertainty and inferences in hydrological studies and water resources management

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Explanation of the title

- **Climatic change certainty**: Climate changes always
  - due to natural reasons
  - more recently due to anthropogenic effects
- **Climatic uncertainty**: Accurate deterministic predictions of future hydro-climatic regimes may be infeasible
  - due to weaknesses of models
  - due to inherent system complexity (uncertainty is probably a structural and inevitable characteristic of hydro-climatic processes)
- **Hydrological studies and water resources management**: require knowledge of future conditions
  - look forward to eliminating uncertainty (probably impossible)
  - can compromise with quantification of uncertainty and risk under future conditions (difficult to achieve)
  - as a first step, should seek for estimates of uncertainty and risk under present and past conditions (not achieved so far)

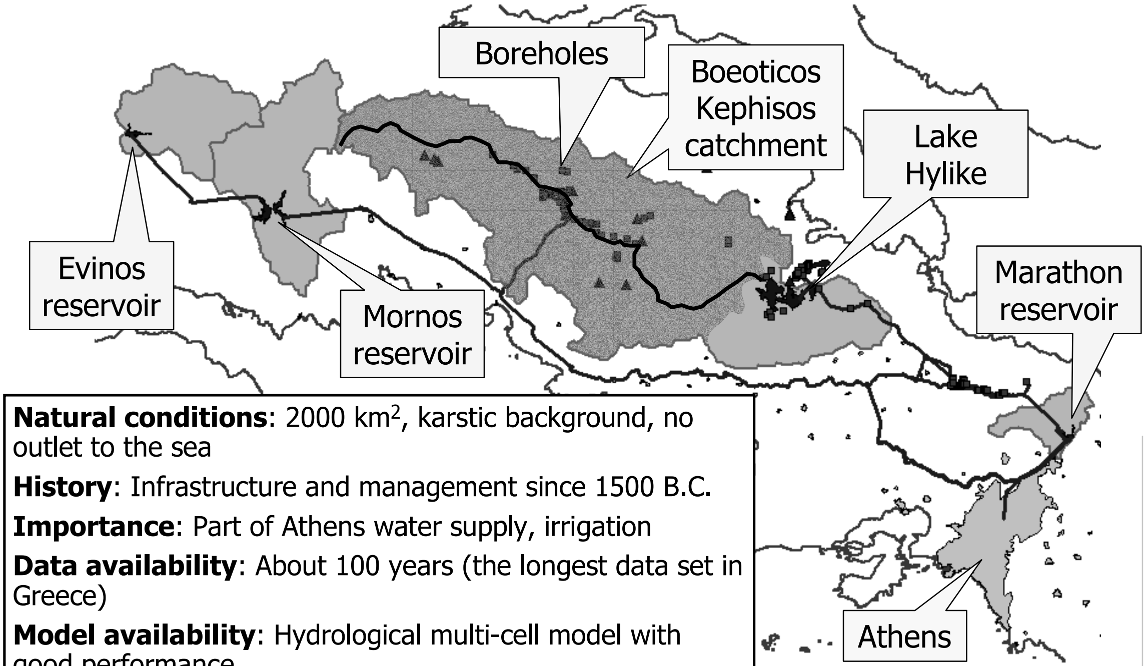
Approaches to quantify uncertainty

- **Scenario-based**: Plausible assumptions about future conditions
  - naïve (e.g. increase/decrease of precipitation by 20%) – no climatic models are required
  - sophisticated (e.g. increase of CO_2 concentration) – coupling with climatic models
- **Probabilistic:** Use of concepts of probability, statistics and stochastic processes
  - with present and past empirical basis (hydro-climatic records)
  - with plausible assumptions about future conditions, utilising stochastic relationships between hydro-climatic processes and factors affecting them

Targets of the presentation

- To show that current methods underrate and underestimate seriously the climatic uncertainty
  - Scenario-based approaches describe a portion of natural variability as climatic models result in interannual variability that is too weak
  - Even probabilistic approaches based on classical statistical analyses of real world data hide some sources of variability and uncertainty
- To show that probabilistic approaches can be adapted to yield estimates of uncertainty that are:
  - more accurate than classical estimates
  - impressively higher than classical estimates

Empirical basis of the study: The Boeoticos Kephisos River basin



Natural conditions: 2000 km^2, karstic background, no outlet to the sea

History: Infrastructure and management since 1500 B.C.

Importance: Part of Athens water supply, irrigation

Data availability: About 100 years (the longest data set in Greece)

Model availability: Hydrological multi-cell model with good performance

Empirical basis in hydrological statistics

A typical "short" time series: Annual runoff (expressed as equivalent depth) of the Boeoticos Kephisos River basin

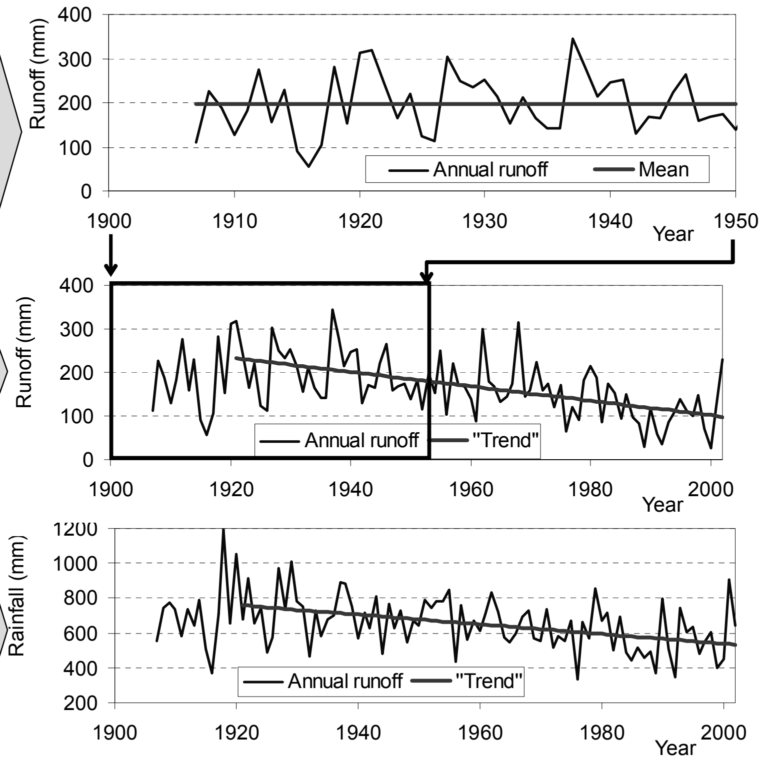
Stable behaviour, annual random fluctuation around a constant mean

The same time series for a longer period

Appearance of overyear "trends"

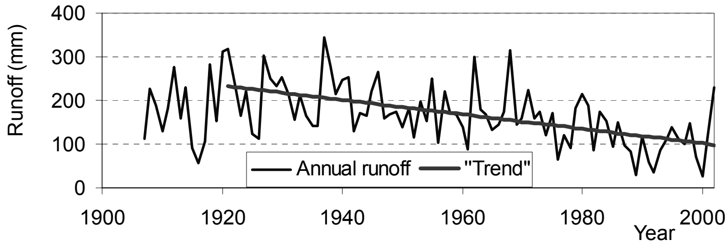
A similar "trend" in the rainfall series of same location

Explains the "trend" in runoff



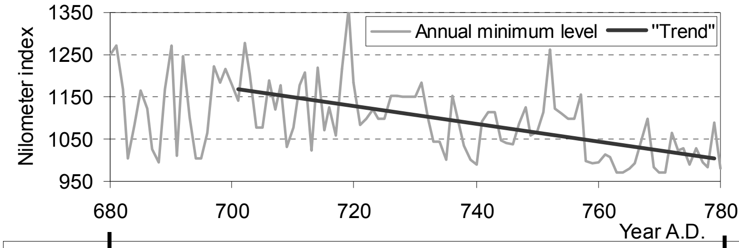
Behaviour of long series

The full Boeoticos Kephisos runoff time series



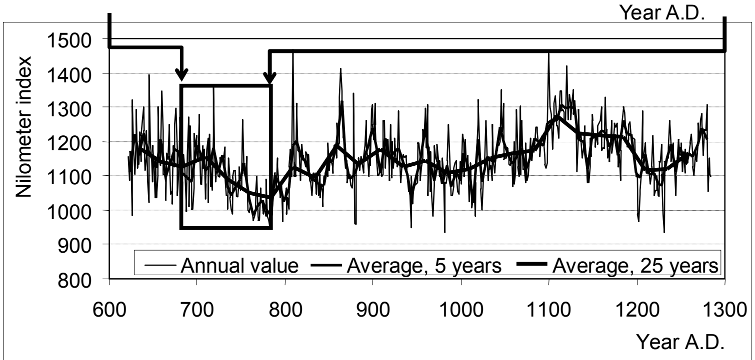
Part of the annual minimum water level of the Nile river (Nilometer)

A similar "trend"



The full Nilometer series for the years 622 to 1284 A.D. (663 years; Beran, 1994)

Upward and downward irregular fluctuations at all time scales



Climatic fluctuations and the Hurst phenomenon

- "Climate changes irregularly, for unknown reasons, on all timescales" (National Research Council, 1991, p. 21)
- Many long time series confirm this motto
- Irregular changes in time series are better modelled as stochastic fluctuations on many time scales rather than deterministic components
- Equivalently (Koutsoyiannis, 2002), these fluctuations can be regarded as a manifestation of the *Hurst phenomenon* quantified through the *Hurst exponent*, *H* (Hurst, 1951)

Original formulation of the Hurst phenomenon

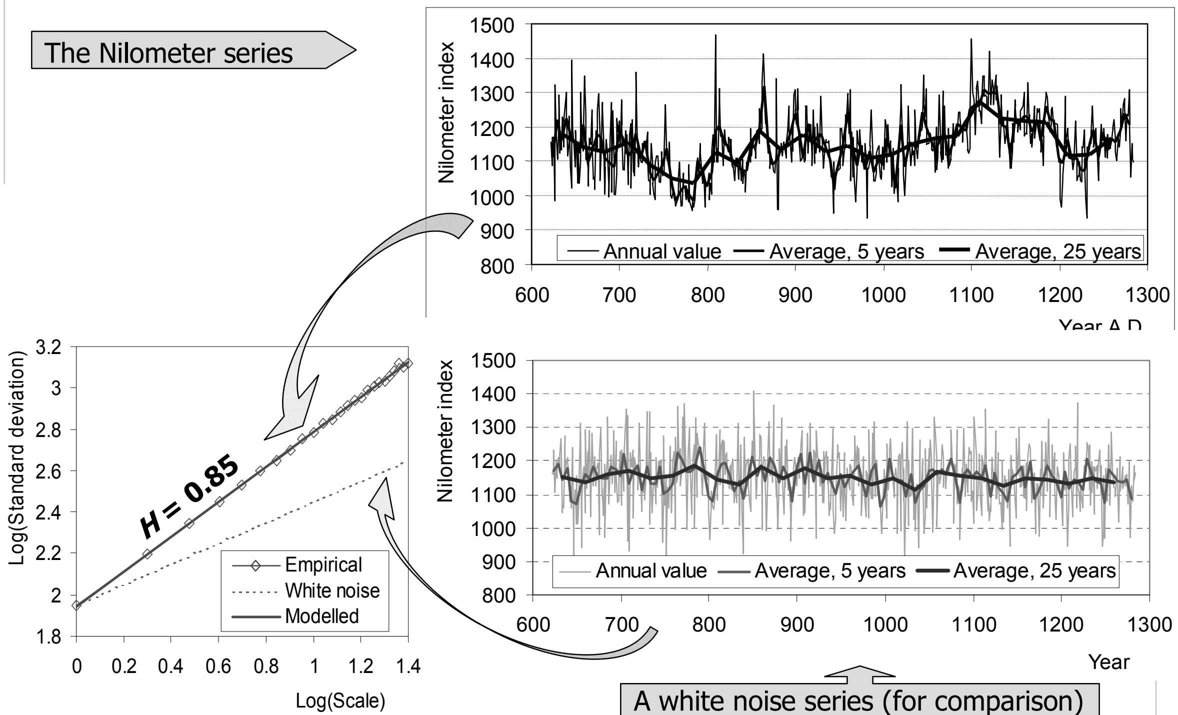
- The Hurst phenomenon is typically formulated in terms of the statistical behaviour of a quantity called "range", (Hurst, 1951) which describes the difference of **accumulated inflows minus outflows** from a hypothetical infinite **reservoir**
- In this respect, it has been regarded that it **affects the reservoir planning, design and operation**, but only when the reservoir performs **multi-year regulation** (e.g. Klemeš et al., 1981)

Simpler formulation of the Hurst phenomenon

A process at the annual scale	X_i
The mean of X_i	$\mu := E[X_i]$
The standard deviation of X_i	$\sigma := \sqrt{\mathrm{Var}[X_i]}$
The aggregated process at a multi-year scale $k \geq 1$	$Z_1^{(k)} := X_1 + \dots + X_k$ $Z_2^{(k)} := X_{k+1} + \dots + X_{2k}$ $\vdots$ $Z_i^{(k)} := X_{(i-1)k+1} + \dots + X_{ik}$
The mean of $Z_i^{(k)}$	$E[Z_i^{(k)}] = k\,\mu$
The standard deviation of $Z_i^{(k)}$	$\sigma^{(k)} := \sqrt{\mathrm{Var}\,[Z_i^{(k)}]}$
if consecutive X_i are independent	$\sigma^{(k)} = \sqrt{k}\,\sigma$
if consecutive X_i are positively correlated	$\sigma^{(k)} > \sqrt{k}\,\sigma$
if X_i follows the Hurst phenomenon	$\boxed{\sigma^{(k)} = k^H \sigma}$ $(0.5 < H < 1)$
Extension of the standard deviation scaling and definition of a simple scaling stochastic process (SSS)	$(Z_i^{(k)} - k\mu) \stackrel{d}{=} \left(\frac{k}{l}\right)^H (Z_j^{(l)} - l\mu)$ for any scales k and l

Tracing and quantification of the Hurst phenomenon: (a) The long Nilometer data set

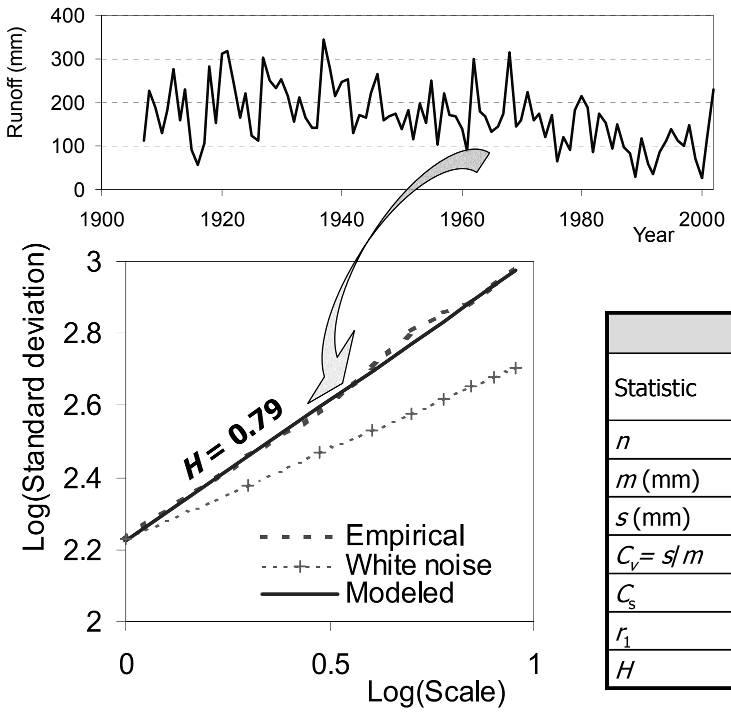
The Nilometer series



A white noise series (for comparison)

Tracing and quantification of the Hurst phenomenon: (b) The time series of the study area

The Boeoticos Kephisos runoff time series



Statistics of all processes			
Statistic	Runoff	Rainfall	Temperature
n	96	96	102
m (mm)	167.7	658.4	16.9
s (mm)	74.5	158.9	0.70
$C_v = s/m$	0.44	0.24	0.04
C_s	0.36	0.44	0.34
r_1	0.34	0.10	0.31
H	0.79	0.64	0.63

Effect of the Hurst phenomenon in statistics

- Fundamental law of classical statistics

$$\mathrm{StD}[\bar{X}] = \frac{\sigma}{\sqrt{n}}$$

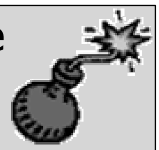
$\bar{X}$ = sample mean
σ = standard deviation
n = sample size

- Modified law for SSS

$$\mathrm{StD}[\bar{X}] = \frac{\sigma}{n^{1-H}}, \; H > 0.5$$

- Example
  To obtain $\mathrm{StD}[\bar{X}] / \sigma = 10\%$
  - n = 100 for classical statistics
  - n = 100 000 for SSS with H = 0.8

A bomb in the foundation of climatology

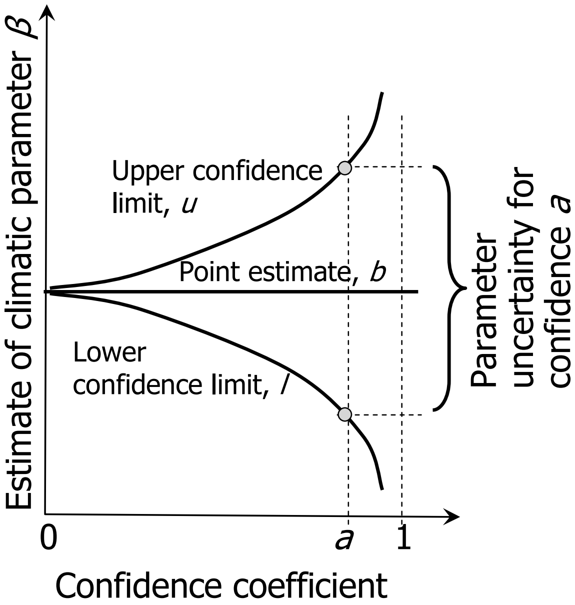


Climatology and the Hurst phenomenon

- **Climatology**: the atmospheric science concerned with long term **statistical properties** of the atmosphere (e.g., **mean values** and **range of variability** of various measurable quantities, and frequencies of various events) (Wallace and Hobbs, 1977)
- **Climate**: Statistical synthesis of the weather elements over a long period of time (typically 30 years)
- **Effect of the Hurst phenomenon**: Increases dramatically the range of climatic variability (Koutsoyiannis, 2003)

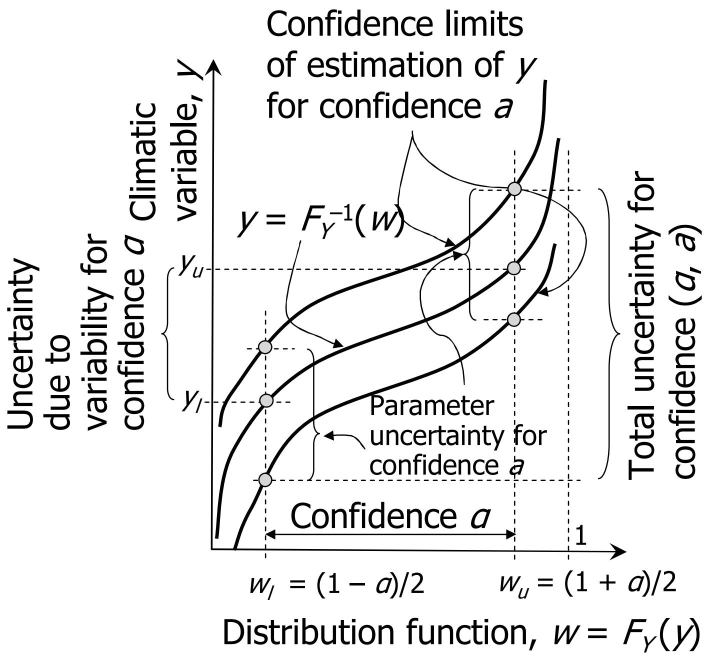
Quantification of uncertainty: Confidence limits for a climatic parameter

- Climatic parameter: β (e.g. mean annual rainfall)
- Random sample $\mathbf{X} = (X_1, \ldots, X_n)$ observation $\mathbf{x} = (x_1, \ldots, x_n)$
- Point estimator of β: $B = g_B(\mathbf{X})$ point estimate of β: $b = g_B(\mathbf{x})$
- Interval estimators of β for confidence coefficient a:
  $U = g_U(\mathbf{X})$ (upper),
  $L = g_L(\mathbf{X})$ (lower) with
  $$P(L \le \beta \le U) = a$$
  interval estimate of β:
  $$(l, u) = (g_L(\mathbf{x}), g_U(\mathbf{x}))$$

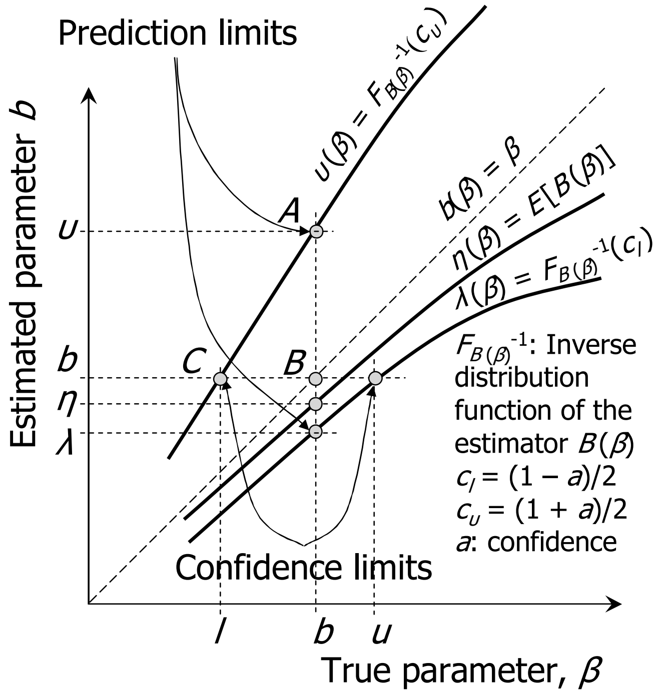


Quantification of uncertainty: Confidence limits for a climatic variable

- Climatic variable: Y (e.g. mean annual rainfall of a 30-year period)
- Distribution function $F_Y(y) = P(Y \le y)$
- For a specified non-exceedence probability w, the corresponding value of Y, i.e. $y = F_Y^{-1}(w)$ is a parameter



Estimation of confidence limits by Monte Carlo simulation – One model parameter



- Method 1 (Ripley, 1987)
  $l = 2b - u$, $u = 2b - \lambda$
- Method 2 (Ripley, 1987)
  $l = b^2 / u$, $u = b^2 / \lambda$
- Method 3

$$\frac{u - b}{b - l} = \frac{\mathrm{AB}}{\mathrm{BC}} \approx \frac{du}{d\beta}$$

$$l = b + \frac{b - u}{du/d\beta}, \quad u = b + \frac{b - \lambda}{d\lambda/d\beta}$$

for $du/d\beta = d\lambda/d\beta = 1$
$\rightarrow$ method 1

for $du/d\beta = u/\beta$,
$d\lambda/d\beta = \lambda/\beta$
$\rightarrow$ method 2

Estimation of confidence limits by Monte Carlo simulation – Many model parameters

The same equations can be used in the multi-parameter case. To implement Method 3, i.e.,

$$l = b + \frac{b - u}{du/d\beta}, \quad u = b + \frac{b - \lambda}{d\lambda/d\beta}$$

the derivatives $d\lambda/d\beta$ and $du/d\beta$ should be evaluated at appropriate directions $\mathbf{d}_\lambda$ and $\mathbf{d}_u$

Let the vector of (unknown) model parameters (distributional, dependence) $\boldsymbol{\theta} = [\theta_1, \ldots, \theta_k]^T$

Let the vector of estimators of $\boldsymbol{\theta}$, $\mathbf{T} = [T_1, \ldots, T_k]^T$

Let $\mathrm{Var}[\mathbf{T}] = \mathrm{diag}(\mathrm{Var}[T_1], \ldots, \mathrm{Var}[T_k])$

Let $\beta = h(\boldsymbol{\theta})$ the parameter whose confidence limits are required

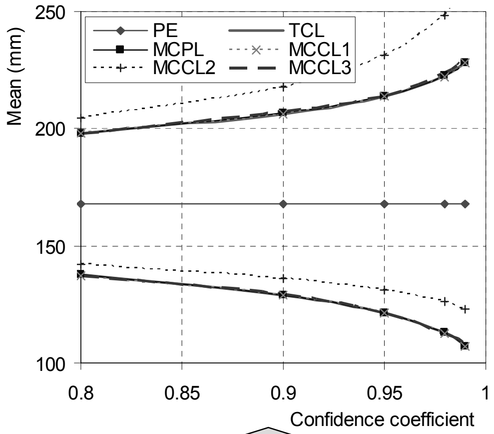
Let $\boldsymbol{\gamma} = [\lambda, \beta, u]^T$ the vector consisting of β and its prediction limits (λ, u) for confidence a

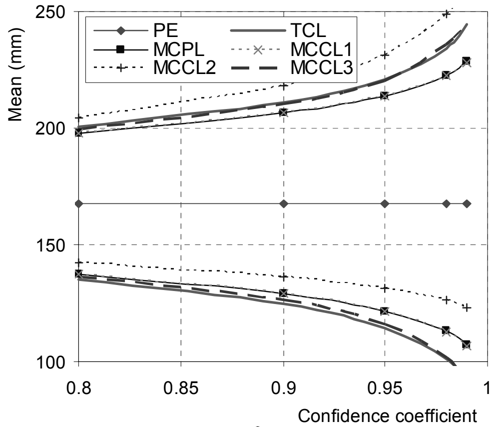
Let $\mathbf{q}$ the 3 × 3 matrix defined as

$$\mathbf{q} := \frac{d\boldsymbol{\gamma}}{d\boldsymbol{\theta}} \mathrm{Var}[\mathbf{T}] \left(\frac{d\boldsymbol{\gamma}}{d\boldsymbol{\theta}}\right)^T, \text{ where } \frac{d\boldsymbol{\gamma}}{d\boldsymbol{\theta}} = \begin{bmatrix} \frac{d\lambda}{d\boldsymbol{\theta}} \\ \frac{d\beta}{d\boldsymbol{\theta}} \\ \frac{du}{d\boldsymbol{\theta}} \end{bmatrix} = \begin{bmatrix} \frac{\partial\lambda}{\partial\theta_1} & \frac{\partial\lambda}{\partial\theta_2} & \cdots & \frac{\partial\lambda}{\partial\theta_k} \\ \frac{\partial\beta}{\partial\theta_1} & \frac{\partial\beta}{\partial\theta_2} & \cdots & \frac{\partial\beta}{\partial\theta_k} \\ \frac{\partial u}{\partial\theta_1} & \frac{\partial u}{\partial\theta_2} & \cdots & \frac{\partial u}{\partial\theta_k} \end{bmatrix}$$

Then $\mathbf{d}_\lambda = \mathbf{q}\,[0, 1, 1]^T$, and $\mathbf{d}_u = \mathbf{q}\,[1, 1, 0]^T$, so that $\frac{d\lambda}{d\beta} = \frac{q_{12} + q_{13}}{q_{22} + q_{23}}$, $\frac{du}{d\beta} = \frac{q_{31} + q_{32}}{q_{21} + q_{22}}$

Verification of method – mean of normal distribution



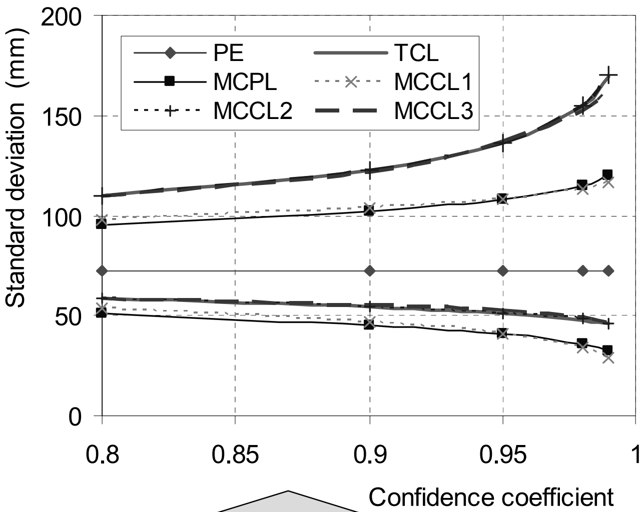


Assumptions
$n = 10$
$m = 167.7$ mm, unknown
$s = 74.5$ mm, known
Normal distribution, independence

Assumptions
$n = 10$
$m = 167.7$ mm, unknown
$s = 74.5$ mm, unknown
Normal distribution, independence

PE: Point estimate
MCPL: Monte Carlo prediction limits
TCL: Theoretical confidence limits
MCCL 1, 2, 3: Monte Carlo confidence limits by methods 1, 2, 3

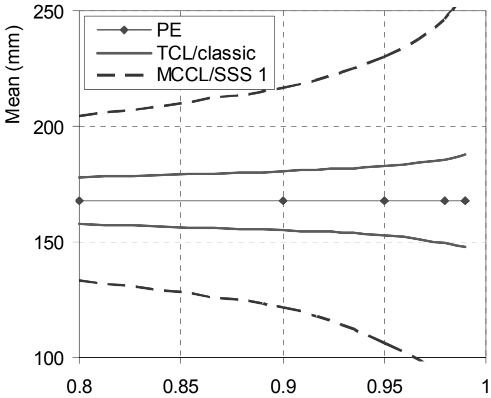
Verification of method – standard deviation of normal distribution

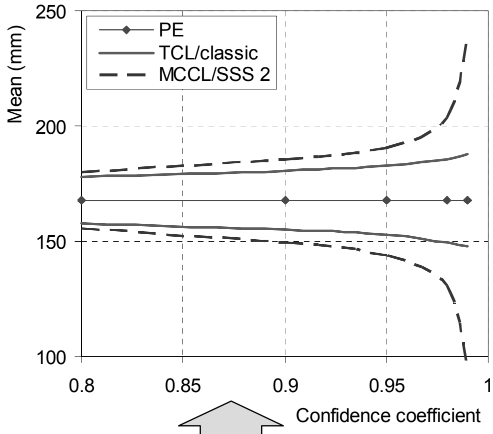


PE: Point estimate
TCL: Theoretical confidence limits
MCPL: Monte Carlo prediction limits
MCCL 1, 2, 3: Monte Carlo confidence limits by methods 1, 2, 3

Assumptions
$n = 10$
$m = 167.7$ mm, unknown
$s = 74.5$ mm, unknown
Normal distribution, independence

Increase of uncertainty in an SSS process



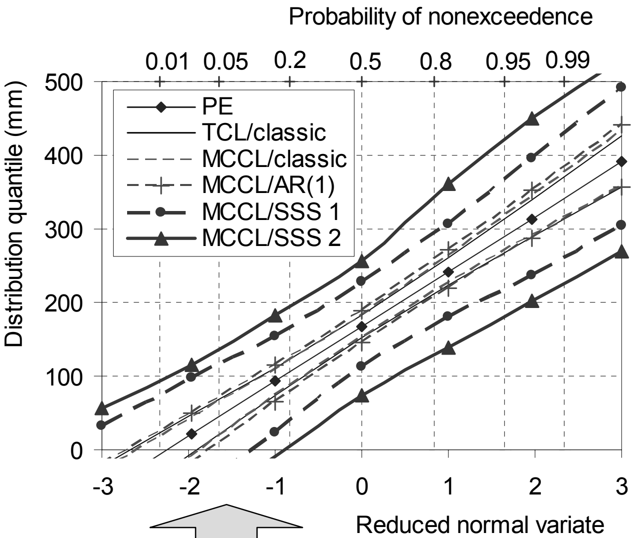


Assumptions
n = 96
m = 167.7 mm, unknown
s = 74.5 mm, unknown
H = 0.79, known
Normal distribution

Assumptions
n = 96
m = 167.7 mm, unknown
s = 74.5 mm, unknown
H = 0.5, unknown
Normal distribution

PE: Point estimate
TCL/classic: Theoretical confidence limits, assuming independence
MCPL/SSS: Monte Carlo confidence limits by method 3 assuming an SSS process with known *H* (case 1) or unknown *H* (case 2)

Uncertainty of runoff: Annual scale

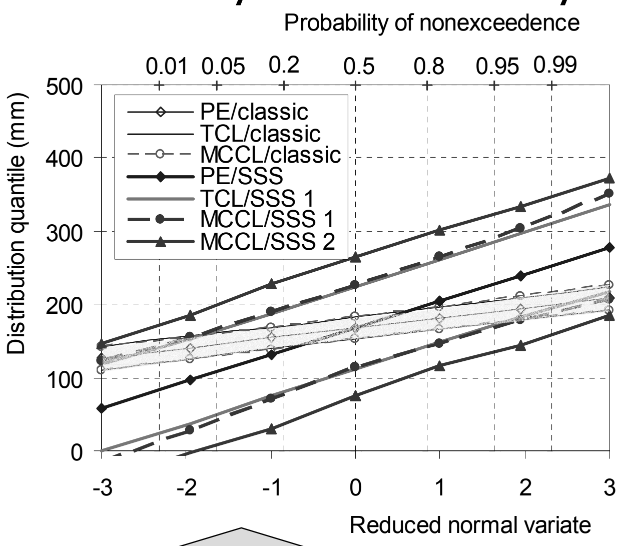


Depend-ence structure	Parame-ters	Total uncertainty, % of mean
Any	*m*, s**	174
IID	*m, s**	204
IID	*m, s*	206
AR(1)	*m, s, r**	210
AR(1)	*m, s, r*	211
SSS	*m, s, H**	236
SSS	*m, s, H*	268
Parameters marked with * are fixed		

Assumptions
n = 96, *a* = *α* = 95%
m = 167.7 mm
s = 74.5 mm
r = 0.34/*H* = 0.79
Normal distribution

PE: Point estimate
TCL/classic: Theoretical CL, IID
MCCL/classic: Monte Carlo CL (method 3), IID
MCCL/AR(1): Monte Carlo CL (method 3), AR(1)
MCPL/SSS: Monte Carlo CL (method 3), SSS
(1: fixed *H*; 2: unknown *H*)

Uncertainty of runoff: 30-year scale ("climate")



Dependence structure	Parameters	Total uncertainty, % of mean
IID	*m**, *s**	32
IID	*m*, *s*	50
SSS	*m**, *s**, *H**	87
SSS	*m*, *s*, *H**	165
SSS	*m*, *s*, *H*	199
Parameters marked with * are fixed		

Assumptions
n = 96, a = α = 95%
m = 167.7 mm
s = 74.5 mm
H = 0.79
Normal distribution

The theoretical confidence limits of the u-quantile of the random variable

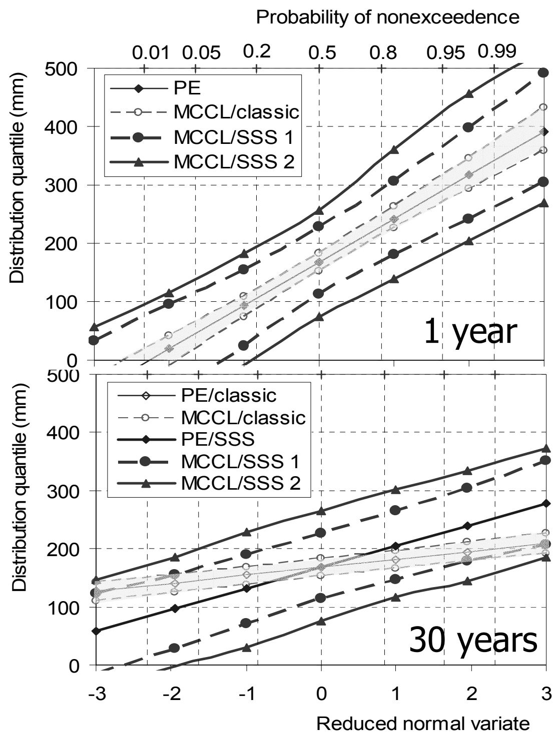
$Y_i^{(k)} := (1/k)\,(X_{(i-1)k+1} + \ldots + X_{ik})$

are based on the following relationship (adapted from Koutsoyiannis, 2003)

$$\mathrm{StD}[Y_u^{(k)}] = \frac{s}{n^{1-H}}\sqrt{1 + \frac{(\zeta_u / k^{1-H})^2}{2}\,\frac{\varphi(n, H)}{n^{2H-1}}}$$

where ζ_u the standard normal u-quantile and $\varphi(n, H) = (0.1\,n + 0.8)^{0.088(4H^2-1)^2}$

Comparisons of runoff uncertainty: 1- and 30-year scales

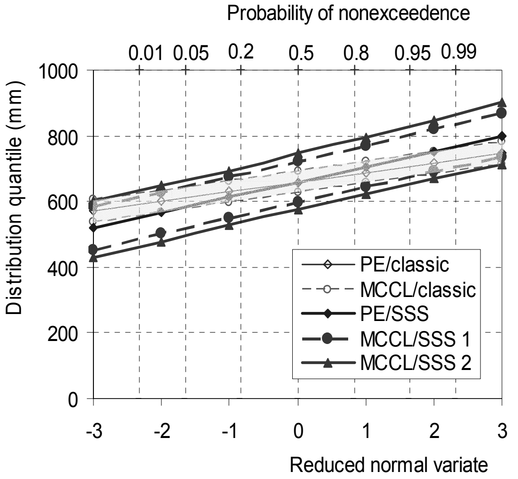


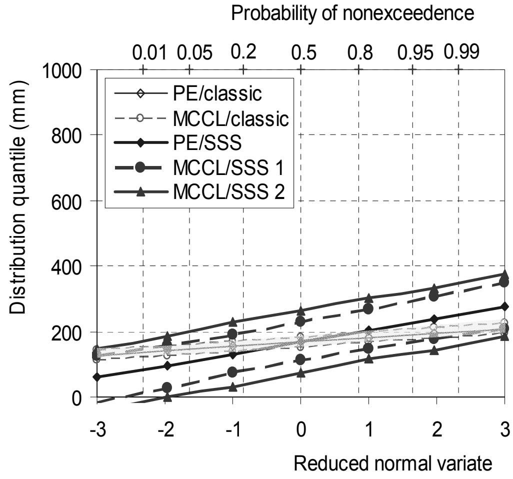
Dependence structure	Parameters	Total uncertainty, % of mean	
		Annual scale	30-year scale
IID	*m**, *s**	174	32
IID	*m*, *s*	206	50
SSS	*m**, *s**, *H**	174	87
SSS	*m*, *s*, *H**	236	165
SSS	*m*, *s*, *H*	268	199
Parameters marked with * are fixed			

Climate is what you expect
Weather is what you get

Weather is what you get
Climate is what you get
… if you keep expecting for many years

Comparison of climatic variability of rainfall and runoff (30-year averages in mm)

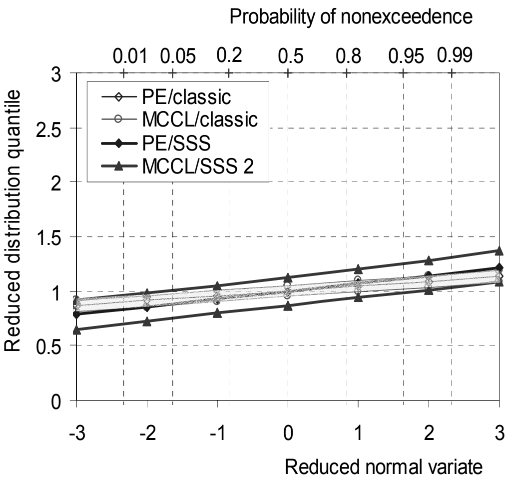


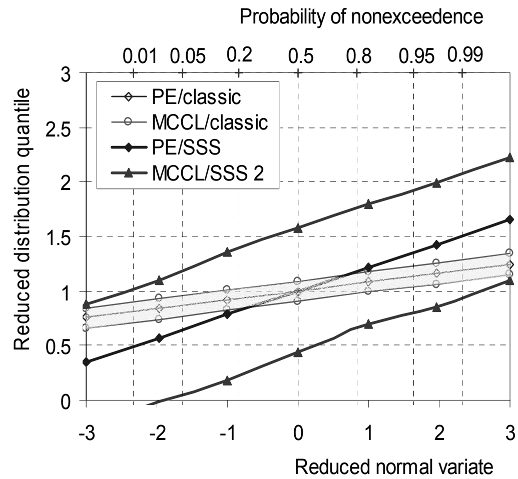


Rainfall (m = 658.4 mm, C_v = 0.24, H = 0.64)

Runoff (m = 167.7 mm, C_v = 0.44, H = 0.79)

Comparison of climatic variability of rainfall and runoff (30-year averages standardised by mean)

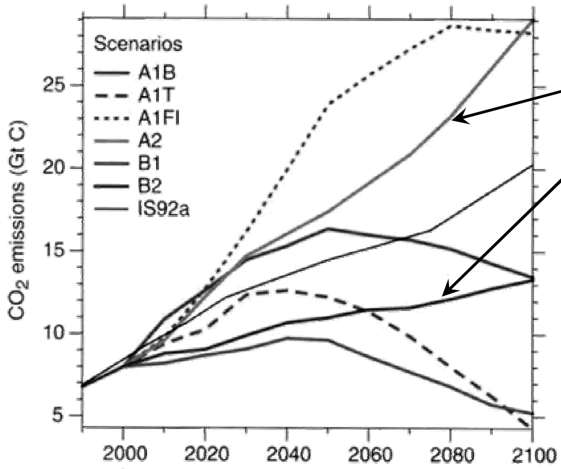




Rainfall (m = 658.4 mm, C_v = 0.24, H = 0.64)

Runoff (m = 167.7 mm, C_v = 0.44, H = 0.79)

Scenario-based approach: Scenarios and climatic models used in this study



Source:
http://ipcc-ddc.cru.uea.ac.uk/asres/emissions_scenarios.jpg

Model results (climatic predictions): Available on-line by the IPCC Data Distribution Centre (http://ipcc-ddc.cru.uea.ac.uk/dkrz/dkrz_index.html)

Scenarios (IPCC)

A2: high energy and carbon intensity, and correspondingly high CO_2 emissions

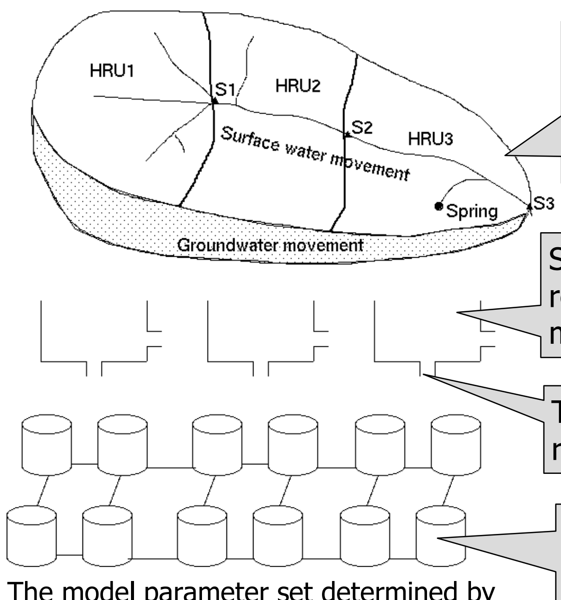
B2: the energy system predominantly hydrocarbon-based but with reduction in carbon intensity

Models

HADCM3: a coupled atmosphere-ocean general circulation model (**GCM**) developed at the Hadley Centre for Climate Prediction and Research (Gordon et al., 2000) Resolution: 2.5°Lat. x 3.75°Long. (73 Lat. x 96 Long.)

CGCM2: a global coupled model developed at the Canadian Centre for Climate Modelling and Analysis (Flato and Boer, 2000) Resolution: 3.75°Lat. x 3.75°Long. (48 Lat. x 96 Long.)

Scenario-based approach: Hydrological model used in the study



The catchment is divided into spatial subunits with similar morphological and hydrological characteristics (hydrologic response units; HRU)

Surface hydrological processes are represented by a modified Thornthwaite model acting on soil moisture reservoirs

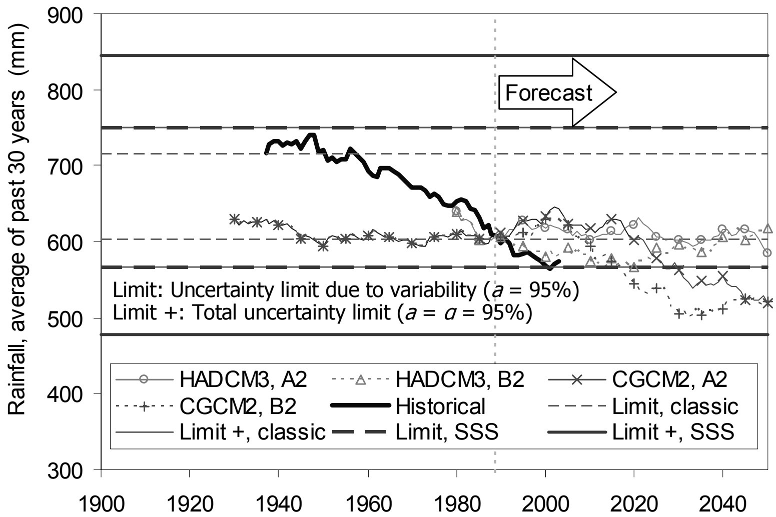
The percolation of each soil moisture reservoir supplies the aquifer

The aquifer is represented as a network of storage elements (tanks) and transportation elements (conduits with Darcian flow equation)

The model parameter set determined by Efstratiadis et al. (2003) and Rozos et al. (2004) was used in this study, too

Calibration period: 1984-1990; Validation period 1990-1994

GCM scenarios of future rainfall

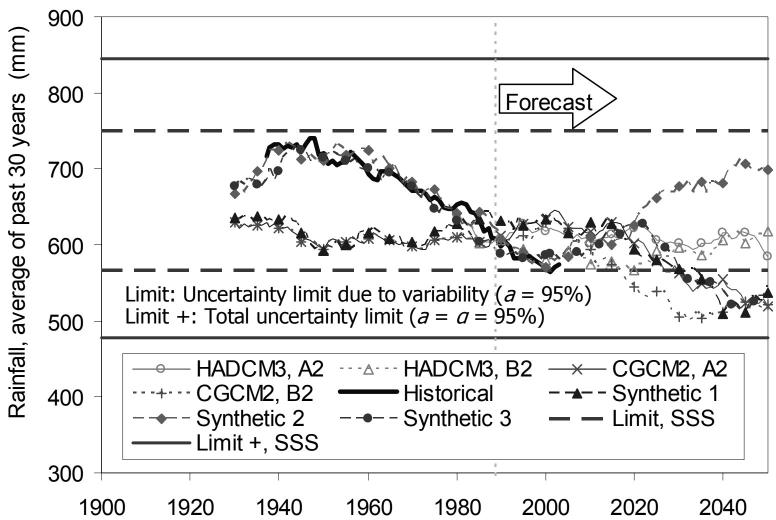


The time series of HADCM3 (A2 and B2) are the averages of the grid points (37°30΄N, 22°30΄E) and (40°00΄N, 22°30΄E), so that they roughly correspond to the point (38°75΄N, 22°30΄E), which lies in the catchment. The time series of CGCM2 (A2 and B2) are for the grid point (38°96΄N, 22°30΄E) which lies in the catchment.

All series were rescaled so as to match the historical average of the 30-year period between the hydrological years 1960-61 to 1989-90.

- Time series of GCM scenarios exhibit low interannual (30-year) variability in the past (Hurst coefficients close to 0.50)
- The departures of GCM time series from historical rainfall are very high in the early part of the observation period
- The future GCM rainfall falls within the SSS uncertainty limits

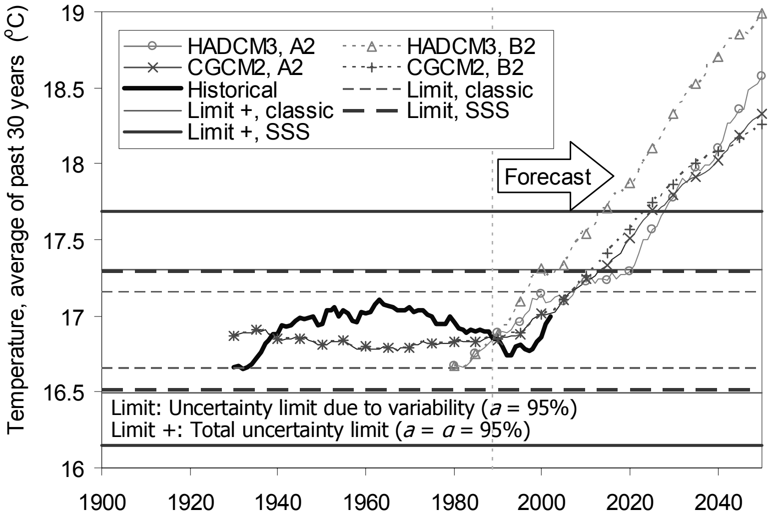
Scenarios of future rainfall: GCM scenarios vs. stochastic scenarios



The "synthetic" time series were drawn from 100 000 records generated from the SSS process with statistics equal to those of historical rainfall

- Synthetic series 1: In close agreement to CGCM2 scenario A2
- Synthetic series 2: In close agreement to historical climate with an upward future "trend"
- Synthetic series 3: In close agreement to historical past climate and to CGCM2 future scenario A2

GCM scenarios of future temperature

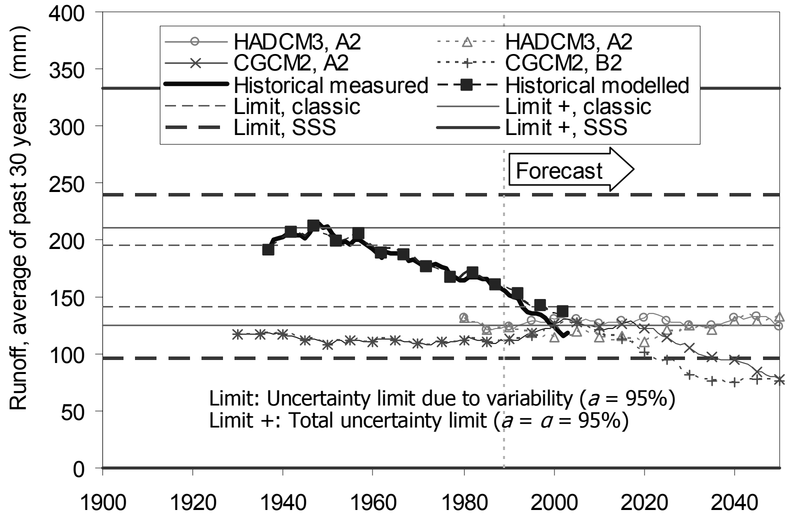


The time series of HADCM3 (A2 and B2) are the averages of the grid points (37°30′N, 22°30′E) and (40°00′N, 22°30′E), so that they roughly correspond to the point (38°75′N, 22°30′E), which lies in the catchment. The time series of CGCM2 (A2 and B2) are for the grid point (38°96′N, 22°30′E) which lies in the catchment.

All series were shifted so as to match the historical average of the 30-year period between the hydrological years 1960-61 to 1989-90.

- Time series of CGCM2 scenarios exhibit low interannual (30-year) variability in the past
- Time series of HADCM3 scenarios exhibit unrealistic upward trends in the past
- The future GCM temperature takes off the SSS uncertainty zone at years 2015-2030

Resulting scenarios of future runoff



Hydrological model inputs

Areal rainfall at the HRUs was estimated by regression based on the single-station rainfall

Potential evaporation at the HRUs was estimated by regression based on the single-station temperature and solar radiation

- Runoff generated from historical rainfall agrees perfectly with historical runoff
- Time series of GCM scenarios exhibit low interannual (30-year) variability in the past
- The departures of GCM time series from historical runoff are very high in the early part of the observation period
- The future GCM runoff falls well within the SSS uncertainty limits

Conclusions

- Classical statistics, applied to climatology and hydrology, describes only a portion of natural uncertainty and underestimates seriously the risk
- Climatic models that are supposed to predict future climate do not capture past climatic variability, i.e. they result in interannual variability that is too weak
- The Hurst phenomenon and simple scaling stochastic (SSS) processes offer a sound basis to adapt hydro-climatic statistics so as to capture interannual variability
- The SSS statistical framework, applied with past hydro-climatic records, is a feasible step towards making more accurate estimates of uncertainty and risk, good for hydrological studies and water resources management
- Anthropogenic climate change increases future uncertainty, but the quantification of the increase is difficult to achieve

This presentation is available on line at http://www.itia.ntua.gr/g/docinfo/606/

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