The role of real-time forecasting models in mitigating the impacts of flooding

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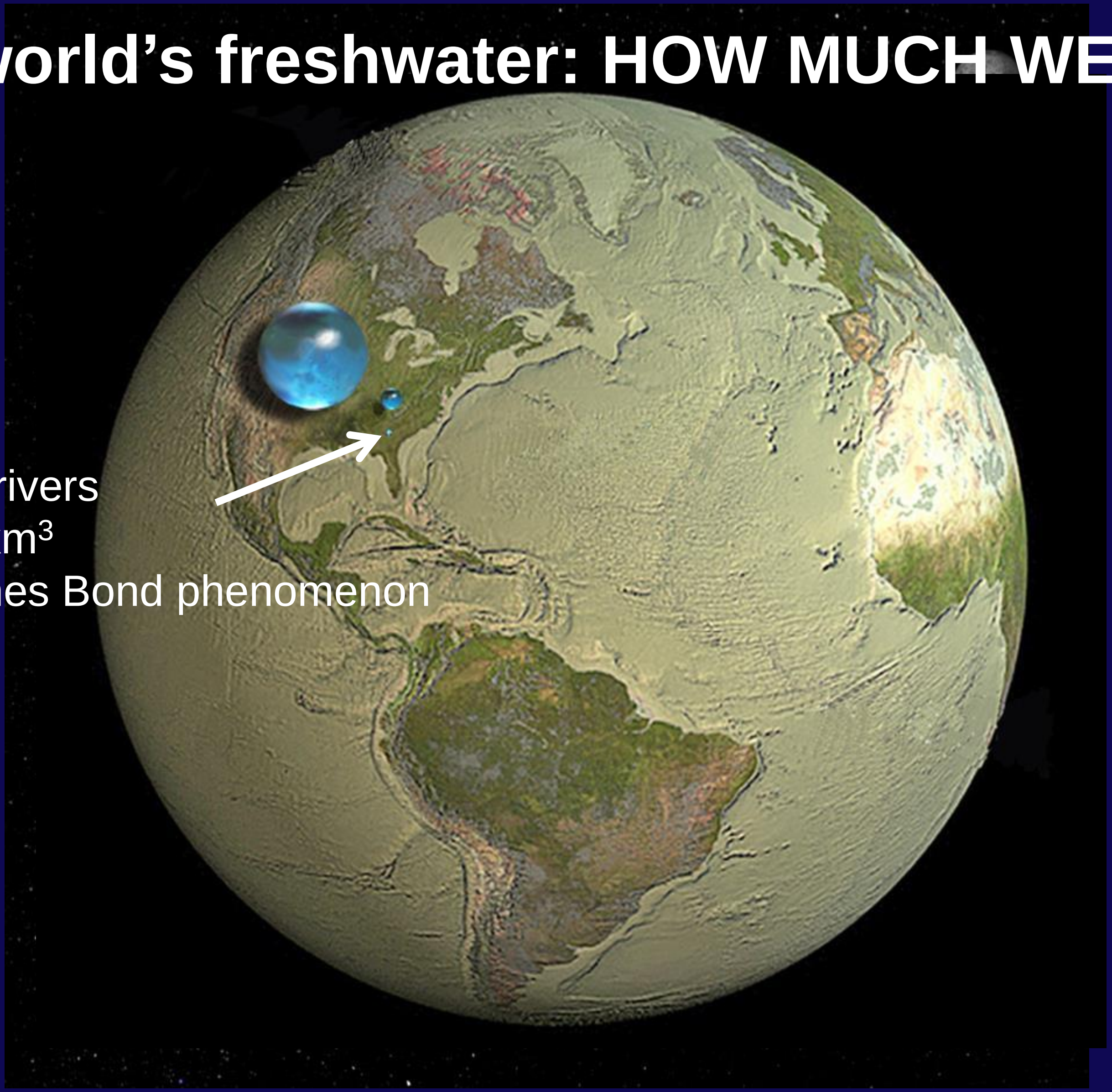
- MAKING THE CASE
- THE DRIVERS
- THE DATA ISSUE
- MODELING
- REAL-TIME FORECASTING TOOLS
- LESSONS LEARNED

The world's freshwater: HOW MUCH WE HAVE?

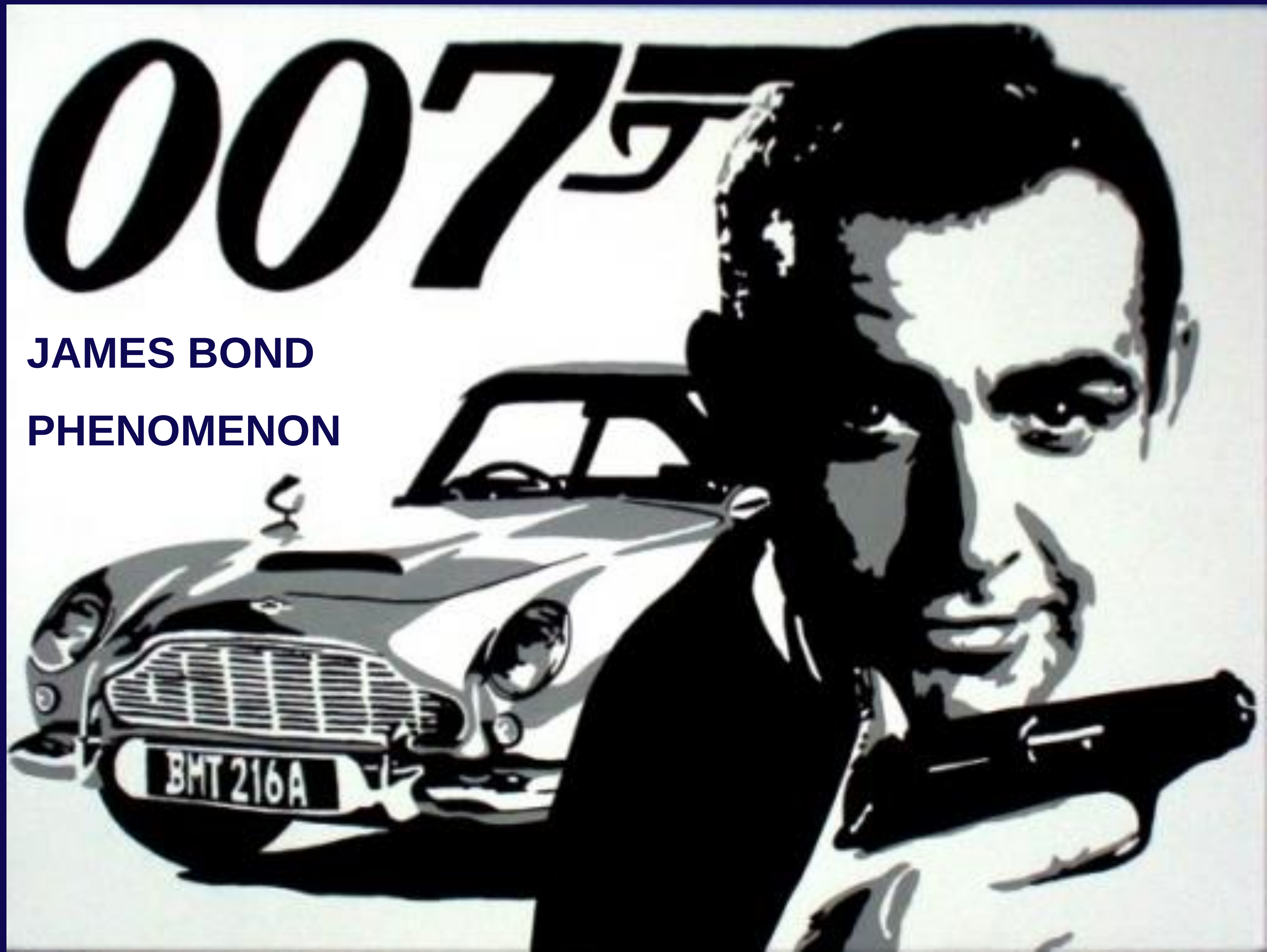


Lakes and rivers

- 41,000 km^3
- The James Bond phenomenon

.007

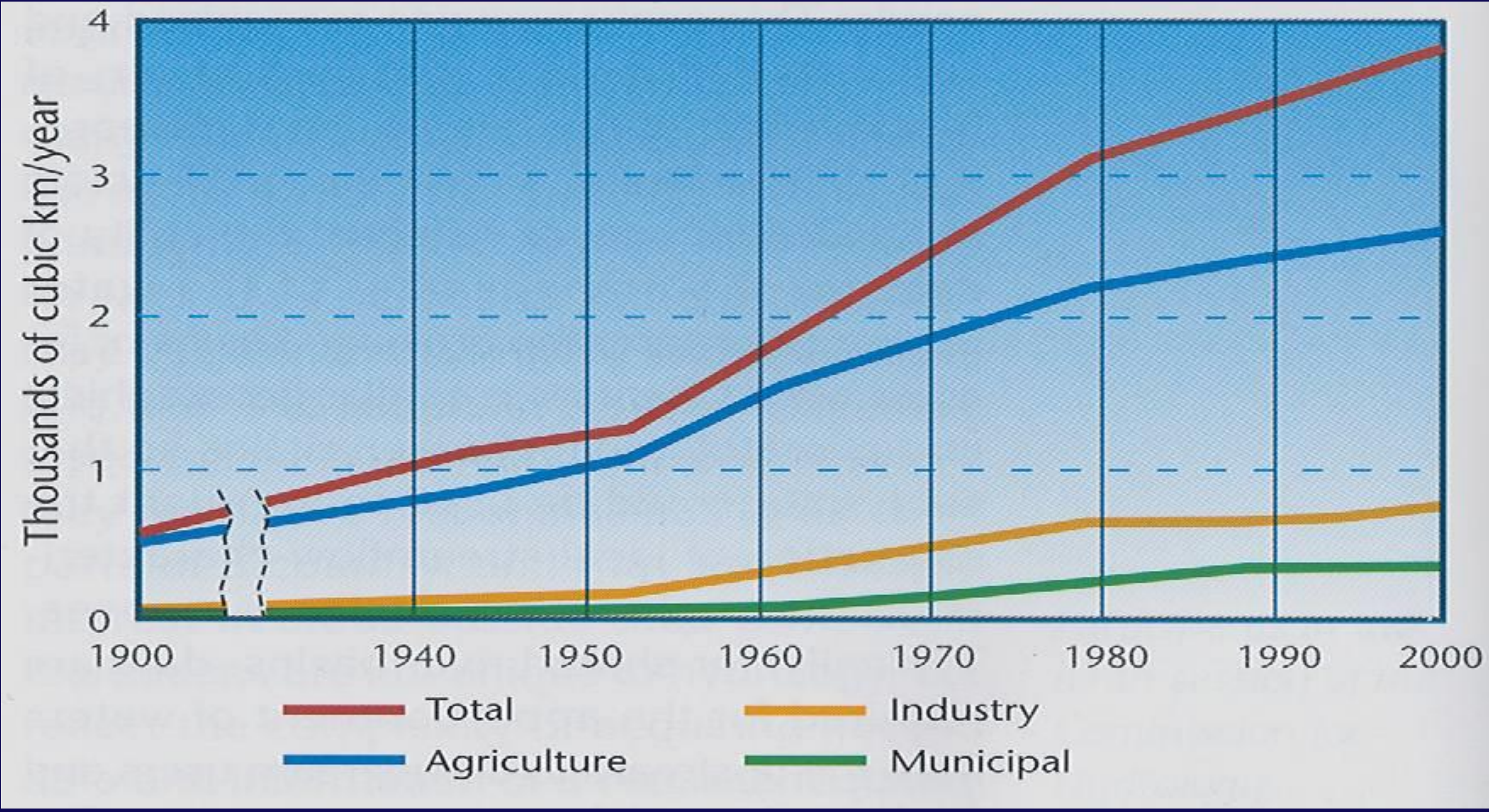
EASILY ACCESSIBLE WATER



JAMES BOND

PHENOMENON

TRENDS OF NON-SUSTAINABLE WATER USE [1000 KM3/YR]

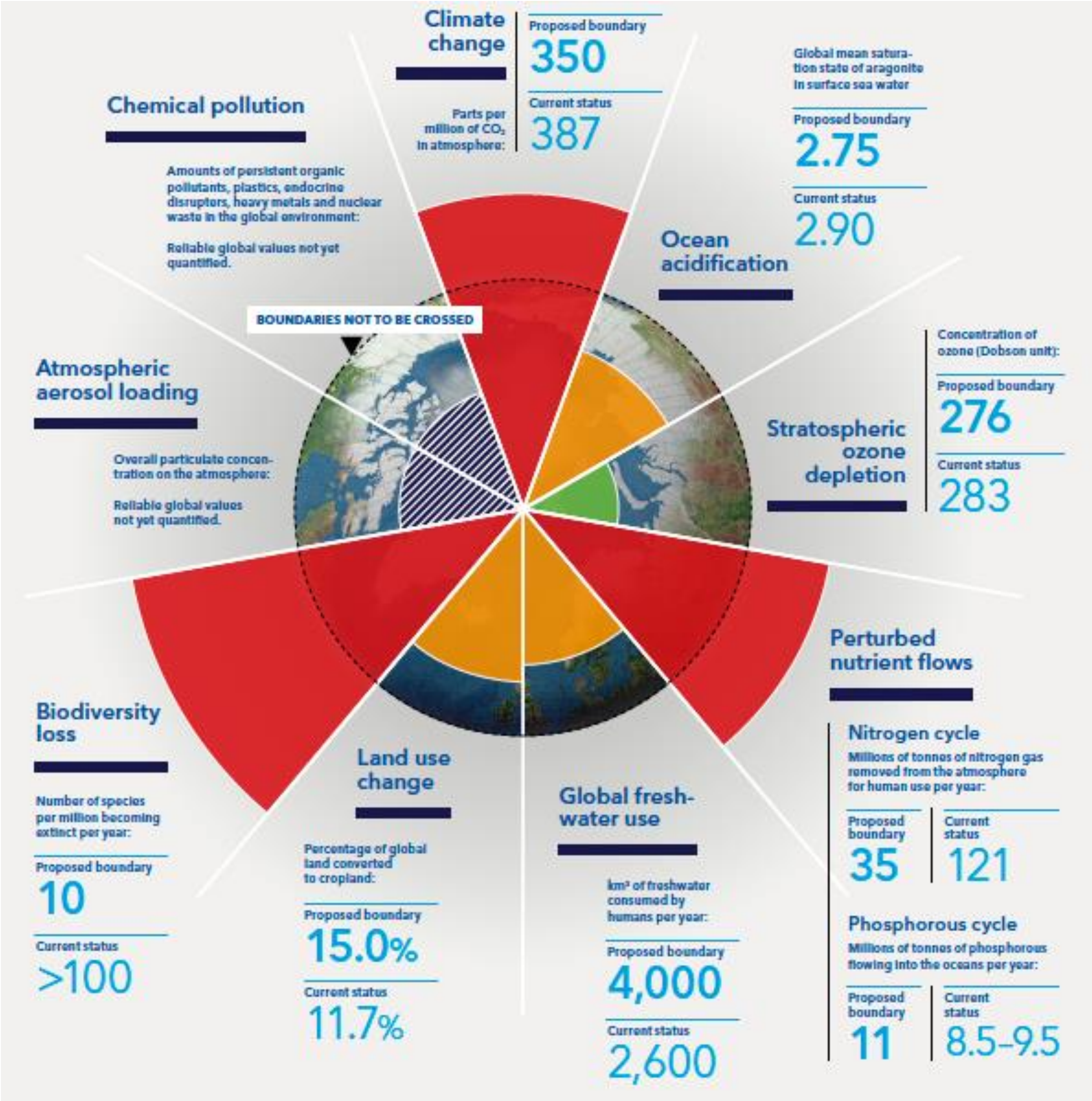


Areas where we have exceeded the boundaries and are continuing to move further beyond them.

Areas where we are still below the boundary values, but are moving towards them.

Area where international political agreements have allowed us to start moving away from a boundary – in the correct direction.

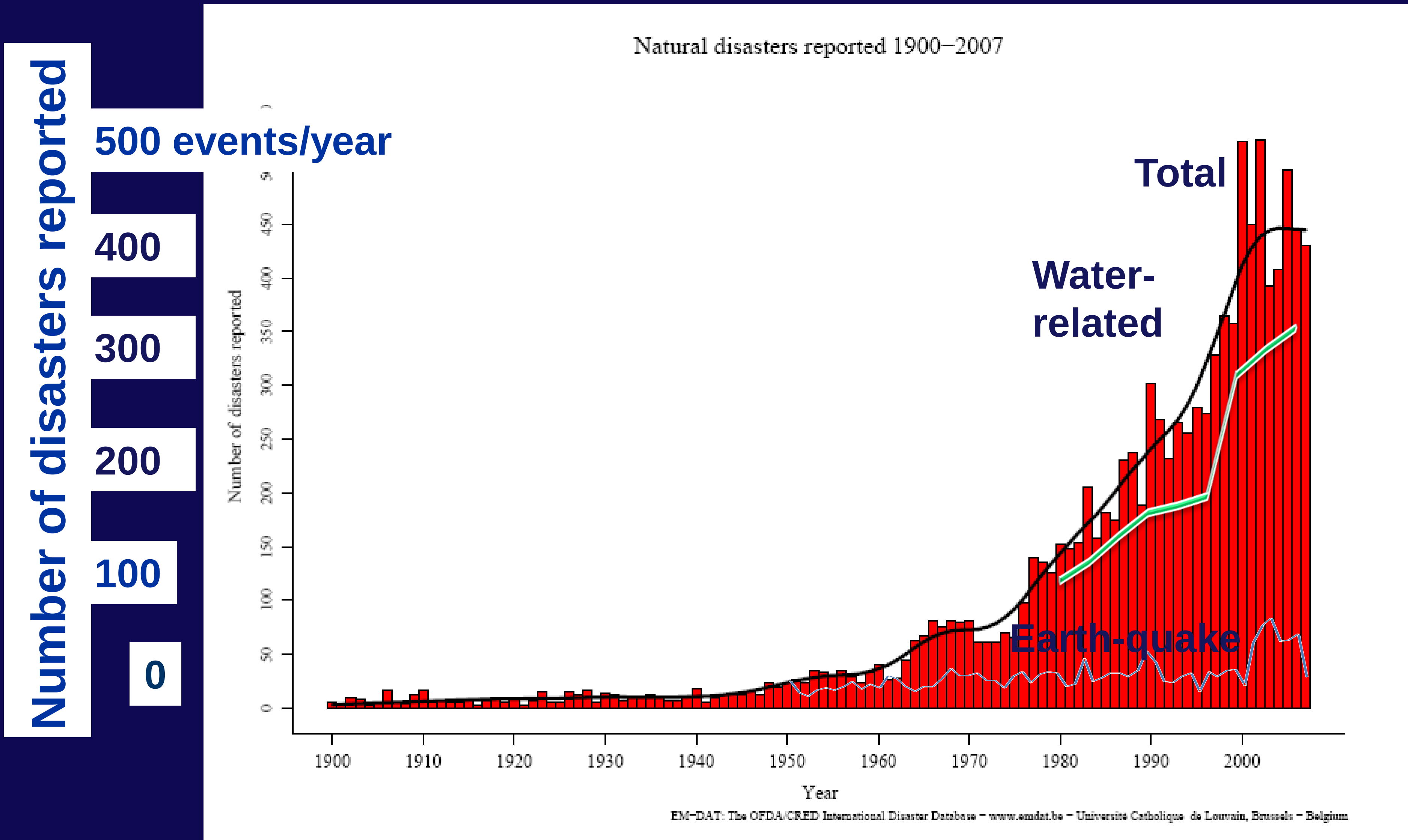
Areas where no boundary values were established.



Rockström, et al., Nature, 2009
DNV GL Report 2014

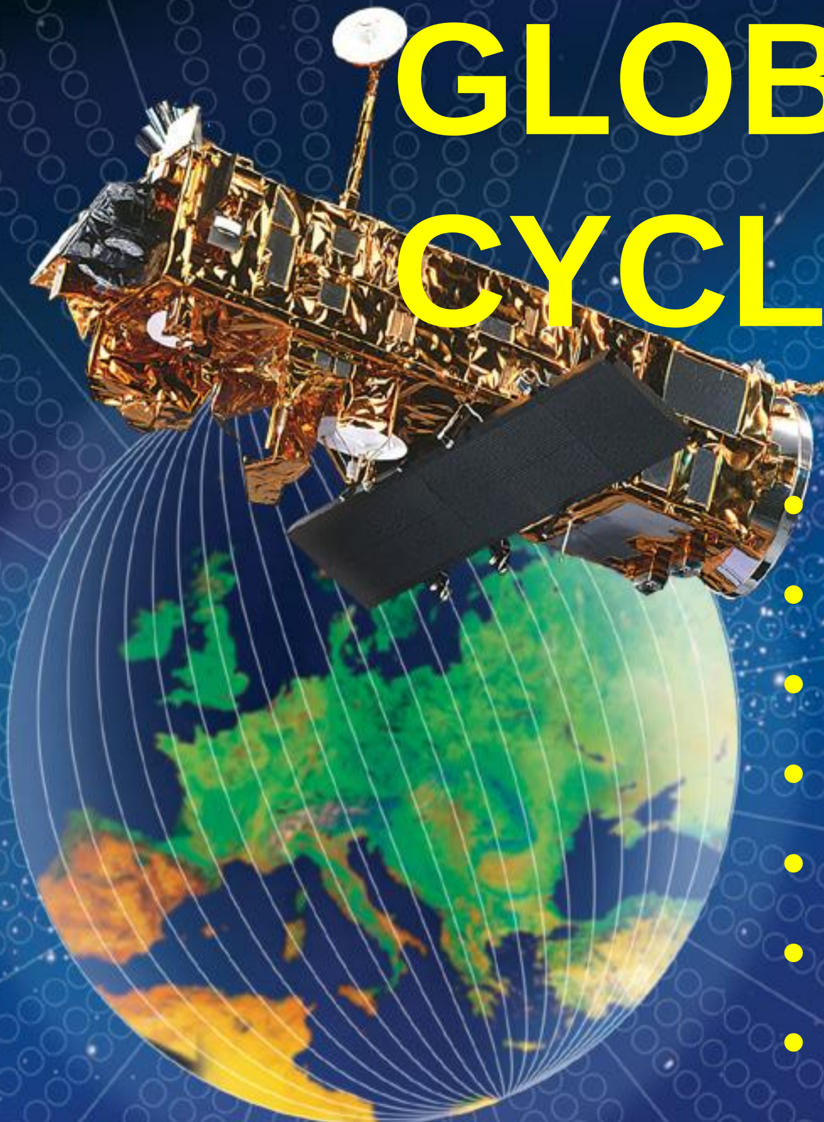
MAKING THE CASE

Number of natural disaster events since 1900 to 2007

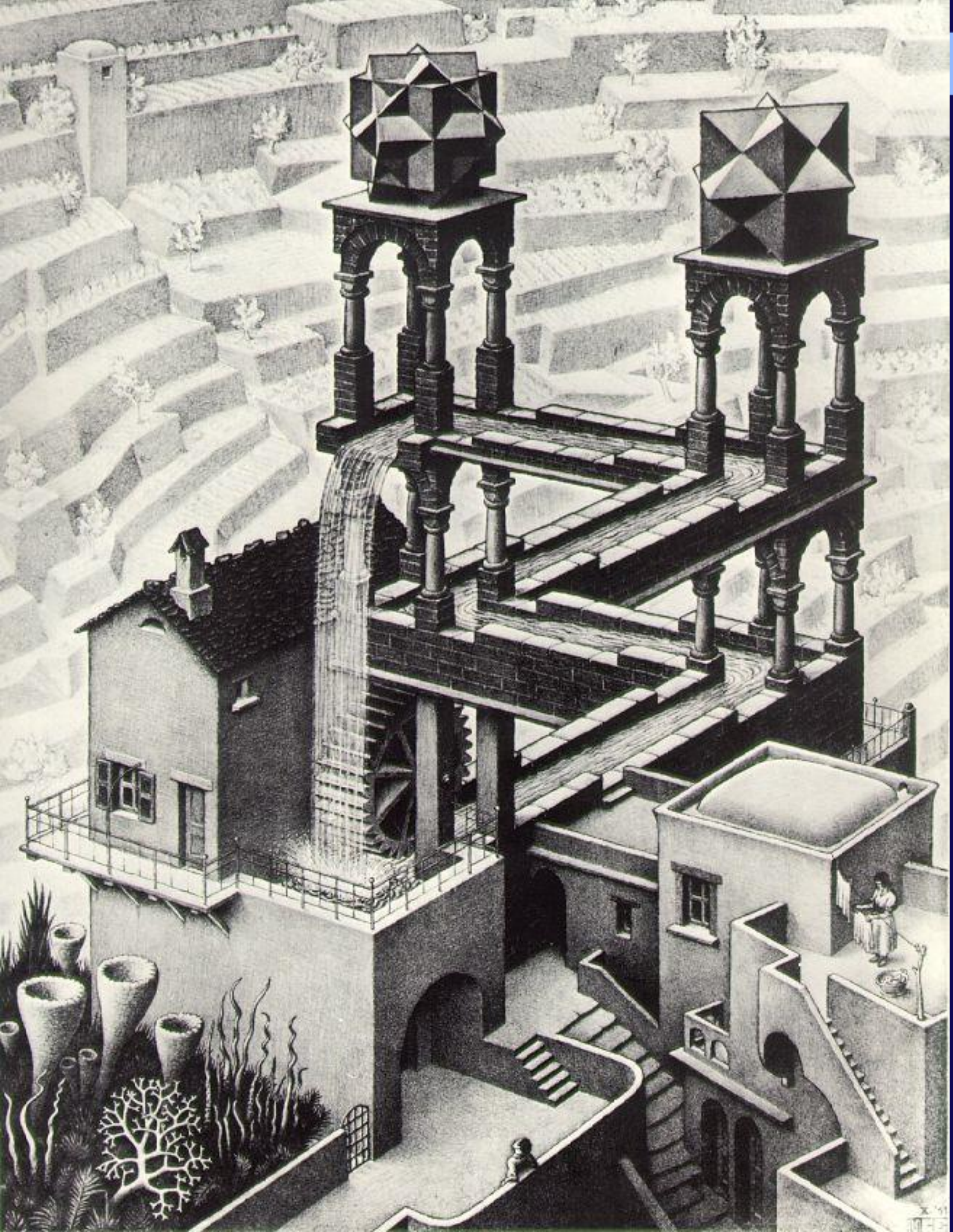


NEGATIVE IMPACT

GLOBAL WATER CYCLE ISSUES



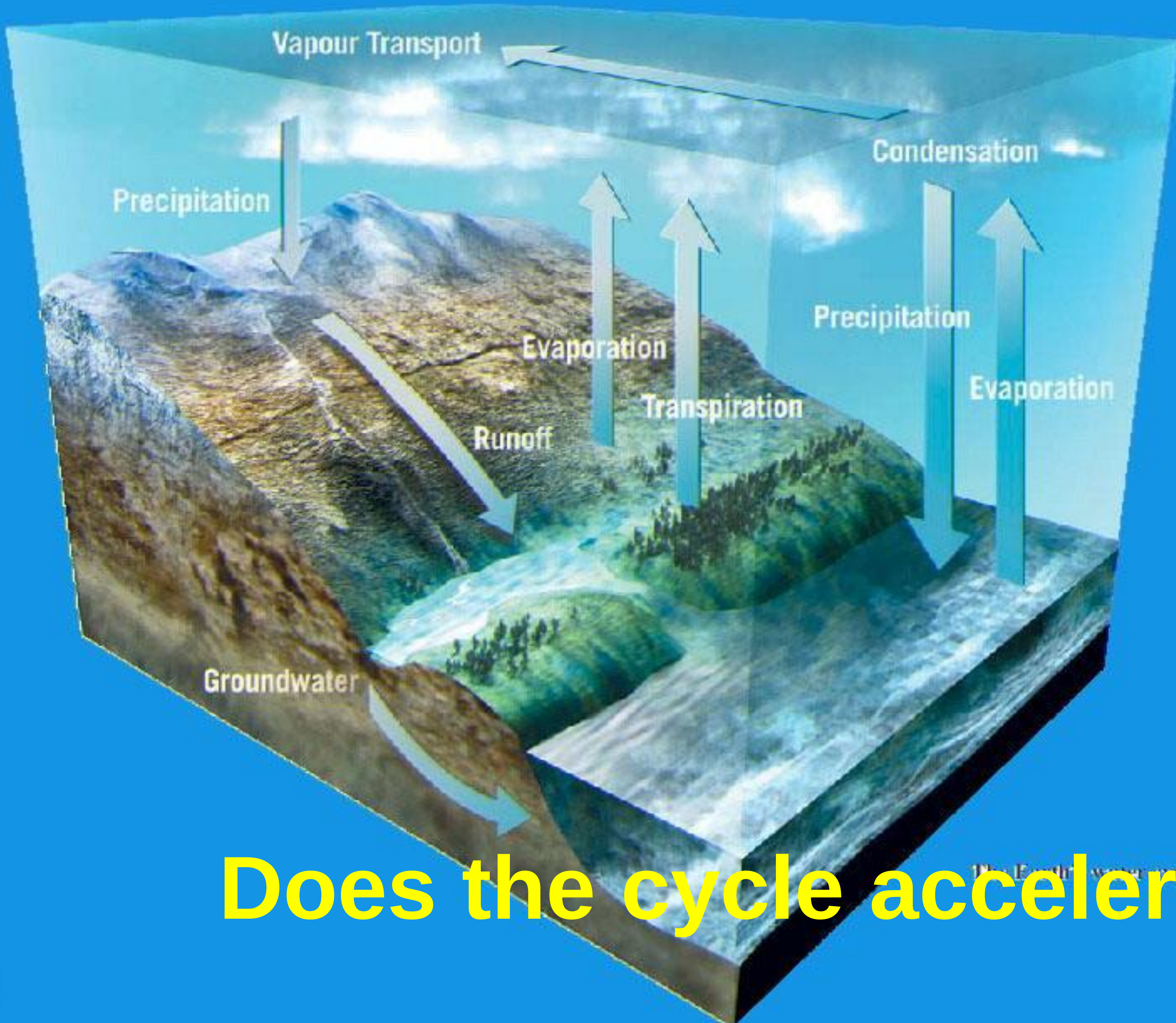
- Is the cycle changing?
- Increased risks?
- Growing vulnerability?
- More disasters ?
- Less water for people?
- Crisis is looming?
- What crisis?
- Resource?
- Governance?
- Global or local?



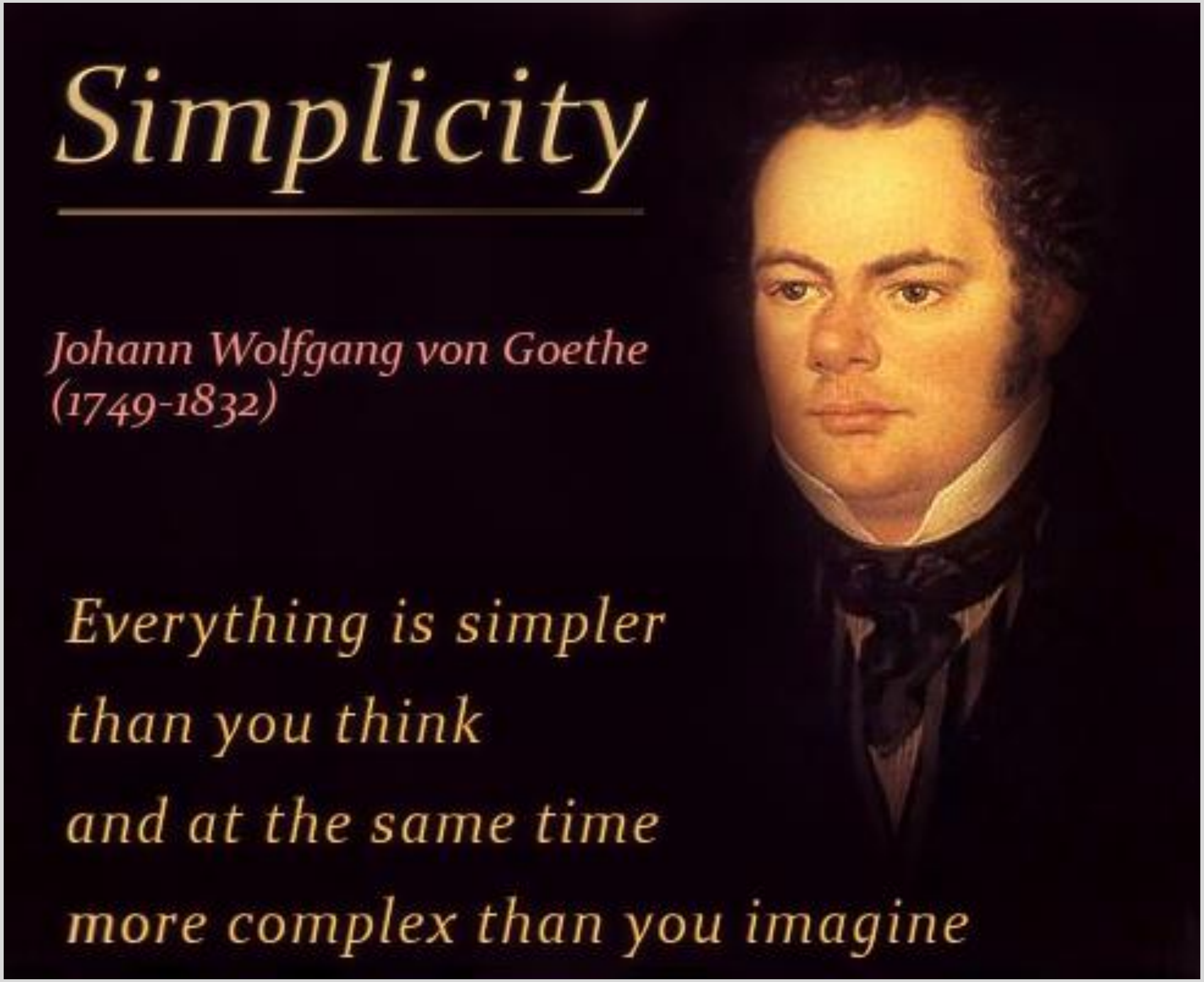
Water cycle

No begin and no end!

Maurits Cornelis Frans Escher



Does the cycle accelerate?


Simplicity
Johann Wolfgang von Goethe
(1749-1832)
Everything is simpler
than you think
and at the same time
more complex than you imagine

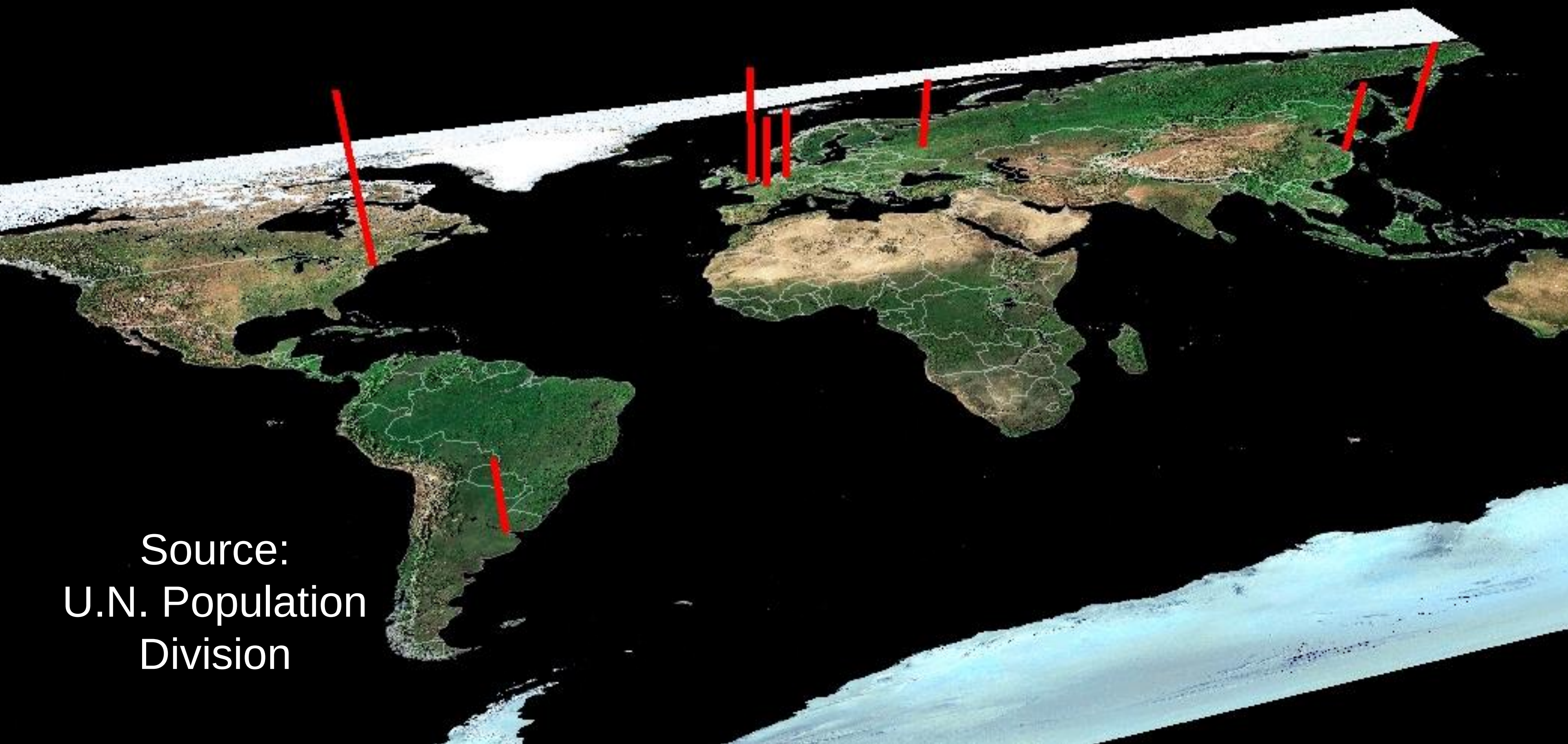
THE DRIVERS

KEY CHANGES SINCE 1900

- **The world's population has increased 3-fold**
- **Water withdrawal has increased 6-fold**
- **The area of cropland has almost doubled**
- **The area of pasture has decreased by about 75%**
- **The area covered by tropical forests has decreased by about 25%.**
- **Dams now intercept ca. 40% of the runoff from the continents**

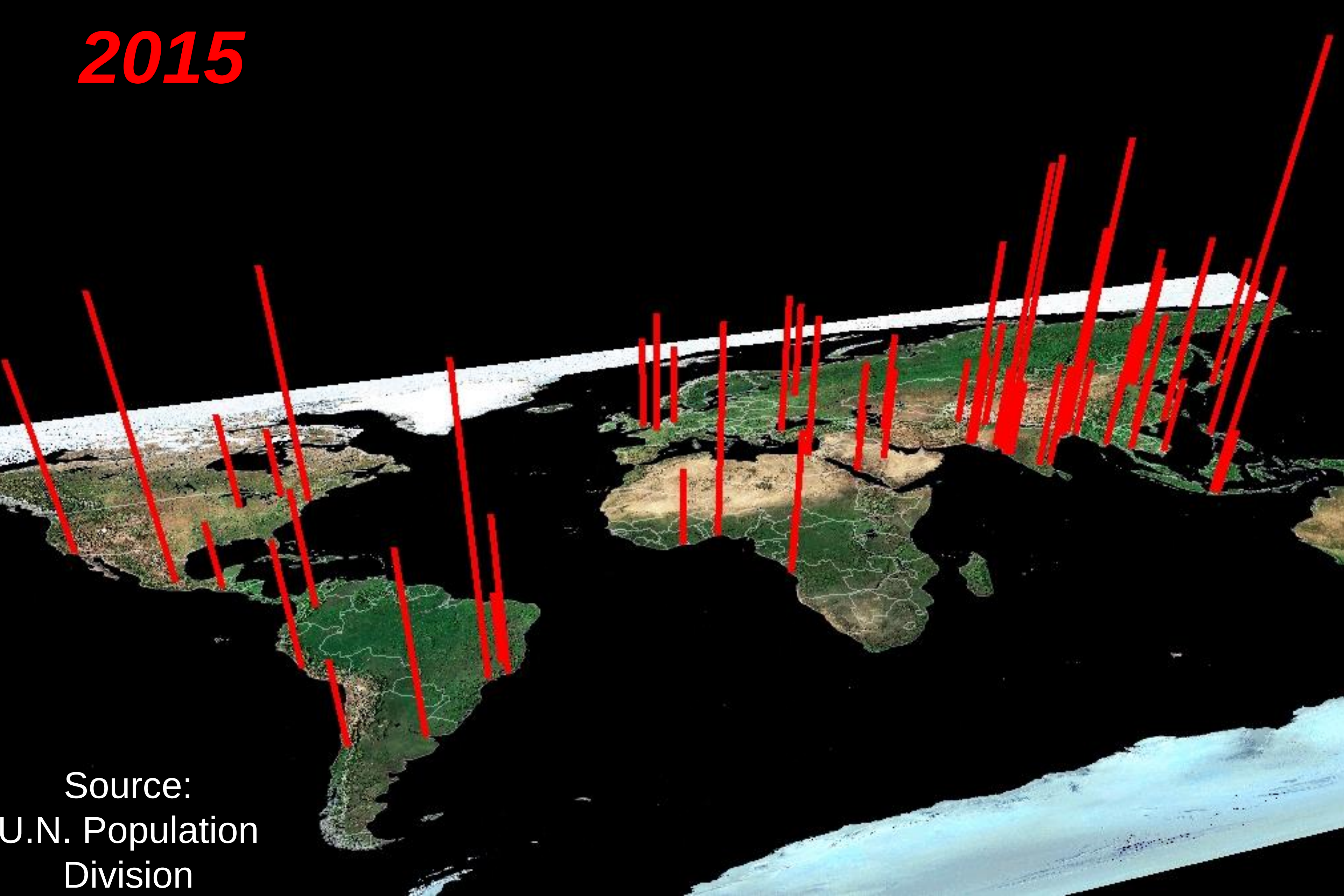
World Cities exceeding 5 million residents

1950



Source:
U.N. Population
Division

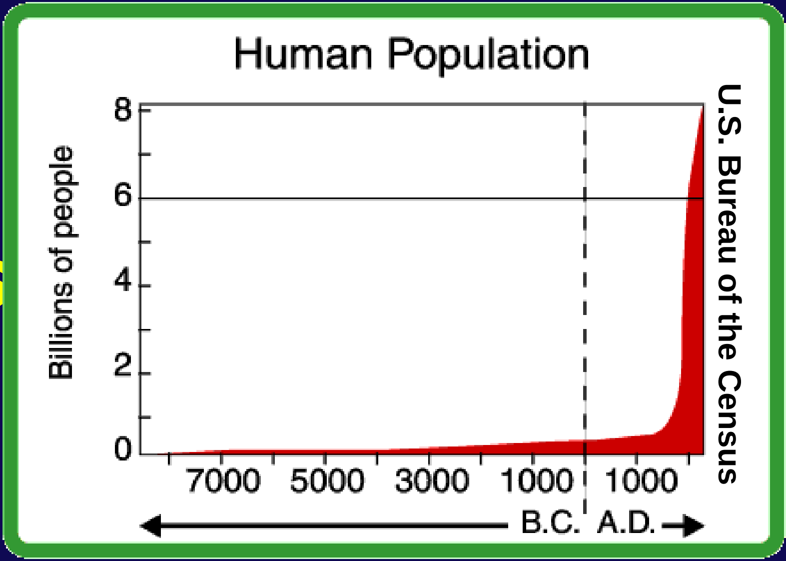
World Cities exceeding 5 million residents



Source:
U.N. Population
Division

Global change drivers:

- **Population growth, movement, migration and age structures**
- **Geo-political changes and realignments**
- **Trade and subsidies**
- **Technological changes**
- **Climate change**




Wallpapers-Junction.Com

SUPERIMPOSED ON THIS …

WATER AND CLIMATE

HEADLINE NEWS!!!!!

The climate is changing !!!

(Yap, for 4 billion years now …)

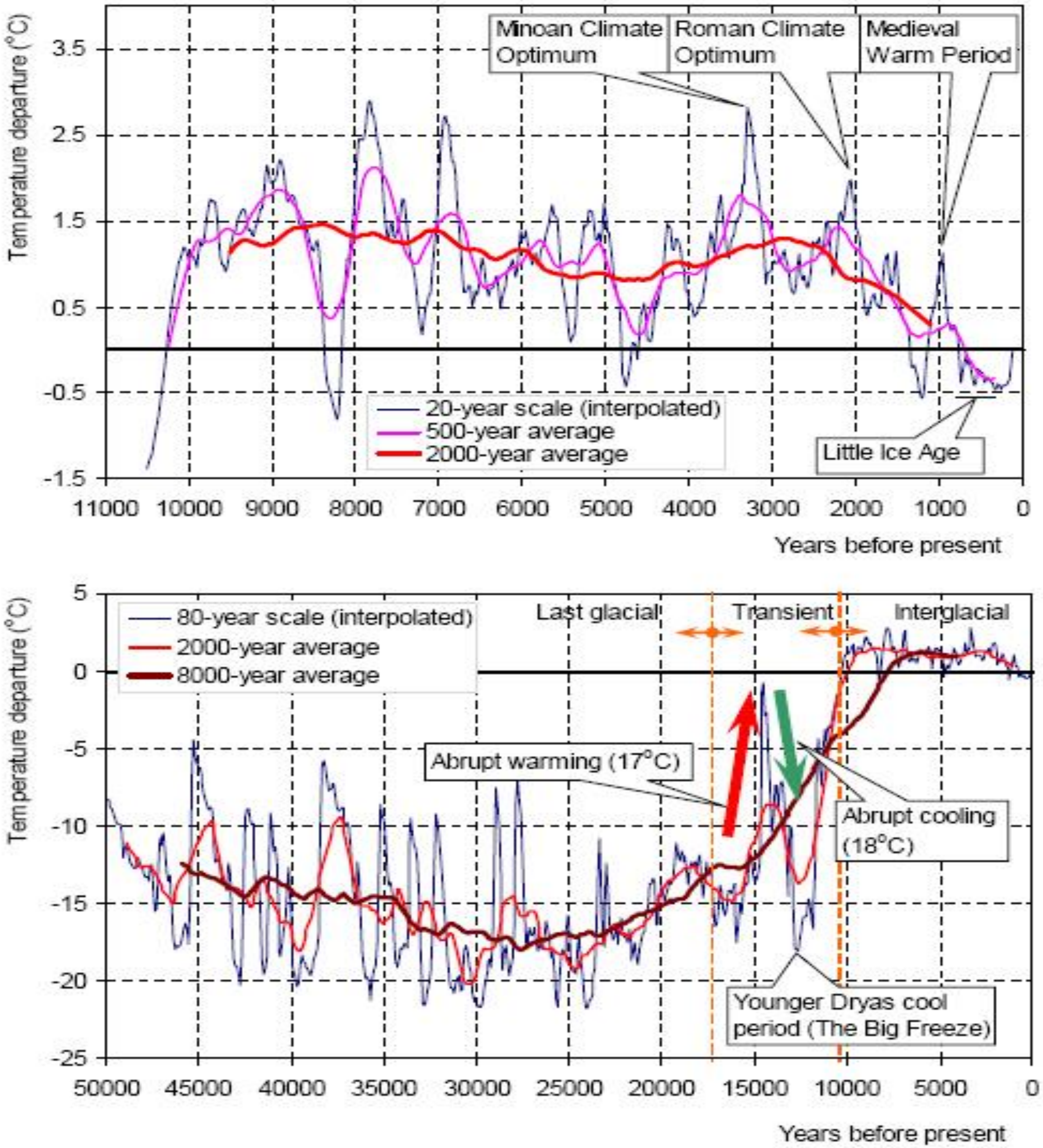
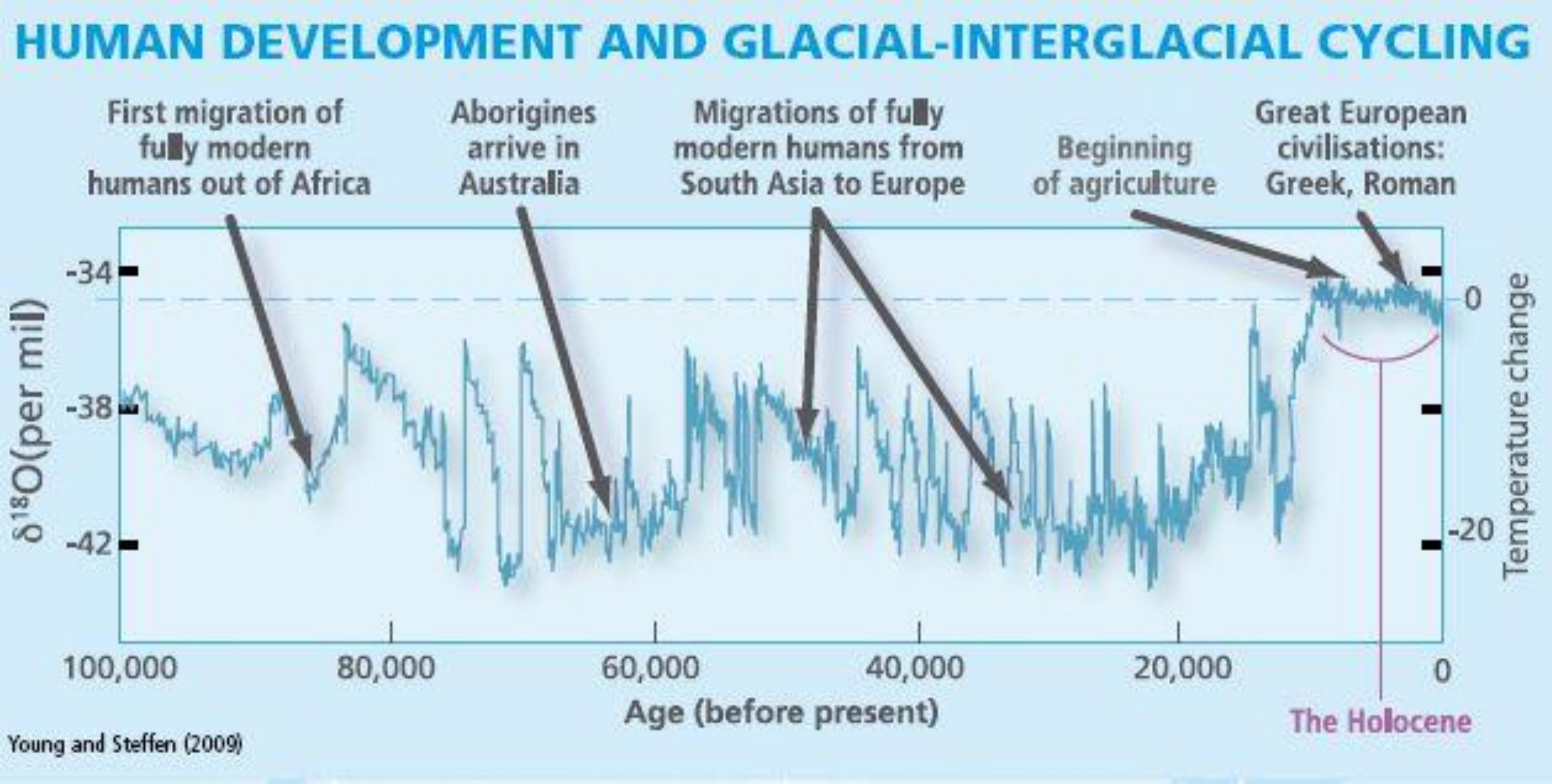


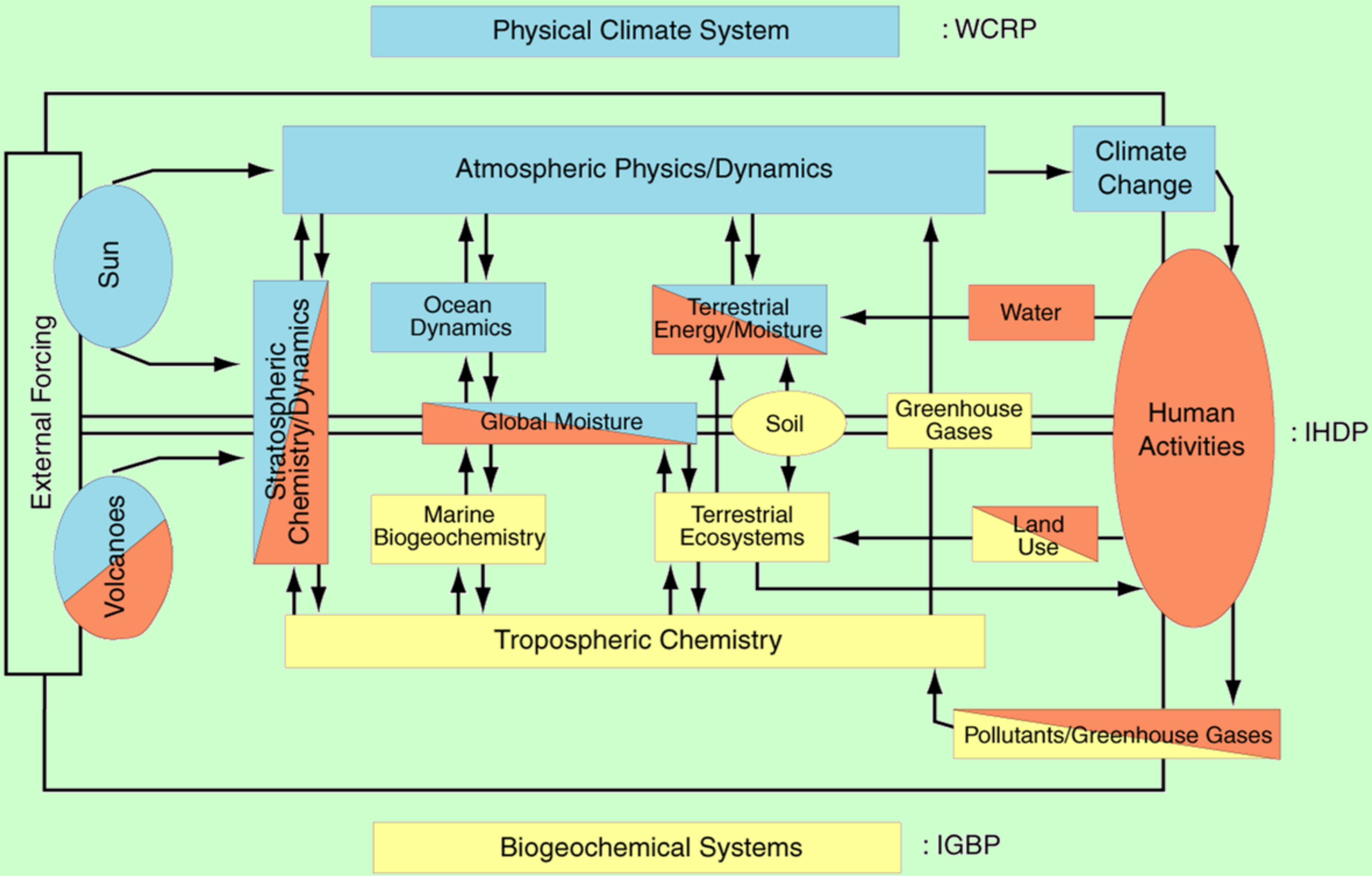
Fig. 3 Times series plot of the temperature in Greenland, as reconstructed from the GISP2 Ice Core (Alley 2000, 2004; temperature departures from the most recent value, which is -31.6°C; data from ftp.ncdc.noaa.gov/pub/data/paleo/icecore/greenland/summit/gisp2/isotopes/gisp2_temp_accum_alley2000.txt): (a) during the Holocene (current interglacial period), with marking of the most prominent recent lows and highs; and (b) the entire record with marking of the most prominent abrupt warming and cooling episodes (in a transient period between the current interglacial and the last glacial period) that ended with the Younger Dryas cool period.

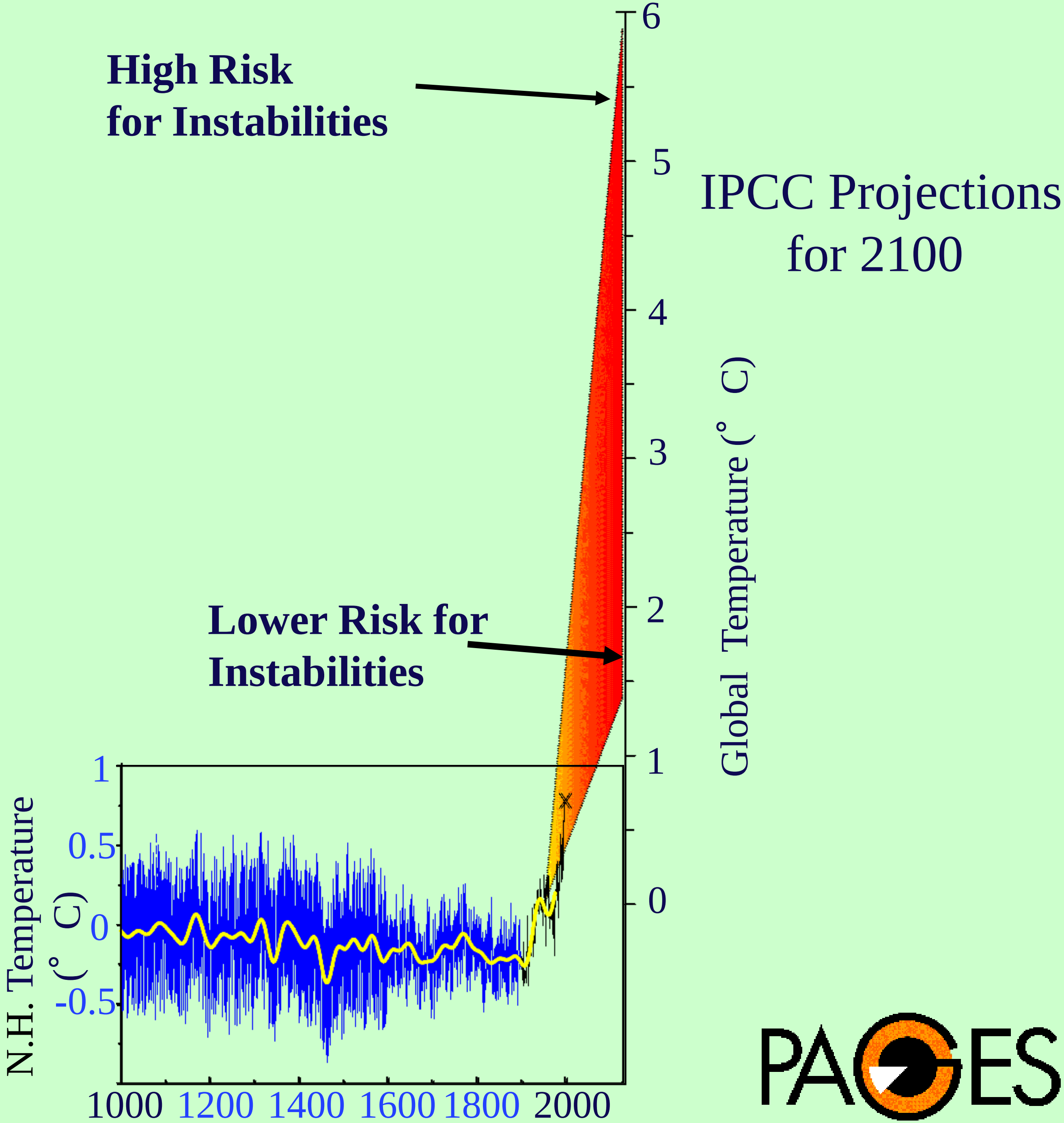
THE GREAT MIGRATION WAVES

OF THE PAST 100,00 YEARS



The Earth System: Coupling the Physical, Biogeochemical and Human Components




High Risk
for Instabilities
Lower Risk for
Instabilities
IPCC Projections
for 2100
Global Temperature (°C)
N.H. Temperature (°C)
6
5
4
3
2
1
0
1
0.5
0
-0.5
1000
1200
1400
1600
1800
2000

THE URBAN HEAT ISLAND:

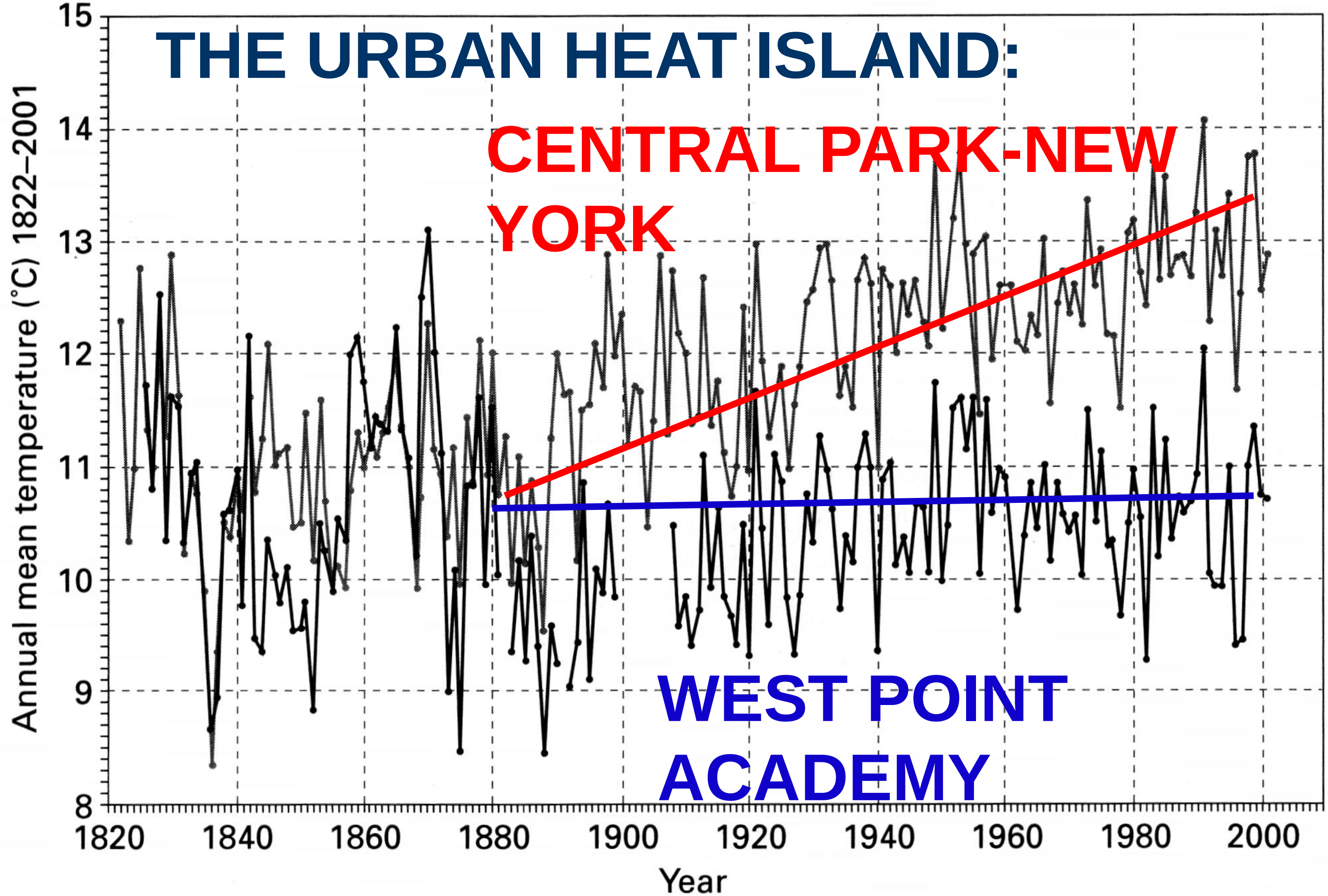
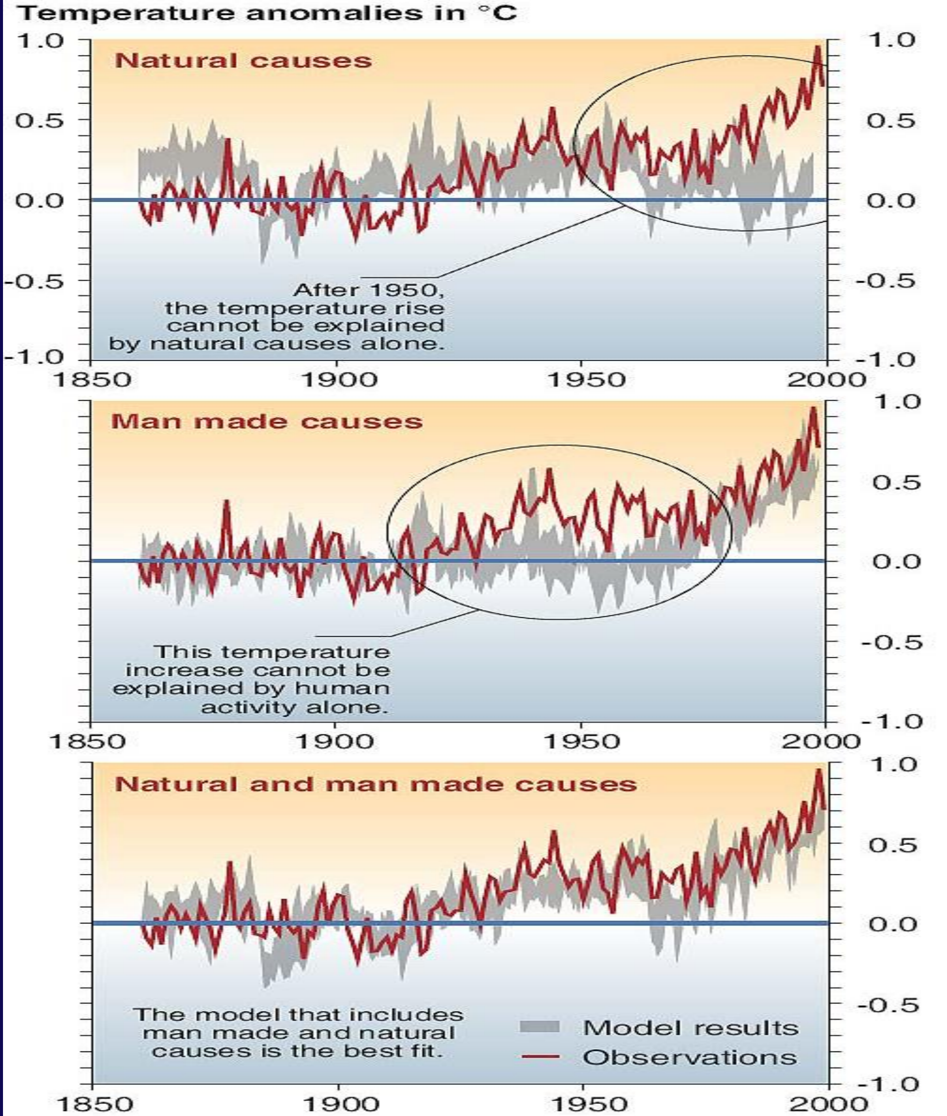


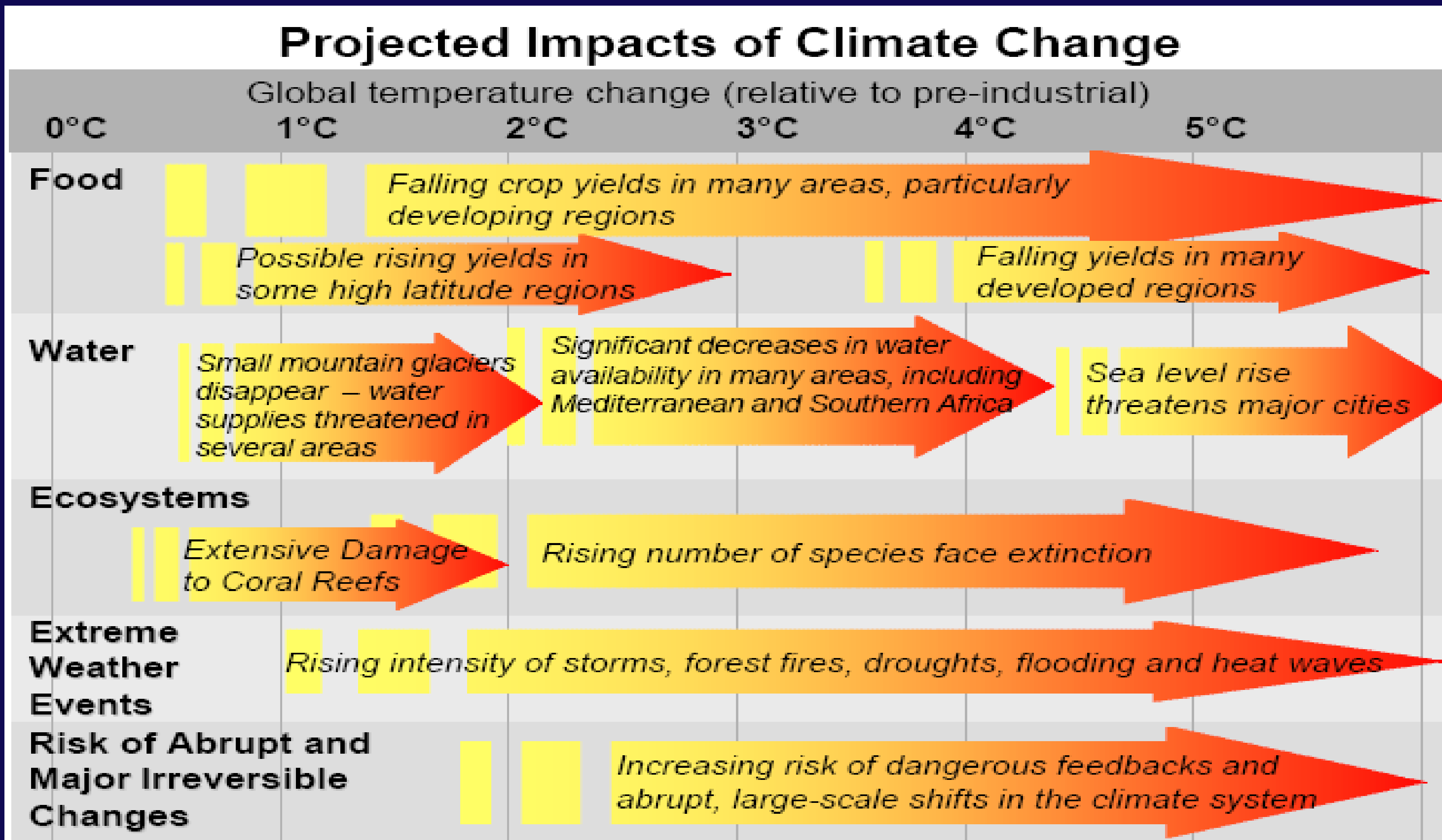
Figure 47. Annual mean temperature (°C), from 1822 to 2001, at: (*top*) Central Park in New York City; and (*bottom*) US Military Academy, West Point, NY.
From Daly (2003).

Climate change: What do we know?

- **Global Mean Temperature have increased**
- **Greenhouse Gases play a role**
- **Reducing Emissions alone will not avoid impacts**



Climate change is effecting our environment, our societies and our cultures



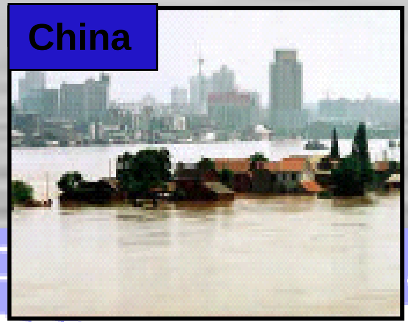
(Source: IPCC)

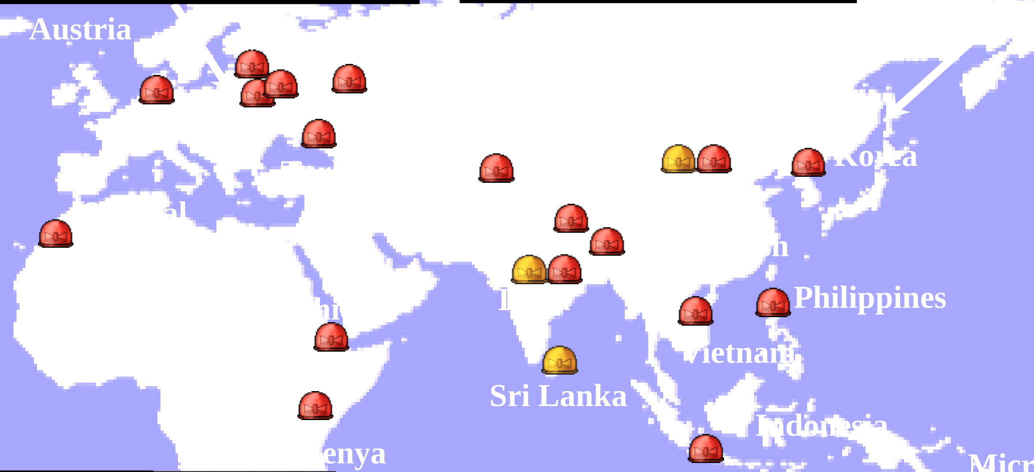
Water hazards and related nexi are major challenges

- **Intensifying and increasing occurrence of water related hazard in many part of the world**

- **Serious concern on climate change such as extreme hydrologic events and sea level rising**

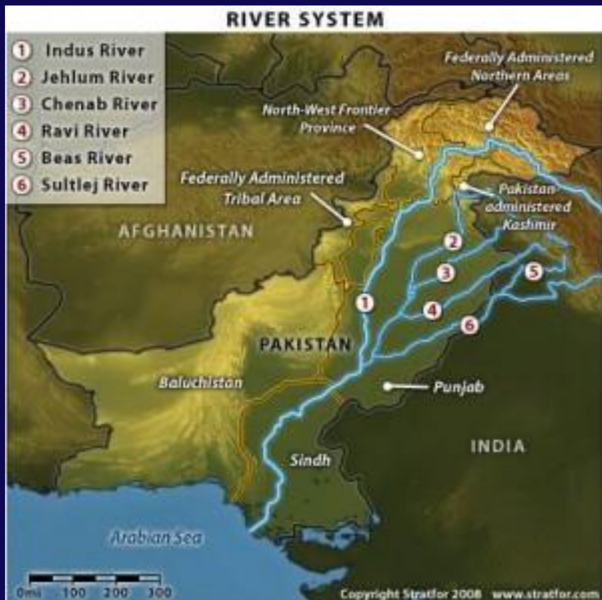
Major floods and droughts worldwide





There is pressing need to develop advanced risk management on water hazard in order to secure human life and ensure sustainable socio-economic development and poverty alleviation.

Flood Disaster in Pakistan (August, 2010)



Flood Disaster in Korea (September 21, 2010)

Rio de Janneiro, Brasil (January, 2011)

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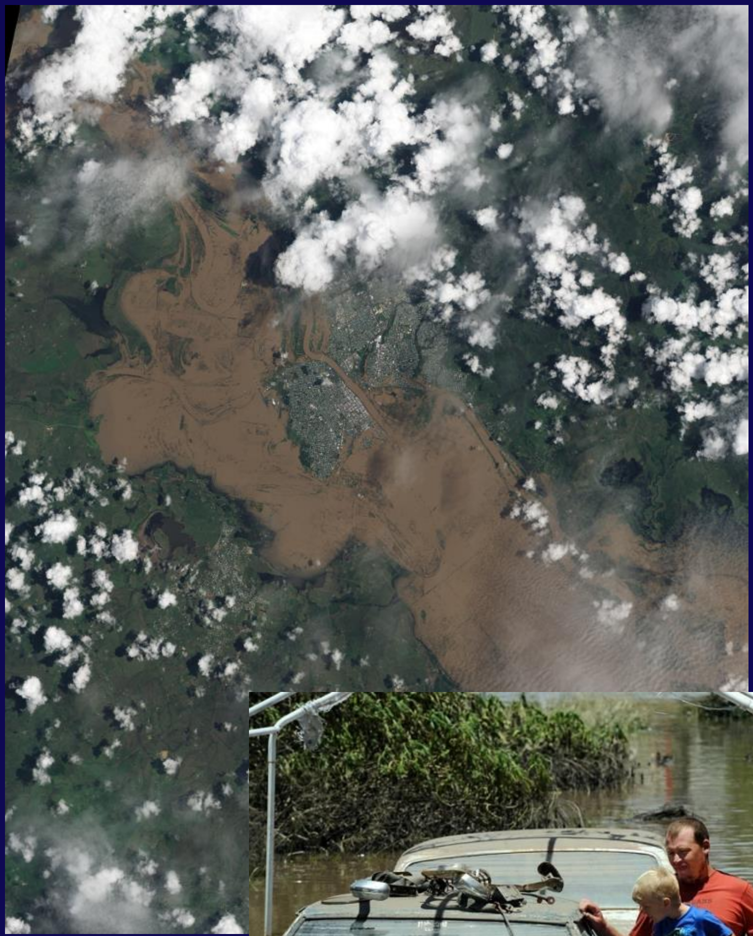
Flood Disaster in Brisbane, Australia (January, 2011)

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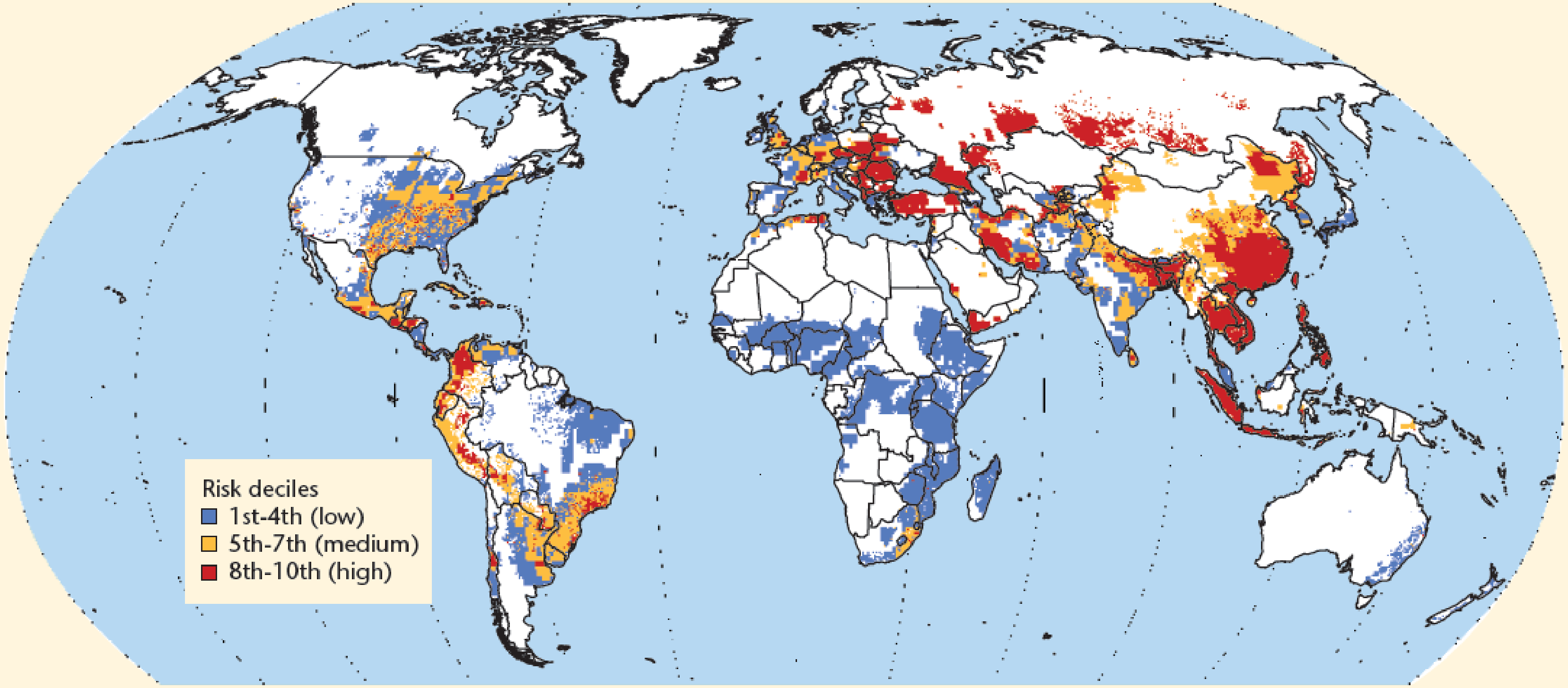
FLOODS


I DON'T BELIEVE IN
GLOBAL WARMING

FLOOD LOSSES IN FUNCTION OF GDP

Map 10.3 **Impact of flood losses (comparative losses based on national GDP)**



Note: Deciles refer to the level of risk, normalized for comparing 10 categories.
Source: Based on Dilley et al. 2005.

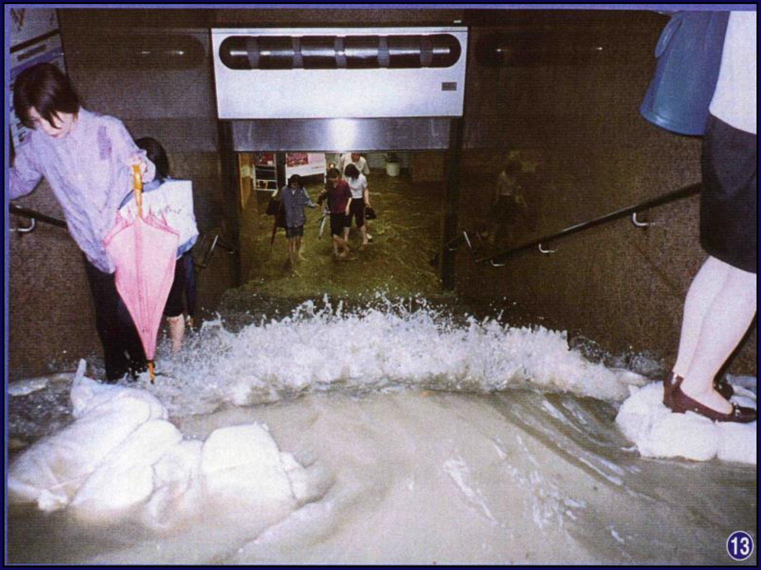
... unpleasant surprises ...

(Source : MLIT)

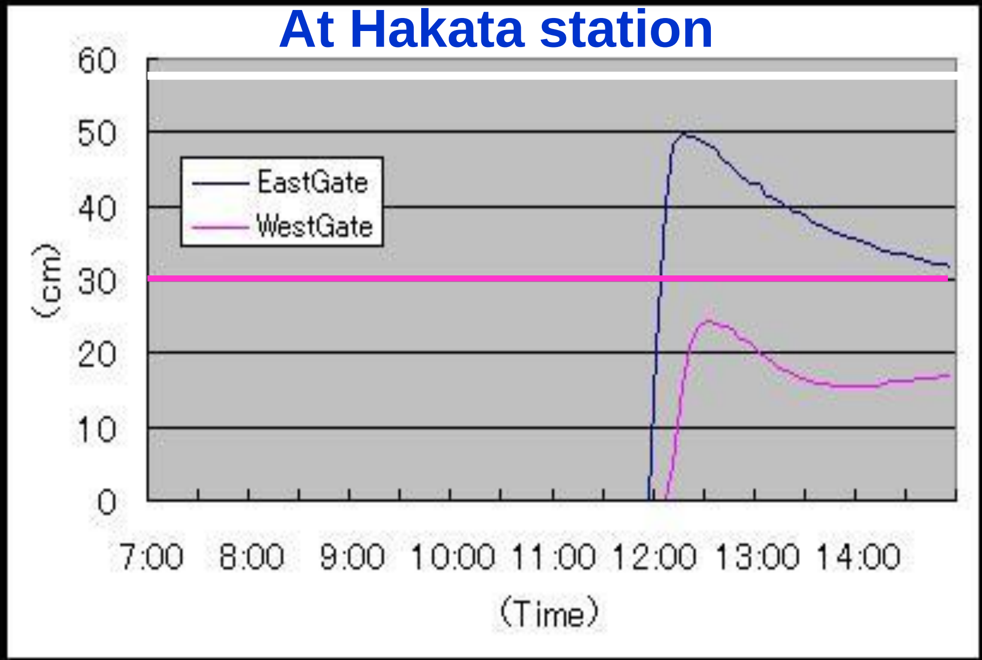
Fukuoka Flash Flood in 1999

- Urban expansion taking place downward → Underground flood risk
- Recent developments → Long term risks are not experienced

(Source: Herat, UNU)



Fukuoka flash flood simulation



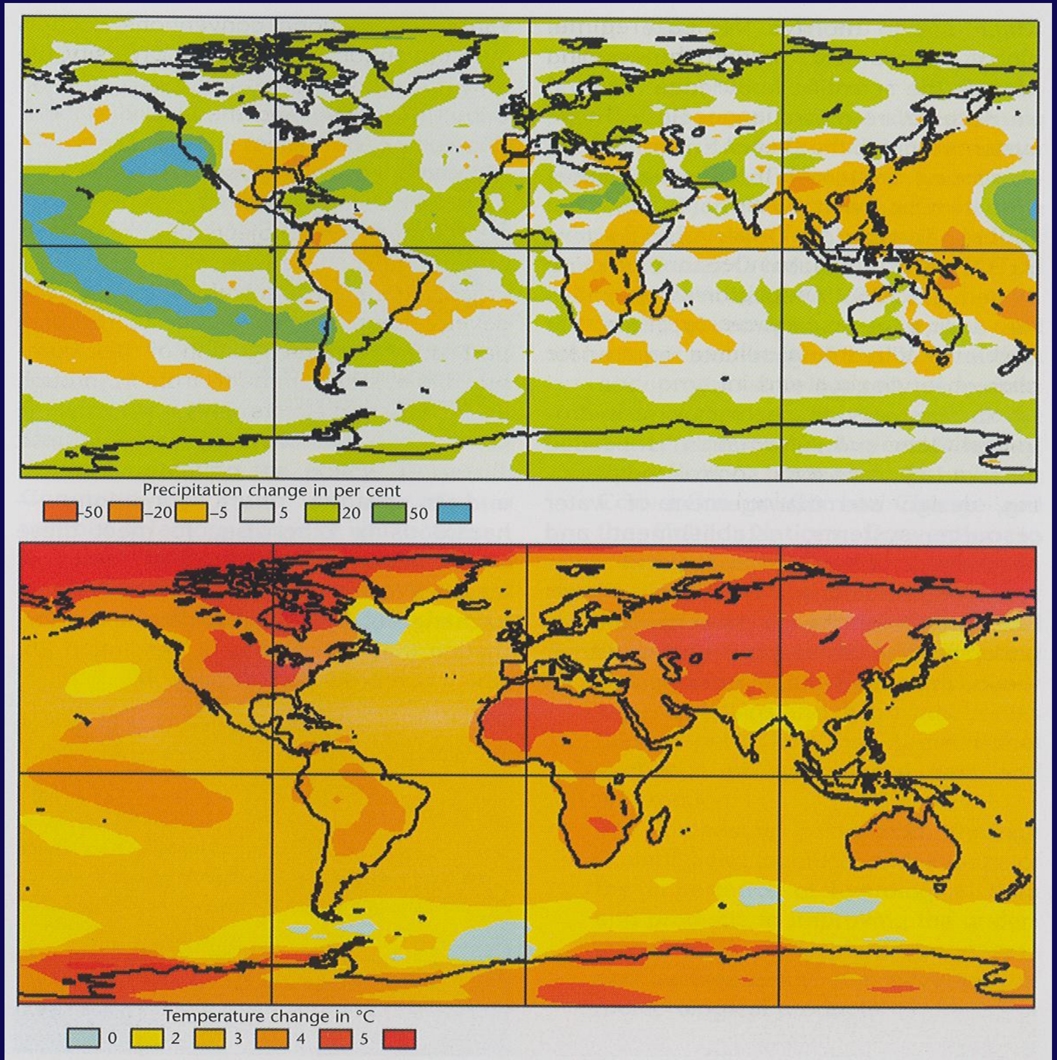
<u>Volume of water entered into underground space:</u>

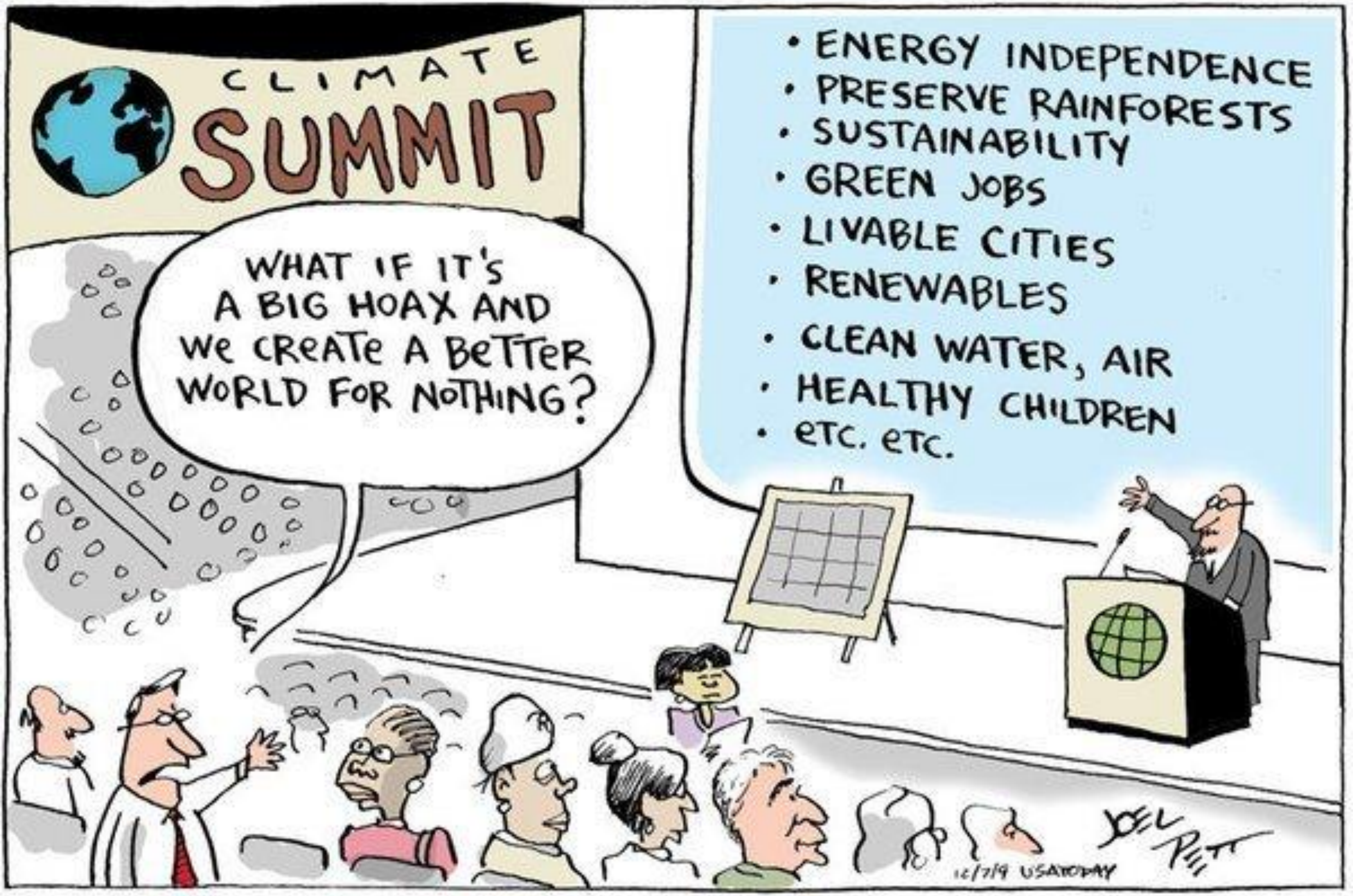
•2,017 m3 (simulated volume)
•1,320 m3 (total pumped water

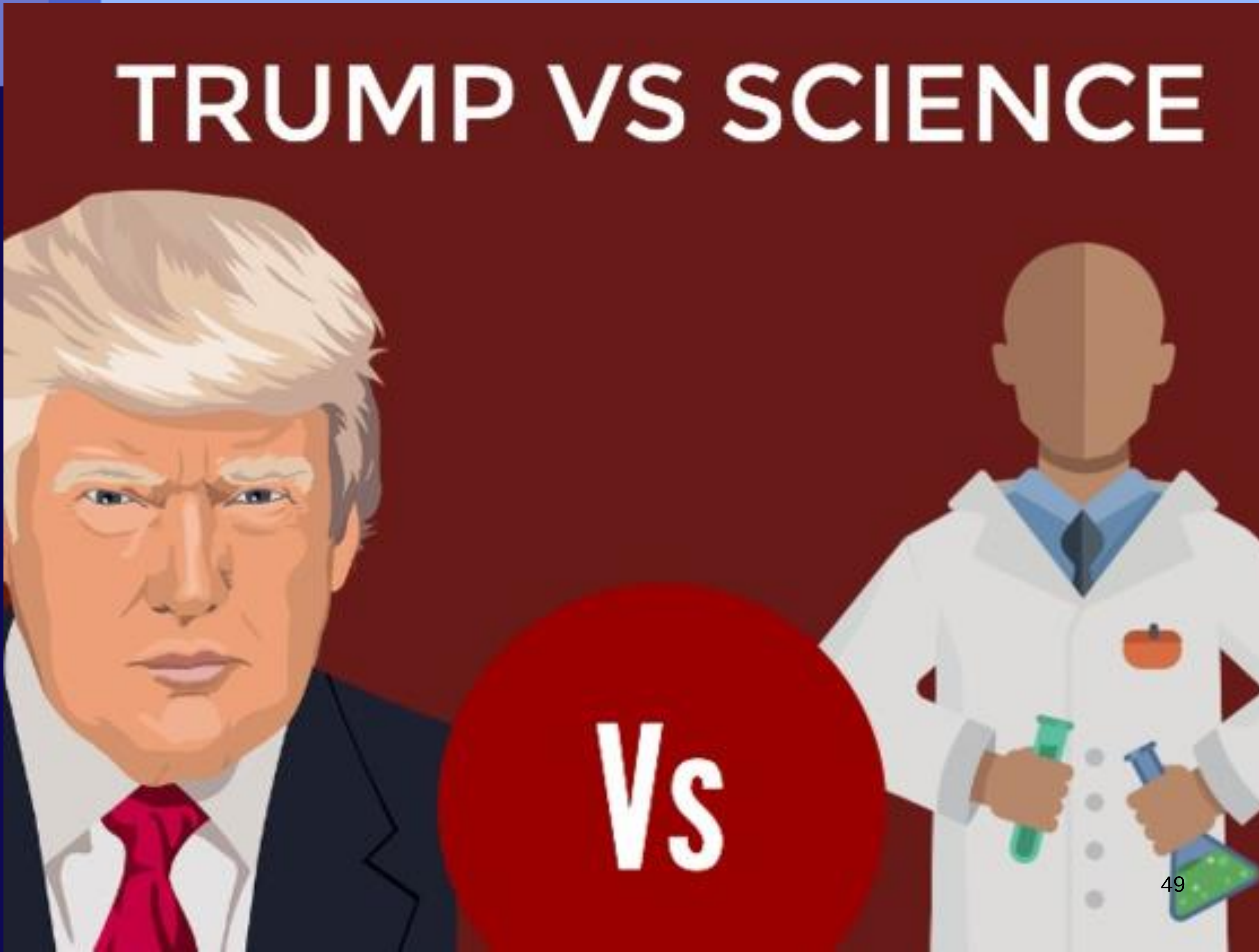
ARIDITY

NOT TOO MUCH HOPE ...

UNLESS POLITICAL LEADERS STICK TO THE PARIS AGREEMENT




CLIMATE SUMMIT
• ENERGY INDEPENDENCE
• PRESERVE RAINFORESTS
• SUSTAINABILITY
• GREEN JOBS
• LIVABLE CITIES
• RENEWABLES
• CLEAN WATER, AIR
• HEALTHY CHILDREN
• etc. etc.
WHAT IF IT'S A BIG HOAX AND WE CREATE A BETTER WORLD FOR NOTHING?
12/7/9 USATODAY
JOEL PETT


TRUMP VS SCIENCE
Vs

CLIMATE CHANGE IS ALL ABOUT WATER

KEY TO SUSTAINABILITY:

CLIMATE ADAPTIVE WATER STRATEGIES

DO WE HAVE A CHOICE?

WE NEED TO INCREASE THE

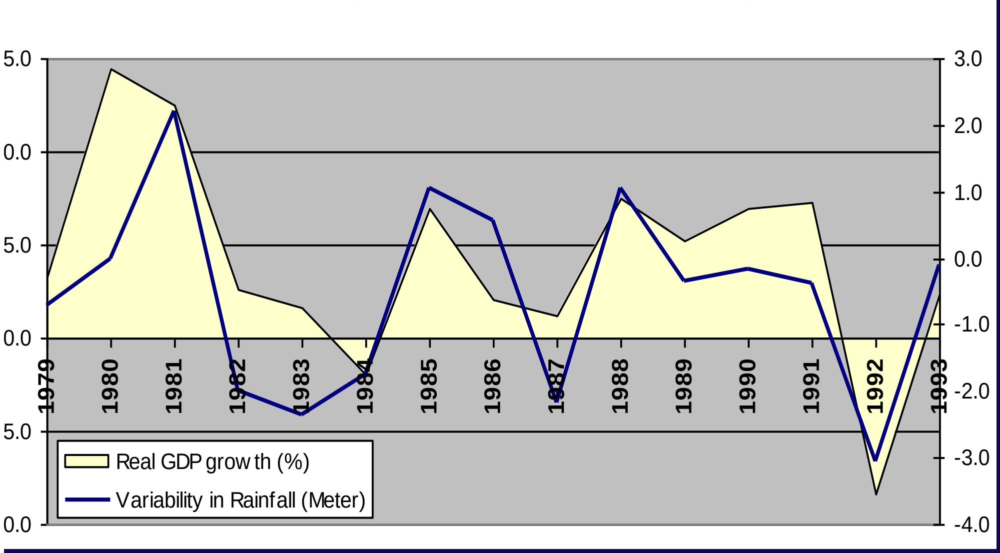
RESILIENCE

OF OUR SYSTEMS

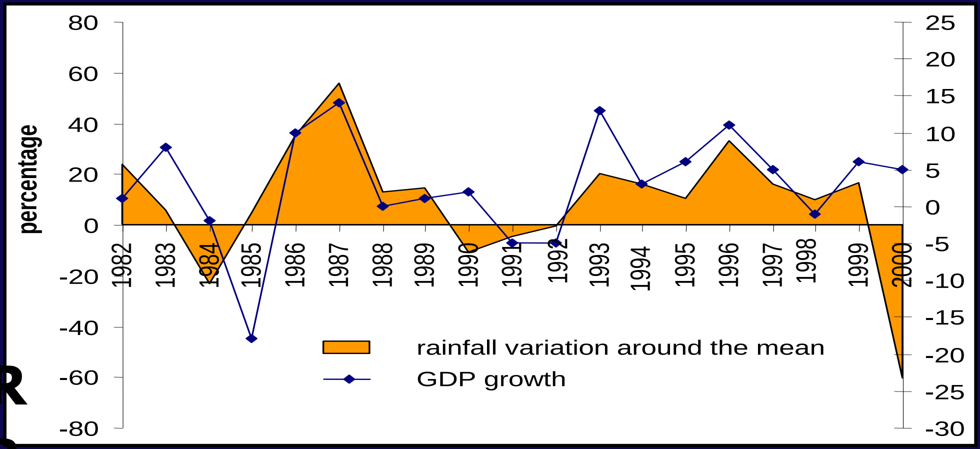
ADAPTATION

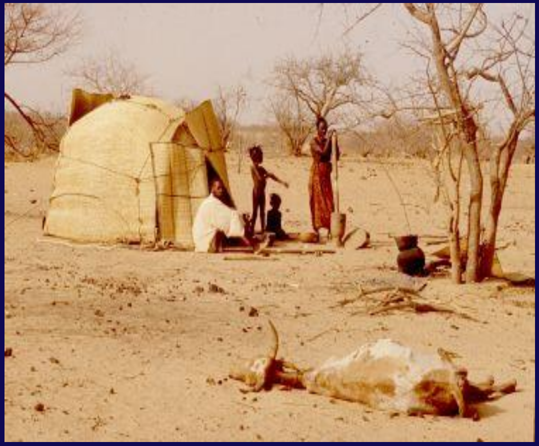
RESILIENCE

Economy-wide impacts



Rainfall & GDP growth: Zimbabwe 1978-1993





R
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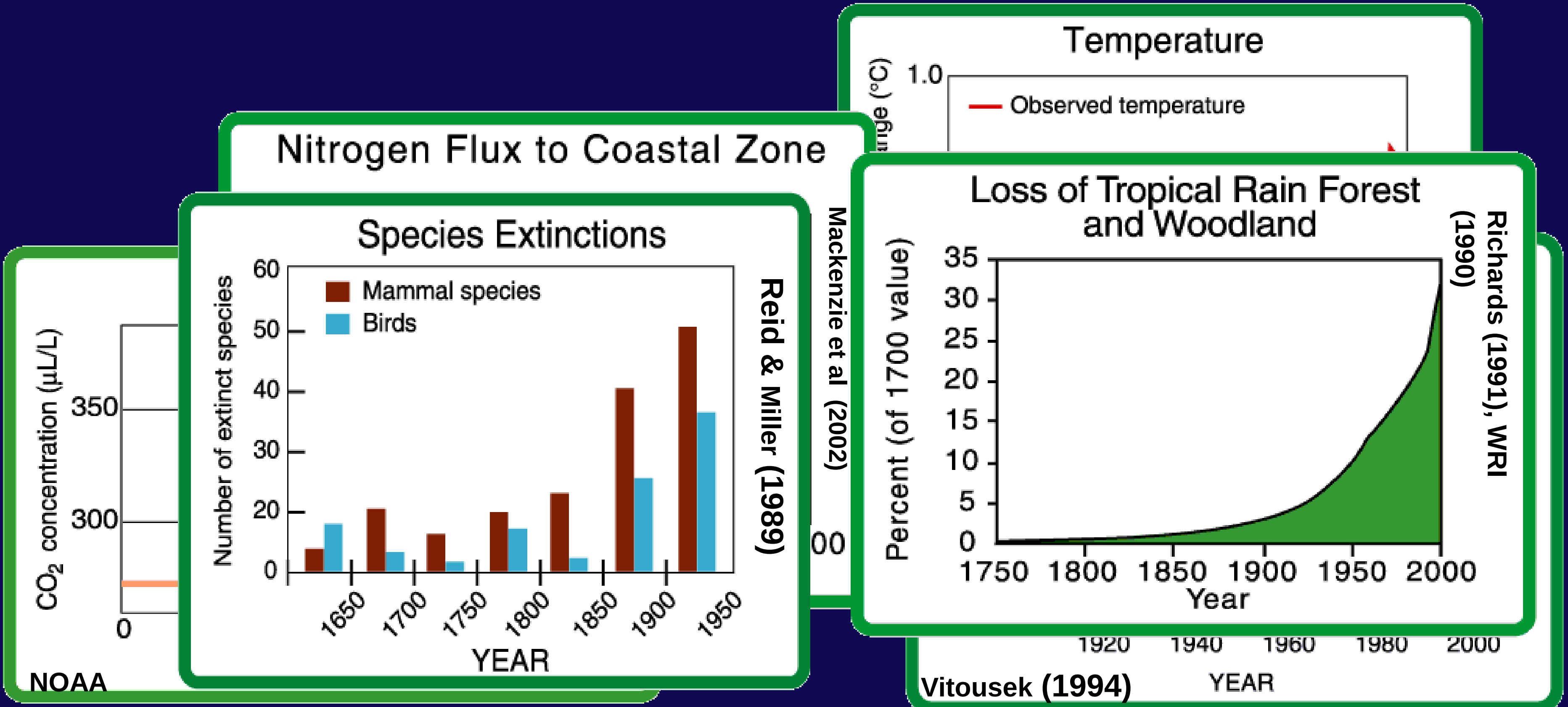
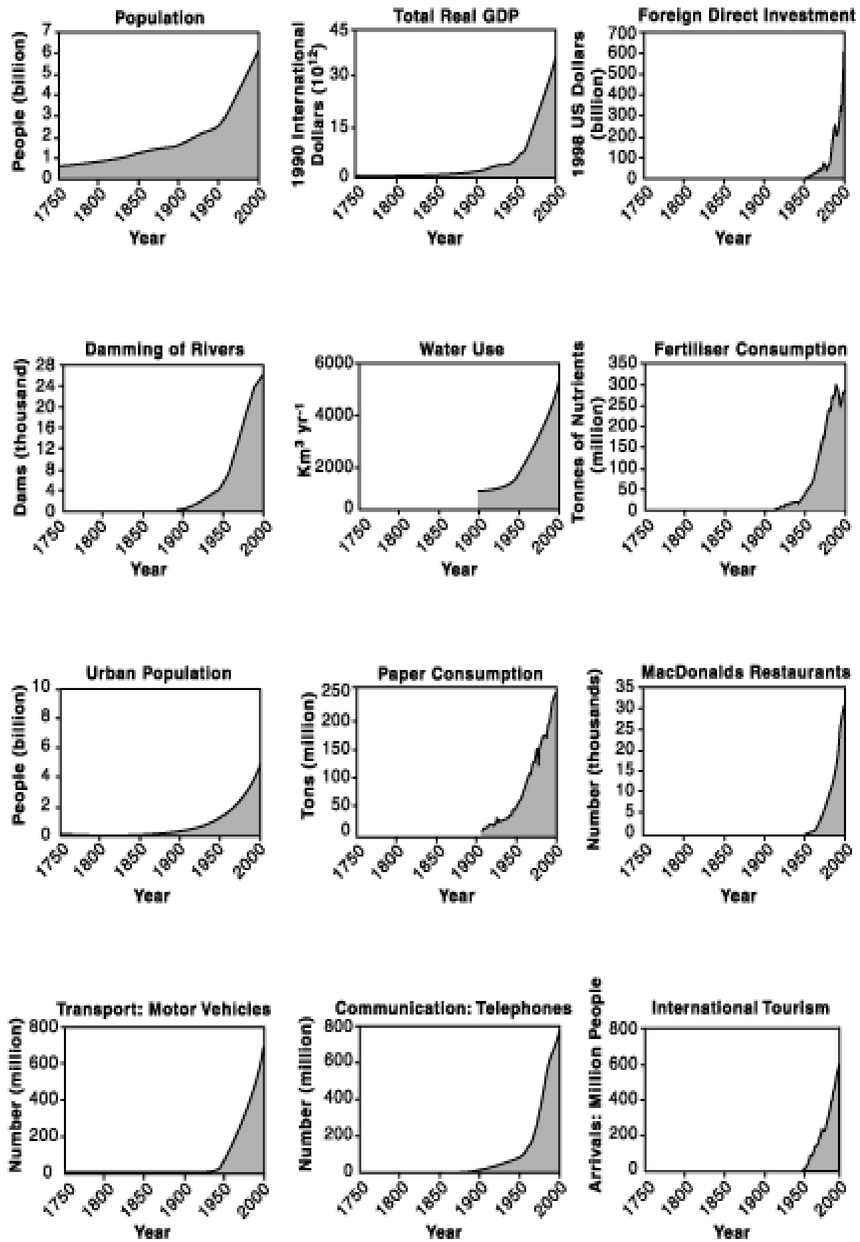
Ethiopia: 1982 - 2000

Global change impacts

- Global change is more than global climate variability/change
- It has natural PLUS human/social dimensions
- A constellation of changes, many global in domain

For example, we see large changes in:





From: Steffen et al. 2004

STATIONARITY IS DEAD

New technologies are needed

Expected Impacts of Global Changes on Water Resource:

WILL WE HAVE MORE FLOODS ?

Outline

- Data issues
- Basic definitions and problems
- Overview of real-time operational hydrological forecasting models
- State space analysis: Discrete models
- Structural-stochastic recursive models
- Lessons learned and outlook

THE DATA ISSUE

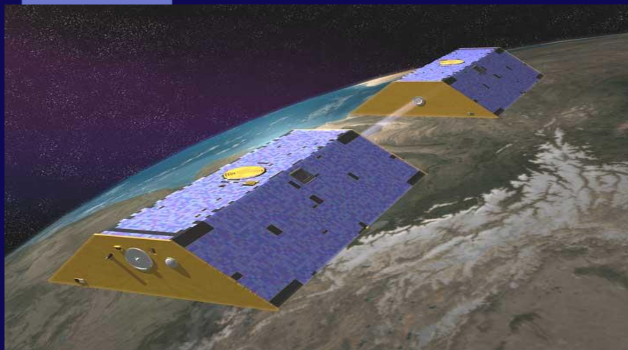
IF YOU CAN'T MEASURE IT REAL TIME

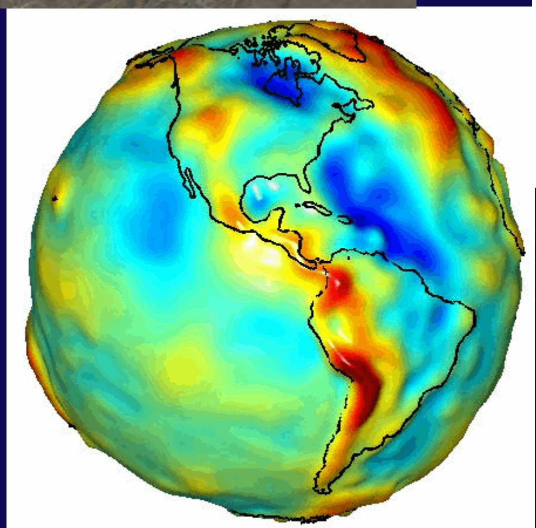
AND IF YOU DON'T HAVE THE

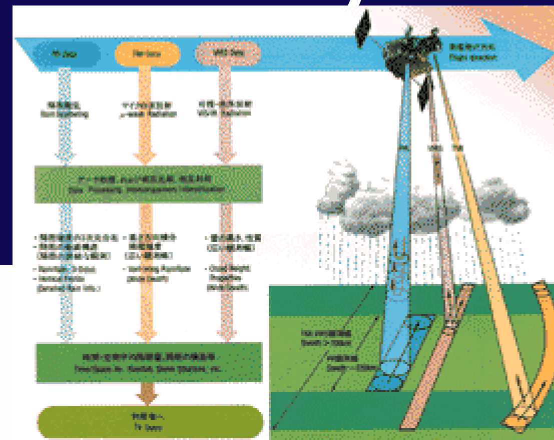
RIGHT DIGITAL TECHNOLOGY

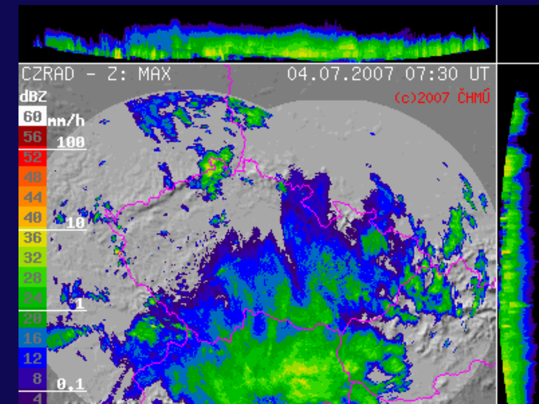
YOU CAN'T MANAGE IT

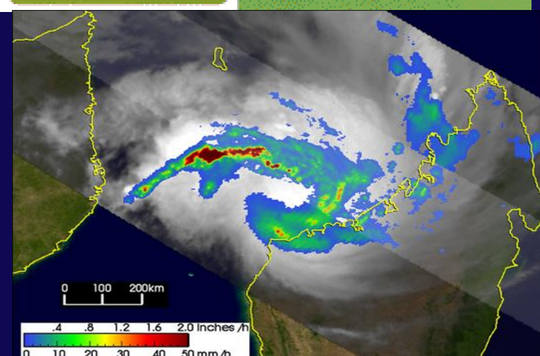
Remotely sensed data

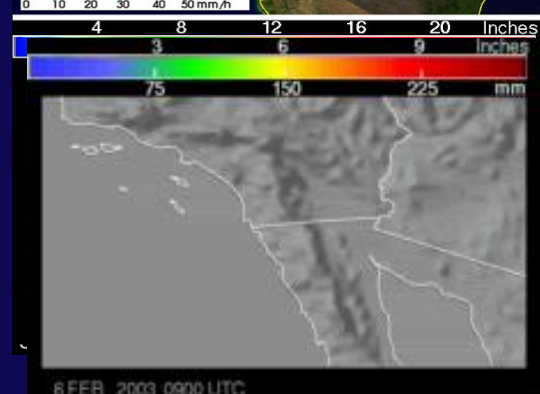


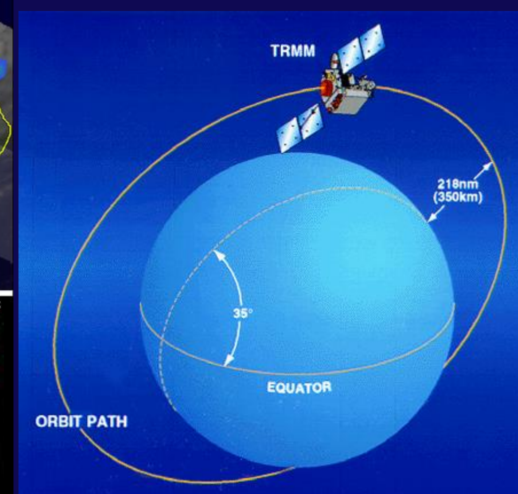












(Source: D. Solomatine)

Flow of information in a Hydroinformatics system

Data → Models → Knowledge → Decisions

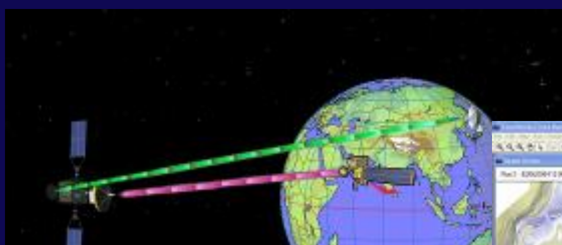
Earth observation, monitoring

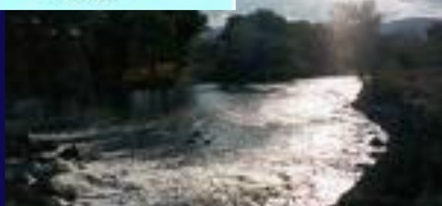
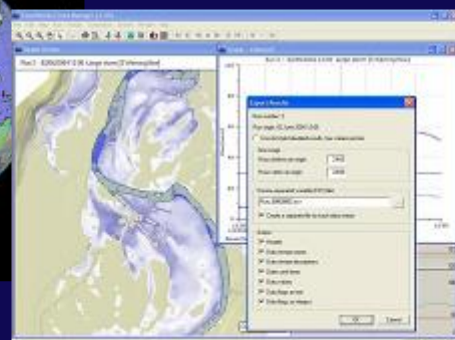
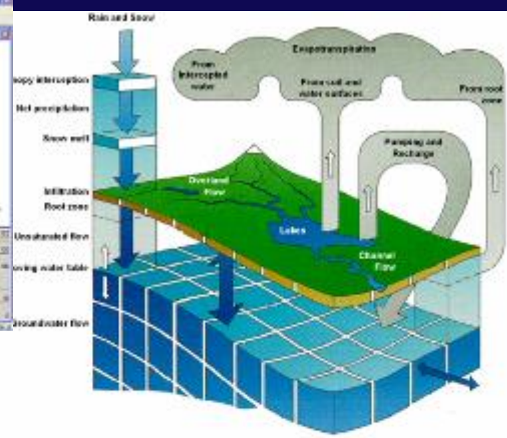
Numerical Weather Prediction Models

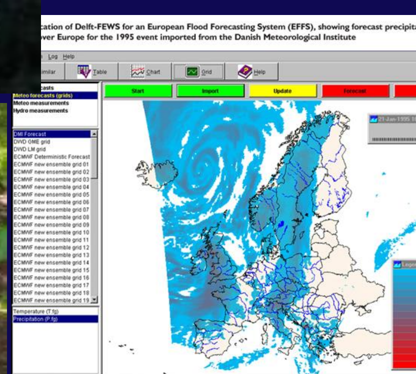
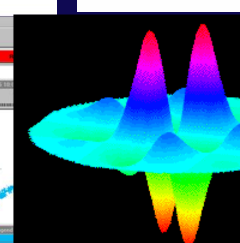
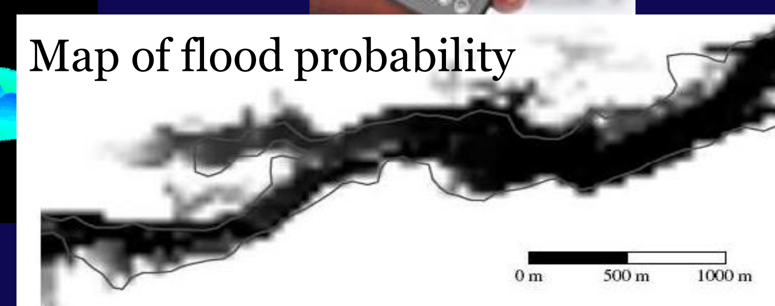
Data modelling, integration with hydrologic and hydraulic models

Access to modelling results

Decision support



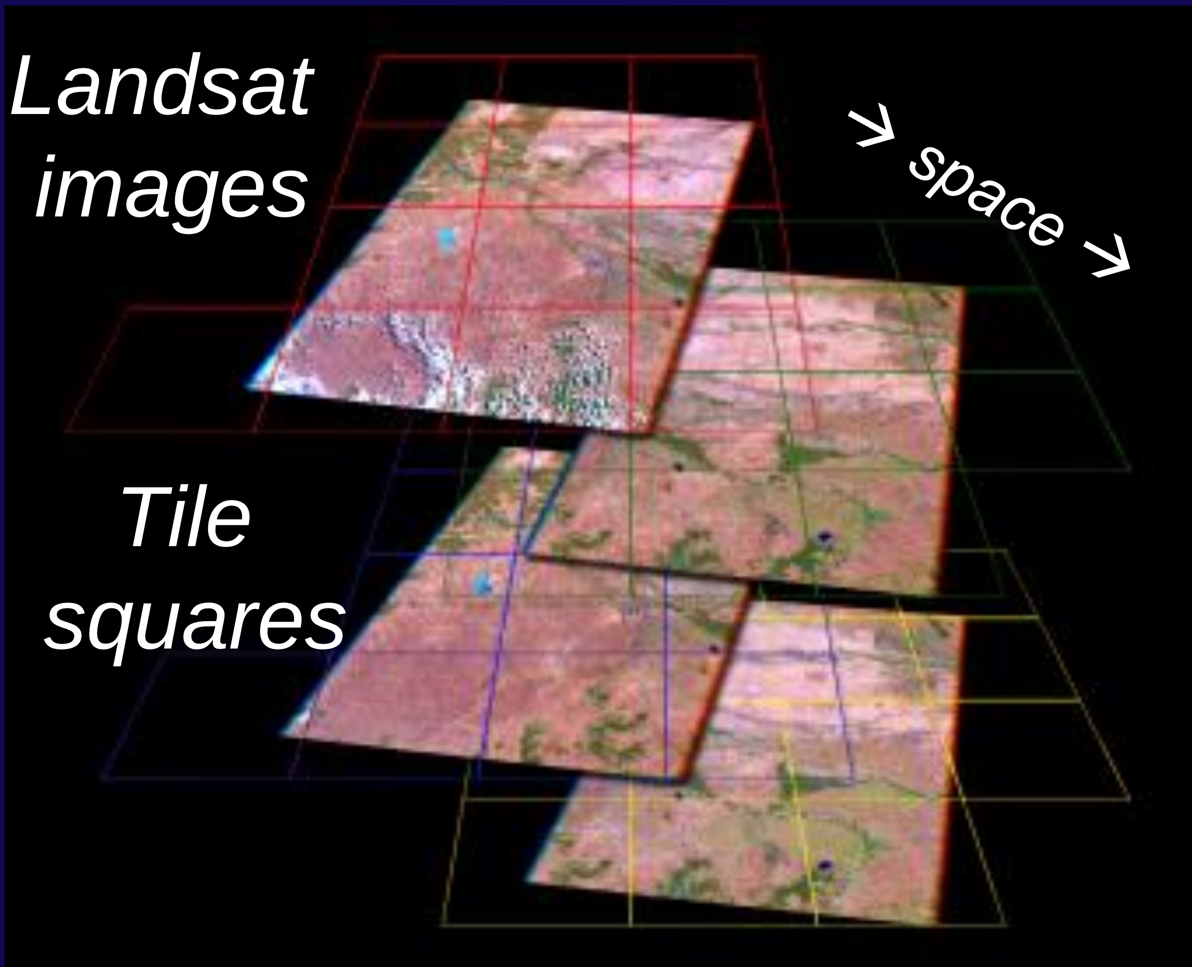




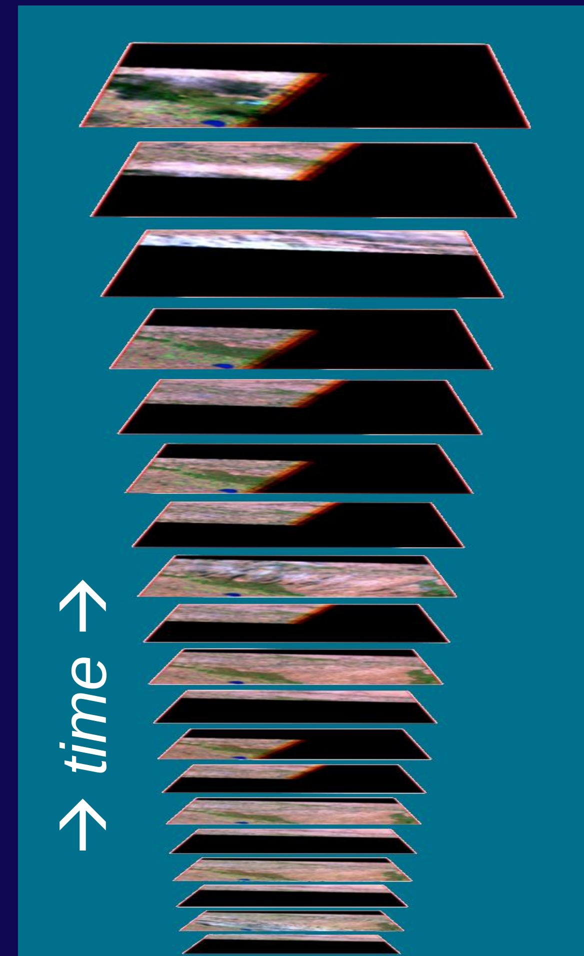





So urce: D. Solomatine

Formulation
Implementation
Primary Ops
Extended Ops
NI-SAR
PACE
SWOT
TEMPO
GRACE-FO (2)
ICESat-2
CYGNSS
SAGE III (on ISS)
SMAP
OCO-2
TRMM
QuikSCAT
SORCE
EO-1
Landsat-7
(USGS)
ACRIMSAT
Aquarius
Terra
Suomi NPP
(NOAA)
Aqua
CloudSat
Landsat-8
(USGS)
CALIPSO
Aura
GPM
GRACE (2)
OSTM/Jason 2
(NOAA)

“Cubing” Landsat images

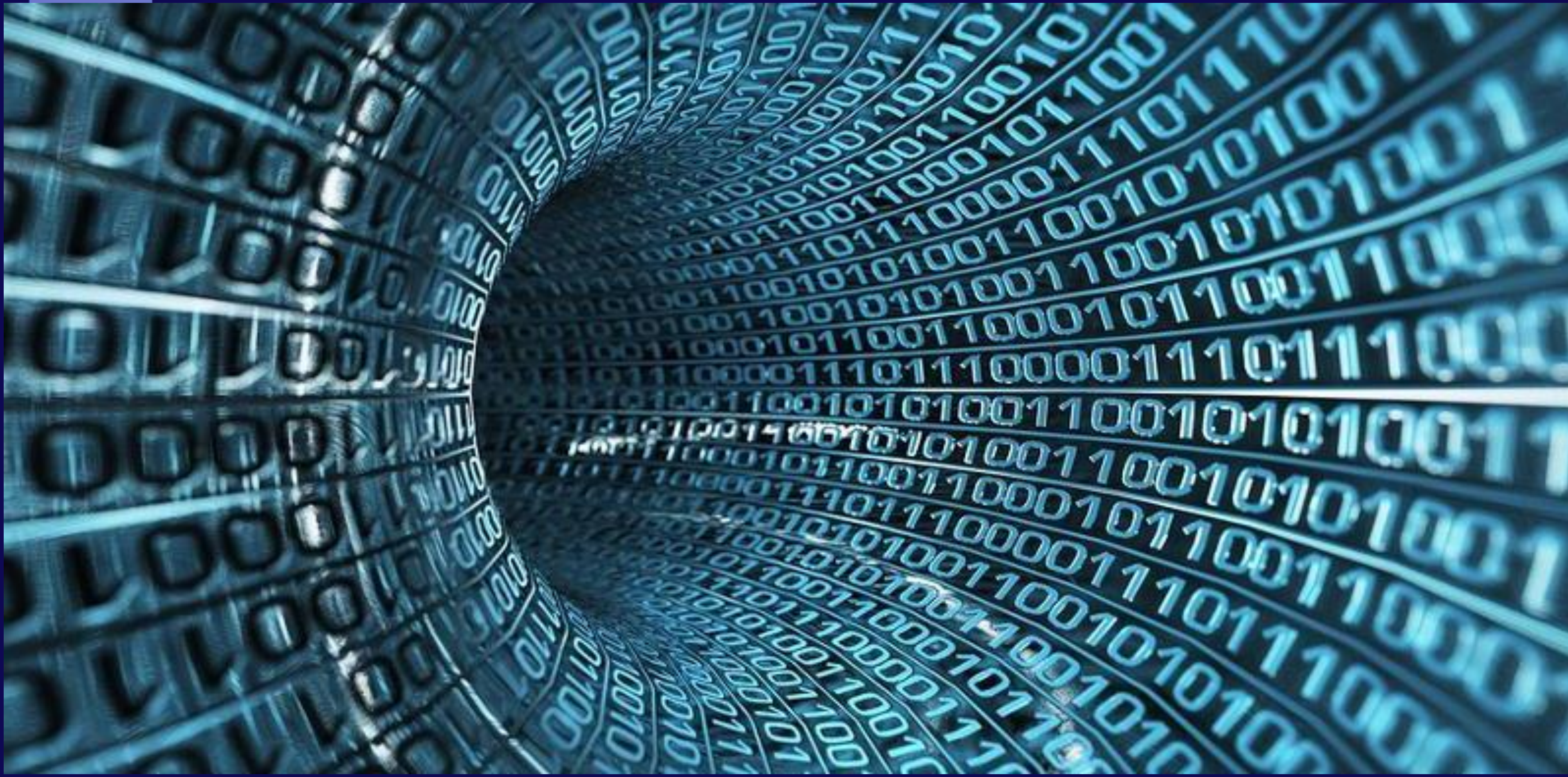




Dice…

Stack

BIG DATA



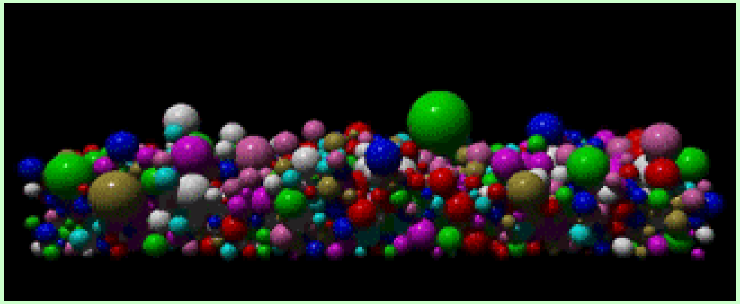
Data revolution:

Terra bytes Petabytes Exabytes … Terra Hertz speed

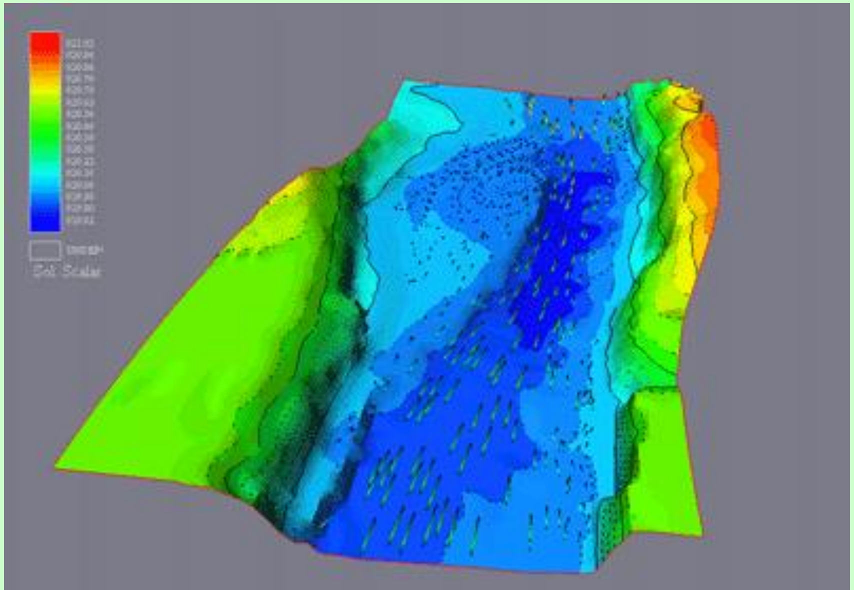
MODELING

Modeling is the heart …

Technologies support the whole information cycle, and *integrate data, models, and humans*



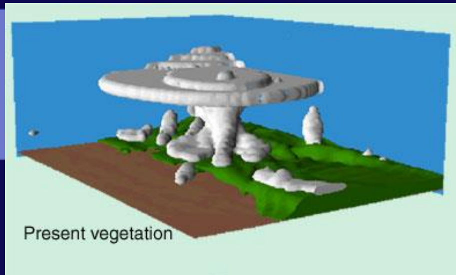
$$\frac{\partial Q}{\partial t}+\frac{\partial}{\partial x}\left(\frac{Q^2}{A}\right)+gA\frac{\partial h}{\partial x}-gAS_o+gAS_f=0$$

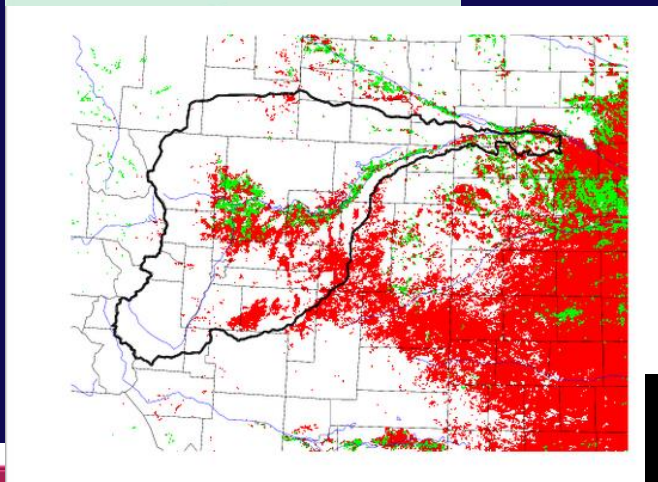


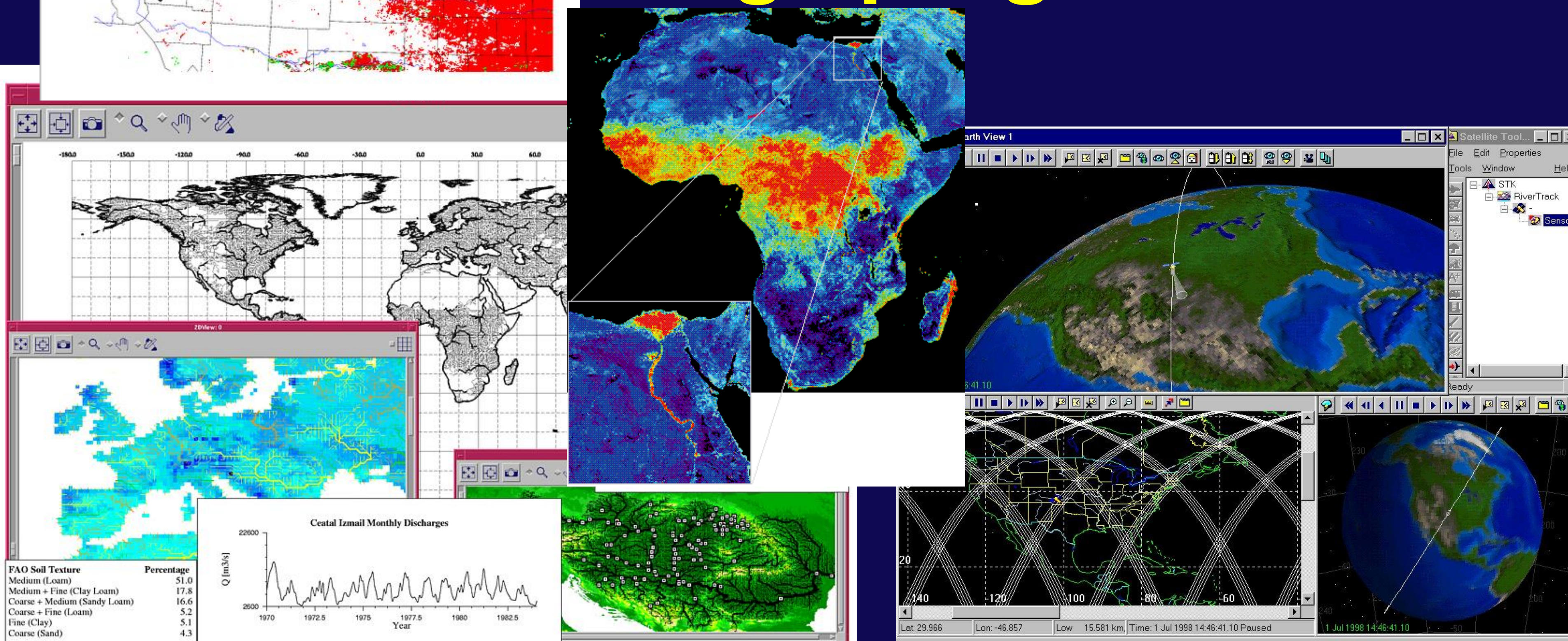
High Precision Earth Systems Tools

- Satellite data
- Data assimilation
- Simulation models
- Geospatial analysis / GIS

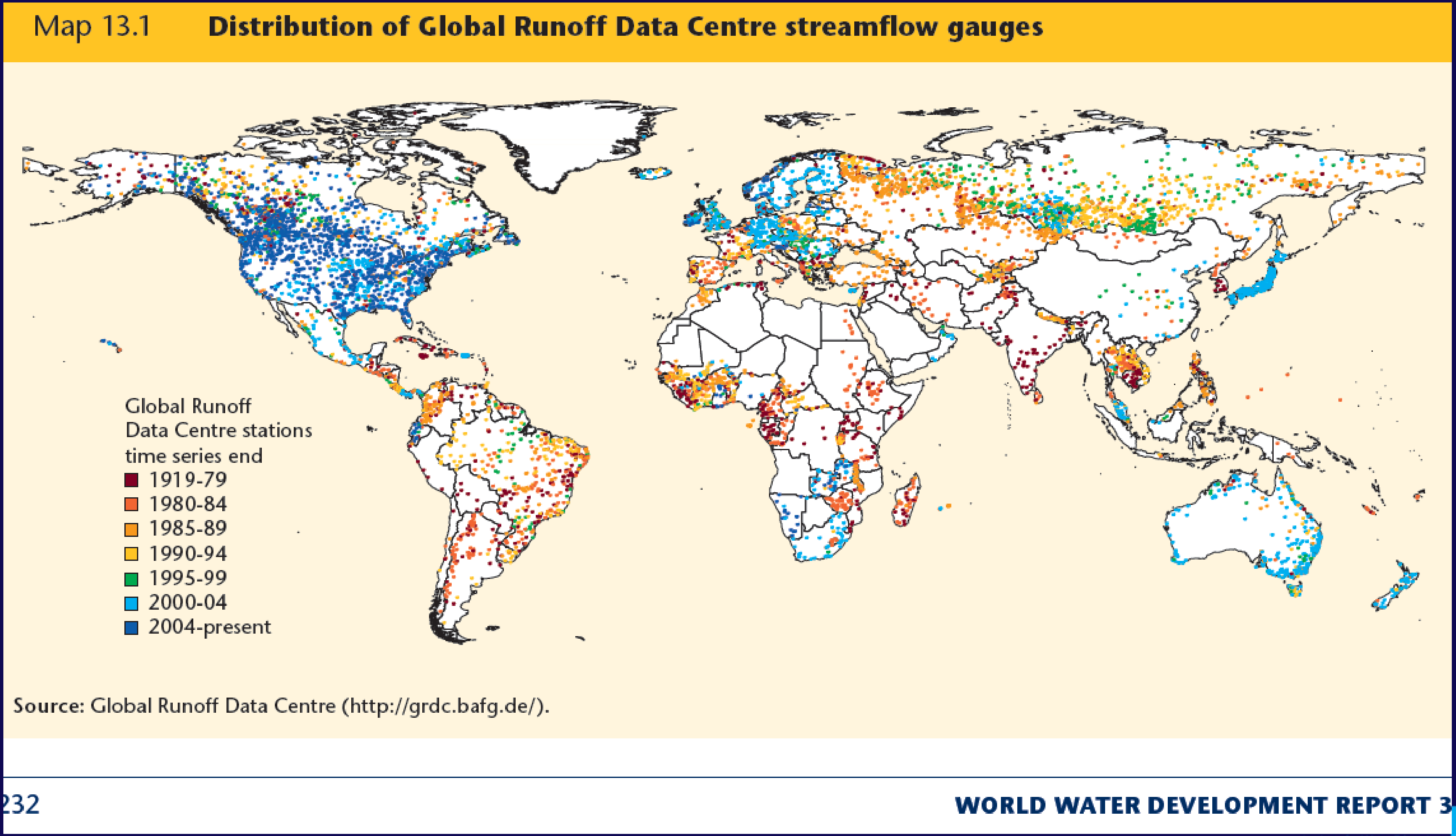
Huge progress but…







Our capacity to monitor remains limited



What is forecasting?

"Though this be madness,
yet there is a method in it"
(Shakespeare)

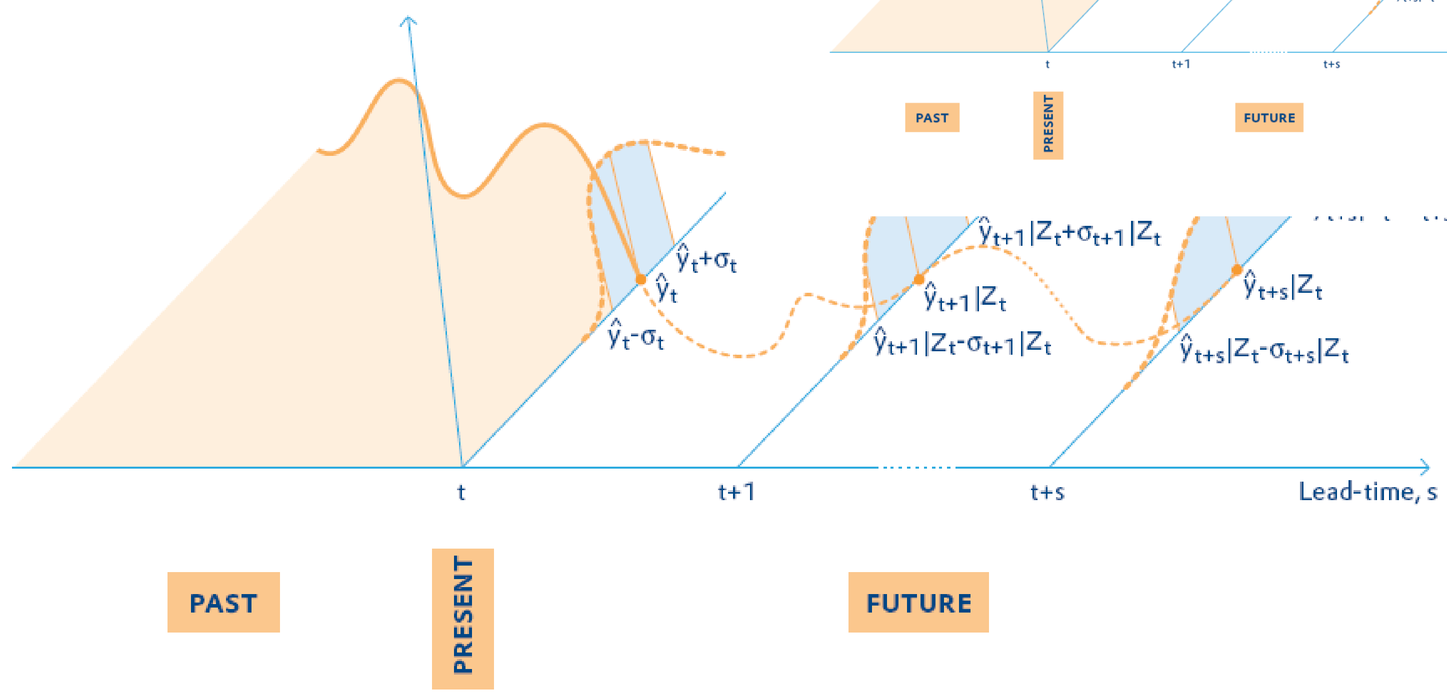
What does forecasting really mean?

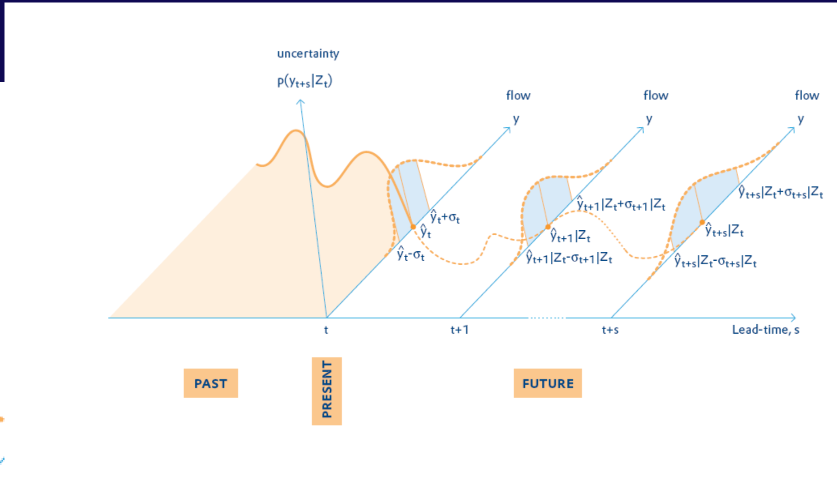
Speaking about probabilities

Forecasting is a difficult thing, particularly when it concerns the future

(attributed to Niels Bohr)

Conditional forecast





- Double faced Ianus, the Greek God

Basic definitions and problems

Forecasting vs.
Statistical prediction

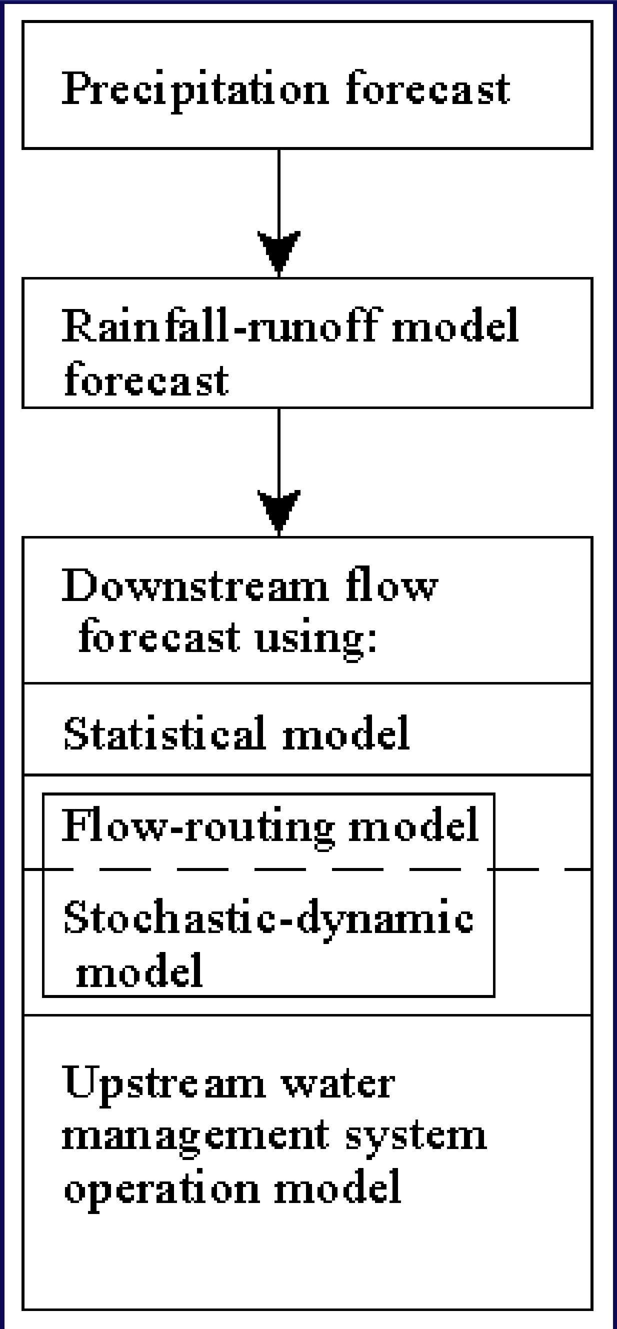
•Real-time operational forecasting is very much a time-critical exercise

•The forecast paradox

Basic requirements:

- Consider the underlying physical principles through appropriate structures
- Consider stochasticity
- Have a minimum number of free parameters to estimate
- Build up in a modular fashion to match complex network topologies
- Provide information on the reliability of the forecast in function of the lead time
- Be fast as forecasting is a time critical exercise

- The models must be mathematically tractable and yet robust
- Adapt to the changing hydrological conditions by having an internal updating mechanism
- Provide uncertainty analysis
- Have minimum site dependence
- Set up of more complex models from simple ones by mapping the topology of a river system in a modular fashion



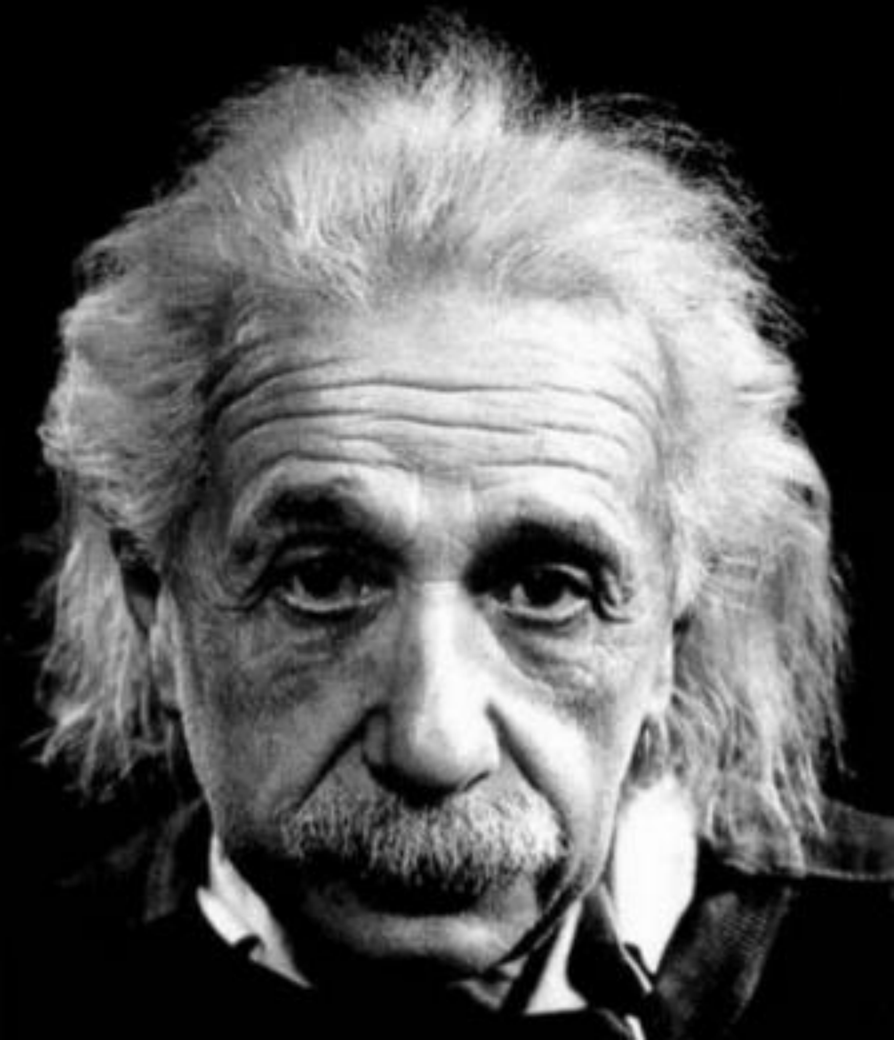
UNESCO-IHE
Institute for Water Education

Overview of real-time operational hydrological forecasting models

Problems of the Week

"Everything should be made as simple as possible, but not simpler."

Albert Einstein



- All our trouble started in 1932 with the UH
- Effective rainfall does not exist in reality
- Nobody observed that IUH as such does not exist

- Where to go?
- Conceptual models / state variables
- Complex vs. simplified
- Time series models / stochastic IUH
- THE WAR: deterministic vs. stochastic –

  Who is right?

A brokered marriage: can it be a good compromise?

Can we arrange a marriage between things of the two schools that are good and rejecting at the same time those things that are not good?;

Can we work on developing combined structural – stochastic models that are applicable for operational forecasting use?

Overview of approaches

- Unit hydrograph
- Soil moisture accounting
  - Coaxials
  - Explicit
  - Implicit

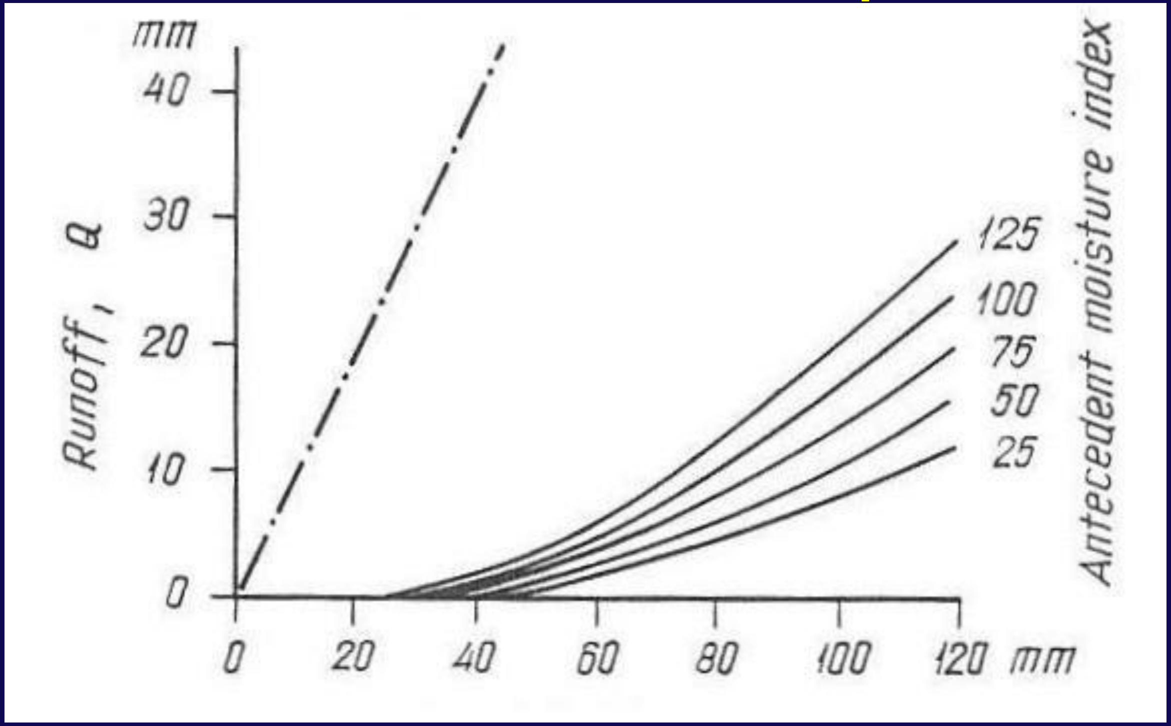
Simplified physical models

Time series analysis based approaches

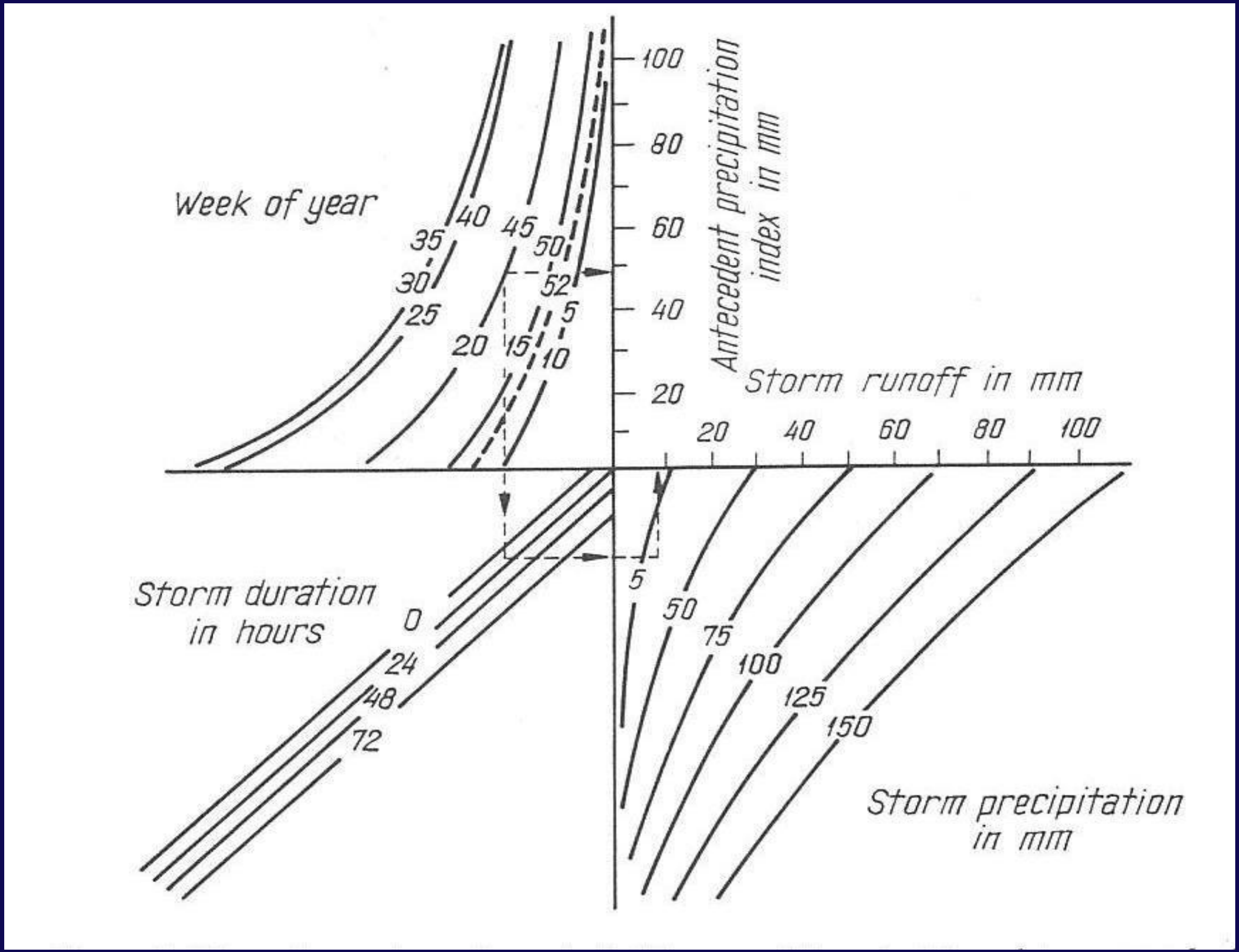
Combined models

API

- Antecedent Moisture/Precipitation Index

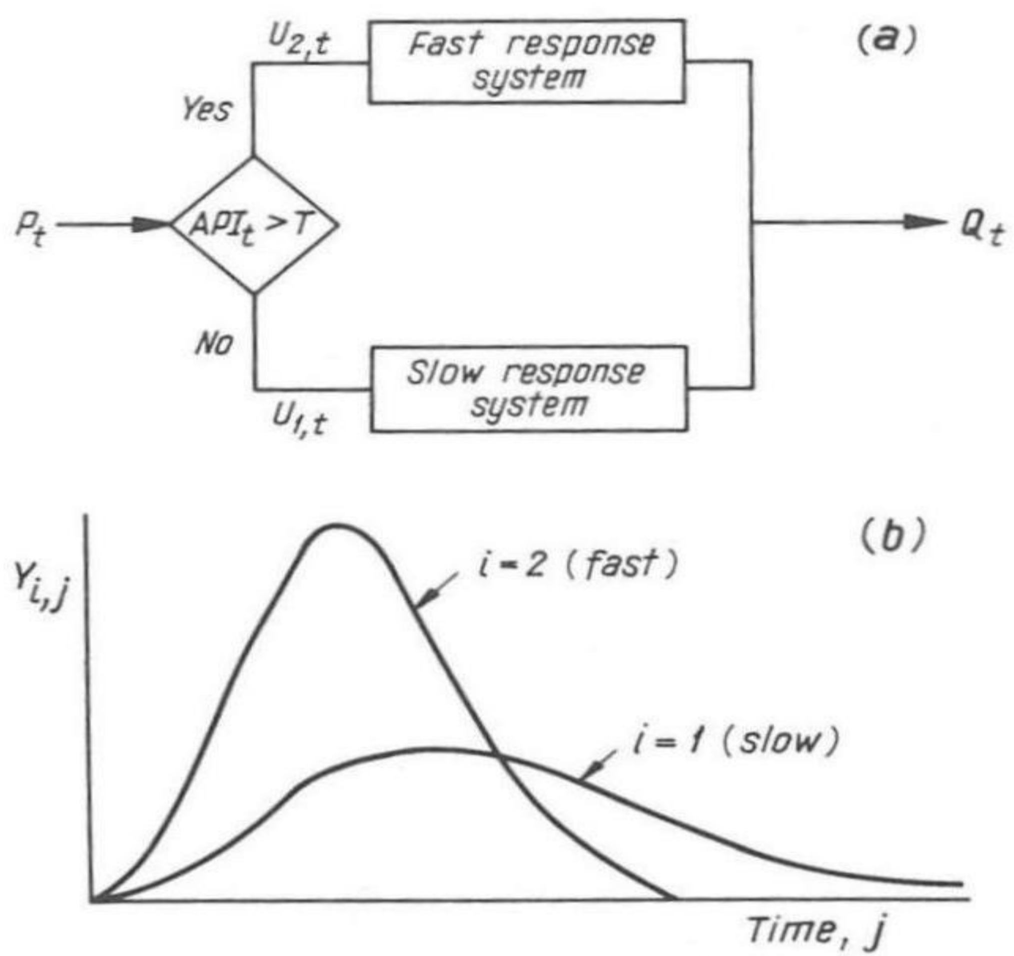


API based coaxials



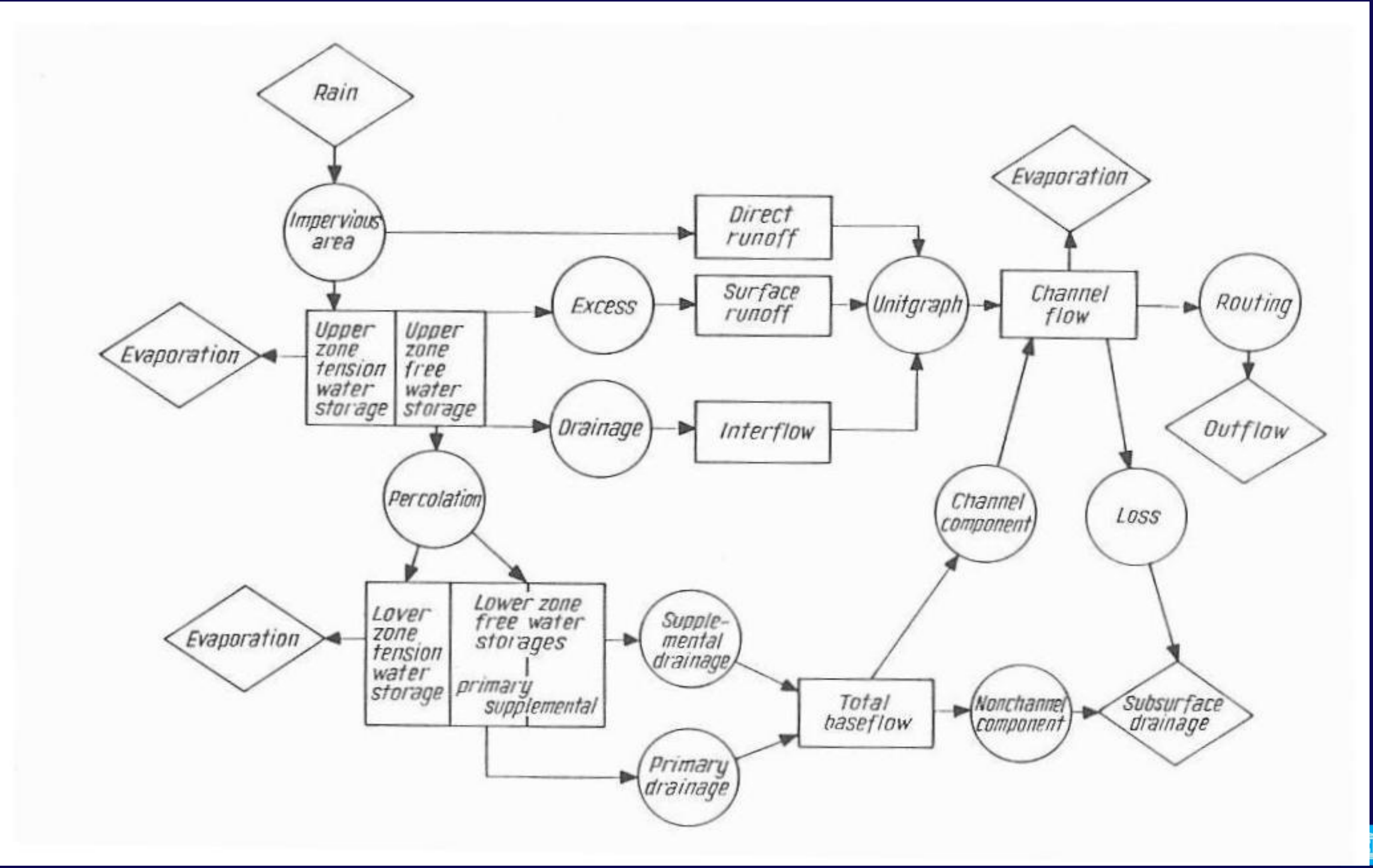
- External vs.
- Internal descriptions

Constrained Linear System (**CLS**) (Todini and Wallis)

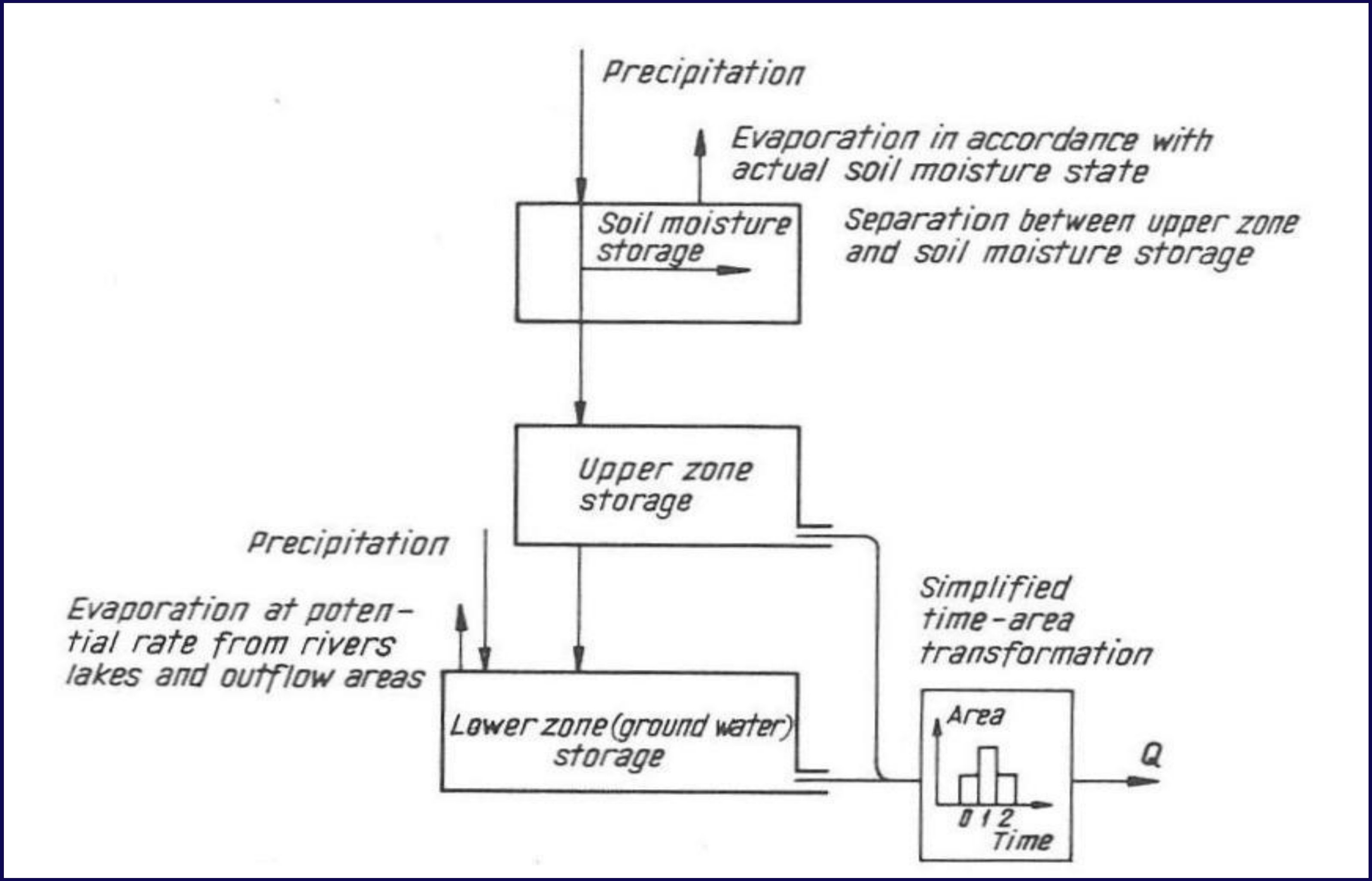


- **API dependent threshold**
- **Two IUHs**

SACRAMENTO rainfall-runoff model

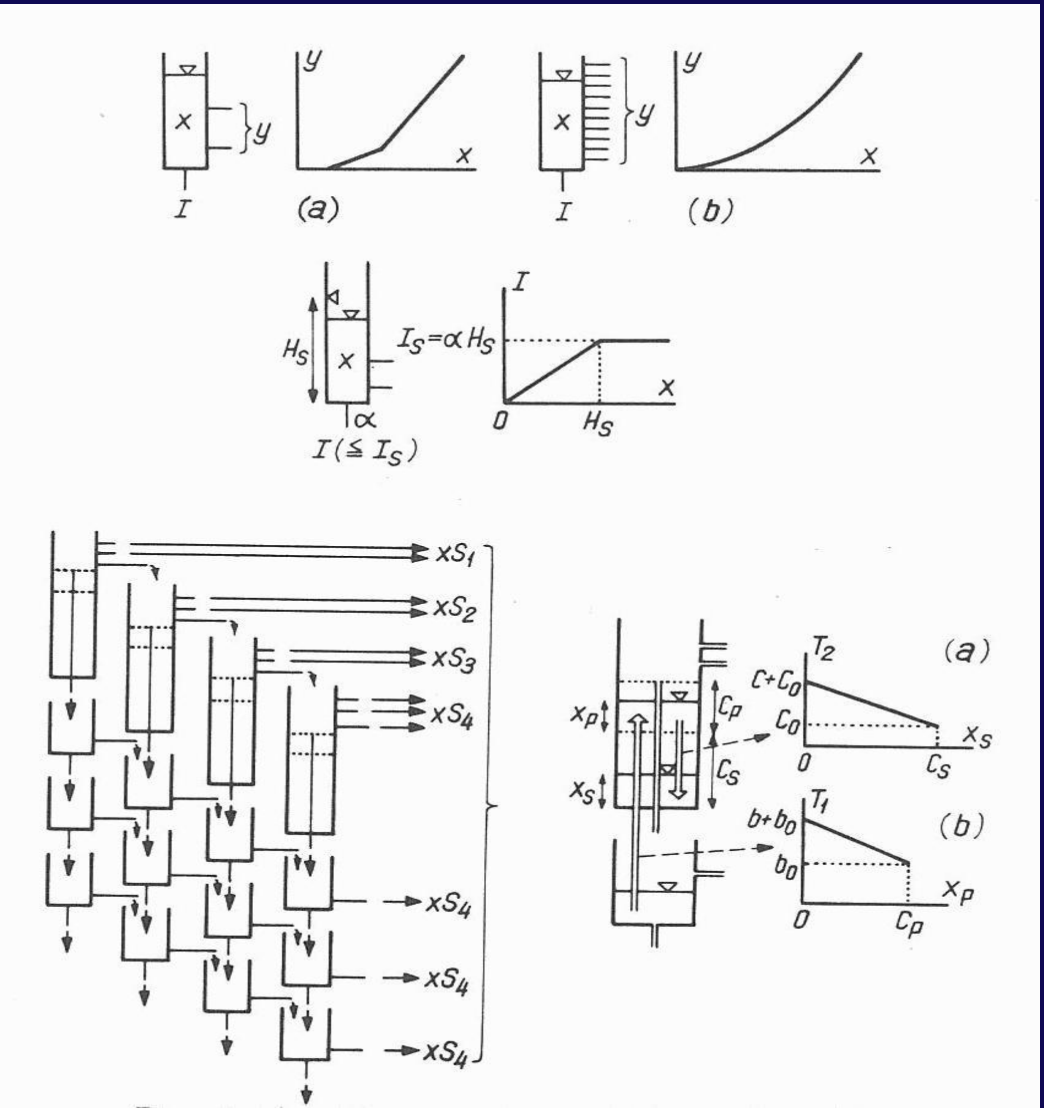


HBV model



Precipitation
Evaporation in accordance with actual soil moisture state
Soil moisture storage
Separation between upper zone and soil moisture storage
Upper zone storage
Precipitation
Evaporation at potential rate from rivers lakes and outflow areas
Lower zone (ground water) storage
Simplified time-area transformation
Area
0 1 2
Time
Q

Sugawara's TANK model



(Implicit soil-moisture accounting)

- External vs.
- SIMPLIFIED internal description

“Make things simple,
but no simpler”
(Einstein)

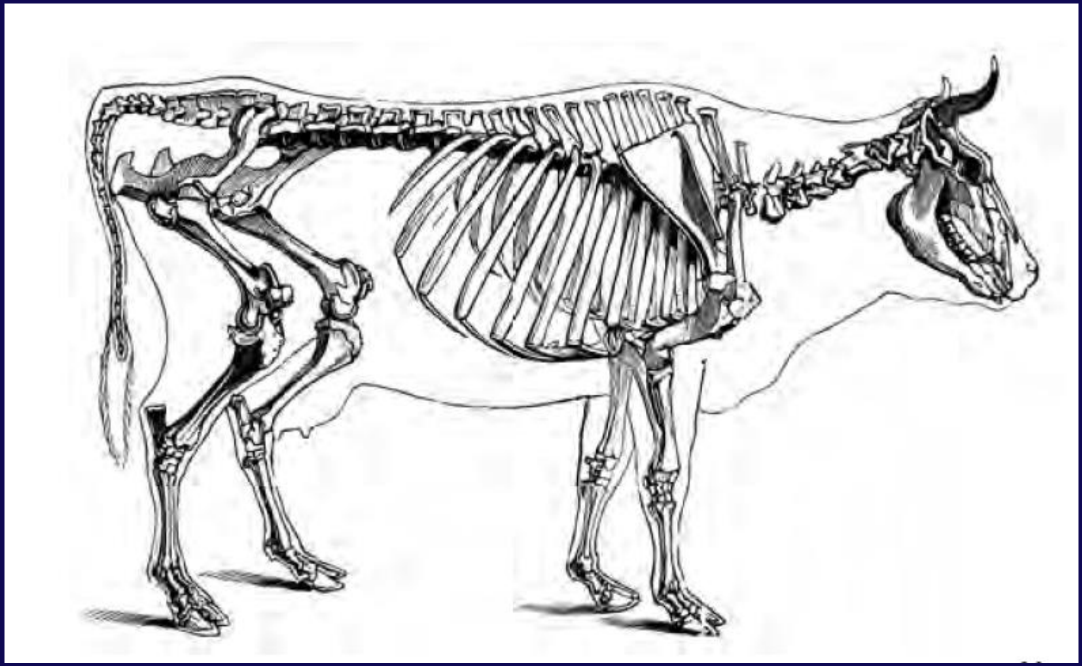
Making things simple

An introduction to the anatomy of cows:

Chopping hydrodynamics down to its bones

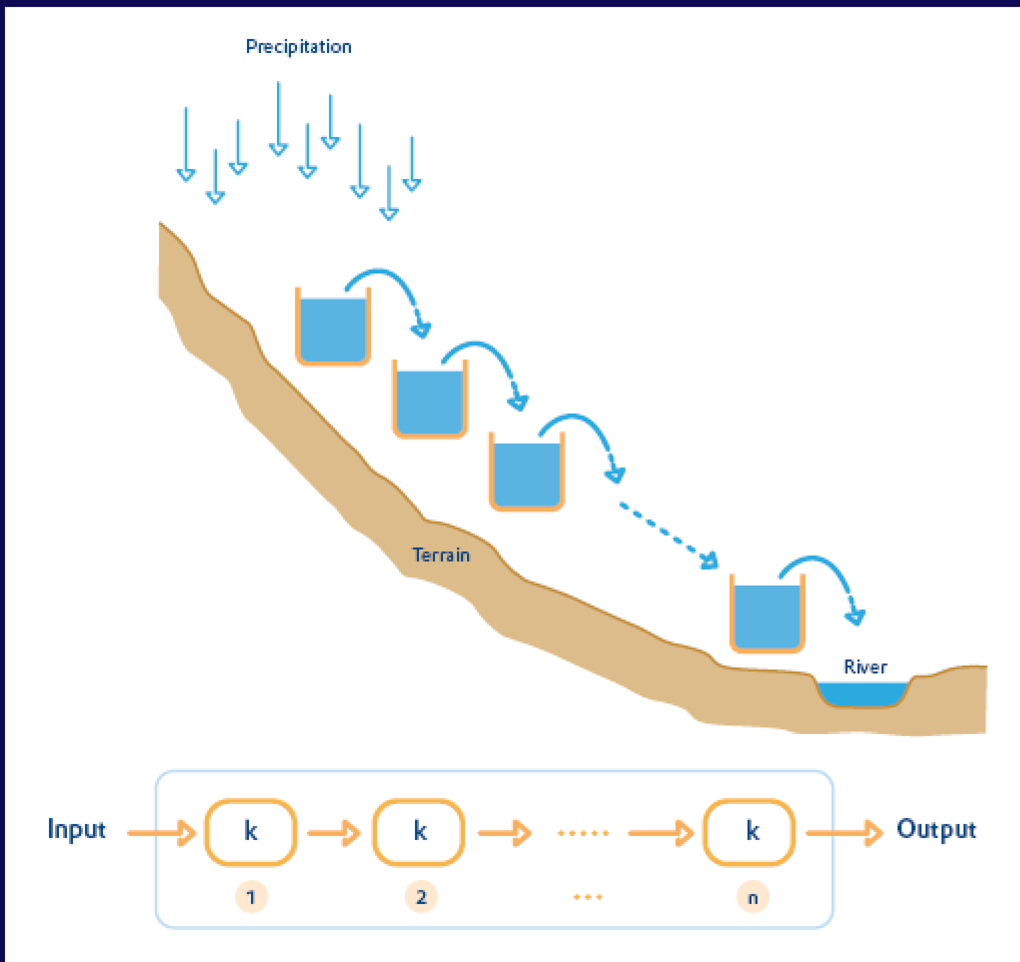
The linear kinematic wave as cow skeleton

Peel the various layers of the hydrodynamic equation off until the principal structure appears

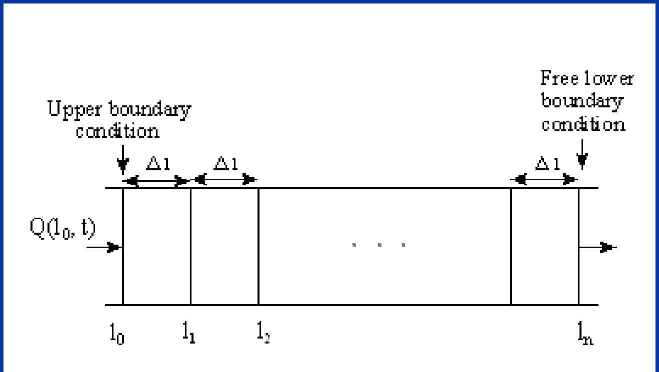


Explains a large portion of the runoff phenomena in terms of its variance

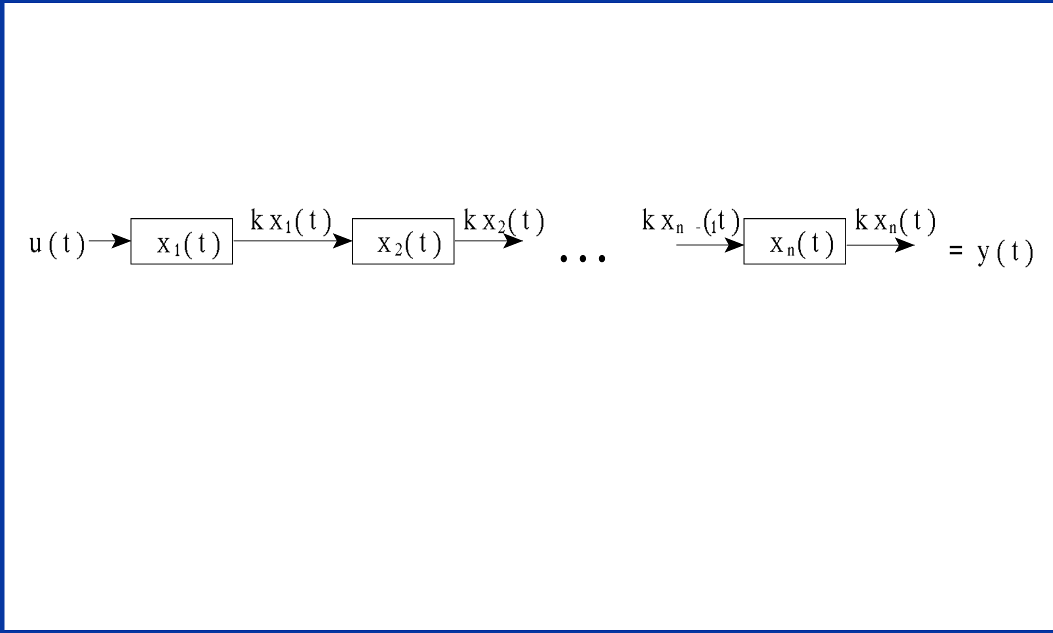
Cascade models



Discretization in space



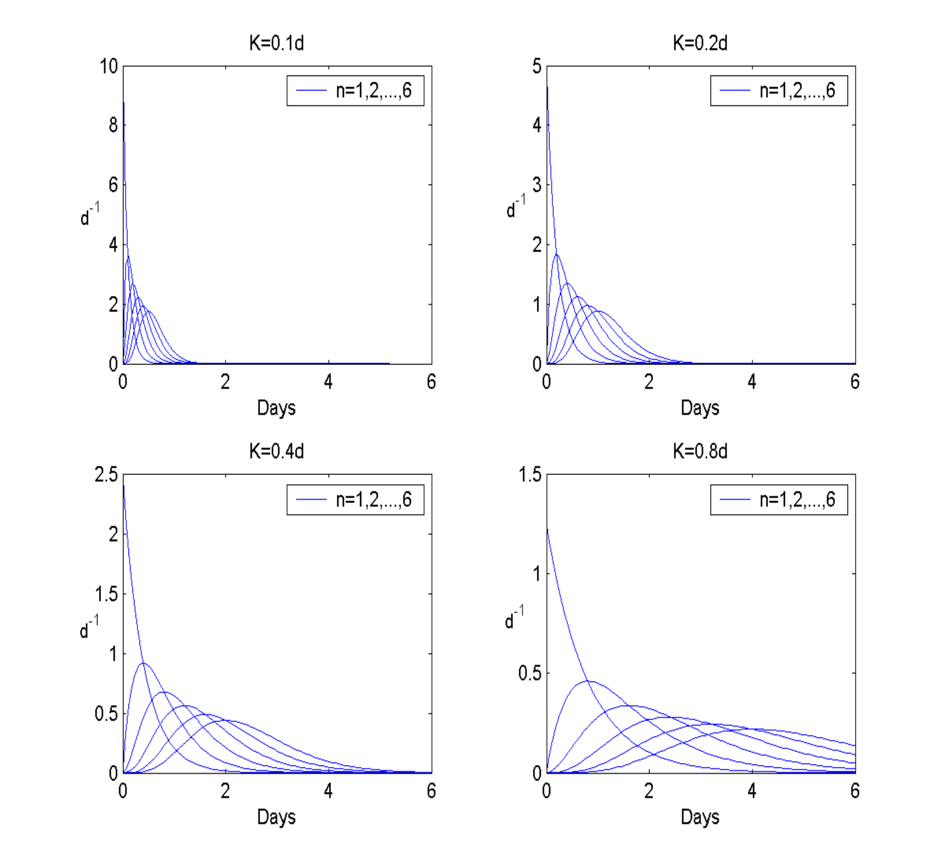
Linear kinematic wave



Kalinin-Milyukov-Nash (KMN) cascade

$$h(t) = \frac{1}{K}\left(\frac{t}{K}\right)^{n-1} \frac{1}{(n-1)!} e^{-t/K}, \qquad t \geqslant 0$$

Impulse responses of the continuous KMN-cascade



n = 1,2, …,6
K = 0.1, 0.2, 0.4, 0.8 days

$$
\begin{aligned}
\dot{\mathbf{x}}(t) &= \mathbf{F}\mathbf{x}(t) + \mathbf{G}\mathbf{u}(t) \\
\mathbf{y}(t) &= \mathbf{H}\mathbf{x}(t)
\end{aligned}
$$

$$\Sigma_{KMN} = (\mathbf{F}, \mathbf{G}, \mathbf{H})$$

State space analysis: The Discrete Linear Cascade Model (DLCM)

From KNM to DCM: time discretisation

- Discrete coincidence
- Dynamic changes between sampling points
- Transitivity

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \\ \dot{x}_3(t) \\ \vdots \\ \dot{x}_n(t) \end{bmatrix} = \begin{bmatrix} -k & & & & 0 \\ k & -k & & & \\ & k & -k & & \\ & & \ddots & \ddots & \\ 0 & & & k & -k \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ \vdots \\ x_n(t) \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix} u(t)$$

$$\dot{\mathbf{x}}(t) = \mathbf{F}\mathbf{x}(t) + \mathbf{G}u(t)$$

$$y(t) = [0, 0, ..., k] \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ \vdots \\ x_n(t) \end{bmatrix}$$

$$y(t) = \mathbf{H}\mathbf{x}(t)$$

$$\mathbf{\Sigma}_{KMN} = (\mathbf{F}, \mathbf{G}, \mathbf{H})$$

$$h(t) = k(tk)^{n-1}\frac{1}{(n-1)!}e^{-tk}$$

$$\mathbf{\Phi}(t) = e^{t\mathbf{F}} = \begin{bmatrix} e^{-tk} & 0 & 0 & \cdots & 0 \\ tke^{-tk} & e^{-tk} & 0 & \cdots & 0 \\ \frac{(tk)^2}{2!}e^{-tk} & tke^{-tk} & e^{-tk} & 0 & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ \frac{(tk)^{n-1}}{(n-1)!}e^{-tk} & \frac{(tk)^{n-2}}{(n-2)!}e^{-tk} & \cdots & tke^{-tk} & e^{-tk} \end{bmatrix}$$

$$\mathbf{x}(t+\Delta t) = \mathbf{\Phi}(t+\Delta t, t)\mathbf{x}(t) + [\int_t^{t+\Delta t} \mathbf{\Phi}(t+\Delta t, \tau)\mathbf{G}(\tau)d\tau]\mathbf{u}(t)$$

$$
\begin{aligned}
\mathbf{x}_t &\triangleq \mathbf{x}(t) \\
\mathbf{u}_t &\triangleq \mathbf{u}(t) \\
\mathbf{\Phi}_t(\Delta t) &\triangleq \mathbf{\Phi}(t+\Delta t, t) \\
\mathbf{\Gamma}_t(\Delta t) &\triangleq \int_t^{t+\Delta t} \mathbf{\Phi}(t+\Delta t, \tau)\mathbf{G}(\tau)d\tau
\end{aligned}
$$

$$
\mathbf{x}_{t+\Delta t} = \mathbf{\Phi}_t(\Delta t)\mathbf{x}_t + \mathbf{\Gamma}_t(\Delta t)\mathbf{u}_t
$$

$$\mathbf{y}_t = \mathbf{H}\mathbf{x}_t$$

$$\mathbf{x}_{t+\Delta t} = \mathbf{\Phi}(\Delta t)\mathbf{x}_t + \mathbf{\Gamma}(\Delta t)u_t$$

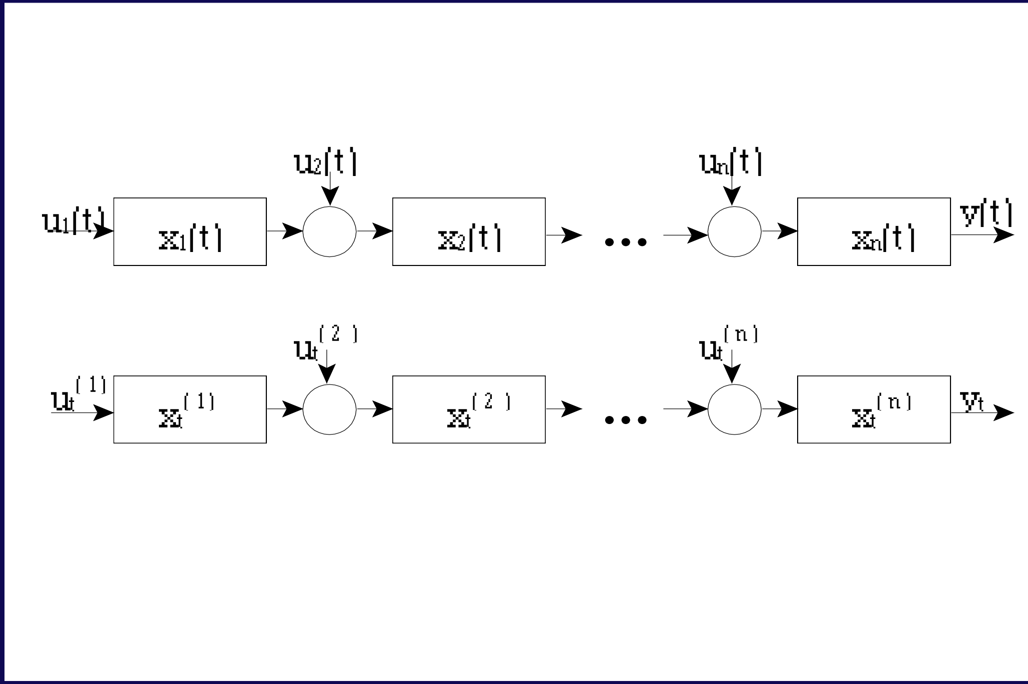
$$\mathbf{\Phi}(\Delta t) \triangleq \mathbf{\Phi}(t + \Delta t, t) = e^{(t+\Delta t - t)\mathbf{F}} = e^{\Delta t \mathbf{F}}$$

$$\mathbf{\Gamma}_t(\Delta t) = \int_t^{t+\Delta t} \mathbf{\Phi}(t + \Delta t - \tau)\mathbf{G}(\tau)d\tau$$

$$\boldsymbol{\Phi}(\Delta t) = \begin{bmatrix} e^{-\Delta tk} & 0 & 0 & \cdots & 0 \\ \Delta tke^{-\Delta tk} & e^{-\Delta tk} & 0 & \cdots & 0 \\ \frac{(\Delta tk)^2}{2!}e^{-\Delta tk} & \Delta tke^{-\Delta tk} & e^{-\Delta tk} & 0 & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ \frac{(\Delta tk)^{n-1}}{(n-1)!}e^{-\Delta tk} & \frac{(\Delta tk)^{n-2}}{(n-2)!}e^{-\Delta tk} & \cdots & \Delta tke^{-\Delta tk} & e^{-\Delta tk} \end{bmatrix}$$

$$
\boldsymbol{\Gamma}(\Delta t) = \left[\begin{array}{c} (1 - e^{-\Delta t k})/k \\ [1 - e^{-\Delta t k}(1 + \Delta t k)]/k \\ [1 - e^{-\Delta t k}(1 + \Delta t k + \frac{(\Delta t k)^2}{2})]/k \\ \vdots \\ (1 - e^{-\Delta t k} \sum_{j=0}^{n-1} \frac{(\Delta t k)^j}{j!})/k \end{array} \right]
$$

Generalizations for lateral inflows



Learn from your errors – if you can!

"From error to error one discovers the entire truth." (Freud)

Learn from your errors

An arranged marriage between

Structure and Chance

A brokered marriage: can it be a good compromise?

Can we arrange a marriage between things of the two schools that are good and rejecting at the same time those things that are not good?;

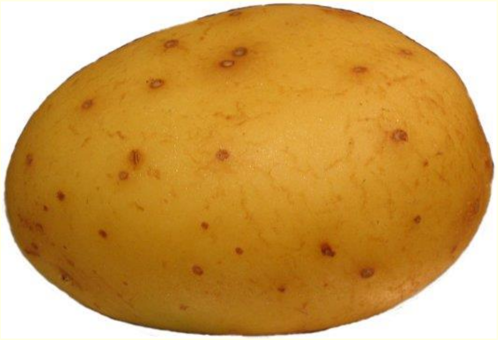
Can we work on developing combined structural – stochastic models that are applicable for operational forecasting use?

Work programme:

Arrange a marriage between things of the two schools that are good and rejecting at the same time those things that are not good;

Work on developing combined structural – stochastic models that are applicable for operational forecasting use

Batch vs. recursive estimates



Noisy potato measurements

$$z_\tau = x + \nu_\tau,\ \tau = 1,2,\ldots\ldots,t$$

$$\hat{x}_t = \frac{1}{t}\sum_{\tau=1}^{t} z_\tau$$

From old to new with updating…

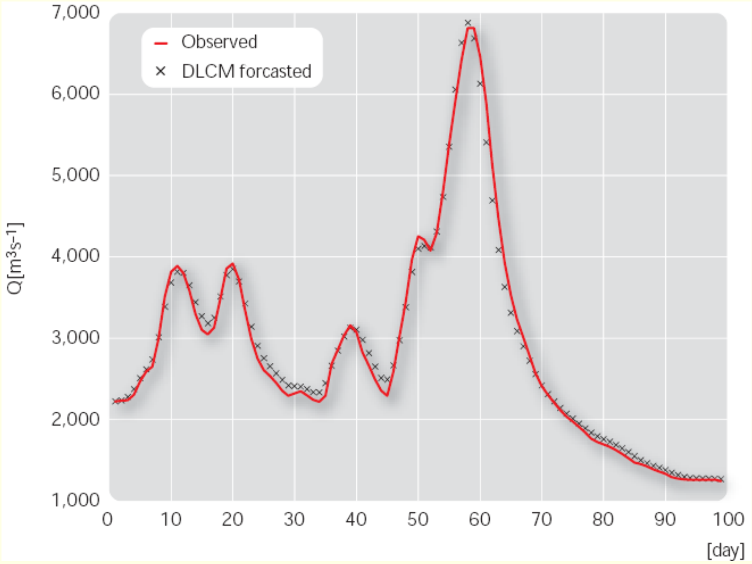
- {new estimate} = {old estimate} & {new measurement data}
- {a posteriori} = {a priori} & {new information}

$$\hat{x}_{t+1} = \hat{x}_t + \frac{1}{t+1}\left(z_{t+1} - \hat{x}_t\right)$$

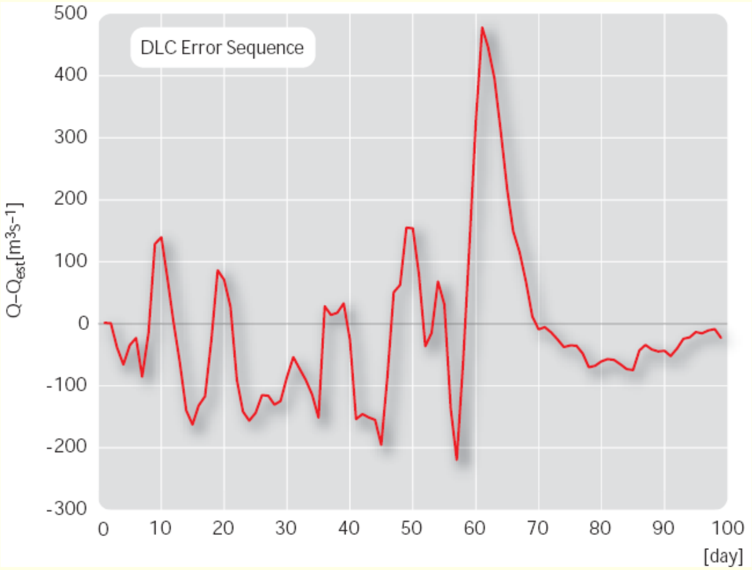
The innovation/error is fed back to the old estimate to get the new one. This feedback mechanism is really the essence of updating.

$$\hat{x}_{t+1} = \hat{x}_t + K_{t+1}\,\nu_t$$

Deterministic forecast by DLCM



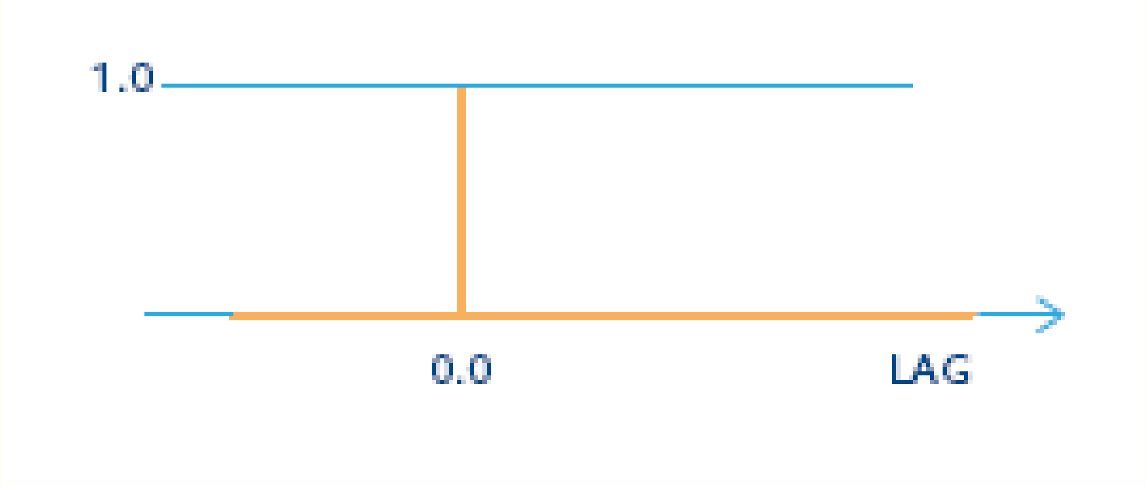
- If errors have memory, they have their own dynamics that could be modeled and forecasted.



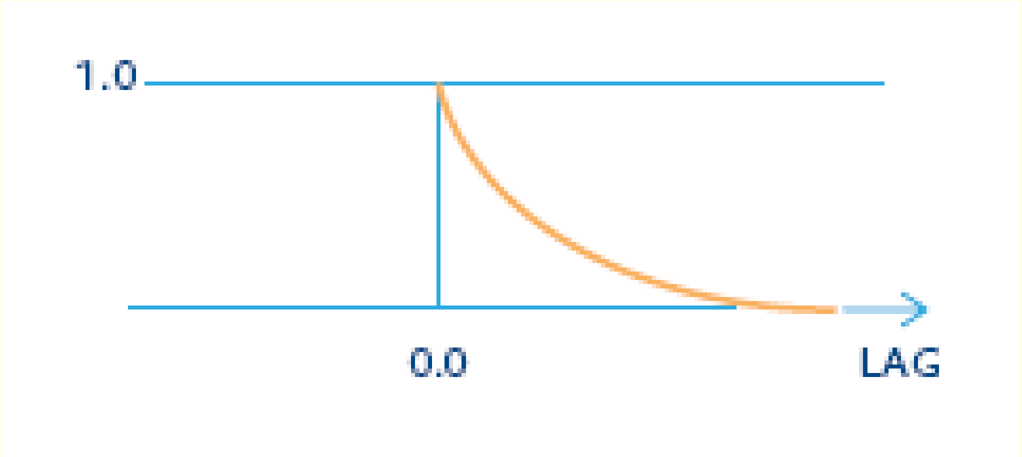
- If there is no internal correlation in a time series, it simply cannot be forecasted.

Autocorrelation functions of noise types

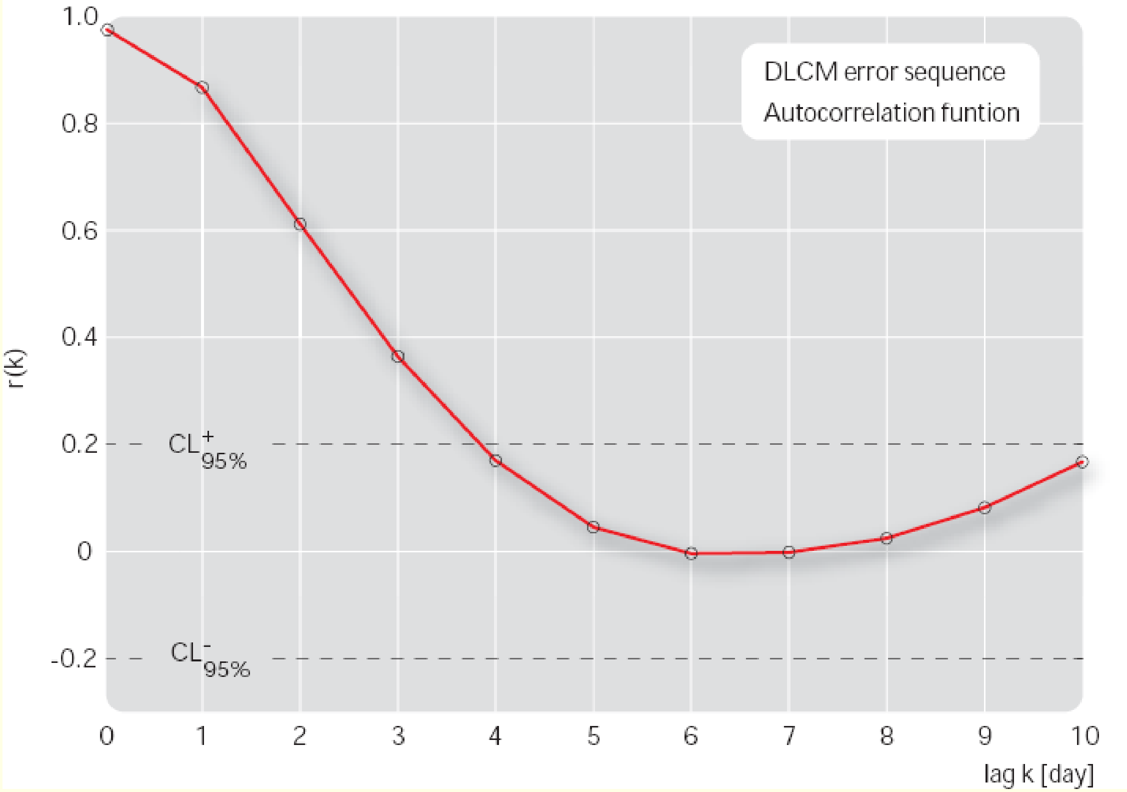
White Gaussian noise



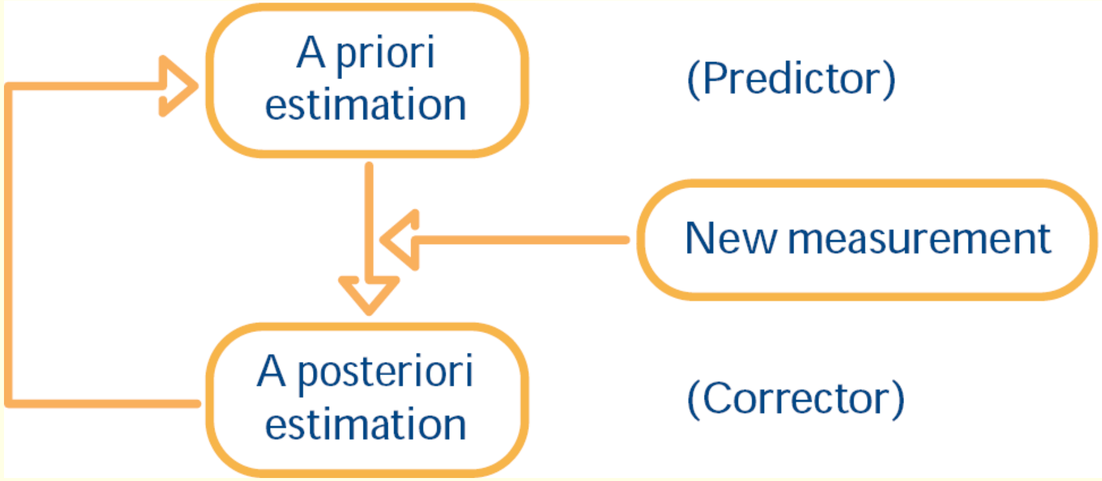
Red (Markovian) noise



Sample autocorrelation function of the DLC one-day-ahead error sequence showing Markovian characteristics

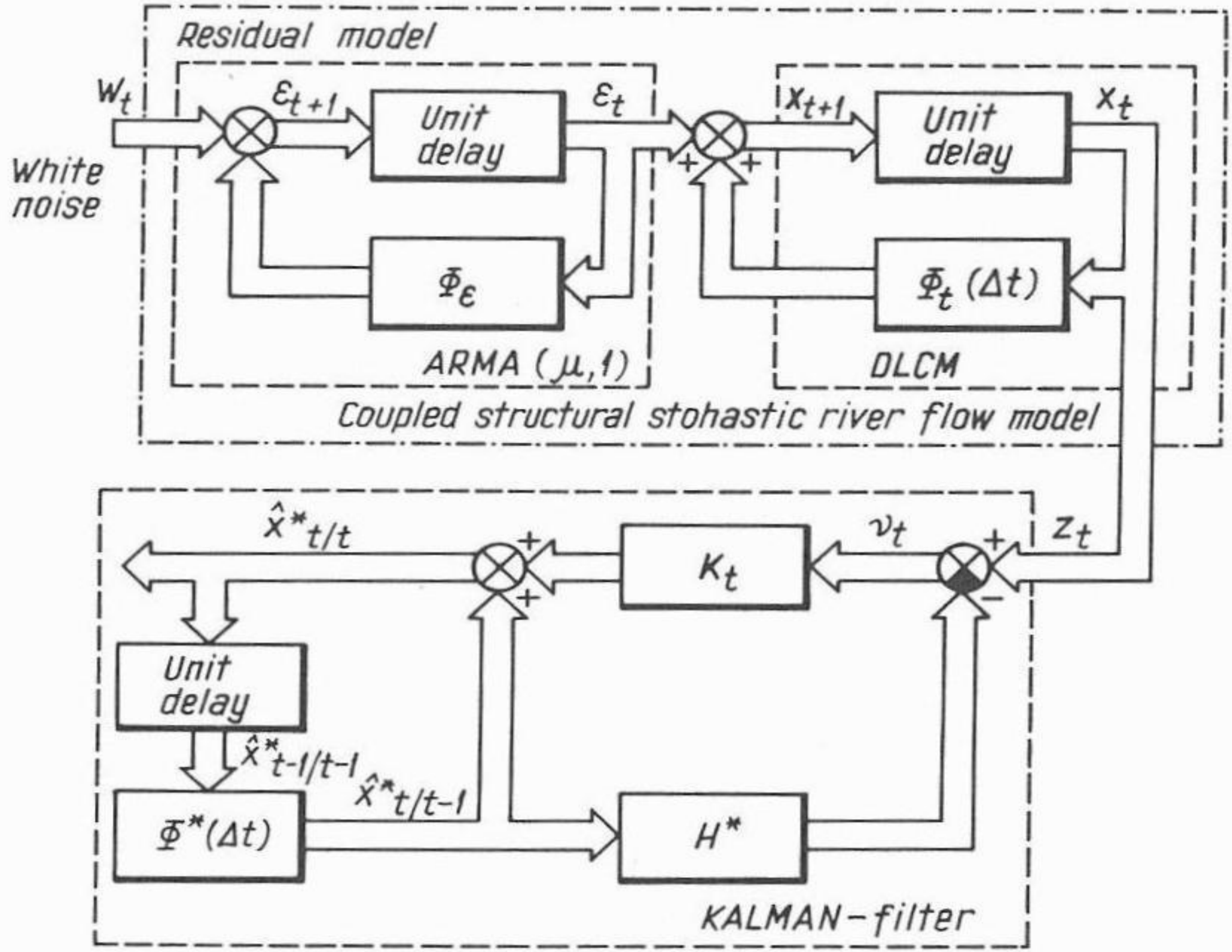


The Kalman filter also functions as a predictor–corrector algorithm connecting *a priori and a posteriori estimates through the information that is brought in by the new measurements*

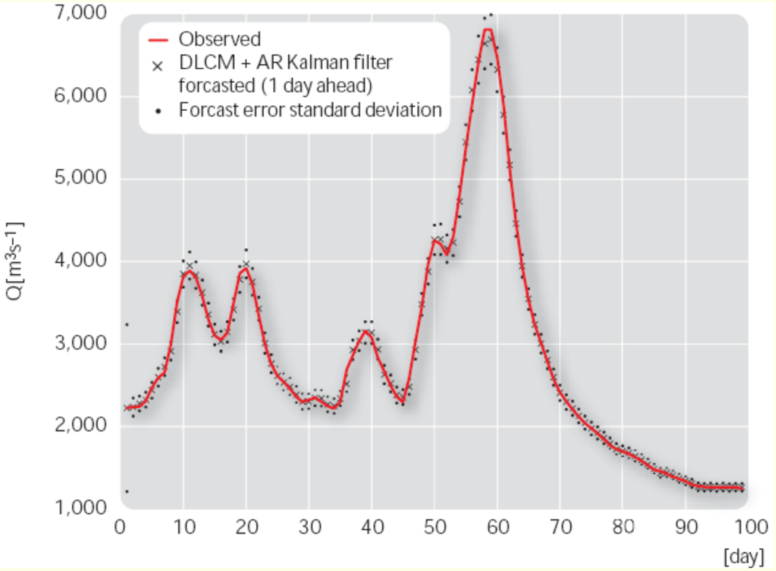


$$
\begin{aligned}
\overset{\wedge}{\mathbf{x}}{}^{*}_{t|t-\Delta t} &= \mathbf{\Phi}^{*}(\Delta t)\overset{\wedge}{\mathbf{x}}{}^{*}_{t-\Delta t|t-\Delta t} + \mathbf{\Gamma}^{*}(\Delta t)u_{t-\Delta t} \\
\mathbf{P}^{*}_{t|t-\Delta t} &= \mathbf{\Phi}^{*}(\Delta t)\mathbf{P}^{*}_{t-\Delta t|t-\Delta t}\mathbf{\Phi}^{*T}(\Delta t) + \mathbf{\Lambda}^{*}Q_{t-\Delta t}\mathbf{\Lambda}^{*T}
\end{aligned}
$$

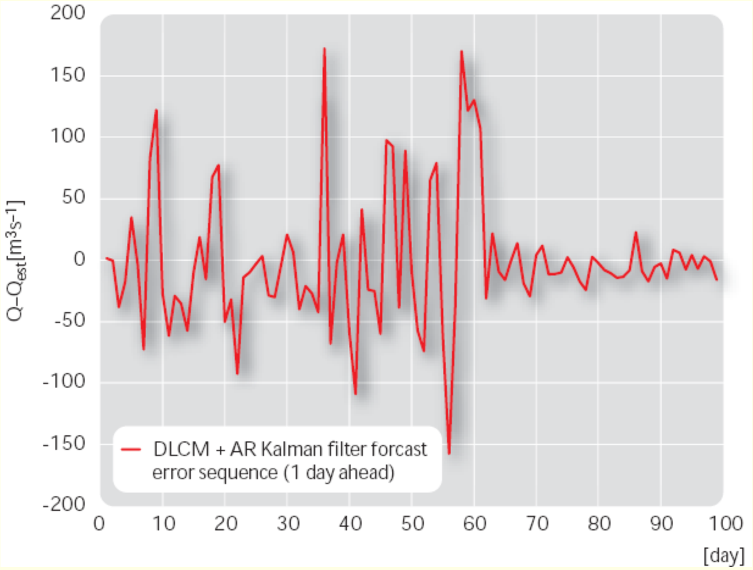
$$
\begin{aligned}
\mathbf{K}^{*}_{t} &= \mathbf{P}^{*}_{t|t-\Delta t}\mathbf{H}^{*T}[\mathbf{H}^{*}\mathbf{P}^{*}_{t|t-\Delta t}\mathbf{H}^{*T} + R_t]^{-1} \\
\overset{\wedge}{\mathbf{x}}{}^{*}_{t|t} &= \overset{\wedge}{\mathbf{x}}{}^{*}_{t|t-\Delta t} + \mathbf{K}^{*}_{t}[z_t - \mathbf{H}^{*}\overset{\wedge}{\mathbf{x}}{}^{*}_{t|t-\Delta t}] \\
\mathbf{P}^{*}_{t|t} &= [\mathbf{I}_{n+\mu} - \mathbf{K}^{*}_{t}\mathbf{H}^{*}]\mathbf{P}^{*}_{t|t-\Delta t}
\end{aligned}
$$


Residual model
W_t
White noise
ε_{t+1}
Unit delay
ε_t
Φ_ε
ARMA (μ,1)
x_{t+1}
Unit delay
x_t
$\Phi_t(\Delta t)$
DLCM
Coupled structural stohastic river flow model
$\hat{x}^*{t/t}$
K_t
ν_t
z_t
Unit delay
$\hat{x}^*{t-1/t-1}$
$\hat{x}^*{t/t-1}$
$\Phi^*(\Delta t)$
H^*
KALMAN-filter

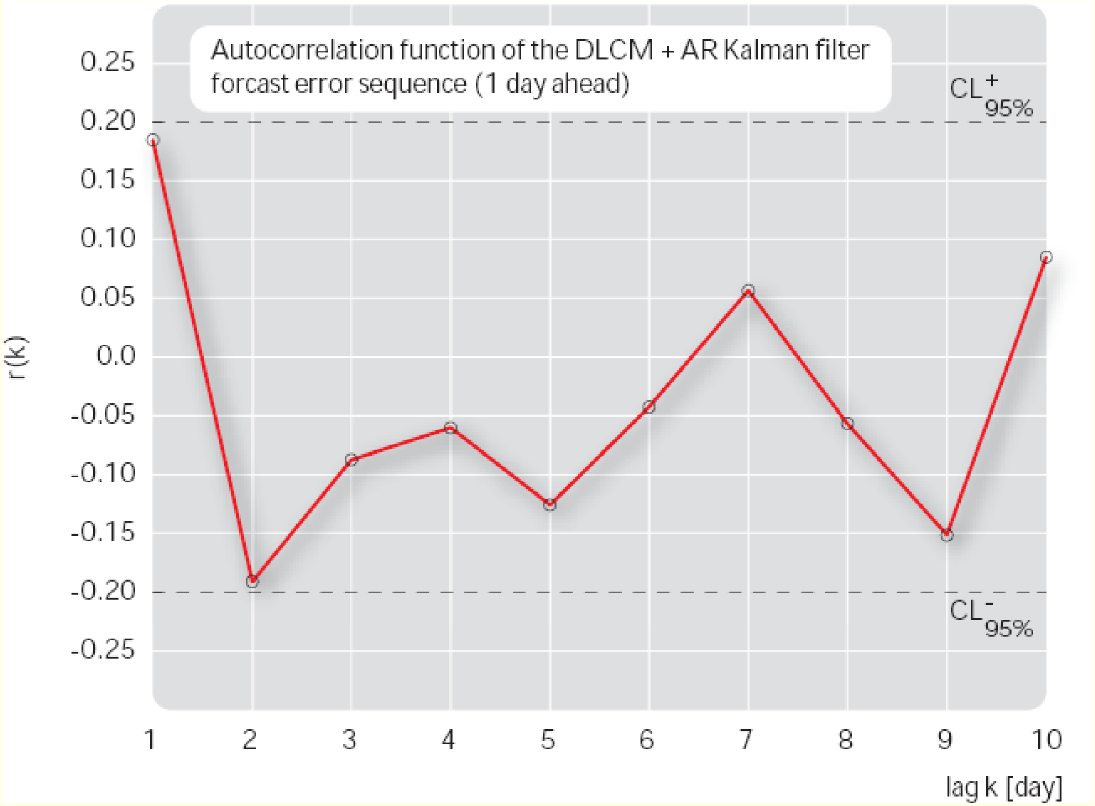
One-day-ahead forecasts of the Kalman-filtered DLCM structural and AR(1) autoregressive (stochastic) combined model with the forecast error standard deviation (+/- σ)



One-day-ahead forecast error sequence.



Autocorrelation function of the Kalman-filtered DLCM and AR(1) autoregressive combined model (White Gaussian Noise sequence at 95 % Confidence Level)



Where do we go from here?

LESSONS

Eight lessons learned:

- Firstly, a forecasting model should always encapsulate, even if in a strongly simplified manner, the physics of the processes involved.
- Secondly, a forecasting model should always encapsulate the treatment of the unavoidable uncertainties as well.
- Thirdly, the deterministic – structural part and the stochastic part, which describes the dynamics of the errors of the previous part, need to be coupled in combined forecasting models.

Eight lessons learned:

- Fourthly, forecasts are to be updated through error feedback whenever a new piece of relevant information becomes available.
- Fifthly, there is no unique forecasting model.
- Sixthly, there is no best forecasting model.
- Seventhly, in operational hydrological forecasting backup systems are always needed (see Murphy's extended relevant Laws).

Eight lessons learned:

- Eighthly, never fully trust your model but trust your oldest technician in the Forecasting Center. Models are excellent decision support tools, yet the human operator should never be excluded from the process of issuing forecast.

The Eight Laws of Hydrological Forecasting (Modified After Mr. Murphy)

§ 1 The flood always hits at Sunday 02:00 AM when there is nobody in the forecasting center.

§ 2 If § 1 does not apply than the flood comes when the staff is windsurfing on the nearby lake.

§ 3 If one is lucky one meets only once in a life time the flood that is greater than the design flood.

The Eight Laws of Hydrological Forecasting

§ 4 If one is unlucky this happens regularly.

§ 5 The 100-year return period flood returns every ten years minimum twice.

§ 6 When the Big Flood comes the on-line data collection system fails within minutes.

§ 7 When the Big Flood comes all our precious hardware breaks down in maximum *K* hours, where *K* is one fifth of the concentration time of the catchment.

The Eight Laws of Hydrological Forecasting

§ 8 The probability of the joint occurrence of unfixable computer bugs in the code of our forecasting model and the Big Flood is one.

Final lessons:

- Model development and usage is only a small fraction of the costs of establishing and running an operational hydrological forecasting system.
- Models play the same role as the heart does in the human body. Small but one just cannot live without them.

SO, WILL THERE BE ENOUGH WATER IN THE 21ST CENTURY?

IS MORE TECHNOLOGY THE ANSWER?

It is part of the answer only ….

We need to generate…

- **The political will** to … **DO IT**
- **The capacity** to … **DO IT RIGHT**
- **The resources** to … **DO IT RIGHT NOW**

17 Sustainable Development Goals

WATER CONNECTS THE SDGs