# Hydrometeorological Forecasting: Model Calibration and parameter Estimation Requirements


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*Center for Hydrometeorology and Remote Sensing*
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*The Abdus Salam ICPT Conference on:*

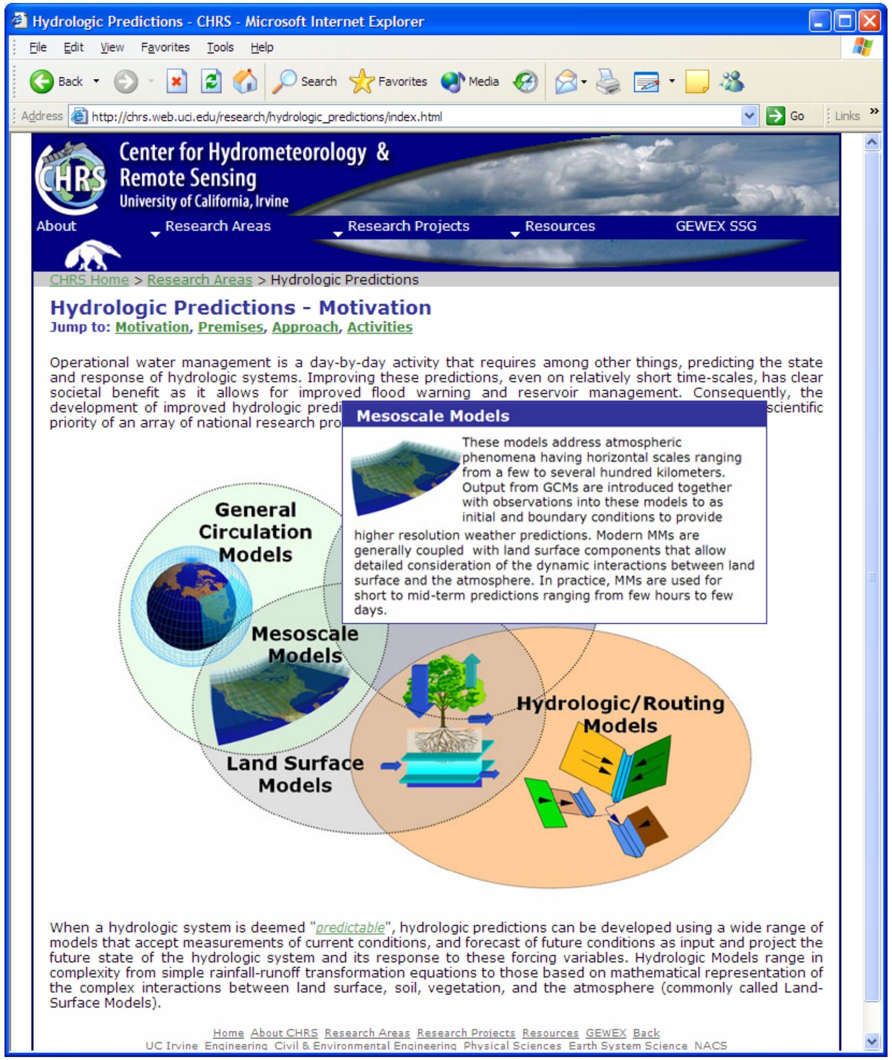
*Water Resources in Developing Countries: Planning & Management under Climate Change Scenario*

*Trieste, Italy: Apr. 27th- May 8th 2009*

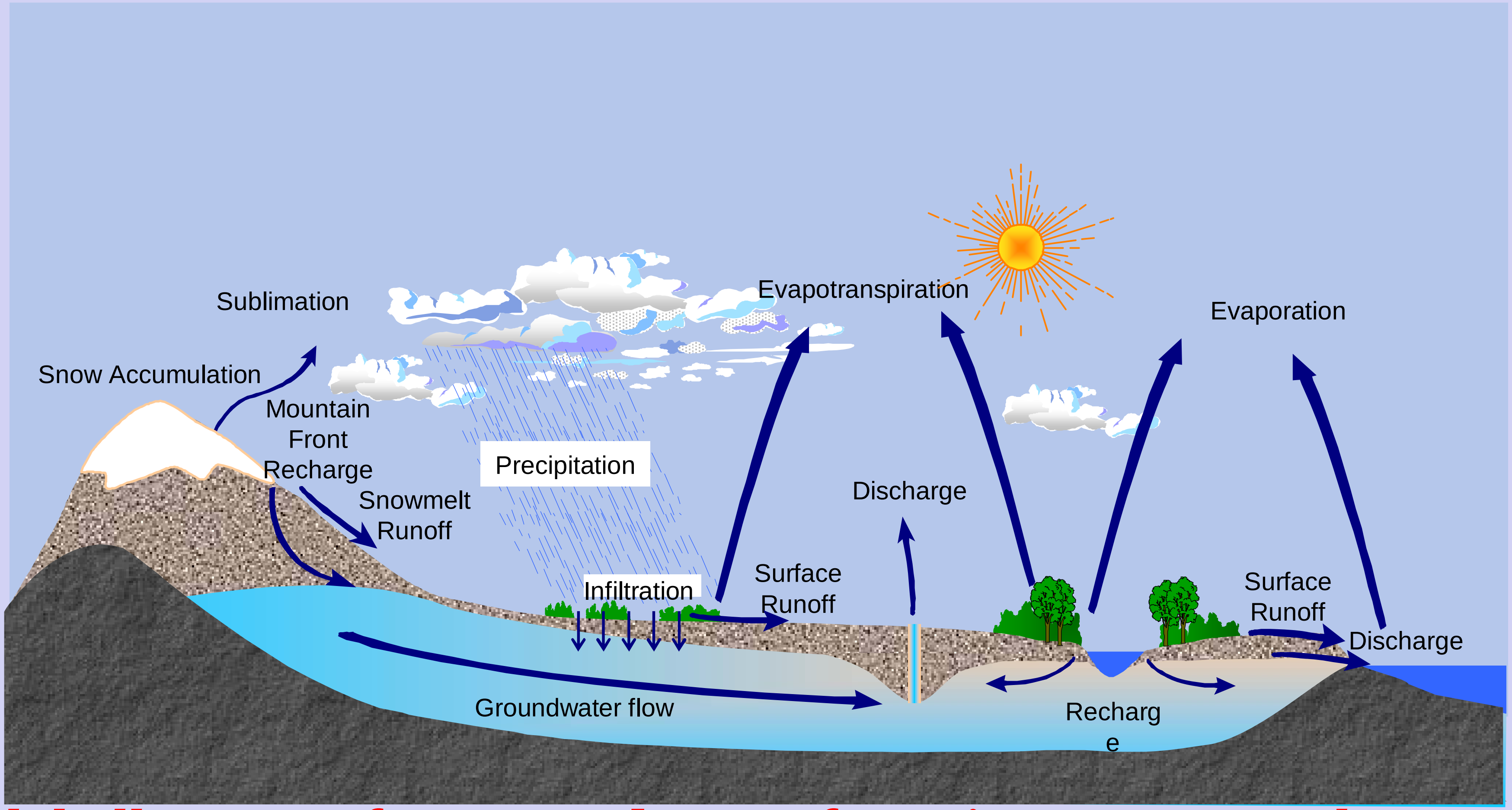
# CHRS & Affiliates: Faculty … University of California, Irvine (UCI) … International Team … University of Arizona (UA)

# SAHRA Web Site

# CHRS Web Site

# Studying the Hydrologic Cycle at Various Scales

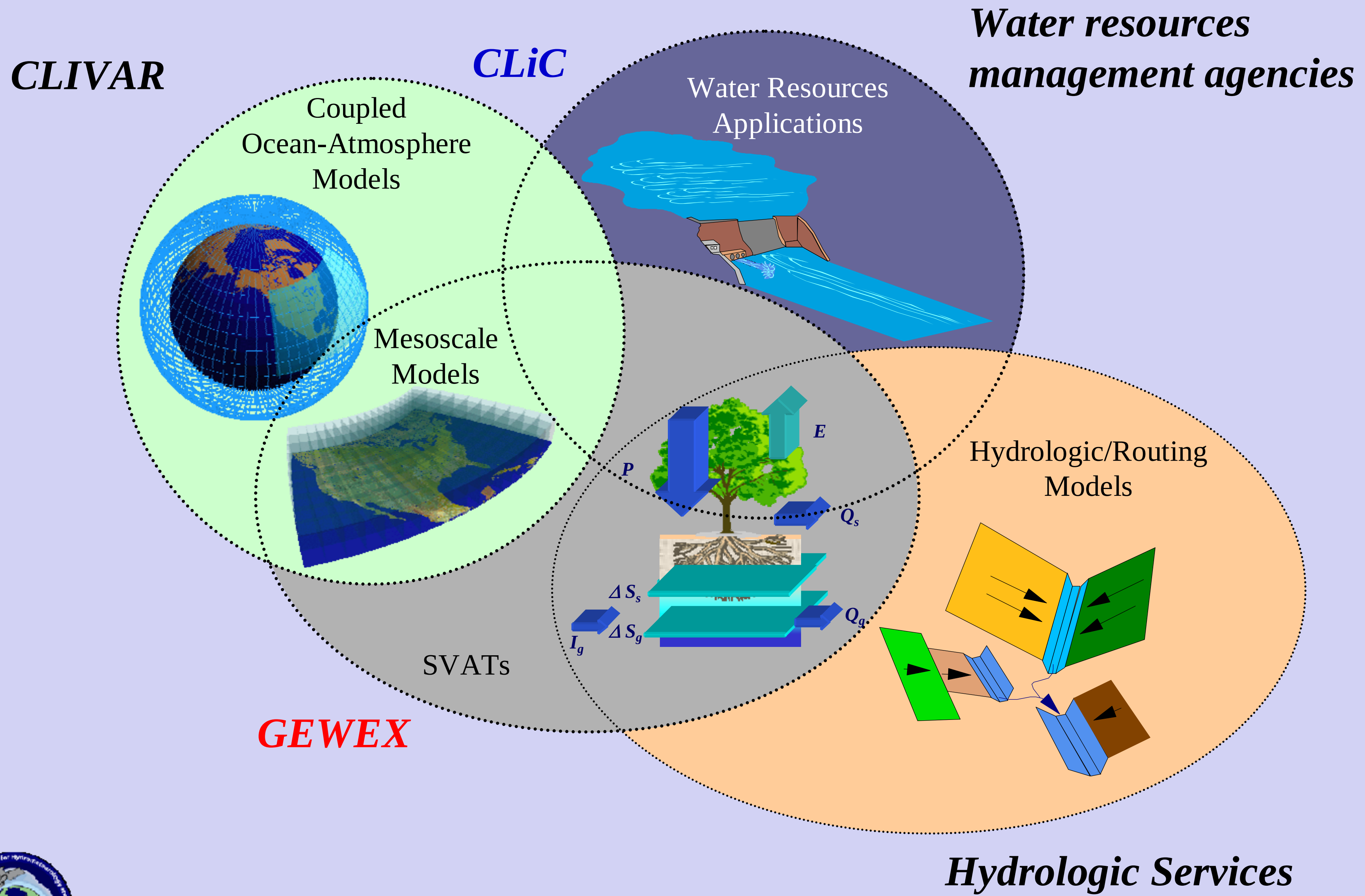



**Globally: 86% of Evap. and 78% of Precip. occur over the oceans**

# Hydrologically-Relevant Climate Variables

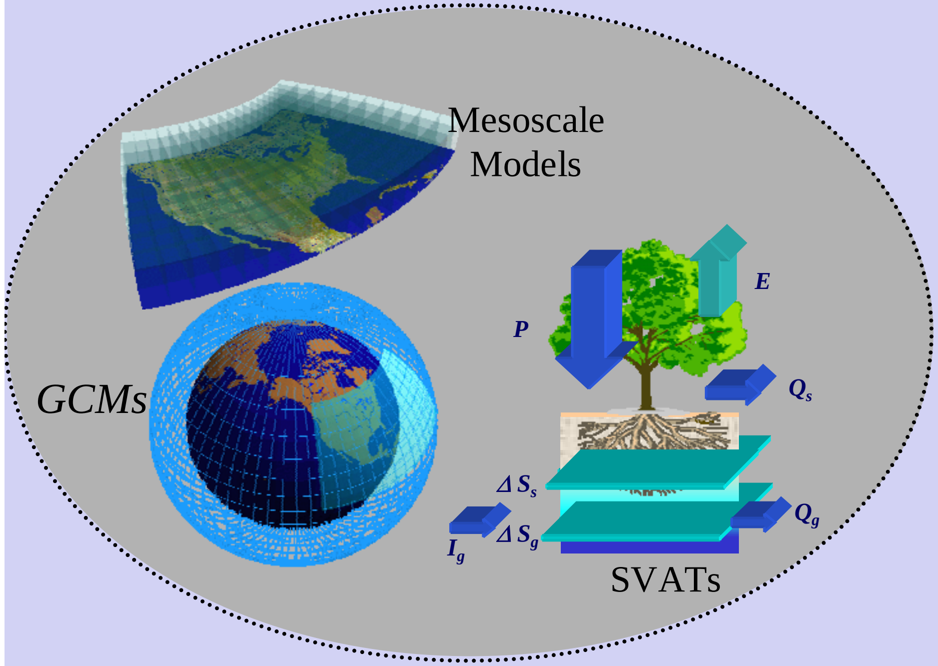
***Hydrologic predication requirements and how well are we satisfying them?***

# From the Global- to Watershed-Scale



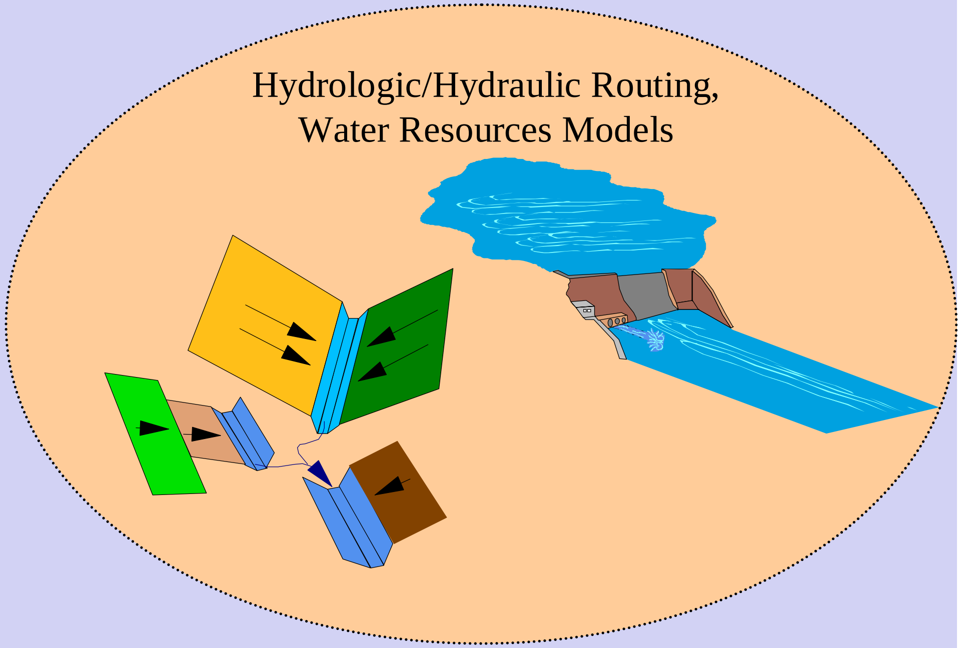
# Hydroclimate Science and Hydrologic/Water Resources Engineering

## SCIENCE




**Hydroclimate Science**

## ENGINEERING




**Hydrologic/Hydraulic and Water Resources Engineering**

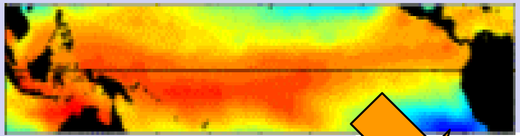
# Example of Prediction: Seasonal to inter-annual

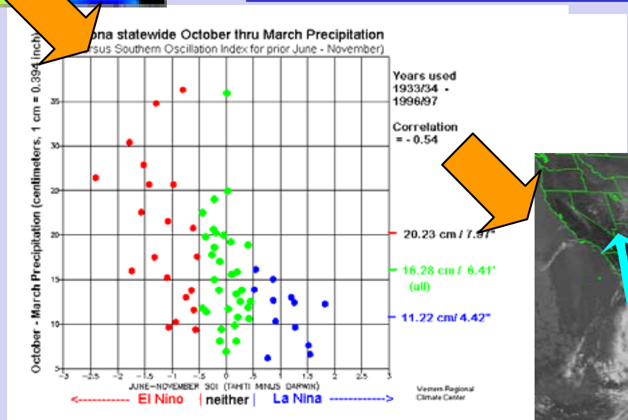
*From climate prediction*

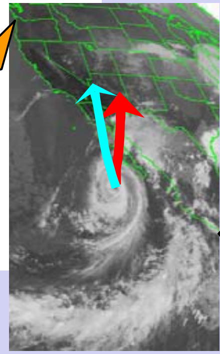
*Decisions*

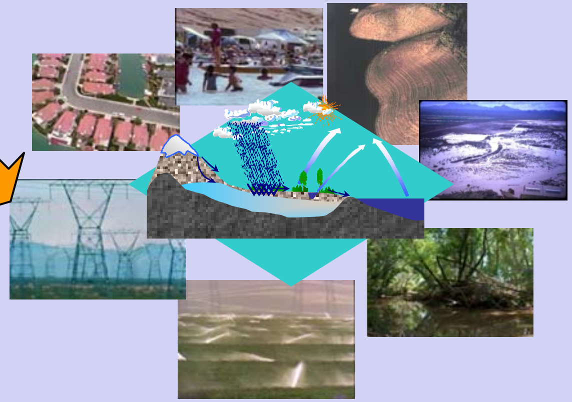
*To Weather predict: the actual event*

*To impact on water resources*



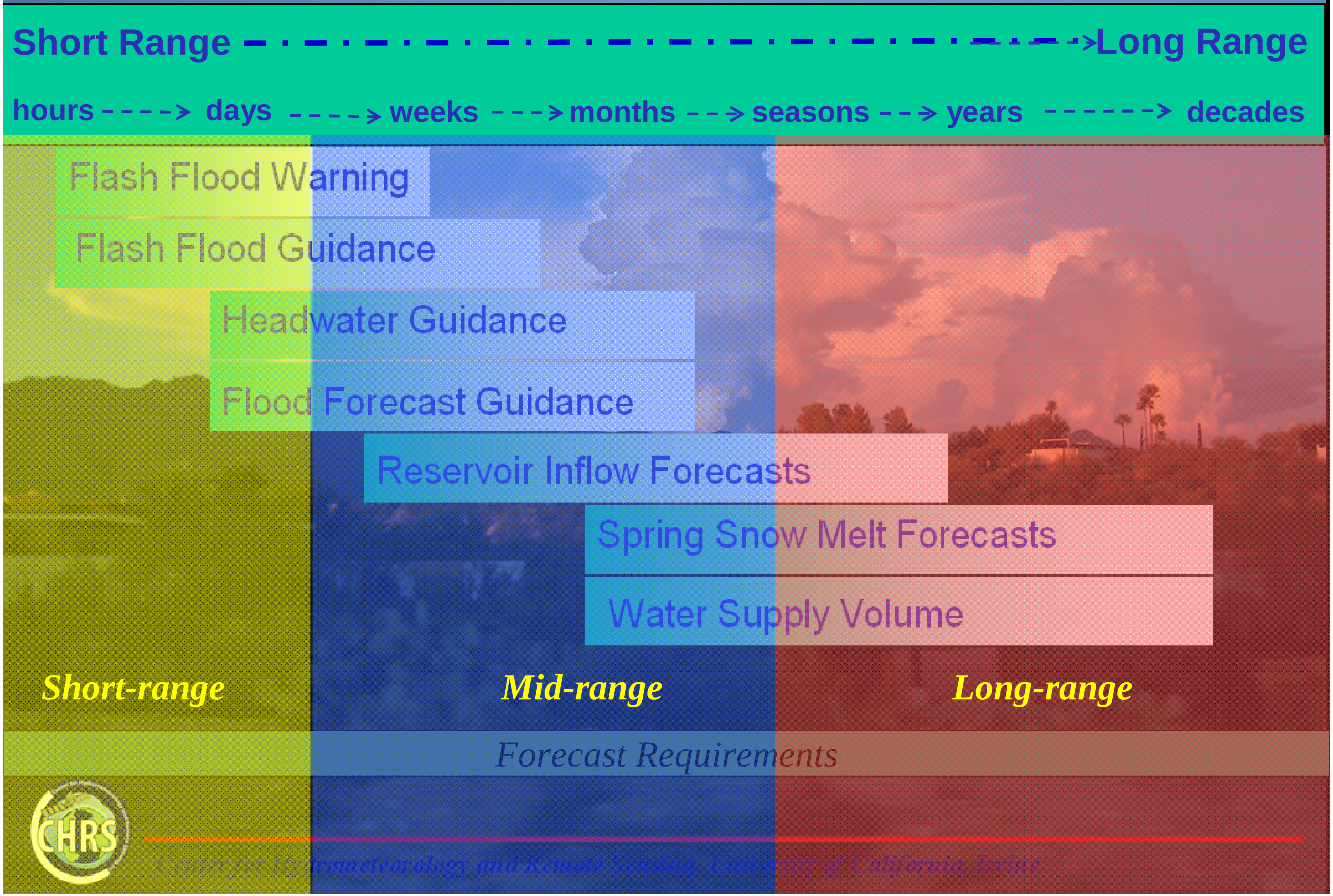


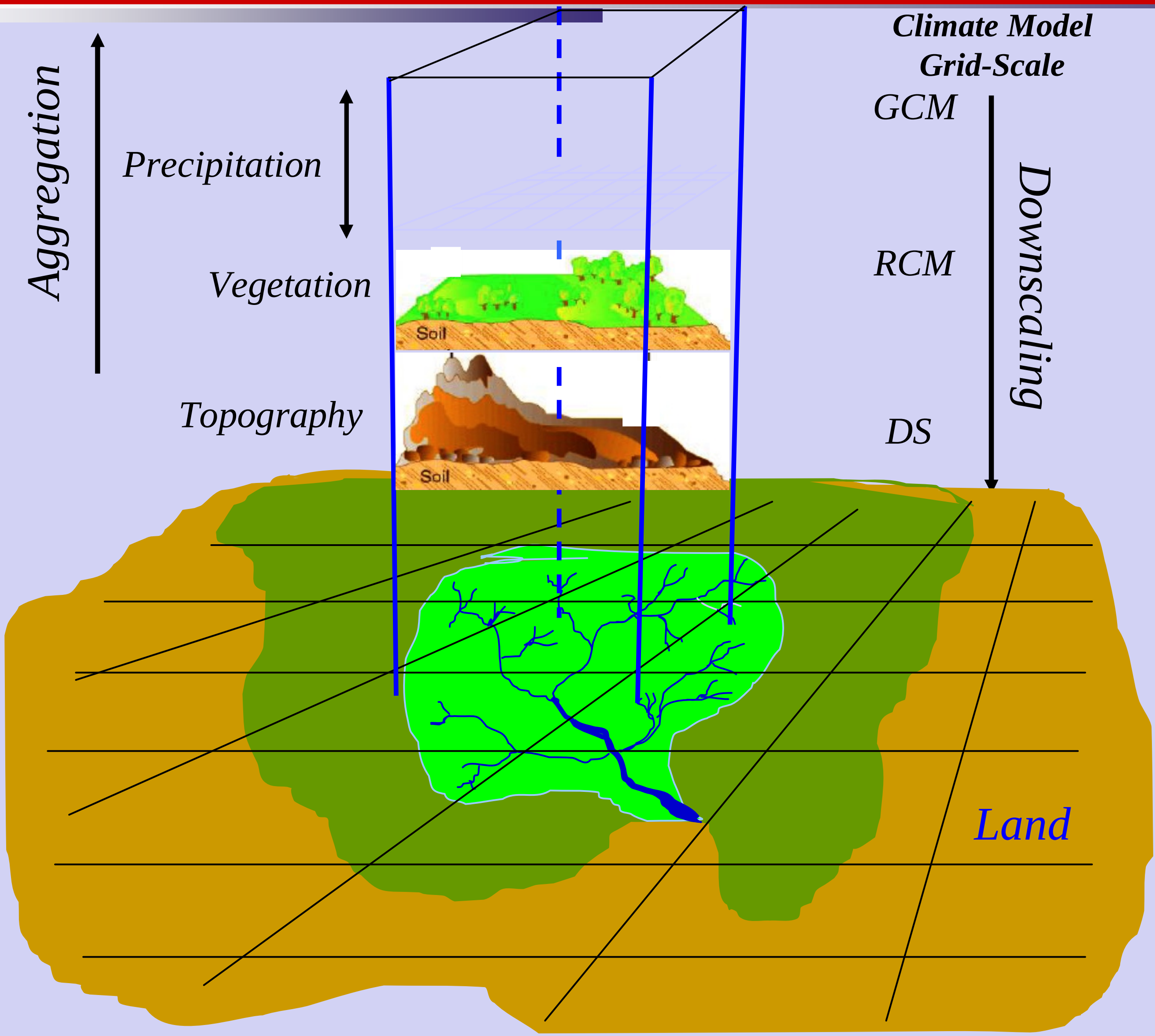


*Source: S. Sorooshian* ***GEWEX-SSG***

# *Required Hydrometeorologic Predictions*

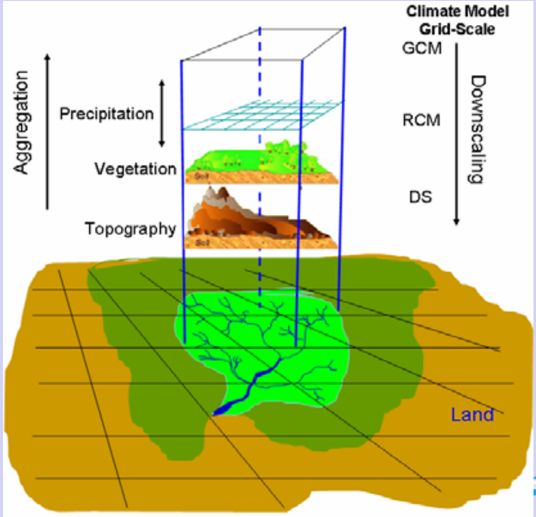


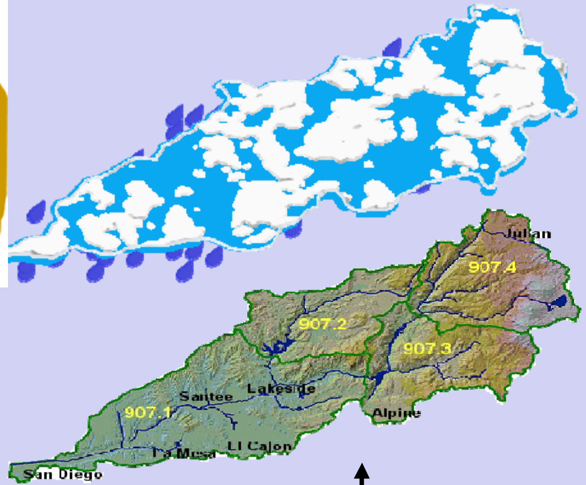
# Climate Model Downscaling to watershed Scale

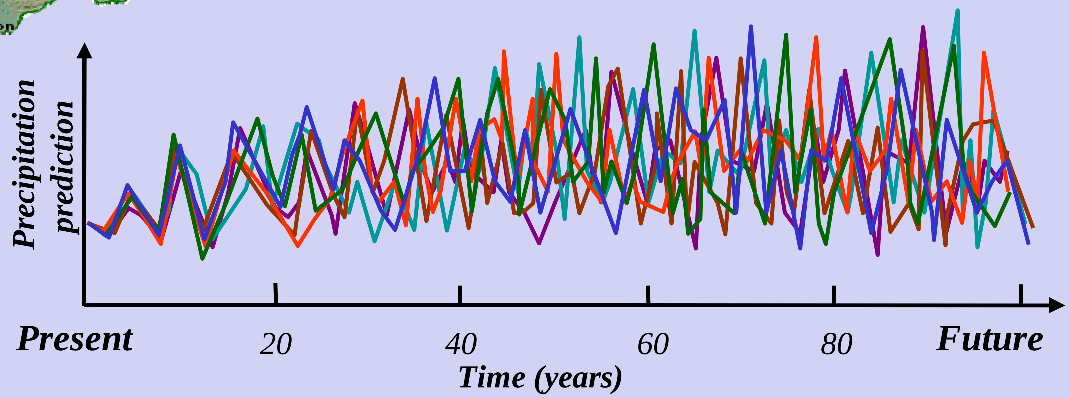


# Climate Model Downscaling to watershed Scale

## *Generation of Future Precipitation Scenarios*

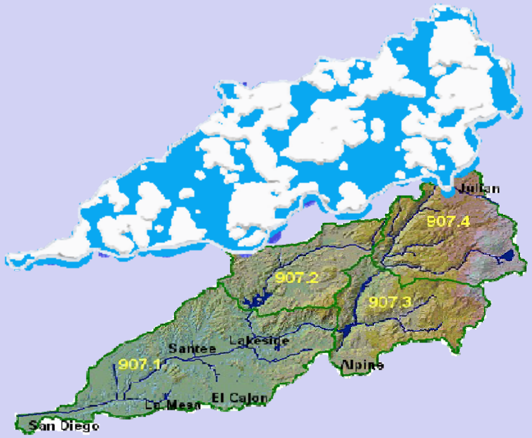


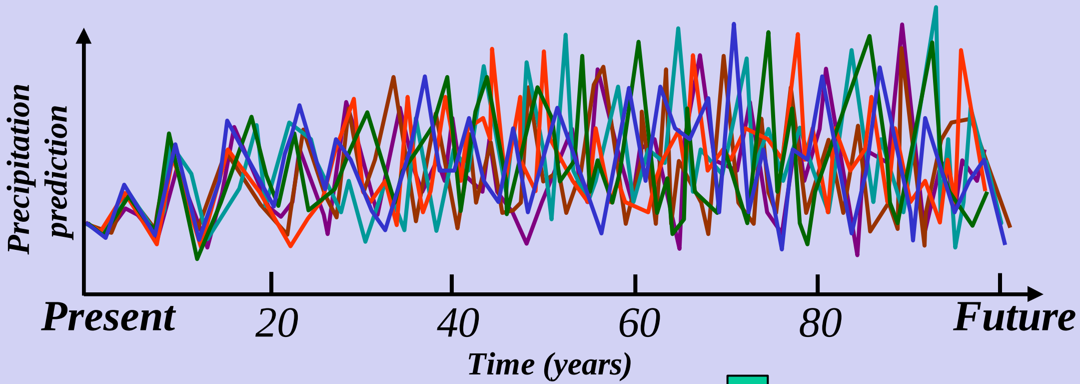



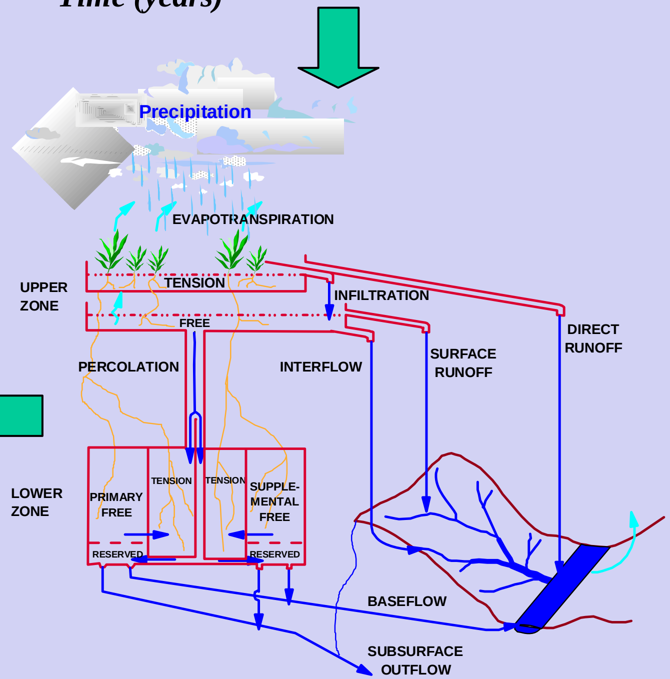



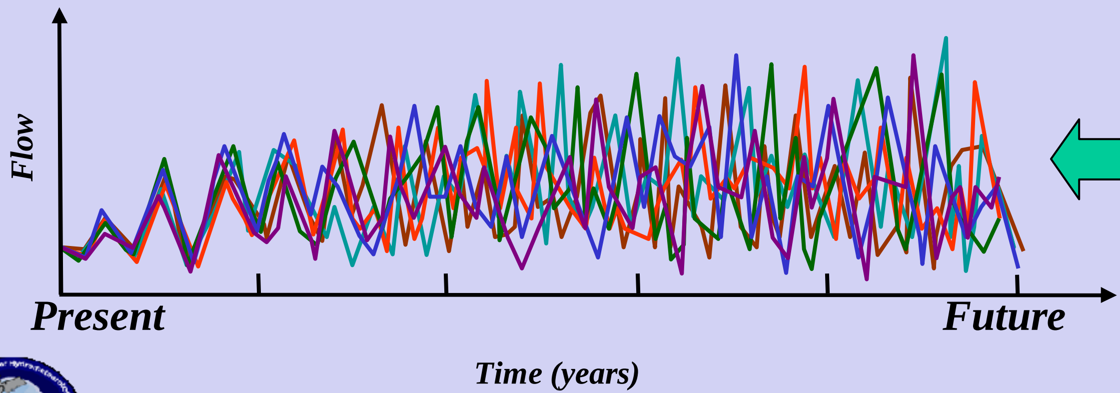
# Downscaled Precipitation to Runoff Generation

## Generation of Future Runoff Scenarios




# *Brief Review of Rainfall Runoff modeling:*

# *Progress in Hydrologic Modeling*

# Hydrologic Modeling Challenges

<u>Continental Scale:</u>

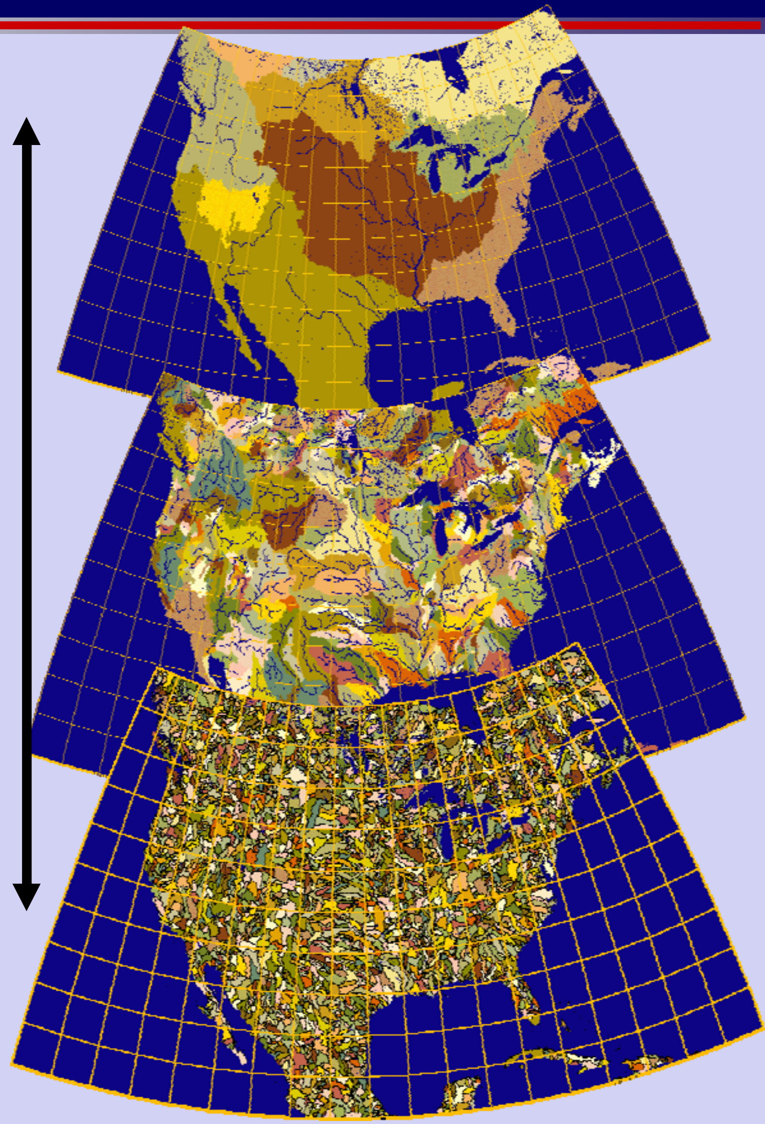
***Focus of Hydro-Climate modelers***

*Different Scales*
*Different Issues*
*Different Stakeholders*

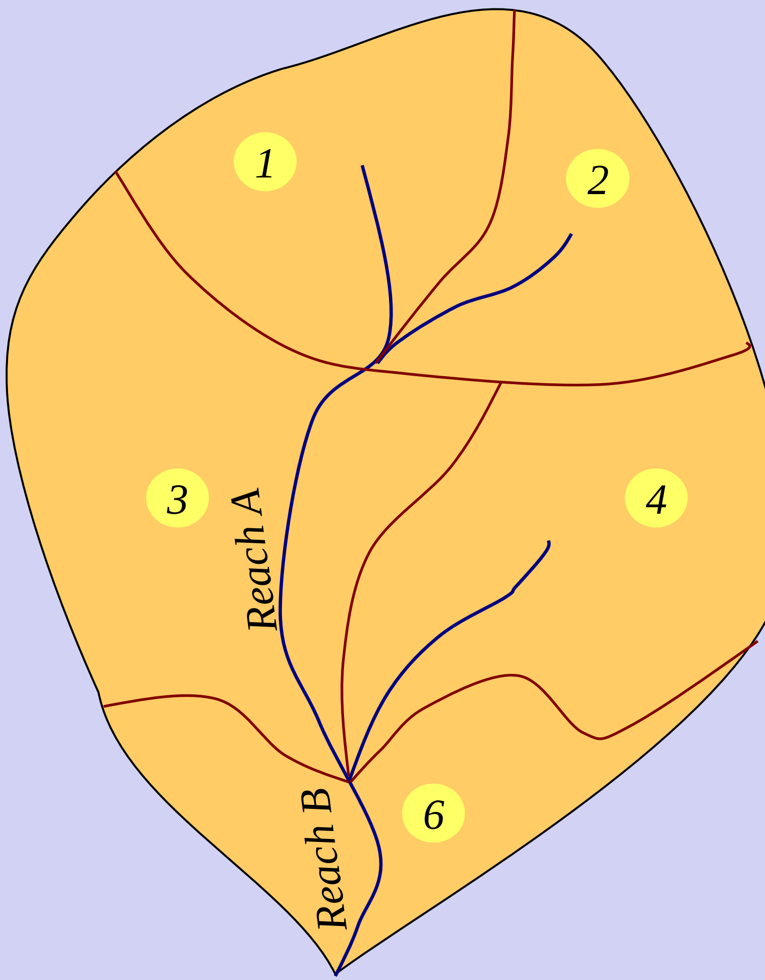
<u>Watershed Scale</u>:

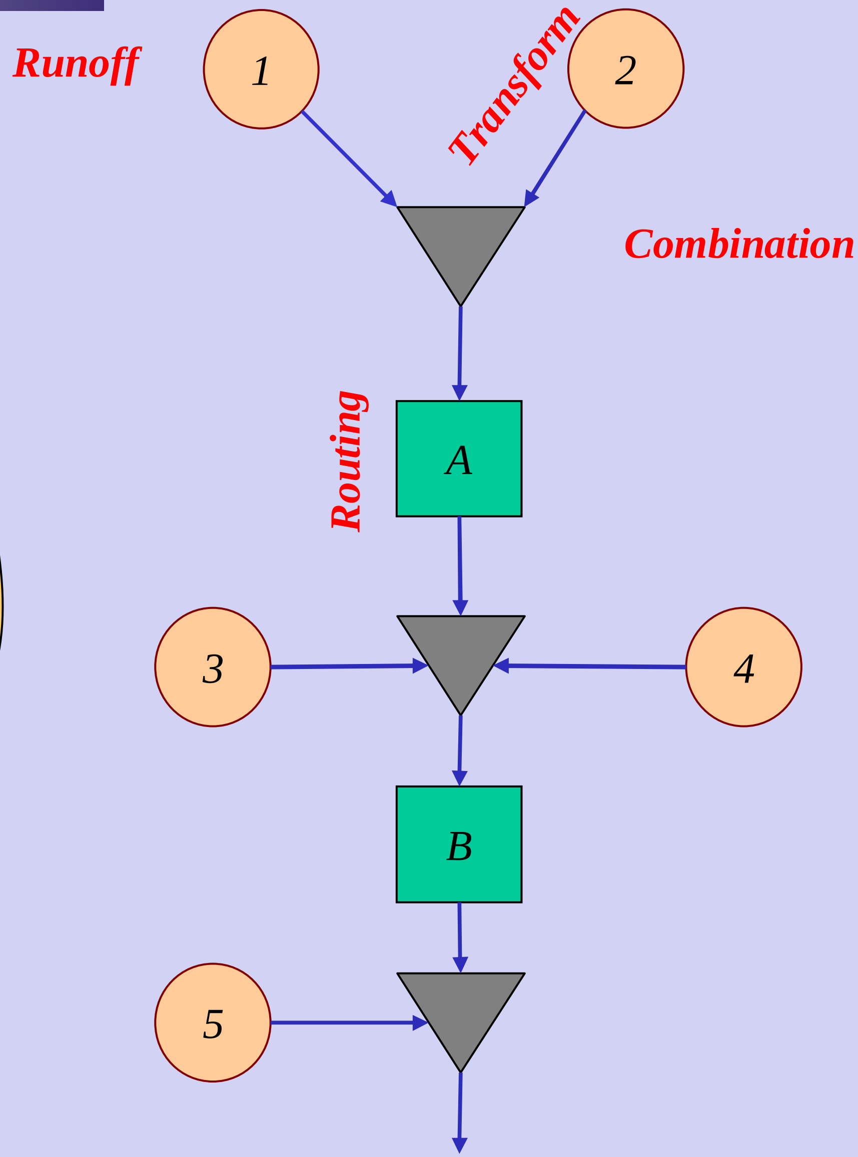
***Focus of Hydro-Met. Modeling***

***Where hydrology happens***

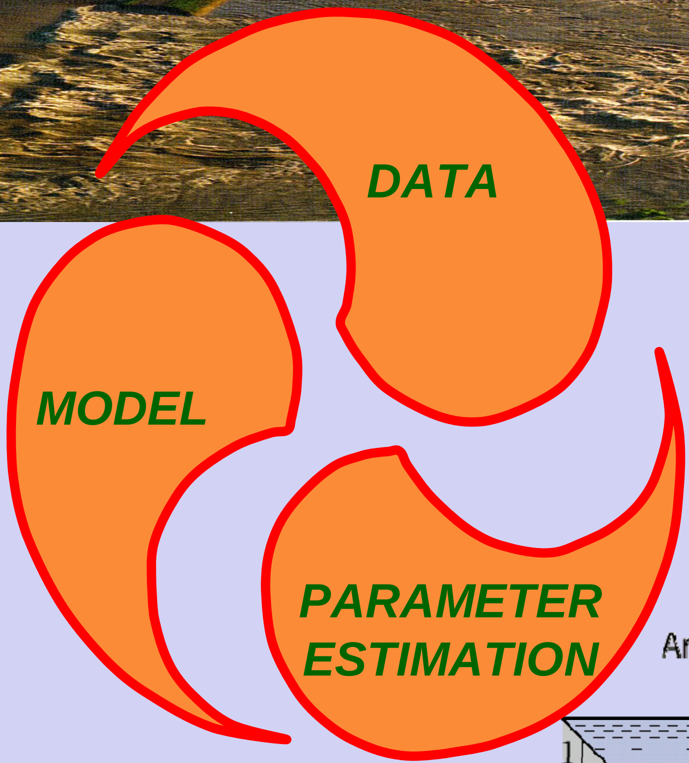


# “Semi-distributed” Hydrologic Models

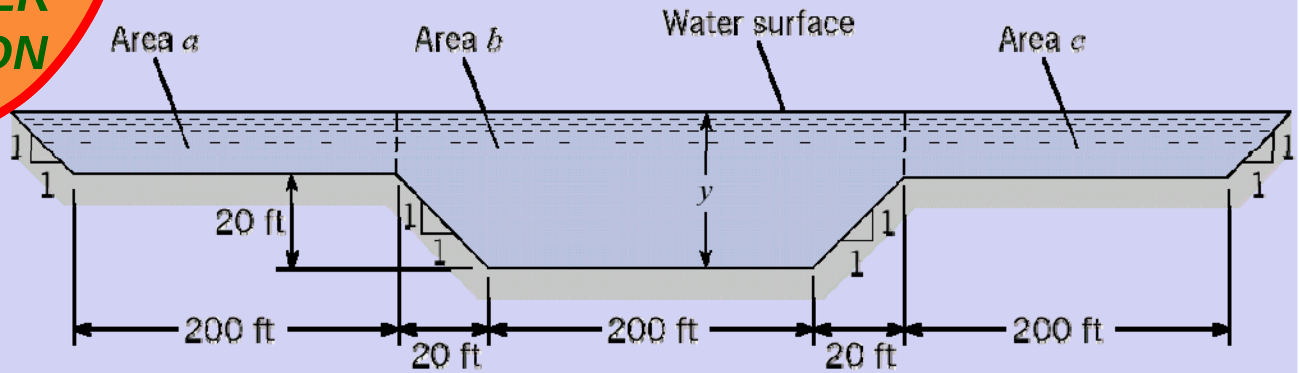


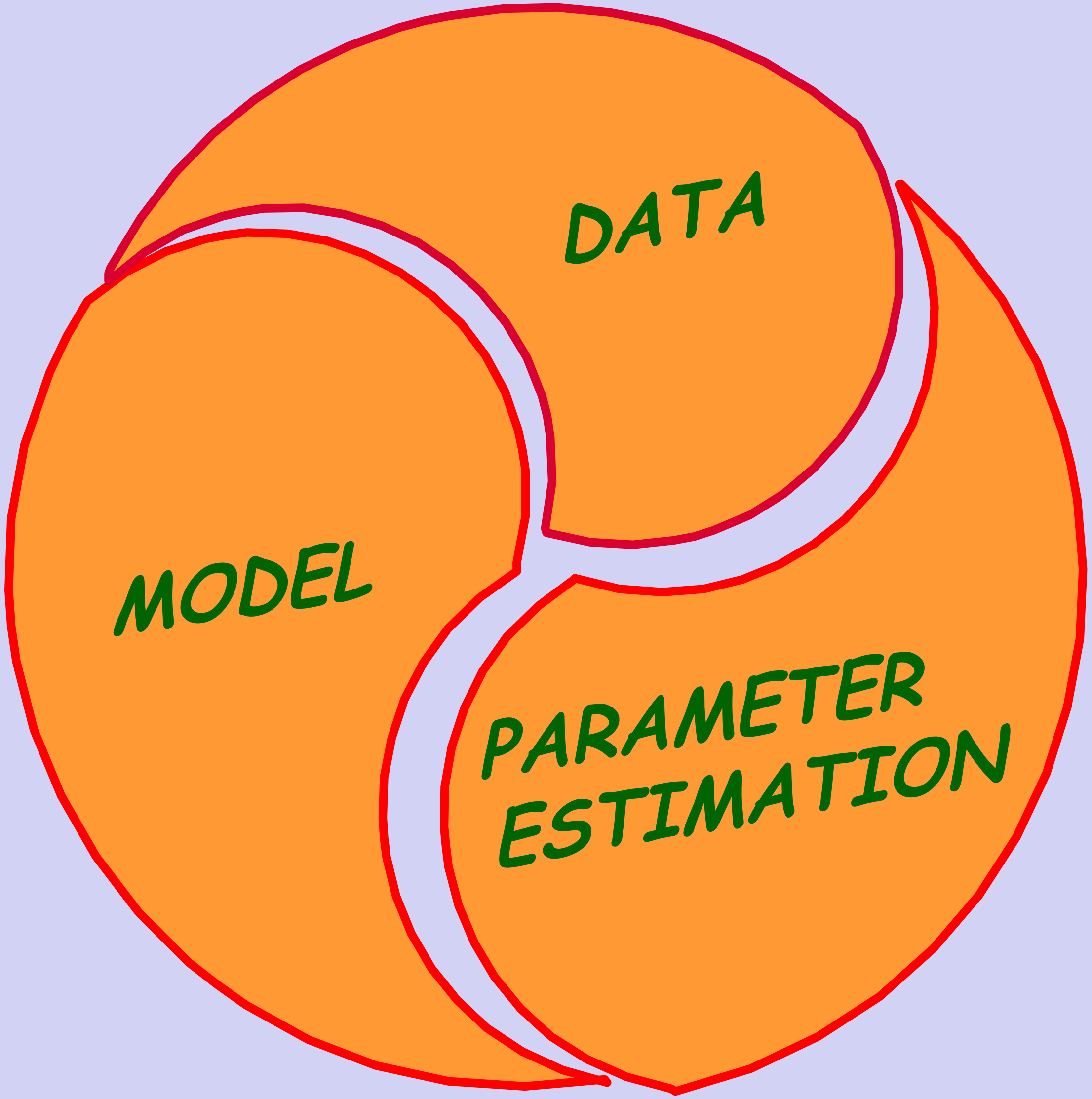
# *Hydrologic Modeling:   3 Elements!*



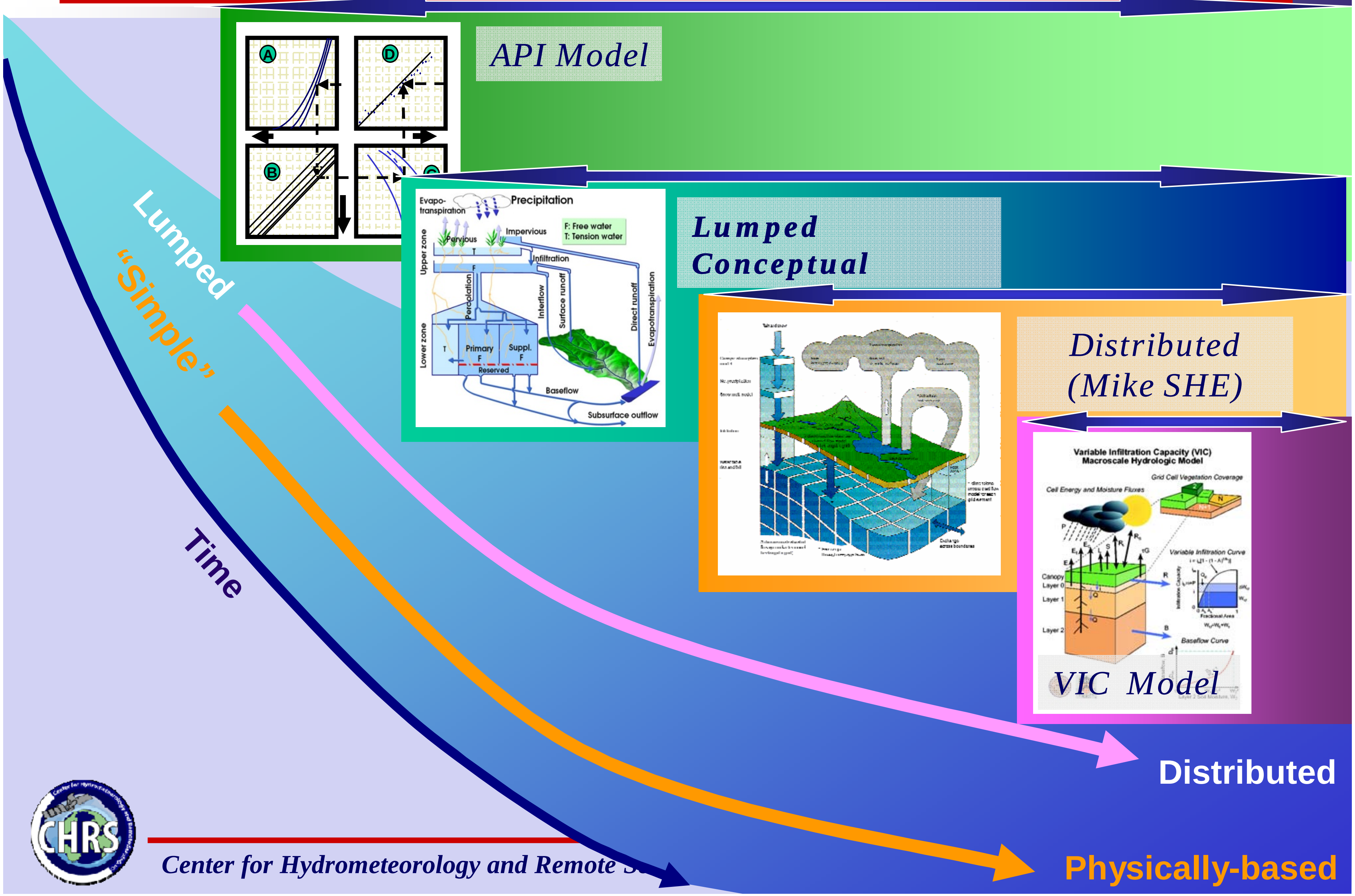

**If the "World" of Watershed Hydrology Was Perfect!**



# Hydrologic Modeling

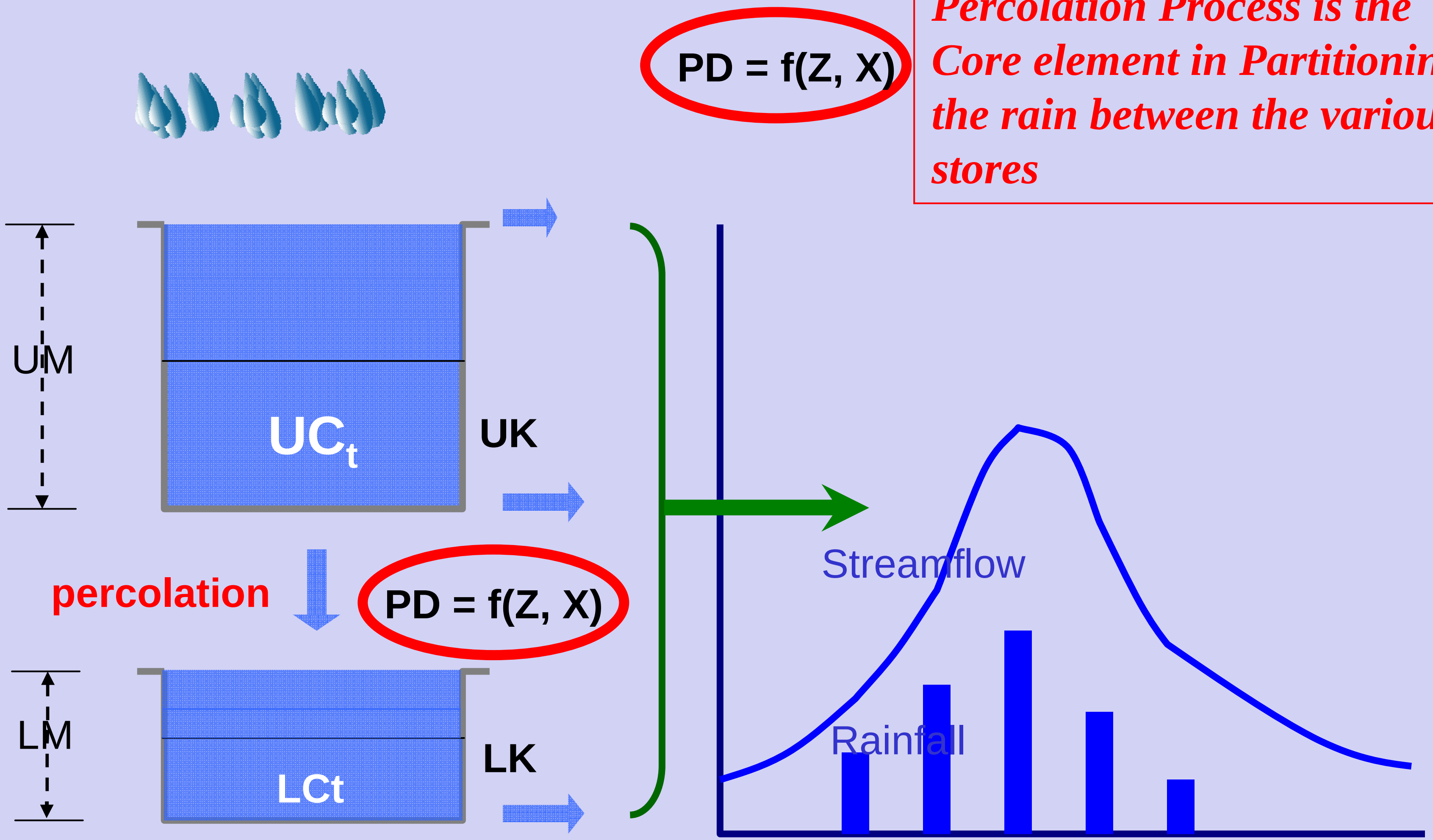


# Evolution of Hydrologic R-R Models

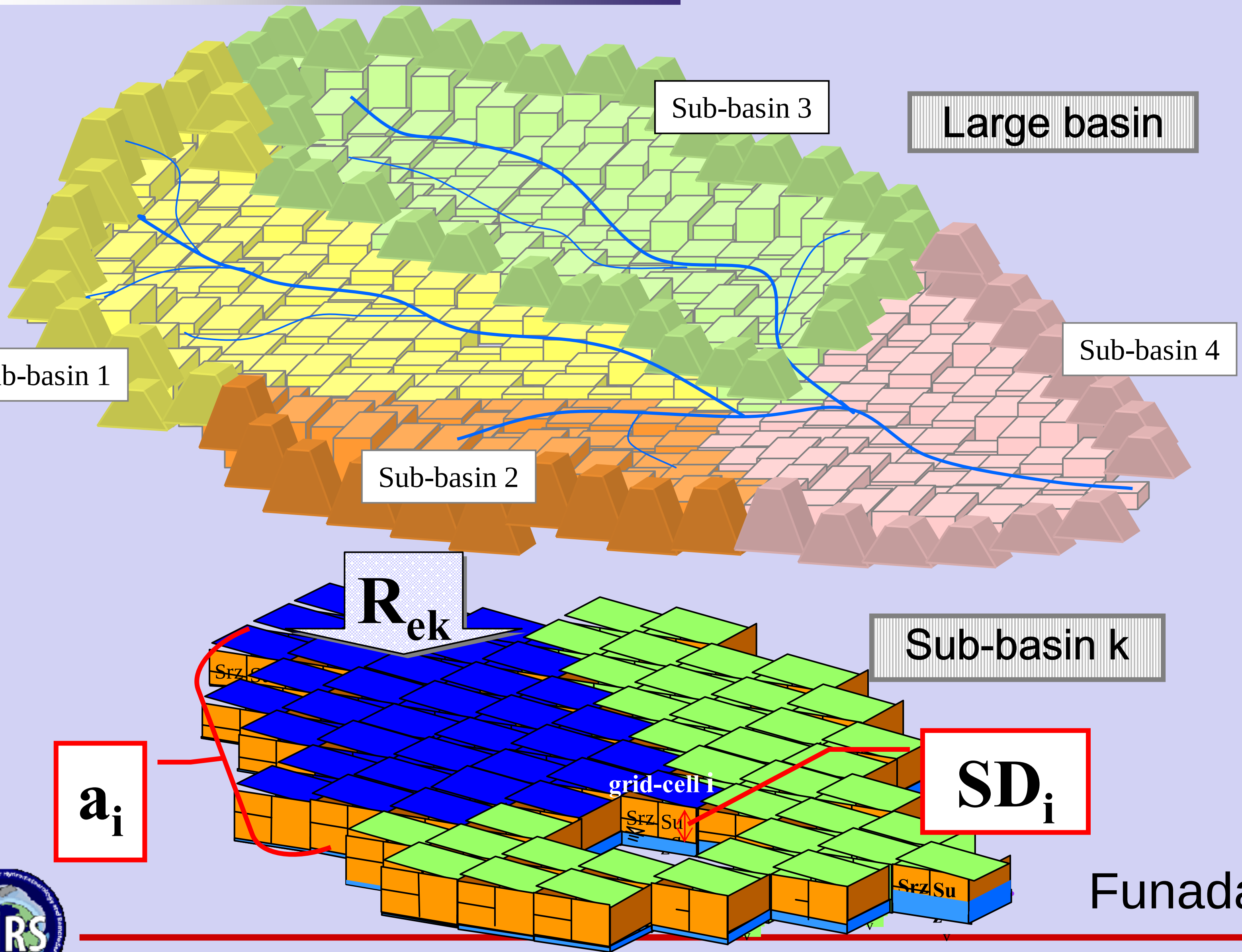


# *A look into the "heart" of R-R Models*

*Percolation Process is the Core element in Partitioning the rain between the various stores*



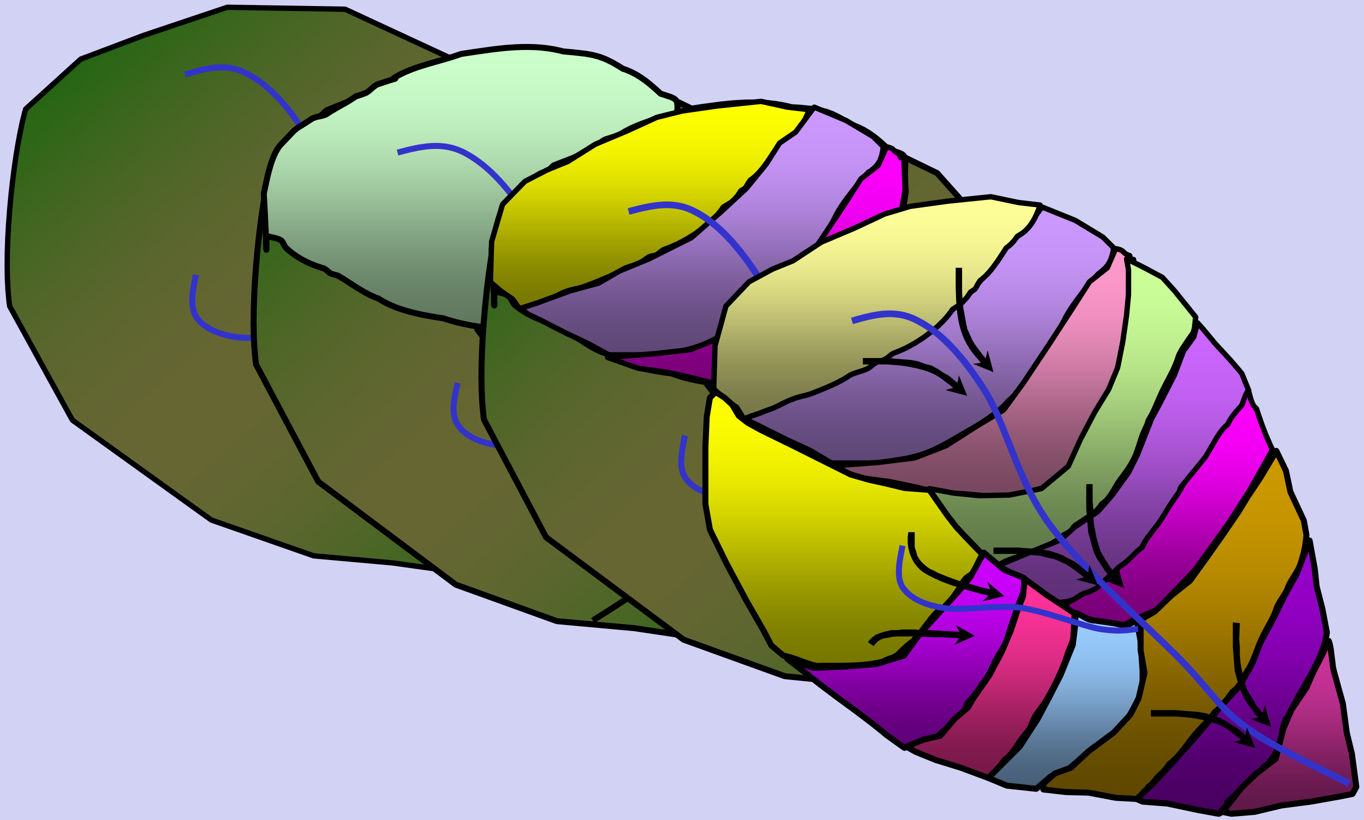
# Example of Distributed Model Appl. in large Basins



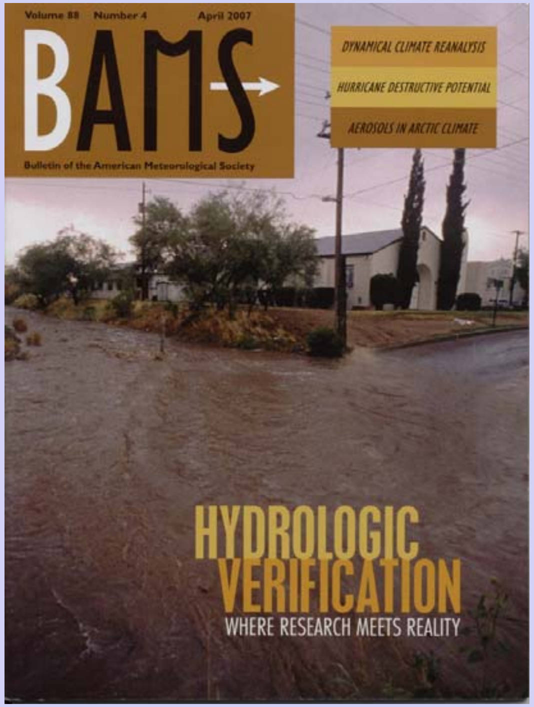

Funada, 2004

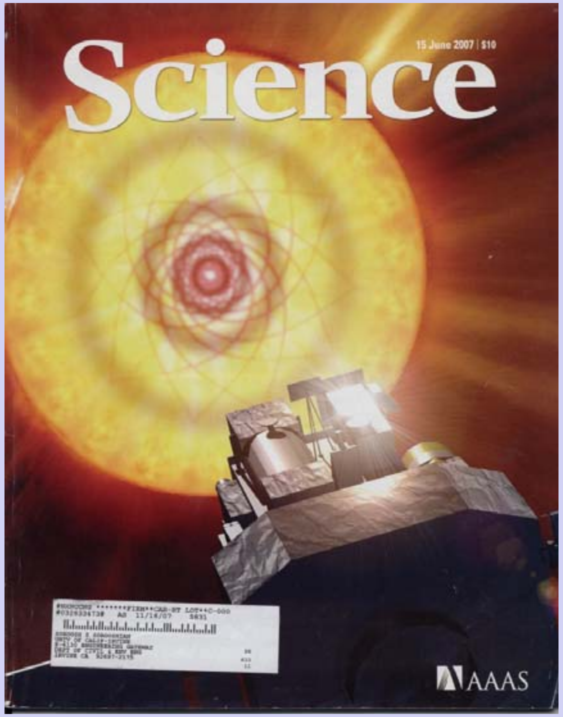
# Alternative Approach to a Fully Distributed Approach

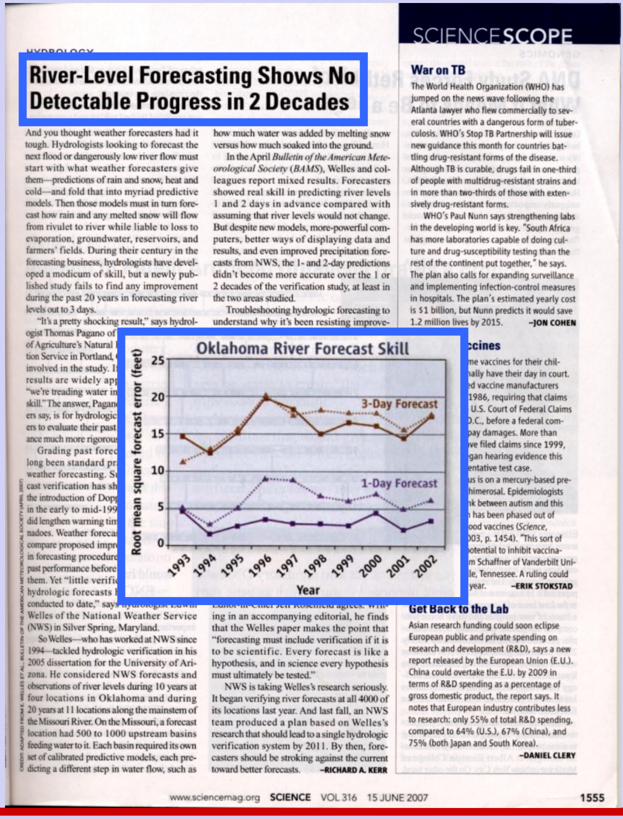
## Segmentation Strategy



# Status of Forecast Skill in Hydrologic Models




HYDROLOGY

## River-Level Forecasting Shows No Detectable Progress in 2 Decades

And you thought weather forecasters had it tough. Hydrologists looking to forecast the next flood or dangerously low river flow must start with what weather forecasters give them—predictions of rain and snow, heat and cold—and fold that into myriad predictive models. Then those models must in turn forecast how rain and any melted snow will flow from rivulet to river while liable to loss to evaporation, groundwater, reservoirs, and farmers' fields. During their century in the forecasting business, hydrologists have developed a modicum of skill, but a newly published study fails to find any improvement during the past 20 years in forecasting river levels out to 3 days.

"It's a pretty shocking result," says hydrologist Thomas Pagano of ... of Agriculture's Natural ... tion Service in Portland, ... involved in the study. I... results are widely app... "we're treading water in ... skill." The answer, Pagan... ers say, is for hydrologic... ers to evaluate their past ... ance much more rigorous...

Grading past forec... long been standard pr... weather forecasting. S... cast verification has sh... the introduction of Dopp... in the early to mid-199... did lengthen warning tim... nadoes. Weather forecas... compare proposed impr... in forecasting procedure... past performance before ... them. Yet "little verific... hydrologic forecasts h... conducted to date," says hydrologist Edwin Welles of the National Weather Service (NWS) in Silver Spring, Maryland.

So Welles—who has worked at NWS since 1994—tackled hydrologic verification in his 2005 dissertation for the University of Arizona. He considered NWS forecasts and observations of river levels during 10 years at four locations in Oklahoma and during 20 years at 11 locations along the mainstem of the Missouri River. On the Missouri, a forecast location had 500 to 1000 upstream basins feeding water to it. Each basin required its own set of calibrated predictive models, each predicting a different step in water flow, such as how much water was added by melting snow versus how much soaked into the ground.

In the April *Bulletin of the American Meteorological Society* (*BAMS*), Welles and colleagues report mixed results. Forecasters showed real skill in predicting river levels 1 and 2 days in advance compared with assuming that river levels would not change. But despite new models, more-powerful computers, better ways of displaying data and results, and even improved precipitation forecasts from NWS, the 1- and 2-day predictions didn't become more accurate over the 1 or 2 decades of the verification study, at least in the two areas studied.

Troubleshooting hydrologic forecasting to understand why it's been resisting improve-...

... ing in an accompanying editorial, he finds that the Welles paper makes the point that "forecasting must include verification if it is to be scientific. Every forecast is like a hypothesis, and in science every hypothesis must ultimately be tested."

NWS is taking Welles's research seriously. It began verifying river forecasts at all 4000 of its locations last year. And last fall, an NWS team produced a plan based on Welles's research that should lead to a single hydrologic verification system by 2011. By then, forecasters should be stroking against the current toward better forecasts. —RICHARD A. KERR

CREDIT: ADAPTED FROM E. WELLES ET AL., BULLETIN OF THE AMERICAN METEOROLOGICAL SOCIETY (APRIL 2007)

SCIENCESCOPE

### War on TB

The World Health Organization (WHO) has jumped on the news wave following the Atlanta lawyer who flew commercially to several countries with a dangerous form of tuberculosis. WHO's Stop TB Partnership will issue new guidance this month for countries battling drug-resistant forms of the disease. Although TB is curable, drugs fail in one-third of people with multidrug-resistant strains and in more than two-thirds of those with extensively drug-resistant forms.

WHO's Paul Nunn says strengthening labs in the developing world is key. "South Africa has more laboratories capable of doing culture and drug-susceptibility testing than the rest of the continent put together," he says. The plan also calls for expanding surveillance and implementing infection-control measures in hospitals. The plan's estimated yearly cost is $1 billion, but Nunn predicts it would save 1.2 million lives by 2015. —JON COHEN

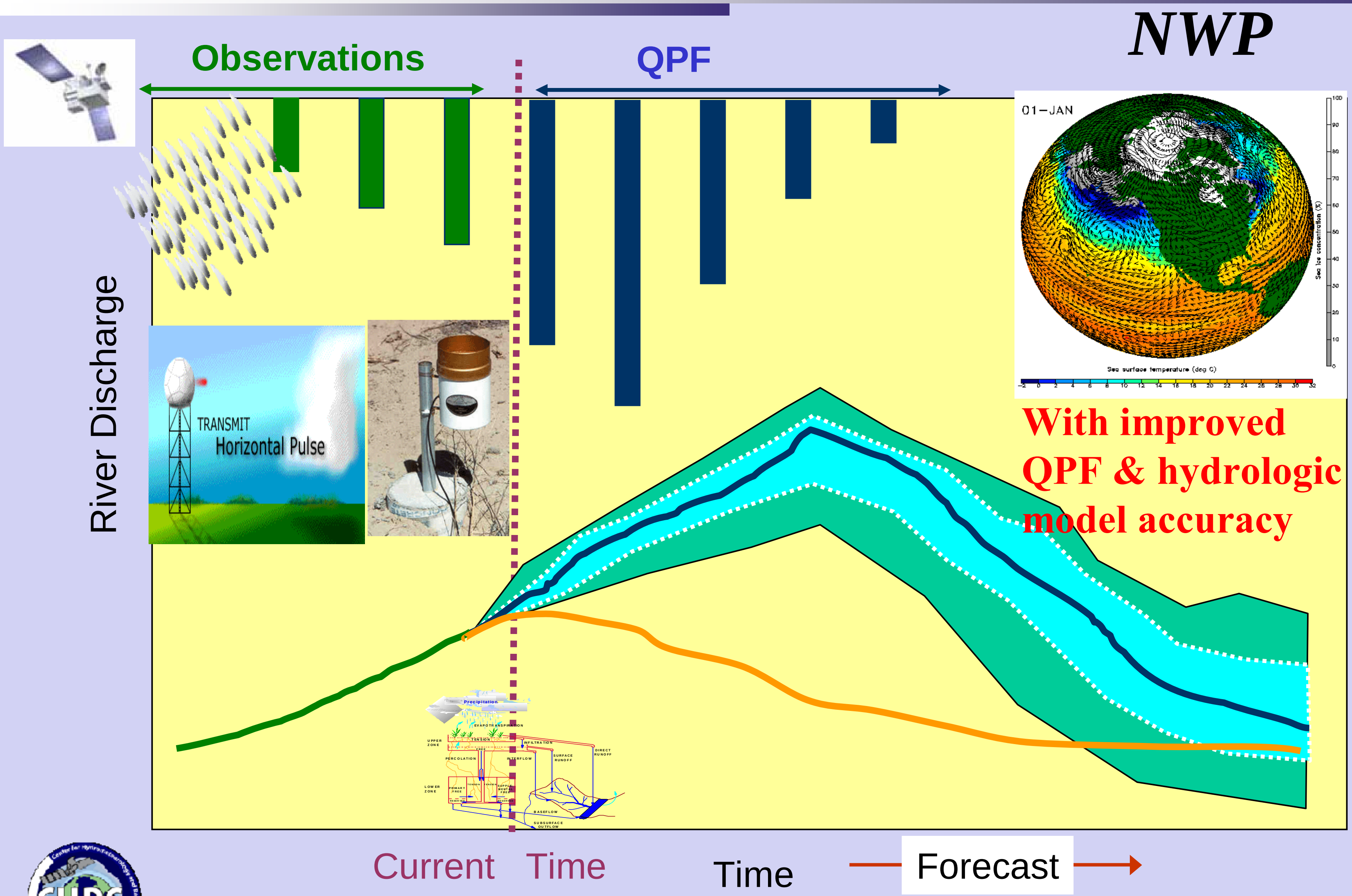
### ...ccines

...me vaccines for their chil-... ...ally have their day in court. ...d vaccine manufacturers ... 1986, requiring that claims ... U.S. Court of Federal Claims ... D.C., before a federal com-... pay damages. More than ... ve filed claims since 1999, ... gan hearing evidence this ... entative test case. ... us is on a mercury-based pre-... himerosal. Epidemiologists ... nk between autism and this ... has been phased out of ... ood vaccines (*Science*, ... 003, p. 1454). "This sort of ... potential to inhibit vaccina-... m Schaffner of Vanderbilt Uni-... le, Tennessee. A ruling could ... year. —ERIK STOKSTAD

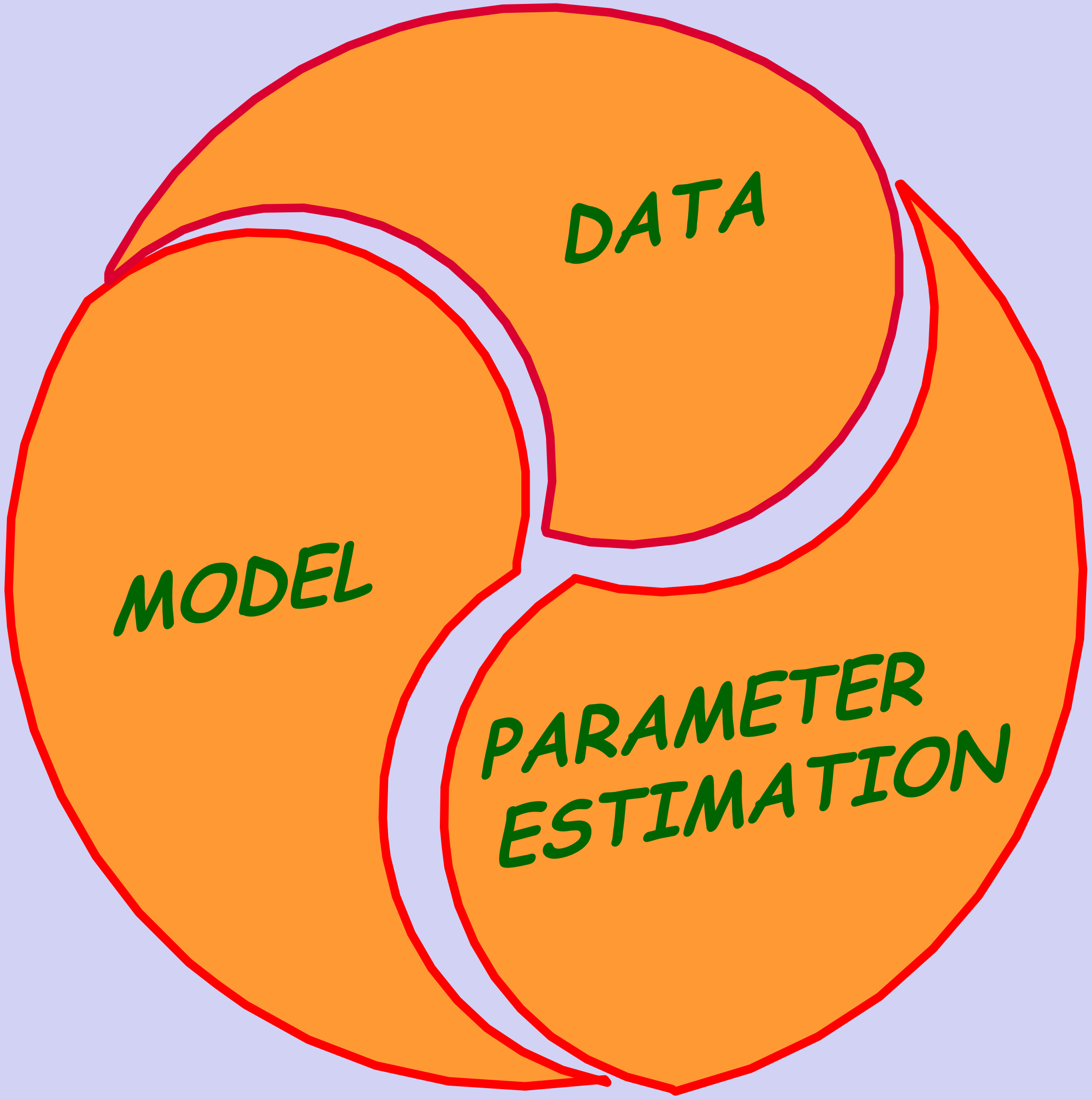
### Get Back to the Lab

Asian research funding could soon eclipse European public and private spending on research and development (R&D), says a new report released by the European Union (E.U.). China could overtake the E.U. by 2009 in terms of R&D spending as a percentage of gross domestic product, the report says. It notes that European industry contributes less to research: only 55% of total R&D spending, compared to 64% (U.S.), 67% (China), and 75% (both Japan and South Korea). —DANIEL CLERY

# *Shorter Time scale: Extending the Forecast Lead time*



# Model Calibration



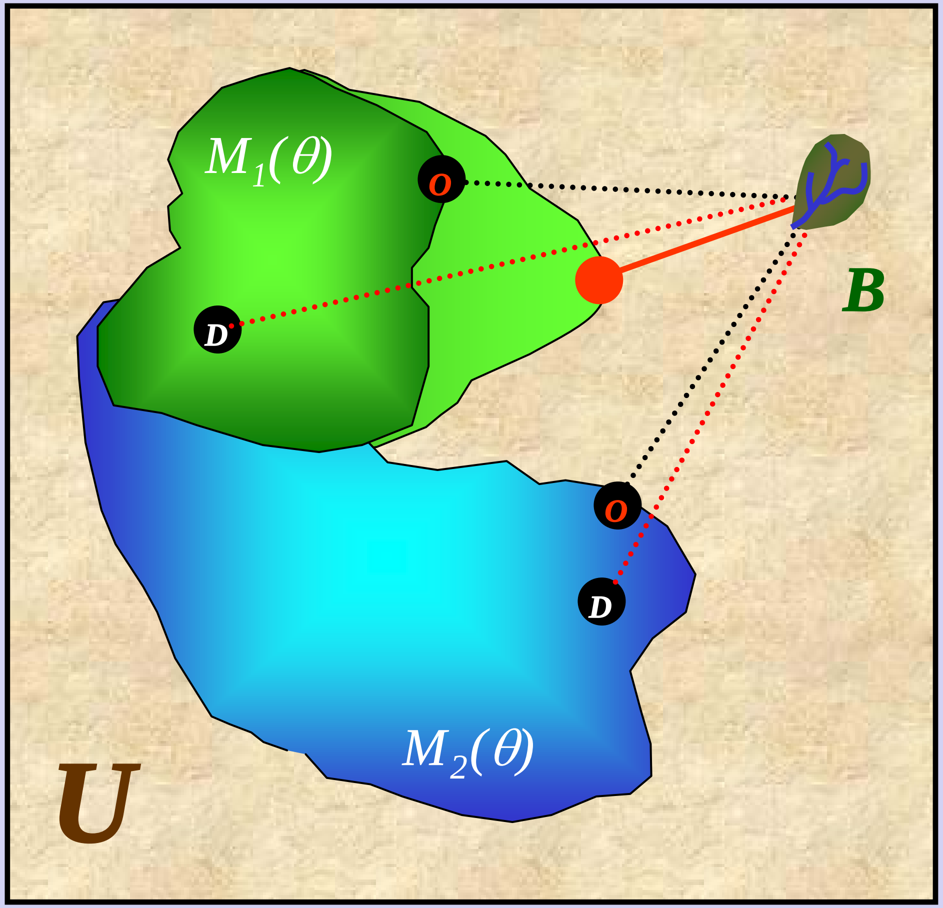
# The Identification Problem

1. **Select a model structure** (Input-State-Output equations)
2. **Estimate values for the parameters**

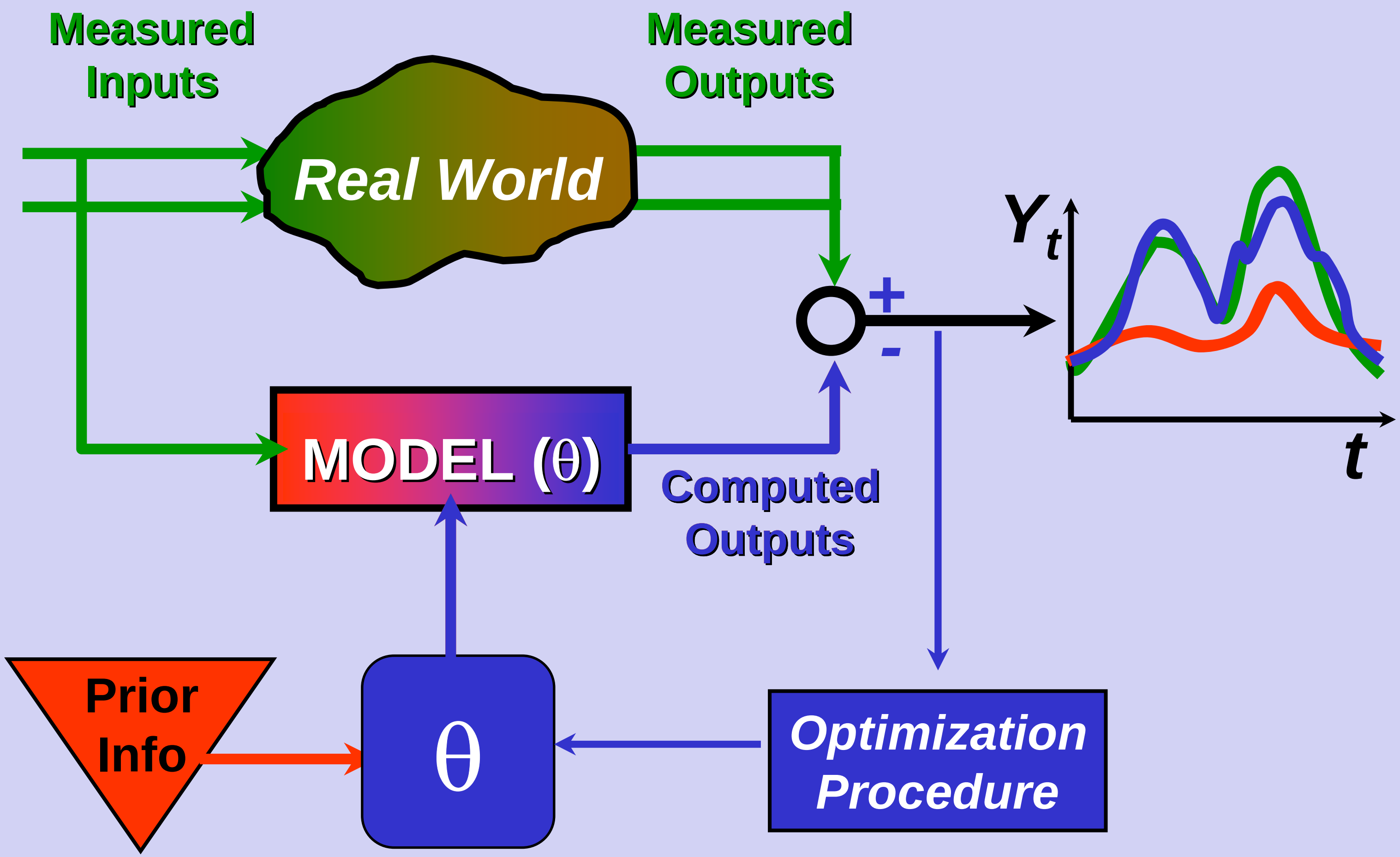
***U* – *Universal Set***

***B* - *Basin***

***$M_i(\theta)$* – *Selected Model Structure***



# The Concept of Model Calibration




*"Calibration: constraining the model to be consistent with observations"*

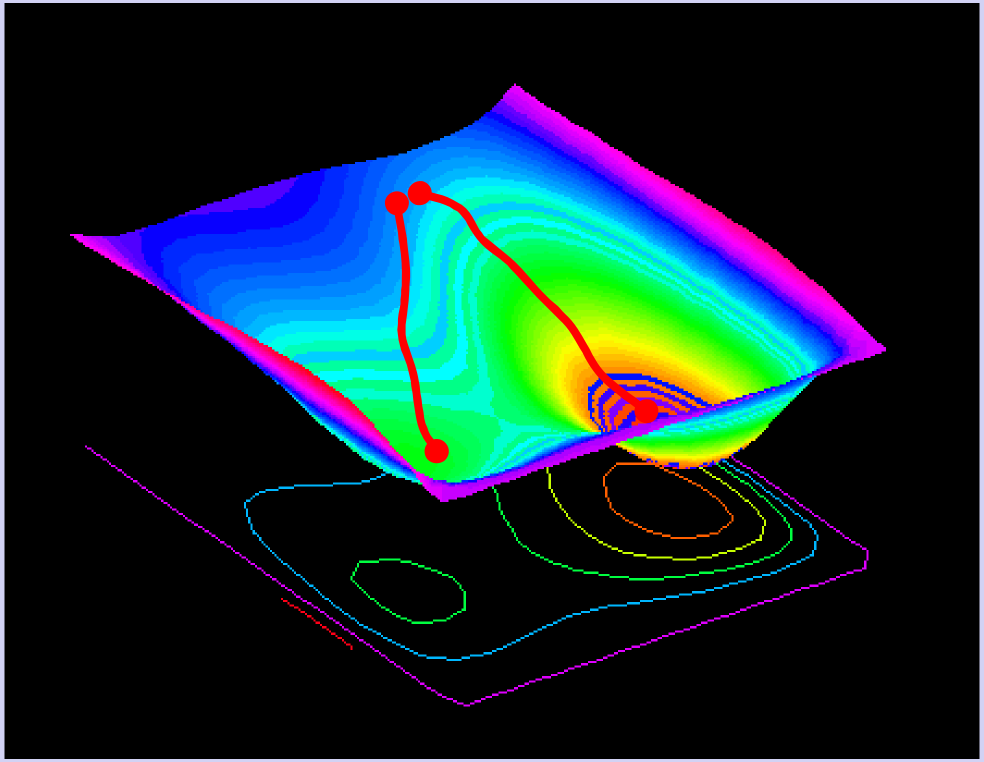
# The Optimization Approach

# Calibration components

*Objective Function*

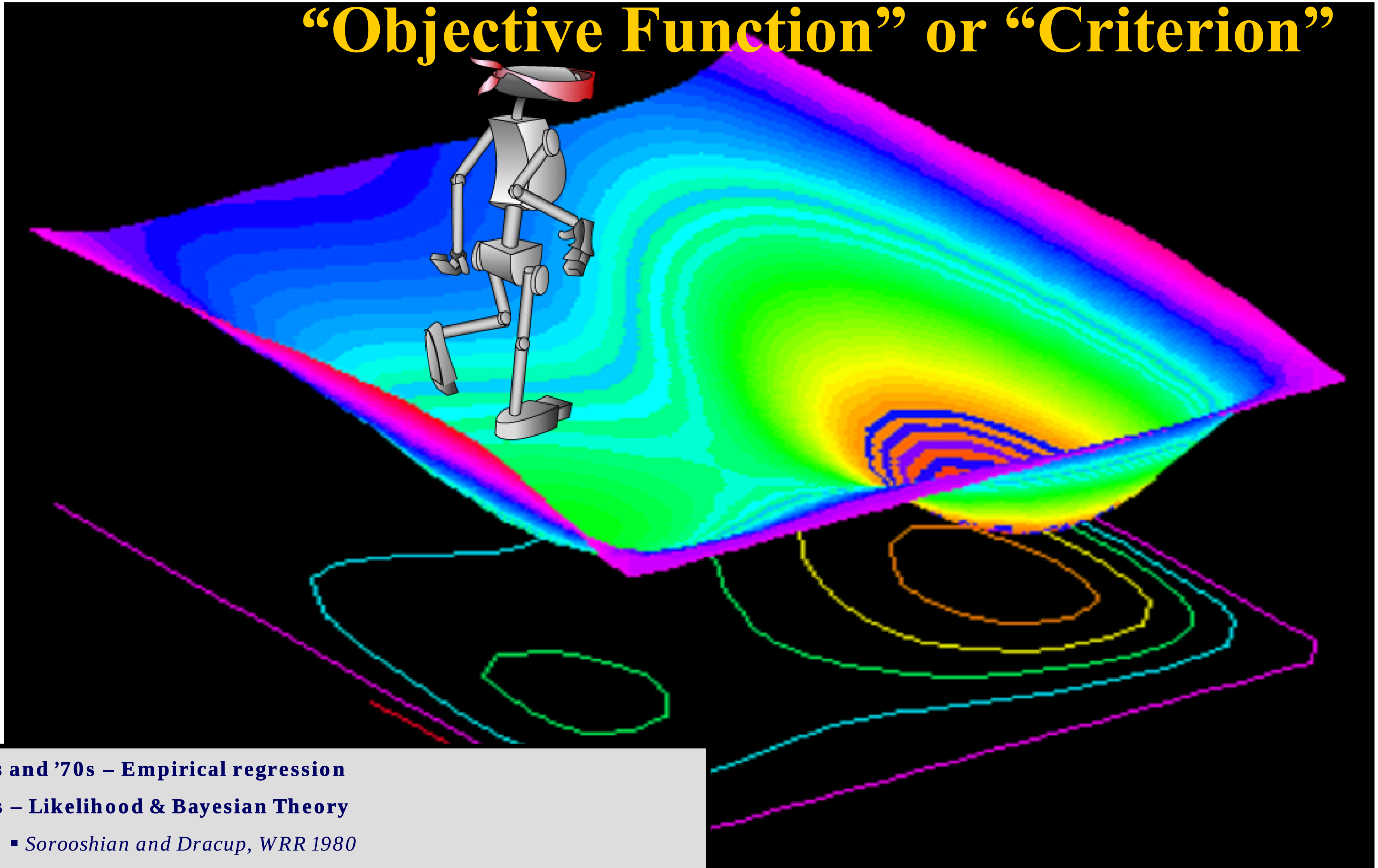
*Search Algorithm*

*Sensitivity Analysis*



*Problems with identifiability*

# The Measure of Closeness …



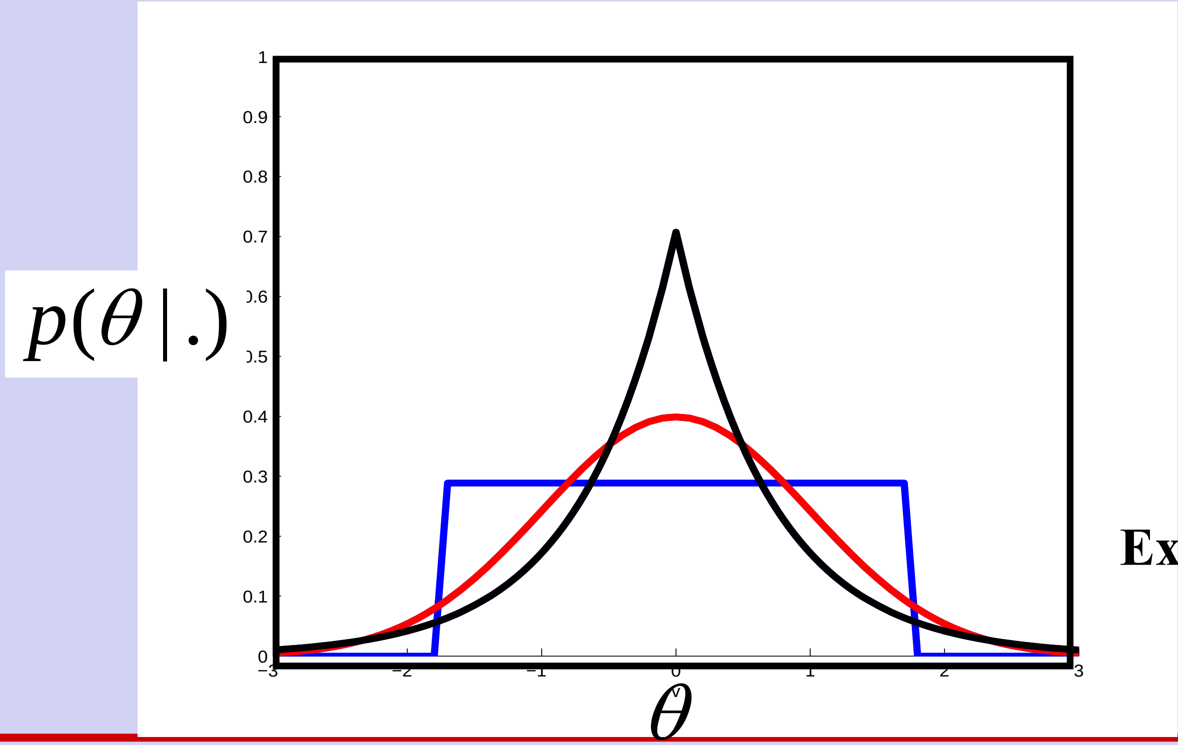

- ❑ '60s and '70s – **Empirical regression**
- ❑ '80s – **Likelihood & Bayesian Theory**
    - *Sorooshian and Dracup, WRR 1980*
    - *Kuczera, WRR 1983*
    - *others …*

# Calibration Criterion

## [General Exponential Power Density]

(Posterior Parameter Probability Distribution Function)

$$p(\theta_i \mid \mathbf{y}, \gamma) = \left[\frac{\omega(\gamma)}{\sigma}\right]^N \exp\left[-c(\gamma)\sum_{j=1}^{N}\left|\frac{e(\theta_i)_j}{\sigma}\right|^{2/(1+\gamma)}\right]$$

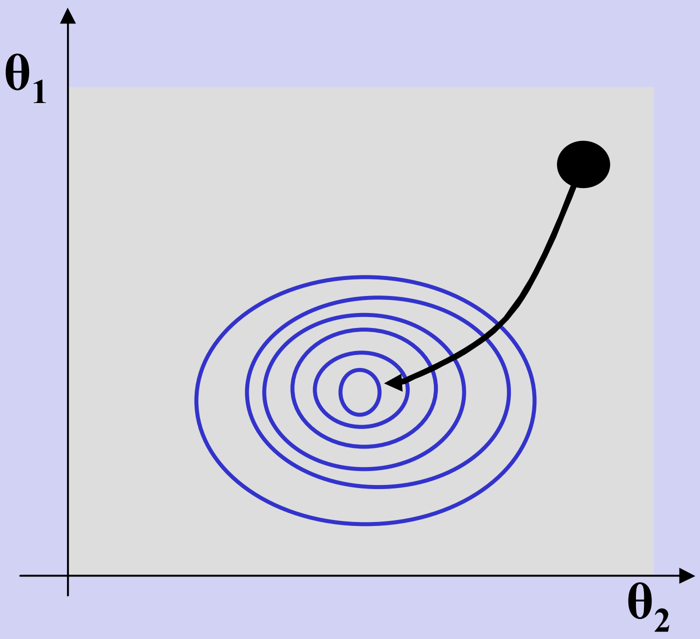



**Uniform** $\gamma \to (-1)$

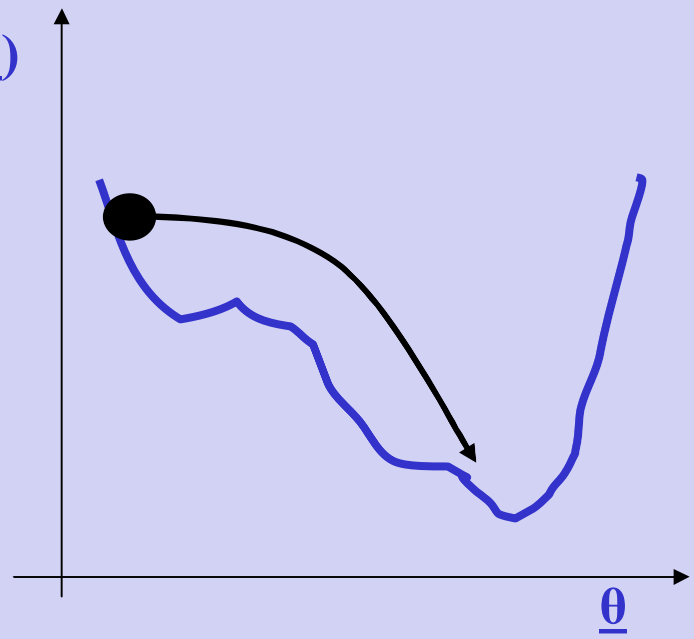
**Normal** $\gamma = 0$

**Exponential** $\gamma = 1$

# *Objective function Parameter Space*

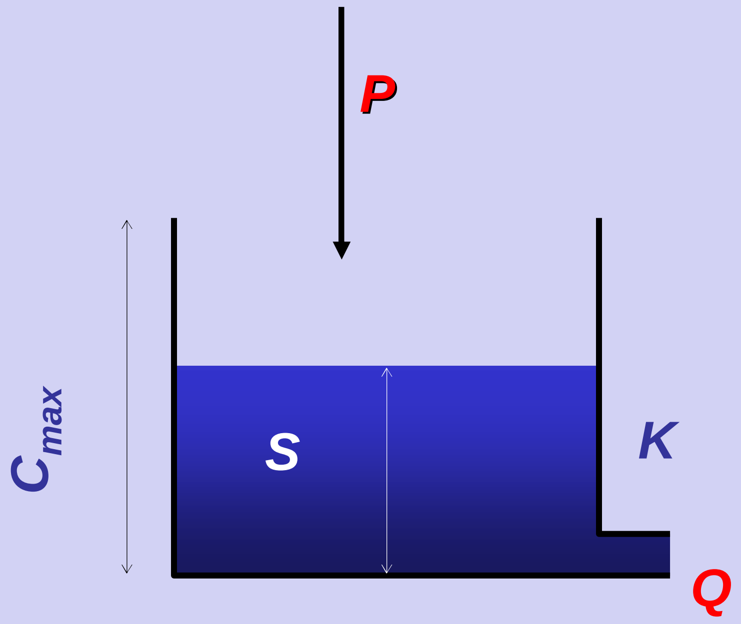



**Parameter Space**



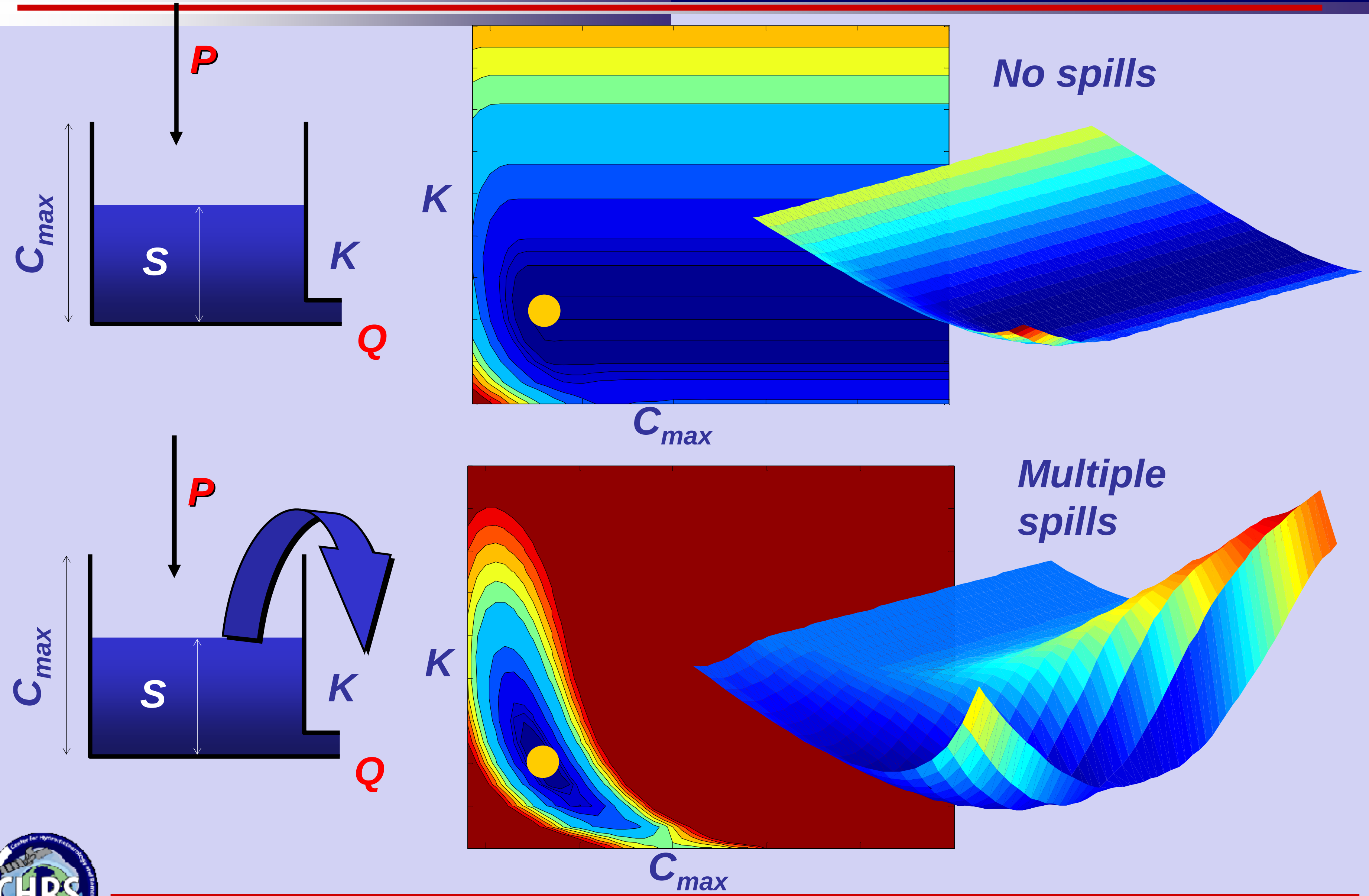

**Objective Function Space**

# Data information content



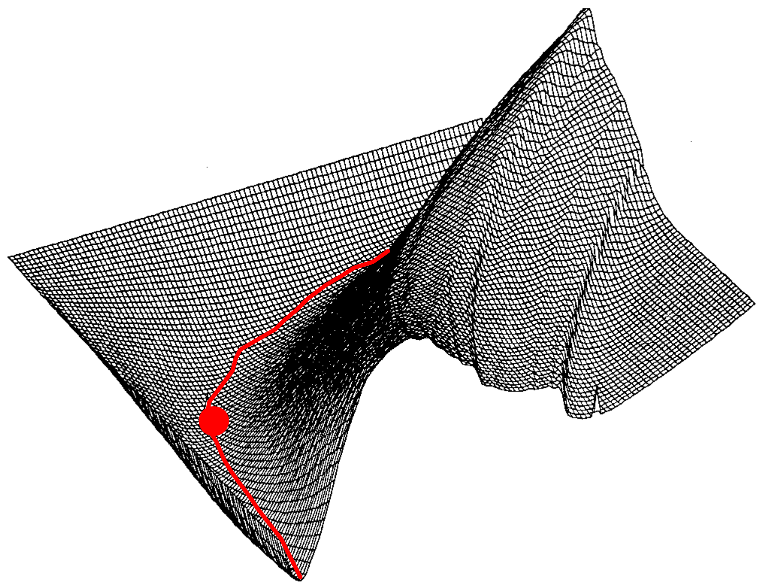

***"Bucket Model"***
***Simple two parameter Model***

# Data information content



# Difficulties in Optimization

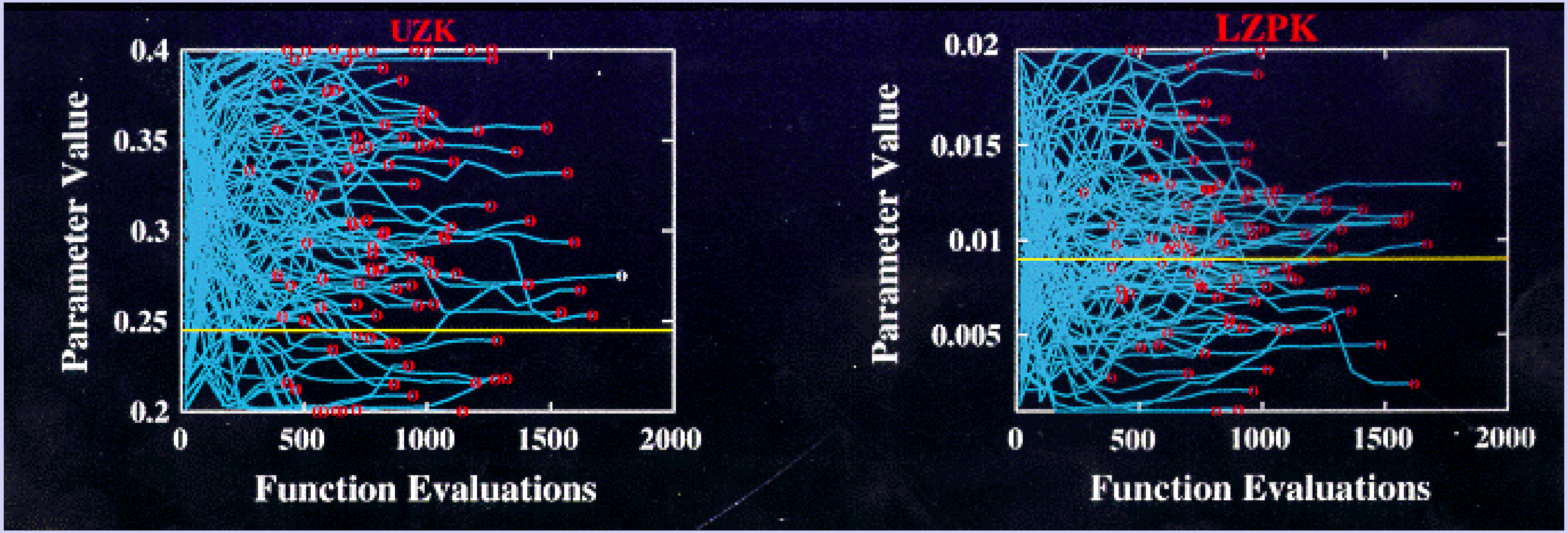
| | |
|---|---|
| 1.- Regions of Attraction | More than one main convergence region |
| 2.- Local Optima | Many small "pits" in each region |
| 3.- Roughness | Rough surface with discontinuous derivatives |
| 4.- Flatness | Flat near optimum with significantly different parameter sensitivities |
| **5.- Shape** | Long and curved ridges |



Duan, Gupta, and Sorooshian, 1992, WRR

# Optimization Strategy – Local Direct Search

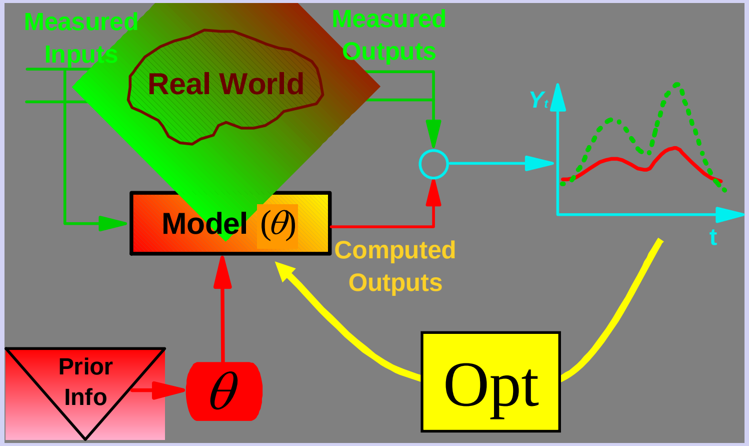
***Calibration of the Sacramento Model***
***Downhill Simplex Method,*** *Nelder & Mead, 1965*




Duan, Gupta, and Sorooshian, 1992, WRR

# Difficulties in Global Optimization

$$Maximize\ p(\theta^t \mid model, data)$$
$$w.r.t.\ \theta$$



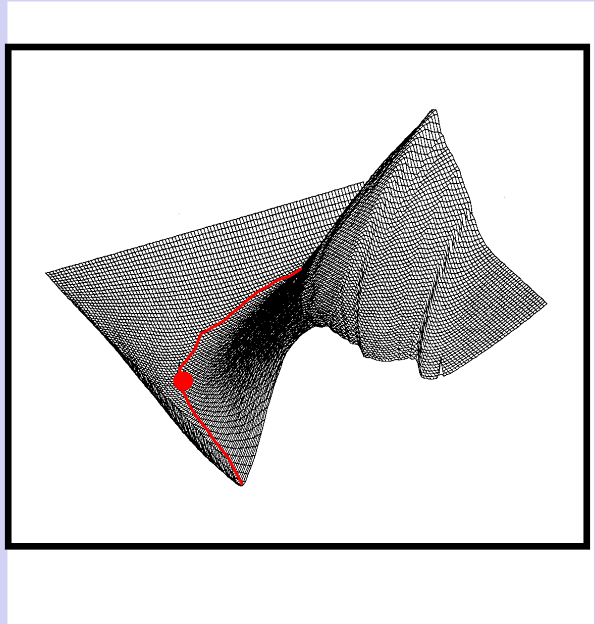

*1 – Multiple regions of attraction*

*2 – UNCOUNTABLE local optima*

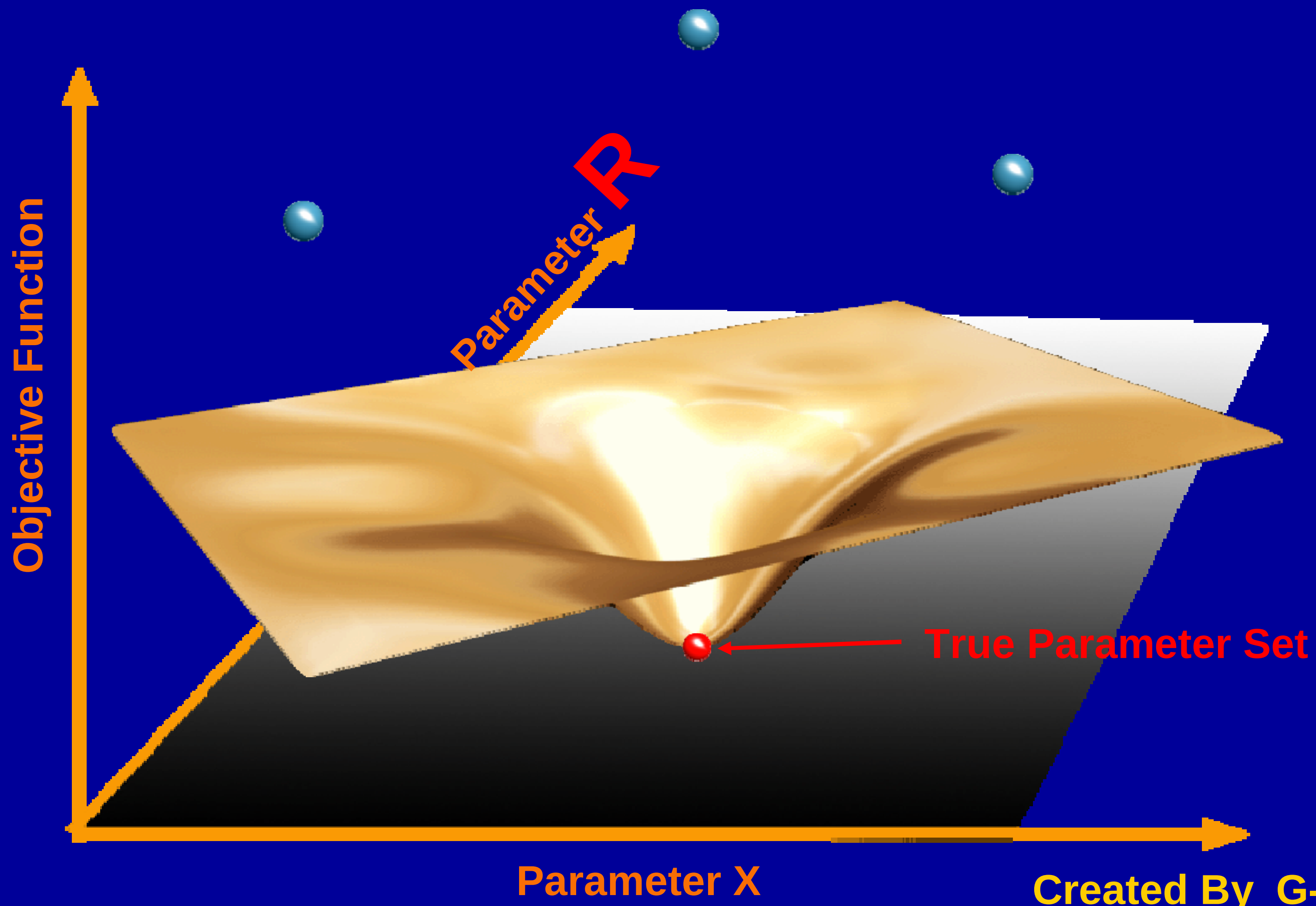
*3 – Discontinuous derivatives*

*4 – Long and curved ridges*

*5 – Poor sensitivity*

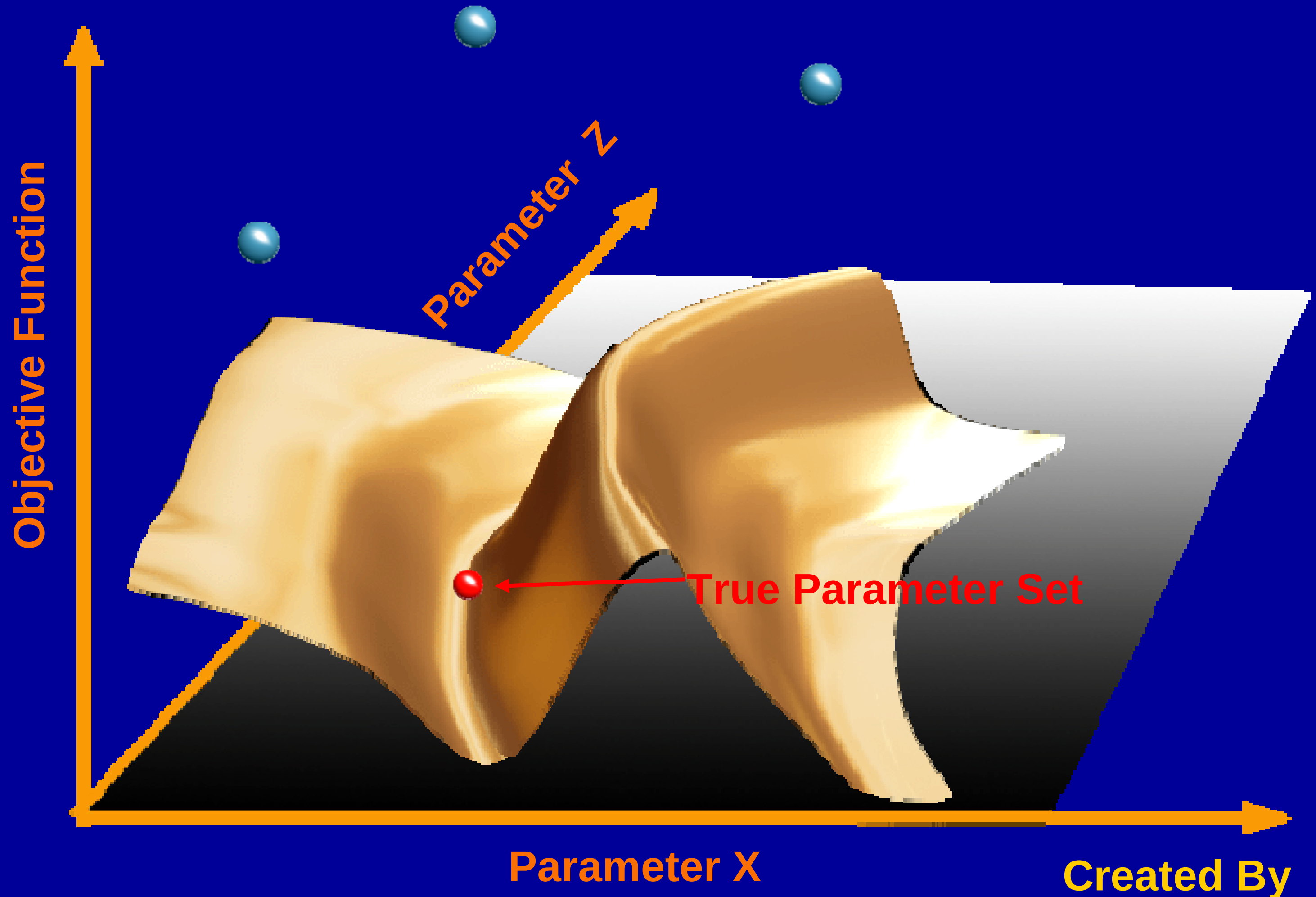


# The Ideal case: Convex Optimization



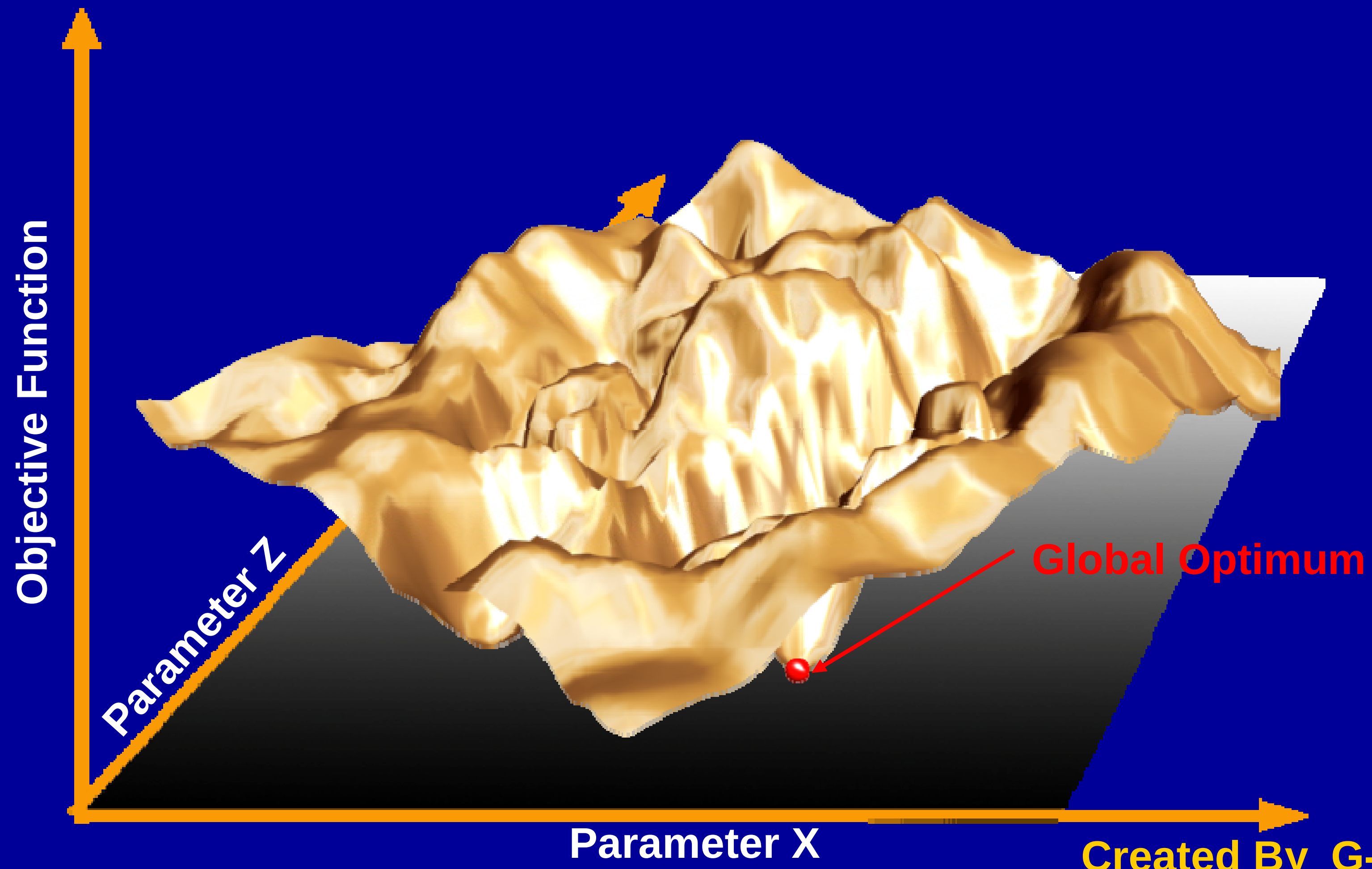

Created By G-H Park

# *Difficulties in Global Optimization*




**Created By G-H Park**

# *Parameter Estimation (non-convex, multi-optima)*

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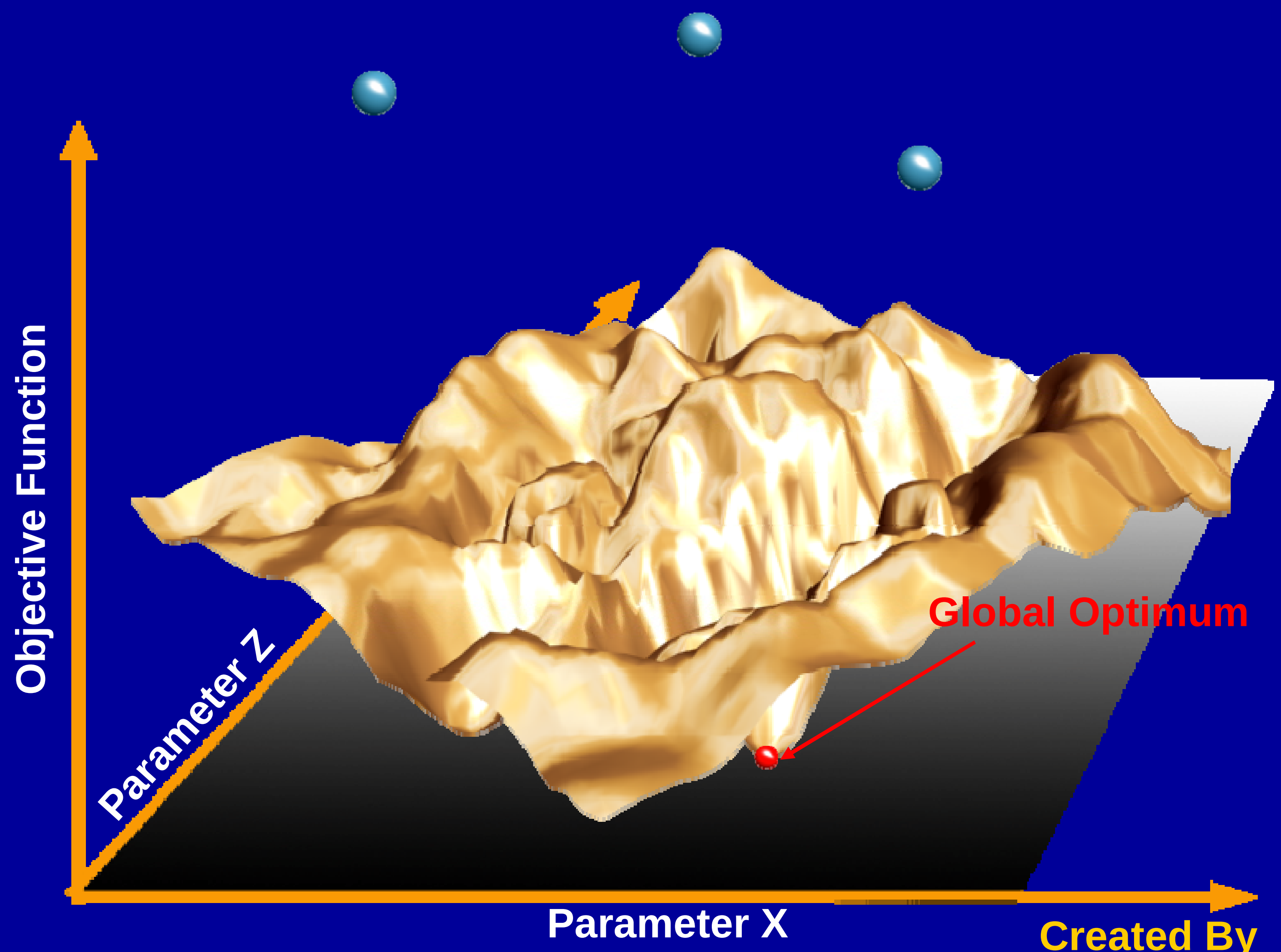


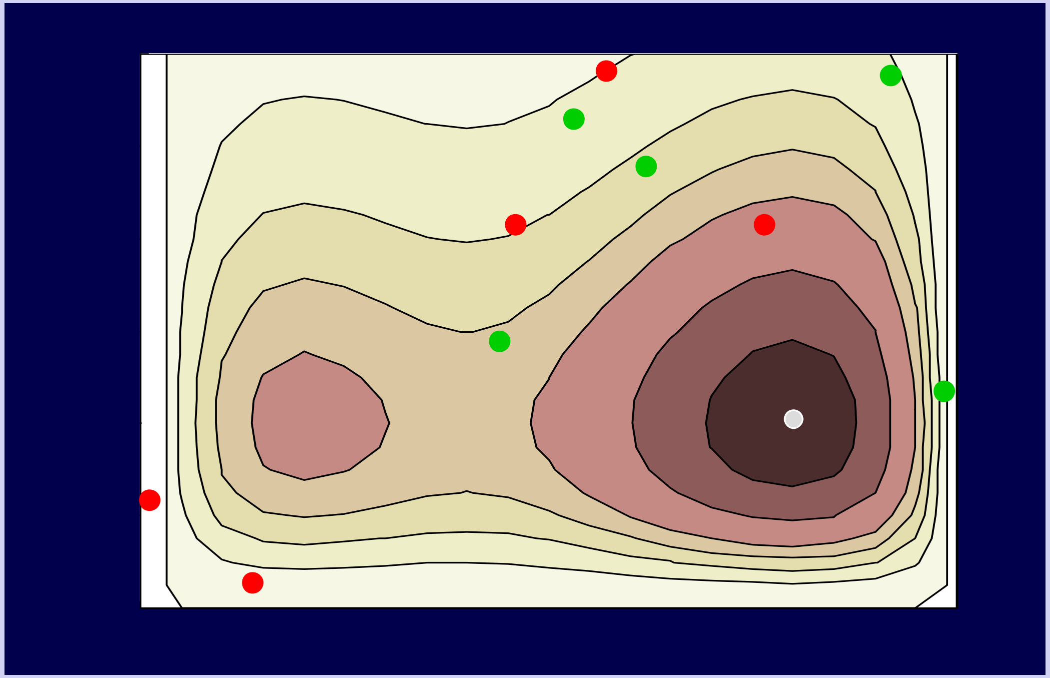

Created By G-H Park

# *The* SCE-UA *Algorithm …* *(1992)*

Duan, Gupta, and Sorooshian, 1992, WRR

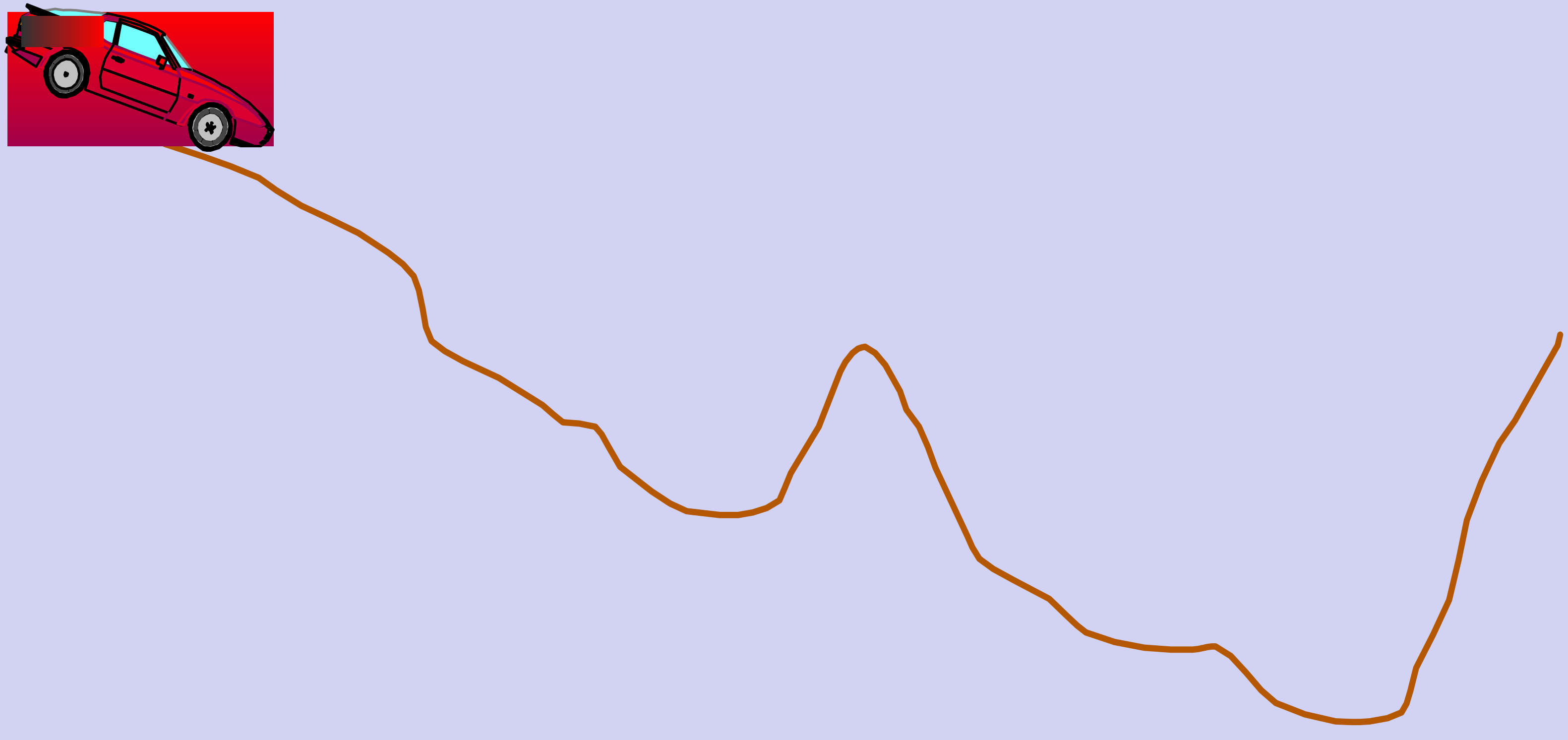
# *The Shuffled Complex Evolution Algorithm*

## *The* SCE-UA *Algorithm …*

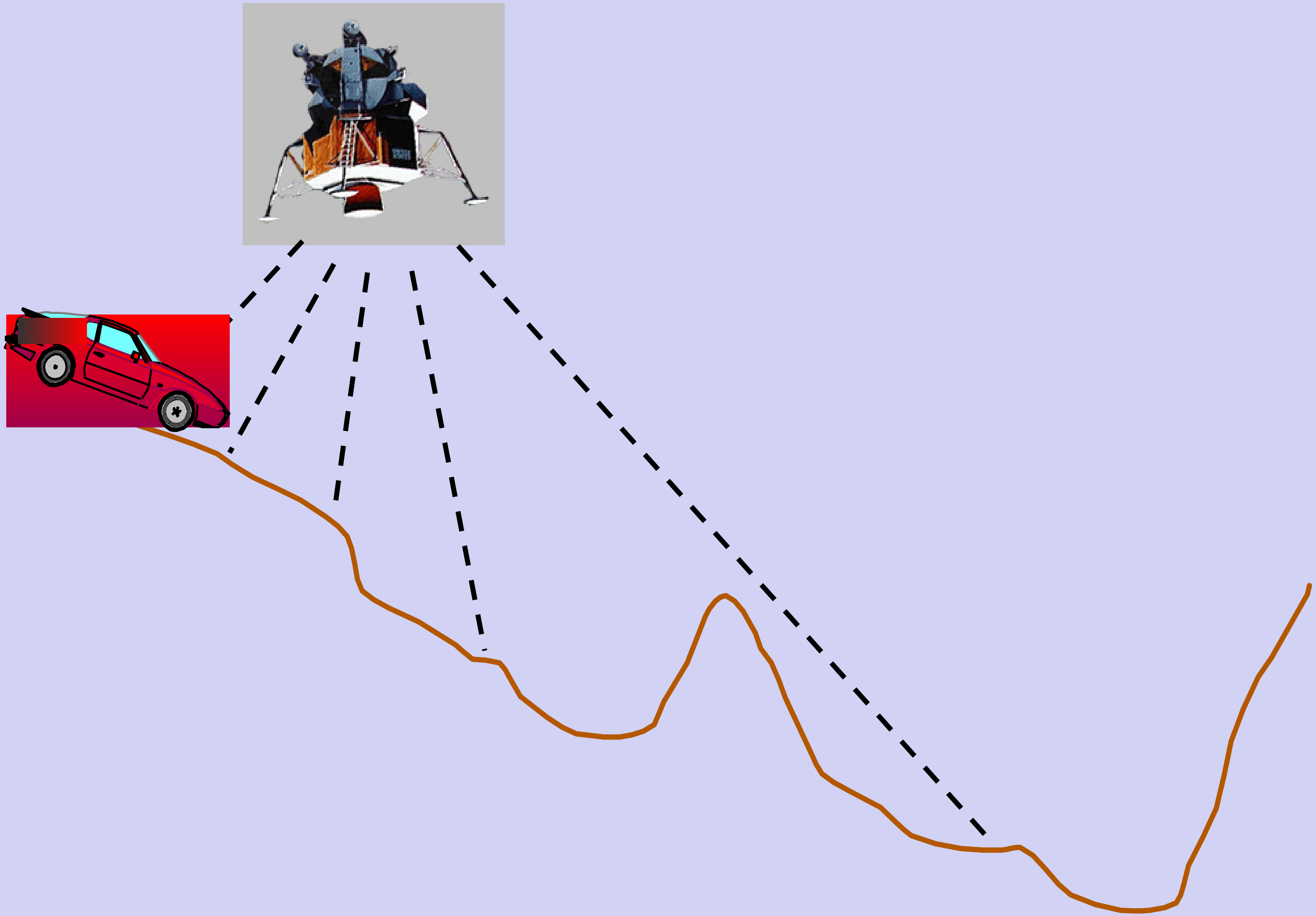


Duan, Sorooshian, and Gupta 1992, WRR

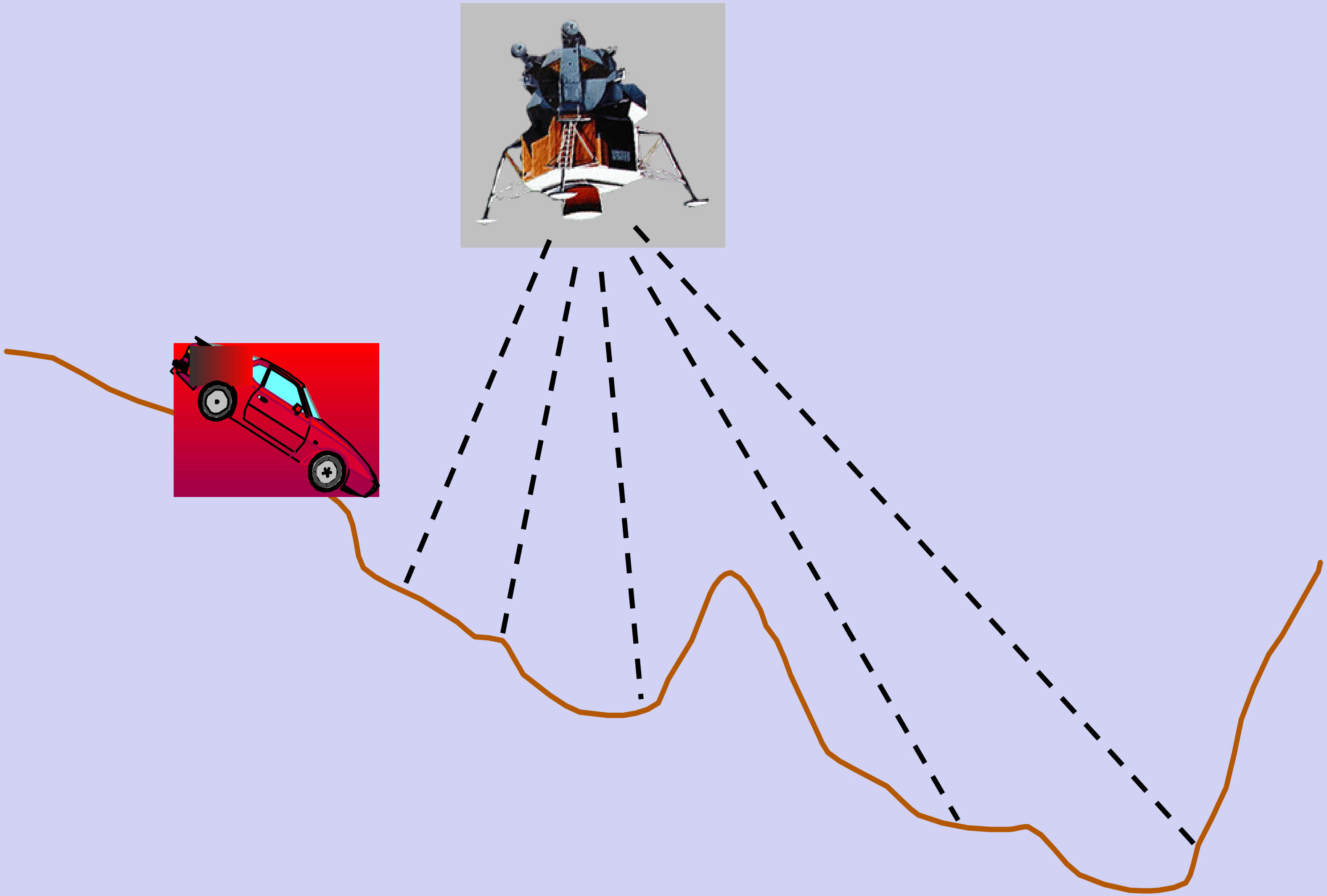
# *The Concept Behind SCE Method*



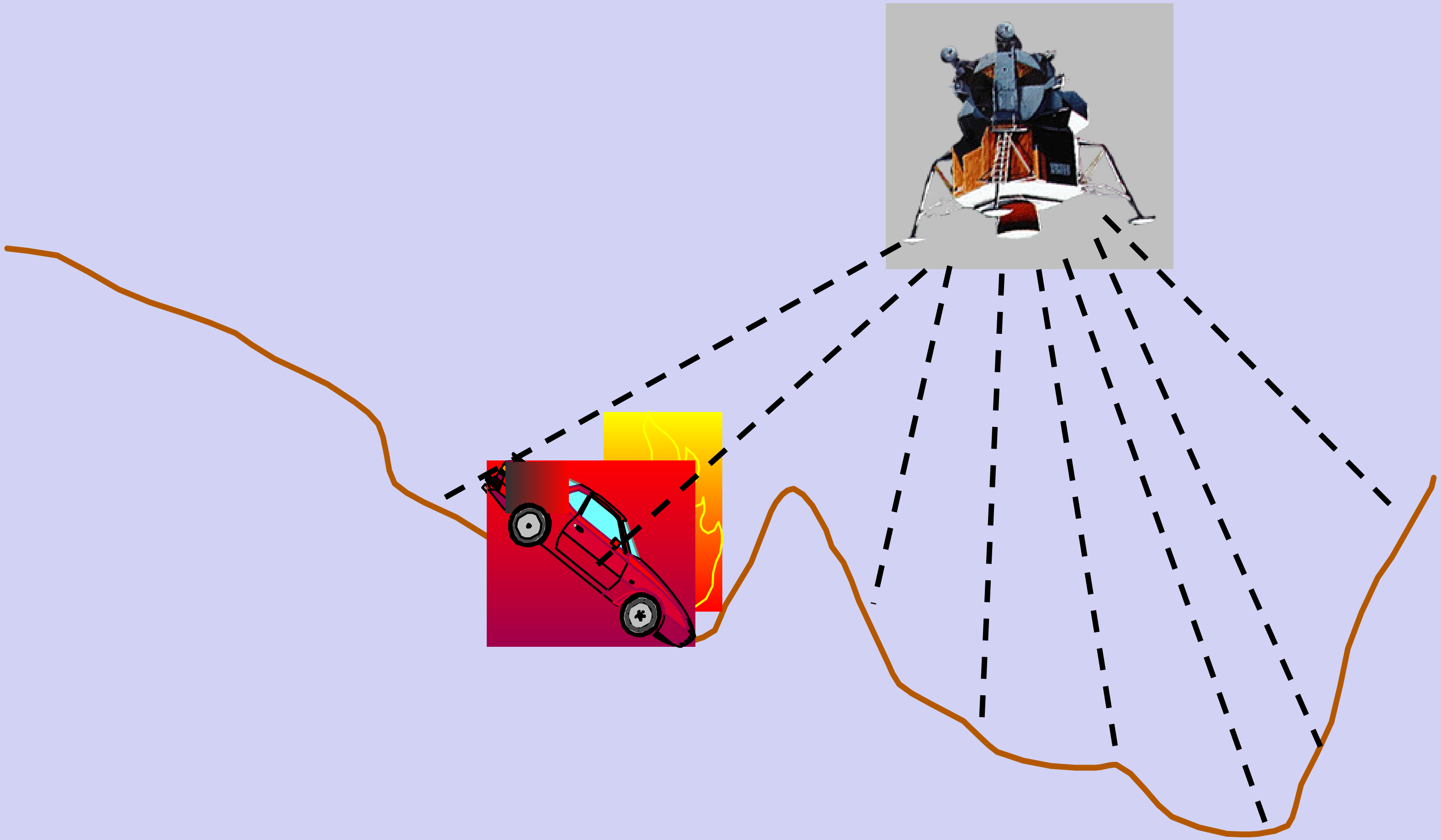
# The Concept Behind SCE Method



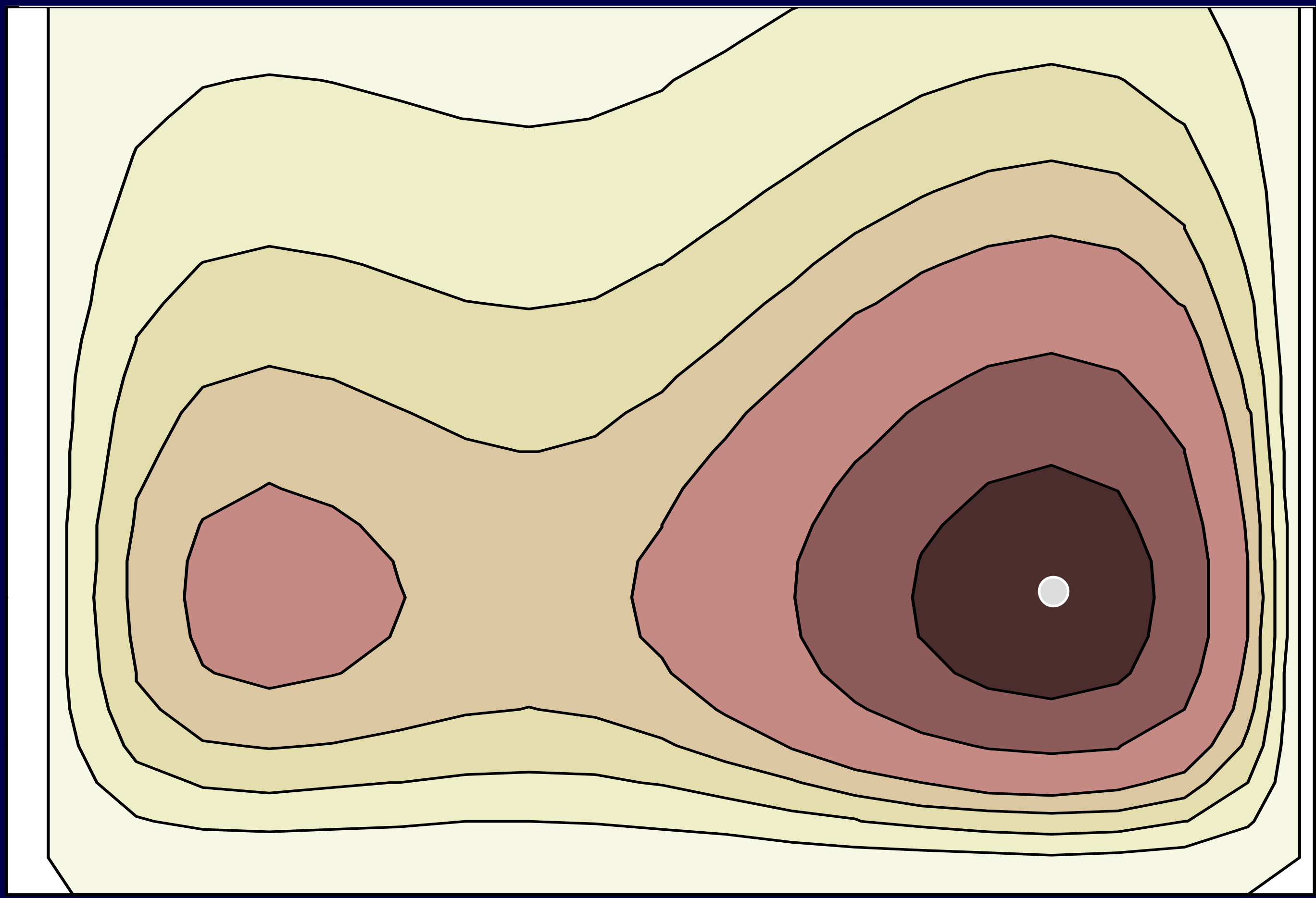
# *The Concept Behind SCE Method*



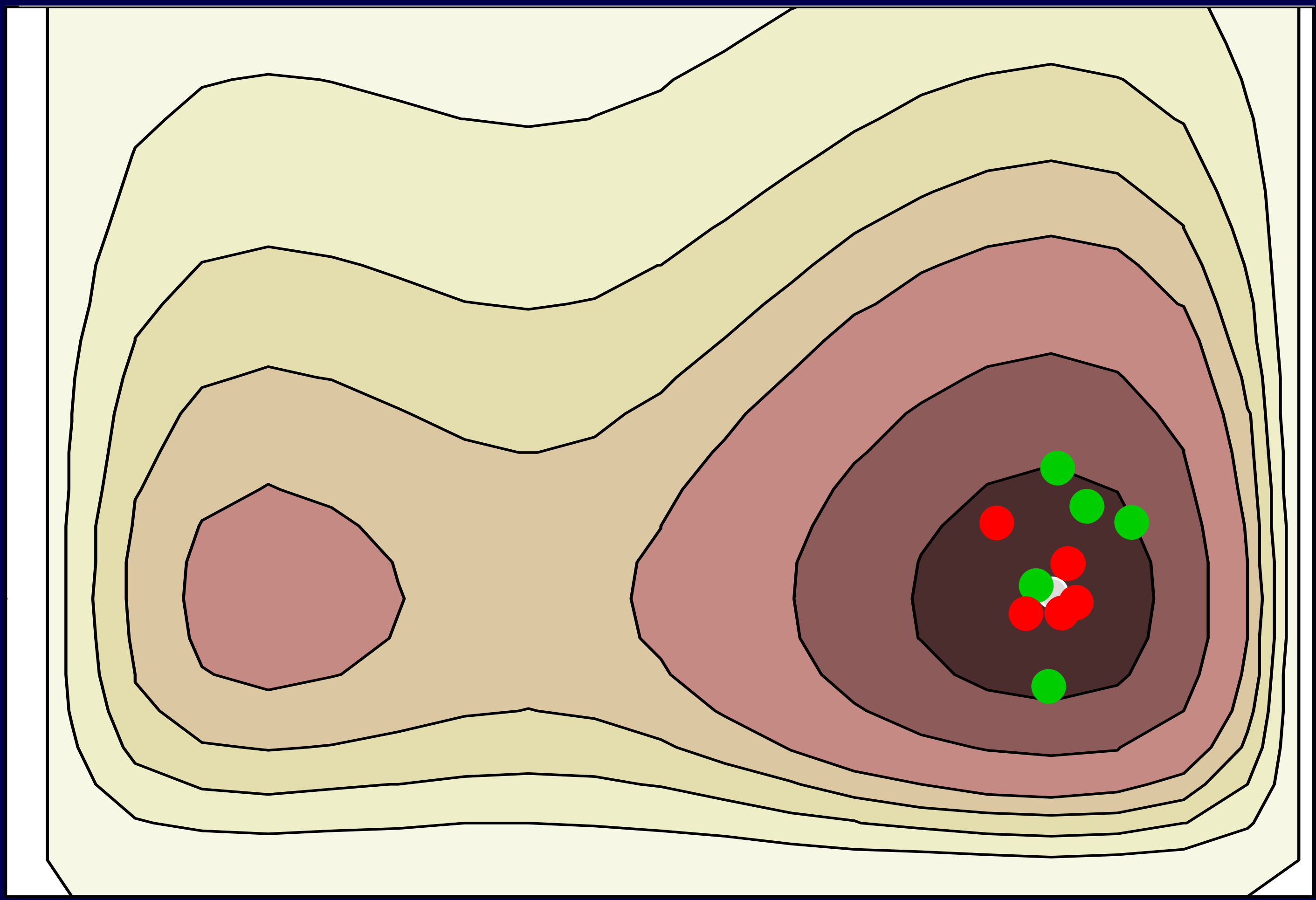
# The Concept Behind SCE Method



# SCE Method – How it works …



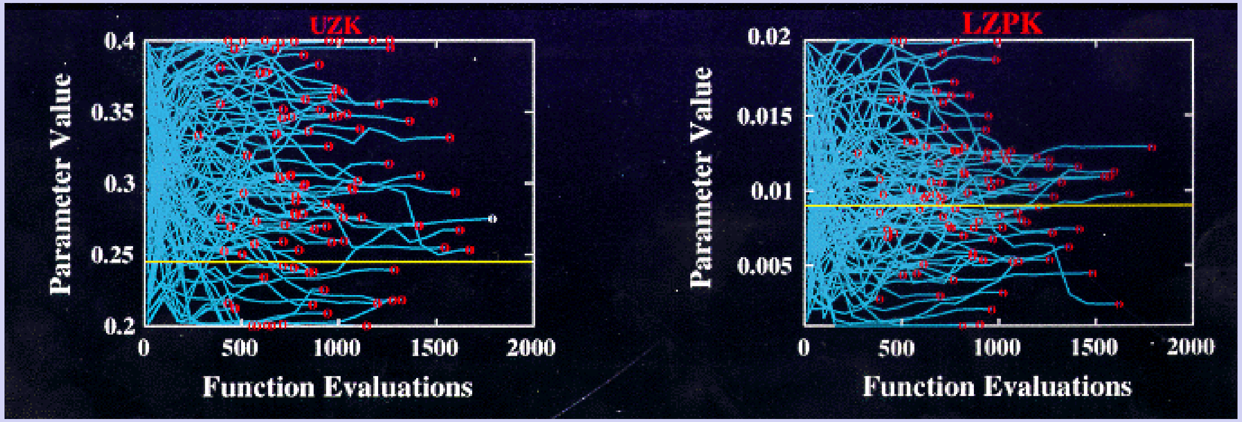
# Shuffled Complex Evolution (SCE-UA)



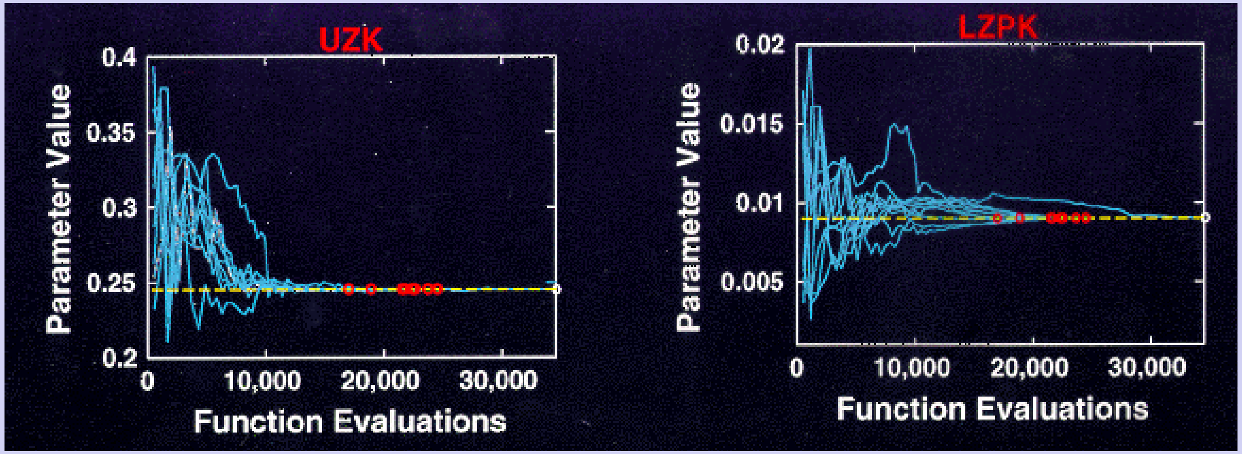
# Global Optimization – The SCE-UA Algorithm

*Duan, Gupta & Sorooshian, 1992, WRR*

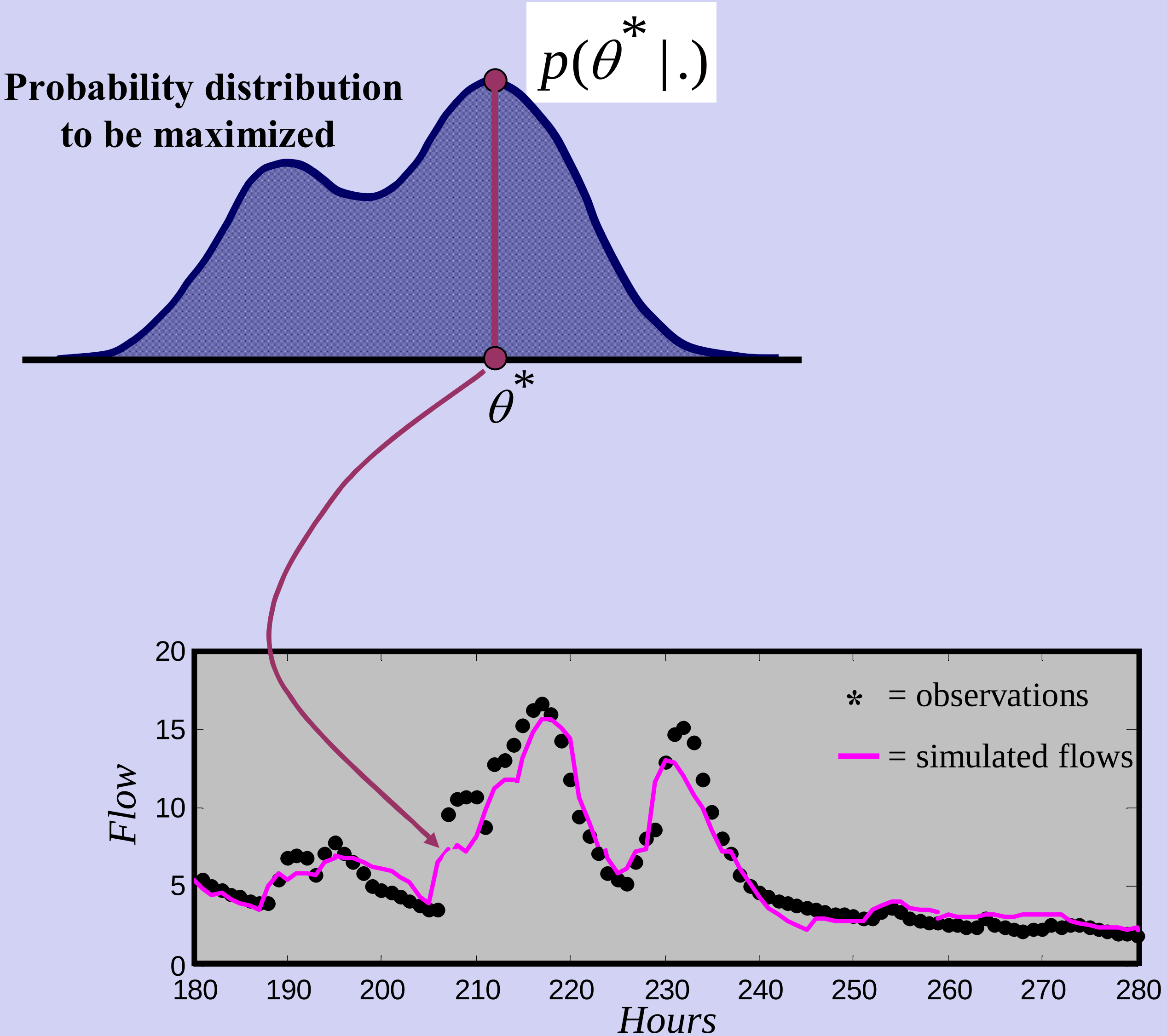
***Simplex Method***




***Shuffled Complex Evolution (SCE-UA)***



# SCE-UA *only solves for Mode of Distribution*

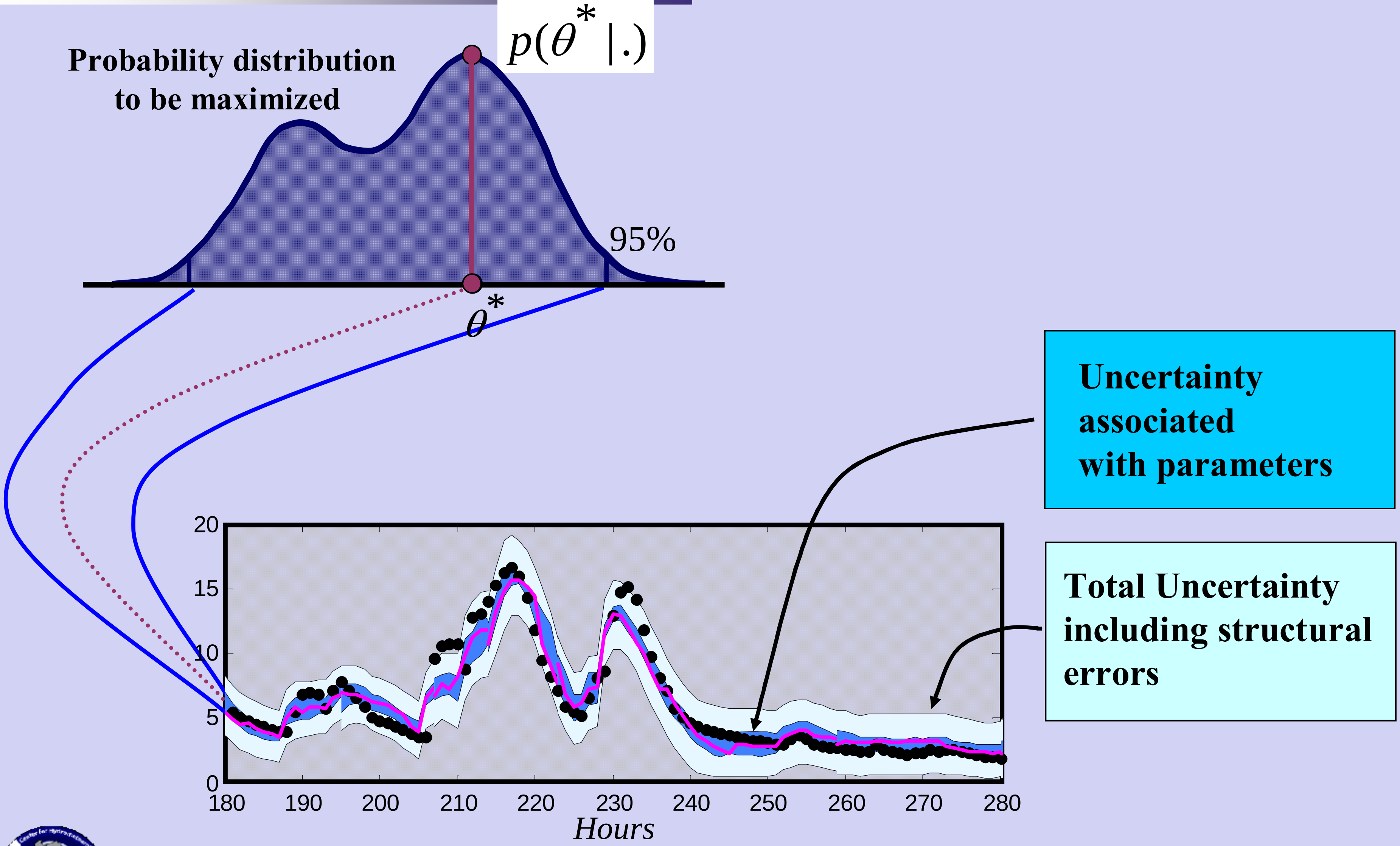


# Shuffled Complex Evolution Metropolis

SCE → SCEM

*Vrugt, Gupta, Bouten & Sorooshian*
*WRR 2003*

# *Need estimates of the prediction uncertainty*

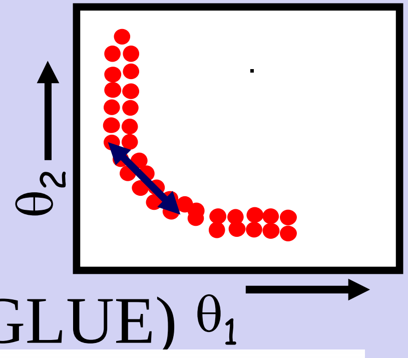


# Parameter Uncertainty Methods

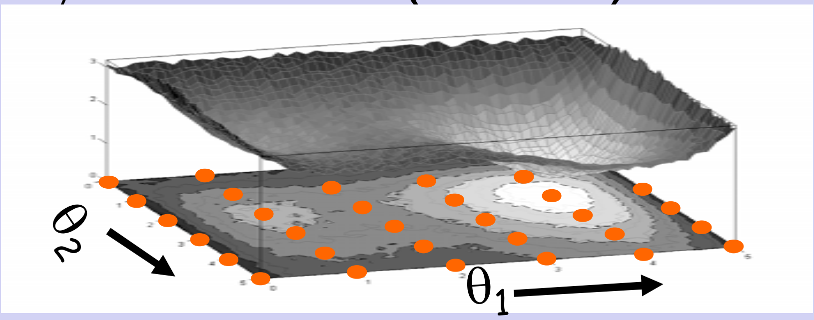
(1) First-order approximations near global optimum (Kuczera etal)

**Limitations**

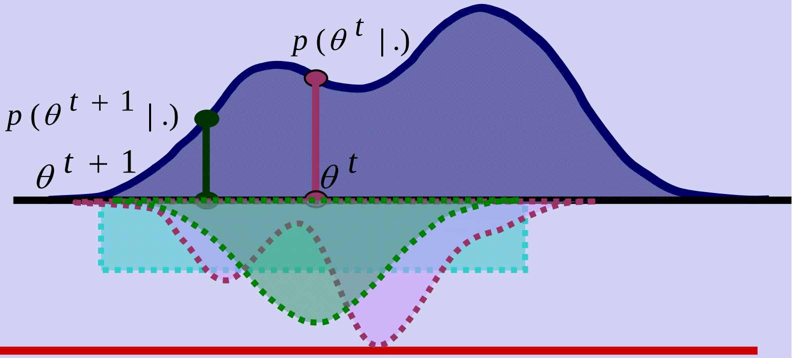
- **Assumes Model is Linear**
- **Assumes Posterior Dist. Guassian**



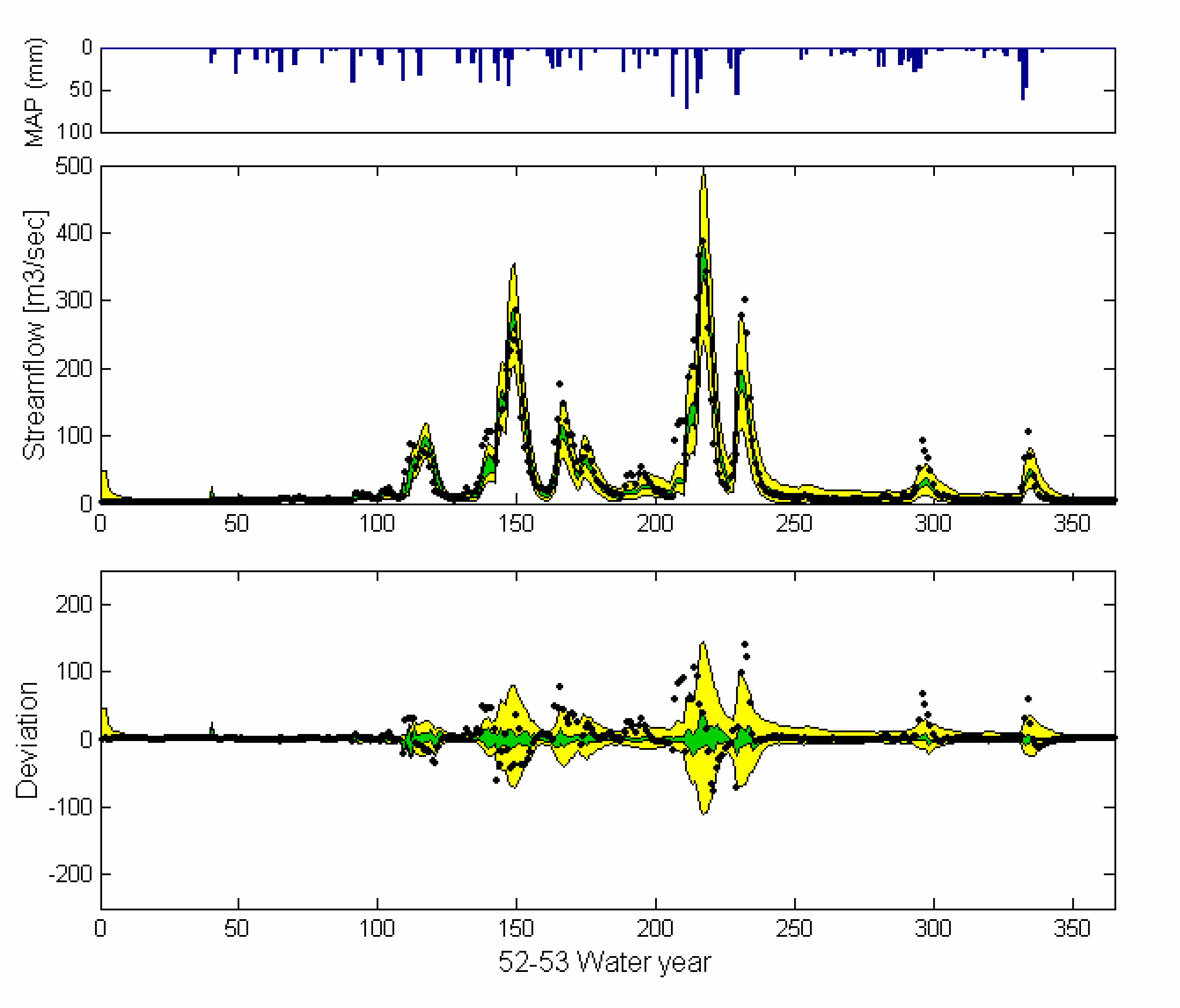

(2) Generalized Likelihood Uncertainty Estimation (GLUE) method (Beven and co-workers)




(3) Markov Chain Monte Carlo (MCMC) methods
(Vrugt and others)



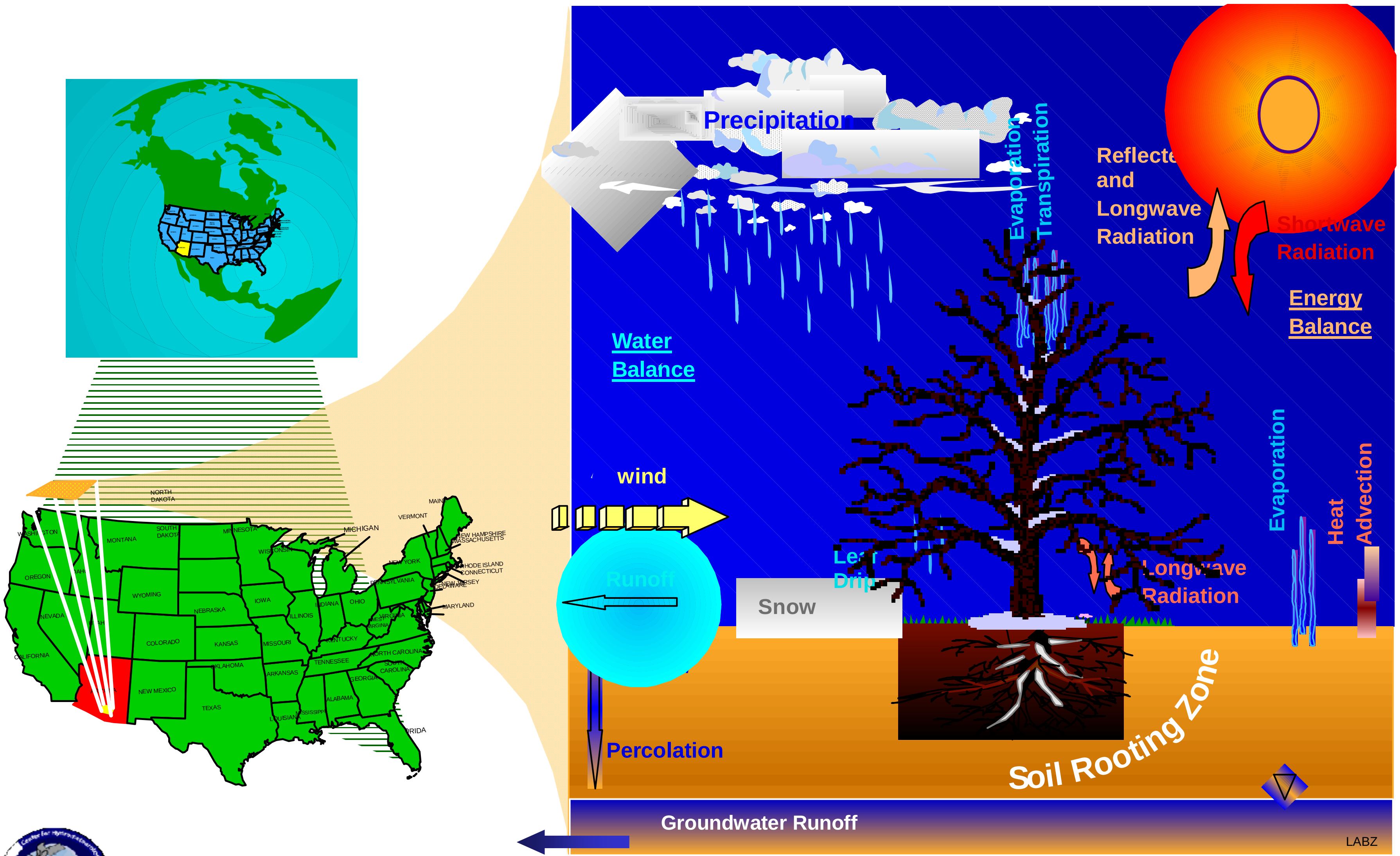
# Flow Ranges instead of point estimates



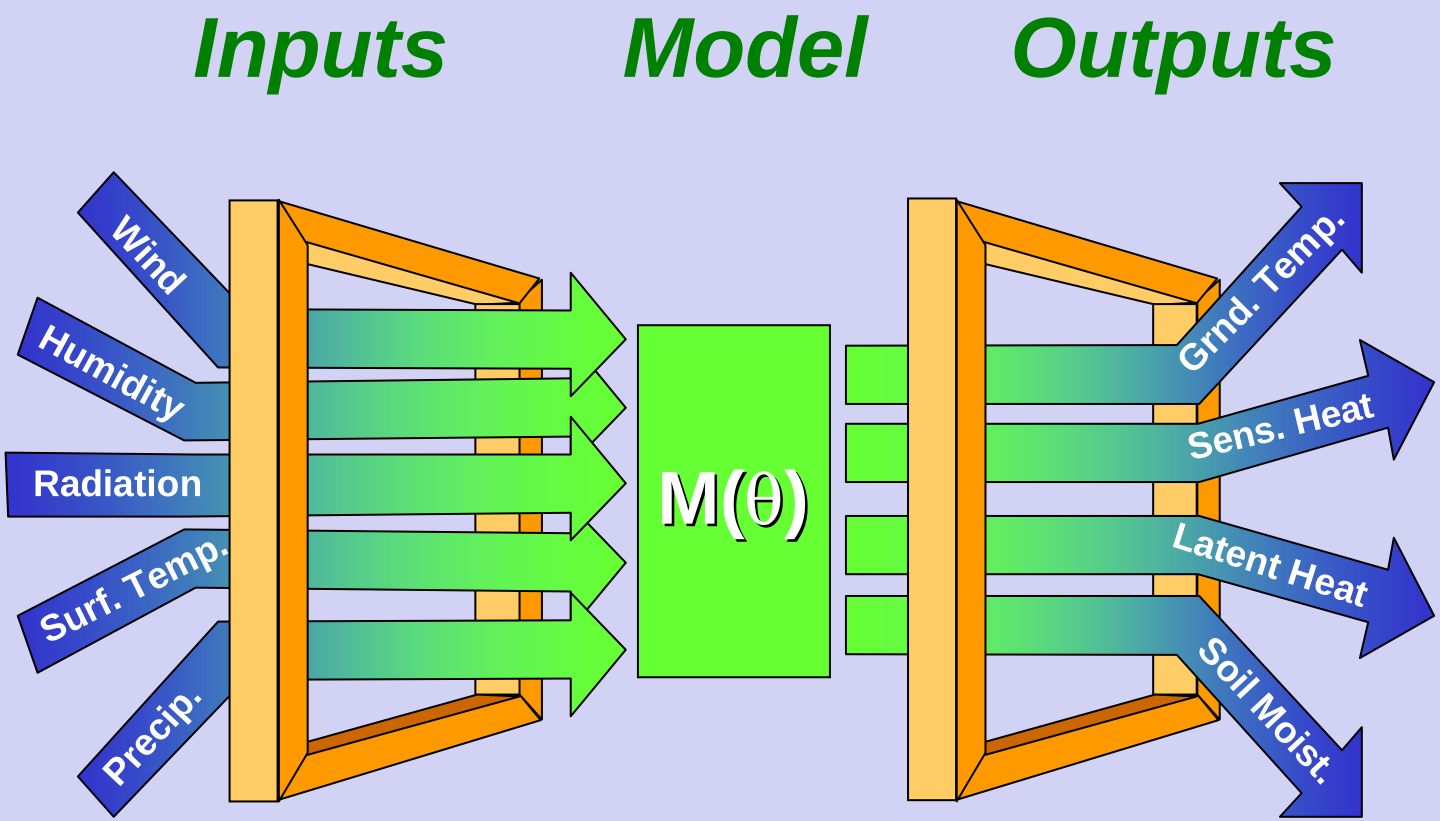
# *Advances in Parameter Estimation*

## *Evolving Directions*

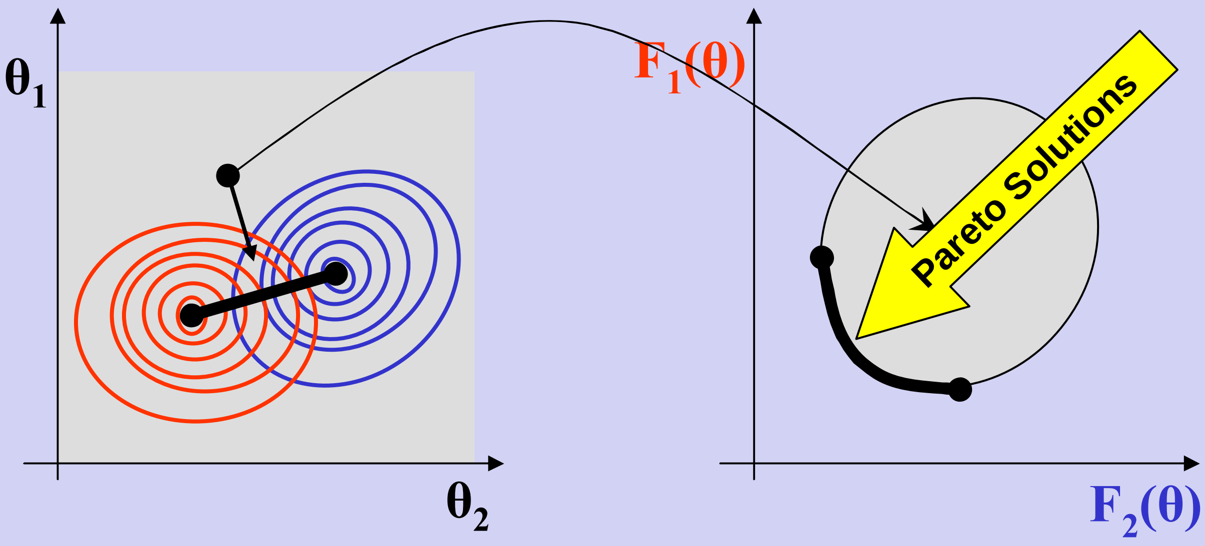
# *Land-Surface Model*



# Multi-Objective Approaches



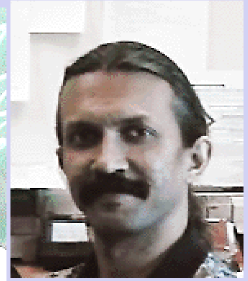
# *Multi-Criteria Calibration Concept*



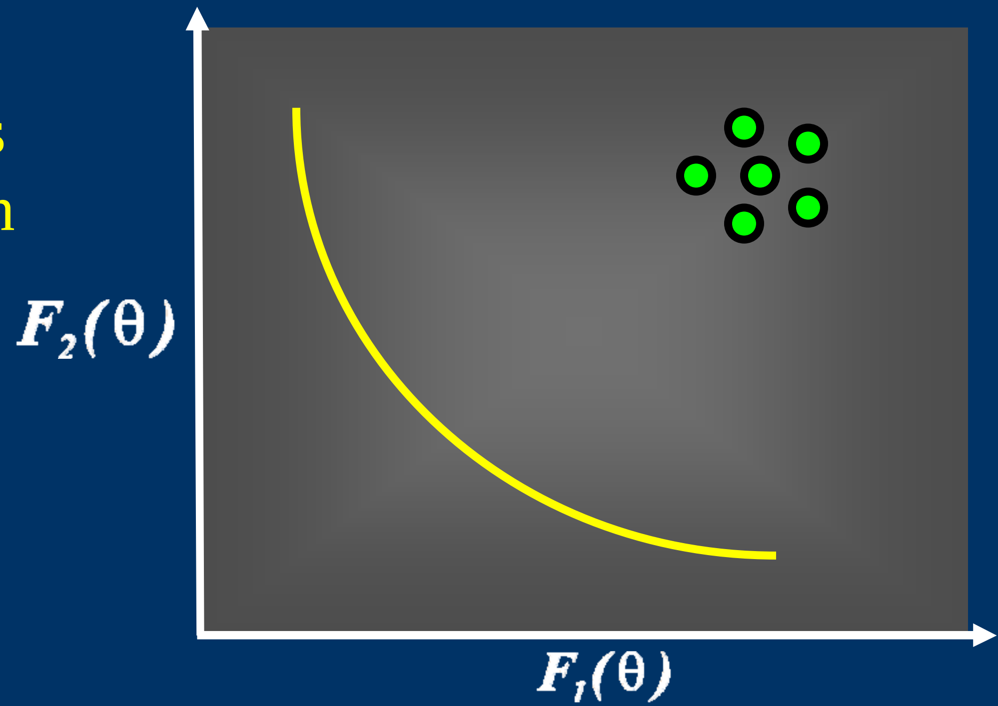
# Multi-Objective Optimization Problem

**Minimize** $F(\theta) = \{ F_1(\theta), \ldots, F_n(\theta) \}$

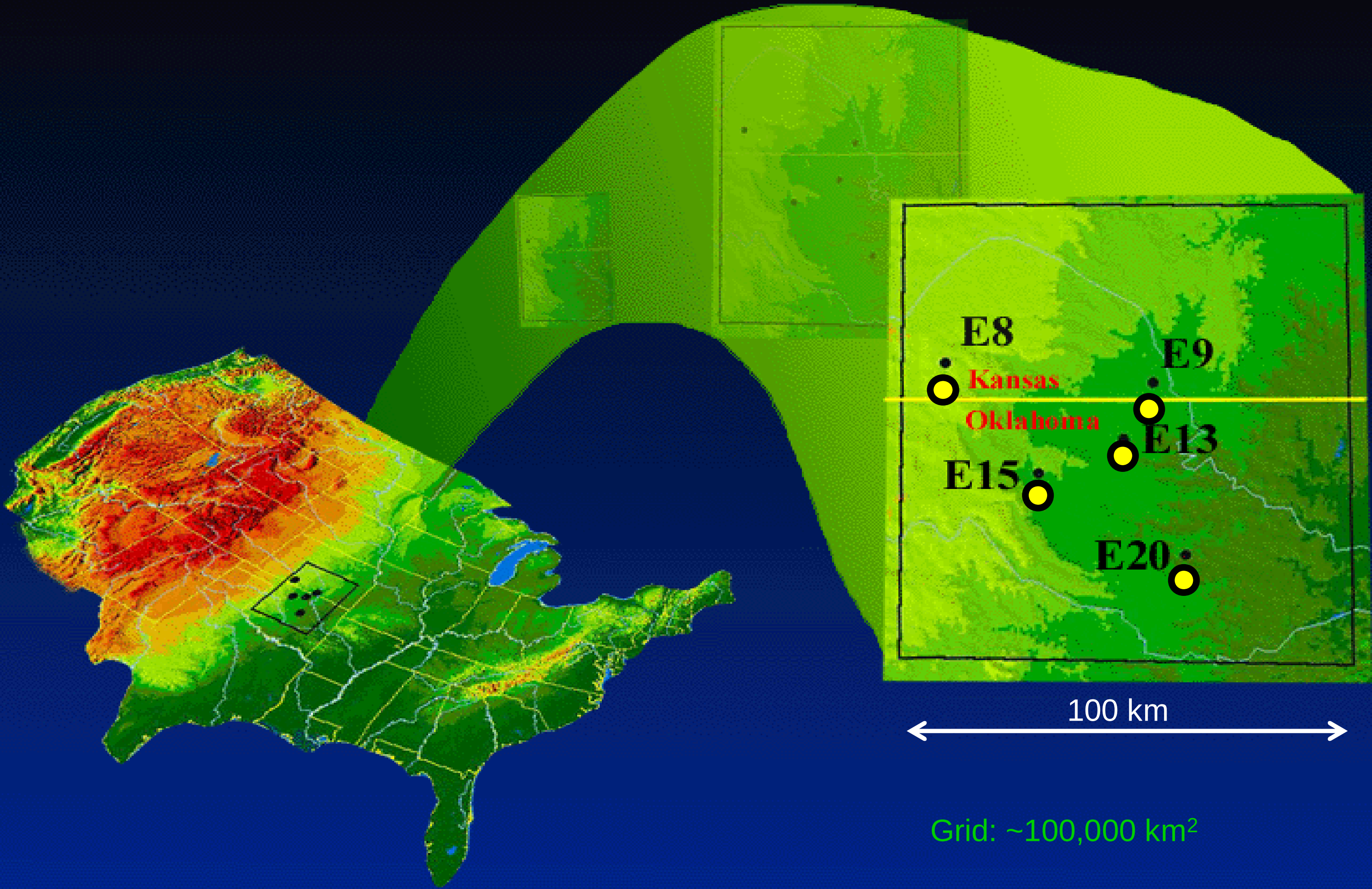
wrt $\theta \subset \Omega$



✓ Simultaneously finds several Pareto Solutions in a Single Optimization

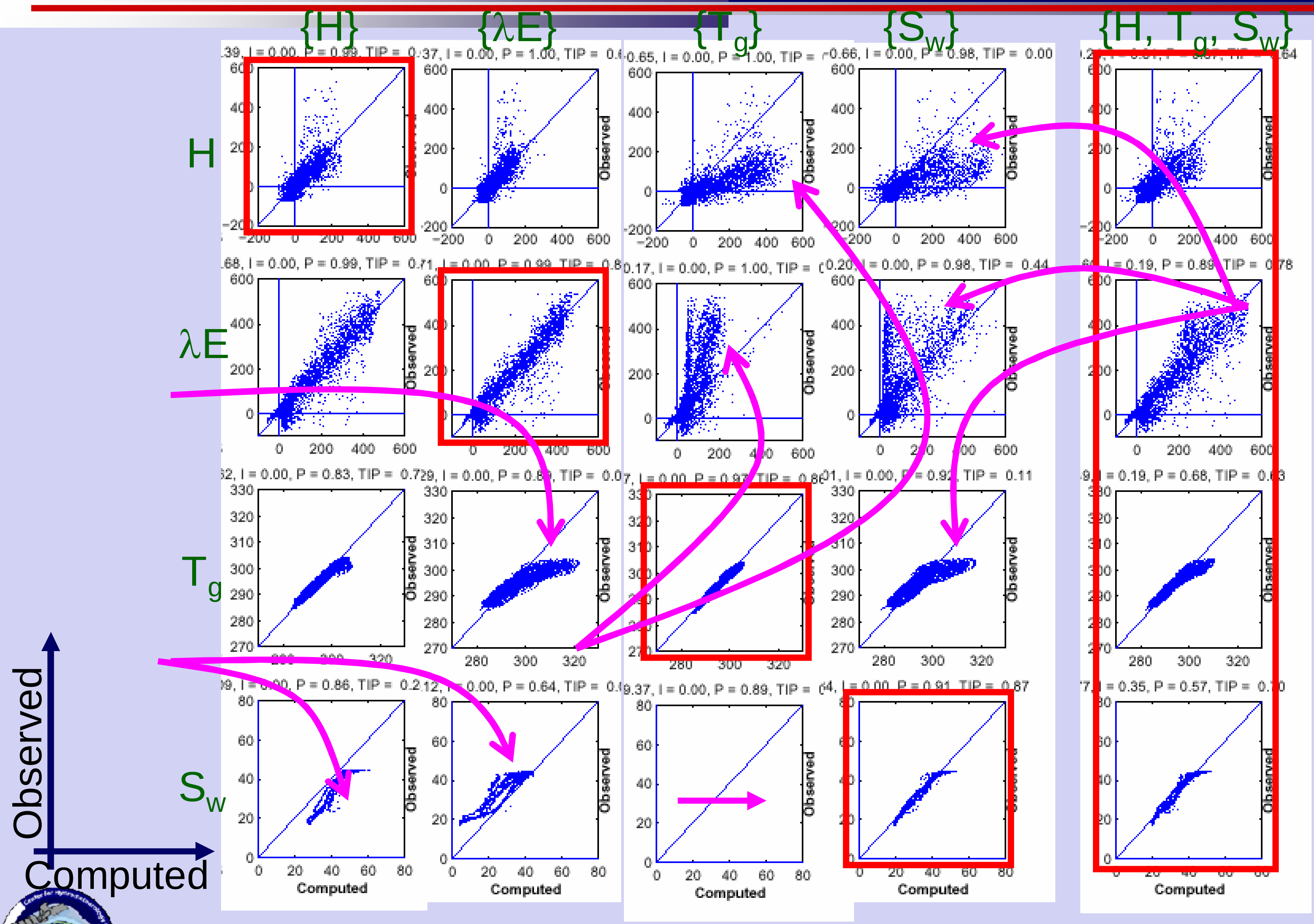


# ARM-CART SGP Site




Grid: ~100,000 km$^2$

# *Single- & Multi-Flux Calibrations*



# *Data Locations Characteristics*

BOREAS (NSA-OJP)
- Type: Evergreen Needleleaf
- Cover: 6.5%
- Precipitation: 242 mm
- Data : Jan 94 - Dec 96

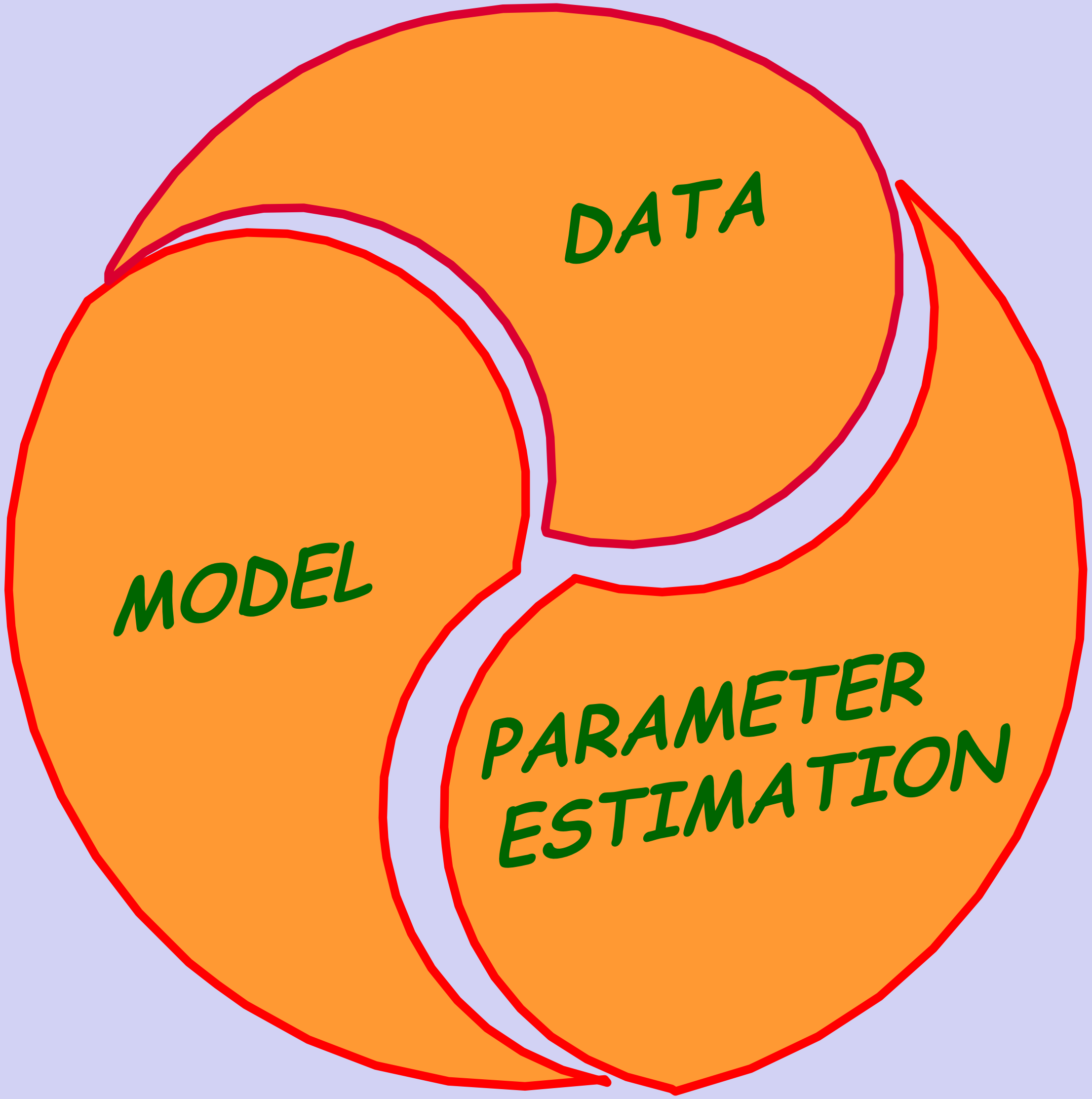
Cabauw
- Type: Short Grass
- Cover: 16.6%
- Precipitation: 776 mm
- Data : Jan 87 - Dec 87

Tucson
- Type: Semi-Desert
- Cover: 9.2%
- Precipitation: 275 mm
- Data : May 93 - Jun 94

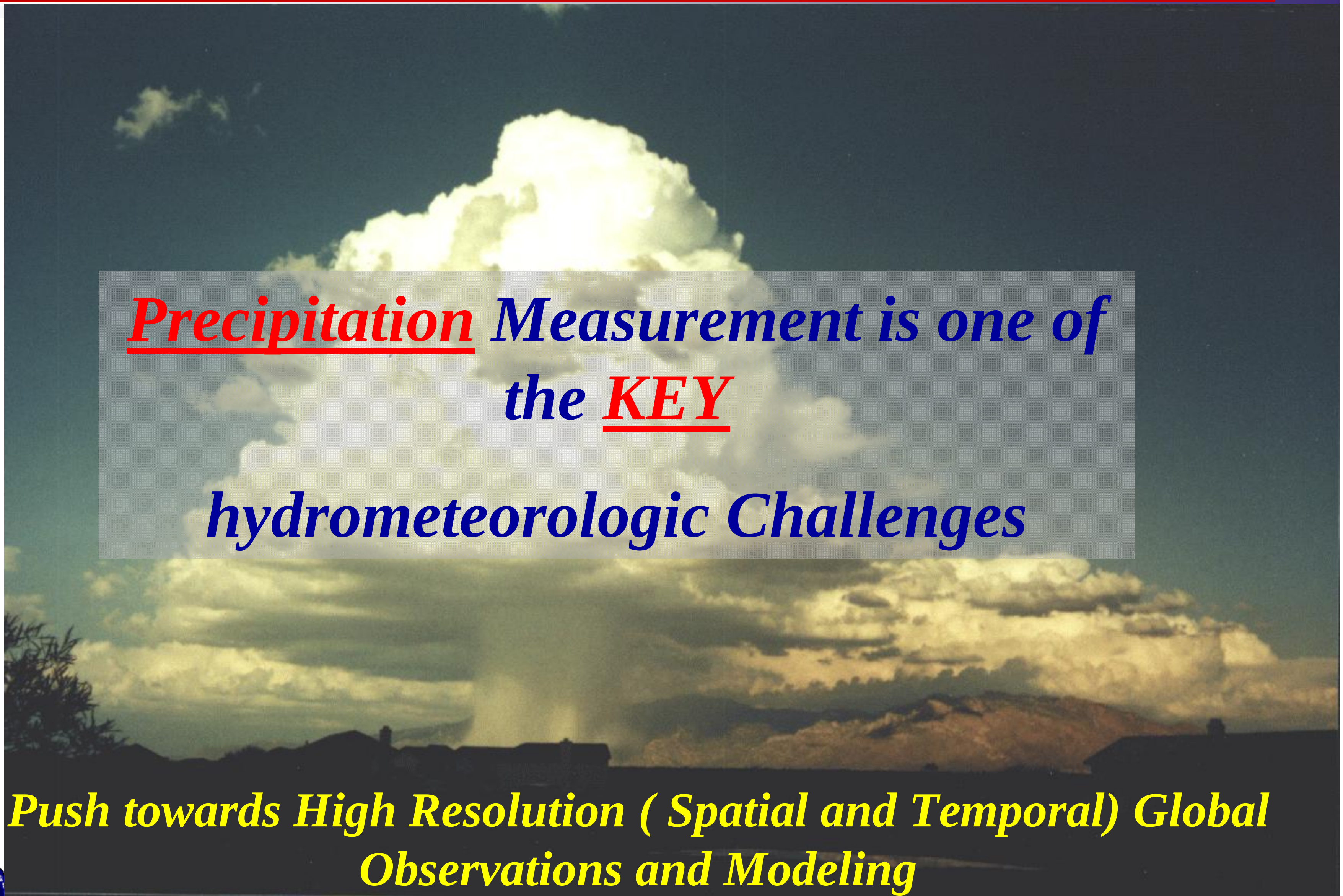
ABRACOS (Reserva Jaru)
- Type: Evergreen Broadleaf
- Cover: 9.7%
- Precipitation: 1600 mm
- Data : May 92 - Dec 93

ARM-CART (E13)
- Type: Mixed Crop / Farm Land
- Cover: 8.1%
- Precipitation: 600 mm
- Data : Apr 95 - Aug 95

# Data



# A Key Requirement!



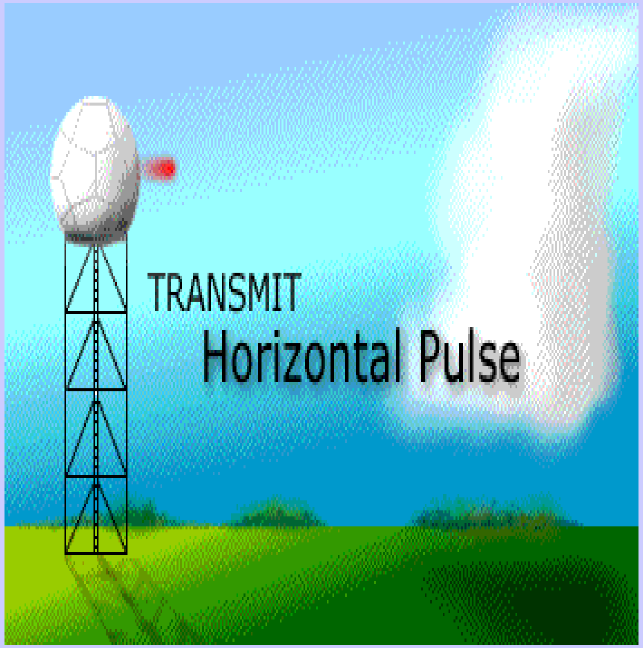
***Precipitation* Measurement is one of the *KEY***

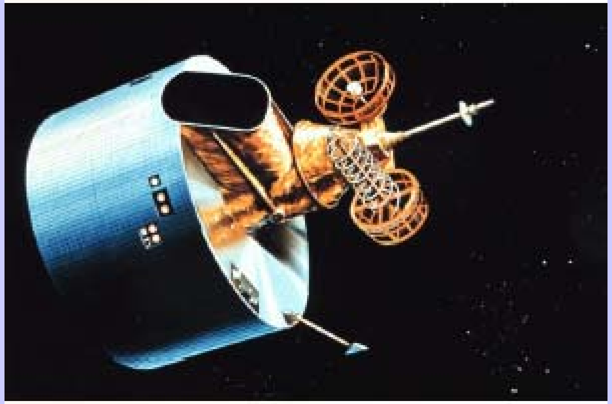
***hydrometeorologic Challenges***

***Push towards High Resolution ( Spatial and Temporal) Global Observations and Modeling***

# *Precipitation Observations: Which to trust??*

Rain Gauges

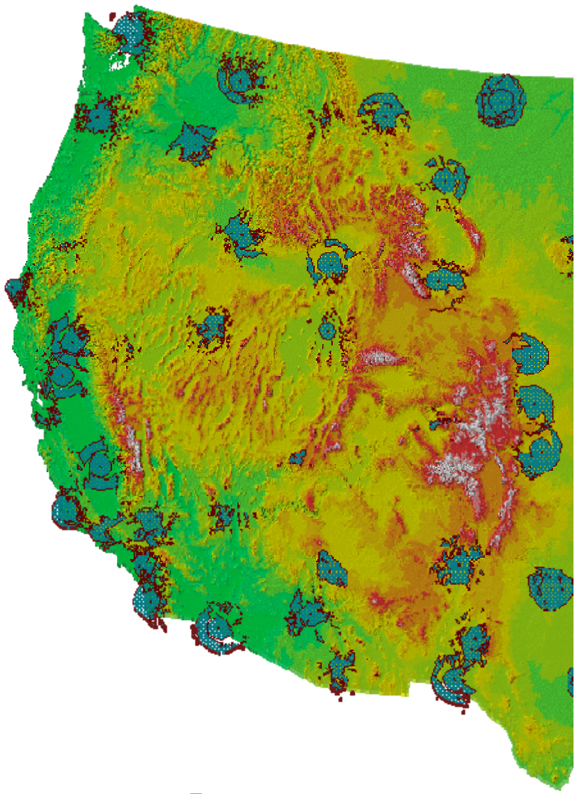


Satellite

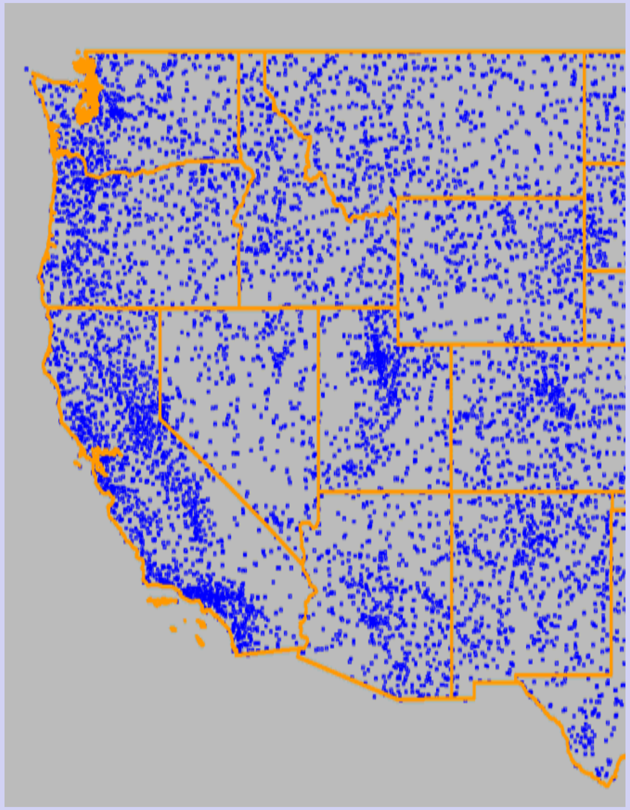
*Sources: R. Fulton, D.-J. Seo. and J. Breidenbach, AMS Short-Course on QPE/QPF, 2002*

# Coverage of the WSR-88D and gauge networks



**1 km AGL**

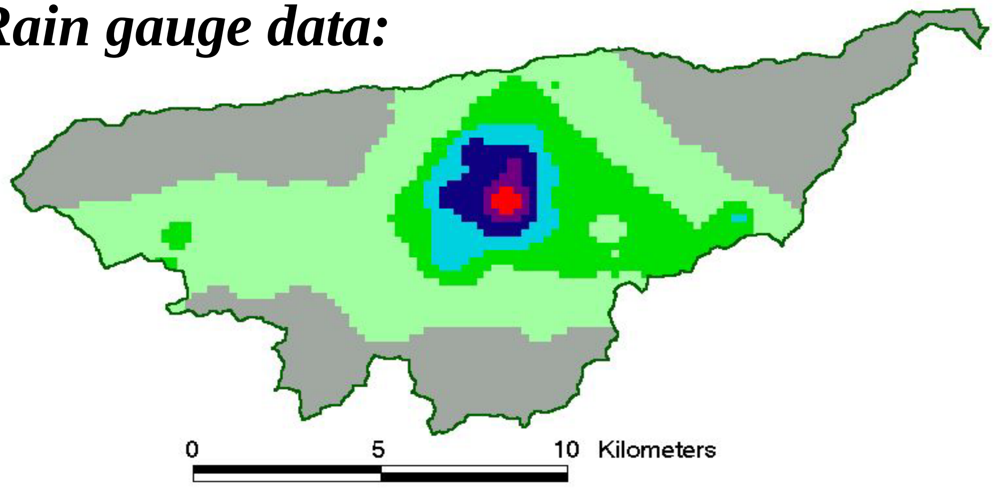
*Maddox, et al., 2002*



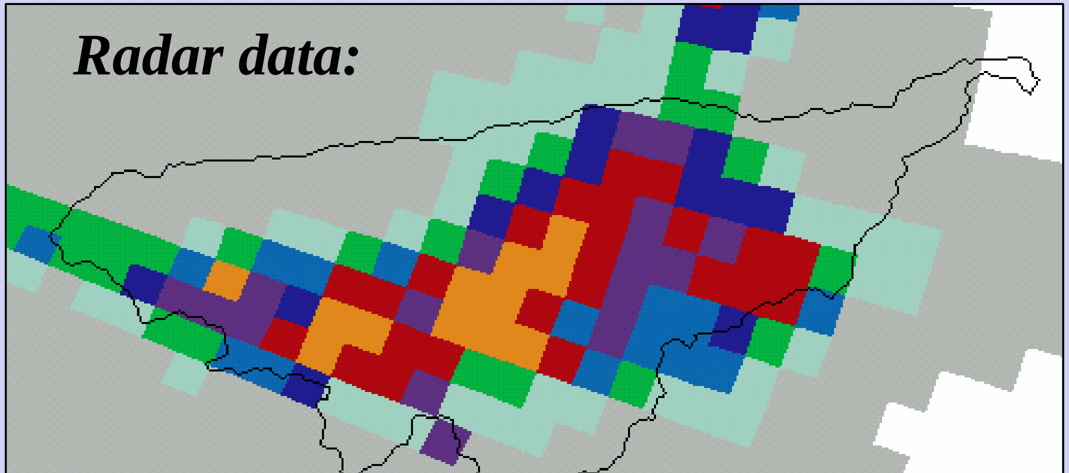
***Daily precipitation gages (1 station per 600 km^2 for Colorado River basin) hourly coverage even more sparse***

# Radar-Gauge Comparison (Walnut Gulch, AZ)

**Rain gauge data:**



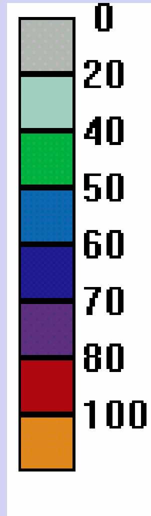

**Radar data:**



**Z=300R$^{1.4}$, 2.4$^{o}$ elevation, HailThresh=56 dbz**

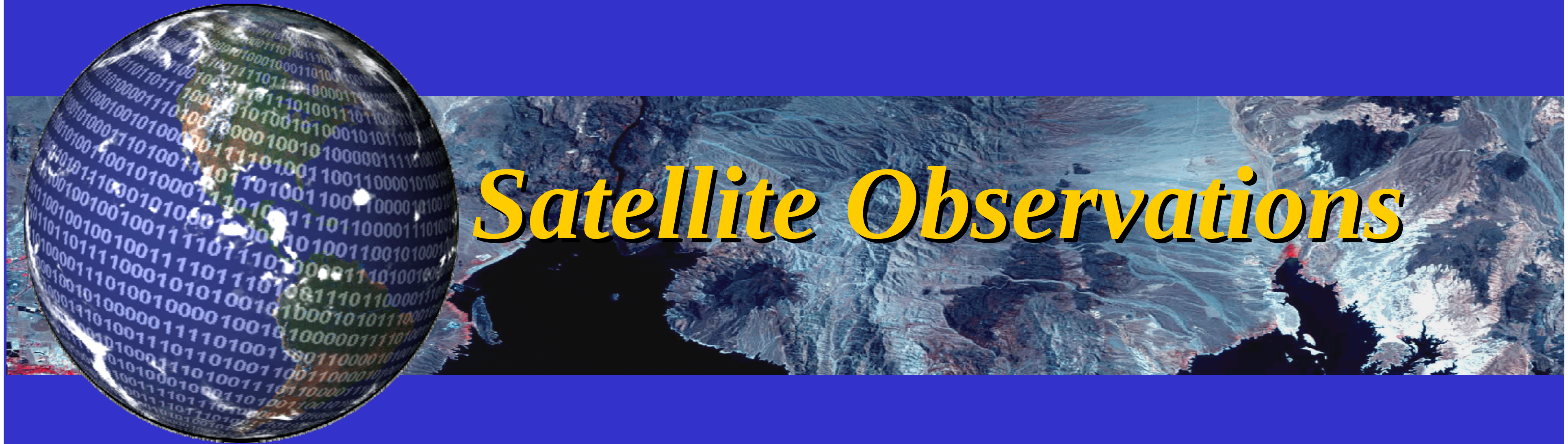
***Precipitation event: Aug. 11, 2000***

*Storm depth (mm)*



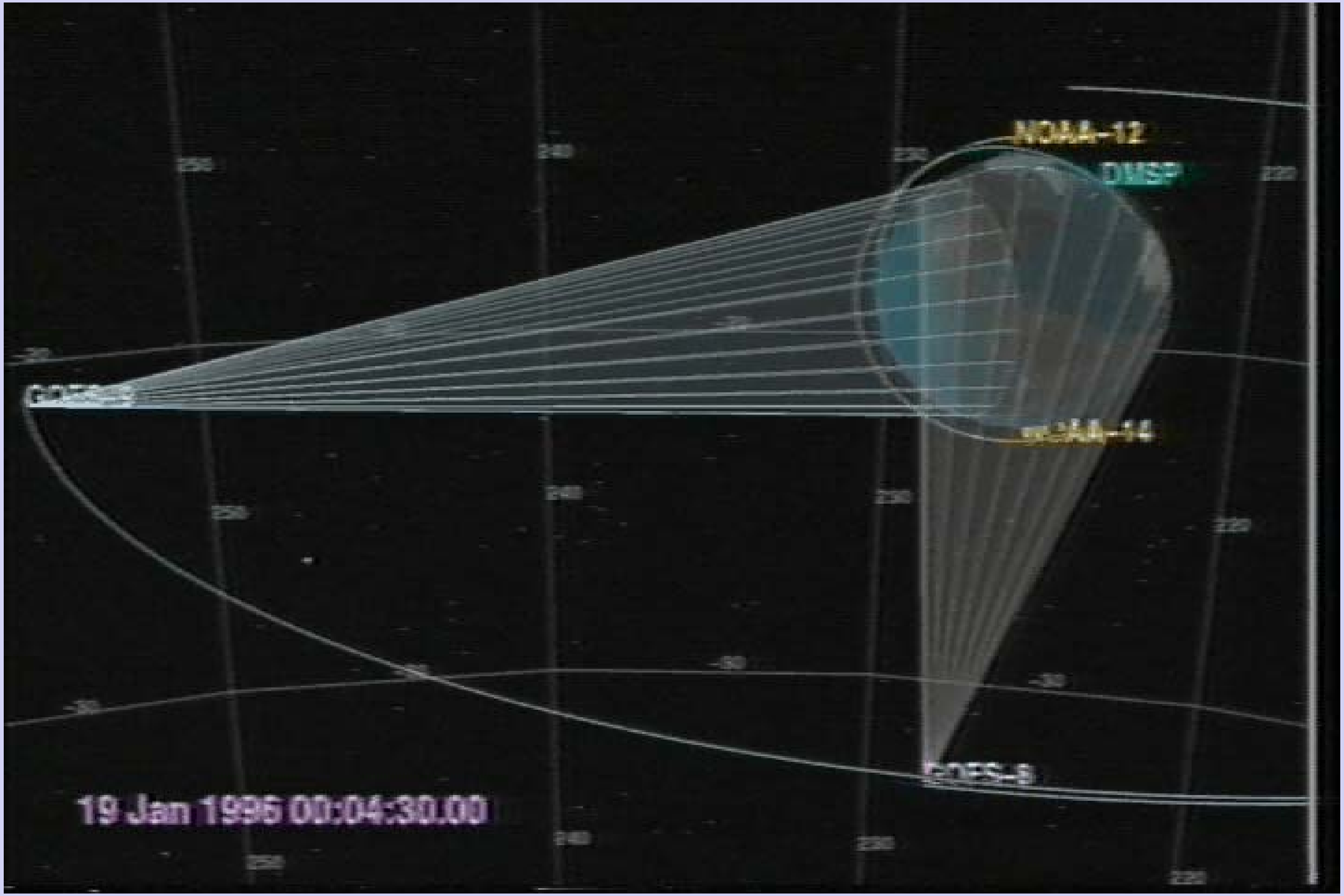

***70% overestimation by the radar!***

# Space-Based Observations

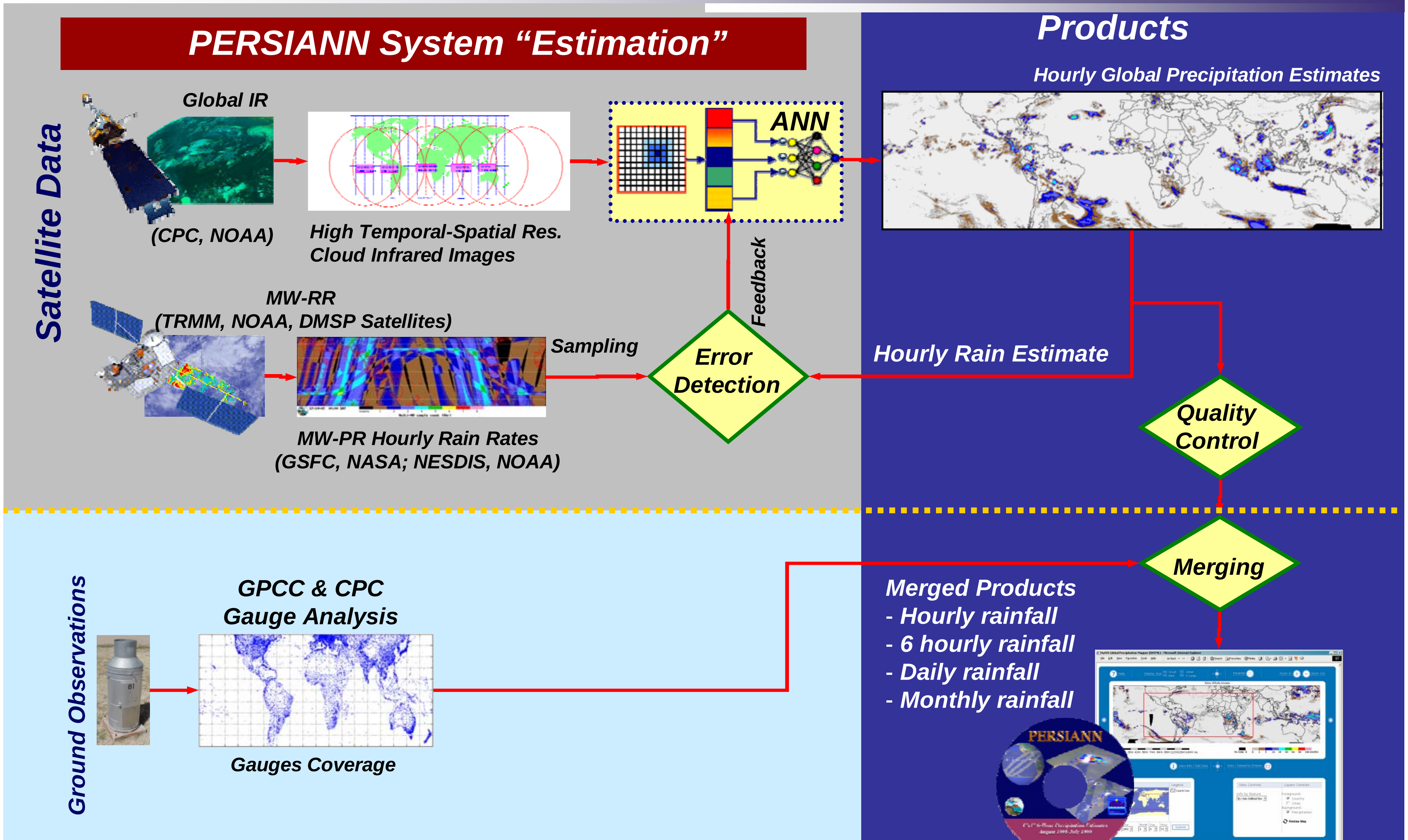


# Geostationary and Polar Satellites

*Courtesy: NASA's ESE*

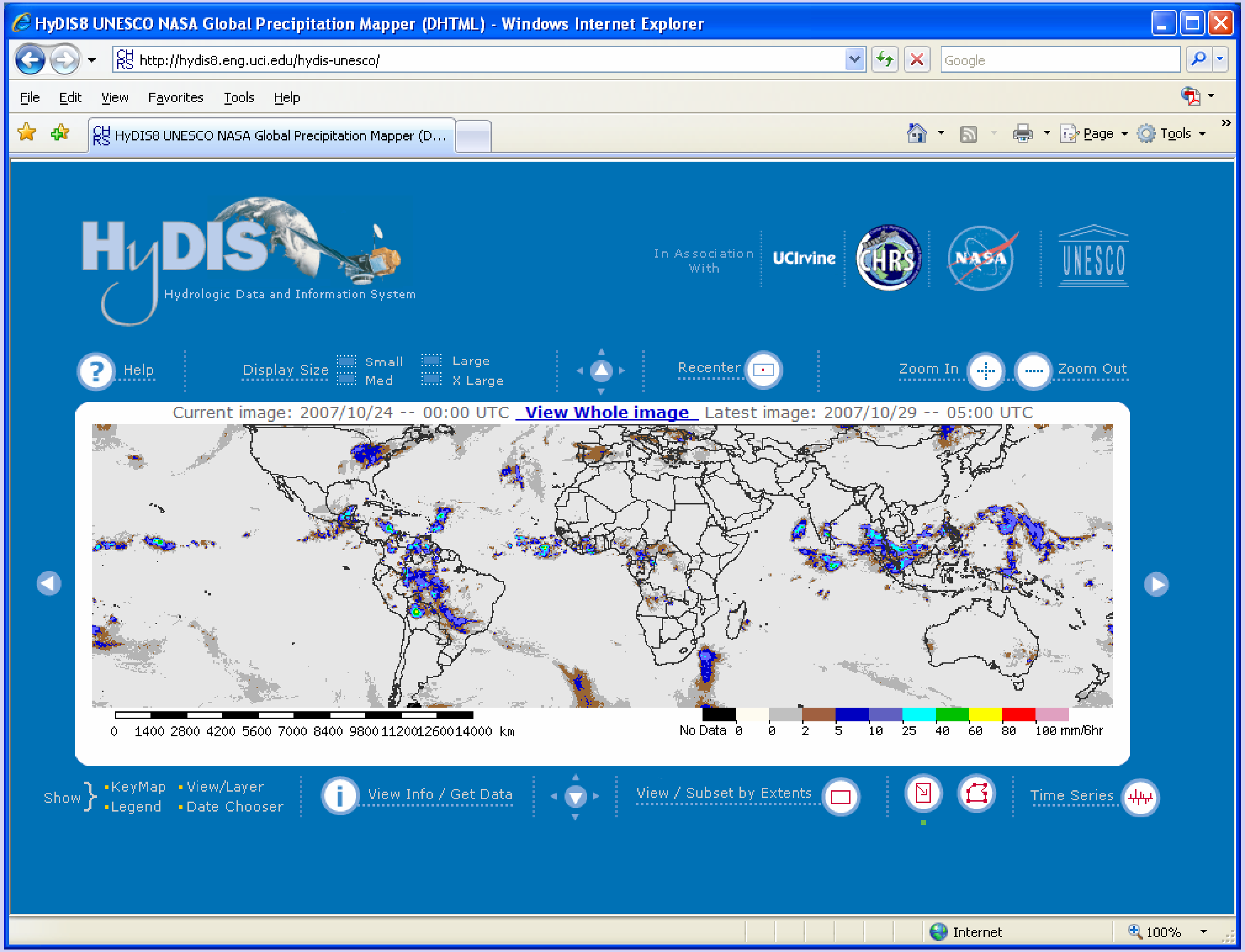


# Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)

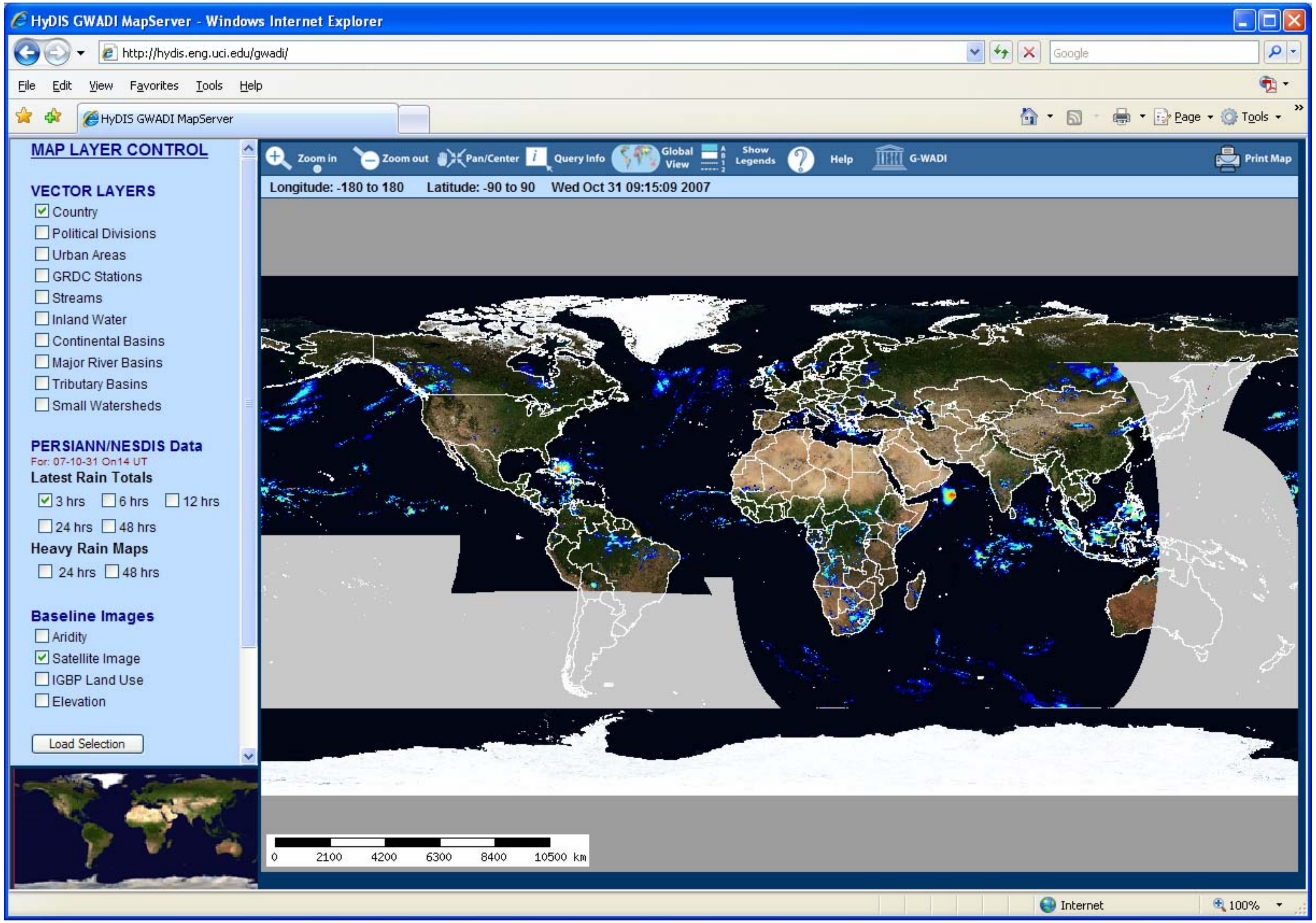



CHRS Center for Hydrometeorology and Remote Sensing, University of California, Irvine

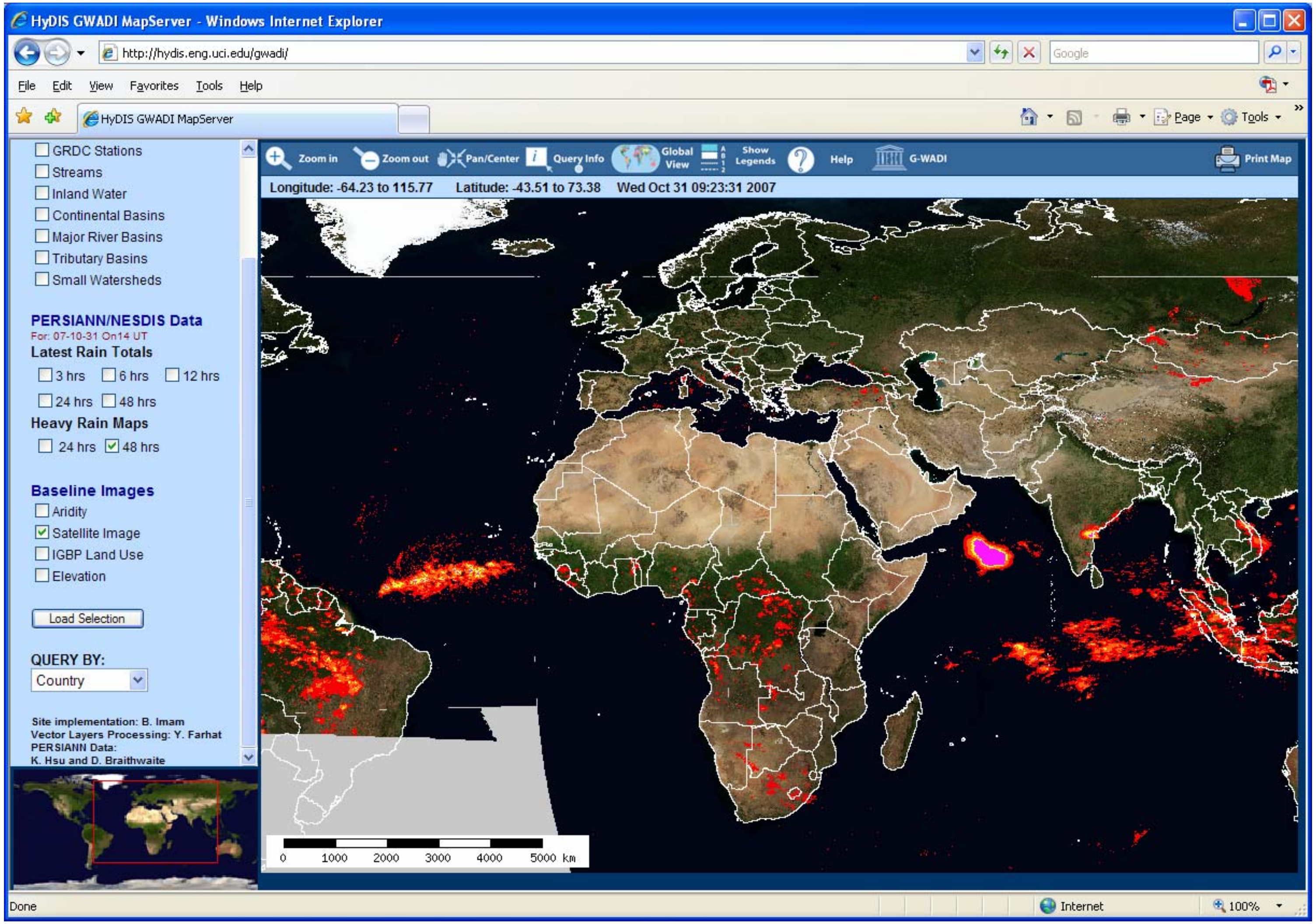
# Satellite Products: Promising future



# Satellite Products: Promising future



# Satellite Products: Promising future

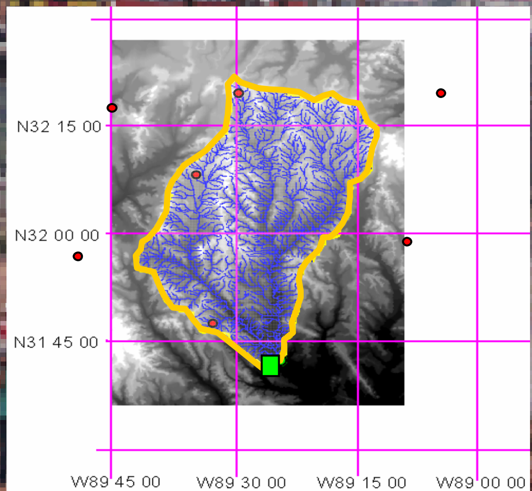


# Satellite Rainfall Estimation: Research at UC Irvine

Streamflow forecasting of a catchment in US using UCI-PERSIANN rainfall Estimates for use in the US National Weather Service Runoff Forecasting System (NWSRFS).

***Promising Potential for Various Applications:***

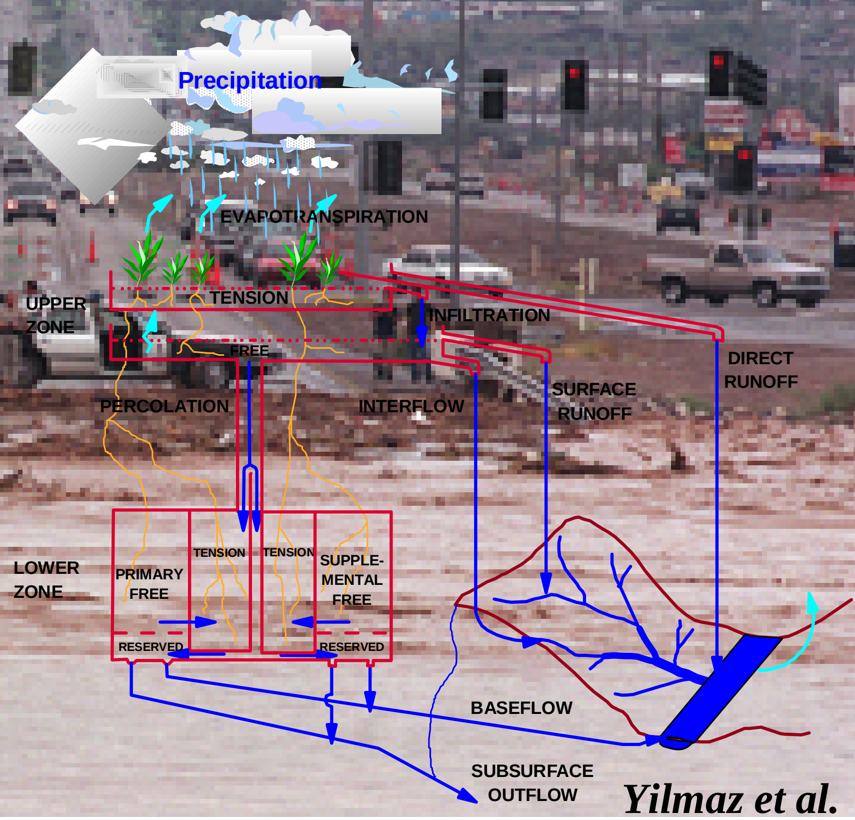
***Flood Forecasting Example***




● Gages used by NWS

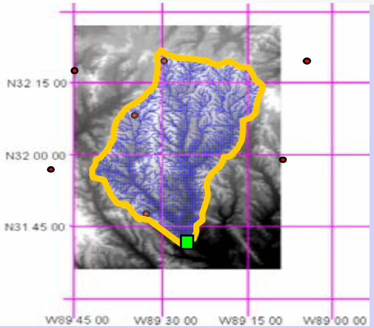
*Leaf River Near Collins*
*Mississippi*
*USGS # 02472000*

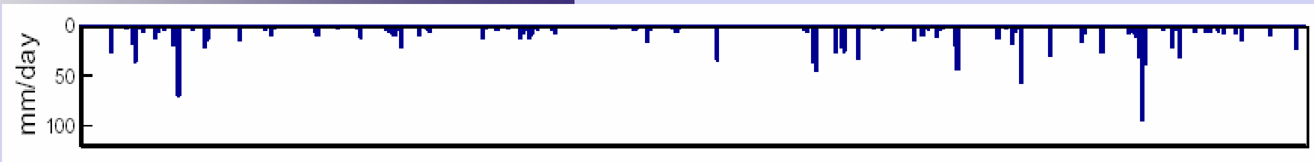
*Basin Area : 753 mi$^2$*

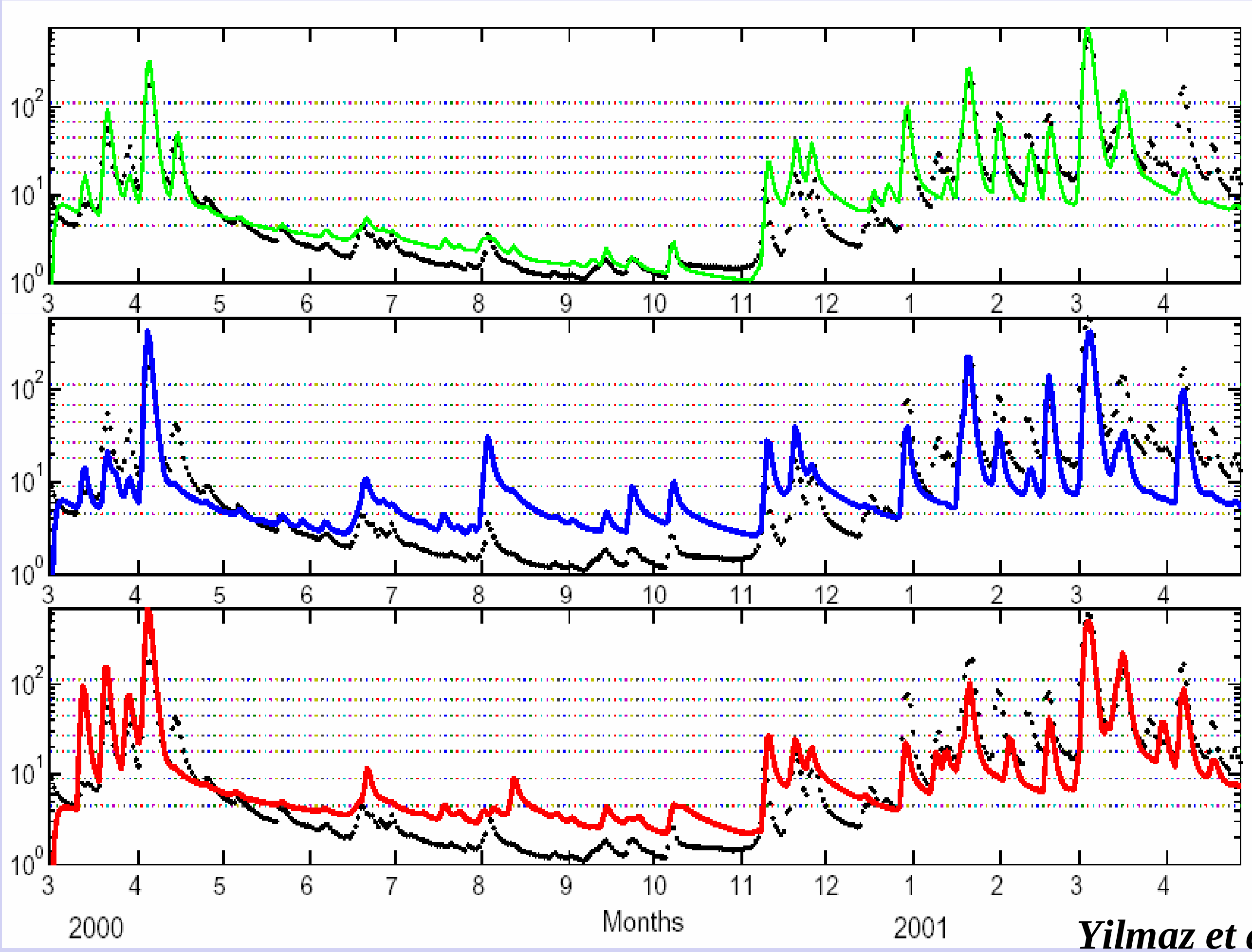



**Yilmaz et al. JHM 2005**

# Satellite Rainfall Estimation: Research at UC Irvine




**RAINGAGE**

Corr =0.95
RMS =23.9
BIAS =-1.32

**RADAR**

Corr =0.92
RMS =28.8
BIAS =-6.74

**PERSIANN**

Corr =0.94
RMS =22.6
BIAS =-5.15

***Yilmaz et al.* *JHM 2005***

# Satellite-Based Precipitation: Any Good for Hydrometeorological Applications???

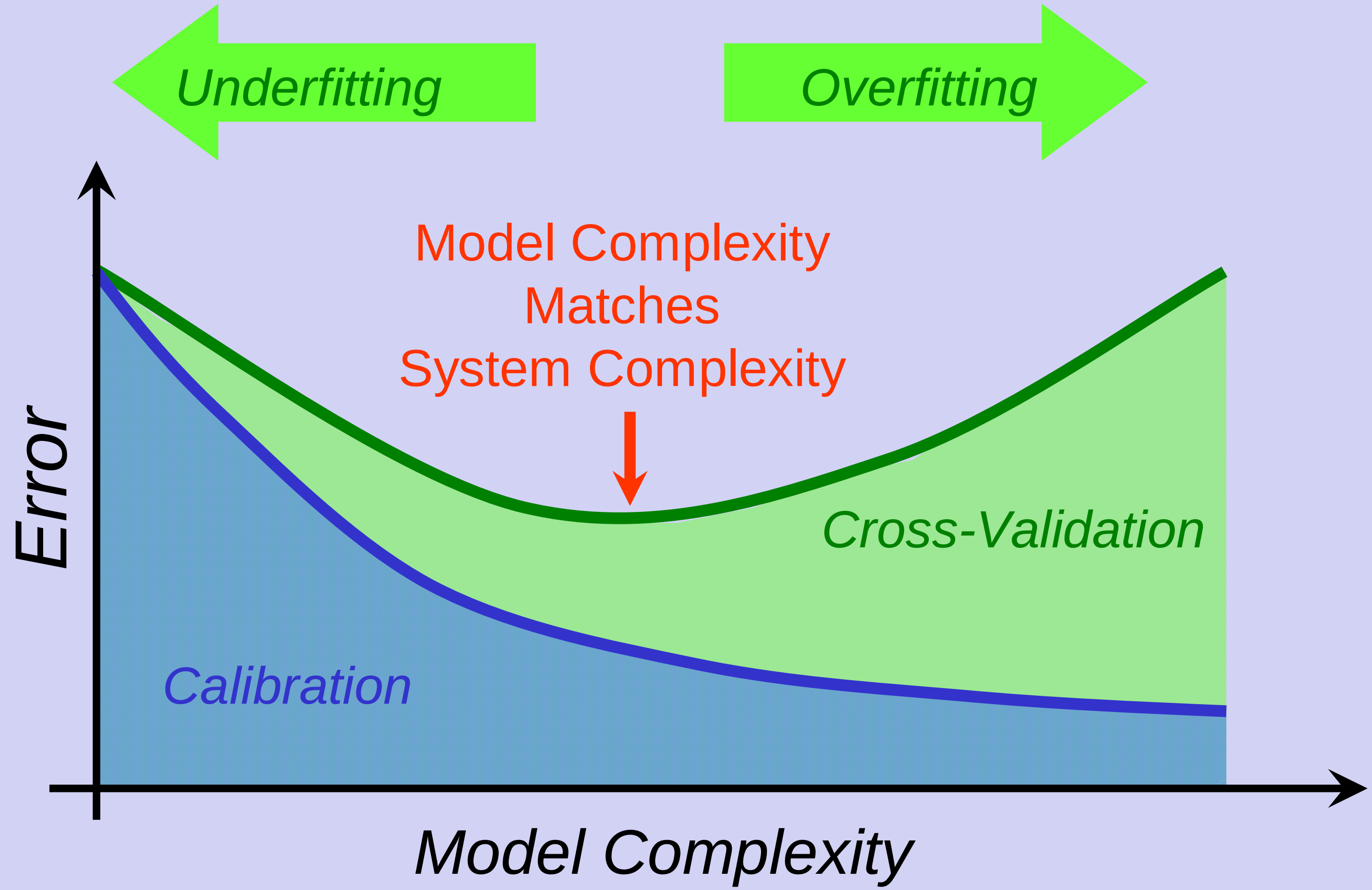

# *Very Promising*

# GPM Mission: Target Date 2012?

**OBJECTIVES**

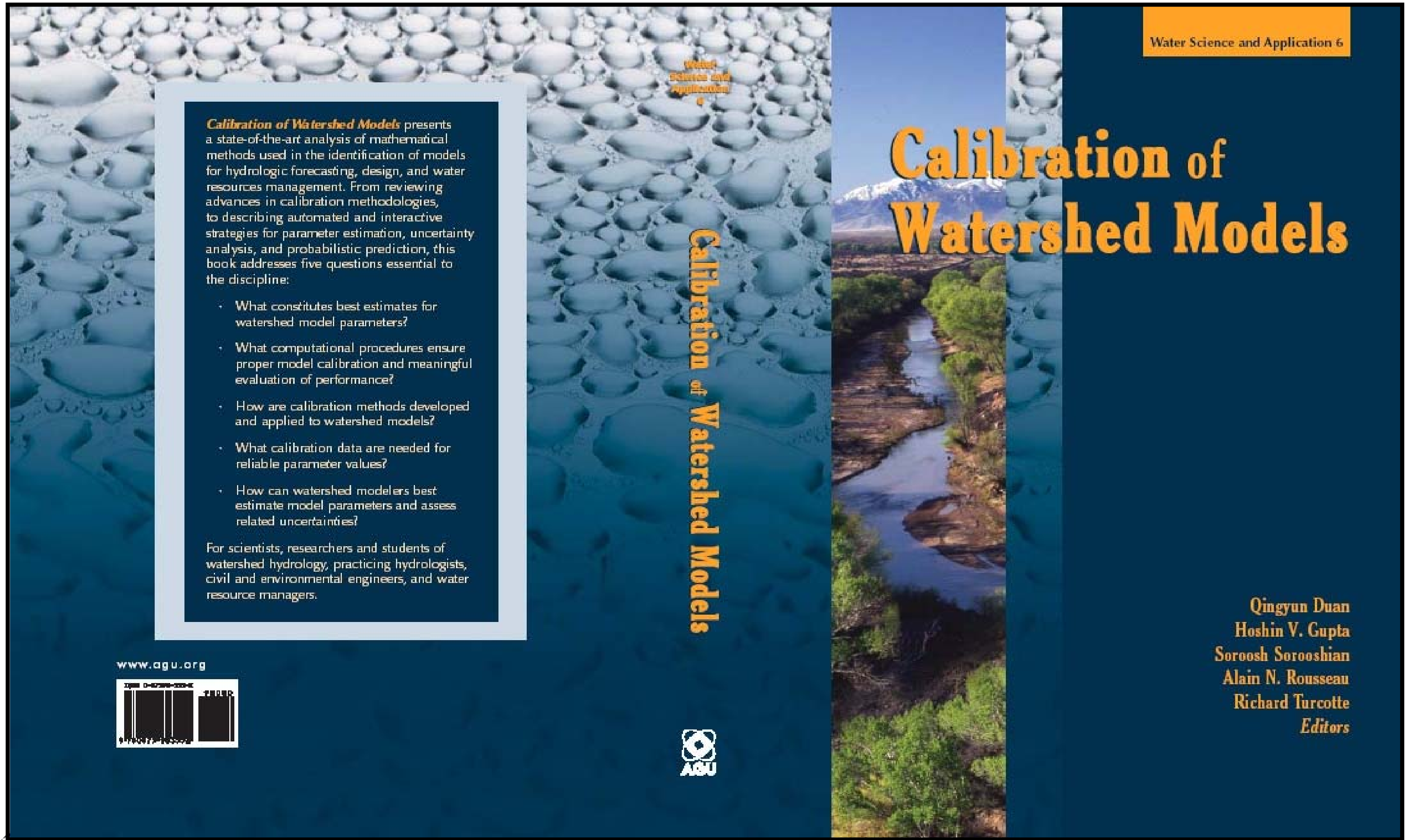
- **1 Main satellite + 8 Smaller Satellites **
- **Provide sufficient global sampling to significantly reduce uncertainties in short-term rainfall accumulations**

# Limit to Model Complexity




Source: Gershenfeld, 1999

# AGU Monograph – Now Available

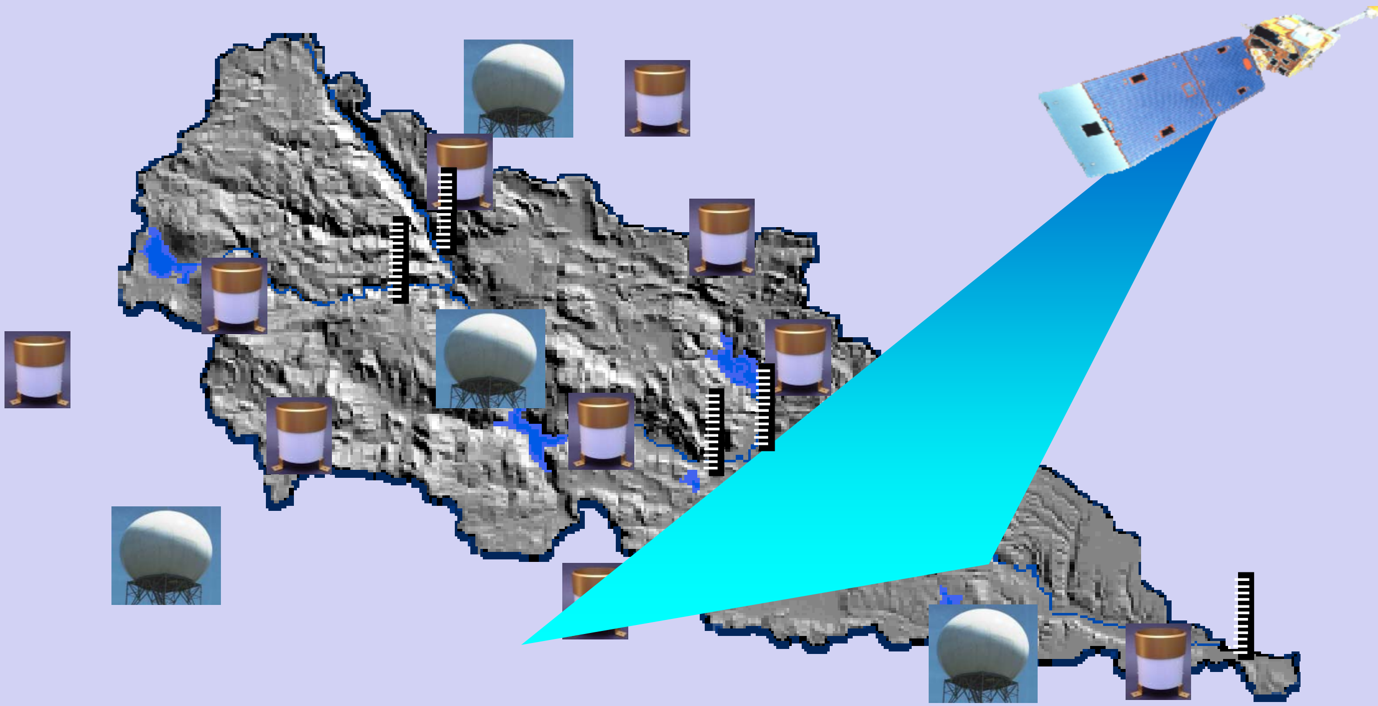



Thank You For Listening
The Rio Grande River, NM Photo: J. Sorooshian 2005

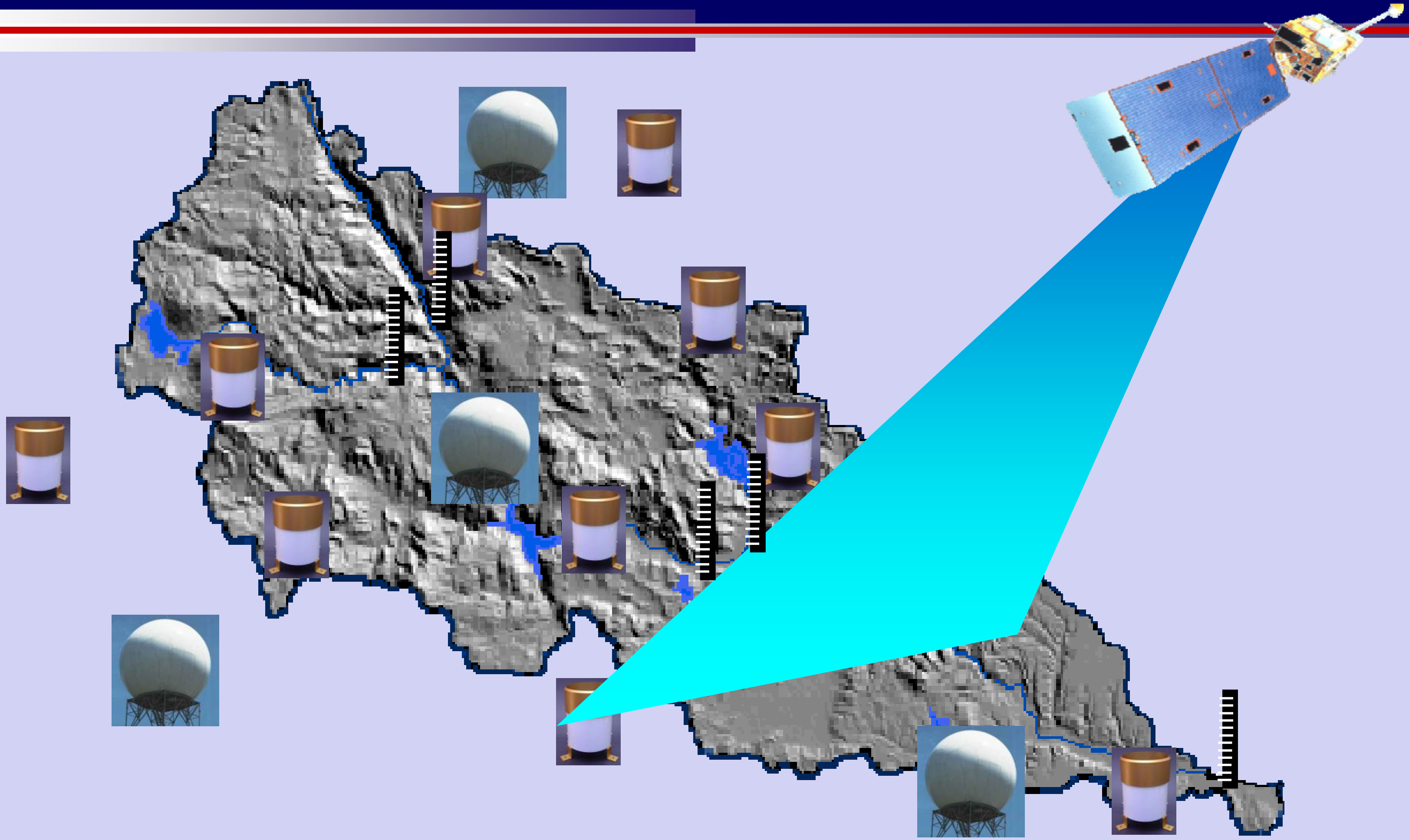
# Data Requirements for Hydrologic Modeling

## Limitations

**prediction** or forecasting of the hydrological responses of given watershed
highly dependant on availability of data for calibration and prediction

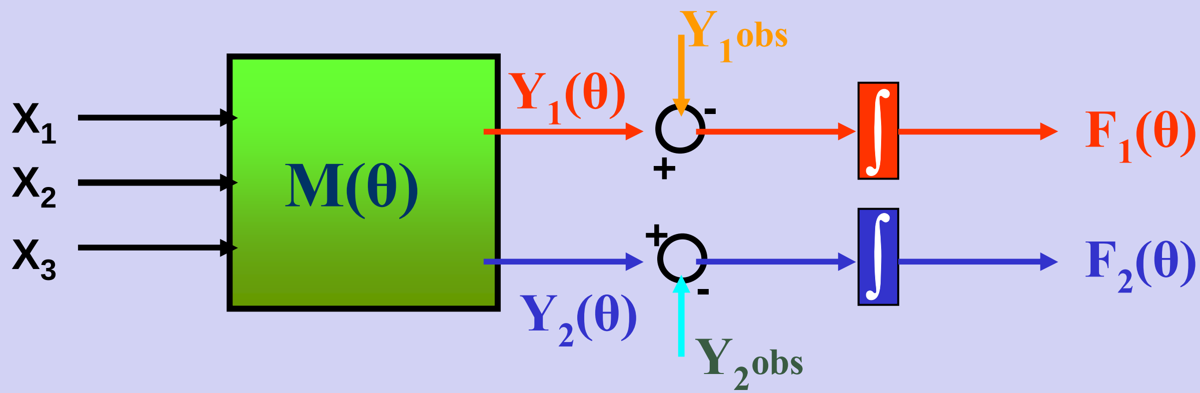


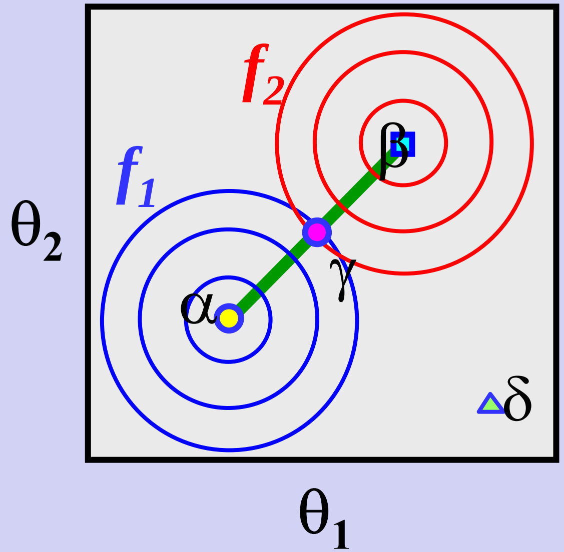
# Data Requirements for Hydrologic Modeling

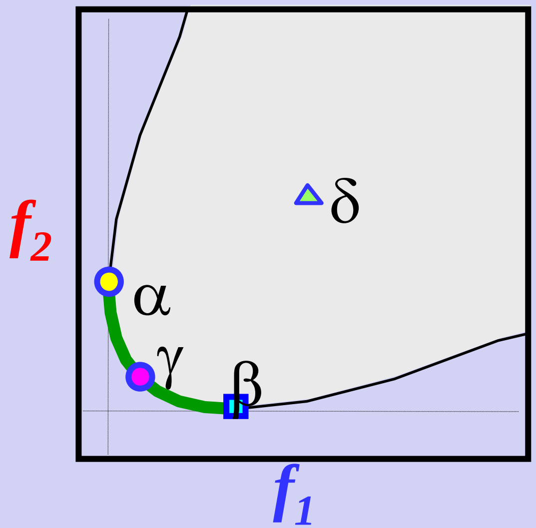


Data Limitation is an Important Factor in Success of Hydrologic Modeling

# *Multi-Criteria Calibration Approach*




*Gupta, Sorooshian, Yapo, WRR, 1998*