Lecture III
Calibration and parameter Estimation Requirements of Hydrologic Models

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The Abdus Salam ICTP Summer School on:

Climate Impact Modeling for Developing Countries:

Water, Agriculture & Health

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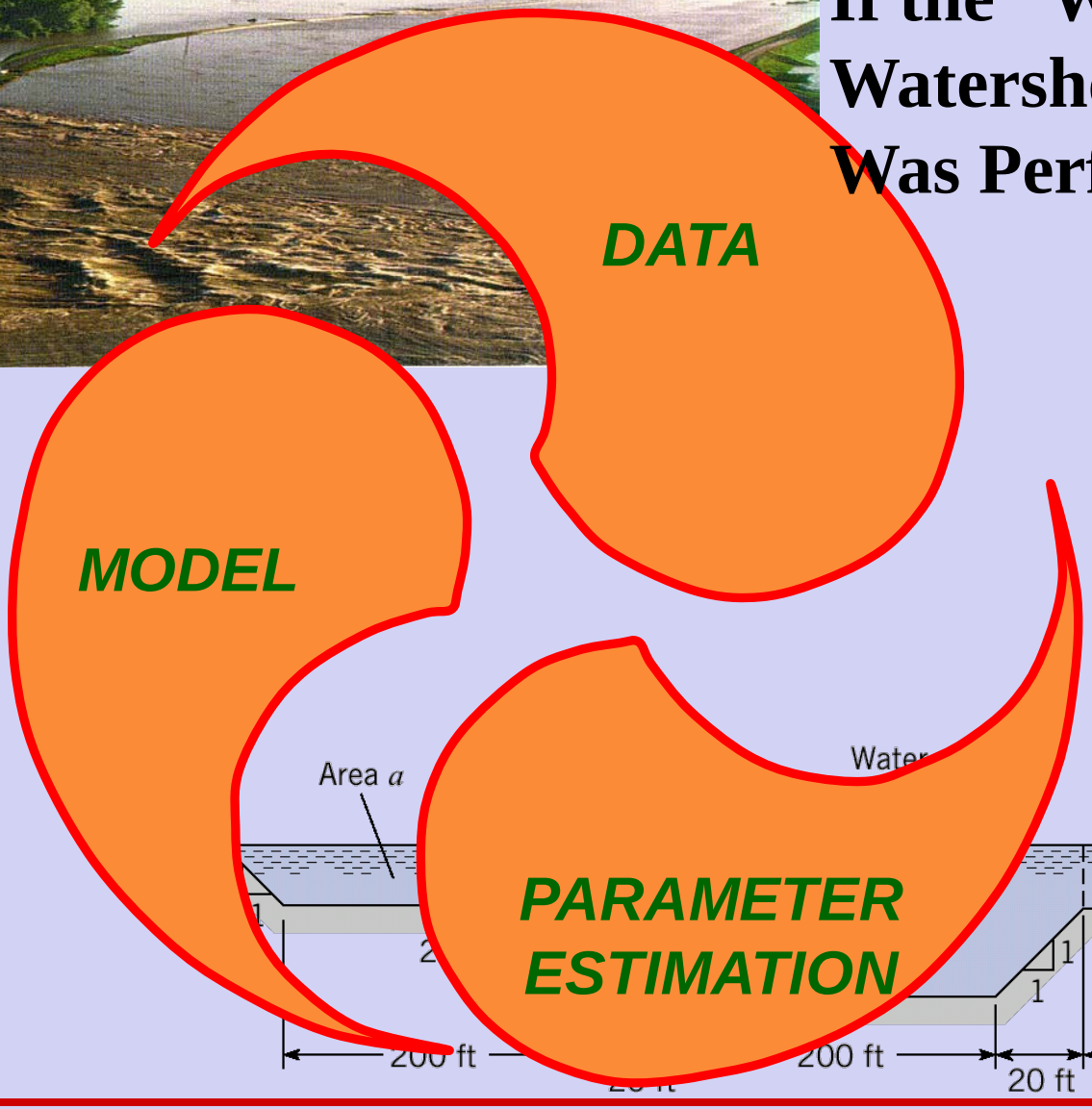
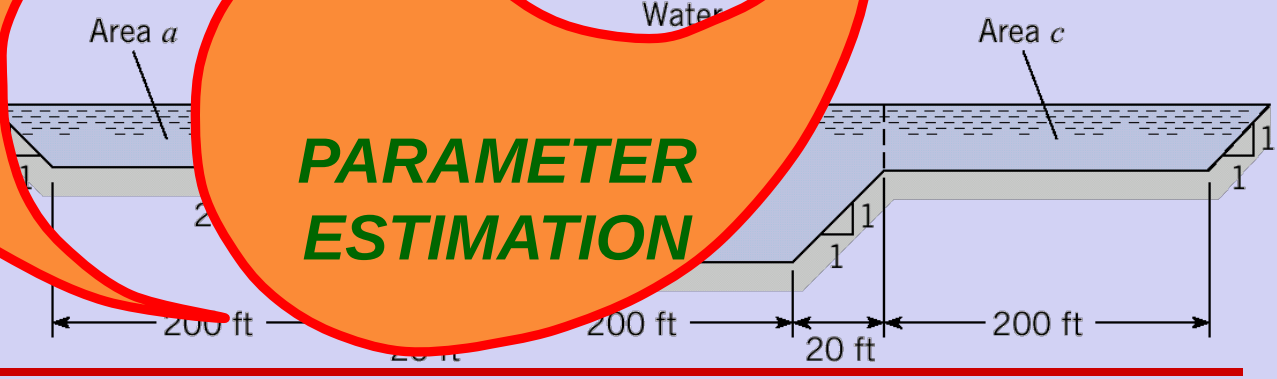
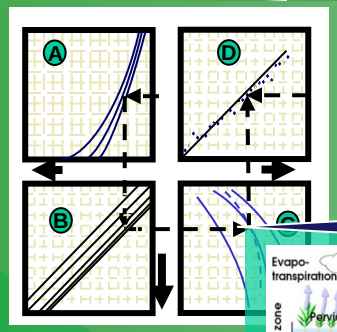
Hydrologic Modeling: 3 Elements!

If the "World" of Watershed Hydrology Was Perfect!

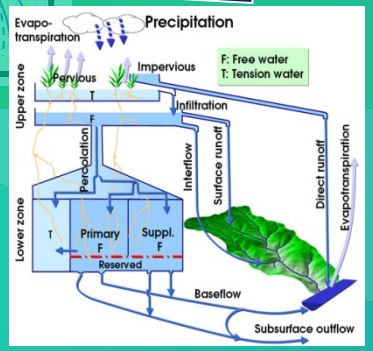




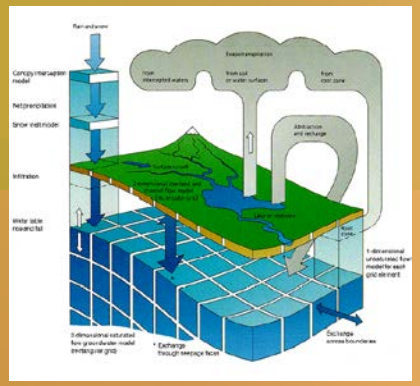
Evolution of Hydrologic R-R Models



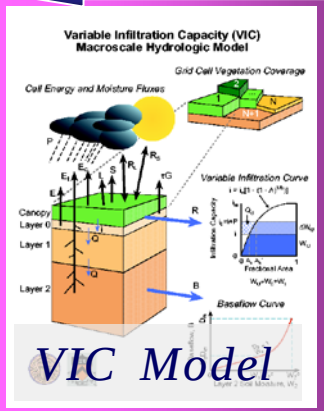
API Model



Lumped Conceptual



Distributed (Mike SHE)



VIC Model

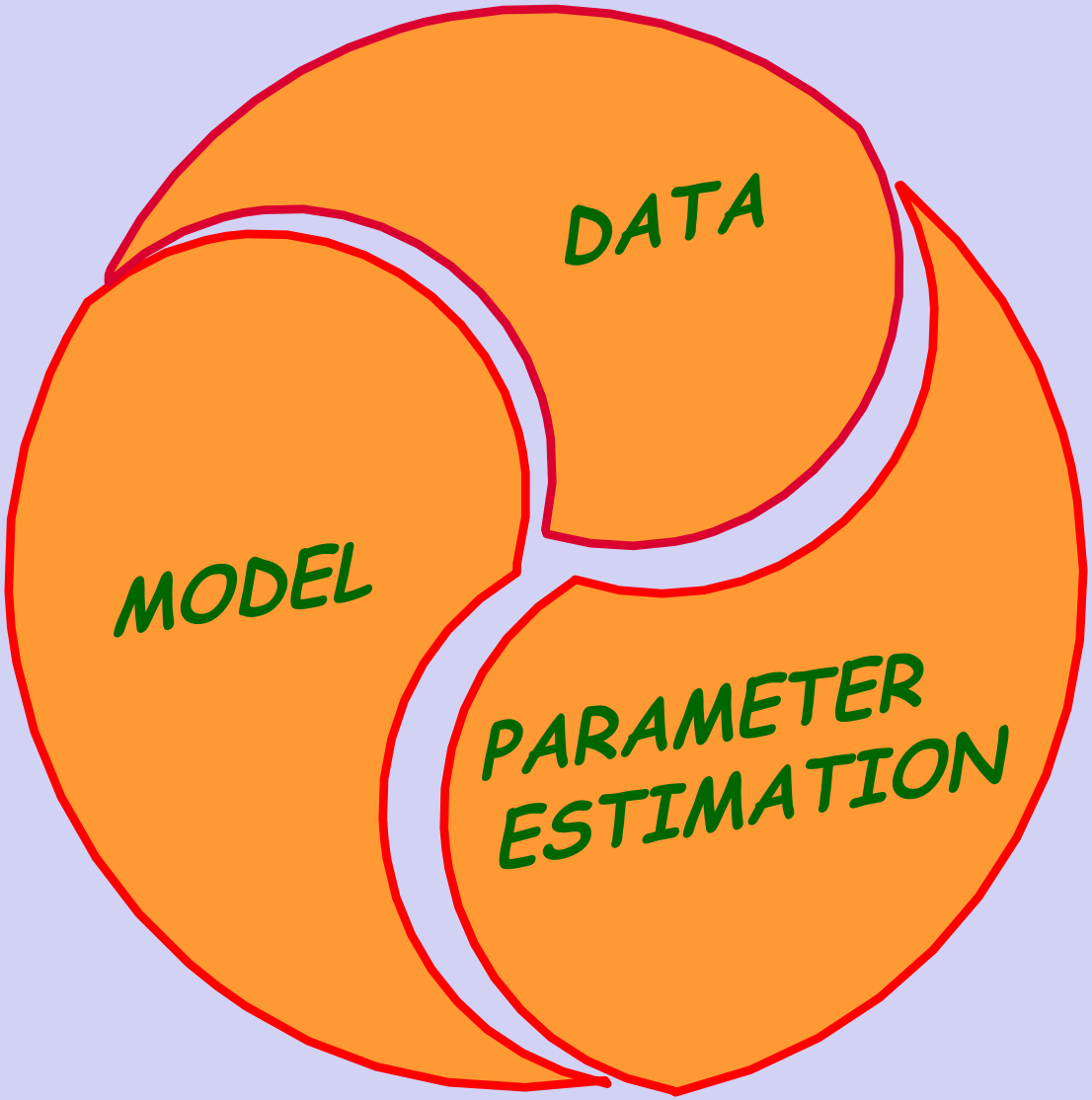
Lumped "Simple"

Time

Distributed

Physically-based

Model Calibration



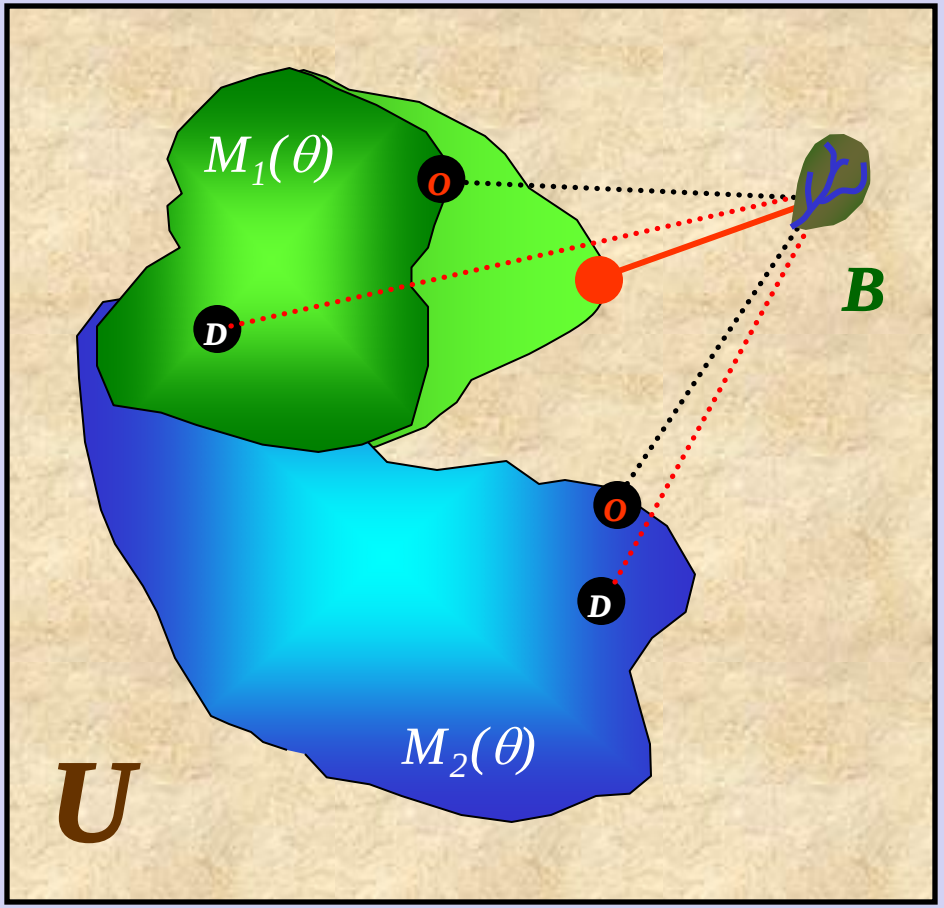
The Identification Problem

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

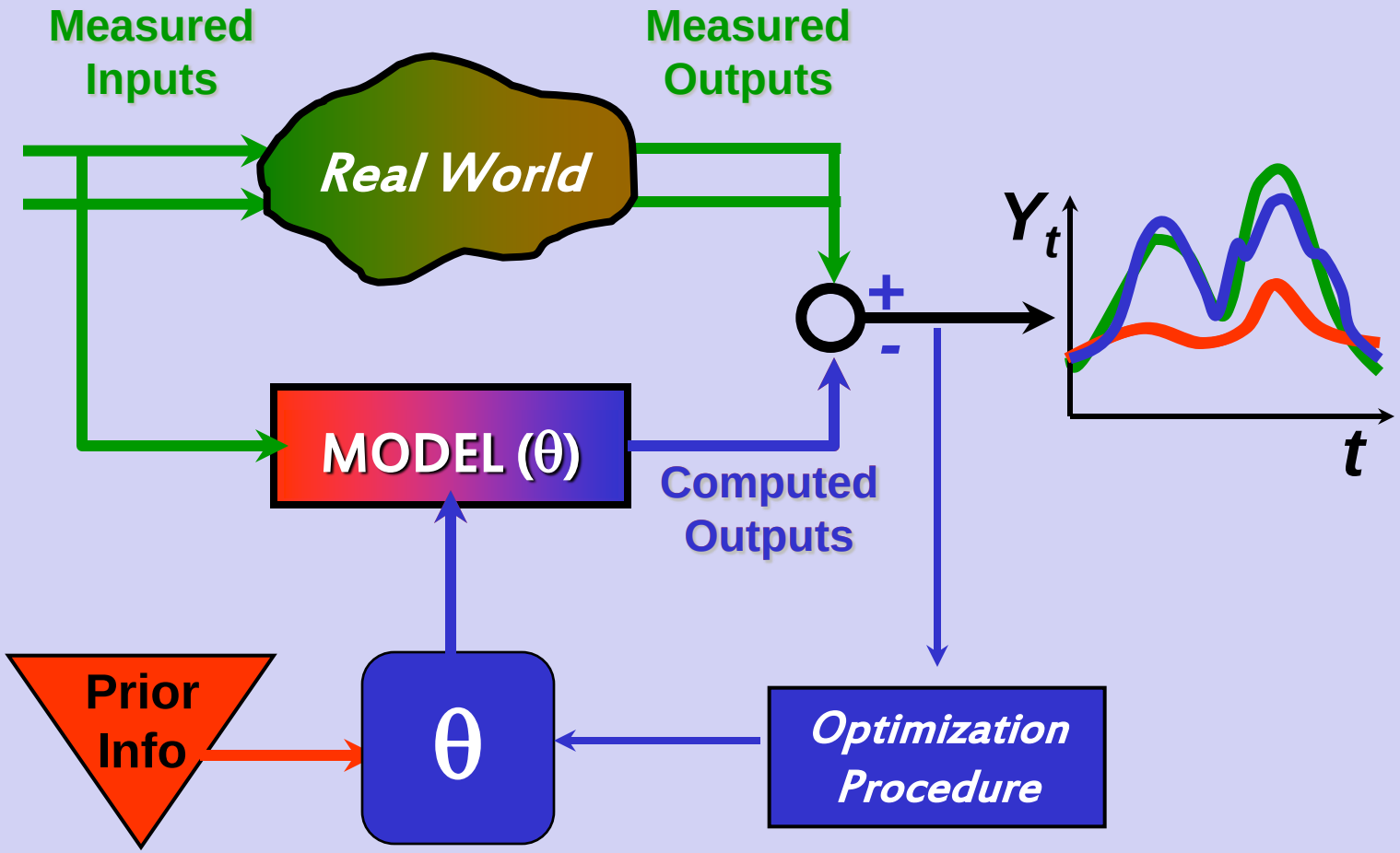
U – Universal Set

B - Basin

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



The Concept of Model Calibration



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

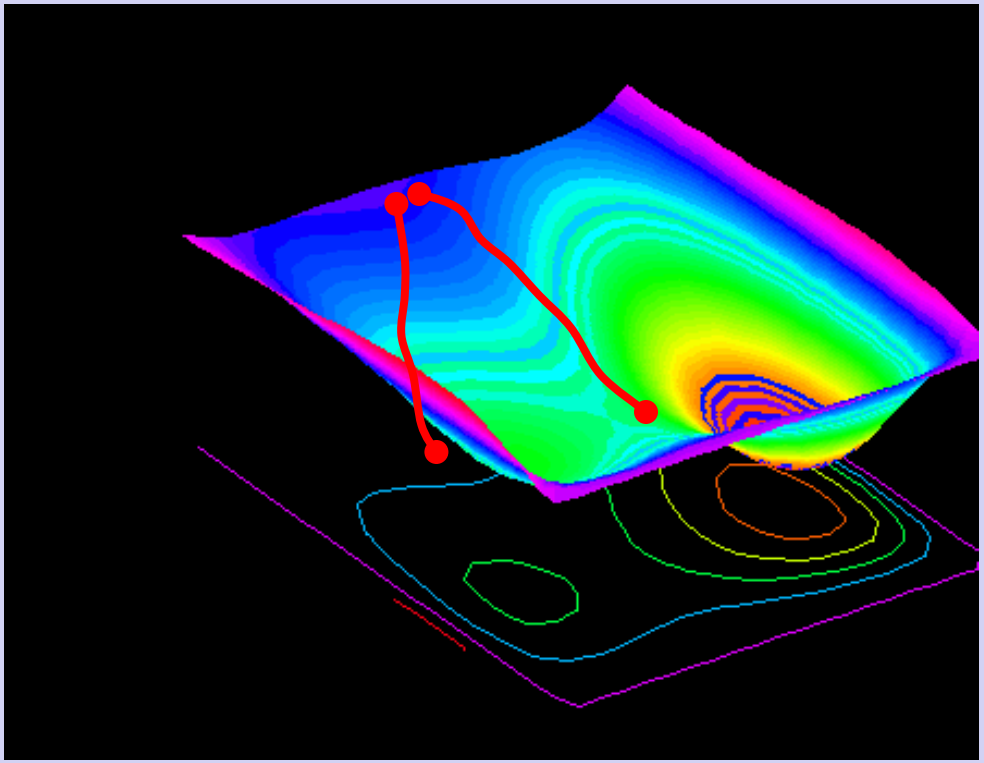
The Automatic Calibration Approach

Calibration components

Objective Function

Search Algorithm

Sensitivity Analysis



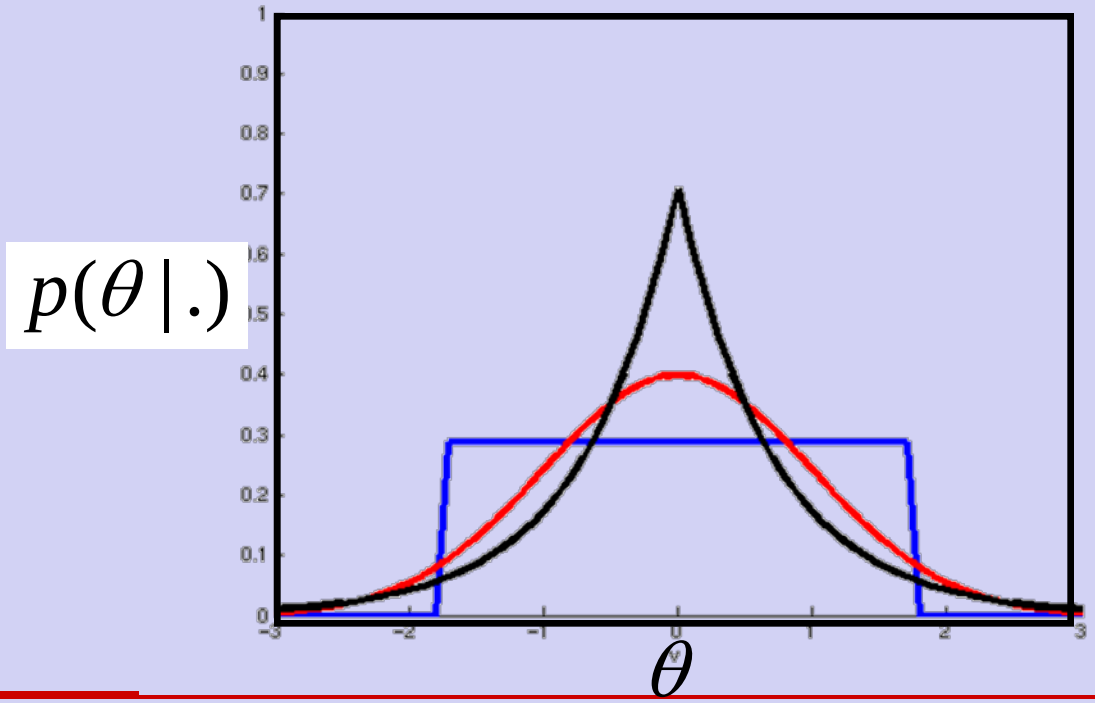
Problems with identifiability

Calibration Criterion

[General Exponential Power Density]

(Posterior Parameter Probability Distribution Function)

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

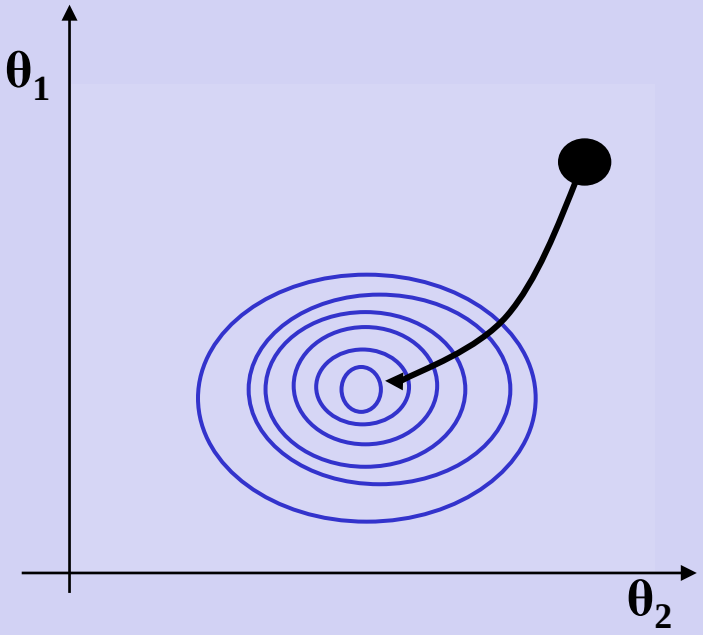


Uniform $\gamma \to (-1)$

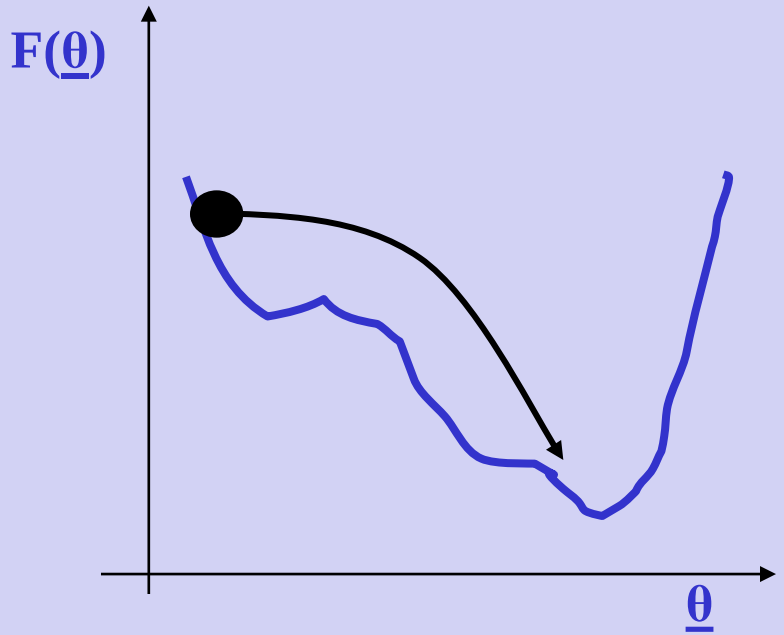
Normal $\gamma = 0$

Exponential $\gamma = 1$

Objective function Parameter Space

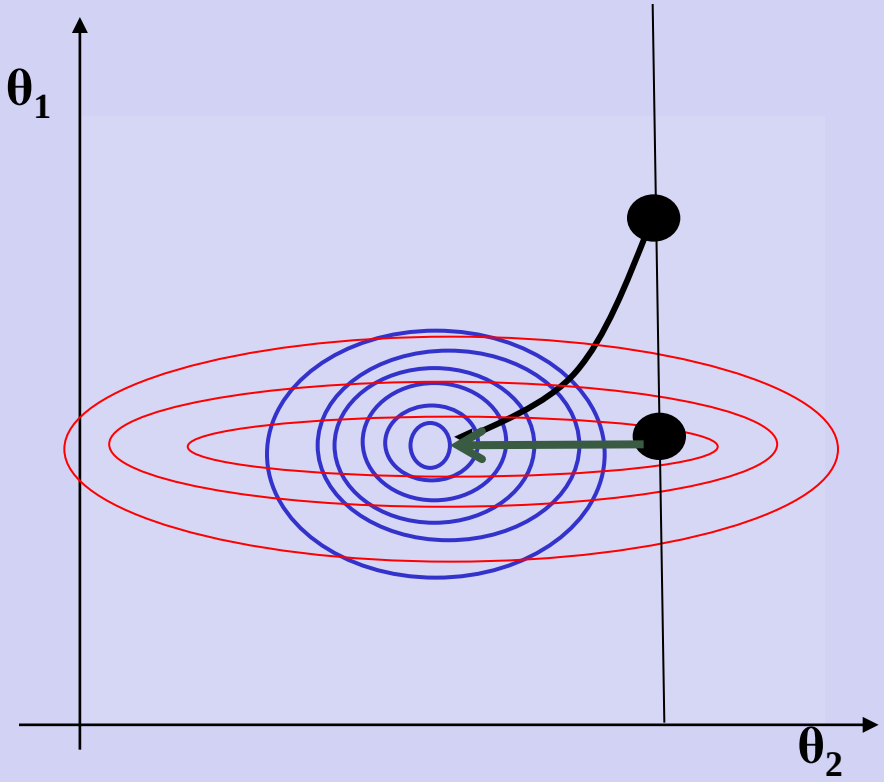


Parameter Space



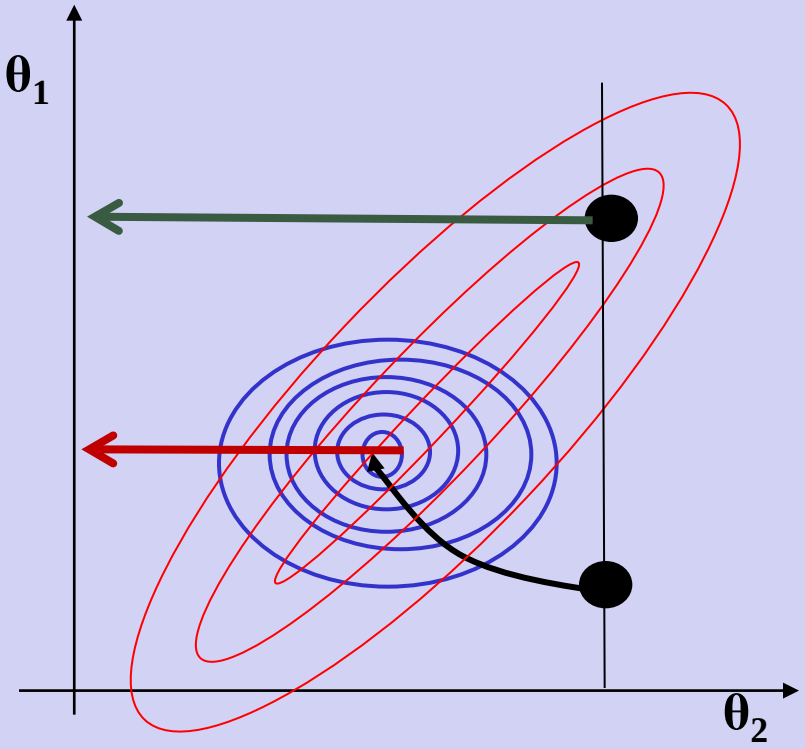
Objective Function Space

Parameter Sensitivity



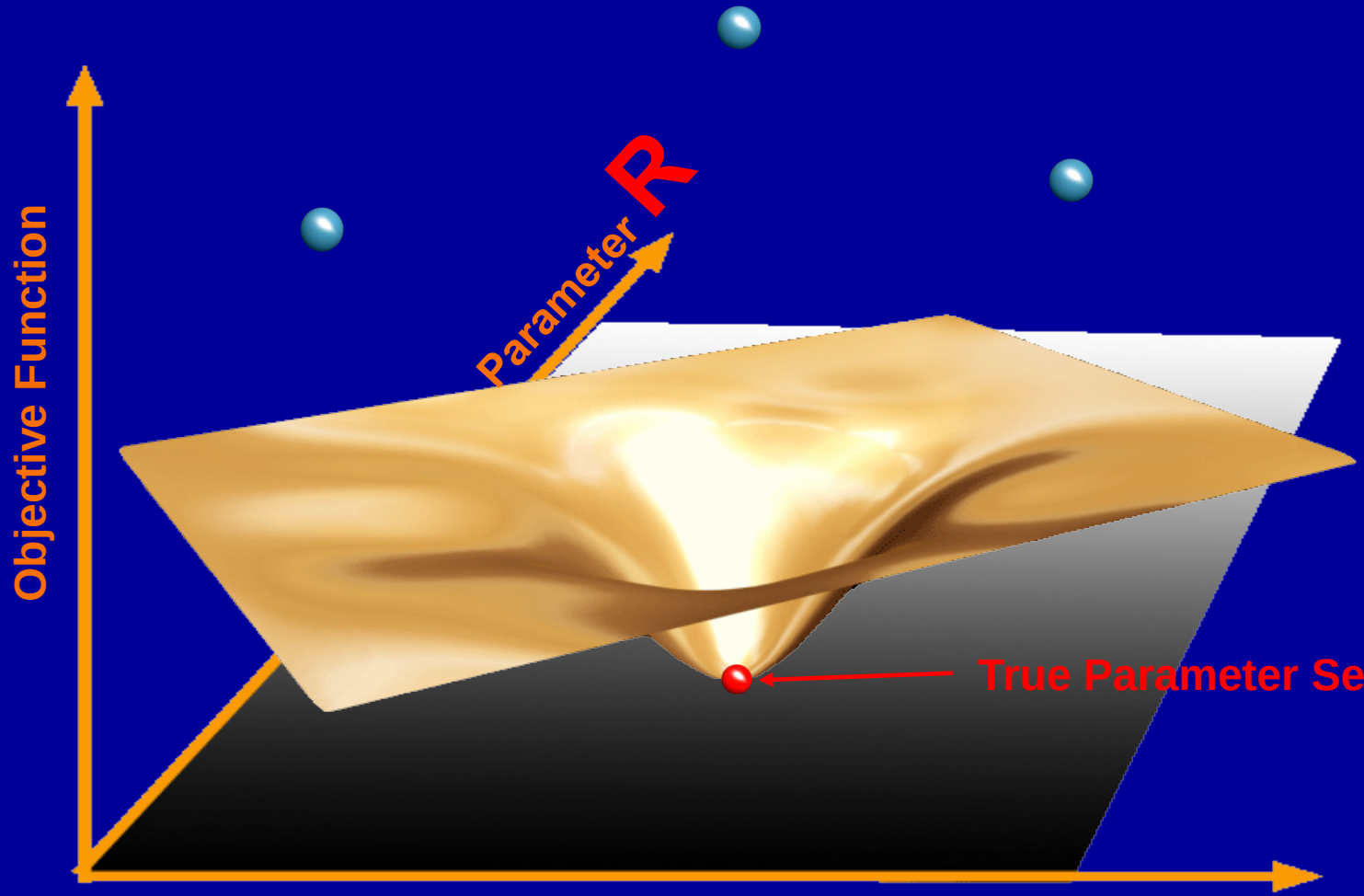
Parmeter Space

Parameter Sensitivity



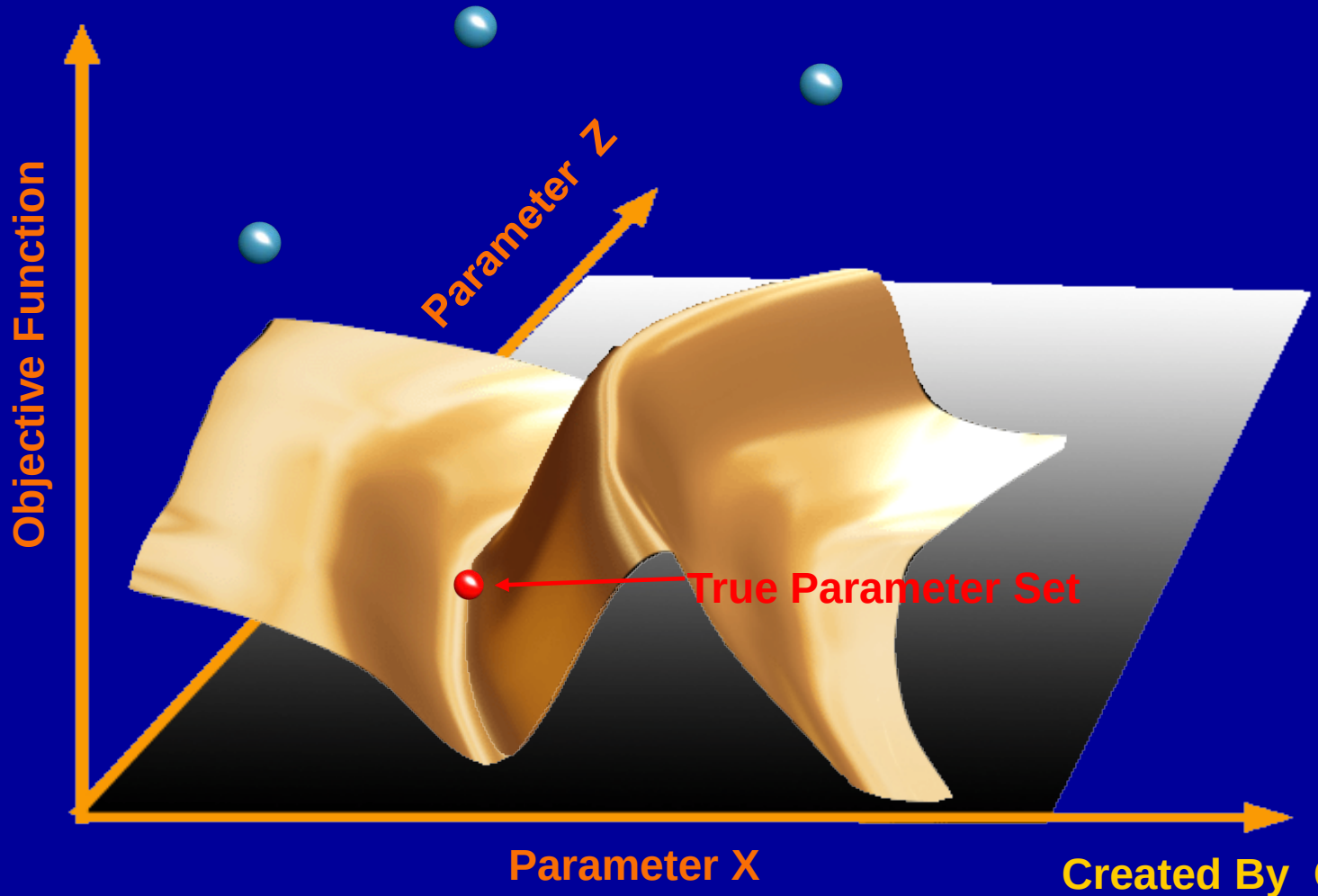
Parameter Space

The Ideal case: Convex Optimization



Created By G-H Park

Difficulties in Global Optimization



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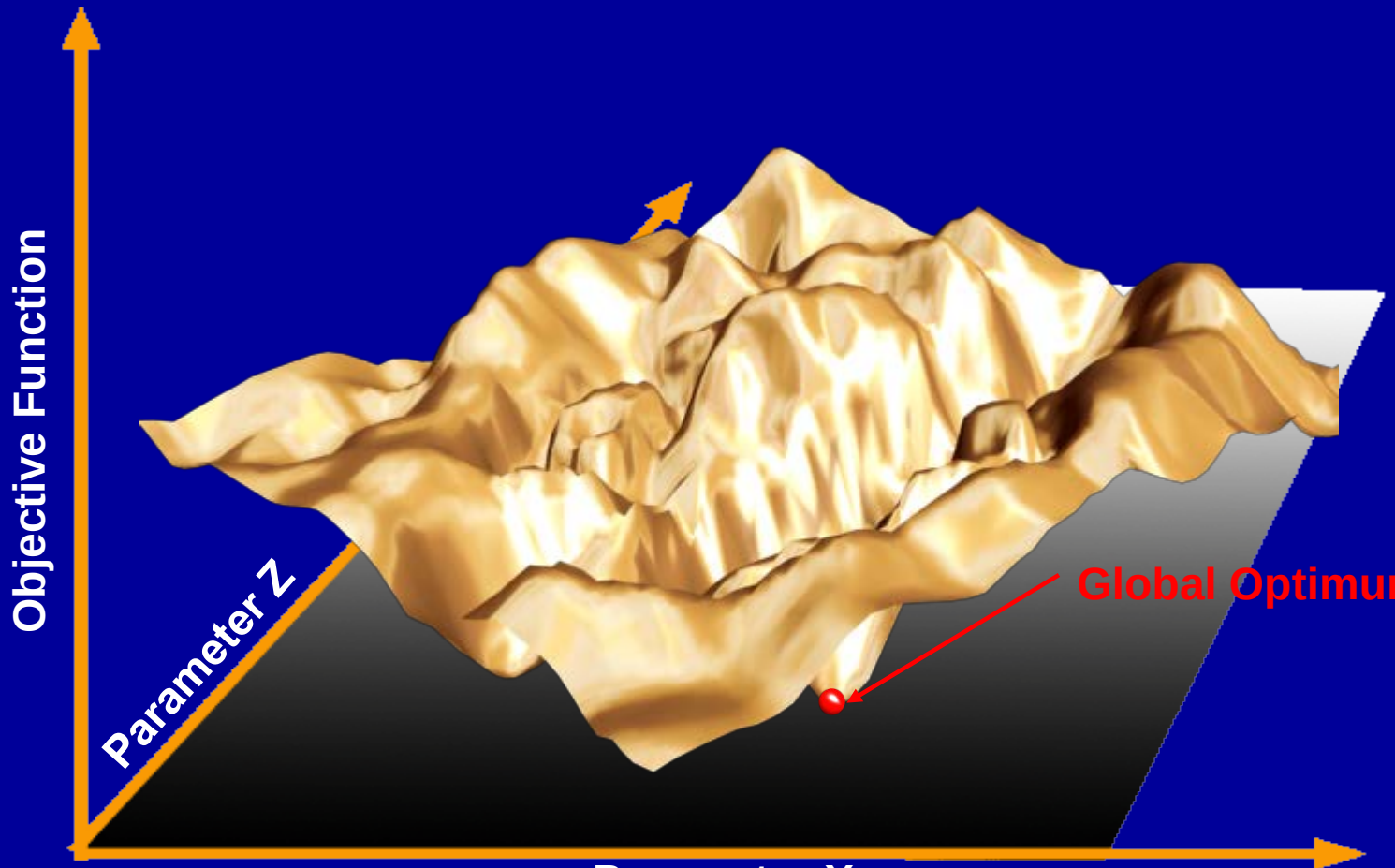
Parameter Estimation (non-convex, multi-optima)



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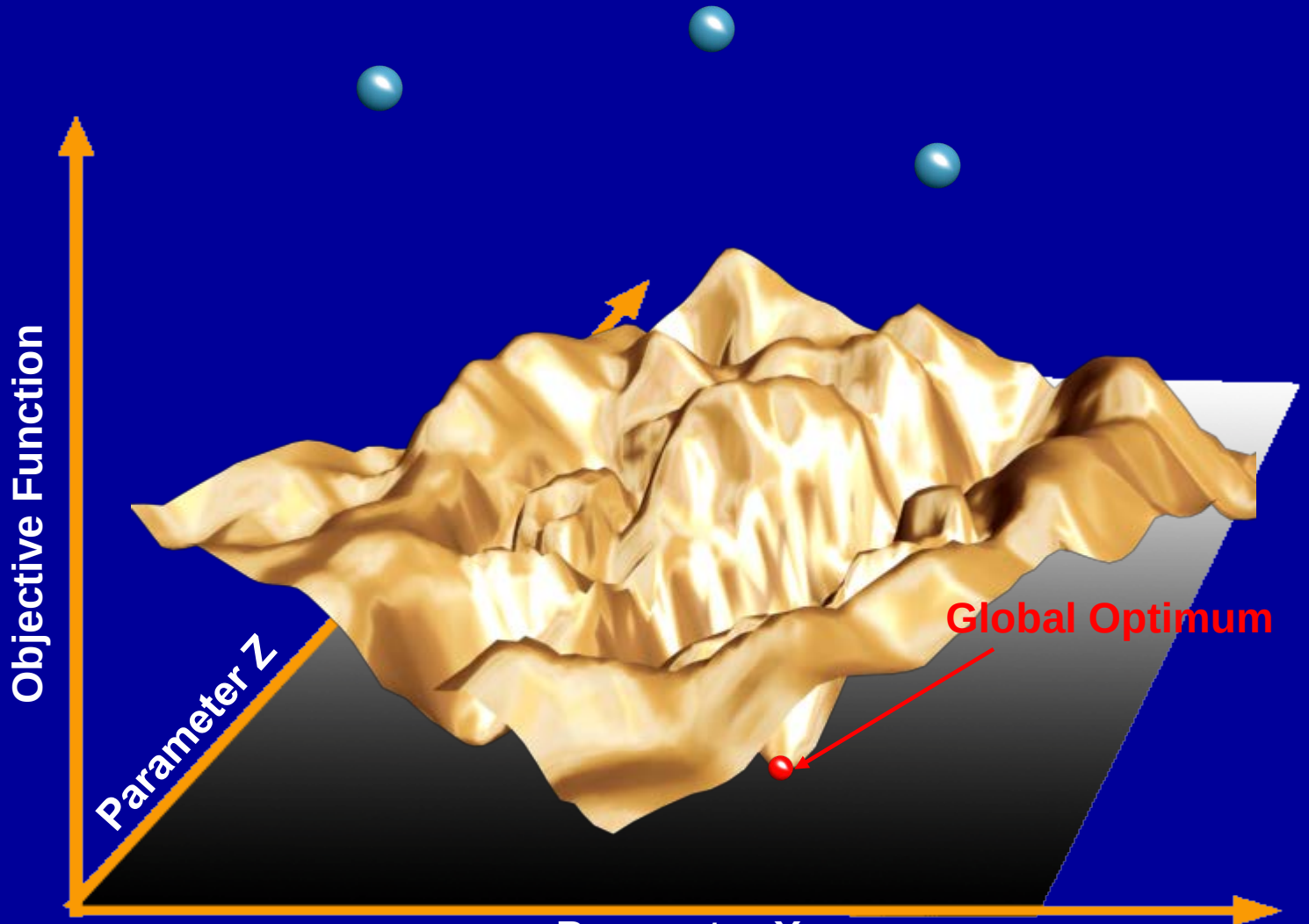

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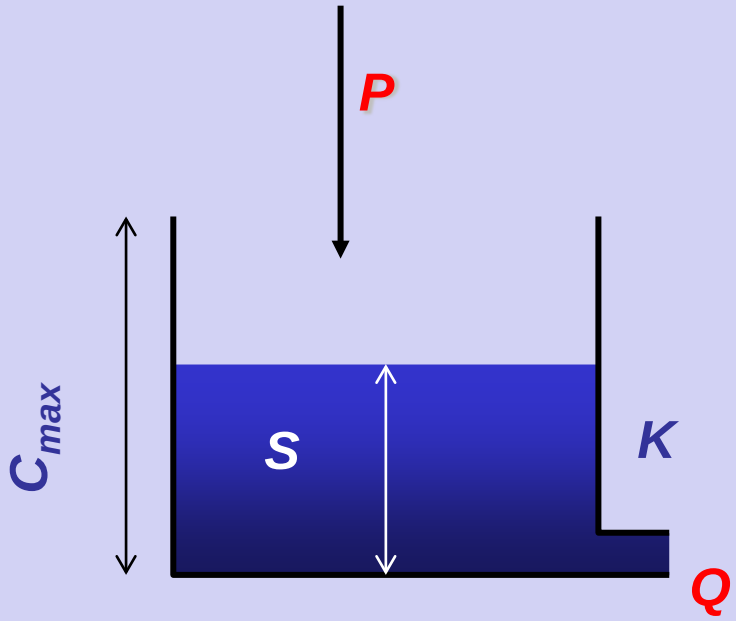
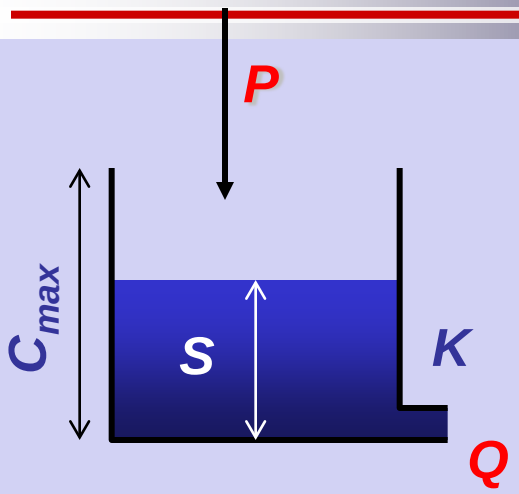
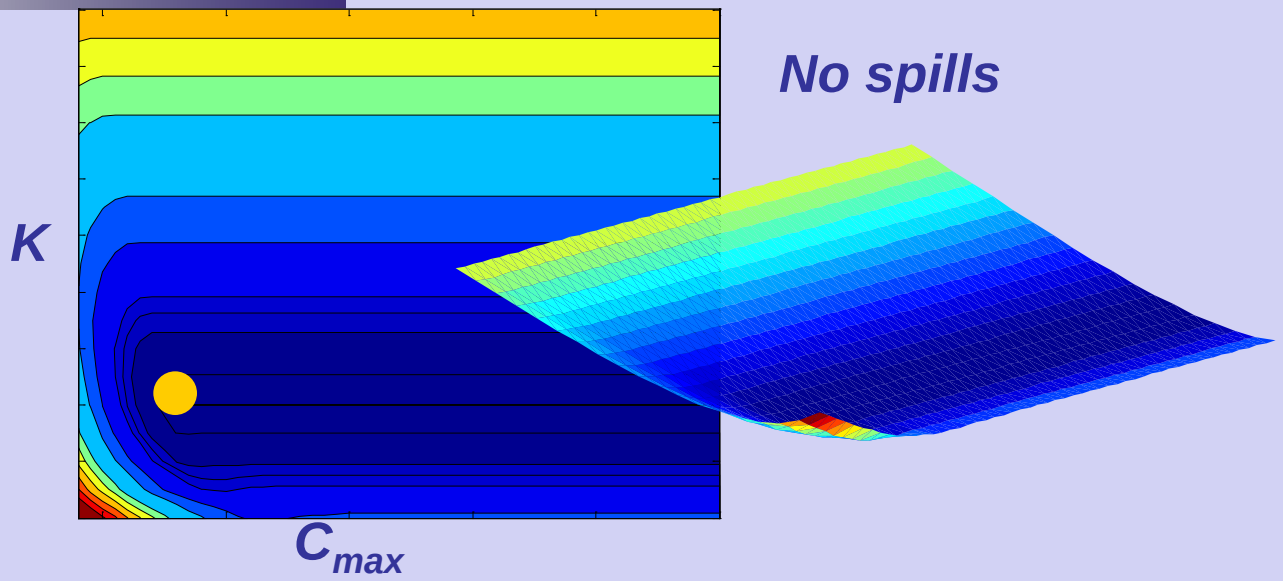
Data information content

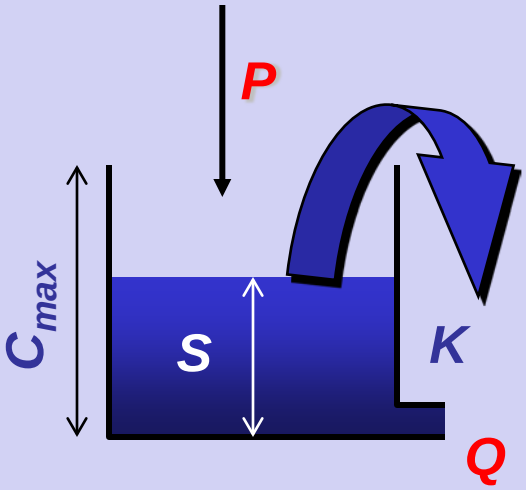


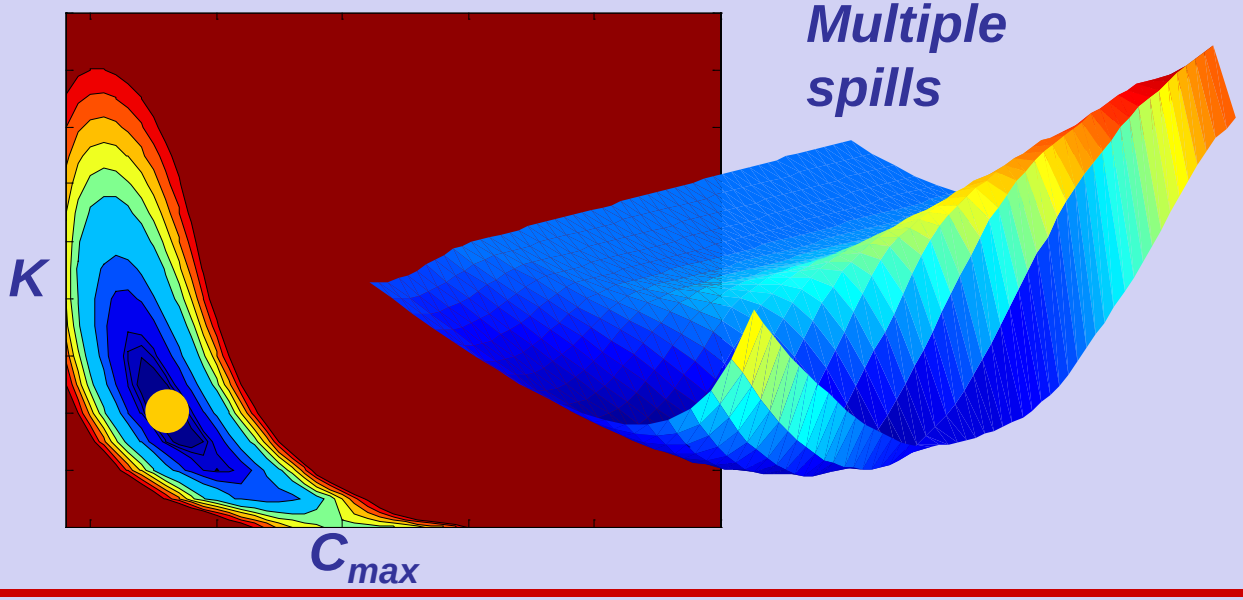
"Bucket Model"
Simple two parameter Model

Data information content





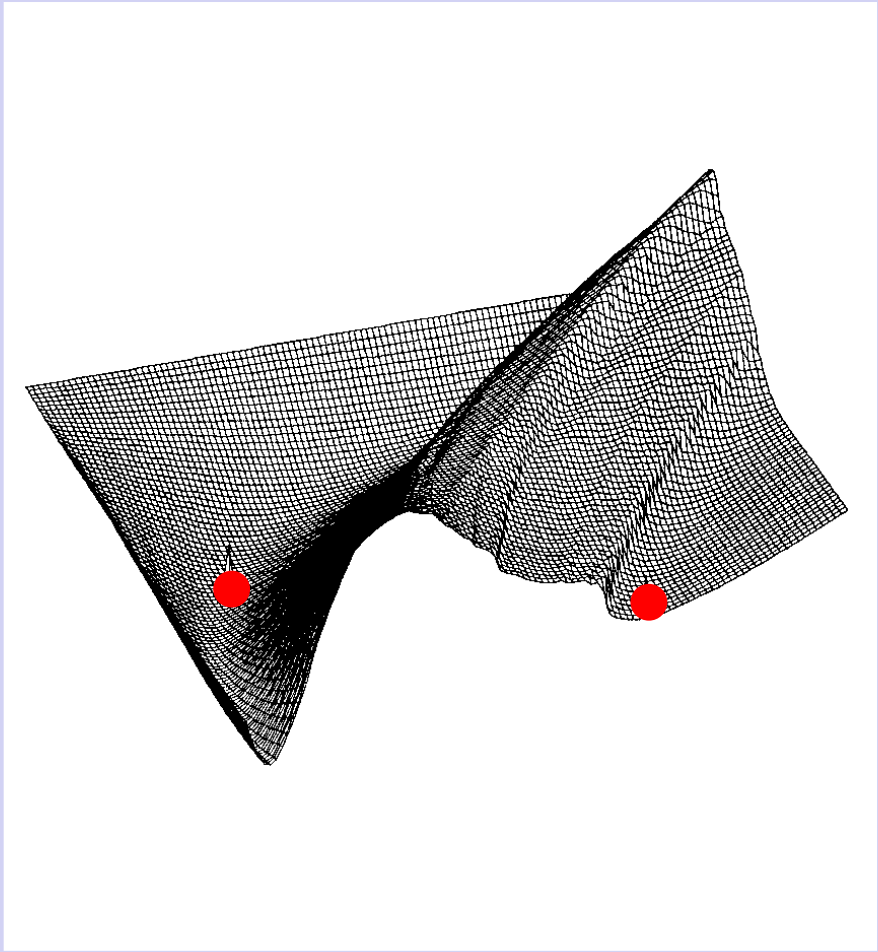




Difficulties in Optimization

1.- Regions of Attraction

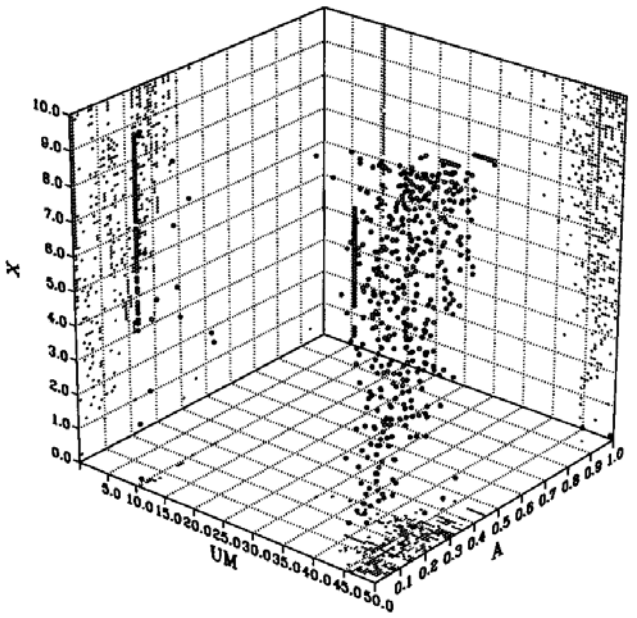
More than one main convergence region



Duan, Gupta, and Sorooshian, 1992, WRR

Difficulties in Optimization

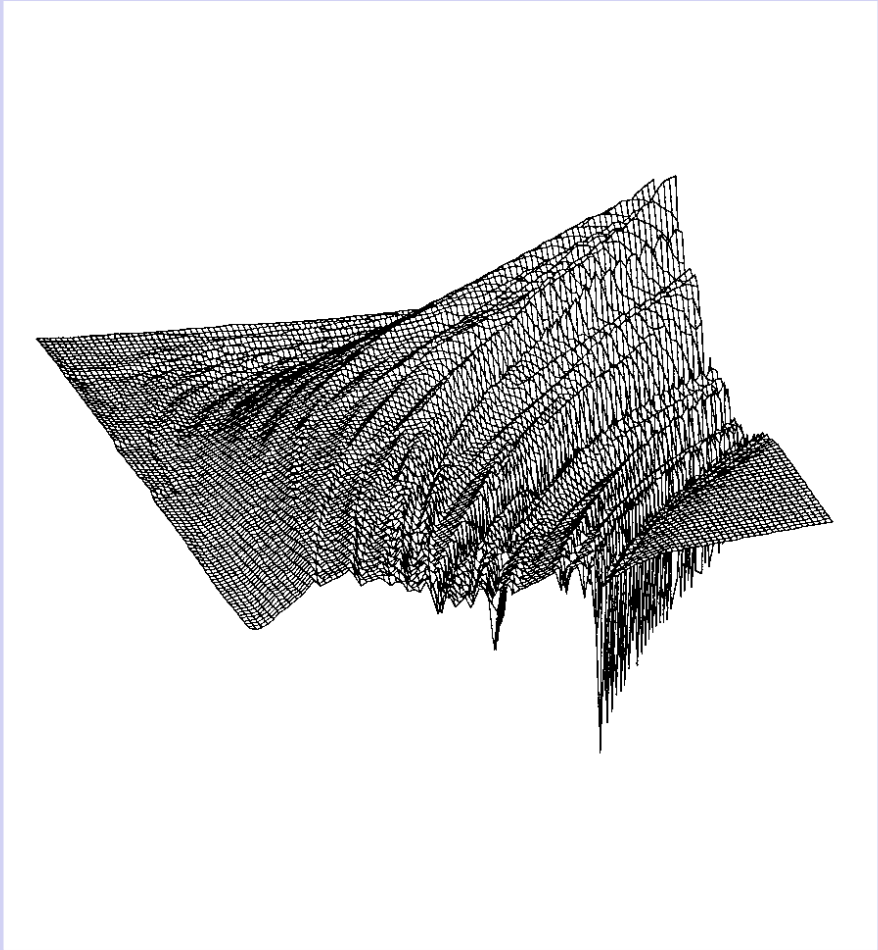
1.- Regions of Attraction	*More than one main convergence region*
2.- Local Optima	*Many small "pits" in each region*



Duan, Gupta, and Sorooshian, 1992, WRR

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*



Duan, Gupta, and Sorooshian, 1992, WRR

Difficulties in Optimization

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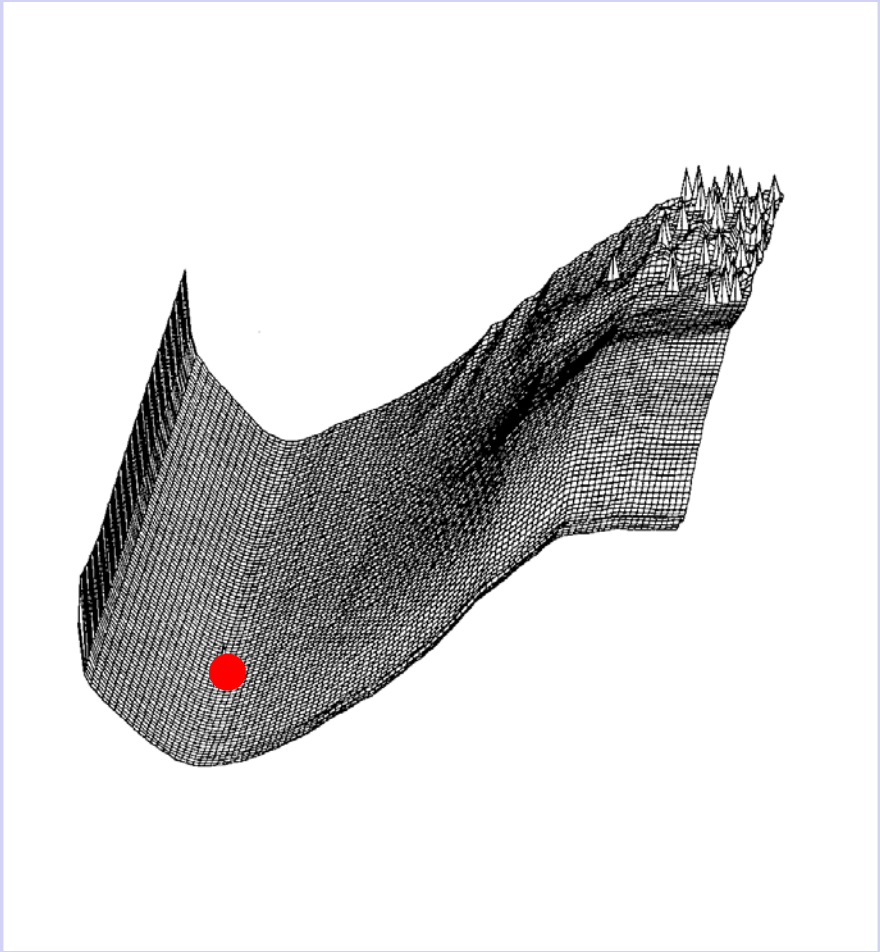

Duan, Gupta, and Sorooshian, 1992, WRR

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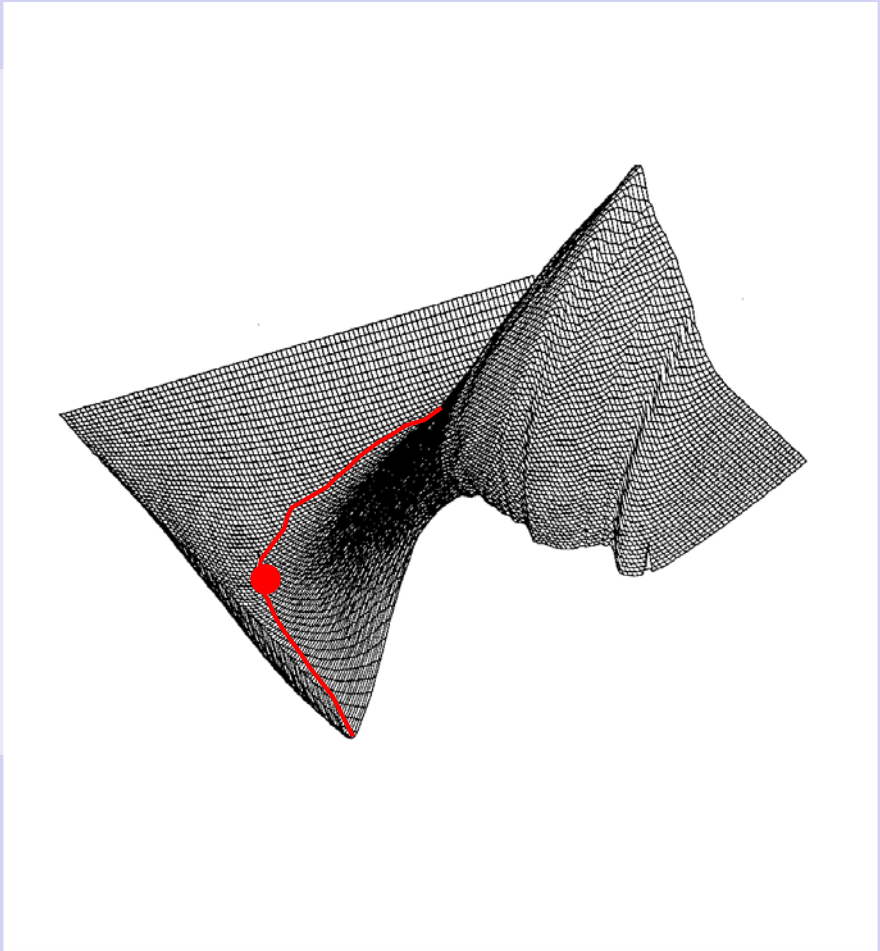
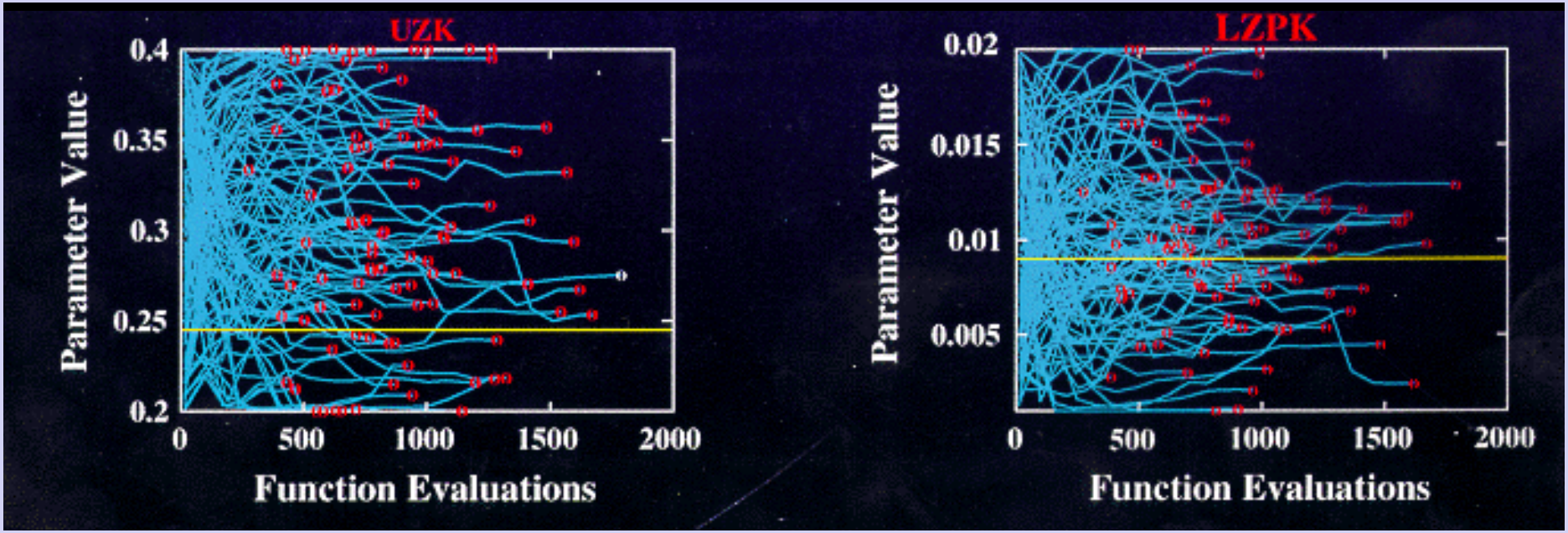
5.- Shape	*Long and curved ridges*



Duan, Gupta, and Sorooshian, 1992, WRR

Optimization Strategy – Local Direct Search

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

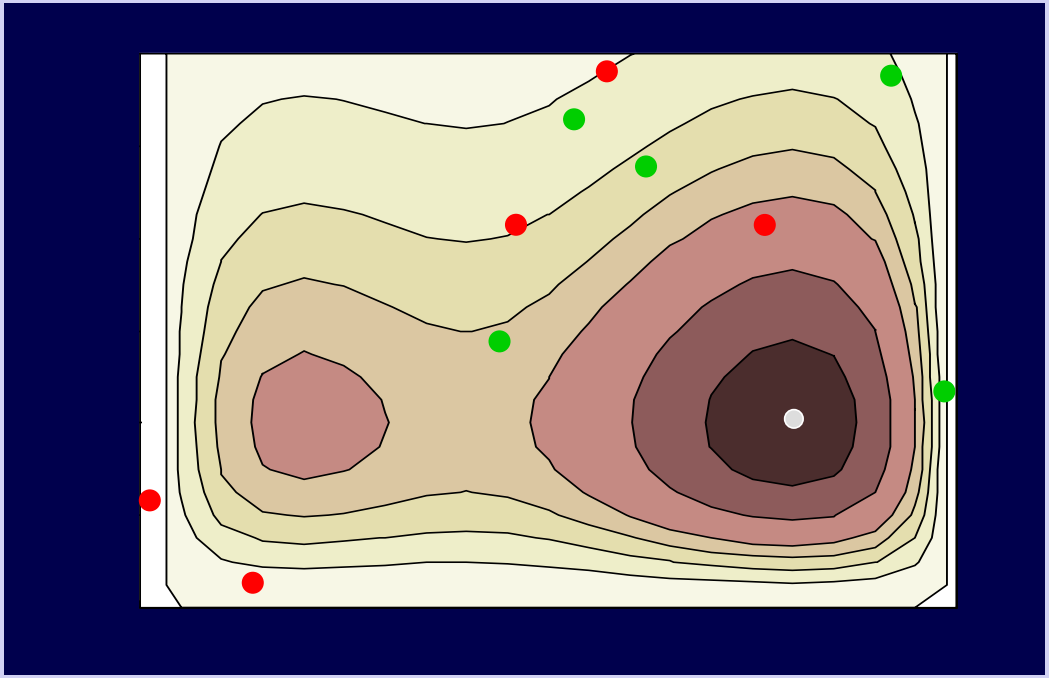


Duan, Gupta, and Sorooshian, 1992, WRR

The SCE-UA *Algorithm …*
(1992)

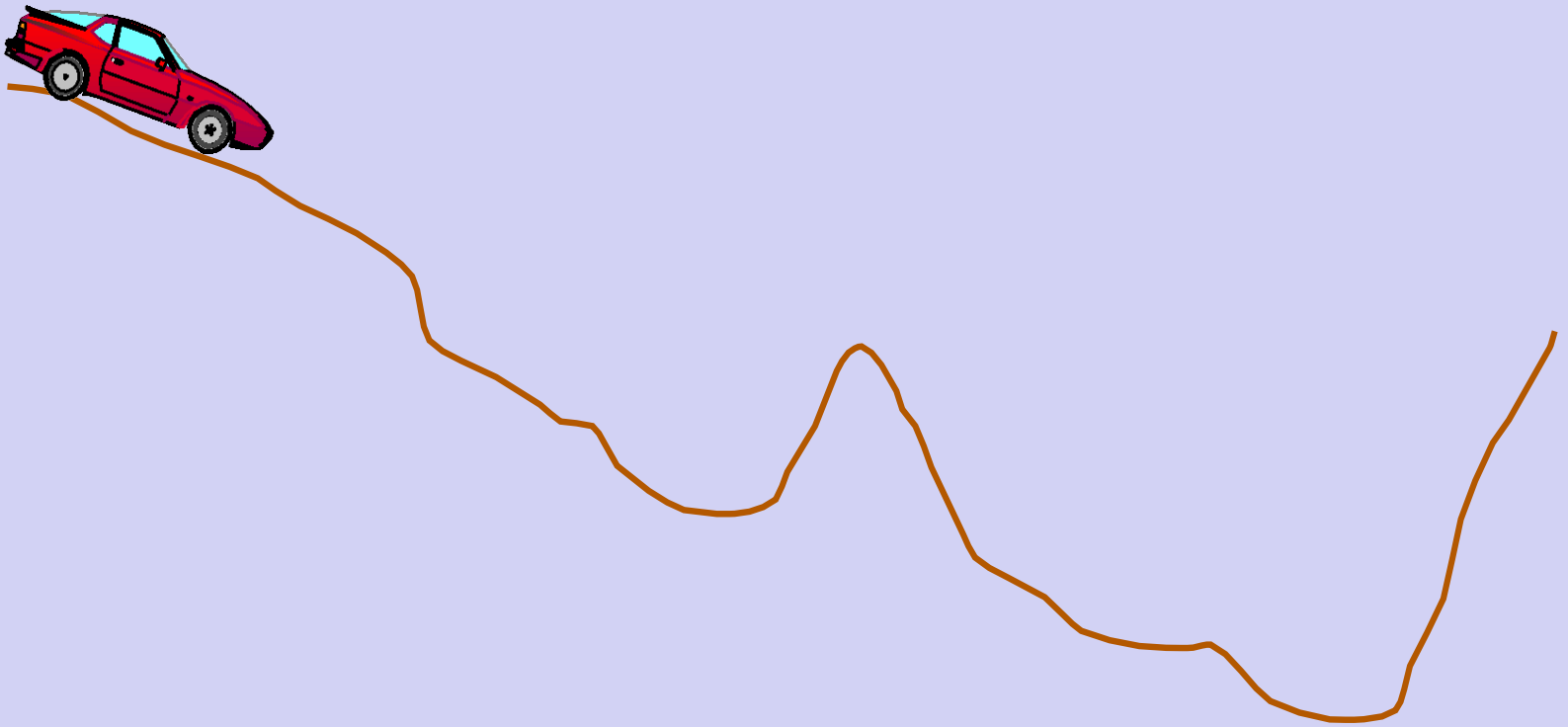
Duan, Gupta, and Sorooshian, 1992, WRR

The SCE-UA *Algorithm …*

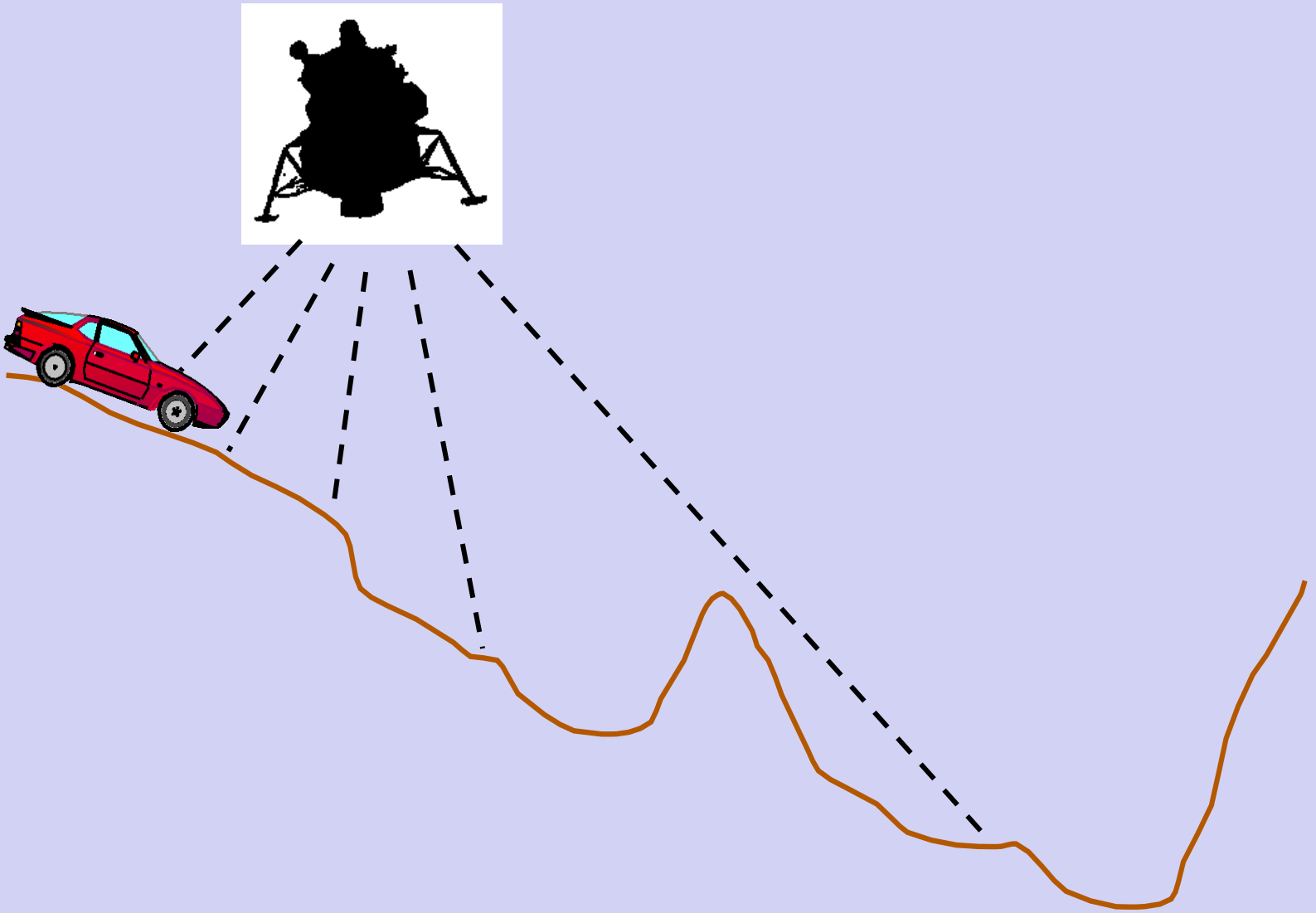


Duan, Sorooshian, and Gupta 1992, WRR

The Concept Behind SCE Method



The Concept Behind SCE Method



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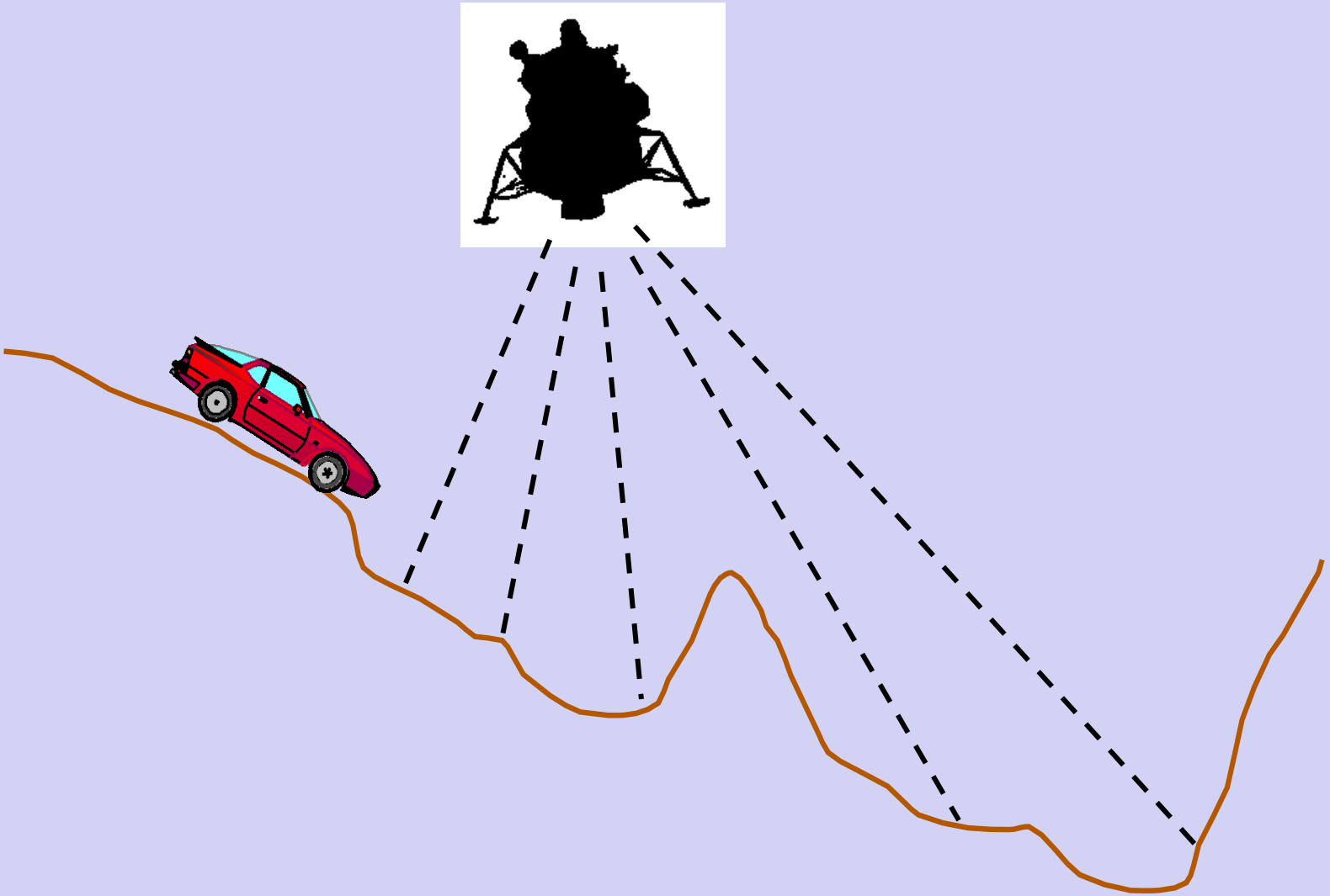

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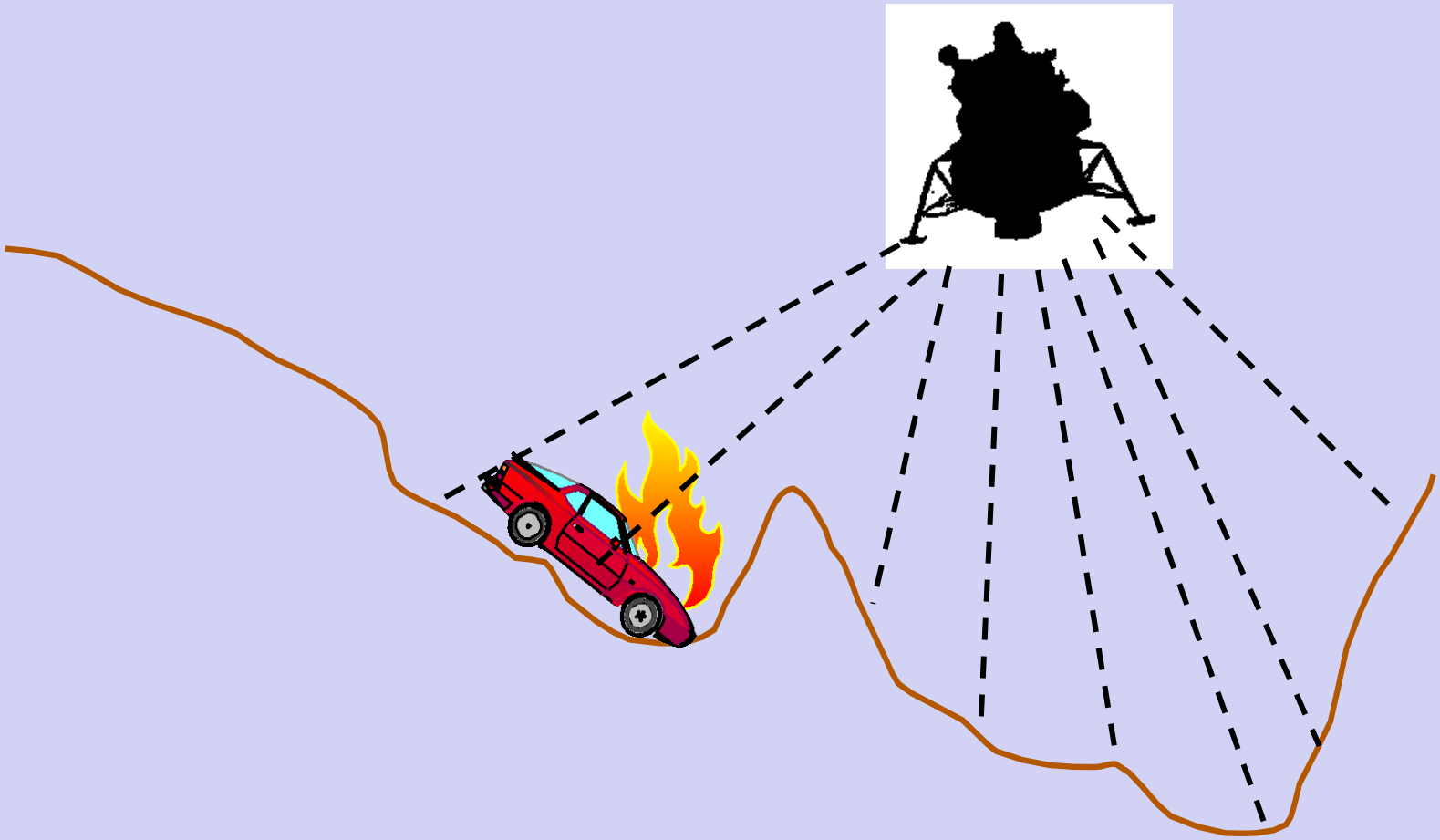
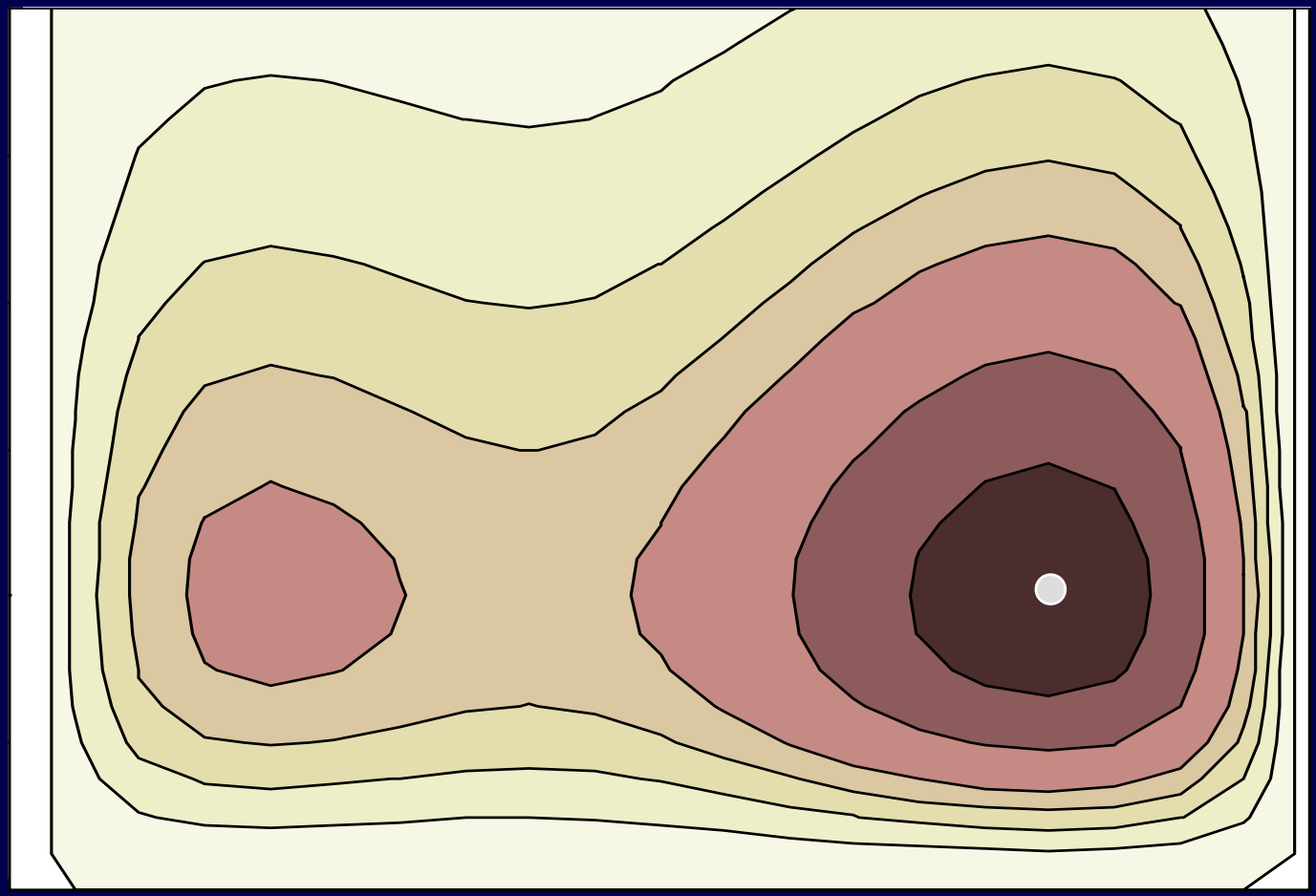
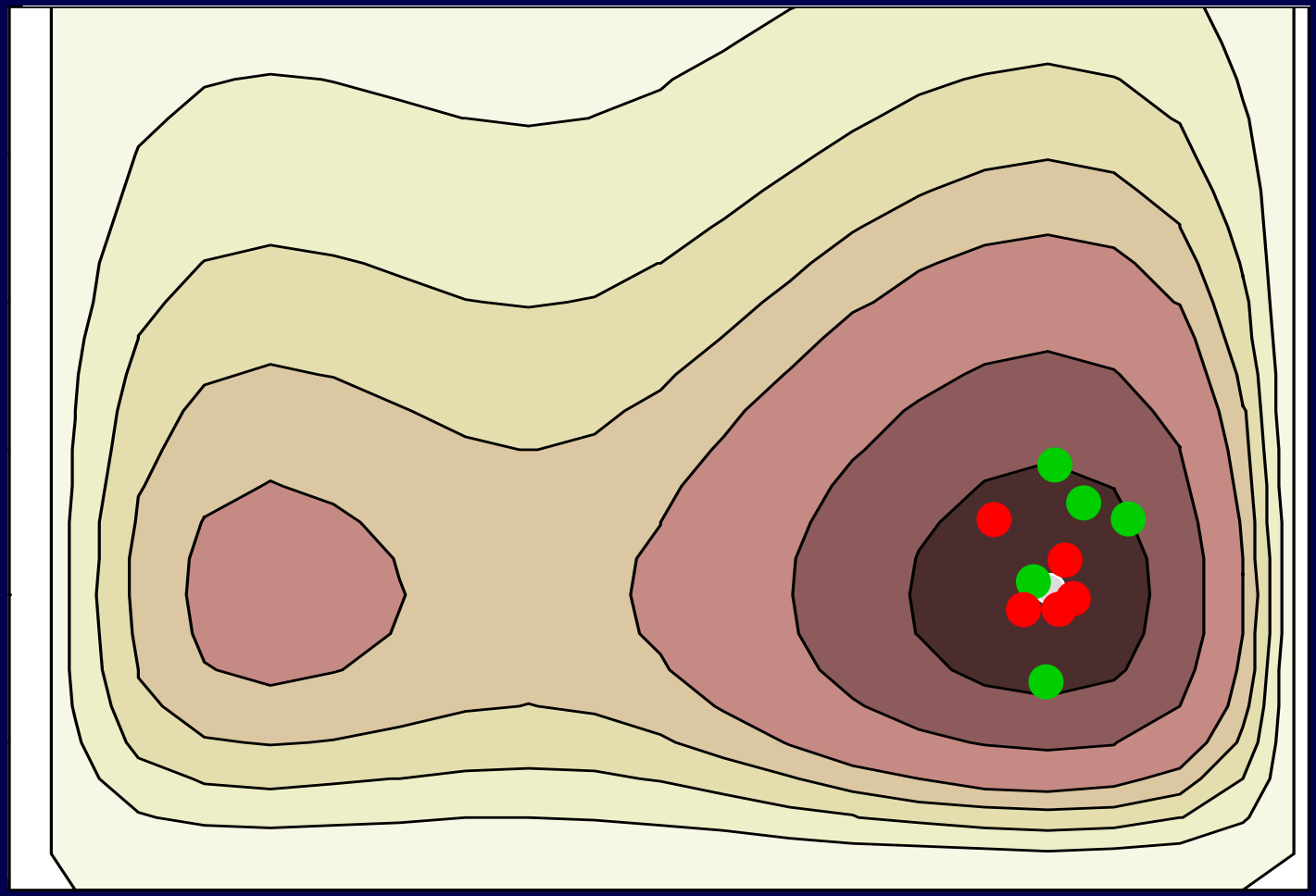


SCE Method – How it works …



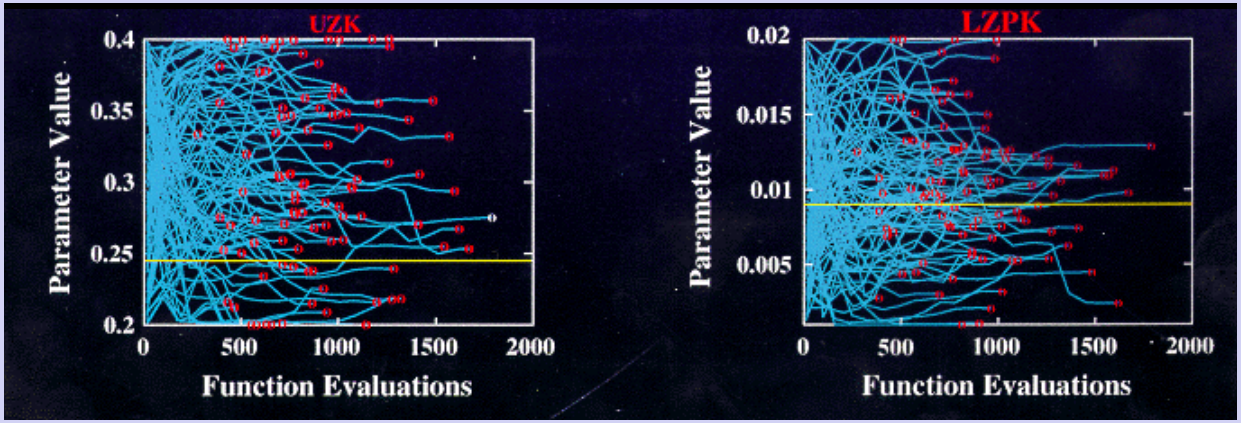
Shuffled Complex Evolution (SCE-UA)



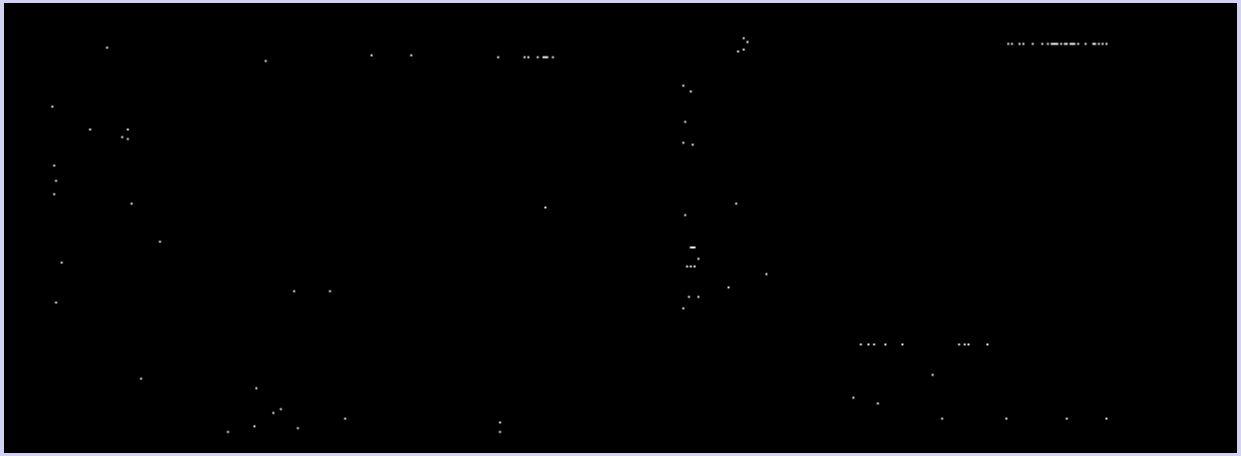
Global Optimization – The SCE-UA Algorithm

Duan, Gupta & Sorooshian, 1992, WRR

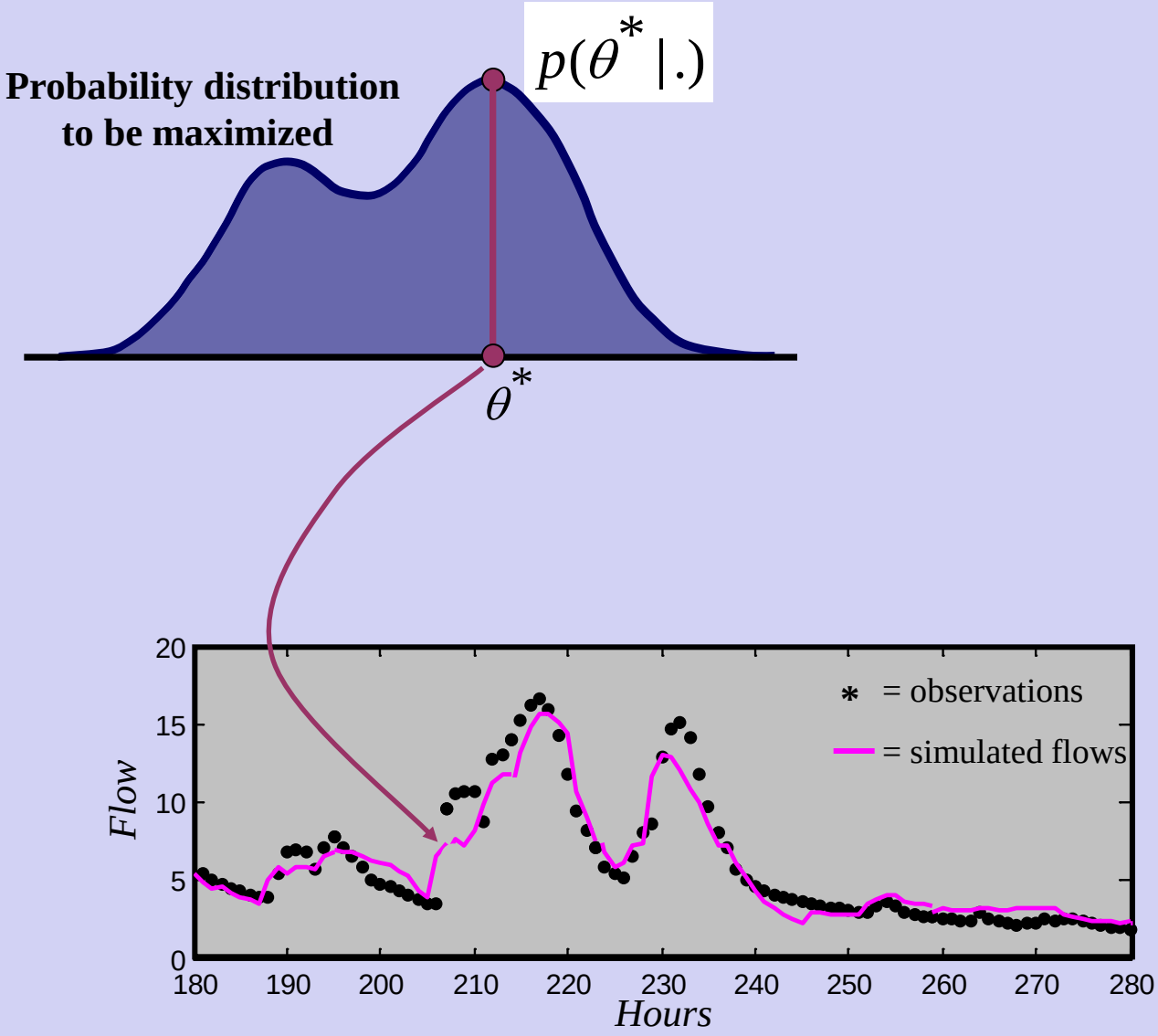
Simplex Method



Shuffled Complex Evolution (SCE-UA)



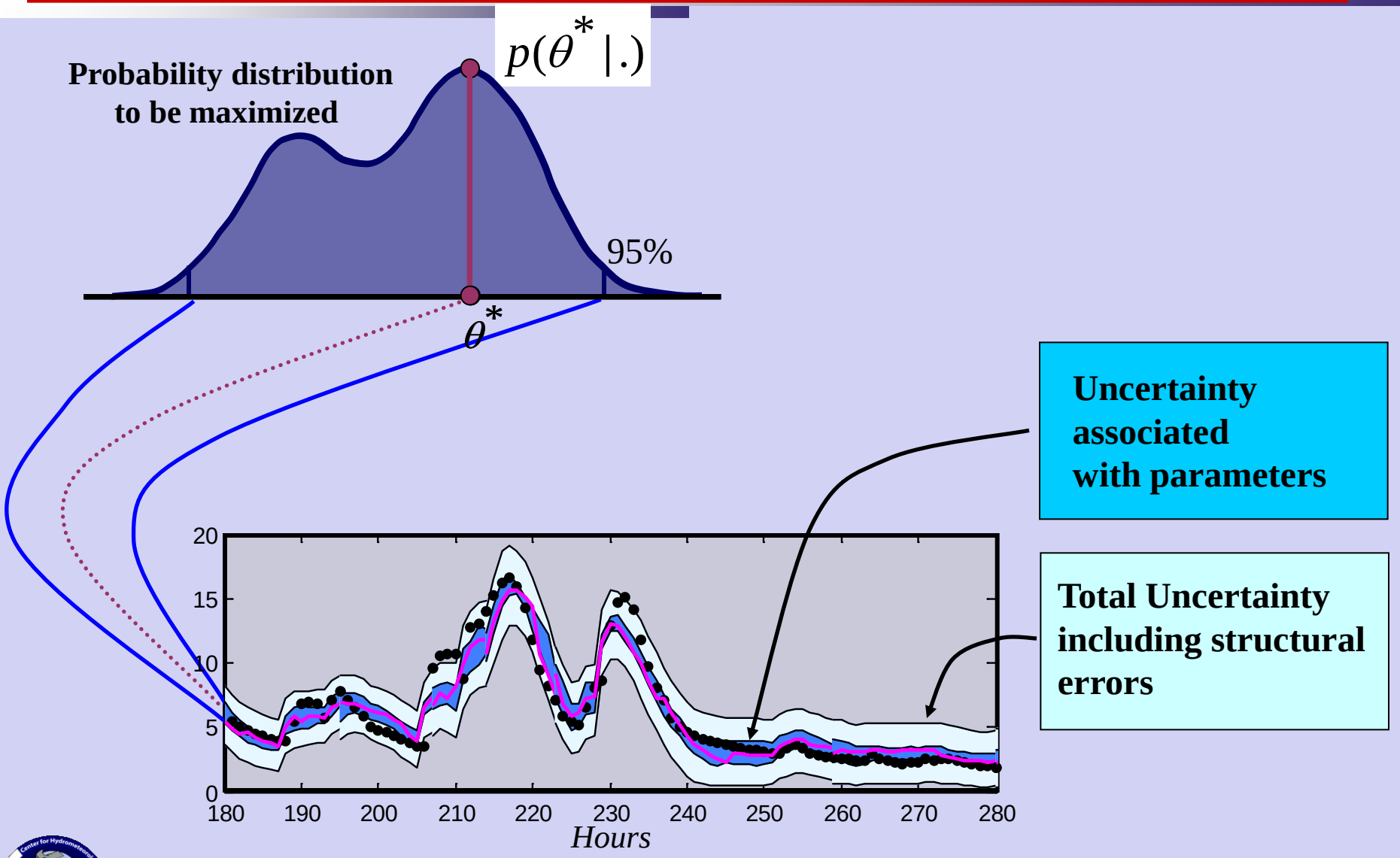
SCE-UA *only solves for Mode of Distribution*



Shuffled Complex Evolution Metropolis

SCE → *Vrugt, Gupta, Bouten & Sorooshian WRR 2003* → SCEM

Need estimates of the prediction uncertainty

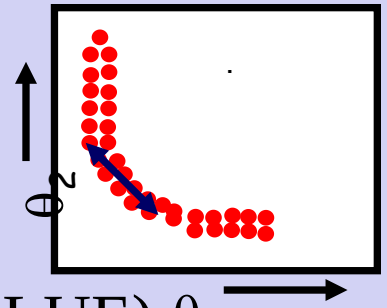


Parameter Uncertainty Methods

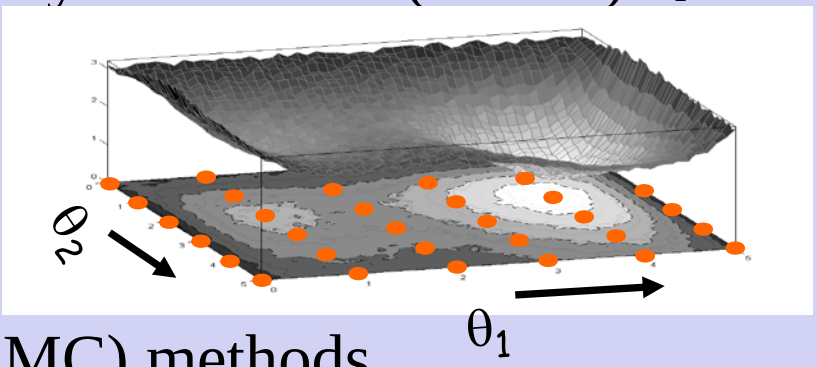
(1) First-order approximations near global optimum (Kuczera etal)

Limitations

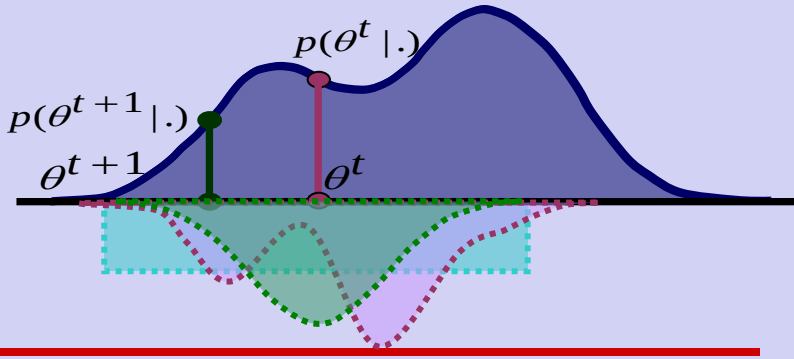
- **Assumes Model is Linear**
- **Assumes Posterior Dist. Guassian**



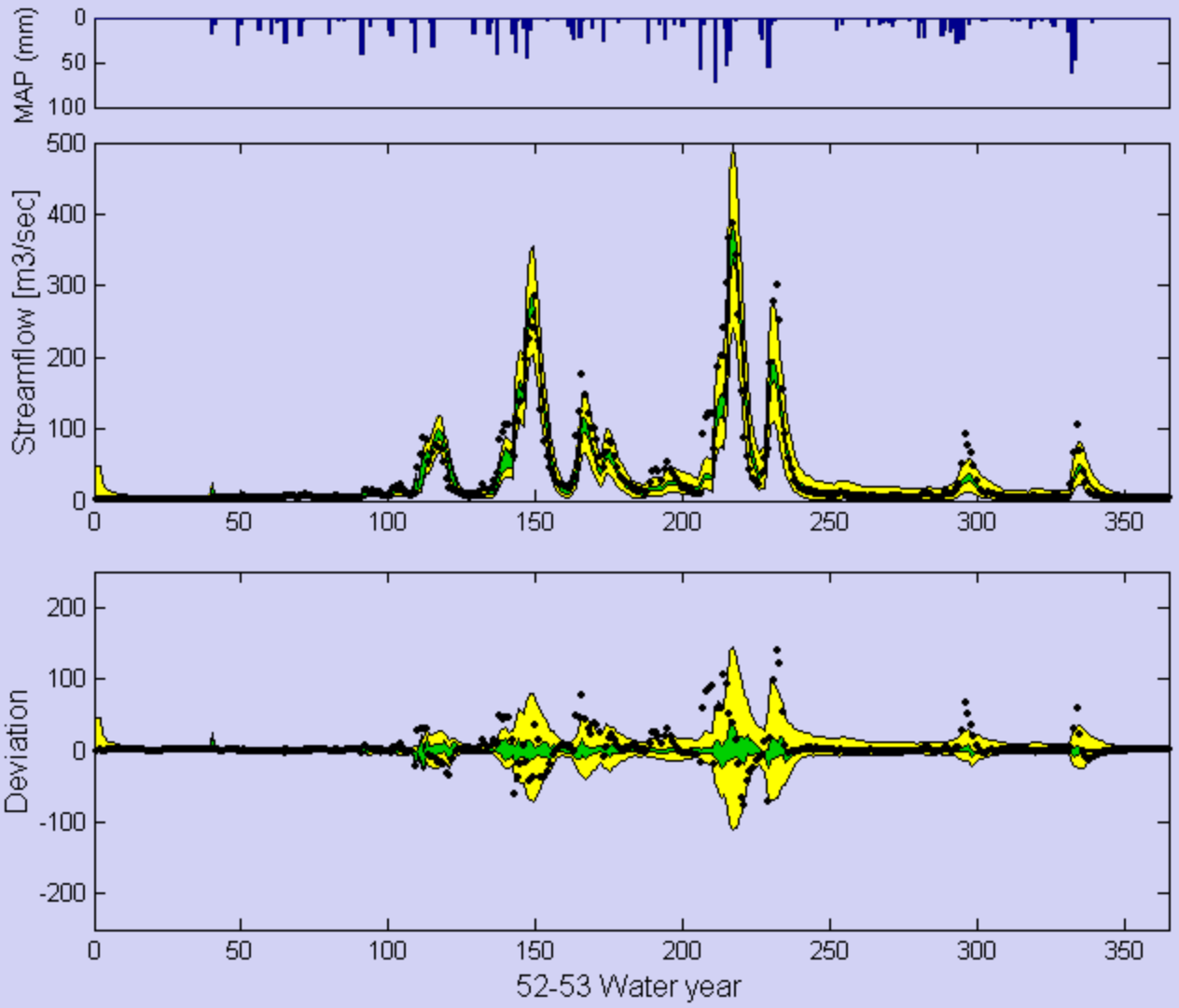
(2) Generalized Likelihood Uncertainty Estimation (GLUE) method (Beven and co-workers)



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



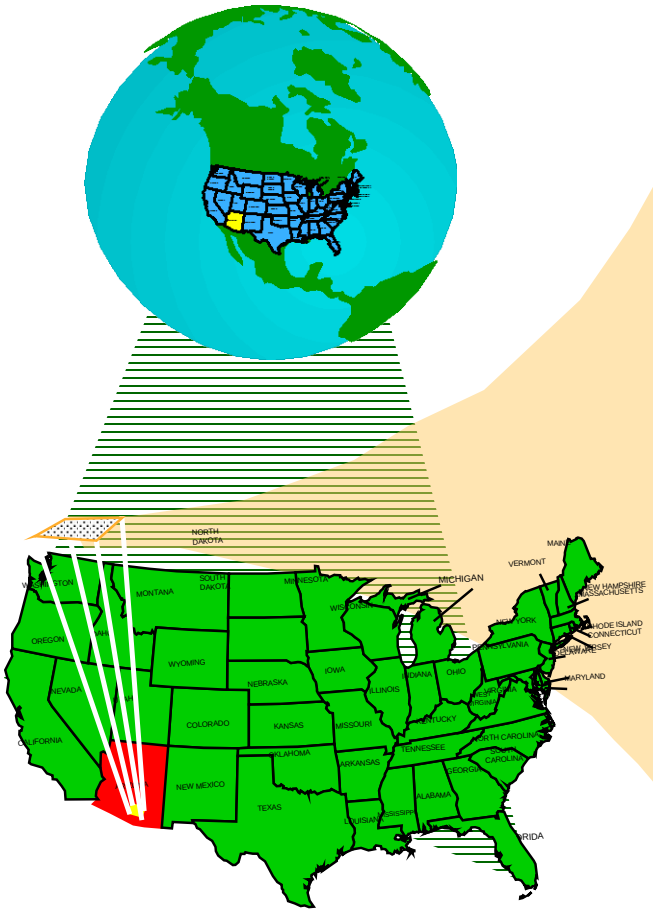
Flow Ranges instead of point estimates

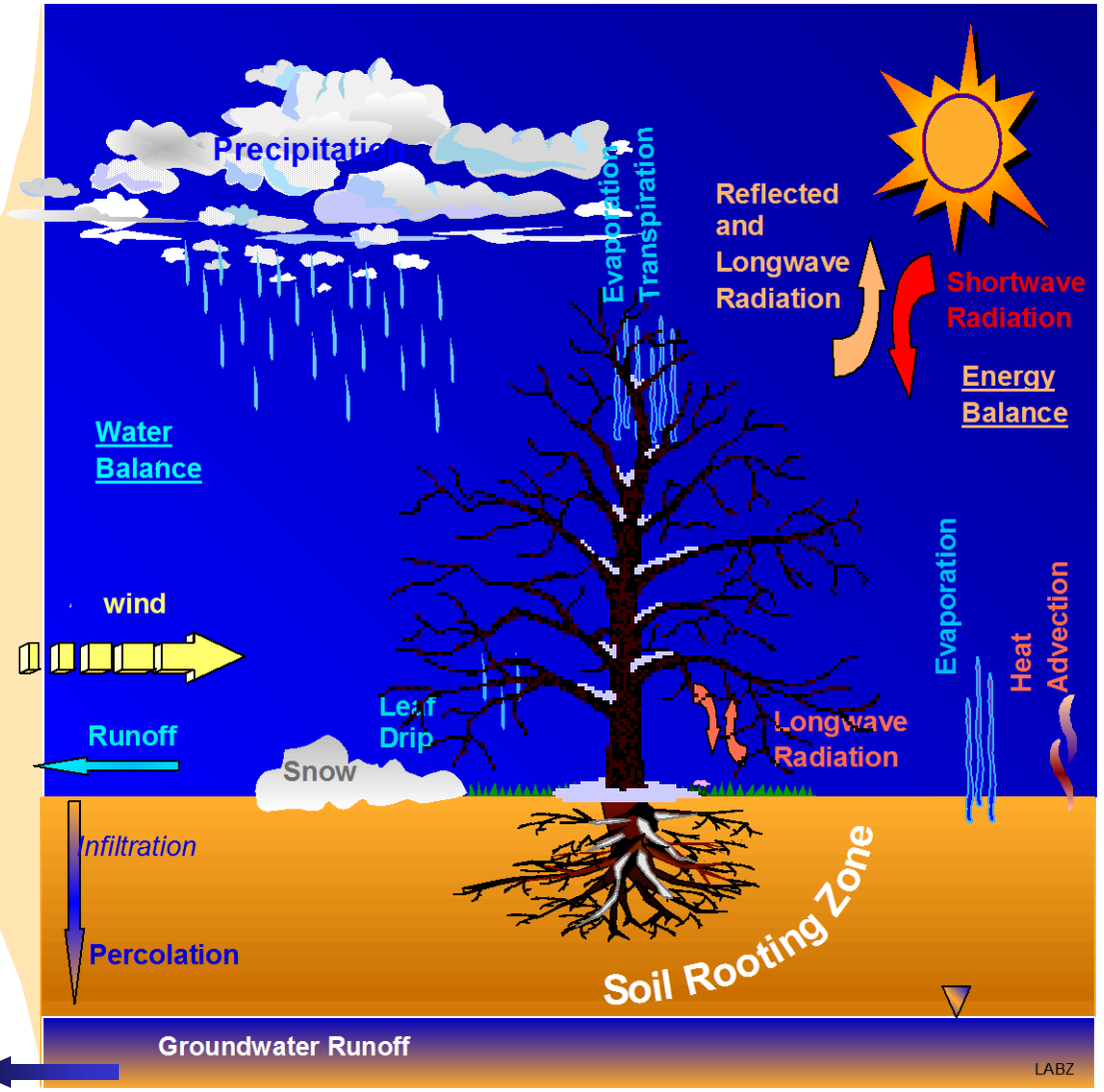


Advances in Parameter Estimation

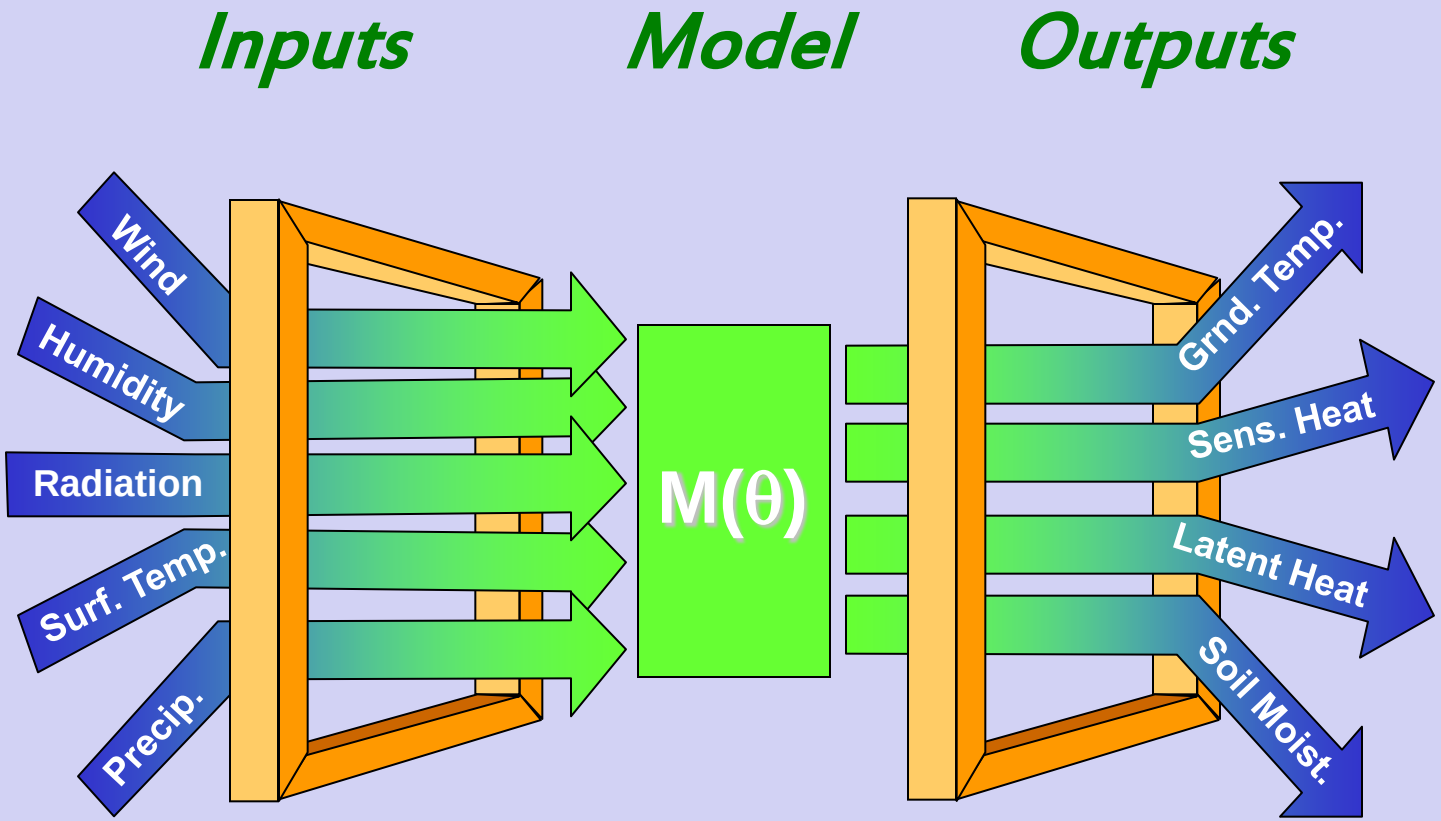
Evolving Directions

Land-Surface Model

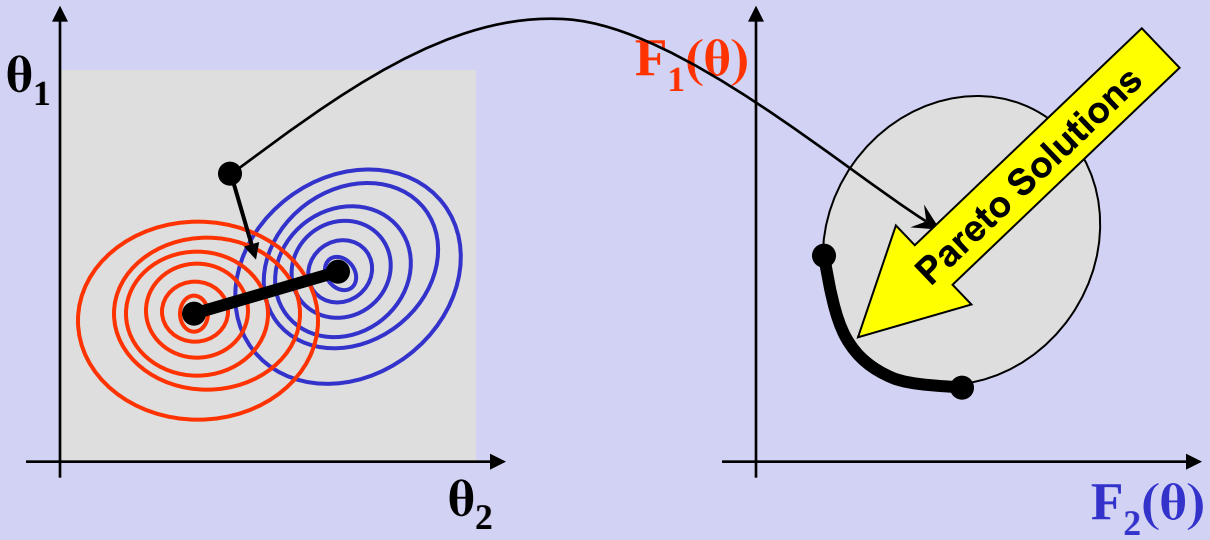




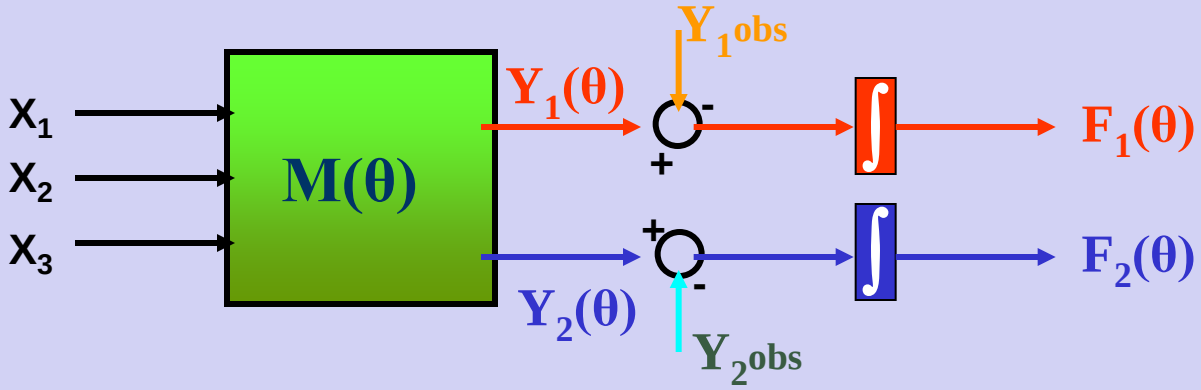
Multi-Objective Approaches

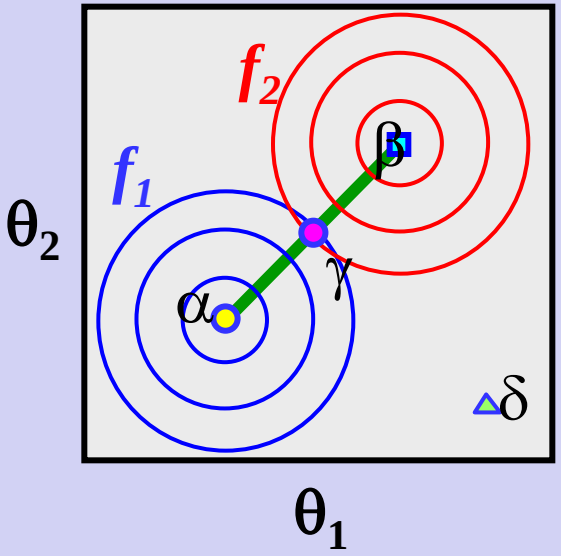


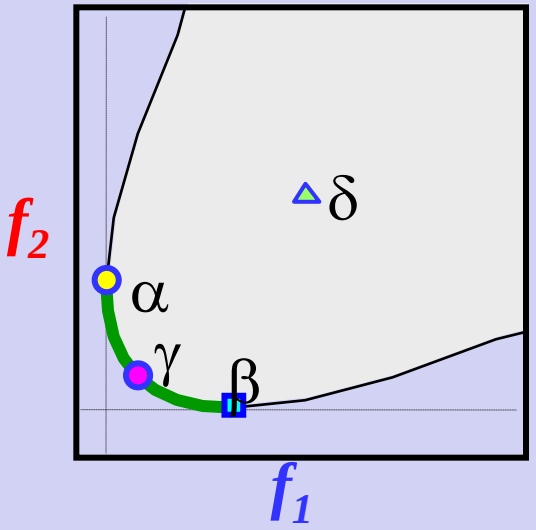
Multi-Criteria Calibration Concept



Multi-Criteria Calibration Approach



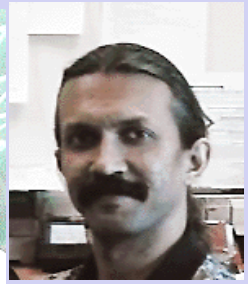




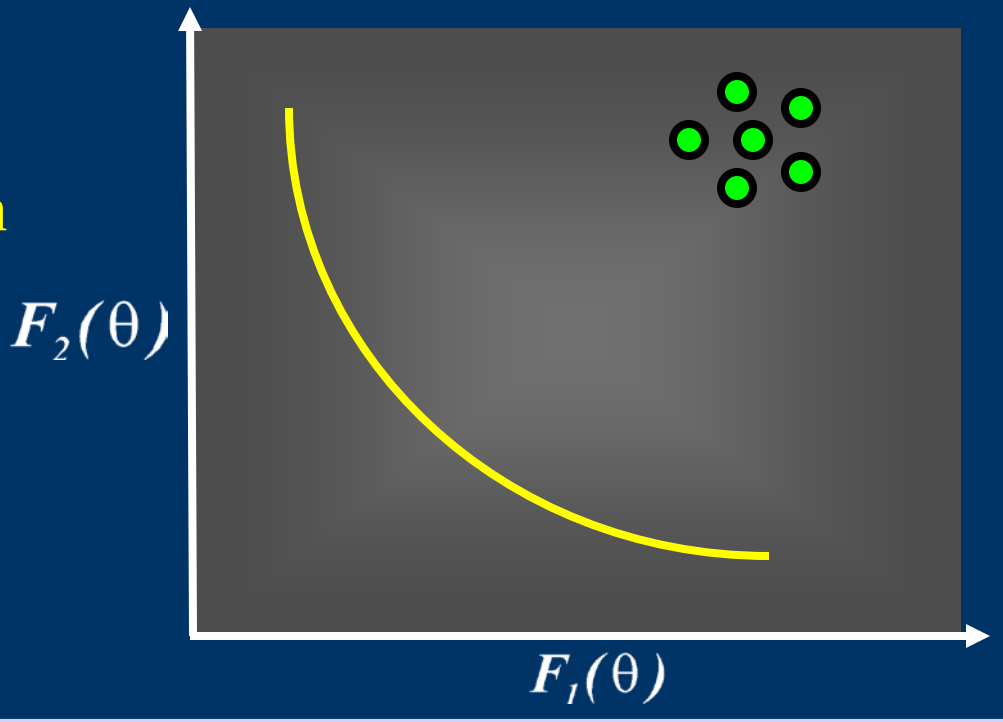
Gupta, Sorooshian, Yapo, WRR, 1998

Multi-Objective Optimization Problem

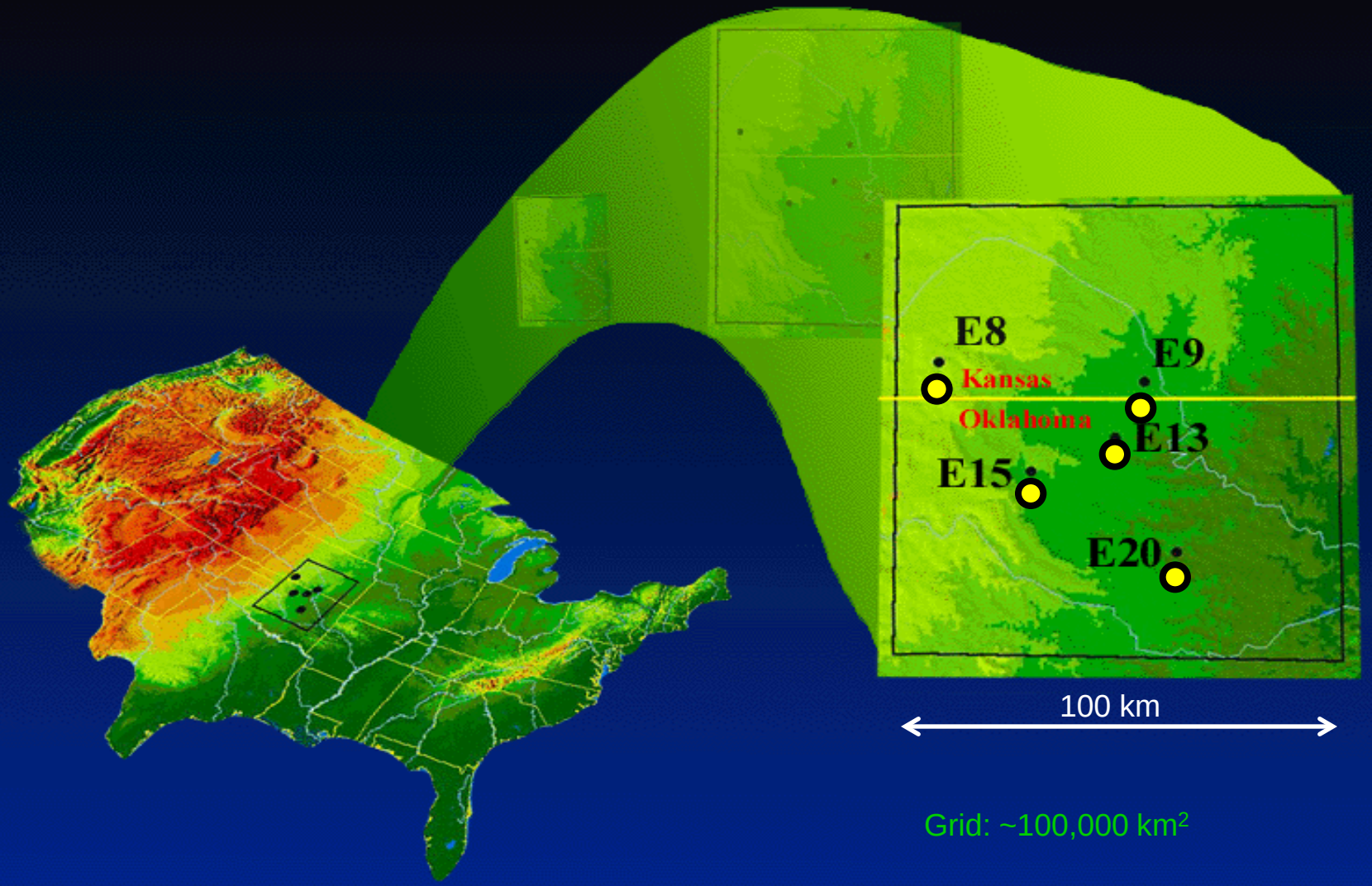
$$\text{Minimize}_{\text{wrt } \theta \subset \Omega} \quad F(\theta) = \{ F_1(\theta), \ldots, F_n(\theta) \}$$



- ✓ Simultaneously finds several Pareto Solutions in a Single Optimization



ARM-CART SGP Site



Grid: ~100,000 km^2

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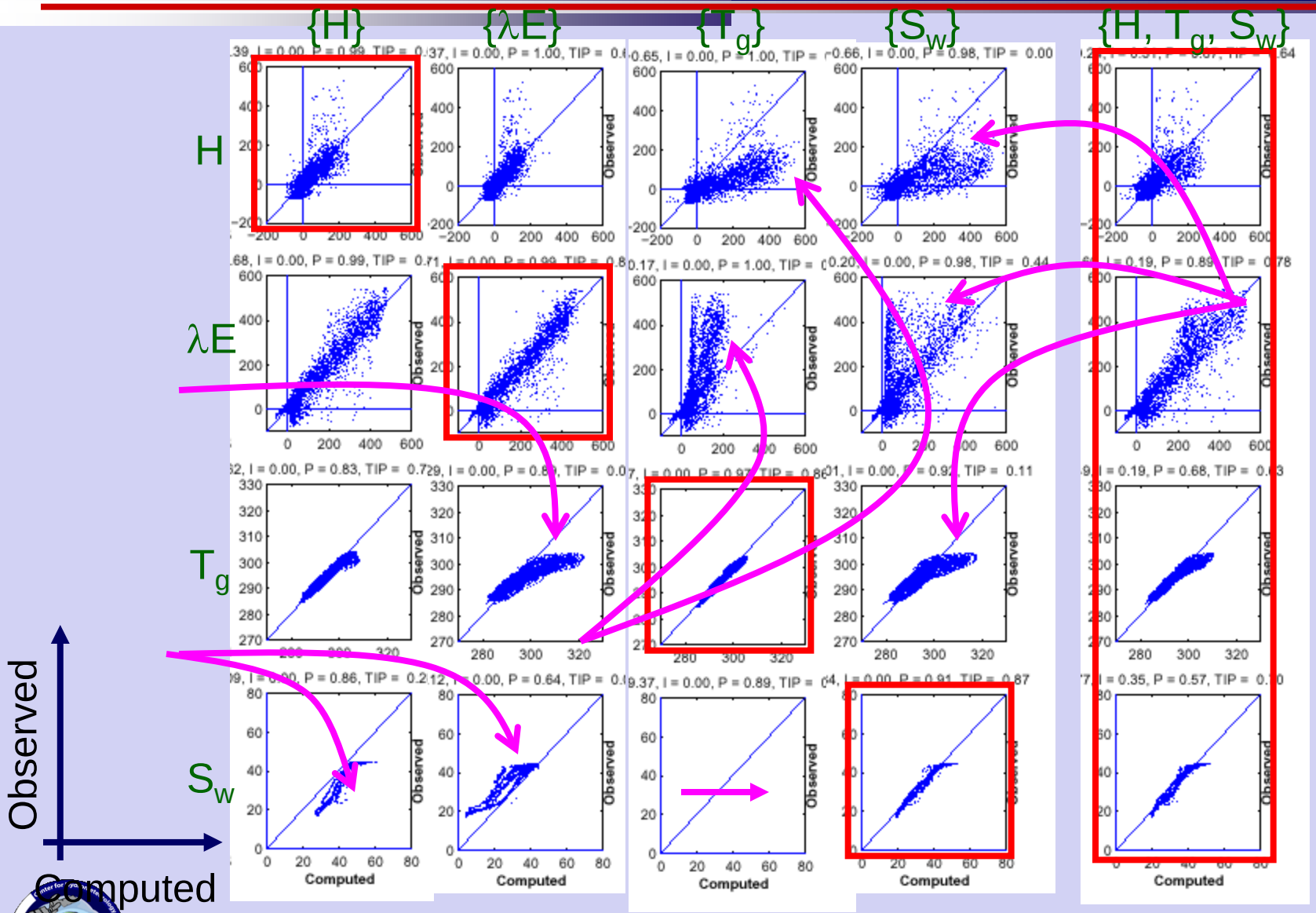
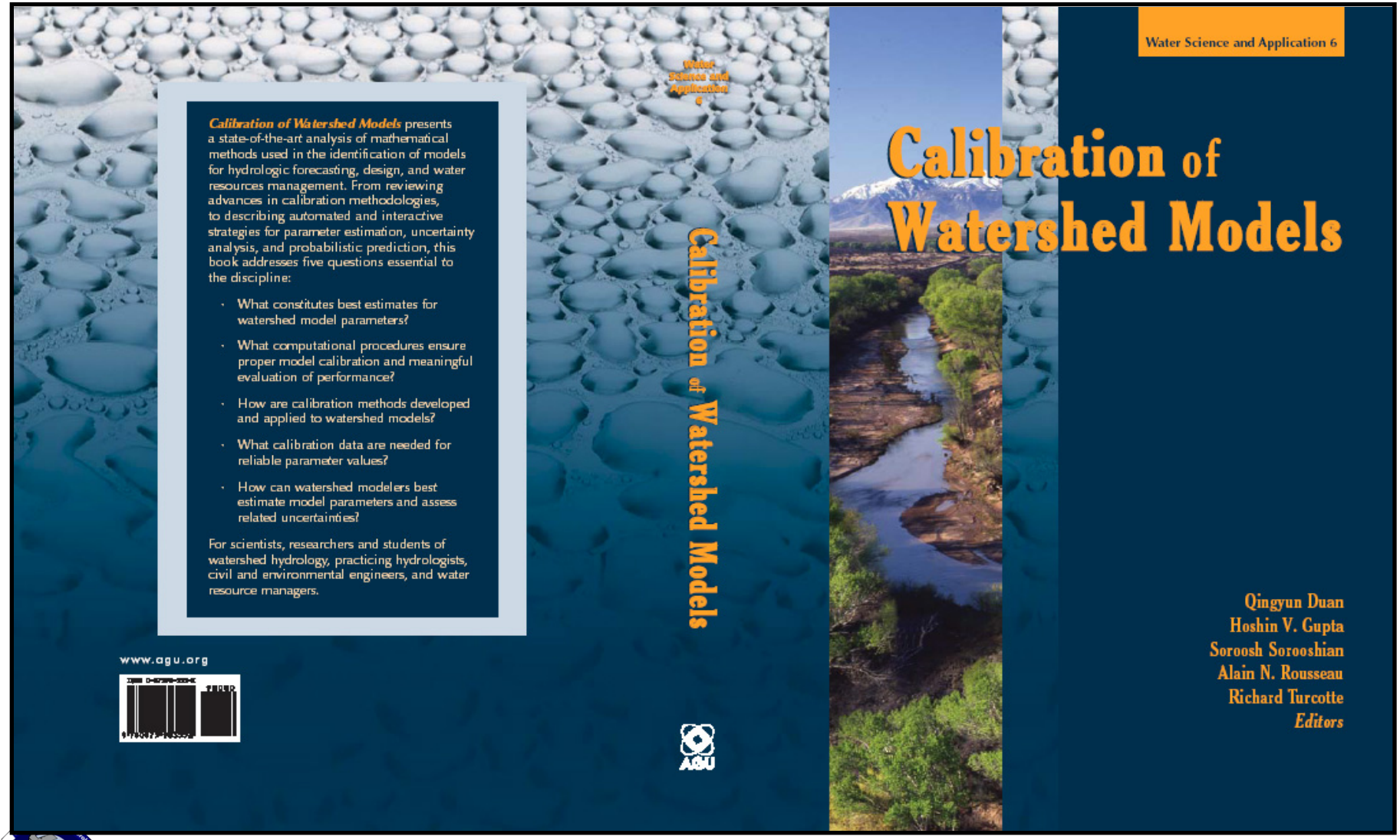
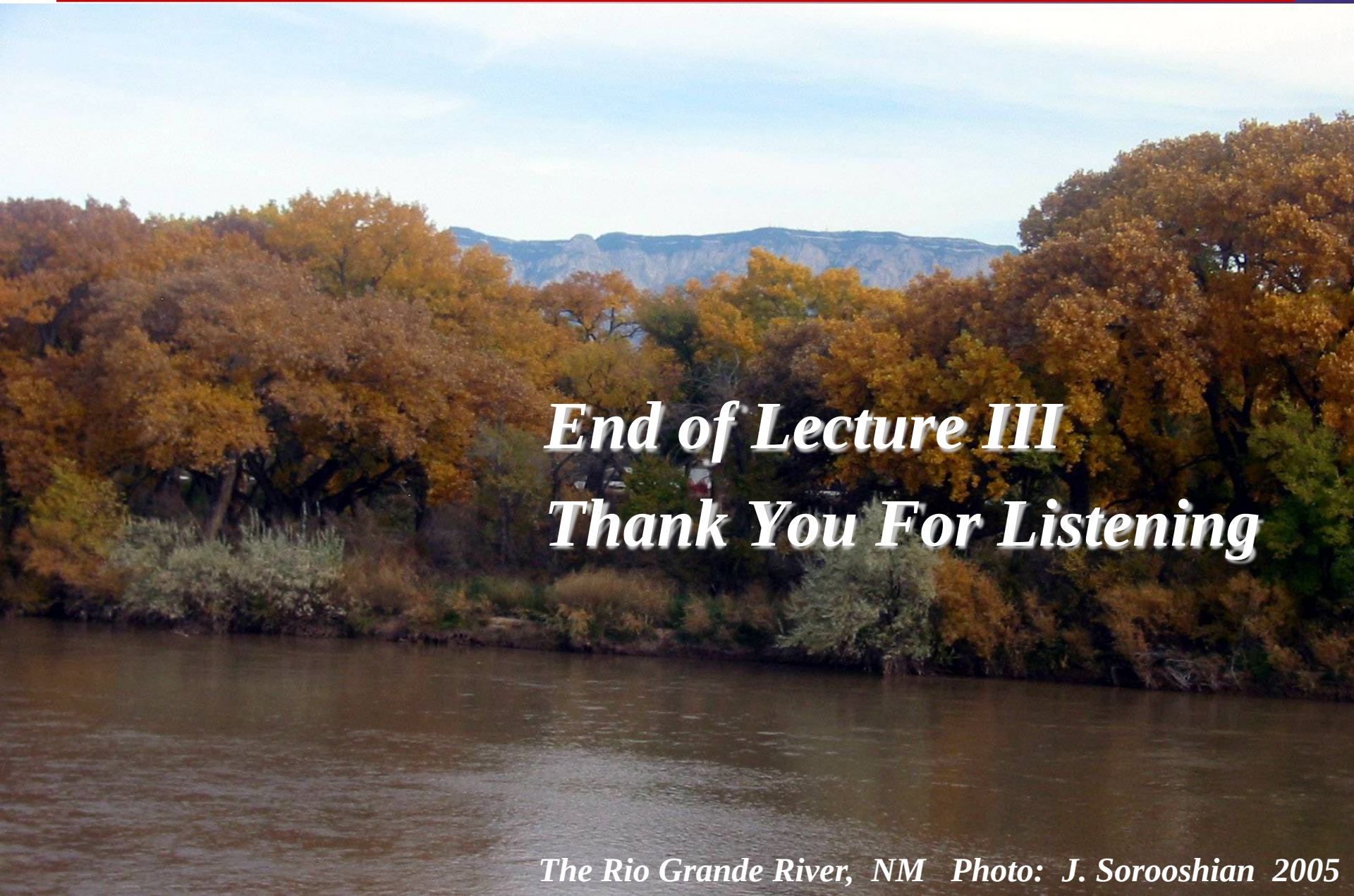
Single- & Multi-Flux Calibrations



AGU Monograph – Now Available





The Rio Grande River, NM Photo: J. Sorooshian 2005