



GOBIERNO
DE ESPAÑA

MINISTERIO
DE ECONOMÍA
Y COMPETITIVIDAD



Instituto Geológico
y Minero de España



A preliminary global assessment of under-catch of solid precipitation in Canales Basin (Sierra Nevada, Spain)

P. Jimeno, M. Pegalajar, **D. Pulido-Velázquez**, AJ Collados-Lara,
Eulogio Pardo. Spanish Geological Survey.
Spanish Geological Survey, IGME

1. INTRODUCTION: Under-catching phenomenon

2. MATERIAL & METHOD (Global assessment of under-catching)

2.0. Location of the study area and data (s/t resolution and **LONG periods**)

2.A. Geostatistical estimation of climatic fields (P & T). Hypothesis

2.B. Automatic calibration of conceptual-hydrological balance model (snow $\subset$):
- **Optimization algorithm** (Automatic calibration)

3. RESULTS

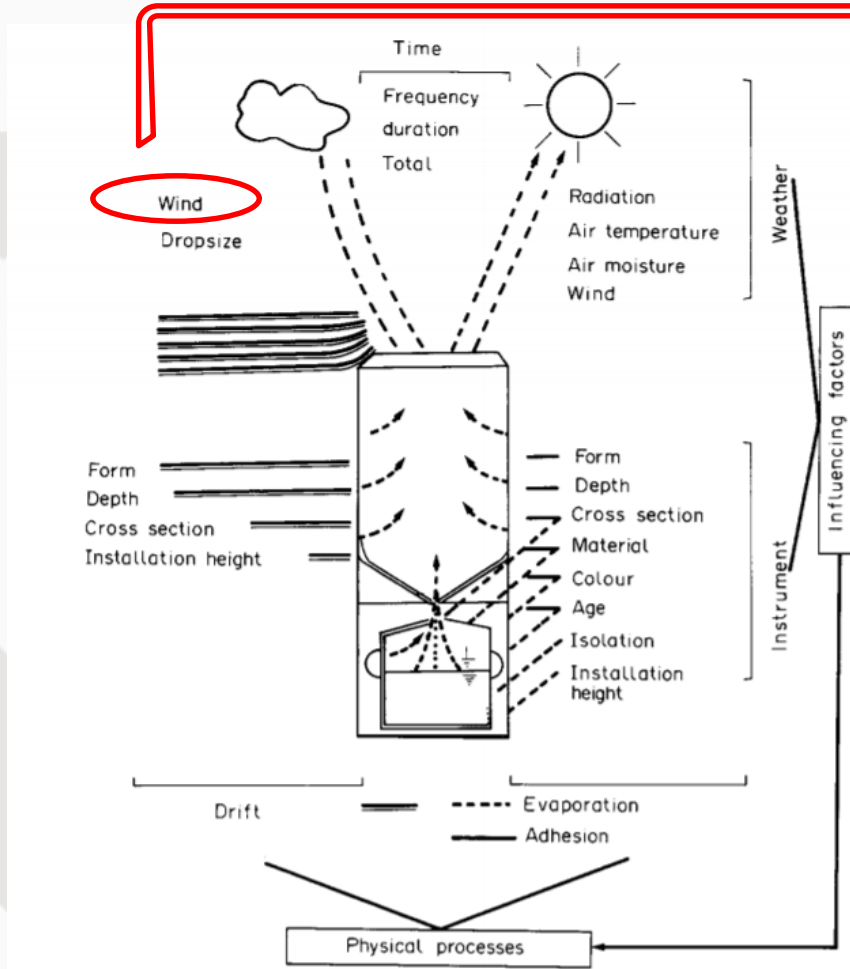
3.1 Best calibration algorithm = $f(\text{longitude of the temporal period})$

3.2 Statistic of **correction factor** for solid (C_s) and liquid (C_r) precipitation

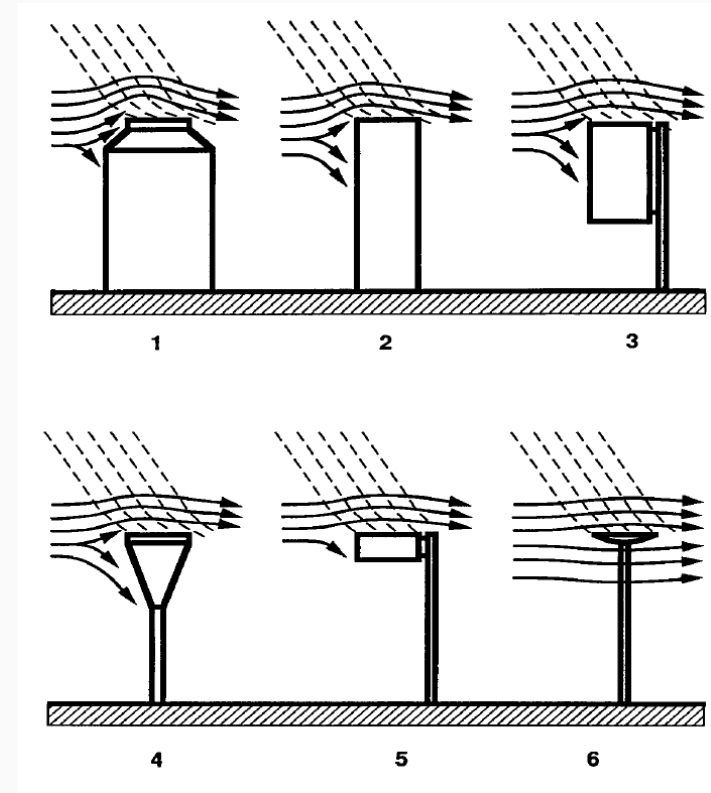
4. FUTURE RESEARCH WORKS

Non constact $C_s(x,t) = f(\text{wind intensity})$; Multi-criteria approaches; Impacts of future CC scenarios & adaptation strategies

1. INTRODUCTION: Under-catching phenomenon



Relevant physical processes affecting the systematic error of precipitation measurement (Sevruk, 1991)



The phenomenon of wind-induced error of precipitation measurement. Arrows show the streamlines and the dashed lines the trajectories of precipitation particles (Goodison et al., 1998)

1. INTRODUCTION: Under-catching phenomenon

- Brown and Peck (**1962**) studying about **challenges of precipitation measurements**.
- Sevruk (**1982**) described the **methods for correcting systematic errors in precipitation measurements** for operational use.
- WMO Solid Precipitation Intercomparison Committee between 1987 and 1993 (Goodison et al., **1998**): assessed and derived **adjustment functions for solid precipitation measurement** configurations used at that time, which to a large extent are manual observations.
- Rasmussen et al. (**2012**): studying the **relative accuracies of different instrumentation**, gauges and windshield configurations to measure snowfall
- Wolff et al. (**2015**): Determine the wind-induced under-catch of solid precipitation. Qualitative analyses and Bayesian statistics are used to evaluate and objectively choose the model that best describes the data.

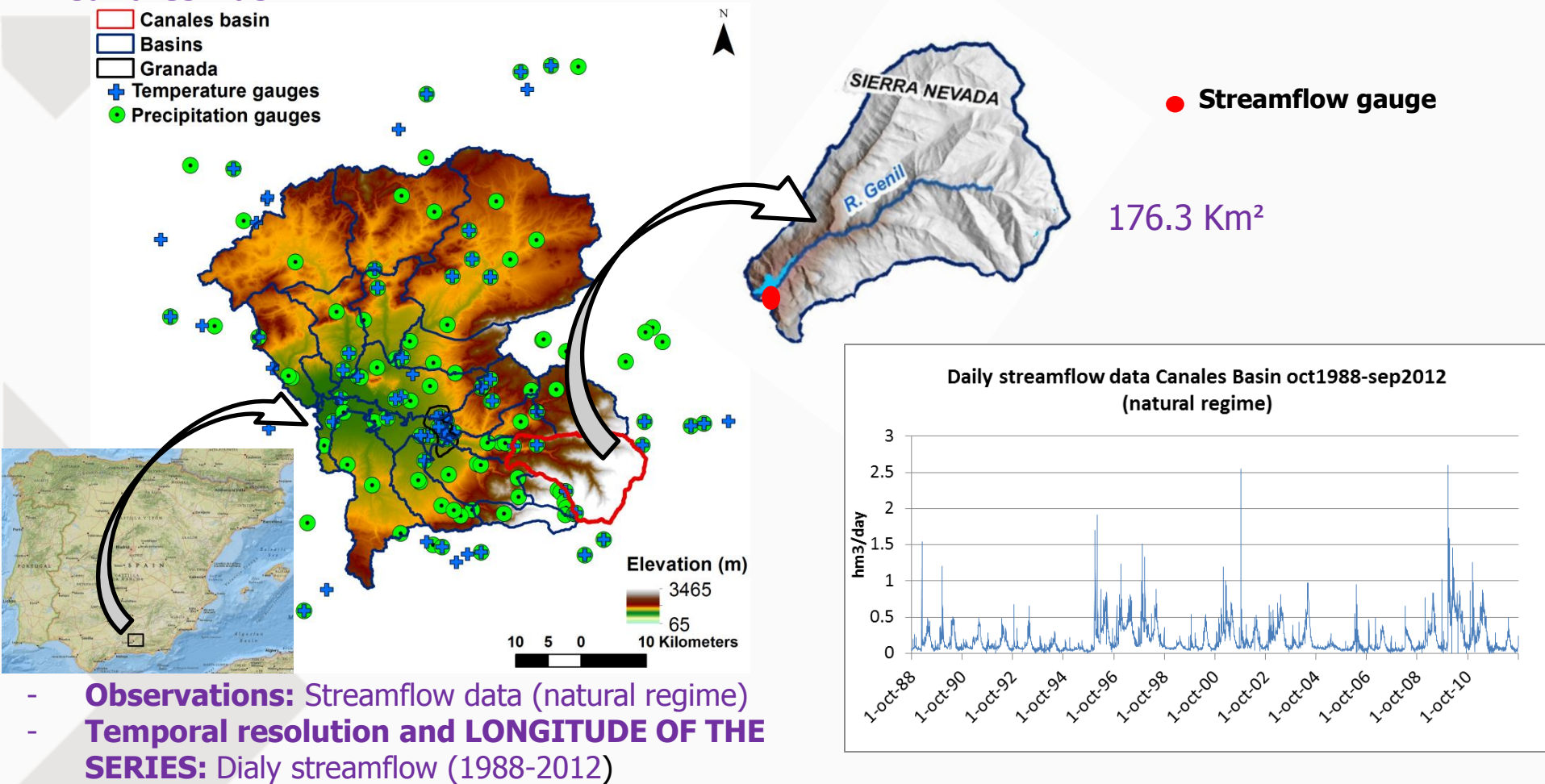


Precipitation gauge with Tretyakov shield
(Rasmussen et al., 2012)

2. MATERIAL & METHOD

2.0. Location of the study area and data (s/t resolution and **LONG periods**)

- Canales Basin:



2. MATERIAL & METHOD

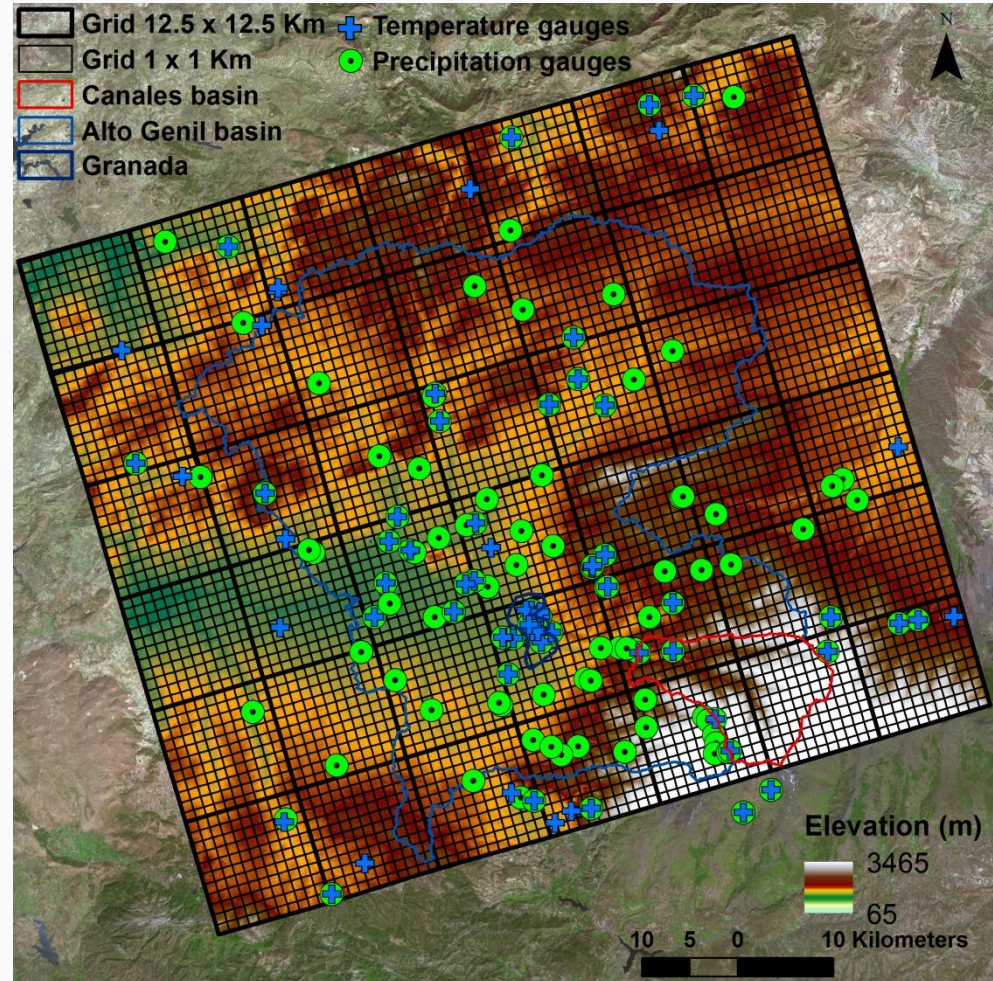
2A. Geostatistical estimation of climatic fields (P & T). Hypothesis

DATA

- 119 Precipitation gauges
- 72 Temperature gauges
- Temporal resolution: **daily**
- Period: **1980-2014 (34 years)**

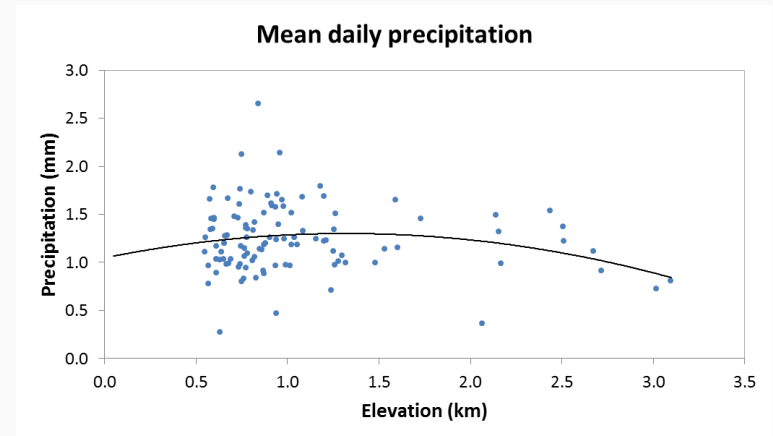
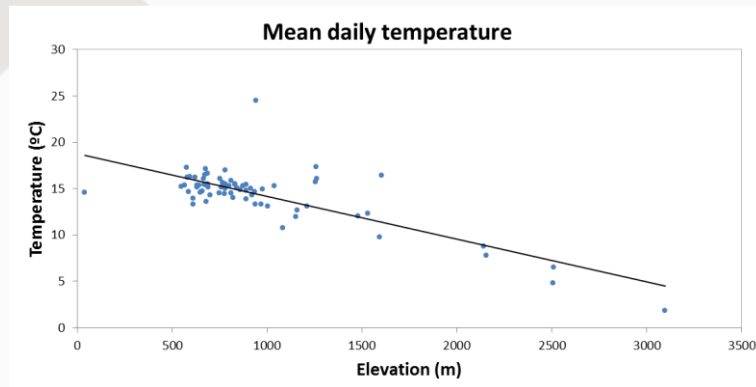
Daily **estimation** 1980-2014:

- Spatial resolution: 1km
- Monthly model vs yearly model



2. MATERIAL & METHOD

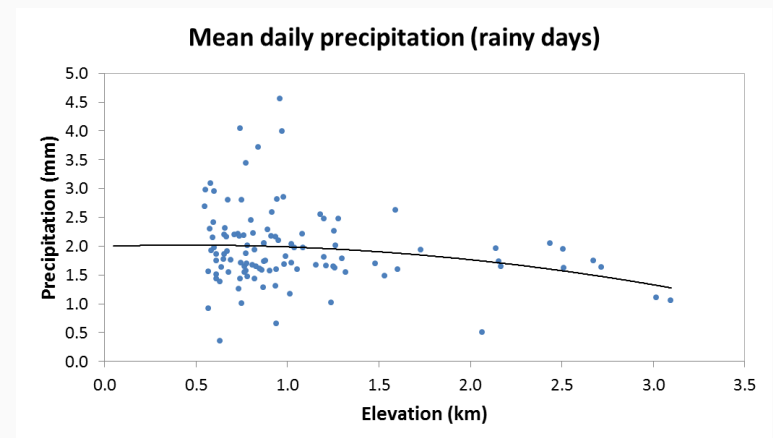
2A. Geostatistical estimation of climatic fields (P & T). Hypothesis



TEMPERATURE: linear relation → KED lineal
Tmin + kriging (Tmax-Tmin)

PRECIPITATION: quadratic relationship →

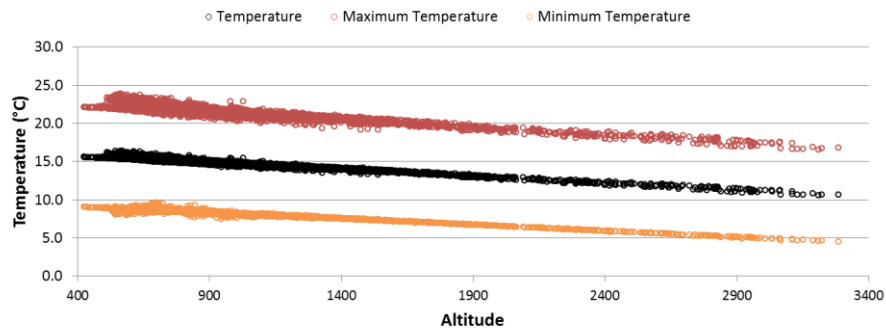
- KED linear
- KED quadratic
- Regression-Kriging using "zeros"
- Regression-Kriging without using "zeros"



2. MATERIAL & METHOD

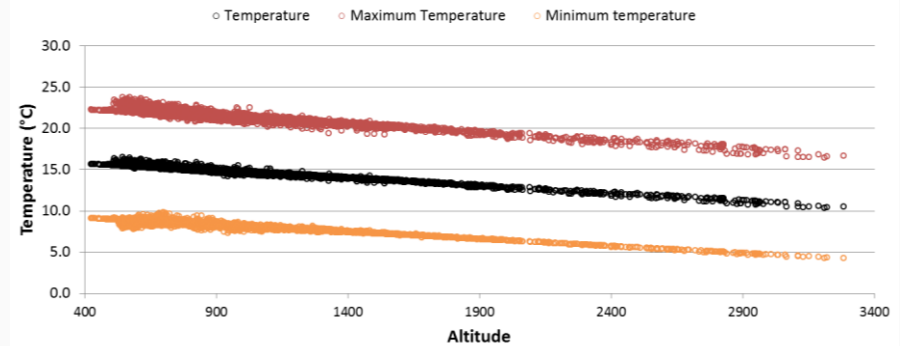
2A. Geostatistical estimation of climatic fields (P & T). Hypothesis

Estimated daily mean temperature for the monthly model



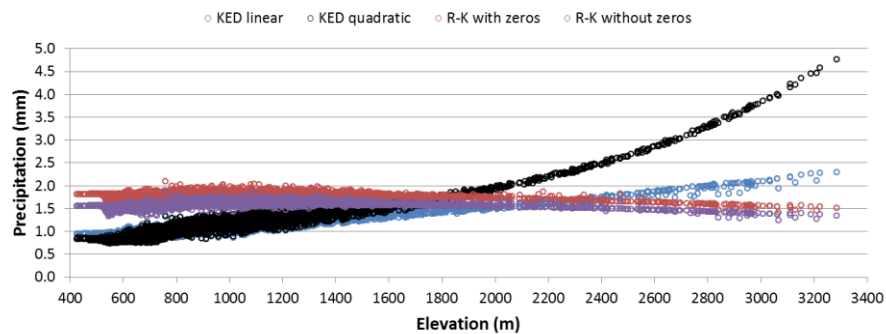
Monthly model

Estimated daily mean rainfall and temperature for the yearly model

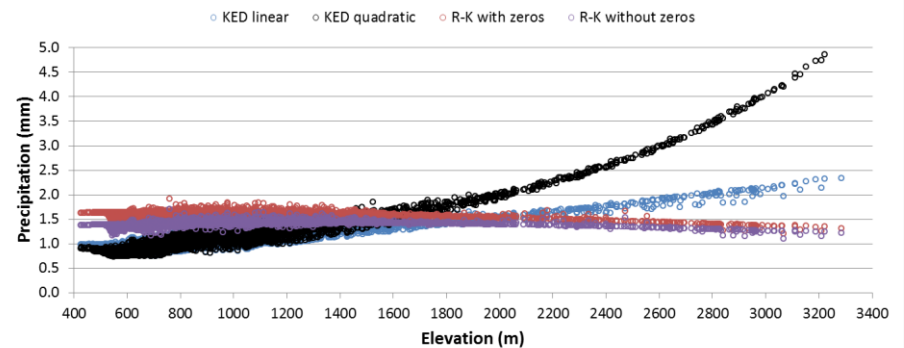


Yearly model

Estimated daily mean precipitation for the monthly model



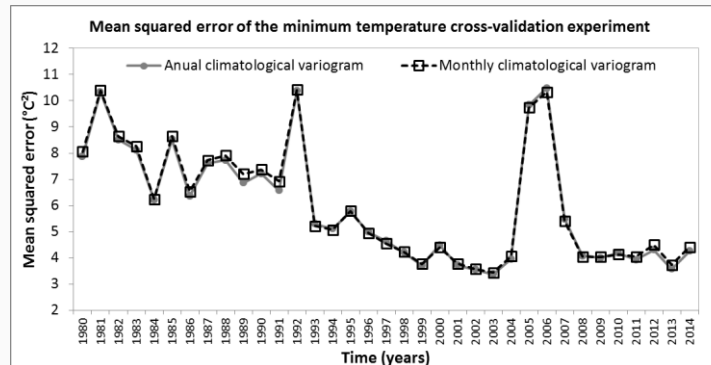
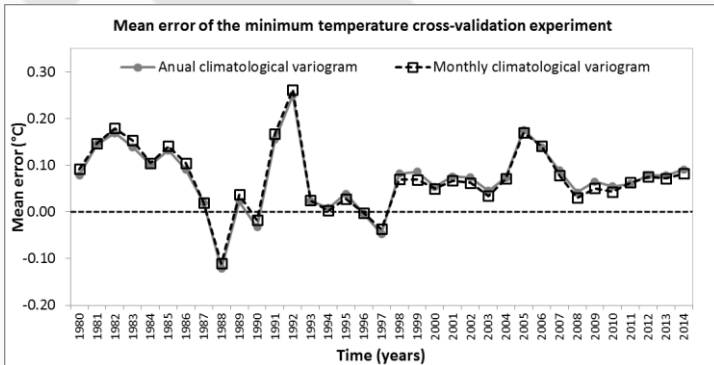
Estimated daily mean precipitation for the yearly model



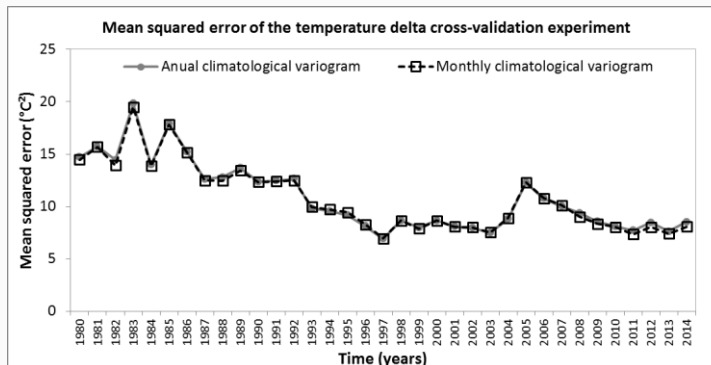
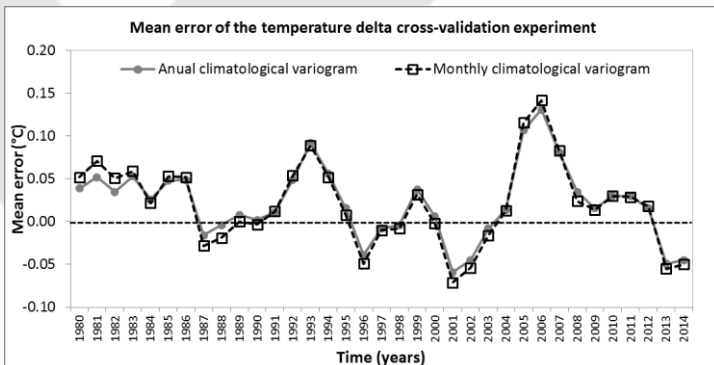
2. MATERIAL & METHOD

2A. Geostatistical estimation of climatic fields (P & T). Hypothesis

CROSS VALIDATION analysis. TEMPERATURE (KED)



KED Tmin
ME (M.M)=0.072
ME (Y.M)=0.072
MSE (M.M)=6.04
MSE (Y.M)= 5.98

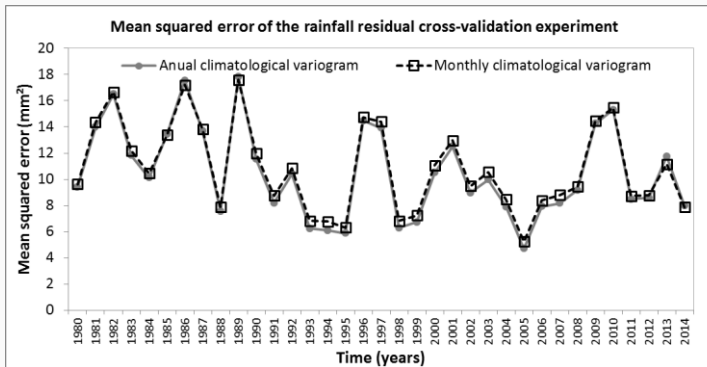
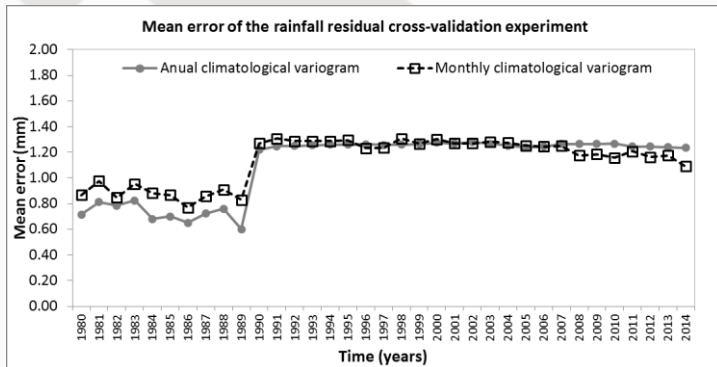


Kriging (Tmax-Tmin)
ME (M.M)=0.020
ME (Y.M)=0.022
MSE (M.M)=10.79
MSE (Y.M)= 10.89

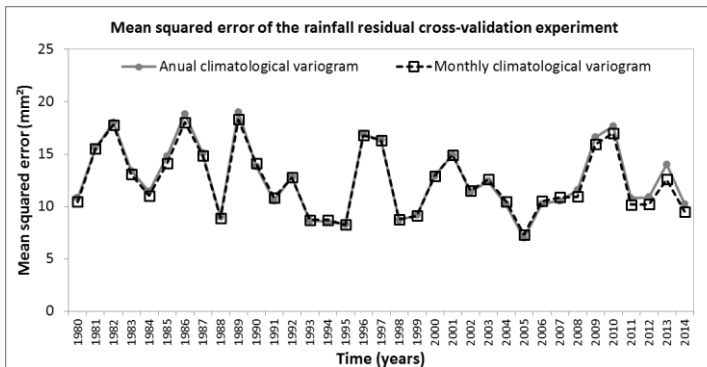
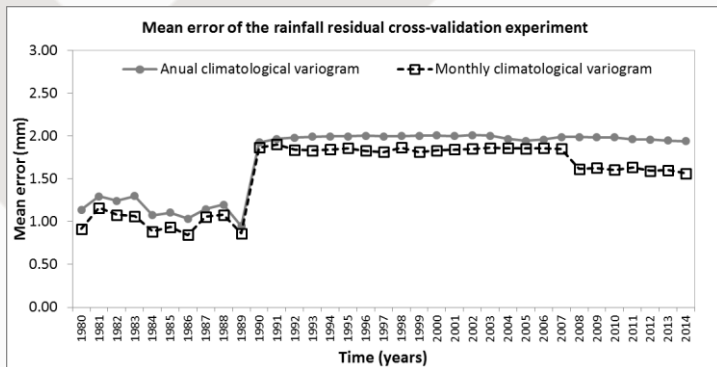
2. MATERIAL & METHOD

2A. Geostatistical estimation of climatic fields (P & T). Hypothesis

CROSS VALIDATION PRECIPITATION (R-K)



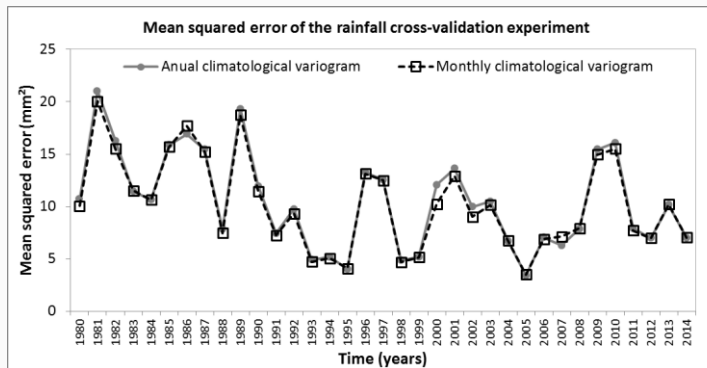
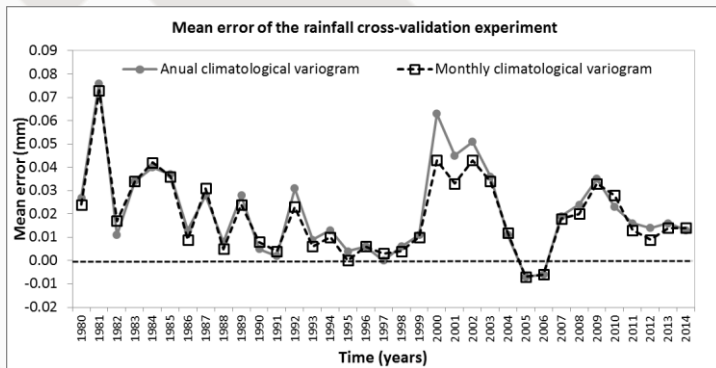
R-K with zeros
ME (M.M)=1.14
ME (A.M)=1.10
MSE (M.M)=10.5
MSE (A.M)=10.8



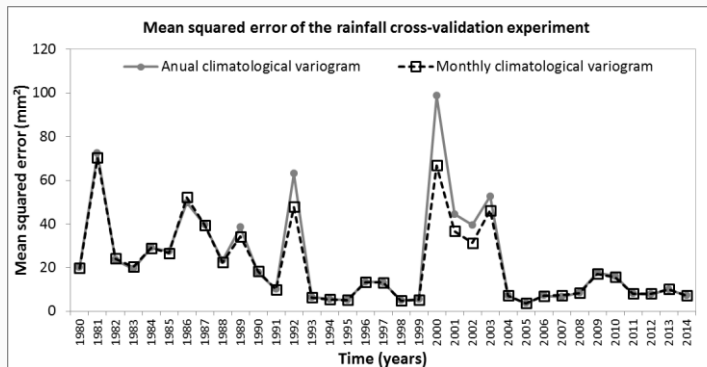
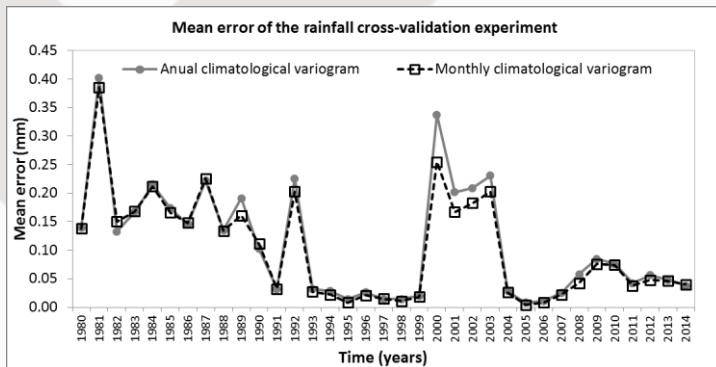
R-K without zeros
ME (M.M)=1.56
ME (A.M)=1.74
MSE (M.M)=12.4
MSE (A.M)=12.6

2. MATERIAL & METHOD

2A. Geostatistical estimation of climatic fields (P & T). Hypothesis CROSS VALIDATION PRECIPITATION (KED)



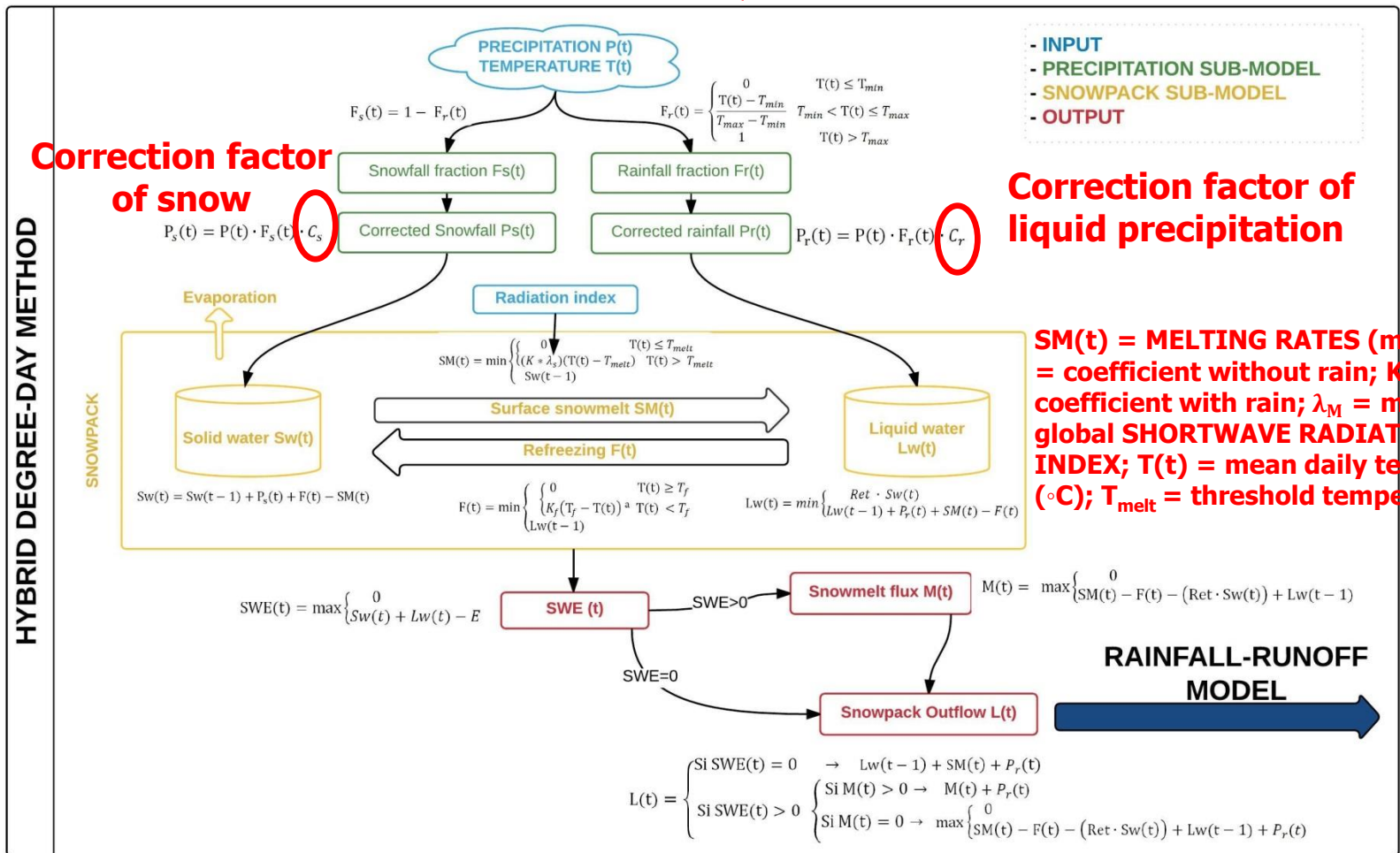
KED linear
ME (M.M)=0.019
ME (Y.M)=0.021
MSE (M.M)=10.19
MSE (Y.M)=10.44



KED quadratic
ME (M.M)=0.103
ME (Y.M)=0.111
MSE (M.M)=21.39
MSE (Y.M)=23.52

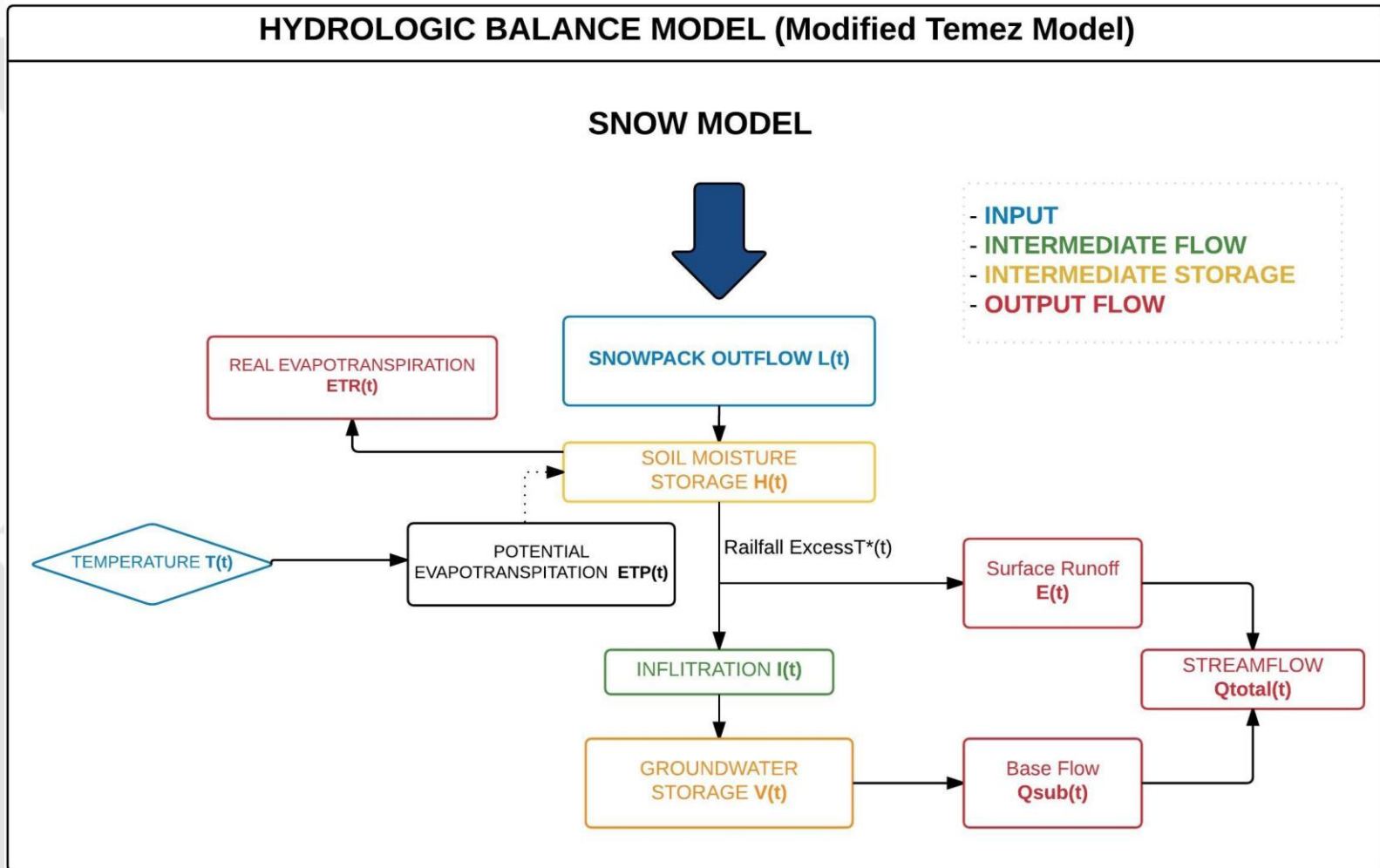
2. MATERIAL & METHOD 2B. Calibration of conceptual hydrological balance model. Sensitivity analysis: Distributed (1x1 kms) snow approach (Modified from Irannezhad et al., 2015 & Orozco, 2014)

Snowmelt approximation = Hybrid degree day method

$$SM(t) = \begin{cases} (K_{1,2} \cdot \lambda_M) \cdot (T(t) - T_{melt}) & \text{if } T(t) \geq T_{melt} \\ 0 & \text{if } T(t) < T_{melt} \end{cases}$$


2. MATERIAL & METHOD 2B. Calibration of conceptual hydrological balance model. Sensitivity analysis:

Lumped hydrological balance model (Témez et al., 1977)



2. METHOD & MATERIAL: Automatic Calibration of conceptual hydrological balance model ()

$$\mathbf{O.F} = \min \sum_{t=1}^n (Q_{sim}(t) - Q_{obs}(t))^2$$

SELECTION OF THE BEST OPTIMIZATION ALGORITHM:

Detailed analysis of optimization techniques has been performed. **IMP:**

-High **computational cost** of our optimization problem: Many **data (long time periods)** + 21 parameters to be optimized

-**Noisy Data** $\Rightarrow$ Risk of **local optimal solutions** as the size of dataset increases

2. METHOD & MATERIAL: Calibration of conceptual hydrological balance model

Objectives/concerns: Which is the best algorithm?

- **How the size of the dataset** affects local optima? => **MSE**
- How the **initial solution affects RESULTS** in classic algorithms? => **MSE**
- **Which** algorithmic methodology **is more robust**? => **SD(MSE)**
- **Which** algorithmic methodology **is more efficient**? => **Computational time**

Tested Algorithms:

- LS – Classic Informed Local Search (trust-region-reflective)
- SA – Simulated Annealing
- SA+LS – The solution of SA is used as initial solution for LS
- GA: Genetic Algorithm
- GA+LS – The solution of GA is used as initial solution for LS

Experimental evaluation:

- Datasets of length: 2 years, 10 years, 20 years
- Stopping criteria: 3000 evaluations

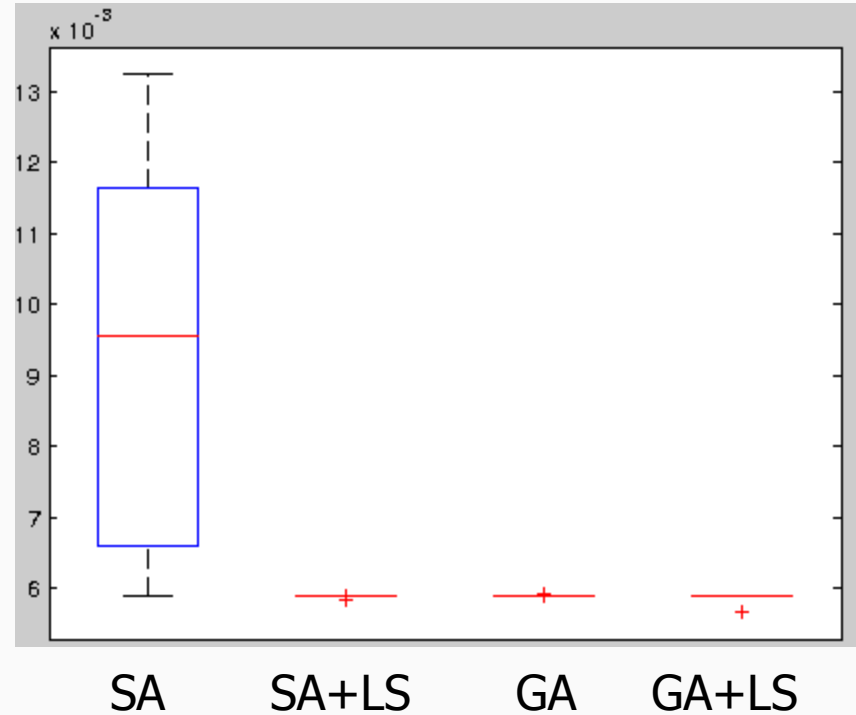
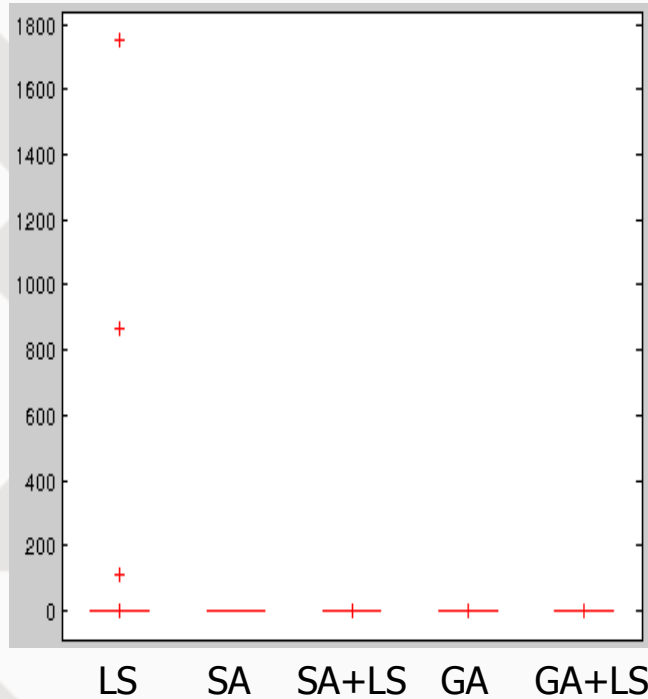
3. RESULTS: 3.1 **Best calibration algorithm** = f(longitude of the temporal period)

Size of dataset: last 2 years

Algorithm	Mean MSE	Median MSE	Best MSE	Worst MSE	S.d.	Average Time per running (s.)	Total time (s.)
LS (local search)	21,66521	0,005883	0,005555	1752,077	173,6847	23,32679	2939,176
SA	0,009551	0,009276	0,005897	0,013242	0,002523	87,48397	2624,519
GA	0,005883	0,005883	0,005838	0,005894	0,000009	105,6492	3169,475
SALS	0,005884	0,005885	0,005883	0,005913	0,000005	97,49557	2924,867
GA+LS	0,005883	0,005876	0,005667	0,005883	0,000039	111,1892	3335,677

3. RESULTS: 3.1 **BEST CALIBRATION ALGORITHM** = $f(\text{longitude of temporal period})$

Size of dataset: last 2 years



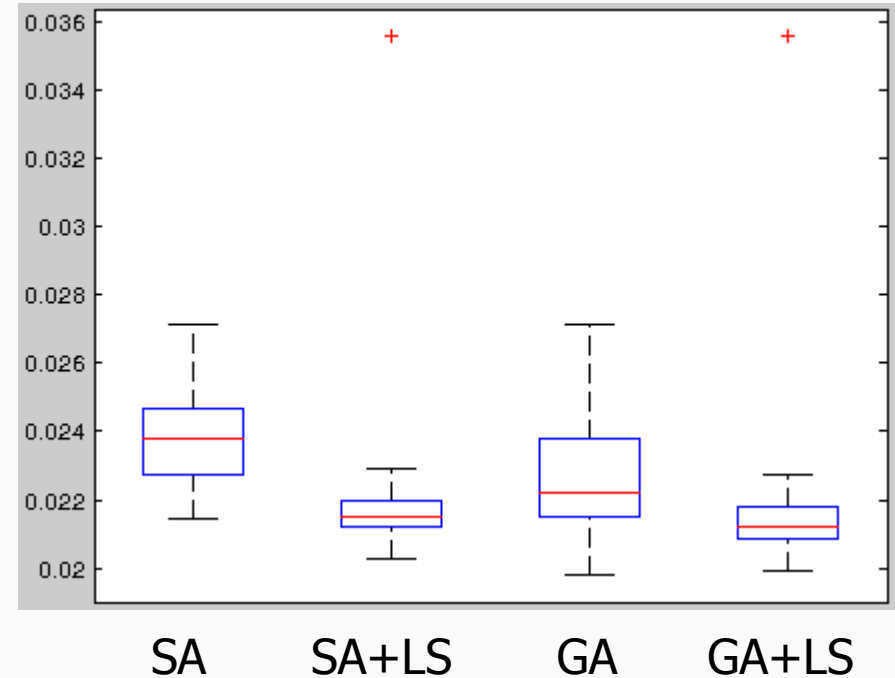
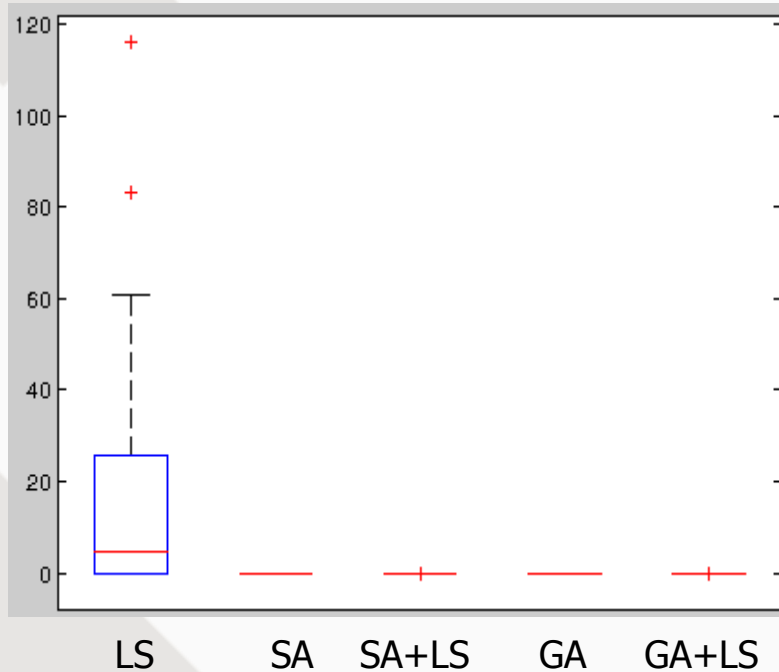
3. RESULTS: 3.1 **BEST CALIBRATION ALGORITHM** = f(longitude of temporal period)

Size of dataset: last 10 years

Algorithm	Mean MSE	Median MSE	Best MSE	Worst MSE	S.d.	Average Time per running (s.)	Total time (s.)
LS (local search)	19,29736	4,537579	0,021985	116,0356	32,22263	477,3874	18618,11
SA	0,023787	0,023804	0,021474	0,027144	0,001375	567,2712	17018,14
GA	0,021516	0,022019	0,020297	0,035567	0,002635	647,34	19420,2
SALS	0,022234	0,022631	0,019804	0,027144	0,001646	615,799	18473,97
GA+LS	0,021218	0,021764	0,019952	0,035567	0,002689	714,357	21430,71

3. RESULTS: 3.1 **BEST CALIBRATION ALGORITHM** = $f(\text{longitude of temporal period})$

Size of dataset: last 10 years



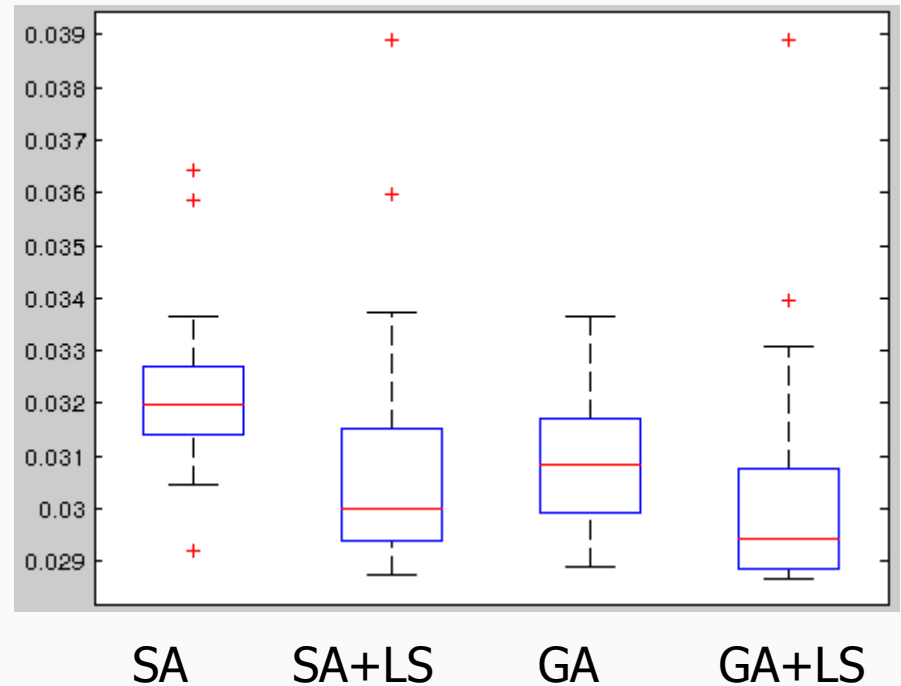
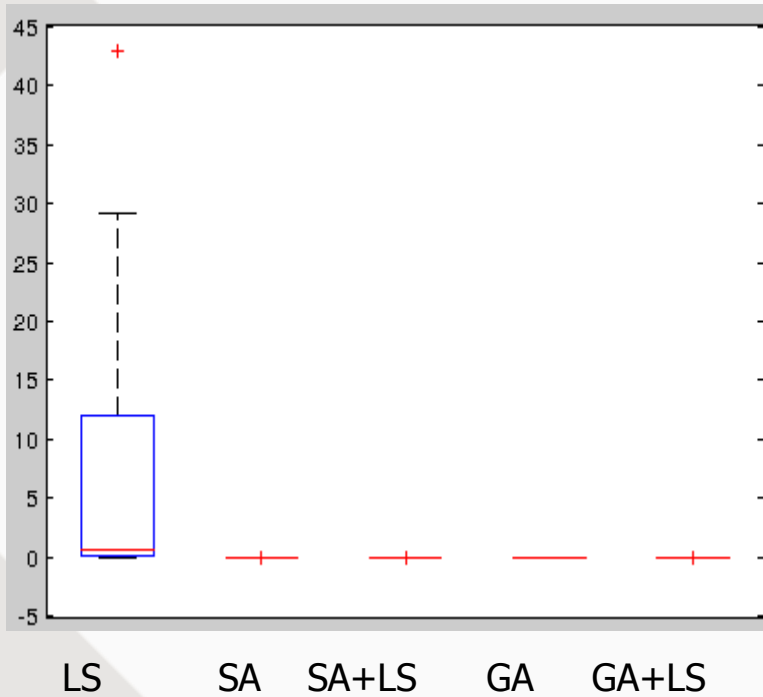
3. RESULTS: 3.1 **BEST CALIBRATION ALGORITHM** = f(longitude of temporal period)

Size of dataset: last 20 years

Algorithm	Mean MSE	Median MSE	Best MSE	Worst MSE	S.d.	Average Time per running (s.)	Total time (s.)
LS (local search)	7,437584	0,68985	0,029464	42,93597	11,04093	1146,329	33243,55
SA	0,03197	0,032112	0,029189	0,036413	0,001525	1013,463	30403,89
GA	0,030008	0,03074	0,028742	0,038906	0,002256	1355,369	40661,08
SALS	0,030823	0,030888	0,028886	0,033639	0,001242	1111,314	33339,42
GA+LS	0,029438	0,030174	0,028656	0,038906	0,002158	1497,698	44930,95

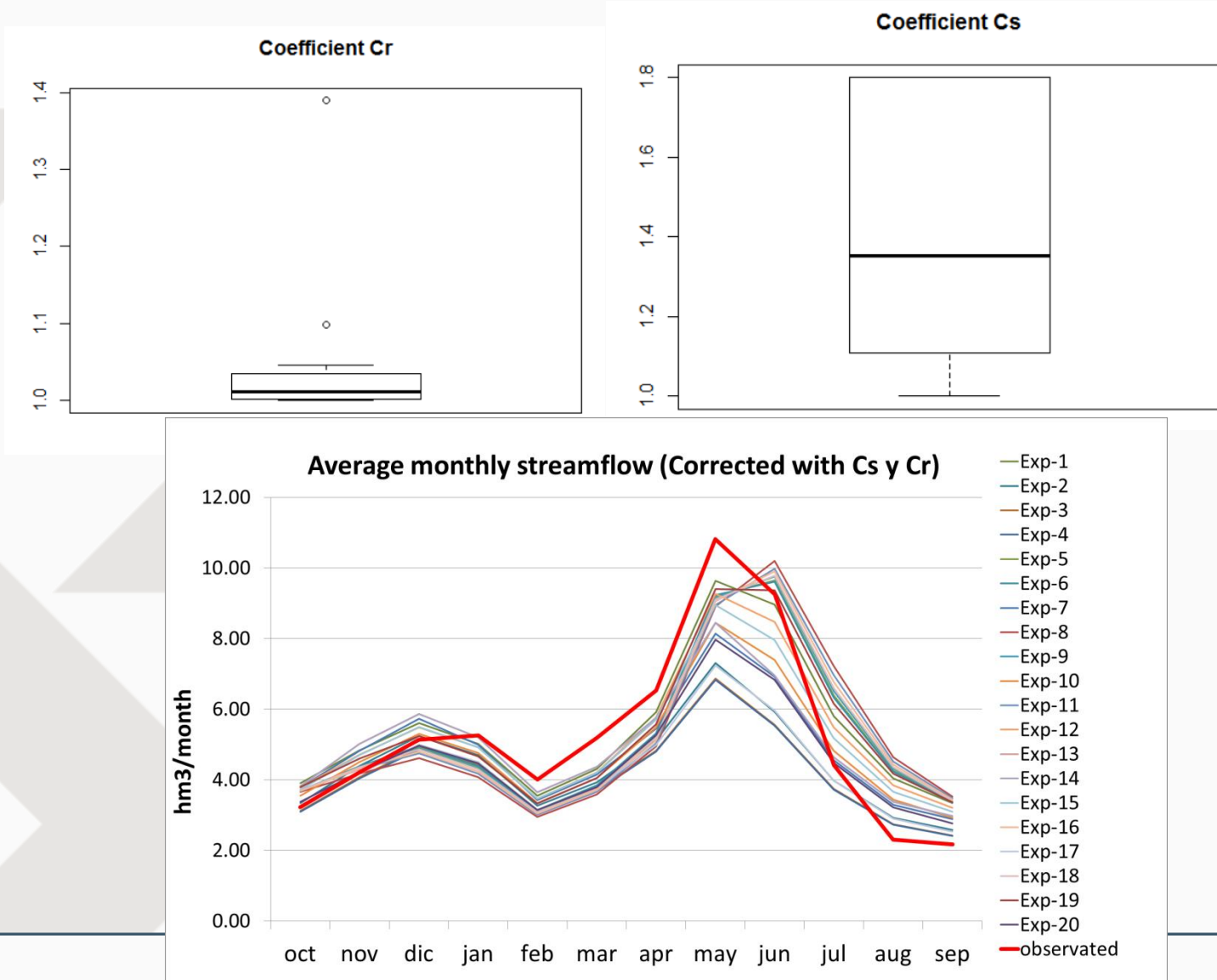
3. RESULTS: 3.1 **BEST CALIBRATION ALGORITHM** = $f(\text{longitude of temporal period})$

Size of dataset: last 20 years



- **GA+LS provided best results in all cases.**
- **Limitation: The computational time is greater, although it is the most robust algorithm.**

3. RESULTS: 3.2 Statistic of **correction factor** for solid (Cs) & liquid (Cr) precipitation



4. FUTURE RESEARCH WORKS.

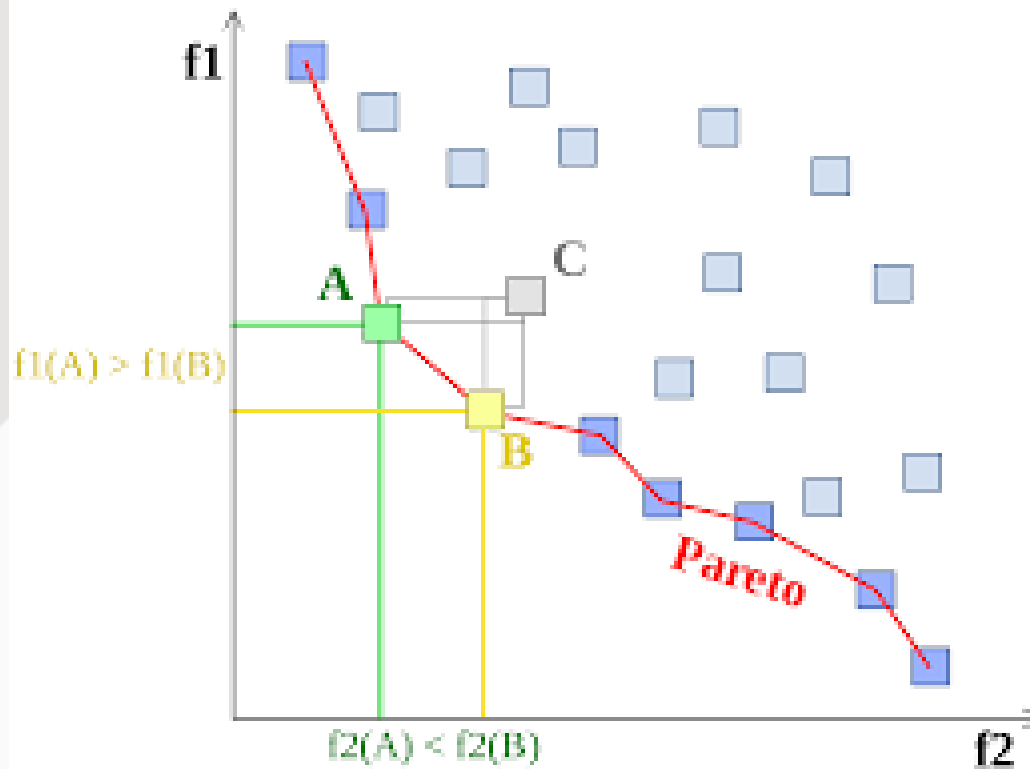
4.0 ANALYSES OTHER HYPOTHESIS IN SNOW MODEL FORMULATION:

- **NON-CONSTANT** correction of snow factor (C_s)
Approaching S/t variability = $f(\text{wind intensity fields})$;
- **Other SNOW MODEL APPROACHES**

4. FUTURE RESEARCH WORKS. 4.1 Multi-criteria calibration approaches.

LONG SERIES: Q & SCA (satellite information + cellular automata simulation where satellite information is not available)

- **Multicriteria approximation: $\text{Min}\{Q, SCA\}$**



4. FUTURE RESEARCH: **Impacts** of future **CC scenarios** & assessment of **adaptation strategies** (classical & Hydro-economic **management models at basin scale**)

■ **BG: Systematic method** to assess **Problems & Solutions** $\Rightarrow$ indices=f(Management model) (Pulido-V, et al., 2011)

114

D. Pulido-Velazquez et al./Journal of Hydrology 405 (2011) 110–122

Table 1

Problems and solutions based on the values of the indices.

		Withdrawal use (I_w)	Withdrawal (I_u)	Demand reliability (I_r)			
				High (I_s^+)		Intermediate (I_s^-)	
				Problems	Solutions	Problems	Solutions
<i>Demand satisfaction (I_s)</i>							
High (I_s^+)	High (I_w^+)	High (I_u^+)	High (I_u^+)			2 ⁺	A ⁺
			Low (I_u^-)			2 ⁺ –4 ⁺	A ⁺ –C ⁺
Intermediate (I_s^-)	Low (I_w^-)	High (I_u^+)	High (I_u^+)			2 ⁺ –3 ⁺	A ⁺ –B ⁺
			Low (I_u^-)	1 ⁺ –4 ⁺	A ⁺ –C ⁺	1 ⁺ –2 ⁺ –4 ⁺	A ⁺ –C ⁺
Low (I_s^-)	High (I_w^+)	High (I_u^+)	High (I_u^+)	1 ⁺ –3 ⁺	A ⁺ –B ⁺	1 ⁺ –2 ⁺ –3 ⁺	A ⁺ –B ⁺
			Low (I_u^-)	1 ⁺ –4 ⁺	A ⁺ –C ⁺	1 ⁺ –2 ⁺ –4 ⁺	A ⁺ –C ⁺
Low (I_s^-)	Low (I_w^-)	High (I_u^+)	High (I_u^+)	1 ⁺ –3 ⁺	A ⁺ –B ⁺	1 ⁺ –2 ⁺ –3 ⁺	A ⁺ –B ⁺
			Low (I_u^-)	1 ⁺ –3 ⁺ –4 ⁺	A ⁺ –B ⁺ –C ⁺	1 ⁺ –2 ⁺ –3 ⁺ –4 ⁺	A ⁺ –B ⁺ –C ⁺

+ High = Intermediate – Low

Problem:

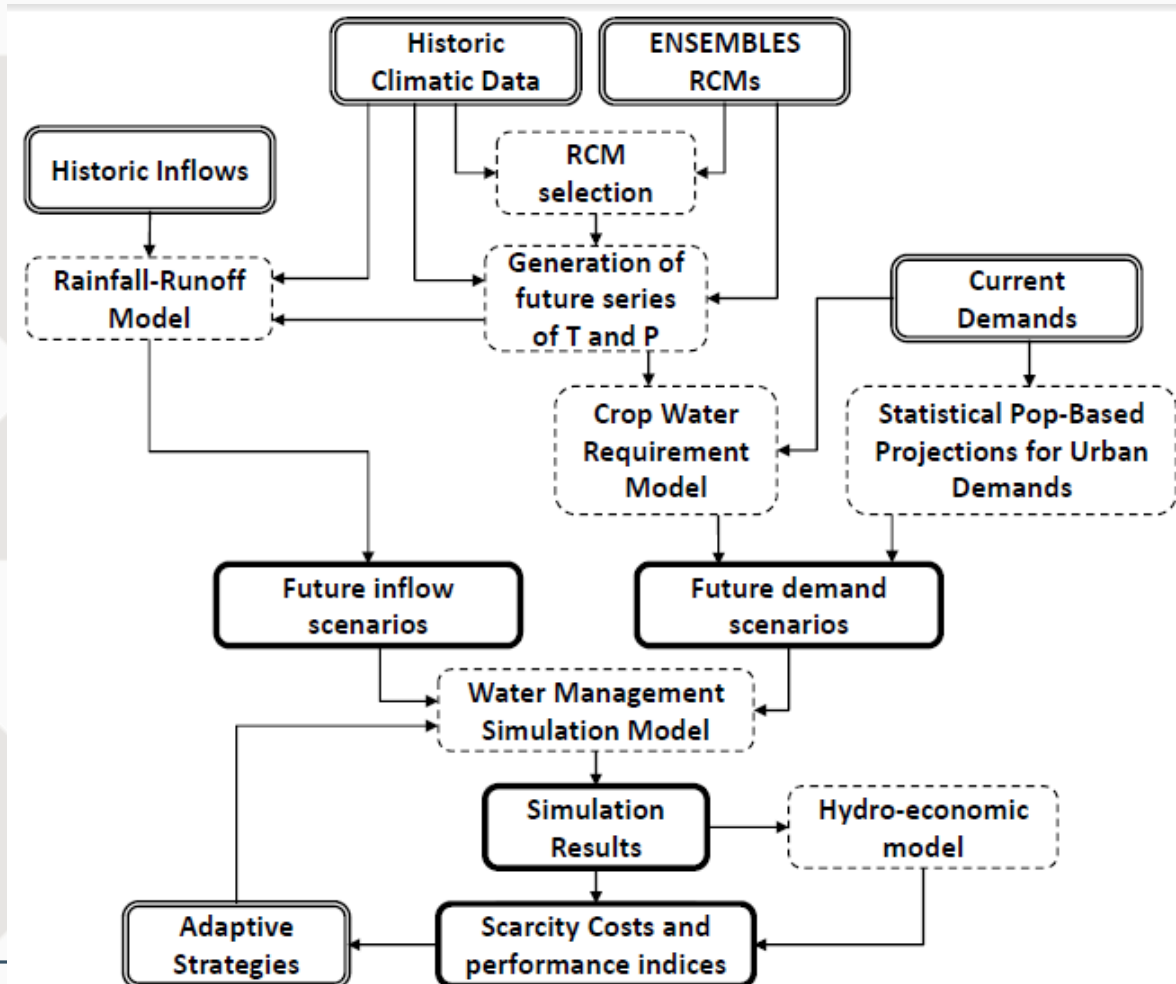
1. Vulnerable: water scarcity may produce significant damages.
2. Unreliable: low intensity droughts may lead to water scarcity.
3. Excess of demand with respect to withdrawal (pumping + natural inflows-depletions produced by pumping).
4. Reduced use of withdrawal.

Solution:

- A. Demand management.
- B. Complementary resources are needed (additional pumping, water transfer, water reuse, etc.).
- C. Increase regulation of the system withdrawal (surface structural works, artificial recharge, water reuse, etc.).

4. FUTURE RESEARCH: **Impacts** of future **CC scenarios** & assessment of **adaptation strategies** (classical & Hydro-economic **management models at basin scale**)

Hydroeconomic assessment of CC impacts & adaptation strategies. Jucar Basin (Escriva-Bou, Pulido-V, et al., 2016)



4. FUTURE RESEARCH: **Impacts** of future **CC scenarios** & assessment of **adaptation strategies** (classical & Hydro-economic **management models at basin scale**)

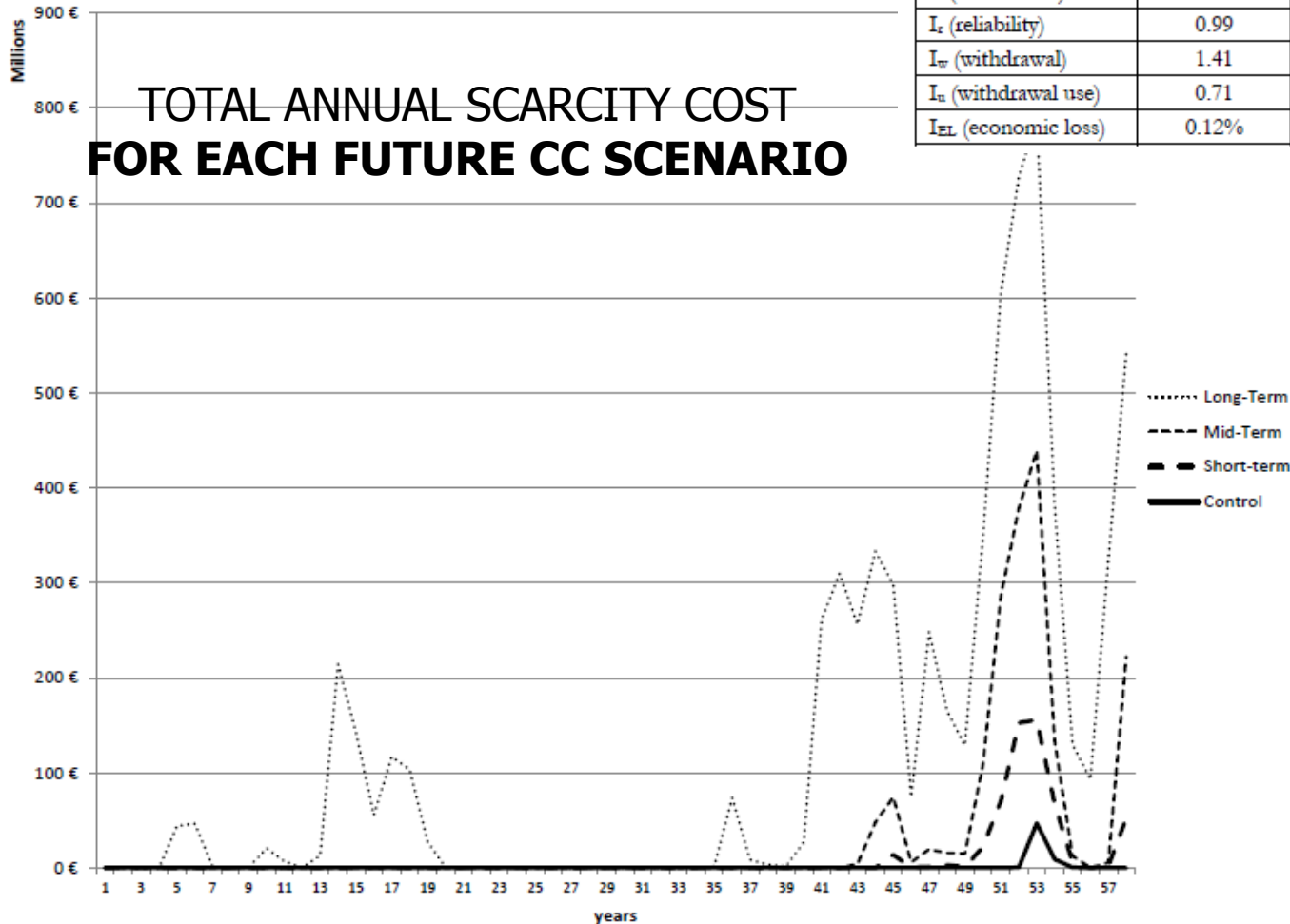
Hydroeconomic assessment of CC impacts & adaptation strategies.

Jucar Basin (Escriva-Bou, Pulido-V, et al., 2016)

Indices (also Economic)

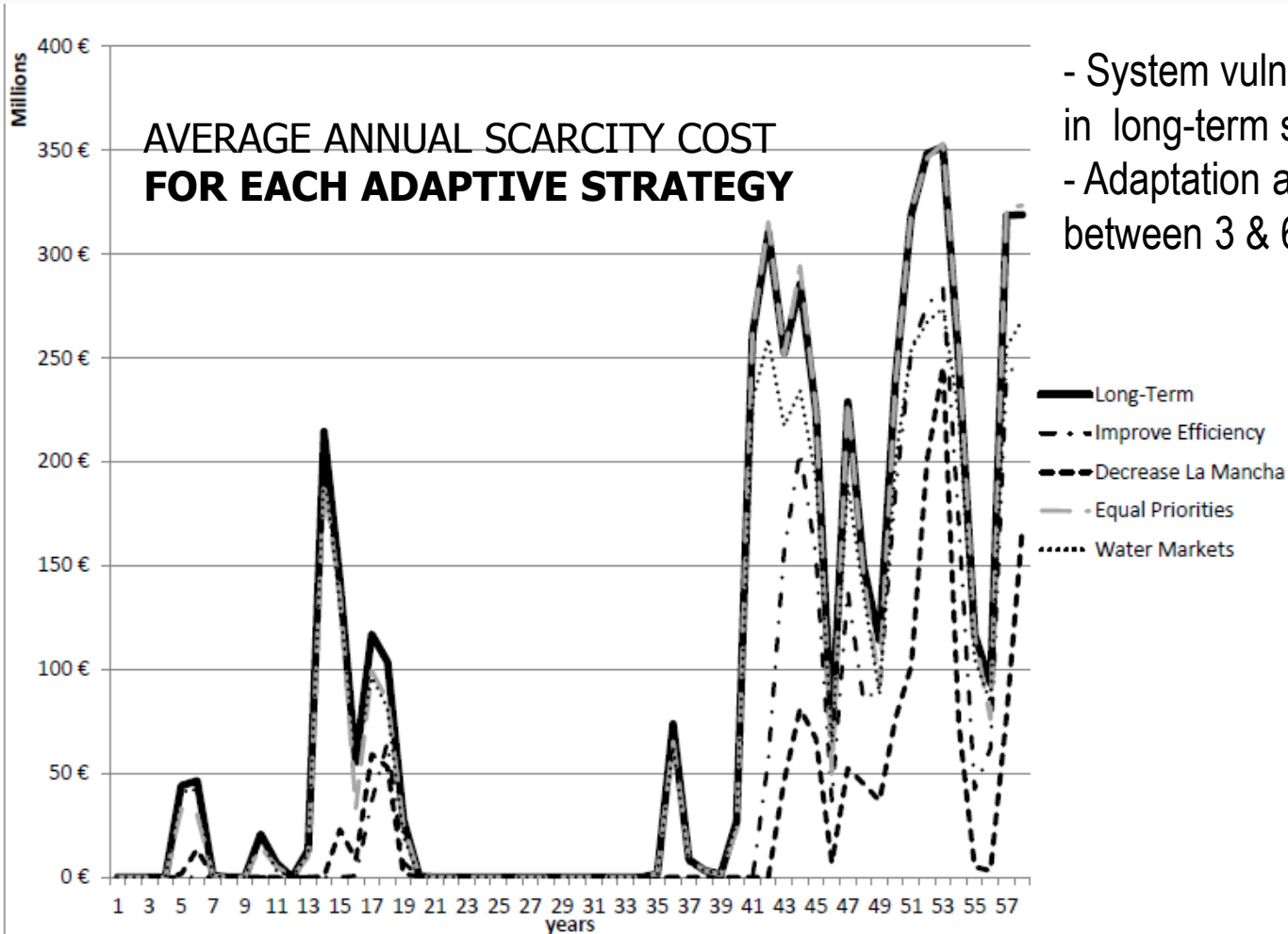
	Control	Short-Term	Mid-Term	Long-Term
I_s (satisfaction)	0.99	0.97	0.95	0.82
I_r (reliability)	0.99	0.95	0.92	0.75
I_w (withdrawal)	1.41	1.27	1.18	0.86
I_u (withdrawal use)	0.71	0.76	0.81	0.95
I_{EL} (economic loss)	0.12%	1.01%	2.26%	9.79%

TOTAL ANNUAL SCARCITY COST FOR EACH FUTURE CC SCENARIO



4. FUTURE RESEARCH: **Impacts** of future **CC scenarios** & assessment of **adaptation strategies** (classical & Hydro-economic **management models at basin scale**)

Hydroeconomic assessment of CC impacts & adaptation strategies. Jucar Basin (Escriva-Bou, Pulido-V, et al., 2016)



- System vulnerable to GC, especially in long-term scenarios (2071-2100)
- Adaptation actions can save between 3 & 65 M€/year.

**THANK YOU
FOR YOUR ATTENTION!!**

David Pulido-Velazquez. (d.pulido@igme.es)
Spanish Geological Survey, IGME