Calibration of a distributed eco-hydrological model using only remotely sensed surface soil moisture

By:

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GIMHA – IIAMA - Universitat Politècnica de València
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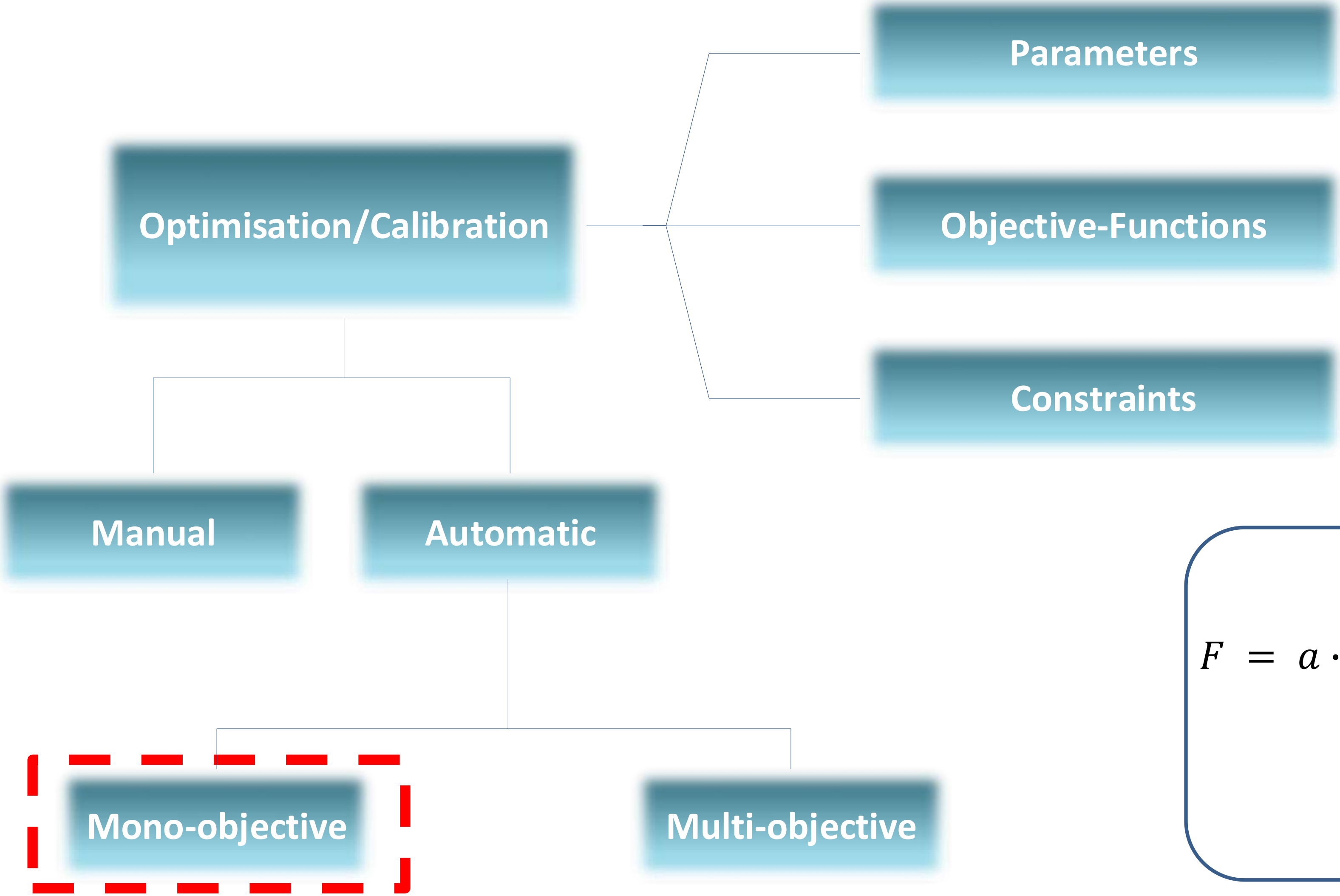
Content

Introduction



Optimisation/Calibration

Parameters

Objective-Functions

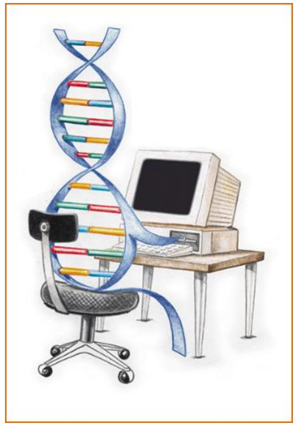
Constraints

Manual

Automatic

Mono-objective

Multi-objective



$$minimise\ F$$

$$F = a \cdot x_1 + b \cdot (x_1)^{1/5} - c \cdot x_2 + d \cdot (x_2)^{-1/7}$$

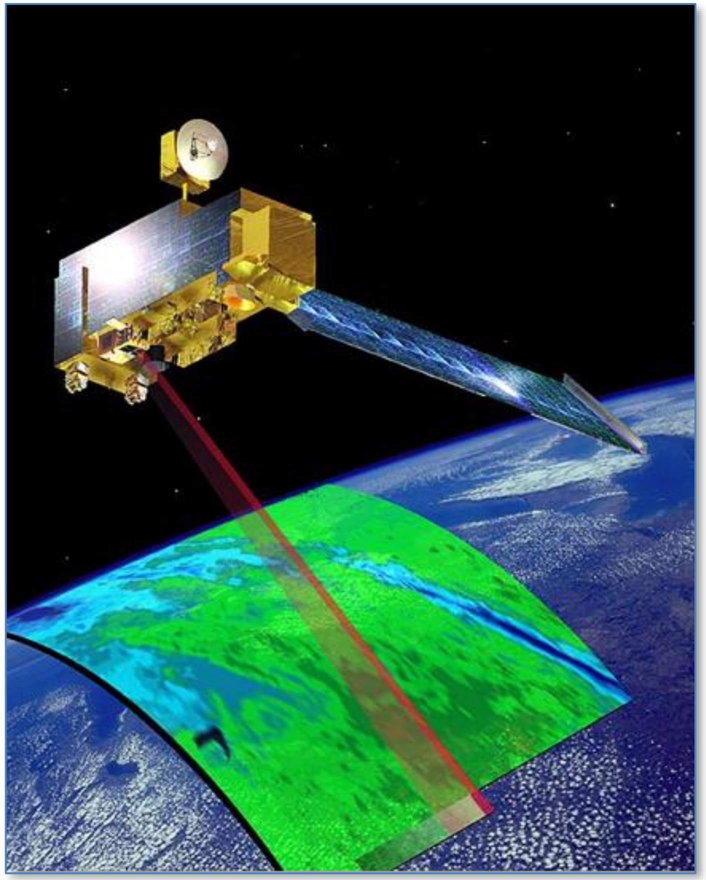
$$\mathrm{R}_1\!: 0 \leq x_1 \leq 1$$

$$\mathrm{R}_2\!: x_2 \geq 0$$

Introduction

- ☐ Use of Remote Sensing (RS) in Hydrological Modelling……(?)

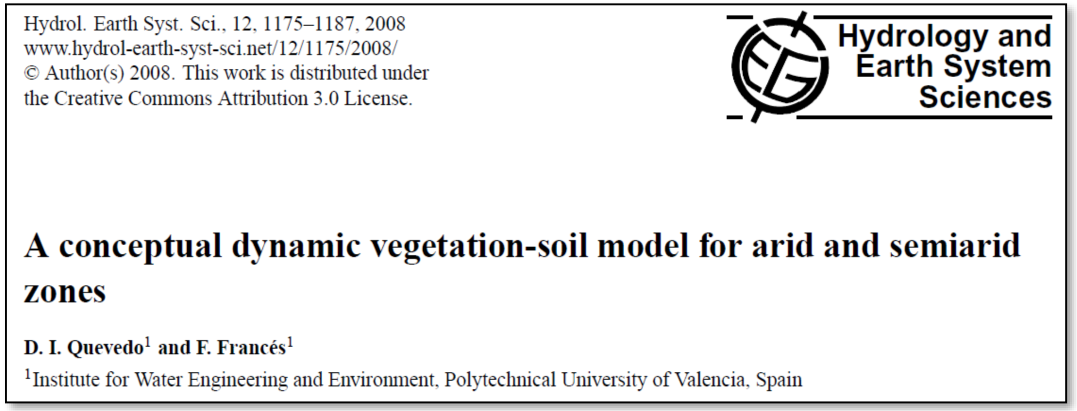
- ➢ Spatial coverage 👍
- ➢ Higher uncertainty than field observations 👎
- ➢ Calibration <- effective parameters
- ➢ **YES** predictions with HM
- ➢ **NOT** data assimilation



Introduction

❑ Use of Remote Sensing (RS) in Hydrological Modelling……(?)

- ➢ NDVI at plot scale:



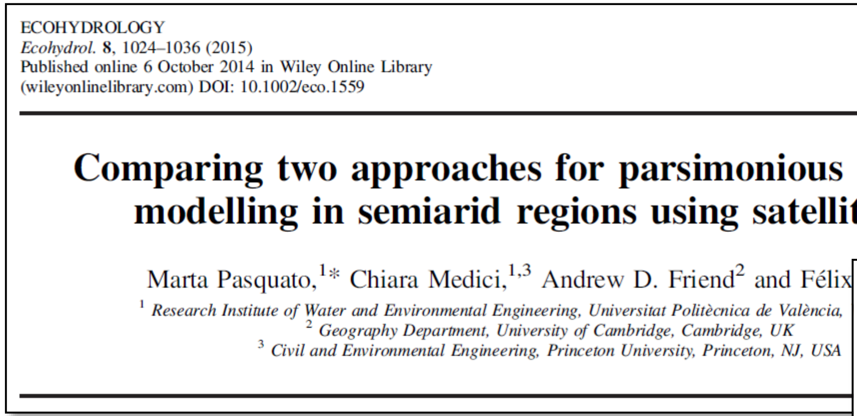
Hydrol. Earth Syst. Sci., 12, 1175–1187, 2008
www.hydrol-earth-syst-sci.net/12/1175/2008/

Hydrology and Earth System Sciences

A conceptual dynamic vegetation-soil model for arid and semiarid zones

D. I. Quevedo[1] and F. Francés[1]

[1]Institute for Water Engineering and Environment, Polytechnical University of Valencia, Spain



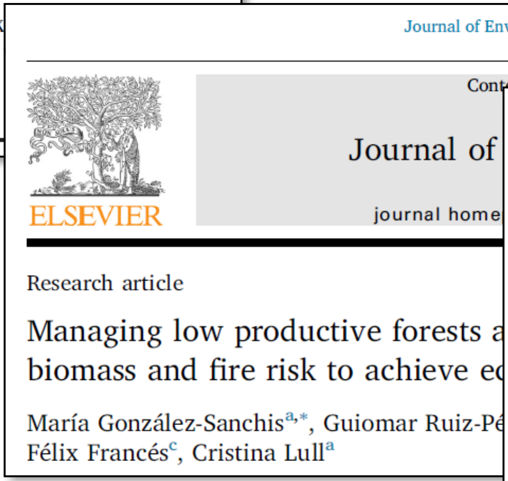
ECOHYDROLOGY
Ecohydrol. **8**, 1024–1036 (2015)
Published online 6 October 2014 in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/eco.1559

Comparing two approaches for parsimonious vegetation modelling in semiarid regions using satellite data

Marta Pasquato,[1]* Chiara Medici,[1,3] Andrew D. Friend[2] and Félix

[1] *Research Institute of Water and Environmental Engineering, Universitat Politècnica de València,*
[2] *Geography Department, University of Cambridge, Cambridge, UK*
[3] *Civil and Environmental Engineering, Princeton University, Princeton, NJ, USA*

- ➢ NDVI at catchment scale:



Journal of Environmental Management 231 (2019) 653–665

Contents lists available at ScienceDirect

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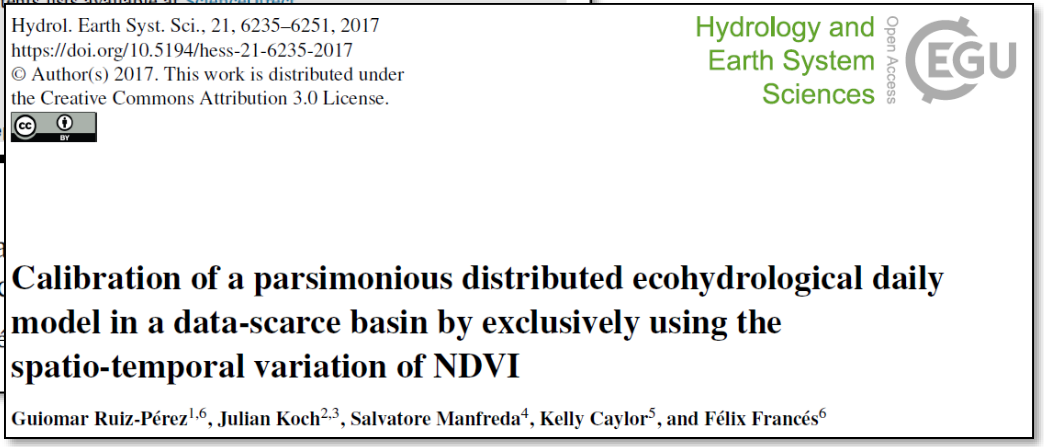
journal home

Research article

Managing low productive forests a
biomass and fire risk to achieve ec

María González-Sanchis[a,*], Guiomar Ruiz-Pé
Félix Francés[c], Cristina Lull[a]



Hydrol. Earth Syst. Sci., 21, 6235–6251, 2017
https://doi.org/10.5194/hess-21-6235-2017

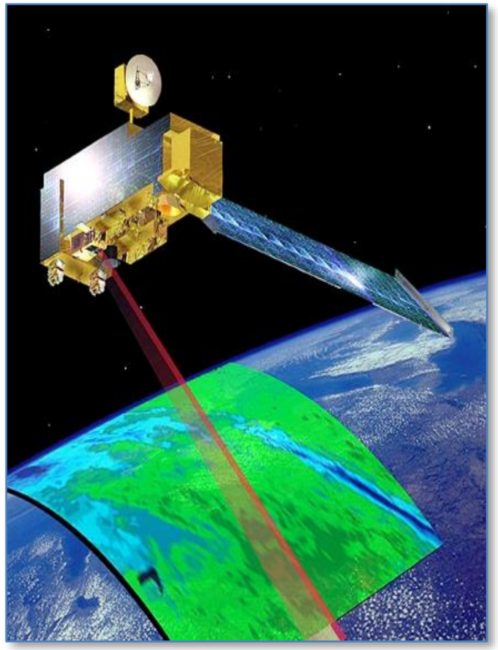
Hydrology and Earth System Sciences
Open Access
EGU

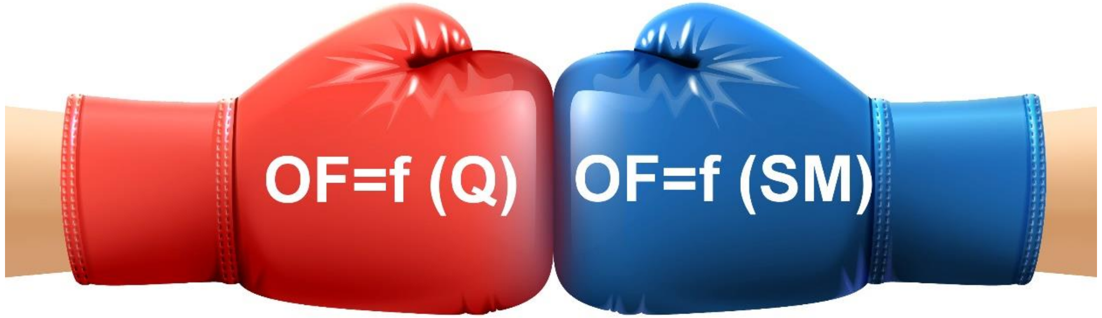
Calibration of a parsimonious distributed ecohydrological daily model in a data-scarce basin by exclusively using the spatio-temporal variation of NDVI

Guiomar Ruiz-Pérez[1,6], Julian Koch[2,3], Salvatore Manfreda[4], Kelly Caylor[5], and Félix Francés[6]

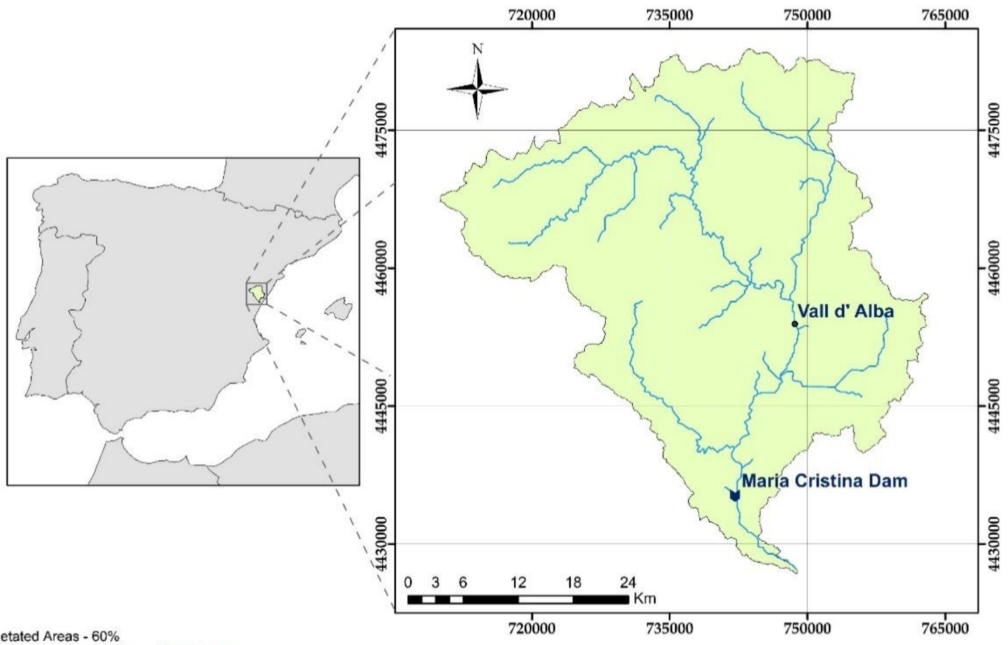
Objectives

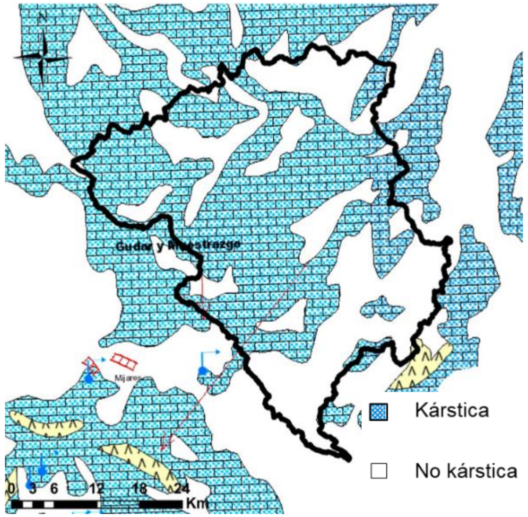
- ❑ Possibility: To use only remotely sensed surface soil moisture at **ungauged basins**
- ❑ Profitability: to assess the value of the **remotely sensed surface soil moisture** as an observed state variable.

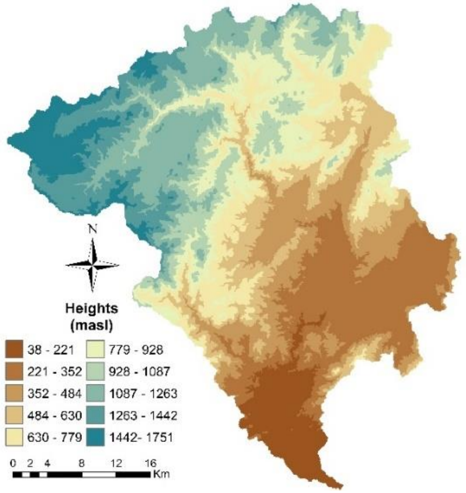


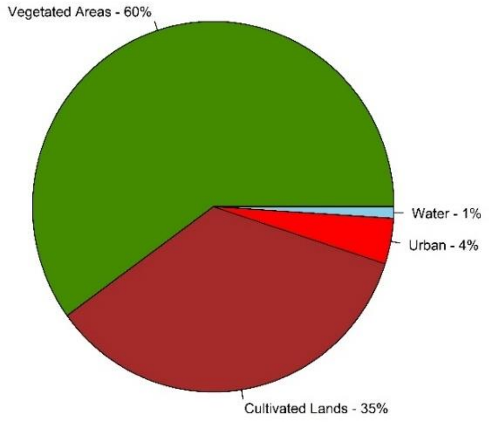


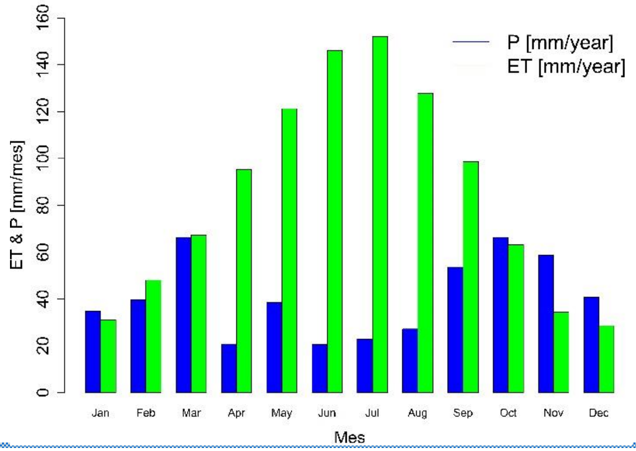
Study Area: Rambla de la Viuda Catchment

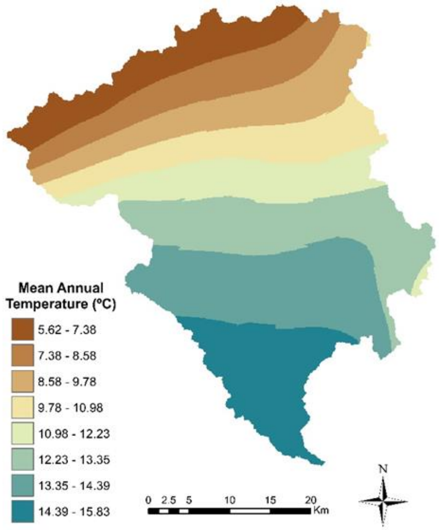


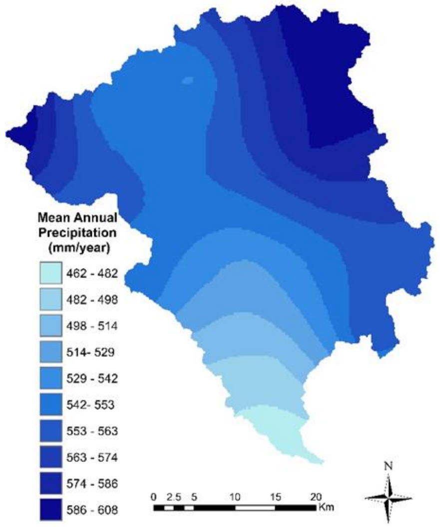








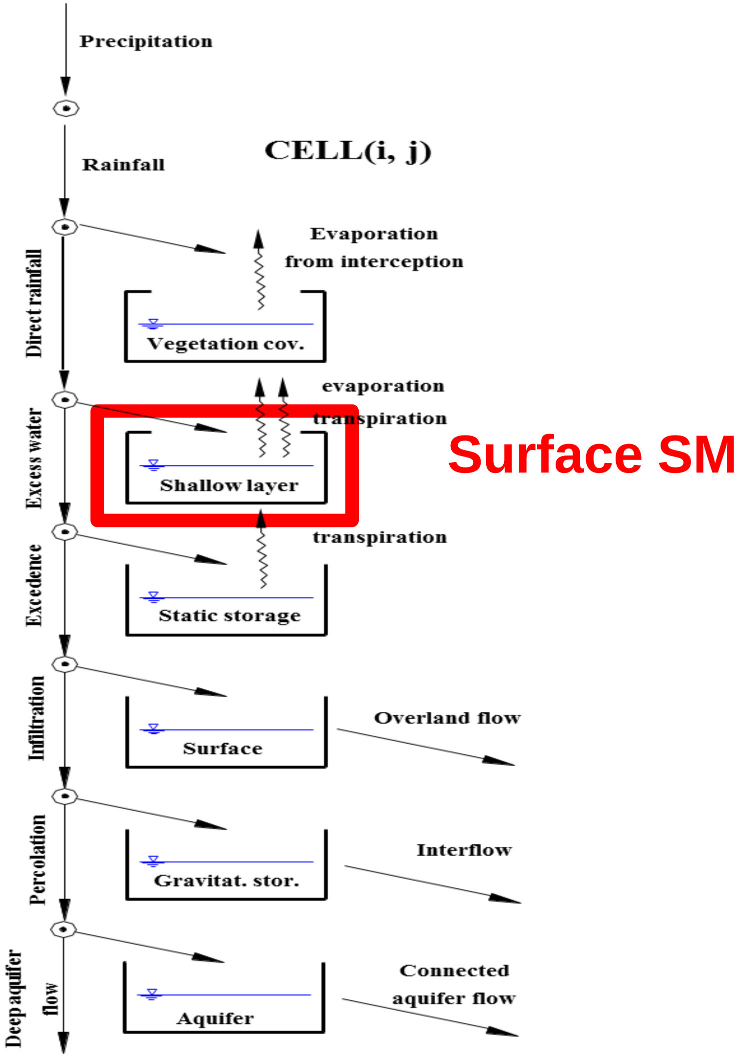




TETIS eco-hydrological model

1
2
3
4

- Developed by our group since 1994 (version 9 on the web)
- Conceptual (tank structure) model, with **physically based parameters**
- **Parsimonious**: 9 parameters for hydrologic sub-model
- **Integral** model: water resources, floods, sediments, dynamic vegetation, crop production, N-C cycle, … and more to come!
- **Distributed** in space
- **Split effective parameter structure**



TETIS eco-hydrological model

- Dynamic vegetation sub-model
  - State variable: leaf biomass
  - Based on the Light Use Efficiency (**LUE**)

$$\frac{dB_l}{dt} = \left(LUE \cdot \varepsilon \cdot APAR - \mathrm{Re}\right) \cdot \varphi_l - \kappa_l \cdot B_l$$

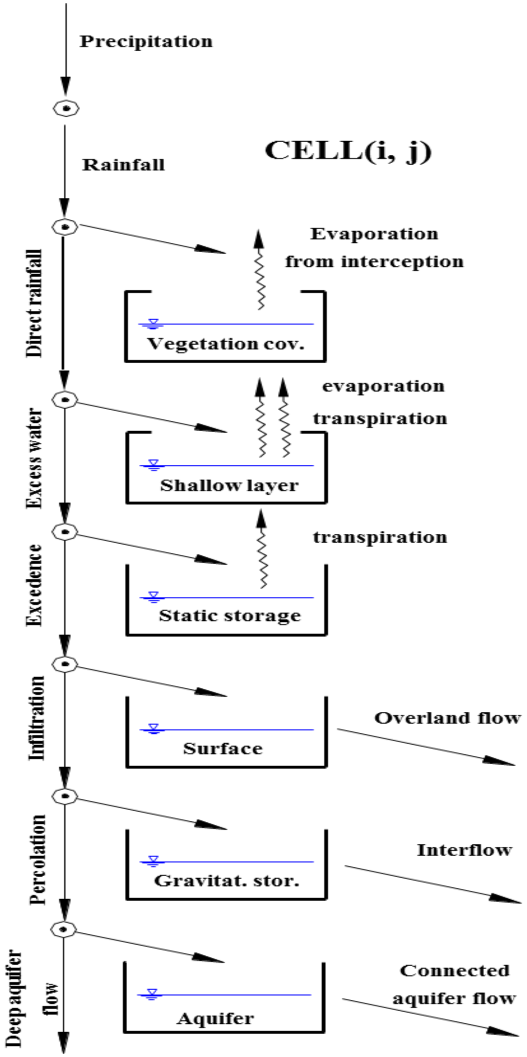
  - Connection with the water cycle:

    ε = stress factor, including water

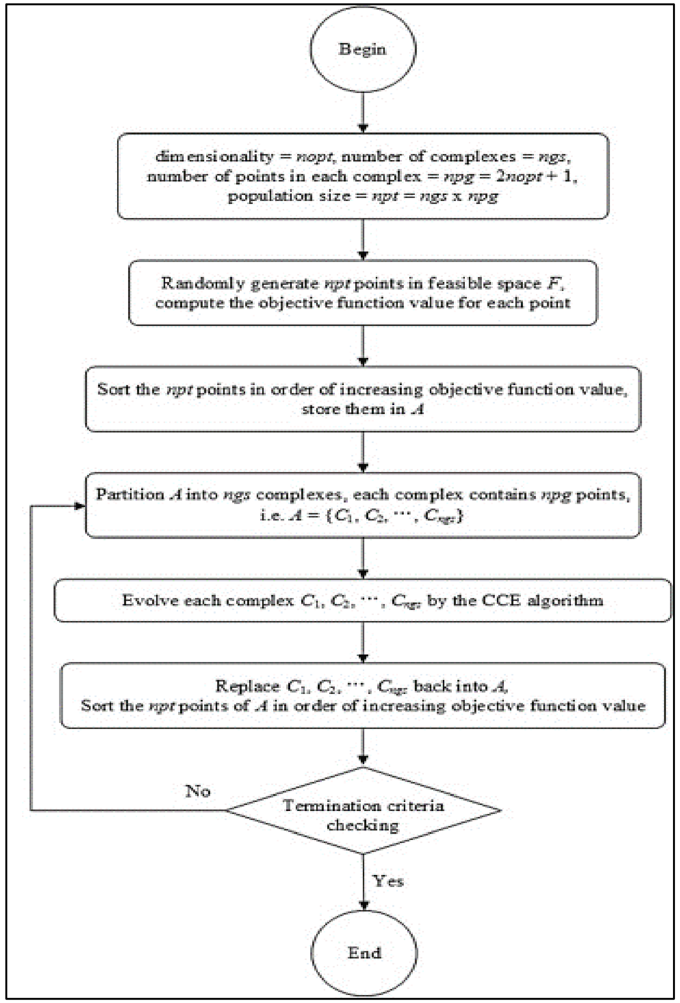
$$T_1 = ET_o \cdot f_t \cdot \min\left(LAI, 1\right) \cdot \beta_t\left(H_1\right) \cdot r_1$$

$$LAI = B \cdot SLA \cdot f_t$$

  - 11 parameters



Optimisation algorithm



Begin

dimensionality = $nopt$, number of complexes = ngs, number of points in each complex = $npg = 2nopt + 1$, population size = $npt = ngs$ x npg

Randomly generate npt points in feasible space F, compute the objective function value for each point

Sort the npt points in order of increasing objective function value, store them in A

Partition A into ngs complexes, each complex contains npg points, i.e. $A = \{C_1, C_2, \cdots, C_{ngs}\}$

Evolve each complex $C_1, C_2, \cdots, C_{ngs}$ by the CCE algorithm

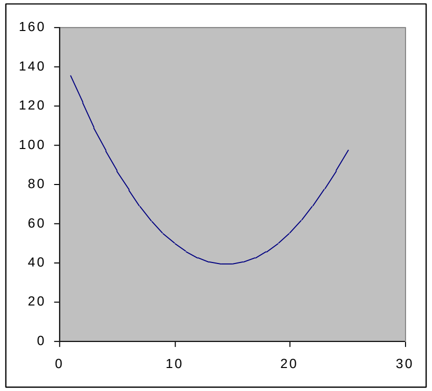
Replace $C_1, C_2, \cdots, C_{ngs}$ back into A, Sort the npt points of A in order of increasing objective function value

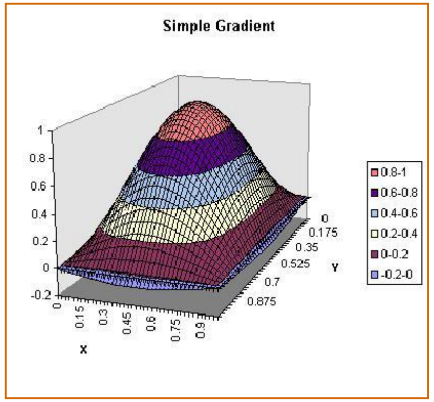
Termination criteria checking

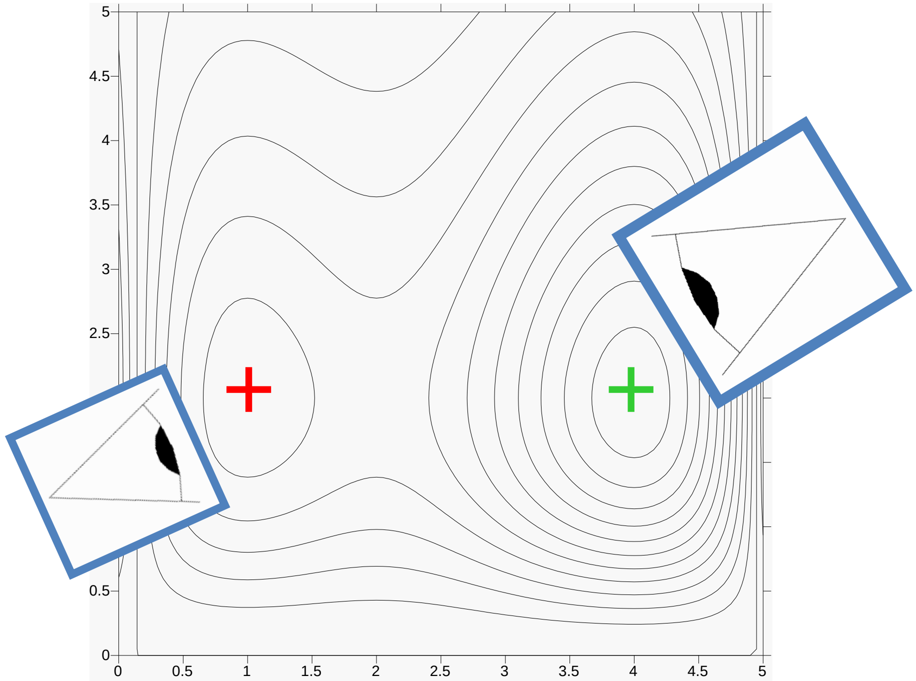
End

Shuffled Complex Evolution (SCE-UA)

Simplex Method + Controlled Random Search + Competitive Evolution + Complex Shuffling







Efficiencies: Objective-Functions

- ❑ Nash-Sutcliffe Efficiency index (NS)

$$NS = 1 - \frac{\sum_{t=1}^{T}\left(Q_{sim}^{t} - Q_{obs}^{t}\right)^2}{\sum_{t=1}^{T}\left(Q_{obs}^{t} - \overline{Q_{obs}}\right)^2}$$

Q_{sim}^{t} is modelled discharge at time t,

Q_{obs}^{t} is observed discharge at time t,

$\overline{Q_{obs}}$ is the mean of observed discharges

- ❑ Spatio-Temporal Efficiency

$$STE = \sum_{p=1}^{N}\left\{w_p * NS\left[\left(loadings(EOF)_p^{obs}, loadings(EOF)_p^{sim}\right]\right\}$$

N = number of principal components that explains at least 95% of the variance;

w_p = portion of explained variance in the **principal component** p;

$loadings(EOF)_p^{obs}$ = loadings of the observed data in the principal component p;

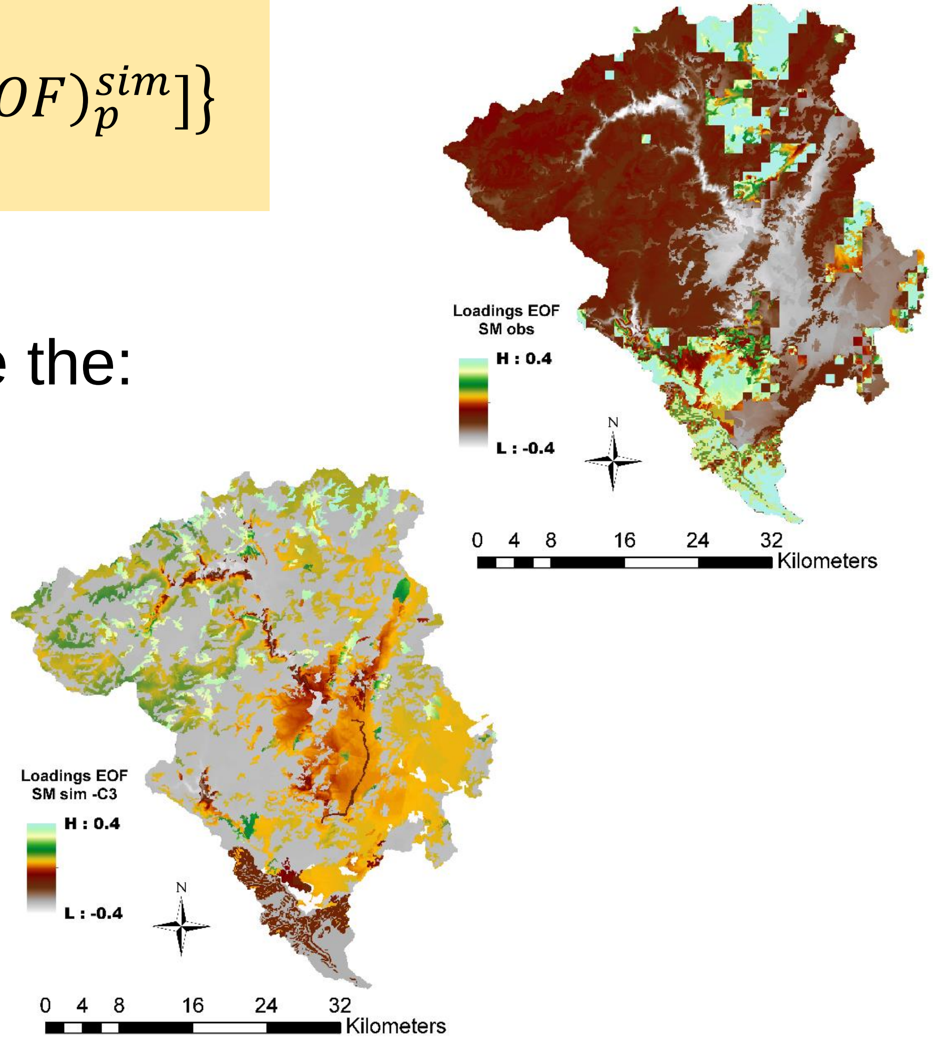
$loadings(EOF)_p^{sim}$ = loadings of the simulated data in the principal component p

Spatio-temporal efficiency (STE)

$$STE = \sum_{p=1}^{N} \{ w_p * NS[(loadings(EOF)_p^{obs}, loadings(EOF)_p^{sim}]\}$$

- ❑ STE (and any other metric) tries to incorporate the:
  - ➢ Spatial pattern
  - ➢ Temporal dynamics

without considering the exact values of the satellite



On the way to STE

$$STE_1 = \frac{\sum_{i=1}^{p}[(NSE_i(sm_{obs}\,, sm_{sim}) \; \forall \; NSE_i \; \geq 0.5\,]}{p}$$

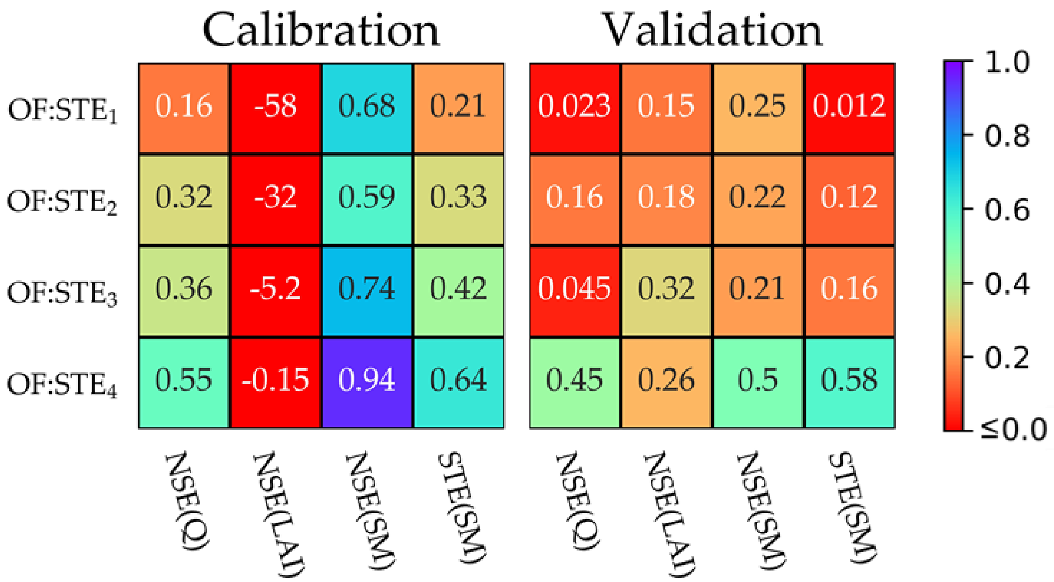
$$STE_2 = \frac{\sum_{i=1}^{pc}\left[(NSE_i(loadings(EOF)^{obs}\,, \; loadings(EOF)^{sim}\,)\right]}{pc}$$

$$STE_3 = \sum_{i=1}^{pc} w_i * \sum_{j=1}^{t}[|loadings(EOF)_{i,j}^{obs} - \; loadings(EOF)_{i,j}^{sim}|]$$

$$STE_4 = \sum_{i=1}^{pc}\{w_i * NSE_i[(loadings(EOF)^{obs}, loadings(EOF)^{sim}]\}$$

Convergence criteria

$$\Delta OF = OF_n - OF_{n-1} \leq 0.001$$



	Calibration				Validation			
	NSE(Q)	NSE(LAI)	NSE(SM)	STE(SM)	NSE(Q)	NSE(LAI)	NSE(SM)	STE(SM)
OF:STE$_1$	0.16	-58	0.68	0.21	0.023	0.15	0.25	0.012
OF:STE$_2$	0.32	-32	0.59	0.33	0.16	0.18	0.22	0.12
OF:STE$_3$	0.36	-5.2	0.74	0.42	0.045	0.32	0.21	0.16
OF:STE$_4$	0.55	-0.15	0.94	0.64	0.45	0.26	0.5	0.58

Model implementation strategy

GENERALITIES

- Common observation period: 2010-2015
  - Warm-up period: 2010
  - Calibration period: 2011-2013
  - Validation period: 2014-2015

- 24 variables for calibration:
  - 9 map correction factors for hydrology
  - 15 (3 x 5 natural land covers) more influent vegetation parameters

Model implementation strategy

1
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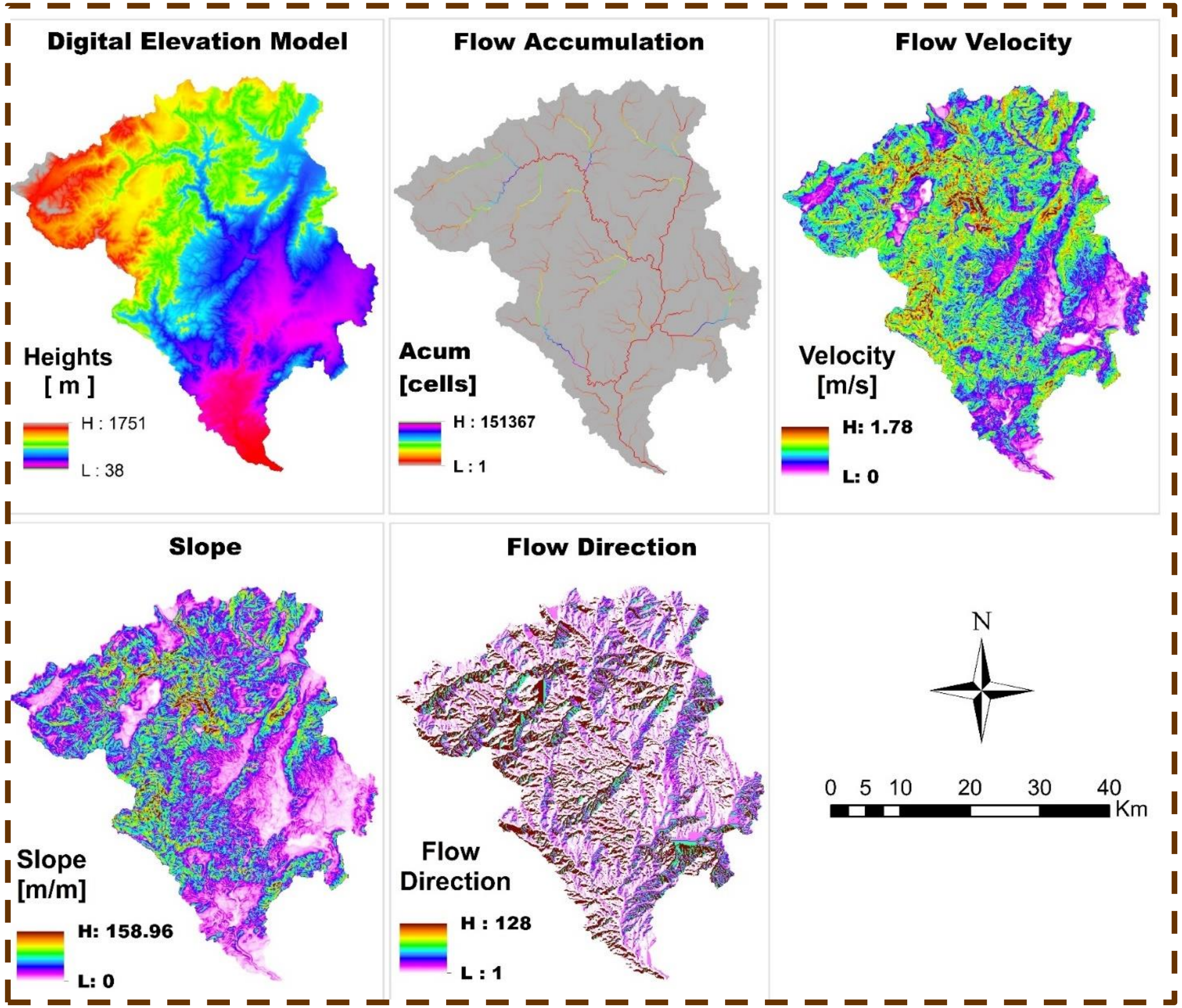
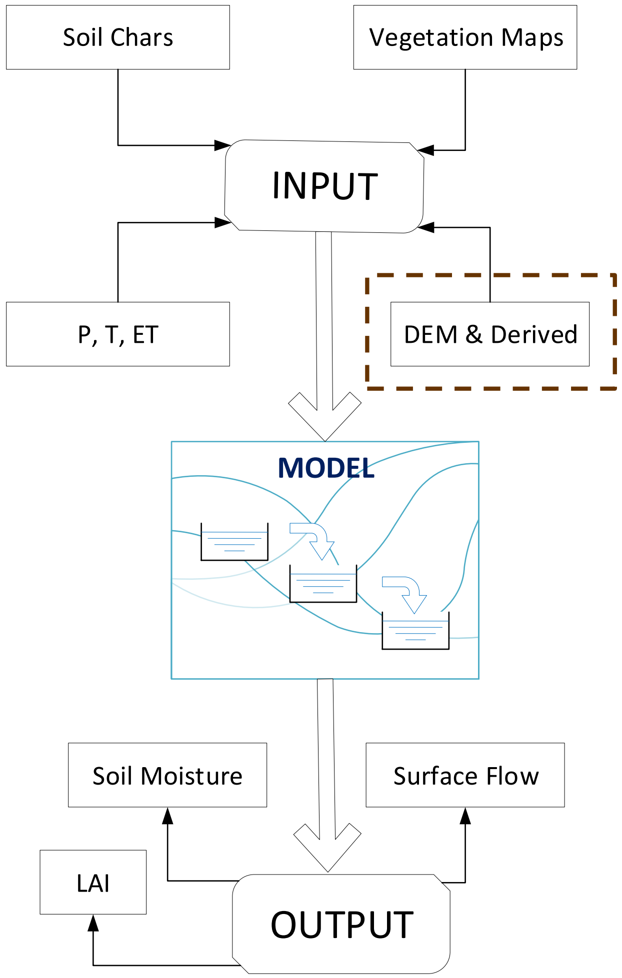



Soil Chars

Vegetation Maps

INPUT

P, T, ET

DEM & Derived

MODEL

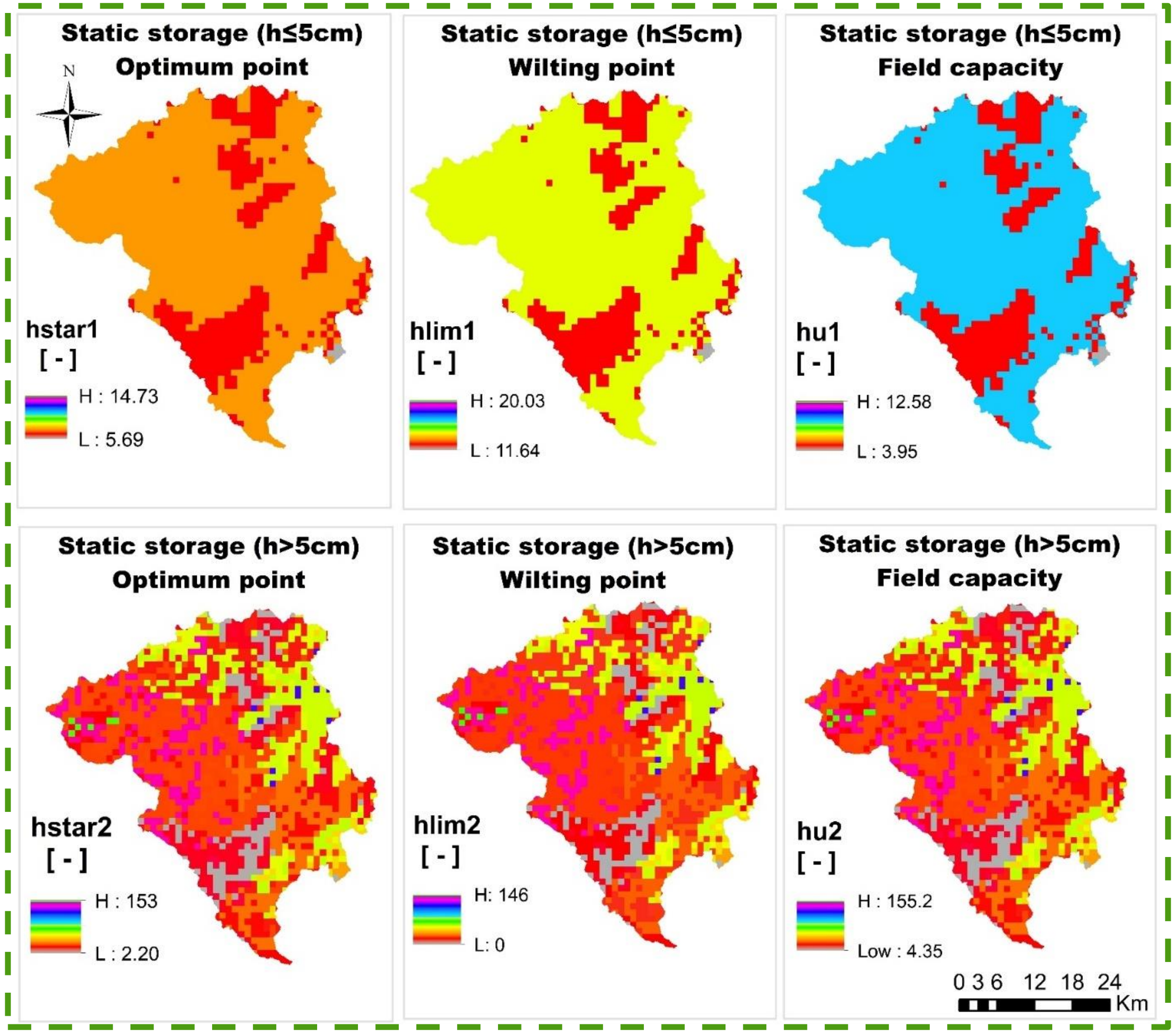
Soil Moisture

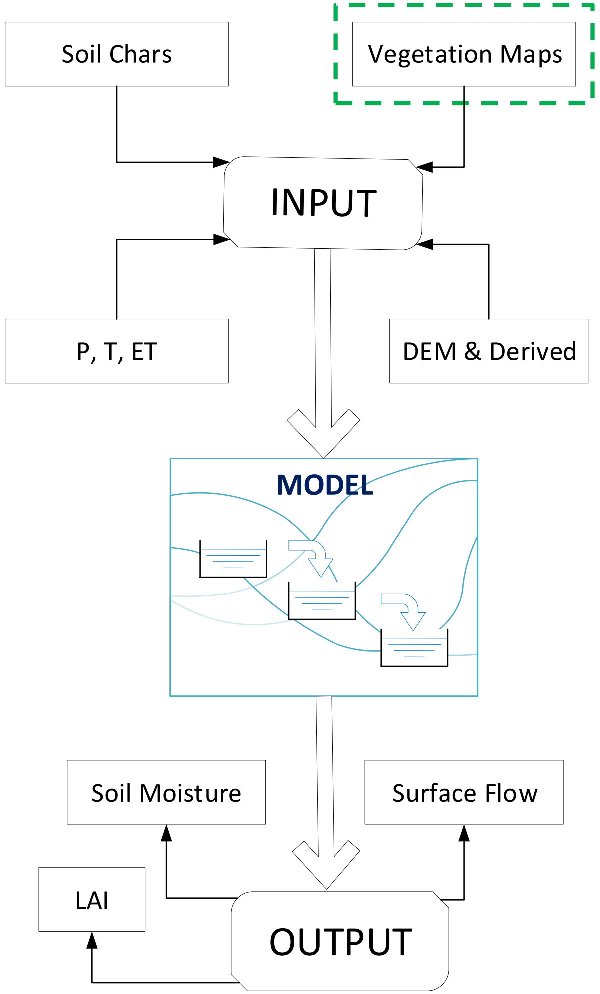
Surface Flow

LAI

OUTPUT

Model implementation strategy





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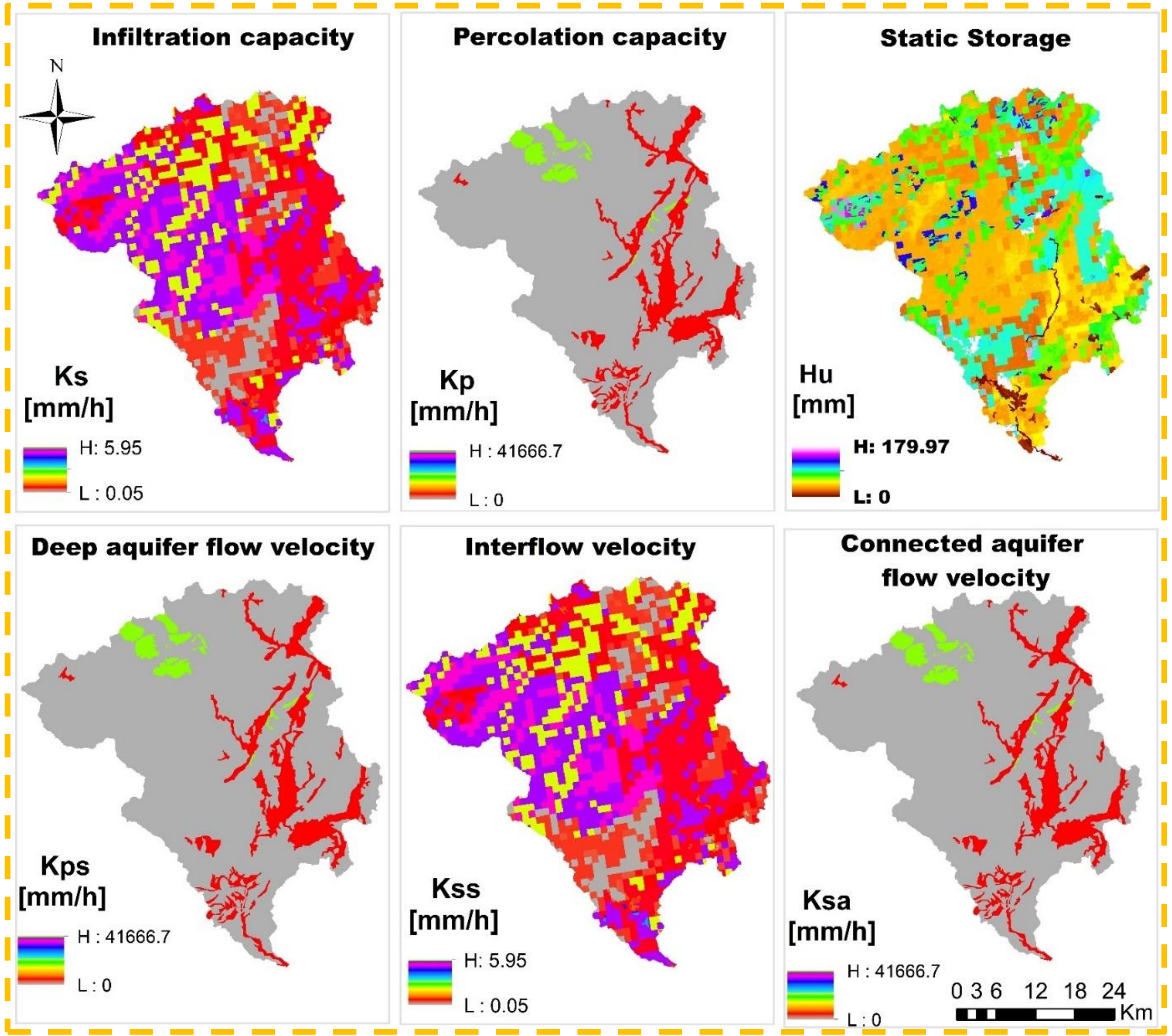

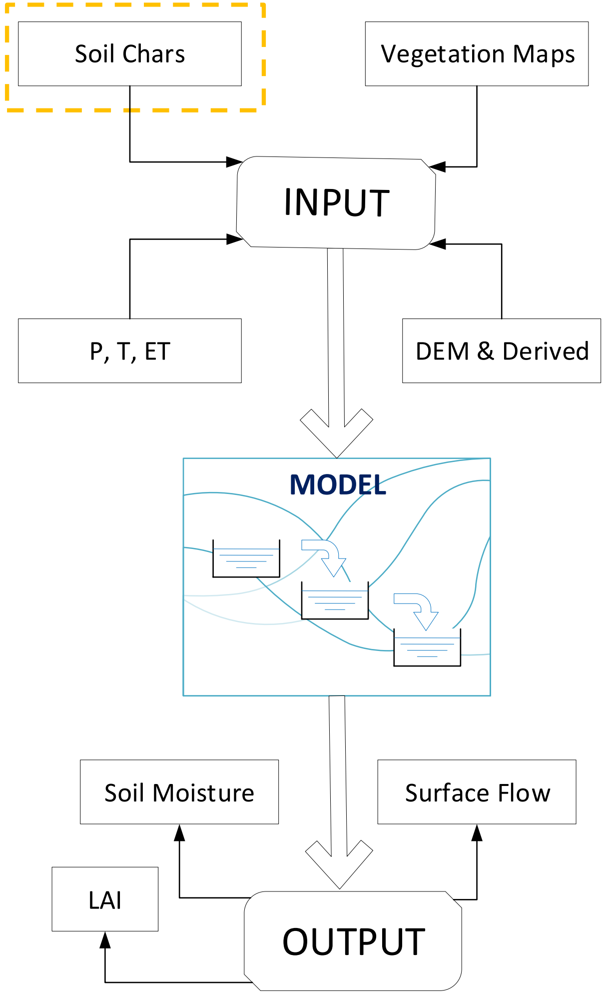
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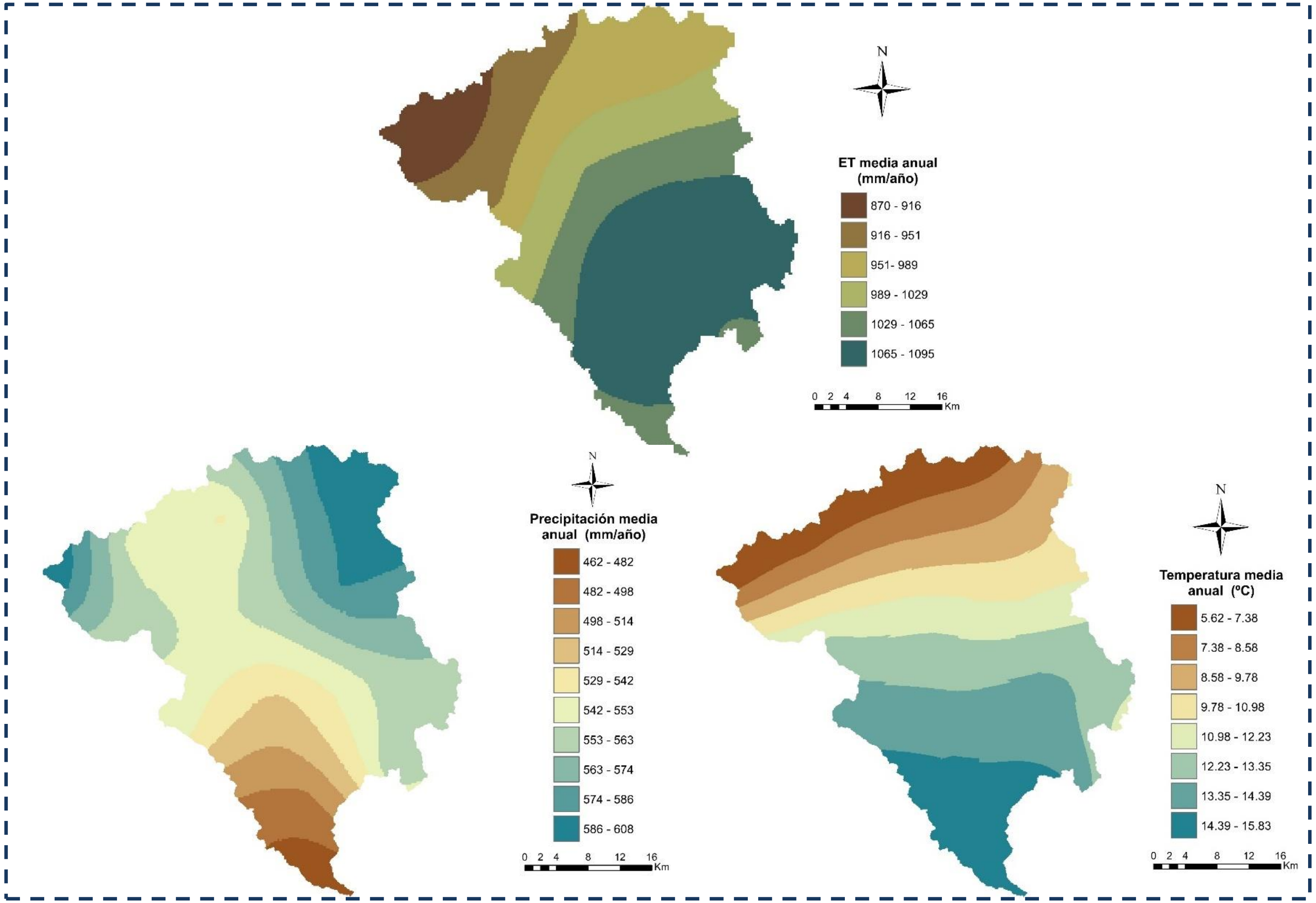

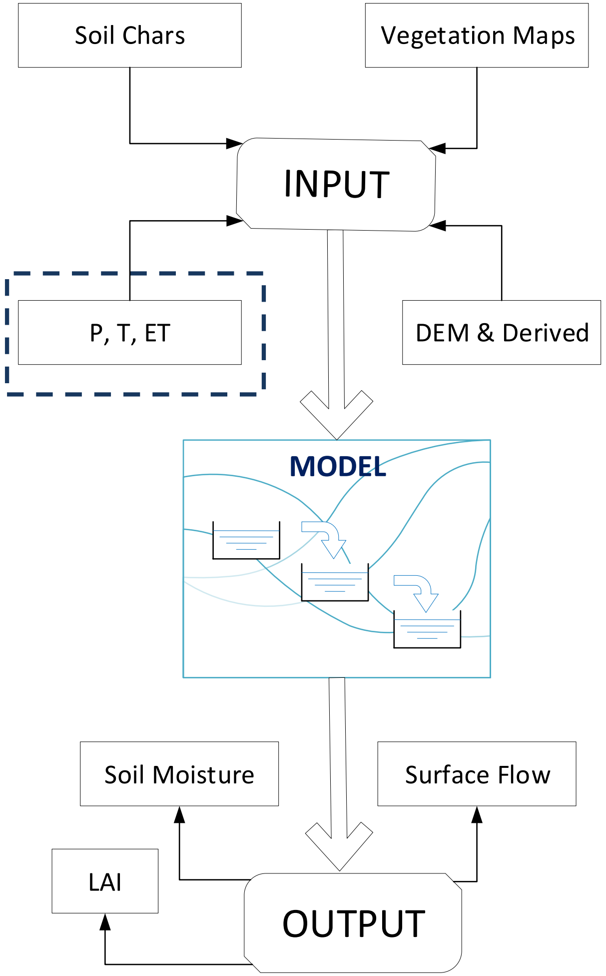

Soil Chars

Vegetation Maps

INPUT

P, T, ET

DEM & Derived

MODEL

Soil Moisture

Surface Flow

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Model implementation strategy

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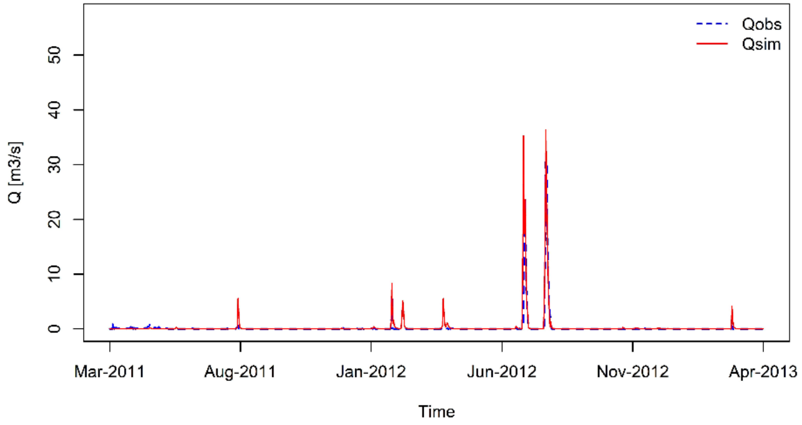
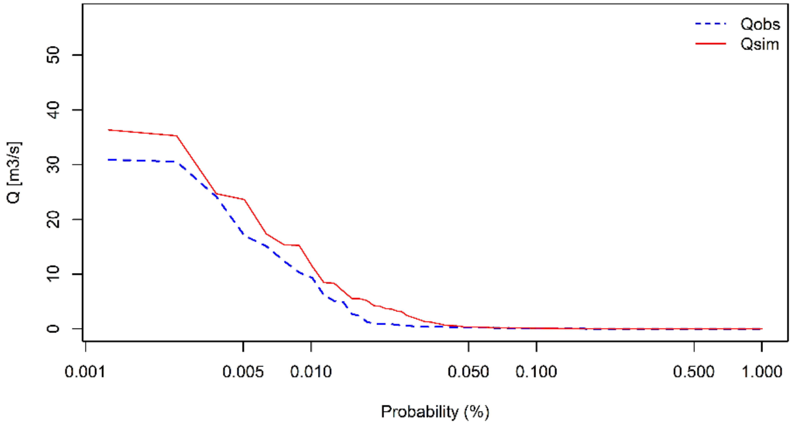
OBSERVED STATE VARIABLES:

- Surface SM: SMOS+MODIS from BEC
- Daily discharge at the outlet from CEH-CEDEX
- LAI: MODIS from NASA (only for spatial validation, NOT for calibration)

Results





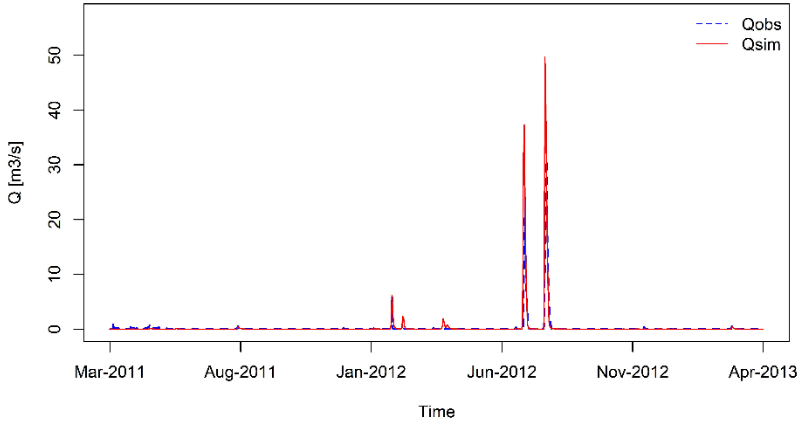
SV: Q

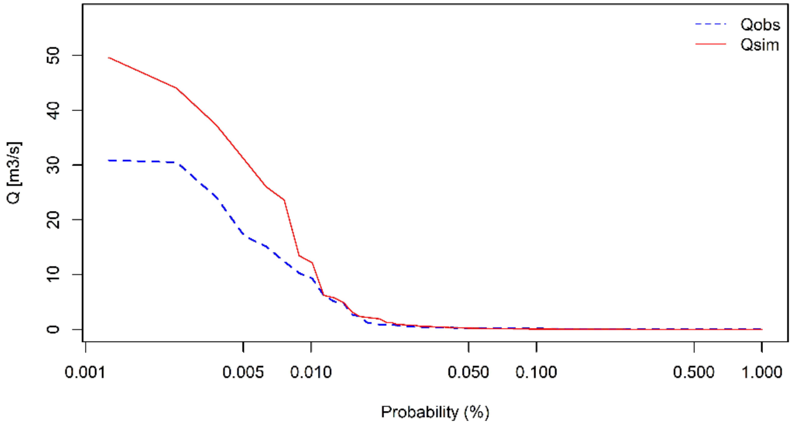
OF= 1 – NS(Q)

Calibration:

NS(Q) = 0.9102

STE(SM) = 0.01





SV: SM

OF= 1 – STE(SM)

Calibration:

NS(Q) = 0.5458

STE(SM) = 0.6369

Results

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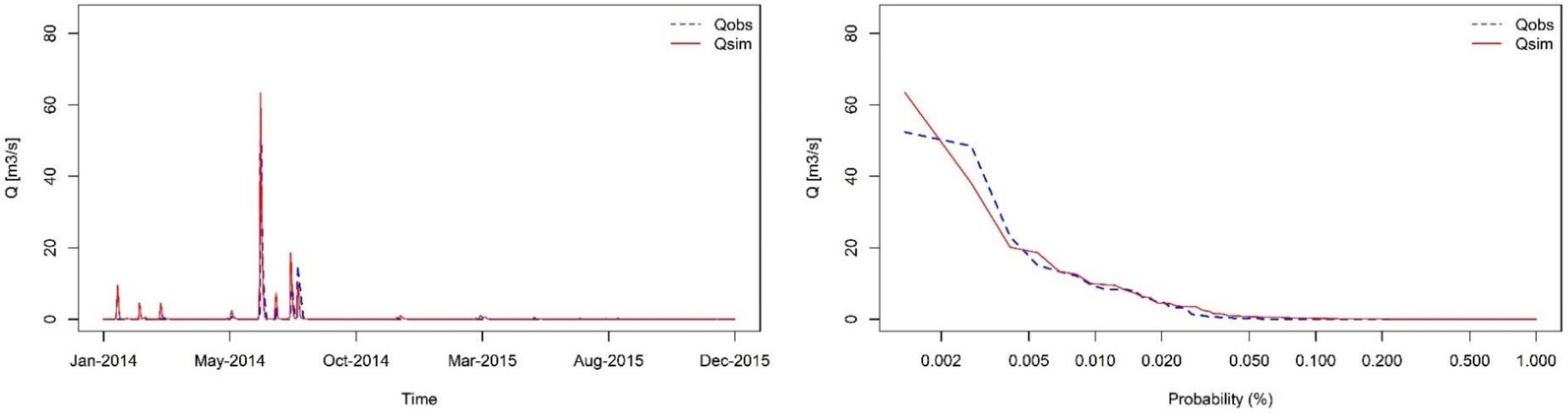


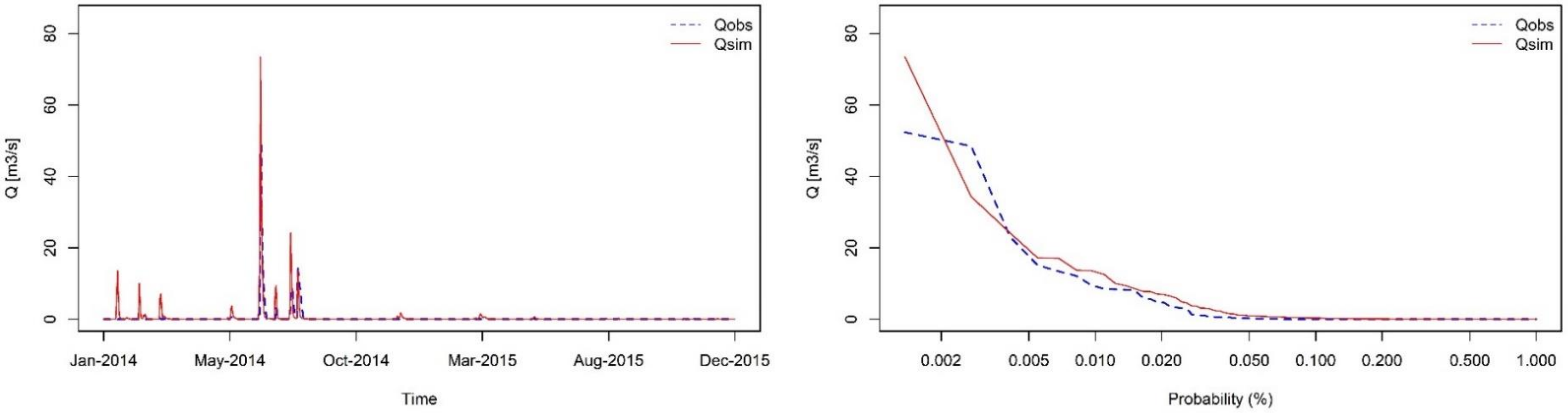
SV: Q

OF= 1 – NS(Q)

Validation:

NS(Q) = 0.4725

STE(SM) = 0.03



SV: Q

OF= 1 – STE(SM)

Validation:

NS(Q) = 0.4452

STE(SM) = 0.5836

Results

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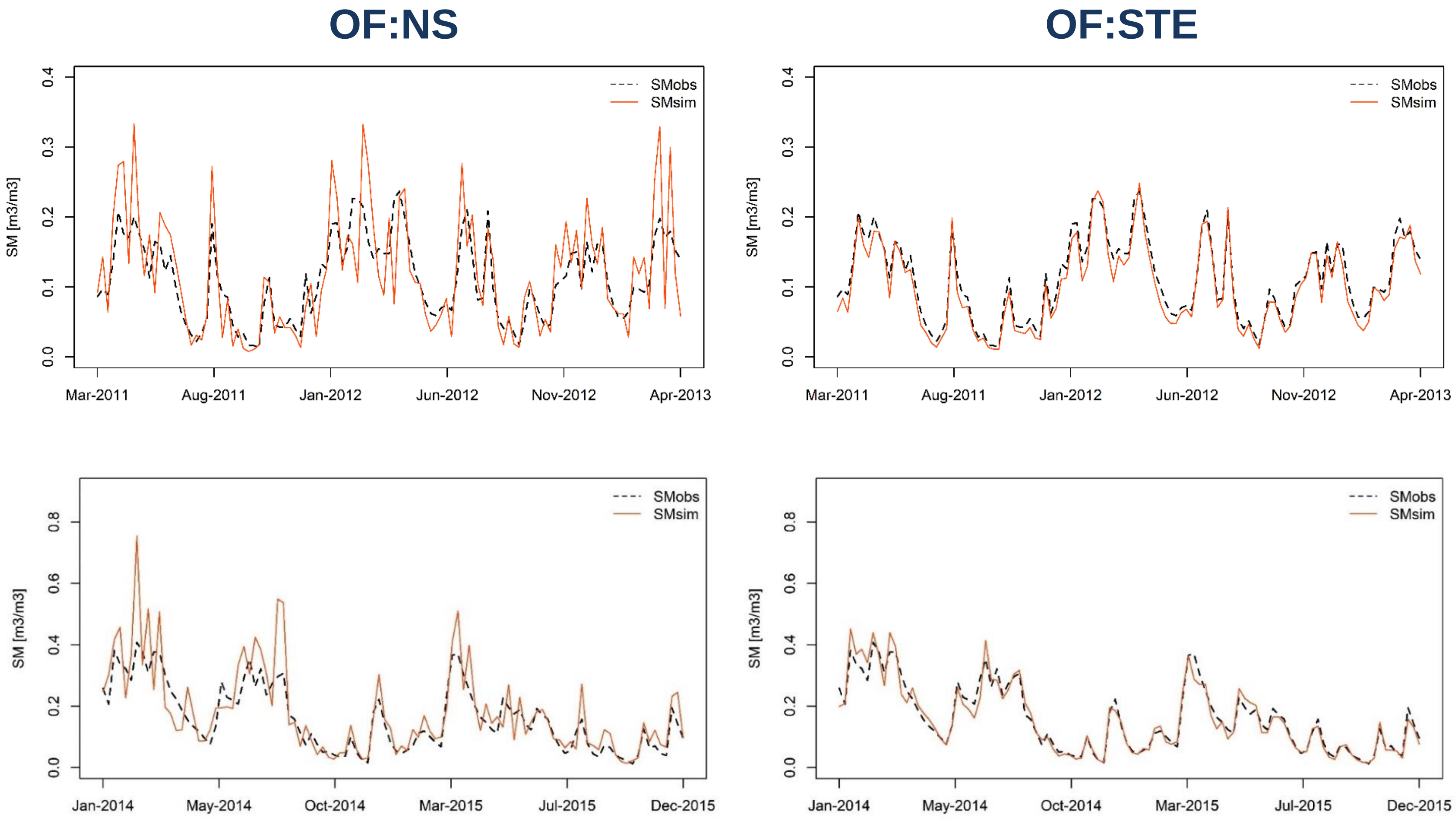
OF:NS

OF:STE

Index	BE (SM_{sim} - SM_{obs})	
Configuration	OF:NSE(Q)	OF:STE(SM)
Calibration	-4.2	-9.5
Validation	-31	-21.4
ΔIndex$_{(cal-val)}$	26.8	11.9

Index	RMSE (SM_{sim} - SM_{obs})	
Configuration	OF:NSE(Q)	OF:STE(SM)
Calibration	0.84	1.387
Validation	6.727	7.461
ΔIndex$_{(cal-val)}$	5.89	6.074

Index	NSE (SM_{sim} - SM_{obs})	
Configuration	OF:NSE(Q)	OF:STE(SM)
Calibration	0.63	0.943
Validation	0.395	0.502
ΔIndex$_{(cal-val)}$	0.235	0.441

Results

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6
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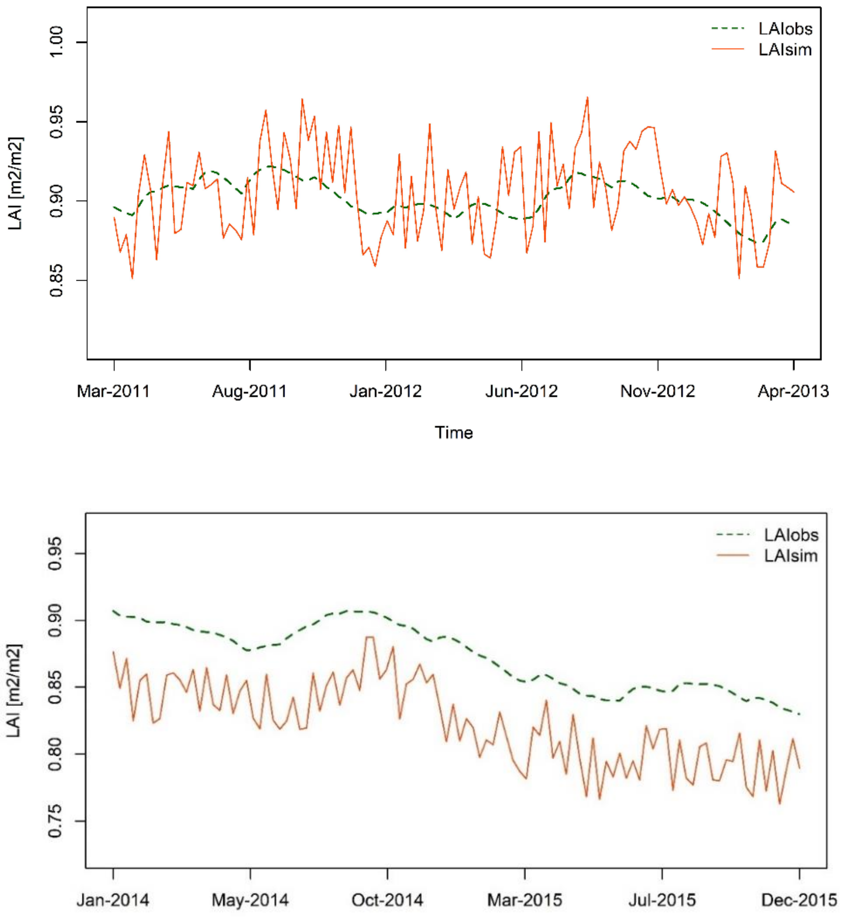
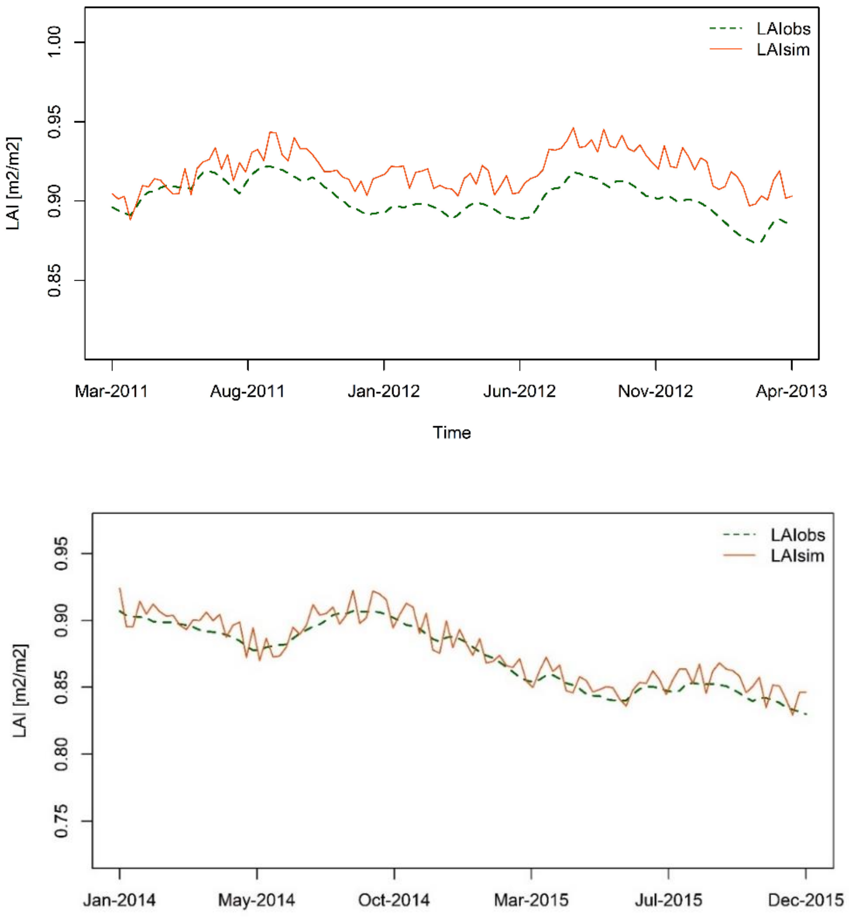
OF:NS



OF:STE

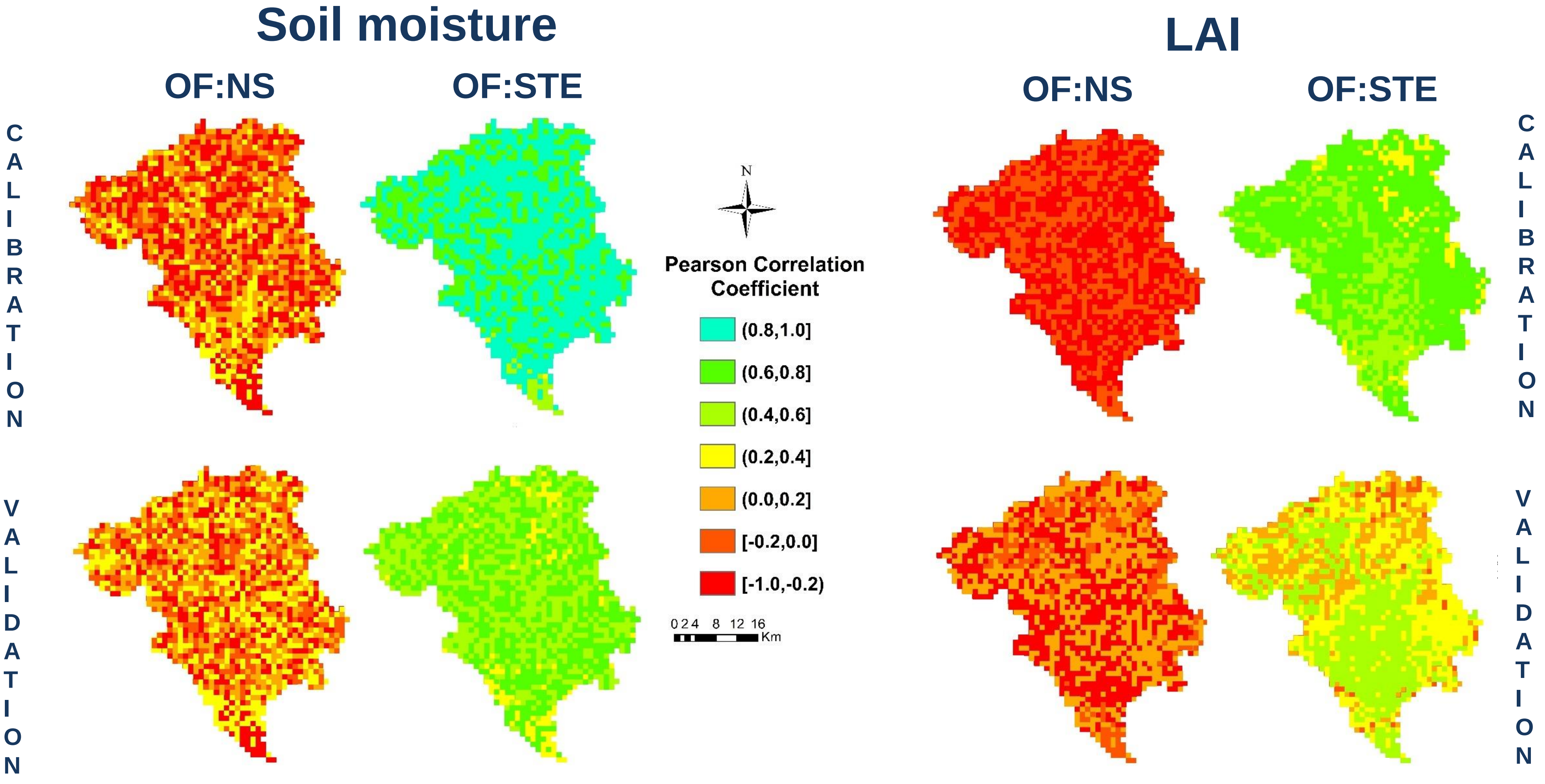


Index	**RMSE (LAI_{sim} - LAI_{obs})**	
Configuration	OF:NSE(Q)	OF:STE(SM)
Calibration	0.95	0.063
Validation	1.1	0.68
ΔIndex$_{(cal\text{-}val)}$	0.15	0.617

Index	**BE (LAI_{sim} - LAI_{obs})**	
Configuration	OF:NSE(Q)	OF:STE(SM)
Calibration	3.9	-6.3
Validation	-25	-24.9
ΔIndex$_{(cal\text{-}val)}$	21.1	18.6

Index	**NSE (LAI_{sim} - LAI_{obs})**	
Configuration	OF:NSE(Q)	OF:STE(SM)
Calibration	-99.01	-0.154
Validation	-0.86	0.32
ΔIndex$_{(cal\text{-}val)}$	98.95	0.474

Results


Soil moisture
LAI
OF:NS
OF:STE
OF:NS
OF:STE
CALIBRATION
VALIDATION
CALIBRATION
VALIDATION
N
Pearson Correlation Coefficient
(0.8,1.0]
(0.6,0.8]
(0.4,0.6]
(0.2,0.4]
(0.0,0.2]
[-0.2,0.0]
[-1.0,-0.2)
0 2 4 8 12 16
Km

Results

1
2
3
4
5
6
7

Summary

	Calibration period								
	01/03/2011-31/12/2013								
	Q_{obs} - Q_{sim}		SM_{obs} - SM_{sim}				LAI_{obs} - LAI_{sim}		
	NS	**BE (%)**	**STE**	**NS**	**RMSE**	**BE (%)**	**NS**	**RMSE**	**BE(%)**
Configuration 1: Q; NS	**0.9102**	-19.32	0.01	0.6310	0.84	-4.2	-99.01	0.95	**3.9**
Configuration 2: SM; STE	0.5458	11.53	**0.6369**	**0.943**	1.387	-9.5	-0.154	0.063	-6.3

	Validation period										
	01/01/2014 - 31/12/2015									01/10/1999 - 01/10/2006	
	Q_{obs} - Q_{sim}		SM_{obs} - SM_{sim}				LAI_{obs} - LAI_{sim}			Q_{obs} - Q_{sim}	
	NS	**BE (%)**	**STE**	**NS**	**RMSE**	**BE (%)**	**NS**	**RMSE**	**BE(%)**	**NS**	**BE (%)**
Configuration 1: Q; NS	0.4725	-21.35	0.03	0.395	6.727	-31	-0.86	1.1	-25	**0.8119**	-22.564
Configuration 2: SM; STE	0.4452	15.36	**0.5836**	0.502	7.461	**-21.4**	**0.32**	0.68	-24.9	0.6321	**14.023**
	Temporal Validation		**Spatio-Temporal Validation**							**Temporal Validation (back)**	

Conclusions

- ☐ Even though challenging, spatio-temporal data, in particular surface SM, can be used as relevant source of information to calibrate process-based models (**ALTERNATIVE**)
- ☐ The SMOS/MODIS remote-sensed fine-scale surface soil moisture data is consistent with observed discharge, however, discharge as SV could not reproduce spatial variability →→→ **EQUIFINALITY**
- ☐ It is possible to use only remote-sensed surface SM to calibrate satisfactorily a distributed hydrological model at ungauged (or with scarce Q data) basins. (**VALUABLE**)

Flood of 1962 in Rambla de la Viuda

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Thanks for your attention

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