Design of a recurrent rainfall-water level model for water management. Application to the karst Plateau of Méjannes-le-Clap (South-eastern France)

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Abstract N° 2347

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Plan

1. **Stakes and aims**

2. ***Cèze* Catchment and Hydrosystem**

3. **Neural networks**

4. **Water level simulations**

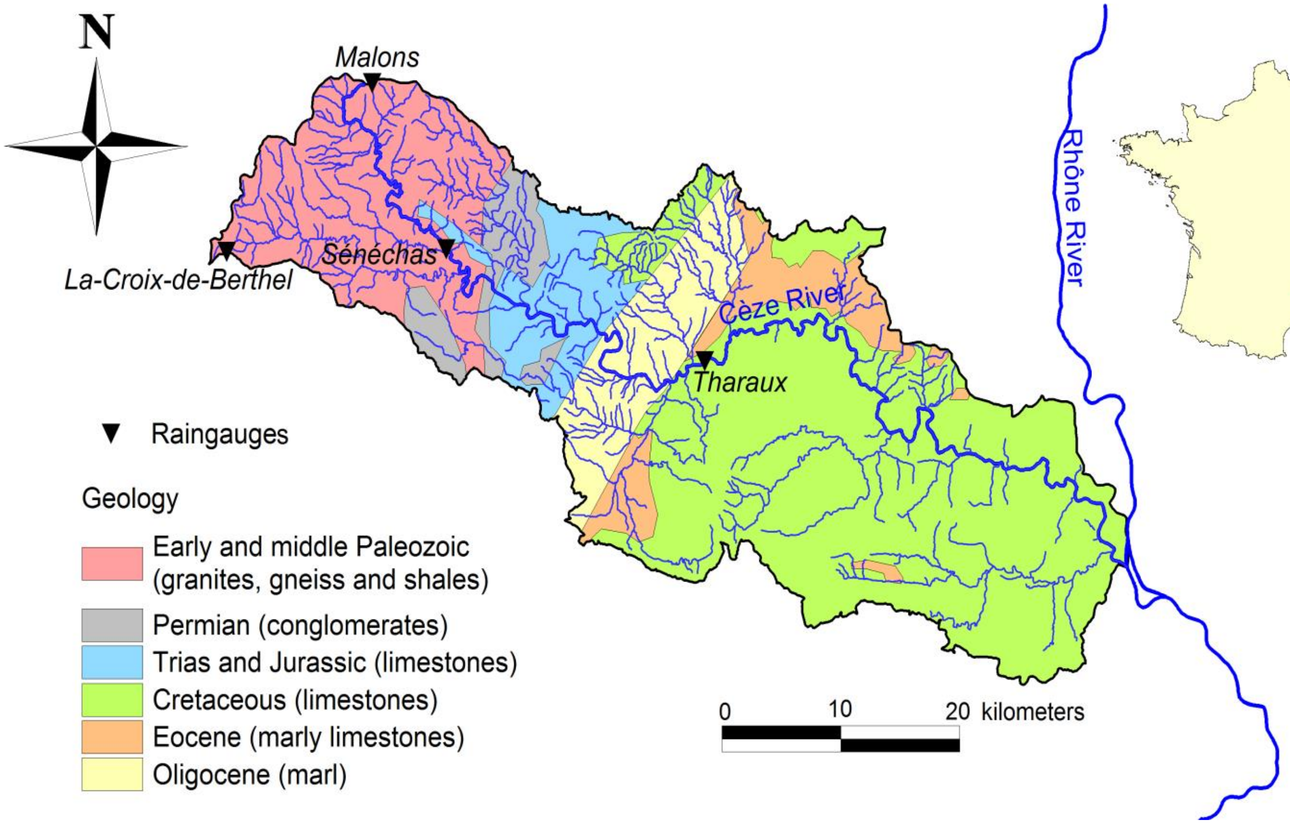
    4.1. Data et hypotheses

    4.2. Forecast

Stakes and aims

- **Karst system modelling**
  - ✓ Water resource subject to anthropogenic pressure
  - ✓ Complex and heterogeneous structure
  - ✓ Relations between river and karst
- **Aim : prediction of water levels using a rainfall scenario**

Cèze catchment an hydrosystem



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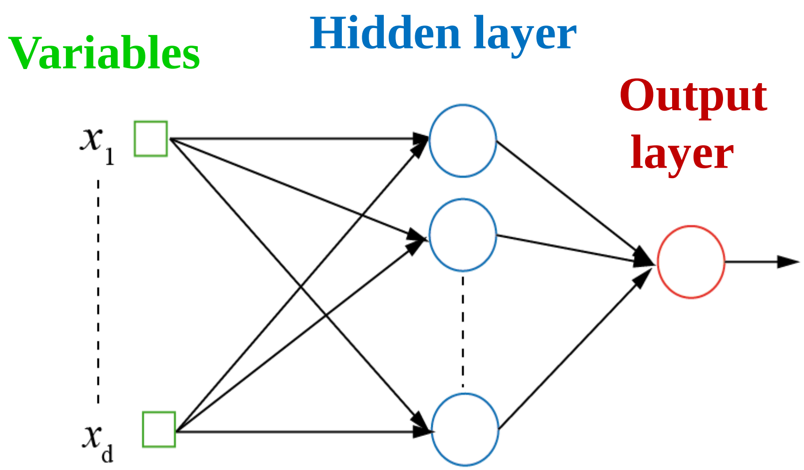
Complexity of the catchment

- ➢Heterogeneous rocks from upstream to downstream
- ➢Heterogeneous rain in time and space
- ➢Numerous and various exchanges between karst and river
- ➢A “ Black box ” model only needs input and output measurments
- ➢Neural networks are able to model nonlinear relations

Neural networks

Multilayer perceptron:

➢Universal Approximators and parcimonious models



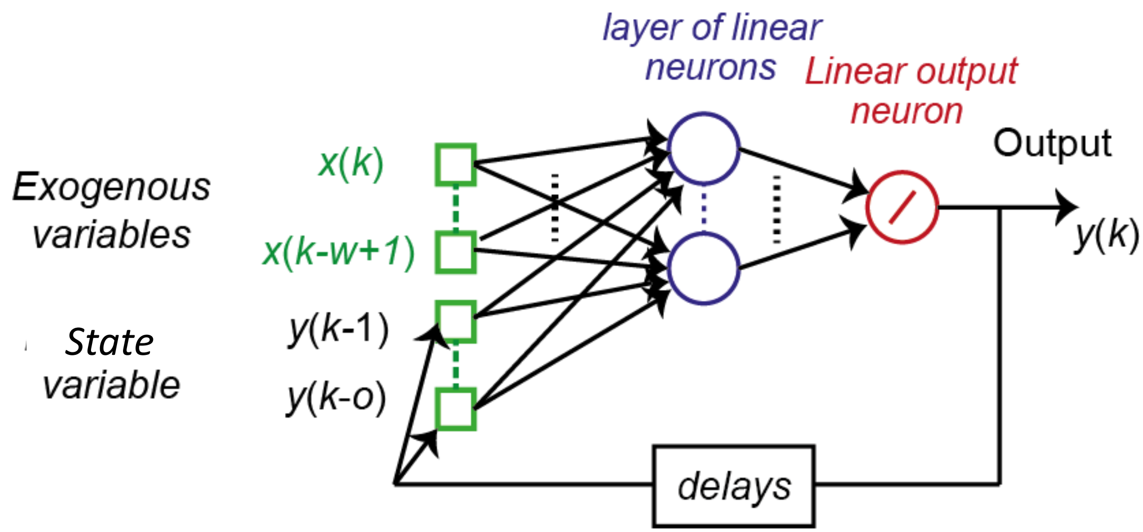
Developpment method

➢Training with Levenberg-Marquardt Algorithm

➢Early stopping and cross-validation method for regularization

➢Median values on 10 parameters initialization

Type of neural networks : the recurrent model



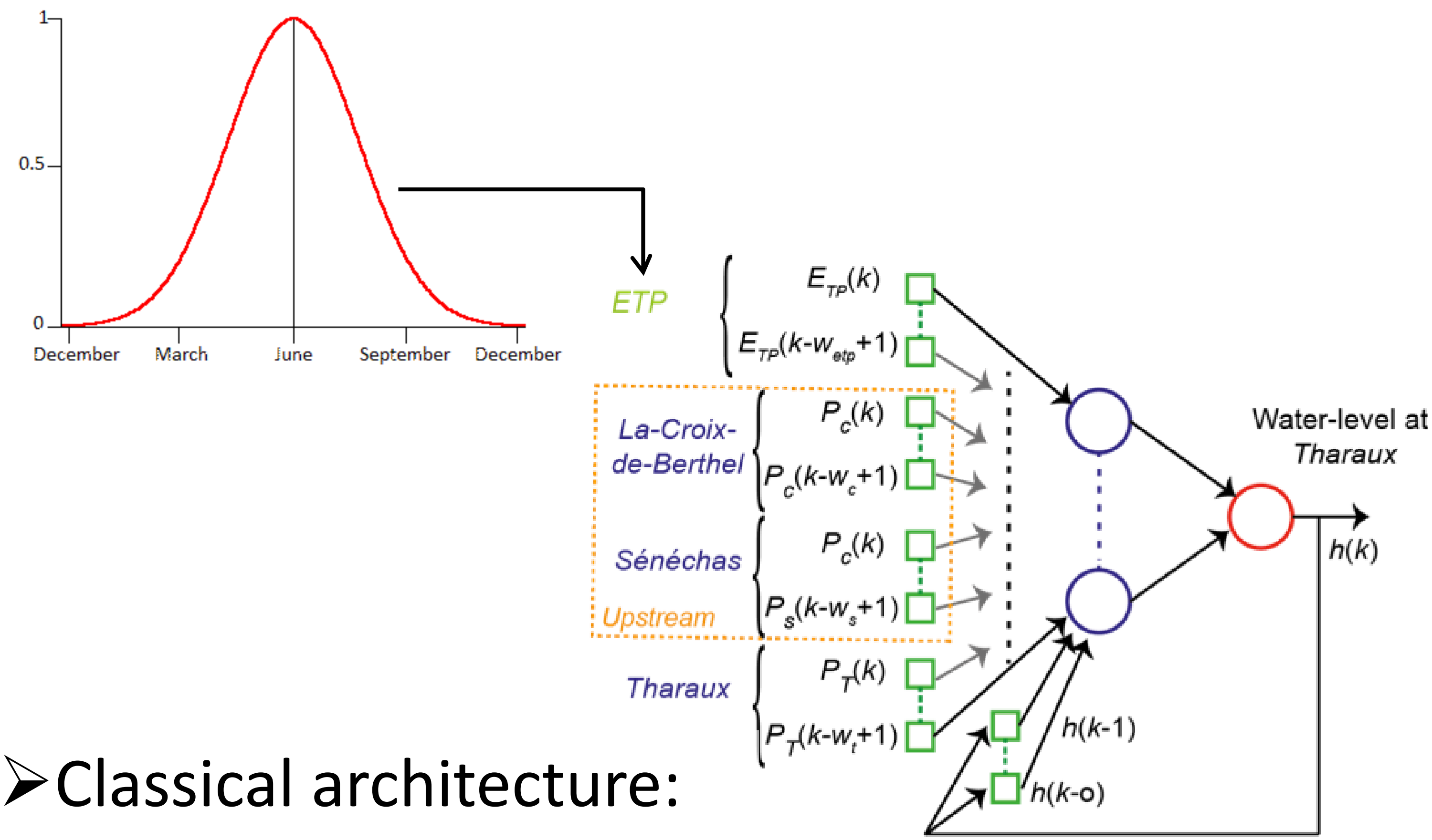
$$R^2 = 1 - \frac{\sum_{k=1}^{n} \left(y^p(k) - y(k)\right)^2}{\sum_{k=1}^{n} \left(y^p(k) - \overline{y^p}\right)^2}$$

- ➢Recurrence is used to get a prediction tool

Database

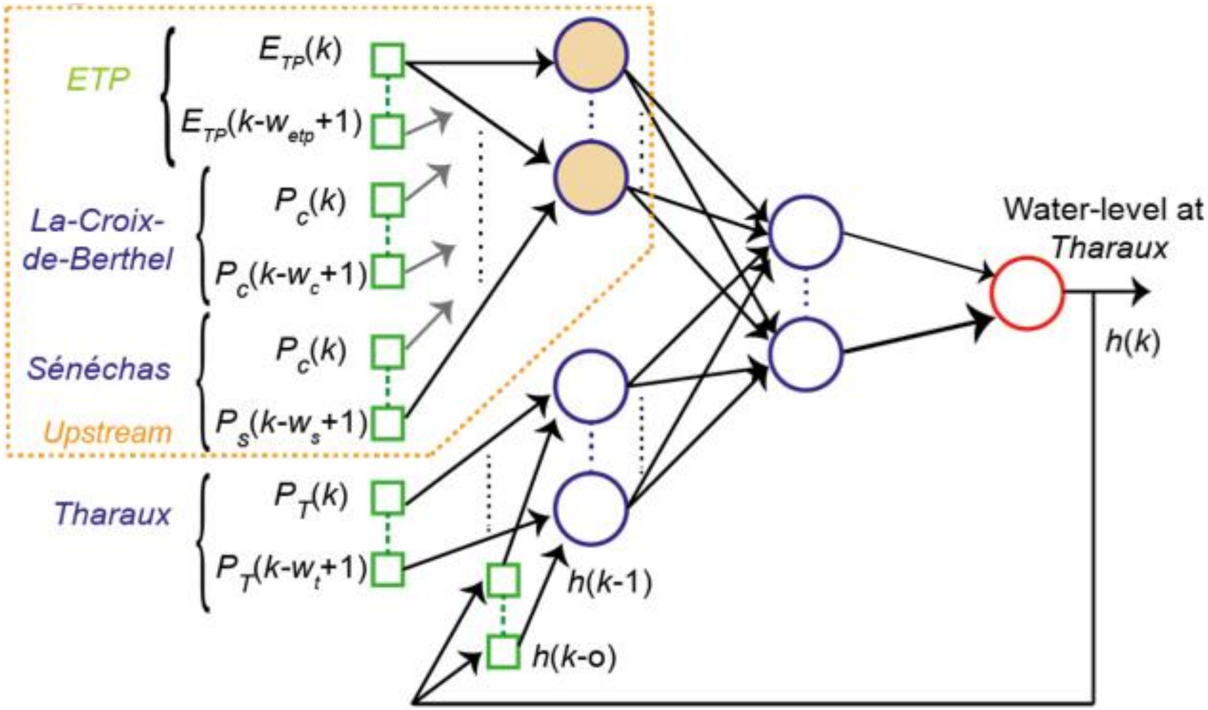
Years	Cumulative rainfall (mm)				Cumulative mean rainfall (mm)	Maximum mean rainfall in a day (mm)	Minimum water level (m)	Maximum water level (m)
	La-Croix-de-Berthel	Malons	*Sénéchas*	*Tharaux*				
1993	1784,00	2039,50	1128,00	844,00	1448,88	143,00	-0,05	6,90
1994	2259,87	2112,02	1399,00	1167,50	1734,60	172,25	0,04	7,92
1995	2179,50	1596,00	753,00	1016,50	1386,25	95,75	-0,16	8,01
1996	2878,75	2366,50	1686,50	1335,00	2066,69	94,75	0,09	6,41
1997	1826,50	1885,50	1622,50	1061,17	1598,92	140,25	0,04	6,47
1998	1443,50	1381,50	1156,00	963,50	1236,13	138,38	0,06	7,15
1999	1668,50	1285,50	1339,50	1007,50	1325,25	78,50	0,08	4,68
2000	1852,50	1875,00	1517,50	1051,50	1574,13	132,50	-0,13	5,36
2003	1426,50	/	1169,50	1087,00	1227,67	95,67	-0,39	6,34
2004	1246,50	/	1129,50	890,00	1088,67	87,33	-0,11	4,80
2005	1253,00	/	846,50	755,00	951,50	176,33	-0,11	4,78
2006	1500,50	/	1166,50	1078,00	1248,33	138,00	0,00	6,16
2007	980,00	/	861,50	724,50	855,33	113,00	0,08	3,14
2008	2585,00	/	2098,00	1217,00	1966,67	115,17	-0,03	7,58
2009	1679,50	1069,40	1422,00	630,50	1200,35	87,63	0,01	5,04
2010	2980,50	1112,50	1641,00	1039,50	1693,38	171,38	0,10	4,87
2011	1712,50	1345,20	1131,00	649,80	1209,63	136,40	0,08	5,82
2012	1065,00	1074,60	1045,50	726,50	977,90	87,00	0,02	2,03
2013	1489,00	1065,00	1462,00	1069,50	1271,38	76,00	-0,02	4,42
Mean	1779,53	1554,48	1293,42	963,89	1371,66	119,96	-0,02	5,68
Standard Deviation	554,19	435,54	325,26	191,53	322,12	31,88	0,11	1,53

Adapting the model architecture to the physical processes



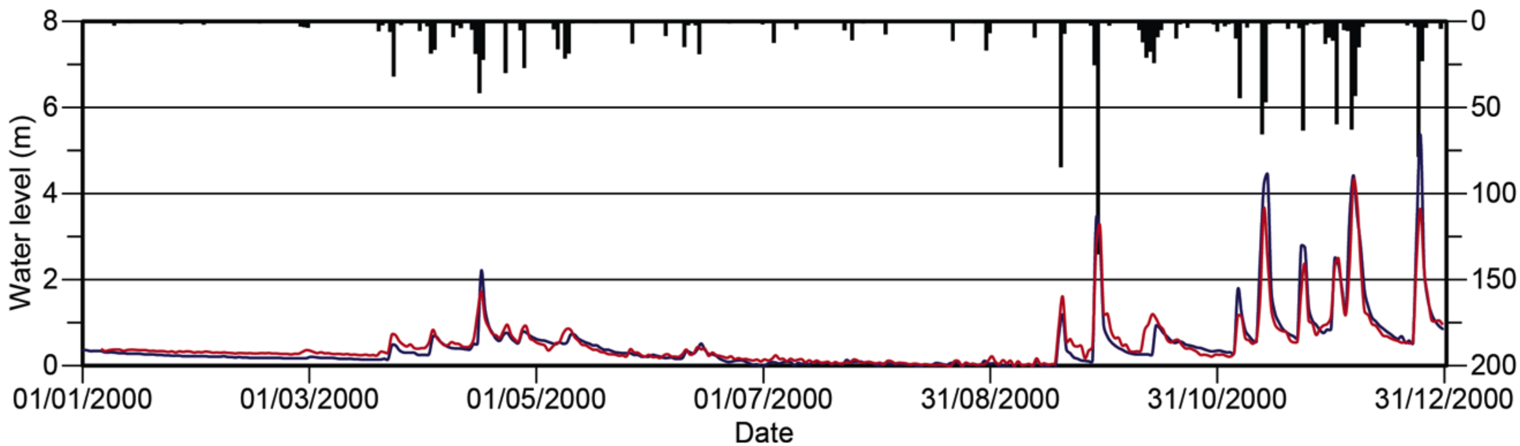
➢Classical architecture: the multilayer perceptron

Adapting the model architecture to the physical processes

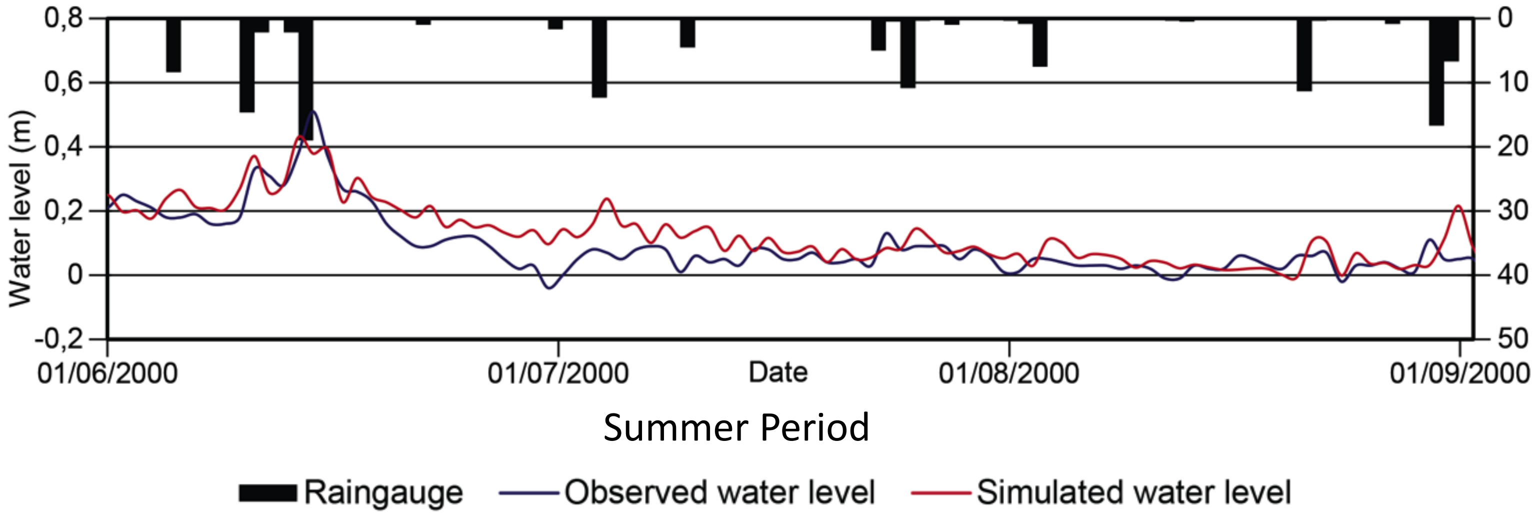


➢Separation of upstream and downstream influence

Results on test year 2000

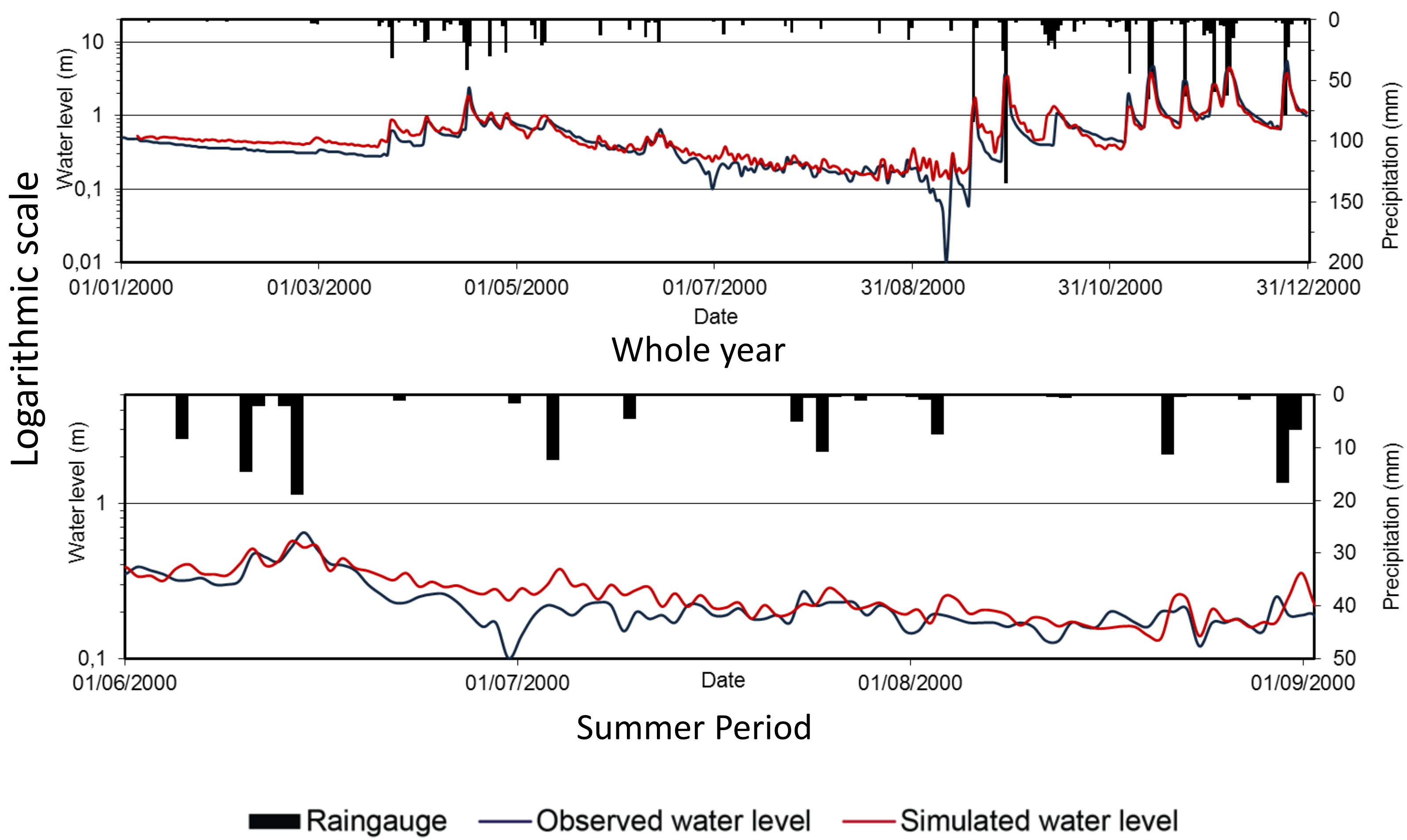


Whole year



Summer Period

Results on test year 2000



Results on test year 2000

- Nash criterion :

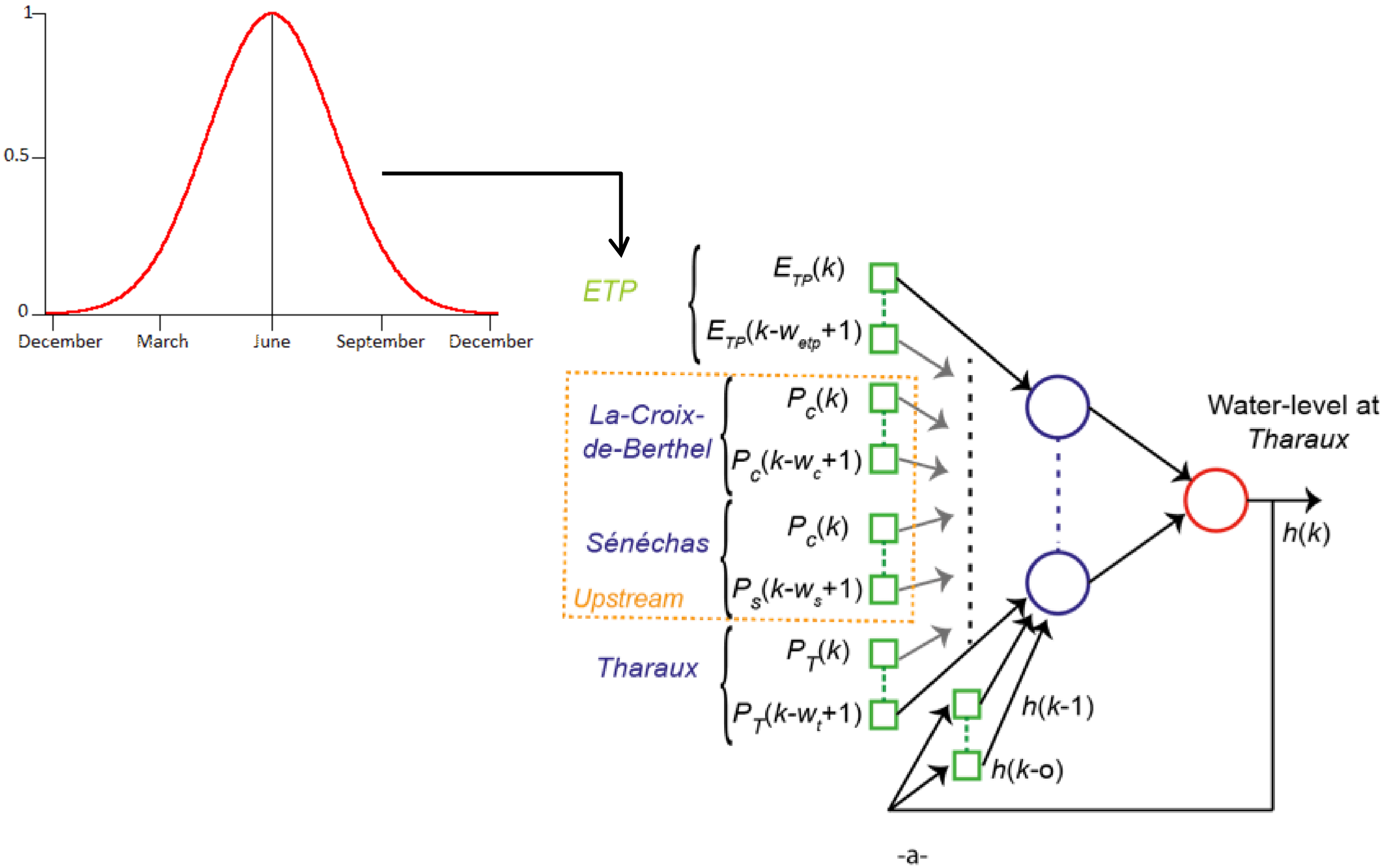
Model	year	summer
MLP	0.84	-0.04
2-branches	0.90	0.63

- Logarithmic Nash criterion :

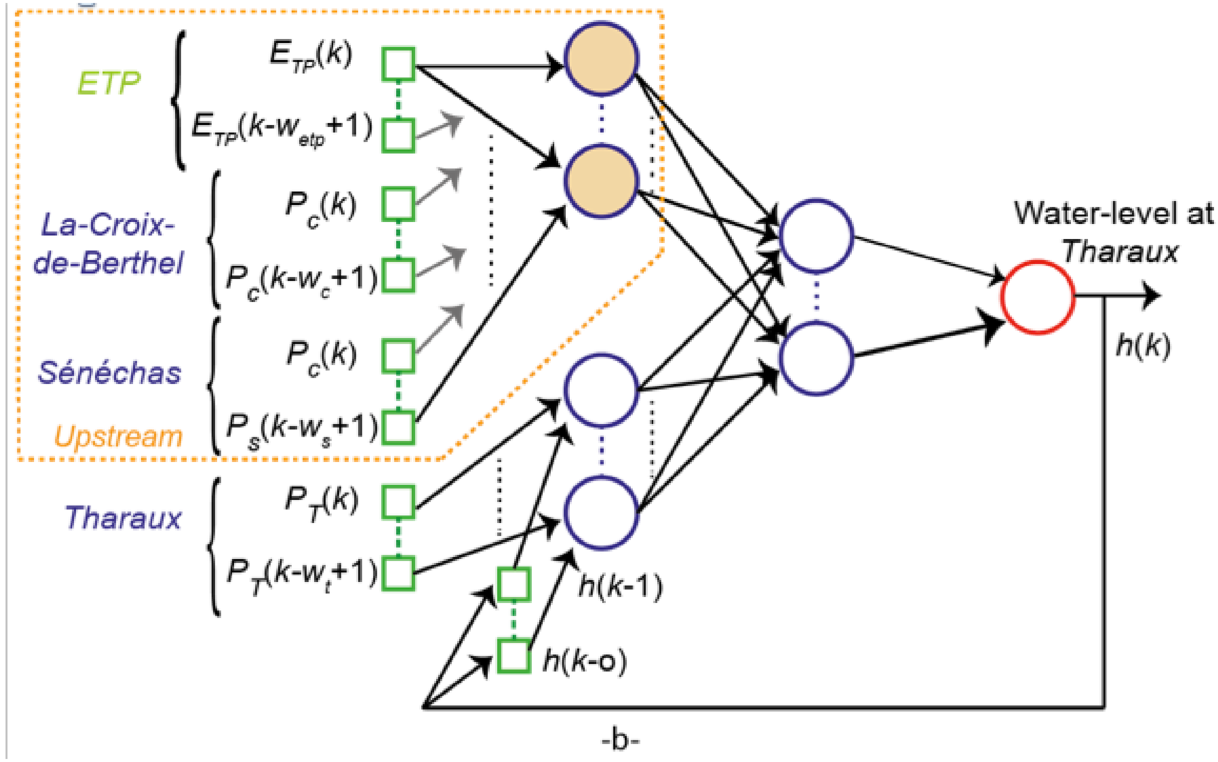
Model	year	summer
MLP	0.76	-0.14
2-branches	0.82	0.48

Conclusions

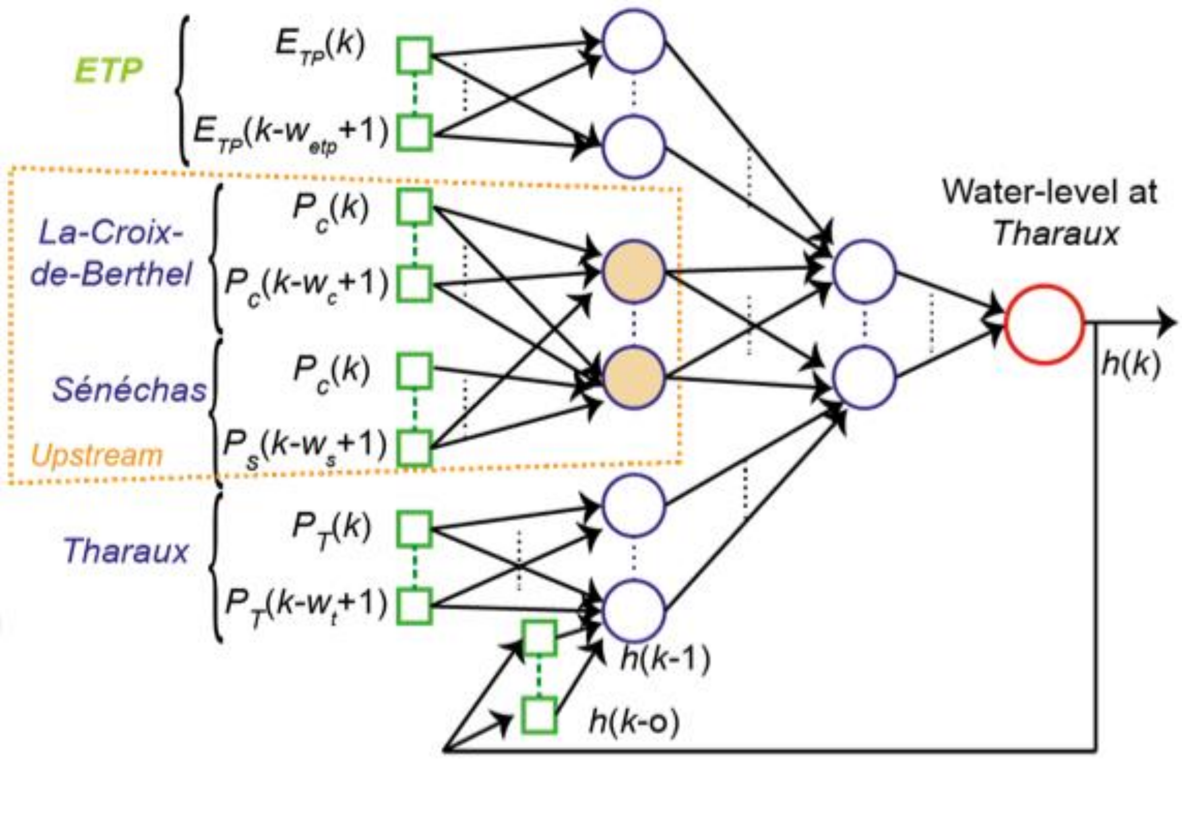
- **Constraining the neural network architecture using assumed physical processes improves the accuracy.**
- **Neural networks are able to simulate both floods and low water level with a single model.**
- **Useful for water managers with rainfall scenarii to anticipate use conflicts.**
- **By comparing with another model at the end of the Cèze canyon, we could estimate the total loss of water.**



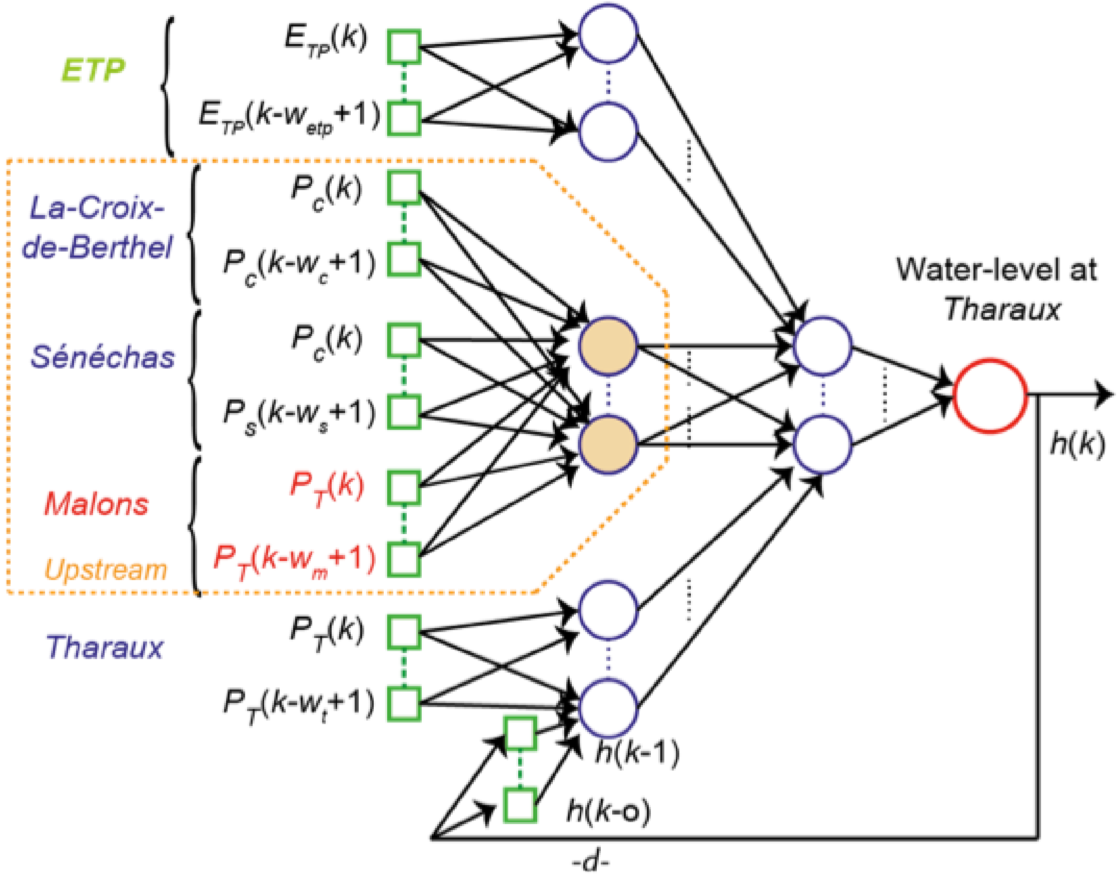
- Multilayer perceptron: model a



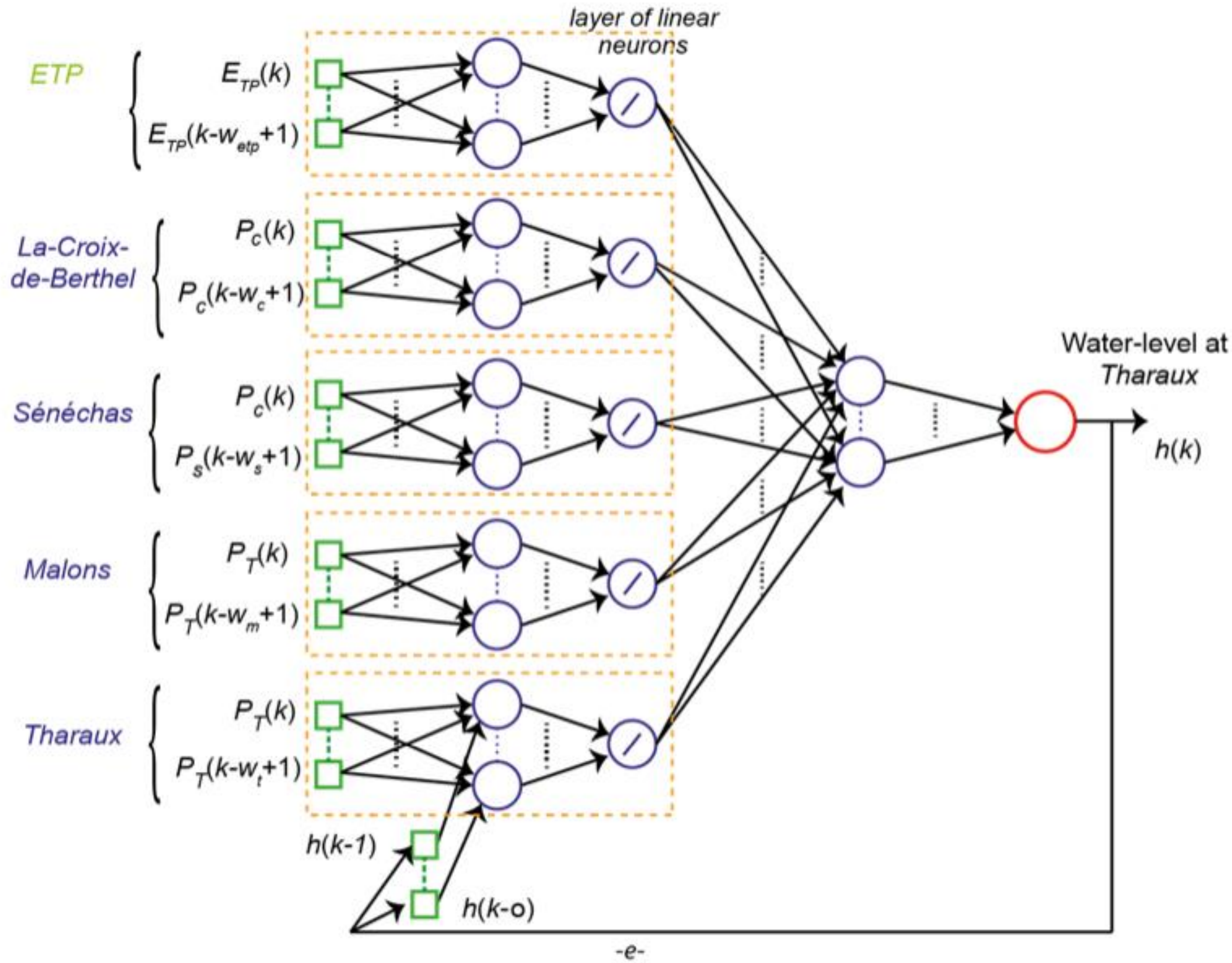
- Clustering of variables to separate upstream influence: model b



- ETP is applied in a third branch: model c



- Adding another raingauge information: model d

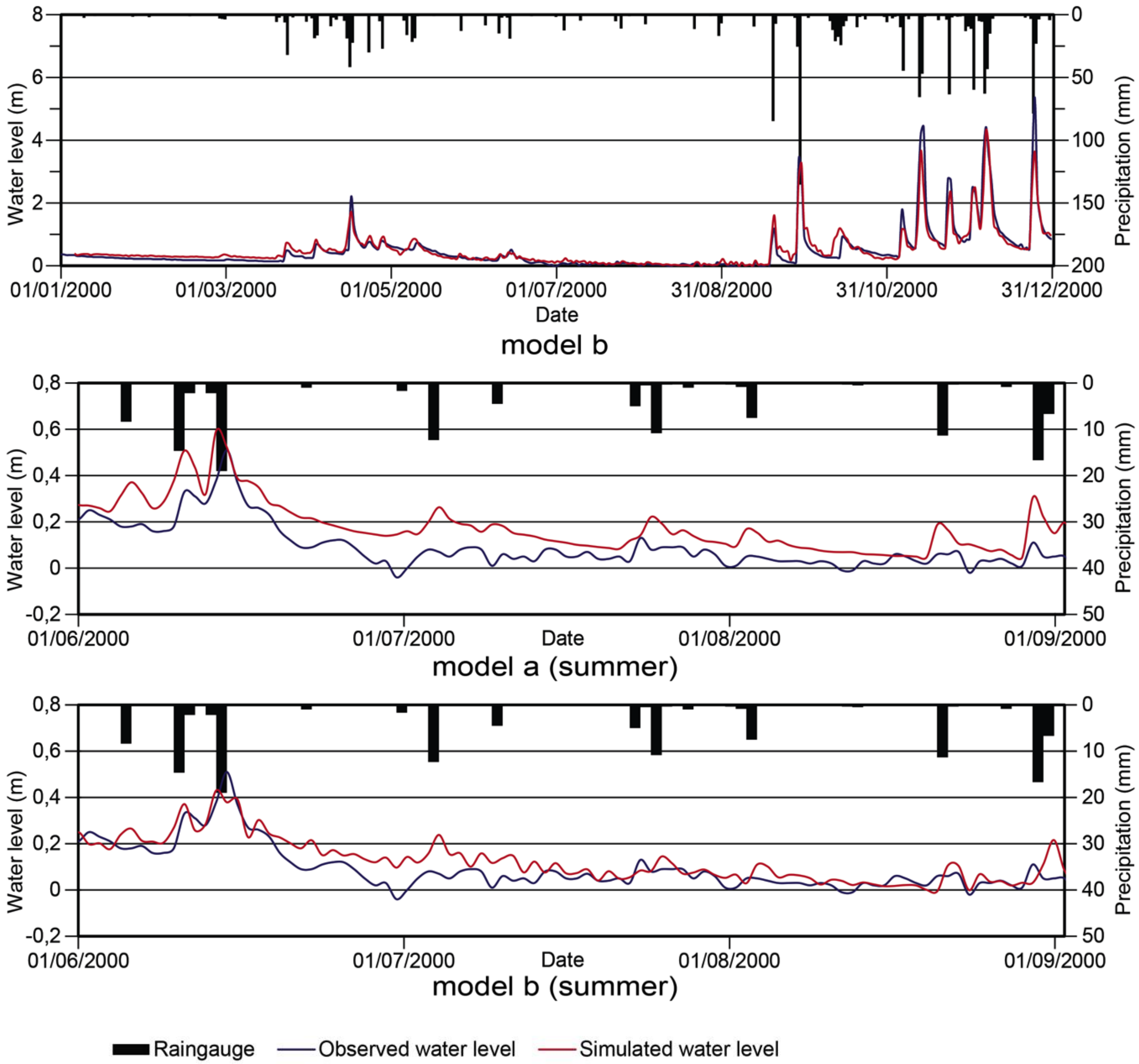


- Separation of each raingauge and ETP: model e

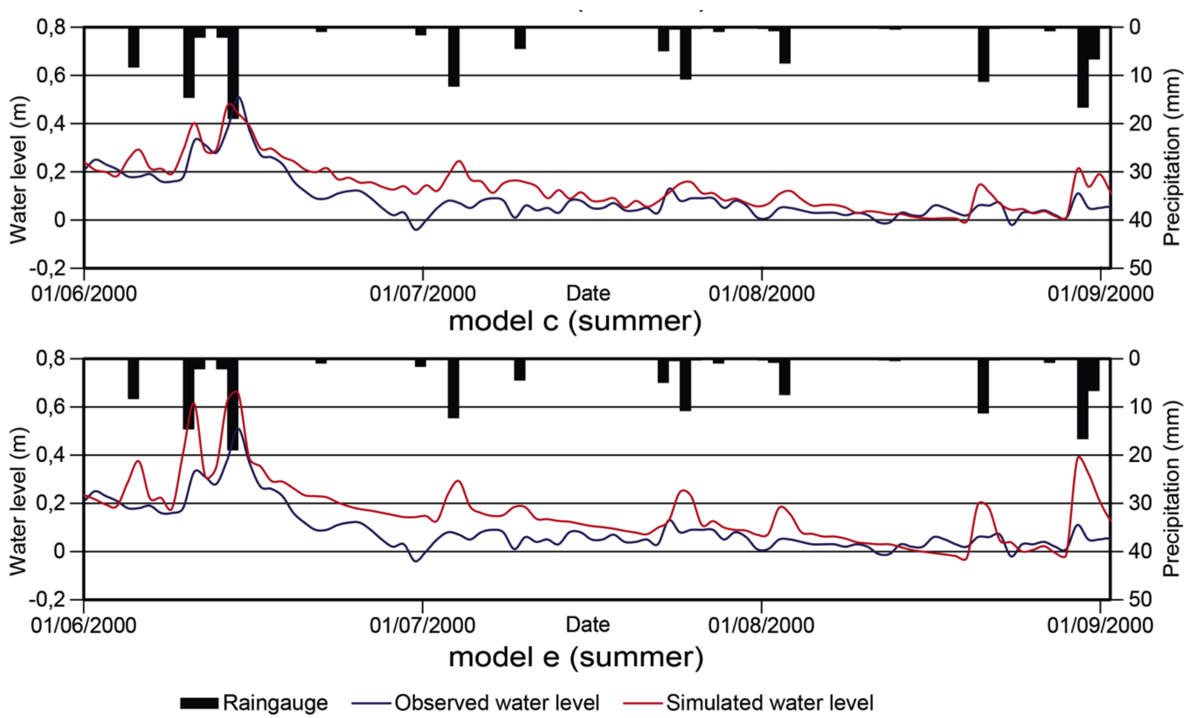
Nash Criterion

Model	year	summer
Model -a-	0.84	-0.04
Model -b-	0.90	0.63
Model -c-	0.87	0.55
Model -d-	0.87	0.47
Model -e-	0.84	-0.02

- b is the best model, ETP is mixed with upstream rain contributions



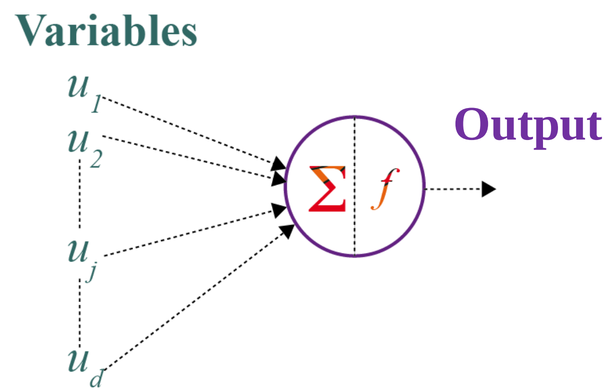
Water level (m)
Precipitation (mm)
01/01/2000
01/03/2000
01/05/2000
01/07/2000
31/08/2000
31/10/2000
31/12/2000
Date
model b
01/06/2000
01/07/2000
Date
01/08/2000
01/09/2000
model a (summer)
01/06/2000
01/07/2000
Date
01/08/2000
01/09/2000
model b (summer)
Raingauge
Observed water level
Simulated water level



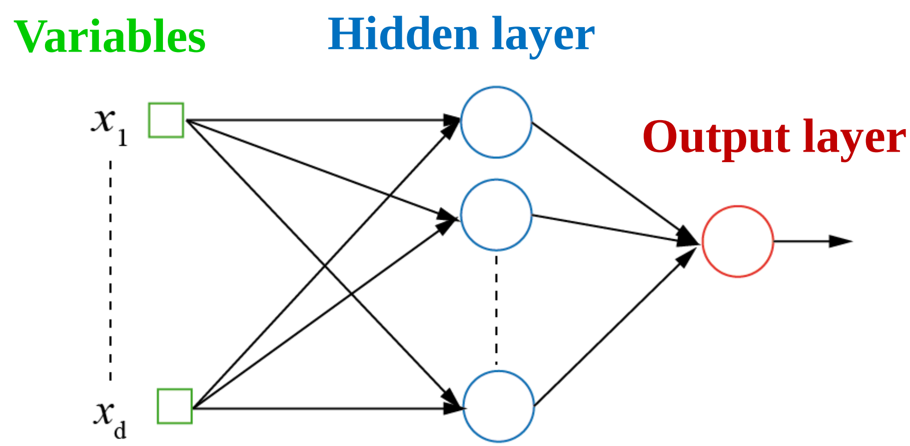
0,8
0,6
0,4
0,2
0
-0,2
Water level (m)
Precipitation (mm)
0
10
20
30
40
50
01/06/2000
01/07/2000
Date
01/08/2000
01/09/2000
model c (summer)
0,8
0,6
0,4
0,2
0
-0,2
Water level (m)
Precipitation (mm)
0
10
20
30
40
50
01/06/2000
01/07/2000
Date
01/08/2000
01/09/2000
model e (summer)
Raingauge
Observed water level
Simulated water level

Neural Networks

- **Neuron model:**



- **Multilayer perceptron:**

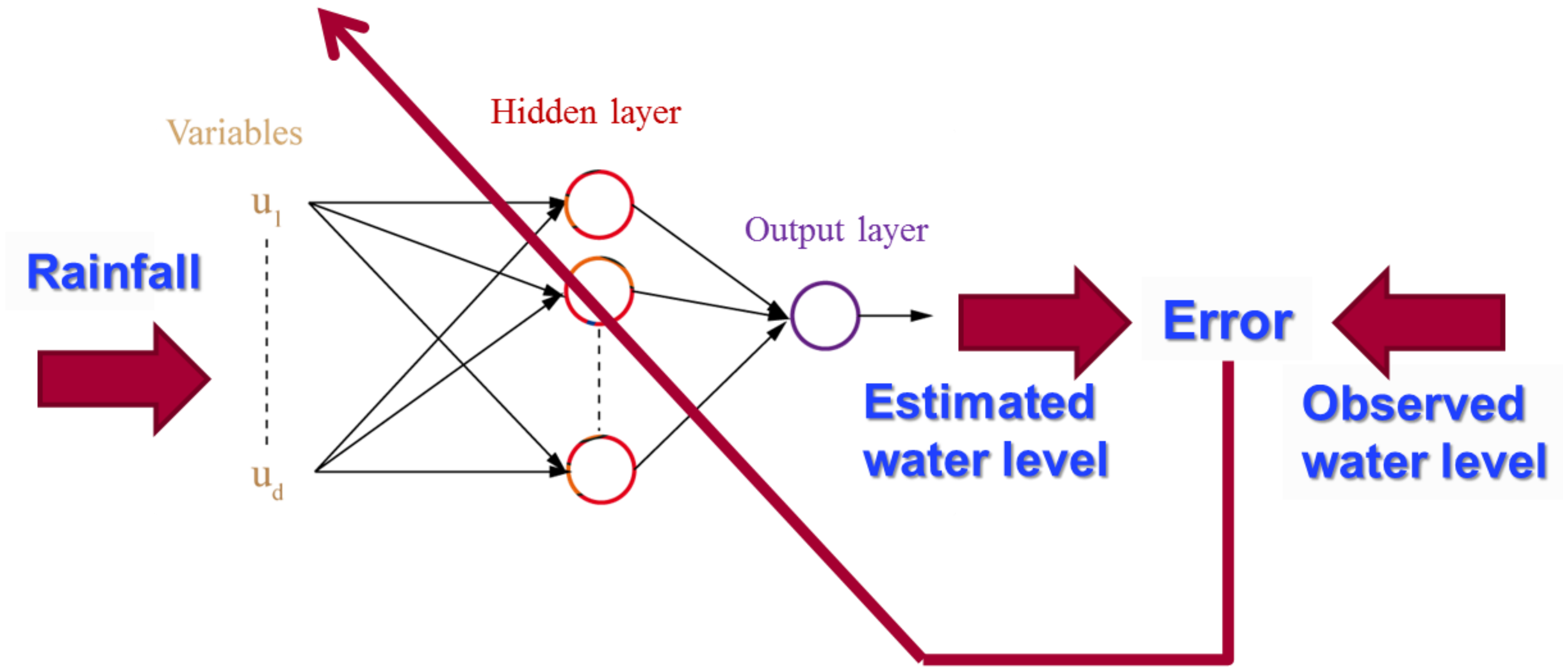


Neural networks : properties and limits

- **Advantages of the multilayer perceptron:**
  - Universal approximators *(Hornik et al. 1989)*
  - Parcimonious *(Barron 1993)*
  - Good efficiency for rainfall-runoff modelling on karst system *(Kong-A-Siou et al. 2011)*

- **Limits:**
  - Bias-variance dilemma: regularization methods to avoid overfitting
  - Sufficient database

Neural networks : training process



Training : minimizing the mean quadratic error using the Levenberg-Marquardt algorithm

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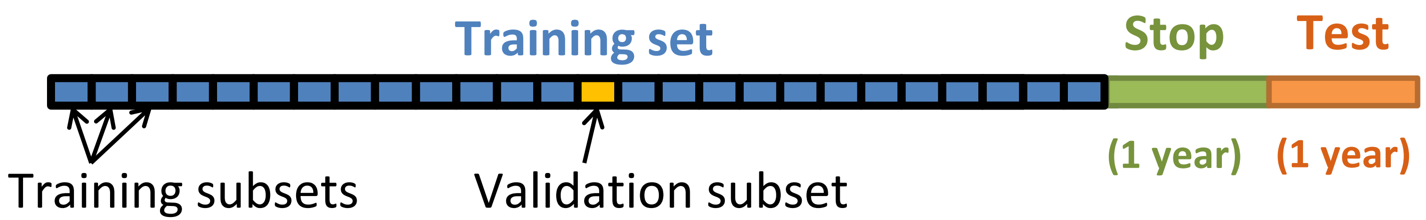
Neural networks : avoiding overfitting

- **Regularization methods:**
  - Early stopping: end of the training process when error in generalization increases *(Sjöberg et al. 1995)*
  - Cross-validation: allows to get the best model with less complexity *(Stone 1974)*



Cross-validation score: mean value of the Quality Criterion on each validation subset