Hydrosystems modelling

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Team ESAH : Eau, Systèmes Anthropiques et Hydrosystèmes
As Water, Anthropogenic Systems and Hydrosystems

(23 persons)

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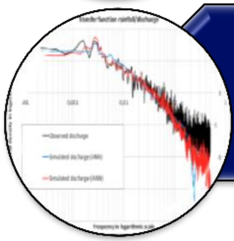
Four methodological domains

Measurement for resource diagnostic

Diagnostic of resources contamination, (persistent pollutants, toxins, bloom algal) in order to better apprehend the state of water (chemical and ecological state) and their probable evolution



Modelling, forecasting

Hydrosystems are generally complex and badly known; besides hydrological modelling, an approach is developed thanks to systemic paradigm

Sustainable management at the scale of the territory

Propose and assess scenarii of development taking into account local features and global changes.

Re-uze and recycling of resources

Circular economy: reuze of used waters (urban, industrial, agricultural) as a function of users constraints

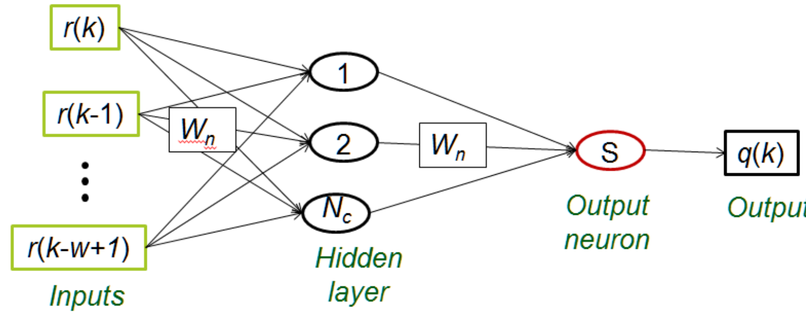
Sections CNU *: 24 (Aménagement de l'espace, urbanisme), 31 et 32 (Chimie analytique et chimie industrielle), 36 (Sciences de la Terre), 61 (Génie informatique, automatique et traitement du signal), 64 et 65 (Biochimie et biologie moléculaire)*

First example: drawdown of the water table of the Lez spring (Hérault-France)

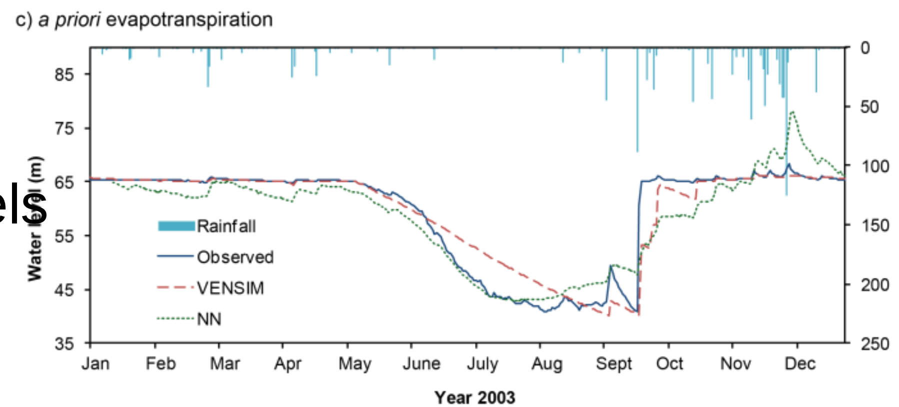
- *Lez* spring feeds *Montpellier* with drinking water (400 000 habitants)
- Karst aquifers (fissured, with huge holes and very different permeabilities) – caves and beautiful landscapes
- Pumping dries up the spring during summer: pumping is thus done in a physical reservoir whose level diminishes

Juillet 2011

- **Rainfall runoff modelling by Neural Networks *(A. Johannet)***



- Data:
  - Precipitations
  - Discharge or water levels
- Springs or rivers

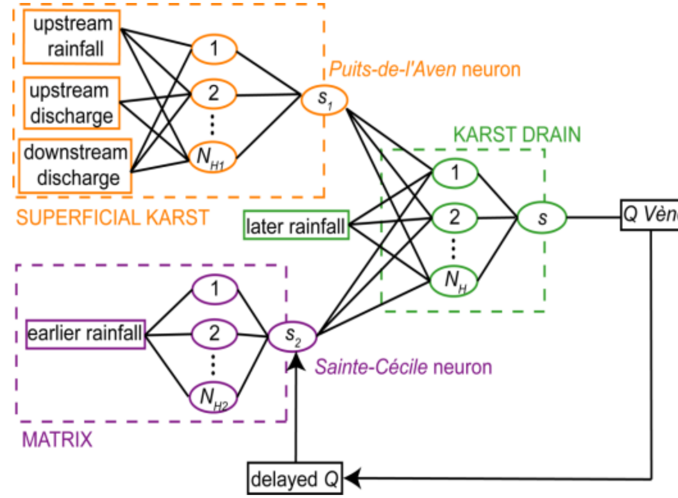


[Kong-A-Siou, J. Hydrology 2014]

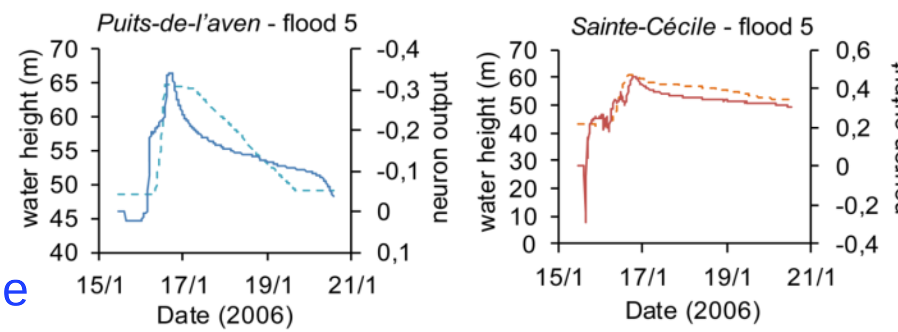
- Goals:
  - Reproduce the observed behaviour;
  - Estimate the response time;
  - Predict impact of global changes on water resources;

Semi supervized estimation of proxies

(EMA : A. Johannet)
Collaboration H. Jourde HSM



- Estimation of proxies representatives of surface – undergroud exchanges for a karst aquifer *Coulazou* (Hérault)
- Proposition of a bloc diagram
  - Bloc « matrix »
  - Bloc « surface contribution »
  - Bloc « drain »
- Extraction of signals inside the model:
  - Good correlation between proxies previously identified: water levels at *Puits-de-l'Aven* and at *Ste-Cécile* well.



[Kong-A-Siou, ISKA Malaga, 2014]

Second example : Inversion of rainfall-runoff relation

- **Compare implementation of discharge-rainfall relation implemented by classical neural network modelling (MLP) and …**
- **Rebuilt of rainfall through a neural model thanks to data assimilation**
  - One event
  - One year
- **First trial : on virtual hydrologic model (without noise and uncertainties)** **[*submitted to IJCNN 2015*]**

The *Lez* spring with water

Inversion of rainfall-runoff relation vs. data assimilation

- **Rainfall-runoff relation depends on a lot of variables :**
  - Evapotranspiration
  - Soils
  - Land use, …
- **Hydrologic data are measured with great uncertainties and noise**
  - Rainfalls (RADAR, raingauges) : 20%
  - Discharge 20%, (30% on peak flow for flash floods)
- **Nonlinear**
- **Non stationary (climate change, anthropogenic effects)**

The *Lez* river with water

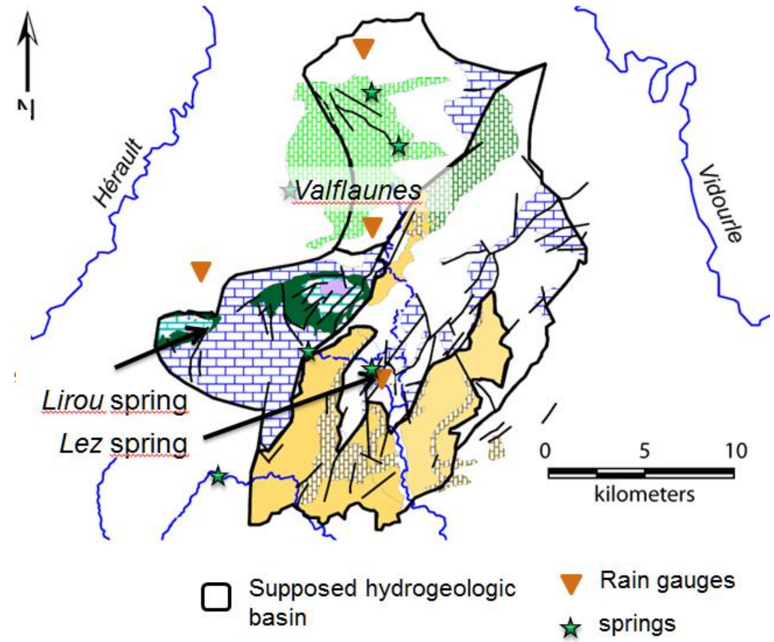
Inversion of rainfall-runoff relation vs. data assimilation

- **Data assimilation is a mathematical framework**
  - set of statistical methods used to integrate recent observations in order to improve systems modeling or knowledge,
  - especially for nonlinear and non-stationary systems
- **Widely used in geosciences: hydrology, agronomy, oceanography, physics of atmosphere, and meteorology.**
- **In hydrology, data assimilation is used to estimate initial conditions**
- **It allows taking into account non stationary (climate change, anthropogenic effects)**

- **In the neural networks formalism:**
  - Adaptivity when parameters are corrected
  - Input correction thanks to minimization of the cost function (as well as for parameters)

Inversion of rainfall-runoff relation vs. data assimilation. Case study : le *Lez* aquifer

- ***Lez* aquifer: complex hydrosystem of 380 km² at the *Lez* spring**
- **Several springs; only one is gauged for a long time**
- **Faults and heterogeneous geology**
- **Heterogeneous rainfalls (space and time variability)**



- **Database:**
  - Discharge and rainfalls: daily time step from 11/11/1987 to 04/06/2007 (20 years)
  - Rainfalls at *Valflaunes* for the same duration

Inversion of rainfall-runoff relation vs. data assimilation. Case study: le *Lez* aquifer

- ***Method : first address a case study without noise***
- **Build an artificial basin with the reservoir model karstmod (http://www.sokarst.org/index.asp?menu=karstmod)**
- **Actual rainfall dataset**
- **Consider estimated discharge of Karstmod as real discharge of the virtual aquifer.**

- **Test on two configurations**
  - One rain event removed
  - One year of rain set to 0

- **Compare direct modelling with ANN and data assimilation**

Inversion of rainfall-runoff relation *vs*. data assimilation. Case study: le *Lez* aquifer

- ***Direct modelling of the inverse relation***
- **Multilayer perceptron**
  - Static (finite impulse response model)

$$y^k = g_{NN}(u^k, \ldots u^{k-w_u+1})$$

  - Feedforwad (finite impulse response model inputted by rainfalls and previous measured output)

$$y^k = g_{NN}(y_p^{k-1}, \ldots, y_p^{k-w_y}, u^k, \ldots u^{k-w_u+1})$$

  - Recurrent model (infinite impulse response)

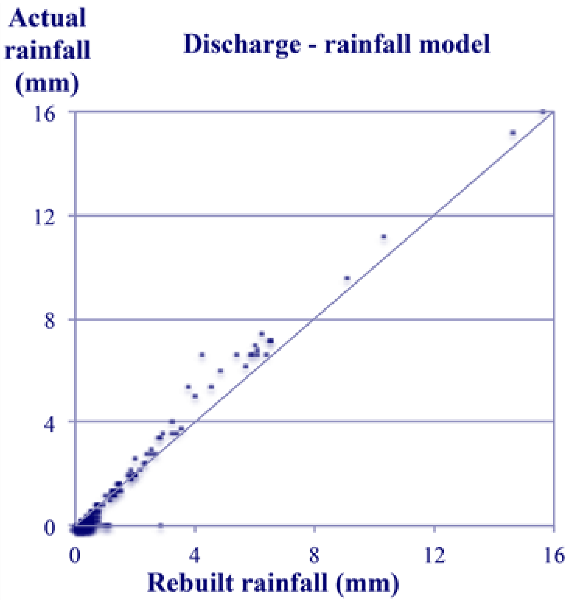
$$y^k = g_{NN}(y^{k-1}, \ldots, y^{k-w_y}, u^k, \ldots u^{k-w_u+1})$$

- **Database**
  - Training 11/11/1987 to 31/12/2003, approximately 16 years
  - Stopping 01/01/2004 to 31/12/2005, 2 years
  - Test 01/01/2006 to 04/06/2007, approximately 1.5 year

$\boldsymbol{y^k}$
: estimated discharge
$\boldsymbol{y_p^k}$
: measured discharge
rainfall u^k,
$\boldsymbol{g_{NN}}$: function implemented by NN

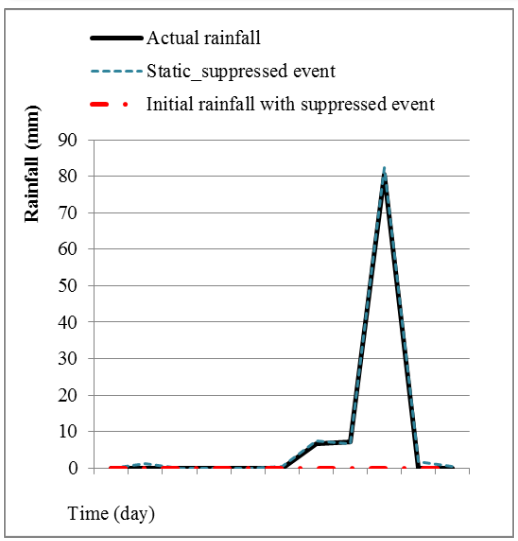
Inversion of rainfall-runoff relation vs. data assimilation. Case study: le *Lez* aquifer

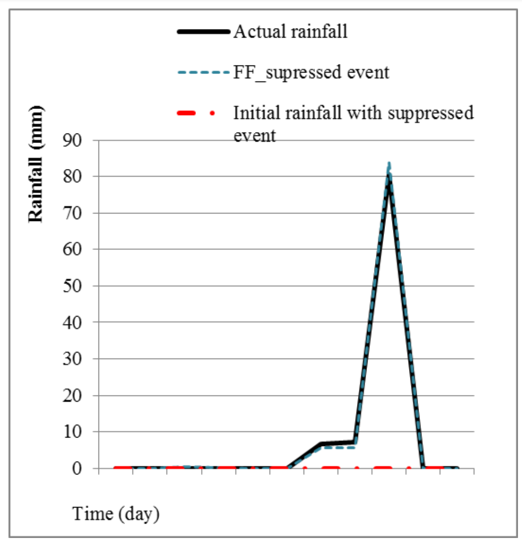
R^2 VALUES FOR RAINFALL-RUNOFF INVERSION	
	R^2 (determination coefficient)
	Test period
Rainfall estimation from discharge	0.98

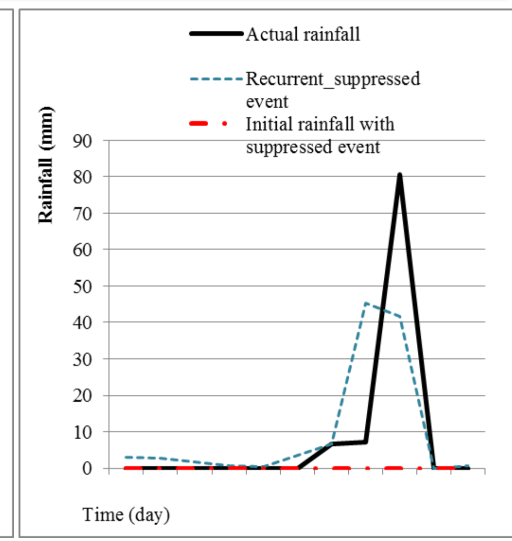


Inversion of rainfall-runoff relation vs. data assimilation. Case study: le *Lez* aquifer

R^2 VALUES FOR DATA CORRECTION			
	R^2		
	Static	Feed-forward	Recurrent
Rainfall correction: Absence of one event	0.96	0.97	0.92
Discharge simulation without assimilation (test set)	0.976	0.819	0.85
Discharge simulation with assimilation (test set)	0.980	0.974	0.976





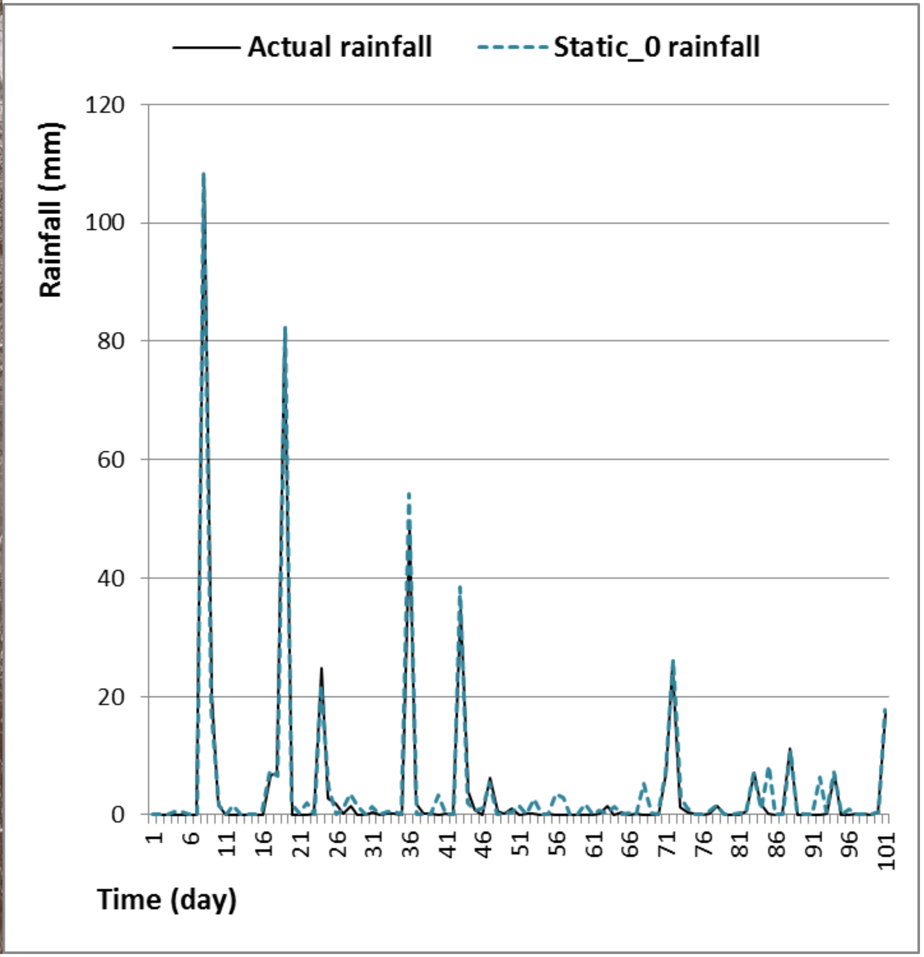


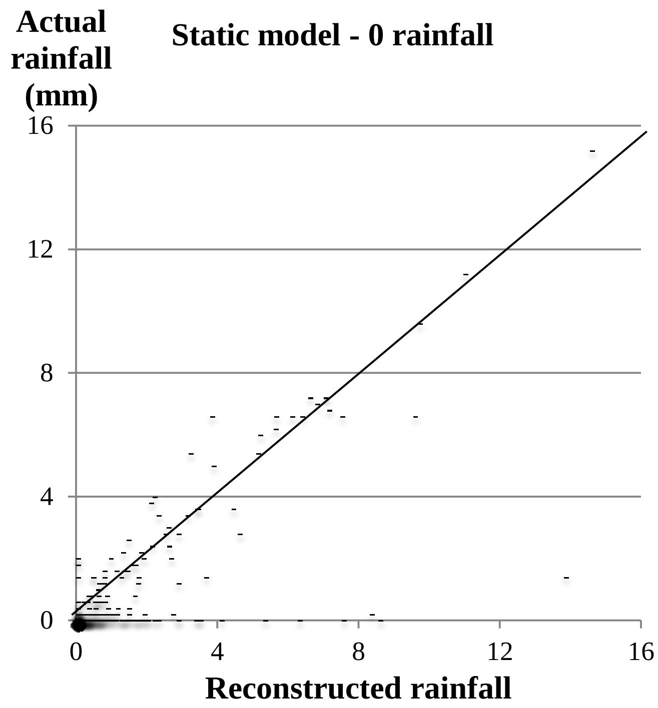
Inversion of rainfall-runoff relation vs. data assimilation. Case study: le *Lez* aquifer

R^2 VALUES FOR DATA REBUILT			
	R^2		
	Static	Feed-forward	Recurrent
Rainfall rebuilt from 0 hypothesis	0.98	0.96	0.60
Discharge simulation without assimilation (test set)	-1.23	0.912	-1.024
Discharge simulation with assimilation (test set)	0.91	0.915	0.909

Inversion of rainfall-runoff relation vs. data assimilation. Case study: le *Lez* aquifer

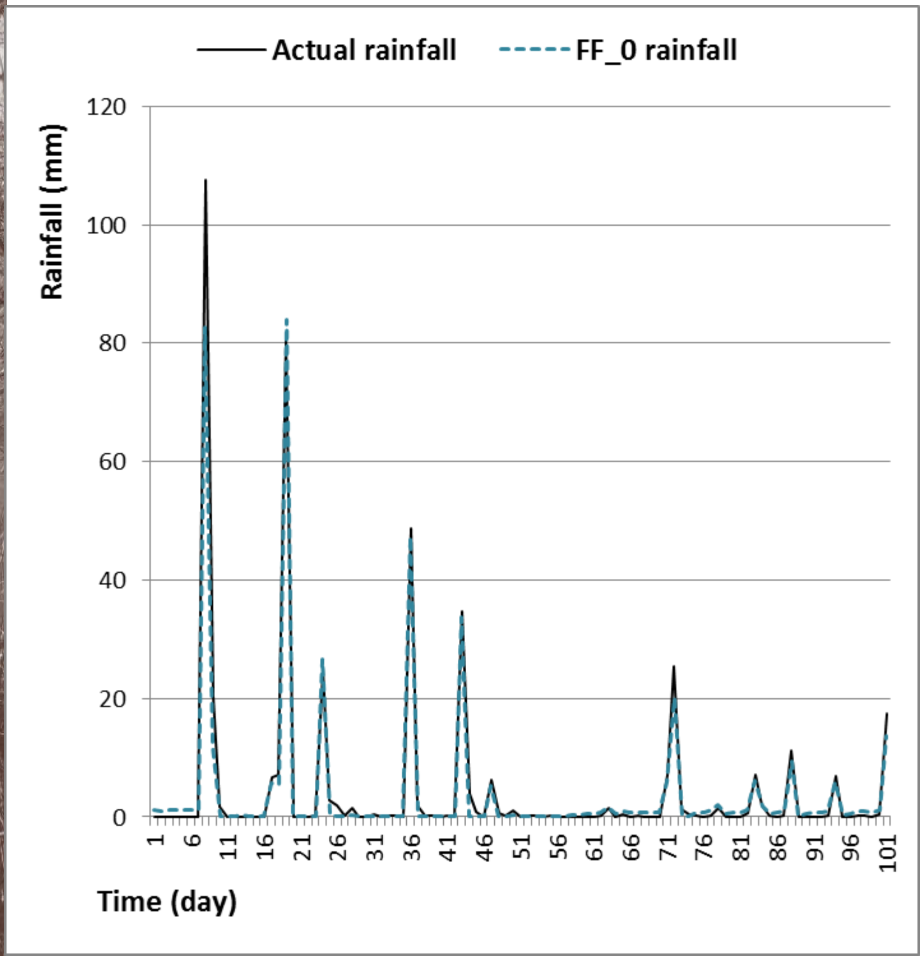
- **Static model**

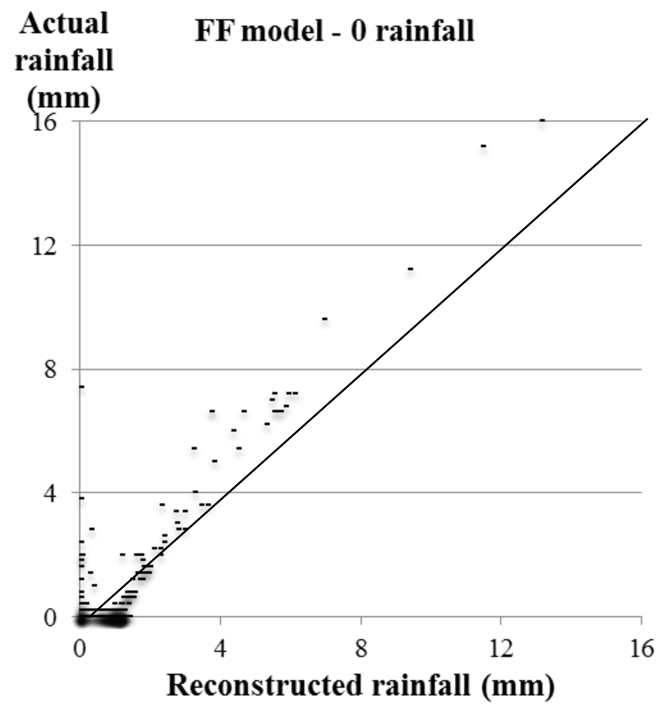




Inversion of rainfall-runoff relation vs. data assimilation. Case study: le *Lez* aquifer

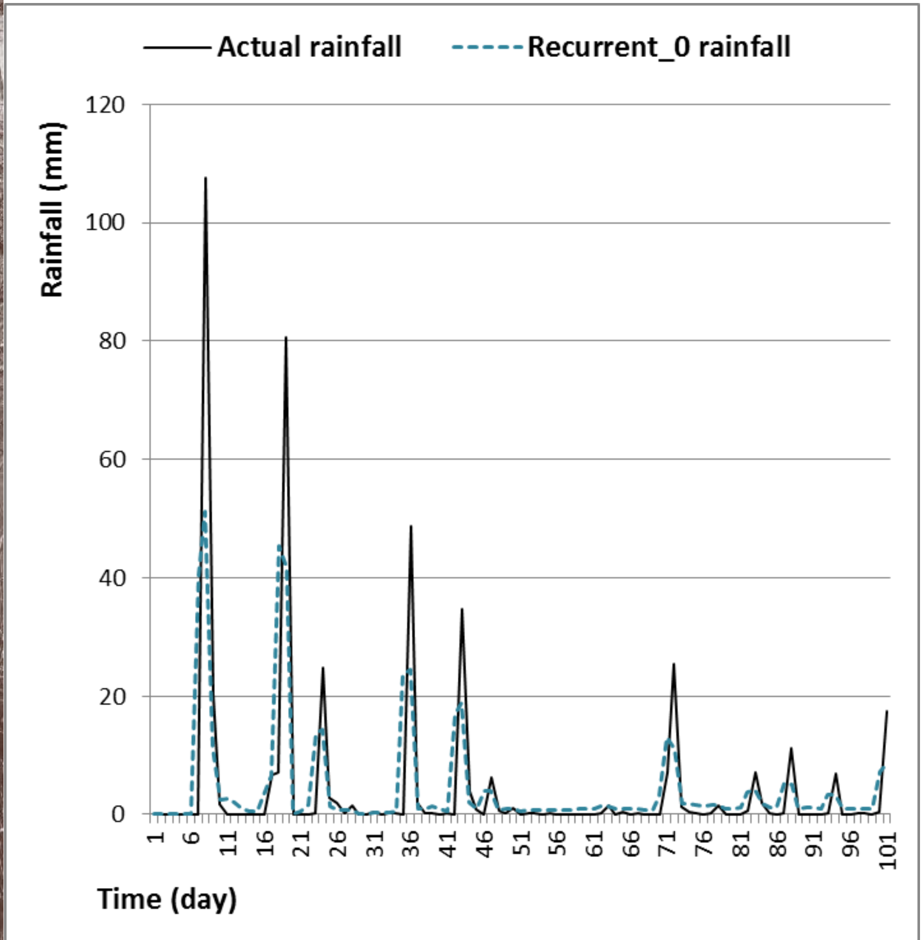
- **Feedforward model**

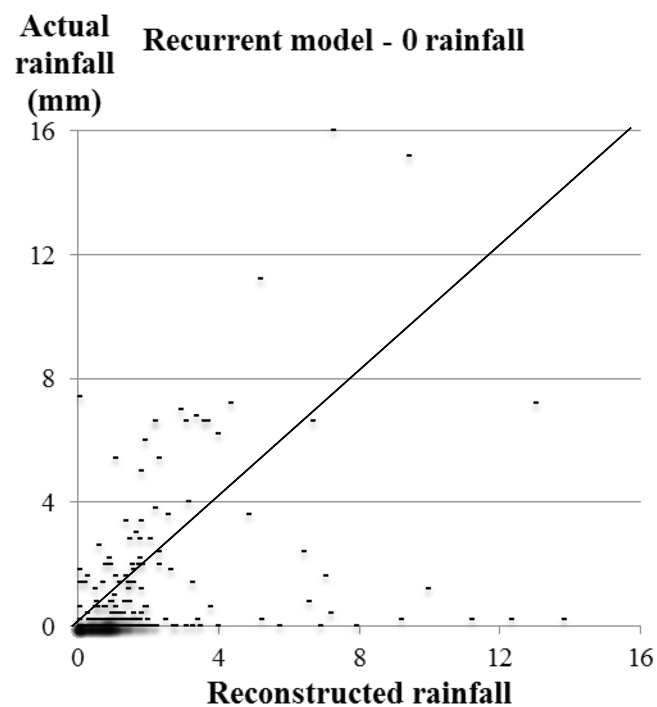




Inversion of rainfall-runoff relation vs. data assimilation. Case study: le *Lez* aquifer

- **Recurrent model**





Inversion of rainfall-runoff relation vs. data assimilation. Case study: le *Lez* aquifer

- **Conclusion**
  - fictitious model without noise
  - inverse direct modelling of rainfall-runoff relation is very efficient and works as well as the best method of data assimilation
- **It would be:**
  - very useful to supplement historical databases
  - adapt databases to more modern instrumentation
- **Before to transpose this method to real cases it would be necessary to better evaluate the role of noise**

Thank you for your attention

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PhD thesis

- Line Kong A Siou, *Modélisation des crues de bassins karstiques par réseaux de neurones,*

Thèse de l'Université Montpellier 2, spécialité Eaux Continentales et Sociétés. École Doctorale SIBAGHE.

soutenue le 21 octobre 2011.

- Denis Maréchal, *Utilisation de l'imagerie satellitale à très haute résolution pour la caractérisation des chemins de l'eau sur des bassins versants cévenols soumis aux crues « éclair ». Ecole des Mines de St Etienne, discipline : Sciences et génie de l'environnement. Soutenue en mai 2011.*
- Guillaume Artigue, *Prévision des Crues Éclair par Réseaux de Neurones : Généralisation aux Bassins non Jaugés.*

Thèse de l'Université Montpellier 2, spécialité Eaux Continentales et Sociétés. École Doctorale SIBAGHE.

Soutenue le 3 décembre 2012

- Audrey Bornancin-Plantier, *Conception de modèles de prévision des crues éclair par apprentissage artificiel*.

Thèse de l'Université Pierre et Marie Curie, spécialité Informatique. École Doctorale EDITE, soutenue le 25 février 2013.

Papers

- «Rainfall-runoff modeling of flash floods in the absence of rainfall forecasts: the case of "Cévenol flash floods" », Toukourou M., Johannet A., Dreyfus G., Ayral P.-A. Journal of Applied Intelligence vol. 35, 2 (2011), pp. 1078-189. doi:10.1007/s10489-010-0210-y.
- Optimization of the generalization capability for rainfall-runoff modeling by neural networks: The case of the Lez aquifer (southern France). Line Kong A Siou, Anne Johannet, Valérie Borrell, Séverin Pistre, in Environmental Earth Sciences, , Volume 65, Issue 8 Pages: 2365-2375.
- Flash flood prediction in poorly gauged basins using neural networks: Case study of the Gardon de Mialet Basin (southern FranceG. Artigue, A. Johannet, V. Borrell, and S. Pistre,), NHESS in press.
- Kong-A-Siou, L., Cros, K., Johannet, A., Borrell-Estupina, V., Pistre, S. (2013) KnoX method, or Kowledge eXtraction from neural network model. Case study on the Lez aquifer (southern France). Journal of Hydrology 507 (19-32).
- Neural Networks model as transparent box: towards extraction of proxies to better assess karst/river interactions (Coulazou catchment, South of France). Line Kong-A-Siou, Hervé Jourde, Anne Johannet. ISKA 2014, Malaga.

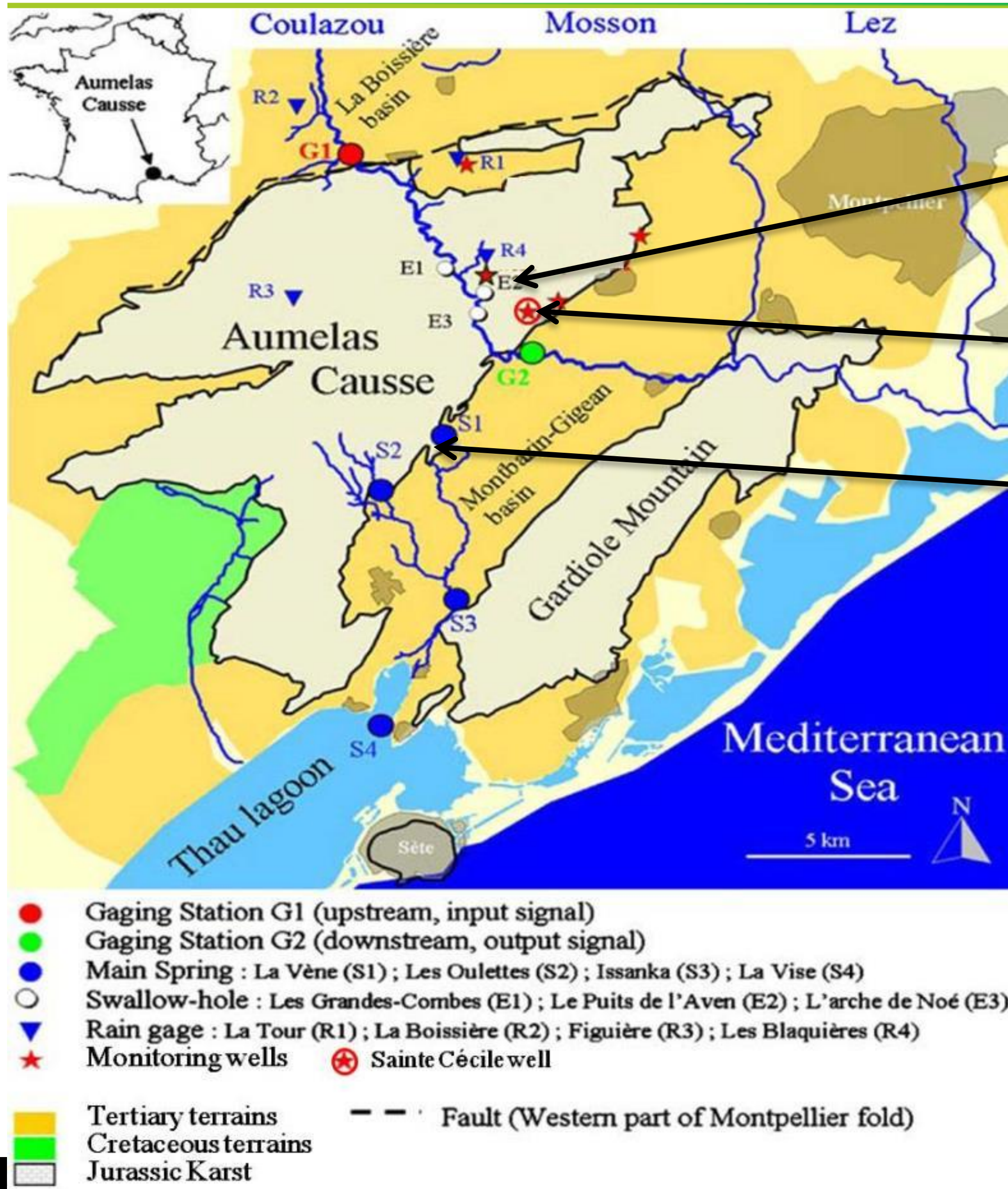
Inversion of rainfall-runoff relation vs. data assimilation. Case study: le *Lez* aquifer

ARCHITECTURE OF DESIGNED MODELS

w_u and w_y are the size of sliding window length of respectively rainfall and recurrent input ; h_n is the number of hidden neurons

	Runoff-rainfall relation (inverse model)		
	Static	**Feed-forward**	**Recurrent**
w_u	-	3	-
w_y	-	9	-
h_n	-	1	-
	Rainfall runoff model with data assimilation		
	Static	**Feed-forward**	**Recurrent**
w_u	50	8	8
w_y	-	2	2
h_n	6	4	4

2. The *Causse d'Aumelas*



Puits de l'aven swallow hole

Sainte Cecile well

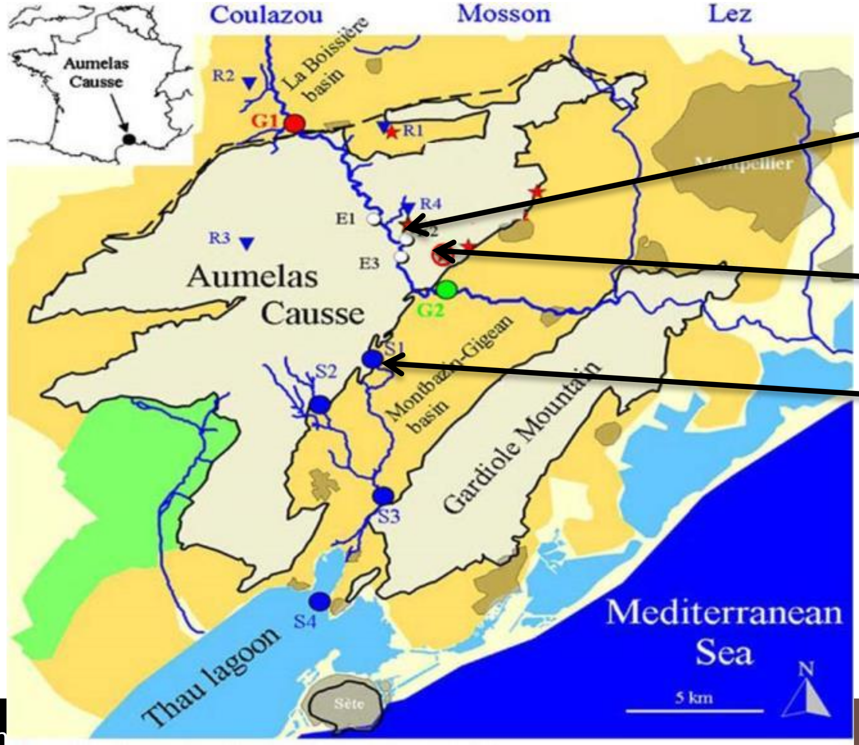
Vène spring

Coulazou Catchement:

- Upstream (non-karst area) :20km²
- Downstream (karst area): 40 km²

Transparent box for the Aumelas hydrosystem

- **Available data**
  - 16 floods with 15 min time step
  - Rainfall (4 rain gauge)
  - Runoff : 3 gauging station (*Coulazou* upstream and downstream, *Vène* spring)
  - Water level in a well and 3 swallow holes

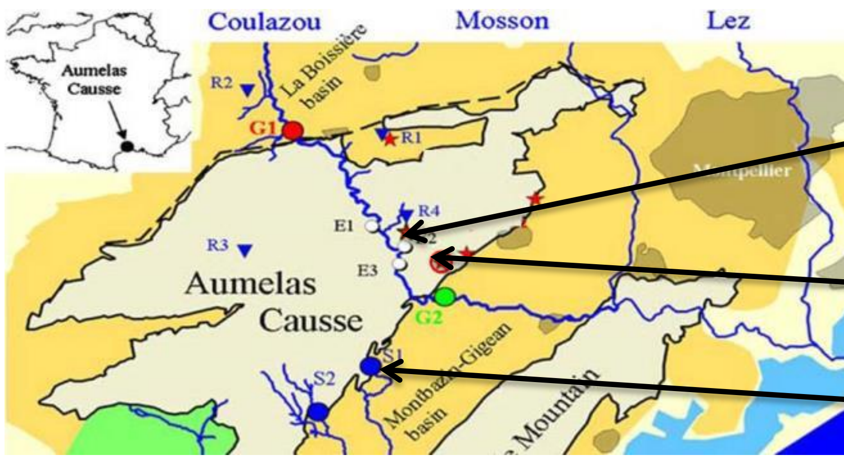


Bailly-Comte V, Jourde H, Pistre S (2009) Conceptualization and classification of groundwater-surface water hydrodynamic interaction in karst watersheds: Case of the karst watershed of the Coulazou River (Southern France). Journal of Hydrology 376:456-462

roxies of karst/river interactions

- **Water level at *Sainte-Cécile* well: hydraulic connection between karst and river**
  - ✓ Perched stream
  - ✓ Connected stream

- **Water level at *Puits-de-l'Aven*: direction of stream**
  - ✓ Gaining stream
  - ✓ Loosing stream



Puits-de-l'Aven swallow hole

Sainte-Cécile well

Vène spring

Postulated model