Note to the Editor.

It seems that Figures were not fully readable in the interactive discussion paper. If necessary, as Figures were designed with the software illustrator they can be provided in high quality, as it appears in the word format.

Revision notes to Anonymous Referee #1 (Received and published: 6 May 2015) on "Identification of spatial and temporal contributions of rainfalls to flash floods using neural network modelling: case study on the Lez Basin (Southern France)" by T. Darras et al.

Note to the first anonymous reviewer.

Comments of the reviewer are recalled in the following and the first response of author is identified in blue; modifications provided on the manuscript are written in red.

Authors first want to thank very much the reviewer for his (her) accurate and interesting work. This will surely improve significantly the paper. To facilitate the link with the questions or thought suggested, we propose to respond to, (or comment) each point just after the text of the reviewer. In order to facilitate the reading, responses will be written in blue. Figures were added.

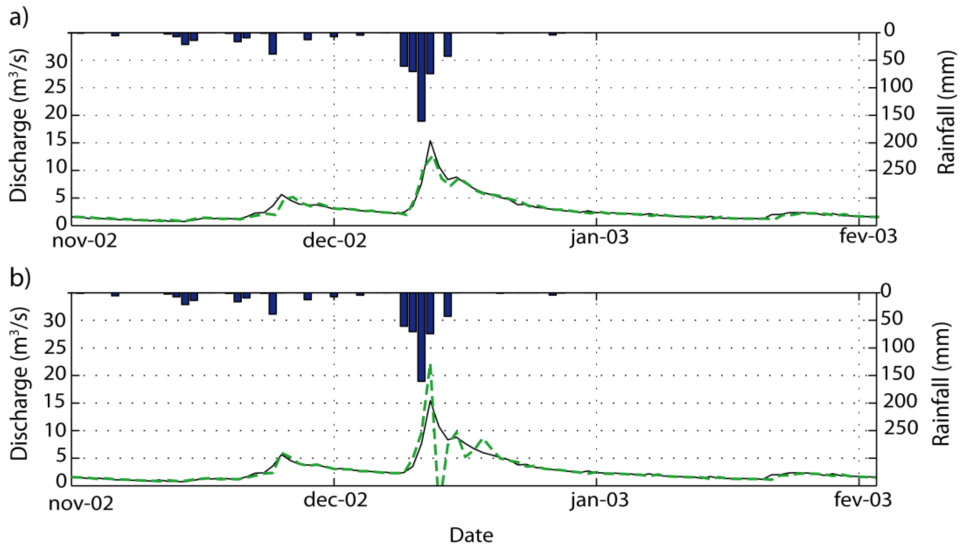
1) This paper focuses on the application of the KnoX modelling methodology to extract knowledge about the contribution and timing of different geographical aquifer zones to flash floods in SE France from artificial neural network models. It is a very worthwhile exercise - the karst aquifers of this region are complex and difficult to model physically. Consequently a knowledge extraction approach using data-driven modelling techniques is a sensible and novel solution. It is also excellent to see an example of the use of ANNs for geographical knowledge extraction, rather than the more commonly attempted (and rather uninteresting) lumped catchment 'curve-fitting' tasks. However, I am concerned that the KnoX methodology (which is essentially a method for assessing model input contributions to the output based on the network weights) is not particularly innovative - network weights have been used for more than a decade to understand the importance of inputs (Olden and Jackson, 2002; Kingston et al., 2003; 2005).

The KNOX method was initially described in the paper (Kong-A-Siou et al, 2013). In this former paper we explained better the origin of the method, without claiming that the idea to consider parameters (or weights) was novel; KNOX was based on the work of Yacoub devoted to variable selection (*Yacoub, B., Bennani, Y., 1997. A heuristic for variable selection in multilayer artificial neural network classifier. Intelligent Engineering Systems Through Artificial Neural Networks 7, 527–532*), which was cited in the previous paper. The main difference with the papers cited previously (Olden and Jackson, 2002; Kingston 2006 (we didn't found Kinston 2003)) is that KNOX is deterministic thanks to the suppression of the random effect due to the initialization of the model. Also the method is different from previous ones: previous ones analyzed variable importance thanks to the strength of the parameters (or weights) aided by sensitivity analysis. In opposition, KNOX it is based on a 2 steps process: first describe the watershed in a block diagram (representing the postulated physical model); Parameters of the model are thus <u>constrained to provide the targeted physical information</u>. Second, each box is implemented using a multilayer perceptron or a unique linear neuron. After that, the contribution of variables can be analyzed and knowledge extracted. In other words, KNOX first constrains the architecture toward the postulated physical model, and second quantifies the physical process. To the best of our knowledge, this two steps procedure is novel. Moreover KNOX was proved (using a virtual artificial aquifer), in the former paper, as sufficiently accurate to extract hydrological knowledge. KNOX method is qualified in L17 as "recent methodology", and the goal of the present paper is "To assess the interest of this methodology" (L20) on another case study. Due to the complexity of both karst aquifer and neural networks, we think that it would be interesting to apply this method to a lot of various configurations in order to assess its efficiency and limitations.

2) What troubles me more, however, is the fact that the KnoX method has been applied to this aquifer before by this authorship team or members thereof (see several citations of work by Kong-A-Siou et al.). The authors make some reference to this in Section 3.5. and in Section 4 cite that the difference with this paper is the hourly data used to drive the model. This leaves me wondering what the contribution to knowledge is in this paper compared to the several other papers by the same (or similar) authorship team. If this is a repeat of previously published work that is largely the same except for a different temporal resolution of input data, then it feels like only a minor contribution to the literature. Therefore, before it can be accepted for publication, I think that the authors need to be very clear about how this paper develops the other papers by Kong- A-Siou et al., 2013 on the Lez Basin, the new findings / insights that result from this paper, and their relevance and importance for hydrologists.

We agree with this questioning, which is fully the role of the referee. As it is impossible to rewrite in a new paper all the work made before and published elsewhere, it is usual to cite previous papers.

- In Kong-A-Siou (2011) we applied NN to perform forecast at Lez spring and validate cross validation as a useful method to select the complexity of the NN.
- In Kong-A-Siou (2012) we focused on regularization methods used to select the best complexity (early stopping and weight decay) and we presented one exemplar figure of what is overfitting due to too high complexity (too many hidden neurons). This figure is the following (top 4 hidden neurons, bottom: 8 hidden neurons). We concluded also that early stopping was efficient.



- In Kong-A-Siou 2014 we compared reservoir model (VENSIM) and recurrent NN to achieve forecasting of discharge and drawdown of water for floods and low water levels. NN was shown efficient for extreme events and VENSIM efficient for intermediate events.

- In Kong-A-Siou 2013 we proposed the KNOX method, explain it, and validate it on a fictitious aquifer. The validation was based on the contributions and time delays of rainfall estimated on 4 zones of the aquifer. The knowledge extracted from the model allows us to have a new vision of the behavior of the aquifer. The study was done on data of the **Lez spring at daily time steps**. Information was useful for water resource (where does the water come from?), and recharge of the aquifer. Only groundwater was considered.

- In the present paper the same basin is considered, with the same delimitation in 4 zones, nevertheless the gauge station is not the same than in 2013: it is the ***Lavalette station*** at the entrance of Montpellier. Also the database is **hourly sampled and includes only flash flood events**. **Addressed processes are thus different.** Flow rate at Lavalette station includes contributions from perennial karstic springs (the most important is Lez spring), temporary karstic springs (Lirou spring can be stronger than Lez spring), diffuse karstic arrivals and also run-off. As the behavior of the basin is very complicated due to surface and underground water floods, and because it is impossible to make measurement during the event (to protect human lives) the application of KNOX method seems interesting to do. After the application of the KNOX method, we found that it was possible to access to a better quantification of processes acting during the flood. We think that this result is really interesting for karst hydrologist as it seems possible to distinguish surface flood and underground flood, thanks to the model as shown in Figure 5. The comparison of contributions and time delays provided in Table 5 allows comparing two different processes acting simultaneously in the aquifer. For us this is interesting, very useful, and we hope that other people redo the same work on other aquifers to explore the potential of this method.

More extensive presentation of the results of previous papers regarding regularization methods (paper of 2011 and 2012) was added in P5L26-31 . Also better presentation of the difference between work of 2013 and this one is also presented P7L29-P8L4.

3) The introduction / literature review is generally well structured and provides a fairly comprehensive and critical overview of the key literature and the arguments from adopting the method used. There are far more examples of the use of the multi-layer perceptron than the two articles cited - a more extensive tabulation would make the review *more complete. Similarly, the application of ANN-based models in a spatially discretized structure to deal with heterogenous and complex hydrological behaviour has also been explored before (e.g. with rainfall-runoff models) and it might be worth mentioning these for completeness (e.g. Tsai et al. 2014, Hyd. Proc., 28(3), 1055). The issue of how to select the 'best' or 'correct' input data sets to the ANN is skipped over a little. The authors might like to consider mentioning the sorts of information-based methods that have emerged for selecting model inputs over the last few years (e.g. the Gamma and Evans tests) and explain their choice of inputs a little more thoroughly in light of these ideas.*

We agree that this presentation could be extended. Our opinion is that a scientific paper must be concise (if possible). The paper has a target, and only the necessary literature, useful to understand and enlighten the methodology and results must be cited. This choice implied, in this case, citing 65 papers. We think it is sufficient but this point can be discussed: it is an editorial choice.

4) I also note that the authors identify ANNs as 'statistical' models. This is, of course, true. However, the term 'data-driven' is perhaps more commonly used to describe ANNs and the authors may wish to alter their terminology.

Yes it could be possible. Nevertheless we observed that the statistical framework is more and more used in the neural network research field, so in our perception (which can be false) "data-driven" sounds a little bit old.

5) Section 2 deals with the basic concepts of ANN design and development. The MLP ANN is chosen, but there is not any real justification for this presented. Why not a RBF ANN or some other variant? I think a stronger justification for the MLP would be useful here.

MLP was chosen (P3686, L3) because of "its properties of universal approximation and parsimony". We thought it was sufficient as well as a lot of authors (also Olden and Jackson, 2002, cited in earlier comments). Moreover, KNOX method was validated in the framework of multilayer perceptron.

6) The terminology 'stop set' is not standard, but I do think it is clear. 'Overtraining' is more commonly referred to as 'overfitting' and this is a term that the authors might like to adjust. The authors do not explain that the issue of overfitting is exacerbated by data splits that are not fully representative of the signals in the data.

Yes we agree.

Actually there is a subtle difference between overfitting and overtraining: overtraining occurs when training is performed too much; it is avoided using early stopping. Overtraining is one the possible cause to overfitting. Another cause of overfitting is for example over parametrization which means that the model has too many parameters. Thus in the manuscript we took care of the word we used (and correct if necessary): overfitting when the problem is the complexity or not well defined; and overtraining when the training is not stopped early (by-heart training).

7) There is a huge literature around methods for achieving representative data splitting to improve the generalisation of ANNs (Holger Maier at the University of Adelaide has published in this area recently) and this literature should at least be cited.

Yes it is possible; nevertheless the goal of the paper is not a review about data splitting. The goal was not to have the best possible generalization, but a good one taking into account the complexity of the basin and uncertainties on input data (that are considerable in this case). Models T7 and T8 (Table 4) can be viewed as excellent taking into account that they are evaluated on the two highest events of the database. We understand that a meticulous hydrologist want to have the best possible generalization. Nevertheless in the context of Mediterranean events, where peaks of flood are measured with an uncertainty of 20% or 30%, we think that the level of quality of models T7 and T8 is sufficient. For us, the great challenge was to extract knowledge quite similar for all various training set. Regarding this challenge, we thought that results (Table 5 and Figure 5) were surprisingly good.

Moreover, regarding flash floods, splitting data following flood events is obvious as time series are not continuous (only flash floods are stored and they can be separated by a long time (several years)).

8) Section 2.1.2. needs a little work. I really struggled to follow what was going on in the method for identifying the stopping point and had to read the text forensically. I think a flow chart is needed to support the text in 2.1.2 and the authors need to work the text up a little more to improve readability and consistency (e.g. the term 'validation set' creeps in here but this could be confused with the other 'sets' presented earlier). The use of a median value from an ensemble of 50 ANNs to avoid the influence of the random initialisation effect is sensible - but it does risk 'damping' the model outputs. It might be worth being explicit about the impacts that using an ensemble median might have.

The “validation set” is simply the one of the cross-validation. This information is lacking; it must be added. For readers interested by cross validation, 2 references were provided. Calculation of the median is not used to calculate the prediction; it is only used to extract parameters and knowledge. We agree that the calculation of the median of the output may induce “damping”; in another work we took this effect into account to make the predictions reliable in case of flash floods (Darras et al 2014, Influence of the Initialization of Multilayer Perceptron for Flash Flood Forecasting: Design of a Robust Model).

This last information was added in the text. Section 2.1.2; was checked and better explained.

9) Section 2.2. deals only briefly with the literature around knowledge extraction. Recent efforts based on partial derivatives have provided useful insights into the physical rationality of ANNs and should probably be mentioned at least (e.g. Mount et al., 2013. HESS, 17, 2827 / Dawson et al., 2014. Jnl Hydroinf. 16(2), 407).

These two papers are thorough, well written and very honest in describing their aims and limits. They address a very interesting issue: how to validate a model calculated thanks to a calibration process? In our opinion this question must be asked also to practitioners of reservoir models. Indeed it is well known that after calibration, parameters of a reservoir model have generally no realistic values. Despite their high quality, these papers haven’t the same goal that KnoX method. Hydrometeorological complexity of the Lez model is incommensurate with the one of the models targeted by these methods. We don’t apprehend the significant added value they could provide to the goal of the paper.

The ref (Mount et al., 2013) is added in P6L29-P7L4 to extend the state of the art.

10) The KnoX method description is not particularly easy to follow - the 4 steps in the text should, perhaps, be revised to improve their readability and specificity. For example, step 3 states ’...and calculate of the median of the absolute value of each parameter over the ensemble models’. What are these ’parameters’? Are they input values? Are they initialization parameters? Are they values associated with the neurons of the network? This is all very unclear. The KnoX method is central to what follows so the authors really do need to revise this section fully and provide clarity.

Parameters are the weights of the model. We choose this word in order to be widely understood by the community of neural networks modelers, see for example the book of Dreyfus G. (Neural Networks), and by modelers in hydrology (reservoir models have parameters that are calculated thanks to a calibration phase as well as parameters of the neural model during training). Nevertheless, the reviewer is right, this term is not so clear at this point of the paper. We will include at least the general equation implemented by the multilayer perceptron and the definition of variables and parameters before this description of KnoX method.

Explanation of the calculation made by the multilayer perceptron was added in P4L27-P5L4. It presents what are the parameters.

11) Again, a flow chart or schematic diagram could be helpful for all readers here. Section 3.5 - please avoid statements such as ’fed by abundant rainfall’. What is the rainfall - please give measurements. One man’s abundance is another’s dearth.

We agree, in Table 1 cumulative rainfall was provided for each event. For example, the maximum is 245 mm in few days.

The previous value is added to better precise what "abundant" means.

12) The legend on Figure 1 is not clear - is the conurbation the hatched area?

Yes it is, in the original Figure it was better readable.

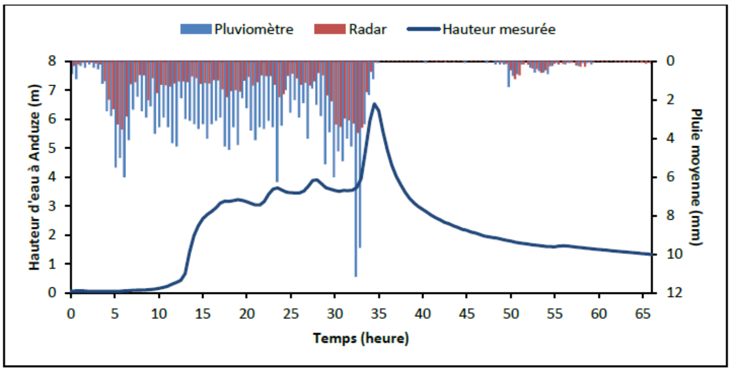
The Figure was modified because the area of the conurbation contains also natural land cover. As it is more interesting to indicate urban area because they accentuate flash floods, we present this information in the new version of Fig. 1.Actually urban zones are downstream of Lavalette that was not obvious in the previous figure.

13) Section 4.1.1 presents the ’postulated model’. I find it somewhat unsatisfying and poorly argued. It relies on the author’s previous papers but little evidence is offered to substantiate the spatial discretisation in the text.

We were afraid to increase the length of the text, and proposed to the reader to read (Kong-A-Siou 2013) where this issue was widely explained.

14) The inputs to the ANNs are simply the mean rainfall values in each of the four zones - as determined by Theissen polygons. This is a rather simplistic method for assigning rainfall inputs and does not account for the spatio-temporal heterogeneity of rainfall in the catchment. Is this a potential issue - I would imagine heterogeneity could be high in *this catchment? RADAR-based rainfall data might be able to help answer this. What might the impact of such a simple assignment of model inputs be on the final model?*

The availability of rainfall spatially and correctly discretized in time is an actual and important issue. These data are not available and RADAR data suffers in this region from several problems: (1) consistency from one event to another, (2) underestimation of rainfall. They are thus not better than rain gauges even if research in this field is very active to improve RADAR rainfall. Don't forget also that radar data are usually calibrated thanks to rain gauges. Personally we demonstrated empirically in a place near the Lez Basin (Gardon d'Anduze) that RADAR data underestimate rainfall by a mean factor of 25% (with important variability) compared to rain gauge data (by comparing only the rain gauge and the pixel of radar corresponding to the rain gauge); see for example the following figure for a cevenol flash flood at Anduze (sorry, it is in French; "pluviomètre" means rain gauge, and "pluie" means rainfall). Thus using rain gauge data in this basin appeared as more robust.



This issue was briefly addressed in P11L29-P12L2.

15) Simply stating that you 'consider the rainfall information sufficient to carry out this study' (Pg 3695, Line 10) doesn't feel an adequate justification to me.

As explained before, rainfall data at hourly time step in the south-east zone doesn't exist anymore. Concerned area (in the south) is impervious; therefore there is no doubt about the influence of karst. Karst contains water table under the impervious layer but has no role on flood as indicated by previous hydrogeological studies. Our questioning is linked to the NE and SO zones; indeed the NO zone (full karst area, and surface water flowing to another river (Vidourle)), seems too far from Lavalette station to be able to contribute to underground Flash Flood. The goal of this study is also to better understand the behavior of the basin in order to develop well suited monitoring strategy (p3682 L16-17).

Important stakes associated with flash flooding in Montpellier imposes us to work on this problematic even if data are not excellent. A sentence added in P13L.17-20. This limitation of the work is pointed out in P17L4-10.

16) Section 4.2. The authors introduce the term 'window-width' in this section and it appears again in Table 3. I simply don't know what this is - I don't recall having seen it in the text before. Similarly, the authors appear to have experimented with developing models using various numbers of hidden neurons - but I don't recall this important process (the model complexity has a major influence on overfitting propensity) being presented in the text earlier. This leaves me rather confused and of the opinion that the methodological descriptions presented earlier in the paper have not been sufficiently clear or detailed enough.

Yes, this information is important. Hidden neurons number is determined by cross-validation as indicated p3687 L4-5 and p3695 L16 and Table 3. Window widths refer to the sliding windows of rainfall vectors and of previous discharge vector. These sliding windows are drawn in Fig. 3; their range of investigation and chosen values are provided in Table 3.

17) I simply can not read Figure 3 and this makes it very difficult to understand the ANN structure that has been used. Similarly, the model outputs in Figure 4 are too small to be useful - I can't see the hydrographs properly. I think that considerably more work is needed here to ensure that the methods and model structure are properly and fully described in the paper and that the model outputs that are being used to validate the model are adequately disclosed.

We are sorry, original figures were designed with Adobe Illustrator. They are good in original png format. They are inserted in the following response. The quality is slightly better when clicking on "printer-friendly Version" and zooming (in the internet HESSD discussion).

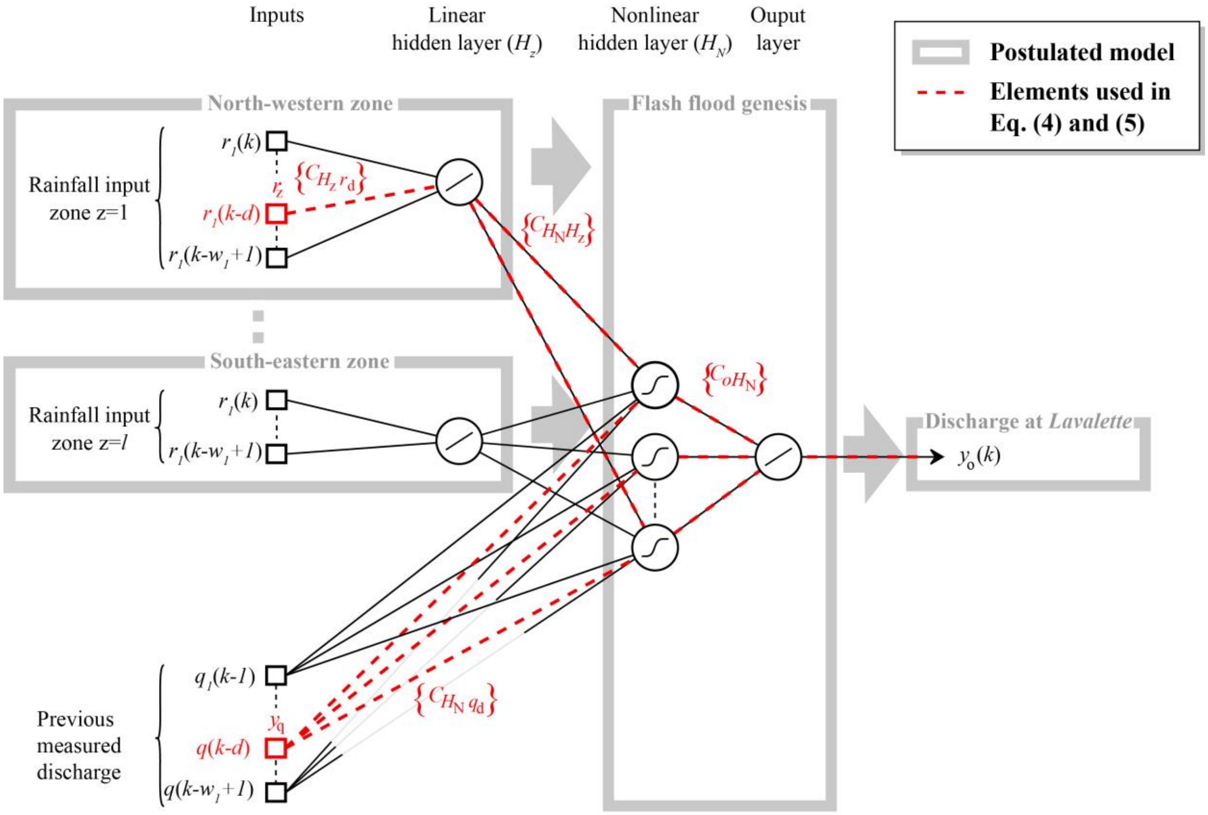


Fig3 Postulated model: grey block-diagram. Three layers multilayer perceptron with linear hidden layer between rainfall inputs and nonlinear layer. Parameters used in Eq. (4) are denoted in red.

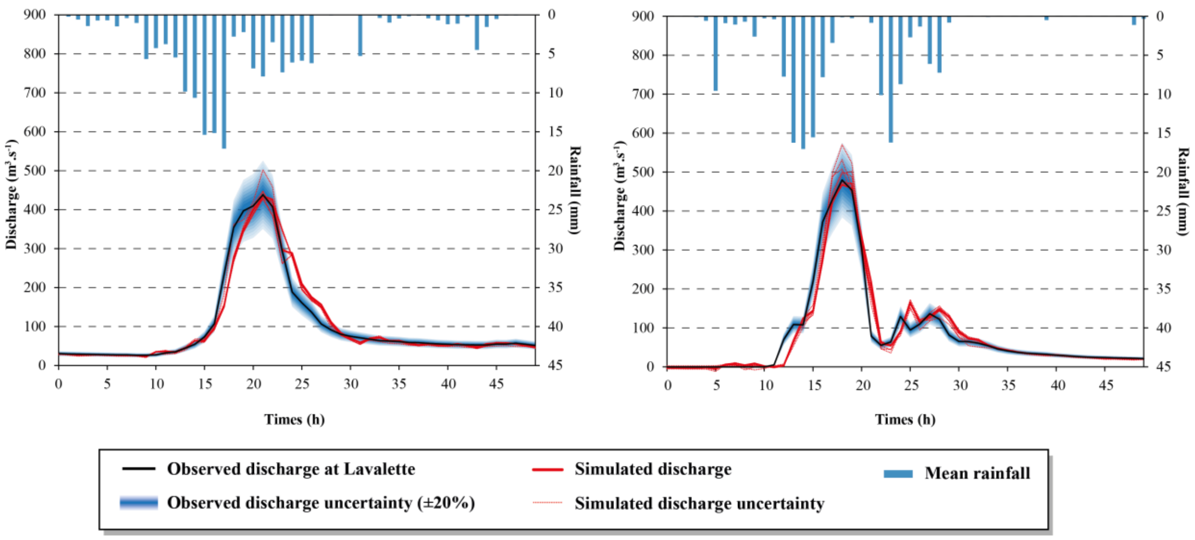


Fig 4. Hydrographs of major events in the database: events 7 and 8. Simulated discharge is the median of outputs coming from the 50 run models (differing by their initialization parameters). Uncertainty on the observed value is the measurement ±20 %. Uncertainty on the simulated value is represented by simulations coming from the 50 run models (differing by their parameters initialization).

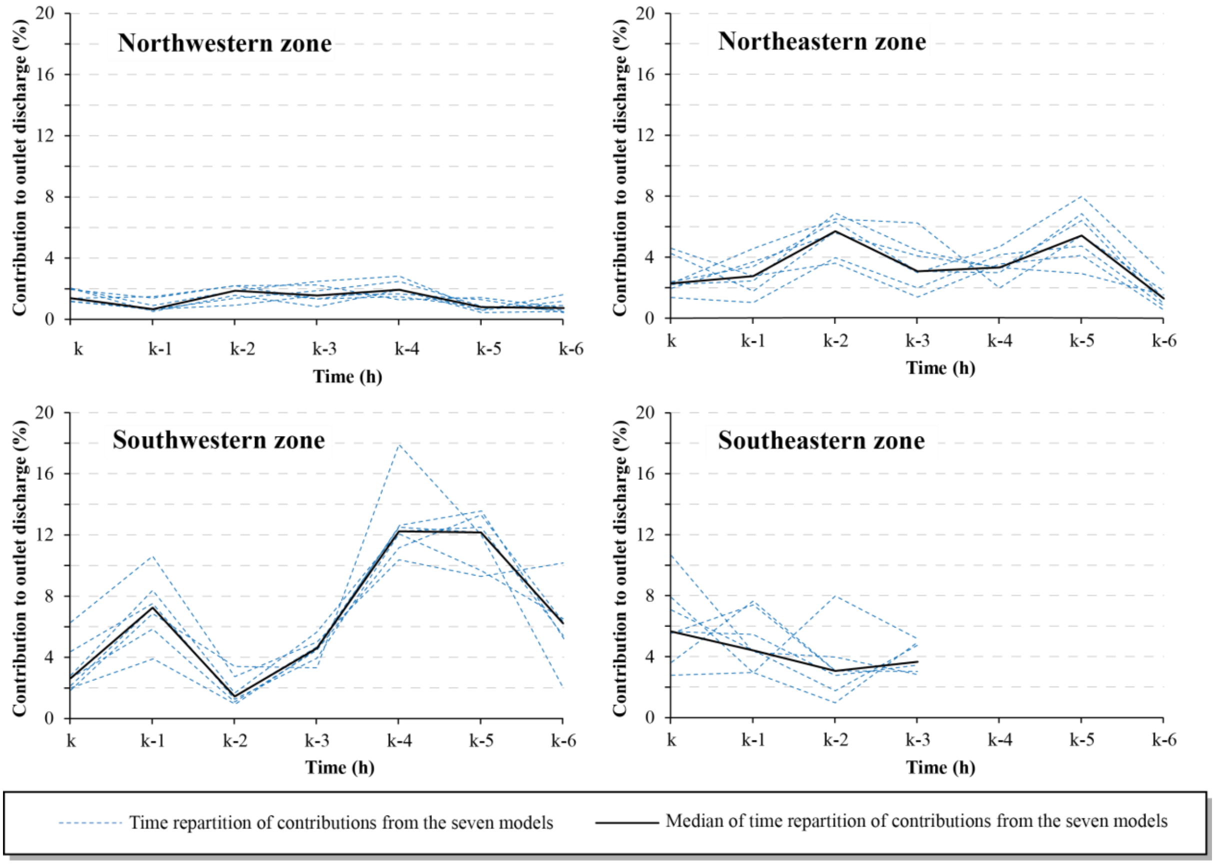


Figure 5. Median and total spread of time distributions of North-western, North-eastern, South-western and South-eastern rainfall inputs contributions calculated from parameters of the 7 designed models

18) In section 4.3 the nature of the KnoX method becomes clearer, along with what the authors meant by 'parameters' earlier in the paper (they are the network weights). Knox is revealed as a method for determining the influence of each input, on the output, at each time step, based upon chaining of the network weights. The use of network weights to explore and quantify the contributions of different inputs is not particularly new. Work by Olden and Jackson (2002) and Kingston et al., (2003, 2006) (which has not been cited) is highly relevant because they did something rather similar. How does KnoX differ from this?

KnoX differs from these methods in several ways: (1) the first step is to **constrain the model** using the "postulated model" established from hydrogeological knowledge. This step **diminishes the number** of parameters and excludes the ones physically impossible. The postulated model **guides the simulation model towards the physical solution** and diminishes the equifinality. Thus the box is no longer totally "black". This proposition is different from the proposition investigated in papers proposed by the reviewer (*Olden and Jackson, 2002; Kingston et al.*) because the constraints are not imposed at the level of the parameters (for example make the parameter linking the evapotranspiration to the hidden neurons positive), but at the level of processes in the case of this paper. Using the block diagram of the postulated model, one says that some processes are possible; others are not. (2) The method takes the median of absolute value of each parameter for 50 different initializations in order to be **independent from one specific initialization**. The sign of the parameter is not important as the product of two negative parameters is positive in the chain of parameters product; for this reason and in order to take profit of the "black box" capabilities of ANN, we didn't want to constrain parameters. (3) Thanks to the postulated model it is possible to **extract temporal information** (Fig. 5) and not only variable contributions. This point is fundamental and allows in the present paper to **characterize the hydrological processes**. (4) KnoX method was validated on a fictitious nonlinear aquifer using actual rainfall data.

These elements are described in detail in the previous paper (Kong-A-Siou, 2013). As it contains 32 pages in Journal of Hydrology, it is not possible to re-write it in the present paper. Nevertheless it is necessary to be red in order to fully understand the contribution of the present work.

The papers of Jackson (2002) and Kingston (2006) present a method which computes a chained product of weights, so called "Connection Weight Approach", this approach was not novel in 2002 and this was not a problem, because other interesting works were done thanks to this CWA. It is the case of KnoX method which proposes a way to smartly perform "pruning" and deterministic knowledge extraction. It can be noted that the CWA approach used in KnoX method was inspired by Yacoub and Bennani, 1997, cited in the previous paper (Kong-A-Siou, 2013).

Nevertheless we would be very interested if we can have another reference about a method able to indicate, for example that there is 3 hours delay between underground flood and surface flood, without measurement of each kind of flood. KnoX provided this information in the present paper.

These considerations are added in section 2.2.

19) Similarly, the quantification of the partial derivatives of MLPs (Mount et al., 2013 and Dawson et al., 2014 - see earlier citations in this report) are arguably more comprehensive methods for understanding the strength and pattern of influence of model inputs on the output response of an ANN. Again, why is KnoX a preferable method?

The response was provided above. Even if cited methods seem more accurate than KnoX to analyze the information provided by each parameter (KnoX only calculates the median). It seems to us that they haven't extracted temporal information on a so complex model (26 input variables highly correlated because they are time-shifted rainfall values, and 5 hidden non-linear neurons).

Moreover the goal is not only to address the importance of input, but also the dynamic of the addressed process thanks to the postulated model.

20) The discussion is simply a summary of the findings of the modelling. This section needs further development to contextualise the KnoX method, its value in hydrological modelling and how it contributes to the range of knowledge extraction methods that have been applied in ANN modelling (see my earlier comments). Moreover, it would be helpful for the readership of HESS to have the contribution of this paper more clearly explained. To help with this, the authors might like to refer to Abrahart et al (2012) (Two decades of anarchy?, Progress in Phys Geog, 36(4), 480) to position their work within the framework set out therein.

Well, we are happy to note that one of the references cited in our paper is also appreciate by the referee. Clearly the contribution is related to the theme 7: "physical interpretation" as it proposes an integrated and simple method to constrain to network (at the level of the whole architecture), and interpret the parameters to extract physical information. Consequently, the discussion has been implemented.

Thank you one more time for the accurate reading of the paper.

Revision notes on "Identification of spatial and temporal contributions of rainfalls to flash floods using neural network modelling: case study on the Lez Basin (Southern France)" by T. Darras et al.

Anonymous Referee #2, Received and published: 11 May 2015

First, authors want to thank the anonymous reviewer #2 for his (her) efforts to understand the paper and his (her) propositions to improve the readability and understandability of the paper. Comments of the reviewer are recalled in the following and the response of author is identified as "response" in blue ; modifications provided on the manuscript are written in red..

General comment: This paper applies KnoX methodology to extracting knowledge from a neural network model to better determine the contributions and time responses of several geographic zones of an aquifer. It is very interesting to read and learn how ANNs can be used to extract the geographical knowledge. The introduction section is nicely rewritten, which is interesting to read, while the remaining parts are difficult to follow and/or easy to lose the points. I do not see a solid conclusion about the extraction of knowledge from ANNs, instead the knowledge and/or inferences presented in the discussion section are mainly based on the authors' geographical senses, not on ANNs. To increase the readability of this manuscript, I make a number of comments and/or suggestion for your consideration.

Response to general comment: One difficulty that was also stressed by the reviewer 1 is that the KnoX method and its validation were not sufficiently explained. This was a choice of the team of authors for 2 reasons: first the detailed explanation was provided in a previous paper (2013). This previous paper also addressed the validation of the method, using a fictitious aquifer with known contributions and known time responses. KnoX method was applied to found the contributions and times responses of this fictitious aquifer; after that, comparisons were done between extracted and known values of the fictitious aquifer. Results were perfect for time response, and jugged acceptable for contributions. Second, this previous paper was very long and it seems better to rewrite it as little as possible. Of course this choice can be discussed.

1. In Section 2 Artificial neural network 9modeling for better characterize processes: (1) There are many kinds of ANNs. It is suggested to mention what kind (type) of ANNs is used in the very beginning (Sec. 2.1) before going into details. (2) A brief presentation of the Knox method and why and how to implement the Knox method in this study should be provided.

Modifications done in the paper P4-5.

Response to comment 1. OK for the propositions. We will also add the equation implemented by the multilayer perceptron in order to make the description of KnoX method more understandable (as underlined by the reviewer 1).

Modification done in the paper P4L27-29-P5L4.

2. In Section 4.1 From postulated model to neural network model: (1) The purpose (reason, logic) of this section should be given. (2) It will be of help to clearly present "The postulated model". (3) What is the point of "Application of the KnoX method would provide this quantification"? Why and how?

Response to comment 2. The postulated model is a conceptual model of how the watershed physically works. It is a block diagram representing the watershed behaviour. It can be drawn only if one has a "high level" idea of this behaviour. Regarding the Lez aquifer, the postulated model was built based on geology. 3 hydrogeological compartments were identified in previous works (during seventies), and a separation was operated on the east compartment regarding the ground properties (impervious or not impervious). This postulated model was indicated in grey boxes in Fig. 3. Starting from the postulated model, it is necessary to implement each box using neural networks. Also in order to make the simulation model better we added a state variable, which consisted in the values of the discharge at previous time step.

Modification done in the paper in section 2.2; and in P12L14-17.

3. Figure 3 is crucial but difficult to follow (also not clear). For instance, what is the "elements used in Eq.4 and 5"? A more detailed description of the corresponding method and process would be helpful.

Response to comment 3. We are sorry if the Figures appear badly in the paper. Original files in png were good. It is possible to access to good figures through the printer-friendly version, and after a zoom of the figures. Elements used in eq. 4 et 5. are the parameters whose notations appeared in eq.4 and eq5. In a scientific paper, when previous works were published, it is always difficult to estimate what have to be re-explained or not. Maybe this point will be more understandable with a readable figure. Please note that figures in good quality are also posted in the response to reviewer 1.

We hope that figures will appear in good quality in the final paper.

4. Model selection is done using cross-validation and a predefined number of training iterations. A more detailed description of cross-validation and the number of iterations should be given.

Response to comment 4. The same problem than previously applies to the description of cross validation. If one wants the paper to be auto-sufficient it must be presented. If one thinks that this method is well known and reference provided, it must not be. Our preference is to not re-write it but we can synthetize it in few sentences.

The process is presented more accurately P6L3-15 and the number of iteration is provided (12).

5. What does the "window-width" mean? Where is the number of hidden neurons? Is there anything to do with the "Optimisation" of the rainfall temporal window widths?

Response to comment 5. Window width refers to the number of delayed rainfall data that are applied to the model. They will be presented at the beginning of the paper with the presentation of the multilayer perceptron. The number of hidden neurons was 5; it was provided in Table 3.

Presentation done with the equation of the multilayer perceptron P4-5.

6. The symbol of variable (for instance, rz(k -d)) in Equation 4 is difficult to learn (read). It is suggested to re-design the symbol and formulation!

Response to comment 6. Sorry, we don't understand as the symbol seems readable in eq 4. But it was not readable in the Fig.3 (please, see response to question 3).

We hope that figures will appear in good quality in the final paper.

7. Page 3697: "The contribution of the previous measured discharges used as input to the model ranges from 21 to 30% (respectively 89 to 70% for total rainfall) depending on the considered model Tn (n = 1, 7). Nevertheless, only rainfall contribution values are considered (for a total of 100 %) because the measured input of discharge plays the role of state variable (Artigue et al., 2012)." How to verify those results?

Response to comment 7. In another life we experienced the design of automatic control schemes using neural networks. In automatic control, it is currently accepted that the values of the targeted variable (the output, here the discharge) can be applied as input at previous times to provide an idea about the state of the system. This is understandable by the simple following reasoning: if the model has the measured value of discharge at time k-1 as input in order to estimate the discharge at time k, it has the information about the level of the flood: schematically high level or low level. If 2 values of discharge are applied at inputs, the models can deduce the slope of the discharge curve and thus it knows if the discharge is increasing or decreasing. If 3 values are applied, the model can deduce the second derivative (acceleration), etc … the set of values of discharge, slope of discharge and second derivative is considered as a "state vector". In Artigue 2012, we showed that the feed-forward model (designed with previous values of discharge as inputs) was very good (this is well known). When designing the recurrent model without measured discharge but estimated discharge as input, this state vector was lacking (estimation of the state vector is not good), thus we had to replace it by another value. To this end we applied the cumulative rainfall from the beginning of the event and this information allows the model to be better. We can consider that the cumulative rainfall provides an information about the level of humidity of the basin: a state information.

Our experience with KnoX method showed us that the purely recurrent model wasn't efficient to simulate the behaviour of the basin; thus knowledge extraction has no interest. But the feed-forward model fed by previous observed discharge is efficient, knowledge can thus be extracted.

8) Section 4.4 Time distribution of contributions: (1) Line 5 on Page 3698: "Figure 4 shows the time distributions ... ,", should it be Figure 5?

Response to comment 8. Yes, sorry. Thank you for the scrupulous reading.

Correction done.

9. Figure 5 displays the Median and total spread of time distributions of North-western, North-eastern, Southwestern and South-eastern rainfall inputs contributions calculated from parameters of the 7 designed models. The fluctuations of North-western and North-eastern parts seem small and flat. How to tell (prove) the difference?!

Response to comment 9. We are not sure to well understand the comment. For us only the contributions of inputs for North-western are small and flat. For North-eastern zone one can see 2 "peaks" (at k-2 and k-5). Each contribution is not very high, but considering the whole zone, the contribution of zone NE reaches 26% (Table 5) thus 3 times the contribution of NW zone.

10. This contribution calculus of Equation 5 is done for each exogenous input: rainfall or measured discharge, and for each designed model. However, in the Conclusion Section, I do not see "Moreover efficient new approaches were demonstrated to extract information from a set of parameters" and "Among these methods, the KnoX method can identify contributions from various geographic zones to discharge at the basin outlet". More to address?

Response to comment 10. We are sorry, but we are not sure to understand the question. We think that the proposition of a method able to address processes characterization in complex hydrosystem is very new and very promising for new research; maybe is it sufficient?

Identification of spatial and temporal contributions of rainfalls to flash floods using neural network modelling: case study on the *Lez* Basin (Southern France)

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Mis en forme : Lien hype1, Couleur de police : Texte 1

Mis en forme : Couleur de police : Texte 1

Abstract

Flash floods pose significant hazards in urbanised zones and have important human and financial implications in both the present and future due to the likelihood that global climate change will exacerbate their consequences. It is thus of crucial importance to better model these phenomena especially when they occur in heterogeneous and karst basins where they are difficult to describe physically. Toward this goal, this paper applies a recent methodology (KnoX methodology) dedicated to extracting knowledge from a neural network model to better determine the contributions and time responses of several well-identified geographic zones of an aquifer. To assess the interest of this methodology, a case study was conducted in Southern France: the *Lez* hydrosystem whose river crosses the conurbation of Montpellier (400,000 inhabitants). Rainfall contributions and time transfers were estimated and analysed in four geologically-delimited zones to estimate the sensitivity of flash floods to water coming from the surface or karst. The *Causse de ~~Viol~~Viols-le-Fort* is shown to be the main contributor to flash floods and the delay between surface and underground flooding is estimated to be three hours. This study will thus help operational flood warning services to better ~~characterise~~characterize critical rainfall and develop measurements to design efficient flood forecasting models. This generic method can be applied to any basin with sufficient rainfall-runoff measurements.

1 Introduction

Flash floods are rapid (they rise in a few hours) and intense floods that occur within small basins. Our current lack of understanding of these floods constitutes a great societal challenge because of their socioeconomic and environmental impacts (Gaume and Bouvier, 2004; Llasat et al., 2010). Over the past 20 years, flash flooding in southeastern France has caused more than 100 fatalities and several billion euros in property damage. In karst basins, the event of June 2010, in the *Var* (southern France) caused 27 casualties and more than one billion euros of damages. Early warning is also a priority (Borga et al., 2011; Price et al., 2011) that could be improved by using forecast models. In recent decades, considerable efforts have been devoted to improving our understanding and forecasting of flash flooding (Gaume et al., 2009; Marchi et al., 2010). In the literature three aspects were investigated: (*i*) the rain event (or other cause of rising water), (*ii*) runoff genesis, and (*iii*) surface and underground geomorphologic and geologic settings that channel the water transfer toward the outlet.

Code de champ modifié

Mediterranean rain events often occur at the meso-scale (Rivrain, 1997) and generate intense localised rainfall. For this reason, Le Lay and Saulnier, (2007), Cosandey and Robinson, (2000) Tramblay et al. (2010) show that flash flood generation is controlled by spatial and temporal variability of rainfall and initial soil moisture conditions. Moreover, sensitivity to rainfall heterogeneity is elevated in small watersheds, which are locations of flash flooding (Krajewski et al., 1991) (Corradini and Singh, 1985) (Raynaud et al., 2015). The hydrodynamic behaviour of hydrosystems subject to intense rain events depends on soil moisture as well as geology, tectonics, and land use (Anctil et al., 2008; Nikolopoulos et al., 2011). Moisture content estimation at the watershed scale has proven beneficial for discharge prediction (Kitanidis and Bras, 1980; Parajka et al., 2006; Wooldridge et al., 2003). Nevertheless, soil moisture measurements are highly dependent on field measurement techniques; they provide relative spatial and temporal distributions (Katul et al., 2007; Lauzon et al., 2004) rather than absolute values.

~~In karst systems, underground water obviously plays a significant role in flooding (Bailly-Comte et al., 2009, 2012; Fleury et al., 2013). Nevertheless, karst systems are intrinsically heterogeneous and their hydrodynamic behaviour generally differs from one system to another (Bakalowicz, 2005). However even if the contribution of karst groundwater to flash flooding is assumed to be negligible because of its longer response time (Borga et al., 2007; Norbiato et al., 2008), other studies emphasize the considerable contribution of groundwater to flash flooding (Bailly-Comte et al., 2012). Faced with the question of the role of karst~~

~~groundwater in flash flooding, this study investigates a method for estimating spatialized contributions from different parts of a heterogeneous aquifer.~~

~~Because of the lack of knowledge regarding the various hydrodynamic behaviours involved in karst systems, a generic blackbox~~In karst systems, underground water obviously plays a significant role in flooding (Bailly-Comte et al., 2009, 2012; Fleury et al., 2013). Nevertheless, karst systems are intrinsically heterogeneous and their hydrodynamic behaviour generally differs from one system to another (Bakalowicz, 2005). However even if the contribution of karst groundwater to flash flooding is assumed to be negligible because of its longer response time (Borga et al., 2007; Norbiato et al., 2008), other studies emphasize the considerable contribution of groundwater to flash flooding (Bailly-Comte et al., 2012). Faced with the question of the role of karst groundwater in flash flooding, this study investigates a method for estimating spatialized contributions from different parts of a heterogeneous aquifer.

Because of the lack of knowledge regarding the various hydrodynamic behaviours involved in karst systems, a generic black box method seems to be adequate. For this reason, neural network modelling seems to be a relevant method (Kong-A-Siou et al., 2011; Kong-A-Siou et al., 2014; Kurtulus and Razack, 2007). For this purpose, in recent decades, the multilayer perceptron has been increasingly used in the field of hydrology (Maier and Dandy, 2000; Toth, 2011). These models have been effective in identifying the rainfall-runoff relationship (Hsu et al., 1995). Their ability to forecast flash floods (Toukourou et al., 2011; Artigue et al., 2012) and model karst system behaviour have also been demonstrated (Kong-A-Siou et al., 2011). To model hydrosystem behaviour efficiently, neural networks need relevant datasets as input and output variables, and rigorous application of regularisation methods (Abrahart and See, 2007; Bowden et al., 2005; Fernando et al., 2009). Rainfall data are obvious inputs; in addition (Anctil et al., 2008) demonstrated that soil-moisture content observations improve prediction performance. Even so, selection of relevant variables to represent moisture content is a difficult task (Darras et al., 2014a). Data quantity and quality are the major limiting factors in the application of neural networks to hydrological modelling (Pereira Filho and Santos, 2006). Because of noisy data, neural networks used to model natural phenomena are sensitive to ~~overtraining~~overfitting; the use of regularization methods to deal with the bias-variance trade-off is thus mandatory (cf. Sect. 3.1.2). Kong-A-Siou et al. (2014) compared neural network models and VENSIM software to simulate flooding or drought; they concluded that neural modelling performed better for extreme events whereas VENSIM worked better for intermediate, more complex events. This statistical approach has been used to propose some interesting hydrological models. Artigue (2012) has proposed a combination of linear and non-linear modelling in the same model. ~~Corzo and Solomatine (2007)~~Corzo and Solomatine (2007) have proposed a combination of specialised neural network to represent isolated processes involved in flood genesis. These methods provided efficient forecasts on rapid hydrodynamic watersheds. Moreover, recent advances have proven that the use of these statistical tools can improve the currently-available knowledge of a system. Based on these recent scientific findings, the *Knowledge eXtraction* (KnoX) methodology was developed to describe contributions and time transfers of spatialized rainfall in any basin. This paper thus proposes to apply this methodology to better apprehend both surface and groundwater processes at the origin of flash flooding in a karst basin. To this end, we focus on the *Lez* karst hydrosystem which feeds the *Lez* River that flows through the conurbation of Montpellier (Southern France) with a population of 400 000. Because of its meteorological and geomorphological setting, the *Lez* River at the *Lavalette* station, located at the entrance to the city of *Montpellier* is the site of flash flooding. In addition, as a karst system, the geomorphological structure of the *Lez* aquifer is strongly heterogeneous, leading to anisotropic water circulation and highly nonlinear hydrodynamic behaviour. Flow rate at *Lavalette* station includes contributions from perennial karst springs (the most important is *Lez* spring), temporary karst springs (*Lirou* spring can be stronger than *Lez* spring), diffuse karst arrivals and also run-off.

The scientific challenge of this study is thus to apply neural networks to better quantify processes operating in flash flooding. For this purpose, after introduction, Sect. 2 presents a discussion of neural network modelling and the KnoX method. Section 3 is a description of the study area. Section 4 presents the application of the KnoX method to the study area and estimate of contributions and time transfers of spatialized rainfalls to discharge at *Lavalette*. Sect. 5 discusses the results and exposes operational and scientific implications. In the conclusion section we discuss innovative perspectives of this generic methodology.

2 Artificial neural network modelling for better characterize processes

2.1 Neural network design

2.1.1 General presentation

Artificial neural networks are statistical black box models that use input-output measurements to identify nonlinear functions of a system. Basics about neural modelling can be found in ~~(Dreyfus, 2005), only specific information, mandatory for a comprehensive presentation of~~

~~this study will be provided hereafter. The chosen model is the multilayer perceptron because of its properties of universal approximation and parsimony (Barron, 1993). The universal approximation is the capability to approximate any differentiable and continuous function with an arbitrary degree of accuracy (Hornik et al., 1989). In our study, the multilayer perceptron is a feed-forward model, a finite impulse response model based on (Nerrand et al., 1993). Designing a multilayer perceptron consists mainly of selecting input variables and the number of hidden neurons. This determines the number of parameters mechanically; model complexity increases with the number of parameters.~~(Dreyfus, 2005), only specific information, mandatory for a comprehensive presentation of this study will be provided hereafter. The chosen model is the multilayer perceptron because of its properties of universal approximation and parsimony (Barron, 1993). The universal approximation is the capability to approximate any differentiable and continuous function with an arbitrary degree of accuracy (Hornik et al., 1989). In our study, the multilayer perceptron is a feed-forward model, a finite impulse response model based on (Nerrand et al., 1993). Designing a multilayer perceptron consists mainly of selecting input variables and the number of hidden neurons. This determines the number of parameters mechanically; model complexity increases with the number of parameters. The general equation of the function calculated by the feed-forward multilayer perceptron is the following:

$$y^k = g_{NN}(y_p^{k-1}, \ldots, y_p^{k-1}, u^k, \ldots, u^k, \mathbf{C}), \qquad (1)$$

where the estimated value of the output at the discrete time k is y^k, the observed value of this variable is y_p^k, the input vector is $\mathbf{u}^k$, the nonlinear function implemented by the neural network is g_{NN}; w_u and w_y are the width of windows used to apply the input time-series, they are linked to the length of the vectors $\mathbf{u}$ and $\mathbf{y}_p$; $\mathbf{C}$ is the matrix of parameters of the model, also called "weights".

As statistical models, neural networks are designed in relation to a database. This database is usually divided into three sets: a training set, a stop set, and a test set. The training set is used to calculate parameters through a training procedure that minimizes the mean quadratic error calculated on output neurons. The training is stopped by the stop set (cf. Sect. 2.1.2), and model quality is estimated by the third part of the database: the test set, which is separate from the training and stopping sets. The model's ability to be efficient on the test set is called generalisation. However, the training error is not an efficient estimator of the generalisation error: the efficiency of the training algorithm makes the model specific to the training set. This specialisation of the neural network on the training set is called ~~overtraining. Overtraining~~overfitting. Overfitting is exacerbated by large errors and uncertainties in field measurements; the model learns the specific realization of noise in the training set. This major issue of neural network modelling is called bias-variance trade-off (Geman et al., ~~1992); Kong-A-Siou et al., (2012) studied it in relation to karst aquifers. To deal with this issue and improve the generalization performance, regularisation methods must be employed (Kong A Siou et al., 2011; Schoups et al., 2008). Three~~1992). Usually regularization methods are used to avoid overfitting; to this end, two regularisation methods were used in this study.

~~2.1.2 Regularisation methods~~

~~In the context of this study, the goal of regularisation methods is to minimize output variance. To this end, cross-validation (Stone, 1974) was used as explained in (Kong-A-Siou et al., 2012) to empirically select input variables and the number of hidden neurons. Cross validation thus minimizes model complexity and therefore output variance.~~

2.1.2 ~~Another regularization method is commonly employed: early-stopping (Sjöberg et al., 1995).~~Regularisation methods

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Another regularization method is commonly employed: early-stopping (Sjöberg et al., 1995).. This method stops training before overtraining occurs. A dedicated set, called a stop-set, is considered separately from the database. ~~In (Kong-A-Siou et al., 2012), early-stopping was used with cross validation for input variables and hidden neuron number sizing. In our study, the database is too limited to extract another set from the database (the stop set). Thus, instead of a stop-set, a predefined maximum number of training iterations was selected to avoid overtraining. For this purpose~~

Working also on the *Lez* aquifer but considering only underground water at the *Lez* spring, Kong-A-Siou et al., (2011) applied multilayer perceptron to perform forecast at *Lez* spring and validated cross validation as a useful method to select the complexity of the model. Moreover, Kong-A-Siou et al., (2012) for the same basin, focused on regularization methods (early stopping and weight decay). They conclude that early stopping used in conjunction with cross validation was efficient.

Nevertheless these results, obtained with 16 years daily database can't be applied directly in the present study because the flash flood database is too limited to extract definitively another set from the database (the stop set). Thus, to apply early stopping without stop-set, a predefined maximum number of training iterations was selected to stop training before the complete convergence and, by this way, avoid overtraining. Nevertheless, for this purpose, the selection of the optimal number of training iterations is done using a stop set. Then afterwards, model is run without stop set using this predefined optimal number of training iterations. In the first stage, the database, not including the test set, was divided into *S* subsets corresponding to flash flood events. Training was performed on *S*-1 subsets with 50 different parameters initialisations. The remaining subset was used as a ~~validation~~ stop set. Each subset was used in turn as a ~~validation~~stop set. For each trial the training iteration with the minimum mean quadratic error over the ~~validation~~stop set is set aside. The median of these numbers of iterations was calculated for all ~~validation~~stop sets and all ~~iterations~~initialisations and selected as the optimal number of training iterations. ~~This maximum~~In a second stage, this optimal number of training iteration: 12 iterations is used in all the following without further utilization of stop-set.

In this study, parameters are iteratively calculated using the Levenberg-Marquardt algorithm (Hagan and Menhaj, 1994).

It is well known also that model performance depends strongly on the parameters initialisation. To define a reliable simulation independent from the initialisation, (Darras et al., 2014b) proposed to establish an ensemble of 50 models trained from different initialisations. The output is calculated at each time step by the median of the 50 outputs. It is well known that this method can smooth the output of the model; nevertheless this is not a drawback in this study as this method improves the robustness of the model, which is very important to extract information.

2.2 Towards knowledge improvement about processes

Even if neural networks generally implement black-box models, several authors have tried to make the model more understandable. For example (Johannet et al., 2008) and ~~(Jain and Kumar, 2009)~~(Jain and Kumar, 2009) demonstrated the possibility of observing physically interpretable information at the output of hidden neurons. Another path would be to exploit parameters values. ~~The~~Several works were done to constrain the model using physical knowledge at the level of the parameter for example to select the best input set, or to select the more physically-plausible model (for example the parameters linked to the evapotranspiration input must be positive) (Olden and Jackson, 2002; Kingston et al., 2006). Considering individual parameter value, another goal would be to assess that the neural network model truly performed physical relation (Mount et al., 2013).

Focusing on parameters, the principal difficulty is the sensitivity of ~~parameters~~their values to ~~their~~the initialisation before training. This dependence can be avoided using statistical treatments as proposed by (Kingston et al., 2006). ~~(Kong-A-Siou et al., 2013) using a multistep procedure~~Kong-A-Siou et al., (2013) used a multistep procedure to extract knowlege: (*i*) proposal of a postulated model that describes the available high-level knowledge about the behaviour of the system to be modelled, (*ii*) implement a neural model architecture that follows this postulated model~~,~~: each box of this diagram is implemented using a multilayer perceptron (or a unique linear neuron), (*iii*) train an ensemble of identical models that differ by their initialisation, and calculate ~~of~~ the median of the absolute value of each parameter over the ensemble models (noted as median-parameter), (*iv*) combine median parameters ~~to quantify the importance of each input variable. Kong-A-Siou et al. (2013) applied this method to a karst aquifer to evaluate the~~in a chain of causality to quantify the role of each input variable. Compared to other works that calculate a similar parameters chain-based calculation, and looked at constrains at the level of parameters or inputs (Kingston et al., 2006), this method is original because it applies constrains at the level of processes identified in the block diagram (postulated model). Using the block diagram of the postulated model indicates that some processes are possible; others are not. It allows thus diminishing the number of parameters, and by this way, the complexity of the model, and the multifinality of parameters value. The sign of the parameter is not important as the product of two negative parameters is positive in the chain of parameters product; for this reason and in order to take profit of the “black box” capabilities of ANN, we don’t want to constrain individual parameters. Kong-A-Siou et al. (2013) applied this method to the *Lez* karst aquifer to evaluate the groundwater contributions from different geographic zones to the discharge at the outlet. This methodology is called: Knowledge eXtraction (KnoX). Its accuracy was assessed on a fictitious model, whose processes were perfectly known, before being applied to a real aquifer.

~~In this study we propose to apply the KnoX method to estimate the contributions of different processes, effective in a heterogeneous aquifer, to flash floods. Regarding the *Lez* basin, we~~

~~thus~~In this study we propose to apply the KnoX method to quantify spatially and temporally the effect of different processes, effective in a heterogeneous aquifer, to flash floods. The considered gauge station is *Lavalette* at the entrance of *Montpellier*, the time step is the hour. Regarding the case study on the *Lez* basin, it is very different from the work made by (Kong-A-Siou et al., 2013), as in the present study we considered flash flooding at *Lavalette* (maximum discharge equal to 480 m^3/s) having an important surface water contribution; whereas the previous work investigated daily runoff of underground water at the *Lez* spring (maximum discharge inferior to 20 m^3/s). In the present study we investigate improvement of knowledge about karst and non-karst (surface) flooding processes.

2.3 Performance criteria

Several criteria were used to model selection and performance assessment. The first is the Nash-Sutcliffe efficiency, hereafter referred to as R^2 (Nash and Sutcliffe, 1970). R^2 is used to perform model selection using cross-validation. The second is specifically flood-oriented: the synchronous percentage of peak discharge, or S_{PPD}. The last, a purely temporal aspect, is the delay between measured and simulated flood peak, hereafter referred to as P_d (Peak delay).

2.3.1 Nash-Sutcliffe efficiency

The Nash-Sutcliffe efficiency is the most widely used criterion for evaluating hydrological models. It is equivalent to the R^2 determination coefficient *i.e.*:

$$R^2 = 1 - \frac{\sum_{k=1}^{n}(y_p^k - y^k)^2}{\sum_{k=1}^{n}(y_p^k - \overline{y^k})^2}, \qquad (\cancel{1}2)$$

where k is discrete time, n the number of time steps used to calculate R^2, y the simulated discharge, y_p the measured discharge, and $\overline{y_p}$ is the measured mean discharge. The Nash score is not really convenient for assessing flood simulations as it takes into account errors on the whole event and not specifically on the peak. For this reason, other criteria were proposed.

2.3.2 Synchronous percentage of peak discharge

Synchronous percentage of peak discharge is especially designed for the evaluation of flash flood modelling. It is the ratio of measured and simulated discharges at the time of the observed peak discharge:

$$S_{PPD} = 100\frac{y^{k_p^{max}}}{y_p^{k_p^{max}}}, \qquad (\cancel{2}3)$$

where k_p^{max} is the time of the measured peak discharge.

2.3.3 Delay between measured and simulated flood peaks

The delay between simulated and measured peak discharge is calculated using Eq. (~~3~~4). A positive delay means a retarded simulated peak discharge. Conversely, a negative lag means advanced simulated peak discharge. The peak delay can be expressed as:

$$P_d = k^{max} - k_p^{max}, \qquad (~~3~~4)$$

where k^{max} is the time of the simulated peak discharge.

3 Case study: The *Lez* aquifer

3.1 Lez hydrosystem

The *Lez* aquifer is a Mediterranean karst system located in southeastern France upstream of *Montpellier* (Fig. 1). Its extent is estimated at about 380 km^2 (Bérard, 1983). The *Lez* spring is the main outlet of this aquifer, hereafter referred to as the "basin". Another major spring is the *Lirou* Spring, which flows only during rain events. Both springs feed the *Lez* River, which crosses *Montpellier* and its conurbation, an area with population of about 400 000. The recharge area, composed of karst outcrops and swallow holes, is estimated at about 130 km^2 (Dörfliger et al., 2008). The surface catchment, an area of about 120 km^2 hereafter referred to as the "watershed", is defined by its topographic setting at the outlet of *Lavalette* gauging station. As often with karst systems, geographical areas of the watershed and the underground basin are not superposed. Due to complex geology, the recharge area extends to only a part of the watershed and underground basin. For this reason, the *Lez* aquifer is considered to be a hydrosystem.

3.2 Geological and tectonic settings

Similar to many karst systems, the *Lez* hydrosystem is composed of karst and non-karst components. The karst component crops out in the upstream part of the system; it underlies impervious formations in the downstream part. The karst component consists of Cretaceous and Jurassic carbonate rocks. The karst in these formations developed under the current Mediterranean Sea level as a result of the Messinian crisis (Hsü et al., 1973). These formations also crop out widely and form the calcareous plateaus of both the *Causse de ~~Hortus~~l'Hortus* and the *Causse de Viols-le-Fort*. The downstream part of the system is composed of Eocene carbonate and clay formations and Tertiary sandstone and conglomerate formations.

Two major tectonic events have affected the geomorphological structure of the *Lez* hydrosystem. The first was Pyrenean compression, which occurred during the Eocene. This south-north compression led to the formation of east-west trending faults. The second tectonic event was the opening of the *Lion* Gulf during the Oligocene. This event led to the formation of northeast-southwest sinistral faults, including the *Corconne* fault that crosses the *Lez* basin.

3.3 Meteorological and hydrogeological setting

The study area is subject to a Mediterranean climate. Mediterranean events often occur at the meso-scale and promote intense and localized rainfall. Daily rainfalls can reach 650 mm, such as one event that occurred in September 2002 in south-eastern France. Such high-volume rainfall events are referred to as Mediterranean episodes.

3.4 Hydrodynamic circulation

Kong-A-Siou et al. (~~2013b~~2013) divided the *Lez* basin into four parts (Fig. 2) to better analyse the rainfall-runoff relationship at the *Lez* Spring at a daily time step. The east-west division is based on the *Corconne* Fault pathway. On the western side of the basin, the south-north division is based on the *Causse de Viols-le-Fort* boundary, which is a cropping part of the principal aquifer. On the eastern side of the basin, a south-north division has been drawn based on its geological setting~~.~~ (impervious or non-impervious soils). The Oligocene and Eocene formations define a well-delineated impervious zone in the southeastern part of the basin. The geological composition of each zone is assumed to be “homogeneous”, which means that the geology within a zone is quite similar and that it differs more from the geology of other zones. Using the KnoX method, (Kong-A-Siou et al., ~~2013a~~2013) were able to estimate both the water contribution from each “homogeneous” geological zone to the *Lez* Spring discharge and the mean time-response. The last study, which was conducted at daily time step, shows the important contribution, more than half, of the northeastern zone to the discharge of the *Lez* Spring. These contributions are presented in Table 5.

3.5 Flash Flooding in the *Lez* basin

Fed by abundant rainfall on the basin~~,~~ (245 mm in few days), the *Lez* receives contributions from surface watershed and also from underground (karst) basin thanks principally to its tributary: the *Lirou* river. The *Lez* can exceed a discharge higher than 500 $m^3.s^{-1}$ at its entrance to Montpellier. This corresponds to a specific discharge greater than 4 $m^3.s^{-1}.km^{-2}$, based on the size of the surface watershed~~,~~ (120 km^2, see Sect. 3.1.), or 1.3 $m^3.s^{-1}.km^{-2}$ considering the whole underground basin~~.~~ (380 km^2, see section 3.1.). These two simple numbers highlight the need to better understand the origin of the water, and water circulations during flash floods at the *Lavalette* station at the entrance to Montpellier.

To this end, two different approaches have been proposed in the literature, using event-based modelling. The first uses data assimilation (Kalman filter) to: (*i*) estimate karst filling at the beginning of the event, (*ii*) adapt transfer velocity at each time step, and (*iii*) correct the lack of accuracy of rainfall measurement. Based on these improvements, R^2 of simulation increased from 0.89 to 0.91 for an event in December 2003, and from 0.72 to 0.98 for an event in September 2005 (~~cf~~ Table 1). The model is based on the Soil Conservation Service production function coupled with a lag and route transfer function (Coustau et al., 2012). The second approach has operational goals and proposes a graphical method (abacus) to estimate flood peaks from forecast rain features and karst filling (Fleury et al., 2013). Using Abacus, authors revised the estimated peak of the September 2005 event down to 460 $m^3.s^{-1}$ from 480 $m^3.s^{-1}$.

Thus, it appears that improved knowledge of karst/river interactions is critical. For this purpose, in the next section we propose to use the KnoX method to estimate the contribution of each zone of the *Lez* basin to flash flood events.

3.6 Database presentation and analysis

3.6.1 Monitoring network

Hourly rainfall data are available at five rain gauges: *Saint-Martin-de-Londres*, *Prades-le-Lez*, *Sommières*, *Vic-le-Fesq* and *Saint-Hippolyte-du-Fort*. The French Weather Forecasting Service (*Météo France)* manages the first two gauges, and the Flood Forecasting Service of the *Grand Delta* (SPCGD) manages the last three gauges. Only the *Prades-le-Lez* rain gauge is inside the *Lez* system, but as pointed out in introduction, it is essential to make use of spatialized rainfall information. In addition, no data at the considered time step is available further south than the *Prades-le-Lez* rain gauge. Spatial rainfall variability is thus not correctly described in the southern part of the basin. This will limit the reliability of this study regarding the southern zone of the basin. Unhopefully it is not convenient to use weather radar information in this basin because; due to the distance of the *Nîmes* radar (50 km), this information is not robust from one event to another and generally underestimate the rainfall value compared to the rain gauge measurements (Marchandise, 2007; Visserot, 2012); also radar information is not available for all events in the database. Discharge data are provided by the *Lavalette* gauging station managed by an office of the French ministry of ecology and sustainable development (DIREN). Both rainfall and discharge data are available at an hourly time step, which is convenient for flash flood modelling.

The data suffers from high noise and uncertainty. The uncertainties of discharge measurements have been estimated at around ± 20% for flash floods. The uncertainty of rainfall measurements, can be as high as ± ~~30~~10% to 20% (Marchandise, 2007). Rainfall and discharge time series are available from 2002 to 2008. Fifteen flood events whose peak discharges exceed 80 $m^3.s^{-1}$ were selected (Table 2). Events 7 and 8 were the most intense; contrary to other intense events, events 13 and 8 occurred on dry soils.

4 Application of the KnoX method to flash flooding at *Lavalette*

4.1 From postulated model to neural network model

As presented in Sect. 2.2, the postulated model represents the schematic high-level information one has about the basin of interest. This *a priori* knowledge must be expressed using a block diagram and each box of this diagram is implemented using a multilayer perceptron (or a unique linear neuron).

4.1.1 Postulated model

The~~As presented in Sect. 2.2, it was necessary to prepare a~~ postulated model describing flash flood genesis at *Lavalette* station~~. The postulated model~~ is based on the work of (~~Kong-A-Siou et al. 2013) as the considered basin is the same (surface + underground). The~~Kong-A-Siou et al. 2013) as the considered basin is the same (surface and underground). Remember that the primary difference is that flash floods are considered at hourly time step at the *Lavalette* station in this study. Using continuous data at daily time step at the *Lez* Spring, (Kong-A-Siou et al., 2013) showed that the north-eastern and north-western zones are the principal contributors to *Lez* spring discharge. To estimate the contributions of each zone to flooding at *Lavalette*, we distinguished the both behaviours: surface (rapid if inside the impervious watershed) and underground (slower if infiltrated into karst outcrops or in faults: faults play the role of a drain in impervious parts of the basin inside and outside of the *Lavalette* surface watershed). Schematically, by looking at the map presented in Fig. 2 and following the previous reasoning, one can propose that the north-western zone would make a minor contribution to flash flooding at *Lavalette* because it is outside the surface (topographic) basin and because its underground time response is ~~great~~high (Table 5). The south-eastern zone would also have a minor impact because its impervious area is mostly outside the *Lavalette* watershed. Regarding the south-western and north-eastern zones, it is difficult to propose an a priori quantification. It is thus not easy to estimate the principal contributors to flash flooding. Application of the KnoX method would provide this quantification. The postulated model of the basin behaviour is thus composed of four branches, each corresponding to a zone of the basin, involving surface and groundwater, and feeding a complex mixing process. The postulated model is represented in Fig. ~~3~~3 in grey block-diagram.

The model used to apply the KnoX method is based on the multilayer perceptron; it follows the postulated model represented in Fig. 3 with four zones contributing to discharge at *Lavalette* station. As suggested by the KnoX method, to be able to identify the contribution of each zone to the discharge, a linear hidden neuron is added between the inputs and the layer of sigmoid neurons. These neurons are intended to represent rain that falls on each zone; they facilitate the estimate of the time response of water falling in each zone.

4.1.2 Input data

Inputs are mean rainfalls for each zone. These rainfalls are calculated using the Thiessen polygon method. Table 2 shows the weight of each rain gauge for each zone. It highlights the sparse spatial distribution of rainfall information in the south of the basin. ~~Nevertheless~~Nevertheless, taking into account the importance of the stakes in this zone, and as the goal of this study is to better understand the behaviour of the basin in order to develop well suited monitoring strategy, we consider the rainfall information sufficient to carry out this study.

4.2 Model design

4.2.1 Model selection

As presented in Sect. 2.1.2, model selection is done using cross-validation and pre-definite number of training iterations. Ranges of investigation and chosen values of various window-width and hidden neurons numbers are provided in Table 3. One can note that the complexity of the model is moderate (small number of hidden neurons). To make the model assessment more reliable on the most intense events 7 and 8, model selection was done without these events (blind assessment).

4.2.2 Model validation

The database presented in Table 4 shows seven ~~rapid~~flash flood events. Because of the small number of events and their heterogeneity it seemed necessary ~~of estimating~~to estimate modelling quality on all events. We thus decided to train seven models, testing each on one event (training performed on the six following events). The model tested on event n is noted as T_n. This is a cross-test operation. Table 4 shows the performance of the seven models in terms of R^2, synchronous percentage of peak discharge (S_{PPD}), and peak delay (P_{d}). After training, we compared the quality of the models: aside from model T_2, R^2 and S_{PPD} scores of model T_{13} are the worst, respectively 0.71 and 138%. The other models show satisfactory R^2 and S_{PPD} scores: R^2 from 0.79 to 0.96 and S_{PPD} from 87% to 99%. Regarding the P_{d}, only model T_2 performed badly. The models T_4, T_7, $T_{8,}$ and T_{14} are efficient regarding the three performance criteria. Model T_{13} over-estimates the flood peak; note that event 13 is the sole event that occurred on dry soils, except event 8 when extremely intense rainfall was observed.

Looking at hydrographs presented in Fig. 4 for the two most intense events and taking into account the scores presented in Table 4, one can suggest that the models are efficient enough to be used for knowledge extraction. In addition, as it will be shown in Sect. 4.3.1, knowledge extraction is independent of outliers as it takes into account all events of the training database.

4.3 Contributions and time transfers of spatial rainfall to discharge at the *Lavalette* station

The KnoX method was used to estimate the contributions of the four previously defined zones to flash flooding at the *Lavalette* station.

4.3.1 Extraction of information from parameters

After training, the median of absolute values of the parameters for 50 different initializations is calculated. It is noted as ${}^{M}\left|C_{ij}\right|$for the parameter C_{ij} linking the neuron (or input) j to the neuron i. The rainfall contribution of zone z to output at time step k-d (k is the discrete time and d a delay) is denoted as $r_z(k\text{-}d)$. It is calculated according to the chain of parameters linking one input: $r_z(k-d)$, to the output $y(k)$. As it is shown in Fig. 3, we have three layers of parameters between the input $r_z(k-d)$ and the output $y(k)$, therefore there is three terms in numerator; denominator corresponds to normalization terms in order to estimate the specific contribution of the input $r_z(k-d)$ relative to the sum of all other parameters of the same layer. There is also three normalisation terms because there is three layers of parameters. Following notations are reported in red in Fig.3. The contribution is calculated as:

$$P\big(r_z(k-d)\big) = \frac{{}^{M}|c_{H_z r_d}|}{\sum_{d=0}^{w_z} {}^{M}|c_{H_z r_d}|} \sum_{H_N=1}^{N_c} \left[\frac{{}^{M}|c_{H_N H_z}|}{\sum_{H_z=1}^{l}\left({}^{M}|c_{H_N H_z}|\right) + \sum_{d=1}^{w_1-1}\left({}^{M}|c_{H_N q_d}|\right)} \frac{{}^{M}|c_{O H_N}|}{\sum_{H_N=1}^{n}\left({}^{M}|c_{O H_N}|\right)} \right] \quad (5)$$

where H_z (H_z=1, 4) is the subscript of the first hidden layer of linear neurons, H_N (H_N =1, N_c) is the subscript of the second hidden layer (of N_c nonlinear neurons); q_d is the subscript of the previously measured discharge inputs y_q, and O is the subscript of the output layer.

The contribution of an entire zone can be expressed as the sum of the contributions of the considered zone at different time steps:

$$P_z = \sum_{d=0}^{w_z} P\big(r_z(k-d)\big) \quad (\cancel{5}6)$$

~~This contribution calculus is done for each exogenous input: rainfall or measured discharge, and for each designed model (T~~~~*n*~~~~, *n*=1, 7). The contribution of the previous measured discharges used as input to the model ranges from 21% to 30% (respectively 89 to 70% for total rainfall) depending on the considered model T~~~~*n*~~~~ (*n*=1, 7). Nevertheless, only rainfall contribution values are considered (for a total of 100%) because the measured input of discharge plays the role of state variable (Artigue et al., 2012). Rainfall contribution medians for the seven models are provided in Table 5. Values obtained by (Kong-A-Siou et al., 2013) are also reported; they show the difference between contributions of the same zones to very different processes (flash flood at *Lavalette* station for this study, and daily aquifer discharge at the *Lez* Spring (in the 2013 study).~~

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4.4 Time distribution of contributions

Figure ~~4~~5 shows the time distributions of contributions by the north-western, north-eastern, south-western and south-eastern rainfall inputs. The percentages expressed in this section are the contribution of the inputs to the output.

Fig. 5 shows that the major contribution comes from the south-western zone, with two peaks at *k*-1 and {*k*-4 to *k*-5}. This means that, on average, for all events and all time steps, water comes principally from the south-western zone via two transfer functions: one associated with rapid surface response (*k*-1) and the other associated with slower karst response (*k*-4) to (*k*-5) (*Causse de Viols-le-Fort*, cf. Fig. 1 and 2). The same reasoning can be applied to the north-eastern zone: fast surface response at *k*-2 and slower karst water at *k*-5 (due to numerous faults in this zone, cf. Fig. 2); nevertheless, contributions from the north-eastern zone are less pronounced than the south-western ones.

5 Discussion

5.1 Rainfalls contributions to discharge

The map shown in Fig. 2 and Table 5 can guide the discussion: Fig. 2 presents the transcription of geological properties in infiltration capabilities.

- Regarding the south-western zone (43% to 54%), it appears that the large extent of karst delayed contribution (24% for {*k*-4 to *k*-5}) comes from the *Causse de Viols-le-Fort*. This property is not observed in daily continuous modelling (Table 5) because the *Lirou* Spring (outlet of the *Causse de Viols-le-Fort*, cf. Fig. 1) is an intermittent spring that flows only in wet conditions; moreover this part of the aquifer is pumped for drinking water during the dry season.
- Regarding the north-eastern zone, the second largest contributor to flash flooding at *Lavalette* (18% to 30%), a careless analysis could lead to the conclusion that it may be the major contributor because it has a large impervious basin within the surface watershed of the *Lez* at *Lavalette*. However, significant losses occur through numerous faults in the southern part of this zone (cf. Fig.2). As in the south-western zone, two contributions play a role: surface (rapid) and underground (slow) (recall that the contribution reflects the behaviour of the entire training database; thus this schematic behaviour can be assumed). Nevertheless the *Lez* Spring, which drains the underground north-eastern zone, has a smaller discharge than *Lirou* Spring, during flood events, and

thus softens the underground flooding. The daily discharge of the north-eastern zone to *Lez* Spring (50% to 54%) can be explained only by infiltration through numerous faults, not limited to the surface watershed but also in the extreme northern part of the underground basin. Indeed, a dye tracing experiment demonstrated water circulation between sinkholes in river tributaries of the *Vidourle* (east of *Lez* Basin, cf. Fig.2) (Bérard, 1983).

- In the north-western zone, both behaviours (flash flooding at *Lavalette* or daily runoff at the *Lez* Spring) ~~differs~~differ greatly. For flash floods at *Lavalette*, the north-western zone has a weak influence, which is consistent with the representation of the basin in Fig. 2. (perched ~~aquifers~~aquifer delaying water transfers and limited infiltration along the *Corconne* fault due to the limited infiltration capability of the fault); for daily run-off at the *Lez* Spring, conversely, delayed transfer and permanent infiltration along faults increases the storage and thus contributes more to daily runoff (28% to 31%).
- Lastly, the south-eastern zone has a lesser effect on flash flooding due to its small area in the watershed at *Lavalette* (12% to 24%). One can observe a relatively large variability on Fig. 5. This may be a limit of the work due to: (i) the high sensitivity of this small fully-impervious area to localised heavy rainfall, combined with the bad representation of the rainfall variability in this zone (Sect. 3.6.1~~).~~), or (ii) the heterogeneity of events that influences the training. For daily runoff at the *Lez* ~~spring~~Spring, this zone can be excluded from the recharge basin (4% to 7%); this is consistent with the Fig. 2 information, as the zone is composed of impervious formations downstream of the spring.

5.2 Time behaviour

Temporal contributions within each zone are shown in Fig.5. As analysed previously, these contributions are consistent with dual behaviours: fast surface water and slower karst water. The sensitivity of these estimations with respect to the different models (7 models) shown by dotted points does not contradict the proposed analysis.

5.3 Flash-flood simulations

Schematically Fig. 5 shows that response times of 2 h (probably surface water) and 5-6 h (probably karst water) are not very different. Consequently it is possible for karst water to add to surface flooding in the event of multi-peak rainfalls. This behaviour was underlined by

(Bailly-Comte et al., 2012; Coustau et al., 2012; Fleury et al., 2007) who focused on the importance of the initial water level inside the karst. Consequently, flash-flood simulations would require real-time piezometric information in both the north-eastern and south-western zones to estimate the influence of karst water in these two zones.

5.4 Limits of the study

The KnoX method is a novel tool for investigating the behaviour of heterogeneous basins. Because this method is currently under discovery and development, the sensitivity of the provided estimations to noise, uncertainty, and small database size have not yet been fully assessed. Nevertheless the overview of the *Lez* aquifer that this method has provided appears to be quite consistent with the current knowledge. Based on the proposed behaviour of the *Lez* aquifer, several fieldwork projects are currently in progress to assess karst and non-karst contributions at the *Lavalette* station.

6 Conclusion

Mediterranean flash floods and mountain floods are responsible for numerous casualties and major property damage. These floods occur in heterogeneous basins, which are difficult to observe and thus to model. For this reason this paper investigates the ability to obtain information on a complex aquifer through global systemic modelling using neural networks. For this purpose we chose as a case study flash flooding at the entrance to the great city of Montpellier (Southern France) where large potential losses are at stake. After recent trends in flash flooding and karst modelling, this paper focuses on hydrological modelling with neural networks and presents the basics of neural network modelling. It was shown that these statistical models can efficiently model unknown relationships using only databases. Moreover efficient new approaches were demonstrated to extract information from a set of parameters. Among these methods, the KnoX method can identify contributions from various geographic zones to discharge at the basin outlet; it also provides better characterisation of processes linked to karst water and surface water. To investigate this capability, a case study was conducted on a complex hydrosystem, the *Lez* hydrosystem. The application to this system shows that the KnoX method consistently estimated the water contributions from four “homogenous” geological zones of the hydrosystem to the discharge at its outlet. The main contributor to flash flooding at *Lavalette* was identified as the *Causse de Viols-le-Fort* karst plateau. Piezometric information within this plateau would thus be of crucial importance to model flooding at the *Lavalette* station. On a more interesting note, several time responses were identified and associated with surface circulations or underground contributions. The lag between these two different response times, estimated at three hours, may thus correspond to synchronization difference between surface and underground flooding. This information may help flood-warning services anticipate the size of a flood in case of a rain event composed of two rain peaks separated by three hours.

This is a generic method that can be applied to any heterogeneous basin as long as a sufficient database is available.

Author contributions

Darras T., Kong-A-Siou L. and Johannet A. designed the experiments and Darras T. conducted them. Borrell Estupina V., Vayssade B. and Pistre S. provided hydrological and meteorological data and their expertise. Darras T. prepared the manuscript with contributions from all co-authors. Johannet A. contributed to the RNF Pro software used to simulate neural networks and extract parameters.

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Table 1. Dates, peak discharges, and mean cumulative rainfalls of flood events contained in the database. Intense events are highlighted by a star. Mean cumulative rainfall is calculated using a weighted average of the five rain gauges with the Thiessen polygon method.

Events	Dates	Peak discharge ($m^3.s^{-1}$)	Mean cumulative rainfalls (mm)
1	24 - 27 August 2002	7	128
2*	***08 - 09 September 2002***	***112***	***171***
3	08 - 13 October 2002	45	118
4*	***09 - 13 December 2002***	***384***	***245***
5	15 - 18 November 2003	68	86
6*	***23 - 25 November 2003***	***95***	***51***
7*	***01 - 05 December 2003***	***438***	***234***
8*	***05 - 07 September 2005***	***480***	***144***
9	27 - 31 January 2006	53	117
10	13 - 15 September 2006	25	147
11	23 - 26 September 2006	23	85
12	02 - 07 May 2007	9	88
13*	***20 - 21 October 2008***	***114***	***123***
14*	***21 - 22 October 2008***	***104***	***72***
15	01 - 08 November 2008	31	127

Table 2. Percentage of each rain gauge to the rainfall for each zone and for the whole *Lez* basin by Thiessen polygons.

Rain gauges	North-eastern zone	North-western zone	South-eastern zone	South-western zone	Whole *Lez* system area
Prades-le-Lez	74%	13%	100%	39%	61%
Sommières	12%	-	-	-	5%
Vic-le-Fesq	14%	3%	-	-	6%
Saint-Martin-de-Londres	-	20%	-	61%	15%
Saint-Hippolyte-du-Fort	-	64%	-	-	13%

Table 3: Optimisation of the rainfall temporal window widths

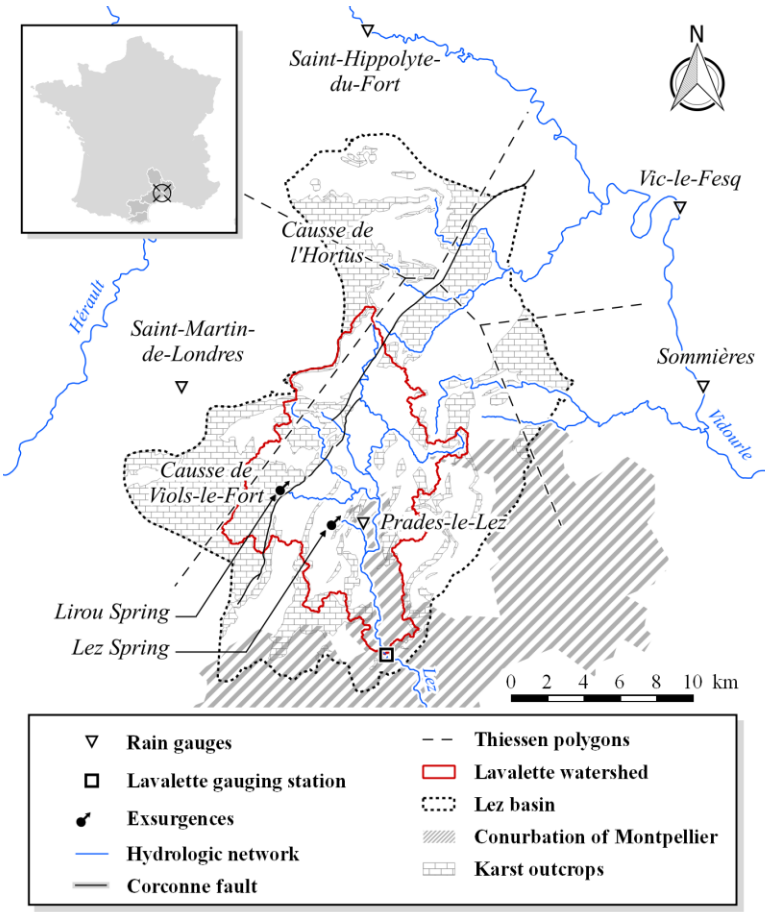
	North-eastern zone	North-western zone	South-eastern zone	South-western zone	Previous discharge	N_C
Temporal window width range (*h*)	3-9	2-8	2-8	3-9	1-5	1-7
Chosen temporal window width (*h*)	7	7	4	7	1	5

Table 4. Performances of models T_2, T_4, T_6, T_7, T_8, T_{13} and T_{14}: Nash criterion (R^2), the synchronous percentage of the peak discharge (S_{PPD}) and the peak delay (P_d). T_7 and T_8 are models tested on the two most intense events.

Models	R^2	S_{PPD} (%)	P_d (h)
T_2	-0.75	22	-5
T_4	0.96	87	-1
T_6	0.84	122 - 89	0 - 0
T_7	***0.96***	***99***	***0***
T_8	***0.93***	***97***	***0***
T_{13}	0.71	138	0
T_{14}	0.79	94	1

Table 5. Contributions of different zones to discharge. Flash-flood contribution is the median of contributions of rainfall inputs to the output of the seven models T_2, T_4, T_6, T_7, T_8, T_{13} and T_{14}. Maximum and minimum values come from the set of 7 models in this study and from 10 experiments of 50 initialisations in ~~(Kong-A-Siou et al., 2013)~~(Kong-A-Siou et al., 2013).

	North-western zone	North-eastern zone	South-western zone	South-eastern zone
Part of the surface water-shed at *Lavalette*	10%	45%	20%	25%
Rainfalls contribution to flash-flooding at *La-valette* (min –max)	**9%** (8% –11%)	**26%** (18%–30%)	**47%** (43% –54%)	**18%** (12%–24%)
Time delay of principal contributions	-	-2h; -5h	-1h; -4h to -5h	0h
Part of the underground basin at *Lez* Spring from (Kong-A-Siou et al., 2013)	22%	36%	18%	24%
Rainfalls contribution to daily discharge at *Lez* Spring from (Kong-A-Siou et al., 2013) (min – max)	**29%** (28%-31%)	**52%** (50%-54%)	**13%** (10%-15%)	**6%** (4%-7%)
Time delay of principal contributions	-1 day to -3 days	-1 day	-1 day	0 day


Saint-Hippolyte-du-Fort
N
Vic-le-Fesq
Causse de l'Hortus
Hérault
Saint-Martin-de-Londres
Sommières
Vidourle
Causse de Viols-le-Fort
Prades-le-Lez
Lirou Spring
Lez Spring
Lez
0 2 4 6 8 10 km
Rain gauges
Lavalette gauging station
Exsurgences
Hydrologic network
Corconne fault
Thiessen polygons
Lavalette watershed
Lez basin
Conurbation of Montpellier
Karst outcrops

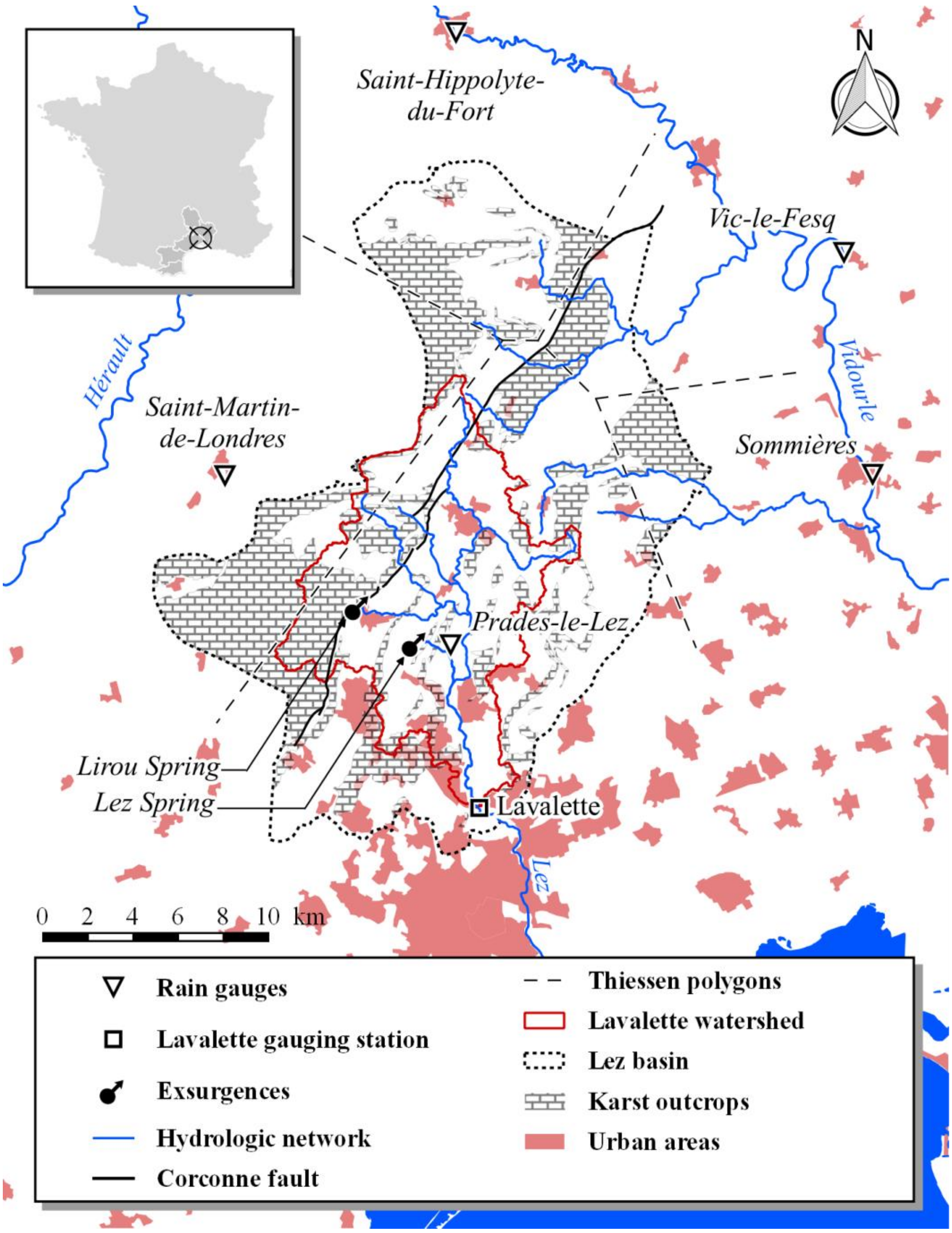


Figure 1. Map of the *Lez* hydrosystem with location of karst outcrops, rain gauges, gauging stations, springs, *causses de Viols-le-Fort* and *de l'Hortus* and of *Corconne* fault. Boundaries of surface watershed~~ and~~, underground basin~~,~~ and ~~the conurbation of Montpellier~~urban zones are also shown.

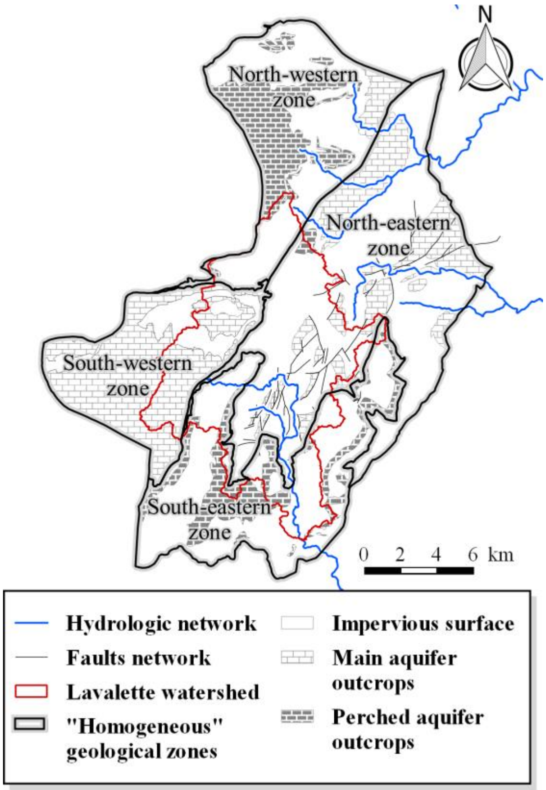


Figure 2. Map of the *Lez* basin: zone boundaries and topographic watershed; impervious and non-impervious formations; faults intensifying infiltration.

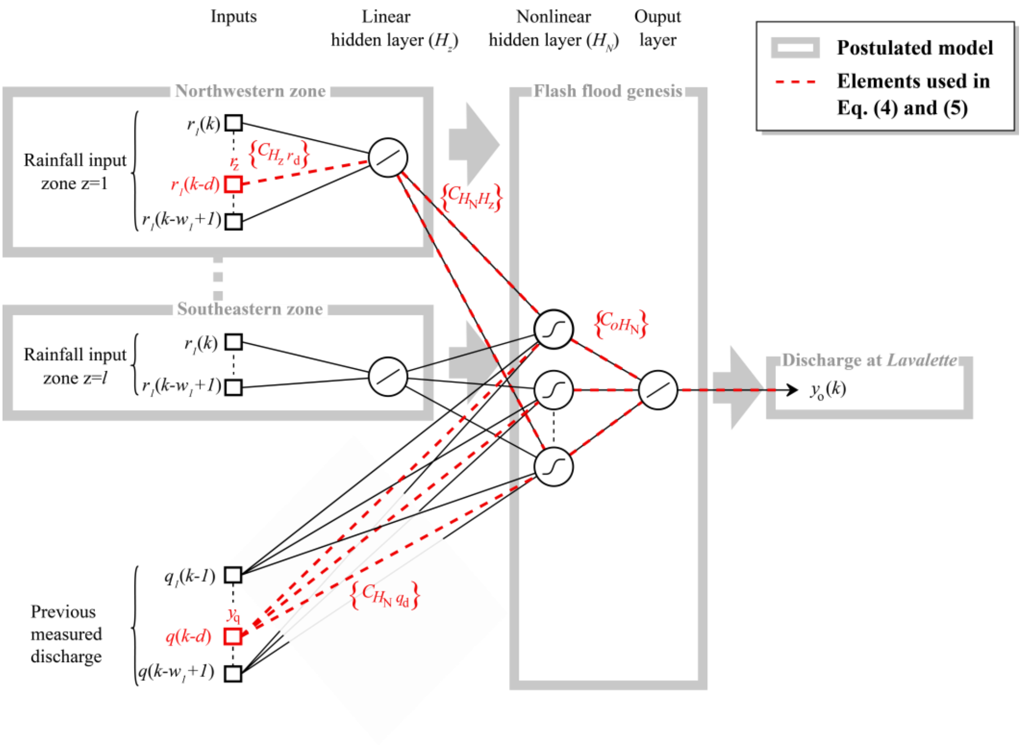
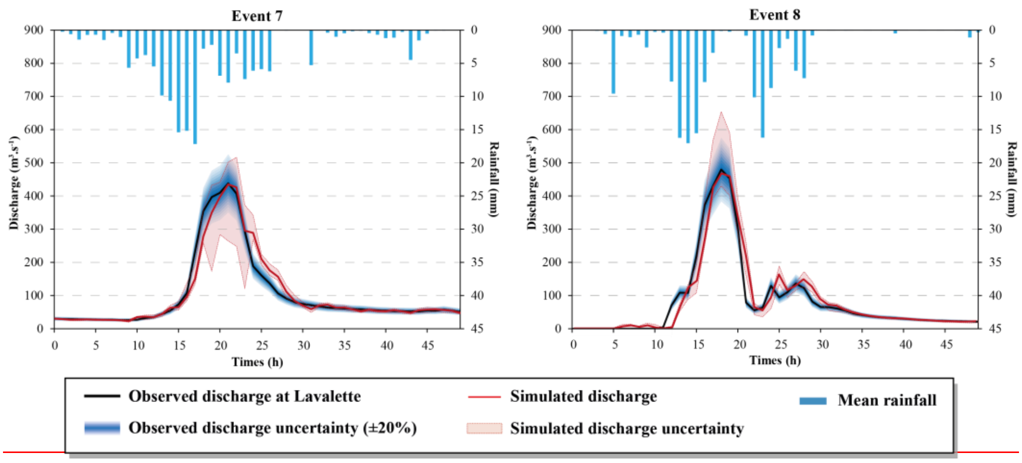


Figure 3. Postulated model: grey block-diagram. Three layers multilayer perceptron with linear hidden layer between rainfall inputs and nonlinear layer. Parameters used in Equ. 4 are denoted in red.



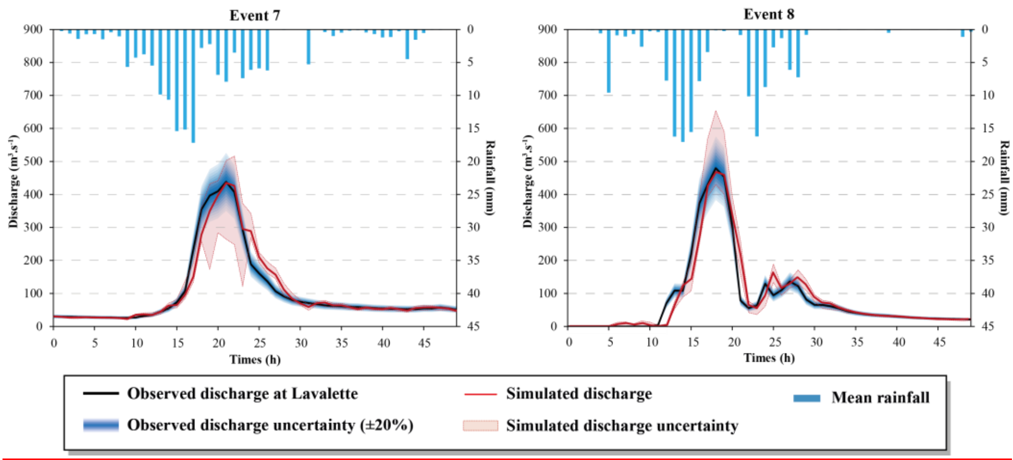
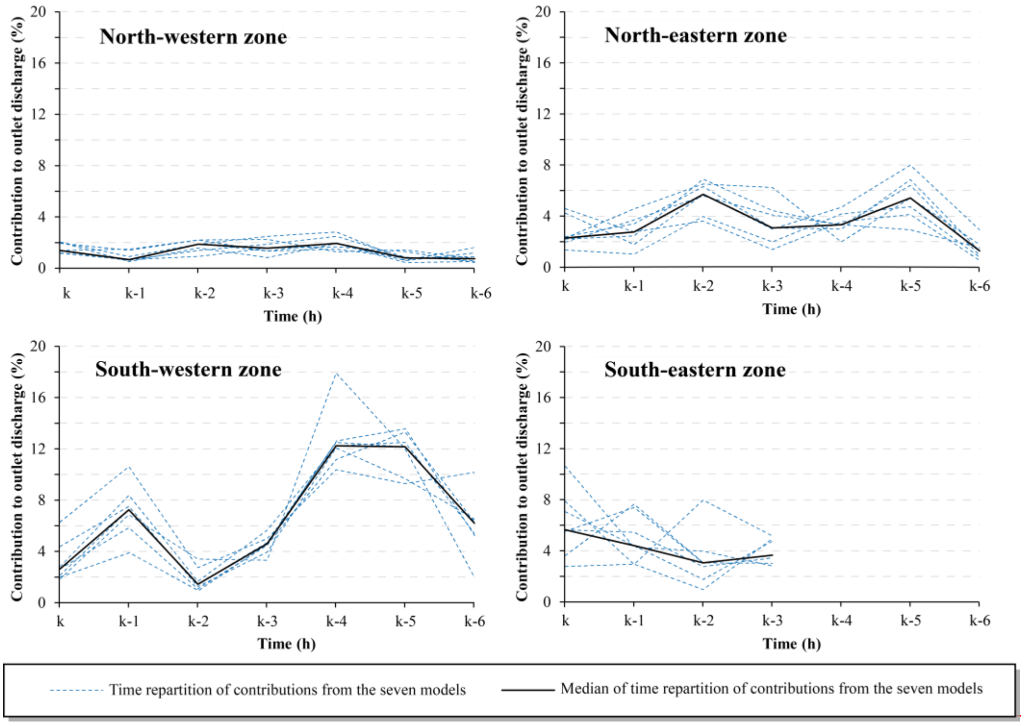


Figure 4. Hydrographs of major events in the database: events 7 and 8. Simulated discharge is the median of outputs coming from the 50 run models (differing by their initialization parameters). Uncertainty on the observed value is the measurement ~~±~~ ± 20%. Uncertainty on the simulated value is represented by simulations coming from the 50 run models (differing by their parameters initialization).


North-western zone
North-eastern zone
South-western zone
South-eastern zone
Contribution to outlet discharge (%)
0
4
8
12
16
20
k
k-1
k-2
k-3
k-4
k-5
k-6
Time (h)
Time repartition of contributions from the seven models
Median of time repartition of contributions from the seven models

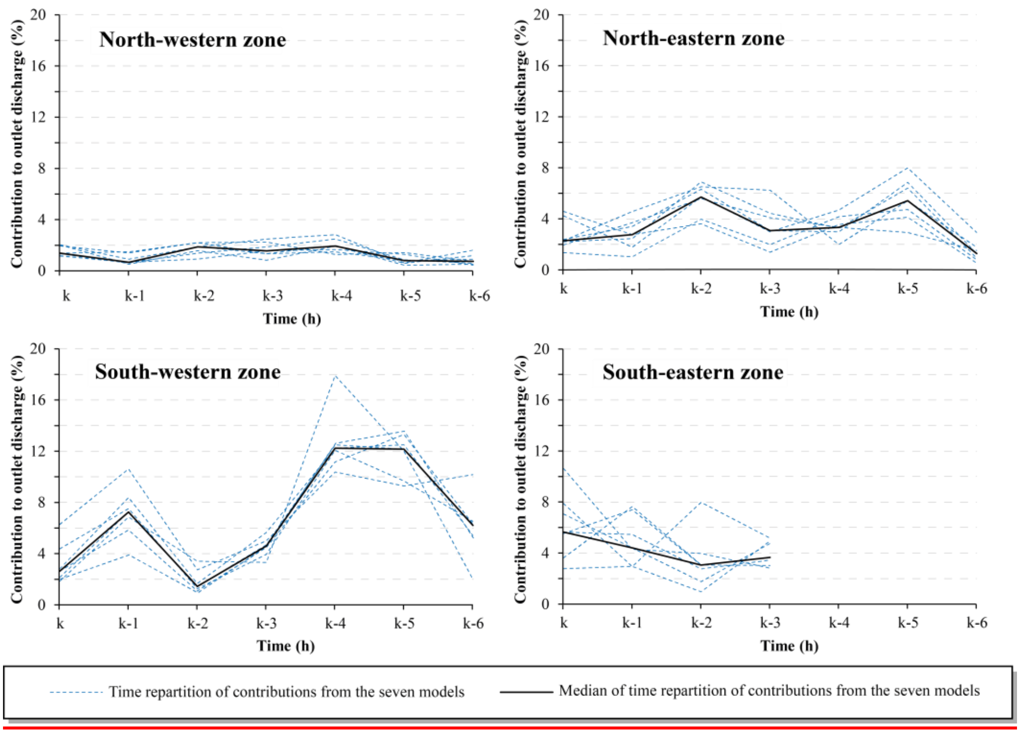


Figure 5. Median and total spread of time distributions of North-western, North-eastern, South-western and South-eastern rainfall inputs contributions calculated from parameters of the 7 designed models.