Discussion of "Generalized regression neural networks for evapotranspiration modelling"*

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There is no doubt that so-called "artificial neural networks" (ANN) are powerful computational tools to model complex nonlinear systems. In my view, an ANN establishes a data-driven nonlinear relationship between inputs and outputs of a system. The fact that such a nonlinear model is generally very complicated (usually one does not even write down the equations) renders it a black-box model. The fact that the model contains numerous parameters makes imperative the use of an advanced optimization method to calibrate its parameters. Once an ANN is fitted, it can be used to predict outputs from known inputs. Thus, there have been numerous successful applications of ANN in forecasting the future evolution of complex systems (e.g. Casdagli & Eubank, 1992; Weigend & Gershenfeld, 1994). However, I am afraid that there has also been an abuse in other cases, indirectly assisted by the numerous technical details, inapproachable for the majority of scientists (in our case hydrologists), and even by the exotic ANN vocabulary. The paper by Kişi (2006) stimulated my "reflex" questions about "neural networks", their use and abuse, and helped me to organize them so that they can be addressed to the "central nervous system".

I start with the vocabulary itself. How "neural" are ANN? This question may be philosophical and related to the nature of the so called "artificial intelligence". I am not prepared to discuss in depth this type of question, for which profound analyses can be found in Dreyfus & Dreyfus (1986), Penrose (1989, 1994, 1996) and Hodges (2000–2002). However, I thought of a simplified version of this question: Is it necessary to call these mathematical models "neural" networks? Structures such as graphs and networks are very common in science (including hydrology, hydraulics and water resources), and consist of nodes (or vertices) and arcs (edges, or arrows in directed graphs and networks). Why in this case should we speak of "neurons" instead of nodes or arcs? After all, while in other cases (e.g. a river network, a water distribution network) the network has a physical hypostasis, in ANN the network is just a convenient pictorial representation of a complicated mathematical nonlinear relationship, which could be handled even without the notion of a network. A lot of similar questions can arise: Why use such terms as "one-pass learning algorithm with a highly parallel structure" or "training vector"? Isn't it more understandable to speak about "model calibration", "model fitting" and "parameter optimization" instead of "learning" or "training"? If yes, why have these anthropomorphized terms been so prevalent?

Furthermore, is an ANN approach appropriate for any type of problem? Kişi (2006) seems to reply positively to this question. His motivation for the paper is simply this: "However, the application of ANN to evapotranspiration modelling is limited in the literature. ... To the knowledge of the author, no work has been reported

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in the literature that addresses the application of generalized regression neural networks (GRNN) to [reference evapotranspiration] ET_0 estimation. This provided an impetus to investigate the potential of the GRNN for better mapping of the process." So, the motivation seems to be a matter of whether others have or have not published research on this issue. Shouldn't one have some thoughts on the utility of the approach in principle for the specific problem, before proceeding to its adoption?

To make these questions clearer, let us see what the author proposed in his paper: "The ET_0 obtained by the FAO-56 [Penman-Monteith] PM was standardized … Finally, these normalized data were used for the calibration of GRNN models. A program code, including ANN toolboxes, was written in MATLAB language for the GRNN simulations." This can be outlined as follows: Take the FAO Penman-Monteith equation. Take the required meteorological inputs (historical time series) and apply the equation to estimate the Penman-Monteith evapotranspiration as output. Then disregard the equation, take only the input and output data and "train" an ANN to produce the output from the input data. On this point, I wonder: If I have the data and the equation (which is simple, explicit, and clear), why do I need to use an ANN (a black-box complicated model whose detailed mathematical behaviour I do not know) to reproduce (approximately) the outputs that the simple equation yields precisely? Certainly, it is justifiable to apply an ANN approach if the relationship of output to inputs is complex and not known. But in this very case isn't it both simple and completely known? I characterize the Penman-Monteith model as simple, because mathematically it is an algebraic equation (as contrasted, for instance, to differential equations without closed solutions that describe most hydrometeorological processes). And I maintain that, in this paper, the relationship of inputs to outputs is completely known because the author has assumed that it is fully described by the Penman-Monteith model, which he applied to estimate the output. That is, in this paper the output is not known from measurements, but from application of the Penman-Monteith equation, which subsequently the author proposes to replace with the ANN built upon the equation. Does the replacement of an explicit equation with a MATLAB code of a black box serve any purpose?

Still, one may argue that, once an ANN model has been fitted, it can serve other purposes, such as approximation of the original equation and sensitivity analysis including the sensitivity to missing data or missing variables. Indeed, such issues are all discussed in Kişi (2006). Again, several questions arise. If our aim is approximation, what is the real value of an ANN? Isn't it more insightful to make an approximation using classical analytical and numerical tools (given that in this case we know the equation describing the system)? Doesn't an explicit equation deserve an explicit approximation? Isn't it more practical to adopt one of the existing empirical approximate equations of evapotranspiration? If our aim is sensitivity analysis, does an ANN approach have any advantage over classical methods? Isn't it more insightful to use, for instance, partial derivatives to assess the influence of a specific input? Isn't it more informative to use a probabilistic description of the inputs and a Monte Carlo simulation to obtain some insight on the degree that the different inputs affect evapotranspiration? Is it really possible for an ANN to provide an insightful sensitivity analysis of the problem at hand?

To shed light on the last question, I will use the results of the sensitivity analysis of Kişi (2006), according to which "[The temperature] *T* seems to be more effective than [the relative humidity] RH and [the wind speed] U_2 in estimation of ET_0 because of the fact that adding T into the input combination … significantly increases the model performance", but later "In contrast to the Pomona Station, RH seems to be more effective than T in estimation of ET_0". We can discuss these results from a theoretical and a practical viewpoint. From a theoretical viewpoint, simple inspection of the Penman-Monteith equation reveals that RH does not appear in it. It is only used to estimate the vapour pressure and finally the vapour pressure deficit, the difference from saturation vapour pressure. All these variables presuppose that the temperature is known, otherwise how can one estimate them? So, what is the meaning of preferring to know RH over T? The same value of RH results in very different vapour pressure deficits in summer and in winter. From a practical viewpoint, it is well understood that any meteorological station includes at least a thermometer, the simplest meteorological instrument. Besides, in conventional meteorological stations, RH is obtained from two temperature readings, dry bulb and wet bulb, and this simple technique is also used even in modern non-conventional stations for testing the sensors consistency and accuracy. It is then difficult to imagine that we may know RH and not T. What is then the meaning of comparing which of T and RH is most effective in estimation of ET_0? Furthermore, in a sensitivity analysis framework, one must have in mind that the measurement of T is much more accurate than that of RH and that the (temporal and spatial) variability of RH exhibits a more random pattern in comparison to T; these are quantifiable by classical methods but seem to be ignored in an ANN approach. This example may indicate that sensitivity analyses performed by ANN can be as black-box, sightless, and inconsistent with physical realism and practical needs, as the ANN itself.

One of the most interesting points of the paper by Kişi (2006) is the comparison of the ANN results with other existing approximations, i.e. simplified empirical methods, such as the Hargreaves and Ritchie equations. Here the natural question is, how fair is it to compare an ANN fitted on a specific site with a general equation applied on this site? One is reminded that the ANN contains numerous adjustable parameters optimized for the site-specific data, whereas Hargreaves and Ritchie equations do not contain any adjustable parameters at all. It is not, then, a surprise to conclude that "the GRNN1 model outperforms all other models in terms of various performance criteria." It is amazing, however, that a simple linear modification of the results of Hargreaves and Ritchie equations (the author calls them calibrated versions of the equations) suffices to make their performance as good as that of the ANN. And the same methods outperform the ANN if some data are missing, filled in from neighbouring stations. Thus, the author correctly suggests that "the results imply that the C_Hargreaves and Ritchie empirical methods may be used instead of GRNN models in cross-station applications."

After all these analyses, I wonder how justified the conclusion is that "The study demonstrated that modelling of daily reference evapotranspiration is possible through the use of the GRNN technique." Wouldn't a negative conclusion, that an ANN approach does not offer too much in evapotranspiration estimation, be more useful? Having said that, I think that the practice of emphasizing negative results in research publications has been regarded as negative itself, while, in my opinion, it is very positive and useful. In this respect, I look forward to reading such assessments of ANNs, in which their usefulness is discussed along with their limitations.

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REPLY to Discussion of "Generalized regression neural networks for evapotranspiration modelling" by D. Koutsoyiannis

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The author would like to express his thanks for the interest shown in his paper and for the discusser's comments on the subject. I have tried to clarify all the points raised below.

The ANN terminologies are used in many papers, proceedings and books in the literature. I should not be the one to whom this question is directed. This question goes especially to those who first published the ANN terminology in the literature. Unfortunately there is not a common terminology in this subject, as in the case of other research areas. If one (e.g. one who is not familiar with the ANN terminology) is not aware that some different terminologies have the same meaning (for example, model calibration and training or learning all have the same meaning), he may think that the terminology he reads for the first time is different from the terminology he already knows. To this author, what is more important is the content of the study rather than its terminology.

The author does not agree with the discusser in that the motivation is not a matter of whether others have or have not published research on this issue. The thoughts on the utility of the ANN approach in principle for the ET_0 estimation were published in the related literature (Kumar *et al.*, 2002; Sudheer *et al.*, 2003; Trajkovic *et al.*, 2003; Trajkovic, 2005; Kisi, 2006a). In these studies the multi-layer feed-forward ANN (FFNN) and radial basis ANN were used. However, in the present study, a different ANN technique, having some advantages over other ANNs, was proposed. The advantages of this ANN technique relative to the others were mentioned in Kişi (2006b). For example, the FFNN method performance is very sensitive to randomly assigned initial weight values. However, this problem was not faced in GRNN simulations (Cigizoğlu, 2005). The GRNN does not require an iterative training procedure, as in the FFNN method explained by Specht (1991). The local minima problem was not faced in GRNN simulations (Specht, 1991). This GRNN model can be embedded as a module for estimating evapotranspiration data in hydrological modelling studies.

Methods for measuring evapotranspiration are based on micrometeorological techniques (aerodynamic method, eddy covariance, etc.), or on the use of lysimeters, tanks filled with soil in which crops are grown under natural conditions to measure the amount of water lost by evaporation and transpiration. The methods for measuring evapotranspiration require complex and very costly instrumental devices and are generally recommended only for specific research purposes (Allen *et al.*, 1998). The evapotranspiration rate from a reference surface is called reference evapotranspiration (ET_0) and expresses the evaporating power of the atmosphere at a specific location and time of the year. The ET_0 is commonly estimated by either physically-based complex methods (Penman, Penman-Monteith, etc.), or by empirical relationships between meteorological variables (Hargreaves, Hargreaves-Samani, Blaney-Criddle, etc.) (Doorenbos & Pruitt, 1977; Jensen *et al.*, 1990; Smith 1992). Recently, the Food and Agriculture Organisation (FAO) recommended a combined model of Penman-Monteith as a standard method for determining ET_0 using meteorological data (Allen *et al.*, 1998). The ET_0 computed from meteorological data by the FAO-56 Penman-Monteith equation was chosen as the true value during training and testing the neural network and empirical models in the study, due to the absence of measured values. There also are many studies in the literature (Tracy *et al.*, 1992; Marino *et al.*, 1993; Hameed *et al.*, 1995, 1997; Trajkovic, 1999) that use the ET_0 values computed by using the FAO-56 Penman-Monteith method as observed ET_0 data.

The author does not agree with the discusser in that the Penman-Monteith is a simple method that yields ET_0 output precisely. The Penman-Monteith method is a physically-based complex method that requires many parameters, as mentioned above (see also Kumar *et al.*, 2002). Some studies in the literature (McKenzie & Craig, 2001; Kumar *et al.*, 2002) compared the ANN and Penman-Monteith methods with the lysimeter ET_0 data and indicated that the ANN performs better than the standard Penman-Monteith method. However, the Penman-Monteith method is difficult to apply because of a lack of data concerning a few model variables (e.g. net radiation) that are missing for some weather stations. In fact net radiation, like other variables, is often estimated from other parameters (Jensen *et al.*, 1990; Llasat & Snyder, 1998). Moreover, values of canopy and aerodynamic resistance can greatly affect the accuracy of Penman-Monteith estimates (Ventura *et al.*, 1999).

The discusser states that "*Certainly, it is justifiable to apply an ANN approach if the relationship of output to inputs is complex and not known. But in this very case isn't it both simple and completely known?* " Evapotranspiration is a sufficiently complex and nonlinear phenomenon to justify the use of the ANN technique, because it depends on several interacting climatological factors, such as temperature, humidity, wind speed, radiation, type, and growth stage of the crop, etc. (Kumar *et al.*, 2002; Keskin & Terzi, 2006). Artificial neural networks are effective tools to model nonlinear systems. A neural network model is a mathematical construct whose architecture is essentially analogous to the human brain. Basically, the highly interconnected processing elements arranged in layers are similar to the arrangement of neurons in the brain. Recently, artificial neural networks (ANN) have been applied in meteorological and agro-ecological modelling; most of the applications reported in the literature concern estimation, prediction and classification problems (Arca *et al.*, 1998; Dowla & Rogers, 1995; Schultz *et al.*, 2000). Neural network applications have diffused rapidly due to their functional characteristics, which provide many advantages over traditional analytical approaches (Paruelo & Tomasel, 1997; Patterson, 1996; Smith, 1996).

It may be noted that the main focus of the paper under discussion was to evaluate the potential of the GRNN approach in estimating evapotranspiration from climatic data. I wish to re-emphasize that this study does not intend to replace or substitute the well-established ET models (based on physical processes) in situations where sufficient and necessary data are available. As stated in the Conclusion section of the study, "The GRNN technique could be of use in water budgeting of basins, design of reservoirs and various other hydrological analyses where other models may be inappropriate".

The aim of the study was not sensitivity analysis, as explained in Kisi (2007). Further, the author does not agree with the statement "we know the equation describing the system". As mentioned before, the Penman-Monteith equation is not a simple method and does not yield ET_0 output precisely.

The authors do not claim that "The concept of ANN as presented in this paper gives the impression that this method is magical and can carry out all kinds of function approximation." The employment of ANN is commendable: for very complex processes, when there is no simple mathematical model or for highly nonlinear processes. The use of ANNs is not a good idea if the conventional theory yields a satisfying result, e.g. if an easily solvable and adequate mathematical model already exists. As stated in Conclusion section of Kisi (2006b), the GRNN technique could be of use in design of reservoirs and various other hydrological analyses where other models may be inappropriate. The GRNN models can be embedded as a module for estimating ET_0 data in hydrological modelling studies.

The RH was found to be more effective for ET_0 estimation than T for the Santa Monica Station. This result, which is different from that of the Pomona Station, may be site-specific, as Santa Monica Station is located in a coastal area. However, in some areas (e.g. developing countries), the only available data may be the solar radiation, R_s, and air temperature, T, due to the difficulty in obtaining the data for the other two parameters. In such cases, two-parameter temperature-based models are preferred. This study indicated that adding RH into the inputs may significantly increase the model accuracy.

The author agrees with the discusser in that the ANN contains numerous adjustable parameters optimized for the site-specific data whereas the Hargreaves and Ritchie equations do not contain any adjustable parameter at all. However, the ANN was found to perform better than the Hargreaves and Ritchie methods for the Santa Monica Station. This result is also justified by the study of Trajkovic (2005), who compared the ANN estimates with the Hargreaves method and its calibrated version and found that the ANN performs much better than the empirical model. He says in his study that "*The calibrated Hargreaves method overestimated ET_0 even after the calibration. So, this method cannot be recommended for utilization*". However, the weakness of these empirical methods is that they have a limited range of applicability because (a) their variables may not be easily measurable in other places, or some existing data may not be utilized; (b) they are usually accurate only in a limited range, for their model structure may be only partially correct; and (c) it is difficult to compare one method with another due to method-specific model variables; for example, the requirements for measurement of temperature and wind speed may be at different heights above the water or ground surface (Singh & Xu, 1997). The author agrees with Trajkovic (2005) in that people should adapt all calculations to their local conditions and they should use their own judgment on the results based on their local experiences and not take the results blindly.

The author agrees with the discusser in that reporting the assessment of a proposed method with its drawbacks and limitations is very important and useful.

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