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Which potential evapotranspiration input for a lumped rainfall–runoff model? Part 2—Towards a simple and efficient potential evapotranspiration model for rainfall–runoff modelling

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Abstract

This research sought to identify the most relevant approach to calculate potential evapotranspiration (PE) for use in a daily rainfall–runoff model, while answering the following question: How can we use available atmospheric variables to represent the evaporative demand at the basin scale? The value of 27 PE models was assessed in terms of streamflow simulation efficiency over a large sample of 308 catchments located in France, Australia and the United States.

While trying to identify which atmospheric variables were the most relevant to compute PE as input to rainfall–runoff models, we showed that the formulae based on temperature and radiation tend to provide the best streamflow simulations. Surprisingly, PE approaches based on the Penman approach seem less advantageous to feed rainfall–runoff models.

This investigation has resulted in a proposal for a temperature-based PE model, combining simplicity and efficiency, and adapted to four rainfall–runoff models. This PE model only requires mean air temperature (derived from long-term averages) and leads to a slight but steady improvement in rainfall–runoff model efficiency.

Keywords: Rainfall–runoff modelling; Sensitivity analysis; Potential evapotranspiration; Parsimony

1. Introduction

For engineers who wish to use a rainfall–runoff model in a catchment study, how to represent the evaporative demand introduced into a model often poses a dilemma. Rainfall–runoff models often use potential evapotranspiration (PE), which is mainly an agronomic concept that lacks a clear definition at the catchment or regional scale. Here, we are interested in finding the most adequate PE input to lumped conceptual rainfall–runoff models with the sole purpose of providing better streamflow simulations.

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The hydrological literature contains a wealth of PE models, each with different data requirements: as Brutsaert (1982) points out, “in the case of evaporation beside sampling, there is also the problem of simply determining it at a point location.” In operational situations, where meteorological stations are scarce, hydrologists often hesitate: should they use a formula with large data requirements (and possibly a poor spatial representation) or a simpler formula, thus providing a better spatial representation of catchment-scale evaporative demand?

In the companion article, Oudin et al. (this issue) showed that rainfall–runoff models are poorly responsive to actually observed classical Penman PE input. They require only mean values, which are sound derivations of the true climatic information. As this previous study was based on the recommended Penman PE estimates, a further interrogation arises: Could other PE models be more relevant than Penman-type models at the catchment scale? Indeed, if rainfall–runoff models are particularly insensitive to PE input, could a different and possibly simpler PE model (i.e. less data-demanding) than Penman be used?

To answer this question, we chose to compare several PE models found in the literature and then assess their respective merits as input to rainfall–runoff models. In Section 2, we first review some of the literature relevant to the use of Penman PE models within rainfall–runoff models. Section 3 mentions the data detailed in the companion article and presents the method. In Section 4, we assess the efficiency of rainfall–runoff models using each PE model with daily data and mean daily values. Then we discuss relevance of PE models for rainfall–runoff modelling. Last, Section 5 proposes a PE model, combining simplicity and efficiency, for the four rainfall–runoff models used in this study.

2. Relevant literature

One of the first studies of sensitivity to errors in potential evapotranspiration input was published by Parmele (1972). The author used three models and a sample of nine catchments to assess the impact of PE errors on model efficiency. He compared streamflows simulated with erroneous PE to synthetic streamflow, obtained with ‘true’ PE. He found that an estimate of PE accurate to better than $\pm 20\%$ may not be necessary. Other sensitivity analysis studies such as those by Paturel et al. (1995) and Nandakumar and Mein (1997) found that compared to errors in rainfall, PE errors induced much smaller output errors.

To observe model sensitivity to the type of PE formulation, many studies also attempted to replace the Penman formula with simpler or more sophisticated methods.

Andersson (1992) compared the effect of seven different methods of PE computation on the output of the HBV rainfall–runoff model, including: Penman PE values, mean monthly Penman PE values and the temperature-based PE model developed by Thornthwaite. He used the same set of calibrated parameters in each case, only allowing the precipitation correction factor to compensate for PE over- or under-estimation to obtain the same total runoff amount for all formulae over the calibration period. Differences between methods, expressed in terms of model efficiency, were marginal: the inclusion of temperature slightly improved the performance of the model while mean Penman PE values yielded better results than time-varying Penman PE.

Lindroth (1993) and Joukainen (2000) also used the HBV model and modified the routine computing actual evapotranspiration (AE) from PE, to better take into account interception by trees and snowmelt, adding several new parameters to the model. They found a very slight improvement in calibration, even though they had largely increased the number of model parameters. Clearly, HBV is not sensitive to such refinements of its AE computation routine.

Evans (2003) tested several regional climate models associated with the CMD-IHACRES model on an experimental site in central USA. He found that the best results were produced by a regional climate model using only precipitation and evapotranspiration determined simply with temperature as a surrogate for PE. This study is another example of the crudeness of the climatic inputs that seems to be favoured by rainfall–runoff models.

Andréassian et al. (2004) used a sample of 62 mountainous catchments and two rainfall–runoff models to test the impact of a regionalized Penman PE on the performance of rainfall–runoff models.

They found that in both models, a very simple assumption on PE input (the same average input for all catchments) yields the same results as a more accurate input obtained from regionalization.

All these studies raise an important question: is the Penman model the most relevant PE model for catchment modelling? Doubts on this topic had already been raised by Morton (1994)—probably the most critical about the use of Penman's approach in rainfall–runoff modelling—who stated: "It seems likely that the use of the Penman–Monteith equation to estimate evaporation from hydrologically significant areas has no real future, being merely an attempt to force reality to conform to preconceived concepts derived from small wet areas." Trying to approve or to refute this statement, we can also put forward a further question: does a relevant and self-contained PE model exist for rainfall–runoff modelling?

3. Data and methods

The data and the model comparison methods used for this research are similar to those used in the companion article. In this section, we briefly mention the main characteristics of the testing framework. For more detailed information, refer to Oudin et al. (this issue).

- A sample of 308 catchments located in Australia, France and the United States was used for this study. Four simple, reliable, continuous daily lumped rainfall–runoff models were used: GR4J, HBV0, IHAC, TOPMO.
- To study the impact of different PE models on rainfall–runoff model efficiency, we followed the split-sample test procedure recommended by Klemeš (1986): for each catchment, data time-series were split into two to six independent (non-overlapping) sub-periods. Then the model was calibrated on each sub-period and tested in validation mode on all the other sub-periods. The periods vary between 4 and 6 years and a total of 2498 validation periods were identified on the 308 catchments.
- The validation criteria used to assess streamflow simulations were the Nash and Sutcliffe (1970) criterion applied to streamflows $N_a(Q)$ and root-square-transformed streamflows $N_a(\sqrt{Q})$, and a water balance criterion CB. Equations and details of these criteria are given in the companion article (Oudin et al., this issue).

4. Comparison of 27 PE models

4.1. Selected PE models

There is a wealth of methods for estimating PE. Overviews of many of these methods can be found in the hydrological literature (Brutsaert, 1982; Jensen et al., 1990; Morton, 1994; Xu and Singh, 2002). These methods can be grouped into several categories, including: empirical, mass transfer, combination, radiation, temperature and measurements. The number of equations and the wide range of data types needed make it difficult to select the most appropriate evaporation method.

The combination method (Penman, 1948) is usually considered as the most physically satisfying by many hydrologists (Jensen et al., 1990; Shuttleworth, 1993; Beven, 2001). The sample of formulae tested in the present study embodies a wide range of methods and conceptions and make it possible to test the Penman formula versus simpler ones. We also tested 10 formulae, which are simple associations of meteorological variables, allowing a comparison with the efficiency of other classical PE models. The 27 formulae used in this study are presented in Table 1.

Several studies have dealt with the search for the best formula to compute PE (Jensen et al., 1990; Amatya et al., 1995; Xu and Singh, 2002). Many of these studies chose the Penman approach as reference, as it seems to give PE estimates of highest adequacy with lysimeter measurements. However, this approach was not possible in our case, since we placed our PE study within a rainfall–runoff perspective, i.e. we wish to judge the value of a PE model based on the quality of the streamflow simulations it yields. In other words, our assessment of a PE model lies only in its capacity to allow the rainfall–runoff models to make better predictions.

The 27 PE formulations used in this study are detailed in Appendix A. Last, it should be mentioned

Table 1
PE formulae selected for the study

Classification	Common method name	Data needed	Reference
Simple associations of meteorological variables	PE α Tmax	T	
	PE α Tmin	T	
	PE α T	T	
	PE α U	U	
	PE α D	D	
	PE α Re	R_e	
	PE α TD	T, D	
	PE α (1−RH)	RH	
	PE α (1−RH)U	RH, U	
	PE α (1−RH)UD	RH, U, D	
Combination	Penman	RH, T, U, D	Penman (1948)
	Penman–Monteith	RH, T, U, D	Monteith (1965)
	Priestley–Taylor	T, D	Priestley and Taylor (1972)
	Kimberly–Penman	RH, T, U, D	Wright (1982)
	Thom–Oliver	RH, T, U, D	Thom and Oliver (1977)
Temperature	Thornthwaite	T	Thornthwaite (1948)
	Blaney–Criddle	T, D	Blaney and Criddle (1950)
	Hamon	T, D	Hamon (1961)
	Romanenko	RH, T	Xu and Singh (2001)
	Linacre	RH, T	Linacre (1977)
Radiation	Turc	RH, T, D	Xu and Singh (2001)
	Jensen–Haise	T	Jensen and Haise (1963)
	McGuinness–Bordne	T	McGuinness and Bordne (1972)
	Hargreaves	T	Hargreaves and Samani (1982)
	Doorenbos–Pruitt (FAO-24)	RH, T, U, D	Jensen et al. (1990)
	Abtew	RH, T, D	Abtew (1996)
	Makkink	T	Makkink (1957)

T, Temperature; U, Wind Speed; D, Insulation/Radiation; RH, Relative Humidity; R_e, Extraterrestrial radiation (depending on the latitude and Julian day).

that the computation of all weather data required for the several PE computations followed the method and procedure given in Appendix C of Morton's article (1983).

4.2. Scaling of PE estimates to avoid systematic biases

Most PE models listed in Table 1 give mean accumulated PE values different from those given by the original Penman formula. These under- or over-estimations may yield systematic errors on streamflow simulations. In order to achieve similar accumulated PE values over the tested periods, we chose to apply a scaling factor for each formula and for each basin in order to fit the annual mean Penman PE value. The scaling factor is given by

$$\mathrm{PE}^{*}_{\mathrm{formula}}(j) = \left[\frac{\sum_{i=1}^{n}\mathrm{PE}_{\mathrm{Penman}}(i)}{\sum_{i=1}^{n}\mathrm{PE}_{\mathrm{formula}}(i)}\right]\mathrm{PE}_{\mathrm{formula}}(j) \tag{1}$$

where $\sum_{i=1}^{n} PE_{Penman}(i)$ is the sum of the daily Penman PE over the entire record period, and $\sum_{i=1}^{n} PE_{formula}(i)$ is the sum of the daily PE values computed with the tested formula over the entire record period.

Hence, all the scaled PE formulae estimates used to feed the four rainfall–runoff models considered here had exactly the same long-term mean as the original Penman values. By introducing this scaling factor, we aimed to test only the relative importance of PE fluctuations over the tested period for each PE formula, and thus to identify which atmospheric parameters would lead to the best temporal fluctuations of the catchment evaporative demand. The scaling factor is similar in its effect to using mean Penman PE as evaporative demand amount, as done by Oudin et al. (this issue), except that the seasonal cycle is captured differently. Hence, this factor allows focusing on the seasonal cycle of each formula, thus avoiding the effects of systematic biases on PE amounts, which were recently assessed in Andréassian et al. (2004).

4.3. Testing PE data versus mean PE

In the companion article, we investigated the validity of using mean Penman PE instead of time-varying PE. The results suggested that rainfall–runoff models were insensitive to time-varying PE information. As the tests were carried out only with the Penman model, we extended the tests to the 27 PE formulae in this section.

PE values were computed with daily observed meteorological variables. Then, using the four rainfall–runoff models, a systematic test with all the PE formulae was done on the catchment sample to compare model efficiency (in validation mode) when fed with PE or mean PE.

Fig. 1 presents the results obtained with both options for each rainfall–runoff model. The results for each PE model are summarized using the median Nash criterion over the 2498 validation periods (a more detailed examination of the distributions of Nash criteria will be made in Section 4.4). Two assessment criteria are presented on Fig. 1 but similar results were obtained for the *CB* criterion.

Fig. 1 confirms that PE time series generally do not obtain better results than mean PE values. The possible gain is limited and rarely exceeds 1% of the Nash criterion for the 27 PE formulations proposed here. These results confirm those obtained by Oudin et al. (this issue): using PE does not allow yielding significantly better streamflow simulations than with mean PE. Thus, time varying data will not be considered hereafter, since they do not improve the efficiency of rainfall–runoff models compared with mean values.

Results were relatively homogenous between the four rainfall–runoff models. None of the rainfall–runoff models presented systematic degradation when using mean PE. However, note that TOPMO seems to have benefitted little from actual daily PE. This is all the more surprising as this model has the most sophisticated routine to compute actual evapotranspiration from PE. This may indicate an overparameterization of the loss module in this

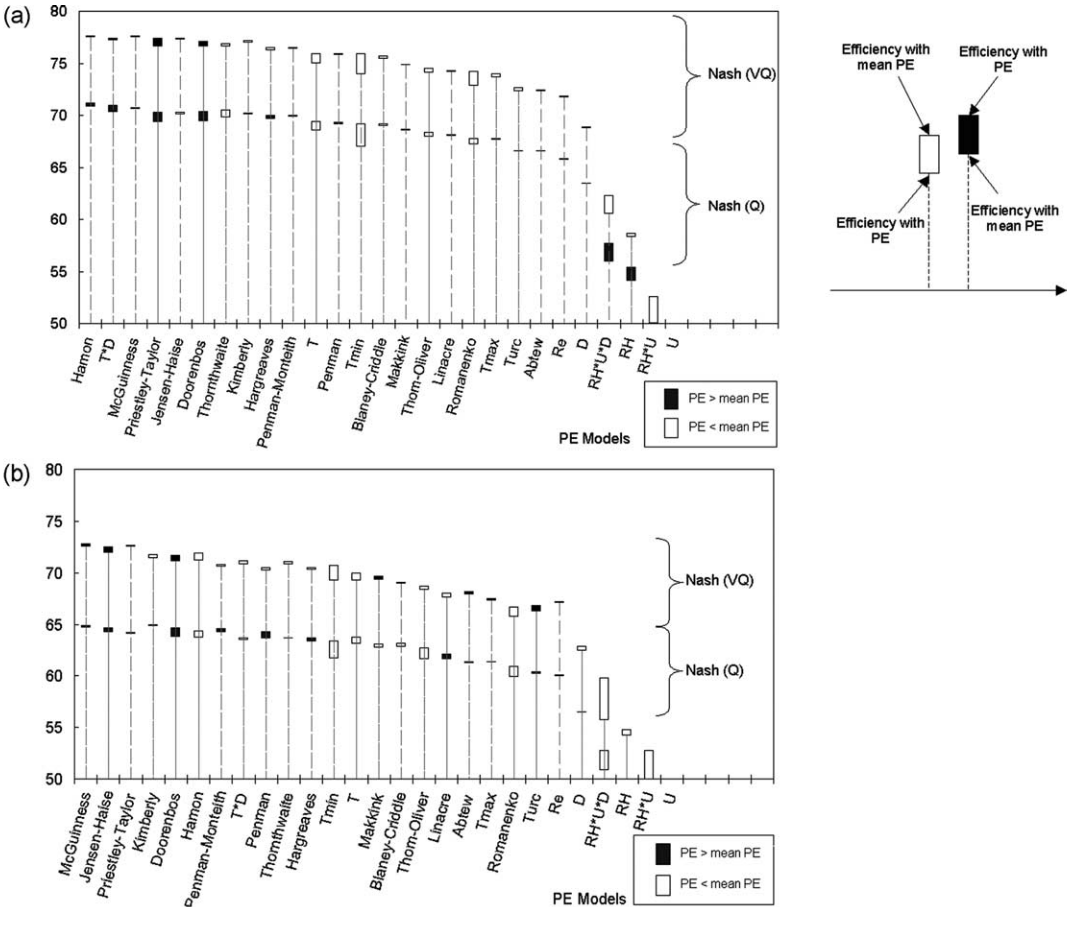

Fig. 1. Differences in rainfall–runoff model performance when using PE and mean PE values for (a) GR4J, (b) HBV0, (c) IHAC and (d) TOPMO. Median of Nash (Q) and Nash ($\sqrt{Q}$) criteria over the 2498 validation periods and sorted in the decreasing order of the median value of Nash criteria.

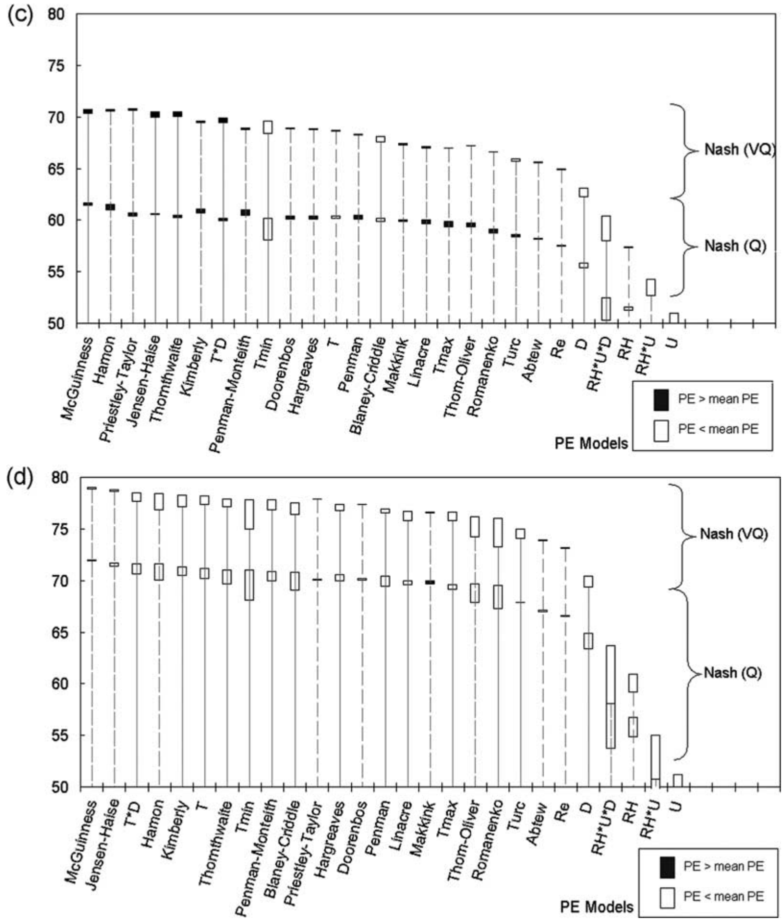

Fig. 1 (*continued*)

model. Moreover, TOPMO has two reservoirs (the interception and production reservoirs) in its evapotranspiration treatment, and it is likely that these two reservoirs contribute to the filtering of the differences between PE and mean PE.

Fig. 2 presents the previous results for GR4J in terms of the aridity index and catchment area. The investigation was not limited to the GR4J model and similar results (not shown here) were obtained for other models and criteria. The catchment sample was split into four groups: the first group was made of catchments with area less than 150 km^2, and the second was made of catchments with an area greater than 150 km^2. Then each group was also split into two sub-groups according to the aridity index (greater or less than 1) of the catchments. Fig. 2 shows that for arid catchments ($PE/P \geq 1$) there was a slight improvement when using actual PE instead of mean PE for almost all PE formulae. Fig. 2 also shows that overall small catchments produced a larger gain than large catchments. However, the improvements observed for arid catchments remained very small and never exceeded 2%; these results confirm and generalize previous results (Calder, 1983; Edijatno, 1991; Fowler, 2002) obtained for other climates. Moreover, note that on these catchments, the performance of the four models was significantly altered compared to other catchments and it is therefore difficult to compare the two groups objectively.

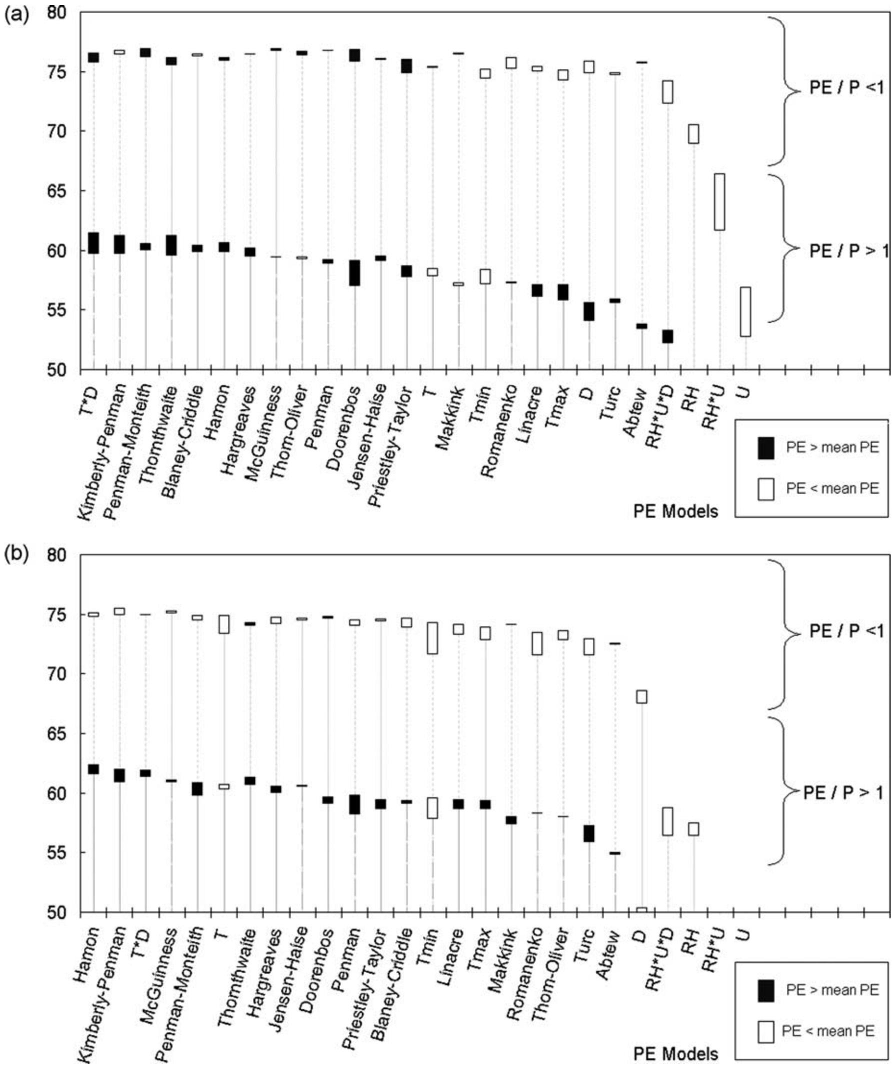

Fig. 2. Differences in GR4J model performance when using PE and mean PE values for (a) catchments with area less than 150 km^2, and (b) catchments with area greater than 150 km^2. Median of Nash (Q) for two groups depending on aridity index, over the 2498 validation periods and sorted in the decreasing order of the median value of Nash criteria.

4.4. Relevance of the 27 tested PE formulae for rainfall–runoff modelling

For each PE model, we extracted the mean PE values and tested them as inputs to the four rainfall–runoff models considered in this study. Fig. 3 presents average performance over all validation periods together with representative percentiles (0.10, 0.25, 0.50, 0.75 and 0.90) for the Nash (Q) criterion, with the four tested rainfall–runoff models. PE models are ranked in decreasing order of median Nash criterion over all basins.

It can be noted that performance was strikingly similar for most PE formulae, confirming results of previous studies that indicated a lack of sensitivity of rainfall–runoff models to PE inputs (Parmele, 1972; Andersson, 1992). Nash criteria appear to be very close for most of the PE formulations used: median efficiencies vary less than 5% for half of the sample of PE formulae. Moreover, distributions of the performance of different models are also similar, suggesting that PE models yield a similarly high or low performance on a number of basins. The small differences between formulae in terms of streamflow calculations give a hint of the lack of accuracy required for PE input to the model since the seasonal cycle of many PE formulae can strongly differ.

Fig. 4 shows the performance obtained by the GR4J model assessed with the two other criteria. Note that the overall ranking of PE formulae and the conclusions on the value of PE formulae for streamflow simulations are similar for all criteria.

Aerodynamic parameters such as wind speed and relative humidity are far from being as efficient as energy-based parameters: the lowest-performance PE formulae are all based on wind speed and/or relative humidity, without energy-based parameters. In contrast, when PE is represented by air temperature, the performance is acceptable. This is probably due to the poor representation of the seasonal cycle of aerodynamics-based formulations. Note also that the Priestley–Taylor formula, which represents the energy-based term of the Penman formula, appears slightly more efficient in a rainfall–runoff context than the latter.

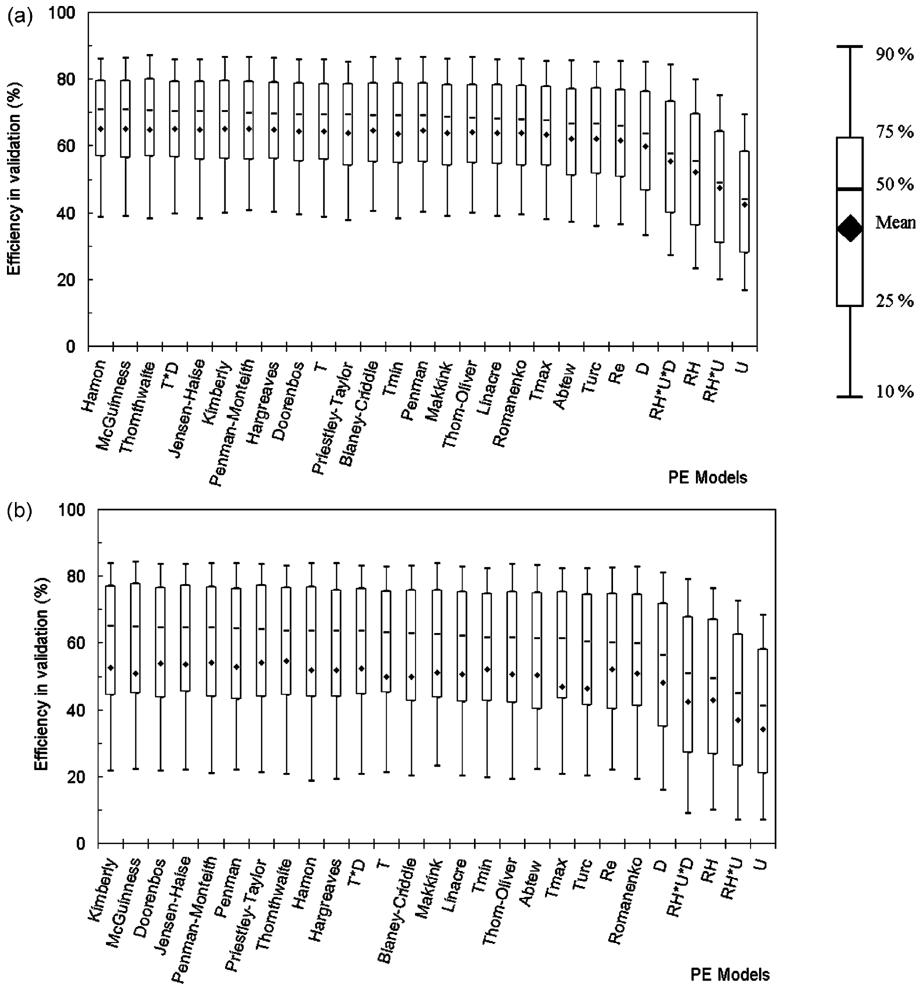

Fig. 3. Average and 0.10, 0.25, 0.50, 0.75 and 0.90 percentiles of Nash (Q) criteria obtained by 27 PE models in validation mode for GR4J model (a), HBV0 (b), IHAC (c) and TOPMO (d). Results are obtained on 2498 validation periods and PE models are sorted in decreasing order of median Nash criterion.

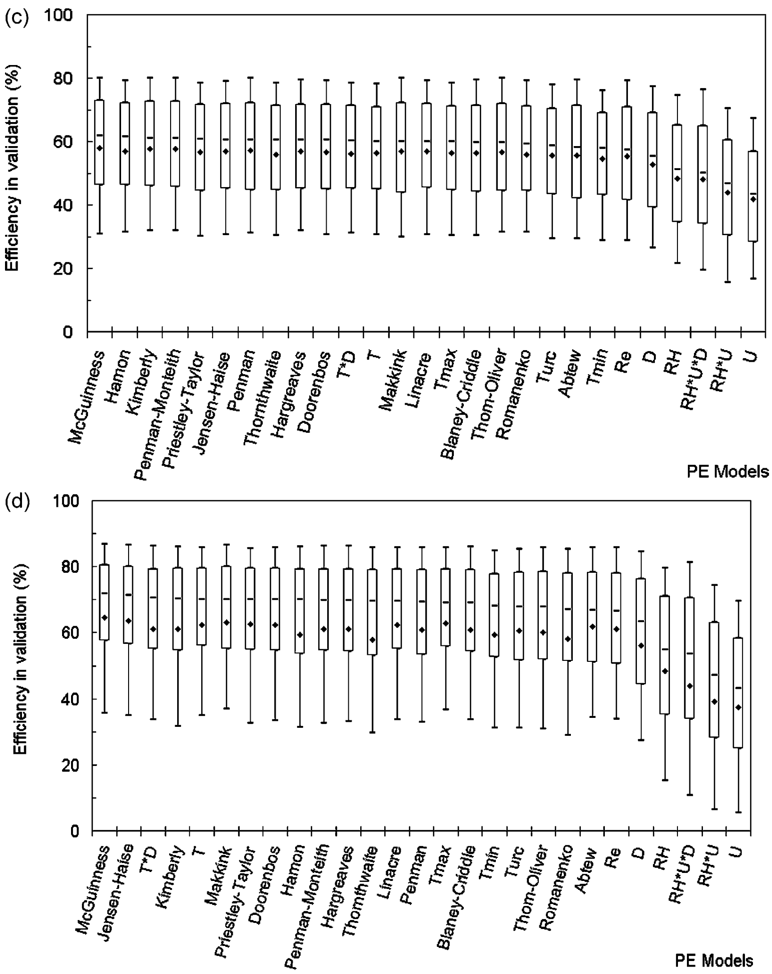

Fig. 3 (*continued*)

Fig. 5 summarizes the ranks obtained by the 27 PE models in validation mode for the four rainfall–runoff models. Figs. 3 and 5 show that there is good albeit not complete agreement in PE model ranking for the four rainfall–runoff models. This is a key point because it suggests that we can propose a PE model that improves the efficiency of all rainfall–runoff models. Fig. 5 also shows that temperature- and radiation-based PE models tend to be more efficient than the others, particularly combination PE models. Here, extra-terrestrial radiation relies only on latitude and Julian day. Thus, the McGuinness or Jensen–Haise models, for example, can be considered more relevant for rainfall–runoff modelling than Penman-type models, which use four climatic parameters. However, it must be kept in mind that all PE formulae are scaled to the Penman PE mean, and so they are not independent; tests without a scaling factor will be performed on specific formulae in Section 5.

From the operational side, these results are very useful because one can quite easily obtain mean monthly temperatures at many locations. Thus, it will be much easier to obtain catchment-scale representative PE estimates with temperature-based methods than with Penman-type methods, for which values are often extrapolated from distant meteorological stations.

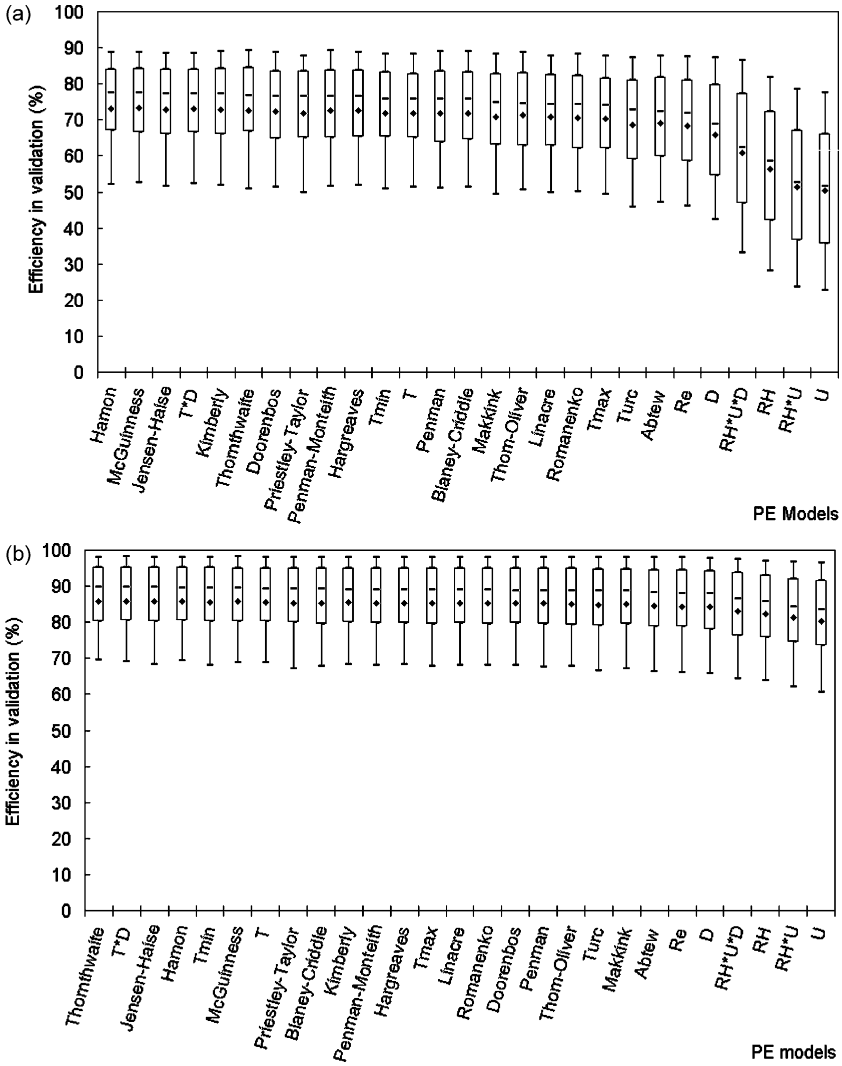

Fig. 4. Average and 0.10, 0.25, 0.50, 0.75 and 0.90 percentiles of Nash ($\sqrt{Q}$) and CB criteria obtained by 27 PE models in validation mode for GR4J model. Results are obtained on 2498 validation periods and PE models are sorted in decreasing order of median Nash criteria.

5. Assessment of a simple and efficient PE model

In Section 4, we showed that from an operational point of view, the commonly used Penman model does not appear to be the most relevant PE model since it requires four climatic variables and provides no better streamflow simulations than other less data-demanding models. Even if some authors focused on the physically based Penman model, we believe that the choice of the PE model to be used for applications of conceptual rainfall–runoff models should be made in terms of efficiency, and in the case of similar efficiency, in terms of simplicity. In Section 4, we have shown that temperature- and radiation-based models give the most valuable seasonal cycle of PE for rainfall–runoff models. However, the PE models used in Section 4 were constrained to yield the same long-term average as the Penman model. In this section, we have attempted to propose simple PE models for the four rainfall–runoff models. The PE models take the form of a radiation-based method, with two adjustment factors, using only mean (long-term averages) climatic data.

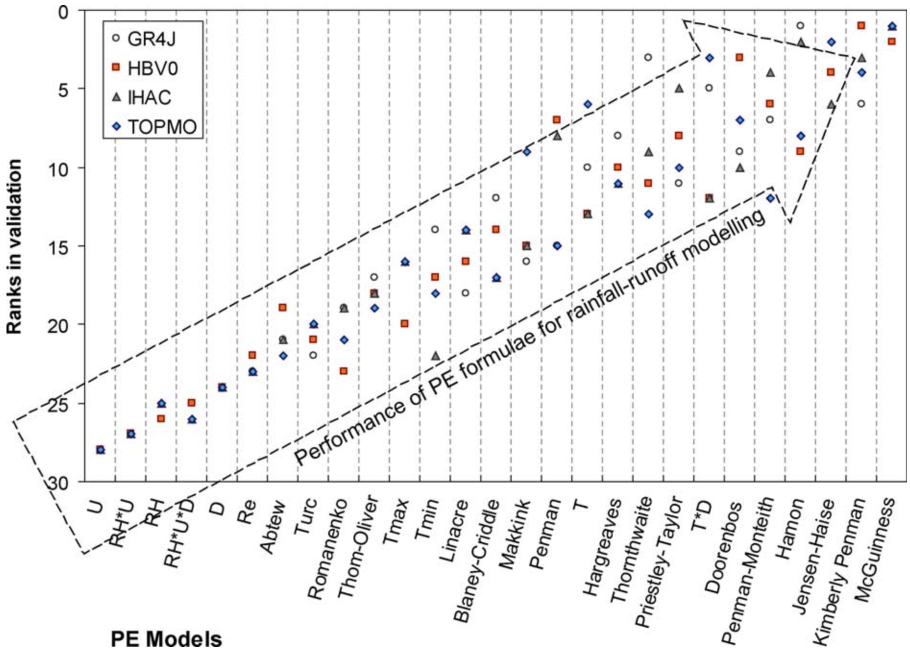

Fig. 5. PE model ranking for the four rainfall–runoff models in validation mode. Results are obtained with the median Nash (Q) criterion over the 2498 validation periods (PE models, scaled to Penman PE, were ranked in this figure by order of decreasing mean efficiency for the four rainfall–runoff models).

One of these adjustment factors refers to the scaling factor presented in Section 4.2, which we now wish to define independently of the Penman formulation.

5.1. Adjusting a simple PE model based on mean temperature data

From the pool of the top ten PE formulae identified in Section 4, we chose to focus our research on two of them, the Jensen–Haise and McGuinness models, which give as satisfactory results as more data-demanding models such as the Kimberly–Penman or the Penman–Monteith models. The Jensen–Haise and McGuinness models only need the climatological mean daily air temperature and extra-terrestrial radiation. They take the following generalized form:

$$\begin{aligned} \mathrm{PE} &= \frac{R_\mathrm{e}}{\lambda\rho}\frac{T_\mathrm{a}+K_2}{K_1} \quad \text{if } T_\mathrm{a}+K_2>0 \\ \mathrm{PE} &= 0 \quad \text{otherwise} \end{aligned} \tag{2}$$

where PE is the rate of potential evapotranspiration (mm day^{-1}), R_e is extraterrestrial radiation (MJ m^{-2} day^{-1}), depending only on latitude and Julian day, λ is the latent heat flux (taken equal to 2.45 MJ kg^{-1}), ρ is the density of water (kg m^{-3}) and T_a is the mean daily air temperature (°C), which is therefore a single function of the Julian day for a given location. K_1 (°C) and K_2 (°C) are new constants to adjust over the catchment sample for each rainfall–runoff model. Clearly, K_1 is the scaling factor, now independent of Penman PE values, and K_2 is the factor making it possible to vary the threshold for air temperature, i.e. the minimum value of air temperature for which PE is not zero. Note that K_1 and K_2 are fixed model parameters since they are adjusted over the whole catchment sample and not specifically calibrated for each catchment. Hereafter, the term ‘adjusted PE model with mean air temperature’ will refer to the PE model described in Eq. (2).

To adjust the two constants, we tested several values of K_1 and K_2 for each rainfall–runoff model and kept the association (K_1, K_2) that gives the best streamflow simulations over the catchment sample. In the Jensen–Haise and McGuinness models (K_1, K_2) are equal to (40, 0) and (68, 5), respectively. Note that the adjustment procedure of K_1 is not applicable for IHAC and HBV0 rainfall–runoff models because they already have a scaling parameter for PE, which is optimized during the calibration phase. So for the HBV0 and IHAC models, we have adjusted only the constant K_2.

Fig. 6 summarizes the results obtained when using the adjusted PE model with mean air temperature for the four rainfall–runoff models. Median model efficiency for several values of K_2 is plotted against the value of the adjustment factor K_1, in order to give some perspective on the models' sensitivity to these factors.

First, it should be noted that rainfall–runoff models are sensitive to the scaling divisor K_1. Scaling factors K_1 are larger than 68 for the TOPMO and GR4J models, suggesting that the original McGuinness model overestimated PE in a rainfall–runoff context. This corroborates the frequent statement found in the hydrological literature about over-estimation of the evaporative demand at the catchment scale by classical PE formulae (Morton, 1983).

The adjustment of the translation factor K_2 generally improves the model by less than 2% for the median of Nash criteria. The optimal value of K_2 is often intermediate (5 or 6). This may be due to the influence given to negative values of air temperature, which are not taken into account when $K_2=0$. On the other hand, when K_2 increases, the relative weight of the temperature term of the equation decreases and the equation does not fully take into account the range of air temperature fluctuations.

Though it appears that the adjusted factors are linked to the structure of rainfall–runoff models,

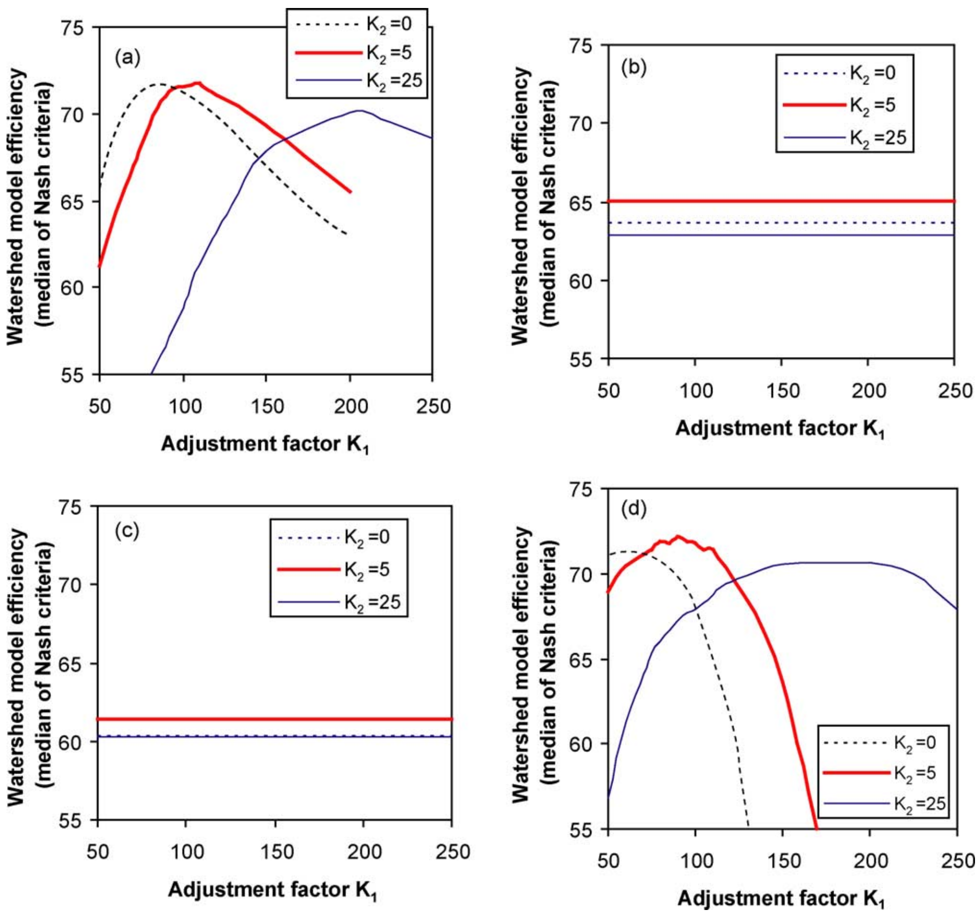

Fig. 6. Variations of rainfall–runoff models efficiency when adjusting factors for a model based on mean temperature and extraterrestrial radiation data. Results obtained with (a) GR4J model, (b) HBV0 model, (c) IHAC model and (d) TOPMO model.

Table 2
Rainfall–runoff model performance with Penman and adjusted PE models—Nash (Q), Nash ($\sqrt{Q}$) and CB criteria (%) obtained in validation mode (results obtained over 2498 validation periods)

Rainfall–runoff models	PE input option	Median of Na (Q) (%)	Median of Na ($\sqrt{Q}$) (%)	Median of CB (%)
GR4J	Penman PE	69.1	75.9	88.9
	Adjusted model with mean air temperature	71.9	78.2	89.9
HBV0[a]	Penman PE	64.3	70.2	89.0
	Adjusted model with mean air temperature	65.0	71.8	89.7
IHAC[a]	Penman PE	60.5	68.4	87.2
	Adjusted model with mean air temperature	61.4	70.3	87.3
TOPMO	Penman PE	69.4	76.6	88.0
	Adjusted model with mean air temperature	72.0	78.8	90.0

[a] IHAC and HBV0 models have their own optimized K_1 adjustment factor during the calibration phase; only K_2 was adjusted.

a common formula can be proposed, which yield results close to the optimum (with a possible decrease less than 0.5% from the maximum value of the Nash criterion). Hence, the values taken by K_1 are between 90 and 115 for GR4J and between 75 and 110 for TOPMO. So the value of K_1, which gives quite satisfying results for both the rainfall–runoff models, is between 90 and 110. Finally, we can propose a simple formula according to the following equation:

$$\begin{aligned} &\mathrm{PE} = \frac{R_\mathrm{e}}{\lambda\rho}\frac{T_\mathrm{a}+5}{100} && \text{if } T_\mathrm{a}+5>0 \\ &\mathrm{PE} = 0 && \text{otherwise} \end{aligned} \tag{3}$$

where PE is the rate of potential evapotranspiration (mm day^{-1}), R_e is extraterrestrial radiation (MJ m^{-2} day^{-1}), λ is the latent heat flux in (MJ kg^{-1}), ρ is the density of water (kg m^{-3}) and T_a is mean daily air temperature (°C), derived from long-term average.

5.2. Model efficiencies obtained with the proposed PE model versus Penman model

Table 2 presents the comparison of streamflow simulation efficiencies in validation mode for two different approaches (the Penman and adjusted PE model). We have used daily computed data for the Penman model because this option is often preferred by hydrologists when daily data are available. For the adjusted PE models, mean data were used since we consider that they do not affect efficiency of rainfall–runoff models compared with daily data.

The median value of the three criteria obtained over the 2498 validation periods are used to summarize the efficiencies of the rainfall–runoff models.

Model efficiencies can be slightly improved with the proposed PE equations, leading to an improvement ranging from 0.7 to 2.8% (median of Nash criteria on streamflow), depending on the rainfall–runoff model used. This is even more remarkable since proposed PE equation data requirements are much lower than Penman model data requirements.

Fig. 7 illustrates the shape of obtained distributions over the 2498 validation periods of Nash criterion values obtained by the rainfall–runoff models, with the Penman PE model and the adjusted PE model.

These results confirm those shown in Table 2. Compared to the Penman model, the adjusted PE models are indeed equivalent for HBV0 and IHAC and slightly more efficient for GR4J and TOPMO.

6. Conclusion

The objective of this study was to investigate the main strategies to input PE into a rainfall–runoff model and to assess their impacts on streamflow simulation efficiency. A 27-formulae sample was tested against data from 308 catchments within a wide range of climatic zones.

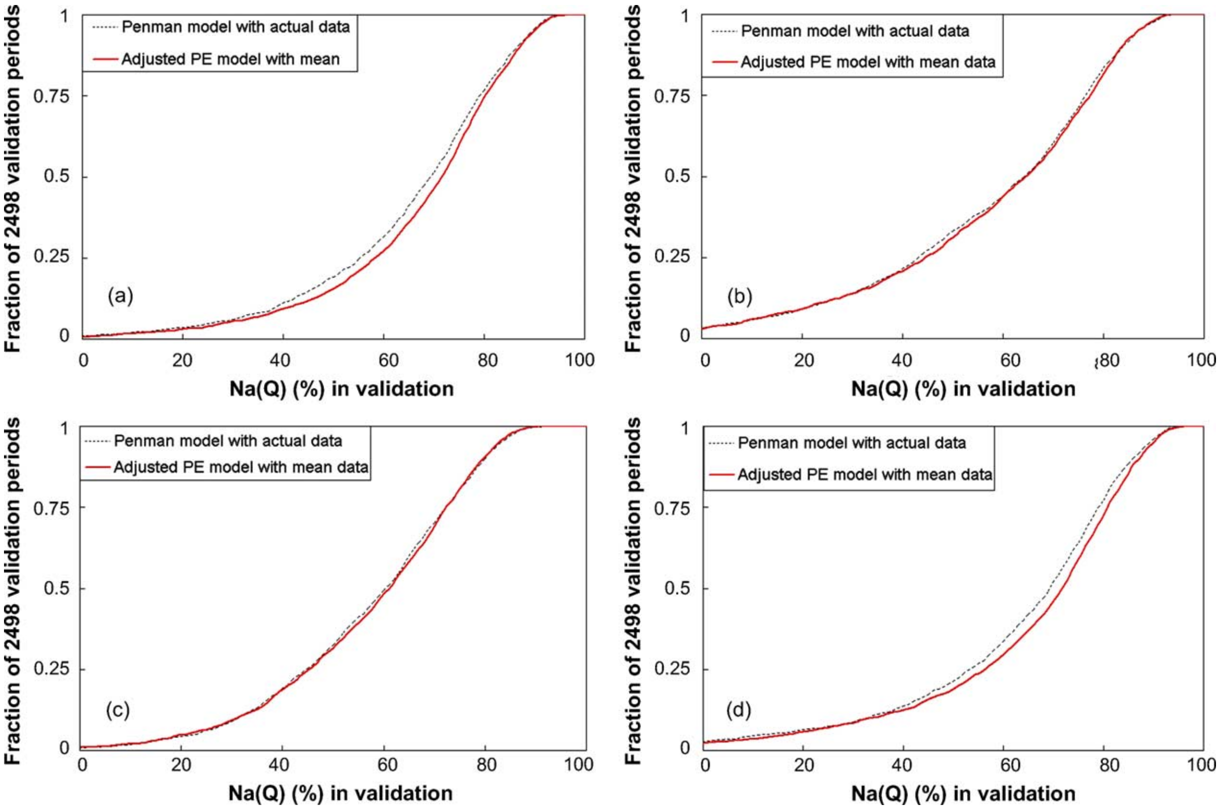

Fig. 7. Distributions of performance per catchment (over the 2498 validation periods) obtained in validation with Nash (Q) criterion with (a) GR4J, (b) HBV0, (c) IHAC and (d) TOPMO using proposed PE model and Penamn PE.

The main result of this study is that very simple models relying only on extraterrestrial radiation and mean daily temperature are as efficient as more complex models such as the Penman model and its variants. The comparison made of 27 tested formulae showed that the McGuinness model can be used instead, without loss of efficiency, for rainfall–runoff modeling, and using average data at that. This is rather convenient from an operational point of view since hydrological studies are often limited by the incompleteness of climate data.

Finally, we found that rainfall–runoff model efficiency can be improved even by using simple temperature-based PE models, which require only mean daily temperature data. Although the adjustment factors to be used could possibly change with the rainfall–runoff model into which PE is inputted, we decided on a single formula.

Overall, we consider these results as encouraging and we hope that this article will stimulate further work on PE model development for use in rainfall–runoff models and/or at the catchment-scale, and encourage the use of a simple PE model. After all, if a simple temperature-based PE estimation works as well as a Penman-type model, why not using a simpler model with lower data requirements?

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Appendix A. Background for PE calculation

A.1. Weather data notations and units

PE	potential evapotranspiration (mm day^{-1})
Δ	Slope of vapor pressure curve (kPa $°C^{-1}$)
λ	latent heat of vaporization (MJ kg^{-1})
ρ	water density (=1000 kg L^{-1})
γ	psychrometric constant (kPa $°C^{-1}$)
$e_s(T_a)$	saturation vapour pressure (kPa)
$e_a(T_d)$	actual vapour pressure (kPa)
r_a	aerodynamic resistance (s m^{-1})
r_s	surface resistance of reference crop (=69 s m^{-1})
U	wind speed 2 m above soil surface (m s^{-1})
T_a	air temperature (°C)
T_d	dew point temperature (°C)
R_e	extraterrestrial radiation (MJ m^{-2} day^{-1})
R_g	global short-wave radiation (MJ m^{-2} day^{-1})
R_n	net solar radiation (MJ m^{-2} day^{-1})
DL	day length (h day^{-1})
D	bright sunshine (h day^{-1})
α	surface albedo
J_D	Julian day

A.2. PE computations

Penman (1948)	$\mathrm{PE}=\frac{\Delta R_n+\gamma(e_a-e_d)W}{\lambda\rho(\Delta+\gamma)}$ with $W=2.6\,(1+0.536U)$
Penman-Monteith (Monteith, 1965)	$\mathrm{PE}=\frac{\Delta R_n+\gamma(e_a-e_d)W}{\lambda\rho\left[\Delta+\gamma\left(1+\frac{r_s}{r_a}\right)\right]}$ with $W=(1500/r_a)$ and $r_a=(208/U)$
Priestley and Taylor (1972)	$\mathrm{PE}=\frac{\alpha_{pt}\Delta R_n}{\lambda\rho(\Delta+\gamma)}$ with $\alpha_{pt}=1.26$
Kimberly–Penman (Wright, 1982)	$\mathrm{PE}=\frac{\Delta R_n+\gamma(e_a-e_d)W}{\lambda\rho(\Delta+\gamma)}$ with: $W=\left[0.4+0.14\exp\left(-\left(\frac{J_D-173}{58}\right)^2\right)\right]+\left[0.605+0.345\exp\left(-\left(\frac{J_D-243}{80}\right)^2\right)\right]U$
Thom and Oliver (1977)	$\mathrm{PE}=\frac{\Delta R_n+2.5\gamma(e_a-e_d)W}{\lambda\rho\left[\Delta+\gamma\left(1+\frac{r_s}{r_a}\right)\right]}$ with $W=2.6(1+0.536U)$
Thornthwaite (1948)	$\mathrm{PE}=\frac{4}{3}DL\left(\frac{10T_m}{I}\right)^K$ with $K=0.49+1.8(I/100)-0.77(I/100)^2+0.67(I/100)^3$, $I=\sum_{k=1}^{12}\left(\frac{T_k}{5}\right)^{1.51}$ where T_k is the mean monthly temperature.
Blaney-Criddle (1950)	$PE=k\cdot D\cdot(0.46T_a)+8.13)$ With k varying from 0.45 to 1.2 according to season and vegetation type (here, $k=0.82$)
Hamon (1961)	$\mathrm{PE}=\left(\frac{DL}{12}\right)^2\exp\left(\frac{T_a}{16}\right)$
Romanenko (1961)	$\mathrm{PE}=4.5\left(1+\frac{T_a}{25}\right)^2\left(1-\frac{e_d}{e_a}\right)$
Linacre (1977)	$\mathrm{PE}=\frac{\frac{500T_h}{(100-A)}+15(T_a-T_d)}{80-T_a}$ with A, latitude of the station $T_h=T_a+0.006\,h$ where h is the altitude (m)
Turc (1961)	$\mathrm{PE}=0.027\left(\frac{T_a}{T_a+15}\right)(R_g(1-\alpha)+24)y$
Jensen and Haise (1963)	$\mathrm{PE}=\frac{R_e}{\lambda\rho}\frac{T_a}{40}$
McGuinness–Bordne (1972)	$\mathrm{PE}=\frac{R_e}{\lambda\rho}\frac{T_a+5}{68}$

Hargreaves and Samani (1975)	$PE=0.0023\frac{R_e}{\lambda\rho}(T_{max}-T_{min})^{1/2}(T_a+17.8)$
Doorenbos-Pruitt (1977) (FAO-24)	$PE=-0.3+\frac{\Delta}{\Delta+\gamma}\frac{R_g}{\lambda\rho}(1-\alpha)W$
	with: $W=1.066-0.13\frac{RH}{100}+0.045U-0.02\frac{RH}{100}U-3.15\left(\frac{RH}{100}\right)^2-0.0011U$
Abtew (1996)	$PE=0.53\frac{R_g}{\lambda\rho}(1-\alpha)$
Makkink (1957)	$PE=\frac{1}{\lambda\rho}\left(\frac{0.63R_g\Delta}{\Delta+\gamma}+14\right)$

References

Abtew, W., 1996. Evapotranspiration measurements and modeling for three wetland systems in south Florida. Water Resources Bulletin 32 (3), 465–473.

Amatya, D.M., Skaggs, R.W., Gregory, J.D., 1995. Comparison of methods for estimating REF-ET. Journal of Irrigation and Drainage Engineering 121 (6), 427–435.

Andersson, L., 1992. Improvement of runoff models. What way to go? Nordic Hydrology 23, 315–332.

Andréassian, V., Perrin, C., Michel, C., 2004. Impact of imperfect potential evapotranspiration knowledge on the efficiency and parameters of watershed models. Journal of Hydrology 286 (1-4), 19–35.

Beven, K.J., 2001. Rainfall–runoff Modelling—The Primer. Wiley, New York. 360 pp.

Blaney, H.F., Criddle, W.D., 1950. Determining water requirements in irrigated areas from climatological and irrigation data. Technical Paper no. 96, US Department of Agriculture, Soil Conservation Service, Washington, DC.

Brutsaert, W., 1982. Evaporation into the Atmosphere. Kluwer, Dordrecht. 299 pp.

Calder, I.R., 1983. An objective assessment of soil-moisture deficit models. Journal of Hydrology 60, 329–355.

Doorenbos, J., Pruitt, W.O., 1977. Crop water requirements. Irrigation and Drainage Paper No. 24. FAO, Rome.

Edijatno, 1991. Mise au point d'un modèle élémentaire pluie-débit au pas de temps journalier. PhD Thesis, Université Louis Pasteur, Strasbourg, France, 242 pp.

Evans, J.P., 2003. Improving the characteristics of streamflow modeled by regional climate models. Journal of Hydrology 284 (1-4), 211–227.

Fowler, A., 2002. Assessment of the validity of using mean potential evaporation in computations of the long-term soil water balance. Journal of Hydrology 256 (3/4), 248–263.

Hamon, W.R., 1961. Estimating potential evaporation, in: Division, J.o.H. (Ed.), Proceedings of the American Society of Civil Engineers, pp. 107–120.

Hargreaves, G.H., Samani, Z.A., 1982. Estimating potential evapotranspiration. Technical note. Journal of Irrigation and Drainage Engineering 108 (3), 225–230.

Jensen, M.E., Haise, H.R., 1963. Estimating evapotranspiration from solar radiation. Journal of Irrigation and Drainage Division, ASCE 89 (LR4), 15–41.

Jensen, M.E., Burman, R.D., Allen, R.G., 1990. Evapotranspiration and water requirements, ASCE Manual 70, New York, USA 1990. 332 pp.

Joukainen, S., 2000. Improving the calculation of potential evapotranspiration of the HBV model: application to the Ounasjoki watershed, in: Nilsson, T. (Ed.), Nordic hydrological conference 2000. Nordic Hydrological Programme Report, 2000. Swedish Hydrological Council, Uppsala, pp. 347–354.

Klemeš, V., 1986. Operational testing of hydrologic simulation models. Hydrological Sciences Journal 31 (1), 13–24.

Linacre, E.T., 1977. A simple formula for estimating evaporation rates in various climate, using temperature data alone. Agricultural Meteorology 18, 409–424.

Lindroth, A., 1993. Potential evaporation—a matter of definition. Nordic Hydrology 24 (5), 359–364.

Makkink, G.F., 1957. Testing the Penman formula by means of lysimeters. Journal of the Institution of Water Engineers 11, 277–288.

McGuinness, J.L., Bordne, E.F., 1972. A comparison of lysimeter-derived potential evapotranspiration with computed values. Technical Bulletin 1452, Agricultural Research Service, US Department of Agriculture, Washington, DC.

Monteith, J.L., 1965. Evaporation and the environment, The state and movement of water in living organisms, XIXth symposium. Cambridge University Press, Swansea.

Morton, F.I., 1983. Operational estimates of areal evapotranspiration and their significance to the science and practice of hydrology. Journal of Hydrology 66 (1–4), 1–76.

Morton, F.I., 1994. Evaporation research—a critical review and its lessons for the environmental sciences. Critical Reviews in Environmental Science and Technology 24 (3), 237–280.

Nandakumar, N., Mein, R.G., 1997. Uncertainty in rainfall–runoff model simulations and the implications for predicting the hydrologic effects of land-use change. Journal of Hydrology 192, 211–232.

Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models. Part I—a discussion of principles. Journal of Hydrology 10, 282–290.

Parmele, L.H., 1972. Errors in output of hydrologic models due to errors in input potential evapotranspiration. Water Resources Research 3 (2), 348–359.

Paturel, J.E., Servat, E., Vassiliadis, A., 1995. Sensitivity of conceptual rainfall–runoff algorithms to errors in input data—case of the GR2M model. Journal of Hydrology 168, 111–125.

Penman, H.L., 1948. Natural evaporation from open water, bare soil and grass. Proceedings of the Royal Society of London 193, 120–145.

Priestley, C.H.B., Taylor, R.J., 1972. On the assessment of surface heat fluxes and evaporation using large-scale parameters. Monthly Weather Review 100, 81–92.

Shuttleworth, W.J., 1993. Evaporation, in: Maidment, D.R. (Ed.), Handbook of Hydrology. McGraw-Hill, New York.

Thom, A.S., Oliver, H.R., 1977. On Penman's equation for estimating regional evaporation. Quarterly Journal of the Royal Metereological Society 103, 345–357.

Thornthwaite, C.W., 1948. An approach towards a rational classification of climate. Geographical Review 38, 55–94.

Turc, L., 1961. Evaluation des besions en eau d'irrigation, évapotranspiration potentielle, Annales Agronomiques, 12, 13–49.

Wright, J.L., 1982. New evapotranspiration crop coefficients. Journal of Irrigation and Drainage Engineering 108 (IR2), 57–74.

Xu, C.-Y., Singh, V.P., 2001. Evaluation and generalization of temperature-based methods for calculating evaporation. Hydrological Processes 15 (2), 305–319.

Xu, C.Y., Singh, V.P., 2002. Cross comparison of empirical equations for calculating potential evapotranspiration with data from Switzerland. Water Resources Management 16 (3), 197–219.