



# Impact of potential and (scintillometer-based) actual evapotranspiration estimates on the performance of a lumped rainfall–runoff model

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**Abstract.** Evapotranspiration (ET) plays a key role in hydrological impact studies and operational flood forecasting models as ET represents a loss of water from a catchment.

Although ET is a major component of the catchment water balance, the evapotranspiration input for rainfall–runoff models is often simplified in contrast to the detailed estimates of catchment averaged precipitation.

In this study, an existing conceptual rainfall–runoff model calibrated for and operational in the Bellebeek catchment in Belgium firstly has been validated and its sensitivity to different available potential ET input has been studied. It has been shown that when applying a calibrated rainfall–runoff model, the model input should be consistent with the input used for the calibration process, not only on the volume of ET, but also on the seasonal pattern. Secondly, estimates of the actual evapotranspiration based on measurements of a large aperture scintillometer (LAS) have been used as model forcing in the rainfall–runoff model. From this analysis, it has been shown that the actual evapotranspiration is a crucial factor in simulating the catchment water balance and the resulting stream flow.

Regarding the actual evapotranspiration estimates from the LAS, it has been concluded that they can be considered realistic in summer months. In the months where stable conditions prevail (autumn, winter and (early) spring), an underestimation of the actual evapotranspiration is made, which has an important impact on the catchment's water balance.

## 1 Introduction

Floods are among the most common natural disasters in the world. Among other infrastructure protecting measures, one indispensable tool to manage floods is the use of operational rainfall–runoff models to predict the arrival of discharge peaks. These rainfall–runoff models are usually forced with continuous time series of the catchment averaged precipitation and evapotranspiration rates. These are then related to the catchment discharge through a number of conceptual equations –representing a number of reservoirs that are connected through a number of flows– of which the parameters are tuned through a comparison of the modeled discharge to observations (Ferret et al., 2010).

Although evapotranspiration is a major component of the catchment's water balance, the evapotranspiration input for rainfall–runoff models is often simplified compared to the detailed estimates of catchment averaged precipitation. However, evapotranspiration rates depend, among other, on land cover type and soil moisture conditions (Samain et al., 2011), and consequently it can be considered important to estimate the watershed-scale evapotranspiration.

Nevertheless, poor attention is given to this date to the ET input for rainfall–runoff models. As an appropriate (continuous) estimate of actual evapotranspiration at the catchment scale is often not available, potential evapotranspiration tends to be used as model forcing. The estimates of potential evapotranspiration ( $ET_p$ ) are usually based on calculations from meteorological data (such as Penman's equation).  $ET_p$  is then converted into actual evapotranspiration through one or more equations (with corresponding parameters) depending on the water content of one or more soil water reservoirs.

Oudin et al. (2005b) studied the impact of different potential ET inputs on the model performance of four different rainfall–runoff models over a large and climatically varied catchment sample of 308 catchments located in France, Australia and the United States. They concluded that looking for daily observed  $ET_p$  data as input for rainfall–runoff models is not necessary and that a long-term average regime curve of  $ET_p$  resulted in an equal stream flow simulation efficiency.

By studying more extensively the rainfall–runoff models and their inner state variables, Oudin et al. (2004) have shown that the insensitivity of rainfall–runoff models to the different  $ET_p$  inputs is due to the low-pass behavior of the soil moisture reservoirs, which smooths the effect of the  $ET_p$  fluctuations. It is important to mention that for these studies, systematic differences between different  $ET_p$  inputs have been eliminated by a rescaling to the same long-term  $ET_p$ . Additionally, Oudin et al. (2006) found that systematic errors in the  $ET_p$  input lead to a proportional degradation of model performance. This can be improved by recalibrating the rainfall–runoff model with the (erroneous)  $ET_p$  input, because the conversion of potential into actual ET compensates for input errors in the potential ET.

In this paper, an existing conceptual rainfall–runoff model, calibrated for and operational in the Bellebeek catchment, is validated, and its sensitivity to different available ET inputs has been studied. Not only the impact on the model performance is studied for different estimates of potential ET as model forcing (as is done earlier by Oudin et al., 2005b), but also for an estimate of the catchment averaged actual ET.

These estimates of  $ET_{act}$  have been obtained indirectly from optical scintillometry, a technique that is quickly emerging in hydrologic applications to estimate surface fluxes continuously across large distances.

The paper is organized as follows. In Sect. 2, the study site and the available data sets are described. In Sect. 3, the probability distributed model (PDM) of the Bellebeek catchment is introduced. This model has formerly been calibrated by Cabus (2008) with a mean seasonally variable  $ET_p$  input (a sinusoidal function throughout the year for daily  $ET_p$  averages).

In Sect. 4, the performance of this PDM on stream flow output is evaluated when other  $ET_p$  inputs are used (based on the Penman–Monteith equations) (Sect. 4.2). Also, the impact of other temporal resolutions for the ET input has been assessed (Sect. 4.3). In addition to the methodology of Oudin et al. (2004), for the Bellebeek catchment, the model performance has also been evaluated on its simulations of the internal model variable  $ET_{act}$  as actual evapotranspiration estimates are available from a large aperture scintillometer.

Finally, in Sect. 5, the performance of the PDM applying the catchment's actual evapotranspiration derived from scintillometer data as model forcing, is evaluated.

## 2 Site and data description

### 2.1 Site description

The study was performed in the Dender catchment in Flanders, the northern part of Belgium. Figure 1 shows the location of the catchment together with a digital elevation model (DEM) of the area. A meteorological station as well as a large aperture scintillometer (LAS) are operational in the subcatchment of the Bellebeek (102.3 km<sup>2</sup>). The elevation in the subcatchment ranges between 10 and 110 m. Soil texture is predominantly loam (74 %), and the land use is predominantly agriculture (63.6 %) and pasture (22.9 %). Urban land cover makes up 8.6 % of the surface and the remaining area consists of forest (4.8 %) and open water (0.1 %).

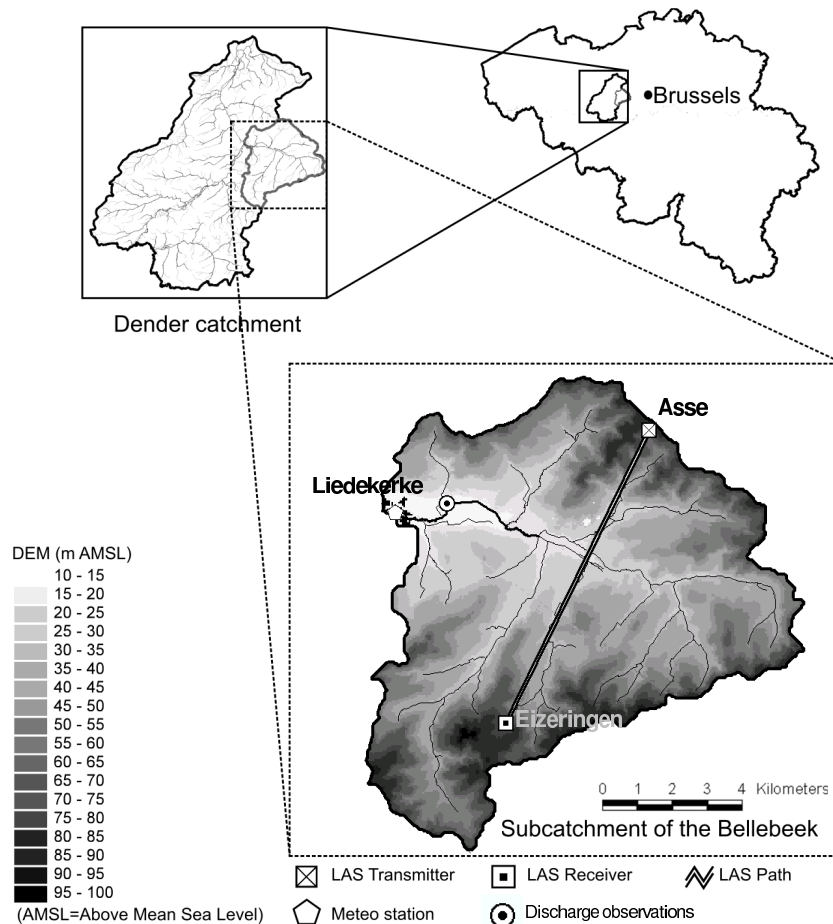
Precipitation rates as model forcing for the PDM are continuously measured at the meteorological station of Liedekerke, situated near the outlet of the catchment and are considered here as uniformly distributed over the catchment. Discharge observations are continuously available at an hourly time step at the outlet of the catchment.

### 2.2 Data sets from the meteorological station

Figure 1 shows the location of the meteorological station of Liedekerke used in this study. Continuous measurements of wind speed and wind direction at 10 m height, as well as precipitation rates, air pressure, and air and dew point temperature at a height of 2 m were available at a 10 min intervals. Further, net radiation ( $R_n$ ) data from a NR-Lite net radiometer (Kipp and Zonen, Delft, Netherlands) at 2 m height and ground heat flux ( $G$ ) observations from two HFP01 soil heat flux sensors (Hukseflux, Delft, Netherlands) at 5 cm depth were also available at this site. Discharge observations were available with an hourly time step at the outlet of the Bellebeek subcatchment.

### 2.3 Scintillometer data

The scintillometer used in this experiment is an LAS type BLS2000 (Scintec AG, Tübingen, Germany). The transmitter is situated in Asse on a water tower at an elevation of 40 m above the surface. The receiver is installed in the church tower in Eizingen at 15 m above the surface (Samain et al., 2011). The LAS is measuring over the subcatchment of the Bellebeek along a 9.5 km path. This allows the beam to cross the basin well above the canopy, the small forests, the valley of the Bellebeek and its tributaries and roads and towns. According to Samain et al. (2011), the effective height ( $z_{eff}$ , m) of the beam is 68 m, calculated following Hartogensis et al. (2003). The BLS2000 has an aperture size of 0.26 m, which makes it suitable for flux measurements on a relatively large spatial scale (up to 10 km). From the 1 min data of observed intensities, 1 min  $H$  values are derived using the calculation procedure explained in Samain et al. (2011).



**Fig. 1.** The location of the study site in Belgium, a DEM of the study area and the location of the meteorologic stations and the LAS in the study area.

As shown in Samain et al. (2011), representative sensible heat fluxes for the heterogeneous catchment of the Bellebeek can be calculated from the LAS data.

Samain et al. (2012a) further describe the construction of an almost continuous series of hourly sensible heat fluxes using an operational algorithm based on the diurnal cycle of the refractive index structure parameter  $C_N^2$  and by ignoring the humidity correction based on the Bowen ratio. This disregard of the humidity correction has been shown to result in an increase of the completeness of the resulting  $H$  series with only a marginal error in  $H$  (Samain et al., 2012a).

For the present study, data of the LAS from 21 February 2008 until 31 December 2010 are used. Unfortunately, due to logging problems, no LAS data were available for approximately 30% of this time series. Using the algorithm for constructing a continuous time series of  $H$  from LAS as explained by Samain et al. (2012a), for the remaining time steps, a reliable estimate of  $H$  could be obtained for 88% of the time steps. The loss of 12% of the data was either due to precipitation, or because no reliable hourly  $C_N^2$  was obtained from LAS data, because the algorithm could not be

applied. The latter problem occurred because no clear  $C_N^2$  minimum could be found around the transition between different stability conditions. In a next step, the energy balance equation has been applied to calculate latent heat fluxes  $LE$  (the energy equivalent of evapotranspiration) from these  $H$  fluxes (Samain et al., 2012b). Therefore, the operational estimates of the catchment available energy ( $AE = R_n - G$ ) are calculated from the point measurements of  $R_n$  and  $G$  from the Liedekerke meteorological station, and adjusted to the catchment scale through the use of the calibrated land surface model TOPLATS (Samain et al., 2012b). Resulting  $LE$  values for a period of 6 months have been compared to results from the remote sensing based surface energy balance algorithm ETLook and the land surface model TOPLATS. Consistency has been shown between daily evapotranspiration rates from ETLook, TOPLATS and the LAS (Samain et al., 2012b), and as such, these LAS-based ET-values can be considered as catchment averaged actual evapotranspiration estimates.

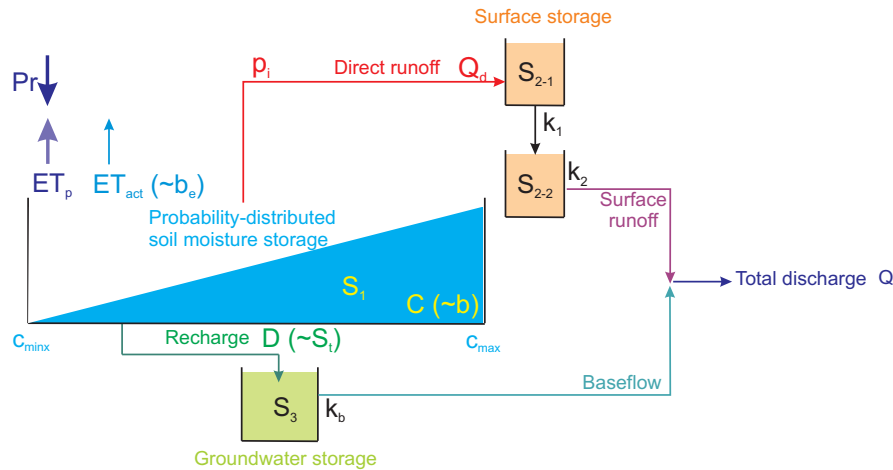


Fig. 2. Schematic of the PDM.

### 3 The probability distributed model

Different conceptual rainfall–runoff models exist to estimate the arrival and the height of discharge peaks, which is an important tool in the management of floods. Certainly in a densely populated and flood-sensitive area as Flanders (part of Belgium), the need for flood predictions is significant (Cabus, 2008). In the operational flood-forecast system of the Flemish government, the hydrological probability distributed model (PDM) is used to predict discharge into the rivers from the rainfall–runoff process, which is further used as forcing for hydraulic models to forecast flood extents.

#### 3.1 Model structure

Figure 2 shows a schematic of the PDM. A detailed description is given in Moore (2007). The PDM uses precipitation  $Pr$  ( $\text{mm h}^{-1}$ ) and potential evapotranspiration  $ET_p$  ( $\text{mm h}^{-1}$ ) as input and is programmed for time steps of 1 h. The conceptual basis of the model is the partitioning of the surface into a number of reservoirs, each with a different storage capacity. The distribution of the moisture content in the soil reservoir is mathematically described by a probability distribution. In most cases, a Pareto distribution is supposed, described by three parameters ( $c_{max}$ ,  $c_{min}$  and  $b$ ):

$$F(c) = 1 - \left( \frac{c_{max} - c}{c_{max} - c_{min}} \right)^b, \quad c_{min} < c < c_{max}, \quad (1)$$

where  $F(c)$  is the saturated fraction of the catchment (–),  $c$  (mm) is the moisture content,  $c_{min}$  (mm) and  $c_{max}$  (mm) are parameters defining the minimum and maximum soil moisture storage capacity, and exponent  $b$  (–) is a model parameter. For the Pareto distribution the moisture content  $c$  at each time step is calculated as

$$c = (c_{max} - c_{min}) \left[ 1 - \left( \frac{S_{max} - S_1}{S_{max} - c_{min}} \right)^{\frac{1}{b+1}} \right]. \quad (2)$$

The maximum storage capacity  $S_{max}$  (mm) of the soil moisture reservoir(s)  $S_1$  (mm) is defined by

$$S_{max} = \frac{c_{max} + bc_{min}}{b + 1}. \quad (3)$$

The drainage  $D$  ( $\text{mm h}^{-1}$ ) to the groundwater is controlled by the groundwater drainage time constant  $k_g$  (h) and is limited by  $S_t$  (mm), the threshold below which water is being held under soil tension:

$$D = \frac{1}{k_g} (S_1 - S_t)^{b_g}, \quad S_t \leq S_1. \quad (4)$$

Actual evapotranspiration is a fraction of the potential evapotranspiration  $ET_p$  ( $\text{mm h}^{-1}$ ) controlled by the water content of the soil moisture reservoir  $S_1$  (mm) and a parameter  $b_e$  (–):

$$ET_{act} = ET_p \left( 1 - \left( \frac{S_{max} - S_1}{S_{max}} \right)^{b_e} \right). \quad (5)$$

The soil moisture reservoirs are filled with the available water  $p_i$  ( $\text{mm h}^{-1}$ ), which is a gain of water due to rainfall, and a loss of water by evapo(transpi)ration  $ET_{act}$  ( $\text{mm h}^{-1}$ ) and by drainage  $D$  ( $\text{mm h}^{-1}$ ) to the groundwater:

$$p_i = Pr - ET_{act} - D. \quad (6)$$

The storage in the soil moisture reservoir(s)  $S_1$  at a time step  $t$ , is the sum of the storage in the previous time step ( $t - 1$ ) with the available water  $p_i$  and the direct runoff  $Q_d$  ( $\text{mm h}^{-1}$ ) when reservoirs overflow with an excess of available water:

$$S_{1,t} = S_{1,t-1} + p_i - Q_d, \quad S_{1,t} \leq S_{max}. \quad (7)$$

The overflow water is conceptually modeled as the surface runoff  $Q_s$  or fast discharge using a succession of two linear

reservoirs with time constants  $k_1$  (h) and  $k_2$  (h), which is expressed as the discretely coincident transfer function model described by O'Connor (1982):

$$Q_{s,t} = -\delta_1 Q_{s,t-1} - \delta_2 Q_{s,t-2} + \omega_0 Q_{d,t} + \omega_1 Q_{d,t-1}, \quad (8)$$

with

$$\delta_1 = \exp\left(\frac{-1}{k_1}\right), \delta_2 = \exp\left(\frac{-1}{k_2}\right), \quad (9)$$

$$\omega_0 = \frac{k_1(\delta_1 - 1) - k_2(\delta_2 - 1)}{k_2 - k_1}, \quad (10)$$

$$\omega_1 = \frac{k_2(\delta_2 - 1)\delta_1 - k_1(\delta_1 - 1)\delta_2}{k_2 - k_1}. \quad (11)$$

The slow discharge or baseflow  $Q_b$  ( $\text{mm h}^{-1}$ ) from the groundwater is modeled using an additional reservoir with time constant  $k_b$  ( $\text{h mm}^{-2}$ ). Following Moore (2007), a cubic form is usually considered most appropriate to represent the groundwater storage  $S_3$ . The baseflow from the groundwater storage is then calculated following:

$$Q_b = k_b S_3^3, \quad (12)$$

in which the groundwater storage  $S_3$  at a time step  $t$  is determined as follows:

$$S_{3,t} = S_{3,t-1} - \frac{1}{3k_b S_{3,t-1}^2} \left[ \exp\left(-3k_b S_{3,t-1}^2\right) - 1 \right] (D - k_b S_{3,t-1}^3). \quad (13)$$

The modeled total discharge  $Q$  ( $\text{mm h}^{-1}$ ) is then the sum of the baseflow  $Q_b$  and the surface runoff  $Q_s$ .

### 3.2 Application to the test site

The PDM has been calibrated in the framework of a consistent and area-covering modeling study for all river-gauging stations on the non-navigable watercourses in Flanders. These models were assessed not only for the accurate simulation of a limited number of storms, but also for their statistical correspondence with high-water events, their total water volume and the total similarity over the complete year-to-year monitoring series (Cabus, 2008).

For the calibration of the PDM for the Bellebeek by Cabus (2008), catchment average rainfall was determined using the Thiessen methodology using different rain gauge stations in and around the catchment. The potential evapotranspiration input was based on daily values from a sine curve with minimum ( $0 \text{ mm day}^{-1}$ ) in January and twice the average ( $2 \times 2 = 4 \text{ mm day}^{-1}$ ) on 4 July. The calibration period lasted from 1973 until 2001. The calibrated parameters are listed in Table 1.

**Table 1.** PDM parameter values for the Bellebeek at Essene.

Area	( $\text{km}^2$ )	88.38
$c_{\text{max}}$	(mm)	400
$c_{\text{min}}$	(mm)	0
$b$	(-)	0.3
$b_e$	(-)	2.5
$k_1$	(h)	10
$k_2$	(h)	4
$k_b$	( $\text{h mm}^{-2}$ )	18
$k_g$	(h)	5174.2
$S_t$	(mm)	45
$b_g$	(-)	1

### 3.3 Model performance

In this study, the PDM of the Bellebeek catchment will be further validated for a 4 yr time period (2007–2010) with special attention to the impact of different ET approaches as model forcing.

A multi-criteria protocol will be used here to evaluate the high frequency (hourly) modeled river flow from these simulations. First, the multiple criteria as described by Willems (2009) are applied. This methodology not only focuses on a good overall correspondence of the total flow, but also on the correspondence of cumulative flow (total outflow volume from the catchment), baseflow, high peak flows and high peak flow distribution, and low flows. As the rainfall–runoff model is operationally used to predict high flows, the main focus is on the peak flows. The plots considered for this model performance evaluation are consequently time series plots of the total flow, the baseflow, the cumulative total and baseflow (Fig. 3), the scatterplot of simulated versus observed peak flows and the empirical extreme value distribution of the peak flows (Fig. 4).

Therefore, the river flow series  $Q(t)$  ( $\text{m}^3 \text{ s}^{-1}$ ) is separated in its subflows (baseflow  $Q_b(t)$  ( $\text{m}^3 \text{ s}^{-1}$ ) and surface flow  $Q_s(t)$  ( $\text{m}^3 \text{ s}^{-1}$ )) applying the filter described by Nathan and McMahon (1990):

$$Q_s(t) = a_1 Q_s(t-1) + a_2 (Q(t) - \alpha_f Q(t-1)), \quad (14)$$

$$Q_b(t) = Q(t) - Q_s(t) = \alpha_f Q_b(t-1) + a_3 (1 - \alpha_f) (Q_s(t-1) + Q_s(t)), \quad (15)$$

where  $a_1$  (-),  $a_2$  (-),  $a_3$  (-) and  $\alpha_f$  (-) are calculated using

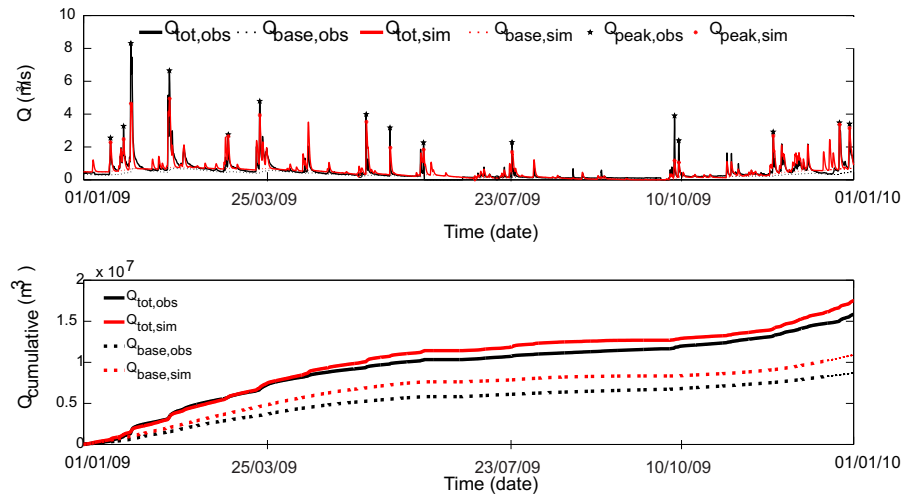
$$a_1 = \frac{(2+v)\alpha_f - v}{2+v-v\alpha_f}, \quad (16)$$

$$a_2 = \frac{2}{2+v-v\alpha_f}, \quad (17)$$

$$a_3 = 0.5v, \quad (18)$$

$$\alpha_f = \exp(-1/K). \quad (19)$$

The recession constant  $K$  (h) equals the time in which the flow is reduced during dry weather flow periods to a fraction  $\exp(-1) = 0.37$  of its original discharge.  $K$  can be quantified



**Fig. 3.** Example of time series and selection of nearly independent peak flow values of the observed and simulated river flow series for the year 2009 (top) and cumulative volume of observed and simulated total and base flow for the year 2009 (bottom).

as the average value of the inverse of the slope of the tangent of  $\ln(Q)$  versus time  $t$ . The second parameter  $\nu$  (–) can be calibrated by visually optimizing the height of the subflow during the recession periods in this graph (Willems, 2009). The result of the baseflow separation on the time series of stream flow of the Bellebeek is shown in Fig. 3.

From the flow series, also nearly independent peak and low flows are extracted in order to evaluate the empirical extreme value distributions of these extreme high and low flows.

To select peak flows, the methodology of Willems (2009) and Van Steenbergen and Willems (2012) is used. To avoid that small noise peaks are selected, in a first step of this methodology, only peaks higher than a minimum peak height are selected. Further, a peak can be considered nearly independent from a consecutive peak when the length of its decreasing limb exceeds a minimum time and the discharge drops down between the peaks to a fraction lower than a threshold fraction value of the peak flow.

A simulated peak flow is paired with an observed peak flow, if the simulated peak appears within a time window of 10 h around the observed peak, allowing small phase errors in the modeling results. Paired peak flows for the observed and simulated stream flows are illustrated in Fig. 3.

In the scatter plots of observed versus simulated peak flows (Fig. 4), the Box–Cox (BC) transformation (Box and Cox, 1964) is applied to both the observed and simulated values in order to reach homoscedastic model residuals. In rainfall–runoff models, the model residual variance or standard deviation typically increases with higher flow values. By performing the transformation, equal weight is given to the higher and lower peak flow values in the standard deviation calculation. The BC transformation, when applied to a variable  $X$ , is given by

$$\text{BC}(X) = \frac{X^{\lambda_{\text{BC}}} - 1}{\lambda_{\text{BC}}}. \quad (20)$$

The value of  $\lambda_{\text{BC}}$  can vary between 0 and 1 and needs to be calibrated. For runoff discharges,  $\lambda_{\text{BC}}$  usually adopts a value around 0.25 (Van Steenbergen and Willems, 2012) and is taken fixed here. After BC transformation, model residuals have a constant standard deviation ( $\text{STDEV}_{Q_{\text{peak}}}$ ) and a given mean residual error ( $\text{ME}_{Q_{\text{peak}}}$ ). These are plotted in Fig. 4 based on lines deviating from the bisector line.

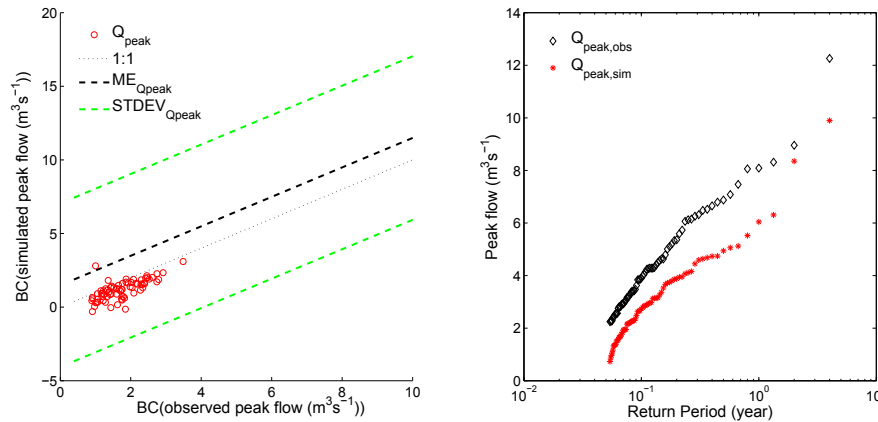
To construct the empirical extreme value distribution, empirical return periods for the peak flows are calculated based on the rank number of each peak flow after sorting of the peak flows. For the  $i$ th highest peak flow in a time series of  $n$  years, the return period of that event is given by

$$T(i) = \frac{n}{i}. \quad (21)$$

Based on this multi-criteria evaluation, a multi-objective set of statistics can be considered. The general equations for these statistics are defined hereafter for a variable  $X$ :

$$\text{RMSE} = \sqrt{\frac{\sum_{j=1}^n (X_{\text{obs},j} - X_{\text{sim},j})^2}{n}}, \quad (22)$$

$$\text{bias} = \overline{X_{\text{obs}}} - \overline{X_{\text{sim}}}, \quad (23)$$



**Fig. 4.** Example of scatter plot of simulated versus observed peak flows during independent quick flow periods after Box–Cox transformation ( $\lambda = 0.25$ ) (left) and the empirical extreme value distribution of peak flows for 4 yr of observations and simulations (2007–2010) (right).

$$CB = \left[ 1 - \text{abs} \left( 1 - \frac{\sum_{j=1}^n X_{sim,j}}{\sum_{j=1}^n X_{obs,j}} \right) \right], \quad (24)$$

$$NS = \left[ 1 - \frac{\sum_{j=1}^n (X_{obs,j} - X_{sim,j})^2}{\sum_{j=1}^n (X_{obs,j} - \bar{X}_{obs})^2} \right]. \quad (25)$$

Concerning the river flow, the RMSE (root mean square error), bias, NS (Nash–Sutcliffe criterion), CB (cumulative balance error) and difference in cumulative flow volume ( $\Delta_{cum} Q$ ) for the total flow as well as for the baseflow are used to evaluate model performance. For the peak flows, the RMSE for the peak flows as well as the standard deviation ( $STDEV_{peak}$ ) and the mean residual error ( $ME_{peak}$ ) of the BC-transformed peak flows are used as evaluation tools. Also the RMSE of the low flows are considered.

In addition to this multi-criteria approach for the modeled river flow, the modeled actual evapotranspiration rates can be validated based on the available actual evapotranspiration data. The considered statistics for  $ET_{act}$  evaluation are RMSE and the difference in cumulative actual evapotranspiration  $\Delta_{cum} ET_{act}$ .

#### 4 Effect of different $ET_p$ inputs on model performance

As the PDM of the Bellebeek catchment has been calibrated with the sinusoidal potential evapotranspiration input as described above, the model performance of the PDM will be evaluated for more detailed and catchment specific ET input. In this study, no recalibration of the rainfall–runoff has been performed because the objective of the study is assessing to

what extent the use of a model with different ET estimates will lead to worse results. This may seem evident, but in many cases ET inputs from different sources are used simultaneously in rainfall–runoff models. It will be shown that using different ET inputs as model forcing without recalibrating the model can lead to a deterioration in the model results.

For this study, the model is validated for 4 yr of simulation (from 1 January 2007 through 31 December 2010). Simulations are initiated in January 2005, in order to initialize all model reservoirs. From February 2008 through December 2010, LAS-based estimates of  $ET_{act}$  are available to validate the model for actual evapotranspiration. For this validation, point measurements of rainfall at the Liedekerke meteorological station are used and considered to be representative for the catchment-averaged rainfall. When comparing simulation results to the discharge measurements, one should keep in mind that there will always be discrepancies between the catchment-averaged rainfall and the point measurement of rainfall, which can result in sometimes overestimations and sometimes underestimations of the simulated discharge.

#### 4.1 Other potential evapotranspiration inputs

Moore (2007) does not specify how the potential evapotranspiration input for the PDM should be calculated. As stated before, for the calibration of the model, daily average values following a sinusoidal curve have been used as potential evapotranspiration input ( $ET_{p,sinus}$ ). As this potential evapotranspiration input cannot be considered catchment specific and not having the temporal variability of the model output (daily averages versus hourly model time step), the calibrated model will be validated with other more catchment specific potential evapotranspiration input with a temporal resolution according to the model time step (hours).

Various empirical evapotranspiration equations can be used to estimate potential evapotranspiration. In accordance with Oudin et al. (2005b), who studied the impact of the degree of detail of potential evapotranspiration input on model performance of rainfall–runoff models, the Penman model (Penman, 1948) is used to calculate hourly potential evapo(transpi)ration based on hourly actual data from the Liedekerke meteorological station.

The Penman equation describes potential evaporation ( $E_p$ ) from an open water surface, while the PDM models the flow from a catchment. Therefore, it is more appropriate to use a potential evapotranspiration equation for a vegetated land area where evaporation as well as transpiration of the catchment surface are considered. Following the recommendations of the FAO (Allen et al., 1998), the Penman–Monteith equation is ranked as the best method for all climatic conditions. The Penman–Monteith  $ET_p$  is defined as the reference evapotranspiration or the rate of evapotranspiration from a hypothetical reference crop with an assumed crop height of 0.12 m, of fixed surface resistance of  $70 \text{ s m}^{-1}$  and an albedo of 0.23, closely resembling the evapotranspiration from an extensive surface of green grass of uniform height, actively growing, completely shading the ground and with adequate water (Allen et al., 1998). As such, hourly Penman–Monteith  $ET_p$  values are calculated based on the hourly actual data from the Liedekerke meteorological station as input for the PDM of the Bellebeek catchment.

In order to evaluate the effect of the temporal resolution of the evapotranspiration input, also daily, monthly and annual averages of potential evapotranspiration calculated with the Penman ( $E_{p,P}$ ) and Penman–Monteith ( $ET_{p,PM}$ ) equations are calculated and distributed hourly so that they can be used as evapotranspiration input (in  $\text{mm h}^{-1}$ ) for the Bellebeek PDM, which is run with a time step of 1 h.

In Fig. 5, the different potential evapotranspiration inputs are illustrated for the year 2007 as well as the cumulative ET volumes for the validation period (2007–2010).

#### 4.2 Is model performance influenced by different $ET_p$ input?

Table 2 shows all considered statistics describing the model performance using different  $ET_p$  inputs. As the model has been calibrated using  $ET_{p,\text{sinus}}$ , which are daily values for ET input, results of the other ET approaches (Penman and Penman–Monteith) are in first instance compared for daily averages ( $E_{p,P,\text{daily}}$  and  $ET_{p,PM,\text{daily}}$ ).

The table shows that the model performs (approximately) equally well using the sinus approach ( $ET_{p,\text{sinus}}$ ) or Penman's equation ( $E_{p,P,\text{daily}}$ ). When using the Penman–Monteith approach ( $ET_{p,PM,\text{daily}}$ ), the general and minima statistics show poorer results, while the peak and  $ET_{\text{act}}$  statistics are better.

From the cumulative volumes shown in Fig. 5, it is clear that the  $ET_{p,PM}$  approach for  $ET_p$  calculation results in an underestimation of the potential evapotranspiration compared

to  $ET_{p,\text{sinus}}$  and  $E_{p,P,\text{daily}}$ . As stated by Oudin et al. (2005a), an under- (or over-) estimation of the  $ET_p$  input, may yield systematic errors on stream flow simulations.

Figure 6b indeed illustrates that when using the underestimated  $ET_p$  input ( $ET_{p,PM}$ ), the resulting stream flow is overestimated. This can be seen from the higher cumulative volume of the stream flow compared to the volume of the observed stream flow and the stream flow volume modeled with the other  $ET_p$  inputs ( $ET_{p,\text{sinus}}$  and  $E_{p,P,\text{daily}}$ ). Using  $ET_{p,PM}$  also results in higher modeled peak flows, which more closely resemble the observed peaks, but which is only caused by a systematic higher modeled stream flow.

Oudin et al. (2005a) introduced a scaling factor to eliminate the systematic error (systematic difference) on  $ET_p$  with the purpose to have exactly the same long-term mean  $ET_p$  from  $ET_{p,PM}$  as the other  $ET_p$  input(s).

For every time step  $j$ , the rescaled  $ET_{p,PM,\text{rescale},j}$  is calculated as

$$ET_{p,PM,\text{rescale},j} = \left( \frac{\sum_{i=1}^n ET_{p,PM,i}}{\sum_{i=1}^n E_{p,P,i}} \right) E_{p,P,j}, \quad (26)$$

where  $\sum_{i=1}^n ET_{p,PM,i}$  is the year's sum of the Penman–Monteith  $ET_p$  and  $\sum_{i=1}^n E_{p,P,i}$  is the year's sum of the Penman  $ET_p$ .

This rescaling of the  $ET_p$  input has been implemented for the hourly  $ET_{p,PM}$  input using the long-term (yearly)  $E_{p,P}$  values. The cumulative values for the rescaled  $ET_{p,PM}$  input are added in Fig. 5 and the model performance statistics can be found in the last column of Table 2. The model performs equally well using the rescaled  $ET_{p,PM}$  input compared to the model results with  $ET_{p,\text{sinus}}$  or  $E_{p,P}$  as model input.

Nash criteria are in accordance with Oudin et al. (2005a) within a less than 5 % difference and confirm the findings of Oudin et al. (2005a) for the PDM: the rainfall–runoff model is slightly sensitive to different  $ET_p$  inputs under the condition that the long-term mean  $ET_p$  is similar for the different  $ET_p$  formulae to have no under- or overestimation of  $ET_p$  for the model.

If not, there can be a systematic error in the  $ET_p$  input, with a consequent poor model performance. If no rescaling of the  $ET_p$  input is performed, the rainfall–runoff model should be recalibrated for the non-rescaled  $ET_p$  input.

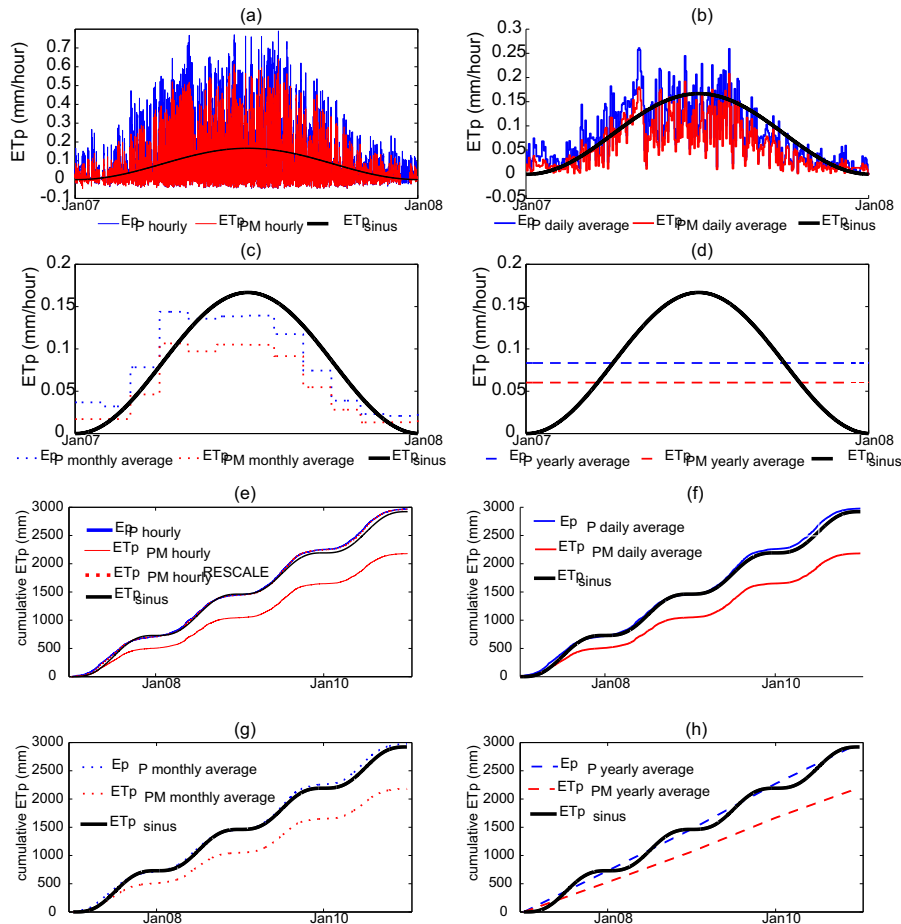
#### 4.3 Is the temporal resolution of $ET_p$ input an issue in river flow prediction from the PDM?

At first sight, it would be obvious that a more accurate evaporative demand input (e.g., daily  $ET_p$  values instead of monthly mean  $ET_p$  values) should have a positive impact on the catchment water balance simulations of a rainfall–runoff



**Table 2.** Statistics of the model performance using different ET<sub>p</sub> approaches as model forcing.

Statistics		ET <sub>p, sinus</sub>			Penman E <sub>p</sub>			Penman–Monteith ET <sub>p</sub>				
		ET <sub>p, sinus</sub>	E <sub>p,P</sub> hourly	E <sub>p,P</sub> daily	E <sub>p,P</sub> monthly	E <sub>p,P</sub> yearly	ET <sub>p,PM</sub> hourly	ET <sub>p,PM</sub> daily	ET <sub>p,PM</sub> monthly	ET <sub>p,PM</sub> yearly	ET <sub>p,PM</sub> hourly, rescale	
Statistics Q <sub>tot</sub>	RMSE	(mm)	0.460	0.430	0.432	0.433	0.589	0.528	0.528	0.643	0.427	
	bias	(mm)	0.064	0.046	0.040	0.035	0.046	0.242	0.242	0.237	0.063	
	NS	(-)	0.717	0.737	0.735	0.734	0.506	0.603	0.603	0.604	0.413	
	CB	(-)	0.910	0.932	0.942	0.949	0.933	0.638	0.645	0.652	0.740	
	Δ <sub>cum</sub> Q <sub>tot</sub>	(mm)	-2346	-1594	-1373	-1198	1582	-8501	-8346	-8182	-6117	-2169
	Δ <sub>cum</sub> Q <sub>base</sub>	(mm)	-4251	-3114	-3088	-3036	-1289	-7502	-7511	-7498	-6325	-3455
Statistics Q <sub>peak</sub>	RMSE (Q <sub>peak</sub> )	(m <sup>3</sup> s <sup>-1</sup> )	1.906	1.850	1.891	1.926	2.453	1.578	1.578	2.160	1.794	
	MEQ <sub>peak</sub>	(BC m <sup>3</sup> s <sup>-1</sup> )	-0.530	-0.544	-0.561	-0.569	-0.680	-0.234	-0.243	-0.250	-0.329	
	STDEV Q <sub>peak</sub>	(BC m <sup>3</sup> s <sup>-1</sup> )	0.506	0.483	0.484	0.492	0.597	0.497	0.496	0.503	0.627	
Statistics Q <sub>low</sub>	RMSE (Q <sub>low</sub> )	(m <sup>3</sup> s <sup>-1</sup> )	0.117	0.082	0.082	0.082	0.149	0.173	0.174	0.215	0.088	
Statistics ET <sub>act</sub>	RMSE (ET <sub>act</sub> from LAS)	(mm)	0.102	0.072	0.106	0.107	0.112	0.058	0.102	0.110	0.068	
	Δ <sub>cum</sub> ET <sub>act</sub> from LAS	(mm)	-438	-410	-394	-377	-430	-262	-249	-243	-290	



**Fig. 5.** Different  $ET_p$  approaches as input for the PDM (illustrated for the year 2007) compared to the  $ET_{p,sinus}$ . Example of a yearly  $ET_p$  cycle (2007) for the different temporal resolutions (**a**, **b**, **c**, **d**) and cumulative evapotranspiration for the different temporal resolutions (**e**, **f**, **g**, **h**).

model. However, in earlier studies, no clear differences in model performance have been seen when using a more detailed, temporally varying  $ET_p$  input compared to e.g., an average monthly estimate of  $ET_p$  (Oudin et al., 2005b).

From a systematic test over a large catchment sample (308 catchments in Australia, France and US) and using four different rainfall–runoff models, Oudin et al. (2005b) concluded that insensitivity to temporally varying  $ET_p$  data is a substantial characteristic of rainfall–runoff models.

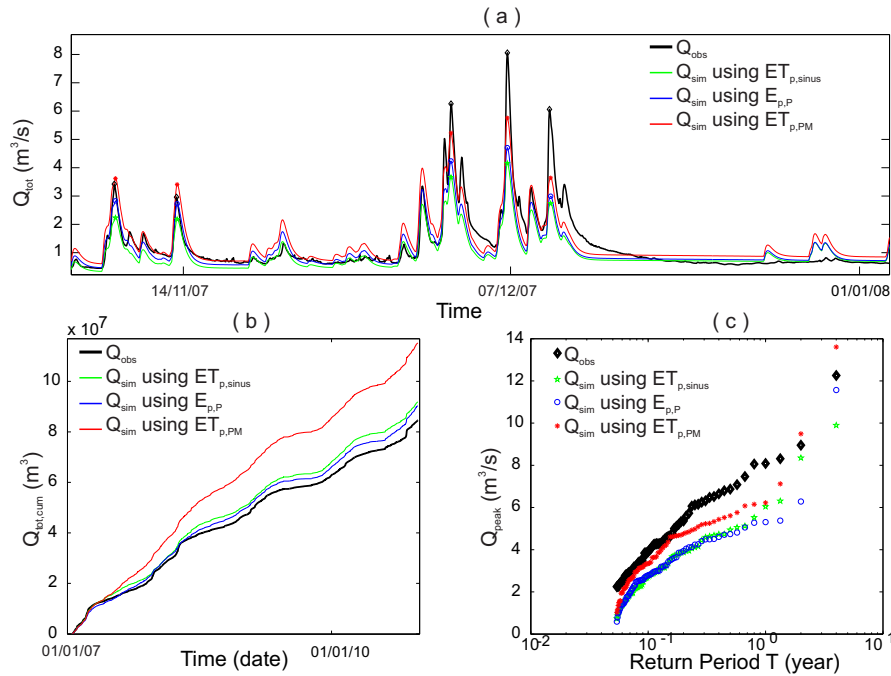
The model performance statistics, e.g., the different time step sizes of  $E_{p,P}$  in Table 2, for the PDM of the Bellebeek confirm in first instance the findings of Oudin et al. (2005b): the resulting stream flow of the PDM does not significantly change with more or less detailed  $ET_p$  input.

However, two additional findings can be seen. Firstly, the use of the yearly average of  $ET_p$  results in a considerable decrease of all model performance statistics compared to the performance statistics from simulations with a detailed hourly  $ET_p$  input (or daily or monthly averages of  $ET_p$ ).

Secondly, from the evaluation of the actual evapotranspiration, it can be seen that the RMSE increases when daily, monthly or yearly averages of  $ET_p$  are used as model input. So, even though the stream flow simulation does not change significantly with a less detailed  $ET_p$  input (daily or monthly average instead of hourly  $ET_p$ ), the model performance decreases in its simulation of the actual evapotranspiration because the model is not able to simulate the diurnal cycle of the actual evapotranspiration (as estimated from the LAS data) when less detailed  $ET_p$  is used as model forcing.

These results are an addition to the results of Oudin et al. (2005b).

Firstly, it is a confirmation for an even more detailed  $ET_p$  input in comparison to earlier studies, as the PDM runs at a time step of 1 h using hourly  $ET_p$  inputs (instead of model time steps and thus model input of 1 day as applied by Oudin et al., 2005b). Secondly, the rainfall–runoff model seems to be insensitive to more or less detailed  $ET_p$  input, unless there is no seasonal cycle present in the  $ET_p$  input as is the case for



**Fig. 6.** (a) Observed and modeled stream flow using  $ET_{p,sinus}$ ,  $E_{p,P}$  and  $ET_{p,PM}$  as  $ET_p$  input for the PDM. (b) Cumulative stream flow using the different  $ET_p$  inputs. (c) Peak flow values using the different  $ET_p$  inputs.

the yearly average values of  $ET_p$ . Finally, the insensitivity of the rainfall–runoff model causes an erroneous simulation of the actual evapotranspiration for the catchment.

Thus, the finding of Oudin et al. (2005b) that model performance does not improve when using a more detailed evapotranspiration input should be differentiated into two aspects. A rainfall–runoff model seems to be insensitive to a more or less detailed  $ET_p$  input, unless there is no seasonal cycle present in the  $ET_p$  input (as is e.g., the case for the yearly average values of  $ET_p$ ), and inner state variables such as the actual evapotranspiration are better simulated when more detailed  $ET_p$  values are used as model forcing.

## 5 Impact of actual evapotranspiration input on model performance

### 5.1 Model performance based on $ET_{act}$

As described in Sect. 2, estimates of the catchment’s actual evapotranspiration are made from measurements of the catchment’s sensible heat flux from the large aperture scintillometer and converted to evapotranspiration estimates using the energy balance approach with values of AE from the Liedekerke ground station upscaled to catchment averages of AE.

These estimates of the catchment’s actual evapotranspiration can be used as model forcing for the PDM model instead of potential evapotranspiration input. As such, the

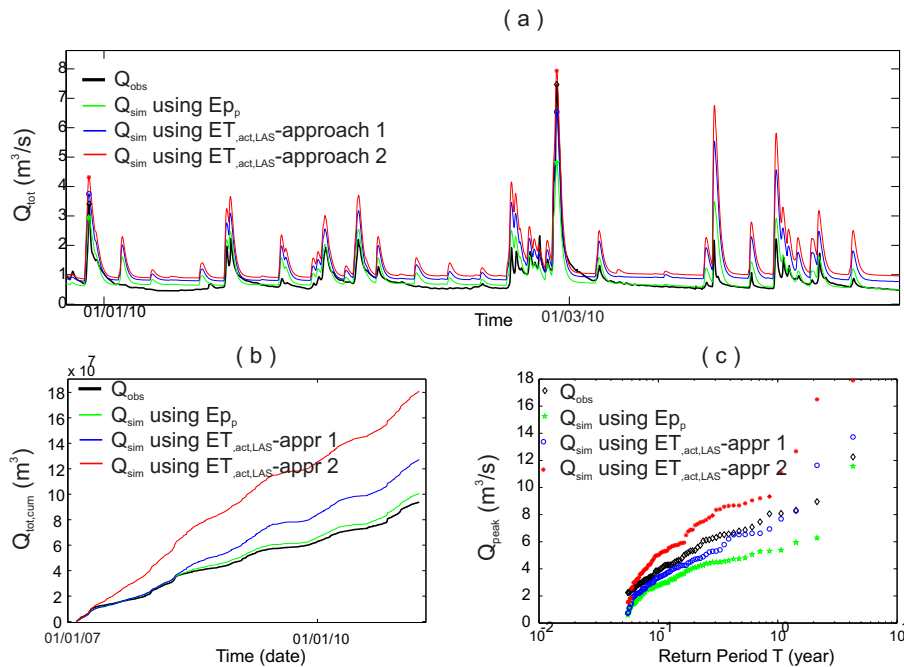
availability of  $ET_{act}$  provides the possibility to simplify the PDM by omitting the calculation from  $ET_p$  to  $ET_{act}$  (Eq. 5) and the according parameter  $b_e$ .

Although the continuity of the  $H$  series from the LAS has been extensively studied and improved as described in Sect. 2, no full continuous time series of  $H$  and hence  $ET_{act}$  could be obtained from LAS data, which is required by the PDM. In order to overcome this problem, two approaches have been followed, and the respective model performances of both approaches have been calculated.

In the first approach, the PDM is used with  $ET_{act}$  from LAS data if these are available, while for time steps when no  $ET_{act}$  from the LAS is available, potential evapotranspiration was used and actual evapotranspiration is calculated based on the soil moisture content  $S_1$  through Eq. (5). As potential evapotranspiration estimates, four types of  $ET_p$  are used in different model runs:  $ET_{p,sinus}$ , hourly  $E_{p,P}$ , and  $ET_{p,PM}$  and rescaled hourly  $ET_{p,PM}$ .

Comparing the model performance statistics of the four model runs for this approach in Table 3 to the results of model performance using the respective four  $ET_p$  values as input (Table 2), it is clear that PDM performs worse with this combination of  $ET_{act}$  and  $ET_p$  as model input: all flow statistics (general, peak as well as low flow statistics) decreased compared to Table 2.

To assess if the cause for this decline in model performance is due to the combination of  $ET_{act}$  with  $ET_p$  as model forcing for the PDM, a second approach is used. The second



**Fig. 7.** Observed and modeled stream flow using  $E_{p,p}$  on the one hand and both approaches of  $ET_{act,LAS}$  on the other hand as ET input for the PDM (a). Cumulative stream flow using the different ET inputs (b). Peak flow values using the different ET inputs (c).

**Table 3.** Statistics of the model performance using  $ET_{act}$  as model forcing.

			$ET_{act,LAS}$ + $ET_{p,sinus}$	$ET_{act,LAS}$ + $E_{p,p}$ ,hourly	Approach 1 $ET_{act,LAS}$ + $ET_{p,PM,hourly}$ , rescale	$ET_{act,LAS}$ + $ET_{p,PM,hourly}$	Approach 2 $ET_{act,LAS}$ completed
Statistics $Q_{tot}$	RMSE	(mm)	0.582	0.597	0.596	0.696	0.996
	bias	(mm)	0.234	0.239	0.245	0.384	0.647
	NS	(-)	0.518	0.493	0.495	0.311	-0.409
	CB	(-)	0.656	0.649	0.641	0.435	0.049
	$\Delta_{cum} Q_{tot}$	(mm)	-8074	-8248	-8446	-13270	-22346
	$\Delta_{cum} Q_{base}$	(mm)	-7393	-7337	-7426	-10394	-15007
Statistics $Q_{peak}$	RMSE (peak)	( $m^3 s^{-1}$ )	1.965	1.981	1.958	1.945	2.599
	ME $Q_{peak}$	( $BC m^3 s^{-1}$ )	-0.303	-0.285	-0.276	-0.067	0.287
	STDEV $Q_{peak}$	( $BC m^3 s^{-1}$ )	0.611	0.634	0.635	0.601	0.636
Statistics $Q_{low}$	RMSE ( $Q_{low}$ )	( $m^3 s^{-1}$ )	0.203	0.217	0.216	0.283	0.415

approach consists of completing the series of  $ET_{act}$  from the LAS by estimating  $ET_{act}$  from potential evapotranspiration data using monthly regressions between  $E_{p,p}$  (Penman approach) and available  $ET_{act}$  from the LAS approach as given in Table 4.

Using this completed  $ET_{act}$  series results in an even worse performance of the PDM (Table 3). Thus, the use of actual evapotranspiration in combination with potential evapotranspiration on the time steps when no  $ET_{act}$  is available (Approach 1) results in better flow simulations than using only  $ET_{act}$  values based on the monthly regressions between  $ET_{act}$  and  $E_{p,p}$  (Approach 2). This means that in approach 1, the

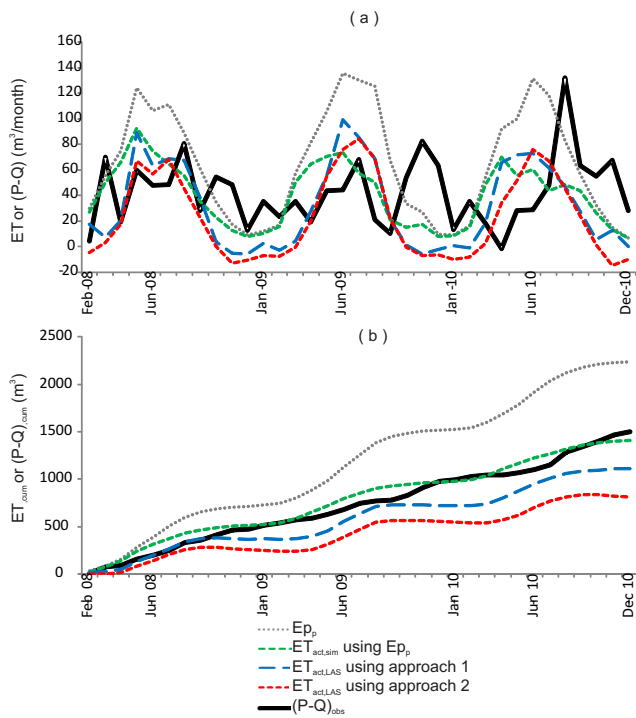
time steps where  $ET_p$  is used, partly correct the erroneous results obtained during the time steps where the model is using the actual evapotranspiration input derived from the LAS data.

## 5.2 The decline in model performance using $ET_{act}$

From the comparison of the model performance based on potential evapotranspiration on the one hand and based on actual evapotranspiration input on the other hand, it is clear that using actual evapotranspiration as input for PDM affects the simulated stream flow.

**Table 4.** Statistics of the monthly regressions between hourly  $ET_{act}$  from the LAS approach ( $s$  axis) and  $E_{p,P}$  ( $y$  axis).

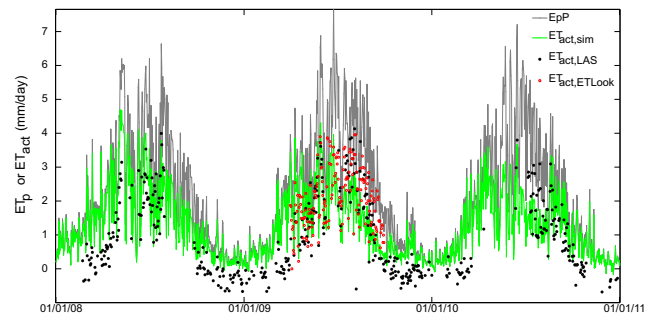
Month	Mean ( $E_{p,P}$ ) ( $mm\ h^{-1}$ )	Mean ( $ET_{act,LAS}$ ) ( $mm\ h^{-1}$ )	Slope (-)	Intercept ( $mm\ h^{-1}$ )	$R$ (-)	RMSE ( $mm\ h^{-1}$ )	$N$ (-)	NS (-)
1	0.021	-0.005	0.030	-0.006	0.044	0.050	679	-0.956
2	0.034	-0.008	0.089	-0.011	0.192	0.071	1164	-0.558
3	0.077	0.004	0.234	-0.014	0.651	0.117	1877	-0.080
4	0.109	0.030	0.415	-0.015	0.877	0.131	1607	0.378
5	0.148	0.078	0.677	-0.023	0.957	0.107	1153	0.740
6	0.171	0.095	0.646	-0.016	0.892	0.131	921	0.648
7	0.162	0.099	0.716	-0.017	0.940	0.104	1884	0.767
8	0.145	0.081	0.717	-0.023	0.957	0.098	1396	0.779
9	0.092	0.036	0.643	-0.023	0.921	0.086	1306	0.656
10	0.049	0.003	0.318	-0.013	0.676	0.087	1899	0.179
11	0.034	-0.011	0.155	-0.017	0.381	0.068	1233	-0.527
12	0.015	-0.009	0.033	-0.010	0.036	0.045	1404	-1.483



**Fig. 8.** Time series of monthly sums of ET inputs and simulations, and observed  $Pr-Q$  (a). Time series of the cumulative ET inputs and simulations, and observed  $Pr-Q$  (b).

In Fig. 7, time series, cumulative stream flow volume and peak discharges from simulations using  $ET_p$  and  $ET_{act}$  (both approaches) are compared to the observed stream flows in the Bellebeek catchment. From this figure, it is clear that higher stream flows are simulated using the  $ET_{act,LAS}$  approaches as ET input for the PDM.

Figure 8 shows the monthly sums and cumulative volumes of the actual evapotranspiration from simulations using  $ET_p$  on the one hand and both approaches for the use of  $ET_{act,LAS}$



**Fig. 9.** Time series of daily  $E_{p,P}$ , simulated  $ET_{act}$  with PDM based on  $E_{p,P}$ ,  $ET_{act}$  from the LAS and  $ET_{act}$  from ETLook.

as PDM input on the other hand. The yearly volumes of actual evapotranspiration and stream flow are also given in Table 5.

In this figure and table, it can be seen that the (cumulative) volume of the actual evapotranspiration as modeled by PDM using the potential  $E_{p,P}$  input is higher than the actual evapotranspiration from both  $ET_{act,LAS}$  approaches, while the volume of stream flow is higher using the latter  $ET_{act,LAS}$  inputs.

From the model description in Sect. 3.1, it is clear that the PDM closes the water balance.

Considering the closed water balance, it is evident that with the given precipitation, lower estimates of  $ET_{act}$  result in higher simulated stream flows  $Q$  and vice versa.

Therefore, to be able to use the actual evapotranspiration estimates as model forcing for the PDM, the estimated  $ET_{act}$  should close the water balance with the observed  $Pr$  and  $Q$ . From the cumulative volumes of the observed difference between precipitation and stream flow  $(Pr-Q)_{obs}$  and the cumulative series of  $ET_{act}$  based on the LAS data using the two approaches (Fig. 7b), it is clear that the estimates of  $ET_{act}$  are too low to close the water balance. As such, the series of  $ET_{act}$  are not suitable for a stream flow simulation with the

**Table 5.** Yearly volumes of observed precipitation (Pr) and stream flow ( $Q_{\text{obs}}$ ) together with yearly sums of actual evapotranspiration ( $ET_{\text{act}}$ ) and simulated stream flow ( $Q_{\text{sim}}$ ) from PDM simulations using the potential  $E_{p,p}$  input and both approaches for the use of  $ET_{\text{act,LAS}}$ .

Year	2008	2009	2010
Pr (mm)	748	681	764
$Q_{\text{obs}}$ (mm)	241	179	246
PDM simulation using $E_{p,p}$			
$ET_{\text{act}}$ (mm)	533	456	441
$Q_{\text{sim}}$ (mm)	260	192	273
PDM simulation using $ET_{\text{act,LAS}}$ – Approach 1			
$ET_{\text{act}}$ (mm)	389	355	385
$Q_{\text{sim}}$ (mm)	356	308	340
PDM simulation using $ET_{\text{act,LAS}}$ – Approach 2			
$ET_{\text{act}}$ (mm)	254	298	260
$Q_{\text{sim}}$ (mm)	532	388	448

PDM (or any other rainfall–runoff model) and a recalibration of the PDM based on the  $ET_{\text{act}}$  cannot solve this problem.

From this, it can be concluded that the actual evapotranspiration is a crucial factor in simulating the catchment’s water balance and the (volume of the) resulting stream flow with a rainfall–runoff model.

By using potential evapotranspiration as model forcing, this problem is bypassed, as the volume of the stream flow can be adjusted by “tuning” (calibrating) the calculation of actual evapotranspiration from the potential evapotranspiration input as to close the water balance for the measured Pr and  $Q$ .

### 5.3 Inverting $ET_{\text{act}}$ from LAS data

To build more realistic rainfall–runoff models, good (better) estimates of the actual catchment evapotranspiration are necessary. In order to explore the shortcomings of the described methodology of  $ET_{\text{act}}$  estimation from LAS data, the daily values of the estimated  $ET_{\text{act}}$  from the LAS are compared to the daily values of the PDM-simulated  $ET_{\text{act}}$  using hourly  $E_{p,p}$  as model forcing. For the LAS approach, only days are considered where 24 hourly values are available. In Fig. 9, time series of  $ET_{\text{act}}$  from the LAS approach are shown together with PDM results of  $ET_{\text{act}}$  and  $ET_{\text{act}}$  estimates from the remote sensing based surface energy balance algorithm, ETLook model, as described in Samain et al. (2012b). Monthly scatterplots are shown in Fig. 10.

From May to August, the estimates of  $ET_{\text{act}}$  based on LAS data and the energy balance approach can be considered to be realistic as they are consistent with the actual evapotranspiration estimates from ETLook and also with the simulated

$ET_{\text{act}}$  values of the calibrated PDM. For those months, the estimated actual evapotranspiration is significantly lower than the potential evapotranspiration as the soil moisture is depleted and the evapotranspiration process is limited by the available soil moisture.

For the other (wetter) months, the opposite is expected: the actual evapotranspiration is not limited by the soil moisture content due to decreased radiation, and evapotranspiration occurs at the potential rate. This can be seen for the PDM simulated  $ET_{\text{act}}$  in Fig. 9. However, the  $ET_{\text{act}}$  based on LAS data for those months generally underestimate the  $ET_{\text{act}}$  as simulated with the PDM. In autumn, winter and (early) spring, the actual evapotranspiration estimates from LAS data are very low and in many cases negative. Even though the evapotranspiration rates can be considered very low in those months (also the potential evapotranspiration is very low) and the absolute values do not differ much, the consistent underestimation of  $ET_{\text{act}}$  by the LAS approach causes a considerable underestimate of the total volume of  $ET_{\text{act}}$  for those months. The proposed energy balance approach to convert the scintillometer measured sensible heat flux into evapotranspiration rates is highly influenced by uncertainties in all terms of the energy balance in winter months. The total underestimate of the actual evapotranspiration based on the LAS data in winter months, causes a closure error in the water balance. As such, for these months, the actual evapotranspiration from the LAS cannot be used as model forcing for rainfall–runoff modeling.

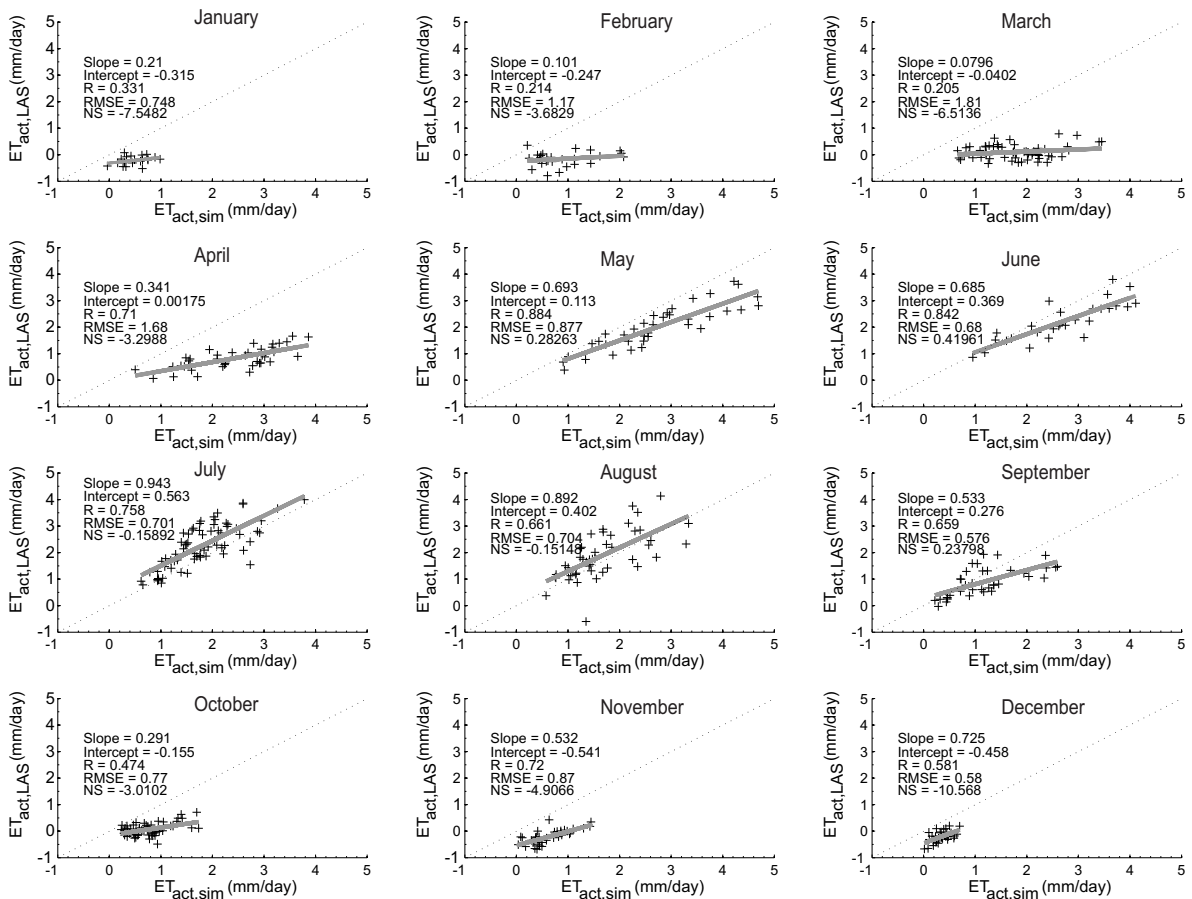
Also, the regressions between potential evapotranspiration and actual evapotranspiration from LAS data in Table 4 for the winter months are an indication that the proposed LAS methodology does not succeed in a proper estimation of actual evapotranspiration in those months. Using these regressions to make continuous series of  $ET_{\text{act}}$  (as is proposed in the second approach) as model forcing, explains the worse model performance as compared to the first approach where  $ET_{\text{act}}$  is calculated from  $E_{p,p}$  when no  $ET_{\text{act}}$  values from the LAS methodology were available.

## 6 Summary and conclusions

In this paper, the performance of the calibrated lumped rainfall–runoff model for the Bellebeek catchment has been evaluated for different evapotranspiration inputs. The effect of different potential and actual evapotranspiration inputs of stream flow simulations has been assessed.

A first conclusion is that when applying a calibrated rainfall–runoff model, the model input should be consistent with the input used for the calibration process. Regarding the evapotranspiration input, it means that the long-term  $ET_p$  should be equal to the long-term  $ET_p$  used for calibration.

Secondly, as a confirmation of earlier studies, it is shown that a rainfall–runoff model as the PDM is relatively insensitive for detailed  $ET_p$  input. Furthermore, it is important to



**Fig. 10.** Monthly scatterplots of the daily values of estimated  $ET_{act}$  from the LAS compared with daily values of simulated  $ET_{act}$  with PDM based on  $E_{p,p}$ .

notice that the  $ET_p$  input must have a correct seasonal pattern, which is shown by a decline in model performance when using yearly averages of  $ET_p$ . A second addition to earlier studies, is the fact that when using less detailed  $ET_p$  input as model input (e.g., daily  $ET_p$  instead of hourly  $ET_p$ ), the inner state variables possibly do not match the detailed course of the corresponding physical variable, which has been shown by the decrease of model performance for actual evapotranspiration.

Finally, using actual evapotranspiration estimates for the catchment as model forcing for the calibrated rainfall–runoff model does not automatically result in better stream flow simulation. As the actual evapotranspiration underestimates the simulated actual evapotranspiration from the calibrated model, this model forcing causes poor stream flow simulations. It has been concluded that the actual evapotranspiration is a crucial factor in simulating the catchment’s water balance and the (volume of the) resulting stream flow.

Using potential evapotranspiration as model forcing provides the opportunity to “tune” the model so that evapotranspiration is used to properly close the water balance. On the

contrary, when using actual evapotranspiration inputs, there is no means to force the water balance to close and the stream flow simulation is highly dependent on correct and representative input data of rainfall and evapotranspiration. As such, a recalibration of the model is based on data that are not able to close the water balance, and cannot help to improve the model performance.

Regarding the actual evapotranspiration estimates from the LAS, it has been concluded that they can be considered realistic in summer months, but are doubtful in the months where stable conditions prevail (autumn, winter and (early) spring). Although the absolute values of the actual evapotranspiration at the hourly time step are only slightly underestimated, the total volume of the actual evapotranspiration over longer time frames (day, month, year) is considerably underestimated and causes a closure error in the water balance. Therefore, further research is required to correct and validate the actual evapotranspiration for these months before they can be used in water balance or hydrologic model studies.

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