HBV-Extended (HBV-E) hydrological model User Manual v1.1

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Model name: **HBV-Extended (HBV-E) hydrological model**
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Language: R
Model type: physically-based / conceptual
Time scales: applications in daily time steps (aims to hourly and monthly scales)
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1. Summary

The HBV-E model is an improved version from traditional HBV model and written in R. In this version, the evapotranspiration and calibration modules have been improved. The original code of HBV-E model is open and available from https://github.com/jeromelau11/Hydro_model/.

2. Model structure

Like many existing hydrological models, the HBV-E model follows the structure of HBV model which consists of snow module, evapotranspiration module, soil moisture model and the runoff routing model. The current version of HBV-E model is focusing on improving the evapotranspiration module.

3. Evapotranspiration

To calculate actual evapotranspiration over the basin, the model requires to provide long-term potential evapotranspiration (PET). The HBV-E model provides several

ways for users to calculate the PET, depending on the available input climate information, including Penman, Thornthwaite's formation, Priestley-Taylor, Hargreaves-Samani. Users can pick up either formation in the HBV-E model to compute the PET based on the availability of the climate data.
Based on the PET, the model estimates the actual evapotranspiration (E_t). However, water loss from a catchment area does not always proceed at the potential rate, since this is dependent on a continuous water supply. When the vegetation is unable to abstract water from the soil, then the actual evaporation becomes less than potential. Thus the relationship between E_t and PE depends upon the soil moisture content.

Here is an example of the relationship between PE and E_t, according to Bergström, (1992):

$E_t = PE$ when $h \geq h_{FC}$

$$E_t = PE.\left[\frac{h - h_{WP}}{h_{FC} - h_{WP}}\right]$$ when $h_{WP} < h < h_{FC}$

$Et = 0$ when $h \leq h_{WP}$

Where:
h is the amount of soil moisture (mm).
h_{FC} is the amount of soil moisture corresponding to field capacity (mm).
h_{WP} is the amount of soil moisture corresponding to the wilting point (mm).

More importantly, unlike traditional HBV model based on PET, the HBV-E model provides another module for estimating the actual evapotranspiration by using the Penman-Monteith formula instead of the PET if the input data available (this module is on progress to be integrated in the HBV-E model).

$$E_T = \frac{\Delta R_n + (e_a - e_d)*\frac{\rho * c_p}{r_a}}{\lambda(\Delta + \gamma*(1+\frac{r_s}{r_a}))}$$

where R_n = net radiation (W/m^2)
ρ = density of air
c_p = specific heat of air
r_s = net resistance to diffusion through the surfaces of the leaves and soil (s/m)
r_a = net resistance to diffusion through the air from surfaces to height of measuring instruments (s/m)
γ = hygrometric constant

Δ = de/dT

e_a = saturated vapour pressure at air temperature

e_d = mean vapour pressure

The further improvement for the evapotranspiration module in HBV-E model is to estimate the actual evapotranspiration based on LAI (Leaf area index) and remote sensing data.

The method is of quite good accuracy and is usually used for calculations of evapotranspiration from farmlands. The good accuracy is due to all the parameters of the equation but still it is not perfect. For instance, the r_s value is a constant depending on what kind of vegetation the area holds. If the equation is used over a large area with different kind of vegetation you have to estimate a value for r_s. The estimation gets even more non accurate if the area contains spots without vegetation. (Ward, 1999; Menzel, 1997)

In the current version, the HBV-E model follows the structure of HBV model to model the snow, soil moisture and the runoff routing. More details about these routines can be found in Bergstrom (1995).

4. Model calibration using Differential Evolution Adaptive Metropolis

Another important improvement in the HBV-E model is that the highly efficient calibration approach is integrated in this model.

In the HBV or HBV-E models, the mathematical formulation of hydrologic processes is simplified using numerous model parameters including both physically-based and empirical ones. Traditional HBV model uses the manual trial and error calibration, which may consume amounts of time and work resources. Later on, HBV-light (Siebert, 1997) provided an automated Monte-Carlo routine to estimate parameters.

The HBV-E model incorporates the Differential Evolution Adaptive Metropolis (DREAM) algorithm into the calibration process. The DREAM algorithm significantly improve the efficiency of Markov chain Monte Carlo (MCMC) simulation can be made by using a self-adaptive Differential Evolution learning strategy within a population-based evolutionary framework. It is able to run multiple different chains simultaneously for global exploration, and automatically tunes the scale and orientation of the proposal distribution in randomized subspaces during the search. Vrugt et al. (2009) proved this algorithm is superior to other adaptive MCMC sampling approaches by using different case studies including nonlinearity, high-dimensionality, and multimodality. It also enhances the applicability of MCMC simulation to complex, multi-modal search problems.

In the HBV-E model, the DREAM algorithm is integrated for the model parameter calibration.

5. Source code and language

The HBV-E model was written in R. The code is public and any user can access to the code by .The authors also encourage users to use the model and report any bugs in the model. Code and documents can be found in
https://github.com/jeromelau11/Hydro_model/

6. Runs and applications

6.1. Data needed to run the model (inputs):

Input data may vary according to different PET method applied in the simulation. IN this case, Penman algorithm is used for the estimate of PET. In this document, as an illustration, the data from a small basin over the upper Xinfengjiang Basin (Guangdong, China) with minimal human-effect are used.

- Pre precipitation
- Ave_T air temperature
- Runoff runoff
- Tmax maximum temperature in degree Celcius
- Tmin minimum temperature in degree Celcius
- uz wind speed in meters per second
- n sunshine hour in hours
- RHmax maximum relative humidity in percentage
- RHmin minimum relative humidity in percentage
- elevation
- basin area
- latitude in radius
- net Radiation (optional)

6.2. Input files

climate.txt; other_para_PET.txt

As an example for the climate input with the format as follows:

Date	uz	n	Tmin	Tmax	RHmin	RHmax	Pre	Runoff	Ave_T
1989/1/1	2.5	0	8.9	10.3	75	79	0	12	9.4
1989/1/2	0	6.4	8.4	19.8	46	78	0.2	9.36	11.5
1989/1/3	0.5	8.4	7.5	22.7	47	81	0	8.49	13.2
1989/1/4	0.3	0	13.7	16.1	76	89	39	8.78	14.5
1989/1/5	0.3	0.2	13	17	73	96	54.6	29.6	13.7

6.3. Model parameters and ranges

Those parameters are from the traditional HBV model (Bergstrom, 1997).

	Symbol	Description	Range
1	SCF	snow correction factor	User setting
2	DDF	degree day factor	User setting
3	tr	threshold temperature above which precipitation is rain	User setting
4	ts	threshold temperature below which precipitation is snow	User setting
5	tm	threshold temperature above which melt starts	User setting
6	lprat	parameter related to the limit for potential evaporation	User setting
7	fc	field capacity	User setting
8	beta	the non linear parameter for runoff production	User setting
9	K0	storage coefficient for very fast response	User setting
10	K1	storage coefficient for fast response	User setting
11	K2	storage coefficient for slow response	User setting
12	lsuz	threshold storage state	User setting
13	cperc	constant percolation rate	User setting
14	bmax	maximum base at low flows	User setting
15	BFIK	free scaling parameter	User setting

6.4. Parameter calibration and run

The improved HBV-E model uses the Differential Evolution Adaptive Metropolis (DREAM) algorithm into the parameter calibration process.

```
# how many data points to be simulated

nn<-8400
Model.main<-function(paras){
  Qobs<-Runoff[1:nn]
  simDist1 <- HBV_E(prec=Pre, airt=Temp, ep=PET,
area=areas/sum(areas),
                    param= paras,incon=c(60,0,1,2.5),iLength=nn)
  Qs<-simDist1$Q
  return(Qs)
}


control <- list(nseq=20,ndraw=50)
calbriate<-dreamCalibrate(
  FUN=Model.main,
  pars=paras_all,
  obs=Qobs,
  control=control
)
```

```
sim_output_medain <- HBV_E(prec=Pre, airt=Temp, ep=PET, area=1,
param=as.numeric(par_median_all),incon=c(60,0,1,2.5),iLength=N
ULL)
```

6. 5. Outputs

6.5.1 Parameter calibration outputs are saved as param_cal_out.txt (also parameter uncertainty interval provided in HBV-E model):

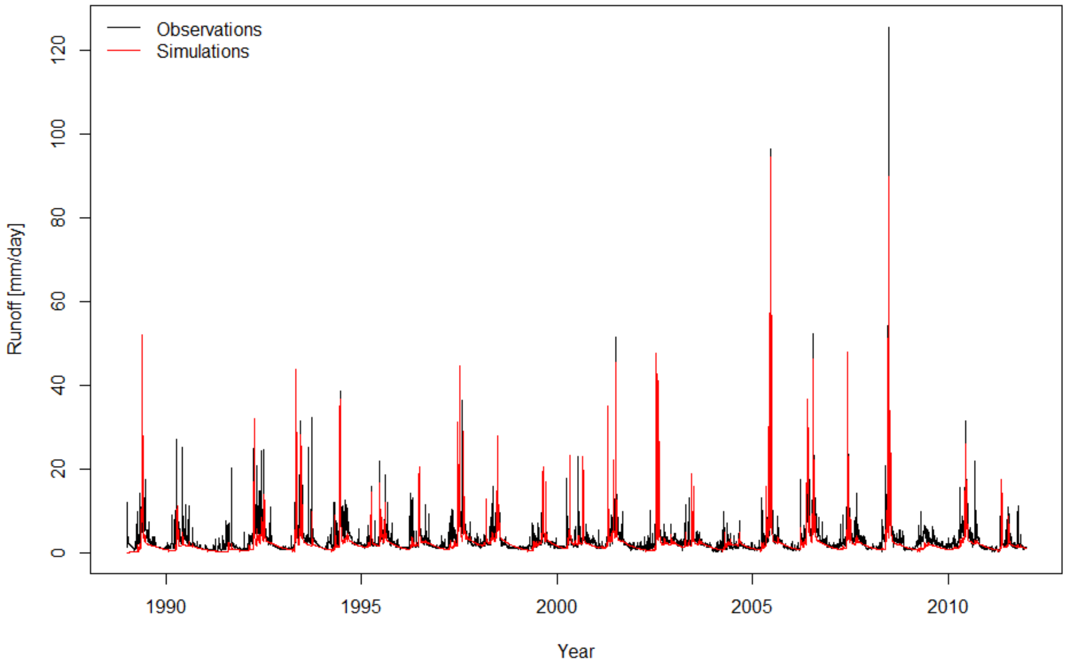
```
CODA summary for last 50% of MCMC chains:

Iterations = 6:10
Thinning interval = 1
Number of chains = 20
Sample size per chain = 5

1. Empirical mean and standard deviation for each variable,
   plus standard error of the mean:

            Mean      SD Naive SE Time-series SE
csf      1.20661   0.1942  0.01942      0.006022
ddf      2.59921   1.2837  0.12837      0.033194
tr       1.94157   0.4792  0.04792      0.012783
ts      -1.46352   1.2155  0.12155      0.043665
tm       0.06984   1.1700  0.11700      0.045732
lprat    0.47402   0.2904  0.02904      0.008827
fc     235.97752 179.0889 17.90889      7.851028
beta     6.15976   6.3992  0.63992      0.260174
k0       0.77784   0.6646  0.06646      0.022529
k1      19.32021   6.4867  0.64867      0.162061
k2     139.96501  62.3142  6.23142      2.519266
lsuz    59.72235  29.7714  2.97714      1.267326
cperc    4.55994   2.3198  0.23198      0.098695
bmax    16.58548   8.9152  0.89152      0.375017
croute  25.21184  11.4723  1.14723      0.508009

2. Quantiles for each variable:

           2.5%     25%     50%     75%   97.5%
csf     0.90138  1.0176  1.2103  1.3804  1.4820
ddf     0.35144  1.5046  2.7246  3.5094  4.4153
tr      1.10032  1.4523  2.0474  2.4016  2.6004
ts     -2.94087 -2.3835 -1.9419 -0.5905  0.9789
tm     -1.58548 -0.9876  0.1137  1.3402  1.9452
lprat   0.03171  0.2524  0.4726  0.7368  0.9552
```

```
fc      7.31255 49.7027 259.7440 381.2412 571.9620
beta    0.01284  0.5187   5.3392  11.6462  19.0774
k0      0.05143  0.2121   0.4820   1.3744   1.9261
k1      7.99403 14.4214  22.2419  23.9747  28.6399
k2     58.23636 76.9793 143.4583 192.2793 241.0098
lsuz    6.86726 30.8622  60.4890  84.7916  97.3720
cperc   0.24052  2.7573   5.0785   6.8121   7.7425
bmax    1.55205  7.3569  18.6253  23.8350  28.6570
croute  2.73266 17.1882  26.9331  33.2725  48.3941
```

6.5.2 Modelled outputs including simulated soil moisture, ETA, runoff, etc are saved as model_output.txt

```
           runoff          soil_moisture  ETA
2008-12-23 1.129985e+00   106.4690049 1.931909e+00
2008-12-24 1.122163e+00   104.5554309 1.913574e+00
2008-12-25 1.114395e+00   102.7500604 1.805370e+00
2008-12-26 1.106681e+00   101.4238561 1.326204e+00
2008-12-27 1.099227e+00   104.8586192 1.035544e+00
2008-12-28 1.092329e+00   116.7992591 9.568866e-01
2008-12-29 1.084765e+00   115.5771101 1.222149e+00
2008-12-30 1.077256e+00   114.3233462 1.253764e+00
2008-12-31 1.069799e+00   112.8391877 1.484158e+00
2009-01-01 1.062393e+00   110.8959900 1.943198e+00
2009-01-02 1.055039e+00   108.9925660 1.903424e+00
2009-01-03 1.047736e+00   107.4295805 1.562986e+00
2009-01-04 1.040483e+00   105.5358389 1.893742e+00
2009-01-05 1.033281e+00   103.7494508 1.786388e+00
2009-01-06 1.026128e+00   101.9136443 1.835806e+00
2009-01-07 1.019025e+00   100.3350942 1.578550e+00
2009-01-08 1.011971e+00    98.9708712 1.364223e+00
2009-01-09 1.004966e+00    96.9739448 1.996926e+00
2009-01-10 9.980093e-01    95.2959308 1.678014e+00
2009-01-11 9.911008e-01    93.7424152 1.553516e+00
```

6.5.3 Validation period plots for runoff (mm).



6.5.4 HBV-E model performance measures:

The RMSE of a model prediction with respect to the estimated variable X_{model} is defined as the square root of the mean squared error:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}}$$

where X_{obs} is observed values and X_{model} is modelled values at time/place i.

Correlation coefficient:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

The correlation is +1 in the case of a perfect increasing linear relationship, and -1 in case of a decreasing linear relationship, and the values in between indicates the degree of linear relationship between for example model and observations. A correlation coefficient of 0 means the there is no linear relationship between the variables.

The square of the Pearson correlation coefficient (**r^2**), known as the coefficient of determination, describes how much of the variance between the two variables is described by the linear fit.

The Nash-Sutcliffe model efficiency coefficient (E) is be used to quantitatively describe the accuracy of model outputs for other things than discharge. It is defined as:

$$E = 1 - \frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model})^2}{\sum_{i=1}^{n}(X_{obs,i} - \overline{X_{obs}})^2}$$

where X_{obs} is observed values and X_{model} is modelled values at time/place *i*.

Nash-Sutcliffe efficiencies can range from -∞ to 1. An efficiency of 1 (E = 1) corresponds to a perfect match between model and observations. An efficiency of 0 indicates that the model predictions are as accurate as the mean of the observed data, whereas an efficiency less than zero (-∞ < E < 0) occurs when the observed mean is a better predictor than the model.
HBV-E model performance:

Table. Statistics

NSE	RMSE	R
0.65	2.83	0.82

7. Future improvement

The next step of HBV-E model is to improve the soil moisture component and response function.

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