Improved Rainfall-Runoff Modeling Combining a Semi-Distributed Model with Artificial Neural Networks

H. Rouhani, D. Gorissen, J. Feyen

SWAT Conference, July 2nd-6th,
2007,The Netherlands

1. Objective

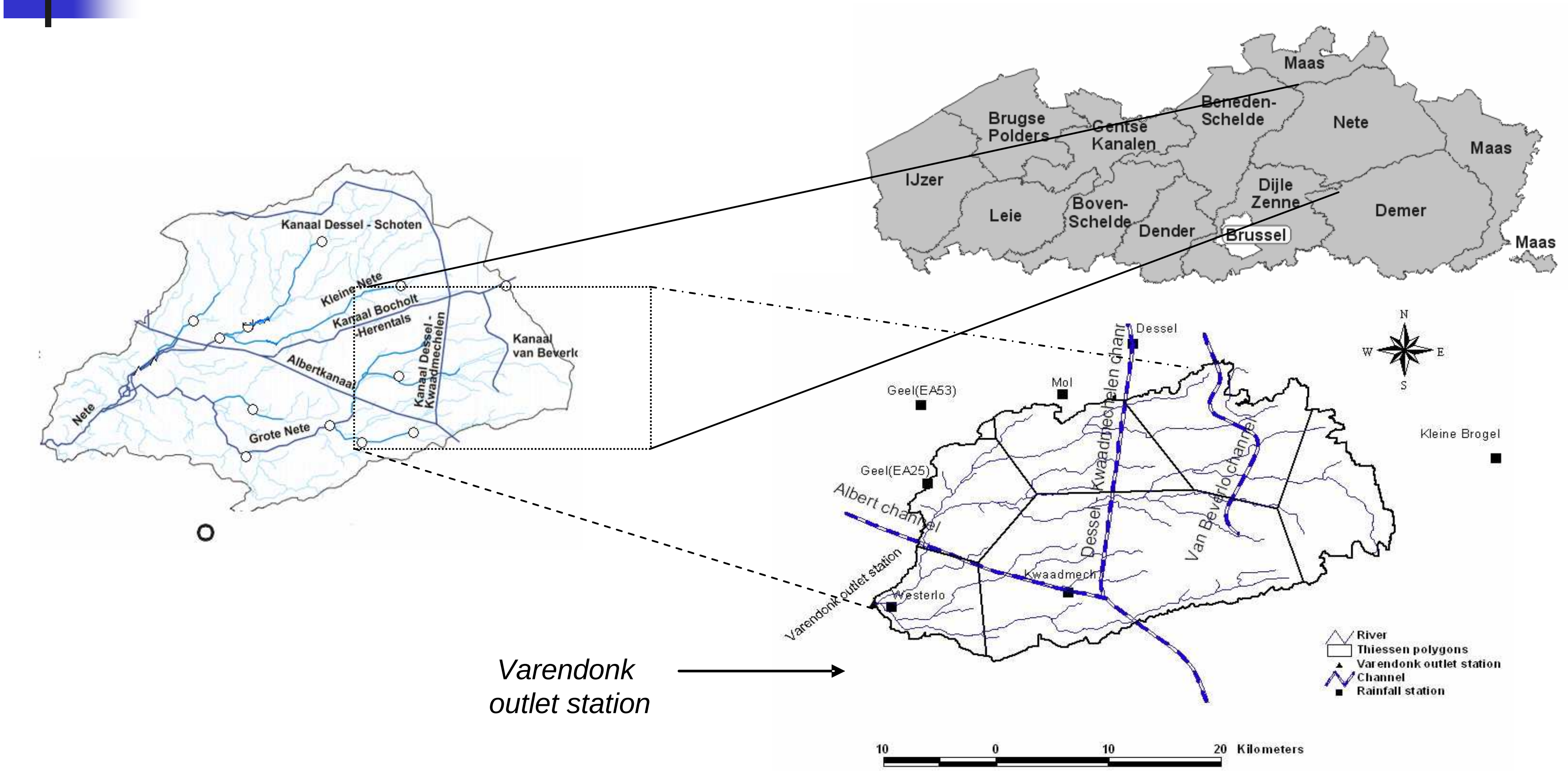
- **Integrated approach to model rainfall-runoff using AVSWAT and Artificial Neural Networks (ANNs).**

☞ Step1: Identify model calibration parameters (LHS-OAT method);

☞ Step2: Optimized model parameters using automatic calibration (SCE-UA) by matching observed and simulated quick and slow flow;

☞ Step3: Fit the black box model to the output of the deterministic rainfall-runoff model to create hybrid and cooperative applications.

2. Study area



Varendonk outlet station

KATHOLIEKE UNIVERSITEIT LEUVEN

3. Model set up and data

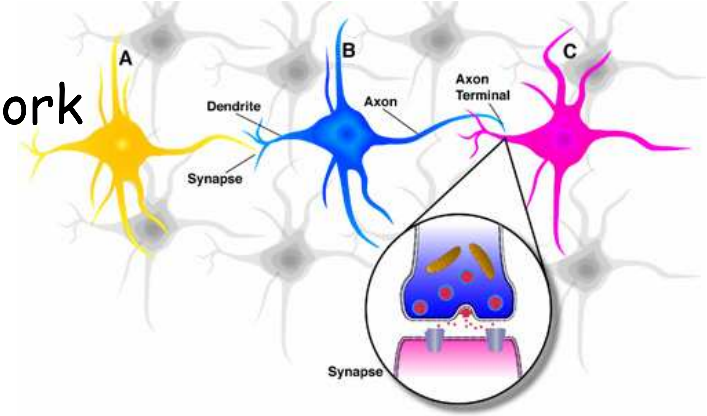
- Daily maximum and minimum air temperature, relative humidity and daily precipitation were gathered from the Royal Meteorological Institute (Belgium);
- Daily stream data flow data made available by the Flemish Water Administration for Land and Water;
- The Penman-Monteith FAO-56 method was used for the calculation of the potential evapotranspiration (Allen et al., 1998);
- The soil map was available at a scale of 1:25.000, and the soil physical data derived from the Aardewerk-SIBIS Soil Information System (Van Orshoven et al., 1993).
- Landuse was derived using the multitemporal LANDSAT 5 TM 1997.

3. Model set up and data

- Four weather stations .
- The annual rainfall for the period 1994-2002 varied from a minimum of 684.1 mm to a maximum of 1089.1 mm.
- The annual rainfall during the calibration period (1999-2002) was 957.6 mm 21% higher than the regional average annual rainfall.
- Validation period (1994-1998), the annual rainfall was 828.1 mm

4. Neural network

- Multi-Layer feed-forward neural network
- Focused time-delay neural network



- Nonlinear time-dependent signals
- It is simply a static multi layer perceptron with a tap delay line between the input and the first layer
- This network is well suited to time-series prediction (MATLAB user guide)

5. Multi-objective functions

- The optimal parameter set for one signal might not be the best parameter set for another signal.

- Two general approaches to multi-objective calibration

  - aggregated to form a single objective function

    the solution is strongly dependent on the way the objectives have been aggregated.

  - concept of Pareto optimality

Vilfredo Pareto, 1848-1923

5.1. Pareto optima1

- A Pareto-optimal solution cannot be improved upon without hurting at least one of the criteria.
- All solutions on the Pareto front equally important and all are the global optimal solutions.
- The user must decide what compromise to make
  - Algorithms: Normal Constraint method, Pattern search, Genetic algorithm, etc…

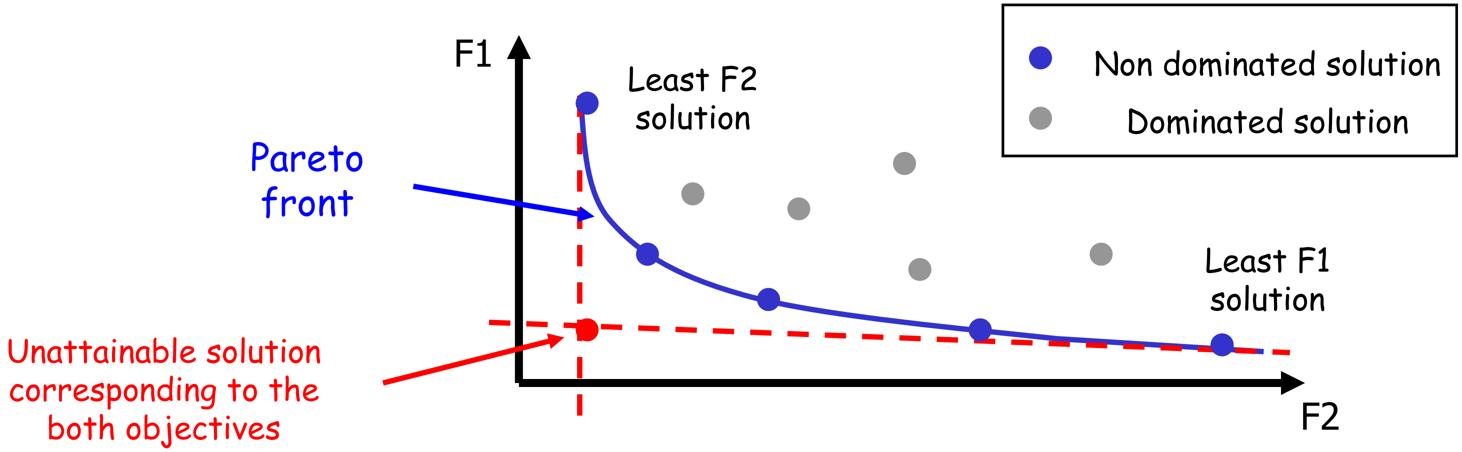


Fig 1. Maping the Preto performance space

5.1. Pareto optima1

- The aggregated objective function:

$$F_{agg} = \omega g_1(F_1) + (1-\omega) g_2(F\ 2) \qquad (1)$$

- Compensate for difference in magnitude between MSE terms

$$g_i(F_i) = \frac{F_i}{\sigma_i} + \varepsilon_i, i = 1,2 \qquad (2)$$

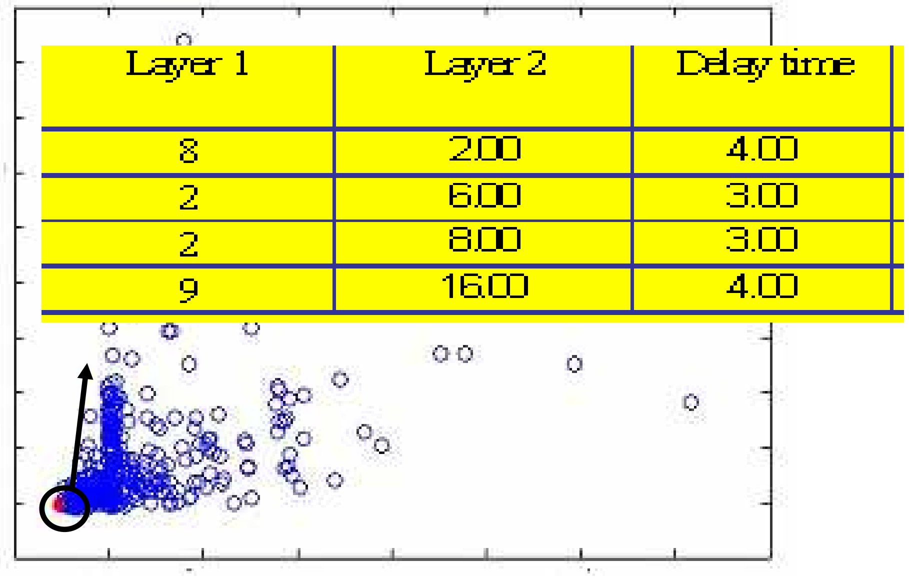
- Transformation constant

$$\varepsilon_i = \max\left\{\min\left\{\frac{F_J}{\sigma_J}\right\}, j = 1,2\right\} - \min\left\{\frac{F_i}{\sigma_i}\right\} \qquad (3)$$

Madsen,H. (2003), Parameter estimation in distributed hydrological catchment modelling using automatic calibration with multiple objective. *Advances in Water Resources, Volume 26, Pages 205-216*

6. Result

Fig 2. Objective function values of evaluated parameter sets.



Layer 1	Layer 2	Delay time
8	2.00	4.00
2	6.00	3.00
2	8.00	3.00
9	16.00	4.00

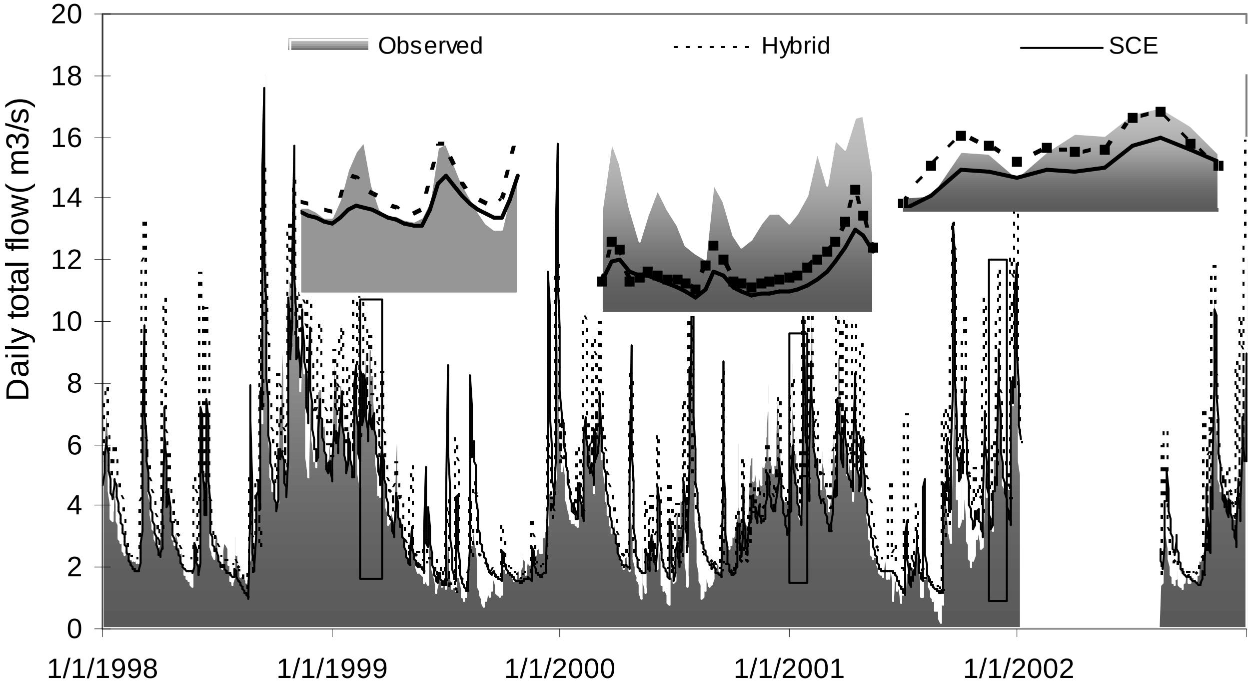
6. Result

Table 1. Summary of the statistics for the daily total water and slow flows in the calibration and validation periods

Statistical criteria	Average daily total water flow				Average daily slow flow			
	Calibration		Validation		Calibration		Validation	
	SCE	Hybrid	SCE	Hybrid	SCE	Hybrid	SCE	Hybrid
RMSE ($m^3 s^{-1}$)	1.45	0.57	1.38	0.68	0.70	0.32	1.11	0.56
EF	0.72	0.83	0.68	0.79	0.80	0.86	0.63	0.84
R^2	0.80	0.89	0.88	0.92	0.81	0.89	0.87	0.91

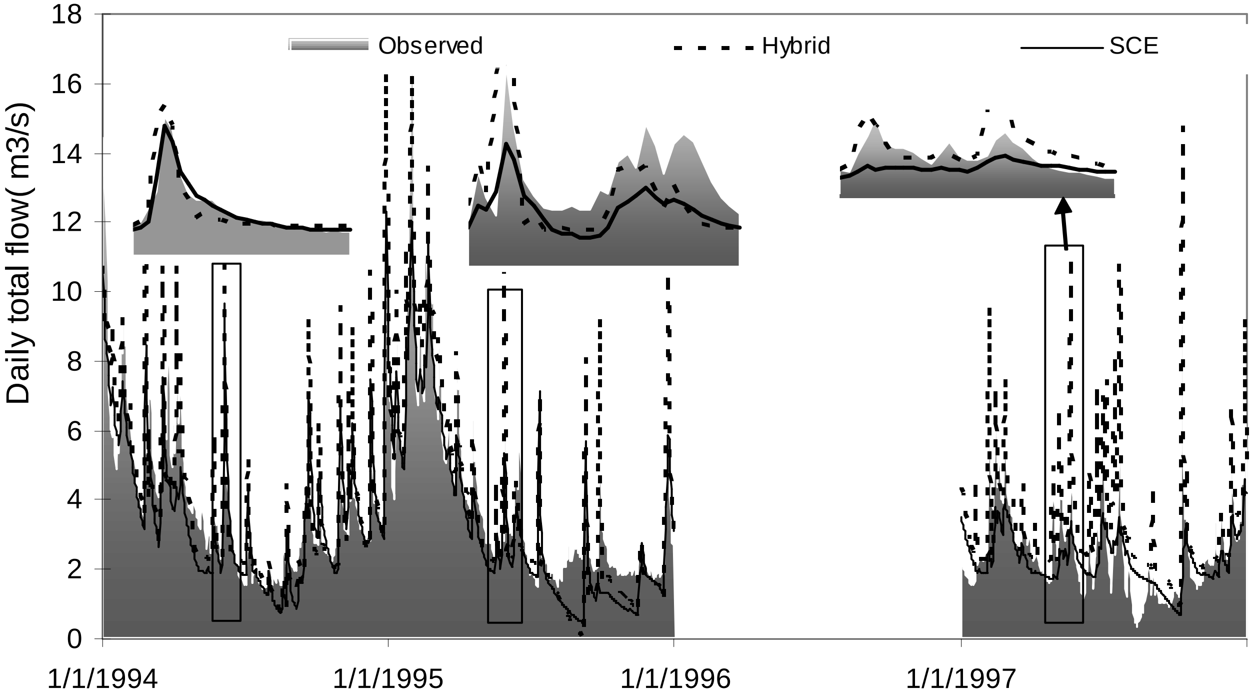
6. Result

Figure 3 : Comparison of observed and simulated daily total flows outlet during the model calibration (1998-2002), for observed, hybrid and SCE methods.



6. Result

Figure 4: Comparison of observed and simulated daily total flows during the model calibration (1994-1997), for observed, hybrid and SCE methods.



7. Conclusion & recomendation

- Recent developments in stochastic analysis, are opening up new horizons in hydrology modelling
- Significant progress is being made in hybrid method.
- This survey is on-going.
- Keep working team work

Thank you for your attention

Question?