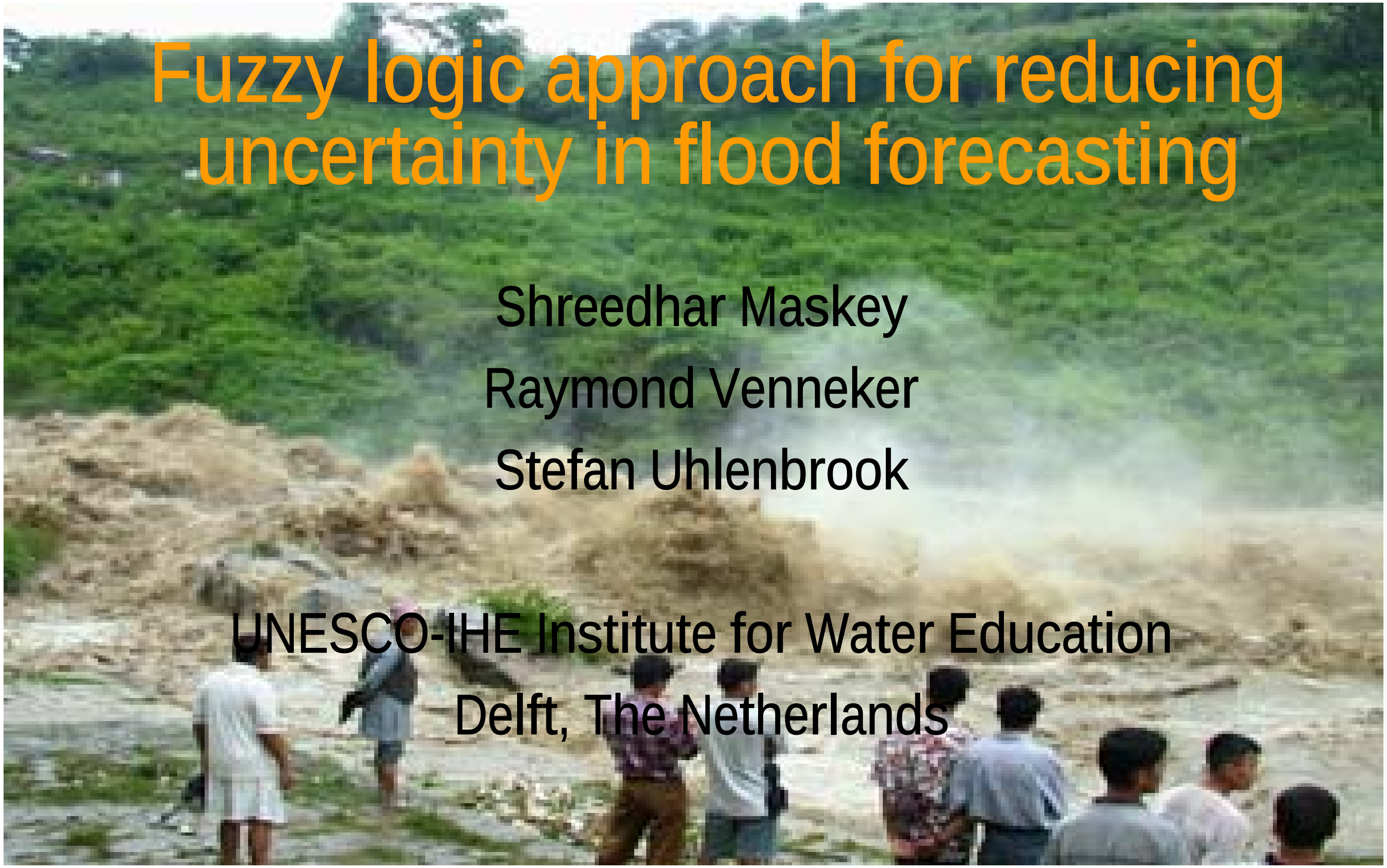

Fuzzy logic approach for reducing uncertainty in flood forecasting

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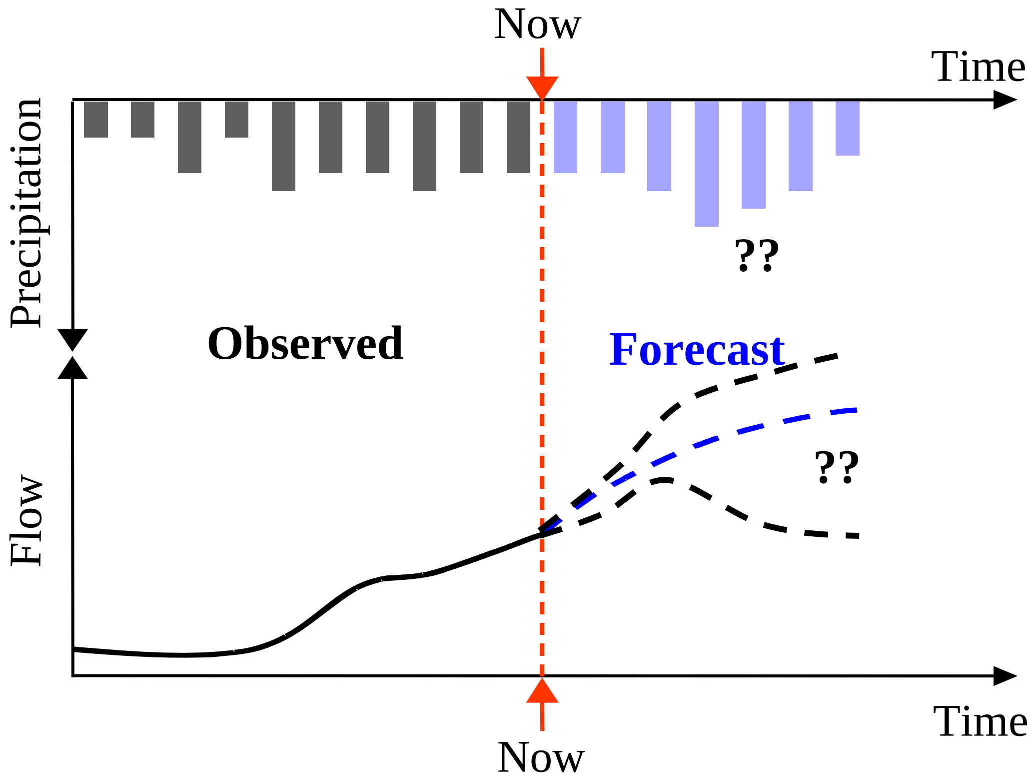
Objectives

- To present an overview of uncertainty related issues in flood forecasting.
- To show the impact of rainfall data uncertainty using disaggregation methodology.
- To introduce a methodology that combines multiple models using fuzzy logic for flood forecasting. The methodology aims to reduce model error/uncertainty.

Modeling for flood forecasting

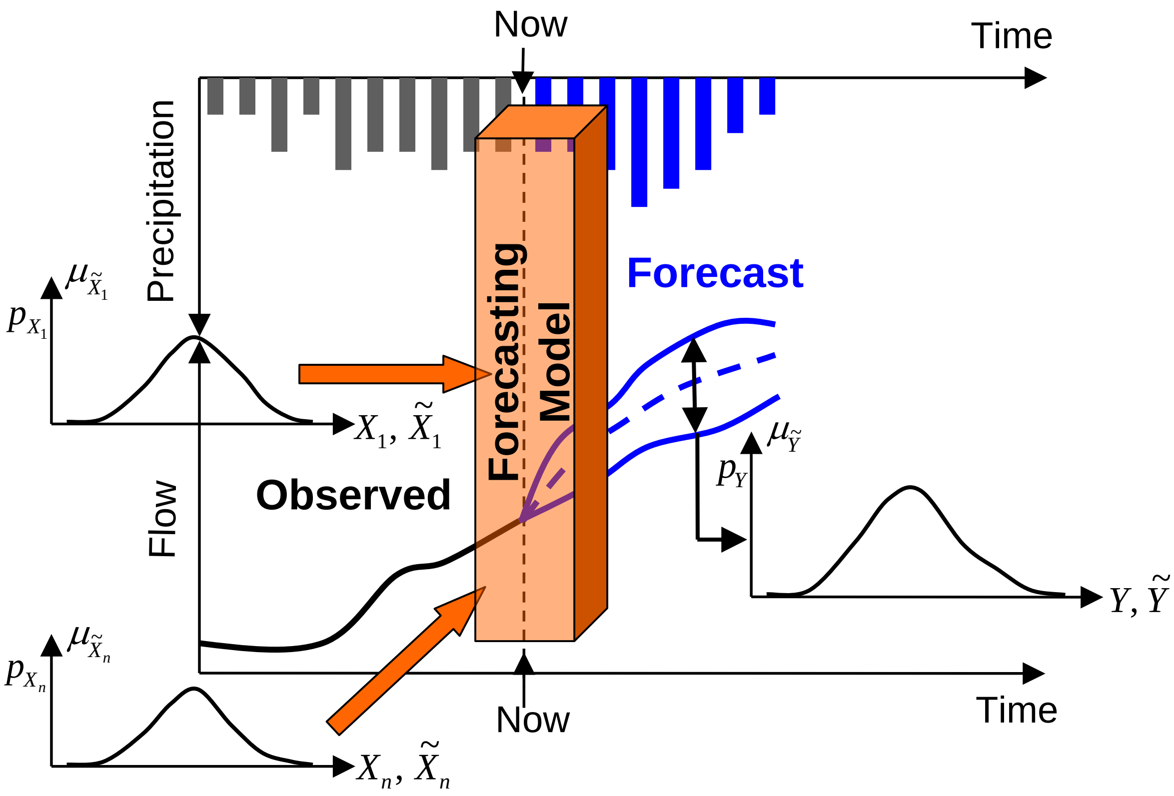
- Types of model
  - Physically-based distributed
  - Lumped/semi-distributed conceptual
  - Data driven



- Role of future rainfall in future floods
  - Integration of weather forecasts into flood forecasting system

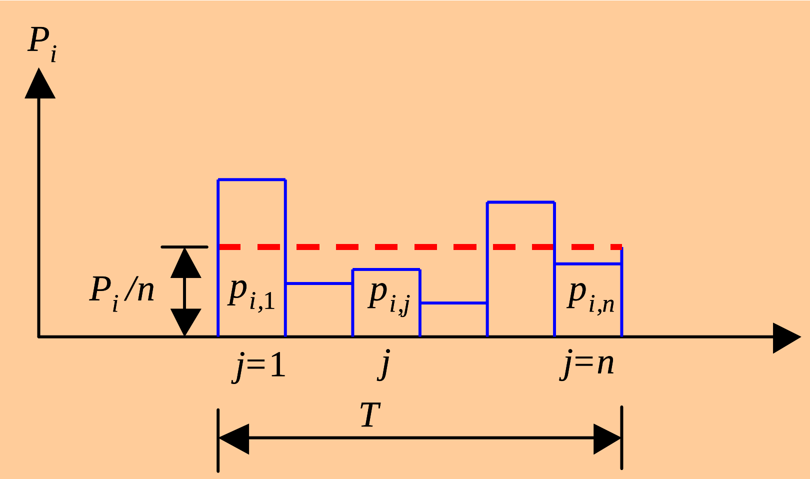
Uncertainty in flood forecasting

- Uncertainty comes from
  - Input data
  - Model parameters
  - Model structure
  - Calibration data
  - Initial state of the system
  - Limited knowledge of the system



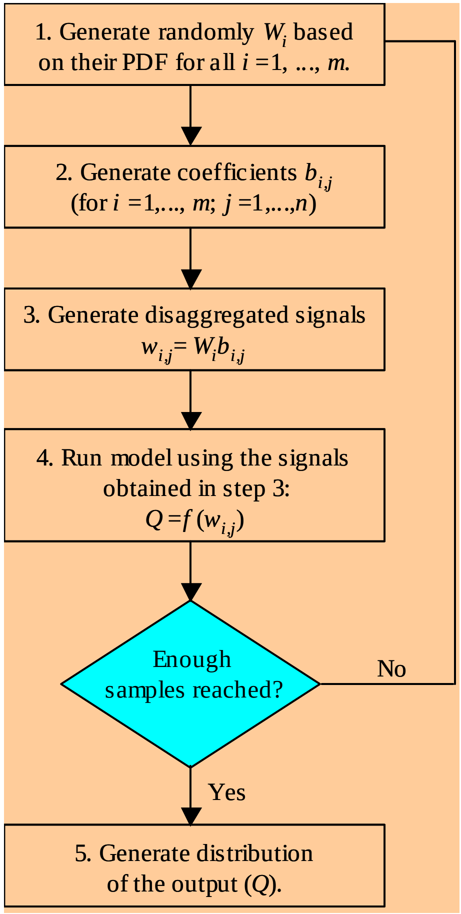
Uncertainty caused by rainfall data

- Uncertainty in rainfall comes from
  - Imprecise quantity
  - Low frequency data
  - Spatial regionalization
- Rainfall data uncertainty propagation using temporal disaggregation
  - Monte Carlo based approach
  - Fuzzy extension principle based approach



$$Q = f([p_{1,1},\dots,p_{1,n}]\times\dots\times[p_{m,1},\dots,p_{mn}])$$

Rainfall disaggregation and uncertainty propagation



1. Generate randomly W_i based on their PDF for all $i = 1, \ldots, m$.

2. Generate coefficients $b_{i,j}$ (for $i = 1,\ldots, m$; $j = 1,\ldots,n$)

3. Generate disaggregated signals $w_{i,j} = W_i b_{i,j}$

4. Run model using the signals obtained in step 3: $Q = f(w_{i,j})$

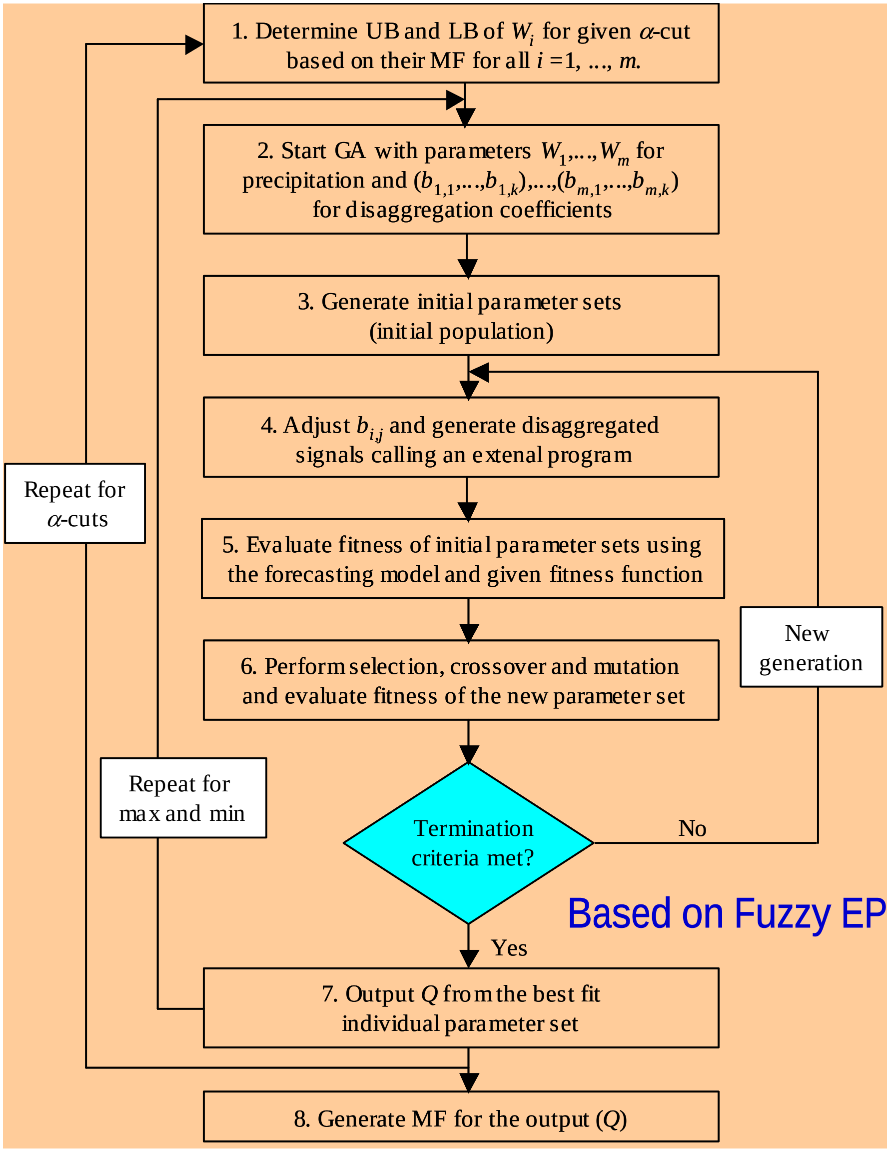
Enough samples reached?

No

Yes

5. Generate distribution of the output (Q).

Based on Monte Carlo method



1. Determine UB and LB of W_i for given α-cut based on their MF for all $i = 1, \ldots, m$.

2. Start GA with parameters $W_1,\ldots,W_m$ for precipitation and $(b_{1,1},\ldots,b_{1,k}),\ldots,(b_{m,1},\ldots,b_{m,k})$ for disaggregation coefficients

3. Generate initial parameter sets (initial population)

4. Adjust $b_{i,j}$ and generate disaggregated signals calling an extenal program

5. Evaluate fitness of initial parameter sets using the forecasting model and given fitness function

6. Perform selection, crossover and mutation and evaluate fitness of the new parameter set

Termination criteria met?

No

New generation

Yes

7. Output Q from the best fit individual parameter set

Repeat for max and min

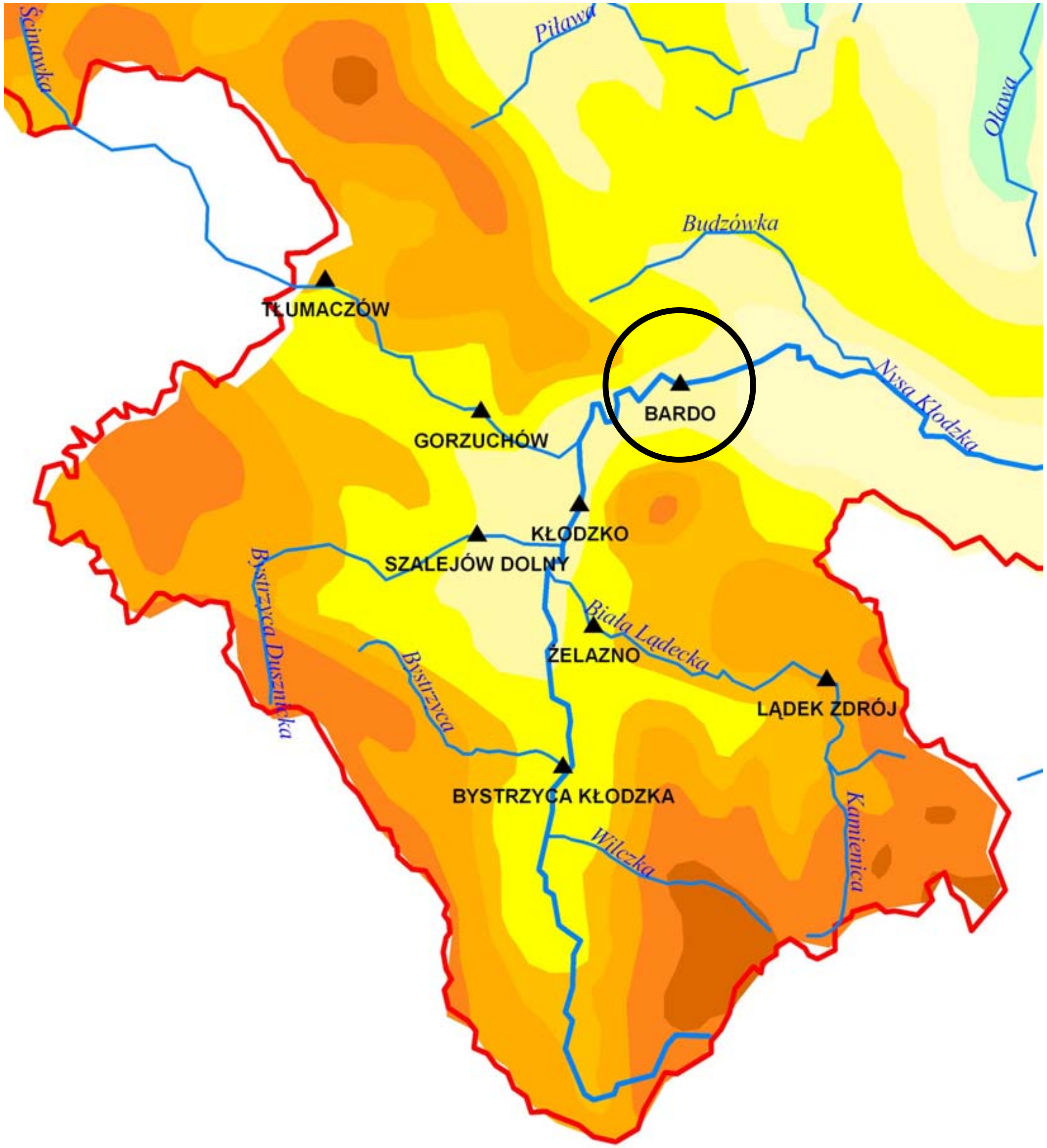
Repeat for α-cuts

8. Generate MF for the output (Q)

Based on Fuzzy EP

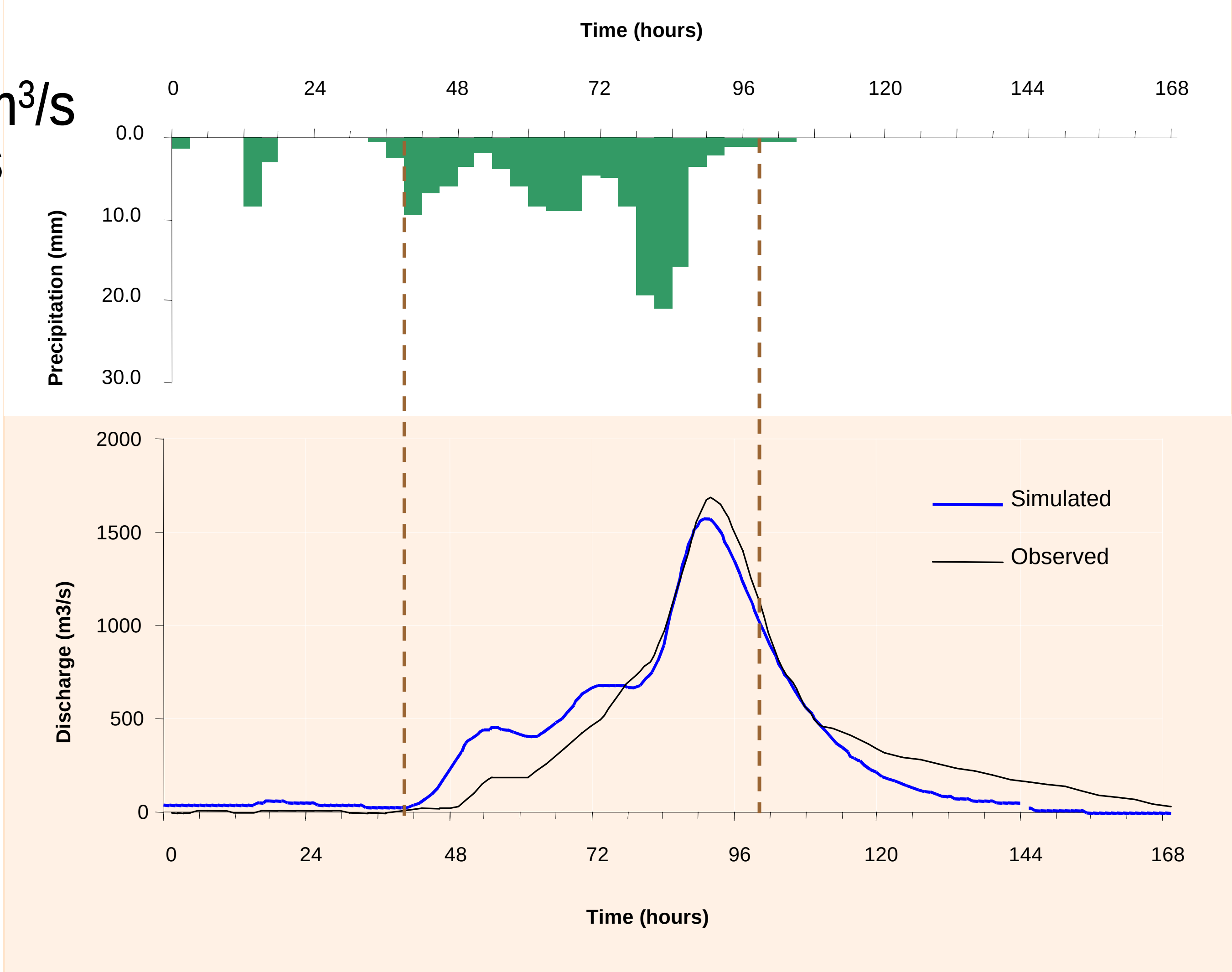
Rainfall disaggregation and uncertainty propagation

- Klodzko valley (Poland)
  - Basin area = 1744 km^2
  - 9 sub-basins
  - Model HEC-HMC
  - Forecast for Bardo on River Nysa Klodzka

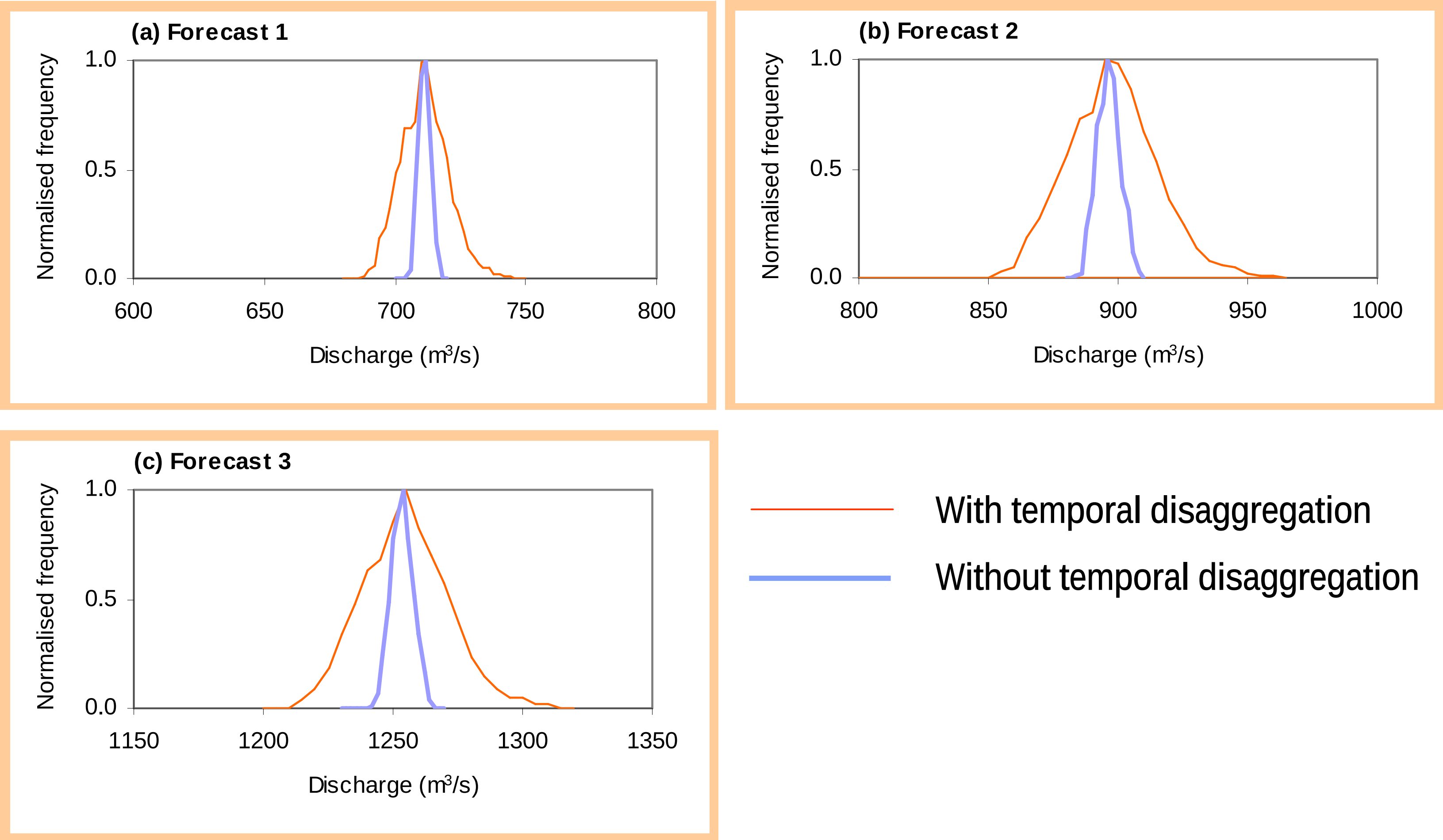


Rainfall disaggregation and uncertainty propagation

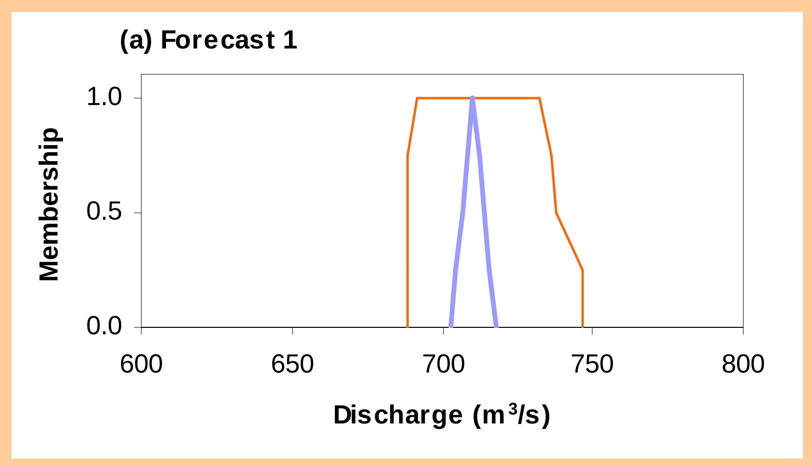
- Flood of July 1997
- Max discharge reached 1700 m^3/s (50 m^3/s 3 days before).

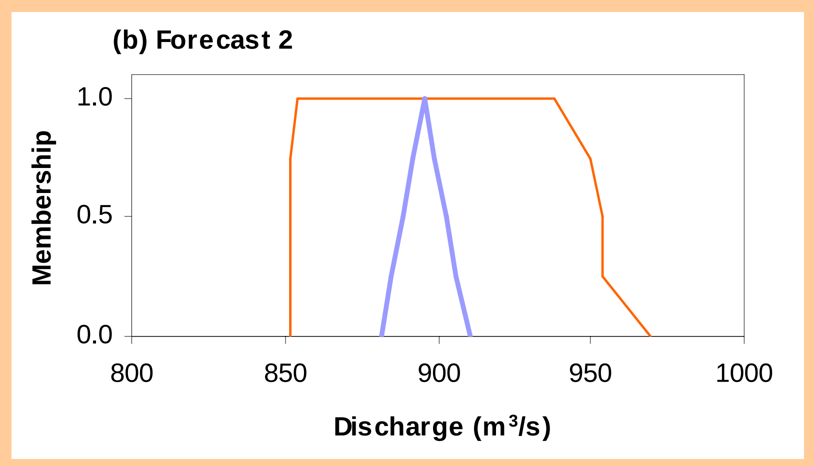


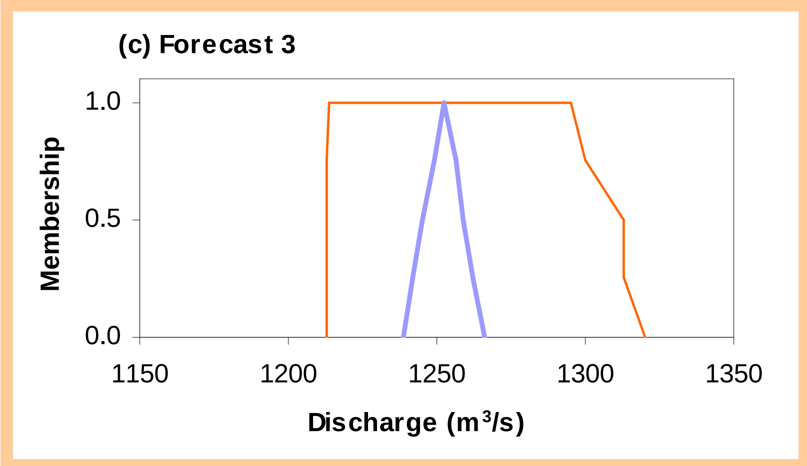
Impact of rainfall uncertainty (Monte Carlo approach)



Impact of rainfall uncertainty (Fuzzy EP approach)


(a) Forecast 1


(b) Forecast 2

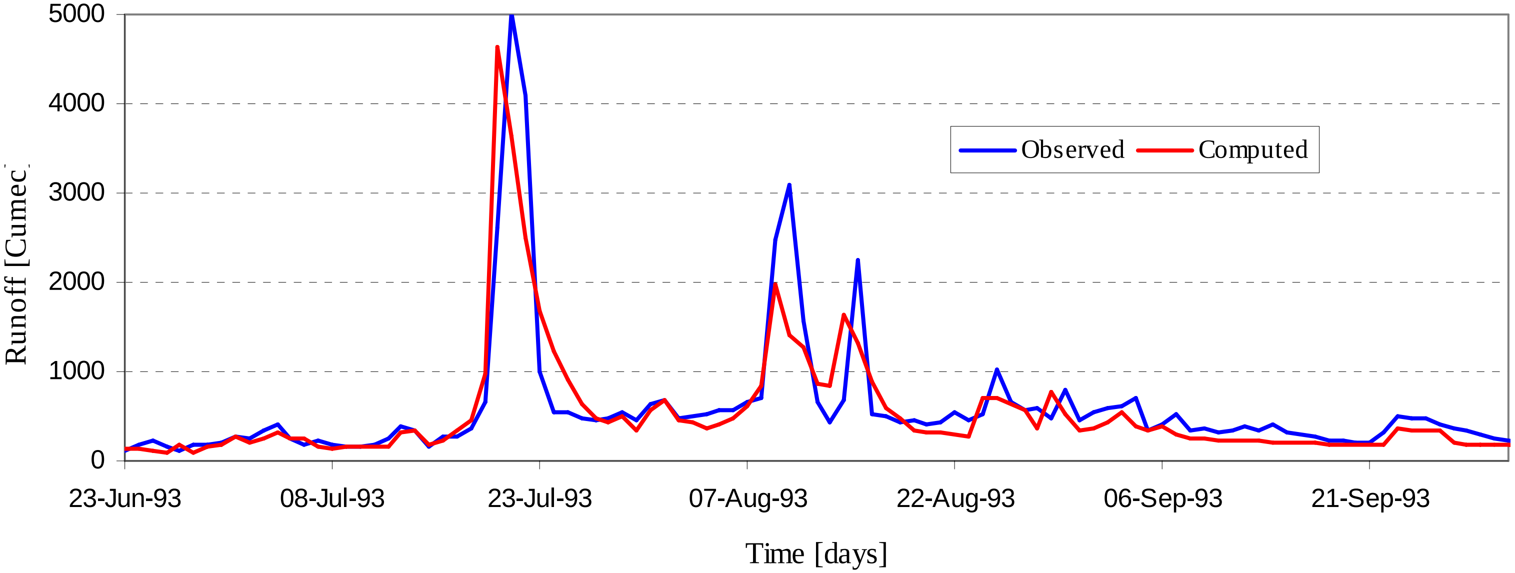

(c) Forecast 3

— With temporal disaggregation

— Without temporal disaggregation

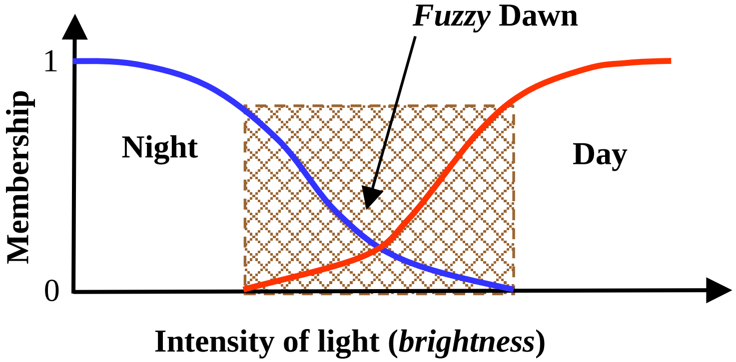
Model calibration

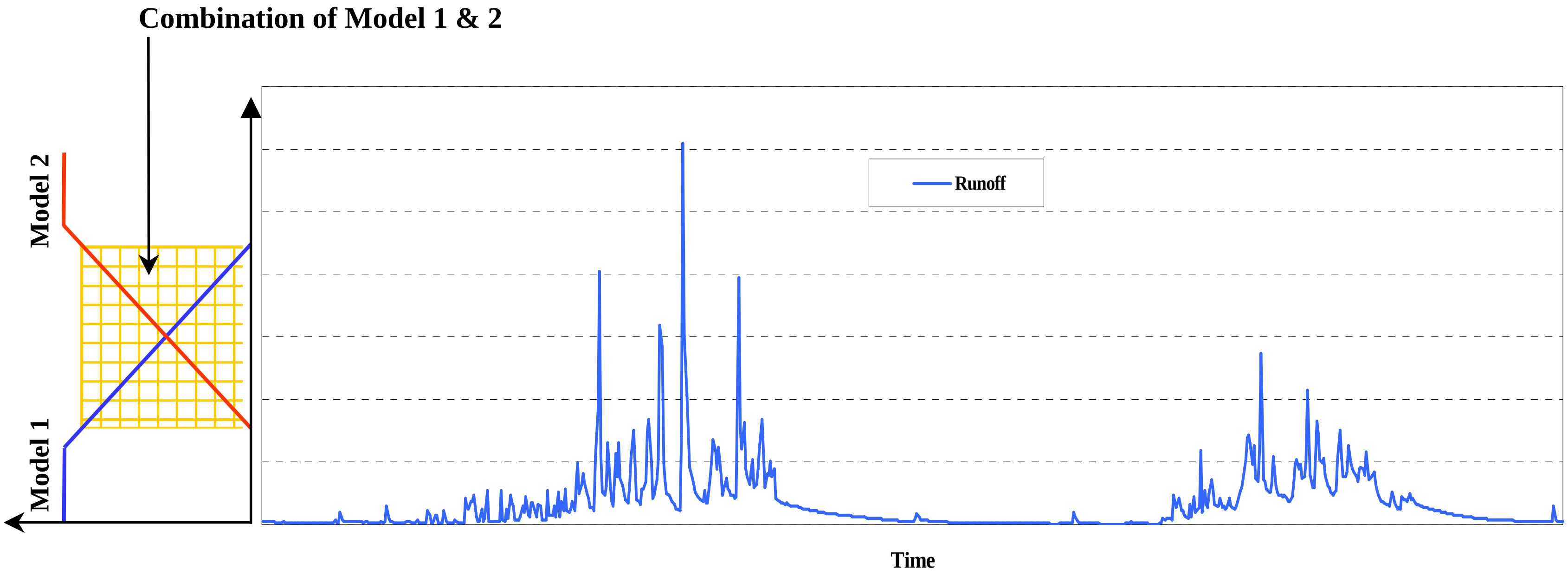
- Plays a vital role in model accuracy (more for conceptual models)
- Problems:
  - Calibrated parameter sets may vary for different flood events. Not a single parameter set satisfies all flood events.
  - Calibration data also possess uncertainty.



Fuzzy logic for reducing error/uncertainty

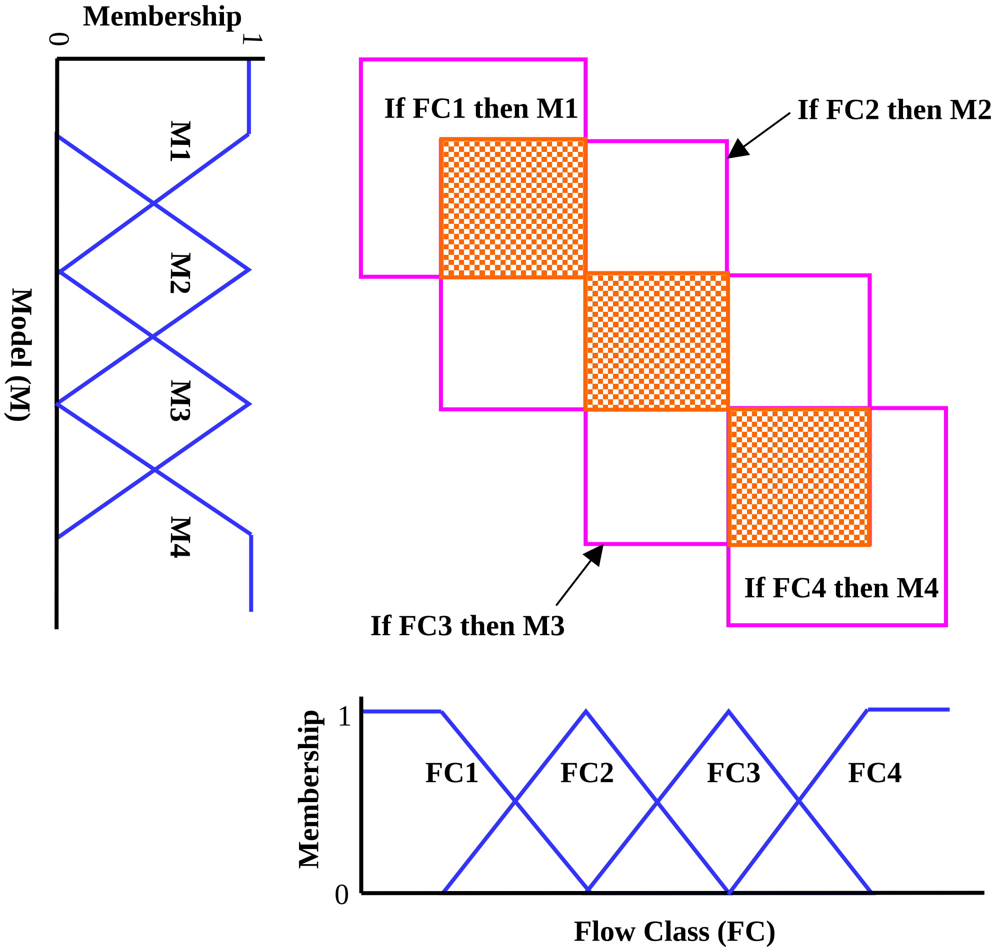
- The basic fuzzy principle:
  Everything is a matter of degree.





Fuzzy logic for reducing error/uncertainty

- Methodology
  - Classify flood events into various classes.
  - Calibrate a model independently for each flood class.
  - Use fuzzy logic to combine the models.



If FC1 then M1

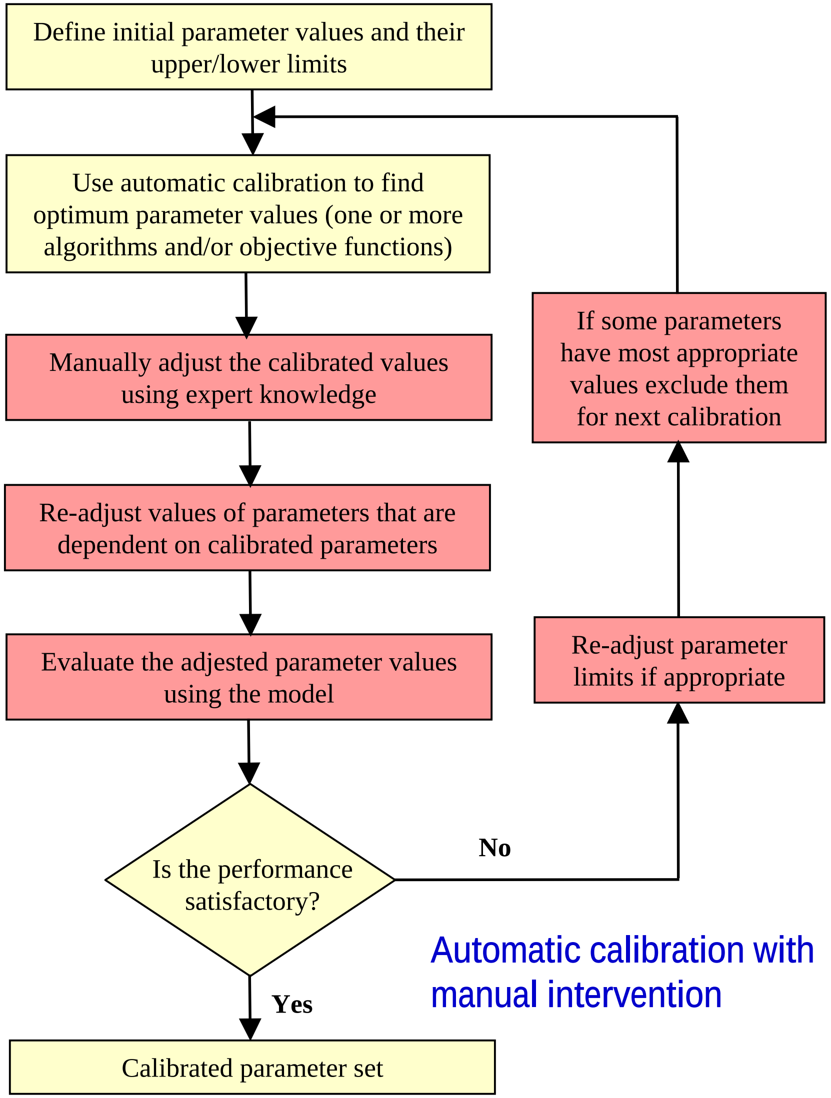
If FC2 then M2

If FC3 then M3

If FC4 then M4

Fuzzy logic for reducing error/uncertainty

- Methodology (contd.)
  - Flow classes can be defined based on antecedent conditions and forecasted rainfall.
  - Requires consistent and robust calibration procedure.
  - Automatic calibration with manual intervention can be used.



Define initial parameter values and their upper/lower limits

Use automatic calibration to find optimum parameter values (one or more algorithms and/or objective functions)

Manually adjust the calibrated values using expert knowledge

Re-adjust values of parameters that are dependent on calibrated parameters

Evaluate the adjested parameter values using the model

Is the performance satisfactory?

No

Re-adjust parameter limits if appropriate

If some parameters have most appropriate values exclude them for next calibration

Yes

Calibrated parameter set

Automatic calibration with manual intervention

Conclusions

- The methodology uses specific models depending on the respective hydrological situation.
- The methodology has potential to enhance forecasting capacity/precision of models using the fuzzy logic approach.
- The methodology provides opportunity to forecast a range of plausible values.