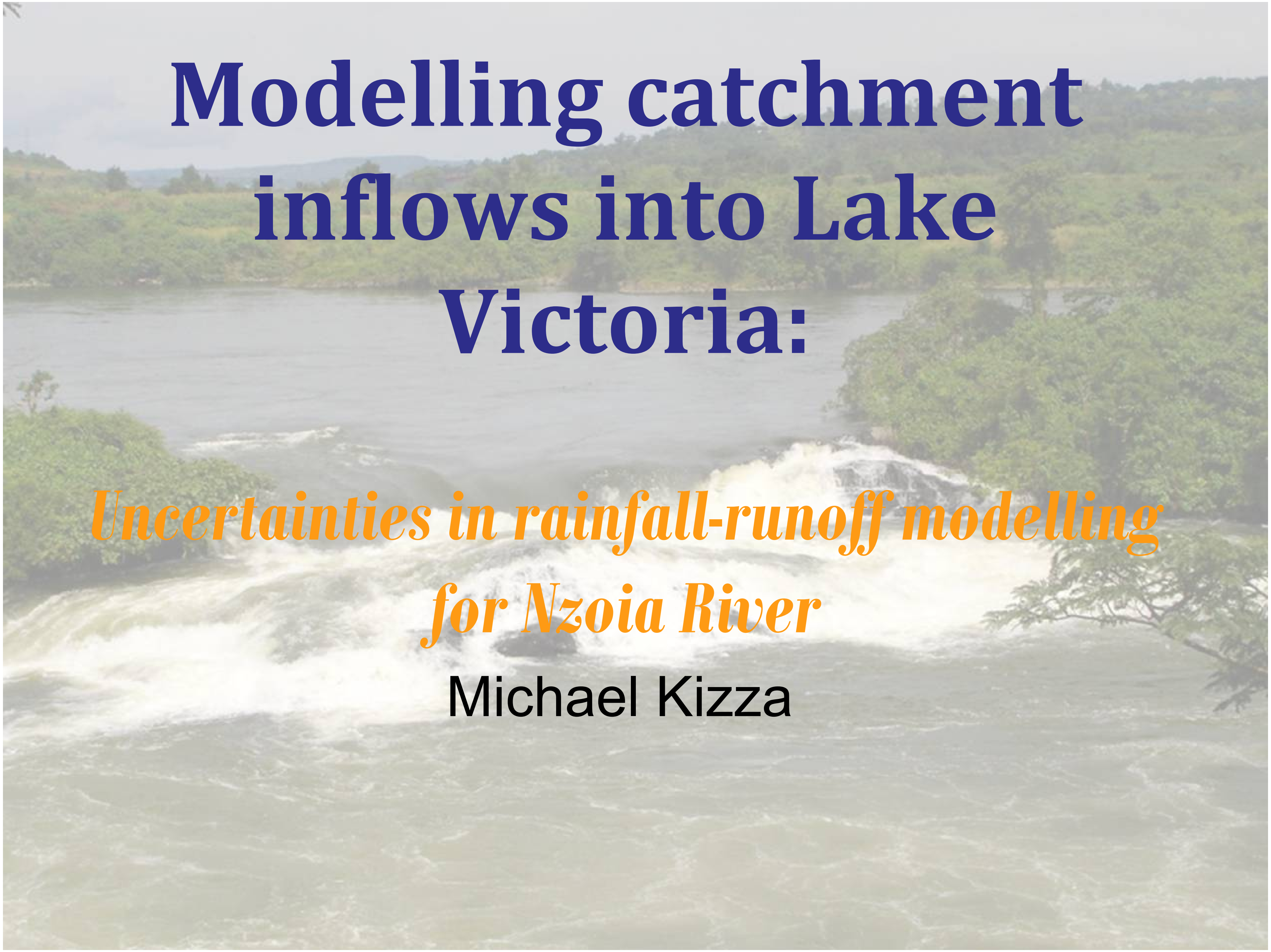
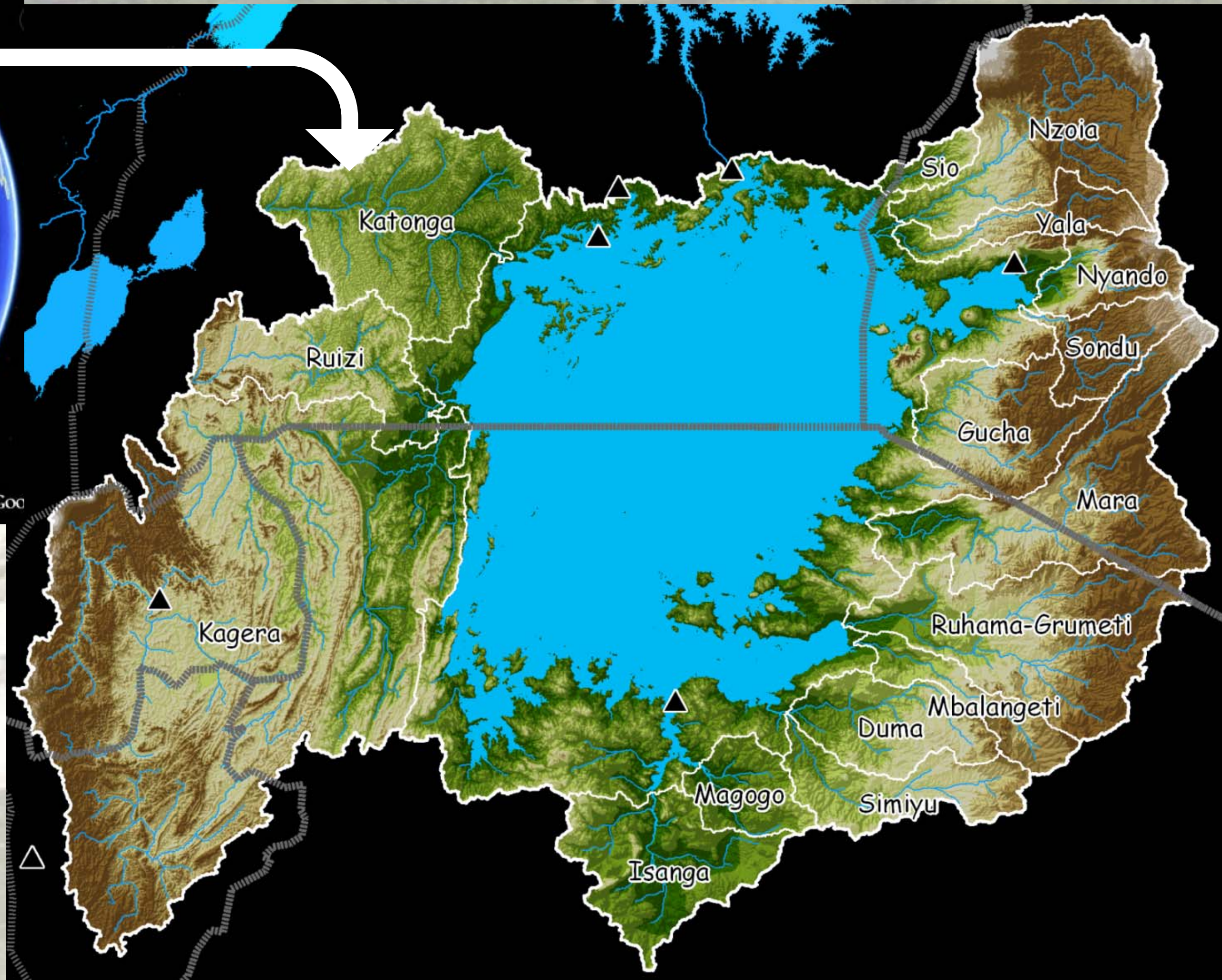


Modelling catchment inflows into Lake Victoria:

Uncertainties in rainfall-runoff modelling for Nzoia River

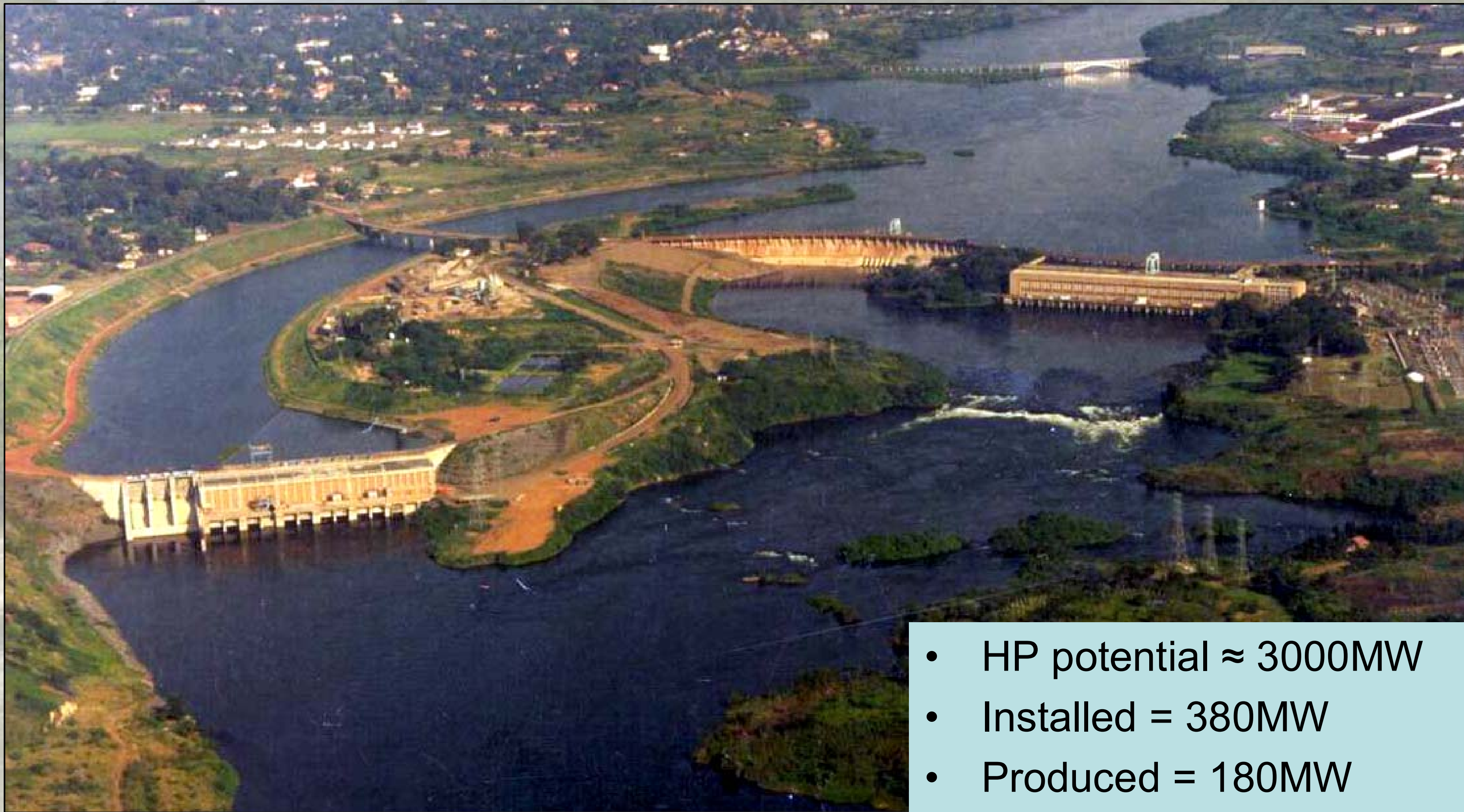
Michael Kizza

Lake Victoria Basin



- Lake: 68,000km^2
- Basin: 190,000km^2
- WB components
  - Rainfall: 1750mm
  - Evaporation: 1600mm
  - Inflow: 300mm
  - Outflow: 450mm

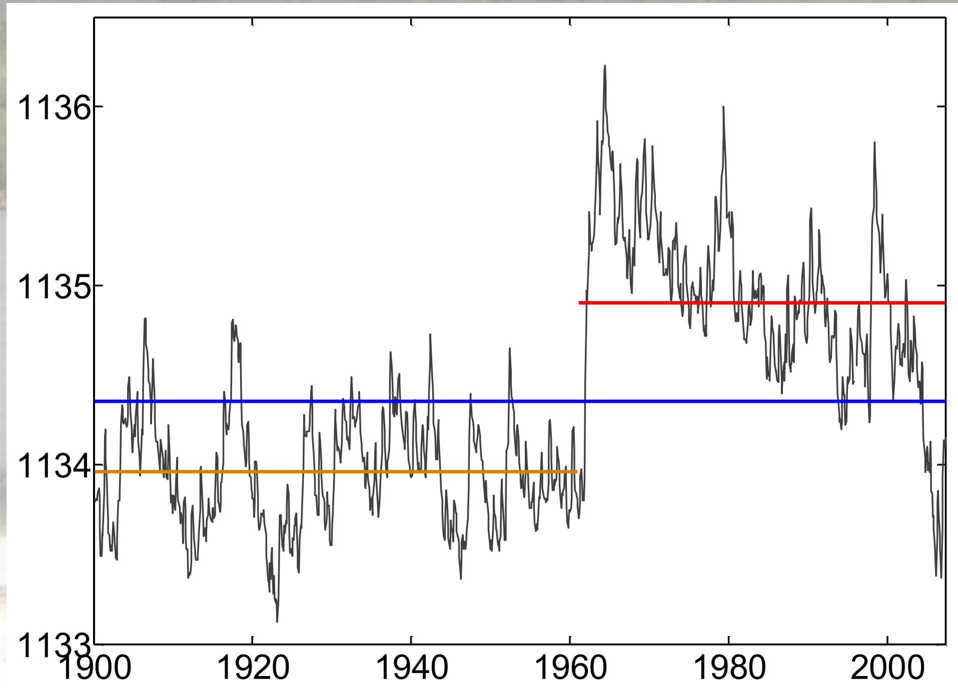
Lake Victoria outflow

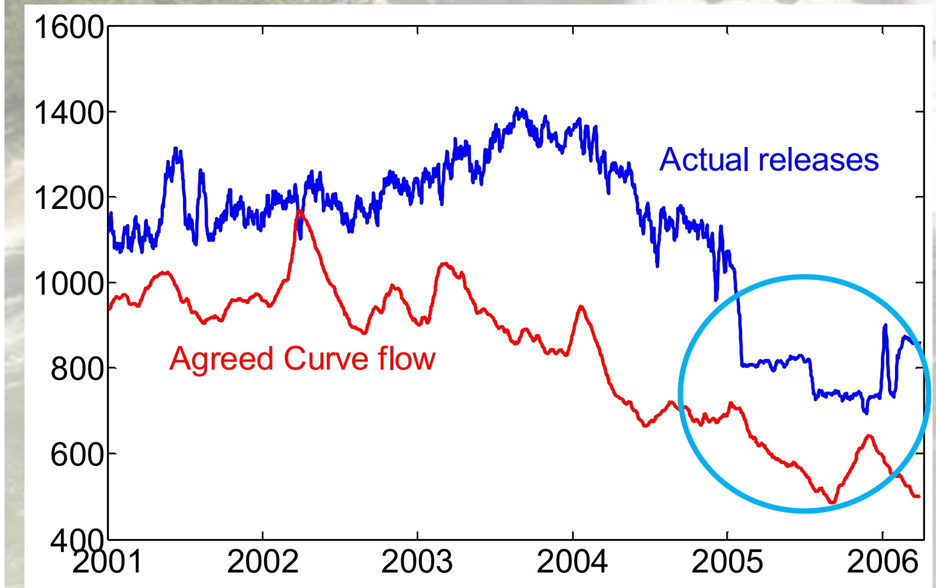


- HP potential ≈ 3000MW
- Installed = 380MW
- Produced = 180MW
- Demand ≈ 800MW
- Growth = 8MW/month

Water balance issues

- Transient water levels
- Agreed curve issues
- Estimation of lake rainfall
- Catchment inflows





Catchment inflow issues

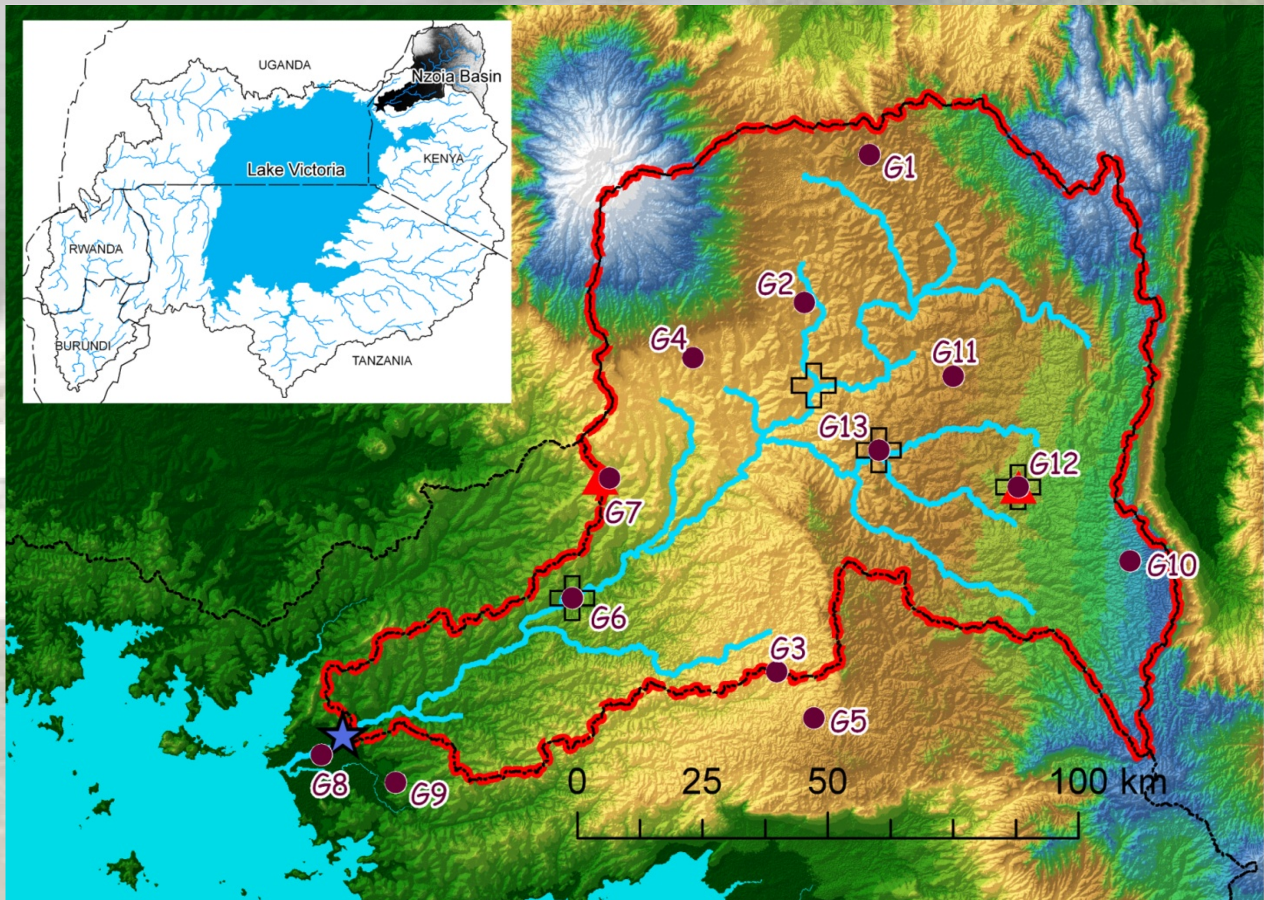
- High spatial and temporal variability in catchment inflows around basin due to variations in
  - Basin climate and rainfall
  - Catchment characteristics (soils, topography etc)
- Data scarcity and reliability issues

- *…. Uncertain estimates of catchment inflows which has an adverse effect on water*

Objective and study area

- to develop a framework for estimating the variability in the catchment inflow into Lake Victoria taking into account issues of unreliable input and calibration data that is a common feature in tropical catchments.

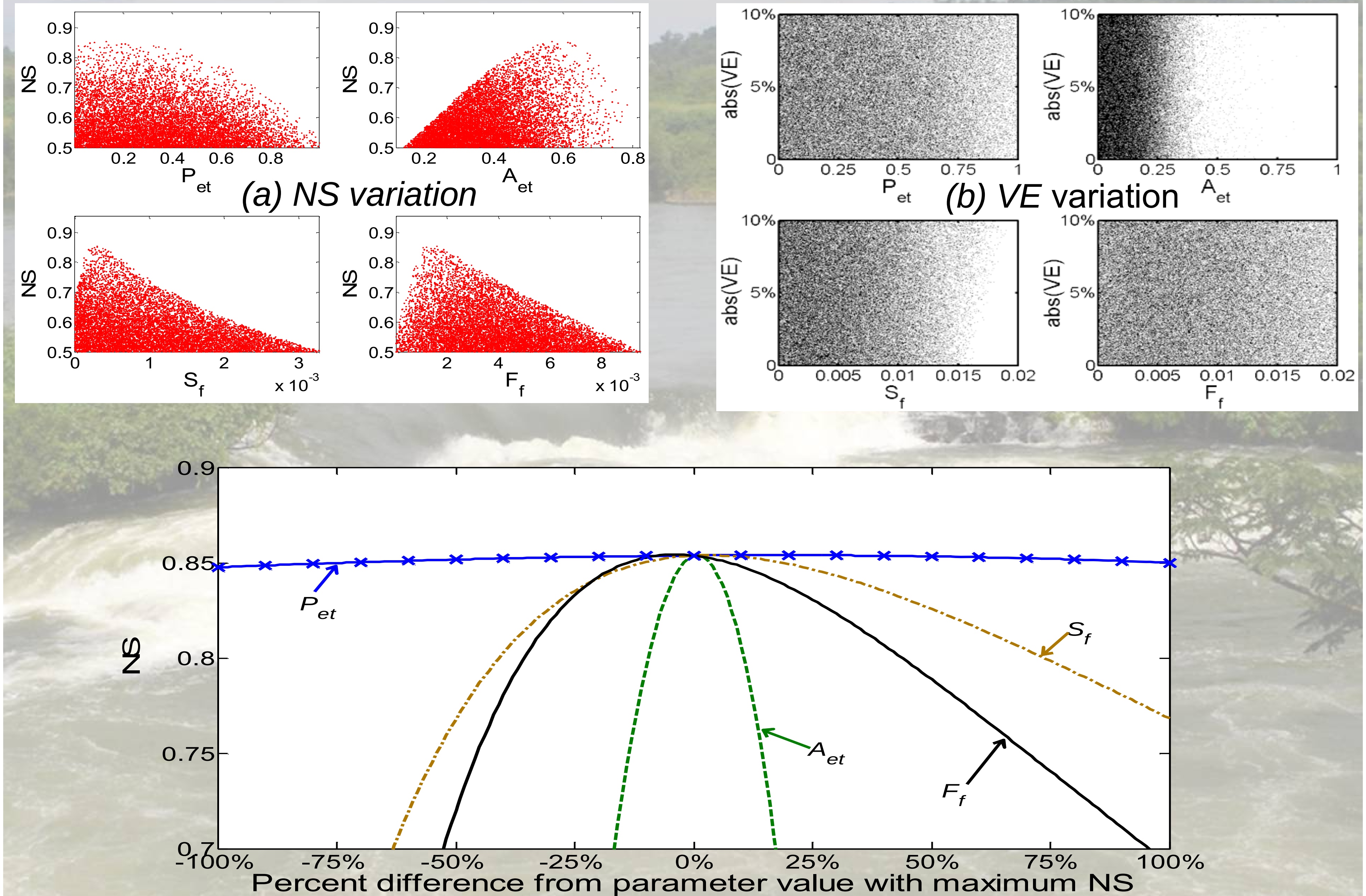
- **Nzoia Basin**



Adopted methodology

- Use of WASMOD (Xu, 2002) model, with 4 parameters for controlling different water balance components; namely P_{et}, A_{et}, S_f and F_f
- Data: monthly values of *rainfall, temperature, evaporation* and *simulated runoff*
- Assessment approach: GLUE approach (Beven and Binley, 1992)
  - •Monte Carlo simulation with 1,000,000 uniformly sampled parameter sets.
  - •Selection of behavioural parameter usingNash-sutcliffe (NS) and Volume Error (VE) criteria.
- *Model Simulation periods*
  - – 1970-1972: warm-up to stabilise moisture content value
  - – 1973-1982: calibration period
  - – 1983-1989: first model conditioning period
  - – 1990-1995: second conditioning period
- The Bayesian model averaging equation was used to combine model performances (likelihoods) from two simulation periods

Parameter sensitivity



Model performance

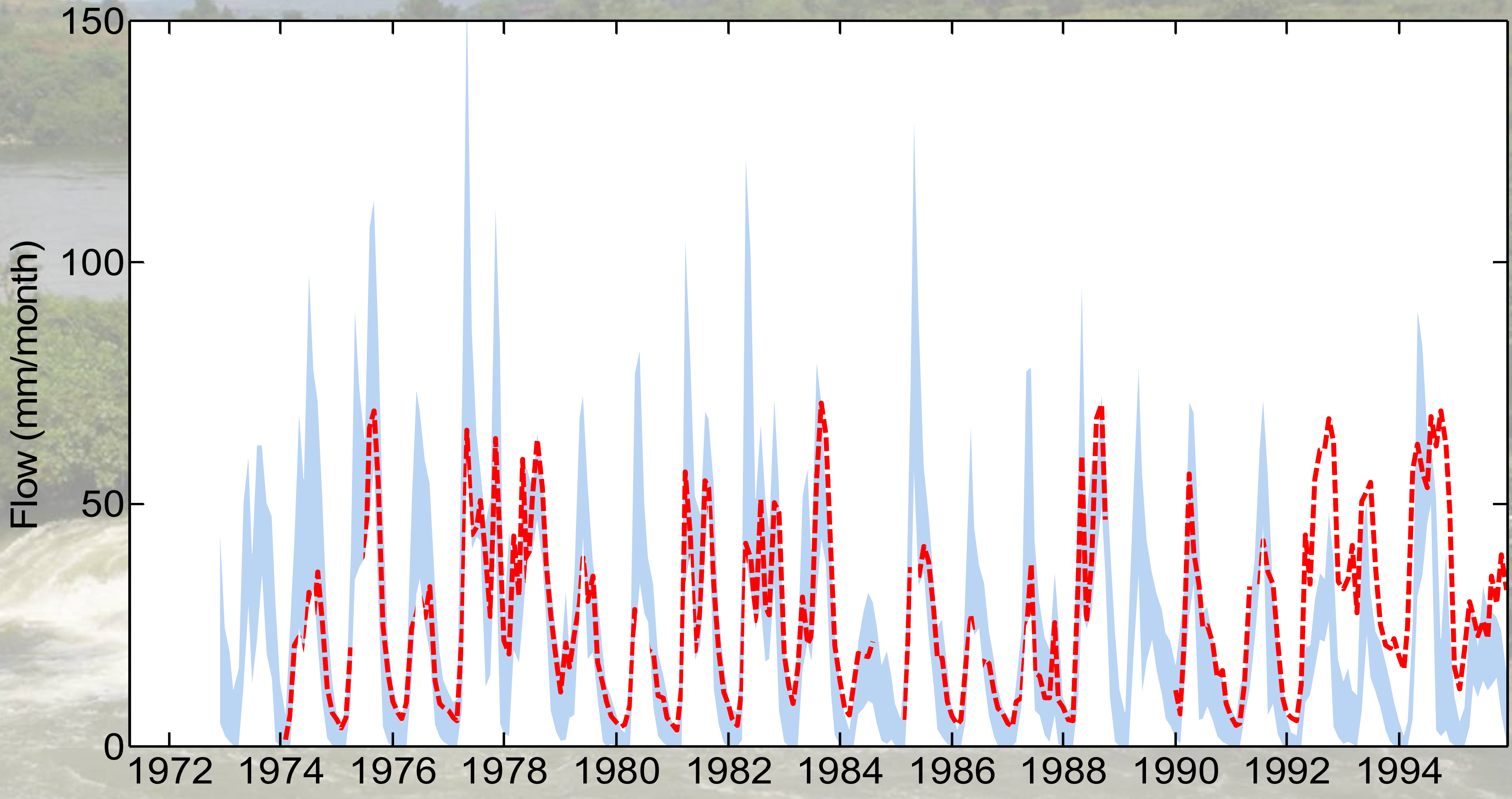
Table 1. Number of behavioural parameter sets after conditioning for different periods

Model Period	No of Behavioural parameter sets
Calibration (1973-1982)	(2,673)
1st Conditioning period (1983-1989)	(1,535)
2nd Conditioning Period (1990-1995)	(-)

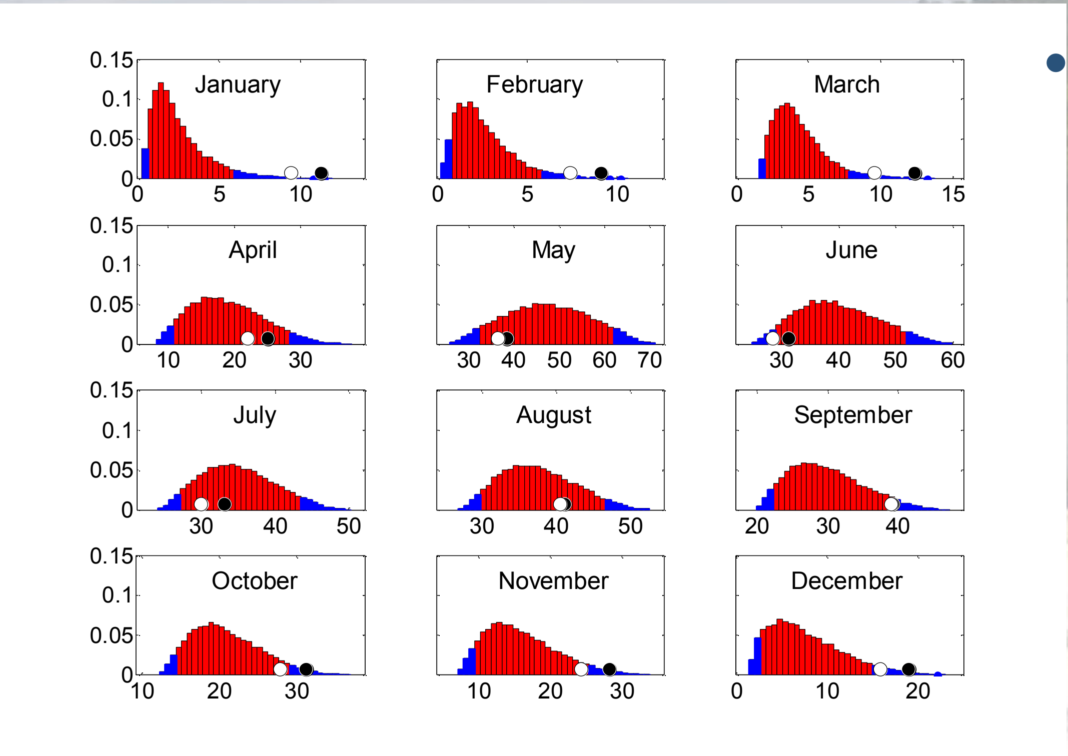
Table 2. Model failures (as a percentage of months when simulated flows fail to bound observed flows) for different simulation periods

Period	Model failure (%)
1973 – 1982	(19)
1983 – 1989	(11)
1973 – 1989	(16)
1990 - 1995	(83)
1973 - 1996	(29)

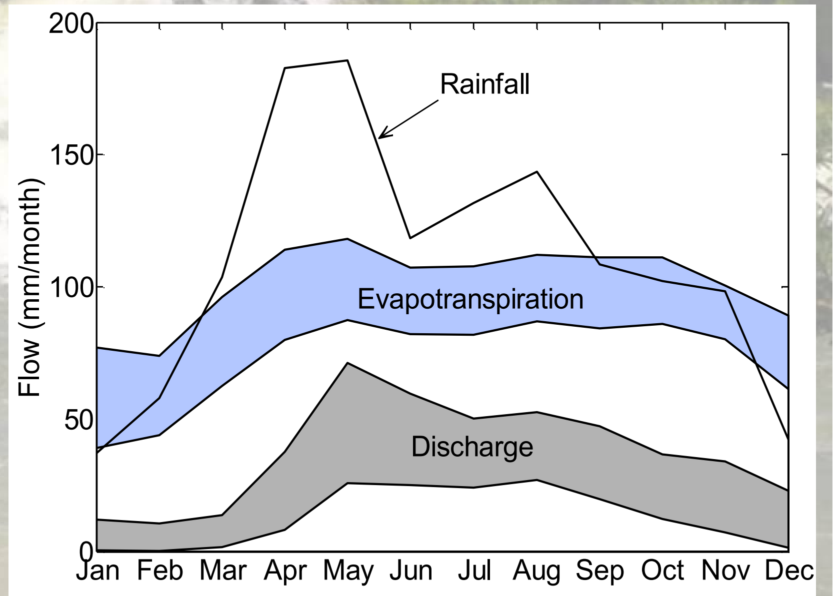
Model performance



Key flow features



- **Annual water balance**
  - R = 1322mm
  - E = 1052mm
  - Q = 257mm

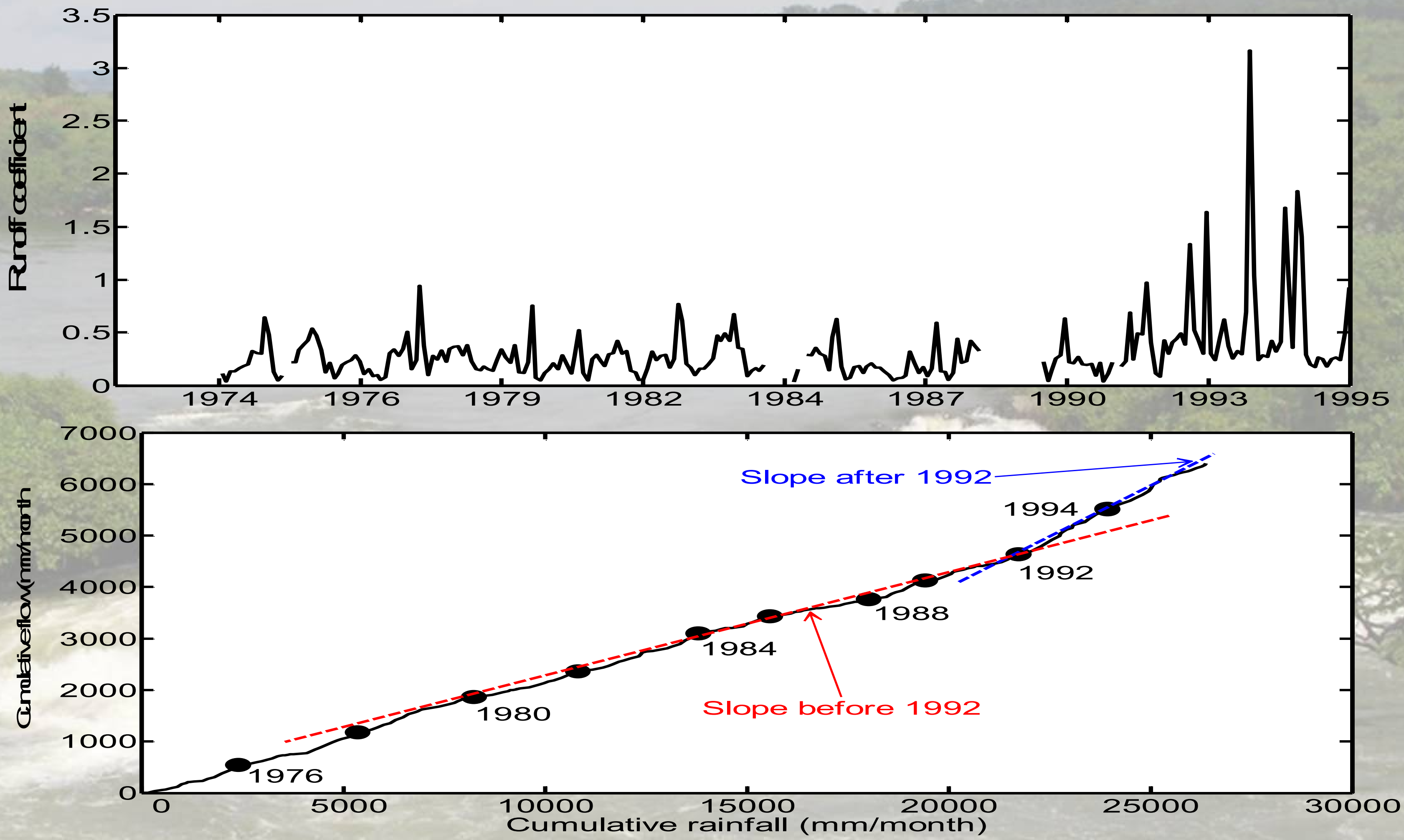


- Bounding of measured flows
  - 1972-1989: 9 out of 12 months
  - 1972-1995: 6 out of 12 months

Discussion

- *NS* performed better than *VE* at constraining the parameters.
- The model output was most sensitive to parameter A_{et} and least sensitive to Pet.
- Model conditioning for the 1983-1989 period resulted in dropping of 1,138 parameter sets (43%). However, model completely failed for the 1990-1995 period when all parameter sets failed to meet the required performance level (Table 1).
- Overall, the model perfomed well with about 70% of the observed flows being bracketted by simulations.
- While high flows were well simulated, there was a general understimation of low flows. This is an expected result when the Nash-Sutcliffe coefficient for model evaluation because, by squaring the model error, emphasis is put on providing a good fit for high flows over low flows.

Cause of model failure for 1990-1995



Uncertainties in measured discharge data were the most likely cause in model failure for 1990-1995

Conclusions

The adopted framework for simulating Lake Victoria inflows using WASMOD model followed by model performance evaluation using the GLUE approach gave acceptable results and was shown to be effective for handling uncertainties in input and calibration data.

The approach was also shown to be useful in identifying gross errors in the data.