Equifinality in calibration of the Variable Infiltration Capacity (VIC) Model Parameters

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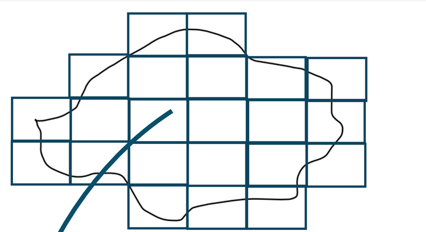
1 : Introduction

- VIC is a large-scale, semi-distributed hydrologic model operating at the grid-cell level.
- An effective application of VIC model requires model calibration (Luo & Li, 2021).
- Equifinality during hydrological model calibration reduces the models simulation and prediction ability (Tang et al., 2023).
- The operational definition of equifinality in hydrological modeling is that various model structures and/or parameter sets produce similar (not necessarily identical) hydrological outcome (Khatami et al., 2019).
- **Objective:**

To explore equifinality in VIC model calibration using Genetic Algorithm (GA).

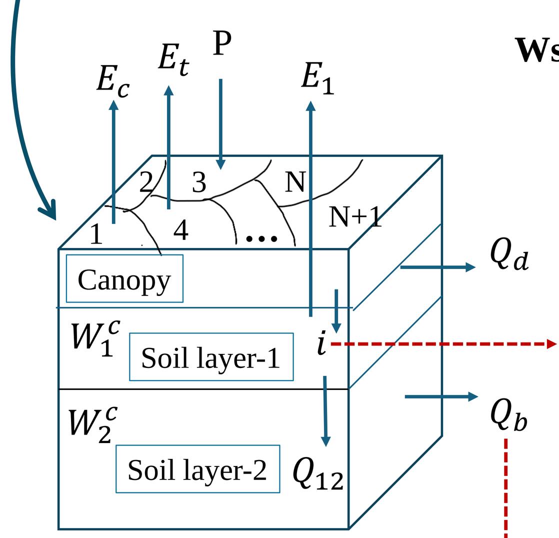
2.1 : Model



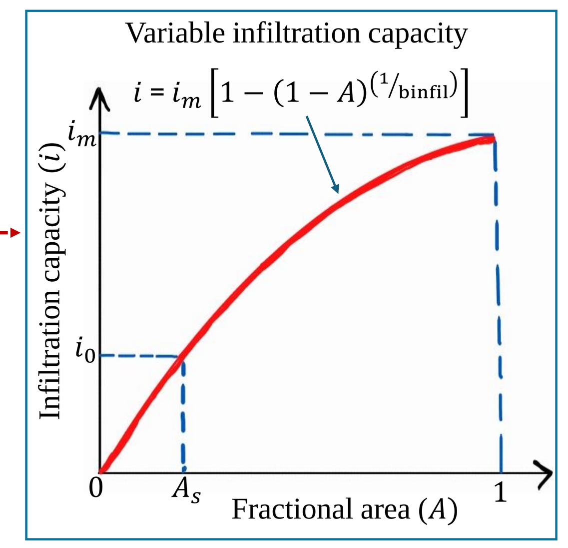
VIC model grids for a catchment

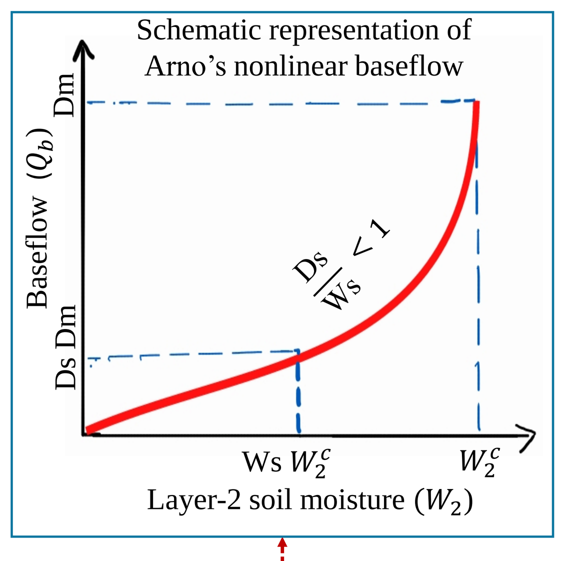
Table 2.1: Description of VIC model parameters selected for calibration

Parameter	Description	Model response	Range
binfil	Soil moisture capacity curve shape parameter	Direct runoff	1×10^{-5} - 0.4
Dm	Maximum baseflow velocity	Baseflow	0-30 mm/day
Ds	Fraction of maximum baseflow velocity for nonlinear baseflow	Baseflow	0-1
Ws	Fraction of maximum soil moisture for nonlinear baseflow	Baseflow	0-1



Schematic representation of surface and subsurface of a grid in VIC model





1, 2, . . . , N: N different types of vegetation; **N+1:** bare soil (**land cover types**); **P:** precipitation; E_c: evaporation from the canopy layer of each vegetation class; E_1: evaporation from bare soil; E_t: transpiration from each of the vegetation class; i: infiltration capacity; i_m: maximum infiltration capacity; i_0: point infiltration capacity corresponding to A_s; A: fraction of an area for which the infiltration capacity is less than i, A_s: fraction of the bare soil that is saturated before start of precipitation; W_1^c: maximum soil moisture content of layer-1, W_2^c: maximum soil moisture content of layer-2; W_2: soil moisture content of layer-2; Q_{12}: drainage from layer-1 to layer-2; Q_d: direct runoff; Q_b: baseflow.

2.2 : Study area and dataset

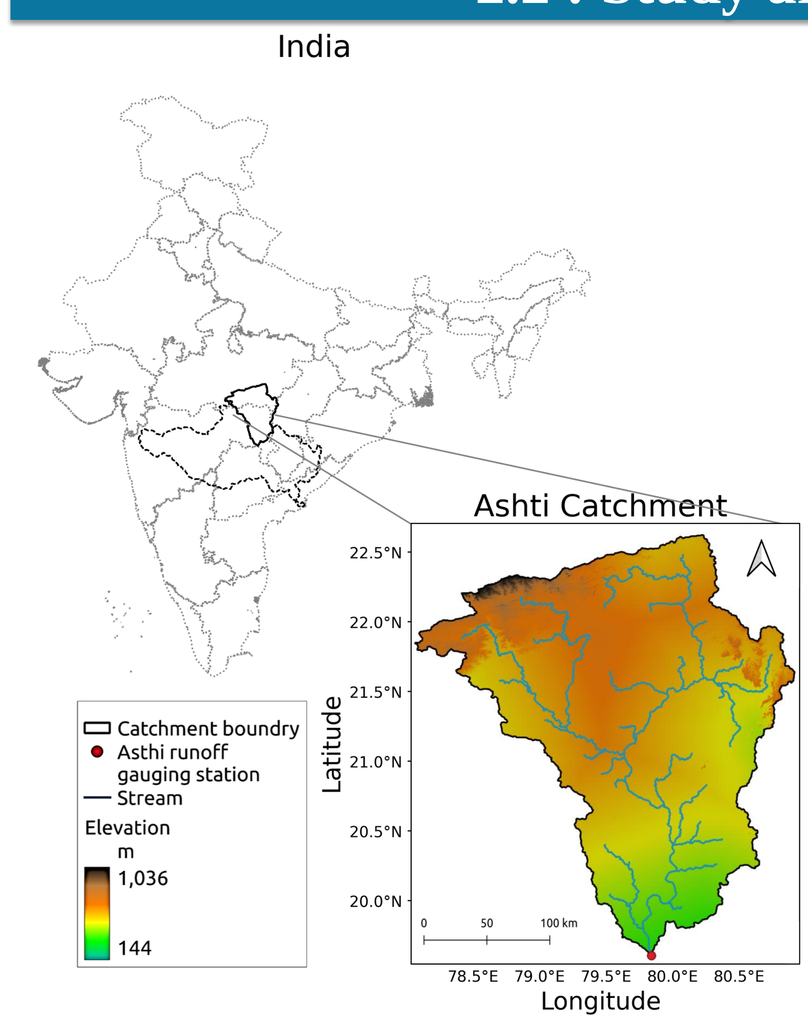


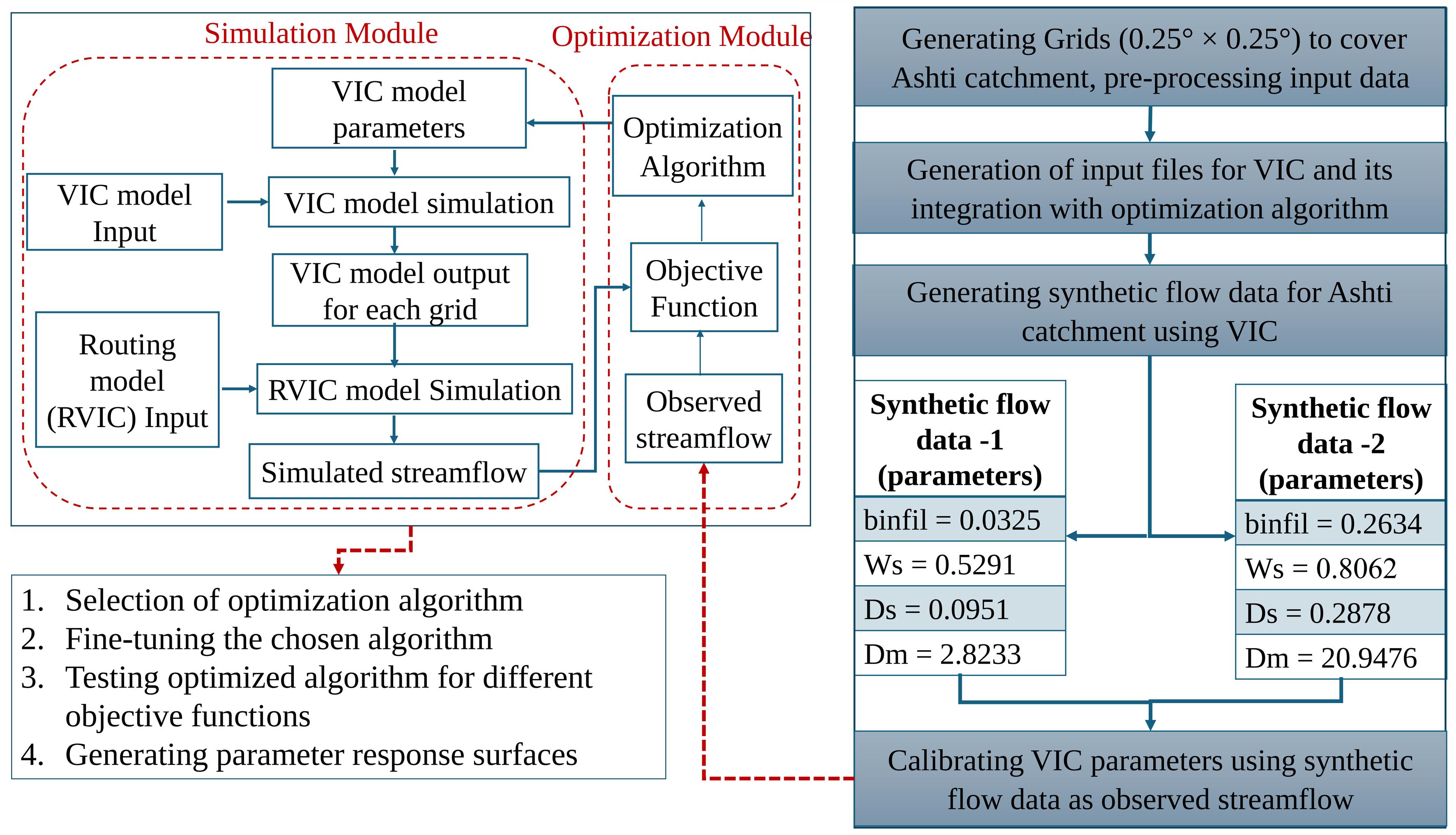
Figure 2.2.1: Ashti catchment (50990 km^2), a tributary of the Godavari river basin

Table 2.2: Input data and their sources

Input Data	Data Source
Digital elevation model	SRTM, 90 m spatial resolution
Soil data	FAO, 1 km spatial resolution
LULC	AVHRR, 1 km spatial resolution
LAI	MODIS, 1 km spatial and 8 days of temporal resolution
Albedo	MODIS, 500 m spatial and 16 days of temporal resolution
Rainfall	IMD, 0.25° × 0.25° spatial resolution, daily
Maximum and Minimum temperature	IMD, 1.0° × 1.0° spatial resolution, daily
Wind speed	NCEP, 2.5° × 2.5° spatial resolution, daily
Streamflow/ discharge	India-WRIS, Ashti gauge point (19.7° N, 79.8° E), daily

SRTM: Shuttle Radar Topography Mission; **FAO:** Food and Agriculture Organization; **AVHRR:** Advanced Very High-Resolution Radiometer; **MODIS:** Moderate Resolution Imaging Spectroradiometer; **IMD:** India Meteorological Department; **NCEP:** National Centers for Environmental Prediction; **India-WRIS:** India Water Resources Information System.

3 : Methodology



1. Selection of optimization algorithm
2. Fine-tuning the chosen algorithm
3. Testing optimized algorithm for different objective functions
4. Generating parameter response surfaces

4 : Results and discussion

1. **Selection of optimization algorithm [genetic algorithm (GA)/ shuffled complex evolution (SCE) algorithm]:**

For the same number of iterations;

- GA performs better in reaching true parameter values compared to SCE.
- GA achieves the lowest value of the objective function, root mean square error (RMSE) in discharge.
- GA takes more computation time compared to SCE.

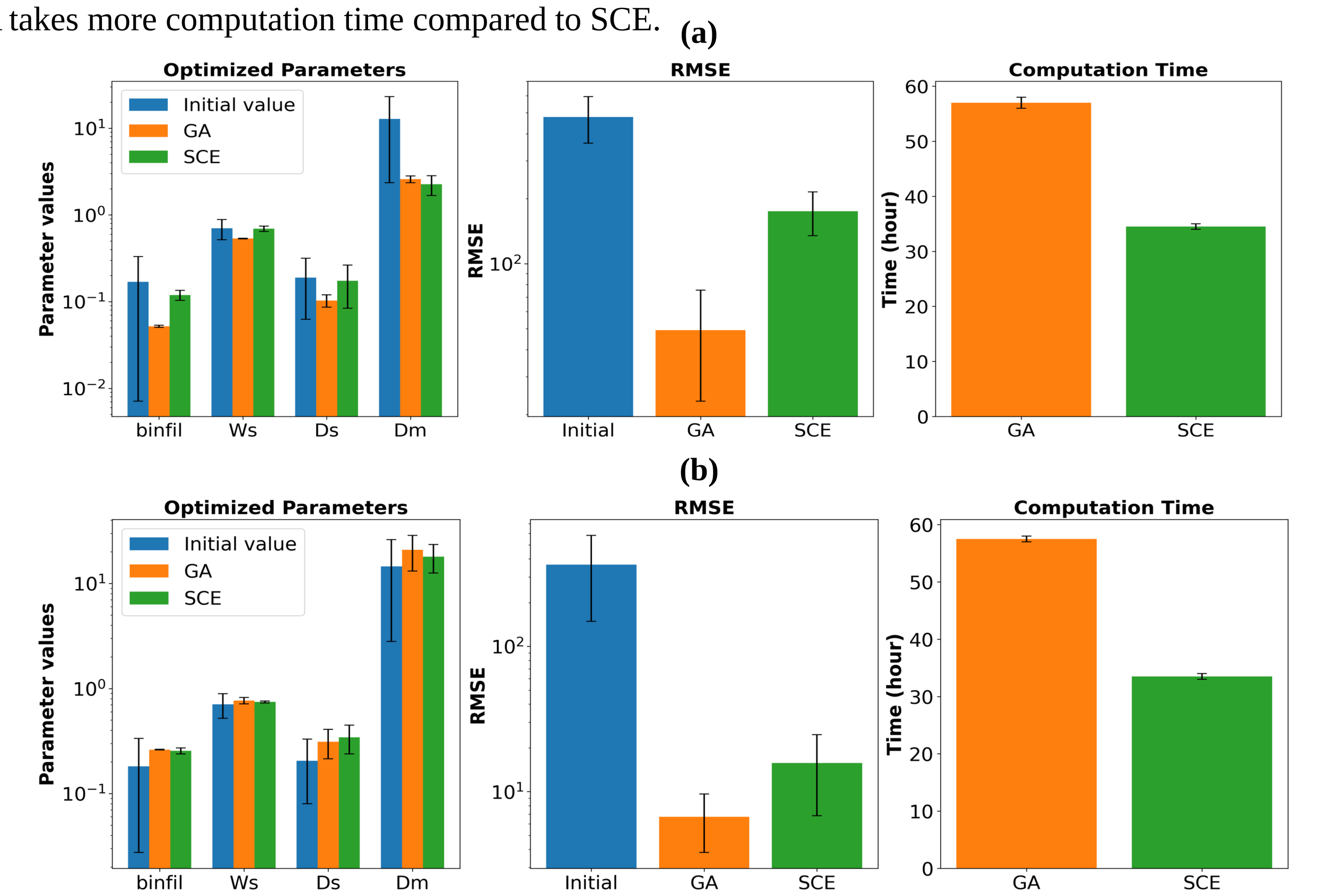


Figure 4.1: Comparison of final value of parameters, RMSE in simulated discharge, and time taken by GA and SCE algorithms for **(a)** synthetic flow data -1, **(b)** synthetic flow data -2 with three sets of initial parameter values

2. **Fine-tuning the GA by changing its parameters:**

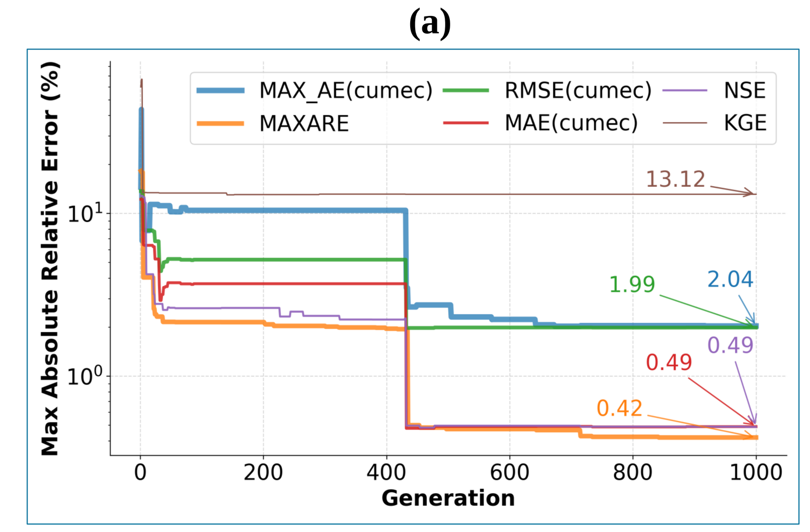
- GA parameters were adjusted within the range specified in Table 4.1, both individually and in combination.
- Results were compared based on maximum absolute relative error (MAXARE) in discharge as well as parameters for both the synthetic flow data.

Table 4.1: GA parameters, their literature-specified ranges (Waheed et al., 2020) and optimum value.

GA parameter	Range	Optimum value
Solution per population	[4, 8, 12, 16, 20, 24, 28, 32]	32
Number of parents mating	[2, 4, 6, 8, 10, 12, 14, 16]	2
Crossover type	["single_point", "two_points", "uniform", "scattered"]	uniform
Crossover probability	[0.6, 0.63, 0.66, 0.7, 0.73, 0.76, 0.8, 0.83, 0.86, 0.9]	0.7
Mutation type	["adaptive", "random", "swap", "inversion", "scramble"]	random
Mutation probability	[0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1]	0.09

3. **Testing optimized GA for six objective functions:**

Maximum absolute error (MAX_AE); maximum absolute relative error (MAXARE); root mean square error (RMSE); mean absolute error (MAE); Nash-Sutcliffe efficiency (NSE); Kling-Gupta efficiency (KGE)



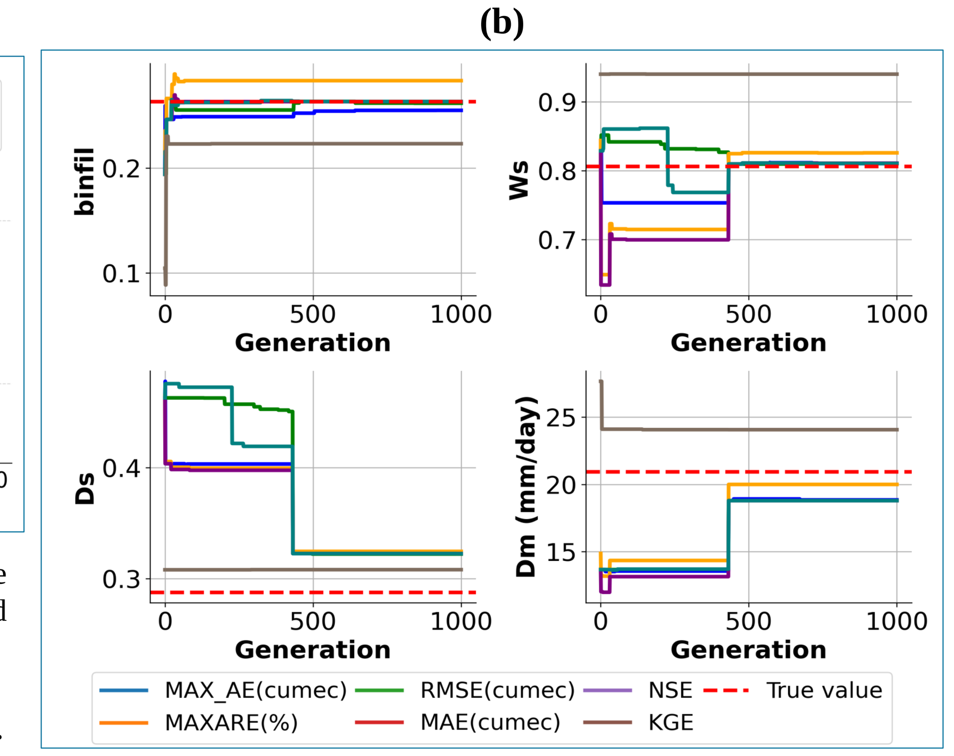


Figure 4.2: **(a)** GA generation vs. MAXARE in discharge and **(b)** GA generation vs. parameters binfil, Ws, Ds and Dm for all objective functions for synthetic flow data - 2

Synthetic flow data – 1 produces similar result.

4. **Generating parameter response surfaces:**

- Parameter response surface for all combination of parameters.
- Threshold: minimum of 10% of the mean and 1% of the maximum observed discharge

Table 4.2: Range of parameters, where MAX_AE(cumec) < threshold

binfil_Ws	binfil: (0.23, 0.30)	Ws: (0.73, 0.88)
binfil_Ds	binfil: (0.23, 0.30)	Ds: (0.27, 0.32)
binfil_Dm	binfil: (0.23, 0.30)	Dm: (19.20, 22.80)
Ws_Ds	Ws: (0.71, 0.90)	Ds: (0.26, 0.34)
Ws_Dm	Ws: (0.70, 0.90)	Dm: (17.70, 25.20)
Dm_Ds	Ds: (0.20, 0.41)	Dm: (13.50, 30.00)

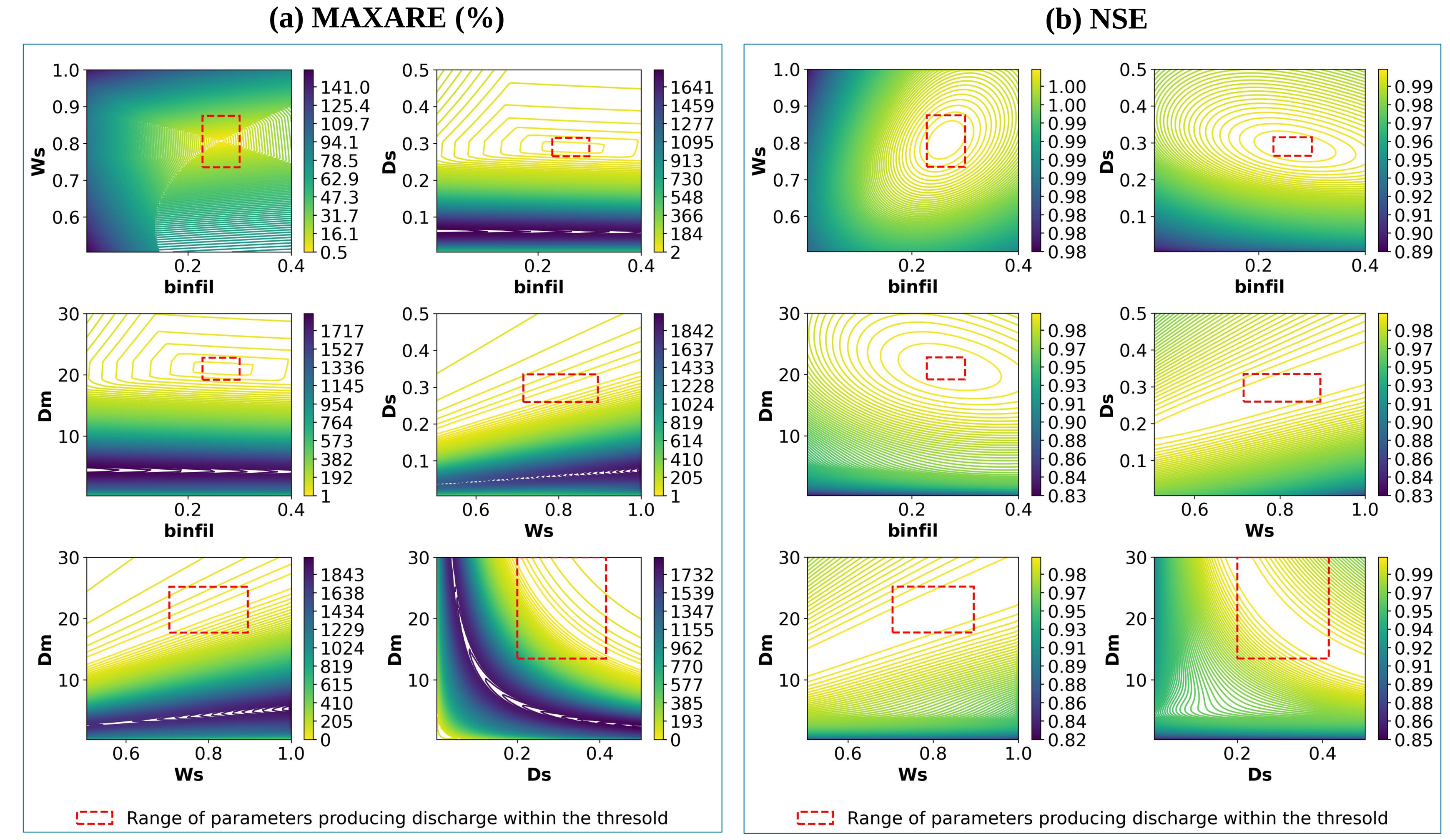


Figure 4.3: Parameter response surfaces for combinations of parameters, **(a)** MAXARE (%) and **(b)** NSE

5 : Conclusion

- **GA outperforms the SCE algorithm** in terms of achieving the true parameter values and reducing RMSE in simulated discharge for both synthetic flow data (Figure 4.1), although it requires more computational time.
- **MAXARE, MAE,** and **NSE** perform similar in reaching the true parameter values for both the synthetic flow data -2 (Figure 4.2).
- The **parameter response surfaces** (Figure 4.3) show that the ranges of parameters can produce simulated discharge within the threshold **showing the presence of equifinality.**

Acknowledgment

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