Daily flow prediction in Ungauged watersheds: SWAT-ANN

Dr. Navideh Noori

Post-Doc, Odum School of Ecology, University of Georgia

&

Dr. Latif Kalin

Prof., School of Forestry and Wildlife Sciences, Auburn University Assoc. Director, Center for Environmental Studies at the Urban-Rural Interface





- CENTER FOR -ENVIRONMENTAL STUDIES - AT THE -URBAN - RURAL INTERFACE



Background

- Streamflow prediction:
 - ✓ Operation and optimization of water resources
 - ✓ Flood control and water resource management
 - ✓ It is complicated: Climate, topology, topography, soil, geology, land use/cover
- Accuracy of different flow prediction models:
 - ✓ Empirical methods are simplistic and are constrained to a functional form between variables prior to the analysis.
 - ✓ Process-based models take into account various processes of the hydrological cycle via mathematical formulation.

Background

- Predictions in ungauged watersheds are more challenging
- ✓ No data for calibration
- Regionalization: Transfer of parameters from neighboring gauged watersheds (donor) to an ungauged (target) watershed.
 - ✓ Regression based
 - ✓ Physical similarity based
 - ✓ Proximity based

Run-off Prediction in Ungauged Basins



Home



National Streamflow Statistics Program

Table 3. Regional flood-frequency relations for urban streams in Alabama.

[Note: Associated mean standard errors of estimate, mean standard errors of prediction, and mean variance of prediction are listed in table 4. Q, flood flow, in cubic feet per second; A, contributing drainage area, in square miles; PD, percentage of basin developed]

Exceedance probability (percent)	Urban regression equations
50	$Q = 95 A^{0.648} PD^{0.407}$
20	$Q = 226 A^{0.670} PD^{0.298}$
10	$Q = 306 A^{0.675} PD^{0.276}$
4	$Q = 417 A^{0.670} PD^{0.253}$
2	$Q = 513 A^{0.663} PD^{0.237}$
1	$Q = 618 A^{0.656} PD^{0.223}$
0.5	$Q = 733 A^{0.650} PD^{0.210}$
0.2	$Q = 897 A^{0.642} PD^{0.196}$

Regional Regression Equation Publications by State

USGS Rural Peak-Flow Regression Equations



SWAT - ANN

- Soil Water Assessment Tool (SWAT)
 - ✓ a large amount of spatial and temporal data needed.



- Calibration and validation processes are time consuming, requires good expertise and could be challenging.
- Artificial Neural Network (ANN)
 - ✓ Select the best combination of the input variables for a parsimonious model.
 - ✓ If an event is beyond their training data range, the predictive model would perform poorly with high uncertainty.
 (nput Layer)
 (Nidden Layer)
 (Output Layer)



Study Area



Study Area



Coupling SWAT with ANN



- Very good: $E_{NASH} \ge 0.70$; $|R_{BIAS}| \le 0.25$
- **Good:** $0.50 \le E_{NASH} < 0.70$; $0.25 < |R_{BIAS}| \le 0.50$
- Satisfactory: $0.30 \le E_{NASH} < 0.50$; $0.50 < |R_{BIAS}| \le 0.70$
- Unsatisfactory: $E_{NASH} < 0.30$; $|R_{BIAS}| > 0.70$

Coupling SWAT with ANN



Results, Warm Season

1.0

0.8

0.6 E^{NASH} 3

0.2

0.0



9

Results, Cool Season



10

Flow Prediction Using SWAT



11

Conclusions

- Performance rates of coupled models:
 - ✓ 62% of the runs for the cool season → Good to Very good
 - ✓ 83% of the runs for the warm season → Good to Very good
- Performance rate of SWAT models:
 - ✓ 34% of the runs → Good to Very good
- As the percent forest cover or the size of test watershed increased, the coupled model performances gradually decreased during both cool and warm.
- Coupled models work better in urbanized watersheds with size <200 km².
- Combining ANN and SWAT could enrich the modeling environment by:
 - Excluding the calibration and sensitivity analysis to adjust the SWAT model parameters
 - \checkmark Narrowing down the number of inputs to ANN.



Thank you for your attention!

For more information please contact: Latif Kalin, Latif@auburn.edu