



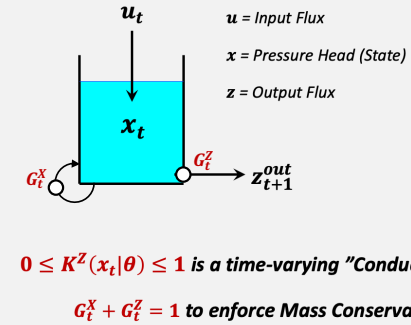
# A Mass-Conserving Perceptron for Modeling the Catchment-Scale Hydrologic System

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## 1. Isomorphism Between GRN and PBM

### Basic Unit of a Physical-Conceptual Model (Mass Conserving Unit)



**Flux Equation**

$$z_{t+1}^{out} = f(x_t|\theta) = \left( \frac{f(x_t|\theta)}{x_t} \right) \circ x_t$$

$$= K^Z(x_t|\theta) \circ x_t$$

$$= G_t^Z \circ x_t$$

**Conservation Equation**

$$\frac{dx(t)}{dt} = u(t) - z(t)$$

$$x_{t+1} = x_t - z_{t+1}^{out} + u_t$$

$$= x_t - G_t^Z \circ x_t + u_t$$

$$= (1 - G_t^Z) \circ x_t + I \circ u_t$$

$$= G_t^X \circ x_t + G_t^U \circ u_t$$

Figure 1 (left): Isomorphism between a generic Gated Recurrent Neuron and a simple physics-based two-parameter hydrological model unit.

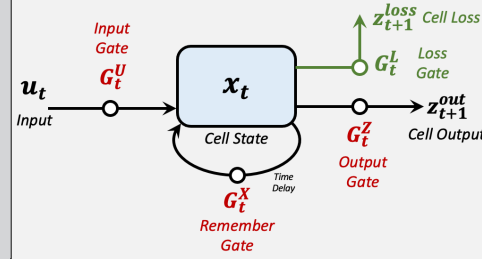
$u[t]$ : system input;  
 $z[t]$ : system output;  
 $x[t]$ : system internal state;  
 $K^Z(x_t|\theta)$ : Conductivity Function;

$G_t^U$ : Input gate  
 $G_t^X$ : output gate;  
 $G_t^Z$ : Remember gate;

Figure 2 (right): The proposed Physically-Interpretable mass-conserving perceptron node (MCPN) for modeling rainfall-runoff processes.

All the notations are kept the same as listed in Figure 1 and with a newly introduced loss gate that is denoted as  $G_t^L$  so as to properly account for the unobserved loss in the hydrological system (catchment).

## 2. Mass-Conserving Perceptron (MCP)



**To enforce Mass Conservation**

$$z_{t+1}^{out} = G_t^Z \circ x_t$$

$$z_{t+1}^{loss} = G_t^L \circ x_t$$

$$x_{t+1} = (1 - G_t^Z - G_t^L) \circ x_t + I \circ u_t$$

$$= G_t^X \circ x_t + G_t^U \circ u_t$$

$$G_t^X + G_t^Z + G_t^L = 1$$

## 3. Results for Leaf River: Single MCP Cases

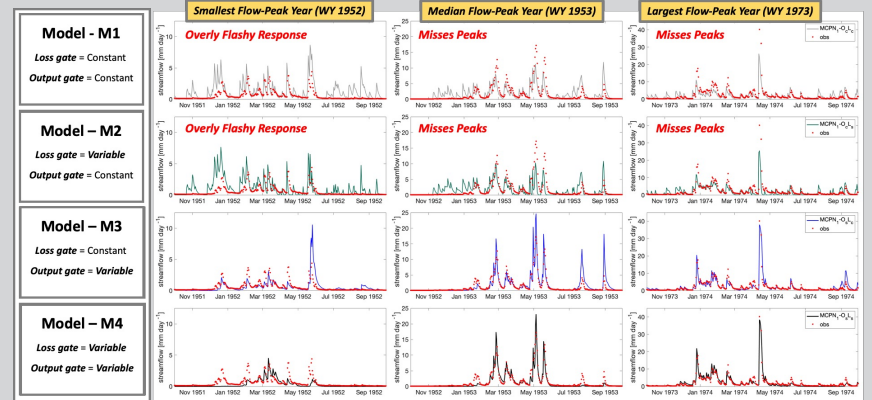


Figure 3: Demonstration of the simulation results for different MCPN implementations applied to the Leaf River catchment. \*Model-M1 is the case with constant conductivities at both the output and loss gates. Model-M2 is the case with a constant output gate and time variable (state-dependent) loss gate. Model-M3 is the case with a time variable (state-dependent) output gate and constant loss gate. Model-M4 is the case with both time variable output and loss gates. The time variable output/loss gates use internal cell state/potential evapotranspiration at the current time step as the only variables for learning the context-dependent gating responses.

## 4. Results for Leaf River: Single MCPN Cases with PET constraint

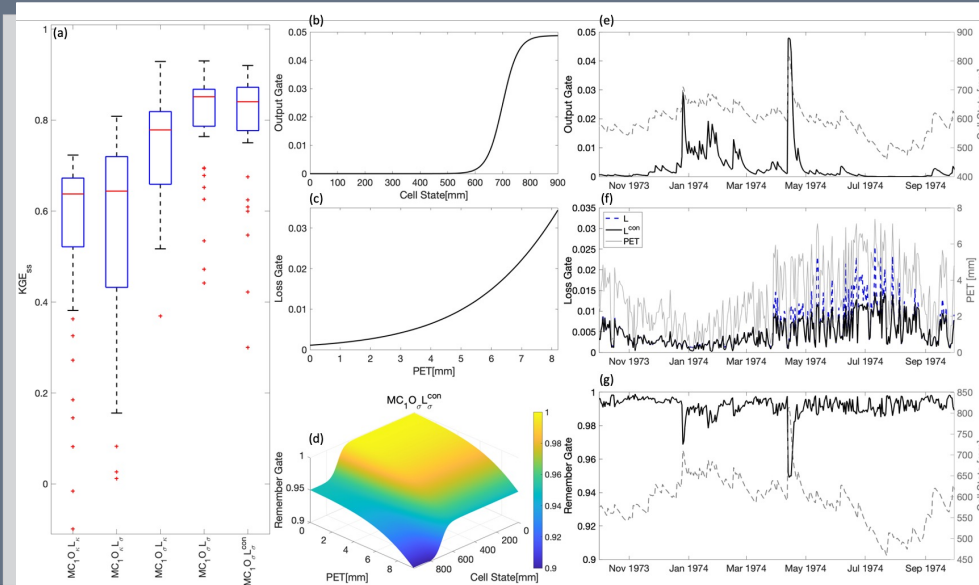


Figure 4 (left): The results for (a) Box and whisker plots of the distributions of annual  $KGE_{65}$  values for various single-node ( $MC_1$ ) architectures. The notation O and L represents the Output and Loss gates, respectively, and the subscripts "c" and "o" indicate Constant and Sigmoid (context-dependent) gating respectively. The notation  $L^{con}$  represents the case where actual Loss  $L_t^c$  is constrained to not exceed the value of the Potential Loss driver  $PL_t$ . The box corresponds to the 25<sup>th</sup> and 75<sup>th</sup> percentiles, the red line indicates the median value, the whiskers indicate the 5<sup>th</sup> and 95<sup>th</sup> percentiles, and the red crosses indicate the outlier years having relatively poor  $KGE_{65}$  skill relative to other years in the distribution. Subplot (b) through (d) show the output, loss and remember gate, and subplot (e) to (g) presents the corresponding gate state for  $MC_1 O_L^{con}$  case

Figure 5 (right): The results of adding mass relaxation gate for the single node  $MC_1(O_L^{con})$  with (a) Box and whisker plots of the distributions of annual  $KGE_{65}$  values for single-node-architectures with various mass relaxation including the cell-state-dependent  $MC_1(O_L^{con} M_{rel}^c)$ , and cell-state-independent  $MC_1(O_L^{con} M_{rel}^o)$  as well as the case ( $MC_1(O_L^{con} M_{rel}^c)$  &  $MC_1(O_L^{con} M_{rel}^o)$ ) without constraining  $MC_{rel}$  to be positive. Subplot (b) to (f) shows the analysis for  $MC_1(O_L^{con} M_{rel}^c)$  case with (b) MR gate function, (c) input precipitation & generated evaporative flux, (d) internal cell state, (e) flux generated through MR gate, and (f) generated output streamflow.

References:  
 Gupta, V.K. and Sorooshian, S., 1983. Uniqueness and observability of conceptual rainfall-runoff model parameters: The percolation process examined. *Water resources research*, 19(1), pp.269-276.  
 Hochreiter, S. and Schmidhuber, J., 1997. Long short-term memory. *Neural computation*, 9(8), pp.1735-1780.  
 Wang, Y.H., 2023. Bridging the Gap Between the Physical-Conceptual Approach and Machine Learning for Modeling Hydrological Systems (Doctoral dissertation, The University of Arizona).

## 5. Results for Leaf River: Allowing Unobserved Mass Exchange with Environment

