Synchronization in hydrologic processes and modeling the response with concepts, physics and neural networks

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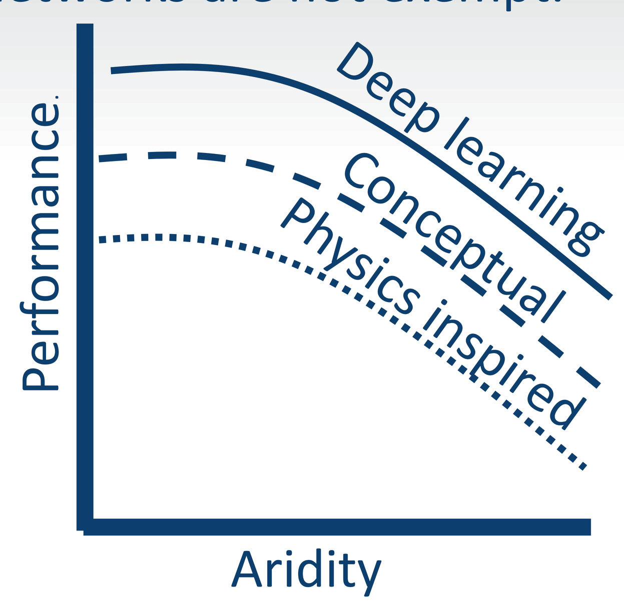
Background

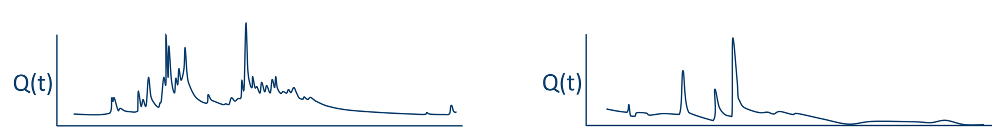
All rainfall-runoff models tend to degrade in performance when used in arid basins. Neural networks are not exempt.



In arid basins, the transition from rainfall to runoff is highly sensitive to initial conditions, often resulting in spontaneous runoff activation.

Arid basins tend to have a flashier runoff response, complicating the prediction of timing, peaks, and recession.

Arid basins typically exhibit lower or zero baseflow, with sparse runoff events — sometimes only a few in a single year.



All types of models can show spontaneous behavior when trained/calibrated for arid regions, but performance metrics suffer.

We propose that there may be an inherent synergy between physics, conceptual and deep learning models.

Differentiable modeling (Shen et al. 2023, Feng et al. 2022 and Bindas et al. 2023) has been proposed as a path forward for merging types of model.

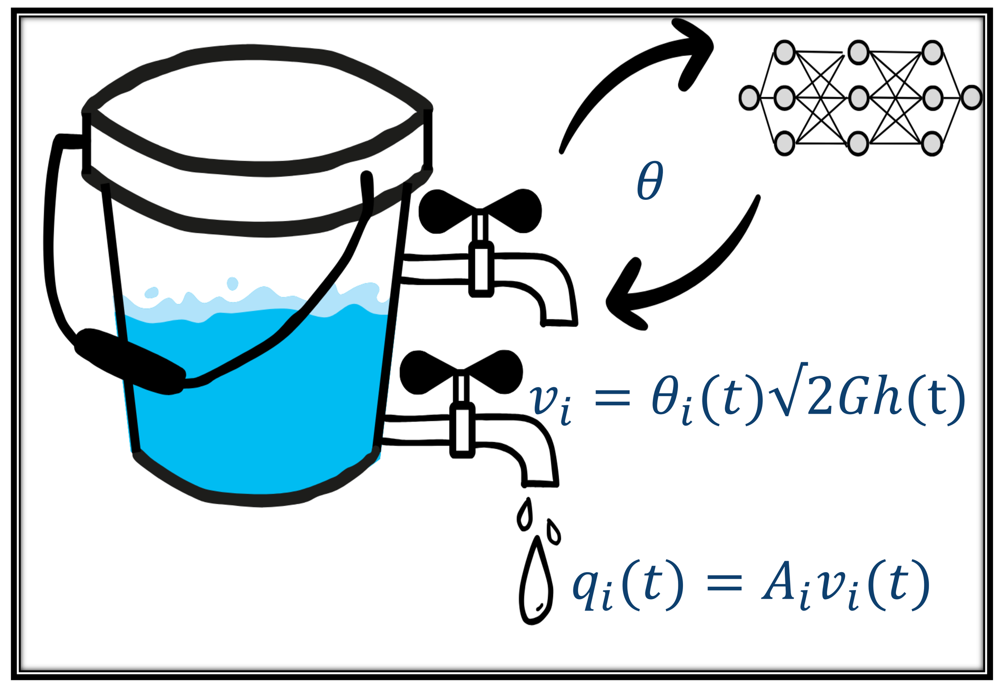
Method

Proposed modeling approach:

- Custom conceptual model designed for differential modeling
- Hydrologically intuitive, extending the Nash Cascade to a network
- Displays synchronistic tendencies of hydrologic processes
- Directly comparable to a neural network

Flow out of each element is controlled by a valve. Differentiable modeling approach to determine the valve position, θ.

Networks can be created arbitrarily or designed with specific dimensions for specific purposes. Adding more layers, and buckets to each layer enables complicated hydrologic responses.

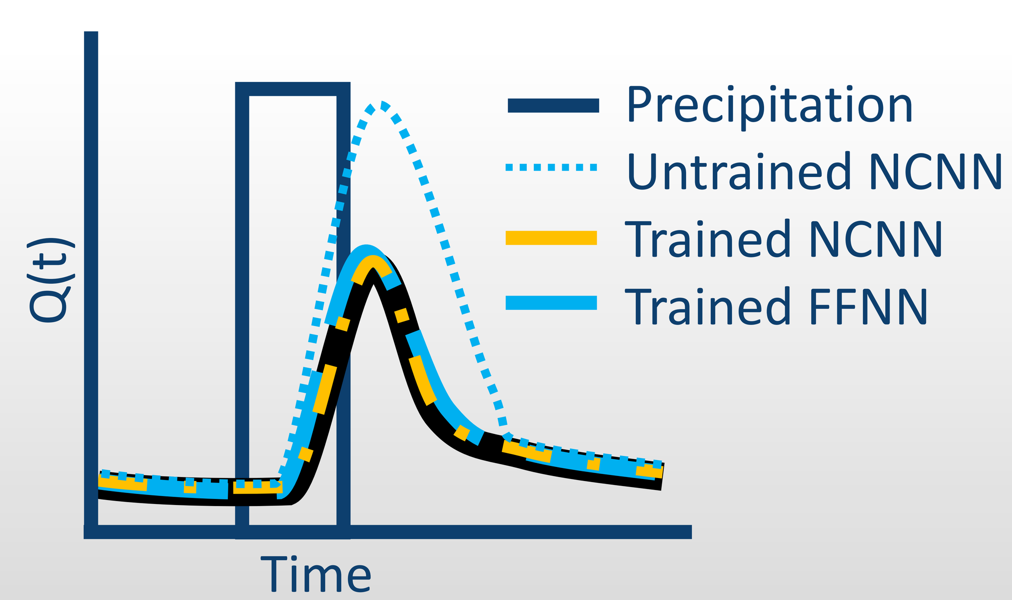


The mass into each bucket (j) include some portion of precipitation and the sum of spigot connections (c), one each from each upstream bucket.

$$I_j = P(t) + \sum_{c=1}^{N_{j-1}} q_{l-1,c}(\mathrm{t}) \qquad Q_l(t) = \sum_{j=1}^{N_b} \sum_{i=1}^{M_{sb}} A_{ij}\theta_{ij}(t)\sqrt{2Gh_{ij}(\mathrm{t})}$$

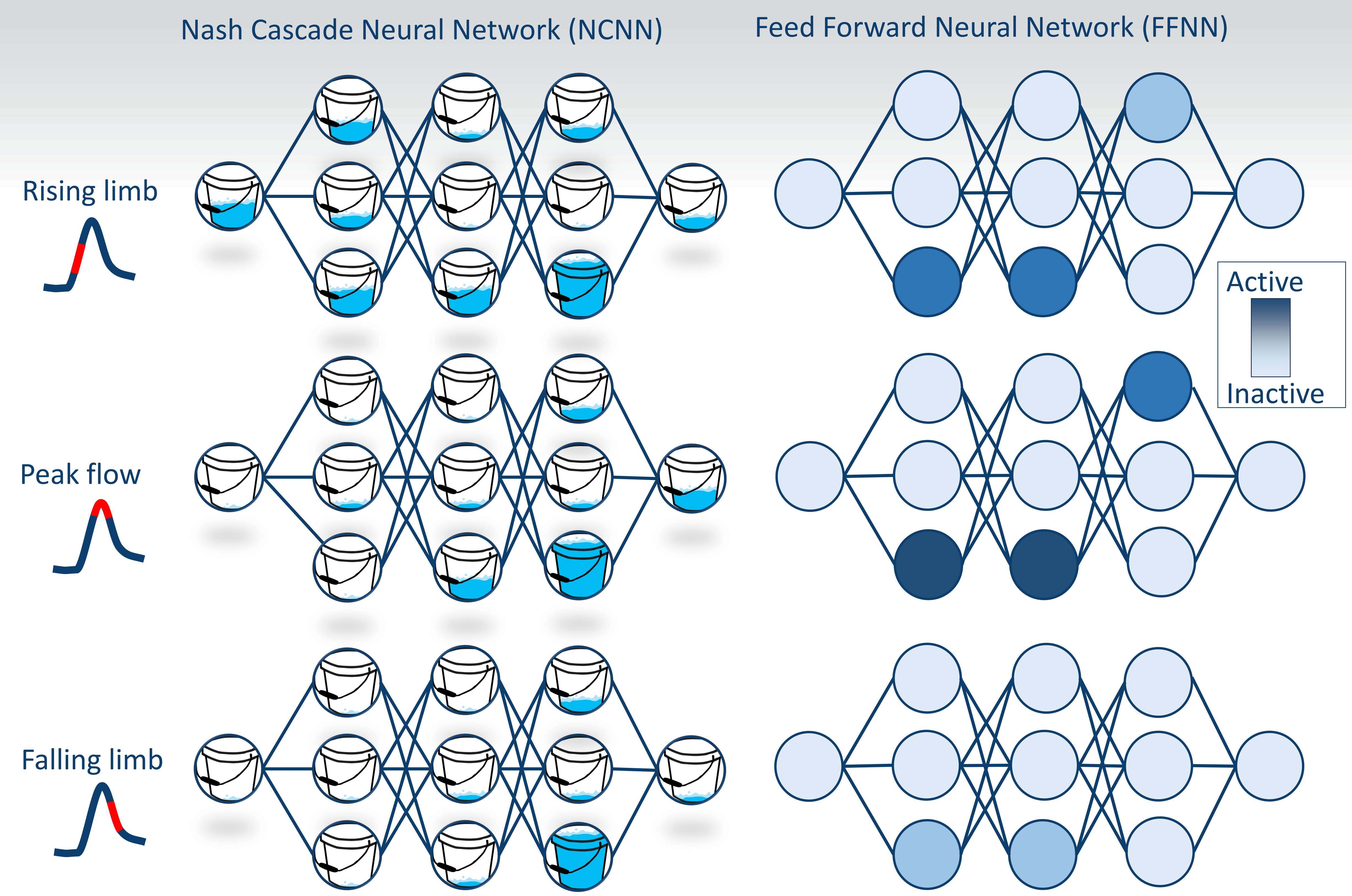
Flow out of each layer (l) is the sum of the spigots (i) on each bucket (j) in each layer. Flow out of the system, $Q(t)$, is the total flow from the n^{th} (downstream) layer (Q_n).

Simple test on a unit hydrograph to understand the similarities in dynamics between the Nash Cascade Neural Network and a simple Feed Forward Neural Network.



References:
Shen, C. et al. Differentiable modelling to unify machine learning and physical models for geosciences.
Feng, D. et al. Differentiable, Learnable, Regionalized Process-Based Models With Multiphysical Outputs can Approach State-Of-The-Art Hydrologic Prediction Accuracy.
Bindas, T. et al. Improving large-basin river routing using a differentiable Muskingum-Cunge model and physics-informed machine learning.
Lees, T. et al. Hydrological concept formation inside long short-term memory (LSTM) networks.

Discussion



The Nash Cascade Neural Network is a hydrologic conceptual model specifically designed for deep learning based differentiable parameter learning. Arbitrarily large networks can be created, and the differentiable parameter learning enables network that can be used to represent any hydrologic system, much the same way that a neural network does, but with hydrologic intuition.

In each scenario and bucket network configuration, a single path within the network tends to dominate the NCNN, with one single bucket often prevailing. In this simple example of the FFNN there is also a dominant path within the network, but the results show two dominant nodes within that path.

Lees et al., 2021, show that a neural network can learn hydrologic sub-processes, which can be probed from the trained model weights and activations. The NCNN can be used to proactively assign a sub-network to a specific sub-process or can be probed post-hoc.

Perhaps, since these two network types behave similarly, the bucket network is an unnecessary complication, and a modeler is likely better off using the neural network, with the assurance that an idealized conceptual hydrological model may end up as quasi neural network itself.