High-resolution rainfall-runoff modeling using graph neural network

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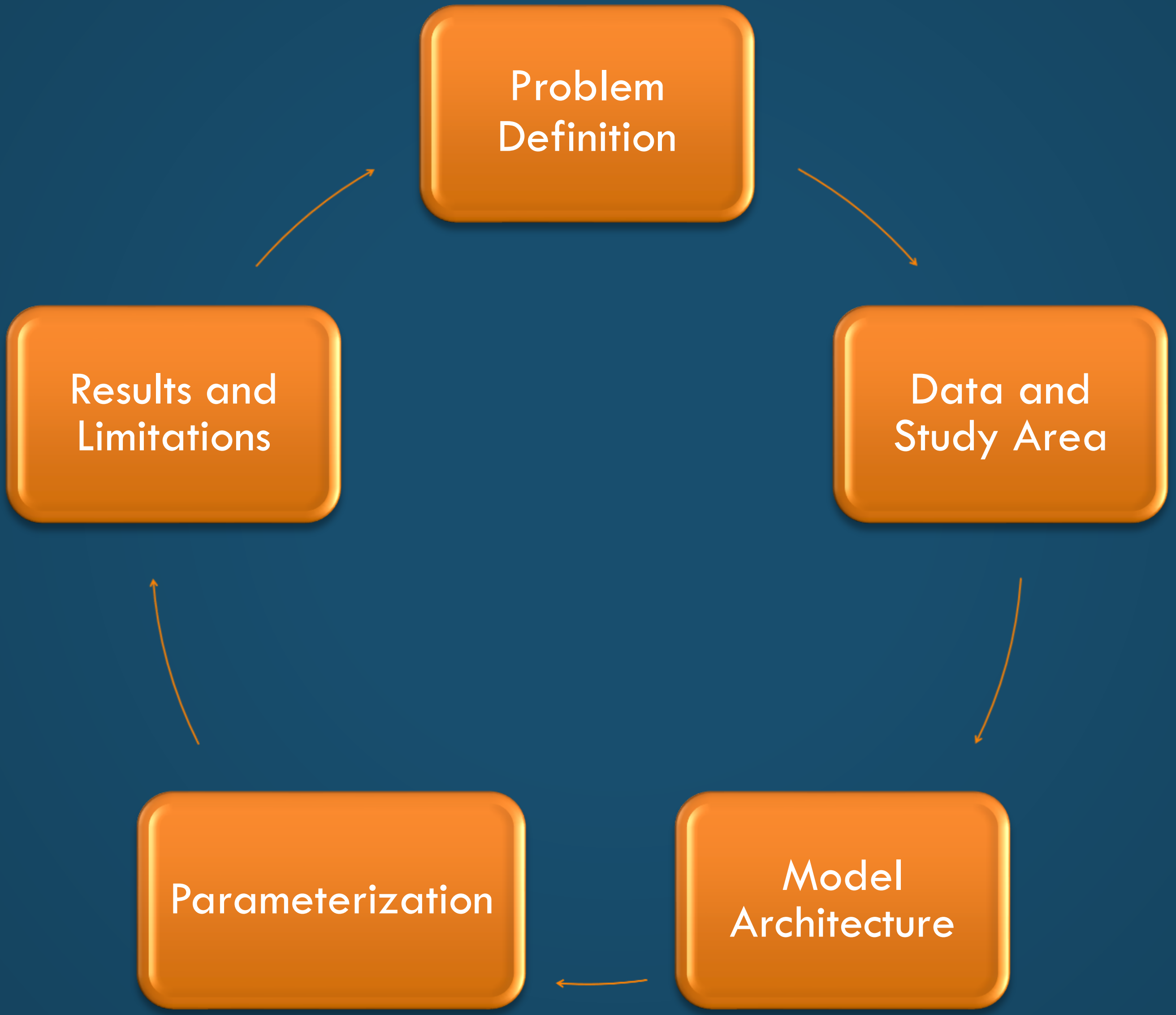
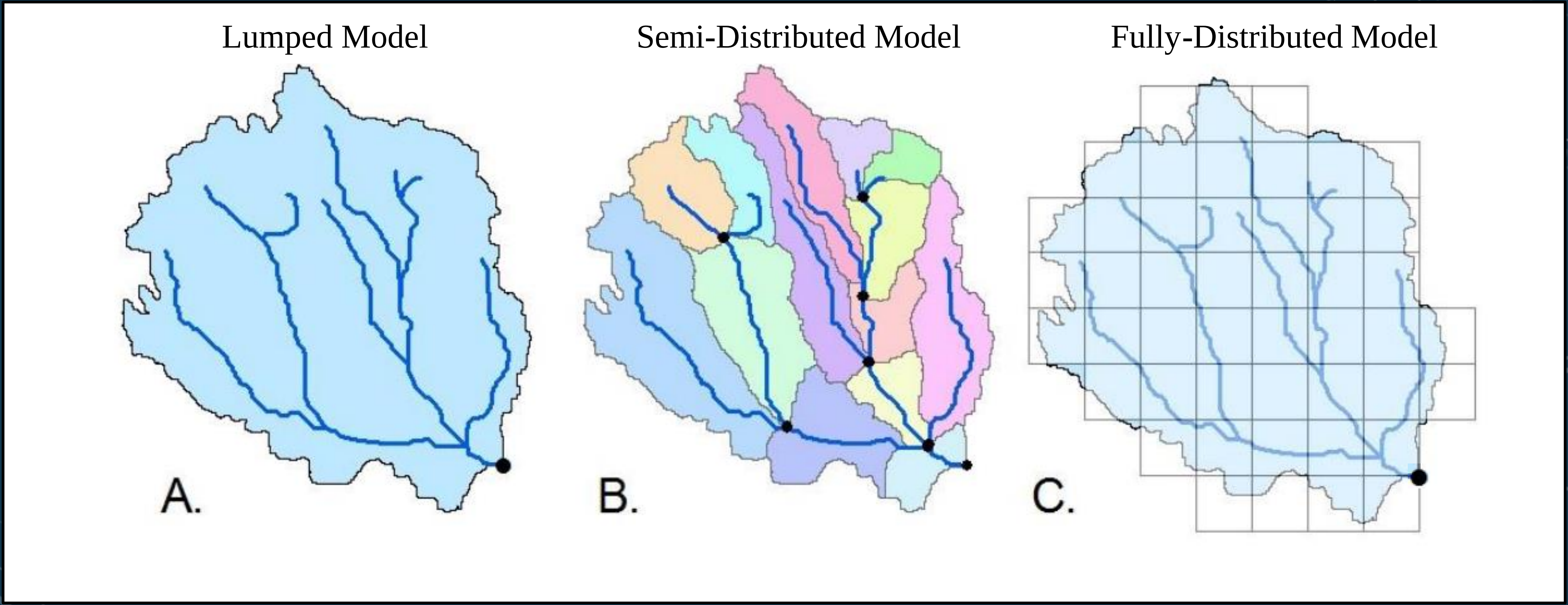
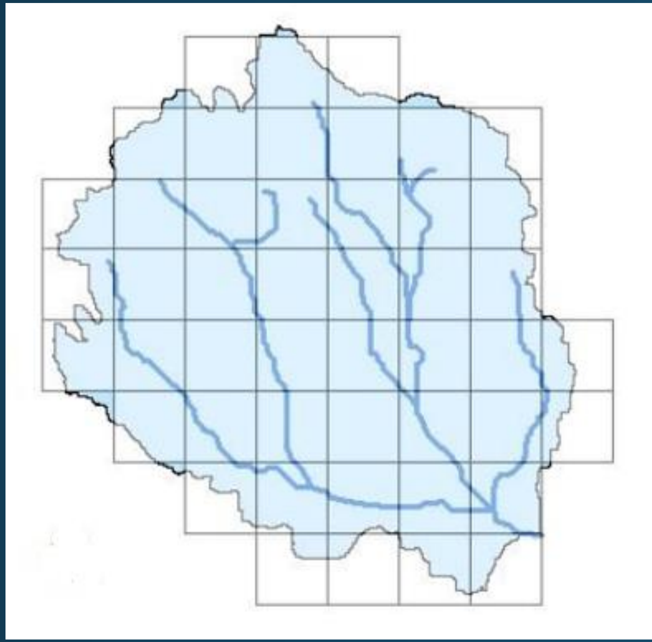
Presentation Outline

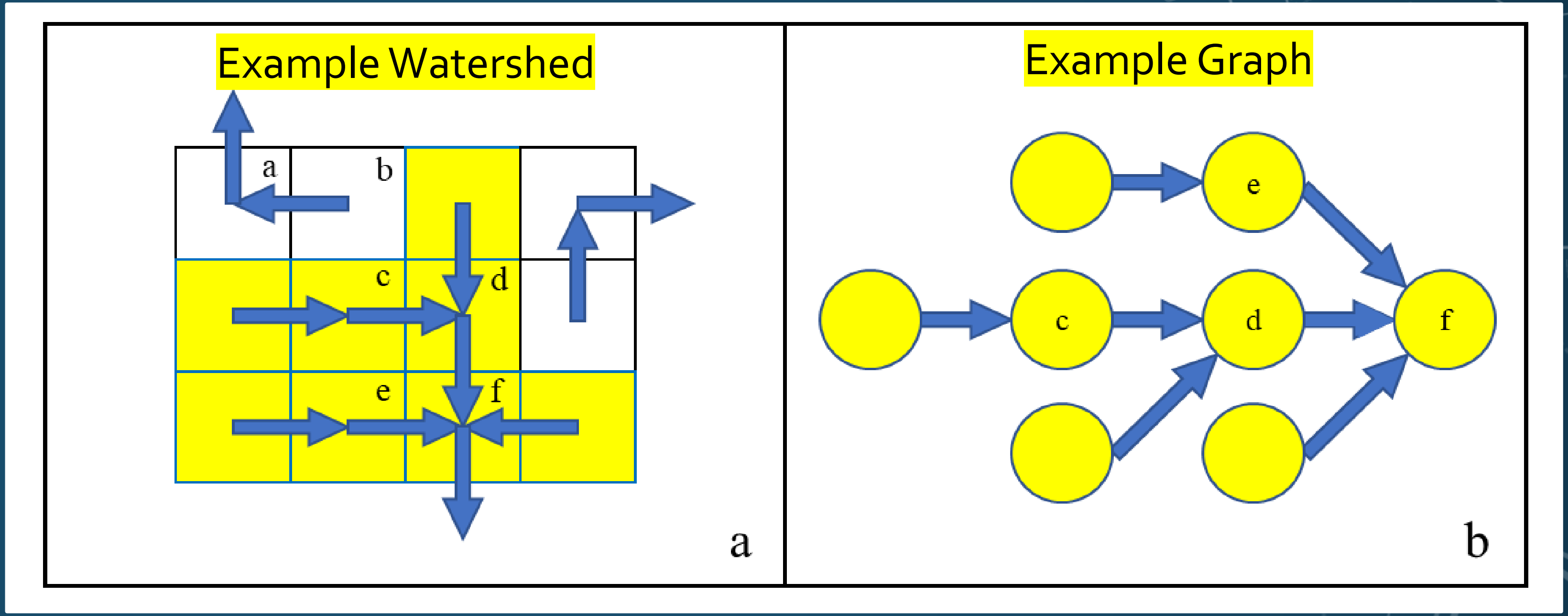


Today's deep learning models are mainly lumped or semi-distributed, making them incapable of dealing with rainfall distributions that are unequal.



We can turn a watershed into a unidirectional directed graph using DEM and flow direction data.



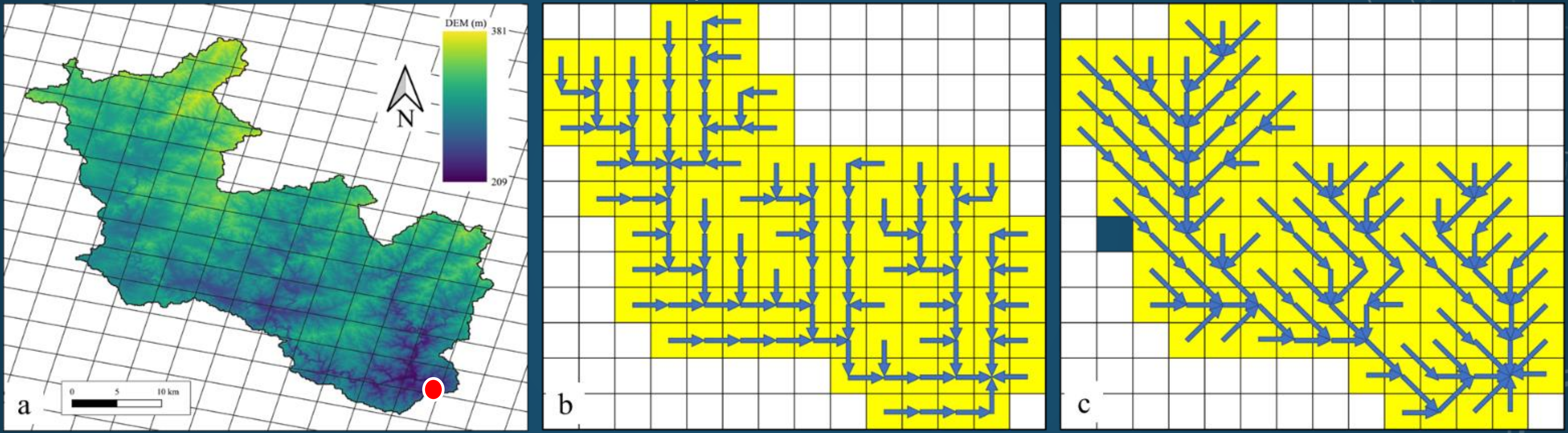


Study Area

A single large (~1,300km^2) watershed without USGS gauges inside.

D4 flow direction

D8 flow direction

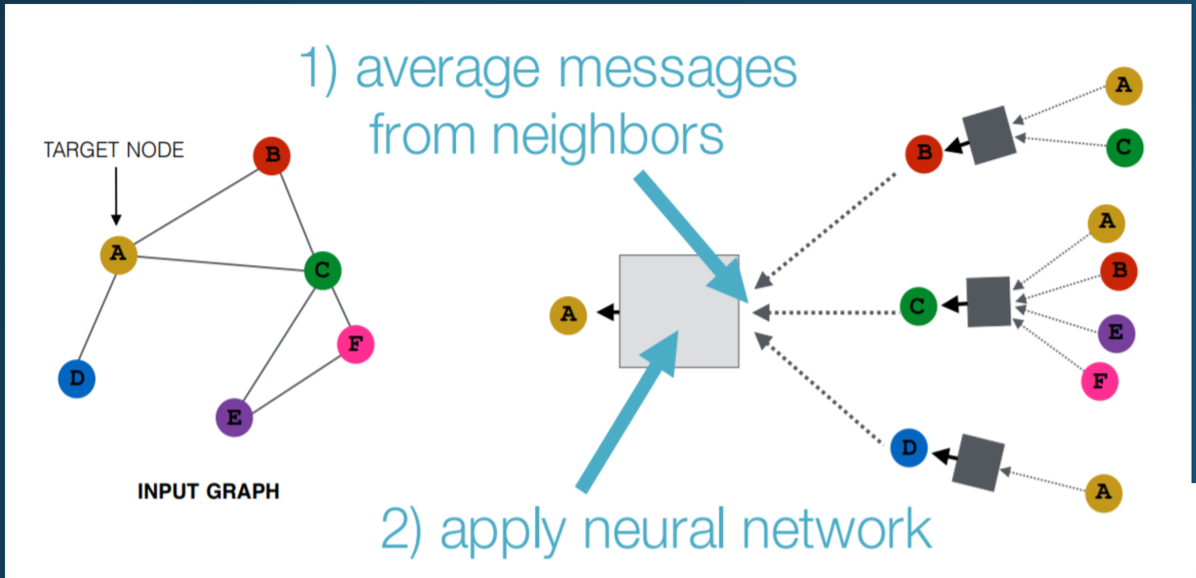


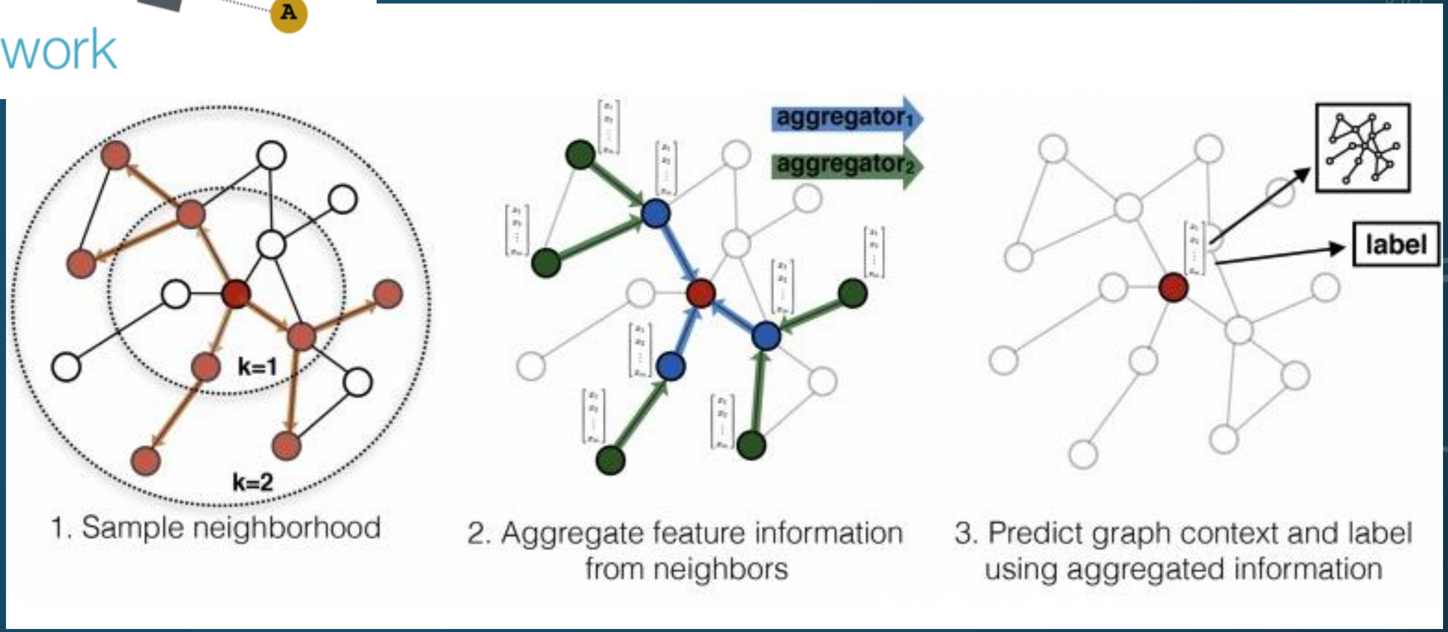
* Time of Concentration is about 45 hours when using an average flow rate of 0.75m/s

Data in Hourly.
7 Water Years (Oct 2011 to Sep 2018). Train/Valid/Test split by 4/2/1.

Datasets	Data Type	Sources	Spatial Resolution	Temporal Resolution	Unit
DEM	GIS shapefile	NASA SRTM 90m	90-m grid	constant	m
Drainage area polygon	GIS shapefile	Iowa Flood Center	Polygon	constant	-
Precipitation intensity	Stage IV multi-sensor measurement	NOAA	4-km grid	60-min	mm/hr
Streamflow rate	USGS gage measurement	USGS	Point	15-min	ft^3/s

Graph Neural Networks



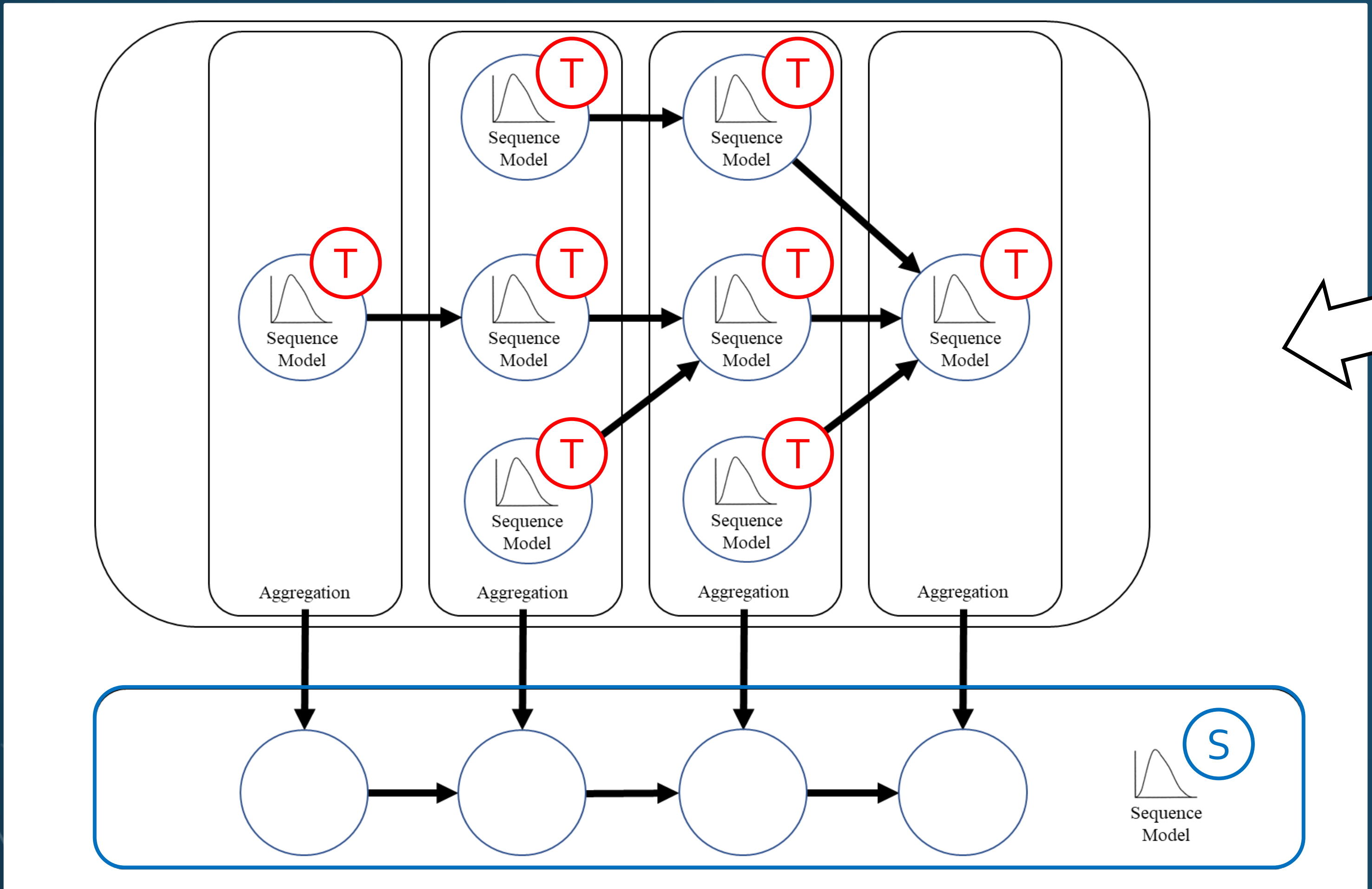


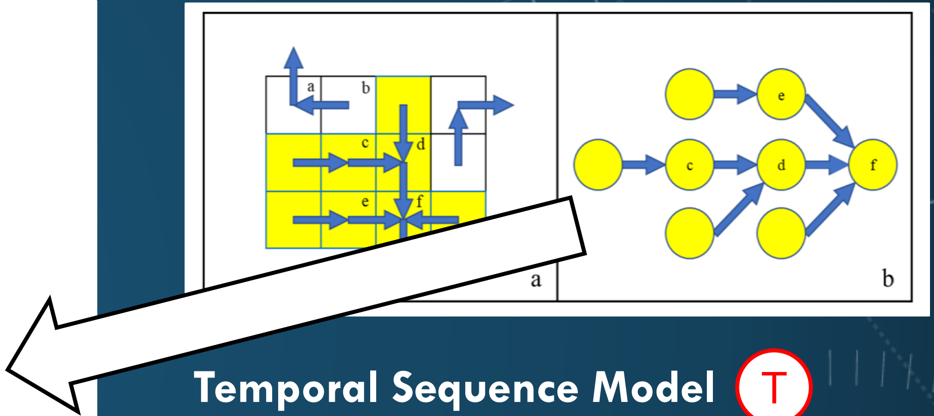
http://snap.stanford.edu/graphsage/

Our Designed Graph Neural Network

Step 1: Temporal Sequence Model (Rainfall-Runoff on Land) T

Step 2: Spatial Sequence Model (Space-time Confluence) S





Temporal Sequence Model T

Multi-Timestep Generalized Model on multiple land and area

Xiang, Z., Demir, I., Mantilla, R., & Krajewski, W. F. (2021). A Regional Semi-Distributed Streamflow Model Using Deep Learning. https://eartharxiv.org/repository/view/2152/

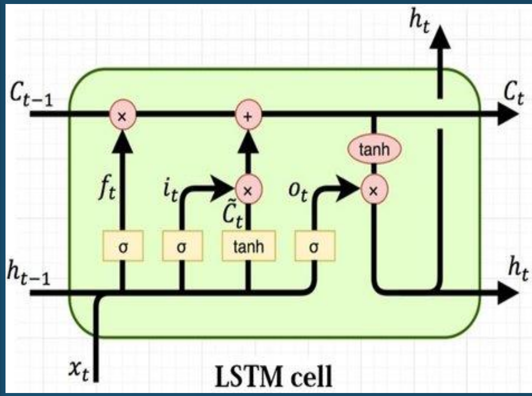
Spatial Sequence Model S

Single-Timestep model with aggregated land information

Parameterization with a 72-hour window

Table 2. Parameters of the sequence model layers for rainfall-runoff modeling at temporal scale in baseline models and GNRRM.

Model	# Layer	# Neurons each layer	k	d	# Length	#Parameters at each hidden layer
LSTM	5	32	-	-	72	8,320
BiLSTM	5	32	-	-	72	24,832
GTCN	5	32	6	1,2,4,8,16	72 (cut off from 96)	12,352
BiGTCN	5	32	6	1,2,4,8,16	72 (cut o from 96)	



$$i_t = \sigma(x_t U^i + h_{t-1} W^i)$$
$$f_t = \sigma(x_t U^f + h_{t-1} W^f)$$
$$o_t = \sigma(x_t U^o + h_{t-1} W^o)$$
$$\tilde{C}_t = \tanh(x_t U^g + h_{t-1} W^g)$$
$$C_t = \sigma(f_t * C_{t-1} + i_t * \tilde{C}_t)$$
$$h_t = \tanh(C_t) * o_t$$

4-layer TCN

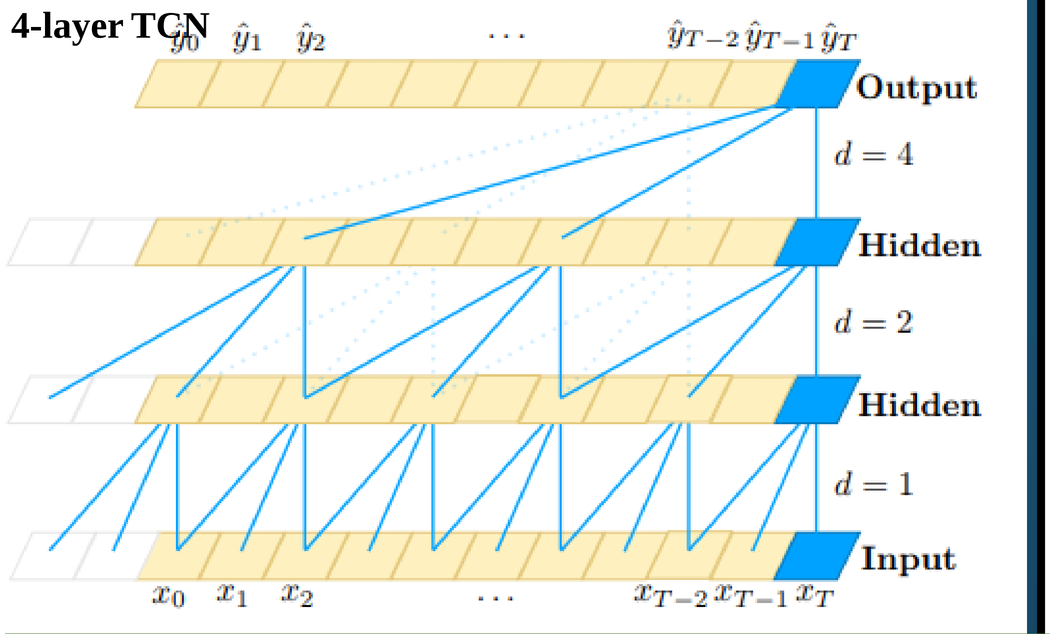
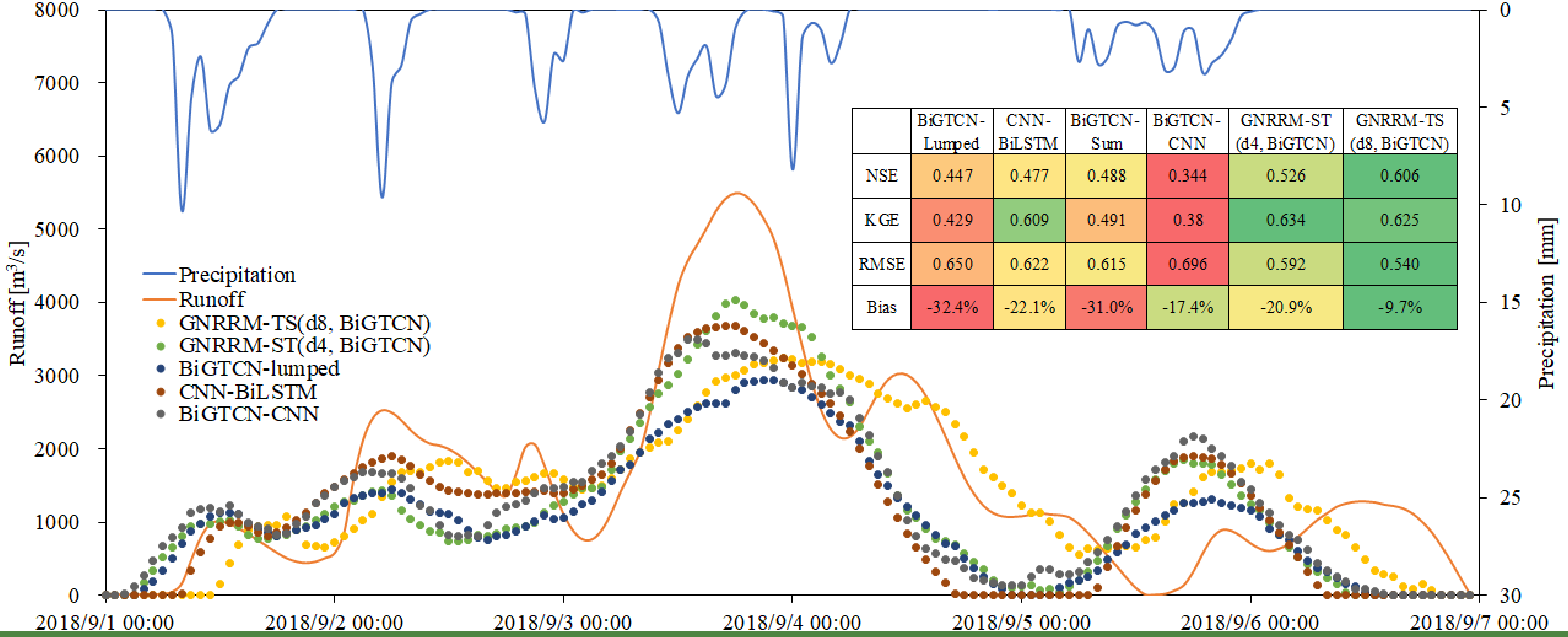


Table 3. Parameters of the sequence model layers for rainfall-runoff modeling at spatial scale in GNRRM.

Model	# Flow directions	# Layer	# Neurons each layer	k	d value each layer	# Length	#Parameters at each hidden layer
LSTM	d4	5	32	-	-	22	8,320
LSTM	d8	5	32	-	-	16	8,320
BiLSTM	d4	5	32	-	-	22	24,832
BiLSTM	d8	5	32	-	-	16	24,832
GTCN	d4	4	32	4	1,2,4,8	22 (cut off from 32)	8,256
GTCN	d8	4	32	4	1,2,4,8	16 (cut off from 32)	8,256
BiGTCN	d4	4	32	4	1,2,4,8	22 (cut off from 32)	32,896
BiGTCN	d8	4	32	4	1,2,4,8	16 (cut off from 32)	32,896

Results

Models	KGE (the higher the better)				NSE (the higher the better)				RMSE [m³/s] (the lower the better)			
	sum	CNN	GNRRM (d4)	GNRRM (d8)	sum	CNN	GNRRM (d4)	GNRRM (d8)	sum	CNN	GNRRM (d4)	GNRRM (d8)
LSTM	0.676	0.657	0.701	0.741	0.527	0.543	0.563	0.604	7.458	7.333	7.172	6.829
BiLSTM	0.778	0.804	0.822	0.809	0.620	0.695	0.643	0.630	6.688	5.989	6.477	6.599
GTCN	0.699	0.736	0.783	0.774	0.641	0.632	0.700	0.669	6.449	6.582	6.119	6.238
BiGTCN	0.704	0.708	0.826	**0.842**	0.559	0.585	0.704	**0.714**	7.203	6.211	**5.786**	5.799



	BiGTCN-Lumped	CNN-BiLSTM	BiGTCN-Sum	BiGTCN-CNN	GNRRM-ST (d4, BiGTCN)	GNRRM-TS (d8, BiGTCN)
NSE	0.447	0.477	0.488	0.344	0.526	0.606
KGE	0.429	0.609	0.491	0.38	0.634	0.625
RMSE	0.650	0.622	0.615	0.696	0.592	0.540
Bias	-32.4%	-22.1%	-31.0%	-17.4%	-20.9%	-9.7%

Thank you

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