Short-term Hourly Streamflow Prediction with Graph Convolutional GRU Networks

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Outline

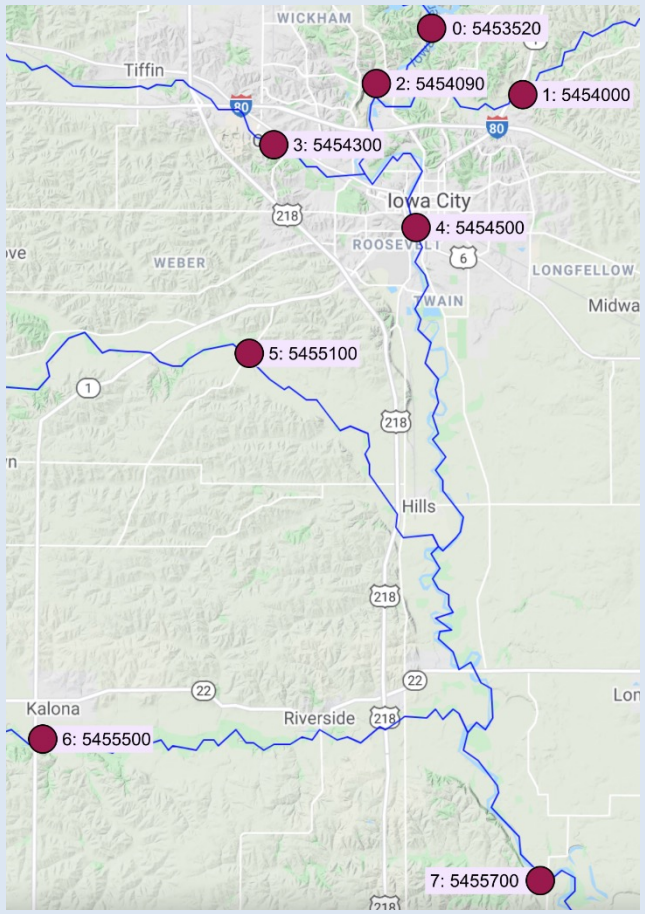
- Introduction
- Graph Convolutional GRUs
- Approach
- Results

Introduction

- The devastating impacts of natural disasters [1]
- Flooding as one of the destructive natural disasters [1, 2]
- The effect of the climate change [3, 4]
- Importance of streamflow prediction [5, 6, 7]

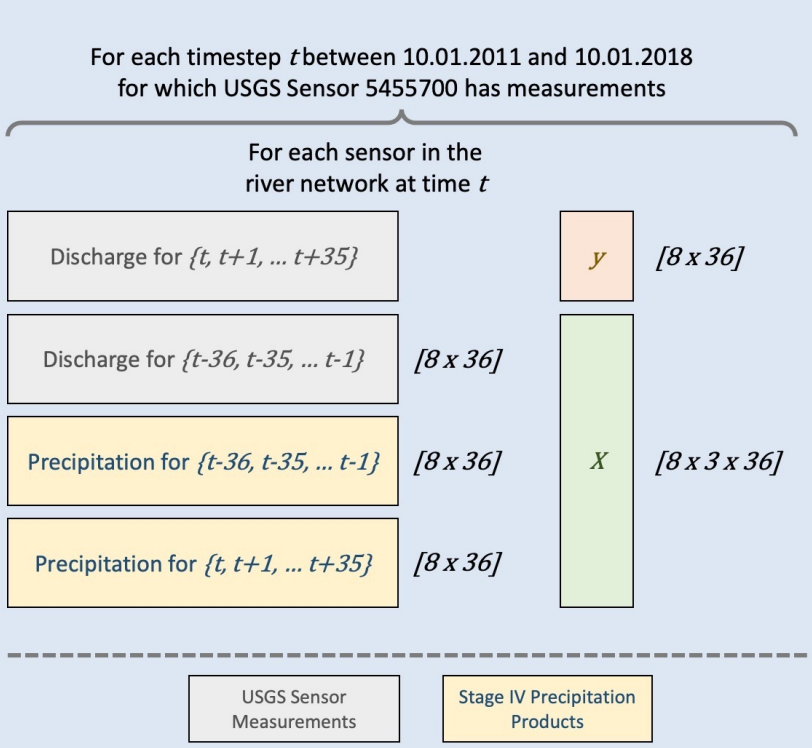
Graph Convolutional GRUs [8]

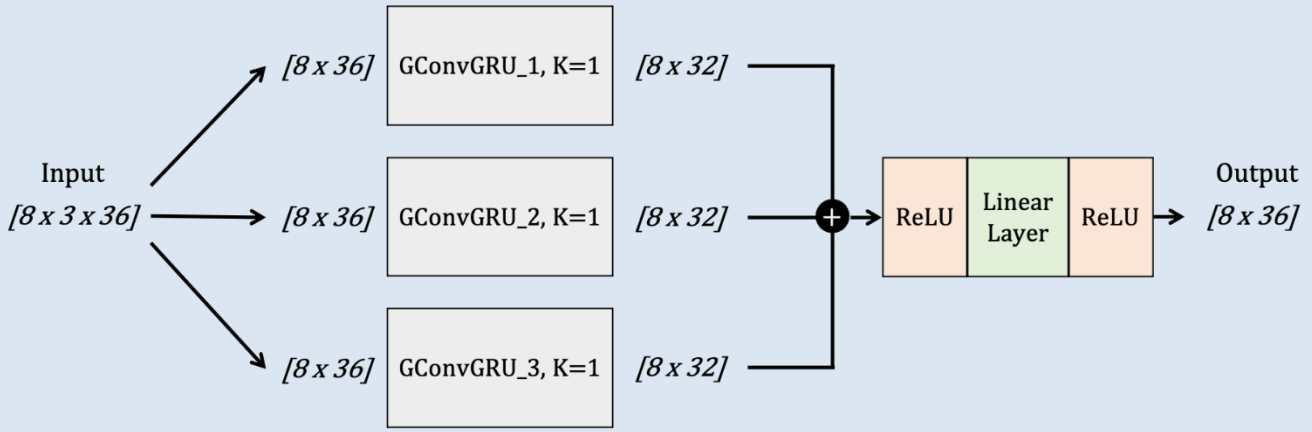
- Captures spatial dependencies with CNNs
- Identifies dynamic patterns with GRUs in the structured data
- Traffic prediction [9], Modeling language [8]
- River network can be expressed as a graph.



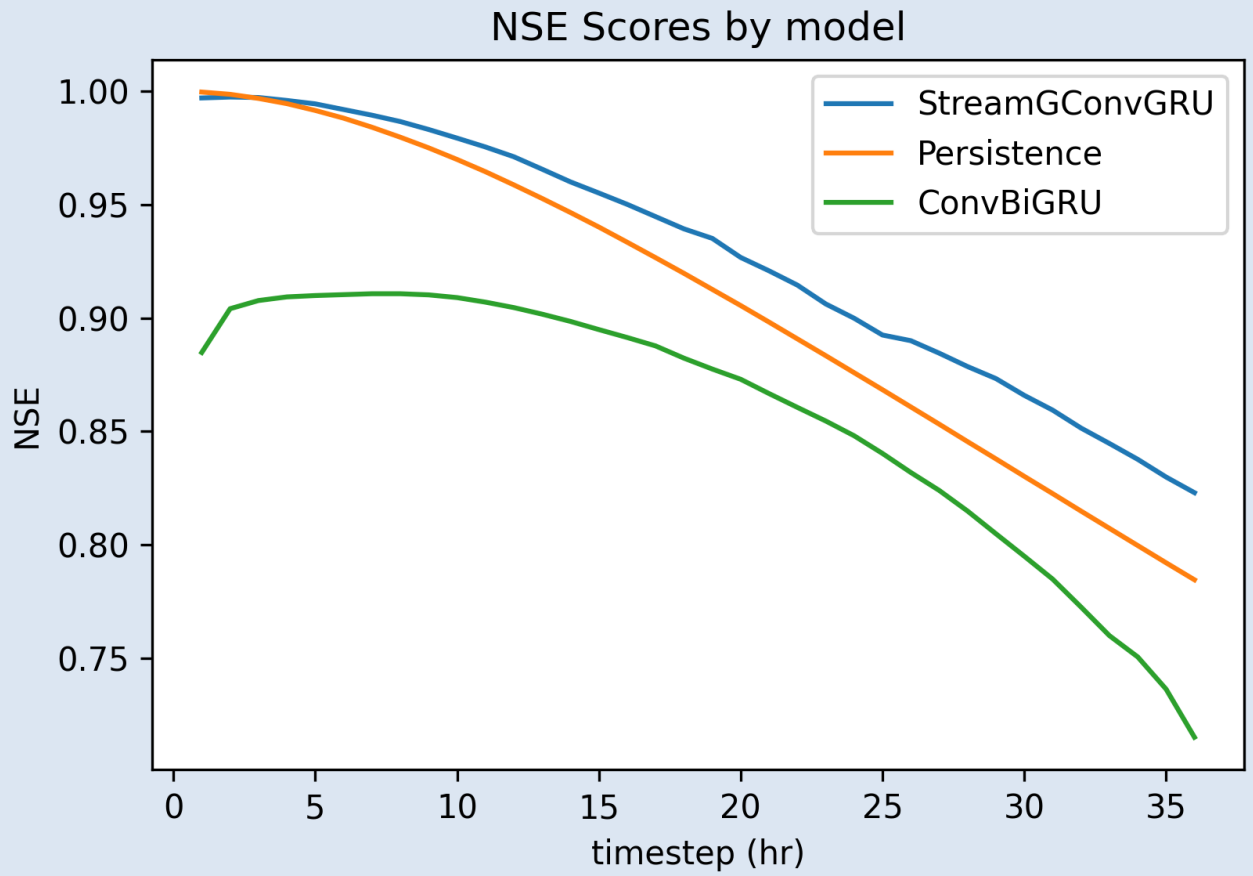
Visualization of this study area (Johnson County, Iowa) and USGS sensor locations on Google Maps with their *id in graph: usgs_id*

Approach


For each timestep t between 10.01.2011 and 10.01.2018
for which USGS Sensor 5455700 has measurements
For each sensor in the
river network at time t
Discharge for {t, t+1, ... t+35}
Discharge for {t-36, t-35, ... t-1}
Precipitation for {t-36, t-35, ... t-1}
Precipitation for {t, t+1, ... t+35}
[8 x 36]
[8 x 36]
[8 x 36]
y
[8 x 36]
X
[8 x 3 x 36]
USGS Sensor Measurements
Stage IV Precipitation Products


Input
[8 x 3 x 36]
[8 x 36]
[8 x 36]
[8 x 36]
GConvGRU_1, K=1
GConvGRU_2, K=1
GConvGRU_3, K=1
[8 x 32]
[8 x 32]
[8 x 32]
ReLU
Linear Layer
ReLU
Output
[8 x 36]

Results



$$NSE = 1 - \frac{\sum_{t=1}^{T}(Q_m^t - Q_o^t)^2}{\sum_{t=1}^{T}(Q_o^t - \overline{Q_o})^2}$$

Q_m^t = mean modeled discharge at time t
Q_o^t = observed discharge at time t
$\overline{Q_o}$ = mean of observed dis- charges

References

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References

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Thank you

Any questions?