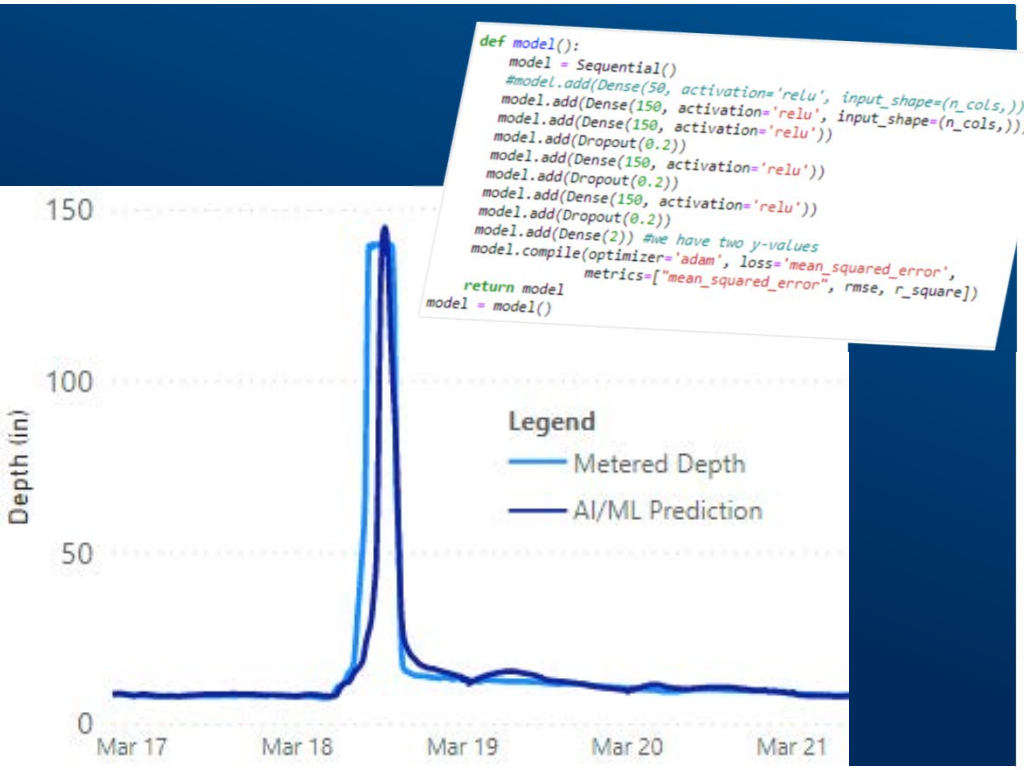
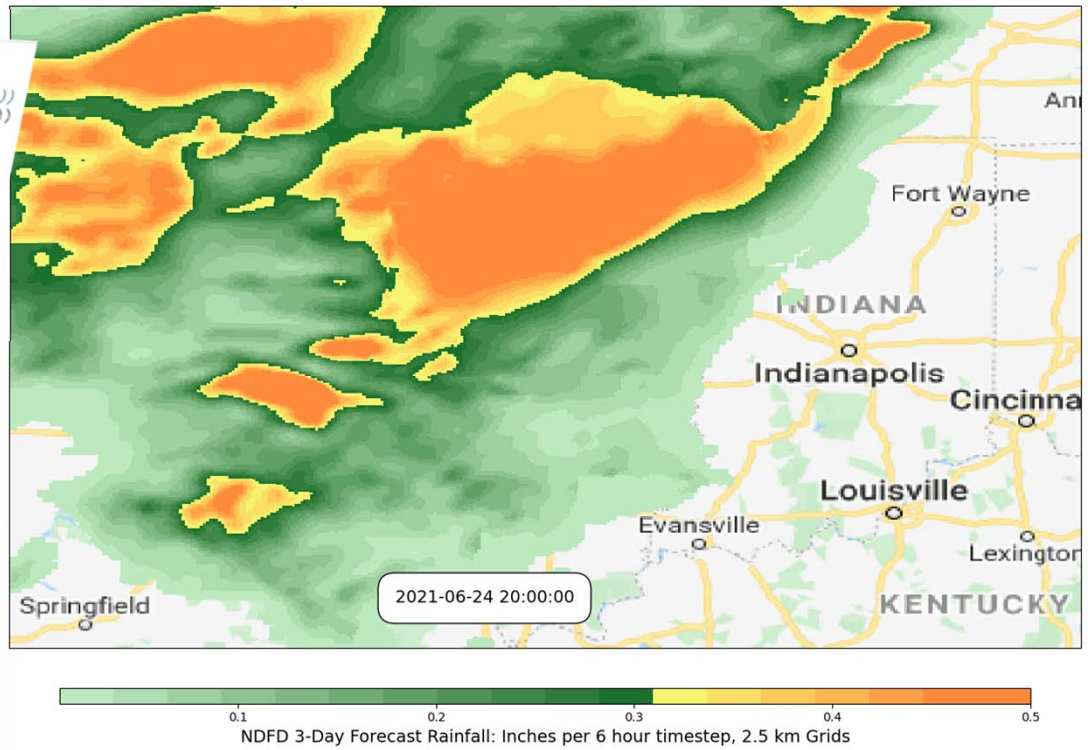




LEVERAGING MACHINE LEARNING FOR PREDICTIVE OPERATIONAL SUPPORT

Chris Ranck, PE, BCEE, D.WRE, ENV SP

September 30, 2021

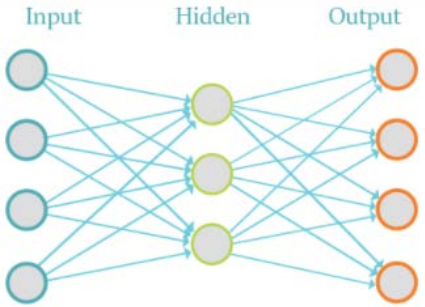
BUILDING A WORLD OF DIFFERENCE®

BLACK & VEATCH

AGENDA

- What is Machine Learning?
- Why Machine Learning?
- How Does it Work?
- Example #1: Wet-Weather Operational Forecast
- Example #2: River Flood Forecast
- Example #3: Sewer Flow Depth
- How to Get Started
- Summary
- Acknowledgements

What is Machine Learning?



A Data-Driven computational process to develop patterns and relationships

If properly deployed, provides tremendous and instantaneous predictive power

A key computational component of a Digital Twin for any type of infrastructure

IBM Cognitive Class.ai, 2018

Why Machine Learning?

Utilities have invested in data collection and models

These answer our questions but only looking backwards

Artificial Intelligence / Machine Learning (AI/ML) leverages this investment to look forwards

Can be implemented at any scale

Can be implemented without any additional software cost

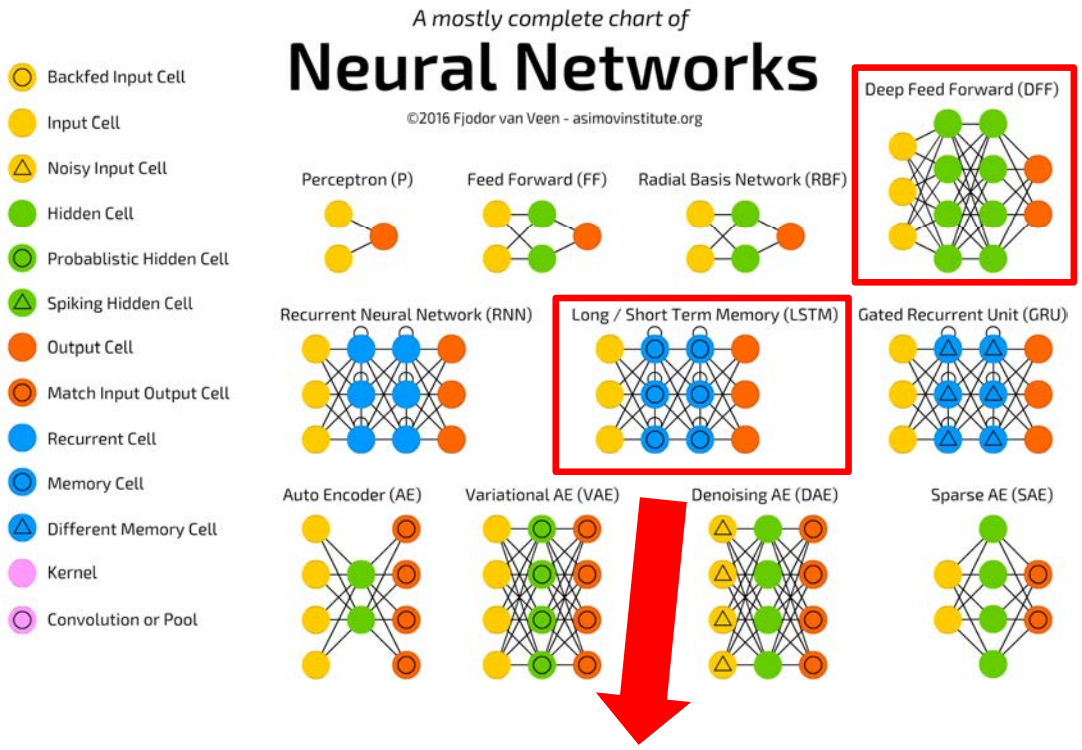
How Does It Work?

First, a few thoughts on AI/ML:

1. In 5 years or less, AI/ML will be part of our everyday workflow (like Excel)
2. Coding a neural network isn't harder than setting up a hydraulic model, GIS overlay, or iterative design calculation
3. No, your neural network will not become sentient and create an army of robots

Image courtesy of Marvel Studios

How Does It Work?



Event Volume Classification

Time Series Forecasting

How Does It Work?

Deep Feed Forward: Train and Test Sets

Event	Rain (in)	CSO (MG)
4/7/19	0.9	12
5/23/19	2.2	15
8/5/19	1.2	5
2/3/20	1.7	9
4/15/20	2.2	24
4/28/20	2.1	22
6/12/20	1.5	13
6/18/20	1.9	16
7/14/20	3.4	40
9/8/20	2.4	11

Train

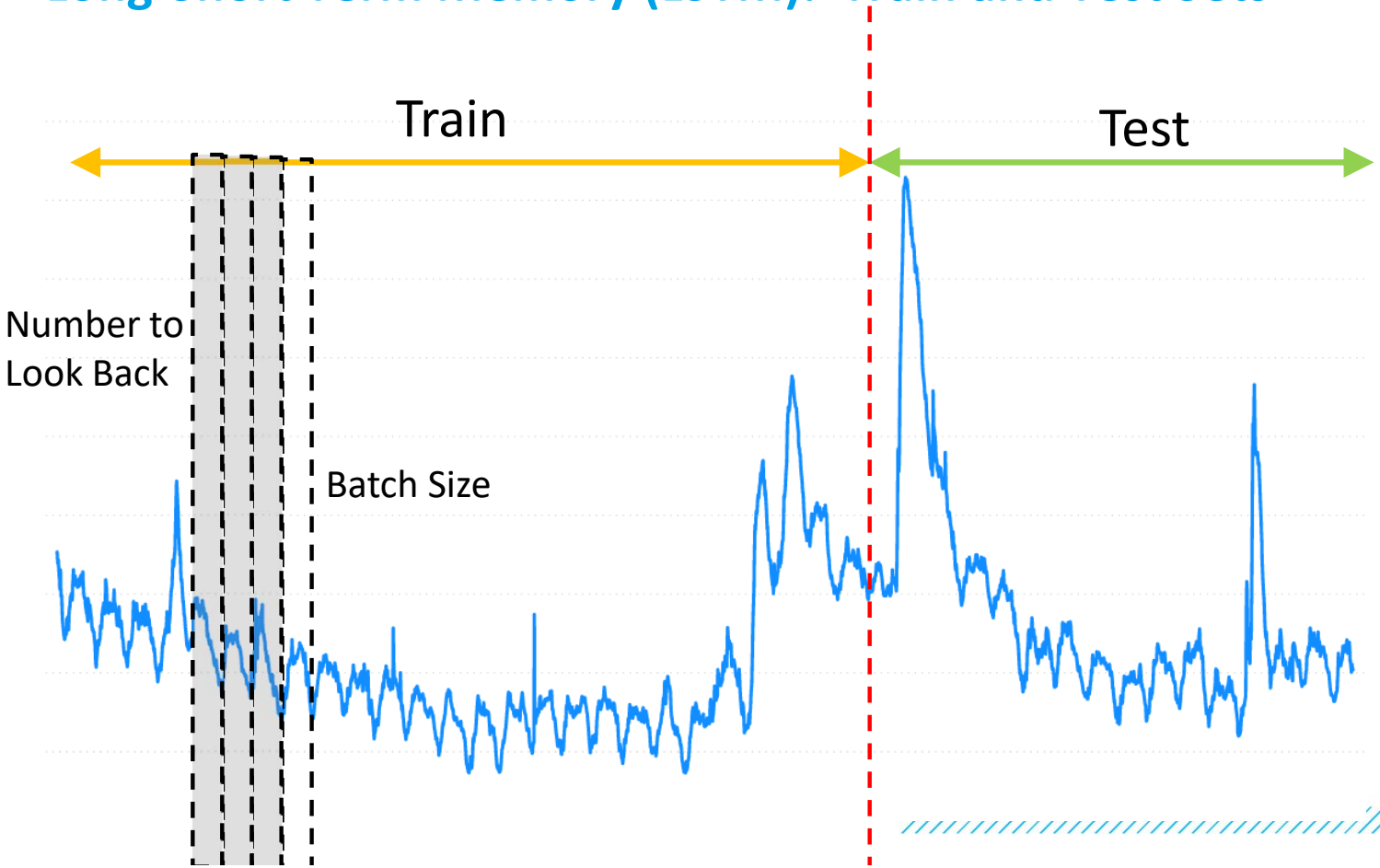
Event	Rain (in)	CSO (MG)
4/7/19	0.9	12
5/23/19	2.2	15
2/3/20	1.7	9
4/15/20	2.2	24
6/12/20	1.5	13
6/18/20	1.9	16
9/8/20	2.4	11

Test

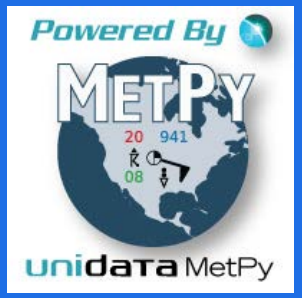
Event	Rain (in)	CSO (MG)
8/5/19	1.2	5
4/28/20	2.1	22
7/14/20	3.4	40

How Does It Work?

Long-Short Term Memory (LSTM): Train and Test Sets



citizens energy group™



Example #1 Wet-Weather Operational Forecast

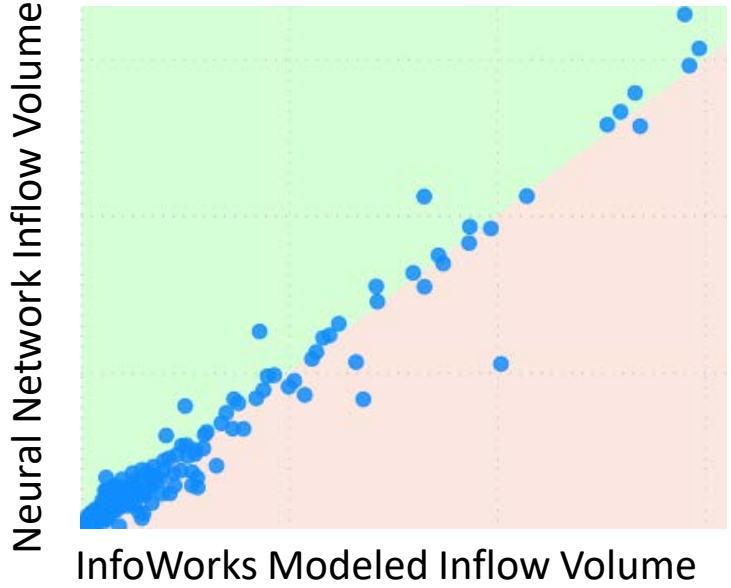
Objective: Can we predict how much flow will come to a future CSO facility before the event happens?

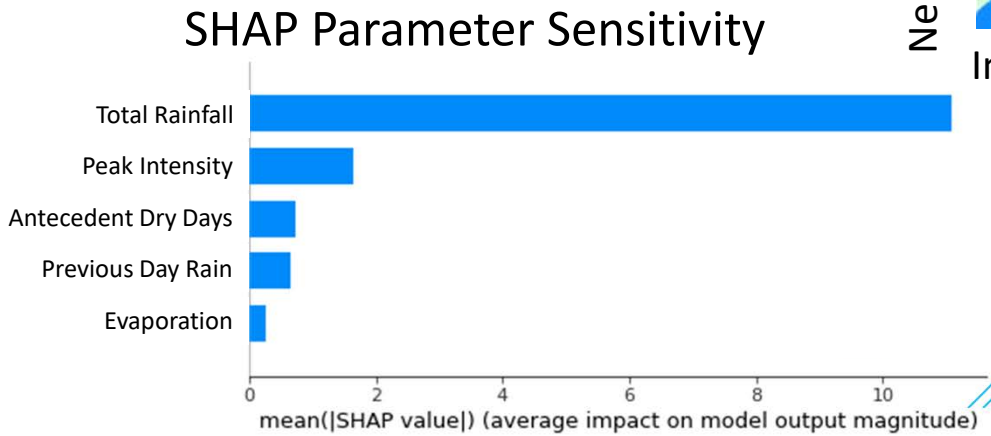
- **Part 1: Fit a neural network to four years of modeled flow, rainfall and evaporation data**
- **Part 2: Harness the MetPy toolkit to obtain the 72-hour NOAA National Digital Forecast Database (NDFD) radar rainfall forecast**
- **Part 3: Connect Parts 1 and 2 in a BI Dashboard**

Example #1 Wet-Weather Operational Forecast

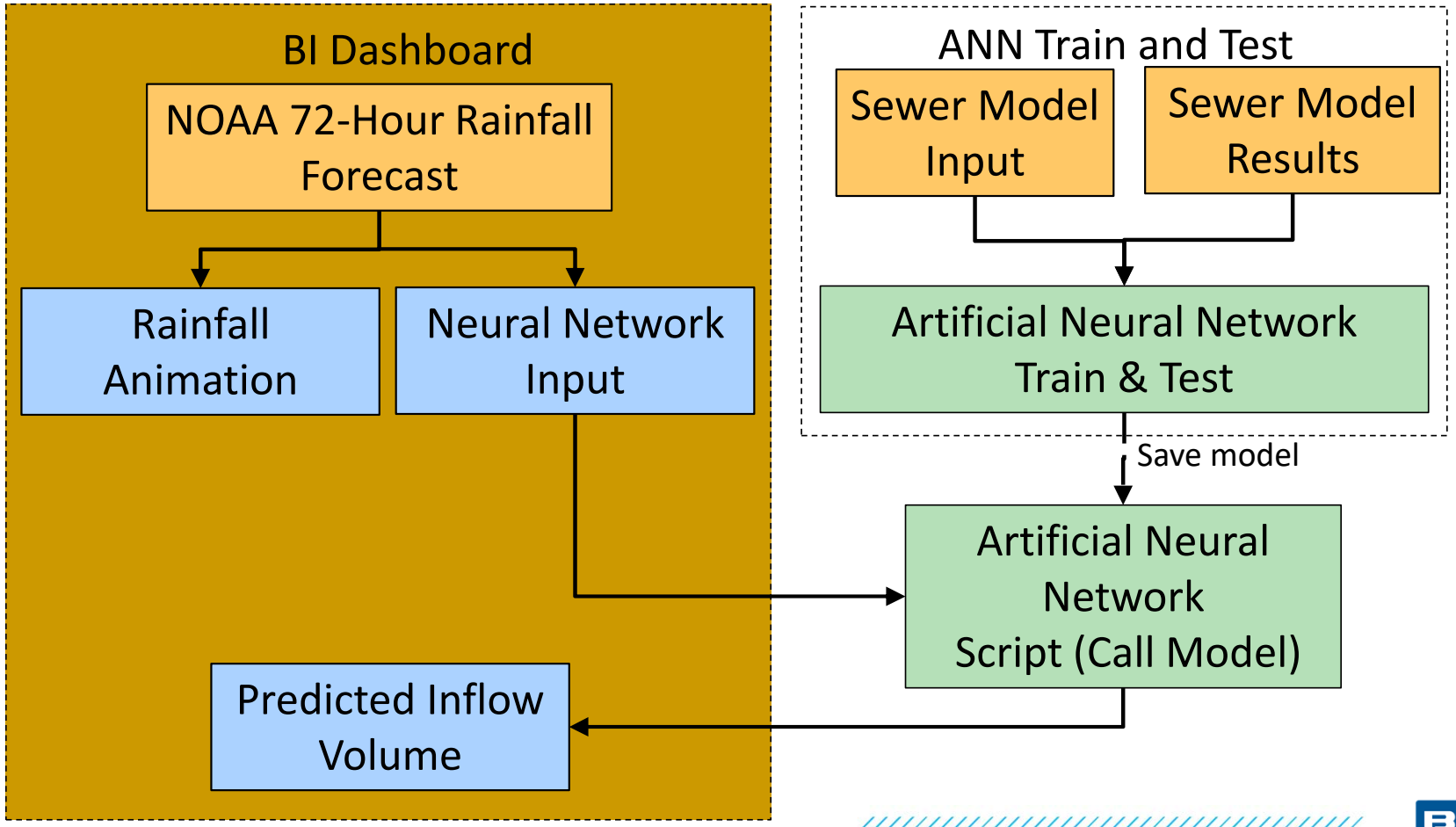
Neural Network Results

- 5 Parameters Carried Forward
- 93% R^2
- Total Volume within 1%

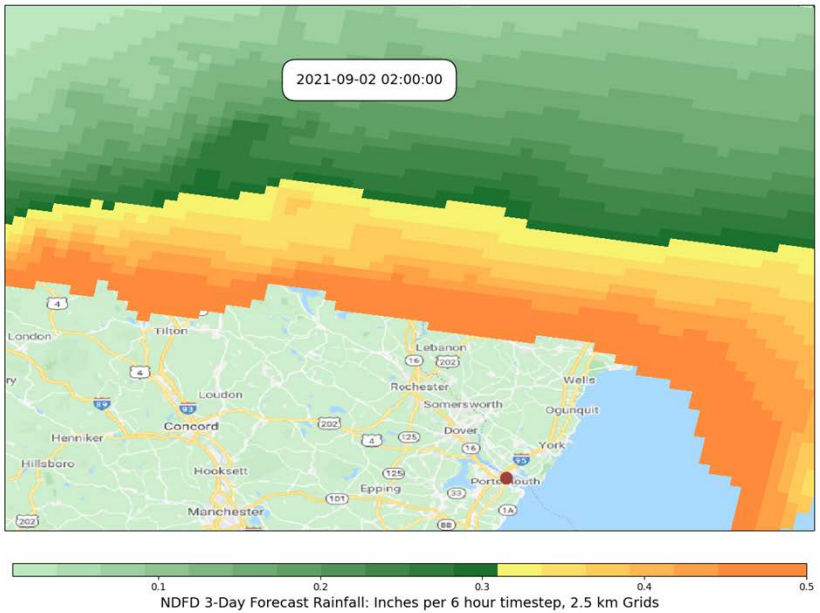


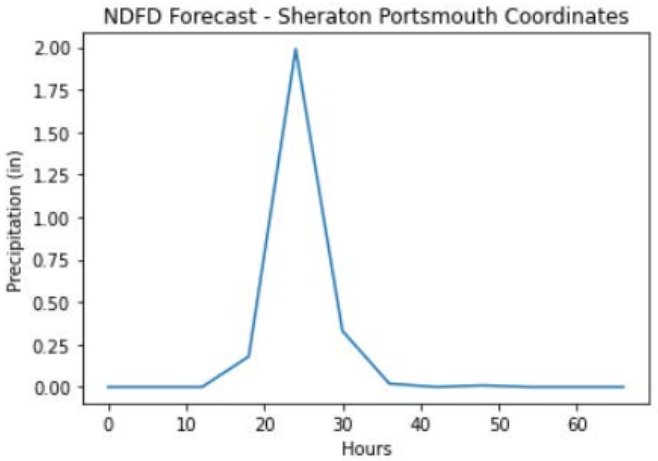


Example #1 Wet-Weather Operational Forecast



Example #1 Wet-Weather Operational Forecast





Forecasted 9/1/21
(mid morning)

Actual Rain: 2.35”
(Weather Underground)

Neural Network Predicted Inflow Volume

Date	Rain (in)	Peak Intensity (in/hr)	Antecedent Dry Days	Inflow Volume (MG)
9/1/21	0.00	0.00	0	0
9/2/21	2.50	0.33	0	23
9/3/21	0.01	0.00	0	0
9/4/21	0.00	0.00	0	0

Example #1 Wet-Weather Operational Forecast

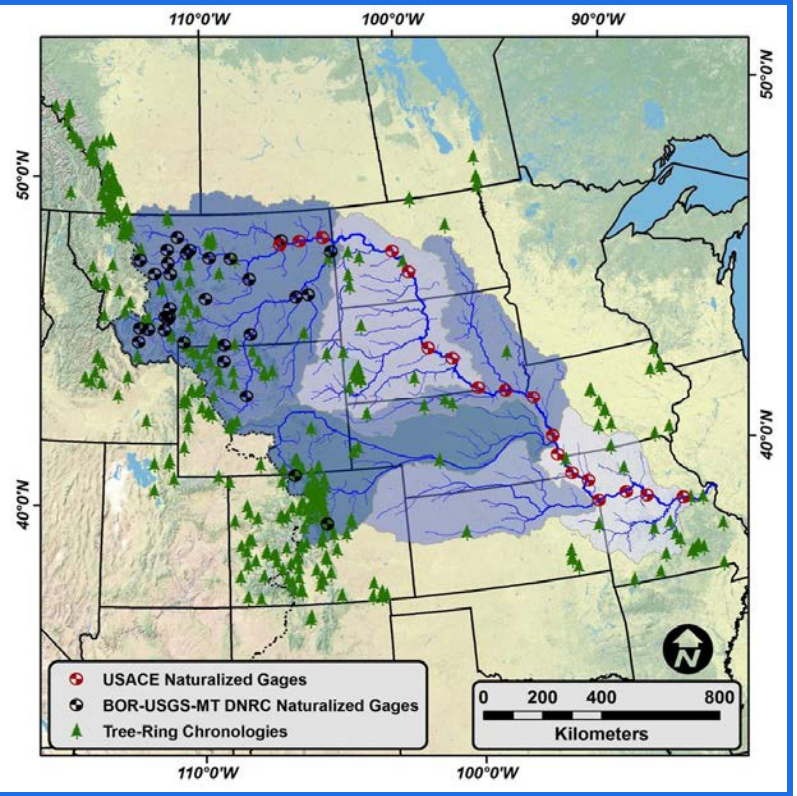
How Good is the NDFD Forecast?

- March –August 2021: 119 Forecast Events
  - 88 Events within 0.2 inches of Actual Gauge Rainfall
  - Total NDFD Rainfall: 26.9 inches
  - Total ADS Gauge Rainfall: 25.4 inches
- May 28, 2021 Rain Event

Forecast Taken	May 25	May 26 AM	May 26 PM	May 27	May 28 AM	Average Gauge Rainfall*
Rainfall (in)	1.48	1.01	0.83	0.41	0.64	0.43

*Max Gauge 0.63 in

Example #2 River Flood Forecast



USGS science for a changing world

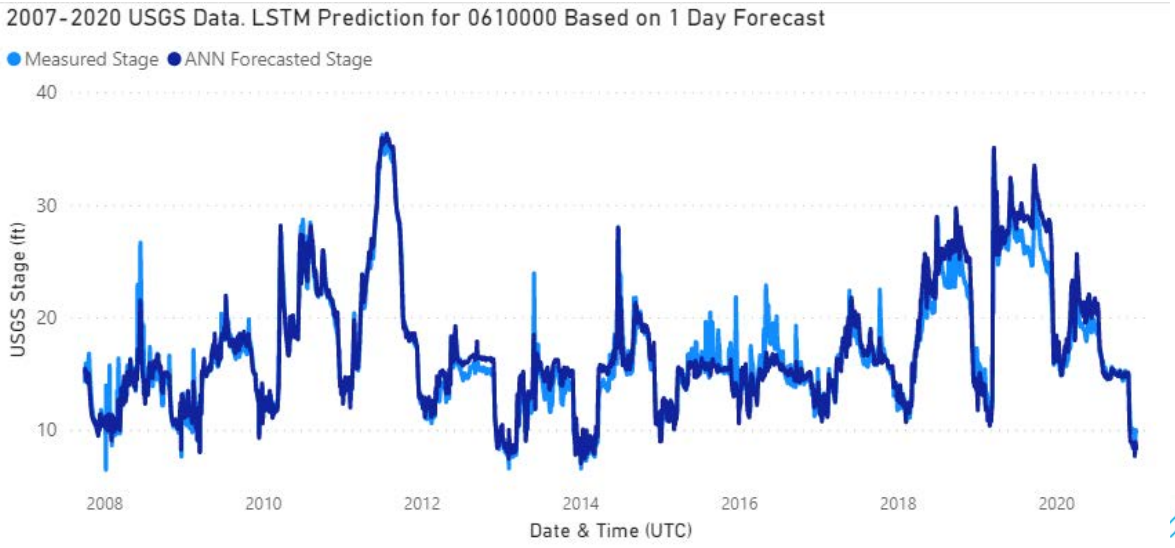
Objective: Can we predict Missouri River floodstage based on four upstream gauges, 1 day in advance?

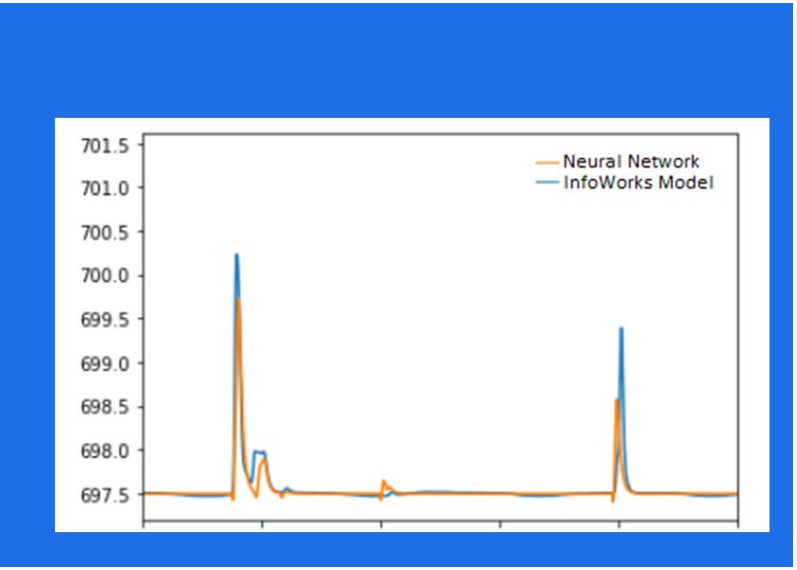
- **Part 1: Fit a LSTM neural network to thirteen years of USGS data**
  - **Target: Missouri River at Omaha**
  - **Upstream Gauges: Decatur, NE; Sioux City, IA; Bismarck, ND; Wolf Point, MT**
- **Part 2: Integrate into BI using the Hydrofunctions library to obtain current data to forecast**

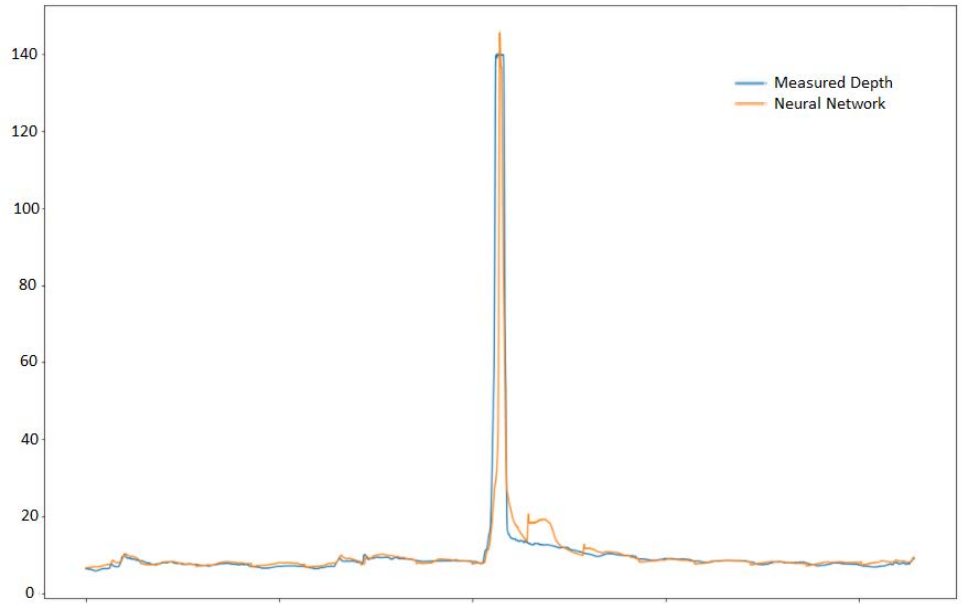
Example #2 River Flood Forecast

Neural Network Results: 1 Day Forecast Offset

- 88% R^2
- 10% Dropout, 1 Hour Batch Size, Looking Back 3 Hours
- USGS data typically available within 2 hours of present







Example #3 Sewer Flow Depth

Two LSTM Case Studies

1. **Modeled Depth**
   - Parameters: Rainfall, Temperature
   - 15-minute batch size
2. **Metered Depth (Different location)**
   - Parameters: Two Upstream Meters
   - 2-Hour Forecast Offset
   - 30-minute batch size, 20% dropout

How to Get Started

Many choices for AI/ML Courses

Unidata online workshop for MetPy

MetPy Mondays on YouTube

Chris' Lessons Learned:

- Confirm data is representative and consistent
- Time series forecasting (LSTM) is inconsistent for CSO discharges and other intermittent flows
- You can do this!

Summary

There is tremendous potential for AI/ML in our profession

- **Predictive Capability leveraging current datasets**
- **Capability for classification and correlation**

AI/ML can be effective in lieu of a traditional model

AI/ML can be an extension of a traditional model

And this can all be done with free software!

Summary

One more bold prediction:

- **In 2001, where would a utility's sewer model be found?**
- **Where would it be found now?**

~~**2001: "Utility Staff can't run their models"**~~

2021: "Utility Staff can't do their own AI/ML"

Acknowledgements

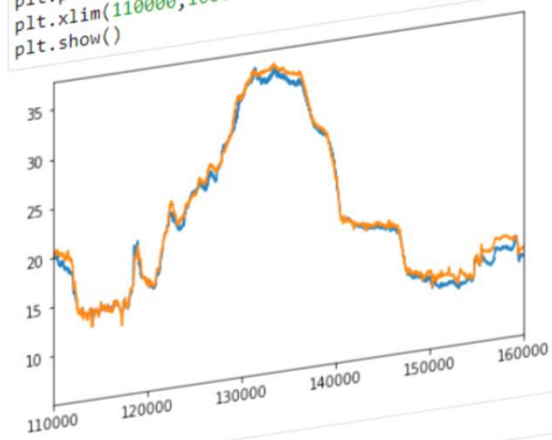
- Citizens Energy Group
- MetPy

Discussion

- **Questions?**

```
#LSTM for River Stage Forecast
model = Sequential()
model.add(LSTM(50, recurrent_dropout=0.1,activation='relu', input_shape=(n_input, n_features)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mean_squared_error', metrics =[ "mean_squared_error",r_square])
model.summary()
```

```
#zoom in on big 2011 event
plt.plot(results2)
plt.xlim(110000,160000)
plt.show()
```




```
results2.max()
```

```
Measured    36.290000
Predicted   36.387341
```