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# Predicting Water Temperature Inside WDS Using Deep Learning

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# AGENDA

Background

Data

Methodology

Outcomes

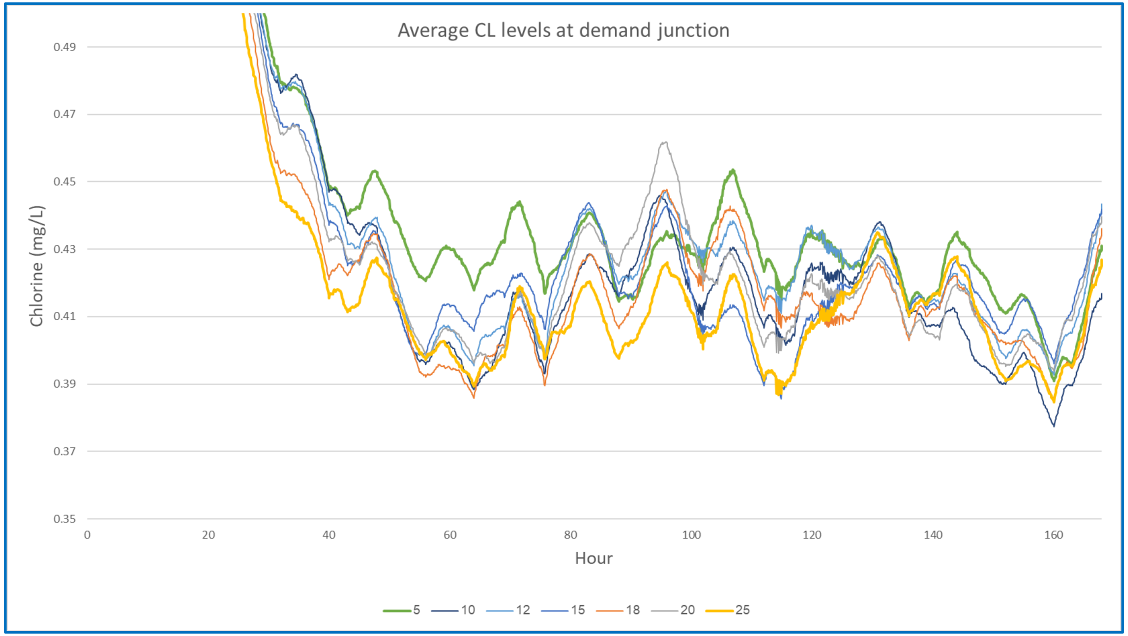
Conclusion and Recommendations

# Why Water Temperature is Important?

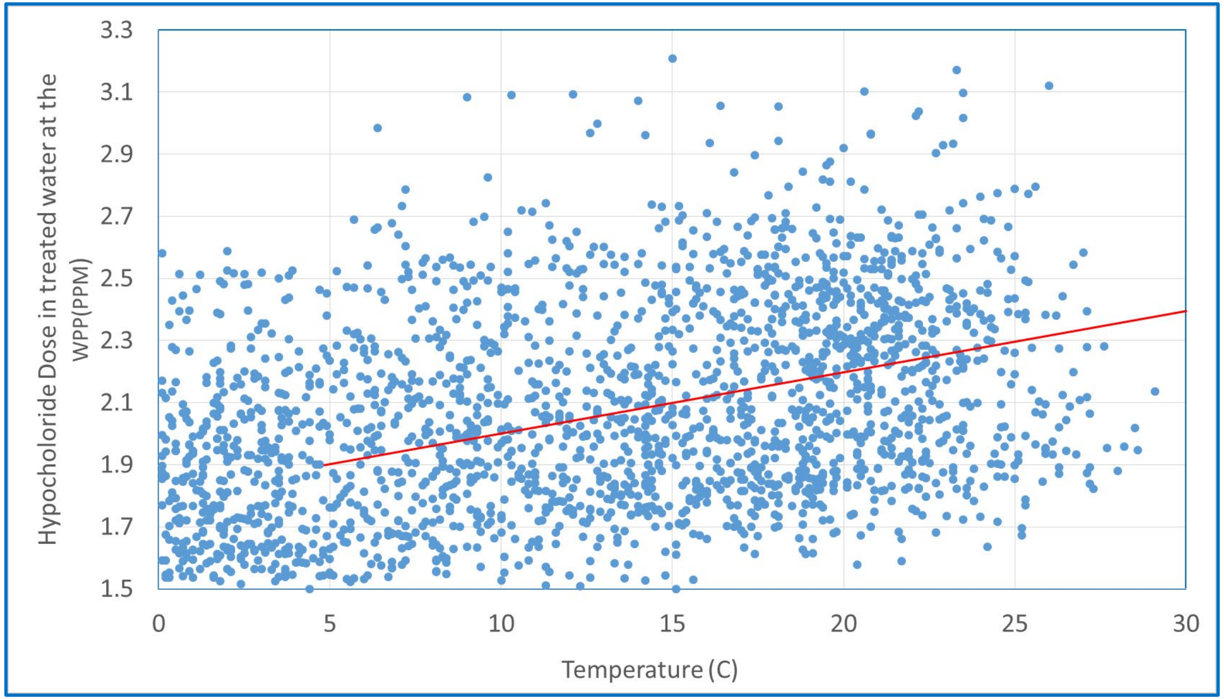
## Water quality:

- Physical, chemical and biological processes.
- Microbial growth and competition,
- Pipe corrosion,
- Chlorine decay

# Why Water Temperature is Important?



# Why Water Temperature is Important?

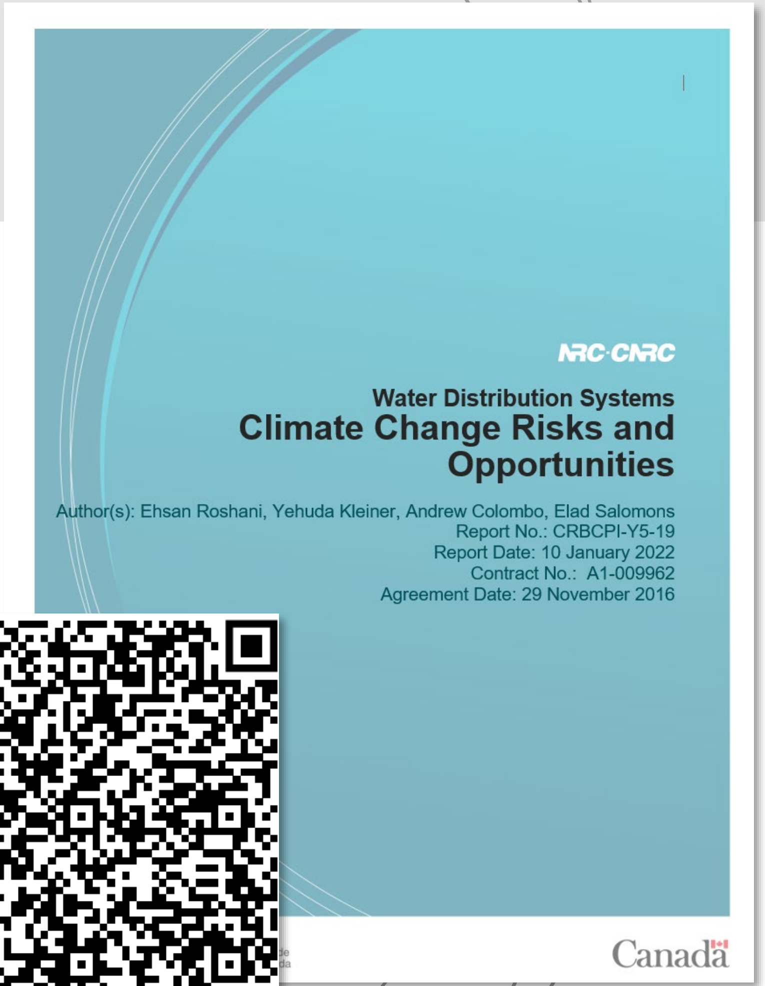



0.02 PPM to the concentration of Hypochlorite per 1 degree increase in the air temperature

# WDS Climate Change Risk & Opportunities

## Impact of Changing Climate on

- Demand
- Watermain Capacity
- Energy
- Pipe Break
- Water Quality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Water Distribution Systems

Climate Change Risks and Opportunities

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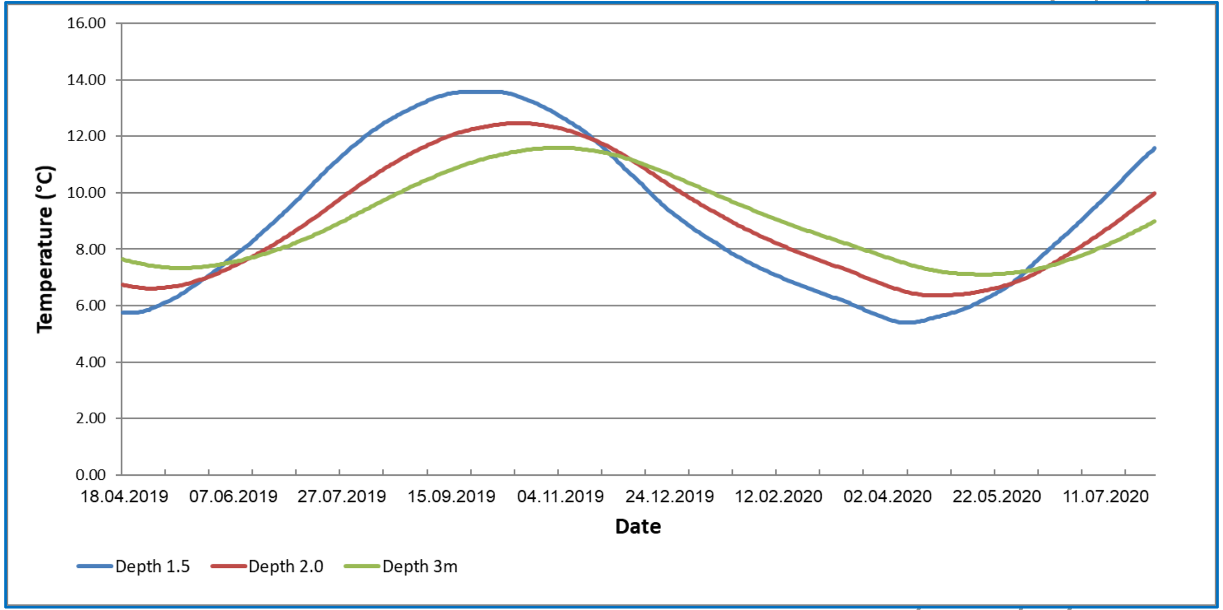
Canada

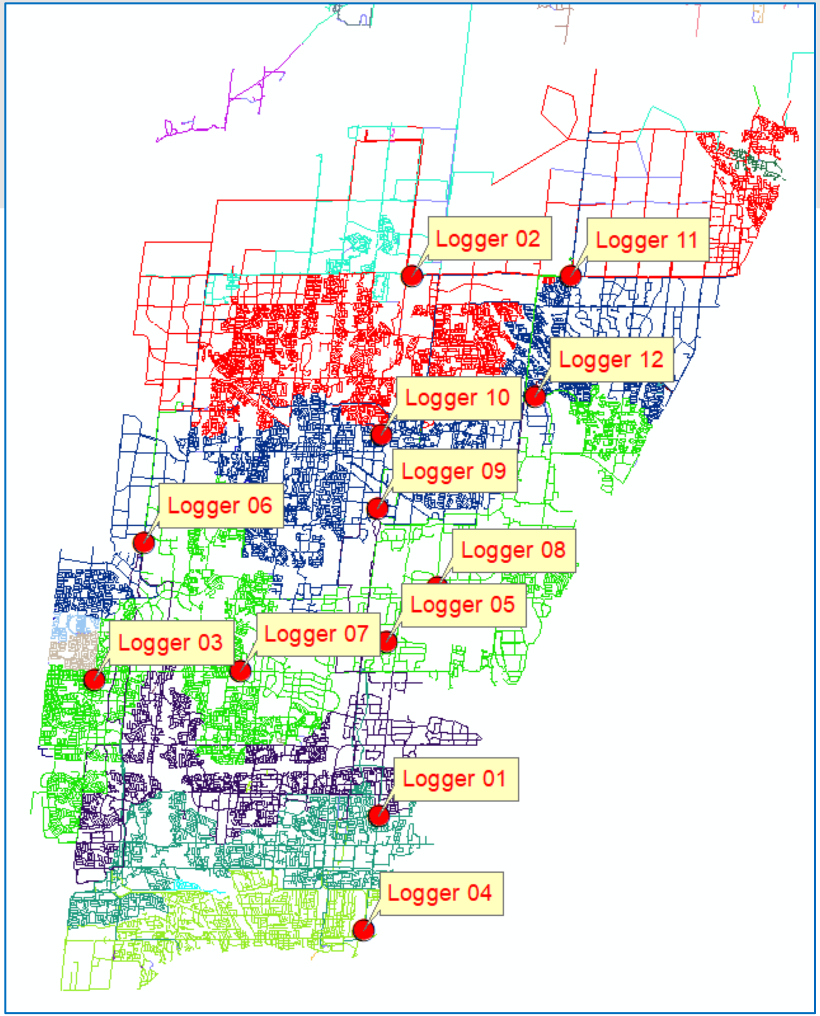
# Previous Works

- The literature in this area is limited (Numerical or Physical Models).
- Heavily relying on soil temperature
- Often use water temperature from the consumer side.

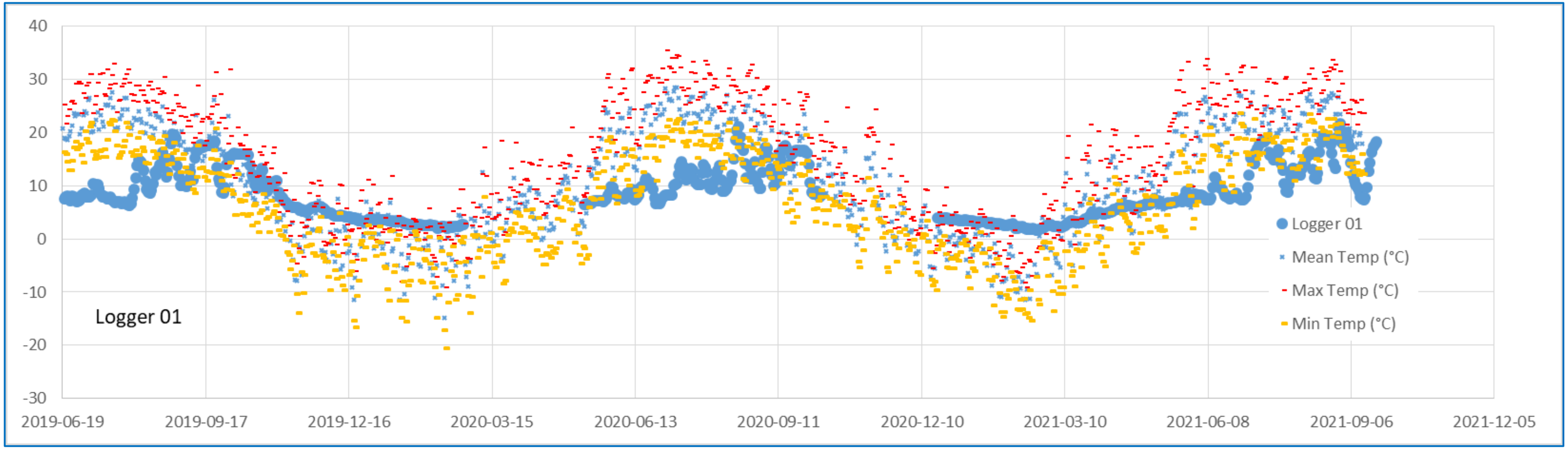


# Getting temperature from inside the WMs


# Logger Locations

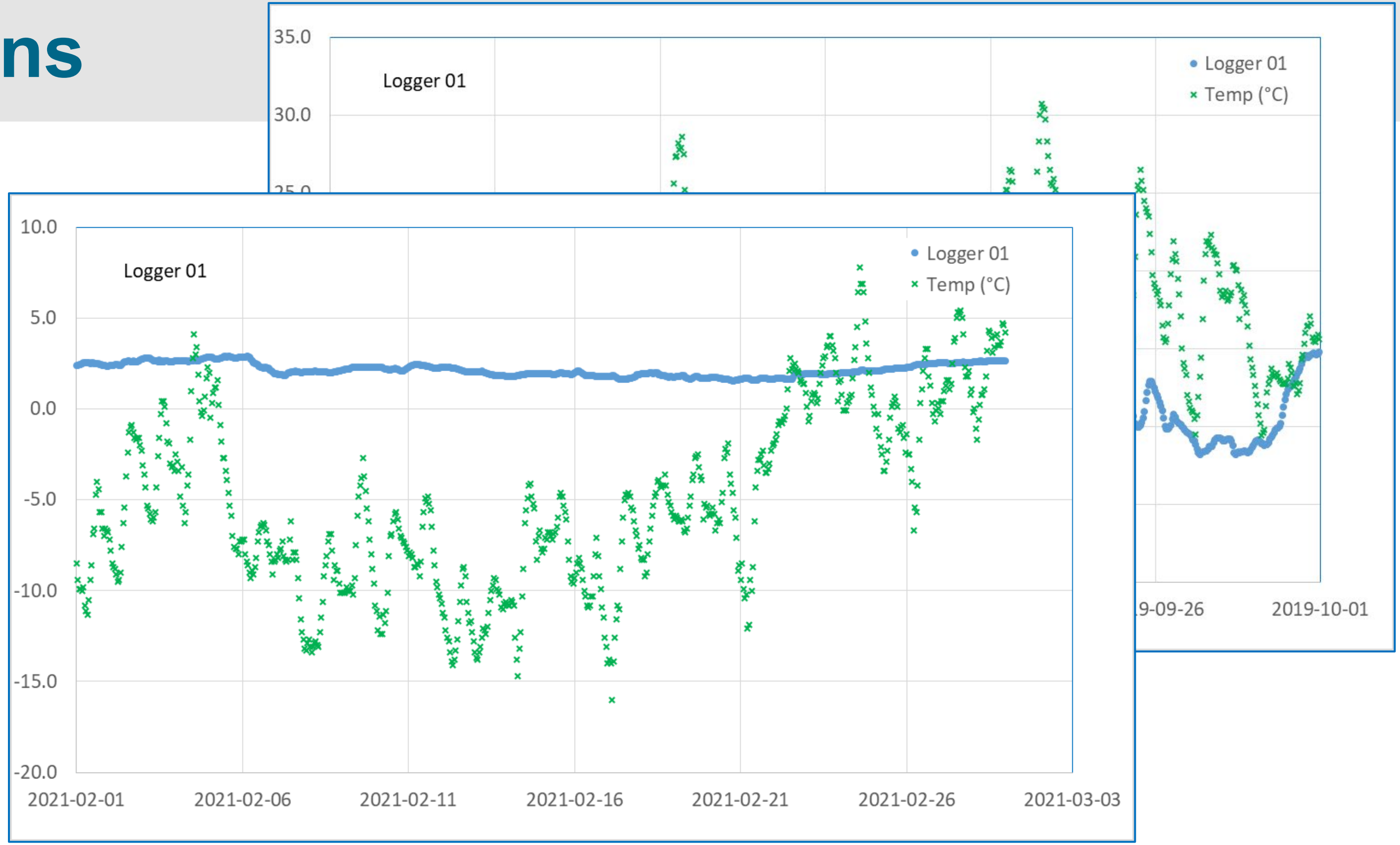



# Observations



# Observations

- **Daily temperature fluctuation is not as important.**



# Long-Short Term Memory (LSTM)

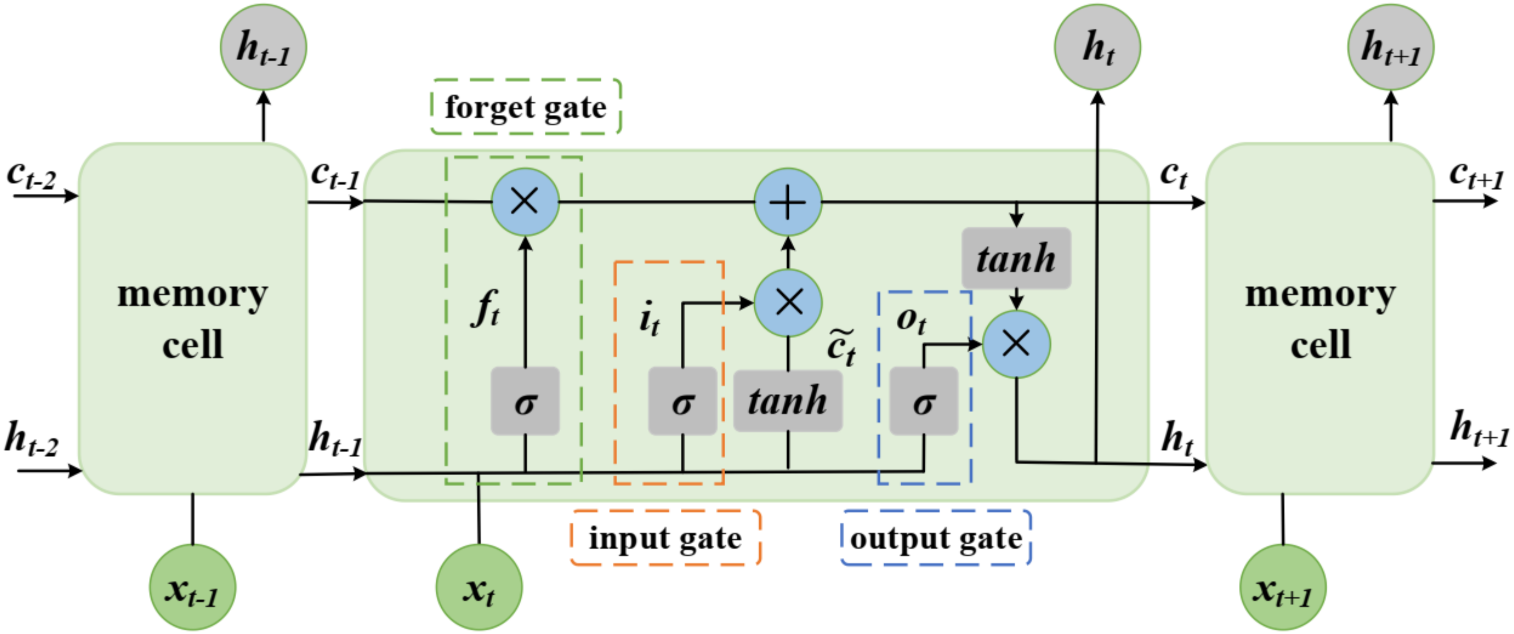
Proven effectiveness in modeling time series.

These models have been shown to often surpass the accuracy of many physics-based models.

LSTMs maintains information over long sequences.

Advanced variant of Recurrent Neural Network (RNN) introduced in 1997!

# Long-Short Term Memory (LSTM)



# Long-Short Term Memory (LSTM)

Data from Logger 1 was used to train the model.

70% for training and validation and 30% for testing.

14 previous time step (based on R2).

Two hidden layers with 256 and 16 LSTM cells, respectively, and the ReLU activation function.

To prevent overfitting, a Dropout layer was included, with a dropout rate of 0.2 during training phase.

# Scenarios

1- Fixed past (previous 14 timesteps) to predict upcoming timestep.

a- Constant dropout of 20%

b- Monte Carlo dropout

2- Fixed past (previous 14 timesteps) to predict upcoming 10 time steps.

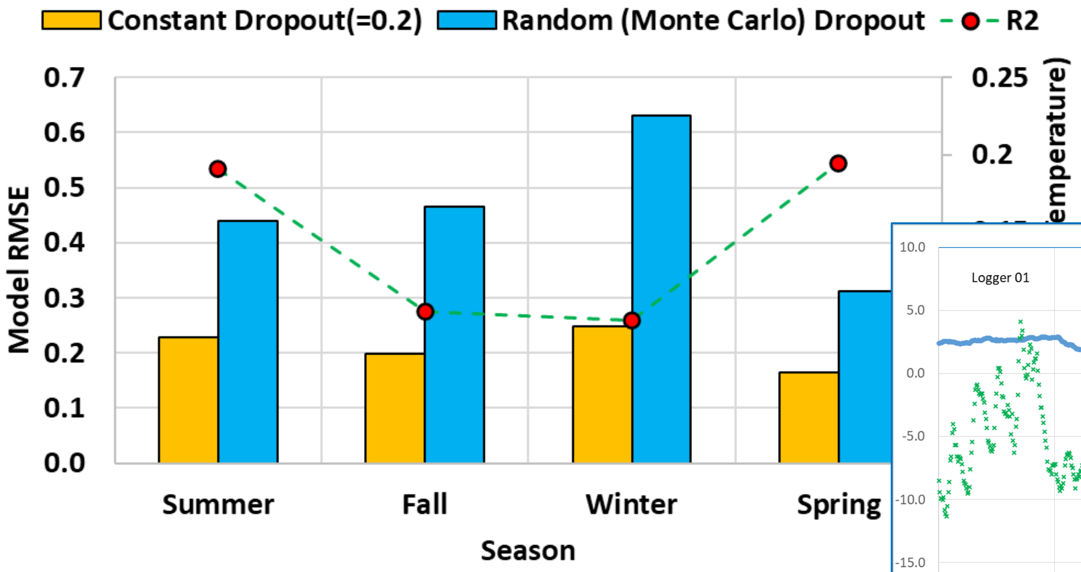
a- Constant dropout of 20%

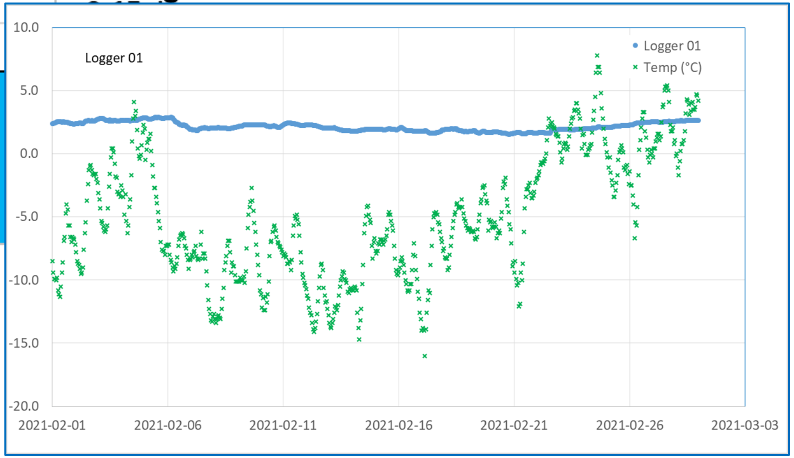
b- Monte Carlo dropout

# First Scenario

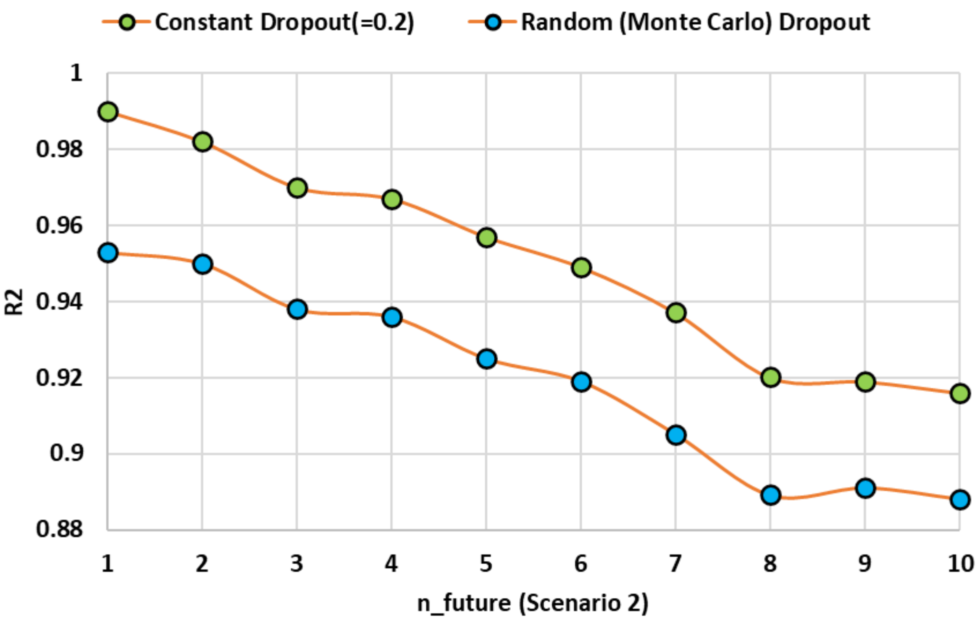
| Dropout method | MSE | RMSE | NRMSE | Average Error (˚C) | Max Error (˚C) | MAE | $R^2$ |
|---|---|---|---|---|---|---|---|
| Constant (=0.2) dropout | 0.014 | 0.119 | 0.014 | 0.075 | 1.1 | 0.075 | 0.993 |
| Random (Monte Carlo) dropout | 0.047 | 0.216 | 0.046 | 0.144 | 1.82 | 0.144 | 0.957 |

# First Scenario



# Second Scenario



# Third Scenario

| Performance Indicator | Scenario 2 – Constant Dropout | Scenario 3 – Constant Dropout | Scenario 2 – Random Dropout | Scenario 3 – Random Dropout |
|---|---|---|---|---|
| **MSE** | 0.067 | 0.075 | 0.099 | 0.108 |
| **RMSE** | 0.26 | 0.27 | 0.32 | 0.33 |
| **MAE** | 0.160 | 0.161 | 0.216 | 0.220 |

# Conclusions

1- Constant dropout led to better accuracy.

2- LSTM perform well in predicting temperatures based on air.

3- It performs much better in summer than in winter.

4- Even for 10 hour forecast the RMSE is 0.3 degree which is very usable.

# THANK YOU

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