IWRA's XVII

WORLD WATER CONGRESS

29 Nov-3 Dec,2021

Exco Daegu, Republic of Korea

Water Level Prediction using LSTM and GRU for Data-Scarce Areas

KAREEM, Kola Yusuff (Speaker)

Dr. Younghun Jung (Advisor)

Department of Advanced Science and Technology Convergence

Kyungpook National University

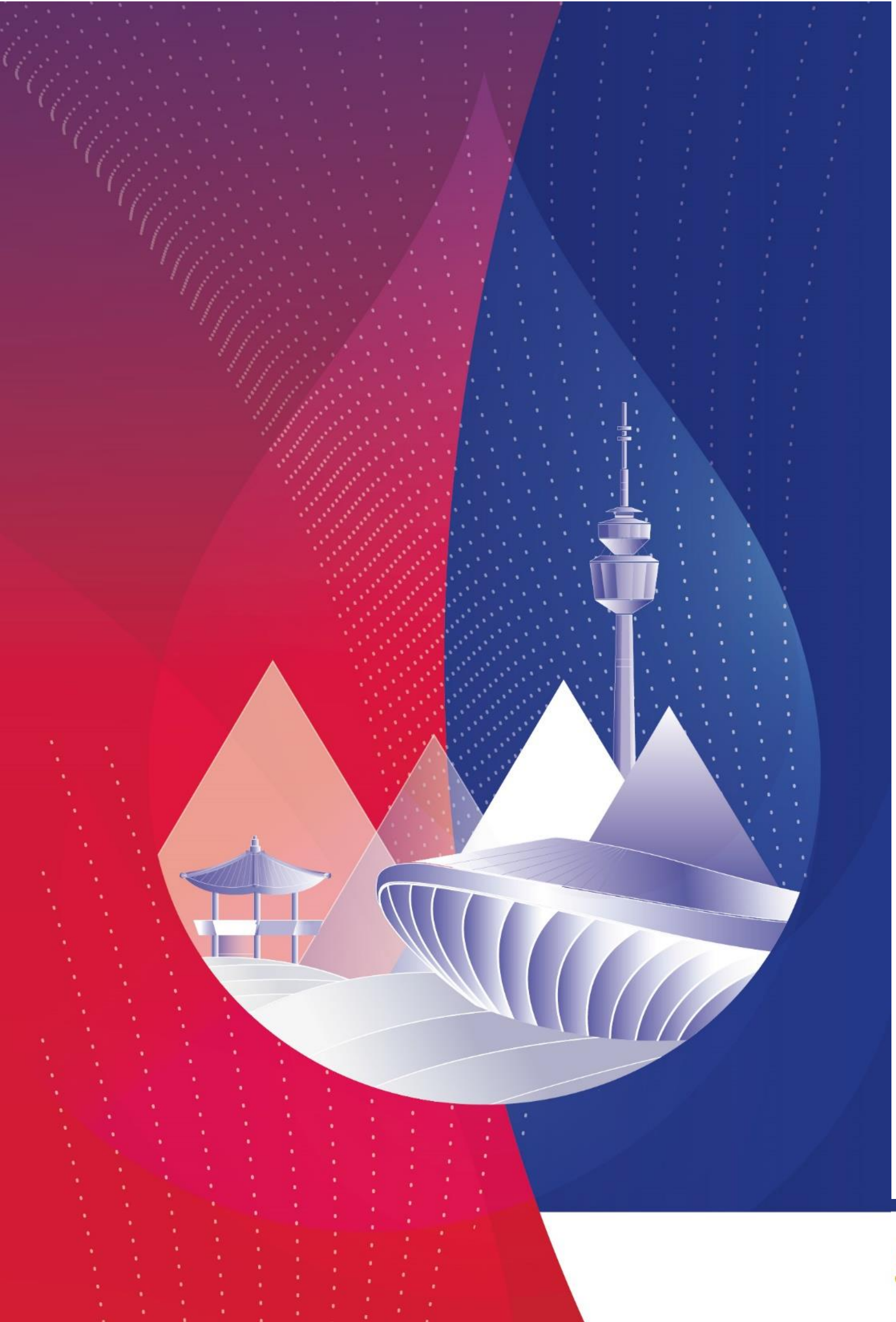
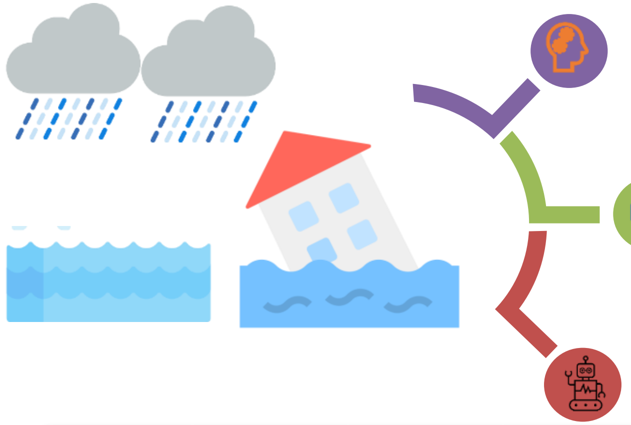


Table of Contents

1. Introduction

1.1 Deep Learning Applications

The goods and services provided by nature that contribute to the well-being of humans.



Application of data-driven machine learning models to hydrologic studies by learning temporal dependencies in data is currently gaining momentum globally.

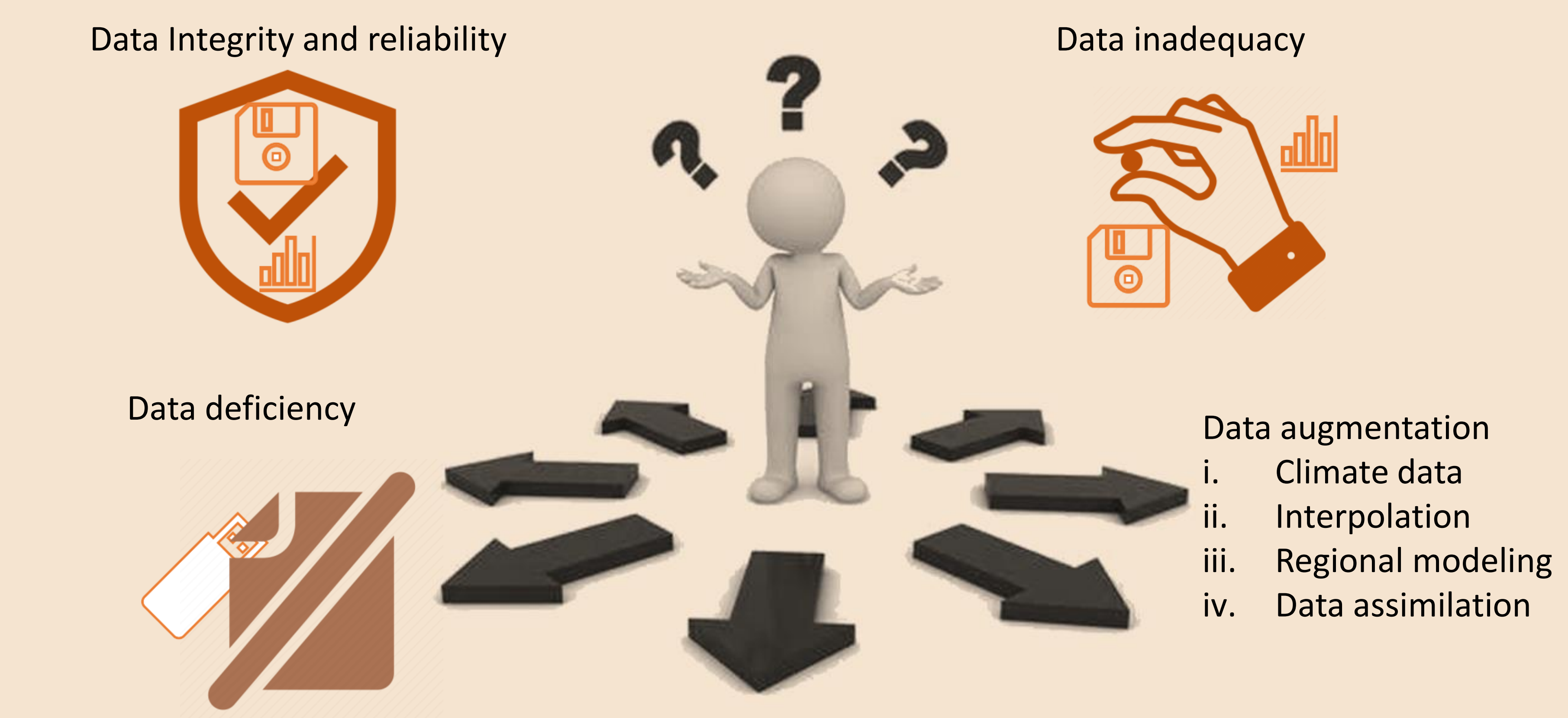
Deep learning models offer more accurate and simpler modeling solutions than traditional physics-based models, as a result of ease of computation.

With applications ranging from:

to

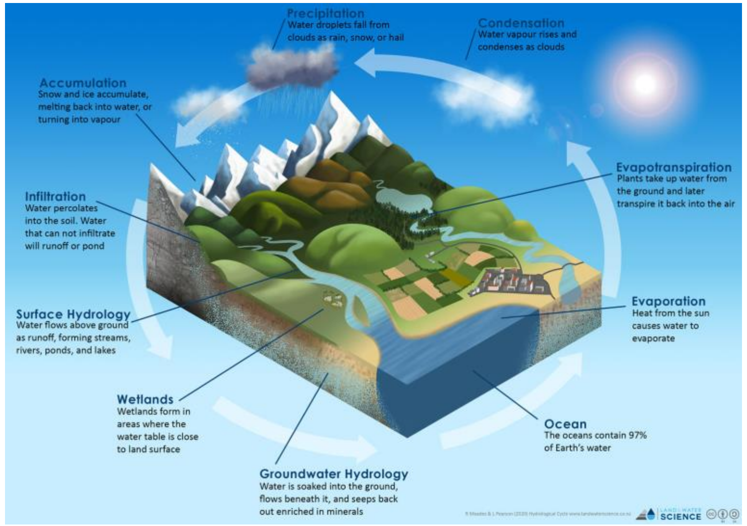
1.2 Data Management in Developing Countries

Problems encountered in data-scarce areas typical of developing countries.



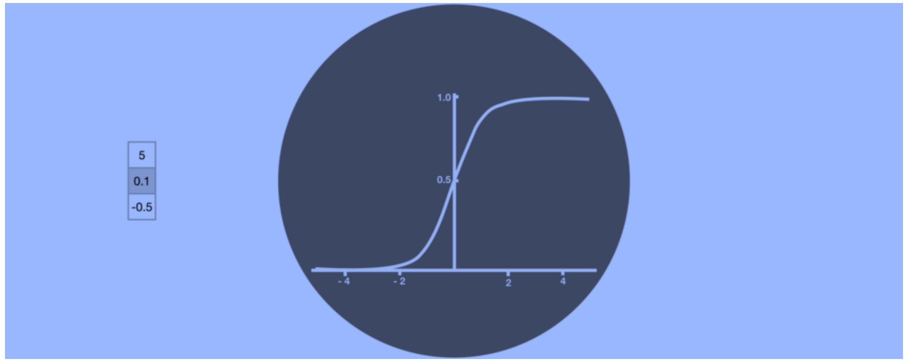
1.3 Interpreting the "Black Box "

Model accuracy or knowledge-based hydrological modeling?



"In hydrology, however, hydrologists are not only interested in obtaining good predictions, but also in explaining the physical drivers of streamflow"

Gauch & Lin (2020)



Gauch, M., & Lin, J. (2020). A Data Scientist's Guide to Streamflow Prediction. http://arxiv.org/abs/2006.12975

1.4 Global Artificial Intelligence Applications in Hydrology

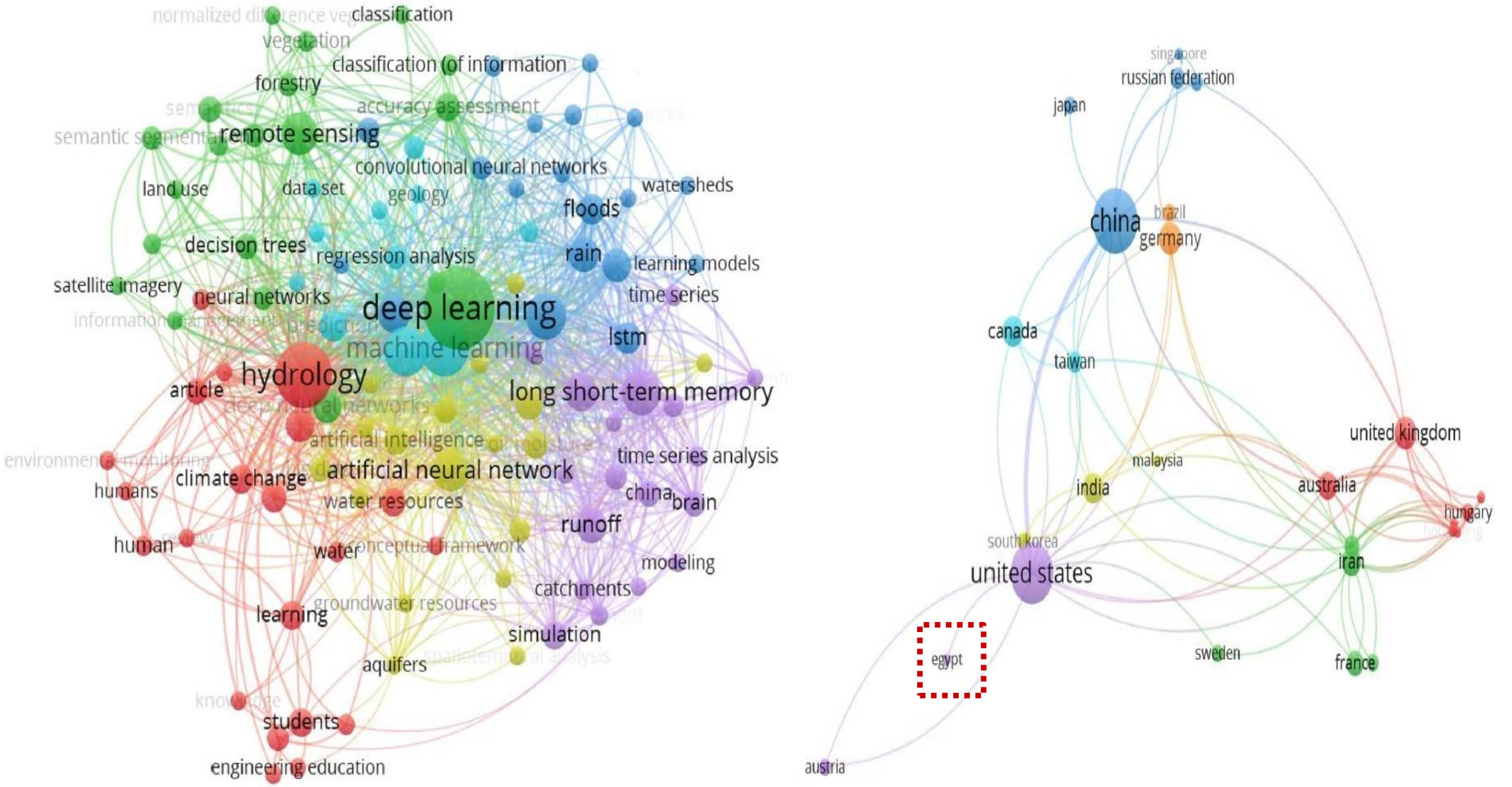
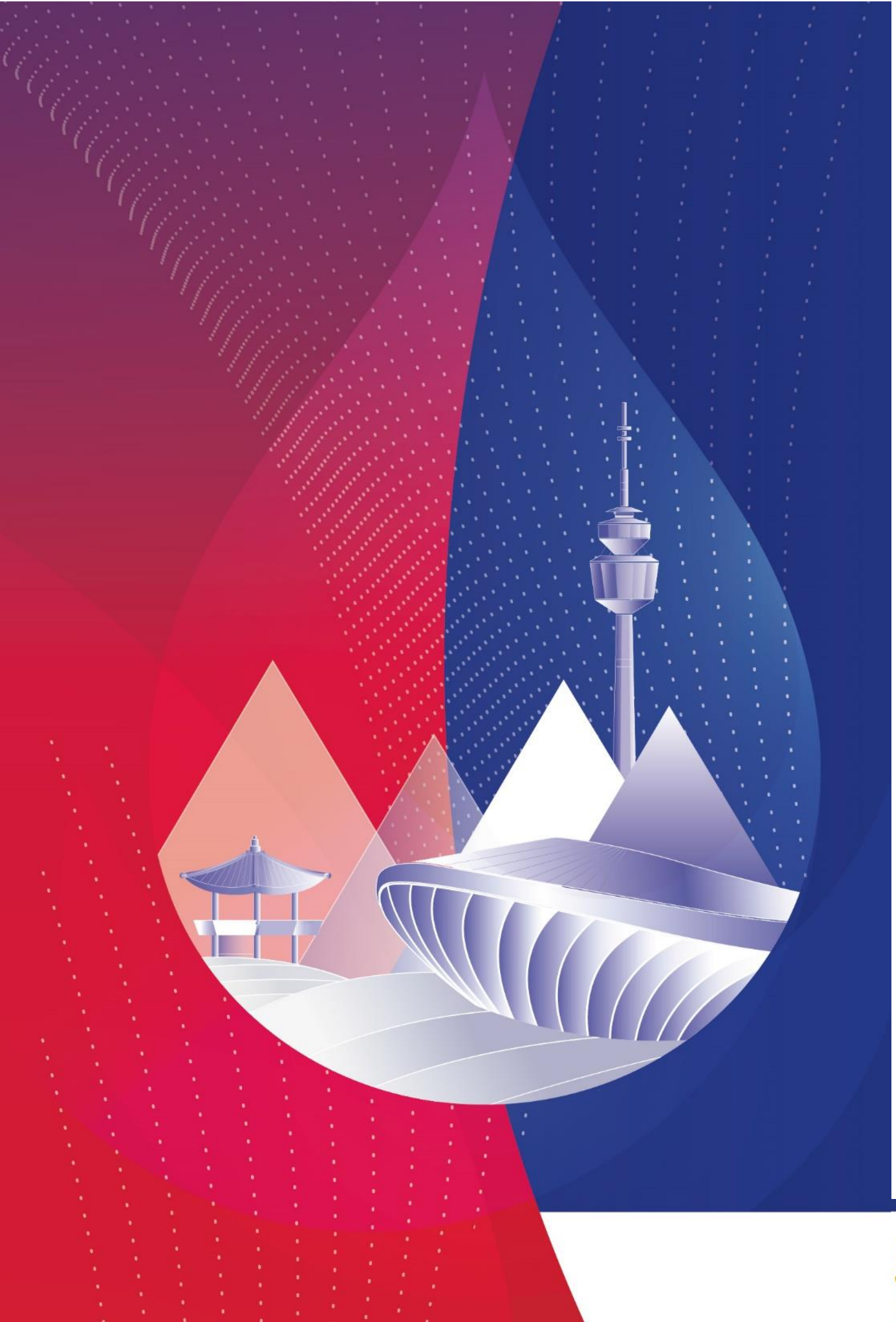


Fig. 1: Specified AI keywords in hydrologic sciences research
Modified from Ghimire *et al.* (2021)

- Over 107 keywords for Wordcloud
- Database: Scopus
- The USA and China claim highest publications in use of LSTM keyword
- South Korea and India have the highest number of publications with the keyword AI and ANN.
- **Sadly, based on this research, only one African country has been able to implement AI in hydrology research**

Ghimire, S., Yaseen, Z. M., Farooque, A. A., Deo, R. C., Zhang, J., & Tao, X. (2021). Streamflow prediction using an integrated methodology based on convolutional neural network and long short-term memory networks. Scientific Reports, 11(1), 1–26. https://doi.org/10.1038/s41598-021-96751-4



2. Methodology

2.1 Study Area

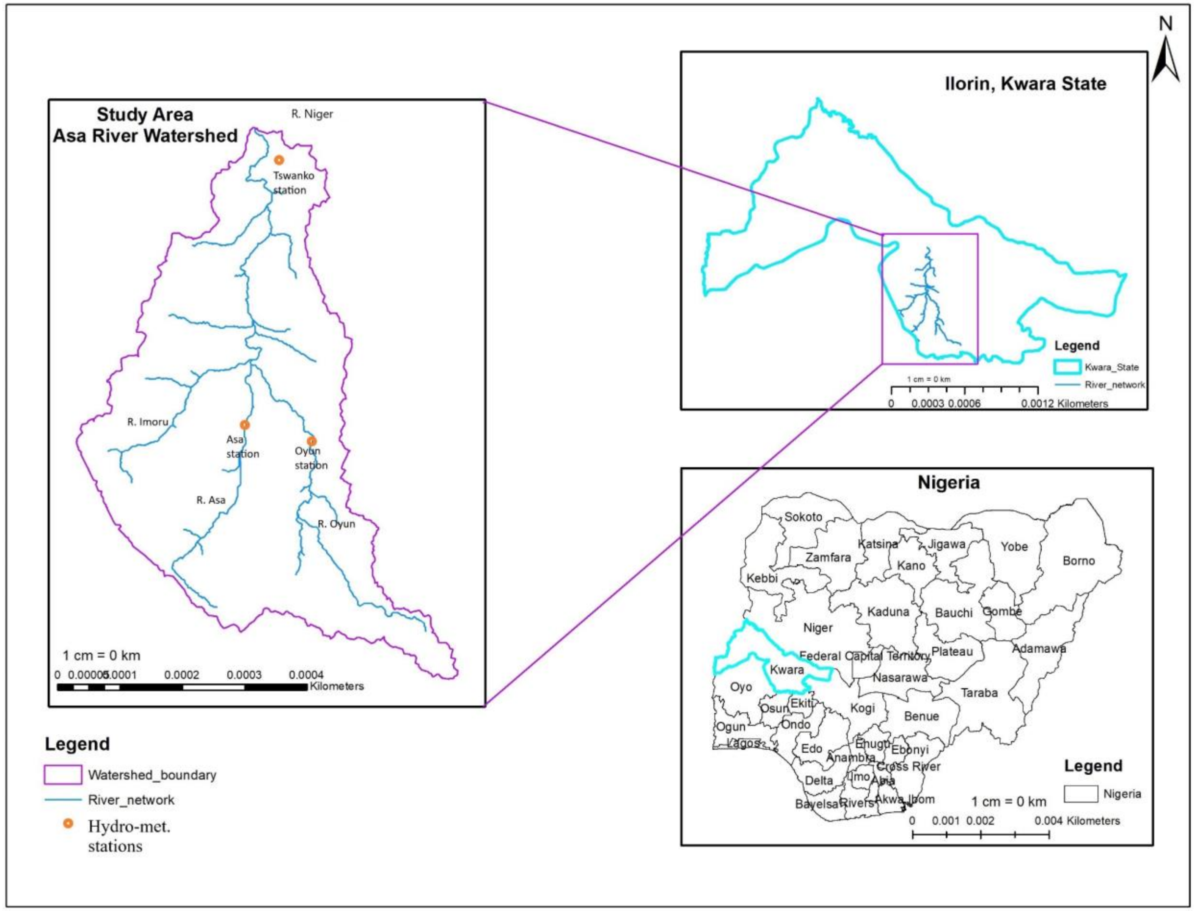


Fig. 2: Asa River Watershed

Asa River

- Location:
  - Ilorin West LGA, Kwara State, Nigeria
  - Lat. 8° 28′ 40.90 N; Long. 4° 34′ 6.60 E
  - 4 km South of Ilorin township
  - Main tributary of River Niger at River Awon estuary
- Total catchment area: 1037 km^2
  - 56 km long; maximum width = 100 m (Ibrahim *et al.*, 2013)
- Significant source of water for agricultural, environmental and economic purposes to locals
- Tributaries: Rivers Agba, Aluko, Odota, Osere, Montile and Atikeke (Ibrahim *et al.*, 2013).

Ibrahim, K. O., Okunlola, I. A. and Abdurrahman, A. (2013). Trace metal indices in the characterization of hydrogeochemical condition of surface water along Asa River, Ilorin, Kwara State, Nigeria. International Journal of Geology, Earth and Environmental Sciences. Vol. 3(1):29-35.

2.2 The Problem *(when it rains, it pours)*

Fig. 3: Rainfall-induced Asa river flood
Source: Saharareporters

- Recurrent perennial river flooding
- Dredging needs, as a result of excessive sediment yield from tributaries
- Residential buildings on floodplains
- Poor maintenance of waterbodies

2.2.1 Aim

- To predict water level elevations of Asa river using Long Short Term Memory and Gated Recurrent Network models with data augmentation

2.3 Methodology

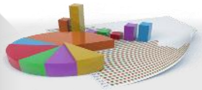
LNRBDA
LOWER NIGER RIVER BASIN DEVELOPMENT AUTHORITY, ILORIN

Datasets (6940)
Streamflow, rainfall and water level data from three stations

Data augmentation through upsampling

Data splitting: Train (80%); Validation (20% of train); and Test (20%)

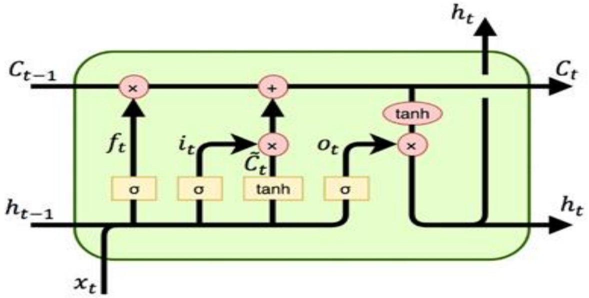
LSTM and GRU modeling
- 1 hidden layer (20 neurons), 2 hidden layers (20 neurons)
- 3 hidden layers (20 neurons)
- 4 hidden layers (20 neurons)



Metrics evaluation and forecasting

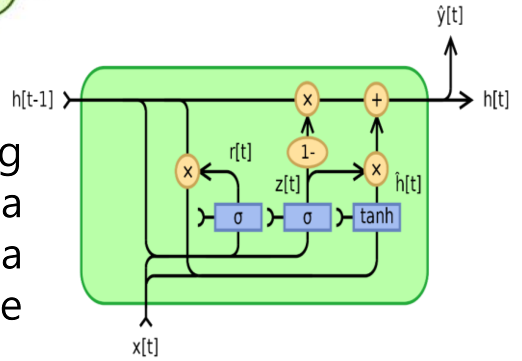
LSTM:

- A type of Recurrent Neural Network (RNN) which learns long term dependencies from time series data using gates and cell state (Hochreiter and Schmidhuber, 1997)



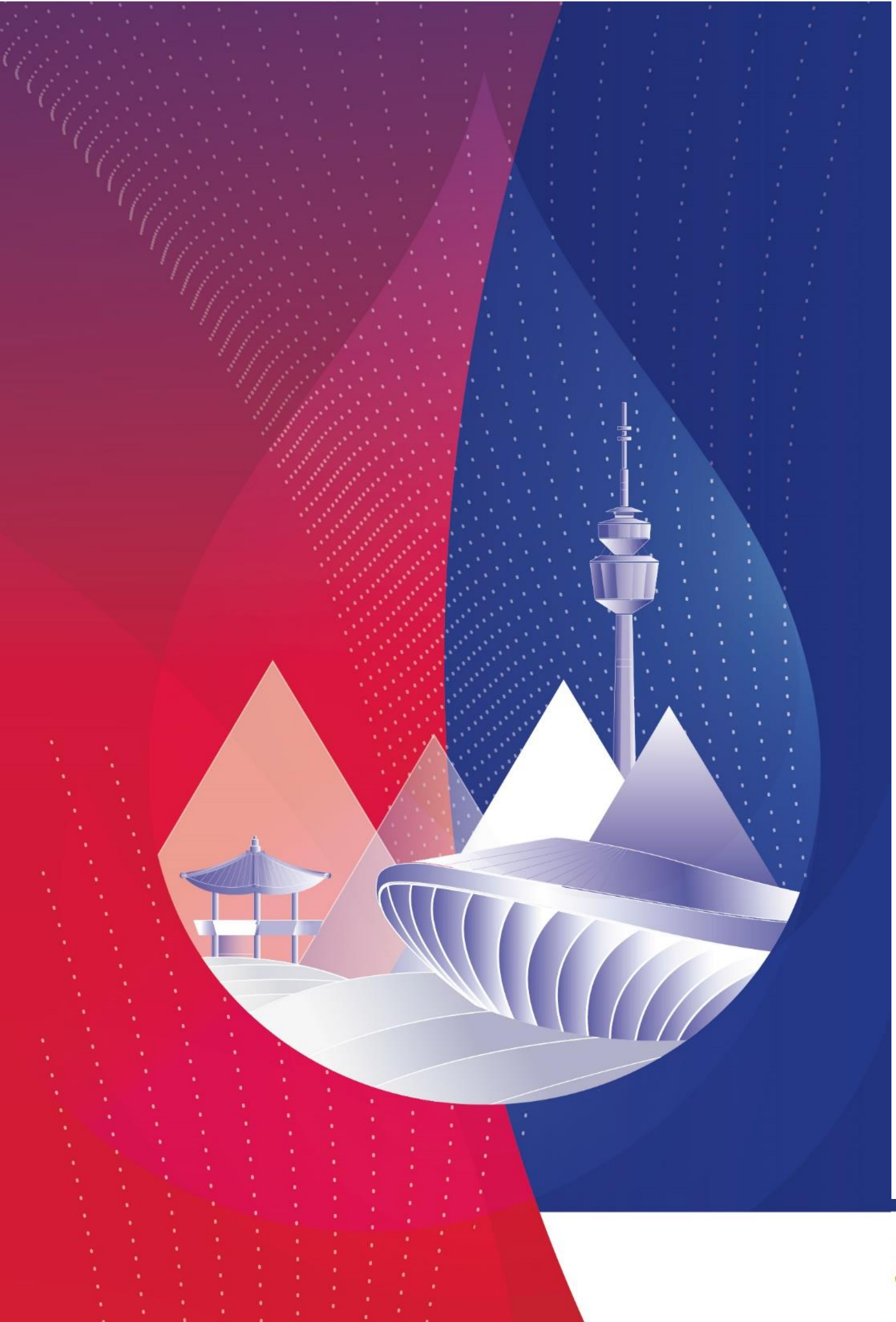
GRU:

- RNN that uses a gating mechanism with a forget gate and has a simpler architecture (Cho *et al.*, 2014)



Hochreiter, S., and Schmidhuber, J. (1997). "Long memory". Neural Computation. 9(8), 1735-1780

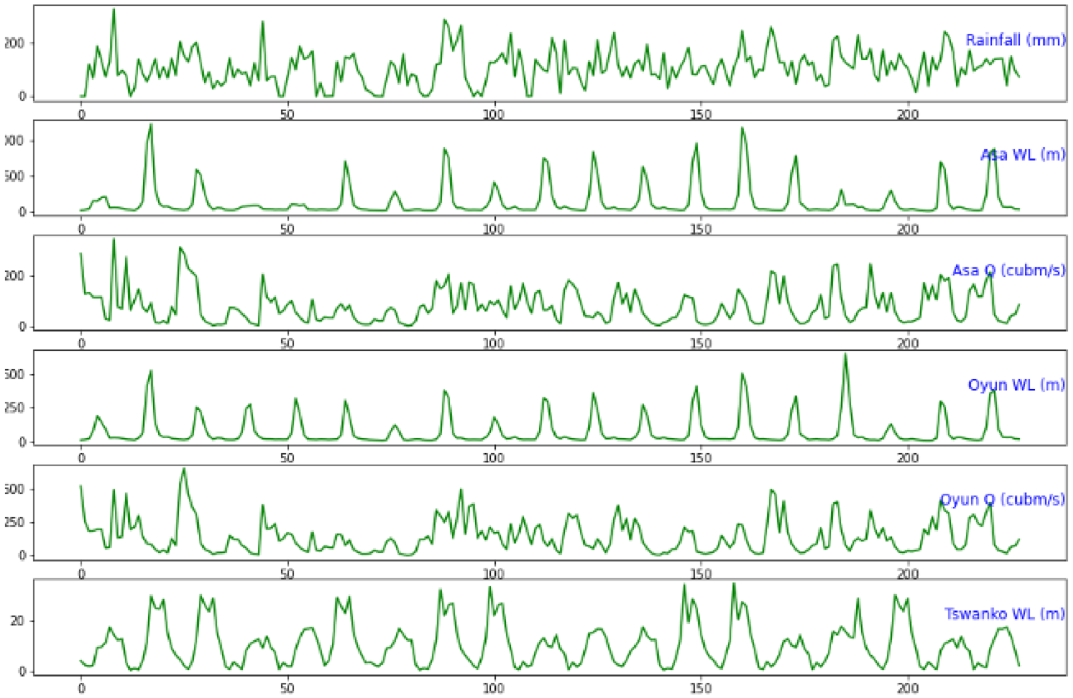
Cho, Kyunghyun; van Merrienboer, Bart; Gulcehre short-term , Caglar; Bahdanau, Dzmitry; Bougares, Fethi; Schwenk, Holger; Bengio, Yoshua (2014). "Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation". arXiv:1406.1078



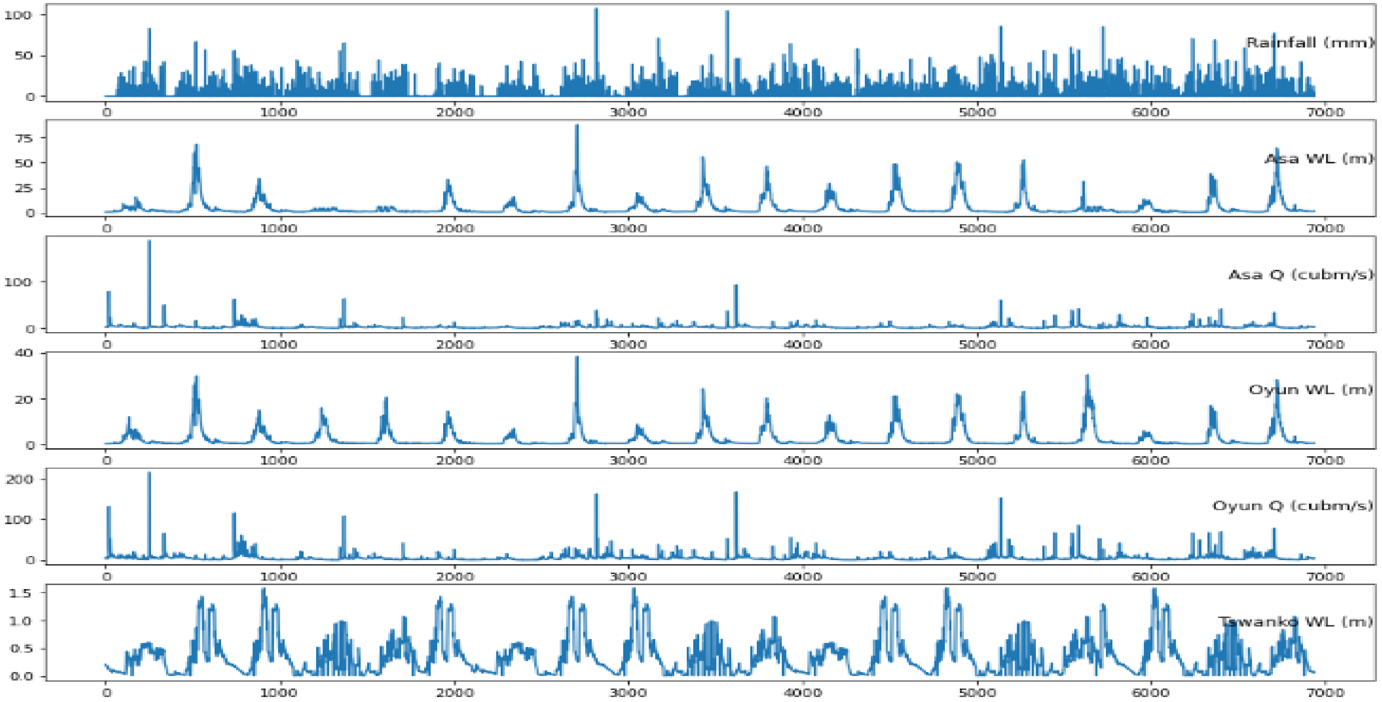
3. Results and Discussion

3.1 DATA UPSAMPLING RESULTS

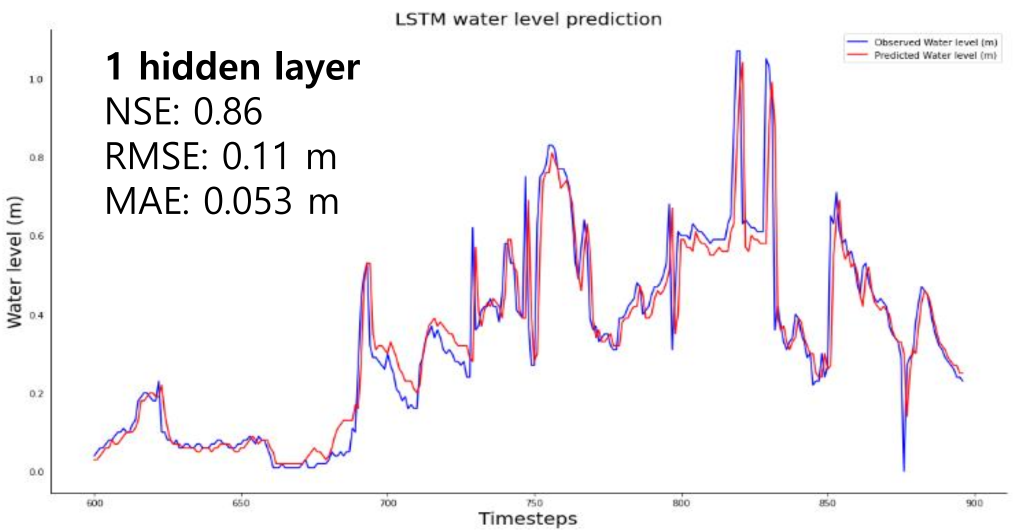
Monthly data

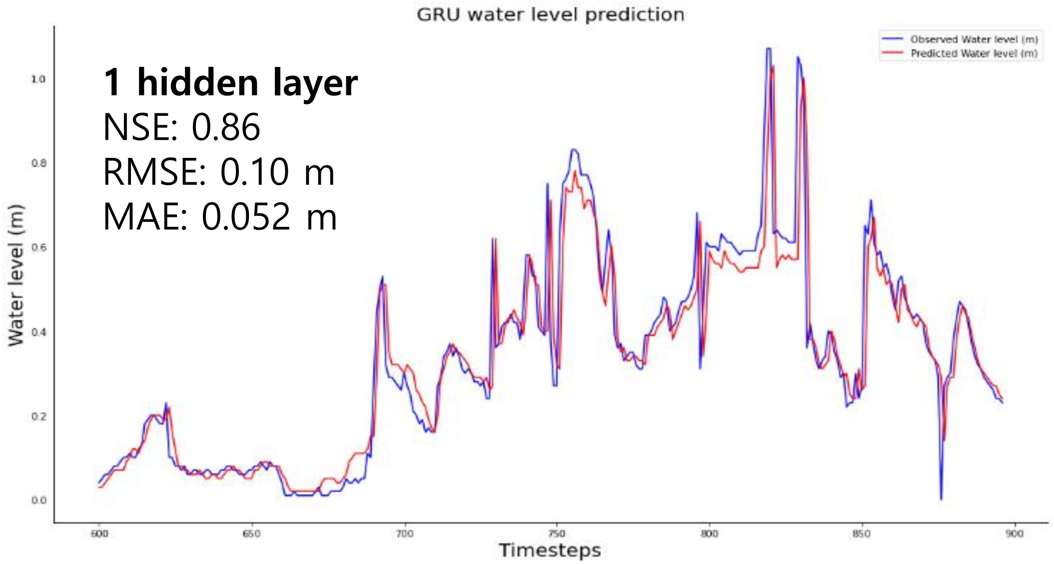


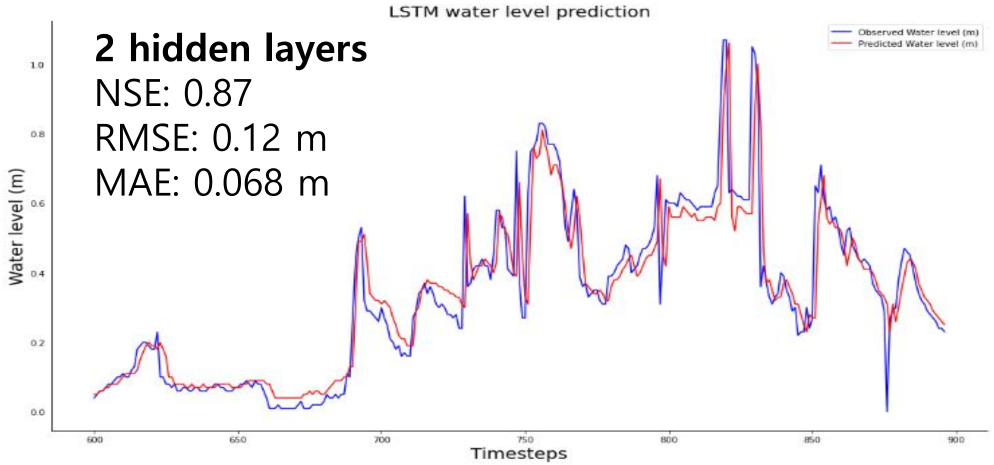
Daily data

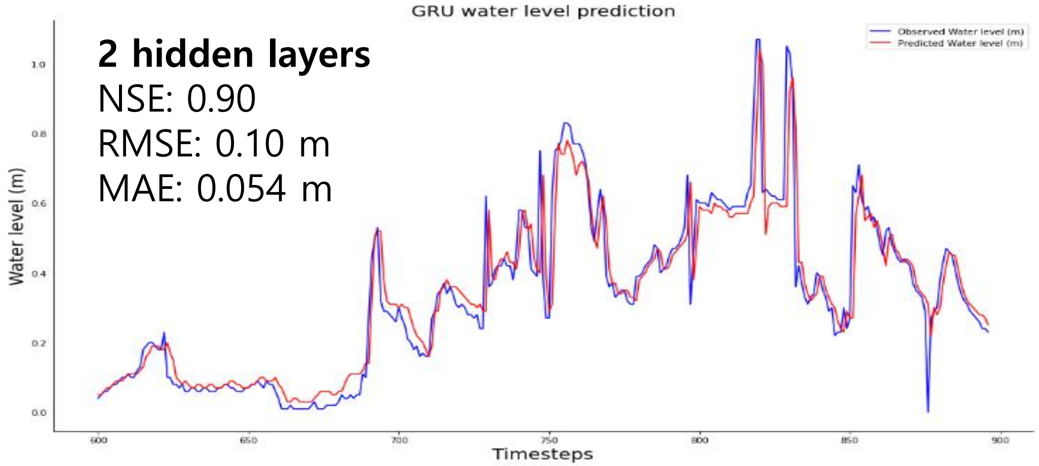


3.2 LSTM and GRU Test Prediction

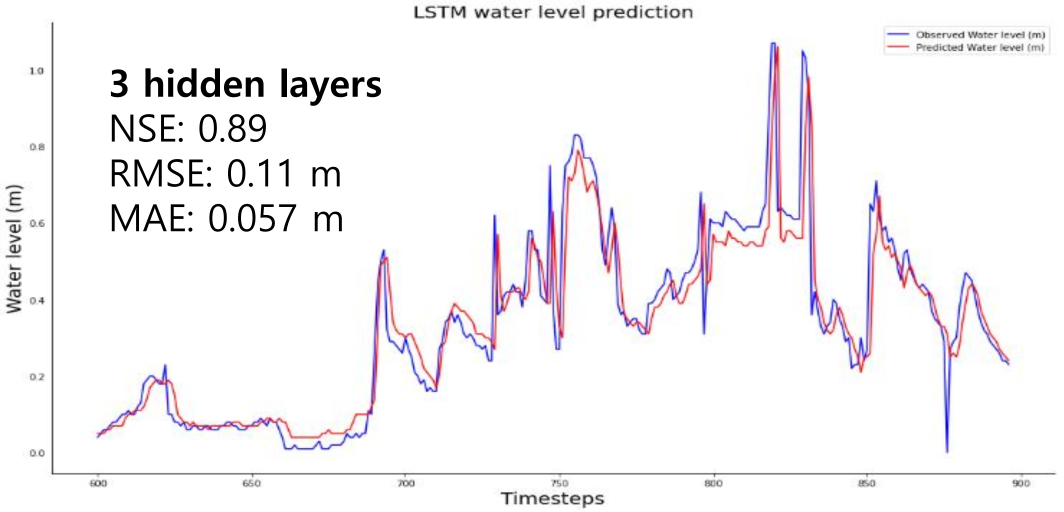


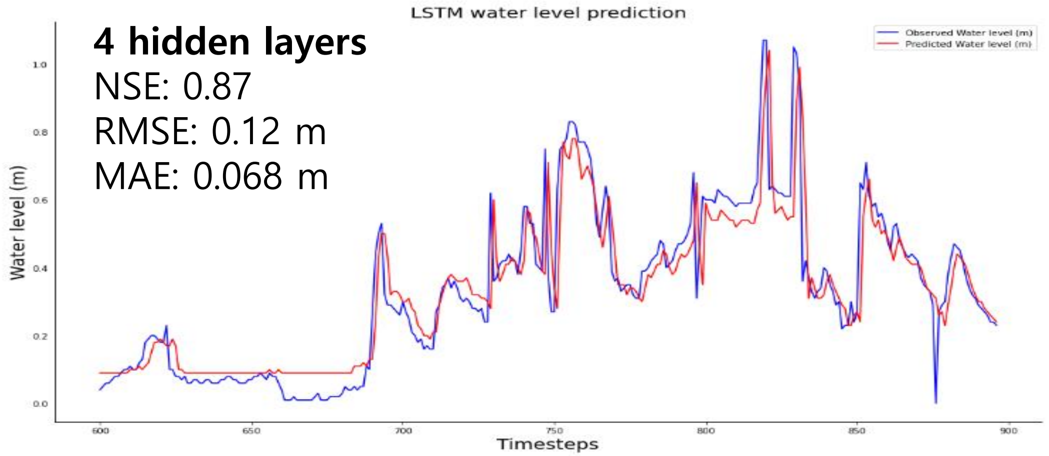


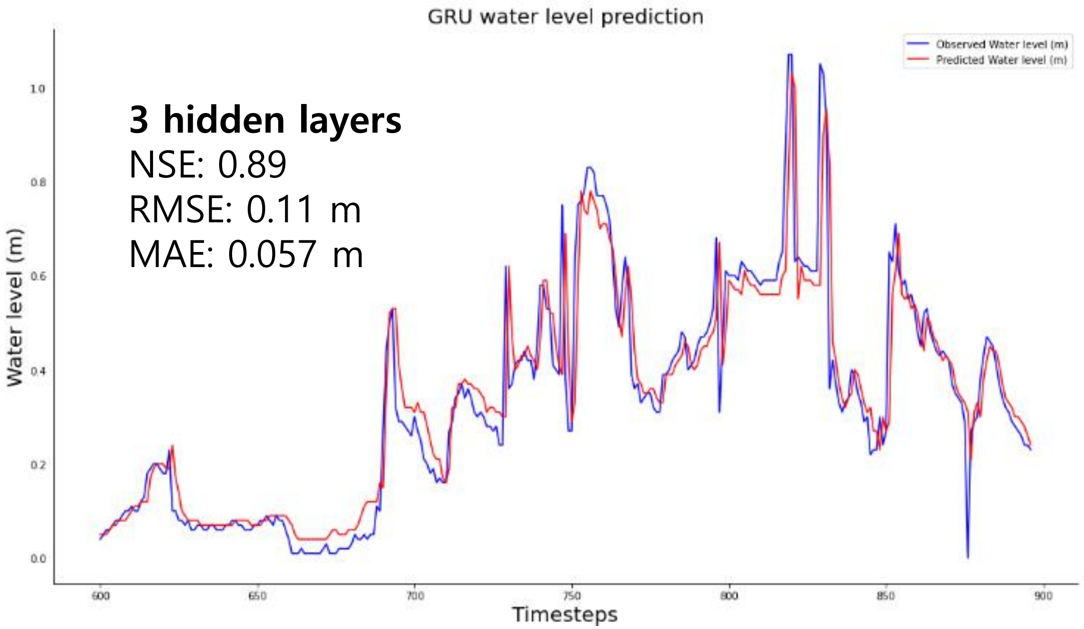


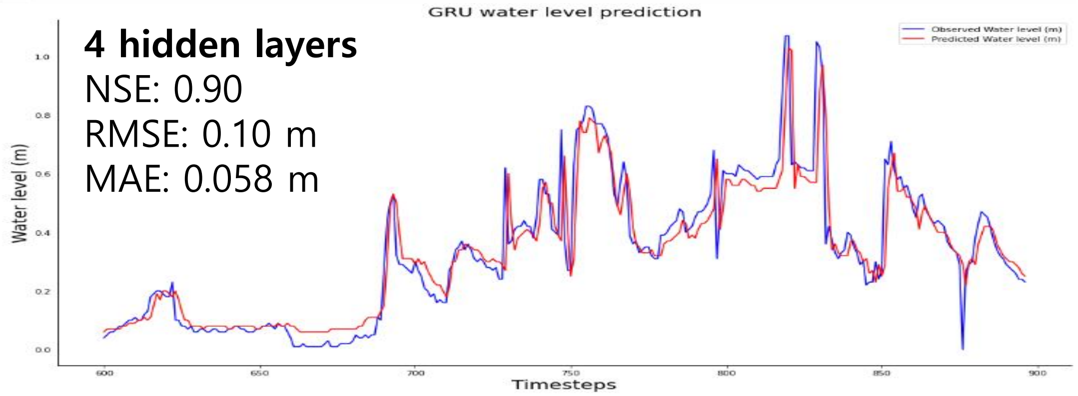


3.3 LSTM and GRU Test Prediction









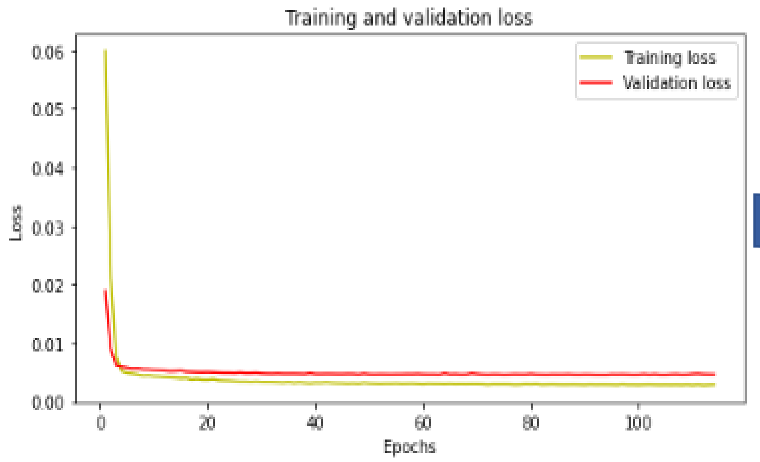
3.4 Computational Cost Analysis

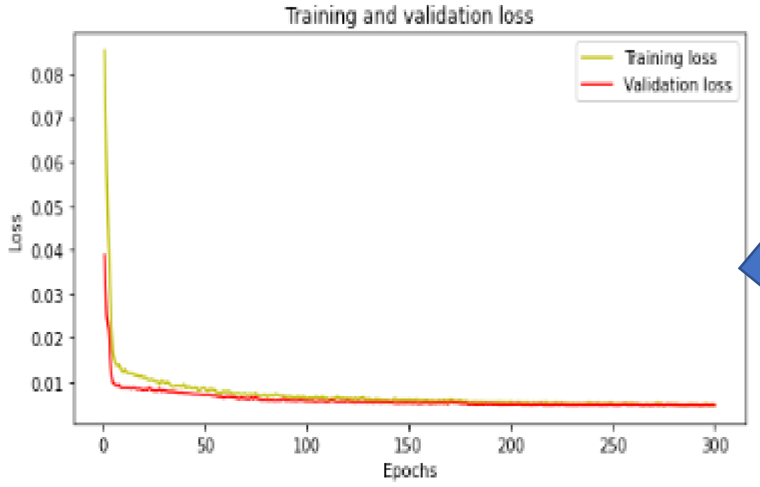
HIDDEN LAYERS	LSTM CC (s)	GRU CC (s)	LSTM Epochs	GRU Epochs
1	25.72	22.58	104	114
2	151.22	115.51	300	162
3	187.55	147.91	300	247
4	196.94	211.30	295	300
Total	561.43 s	497.30	999	823

CC: Computational Cost

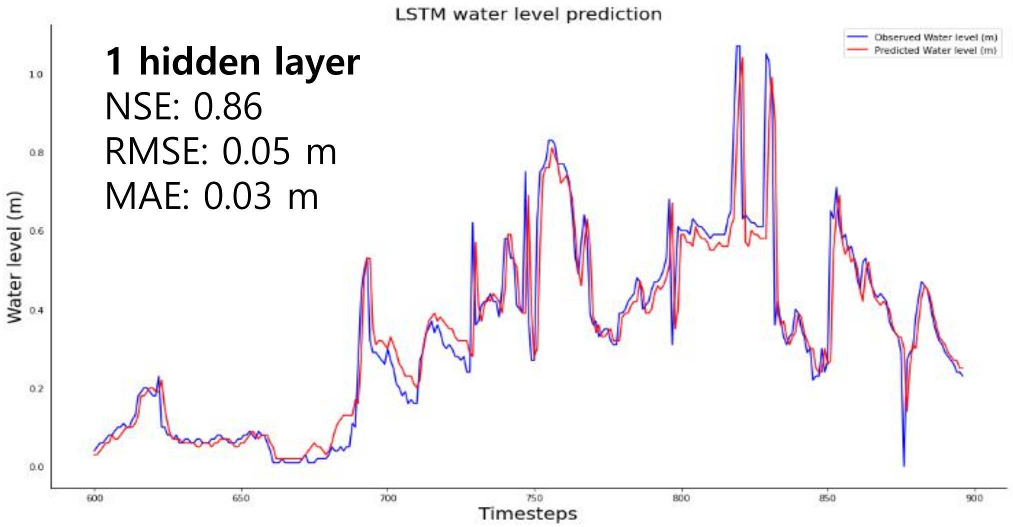
PC specifications:
Intel (R) Core ™ i7 dual core 3.80 GHz, 3.79 GHz processor, 64 GB RAM

Model Loss Evolution

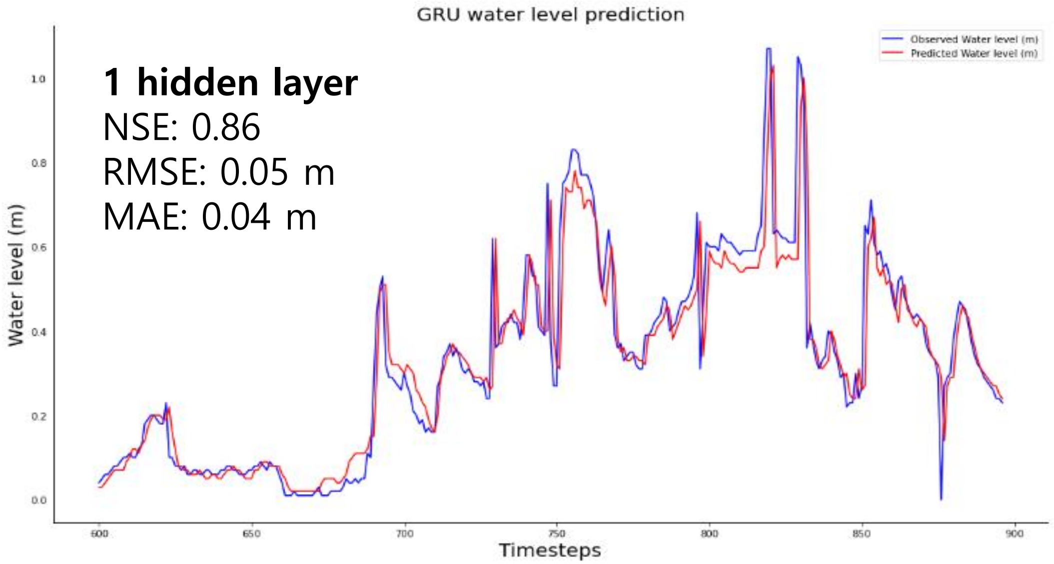




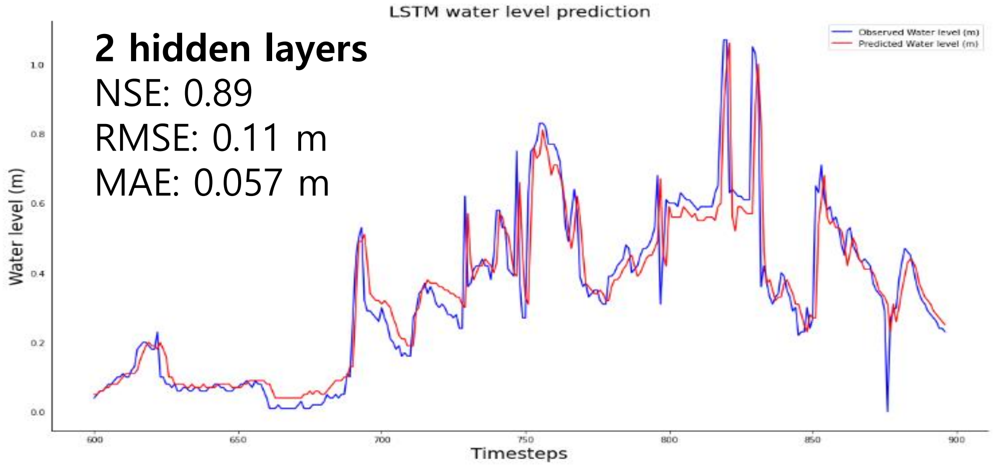
3.5 LSTM and GRU Test Prediction



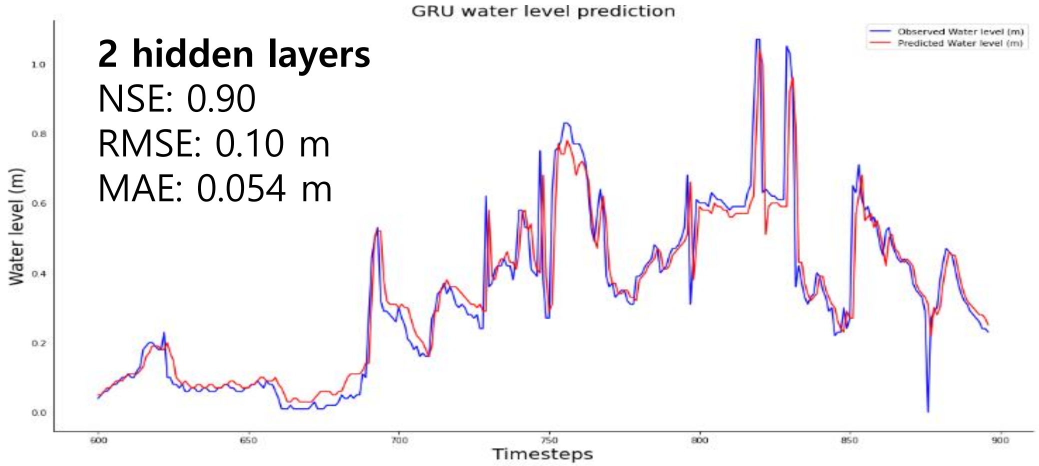
1 hidden layer
NSE: 0.86
RMSE: 0.05 m
MAE: 0.03 m



1 hidden layer
NSE: 0.86
RMSE: 0.05 m
MAE: 0.04 m

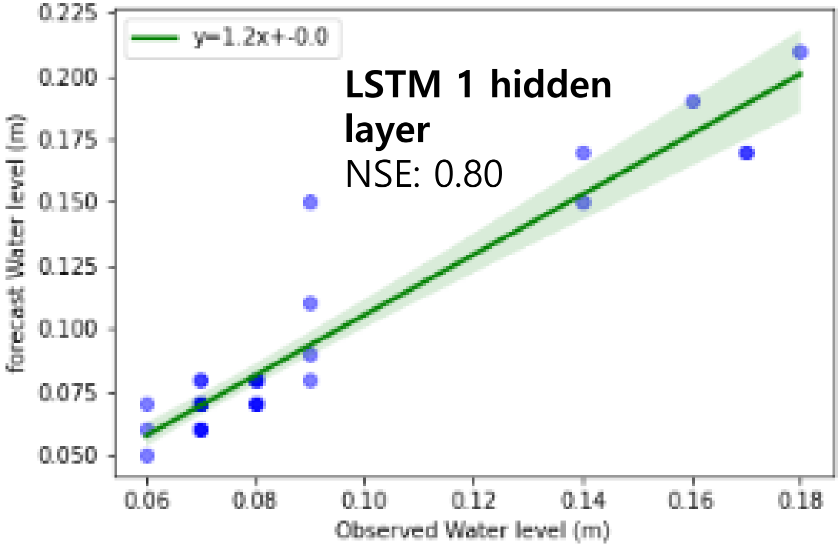


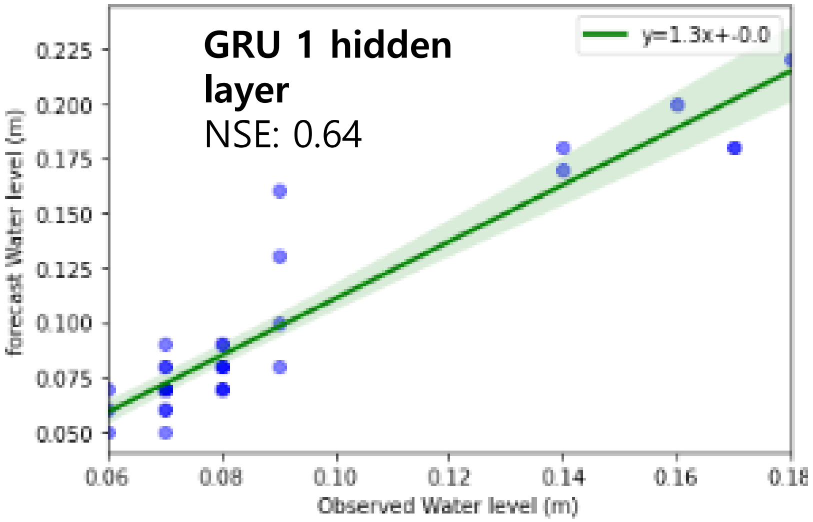
2 hidden layers
NSE: 0.89
RMSE: 0.11 m
MAE: 0.057 m

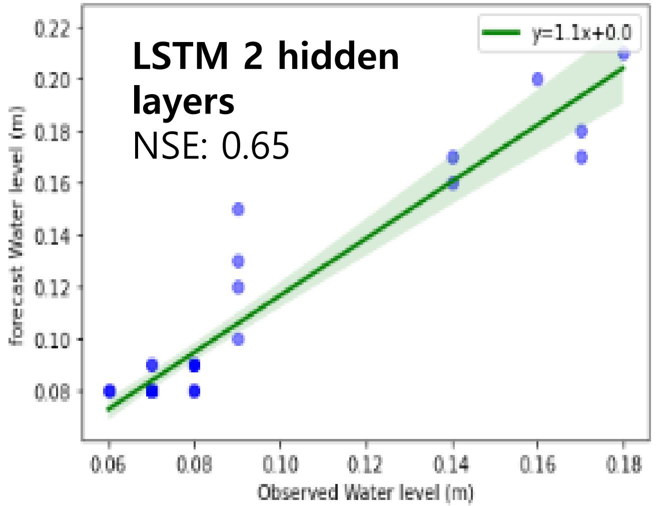


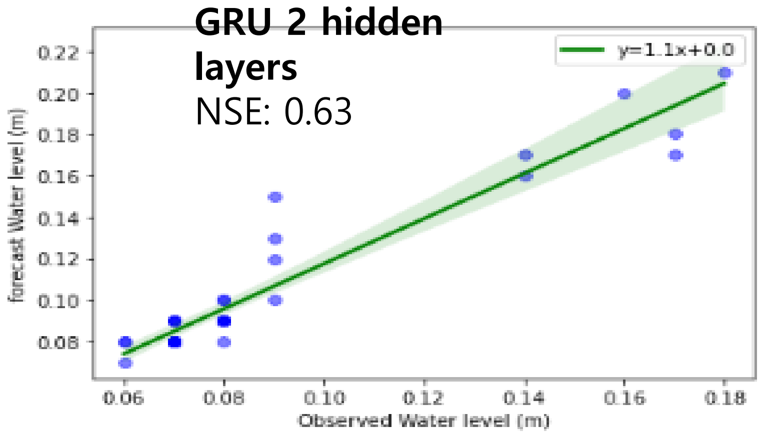
2 hidden layers
NSE: 0.90
RMSE: 0.10 m
MAE: 0.054 m

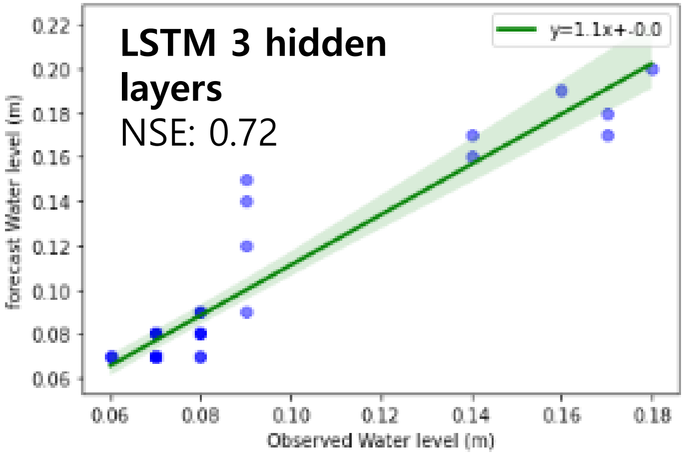
3.6 LSTM and GRU Water Level Forecast for the Next 30 Days

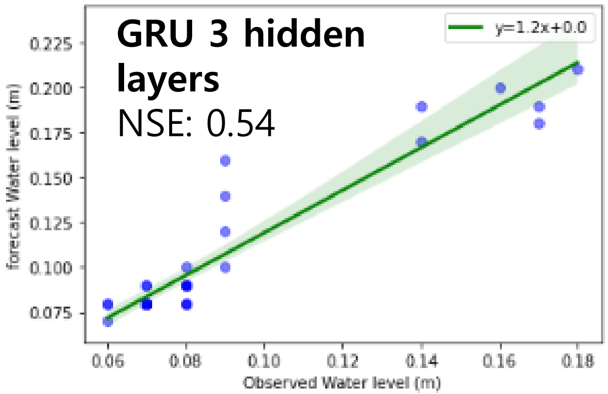




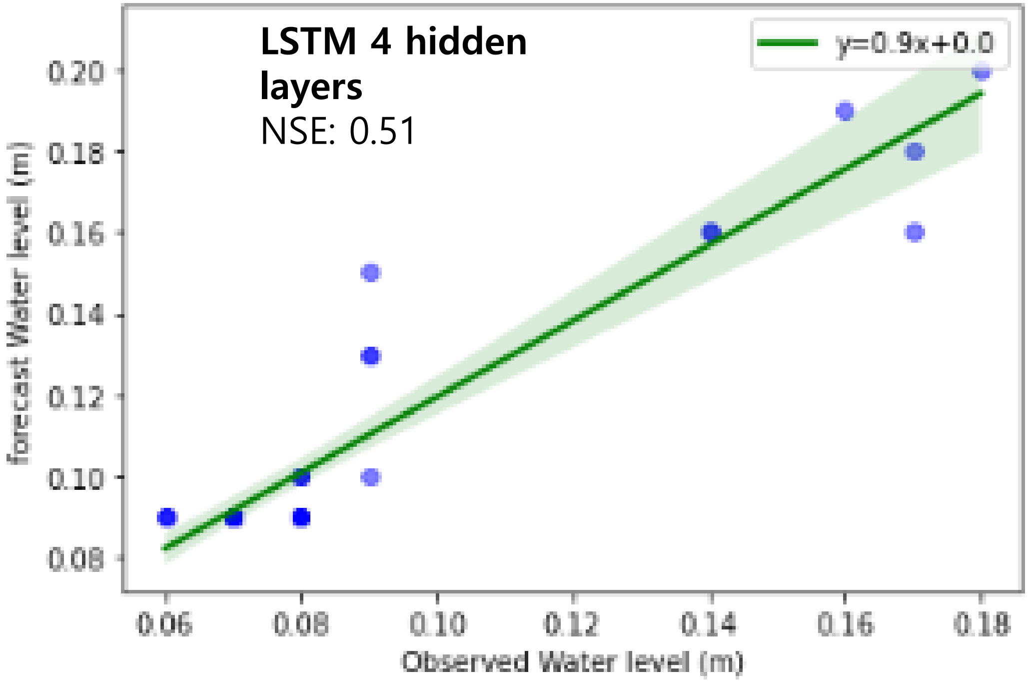


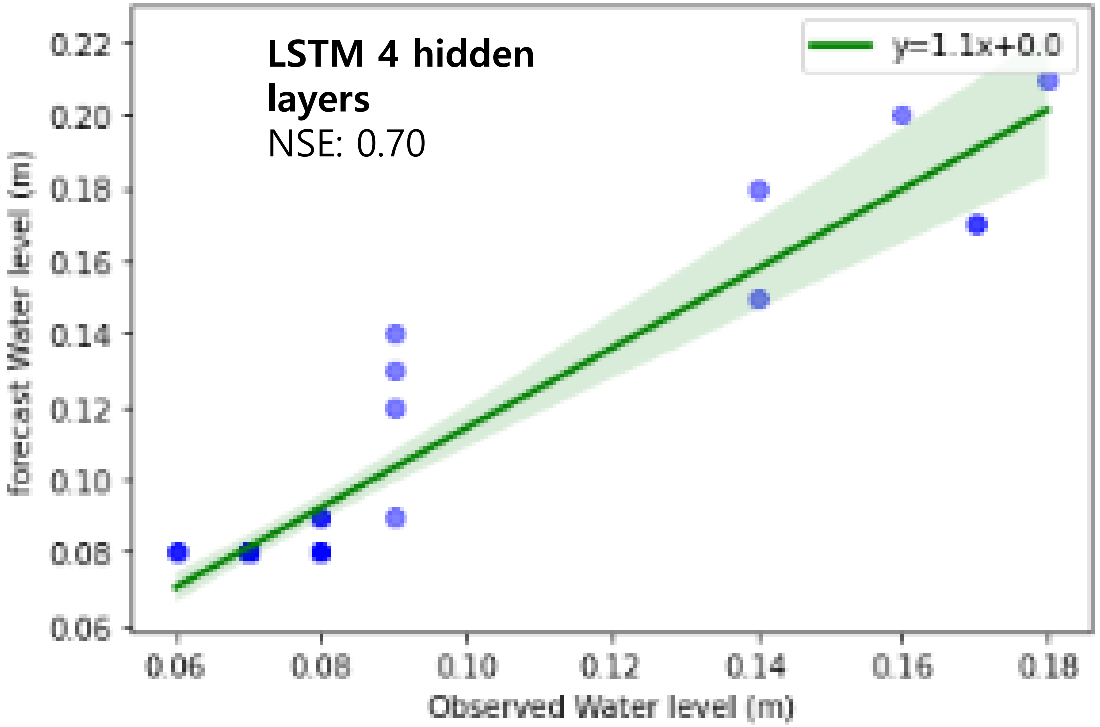






3.6 LSTM and GRU Water Level Forecast for the Next 30 Days





KNU KYUNGPOOK NATIONAL UNIVERSITY

4 Conclusion

- LSTM and GRU models predicted water level optimally using a hidden layer with 20 neurons.
- Results of model forecast show that LSTM model with a single hidden layer and an NSE of 0.80 forecasts water level of Asa river optimally than other deep models.
- Model accuracy reduced with processing time but is still sufficient to quantify water level elevation adequately
- If the goal is to reduce computational cost, GRU models with one hidden neuron may be adopted for the study area.
- If the goal is to achieve better accuracy metrics, LSTM models may be selected
- Developing countries experiencing inadequate data can augment data and employ domain knowledge to implement artificial intelligence.
- Data assimilation and model regionalization can be used in ungauged watersheds rampant in developing countries.

Thank you for listening