A Deep learning based approach in developing temporal & spatially independent irrigation dataset

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SURI

1 Introduction

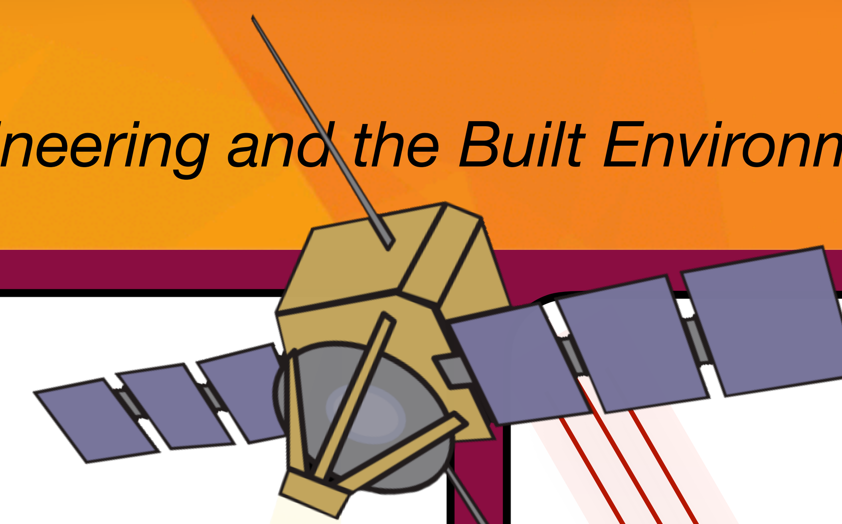
- Groundwater-based irrigation has grown significantly over the past few decades, and this has profound effects on the flow of energy and terrestrial water flow, food production, and the climate.
- In the SURI'22 program, we aimed to estimate the annual irrigation amount using Deep learning methods to integrate "in situ" pumping records, remote sensing products, and climate data in the Kansas High Plains.
- The novelty of the work lies in the strategies we adopted to incorporate both temporal and spatial variables in determining the annual irrigation amount.

Figure 1: Water cycle [6]

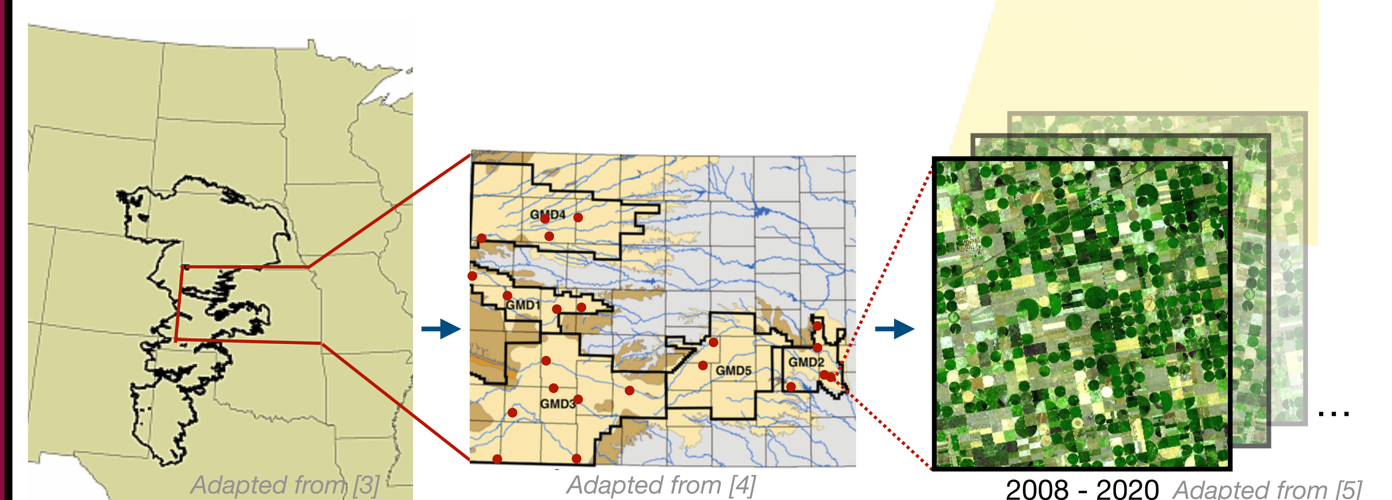
Applications:

- Water cycle is the perpetual movement of water in its various states of matter within the Earth and atmosphere. To model this phenomenon, there are multiple factors such as evapotranspiration, surface runoff, and infiltration which are difficult to quantify. We believe that by accurately estimating the irrigation amount and timing, we can better estimate and quantify other variables in the water cycle equation.

2 Study Area

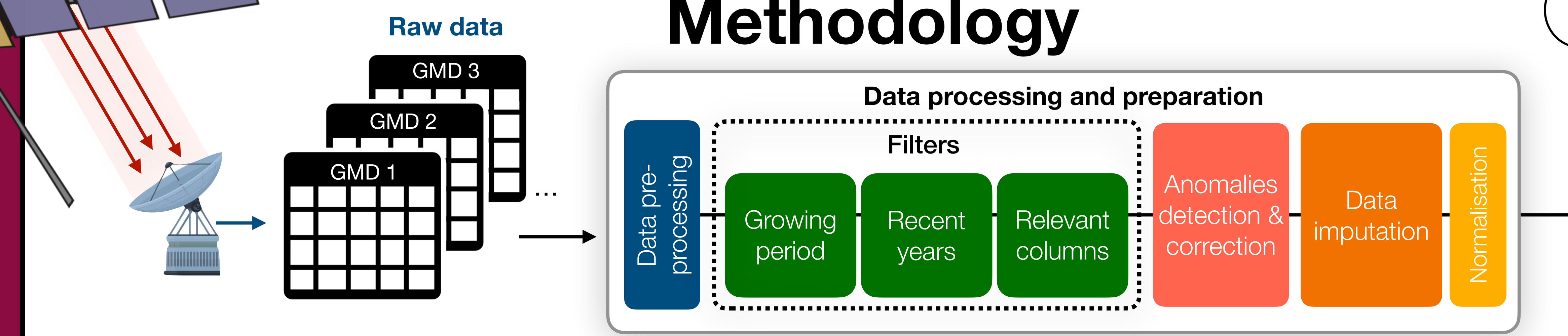


- For this study, the Kansas High Plain Aquifer (HPA) was chosen. The region of study is further classified into 5 regions known as GMDs and contains 24 bases.
- Various data were compiled including hydroclimatic data (precipitation, VPD), land cover, and remote sensing data from MODIS, Landsat, and SENTINEL to quantify vegetation, humidity, precipitation, and ancillary information for each of the 24 base locations, between the years 2008 and 2020 [1].
- Since not all places around the world have the capable high frequency groundwater level measurement systems, our model must be spatially transferable and be able to generate irrigation sequence only with data readily available at CONUS to global scales.
- For this study, we filtered the crop "*Growing period*" (Apr - Oct) and used only the "*Recent years*" (2015 - 2020) for analysis.



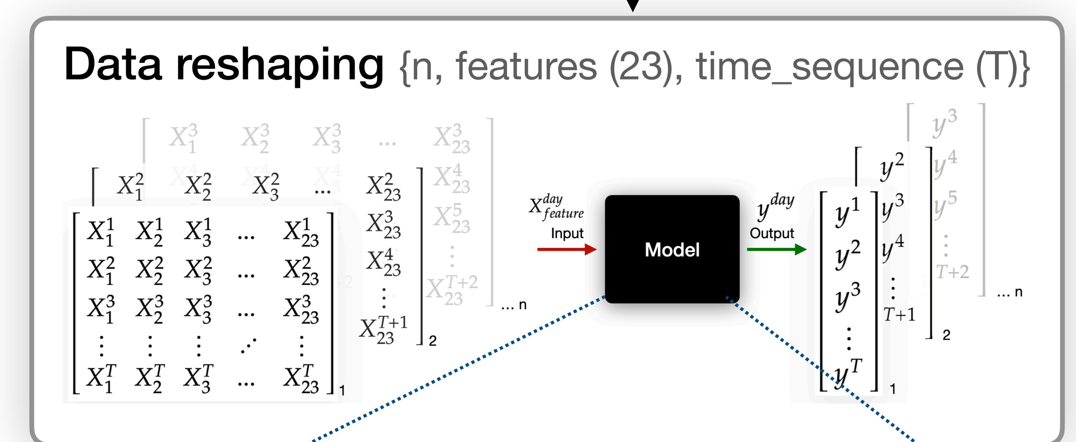
Kansas | **High Plain Aquifer** (HPA) map - 24 bases | **Remote sensing data collection** of 25 locations over 12 years

3 Methodology



Data processing and preparation:

- **Raw data** undergoes basic *data pre-processing*, after which we apply three filters: *Growing period, Recent years, and Relevant columns* (raw satellite features and significant attributes)
- Then, the anomalies of the label is rectified using a custom procedure and the missing data is imputed.
- Finally, after normalising the data, we can reshape it to be passed into the Transformer architecture.

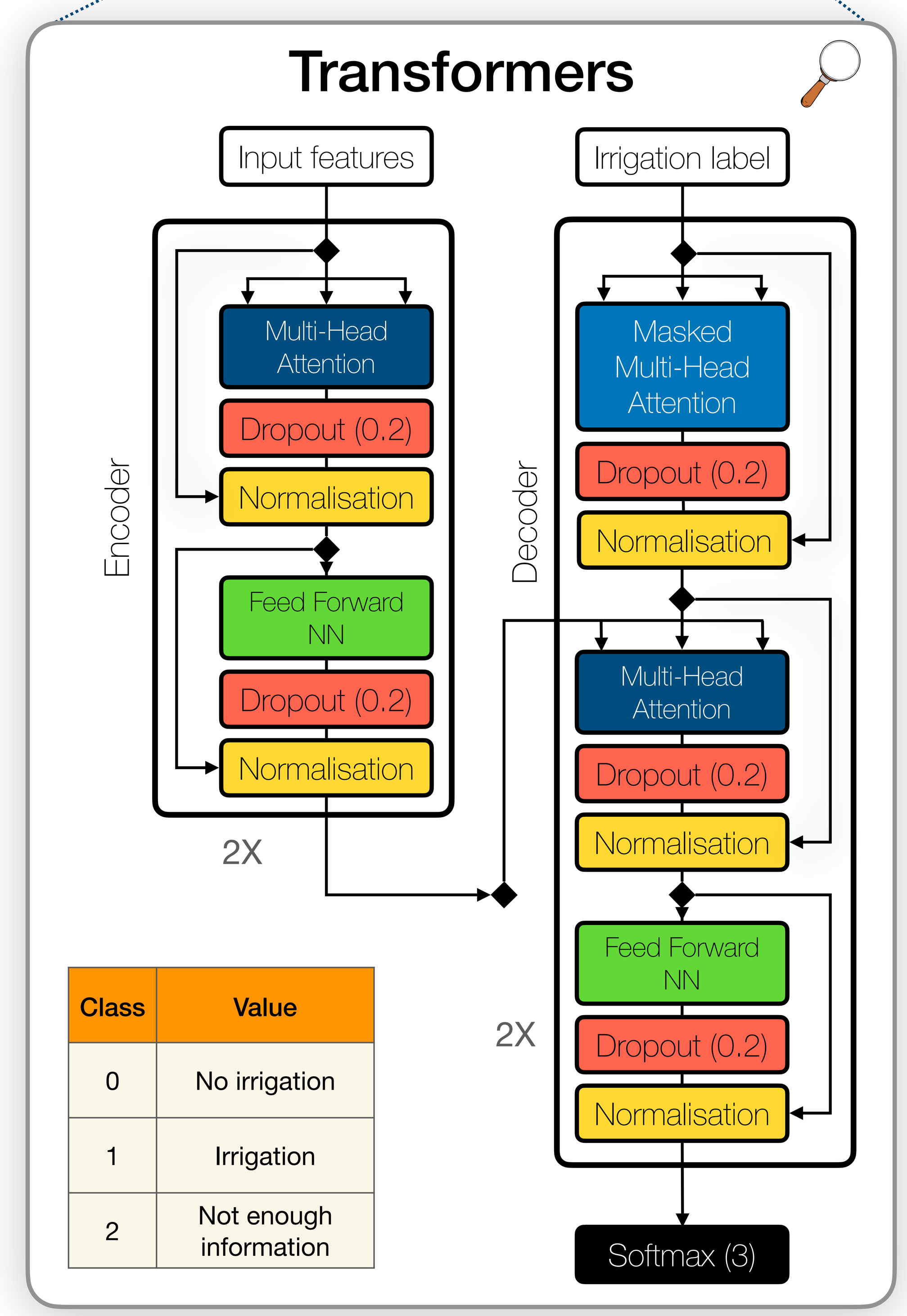


Input and output (data reshaping):

- The data was prepared using a moving window of Time sequence = T. Hence, the input is a 3D-tensor with "n" rows containing "T" time sequences and 23 features (n, T, 23). The output is also a 3D-tensor with "n" rows containing "T" time sequences (n, T, 1).

Transformers:

- lrate $= d^{-0.5} \cdot min(\text{step num}^{-0.5}, \text{step num} \cdot \text{warmup steps}^{-1.5})$ [2]
- The softmax output represents the probability distribution of the three classes (0, 1, 2) for "T" time sequences.



Class	Value
0	No irrigation
1	Irrigation
2	Not enough information

Results:

The Loss unfortunately does not converge to minimum over 500 epochs as of the final week of SURI'22 program, and we are in the process of rectifying this. Hence, the model accuracy appears to fluctuate randomly. After refining and debugging the code, we are hoping to acquire better performance and results.

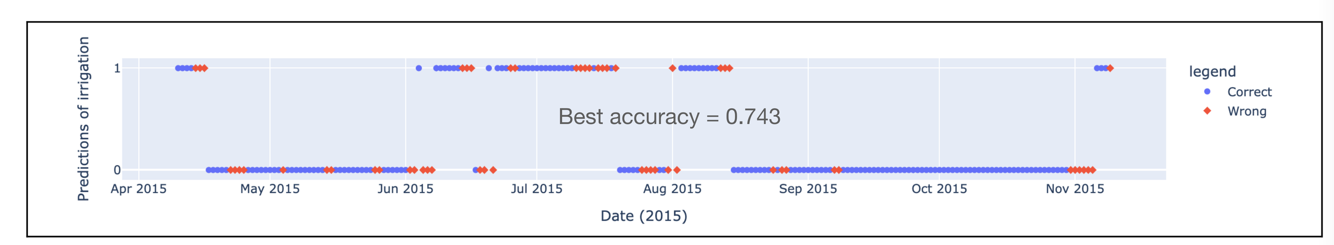


Figure 2: Prediction of irrigation in 2015

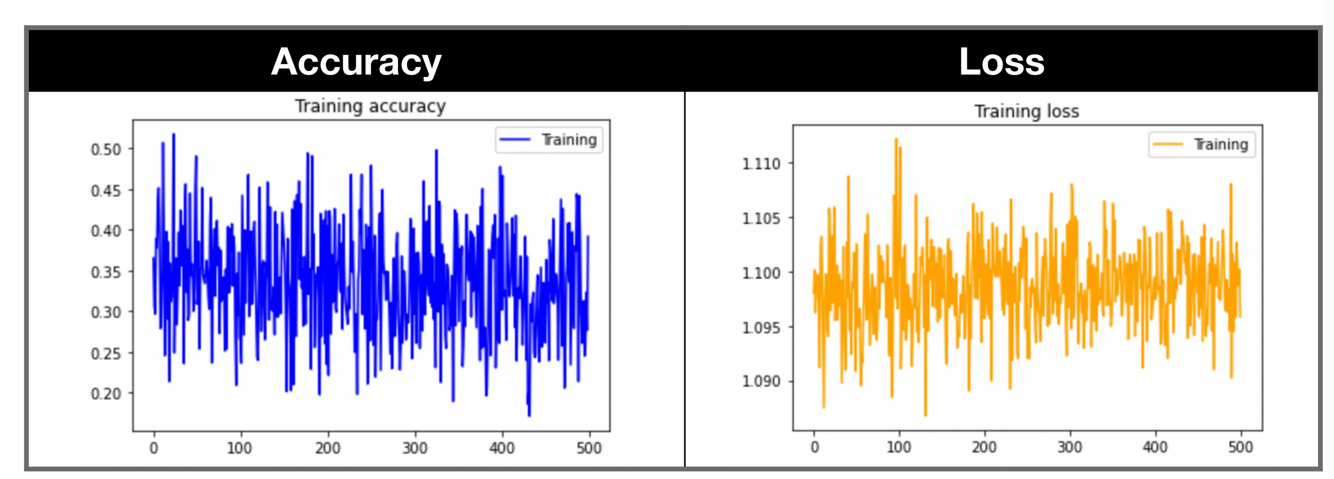
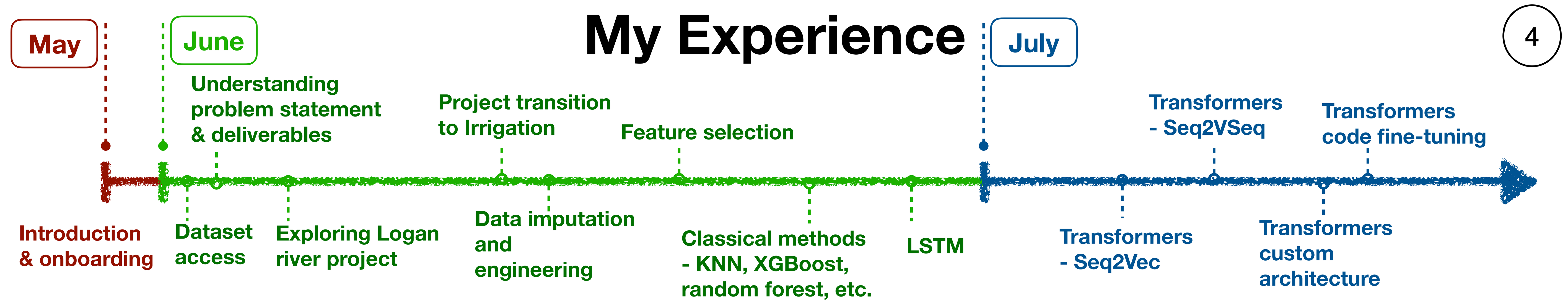


Figure 3: Accuracy and Loss of Transformers

4 My Experience



Although I applied for "Logan river" project, I transitioned into "Irrigation" after realising the profound real-world impact I can impart on the community in doing this project. Over the past 8 weeks, I have conducted many experiments in pursuit to creating a spatially and temporally independent model that can accurately predict the annual irrigation amount using remote sensing data. I encountered many challenges along the way, but with the constant support and guidance from **Dr. Xu** and PhD student **Shiqi Wei**, I was able to address them systematically, and think creatively around the problems. Our work is not yet complete, and we are continually working towards refining our model. By working with people from various backgrounds and interdisciplinary domains, the SURI program has provided me with an opportunity to gain international exposure, learn and contribute to ongoing research in applications of Deep learning in Hydrology. I am grateful and glad to have been a part of it. I hope that you enjoyed reading about my work as much as I loved doing it!