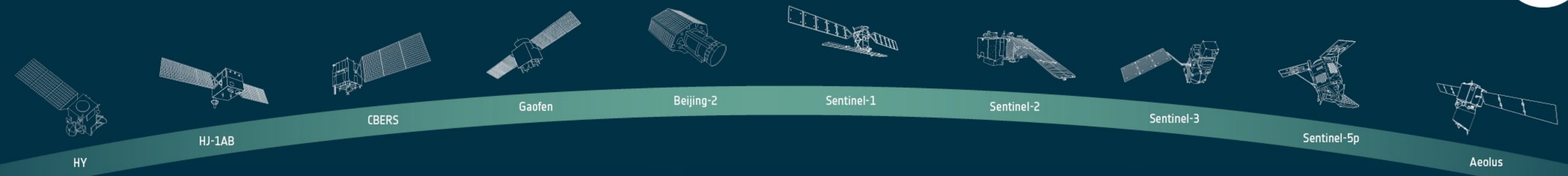



# 2022 DRAGON 5 SYMPOSIUM

## MID-TERM RESULTS REPORTING

17-21 OCTOBER 2022

**[PROJECT ID. 59308]**

[SEISMIC DEFORMATION MONITORING AND ELECTROMAGNETISM ANOMALY DETECTION BY BIG SATELLITE DATA ANALYTICS WITH PARALLEL COMPUTING (SMEAC)]

# Dragon 5 Mid-term Results Project

< Thursday, 20/Oct/2022>

**ID. 59038**

**PROJECT TITLE: SEISMIC DEFORMATION MONITORING AND ELECTROMAGNETISM ANOMALY DETECTION BY BIG SATELLITE DATA ANALYTICS WITH PARALLEL COMPUTING (SMEAC)**


**PRINCIPAL INVESTIGATORS: [DR YAXIN BI, PROF JIANBO SUN]**

**CO-AUTHORS: [PROF XUEMIN ZHANG, PROF MINGJU HUANG, DR CECILE LASSERRE]**

**PRESENTED BY: [DR YAXIN BI]**

- The project's objectives
- Detail the ESA, Chinese and ESA Third Party Mission data utilised after 2 years
- Inform on the results after 2 years of activity
  - ✓ Predicting the Swarm data with the application of DL techniques
  - ✓ Investigating the longest period of time for which we are able to predict the Swarm data
  - ✓ Studying the data framing impact on predicting the Swarm data
  - ✓ Applying two conventional machine learning techniques to detect anomalies from the predicted Swarm data
- Publications and planning
- Plan for academic exchanges

# Background: objectives

- The project aims to develop and apply innovative data analytic methods underpinned with deep learning technology to analyze and detect seismic anomalies from electromagnetic data observed by the SWARM and CSES satellites along with CSELF network. The objectives are
  - ✓ Characterise electromagnetic signals and variations of signal spectrums by features; characterise abnormal signal patterns detected from electromagnetic data, which are likely related to earthquakes.
  - ✓ Improve the performance of the anomaly detection algorithms previously developed and scale up data analysis using these algorithms.
  - ✓ Develop more sophisticated anomaly detection algorithms based on deep machine leaning
  - ✓ Use the new algorithms to analyse the Swarm, CSES and CSELF data
  - ✓ Discover electromagnetic signatures detected before earthquakes from the ground to the ionosphere.
  - ✓ Perform correlation analysis between anomalies and large earthquakes in depth, identify times of anomalies appearing before, during and after earthquakes, anomaly cycles and time they last.

# EO Data Delivery

Data access (list all missions and issues if any). NB. in the tables please insert cumulative figures (since July 2020) for no. of scenes of high bit rate data (e.g. S1 100 scenes). If data delivery is low bit rate by ftp, insert "ftp"

| ESA Third Party Missions | No. Scenes |
|---|---|
| 1. | |
| 2. | |
| 3. | |
| 4. | |
| 5. | |
| 6. | |
| Total: | |
| Issues: | |

| ESA Third Party Missions | No. Scenes |
|---|---|
| 1. Swarm satellite data | |
| 2. Sentinel 1 | |
| 3. | |
| 4. | |
| 5. | |
| 6. | |
| Total: | |
| Issues: | |

| Chinese EO data | No. Scenes |
|---|---|
| 1. CSES satellite data | |
| 2. CSELF network | |
| 3. | |
| 4. | |
| 5. | |
| 6. | |
| Total: | |
| Issues: | |

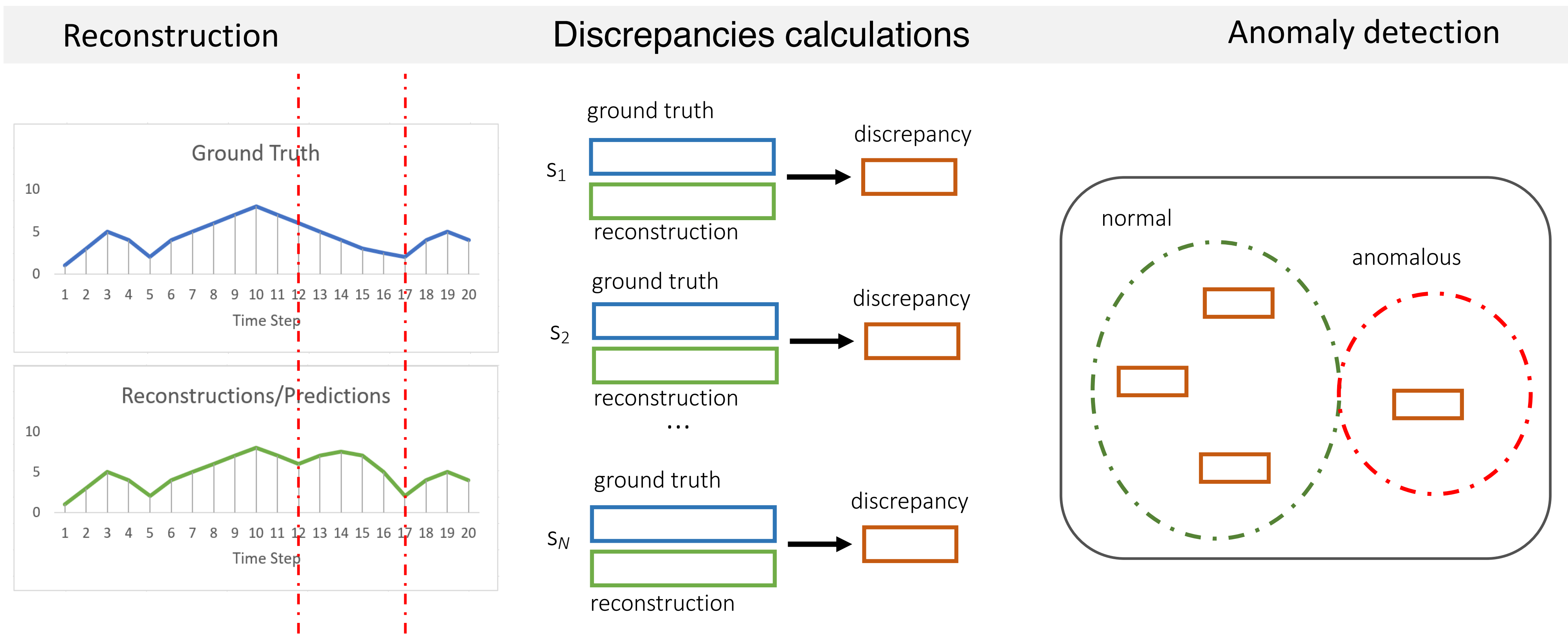
# European Young scientists contributions in Dragon 5

| Name | Institution | Poster title | Contribution |
|---|---|---|---|
| Ms Maja Pavlovic | Ulster University | Long-short Term Memory Neural Network for Pre-earthquake Geomagnetic Anomaly Detection From Principal Component Time Series | First author (223) |
| Dr Wei Zhai | Gansu Earthquake Agency; Ulster University | Recognition and Assessment of Building Damage in Earthquake-stricken Areas Using Post-earthquake Sentinel-1 SAR images | First author (157) |
| Mr Christopher O'Neill | Ulster University | | |

# Chinese Young scientists contributions in Dragon 5

| Name | Institution | Poster title | Contribution |
|---|---|---|---|
| Mr Xiaohui Du | Institute of Earthquake Forecasting, China Earthquake Administration; Wuhan University | Statistical Analysis of Electron Density Disturbances in the Ionosphere Caused by Earthquakes Using China Seismo-Electromagnetic Satellite | First author (226) |
| Mr. Yulin Zhou | Institute of Earthquake Forecasting, China Earthquake Administration | | |
| Miss Bing Han | Institute of Geology, China Earthquake Administration | | |

# Deep Learning Approaches for Prediction and Anomaly Detection



# Why Recurrent Neural Networks (RNN)

- Given vectors *x*, they can be processed by applying a recurrence formula of RNN at every time step:

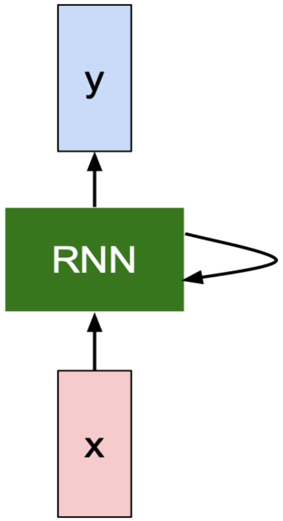
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

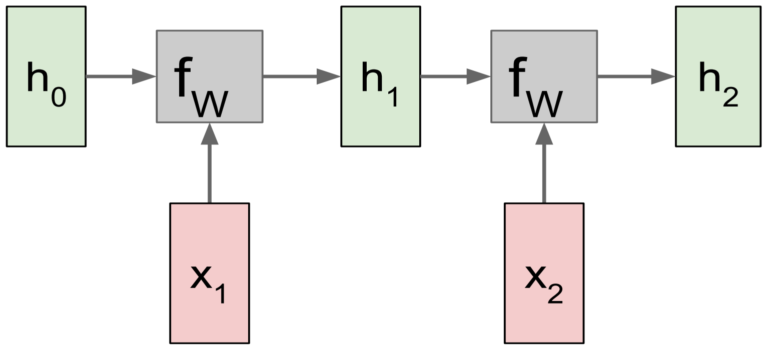
new state

old state

input vector at some time step

some function with parameters W




- The same function and the same set of weights and bias are used at every time step.

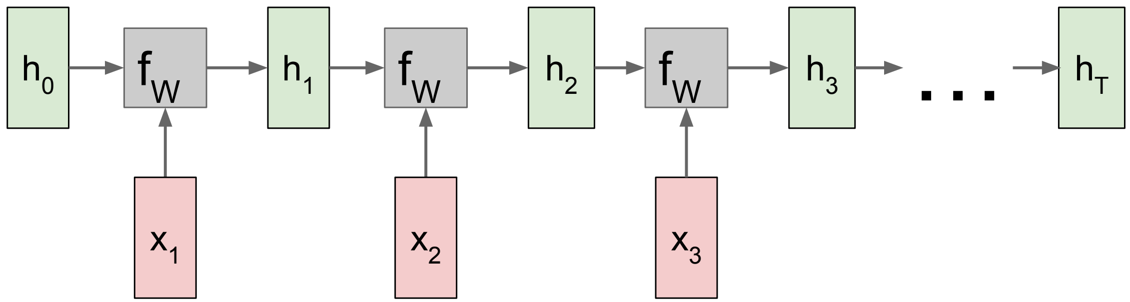
# Why Recurrent Neural Networks (RNN) (cont'd)

- In a Simple Vanilla RNN, the state consists of a single "hidden" vector $h_t$:

$$h_t = f_W(h_{t-1}, x_t)$$

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

$$y_t = W_{hy}h_t$$



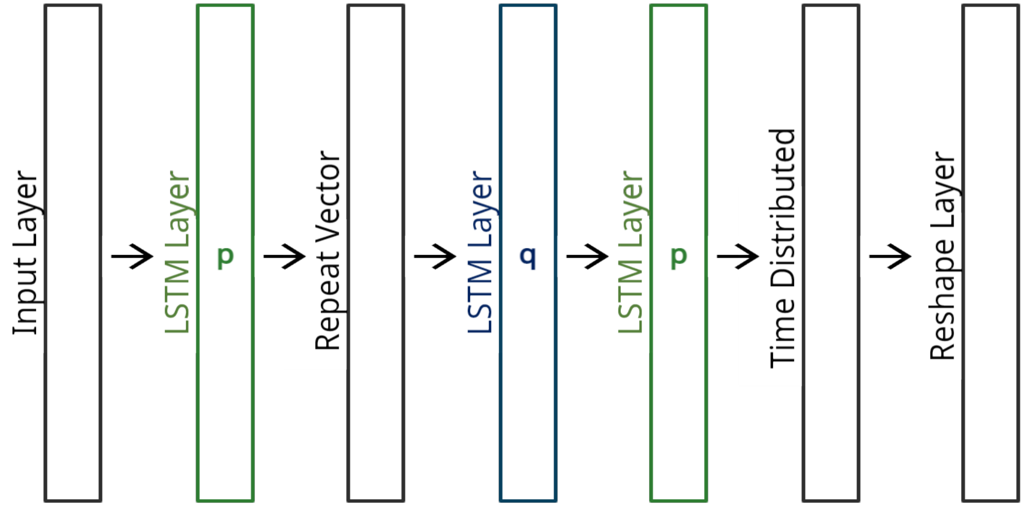

where the activation function is **tanh**, the weight at the recurrent neuron is $W_{hh}$ and the weight at the input neuron is $W_{xh}$, the output state is $y_t$.

# Issues with RNN

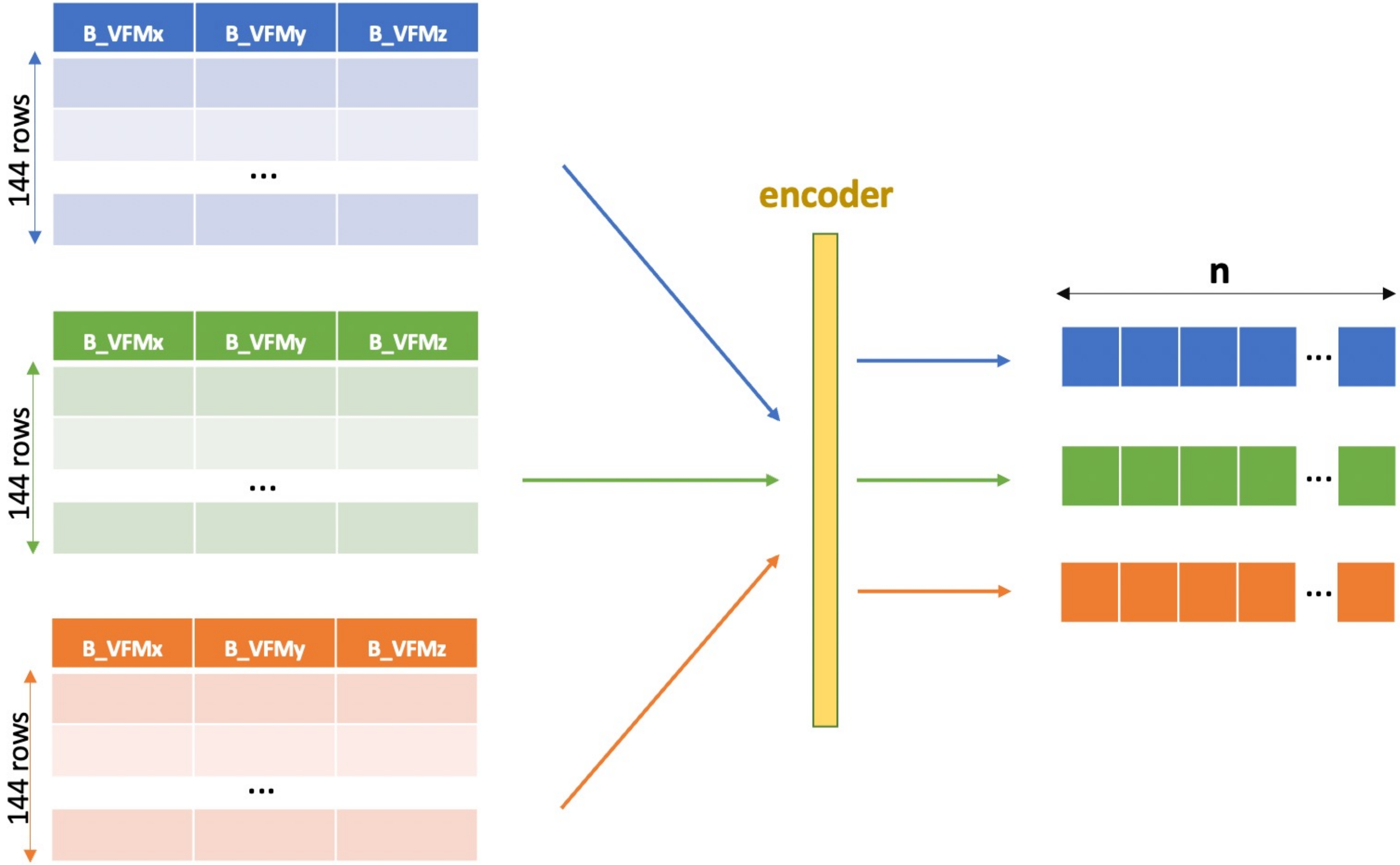
- In theory, RNNs are capable of handling “long-term dependencies”, i.e. through carefully picking parameters for them. Unfortunately, it is not practical to manually picking parameters, RNNs don’t seem to be able to learn them.
- Long-Short Term Memory networks (LSTMs) – are a special kind of RNNs, capable of learning long-term dependencies.
- LSTMs are designed with the following features to handle the long-term dependency problem:
  - ✓ Repeating modules (neurons) with very simple structure such as a single tanh layer
  - ✓ Remembering information for long periods of time as their default behavior, which is not something they struggle to learn
- They work tremendously well on handling time series data, which are now widely used.

# Design of LSTM Layers

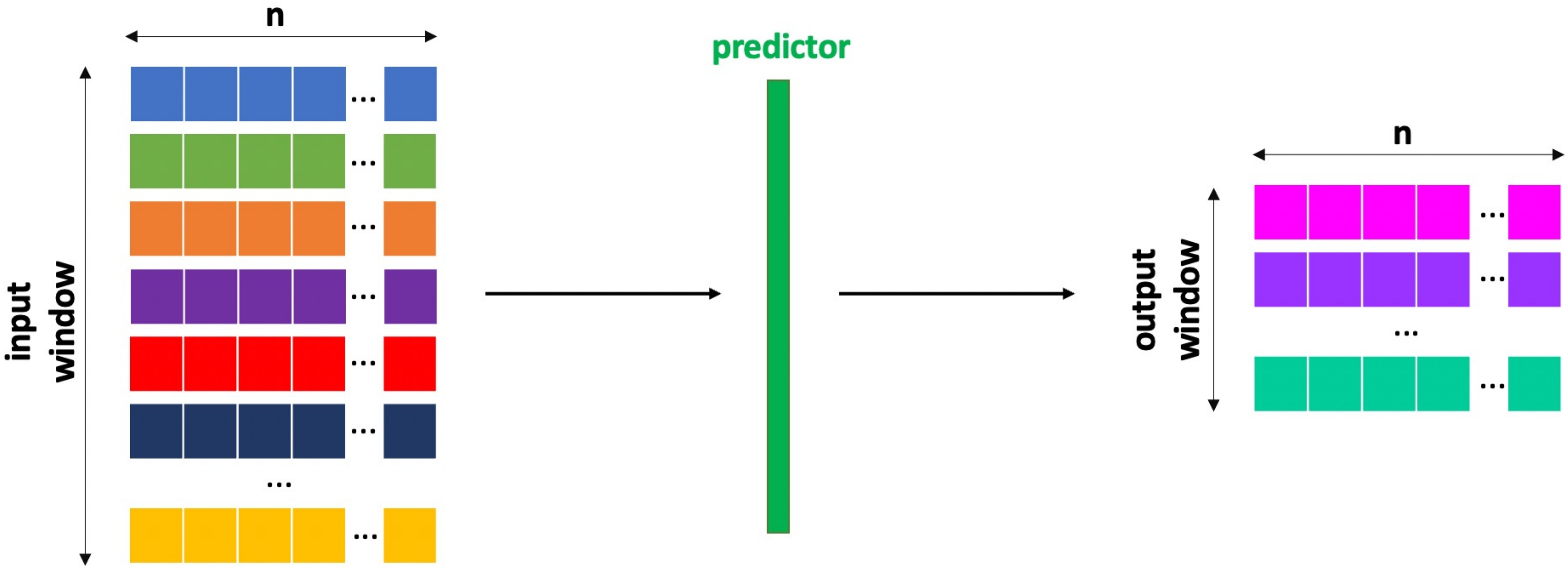
- Three LSTM layers with *p*, *q* and p number of neurons respectively.
- Repeat Vector, Time Distributed and Reshape layers to adjust the shape of data.
- Activation function: tanh with glorot uniform kernel initialiser.
- Loss functions (error metrics): Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE).



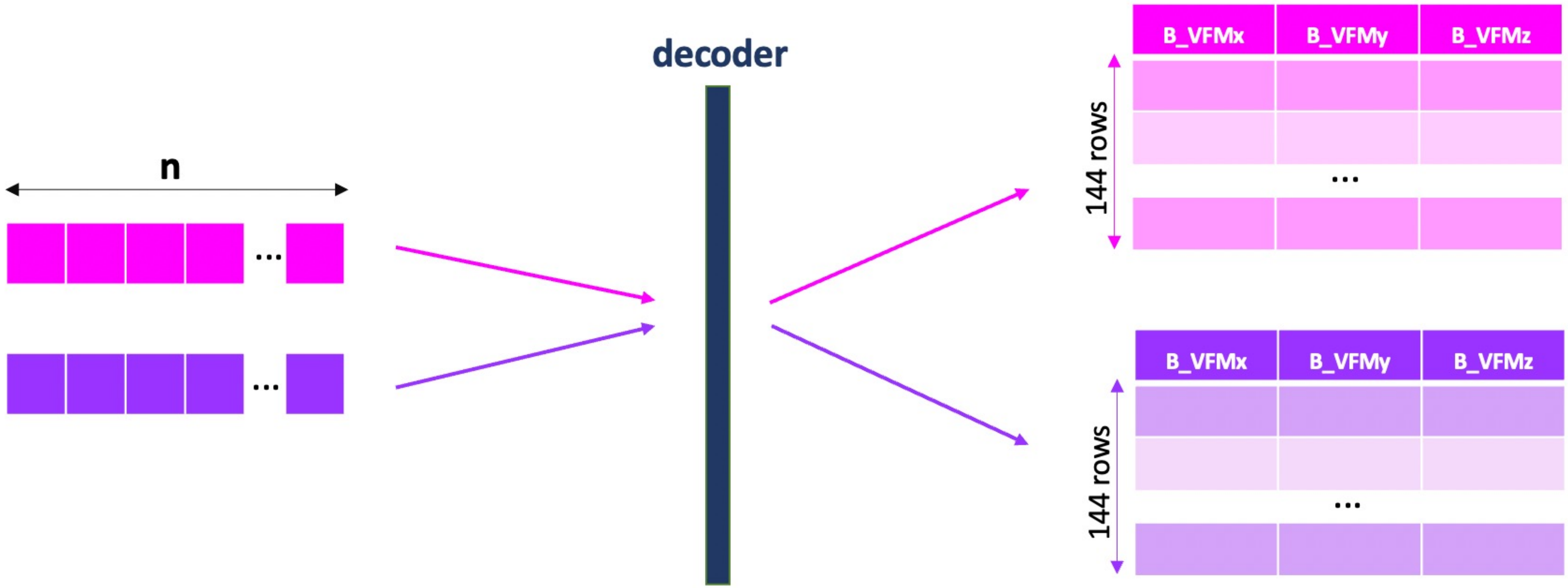
# Incorporating LSTMs into Developing an Encoder-Predictor-Decoder



# Approach II: Encoder-Predictor-Decoder



# Approach II: Encoder-Predictor-Decoder (cont'd)



# Prediction Frames

TABLE I: I/O lengths of the windows tested for the predictors

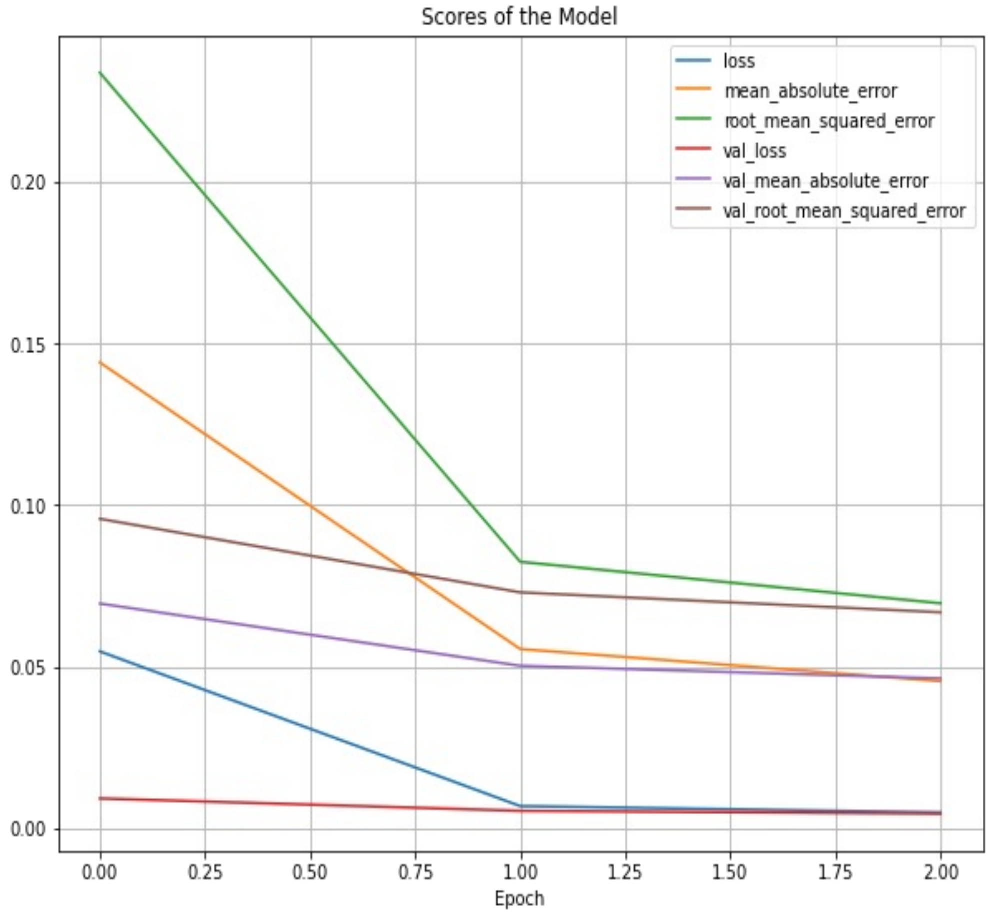
| Target | Input A | Input B | Input C | Input D | Output |
|---|---|---|---|---|---|
| 1 week | 7 | 21 | 30 | - | **7** |
| 1 month | 7 | 30 | 60 | - | **30** |
| 6 months | 30 | 90 | 120 | 180 | **180** |
| 8 months | 180 | 320 | - | - | **240** |

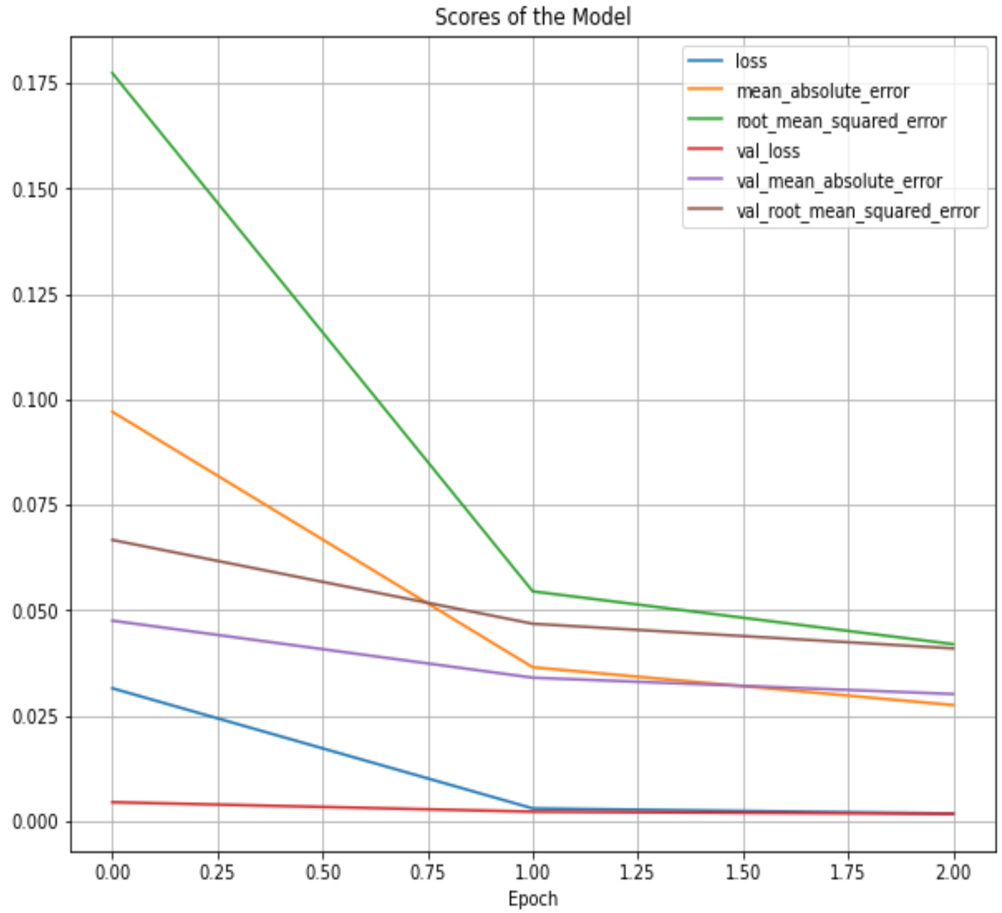
days

# Prediction Frames (cont'd)

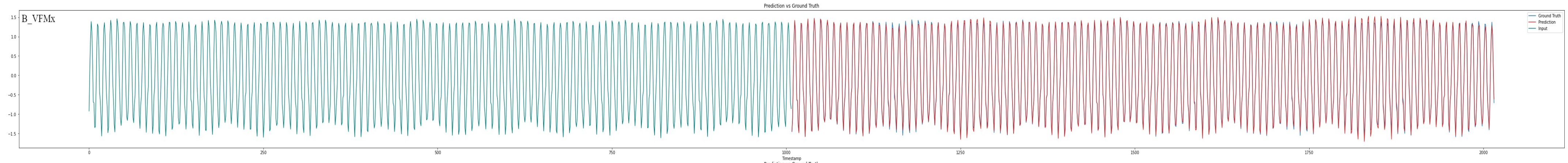
- Our experiments cover four prediction targets: 1 week, 1 month, 6 months and 8 months.
- We examine multiple input/output data windows.
- For our analysis, we gather all available *MAGx LR* packages between January 2014 and July 2021. As we acquire measurements recorded by Swarm A. All the mentioned packages belong to the *Level 1B* type

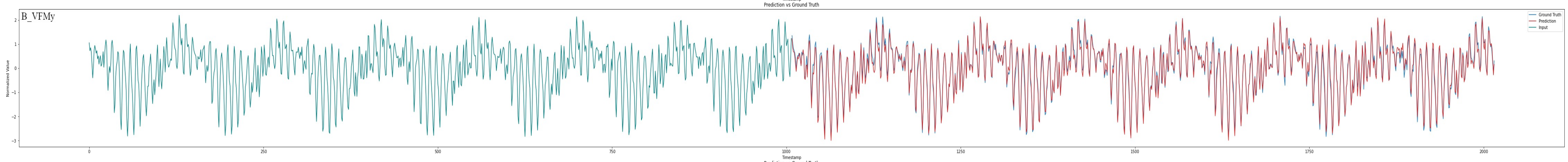
# Training for Model Selection

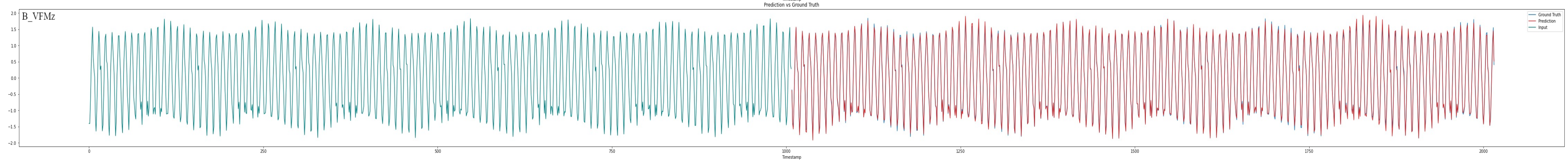


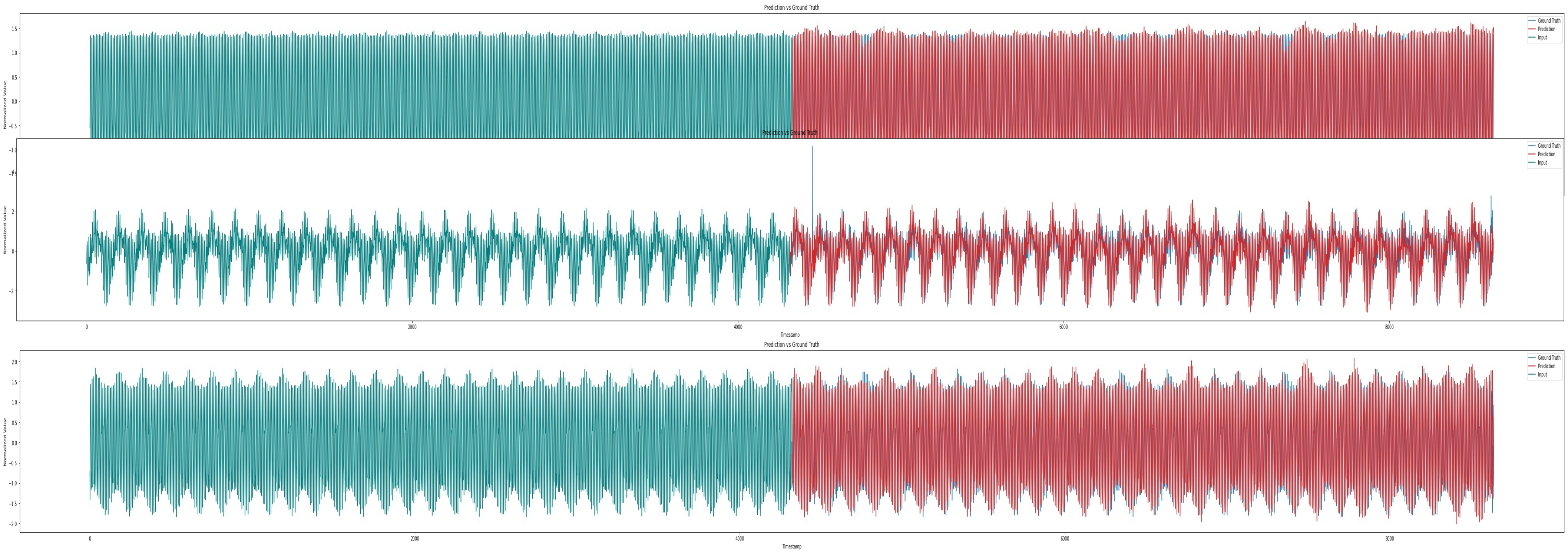
# Prediction: 7 days -> 7 days



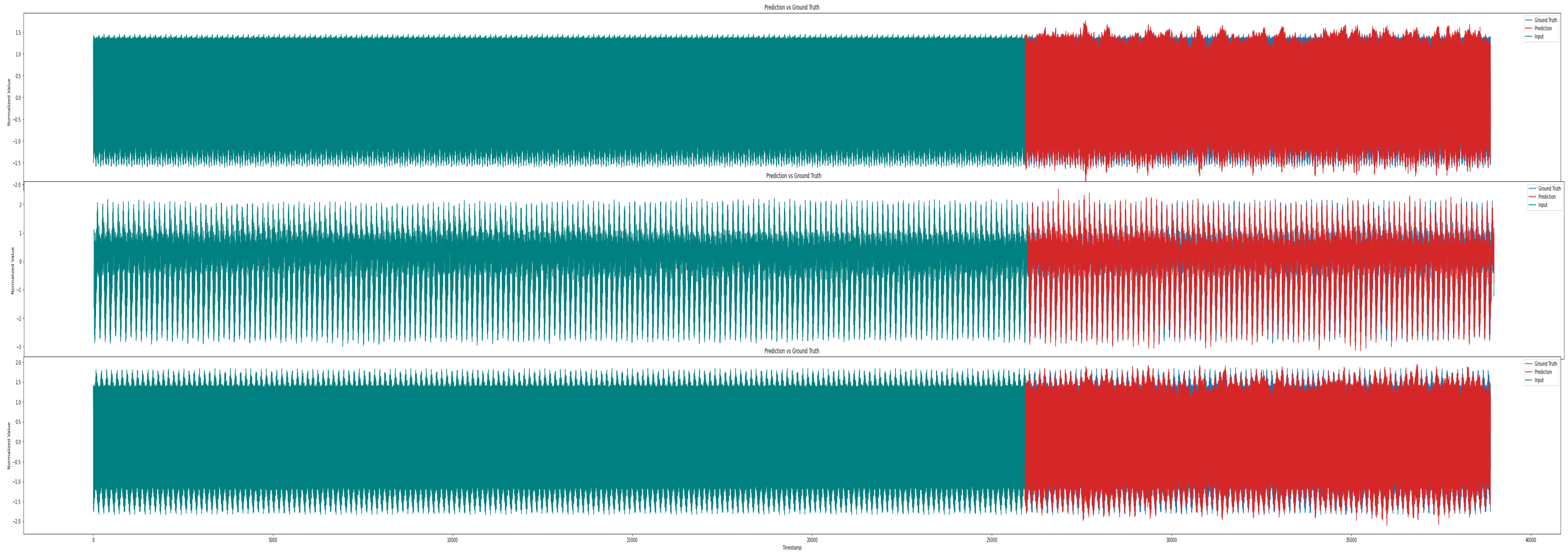



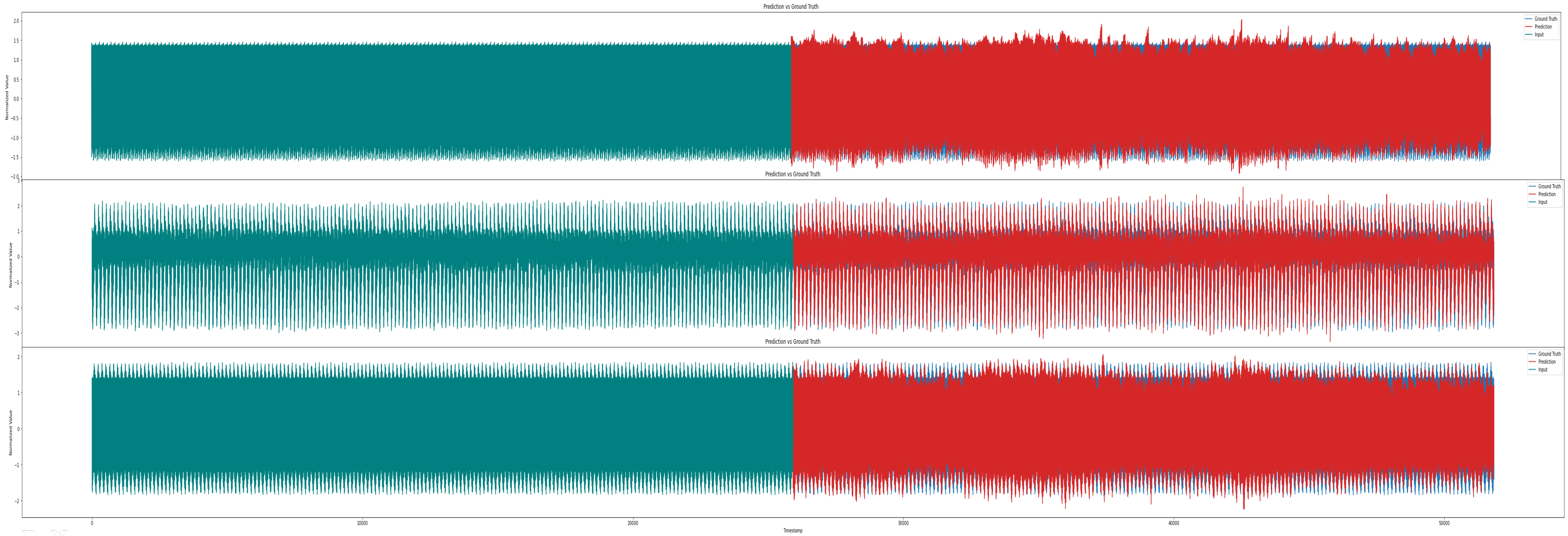
# Prediction: 30 days -> 30 days



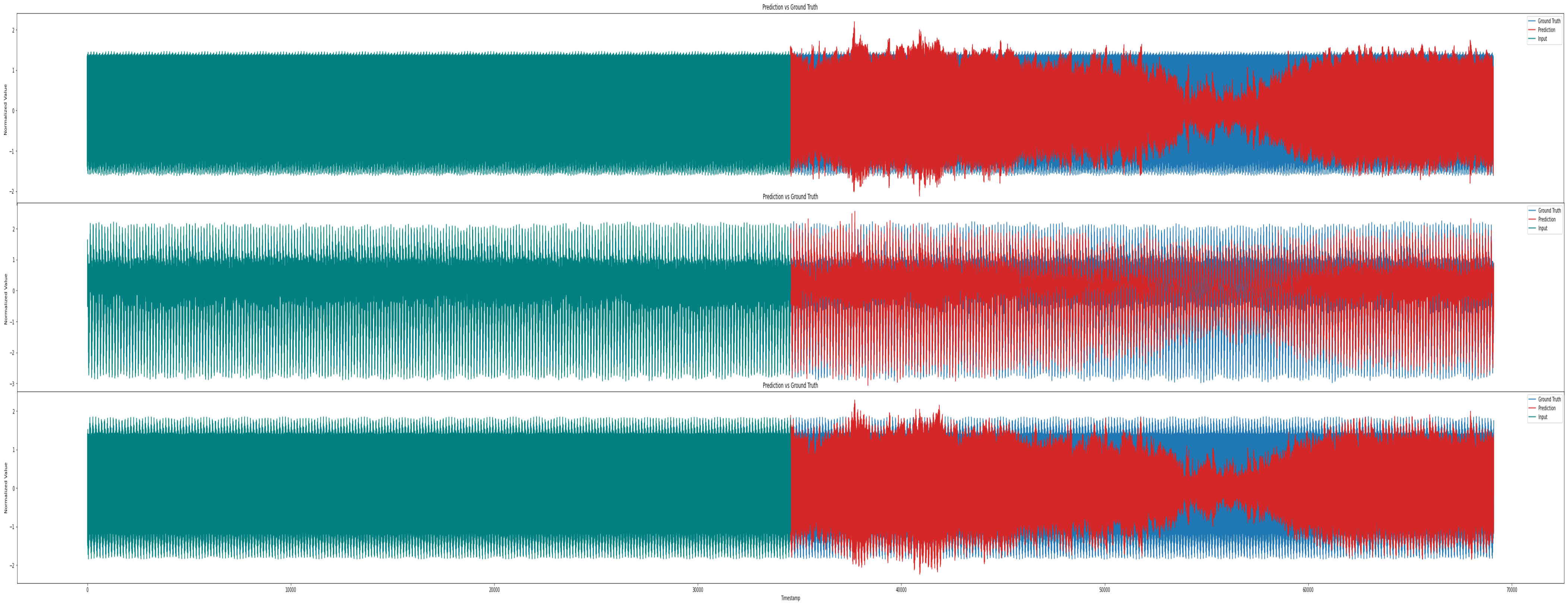
# Prediction: 6 months -> 3 months



# Prediction: 6 months -> 6 months



# Prediction: 8 months -> 8 months



# Similarity Metrics for Calculating Discrepancies

- To calculate the discrepancies between reconstructed or predicted data and the ground-truth data, we use three metrics: Absolute Error, Area Error and Dynamic Data Warping (DTW).
- Absolute Error allows for examining point discrepancies.
- Area Error and DTW are more useful for detecting collective discrepancies in data.
- Plots of these metrics over time provide an understanding about a similarity between predictions and ground-truth data.

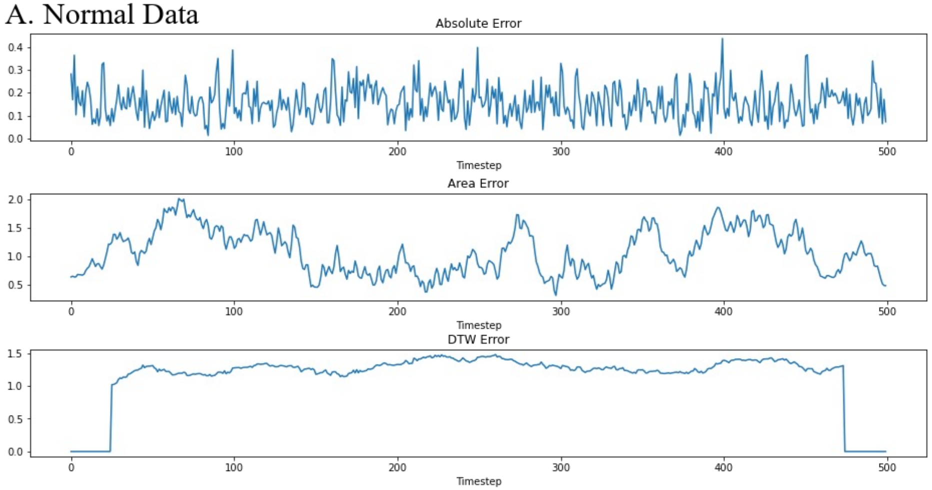
$$AbsoluteError = |x^t - \hat{x}^t| \tag{1}$$

$$AreaError = \frac{1}{2 * l} \left| \int_{t-l}^{t+l} x^t - \hat{x}^t dx \right| \tag{2}$$

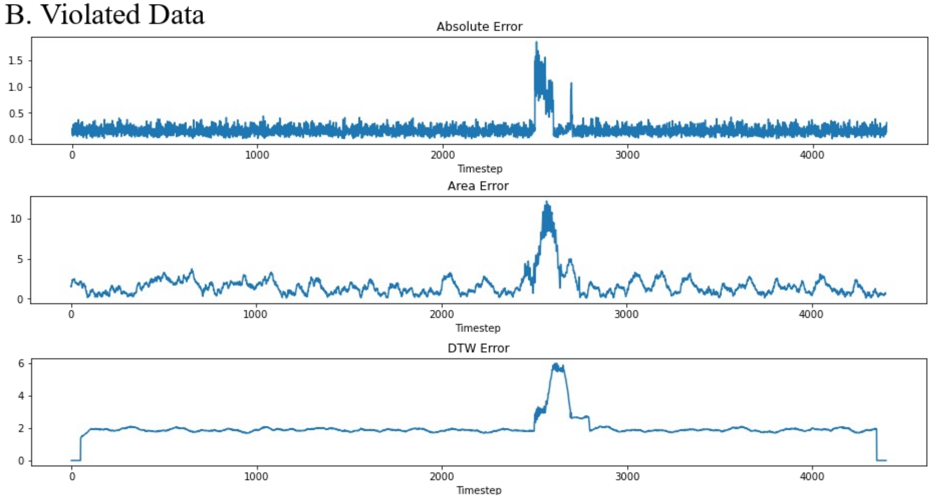
$$DTW = \min_W \left[ \frac{1}{K} \sqrt{\sum_{k=1}^{K} w_k} \right] \tag{3}$$

# Sample Usage of Similarity Metrics

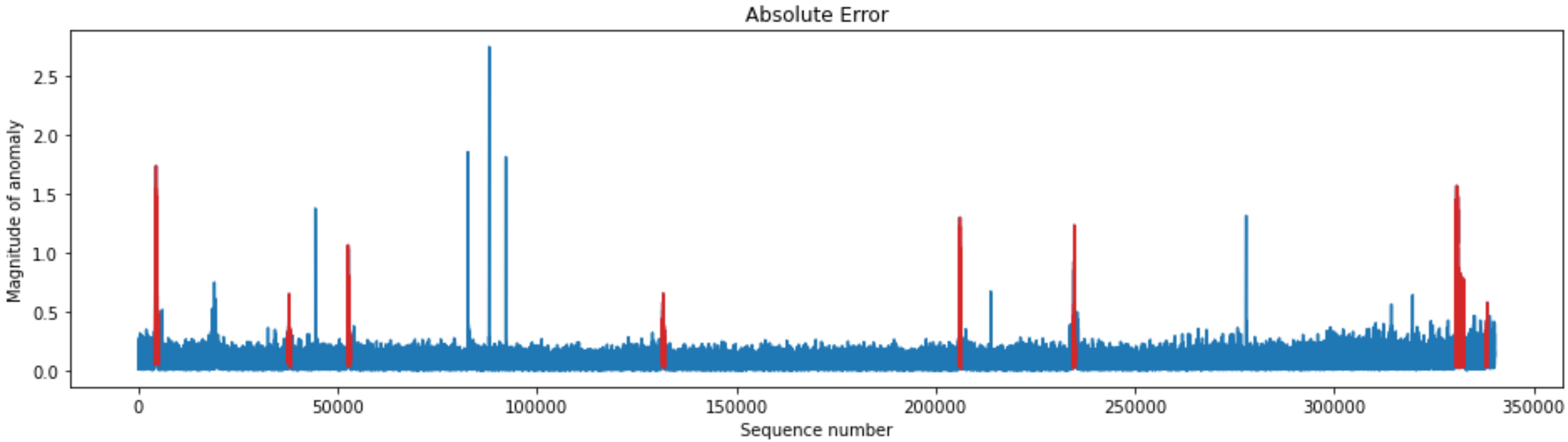
A. Normal Data




B. Violated Data



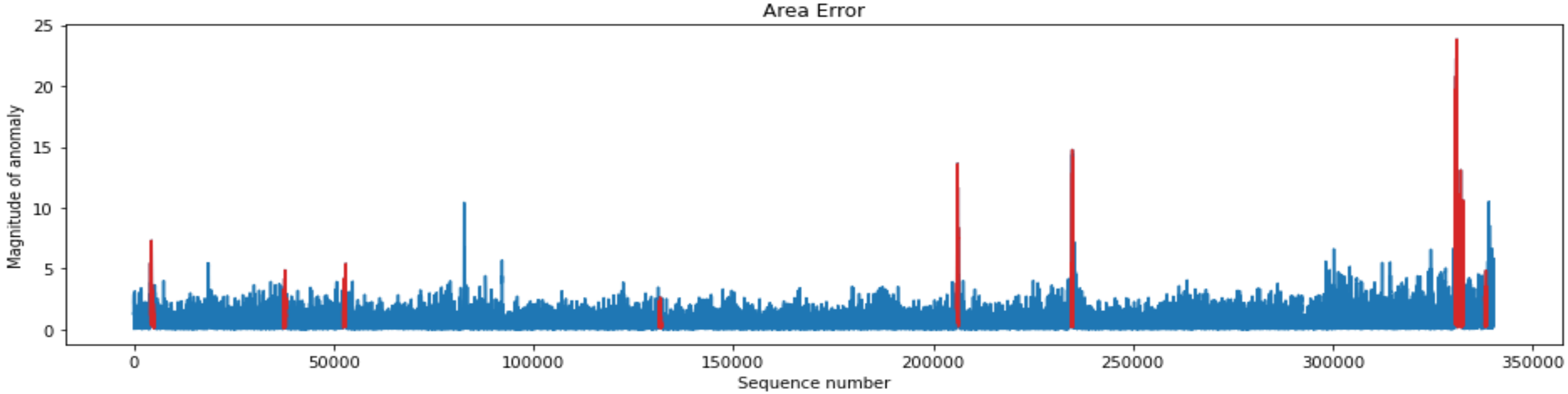
## Anomaly Detection

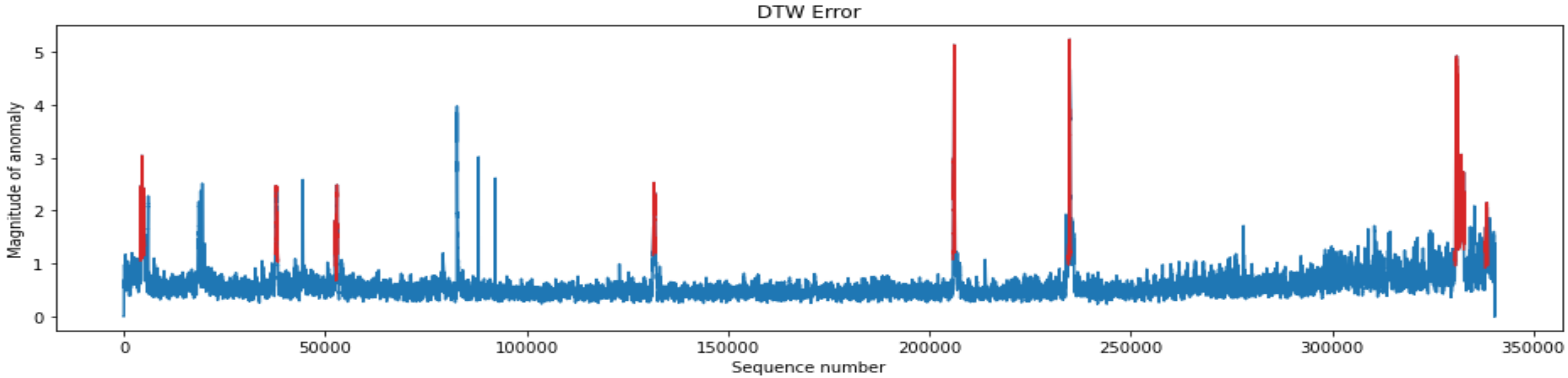



```
Sequence; Timestamp; Length: 584
  4152     29/07/2014 20:00
  4153     29/07/2014 20:10
  4154     29/07/2014 20:20
  4155     29/07/2014 20:30
  4156     29/07/2014 20:40
                  ...
```

```
Sequence; Timestamp; Length: 695
 52419     30/06/2015 01:30
 52420     30/06/2015 01:40
 52421     30/06/2015 01:50
 52422     30/06/2015 02:00
 52423     30/06/2015 02:10
```

# Anomaly Detection (cont'd)



# Results and discussions

- We proposed an approach – incorporating LSTM layers to build an Encoder-Predictor-Decoder architecture.
- The experiments demonstrate that Encoder-Predictor-Decoder allows for predicting and reconstructing Swarm data for longer periods of time and also outperforms a Stacked LSTM layers approach which started to perform poorly after 500 time steps and the training process became extremely slow.
- We have achieved good results for 1 week, 1 month, 6 and 8 months predictions.
- The maximum summarised period of input and output data that allowed for predictions was equal to 8 months.
- We examined 4 prediction targets with 12 different data frames, the experiments usually gave the best results for windows of the same input and output size.

# Results and discussions (cont'd)

- Anomaly Detection – Classification Model
  - ✓ Examining the whole Swarm dataset by a reconstruction model.
  - ✓ Implementing three similarity metrices for computing discrepancies between predicted results and ground truth Swarm data.
  - ✓ Integrating two existing anomaly detection methods of local factor and isolation tree forest for detecting anomalies based on the created representation for detecting anomalies in Swarm data
  - ✓ Conduct large scales of comparisons based on the detected anomalies in Swarm data with the ground-truth entries from the earthquake repository.

# Planning and achievements

- The project has been at the end of Milestone 2 and will start on Milestone 3 with a focus of comparative study on deep learning algorithms with the algorithms previously developed on a number of earthquakes-prone regions in 2023
- New young scientist Christopher O'Neill has been recruited
- One paper has been published by Maja Pavlovic, Yaxin Bi, Peter N. Nicholl, in the 14$^{th}$ International Conference of Knowledge, Science, Engineering and Management (KSEM), 394-405, 2021.
  - ✓ "Extracting Anomalous Pre-earthquake Signatures from Swarm Satellite Data Using EOF and PC Analysis"
- Mutual academic exchanges have been planned, which are subject to the restrictions of Covid-19 in China

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Thanks for your attention!