Predicting Ionospheric Parameters Using Convolutional Neural Networks on AIA / SDO Images

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DLR

Outline

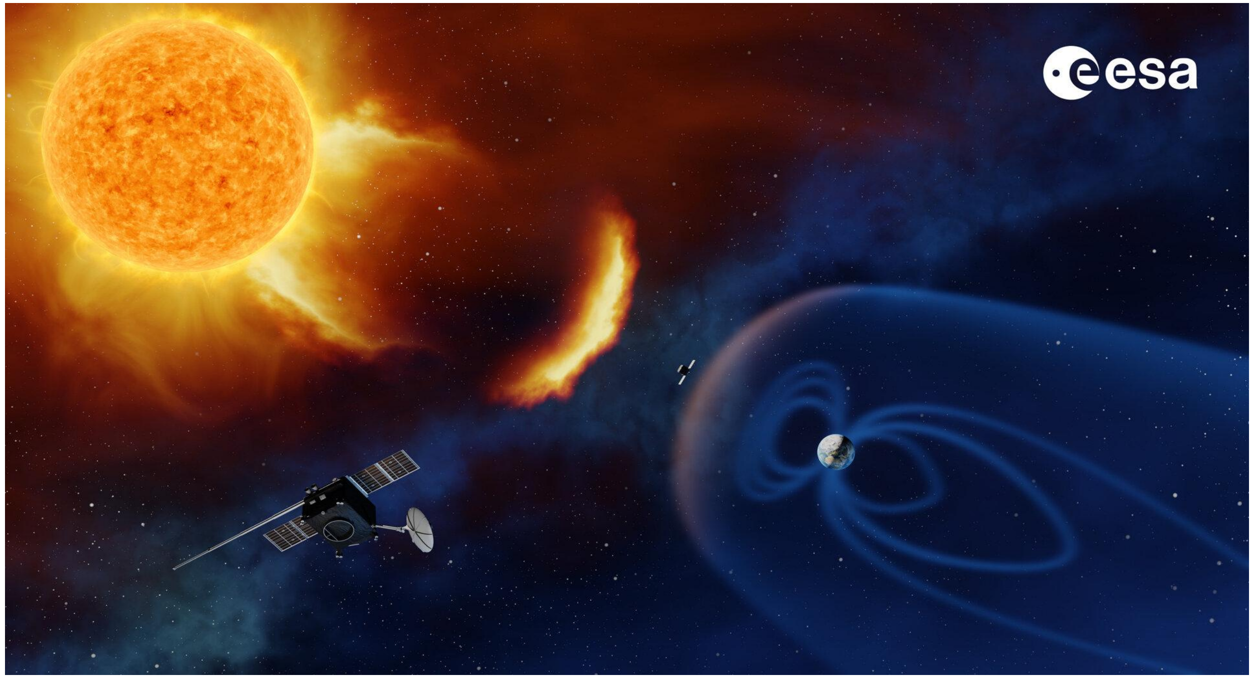
- Motivation
- Ionospheric parameters
- Introduction to Machine Learning
- Methods
    - Gathering data from SDO and OMNI
    - Data cleaning protocols
- Convolutional Neural Network (CNN) model
- Results
- Conclusions

Motivation

Motivation

- Solar activity effects the physical properties in the Earth’s upper atmosphere

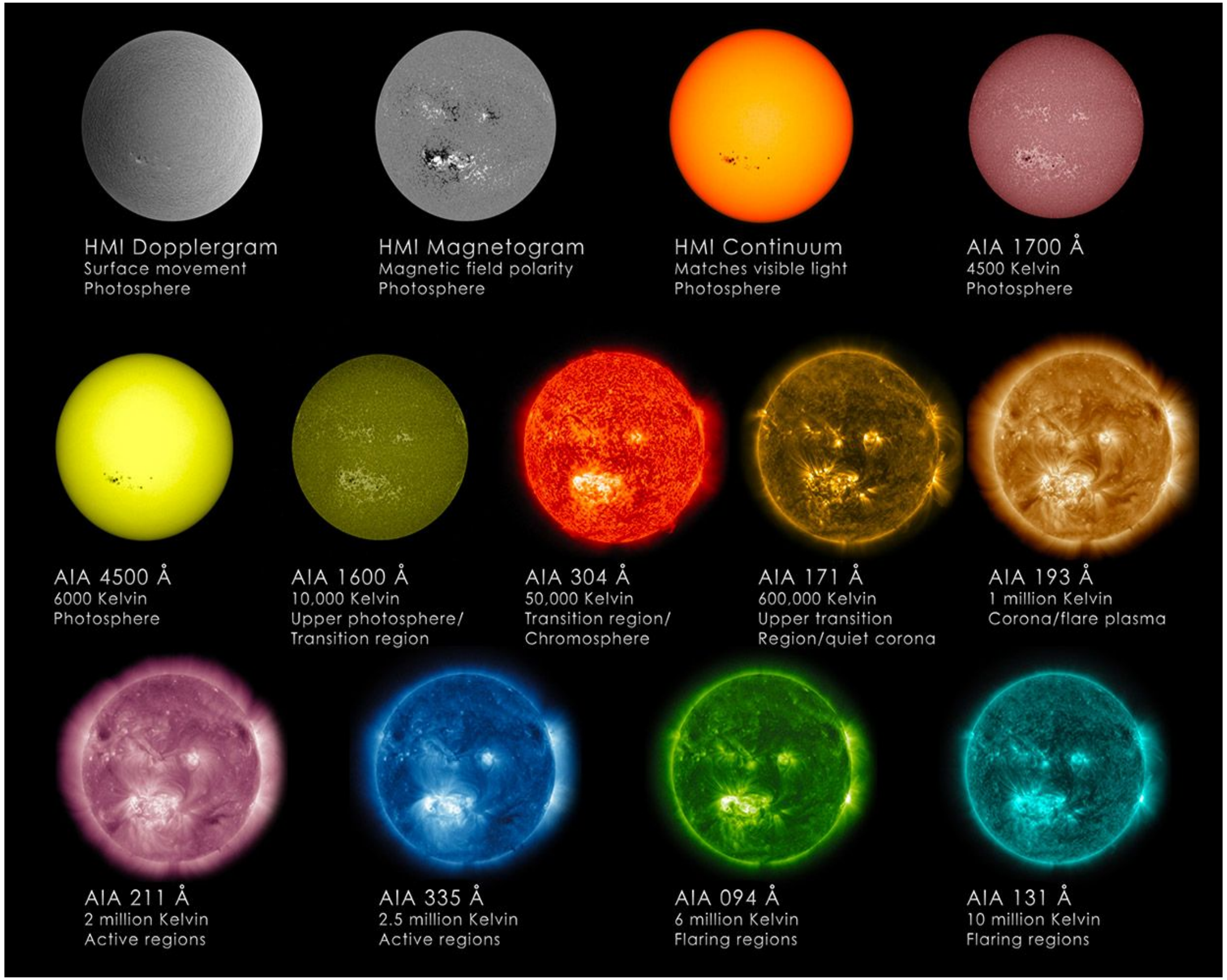
- Full-disk observations of the Sun to capture global variations – Atmospheric Imaging Assembly (AIA)



Can solar images serve as input to machine learning algorithms to predict ionospheric responses to solar radiation?

Motivation

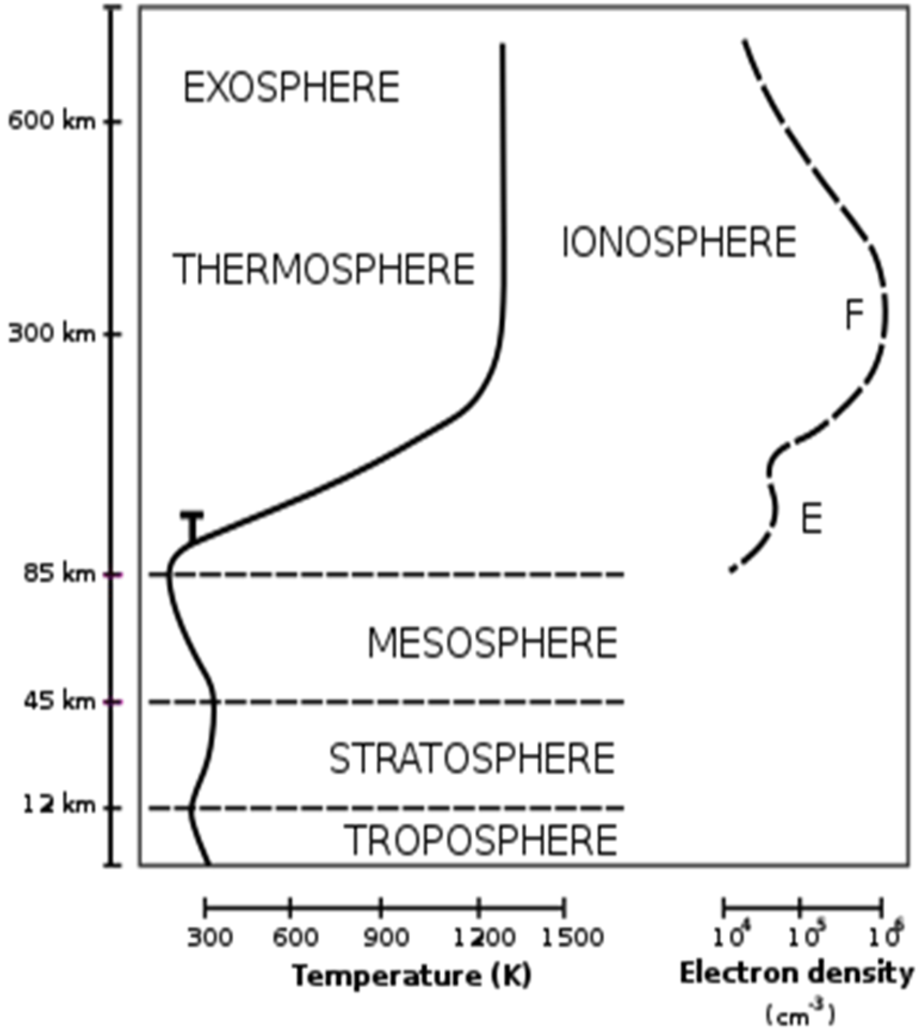
- Atmospheric Imaging Assembly (AIA)
- Energy input, storage, and release
- These variations drive density and ionization changes in the ionosphere



source: SDO website

Ionospheric Parameters

Ionosphere - General Structure and Parameters



- High densities charged particles due to solar radiation
- Different layers: characterized by electron density
- Crucial for radio communication and satellite navigation
- Highly sensitive to space weather events
- <u>**Parameters**</u>:
  - **Geomagnetic activity**:
    - Kp (0-9; storm if Kp>5) and
    - Dst (storm if Dst < -50nT)
  - **Solar activity**:
    - Number of sunspots: Indicator of solar activity
    - F10.7: Solar radio flux at 10.7 cm

Introduction to Machine Learning

Machine Learning

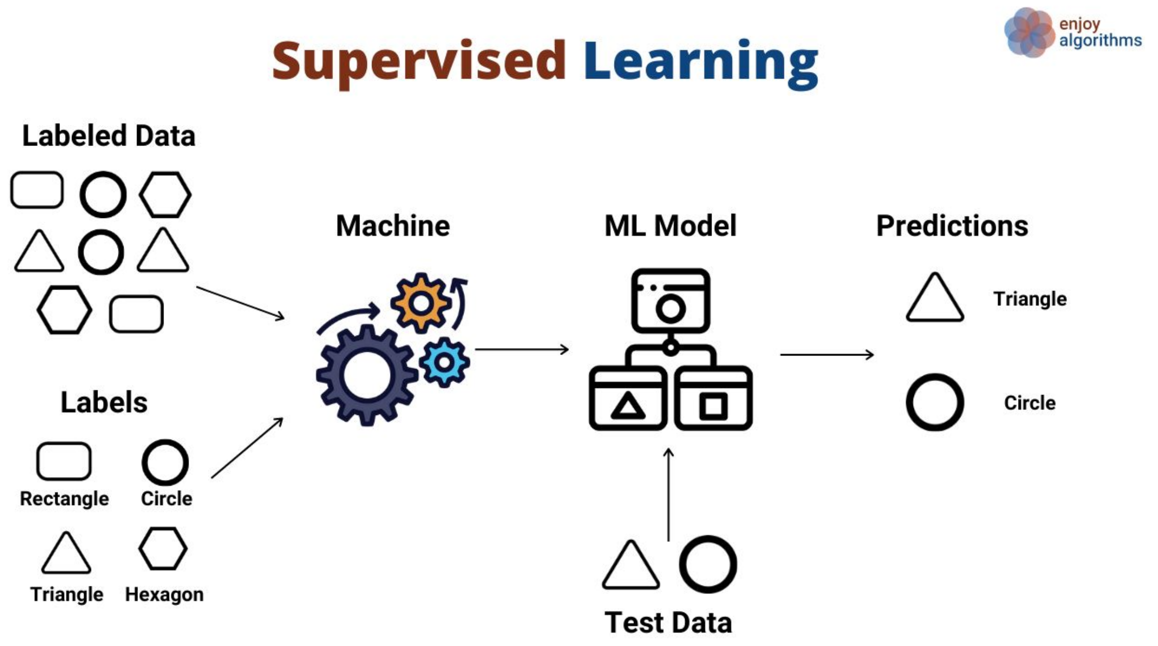
Type of learning - Supervised learning

- Feed inputs (features) and a corresponding output (target)
- Model "learns" a function that maps the inputs to the desired output
- This "function" must minimize some cost function (in our case MSE)

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

- *What would happen is MSE went to zero for the training set?*

- Unsupervised learning - unlabeled data, no explicit guidance

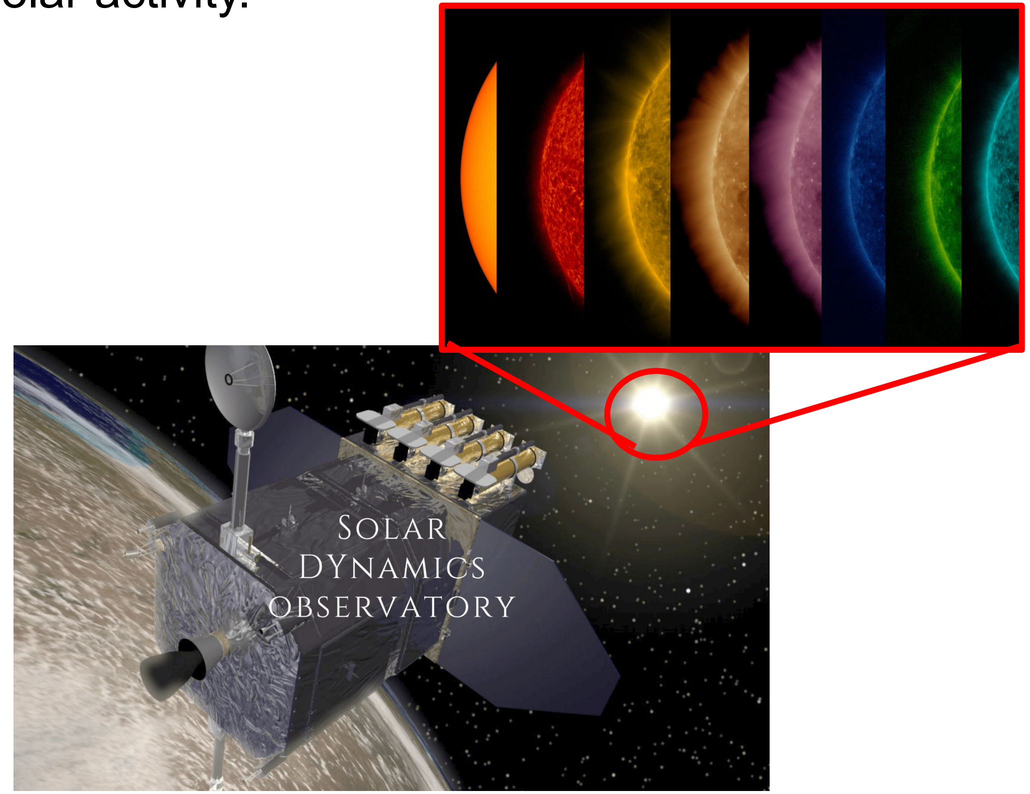


Methods

Obtaining the data

Solar Dynamics Observatory (SDO):

NASA mission launched in 2010 to study the sun and its influence on space weather. Observes the sun, capturing images and data in various wavelengths to understand solar activity.



Source: The Space Collective

OMNIWeb NASA:

Compilation of hourly-averaged, near-Earth solar wind magnetic field and plasma parameter data → F10.7, Dst, Kp, Number of Sunspots

Source: OMNIWeb

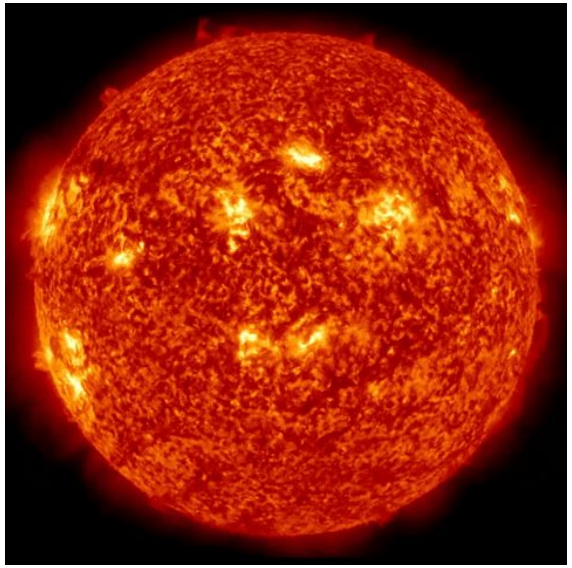
Data cleaning protocols

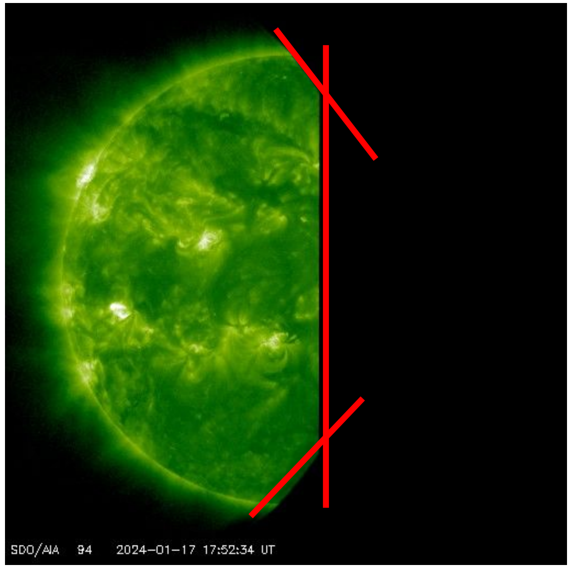
Time period: 2024-01-01 → 2024-05-31

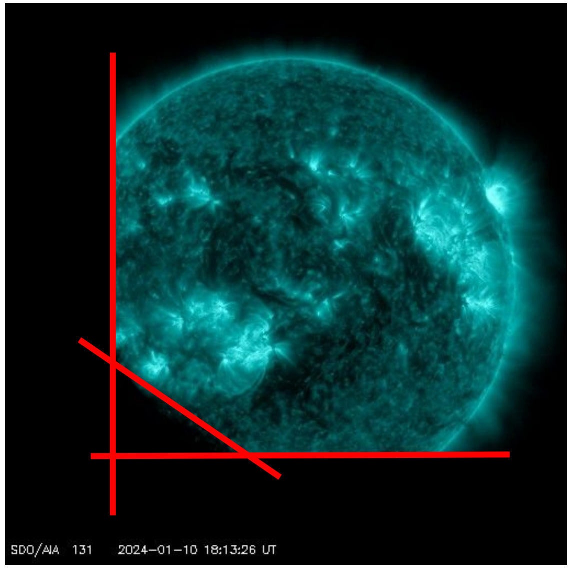
Three data points: 6:00am, 12:00pm, and 6:00pm

Removed faulty data images by hand:

- January 10, 2024
- January 17, 2024
- April 10, 2024







Train-Validation-Test

Model is trained on labeled data, then evaluated on unseen test images to predict parameters.

🧠 **Training** (80% of data)

Feed:
📷 SDO / AIA Images
🔢 Known Output (Parameter values)

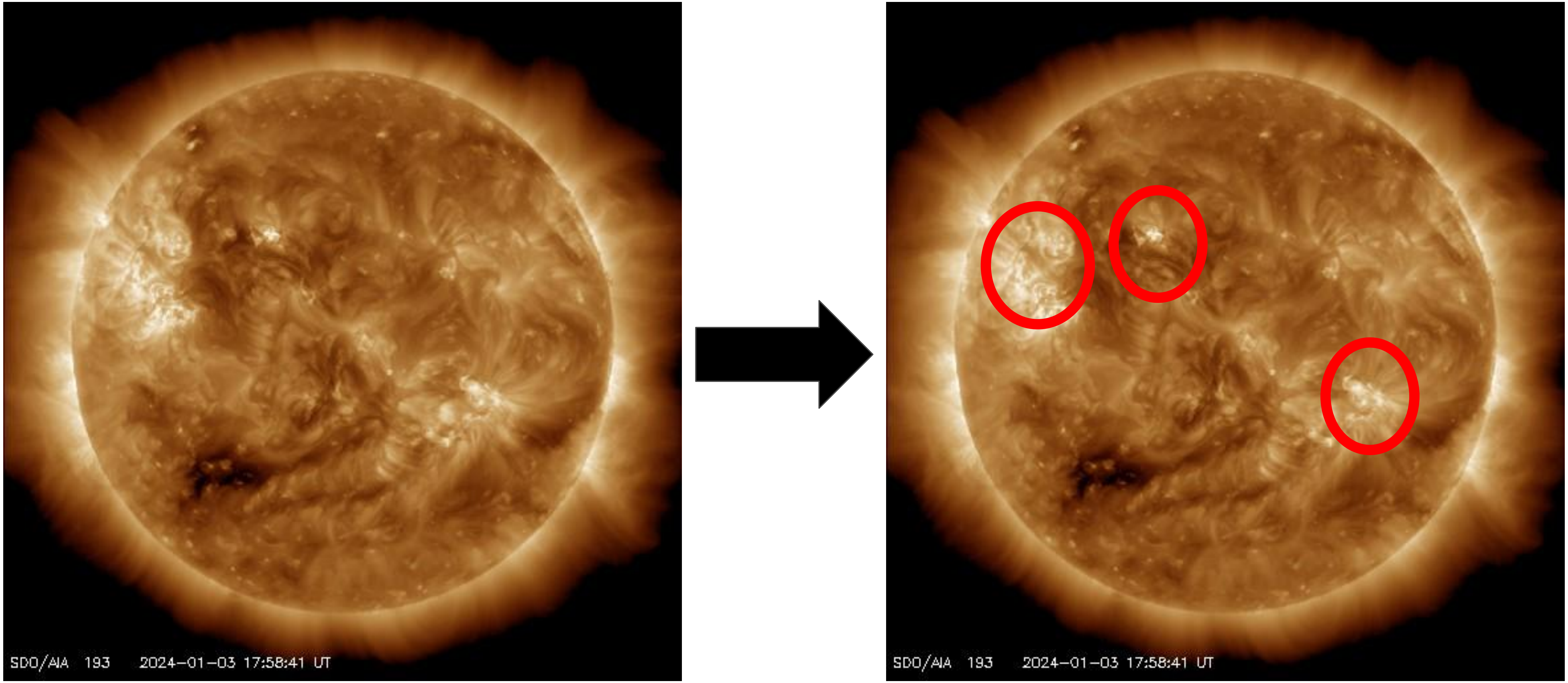
Outcome:
📊 Trained Model

🔎 **Testing** (20% of data)

Input:
📷 Unseen Images

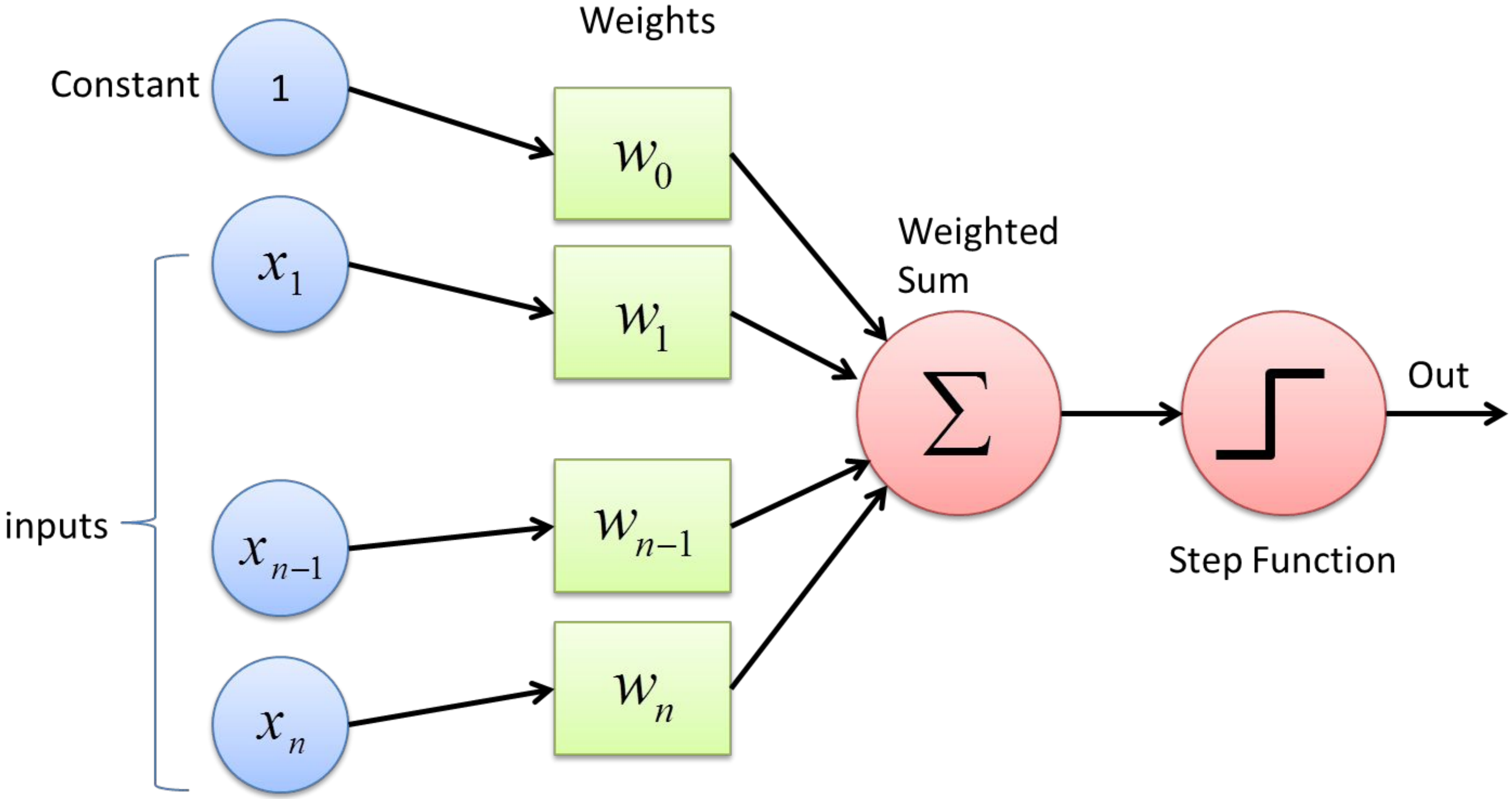
Output:
🔢 Predicted Indices / Parameters

Convolutional Neural Network

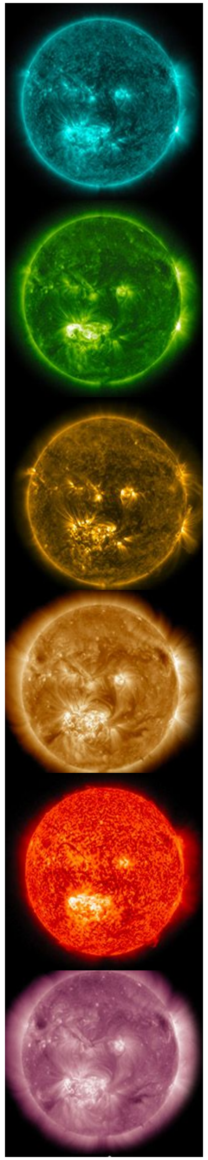


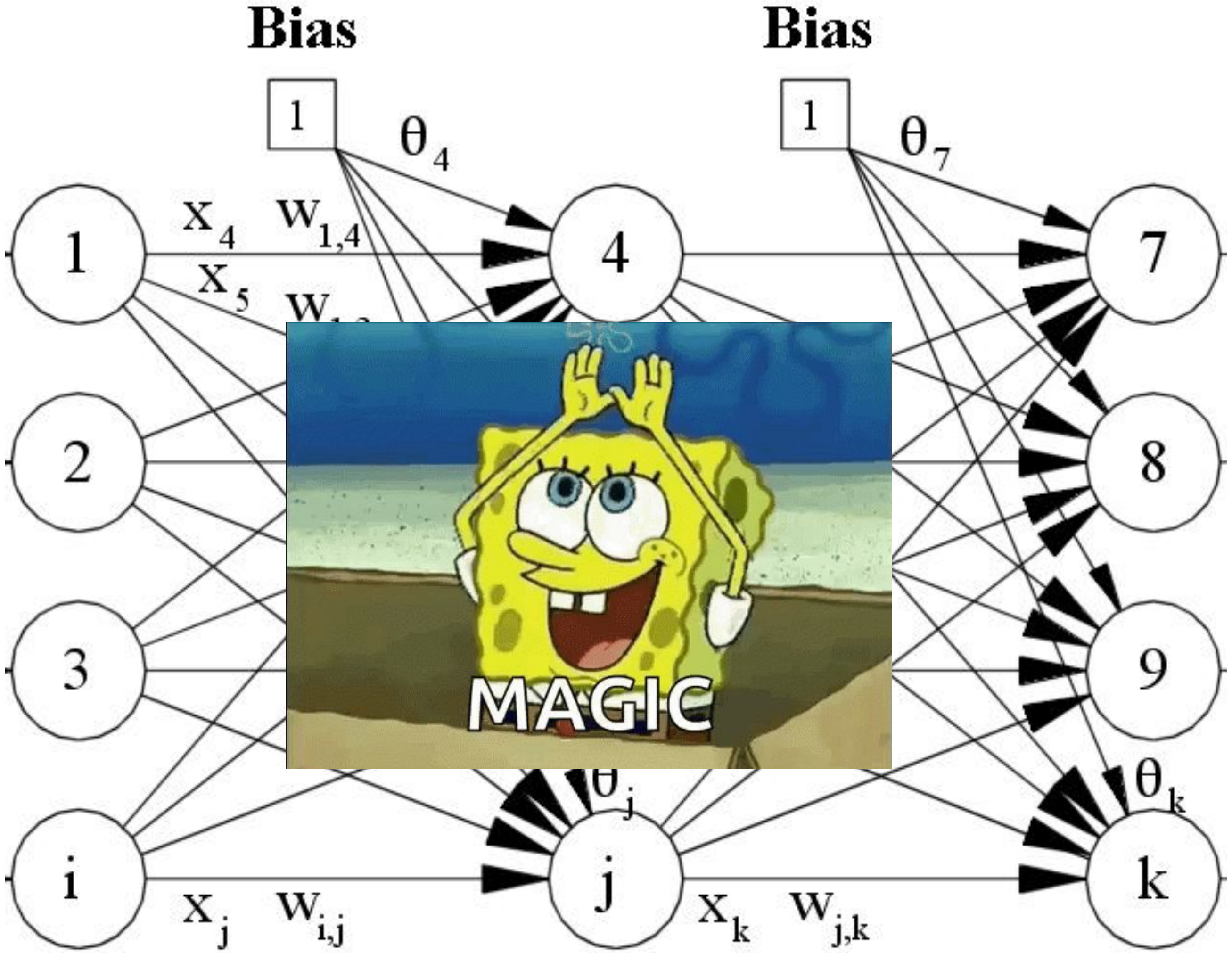
Using an image of the sun, the model will look at the features and predict the ionospheric parameters

Neural Network



Neural Network





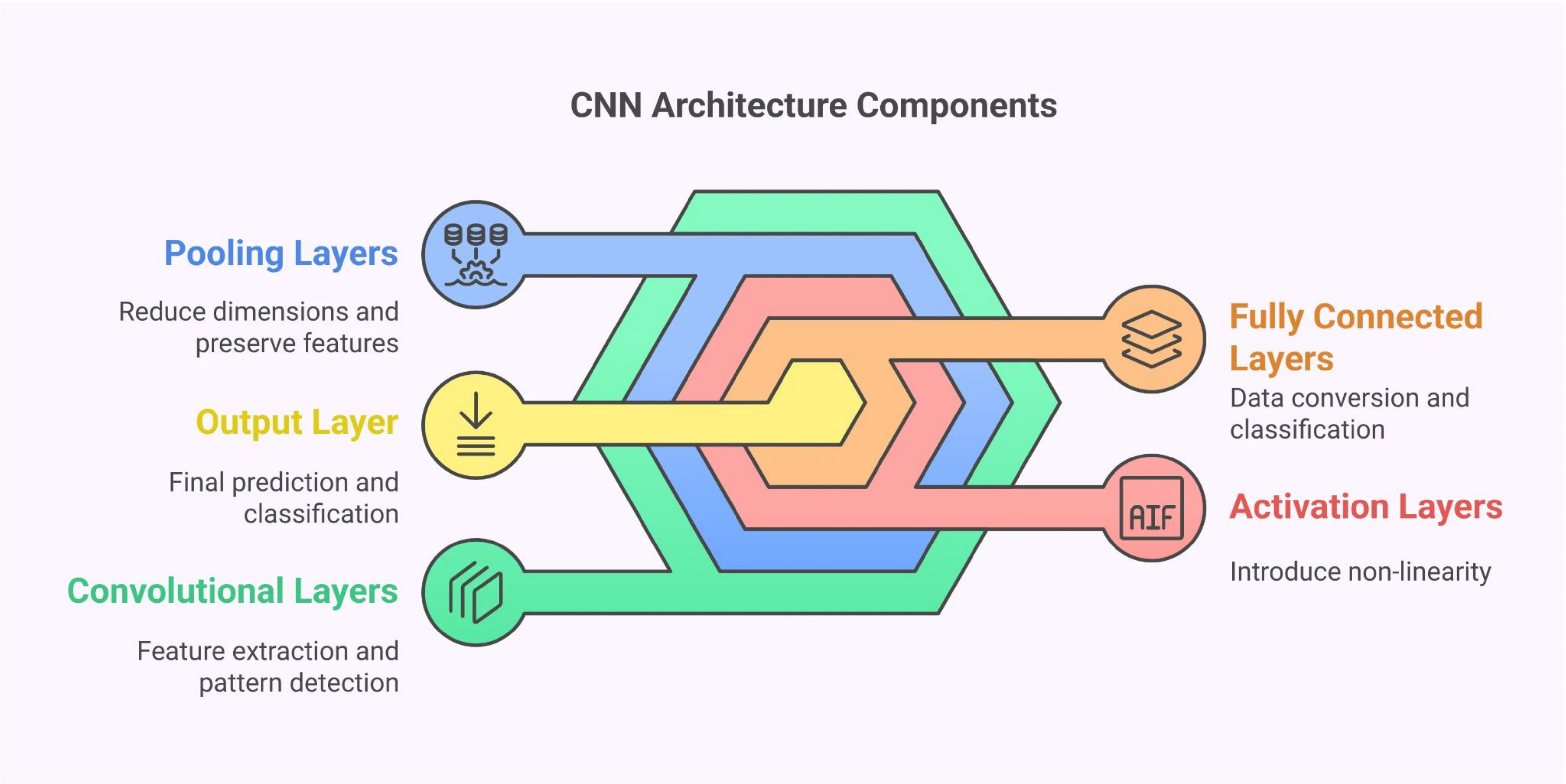
f107

dst

kp

sunspot

Convolutional Neural Network



Source:Image Kit

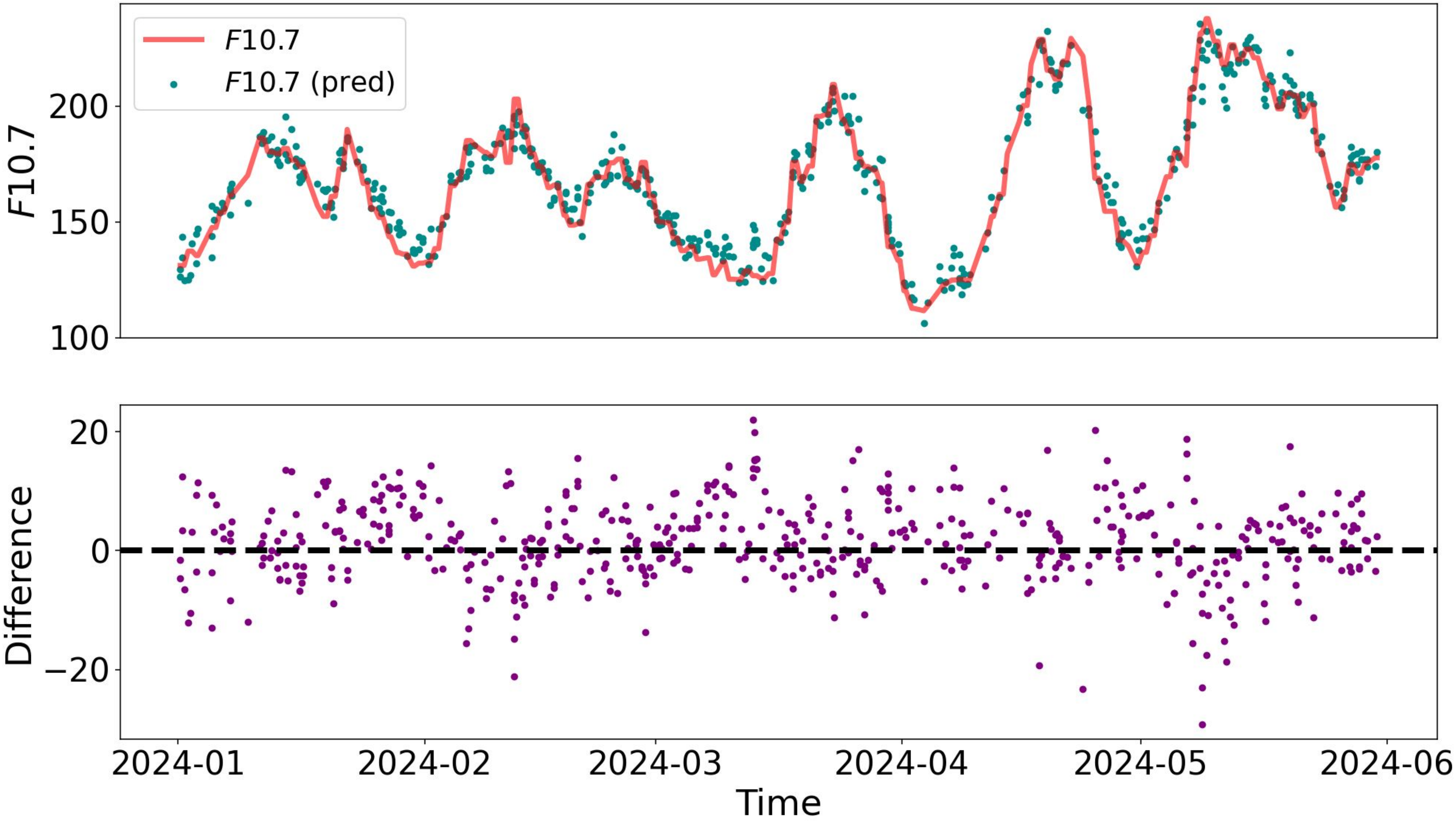
Models

- Model 1:
  - **Layers:** 8 (including input)
  - **Neurons:** 64 (hidden layer) + 4 (output)
  - **Conv2D filters:** 16 in first, 32 in second
  - **Output layer:** 4 regression values
  - **Epochs**: 10

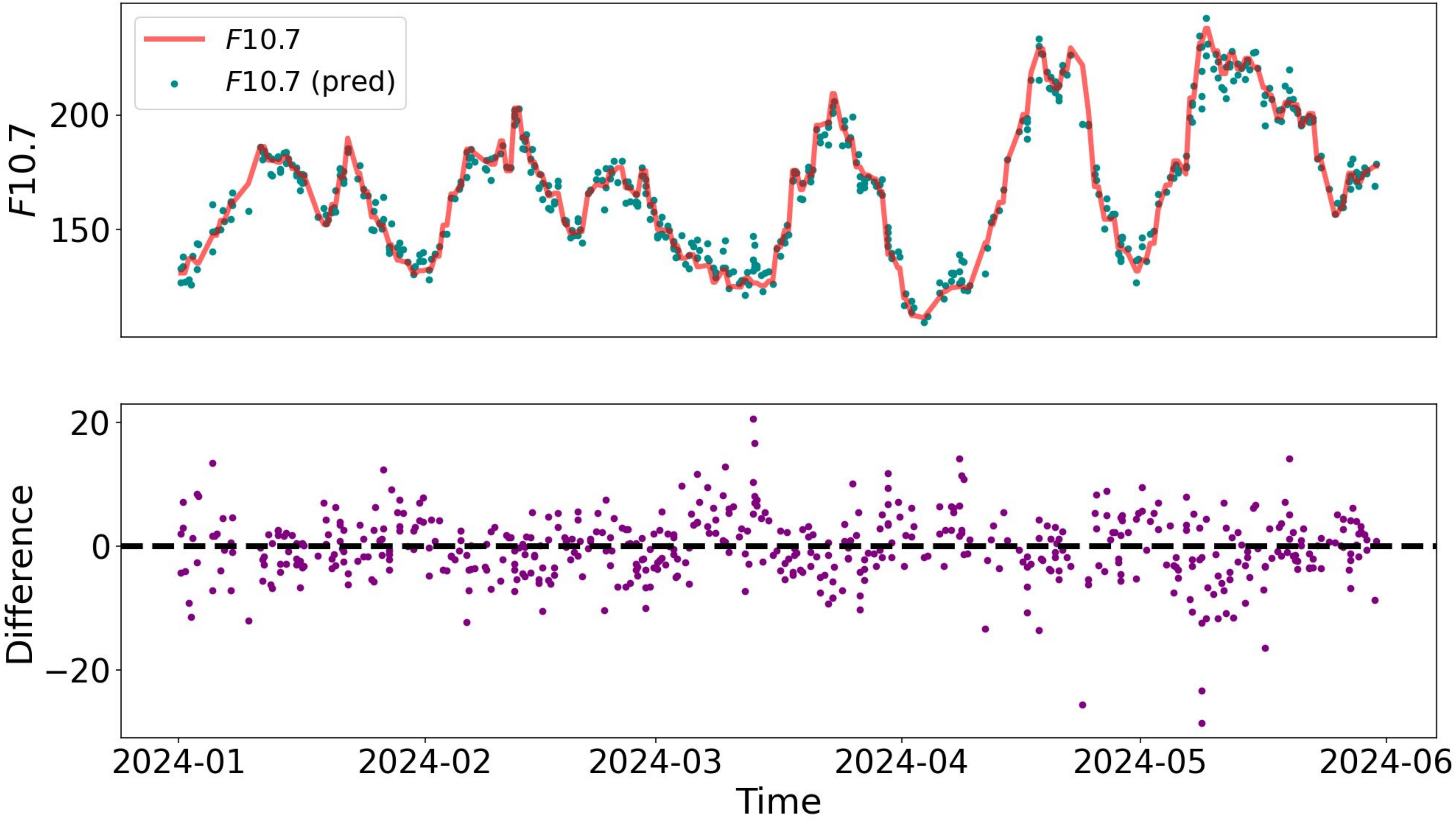
- Model 2:
  - **Layers:** 8 (including input)
  - **Neurons:** 32 (hidden layer) + 4 (output)
  - **Conv2D filters:** 64 in first, 32 in second
  - **Output layer:** 4 regression values
  - **Epochs:** 100

Results and Conclusions

F10.7 Prediction - Model 1

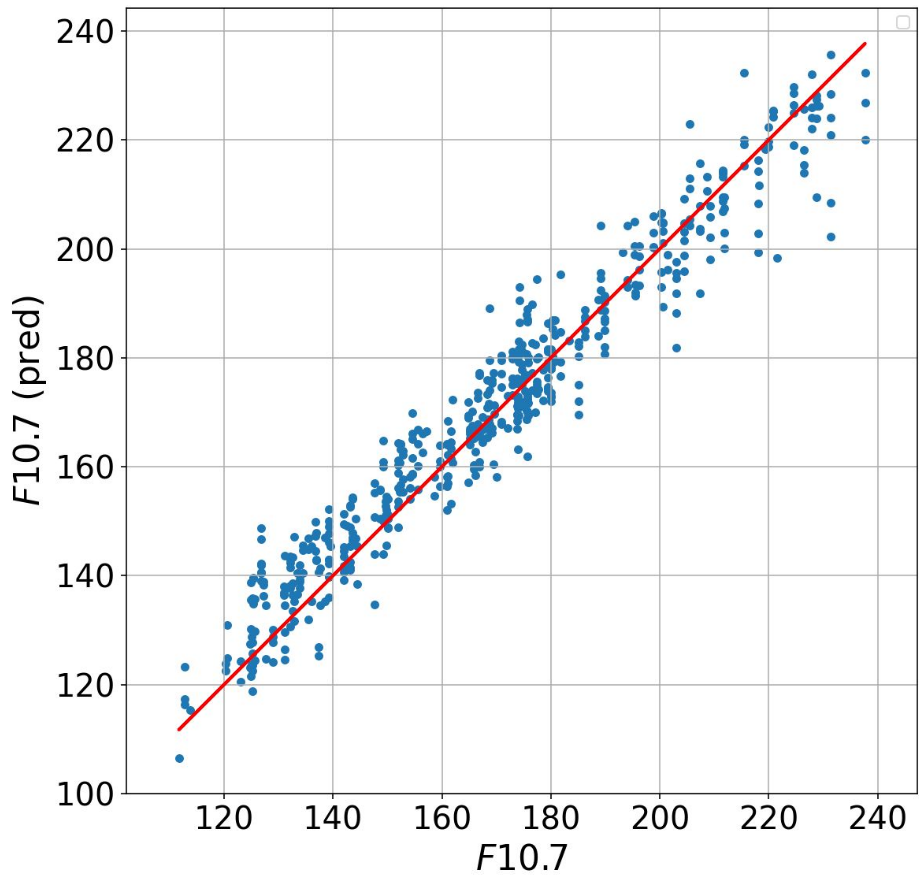


F10.7 Prediction - Model 2



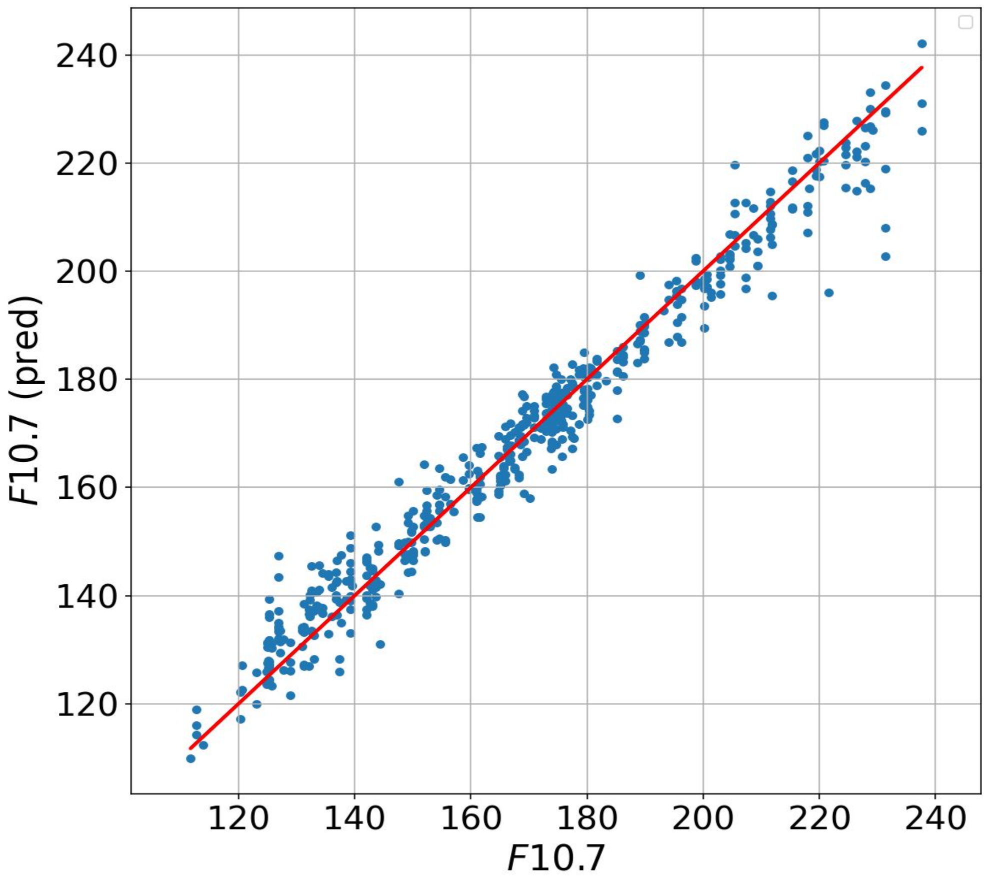
F10.7 Prediction

Model 1



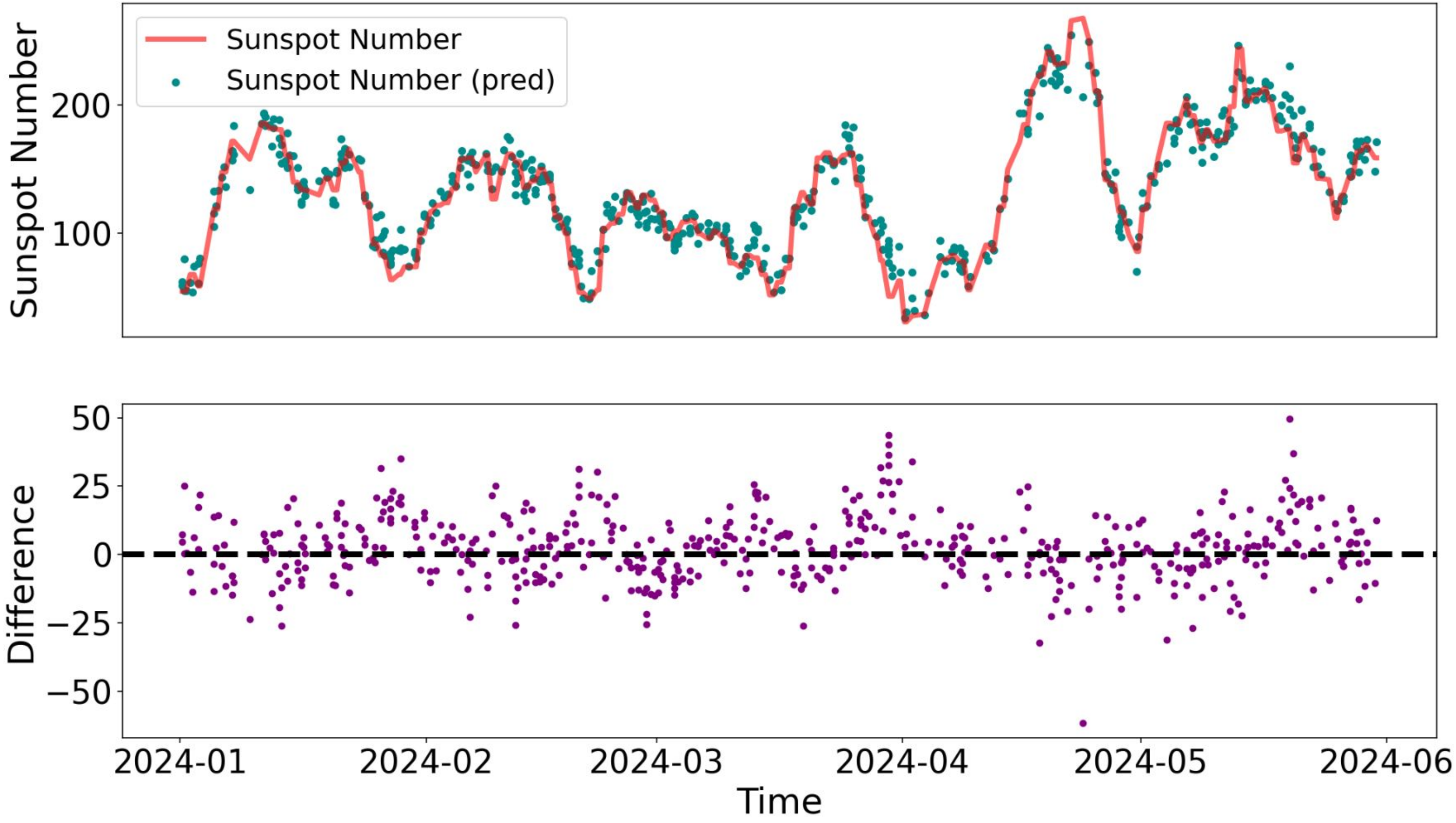
MSE ≈ 103.86

Model 2

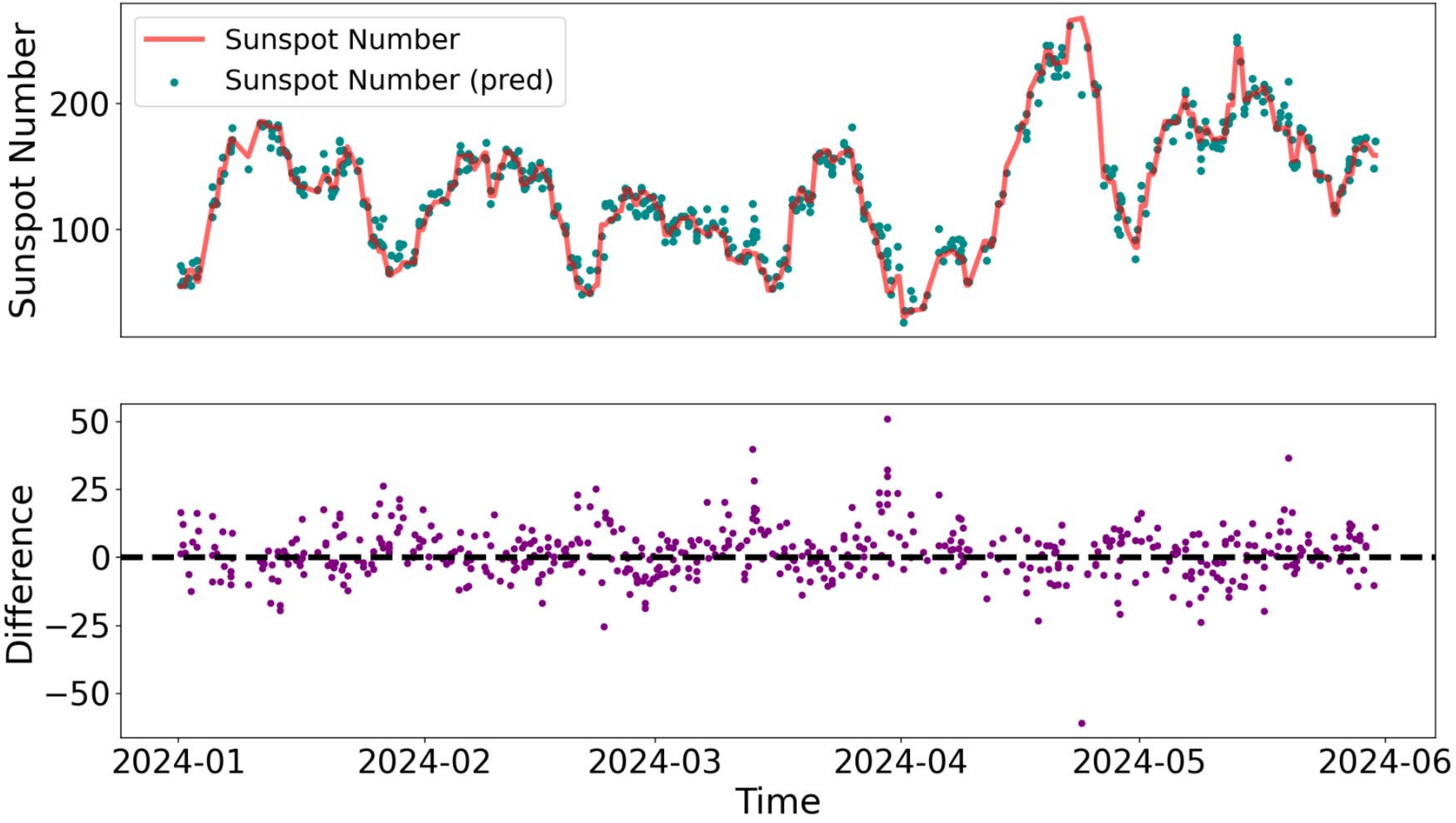


MSE ≈ 46.16

Sunspot Number Prediction - Model 1

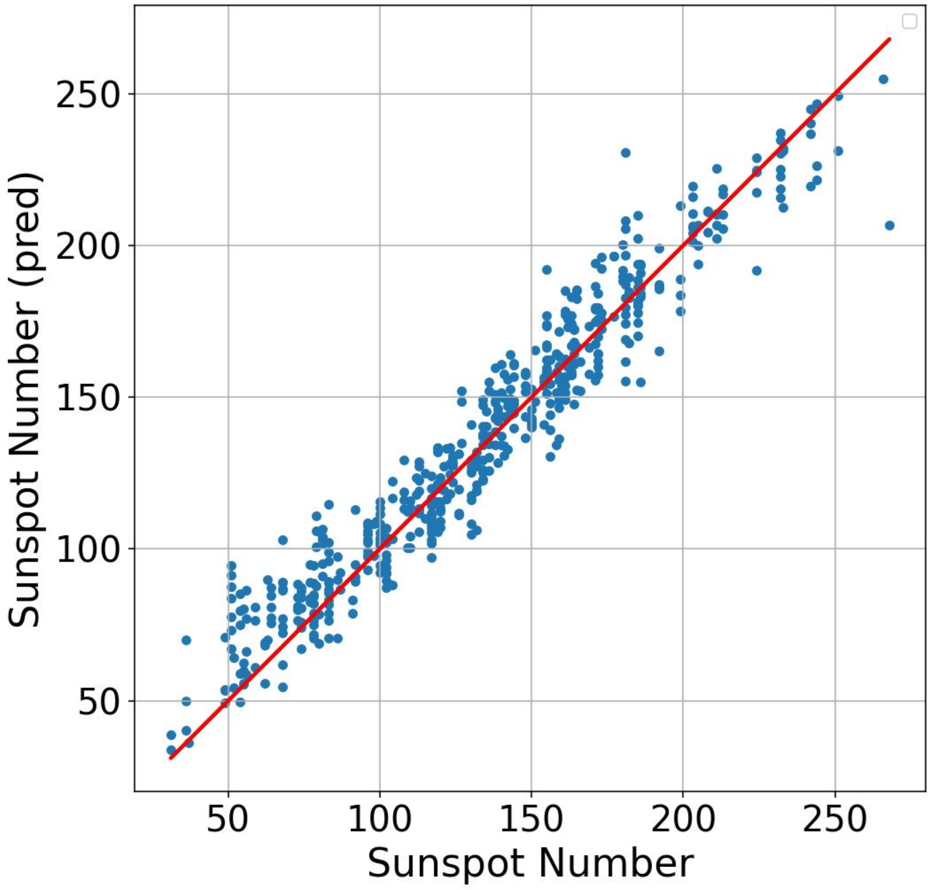


Sunspot Number Prediction - Model 2



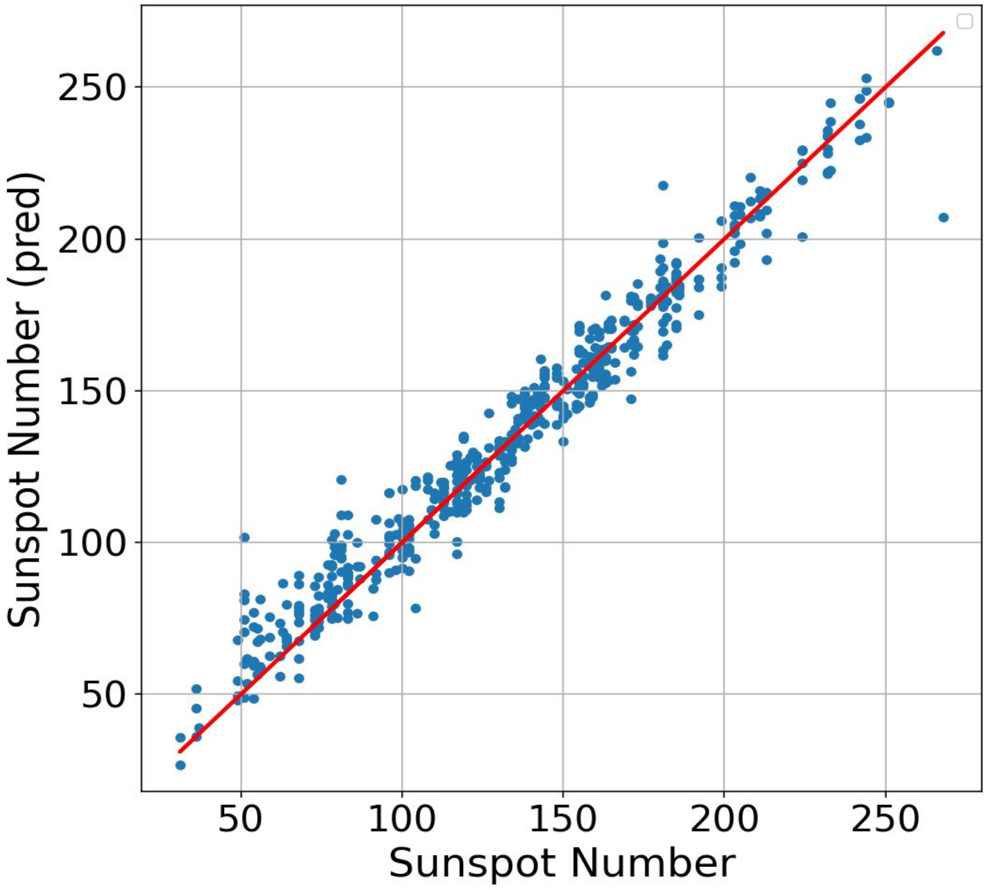
Sunspot Number Prediction

Model 1



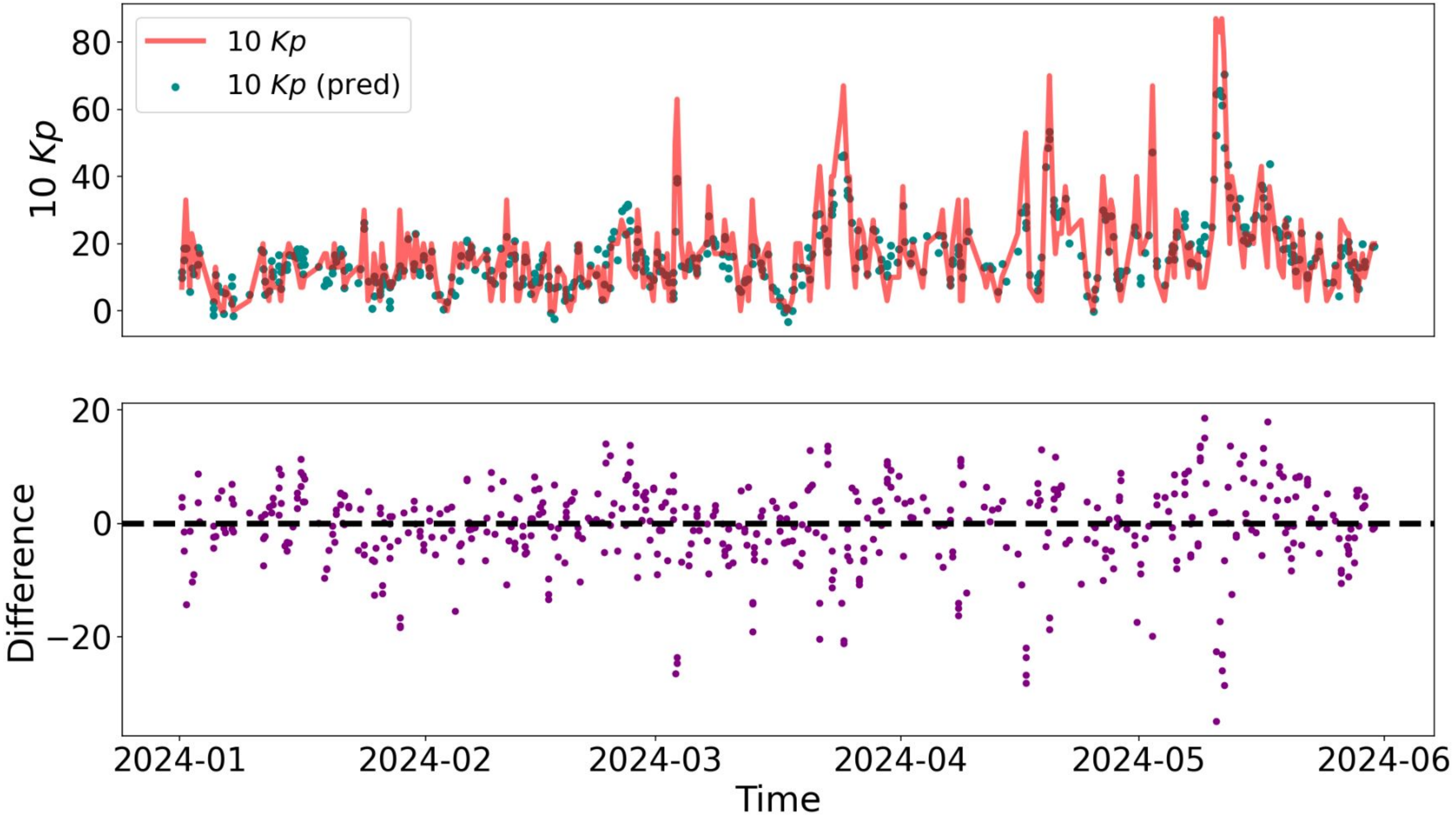
MSE ≈ 103.86

Model 2

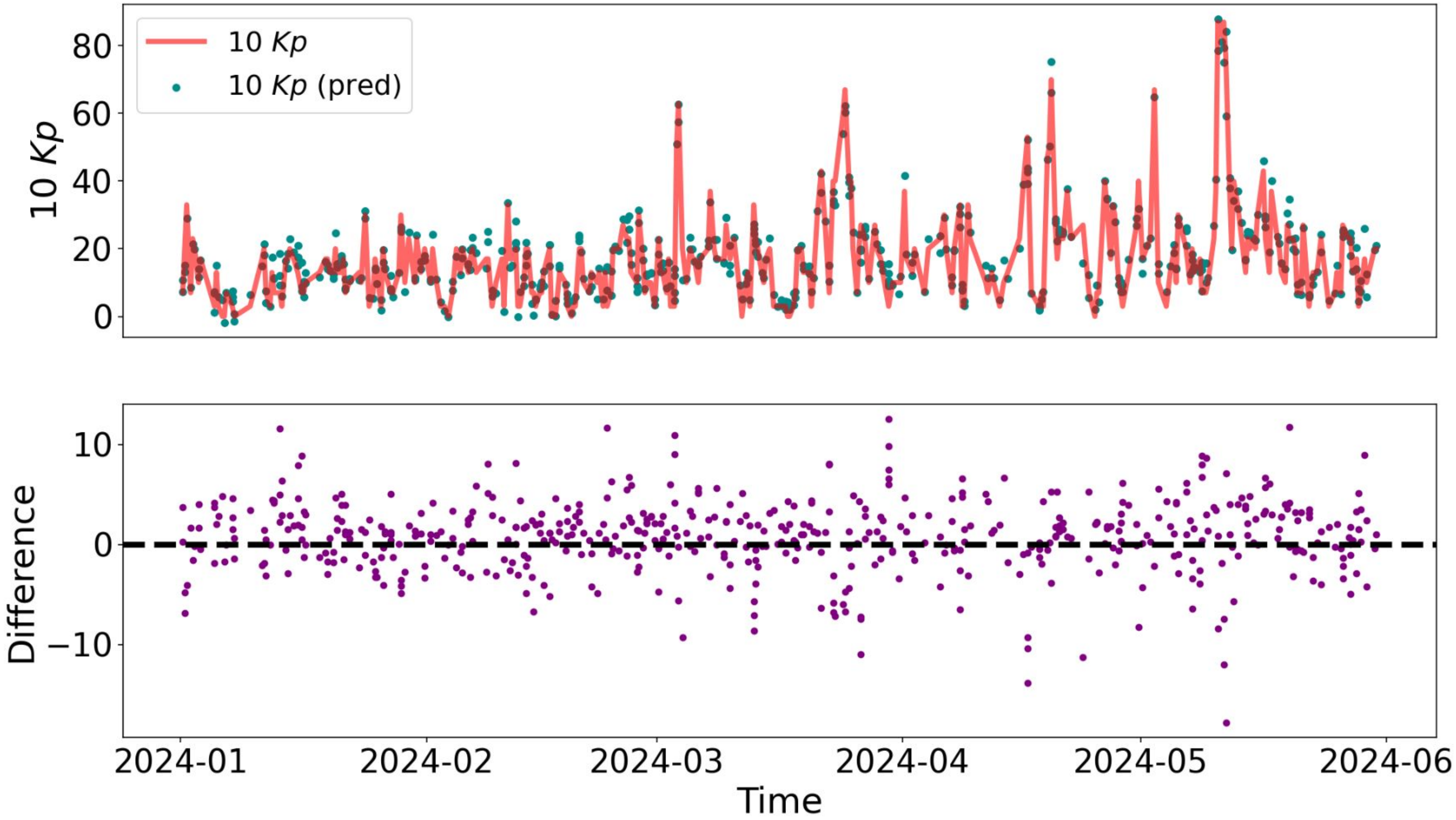


MSE ≈ 46.16

K_p Prediction - Model 1

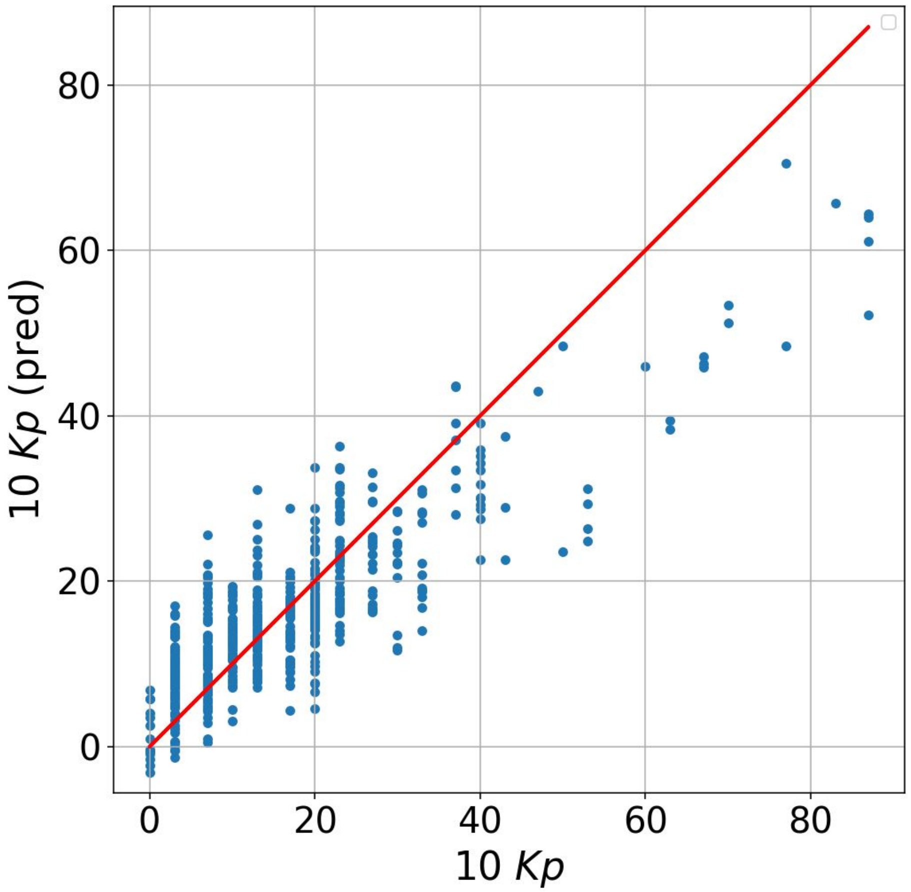


K_p Prediction - Model 2



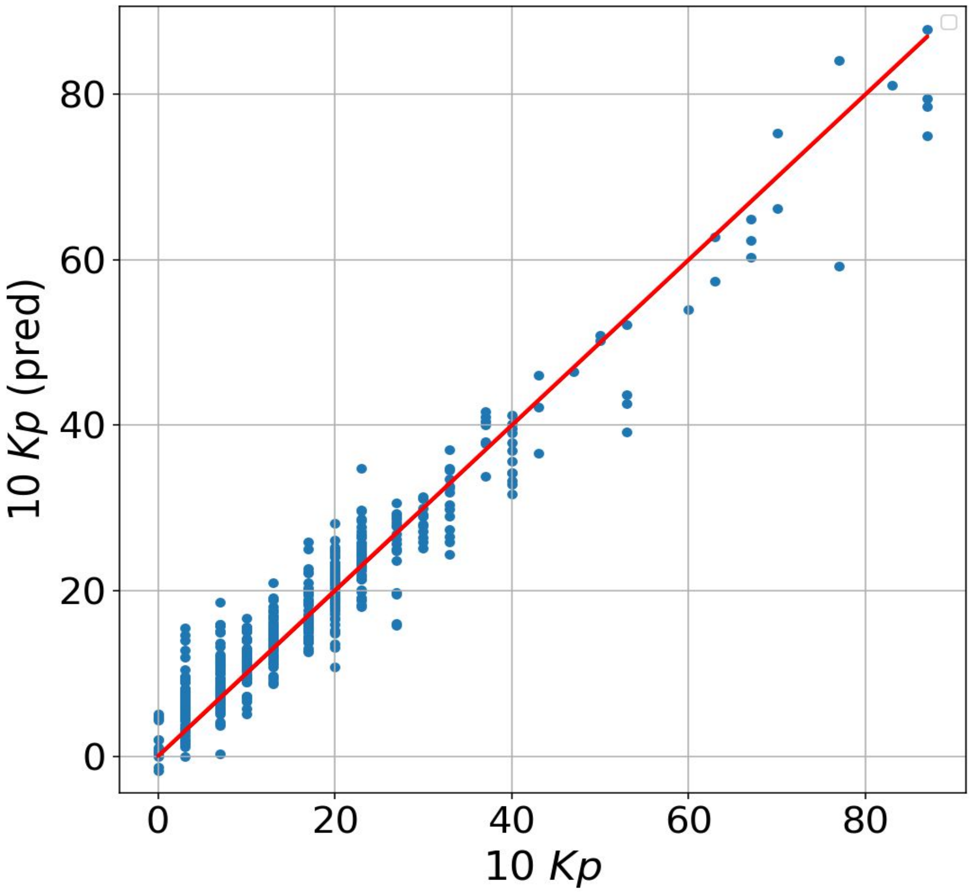
K_p Prediction - Model 2

Model 1



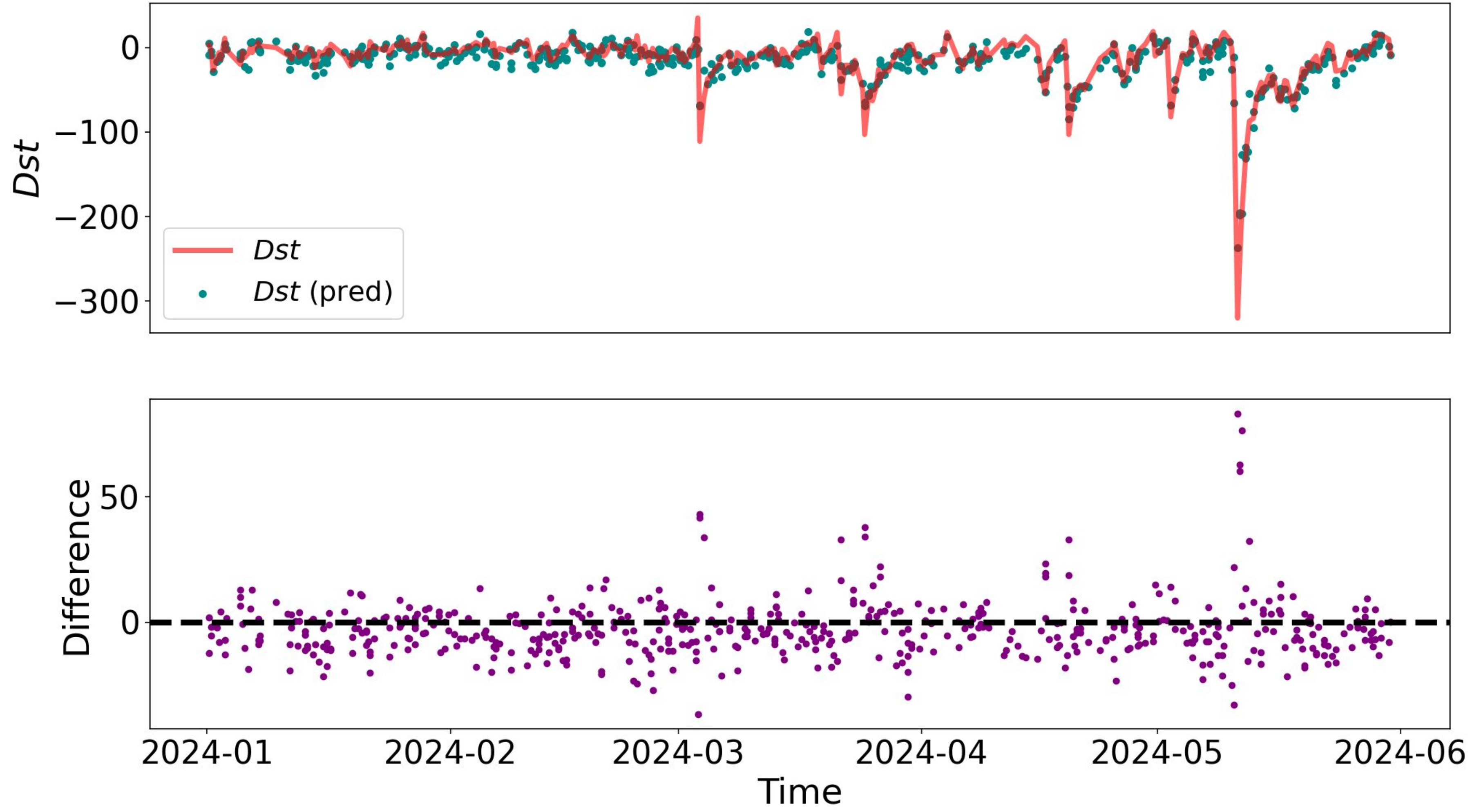
MSE ≈ 103.86

Model 2

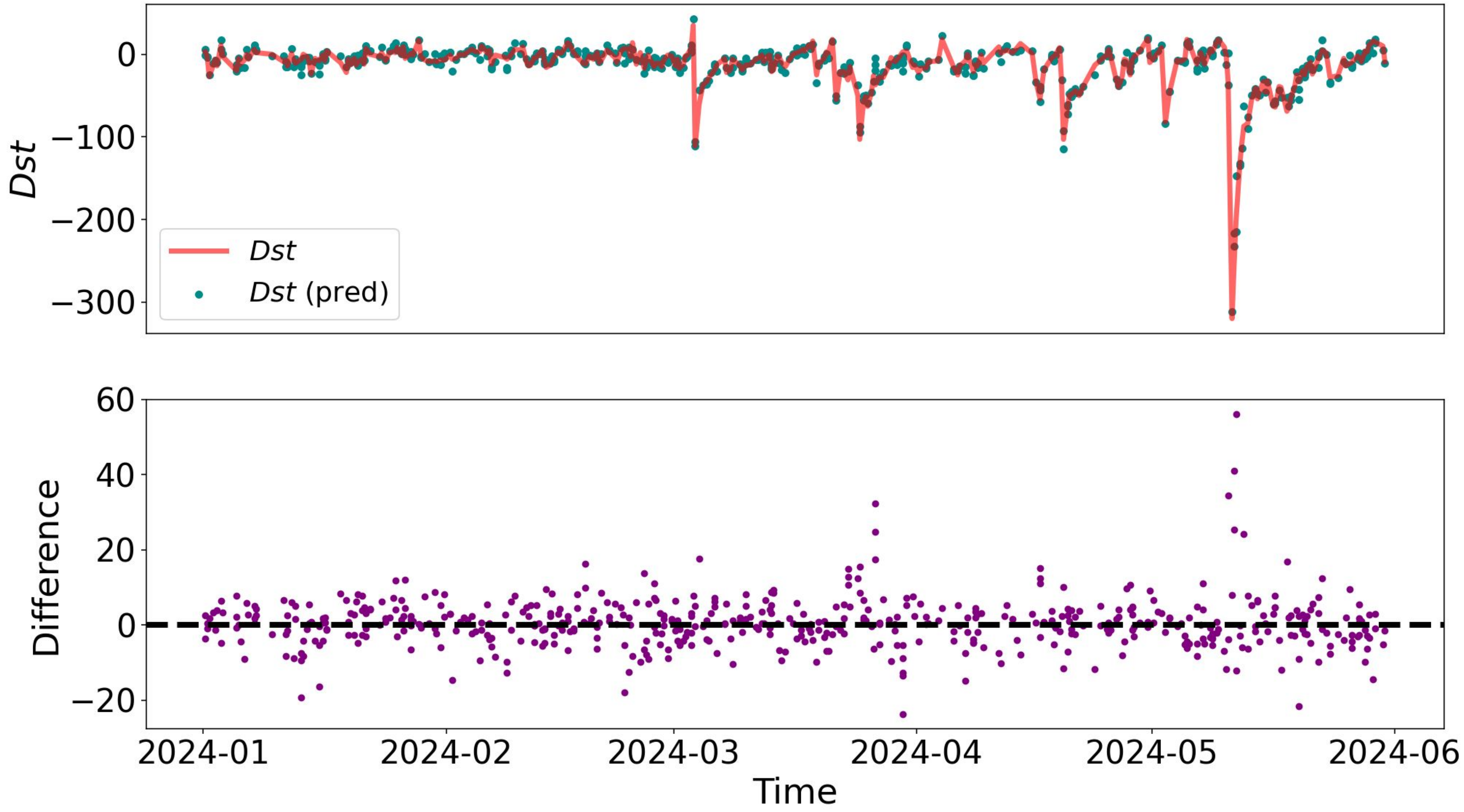


MSE ≈ 46.16

Dst Prediction - Model 1

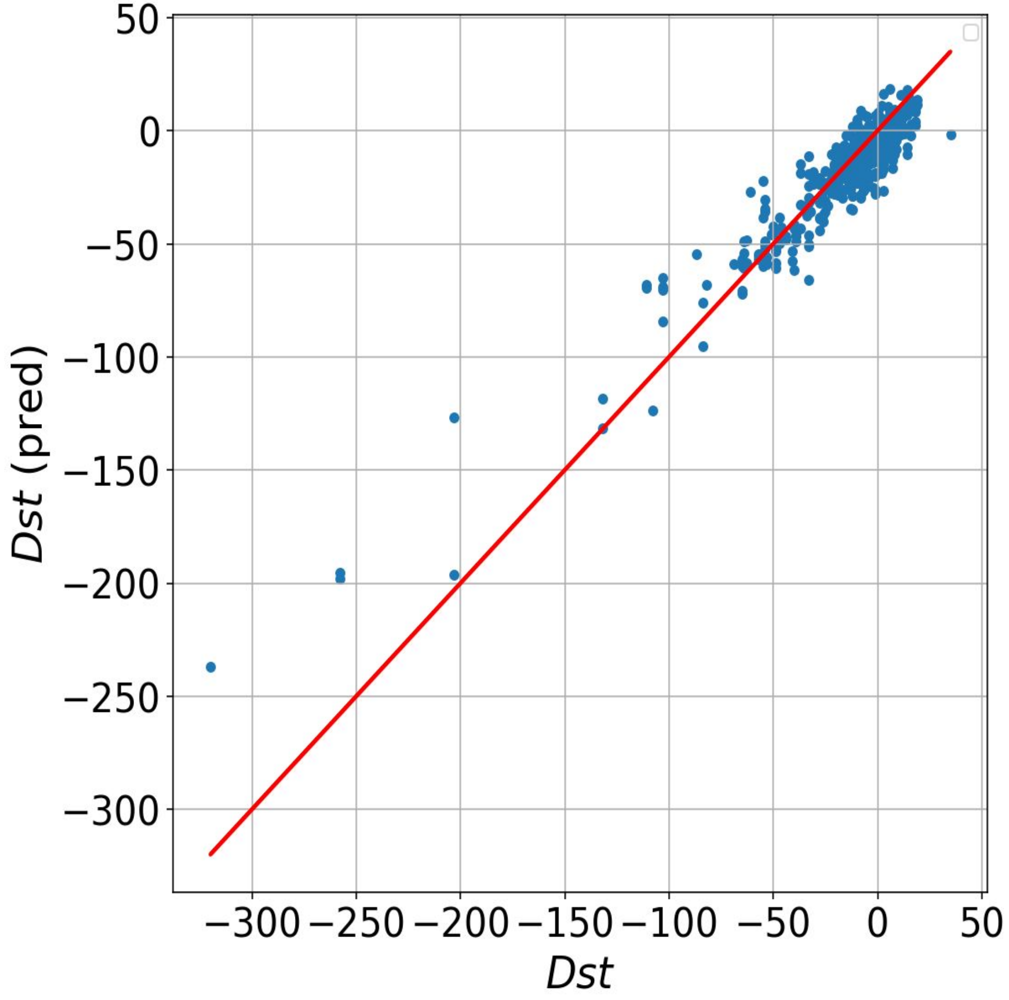


Dst Prediction - Model 2



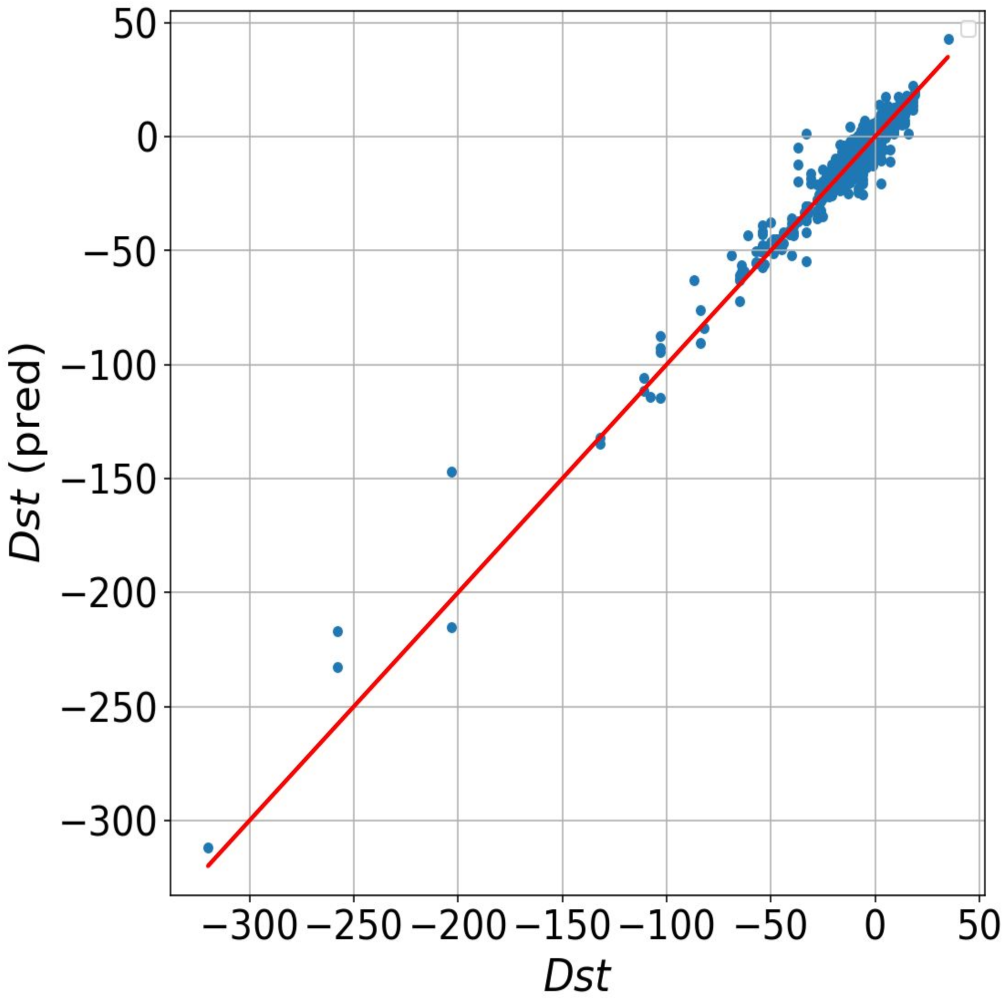
Dst Prediction

Model 1



MSE ≈ 103.86

Model 2



MSE ≈ 46.16

Conclusion

- A CNN model was created that predicts Ionospheric indices using Solar images in different wavelengths

- Model 2, that contains more neurons, filters, and training phases (epochs) ***outperformed*** Model 1

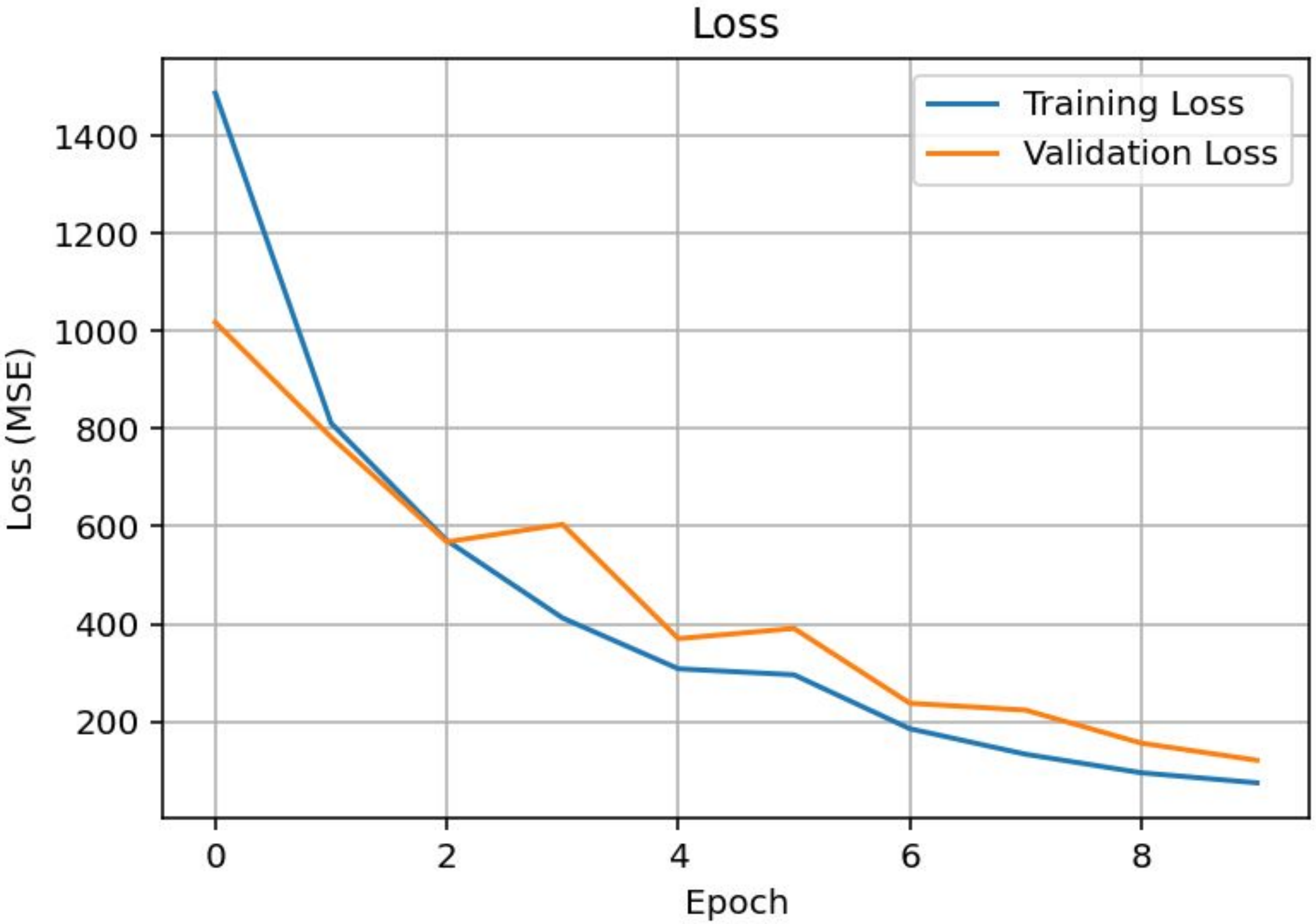
- We were able to capture the geomagnetic indices during storm time

Future Work

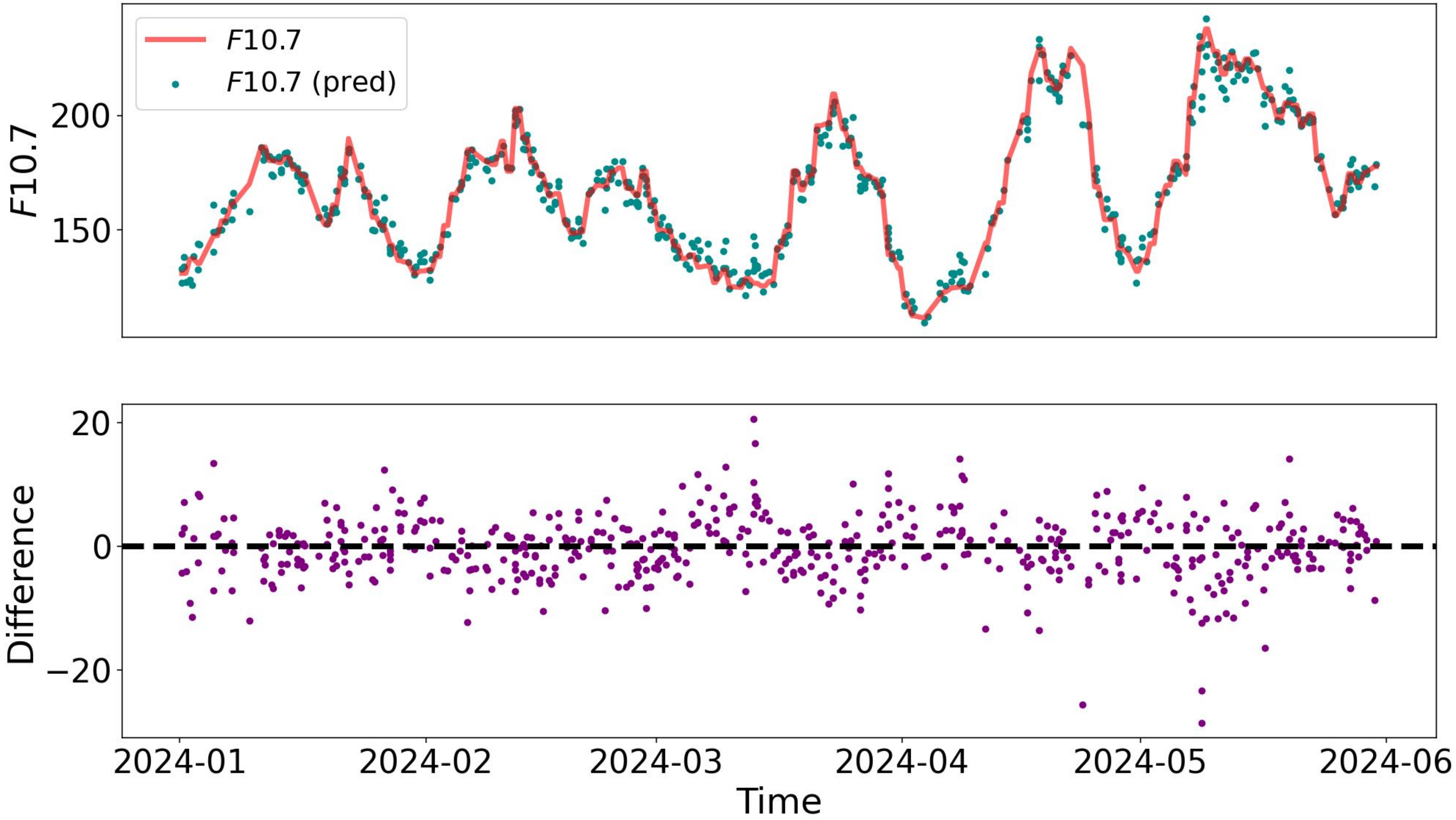
- Train the models more during storm times to predict geomagnetic indices
- Extend the dataset and validate the models on larger data

Backup Slides

Loss & Validation Loss Function of Model 1

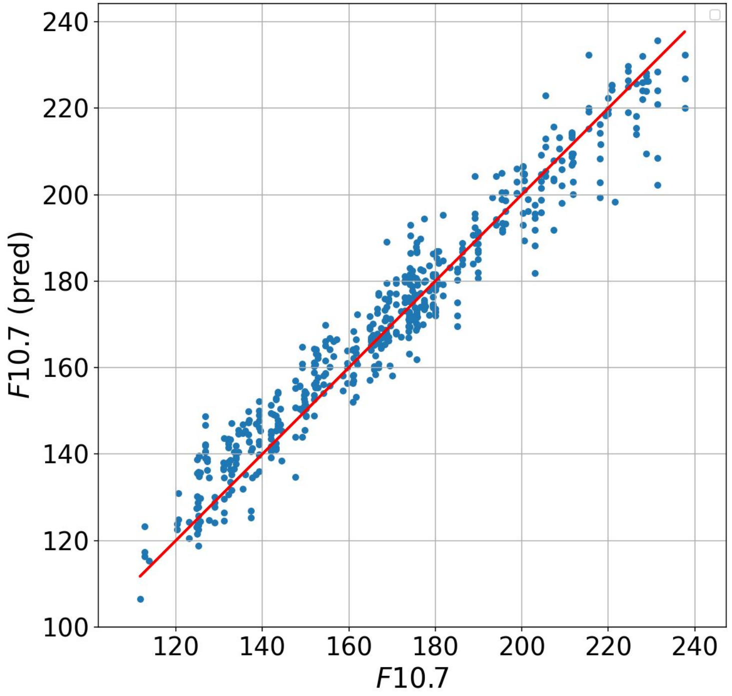


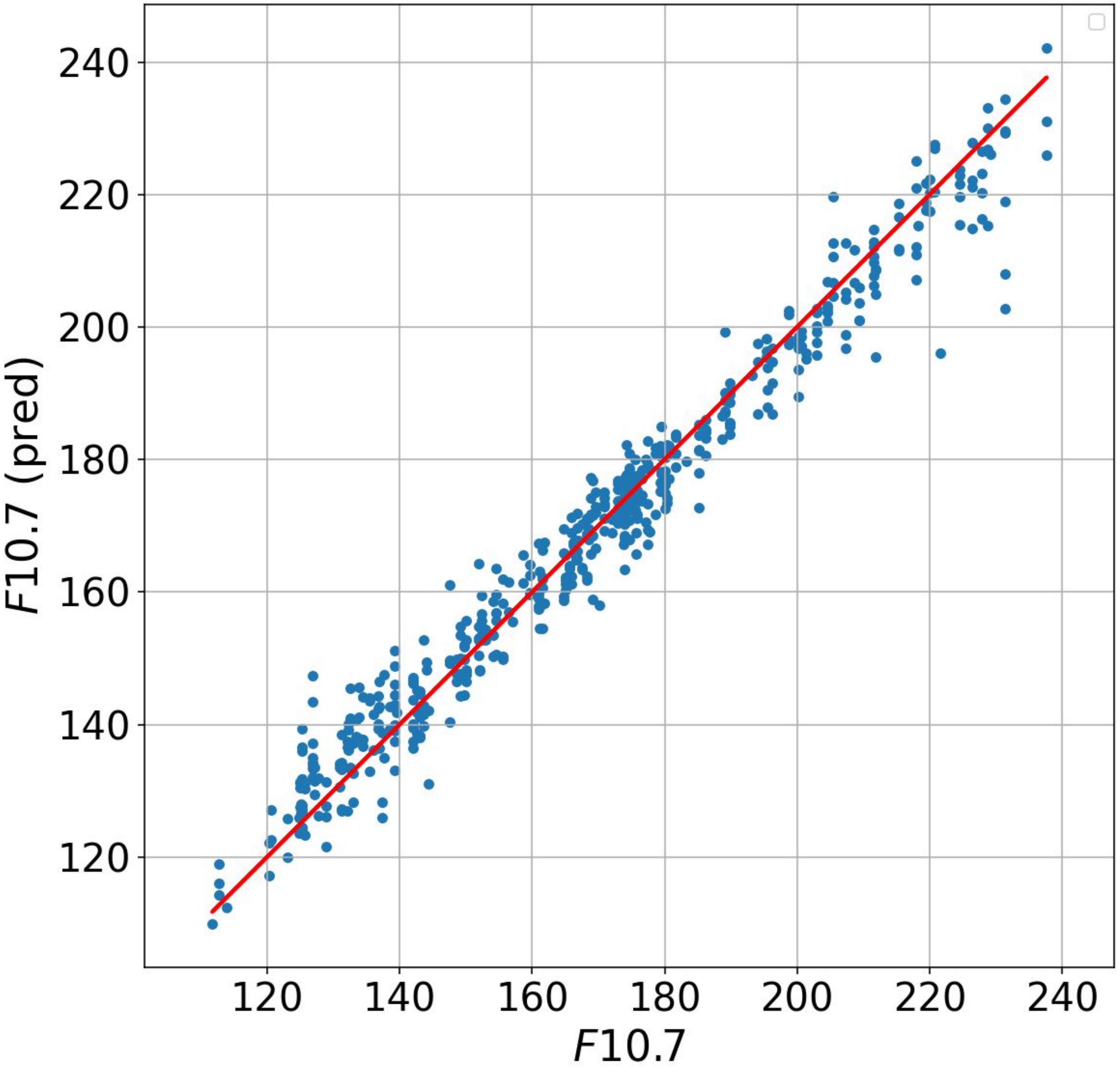
F10.7 Prediction - Model 2a



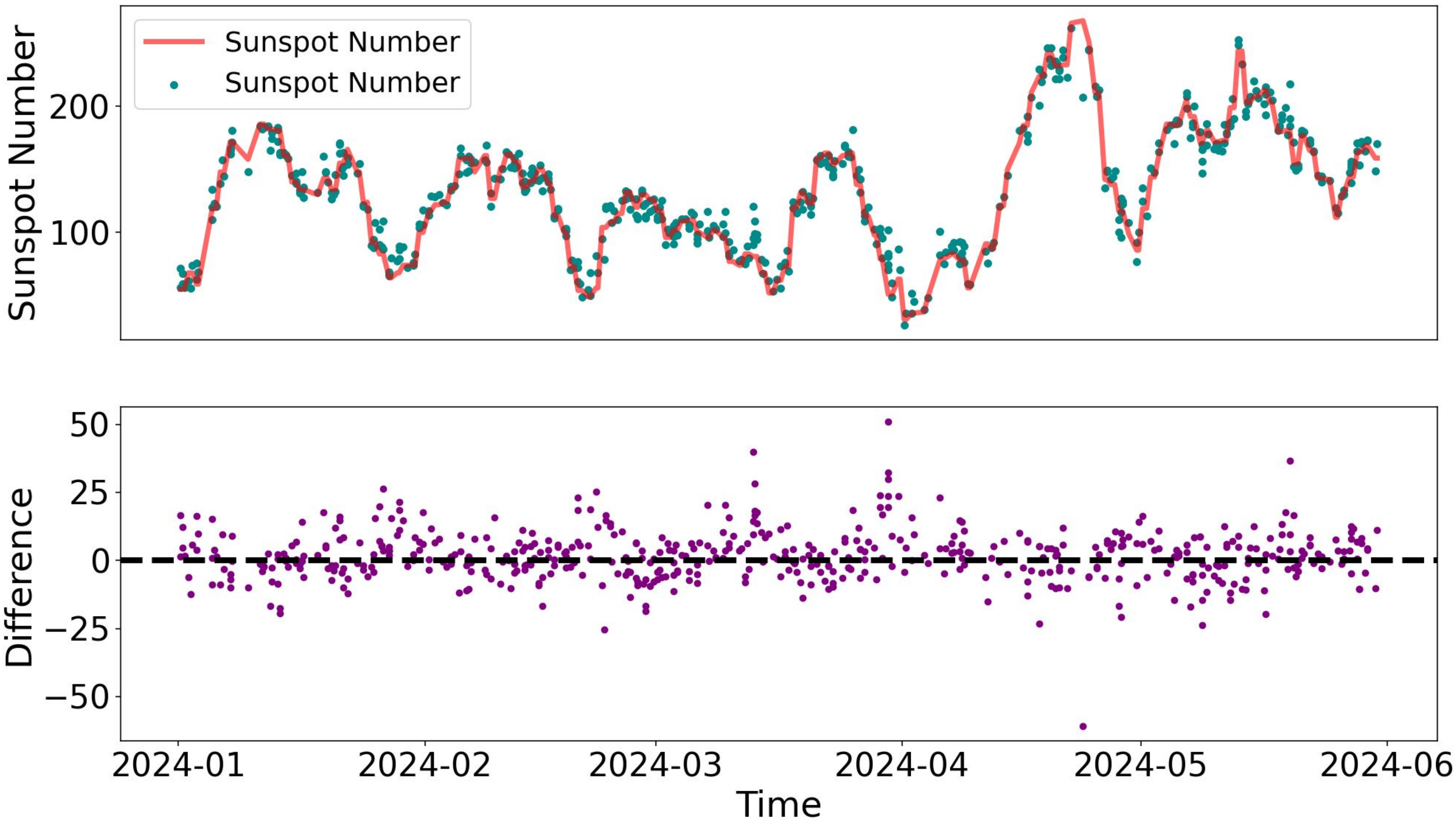
F10.7 Prediction - Model 2a

Model 1

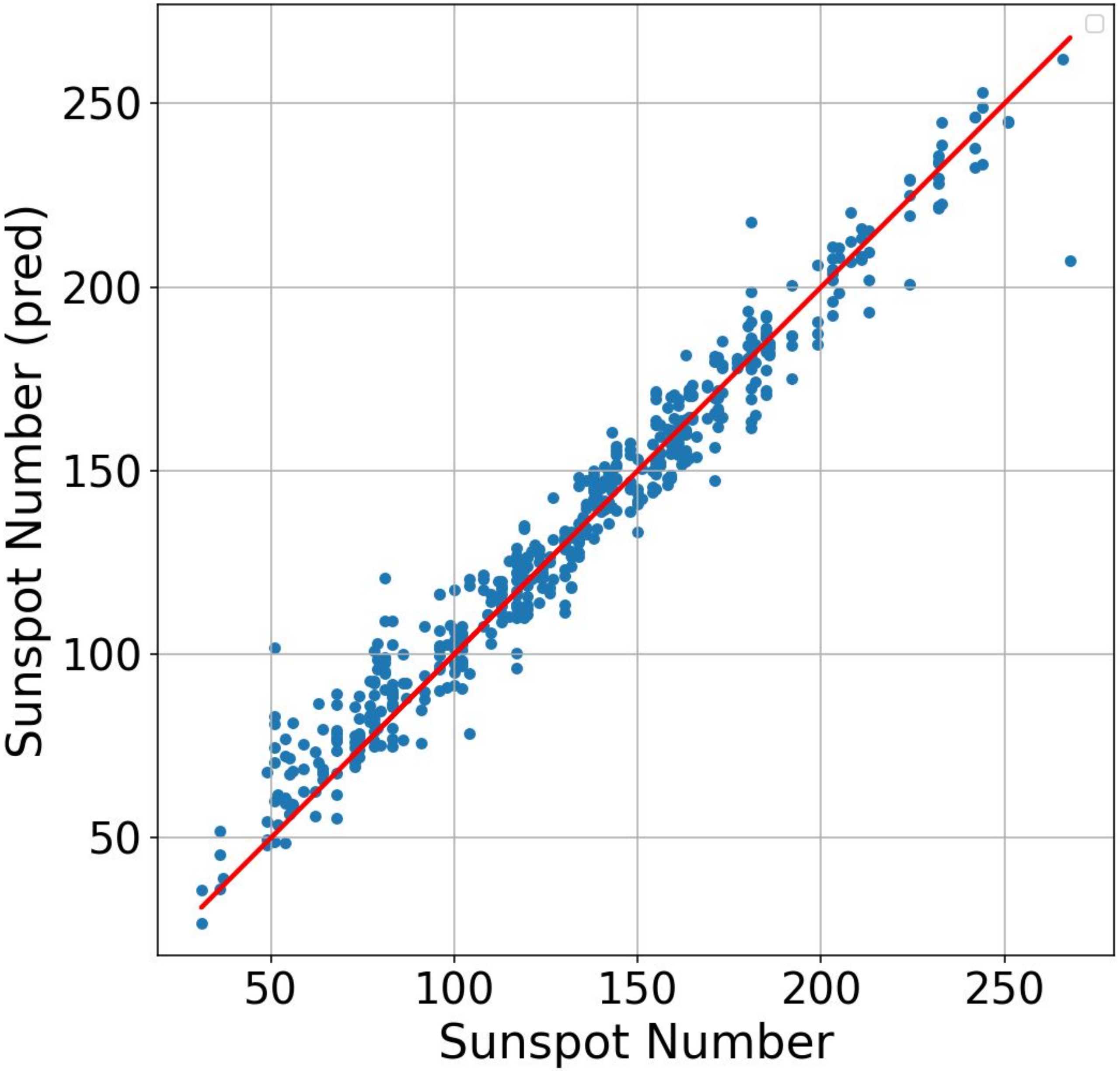




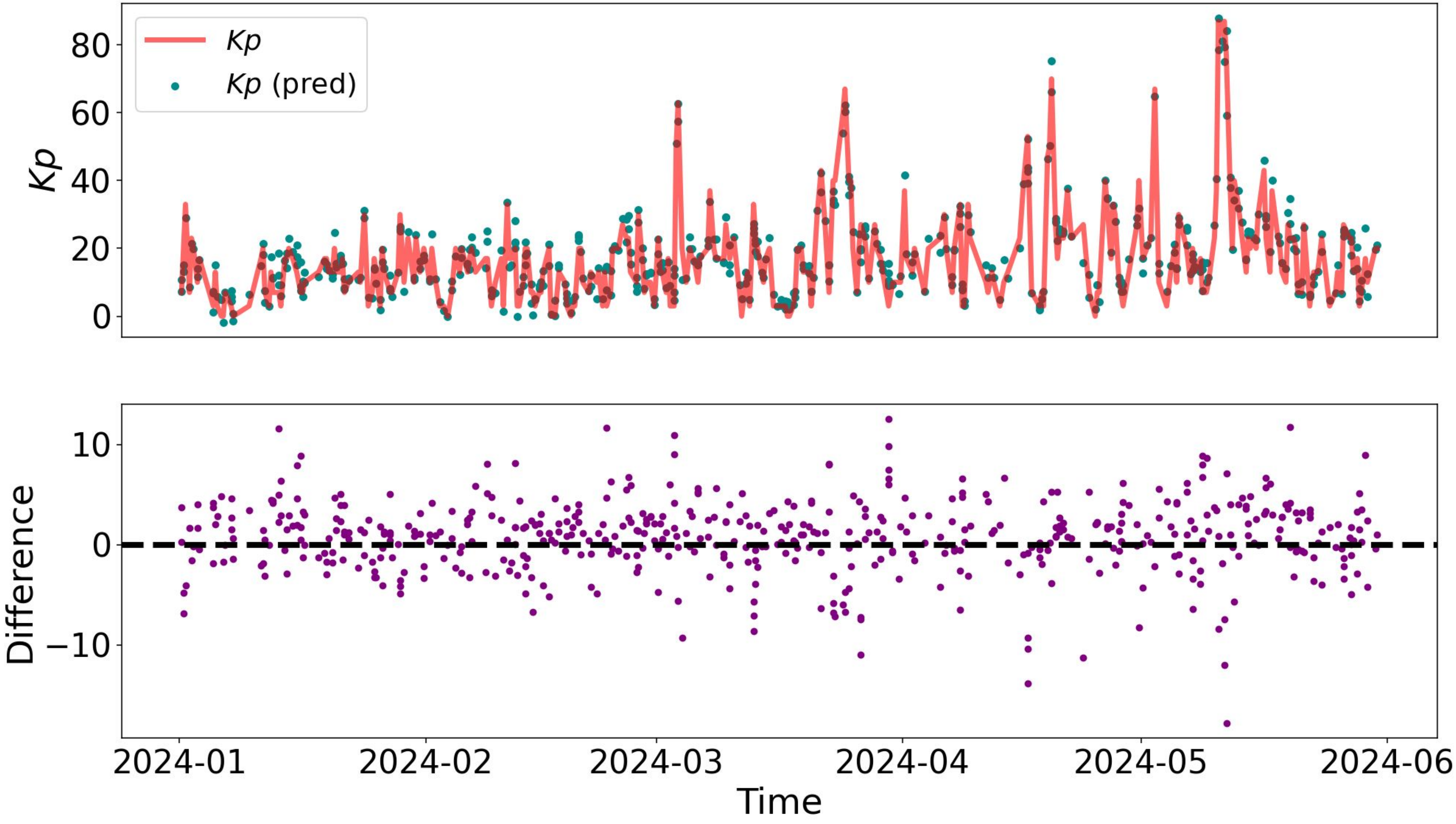
Sunspot Number Prediction - Model 2a



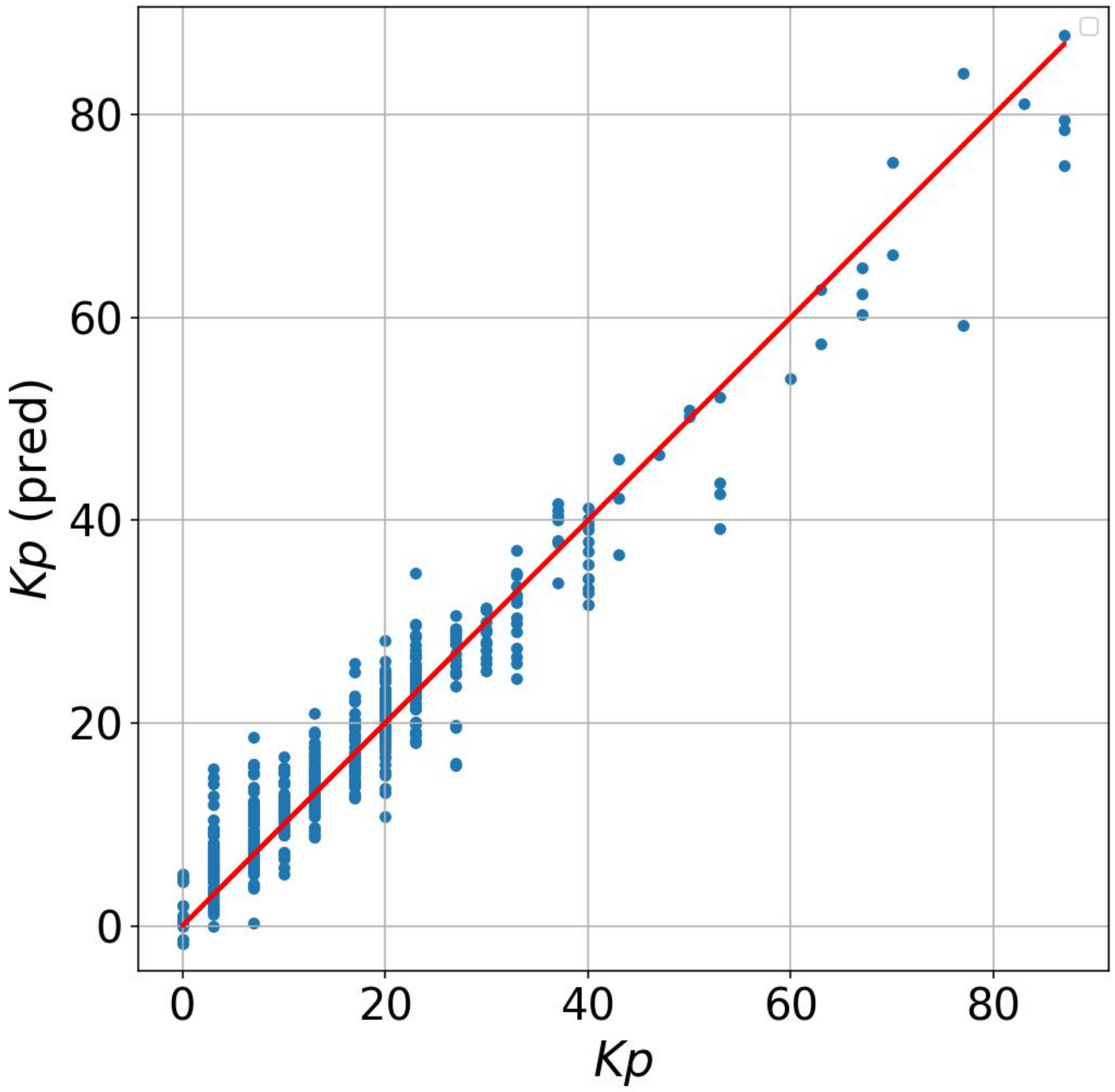
Sunspot Number Prediction - Model 2a



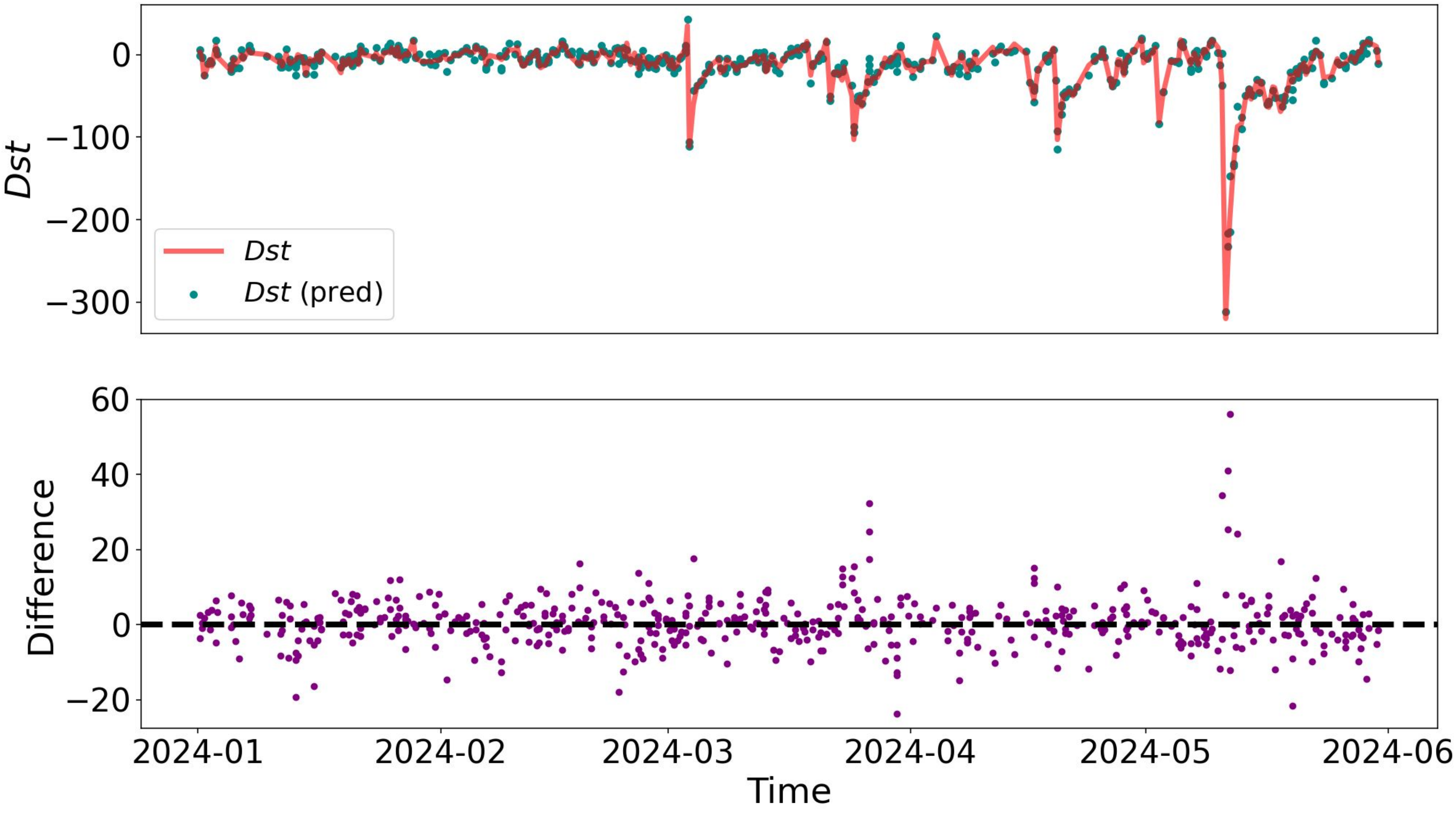
K_p Prediction - Model 2a



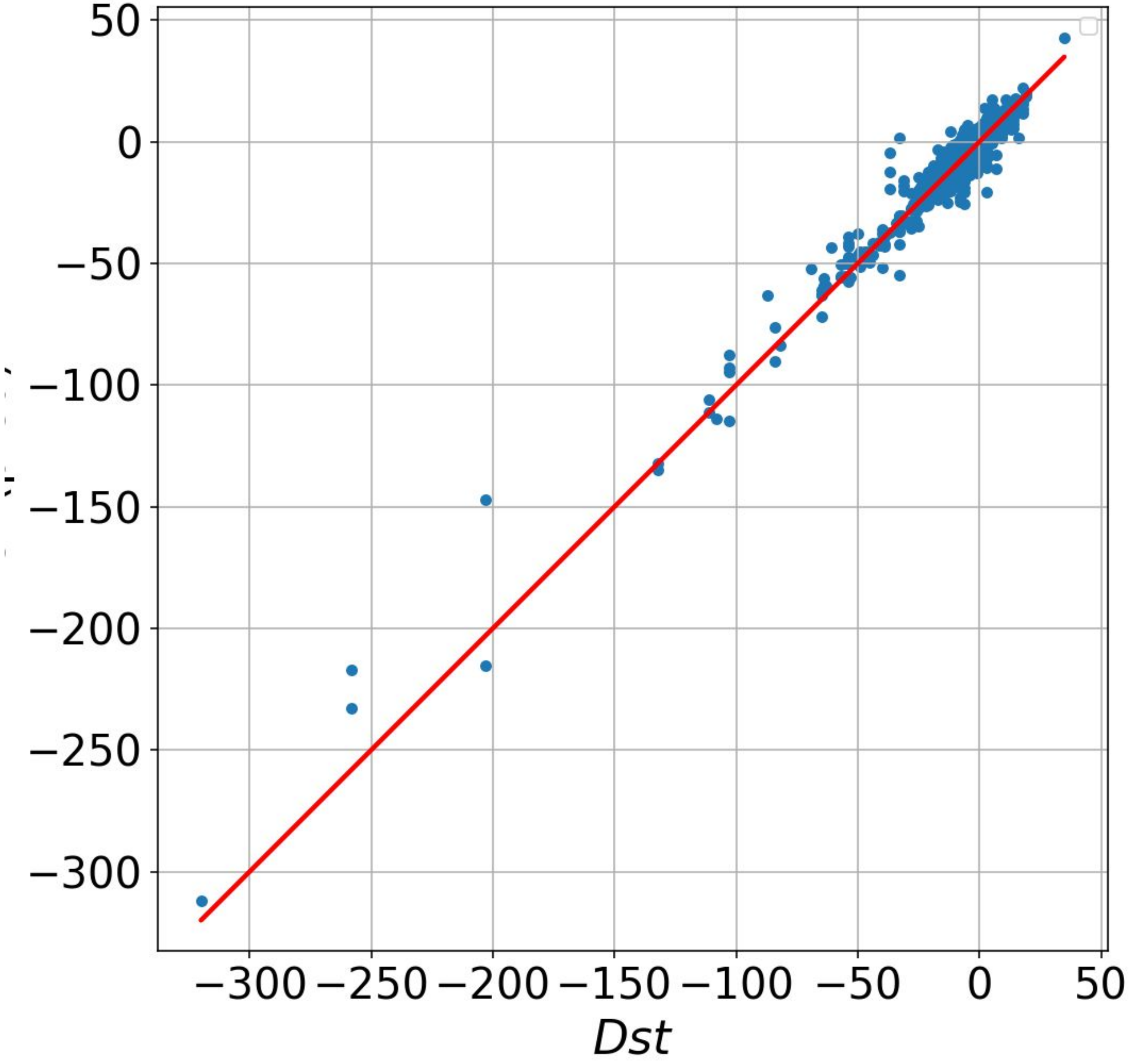
K_p Prediction - Model 2a



Dst Prediction - Model 2a



Dst Prediction - Model 2a



References

https://ik.imagekit.io/upgrad1/abroad-images/imageCompo/images/Basic_CNN_Architecture__A_Detailed_Explanation_of_the_5_Layers_in_Convolutional_Neural_Networks_visual_selectionO0WIL1.png