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IFT6759 - Project 1
Solar Irradiance Prediction

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Project Description

With the surge of perturbations that climate change has brought in the last years, the need for energy diversification has risen.

Better solar irradiance forecasting would ensure efficient management of photovoltaic energy, i.e storing energy while in maximum solar irradiance.

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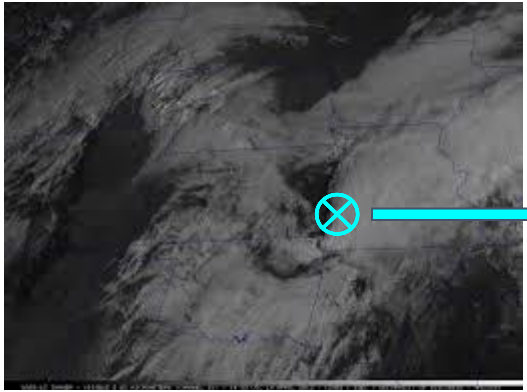
Project Description

Solar Irradiance : power per unit area (watt per square meter, W/m^2), received from the Sun in the form of electromagnetic radiation” - Wikipedia

Using satellite imagery and other metadata such as datetime, station ID, etc., predict GHI values up to 6 hours in the future at specific points on the map.

$T = T_0$, $T = T_0 + 1h$, $T = T_0 + 3h$, $T = T_0 + 6h$.



GHI values:

$T_0 = 433.2\ W/m^2$
$T_0 + 1h = 443.5\ W/m^2$
$T_0 + 3h = 263.1\ W/m^2$
$T_0 + 6h = -3.2\ W/m^2$

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Data Ingestion/Preprocessing

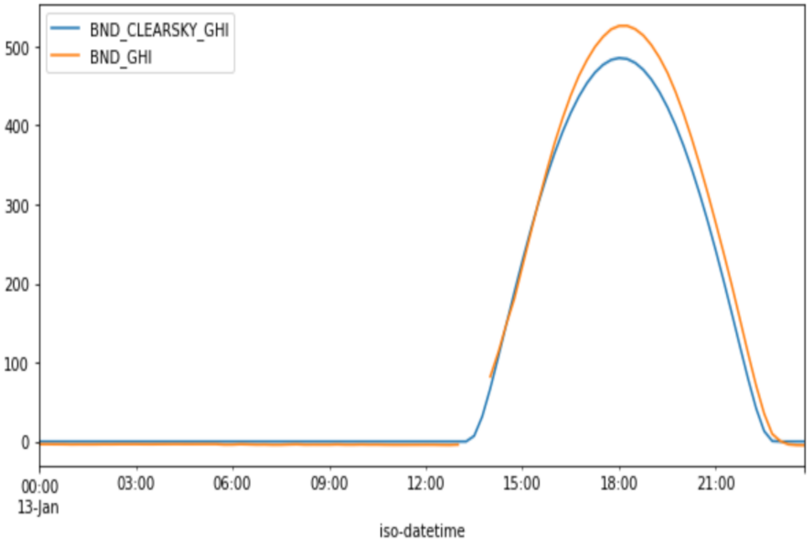
Dealing with NaNs

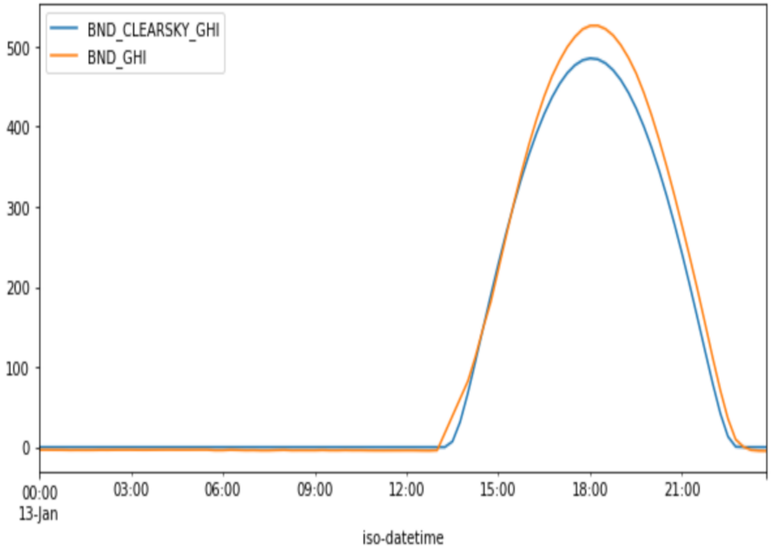
Features	Missing percentage
ncdf_path	17.4098%
hdf5_8bit_path	0.015%
hdf5_16bit_path	0.015%
BND_GHI	0.086%
TBL_GHI	0.2444%
DRA_GHI	0.5980%
FPK_GHI	0.2696%
GWN_GHI	1.2242%
PSU_GHI	0.1084%
SXF_GHI	0.362753%

Even though hdf5_path has less NaN we should only consider dataframe observations where the ncdf_path is not null.

Dealing with NaNs

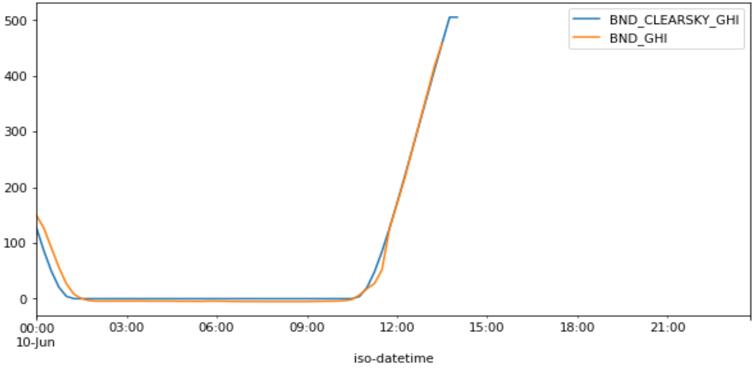
We interpolated missing GHIs using a linear interpolation based on the previous and next occurrence of valid data.



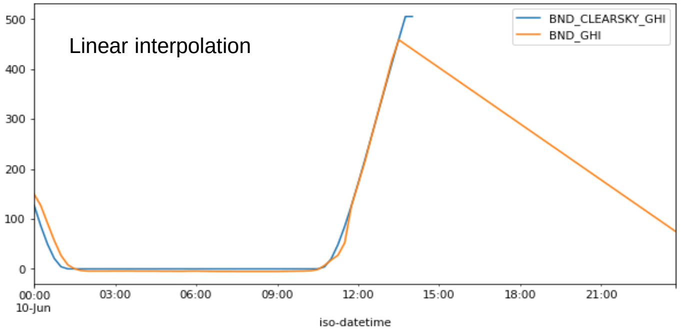


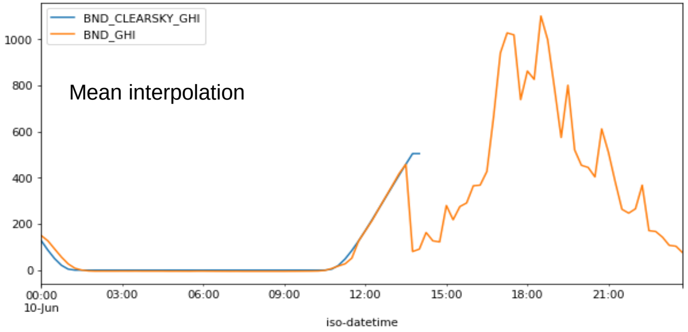
Dealing with NaNs

We interpolated missing GHIs using a mean interpolation based on the previous and next day of valid data.



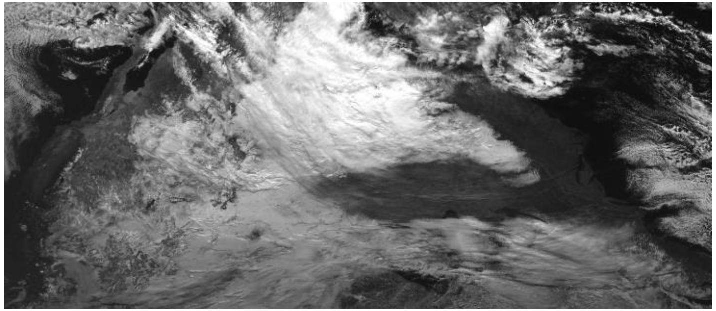
Several missing hours



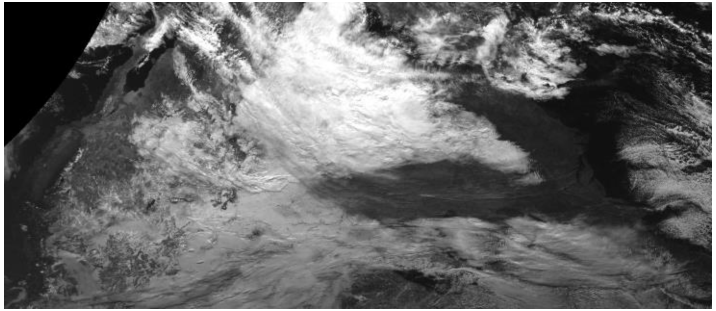


Dealing with missing images

We experienced with interpolating missing images by using a linear interpolation pixels-wise from previous and next available images:

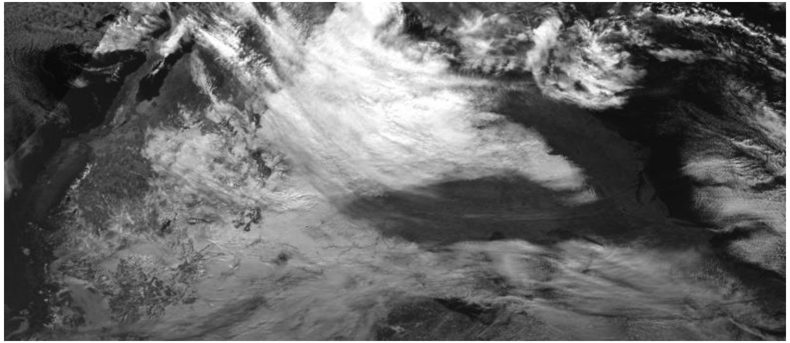


Previous image



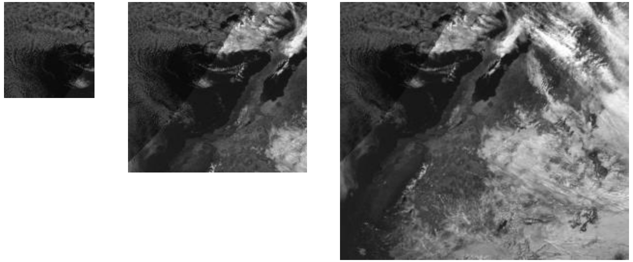
Next image

Interpolate missing image



Interpolated image

Cropping Strategy



How many pixels to keep?

Over how many pixels a cloud can travel in 6 hours?

½ Ideal image size =
6 hours * Cloud speed km/hr * pixels/km

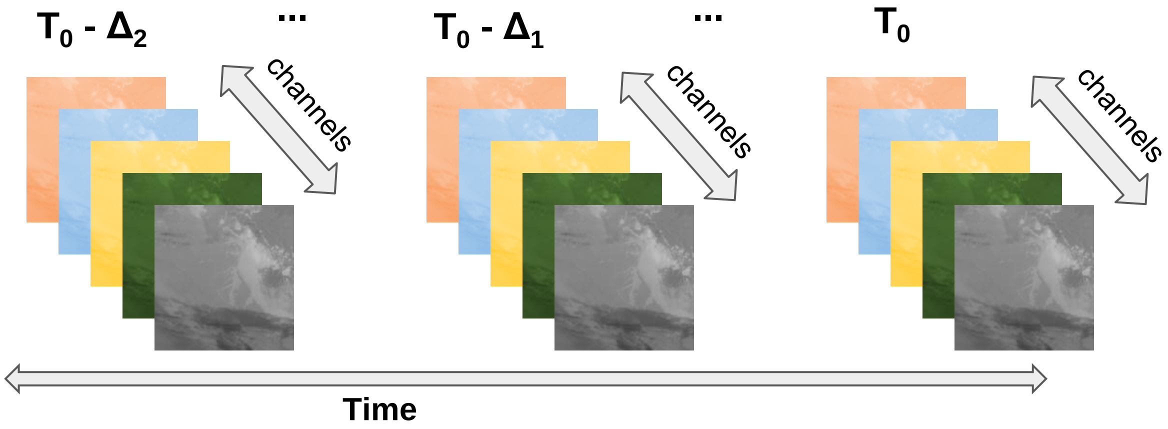
Average cloud speed: 64km/hr
Max cloud speed: 160km/hr

GOES-13 Pixel density:
16km/px

Image sizes:
Average case: 48 pixels
Worst case: 120 pixels

Cropping

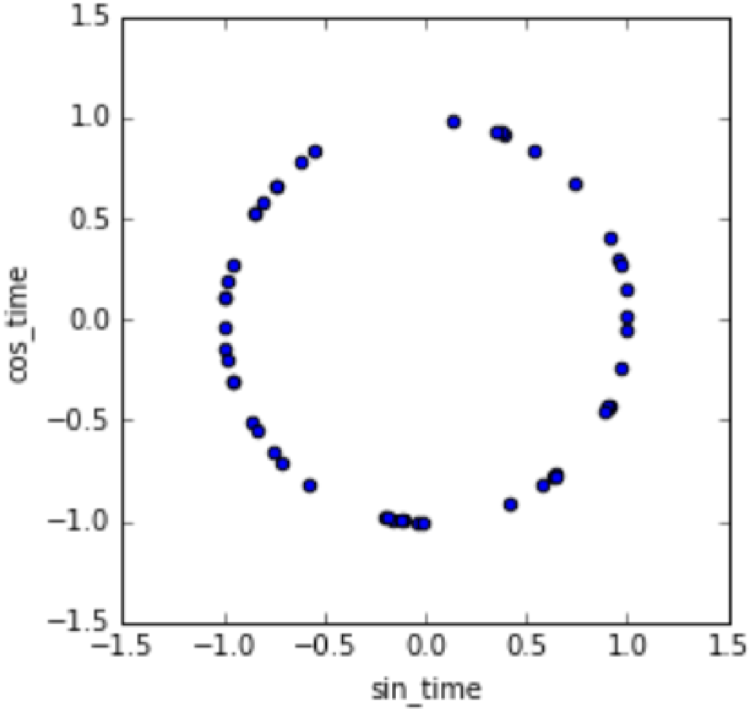
In order to capture the dynamics of atmospheric phenomena, we considered a sequence length of past 2 images with a window size of 41. Thus, our input image is of size (82,82,5).



If there was any missing image in the pre-defined sequence length, we replaced those with the image at T_0

Encoding cyclical features

Sin and cosine transformation - time of day & day of year



$$t_d = \sin\left(\frac{\text{sec in day}}{\text{sec per day}} * 2\pi\right)$$

$$t_y = \sin\left(\frac{\text{day in year}}{\text{days per year}} * 2\pi\right)$$

$$\text{cyclical time of day} = (\sin t_d, \cos t_d)$$

$$\text{cyclical time of year} = (\sin t_y, \cos t_y)$$

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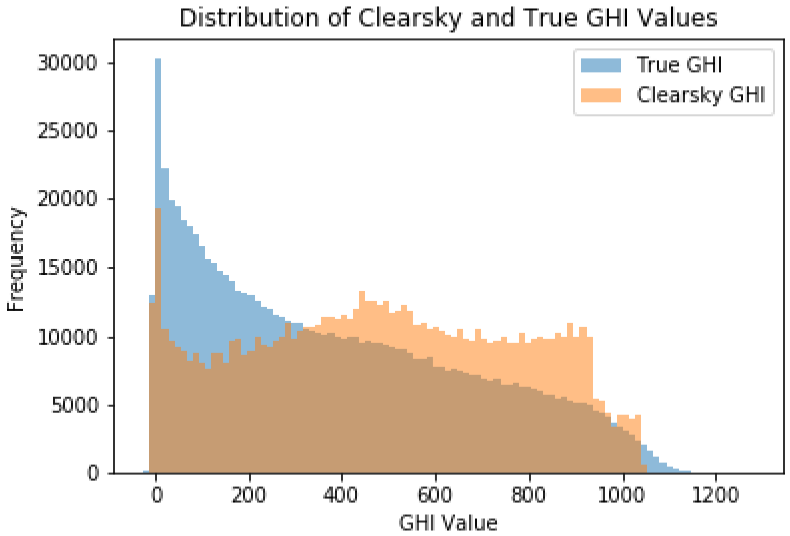
Models + Architectures

Loss Function Definition

Metric of Interest: GHI RMSE

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



Model Target: Clearsky ratio!

Clearsky ratio

$$k_{true} = \frac{ghi_{true}}{ghi_{cs}}$$

MSE Loss:

$$\mathrm{loss} = (k_{true} - k_{pred})^2$$

Use **sigmoid** output activation function to predict k!

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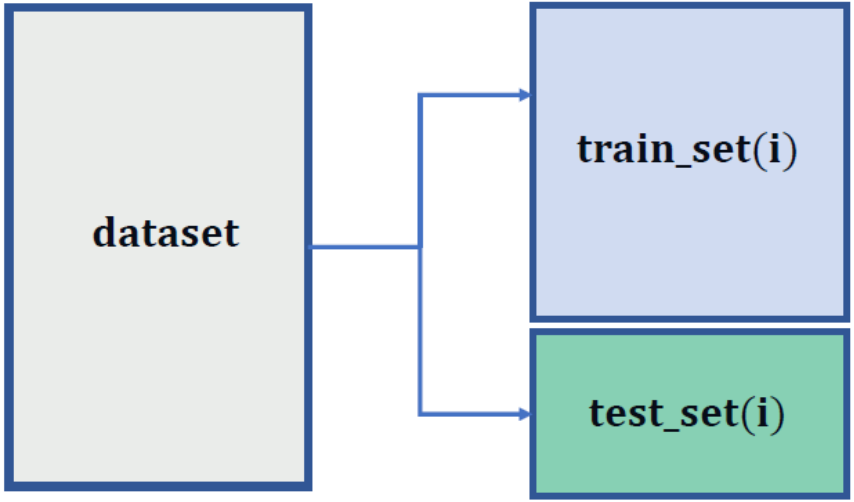
Cross-Validation Strategy

Train on all data from 2010-2014

Hold out 2015 for validation



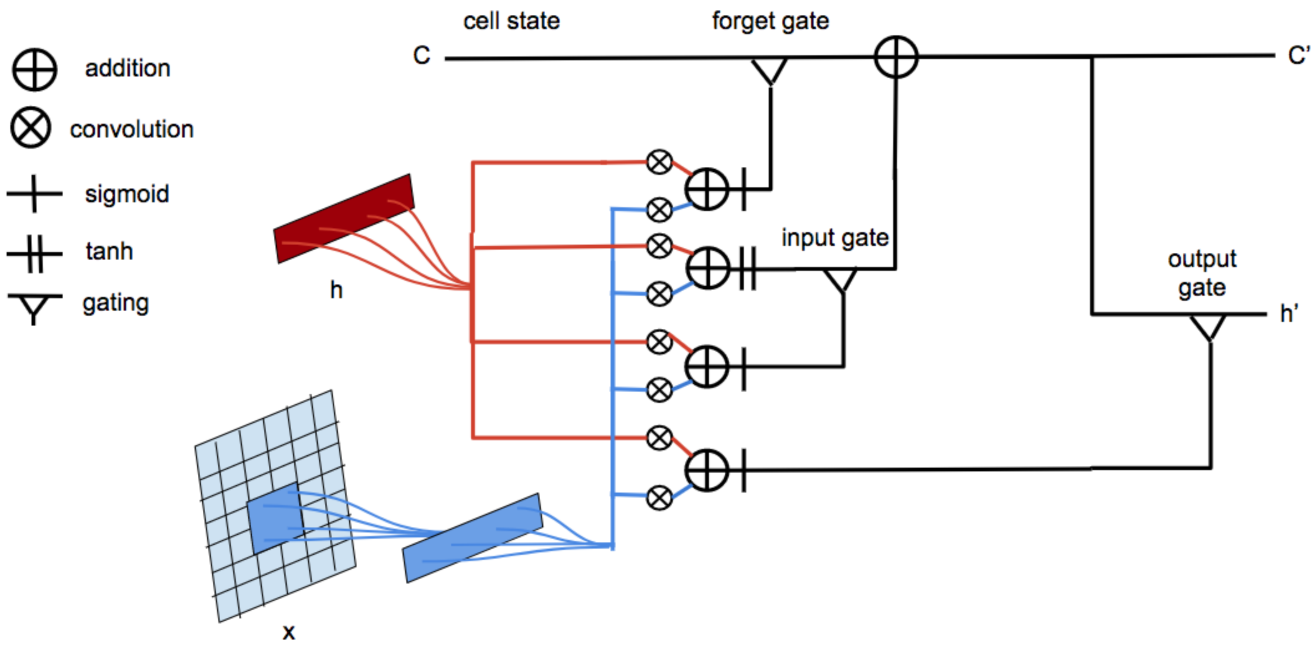
Input Features

Input features :

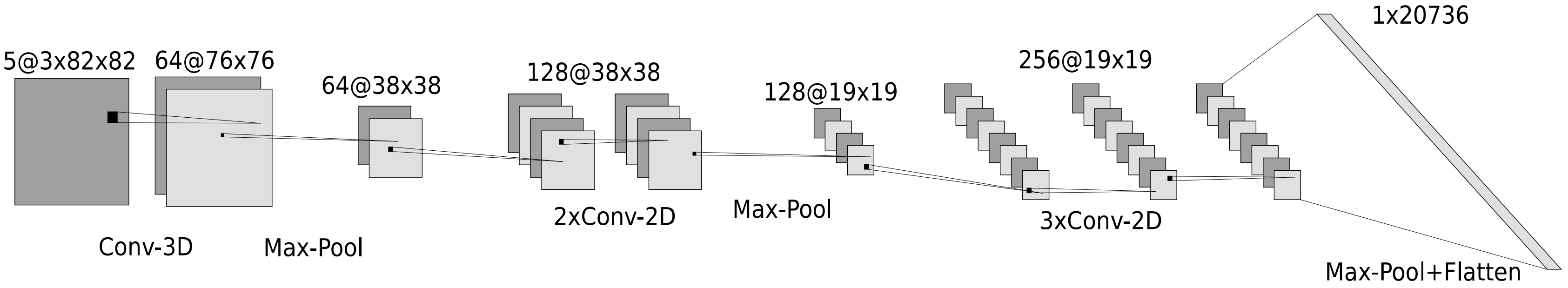
- Past 3 cropped images centered around station coordinates
- Clearsky value GHIs for $T_{0,}$ $T_{1,}$ $T_{3,}$ T_6
- Cyclical time of day
- Cyclical time of year

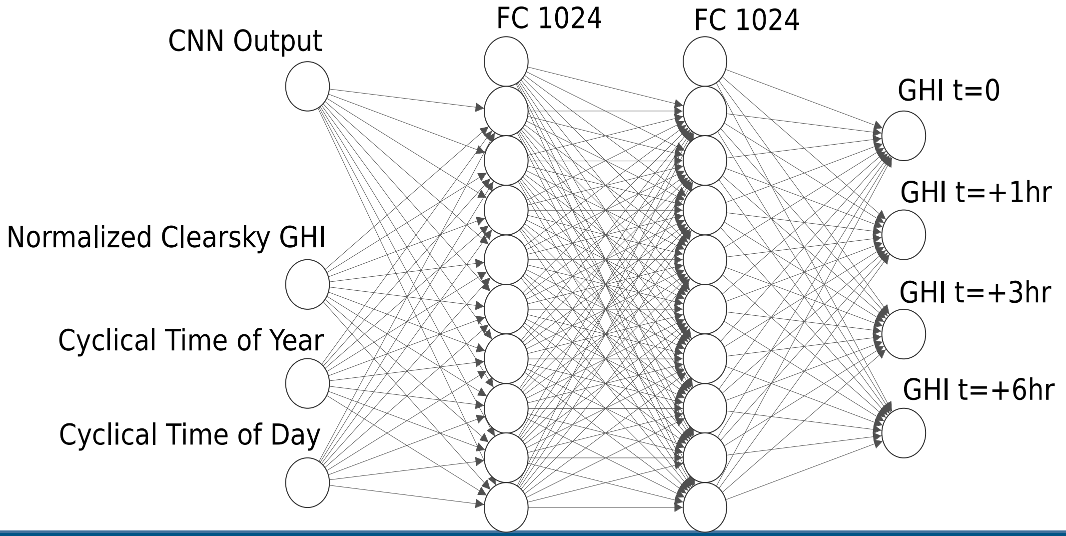
Models tried

Convolutional LSTM



3D CNN - Architecture

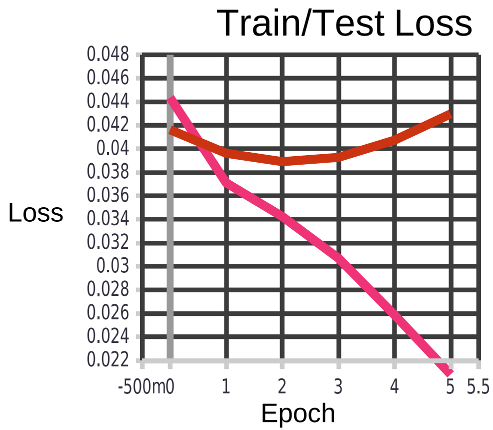


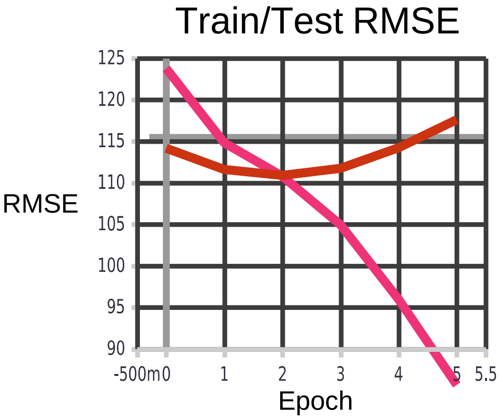


Other notes:

- Batch normalization after all CNN, FC layers
- RELU activation after batch normalization
- Sigmoid activation for output layer

Results





Model hyperparameters:

K-inflation: 10%
1024 Dense Units
3 Input Images @ t=0, -30 min, -60 min
1 Conv3D, 5 Conv2D layers

Other hyperparameters searched:

Model Description	Best Validation RMSE
Best Model (above)	110.2
Use 2048 Dense Units	111.5
Use 5 Input Images	112.2
Use onehot station IDs	110.9

Conclusion

Best model : 3D-CNN

Future work :

- Hyperparameter tuning with Orion
- Include image interpolation
- Weather API
- Other models (ResNet, etc.)