SUNCAST

Nowcast Solar Irradiance

Using Computer Vision and Deep Learning on Satellite Images

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Solar Energy

- Solar power generation account for almost 80% of the increase in renewable energy generation through 2050[1]
- Solar power is required to reduce global greenhouse gas emissions that stem from the energy sector each year[2,3]

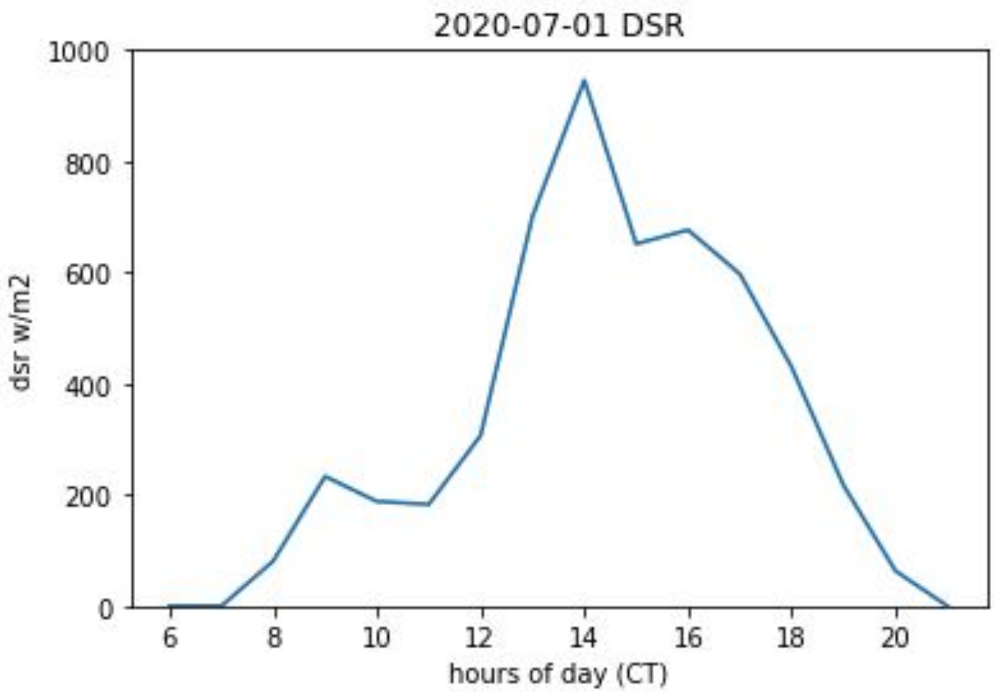
[1] Bipartisan Policy Center. Annual energy outlook 2021.Energy Information Administration,Washington, DC, 2021.

[2] Phebe Asantewaa Owusu and Samuel Asumadu-Sarkodie. A review of renewable energysources, sustainability issues and climate change mitigation.Cogent Engineering, 3(1):1167990,2016

[3] D Elzinga, S Bennett, D Best, K Burnard, P Cazzola, D D'Ambrosio, J Dulac, A Fernandez Pales,C Hood, M LaFrance, et al. Energy technology perspectives 2015: mobilising innovation toaccelerate climate action.Paris: International Energy Agency, 2015.

Solar Energy Prediction

- Solar power is volatile and intermittent



Existing Solutions

Use ground-based images to predict production at a solar plant in Hangzhou,China 1.

Deep learning model on satellite images to predict total daily PV for the entire nation of Germany.

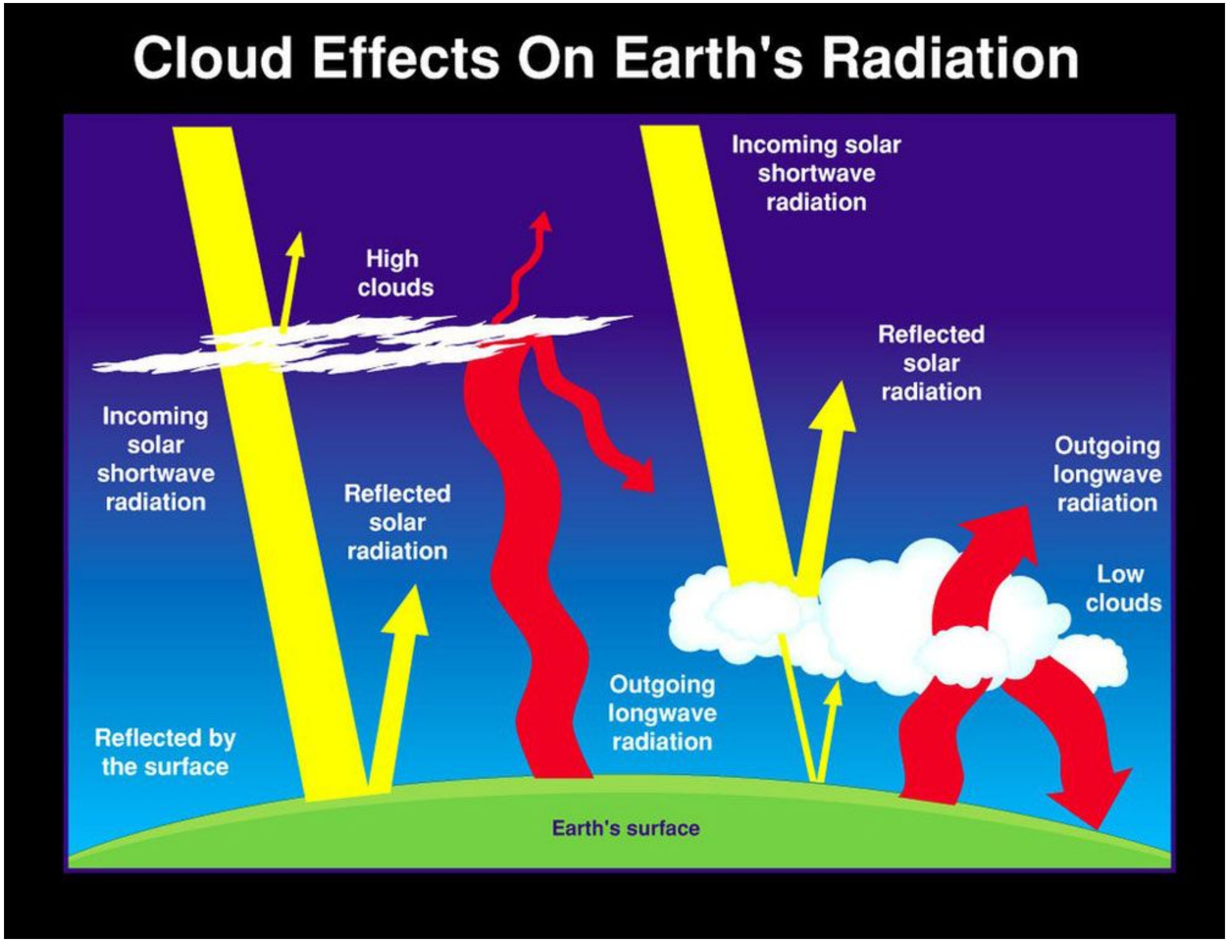
Numerical weather prediction(NWP) models

Keyong Hu, Shihua Cao, Lidong Wang, Wenjuan Li, and Mingqi Lv. A new ultra-short-termphotovoltaic power prediction model based on ground-based cloud images.Journal of CleanerProduction, 200:731–745, 2018

Nicolas Sebastien Jeremie Lequeux. Johan Mathe, Nina Miolane. Pvnet: A lrcn architecturefor spatio-temporal photovoltaic powerforecasting from numerical weather.arXiv preprintarXiv:1902.01453, 2019.

Hadrien Verbois, Robert Huva, Andrivo Rusydi, and Wilfred Walsh. Solar irradiance forecastingin the tropics using numerical weather prediction and statistical learning.Solar Energy, 162:265–277, 2018.

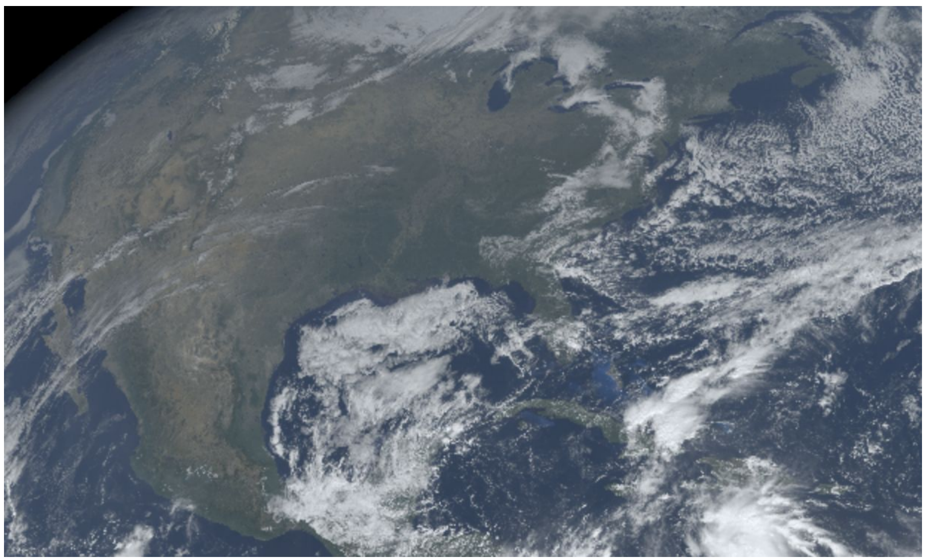
Factors that affect Solar Irradiation



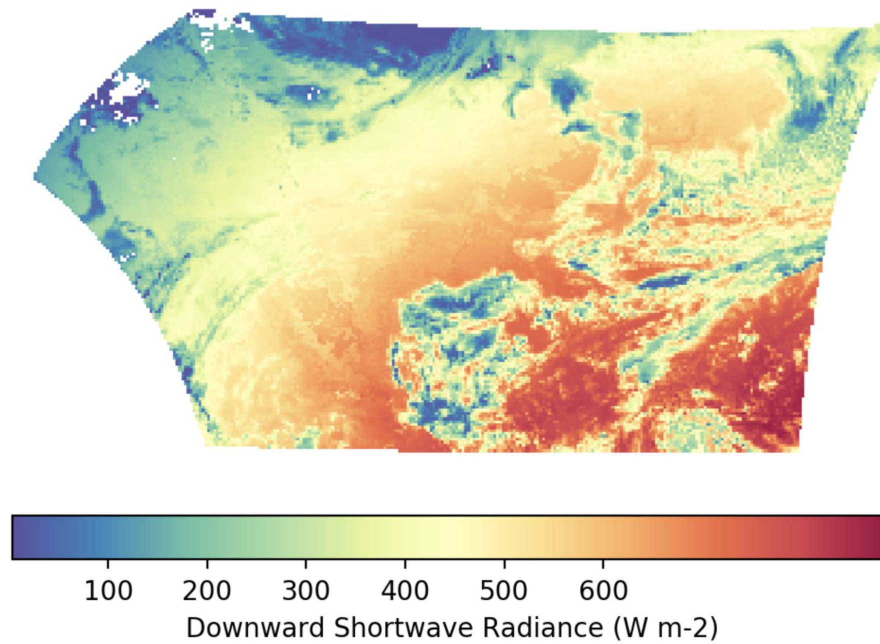
Ref: https://www.goes-r.gov/featureStories/solarEnergyForecasts.html

NOAA GOES Satellite Images

True Color Image



DSR

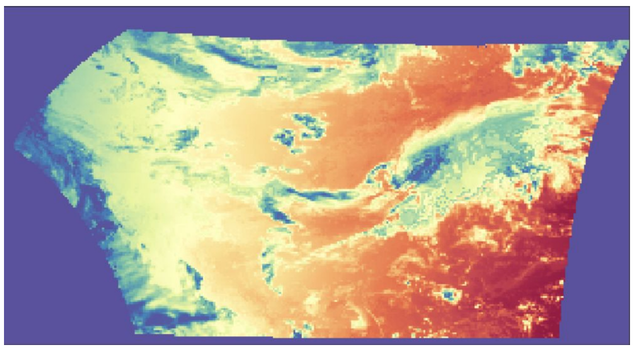


Satellite images available on “Open Data on AWS”
https://registry.opendata.aws/noaa-goes/
File Format: netCDF

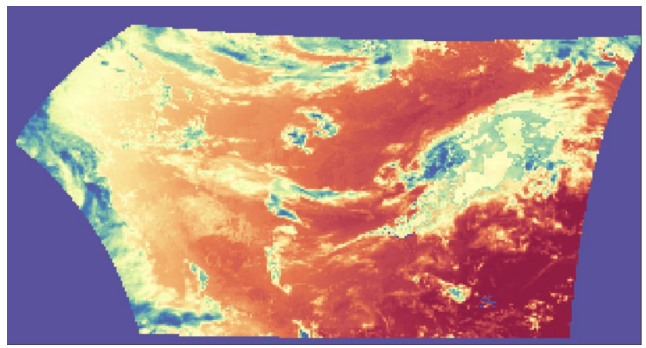
Model Features & Label

X

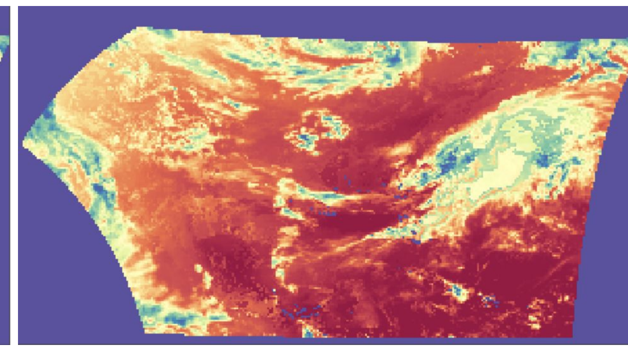
t - 2



t - 1

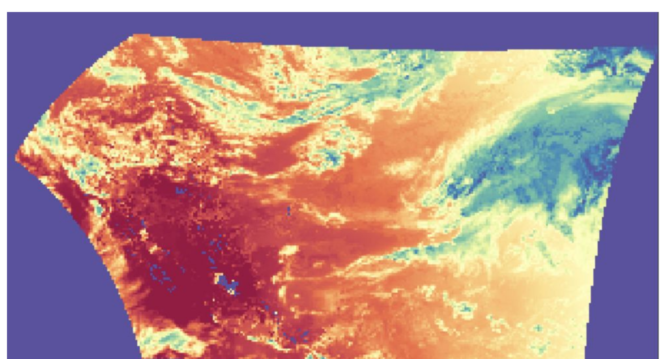


t

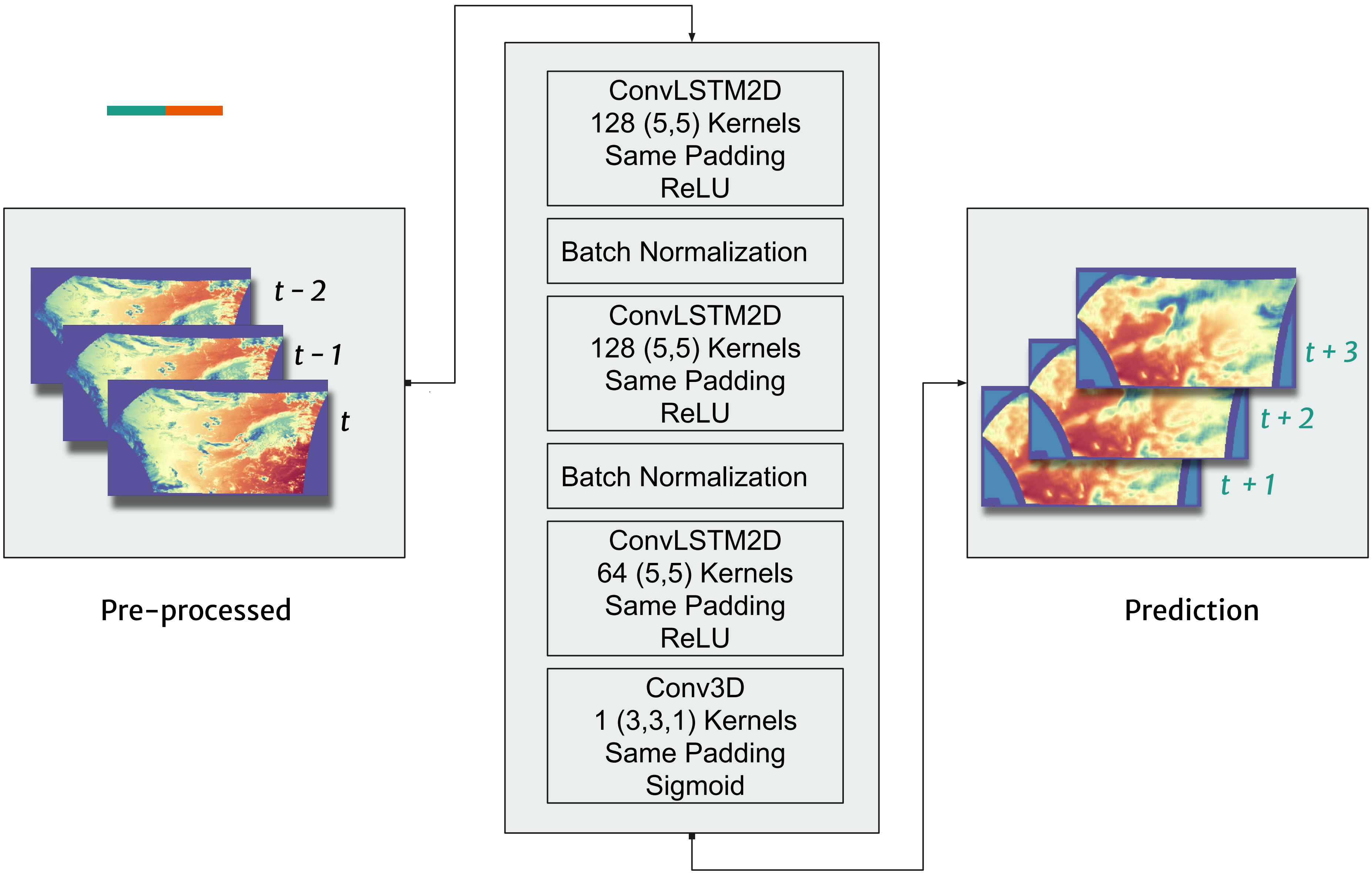


y

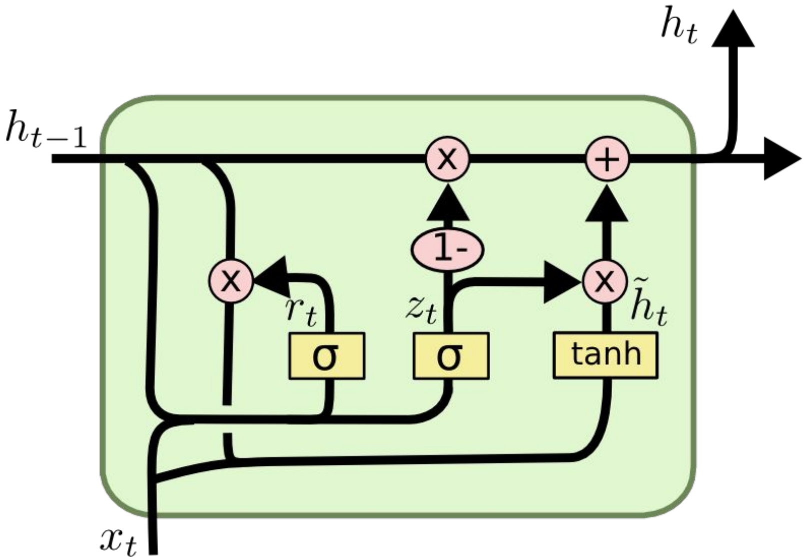
t + 1



Model Architecture



Cell Variation - ConvGRU



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

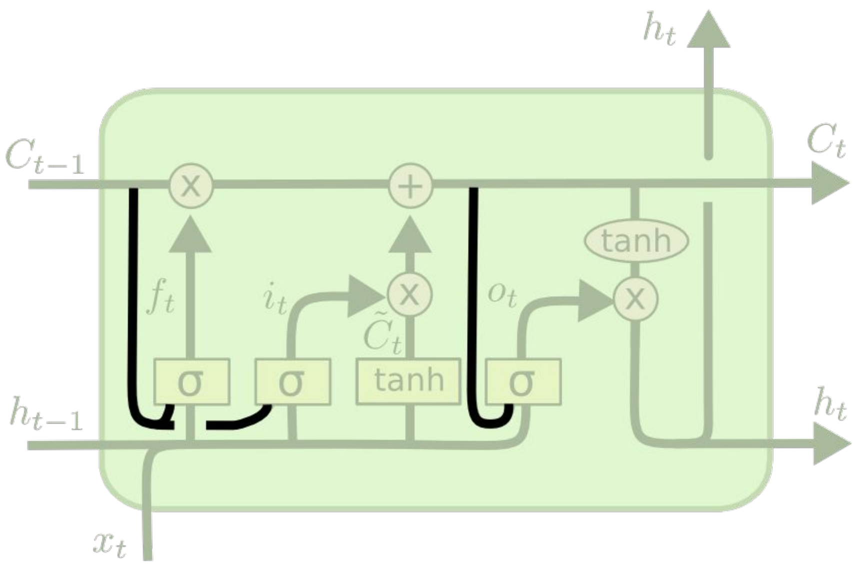
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Reference: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Cell Variation - ConvLSTMPeepHole

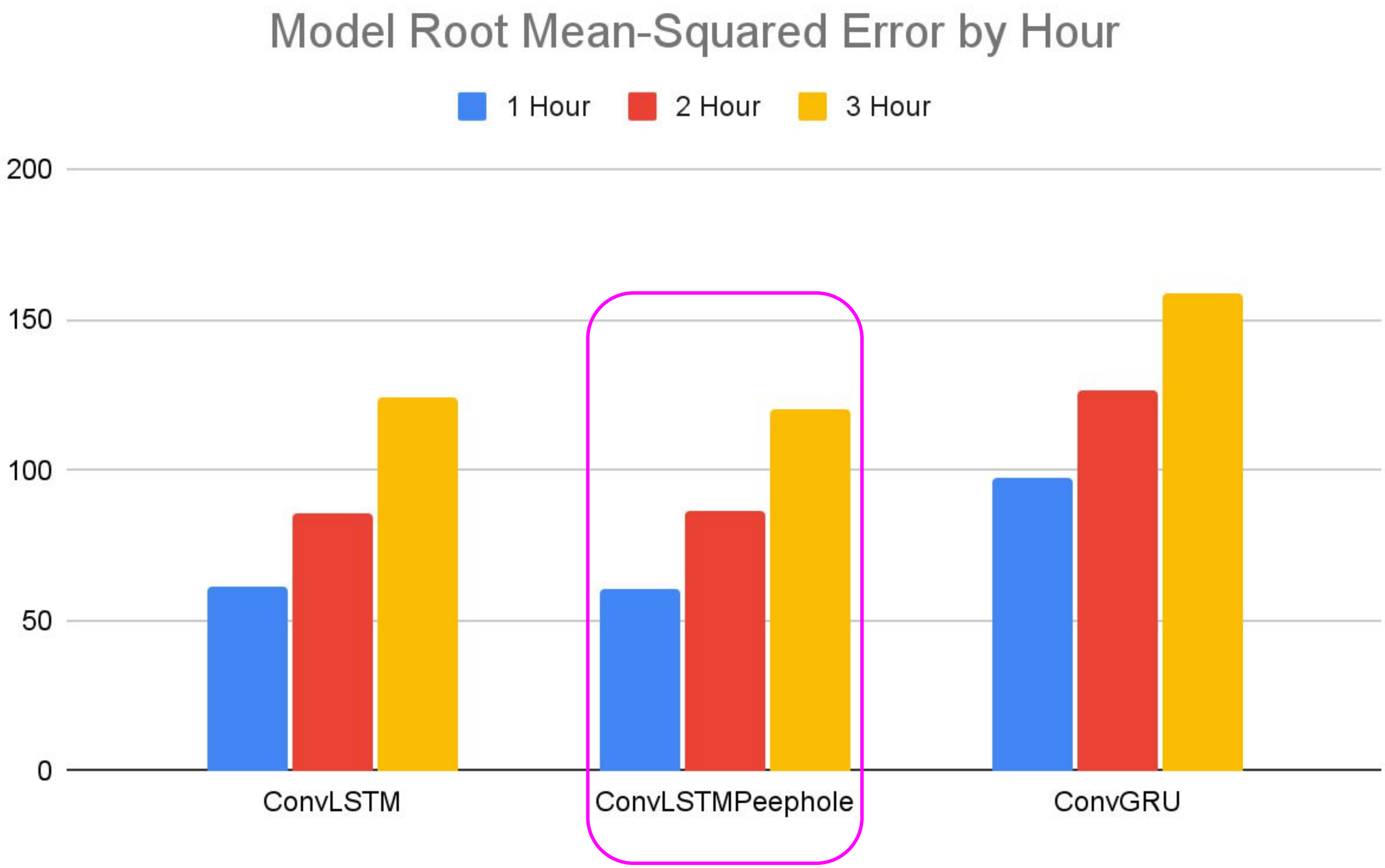


$$f_t = \sigma\left(W_f \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \ + \ b_f\right)$$

$$i_t = \sigma\left(W_i \cdot [\boldsymbol{C_{t-1}}, h_{t-1}, x_t] \ + \ b_i\right)$$

$$o_t = \sigma\left(W_o \cdot [\boldsymbol{C_t}, h_{t-1}, x_t] \ + \ b_o\right)$$

Reference: https://colah.github.io/posts/2015-08-Understanding-LSTMs/



Model Root Mean-Squared Error by Hour
1 Hour
2 Hour
3 Hour
200
150
100
50
0
ConvLSTM
ConvLSTMPeephole
ConvGRU

HRRR vs ConvLSTMPeephole Model

Group	HRRR RMSE	Model RMSE
Overall	124.9	108.6
Low DSR (0-300)	165.3	135.3
Medium DSR (300-600)	170.7	131.7
High DSR (600+)	103.5	98.3

ConvLSTM vs HRRR performance for predictions made for 22 locations between 10:00AM-3:00PM PST for four weeks of the test set (RMSE,W/m2)

Future Work

- Add more number of images to model input
- Add channels to each of these images (e.g. infrared, near-infrared and visible)
- Train for other regions around the world

Thank you!

Appendix

Detail Model Performance

First Hour Prediction				
Model	Overall	Low DSR (0-300)	Medium DSR (300-600)	High DSR (600+)
ConvLSTM	61.4	56.3	74.6	67.5
ConvLSTMPeephole	**60.2**	**55.2**	**73.1**	**66.1**
ConvGRU	97.2	77.3	152.1	107.1
Second Hour Prediction				
Model	Overall	Low DSR (0-300)	Medium DSR (300-600)	High DSR (600+)
ConvLSTM	**85.7**	**76.3**	**117.8**	**88.1**
ConvLSTMPeephole	86.5	77.9	119.1	86.3
ConvGRU	126.9	96.9	209.5	137.9
Third Hour Prediction				
Model	Overall	Low DSR (0-300)	Medium DSR (300-600)	High DSR (600+)
ConvLSTM	123.8	102.3	**184.6**	136.2
ConvLSTMPeephole	**120.6**	**88.2**	205.9	**132.5**
ConvGRU	159.2	93.5	267.7	223.9

Table 1: Model Performance on the 2-month test set(RMSE, W/m^2).