Self-Supervised Learning on Multispectral Satellite Data for Near-Term Solar Forecasting


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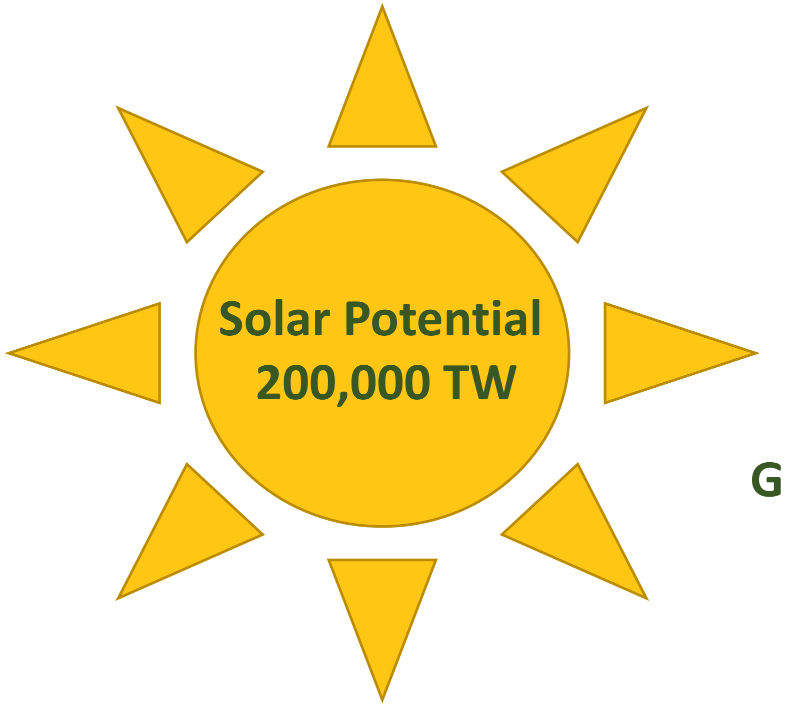
UMass Amherst

Harnessing Solar Potential To Power the Planet



Global Energy Demand is 20 TW

Source: Varun Sivaraman

Harnessing Solar Potential To Power the Planet

Solar Potential 200,000 TW

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Now

< 2% of Global Electricity Demand

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2030
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Harnessing Solar Potential To Power the Planet

Solar Potential 200,000 TW

Global Energy Demand is 20 TW

Now
< 2% of Global Electricity Demand

2030
10% of Global Electricity Demand

2050
33% of Global Electricity Demand

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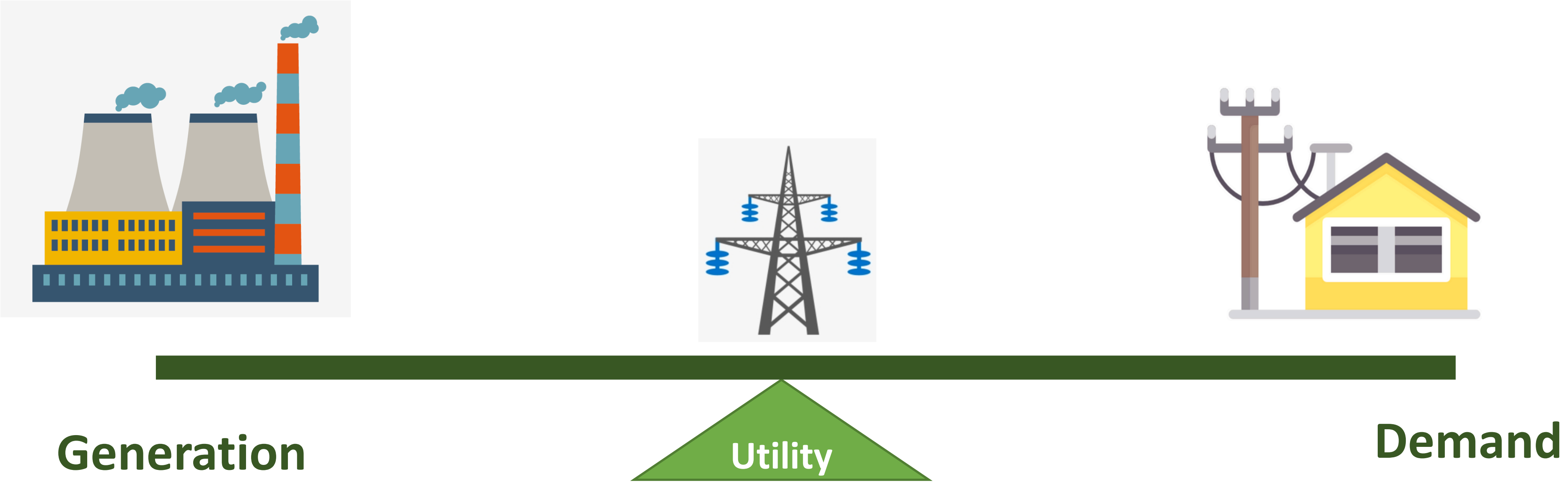
Energy and the Grid: A difficult balancing act

- **Tight balance between varied generators and consumers**
  - Failure to do so causes – power surge or power outage



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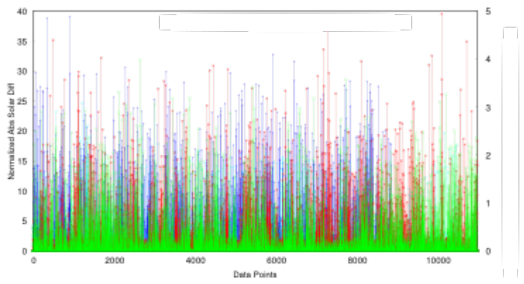


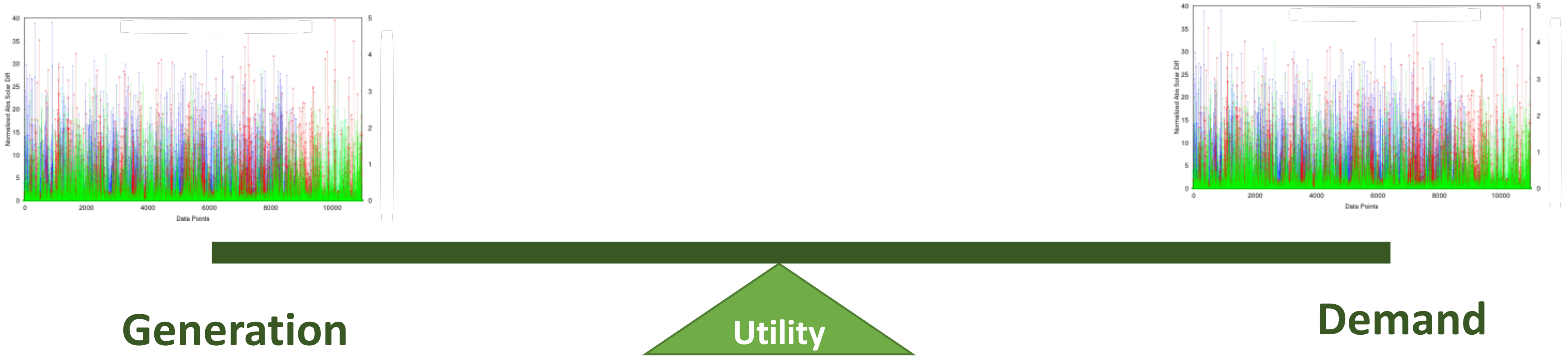
Generation

Utility

Demand

Energy and the Grid: A difficult balancing act

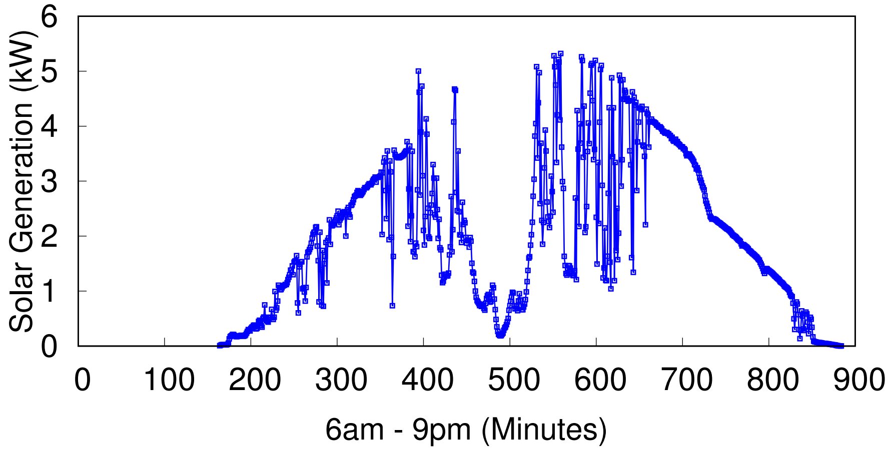
- **Tight balance between varied generators and consumers**
- Failure to do so causes – power surge or power outage
- **Solar is diffused, intermittent and volatile**
  - Making it unreliable source of energy



Solar Forecasting

- Solar is intermittent and its output can change in matter of minutes to hours considerably

Actual Solar



Highest variation = 75% of max solar generation

Minute-level Solar generation day from single day and single site

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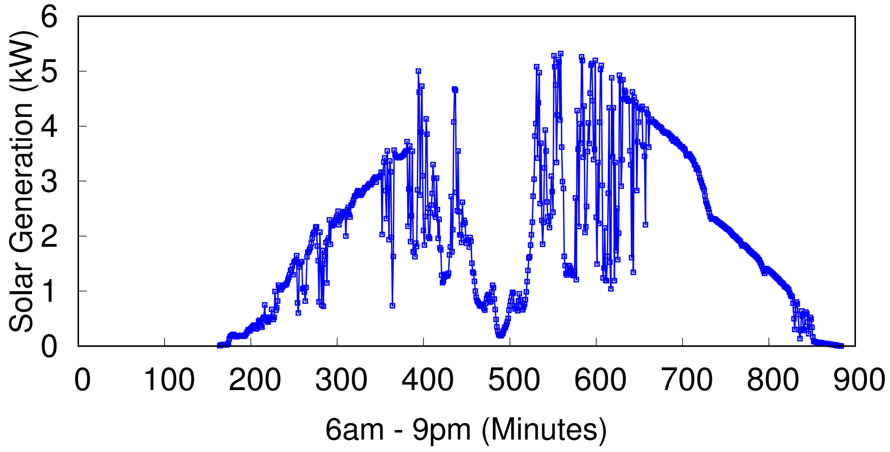

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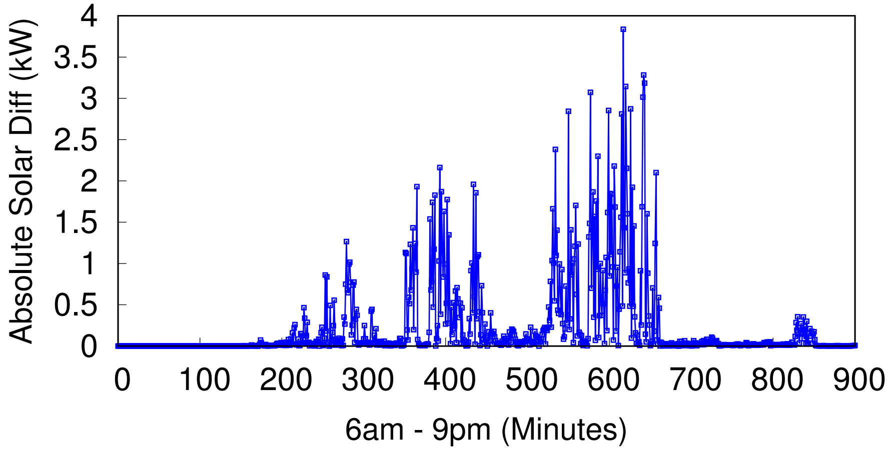
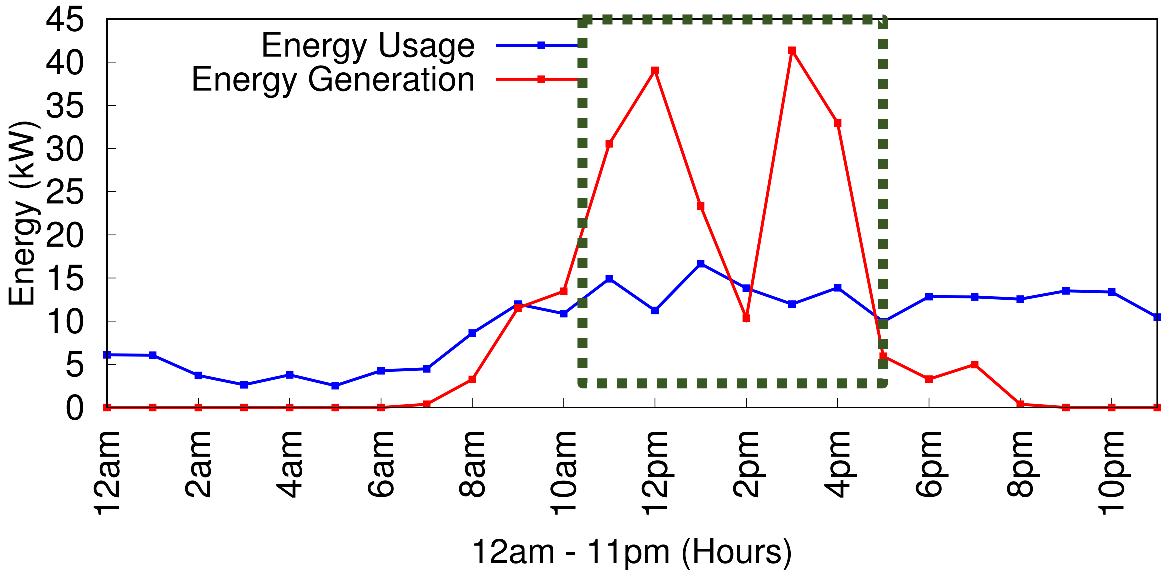
Solar Difference



Minute-level Solar generation day from single day and single site

Solar Power is Intermittent



Solar Forecasting

- *Solar forecasts* - **predict future** solar output based on **forecasts** of physical factors
  - e.g., location, time-of-day, day-of-year, cloud cover, temperature

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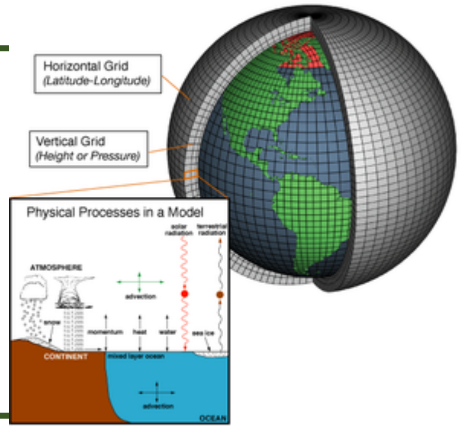
- **Near-term solar forecasts**
  - Solar output predictions on a scale of minutes to hour
  - Allow homes and grid to adapt to large sudden changes in solar output

Solar Forecasting: Prior Approaches

- **Numerical Weather Predictions (NWP) Models**
  - Exploit meteorological physics or atmospheric trends
  - Limited capability to predict smaller changes or clouds
  - Appropriate for hours to days ahead predictions



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  - Requires additional infrastructure like sky camera
  - Site-specific & not scalable

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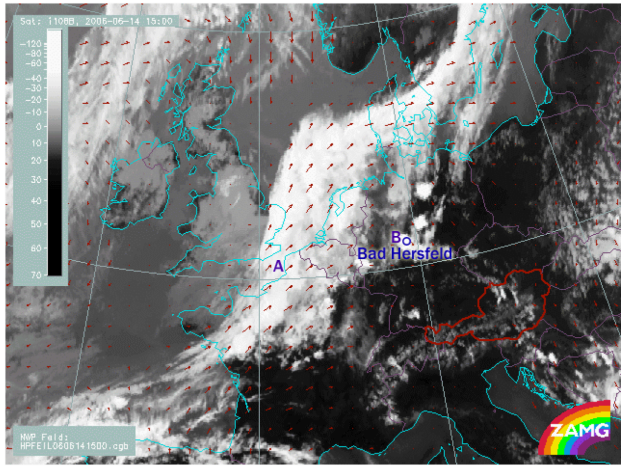

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- **Cloud motion vector models**
  - Forecasts based solely on the recent past motion
  - Does not capture atmospheric dynamics

Solar Forecasting: New Approach

- **Use multispectral GOES-R satellite data directly to predict solar**
  - Satellite data is made publicly available in near real-time

- **Exploit spatio-temporal aspects of multispectral channel data**

A New Opportunity: Launch of GOES-R Satellites

- **NOAA launching new generation of geostationary satellites**
  - GOES-16 launched 12/17, GOES-17 launched 2/18
  - Satellite data is made publicly available in near real-time

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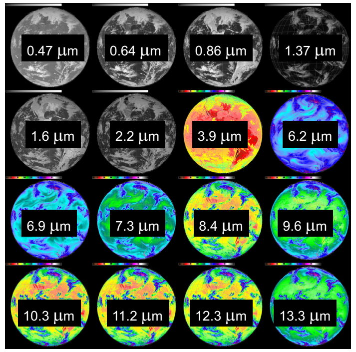
- **Multi-Spectral Data offers unprecedented resolution**
  - Senses *16 different spectral bands of light*
  - *Spatial* – every 0.5-2km^2 across U.S.
  - *Temporal* – released every 5 minutes



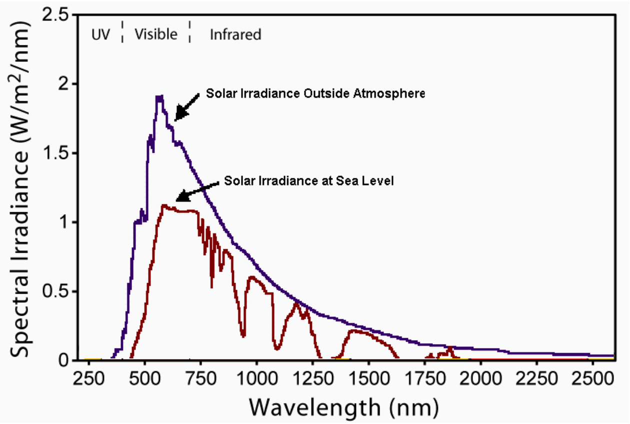
GOES-R Series – 16 Channels, 2 VIS, 4 Near-IR, 10 IR

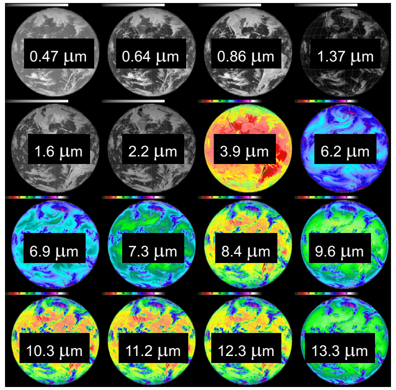
19

NOAA	WEATHER UNDERGROUND
5 mins	**60 mins**
0.5 – 2 km^2	**~42 km^2**

Satellite Data Contains Information about Changes in Solar Output

- **Solar generation synchronizes with first three channel**





Source: Luciano Mescia

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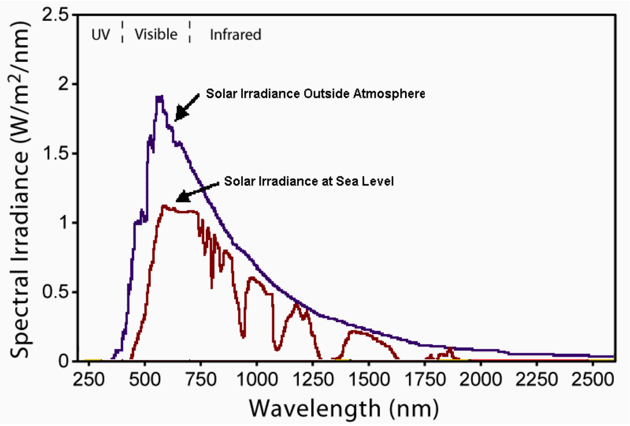

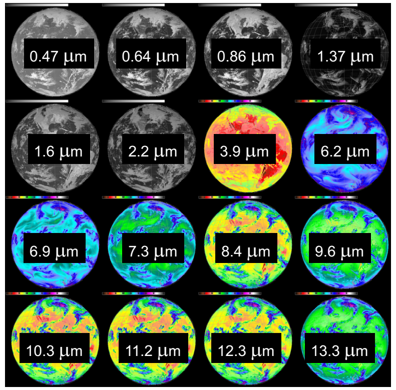

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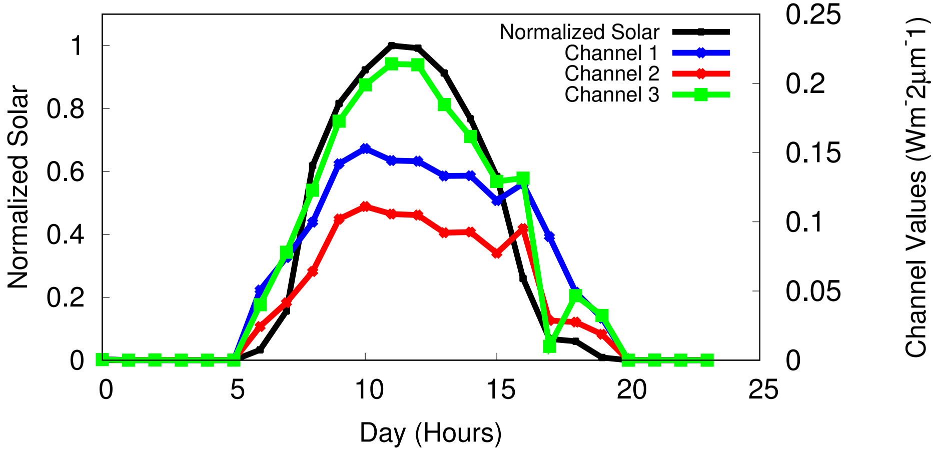
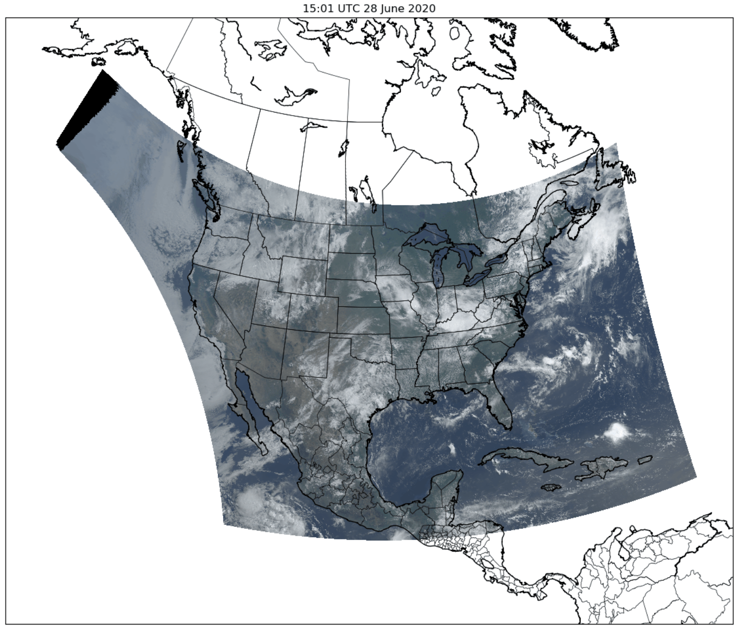
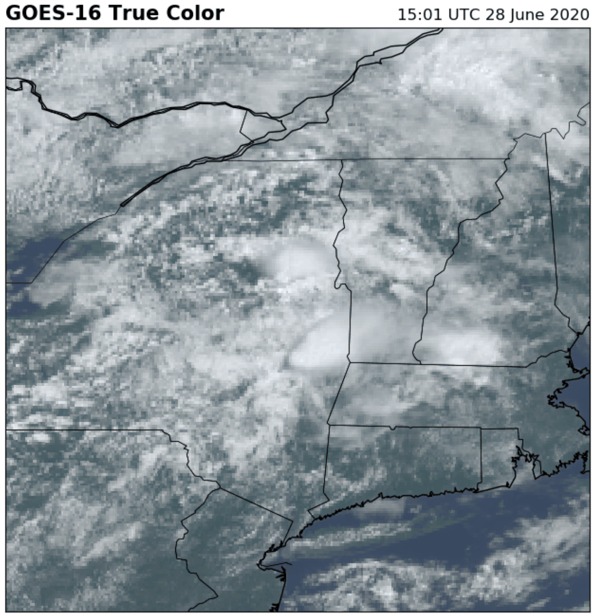
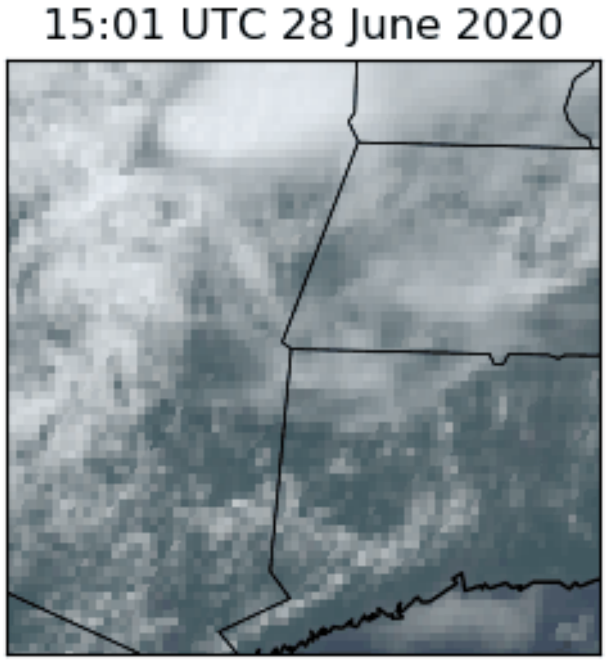


Satellite Data Contains Information about Changes in Solar Output

- **Multispectral channel data captures information about small changes**





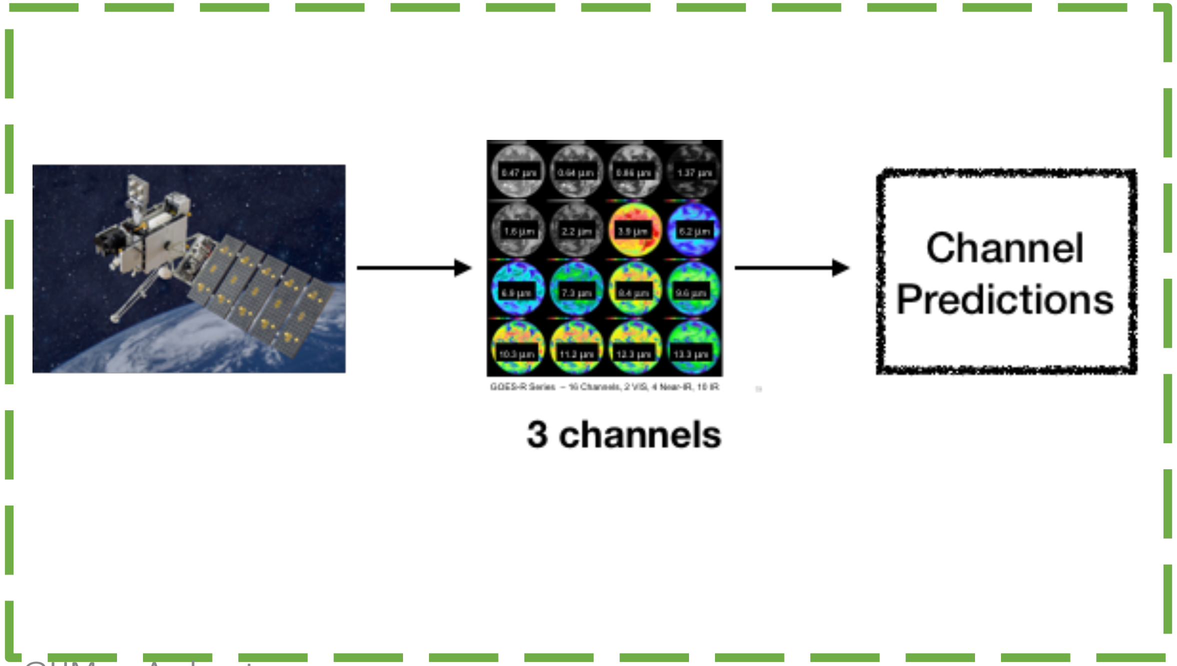


5-Minute True Color (RGB) Imagery from GOES-16 (1-hour window)

End to End Solar Forecasting Framework

- Spatio-temporal aspects of channel data capture information about-
  - Atmospheric changes
  - Cloud movements

Near-Term Channel Forecast



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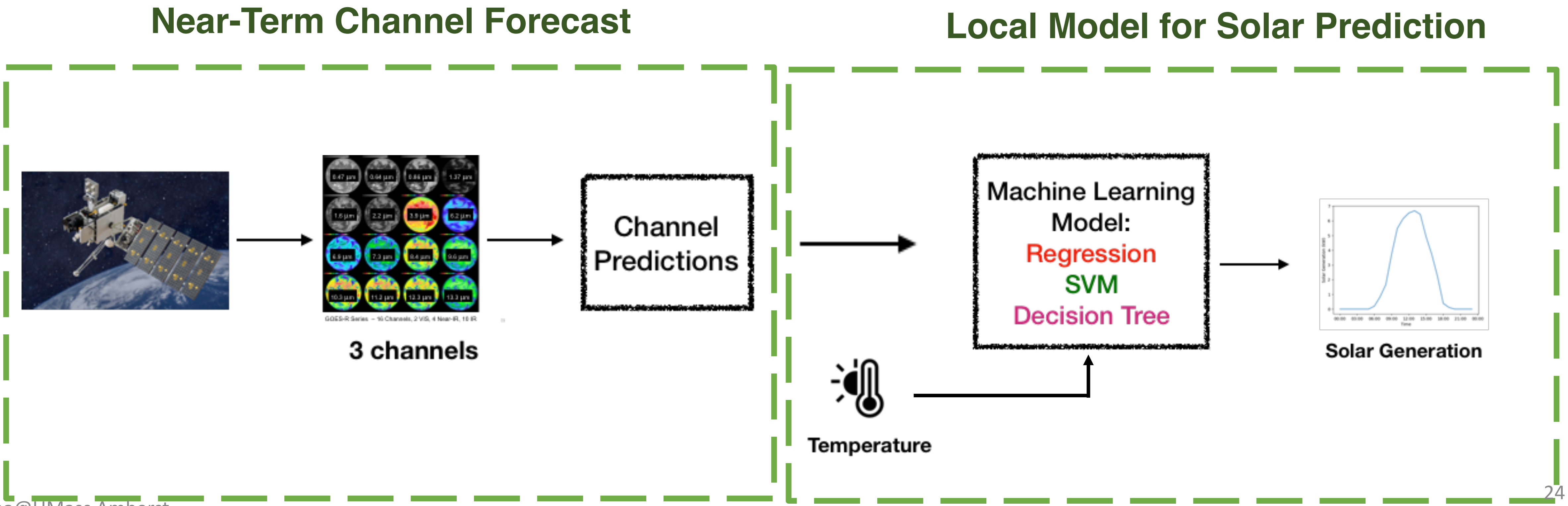
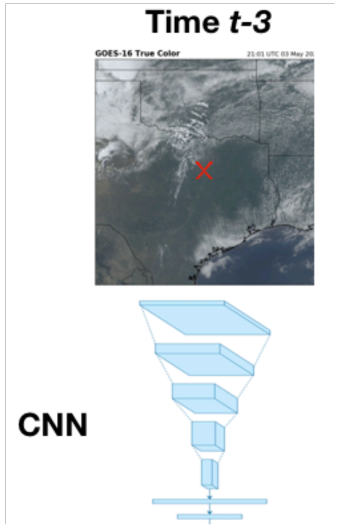


Self- Supervised Models on Time Series Data

- **Convolution Neural Networks**
  - Extracting features for one location



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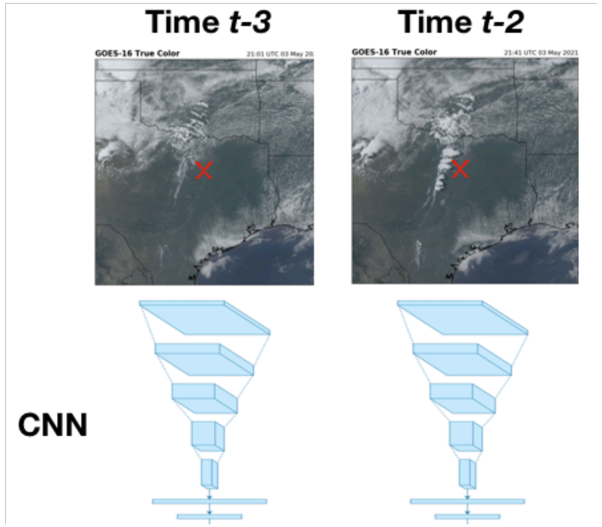

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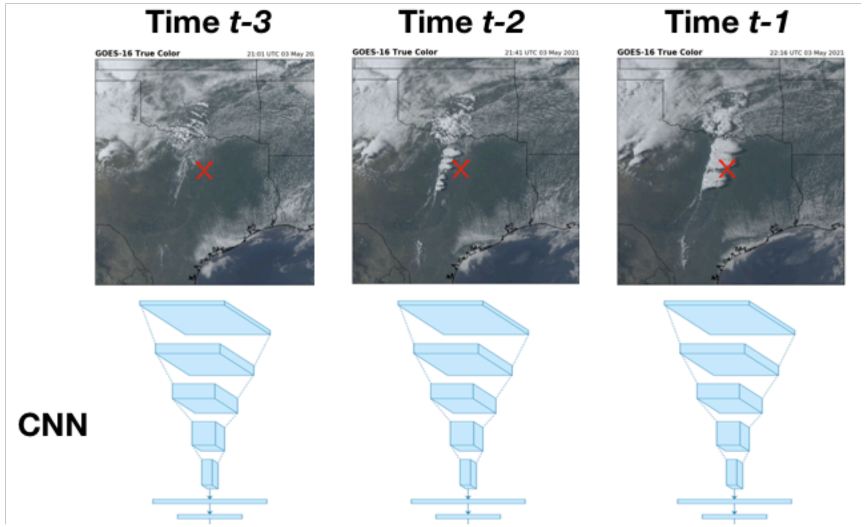

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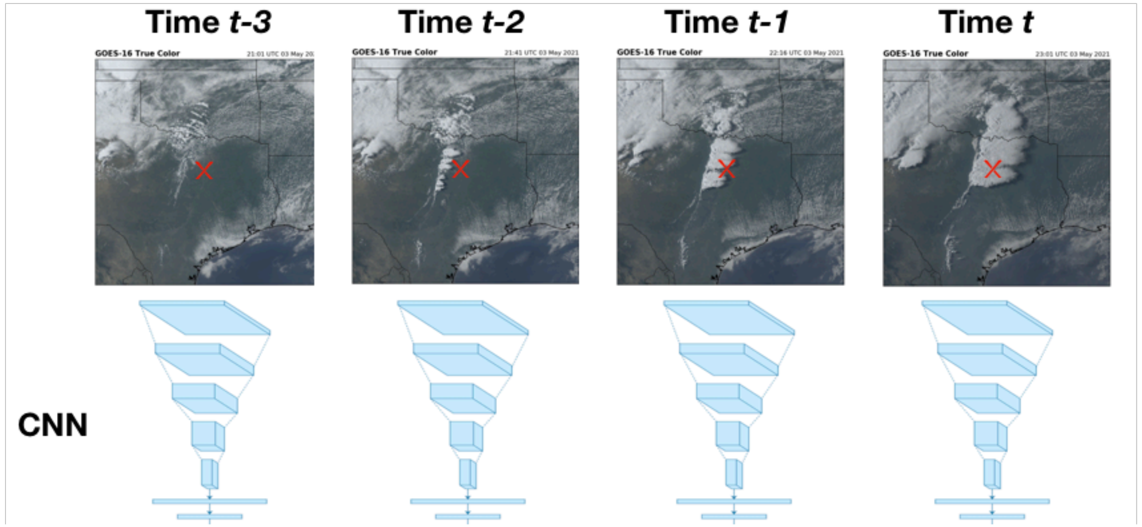
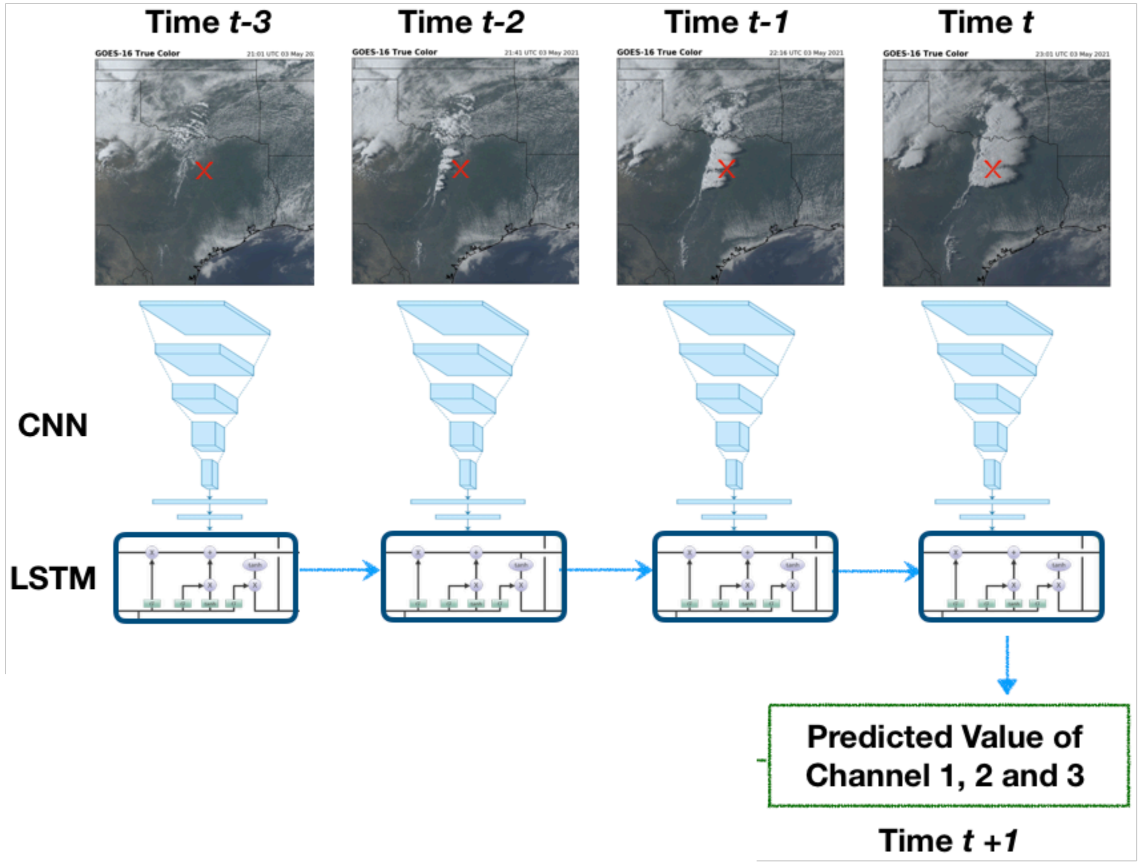


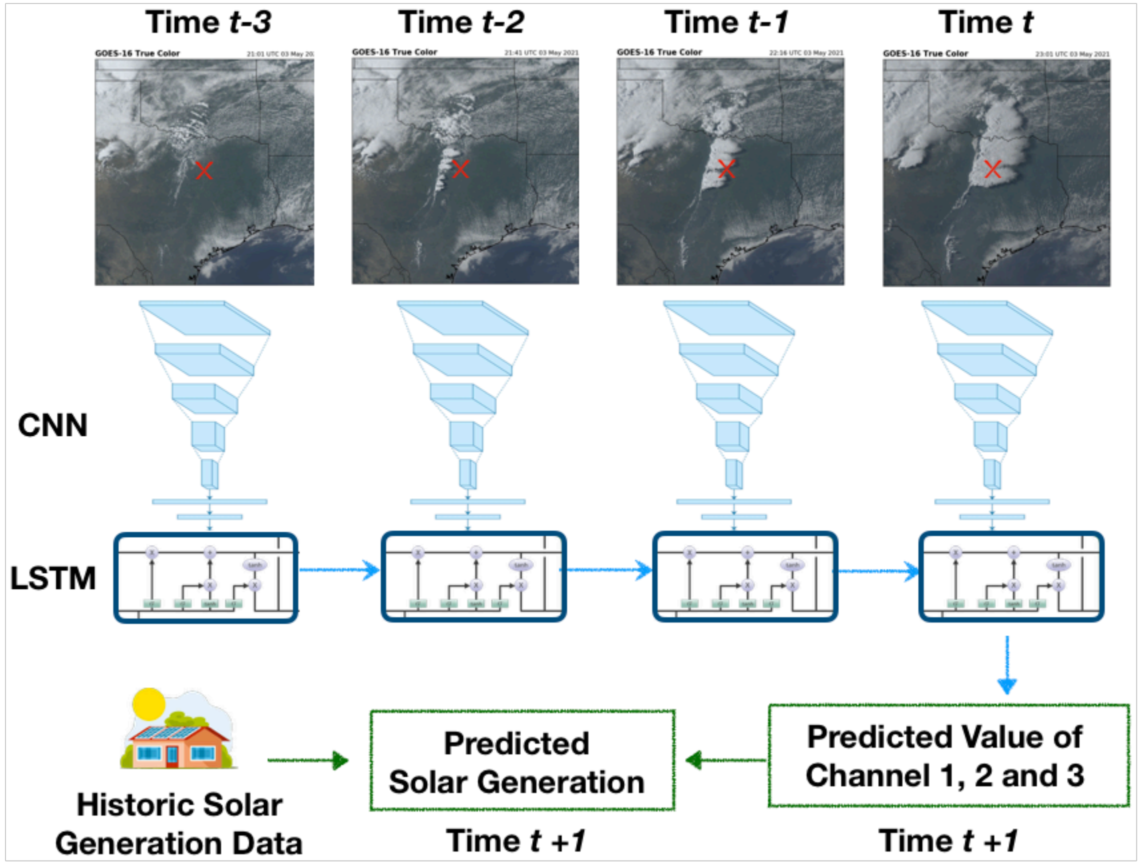
Self- Supervised Models on Time Series Data

- **Convolution Neural Networks with LSTM**

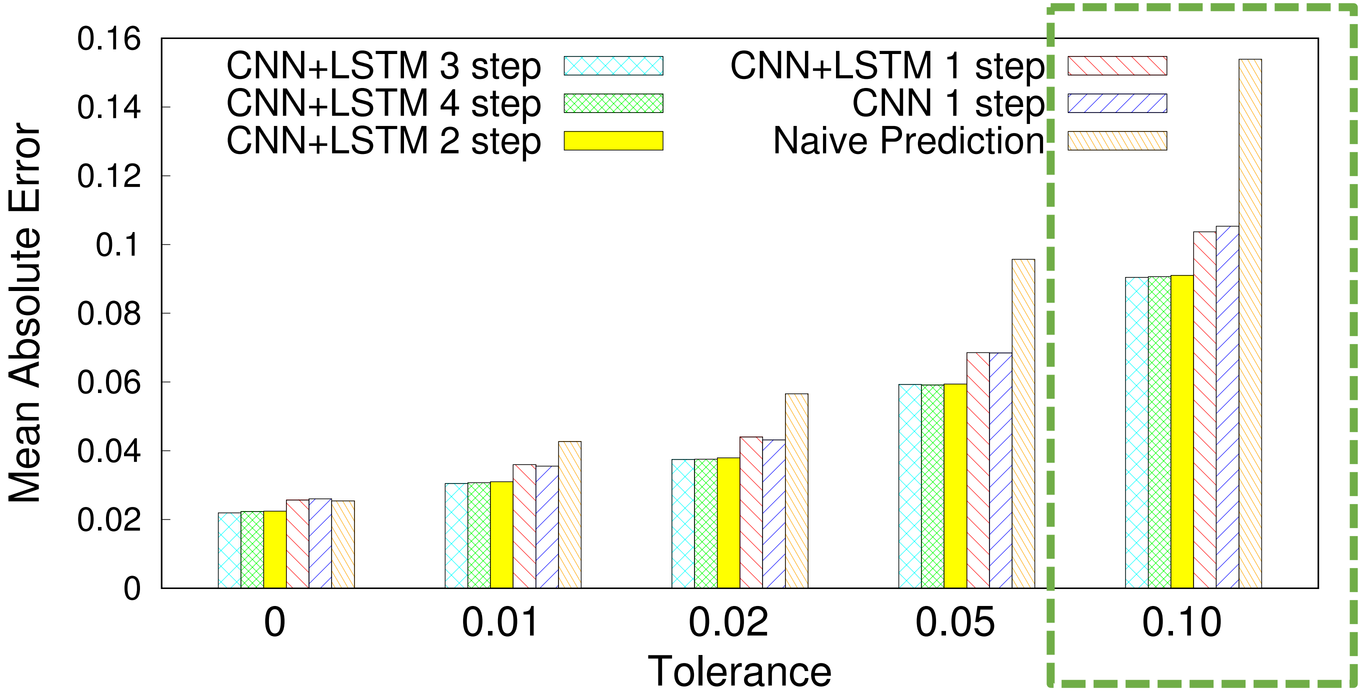


Self- Supervised Models on Time Series Data

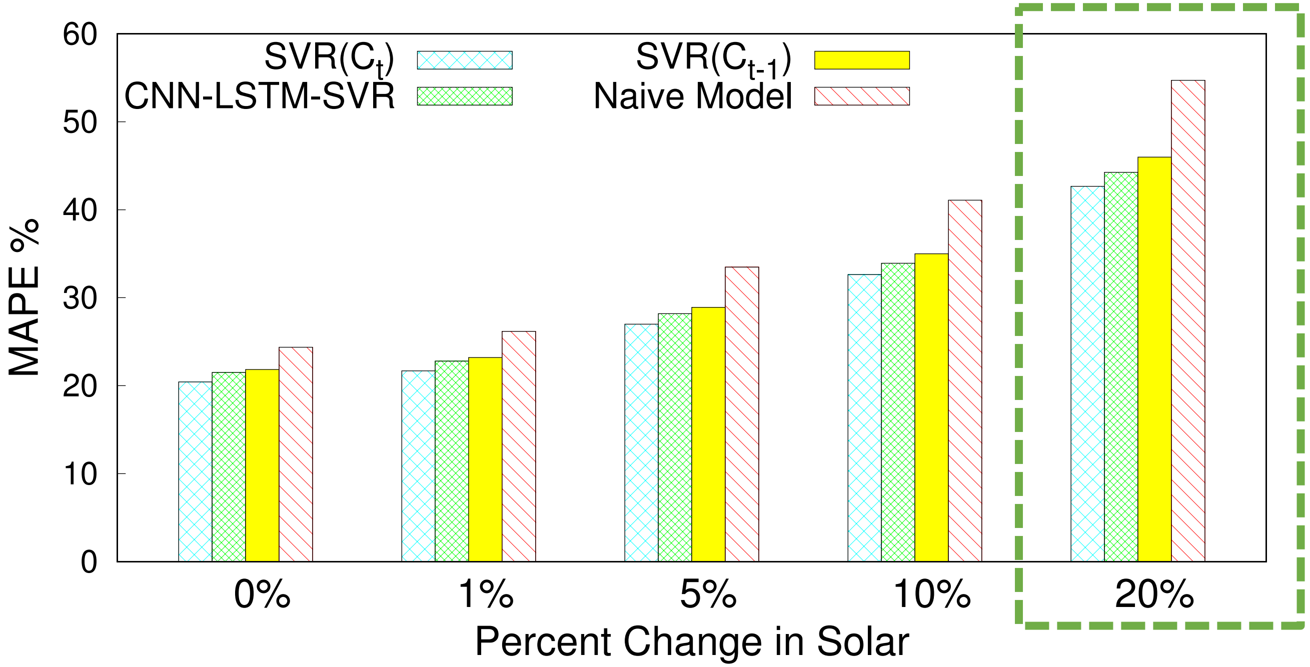
- **End to end near-term solar forecasting**



Results from Channel Prediction Models



Results from end-to-end Solar Prediction Models



SVR(C_t) Upper-bound using ground truth observation

CNN-LSTM-SVR Using forecasted channel values through CNN-LSTM model

SVR(C_{t-1}) Lower-bound using $C_{(t-1)}$ as naïve forecast

Naive Model Past predicts future baseline

Thank You!

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www.akanshasinghbansal.com