Intra-day solar power forecasting using cloud images from Himawari satellite

NATANON TONGAMRAK ID 6232007121

NATTHAPOL DEJTRAKULWONGSE ID 6232011621

ADVISOR : ASSOCIATE PROFESSOR JITKOMUT SONGSIRI

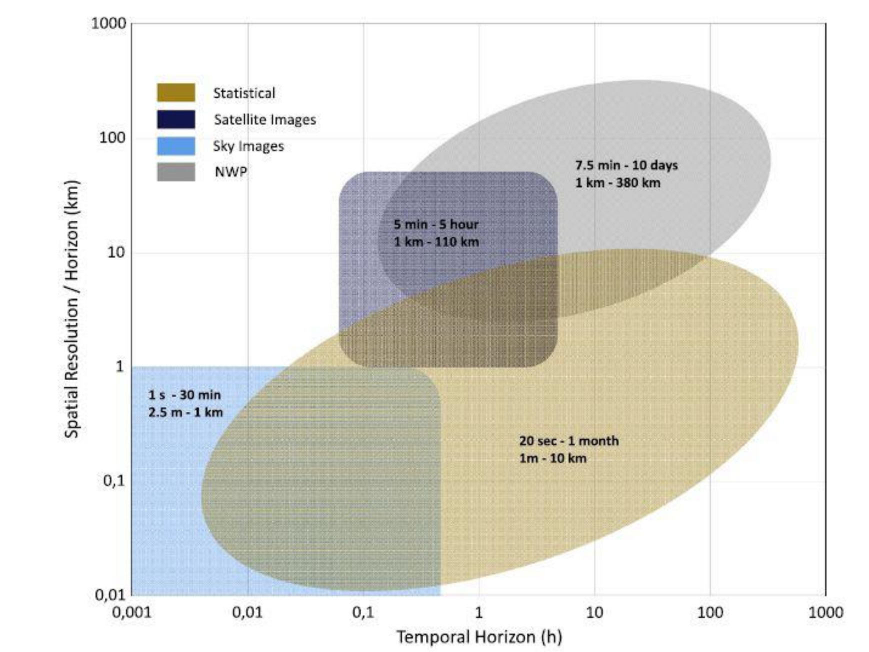
DEPARTMENT OF ELECTRICAL ENGINEERING

FACULTY OF ENGINEERING, CHULALONGKORN UNIVERSITY

Table of contents

Introduction : Motivation

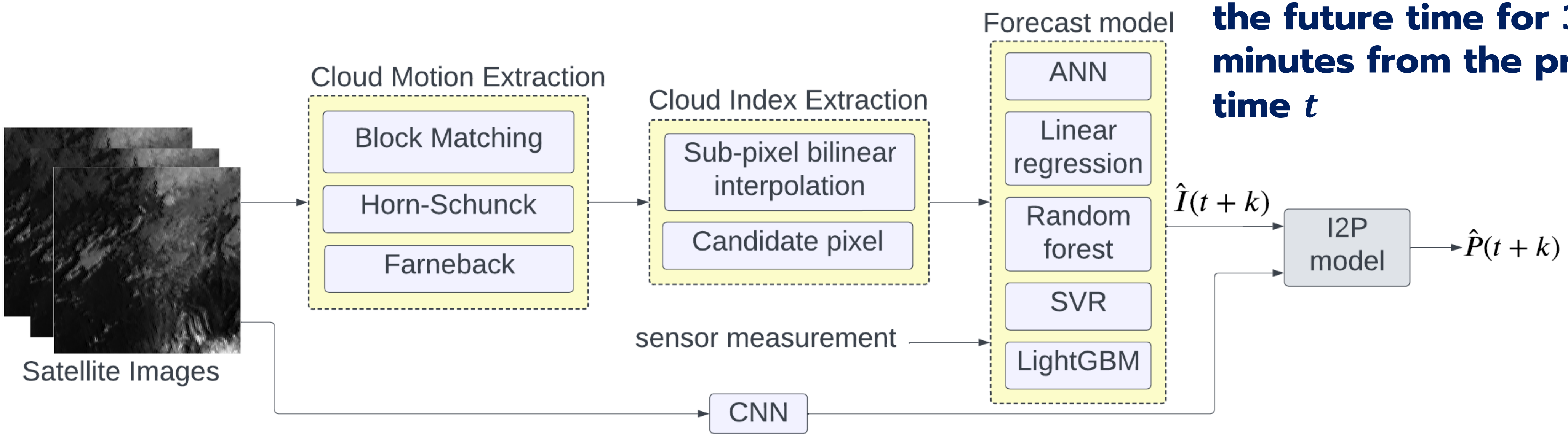
- The forecast horizon of around 1 - 6 hours (Intra-day) can help grid operation management e.g. load-following.
- Cloud information is necessary to estimate the future irradiance in the horizon of an Intra-day which can be extracted from satellite images.



Source : J. Antonanzas et al. "Review of photovoltaic power forecasting," Solar energy, vol. 136, pp. 78–111, 2016. [5]

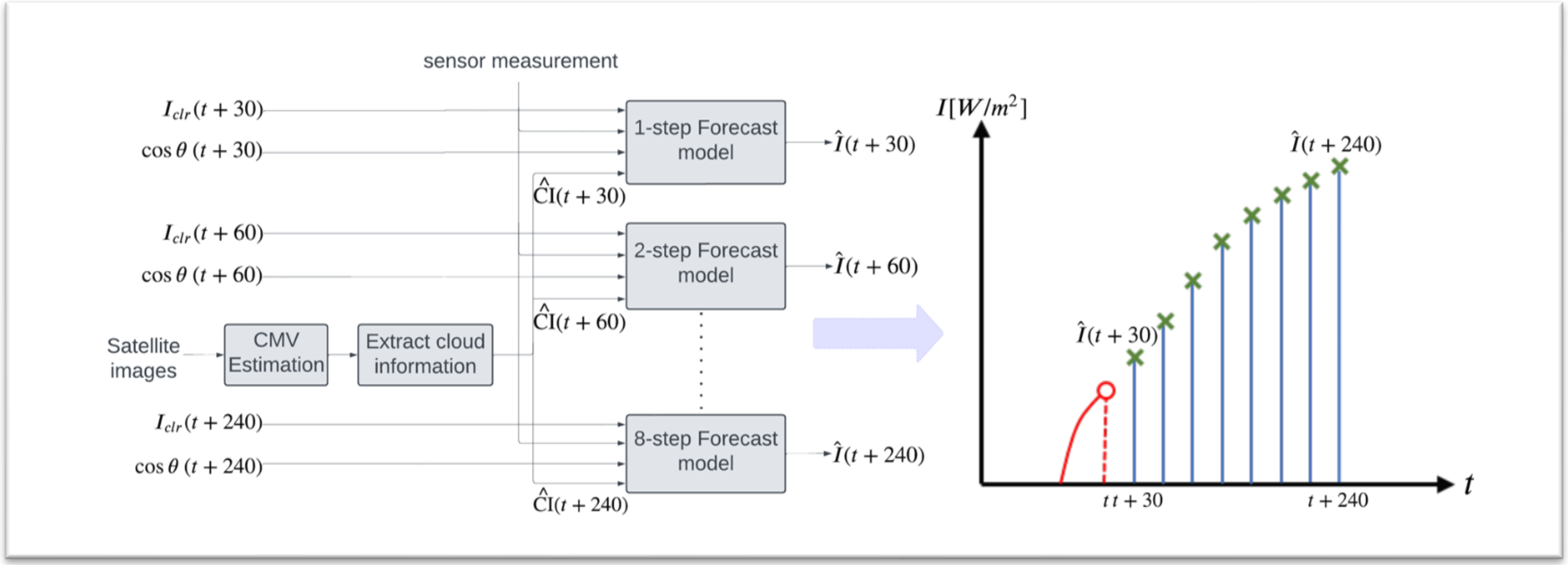
Introduction : Overall scheme

The argument $t+k$ denotes the future time for $30 \times k$ minutes from the present time t



- Compare the forecasting performance of a traditional ML model that utilizes extracted cloud information feature with CNN models that extracts relationships from input cloud image data.
- Utilize the PV conversion model (I2P) to convert the forecasted Irradiance (I) into Generated Power (P) at each site.

Introduction : Forecasting in each horizon



- In this project, we will forecast the irradiance in 30, 60, ..., 240 minutes ahead (8 steps), the estimated irradiance comes from separated forecast models

Methodology

Data Preprocessing

Clear sky model

Cloud index estimation

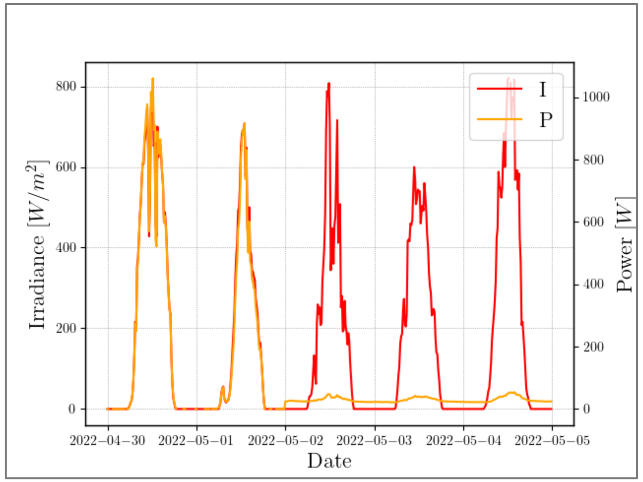
Forecasting models

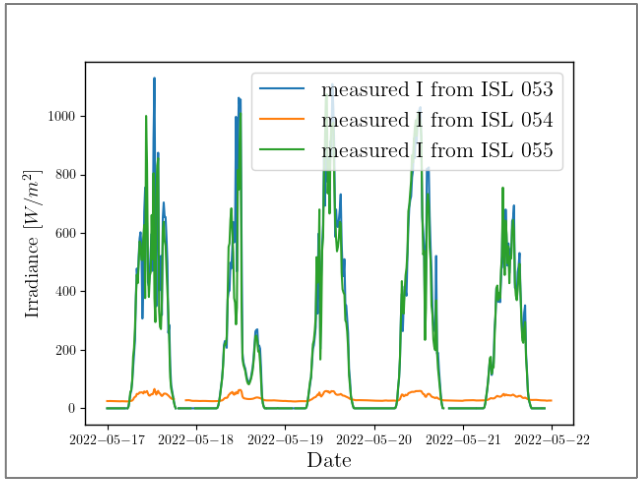
PV conversion model

Methodology : Data preprocessing

Impact solar data

IMPACT SOLAR GROUP



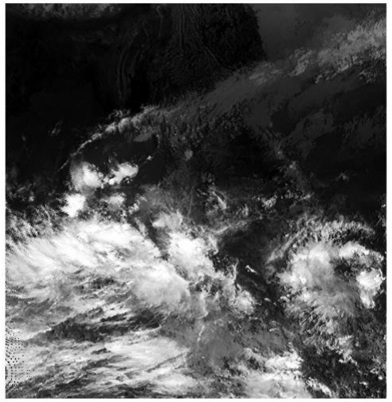


- Available measurement : $P\ [kW]$, $I\ [W/m^2]$, Temperature ($T\ [°C]$) with a period of 15 minutes from 56 site stations.
- The recorded data that have a measured I nearly zero but P in the normal range, such as those shown at site 32 and 54, are marked as erroneous data.
- They are excluded from the analysis.

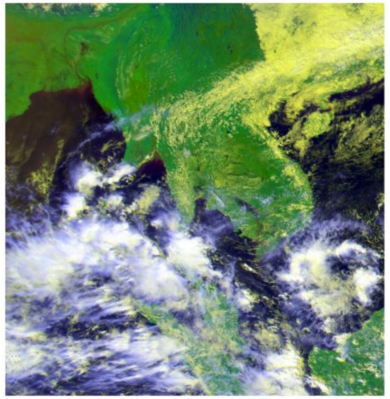
Methodology : Data preprocessing

SGRU

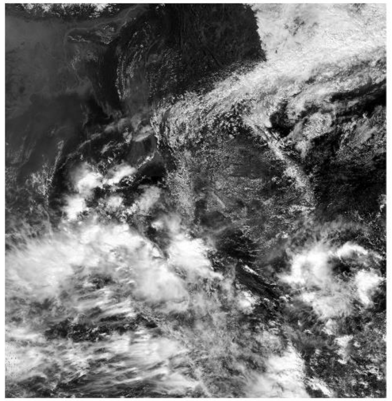
- Cloud images from Himawari satellite were received at the ground station located at CUEE by SGRU.
- The images came with a period of 10 minutes, resolution of 1725x1670 pixels and each pixel represents area with size 2x2 km^2. The images are categorized into 2 types including cloud mask and overview RGB
- If the images contain black stripe, then it will be removed during the preprocessing.



Cloud mask



Overview RGB



Overview R channel

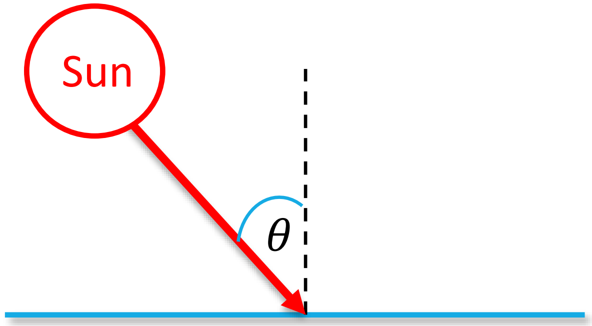
Bad image

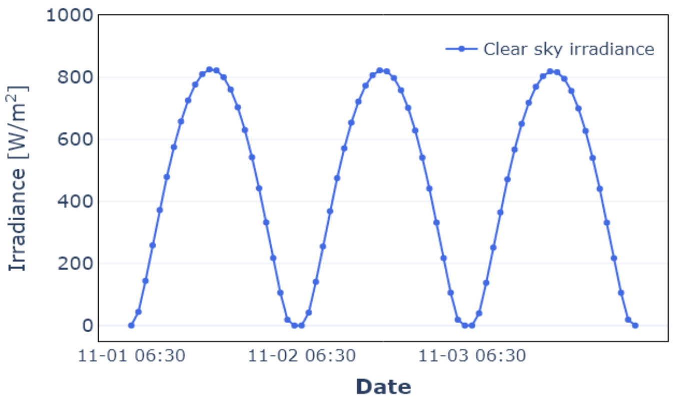
Methodology : Clear sky model

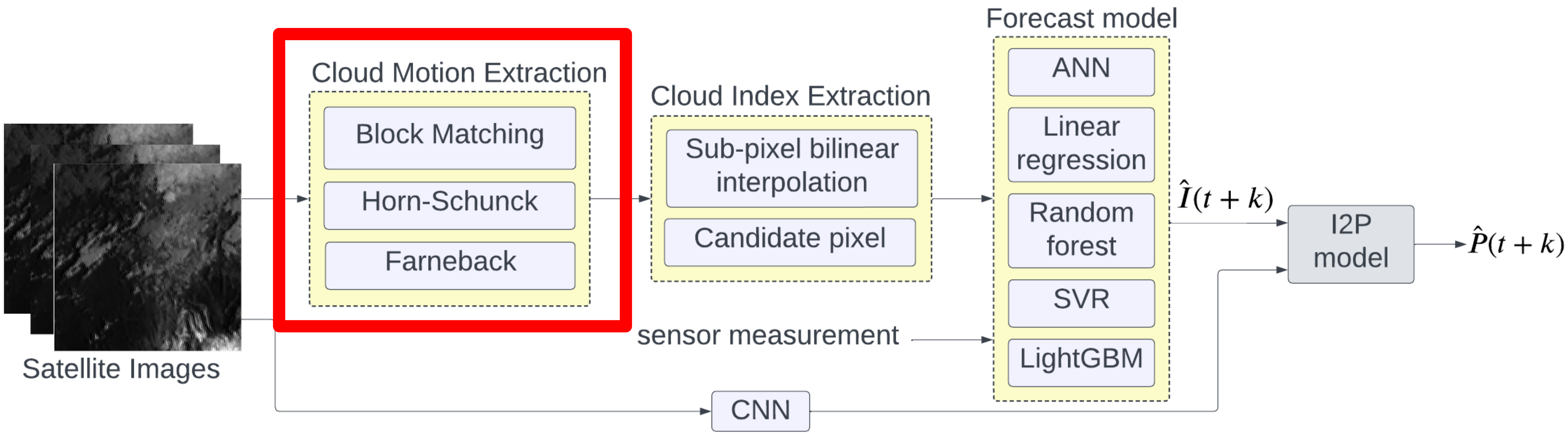
Clear sky model estimates the irradiance on the clear-sky conditions with physical-based knowledge. The model is proposed in various form but the one we use is from P. Ineichen and R. Perez. [1]

$$I_{\mathrm{clr}}(t) = a_1 I_0 \cos\theta(t)\, e^{-a_2(f_{h_1}+f_{h_2}(T_L-1)AM(t))}$$

- h is the elevation from sea level
- $a_1, a_2, f_{h_1}, f_{h_2}$ is a parameter that depends on h
- T_L is Linke turbidity factor
- $AM(t)$ is air mass coefficients
- $\theta(t)$ is zenith angle





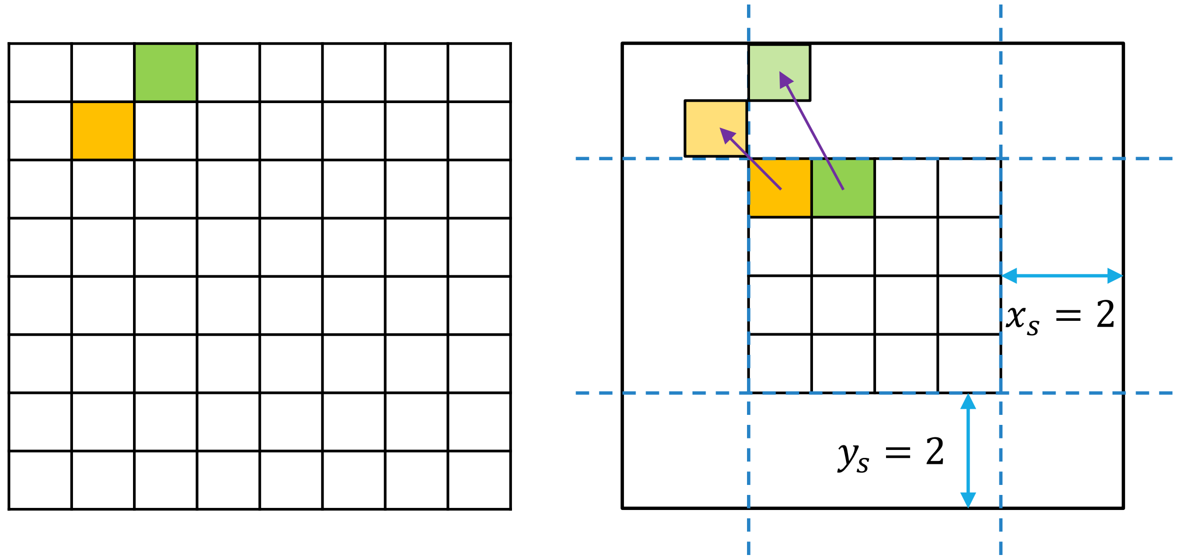

Cloud Motion Extraction
Block Matching
Horn-Schunck
Farneback
Cloud Index Extraction
Sub-pixel bilinear interpolation
Candidate pixel
Forecast model
ANN
Linear regression
Random forest
SVR
LightGBM
$\hat{I}(t+k)$
I2P model
$\hat{P}(t+k)$
sensor measurement
Satellite Images
CNN

Methodology : Cloud index estimation

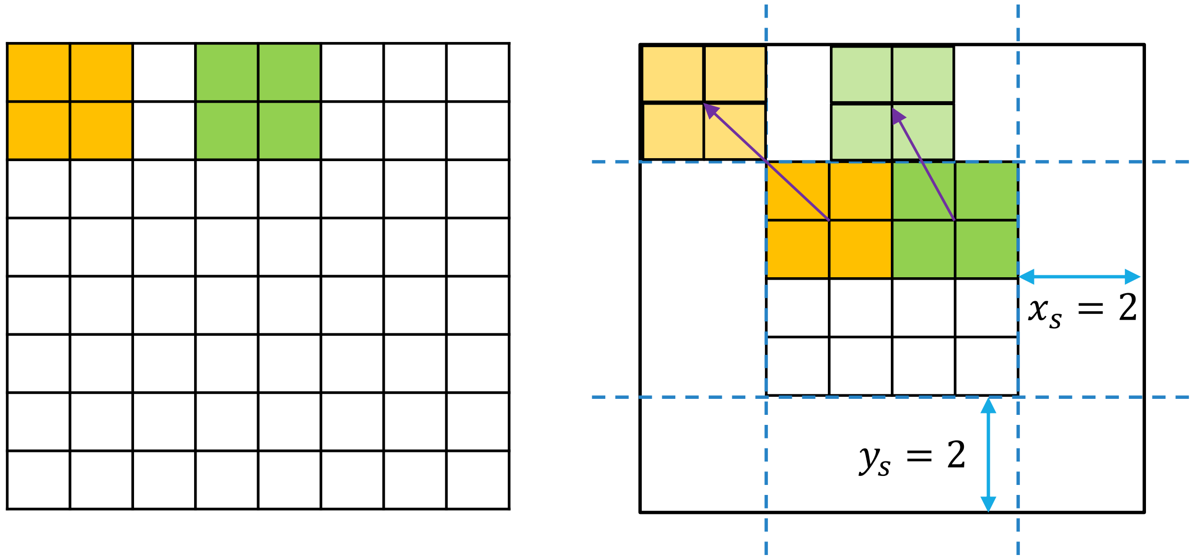
CMV extraction

CMV extraction is a technique for tracking a movement of cloud (v_x, v_y). It includes 2 methods

(1) Block-matching: This method will find a pair of block with highest cross-correlation coefficient. The algorithm also incorporates x_s and y_s to ensure that the search does not exceed the boundaries of the image.



Exhaustive search



Box search

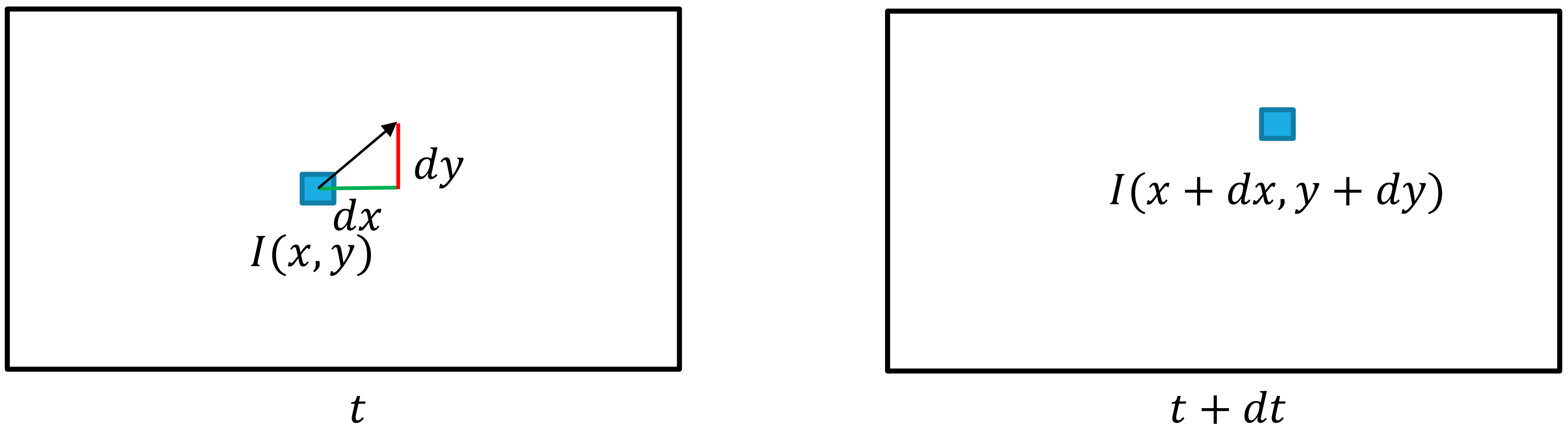
Methodology : Cloud index estimation

CMV extraction

(2) Optical flow: This method wants to find the flow of intensity of pixel (I) with the assumption that

- The intensity remains the same between two consecutive images.
- No formation/deformation and spreading of cloud.

$$I(x+dx, y+dy, t+dt) = I(x,y,t) \longrightarrow \frac{\partial I(x,y,t)}{\partial x} v_x + \frac{\partial I(x,y,t)}{\partial y} v_y + \frac{\partial I(x,y,t)}{\partial t} \approx 0$$

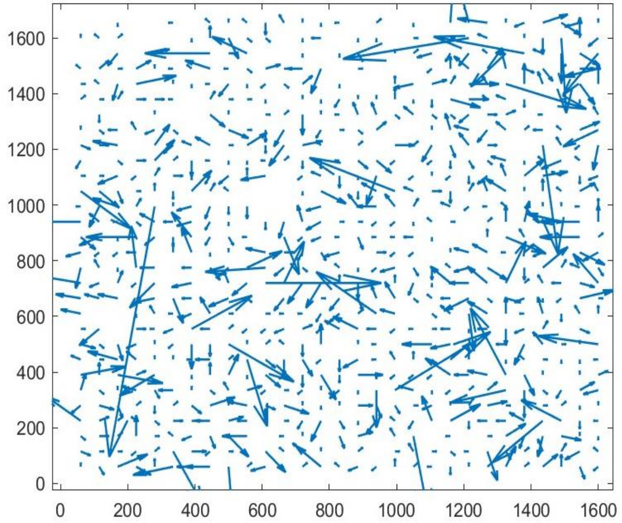


Methodology : Cloud index estimation

CMV extraction

(2.1) Horn-Schunck method: This method starts by assuming optical flow assumption and aims to maximize the smoothness of the velocity. [3]

$$\underset{v_x, v_y}{argmin} \int \underbrace{||\nabla v_x||^2 + ||\nabla v_y||^2}_{\text{smoothness}} + \lambda \left(\frac{\partial I(x,y,t)}{\partial x} v_x + \frac{\partial I(x,y,t)}{\partial y} v_y + \frac{\partial I(x,y,t)}{\partial t} \right)^2$$

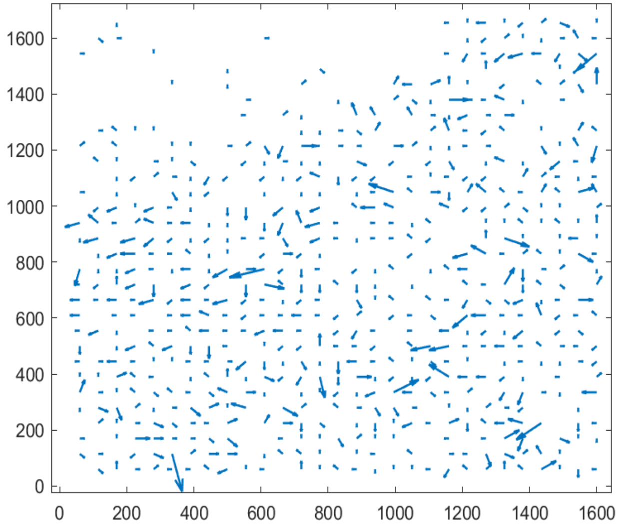


$\lambda \downarrow$

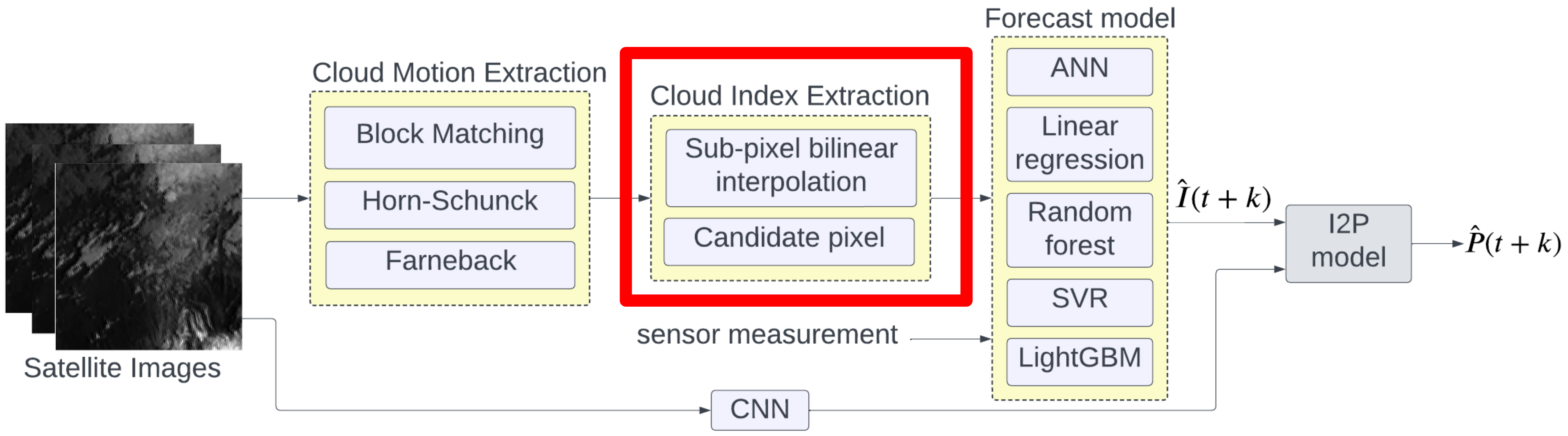
(2.2) Farneback method: This method tries to express the intensity as a quadratic function of position $z = (x, y) \in \mathbb{R}^2$. Then, the intensity at time $t-1$ and position z is

$$I_{t-1}(z) = z^T A_1 z + b_1^T z + c_1$$

By using the optical flow assumption, the intensity at time t is then $I_{t-1}(z-d) = I_t(z)$ where $d = (v_x, v_y) \in \mathbb{R}^2$ is displacement of the intensity which can be calculated by equating the coefficients. [2]



$\lambda \uparrow$

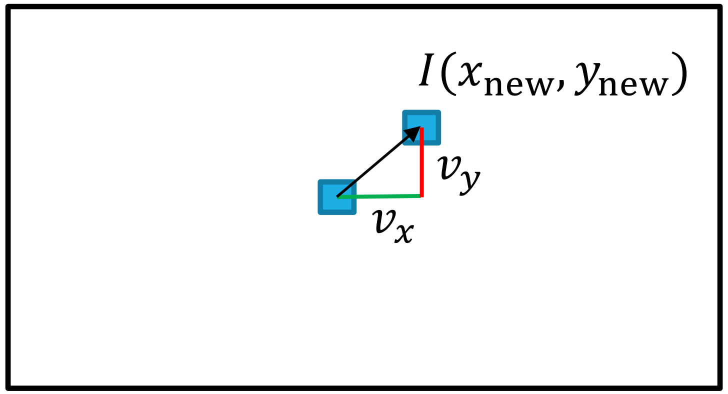


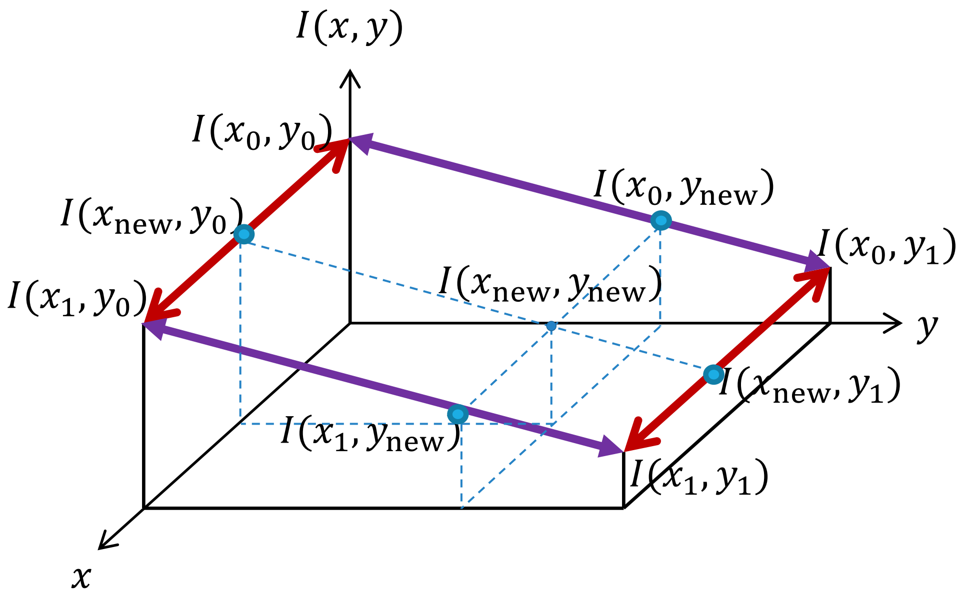
Forecast model
Cloud Motion Extraction
Cloud Index Extraction
ANN
Block Matching
Linear regression
Sub-pixel bilinear interpolation
Horn-Schunck
$\hat{I}(t+k)$
Random forest
I2P model
$\hat{P}(t+k)$
Candidate pixel
Farneback
SVR
sensor measurement
LightGBM
Satellite Images
CNN

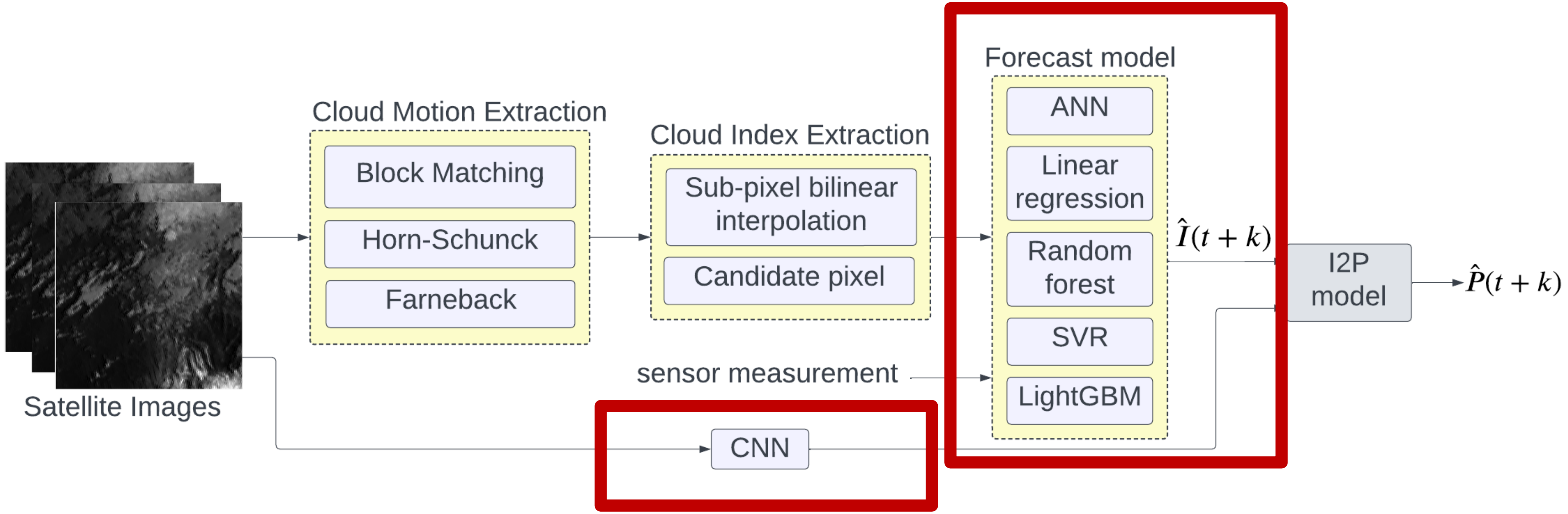
Methodology : Cloud index estimation

Sub-pixel bilinear interpolation

After the CMV is calculated and the intensity is displaced, the estimated cloud index (intensity) will be calculated by weighted averaging with respect to the distance around the neighborhood with integer position. [4]






Satellite Images
Cloud Motion Extraction
Block Matching
Horn-Schunck
Farneback
Cloud Index Extraction
Sub-pixel bilinear interpolation
Candidate pixel
sensor measurement
CNN
Forecast model
ANN
Linear regression
Random forest
SVR
LightGBM
$\hat{I}(t+k)$
I2P model
$\hat{P}(t+k)$

Methodology : Forecasting model

Forecasting model can be categorized into 3 sections including

1. **Baseline time-series model** : SARIMAX

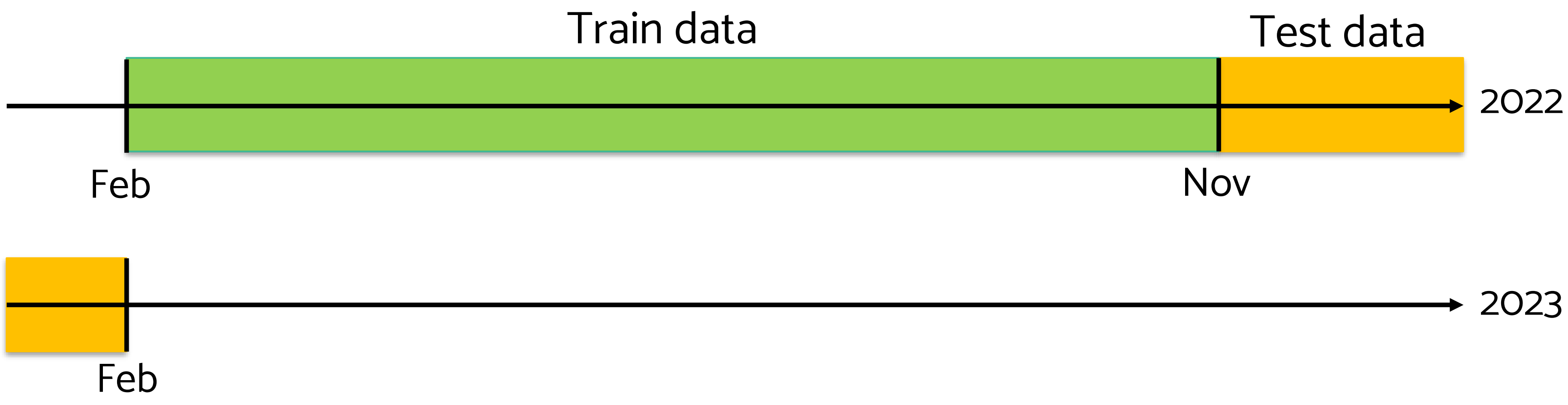
2. **Traditional ML model** : Linear regression, SVR, Random forest, LightGBM

3. **Deep neural networks model** : ANN, 3D-CNN, CNN LSTM

Methodology : Forecasting model

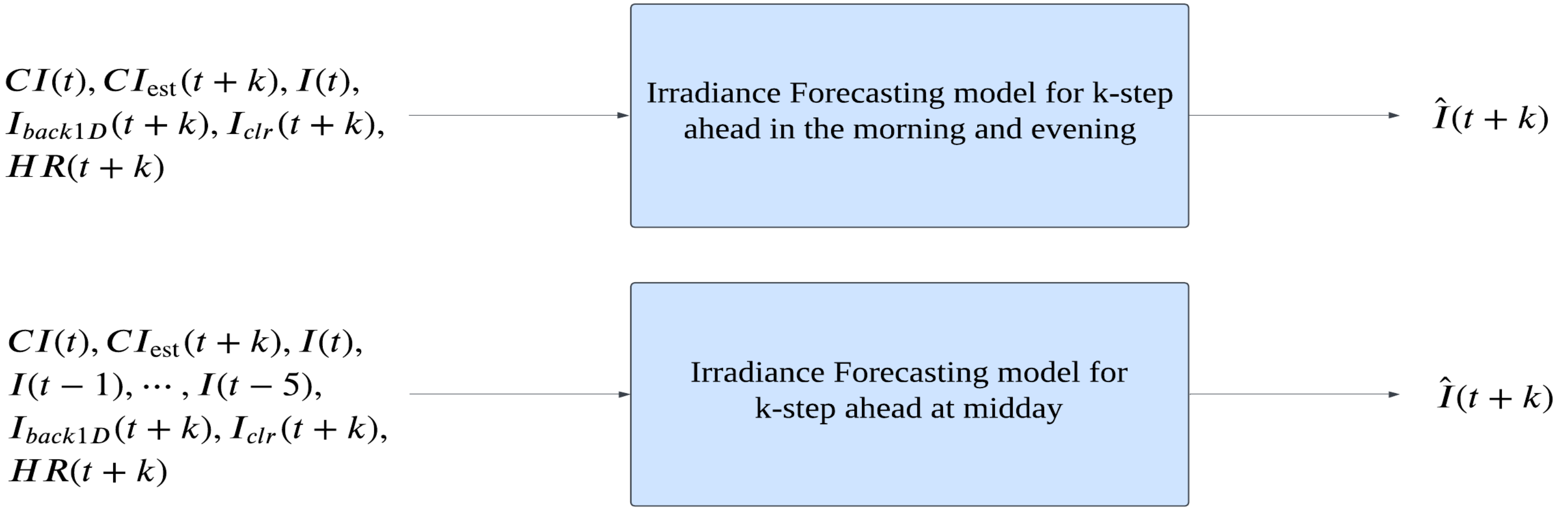
Baseline time-series model

Since our baseline model is time-series, we then split the data into first 9 months as the training and the last 3 month as the testing. For ideally, the training should contain 1 year data in order to capture all of the seasonality of irradiance.



Methodology : Forecasting model

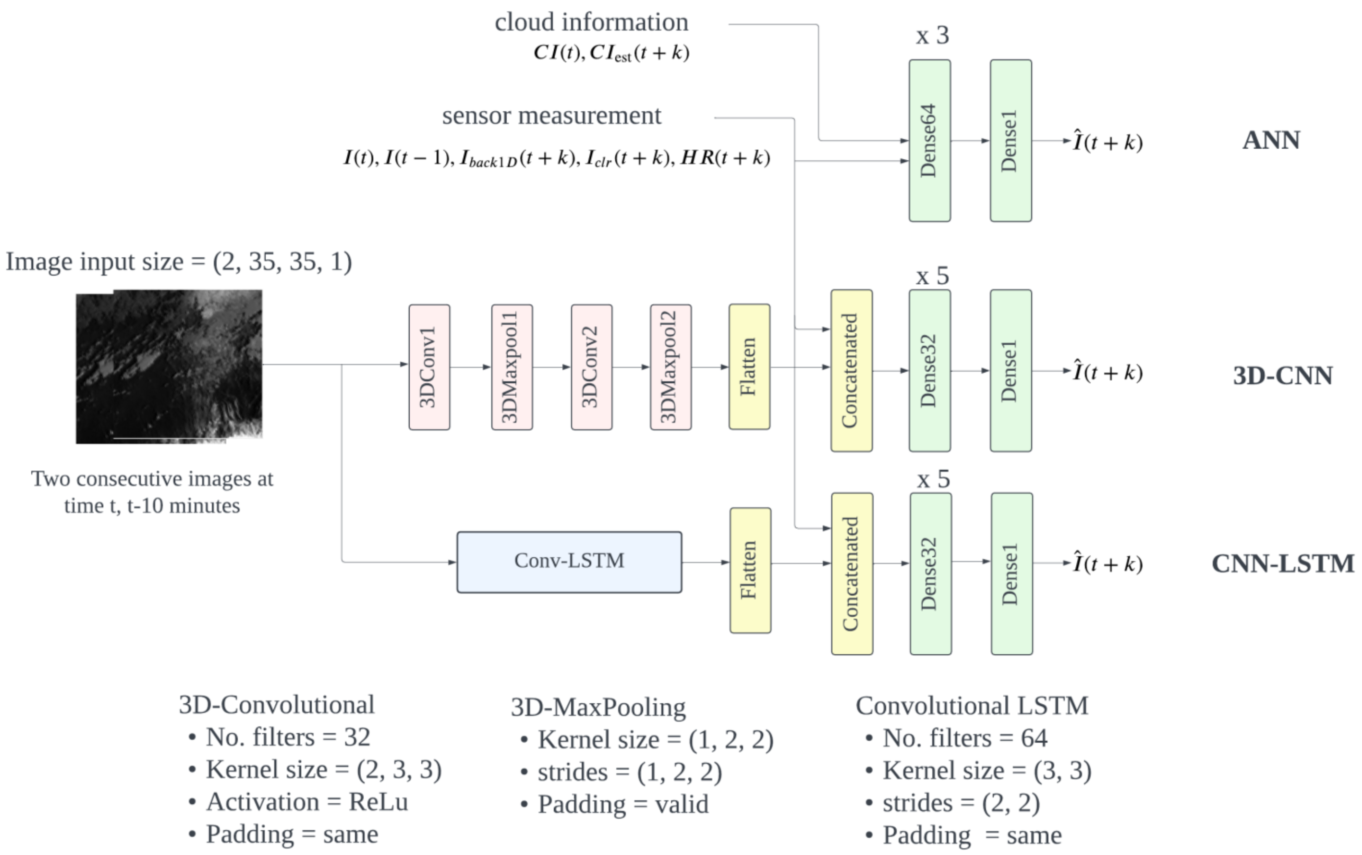
Traditional ML model mapping



- We categorized each lead-time model into three sub-models corresponding to the forecasted values in the morning times, midday times, and evening times.
- The time intervals for each of the sub-models are as follows: 07:00 - 09:00, 09:30 - 15:30 and 16:00 - 17:00 for the morning, midday and evening sub-model respectively, Features mappings are expressed above.

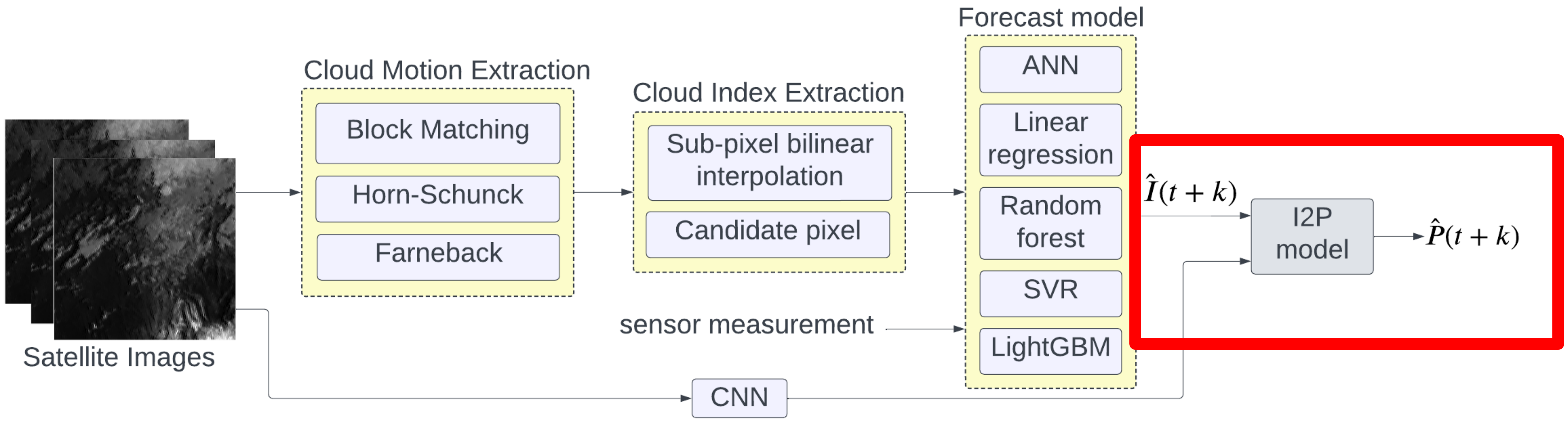
Methodology : Forecasting model

Deep neural networks model mapping



The ANN model consists of 3 difference model structures

- DNN uses estimated cloud index feature along with sensor measurement similar to previous model.
- 3D-CNN extracts spatiotemporal relationship from cloud images through convolution across all spatial and temporal axes
- CNN-LSTM utilizes LSTM cells to extract temporal information from the convoluted cloud image data.



- Linear regression

$\hat{P} = \alpha_0 + \alpha_1 \hat{I}$ with

  - MSE Loss
  - Huber loss

- Polynomial regression

$\hat{P} = \beta_0 + \beta_1 \hat{I} + \beta_2 \hat{I}^2$ with MSE Loss

The training dataset consists of the actual I and P data while the forecasted $\hat{I}$ from CNN-LSTM will be used as a testing dataset.

Results & Discussion

Cloud index estimation

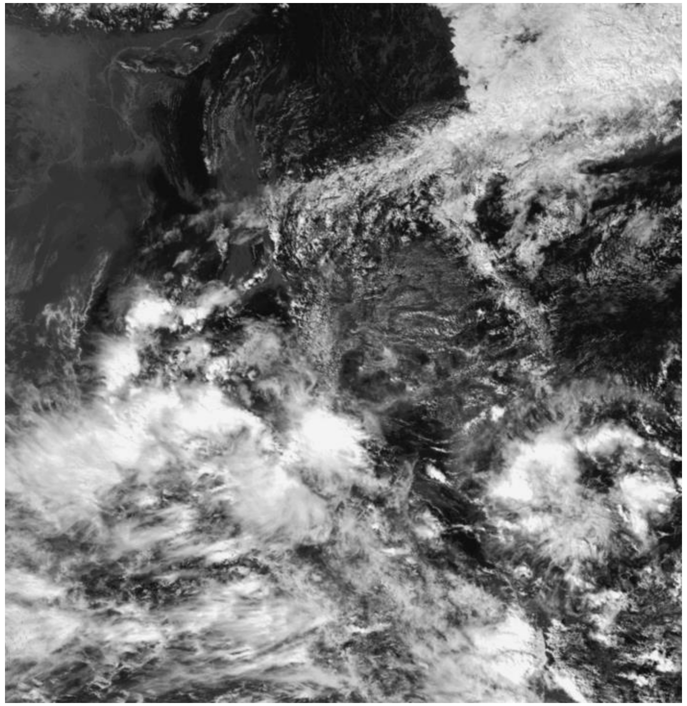
Irradiance forecasting

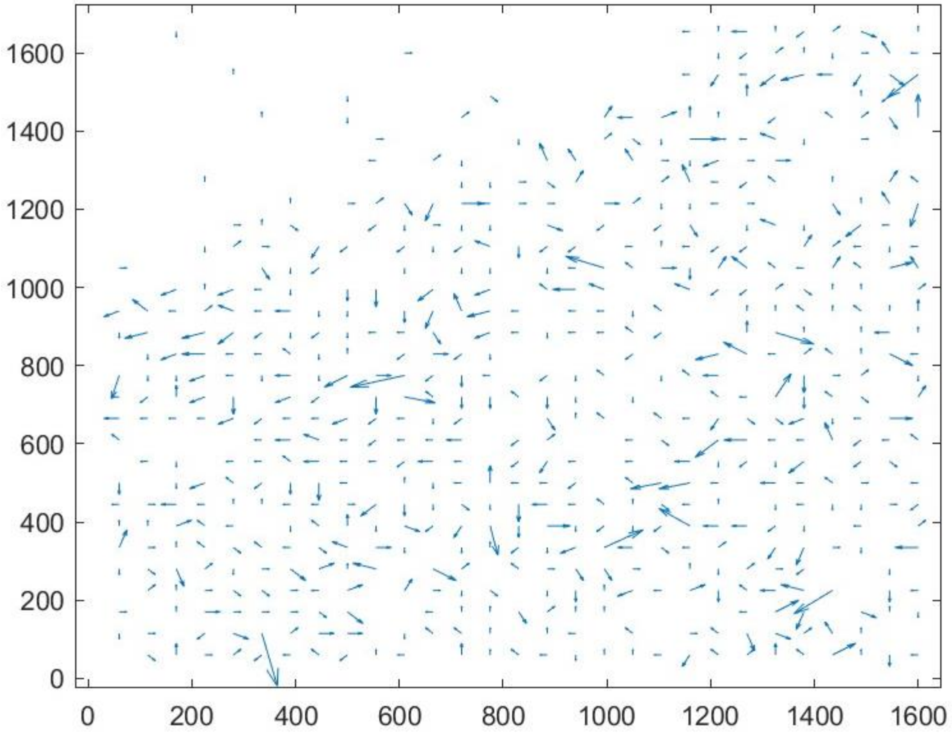
PV conversion

Result & Discussion : Cloud index estimation

Examples of CMV extraction

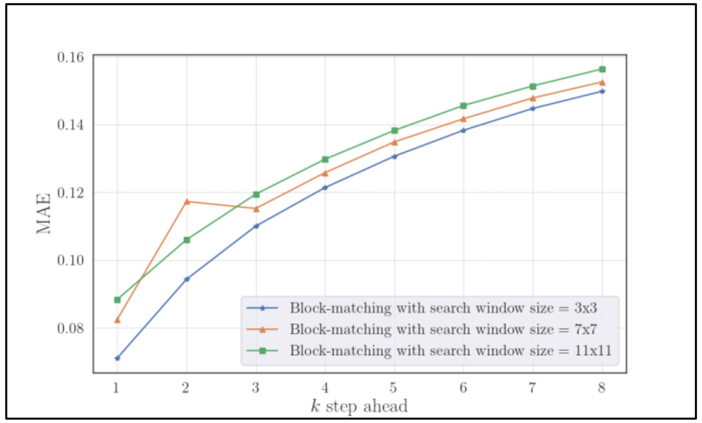
The example of CMV extraction are shown below as GIF. The CMV tends to point toward the same direction as those of cloud in overview R channel.

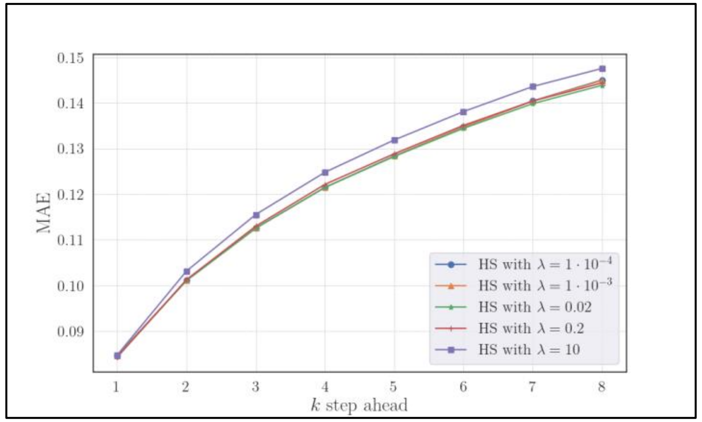


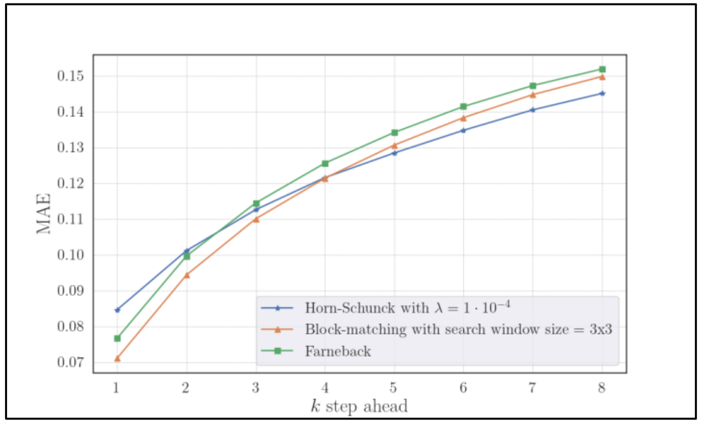


Result & Discussion : Cloud index estimation

hyperparameters tuning of each method



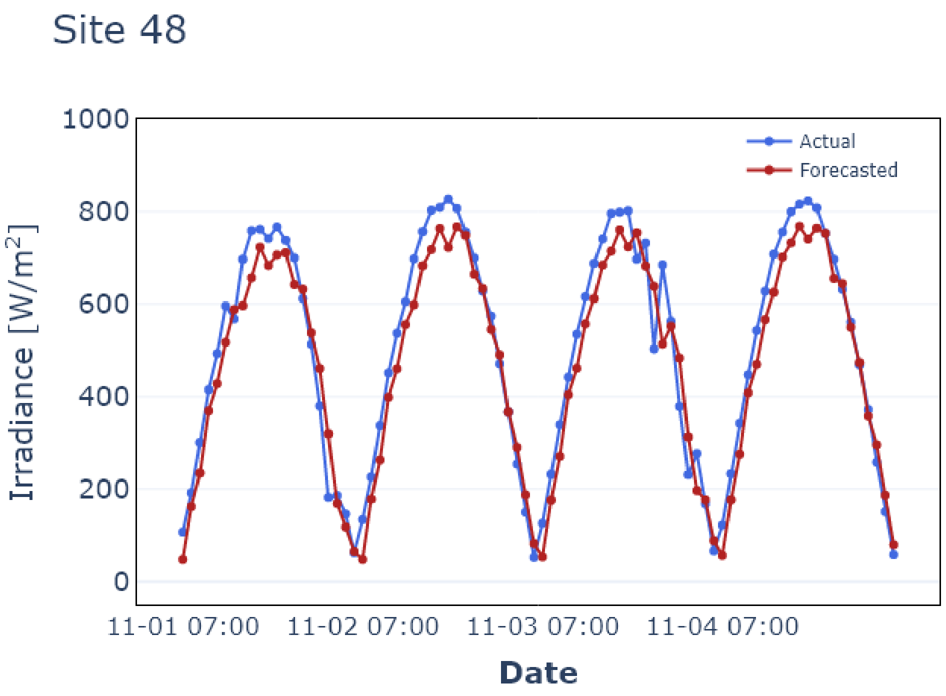


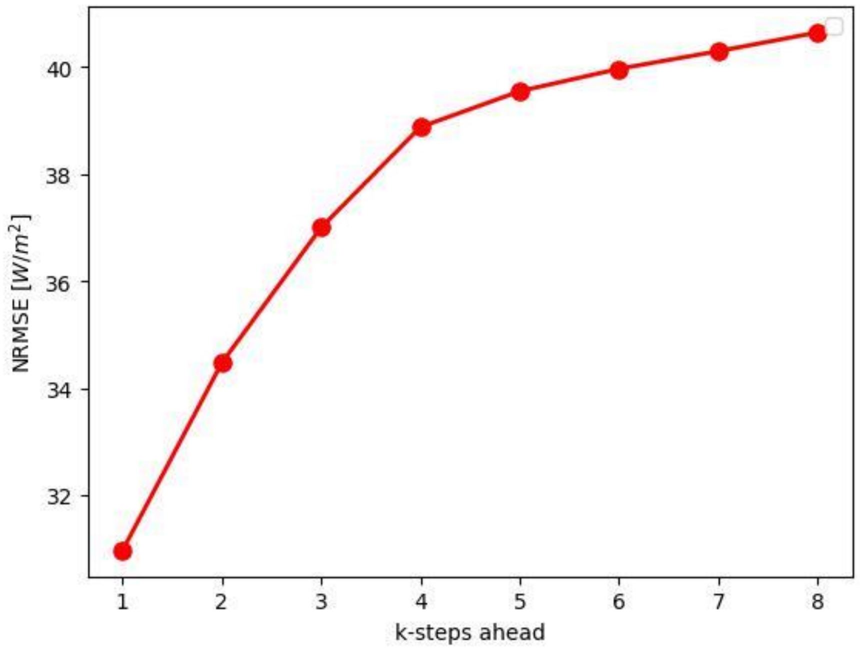


- As the search size increases in the block-matching method, the MAE also increases.
- At different k values, the optimal λ for each k are also different. But at $k = 8$ the best smoothness factor is $\lambda = 0.1$
- For k is 1, 2, 3, and 4, the Block-matching method demonstrates superior performance, whereas for k is 5, 6, 7, and 8, the Horn-Schunck method outperforms others.

Result & Discussion : Irradiance forecasting

Baseline performance by SARIMAX model

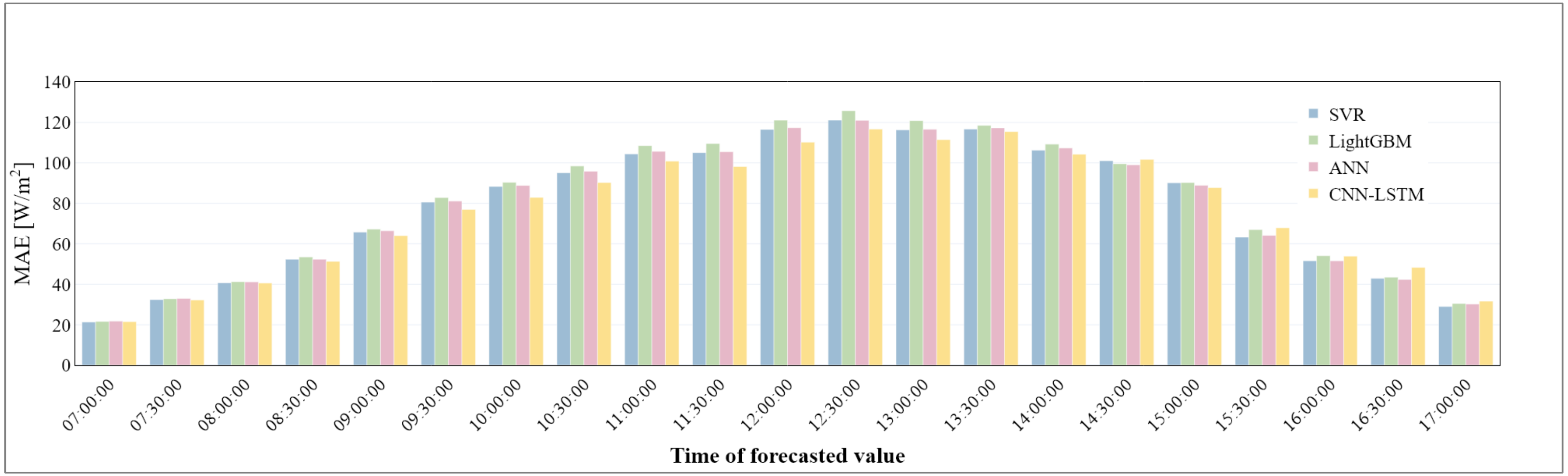




- The forecasted irradiance can not catch up with the actual at midday.
- NRMSE ranges from 30.96% to 40.65%

Result & Discussion : Irradiance forecasting

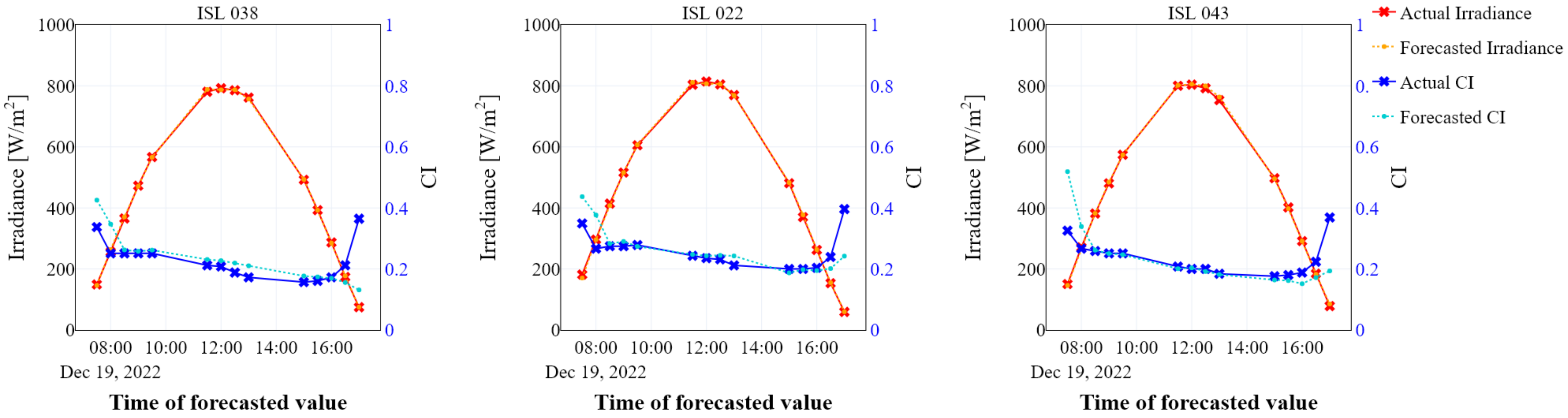
Hourly MAE of 30-minutes ahead model



- The CNN-LSTM model demonstrates the best performance compared to all other models, as indicated by the lowest MAE $= 77.64\ \mathrm{W/m^2}$
- Among the ML models that utilized the estimated cloud index feature, the best-performing model is SVR with MAE $= 79.09\ \mathrm{W/m^2}$

Result & Discussion : Irradiance Forecasting

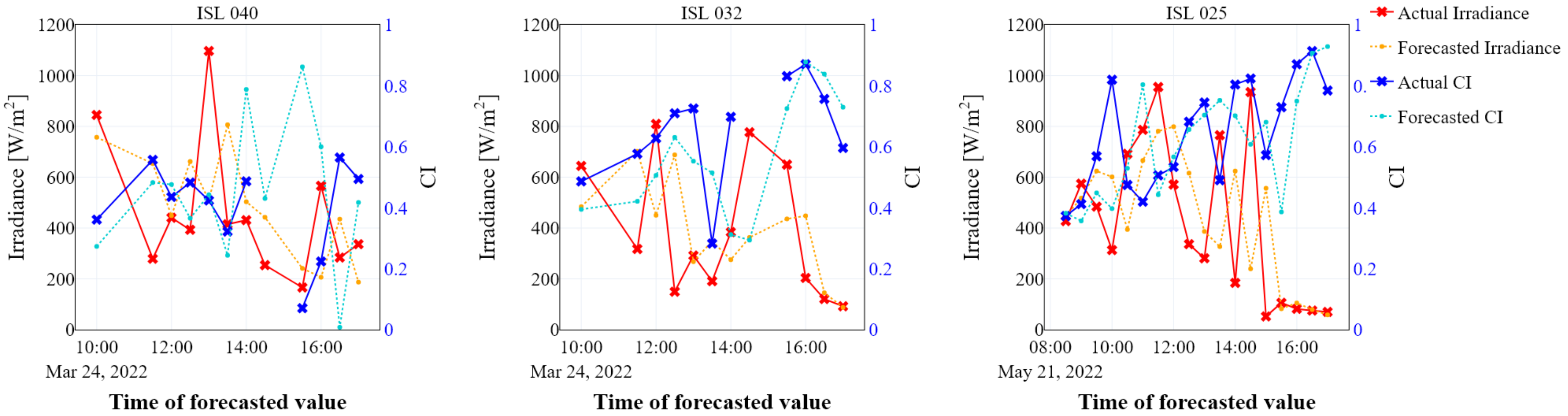
Satisfactory estimation by SVR



- On the day with the lowest MAE of the forecasting results, the cloud index remains consistently low throughout the day, and the Irradiance shows less fluctuations.
- The forecasted cloud Index feature can accurately track the actual values.

Result & Discussion : Irradiance Forecasting

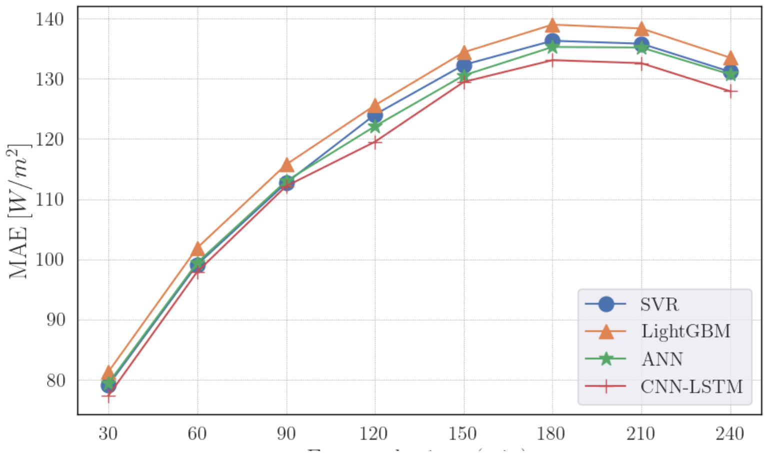
Unsatisfactory estimation by SVR

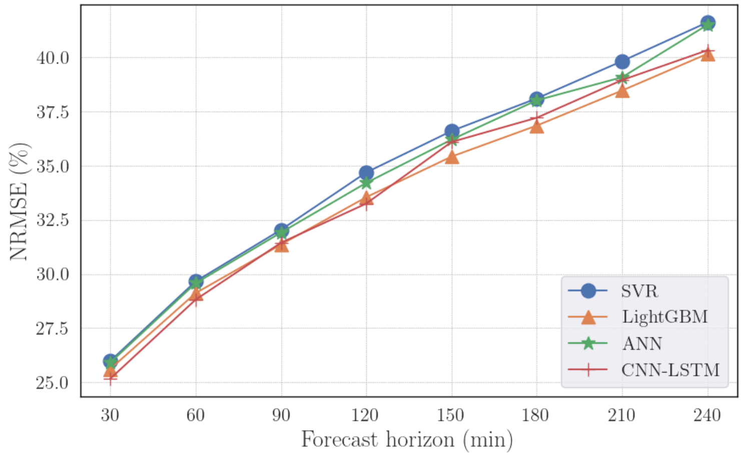


- On the day with the highest MAE of the forecasting results, both the measured Irradiance and actual cloud index exhibit significant fluctuations. Where, The expected anti-correlation between I and CI still show.
- The forecasted cloud Index feature cannot accurately capture the actual values.

Result & Discussion : Irradiance forecasting

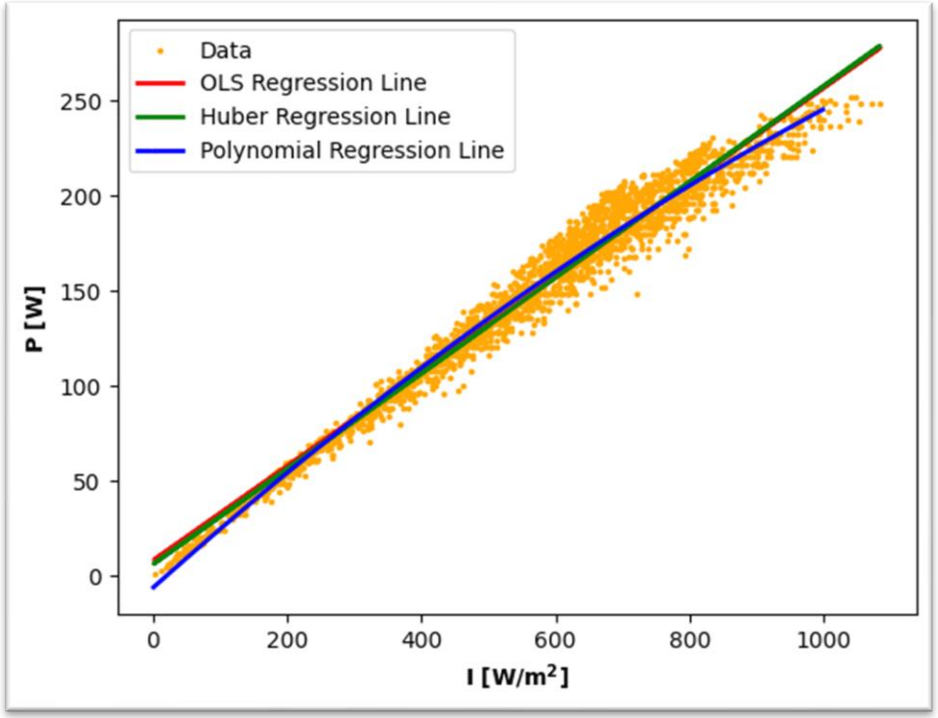
Comparing all models

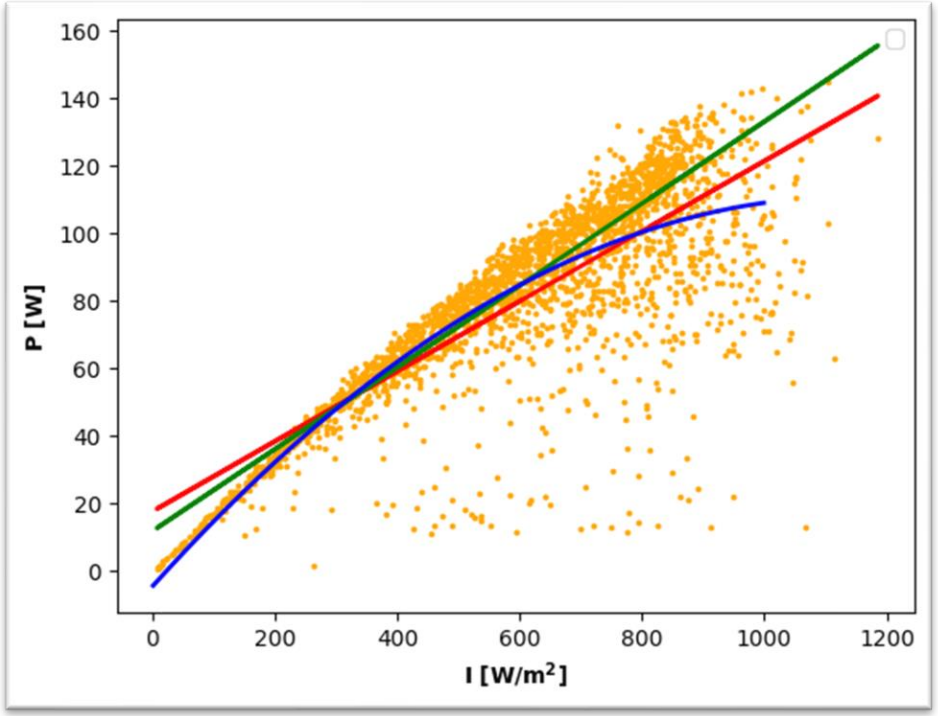




- The models that employ convolutional methods outperform the traditional ML models that used estimated cloud index up to a 120-minutes ahead with MAE ranges from 77.34 to 119.52 $\mathrm{W/m^2}$, approximately 4-6 $\mathrm{W/m^2}$ better than the others.
- Beyond 150 minutes-ahead, conflict occurred from using different metrics, If we consider MAE, CNN models continue to have better performance more than ML models.
- If NRMSE are considered, the tree-based models achieve a slightly better score with an NRMSE of 40.15 % compared to the CNN's NRMSE of 40.26 % example at 240-minutes ahead.

Result & Discussion : PV conversion





By using simple model to predict P from I, it turns out that linear regression yields the best performance with NRMSE = 22.75%

Conclusion

- ❖ The results of irradiance forecasting indicate that extracting spatiotemporal relationships from cloud images through convolution yields favorable outcomes compared to traditional ML methods that use estimated cloud index, particularly for shorter 2-hour forecasts.
- ❖ For longer horizons, both extracting methods exhibit similar performance, with the tree-based method slightly better performance.
- ❖ Due to these results, the computational cost becomes a factor that must be considered during the model implementation process. For forecast horizons of 150-240 minutes ahead, it is recommended to utilize only traditional ML models.

Conclusion : Compare to other researches

Model	MAE $(\mathrm{W/m^2})$	NRMSE(%)
IrradianceNET [6]	107.329	-
Proposed model from G. Raimondo [7]	-	0.52
Best model from our experiment	127.27	0.40

- There are several factors that contribute to the difference in performance scores, such as the type of image, the amount of data available and the weather conditions in each area.
- Irradiance data use cloud albedo images with 5 years data.
- Both models above do not use measurement features.

Reference

[1] P. Ineichen and R. Perez, "A new airmass independent formulation for the linke turbidity coefficient," Solar Energy, vol. 73, no. 3, pp. 151–157, 2002.

[2] G. Farnebäck, "Two-frame motion estimation based on polynomial expansion," in Scandinavian conference on Image analysis, pp. 363–370, Springer, 2003.

[3] B. K. Horn and B. G. Schunck, "Determining optical flow," Artificial intelligence, vol. 17, no. 1-3, pp. 185–203, 1981.

[4] Y. Lv, Q. Feng, and L. Qi, "A study of sub-pixel interpolation algorithm in digital speckle correlation method," in 2008 International Conference on Optical Instruments and Technology: Optoelectronic Measurement Technology and Applications, vol. 7160, pp. 740–748, SPIE, 2009.

[5] J. Antonanzas , N. Osorio, E. Natalia, R. Escobar, R. Urraca and F. Martinez-de-Pison, "Review of photovoltaic power forecasting," Solar energy, vol. 136, pp. 78–111, 2016.

Reference

[6] A. H. Nielsen, A. Iosifidis, and H. Karstoft, "Irradiancenet: Spatiotemporal deep learning model for satellite-derived solar irradiance short-term forecasting," *Solar Energy*, vol. 228, pp. 659–669, 2021.

[7] R. Gallo, M. Castangia, A. Macii, E. Macii, E. Patti, and A. Aliberti, "Solar radiation forecasting with deep learning techniques integrating geostationary satellite images," *Engineering Applications of Artificial Intelligence*, vol. 116, p. 105493, 2022.