CHULA ENGINEERING
Foundation toward Innovation

Database and image preprocessing for solar energy forecasting

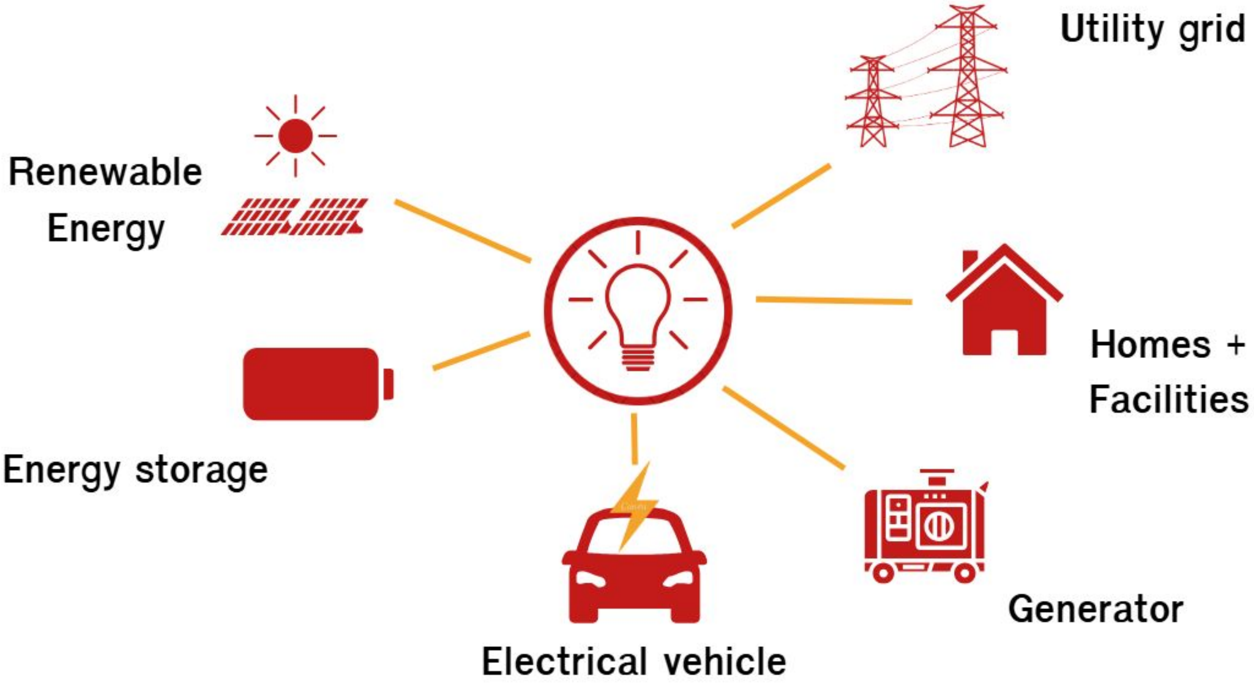
Advisor Dr. Suwichaya Suwanwimolkul

Kanawut Suwandee 6430031021

Kongpob In-odd 6430015021

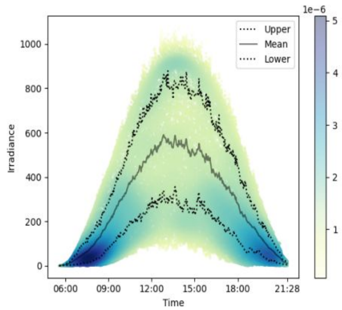
Introduction

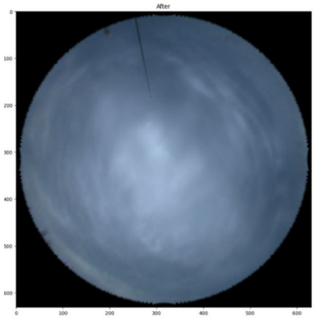
CHULA ΣNGINEERING
Foundation toward Innovation

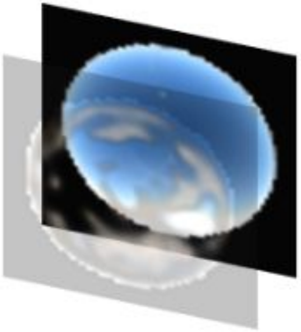


Objectives

- Analyze and examine the characteristics of three different datasets: SKIPP'D, CUEE, SIRTA.
- Evaluate the performance of SUNSET, SolarNet, Unet, on the three datasets.
- Process and extract additional features, e.g., cloud volume, and cloud mask.
- Gauge the impact of additional features from sky images on the SIRTA dataset and record any challenges occurred during building the benchmarking system.

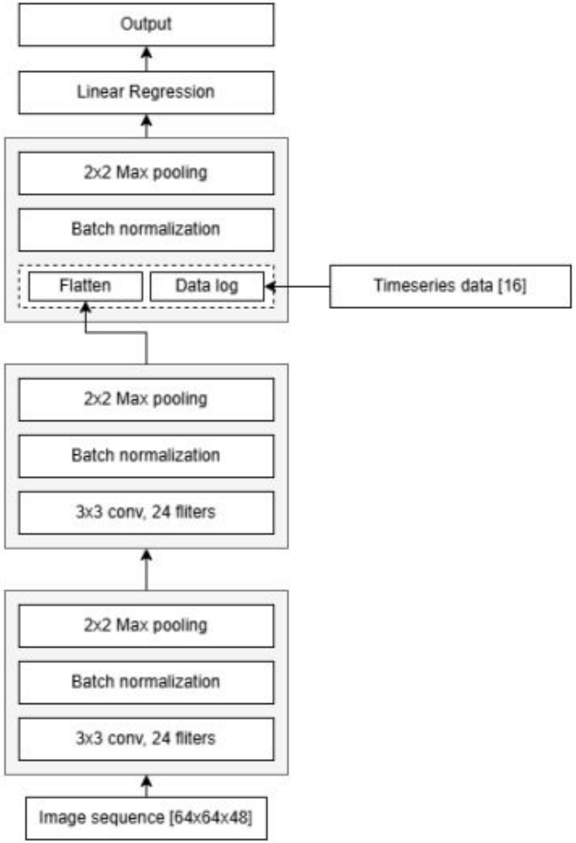




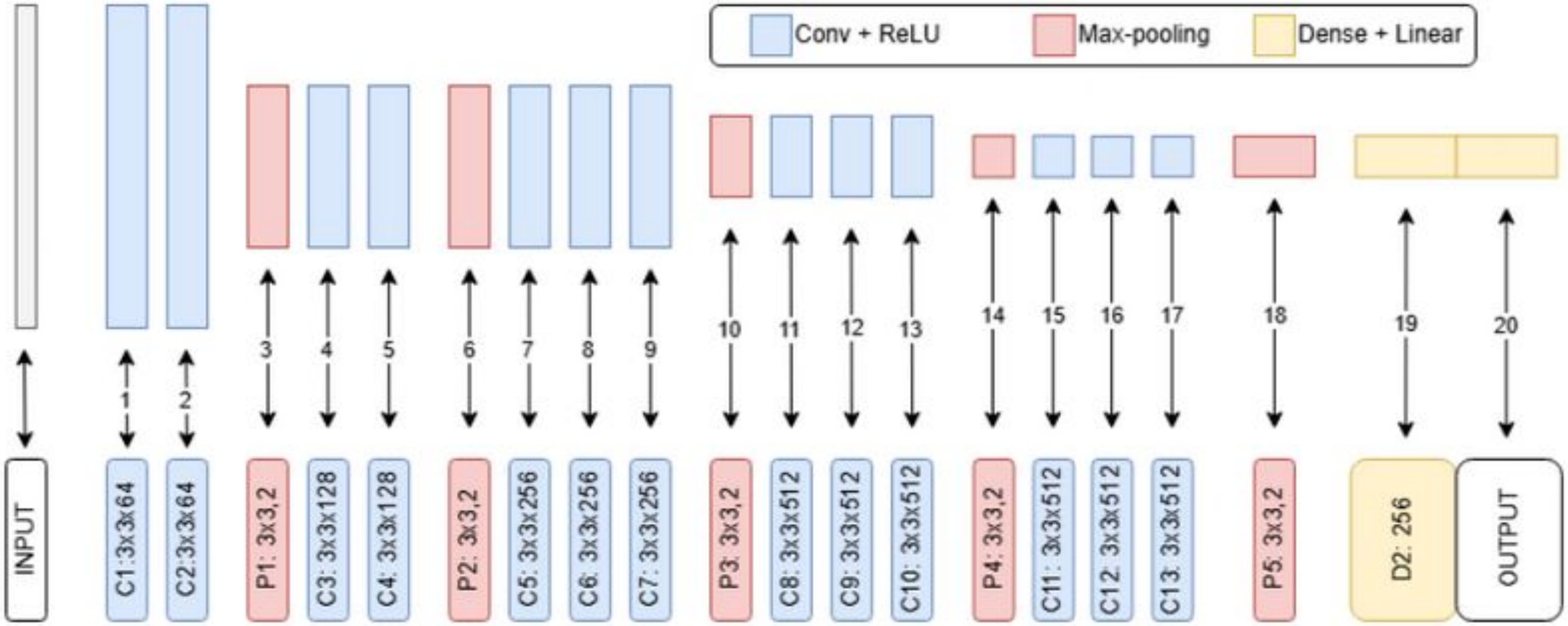


Background

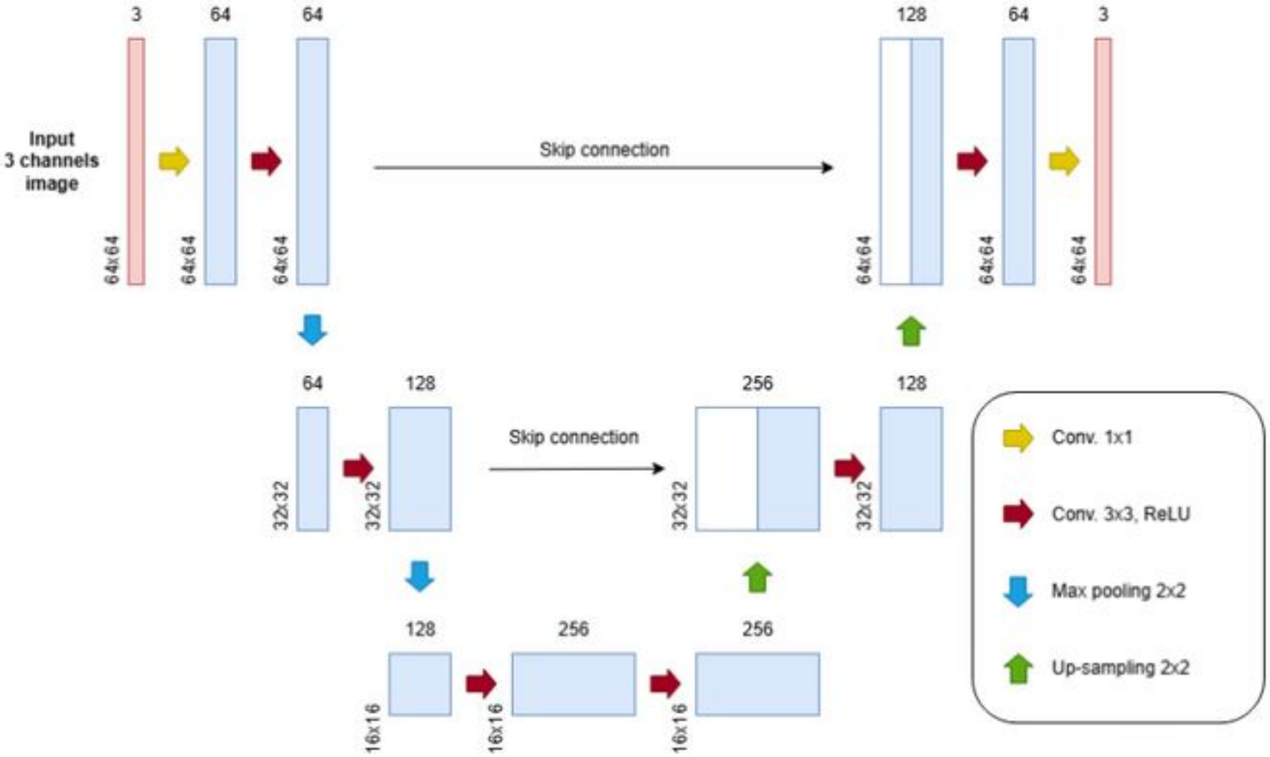
SUNSET (Sun et al., 2019)



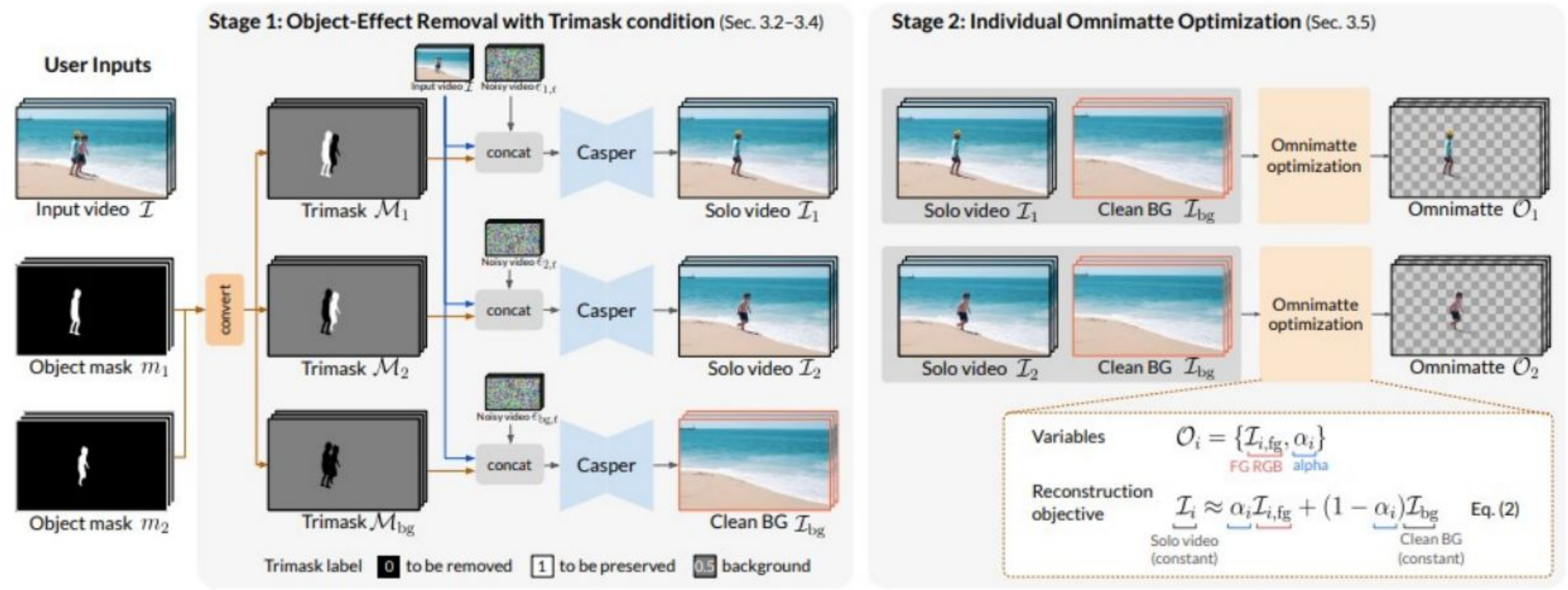
SolarNet (Feng et al., 2020)



Unet (Nie et al., 2020)



Generative omnimatte (Lee et al., 2024)



Methodology
& results

Outcomes

1. Data exploratory :

1.1) Data exploratory on SKIPP’D, CUEE, SIRTA datasets.

2. Image processing techniques :

2.1) Perform RoI extraction and lens distortion correction.

2.2) Training with baseline settings.

2.3) Training with image processing techniques.

3. Cloud mask and cloud foreground :

3.1) Cloud mask and cloud foreground extraction using a baseline method.

3.2) Cloud mask and cloud foreground extraction using a generative omnimatte.

3.3) Training with cloud mask and cloud foreground.

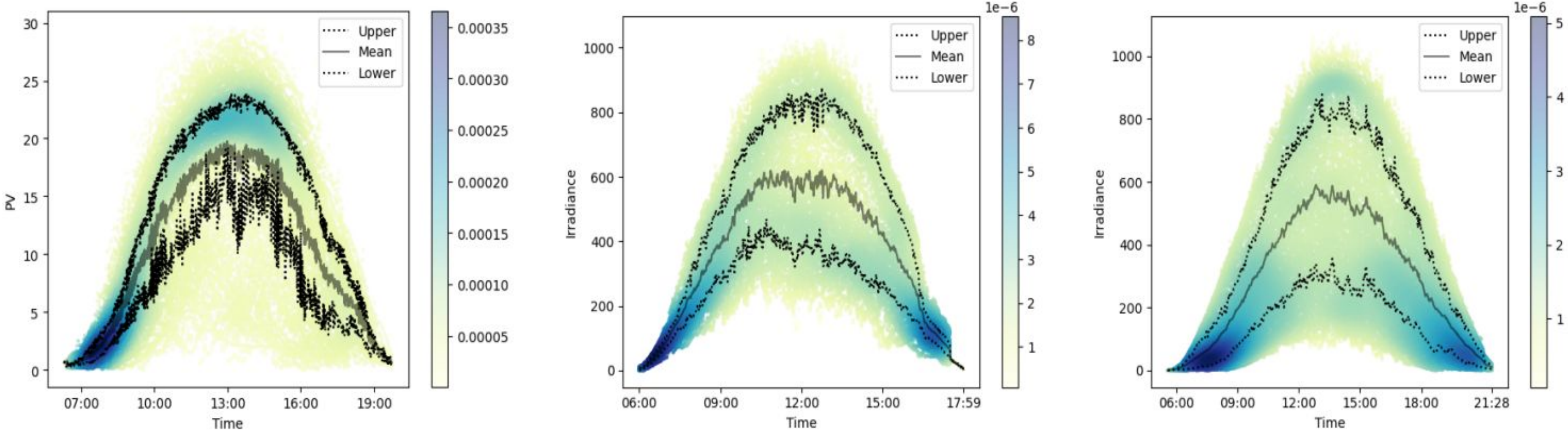
Data exploration

Data exploration

Dataset	SKIPP'D	CUEE	SIRTA
Camera Model	DS-2CD6365G0E-IVS	DS-2CD1021G0-I	EKO SRF-02
Resolution	64 × 64	1920 x 1080	64 × 64
Lens Type	Fisheye lens	DSLR lens	Fisheye lens
Capture Interval	1 minute	1 minute	1-2 minute
Start Date	09/03/2017	15/03/2023	01/01/2023
End Date	26/10/2019	03/11/2023	31/12/2023
Start Time	06:00	06:00	05:00
End Time	Not over 20:00	18:00	Not over 22:00

Data exploration

CHULA ΣNGINEERING
Foundation toward Innovation



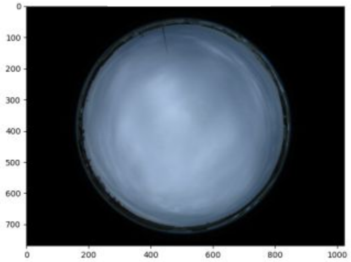
(a) SKIPP'D [KW] (b) CUEE [Watt/m^2] (c) SIRTA [Watt/m^2]

Image processing technique

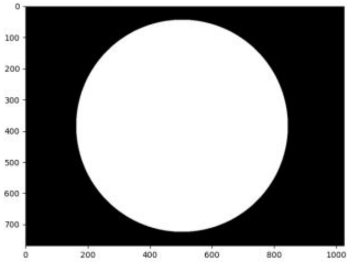
Image processing technique

RoI extraction

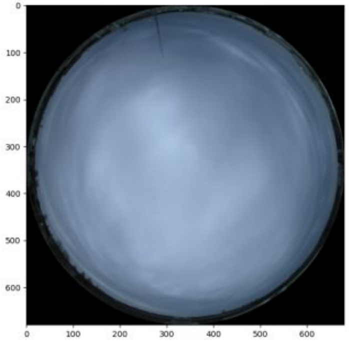
Before



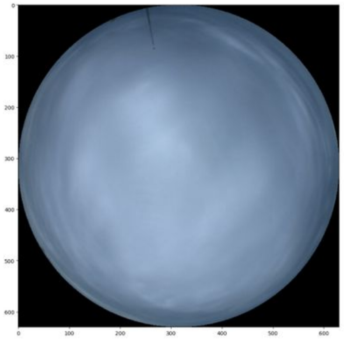
RoI



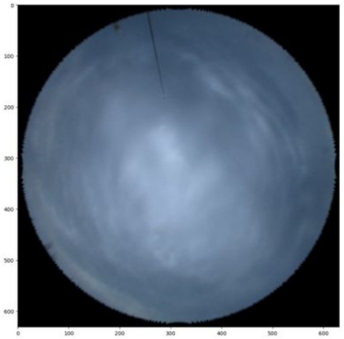
After



Before



After



Distortion correction

$$\begin{pmatrix} \rho\cos\theta \\ \rho\sin\theta \\ h \end{pmatrix} = \gamma(s)\left[\frac{2}{R_m}\begin{pmatrix} s\cos\theta \\ s\sin\theta \\ \sqrt{R_m^2 - s^2} \end{pmatrix} - \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} + \begin{pmatrix} s\cos\theta \\ s\sin\theta \\ \sqrt{R_m^2 - s^2} \end{pmatrix}\right]$$

Training with processed data result

CHULA ΣNGINEERING
Foundation toward Innovation

Then trained SUNSET, SolarNet, Unet on processed SIRTA dataset.

Baseline model

Model	Learning loss.	Parameter setting	Model parameters	Train on AE		Train on SE	
				MAE	RMSE	MAE	RMSE
SUNSET	MAE	Dense Size: 1024, Div num filter: 1	26296497	38.97	84.41	-	-
	RMSE	Dense Size: 1024, Div num filter: 4	7367373	-	-	45.04	86.24
Unet	MAE	Batch Size: 128, Drop rate: 0.4	306120	24.99	39.89	-	-
	RMSE	Batch Size: 128, Drop rate: 0.4	306120	-	-	24.08	41.02
Solarnet	MAE	Batch Size: 64, Num layer: 4	14867974	72.65	121.16	-	-
	RMSE	Batch Size: 16, Num layer: 4	14867974	-	-	65.03	106.86

Processed image

Model	Learning loss.	Parameter setting	Model parameters	Train on AE		Train on SE	
				MAE	RMSE	MAE	RMSE
SUNSET	MAE	Dense Size: 1024, Div num filter: 1	26296497	42.91	88.45	-	-
	RMSE	Dense Size:1024, Div num filter: 4	3237081	-	-	45.86	85.65
Unet	MAE	Batch Size:128, Drop rate:0.4	306120	29.01	48.46	-	-
	RMSE	Batch Size:128, Drop rate:0.4	306120	-	-	29.66	48.12
Solarnet	MAE	Batch Size:16, Num layer: 4	14867974	66.79	116.81	-	-
	RMSE	Batch Size:16, Num layer: 4	14867974	-	-	67.50	110.16

Cloud mask and cloud foreground extraction

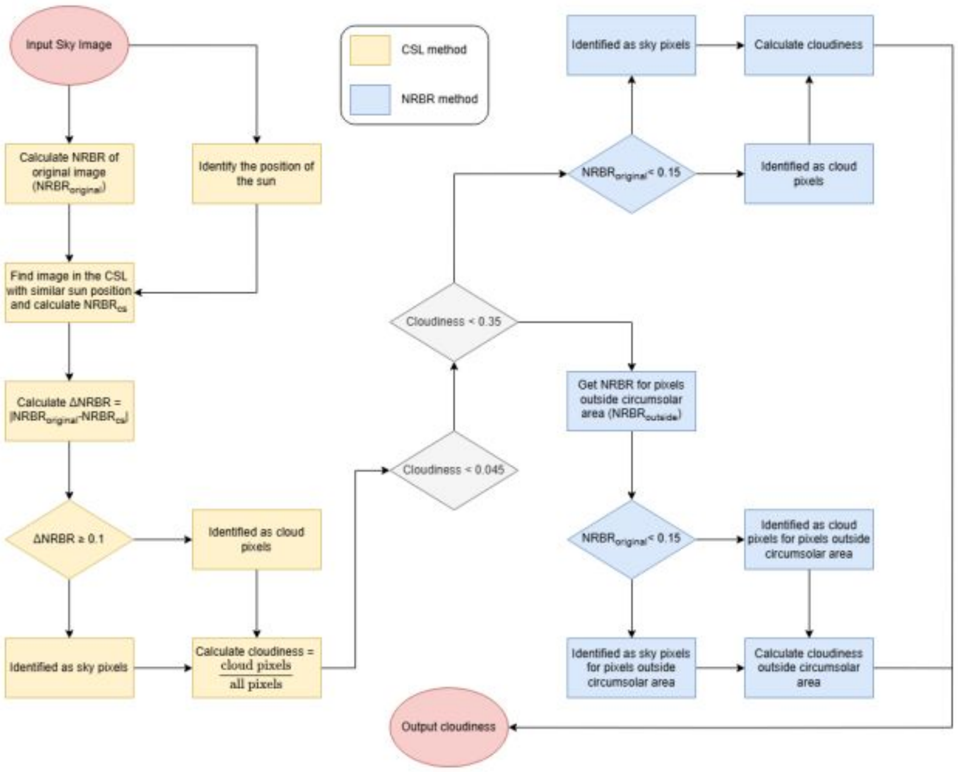
Improve model performance with additional cloud masking channels

This study, we have extracted additional information from sky image as cloud mask to improve model performance (4 cloud masking methods).

1. Cloud mask extraction with baseline (Nie et al., 2020)
2. Cloud foreground extraction with baseline (Nie et al., 2020)
3. Cloud mask extraction using **generative omnimatte** (Lee et al., 2024)
4. Cloud foreground extraction using **generative omnimatte** (Lee et al., 2024)




Cloud mask extraction (Nie et al., 2020)



Cloud mask
(Nie et al., 2020)

Cloud foreground extraction (Nie et al., 2020)

Sky image

*

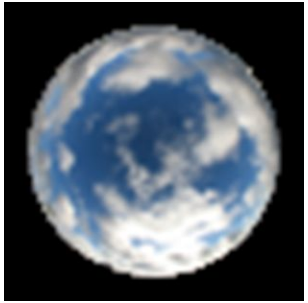
Cloud mask

=

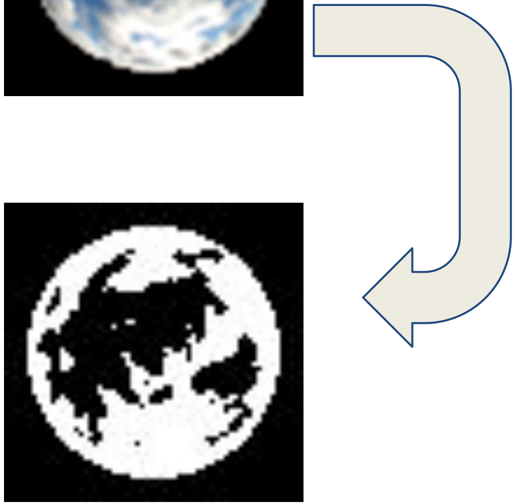
Cloud foreground

Nie et al. method and generative omnimatte

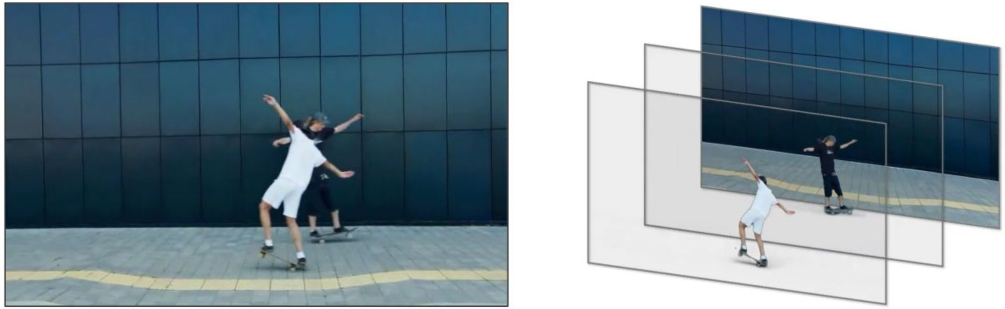
Nie et al. method



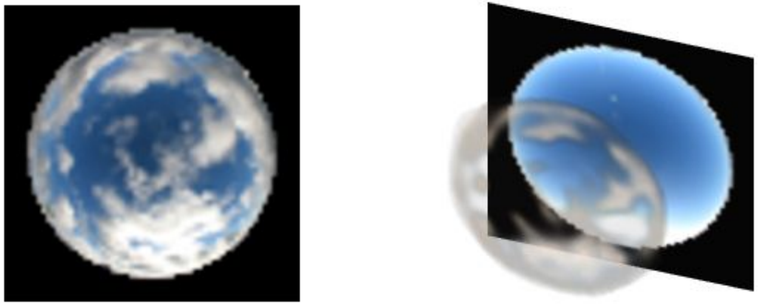
Classifie pixels by calculating NRBR



Generative omnimatte



Extract foreground from image into a separate layer.



Improve cloud cover extraction

1. Preprocessing sky image :

Preprocessing sky image on SIRTA datasets.

2. Train text-to-image generation model :

To generate a clear sky image by specifying brightness and clarity through text.

3. Train generative omnimatte :

To generate cloud mask and cloud foreground layer by using sky image and clear sky image as inputs

Improve cloud cover extraction

Sky images

Nie et al. method

0 and 1

Improve

Sky images

Clear sky image

Generative omnimatte

0 to 1

Data exploration | Image processing technique | Cloud mask and cloud foreground extraction

Generative omnimatte learning loss

Loss function

$$\lambda_{sparsity} L_{sparsity} + L_{mask}$$

(Base model)

Mask loss

$$L_{mask} = ||m - \alpha||_2$$

Sparsity loss

$$L_{sparsity} = ||\alpha||_1$$

$$\lambda_{sparsity} = 0.001$$

Generative omnimatte learning loss

CHULA ENGINEERING
Foundation toward Innovation

Loss function

$$\lambda_{sparsity} = \lambda_{mask} = 0.001$$

$$L_{recon} + \lambda_{sparsity} L_{sparsity} + \lambda_{mask} L_{mask}$$

(Tranfer model)

Reconstruction loss

$$L_{recon} = ||I - I_{recon}||_2 = ||I - \alpha I_{fg} + (1 - \alpha) I_{bg}||_2$$

(Comb-off)

$$L_{recon} = ||I - I_{recon}||_2 = ||I - \alpha\,(I_{fg} + I_{bg}) + (1 - \alpha) I_{bg}||_2$$

(Comb-on)

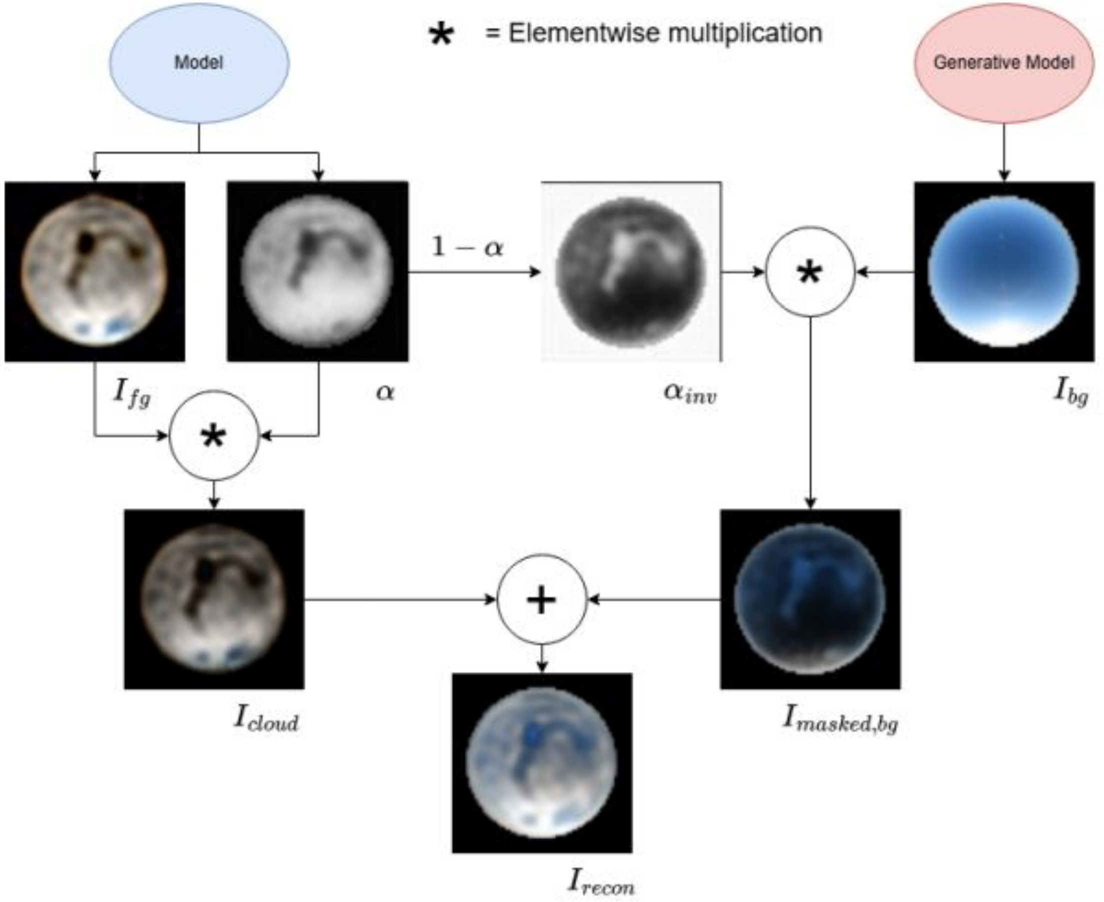
Sparsity loss

$$L_{sparsity} = ||\alpha||_1$$

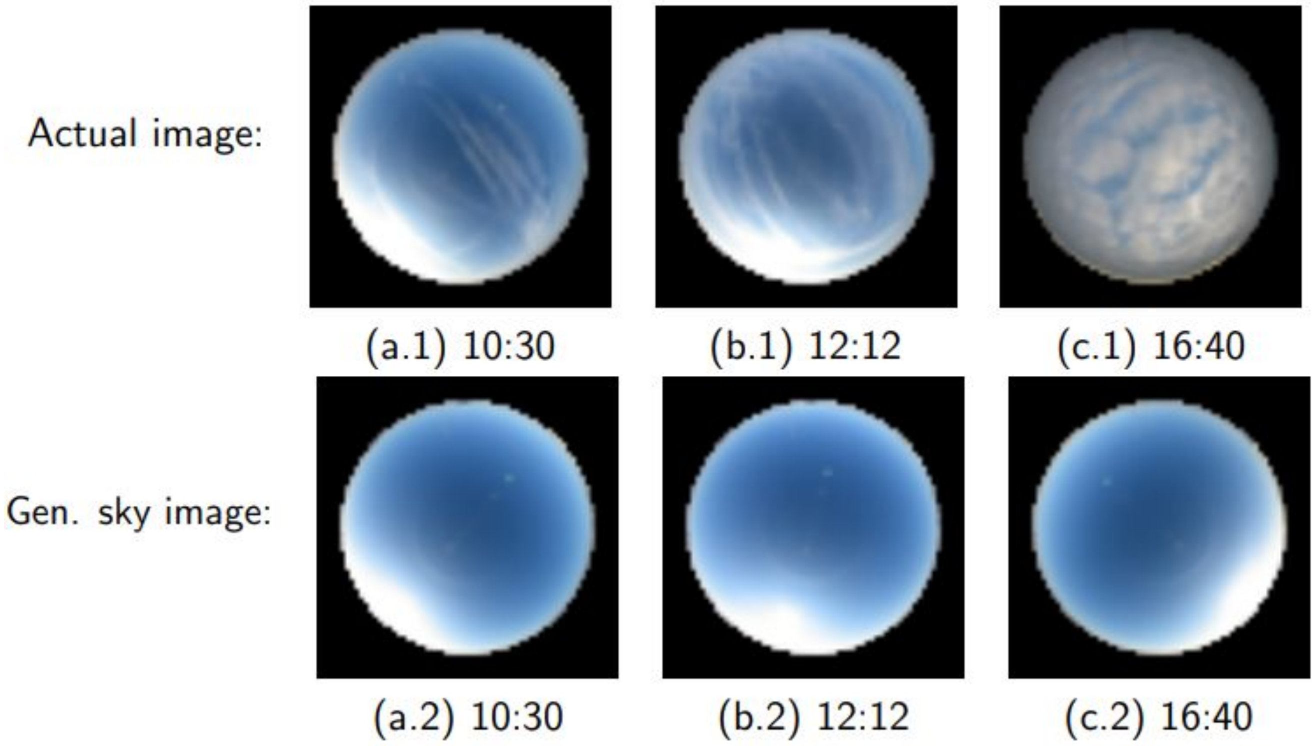
Mask loss

$$L_{mask} = ||m - \alpha||_2$$

Generative omnimatte learning loss



Clear-sky image generation



Cloud mask and foreground extraction using generative omnimatte

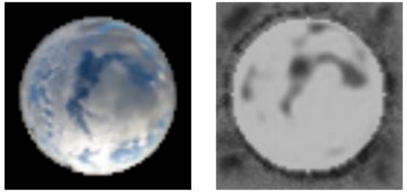
CHULA ΣNGINEERING
Foundation toward Innovation

Sky image

Cloud mask
(Generative omnimatte)

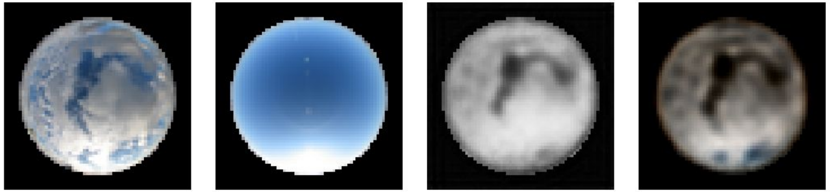
Cloud foreground
(Generative omnimatte)

Cloud mask and cloud foreground extraction results



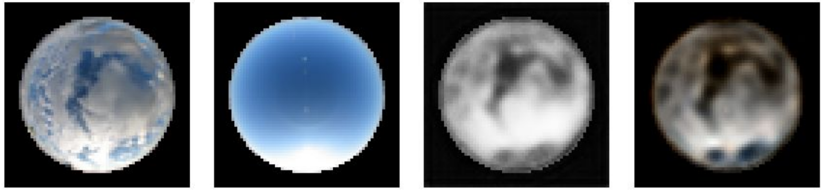
(a) Sky image (b) Cloud mask

Baseline model



(a) Sky image (b) Clear sky image (c) Cloud mask (d) Cloud foreground

Comb-off model

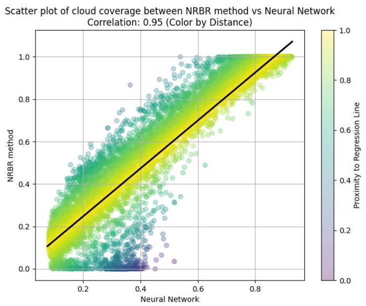


(a) Sky image (b) Clear sky image (c) Cloud mask (d) Cloud foreground

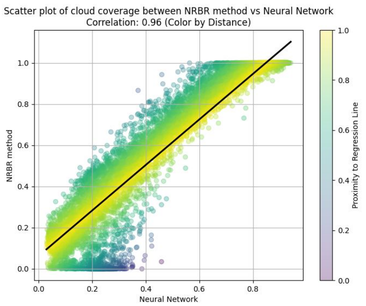
Comb-on model

Generative omnimatte results

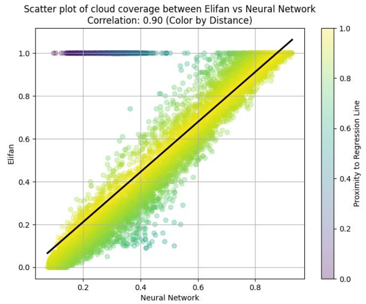
Quality of the predicted soft-decision mask



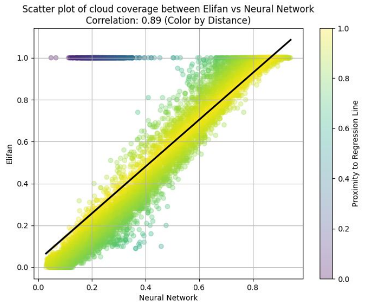
Comb-on model vs. [Nie et al., 2020]



Comb-off model vs. [Nie et al., 2020]



Comb-on model vs. Elifan

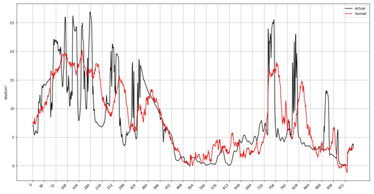


Comb-off model vs. Elifan

Training with cloud mask and cloud foreground

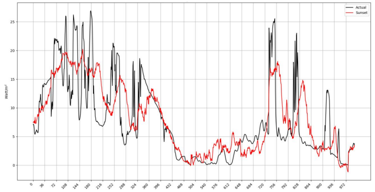
We have trained SUNSET on SIRTA dataset with additional cloud masking channels to improve model performance.

Original images → Neural Network →



Improve

Original images + Cloud mask → Neural Network →

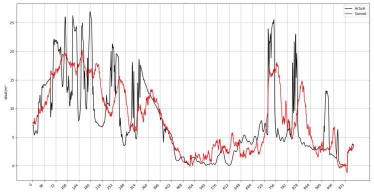


Training with cloud mask and cloud foreground

Due to limited CPU RAM, we have trained the new SUNSET model using only the first 6 months of the SIRTA dataset for the baseline model and all cloud mask experiments.

64x64x3 (unit8)	64x64x3 (unit8)	64x64x6 (float32)
Original images	Processed images	Original images + Cloud mask

Neural Network



Irradiance

Training with cloud mask and cloud foreground

Experiment 1 : Cloud mask extraction with baseline (Nie et al., 2020)
Experiment 2 : Cloud foreground extraction with baseline (Nie et al., 2020)
Experiment 3 : Cloud mask extraction using generative omnimatte (Lee et al., 2024)
Experiment 4 : Cloud foreground extraction using generative omnimatte (Lee et al., 2024)

Evaluation	Learning loss: MAE				
	Original	Experiment 1	Experiment 2	Experiment 3	Experiment 4
MAE	32.74	36.51	33.93	33.28	36.79
RMSE	76.25	78.80	75.77	75.22	80.22

Evaluation	Learning loss: RMSE				
	Original	Experiment 1	Experiment 2	Experiment 3	Experiment 4
MAE	42.91	34.76	38.83	36.82	39.12
RMSE	79.03	73.32	77.06	74.08	76.69

Conclusion

Conclusion

- SUNSET consistently achieves the best performance in the forecasting task due to receive both Image and timeseries data as a input
- This study can enhance the SUNSET model's performance on the SIRTA dataset by incorporated an additional cloud mask channel method 1, resulting in an approximate 3% improvement in RMSE

Problems, obstacles, and solutions

- Limited memory on the CPU and GPU RAM poses a significant challenge in the handling of high-resolution images. Consequently, the original images, stored in the database at full resolution, must be downscaled to 64×64 pixels for model training. This reduction in resolution can lead to a loss of image quality and critical features, which may affect the accuracy of the results and complicate their interpretation. To overcome this limitation, an on-the-fly data generation approach can be employed.

CHULA ENGINEERING
Foundation toward Innovation

Thank you

During the preparation of this work, ChatGPT has been used solely for enhancing the readability and language.

After using this tool, we have reviewed and edited the content as needed and take the full responsibility for the content.

Kanawut Suwandee
Kongpob In-odd

Reference

C. Feng and J. Zhang, “Solarnet: A sky image-based deep convolutional neural network for intra-hour solar forecasting,” Solar Energy, vol. 204, pp. 71–78, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0038092X20303285

Y. Sun, V. Venugopal, and A. R. Brandt, “Short-term solar power forecast with deep learning: Exploring optimal input and output configuration,” Solar Energy, vol. 188, pp. 730–741, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0038092X19306164

Y. Nie, Y. Sun, Y. Chen, R. Orsini, and A. Brandt, “Pv power output prediction from sky images using convolutional neural network: The comparison of sky-condition-specific sub-models and an end-to-end model,” Journal of Renewable and Sustainable Energy, vol. 12, no. 4, p. 046101, 08 2020. [Online]. Available: https://doi.org/10.1063/5.0014016

Y.-C. Lee, E. Lu, S. Rumbley, M. Geyer, J.-B. Huang, T. Dekel, and F. Cole, “Generative omni-matte: Learning to decompose video into layers,” arXiv preprint arXiv:2411.16683, 2024.