

**POLITECNICO**  
MILANO 1863

# Photovoltaic power generation nowcasting: cloud type classification forecast through satellite data and imagery

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# Introduction

## FRAMEWORK

Grid connected PV systems (and RES) are expected to **grow in number**

## PROBLEM

Sudden variations in **weather conditions** may cause significant variations in RES power production. In PV systems this is mainly due to **moving clouds** which are affecting **solar radiation**.



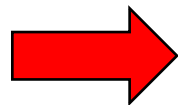
In **national electrical grids sudden power inflows raise issues of stability and reliability**. These fluctuations on **small scale**, i.e. in **microgrids**, affect **dispatchability**.

## ACTUAL SOLUTION

Usually, two technologies are adopted to mitigate this issue:

- **Battery energy storage system (ESS)**, which should be properly sized and coordinated “a priori”
- Backup generators (usually carbon based) are included

## GAP

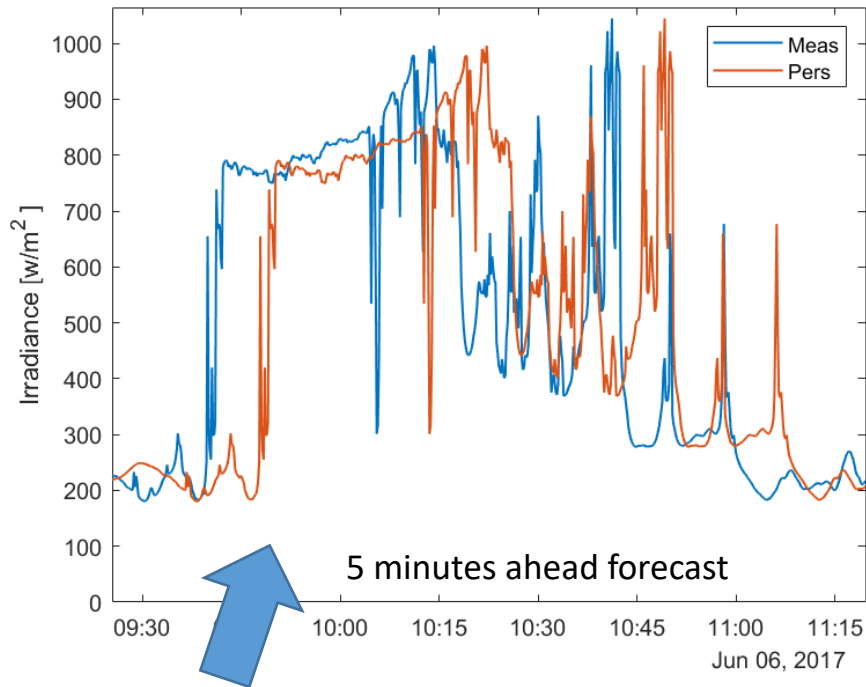


**An accurate short-term solar radiation forecast is needed!**

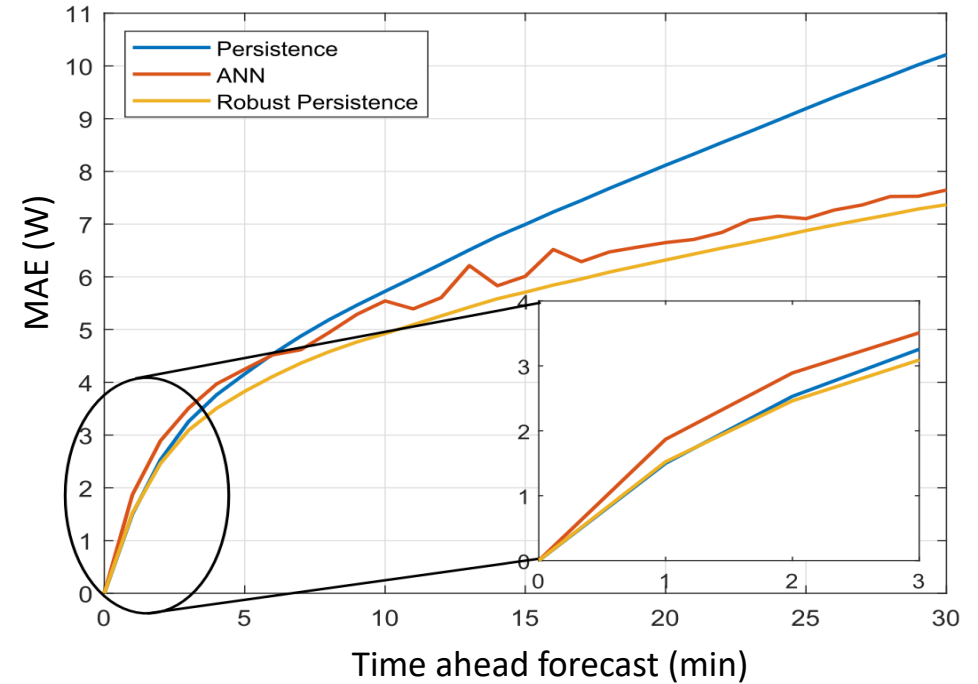


# Nowcasting: Persistence vs ANN

**Persistence and ANN** are typical methods for day-ahead and intraday forecasting of solar radiation.



**Persistence fails in predicting sudden ramps and drops of solar irradiance**



**After 5 minutes ahead forecast robust persistence shows good accuracy**

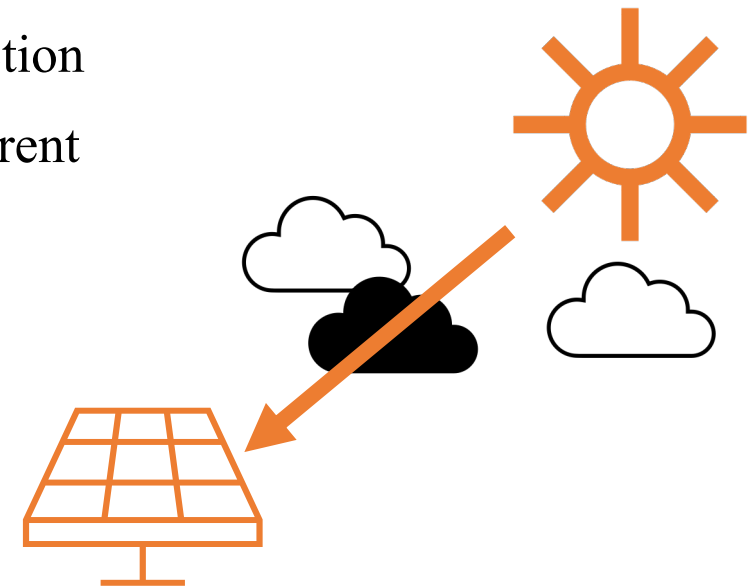
*S. Leva, A. Nespoli, S. Pretto, M. Mussetta and E. Ogliari, "PV Plant Power Nowcasting: A Real Case Comparative Study With an Open Access Dataset," in IEEE Access, vol. 8, pp. 194428-194440, 2020*





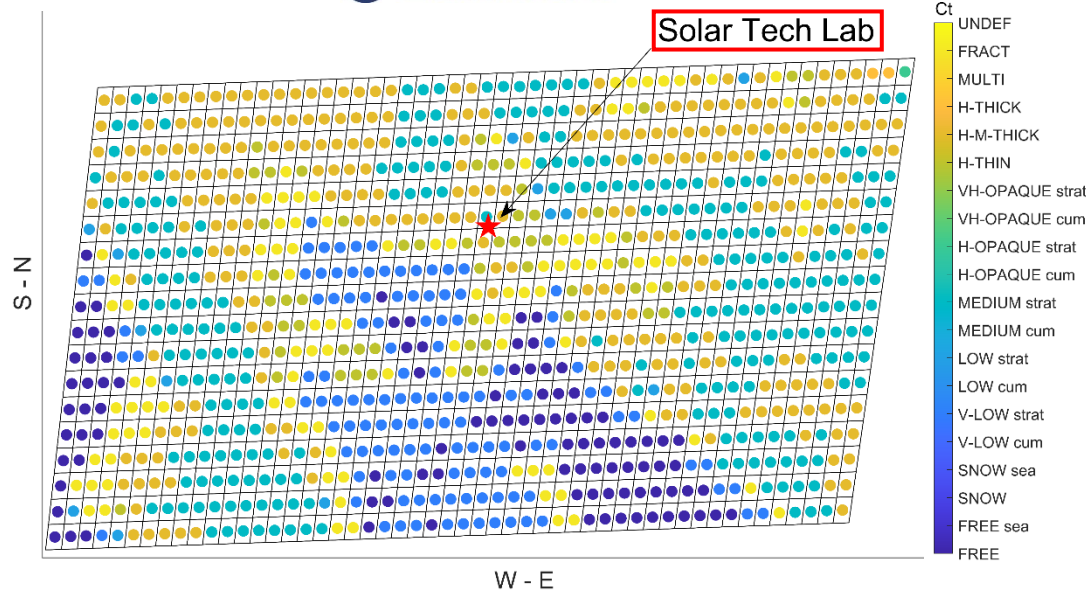
**TARGET:** to set a simplified methodology for 15 minutes ahead forecast (nowcasting) of the sudden variations (peaks and drops) of solar irradiance on a given location through satellite images.

1. Dynamic Cloud model development: cloud-to-Sun solar irradiance interaction
2. Cloud type classification forecast through satellite data and imagery: different training layout comparison and reduced satellite data classification
3. Most effective Machine Learning techniques (ANN and Random Forest) for Nowcasting setting up: sizing and performance assessment





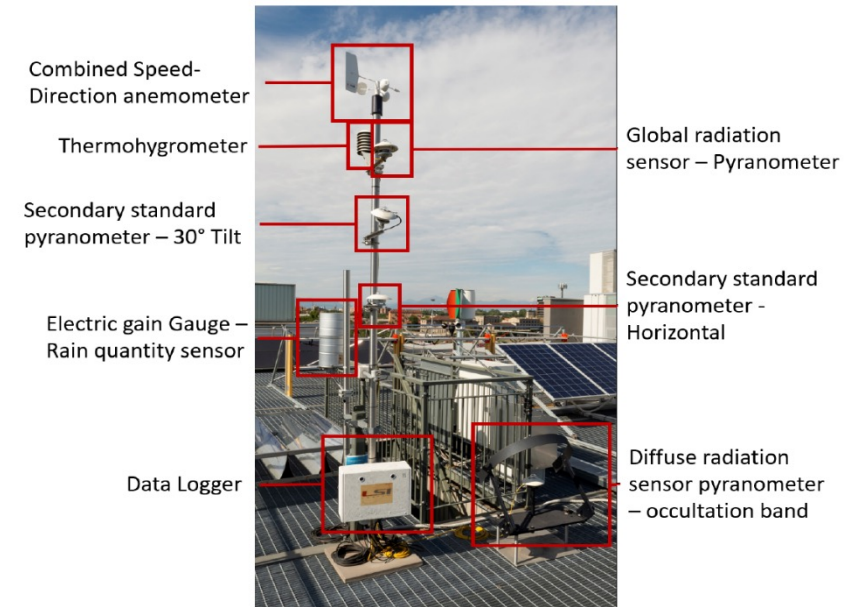
## • SATELLITE DATA (15 min.)



- Size: 18x51 pixel (1 pixel = 3x5 km)
- Cloud type (19 classes) & Cloud top altitude
- Latitude and longitude
- 385 images available (~10 days)



## • WEATHER STATION MEASUREMENTS (10 sec.)



- Global Horizontal Irradiance (GHI) [ $\text{W}/\text{m}^2$ ]
- Wind speed [ $\text{m}/\text{s}$ ] and direction [ $^\circ$ ]
- Rain [ $\text{mm}$ ]



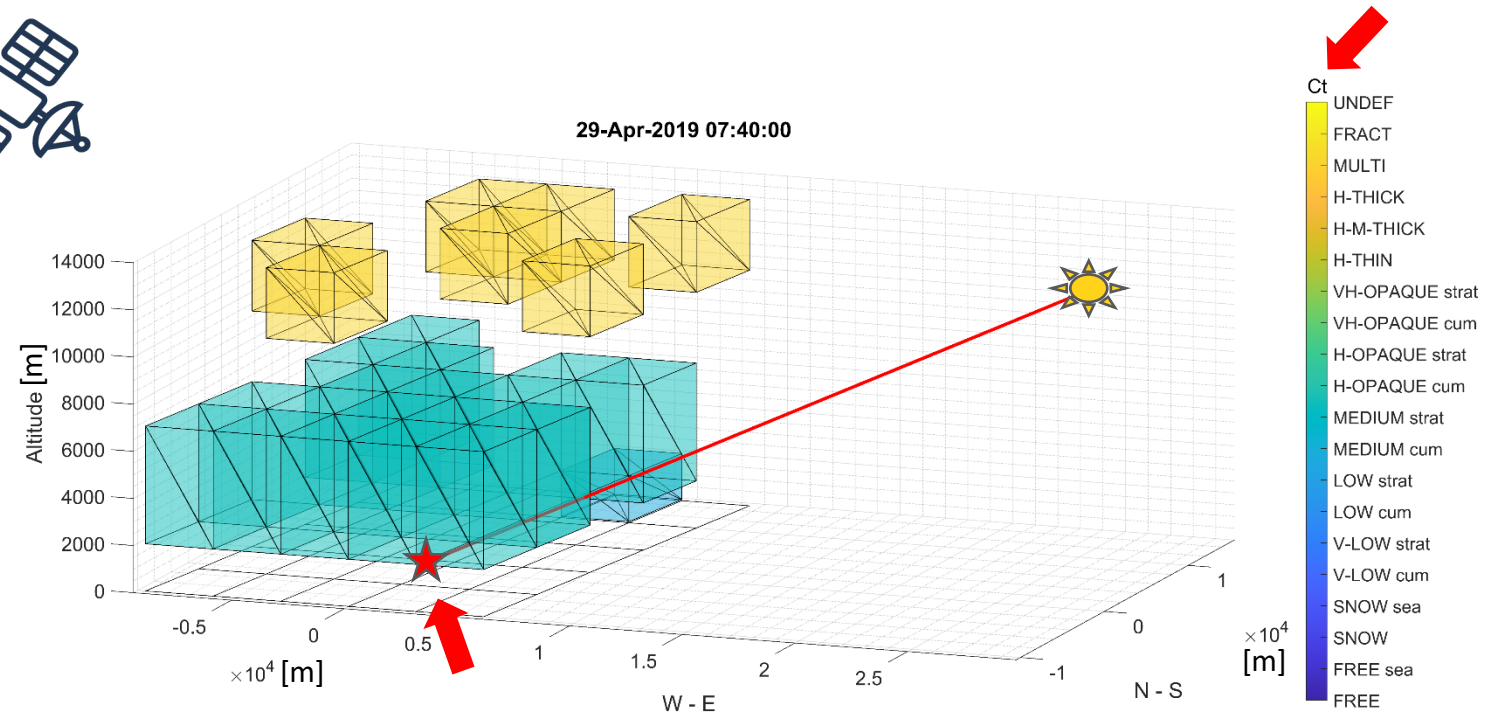
# Dynamic Cloud model 1/2



The aim of this model is to identify the cloud position (pixel) that could mitigate the beam component of solar radiation on a given location

## Available information:

- Latitude and longitude of each pixel
- Cloud type
- Cloud top altitude measure
- Cloud bottom altitude (from literature)
- Solar altitude and azimuth angles
- Clear Sky  $GHI_{CS}$



★ : Solar Tech Lab



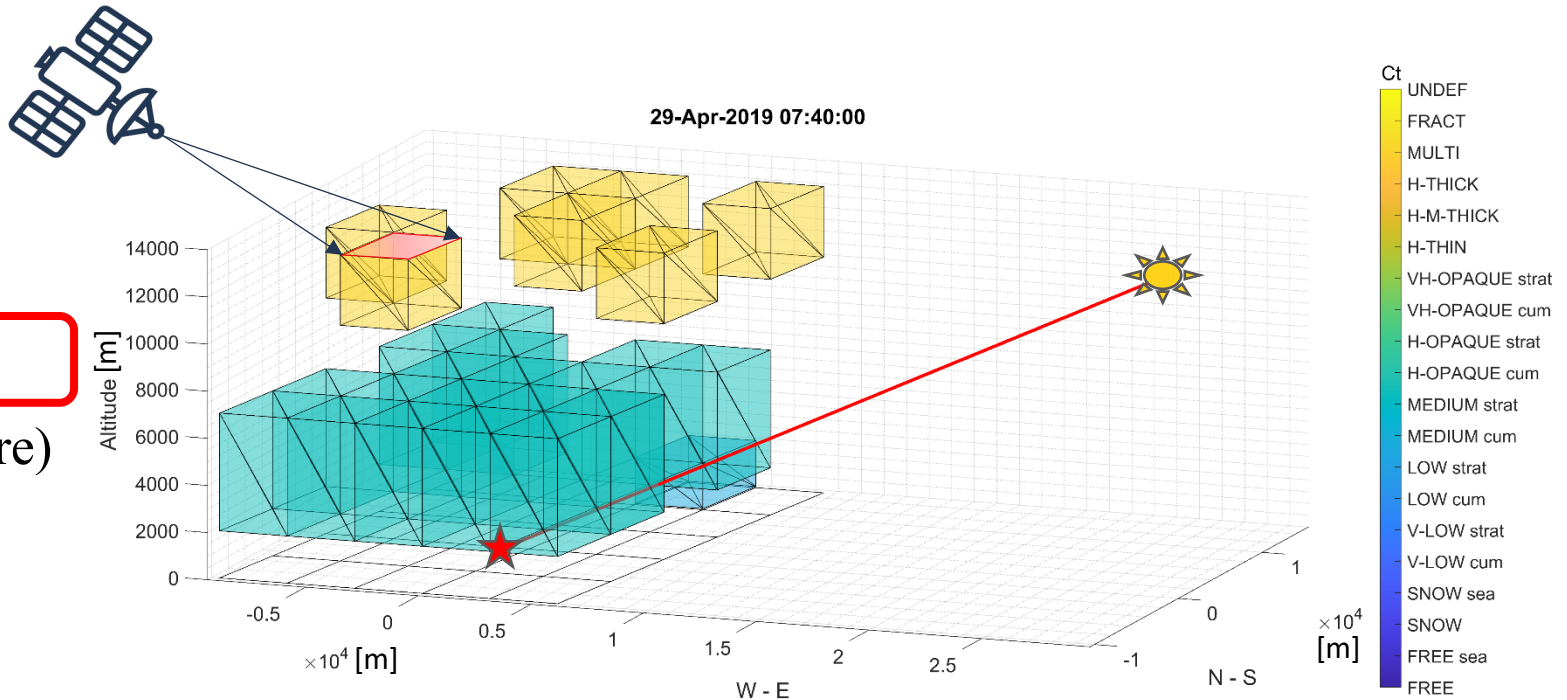
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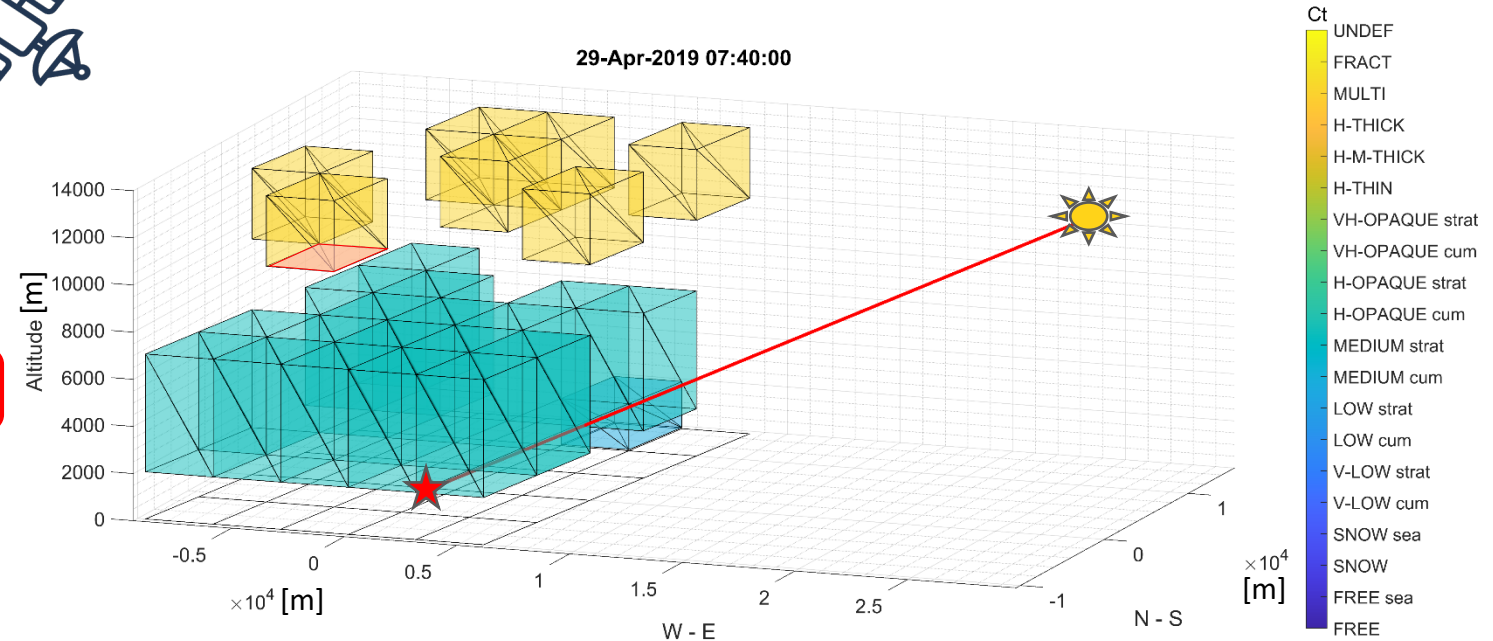
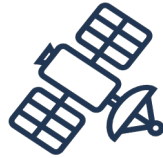
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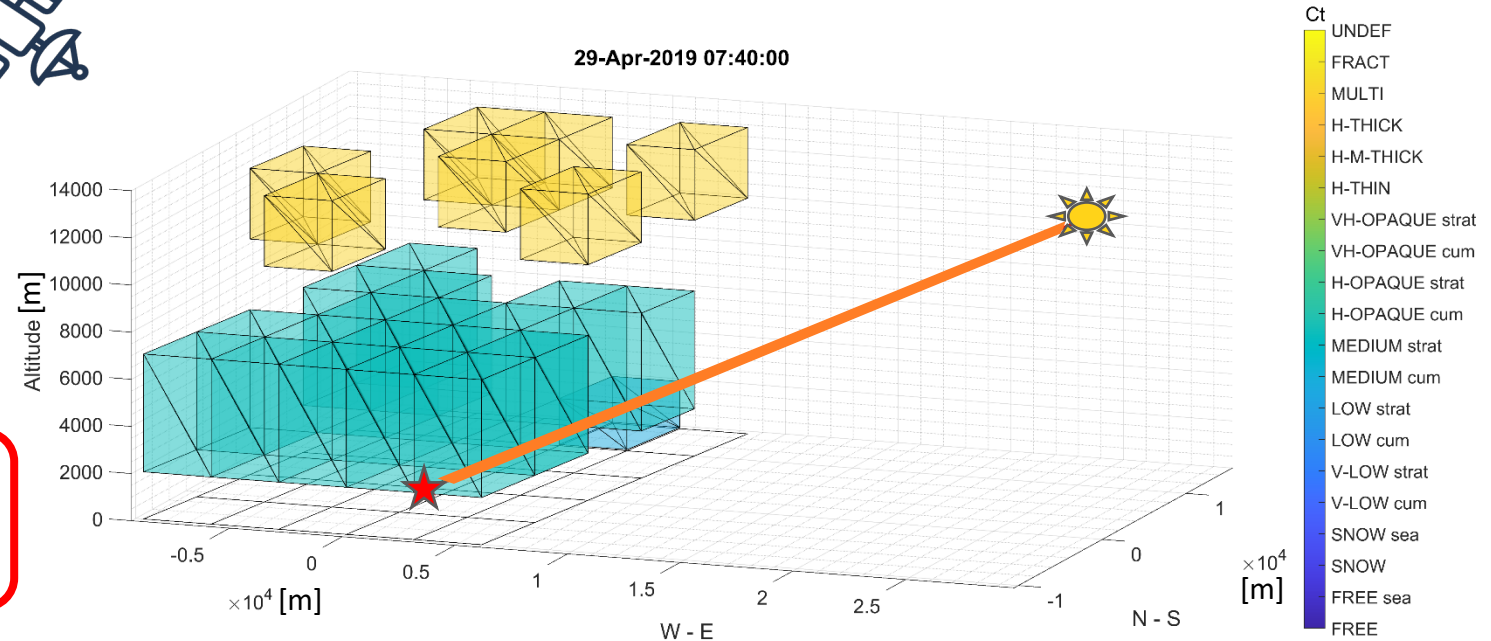
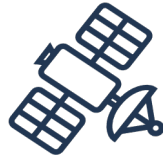
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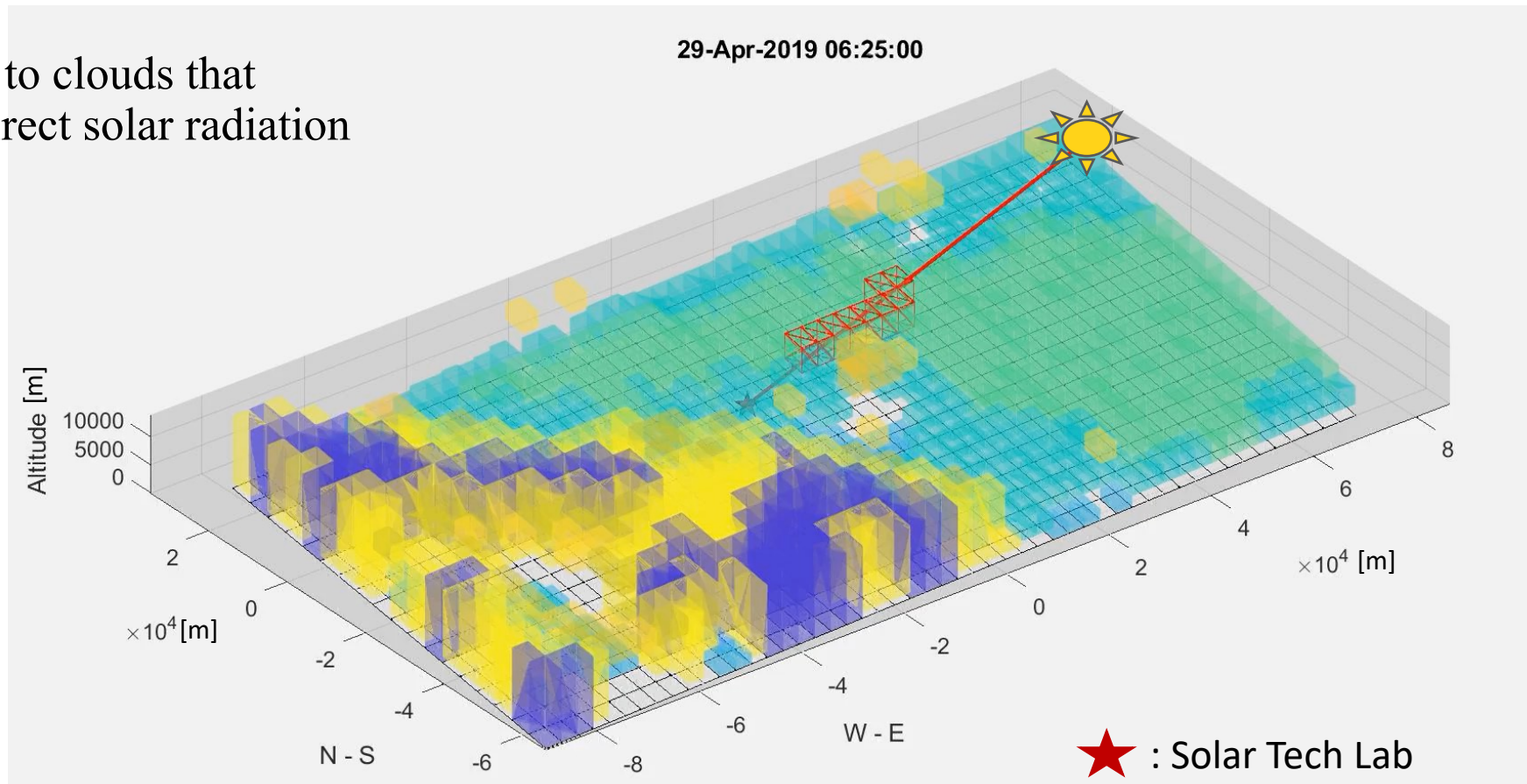
★ : Solar Tech Lab





## Complete model

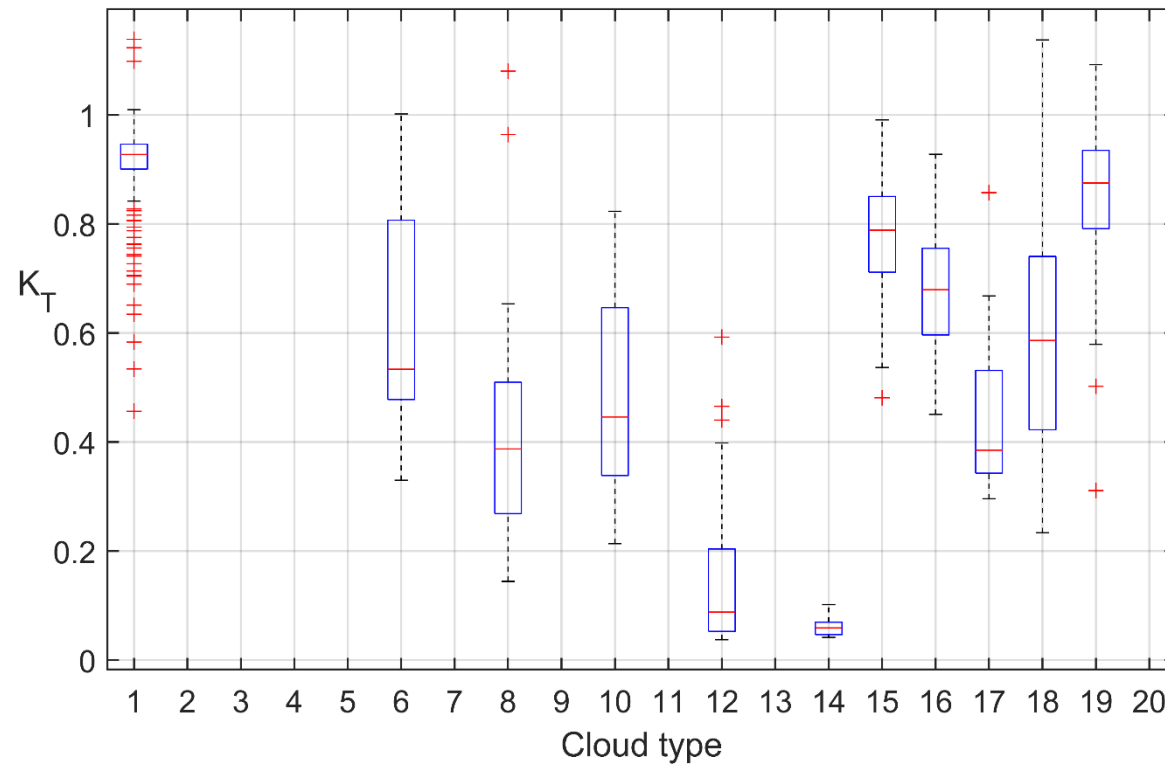
**red pixels** refer to clouds that interfere with direct solar radiation



# Cloud type classification 1/2



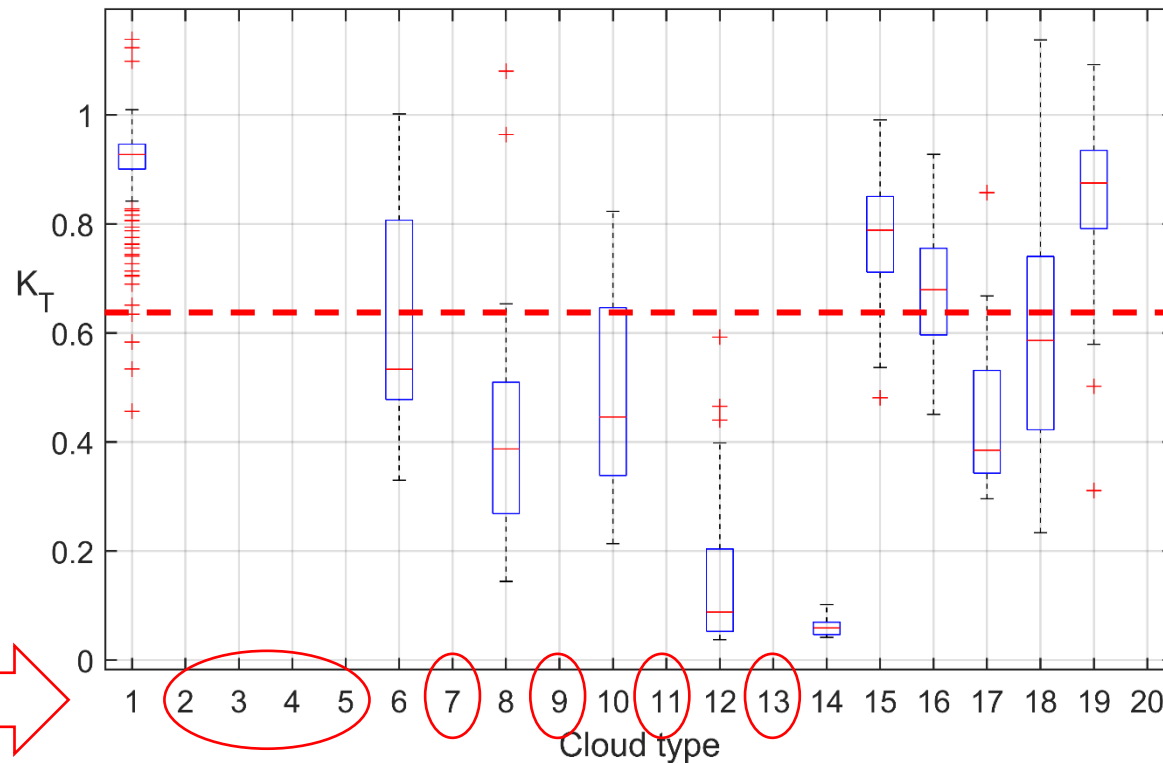
**red pixels** from the Cloud model  $\longrightarrow$  Clearness index ( $K_T = \frac{GHI_{measured}}{GHI_{clear\ sky\ model}}$ )



# Cloud type classification 1/2



**red pixels** from the Cloud model  $\longrightarrow$  Clearness index ( $K_T = \frac{GHI_{measured}}{GHI_{clear\ sky\ model}}$ )



Different Cloud types with overlapping  $K_T$

Some classes with few samples

Missing Cloud types  $\longrightarrow$

**A reduced satellite data classification is needed!**

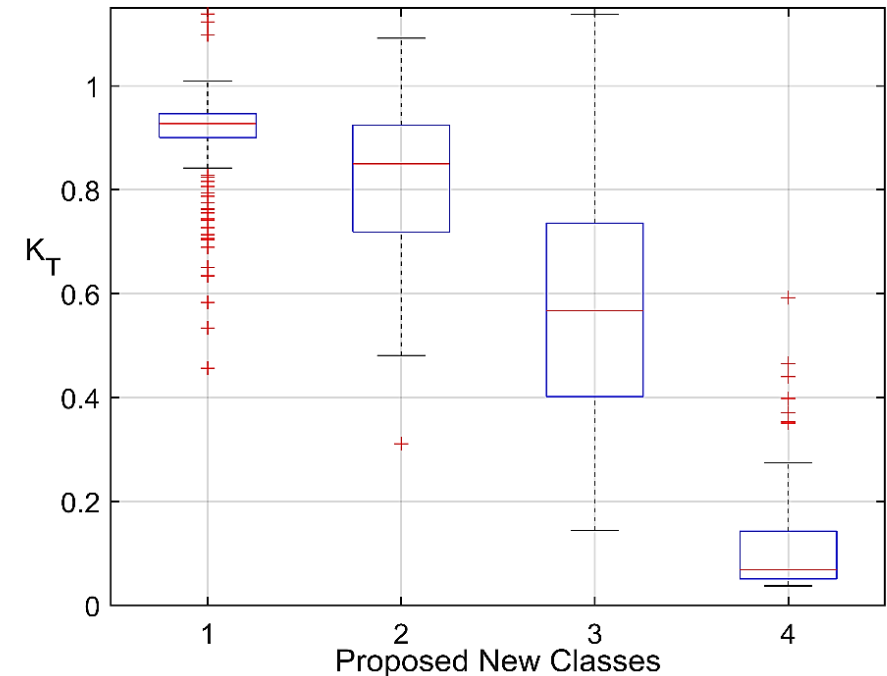
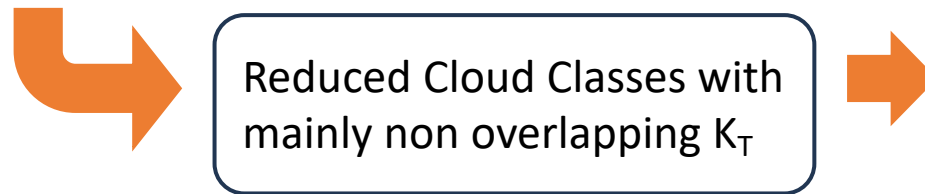


# Cloud type classification 2/2



- 4 New Classes proposed by merging different Cloud Classes from the previous 19

Original classes Conf. 1	Aggregated classes Conf. 2	Hot encode Conf. 3
1	1	[1, 0, 0, 0]
15, 19	2	[0, 1, 0, 0]
6, 8, 10, 16, 17, 18	3	[0, 0, 1, 0]
12, 14	4	[0, 0, 0, 1]



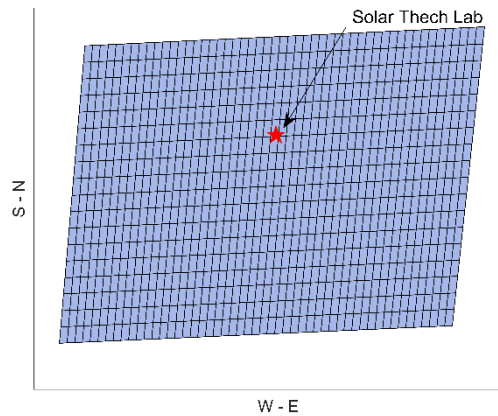
# Input dataset selection



5 proposed input scenarios:

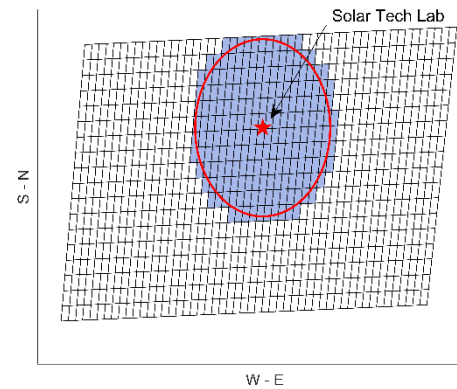
Exploited pixel

Full available dataset

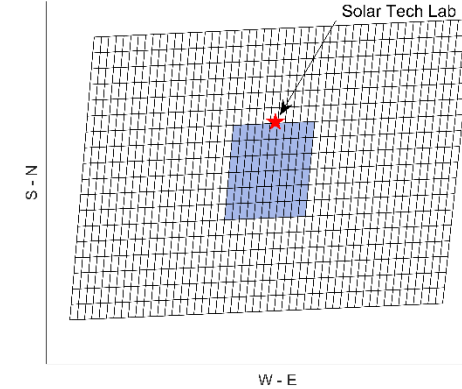


Full Frame

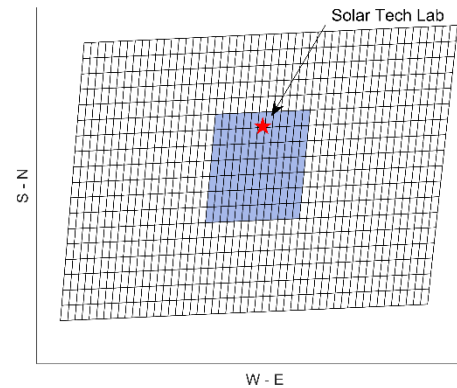
4 Reduced datasets



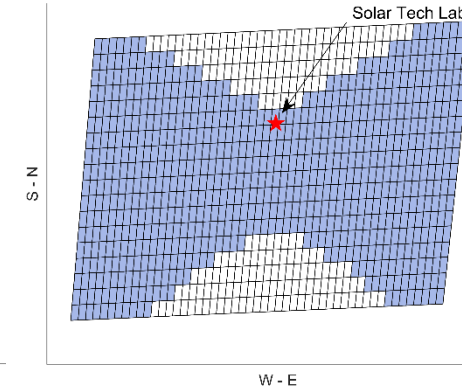
Circle, radius 30 Km



Area 11x6



Area 13x7



Butterfly





## Input

Satellite data provided in three different configurations for each previous scenario (3 conf. x 5 scenarios = 15)

- Conf. 1 = Original classification (1-19)
- Conf. 2 = Reduced classification (1-4)
- Conf. 3 = Reduced classification (1-4) in One-Hot-Encode

Common data
Solar altitude angle
Solar azimuth angle
Wind speed
Wind direction
Rain
Clearness Index



## Target

Clearness Index ( $K_T$ ) Membership Class

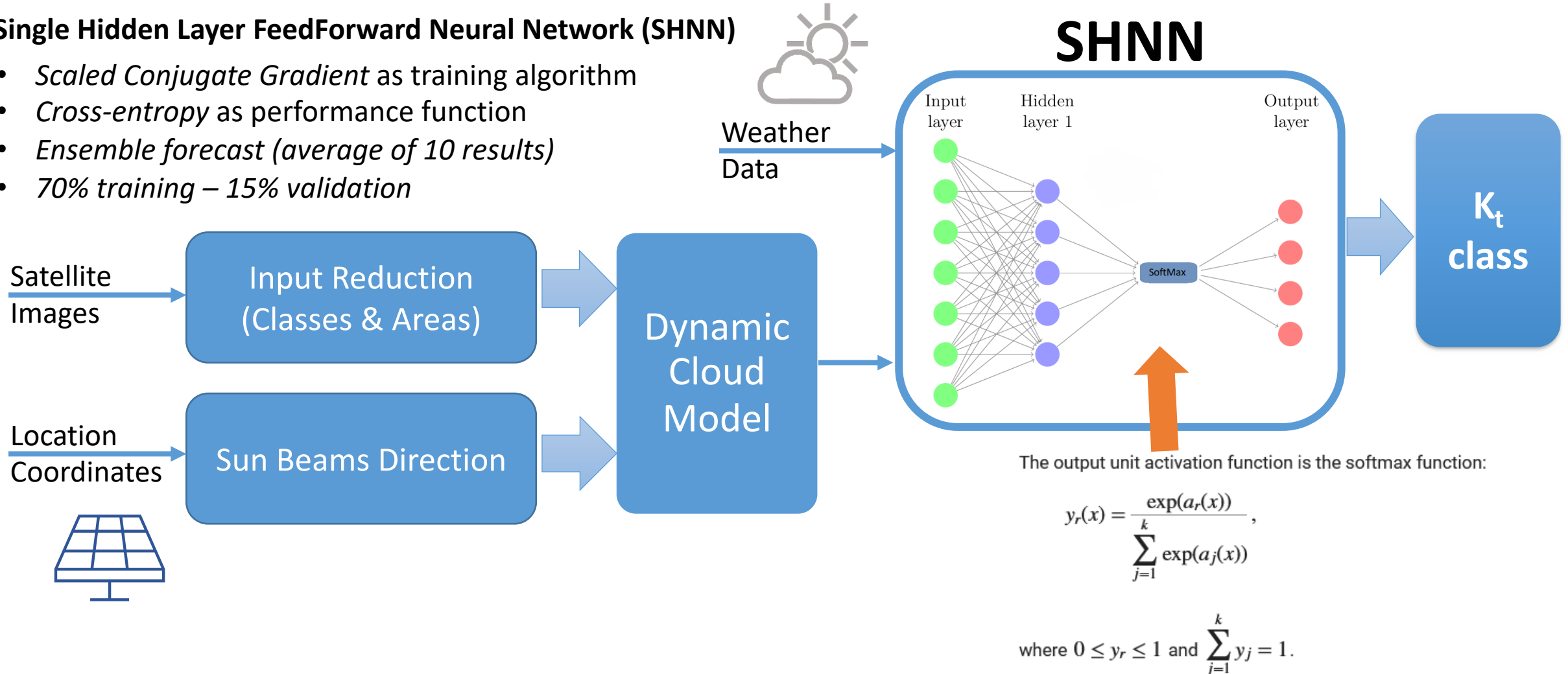
Label	Interval
<b>C1</b>	$0 \leq K_T < 0.20$
<b>C2</b>	$0.20 \leq K_T < 0.45$
<b>C3</b>	$0.45 \leq K_T < 0.75$
<b>C4</b>	$K_T \geq 0.75$

$K_T$  Classes from bibliography

# ANN Layout

## Single Hidden Layer FeedForward Neural Network (SHNN)

- *Scaled Conjugate Gradient* as training algorithm
- *Cross-entropy* as performance function
- *Ensemble forecast (average of 10 results)*
- *70% training – 15% validation*

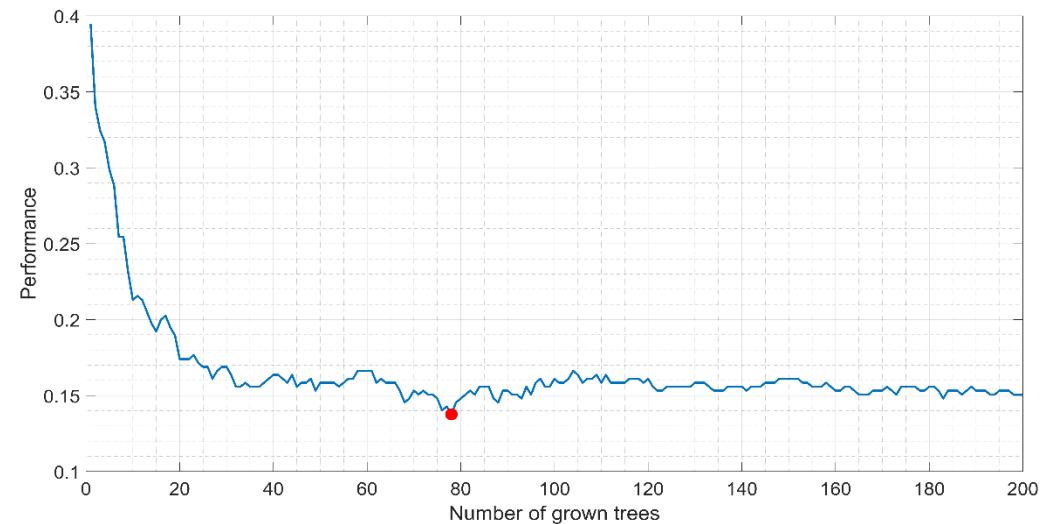
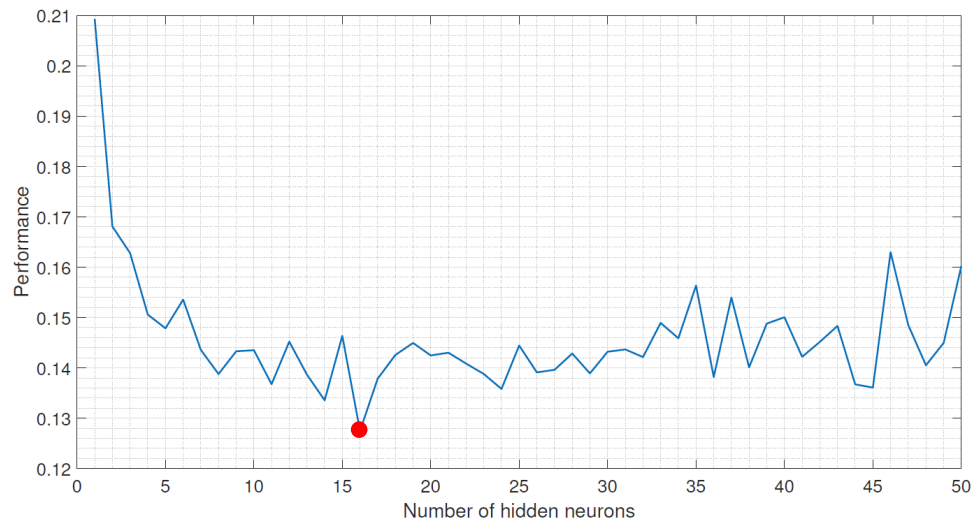




# Sizing and Performance evaluation

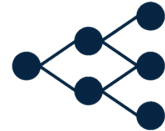


**Sizing:** Identification of the optimal number of Hidden neurons or trees with Out Of Bag (OOB) algorithm



**Performance:** Identification of the classification performance of each Machine Learning model with OOB algorithm





Single Hidden layer FFNN	Conf. 1	Conf. 2	Conf. 3
Circumference 30	68.1%	75.8%	73.2%
Area 11x6	72.5%	77.9%	74.0%
Area 13x7	72.5%	76.6%	74.3%
Butterfly	69.6%	79.7%	80.3%
Full Frame	72.5%	79.0%	79.0%



- Increased Classification Accuracy with reduced dataset
- Less accurate than Random Forest



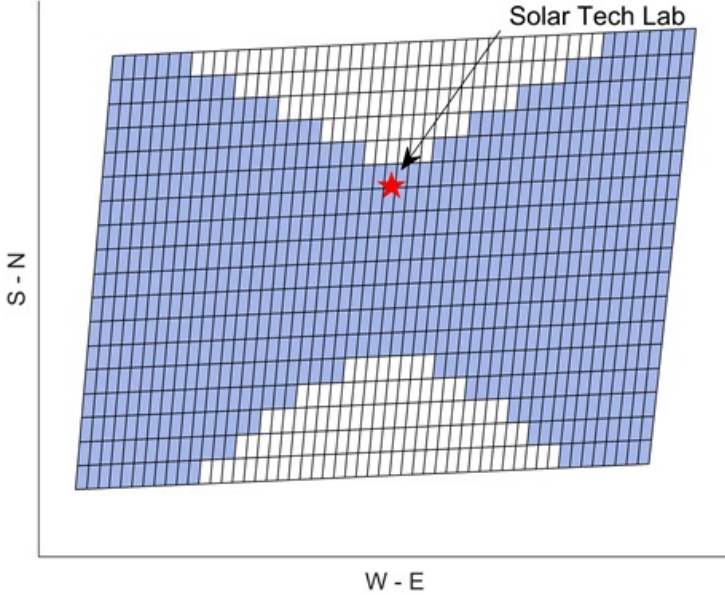
Random Forest	Conf. 1	Conf. 2	Conf. 3
Circumference 30	83.1%	81.6%	81.0%
Area 11x6	82.9%	82.3%	82.3%
Area 13x7	84.2%	83.1%	81.0%
Butterfly	81.6%	82.6%	83.1%
Full Frame	81.8%	81.8%	81.6%



- Best Classification Accuracy
- Globally Robust (always >81%)



## Single Hidden layer FFNN



Reduced classification (1-4)  
One-Hot-Encode

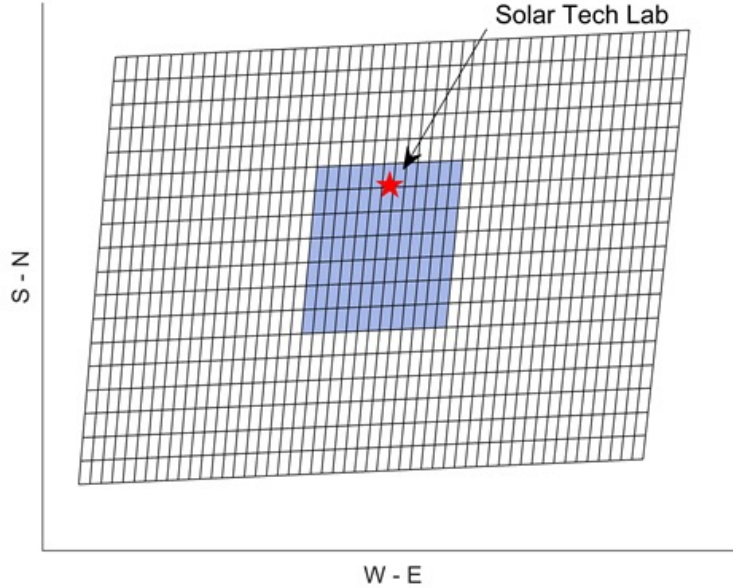
1	36 9.4%	3 0.8%	0 0.0%	0 0.0%	92.3% 7.7%
2	4 1.0%	23 6.0%	4 1.0%	4 1.0%	65.7% 34.3%
3	2 0.5%	10 2.6%	68 17.7%	21 5.5%	67.3% 32.7%
4	0 0.0%	6 1.6%	22 5.7%	182 47.3%	86.7% 13.3%
	85.7% 14.3%	54.8% 45.2%	72.3% 27.7%	87.9% 12.1%	80.3% 19.7%
	1	2	3	4	
	Target Class				



# Best Results



## Random Forest



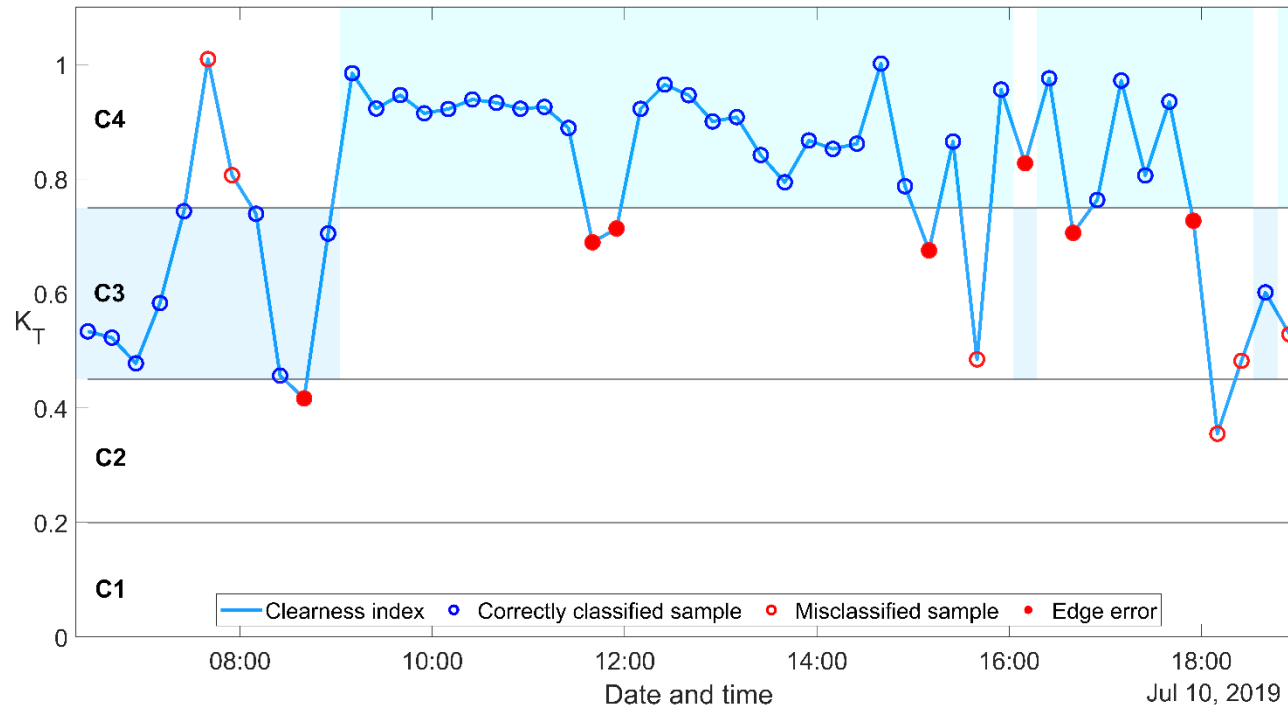
Original classification (1-19)

1	36 9.4%	2 0.5%	0 0.0%	0 0.0%	94.7% 5.3%
2	6 1.6%	28 7.3%	4 1.0%	0 0.0%	73.7% 26.3%
3	0 0.0%	12 3.1%	65 16.9%	12 3.1%	73.0% 27.0%
4	0 0.0%	0 0.0%	25 6.5%	195 50.6%	88.6% 11.4%
	85.7% 14.3%	66.7% 33.3%	69.1% 30.9%	94.2% 5.8%	84.2% 15.8%
	1	2	3	4	
	Target Class				





## Most common errors are due to rigid classification



## Mitigation strategies

- I. Fuzzy logic classification
- II. Confidence interval
- III. From Classes to continuous values



## Simplified methodology for the 15 minutes ahead forecasting (nowcasting) of the solar irradiance on a given location through satellite images



### Dynamic Cloud model development

- Cloud model able to identify the Cloud typology interacting with the direct sun beams
- Reduced Cloud type classification (from 19 to 4), based on Clearness Index, improved the neural network performance up to 10%

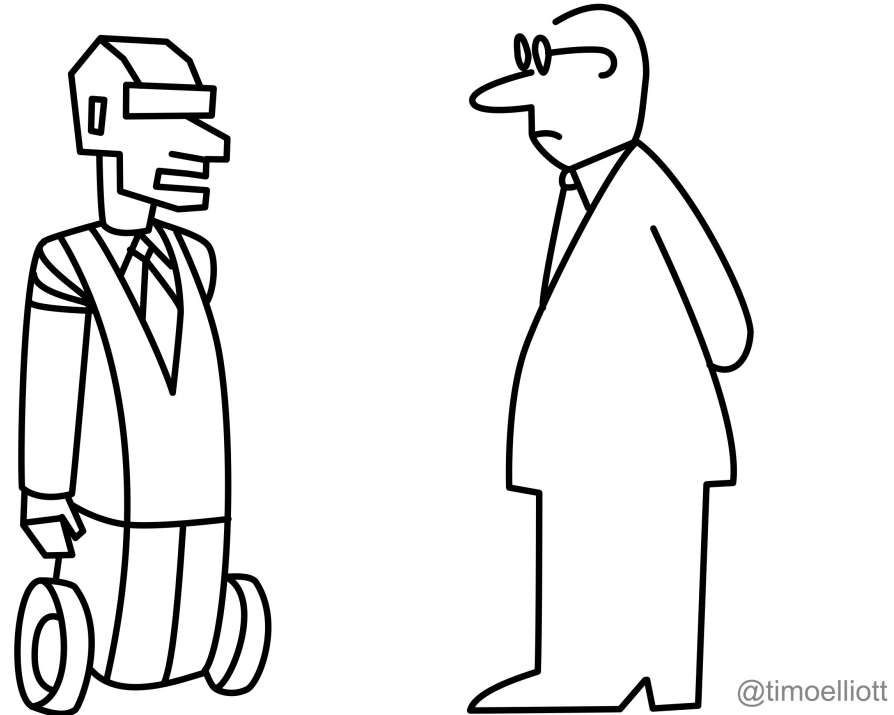


### Solar irradiance nowcasting through Machine Learning Techniques

- Random forest results are more accurate than Artificial Neural Networks
- Reduced dataset scenarios (Area 13x7 & Butterfly) always provided the best training accuracy (> 2%)
- Satellite data and imagery, combined with weather measurements, improved the prediction of the solar radiation 15 minutes ahead on a specific geographic target up to 84.2% using Random Forests (Area 13x7)

Nespoli, A., Niccolai, A., Ogliari, E., Perego, G., Collino, E., & Ronzio, D. (2022). Machine Learning techniques for solar irradiation nowcasting: Cloud type classification forecast through satellite data and imagery. *Applied Energy*, 305, 117834.





*“The good news is I have discovered inefficiencies.  
The bad news is that you’re one of them.”*