# Photovoltaic and Solar Power Forecasting

## Pearl PV – 4th Training School

University of Twente, The Netherlands
Eli Shirazi

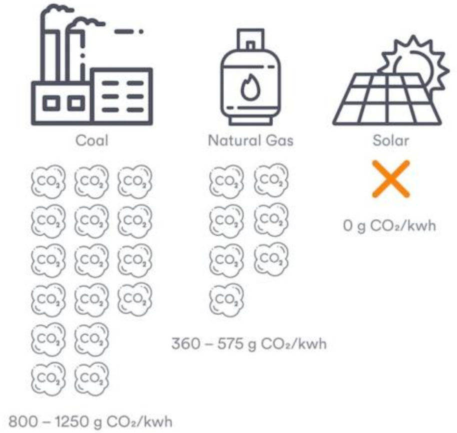
# Introducing myself

- Main research topics
  - PV generation forecast
  - Energy management
  - Grid integration of PV generation
  - Digitalization of the energy system
- Short resume
  - Assistant Professor, Sustainable Energy Technology Systems Group, Dept. of Design Production and Management, Fac. of Engineering Technology, University of Twente, 2021 - present
  - Postdoctoral Researcher, Dept. of Electrical and Electronic Engineering, Fac. of Engineering Science, KU Leuven.
    - Projects:
      - PV power forecast
      - Energy management
    - PhD thesis: "Self-healing in Smart Distribution Networks with PV penetration by Distributed Control"

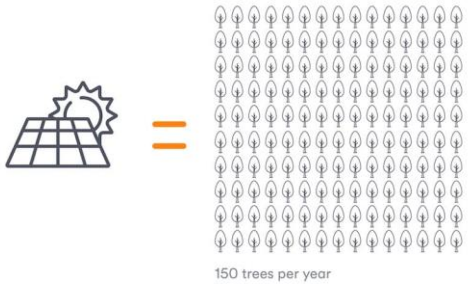
Dr. Dipl.-Ing. Eli (Elham) Shirazi

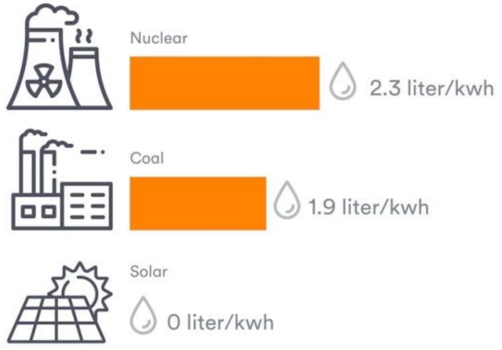
# Table of contents

# Why Solar Energy?

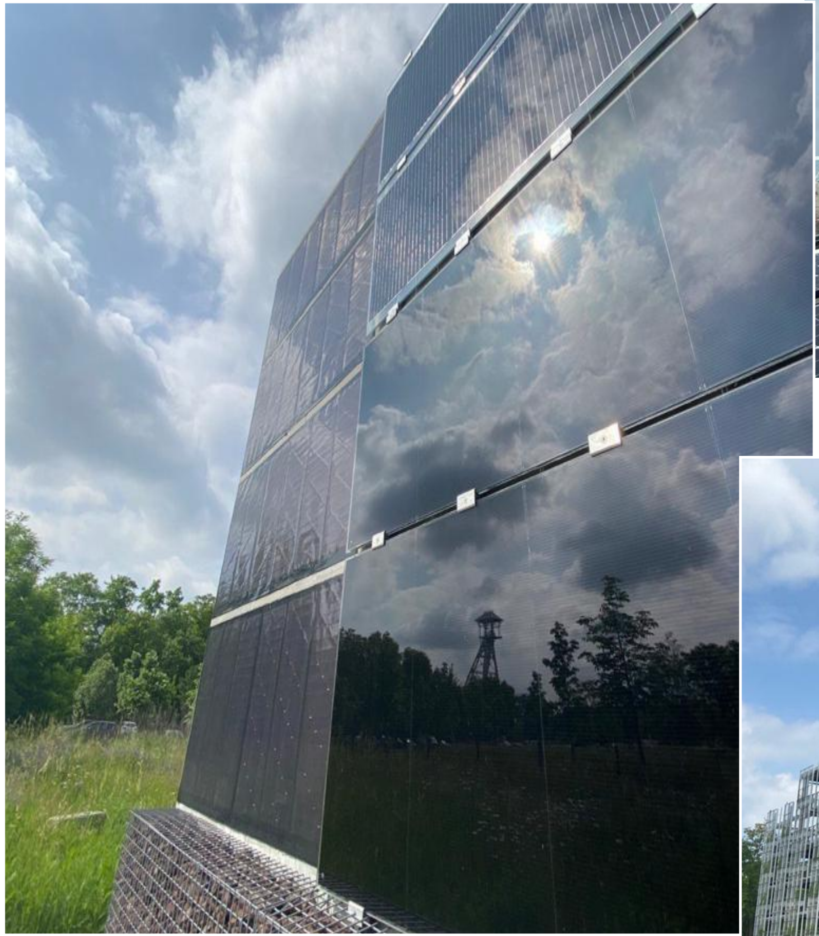







Images courtesy: Vivint solar

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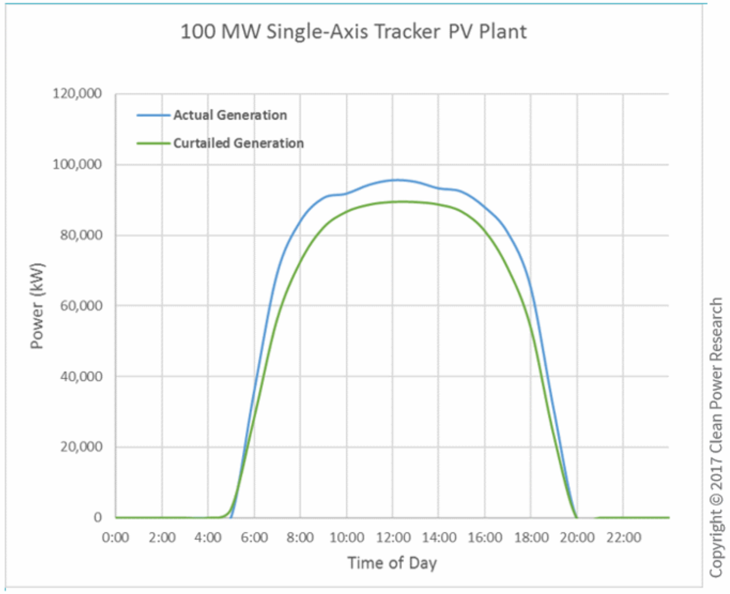
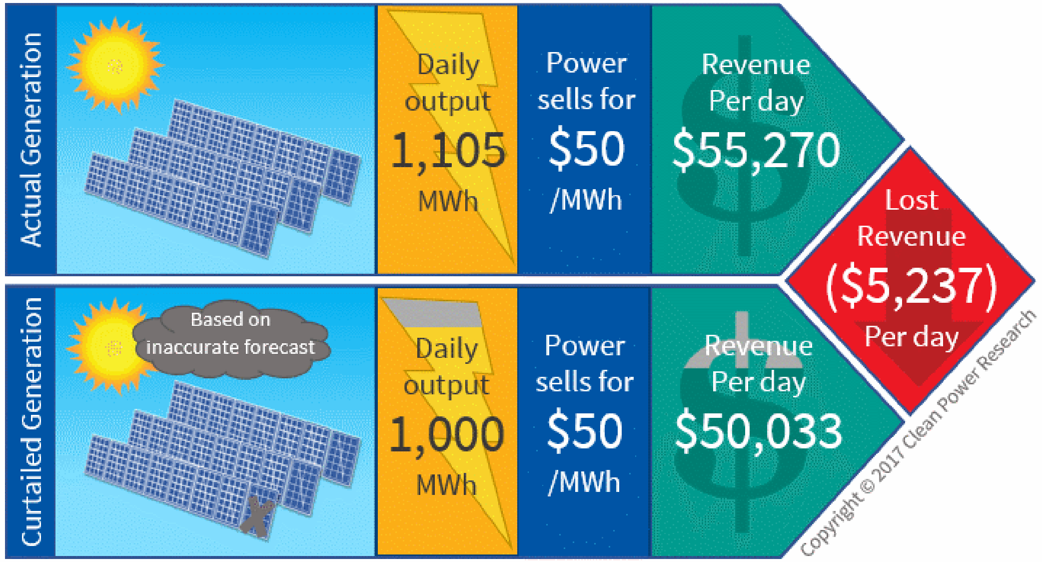
# 3 Key Questions To Ask?

- Why Solar Forecasting?
- Where do solar forecasts go wrong?
- What happens when solar forecasts go wrong?





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# PV Power Forecast Procedure

- Direct Normal Irradiance (DNI)

- Diffuse Horizontal Irradiance (DHI)


- Global Horizontal Irradiance (GHI)

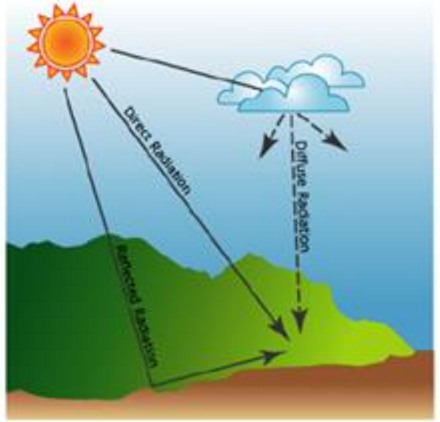



Image courtesy: esri.com

$$GHI = DHI + DNI \cdot cos(\theta_Z)$$

**Weather Forecast**

- Solar irradiance ( GHI, DHI, DNI)
- Ambient Temperature
- Wind speed/direction
- Humidity
- …

+

**PV System Data**

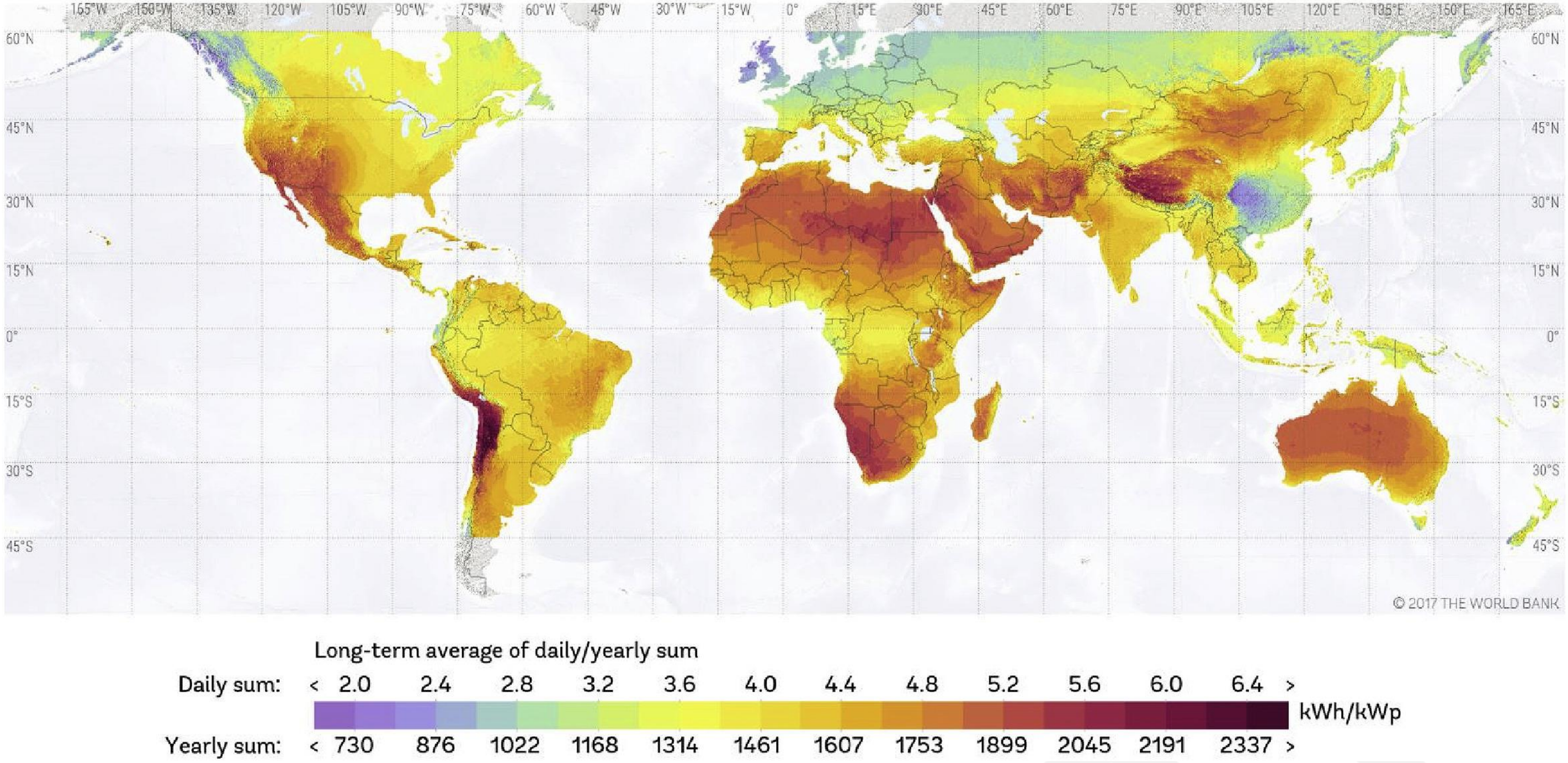
- System location and orientation
- Module temperature
- Historical Data or Manufacturer Specification
- …

→

**Forecast:**

- PV Power Forecast

# The solar resources map



# PV power forecasting methods classification

Criteria for PV power forecast classification:

- Forecasting horizon (short-, long-term, ...)
- Forecasting method (physics based, machine learning based,...)
- Input data (sky imager, satellite,...)

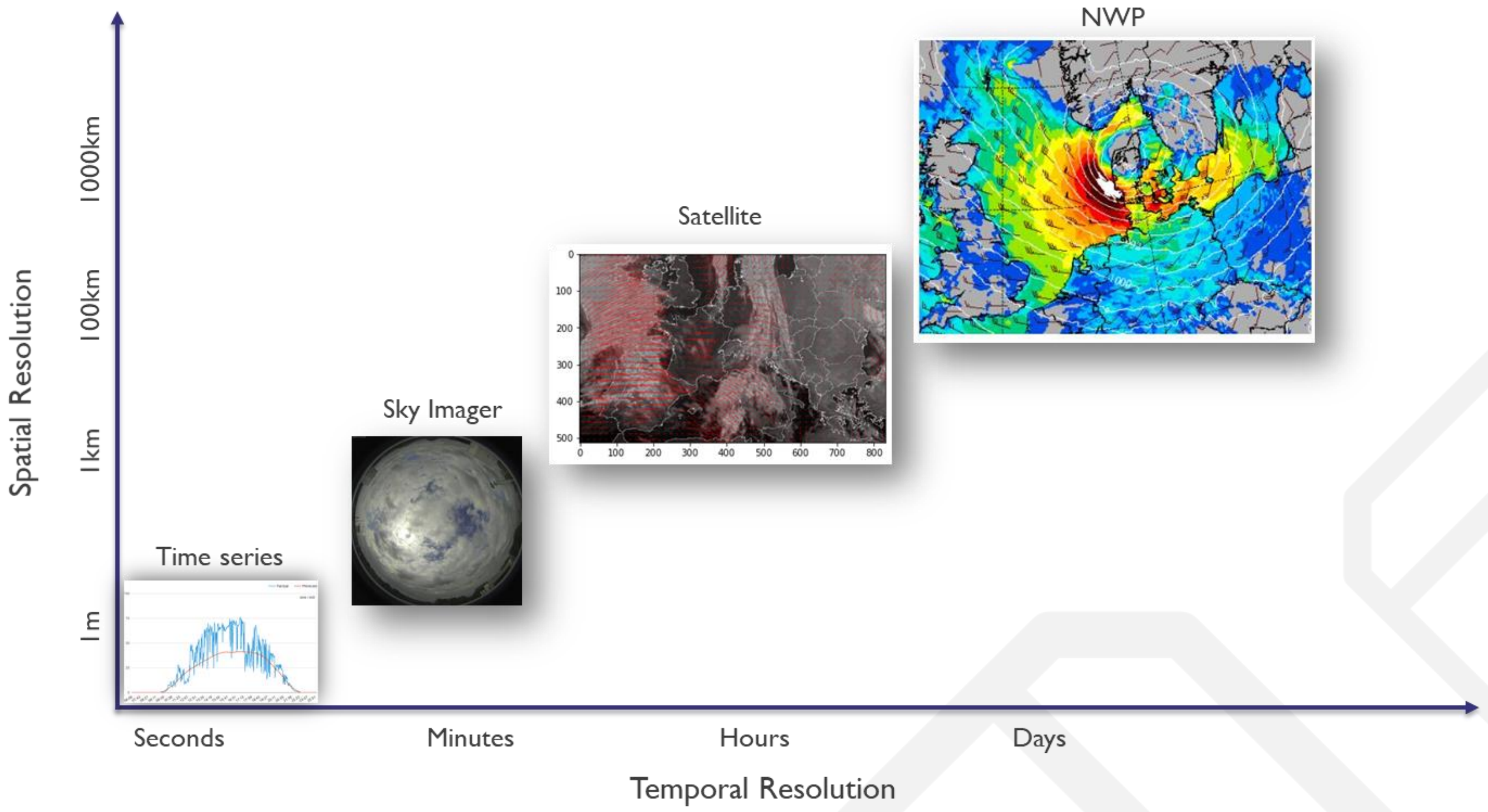
# Classification of PV power forecasting

## Based on forecasting horizon

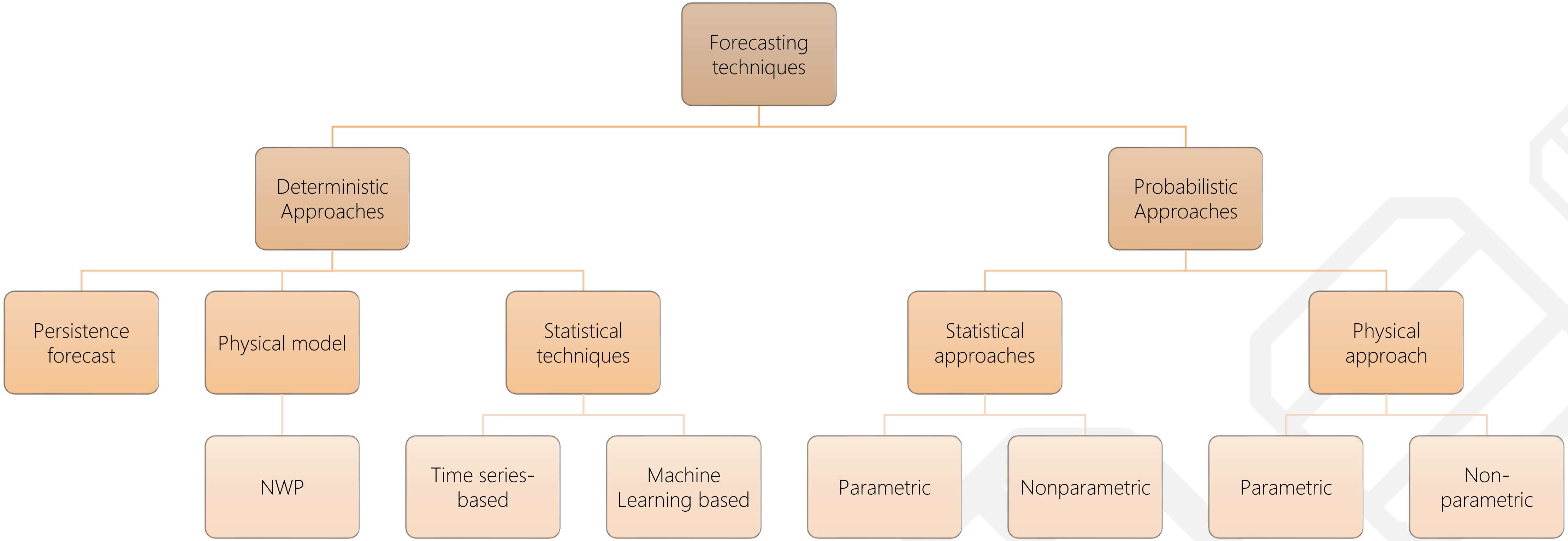
Forecast Techniques

- Very Short Term
  ( 1s – 1<h)
- Short Term
  ( 1h – 24 h / 2-3 d)
- Medium Term
  ( 2-3 d /1w – 1m)
- Long Term
  (1m – 1y/10y)

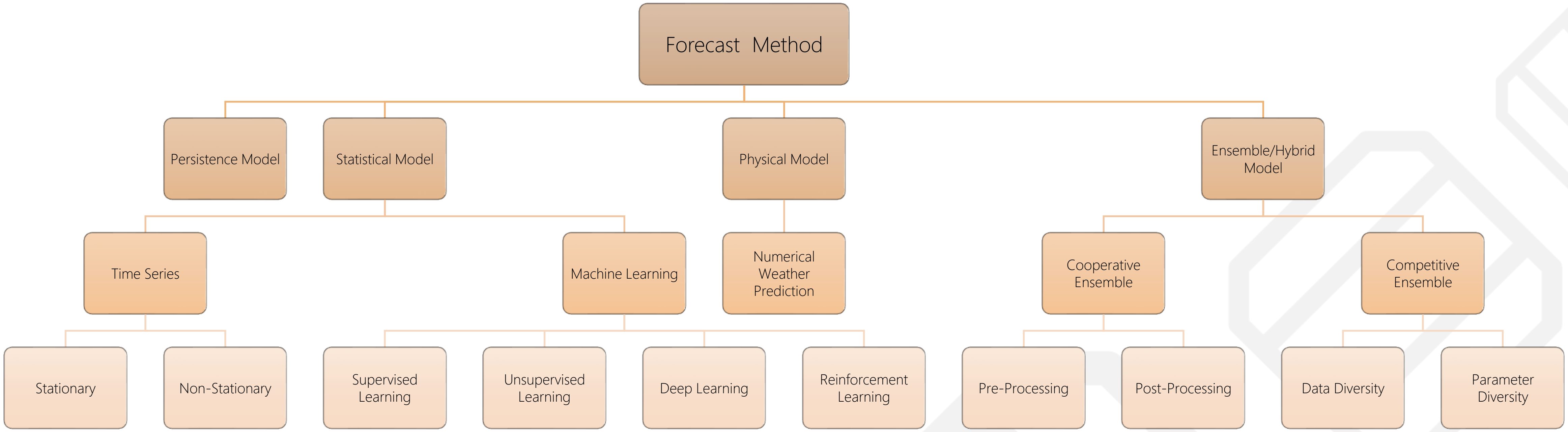
# The horses for courses approach



# Classification of PV power forecasting based on APPROACHES/MODEL



# Classification of PV power forecasting
## based on APPROACHES/MODEL (Deterministic)



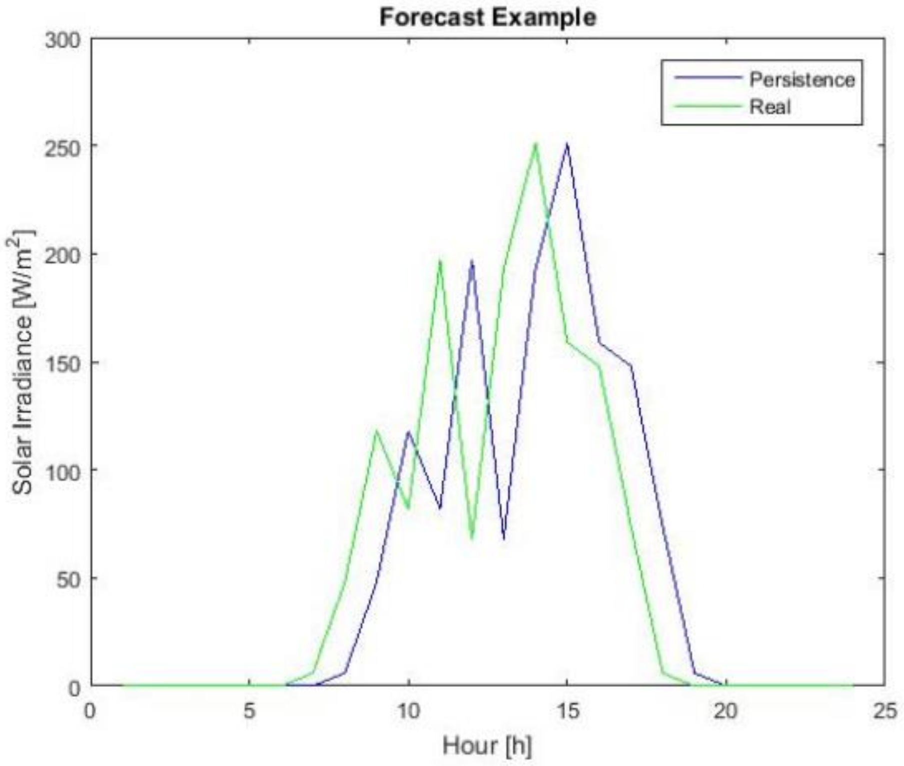
# Persistence model

- The persistence model considers that the solar radiation at $t + 1$ is equal to the solar radiation at $t$.
- It assumes that the atmospheric conditions are stationary.
- It is also called the naïve predictor.

$$G_{t+1} = G_t$$

- An improved version of this model is the scaled persistence model.
- To take into account the fact that the apparent position of the sun is not identical between $t$ and $t + 1$, the persistence model is corrected with a clear-sky ratio term.

$$G_{t+1} = G_t \frac{G_{t+1}^{Clear\ Sky}}{G_t^{Clear\ Sky}}$$

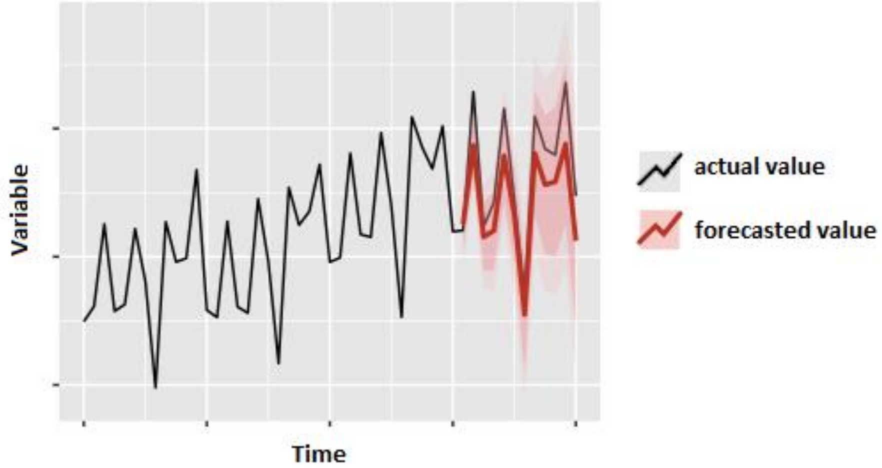



J. D. Marques do Rego et. al, Solar Irradiance Forecast Using Artificial Intelligence Techniques

# Statistical models-Time series

Image courtesy: www.bounteous.com

- Time series: A discrete time series is a sequence of time ordered data values, measured in general at fixed time intervals.
- A time series model presumes that past pattern will appear in the future.
- Time series forecasting means the use of a model to predict future values based on past values.
- AR (auto regressive) ,MA (moving average), ARMA, ARMAX, …



# Statistical models -Time series

- AR (Autoregressive model)
  - The current value of the process can be expressed as a finite, linear combination of the previous values of the process and a single shock. Thus, the process is said to be regressed on the previous values. AR(p)

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t.$$

- MA (Moving Average model)
  - While the AR techniques model the stochastic portion of the time series as a weighted sum of previous values, MA methods model it as a finite sum of previous shocks. MA(q)

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

- ARMA (Autoregressive moving average model)
  - ARMA models provide a parsimonious description of a (weakly) stationary stochastic process in terms of two polynomials, one for the autoregression (AR) and the second for the moving average (MA). ARMA(p,q)

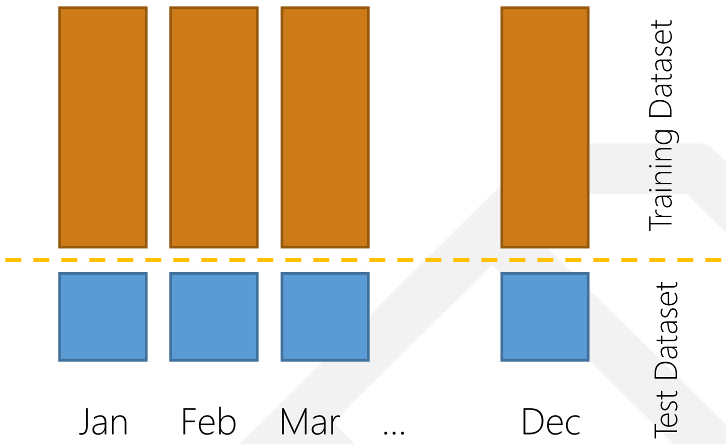
$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}.$$

- ARMAX (Autoregressive moving average models with exogenous variables)
  - ARMAX(p,q,b) refers to the model with p autoregressive terms, q moving average terms and b exogenous inputs terms. This model contains the AR(p) and MA(q) models and a linear combination of the last b terms of a known and external time series.

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \sum_{i=1}^{b} \eta_i d_{t-i}.$$

# Statistical models - Machine learning

- Machine learning (ML) is a subfield of computer science, and it is classified as an artificial intelligence (AI) method.
- The machine learning models find relations between inputs and outputs
- this characteristic allow the use of machine learning models in many cases:
  - pattern recognition,
  - classification problems,
  - data mining,
  - forecasting problems.



# Statistical models - Machine learning

- ML concerns the construction and study of systems that can learn from data sets, giving computers the ability to learn without being explicitly programmed.
- In the predictive learning problems, the system consists of:
  - a random “output” or “response” variable y
  - a set of random “input” or “explanatory” variables x

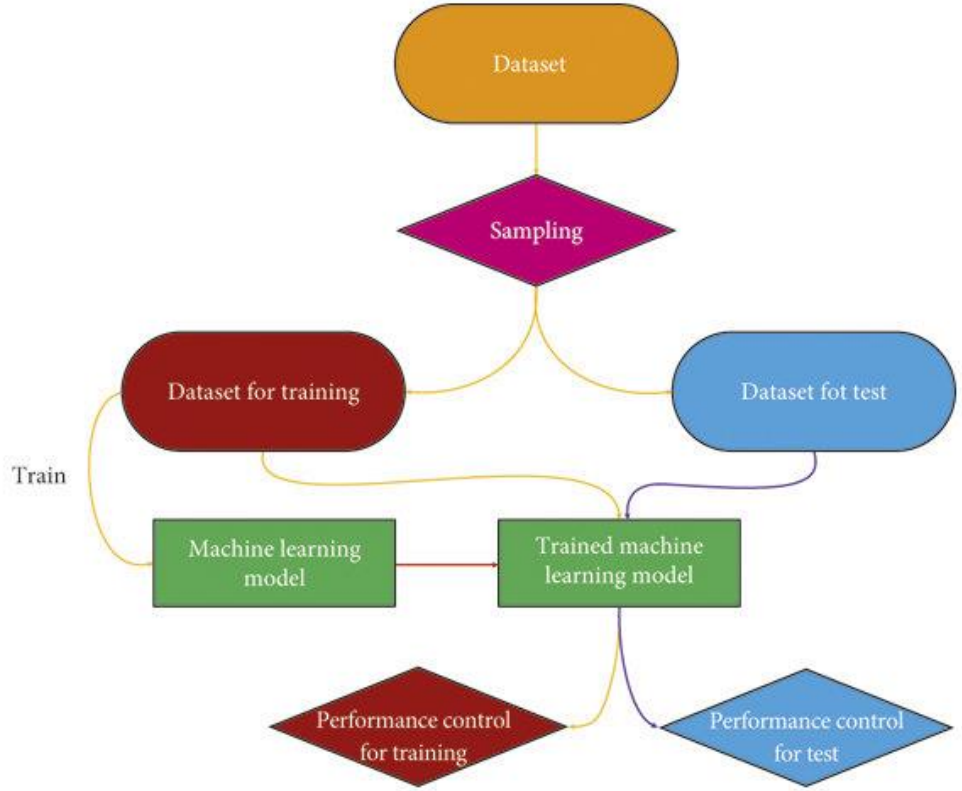
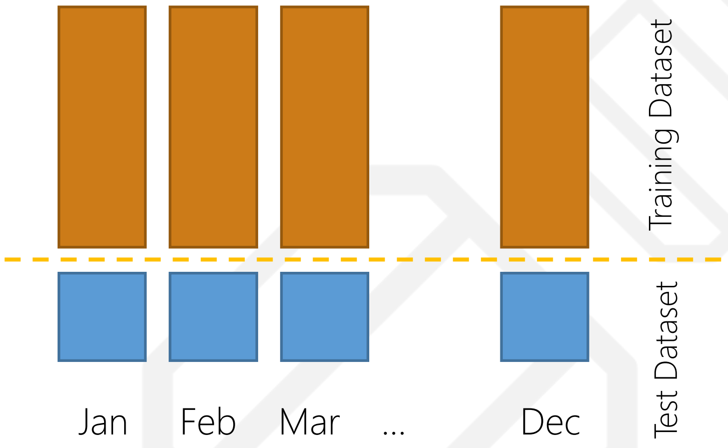



Image courtesy: Uçar et. al.(2020)

# Statistical models - Machine learning

- Large dataset is essential for the learning algorithm to understand the behavior of the system.
- First step for machine learning based system is data procurement.
- Collected data has been divided from different perspective and summarizes in useful information. The steps included in this process is data cleansing and data segregation.
- Data has been segregated in three disjoint sets, training, testing and validation.
  - Training dataset has been applied for model training
  - Testing dataset has been used for model optimization and evaluation.



# Machine learning based PV power forecasting

- Supervised
- Unsupervised
- Reinforcement learning
- Deep learning
- Ensemble

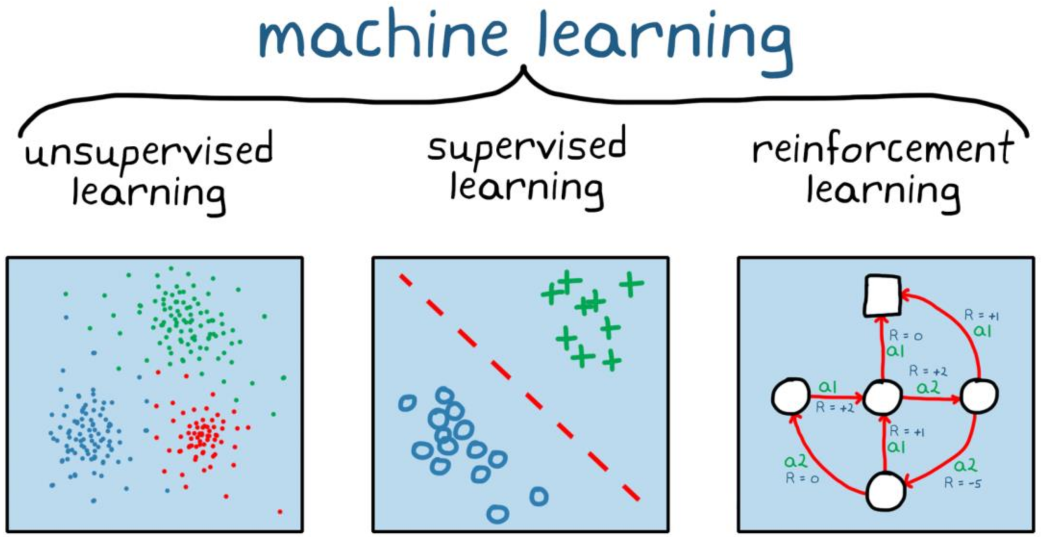



Image courtesy: MathWorks

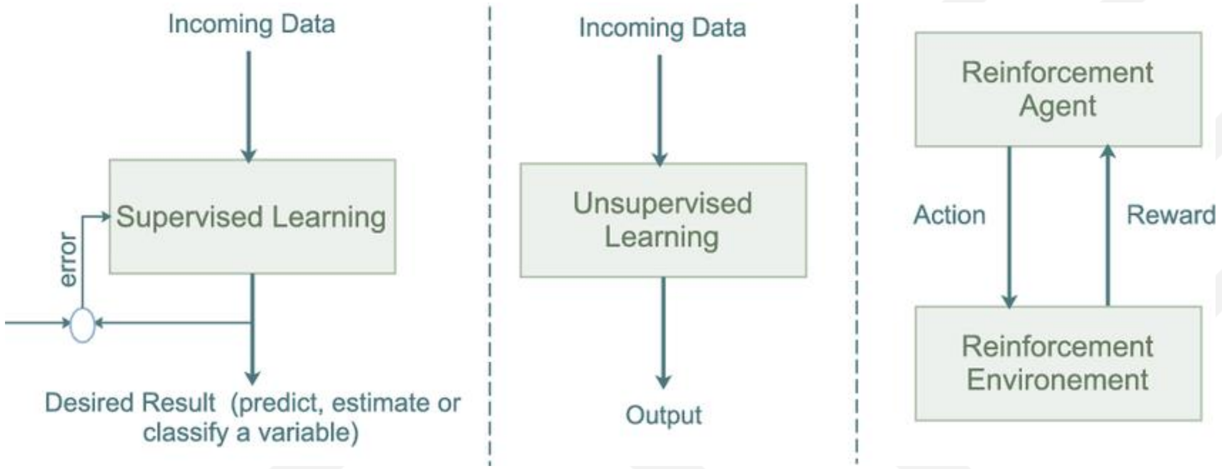
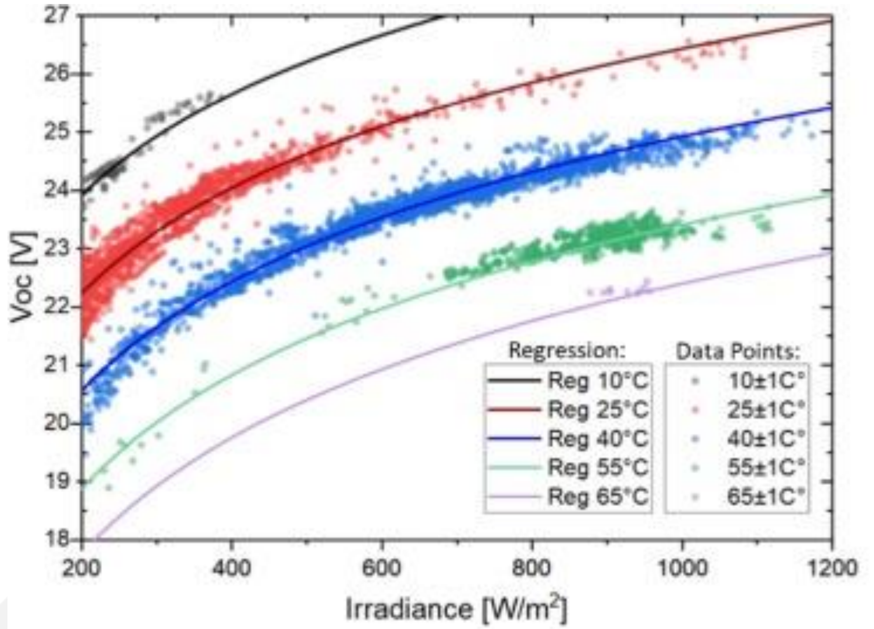



Image courtesy: Fourati et. al (2021)

# Statistical models - Machine learning

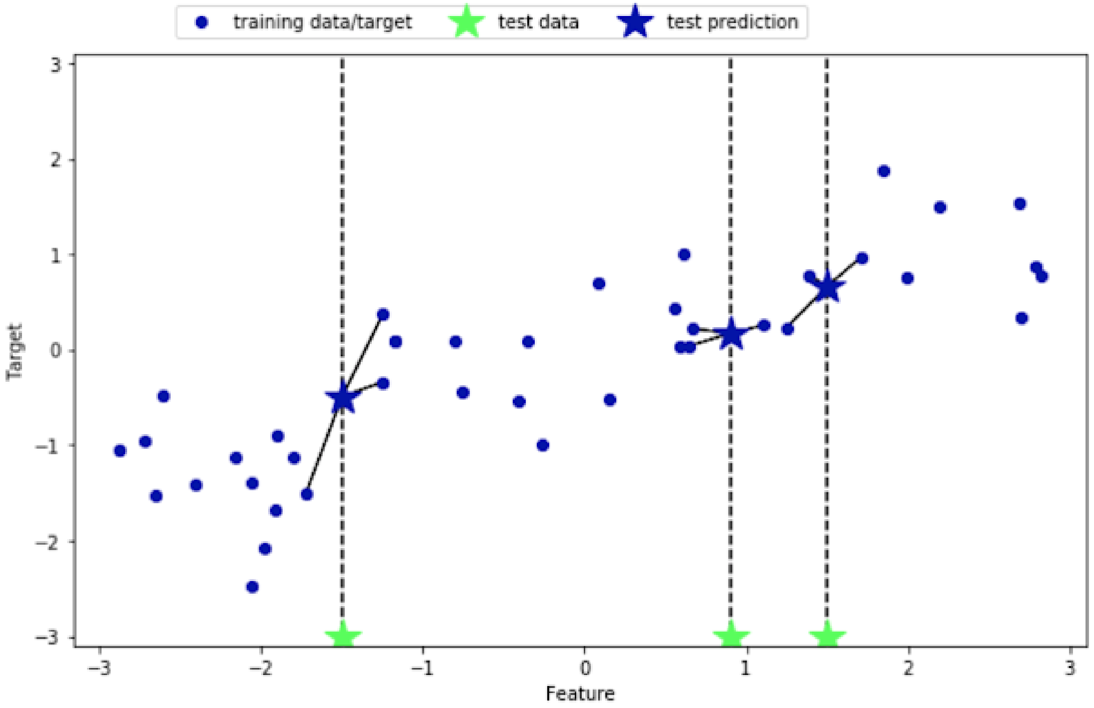
- Linear Regression
- In most linear regression models, the objective is to minimize the sum of squared errors. The objective function with one predictor (feature) is as follows:

$$MIN \sum_{i=1}^{n} (y_i - w_i x_i)^2$$



# Statistical models - Machine learning

- Nearest Neighbor (kNN)
- For both classification and regression
- A function is only approximated locally
- It assign a weight to the contributions of the neighbors, so that the nearest neighbors contribute more to the average than the distant ones.
- weight = 1/d, where d is the distance to the neighbor




Andreas C. Müller, Sarah Guido, Introduction to Machine Learning with Python, 2016

# Statistical models - Machine learning

- Artificial Neural Network (ANN)
- inputs $x_1$, $x_2$and $x_3$
- weighted by $\omega_1$, $\omega_2$ and $\omega_3$
- Bias $\beta$
- Embedded net function $\mathrm{y} = \beta + \sum_{i=1}^{3} \omega_i x_i$
- transfer function $f(.)$
- output $z$

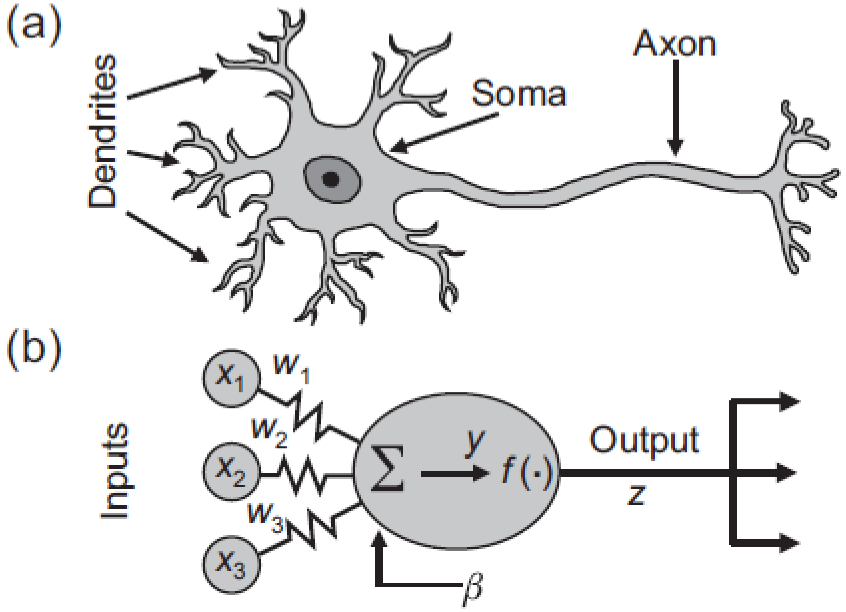
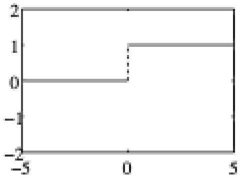
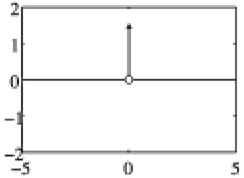
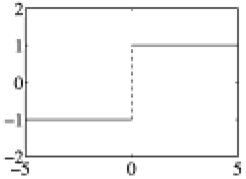
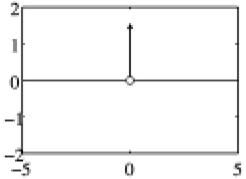
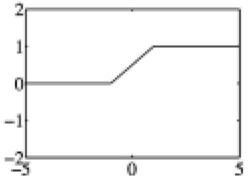
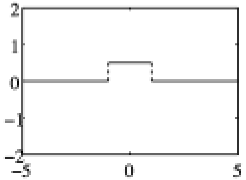
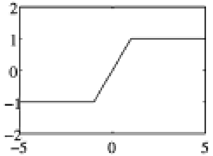
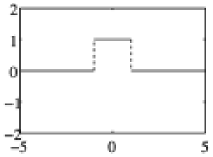
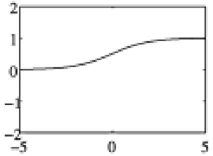
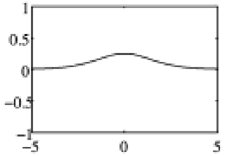
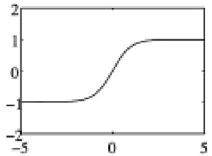
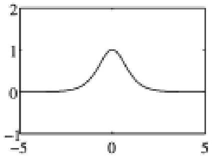
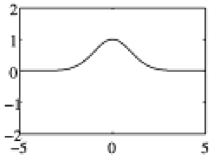
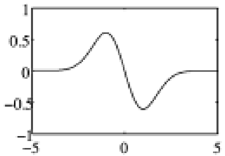



Image courtesy: G. Kariniotakis, Renewable Energy Forecasting, from models to applications. Elsevier Inc., 2017

# Statistical models - Machine learning

## ANN – transfer functions

| Classification | Expression | Derivative | $f(z)$ | $f'(z)$ |
|---|---|---|---|---|
| Unipolar step or heaviside (threshold) | $f(y) = H(y) = \begin{cases} 1, & \text{if } y > 0 \\ 0, & \text{if } y < 0 \end{cases}$ | $\delta(y) = \begin{cases} 0, & \text{if } y \neq 0 \\ \infty, & \text{if } y = 0 \end{cases}$ |  |  |
| Bipolar step (threshold) | $f(y) = \text{sign}(y) = 2H(y) - 1$ | $\delta(y) = \begin{cases} 0, & \text{if } y \neq 0 \\ \infty, & \text{if } y = 0 \end{cases}$ |  |  |
| Unipolar linear | $f(y) = \begin{cases} 0, & \text{if } y < -1 \\ \frac{1}{2}(y+1), & \text{if } \lvert y \rvert < 1 \\ 1, & \text{if } y > 1 \end{cases}$ | $\frac{1}{2}[H(y+1) - H(y-1)]$ |  |  |
| Bipolar linear | $f(y) = \begin{cases} -1, & \text{if } y < -1 \\ y, & \text{if } \lvert y \rvert < 1 \\ 1, & \text{if } y > 1 \end{cases}$ | $H(y+1) - H(y-1)$ |  |  |
| Unipolar sigmoid (logistic) | $f(y) = (1/1 + e^{-y})$ | $f(y)(1 - f(y))$ |  |  |
| Bipolar sigmoid (hyperbolic tangent) | $f(y) = \tanh(y)$ | $(1 - \lvert f(y)^2 \rvert)$ |  |  |
| Gaussian radial basis | $f(y) = \exp(-\lVert y - m \rVert^2/\sigma^2)$ | $-2(y-m)f(y)/\sigma^2$ |  |  |

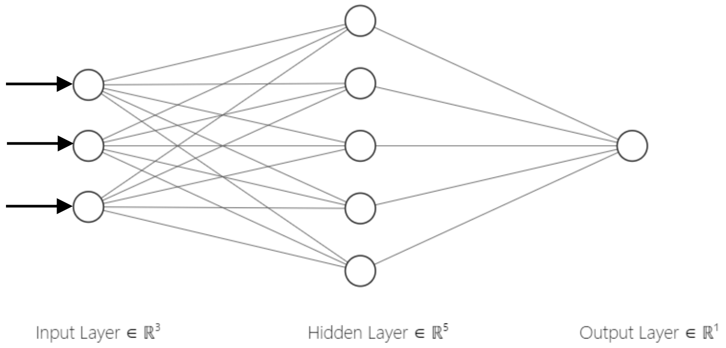
# Statistical models - Machine learning

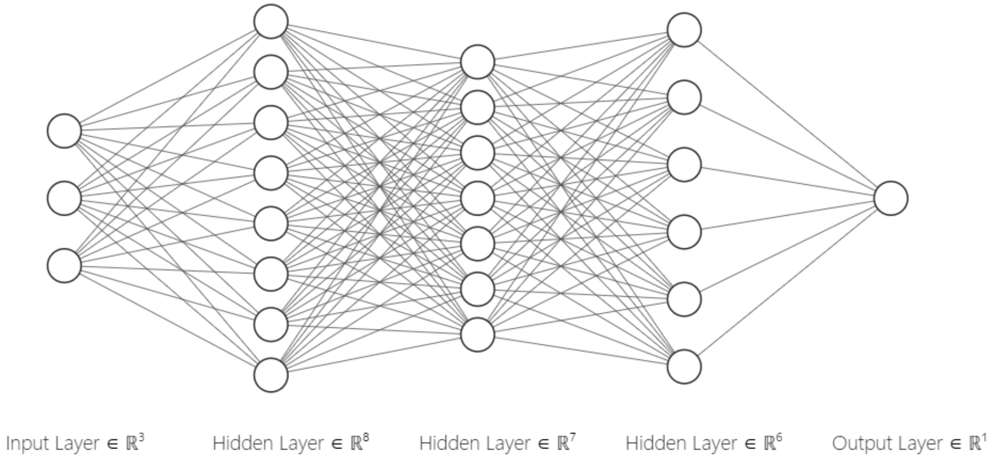
- ANN – Multi Layer Perceptron (MLP)
- A MLP is a class of feedforward ANN
- Supervised Learning
- Shallow/Deep architecture

solar irradiance

air temperature

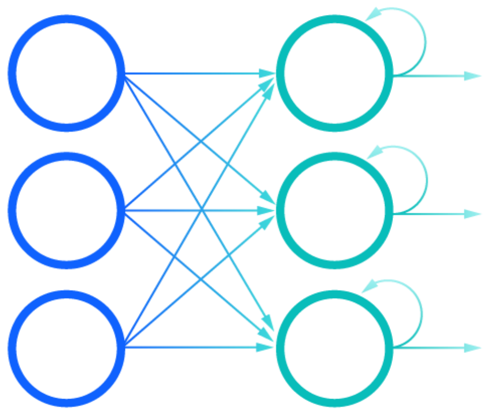
…, cloud cover



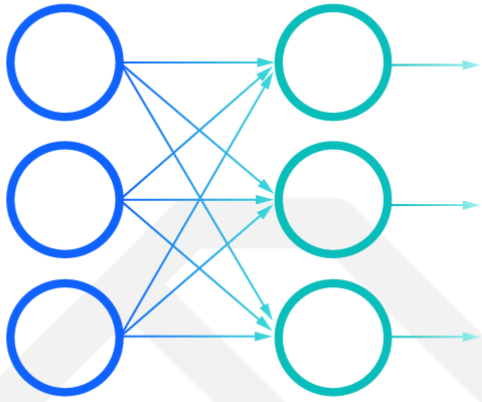



# Statistical models - Machine learning

- ANN - Recurrent neural network (RNN)
- RNN is a prominent class of ANN which relies on time series data by feedback system to inherit the previous time step values; demonstrating temporal dynamic characteristics.
- built-in feedback loop



RNN

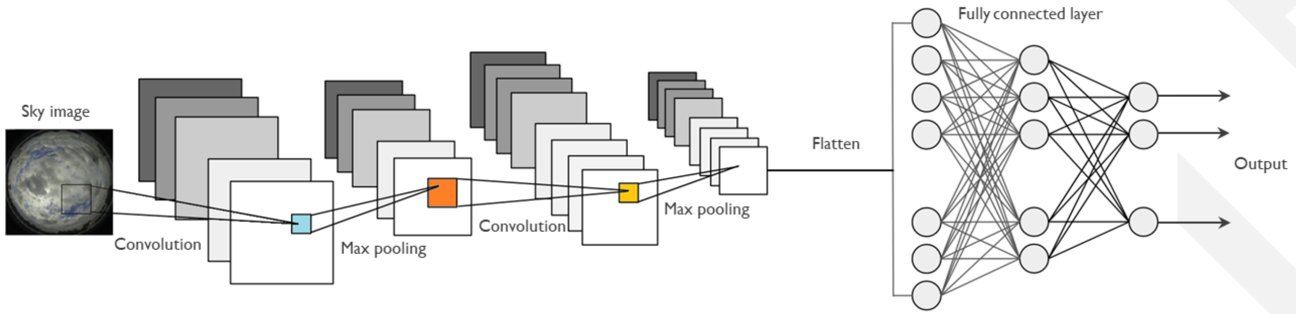


Feed-forward

# Statistical models - Machine learning

## ANN - Convolutional Neural Network (CNN)

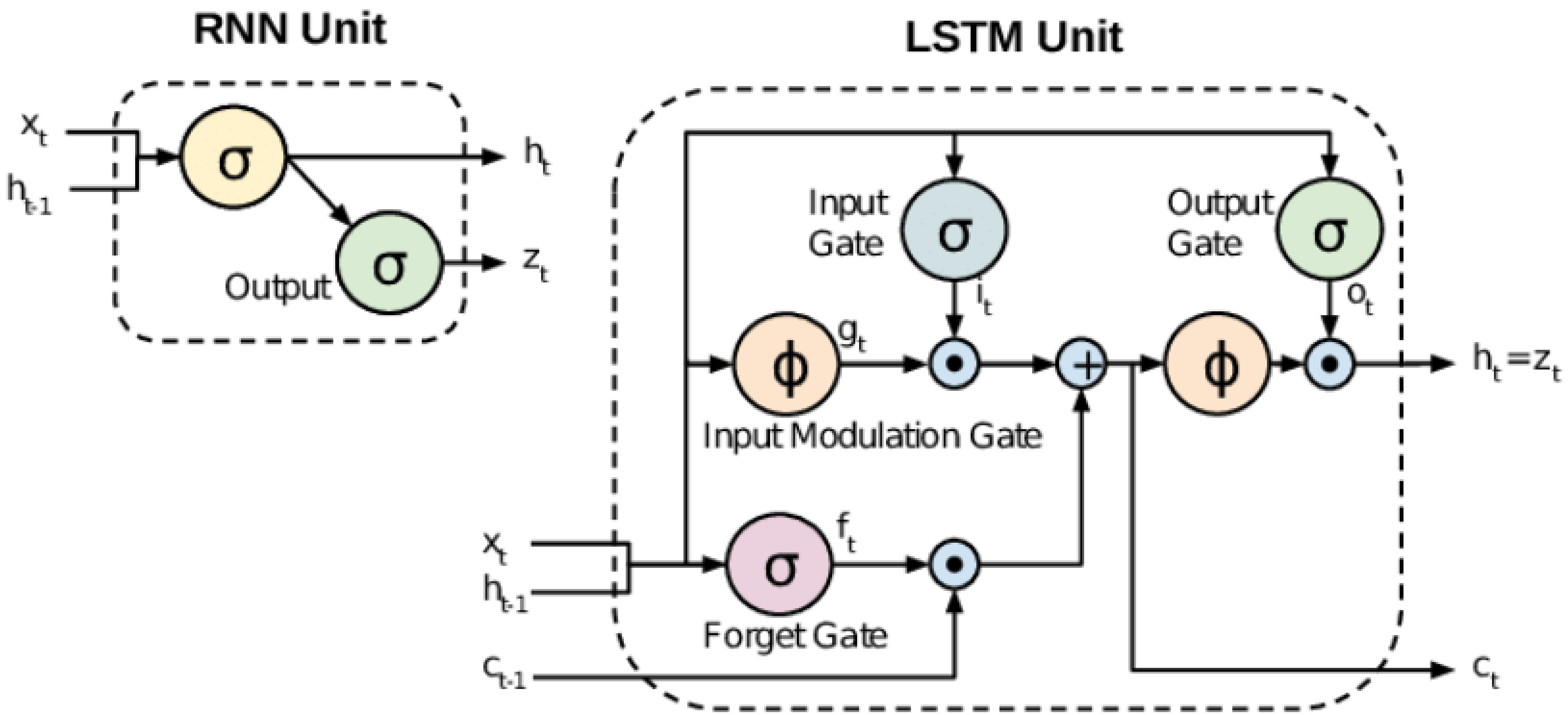
- Deep, supervised learning, specialized type of ANN that use convolution in place of general matrix multiplication
- analyze visual data
- Input layer: An Image, a tensor with a shape: (number of inputs) x (input height) x (input width) x (input channels)
- Convolutional layers: After passing through a convolutional layer, the image becomes abstracted to a feature map, also called an activation map, with shape: (number of inputs) x (feature map height) x (feature map width) x (feature map channels). Convolutional layers convolve the input and pass its result to the next layer.
- Pooling Layers reduce the dimensions of data by combining the outputs of neuron clusters at one layer into a single neuron in the next layer.
- Flatten Layer converts the data into an array to be used as an input for the concluding layer



# Statistical models - Machine learning

## Long-Short Term memory (LSTM)

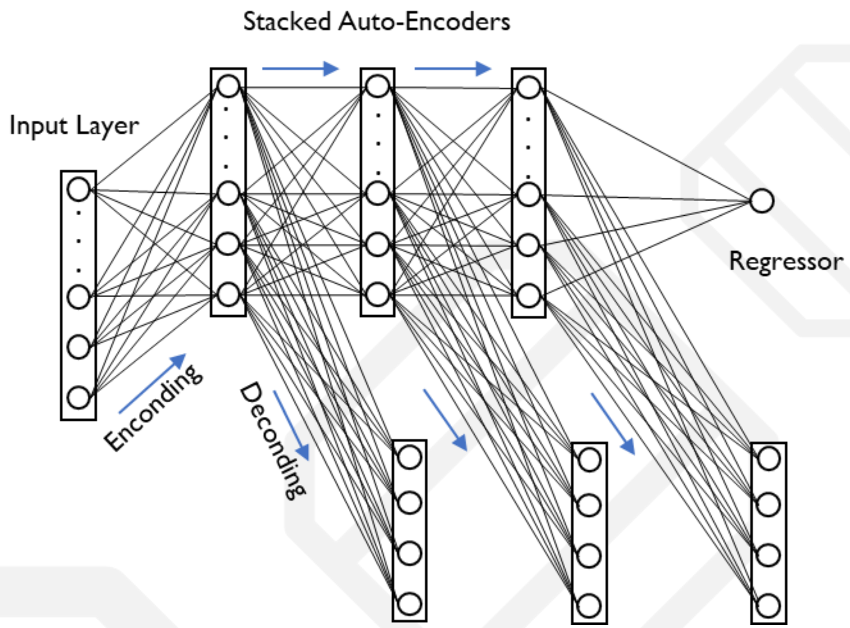
- input gate,
- output gate




- input gate,
- forget gate,
- output gate
- candidate value

# Statistical models - Machine learning

- Stacked auto-encoder
- A stacked auto-encoder (SAE) is a deep, unsupervised learning structure and a form of NNs. SAE tries to generate a compact representation of the input dataset by learning how to keep the most influential and essential features.
- These feature extraction capability makes SAE a powerful algorithm for PV power forecasting

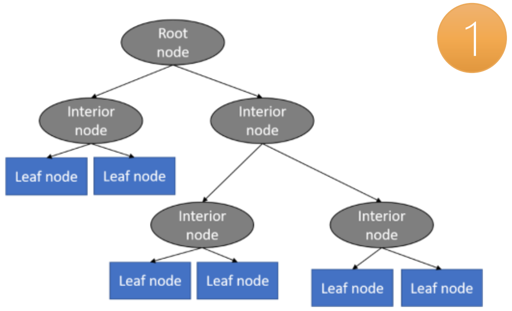


# Statistical models
# Machine learning

Some other Machine learning methods which can be applied for PV power forecast:

1. Decision tree
2. LSTM
3. SVR
4. RL
5. CNN

1

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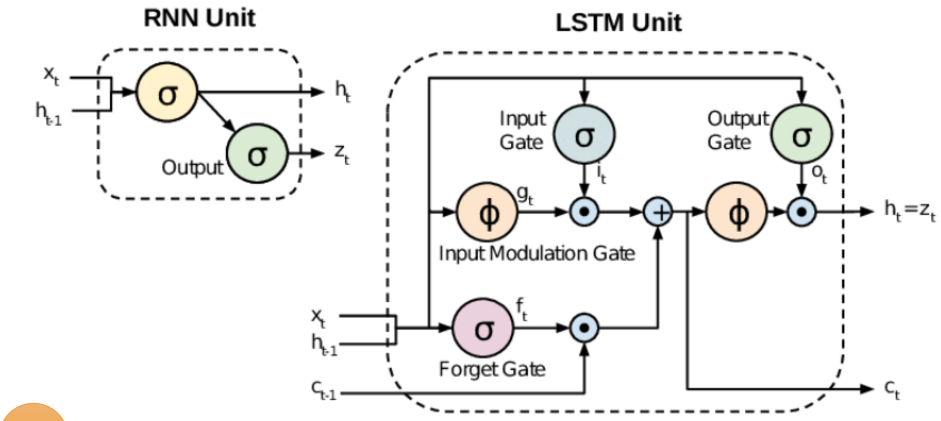


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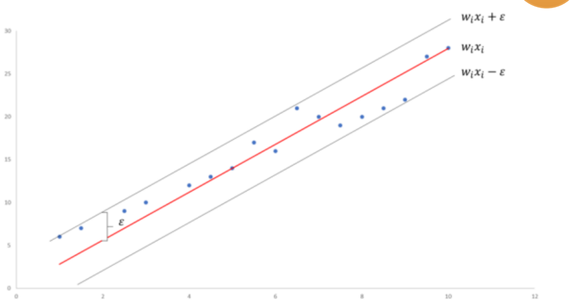

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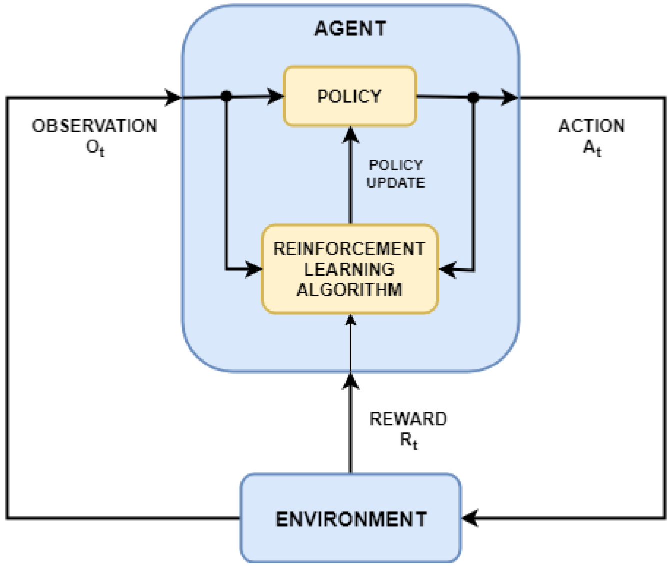


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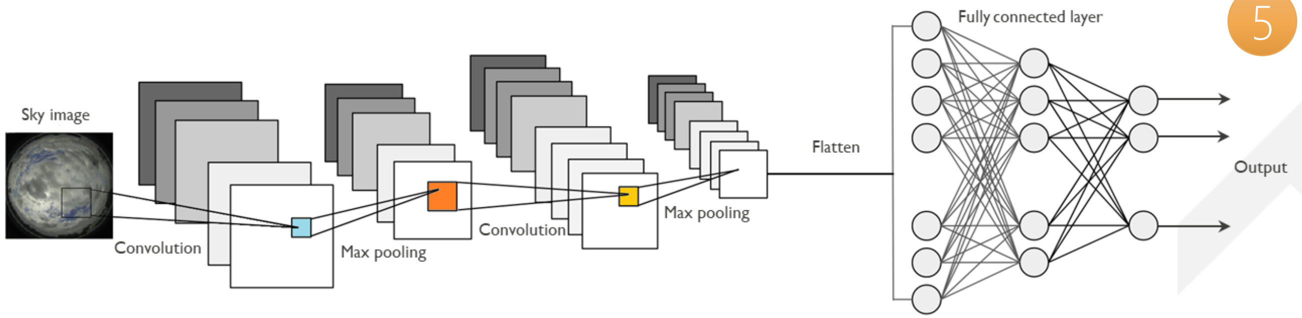
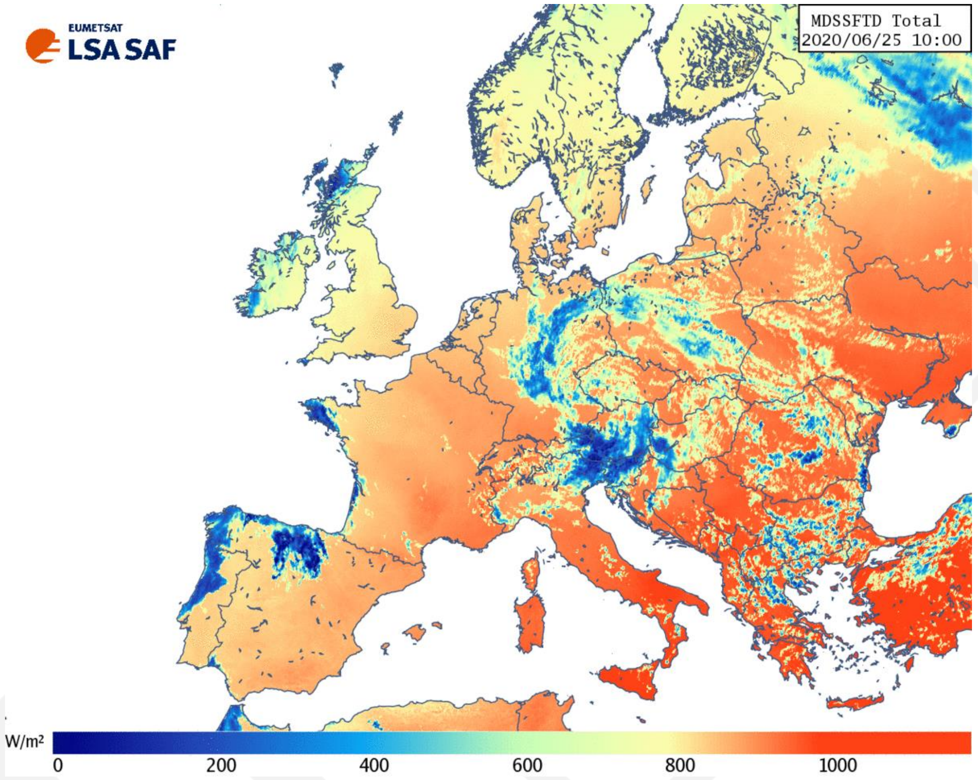
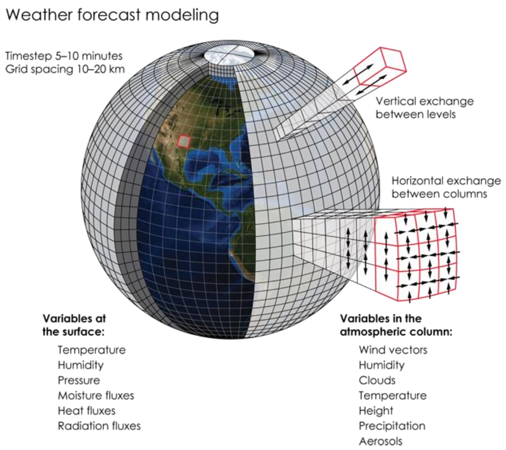


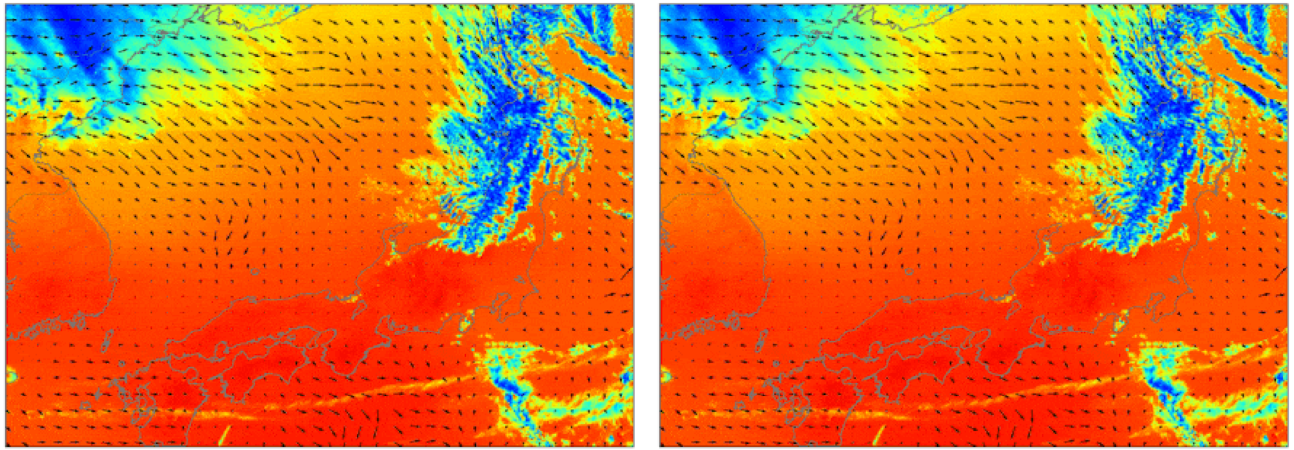
# Physical model

- Understanding the atmospheric physics and dynamics that ultimately cause the wind and solar resource to vary is key to modeling and forecasting for renewable energy.
- Mathematical models based on the same physical principles can be used to generate either short-term weather forecasts or longer-term climate predictions.
- Numerical weather prediction (NWP) uses mathematical models of the atmosphere and oceans to predict the weather based on current weather conditions.
- NWP computer models process current weather observations to forecast future weather.
- All NWP models parameterize a number of physical processes. These include atmospheric radiation, land surface interactions, turbulent mixing, convective clouds, and cloud microphysics.



# Numerical Weather Prediction (NWP)

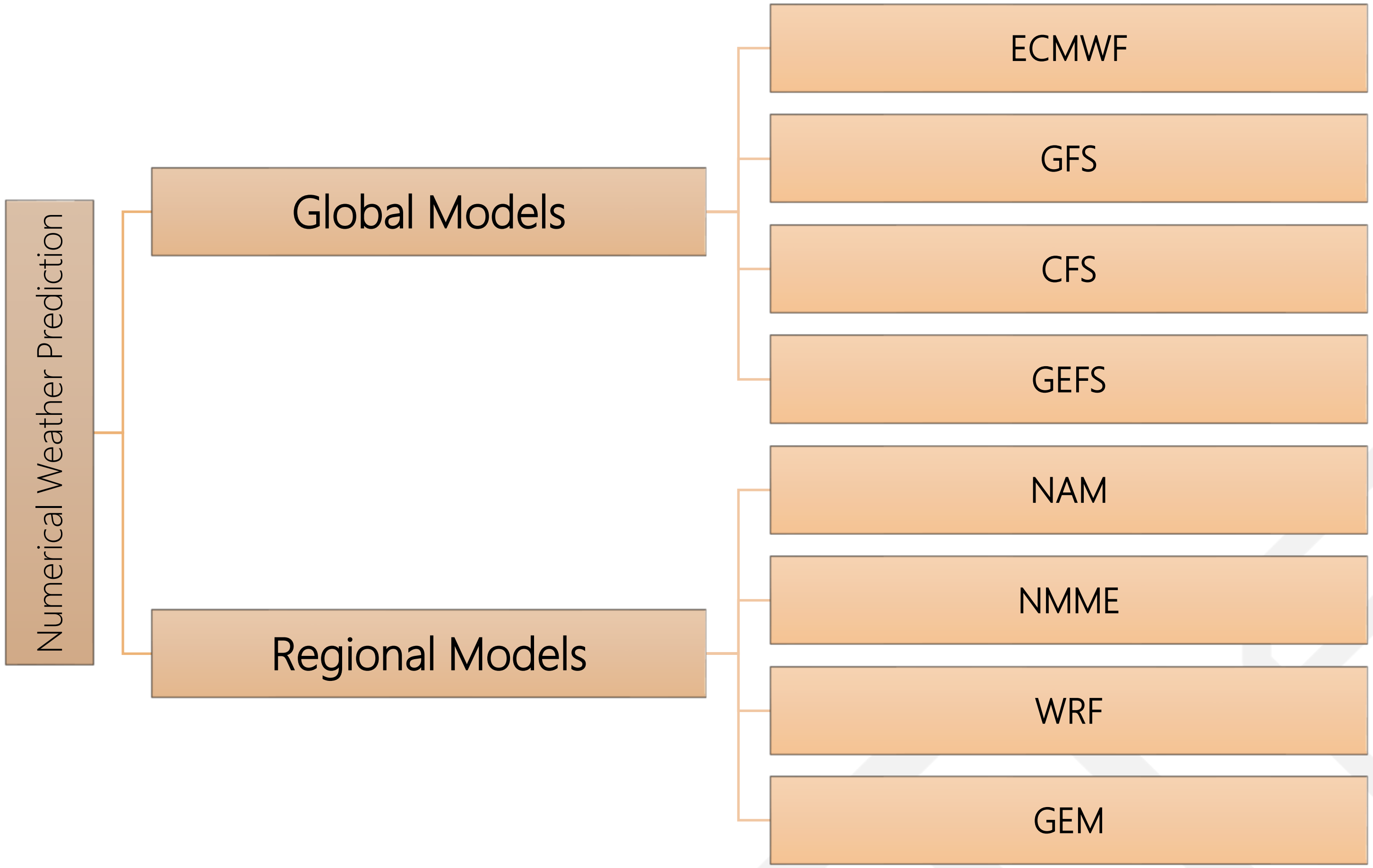


1/19

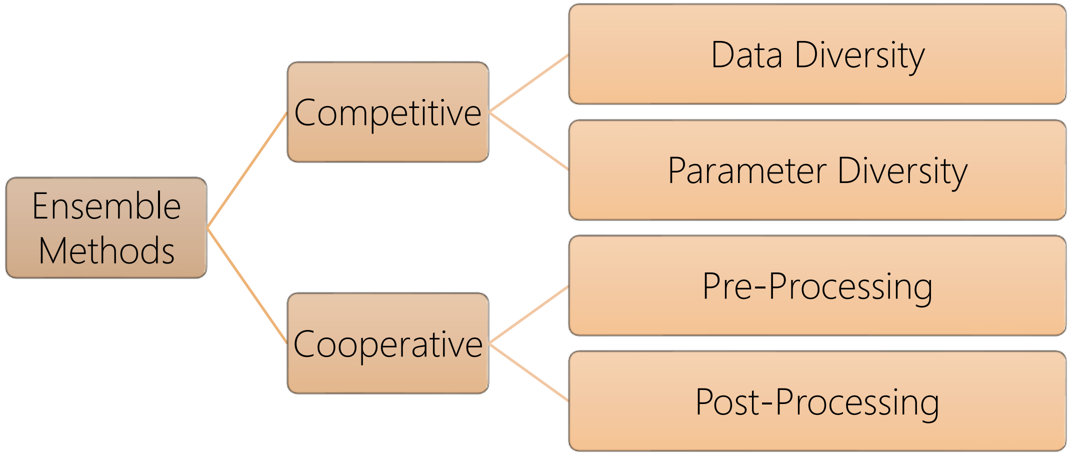
- The equations of physical models for atmosphere are ***nonlinear partial differential equations*** which are impossible to solve exactly through analytical methods. NWP uses ***numerical methods*** to obtain approximate solutions.
- To forecast PV output power, the NWP model employs specific weather features such as GHI, relative humidity, wind speed and direction.
- NWP models are the basis of solar resource forecasts in the time horizon ranging between 6 and 72 hours.

# NWP Models


Numerical Weather Prediction
Global Models
Regional Models
ECMWF
GFS
CFS
GEFS
NAM
NMME
WRF
GEM

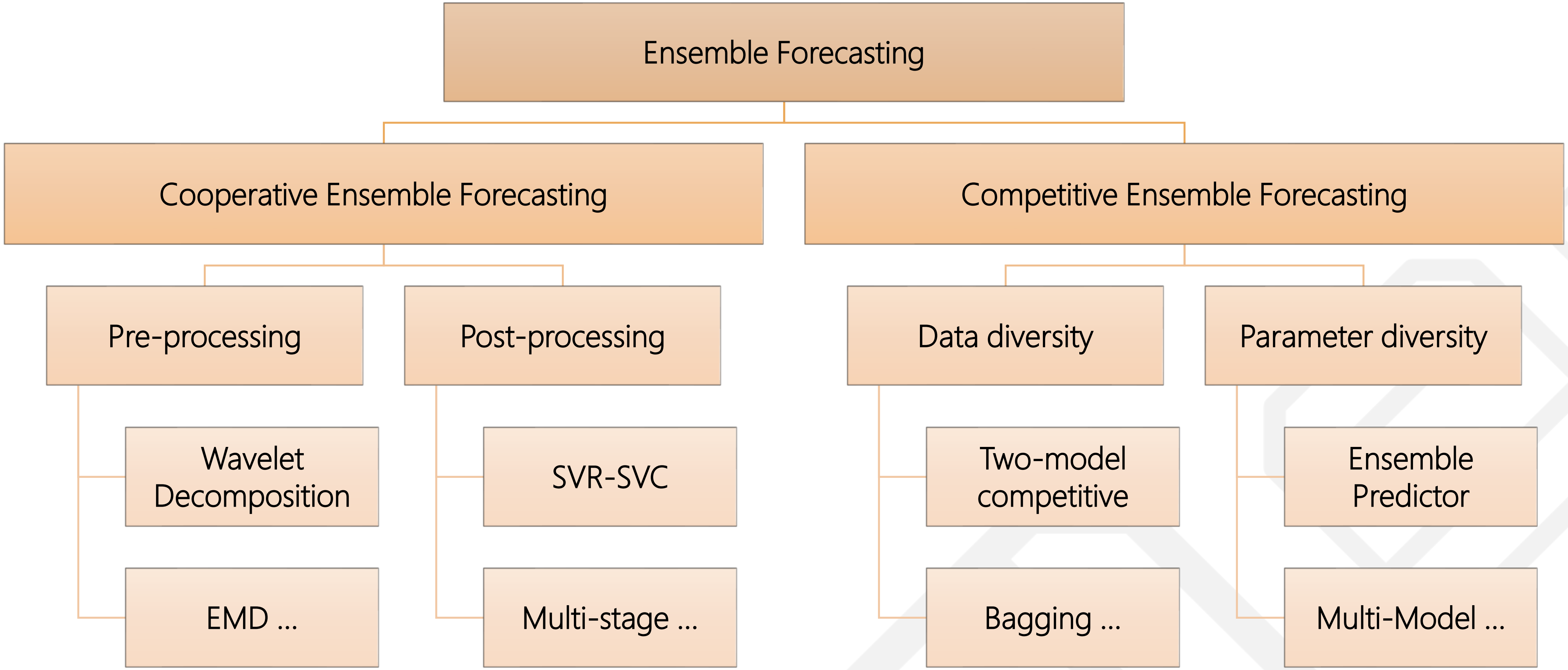
# Ensemble methods

An ensemble method uses multiple predictors to obtain an aggregated decision which is better than any of the base predictors.




- Competitive ensemble forecasting approach uses multiple predictors constructed with slightly different initial conditions or different parameters that are able to construct individual forecast models to form an ensemble forecast model. The forecasting results from all models or selected models after pruning are aggregated by averaging. Diversity is a key feature in competitive ensemble forecasting.
- Cooperative ensemble forecasting divides a prediction task into several sub-tasks and solves each sub-task individually. The overall forecasting results are obtained by aggregating the forecast values of all predictors.

# Ensemble Forecasting



# Probabilistic forecasts

providing some uncertainty measure for the forecast

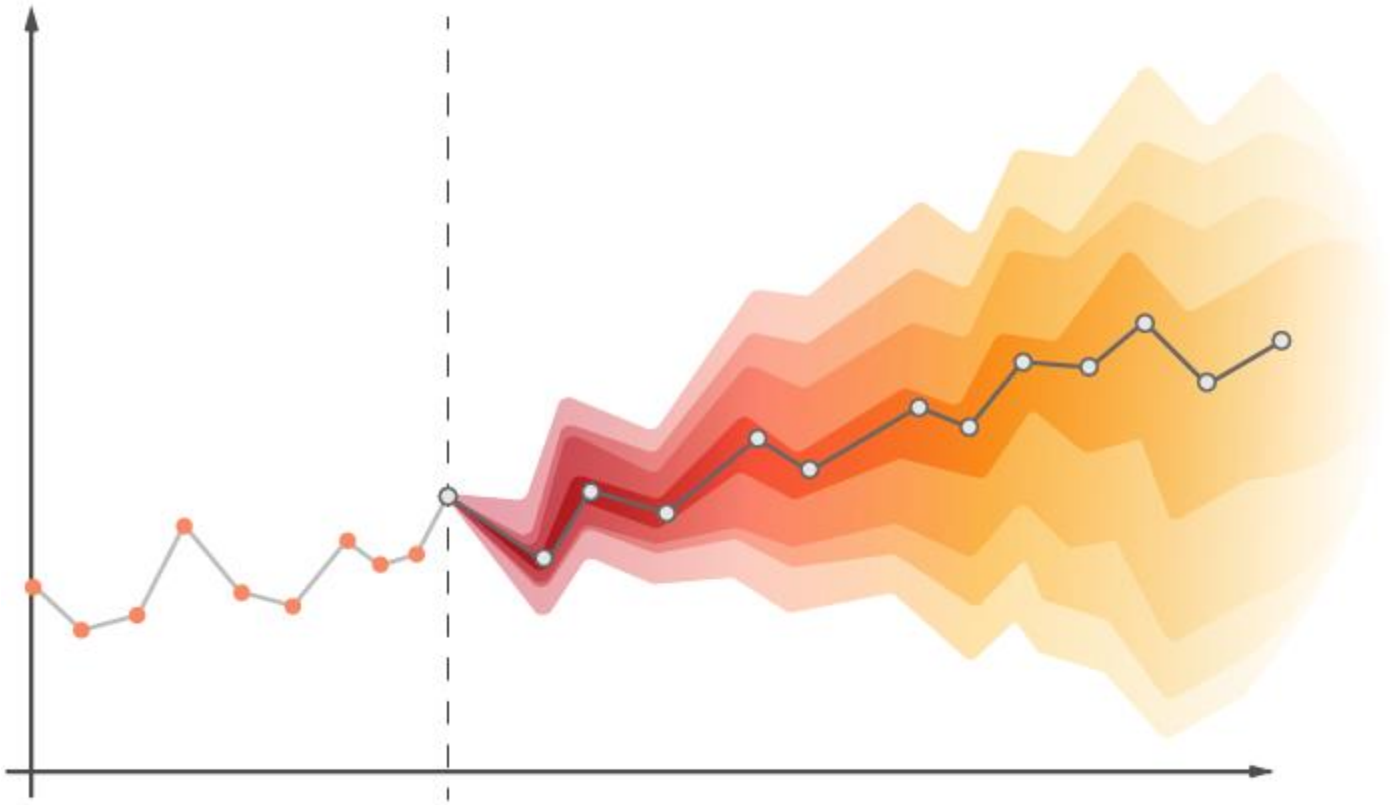
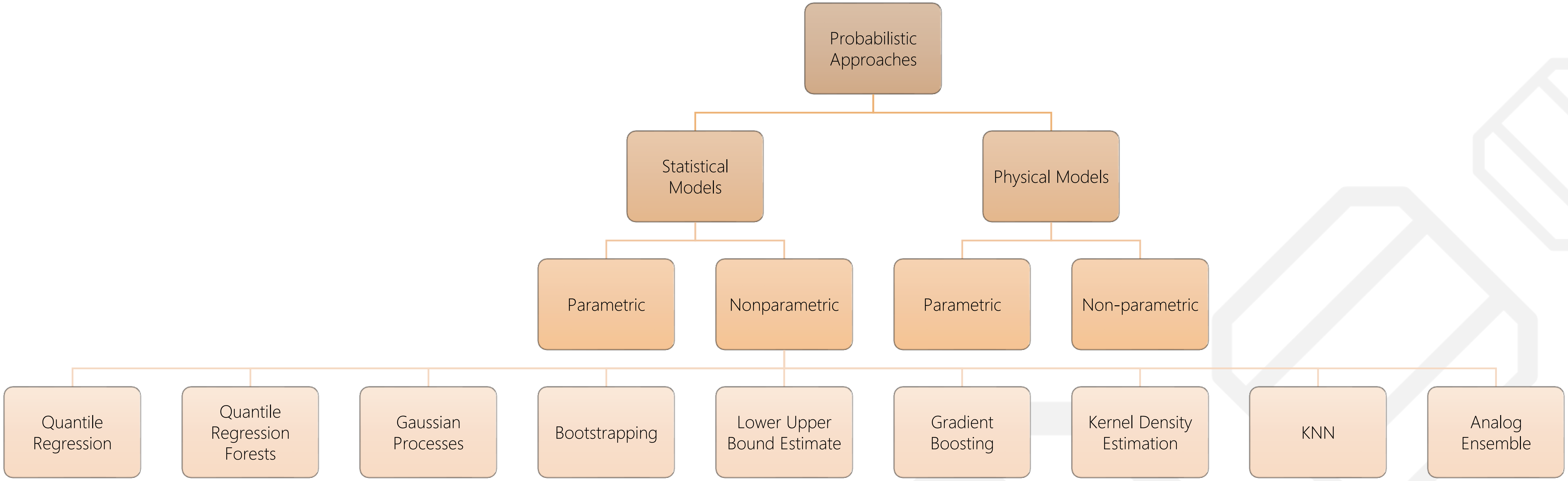


Image courtesy: lokad.com

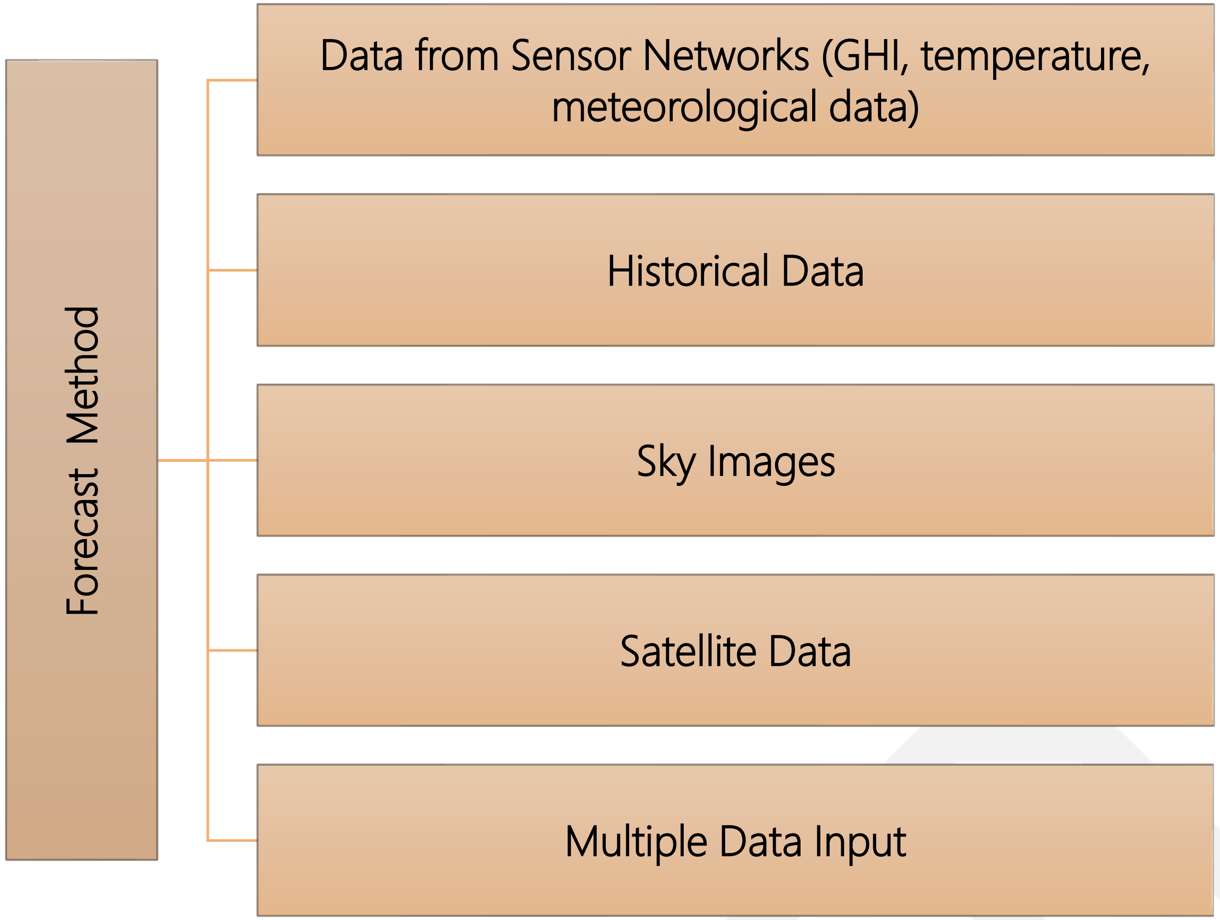
# Classification of PV power forecasting

## based on APPROACHES/MODEL (Probabilistic)



# Classification of pv power forecasting methods

Based on INPUT DATA



# Sky imager-based forecasting

- Sky camera systems
- The total sky imager (TSI) or whole sky imager (WSI) is a ground-based camera which provides time series of hemispheric sky images during daylight hours and retrievals of fractional sky cover for periods when the solar elevation is greater than 10 degrees.

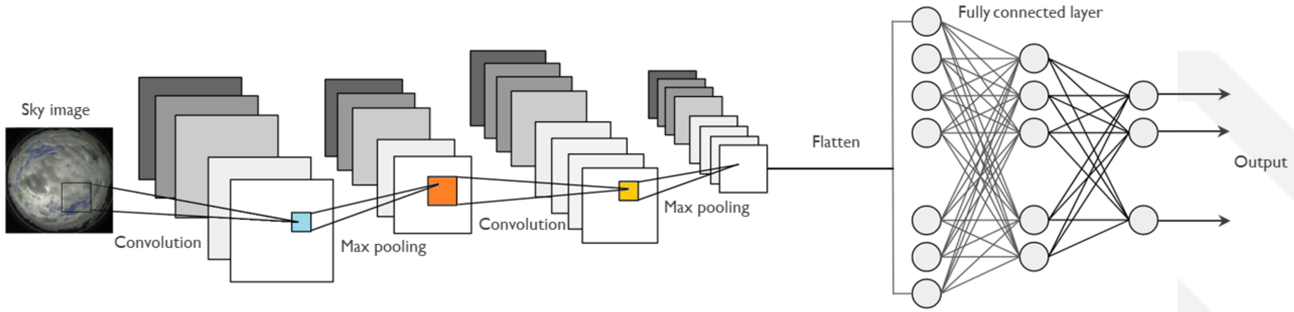
sky camera system operating in the visible spectral range with a fish-eye lens, KU Leuven


Image courtesy of the U.S. Department of Energy Atmospheric Radiation Measurement (ARM) user facility.

P A R L P V

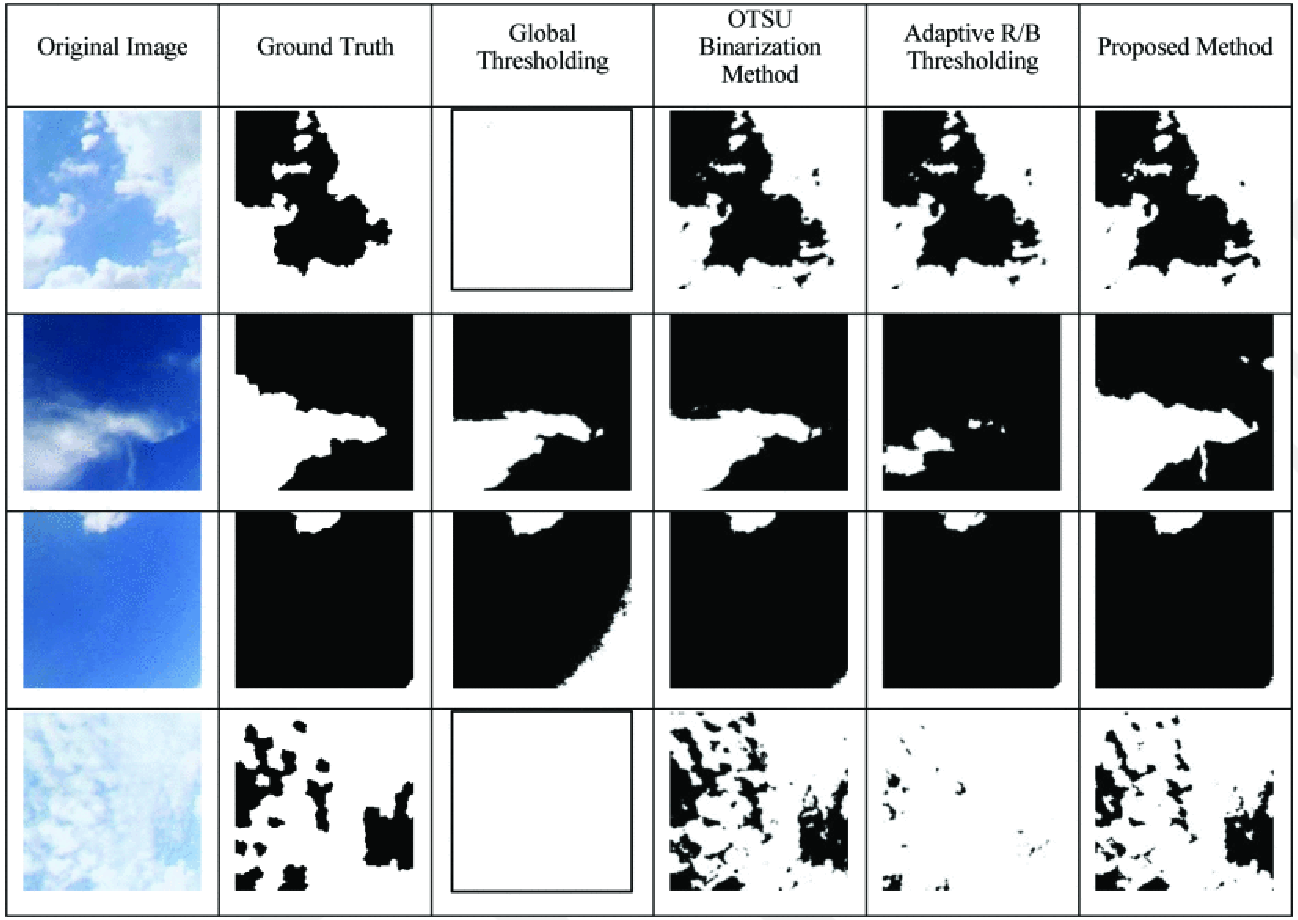
# Sky imager-based forecasting

- Apply image processing and cloud tracking techniques to sky photos.
- The method generally assumes a persistence of the opacity, direction, and velocity of cloud movements.
- Clouds are detected and segmented on successive images and their past displacements are estimated to anticipate their next moves.
- Calculate the sun irradiation and forecast the PV power afterwards.



# Sky imager-based forecasting

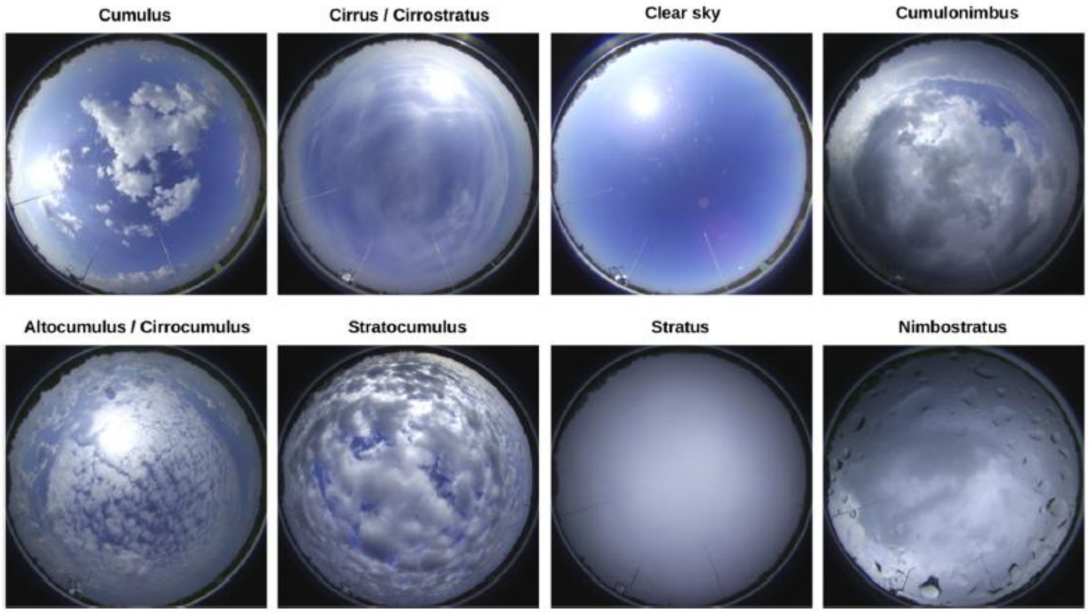
- Cloud detection/cloud coverage:
- Clouds have the highest impact on fluctuations in the PV power output specifically in very short-term horizon, so sky imagers can provide images to track cloud motion and calculate cloud cover.
- The cloud detection algorithms are mostly based on R and B channels because clouds predominantly scatter B and R channels, while clear sky scatters higher values of B channel.




E. Shirazi et al., "Cloud Detection for PV Power Forecast based on Colour Components of Sky Images," 2021

# Sky imager-based forecasting

## Cloud classification



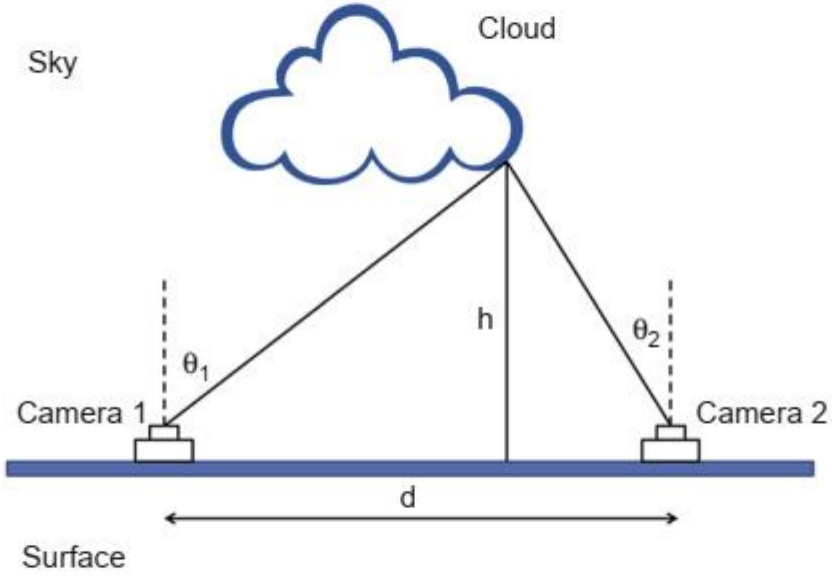

| Features | | Name | Role |
|---|---|---|---|
| 1 | **Spectral** | Mean R | They describe the average color and total variation of an image. They are useful to distinguish between thick dark clouds and brighter clouds and to separate high and transparent cirrus clouds from others. Due to the color of the sky and the different translucency of clouds, the color component B has the highest separation power |
| 2 | | Mean B | |
| 3 | | Standard deviation B | |
| 4 | | Skewness B | |
| 5 | | Difference R-G | |
| 6 | | Difference R-B | |
| 7 | | Difference G-B | |
| 8 | **Textural** | Energy B | It shows the homogenity of gray level differences |
| 9 | | Contrast B | It measures the local variation of gray level differences |
| 10 | | Homogenity B | It reflects the similarity of adjacent gray levels |
| 11 | | Cycle factor | It is used for the detection of raindrops in the image |
| 12 | | Cloud cover | It is a measure of the average cloudiness |

G. Kariniotakis, Renewable Energy Forecasting (2017)

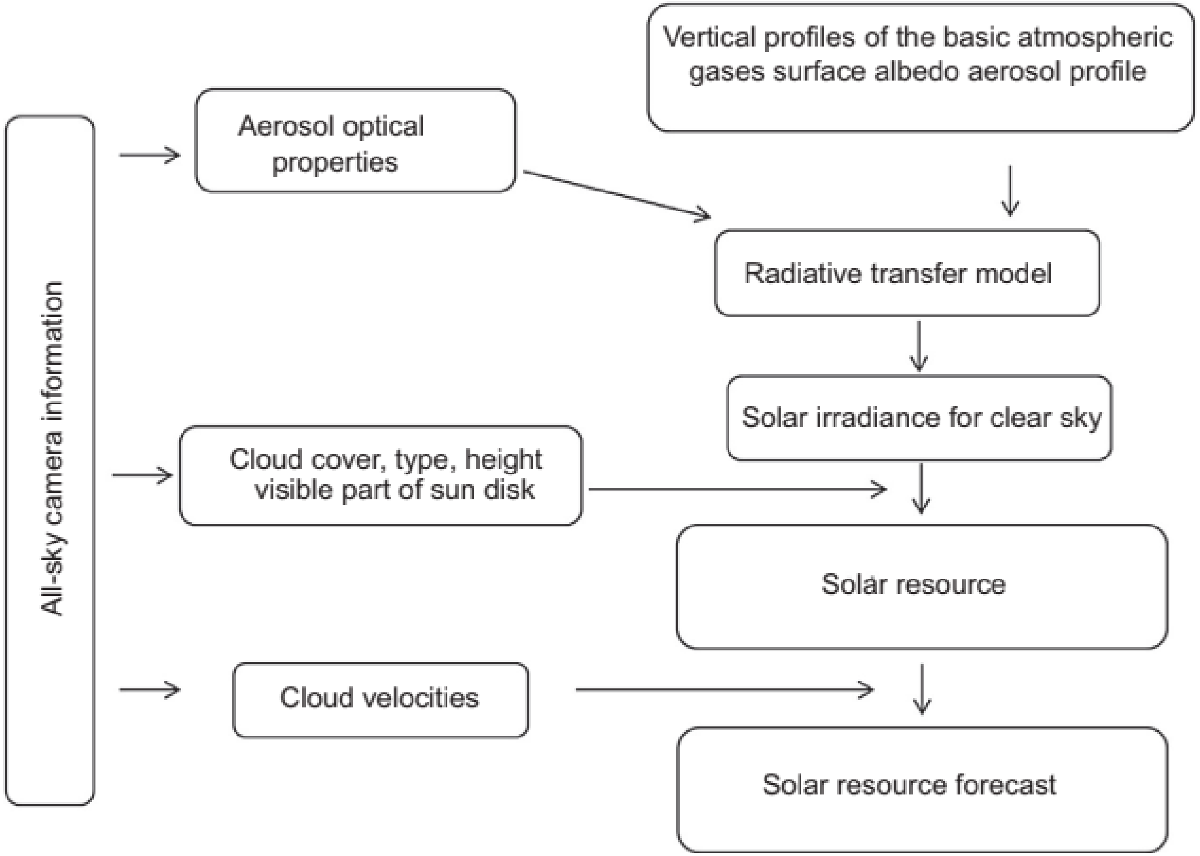
# Sky imager-based forecasting

- Cloud height estimation
- The triangulation procedure to estimate the cloud base height (CBH)
- Two pictures of the overhead sky are obtained from ground-based cameras 1 and 2.
- The distance between the two cameras and the CBH are d and h, respectively. The same cloud feature is identified on the pictures obtained from the two sites and the
- zenith angles $\theta_1$ and $\theta_2$ can be calculated. The CBH is given by:

$$h = \cos(\theta_1) coss(\theta_2) d / \sin(\theta_1 + \theta_2)$$



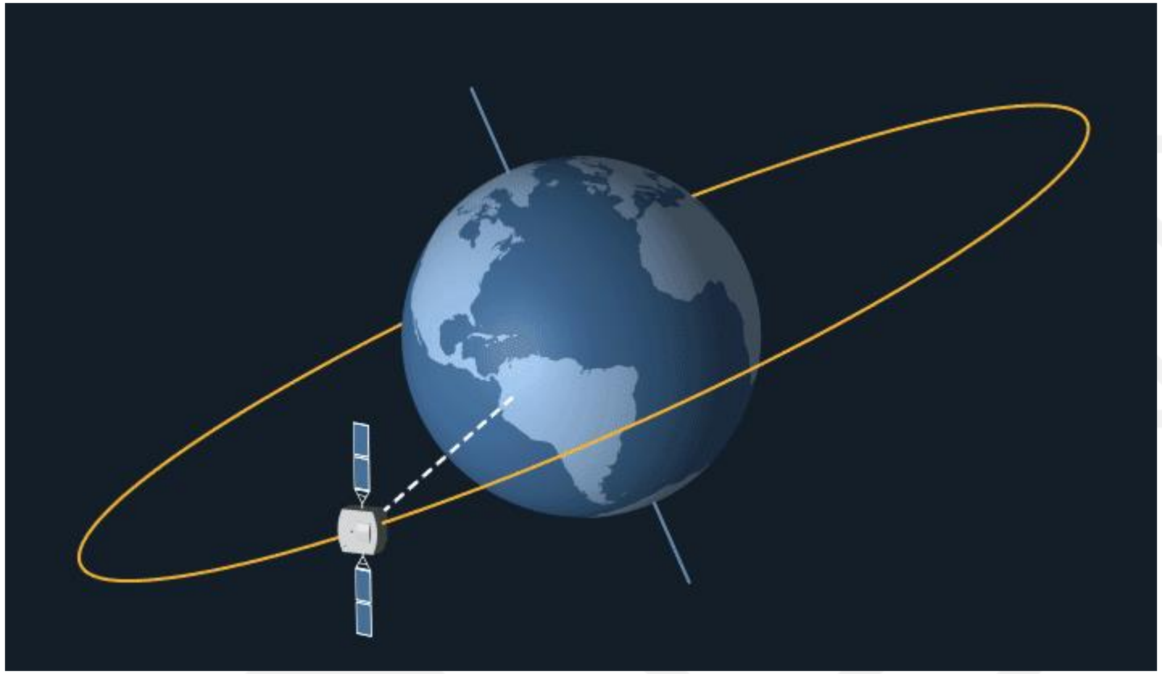
# Sky imager-based forecasting



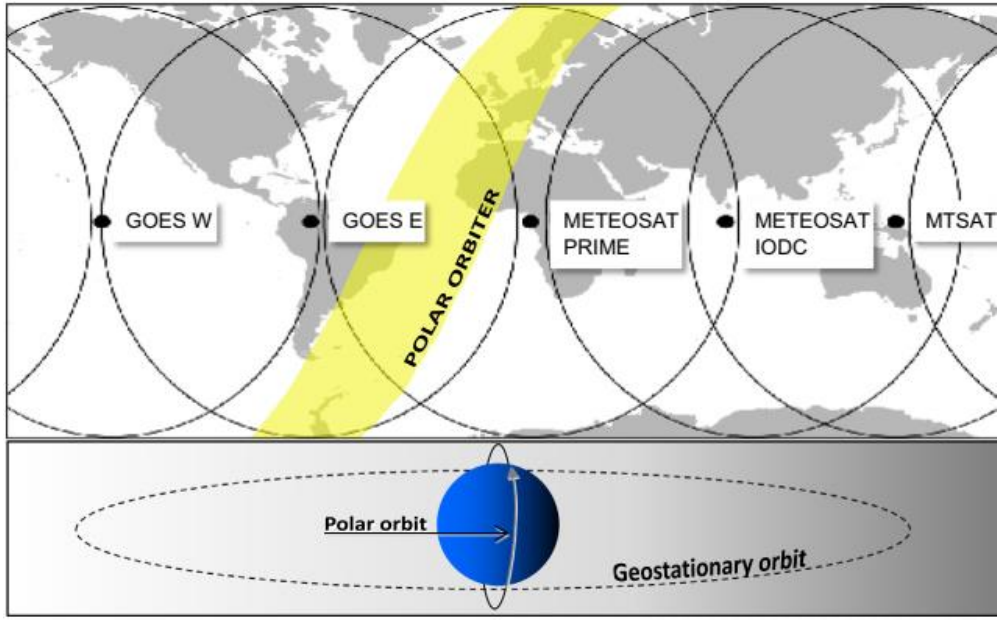

G. Kariniotakis, Renewable Energy Forecasting (2017)

# Satellite based forecasting

- normal spatial resolution:
  - 2-10 km
- normal temporal resolution:
  - 15 mins
- the main advantage:
  - better location of clouds



# Satellites and spectral bands



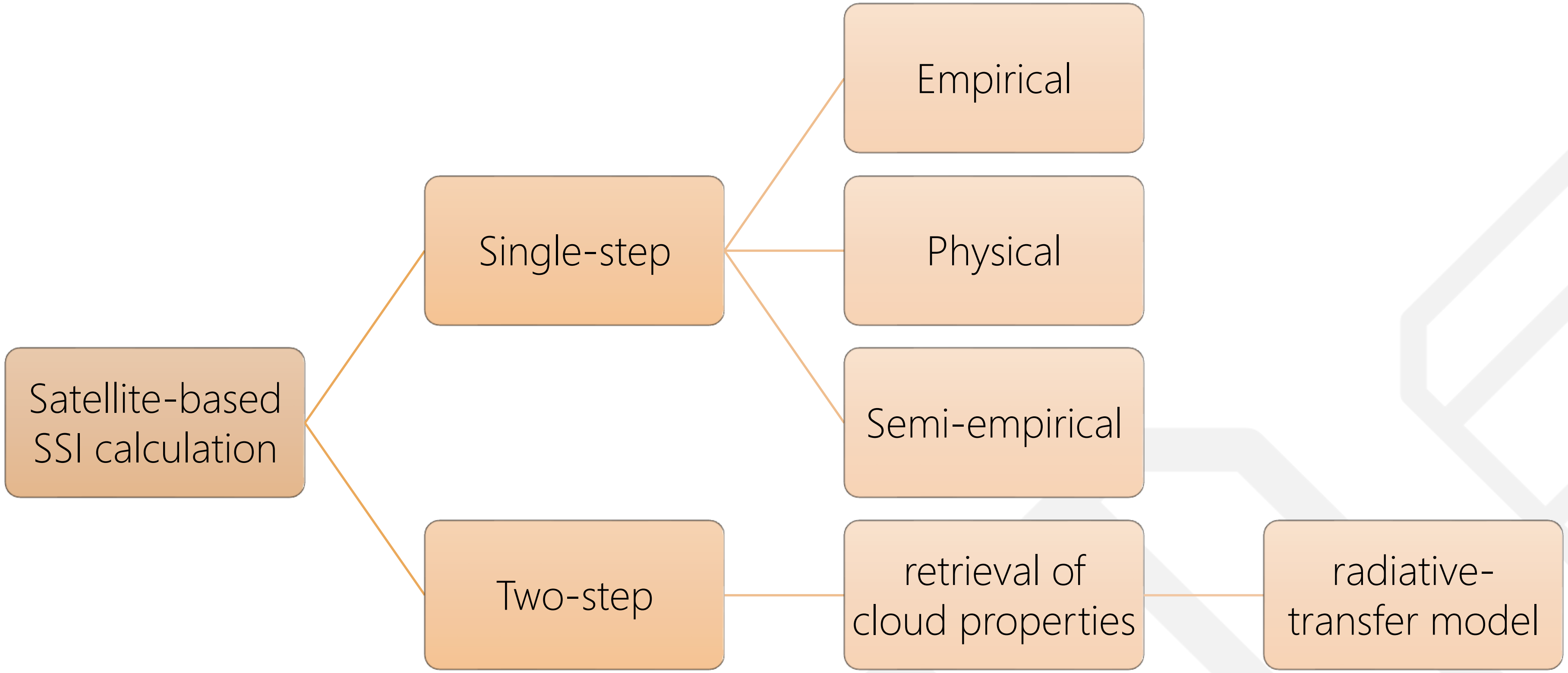

**Spectral Channels in the Current GOES Satellite Series**

| Satellite imager channel | Wavelength range (μm) | Ground resolution at nadir | Primary detection |
|---|---|---|---|
| 1 Visible | 0.55–0.75 | 1 km | Clouds, albedo, smoke |
| 2 Shortwave IR | 3.80–4.00 | 4 km | Clouds, smoke |
| 3 Moisture IR | 6.30–6.70 | 8 km | Clouds, water vapor |
| 4 Surface Temperature IR | 10.20–11.20 | 4 km | Clouds, water vapor, surface temperature |
| 6 Longwave IR* | 12.80–13.80 | 4 km | Clouds, water vapor |

# Satellite based forecasting

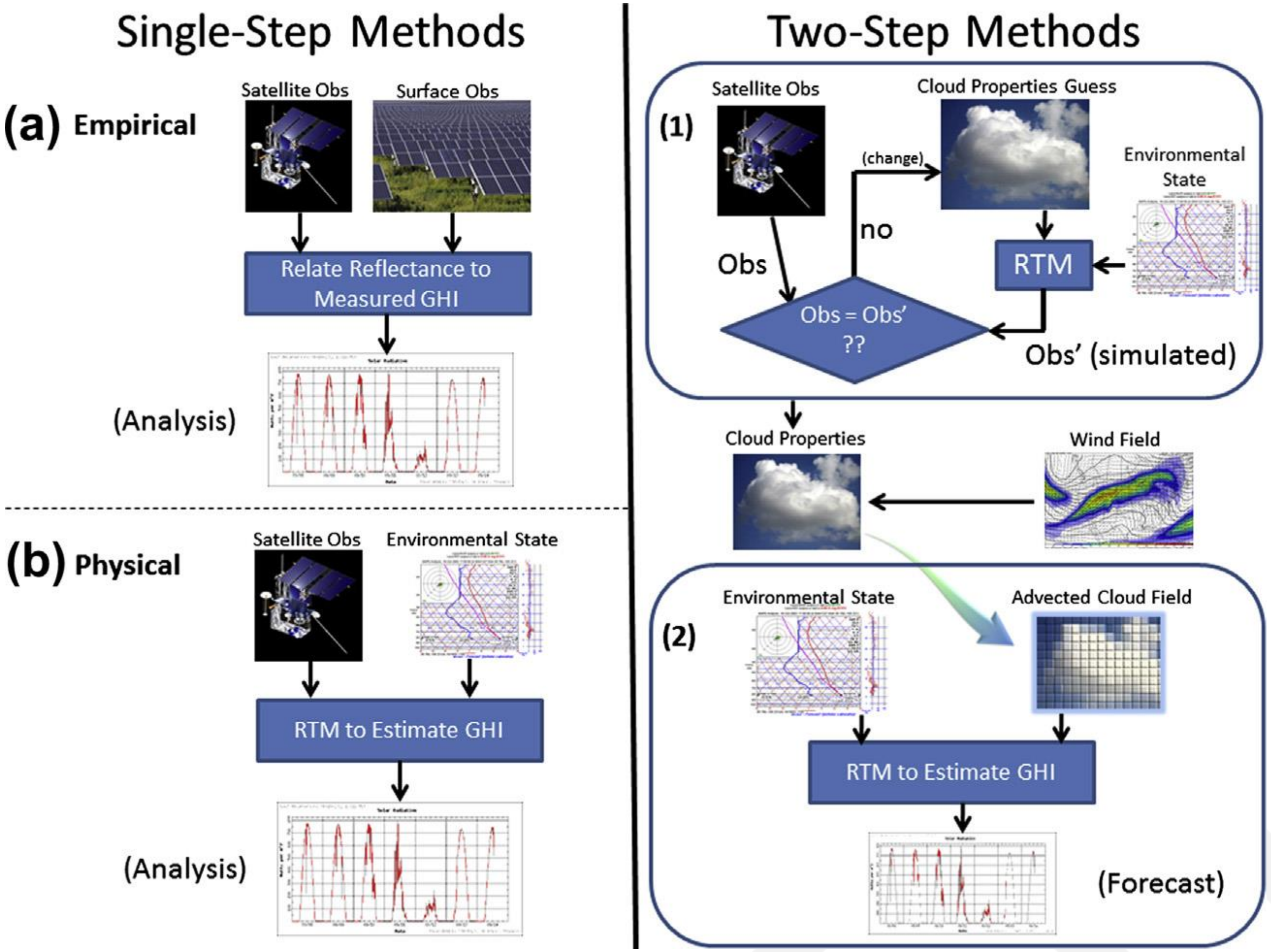
## Calculating solar surface irradiance

- Satellite measurements can be converted to down-welling solar radiation at the surface using various methods that combine radiative transfer theory and observations.



# Satellite based forecasting

## Calculating solar surface irradiance



# Satellite based forecasting- Empirical Models

- Empirical models use relationships between satellite and ground measurements to estimate surface radiation.
- Most empirical methods assume a pseudolinear relationship between atmospheric transmittance and satellite measurement

$$GHI = GHI_{max} \times (1 - N) + GHI_{min}$$

- with $GHI_{max}$ being the clear-sky equivalent value and $GHI_{min}$ being a low value corresponding to dense overcast conditions; N is a cloud index defined by

$$N = \frac{C - C_{min}}{C_{max} - C_{min}}$$

- where $C$, $C_{min}$ and $C_{max}$ are values of the current, minimum (usually a clear-sky background value) and maximum observed satellite visible radiance (satellite count)

# Satellite based forecasting- Physical Models

- Physical models use Radiative Transfer Model (RTM) to estimate surface radiation directly from satellite observations
- RTM calculations could involve a single broadband calculation or multiple calculations in different wavelength bands.
- The clear-sky model initially included water vapor and Rayleigh scatter, but progressively added ozone and aerosols.

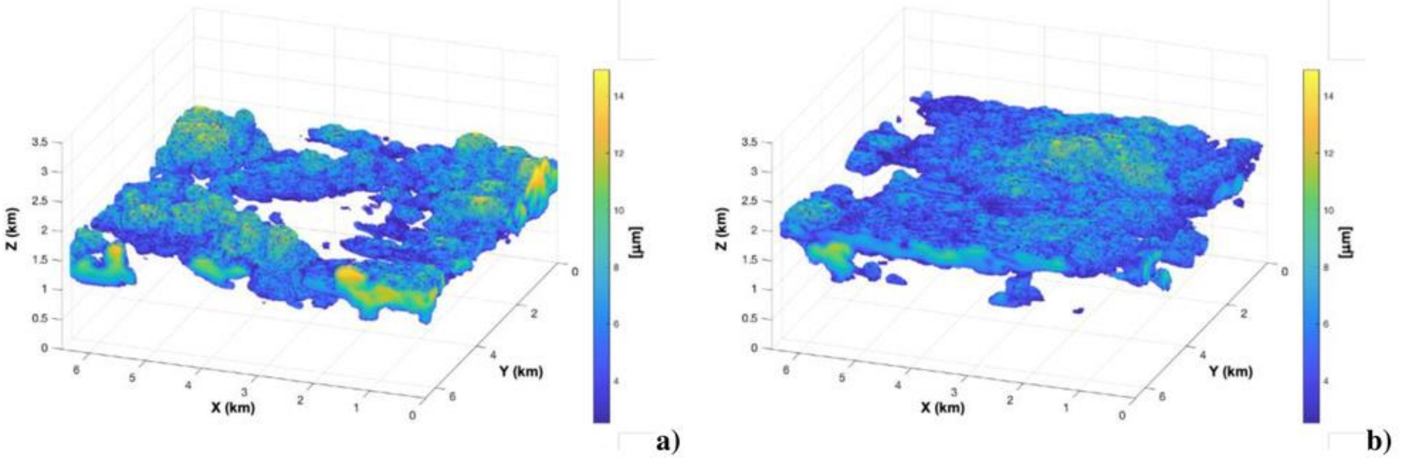



Image courtesy: C. P. Ferrús, et. al., "Retrieval of cloud optical depth through radiative transfer and remote sensing: from 1D to 3D approach, 2021

# Satellite based forecasting- semiempirical models

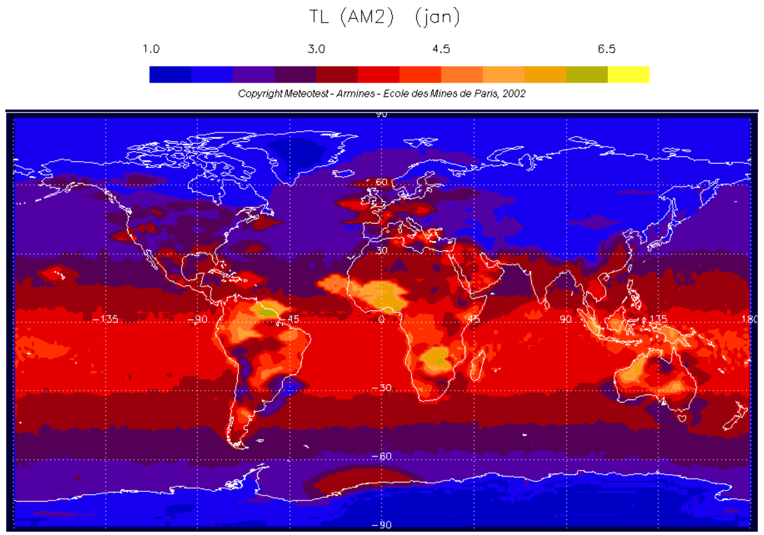
- Semi-empirical models are typically designed to exploit data recorded by a satellite *visible channel*.
- *The underlying principle:* The visible Earth radiance seen by the satellite is approximately proportional to cloud opacity and to the cosine of the solar-zenith angle.
- For a given solar-zenith angle, the visible radiance is inversely proportional to the global horizontal irradiation (GHI) at the surface.
- Semi-empirical models typically include two operationally distinct parts:
  - Clear-sky irradiance background $GHI_{clear}$ (derived independently from other sources)
  - Cloud attenuation superimposed on the background (determined from the visible radiance)

# Satellite based forecasting- semiempirical models

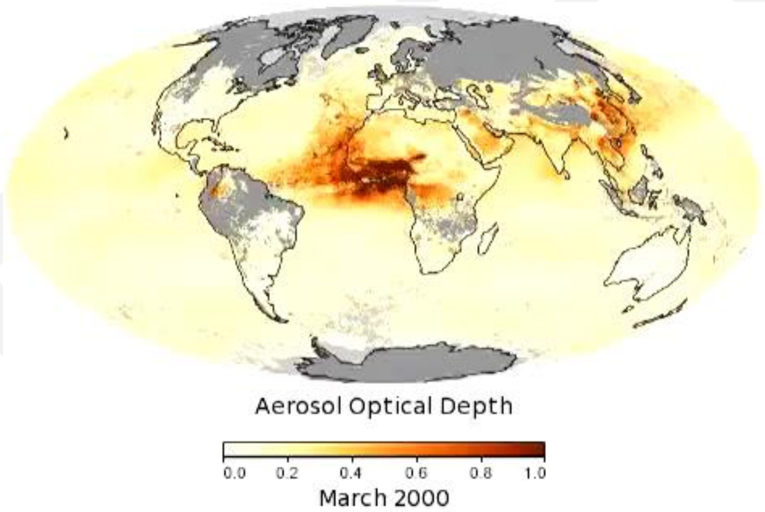
## Clear sky background

Clear-sky irradiance is a function of:

- Extra-terrestrial irradiance (a function of Earth–Sun distance) ~1366 W/m2
- Position of the Sun in the sky quantified by the solar-zenith angle
- Elevation above sea level
- Composition of atmospheric gases, especially water vapor and ozone content
- Atmospheric aerosol content,  AOD ( aerosol optical depth)
- Linke turbidity factor (TL) quantifies all non-Rayleigh effects in the clear atmosphere (combined effect of aerosols and water vapor)




Average Linke turbidity factor (TL) map,Image Courtesy: Ecole de Mines de Paris




Average monthly AOD (2000-2015) map,Image Courtesy: NASA

# Satellite based forecasting- semiempirical models

## Clear sky background

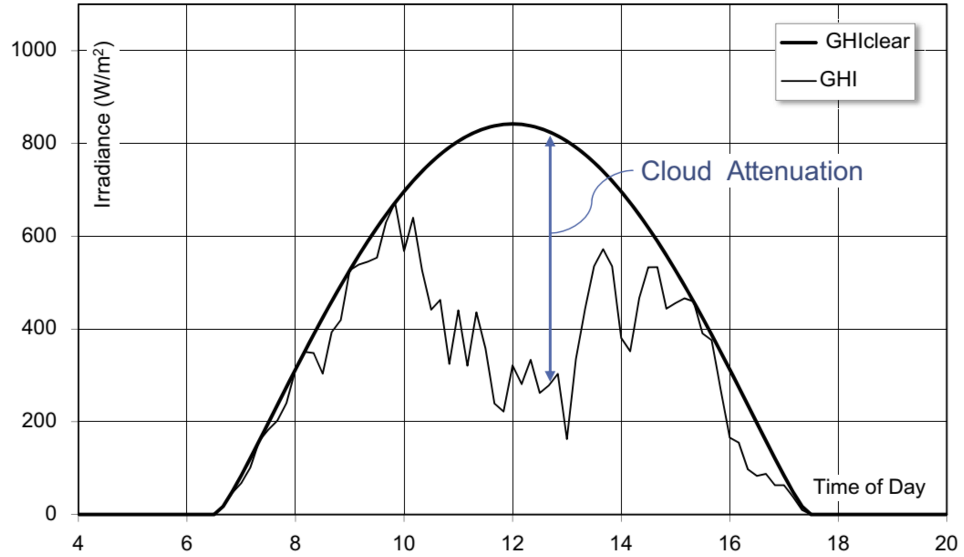
There are many clear sky models, such as Bird, REST2, NREL CSR, HelioClim, Ineichen.

Clear-sky Ineichen model

$$GHI_{clear} = I_0' \cos(Z)\, e^{\left(\tau_g / \cos(Z)\right)^{a}}$$

- $I_0'$ : a reference-modified normal-incident irradiance incorporating precipitable-water and site-elevation effects,
- $Z$: solar zenith angle,
- $\tau_g$ : an aerosol-attenuation coefficient also incorporating site elevation effects
- $a$ : parameter as a function of elevation and AOD.

$$DNI_{clear} = I_0' e^{\left(\tau_b / \cos(Z)\right)^{b}}$$



# Satellite based forecasting- semiempirical models

## Cloud attenuation: cloud index

- Cloud attenuation calculations determine a cloud index (CI) from satellite images, applying the quasi-linear relationship between satellite count and surface GHI.
- For a given time and location, CI is determined by the value of the cosine corrected count, CCC, with respect to the local dynamic range per equation

$$CI = \frac{UB - CCC}{UB - LB}$$

UB and LB represent, the upper and lower bound of the dynamic range at a given point in time and space.

# Satellite based forecasting- semiempirical models

- Computing global irradiance
- The CI should be proportional to the global clear-sky index.
- A linear relationship is indeed used in several semiempirical model implementation, Heliosat:

$$kt^* = \frac{GHI}{GHI_{clear}}$$

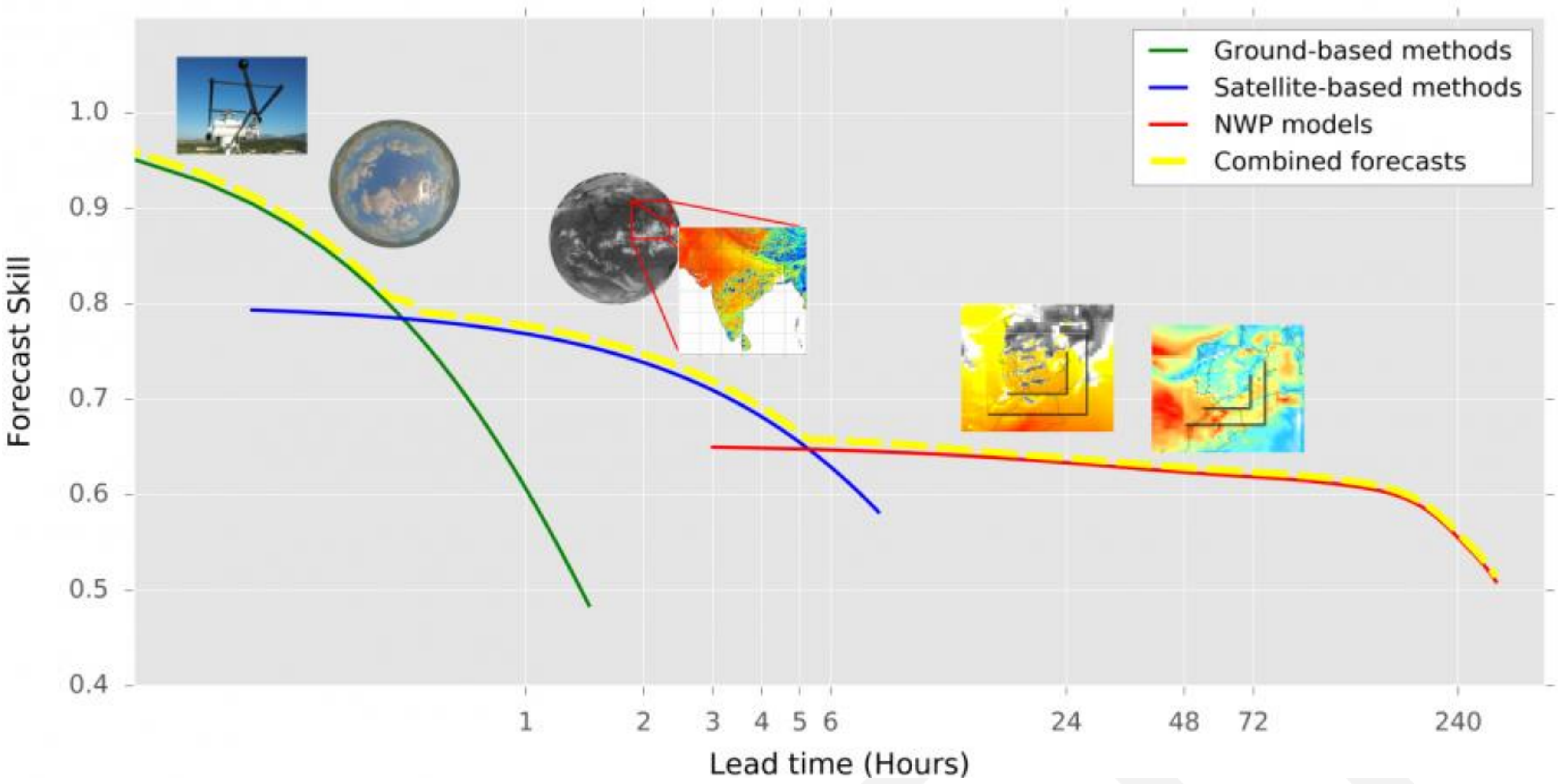
- SUNY model

$$kt^* = 2.36CI^5 - 6.3CI^4 + 6.22CI^3 - 2.63CI^2 - 0.58CI + 1$$

- SolarGIS model

$$kt^* = CI\Big(CI\Big(CI\Big(CI\big((0.100303CI) - 0.189451\big) + 0.596357\Big) - 0.714985\Big) - 0.663526\Big) + 1$$

# Sky camera, satellite and NWP methods comparison



# Performance matrixes

To precisely evaluate the prediction accuracy of previously described models, four statistical quality measures has been adopted. These measures are executed by the following equations:

- To calculate the difference between real time measurements and specific model predicted values, root mean square error (RMSE) or root mean square deviation (RMSD) has been used:

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t^{actual} - x_t^{predicted})^2}$$

- Accuracy measures the proximity of the analytical results to the actual value.

$$Accuracy = \frac{1}{T}\sum_{t=1}^{T}|x_t^{actual} - x_t^{predicted}|$$

- "R squared", the coefficient of determination, is the proportion of the variation in the dependent variable that is predictable from the independent variable. (0,1) or (0,100%)

$$R^2 = 1 - \frac{\sum_{t=1}^{T}(x_t^{actual} - x_t^{predicted})^2}{\sum_{t=1}^{T}(x_t^{actual} - \frac{1}{T}\sum_{t=1}^{T} x_t^{actual})^2}$$

# Commercial forecast

SOLARGIS

Reuniwatt

SolarAnywhere®

SOLCAST

steadysun

DNV

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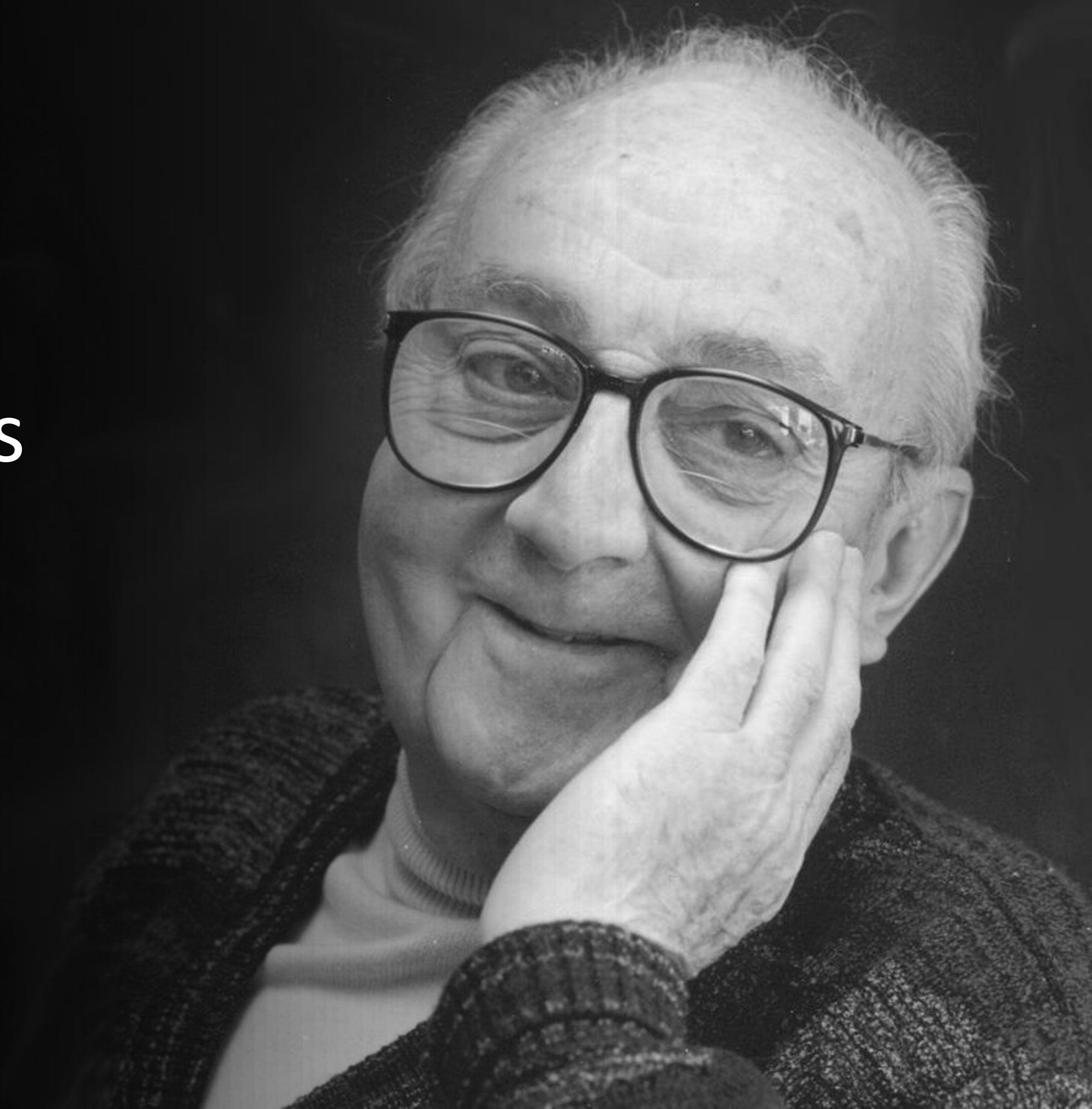
“Essentially, all models are wrong, but some are useful”

-George E.P. Box



P E A R L P V

# Thank you for your attention

**Question or comments?**

**Feel free to contact me at e.shirazi@utwente.nl**