



Solar Irradiance Forecast from satellite images

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Why solar irradiance forecast?

PV Power Forecast



Solar Thermal Forecast



Weather Forecast

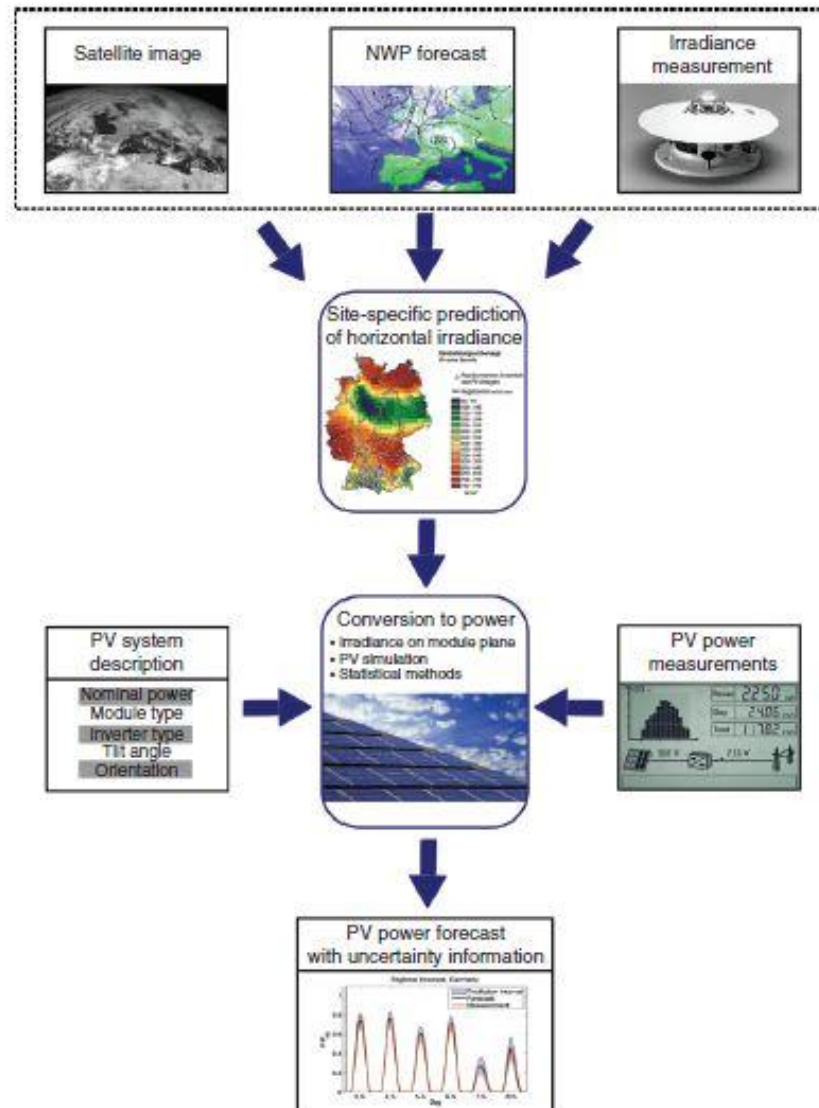


Agriculture Forecast

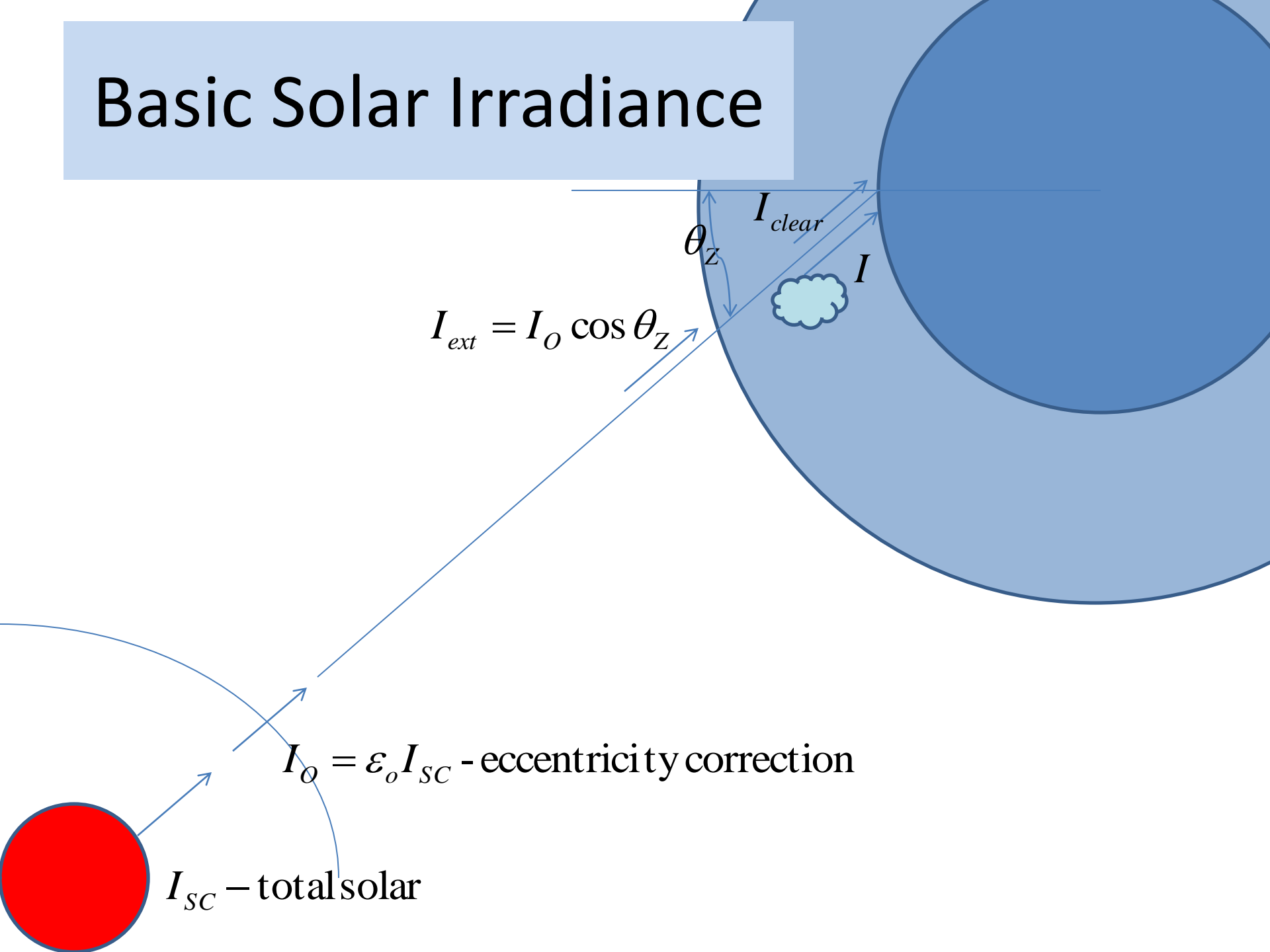


Load Forecast

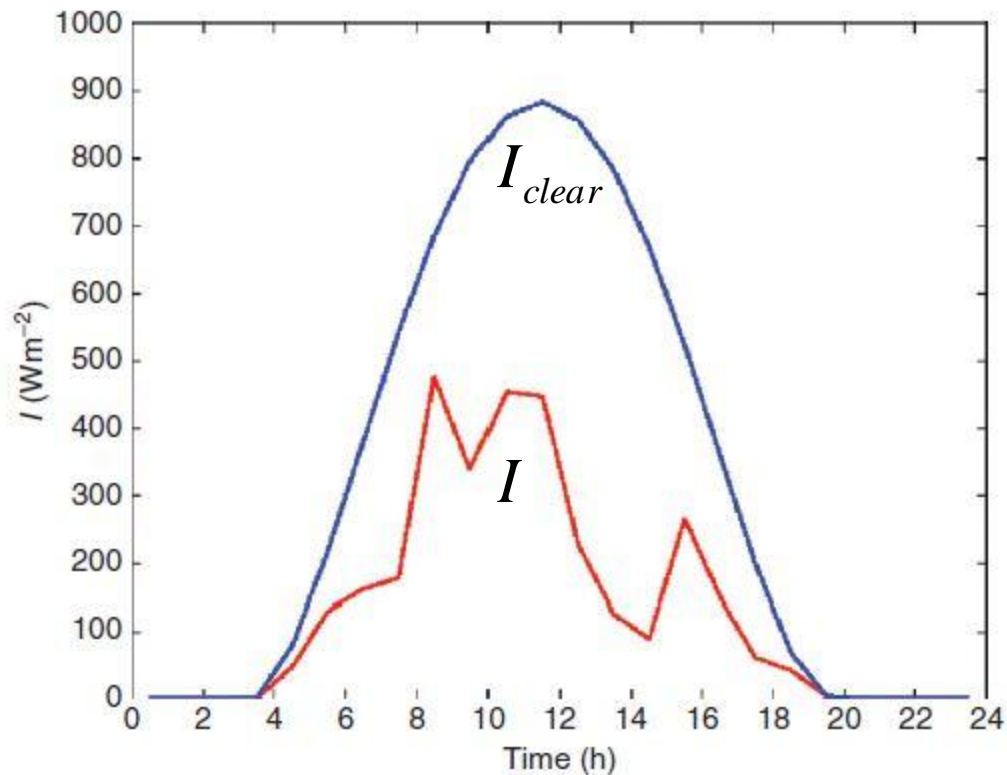
PV Power Forecast System



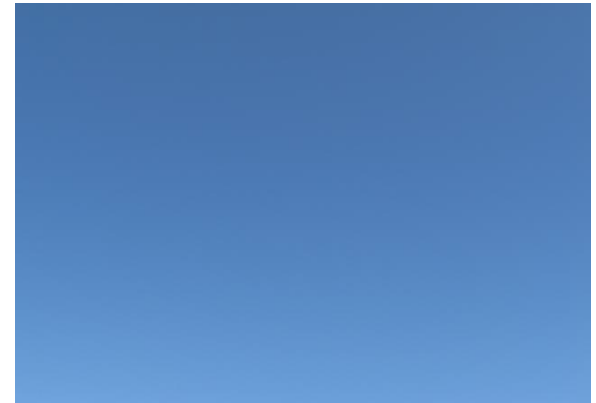
Basic Solar Irradiance



Basic Solar Irradiance (cont.)



$$\text{Clear Sky Index} : k^* = \frac{I}{I_{clear}}$$



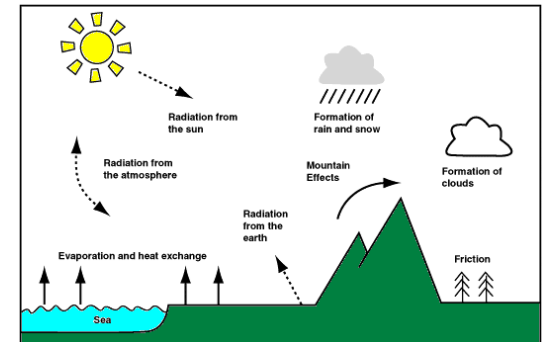
Basic Solar Irradiance Forecast

Time Series/Persistence
(good if no cloudiness change)



Ground-based Sky Imagers
(15-30 min)

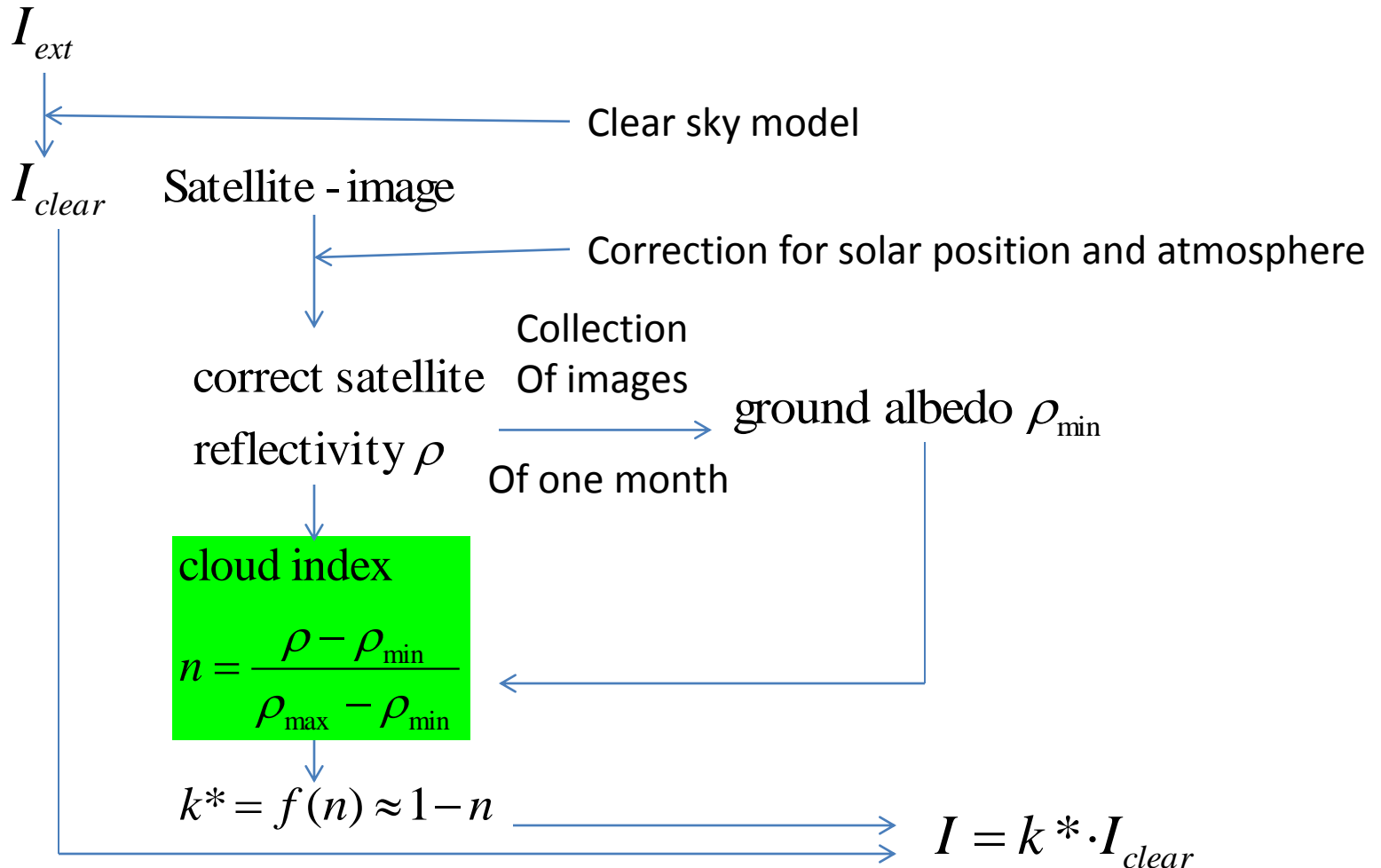
Satellite Imagers
(1-5 hr)



Numerical Weather Prediction
(NWP) (> 5 hr)

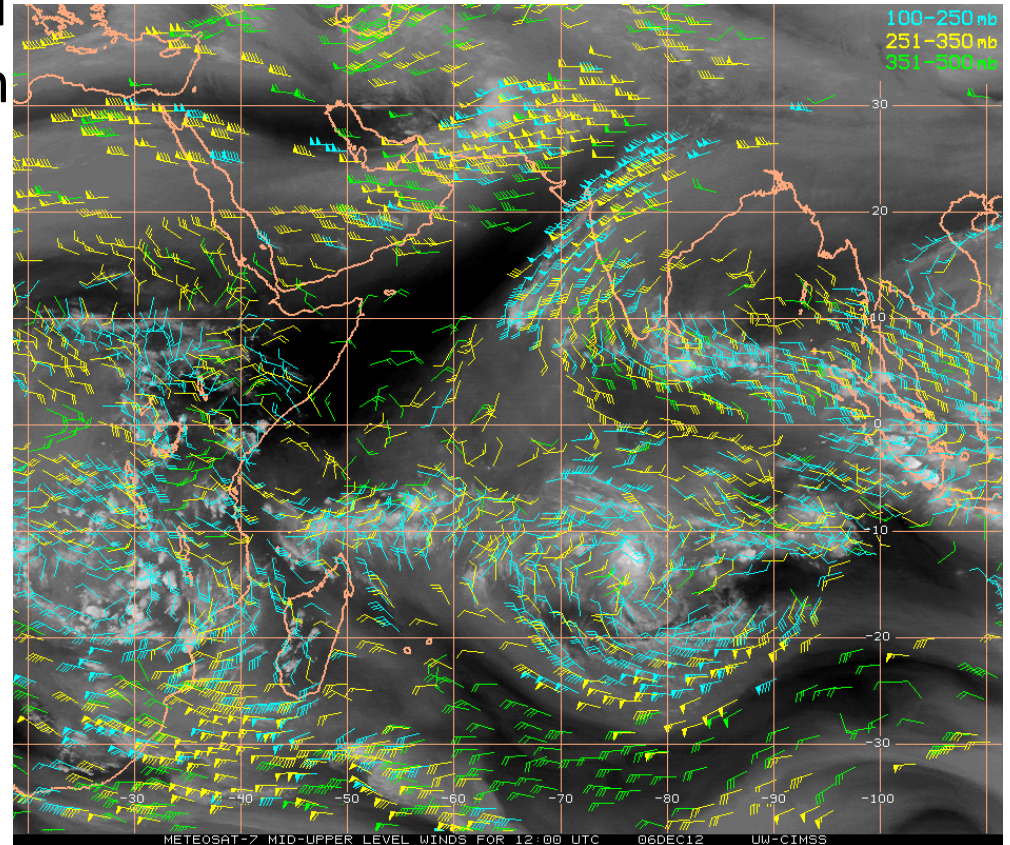
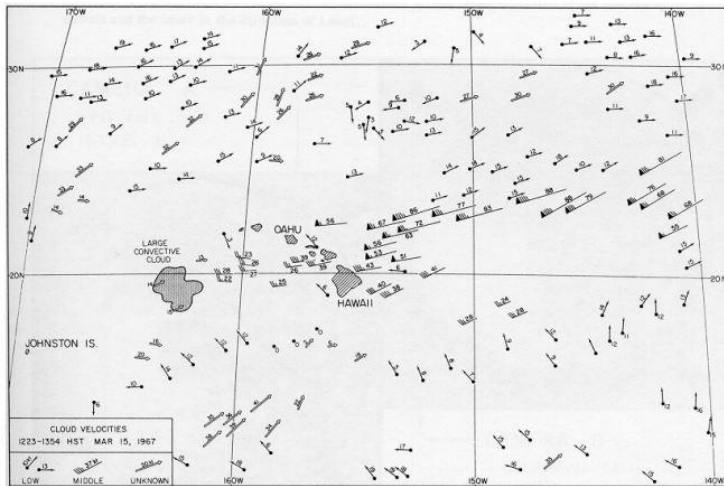
Irradiance from satellite data: HELIOSAT

(simplified from Hammer et al 2003)



Cloud tracking

- Since 1960s (PV ~1970s)
- 2001, National Environmental Satellite, Data and Information Service (NESDIS) – 3-hrly automatically generate winds



Cloud tracking (cont.)

Velocity Assessment –

small cloud ->

Tracer selection->

Spatial-correlation analysis

Height Assignment –

-> shadow

-> Infrared Window technique,

CO2 slicing technique,

water vapor intercept technique

Properties–

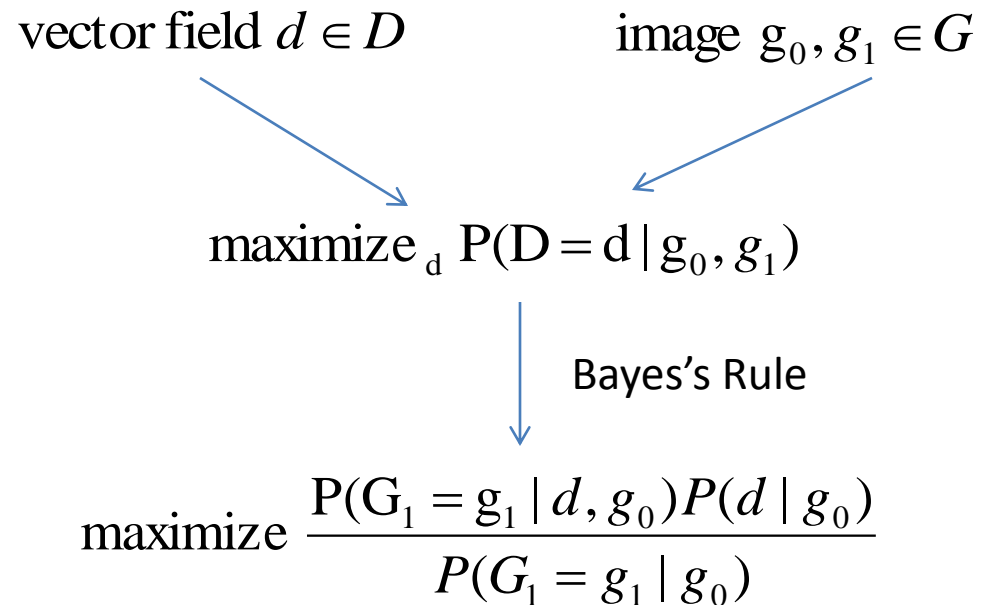
-> cloud motion vectors not for all pixels

-> height assessment needed extra analysis

-> Constancy assumption

Cloud Motion Vectors I

- Statistical method for the estimation of motion (Hammer et al 1999, Konrad and Dubois 1992)
- Probabilistic model of random vector fields



Cloud Motion Vectors I (cont.)

Constancy: $n_1(x+d) = n_0(x)$ \longrightarrow $P(r) \approx \exp(\sum -r_i^2 / 2\sigma^2)$:
 $r_i = n_1(x_i + d_i) - n_0(x_i)$

$P(G_1 = g_1 | d, g_0)$

Gaussian Random Surface w/ zero mean

Gradient Constancy:

$\text{grad}(n_1)(x+d) =$
 $\text{grad}(n_0)(x)$



$P(r_g) \approx \exp(\sum -r_{g,i}^2 / 2\sigma^2)$:
 $r_i = \text{grad}(n_1)(x_i + d_i) - \text{grad}(n_0)(x_i)$

$P(D = d | g_0)$

Theory of Markov Random Fields



$P(D = d | g_0) = c_3 \exp(-U_d / \beta)$

$U_d = \sum_{i,j \in N} \|d(x_i) - d(x_j)\|^2$

Cloud Motion Vectors I (cont.)

$$\text{maximize}_d P(D = d/g_0, g_1) \equiv \text{maximize}_d \frac{1}{Z} \exp(-U);$$

$$U = \lambda_1 U_n + \lambda_2 U_{grad(n)} + \lambda_3 U_d$$

$$U_n = \sum_i (n_1(x_i + d_i) - n_0(x_i))^2$$

$$U_{grad(n)} = \sum_i (\text{grad}(n_1)(x_i + d_i) - \text{grad}(n_0)(x_i))^2$$

Solved by Simulated Annealing: extend probability by 'temperature' T and do random search w/ scheme to escape from local minima

Comment: Constancy, Gradient Constancy, Continuous flow, Initial condition Problem

Cloud Motion Vectors II

- Optical Flow computation (Koltakov et al. 2012)
- Lucas-Kanade Algorithm (1961)
- Constancy assumption

Constancy:

$$n(x_1, x_2, t) = n(x_1 + \delta x_1, x_2 + \delta x_2, t + \delta t)$$

↓ Taylor Expansion

$$\frac{\partial n}{\partial x_1} \delta x_1 + \frac{\partial n}{\partial x_2} \delta x_2 + \frac{\partial n}{\partial t} \delta t = 0$$

$$\text{grad}(n)^T V = -n_t$$

$V = d$ in one time step

One equations with 2 unknowns!

Cloud Motion Vectors II (cont.)

Assume a group of pixels has same velocity V

$$\text{grad}(n)^T V = -n_t$$

If number of pixels in group > 2 ,
Not simultaneously solvable

$$\text{grad}(n(x_1))^T V = -n_t(x_1)$$

...

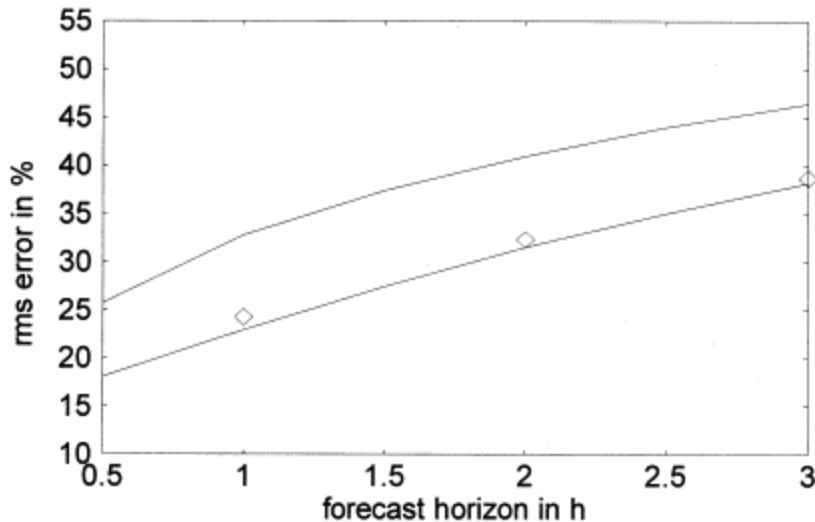
$$\text{grad}(n(x_k))^T V = -n_t(x_k)$$

Convert it to weighted least-square problem $\min \sum_{x_i \in \Omega} W(x_i) [\text{grad}(n(x_i))^T V + n_t(x_i)]^2$

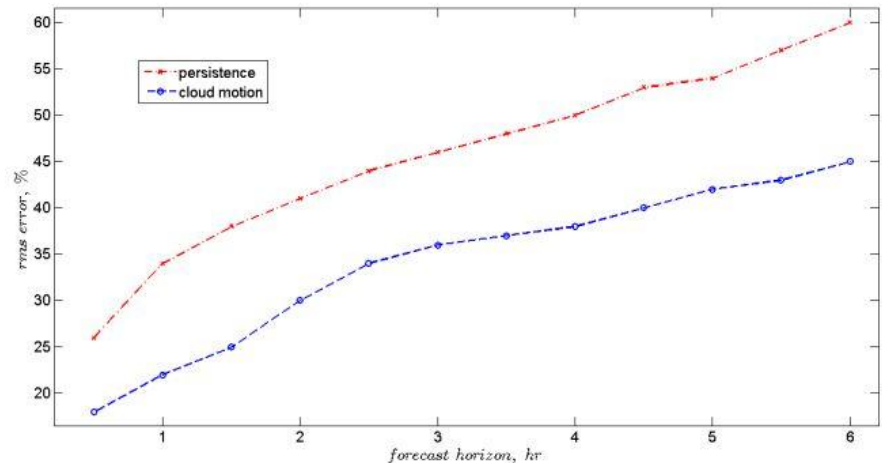
Comment: Constancy, Continuous flow, No Gradient constancy, Large Motion Problem (solved by multi-resolution image), Choice of group (nxn squares)

Cloud Cover Forecast

- Use velocity vector – simply first order equation of motion



Hammer et al (1999)



Koltakov (2012)

Comment: Same Accuracy, Better computation efficiency
Constancy assumption

Some Thoughts

- Constancy assumption
- Height, thickness of clouds
- Correlation between pixels
- Vector Calculus
- Other forms of optimization problem
- Utilization of Cloud Tracking Techniques
- How to cooperate with other prediction methods & other parameters