Short-term solar forecasting with statistical models and combination of models

Philippe Lauret, Mathieu David
PIMENT Laboratory, University of La Réunion
L. Mazorra Aguiar
University of Las Palmas de Gran Canaria

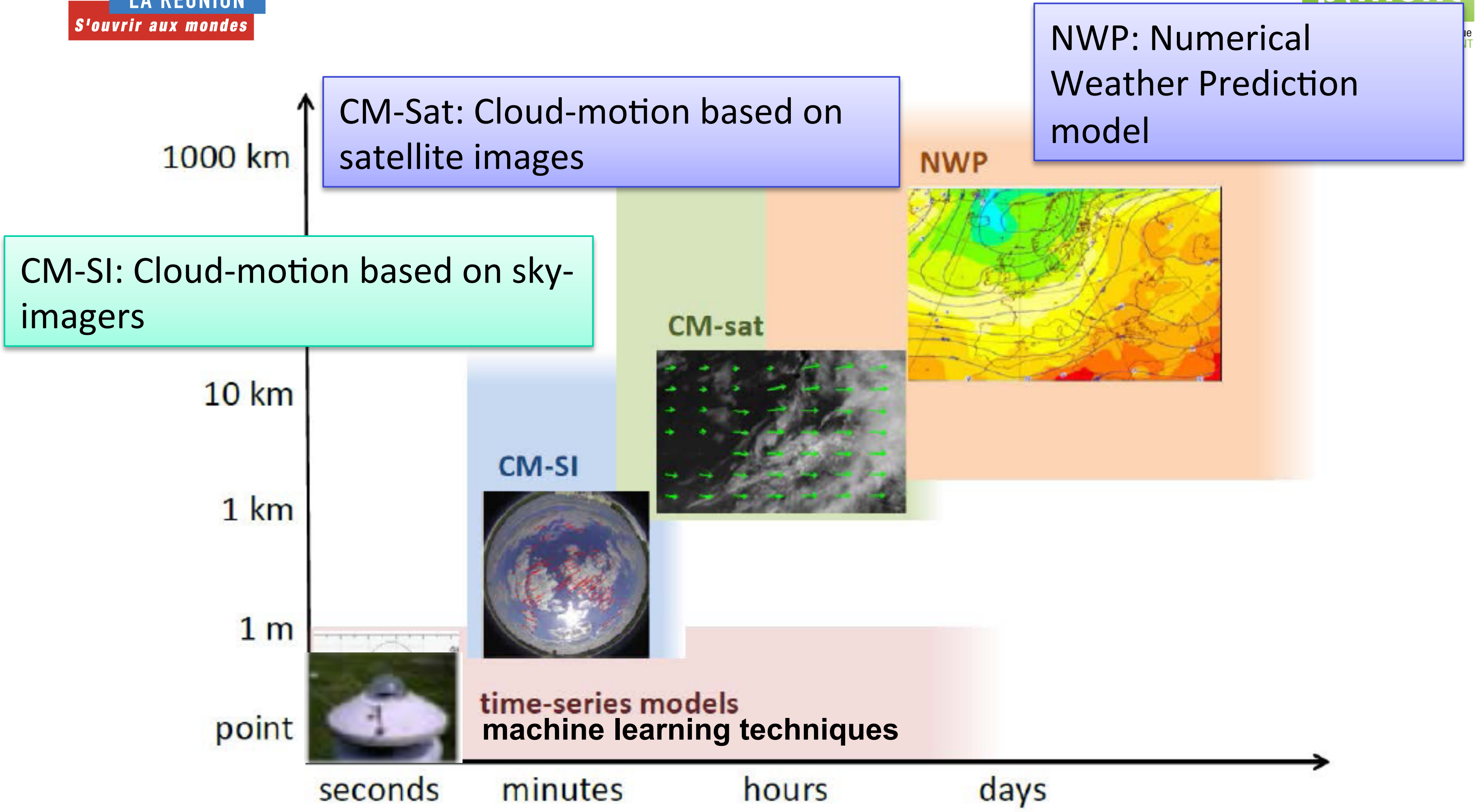
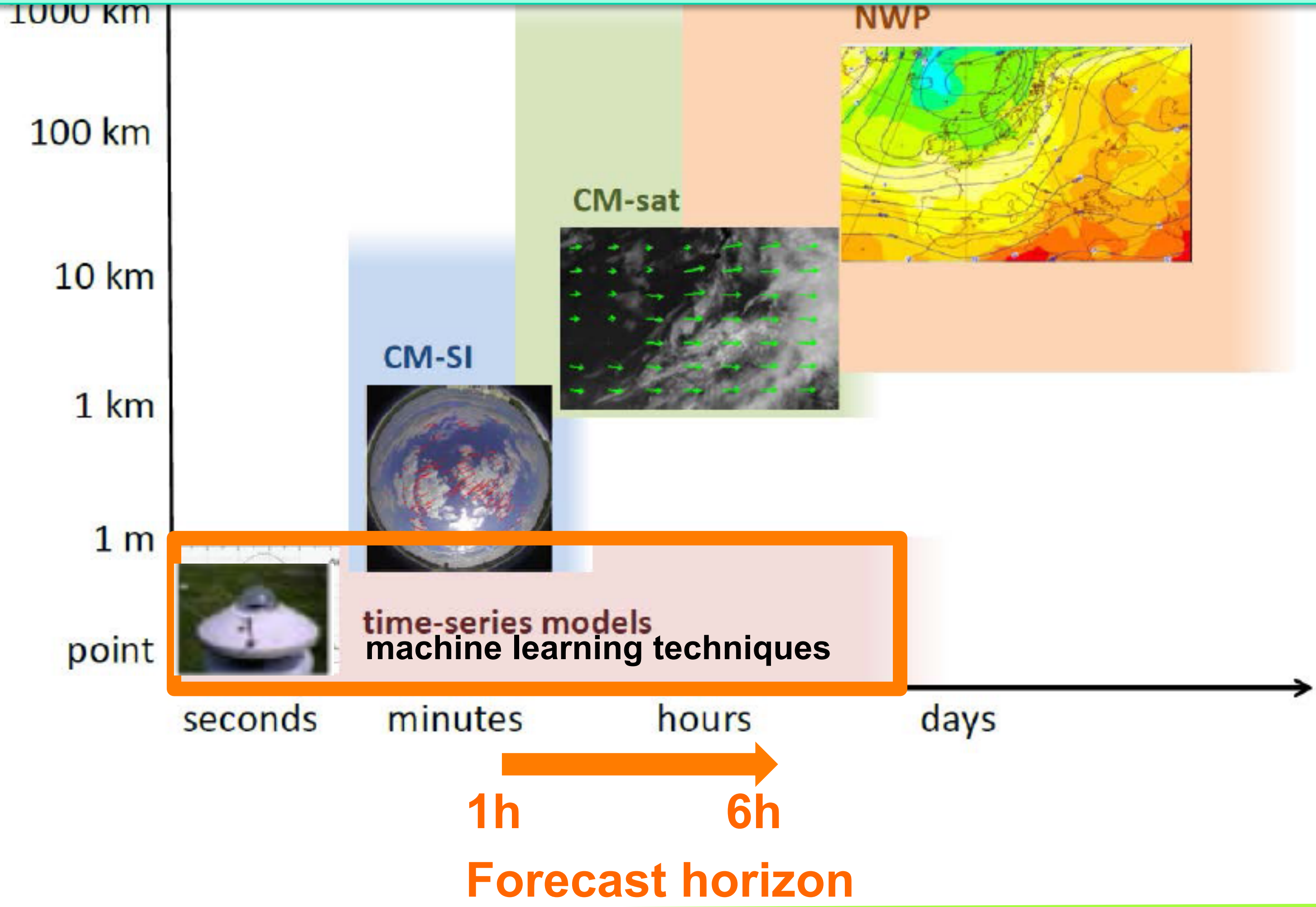
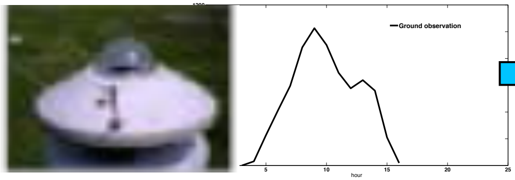


Figure from "Best Practices Handbook for the Collection and Use of Solar Resource Data for Solar Energy Applications", Tech. Report, NREL/TP-5D00-63112. Available online:http://www.nrel.gov/docs/fy15osti/63112.pdf

Focus on intra-day solar forecasting i.e predictions of the solar irradiance from 1h up to 6 hours in the future

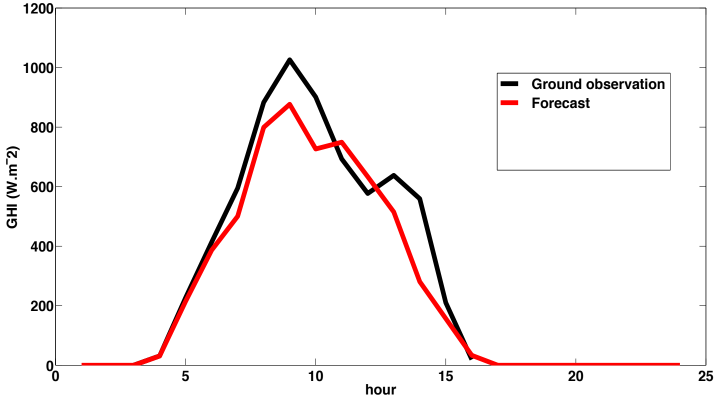


Past ground measurements of GHI



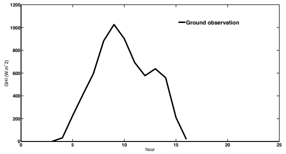
Forecasting model

GHI forecasts



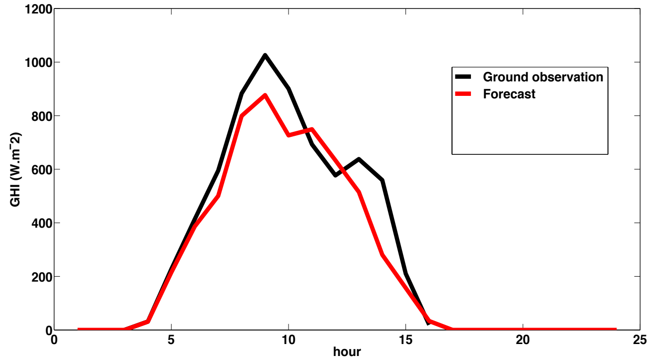
GHI: Global Horizontal Irradiance

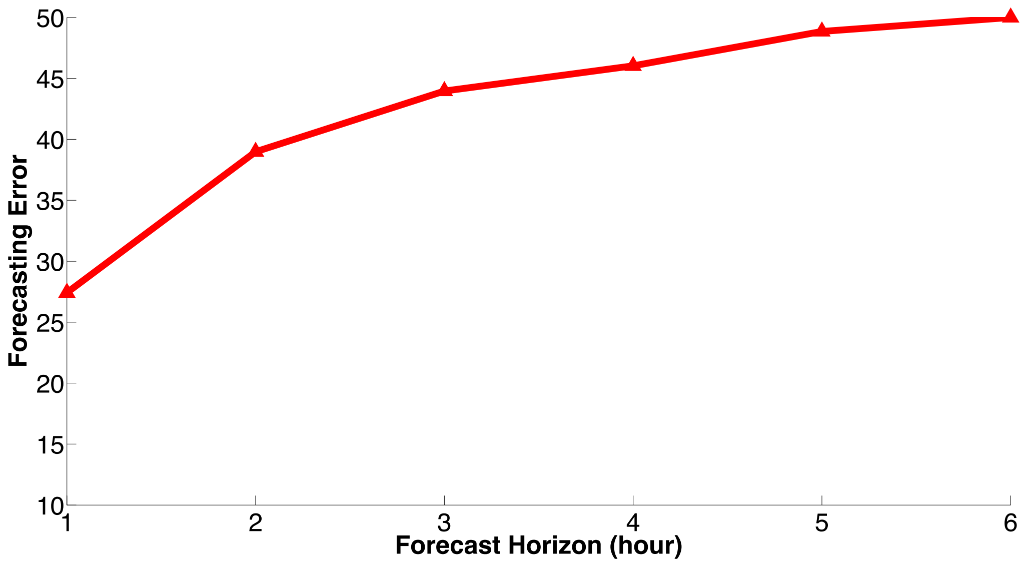
Past ground measurements of GHI



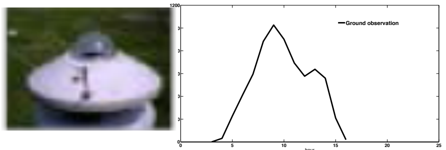
Forecasting model

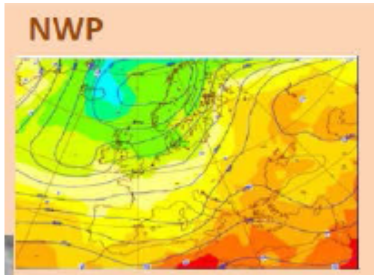
GHI forecasts





Past ground measurements of GHI





Forecasting model

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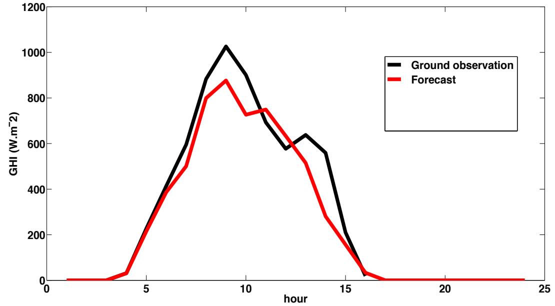
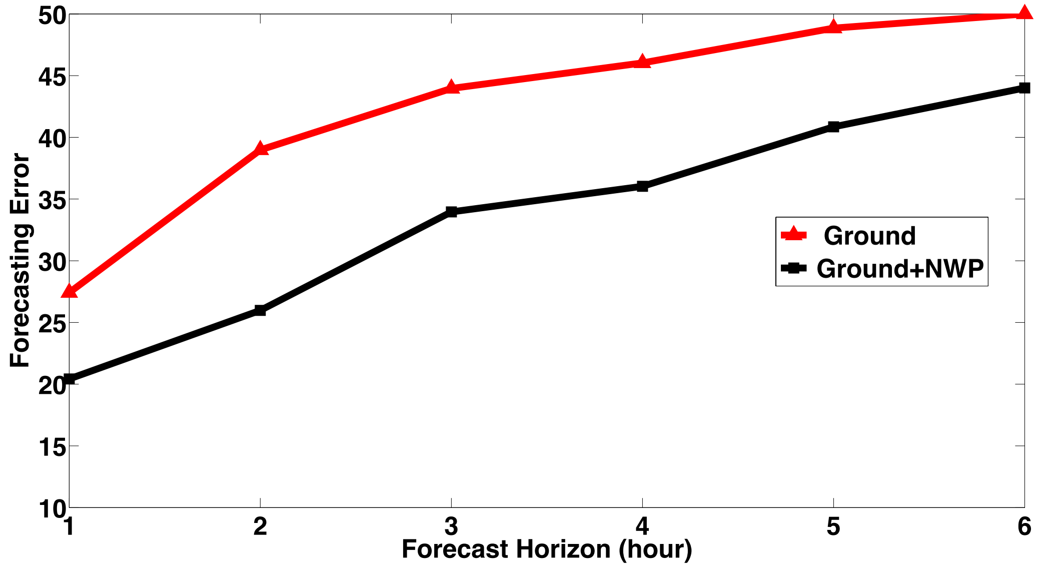
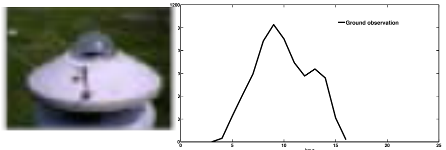
GHI forecasts

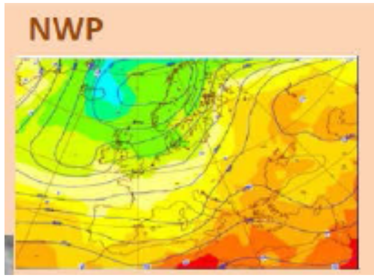




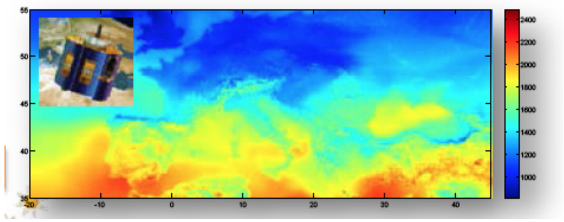
Past ground measurements of GHI



NWP



Satellite data



Forecasting model

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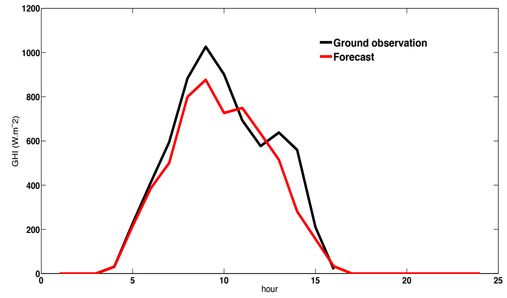
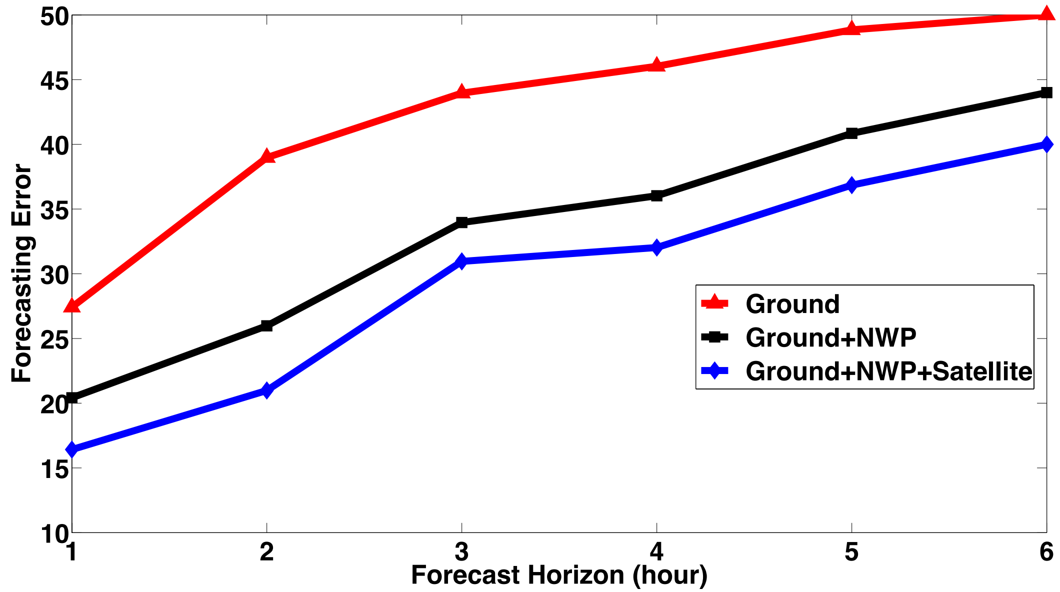
GHI forecasts



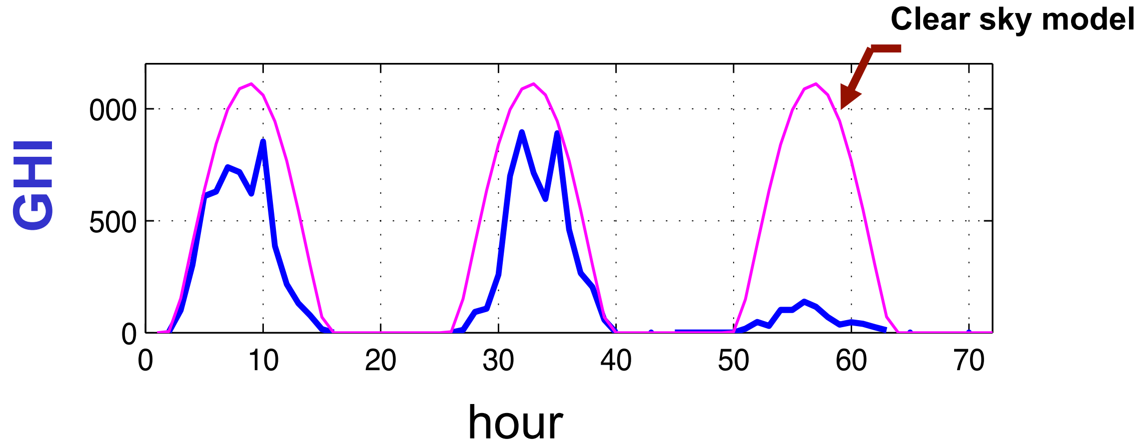


2 stations from the SURFRAD network:
Desert Rock and **Fort Peck**

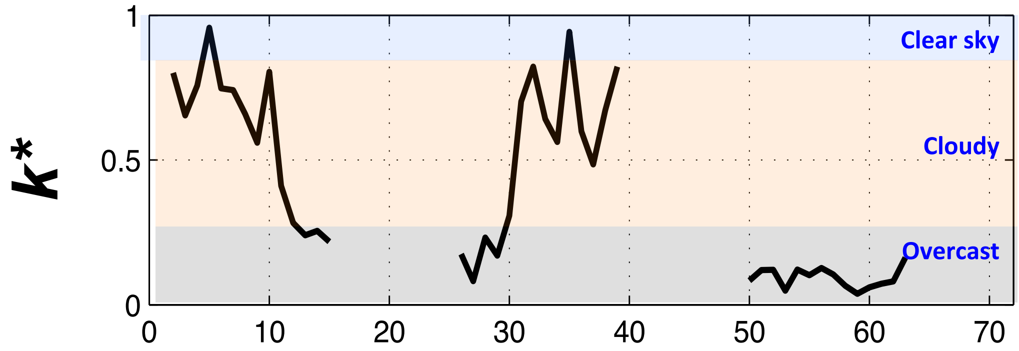
SURFRAD Network, Monitoring Surface Radiation in the Continental United States. Available online: http://www.esrl.noaa.gov/gmd/grad/surfrad/index.html

Sites for intra-day solar forecasting

3 insular sites: La Réunion island (2) and Gran Canaria island

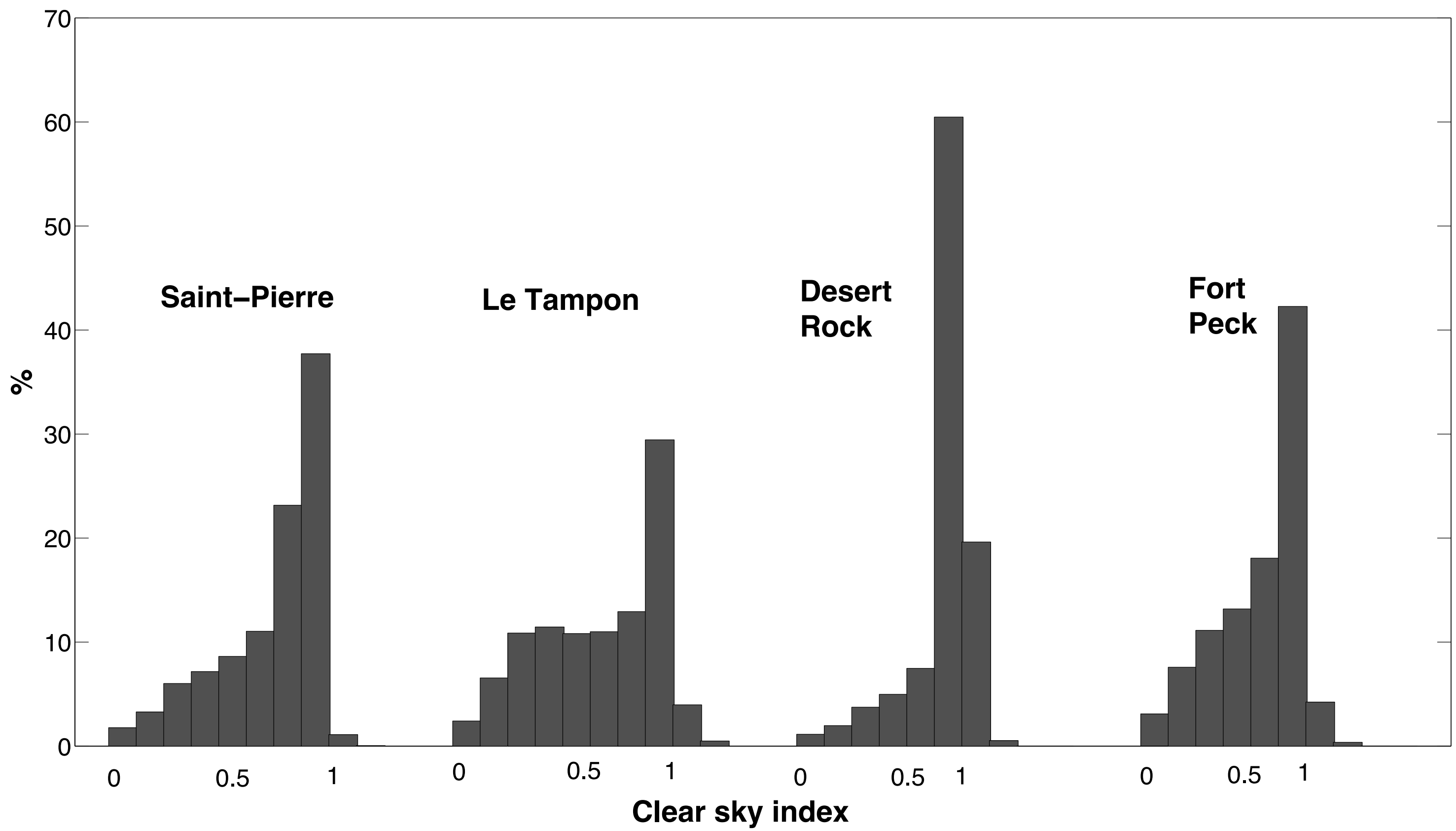


Clear sky index: $$k^* = \frac{GHI}{GHI_{Clear}}$$



Forecasting models are fitted to the clear sky index time series

Sky conditions analysis



Solar variability	intermediate	high	low	intermediate

Benchmarking of the forecasting models

2 references models: Persistence and climatological mean

1 time series model model (ARMA model) with recursive estimation of the parameters

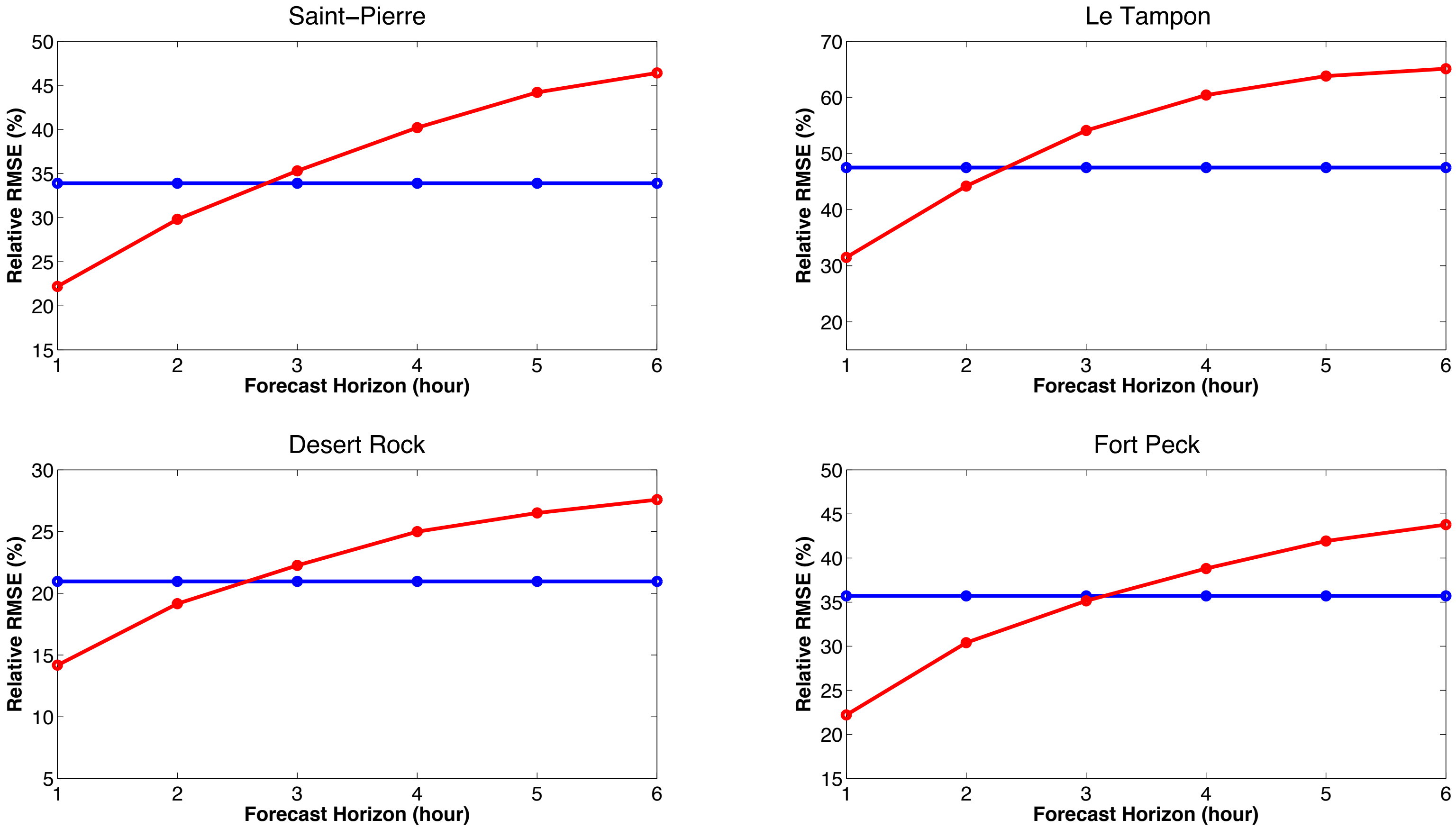
1 machine learning technique (Artificial Neural Network)

Evaluation of the forecasting performance :

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(GHI_{forecast.i} - GHI_{measured.i}\right)^2}$$

Forecast skill parameter: $s(\%) = \left(1 - \frac{RMSE_{method}}{RMSE_{pers}}\right)\times 100$

Results - Reference models

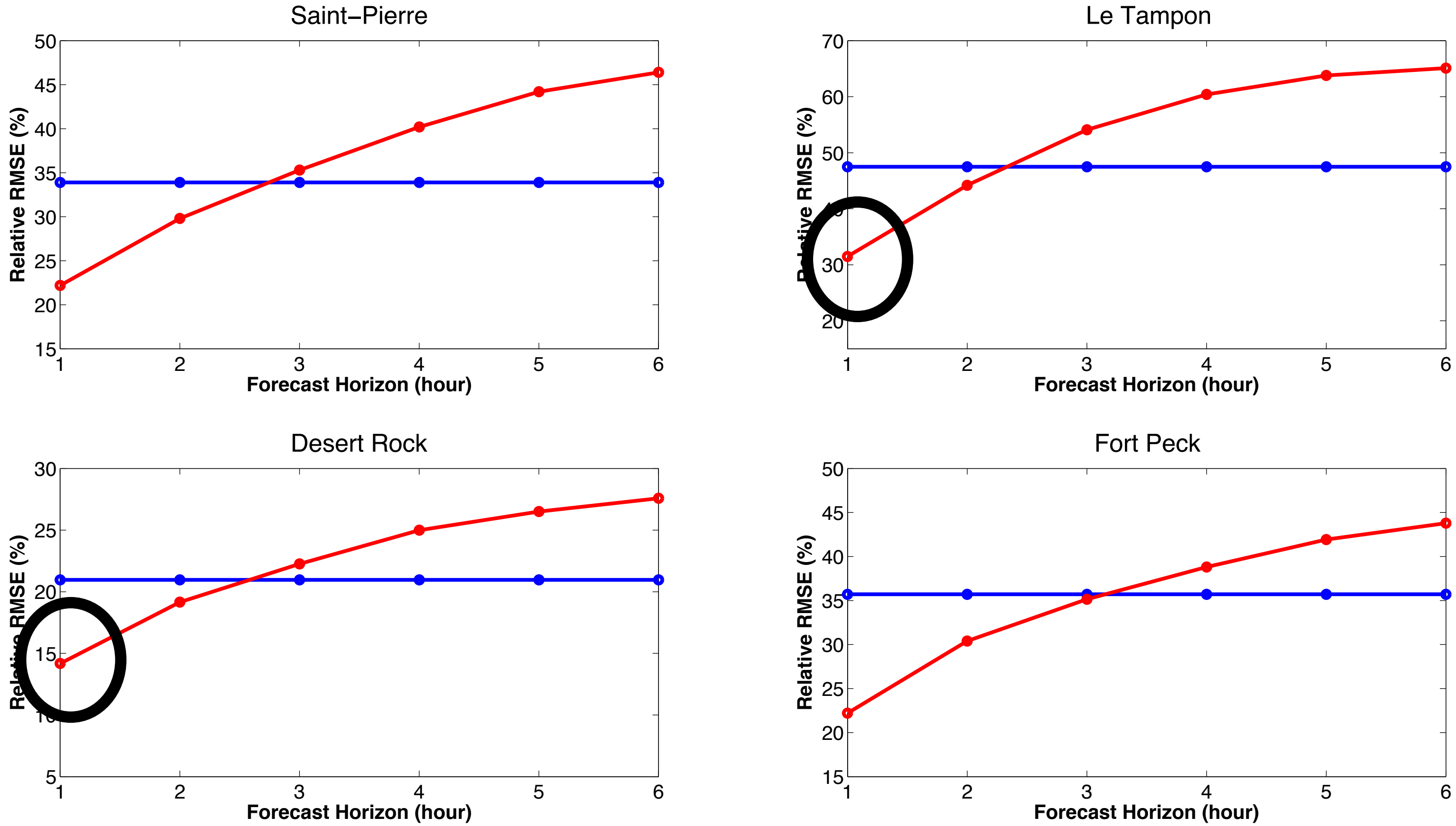


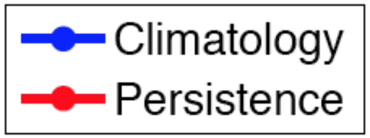
Climatology
Persistence

$$\widehat{k^*}(t+h) = mean\ (k^*)$$

$$\widehat{k^*}(t+h) = k^*(t)$$

Results - Reference models



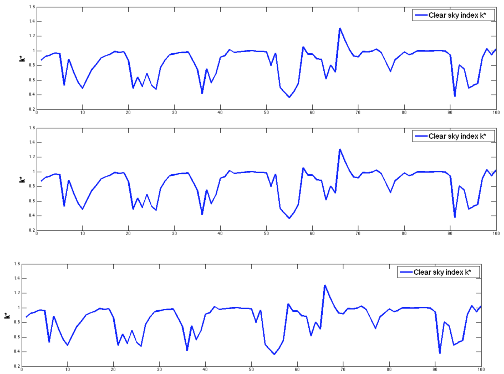


$$\widehat{k^*}(t+h) = mean\ (k^*)$$

$$\widehat{k^*}(t+h) = k^*(t)$$

Past ground measurement values of *k**

Forecasted *k** for time horizon *h*



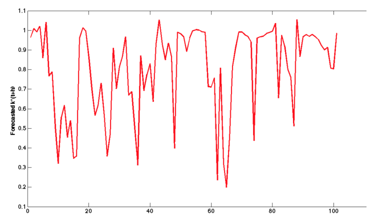
$k^*(t)$

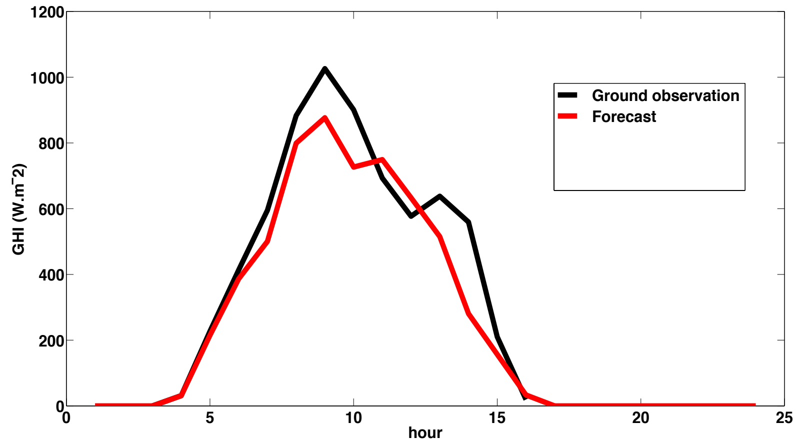
$k^*(t-1)$

$k^*(t-2)$

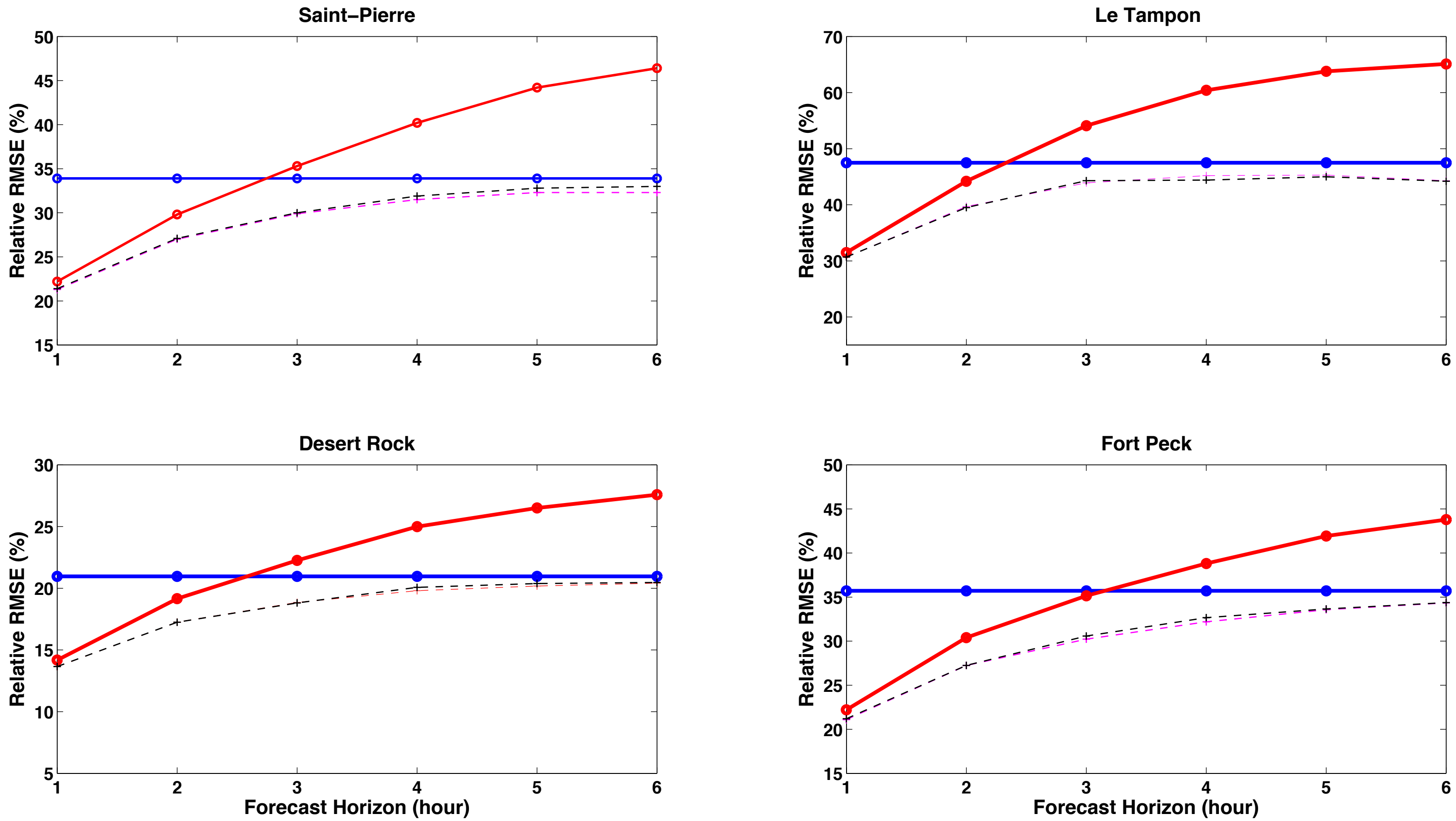
Forecasting model

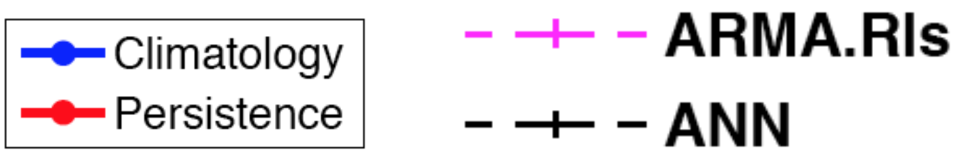
$k^*(t+h),\ h=1,2,3\ldots,6$

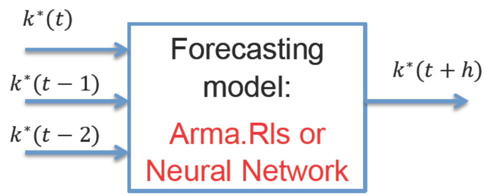




Results – Use of ground data only



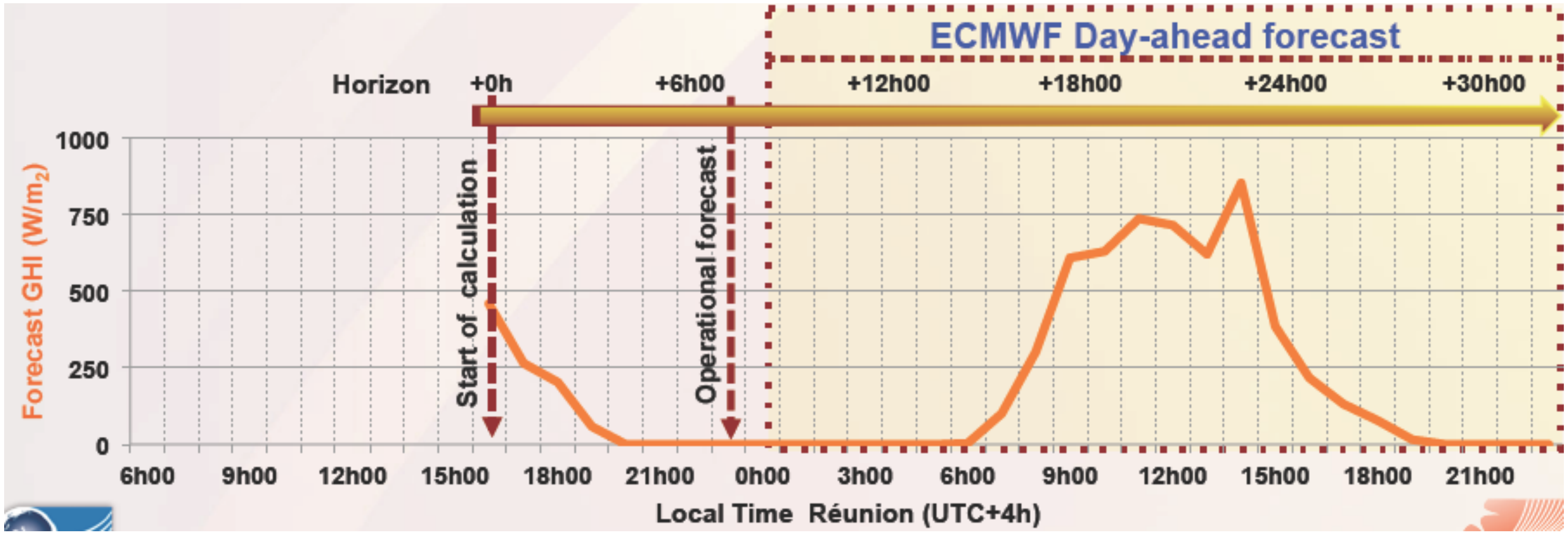




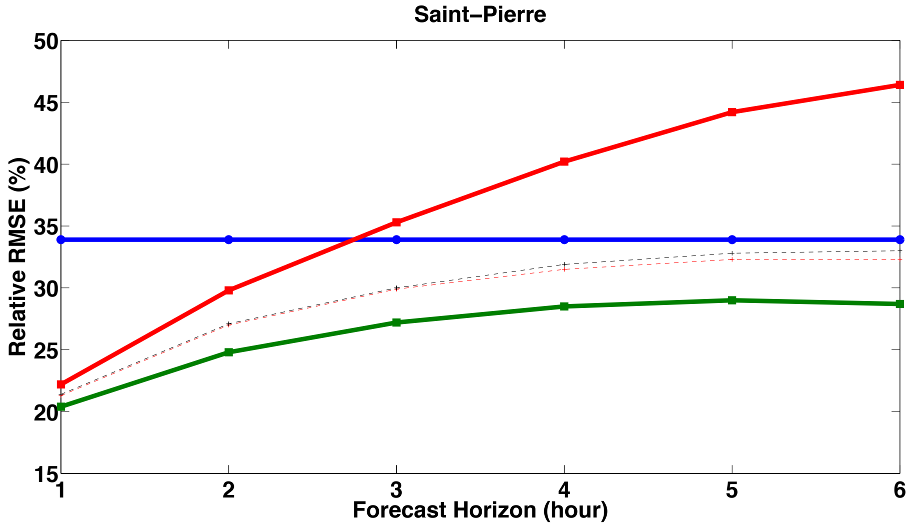
Use of exogenous inputs provided by NWP models

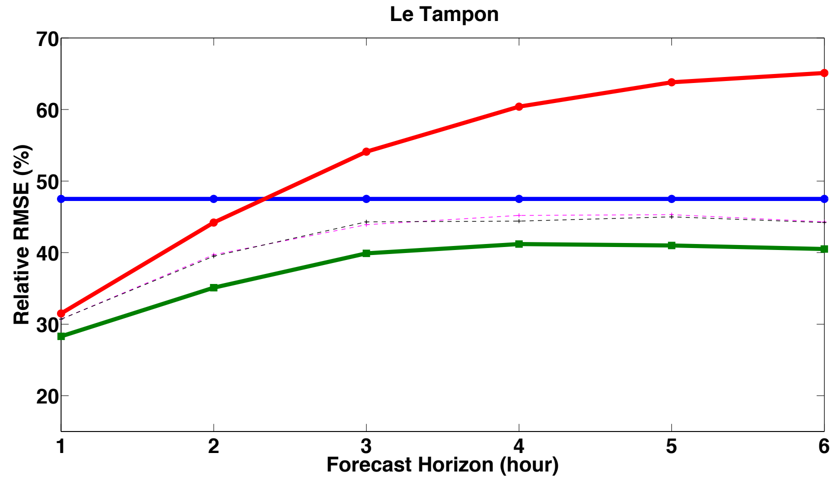
GHI and TCC forecasts provided by the European Centre for Medium Range Weather Forecasts (ECMWF)

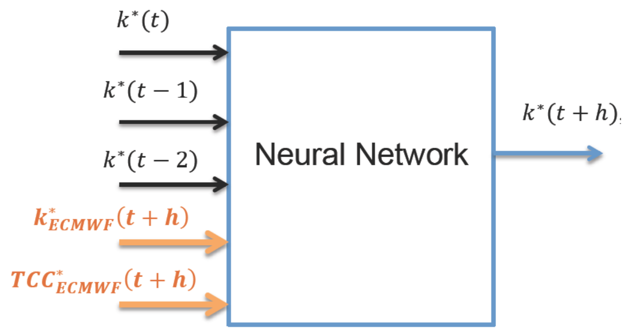
- IFS model
- Generated at 12h00 UTC (16h00 in Reunion)
- Available at 18h55 UTC (22h55 in reunion)
- Spatial resolution: 0.125° x 0.125° (≈ 14 x 14 km near Reunion)
- Temporal resolution: 1 hour



Results – Combination of Ground and ECMWF data







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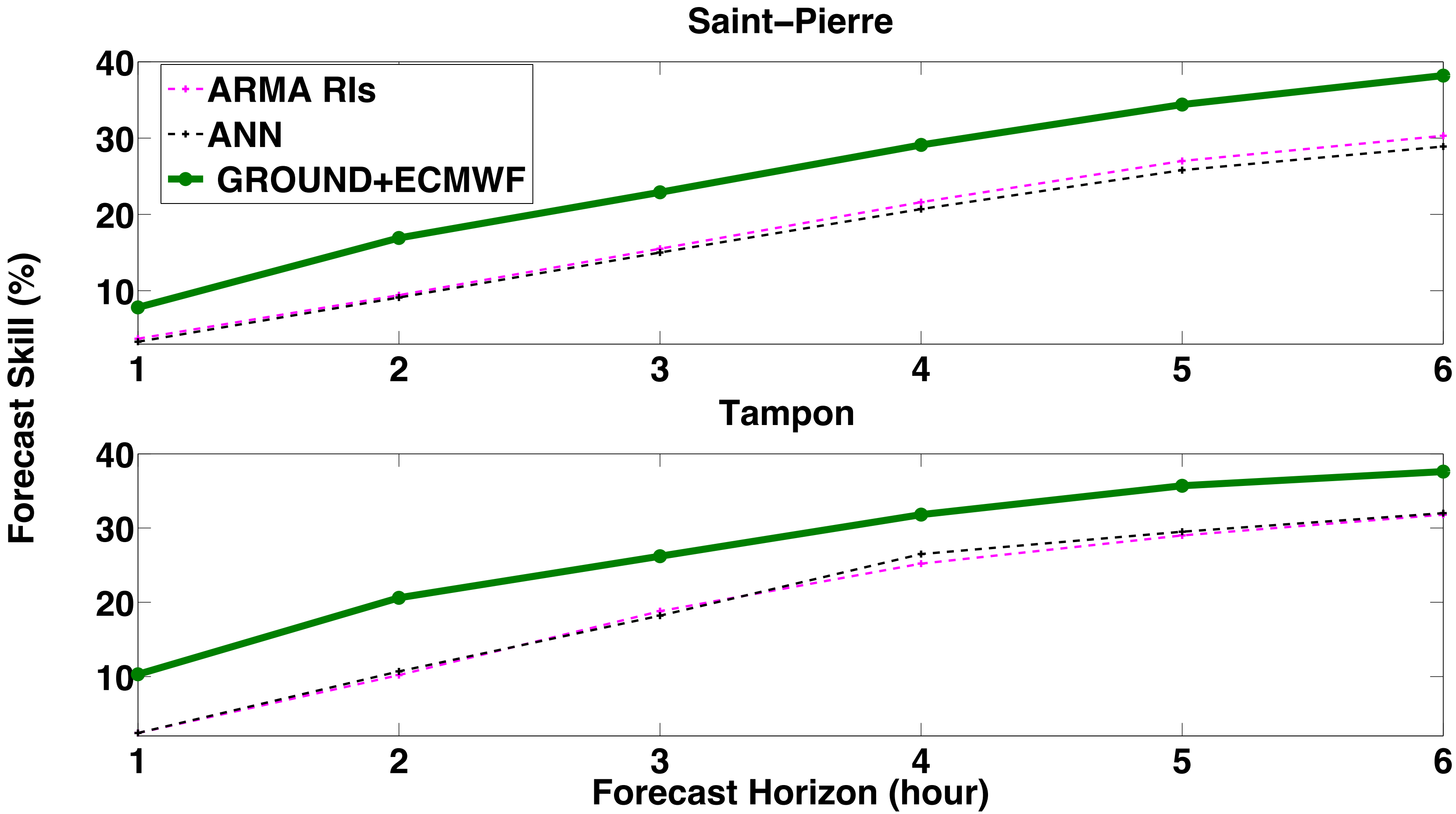


✓ higher values of s-skill scores are obtained with the combination of on-site measured irradiance and NWP model output

Exogenous inputs provided by Satellite data

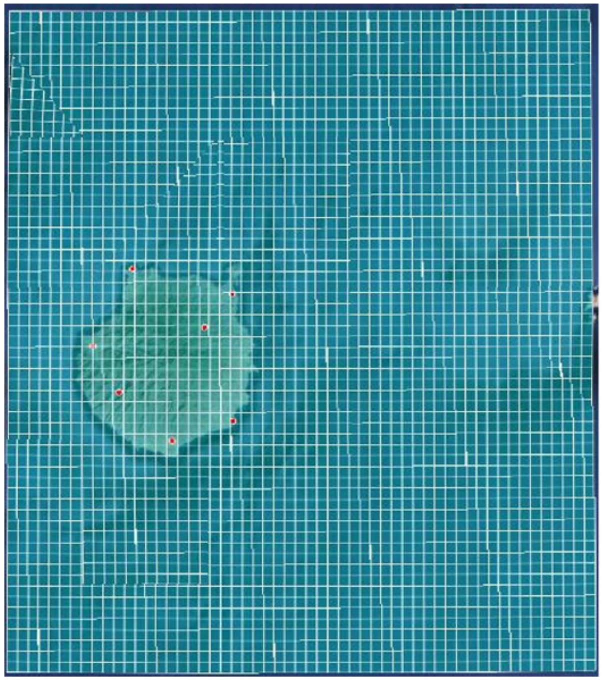


Fig. 1. Geographic distribution of satellite-derived data obtained from HC3v5 for Gran Canaria Islands. Courtesy of *MINES ParisTech/ ARMINES.*

Satellite-derived GHI for Gran Canaria obtained from HelioClim solar radiation databases

- Spatial resolution: 3 km x 3km
- Temporal resolution: 15 mins

Selection of Satellite pixels

Selection of satellite pixels by calculating the cross-correlation between ground clear sky index and satellite clear sky indices:

$$C_{k^*}(i,j)_h = corr\left(k^*_{ground}(t), k^*_{satellite}(t-h)\right) \quad for \quad h = 0, 1, 2 \;\&\; 3$$

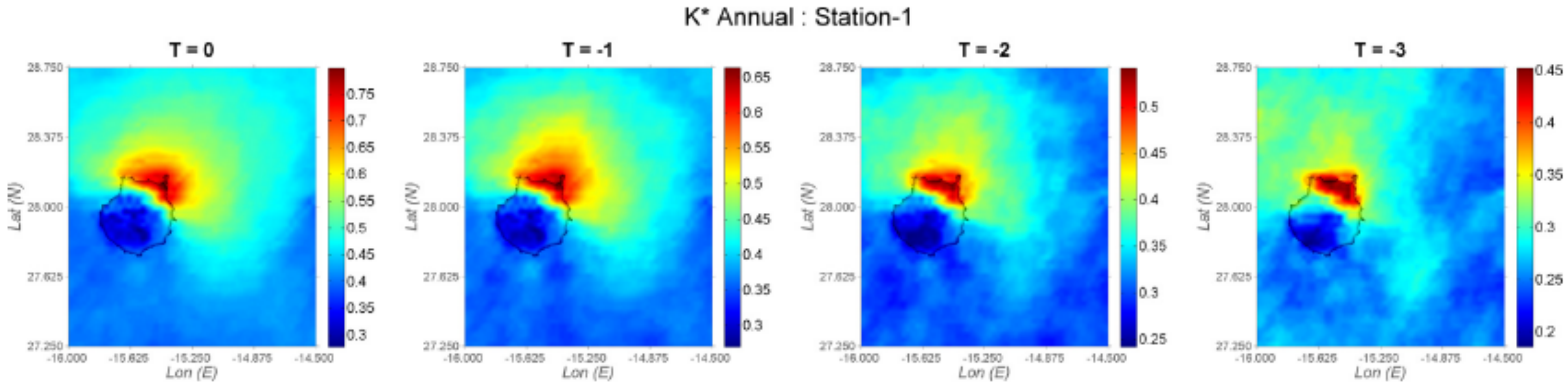
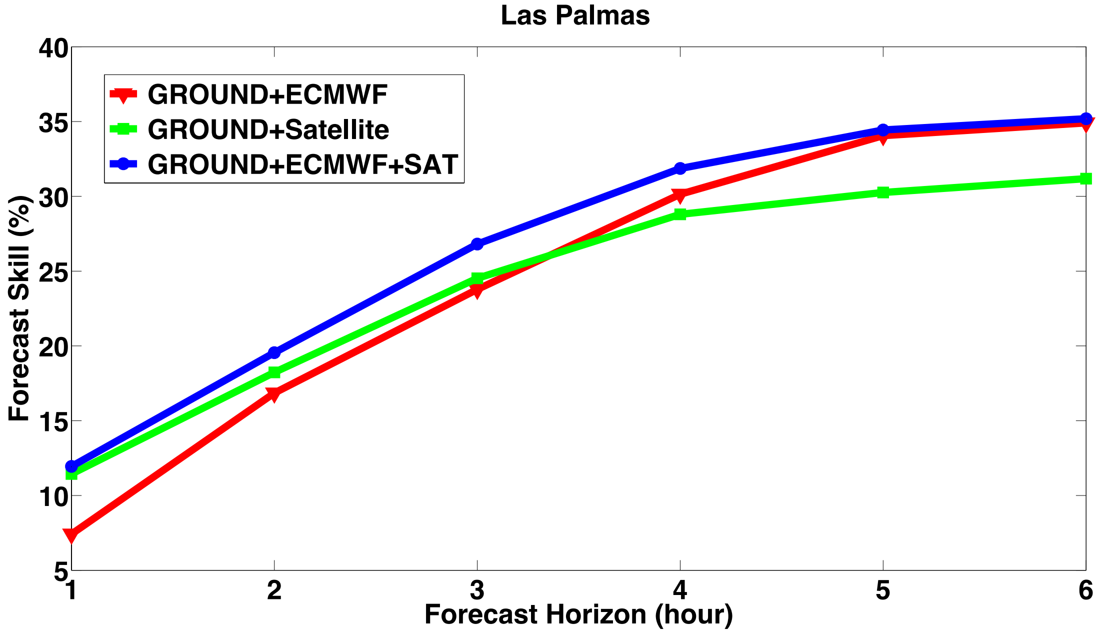
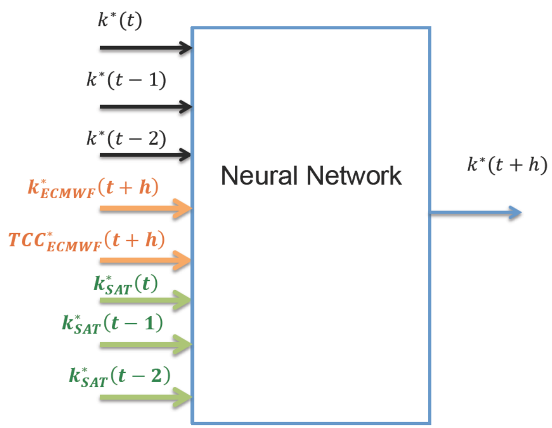


Fig. 8. Intercorrelation annual map for clear sky index between ground measurement and each satellite pixel around the measurements at station C1 – Las Palmas for time lag $h = 0$, 1, 2 and 3 h.





- ✓ Overall, the forecast skill of the combination GROUND+ECMWF+SAT is better than the forecast skill of the two other models GROUND+ECMWF and GROUND+SAT

✓ Use of exogenous inputs (such as those provided by NWP models or Satellite data) improve the accuracy of the intra-day solar forecasts.

Further investigations:

◆ Use of other input paramters e.g. wind fields, humidity, cloud height provided by a NWP model

◆ Implementation of ECMWF forecasts in an ARMAX Recursive Least Square model

Further readings: Use of exogenous inputs in forecasting models:

A. Zagouras, H. Pedro and C. Coimbra, "On the role of lagged exogenous variables and spatio-temporal correlations in improving the accuracy of solar forecasting methods," Renewable Energy, vol. 78, pp. 203-2018, 2015.

B. Marquez, R., Coimbra, C.F.M., 2011. Forecasting of global and direct solar irradiance using stochastic-learning methods, ground experiments and the NWS database. Solar Energy 85, 746–756.

C. R. Dambreville, P. Blanc, J. Chanussot and D. Boldo, "Very short term forecasting of the Global Horizontal Irradiance using a spatio-temporal autoregresive model," Renewable Energy, vol. 72, pp. 291-300, 2014.

D. C.Voyant, M. Muselli, C. Paoli and M.L Nivet, « Numerical weather prediction (NWP) and hybrid ARMA/ANN model to predict global radiation", Energy, Energy, Volume 39, Issue 1, March 2012, Pages 341-355.

E. L. Mazorra Aguiar, B. Pereira, M. David, F. Diaz and P. Lauret, «Use of satellite data to improve solar radiation forecasting with Bayesian Artificial Neural Networks,» Solar Energy, vol. 122, pp. 1309-1324, 2015.

F. Bacher, P.; Madsen, H.; Nielsen, H.A. (2009). "Online Short-Term Solar Power Forecasting." Solar Energy (83); pp. 1,772–1,783.

G. P. Lauret, E. Lorenz, M. David. «Solar Forecasting in a Challenging Insular Context» accepted for publication in Atmosphere journal, ISSN 2073-4433, www.mdpi.com/journal/atmosphere.