Solar Energy Forecasting Advances and Impacts on Grid Integration

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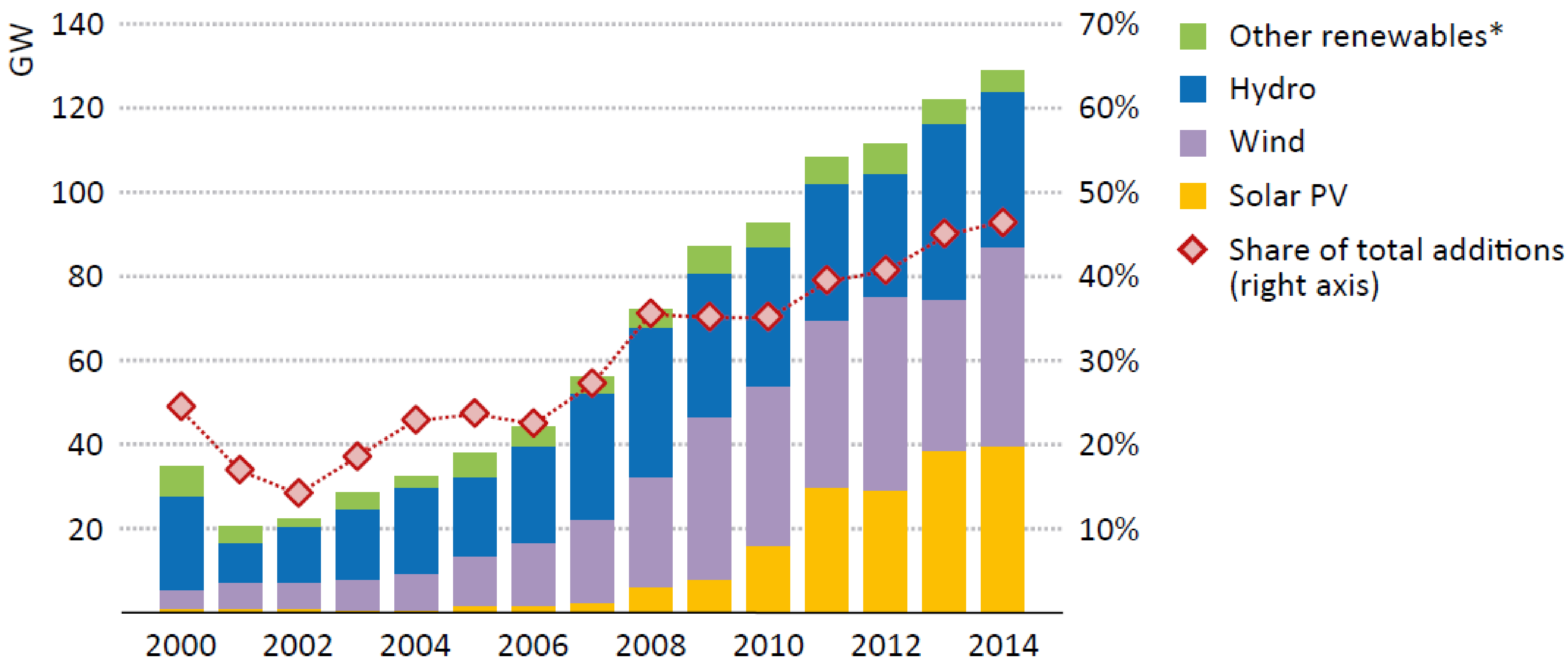
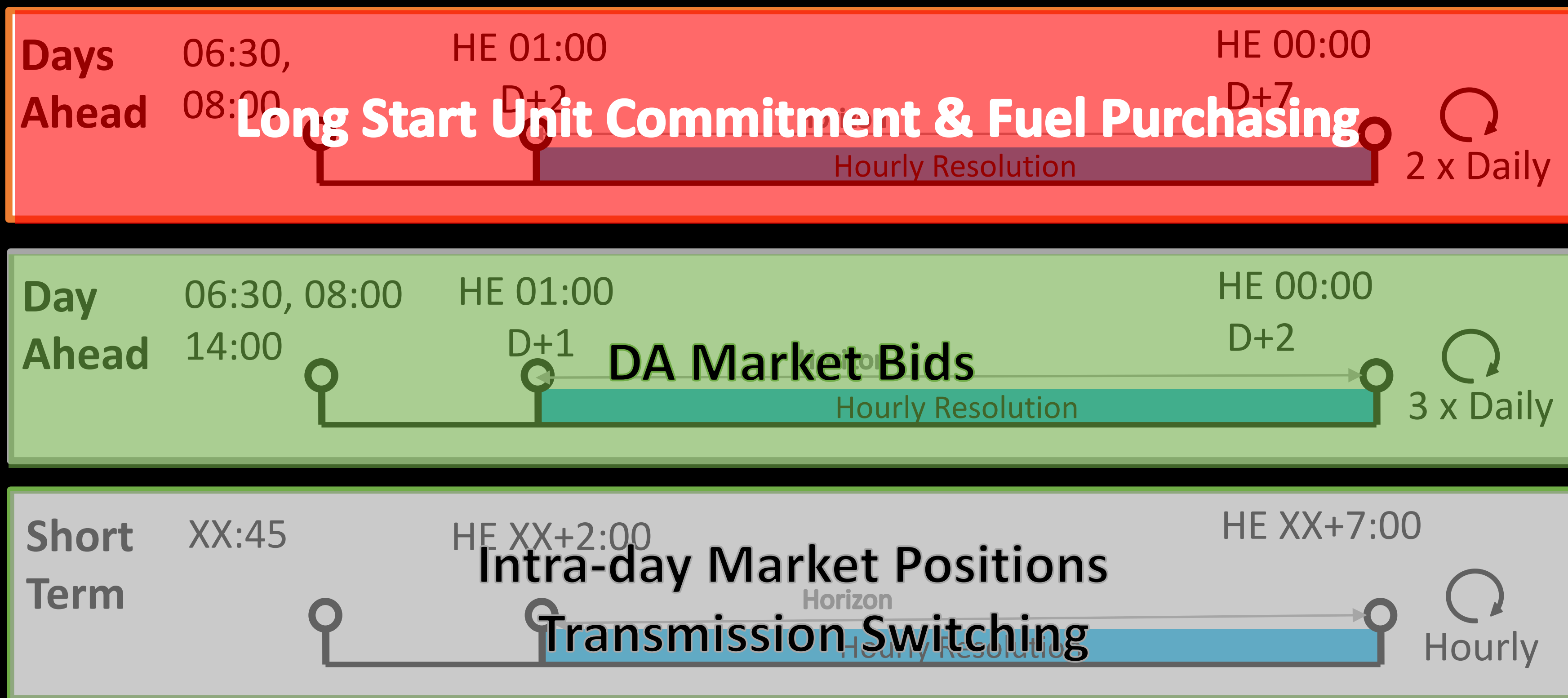
Global renewables-based power capacity additions by type and share of total capacity additions



* Includes geothermal, marine, bioenergy and concentrating solar power.

Source: International Energy Agency (IEA) – Energy and Climate Change – World Energy Outlook Special Report (2015).

Time Horizons for Energy Markets



Lannoye, Tuohy, EPRI (2015)

Outline

- Grid Integration Case Studies
  - Day-ahead forecast for unit commitment
  - Storage operation for PV smoothing
  - Sky imager forecast for distribution system voltage control
- Solar Forecasting Advances
  - Forecast Accuracy Metrics
  - Forecast Technologies
    - Numerical Weather Prediction
    - Sky imager
    - Satellite
  - IEA Task 46
- Future Research

- What is the value of improving DA solar power forecasts?
- And what are the impacts on bulk power system operations?

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Solar Energy 129 (2016) 192–203
SOLAR ENERGY
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The value of day-ahead solar power forecasting improvement

Carlo Brancucci Martinez-Anido [a], Benjamin Botor [a], Anthony R. Florita [a], Caroline Draxl [a], Siyuan Lu [b], Hendrik F. Hamann [b], Bri-Mathias Hodge [a,*]

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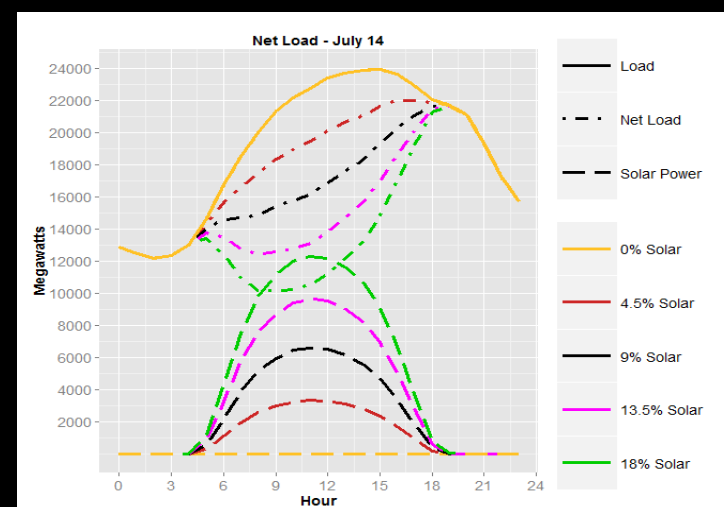
Received 25 November 2015; received in revised form 21 January 2016; accepted 25 January 2016
Available online 17 February 2016

Communicated by: Associate Editor Jan Kleissl

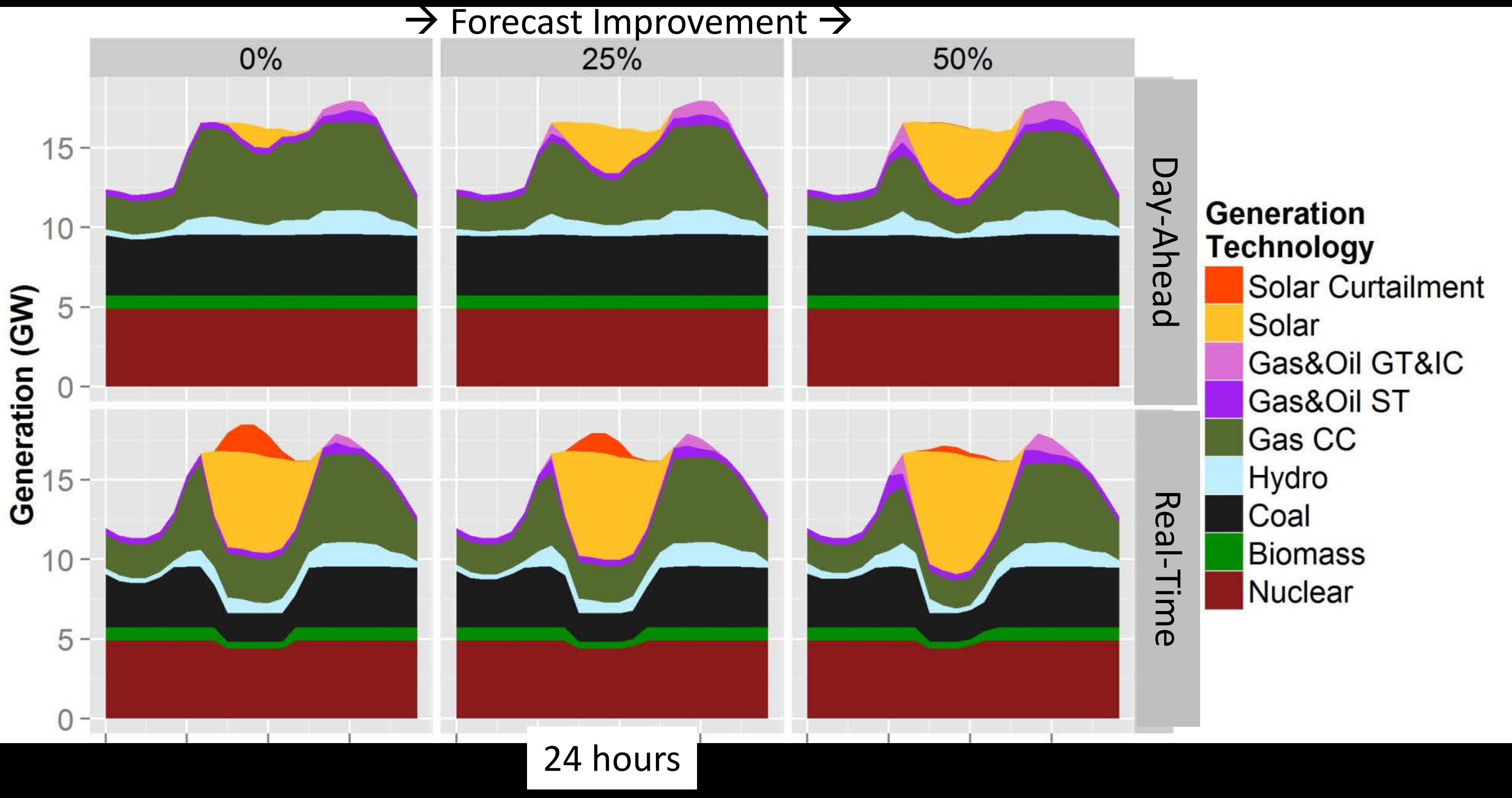
Scenarios for each solar power penetration level (4.5% / 9.0% / 13.5% / 18.0%)

- DA forecasts: 25% uniform improvement
- DA forecasts: 50% uniform improvement
- DA forecasts: 75% uniform improvement
- DA forecasts: 100% uniform improvement



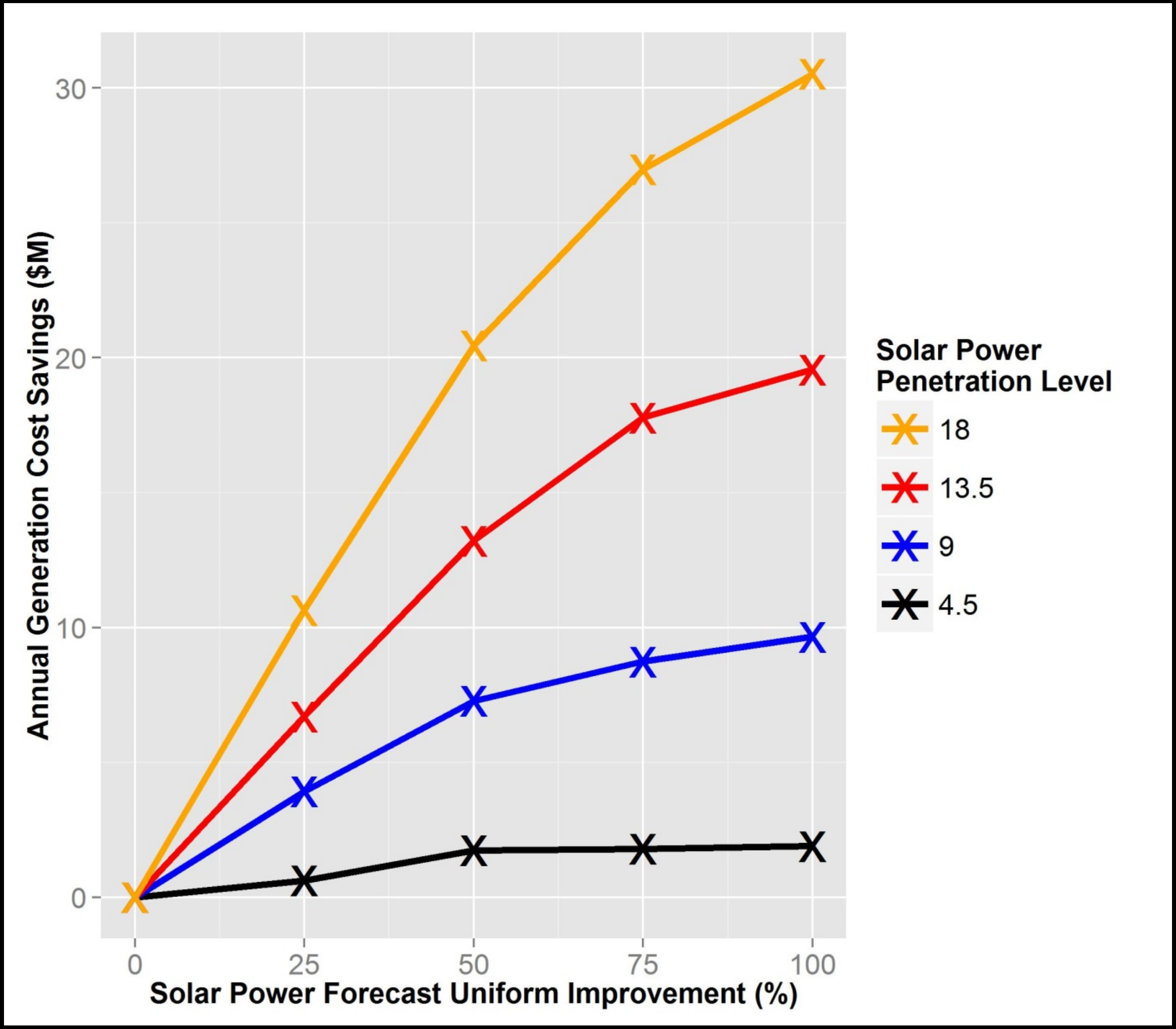
Carlo Brancucci Martinez-Anido, NREL

Underforecast Event



Reduced curtailment
Reduced fossil fuel generation
Reduced Gas CC ramping

Value of DA Solar Power Forecasting Improvement



Impacts of Day-Ahead Solar Forecast Improvements

Solar power forecasting improvements

- Reduces electricity generation from the fast reacting and lower efficiency power plants, such as gas and oil GT and IC.
- Decrease ramping of all generators, start and shutdown costs, and solar power curtailment.
- Provides an annual economic value.

The marginal value of solar power forecasting improvement increased with solar power penetration, while it decreased with additional improvement levels.

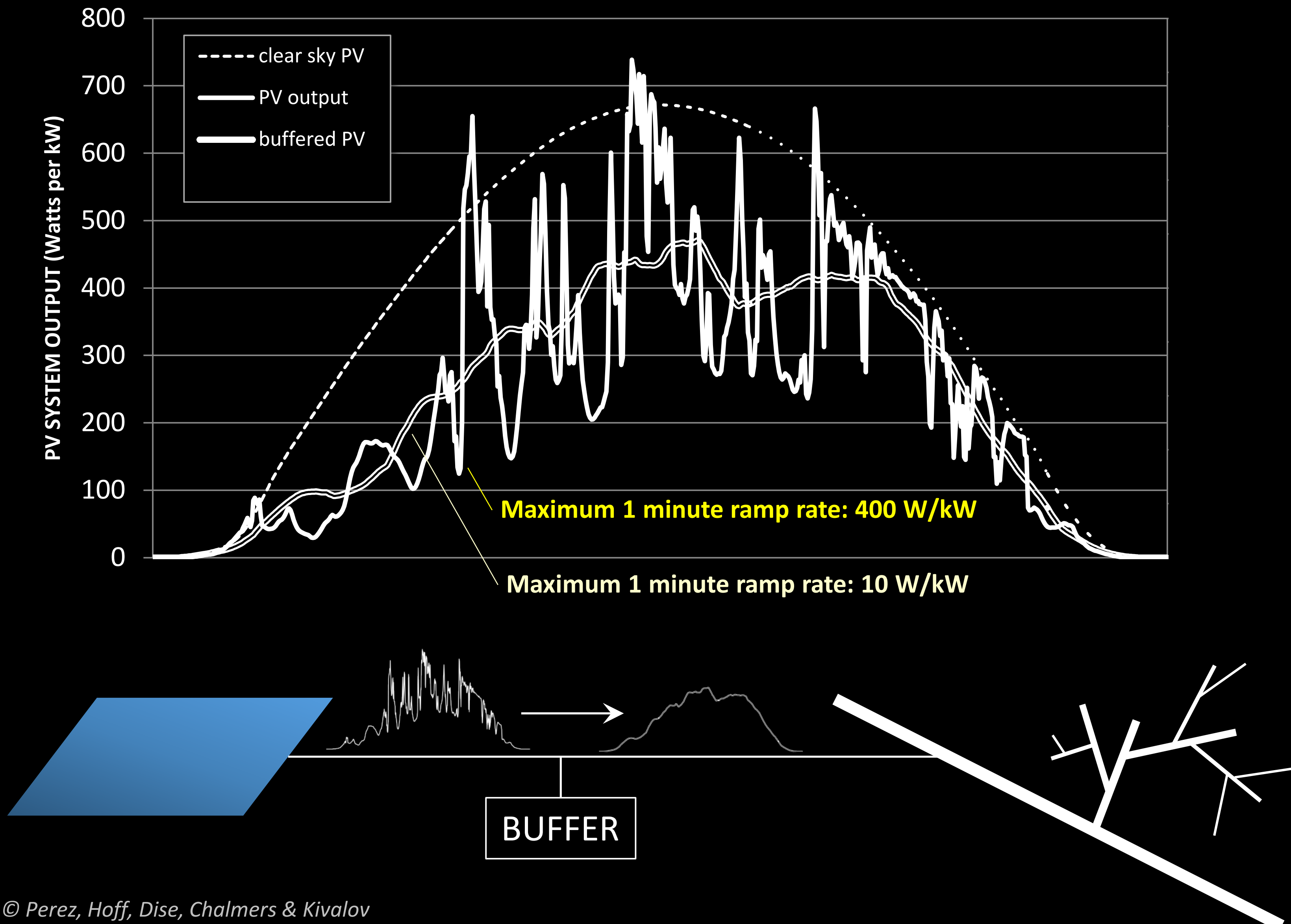
and in reality …

Impact of DA Forecast Errors on Intraday Spot Pricing in Germany

Sample Application

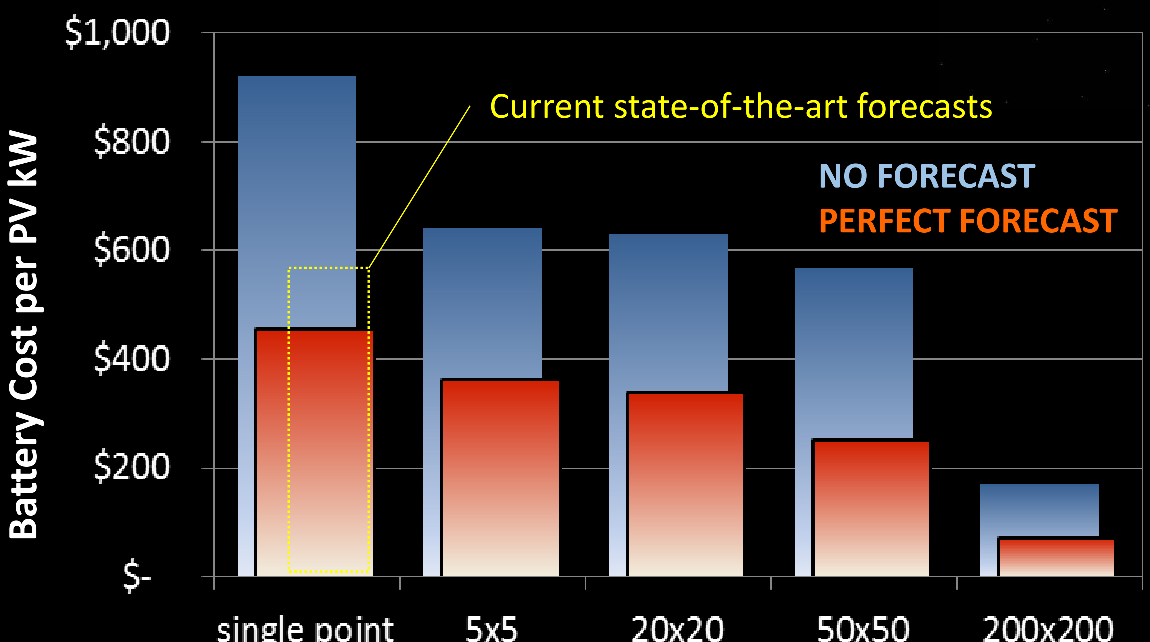
Smoothing Solar with Forecast and Storage

THE PROBLEM A SOLUTION



OPERATIONAL MITIGATION SCENARIO

1 minute ramp rate	< 5% installed capacity
5 minute ramp rate	< 10% installed capacity
15 minute ramp rate	< 15% installed capacity
60 minute ramp rate	< 25% installed capacity

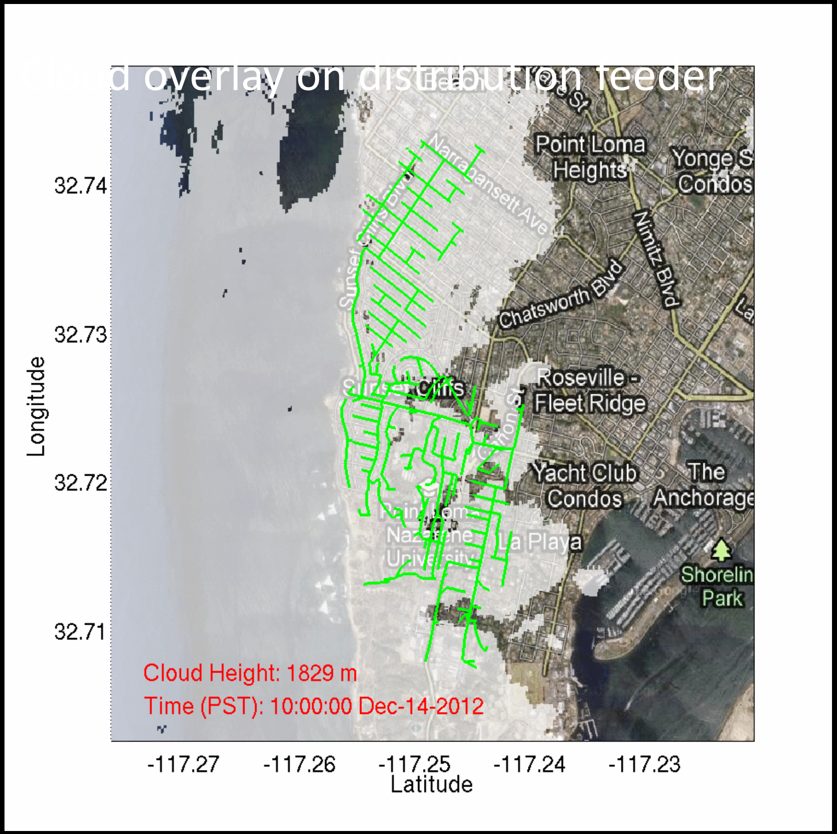


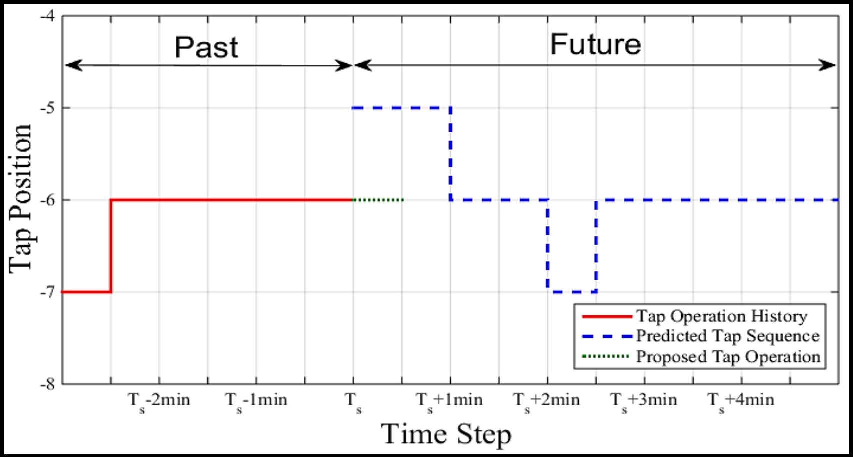
Sample Application

Reduce Distribution Feeder Transformer Tap Operations

Sky Imagery for Distribution Systems

- High resolution and distributed PV generation profiles
- Up to 15 min forecasts
- Tap changes designed to manage voltage
    - Time lag
    - Cost



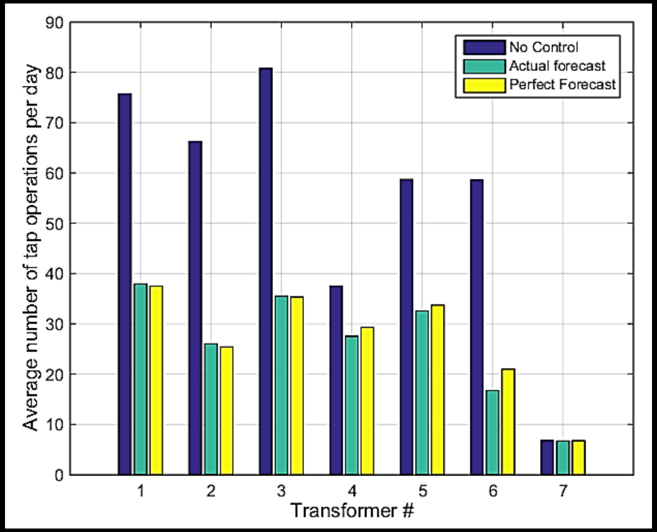


- Avoid unnecessary tap operations

Simulated TO Reduction

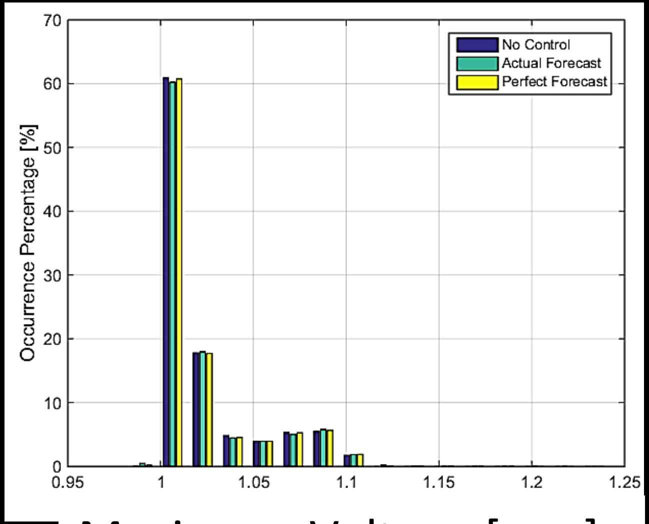
- 100% PV penetration
- #TO on Jan 19, 1000 – 1230 h
  - No control: 125 TO
  - Actual forecast: 46 TO
  - Perfect Forecast: 15 TO

TO Depth

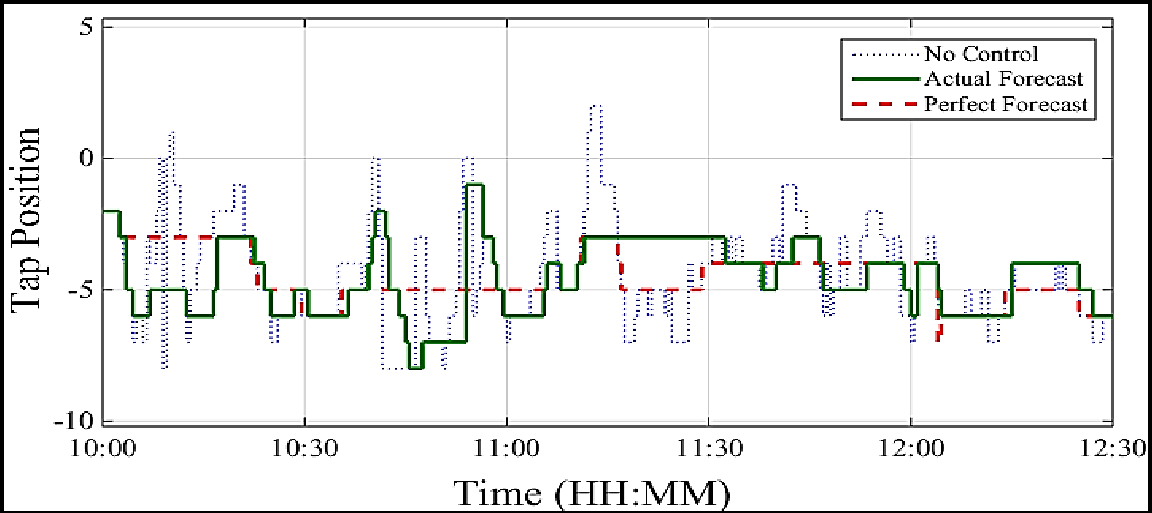


Voltage Quality Impacts

Histogram

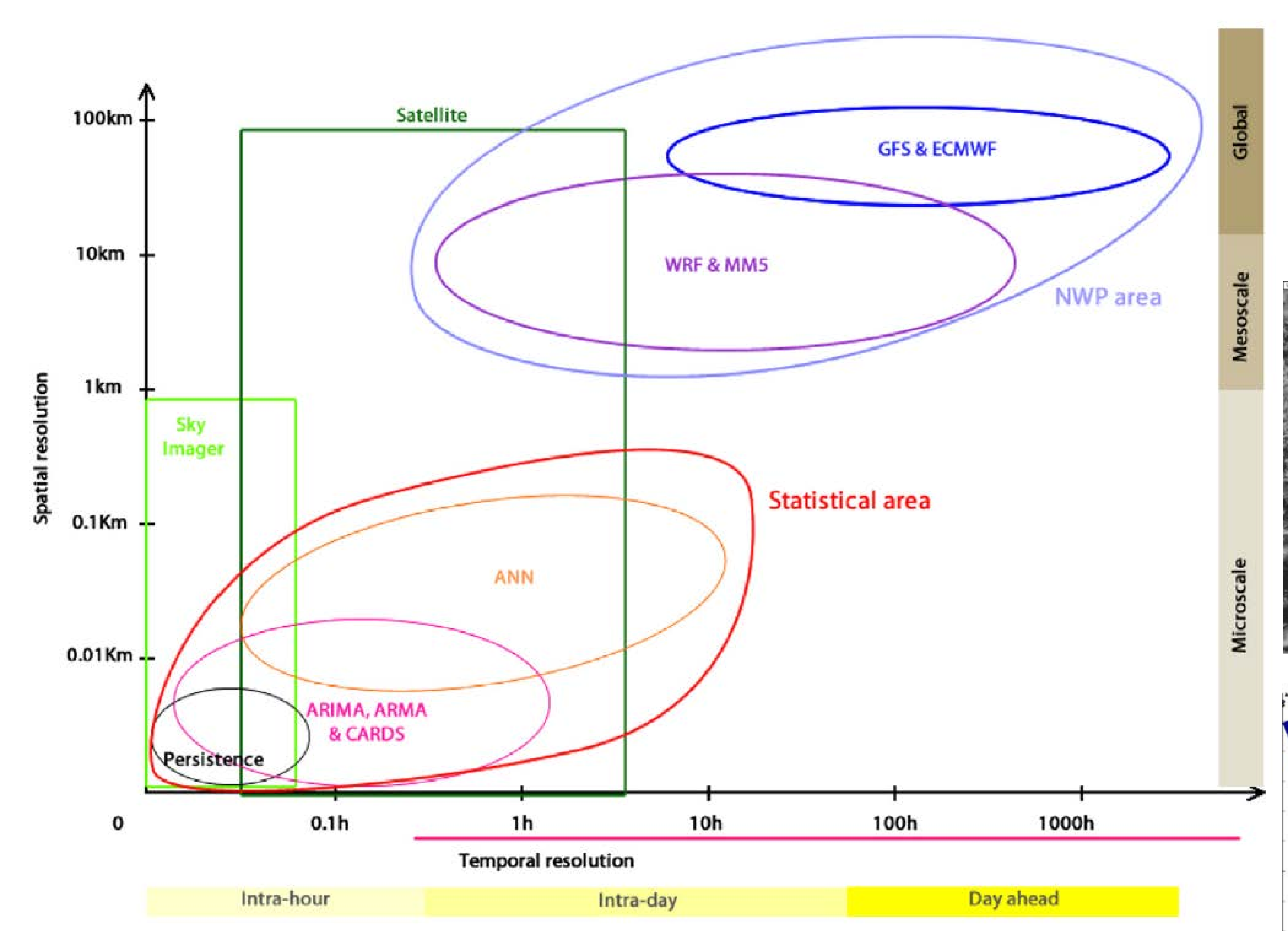


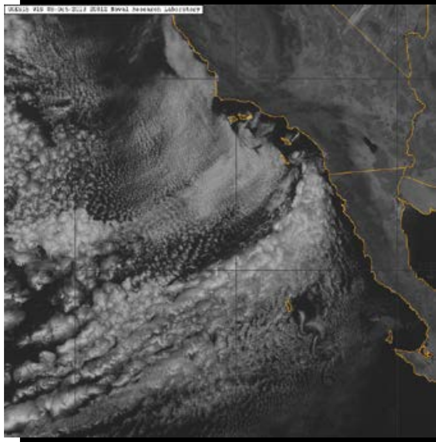
Maximum Voltage [p.u.]

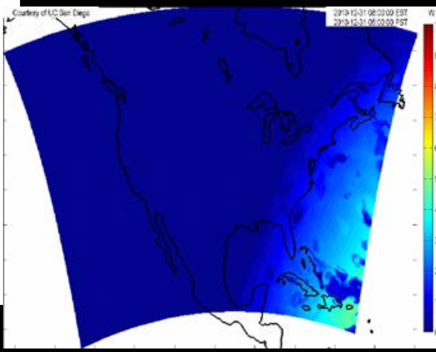


Solar Forecasting Improvements

Solar Forecast Types and Horizons







Diagne *et al.*, 2013, Inman *et al.*, 2013

Solar Forecast Accuracy Metrics

- Absolute
  - MAE, RMSE [W m^{-2}]
  - MBE
- Relative
  - MAPE [%]
- But: Higher variability, higher random errors
  - Penalizes point forecast, minute forecasts, cloudy climates
- Solution: Forecast Skill:
  - FS = 1 – RMSE / RMSE of Smart Persistence
  - “Smarter” IEA Task 46 definition

Further Reading:

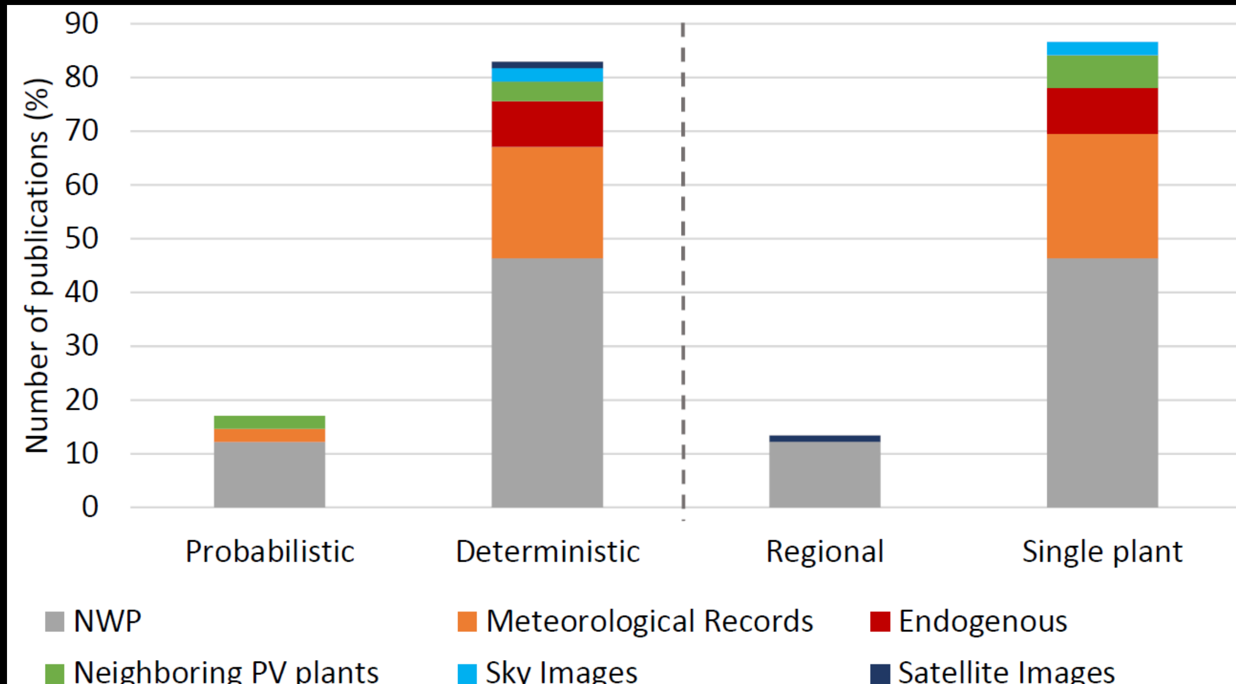
Hoff, T. E., Perez, R., Kleissl, J., Renne, D. and Stein, J. (2012), Reporting of irradiance modeling relative prediction errors. Prog. Photovolt: Res. Appl.. doi: 10.1002/pip.2225

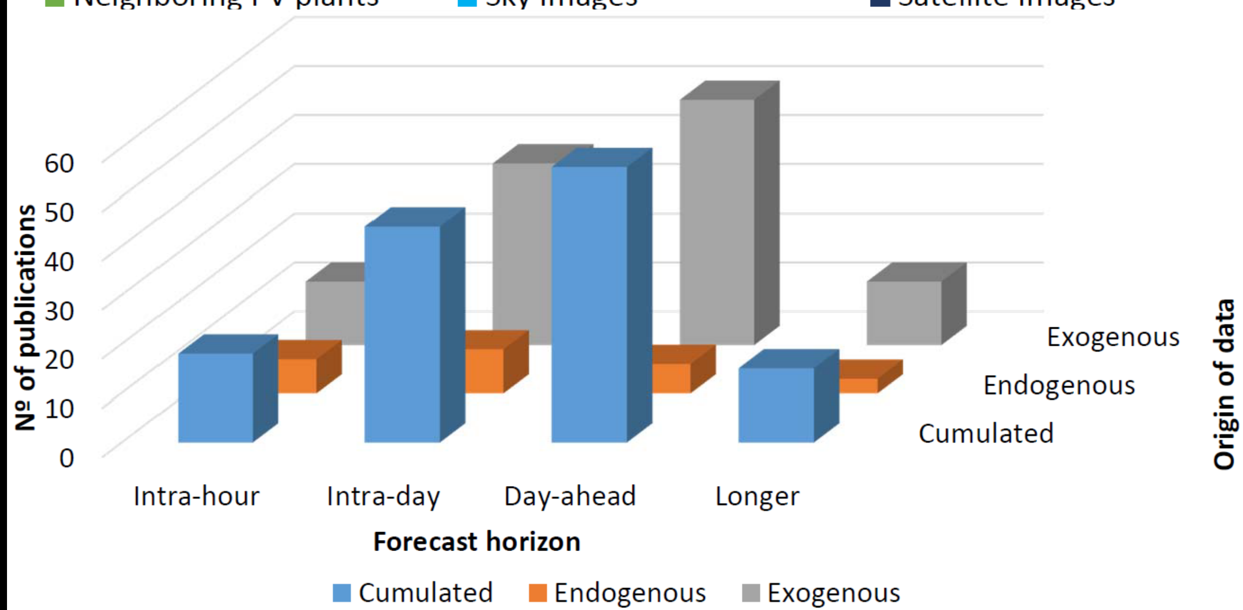
Zhang, J., Florita, A., Hodge, B.M., Lu, S., Hamann, H.F., Banunarayanan, V. and Brockway, A.M., 2015. A suite of metrics for assessing the performance of solar power forecasting. *Solar Energy*, *111*, pp.157-175.

Coimbra, C., J. Kleissl, and R. Marquez. "Overview of solar forecasting methods and a metric for accuracy evaluation." *Solar Resource Assessment and Forecasting, edited by: Kleissl, J., Elsevier, Waltham, Massachusetts* (2013).

RMSE	Desert Rock		Fort Peck		Boulder		Sioux Falls		Bondville		Godwin Creek		Penn State	
Clearness index*	90%		80%		70%		79%		70%		81%		66%	
Satellite model error	99	Persist.	99		124	Persist.	80		100		97		113	
1 h ahead	99	100	91	111	143	170	80	97	100	108	92	103	112	131
	FS = 1%				FS = 18%									
2 h ahead	110	119	109	149	175	214	98	127	115	145	113	135	127	164
	FS = 8%				FS = 18%									

Review of Solar Power Forecast Research





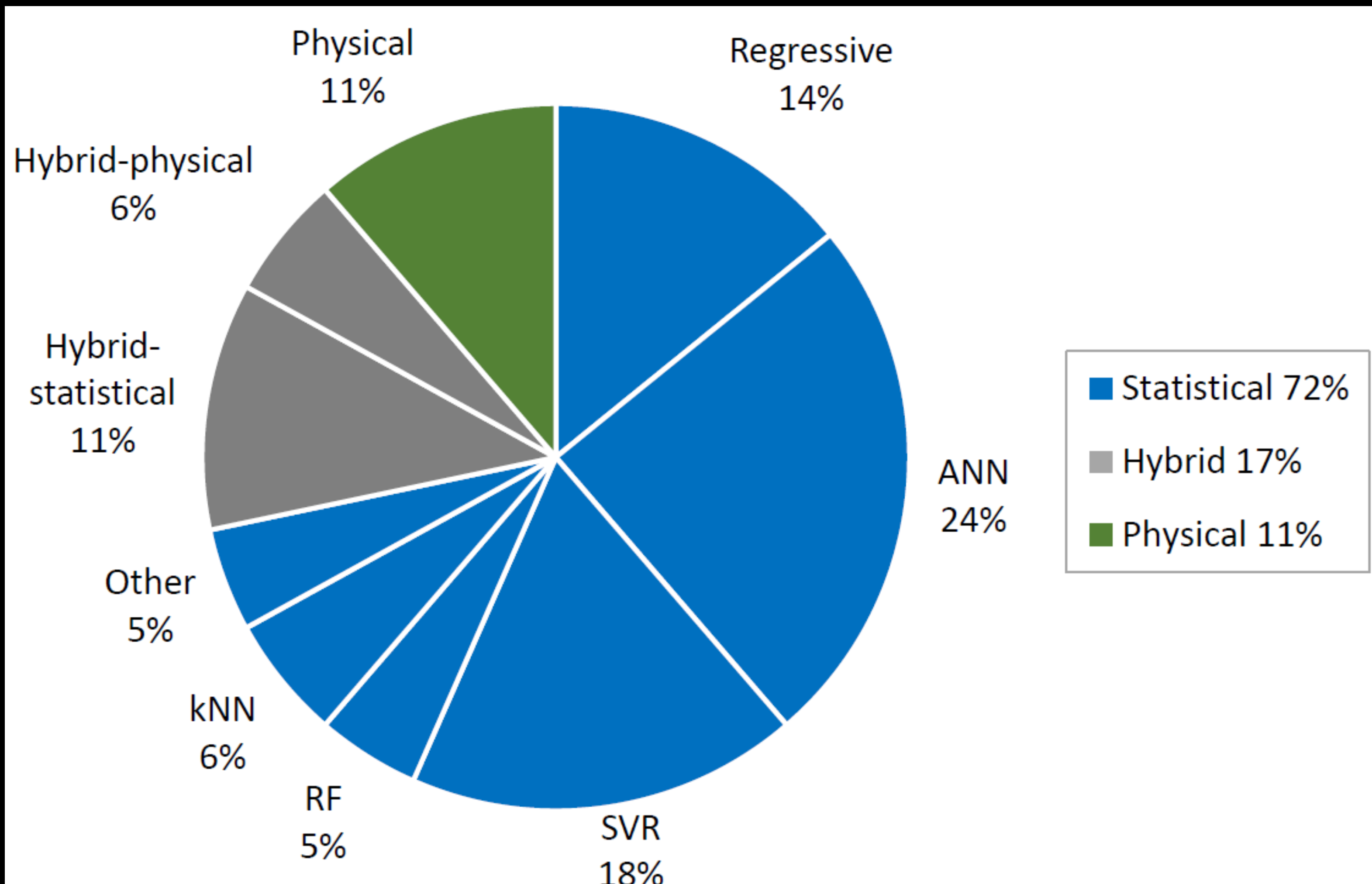
Javier Antonanzas; Natalia Osorio, Master; Rodrigo Escobar, Ruben Urraca; Francisco Javier Martínez de Pisón, State of the art of power forecasting on photovoltaics, Solar Energy, under review

Progress

Machine Learning Techniques

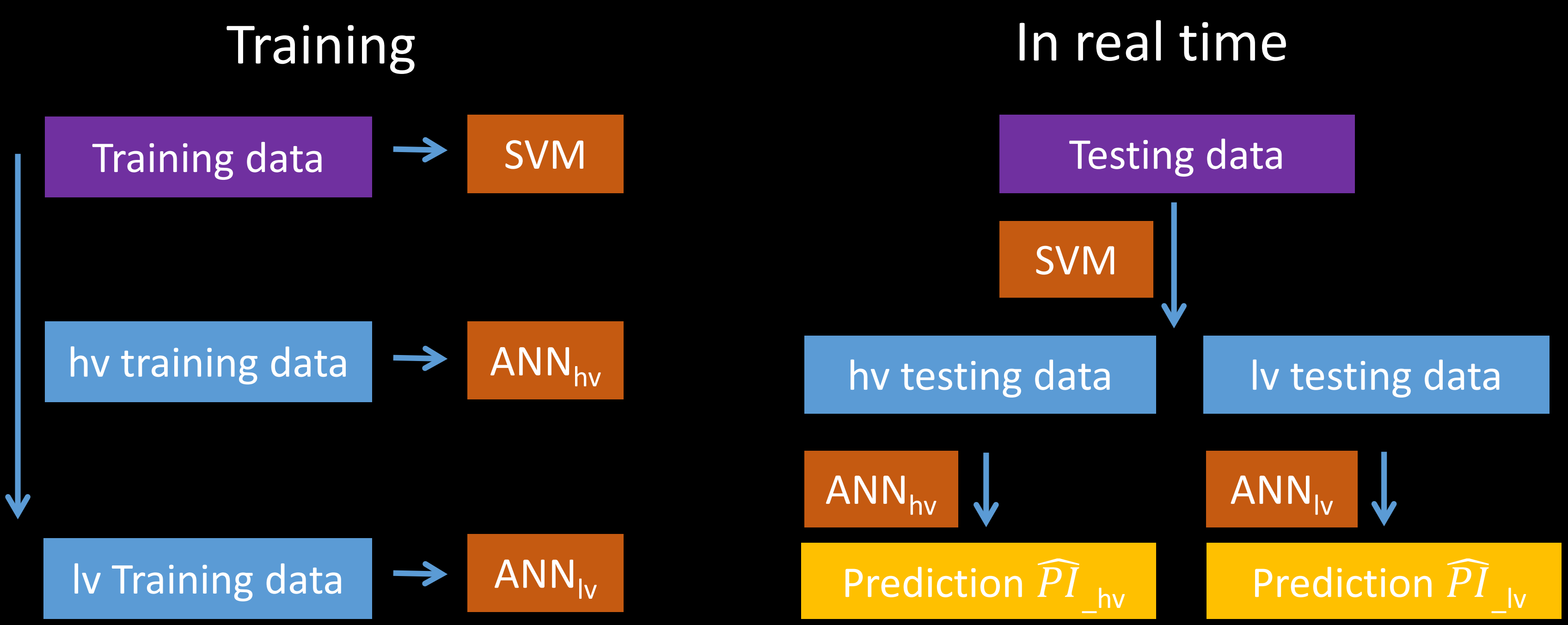
2010: Unsophisticated postprocessing

Review of Solar Power Forecast Research



Javier Antonanzas; Natalia Osorio, Master; Rodrigo Escobar, Ruben Urraca; Francisco Javier Martínez de Pisón, State of the art of power forecasting on photovoltaics, Solar Energy, under review

Smart Probabilistic Forecasts with SVMs and ANNs



The proposed smart model first uses a SVM to classify the weather condition into either low DNI variance period (lv) or high DNI variance period (hv) [1] and then adaptively applys the more suitable ANN schemes to construct the PIs of 90% confidence level for 5-, 10-, 15-, and 20-minute horizons.

Y. Chu, H. T.C. Pedro, and C.F.M. Coimbra (2013) "Hybrid Intra-Hour DNI Forecasts with Sky Image Processing Enhanced by Stochastic Learning." ***Solar Energy*** (**98**) pp. 592-603.

Assessment and Progress

Numerical Weather Prediction

2010: Poor clear sky modeling

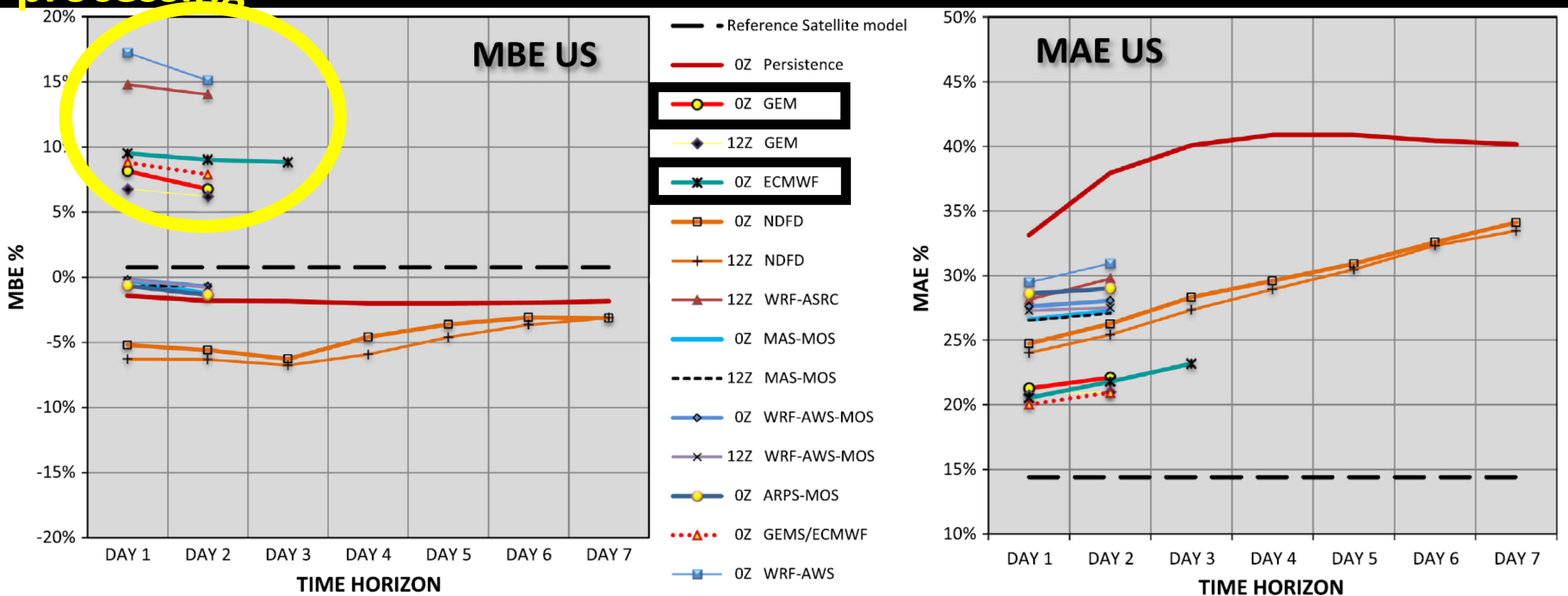
Perez et al. Solar Energy, 2013

Numerical Weather Prediction (NWP)

- Physics-based modeling important for long time horizons

- But: Large biases
- Accurate native forecasts low NOAA priority
- Europeans outperform

No post-processing



NWP Clear Sky Modeling

- Aerosol climatological dataset (SCS-LIM)
  - Removed stubborn satellite errors over desert South-West
- Online AOD data (GEOS5 AOD)

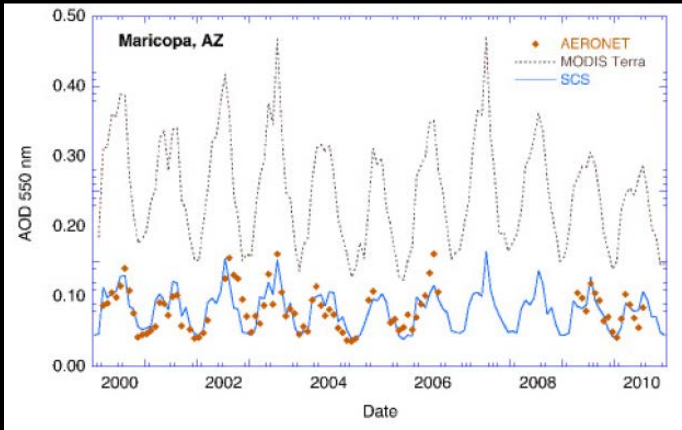


TABLE 2. RMSE in the surface irradiance components ($W\ m^{-2}$). The relative improvement with respect to the NO-AEROSOL experiment is shown in parenthesis.

Irradiance	*NO – AEROSOL*	*ECMWF – CLIM*	*SCS – CLIM*	*GOCART – CLIM*	*MACC – AOD*	*GEOS5 – AOD*
GHI	21	16 (23 %)	16 (23 %)	16 (23 %)	20 (5 %)	15 (28 %)
DIF	44	20 (54 %)	19 (57 %)	26 (41 %)	42 (4 %)	12 (73 %)
DNI	103	66 (36 %)	52 (50 %)	58 (44 %)	120 (-16 %)	41 (60 %)

Jimenez, Pedro A., et al. "WRF-Solar: An augmented NWP model for solar power prediction. Model description and clear sky assessment." *Bulletin of the American Meteorological Society* 2015.

Progress

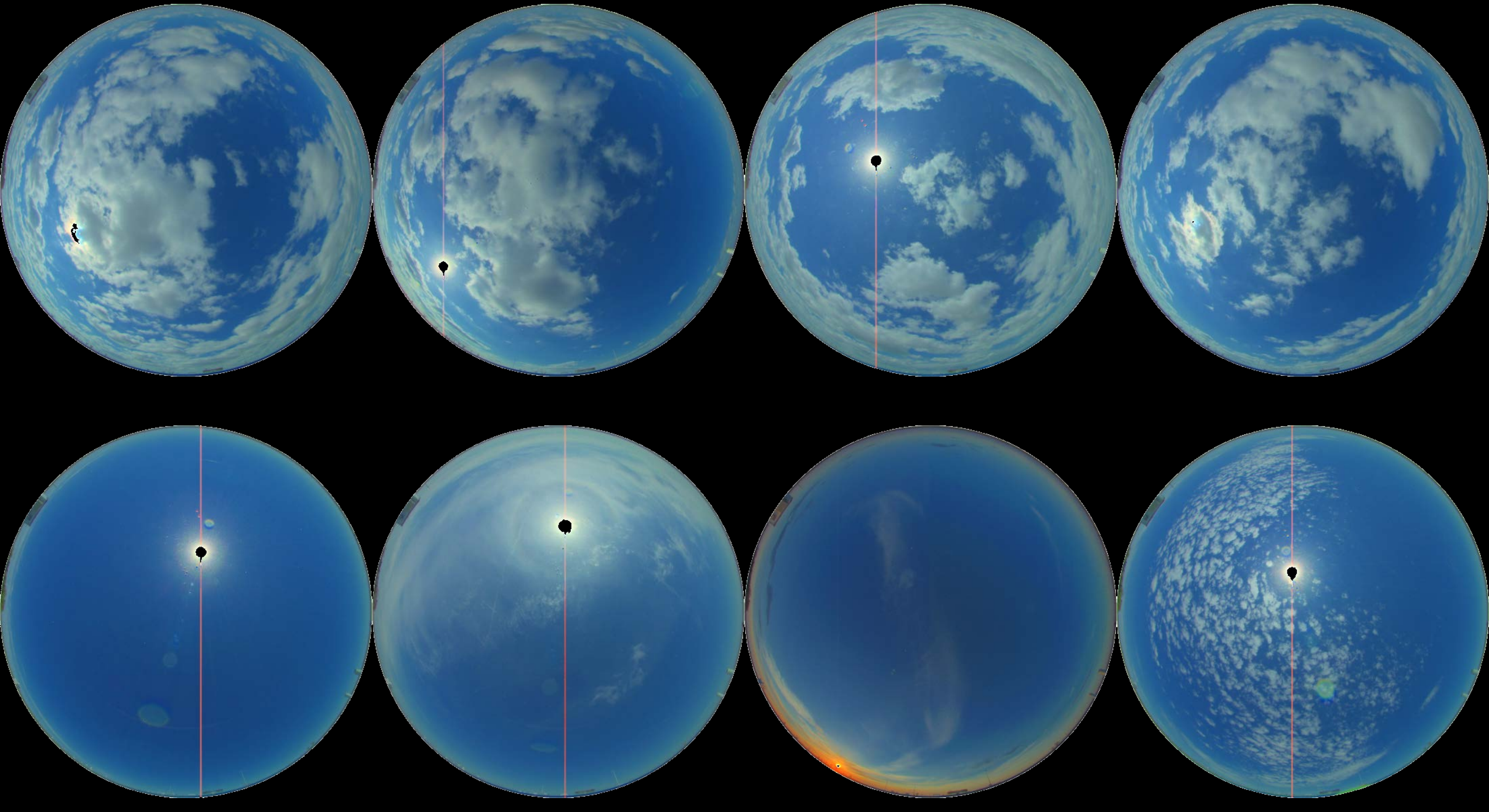
Sky Imager Solar Forecasting

Design and application of a high dynamic range sky imaging system for solar forecasting

Chi Wai Chow
S. M. Iman Gohari
Bryan Urquhart
Handa Yang
Ben Kurtz
Dung Nguyen
Mohamed Ghonima
Felipe Mejia
Guang Wang
Jan Kleissl

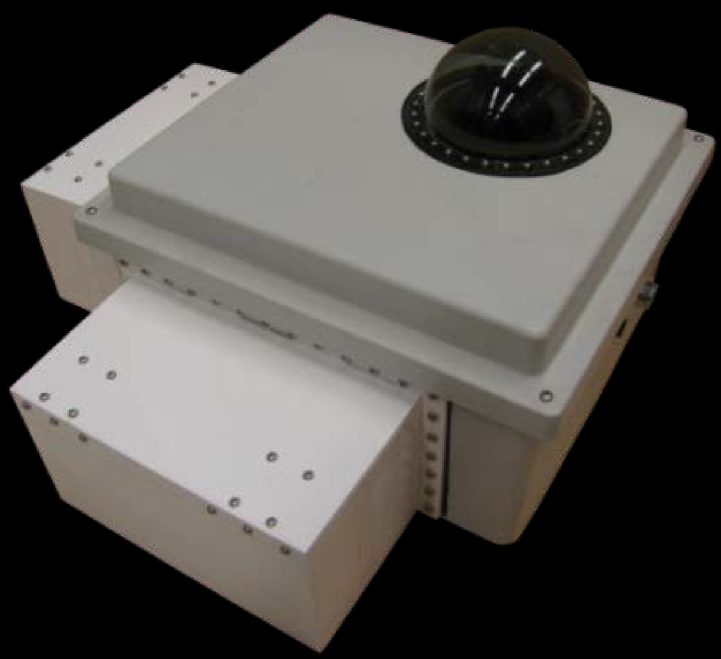
University of California, San Diego, Department of Mechanical and Aerospace Engineering, La Jolla, California, USA

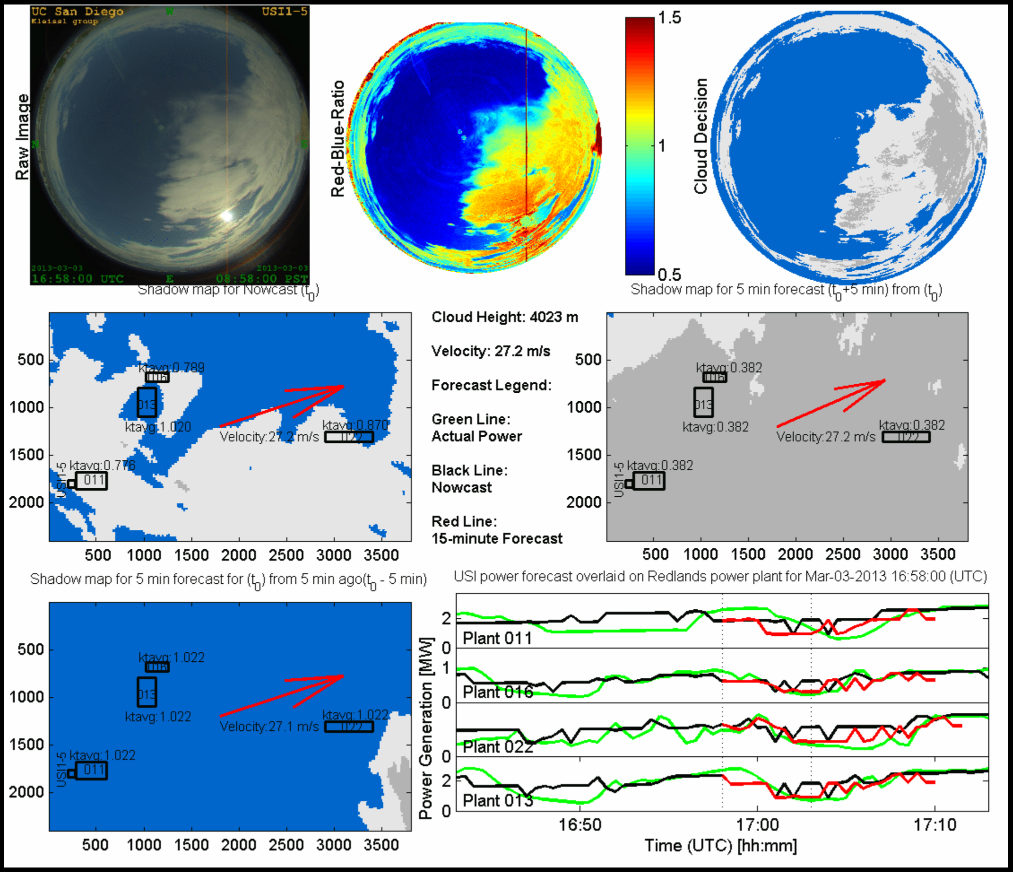
Images



Solar forecasting with sky imager

- 30 sec, 10m x 10m resolution.
- Basic steps
  - Cloud detection
  - Cloud height determination
  - Cloud motion vectors
  - Projection on the ground for irradiance maps
  - Convert from irradiance to power



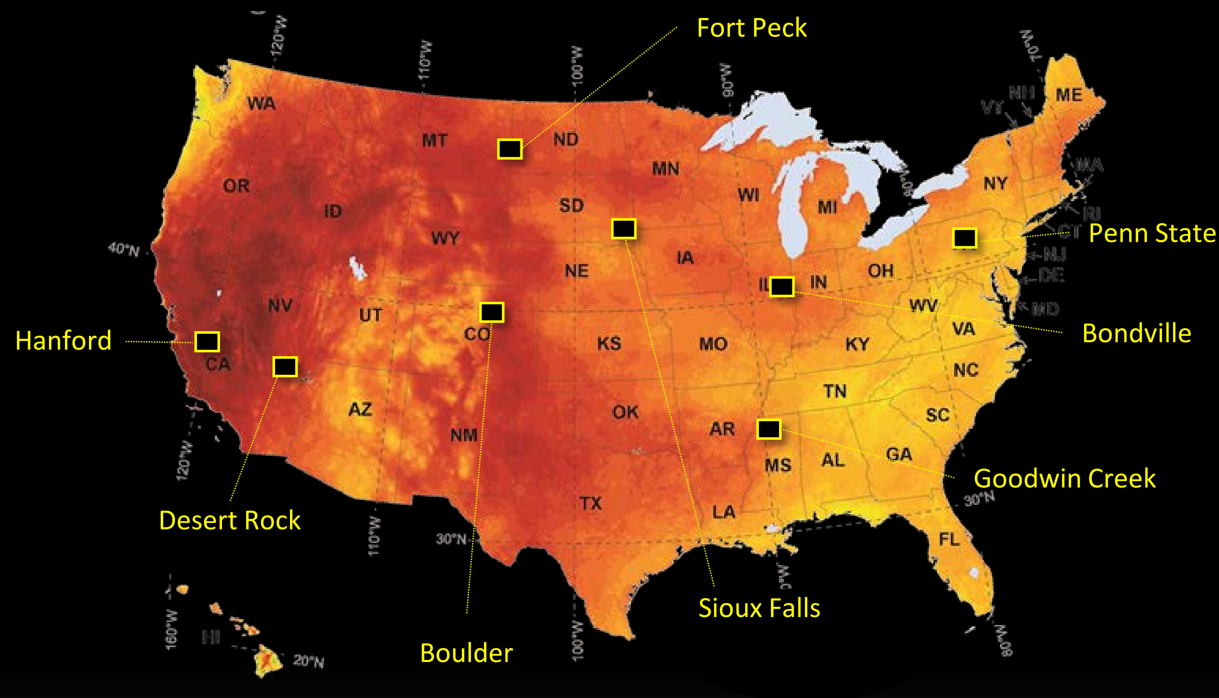


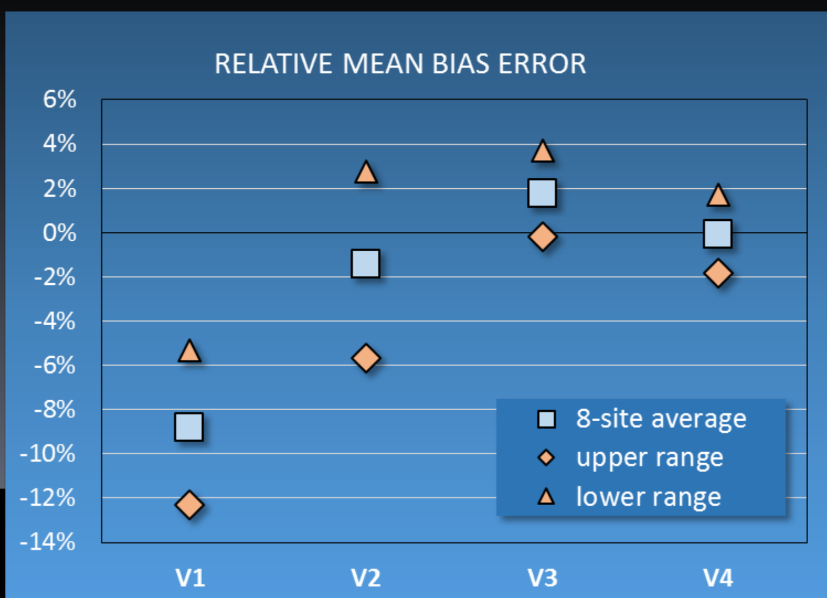
Sample of the forecasting process with sky imager

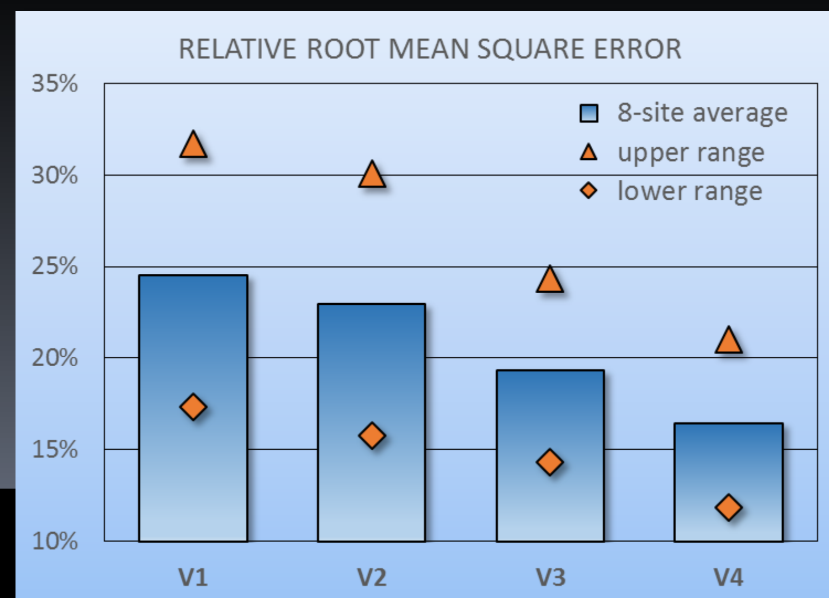
Progress

Satellite Solar Forecasting

SolarAnywhere Satellite Irradiance Model Accuracy







2005 2010 2015 2016

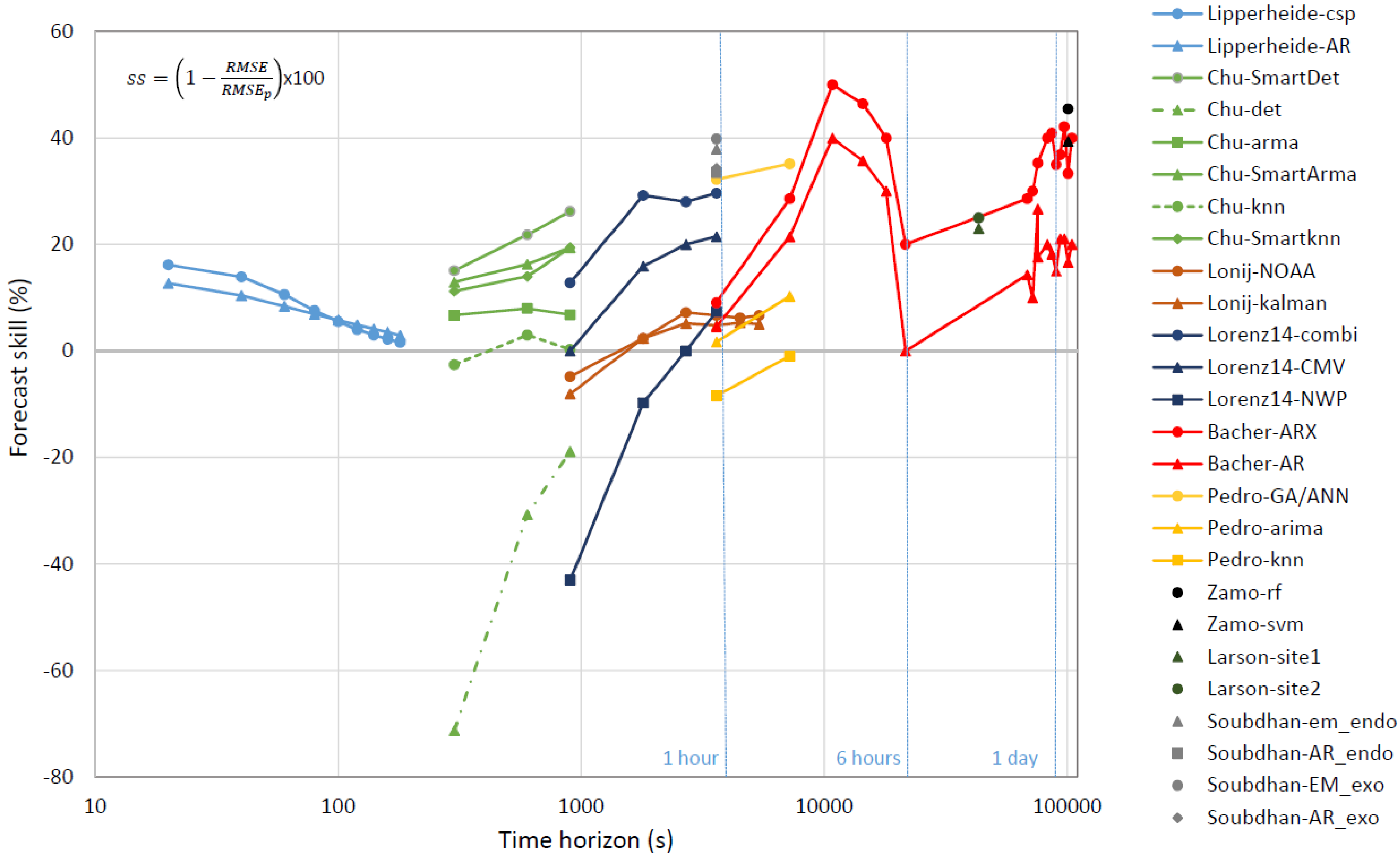
Progress

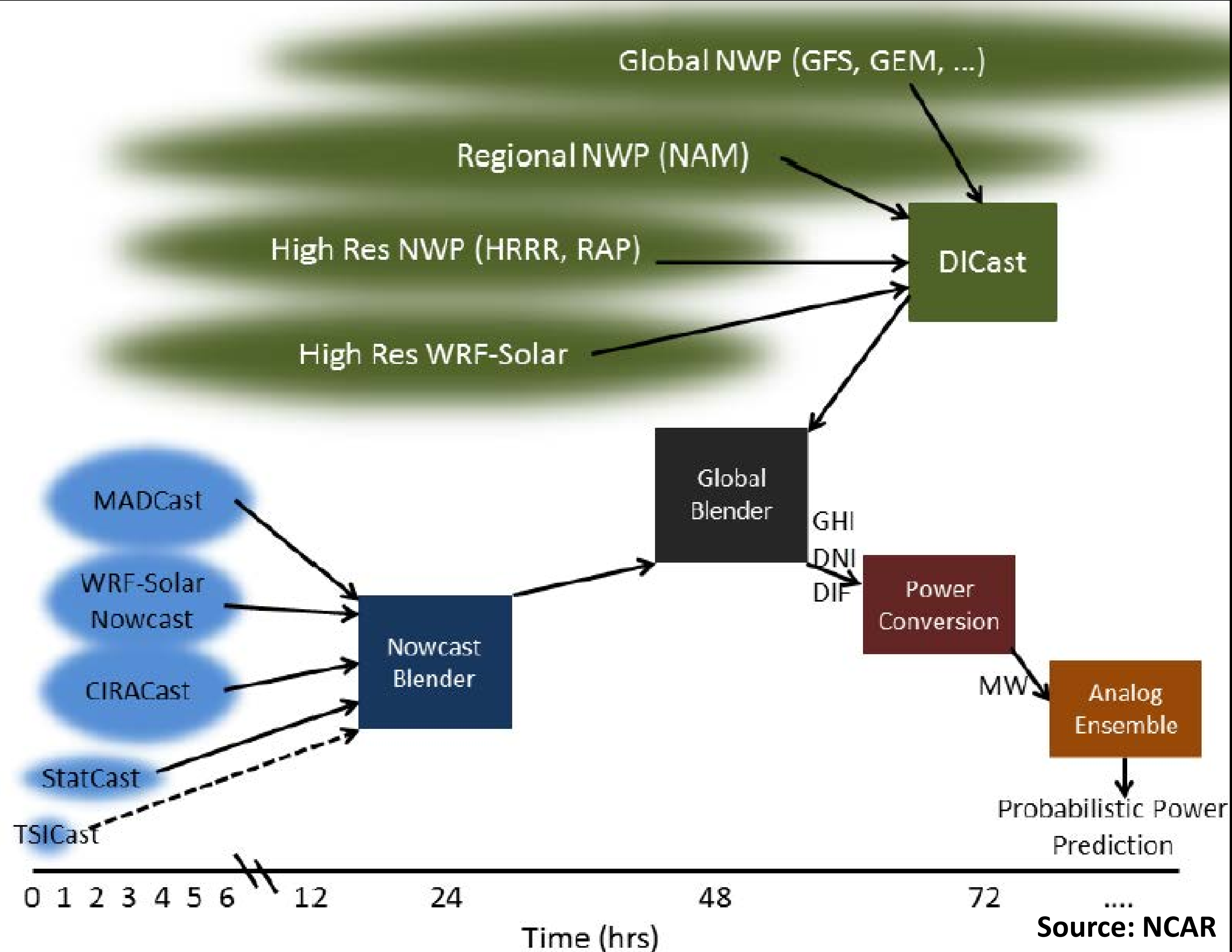
Putting it all together

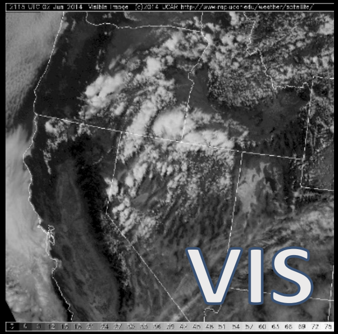
Example NCAR

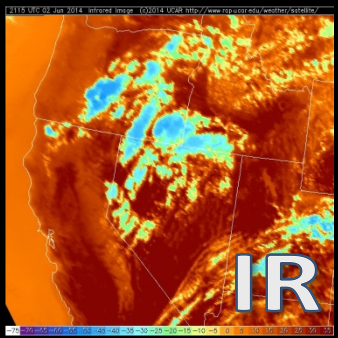
Example SolarAnywhere

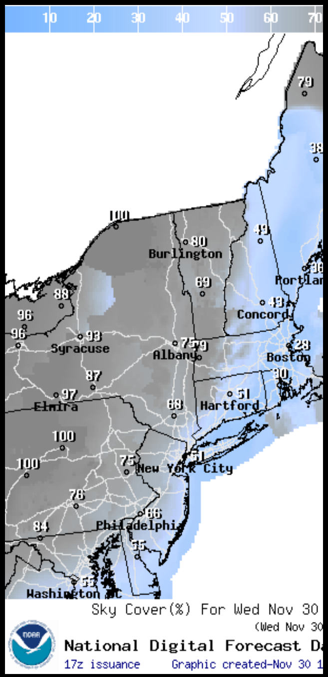
State-of-the-Art Forecast Skills




Global NWP (GFS, GEM, ...)
Regional NWP (NAM)
High Res NWP (HRRR, RAP)
High Res WRF-Solar
DICast
Global Blender
GHI
DNI
DIF
Power Conversion
MW
Analog Ensemble
Probabilistic Power Prediction
MADCast
WRF-Solar Nowcast
CIRACast
StatCast
TSICast
Nowcast Blender
0 1 2 3 4 5 6 12 24 48 72 ....
Time (hrs)
Source: NCAR







<u>GLOBAL SCALE MODELS</u>

- NCEP GFS
- ECMWF

<u>CONTINENTAL SCALE MODELS</u>

- NAM

<u>HIGH RESOLUTION ASSIMILATION MODELS</u>

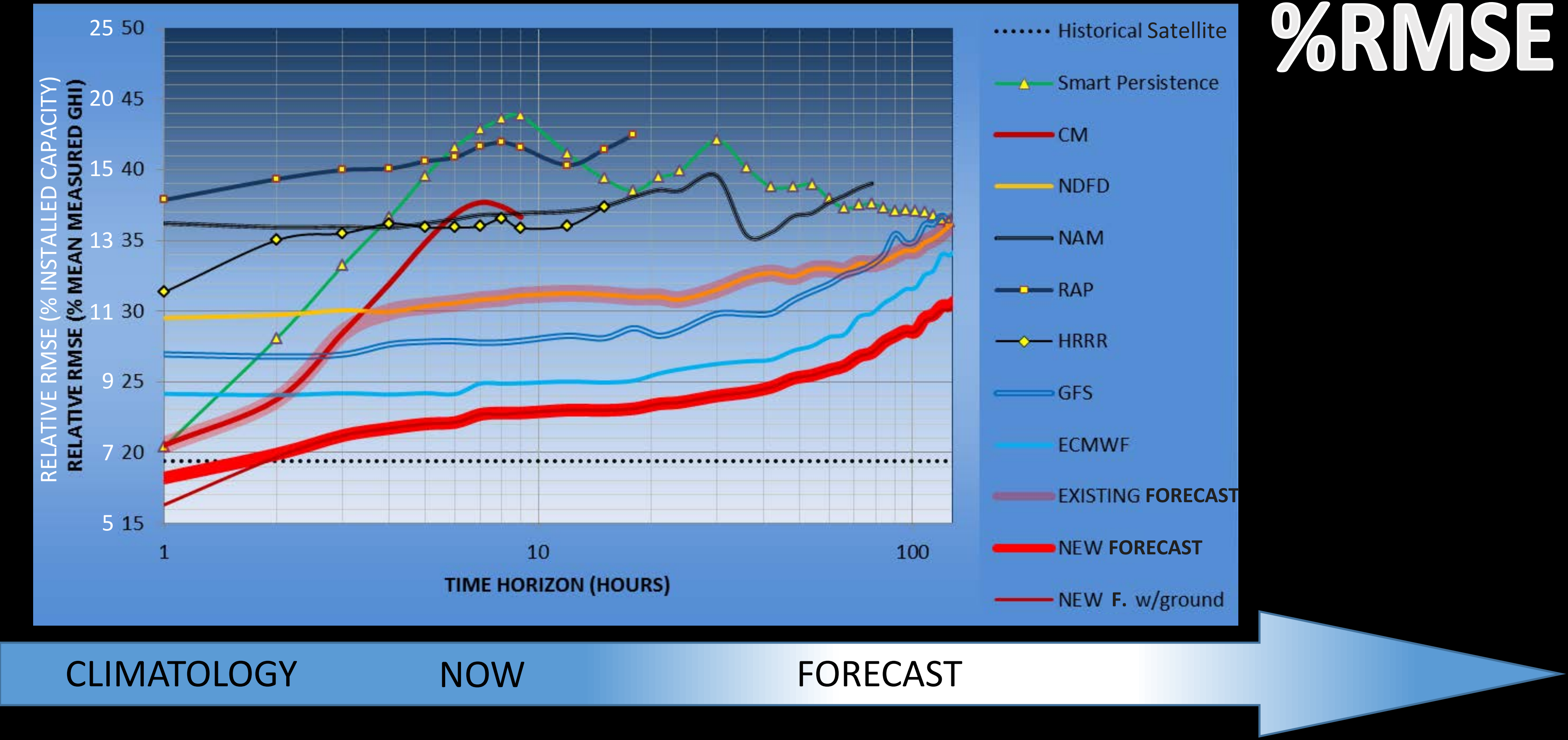
- RAP
- HRRR

Cloud motion *NDFD* *Operational NWP models*

CLIMATOLOGY NOW FORECAST

NEW SolarAnywhere
OPTIMUM MIX

%RMSE



RELATIVE RMSE (% INSTALLED CAPACITY)
RELATIVE RMSE (% MEAN MEASURED GHI)
25 50
20 45
15 40
13 35
11 30
9 25
7 20
5 15
1
10
100
TIME HORIZON (HOURS)
Historical Satellite
Smart Persistence
CM
NDFD
NAM
RAP
HRRR
GFS
ECMWF
EXISTING FORECAST
NEW FORECAST
NEW F. w/ground
CLIMATOLOGY
NOW
FORECAST

The Future

GOES-R Satellite Launch Oct 2016

GOES-R IMPROVEMENTS OVER CURRENT GOES

GOES-R will feature the following improvements over current GOES capabilities:

Capability	Current GOES	GOES-R
Full Disk Image	30 minutes	5 minutes
Imager bands	5	16
Visible	~1 kilometer	0.5 - 1 kilometer
Near Infrared	N/A	1 -2 kilometer
Infrared	4-8 kilometer	2 kilometer
Bit Depth	10 bits	12 bits – Visible, 14 bits IR

- GOES-R mitigates main sky imager advantages

Virtual Sky Imager Testbed

Mejia et al. (2015)

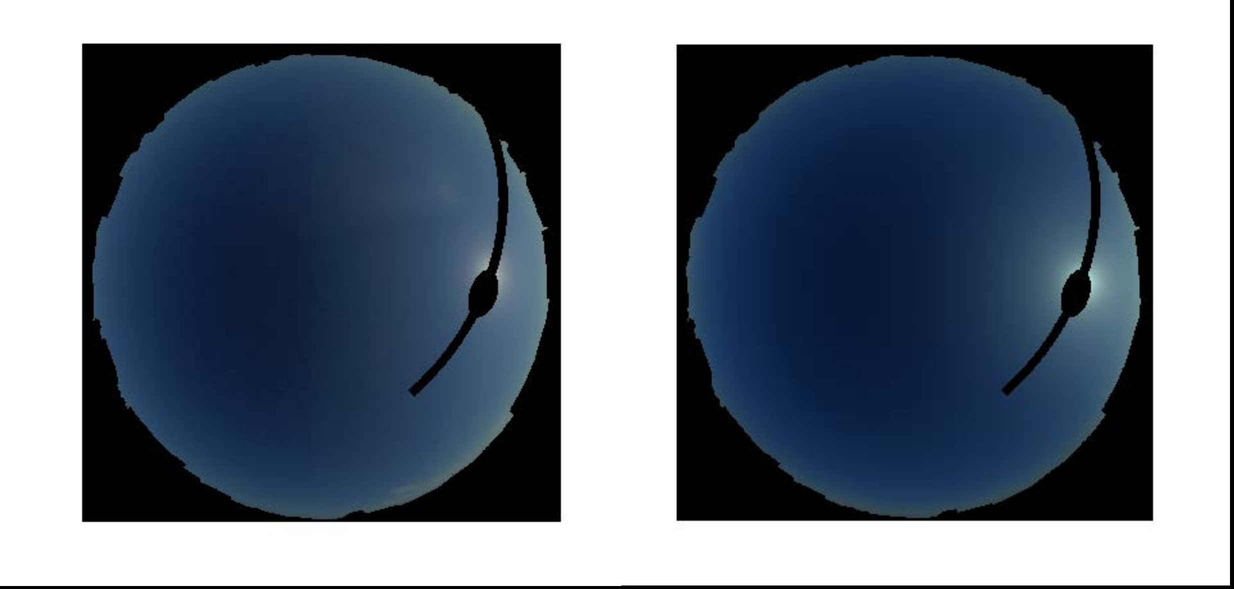
3D Radiative Transfer Models – Image Tomography

Real Sky Images are difficult to control and analyze systemically:

- Dirt - 3D cloud effects - Stray light effects - Many dependent variables

→ **Create Virtual Sky Imager Testbed**

Spherical Harmonic Discrete Ordinate Method (SHDOM) 3D Radiative Transfer Model

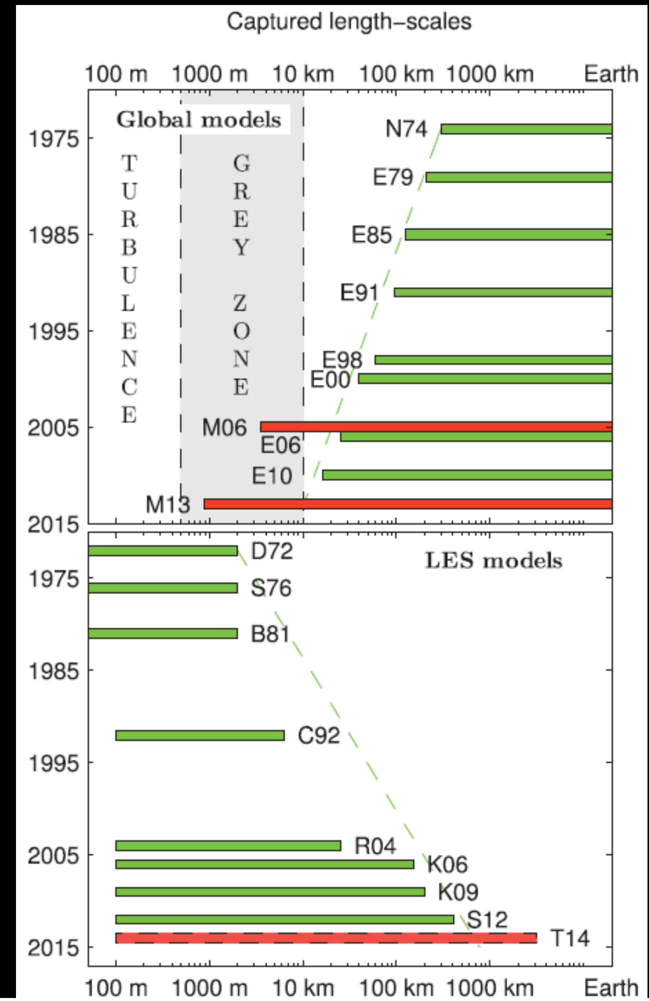


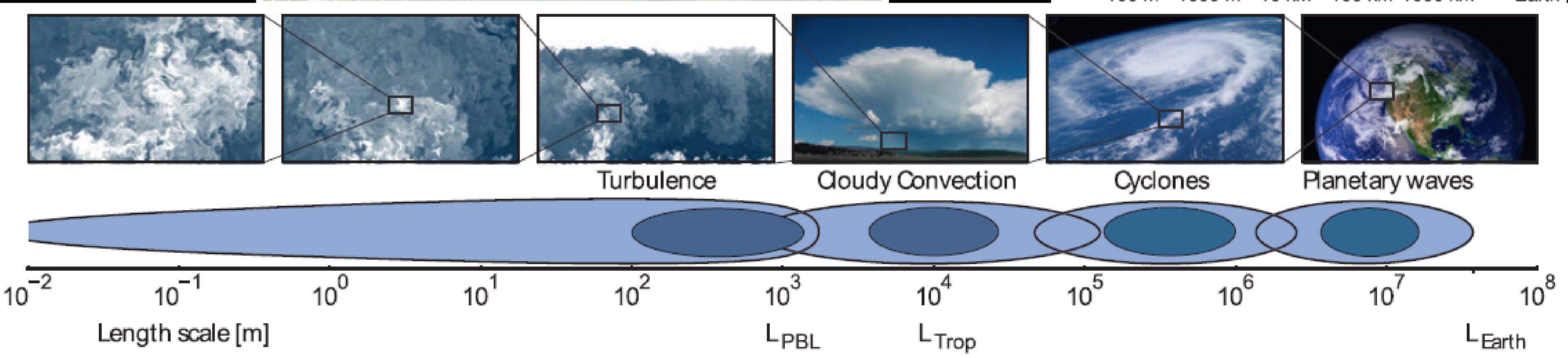
USI image taken at UCSD. SHDOM simulated sky image.

Goal: Robust and accurate cloud detection and cloud optical depth estimation

Schalkwijk et al. (BAMS, 2015)

Cloud Resolving GPU-LES





IEA Task 46 Solar Resource Assessment and Forecasting

- Lead: David Renne
- International Coordination
  - Germany, Spain, Australia, Chile
- Joint model evaluations
- Benchmarking and metrics

From the stone age 2010 to 2015

- NWP: Poor clear sky modeling
  - No cloud liquid water output
- No satellite forecasts pre-sunrise
- Unsophisticated postprocessing
  - Bias removal
- Deterministic forecasts
- Solar forecasts not used operationally

- Dynamic aerosols and cloud interactions
  - RAP outputs cloud liquid water
- Infrared satellite channels for pre-sunrise forecasts
- Sophisticated postprocessing
  - Regime-based corrections, Deep machine learning
- Probabilistic forecasts
- Solar forecasts widely used operationally

Final Word – Persistence is a tough competitor in the industry!

SOLAR PLANTS

FORECASTERS

Forecaster ID	ALA1	ALA2	BWNG	SINKIN	SOMERSET
BONN3027	68%	66%	77%	74%	72%
RIGA6629	62%	54%	66%	67%	67%
OSLO9582	61%	62%	56%	49%	53%
PERSIST1	56%	52%	57%	53%	53%
LYON1996	55%	56%	59%	52%	50%
MESA4145	50%	37%	64%	63%	63%
BAKU7743	49%	50%	51%	48%	48%
PUNE6437	49%	50%	53%	48%	48%
PERSIST2	48%	44%	50%	47%	44%
KANO4083	48%	49%	53%	47%	47%
LYONCORR	47%	49%	49%	47%	47%
MESAADD1	46%	45%	33%	41%	42%
LIMAADD1	43%	43%	38%	45%	46%
KOBE8145	39%	41%	41%	39%	38%
LIMA2463	38%	42%	35%	39%	41%
GIZA2169	29%	31%	26%	28%	29%
ROME1995	18%	22%	23%	20%	19%

Lannoye, Tuohy, EPRI (2015)