A Probabilistic Forecasting System for Solar Power Generation

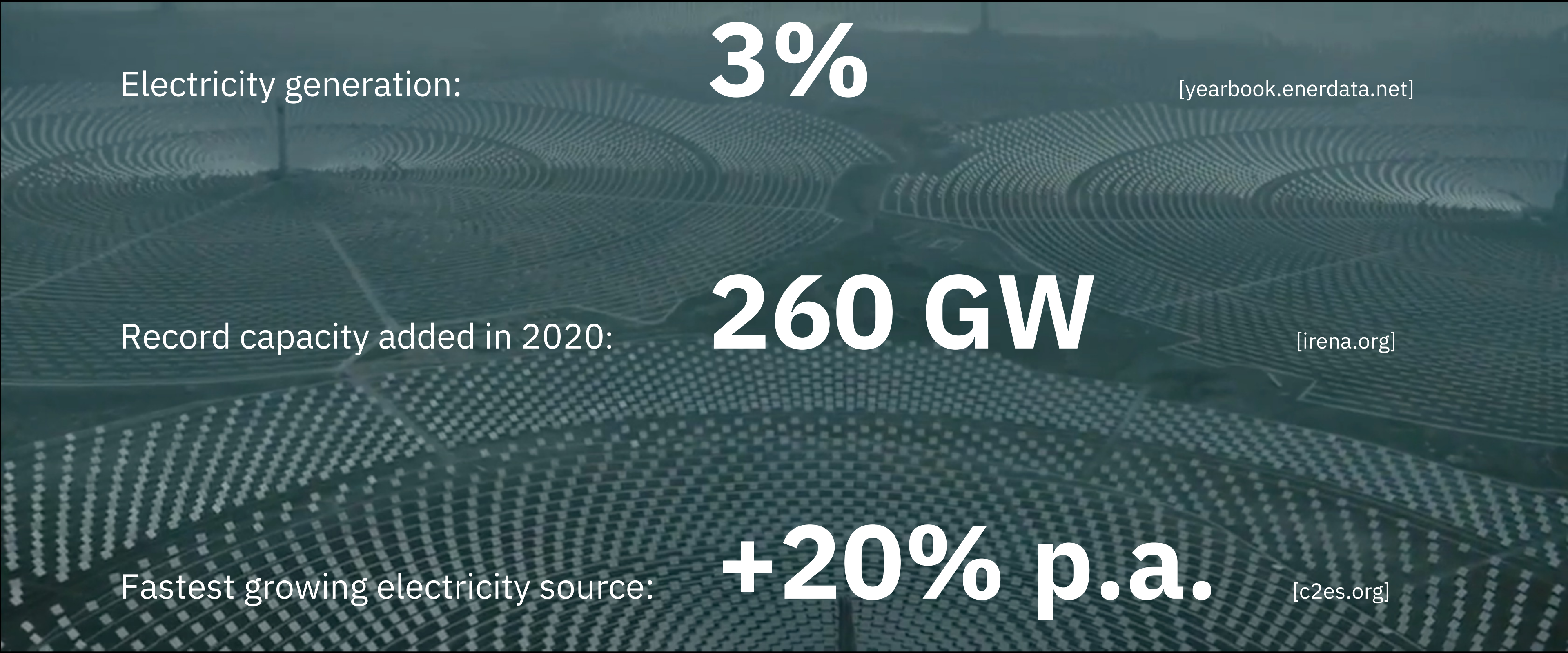
Carlo Siebenschuh,
Hendrik Hamann, Rui Zhang

06-08-2021

IBM

This material is based upon work supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under Solar Energy Technologies Office (SETO) Agreement Number EE0008215.

Solar Power Generation: Global



Electricity generation: **3%** [yearbook.enerdata.net]

Record capacity added in 2020: **260 GW** [irena.org]

Fastest growing electricity source: **+20% p.a.** [c2es.org]

Renewables add Uncertainty

- ISOs balance power in real-time
- renewables intensify this balancing challenge
- uncertainty necessitates more ramp
- higher ramp requirement (regulation) could offset the economic benefits of renewables
- maximize renewable penetration s.t. a balanced power network

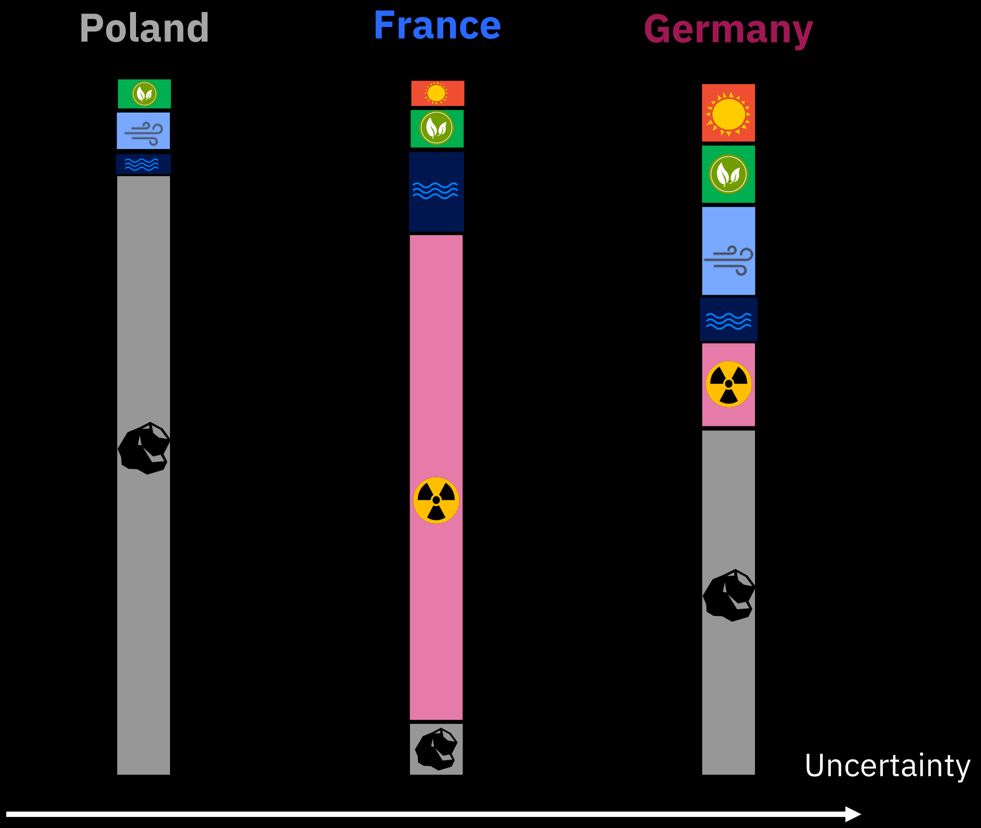


Fig. 1: Relative energy generation mix by country

Deterministic Solar Forecasting

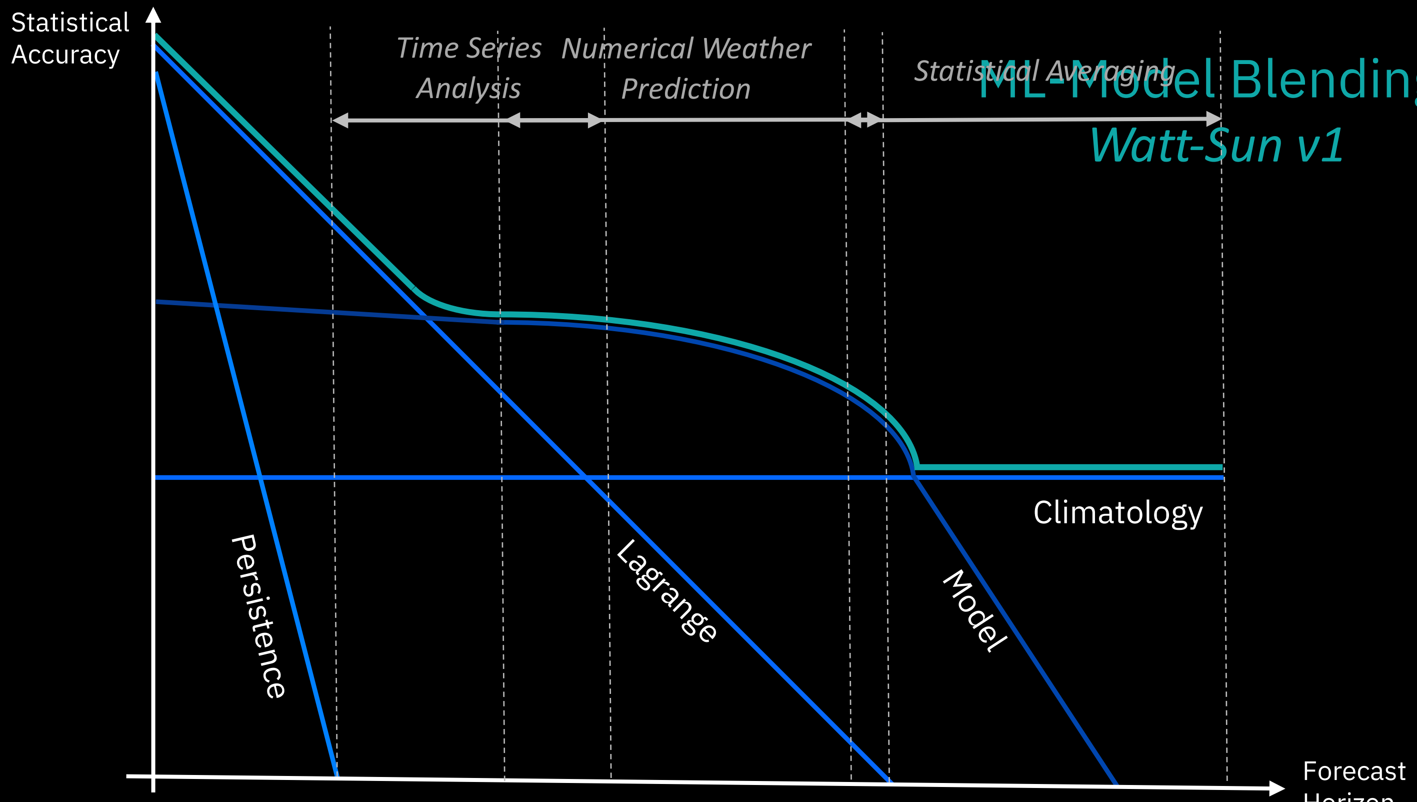


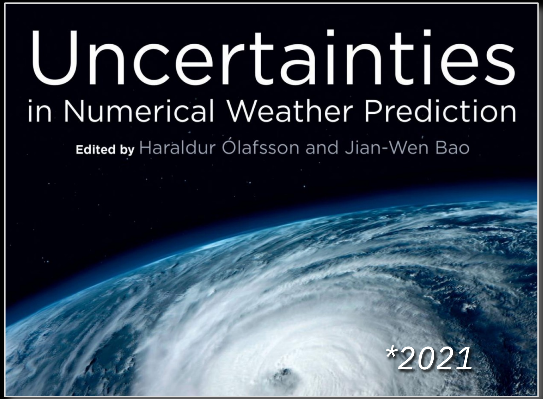
Fig. 2: Forecasting Accuracy across Methodologies

Uncertainty in Solar Forecasting

The definition of 'truth' for Numerical Weather Prediction error statistics

Rod FREHLICH

*2011



Strictly Proper Scoring Rules, Prediction, and Estimation

Tilmann GNEITING and Adrian E. RAFTERY

*2007

Measurements

Numerical Weather Prediction

Statistical Post-Processing

R_{t-l} → X_t —*Watt-Sun*→ Y_{t+h}

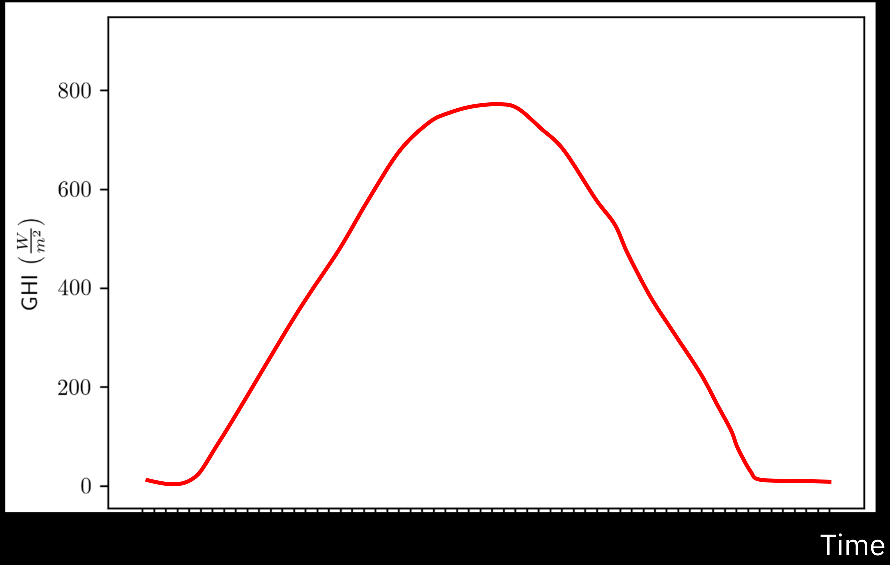
(Raw) Measurements

Temperature,
Precipitation Rate,
…

Global horizontal irradiance,
Solar Power Generation,
…

Watt-Sun: From *v1* to *v2*

v1 : Deterministic (’*Point*’) Forecast



v2: Probabilistic (‘*Interval*’) Forecast

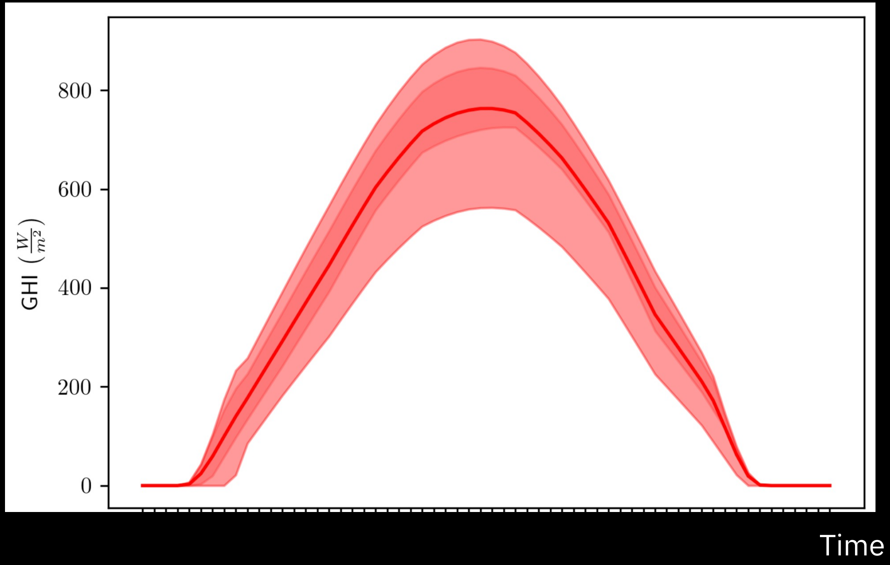


Fig. 3: 24h ahead forecasts of global horizontal irradiance (GHI),
Las Topaz (CA), April 1st 2020

Watt-Sun v1 : The Model

Regression:
global horizontal irradiance

Input Data:
Meteorological, Climatological, Topographical Data

$$Y_{t+h,s} = \sum_{c=1}^{C} \left(f_{t,s,h,c}(X_t; \theta_{t,s,h,c}) \right)$$

Legend

t	current time
h	forecast horizon
s	space (lat/lon)
c	weather category

Model instance:

- weather category-aware
- physical interpretability
- machine-learnt model blending

Watt-Sun v2 : The Model

Quantile Prediction:
global horizontal irradiance

Input Data:
Meteorological, Climatological, Topographical Data

$$F^{-1}(p; Y_{t+h}) = \sum_{m=1}^{M} \left(f_{t,h,m}(X_t; \theta_{t,h}) \right)$$

Model Instance:

- automatic filtering (diurnal/seasonal)
- space-time embedding learning
- rasterized output

Legend

t	current time
h	forecast horizon
m	model instance
F	CDF

Watt-Sun: Training and Test Data

- Y
- ☐ X

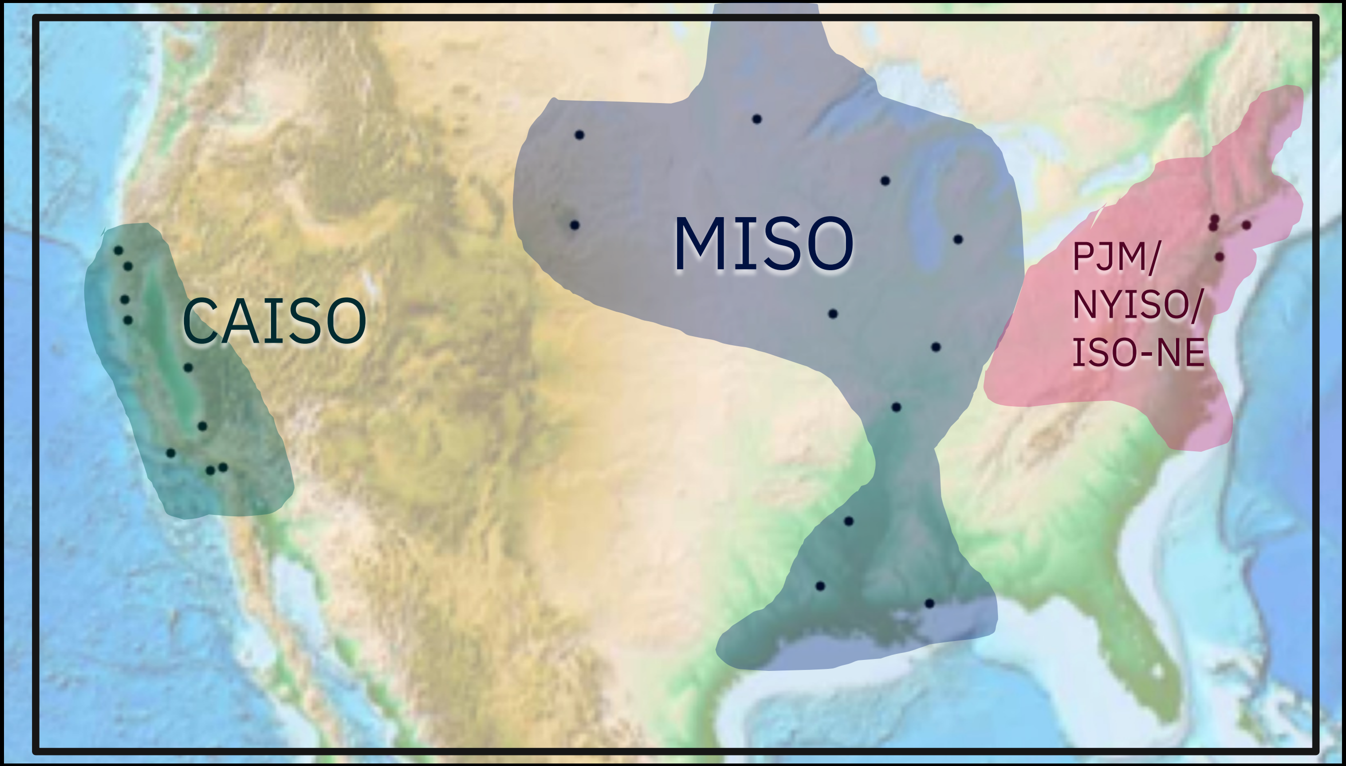
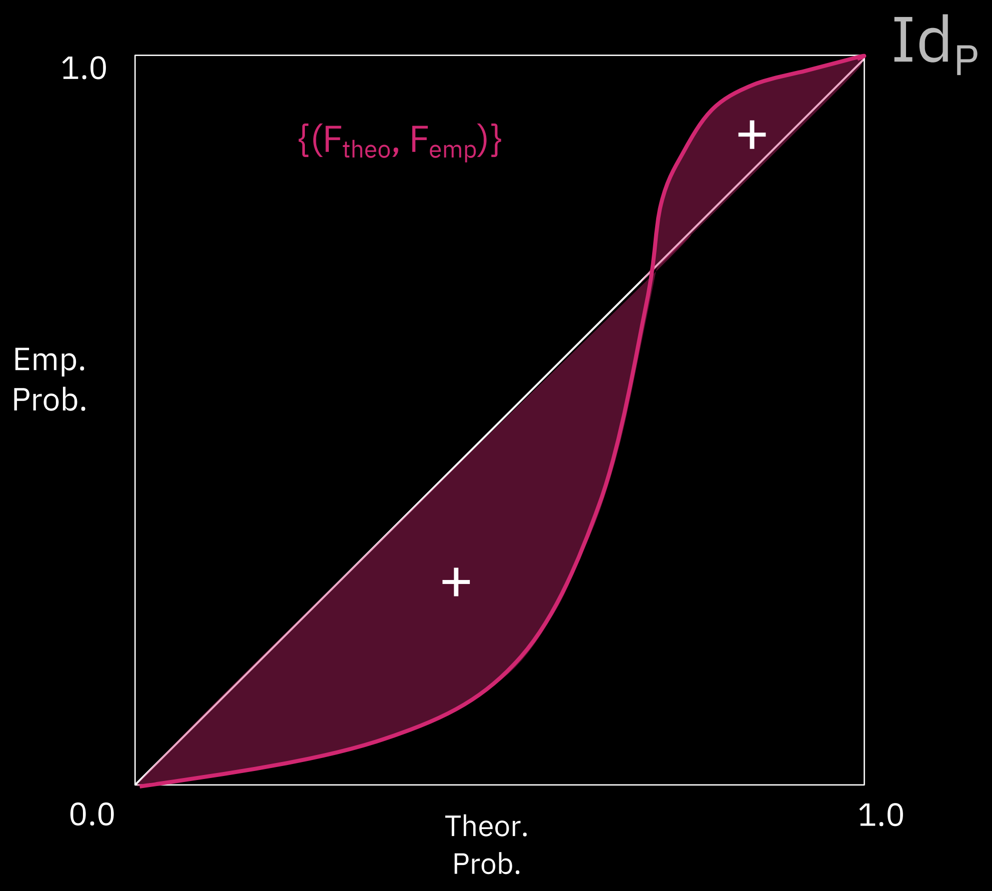
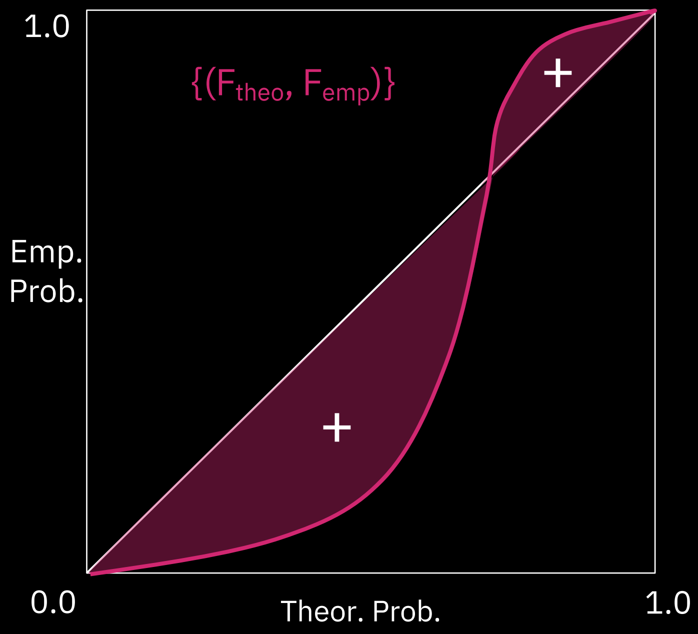


Fig. 4: 24 GHI reference stations, and NOAA High-Resolution Rapid

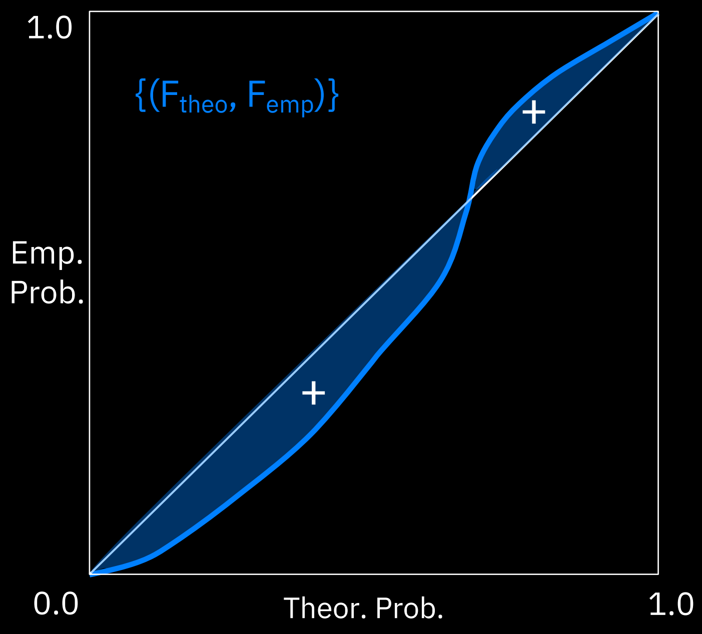
Performance: PP-Plot



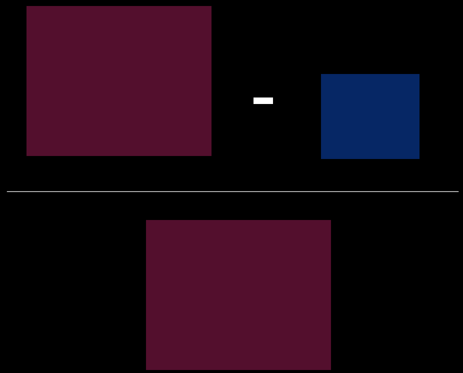
Performance: PP-Plot Metric



A. Baseline



B. Watt-Sun v2



C. PP-Plot Metric

Computational Challenges

Storage

- temporal resolution: sub-hourly data
- spatial resolution: 3 km
- extent: North America

IBM PAIRS Geoscope

Computation

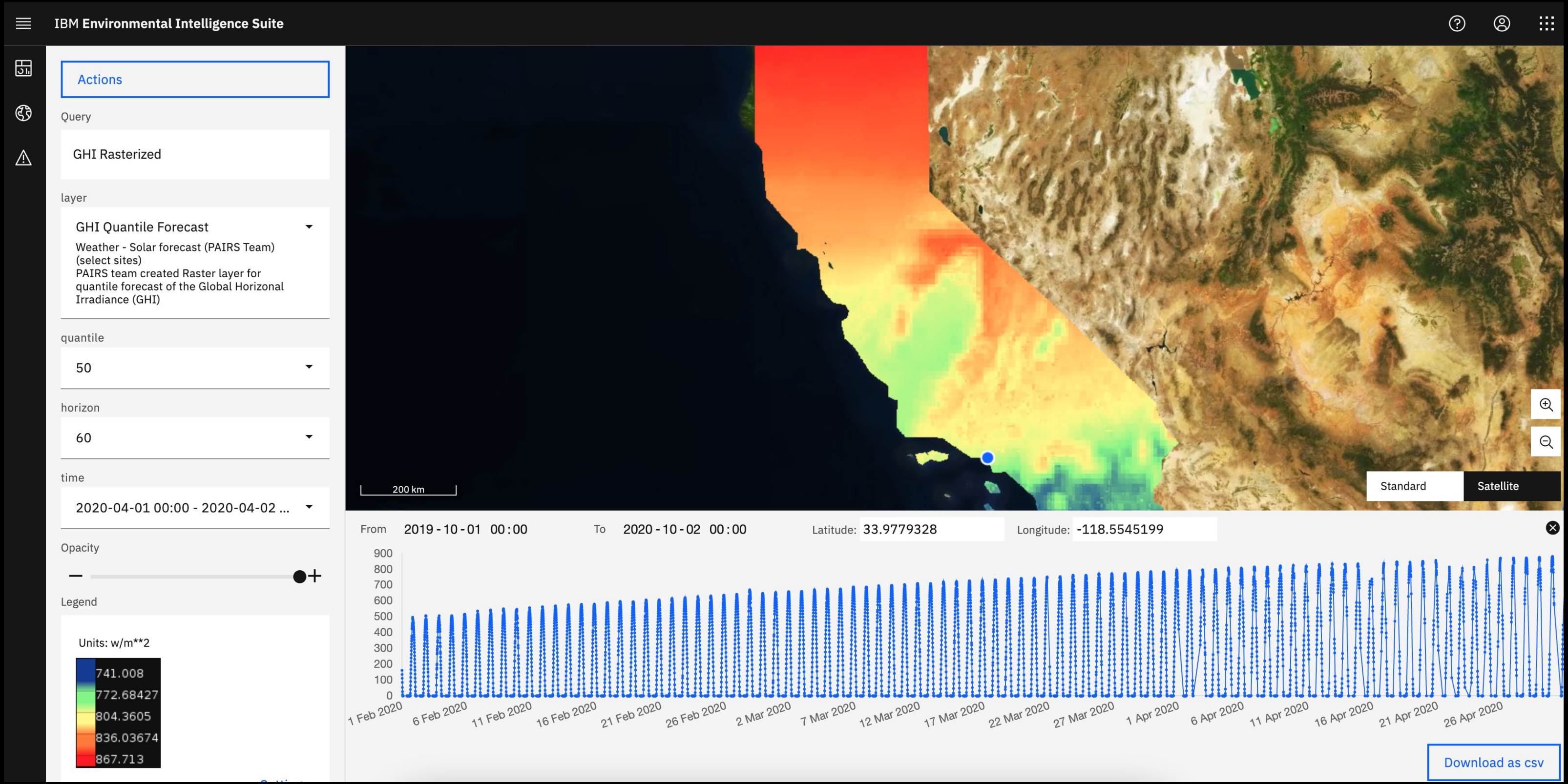
- infer thousands of parameters
- multiple optimization problem
- continuous deployment

IBM Cloud

IBM PAIRS : Graphical User Interface

Output: GHI, 50% quantile

Input Data: GOES 16



IBM COS: Cloud Object Storage

IBM Cloud

Model Estimation

- integrated ML frameworks
- distributed deep learning

Model Deployment

- customizable environments (e.g. Python, R)
- reliable inference
- logging

Thank you!

carlo.siebenschuh@ibm.com