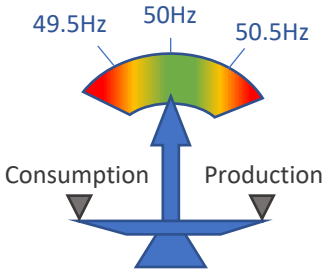
Combination of post-processing methods to improve high resolution solar irradiance forecasts in French Guiana

Rafael Alvarenga, Hubert Herbaux and Laurent Linguet

Jun 2022

CONTEXT



Power grid stability: balance between production and consumption

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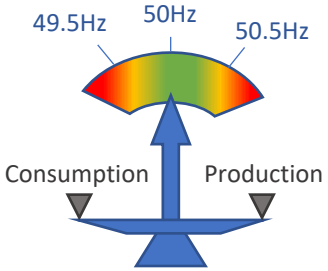

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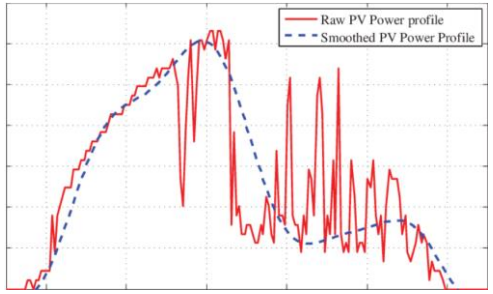

Renewables may deliver a particular intermittent power

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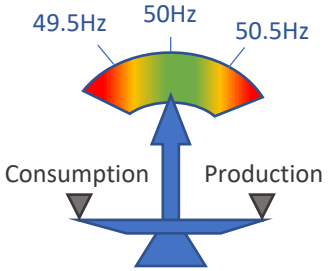

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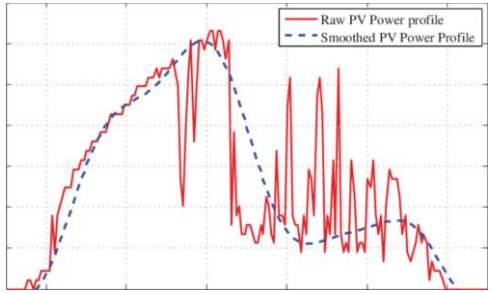

Renewables may deliver a particular intermittent power

Challenge: reduce grid carbon intensity maintaining the supply reliability

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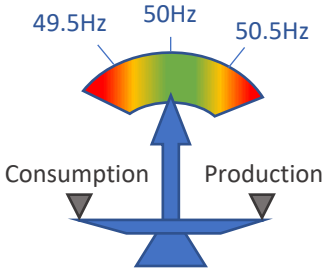

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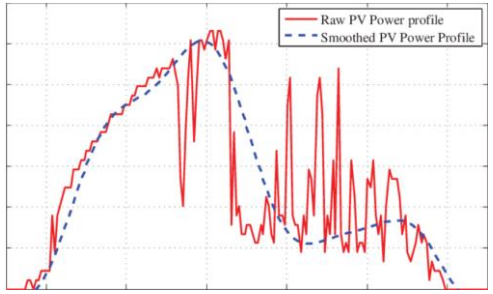

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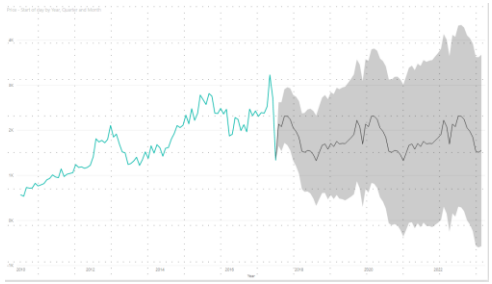
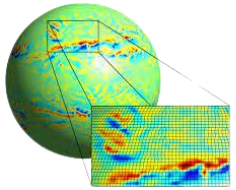


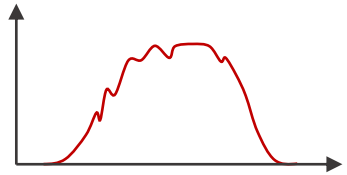
Intermittent producers are encouraged to issue reliable forecasts of their production

OBJECTIVES

In the case of PV power plants, the energy production is highly correlated with the solar irradiance

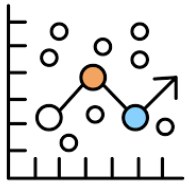
Numerical Weather Prediction (NWP)

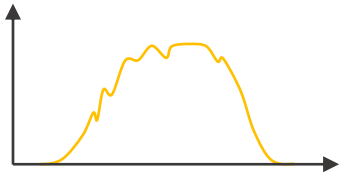




Solar irradiance forecasts

Statistical model





PV power forecasts

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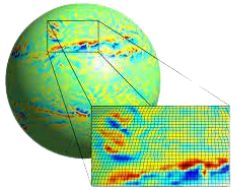
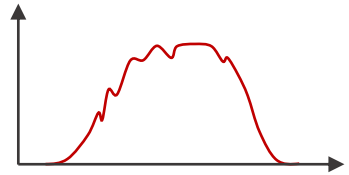


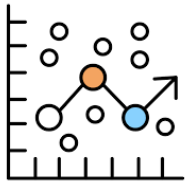
Approximations during modeling

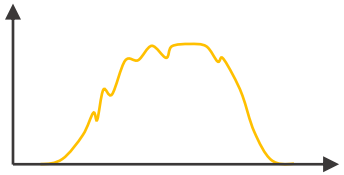


Solar irradiance forecasts

Cause forecast errors

Statistical model





PV power forecasts

Biased forecasts

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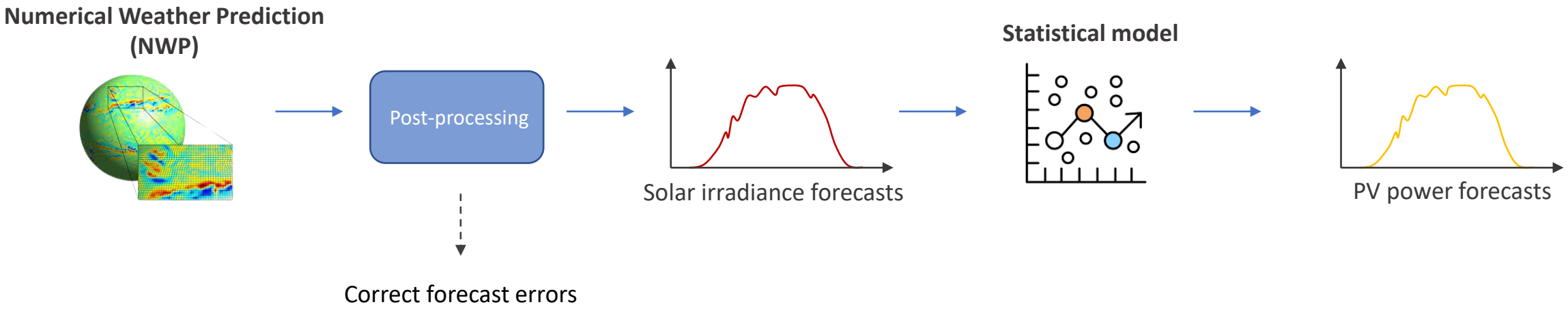

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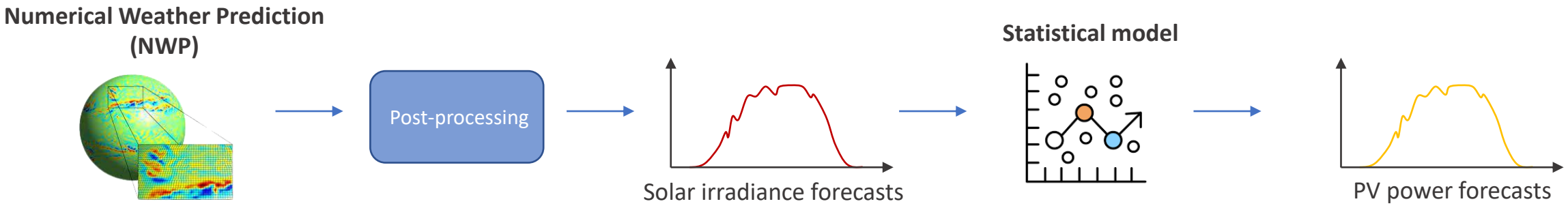
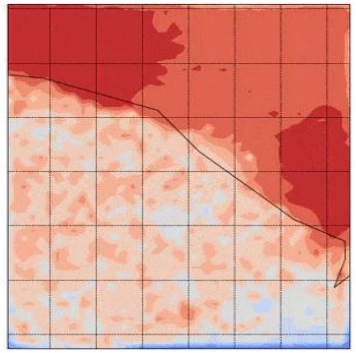


In this study, multiple methods and their combinations were tested to improve high-resolution solar irradiance forecasts

The forecasts are used to predict the meteorology over a PV power plant in French Guiana

Forecasts

Two years of daily solar irradiance forecasts with a 24h horizon, generated using the Weather Research and Forecasting (WRF) numerical model.



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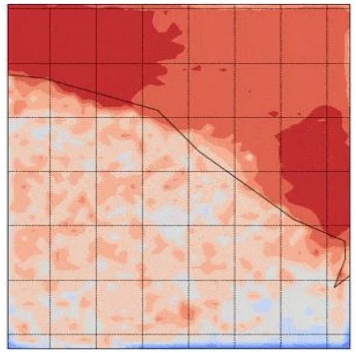
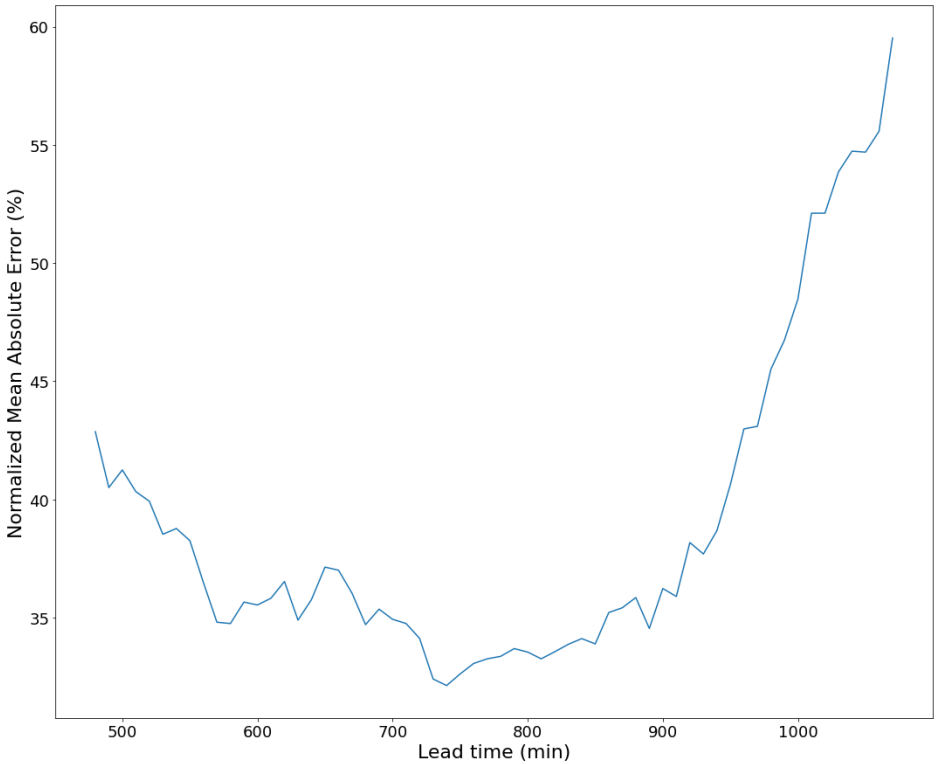
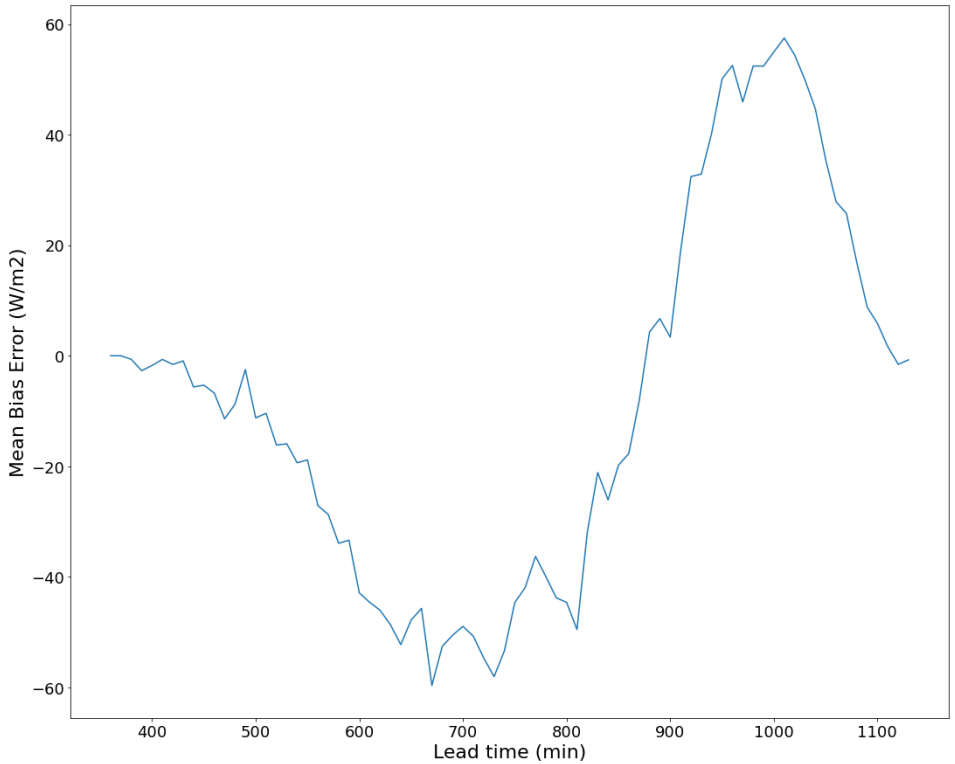
The original forecasts contain two types of errors, a **random error** and a **systematic error**.







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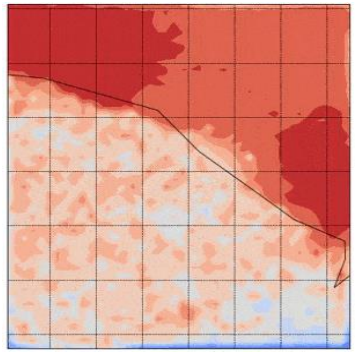
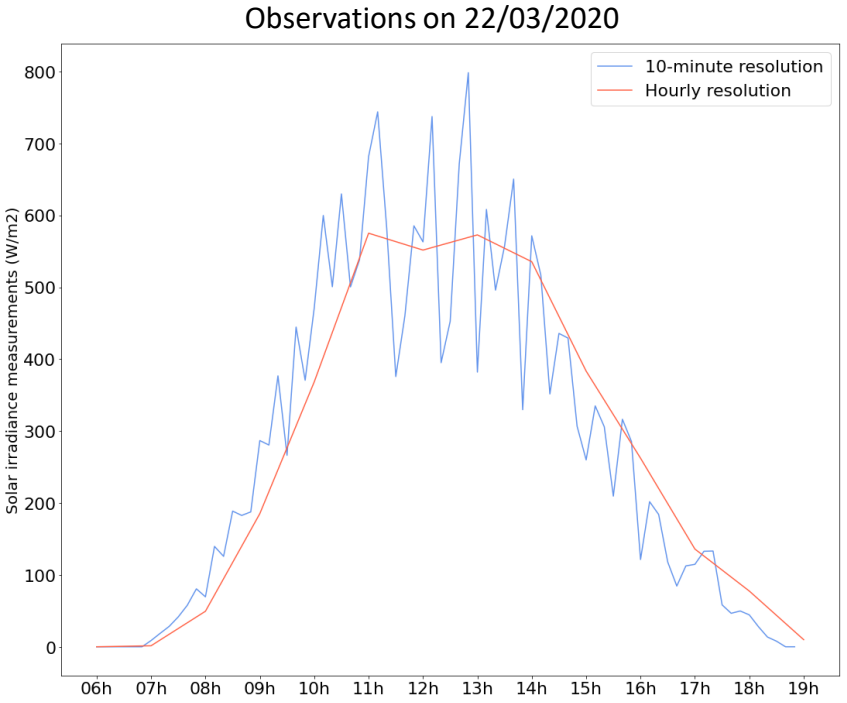


Observations

Ground truth is used to build post-processing models and to assess their performance.



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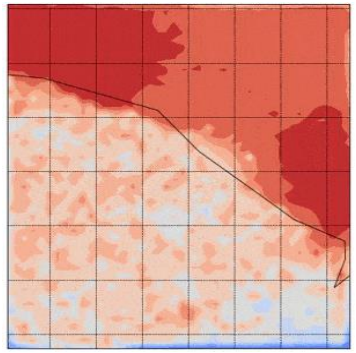

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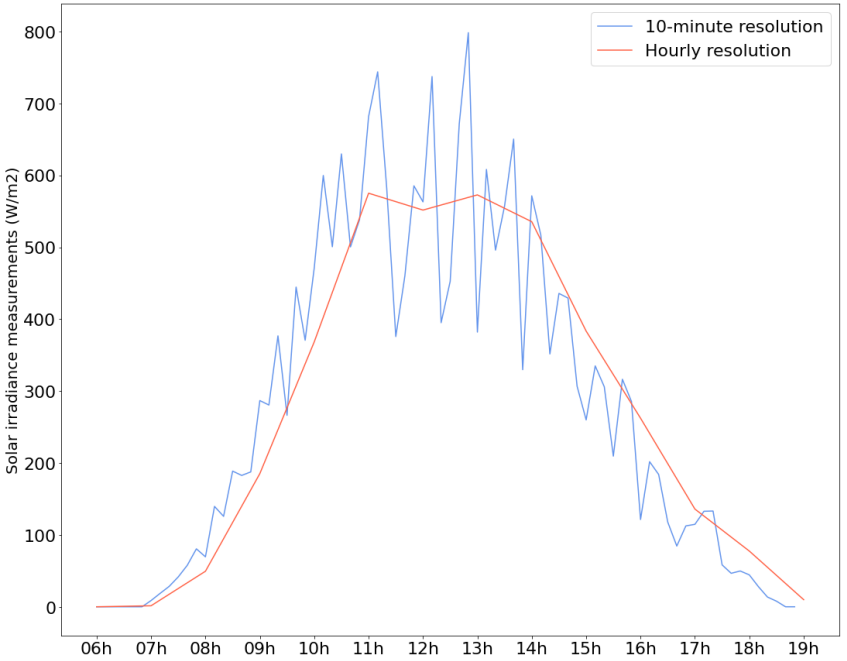
Observations on 22/03/2020



Two time-resolutions

The methods are tested in both **10-minute** and **hourly resolution**, in order to analyze the differences in modeling and results according to the time resolution.

METHODOLOGY

3 methods were tested for the post-processing of the solar irradiance forecasts:

Model Output Statistics (MOS) **Kalman Filter** **Kernel Conditional Density Estimation**

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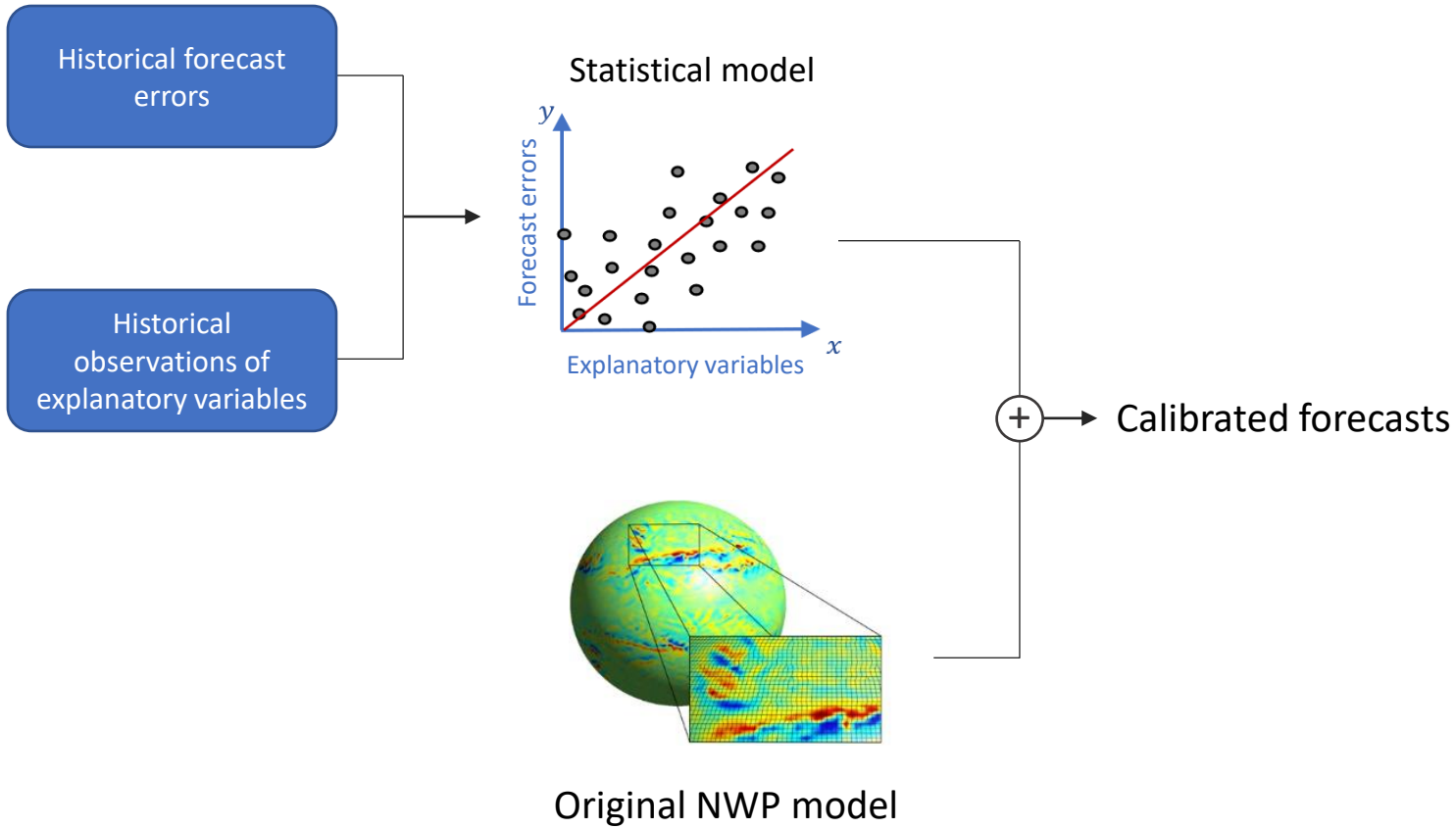

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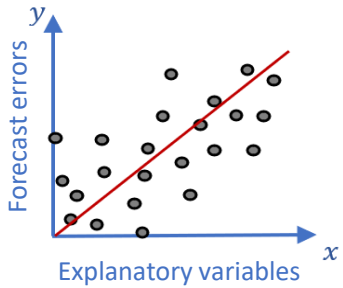
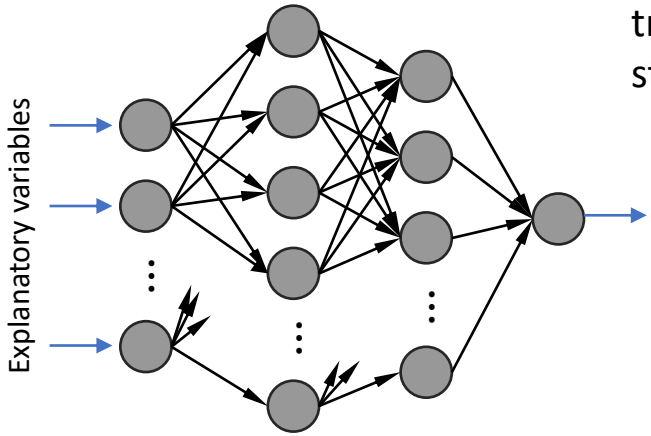
Historical forecast errors

Historical observations of explanatory variables

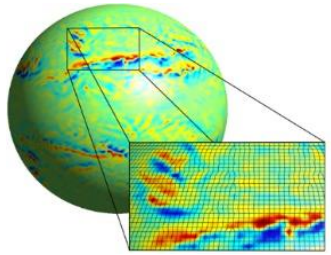
Statistical model



MLP neural network



Parameters estimated with training based on stochastic gradient descent



Original NWP model

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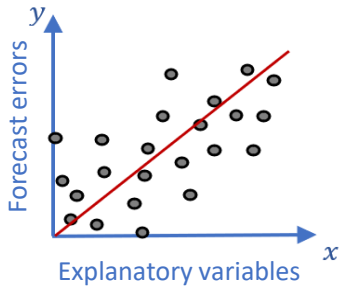

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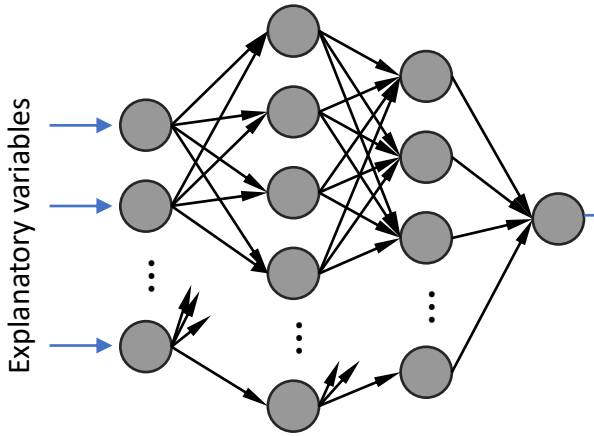

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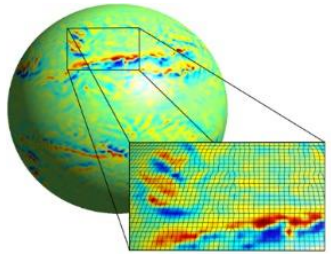

Original NWP model

Lorenz 4th-order polynomial

$$e = a_1 \cos^4(\hat{Z}) + a_2(\hat{k})^4 + a_3 \cos^3(\hat{Z}) + \cdots + a_0(\hat{k})$$

Explanatory variables

Parameters estimated directly with MSE minimization

METHODOLOGY

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Model Output Statistics (MOS) **Kalman Filter** Kernel Conditional Density Estimation

The method is based on two group of equations:

Time update

1) Project the last error predicted

$$\hat{x}_t = A\hat{x}_{t-1}$$

2) Project the error covariance

$$P_t^- = A.P_{t-1}.A^T + Q$$

Measurement update

1) Compute the Kalman gain

$$K_t = P_t^-.H^T(H.P_t^-.H^T + R)^{-1}$$

2) Update estimate with measurement z_t

$$\hat{x}_t = \hat{x}_t + K_t(z_t - H\hat{x}_t)$$

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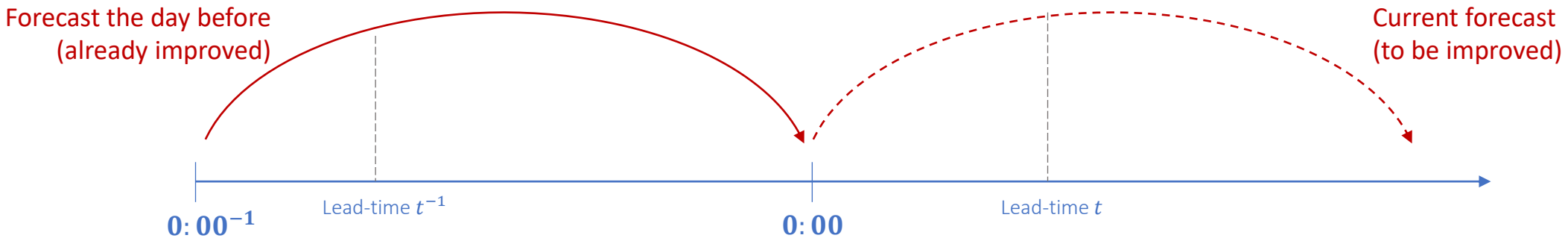

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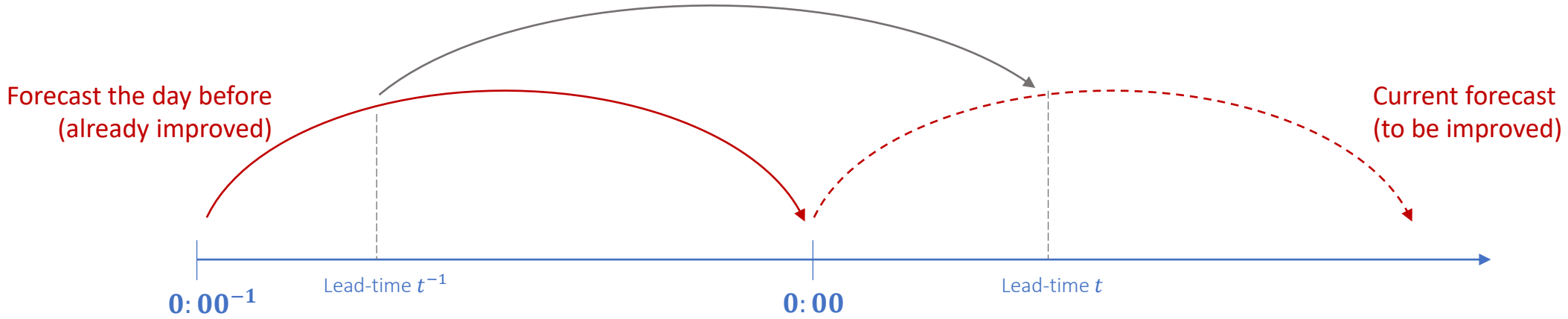
Project the last error predicted for this lead-time and its error covariance matrix



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Project the last error predicted for this lead-time and its error covariance matrix

Improve the declared forecast (to be used to post-process the following forecast)

Forecast the day before (already improved)

Current forecast (to be improved)

$0{:}00^{-1}$ Lead-time t^{-1} $0{:}00$ Lead-time t

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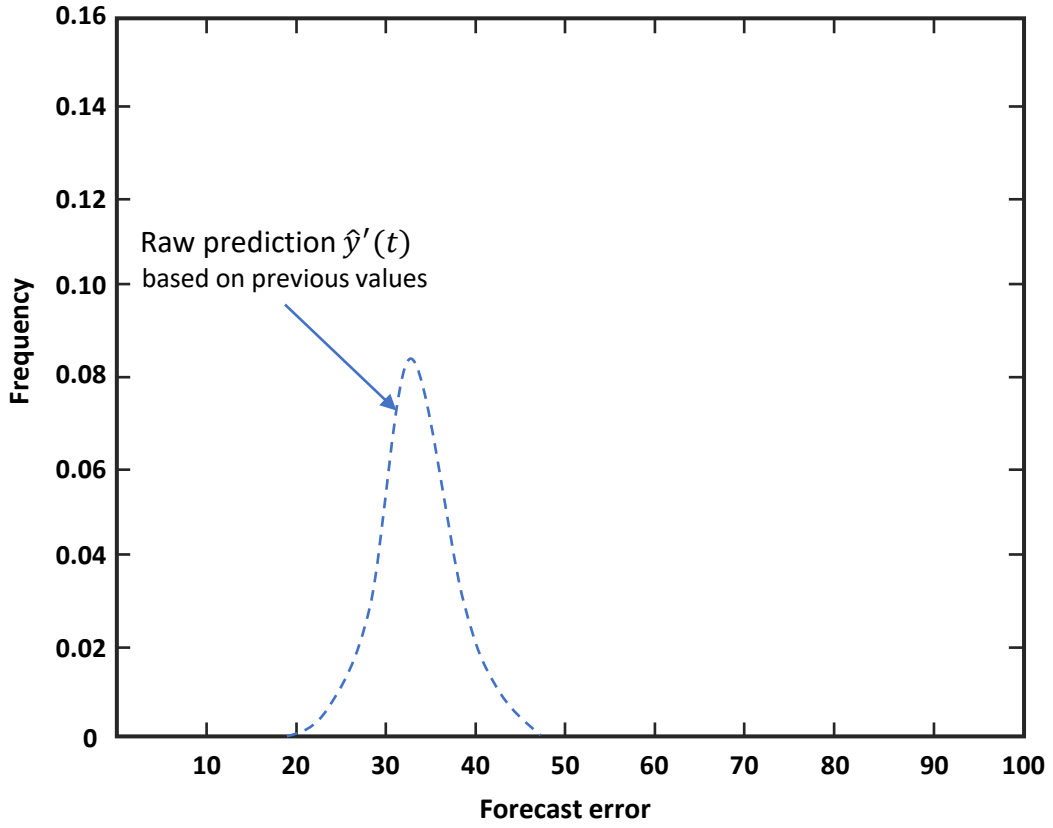

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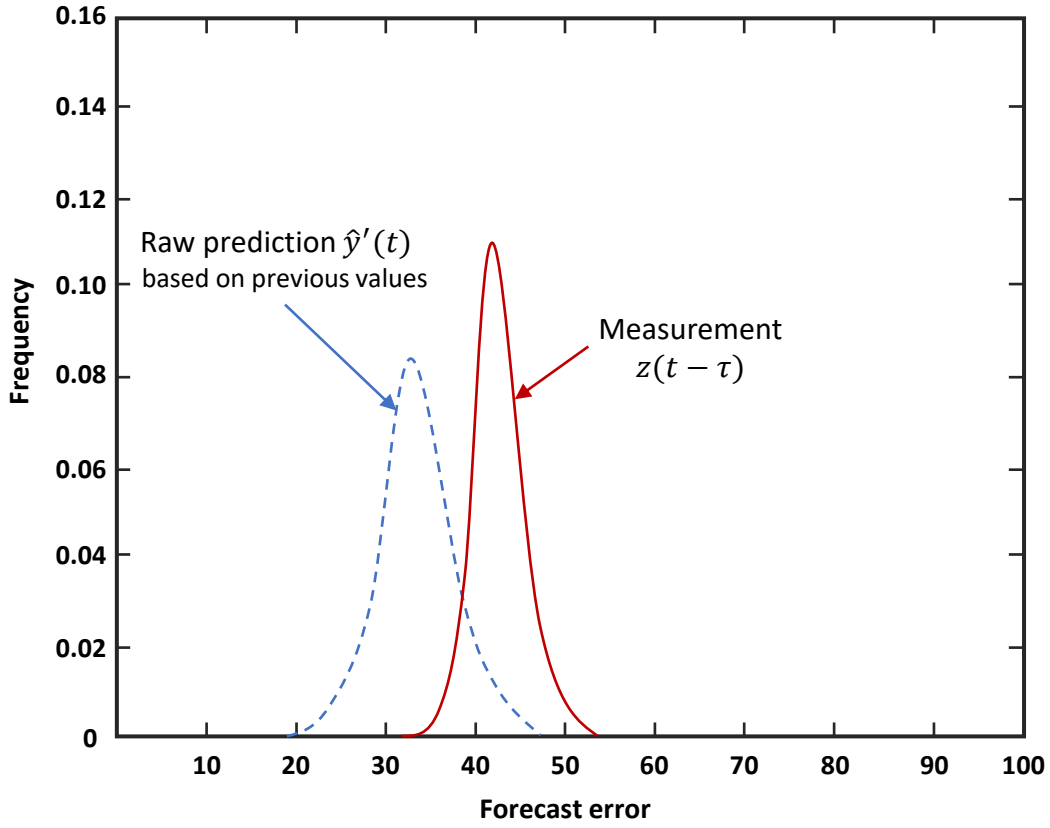

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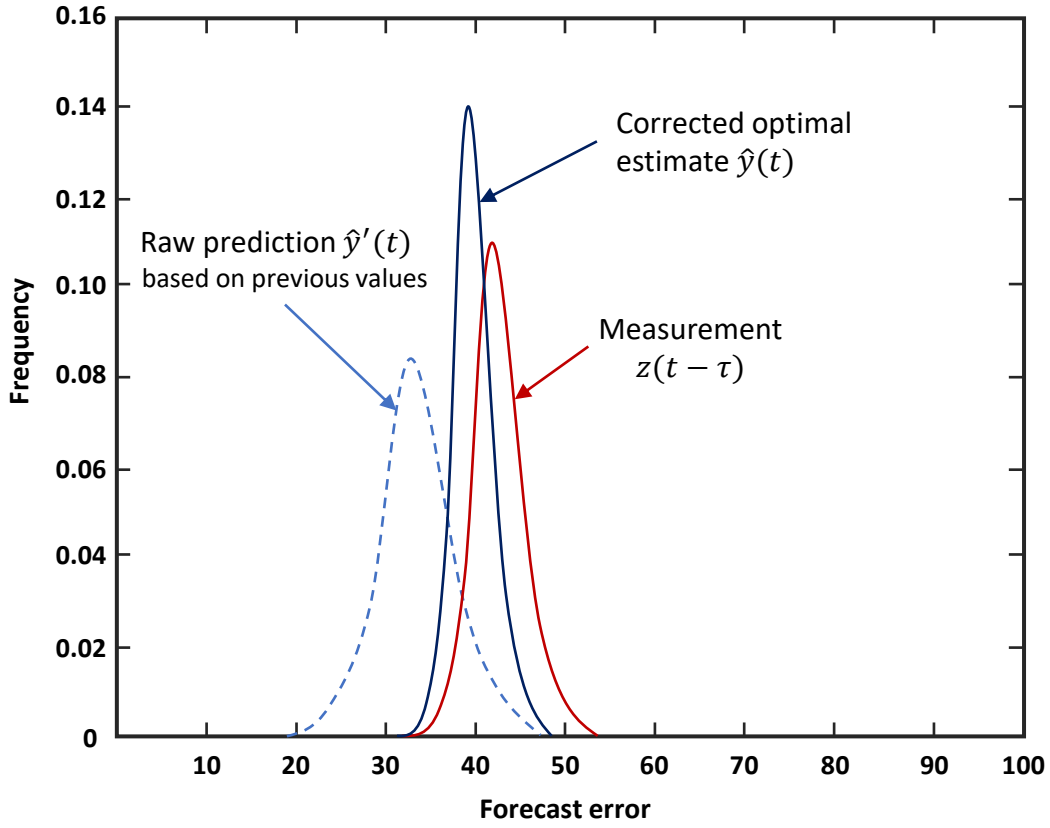

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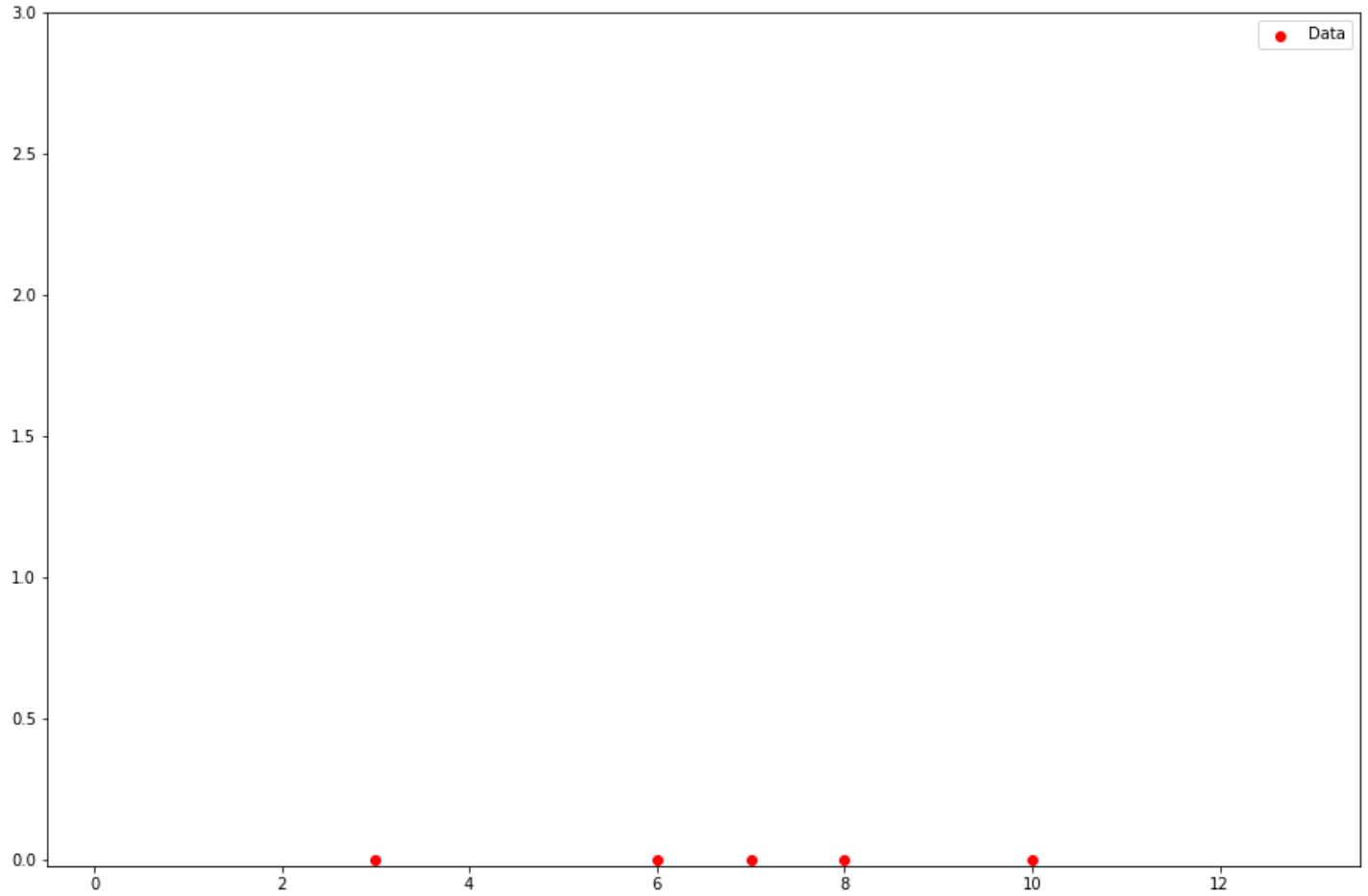

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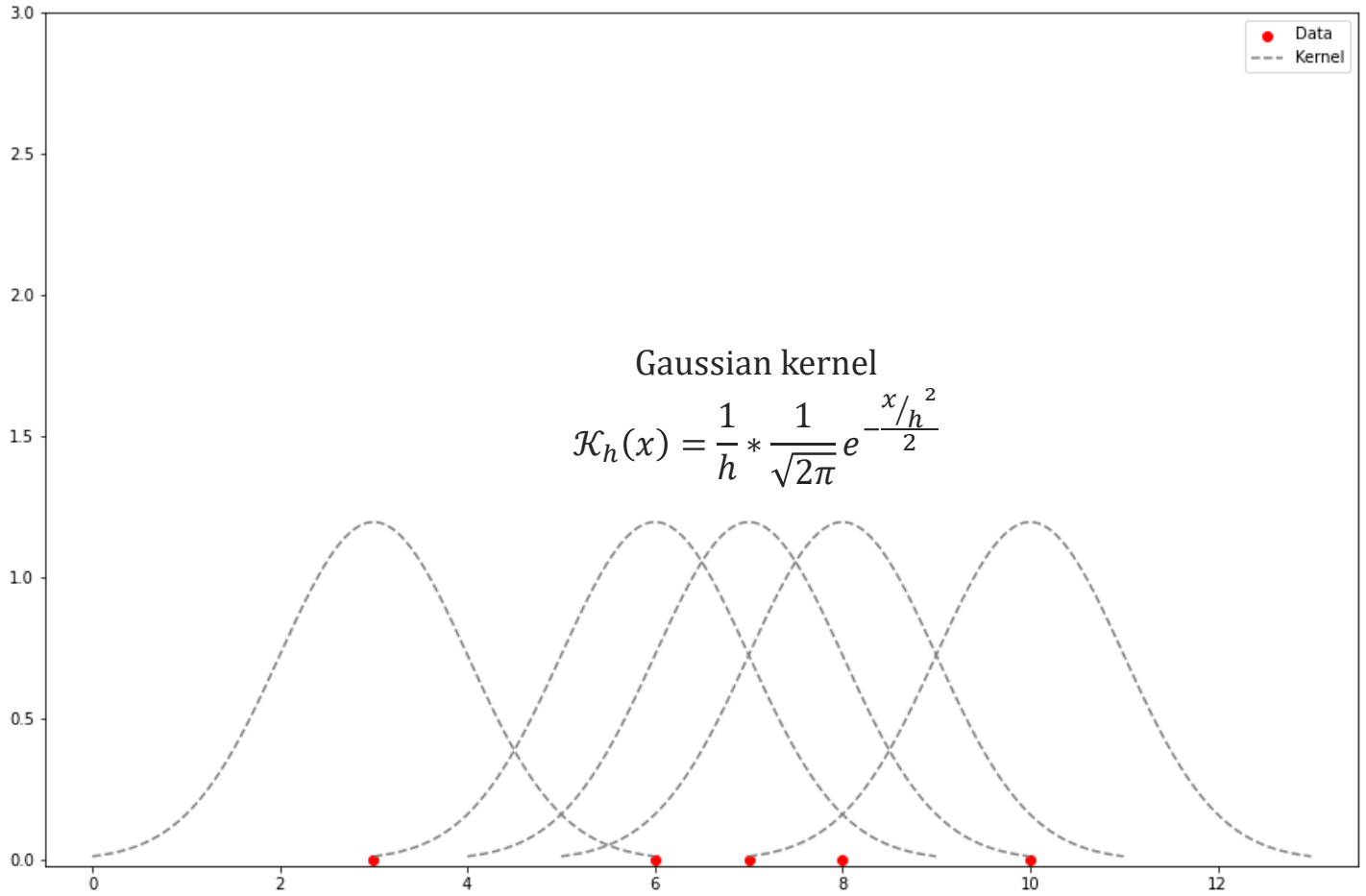

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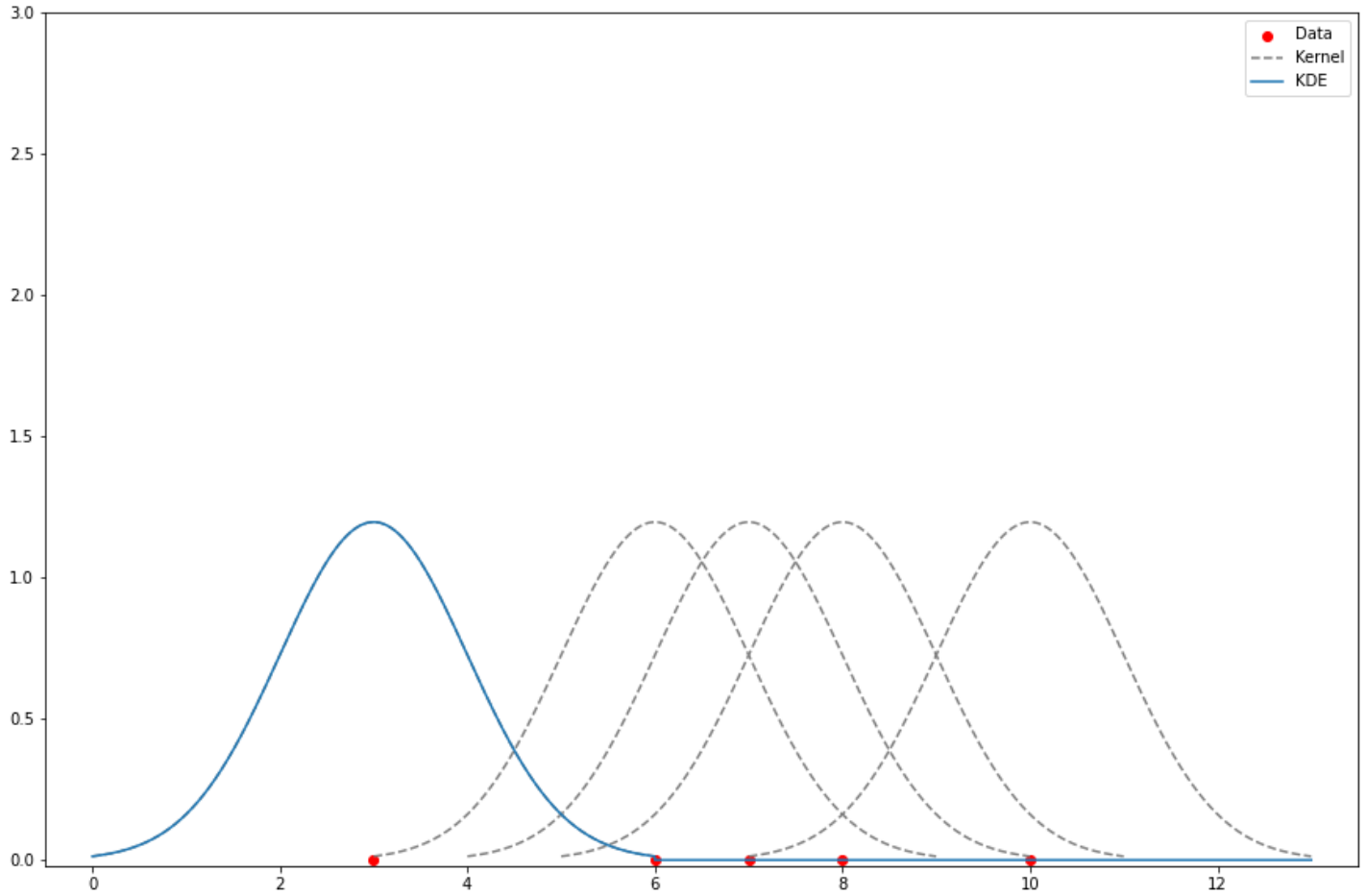

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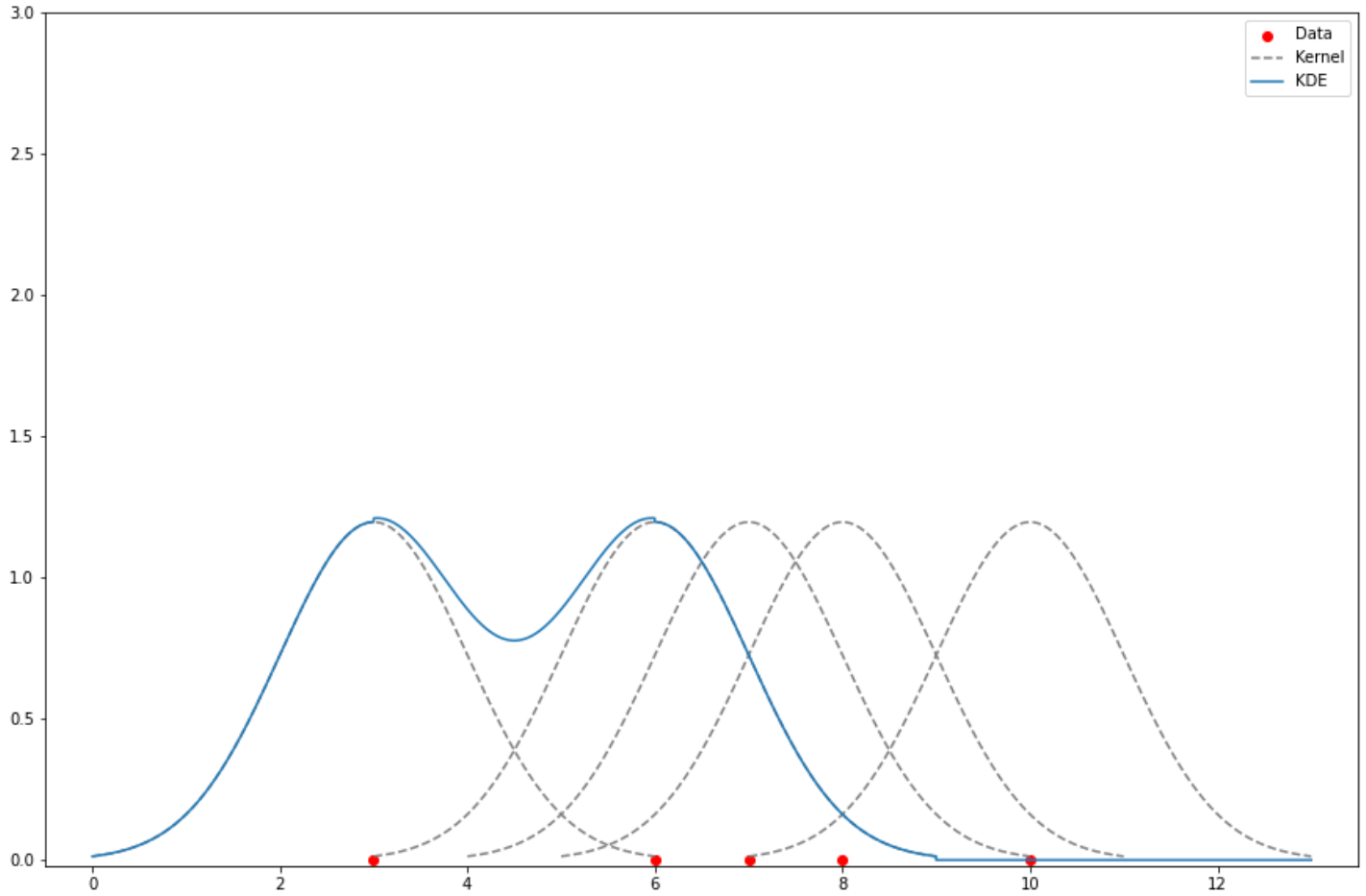

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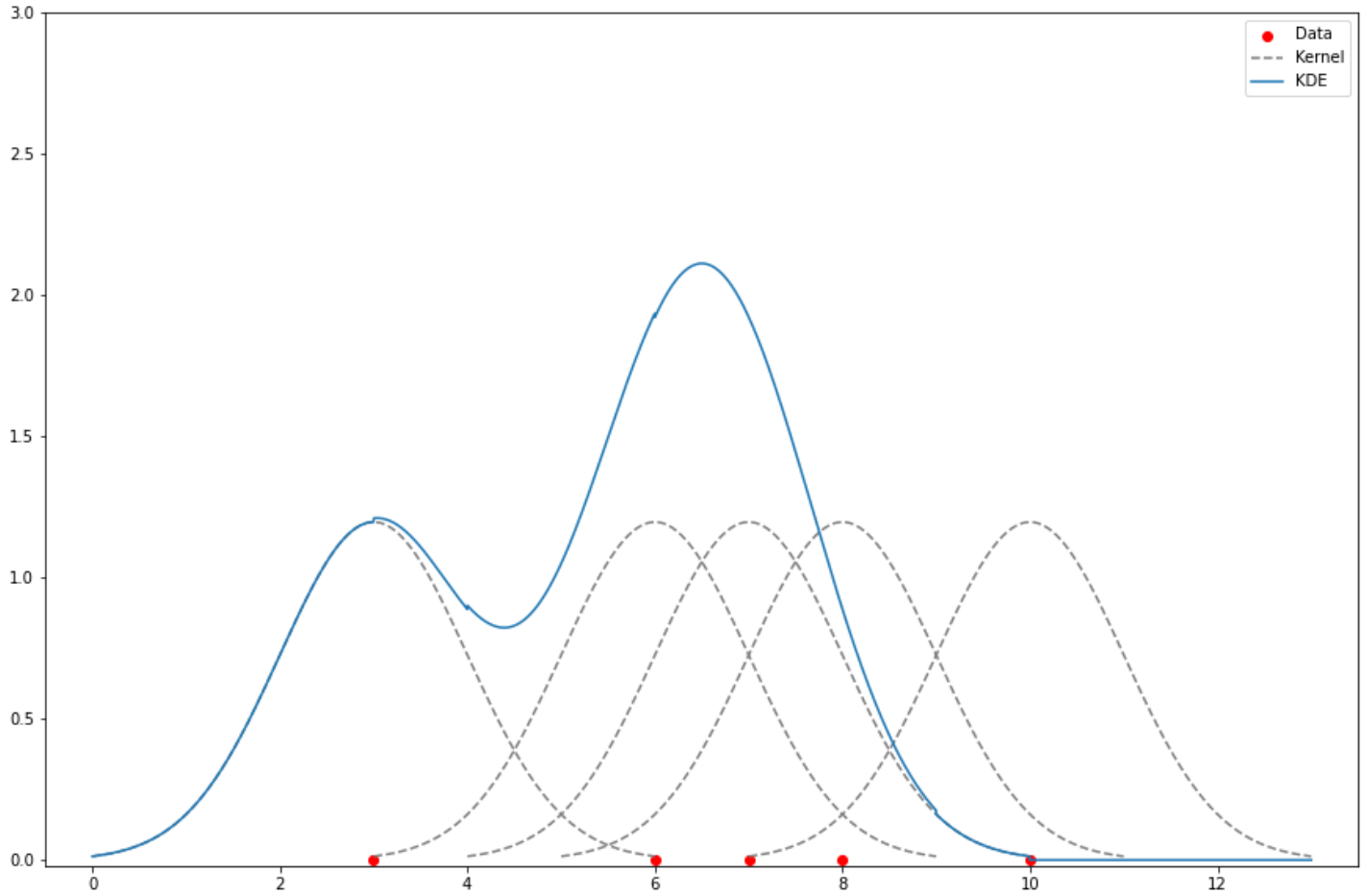

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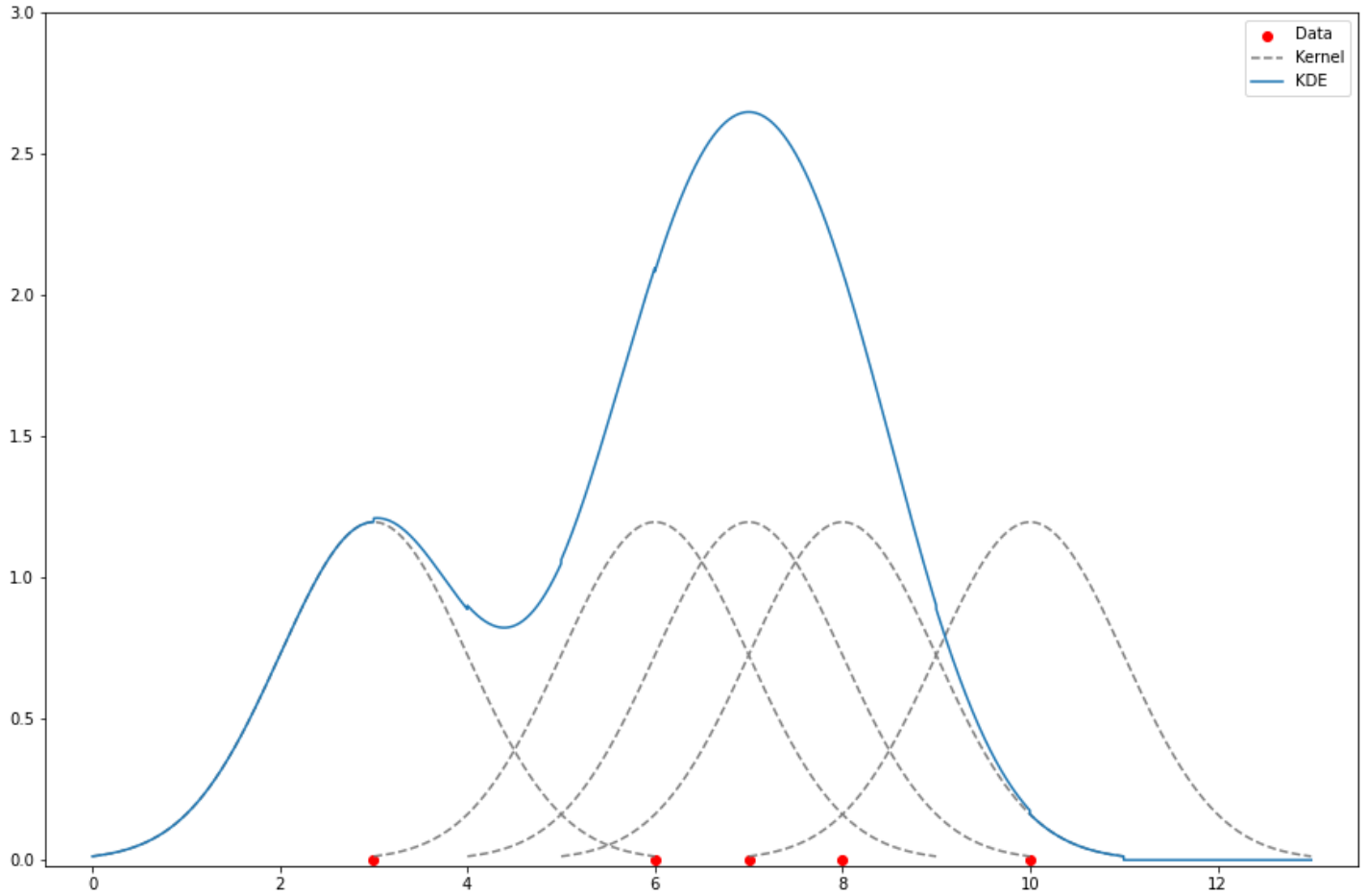

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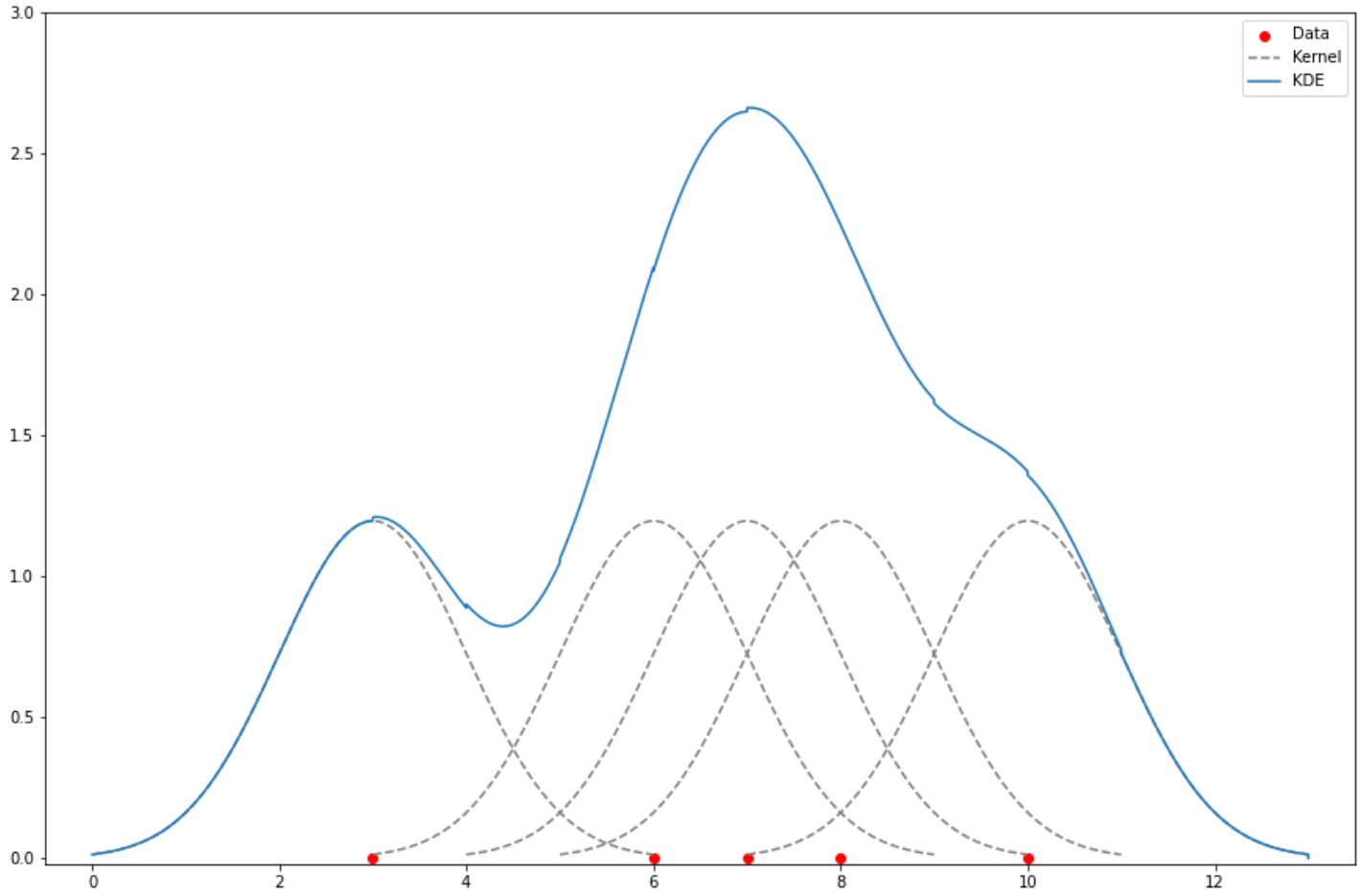

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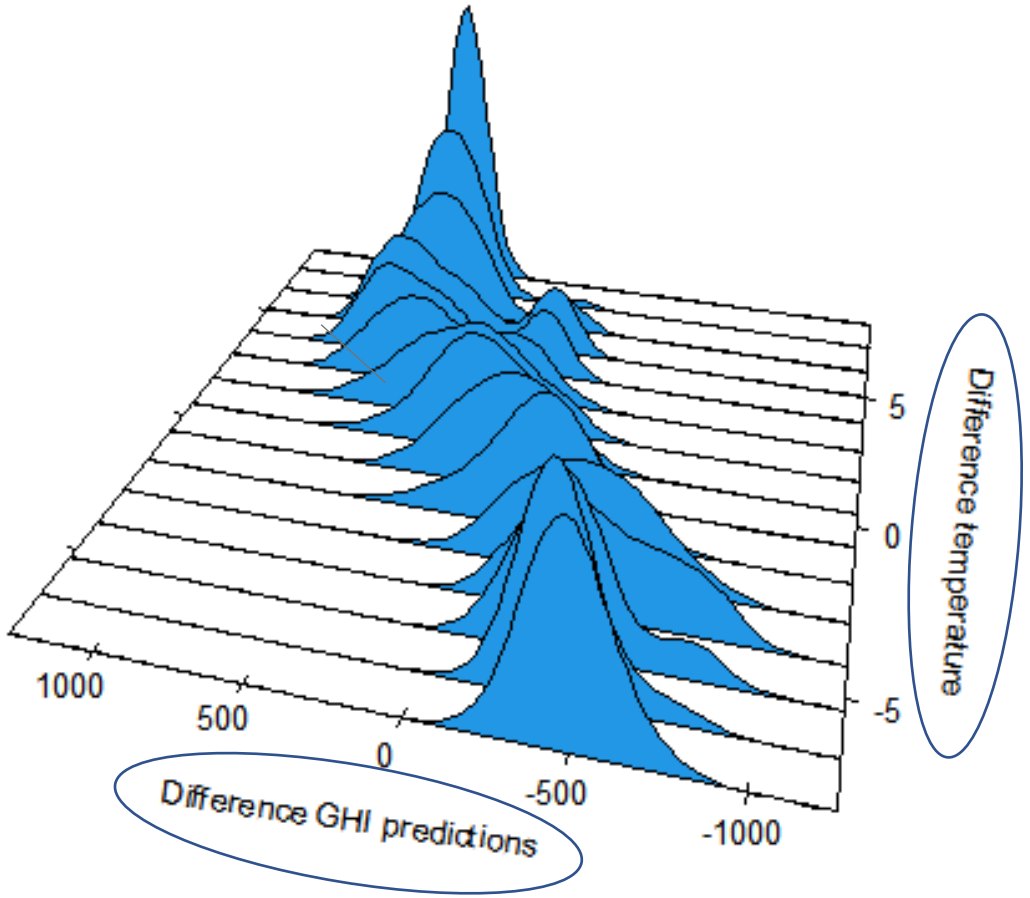
Adding conditionals to the process…



Difference between conditionals of a historical dataset and current conditionals

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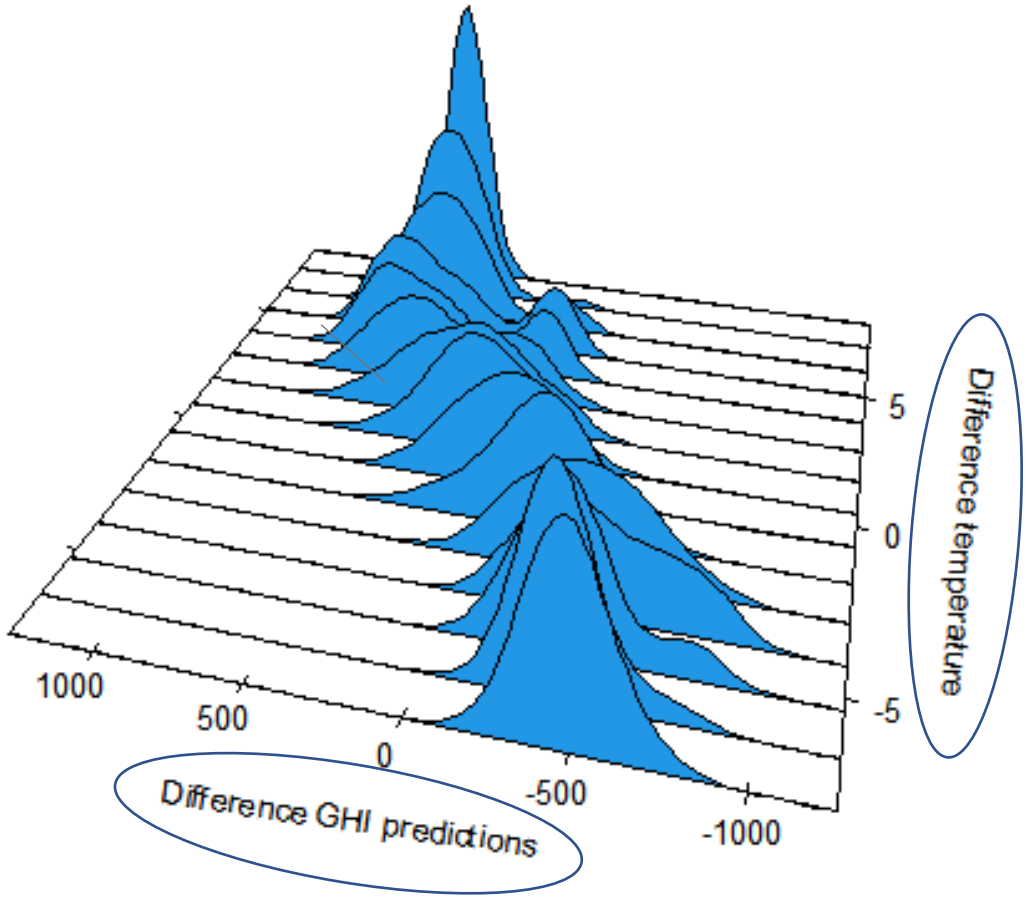

$\mathbb{E}$ { Difference between conditionals of a historical dataset and current conditionals } $\times$ historical forecast errors

$=$ current forecast error estimation

RESULTS

Modeling

Forecast improvement

Modeling Forecast improvement

Best group of predictors per method per time resolution

Resolution	ANN	Lorenz	KCDE	Kalman filter
10-minute	$Irradiance_{pred}$ Wind speed (x) Wind speed (y) Cloud-coverage Temperature Humidity	$Irradiance_{pred}$ Cloud-coverage Sun zenith angle Pressure Temperature Wind speed (x)	$Irradiance_{pred}$ Cloud-coverage Sun zenith angle Pressure	$Irradiance_{pred}$ Cloud-coverage
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No significant difference

More significant difference

Modeling Forecast improvement

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→ Allows to explain forecasts errors for hourly resolution only

RESULTS

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Forecast improvement

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Forecast improvement

10-minute resolution improvement (%)

Method	MAE	RMSE	MBE
MOS_{ANN}	22	12	-95
MOS_{Lorenz}	7	10	48
KF	8	7	**95**
KCDE	6	9	27
KF + MOS_{ANN}	32	17	-31
MOS_{ANN} + KF	**45**	**41**	91

Hourly resolution improvement (%)

Method	MAE	RMSE	MBE
MOS_{ANN}	37	36	-49
MOS_{Lorenz}	9	10	43
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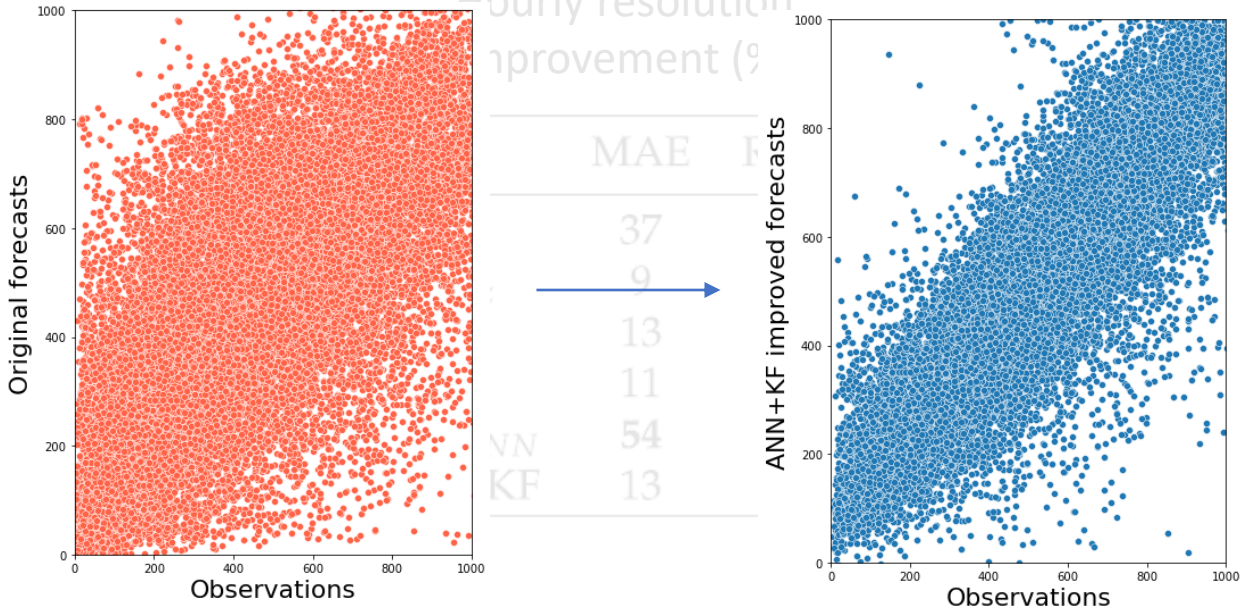

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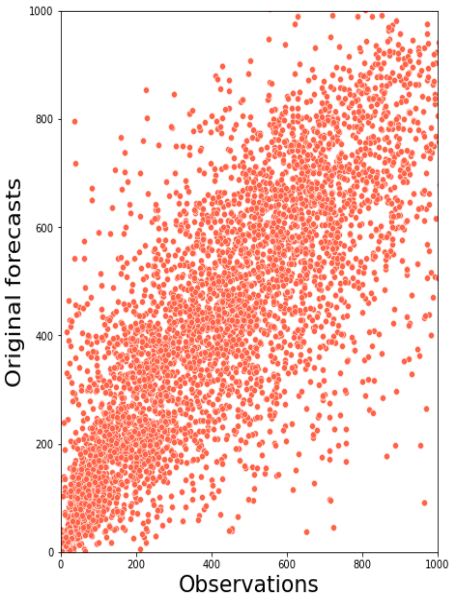

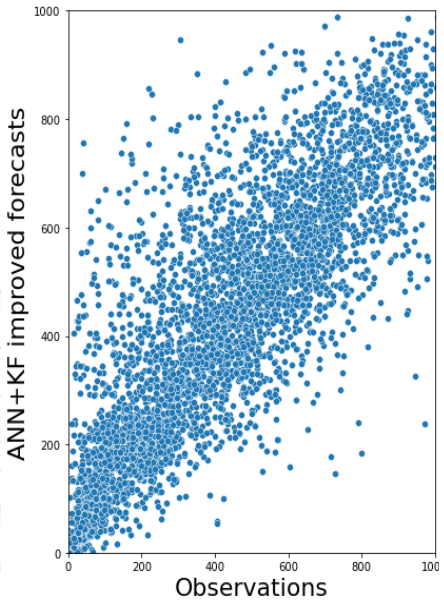

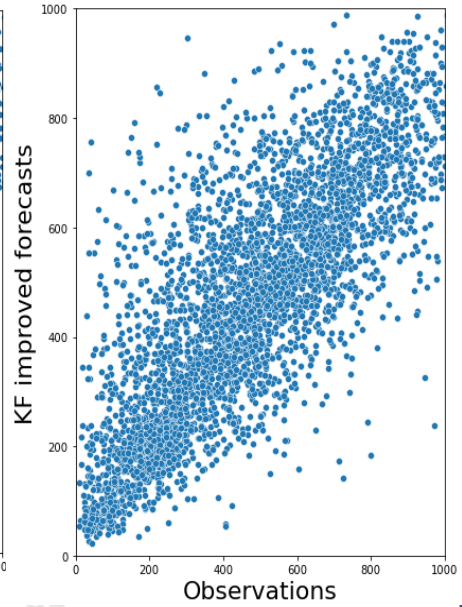

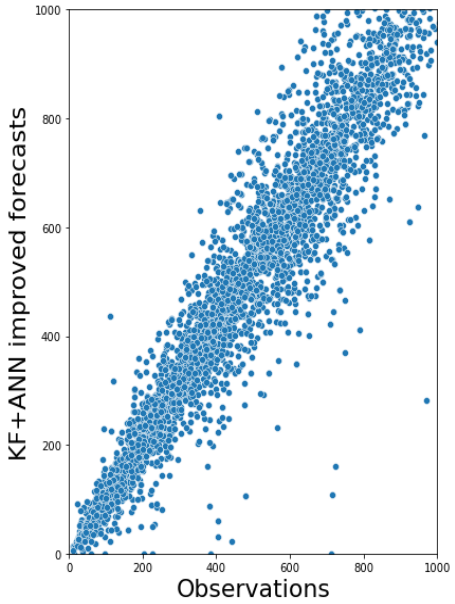

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- 10-minute resolution post-processing: the combination of a neural network MOS followed by a Kalman filter improve significantly both errors;
- Hourly resolution post-processing: the combination Kalman filter + neural network MOS improves the best the random error, however the Kalman filter can be used individually if the focus is on improving the systematic error;