Predicting Photovoltaic Power Production using High-Uncertainty Weather Forecasts

Supplementary Materials

Tomas Polasek[a,*] (Researcher), Martin Cadik[a] (Researcher)

[a]Faculty of Information Technology, Brno University of Technology, Brno, Czech Republic

ARTICLE INFO

Keywords:
Solar Power Forecasting
Photovoltaic Dataset
Prediction Uncertainty
Machine Learning Model

ABSTRACT

A growing interest in renewable power increases its impact on the energy grid, posing significant challenges to reliability, stability, and planning. Weather-based prediction methods help relieve these issues. However, their real-world accuracy is limited by weather forecast errors. To help resolve this limitation, we introduce the SolarPredictor model. Publicly available weather forecasts are used to predict solar power production by a target photovoltaic power plant. To achieve high prediction accuracy, the model is trained on genuine weather forecasts, including errors and mispredictions. Further, we introduce the SolarDB dataset, comprising one year of power production data for 16 power plants. The dataset includes hourly weather forecasts with seven days of history, allowing our model to anticipate errors in the meteorological features. The prediction accuracy is evaluated on a wide range of weather forecast ages, accurately reflecting real-world performance. The SolarPredictor model is compared against 17 techniques, reaching an average RRMSE of 6.15 for 1-day, 8.54 for 3-day, and 8.89 for 7-day predictions on the SolarDB dataset. Finally, we analyze the effects of weather forecast uncertainty on prediction accuracy, showing there is at least a 23 % performance gap compared to using zero-error weather. Data and additional resources are available at cphoto.fit.vutbr.cz/solar.

1. Introduction

This document contains supplementary materials which were omitted from the main text for reasons of brevity. We include additional data concerning the SolarDB dataset (Sec. 2), SolarPredictor model (Sec. 3), and experiments (Sec. 4).

2. The SolarDB Dataset

2.1. Data Overview

We provide a detailed overview of the SolarDB dataset in Fig. 1. In Fig. 3, each of the 16 power plants is represented by an overview (left) and a set of features (right). Apart from Power (top), we also provide the following features in order: Precipitation Intensity (1), Precipitation Probability (2), measured Temperature (3), Perceived Temperature (4), Dew Point temperature (5), Humidity (6), Pressure (7), Wind Speed (8), Wind Bearing (9), Cloud Cover (10), Visibility (11), Sun Altitude (12), Sun Azimuth (13), and Sun Irradiance (14).

2.2. Data Description

In the left of Fig. 2, we provide a full listing of data available in the SolarDB dataset. The status and error codes sent by the reporting systems are aggregated into the categories enumerated in the top-right of Fig. 2 and provided for every production record. Status codes are attached to the first record after a condition arises. For example, external error conditions may be caused by weather, power grid anomalies, or other connection-related problems. Conversely, the internal errors represent problems within the inverter or photovoltaic system itself – e.g., battery malfunction or overheating. We also provide a visualization of the available features in the bottom-right of Fig. 2.

*Corresponding author
ipolasek@fit.vutbr.cz (T. Polasek); cadik@fit.vutbr.cz (M. Cadik)
cphoto.fit.vutbr.cz (T. Polasek); cphoto.fit.vutbr.cz (M. Cadik)
ORCID(s): 0000-0002-1441-0241 (T. Polasek); 0000-0001-7058-9912 (M. Cadik)

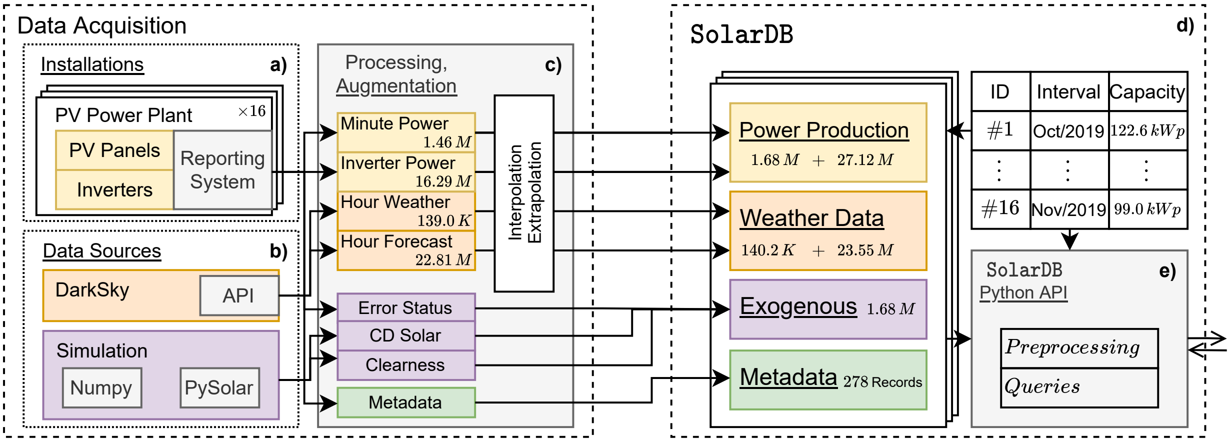

Figure 1: (Color, 2-column) Data Collection Overview: A diagram of the SolarDB dataset collection procedure. Each of the 16 installations reports production data **(a)** at 5, 10, or 15-minute intervals (Tab. **??**), both at the power plant and per-inverter levels. Secondary data sources **(b)** include the Dark Sky [1] API for weather forecasts. The raw data containing over 40.7 M records is pre-processed and augmented **(c)**, creating the uniform SolarDB dataset **(d)** with over 53.5 M records. Additional power plant meta-data is provided. Finally, the dataset is accessed through the Python API **(e)**

Type	Name	Unit	Range	Description
Power	Power_{AC}	W	$\mathbb{R}$	Final output after conversion
	Power_{DC}	W	$\mathbb{R}$	Pure output of the panels
	Energy_{Int}	Wh	$\mathbb{R}$	Energy produced over interval
Weather	Summary	–	str	String summary of weather
	PrecipInt	mm/h	$\mathbb{R}$	Precipitation intensity
	PrecipProb	$\%$	$[0,1]$	Precipitation probability
	Temp	$°C$	$\mathbb{R}$	Measured temperature
	ApparentTemp	$°C$	$\mathbb{R}$	Perceived temperature
	DewPoint	$°C$	$\mathbb{R}$	Dew point temperature
	Humidity	$\%$	$[0,1]$	Humidity from dry (0) to humid (1)
	Pressure	hPa	$\mathbb{R}$	Pressure at ground level
	WindSpeed	km/h	$\mathbb{R}$	Average wind speed
	WindBearing	°	$[0,359]$	Wind bearing, north at 0°, clockwise
	CloudCover	$\%$	$[0,1]$	Cloud cover, clear (0) to overcast (1)
	Visibility	km	$[0,16]$	Visibility up to 16 km
Exogenous	Interpolated	–	$\{0,1\}$	Flag for original (0), interpolated (1)
	Extrapolated	–	$\{0,1\}$	Flag for original (0), extrapolated (1)
	Year	$year$	$\mathbb{Z}$	Year of observation
	Day	day	$[0,366]$	Observation Day of the year
	Time	sec	$[0,86400]$	Observation second of the day
	Age	$hour$	$\mathbb{R}_{\geq 0}$	Age of forecast, 0 for measured
	SunAltitude	rad	$[-\frac{\pi}{2},\frac{\pi}{2}]$	Sun altitude from ground plane
	SunAzimuth	rad	$[0,2\pi]$	Sun azimuth, north at 0, clockwise
	SunIrradiance	W/m^2	$\mathbb{R}$	Estimated clear sky irradiance
	Status	–	$\mathbb{Z}$	Status code for power record
	Error	–	$\mathbb{Z}$	Error code for power record
	Clear	–	$\{0,1\}$	Daily clarity, clear (0) or overcast (1)
Meta	Freq	min	$\mathbb{Z}$	Frequency of power observation
	Capacity	kWp	$\mathbb{R}$	Installed capacity
	Inverters	–	$\mathbb{Z}$	Number of inverters
	Latitude	°	$[-90,90]$	Anonymized latitude
	Longtitude	°	$[-180,180]$	Anonymized longtitude

ID	Name	Description
1	info	Information message not critical for device operation
2	warning	Warning message signalling abnormal conditions
3	error	Error message, device not operating correctly
4	wait	Device is waiting, operation will be resumed later
5	under	Under-current or under-voltage condition
6	over	Over-current or over-voltage condition
7	ext_error	Error caused by external conditions
8	int_error	Error caused by internal conditions
9	unknown	Unknown status or error condition

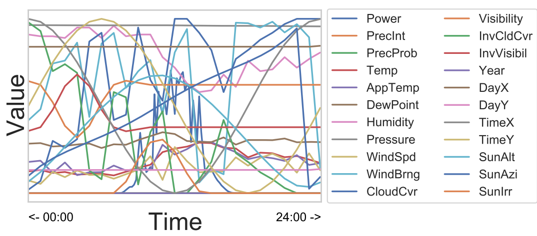

Figure 2: Dataset Quantities (left): Categorization of data included in the SolarDB dataset including their units and ranges. **Status Codes (right, top):** The message identifiers for status and error codes. **Feature Sample (right, bottom):** A single day-worth of power data from the SolarDB dataset along with a complete set of augmented features. Inverse and temporal values are calculated from the corresponding weather data. Sun features are calculated using PySolar [2].

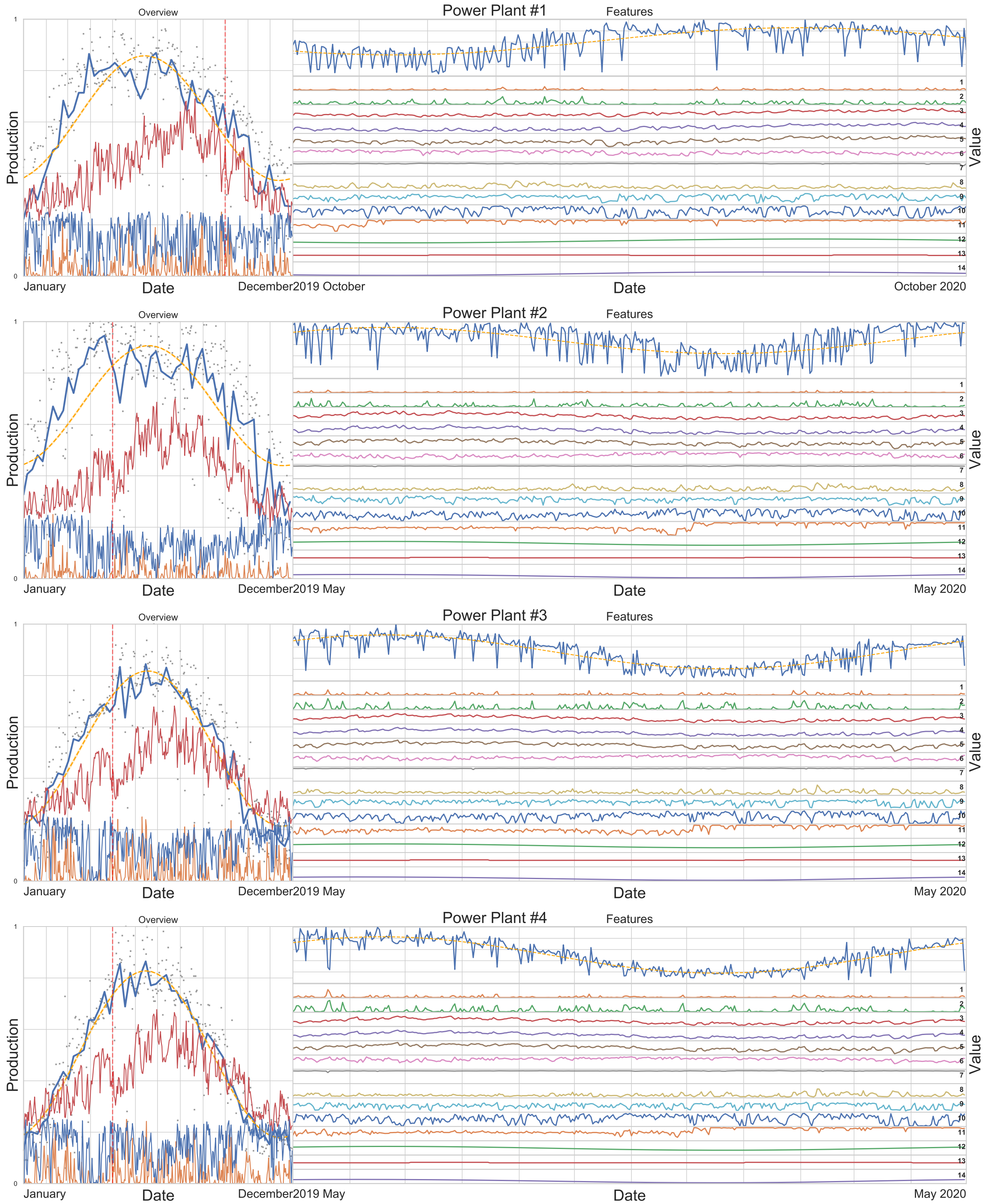

Figure 3: Power Plant Details (continued)

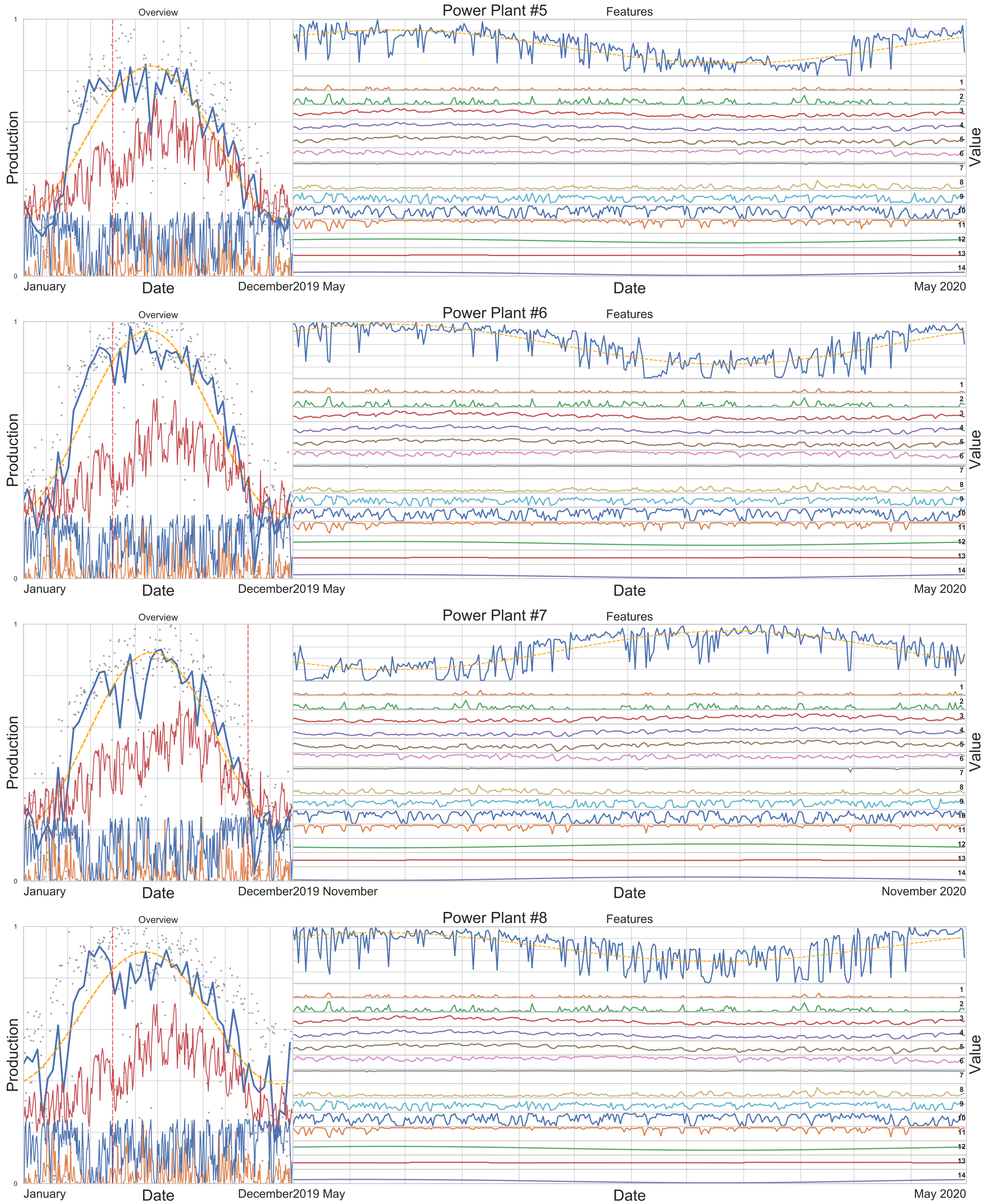

Figure 3: Power Plant Details (continued)

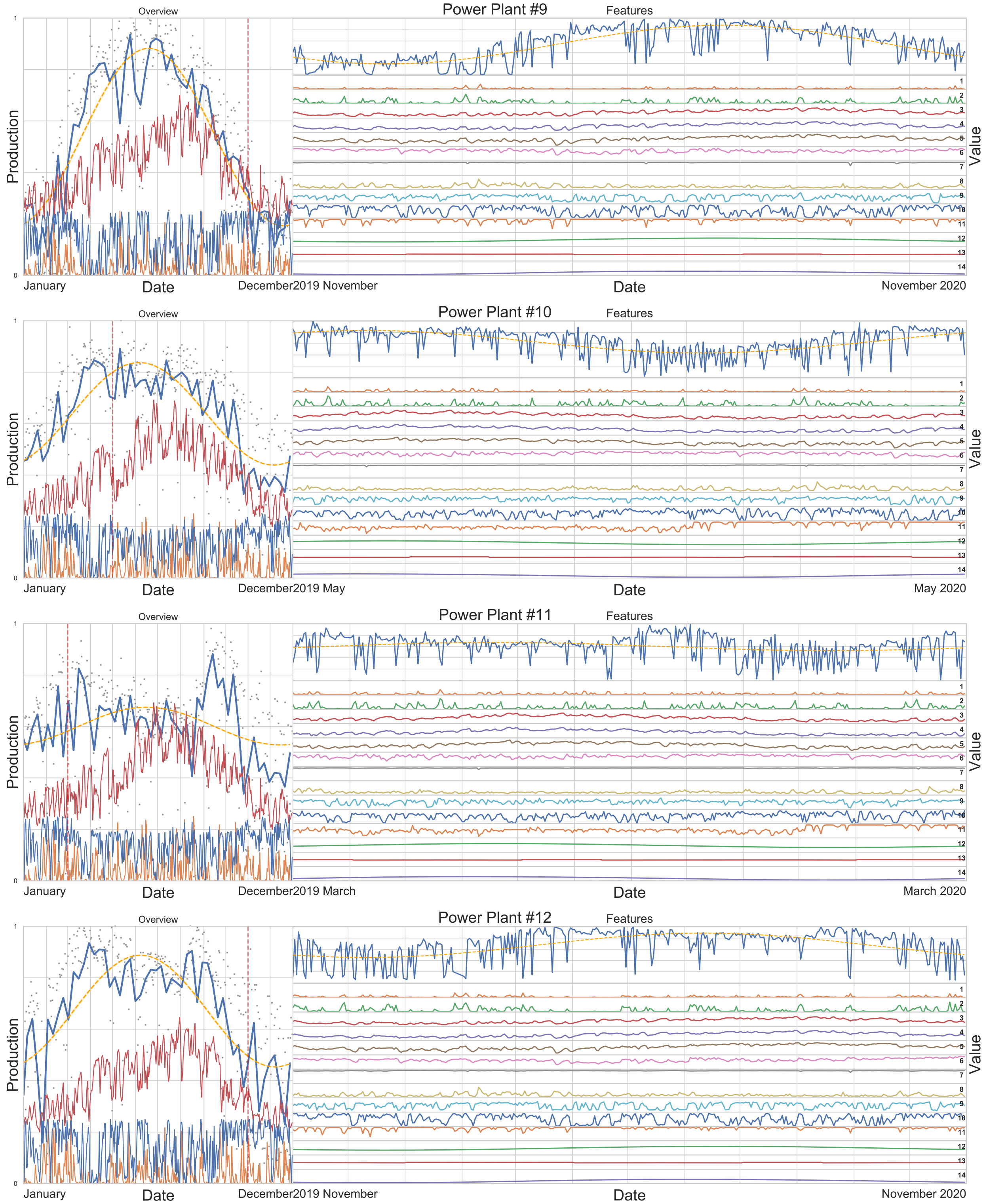

Figure 3: Power Plant Details (continued)

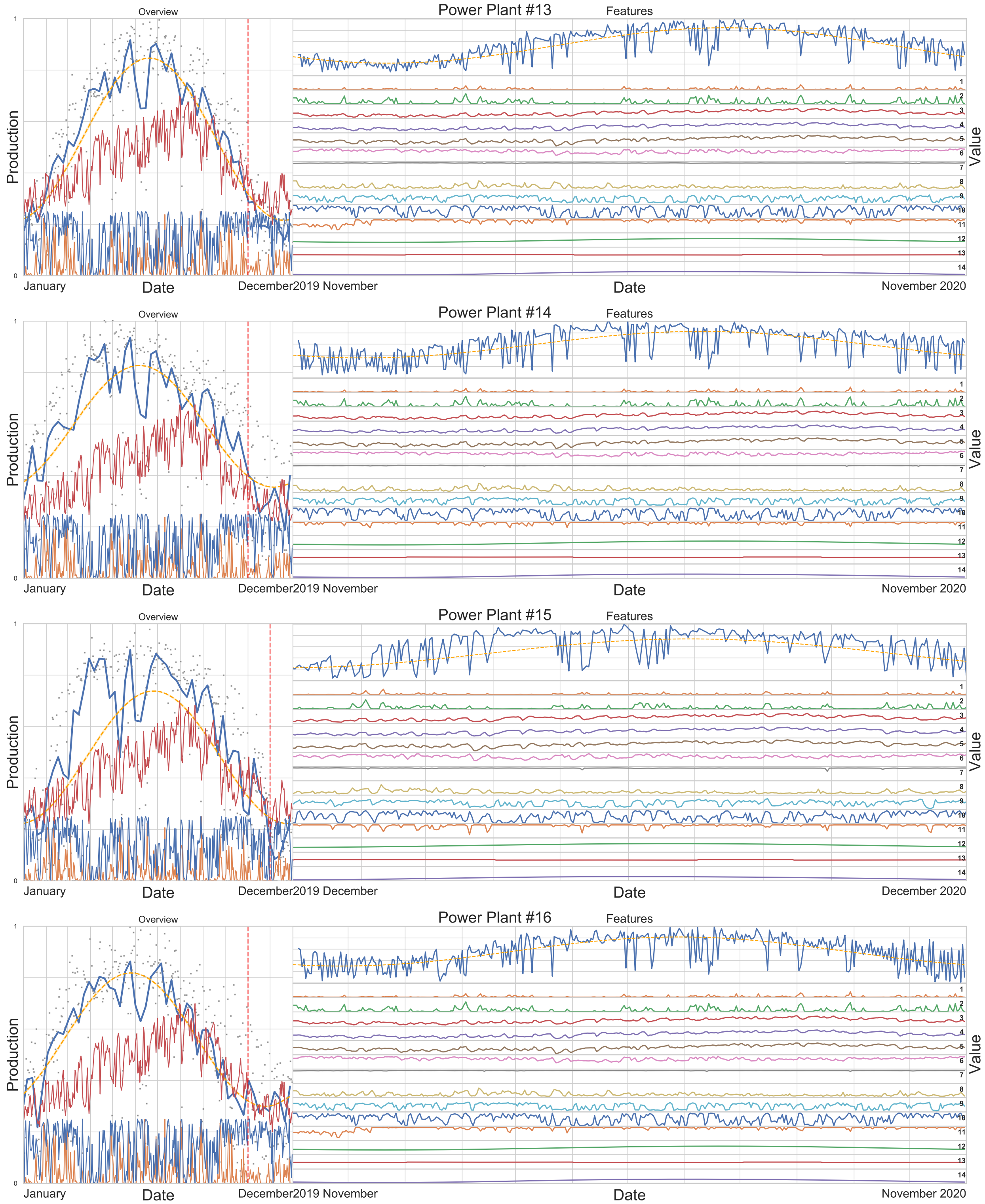

Figure 3: Power Plant Details (continued): The summary of the complete set of 16 power plants included in the SolarDB dataset. Overview of the production with synchronized dates is shown on the **left**, including weekly Power (**blue**) and daily Power (**grey**) on **top**, and Temperature (**red**), Cloud Cover (**blue**), Precipitation (**Orange**) on the **bottom**. Feature values are presented on the **right**, starting with Power (**top**), followed by: Precipitation Intensity (1), Precipitation Probability (2), Temperature (3), Perceived Temperature (4), Dew Point (5), Humidity (6), Pressure (7), Wind Speed (8), Wind Bearing (9), Cloud Cover (10), Visibility (11), Sun Altitude (12), Sun Azimuth (13), and Sun Irradiance (14).

3. The SolarPredictor System

3.1. Predictor Architecture

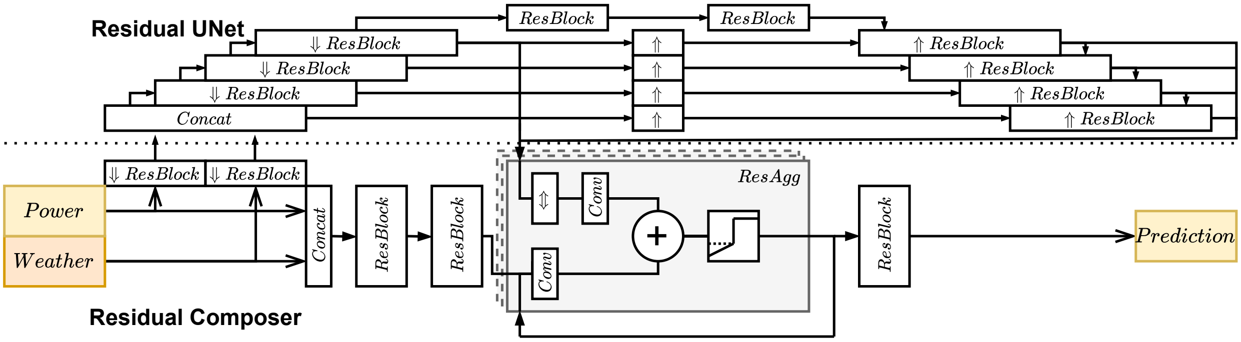

Figure 4: SolarPredictor Model: The model combines a Residual UNet for spatiotemporal analysis in the **upper** part, while the **lower** Residual Composer path is used for the composition of the final signal.

In this section, we provide additional details for the SolarPredictor model (Fig. 4). We implemented the models using the Tensorflow framework [3]. We use the AMSGrad [4] variant of the ADAM [5] optimizer with initial $lr = 0.005$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, mini-batch size of 256, modifying the learning rate with reduce-on-plateau technique ($f = 0.1$, $p = 5$). We train the model for 60 epochs with the Smooth Loss objective. We provide 288 values of reduced selection of weather features and 288 historical power values, producing 288 values at each prediction step. The Conv1D layers comprise causal dilated 1D convolutions [6] using the LeakyReLU ($\alpha = 0.3$) activation function. We use Glorot normal and uniform [7] initialization for kernel and bias, respectively. Additionally, we use kernel regularization, setting $l_2 = 0.005$. In combination with Fig. 4, the model consists of the following modules:

- $\Downarrow$ ResBlock [F]: In → Conv1D[F, 3] → BatchNormalization → Conv1D[F, 3] → BatchNormalization → AveragePooling1D[$s = 2$]] → Add[In → Conv1D[F, 1, $s = 2$] → BatchNormalization] → Out

- ResBlock [F]: In → Conv1D[F, 3] → BatchNormalization → Conv1D[F, 3] → BatchNormalization → Add[In → Conv1D[F, 1] → BatchNormalization] → DropoutOut

- $\Uparrow$ ResBlock [F]: In → UpConv1D[$s = 2$] → Conv1D[F, 3] → BatchNormalization → Concatenate[Skip] → Conv1D[F, 3] → BatchNormalizationConv1D[F, 3] → BatchNormalization → Add[In → Conv1DTranspose[F, 1, $s = 2$] → BatchNormalization] → Out

- ResAgg: In → UpDownConv1D[288] → Conv1D[1, 1] → Add[In] → Out

- RUNet: Concatenate[Power History →$\Downarrow$ ResBlock[4], Weather Features →$\Downarrow$ ResBlock[4]] →$\Downarrow$ ResBlock[8] →$\Downarrow$ ResBlock[16] →$\Downarrow$ ResBlock[32] → ResBlock[64] → ResBlock[64] →$\Uparrow$ ResBlock[32] →$\Uparrow$ ResBlock[16] →$\Uparrow$ ResBlock[8] →$\Uparrow$ ResBlock[4]

- RComposer [UN]: Concatenate[Power History →$\Downarrow$ ResBlock[4], Weather Features →$\Downarrow$ ResBlock[4]] → ResBlock[16] → ResBlock[8] → ResAgg[Concatenate[$\Downarrow$ ResBlock[4]$_{\mathrm{UN}}$, $\Downarrow$ ResBlock[4]$_{\mathrm{UN}}$]] → ResAgg[$\Downarrow$ ResBlock[8]$_{\mathrm{UN}}$] → ResAgg[$\Downarrow$ ResBlock[16]$_{\mathrm{UN}}$] → ResAgg[$\Downarrow$ ResBlock[32]$_{\mathrm{UN}}$] → ResAgg[$\Uparrow$ ResBlock[32]$_{\mathrm{UN}}$] → ResAgg[$\Uparrow$ ResBlock[16]$_{\mathrm{UN}}$] → ResAgg[$\Uparrow$ ResBlock[8]$_{\mathrm{UN}}$] → ResAgg[$\Uparrow$ ResBlock[4]$_{\mathrm{UN}}$] → ResBlock[4] → Out

- SolarPredictor: Input → RComposer[RUNet] → Output

					Clear Days			Overcast Days			All Days					
	Model	Power	Weather	Out	RRMSE	PError	cor_p	RRMSE	PError	cor_p	RMSE	RRMSE	R^2	PError	cor_p	cor_s
Classical	SVMSin	0	1:1	1:1	19.09	70.361	0.207	42.17	83.056	0.095	7031	29.66	0.004	78.882	0.227	0.207
	TreeSin	0	1:1	1:1	9.71	29.860	0.365	31.42	59.199	0.483	4446	21.99	0.245	49.464	0.570	0.572
	TreeSeq	0	288:1	288:1	9.39	26.909	0.400	24.19	55.075	0.605	4028	18.05	0.275	45.717	0.682	0.684
	TreeSeH	288:1	288:1	288:1	9.37	**21.992**	**0.516**	24.31	51.305	0.662	3975	17.99	0.291	41.479	0.745	0.747
	RForSin	0	1:1	1:1	8.56	22.955	0.358	33.65	62.592	0.510	3973	21.80	0.347	49.384	0.610	0.610
	RForSeq	0	288:1	288:1	7.47	26.175	0.467	25.92	53.353	0.649	3288	17.46	0.443	44.248	0.720	0.731
	RForSeH	288:1	288:1	288:1	**7.42**	24.373	0.494	**19.30**	**50.026**	**0.699**	**3050**	**13.82**	**0.448**	**41.311**	**0.761**	**0.766**
DNN	DNNSin	0	1:1	1:1	17.09	42.106	0.245	30.29	60.910	0.199	5607	23.69	0.154	54.403	0.255	0.506
	DNNSeq	0	288:1	288:1	12.62	25.500	0.436	28.10	70.295	0.511	4758	21.18	0.186	55.558	0.622	0.625
	DNNSeH	288:1	288:1	288:1	**11.36**	**24.291**	**0.516**	**19.19**	**52.701**	**0.630**	**3894**	**15.52**	**0.304**	**43.169**	**0.704**	**0.733**
Recurrent	LSTMVan	288:1	288:1	288:1	17.02	40.179	0.026	31.31	61.396	0.148	5658	24.39	0.053	54.240	0.169	0.181
	LSTMSta	288:1	288:1	288:1	17.08	40.796	0.028	31.03	61.867	0.147	5657	24.20	0.072	54.716	0.158	0.158
	LSTMCNN	288:1	288:1	288:1	16.97	36.410	0.378	24.78	57.747	0.392	5416	20.86	0.130	50.532	0.524	0.492
	LSTMCon	288:1	288:1	288:1	17.38	36.264	0.069	34.56	63.265	0.158	5920	26.35	0.090	54.187	0.194	0.191
	LSTMBid	288:1	288:1	288:1	10.03	19.818	0.433	31.69	66.416	0.495	4340	22.07	0.301	51.051	0.623	0.628
	SPredSeRc	36:8	4:2	8:1	16.34	47.334	0.200	26.68	**56.843**	0.409	5399	21.89	0.059	53.636	0.408	0.433
	SPredPaRc	36:8	36:1	36:1	**10.24**	**16.051**	**0.701**	**20.86**	60.477	**0.599**	**3710**	**16.00**	**0.365**	**45.508**	**0.755**	**0.767**
Convolutional	SPredCNN	288:1	72:4	288:1	9.18	38.394	0.562	15.85	46.770	0.711	3311	13.11	0.422	43.820	0.767	0.768
	SPredCNNO	288:1	288:1	288:1	8.06	30.601	0.416	20.25	58.196	0.595	3507	15.41	0.372	49.032	0.666	0.690
	SPredUNet	288:1	288:1	288:1	7.85	28.160	0.345	20.64	51.936	0.539	3376	15.47	0.385	44.066	0.609	0.682
	SPredTCN	288:1	288:1	288:1	7.46	28.643	0.442	19.03	51.032	0.641	3173	14.38	0.424	43.542	0.705	0.729
	SPredWave	288:1	288:1	288:1	7.89	25.623	0.443	24.85	55.232	0.620	3439	17.23	0.397	45.317	0.685	0.711
	SPredTrf	288:1	288:1	288:1	9.50	27.625	0.478	18.29	53.575	0.649	3573	14.69	0.361	44.997	0.720	0.721
	SPred	288:1	288:1	288:1	**5.68**	**16.886**	**0.610**	**16.16**	**44.351**	**0.780**	**2533**	**11.78**	**0.564**	**35.097**	**0.812**	**0.842**
Enh	RForEnh	288:1	288:1	288:1	6.90	19.838	0.561	17.34	44.982	0.710	2775	12.46	0.445	36.468	0.785	0.796
	SPredEnh	288:1	288:1	288:1	**4.50**	**15.308**	**0.849**	**11.29**	**32.480**	**0.878**	**1897**	**8.45**	**0.690**	**26.304**	**0.921**	**0.926**

Table 1
(2-column) Prediction Models: A quantitative comparison of model prediction accuracy. The models are split into the baseline experiments covering Classical, DNN, RNN, CNN, and Enhanced models. The table contains information on the sizing of the vectors, specifically the power history (Power), weather (Weather), and output (Out). Each value represents the number of time steps n and its stride s as $n : s$, where zero represents unused input. Three categories of performance are considered: clear, overcast, and all days. The metrics are calculated as an average over predictions for 1–10 days ahead.

4. Dataset Evaluation and Experiments

4.1. Model Comparison

Tab. 1 presents full quantitative evaluation of the 24 evaluated models, while Fig. 5 shows a qualitative comparison and Fig. 6 presents their calendar data, showing overall prediction performance on power plant #8. We follow with a description of each of the 24 experimental models and their training procedures.

Support Vector Machine: The SVMSin model is based on the Support Vector Regressor from the SciKit-Learn library [8]. We use polygonal kernel, setting $C = 1000.0$, $gamma = 100.0$ and $degree = 2$. Input consists of all of the weather features, predicting one step ahead.

Decision Tree: The TreeSin, TreeSeq, and TreeSeH models use the Decision Tree Regressor implementation from the SciKit-Learn library [8]. We set the maximum depth of all trees to $d = 50$, using the Mean Squared Error criterion. Input consists of all weather features, predicting 1 (TreeSin) or 288 (TreeSeq, TreeSeH) steps ahead. Additionally, we also provide 288 historical power production values to the TreeSeH model.

Random Forest: The RForSin, RForSeq, RForSeH, and RForEnh models use the Random Forest Regressor from the SciKit-Learn library [8]. We set the number of estimators to $u = 1000$, keeping the maximum depth unlimited. We use Mean Squared Error as the split criterion. Input consists of all weather features, predicting 1 (RForSin) or 288 (RForSeq, RForSeH, and RForEnh) steps ahead. Both the RForSeH and RForEnh are additionally provided with 288 historical power production values.

Deep Neural Network: The DNNSin, DNNSeq, and DNNSeH models use a simple Deep Neural Network architecture built in Tensorflow [3]. We train the model for 200 epochs using the Mean Squared Error loss function. We use the AMSGrad [4] variant of the ADAM [5] optimizer with initial $lr = 0.005$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, and mini-batch size of 256. We also use the reduce-on-plateau technique with factor $f = 0.1$ and patience $p = 5$. Input to the model consists of all weather features, predicting 1 (DNNSin) or 288 (DNNSeq, DNNSeH) steps ahead. The DNNSeH model is additionally provided with 288 historical power production values concatenated to the weather input. It consists of dense neurons, including an input layer with 576 neurons, a hidden layer with 288 neurons, and an output layer with

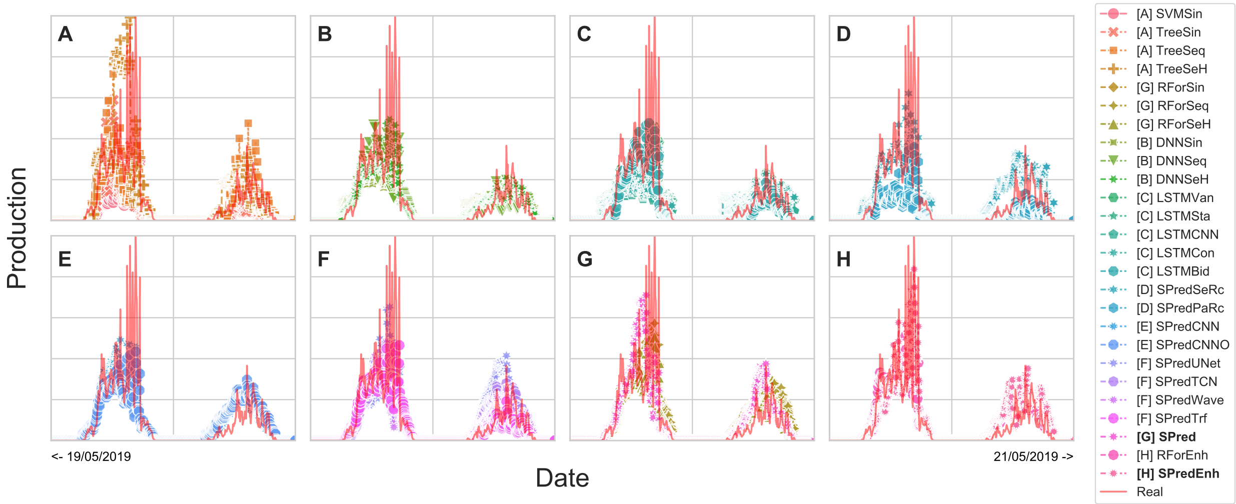

Figure 5: Qualitative Comparison: Samples of predicted waveforms for each prediction model, categorized **A** through **H** in the legend. Each graph contains predictions calculated for power-plant #8 from May 19th 00:00 to May 21st 00:00 of 2019, including **solid red** ground truth. Notably, the RNN (**C**, **D**) and CNN (**E**, **F**) models produce more smoothed outputs. Conversely, the DNN (**A**) and classical (**B**) approaches attempt to match the high-frequency training waveforms, while both the RFor and SPred models (**G**, **H**) output balanced waveforms.

1 (DNNSin) or 288 (DNNSeq, DNNSeH) neurons. We also add a Dropout layer between the input and hidden layers with a probability of $p = 0.3$. All neurons use Glorot uniform initialization [7] combined with LeakyReLU activation function with $\alpha = 0.3$, except for the output layer, which uses a linear activation function.

Long Short-Term Memory: The LSTMVan, LSTMSta, LSTMCNN, LSTMCon, and LSTMBid use varying architectures based on the LSTM recurrent unit from the Tensorflow framework [3]. For all of the variants, we use the AMSGrad [4] variant of the ADAM [5] optimizer with initial $lr = 0.005$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, and mini-batch size of 256, except for the LSTMBid for which we use $lr = 0.001$. We automatically anneal the learning rate using the reduce-on-plateau technique with factor $f = 0.1$ and patience $p = 5$. Each model is trained with the Mean Squared Error loss for 200 epochs, which is sufficient to reach convergence. Inputs include all weather features and 288 historical power production values, always predicting for 288 steps ahead. All LSTM units are regularized ($l_1 = 0.005$), using Tanh activation function and a sigmoid as the recurrent activation function. Additionally, all dense layers utilize the LeakyReLU activation with $\alpha = 0.3$, while dropout layers use the probability of $p = 0.3$. Specifically, the model architectures are following:

- LSTMVan: Input → ReturnSequences[LSTM[25]] → Dense[288] → Output
- LSTMSta: Input → TimeDistributed[Dense[25]] → ReturnSequences[LSTM[25]] → Dropout → ReturnSequences[LSTM[25]] → ReturnSequences[LSTM[25]] → Dropout → Dense[288] → Output
- LSTMCNN: Input → Conv1D[25, 3] → ReturnSequences[LSTM[25]] → Dropout → Dense[288] → Output
- LSTMCon: Input → *Conv*LSTM[64] → Dense[288] → Output
- LSTMBid: Input → Bidirectional[ReturnSequences[LSTM[32]]] → Dropout → Dense[288] → Output

Serial Recurrent Predictor: The SPredSeRc model combines LSTM units for signal pre-processing with a dense neural network in series. We used the Tensorflow framework [3] in its implementation. We use the AMSGrad [4] variant of the ADAM [5] optimizer with initial $lr = 0.005$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $decay = 0.01$ and mini-batch size of 256. The learning rate is automatically modified by the reduce-on-plateau technique with factor $f = 0.1$ and patience $p = 5$. We train the model for 20 epochs with the Mean Squared Error loss, which is sufficient for convergence. The model is provided with all weather features of 4 steps ahead with a stride of 2 and 36 historical power production values with a stride of 8. The output consists of 8 values with a stride of 1. All of the LSTM units use the tanh activation function and a sigmoid recurrent activation function. The dense layers use the Glorot uniform initialization [7] along with a LeakyReLU activation ($\alpha = 0.3$). The model architecture consists of the following three parts:

- LSTM: In → Bidirectional[ReturnSequences[LSTM[32]]] → Dropout → Dense[128] → Out
- DNN: In → Dense[1920] → Dense[1600] → Dense[1280] → Dense[640] → Dense[320] → Dense[64] → Out
- Joined: Concatenate[Power History → LSTM, Weather Features → DNN] → Dense[1920] → Dropout → Dense[64] → Dense[8] → Output

Parallel Recurrent Predictor: The SPredPaRc model uses a combination of LSTM units with a dense neural network in parallel, utilizing the Tensorflow framework [3]. For training, we use the AMSGrad [4] variant of the ADAM [5] optimizer with initial $lr = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $decay = 0.01$ and mini-batch size of 256. The learning rate is modified during training by the reduce-on-plateau technique with factor $f = 0.1$ and patience $p = 5$. We use the Smooth Loss, defined in the main text, training the model for 20 epochs, which is sufficient to reach convergence. The model is provided with the complete set of weather features in 36 values with a stride of 1 with additional 36 power history values with a stride of 8, producing 36 predictions each step. The LSTM units use the tanh activation function and a sigmoid recurrent activation function, while the dense layers use the LeakyReLU activations ($\alpha = 0.3$) along with the Glorot uniform initialization [7]. The model consists of the following parts:

- LSTM: In → ReturnSequences[LSTM[32]] → Dropout → ReturnSequences[LSTM[32]] → Dropout → TimeDistributed[Dense[32]] → Out
- Joined: Concatenate[Power History → LSTM, Weather Features] → Dense[400] → Dense[200] → Dense[36] → Output

Convolutional Neural Network: The SPredCNN model combines convolutional layers with dense neural network elements. We use the Tensorflow framework [3] in its implementation. We train the model using the RMSPROP [9] optimizer, setting the initial learning rate to $lr = 0.003$, $\rho = 0.9$, clipping the gradients at $c = 1.0$, and setting the mini-batch size to 128. The initial learning rate is annealed during training by using linear falloff. We use the Huber loss function, as defined in the primary text. The training procedure consists of three steps, gradually training the Pure Power Predictor, Pure Weather Predictor, and Joined Predictor. Each training consists of 40 epochs. During the final Joined Predictor training, we do not freeze weights of the Power and Weather segments, training them jointly. All weather features consisting of 72 values with a stride of 4 are provided to the model combined with 288 power history values with a stride of 1, producing 288 values at each prediction step. The dense layers use the LeakyReLU activation with $\alpha = 0.3$ except for the output layers, which use a linear activation function. The convolutional layers consist of 1D causal convolutions [6] combined with the LeakyReLU activation ($\alpha = 0.3$). We use Glorot uniform [7] initialization for dense neurons, while Glorot normal [7] initialization is used in the convolutional layers. The model architecture contains the following parts:

- Power Predictor: In → Conv1D[32, 8, $s = 1$, $d = 2$] → Conv1D[32, 8, $s = 2$, $d = 1$] → Conv1D[32, 8, $s = 1$, $d = 2$] → Conv1D[32, 8, $s = 8$, $d = 1$] → Dropout → Out
- Pure Power Predictor: Power History → Power Predictor → Dense[288] → Output
- Weather Predictor: In → Conv1D[32, 8, $s = 1$, $d = 2$] → Conv1D[32, 8, $s = 2$, $d = 1$] → Conv1D[32, 8, $s = 1$, $d = 2$] → Conv1D[32, 8, $s = 8$, $d = 1$] → Dropout → Out
- Pure Weather Predictor: Weather Features → Weather Predictor → Dense[288] → Output
- Joined Predictor: Concatenate[Power History → Power Predictor, Weather Features → Weather Predictor] → Dense[360] → Dropout → Dense[288] → Dropout → Dense[288] → Output

Feature Selection CNN: The SPredCNNO model is functionally similar to the SPredCNN model, combining convolutional and dense neural networks. However, in contrast to the original model, we used feature selection presented in the primary text to reduce the number of utilized weather features, allowing us to provide the model with non-strided inputs. We used the Tensorflow framework [3] in its implementation. For training, we use the AMSGrad [4] variant of the ADAM [5] optimizer with initial $lr = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $decay = 0.01$ and mini-batch size of 256. The training rate is modified during the training by using a linear falloff. We use the Huber loss function, as defined in the primary text. The training procedure is similar to the SPredCNN model, consisting of three stages: Pure Power Predictor, Pure Weather Predictor, and Joined Predictor. The inputs to the model consist of 288 weather features along with 288 power history values, all with a stride of 1. In each step, the model produces 288 predictions. All dense layers use the LeakyReLU activation function with $\alpha = 0.3$ combined with the Glorot uniform [7] initialization. Conversely, the convolutional layers consist of 1D causal convolutions [6] with the Glorot normal [7] initialization. Additionally, we also use the Alpha Dropout [3] with $\alpha = 0.1$. The model architecture is as follows:

- Power Predictor: In → Conv1D[32, 8, $s = 1$, $d = 2$] → Conv1D[32, 8, $s = 2$, $d = 1$] → Conv1D[32, 8, $s = 1$, $d = 2$] → Conv1D[32, 8, $s = 8$, $d = 1$] → AlphaDropout → Out
- Pure Power Predictor: Power History → Power Predictor → Dense[288] → Output
- Weather Predictor: In → Conv1D[32, 8, $s = 1$, $d = 2$] → Conv1D[32, 8, $s = 2$, $d = 1$] → Conv1D[32, 8, $s = 1$, $d = 2$] → Conv1D[32, 8, $s = 8$, $d = 1$] → AlphaDropout → Out
- Pure Weather Predictor: Weather Features → Weather Predictor → Dense[288] → Output
- Joined Predictor: Concatenate[Power History → Power Predictor, Weather Features → Weather Predictor] → Dense[1152] → Dense[576] → Dense[288] → Output

UNet Predictor: The SPredUNet model is based on the UNet [10] architecture. We adjust the base architecture to better work with time-series 1D signals, implementing our modifications in Tensorflow [3]. We use the AMSGrad [4] variant of the ADAM [5] optimizer with initial $lr = 0.005$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, $decay = 0.01$, mini-batch size of 256, modifying the learning rate with reduce-on-plateau technique ($f = 0.1$, $p = 5$). We train the model for 60 epochs with the Mean Squared Error loss. The model is provided with 288 values of reduced weather features and 288 power history values, producing 288 predictions each step. We modify the base UNet units by transforming all 2D convolutions to 1D causal dilated convolutions [6], using the LeakyReLU ($\alpha = 0.3$) activation functions, adding residual connections with projection, and adding dropout ($p = 0.35$) along with batch and weight normalization. We use Glorot normal and uniform [7] initializations for kernel and bias, respectively. The UpBlock modules are provided with outputs after the second convolution from DownBlock from the corresponding level. The primary parts making up the model architecture are:

- DownBlock [F]: In → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → Conv1D[F, 1, $s = 2$]] → Add[In → Conv1D[F, 1, $s = 2$]] → Out
- Bottleneck [F]: In → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → Add[In → Conv1D[F, 1]] → Out
- UpBlock [F]: In → UpConv1D[$s = 2$] → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → Concatenate[DownBlock_Out] → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → Add[In → Conv1DTranspose[F, 1, $s = 2$]] → Out
- UNet: Input → DownBlock[64] → DownBlock[128] → Bottleneck[256] → Bottleneck[256] → UpBlock[128] → UpBlock[64] → Conv1D[2, 3] → Conv1D[1, 1] → Output

TCN Predictor: The SPredTCN model is based on the Temporal Convolutional Networks [6] architecture. We modify the base architecture to better adapt it to the time-series prediction task, using the Tensorflow framework [3]. The training procedure and the convolutional layers use the same parameters as the SPredUNet model. The architecture consists of:

- DownTCN [F]: In → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → Dropout → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → Dropout → Conv1D[F, 1, $s = 2$]] → Add[In → Conv1D[F, 1, $s = 2$]] → Out

- MiddleTCN [F]: In → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → Dropout → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → Dropout → Add[In] → Out

- UpTCN [F]: In → Conv1DTranspose[F, 1, $s = 2$] → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → Dropout → WeightNormalization[Conv1D[F, 3]] → BatchNormalization → Dropout → Add[In → Conv1DTranspose[F, 1, $s = 2$]] → Out

- TCN: Input → DownTCN[64] → DownTCN[128] → MiddleTCN[256] → MiddleTCN[256] → UpTCN[128] → UpTCN[64] → Conv1D[2, 3] → Conv1D[1, 1] → Output

WaveNet Predictor: The SPredWave model is based on the WaveNet model [11], which we modify to improve its ability to process time-series power data. We use the Tensorflow framework [3] for its implementation. The training procedure uses the same parameters as the SPredUNet model. The convolutional layers use dilated causal 1D convolutions [6] and Glorot uniform [7] initialization, while activation functions are specified for each layer. The architecture consists of stacks of WaveBlocks, which are finally aggregated by adding all their residual signals, using the output of the third convolutional layer in each WaveBlock. The model consists of the following parts:

- WaveBlock [D]: Multiply[In → Conv1D[128, 2, $d = D$, tanh], In → Conv1D[128, 2, $d = D$, sigmoid]] → Conv1D[128, 1, linear] → Add[In → Conv1D[128, 1, linear]] → Out

- WaveStack:In → WaveBlock[2] → WaveBlock[4] → WaveBlock[8] → WaveBlock[16] → WaveBlock[32] → Out

- WaveNet: Input → WaveStack → WaveStack → WaveStack → WaveStack → Output

Transformer Predictor: The SPredTrf model is based on the Transformer architecture [12], which we modify to allow it to work on time-series prediction data using the Tensorflow framework [3]. The training procedure is the same as for the SPredUNet model, but we use the Smooth Loss instead of the Mean Squared Error. The convolutional layers use causal 1D convolutions [6] combined with Glorot uniform [7] initialization. We use the ReLU activation for most convolutional layers, except for the output layer, in which case we use LeakyReLU with $\alpha = 0.3$. The dropout layers use a drop probability of $p = 0.3$. The model architecture consists of an input encoder, output encoder, and output decoder:

- InpEncoder: In → MultiHeadAttention[$c = 2$, $s = 64$] → Dropout → Add[In] → LayerNormalization → Out

- InpFeedForward: In → InpEncoder → Conv1D[64, 3] → Conv1D[288, 1] → Dropout → Add[In → InpEncoder] → LayerNormalization → Out

- OutEncoder: In → MaskedMultiHeadAttention[$c = 2$, $s = 64$, causal] → Dropout → Add[In] → LayerNormalization → Out

- OutEncoderMemory: In → Concatenate[OutEncoder, In → InpFeedForward] → Dropout → Add[In → OutEncoder] → LayerNormalization → Out

- OutFeedForward: In → OutEncoderMemory → Conv1D[64, 3] → Conv1D[288, 1] → Dropout → Add[In → InpEncoder] → LayerNormalization → Out

- Transformer: Input → OutFeedForward → Conv1D[2, 3] → Conv1D[1, 1] → Output

Solar Predictor: Both the SPred and SPredEnh models use the SolarPredictor architecture described in the primary text. For further details, also see Sec. 3 in this supplementary material.

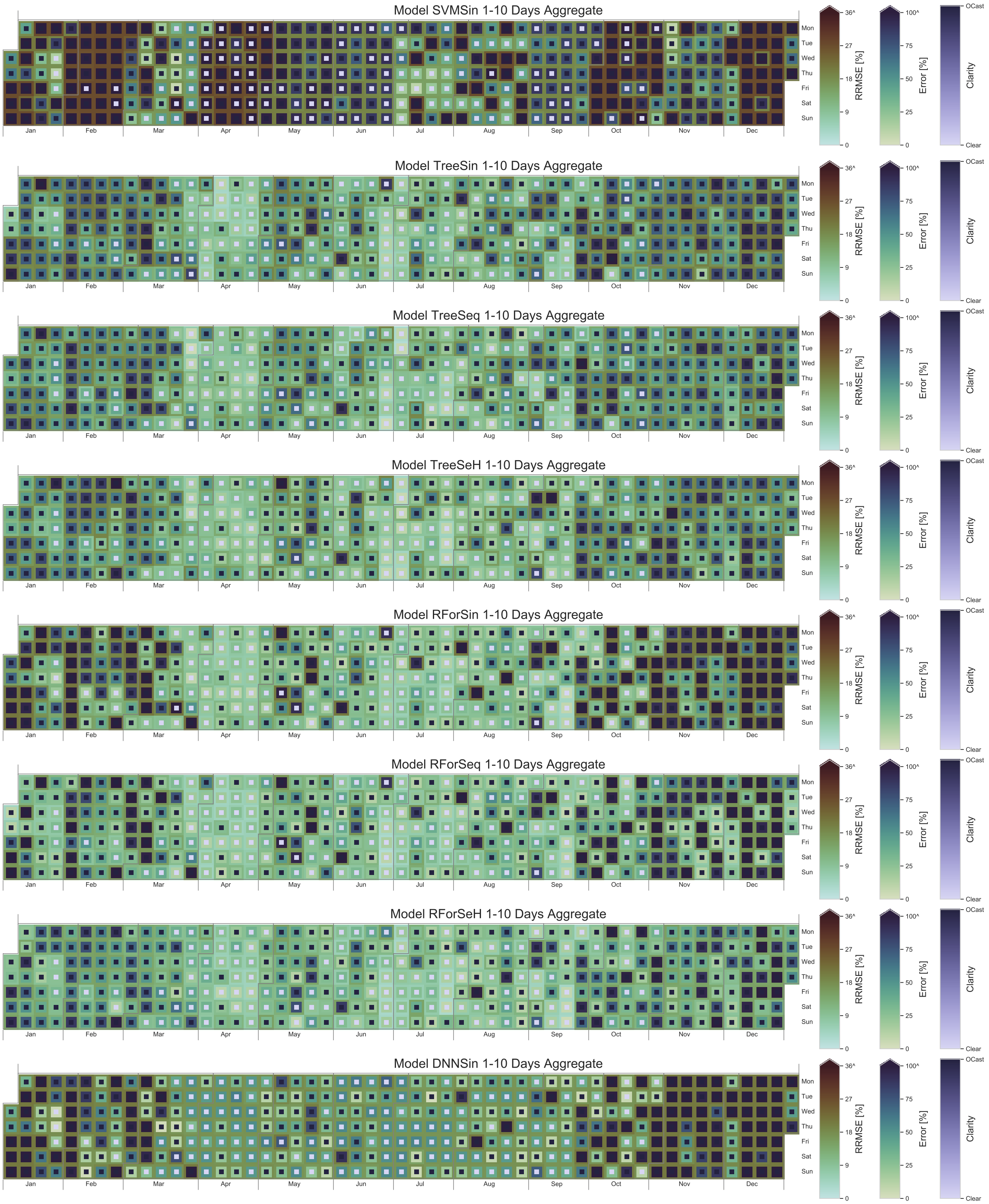

Figure 6: Model Prediction Error (continued)

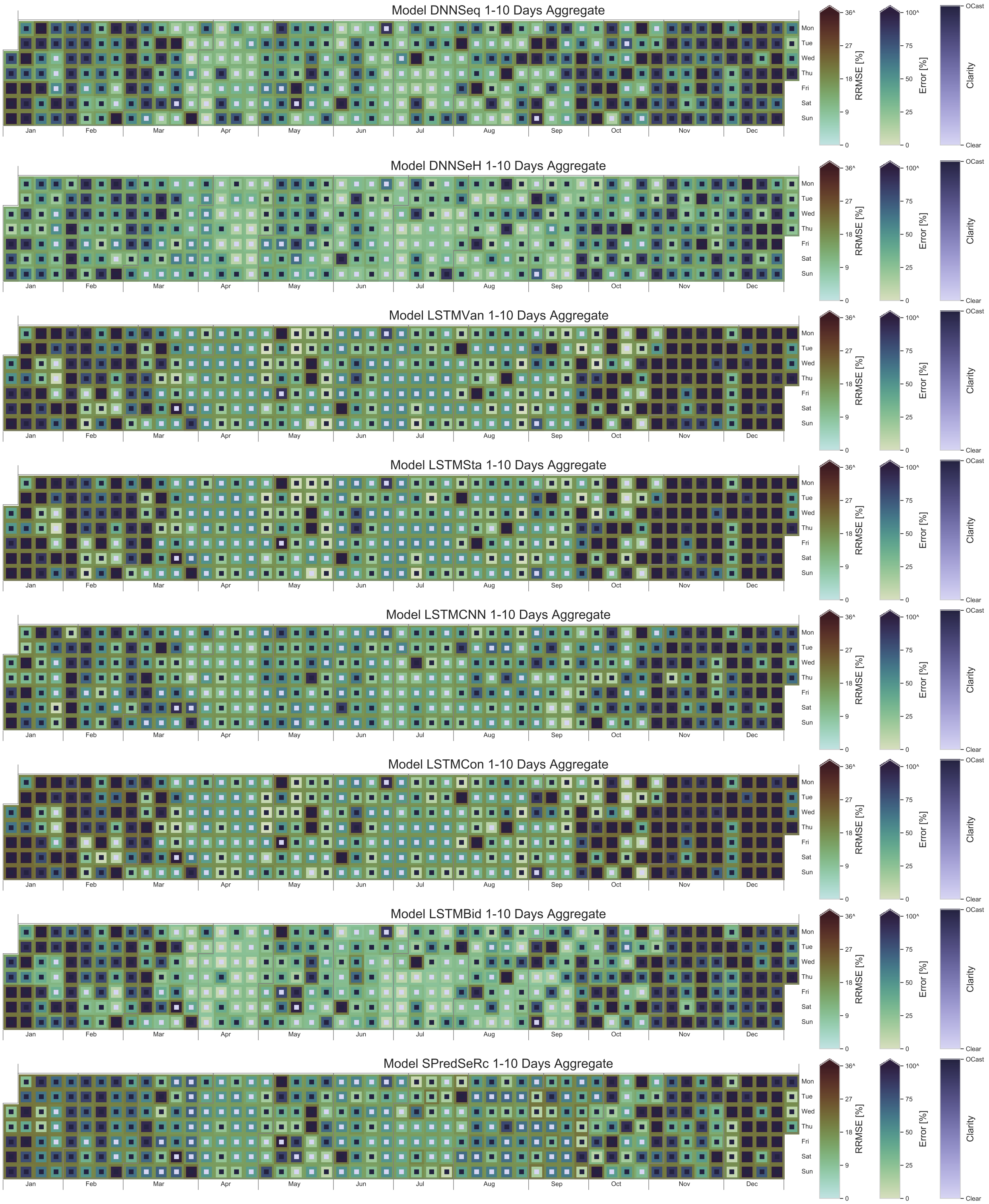

Figure 6: Model Prediction Error (continued)

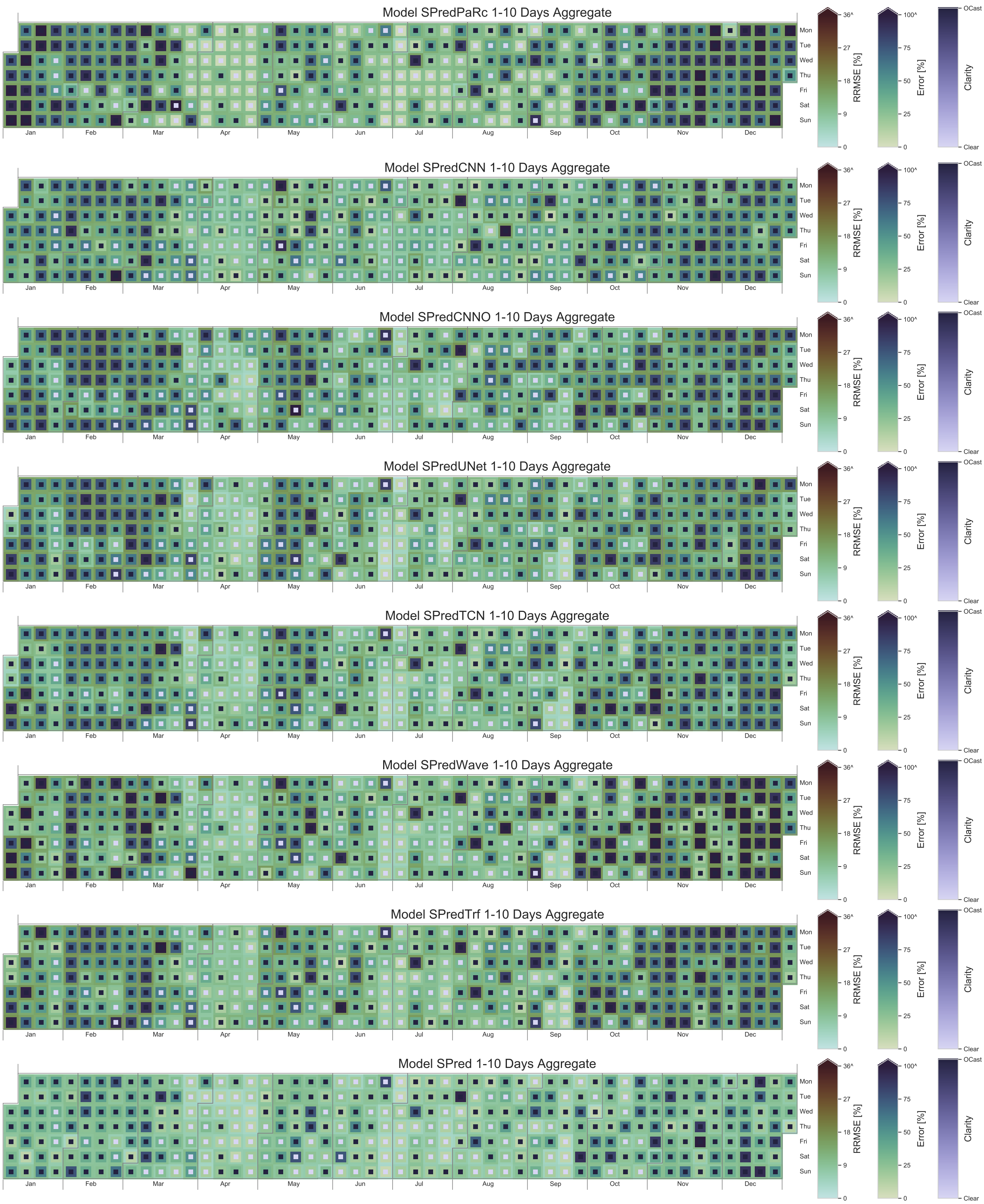

Figure 6: Model Prediction Error (continued): The summary of prediction errors for the complete set of 24 tested models, calculated for power plant #8. Cells in the calendar represent individual days. Each cell conveys three types of information, from outside to inside: RRMSE, prediction Error, and Clarity – light color for clear days and dark color for overcast days.

									Clear Days			Overcast Days			All Days					
	Model	Scl	Sel	Aug	Smpl	Meas	Fore	Real	RRMSE	PError	cor_p	RRMSE	PError	cor_p	RMSE	RRMSE	R^2	PError	cor_p	cor_s
	SPredBaseline	✗	✗	✗	✗	✓	✗	✗	9.13	20.265	0.657	32.33	74.819	0.659	4005	21.30	0.323	56.980	0.750	0.765
Feature	SPredScaler	✓	✗	✗	✗	✓	✗	✗	6.63	20.397	0.656	17.13	45.412	0.711	2755	12.57	0.514	37.036	0.792	0.808
Feature	SPredOutliers	✓	O	✗	✗	✓	✗	✗	6.75	18.906	0.666	17.20	45.919	0.778	2756	12.75	0.508	36.977	0.822	0.831
Feature	SPredWeights	✓	O+W	✗	✗	✓	✗	✗	6.59	18.945	0.672	17.22	47.076	0.758	2749	12.71	0.512	37.662	0.814	0.827
Feature	SPredCyclicAge	✓	O+W	C	✗	✓	✗	✗	**5.62**	18.099	0.590	16.98	**43.323**	**0.773**	**2496**	**11.79**	**0.565**	**34.857**	**0.799**	**0.835**
Feature	**SPredAugmented**	✓	O+W	C+F	✗	✓	✗	✗	**5.68**	**16.886**	**0.610**	16.16	**44.351**	**0.780**	**2533**	**11.78**	**0.564**	**35.097**	**0.812**	**0.842**
Forecast	SPredMeasured	✓	O+W	C+F	Day	✓	✗	✗	16.63	55.805	0.174	26.92	58.248	0.494	5503	22.56	0.358	57.451	0.463	0.718
Forecast	SPredAllData	✓	O+W	C+F	All	✓	✗	✗	5.54	17.911	0.710	15.63	45.557	0.791	2377	11.24	0.582	36.322	0.842	0.845
Forecast	SPredForecast	✓	O+W	C+F	All	✓	0D	✗	6.26	21.286	0.682	13.76	41.379	0.789	2418	10.45	0.601	34.523	0.839	0.845
Forecast	SPredMultiple	✓	O+W	C+F	All	✓	7D	✗	**4.65**	**12.878**	0.779	15.63	42.795	0.813	2274	10.98	0.600	32.785	0.869	0.873
Forecast	**SPredRealistic**	✓	O+W	C+F	All	✓	7D	7D	**4.50**	15.308	**0.849**	**11.29**	**32.480**	**0.878**	**1897**	**8.45**	**0.690**	**26.304**	**0.921**	**0.926**

Table 2

(2-column) Ablation Study: Experimental results dealing with the efficacy of the proposed augmentations. The baseline model (**top**) is first (**middle**) enhanced with scaling (Scl), sample selection (Sel: **O**utliers, **W**eights), and augmentation (Aug: **C**yclic, **F**eature selection). This improves Clear Day performance. Next, training data augmentation is introduced (**bottom**) with sampling (Smpl: single per Day, All), measured weather (Meas), forecasts of up to given age (Fore), and realistic samples (Real). Using the realistic sampling scheme leads to improvements both in Clear and Overcast days.

				Clear Days			Overcast Days			All Days					
Model	Meas	Fore	Real	RRMSE	PError	cor_p	RRMSE	PError	cor_p	RMSE	RRMSE	R^2	PError	cor_p	cor_s
SPredAugmented	✓	✗	✗	5.68	16.886	0.610	16.16	44.351	0.780	2533	11.78	0.564	35.097	0.812	0.842
SPredW1D	✓	1D	✗	5.41	18.022	0.690	14.84	41.780	0.788	2321	10.77	0.600	33.776	0.841	0.841
SPredW2D	✓	2D	✗	5.75	19.930	0.628	14.71	41.033	0.783	2420	10.77	0.599	33.927	0.818	0.837
SPredW3D	✓	3D	✗	5.73	19.493	0.571	13.72	38.559	0.802	2324	10.26	0.611	32.128	0.806	0.851
SPredW4D	✓	4D	✗	5.42	18.216	0.661	15.13	40.635	0.797	2307	10.92	0.602	33.112	0.834	0.844
SPredW5D	✓	5D	✗	5.25	17.278	0.599	15.65	42.922	0.795	2324	11.14	0.597	34.306	0.813	0.851
SPredW6D	✓	6D	✗	5.97	18.680	0.644	14.82	40.753	0.797	2434	10.90	0.588	33.354	0.827	0.846
SPredRealistic	✓	7D	✗	**4.65**	**12.878**	0.779	15.63	42.795	0.813	2274	10.98	0.600	32.785	0.869	0.873
SPredW7R	✓	7D	7D	**4.50**	15.308	**0.849**	**11.29**	**32.480**	**0.878**	**1897**	**8.45**	**0.690**	**26.304**	**0.921**	**0.926**

Table 3

(2-column) Weather Ablation: Investigation of training the model on weather forecast data, starting with the SPredAugmented (Tab. 2). Starting with only measured weather (Meas), additional forecast ages (Fore) are added in the **middle** section. Diminishing effects are notable at around five days of data. The deterioration is corrected by using the realistic sampling (Sec. **??**, which better represent the real-world data.

4.2. Ablation Study

We provide the full results of our ablation experiments on the RForEnh and SPredEnh models. Full experiments concerning feature augmentation and training on weather forecasts are presented in Tab. 2 and Tab. 3. Evaluation of the sizing ablation study can be found in Tab. 4, Tab. 5. The sampling experiment results can be found in Tab. 6.

4.3. Cross-Validation Results

Tab. 7 provides a detailed evaluation for each of the 16 power plants, using both the RForEnh and SPredEnh models. Fig. 7 and Fig. 8 provide an overview of average weather error over a 10-day interval.

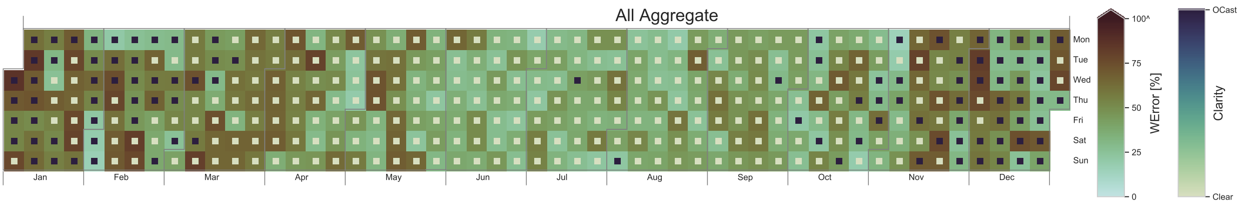

Figure 7: Overall Weather Error: A calendar graph containing the aggregate weather error for all 16 power plants. Cells in the calendar represent individual days. Each cell contains two types of information $WeatherError$ on the outside and $Clarity$ on the inside – light for clear days and dark for overcast days.

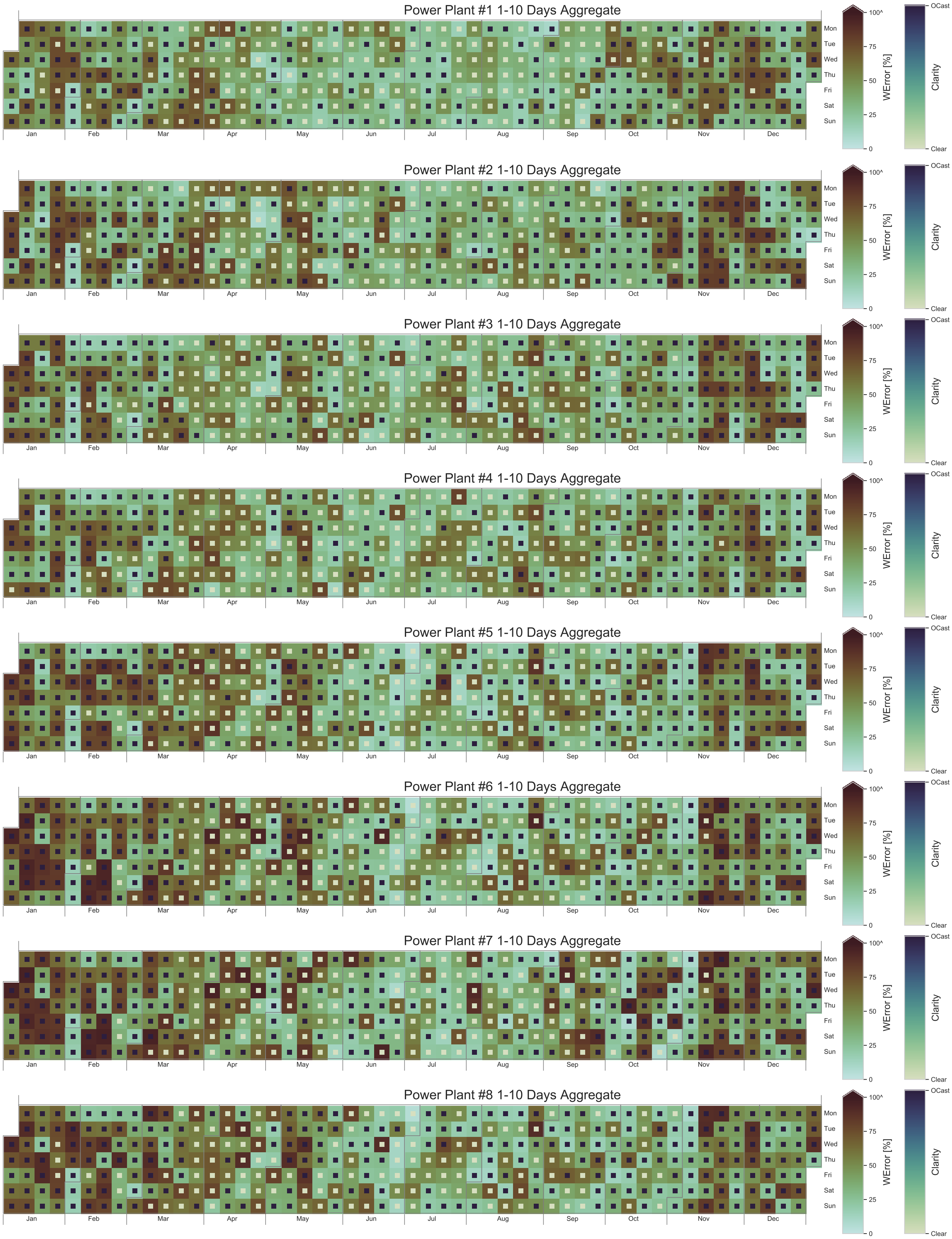

Figure 8: Power Plant Weather Error (continued)

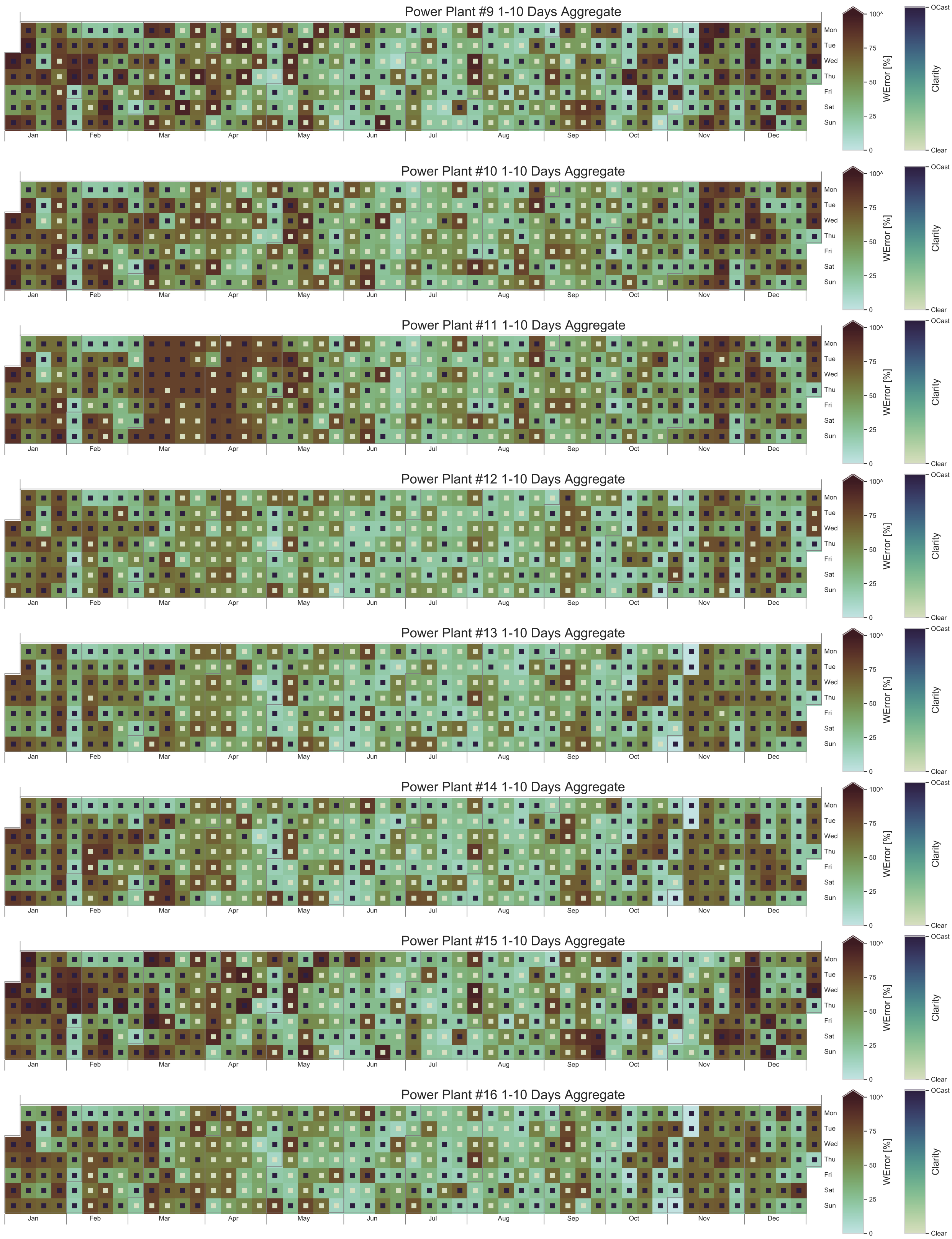

Figure 8: Power Plant Weather Error (continued): A summary of the weather errors for the complete set of 16 power plants included in the SolarDB dataset. Cells in the calendar charts represent individual days. Each cell contains two types of information Weather Error on the outside and Clarity on the inside – light for clear days and dark for overcast days.

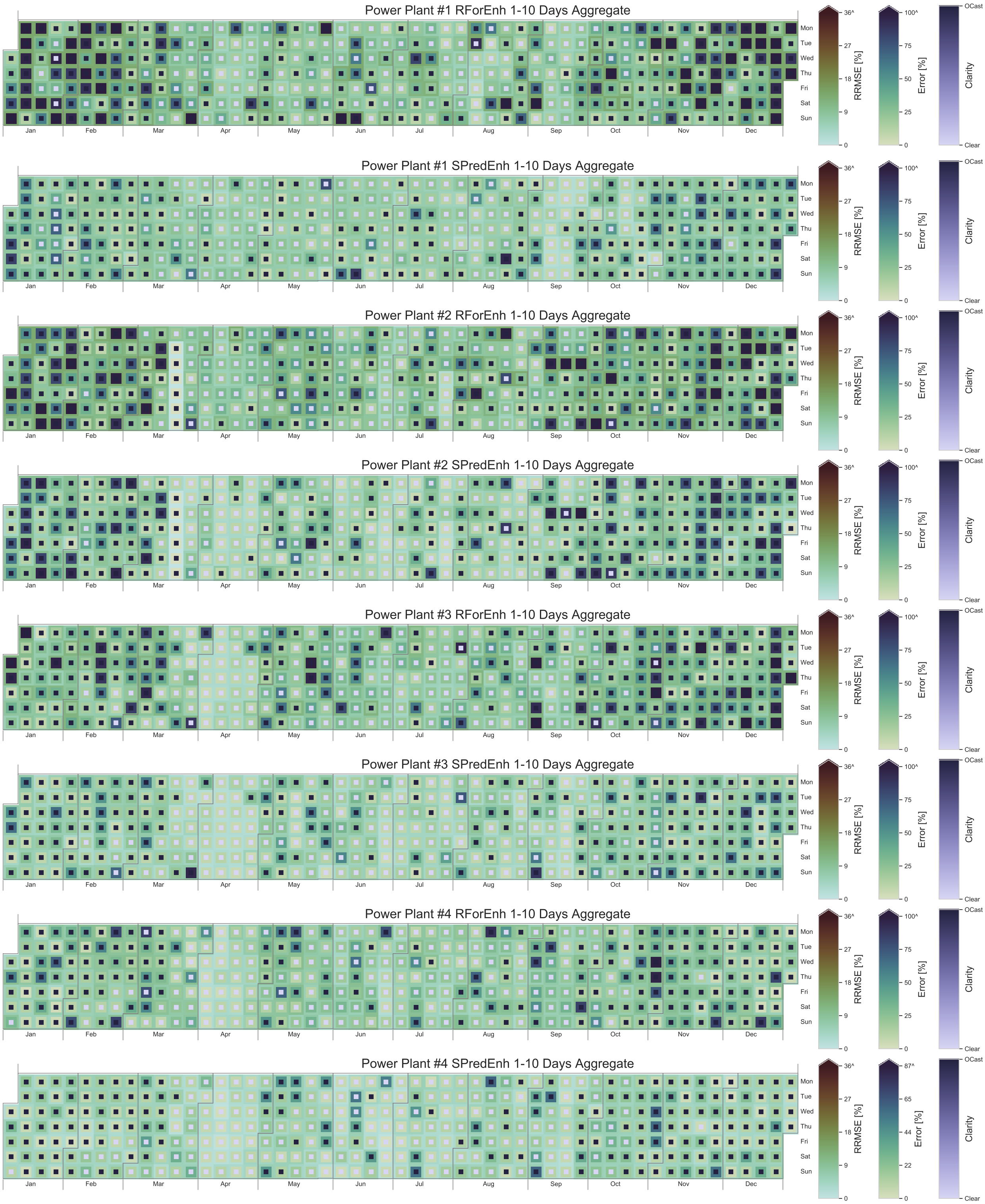

Figure 9: Model Prediction Error (continued)

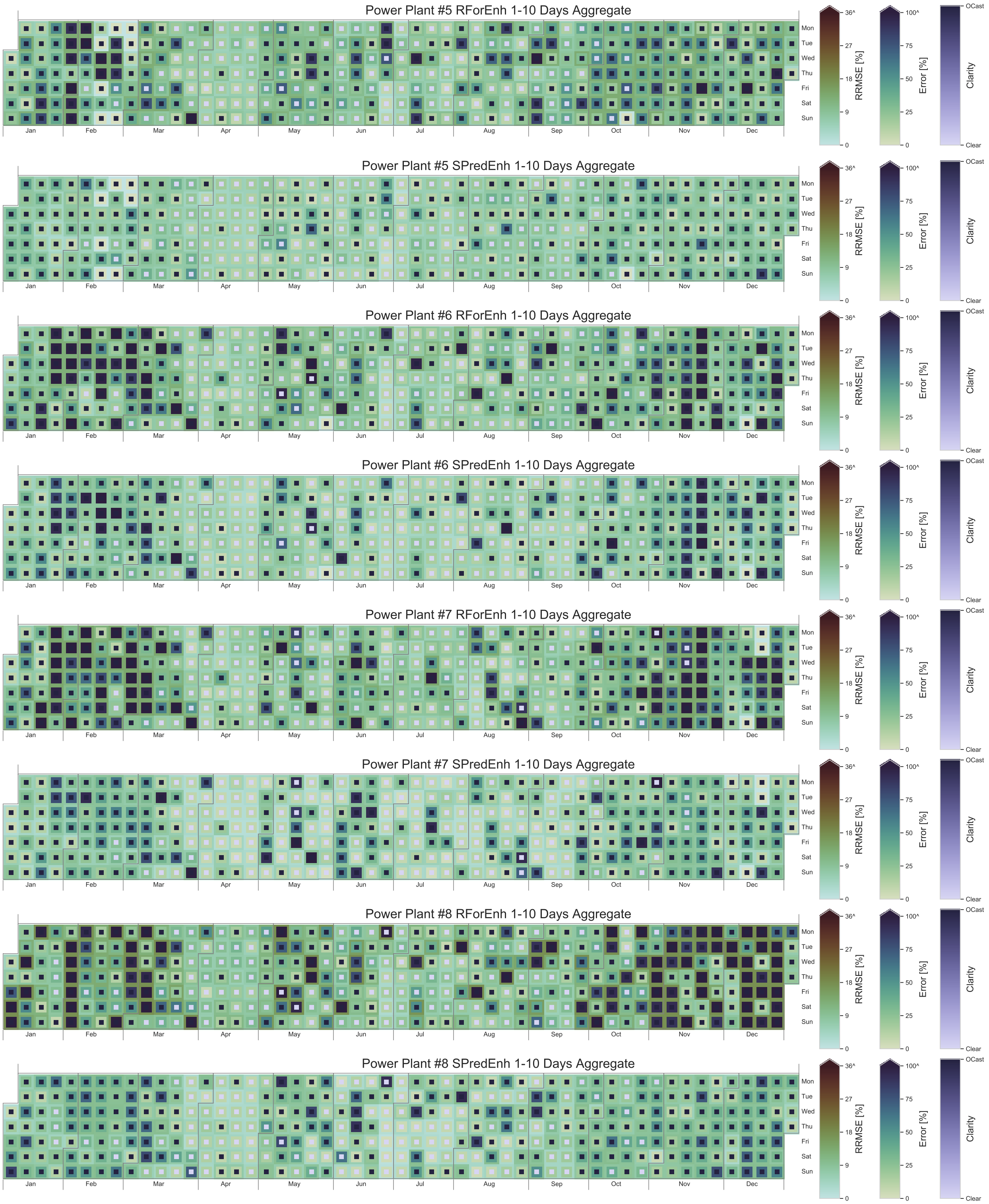

Figure 9: Model Prediction Error (continued)

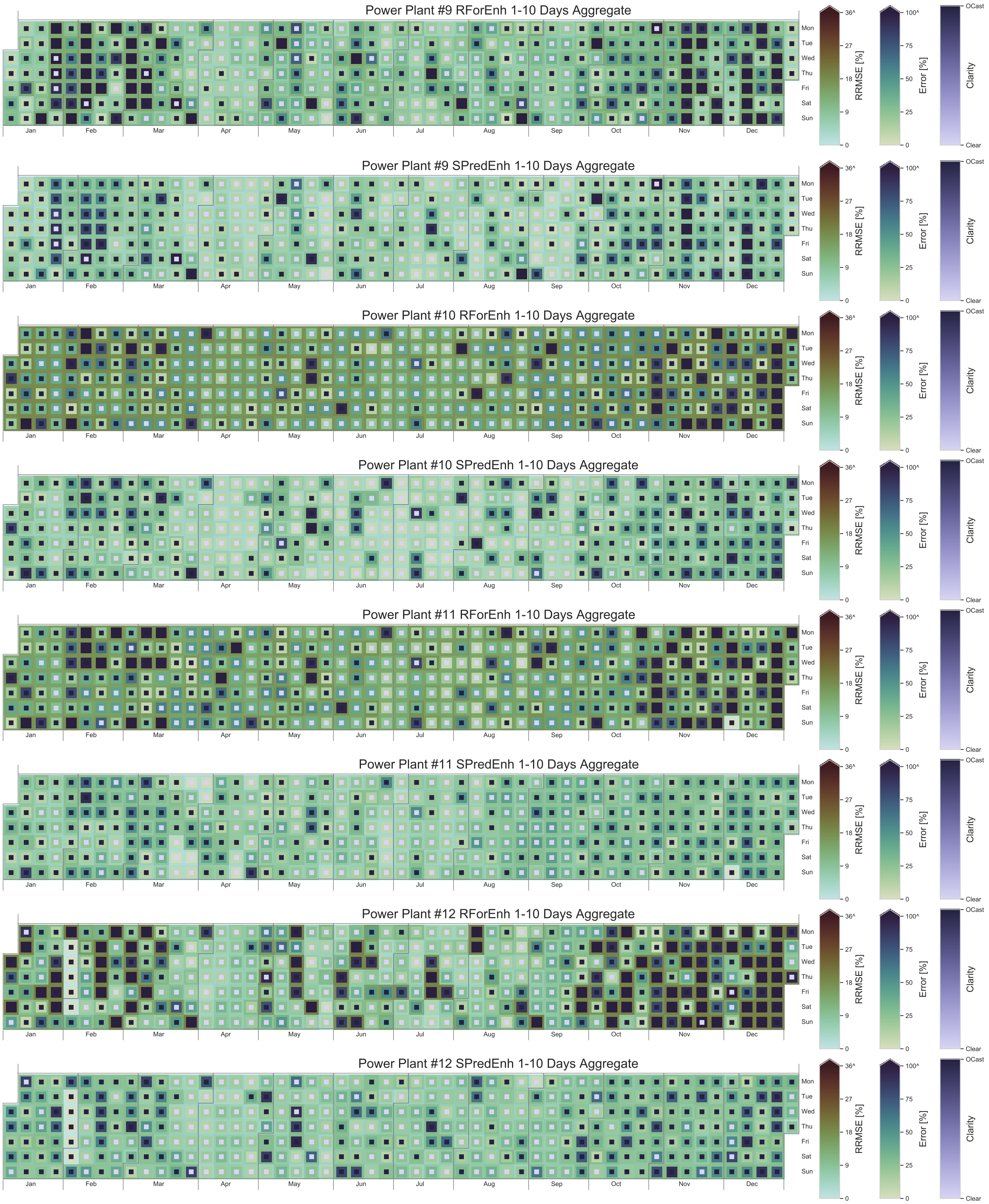

Figure 9: Model Prediction Error (continued)

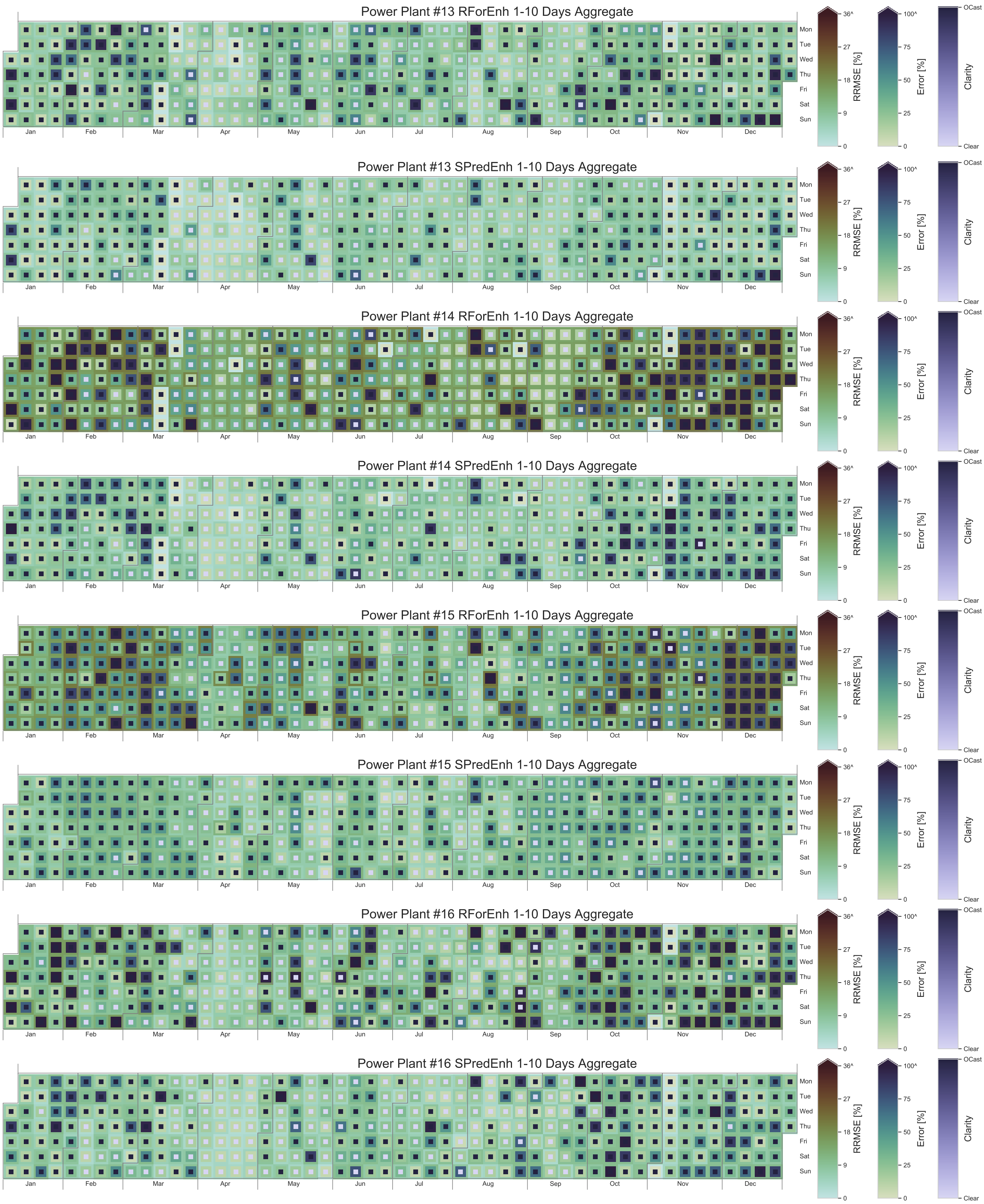

Figure 9: Model Prediction Error (continued): A summary of prediction errors for the complete set of 16 power plants included in the SolarDB dataset, covering both the RForEnh and SPredEnh models. Cells in the calendar represent individual days. Each cell conveys three types of information, from outside to inside: RRMSE, prediction Error, and Clarity – light color for clear days and dark color for overcast days.

				Clear Days			Overcast Days			All Days					
Model	Power	Weather	Out	RRMSE	PError	cor_p	RRMSE	PError	cor_p	RMSE	RRMSE	R^2	PError	cor_p	cor_s
RForSeH	0	1:1	1:1	17.44	54.197	0.267	77.27	92.925	0.037	8486	48.87	0.000	80.191	0.101	0.121
RForSeH	0	36:1	36:1	20.40	77.142	0.105	88.19	93.448	0.157	10085	57.80	0.047	88.086	0.234	0.242
RForSeH	0	72:1	72:1	19.22	74.605	0.145	80.86	93.224	0.194	9397	53.13	0.049	87.102	0.282	0.279
RForSeH	0	72:4	72:4	8.96	22.679	0.359	34.03	63.160	0.500	4094	22.34	0.326	49.681	0.603	0.601
RForSeH	0	144:1	144:1	12.58	33.540	0.267	52.30	83.085	0.299	6017	34.29	0.154	66.794	0.419	0.410
RForSeH	0	144:2	144:2	8.71	22.232	0.384	33.74	62.784	0.513	4008	21.96	0.341	49.223	0.617	0.616
RForSeH	0	288:1	288:1	8.56	22.955	0.358	33.65	62.592	0.510	3973	21.80	0.347	49.384	0.610	0.610
RForSeH	0	576:1	576:1	7.87	25.768	0.412	27.15	55.965	0.643	3505	18.35	0.420	45.923	0.682	0.684
RForSeH	72:1	1:1	1:1	17.79	49.778	0.070	75.64	93.507	0.176	8238	46.40	0.000	79.128	0.076	0.057
RForSeH	72:1	36:1	36:1	21.06	25.846	0.487	38.58	54.749	0.662	7157	30.15	0.000	44.943	0.741	0.748
RForSeH	72:1	72:1	72:1	21.63	19.888	0.519	39.76	55.793	0.704	7396	31.32	0.000	43.738	0.778	0.785
RForSeH	72:1	72:4	72:4	19.65	25.487	0.490	32.64	52.456	0.678	6520	26.29	0.000	43.309	0.755	0.761
RForSeH	72:1	144:1	144:1	21.30	23.055	0.472	34.69	53.635	0.673	6977	28.09	0.000	43.288	0.750	0.759
RForSeH	72:1	144:2	144:2	19.50	25.931	0.483	32.83	52.525	0.685	6482	26.32	0.000	43.511	0.757	0.765
RForSeH	72:1	288:1	288:1	19.61	26.227	0.481	32.39	52.034	0.690	6475	26.06	0.000	43.265	0.758	0.765
RForSeH	72:1	576:1	576:1	19.14	28.133	0.386	34.08	53.344	0.676	6499	27.13	0.000	44.958	0.698	0.706
RForSeH	144:1	1:1	1:1	18.03	53.623	0.043	43.04	75.531	0.128	6783	30.27	0.000	68.318	0.068	0.170
RForSeH	144:1	36:1	36:1	23.74	31.873	0.461	47.17	56.733	0.567	8243	36.04	0.000	48.216	0.672	0.663
RForSeH	144:1	72:1	72:1	24.94	23.383	0.472	47.27	58.441	0.662	8552	36.62	0.000	46.666	0.730	0.741
RForSeH	144:1	72:4	72:4	21.03	28.308	0.475	36.44	56.182	0.628	6971	28.99	0.004	46.734	0.723	0.726
RForSeH	144:1	144:1	144:1	24.15	27.348	0.507	45.33	56.174	0.633	8240	35.24	0.000	46.357	0.722	0.722
RForSeH	144:1	144:2	144:2	21.13	28.365	0.471	37.07	56.785	0.620	6974	29.33	0.007	47.177	0.714	0.715
RForSeH	144:1	288:1	288:1	21.21	28.223	0.454	37.61	57.075	0.610	7046	29.63	0.005	47.289	0.710	0.713
RForSeH	144:1	576:1	576:1	22.03	27.663	0.396	35.49	53.971	0.678	7237	29.20	0.000	45.182	0.707	0.715
RForSeH	144:2	1:1	1:1	23.51	88.882	0.179	101.47	98.770	0.178	11550	65.90	0.000	95.519	0.294	0.295
RForSeH	144:2	36:1	36:1	23.51	88.882	0.179	101.47	98.770	0.178	11550	65.90	0.000	95.519	0.294	0.295
RForSeH	144:2	72:1	72:1	23.10	88.753	0.089	92.66	96.020	0.162	10975	61.26	0.000	93.630	0.247	0.320
RForSeH	144:2	72:4	72:4	13.32	28.528	0.347	29.09	60.018	0.396	4692	21.26	0.159	49.437	0.518	0.513
RForSeH	144:2	144:1	144:1	17.44	49.111	0.191	62.30	88.941	0.253	7783	41.92	0.012	75.844	0.365	0.384
RForSeH	144:2	144:2	144:2	8.89	22.775	0.392	33.44	61.702	0.511	4051	22.00	0.326	48.713	0.619	0.615
RForSeH	144:2	288:1	288:1	13.17	27.732	0.371	28.27	58.955	0.444	4634	20.73	0.164	48.424	0.561	0.556
RForSeH	144:2	576:1	576:1	7.95	25.573	0.413	26.68	55.333	0.659	3493	18.13	0.418	45.420	0.697	0.700
RForSeH	288:1	1:1	1:1	7.66	22.042	0.561	19.27	49.980	0.710	3083	13.84	0.445	40.520	0.785	0.796
RForSeH	288:1	36:1	36:1	7.21	20.846	0.543	19.94	50.544	0.713	3048	14.05	0.439	40.529	0.785	0.787
RForSeH	288:1	72:1	72:1	7.28	23.328	0.539	19.23	48.598	0.709	3000	13.73	0.449	40.020	0.783	0.785
RForSeH	288:1	72:4	72:4	7.39	23.994	0.496	19.86	50.959	0.692	3056	14.07	0.443	41.855	0.759	0.763
RForSeH	288:1	144:1	144:1	7.42	23.242	0.522	19.66	49.557	0.701	3039	13.93	0.443	40.638	0.776	0.777
RForSeH	288:1	144:2	144:2	7.33	23.891	0.493	19.59	50.723	0.697	3045	13.93	0.445	41.622	0.762	0.766
RForSeH	288:1	288:1	288:1	7.42	24.373	0.494	19.30	50.026	0.699	3050	13.82	0.448	41.311	0.761	0.766
RForSeH	288:1	576:1	576:1	7.83	27.894	0.381	22.29	52.939	0.682	3250	15.72	0.437	44.601	0.701	0.710

Table 4
Sizing Ablation: The results of sizing ablation experiments for the Random Forest model. Each value represents the number of values n and its stride s as $n : s$.

4.4. Prediction Difficulty

Tab. 8, Tab. 9, and Tab. 10 provide a complete model evaluation for clear, overcast, and all days, respectively.

				Clear Days			Overcast Days			All Days					
Model	Power	Weather	Out	RRMSE	PError	cor_p	RRMSE	PError	cor_p	RMSE	RRMSE	R^2	PError	cor_p	cor_s
SPred	0	1:1	1:1	5.63	20.239	0.008	13.31	40.609	0.077	2176	10.25	0.632	33.699	0.074	0.878
SPred	0	36:1	36:1	5.33	19.833	0.796	11.20	36.120	0.850	2049	8.68	0.675	30.278	0.896	0.901
SPred	0	72:1	72:1	5.52	20.299	0.742	12.26	39.233	0.817	2135	9.27	0.647	32.620	0.864	0.879
SPred	0	72:4	72:4	5.51	19.531	0.748	12.95	39.717	0.815	2189	9.74	0.640	32.607	0.869	0.883
SPred	0	144:1	144:1	5.55	21.279	0.745	12.66	39.166	0.810	2177	9.66	0.632	32.834	0.862	0.879
SPred	0	144:2	144:2	5.73	20.540	0.757	12.54	38.756	0.822	2193	9.67	0.638	32.263	0.870	0.886
SPred	0	288:1	288:1	5.77	20.515	0.761	13.00	40.674	0.813	2245	9.90	0.620	33.511	0.868	0.879
SPred	0	576:1	576:1	5.60	20.400	0.731	12.75	39.022	0.811	2224	9.73	0.630	32.437	0.862	0.876
SPred	72:1	1:1	1:1	12.86	22.348	0.859	16.71	31.620	0.897	4004	14.80	0.264	27.913	0.934	0.939
SPred	72:1	36:1	36:1	12.47	27.450	0.864	15.91	32.202	0.908	3842	14.21	0.300	29.966	0.935	0.939
SPred	72:1	72:1	72:1	12.94	17.962	0.822	16.77	32.159	0.893	4051	14.97	0.252	26.883	0.923	0.934
SPred	72:1	72:4	72:4	12.90	18.775	0.812	16.55	30.512	0.886	4031	14.83	0.257	26.052	0.917	0.930
SPred	72:1	144:1	144:1	13.81	15.946	0.767	18.17	34.430	0.862	4372	16.13	0.197	27.889	0.896	0.912
SPred	72:1	144:2	144:2	13.51	16.691	0.787	17.94	32.017	0.875	4242	15.80	0.214	26.417	0.908	0.919
SPred	72:1	288:1	288:1	13.93	17.087	0.754	19.19	34.338	0.843	4482	16.75	0.174	28.116	0.885	0.902
SPred	72:1	576:1	576:1	13.76	17.513	0.645	18.28	32.916	0.847	4359	16.21	0.195	27.290	0.852	0.909
SPred	144:1	1:1	1:1	14.92	20.807	0.774	19.39	34.190	0.871	4665	17.32	0.129	29.260	0.901	0.913
SPred	144:1	36:1	36:1	14.78	20.448	0.845	19.08	31.944	0.892	4577	16.93	0.127	27.550	0.928	0.933
SPred	144:1	72:1	72:1	15.63	16.050	0.814	20.50	34.094	0.878	4877	18.14	0.092	27.596	0.916	0.923
SPred	144:1	72:4	72:4	15.19	18.567	0.821	19.85	34.807	0.886	4723	17.63	0.109	28.912	0.920	0.926
SPred	144:1	144:1	144:1	15.42	18.858	0.800	19.71	33.001	0.878	4743	17.56	0.110	27.698	0.911	0.923
SPred	144:1	144:2	144:2	15.53	17.483	0.799	20.38	34.659	0.875	4865	18.11	0.099	28.542	0.910	0.921
SPred	144:1	288:1	288:1	15.94	16.129	0.801	20.58	34.179	0.868	4974	18.44	0.095	27.699	0.908	0.915
SPred	144:1	576:1	576:1	15.78	17.713	0.792	21.37	33.837	0.869	4995	18.76	0.088	28.066	0.902	0.914
SPred	144:2	1:1	1:1	5.93	22.146	0.758	10.90	36.308	0.830	2133	8.76	0.668	31.144	0.877	0.902
SPred	144:2	36:1	36:1	5.77	20.591	0.779	11.89	38.625	0.834	2126	9.10	0.657	32.270	0.880	0.900
SPred	144:2	72:1	72:1	5.49	19.601	0.791	12.18	38.783	0.838	2100	9.27	0.657	31.983	0.888	0.898
SPred	144:2	72:4	72:4	5.86	18.518	0.646	12.31	42.431	0.792	2269	9.67	0.627	34.308	0.829	0.864
SPred	144:2	144:1	144:1	5.42	19.367	0.736	12.15	39.054	0.810	2128	9.30	0.649	32.148	0.859	0.882
SPred	144:2	144:2	144:2	5.62	18.544	0.738	13.27	40.559	0.805	2212	9.94	0.632	32.892	0.863	0.875
SPred	144:2	288:1	288:1	6.15	21.512	0.740	11.38	38.783	0.809	2308	9.30	0.632	32.705	0.854	0.886
SPred	144:2	576:1	576:1	5.68	20.190	0.739	12.74	38.327	0.814	2225	9.70	0.634	31.946	0.864	0.881
SPred	288:1	1:1	1:1	9.09	39.974	0.922	9.52	32.600	0.943	2709	9.25	0.640	34.288	0.964	0.968
SPred	288:1	36:1	36:1	9.01	39.676	0.933	9.66	32.918	0.954	2694	9.21	0.641	34.417	0.971	0.974
SPred	288:1	72:1	72:1	5.18	17.854	0.824	10.66	33.461	0.885	1915	8.12	0.698	27.698	0.919	0.933
SPred	288:1	72:4	72:4	5.42	18.672	0.811	10.36	33.192	0.879	1955	8.13	0.697	27.821	0.916	0.928
SPred	288:1	144:1	144:1	5.02	17.964	0.751	10.79	33.733	0.852	1959	8.35	0.684	28.135	0.889	0.906
SPred	288:1	144:2	144:2	5.05	17.168	0.765	11.41	34.937	0.864	1966	8.60	0.677	28.551	0.897	0.909
SPred	288:1	288:1	288:1	5.00	16.796	0.775	10.78	31.945	0.869	1952	8.33	0.679	26.388	0.903	0.916
SPred	288:1	576:1	576:1	5.11	17.123	0.776	11.43	33.093	0.851	2003	8.62	0.672	27.360	0.896	0.910

Table 5
Sizing Ablation: The results of sizing ablation experiments for the SolarPredictor model. Each value represents the number of values n and its stride s as $n : s$.

				Clear Days			Overcast Days			All Days					
Model	Day	Hour	Smooth	RRMSE	PError	cor_p	RRMSE	PError	cor_p	RMSE	RRMSE	R^2	PError	cor_p	cor_s
SPred	$0.0 : 0.0$	$0.0 : 0.0$	$0.0 : 0.0$	21.77	60.687	0.116	54.14	55.106	0.004	9237	36.48	0.345	56.941	0.002	0.727
SPred	$0.0 : 1.0$	$0.0 : 0.0$	$0.0 : 0.0$	6.98	26.913	0.842	10.91	35.741	0.883	2284	9.02	0.661	32.206	0.917	0.929
SPred	$0.0 : 1.0$	$0.0 : .50$	$0.0 : .01$	4.91	16.738	0.812	13.21	38.101	0.855	2073	9.73	0.654	30.601	0.903	0.912
SPred	$0.0 : 1.0$	$0.0 : .50$	$0.0 : .05$	4.99	17.168	0.799	12.22	35.226	0.859	2024	9.09	0.671	28.715	0.902	0.910
SPred	$1.0 : 0.0$	$0.0 : 0.0$	$0.0 : 0.0$	5.26	18.853	0.863	11.37	36.023	0.886	2022	8.62	0.677	29.738	0.928	0.932
SPred	$1.0 : 0.0$	$.50 : 0.0$	$0.0 : 0.0$	4.50	13.382	0.847	12.17	35.928	0.857	2008	9.04	0.664	28.064	0.907	0.914
SPred	$1.0 : 0.0$	$.50 : 0.0$	$.01 : 0.0$	4.69	15.328	0.632	13.15	38.958	0.851	2050	9.69	0.646	30.696	0.843	0.901
SPred	$1.0 : 0.0$	$.50 : 0.0$	$.05 : 0.0$	4.60	14.473	0.806	11.65	36.365	0.861	1969	8.92	0.659	28.890	0.901	0.909
SPred	$1.0 : 0.0$	$1.0 : 0.0$	$0.0 : 0.0$	4.71	14.661	0.859	13.05	36.034	0.870	2067	9.55	0.653	28.500	0.918	0.920
SPred	$1.0 : 1.0$	$.50 : 0.0$	$0.0 : 0.0$	4.39	12.623	0.822	13.85	39.515	0.843	2066	9.98	0.642	30.313	0.893	0.902
SPred	$1.0 : 1.0$	$.50 : 0.0$	$.01 : 0.0$	4.68	15.122	0.824	12.76	36.178	0.866	2004	9.34	0.662	28.753	0.909	0.914
SPred	$1.0 : 1.0$	$.50 : 0.0$	$.05 : 0.0$	4.69	14.961	0.832	12.54	36.142	0.860	2008	9.22	0.666	28.760	0.907	0.910
SPred	$1.0 : 1.0$	$.50 : .50$	$0.0 : 0.0$	4.84	16.831	0.809	12.56	36.642	0.867	2006	9.27	0.660	29.572	0.904	0.914
SPred	$1.0 : 1.0$	$.50 : .50$	$.01 : 0.0$	5.15	17.549	0.776	11.44	34.113	0.843	2028	8.68	0.676	28.079	0.894	0.904
SPred	$1.0 : 1.0$	$.50 : .50$	$.01 : .01$	5.00	16.796	0.775	10.78	31.945	0.869	1952	8.33	0.679	26.388	0.903	0.916
SPred	$1.0 : 1.0$	$.50 : .50$	$.05 : 0.0$	4.34	13.349	0.835	12.66	37.181	0.867	1993	9.26	0.659	28.921	0.909	0.912
SPred	$1.0 : 1.0$	$.50 : .50$	$.05 : .01$	4.53	14.640	0.832	13.09	36.709	0.853	2017	9.42	0.654	28.951	0.904	0.908
SPred	$1.0 : 1.0$	$.50 : .50$	$.05 : .05$	4.65	14.982	0.805	12.27	36.167	0.855	2015	9.05	0.664	28.823	0.899	0.907
SPred	$1.0 : 1.0$	$1.0 : 0.0$	$0.0 : 0.0$	4.54	13.901	0.850	13.35	38.154	0.862	2042	9.75	0.644	29.748	0.910	0.914
SPred	$1.0 : 1.0$	$1.0 : .50$	$0.0 : 0.0$	4.89	16.714	0.803	12.07	34.337	0.863	2008	8.95	0.675	28.082	0.900	0.907
SPred	$1.0 : 1.0$	$1.0 : 1.0$	$0.0 : 0.0$	4.81	15.380	0.814	13.58	38.110	0.847	2090	9.82	0.647	30.163	0.895	0.898

Table 6
Sampling Ablation: The results of the sampling experiments for the SolarPredictor model. Random selection of daily, hourly, and smooth (per-minutely) training vectors are selected, covering the given ratio of all data. The ratio of weather w and realistic r data is specified as $w : r$.

	Model	Clear Days RRMSE	Clear Days PError	Clear Days cor_p	Overcast Days RRMSE	Overcast Days PError	Overcast Days cor_p	All Days RMSE	All Days RRMSE	All Days R^2	All Days PErr	All Days cor_p	All Days cor_s
#1	RForEnh	6.97	22.064	0.546	19.89	51.448	0.682	11994	13.78	0.500	39.250	0.743	0.740
	SPredEnh	5.22	17.721	0.805	9.54	28.775	0.873	7662	7.44	0.724	23.616	0.911	0.911
#2	SPredEnh	4.34	10.939	0.883	10.50	35.217	0.851	70093	8.29	0.658	26.965	0.923	0.922
	RForEnh	7.56	25.530	0.449	15.09	42.511	0.624	110205	12.39	0.478	36.711	0.737	0.744
#3	SPredEnh	3.64	11.799	0.733	8.34	28.697	0.895	1762	6.10	0.769	20.493	0.889	0.948
	RForEnh	5.97	19.621	0.613	14.52	44.842	0.773	2890	10.31	0.588	33.375	0.832	0.832
#4	RForEnh	5.69	16.717	0.772	10.09	31.626	0.833	629	7.90	0.683	24.390	0.869	0.881
	SPredEnh	3.40	9.328	0.943	6.16	19.386	0.914	377	4.80	0.831	14.194	0.953	0.958
#5	RForEnh	7.07	21.845	0.600	13.95	42.401	0.755	4851	10.90	0.520	34.684	0.802	0.779
	SPredEnh	5.05	18.013	0.887	8.02	24.807	0.919	3063	6.70	0.736	21.395	0.942	0.942
#6	RForEnh	6.67	19.484	0.685	24.48	48.901	0.760	13578	14.62	0.534	36.858	0.821	0.820
	SPredEnh	4.49	13.612	0.914	13.12	35.662	0.882	8756	8.33	0.705	26.336	0.939	0.935
#7	RForEnh	6.49	18.821	0.677	30.61	51.115	0.740	20684	18.08	0.496	39.278	0.826	0.815
	SPredEnh	3.37	8.505	0.936	12.00	35.548	0.904	11614	8.15	0.698	25.359	0.943	0.949
#8	RForEnh	6.90	19.838	0.561	17.34	44.982	0.710	2775	12.46	0.445	36.468	0.785	0.796
	SPredEnh	4.50	15.308	0.849	11.29	32.480	0.878	1897	8.45	0.690	26.304	0.921	0.926
#9	SPredEnh	4.63	15.068	0.685	13.33	31.602	0.626	3751	9.18	0.701	25.549	0.626	0.939
	RForEnh	8.03	27.227	0.701	29.49	44.970	0.073	6330	17.24	0.513	38.604	0.040	0.804
#10	SPredEnh	4.53	11.614	0.871	13.25	39.326	0.797	53427	8.77	0.651	25.943	0.916	0.915
	RForEnh	16.74	34.622	0.566	20.54	45.661	0.557	138859	18.42	0.001	39.995	0.733	0.732
#11	RForEnh	14.66	31.712	0.271	18.95	48.346	0.373	75139	17.01	0.130	41.610	0.566	0.593
	SPredEnh	5.85	22.767	0.667	10.46	30.714	0.710	35157	8.47	0.663	27.121	0.806	0.858
#12	SPredEnh	6.08	21.697	0.107	13.18	42.529	1.000	60797	9.50	0.612	32.579	1.000	0.881
	RForEnh	7.04	23.309	0.616	29.17	63.972	0.167	86489	17.96	0.429	45.672	0.071	0.733
#13	SPredEnh	4.42	15.384	0.827	8.07	27.355	0.303	36151	6.38	0.724	22.120	0.639	0.779
	RForEnh	6.20	20.374	0.606	11.93	36.782	0.653	50490	9.51	0.583	30.259	0.778	0.778
#14	SPredEnh	5.14	19.282	0.849	11.36	35.146	0.322	43859	8.45	0.644	28.370	0.720	0.765
	RForEnh	15.53	25.794	0.443	23.53	51.872	0.426	108198	20.03	0.055	41.557	0.686	0.671
#15	SPredEnh	6.35	23.854	0.799	11.13	34.172	0.836	119581	9.24	0.629	30.271	0.849	0.891
	RForEnh	9.48	30.959	0.616	23.97	52.625	0.484	184752	18.19	0.280	45.546	0.601	0.655
#16	RForEnh	6.90	21.285	0.539	19.86	53.652	0.623	8920	14.07	0.463	41.559	0.744	0.737
	SPredEnh	4.54	15.840	0.862	14.45	37.906	-0.088	5905	9.30	0.640	28.994	-0.041	0.803

Table 7

Cross-Validation Experiments: The quantitative evaluation of yearly predictions for each of the 16 power plants, using the two best-performing models – RForEnh and SPredEnh.

		1D		2D		3D		4D		5D		6D		7D		8D		9D		10D	
	Model	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError
Classical	SVMSin	19.02	70.632	19.01	70.352	18.99	70.351	19.03	70.507	19.08	70.930	19.09	70.738	19.07	70.733	18.99	69.736	19.30	69.273	19.33	70.363
	TreeSin	8.28	22.165	8.82	24.182	8.88	26.773	9.07	24.910	9.54	29.689	9.33	28.319	9.75	29.725	10.80	34.734	11.18	38.243	11.48	40.021
	TreeSeq	8.04	19.334	8.08	20.577	8.37	19.817	8.36	21.920	8.64	21.589	9.01	24.217	8.98	25.575	9.94	30.490	12.20	43.212	12.34	44.687
	TreeSeH	8.57	14.890	8.19	13.524	8.46	15.171	8.55	16.491	9.00	18.803	9.21	19.818	9.28	21.467	9.47	23.876	11.39	38.532	11.90	41.901
	RForSin	7.08	22.775	7.19	19.550	7.46	19.494	7.69	18.894	8.03	20.218	8.25	20.095	8.67	22.079	9.93	27.497	10.46	28.708	10.88	30.412
	RForSeq	6.80	22.863	6.87	22.308	6.89	22.539	6.78	21.656	6.95	22.962	6.95	22.745	7.42	25.742	8.27	31.537	8.64	33.466	9.15	36.266
	RForSeH	6.01	15.777	5.99	15.949	6.17	16.762	6.36	18.399	6.47	19.722	6.84	21.747	6.86	20.973	7.54	25.170	11.00	45.294	11.52	47.719
DNN	DNNSin	17.08	41.351	17.05	40.953	17.06	41.133	17.05	41.603	17.05	41.723	17.07	42.040	17.11	42.669	17.12	43.887	17.13	42.935	17.24	44.899
	DNNSeq	8.05	19.803	9.53	17.304	10.63	15.749	11.86	19.324	12.91	24.111	13.62	26.613	14.06	28.813	14.77	32.991	15.17	33.322	15.96	39.906
	DNNSeH	10.34	18.815	10.37	19.027	10.46	19.693	10.51	20.117	10.56	20.155	10.72	22.079	11.01	23.177	11.21	25.766	14.39	37.446	14.86	42.490
Recurrent	LSTMVan	16.99	39.493	17.04	40.800	17.00	39.687	17.02	40.040	16.99	39.976	17.01	40.991	17.05	41.187	17.01	39.884	17.01	39.884	17.02	39.911
	LSTMSta	17.08	40.694	17.08	40.696	17.07	40.605	17.08	40.695	17.08	40.695	17.09	41.066	17.08	41.242	17.07	40.605	17.08	40.608	17.09	41.092
	LSTMCNN	16.76	32.583	16.87	34.805	16.86	33.989	16.90	35.813	17.01	37.673	16.87	35.009	17.05	38.462	16.91	34.173	17.14	38.811	17.32	43.149
	LSTMCon	16.41	38.949	17.49	35.611	17.49	35.596	17.50	36.481	17.49	35.744	17.49	36.047	17.50	36.717	17.47	35.674	17.50	36.035	17.46	35.999
	LSTMBid	7.16	20.700	7.97	17.134	9.11	17.268	9.79	18.067	10.28	18.960	10.49	18.300	10.75	19.497	11.22	20.647	11.57	21.423	12.39	28.811
	SPredSeRc	12.65	48.163	13.51	46.878	14.87	48.527	16.01	48.039	16.91	47.635	17.49	45.130	17.76	48.012	18.04	46.460	18.22	47.561	18.37	47.269
	SPredPaRc	9.85	25.197	10.15	12.964	10.12	14.348	10.18	14.789	10.24	14.204	10.25	13.864	10.32	14.314	10.42	15.719	10.40	16.012	10.55	18.736
Convolutional	SPredCNN	7.02	26.720	8.02	32.187	8.18	33.304	8.23	33.825	8.49	35.202	8.53	35.319	8.85	37.009	10.78	47.124	11.69	50.781	12.13	53.248
	SPredCNNO	6.67	24.247	6.58	22.904	6.82	24.789	6.66	23.244	7.14	25.823	7.22	26.418	7.72	29.052	9.80	39.546	10.55	42.911	11.60	48.050
	SPredUNet	6.19	19.057	6.53	21.044	6.47	21.202	6.22	20.480	6.61	21.768	6.71	22.252	7.55	26.433	9.52	37.520	10.55	41.289	12.43	52.597
	SPredTCN	5.97	19.387	6.32	22.124	6.37	22.092	6.17	21.718	6.60	23.496	6.87	25.267	7.37	27.838	9.31	39.739	9.43	40.079	10.56	46.455
	SPredWave	6.38	19.096	6.66	20.259	6.91	20.847	6.75	20.427	7.27	22.894	7.46	23.482	7.66	23.412	9.31	32.072	9.96	34.676	10.82	40.440
	SPredTrf	7.76	23.346	8.29	23.615	8.32	22.756	8.41	22.193	8.82	23.323	9.05	24.692	9.44	25.612	11.20	35.170	11.64	36.320	12.66	42.820
	SPred	4.02	10.994	4.58	12.057	4.78	12.582	4.69	12.600	4.79	12.507	4.89	13.216	5.38	15.592	8.45	31.097	8.16	30.139	8.28	31.429
Enh	RForEnh	5.56	11.652	5.53	11.437	5.75	12.540	5.91	14.604	6.07	15.855	6.32	17.940	6.36	17.214	6.99	21.187	10.25	38.112	10.58	40.018
	SPredEnh	2.94	7.907	3.77	11.573	4.19	14.040	4.08	13.535	4.25	13.979	4.27	13.991	4.28	14.140	5.61	20.723	5.25	18.862	6.05	22.974

Table 8

Clear Day Interval Length: The evaluation of prediction accuracy with respect to the length of the prediction, showing average prediction accuracy of up to 10 days ahead for *clear* days.

		1D		2D		3D		4D		5D		6D		7D		8D		9D		10D	
	Model	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError
Classical	SVMSin	42.50	83.291	42.11	83.302	42.09	82.841	41.60	83.014	40.58	83.371	39.92	82.750	39.96	82.915	42.23	82.807	40.10	83.479	38.88	82.278
	TreeSin	27.25	56.774	30.15	59.797	32.05	59.406	32.52	59.470	33.61	59.321	32.86	59.321	28.99	59.647	29.84	56.645	32.46	62.034	30.21	58.344
	TreeSeq	20.36	49.814	20.19	48.580	21.30	50.931	22.61	51.844	23.74	55.386	24.37	54.302	25.49	58.227	26.58	59.434	28.79	60.392	29.13	60.481
	TreeSeH	20.26	43.567	21.70	44.373	22.86	50.068	22.17	46.801	23.35	50.702	25.39	50.388	25.73	52.806	27.71	54.464	24.69	58.495	27.07	59.918
	RForSin	22.05	51.535	29.53	59.998	33.24	63.188	34.94	63.132	34.69	66.041	34.83	64.280	35.51	65.635	34.00	63.313	35.12	63.648	35.19	64.024
	RForSeq	23.93	50.537	25.63	54.376	25.84	54.344	26.50	54.597	26.10	54.577	25.40	53.463	25.91	53.071	23.66	51.631	24.89	52.210	25.07	53.320
	RForSeH	17.13	46.802	17.51	47.465	17.56	49.222	18.03	48.599	19.00	50.143	19.10	51.632	20.16	50.759	20.86	51.088	20.26	52.212	20.09	50.825
DNN	DNNSin	29.64	59.830	29.64	60.396	29.98	60.095	29.70	60.651	30.05	60.707	29.60	61.013	29.38	60.574	30.34	61.107	29.06	61.933	29.47	61.610
	DNNSeq	19.43	50.952	19.71	52.617	20.88	58.129	23.27	65.951	25.03	71.340	27.23	75.286	32.37	79.768	35.31	79.271	38.09	83.248	40.49	85.490
	DNNSeH	17.30	46.870	17.56	47.289	17.40	49.206	17.73	51.234	18.39	50.329	18.57	53.762	20.04	55.206	22.57	56.549	20.57	56.820	20.80	58.314
Recurrent	LSTMVan	28.63	61.807	29.32	60.529	30.53	61.305	30.31	61.421	31.03	61.411	29.44	59.824	30.83	60.316	33.01	61.658	31.99	62.287	32.16	62.068
	LSTMSta	29.34	60.983	30.20	60.689	29.52	61.645	29.58	61.972	30.56	61.910	29.61	61.081	31.51	62.211	31.24	62.444	30.72	61.942	30.98	61.987
	LSTMCNN	25.31	59.881	24.32	57.930	24.53	56.866	24.51	58.699	24.85	56.130	24.08	57.745	24.65	56.135	23.84	57.931	23.89	56.248	24.05	58.632
	LSTMCon	28.79	60.373	32.93	62.838	33.77	62.998	34.81	63.068	33.14	63.566	33.46	61.552	34.27	63.415	35.60	64.225	35.94	65.000	35.54	64.506
	LSTMBid	19.82	51.488	21.93	59.685	26.25	63.514	28.81	66.214	30.77	67.814	33.44	67.076	36.63	70.339	39.86	70.677	39.69	71.368	40.29	74.967
	SPredSeRc	17.67	46.859	20.77	49.216	23.06	54.045	26.62	57.877	27.16	58.000	29.26	59.895	30.21	60.626	29.95	58.750	30.19	60.998	31.14	60.862
	SPredPaRc	17.49	46.218	21.70	60.666	21.54	59.177	20.78	60.864	20.55	58.885	21.96	59.306	21.87	60.032	20.40	64.510	20.34	67.163	20.96	67.450
Convolutional	SPredCNN	15.50	45.664	15.23	46.874	15.22	45.022	15.63	45.973	15.68	47.662	15.11	44.673	16.11	47.306	16.16	47.364	15.89	46.519	16.50	49.040
	SPredCNNO	20.82	59.910	21.84	62.025	21.12	60.026	22.43	62.286	21.27	56.783	20.36	56.147	20.50	58.295	17.11	54.291	17.21	54.996	18.01	55.934
	SPredUNet	19.46	49.488	20.78	53.223	22.12	52.038	21.73	53.357	21.14	51.613	20.50	49.090	20.40	51.019	18.58	51.990	18.92	52.170	20.74	53.924
	SPredTCN	18.48	51.772	19.07	51.119	19.15	50.220	19.58	51.422	19.29	50.798	18.83	49.456	18.80	50.360	17.61	52.095	18.01	50.043	19.28	51.559
	SPredWave	19.58	53.445	22.20	52.868	23.22	53.754	24.83	54.252	25.64	55.919	25.27	56.134	26.47	56.958	25.52	54.976	25.29	54.920	26.61	57.744
	SPredTrf	17.05	52.013	16.81	51.880	16.87	51.140	17.04	52.484	17.99	51.126	17.13	51.953	17.83	52.781	18.99	52.550	20.04	57.051	22.12	61.375
	SPred	11.43	35.840	13.20	38.277	12.39	36.648	12.54	37.036	12.46	37.691	12.04	38.486	12.30	37.757	11.10	35.704	11.12	35.510	11.45	37.277
Enh	RForEnh	15.45	41.633	15.53	41.869	15.20	41.918	16.12	43.826	16.17	45.046	17.23	45.587	17.73	45.195	19.52	47.527	18.45	47.215	18.56	48.644
	SPredEnh	8.31	25.620	11.47	32.621	11.56	33.366	12.28	33.492	11.90	32.140	11.65	33.527	11.95	34.106	10.66	31.118	11.47	34.104	11.50	33.868

Table 9
Overcast Day Interval Length: The evaluation of prediction accuracy with respect to the length of the prediction, showing average prediction accuracy of up to 10 days ahead for *overcast* days.

		1D		2D		3D		4D		5D		6D		7D		8D		9D		10D	
	Model	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError	RRMSE	PError
Classical	SVMSin	29.56	79.120	29.45	79.035	29.54	78.726	29.40	78.893	29.34	79.272	29.45	78.792	28.69	78.901	29.38	78.501	29.45	78.798	29.07	78.352
	TreeSin	19.18	45.261	21.03	47.989	21.46	48.557	22.44	48.010	23.13	49.550	22.76	48.984	21.24	49.710	21.62	49.318	22.81	54.053	22.46	52.188
	TreeSeq	15.50	39.371	15.54	38.991	16.14	40.461	16.91	41.755	17.66	44.084	18.15	44.246	18.70	47.370	19.68	49.843	21.45	54.682	21.47	55.265
	TreeSeH	15.36	**33.566**	15.99	**33.586**	16.57	**38.137**	16.69	**36.526**	17.40	**39.708**	18.42	**39.884**	19.14	42.224	20.19	44.320	19.07	51.746	20.55	53.906
	RForSin	15.83	41.825	19.19	46.498	21.33	48.588	22.37	48.432	22.54	50.747	22.34	49.619	23.08	51.154	22.69	51.254	23.63	51.897	23.60	52.802
	RForSeq	16.38	41.190	17.28	43.699	17.31	43.748	17.68	43.643	17.51	43.952	16.90	43.246	17.59	43.970	16.86	44.664	17.38	**45.682**	17.90	**47.557**
	RForSeH	**11.90**	35.763	**12.04**	36.375	**12.36**	**38.130**	**12.78**	38.344	**13.25**	**39.658**	**13.57**	41.346	**14.63**	**40.633**	**15.06**	**42.266**	**15.70**	49.741	**15.75**	49.665
DNN	DNNSin	23.41	53.103	23.42	53.370	23.45	53.226	23.50	53.824	23.66	54.038	23.53	54.417	23.40	54.364	23.75	55.222	23.23	55.532	23.61	56.016
	DNNSeq	15.04	40.396	15.28	40.748	16.57	43.921	18.17	50.556	19.89	55.779	21.37	59.249	24.16	62.954	26.24	63.994	27.74	66.786	29.87	70.298
	DNNSeH	**13.98**	**36.917**	**14.16**	**37.319**	**14.09**	**39.027**	**14.41**	**40.515**	**14.80**	**39.792**	**14.88**	**42.779**	**15.72**	**44.376**	**16.92**	**46.332**	**17.58**	**50.382**	**17.88**	**53.100**
Recurrent	LSTMVan	22.91	54.023	23.37	53.840	23.97	53.868	23.97	54.196	23.87	54.005	23.49	53.456	24.14	53.816	25.03	54.137	24.82	54.559	24.97	54.515
	LSTMSta	23.56	53.994	23.51	53.847	23.62	54.355	23.61	54.731	24.20	54.687	23.57	54.238	24.35	55.043	24.37	54.891	24.02	54.554	24.22	54.992
	LSTMCNN	20.94	50.688	20.76	50.132	20.70	49.118	20.81	51.025	20.91	49.856	20.69	49.971	20.90	49.988	20.58	49.832	20.65	50.251	20.82	53.461
	LSTMCon	22.47	53.195	25.76	53.599	26.16	53.755	26.25	54.141	25.61	54.159	25.96	52.957	26.38	54.247	26.86	54.599	26.90	55.330	26.61	54.962
	LSTMBid	14.94	41.109	16.39	45.417	18.65	48.154	20.19	50.308	21.95	51.611	22.93	50.926	25.25	53.391	26.81	54.144	27.27	54.901	28.31	59.554
	SPredSeRc	15.51	46.975	17.54	48.281	19.36	52.129	21.75	54.618	22.59	54.565	23.96	54.957	24.27	56.395	24.48	54.630	24.49	56.496	25.04	56.375
	SPredPaRc	**13.98**	**38.953**	**16.26**	**44.618**	**16.37**	**44.119**	**16.14**	**45.598**	**15.99**	**43.887**	**15.56**	**44.085**	**16.68**	**44.660**	**15.85**	**48.127**	**15.96**	**49.673**	**16.41**	**51.208**
Convolutional	SPredCNN	12.14	39.142	12.37	41.731	12.55	40.954	12.70	41.700	12.80	43.302	12.55	41.378	13.12	43.712	13.83	47.051	13.95	47.745	14.50	50.347
	SPredCNNO	15.30	47.982	15.92	48.940	15.55	48.246	16.40	49.378	15.70	46.477	15.17	46.184	15.49	48.568	14.24	49.317	14.45	50.890	15.34	53.303
	SPredUNet	14.24	39.286	15.12	42.372	15.73	41.715	15.62	42.482	15.29	41.546	14.89	40.054	15.27	42.873	14.96	47.170	15.46	48.553	17.17	53.480
	SPredTCN	13.60	40.807	13.92	41.324	14.11	40.779	14.33	41.459	14.30	41.557	14.02	41.212	14.27	42.729	14.36	47.876	14.39	46.658	15.53	49.877
	SPredWave	14.46	41.933	15.28	41.778	16.22	42.715	17.01	42.865	17.64	44.742	17.19	45.125	18.03	45.549	17.86	47.258	18.18	48.056	19.39	52.043
	SPredTrf	13.34	42.462	13.40	42.234	13.47	41.464	13.77	42.348	14.24	41.728	14.00	42.808	14.37	43.697	15.72	46.799	16.27	50.217	17.89	55.096
	SPred	**8.56**	**27.301**	**9.53**	**29.255**	**9.00**	**28.486**	**9.34**	**28.652**	**9.28**	**28.945**	**9.27**	**29.755**	**9.56**	**30.096**	**9.78**	**33.732**	**9.68**	**33.437**	**9.83**	**34.964**
Enh	RForEnh	10.85	31.166	10.76	31.281	10.88	31.886	11.55	33.885	11.55	35.156	12.20	36.101	12.86	35.711	13.99	38.680	14.44	44.047	14.61	45.684
	SPredEnh	**6.15**	**19.057**	**8.26**	**25.195**	**8.54**	**26.514**	**8.83**	**26.524**	**8.63**	**25.752**	**8.65**	**26.720**	**8.89**	**27.228**	**8.46**	**27.182**	**8.97**	**28.728**	**9.29**	**29.933**

Table 10
All Day Interval Length: The evaluation of prediction accuracy with respect to the length of the prediction, showing average prediction accuracy of up to 10 days ahead for *all* days.

References

[1] Dark Sky. Darksky weather api, 2021. URL `https://darksky.net/dev`. Last visited 2021-04-22.

[2] Brandon Stafford. Pysolar documentation, 2015. URL `https://pysolar.readthedocs.io/`.

[3] Martín Abadi et al. TensorFlow: Large-scale machine learning on heterogeneous systems, 2015. URL `https://www.tensorflow.org/`. Software available from tensorflow.org.

[4] Sashank J. Reddi, Satyen Kale, and Sanjiv Kumar. On the convergence of adam and beyond. *CoRR*, abs/1904.09237, 2019. URL `http://arxiv.org/abs/1904.09237`.

[5] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In Yoshua Bengio and Yann LeCun, editors, *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*, 2015. URL `http://arxiv.org/abs/1412.6980`.

[6] Colin Lea, Michael D Flynn, Rene Vidal, Austin Reiter, and Gregory D Hager. Temporal convolutional networks for action segmentation and detection. In *proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 156–165, 2017.

[7] Xavier Glorot and Yoshua Bengio. Understanding the difficulty of training deep feedforward neural networks. In Yee Whye Teh and Mike Titterington, editors, *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics*, volume 9 of *Proceedings of Machine Learning Research*, pages 249–256, Chia Laguna Resort, Sardinia, Italy, 13–15 May 2010. PMLR. URL `http://proceedings.mlr.press/v9/glorot10a.html`.

[8] Fabian Pedregosa et al. Scikit-learn: Machine learning in python. *the Journal of machine Learning research*, 12:2825–2830, 2011.

[9] Tijmen Tieleman and Geoffrey Hinton. Lecture 6.5-rmsprop: Divide the gradient by a running average of its recent magnitude. *COURSERA: Neural networks for machine learning*, 4(2):26–31, 2012.

[10] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[11] Aäron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew W. Senior, and Koray Kavukcuoglu. Wavenet: A generative model for raw audio. *CoRR*, abs/1609.03499, 2016. URL `http://arxiv.org/abs/1609.03499`.

[12] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Rob Fergus, S. V. N. Vishwanathan, and Roman Garnett, editors, *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 5998–6008, 2017. URL `https://proceedings.neurips.cc/paper/2017/hash/3f5ee243547dee91fbd053c1c4a845aa-Abstract.html`.