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Review

Review on Spatio-Temporal Solar Forecasting Methods Driven by In Situ Measurements or Their Combination with Satellite and Numerical Weather Prediction (NWP) Estimates

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Abstract: To better forecast solar variability, spatio-temporal methods exploit spatially distributed solar time series, seeking to improve forecasting accuracy by including neighboring solar information. This review work is, to the authors' understanding, the first to offer a compendium of references published since 2011 on such approaches for global horizontal irradiance and photovoltaic generation. The identified bibliography was categorized according to different parameters (method, data sources, baselines, performance metrics, forecasting horizon), and associated statistics were explored. Lastly, general findings are outlined, and suggestions for future research are provided based on the identification of less explored methods and data sources.

Keywords: solar forecasting; spatio-temporal; in situ measurements; review; statistical methods; physical methods; machine learning methods; deep learning methods; hybrid methods

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1. Introduction

Solar forecasting, namely the forecasting of the solar resource or photovoltaic power, has been described as a fast-advancing field [1] and is becoming a consolidated research topic with abundant literature [2]. One of the main drivers for solar variability [3] and forecast uncertainty is the change in cloud cover caused by cloud advection, which is essentially a spatio-temporal phenomenon. Thus, it is only natural that several forecasting frameworks aim to grasp these spatio-temporal dynamics [4]. On one hand, Numerical Weather Prediction (NWP) explores a myriad of data sources which are horizontally and vertically distributed in space, together with numerical approximations of the atmospheric equations of motion and parametrizations of unresolved processes, to describe the physical state of the atmosphere and simulate its dynamic behavior [5]. On the other hand, image-based approaches explore sequences of satellite [6,7] or sky-camera [8,9] images to infer cloud motion vectors and extrapolate cloud advection. The different solutions resort to different data inputs and, consequently, offer different operational characteristics [10] (e.g., spatial coverage, spatial and temporal resolution, optimal forecast horizon range, latency associated with data acquisition and processing). For example, when shifting from NWP to satellite and sky-camera, the achieved level of detail grows considerably, with the compromise of it performing best for shorter forecast horizon windows. Naturally, there have also been works proposing hybrid approaches which seek to benefit from this diversity and achieve optimal results [11]. It is also important to note that there are works that combine these approaches to improve forecasting performance [11]. In contrast, others focus on exploring previous values of the forecasted variable only from the location of interest [12], which is often complemented with exogenous weather variables [13].

In a recent review, Yang et al. [2] identified the use of measurements from ground sensing networks in spatio-temporal solar forecasting as a promising application for shorter-term horizons (from a few seconds to one hour ahead). Here, the authors refer to the use of either statistical (e.g., [14]) or advective (e.g., [15]) approaches with spatially distributed global horizontal irradiance (GHI) or photovoltaic (PV) generation data. It should be noted that GHI can either be measured using pyranometers estimated from satellite imagery or predicted by NWP models. The main reasons for this are to exploit higher resolution data (when compared to satellite or NWP) and bypass the uncertainty associated with the conversion of a cloud image to an irradiance forecast, especially with sky imagers. Furthermore, [16,17] have already highlighted the potential of ground sensing networks to improve solar forecasting, with the oldest reference being from 2013, namely Diagne et al. [16]. Additionally, there is already a considerable number of publications applying such approaches [18–23]. At the same time, there seems to be a growing trend of publications which explore statistical-based spatio-temporal approaches using gridded data sources such as satellite-derived irradiance [11,24–28] and NWP irradiance forecasts [29–34]. However, there is yet to be published a literature review addressing this topic.

The most important review works identified explore different research perspectives. Some focus on broader coverage (e.g., [2,35,36]), addressing both solar irradiance and power as well as different forecasting methods (e.g., NWP [37,38], statistical approaches such as traditional statistical [39,40], machine learning [29,41] and deep learning [32,42], and advective approaches [43,44]) and spatio-temporal scales (from seconds ahead in a 100×100 m^2 [14] to days ahead in a 200×400 m^2 [45]). Others are more specific, either focusing on solar irradiance [16,46–48] or in solar power forecasting [10,49–53]. There are also those that target specific forecasting approaches, such as machine learning [46,48,54], deep learning [47,55] or hybrid algorithms [53] or even a specific forecast horizon range [10]. Even though some of these works point out the importance of the spatio-temporal characteristic of the solar variability to improve forecasting performance, in the aforementioned reviews, only 5% of the total number of references correspond to works exploring spatially distributed solar time series as inputs.

On the other hand, publications that propose spatio-temporal solar forecasting approaches tend to only include brief accounts of the state-of-the-art of this research field [9,30,56]. André et al. [40] gave a more detailed account regarding spatio-temporal works, identifying the considered spatial and temporal resolution while also making a distinction between correlation and statistical-based forecasting methods. This work includes 11 references published between 2000 and 2015. Silva et al. [57] made a noteworthy contribution summarizing in a table the descriptions of a set of works exploiting spatially distributed solar time series. These are described in terms of the model, data source, location, time resolution, coverage area, the forecast horizon considered, and the maximum forecast skill achieved. Listing 25 references, it is, to this date, the largest compilation found in the literature. In [58], Tascikaraoglu discussed the benefits of using spatio-temporal approaches in several smart city applications, renewable forecasting (among which, solar) being one of them. For solar forecasting, Tascikaraoglu included 17 references (published between 2011 and 2016) studied according to the characteristics of the model (statistical or physical), taking into account forecasting horizons and particularities.

Despite the substantial number of references mentioned above, in most cases, they focus only on mentioning the applied methods. Even the most descriptive case [57] is limited to presenting a table with little analysis and discussion of its contents. Additionally, most of the references mentioned in the preceding paragraph (that dedicated a space to mention works with a spatio-temporal approach) were published before 2016, with few exceptions from 2017 and 2018. Therefore, the main contribution of this work to the existing literature is two-fold:

1. To provide, to the best of the authors' knowledge, the first review on spatio-temporal solar forecasting, namely on GHI and PV generation, using in situ ground measurements or their combination with satellite or NWP estimates.

2. Comprehensive overview of recent advances using such approaches. The goal here is to categorize and provide statistics and temporal patterns regarding the different models used, the different types of data exploited, and the various forecasting horizons addressed.

The references from this manuscript were identified by conducting a keyword-based search in the following databases: Web of Science (https://www.webofscience.com/wos/alldb/basic-search, accessed on 25 February 2022), Scopus (https://www.scopus.com/search/form.uri?display=basic#basic, accessed on 25 February 2022), and Google Scholar (https://scholar.google.com/, accessed on 25 February 2022). The most effective keywords were "spatio-temporal solar forecasting", "PV forecasting", "irradiance forecasting", "solar forecasting", "neighboring", "multiple sites" and a combination of the mentioned keywords. The authors emphasized in their work's title a few spatial characteristics that were found to be referred differently. For instance, the most used was spatio-temporal, being found written differently as "spatial-temporal" [59–61], "spatiotemporal" [7,23,62–64], and "spatial and temporal" [65,66]. To achieve a compilation as complete as possible, the spatio-temporal references of these works were also included.

Regarding forecasting horizon, while various classifications can be found in the literature [10,36,47,52,53,67,68], this work considers the one proposed by Antonanzas et al. [49] (found in Table 1) as it is easy to interpret (i.e., avoids abstract expressions, such as "short", "medium", "long-term", to which different authors often associate different horizon ranges) and ensures that shorter-term forecasting is differentiated from larger intra-day horizons.

Table 1. Classification of solar forecasting based on temporal resolution.

Forecast Horizon Class	Range
Intra-hour	A few seconds to 1 h ahead
Intra-day	1 to 6 h ahead
Six hours to one day ahead	6 to 48 h ahead
Two days ahead or longer	48 h ahead

The present paper is structured as follows: Section 2 discusses the references on spatio-temporal solar forecasting found in previous works or reviews; Section 3 identifies, analyzes and discusses the works that exploit spatially distributed solar data, which are grouped according to the type of approach pursued; Section 4 adds a discussion on the data sources, methods, metrics, horizons and baselines used; while Section 5 presents the conclusions.

2. Remarks on Spatio-Temporal Solar Forecasting Found in Previous Relevant Review Works

In 2013, Inman et al. [35] anticipated the importance of ground sensing networks and imagery to improve predictions by taking into account a spatial component, since NWP models and satellite imagery lacked the spatial and temporal resolution to provide information on high-frequency solar fluctuations. The authors consider that such approaches can be integrated into the existing solutions to cover a broader range of temporal and spatial scales.

The review of Antonanzas et al. [49] focused exclusively on PV energy forecasting. The authors grouped research works based on the type of data sources exploited, with one group named "neighboring PV plants" exploring PV power data from the target plant and its neighbors. However, less than seven references (i.e., less than 6% of the total of references of the paper) were mentioned. The discussion on forecasting at either point and regional spatial scales highlighted the performance gains from considering a larger spatial region of interest as it benefits from a smoothing effect (i.e., lower overall variability, as less correlated generation profiles are aggregated). Focusing on PV as well, Barbieri et al. [10] dedicated their study to very short-term horizons. The authors discussed how different data sources (sky imagers, a network composed by several sensors, satellite imagery and

NWP) are best suited to target different spatio-temporal scales. Providing references only up to 2014, the authors argued that the ground sensing network is an ideal source of data, as irradiance is directly measured and not indirectly inferred (e.g., from an image).

Finally, as mentioned in the introduction, Yang et al. [2], stated that ground sensing networks will play an increasingly important role in solar forecasting, especially for short-term predictions, due to the increasing deployment of distributed PV systems and the growing need of ground sensing networks data (although ensuring proper quality-check procedures are put in place [69]). In this work, some of the most commonly used methods—such as regressions, spatio-temporal kriging, and partial differential equations—are identified.

3. Spatio-Temporal Approaches

The works exploiting spatially distributed solar data use well-known forecasting approaches such as the more traditional statistical methods, physical methods, machine learning, and hybrid variations. To facilitate the reading and understanding of the different proposals, each approach is discussed separately, with all the identified references being compiled in a table and one work per type of model described in more detail as an illustrative example.

3.1. Traditional Statistical Methods

Table 2 compiles all the references identified in this category. It is observed that the most frequently used methods are Auto-Regressive models with eXogenous inputs (ARX) [39,57,61,70–73], Vector Auto-Regressive model using eXogenous inputs (VARX) [74], Kriging [59,75–77], and Least Absolute Shrinkage and Selection Operator (LASSO) [14,17,30,78,79].

In [45], Amaro e Silva et al. explored a linear ARX model to forecast GHI using ground data and satellite estimates. The authors showed that spatio-temporal methods are valid for a broad range of spatio-temporal scales, from seconds to days ahead and from a small to a to country-sized region. In particular, for intra-hour forecasting, the model coefficients are coherent with the known local advection patterns, upwind locations providing the most relevant information. The relevance of neighboring solar information is shown to depend on the considered forecast horizon, with the authors proposing a normalized weighted average distance (nWAD) metric as a form of characterization. In following works, the authors extended this study to an ensemble of small-scale PV systems [57] and highlight the limitations of a static linear ARX model (since the spatio-temporal cloud dynamics depend on the local advection patterns, which vary with time [80]). To address this, a regime-based approach is proposed where different models are trained for different wind regimes. Lastly, the surface geometry (i.e., tilt and orientation) of the sensor network is shown to impact the performance of spatio-temporal approaches [31], which is particularly relevant for spatially distributed urban-scale PV data. The authors simulated global tilted irradiance assuming rooftop and facade geometries are using state-of-the-art decomposition and transposition models.

In [14], Yang et al. performed very short-term GHI forecasting using a LASSO [81] model. This approach can be seen as an extension of the linear ARX model, as it included a regularization component to perform variable selection and mitigate overfitting. Here, and in related works (such as [17,82]), Yang proposed to complement LASSO with a pre-selection step based on different parameters, such as distance to target site, wind information and statistical criteria. The proposed algorithm is capable of selecting the most important predictors from thousands of potential predictors. Agoua et al. [30] tested a variant where quantile regression has been adapted to include a LASSO variable selection process. In a later work [78], the authors combined different data sources and demonstrate that LASSO is effective in handling the high dimensionality of the input set.

Kriging is an interpolation method capable of forecasting for unsampled sites [75], where its best-known variants are simple, ordinary, and universal kriging. Other variations have been proposed, such as in Heidari Kapourchali et al. [77], where a multivariate extension designated as co-kriging is proposed, or Jamaly and Kleissl [76], where isotropic and anisotropic spatial kriging are compared.

Other identified approaches, such as the Analog method proposed by Berdugo et al. [83], take data privacy (a relevant topic for PV systems) into consideration and seek to minimize information exchanges between sites, while keeping local measurements private. Moreover, Elsinga et al. [84] proposed a spatio-temporal correlation-based method (described as a peer-to-peer (P2P) forecasting algorithm) to address short-term PV power prediction by exploiting data from 11 PV systems.

Table 2. Summary of available literature (2011–2021) for the application of statistical methods regarding spatio-temporal solar forecasting applications.

Reference	Year	Model	Location	Data Source	Time Resolution	Forecast Horizon	Area
[83]	2011	Analog	N.D.	PV	10 min 1 h	10–30 min 1–3 h	N.D.
[59]	2013	Kriging	Singapore	GHI (in situ)	1 h	1–3 h	30×20 km^2
[82]	2014	Kriging, VARX, LASSO	Singapore	GHI (in situ)	5 min	5 min	30×20 km^2
[71]	2014	ARX	Australia	PV	1 h 24 h	1–24 h	0.25×0.4 km^2
[70]	2014	ARX	France	GHI (in situ) GHI (satellite)	15 min	15 min–2 h	N.D.
[74]	2015	VARX	Portugal	PV	1 h	1–6 h	40×45 km^2
[14]	2015	LASSO	USA	GHI (in situ)	10 s	10 s–5 min	1×1 km^2
[75]	2015	Kriging	USA	GHI (in situ)	10 s	10 s–5 min	1×1 km^2
[72]	2015	ARX	France	PV	15 min	15 min–6 h	N.D.
[61]	2015	ARX	Guadalupe Island	GHI (in situ)	10 min 1 h	10 min–1 h	N.D.
[39]	2015	AR, ARX	USA	GHI (in situ)	1 min 1 h	1–120 min	51.471 km^2
[40]	2016	VAR	Guadalupe Island	GHI (in situ)	1 s	10 min–1 h	N.D.
[85]	2016	Linear regression	generated data	PV	10 min	5–60 min	N.D.
[86]	2016	LVARr	USA	GHI (in situ)	1 min	5 min	N.D.
[87]	2016	ARIMAX	Singapore	GHI (in situ), PV	15 min 30 min	15–30 min	30×20 km^2
[88]	2016	CSTF	Italy	GHI (in situ), PV	10 min	10 min	113×77 km^2
[76]	2017	Kriging (SP, IST, AST)	USA	PV	1 min 5 min 15 min	1–15 min	N.D.
[84]	2017	P2P method	The Netherlands	GHI (in situ)	60 s	1–60 min	1400 km^2
[57]	2018	ARX	USA UK	GHI (in situ), PV	10 s 30 min	10 s–2 h	N.D.

Table 2. *Cont.*

Reference	Year	Model	Location	Data Source	Time Resolution	Forecast Horizon	Area
[17]	2018	LASSO ultra-fast pre-selection algorithm	USA	GHI (in situ)	10 s 1 min	10 s–1 min	N.D.
[89]	2018	ST model	France	PV	15 min	1–6 h	230 km^2
[90]	2018	OLS, LAD, LASSO, Avg, VAR	USA Brazil Singapore	GHI (in situ)	30 min 1 h 24 h	30–60 min 24 h	N.D.
[30]	2019	QR-LASSO	France	NWP, PV	15 min	1–6 h	191 × 130 km^2
[80]	2019	ARX	USA	GHI (in situ)	10 s	10 s	N.D.
[31]	2019	ARX	USA	GHI (in situ), NWP	10 s	10 s	N.D.
[77]	2019	co-Kriging	USA	GHI (in situ)	1 h	6 h	N.D.
[91]	2019	SRP-Enet	N.D.	PV	10 s	10 s	N.D.
[79]	2019	LASSO	USA	GHI (in situ), GHI (satellite)	30 min	30–120 min	30 km^2
[33]	2020	ARIMAX	South Korea	GHI (satellite) PV, NWP	1 h	1 h	N.D.
[92]	2020	ST-AR	Switzerland	GHI (in situ), PV, NWP	15 min	6 h	N.D.
[73]	2020	ARX	Spain	GHI (in situ)	30 min	0.5–4 h	94,226 km^2
[78]	2021	LASSO	France	GHI (satellite) PV, NWP	15 min	1–6 h	191 × 130 km^2
[93]	2021	e-MVFTS	USA	GHI (in situ)	15 min	30–60 min	N.D.

Abbreviations. (SP) spatial kriging; (IST) isotropic spatiotemporal kriging; (AST) anisotropic spatiotemporal kriging; QR-LASSO: quantile regression LASSO; ST model: spatio-temporal model; LVAR: Local Vector Auto-Regressive; OLS: ordinary least squares; LAD: least absolute deviations; P2P: peer-to-peer method; SRP-Enet: scenario-recognizable preselection-based elastic-net; CSTF: Compressive Spatio-Temporal Forecasting; STVAR: Spatio-Temporal Vector Auto-Regressive method; USA: United States of America; e-MVFTS: evolving Multivariate Fuzzy Time Series; N.D.: not disclosed.

3.2. Machine Learning Methods

For several decades, machine learning (ML) techniques and algorithms have enabled the analysis and processing of various types of information in tasks varying from pre-processing and cleaning of data to the extraction of relevant information and the subsequent interpretation and solution of complex tasks. Deep learning (DL) emerged as a part of machine learning study techniques that allows the achievement of higher performance results in scenarios where it is necessary to analyze massive amounts of data to find complex relationships and patterns due to its higher generalization capabilities. For a better understanding, the methods are presented separately, traditional machine learning and deep learning.

3.2.1. Traditional Machine Learning and Multilayer Perceptrons

The most commonly used machine learning methods in the studies reviewed are Artificial Neural Networks (ANN) [11,94–98], Random Forest (RF) [41,65,73,99], Gradient

Boosted Trees (GBT) [29,100], and Support-Vector Machine (SVM) [65,79,101]. All studies that used machine learning methods were compiled in Table 3.

Persson et al. [100] used the Gradient Boosted Regression Trees (GBRT) model to include data from 42 PV installations sites and allow the automatic availability of spatial information so that the prediction of solar power generation in a station could be based on similar patterns in other stations. The prediction horizon was from 1 to 6 h—the same as the one used by Mazorra Aguiar et al. [97] who proposed an ANN model to forecast GHI for a time horizon from 1 to 6 h ahead for two stations, using satellite-derived data from the surrounding area. In a subsequent paper, the authors [11] included a third source of information by adding NWP data and performed experiments with the ANN model over the satellite and NWP data, first separately, and then, with the combination of both, achieving better results when combining all data sources.

Licciardi et al. [62] trained Auto-Associative Neural Network (AANN) using past measurements from satellite images as input, and ground measurements—obtained by a sensor on the same location—as output. The model was trained using not only the information from the pixel corresponding to the ground measurements but also the pixels surrounding it, forecasting GHI 15 to 60 min ahead.

Eschenbach et al. [73] evaluated ANN, RF, Regression Trees, and ARX models for GHI forecasting using 30-min data from 50 weather stations for a forecast horizon between 30 min and 4 h and concluded that for dense sensor networks, machine learning methods perform better for shorter horizons, while for sparser networks, simpler statistical methods are more effective. Huang et al. [79] tested GBRT, ANN and SVM methods for GHI forecasting over one site complementing 30-min in situ data with neighboring information from 55 points obtained from satellite, considering a forecast horizon from 30 to 2 h with single-step and multi-step prediction and for all them concluded that the best performing model was GBRT.

To forecast solar radiation for the next 24 h, Lan et al. [19] applied Self-Organizing Map Back Propagation (SOM-BP) hybrid neural networks to data coming from a ship moving across a shipping line that had PV panels mouthed and data from near-shore ground stations. In this work, Ensemble Empirical Mode Decomposition (EEMD) was used to decompose the data into frequency bands.

3.2.2. Advanced Deep Learning Methods

While the literature review of the spatio-temporal references mentioned in the introduction refers to traditional machine learning and multilayer perceptron works, none of the included publications explored advanced deep learning techniques such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN). Table 4 compiles identified publications that featuring deep learning methods.

Brahma and Wadhavani [106] explored ground-based and satellite-derived irradiance data using an LSTM model to predict the daily solar irradiance for 1 to 10 days ahead. The authors compared different variants of LSTM, the simple model, the bidirectional model, and the model with an attention mechanism, with the latter configuration achieving the best performance.

Lago et al. [24] proposed a Deep Neural Network (DNN) that combines satellite and NWP data with time series from five stations to predict GHI for a given region up to the next 6 h. Although five stations are used in the training process, the model is then able to predict at any point in the region. To evaluate the performance of the trained model, the authors used data from 25 stations and compare the results with those obtained by other models—Persistence model, Linear model, Gradient Boosting Tree, local DNN— trained with ground measurements. The proposed model matched or slightly improved the prediction while maintaining stability across prediction sites.

Table 3. Summary of available literature (2013–2021) for the application of traditional machine learning methods regarding spatio-temporal solar forecasting applications.

Reference	Year	Model	Location	Data Source	Time Resolution	Forecast Horizon	Area
[94]	2013	ANN	USA	GHI (in situ), GHI (satellite)	30 min	30 min–2 h	N.D.
[95]	2014	ANN	France	GHI (in situ), GHI (satellite)	3 h	3 h	N.D.
[97]	2015	ANN	Spain	GHI (in situ), GHI (satellite)	1 h	1–6 h	N.D.
[101]	2015	k-NN, SVR	Italy	GHI (in situ)	1 h	1 h	9×6 km^2
[62]	2015	AANN	France	GHI (in situ), GHI (satellite)	15 min	15–60 min	123×123 km^2
[11]	2016	ANN	Spain	GHI (in situ), GHI (satellite), NWP	1 h	1–6 h	183×165 km^2
[98]	2016	ANN	N.D.	GHI (in situ)	5 min	60 min	N.D.
[102]	2016	GCRF	USA	GHI (in situ)	1 h	2–10 h	N.D.
[103]	2016	ANN	Spain	GHI (in situ)	15 min	1–6 h	9503 km^2
[104]	2016	WNN	Singapore	GHI (in situ)	1 h	15–60 min	N.D.
[18]	2016	ANN	The Netherlands	PV	15 min	15 min 1 months	11×11 km^2
[29]	2017	GBT	Portugal	PV, NWP	1 h	1–24 h 24–48 h 48–72 h	2400 km^2
[41]	2017	Linear regression RF	Australia	GHI (in situ)	5 min	5 min–3 h	N.D.
[100]	2017	GBT	Japan	PV, NWP	1 h	1–6 h	5×5 km^2
[99]	2017	RF, GBT	USA	NWP GHI (in situ)	1 h	24 h	N.D.
[65]	2018	ensemble (ridge regression GBM, SVM GP, NN, RF, BAG)	USA	GHI (in situ), NWP	N.D.	24 h	N.D.
[79]	2019	SVM BRT MLP	USA	GHI (in situ), GHI (satellite)	30 min	30–120 min	30 km^2
[22]	2020	MGGP, MLP	USA, Italy, Brazil	GHI (in situ)	60 s	15–120 min	N.D.
[21]	2020	CCN	USA	GHI (in situ)	1 min	5–15 min	N.D.
[20]	2020	CESN	USA	GHI (in situ)	1 h	1 h	N.D.
[73]	2020	ANN RF RT	Spain	GHI (in situ)	30 min	0.5–4 h	94,226 km^2
[105]	2021	SVM, GBDT	China	PV	15 min	15 min 1–4 h	N.D.
[19]	2018	BPNN	China	GHI (in situ)	1 h	1 h	N.D.
[33]	2020	SVR ANN DNN	South Korea	GHI (satellite), PV, NWP	1 h	1 h	N.D.

Abbreviations. ANN: Artificial Neural Network; k-NN: k-nearest neighbors; SVR: Support Vector Regression; AANN: Auto-Associative Neural Network; GCRF: Gaussian Conditional Random Fields; WNN: Wavelet Neural Network; GBT: Gradient Boosting Trees; RF: Random Forest; RT: Regression Trees; MGGP: Multigene Genetic Programming; MLP: Multilayer Perceptron; CCNs: Cellular Computational Networks; CESN: Chain-structure Echo State Network; GBDT: Gradient Boosted Decision Trees; BPNN: Back-Propagation Neural Network N.D.: not disclosed.

There are also works implementing different deep learning models based on convolutional layers. For example, Jeong and Kim [107] proposed a Space–Time Convolutional Neural Network (STCNN) to forecast short-term PV power. The authors considered one year of data from 238, 67, and 103 PV sites from three different cities—the model was capable of obtaining indirectly the cloud cover and cloud movement without using more complex structures. Khodayar et al. [108] built a Convolutional Graph Autoencoder (CGAE) to predict solar irradiance for 75 solar plants within a time horizon of 30 min to 6 h. They performed the extraction of spatial characteristics through convolutional graphs with the information being processed in the encoder and decoder layers to calculate the distribution of the solar data to be predicted. Prado-Rujas et al. [42] used a Convolutional Long Short-Term Memory (Conv-LSTM) model to predict solar irradiance using data collected from 17 sensors; the model used a sequence of irradiance maps (obtained through a nearest-neighbor interpolation) as input. The authors worked with a prediction horizon of up to 1 h and analyzed how the location influenced the ability of the system to achieve better performance, resulting in increased robustness and flexibility, as the model was capable of handling missing data events where information from one or more sensors is not available.

Simeunovic et al. [34] proposed two graph-based deep learning models to capture the spatio-temporal correlation of PV plants with a horizon of 6 h ahead. Two datasets were used, a real dataset with 304 sites and a generated dataset of 1000 sites, with the proposed models displaying overall better results. These models surpassed single-site approaches for horizons above 4 h, since they used data from NWP models for training (which provide better results for longer horizons).

Benamrou et al. [26] applied a Recursive Feature Elimination (RFE) algorithm for the selection of relevant pixels based on information from the surrounding pixels found for a station, with cross-validation being used with XGBoost [109] to choose the best selection variant. The output of this process is the input of the deep learning method LSTM for the prediction of GHI for the next 1 to 4 h.

Table 4. Summary of available literature (2018–2021) for the application of deep learning methods regarding spatio-temporal solar forecasting applications.

Reference	Year	Model	Location	Data Source	Time Resolution	Forecast Horizon	Area
[24]	2018	DNN	The Netherlands	GHI (in situ), GHI (satellite), NWP	N.D.	1–6 h	41,543 km^2
[107]	2019	STCNN	USA	PV	1 h	1–6 h	N.D.
[32]	2020	LRCN	Germany	PV, NWP	3 h	24 h	357,386 km^2
[108]	2020	CGAE	USA	GHI (in situ)	30 min	1–6 h	N.D.
[106]	2020	LSTM, GRU, CNN, Bidir-LSTM, Attention-LSTM	India	GHI (in situ), GHI (satellite)	24 h	1–10 days	4.5 × 4.5 degrees
[26]	2020	LSTM	Morocco	GHI (in situ), GHI (satellite)	1 h	1 h	40 × 40 km^2
[63]	2020	ConvLSTM	USA	PV	5 min	15–60 min	N.D.
[110]	2020	LSTM	N.D.	PV	15 min	20–80 min	8 × 8 km^2

Table 4. *Cont.*

Reference	Year	Model	Location	Data Source	Time Resolution	Forecast Horizon	Area
[111]	2020	ResNet-LSTM	USA	GHI (in situ)	30 min	1–12 h	N.D.
[34]	2021	GCLSTM, GCTrafo	Switzerland	GHI (in situ), PV, NWP	15 min	6 h	N.D.
[42]	2021	Conv-LSTM	USA	GHI (in situ)	1 min	1–61 min	1×1 km^2
[23]	2021	ST-GNN	USA	PV	5 min	15–120 min	N.D.
[112]	2021	GSINN	USA	GHI (in situ)	1 s	10–40 s	N.D.
[113]	2021	DeepSTGDL	USA	PV	15 min	1–24 h	N.D.
[114]	2021	CGRVAE	USA	PV	5 min	10–30 min 1–6 h	N.D.
[115]	2021	STGANet	China	PV, GHI (in situ)	1 h	24 h	N.D.

Abbreviations. DNN: Deep Neural Network; LSTM: Long Short-Term Memory; STCNN: Space–Time Convolutional Neural Network; ConvGRU-VB: Variational Bayesian Convolutional Gated Recurrent Unit; LRCN: Long-Term Recurrent Convolutional Network; CGAE: Convolutional Graph Autoencoder; GRU: Gated Recurrent Unit; Bidir-LSTM: bidirectional LSTM; Attention-LSTM: LSTM with attention mechanism; GCLSTM: Graph-Convolutional LSTM; GCTrafo: Graph-Convolutional Transformer; Conv-LSTM: Convolutional LSTM; ST-GNN: Spatio-Temporal Graph Neural Network; CSWLSTM: Convolutional Shared Weight LSTM; GSINN: Group Solar Irradiance Neural Network; DeepSTGDL: Deep Spatio-Temporal Graph Dictionary Learning; CGRVAE: Convolutional Graph Rough Variational Auto-Encoder; ResNet-LSTM: Residual Network LSTM; N.D: not disclosed.

3.3. Physical Methods

The physical methods considered in this review work are mainly advective models where a spatially resolved description of sky cloudiness is advected in space and time according to a cloud motion vector (CMV), which is often under the assumption that clouds keep a constant shape, optical thickness and motion during the forecast horizon under consideration. While CMV-based forecasting traditionally explore satellite [6,7] and sky-camera [8,9] imagery, this review work only considered publications that implement this method using spatially distributed ground data—the potential for such datasets to infer CMV has already been discussed in [116,117]. Table 5 lists the related publications, which are identified in this manuscript.

Most works assume the persistence of the CMV for the duration of the considered forecast horizon [15,118,119]. However, Inage [120,121] implemented more complex advection-describing equations. In the first work [120], the author used advection equations to predict the PV net output in an area of tens of square kilometers in northern Kyushu, Japan. In the following publication [121], the author introduced a modification to the equations and evaluated the behavior for different time horizons and a wider area, validating the forecasts against irradiance measurements.

Nomura et al. [122] predicted PV power generation for a plant with more than 2 MW in a very short-term horizon. Using four sensors positioned in front of the PV plant toward the wind direction, the authors inferred the behavior of cloud shadowing. They considered different positioning distances between sensors (20 m between sensors at 300 m away from the plant and 3 km away from the plant) and concluded that sensors must be placed around the plant so that the forecasting model has information available for different upwind directions.

Table 5. Summary of available literature (2013–2019) for the application of physical methods regarding spatio-temporal solar forecasting applications.

Reference	Year	Model	Location	Data Source	Time Resolution	Forecast Horizon	Area
[15]	2013	Advective	USA	PV	15 min	15–90 min	50 × 50 km^2
[43]	2014	Advective	USA	GHI (in situ), PV	5 min	5–30 min	37 × 44 km^2
[119]	2015	Advective	USA	GHI (in situ), PV	1 min	1 s–30 min	40 × 30 km^2
[118]	2015	Advective	USA	PV	1 s	1–150 min	1.8 × 0.5 km^2
[123]	2017	Coupled stochastic differential equations	USA	PV	1 s	5–120 s	N.D.
[122]	2017	Advective	Japan	PV	1 s	1 s	6 × 6 m^2
[120]	2017	Advective	Japan	GHI (in situ), PV	5 s 150 s	10 min 50 s	1.2 × 1.1 km^2 160 × 40 km^2
[44]	2019	Advective	The Netherlands	GHI (in situ)	15 min	0–4 h	6 × 4 km^2
[121]	2019	Advective	Japan	GHI (in situ)	10–60 min	10–60 min	170 × 60 km^2

Abbreviations. N.D.: not disclosed.

3.4. Hybrid Methods

Hybrid methods relate to works that exploit more than one type of model to deliver a single prediction. Only four papers employing this approach were identified and are compiled in Table 6. Nam and Hur [124] employed Kriging to estimate the meteorological data associated with various solar farms using data from nearby weather stations. These data are fed afterwards into a naive Bayes classifier forecasting method. To calculate a probability distribution, the authors used the Kernel density estimation function, having Gaussian distribution being tested in a later work [125].

Kim et al. [126] proposed an interpolation by Kriging or Inverse Distance Weighting (IDW) to obtain the irradiance at the site of interest. Then, the data are restructured through grouping by similarity to forecast PV energy from irradiance and NWP data, from 12 to 52 h ahead. The authors used a multi-step strategy to achieve their objectives. In the forecasting step, four algorithms were used: Gradient Boosting Machine, Gaussian Process Regression, Random Forest and Bootstrap Aggregating. The four standard algorithms mentioned are evaluated and compared by selecting the best of four model ensembles proposed in the framework. Probabilistic analysis was then performed to improve forecasting accuracy by selecting the most suitable criteria: error observations, graphical model, conditional distribution, sampling, and irradiation scenarios (with irradiation referring to the integral of solar irradiance during a given time interval).

In [28], PV power forecasting is completed in two steps: a preliminary forecast is predicted using a SARIMAX model with PV power plant, meteorological, and air pollutant measurements as inputs; then, this same forecast is used as input to an LSTM network, together with the variables obtained from the satellite and NWP data to obtain a final forecast.

In the works found [28,124–126], the final prediction is based on previous predictions obtained with other methods. The approach presented by [126] is more robust, as it uses an ensemble of methods and evaluates, through probabilistic metrics, the cost of using an interpolation method in the pre-processing. It is observed that using more than one processing method could drastically improve the results, as hybrid methodologies leverage the strengths of different models for accomplishing a common objective. It was identified that few works have applied hybrid methods in applications where the spatial characteristic is highlighted through the use of information from neighbors.

Table 6. Summary of available literature (2018–2021) for the application of hybrid methods regarding spatio-temporal solar forecasting applications.

Reference	Year	Model	Location	Data Source	Time Resolution	Forecast Horizon	Area
[124]	2018	Naïve Bayes Classifier, Kriging	South Korea	GHI (in situ), PV	1 h	24 h	N.D.
[125]	2019	Naïve Bayes Classifier, Kriging	South Korea	GHI (in situ), PV	1 h	24 h	N.D.
[126]	2021	Ensemble variations (GBM + GPR + RF + BAG)	South Korea	GHI (in situ), PV, NWP	1 h	12–52 h	N.D.
[28]	2021	SARIMAX-LSTM	South Korea	GHI (in situ), GHI (satellite), PV, NWP	1 h	3 h	N.D.

Abbreviations. GBM: Gradient Boosting Machine; GPR: Gaussian Process Regression; RF: Random Forest; BAG: Bootstrap Aggregating; SARIMAX: Seasonal Auto-Regressive Integrated Moving Average with eXogenous factors; N.D.: not disclosed.

4. Discussion

Throughout this section, various nuances of the analyzed content and observed trends are highlighted and discussed.

4.1. Number of Publications

For carrying out this review work, 84 papers relevant to the spatio-temporal solar foresting research field, covering the period between 2011 and 2021, were identified and analyzed. Figure 1 shows the annual number of publications derived from this compilation. It can be observed that until 2015, no more than five publications were published in a single year—from 2015 onwards, the annual publication rate increased to an average of 11 publications per year. In addition to a peak in the number of publications in 2015, a growing trend can be found from 2019 onwards.

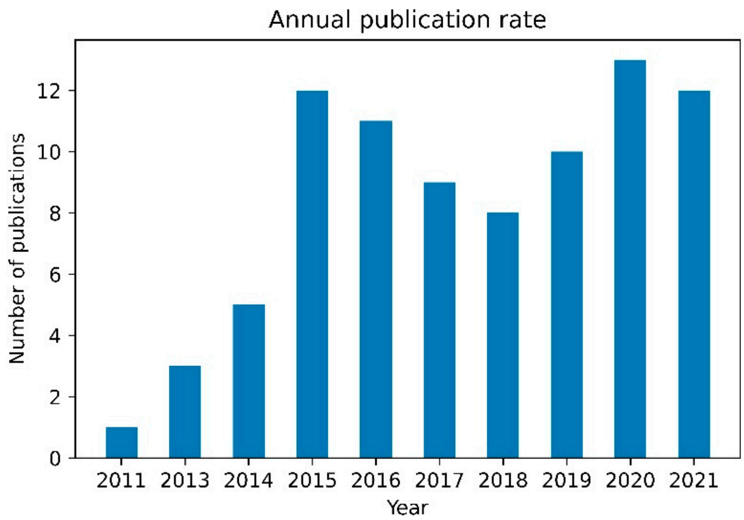

Figure 1. Histogram describing the amount of research works tackling spatio-temporal solar forecasting published from 2011 to 2021.

4.2. Data Sources

From the used data sources perspective, it is observed that 66.6% of the compiled papers exploit ground measurement data (GHI and PV energy). The remainder is divided between satellite-based irradiance estimates (13.6%) or the combination of ground data with satellite data or NWP predictions (19.8%). Ground measurements started to be used in spatio-temporal methods earlier than satellite and NWP data, and in more recent years, the use of each source seems to be growing in a rather stable linear manner. It can also be noticed that most works consider a single data source over the years.

It is also interesting to note that several works that propose forecasting methods assume different data representations to capture the spatio-temporal component of solar variability. There are authors that use as input a sequence of irradiance maps [42], a matrix representation of the spatial–temporal relationship between the sites [107], a graph structure where the nodes are the measurements locations and the vertices are the distance [108] or the correlation relationship between them [34]. The works considered in this review study refer to spatially distributed ground sensors (e.g., [15,103,127]), complemented with gridded satellite estimates (e.g., [97]), or NWP forecasts (e.g., [29,32,65,99]), or a combination of these (e.g., [11,24,29]). The numbers of sites or pixels considered in a model can vary from less than 10 (e.g., [41,60,127]) to more than 100 (e.g., [23,30,34]). Meanwhile, Karimi et al. [23] considered the highest number of ground sites, with power measurements from 316 PV systems.

It is believed that spatio-temporal statistical methods need to ingest a larger amount of information than these numbers may suggest. Firstly, several lags (i.e., previous observations) can be considered for each site. Secondly, complementary variables can also be considered (e.g., [41,98,103]), such as air temperature or wind speed and direction. This can raise dimensionality issues, potentially compromising model performance and computational viability. In fact, the forecast of variable renewable generation has been classified as a big data problem [128], and Yang et al. frame spatio-temporal solar forecasting as a "many-predictor regression problem" [17]. Thus, naturally, the exploitation and proposal of different strategies can be found in various spatio-temporal solar forecasting works. In this line, many works implement input selection methods based on user-defined criteria, such as distance (e.g., [89,103,129]) or the degree of correlation (e.g., [41,105,106]) to the target site, the importance of features [26,106], usually derived from a model, or according to local wind patterns (e.g., [14,40,85]).

Gutierrez et al. [103] subsample a set of 50 weather stations down to 10 based on a circumference with a 55 km diameter—the reduction in stations and even the definition of the diameter of the circumference being driven by the limited processing capacity of the database used. In [89], the authors aim to reduce the dimensionality of the data using a two-step approach. First, a selection of neighboring sites is made based on a distance threshold to the location of interest. Then, the chosen neighboring sites are further filtered based on Akaike information criterion (AIC).

Other works explore forecasting models, which intrinsically perform feature selection, such as the LASSO [14,17,30,78]. In this line, Yang et al. [14] deployed a LASSO model to process up to 256 inputs (16 lags from 16 ground GHI sensors) and test the impact of varying the number of neighboring sites and lags considered; the use of wind information to select which neighbors to include in the model is also explored. There are also works that explore lower-dimension representations of the whole input set, seeking to retain the most relevant information, by using methods such as Self-Organizing Map (SOM) [19], Recursive Feature Elimination (RFE) [26], and Principal Component Analysis (PCA) [62,65]. In this regard, Licciardi et al. [62] reduced the dimensionality of a set of 125 inputs (a 5-by-5 satellite-derived GHI grid, with 5 lags for each pixel) down to five inputs using a neural network-based non-linear PCA, which was shown to surpass three linear variations of PCA.

4.3. Methods

Figure 2a shows how frequent each forecasting approach is explored in the publications identified and reviewed in this work. Analyzing the methods used, the statistical method stands out as the most, being followed by machine learning, physical, deep learning, and hybrid methods. When analyzing the frequency of use of the methods applied by the authors distributed over the years reviewed (presented in Figure 2b), it can be observed that deep learning and hybrid methods are starting to gain ground, with deep learning showing a pronounced growth, although statistical and machine learning methods remain relevant.

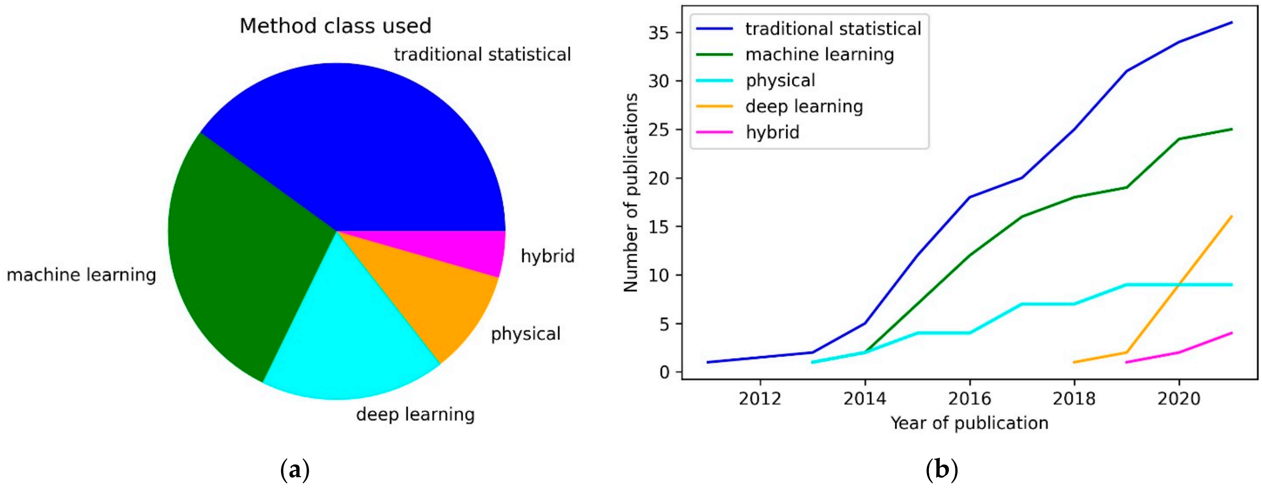

Figure 2. (**a**) Frequency of use of the forecasting methods applied in the reviewed studies; (**b**) corresponding cumulative number of publications through time.

4.4. Forecasting Horizon

As for forecast horizon ranges, the following were considered: intra-hour, intra-day, six hours to one day ahead and two days ahead or longer, as discussed in more detail in the end of the Introduction section.

In the analysis, it was observed that most studies focus on intra-hour (44%) and intra-day (43%) forecasting, longer-term horizons having a modest expression (10% for six hours to one day ahead, 3% for two days ahead or longer). This is coherent with the perspective that spatio-temporal methods can leverage high-resolution solar data to detect and predict cloud dynamics, leading to better forecasts. However, when focused on the corresponding temporal trends (Figure 3), it was found that research efforts aimed at exploring longer-term horizons (leveraging a combination of satellite and NWP data) are gaining importance in recent years.

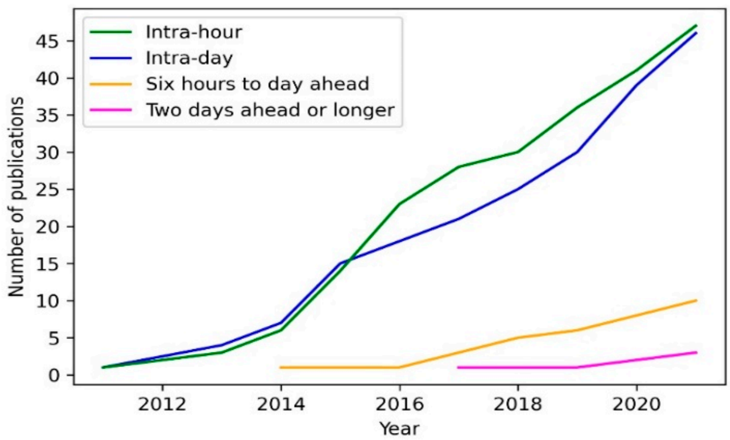

Figure 3. Cumulative evolution of the number of publications addressing a given forecast horizon range.

4.5. Evaluation Metrics

It is standard to evaluate forecasting methods using a set of performance metrics in order to define the goodness of the implementation [130,131]. It is also found that it is common for baseline methods to be implemented, establishing reference values for which other, more complex, methods can be better assessed. Additionally, we identified works aimed at comparing (i.e., benchmarking) a broad range of models using the same data [12,132,133], although none of them explore spatio-temporal approaches.

The works considered in this review compute a broad range of metrics, as presented in Figure 4. For deterministic forecasts, the most common metrics used were the Root Mean Square Error (RMSE), Normalized Root Mean Square Error (nRMSE), Relative Root Mean Square Error (rRMSE), Mean Absolute Error (MAE), Mean Bias Error (MBE), coefficient of determination (R), and Forecast Skill (FS). From the small sample on probabilistic forecasting (10 publications), was observed that the only frequent metric is the Continuous Ranked Probability Score (CRPS), while others such as reliability, sharpness, entropy, or Pinball Loss only appear once. However, it is interesting to note that some of these probabilistic publications actually end up conducting a deterministic assessment of a predefined quantile [77,125,126]. For a more detailed description of most of these metrics, please refer to [2,130].

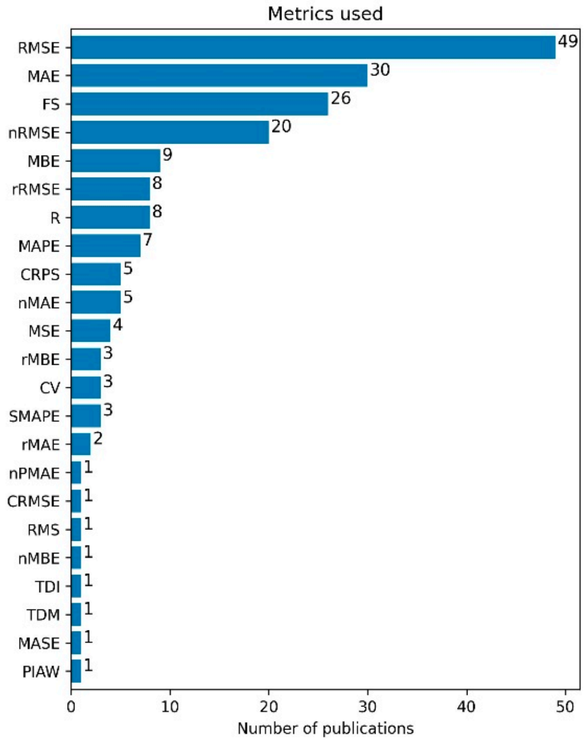

Figure 4. Histogram describing the frequency of use of the metrics from works tackling spatio-temporal solar forecasting. Publications that consider more than one metric will contribute at the same time to different bins of the histogram.

4.6. Considered Baseline

It is also of interest to understand which baseline models are generally used in spatio-temporal solar forecasting works. The choice of a baseline impacts the perception of model performance, since these define a performance reference against which a given model is evaluated, be it in the calculation of the Forecasting Skill metric or by visual comparison in a table or figure.

The simplest forecasting approach is the persistence, where it is assumed that the forecasted solar variable will remain unchanged in the future, as defined by Equation (1), where the left side of the equation refers to the forecast of variable $\hat{y}$ produced in instant t and for the horizon h and the right side to the latest measured value of y.

$$\hat{y}(t+h) = y(t) \tag{1}$$

Most works apply the persistence approach, although we also identified works that consider the slightly more complex Smart Persistence [9,17,22,31,44,80,121]. In this approach, the same Equation (1) is used, but a detrended version of solar irradiance or PV generation (e.g., clearness index and clear sky index) is persisted and then converted back to the original. This allows the predictable daily solar pattern to be considered. It is also interesting to note that many authors designate this approach as a Scaled Persistence [40,79].

Chen and Troccoli [41] presented a modified version of persistence, referred as the as Gap Persistence, which considers the difference between irradiance and clear sky value. Lipperheide et al. [118] proposed another variation named Ramp Persistence, which considers power ramp values (i.e., the difference between consecutive PV power values). Gutierrez-Corea et al. [103] used, besides its basic version, two other persistence approaches based on the clear sky index, named the clear sky expectations persistence forecast (CSEP-F) and the clear sky index persistence forecast (CSIP-F). In CSEP-F, a selection of clear sky days is made and set as expected values, while in CSIP-F, the clear sky is calculated as a function of solar elevation angle. Lastly, two works considered a climatological mean [11,100], where a long-term average of past observations (e.g., GHI, PV generation, clear-sky index) is calculated.

5. Conclusions

Spatio-temporal solar forecasting methods leverage spatially distributed solar data to better grasp and predict solar variability driven by cloud advection patterns. In the reviewed literature, which addresses particularly global horizontal irradiance (GHI) and photovoltaic (PV) generation, we observed that this information is most often obtained from pyranometer networks, satellite imagery and PV systems (either a portfolio of small-scale systems, or a set of sub-sections of a large PV farm). In this line, it is observed that initial works were mostly based on ground sensing networks, with PV and satellite data becoming more commonly used through time—this is to be expected, given the increasing deployment of PV systems which not only generate revenue but imply considerably lower operational and maintenance costs when compared to pyranometer arrays. It is expected that in a world where PV data and higher-resolution satellite information are becoming ever more available, more complex, hybrid solutions combining information from multiple data sources are expected to increase in number. It is relevant to note that the cases where data sources with different spatio-temporal resolution and coverage are used, the models are able to address a broader range of horizons and spatial scales without compromising performance.

It is considered that a strong spatio-temporal application requires the creation of very large-scale datasets, far bigger than that considered in current studies, as a model with high generalization capacity requires large amounts of data from varied and representative areas for the training procedure. We found works with datasets that explored a small number of stations (below 5) or works modeling information from a time window of only 25 days—almost half of the works presented used less than 20 locations, which were values hardly representative for the correct training of a model. Nonetheless, we also found works using satellite data and PV systems that presented a higher density in the network of points used, as discussed in Section 4.2. We believe it is necessary to ensure the traceability of the data employed and promote the use of datasets provided by public agencies that passed quality controls that guarantee the completeness, consistency, accuracy, and veracity of the information in order to allow predictions closer to the ground truth. Another strong line of improvement would be that the authors openly publish the datasets used in their research and the corresponding quality control considered to enable better comparisons between the performance of the models.

We noticed that a considerable part of the works identified address intra-hour forecasting by exploiting high-resolution ground-based data to obtain models with a greater forecasting capability of short-term variability of solar radiation and PV generation. With a similar presence in the compiled literature, the use of ground data and satellite estimates is commonly used to address intra-day forecasting; only a residual amount of applications address longer-term horizons through the incorporation of NWP outputs. We believe that the spatio-temporal characteristic will be extended to longer horizons, as there is an increasing demand in the exploration of long-term horizons as well as advancements in the field toward the addressing of this task.

We also perceived the emergence of novel techniques for representing spatially distributed solar time series datasets in forecasting methods with data with a wider spatial scope (such as matrices, graphs, irradiance maps). These techniques enable a better processing of large amounts of data with deep learning and the conversion of time series data to image data mages. For example, irradiance maps allow us to work with a time-varying number of stations due to their use of interpolated values and not of values from a particular station (nonetheless, they are dependent on the amount of data points from the considered region). In another line, graphs allow the grouping and integration of features as part of the data structure. They are also capable of improving performance and handling large volumes of information. When it comes to choosing one representation over another, there is no set formula—the decision depends largely on the particular dataset the user is going to work with, as both proved to be a more effective prediction of regions.

In our literature review, we also found that the most commonly used baselines are Persistence and Smart Persistence. However, there are others such as Climatology, Probabilistic Persistence, Ramp Persistence, and Gap Persistence. Some authors also explore more complex baselines such as Numerical Weather Predictions (NWP), Artificial Neural Networks (ANN), Auto-Regressive (AR), Cloud motion forecast, Quantile Gradient Boosting and Auto-Regressive models with eXogenous inputs (ARX). Using better baseline models puts in place a higher demand on forecasting ability from the proposed methods, which then is reflected in the achieved Forecasting Skill values.

However, one of the main challenges that still demands further exploration concerns the use of large volumes of data generated from the spatial dimension. It is considered that in spatio-temporal methods, high dimensionality can easily become a modeling issue, since the input pool is composed by various time lags per location. As discussed in Section 4.2, we found several works that already address this by searching for lighter representations of the data through the application of input selection (distance or correlation degree with the target site to build of input subsets) or dimensionality reduction strategies (Principal Component Analysis to infer a lighter representation of the data). These feature selection operations can optimize the performance and usability of the models, since only the most important features are used in training.

We perceived a lack of research on probabilistic spatio-temporal solar forecasting, longer-term forecasting and on hybrid or ensemble methods in the reviewed literature, and it is believed that the exploration of deep learning techniques to handle the spatial and temporal distribution of irradiance data will receive more interest from the scientific community in the following period. As discussed in Section 3.2.2, the most popular deep learning networks are Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN) and Gated Recurrent Units (GRU). However, we are confident that novel architectures specialized in processing times series can be proposed by leveraging recent advances in dilated Convolutional Neural Network, graphs, transformers, or by adding more complexity to the models to take advantage of the advancements in available computing power (graphical units). In this line, it is observed that using more than one processing method could drastically improve the results, as hybrid methodologies leverage the strengths of different model for accomplishing a common objective.

Lastly, it is considered that solar forecasting is an important and constantly evolving research field, having moved from univariate to multivariate time series forecasting and from using single data sources to the combination of several datasets. In the past, the spatio-temporal methods used on ground measurements were less explored due to the lack of data; however, these are beginning to stand out toward the improvement of results from state-of-the-art methods. In this review work, it is observed that classical physical and statistical methods have been reinforced with contributions from other research areas such as artificial intelligence. In our view, the combination of different solar data sources, such as coupling ground data with satellite imagery and NWP, is of essence to address a broader range of temporal and spatial scales. In addition, ensemble methods have been pointed out in the literature as an efficient means to improve forecasting accuracy by taking advantage of different methods. For example, the use of machine learning and deep learning techniques delivered models capable of more efficient handling of large amounts of data while increasing the performance metrics obtained. However, it is considered that in a world with a constant demand for better predictions, we must explore new ways based on deep learning that are better suited to model the complexity of the phenomenon.

To take advantage of the identified research opportunities, we plan to work on spatio-temporal solar forecasting using ground-based measurements and, in particular, explore novel forms of data representation and apply novel deep learning methods such as transfer learning. To achieve this, we will start studying the influence of several pre-processing and prediction techniques on a large-scale dataset from a public data source. The end goal is the obtaining of a deep learning model capable of predicting the solar irradiance from extended regions of the Spanish territory considering the spatio-temporal characteristic.

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