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Solar Radiation Estimation Algorithm and Field Verification in Taiwan

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Abstract: The power generation potential of a solar photovoltaic (PV) power generation system is closely related to the on-site solar radiation, and sunshine conditions are an important reference index for evaluating the installation of a solar PV system. Meanwhile, the long-term operation and maintenance of a PV system needs solar radiation information as a reference for system performance evaluation. Obtaining solar radiation information through the installation of irradiation monitoring stations is often very costly, and the cost of sustaining the reliability of the monitoring system, Internet stability and subsequent operation and maintenance can often be alarming. Therefore, the establishment of a solar radiation estimation model can reduce the installation of monitoring stations and decrease the cost of obtaining solar radiation information. In this study, we use an inverse distance weighting algorithm to establish the solar radiation estimation model. The model was built by obtaining information from 20 solar radiation monitoring stations in central and southern Taiwan, and field verification was implemented at Yuan Chang Township town hall and the Tainan Liujia campus. Furthermore, a full comparison between Inverse Distance Weighting (IDW) and the Kriging method is also given in this paper. The estimation results demonstrate the performance of the IDW method. In the experiment, the performance of the IDW method is better than the Ordinary Kriging (OK) method. The Mean Absolute Percentage Error (MAPE) values of the solar radiation estimation model by IDW at the two field verifications were 4.30% and 3.71%, respectively.

Keywords: solar PV system; solar radiation; inverse distance weighting algorithm

1. Introduction

As global warming is worsening and human dependence on energy is on the rise, global growth in solar PV system development is accelerating. From global installed capacity statistics, solar energy installation capacity reached 79.4 GW in 2016, compared to 55.4 GW installed capacity in 2015; the annual growth rate is 43%, exceeding 30% annual growth for the second consecutive year. This figure is much higher than the original forecast, with the main difference coming from China's installation volume of 34 GW, which is significantly higher than expected [1,2]. Moreover, in recent years there have been many studies on photovoltaic power generation. Jurasz and Ciapała proposed a new method of smoothing the energy exchange with the grid based on fixed volumes of energy [3]. In addition, such a method can also be applied to deal with the problem of larger-scale hydropower plants. The literature [4] indicates that a combination of the cost–benefit calculation and the nesting model can be used to optimize the PV plant size. Furthermore, it can be integrated into other renewable energy sources to improve performance. As increasingly high amounts of solar PV power are connected to the grid, solar power output volatility and randomness are presenting greater challenges for the stability and economical operation of the central power system. Solar radiation is the main factor affecting solar PV output; by measuring solar radiation we could more accurately calculate energy output from centralized and distributed solar PV systems. The most direct way to detect solar radiation is to set up solar radiation monitoring stations; however, this is costly and requires huge manpower, so the density of solar radiation monitoring stations is often insufficient. With government promotion of solar PV systems in recent years, there is increasing public demand to understand and acquire solar radiation and insolation values in areas without monitoring stations, and various statistical methods and interpolation and extrapolation algorithms have emerged. The following is a literature review of the common calculation methods.

IDW [5–11] interpolation applies a linear combination of weights to a set of sample points to determine the estimate. Weighting is an inverse distance function, so inverse distance weighting is the simplest interpolation method. Kriging [12] is an interpolation method similar to inverse distance weighting; it is based on a simplified minimum self-forming algorithm, and uses a variogram as a weight function. The method is named after South African mining geologist D. G. Krige, who developed the fundamental version of this method. At present, there are many variations on the Kriging method for general use, including simple kriging, ordinary kriging, universal kriging, local kriging, co-kriging, and disjunctive kriging. The kriging tool could determine the output value of each position by fitting mathematical functions to a certain number of points or to all points within a specified radius. The kriging method is a multi-step calculation process; it includes exploratory statistical analysis of data, variogram modeling, and creating surfaces. When there are spatial distances or directional deviations in data, the kriging method is often considered the most suitable method.

The most commonly used algorithm [13–15], Ordinary Kriging, is used for solar radiation estimation in this study; regression function and geographic parameters (latitude, longitude, and altitude) are also used to determine the correlation between solar radiation and measured climate variables and geographic indicators. Behrang and Rumbayan [16,17] proposed using latitude, longitude, altitude, monthly mean temperature, average sunshine hours, and relative humidity as independent variables to develop an Artificial Neural Network (ANN) model to estimate solar radiation. Mohamed [18] proposed the Particle Swarm Optimization algorithm to train a Neural Network (PSO-NN) to develop a solar radiation estimation model. The input information used include month, sunshine hours, latitude, longitude, and altitude. Cambodian scholar Janjai [19] proposed using satellite cloud imagery to estimate the Monthly Average Daily Solar Radiation (MADSR) model, whose Root-Mean-Square Deviation (RMSD) is 6.3%. Chinese scholar Wu [20] uses the Support Vector Machines method to estimate MADSR, using highest temperature, lowest temperature, and average temperature as independent variables. The Root-Mean-Square Error (RMSE) value and Nash–Sutcliffe coefficient of this model are 1.637 MJm-2 and 0.813 MJm-2, respectively.

In general, the ANN algorithm has most often used in previous studies, as this method has a high predictive accuracy, but its estimation process is a "black box," making it difficult to interpret the predictions. Therefore, the inverse distance weight algorithm is applied in this paper to estimate solar radiation through a simple distance concept.

The major contributions of this paper are as follows: (1) a high-precision inverse distance weighting algorithm is designed to solve the problem of solar radiation estimation; (2) the field test of the IDW algorithm in solar radiation estimation is demonstrated; (3) comparisons with other solar radiation estimation methods are provided; (4) the advantages and the performance analysis of the proposed verification method are also discussed. The remainder of the paper is organized as follows. The horizontal solar radiation monitoring sites are introduced in Section 2. In Section 3, the algorithm of the inverse distance weighting is described. The experimental results are presented in Section 4. The discussion are mentioned in Section 5. Finally, the conclusions are given in Section 6.

2. Horizontal Solar Radiation Monitoring Sites

Taiwan is about 395 km in length from north to south, and about 144 km in width from east to west. The geographical scope of this experiment is in central and southern Taiwan, the maximum distance between monitoring stations from north to south is about 212 km, and the maximum distance between monitoring stations from east to west is about 66 km. The monitoring stations selected are in central and southern Taiwan, and the Solmetric Sun Eye is used to evaluate shading to ensure that the solar gauges installed at the monitoring stations would not be affected by shade from external environment factors such as buildings or trees. On-site survey and installation of horizontal solar radiation monitoring stations are done in 22 sites. The locations of the monitoring stations are displayed in Figure 1.

Figure 1. Global horizontal irradiation monitoring station installed locations map.

The computer monitoring system collects solar radiation intensity data through an A/D signal converter (I-7188XA, ICP DAS, Hsinchu, Taiwan) by a solar radiometer complying with ISO 9060 Class 2 certifications. At least one datum is recorded every minute and stored in the Internet gateway storage media. Data are transmitted through File Transfer Protocol (FTP) from the data gateway to the backend network server through an Internet connection. The data are supplemented through data synchronization and inspection function, and subsequently processed through the solar radiation estimation model. Among the various monitoring stations, those that do not have an Internet connection resolve the data transmission issue through a 3G network. The monitoring system architecture is detailed in Figure 2.

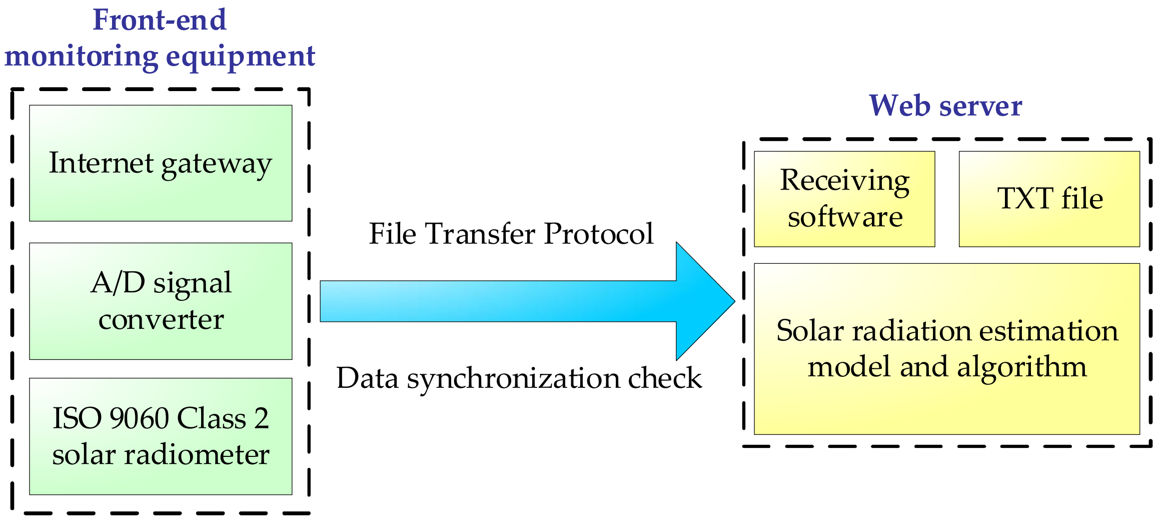

Figure 2. Horizontal solar radiation monitoring system architecture.

The 22 horizontal solar radiation monitoring systems collect local horizontal solar radiation information and establish a solar radiation data bank. The longitude and latitude information of the monitoring systems is detailed in Table A1.

Some installed monitoring stations are shown in Figures 3 and 4. The red circle in the picture on the left indicates the installed location of the solar radiometer; the red circle in the picture on the right indicates the monitoring system box, which includes an Internet gateway and an A/D signal converter. The longitude and latitude information of the 22 monitoring systems is detailed in Table A1.

Figure 3. Tainan Liujia Campus monitoring equipment installation location.

Figure 4. Wuwang Elementary School monitoring system location.

3. Inverse Distance Weighting Algorithm

The study uses horizontal solar radiation data from monitoring stations 1–20, and applies the inverse distance weighting algorithm to establish a zonal solar radiation estimation model. Meanwhile, the study uses solar radiation data from stations 21 and 22 to verify the results of the estimation model. The inverse distance weighting algorithm is shown in Equation (1):

$$SI_0 = \sum_{i=1}^{s} SI_i \frac{1}{d_i^k} / \sum_{i=1}^{s} \frac{1}{d_i^k}, \tag{1}$$

where SI_0 is the estimate value of Point 0, SI_i is the value of known Point i, d_i is the distance between Point i and Point 0, s is the known point used for estimation, and k is the self-determined weight value.

The solar radiation values collected at the 22 horizontal solar radiation monitoring stations are displayed in Table A2, and the chart of peak sum hours at 22 monitoring stations is shown in Figure 5. Solar energy is generally calculated based on a unit of 1000 W/m^2 and converted to equivalent daily Peak Sum Hours (PHS). This represents the total number of effective hours per unit in which the sun releases energy. PSH is defined as follows: solar radiation (PSH) = daily accumulated radiation/1000 (W/m^2).

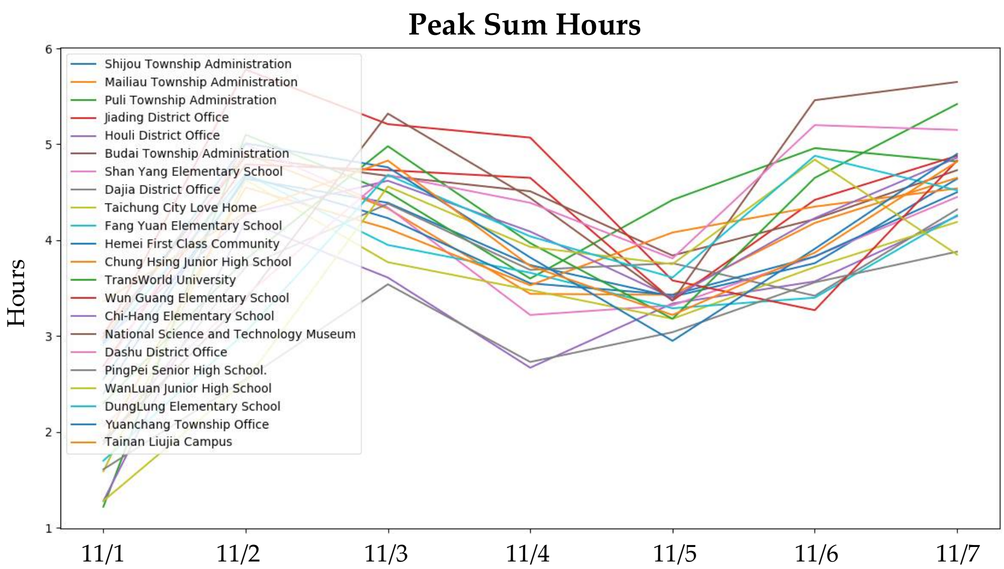

Figure 5. The chart of peak sum hours at 22 monitoring stations.

4. Verification Results

The Mean Absolute Percentage Error (MAPE) is often used as an indicator of estimation error and is defined as follows:

$$\mathrm{MAPE} = \frac{1}{N}\sum_{n=1}^{N}\left|\frac{y_n - \hat{y}_n}{y_n}\right|, \quad (2)$$

where y_n is the actual value, $\hat{y}_n$ represents the estimated value, N is the number of estimations within the evaluation period. This paper selected two monitoring stations to verify the accuracy of the estimation results and used the inverse distance weighting algorithm to establish the zonal solar radiation estimation model. The paper compares and verifies the actual irradiation value against the estimated value at Yuan Chang Township Administration and the Tainan Liujia Campus. Figure 6 represents the comparison results in Yuan Chang Township Administration and Tainan Liujia Campus by IDW and OK method. The comparison results show that the performance is better than with the Kriging method. Table 1 shows the verification results for Yuan Chang Township Administration; with respect to the IDW method, we find that during the verification period the maximum MAPE is 9.50% and the minimum MAPE is 1.15%. Table 2 shows the verification results for Tainan Liujia Campus; with respect to the IDW method, we find that during the verification period the maximum MAPE is 9.26%, and the minimum MAPE is 0.72%. During the verification period, the average MAPE of solar radiation estimation of Yuan Chang Township Administration and Tainan Liujia Campus was 4.30% and 3.71%, respectively. The detailed results shown in Tables 1 and 2 also demonstrate that the performance of the IDW method is better than that of the OK method. The current verification data do not provide a sufficient explanation for such differences; this is an issue that should be addressed in the future.

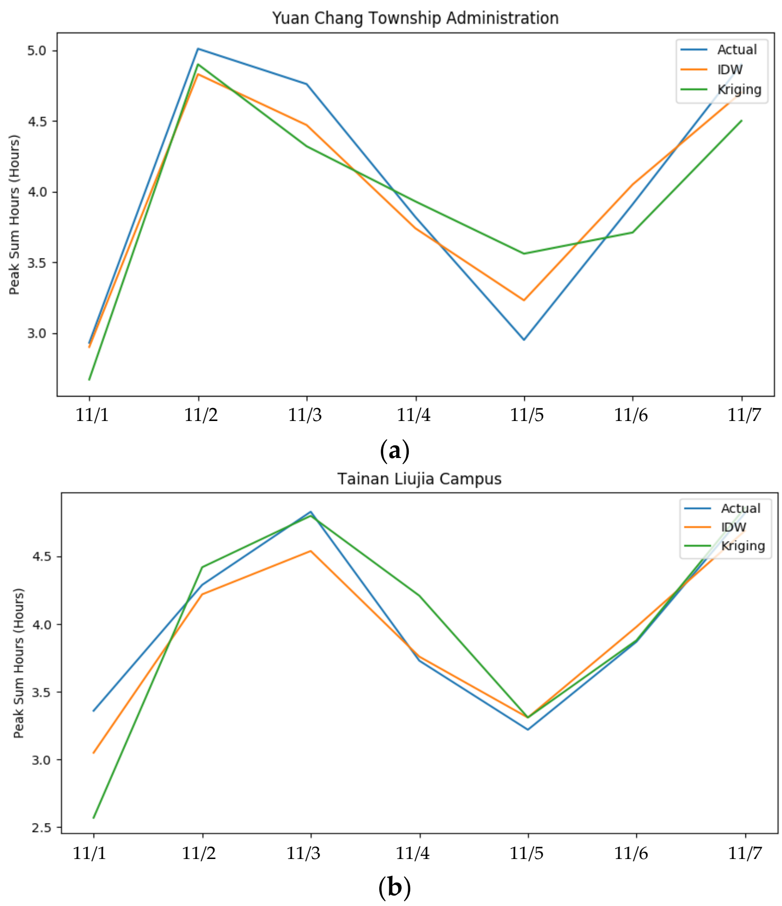

Figure 6. The comparison results: (**a**) Yuan Chang Township Administration; (**b**) Tainan Liujia Campus.

According to studies completed in 2000, Lee et al. proposed a MAPE accuracy classification to assess the estimation accuracy of proposed models. In this experiment, the IDW algorithm proposed in this paper was compared with the OK algorithm (redesign simulation), which is commonly used in solar radiation estimation. The comparison showed that the performance of the IDW is better than that of the OK algorithm; namely, IDW had the lowest MAPE value. The classification criteria are described in Table 3. According to the classification, the proposed model of this study on the estimation of solar radiation has very good accuracy. The geographic research scope of this study is concentrated in the central and southern part of the country; the research results propose a solar radiation estimation model and verification for central and southern counties. It is hoped that this solar radiation estimation model could be promoted rapidly to other counties in Taiwan in order to establish a national solar radiation distribution map. Hopefully a central and southern Taiwan contour map could be drawn according to actual data collected from horizontal solar radiation stations, and estimated values calculated with the inverse distance weighting algorithm. Figure 7 shows the central and southern Taiwan solar radiation distribution map; with this map we could observe fluctuation trends in solar radiation resources in different counties, which can serve as a reference for investment in solar PV system installation, system performance evaluation, and long-term operation and maintenance.

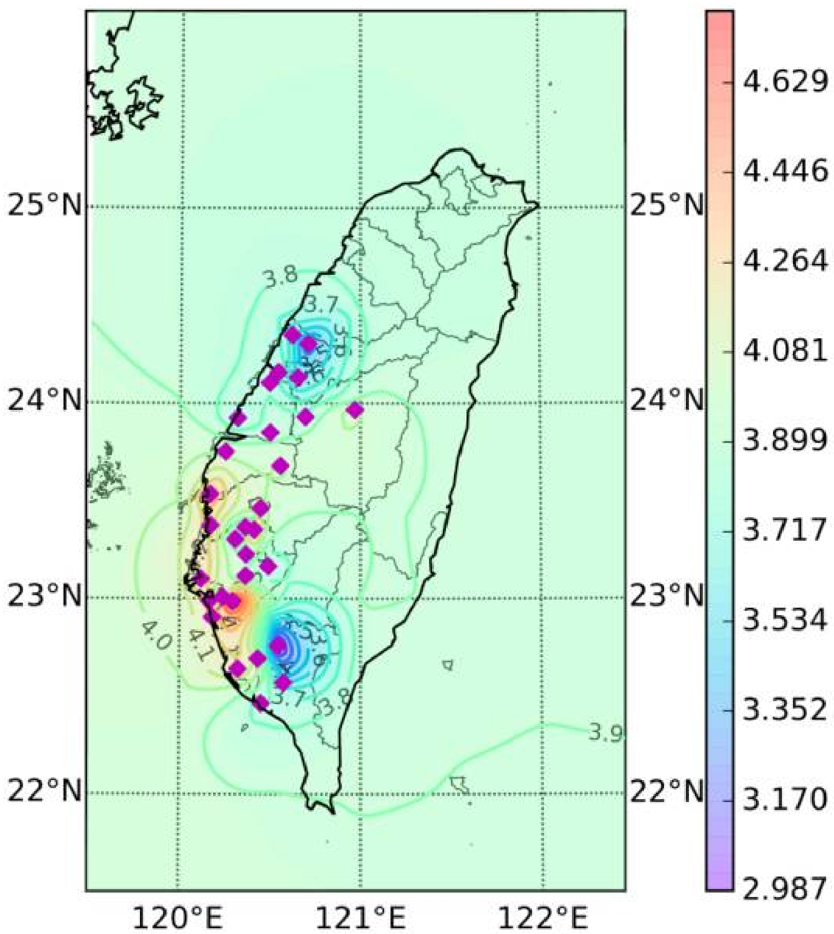

Figure 7. Central and southern Taiwan solar radiation distribution map for Inverse Distance Weighting (IDW) (kWh/m^2).

Table 1. Solar radiation estimation model verification—Yuan Chang Township Administration.

Date	Actual Value	Estimated Value (IDW)	MAPE (IDW)	Estimated Value (OK)	MAPE (OK)
11/1	2.93	2.90	1.15%	2.67	8.79%
11/2	5.01	4.83	3.53%	4.90	2.17%
11/3	4.76	4.47	6.17%	4.32	9.03%
11/4	3.82	3.74	2.01%	3.93	2.94%
11/5	2.95	3.23	9.50%	3.56	20.7%
11/6	3.91	4.05	3.65%	3.71	5.02%
11/7	4.90	4.70	4.04%	4.50	8.03%
Average	3.78	3.99	4.30%	3.94	8.10%

Table 2. Solar radiation estimation model verification—Tainan Liujia campus.

Date	Actual Value	Estimated Value (IDW)	MAPE (IDW)	Estimated Value (OK)	MAPE (OK)
11/1	3.36	3.05	9.26%	2.57	23.28%
11/2	4.29	4.22	1.63%	4.42	3.24%
11/3	4.83	4.54	6.06%	4.80	0.42%
11/4	3.73	3.76	0.72%	4.21	13.00%
11/5	3.22	3.31	2.65%	3.31	2.94%
11/6	3.87	3.98	2.88%	3.88	0.38%
11/7	4.82	4.69	2.76%	4.86	1.01%
Average	4.02	3.94	3.71%	4.01	6.32%

Table 3. Mean Absolute Percentage Error (MAPE) estimation accuracy classification.

MAPE Value	Model Accuracy
MAPE < 10%	Very Good (The closer to 0 the better)
10% < MAPE < 20%	Good
20% < MAPE < 50%	Reasonable
50% < MAPE	False

5. Discussion

Despite the fact that satellite-derived irradiation is quite easy and can be done at low cost, ground measurements from stations are still important for the solar radiation estimation process. In general, irradiation data from satellites cover the whole planet and have a reasonably good spatial and temporal resolution. In Africa, Europe, China, etc., the spatial and temporal resolution provided by satellites is sufficient. However, in some special cases with small land area, such as Taiwan, a much higher spatial resolution for solar radiation monitoring is needed. Furthermore, the information derived from the satellite may be influenced by the current atmospheric and cloud conditions. Therefore, data verified by ground monitoring stations are also important and cannot be ignored. Moreover, PV power generators are also built on the ground. The information from the monitoring stations is closest to the actual situation. We included data from a large number of monitoring stations in Taiwan in this paper, and the estimations of the generated PV power can also be improved by the setting of the ground monitoring stations.

According to the characteristics of the IDW method, the distances between the monitoring stations and the locations of where we want to estimate are the main factors determining the estimation results. Monitoring stations closer to the estimation points have higher influence during the estimation process. Therefore, input stations with minimal distance played the most important role in simulating irradiation in stations 21 and 22. In our experience, monitoring stations within 30 km of the estimation point may have a great influence on the estimation result. In other words, the decreasing number of input stations may impact the irradiation modeling precision, but the degree of impact depends on the distance between the estimation point and the removed monitoring stations. The closer the referencing monitoring station, the greater the impact on the estimation results, and vice versa.

The selection criteria for stations 21 and 22 as verification stations are simply that they are located in the central and southern region of Taiwan, respectively. We have carefully considered various sensitive influence factors; if other stations were selected and their distance between other reference stations was within 30 km, there would be little effect on our research results.

The geographical scope of this experiment is central and southern Taiwan; the maximum distance between monitoring stations from north to south is about 212 km, and the maximum distance between monitoring stations from east to west is about 66 km. In the paper, the distance is very short so that the self-determined k parameter value was established to equal 1. The solar radiation estimation employed the IDW algorithm on the input dataset, which is PSH data from monitoring stations 1–20. Then, monitoring stations 21 and 22 are verification stations. Finally, the verification period in this article is the experimental verification period from 1 November to 7 November.

6. Conclusions

This paper presents a simple method for establishing a solar radiation estimation model by setting up 22 horizontal solar radiation computer monitoring systems to collect solar radiation data, and applying inverse distance weighting algorithm to 20 locations to establish the estimation model. The paper compares the actual solar radiation data of Yuan Chang Township Administration and Liujia Sewage Treatment Plant with the estimated values calculated by the proposed model to verify the hypothesis. The experiments compare the estimation results done by the IDW and Ordinary Kriging methods. The comparison results show that IDW has better performance than the Kriging method. The MAPE of the IDW solar radiation estimation model applied at Liujia Sewage Treatment Plant and Wuwang Elementary School are 4.30% and 3.71%, respectively, confirming that this model has very good estimation accuracy. The experimental results also validate the feasibility and practicality of the IDW method. In the future we hope to make these experimental results more widely available in Taiwan, and, as more data are collected in the horizontal solar radiation monitoring database, longer verification periods could be applied. As the climate in Taiwan has four distinct seasons, the solar radiation estimation model could also be broken down into four models for more in-depth research to improve the accuracy of future estimates.

Author Contributions: P.-H.K. wrote the program and designed the solar radiation estimation model. C.-J.H. planned this study and collected the solar radiation dataset. P.-H.K., H.-C.C. and C.-J.H. contributed to the realization and revision of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Geographic locations of the 22 horizontal solar radiation computer monitoring systems.

No.	Location Name	Longitude and Latitude	No.	Location Name	Longitude and Latitude
1	Taichung City Love Home	24.131594, 120.653725	12	Wun-Guang Elementary School Hu-Kou Branch	23.534850, 120.165990
2	Dajia District Office	24.349143, 120.622465	13	Budai Township Office	23.376099, 120.169879
3	Houli District Office	24.304839, 120.710660	14	Chih-Hang Elementary School	23.462219, 120.445861
4	Shan Yang Elementary School	24.159267, 120.544885	15	Jiading District Office	22.905872, 120.180293
5	Hemei Township First-Class Community	24.105946, 120.497144	16	National Science and Technology Museum	22.641431, 120.322551
6	Shijou Township Administration	23.851281, 120.499099	17	Dashu District Office	22.693476, 120.432831
7	Fang Yuan Elementary School	23.924819, 120.319233	18	PingPei Senior High School.	22.759382, 120.543578
8	Chung Hsing Junior High School	23.931503, 120.693683	19	WanLuan Junior High School	22.571429, 120.574788
9	Puli Township Administration	23.966574, 120.969214	20	DungLung Elementary School	22.464138, 120.451289
10	Mailiau Township Administration	23.753435, 120.252098	21	Yuanchang Township Office	23.649667, 120.314859
11	TransWorld University	23.680371, 120.555737	22	Tainan Liujia Campus	23.225857, 120.366523

Table A2. Solar radiation (PSH) of 22 horizontal solar radiation monitoring stations in central and southern Taiwan.

No.	Station Name	PSH (Unit: Hours)						
		11/1	11/2	11/3	11/4	11/5	11/6	11/7
1	Shijou Township Administration	2.55	4.64	4.39	3.74	3.41	3.76	4.64
2	Mailiau Township Administration	2.98	4.90	4.33	3.44	3.43	4.18	4.65
3	Puli Township Administration	1.22	5.10	4.50	3.60	4.42	4.96	4.82
4	Jiading District Office	2.69	4.79	4.73	4.65	3.37	4.42	4.88
5	Houli District Office	1.28	4.20	3.61	2.67	3.34	3.57	4.25
6	Budai Township Administration	3.03	4.87	4.67	4.51	3.84	4.22	4.73
7	Shan Yang Elementary School	2.63	5.00	4.34	3.22	3.32	3.83	4.45
8	Dajia District Office	1.87	3.72	4.38	3.69	3.76	3.42	4.32
9	Taichung City Love Home	1.59	4.63	3.77	3.48	3.18	3.72	4.19
10	Fang Yuan Elementary School	2.91	4.69	3.95	3.66	3.29	3.40	4.26
11	Hemei First Class Community	2.40	4.67	4.23	3.55	3.43	3.83	4.50
12	Chung Hsing Junior High School	1.89	4.55	4.12	3.53	4.08	4.35	4.54
13	TransWorld University	2.30	3.80	4.98	3.97	3.18	4.65	5.42
14	Wun Guang Elementary School	2.99	5.78	5.21	5.07	3.58	3.27	4.83
15	Chi-Hang Elementary School	2.95	4.27	4.62	4.09	3.40	4.23	4.86
16	National Science and Technology Museum	1.91	3.38	5.32	4.44	3.37	5.46	5.65
17	Dashu District Office	2.06	3.42	4.68	4.39	3.81	5.20	5.15
18	PingPei Senior High School.	1.61	2.55	3.54	2.73	3.04	3.56	3.88
19	WanLuan Junior High School	1.28	2.53	4.56	3.93	3.75	4.84	3.85
20	DungLung Elementary School	1.70	3.04	4.68	4.04	3.61	4.88	4.52
21	Yuanchang Township Office	2.93	5.01	4.76	3.82	2.95	3.91	4.90
22	Tainan Liujia Campus	3.36	4.29	4.83	3.73	3.22	3.87	4.82

Table A3. Acronym list.

Full Name	Acronyms
Artificial Neural Network	ANN
File Transfer Protocol	FTP
Inverse Distance Weighting	IDW
Mean Absolute Percentage Error	MAPE
Monthly Average Daily Solar Radiation	MADSR
Ordinary Kriging	OK
Particle Swarm Optimization Neural Network	PSO-NN
Peak Sum Hours	PHS
Root-Mean-Square Deviation	RMSD
Root-Mean-Square Error	RMSE
Solar Photovoltaic	PV

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