Agricultural Sciences, 2024, 15, 36-53
https://www.scirp.org/journal/as
ISSN Online: 2156-8561
ISSN Print: 2156-8553

Evaluation of a Wireless Solar Powered Personal Weather Station

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How to cite this paper: Lascano, R.J., Goebel, T.S., Gitz III, D.C. and Stout, J.E. (2024) Evaluation of a Wireless Solar Powered Personal Weather Station. *Agricultural Sciences*, **15**, 36-53.
https://doi.org/10.4236/as.2024.151003

Received: September 13, 2023
Accepted: January 9, 2024
Published: January 12, 2024

Abstract

We are evaluating dryland cotton production in Martin County, Texas, measuring cotton lint yield per unit of rainfall. Our goal is to collect rainfall data per 250 - 400 ha. Upon selection of a rainfall gauge, we realized that the cost of using, for example, a tipping bucket-type rain gauge would be too expensive and thus searched for an alternative method. We selected an all-in-one commercially available weather station; hereafter, referred to as a Personal Weather Station (PWS) that is both wireless and solar powered. Our objective was to evaluate average measurements of rainfall obtained with the PWS and to compare these to measurements obtained with an automatic weather station (AWS). For this purpose, we installed four PWS deployed within 20 m of the Plant Stress and Water Conservation Meteorological Tower that was used as our AWS, located at USDA-ARS Cropping Systems Research Laboratory, Lubbock, TX. In addition, we measured and compared hourly average values of short-wave irradiance (R_g), air temperature (T_{air}) and relative humidity (RH), and wind speed (WS), and calculated values of dewpoint temperature (T_{dew}). This comparison was done over a 242-day period (1 October 2022-31 May 2023) and results indicated that there was no statistical difference in measurements of rainfall between the PWS and AWS. Hourly average values of R_g measured with the PWS and AWS agreed on clear days, but PWS measurements were higher on cloudy days. There was no statistical difference between PWS and AWS hourly average measurements of T_{air}, RH, and calculated T_{dew}. Hourly average measurements of R_g and WS were more variable. We concluded that the PWS we selected will provide adequate values of rainfall and other weather variables to meet our goal of evaluating dryland cotton lint yield per unit rainfall.

Keywords

Automation, Sensors, Citizen Weather Station, Mesonet, Rainfall, Weather Variables

1. Introduction

In meteorology, a mesoscale network is referred to as a Mesonet, which consists of a series of linked automated environmental monitoring stations to measure meteorological variables [1]. Mesonets are used for a wide range of applications, including weather forecasting, fire, flood, and freeze warnings and in many cases, they provide agricultural information related to, e.g., crop water requirements and thermal heat units. A history of the development of weather networks to aid producers in crop irrigation is given by [2]. Briefly, the 1930's drought that afflicted the Great Plains of the USA prompted the USDA to initiate a weather forecasting program [3]. In recent years, weather Mesonets have proliferated across the USA [4] and in other countries as well [5] [6] [7] [8]. This expansion was mainly due to the increased availability of commercial weather stations with data-loggers, advances in cellular communication, the Internet, and the demand for weather-related data [2].

In general, automated weather stations (AWS) are categorized based on their application [1] [9]. These AWS include home weather stations, *i.e.*, personal (PWS) or so-called citizen stations [10] [11] [12], and professional weather stations used for specialty applications, such as agricultural, marine, forecasting, and educational purposes. The requirements of all AWS are that they must have meteorological sensors that deliver an analog signal, electronics that convert these signals to a digital value, and the capacity to store and transmit the measured data [1]. The cost of commercially AWS can range several orders of magnitude (10^2 to 10^4) and price is primarily determined by the choice of meteorological sensors, datalogger, and associated hardware and software to measure, store and process data. Most AWS measure air temperature and humidity, wind speed and direction, short-wave irradiance, and rainfall [13].

We are engaged in a field campaign in the southern region of the Texas High Plains (THP) where we are evaluating dryland cotton lint yield as a function of rainfall [14]. For this purpose, we calculate crop water productivity (CWP, kg/m^3), defined as the crop yield [kg/m^2] per unit of crop evapotranspiration (ET, m), and in this calculation we used long-term county data for both the dryland cotton lint yield and rainfall for sixteen southern counties in the THP. In our calculation of CWP, we assumed that the annual crop ET was approximated by annual rainfall [15] [16]. Results showed that the top four counties with the highest CWP were Lubbock, Martin, Lynn, and Howard and of these counties Martin and Howard are in the most southern region of the THP. This is a significant result as these counties are subject to extreme environmental conditions and the management production methods used by dryland producers represent the future schemes that will need to be adopted in other counties to sustain the emerging dryland cropping systems across the THP [14].

As a follow-up study we wanted to measure crop yield and rainfall in specific producer's fields in Martin County, TX which has a surface area of 2400 km^2. Rainfall is spatially variable and the annual average precipitation for Martin

County is 445 mm (https://www.weatherwx.com/climate-averages/tx/martin+county.html) and a typical dryland cotton field is 250 ha or larger. We wanted to maximize the number of fields included in our analysis but came to the realization that the cost associated with measuring rainfall with automatic and wireless rain gauges limited the number of cotton fields that we could include in our analysis. Our aim was to have at least one weather station per 400 ha as we have limited availability of weather data. The coverage provided by the West Texas Mesonet [17] in Martin County is limited to one site (https://www.mesonet.ttu.edu). Thus, we initiated a search for an inexpensive and commercially available rain sensor that would automatically record rainfall and preferably was also wireless.

Rainfall can be measured with a variety of sensors [13] [18] [19] [20] and the conventional rain gauge is the most widely used instrument worldwide. Modifications of these gauges include a tipping bucket rain gauge, which consists of a collector funnel with a sharp edge that diverts rainfall to a tipping bucket mechanism and a tip of the bucket occurs for each 0.2-mm of rainfall accumulation. Another rain gauge is based on an impact sensor, which detects the impact of individual raindrops. The signals due to the impacts are proportional to the volume of the drops. Precipitation can also be measured with a 24 GHz Doppler radar, which measures the drop speed of an individual rain drop. Rainfall amount and rate are calculated from the correlation between drop size and speed. Further, with advances in optical and electronic hardware a variety of instruments based on different principles are commercially available and these can measure the size, shape, and velocity of precipitation particles. These instruments are called disdrometers [21]. Similarly, to the cost of AWS, the expense of commercially available rain sensors can range several orders of magnitude in price. Therefore, we made the decision to explore the use of so-called personal and/or citizen weather stations (PWS) to not only measure rainfall but to also measure other weather variables on as many producer's fields that wanted to participate in our project. The only requirement was that the producers needed to have access to Internet so that weather data could be remotely accessed and downloaded via the Weather Underground web site (https://www.wunderground.com/).

Our first order of business was to search for commercially available PWS that were solar powered and could transmit data wirelessly, and that met our requirements of measuring air temperature and relative humidity, solar shortwave irradiance, wind speed and direction, and rainfall. Once we selected a PWS that suited our needs our objective was to compare hourly and daily measurements of the weather variables measured with our PWS to corresponding values measured with a standard AWS.

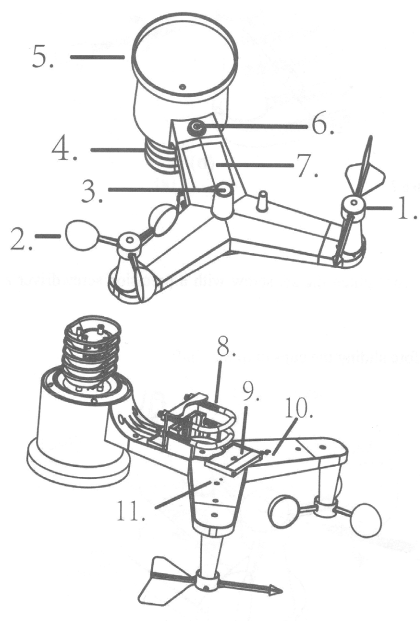
2. Materials and Methods

Our experimental objective was to evaluate weather variables measured with a commercially available PWS by comparing these measurements to values measured with an AWS. For this purpose we selected and used four PWS and compared the average measured values of air temperature (T_{air}) and relative humidity (RH), short-wave irradiance (R_g), calculated dewpoint temperature (T_{dew}), windspeed (WS), and rainfall to equivalent values measured with an AWS located at the facilities of the USDA-ARS, Lubbock, TX (33.59˚N, 101.89˚W and average elevation of 960 m above sea level). The comparison was done for a period of 242 days from 1 October 2022 to 31 May 2023. A description of the PWS and AWS used in our evaluation follows.

2.1. Personal Weather Station (PWS)

A web search of commercially available PWS (https://www.weatherstationadvisor.com/; https://www.wunderground.com/pws/buying-guide) indicated a variety of choices and based on our requirements we selected the Ambient Weather Station (WS-2902C Wi-Fi OSPREY Solar Powered Wireless Weather Station). This PWS consists of an indoor display console (receiver and Wi-Fi transmitter) and of all-in-one outdoor weather sensor array, shown in **Figure 1**.

To evaluate measurements of T_{air} and RH, WS, R_g and rainfall we installed four of the PWS about 20 m from the AWS located at USDA-ARS Plant Stress and Water Conservation Laboratory, Lubbock, TX. The four PWS were installed at a screen-height of 2 m and were situated in the corner of a rectangle, about 10 m apart, in a North, South, East and West orientation. The four PWS were



No.	Description
1	Wind vane
2	Wind speed sensor
3	UV/Light sensor
4	Thermometer-hygrometer sensor
5	Rain collector
6	Bubble level
7	Solar panel
8	U-Bolt
9	Battery Compartment
10	Reset Button
11	LED transmitter indicator

Figure 1. Sensors of the all-in-one PWS (Model Ambient Weather WS–2902C). The numbers on the right hand side correspond to the sensors on the left hand side showing the different components of the weather station (Source: Ambient Weather WS-2902C User's Manual).

installed on 21 August 2022. In our evaluation and comparison we used the average hourly value of weather variables measured with the four PWS.

2.2. Automatic Weather Station (AWS)

For our comparison we selected the Plant Stress and Water Conservation Meteorological Tower as our AWS, which is located at USDA-ARS Cropping Systems Research Laboratory, Lubbock, TX, and has been in operation since 2001. A list of sensors used to measure weather variables are given in **Table 1**. All these weather sensors were at a screen-height of 2 m and the weather station tower has adequate fetch in all directions in a field planted with buffalo grass (*Bouteloua dactyloides*). The meteorological tower with the AWS is shown in **Figure 2**. All sensors are routinely checked and calibrated, and replaced as

Table 1. Weather sensors and datalogger used in the AWS at the USDA-ARS, Lubbock, TX.

Sensors and Datalogger	Manufacturer	Model No.
Silicon Pyranometer (Short-Wave Irradiance) R_g	LI-COR Biosciences, Lincoln, NE	LI-200R
Air Temperature (T_{air}) and Relative Humidity (RH)	Vaisala, Woburn, MA	HMP60-ET
Wind Speed (WS) Monitor	R. M. Young, Traverse City, MI	05305-L
Rain Gauge (Tipping Bucket)	Texas Electronics Inc., Dallas, TX	TR-525USW
Datalogger	Campbell Scientific, Logan, UT	CR-3000

Figure 2. Automatic weather station (AWS) used to measure hourly values of weather variables and compared to measurements obtained with four PWS located at the Cropping Systems Research Laboratory, Lubbock, TX (Photo courtesy of Dr. John E. Stout).

needed. Hourly and daily weather from this station can be downloaded at the Wind Erosion and Water Conservation web site of the USDA-ARS (https://www.ars.usda.gov/plains-area/lubbock-tx/cropping-systems-research-laboratory/wind-erosion-and-water-conservation-research/).

2.3. Calculations

2.3.1. Dewpoint Temperature (T_{dew})

Hourly values of T_{air} and RH measured with the PWS and AWS were used to calculate hourly values of T_{dew} with the procedure given by [22].

$$e_s = 6.1078 \times \exp\left(\frac{17.269 \times T_{air}}{T_{air} + 237.3}\right) \tag{1}$$

where e_s is the saturation vapor pressure (mbar, 1 mbar = 0.1 kPa) and T_{air} is the measured air temperature [˚C]. The actual vapor pressure (e_a, mbar) is given by:

$$e_a = e_s \times \left(\frac{RH}{100}\right) \tag{2}$$

where RH is the measured air relative humidity (%). The hourly dewpoint temperature (T_{dew}, ˚C) was calculated as:

$$T_{dew} = \frac{\left(237.3 \times \ln \times \left(\frac{e_a}{6.1078}\right)\right)}{\left(17.269 - \ln \times \left(\frac{e_a}{6.1078}\right)\right)} \tag{3}$$

2.3.2. Statistical Analysis

We used average hourly weather data obtained from the four PWS and compared these to the hourly values measured with the single AWS. We also calculated and compared daily values of R_g and rainfall. Average and daily values from the PWS were plotted as a function of the corresponding and single value measured with the AWS. In our regression analysis, we plotted PWS values as the y-variable and AWS values as the x-variable and forced these relations through the origin (0, 0). Further the slope (m) of the regression line, $y = mx$ was tested if significantly different than 1 with a *P-Value* of 0.05 (Microsoft Excel for Mac. version 16.17.27).

3. Results and Discussion

Examples of the evaluation of commercially available PWS are given by [23] [24] [25] [26] [27]. These evaluations differed in the length of time and PWS used. Further, there was no consistency regarding which weather variable was evaluated. Regardless, we were unable to find any publications on the PWS we used in our evaluation. We compared average measurements of weather variables measured with the four PWS to corresponding values measured with the AWS for a period of 242 days from 1 October 2022 to 31 May 2023. Of this period, we selected 6 days, 1 and 5 October 2022, 20 November 2022, 7 April 2023, and 4 and 25 May 2023 as examples to illustrate the wide range of measured values. In our analysis, we are comparing two measurements, PWS vs. AWS, and we are not evaluating which value is more accurate, *i.e.*, close to the "true" value [28].

3.1. Diurnal Comparison

Short-wave Irradiance (R_g). Hourly values of short-wave irradiance (R_g) for the six days are shown in **Figure 3**. In general, the average hourly values, range 0 to 1100 W/m^2, measured with the PWS are in better agreement to values measured with the AWS on clear days (1 October, 20 November and 7 April) than on cloudy days (5 October, 4 May). The daily integrated value of R_g measured on 20 Nov 2022 is in close agreement, 13.4 ± 0.4 MJ/m^2 for the PWS vs. 13.0 MJ/m^2 for the AWS and for the 7 April 2023, the average R_g for the PWS is 23.0 ± 1.2 MJ/m^2 compared to 22.4 MJ/m^2 for the AWS. However, the discrepancy between the two measured values increases on cloudy days. For example, on 5 October 2022 the measured average value with the PWS was almost twice the value measured with the AWS, *i.e.*, 9.1 ± 0.5 MJ/m^2 vs. 5.0 MJ/m^2. A similar result was measured on 25 May, with an average daily R_g of 32.1 ± 0.3 MJ/m^2 measured with the PWS, which was 29% higher than the value of 22.7 MJ/m^2 measured with the AWS. Results from this 6-day comparison show that on cloudy days, values measured with the PWS where larger than hourly values measured with the AWS. Examples of comparing R_g measured with different PWS are given by [25] [29]. For example, [29] evaluated three PWS deployed next to a high-performance reference AWS over a ninety-day period. The PWS showed good performance compared to the AWS, and close agreement among the three stations for most standard weather variables. However, measured R_g was underestimated by 3%, which could be corrected with a locally obtained linear regression function.

Air-Temperature (T_{air}). Hourly values of air temperature (T_{air}) for the six days are shown in **Figure 4**. This comparison for a wide range of values, from a low of −5˚C (20 November) to a high of 30˚C (4 May) shows an agreement of ± 0.5˚C for a majority of values measured with both the PWS and AWS. Further, the standard deviation of the average values of T_{air} measured with the four PWS was <0.5˚C for all hourly values. The largest discrepancy between PWS and AWS values was on the 7 April, between 400 and 800 hours where the PWS was about 2˚C - 4˚C warmer than the AWS. Examples of comparing T_{air} with different PWS are given by [26] [27] [28]. In general, these comparisons show good agreement; however, [28] compared two popular PWS and concluded that nighttime measured T_{air} showed a good agreement, but by day differences of 4˚C or more were observed.

Air Relative Humidity (RH). Hourly values of relative humidity (RH) for the six days are shown in **Figure 5**. Measured hourly values ranged from a low of 10% (7 April) to a high of 100% (25 May). The standard deviation of the average value of RH measured with the four PWS was <1% for all hourly values. In general,

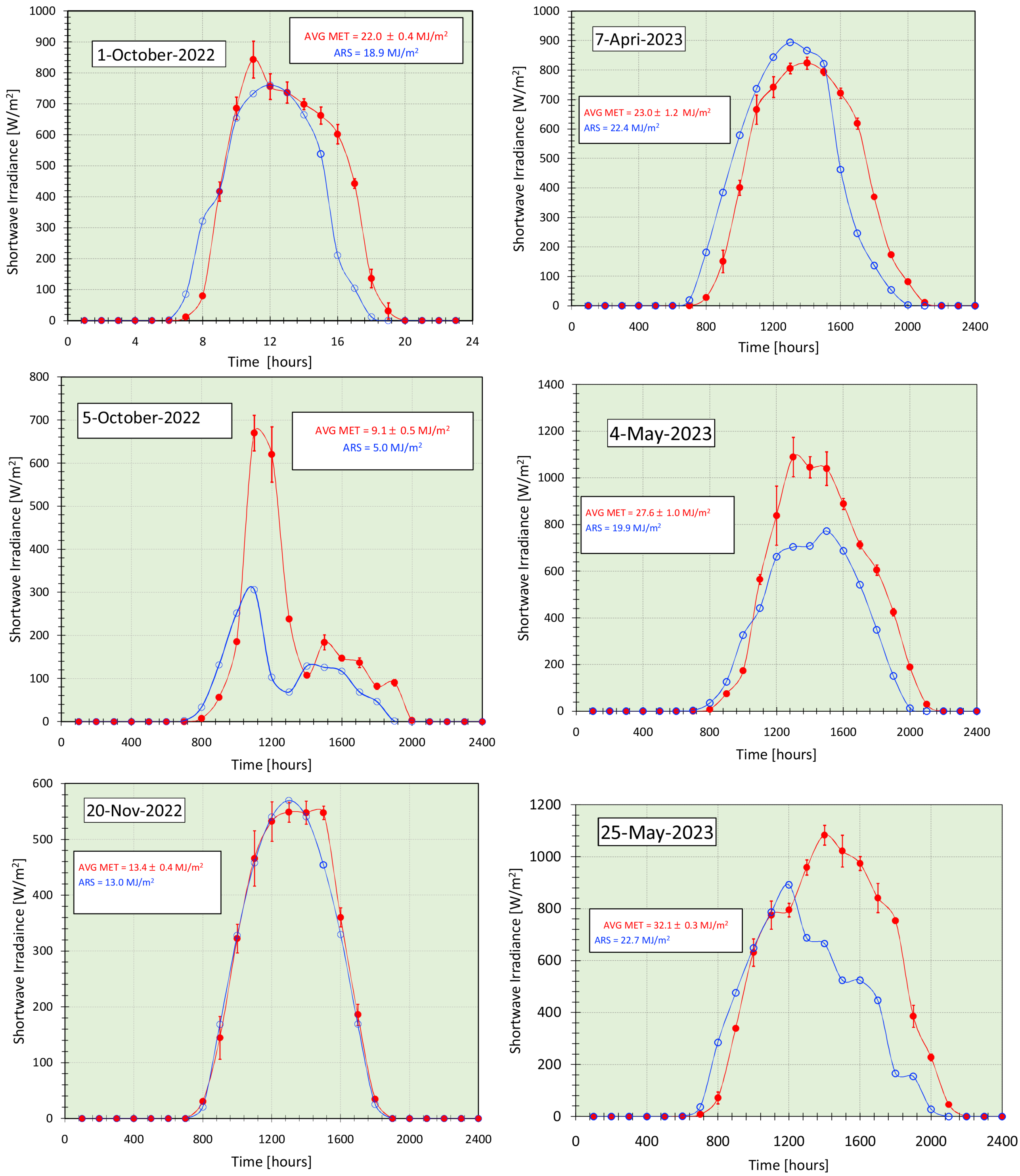


Figure 3. Hourly values of R_g measured with the PWS and AWS for six days. The integrated daily value of R_g is given for each day. Values of the PWS are the average ± standard deviation shown in red and values of the AWS are shown in blue.

the trend of the hourly measured values of RH measured with the PWS is slightly larger, <1%, than values measured with the AWS. A discrepancy of <5% is seen on 4 May between 800 and 1800 hours and on 20 November the two

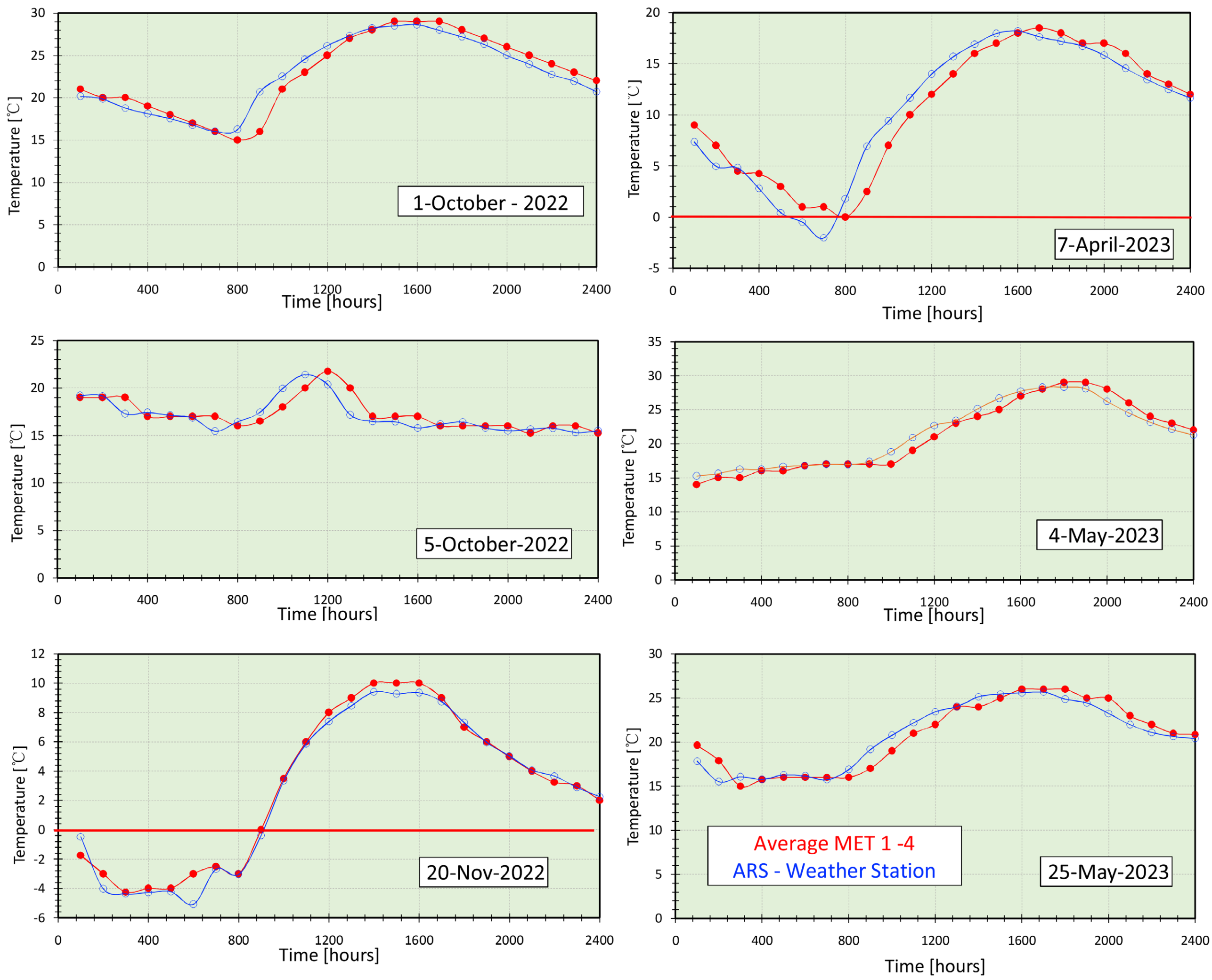


Figure 4. Air temperature as a function of time of day for 6 days. Values measured by the four PWS are plotted in red and values measured by the AWS are plotted in blue.

measurements are in close agreement, *i.e.*, <2% between 800 and 2400 hours. Examples of RH measured with other PWS are given by [23] [24] [30] and they reported close agreement with some exceptions of differences of 5% during day-time hours.

Dewpoint Temperature (T_{dew}). Hourly values of calculated dewpoint temperature (T_{dew}) for the PWS and AWS obtained with Equations (1)-(3) for the six days are given in Figure 6. The standard deviation of the average hourly T_{dew} calculated from the four PWS was <0.5˚C for these six days. Again, in general this comparison shows that the average PWS calculations of T_{dew} tend to be larger than corresponding values of the AWS. For example, on 4 May between 1400 and 1800 hours this discrepancy is about 4˚C and on 25 May the hourly overestimation of the T_{dew} is about 1˚C for the diurnal cycle. An example of evaluating T_{dew} from measured values of T_{air} and RH as part of a PWS is given by [31] and they show close agreement when compared to other sources.

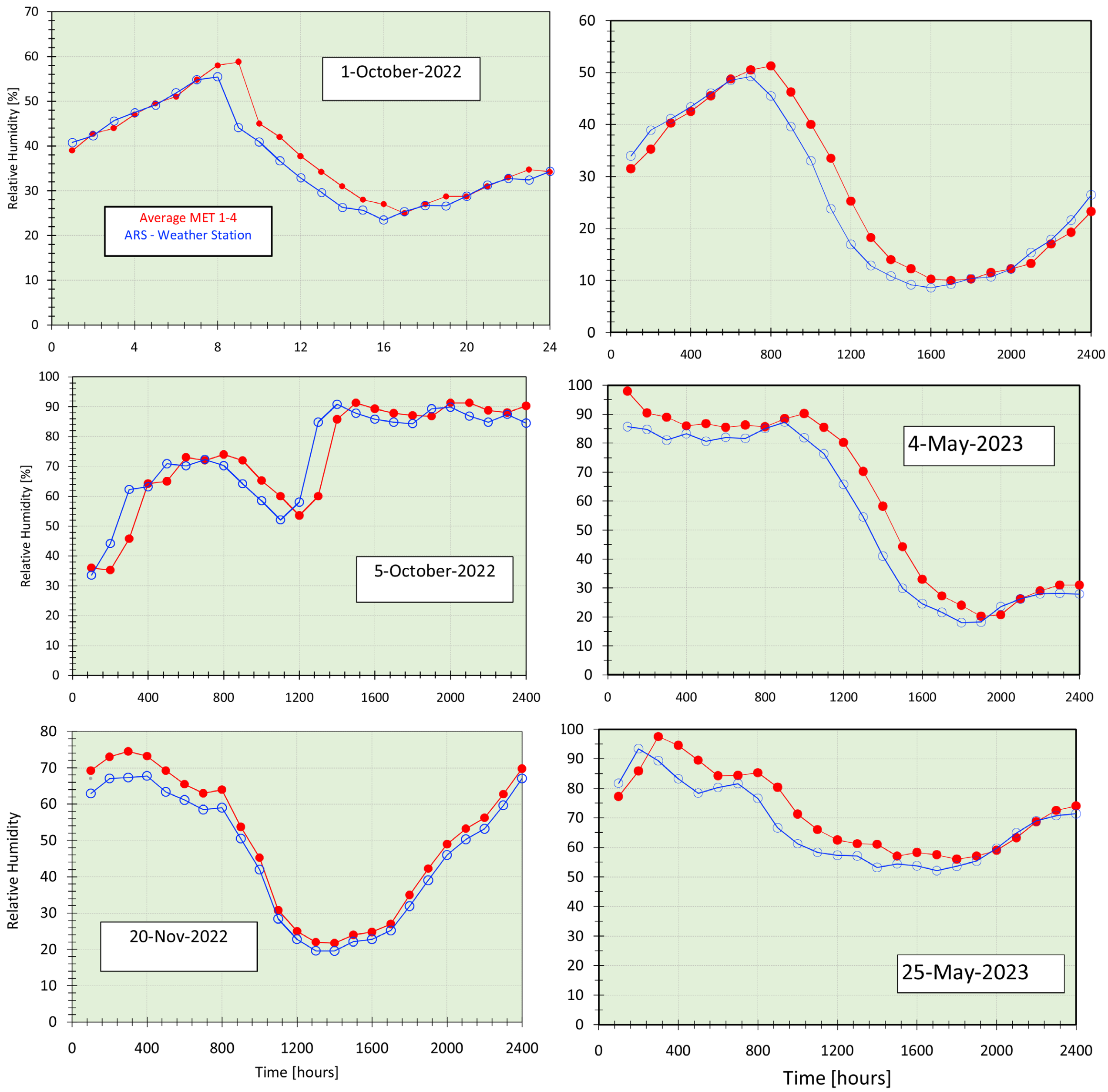


Figure 5. Relative humidity as a function of time of day for 6 days. Values measured by the four PWS are plotted in red and values measured by the AWS are plotted in blue.

Wind-speed (WS). Hourly values of measured wind speed (WS) of the six days is shown in Figure 7. In this six-day comparison, the average WS measured with the PWS tends to be less than the value measured with the AWS. On 4 May the standard deviation of the average WS for the day was ~ ±0.8 m/s and about ±1.0 m/s on 25 May. The overall trend is for the PWS to measure lower hourly value of WS compared to the AWS. Jenkins [30] compared measured WS from two PWS and concluded that WS from one PWS was in good agreement but the other read about 12% low. Dombrowski *et al.* [29] evaluated three PWS and compared these values to an AWS nearby and reported close agreement.

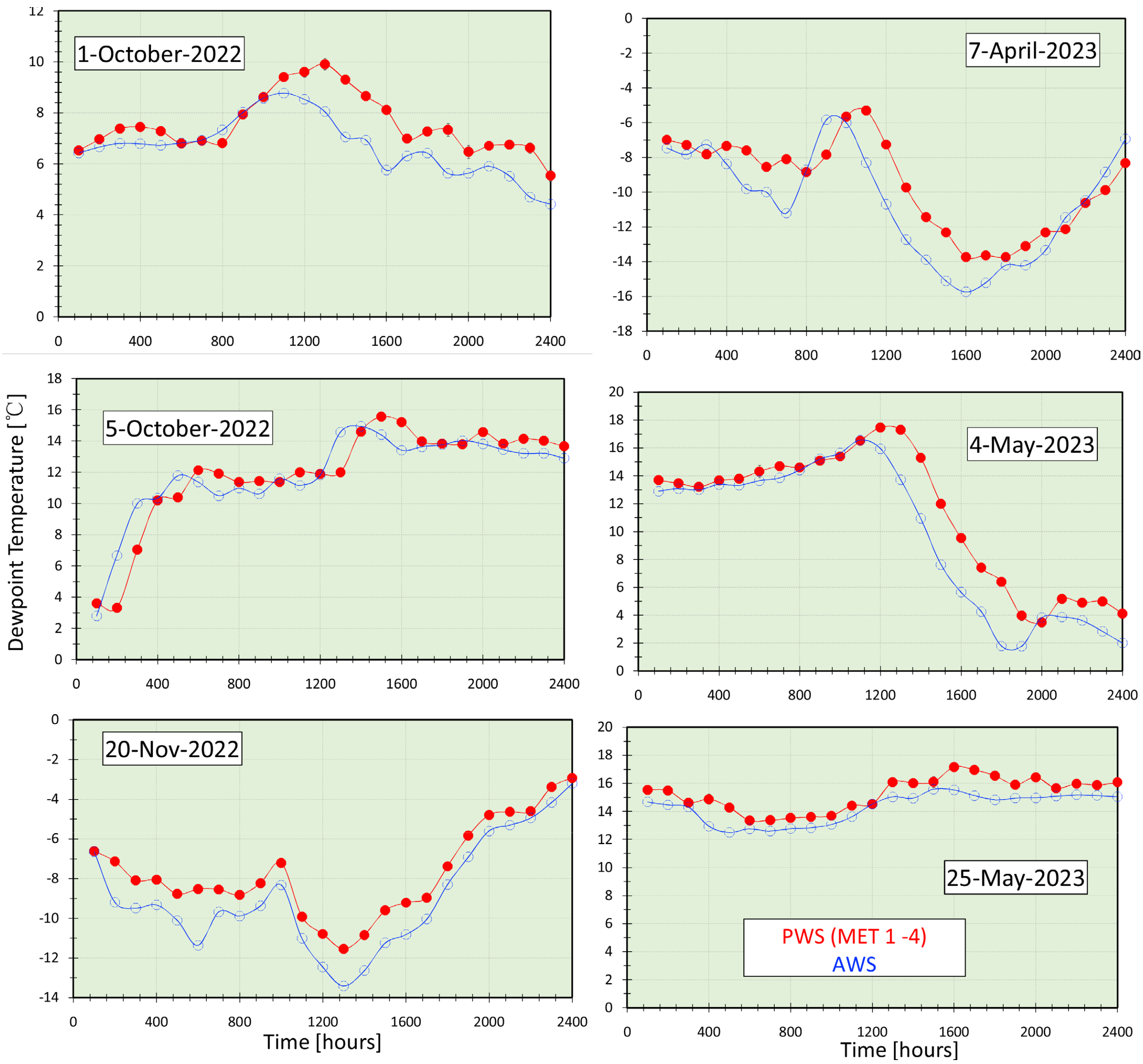


Figure 6. Calculated values of dewpoint temperature for six days. Values measured by the four PWS are plotted in red and values measured by the AWS are plotted in blue.

3.2. Daily Comparison

Daily values of R_g for the 242-day evaluation period were calculated and compared for the PWS and AWS and are shown in **Figure 8**, and linear regression analysis is plotted in **Figure 9**. Daily values of rainfall for the same period are shown in **Figure 10**.

Short-wave Irradiance (R_g). The integrated daily values of R_g for the 242-d measurement period for the PWS and AWS is shown in **Figure 8** and the linear regression of PWS vs. AWS for the same time period is given in **Figure 9**. Gaps in the daily values of R_g were due to loss of communication between the PWS and the datalogger, which occurred on 21 days or about 10% of the measurement

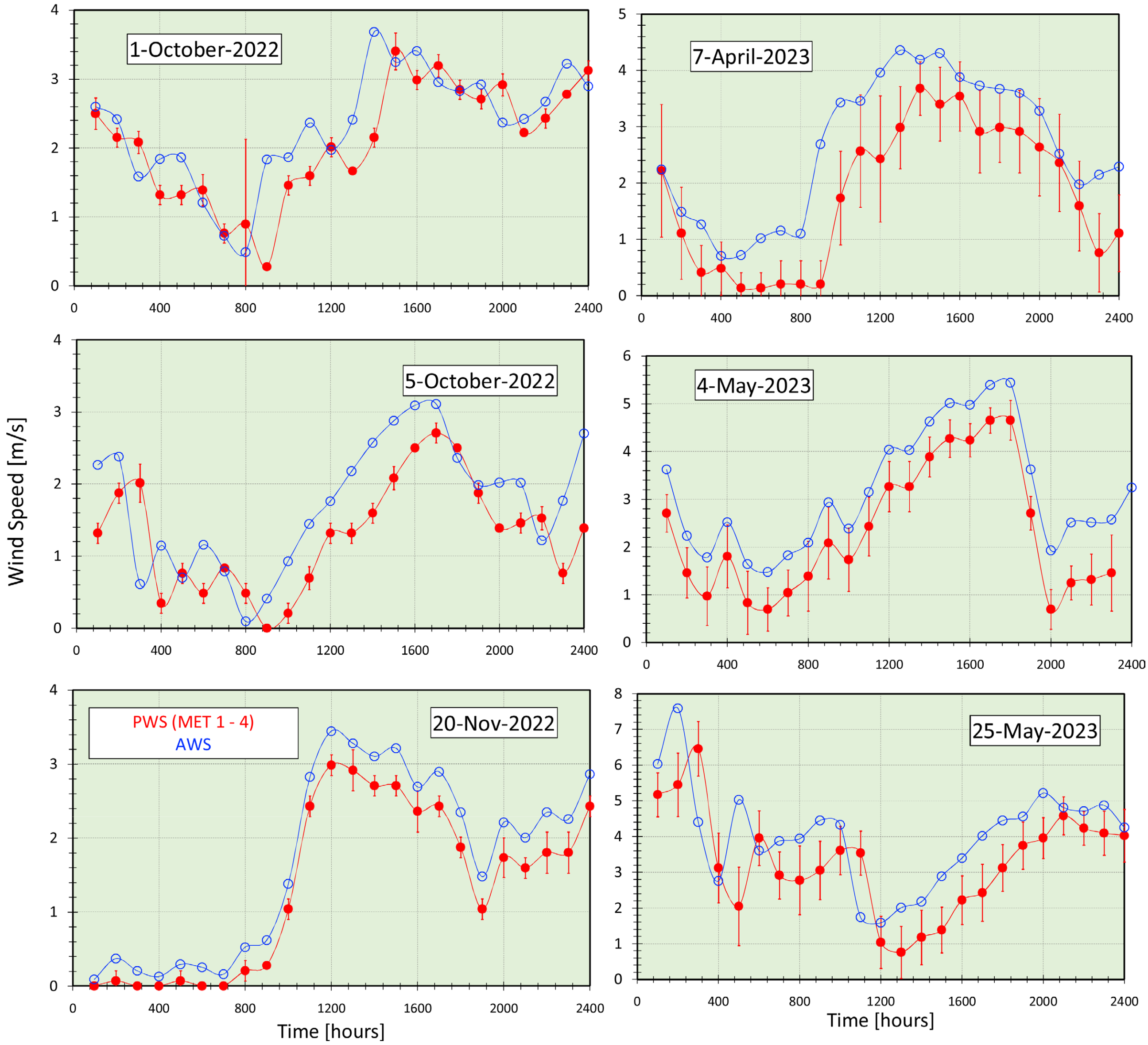


Figure 7. Wind speed as a function of time of day for 6 days. Values measured with the PWS are the average ± standard deviation indicated in red and values measured with the AWS are in blue.

period. The range of daily values of R_g measured with the PWS was from a low of 2.7 MJ/m^2 on 7 Dec 2022 to a high of 34.5 MJ/m^2 on 19 May 2023 and the corresponding low for the AWS was 1.8 MJ/m^2 on 7 Dec 2022 and a high of 28.4 MJ/m^2 on 8 May 2023 (**Figure 8**). The linear regression analysis yielded a slope of 1.15 and a coefficient of determination (R^2) of 0.81 (**Figure 9**). Also plotted is the 1:1 line and shows that the daily value of R_g measured with the PWS were 15% higher compared to values measured with the AWS.

Rainfall. The plot of daily rainfall measured with the PWS vs. daily rainfall measured with the AWS is shown in **Figure 10**. The slope of the line was 1.08 and the R^2 was 0.96. This result indicates close agreement between PWS and AWS; however, note that the maximum measured daily rainfall was 25 mm and

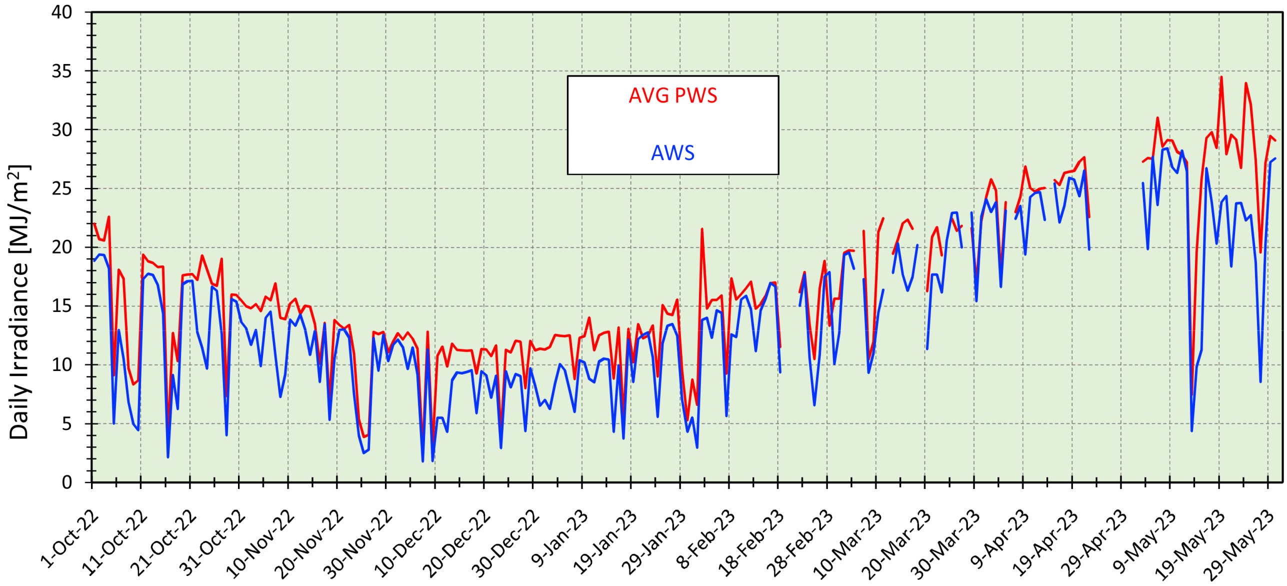


Figure 8. Daily integrated values of R_g as a function of time for the 242-day measurement period. The average of PWS is in red and the AWS value is in blue.

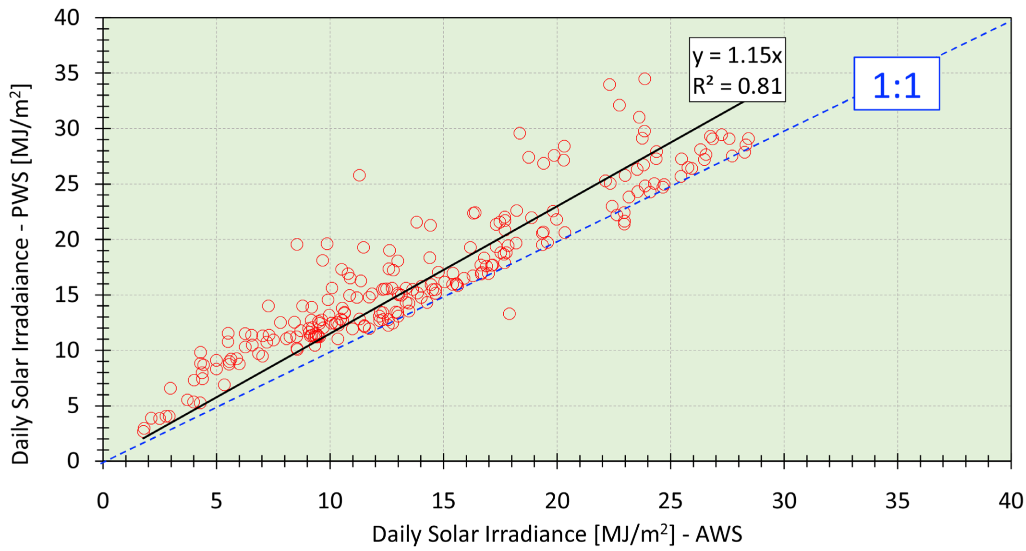


Figure 9. Daily solar irradiance measured with the PWS as a function of daily values measured with the AWS. Plotted are the linear regression and 1:1 line between the two variables.

we expect that for rainfall > 25 mm the discrepancy between measurements would increase. Nevertheless, our primary objective was to evaluate a PWS to measure rainfall with an inexpensive sensor to maximize the number of measurement sites. This result encourages to use the PWS rather than rainfall sensors that cost 2 - 5 times the cost of the PWS. We continue to monitor rainfall measured with both the PWS and AWS but this region is experiencing an unprecedented drought that has prevented us from additional comparisons. In our project we have installed stand-alone rain gauges in close proximity to PWS and we continue to monitor these measurements. Comparisons of the measurement

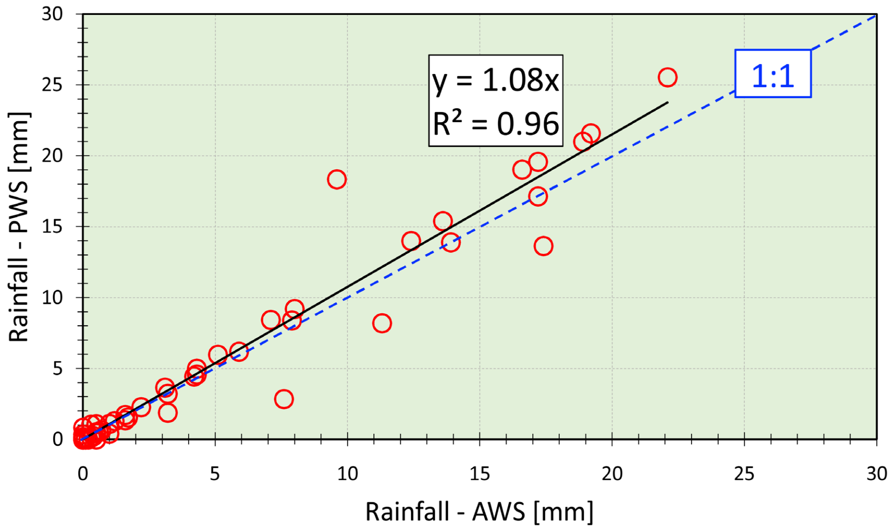


Figure 10. Daily measured rainfall with the PWS as a function of daily values measured with the AWS. Plotted are the linear regression and 1:1 line between the two variables.

of rainfall with PWS are given by [23] [24] [26] [27]. A quality control method that detects and filters typical errors of measuring rain using spatial consistency checks was proposed by [27]. Their method improved the accuracy of a 1-year data set of rainfall measurement of all PWS in the Amsterdam metropolitan area while removing only 12% of the raw measurements.

3.3. Hourly Comparison—Linear Regression

In our evaluation of weather variables measured with the PWS and AWS we compared hourly values of R_g, T_{air}, RH, T_{dew} and WS by plotting the average of four PWS measurements (y-axis) as a function of AWS (x-axis) and performed linear regression forcing the line through the origin (0, 0) and thus $y = mx$ and calculated R^2. In this analysis we are not assuming that the values measured with the AWS are more accurate than those measured with the PWS but rather we are simply comparing the two measurements. A summary of this regression analysis is shown in **Table 2**. The slopes of the lines indicated that hourly values of T_{air}, RH, and T_{dew} measured with the PWS and AWS were statistically the same (P-$value > 0.05$), and hourly values of R_g and WS were the same at a P-$Value >$ 0.10.

As expected the hourly values of R_g and WS showed the largest variability between measurements obtained with the PWS and AWS, and measurements of T_{air}, RH and T_{dew} were in close statistical agreement. We emphasize that this comparison makes no inference as to which value is accurate. A general discussion on the use of PWS is given by [32] and they concluded that the ongoing development of quality control procedures and software packages increases the interest in PWS data and their usage for specific applications. Dombrowski *et al.* [29] showed that even though there was considerable variability in rainfall, with differences of ±7.5% compared to the reference gauge, they concluded that the

Table 2. Linear regression analysis of the hourly weather variable measured with the PWS as the y-axis and corresponding value measured with the AWS as the x-axis. Given are the slope (m) of the line, coefficient of determination (R^2), and number of observations (n). *P-Value* is the probability of the significance of slope not equal to 1.0.

Weather Variable	$y = mx$ Slope (m)	Coefficient of Determination (R^2)	n	*P-Value*
Short-Wave Irradiance (R_g)	1.10	0.86	5500	>0.12
Air Temperature (T_{air})	1.00	0.99	5492	>0.05
Relative Humidity (RH)	1.05	0.97	5492	>0.05
Dewpoint Temperature (T_{dew})	0.94	0.97	5539	>0.05
Wind Speed (WS)	0.85	0.88	5540	>0.10

PWS is well suited for private user applications such as farming. A comparison of several PWS given by [11] showed significant instrument bias that can be parameterized and corrected; however, this requires a reliable estimate of the weather measurement at each location. Further, [12] proposed dynamically learning the quality of individual sensors by optimizing a weighted Gaussian process regression using an evolutionary algorithm. They showed a 12.5% improvement on the mean absolute error.

4. Summary and Conclusions

We conclude that measurements of weather variables obtained with the all-in-one PWS we selected for our analysis is more than adequate for the purpose of not only obtaining daily values of rainfall, but also to measure hourly and daily values of R_g, T_{air}, RH, T_{dew} and WS. However, a word of caution regarding the measurement of daily rainfall needs to be considered. This region is experiencing a severe drought and the largest daily rainfall event we measured over our measurement period was 25 mm and we would expect that any discrepancy would increase for larger values. Further, hourly values of R_g measured with the PWS were in good agreement on clear days but not on cloudy days; however, as suggested by others, local calibration functions could be used to correct the data and reflect the measurement obtained with the AWS. Further, others have suggested that ongoing development of quality control methods and instrument bias can be used to correct errors.

One advantage of the PWS is cost compared to AWS. The all-in-one PWS is for practical purposes a disposable unit and if a sensor fails the best and practical course of action is to replace the entire unit. Our experience is that lightning strikes and blowing sand are the two common causes for instrument failure. On several occasions we lost connectivity to the Internet, which interrupts data collection and sometimes requires a reboot of the system. With the proliferation of inexpensive PWS and availability of Internet on rural areas the use of PWS to collect agriculturally related data will increase. The use of PWS requires an understanding of what is being measured and realization that these are not weather stations that would substitute so-called research stations. Nevertheless, we conclude that the PWS we used in our evaluation provides not only adequate values of rainfall but of other weather variables that can be used for a variety of applications. Further, weather variables values measured with a PWS, and depending on their application, should periodically be checked for quality control of the variable of interest.

Acknowledgements

This research is in part supported by a grant from Cotton Inc.

Declarations

Mention of trade names or commercial products in this publication is solely for the purpose of providing specific information and does not imply recommendations or endorsement by the US Department of Agriculture. The USDA is an equal opportunity provider and employer.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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