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Estimating hourly incoming solar radiation from limited meteorological data

Kurt Spokas
Corresponding Author. U.S. Department of Agriculture—Agricultural Research Service (USDA-ARS) North Central Soil Conservation Research Laboratory, 803 Iowa Avenue, Morris, MN 56267; spokas@morris.ars.usda.gov

Frank Forcella
USDA-ARS North Central Soil Conservation Research Laboratory, 803 Iowa Avenue, Morris, MN 56267

Two major properties that determine weed seed germination are soil temperature and moisture content. Incident radiation is the primary variable controlling energy input to the soil system and thereby influences both moisture and temperature profiles. However, many agricultural field sites lack proper instrumentation to measure solar radiation directly. To overcome this shortcoming, an empirical model was developed to estimate total incident solar radiation (beam and diffuse) with hourly time steps. Input parameters for the model are latitude, longitude, and elevation of the field site, along with daily precipitation with daily minimum and maximum air temperatures. Field validation of this model was conducted at a total of 18 sites, where sufficient meteorological data were available for validation, allowing a total of 42 individual yearly comparisons. The model performed well, with an average Pearson correlation of 0.92, modeling index of 0.95, modeling efficiency of 0.80, root mean square error of 111 W m^{-2}, and a mean absolute error of 56 W m^{-2}. These results compare favorably to other developed empirical solar radiation models but with the advantage of predicting hourly solar radiation for the entire year based on limited climatic data and no site-specific calibration requirement. This solar radiation prediction tool can be integrated into dormancy, germination, and growth models to improve microclimate-based simulation of development of weeds and other plants.

Key words: Energy balance, germination modeling, light, microclimate, weed development.

The quantity of solar radiation reaching the earth's surface varies dramatically as a function of changing atmospheric conditions as well as the changing position of the sun through the day. Solar radiation controls both thermal and moisture balances of the soil system, and accordingly it is a major variable in soil physic models (Flerchinger and Saxton 1989). Additionally, the amount of radiation is a primary factor for plant growth (Steckel et al. 2003; van Dijk et al. 2005), is a component in crop–weed interactions (Lindquist 2001), and influences weed seed germination rates (Miles et al. 2002). Thus, solar radiation is a deterministic quantity that can be used for improving current efforts on weed seed germination and growth modeling.

Previous modeling efforts of total incoming solar radiation (R_s) have been conducted. The simplest assumption is that solar radiation varies as a sine function through the day (Liu 1996; Monteith 1965):

$$R_s = S_{noon}\sin\left(\frac{t}{L_{day}}\right), \qquad [1]$$

where R_s is the solar radiation at time t, S_{noon} is the solar radiation at solar noon, and L_{day} is day length. The major limitation is that the S_{noon} value is still needed.

Bristow and Campbell (1984) developed an empirical algorithm for estimating R_s using daily maximum and minimum air temperatures. Their model reduces the total daily solar radiation incident at the top of the atmosphere (R_a) by a correction factor calculated from the temperature extremes and is given by:

$$R_s = R_a[A[1 - \exp(-B(\Delta T)^C)] \qquad [2]$$

where A, B, and C are empirical coefficients unique to each location and ΔT is the difference between $T_{\max}$ and $T_{\min}$. Because of the empirical constants, the Bristow and Campbell model requires calibration, which involves a large amount of meteorological data (including solar radiation) and is numerically complex (McVicar and Jupp 1999). Despite these factors, the Bristow and Campbell model has been the basis for a large variety of derivative models (e.g., Ball et al. 2004; Donatelli et al. 2003; Goodwin et al. 1999; Wong and Chow 2001) and some that have tried to reduce the amount of site-specific calibration (Antonić 1998).

Another model that estimates daily total radiation was formulated by Hargreaves and Samani (1985). They observed that total solar radiation was related directly to the square root of the differences between daily temperature extremes ($T_{\max} - T_{\min}$) as well as geographical information. This relationship is given by:

$$R_s = R_a(k_R)\sqrt{(T_{\max} - T_{\min})}, \qquad [3]$$

where R_a is the extraterrestrial radiation (W m^{-2}), which is calculated from geometric relationships; $T_{\max}$ is maximum air temperature (C); $T_{\min}$ is minimum air temperature (C); and k_R is an adjustment coefficient (0.16–0.19 C$^{-0.5}$). The correction factor (k_{R_s}) is empirical and is determined by the geographical location with recommended values of 0.16 for sites away from water bodies (interior) and 0.19 for locations near water bodies (coastal) (Hargreaves and Samani 1985). Gautier et al. (1980) have developed algorithms for estimating daily solar radiation from satellite imagery. However, satellite data are expensive and not typically available for the field-scale predictions.

More complex equations to estimate solar radiation also exist but require extensive amounts of detailed meteorological data, such as wind speed, relative humidity, dew point temperature, and cloud cover (e.g., Monteith 1965; Nikolov and Zeller 1992). However, application of these complex relationships for an agricultural weed model is limited since detailed meteorological data (e.g., cloud cover and dew point temperatures) are not typically available. An example of this limited availability is illustrated in Texas, where there is only one weather station for every 40,000 ha of irrigated farmland (Henggeler et al. 1996). Globally, it has been estimated that the ratio of the weather stations monitoring solar radiation compared to those that do not is around 1:500 (Thornton and Running 1999).

Empirical models for the prediction of total solar radiation have been used successfully in water balance models (ASCE-EWRI 2004) but to date have not been implemented for weed seed germination modeling. Another drawback is that a majority of the developed empirical models have used daily time steps, which do not lend themselves to model the soil microclimate conditions that do change drastically diurnally and to which the seeds of many species respond (Lang 1996). The goal of this paper is to present a revised model that will extend the empirical-mechanistic relationships to include precipitation events as well as predictions of total solar radiation on an hourly basis for the ultimate purpose of improving weed development models.

Materials and Methods

Total radiation energy from the sun can be separated into two basic components: direct beam radiation (S_b) and diffuse solar radiation (S_d). The sum of these two results in the total incident solar radiation (R_s) and is represented by

$$R_s = S_b + S_d \qquad [4]$$

The local intensity of solar beam radiation is determined by the angle between the direction of the sun's rays and the earth's surface. The location of the sun is given by the angle between the sun location and the normal to the surface, referred to as the zenith angle (Ψ). Zenith angles vary temporally and geographically but are a function of the time of day, latitude, and time of year by the following relationship (Campbell and Norman 1998):

$$\cos\Psi = \sin(\Phi)\sin(\delta_{SD}) + \cos(\Phi)\cos(\delta_{SD})\cos[0.0833\pi^*(t - t_{sn})] \qquad [5]$$

where Ψ is the zenith angle (radians), Φ is the latitude of the site (radians), t is the time (standard time), t_{sn} is the time of the solar noon, and δ_{SD} is the solar declination angle (radians; Equation 6). Zenith angle will change during the day and is a function of latitude as well as seasonal differences as captured by the solar declination angle. Solar declination ranges from $+0.130\pi$ to -0.130π radians, with the extremes occurring on summer and winter solstices, respectively. Solar declination angle can be found by the following formula (Campbell and Norman 1998):

$$\sin(\delta_{SD}) = 0.39785\sin[4.869 + 0.0172J + 0.03345\sin(6.2238 + 0.0172J)], \qquad [6]$$

where J is the calendar day with $J = 1$ on January 1 and $J = 365$ on December 31 (or 366 during leap years).

The model chosen for the beam radiation is from Liu and Jordan (1960), where the beam radiation (Sp) is given by:

$$Sp = Sp_o\tau^m \qquad [7]$$

where Sp_o is the solar constant (1,360 W m^{-2}), τ is the atmospheric transmittance, and m is the optical air mass number. The optical mass number (m) is found from the following relationship (Campbell and Norman 1998):

$$m = \frac{P_a}{101.3(\cos\Psi)}, \qquad [8]$$

with P_a being the atmospheric pressure (kPa) at the site and Ψ the zenith angle from Equation 5. Average barometric pressure was estimated from the relationship (Campbell and Norman 1998):

$$P_a = 101.3e^{-(a/8,200)}, \qquad [9]$$

where a is the elevation of the site (m).

Atmospheric transmittance (τ) is the percentage of the beam (direct) radiation that will penetrate the atmosphere without being scattered. Gates (1980) suggested values of 0.6 to 0.7 for clear sky conditions. Additional values for atmospheric transmittance for a variety of conditions and topographic slopes can be found in Sellers (1965) and Nikolov and Zeller (1992). For this model, 0.70 was used for clear skies and was the same value used for all sites. Clouds are the primary variable that determines the amount of direct beam solar radiation reaching the surface of the earth. Consequently, regions with higher cloud density (e.g., humid regions) receive less solar radiation than the cloud-free climates (e.g., deserts). For any given location, solar radiation reaching the earth's surface decreases with increasing cloud cover. The range in daily temperature extremes was assumed to be an important factor in determining the presence or absence of clouds (Mahmood and Hubbard 2002), along with precipitation. Table 1 presents the decision matrix that was established to determine the atmospheric transmittance for the modeled day. This matrix is based on the concept that wet and dry days affect solar radiation through influences on cloud cover, which is in agreement with other models (Acock and Pachepsky 2000; Bristow and Campbell 1984; Winslow et al. 2001; Yin 1996). Acock and Pachepsky (2000) observed that the addition of an indicator variable for the presence or absence of precipitation improved the prediction of solar radiation (r^2 improved from 0.3 to 0.6). The major difference in our model is in the magnitude of the reductions; that is, τ was reduced by 0.3 for precipitation on a single day as well as reduced by an additional 0.10 if precipitation occurred the previous day (Table 1). These reductions are higher than those used by Winslow et al. (2001) but result in better predictability and fit with the concept that

Table 1. Decision matrix used to assign value for atmospheric transmitivity (τ).

Conditions	Value of τ
No precipitation at $\Delta T > 10$C (assumed clear sky conditions)	$\tau = 0.70$
No precipitation today, but precipitation fell the previous day	$\tau = 0.60$
Precipitation occurring on present day	$\tau = 0.40$
Precipitation today and also the previous day	$\tau = 0.30$

[a] ΔT is defined as ($Tair_{max} - Tair_{min}$).

water vapor and clouds reduce the incoming radiation. Following the assignment of τ, τ was modified if $\Delta T \leq 10$ C by the following relationship provided that the site was not near the poles ($|latitude| < 60$ C):

$$\tau = \tau/(11 - \Delta T) \quad [10]$$

However, not all of the beam radiation reaches the earth's surface. Radiation is reflected or absorbed by atmospheric gases, clouds, and dust particles (Idso 1980). Some of this radiation is scattered toward earth and is referred to as diffuse radiation (S_d). Campbell and Norman (1998) devised an empirical relationship based on work of Liu and Jordan (1960) for an estimation of diffuse radiation. This relationship is given by:

$$S_d = 0.30(1 - \tau^m)Sp_o\cos\Psi \quad [11]$$

As transmittance of the atmosphere decreases, the importance of the diffuse radiation in the overall energy balance increases. In the previous model, there are no empirical constants that are required to be fitted (e.g., Bristow and Campbell 1984; Mahmood and Hubbard 2002), which improves ease of use. However, as seen later, accuracy was not compromised by this developed decision matrix. The previous equations were implemented in JAVA, and the resulting program (SolarCalc) is freely available at www.ars.usda.gov/mwa/ncscrl.

Statistical Model Validation

Pearson correlation coefficients (r) were calculated since this is a routine measure of correlation in past model comparisons (e.g., Acock and Pachepsky 2000). However, good correlation coefficients do not automatically indicate good model accuracy (Willmott 1982). Therefore, additional statistical parameters were used to assess model performance. An "index of agreement" or modeling index (d) was calculated with the following expression:

$$d = 1 - \left[\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(|x_i - \bar{x}_i| + |y_i - \bar{x}_i|)^2}\right], \quad [12]$$

where x_i are the observed solar radiation values with a mean of $\bar{x}$ and y_i are the modeled values (Mayer and Butler 1993; Willmott 1981). The value of d will vary between 0 and 1, with a value of 1 indicating perfect model agreement (Willmott 1981). The coefficient of modeling efficiency (ME) was calculated by the following formula:

$$\mathrm{ME} = 1 - \left[\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x}_i)^2}\right], \quad [13]$$

where x_i are the observed solar radiation values with a mean of x_i and y_i are the corresponding modeled values (Legates and McCabe 1999; Mayer and Butler 1993). ME will vary between minus infinity and 1 with higher values (closer to 1) indicative of superior model performance (Willmott 1982). Two other statistical measures were calculated and are useful since the units are the same for the parameter as the observed quantity. Therefore, this allows a better assessment of the model's accuracy. The first of these is the root mean square error (RMSE), which was calculated from the following:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum\left[\sum_{i=1}^{n}(x_i - y_i)^2\right]}, \quad [14]$$

where x_i are the observed and y_i are the modeled solar radiation values and n is the number of observations (Mayer and Butler 1993). The second parameter was mean absolute error (MAE) that was calculated by the following:

$$\mathrm{MAE} = \frac{1}{n}\left[\sum_{i=1}^{n}|x_i - y_i|\right], \quad [15]$$

where x_i are the observed solar radiation values and y_i are the modeled values (Willmott 1982). These statistical measures have been used in other modeling comparisons (Diekkrüger et al. 1995; Eitzinger et al. 2004; Legates and McCabe 1999; Wegehenkel 2000; Winslow et al. 2001) and are recommended measures in assessing model performance (Willmott 1982).

Results and Discussion

A total of 18 sites were selected for model validation (Table 2). The sites had sufficient geographical information (latitude, longitude, and elevation) as well as the ability to obtain the required climate data to allow model evaluation during differing seasons. Seasonality was an important consideration because weed emergence modeling can involve seed dormancy during cold or dry seasons as well as growth during warm or wet seasons. Climate data were kept to the simple set of daily precipitation as well as daily air temperature extremes. Hourly solar radiation data were required to be measured at the site to permit model validation. These 18 sites selected gave a range in latitude, longitude, and elevation as well as climates. Statistical results are shown in Table 3. As can be seen in the table, the model performed well overall at predicting the solar radiation for the various sites tested. Figure 1 displays the graphical comparison of the modeled versus measured solar radiation at four randomly selected sites and time periods. As can be seen in the figure, the model essentially duplicates the pattern of diurnal cycles. In addition, the model does simulate the days with lower solar radiation, even though there still are occasional over- and underestimations (Figure 1). There is large scatter when comparing all the modeled versus observed values, with a general clustering around the 1:1 line (Figure 2). Overall, a slight positive bias is observed, with more modeled points being overpredicted than underpredicted (Figure 2). These events most likely can be attributed to other causes of reduced solar radiation, such as partly cloudy days without precipitation, airborne contaminations (e.g., aerosols and dust), or increased humidity levels (Winslow et al. 2001). These sporadic events would be very difficult to predict in a model with the limited climatic inputs we used here. However, despite this limitation, the model still performs adequately, as shown in Table 3. Variability in the number of samples compared was a result of missing data values in the available weather data sets. The other noteworthy item is that prior solar radiation models commonly assessed model performance strictly on cloud-free days (e.g.,

Table 2. Description of experimental sites along with geographical information and years of data used for model validation.

ID	Description	Latitude	Longitude	Elevation (m)	Years	Data source
1	Institute of Ecosystem Studies, Environmental Monitoring Station (Millbrook, NY)	+41.79	−73.74	128	1997–2000	http://www.ecostudies.org
2	Swan Lake Research Farm (Stevens Co., MN)	+45.68	−95.80	335	2000–2001	http://www.morris.ars.usda.gov/
3	Macquarie University (N. Ryde, Sydney, Australia)	−33.77	+151.17	55	2000–2004	http://aws.mq.edu.au/index.html
4	Nevada Desert Research Center	+36.77	−115.97	965	2000–2004	http://www.unlv.edu/Climate_Change_Research/Data_Bases/data_index.htm
5	Albuquerque Airport (New Mexico State University [NMSU] Climate Center)	+35.05	−106.62	1,618	1996, 1999	http://weather-mirror.nmsu.edu/map/
6	Los Lunas—Agriculture Research Center (NMSU)	+34.77	−106.75	1,476	2000–2004	http://weather-mirror.nmsu.edu/map/
7	Carlsbad Caverns (NMSU)	+32.35	−104.21	945	1996, 1999	http://weather-mirror.nmsu.edu/map/
8	Farmington-Agricultural Science Center (NMSU)	+36.75	−108.31	1,700	1999	http://weather-mirror.nmsu.edu/map/
9	Tucumcari-Agricultural Science Center (NMSU)	+35.20	−103.68	1,247	2002	http://weather-mirror.nmsu.edu/map/
10	Ames, IA (Iowa State University)	+42.03	−93.80	354	2003	http://mesonet.agron.iastate.edu/
11	Abisko Naturvetenskapliga Station (Abisko Scientific Research Station) Abisko Sweden	+68.35	−18.82	385	2000–2005	http://www.ans.kiruna.se/home.htm
12	Waterloo Micrometeorology Station, University of Waterloo, Ontario, Canada	+43.47	−80.56	334	1999–2003	http://weather.uwaterloo.ca/data.htm
13	Alachua Station (University of Florida)	+29.80	−82.41	42	2003	http://fawn.ilas.ufl.edu/data/
14	Quincy Station (University of Florida)	+30.54	−84.60	76	2003	http://fawn.ifas.ufl.edu/data/
15	Sebring Station (University of Florida)	+27.42	−81.40	10	2003	http://fawn.ifas.ufl.edu/data/
16	Fargo, ND (North Dakota State University)	+46.90	−96.82	275	1999–2003	http://ndawn.ndsu.nodak.edu
17	Miami University (OH)	+39.53	−84.73	287	2003	http://www.oardc.ohio-state.edu/centernet/weather.htm
18	Oak Ridge, TN (NOAA-ATDD)	+36.0	−84.15	267	1997	Lettenmaier and Nijssen (2001)

TABLE 3. Statistical measures of validation for the modeled hourly solar radiation values at the sites listed in Table 2.[a]

Station ID	Year	n	r	d	ME	RMSE ($W\ m^{-2}$)	MAE ($W\ m^{-2}$)
1	1997	8,721	0.911	0.953	0.812	111.1	58.2
	1998	8,745	0.915	0.954	0.810	107.8	55.2
	1999	7,869	0.916	0.954	0.808	112.8	60.1
	2000	8,783	0.904	0.941	0.736	115.8	58.6
2	2000	8,784	0.915	0.954	0.834	100.8	51.7
	2001	8,784	0.912	0.954	0.828	103.5	51.8
3	2001	7,849	0.919	0.957	0.827	105.2	54.1
	2002	7,974	0.928	0.963	0.852	103.0	54.9
	2003	8,316	0.904	0.942	0.765	125.2	72.2
4	2000	8,742	0.977	0.983	0.926	78.7	36.1
	2001	8,742	0.977	0.984	0.930	77.1	36.3
	2002	8,732	0.955	0.930	0.598	145.1	74.8
5	1996	8,040	0.952	0.974	0.893	102.6	55.5
	1999	8,094	0.872	0.933	0.734	160.4	91.1
6	2000	8,511	0.950	0.974	0.902	105.8	53.4
	2001	5,888	0.948	0.974	0.897	107.3	54.6
	2002	5,771	0.954	0.969	0.861	111.9	62.4
7	1996	7,150	0.948	0.973	0.891	104.4	51.3
	1999	7,346	0.942	0.969	0.873	115.1	55.3
8	1999	7,648	0.934	0.966	0.866	112.8	54.4
9	2002	5,134	0.963	0.981	0.924	92.3	46.5
10	2003	7,945	0.908	0.932	0.787	124.8	68.1
11	2000	8,784	0.868	0.925	0.694	60.0	53.0
	2001	8,627	0.847	0.914	0.646	64.2	50.7
	2002	8,700	0.897	0.945	0.779	53.6	43.7
	2005	3,918	0.860	0.864	0.656	93.5	46.0
12	1999	8,746	0.910	0.953	0.811	106.6	52.9
	2000	8,783	0.906	0.950	0.804	101.2	50.2
	2001	8,342	0.915	0.955	0.819	102.0	50.2
	2002	7,176	0.901	0.948	0.804	97.3	48.2
	2003	8,689	0.913	0.954	0.818	100.8	49.6
13	2003	7,025	0.888	0.929	0.679	134.9	64.0
14	2003	8,723	0.930	0.954	0.791	116.4	59.1
15	2003	6,656	0.919	0.936	0.689	151.7	74.1
16	1999	8,760	0.901	0.948	0.797	105.9	50.9
	2000	8,784	0.908	0.952	0.813	100.4	48.3
	2001	8,784	0.910	0.953	0.812	101.2	49.0
	2002	8,784	0.919	0.958	0.834	95.4	46.3
	2003	8,783	0.841	0.913	0.654	135.7	64.8
	2004	8,784	0.920	0.956	0.816	97.9	46.9
17	2003	8,784	0.847	0.912	0.635	166.8	92.4
18	1997	8,749	0.837	0.911	0.648	146.3	75.0

[a] Abbreviations: n, number of samples compared; r, Pearson's correlation; d, modeling index; ME, model efficiency; RMSE, root mean square error; MAE, mean absolute error. These statistical measures are defined in the model validation section.

Liu 1996; Wang et al. 2002). The assessments conducted here were based on all available solar data for the year, and evaluations were not screened for cloud-free days.

Figure 3 compares the model output for 4 mo across the seasons at Ames, IA, in 2003. From the figure, the model tended to overpredict solar radiation values during the spring and summer (Figures 3B and 3C) and underpredict during the fall and winter (Figures 3A and 3D). There were selected days with significant differences (e.g., March 19, March 20, March 27, June 3, June 26, and November 22) when the model did not predict the reduced solar radiation observed on those days. The reason for the overestimation could be due to increased reflection of solar radiation from snow cover or a decreasing role of atmospheric scattering due to lower solar declination angles. These effects were not further investigated.

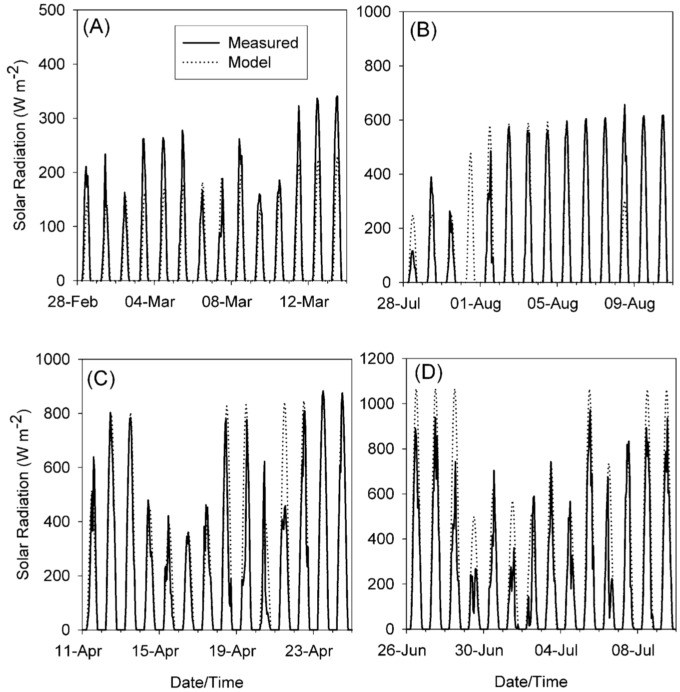

FIGURE 1. Graphical comparison of measured versus modeled solar radiation at four randomly selected sites and time periods. (A) represents the comparison at Abisko Naturvetenskapliga Station in Sweden for the period of February 28–March 14, 2005; (B) is the comparison for Sydney Australia for July 28–August 11, 2001 (no readings recorded on July 31, 2001); (C) is the comparison at Fargo, ND, for April 11–25, 1999; and (D) is the comparison at Quincy Agriculture Station (University of Florida) for June 26–July 10, 2003.

There were no significant differences observed between r, d, and ME across climatic seasons at the Ames site (Table 4), even though there is a drastic difference in the water vapor present in the atmosphere (increased solar scattering) during summer than winter (Winslow et al. 2001). However, RMSE and MAE do fluctuate because of the reduced incident solar radiation in fall/winter compared to summer/spring, with larger errors corresponding to months with

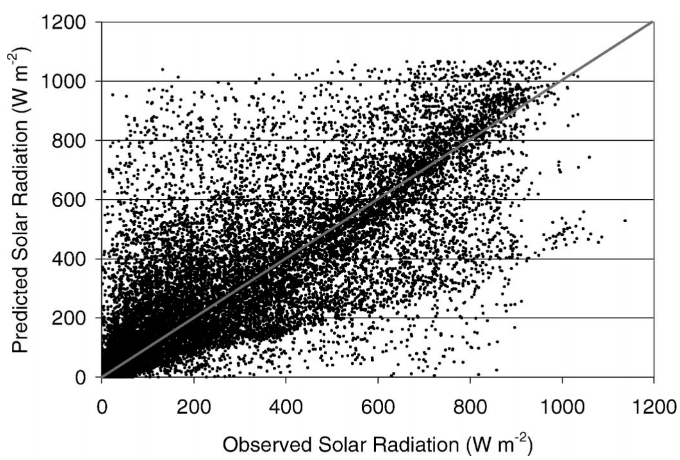

FIGURE 2. Correlation between the predicted and measured solar radiation values for the pooled data from the four stations (Abisko Naturvetenskapliga, Sweden; Sydney, Australia; Fargo, ND; and Quincy Agriculture Station, FL) shown in Figure 1 (n = 29,250).

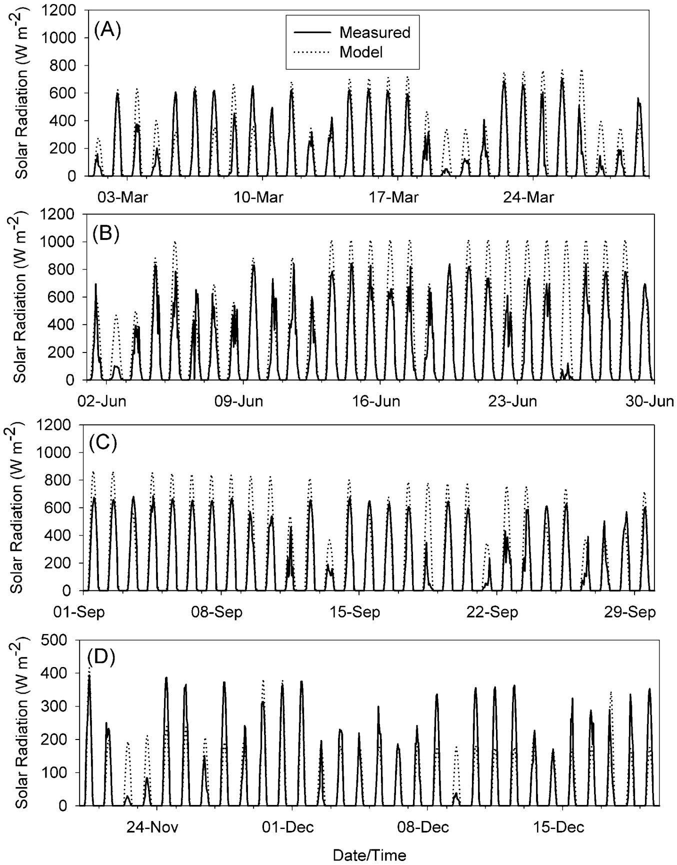

FIGURE 3. Graphical comparison of the model's performance at Ames, IA, for 4 mo during the (A) vernal equinox (spring), (B) summer solstice (summer), (C) autumnal equinox (fall), and (D) winter solstice (winter) in 2003. Last measurement available for 2003 was December 20.

higher incident solar radiation values. As seen in the other statistical measures (*r, d,* and ME), no significant differences exist in the model performance based on season. Therefore, the model does provide an overall reasonable agreement to the measured solar radiation data throughout the year (Figure 3).

The average correlation coefficient for all validation sites is 0.92 with a range of 0.84 to 0.98. Results for the correlation coefficients compare favorably to results from other empirical radiation models in the literature. Ball et al. (2004) achieved a range of regression coefficients (r^2) of 0.56 to 0.77 (r = 0.75–0.85) for daily correlations at 13 sites for five different empirical models following site-specific calibrations. These correlations improved further (r^2 ranged 0.70–0.88) when 7-d averages were compared. Acock and Pachepsky (2000) used hierarchical polynomial regression networks to simulate missing solar radiation values from weather data sets and found model correlation coefficients (r) of 0.4 to 0.5 without site-specific training sets that improved to 0.71 to 0.77 with training sets. As seen in Table 3, our model possesses higher correlation coefficients, ranging from 0.816 to 0.977, without any site-specific calibration. Thornton and Running (1999) observed an r^2 of 0.84 (r = 0.92) for a cross-validation of 40 stations across the United States. We also achieved this value (r = 0.92) with our model, with the exception of not requiring site-specific calibration. However, as indicated by Willmott (1982), the simple correlation does not guarantee good model agreement, and therefore other statistical parameters were calculated.

The average *d,* or modeling index, for the developed solar model is 0.95, with a range from 0.86 to 0.98. This indicates good agreement with the measured solar radiation observations at all validation sites. These *d*-index values place this model in the same accuracy as other empirical models (e.g., Mahmood and Hubbard 2002) but without the requirement of site-specific empirical constants. The Mahmood and Hubbard model had a *d*-index range of 0.90 to 0.94 for nine central U.S. sites for daily predictions. Mahmood and Hubbard (2005) also found that the Bristow and Campbell (1984) model resulted in a *d*-index range of 0.56 to 0.68 for the same sites. This indicates that our model outperforms the current non–site-calibrated empirical models.

The range of ME, or goodness of fit, was from 0.60 to 0.93, with an average of 0.79. This range is slightly lower than other empirical models. This reduced accuracy could be a result of the fact that our model compared solar radiation values on an hourly basis. Typically, model accuracy increases with the longer the time step for the comparison (e.g., Ball et al. 2004). Mahmood and Hubbard (2005) achieved ME values in the range of 0.90 to 0.94 for their daily models following site-specific calibration. An interesting fact in our comparisons is that the maximum and minimum ME occurred at the same site (Nevada Desert Research Center, ID = 4), with the maximum (ME = 0.93) in 2001 and minimum (ME = 0.60) in 2002 (Table 3). This observation illustrates that there was no significant bias in accuracy of predictions based on geographical location.

RMSE values ranged from 77 to 167 W m^{-2}, with an average RMSE of 112 W m^{-2}. MAE values ranged from 36 to 92 W m^{-2} with an average value of 57 W m^{-2} for the sites evaluated. This initially appears high; however, other hourly radiation models have had similar ranges. Perez et al. (1986) observed RMSE of 85 to 100 W m^{-2} for a group of three evaluated hourly radiation models. Therefore, the presented model does fall within the same range as other empirical models. Because of the large amount of weather data that were used to validate the model, different manu-

TABLE 4. Seasonal variability in the model's performance at Ames, IA, for 2003.[a]

Station ID	*n*	*r*	*d*	ME	RMSE (W m^{-2})	MAE (W m^{-2})
Winter (December–March)	1,829	0.863	0.924	0.729	69.0	33.9
Spring (March–June)	2,052	0.894	0.924	0.648	139.8	81.6
Summer (June–September)	2,026	0.927	0.929	0.642	156.9	98.8
Fall (September–December)	2,038	0.909	0.938	0.706	98.5	52.1

[a] Abbreviations: *n,* number of samples compared; *r,* Pearson's correlation; *d,* modeling index; ME, model efficiency; RMSE, root mean square error; MAE, mean absolute error. These statistical measures are defined in the model validation section.

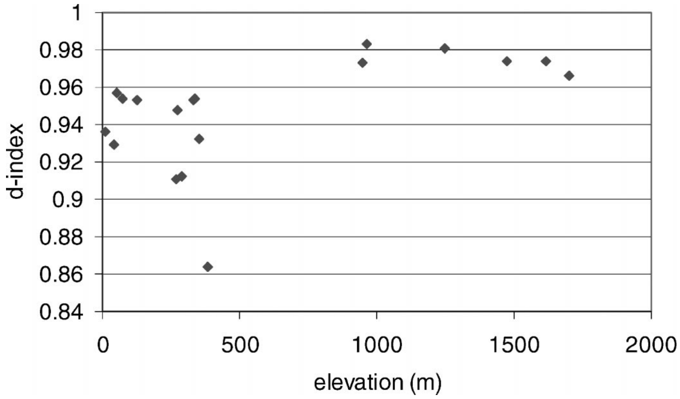

FIGURE 4. Graphical comparison of *d*-index versus site elevation.

facturers and physical conditions of the radiation sensors most likely were encountered. Meyers (2005) estimated that the absolute uncertainties in pyranometer measurements are on the order of 25 to 100 W m^{-2}, indicating that the range in the RMSE and MAE found for the modeled results are close to these instrumentation errors. However, the quality of each individual radiation reading could not be established. Another potential cause of discrepancies is that the developed model predicts the absolute solar radiation at a set time, whereas the collected data represent an hourly average of the solar radiation readings. As a further complication, weather data were collected at different rates at the various sites for the hourly average. Despite these numerical differences, the model still performed well in duplicating the measured results. For a truly accurate comparison, the model should have been run at the same time steps as the collected data and the results averaged over an hour for direct comparison. These comparisons were not conducted in this study.

Figure 4 illustrates the relationship between the *d*-index and site elevation. As seen in the figure, the accuracy of the model improves with increased elevation (>1,000 m). This indicates that the atmospheric scattering is a major uncertainty in the model since the modeling improves with increased elevation. Higher elevations have less atmospheric column through which radiation must travel. There were no significant relationships observed between accuracy of the model and geographical locations (Table 3).

The amount of incoming radiation from the sun is a major driving force for soil temperature and moisture profiles in the shallow soil surface. This is critical for weed modeling, as radiation controls growth and as microclimate conditions present within the soil control the potential germination of weed seeds. This solar radiation model was developed primarily for the future incorporation into the next generation of weed seedling emergence models. Based on the statistical measures assessed here, there is reasonable agreement between the model and measured incoming short-wave radiation achieved without site-specific model calibration. In addition, this model also could be used to fill gaps for solar radiation readings in weather station records (e.g., Acock and Pachepsky 2000). The accuracy of these predictions would be particularly high if precipitation and temperatures were recorded during the gaps in the radiometer readings.

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