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Estimating hourly net radiation for leaf wetness duration using the Penman-Monteith equation

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With 3 Figures

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Summary

Leaf wetness duration (LWD) is related to plant disease occurrence and is therefore a key parameter in agrometeorology. As LWD is seldom measured at standard weather stations, it must be estimated in order to ensure the effectiveness of warning systems and the scheduling of chemical disease control. Among the models used to estimate LWD, those that use physical principles of dew formation and dew and/or rain evaporation have shown good portability and sufficiently accurate results for operational use. However, the requirement of net radiation (Rn) is a disadvantage for operational physical models, since this variable is usually not measured over crops or even at standard weather stations. With the objective of proposing a solution for this problem, this study has evaluated the ability of four models to estimate hourly Rn and their impact on LWD estimates using a Penman-Monteith approach. A field experiment was carried out in Elora, Ontario, Canada, with measurements of LWD, Rn and other meteorological variables over mowed turfgrass for a 58 day period during the growing season of 2003. Four models for estimating hourly Rn based on different combinations of incoming solar radiation (Rg), air temperature (T), relative humidity (RH), cloud cover (CC) and cloud height (CH), were evaluated. Measured and estimated hourly Rn values were applied in a Penman-Monteith model to estimate LWD. Correlating measured and estimated Rn, we observed that all models performed well in terms of estimating hourly Rn. However, when cloud data were used the models overestimated positive Rn and underestimated negative Rn. When only Rg and T were used to estimate hourly Rn, the model underestimated positive Rn and no tendency was observed for negative Rn. The best performance was obtained with Model I, which presented, in general, the smallest mean absolute error (MAE) and the highest C-index. When measured LWD was compared to the Penman-Monteith LWD, calculated with measured and estimated Rn, few differences were observed. Both precision and accuracy were high, with the slopes of the relationships ranging from 0.96 to 1.02 and R^2 from 0.85 to 0.92, resulting in C-indices between 0.87 and 0.93. The LWD mean absolute errors associated with Rn estimates were between 1.0 and 1.5 h, which is sufficient for use in plant disease management schemes.

1. Introduction

Net radiation (Rn) is the energy available at an underlying surface, which is the result of the budget between total upward and downward radiation (shortwave and longwave) fluxes (Rosenberg et al., 1983). It is the fundamental parameter that governs the climate of the lower atmosphere, being the driving force for several processes, such as evapotranspiration, air and soil heating, and photosynthesis. However, Rn is not strictly a macroclimatological parameter, since it depends on the temperature, emissivity and reflectivity of a surface (Monteith and Unsworth, 1990).

A general form used to express Rn for a continuous horizontal surface, which receives radiation only from above, can be stated as,

$$Rn = (1 - \alpha)Rg + Ld - Lu \quad (1)$$

where α is the surface reflection coefficient (albedo), which depends on the surface optical characteristics, Rg is the incoming solar radiation (shortwave), and Ld and Lu are the downward and upward longwave radiations, respectively. Lu depends on surface temperature and emissivity, while Ld is influenced by atmospheric temperature, humidity, and cloud cover. According to Monteith and Unsworth (1990), under overcast conditions Ld $\approx$ Lu so Rn is almost zero at night and around [$(1 - \alpha)$ Rg] during the day.

Rn is important for studies focussed on the surface energy balance, where its magnitude is mainly related to the sensible and latent heat fluxes (Jegede, 1997; Kalthoff et al., 2006). In agrometeorology, Rn is a common parameter used to estimate reference evapotranspiration and leaf wetness duration from physical models (Allen et al., 1998; Huber and Gillespie, 1992). Despite its importance in agrometeorological studies and the relatively simple instrumentation needed for its measurement, Rn is not measured frequently and few historic data are available in the majority of standard meteorological station networks. One option is to solve the lack of data by modelling Rn based on surface weather data, and cloud cover and height, in hybrid models involving physical principles, empirical relationships, and statistical techniques (Pedro, 1980; Jegede, 1997; Iziomon et al., 2000; Madeira et al., 2002).

For the estimation of reference evapotranspiration by physical models, daily Rn data are sufficient. Models for such estimates are relatively simple and normally perform very well under several climatic conditions (Allen et al., 1998; Pereira et al., 1998, 2002). However, for the estimation of leaf wetness duration using physical models, such as the Penman-Monteith approach, hourly Rn data are required. These data are uncommon and are only measured at a few locations. When hourly Rn data are unavailable for use in physical leaf wetness duration models, they can be estimated based on simplified relationships (Madeira et al., 2002).

Leaf wetness duration is a very important agrometeorological parameter, influencing the development of several bacterial and fungal plant diseases, so its estimation is fundamental to the efficient performance of weather-based plant-disease management schemes which rationalize the timing of chemical controls (Huber and Gillespie, 1992). As leaf wetness duration is not widely available, several methods have been developed to estimate LWD from measured meteorological data (Pedro and Gillespie, 1982a, b; Huber and Gillespie, 1992; Gleason et al., 1994; Rao et al., 1998; Sentelhas et al., 2004a). Methods based on the physical principals of dew deposition and dew or intercepted rain evaporation have shown good portability and sufficiently accurate results for operational use in plant disease warning schemes (Pedro and Gillespie, 1982a, b; Gillespie and Barr, 1984; Rao et al., 1998; Luo and Goudriaan, 1999, 2000). Among the physical models used to estimate wetness deposition and evaporation, those based on the Penman-Monteith equation (Monteith and Unsworth, 1990) have some advantages over those based on the energy balance approach, e.g., they do not require a leaf temperature estimate (Rao et al., 1998), which makes them easily applicable using data from nearby weather stations (Sentelhas et al., 2006).

Considering the importance of leaf wetness duration for plant disease warning systems and the lack of Rn data available to run physical models which estimate LWD, our study aimed to evaluate the performance of four methods used to estimate hourly Rn and their impact on leaf wetness duration estimates with a Penman-Monteith model.

2. Material and methods

2.1 Experimental site and measurements

The field experiment was carried out in Elora, Ontario, Canada (43°49′N, 80°35′W, elevation 376 m above M.S.L.), in a turfgrass field for a 58 day period during the growing season of 2003 (from July 28 to October 5). Twelve days were removed from the analysis because of problems with the leaf wetness sensor.

The following meteorological variables were measured: air temperature – T and relative humidity – RH (T and RH probe, Vaisalla, model HMP35A); incoming solar radiation – Rg and net radiation – Rn (CNR1 net radiometer, Kipp &

Zonen); wind speed – U (Met-One anemometer, model 014A); rainfall – R (tipping bucket rain gauge, resolution of 0.254 mm), and leaf wetness duration – LWD (Model 237, Campbell Scientific). T, RH, and U sensors were installed at 1.9 m above the turfgrass while Rg and Rn sensors were located at a height of 1.6 m. The rain gauge was installed on the ground, with the top of the measuring orifice at 0.8 m. The LWD sensor was deployed at 1.9 m height over turfgrass, with an inclination angle of 30° facing north. This "mock leaf" sensor was painted with two coats of off-white latex paint to increase its ability to detect small amounts of wetness, and heat-treated (60–70 °C for 12 h) to remove or deactivate hygroscopic components of the paint (Sentelhas et al., 2004b). The threshold logger reading for the LWD sensor was determined in a laboratory, and values smaller than or equal to this threshold (generally about 9000 kΩ) were considered wet while greater values were considered dry.

All sensors were connected to a datalogger (model 21X, Campbell Scientific) programmed to measure each variable each second and to store the averages and/or totals at the end of each 15-minute interval. Later, 15-minute data were converted to hourly data. Hourly cloud data (% of cover and height) were obtained from observations at Toronto International Airport, about 60 km east of Elora.

2.2 Net radiation models

Net radiation was estimated using four different models. These models differ from each other in terms of the complexity of the required meteorological data. The following models were evaluated.

2.2.1 Model I

Model I is based on the physical principles of radiation balance and empirical coefficients present in the literature. This model was parameterized by Pedro (1980) and is the most complex among the models evaluated in our study. It assumes that the turf is near air temperature, and has an albedo of 30% (solar absorptivity = 0.7) and emissivity of 0.95. It requires the following meteorological data: Rg, T, RH (to obtain air vapour pressure – ea), the fraction of the sky covered by clouds (CC) and cloud height (CH), which are combined in the following equations.

$$Rn = 0.7 * Rg + 0.95 * RLc - 0.95 * 5.67 * 10^{-8} * (T + 273)^4 \quad 2$$

where Rn and Rg are in Wm^{-2}, T is in °C, and RLc is the radiation emitted by the atmosphere, adjusted by the fraction of cloud cover, in Wm^{-2}:

$$RLc = RL * (1 + K * CC^2) \quad (3)$$

where RL is the radiation emitted by the atmosphere under clear sky conditions (Eq. 4) and K is a coefficient which depends on the cloud height (Eq. 5):

$$RL = 5.67 * 10^{-8} * (T + 273)^4 * [0.82 - 0.25EXP(-0.2162 * ea)] \quad (4)$$

$$K = 0.2462 - 0.02 * CH \quad (K = 0 \text{ for clear sky}) \quad (5)$$

where: ea is in hPa and CH in km.

2.2.2 Model II

Model II was parameterized by Madeira et al. (2002) and is based on estimated sky temperature:

a) Temperature of cloudless skies (T_{clear})

$$T_{clear} = T - 20\,°C \quad (6)$$

b) Temperature of cloudy skies (T_{cloudy})

$$T_{cloudy} = T - 15\,°C \quad \text{(for high altitude clouds)} \quad (7)$$

$$T_{cloudy} = T - 10\,°C \quad \text{(for low altitude clouds)} \quad (8)$$

In Equations 7 and 8, cloud heights were classified as high when CH > 3 km and as low when CH ≤ 3 km. From these temperatures, downward longwave radiation (Ld) was calculated by:

$$Ld = [5.67 * 10^{-8} * (1 - CC) * (273 + T_{clear})^4] + [5.67 * 10^{-8} * CC * (273 + T_{cloudy})^4] \quad (9)$$

The upward longwave radiation (Lu) was calculated assuming the sensor was emitting as a blackbody at a temperature similar to the dew point temperature (Td):

$$Lu = 5.67 * 10^{-8} * (273 + Td)^4 \tag{10}$$

Finally, Rn was calculated using Eq. (1), with the same total shortwave absorptivity considered in Model I:

$$Rn = 0.7 * Rg + Ld - Lu \tag{11}$$

2.2.3 Model III

Model III was also parameterized by Madeira et al. (2002) and is based on different sky apparent emissivities (ε) for clear skies (Gates, 1980):

$$\varepsilon_{\text{clear}} = 0.674 + 0.007 * T \tag{12}$$

and for overcast skies (Monteith and Unsworth, 1990):

$$\varepsilon_{\text{cloudy}} = (1 - CC) * \varepsilon_{\text{clear}} + \left[1 - (1 - \varepsilon_{\text{clear}}) * \frac{4 * \Delta T}{T}\right] \tag{13}$$

where ΔT is the difference between cloud base temperature and air temperature, which was assumed to be 5 °C. Ld was calculated using the Stefan-Boltzman equation, as follows:

$$Ld = 5.67 * 10^{-8} * \varepsilon_{\text{cloudy}} * (273 + T)^4 \tag{14}$$

and Lu and Rn were calculated using Equations 10 and 11.

2.2.4 Model IV

Model IV is the simplest model evaluated. It was parameterized for mid-latitudes by Iziomon et al. (2000) and is based on Rg and T data. Net shortwave radiation is given as a function of Rg and α, and net longwave radiation is given as a function of T, as follows:

$$Rn = 0.837 * (Rg * 0.77) - 0.0275 * \left[5.67 * 10^{-8} * (273 + T)^4\right] - 37.7 \tag{15}$$

The empirical coefficients used in Eq. (15) were the average of the coefficients obtained by Iziomon et al. (2000) for three locations around latitude 47°55′N. No change of the coefficients in the first term of Eq. (15) was made in this model, considering its empiricism, but their product (0.65) is similar to the value used in the other models (0.7).

2.3 Penman-Monteith model to estimate leaf wetness duration

The Penman-Monteith model was applied to estimate the latent heat flux (LE), which was used to determine the period of wetness for a sensor over turfgrass (Rao et al., 1998; Sentelhas et al., 2006). The latent heat flux (LE) for a mock leaf was calculated with the following equation (Monteith and Unsworth, 1990):

$$LE = -\frac{\left\{s\,Rn + \left[\frac{1200(es_{\text{Ta}} - ea)}{rb}\right]\right\}}{(s + \gamma^*)} \tag{16}$$

where s = the slope of the saturation vapour pressure curve (hPa °C^{-1}), Rn = net radiation of the mock leaf, es_{Ta} = the saturated vapour pressure at the weather station air temperature (hPa), ea = the actual air vapour pressure (hPa), γ^* = the modified psychrometer constant (assumed to be 0.64 kPa K^{-1} with moisture and heat transfer for both sides of the sensor during dew, and 1.28 kPa K^{-1} for evaporation from one side of a sensor after rain), and rb the boundary layer resistance for heat transfer (sm^{-1}), given by Monteith and Unsworth (1990):

$$rb = 307\left(\frac{d}{U}\right)^{1/2} \tag{17}$$

where d = the effective dimension of the mock leaf (LWD flat plate sensor), equal to 0.07 m, and U = the wind speed at the weather station (m s^{-1}). The model divides rb by 2, considering two sides of the sensor in parallel. The maximum holding capacity of the mock leaf was considered to be 0.8 m for dew. When there is rainfall, it initiates or increases wetness and is added to the positive LE reservoir up to 0.6 mm. The model simply treats rain interception using measured rainfall amount and a fixed maximum amount of water in the rain reservoir (0.6 mm). This simplification ignores the effect of rainfall rate on interception, but does not lead to serious errors since the maximum intercepted water amount is very small.

Using the same procedure adopted by Pedro and Gillespie (1982a, b), wetness onset and dry-off in this model was considered as:

a) wetness onset occurs when LE > 0 or rain begins;
b) wetness dry-off occurs when the condensation and/or rain accumulated by the model is consumed by an equivalent amount of evaporation.

LWD was computed considering the number of hours, between 13:00 h of day n and 12:00 h of day n + 1, when the model estimated the presence of wetness. Daily periods were started at 13:00 rather than midnight to avoid splitting dew events.

2.4 Data analysis

Estimated and measured hourly Rn data were compared by regression analysis, and the performance of the models was also evaluated using the following statistical indices and measures of errors. The coefficient of determination (R^2) indicates the precision of the estimates in relation to measured Rn, the agreement index (D) indicates the accuracy of the estimates in relation to measured Rn (Willmott et al., 1985), ranging from 0 (without agreement) to 1 (perfect agreement), the mean error (ME) describes the direction of the error bias, the mean absolute error (MAE) indicates the magnitude of the average error, and the absolute maximum error (MAXE):

$$D = 1.0 - \left\{ \frac{\sum (O_i - P_i)^2}{\sum (|P_i - Om| + |O_i - Om|)^2} \right\} \tag{18}$$

$$ME = \frac{\sum (P_i - O_i)}{N} \tag{19}$$

$$MAE = \frac{\sum (|P_i - O_i|)}{N} \tag{20}$$

$$MAXE = MAX(|P_i - O_i|) \tag{21}$$

where P_i is the estimated Rn, O_i the measured Rn, and Om the average of measured Rn. Another index, named the confidence index – C (Camargo and Sentelhas, 1997), was also used. This index is obtained by multiplying together D, a measurement of accuracy, and the coefficient of correlation (r), a measurement of precision. C-values range from 0, for poor confidence, to 1 for very good confidence.

Two characteristic conditions, one with clear sky (when $Rn \geq 400\,Wm^{-2}$ between 11:00 and 15:00), and another with overcast weather (when $Rn \leq 200\,Wm^{-2}$ between 11:00 and 15:00), were also used to illustrate the ability of the models to simulate hourly Rn throughout the day. Five days of each condition were selected from the database, considering that just five days of overcast weather were available. From these days, just two, one with a clear sky (30/07/2003) and another with an overcast sky (03/08/2003), were presented graphically.

The models used to estimate Rn were also evaluated by considering their impact on LWD estimates from the Penman-Monteith equation. Measured LWD data were correlated with LWD values obtained with the Penman-Monteith model using hourly Rn input values measured with CNR1 and values estimated by the four models. For these evaluations the same statistical indices and errors presented in Equations 18–21, and the C-index were used. In this case, P_i is estimated LWD, O_i is the measured LWD, and Om is the average of measured LWD.

3. Results

3.1 Performance of hourly Rn models

The relationships between measured and estimated hourly Rn are presented in Fig. 1. All methods estimated hourly Rn quite well, however Models I and IV presented less data dispersion than Models II and III. In general, the models based on cloud data showed a tendency to overestimate positive Rn and to underestimate negative Rn. However, when only Rg and T data were used to estimate hourly Rn (Model IV), the tendency was to underestimate positive Rn; while for negative values no tendency was observed.

Analyzing only negative Rn, all models estimated values with a high dispersion (Fig. 1). Models I and IV presented a baseline for minimum Rn around $-90\,Wm^{-2}$ and $-50\,Wm^{-2}$, respectively, while Models II and III did not present a clear baseline.

Considering the errors and indices presented in Table 1, Models I and II presented a very slight hourly Rn overestimation (ME of +1.5 and $+0.2\,Wm^{-2}$, respectively), and Models III and IV showed a moderate underestimation (ME of -10.0 and $-17.1\,Wm^{-2}$). The mean absolute error (MAE) ranged from $20.3\,Wm^{-2}$ for Model I to $41.9\,Wm^{-2}$ for Model III. The maximum absolute error (MAXE) had the same tendency, ranging from $97.7\,Wm^{-2}$ for Model I to $166.5\,Wm^{-2}$ for Model III. Considering the precision and accuracy of the estimates, it is clear that Model I,

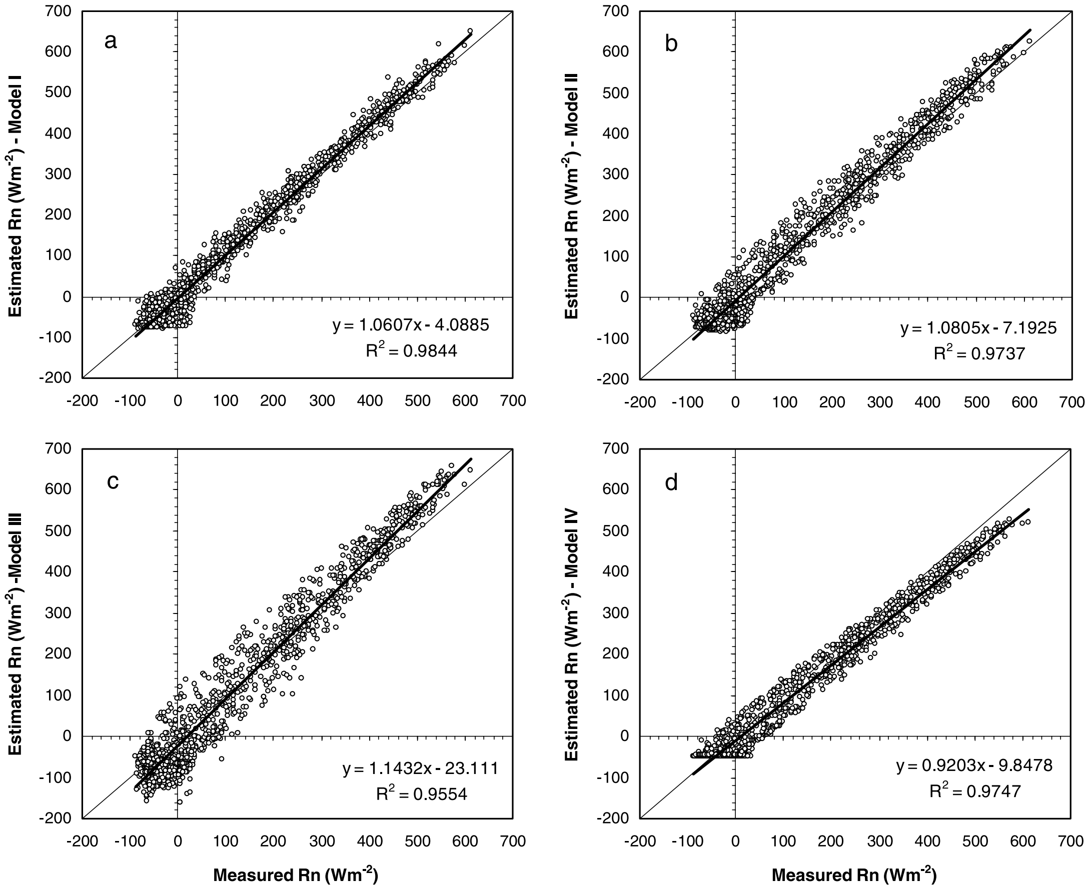

Fig. 1. Relationship between measured and estimated hourly net radiation (Rn), using four different estimation models: **a**) Model I – Pedro (1980), **b**) Model II – Madeira et al. (2002), **c**) Model III – Madeira et al. (2002), and **d**) Model IV – Iziomon et al. (2000), for Elora, Canada, during the summer of 2003

Table 1. Mean (ME), mean absolute (MAE) and maximum (MAXE) errors for hourly Rn estimated by Models I–IV. Coefficients of determination (R^2), and agreement (D) and confidence (C) indices are also shown for the relationship between measured and estimated hourly Rn

Error/ index	Hourly Rn Models			
	I	II	III	IV
ME	+1.47	+0.18	−9.99	−17.14
MAE	20.33	27.89	41.86	27.93
MAXE	97.72	103.05	166.50	102.64
R^2	0.9844	0.9737	0.9554	0.9747
D	0.9949	0.9913	0.9818	0.9899
C	0.9871	0.9782	0.9596	0.9773

the most complex, presented the best performance, with $R^2 = 0.9844$ and $D = 0.9949$, resulting in a C-index of 0.9871, which is classified by Camargo and Sentelhas (1997) as very good performance. Models II and IV also showed good performance, with a C-index around 0.978. Model III had the worst performance, but still showed high indices of precision ($R^2 = 0.9554$) and accuracy ($D = 0.9818$), resulting in a C-index of 0.9596.

To illustrate the performance of the models when estimating hourly Rn under contrasting weather conditions, two days – one with clear sky (30/07/2003) and another overcast sky (03/08/2003) – were chosen (Fig. 2). Again, Model I presented the best performance, estimating hourly Rn with high accuracy and precision for both days (Fig. 2a, b). For a clear sky day, Models II and III overestimated hourly Rn during the day and underestimated it at night (Fig. 2c, e), while Model IV had very good performance all day except for the hours around midday, when Rn was underestimated (Fig. 2g). For overcast weather, Models II, III, and IV underestimated hourly Rn throughout the day (Fig. 2d, f, and h). This is expected for Model IV, which does not

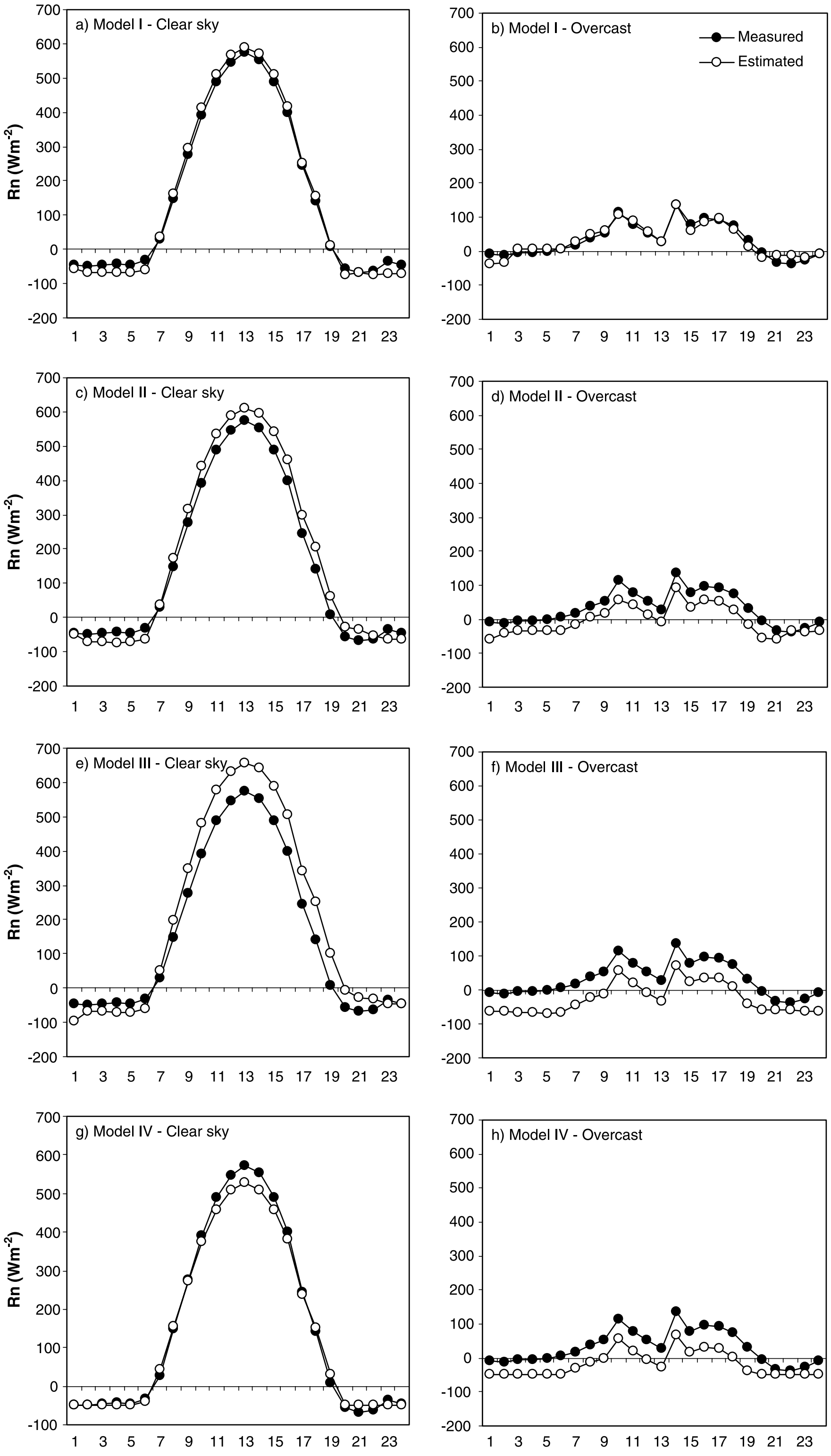

Fig. 2. Hourly variation of net radiation flux (Rn) as measured by CNR1 sensor and estimated by Models I–IV for two characteristic days: under clear sky, with more than 400 Wm^{-2} between 11:00 and 15:00 (**a**, **c**, **e**, **g**), and under overcast sky, with less than 200 Wm^{-2} between 11:00 and 15:00 (**b**, **d**, **f**, **h**), at Elora, Canada, during the summer of 2003

take into account cloud data, but not for Models II and III, since they use cloud data in their formulation. To reinforce the models' performance, statistical errors and indices were determined using five days for each condition. For clear sky conditions, the smallest MAEs were observed for Models I and IV, 21.60 and 17.36 Wm^{-2}, respectively; which agrees with the highest C-indices

Table 2. Mean (ME), mean absolute (MAE) and maximum (MAXE) errors for hourly Rn estimated by Models I–IV. Coefficient of determination (R^2), and agreement (D) and confidence (C) indices are also shown for the relationship between measured and estimated hourly Rn, for five days with clear and overcast sky conditions

Error/ index	Hourly Rn Models			
	I	II	III	IV
Clear sky				
ME	+8.40	+17.99	+23.18	+0.50
MAE	21.60	31.43	44.85	17.36
MAXE	97.72	95.92	118.90	−66.18
R^2	0.9919	0.9874	0.9763	0.9948
D	0.9964	0.9932	0.9869	0.9971
C	0.9883	0.9807	0.9635	0.9919
Overcast				
ME	−2.11	−27.89	−62.22	−38.78
MAE	12.57	30.69	62.30	40.49
MAXE	−53.55	−65.40	−104.85	−74.84
R^2	0.9313	0.8915	0.8538	0.8809
D	0.9799	0.9189	0.7602	0.8478
C	0.9125	0.8192	0.6500	0.7468

of 0.9883 and 0.9919, respectively (Table 2). For overcast conditions, the smallest MAEs were obtained when Models I and II were used. For this case, both precision and accuracy of the estimates were smaller than for clear sky conditions, with a C-index no greater than 0.92 (Table 2).

An overall analysis showed that all evaluated models had performance varying from good to very good, despite the differences presented above. The magnitude of the errors presented in Tables 1 and 2 were expected, since models are only a representation of the real processes involved in the radiation budget. However, the magnitude of these errors must be analyzed for their impact on each kind of model that uses hourly Rn as input, such as estimates of ET or LWD.

3.2 Impact of hourly Rn estimates on Penman-Monteith LWD

LWD was estimated by the Penman-Monteith model using hourly Rn input data measured by the CNR1 sensor, and data estimated by the four Rn models evaluated previously. Use of the measured and modelled net radiation values over turf as good net radiation estimates for the wetness sensor in the Penman-Monteith approach is justified as follows. The sensor was designed to have a solar absorptivity similar to that of a single leaf, which is about 50%. So, for the top surface the sensor absorbs 0.5Rg and at the bottom it absorbs 50% of the reflected shortwave radiation. For a grass surface with albedo (α) of 30%, the sensor absorbs 0.5α Rg at the bottom plus 0.5Rg at the top, which we round off to a total absorption of 0.7Rg. The longwave exchange between the bottom side of the sensor and the turf is neglected since the temperature and emissivity of the sensor and the underlying grass are similar. Therefore, sensor net radiation is very similar to that of measured turf net radiation, and to the model as expressed in Eq. (2).

Estimated LWD was correlated with measured LWD and the results are presented in Fig. 3. The relationships between measured and estimated LWD showed that the Penman-Monteith model estimated LWD with high accuracy and precision, independent of the source of hourly Rn data, with slopes ranging from 0.95 to 1.02 and R^2 values from 0.8468 to 0.9245. Differences observed among LWD estimates with measured and estimated hourly Rn were small, and the best performance resulted from hourly Rn estimated by Models I and II (Fig. 3b, c), with ME of −0.41 h and −0.21 h, MAE of 1.0 h and 1.07 h, and MAXE of 2 h and 3 h, respectively (Table 3). These errors are of the same magnitude as for LWD estimated with measured hourly Rn (Fig. 3a and Table 3).

When LWD was estimated using hourly Rn data from Model I (Fig. 3b), a better precision of the estimates was obtained ($R^2 = 0.9245$), but with an underestimation of around 3.3%. When LWD was estimated with Rn data from Model III, the overestimation was only 1.7%, but with smaller precision, $R^2 = 0.8683$ (Fig. 3d). The LWD errors associated with Model III were higher than for Models I and II, with MAE of 1.29 h and MAXE of 6.0 h, the biggest errors among all the models evaluated (Table 3).

LWD estimated with hourly Rn data from Model IV showed the biggest MAE, 1.53 h, but the MAXE = 4 h was very close to the value obtained when LWD was estimated with Rn from Model II and the CNR1 sensor. The use of Rn from Model IV resulted in an underestimation of 4.3%, with the highest dispersion, $R^2 = 0.8468$ (Fig. 3e). For Model IV, such performance was

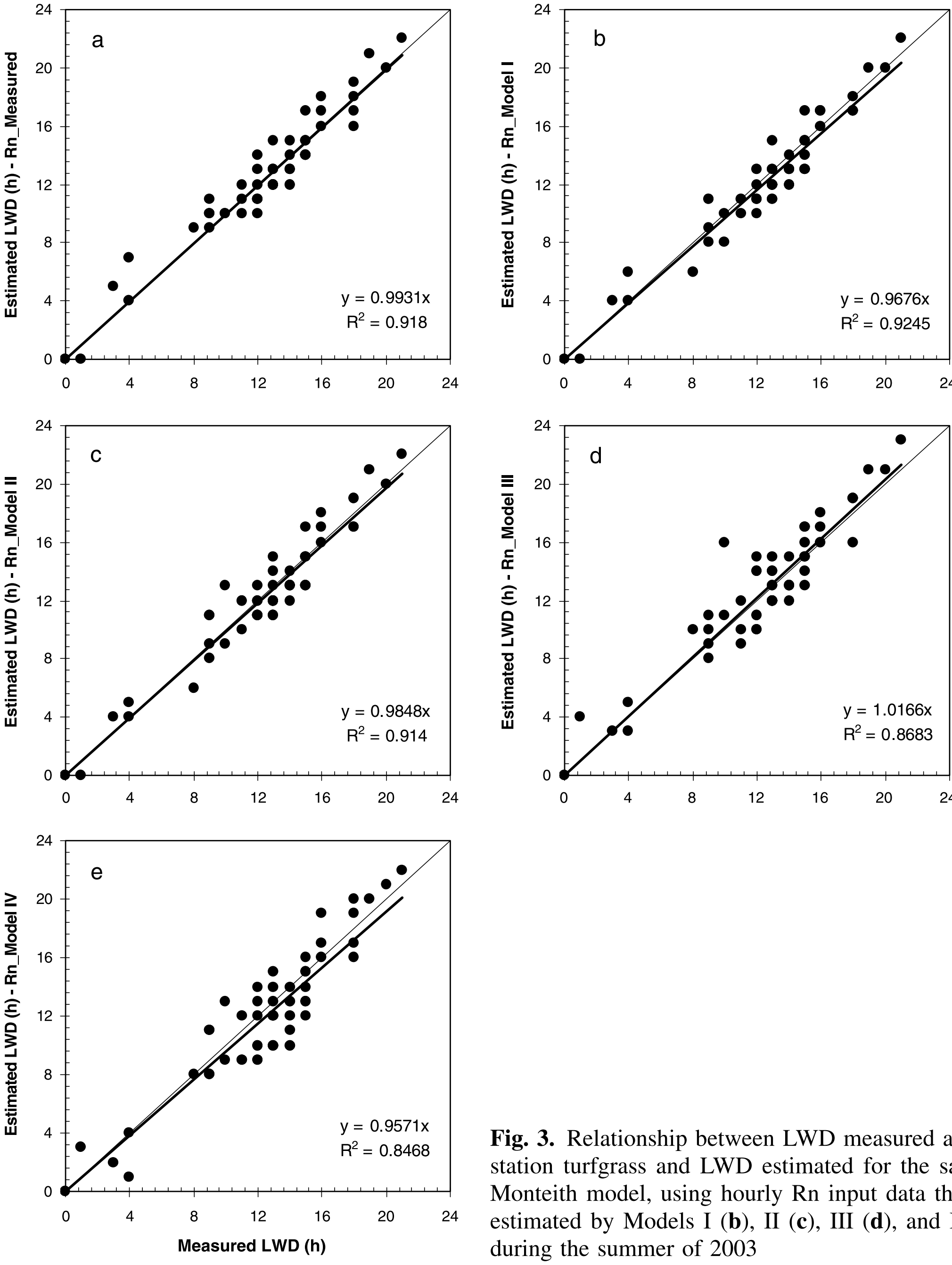

Fig. 3. Relationship between LWD measured at 1.9 m above the weather station turfgrass and LWD estimated for the same height by a Penman-Monteith model, using hourly Rn input data that were measured (**a**) and estimated by Models I (**b**), II (**c**), III (**d**), and IV (**e**), for Elora, Canada, during the summer of 2003

expected considering that it only uses T and Rg data as inputs.

4. Discussion

Net radiation is a very complex parameter since it is influenced by several factors, such as incoming solar radiation, atmospheric temperature and humidity, surface temperature, emissivity and reflectivity (albedo), and cloud cover, type and height (Rosenberg et al., 1983; Monteith and Unsworth, 1990). Its modelling is also complex, especially for estimating hourly data. In this case, the shortwave radiation budget is not very complex, requiring only incoming solar radiation and albedo data. In contrast, the longwave radiation budget normally requires atmospheric temperature and humidity, surface temperature and emissivity, and cloud data. From these, the two most difficult to obtain are cloud data, which are only available at airports and sometimes do not represent nearby regions; and atmospheric and surface temperatures,

Table 3. Mean (ME), mean absolute (MAE) and maximum (MAXE) errors for leaf wetness duration (LWD) estimated with the Penman-Monteith equation using hourly Rn input data that were measured and data estimated by Models I–IV. Coefficients of determination (R^2), and agreement (D) and confidence (C) indices are also shown for the relationship between measured and estimated LWD

Error/ index	Hourly Rn input				
	Measured	Model I	Model II	Model III	Model IV
ME	−0.03	−0.41	−0.21	+0.26	−0.60
MAE	0.93	1.00	1.07	1.29	1.53
MAXE	3.00	2.00	3.00	6.00	4.00
R^2	0.9180	0.9245	0.9140	0.8683	0.8468
D	0.9763	0.9559	0.9739	0.9575	0.9505
C	0.9354	0.9191	0.9311	0.8922	0.8747

normally represented by screen air temperature (Rosenberg et al., 1983).

The purpose of this study was to evaluate the performance of four models of varying complexity to estimate hourly Rn: the most complex model uses Rg, T, RH, CC and CH data and the simplest is based only on Rg and T; and to evaluate the impact of estimated Rn on LWD modelling with a Penman-Monteith equation.

Our results have shown that all evaluated models estimated hourly Rn quite well, with similar performances as obtained by Iziomon et al. (2000) with empirical models in Germany; and by Jegede (1997), with the Fourier transform technique in Nigeria. The C-index, which expresses a measurement of both precision and accuracy, was above 0.95 for all models, representing a very high confidence in the estimates. However, when two characteristic conditions (clear and overcast skies) were evaluated, it was observed that the models estimated hourly Rn better in clear sky conditions, with a C-index ranging from 0.96 to 0.99, than in overcast conditions, with a C-index varying between 0.65 and 0.92. The poorer performance of the models in overcast weather was expected, since the expressions which account for clouds in the longwave budget are based on empirical relationships and the cloud data were obtained for a location approximately 60 km away from the field site. Even the models which consider cloud data in detail, mainly Models II and III, presented errors which are related to different effects of distinct types of clouds covering the same amount of sky and to imprecision in the measurements of their heights. The use of air temperature to represent surface and atmospheric temperature can also be another source of systematic errors (Rosenberg et al., 1983), but these errors could apply to both sky conditions.

When the impact of hourly Rn data on LWD estimates was evaluated, results showed that the source of the hourly Rn data had only a small influence on the performance of the Penman-Monteith model. MAE values ranged from 1.0 to 1.5 h, which are smaller than the values of 1.8 h obtained with the same Penman-Monteith model by Rao et al. (1998), and of 2 h obtained by Sentelhas et al. (2004a), when measured hourly Rn was used. Pedro and Gillespie (1982a, b), using Model I to estimate hourly Rn and a physical model, based on an energy balance approach, to estimate LWD, found MAE of less than 1 h. Madeira et al. (2002) found mean absolute errors of around 1.5 and 1.6 h when LWD was estimated with an energy balance model having as hourly Rn data those estimated by Models II and III, respectively. Even the use of a very simple Model IV to estimate hourly Rn produced good LWD estimates. However, as this simple Rn model is based on empirical coefficients, local adjustments could be required for lower latitudes.

Results presented in this study are important to show that methods based on the physical principals of dew deposition and dew or rain evaporation, which have good portability and accurate results, can be used to run weather-based plant-disease management schemes, even in places where only a modest meteorological data set is available.

5. Conclusions

It has been demonstrated that hourly Rn can be estimated from meteorological data with high precision and accuracy for Canadian mid-latitudes. The best performance was obtained with Model I, which presented, in general, the smallest MAE and the highest C-index. For the simplest Rn model, based on T and Rg, the empirical coefficients of the equation may require re-evaluation for new sites at lower latitudes. The use of estimated hourly Rn from the four evaluated models did not significantly affect LWD estimated by a Penman-Monteith model, although Model I gave the best performance. Mean absolute errors for LWD estimated with hourly Rn from the models ranged from 1.0 when Model I was used, to 1.5 h when Rn data was estimated by Model IV, which are accurate enough to be used in weather-based plant-disease warning systems which use only hourly data from nearby standard weather stations. Therefore, a Penman-Monteith model can be used to estimate LWD with high confidence even in places were a modest hourly weather data set (T, RH, Rg and U) is available.

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