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# On the dynamics of canopy resistance: Generalized linear estimation and relationships with primary micrometeorological variables

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[1] The 1-D and single layer combination-based energy balance Penman-Monteith (PM) model has limitations in practical application due to the lack of canopy resistance ( $r_c$ ) data for different vegetation surfaces.  $r_c$  could be estimated by inversion of the PM model if the actual evapotranspiration ( $E_{Ta}$ ) rate is known, but this approach has its own set of issues. Instead, an empirical method of estimating  $r_c$  is suggested in this study. We investigated the relationships between primary micrometeorological parameters and  $r_c$  and developed seven models to estimate  $r_c$  for a nonstressed maize canopy on an hourly time step using a generalized-linear modeling approach. The most complex  $r_c$  model uses net radiation ( $R_n$ ), air temperature ( $T_a$ ), vapor pressure deficit (VPD), relative humidity (RH), wind speed at 3 m ( $u_3$ ), aerodynamic resistance ( $r_a$ ), leaf area index (LAI), and solar zenith angle ( $\Theta$ ). The simplest model requires  $R_n$ ,  $T_a$ , and RH. We present the practical implementation of all models via experimental validation using scaled up  $r_c$  data obtained from the dynamic diffusion porometer-measured leaf stomatal resistance through an extensive field campaign in 2006. For further validation, we estimated  $E_{Ta}$  by solving the PM model using the modeled  $r_c$  from all seven models and compared the PM  $E_{Ta}$  estimates with the Bowen ratio energy balance system (BREBS)-measured  $E_{Ta}$  for an independent data set in 2005. The relationships between hourly  $r_c$  versus  $T_a$ , RH, VPD,  $R_n$ , incoming shortwave radiation ( $R_s$ ),  $u_3$ , wind direction, LAI,  $\Theta$ , and  $r_a$  were presented and discussed. We demonstrated the negative impact of exclusion of LAI when modeling  $r_c$ , whereas exclusion of  $r_a$  and  $\Theta$  did not impact the performance of the  $r_c$  models. Compared to the calibration results, the validation root mean square difference between observed and modeled  $r_c$  increased by  $5 \text{ s m}^{-1}$  for all  $r_c$  models developed, ranging from  $9.9 \text{ s m}^{-1}$  for the most complex model to  $22.8 \text{ s m}^{-1}$  for the simplest model, as compared with the observed  $r_c$ . The validation  $r^2$  values were close to 0.70 for all models, and the modeling efficiency ranged from 0.61 for the most complex model to  $-1.09$  for the simplest model. There was a strong agreement between the BREBS-measured and the PM-estimated  $E_{Ta}$  using modeled  $r_c$ . These findings can aid in the selection of a suitable model based on the availability and quality of the input data to predict  $r_c$  for one-step application of the PM model to estimate  $E_{Ta}$  for a nonstressed maize canopy.

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## 1. Introduction and Background

[2] Physically and combination-based calculations of actual evapotranspiration ( $E_{Ta}$ ) [i.e., Penman-Monteith [Monteith, 1965]] require quantification of the canopy resistance ( $r_c$ ). Water vapor from vegetative surfaces has to overcome diffusive resistances as it transpires from the stomatal cavities and through the boundary layer to the atmosphere. The term stomatal resistance ( $r_s$ ) is used to describe the diffusive resis-

tance to water vapor flux from the epidermal stomatal cavities to the leaf surface. Soil moisture also encounters capillary resistance as it evaporates and diffuses from the soil surface to the microclimate. Monteith [1965] conceptualized these resistances and combined them into a  $r_c$  term which was originally integrated into the Penman-Monteith (PM) “big leaf” model as an extension of a combination-based model by Penman [1948]. Monteith [1965] noted that  $r_c$  is not purely physiological because it includes the external resistance across the boundary layer, which are variable with wind speed and other environmental factors. While conceptually innovative, the gap of knowledge between the single leaf and plant canopy created difficulty in the development of reliable methods to combine the dynamic diffusive processes in the stomata and the boundary layer into a simple model [Lhomme, 1991].

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[3] Quantifying  $r_c$  has been the subject of many studies. Applying the Ohm's law analogy, *Monteith* [1965] illustrated  $r_c$  as being proportional to the vapor pressure difference (potential difference) between the leaf surface and the microclimate surrounding the canopy and inversely proportional to the water vapor flux [current,  $e_s(T)$ ] and leaf temperature ( $T_L$ ). In the PM method, the surface temperature and humidity are eliminated by combining the bulk aerodynamic and heat balance relationships [*Webb*, 1984]. Although the analogy is physically sound, it is practically difficult to quantify  $T_L$  and  $e_s(T)$  at a specific level within the canopy continuously. The spatial and temporal variation in  $e_s(T)$  and  $T_L$  in the canopy further compound the complexity of using the analogy. The complexity to comprehend and quantify  $r_c$  has compelled researchers [*Tanner*, 1963; *Brutsaert*, 1982] to even question its physical significance. *Philip* [1966] suggested, "canopy resistance is an artifact of a somewhat unrealistic analysis, and its physiological significance is questionable." Despite the lack of a practical and physically sound methodology to estimate  $r_c$  for a variety of vegetation, climatic, soil water status, and management conditions, the PM method has been widely regarded by the scientific community as one of the most robust and accurate approaches to quantify evaporative losses from plant communities.

[4] Considering the simpler *Monteith's* one-layer and 1-D "big leaf" approach, *Szeicz and Long* [1969] introduced a widely applied procedure to estimate  $r_c$  as a quotient of mean  $r_s$  and effective green leaf area index (LAI). They assumed that when soil evaporation is negligible  $r_c$  represents effective  $r_s$  of all leaves acting as resistances in parallel. *Jarvis* [1981] proposed a novel approach for estimating  $r_c$  as the sum of the  $r_s$  values of all individual leaves in an imaginary column through the canopy standing on a unit area of ground. This proposal was further investigated by *Leverenz et al.* [1982], *Whitehead et al.* [1984], and *Beadle et al.* [1985] toward developing a multilayer approach. A multilayer approach, independent of wind speed, to estimate  $r_c$  was presented by *Lhomme* [1991], and the resulting observed  $r_c$  value was considered as a good physiological parameter when soil evaporation is negligible. Another multilayer model of  $r_c$  represents and captures the radiant energy at several levels in the canopy and the heat exchanges between leaves and air at these levels in terms of the layer average  $r_s$  to water vapor flow and leaf boundary layer resistance to water vapor and sensible heat flow [*Shuttleworth*, 2006]. *Juang et al.* [2008] present the results of extensive analyses and interpretation of first-, second-, and third-order closure models to investigate the radiative and turbulence transfer scheme for within and above canopy scalar transfer. Using a fixed  $r_s$  value for well-watered plants has also been suggested [*Monteith*, 1965; *Szeicz and Long*, 1969]. However, computing  $r_c$  by simply averaging different layers of  $r_s$  can be problematic since  $e_s(T)$  and vapor pressure deficit (VPD) are dynamic within the canopy, and changes in VPD and  $e_s(T)$  would influence  $r_c$ . Another foremost methodology to estimate  $r_c$  and evaporative losses from plant communities is the sap flux method. This method provides a unique intermediate between leaf and whole canopy level measurements, and it has been shown recently that the sap flux and porometer measurements of stomatal and canopy conductance match well [*Meinzer and Grantz*, 1990; *Meinzer et al.*, 1995; *Saliendra et al.*, 1995; *Sperry*, 2000; *Ewers et al.*, 2007]. Furthermore, research on the VPD and soil moisture response of  $r_c$  has been shown to

match plant hydraulic theory well [*Whitehead*, 1998; *Oren et al.*, 1999; *Ewers et al.*, 2005; *Franks*, 2004], which is recently being integrated into models of transpiration and by implication of  $E_{Ta}$  [*Mackay et al.*, 2003; *Pataki and Oren*, 2003; *Ewers et al.*, 2008]. The plant hydraulic theory and its functions, especially the relationship between soil water, xylem properties, and leaf conductance ( $g$ ), are presented and discussed in detail by *Meinzer and Grantz* [1990], *Sperry et al.* [1993], *Sperry and Pockman* [1993], *Saliendra et al.* [1995], *Sperry et al.* [1998], *Sperry* [2000], and *Franks* [2004]. The sap flux method has an advantage over the porometric measurements of  $g$  in that it does not disturb the leaf boundary layer. However, the practical application of the sap flux method is somewhat more widespread for woody vegetation rather than agronomic plants.

[5] Following the milestone multiplicative empirical  $r_s$  model from the study of the response of  $r_s$  to environmental variables by *Jarvis* [1976], a different approach to estimating  $r_c$  is the scaling-up of measured or estimated  $r_s$  to  $r_c$ . The fortunate capability of porometers to measure  $r_s$  has made the "scaling-up" approach a motivating and worthy subject to research. *Baldocchi et al.* [1991], *Rochette et al.* [1991], *Ehleringer and Field* [1993], and most recently *Irmak et al.* [2008] presented unique approaches of scaling-up  $r_s$  to  $r_c$ . The majority of these approaches, however, overlook the impact of atmospheric  $CO_2$  levels on stomatal control of water loss from plant communities in the scaling-up process. Following up on a steady-state coupled water and carbon model developed by *Katul et al.* [2003], recently, *Katul et al.* [2009a] developed a stomatal optimization theory describing the effects of atmospheric  $CO_2$  levels on leaf photosynthesis and transpiration rates that can be implemented in large-scale climate models. They showed that the cost of unit of water loss increases with atmospheric  $CO_2$ . Comparisons of their formulation results against gas exchange data collected in a pine forest showed that the formulation correctly predicted the condition under which  $CO_2$ -enriched atmosphere will cause increasing assimilation and decreasing  $g$ .

[6] In the scaling-up approach, each researcher scaled up  $r_s$  to  $r_c$  as a function of different microclimatological and/or physiological variables with successful applications. Nevertheless, difficulties and availability of  $r_c$  data for a variety of vegetation surfaces at different development stages and for a range of soil water and climatic conditions impose impediments to the practical application of the PM model to estimate evaporative losses from certain vegetation surfaces. Even if the  $r_s$  values of a given vegetation surface can be predicted with a reasonable accuracy, the challenge is still overcoming the added difficulties in the process of scaling up leaf level  $r_s$  to  $r_c$  to represent an integrated resistance from plant communities to quantify field-scale evaporative losses using the PM model [*Irmak et al.*, 2008]. *Jarvis* model estimates  $r_s$ , but  $r_c$  rather than  $r_s$  is needed as an input for the PM model. Any contributions to estimate  $r_c$  from more easily obtainable climatic variables, while maintaining the scientific merit and validity and robustness of the approach, can significantly augment the utilization of the *Jarvis* and PM models in practice by the water resource community. As an alternative to the physically based model scaling-up approach, an empirical approach is to estimate  $r_c$  from microclimatic observations. Our specific objectives with this research were to (1) develop a set of generalized-linear empirical models to estimate  $r_c$  as a function of

microclimatic variables for a nonstressed maize canopy, (2) investigate the relationships between primary microclimatic factors and  $r_c$ , and (3) present the practical implementation of the new models via experimental validation using scaled-up  $r_c$  data of porometer-measured leaf stomatal resistance data that were measured through an extensive field campaign in 2006. For further validation of the developed  $r_c$  models, we estimated actual evapotranspiration ( $E_{Ta}$ ) for maize canopy on an hourly basis using modeled  $r_c$  from all models and compared the  $E_{Ta}$  estimates with the Bowen ratio energy balance system (BREBS)-measured  $E_{Ta}$  for an independent data set in 2005.

## 2. Materials and Methods

### 2.1. General Field Experimental Procedures

[7] Detailed descriptions of experimental procedures were presented by *Irmak and Mutiibwa* [2009], and only a brief description will be provided here. Extensive field data collection campaigns on  $r_s$ , leaf area index (LAI), plant height ( $h$ ), and microclimatic variables, including incoming shortwave radiation ( $R_s$ ), net radiation ( $R_n$ ), leaf level photosynthetic photon flux density (PPFD), VPD, wind speed at 3 m ( $u_3$ ), air temperature ( $T_a$ ) at 2 m, relative humidity (RH) at 2 m, and other variables, were carried out in the summer of 2005 and 2006 at the South Central Agricultural Laboratory near Clay Center, Neb (latitude 40°34'N, longitude 98°08'W, and is 552 m mean sea level). Data were collected from a 13.5 ha maize (*Zea mays* L.) field irrigated with a subsurface drip irrigation system. Field maize hybrid Pioneer 33B51 with a comparative relative maturity of 113 to 114 days was planted at 0.76 m row spacing with a seeding rate of approximately 73,000 seeds ha<sup>-1</sup> and planting depth of 0.05 m. Maize was planted on 22 April, emerged on 12 May, and reached full canopy closure on 4 July 2005. It reached silking stage on 12 July, matured on 7 September, and was harvested on 17 October in 2005. In 2006, maize was planted on 12 May with a planting density of 74,130 seeds ha<sup>-1</sup>. Plants emerged on 20 May, reached complete canopy closure on 8 July, reached the silking stage on 15 July, started to mature on 13 September, and were harvested on 5 October 2006. The experimental field was irrigated two or three times a week to meet full plant water requirements. In 2005, total rainfall from 22 April to 30 September was 307 mm, and a total of 225 mm irrigation water was applied with the first irrigation starting on 30 June [69 days after planting (DAP)]. In 2006, total rainfall during the growing season (12 May to 30 September) was 362 mm, and a total of 172 mm of irrigation water was applied with the first irrigation starting on 16 June (35 DAP). The plant-available soil water in the effective plant rooting depth in the top 0.90 m soil layer was kept between near field capacity and the maximum allowable depletion to avoid plant water stress. Plants were fertilized based on soil samples taken prior to planting to determine the fertilizer needs with regular pest and disease control being undertaken when appropriate.

### 2.2. Evapotranspiration and Other Surface Energy Flux Measurements

[8] The surface energy balance components, including  $E_{Ta}$  and microclimatic variables were measured using a deluxe version of a Bowen ratio energy balance system (BREBS,

Radiation and Energy Balance Systems, REBS, Inc., Bellevue, Wash) that was installed in the middle of the experimental field with a fetch distance of 520 m in the north-south direction and 280 m in the east-west direction. Net radiation was measured using a REBS Q\*7.1 net radiometer that was installed approximately 4.5 m above the soil surface. Incoming and outgoing shortwave radiation envelopes were measured simultaneously using a REBS model THRDS7.1 (Radiation and Energy Balance Systems, REBS, Inc., Bellevue, Wash) double-sided total hemispherical radiometer that was sensitive to wavelengths from 0.25 to 60  $\mu$ m. The chromel-constant and thermocouple for the  $T_a$  and RH probes (model THP04015 for  $T_a$  and THP04016 for RH; REBS, Inc., Bellevue, Wash), with a resolution of 0.0055°C for  $T_a$  and 0.033% for RH, were used to measure  $T_a$  and RH gradients. The BREBS used an automatic exchange mechanism that physically exchanged the  $T_a$  and RH sensors at two heights above the canopy.  $T_a$  and RH sensors were exchanged during the last 2 min of each 15 min interval. The left exchanger tube that houses the  $T_a$  and RH probes was in the lower position during the first and third 15 min periods of each hour, and the right tube was in the lower position during the second and fourth 15 min periods of each hour. Rainfall was recorded using a model TR-525 rainfall sensor (Texas Electronics, Inc., Dallas, Tex). Soil heat flux density ( $G$ ) was measured using three REBS HFT-3.1 heat flux plates and three soil thermocouples. Each plate was placed at a depth of 0.06 m below the soil surface. The REBS STP-1 soil thermocouple probes were installed in close proximity to each plate at a depth of 0.06 m below the soil surface. Measured  $G$  values were adjusted to soil temperatures and soil water content as measured using three REBS SMP1R soil moisture probes. One soil moisture probe was installed in close proximity to each soil heat flux plate. Wind speed and direction at 3 m were monitored using a model 034B cup anemometer (Met One Instruments, Grant Pass, Ore). All variables were sampled every 60 s, averaged, and recorded every hour for energy balance calculations using a model CR10X datalogger and AM416 Relay Multiplexer (Campbell Scientific, Inc., Logan, Utah). The BREBS was closely supervised and general maintenance was provided at least once a week. Maintenance included cleaning the thermocouples and housing units (exchanger tubes), servicing radiometers by cleaning domes, checking/replacing the desiccant tubes, and making sure that the radiometers were properly leveled. The radiometer domes were replaced every 3–4 months. The lower exchanger tube was always kept at least about 1.0 m above the canopy throughout the growing season. The distance between the lower and upper exchanger tubes was kept at 0.90 m throughout the season [*Irmak et al.*, 2008; *Irmak and Mutiibwa*, 2008; *Irmak and Irmak*, 2008].

### 2.3. Stomatal Resistance and Plant Physiological Measurements

[9] A model AP4 dynamic diffusion porometer (Delta-T Devices, Ltd., Cambridge, UK) that was equipped with an unfiltered GaAsP photodiode light sensor with a spectral response similar to photosynthetically active radiation response was used to measure  $r_s$  on randomly selected green, healthy, and fully expanded leaves. Detailed description of number of  $r_s$  measurements, dates, and measurement protocols were presented by *Irmak et al.* [2008] and *Irmak and Mutiibwa* [2009]. Precautions were taken to maintain each leaf's natu-

ral orientation during the  $r_s$  measurements. Each reading corresponded to one complete diffusion cycle in which the sensor and leaf reached equilibrium with the RH. Readings were taken by orienting the position of the instrument user behind the plant and sunlight shadow (i.e., the plant leaves that were being measured were always between the instrument user and the sunlight) so that the shading of the sensors and the leaf was prevented. The readings were taken from the near-central portion of young and mature leaves. LAI was measured using a model LAI-2000 plant canopy analyzer (LI-COR Biosciences, Lincoln, Neb). Once a week, the field measurements were taken starting when LAI was about 1.2. On average, a total of 60 LAI measurements were taken on each measurement day and averaged for the day. Plant height was also measured from the soil surface to the tip of the tallest leaf from approximately 50 randomly selected plants.

## 2.4. Modeling Canopy Resistance

[10] Here we strategically evaluated the estimation of  $r_c$  from several directly measured environmental variables such as  $R_n$ , RH,  $T_a$ ,  $u_3$ , and LAI. Readily available field-measurable variables ( $R_n$ ,  $T_a$ , and RH) were given priority in modeling  $r_c$  by including them in all models developed. In addition, computed variables such as aerodynamic resistance ( $r_a$ ), VPD, and solar zenith angle ( $\Theta$ ) were incorporated into the analysis to determine their role in the variation in  $r_c$ . Solar zenith angle was included with the hypothesis that it can help to capture temporal variability in  $r_c$  arising from the diurnal solar movement across the sky, such that as the sun moves across the horizon, there is a continuous redistribution of direct and diffuse sunlight in the canopy, subsequently affecting  $r_c$ . The  $r_a$  was evaluated with an expression that is derived from turbulent transfer and assuming a logarithmic wind profile [Thom, 1975; Monteith and Unsworth, 1990]. Following Brutsaert and Stricker [1979], we computed  $r_a$  ( $\text{s m}^{-1}$ ) as

$$r_a = \frac{\ln\left[\frac{z_m-d}{z_{om}}\right] \ln\left[\frac{z_h-d}{z_{oh}}\right]}{k^2 u_z}, \quad (1)$$

where  $z_m$  is the height of wind measurements (3 m),  $z_h$  is the height of humidity measurements (2 m),  $d$  is the zero plane displacement height (m),  $z_{oh}$  is the roughness length governing transfer of heat and water vapor (m),  $z_{om}$  is the roughness length governing momentum transfer (m),  $k$  is von Karman's constant (0.41), and  $u_z$  is the wind speed at height  $z$  (3 m;  $\text{m s}^{-1}$ ). We used measured plant height ( $h$ , m) to compute  $d$ ,  $z_{om}$ , and  $z_{oh}$  following the study of Monteith *et al.* [1965], Plate [1971], and Brutsaert [1982]

$$d = 0.67h, \quad (2)$$

$$z_{om} = 0.123h, \quad (3)$$

$$z_{oh} = 0.10z_{om}. \quad (4)$$

Since wind speed may induce temporary stomatal closure [Salisbury and Ross, 1992; Kramer, 1983], in addition to transfer of vapor and heat in the canopy,  $r_a$  may have an indirect effect on  $r_c$ . Thus, we incorporated  $u_3$  into the models. Net radiation was included in all models because

stomata generally do not respond to changes in the other environmental variables unless there is sufficient light for photosynthesis to occur [Norman, 1979; Campbell, 1982; Massman and Kaufmann, 1991; Irmak *et al.*, 2008].

[11] The observed  $r_c$  data used in this study as the reference  $r_c$  values to develop the models were scaled up from measured  $r_s$  values that were previously presented by Irmak *et al.* [2008] and Irmak and Mutiibwa [2009]. The modeling in this study is for empirically predicting  $r_c$  and not for scaling up  $r_s$  to  $r_c$ . Irmak *et al.* [2008] presented a methodology for scaling up  $r_s$  to  $r_c$  utilizing  $r_s$  versus a leaf level PPFD response curve that was measured through an extensive field campaign for a nonstressed maize canopy in 2006. Irmak and Mutiibwa [2008] measured  $r_s$  for subsurface drip-irrigated nonstressed maize plants and integrated a number of microclimatic and in-canopy radiation transfer parameters to scale up  $r_s$  to  $r_c$ . With the espousal of microclimatic and plant factors such as LAI for sunlit and shaded leaves,  $\Theta$ ,  $h$ , and direct and diffuse solar radiation, they scaled up  $r_s$  on an hourly basis as a main function of measured PPFD.

[12] The proposed  $r_c$  models of this study were developed using STATISTICA™ software (version 7.1, StatSoft, Inc., Tulsa, Okla) utilizing the generalized-linear/nonlinear model tool. The module is a comprehensive implementation of the general linear model. With this approach, both linear and nonlinear effects for any number and type of predictor variables ( $R_n$ , RH,  $u_3$ ,  $T_a$ , VPD, LAI,  $r_a$ , and  $\Theta$ ) on a discrete or continuous dependent variable ( $r_c$ ) can be analyzed [McCullagh and Nelder, 1989]. The generalized model is a generalization of the linear regression model, such that effects of climatic variables on  $r_c$  can be tested for categorical predictor variables, as well as for effects for continuous predictor variables. A categorical predictor variable is a variable, measured on a nominal scale, whose categories identify class or group membership, which is used to predict responses on one or more dependent variables. The general form of the generalized-linear equation we used was built upon Jarvis-type parameterization and relates a dependent variable ( $r_c$ ) to a set of quantitative independent variables ( $R_n$ , RH,  $u_3$ ,  $T_a$ , VPD, LAI,  $r_a$ , and  $\Theta$ )

$$Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_kX_k + e, \quad (5)$$

where  $e$  is the error variability that cannot be accounted for by the predictors; note that the expected value of  $e$  is assumed to be zero, while the relationship in the generalized-linear model is assumed to be

$$Y = z(b_0 + b_1X_1 + b_2X_2 + \dots + b_kX_k) + e, \quad (6)$$

where  $e$  is the error, and  $z(\dots)$  is a function. Formally, the inverse function of  $z(\dots)$ , say  $f(\dots)$ , is called the link function. The models were developed systematically and had a decreasing number of predictor variables from a maximum of eight predictors to a minimum of three. The form of the equations can be expressed as

$$r_{c,1} = \exp(a + bR_n + cT_a + dVPD + eRH + fu_3 + gr_a + hLAI + k\Theta), \quad (7)$$

$$r_{c,2} = \exp(a + bR_n + cT_a + dVPD + fu_3 + gr_a + hLAI + k\Theta), \quad (8)$$

$$r_{c,3} = \exp(a + bR_n + cT_a + eRH + fu_3 + gr_a + hLAI + k\Theta), \quad (9)$$

$$r_{c,4} = \exp(a + bR_n + cT_a + eRH + fu_3 + hLAI + k\Theta), \quad (10)$$

$$r_{c,5} = \exp(a + bR_n + cT_a + eRH + fu_3 + hLAI), \quad (11)$$

$$r_{c,6} = \exp(a + bR_n + cT_a + eRH + fu_3), \quad (12)$$

$$r_{c,7} = \exp(a + bR_n + cT_a + eRH), \quad (13)$$

where  $r_{c,i}$  is the canopy resistance estimated from model  $i$  ( $s\ m^{-1}$ ),  $R_n$  is net radiation ( $W\ m^{-2}$ ),  $T_a$  is air temperature ( $^{\circ}C$ ), RH is relative humidity (%),  $u_3$  is wind speed measured at 3 m ( $s\ m^{-1}$ ),  $r_a$  is aerodynamic resistance ( $m\ s^{-1}$ ), LAI is green leaf area index,  $\Theta$  is the solar zenith angle (degrees),  $a$  is the intercept, and  $b, c, d, e, f, g, h,$  and  $k$  are the coefficients of  $R_n, T_a, VPD, RH, u_3, r_a, LAI,$  and  $\Theta$ , respectively, with all micrometeorological variables having hourly units.

## 2.5. Calibration and Validation of Proposed Canopy Resistance Models

[13] The scaled up hourly  $r_c$  data set used for calibration ranged from 19 June 2006 to 15 July 2006, and the data set for validation covered the period from 16 July 2006 to 31 August 2006. The coefficients of the models were optimized for the best fit of predicted values to observed values, i.e., maximizing the coefficient of determination ( $r^2$ ) and minimizing the root mean square difference (RMSD) between measured and model-estimated  $r_c$ . In the calibration and validation, the  $r_c$  values that were observed from measured and scaled-up  $r_s$  values that were presented by Irmak *et al.* [2008] were used as the actual (reference)  $r_c$  values. These data sets were used to estimate (optimize) parameters for all seven  $r_c$  models. New parameters were estimated by searching over the parameter space to minimize the RMSD between observed (scaled-up) and model-estimated  $r_c$ . The optimized parameters replaced the original parameters and new  $r_c$  values were calculated for each model. The assumption we made in the model development was that there was no interaction effect of independent variables on  $r_c$ ; thus, the variables act independently. All models were developed for an hourly time step using hourly input variables.

[14] Hourly  $r_c$  values computed from the seven models were compared to hourly  $r_c$  values (scaled up from measured  $r_s$  by Irmak *et al.*, 2008) for the 2006 growing season for validation. We further extended the validation of these models using the 2005 growing season. However, there was no measured  $r_s$  or scaled-up  $r_c$  data available in 2005. For further validation of our models in 2005, we estimated  $r_c$  values from the seven models from measured input variables to solve the PM model for hourly actual evapotranspiration ( $E_{Ta}$ ) and compared the estimated  $E_{Ta}$  values with the BREBS-measured  $E_{Ta}$ . The form of the PM equation we used is

$$\lambda E_{Ta} = \frac{\Delta(R_n - G) + \rho c_p \frac{e_s - e_a}{r_a}}{\Delta + \gamma \left(1 + \frac{r_a}{r_a}\right)}, \quad (14)$$

where  $\lambda E_{Ta}$  is the latent heat flux density ( $W\ m^{-2}$ ),  $G$  is the soil heat flux density ( $W\ m^{-2}$ ),  $\Delta$  is the slope of the saturation vapor pressure and air temperature curve ( $Pa\ ^{\circ}C^{-1}$ ),  $\rho$  is the air density ( $kg\ m^{-3}$ ),  $c_p$  is the specific heat of air ( $J\ kg^{-1}\ ^{\circ}C^{-1}$ ),  $\gamma$  is the psychrometric constant ( $Pa\ ^{\circ}C^{-1}$ ),  $e_s$  and  $e_a$ , respectively, are the saturation and actual vapor pressure of air (Pa) where  $e_s - e_a$  represents VPD, and  $R_n$  is the net radiation ( $W\ m^{-2}$ ).

## 2.6. Statistical Analyses

[15] The ability of the proposed  $r_c$  models to predict the resistances was analyzed using three statistics. The  $r^2$  was used as a measure of goodness of fit (i.e., the measure of total variance accounted for by the model). The RMSD was used as a measure of the total difference between the predicted and observed  $r_c$  values. We used modeling efficiency (EF) to assess the fraction of the variance of the observed values which is explained by the model, so EF provides good measure of model performance. In the EF, the higher values indicate better agreement and the best model is the one with a value of EF closest to unity. Physically, EF is the ratio of the mean square error to the variance in the observed data and subtracted from unity. The EF is an improvement in model evaluation in that it is sensitive to differences in the observed and model-simulated means and variances. However, because of the squared differences, EF can be overly sensitive to extreme values. The EF is expressed as

$$EF = 1 - \frac{\sum (O_i - P_i)^2}{\sum (O_i - \bar{O})^2}, \quad (15)$$

where  $O_i$  and  $P_i$  are the observed and predicted  $r_c$  values, respectively, and  $\bar{O}$  is the mean of observed data. All statistical analyses were performed using STATISTICA™ (ver. 7.1, StatSoft, Inc., Tulsa, Okla.).

## 3. Result and Discussion

### 3.1. Climatic Conditions

[16] A summary of the measured meteorological data for the 2005 and 2006 growing seasons and long-term (32 year) average values are presented in Table 1. During 2006, the year used for model calibration, rainfall from April through July (245 mm) was less than the long-term average (374 mm). August was wetter than average (119 mm versus 83 mm), and daily average incoming shortwave solar radiation ( $R_s$ ) was less ( $224\ W\ m^{-2}$ ) as compared with the previous 4 months of the growing season. Maximum  $T_a$  was 1.5 to 3.5 $^{\circ}C$  higher than the long-term average from May to July. Similarly,  $R_s$  was 18 to 31  $W\ m^{-2}$  greater than the long-term average in the same time period. Relative humidity was also less in 2006 than in an average year. Average wind speed was very similar to long-term average values. From March to August 2006, the  $T_{a\_min}$  was, on average, 1.3 $^{\circ}C$  higher than the long-term average. Overall, 2006 was warmer and drier than an average year. Year 2005, which was used for model validation, was drier than a normal year with 72% normal total rainfall. On a seasonal average  $T_{a\_max}$  in 2005 was 0.6 $^{\circ}C$  higher than the average with  $T_{a\_max}$  in September averaging 2.2 $^{\circ}C$  higher than the average. The warmest month was July with an average  $T_{a\_max}$  of 30.4 $^{\circ}C$ . The seasonal average  $T_{a\_min}$  was 1.4 $^{\circ}C$  higher, and  $R_s$  was 14  $W\ m^{-2}$  higher than the average.

**Table 1.** Meteorological Parameters Measured for the Period of March–October at Clay Center, Neb<sup>a</sup>

Period	Meteorological Variable	March	April	May	June	July	August	September	October
2005	$u_3$ (m s <sup>-1</sup> )	4.7	5.1	5.0	3.7	2.4	1.7	2.4	3.1
	$T_{a\_max}$ (°C)	11.6	17.3	23.3	28.4	30.4	27.8	27.5	19.4
	$T_{a\_min}$ (°C)	-1.9	4.5	9.6	16.5	17.8	16.7	13.4	5.7
	RH <sub>avg</sub> (%)	66.8	68.5	63.6	71.2	70.7	78.3	68.2	67.2
	$R_s$ (W m <sup>-2</sup> )	150.4	206.5	259.0	279.3	283.0	223.1	207.8	145.6
	$R_n$ (W m <sup>-2</sup> )	71.0	108.5	138.7	172.1	174.4	132.8	111.2	59.2
	Rainfall (mm)	52.4	64.4	41.7	77.1	69.6	60.4	42.6	32.2
2006	$u_3$ (m s <sup>-1</sup> )	4.6	4.9	4.7	3.2	1.7	1.5	1.9	3.4
	$T_{a\_max}$ (°C)	9.1	20.5	24.3	29.6	30.3	27.8	22.9	16.1
	$T_{a\_min}$ (°C)	-2.7	5.2	10.8	15.9	18.3	17.0	9.7	3.4
	RH <sub>avg</sub> (%)	72.7	64.6	61.0	65.2	73.4	79.8	71.3	70.3
	$R_s$ (W m <sup>-2</sup> )	157.6	214.0	256.3	288.4	278.4	224.8	181.8	120.4
	$R_n$ (W m <sup>-2</sup> )	72.0	111.4	141.8	169.5	174.0	142.1	108.5	53.8
	Rainfall (mm)	4.3	46.5	60.1	54.2	83.8	118.9	75.9	21.8
Long-term average (1975–2007)	$u_3$ (m s <sup>-1</sup> )	4.1	4.4	4.0	3.5	2.9	2.6	3.1	3.3
	$T_{a\_max}$ (°C)	10.5	17.0	22.5	28.1	30.3	29.2	25.3	18.3
	$T_{a\_min}$ (°C)	-3.2	2.4	9.3	14.6	17.3	16.3	10.7	3.6
	RH <sub>avg</sub> (%)	69.8	66.3	71.3	70.2	73.2	74.5	68.8	67.2
	$R_s$ (W m <sup>-2</sup> )	156.6	196.0	225.0	259.8	259.8	228.5	184.4	131.1
	$R_n$ (W m <sup>-2</sup> )	40.0	59.0	112.0	110.0	93.0	83.0	63.0	45.0

<sup>a</sup>Wind speed at 3 m ( $u_3$ ), maximum and minimum air temperature ( $T_{a\_max}$  and  $T_{a\_min}$ ), average relative humidity (RH<sub>avg</sub>), average incoming shortwave radiation ( $R_s$ ), average net radiation ( $R_n$ ), and total rainfall.

Wind speed and relative humidity values were similar to the long-term average values.

### 3.2. Seasonal Patterns of Hourly Canopy and Aerodynamic Resistances

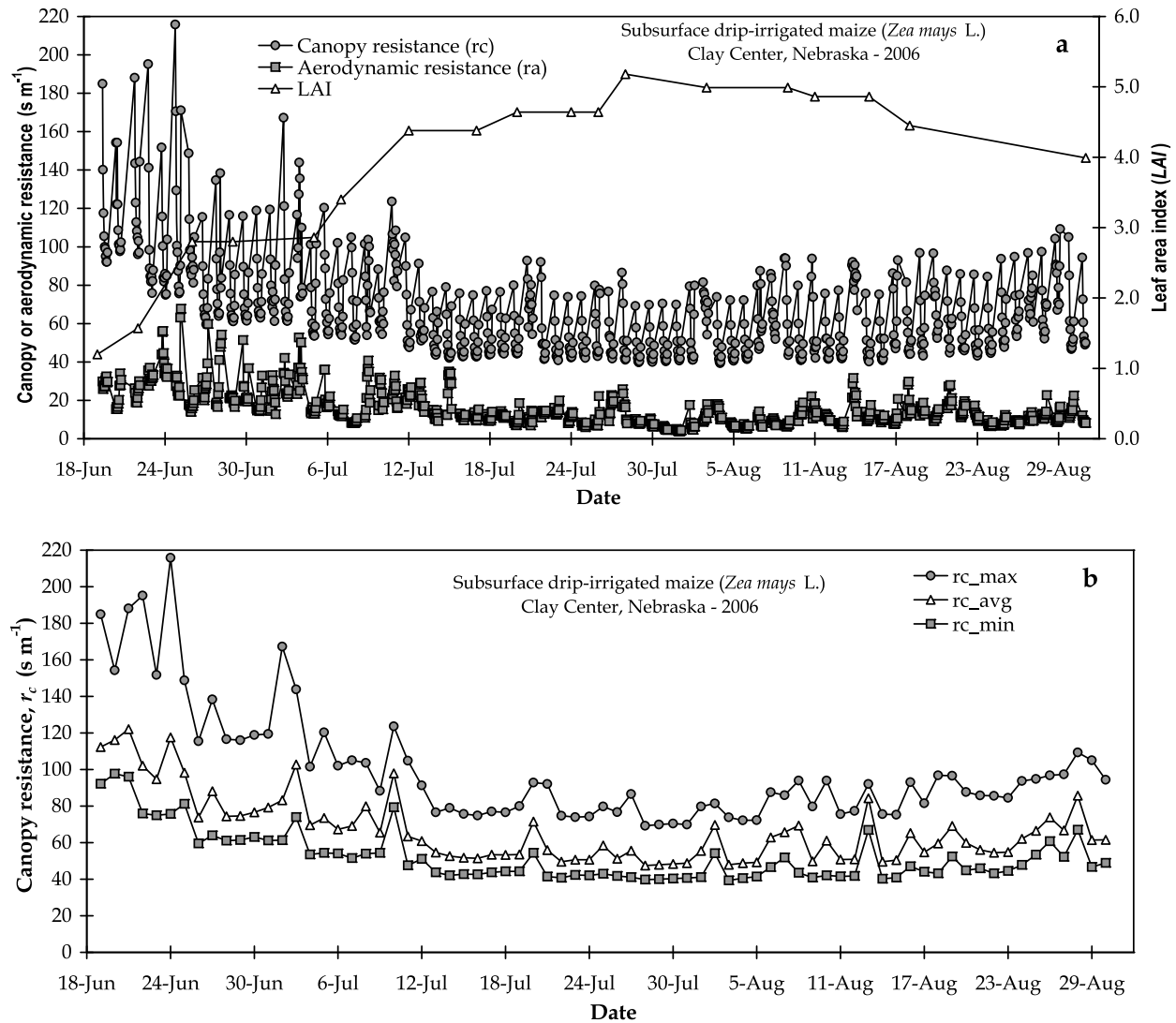
[17] Hourly  $r_c$  decreased from early season during partial canopy toward midseason in early July, remained relatively stable until mid-August, and increased again, slightly, until late August (Figure 1a). Similar to other studies [Monteith, 1995; Alves *et al.*, 1998; Perez *et al.*, 2006], we observed a typical theoretically expected parabolic variation in the diurnal trend of  $r_c$  in Figure 1a, characterized by a high resistance in the morning, gradually decreasing to a minimum in between 13:00 and 16:00 pm and gradually increasing in the afternoon until sunset. The profile of the graph is explained by the soil-plant-atmosphere continuum such that as long as the soil profile can supply the water to meet the evaporative atmospheric demand,  $r_c$  will decrease with increasing radiation. However, when the evaporative demand exceeds the rate of soil water absorption at the root zone, typically in the afternoon,  $r_c$  may increase to reduce transpiration.

[18] From 19 June until first week of July,  $r_c$  was at its greatest values ranging from a daily minimum of 50–60 s m<sup>-1</sup> to around 200 s m<sup>-1</sup>. The  $r_c$  and LAI showed an inverse relationship, where  $r_c$  decreased as LAI increased.  $r_c$  remained relatively stable when LAI reached 3.5–4.0. The maximum  $r_c$  occurred on 24 June at 09:00 am as 216 s m<sup>-1</sup>. During that hour, the following conditions were observed: LAI = 1.6,  $u_3$  = 3.3 m s<sup>-1</sup>,  $T_a$  = 17.9°C, RH = 93.9%,  $R_s$  = 109.3 W m<sup>-2</sup>, and  $R_n$  = 57.4 W m<sup>-2</sup>, with a moderate atmospheric demand (VPD = 0.80 kPa). This high  $r_c$  value (216 s m<sup>-1</sup>) can also be a result of dew formation on the leaves. On average,  $r_c$  fluctuated within a magnitude of about 50 s m<sup>-1</sup> diurnally. Diurnal fluctuations were greatest (>70–75 s m<sup>-1</sup>) early in the season and least (≈30 s m<sup>-1</sup>) in the midseason. The maximum diurnal fluctuation range of  $r_c$  was observed on 24 June as 140 s m<sup>-1</sup>.  $r_a$  followed a similar trend as  $r_c$  throughout the season with lower mag-

nitudes (Figure 1a).  $r_a$  was also high during the early season when plant was short, gradually decreased toward mid-season, and slightly increased again after mid-August.  $r_a$  ranged from approximately 3 s m<sup>-1</sup> in midseason to around 60 s m<sup>-1</sup> in early season. The maximum  $r_a$  was obtained on 25 June as 67.7 s m<sup>-1</sup> when  $h$  = 1.8 m, LAI = 1.57, and within a daily average  $r_c$  = 98.3 s m<sup>-1</sup>.  $r_a$  remained relatively constant during the mid season due to constant  $h$  (ranging between 2 and 2.2 m), fluctuating in a narrow range between 10 to 20 s m<sup>-1</sup>. The seasonal average  $r_a$  was 15.9 s m<sup>-1</sup>.

### 3.3. Relationship Between $r_c$ and Micrometeorological Variables

[19] The relationships between  $r_c$  versus  $T_a$ , RH, VPD,  $R_n$ ,  $R_s$ ,  $u_3$ , wind direction, LAI,  $\Theta$ , and  $r_a$  on an hourly basis are presented in Figures 2a–2j, respectively. We used linear regression, exponential, or power functions as the best-fit functions, depending on the distribution of the data. The relationships between  $r_c$  versus  $u_3$ , wind direction, and  $\Theta$  were weak. There was a strong relationship between  $r_c$  and  $T_a$ , and the  $T_a$  range during the season was between 15.7°C to 39°C (Figure 2a). We found larger values and a larger range of values of  $r_c$  for  $T_a$  values <29°C.  $r_c$  responded to  $T_a$  in a much narrower range for temperatures >29°C. Although there was a general trend of increasing  $r_c$  with increasing RH, this relationship is not strong ( $r^2$  = 0.12, Figure 2b). The response of  $r_c$  to VPD was stronger than to RH with  $r^2$  = 0.23. Aphalo and Jarvis [1991] investigated the response of stomata to leaf surface humidity and temperature and showed that the relationship between  $g$  and RH was different when measured at the same temperature rather than at different temperatures. They observed a reversible response to RH under constant temperature and that there was also a response to temperature under constant RH. An inversely proportional response was consistently obtained when  $g$  was expressed in relation to VPD. Mott and Parkhurst [1991] and Oren *et al.* [1999] showed that the response of stomata is not to VPD (or RH) directly, but it is the transpiration rate which responds directly to VPD. However, this may not be the only mecha-



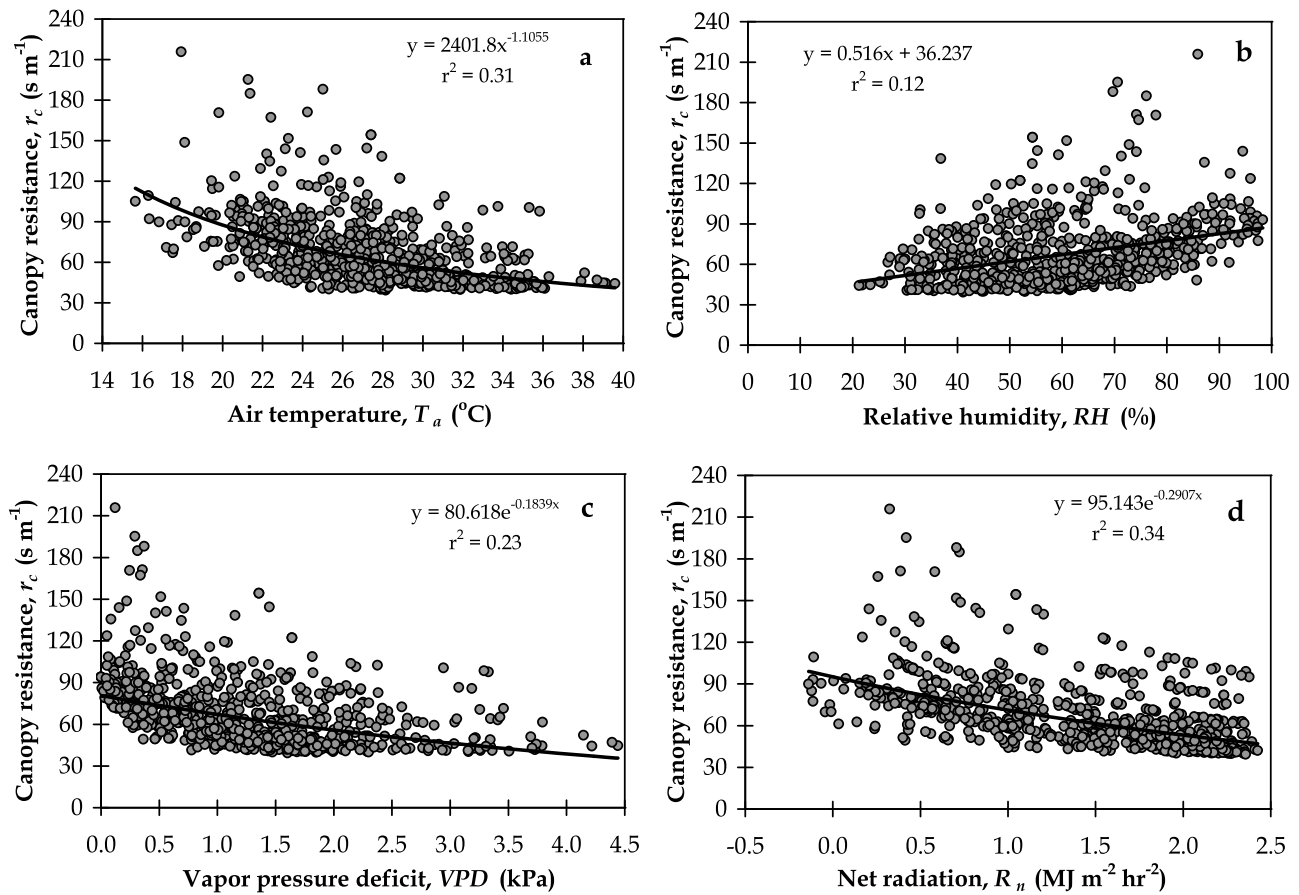
**Figure 1.** (a) Seasonal pattern of hourly canopy resistance ( $r_c$ ) and aerodynamic resistance ( $r_a$ ) in relation to leaf area index (LAI), and (b) and seasonal daily pattern of maximum, average, and minimum canopy resistance for a nonstressed maize canopy.

nism that causes changes in  $r_s$ . Other factors such as change in leaf water potential as a result of transpiration responding to VPD is most likely responsible for changes in  $r_s$  due to this signal (respond to change in water potential) transferring to the guard cells. A number of leaf-level semi-empirical models used different forms of functions of either RH or VPD when modeling stomatal response. For example, the models proposed by *Ball et al.* [1987] (Ball-Berry model) and *Collatz et al.* [1991] suggest that  $g$  is somewhat linear in RH. Others semiempirical in VPD (based on *Leuning et al.* [1995]) and a new class of models based on optimization theories suggest a  $VPD^{0.5}$  dependence of  $g$  (i.e., a power-law versus exponential). Another study showed a  $\log(VPD)$  dependence of  $g$  [*Oren et al.*, 1999]. *Oren et al.* [1999] also showed that stomatal sensitivity is proportional to the magnitude of  $g$  at low VPD ( $\leq 1$  kPa) and concluded that plant species with high  $g$  at low VPD show a greater sensitivity to VPD. The linear model presented by *Katul et al.* [2009b] is consistent with aforementioned studies in terms of the dependency of  $g$  to VPD.

The main rationale of using RH rather than VPD in our models will be discussed in section 3.4.

[20] As expected, the response of  $r_c$  to  $R_n$  was much stronger than for  $R_s$  (Figures 2d and 2e) ( $r^2 = 0.34$  for  $R_n$  versus  $r^2 = 0.10$  for  $R_s$ ), since  $R_n$ , rather than  $R_s$ , represents the amount of energy intercepted at the canopy level that cause a response in stomata. Higher  $r_c$  values were observed at lower  $R_n$  values due to the larger magnitude of stomatal closure at lower  $R_n$  even when other environmental factors change. The maximum  $r_c$  ( $216\ s\ m^{-1}$ ) occurred at  $R_n = 0.33\ MJ\ m^{-2}\ h^{-1}$ , and the minimum usually occurred when  $R_n$  was greater than  $2\ MJ\ m^{-2}\ h^{-1}$ . There were many hours when  $r_c$  did not respond to changes in  $R_n$  due to the control of  $r_c$  by other microclimatological variables. Even though there is enough  $R_n$ , high  $u_3$ , low VPD, small LAI, and low  $T_a$  will have an impact in controlling the opening or closure of stomata. Stomatal response to both  $R_n$  and  $R_s$  was discussed in detail by *Irmak and Mutiibwa* [2009]. We observed several different groupings of  $r_c$  with  $R_n$  in Figure 2d





**Figure 2.** Relationship between canopy resistance ( $r_c$ ) and primary microclimatic variables: (a) air temperature ( $T_a$ ), (b) relative humidity (RH), (c) vapor pressure deficit (VPD), (d) net radiation ( $R_n$ ), (e) incoming shortwave radiation ( $R_s$ ), and (f) wind speed at 3 m ( $u_3$ ) ( $n = 755$  for each case). Relationship between canopy resistance ( $r_c$ ) and main microclimatic variables: (g) wind direction, (h) leaf area index (LAI), (i) solar zenith angle ( $\Theta$ ), and (j) aerodynamic resistance ( $r_a$ ) ( $n = 755$  for each case).

that does not occur as much with  $R_s$  in Figure 2e. The reason for this fluctuation or groupings is not clear to the authors. While the relationship between  $r_c$  and  $u_3$  is not very clear, there was a tendency of increasing  $r_c$  with increasing  $u_3$ . The highest  $r_c$  values were obtained in the  $u_3$  range of 2 to 4 m s<sup>-1</sup> (Figure 2f). As observed by *Monteith et al.* [1965], there is slight evidence in Figure 2f that the  $r_c$  responds to  $u_3$  at higher wind speeds, but the changes in  $r_c$  are too small.

[21] Figure 2h presents the relationship between daily LAI and hourly  $r_c$ . The relationship between the  $r_c$  and LAI is the strongest among all variables ( $r^2 = 0.41$ ).  $r_c$  decreased gradually as LAI increased from 1.20 to 5.30. The magnitude of diurnal fluctuation in  $r_c$  was greater in the early season than in the middle and late season. The larger variations in  $r_c$  at lower LAI and partial canopy cover early in the season were caused by the dry soil surface and higher soil evaporation. The inverse relationship between LAI and  $r_c$  did not hold after approximately LAI = 4.0, although diurnal fluctuation in  $r_c$  was still present. Both variables remained relatively stable for the rest of the season. While the impact of soil surface evaporation on  $r_c$  is not fully understood,  $r_c$  usually increases as soil water is depleted. *Ham and Heilman* [1991] showed that the within-canopy aerodynamic and soil resistance to water vapor transport from the soil surface were greater than

those for the canopy even at low wind speeds. Although *Tanner* [1963] suggested that  $r_c$  contains an aerodynamic component depending on wind speed, our findings support the suggestion of *Monteith et al.* [1965] that resistance is governed primarily by LAI (Figure 2h), light (Figure 2d), temperature (Figure 2a), and VPD (Figure 2c) and is independent of the intensity of turbulent mixing above or within the canopy. This may suggest a high canopy coupling (omega factor,  $\Omega$ ) [*McNaughton and Jarvis*, 1983; *Jarvis and McNaughton*, 1986] between canopy and microclimate above the canopy surface. While quantification of  $\Omega$  was beyond the scope of this study, it is a powerful parameter that describes how strongly the VPD at the canopy surface is linked the boundary layer above the canopy and examines the contribution of radiation and VPD to the transpiration rate [*Jarvis and McNaughton*, 1986].

[22] The relationship between  $r_c$  and  $r_a$  is presented in Figure 2j. The deviation between both resistances is smaller in the low resistance range, while  $r_c$  is always larger than  $r_a$ . On a seasonal average,  $r_c$  was 3.5 times larger than  $r_a$ . It is expected that  $r_a$  would be smaller than  $r_c$  because the evaporative loss is mainly controlled by  $r_c$ . Thus, higher resistance exists at the canopy level for vapor transport. Also,  $r_a$  is often the dominant mechanism for the absorption

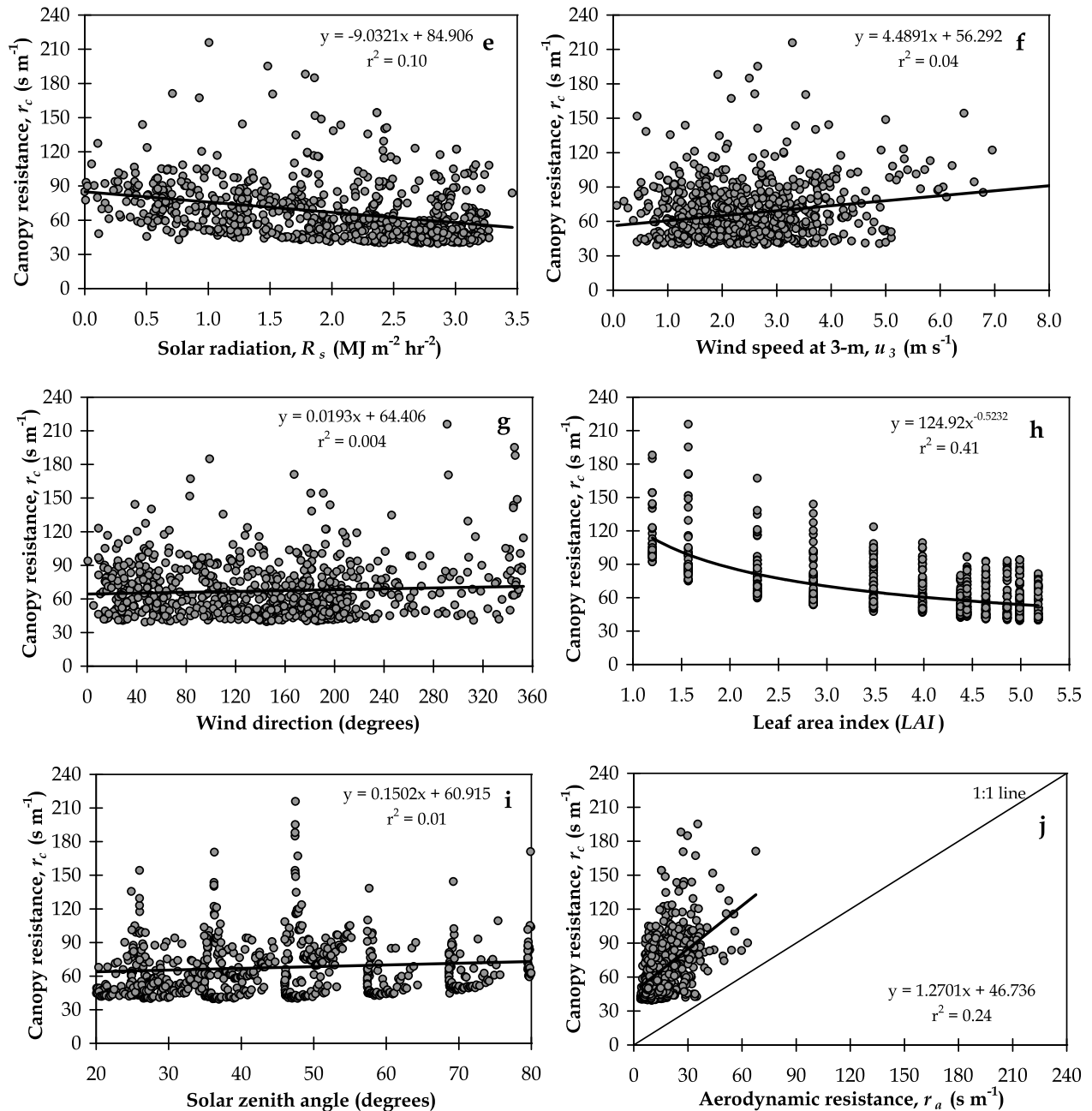
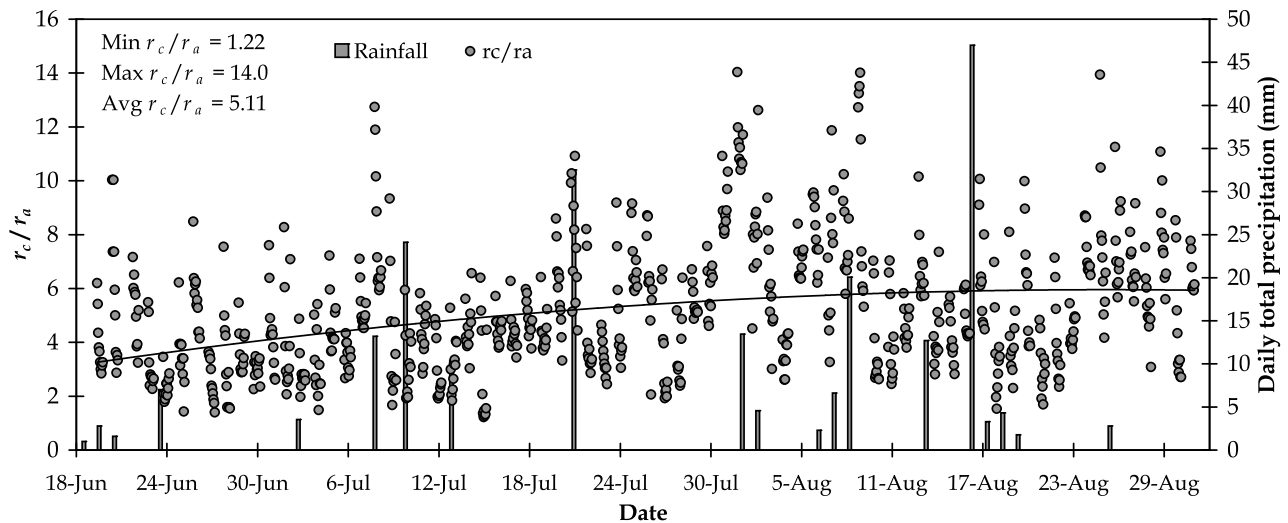


Figure 2. (continued)

of momentum by vegetation so that the resistance to the exchange of momentum between the canopy and surrounding air is smaller than the corresponding resistances to the exchange of heat and vapor, which depend on molecular diffusion alone [Monteith and Unsworth, 1990]. Monteith and Unsworth [1990] analyzed the ratio  $r_c/r_a$  for several mature forest sites and found that the ratio  $r_c/r_a$  is about 50. The ratio can be used as an indicator of the evaporative ratio from wet versus dry canopies. They stated that larger ratios of  $r_c/r_a$  (e.g., 50) would show that evaporation from forest canopies wet with rain would proceed much faster than from

dry canopies exposed to the same microclimatic conditions. Consequently, forests in regions where rain is frequent tend to use more water by evaporation from foliage and transpiration than shorter plants growing nearby. They reported that this contrasts with the situation for many agricultural plants, such as maize, for which minimum values of  $r_c$  are typically  $100 \text{ s m}^{-1}$  but  $r_c/r_a$  is often close to unity. In our case, the minimum  $r_c$  ranged from 40 to  $100 \text{ s m}^{-1}$  (Figure 1b). We found that the hourly  $r_c/r_a$  ratios for our experimental conditions ranged from 1.2 to 14 (Figure 3) with a seasonal average ratio of 5.1, which is much lower than the forest



**Figure 3.** Hourly ratios of canopy resistance ( $r_c$ ) to aerodynamic resistance ( $r_a$ ) ( $r_c/r_a$ ) in relation to precipitation for a nonstressed maize canopy.

canopy as reported by *Monteith and Unsworth* [1990]. Although we did not observe a distinct pattern in the ratio throughout the season, it was lower early in the season, ranging from 1.0 to 8.0; greater in the midseason, fluctuating between 2 and 14, and remained relatively stable around 6.0 from mid-August to the end of the season, although fluctuations were still present. In general, we found that the  $r_c/r_a$  ratio tended to decrease sharply after rain events.

### 3.4. Canopy Resistance Model Calibration and Validation Results

[23] The calibration coefficients  $b$ ,  $c$ ,  $d$ ,  $e$ ,  $f$ ,  $g$ ,  $h$ , and  $k$  and the intercepts ( $a$ ) for the 2006 growing season for the seven models (equations 7–13) are presented in Table 2. Model calibration performance results are presented in Figures 4a–4g. Models  $r_{c\_1}$ ,  $r_{c\_2}$ ,  $r_{c\_3}$ , and  $r_{c\_4}$  had very similar  $r^2$  ( $\sim 0.95$ ) and RMSD ( $\sim 5.0$  s  $m^{-1}$ ). Model  $r_{c\_1}$  had the highest number of modeling variables ( $R_n$ ,  $T_a$ , VPD, RH,  $u_3$ ,  $r_a$ , LAI, and  $\Theta$ ). Models  $r_{c\_6}$  and  $r_{c\_7}$  had very similar performance and had the poorest  $r^2$  of 0.44 and highest RMSD of 17.4 s  $m^{-1}$ . These two models had the least number of modeling variables,  $r_{c\_6}$  with 4 variables ( $R_n$ ,  $T_a$ , RH, and  $u_3$ ) and  $r_{c\_7}$  with 3 variables ( $R_n$ ,  $T_a$ , and RH). The model  $r_{c\_5}$  had a good  $r^2$  of 0.93 and low RMSD of 6.3 s  $m^{-1}$ . The observed seasonal mean  $r_c$  was 75 s  $m^{-1}$ , and the means from all seven models were very similar to the observed value. Estimates from the first five models were very good with very little scatter in the data around the 1:1 line. Models  $r_{c\_6}$  and  $r_{c\_7}$  overestimated in the range of 0 to around 90 s  $m^{-1}$  and underestimated at greater values. The data scatter increased for both models in the higher  $r_c$  range. The coefficients for  $T_a$  and RH for models  $r_{c\_6}$  and  $r_{c\_7}$  are different than other models, whereas the coefficients for other variables were similar for most models. The variation in coefficients for  $T_a$  and RH for models  $r_{c\_6}$  and  $r_{c\_7}$  may be due to exclusion of LAI from these two models such that the influence of  $T_a$  and RH on  $r_c$  was different than other models in the absence of LAI in estimating  $r_c$ .

[24] The seasonal distribution of the hourly residuals that were calculated from the regression between the model estimates of  $r_c$  ( $r_{c\_1}$  through  $r_{c\_7}$ ) versus observed  $r_c$  for the calibration data set are presented in Figure 5. Models  $r_{c\_1}$  through  $r_{c\_5}$  had lower residuals than the models  $r_{c\_6}$  and  $r_{c\_7}$ . The residuals for the models  $r_{c\_1}$  through  $r_{c\_5}$  showed similar trends and tend to fluctuate between similar ranges of  $-20$  to 20 s  $m^{-1}$ . The residuals were higher early in the growing season and fluctuated in a narrower range towards the end of the season. Models  $r_{c\_6}$  and  $r_{c\_7}$  had larger residual fluctuations ranging from  $-35$  to 65 s  $m^{-1}$ . The residuals for these two models were high early in the season, gradually decreased toward the midseason, and remained negative from early July to the end of July. Model  $r_{c\_1}$  had the lowest and models  $r_{c\_6}$  and  $r_{c\_7}$  had the largest residuals. Overall, the sum of squares of the residuals were 8470, 9331, 8649, 8768, 12,754, 45,345, and 45,472 for the models  $r_{c\_1}$  through  $r_{c\_7}$ , respectively. The mean squares of the residuals were 24.8, 27.7, 25.7, 26, 37.8, 134.6, and 135 for the same models, respectively. Except LAI, we did not observe any clear trend of the residuals with respect to any of the micrometeorological drivers measured.

### 3.5. Validation of $r_c$ Models for Estimating Observed $r_c$ in 2006

[25] We validated the models in two ways. First, the models were used to estimate  $r_c$  from 21 July to 30 August in 2006 growing season and the validation results are presented in Figure 6. Compared to the calibration results, the validation RMSD values increased by about 5 s  $m^{-1}$  for all models, and the  $r^2$  decreased to a range of 0.69 to 0.73. The  $r^2$  of 0.71 and 0.70 was a significant improvement in performance for models  $r_{c\_6}$  and  $r_{c\_7}$ , which had a calibration  $r^2$  of 0.44. Models  $r_{c\_1}$ ,  $r_{c\_2}$ ,  $r_{c\_3}$ ,  $r_{c\_4}$ , and  $r_{c\_5}$  had means ranging from 50.3 to 51.5 s  $m^{-1}$ , which was close to the observed mean (55.9 s  $m^{-1}$ ). The means of  $r_{c\_6}$ , and  $r_{c\_7}$  were 76.1 and 75.9 s  $m^{-1}$ . With the EF ranging from 0.57 to 0.65, models  $r_{c\_1}$ ,  $r_{c\_2}$ ,  $r_{c\_3}$ ,  $r_{c\_4}$ , and  $r_{c\_5}$  demonstrated a

**Table 2.** Calibration Coefficients<sup>a</sup> for the Seven Models Developed to Predict Canopy Resistance as a Function of Net Radiation, Air Temperature, Vapor Pressure Deficit, Relative Humidity, Wind Speed at 3 m, Aerodynamic Resistance, Leaf Area Index, and Solar Zenith Angle

Coefficient	Variable	Models and Coefficients						
		$r_{c\_1}$	$r_{c\_2}$	$r_{c\_3}$	$r_{c\_4}$	$r_{c\_5}$	$r_{c\_6}$	$r_{c\_7}$
	Mean $r_c$	74.9	74.8	74.9	74.9	74.9	75.0	75.0
<i>a</i>	Intercept	5.12	5.31	5.17	5.27	5.07	5.59	5.67
<i>b</i>	$R_n$	-0.39	-0.40	-0.39	-0.40	-0.34	-0.19	-0.20
<i>c</i>	$T_a$	0.01	0.01	0.01	0.01	0.0035	-0.03	-0.03
<i>d</i>	VPD	-0.04	-0.09	-	-	-	-	-
<i>e</i>	RH	0.0027	-	0.00357	0.00344	0.0046	-0.00207	-0.0025
<i>f</i>	$u_3$	0.03	0.03	0.03	0.02	0.03	0.01	-
<i>g</i>	$r_a$	0.0016	0.0016	0.0012	-	-	-	-
<i>h</i>	LAI	-0.24	-0.24	-0.24	-0.25	-0.24	-	-
<i>k</i>	$\Theta$	-0.0023	-0.0022	-0.0027	-0.00277	-	-	-

<sup>a</sup>*a*, *b*, *c*, *d*, *e*, *f*, *g*, *h*, and *k*; measured mean  $r_c$  was 75 s m<sup>-1</sup>.

high efficiency since values of EF close to 1 signify a good modeling performance. Although the RMSD and  $r^2$  results of models  $r_{c\_6}$ , and  $r_{c\_7}$  were acceptable, the EF values were -1.096 and -1.087, respectively. A negative EF indicates that the squared difference between the model predictions and the observed values is larger than the variability in the observed data. Thus, the observed mean is a better predictor than the model. The poor EF of models  $r_{c\_6}$  and  $r_{c\_7}$  was further depicted by the slopes, which showed an overestimation of 33% by both models (Figure 6). Model  $r_{c\_6}$  is different from  $r_{c\_7}$  because of the inclusion of  $u_3$ ; however, from the statistical results in Table 2, the two models presented similar performance. It appears that the performance of models  $r_{c\_6}$  and  $r_{c\_7}$  was compromised by using fewer variables that influence  $r_c$ .

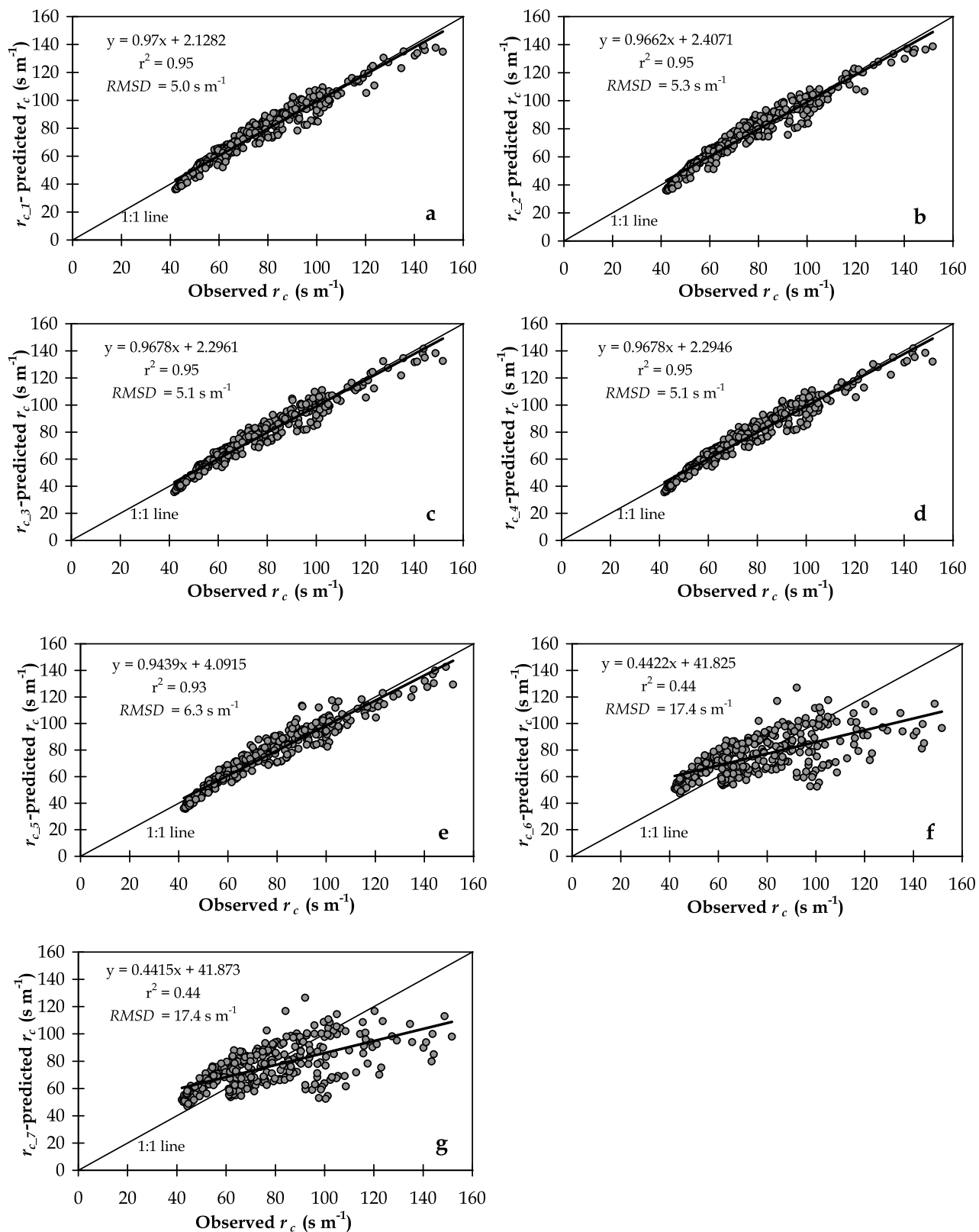
[26] Overall, model  $r_{c\_5}$  performance had the best agreement with the data. The model had the smallest RMSD of 9.3 s m<sup>-1</sup>, highest  $r^2$  of 0.73, the highest EF of 0.65 with only 6% underestimation. Model  $r_{c\_5}$  has 5 variables ( $R_n$ ,  $T_a$ , RH,  $u_3$ , and LAI) with the latter being the only variable not measured by a typical weather station. This is an encouraging performance of the model using readily available weather station data. LAI has been used in both single and multiple layered models as a weighting or scaling factor of  $r_s$  to estimate  $r_c$  [Szeicz and Long, 1969; Sinclair et al., 1976; Whitehead and Jarvis, 1981; Bailey and Davies, 1981; Seller et al., 1986]. Similar to the results presented by Beadle et al. [1985], we observed that the  $r_c$  is considerably influenced by seasonal changes in LAI, and we demonstrated the negative impact of exclusion of LAI, the only plant physiological variable, on  $r_c$  in the performance of models  $r_{c\_6}$ , and  $r_{c\_7}$ , where performance statistics were poor compared to the other models that included LAI.

[27] The performance of model  $r_{c\_1}$ , which used eight variables, was not different from models  $r_{c\_2}$ ,  $r_{c\_3}$ ,  $r_{c\_4}$ , and  $r_{c\_5}$ , which used 5 to 7 variables. To select the better variable between VPD and RH for modeling  $r_c$ , models  $r_{c\_2}$  and  $r_{c\_3}$  were developed with the same number of variables but with one, model  $r_{c\_2}$ , using VPD and the model  $r_{c\_3}$ , using RH. Clearly, the results in Figure 6b versus 6c suggest that RH was a better predictor than VPD with a smaller RMSD and greater  $r^2$  and EF. In model  $r_{c\_3}$ , using RH instead of VPD resulted in 4%, 6%, and 8% improvement in  $r^2$ , RMSD, and EF, respectively. However, the residuals for model  $r_{c\_2}$  and  $r_{c\_3}$  were similar in magnitude and distribution and the improvement in predicted  $r_c$  using  $r_{c\_3}$  was

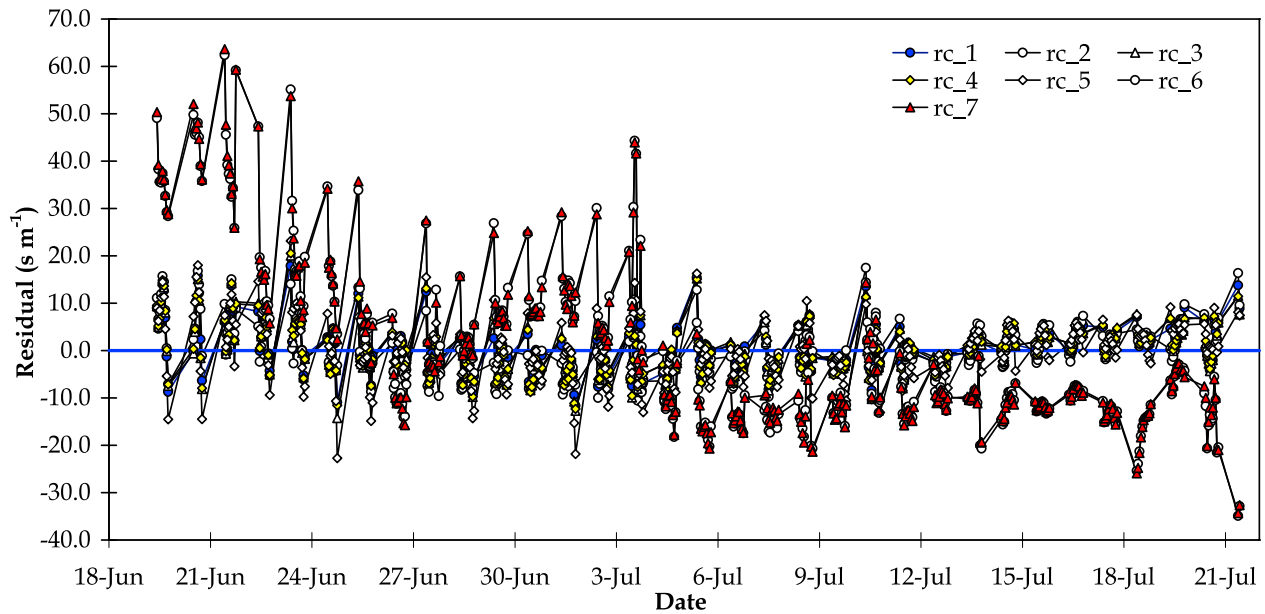
not statistically significant ( $P > 0.05$ ) than predictions of  $r_{c\_2}$ . Nevertheless, since the objective of the study was to model  $r_c$  from weather station-measured climate variables, this was an important finding, and as such, RH rather than VPD was used as a variable for the rest of the models ( $r_{c\_3}$ ,  $r_{c\_4}$ ,  $r_{c\_5}$ ,  $r_{c\_6}$ , and  $r_{c\_7}$ ).

[28] Baldocchi et al. [1991], Finnigan and Raupach [1987], Alves et al. [1998], and Alves and Pereira [2000] have pointed out that  $r_c$  contains additional non-physiological information pertaining to the  $r_a$  in the canopy. Therefore, model  $r_{c\_3}$  was set up to be different from model  $r_{c\_4}$  by the inclusion of  $r_a$ . However, similar to the results obtained by Finnigan and Raupach [1987], the results ( $r^2$  and EF) in Figures 6c and 6d showed that  $r_a$  added a minimal improvement in estimating  $r_c$ . Conversely, elimination of  $\Theta$  as an independent variable from the model  $r_{c\_5}$  resulted in an improvement in RMSD,  $r^2$ , and EF. This suggests that  $r_a$  and  $\Theta$  are of minimal importance in the modeling of  $r_c$ . The results demonstrate that models like  $r_{c\_5}$ , with the variables  $R_n$ , RH,  $T_a$ ,  $u_3$ , and LAI rather than including all variables, such as in model  $r_{c\_1}$ , can provide good performance. This might be due to the fact that inclusion of many independent variables in  $r_c$  modeling can also increase the variability, error, and uncertainty associated with obtaining those variables, thus, negatively impacting the model performance. On the other hand, enough independent variables must be accounted for when modeling  $r_c$  and our results indicated that the model  $r_{c\_5}$  seems to represent this balance (number of variables versus performance).

[29] Figures 6a–6g show a cluster of points of small  $r_c$  values which gradually spread out and decrease in number with increasing variability as the resistances increase. This shows that for a well-watered field,  $r_c$  is dominated by small resistance values, with a few high resistance values generally observed in the morning, late afternoon, and during advection and extreme conditions. In comparison to the 1:1 line, the graphs show that models  $r_{c\_1}$ ,  $r_{c\_2}$ ,  $r_{c\_3}$ ,  $r_{c\_4}$ , and  $r_{c\_5}$  underestimated resistance, whereas  $r_{c\_6}$  and  $r_{c\_7}$  overestimated observed  $r_c$ . Models,  $r_{c\_1}$ ,  $r_{c\_2}$ ,  $r_{c\_3}$ ,  $r_{c\_4}$ , and  $r_{c\_5}$  underestimated observed  $r_c$  by 8%, 10%, 8%, 8%, and 6%, respectively. Both  $r_{c\_6}$  and  $r_{c\_7}$  overestimated by 33%. In Figures 6a–6g, we observed an increase in variability with increasing  $r_c$  for all models. Increased variability could be associated with the rigidity of the models to adjust and depict the limiting variables during extreme conditions. For instance, in the morning hours,  $R_n$  is the limiting factor of  $r_c$ .



**Figure 4.** Calibration (19 June to 15 July 15) performance results for the seven canopy resistance ( $r_c$ ) models ( $n = 405$  for each case).



**Figure 5.** Distribution of residuals of regression between modeled canopy resistance ( $r_{c\_1}$  through  $r_{c\_7}$ ) and observed  $r_c$  for the growing season (19 June to 15 July 2006) for the calibration data set ( $n = 339$ ).

In the afternoon, studies [Adams *et al.*, 1991] have shown that VPD, which is regulated by RH, is typically the limiting factor.

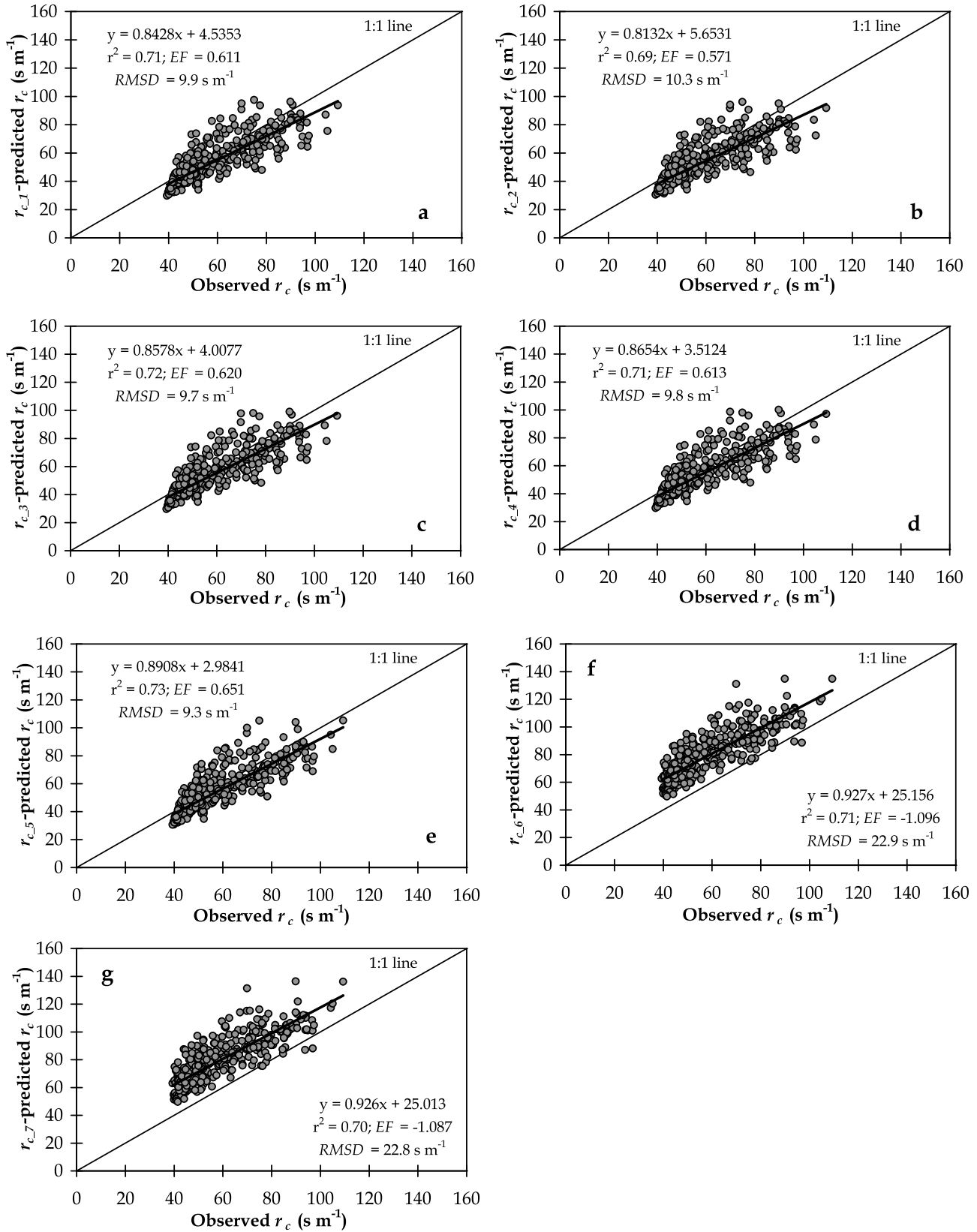
### 3.6. Validation of $r_c$ Models for Estimating $E_{Ta}$ in 2005

[30] Further validation of  $r_c$  model performance was done on an independent data set by estimating  $r_c$  from each model on an hourly basis and then using the PM model as a one-step procedure to estimate  $E_{Ta}$  from modeled  $r_c$ . We then compared the PM-estimated  $E_{Ta}$  to the BREBS-measured  $E_{Ta}$  on an hourly basis. The seasonal distribution of hourly BREBS-measured  $E_{Ta}$  data from 1 May to 31 August that were used is presented in Figure 7. Hourly  $E_{Ta}$  ranged from near zero to  $1.16 \text{ mm h}^{-1}$ . There was a strong agreement between the BREBS-measured and the PM-estimated  $E_{Ta}$  (Figure 8a–8g for models  $r_{c\_1}$  through  $r_{c\_7}$ , respectively). The results show that the performance of all models is similar with  $r^2$  ranging from 0.88 to 0.90. The RMSD ranged from  $0.09 \text{ mm h}^{-1}$  for models  $r_{c\_6}$  and  $r_{c\_7}$  to  $0.13$  to  $0.15 \text{ mm h}^{-1}$  for other models. The  $E_{Ta}$  estimated with  $r_c$  from models  $r_{c\_6}$  and  $r_{c\_7}$  marginally underestimated BREBS-measured  $E_{Ta}$  by only 1%, performing better than the models  $r_{c\_1}$ ,  $r_{c\_2}$ ,  $r_{c\_3}$ ,  $r_{c\_4}$ , and  $r_{c\_5}$ , which overestimated BREBS-measured  $E_{Ta}$  by 17%, 18%, 16%, 16%, 16%, and 16%, respectively. The  $E_{Ta}$  predicted with  $r_c$  models  $r_{c\_6}$  and  $r_{c\_7}$  had a mean of  $0.52$  which was closely similar to the mean of measured  $E_{Ta}$  ( $0.53 \text{ mm h}^{-1}$ ). The means of  $E_{Ta}$  predicted with canopy resistance estimated from models  $r_{c\_1}$ ,  $r_{c\_2}$ ,  $r_{c\_3}$ ,  $r_{c\_4}$ , and  $r_{c\_5}$  were  $0.61$ ,  $0.62$ ,  $0.61$ ,  $0.61$ , and  $0.61 \text{ mm h}^{-1}$ , respectively. The  $E_{Ta}$  predicted using  $r_{c\_6}$  and  $r_{c\_7}$  had a standard deviation of  $0.24 \text{ mm h}^{-1}$  which was less than the standard deviation of the other five models ( $0.27 \text{ mm h}^{-1}$ ).

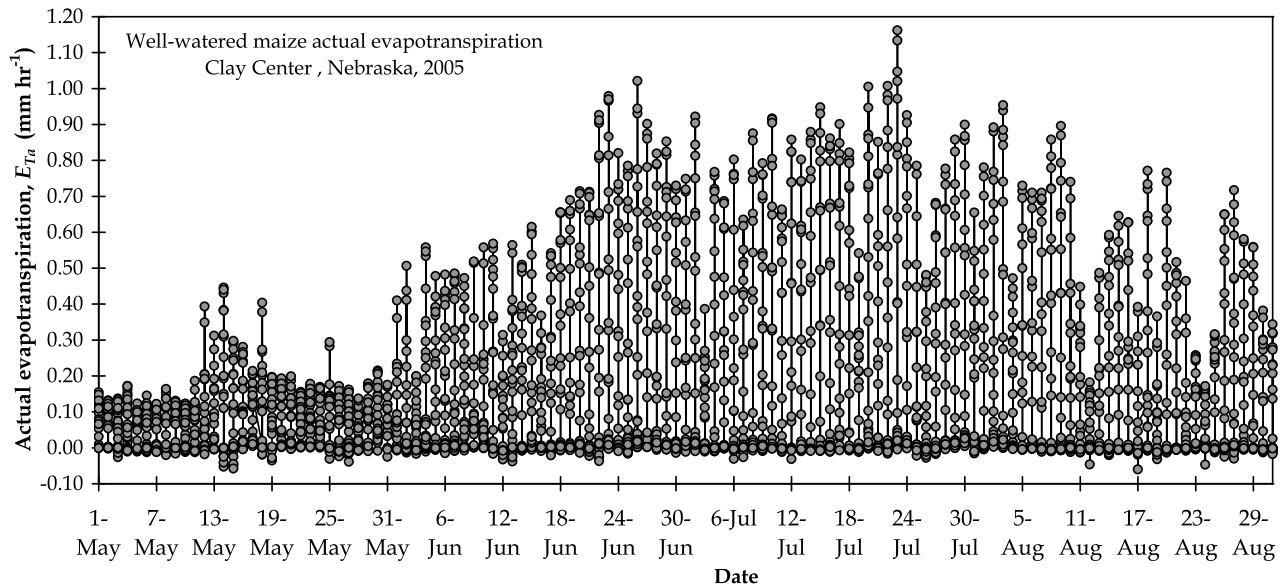
[31] Unlike the results of  $r_c$  validation in 2006, the 2005 results clearly demonstrate that estimating  $E_{Ta}$  using  $r_c$  estimated from models  $r_{c\_6}$  and  $r_{c\_7}$  performed better than using the rest of the models. However, models  $r_{c\_6}$  and  $r_{c\_7}$  overestimated observed  $r_c$  (Figures 6f and 6g, respectively). Thus,

one would have expected these models to estimate lower  $E_{Ta}$  as compared with the BREBS-measured  $E_{Ta}$ , but the  $E_{Ta}$  estimates of both models were within 1% of the BREBS  $E_{Ta}$ . This may be due to the combination of three reasons. First, it is likely that the PM model overestimated  $E_{Ta}$ , but since the  $r_{c\_6}$  and  $r_{c\_7}$  models were producing lower  $E_{Ta}$  due to overestimation of  $r_c$ , this offset the overestimation by the PM model as compared with the BREBS measurements. Steduto *et al.* [2003] and Rana *et al.* [1994] showed that the PM equation overestimates in cases with low ET values. Perez *et al.* [2006], Zhang *et al.* [2008], and Irmak and Mutiibwa [2009] showed that the PM equation can overestimate  $E_{Ta}$  during full canopy cover, especially during periods of high evaporative atmospheric demand. This is because during complete canopy cover and especially during periods with high evaporative atmospheric demand conditions when there is available soil water supply, the variable  $r_c$  approach in the PM model assigns a small resistance value which is assumed to be homogeneous for the whole canopy when in reality some leaves in the canopy are shaded and/or aged and may not contribute to the transpiration rate at the same level as the sunlit and young leaves [Irmak and Mutiibwa, 2009]. Younger and sunlit leaves would have lower  $r_c$  values than the older and shaded leaves, thus, transpiring at different levels and contributing differently to the total evaporative losses estimated by the PM model. It would be expected that the  $E_{Ta}$  rate estimated from the PM model to be less than those measured values. Thus, the  $E_{Ta}$  measured by the BREBS may better represent the total evaporative losses from the whole canopy accounting for  $E_{Ta}$  from various levels of shading and leaves with different ages.

[32] The second possible explanation is, especially in relation to the performance of the PM model in high atmospheric demand conditions, that the  $r_c$  may have been underestimated by models  $r_{c\_6}$  and  $r_{c\_7}$  in our case rather than the PM model itself overestimating during high evaporative demand conditions. The underestimation of  $r_c$  in our case might be due to not accounting for the VPD by Irmak *et al.*



**Figure 6.** Validation (16 July to 31 August 2006) performance results for the seven canopy resistance ( $r_c$ ) models ( $n = 405$  for each case).



**Figure 7.** Seasonal (1 May to 31 August 2005) distribution of Bowen ratio energy balance system (BREBS)-measured hourly actual evapotranspiration ( $E_{Ta}$ ) for well-watered maize canopy ( $n = 2952$ ).

[2008] during the scaling-up  $r_s$  to  $r_c$  process, which is especially important during high evaporative demand settings. Furthermore, some variables may have been misestimated due to experimental and instrumental errors. Relative humidity, for example, is never perfectly estimated [Ewers and Oren, 2000] and the  $R_n$  measurements may not have been perfect. In addition, the BREBS-measured  $E_{Ta}$  contains some measurement error as well. The third possible explanation is the potential insensitivity of  $E_{Ta}$  to  $r_c$ . It has been suggested that  $E_{Ta}$  is estimated more accurately than estimated  $r_c$  because  $E_{Ta}$  depends only in part on  $r_c$  [Stewart, 1988; Stewart and Gay, 1989; Gash *et al.*, 1989]. The sensitivity analyses by Finnigan and Raupach [1987], Stewart [1988], and Gash *et al.* [1989] indicate that the  $E_{Ta}$  is fairly insensitive to  $r_c$  for agronomical plants. If the  $E_{Ta}$  is insensitive to  $r_c$ , then the better performance of models  $r_{c,6}$  and  $r_{c,7}$  in estimating  $E_{Ta}$  could be an artifact of a random performance based on the 2005  $E_{Ta}$  and climate data set. We further tested this by evaluating the sensitivity of  $E_{Ta}$  to  $r_c$  for our data set in the next section.

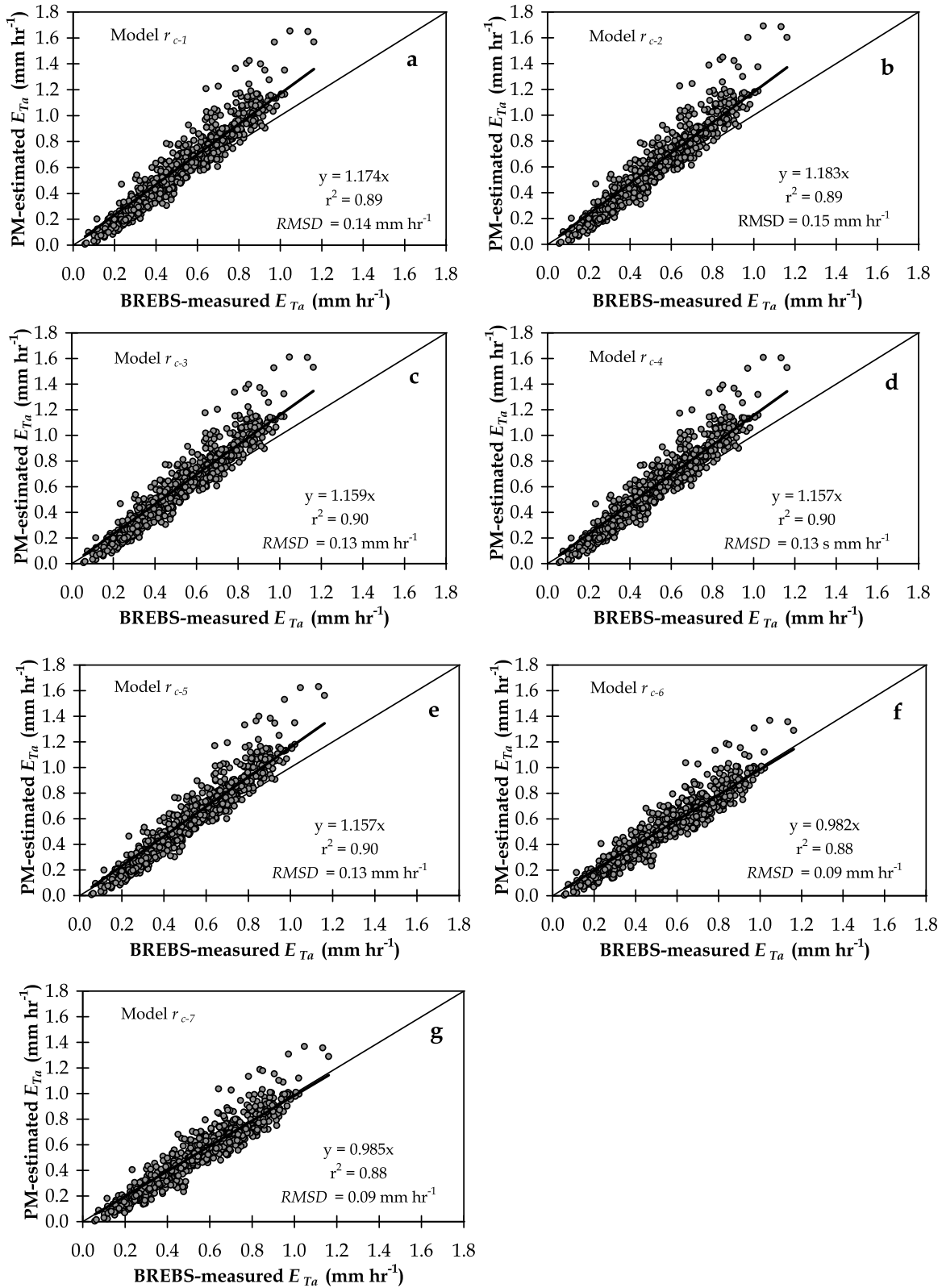
### 3.7. Sensitivity of PM Model to $r_c$

[33] Figure 9 presents the change in  $E_{Ta}$  ( $\text{mm h}^{-1}$ ) as estimated from the PM model per  $10 \text{ s m}^{-1}$  increase in observed  $r_c$ . The cumulative percent change in PM-estimated  $E_{Ta}$  versus changes in  $r_c$  for a morning and noon hour of the same day are also included in the same figure. While we kept all the variables constant during the analyses, we conducted the sensitivity analyses for a randomly selected day (19 June), and analyzed the sensitivity of  $E_{Ta}$  to  $r_c$  for a morning hour (09:00 am) and a noon hour (1:00 pm) for the same day to assess whether the  $E_{Ta}$  shows different response in two different microclimatic conditions for a canopy in the same environment. The observed  $r_c$  was increased from zero to  $300 \text{ s m}^{-1}$  with  $10 \text{ s m}^{-1}$  increments, and the  $E_{Ta}$  rate and the percent change in  $E_{Ta}$  from the PM model were calculated for

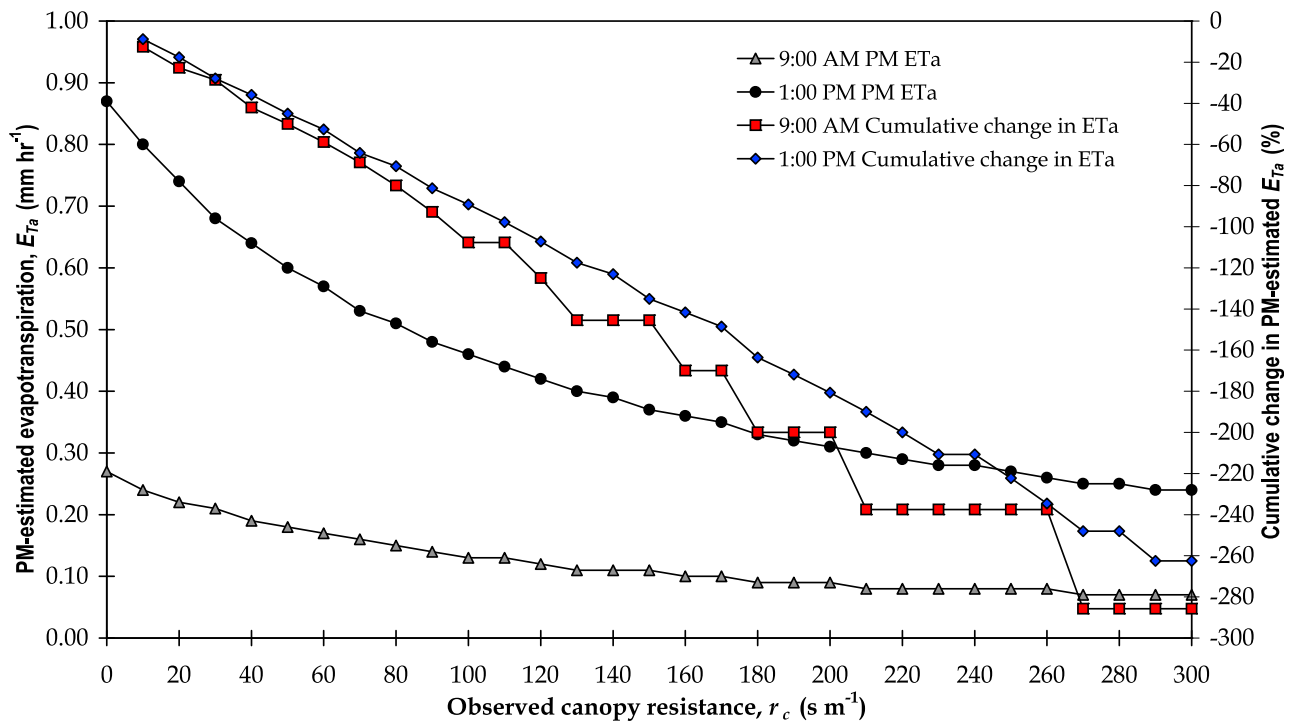
both hours. The initial (base)  $E_{Ta}$  and  $r_c$  values along with the other microclimatic variables measured at 09:00 am and 1:00 pm are presented in Table 3. The response of  $E_{Ta}$  to changes in  $r_c$  was similar for morning and noon hours with decreasing trend in  $E_{Ta}$  as  $r_c$  increased. With the initial  $r_c$  ( $185 \text{ s m}^{-1}$  for 09:00 am and  $100 \text{ s m}^{-1}$  for 1:00 PM) and other measured microclimatic variables, the PM-estimated  $E_{Ta}$  at 09:00 and 1:00 pm, respectively, were  $0.09 \text{ mm h}^{-1}$  and  $0.46 \text{ mm h}^{-1}$ . A unit ( $10 \text{ s m}^{-1}$ ) increase in  $r_c$  had slightly higher decrease in  $E_{Ta}$  for 1:00 pm, and the exponent of the  $E_{Ta}$  versus  $r_c$  lines for 1:00 pm was slightly higher ( $-0.0041$ ) than the one for 09:00 am ( $-0.0043$ ) (Figure 9). The  $a$  values in the exponential functions (equations are not shown on Figure 9) ( $0.738$  and  $0.2203$ ) are analogous to an intercept because these are the values of the functions when  $X=0$  since  $\exp(0) = 1$ . Since the exponents are similar,  $a$  value is more influential on the rate of change (the derivatives of the exponential functions) in  $E_{Ta}$ . The magnitude of the average rate of change in  $E_{Ta}$  at 1:00 pm was greater [ $-0.001744 \text{ mm h}^{-1}$  decrease in  $E_{Ta}$  (negative sign indicates decrease) per  $1 \text{ s m}^{-1}$  increase in  $r_c$ ] than for 09:00 am ( $-0.00053 \text{ mm h}^{-1}$  decrease in  $E_{Ta}$  per  $1 \text{ s m}^{-1}$  increase in  $r_c$ ).  $E_{Ta}$  did not respond to changes in  $r_c$  after about  $210 \text{ s m}^{-1}$  in the morning and after  $270 \text{ s m}^{-1}$  at 1:00 pm. Even though the rate of change was greater for the 1:00 pm curve, a unit increase in  $r_c$  had slightly higher percentage decrease in  $E_{Ta}$  in the morning. This is due to the solar radiation being significantly higher at noon than in the morning ( $888$  versus  $283 \text{ W m}^{-2}$ ). Since the solar radiation is the primary regulator of  $r_c$ , when there is sufficient light to keep stomata fully open, a unit increase in  $r_c$  would be expected to have lower impact on  $E_{Ta}$  under the same amount of radiation when the radiation is kept constant. This is because the role of other environmental variables in controlling stomata would be greater when there is no sufficient light in the morning.

[34] The cumulative percent change in  $E_{Ta}$ , reached  $-286\%$  for morning and  $-262\%$  at 1:00 pm (Figure 9) with





**Figure 8.** Comparison of Penman-Monteith (PM)-estimated hourly actual evapotranspiration ( $E_{Ta}$ ), using estimated canopy resistance ( $r_c$ ) from the seven models developed in this study, and the Bowen ratio energy balance system (BREBS)-measured hourly  $E_{Ta}$  for a well-watered maize canopy.



**Figure 9.** Response of Penman-Monteith (PM) model-estimated actual evapotranspiration ( $E_{Ta}$ ) to changes in canopy resistance ( $r_c$ ) for a morning and noon hour of the same day (19 June 2006) for a non-stressed maize canopy and cumulative percent change in Penman-Monteith (PM) model-estimated actual evapotranspiration ( $E_{Ta}$ ) versus changes in canopy resistance ( $r_c$ ) for a morning and noon hour of the same day (19 June 2006) for a nonstressed maize canopy.

the negative sign indicating decrease in  $E_{Ta}$ . In total, the  $E_{Ta}$  decreased from 0.27 to 0.07 mm at 09:00 am and from 0.87 to 0.24 mm  $h^{-1}$  at 1:00 pm when  $r_c$  increased from 0 to 300  $s m^{-1}$ . Until 100  $s m^{-1}$ , the response of  $E_{Ta}$  to change in  $r_c$  was never zero and was very similar for both the morning and noon hour (Figure 9). After 100  $s m^{-1}$  for the morning and 200  $s m^{-1}$  for the noon hour, the PM model sometimes showed no response (zero decrease in  $E_{Ta}$ ) to increase in  $r_c$  every 10 or 20  $s m^{-1}$ ; thus,  $E_{Ta}$  response fluctuated in a wider range for the morning hour. Zero decrease in  $E_{Ta}$  was observed only three times for 1:00 pm at higher  $r_c$  values (240, 280, and 300  $s m^{-1}$ ). While we conducted the sensitivity analyses for only 1 day with morning and noon hours, the sensitivity of the PM  $E_{Ta}$  may show variation with time of the season due to changes in canopy and due to aerodynamic and energy terms of the model showing different sensitivities to dynamic micrometeorological conditions. However, while the magnitude of the sensitivity of the model may show variations, the trend and the relative sensitivity of the PM  $E_{Ta}$  to  $r_c$  should be similar throughout the season.

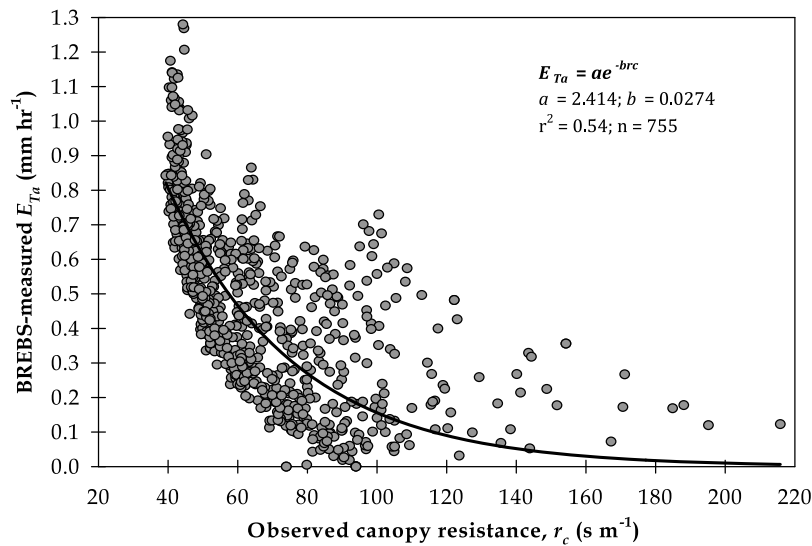
[35] To evaluate the relationship between observed  $r_c$  and  $E_{Ta}$  throughout the season in 2006, we graphed observed scaled-up hourly  $r_c$  values against BREBS-measured hourly  $E_{Ta}$  in Figure 10 and found a strong relationship between the two variables. The  $r_c$  and  $E_{Ta}$  data points in Figure 10 include those measured diurnally, usually from 09:00 am to 5:00 or 6:00 pm, from 19 June through 31 August 2006. The relationship was explained with an exponential decay function ( $Y = ae^{-bx}$ ;  $a = 2.414$  and  $b = 0.0274$ ). On an hourly time step,  $r_c$  alone was able to explain 54% of the

variability ( $r^2 = 0.54$ ) in  $E_{Ta}$ , further indicating a strong dependence of  $E_{Ta}$  on  $r_c$ . The terms  $a$  and  $b$  had standard deviation of 0.1435 and 0.0011, respectively, with both terms being statistically significant ( $P < 0.0001$ ). Figure 10 shows that most of the higher  $E_{Ta}$  rates were observed at the lower  $r_c$  range (40 to 100  $s m^{-1}$ ). The  $E_{Ta}$  rate decreased gradually as  $r_c$  increased. The highest BREBS-measured  $E_{Ta}$  rate (1.28 mm  $h^{-1}$ ) occurred when observed  $r_c$  was 44.3  $s m^{-1}$ . The higher  $r_c$  and lower  $E_{Ta}$  values in Figure 11 were observed in early morning hours and cloudy days with low solar radiation. These results and the sensitivity analy-

**Table 3.** Measured Environmental Variables at 09:00 am and 1:00 pm Where the Sensitivity of Penman-Monteith-Estimated Actual Evapotranspiration to Canopy Resistance was Determined<sup>a</sup>

Measured Variable	Unit	09:00 am	1:00 pm
$T_a$	°C	19.4	25.8
$R_s$	W $m^{-2}$	283.2	888.4
$R_n$	W $m^{-2}$	200.0	638.9
$G$	W $m^{-2}$	19.4	63.8
VPD	KPa	0.31	1.02
RH	%	85.7	68.4
$r_a$	$s m^{-1}$	29.8	27.3
$u_3$	$m s^{-1}$	2.5	4.1
$u_3$ direction	Degrees	East-southeast	East
Base $r_c$	$s m^{-1}$	185	100
Base $E_{Ta}$	mm $h^{-1}$	0.09	0.46

<sup>a</sup>The variables included air temperature ( $T_a$ ), incoming shortwave radiation ( $R_s$ ), net radiation ( $R_n$ ), soil heat flux ( $G$ ), vapor pressure deficit (VPD), relative humidity (RH), aerodynamic resistance ( $r_a$ , calculated from equation 1), wind speed at 3 m ( $u_3$ ), wind direction, and base values for  $r_c$  and  $E_{Ta}$ .



**Figure 10.** Relationship between observed scaled-up canopy resistance ( $r_c$ ) and Bowen ratio energy balance system (BREBS)-measured actual evapotranspiration ( $E_{Ta}$ ) for a nonstressed maize canopy. The  $r_c$  values were obtained from measured and scaled-up leaf stomatal resistance values as reported by Irmak *et al.* [2008] and Irmak and Mutiibwa [2009].

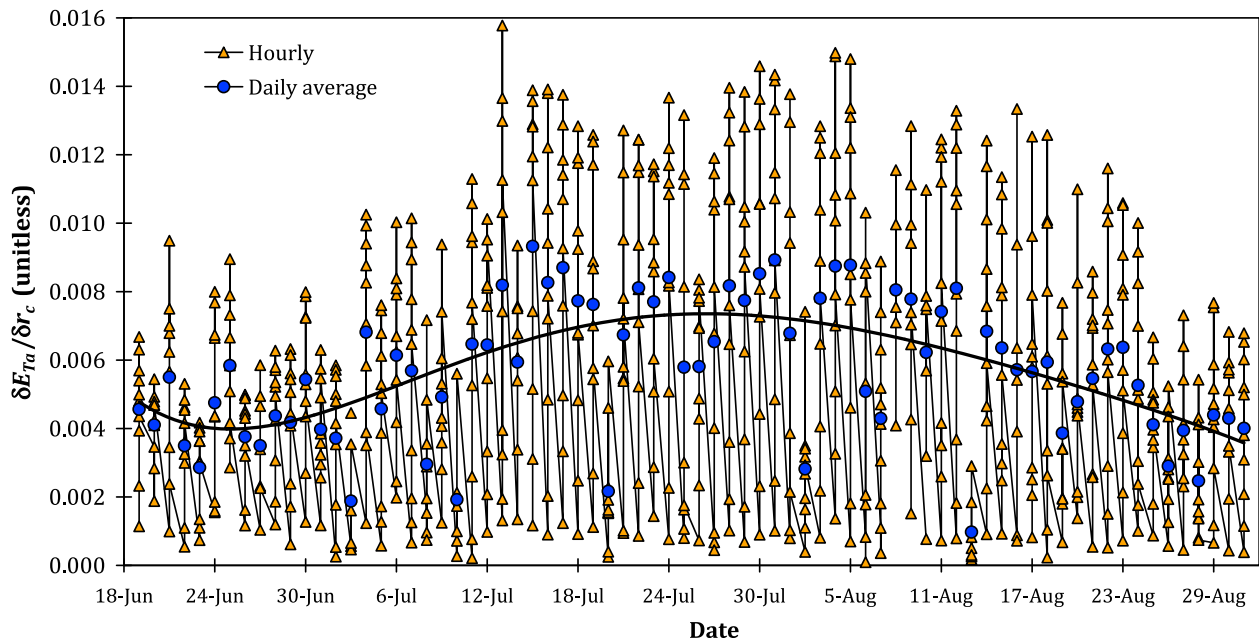
ses demonstrate that the PM-estimated  $E_{Ta}$  is very sensitive to changes in  $r_c$ , but this response is dynamic and is impacted by other factors, but more so by the amount of light (radiation). Thus, it appears that the good performance of model  $r_{c\_6}$  and  $r_{c\_7}$  in Figure 8 is most likely due to the overestimation of the PM model, likely due to underestimation of  $r_c$  by models  $r_{c\_6}$  and  $r_{c\_7}$ , as compared with the BREBS-measured  $E_{Ta}$  and not due to the insensitivity of the  $E_{Ta}$  to  $r_c$ .

[36] Figures 9 and 10 investigate the sensitivity of the PM  $E_{Ta}$  to  $r_c$  implicitly. To explicitly determine the sensitivity of the PM model-estimated  $E_{Ta}$  to  $r_c$ , we solved the following

equation (all variables have been previously defined in equation 14):

$$\frac{\partial \lambda E_{Ta}}{\partial r_c} = \frac{\gamma \left( \Delta (R_n - G) + \rho c_p \frac{e_s - e_a}{r_a} \right)}{r_a \left( \Delta + \gamma \left( 1 + \frac{r_c}{r_a} \right) \right)^2} \quad (16)$$

The ratio of  $\partial \lambda E_{Ta} / \partial r_c$  essentially represents the sensitivity coefficients of the PM with respect to  $r_c$ . We plotted the hourly ratios (09:00 am to 6:00 pm) as a function of time in Figure 11. Daily average ratios also included in the figure. The hourly ratios ranged from near zero to 0.016 with a



**Figure 11.** Sensitivity of the Penman-Monteith (PM) model to canopy resistance ( $r_c$ ) ( $\lambda E_{Ta} / r_c$ , equation 16).

seasonal average of 0.006. The ratio was lowest early in the morning, was at maximum during midday, and started to decrease toward late afternoon. This diurnal trend is due to response of  $r_c$  to increase magnitude of the radiation, temperature, and other micrometeorological variables with time. The ratios were lower early in the season and largest in midseason during complete canopy cover and maximum LAI from mid-July to early August and decreased again toward the end of the season. The lower values in the late season is most likely due to insensitivity of the PM model to  $r_c$  as a result of physiological maturity and leaf senescence as the influence of the  $r_c$  on  $E_{Ta}$  is minimal in these conditions.

#### 4. Conclusions

[37] We investigate the relationships between primary micrometeorological parameters and canopy resistance ( $r_c$ ) and present seven models using a generalized-linear model approach to estimate  $r_c$  for a nonstressed maize canopy. The most complex  $r_c$  model uses net radiation ( $R_n$ ), air temperature ( $T_a$ ), vapor pressure deficit (VPD), relative humidity (RH), wind speed at 3 m ( $u_3$ ), aerodynamic resistance ( $r_a$ ), leaf area index (LAI), and solar zenith angle ( $\Theta$ ) as inputs. The simplest model requires  $R_n$ ,  $T_a$ , and RH. The relationship between  $r_c$  versus  $u_3$ , wind direction, and  $\Theta$  was weak. There was a strong relationship between  $r_c$  and  $T_a$ . Although there was a general trend of increasing  $r_c$  with increasing RH, this relationship was not strong. While the relationship between  $r_c$  and  $u_3$  is not very clear, there was a tendency of increasing  $r_c$  with increasing  $u_3$ . The highest  $r_c$  values were obtained in the  $u_3$  range of 2 to 4 m s<sup>-1</sup>. The relationship between the  $r_c$  and LAI is inverse and is the strongest among all variables. Upon validation, the  $r_c$  model that used  $R_n$ ,  $T_a$ , RH,  $u_3$ , and LAI had the best agreement with the observed  $r_c$  data. Exclusion of LAI resulted in reduced performance and exclusion of  $r_a$  and  $\Theta$  from models did not impact the performance of the  $r_c$  models. The BREBS-measured and the PM-estimated  $E_{Ta}$ , using modeled  $r_c$ , were in close agreement. Given that most of the micrometeorological variables needed for the  $r_c$  models could be measured with a typical weather station, and the physiological variables, such as LAI, could be estimated with a reasonable accuracy, the performance obtained from all  $r_c$  models is an encouraging step toward empirical modeling of  $r_c$  for one-step application of the PM model for estimating  $E_{Ta}$  for nonstressed maize canopy. The purpose of the study was not to rank the models but rather to present empirical models predicting  $r_c$  with different numbers of environmental variables and evaluate their performances to better understand the impact of different environmental variables on  $r_c$ . Our findings could aid in the selection of a suitable model based on the availability and quality of the input data to predict  $r_c$  for one-step application of the PM model to estimate  $E_{Ta}$ .

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