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Allometric Method to Estimate Leaf Area Index for Row Crops

Paul D. Colaizzi,* Steven R. Evett, David K. Brauer, Terry A. Howell, Judy A. Tolk, and Karen S. Copeland

ABSTRACT

Leaf area index (LAI) is critical for predicting plant metabolism, biomass production, evapotranspiration, and greenhouse gas sequestration, but direct LAI measurements are difficult and labor intensive. Several methods are available to measure LAI indirectly or calculate LAI using allometric methods (i.e., exploiting relationships between LAI and more easily measured plant variables), but these depend on other measurements not widely available, and have limited transferability to different seasons. A new allometric method using a log normal function was developed to calculate LAI. Input variables were normalized cumulative growing degree days (CGDD), canopy height (CH), and plant population (PP), which were usually more widely available in crop production datasets. Destructive LAI measurements were obtained over multiple growing seasons for corn (*Zea mays* L.), cotton (*Gossypium hirsutum* L.), sorghum (*Sorghum bicolor* L.), and soybean [*Glycine max* (L.) Merr.] at USDA-ARS, Bushland, TX. Log normal functions were calibrated to LAI measurements from a single season of each crop, and tested using independent LAI measurements from all remaining crop seasons. For all crops, discrepancies between calculated and measured LAI resulted in coefficients of determination from 0.23 to 0.85, model indices of agreement from 0.52 to 0.84, root mean square errors from 0.76 to 1.4, mean absolute errors from 0.57 to 1.2, and mean bias errors from -0.46 to 0.60. The new allometric method can mitigate missing or sparse LAI data, which will enhance the value of large ecological datasets.

Core Ideas

- A new allometric method was developed to estimate LAI for row crops.
- Good agreement resulted for four crops over multiple seasons.
- Best agreement resulted using GDD, plant population, and canopy height.

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Leaf area index is a fundamental plant physiological variable, but is one of the most challenging to measure or estimate (Bréda, 2003). For most applications involving broadleaf plants (i.e., crops), LAI is defined as the one-sided leaf tissue area per unit ground area (Watson, 1947). Leaf area index interacts with practically every aspect of the mass and energy balance of vegetated surfaces. Therefore, LAI has direct bearing on the radiation balance, net primary production, evapotranspiration (ET), and carbon and other gas exchange (Norman and Campbell, 1989). It follows that the quality of LAI measurements or estimates will impact any model involving the mass or energy balance of vegetated surfaces.

Ground-based or in situ methods to quantify LAI have been broadly described as direct, semi-direct, or indirect (Chen et al., 1997; Bréda, 2003; Jonckheere et al., 2004; Weiss et al., 2004). Direct and semi-direct methods include destructive plant harvesting and nondestructive methods, such as litter collection and allometric methods. Destructive plant harvesting is the most direct and usually accurate method, but it is limited to smaller plants (i.e., crops, pasture, shrubs) and limited areas (i.e., a few point samples in a field due to its destructive nature and substantial labor requirements). Litter collection, while nondestructive, is limited to deciduous species and requires careful siting and maintenance of litter traps. Allometric methods are also nondestructive, have been successfully used for many vegetation types, and can be applied to larger areas. However, allometric methods are based on empirical relationships with some other (more easily measured) morphometric variable(s), such as leaf size, leaf shape, dry matter, or diameter at breast height, and hence may be site- and season-specific (Bréda, 2003). In contrast with direct and semi-direct methods, indirect methods usually entail non-contact approaches, such as irradiance extinction or optical analysis (e.g., hemispherical photography), and infer LAI based

P.D. Colaizzi, S.R. Evett, D.K. Brauer, and K.S. Copeland, USDA Agricultural Research Service, Conservation and Production Research Laboratory, P.O. Drawer 10, Bushland, TX 79012; T.A. Howell and J.A. Tolk, Retired, USDA Agricultural Research Service, Conservation and Production Research Laboratory, P.O. Drawer 10, Bushland, TX 79012. Mention of company or trade names is for description only and does not imply endorsement by the USDA. The USDA is an equal opportunity provider and employer. *Corresponding author (paul.colaizzi@ars.usda.gov).

Abbreviations: CGDD, cumulative growing degree days; DOY, day of year; ET, evapotranspiration; E-W, East–West; GDD, growing degree days; CH, canopy height; IAO, index of agreement; LA, leaf area; LAPP, leaf area per plant; LAPPCH, leaf area per plant per canopy height; LAI, leaf area index; LAICH, leaf area index per canopy height; MAE, mean absolute error; MBE, mean bias error; PP, plant population; RMSE, root mean square error; SDI, subsurface drip irrigation; SEE, standard error of the estimate.

on gap fraction and radiative transfer models. Several instruments designed to estimate LAI based on indirect methods have been commercially available for decades (see, for example, Table 1 in Wilhelm et al., 2000; Table 2 in Bréda, 2003; and Table 2 in Jonckheere et al., 2004). Indirect methods tend to underestimate LAI, mainly due to vegetation non-randomness (e.g., clumping) and simplifying assumptions of radiation scattering. However, algorithms designed for indirect methods continue to improve (e.g., Kobayashi et al., 2013; Hu et al., 2014), and have been adopted in instrument firmware (Li-Cor, 2016).

Remote sensing approaches to quantify LAI, while outside the scope of the present study, also warrant brief mention. These typically include digital photography, reflectance, or active laser measurements from aboard a stationary (e.g., boom) or moving (e.g., unmanned aerial vehicle, aircraft, or satellite) platform above the canopy (Zheng and Moskal, 2009). Remote sensing can map large areas rapidly and nondestructively, but require calibration with independent ground-based LAI measurements, which have different (usually smaller) spatial scales. Also, ground-based LAI measurements are site- and season-specific, and have often lacked the spatial resolution or repeat frequency required to support overarching terrestrial studies (Chen et al., 2002). Nonetheless, studies using unmanned aerial vehicles, high spatial resolution satellites, active lasers, and novel algorithms have demonstrated that remote sensing can provide meaningful LAI estimates (provided these can be tied to minimal ground-truth estimates). Some examples include row crops (Marshall and Thenkabail, 2015; Kross et al., 2015), vineyards (Mathews and Jensen, 2013; Kalisperakis et al., 2015), spruce forests (Solberg et al., 2009), and rugged terrain dominated by mixed pine forests (Morsdorf et al., 2006).

With recent efforts to synthesize and make available large datasets, the need for new systematic approaches to address data gaps and uncertainties will become increasingly important for the agricultural and natural sciences (Xie et al., 2015). This is particularly true for LAI. Datasets at within field-scales (i.e., ≤10 m) typically include several plant physiological variables that are relatively easy to measure, such as some aspect of plant size, biomass, yield, or fraction of cover, but relatively few datasets include direct, semi-direct, or indirect methods where LAI is quantified (a notable exception is Scurlock et al., 2001). For example, in agricultural crop production, high spatial resolution yield data measured by monitors aboard harvesting machinery is now widely available (Ross et al., 2008, and references therein). For research and intensively managed commercial production, yield data is likely to be accompanied by sparse but periodic measurements of plant height and fraction of vegetation cover, along with other static agronomic data, such as planting date, seed population, and plant row spacing (Kersebaum et al., 2015). Given the relative availability of these different types of data, LAI estimates for agricultural crops based on allometric approaches would appear to have substantial, but unrealized potential to further develop large agro-ecosystem datasets.

Allometric approaches have been widely used to estimate LAI for forests (e.g., Law et al., 2001; Vyas et al., 2010; Khosravi et al., 2012), and a number of studies have also used the approach for crops. Aase (1978) showed significant correlations between leaf area and aboveground dry matter of winter wheat. McKee (1964) and Wiersma and Bailey (1975) used leaf length and width to estimate leaf area of corn and soybean, respectively. Stewart and Dwyer (1999) developed polynomials describing leaf width for different corn hybrids, and integrated the polynomials to calculate leaf area. Blanco and Folegatti (2003) estimated LAI for cucumber (*Cucumis sativus* L.) and tomato (*Solanum lycopersicum* L.) by fitting a quadratic equation to leaf length and width and their relative height on a plant. Kathirvelan and Kalaiselvan (2007) used a power function to relate leaf area to leaf length and width of groundnut (*Arachis hypogaea* L.). Rouphael et al. (2007) also used leaf length and width as independent variables in first- and second-order linear equations to calculate leaf area of sunflower (*Helianthus annuus* L.). Nehbandani et al. (2013) established relationships for soybean, including LAI and leaf dry mass using a single relationship for different cultivars and plant populations, along with LAI and days after planting, and LAI and main stem node number. Soltani et al. (2006) also related plant leaf area (LA) to stem node number for chickpea (*Cicer arietinum* L.). Other studies considered number of leaves (e.g., plastochron index) for soybean (Sinclair, 1984), chickpea (Soltani et al., 2006); legume (Pengelly et al., 1999), and sorghum (Hammer et al., 1993; Carberry et al., 1993), where the number of leaves was often related to thermal time. Most studies found that leaf length and width were strong predictors of leaf area or LAI using straight-forward allometric equations. However, agricultural production datasets more typically include measurements of plant height, width, population, or row spacing rather than leaf length or width. Therefore, a need exists to investigate allometric approaches using these former variables to estimate LAI.

The objective of this study was to develop and test a general allometric model to estimate LAI using cumulative growing degree days with different combinations of canopy height and plant population for four row crops, including corn, cotton, sorghum, and soybean over multiple growing seasons.

MATERIALS AND METHODS

Field Measurements

All field measurements were obtained at the USDA Agricultural Research Service Conservation and Production Research Laboratory, Bushland, TX (35°11′ N, 102°6′ W, 1170 m above MSL). Soils are classified as Pullman clay loam (fine, mixed, super active, thermic Torrertic Paleustolls) (USDA-NRCS, 2016) with slow permeability, a dense B2 horizon from 0.15- to 0.40-m depth, and a calcic horizon beginning at approximately the 1.3-m depth. The climate is semiarid, with approximately 450 mm mean annual precipitation, 2600 mm Class A pan evaporation, and strong regional advection predominately from the South and South–Southwest during the summer crop growing season.

Destructive plant samples were obtained from four 4.7-ha fields arranged in a square pattern, designated Northeast, Southeast, Northwest, and Southwest. The centers of each field contain large monolithic weighing lysimeters, which have been in operation since 1987 (Evett et al., 2016a). Each lysimeter includes measurements of micrometeorological, soil water, and soil energy variables. Plant samples where obtained at three or more locations in each field at key crop development stages. The locations were selected to avoid the lysimeter areas and other instrumented sites (such as neutron probe access tubes), but away from field edges where crop growth and development may differ from the majority of the field. Plant samples were obtained from 1.0- to 1.5-m^2 areas, placed in coolers, and transported indoors for processing. Following mass, size, and other relevant physiological measurements, leaves were stripped and total leaf area (green and senesced) was measured by a leaf area meter (model LI-3100, LI-COR, Lincoln, NE). Calibration of the meter was checked with a 0.005-m^2 reference disk.

Leaf area and other plant measurements were obtained for corn (Table 1), cotton (Table 2), sorghum (Table 3), and soybean (Table 4). A subset of data (single season) was selected for each crop for model calibration (described in a later section), and the remaining data (excluding the data used for model calibration) were used to test each model. Seasons were selected for model calibration that had the largest range of measured LAI and included relatively frequent plant samples (Tables 1–4).

Agronomic practices were similar to those used in commercial crop production in the region. Crop seasons included multiple cultivars, plant populations, and irrigation treatments. Nearly all crops were planted on east–west (E-W) raised beds spaced at 0.76 m, and furrow dikes were installed across interrows following crop establishment to control run on and run off of irrigation and precipitation water (Schneider and Howell, 2000). The majority of crop seasons were irrigated by a hose-fed lateral move sprinkler system equipped with mid-elevation spray applicators (MESA) spaced at 1.52 m and at a 1.5-m height above alternate interrows. Beginning in 2013, however, the Northeast and Southeast fields were irrigated by subsurface drip irrigation (SDI), with laterals installed approximately 0.22 to 0.25 m deep in alternate interrows (Evett et al., 2016b). Most crops were irrigated to fully meet crop water demands (100% of crop evapotranspiration), but some seasons included deficit irrigation (<100% irrigation rate) and dryland production (0% irrigation rate) (Tables 1–4). The multiple production practices and seasons allowed models to be tested under a wide range of inter-annual climatic and growing conditions that are typical of the region (Baumhardt et al., 2014, 2015, 2016).

Model Development

Given the dependency of plant growth and development on CGDD (McMaster and Wilhelm, 1997), a rational first step is to include CGDD as the primary driver of LAI. In addition, normalizing CGDD for each crop season may be more robust to differences in cultivar maturity rates and inter-annual climatic conditions compared to CGDD alone. Using normalized CGDD as the exploratory variable, a preliminary analysis explored several response variables, including LAI, LAI per canopy height (LAICH), leaf area per plant (LAPP), and leaf area per plant per canopy height (LAPPCH). These four variables each exhibited bell shaped responses (with a single peak) vs. normalized CGDD (data shown later). Assuming that functions exist to describe these responses, a set of allometric models were written as:

$$\mathrm{LAI} = f\left(P_{\mathrm{LAI,crop}}, \theta\right) \quad [1]$$

$$\mathrm{LAI} = \mathrm{CH} \times f\left(P_{\mathrm{LAICH,crop}}, \theta\right) \quad [2]$$

$$\mathrm{LAI} = \mathrm{PP} \times f\left(P_{\mathrm{LAPP,crop}}, \theta\right) \quad [3]$$

$$\mathrm{LAI} = \mathrm{PP} \times \mathrm{CH} \times f\left(P_{\mathrm{LAPPCH,crop}}, \theta\right) \quad [4]$$

$$\theta = \mathrm{CGDD}/\mathrm{CGDD}_{\max} \quad [5]$$

where $f(P_{x,\mathrm{crop}}, \theta)$ is some bell shaped function, P_x is a set of parameters specific to the allometric model version (x) and crop, θ is the exploratory variable (i.e., normalized CGDD), CGDD_{max} is maximum CGDD (i.e., CGDD at harvest or some other terminal point in the season), CH is canopy height (m), and PP is plant population (plants m^{-2}).

Table 1. Corn year, cultivar, field, plant and harvest day of year (DOY), maximum cumulative growing degree days (CGDD), irrigation method, irrigation rate (% of full crop evapotranspiration), row orientation, seed population, and references.

Year	Field†	Cultivar	Plant	Harvest (or max CGDD)	Max CGDD	Irrig. method‡	Irrig. rate	Row orientation	Seed pop.	Reference
			——DOY ——		°C		%		no. m^{-2}	
1989§	NE and SE	PIO 3321	116	297	1817	MESA	100	E-W	6	Howell et al. (1996, 1997)
1990	NE and SE	PIO 3124	129	289	1841	MESA	100	E-W	6	Howell et al. (1996, 1997)
1994	NW and SW	PIO 3737	103	249	1647	na	0	E-W	4	Howell et al. (1996)
1994	NE	PIO 3737	105	259	1722	MESA	100	E-W	8.5	Howell et al. (1996)
1994	SE	PIO 3245	105	270	1850	MESA	100	E-W	7.8	Howell et al. (1996)
2013	NE and SE	PIO 1151HR	142–143	296	1793	SDI	100	E-W	8.2	Evett et al. (2016b)
2013	NW	PIO 1151HR	136–137	294	1855	MESA	75	E-W	8.2	Evett et al. (2016b)
2013	SW	PIO 1151HR	136–137	294	1855	MESA	100	E-W	8.2	Evett et al. (2016b)

† NE, northeast; SE, southeast; SW, southwest; NW, northwest.

‡ MESA, irrigation by mid-elevation spray applicators; SDI, irrigation by subsurface drip irrigation.

§ Calibration data not used to test model.

Table 2. Cotton year, cultivar, field, plant and harvest day of year (DOY), maximum cumulative growing degree days (CGDD), irrigation method, irrigation rate (% of full crop evapotranspiration), row orientation, seed population, and references.

Year	Field†	Cultivar	Plant	Harvest (or max CGDD)	Max CGDD	Irrig. method‡	Irrig. rate	Row orientation	Seed pop.	Reference
			—— DOY ——				%		no. m^{-2}	
2000	NE	PM 2145RR	137	307	1365	MESA	50	E-W	21	Howell et al. (2004)
2000	SE	PM 2145RR	137	307	1365	MESA	100	E-W	21	Howell et al. (2004)
2000	NW	PM 2145RR	136	293	1330	na	0	E-W	17	Howell et al. (2004)
2000	SW	PM 2145RR	136	293	1330	na	0	E-W	12	Howell et al. (2004)
2001	NE	PM 2145RR	136	303	1377	MESA	50	E-W	20	Howell et al. (2004)
2001	SE	PM 2145RR	136	303	1377	MESA	100	E-W	20	Howell et al. (2004)
2001	NW	PM 2145RR	137	295	1335	na	0	E-W	17	Howell et al. (2004)
2001	SW	PM 2145RR	137	295	1335	na	0	E-W	17	Howell et al. (2004)
2002	NE and SE	PM 2145RR	138	317	1065	MESA	100	E-W	20	
2008§	NE	DP 117	141	299	1150	MESA	100	N-S	15.8	Colaizzi et al. (2012); Evett et al. (2012)
2008§	SE	DP 117	141	299	1150	MESA	100	E-W	15.8	Colaizzi et al. (2012); Evett et al. (2012)
2008	NW and SW	DP 117	157	299	991	na	0	E-W	15.8	
2010	NE and SE	DP 104	146	298	1303	MESA	100	E-W	20	
2012	NW and SW	DP 1212 B2RF	140	300	1285	MESA	100	E-W	19	

† NE, northeast; SE, southeast; SW, southwest; NW, northwest.

‡ MESA, irrigation by mid-elevation spray applicators; SDI, irrigation by subsurface drip irrigation.

§ Calibration data not used to test model.

Table 3. Sorghum year, cultivar, field, plant and harvest day of year (DOY), maximum cumulative growing degree days (CGDD), irrigation method, irrigation rate (% of full crop evapotranspiration), row orientation, seed population, and references.

Year	Field	Cultivar	Plant	Harvest (or max. CGDD)	Max. CGDD	Irrig. method	Irrig. rate	Row orientation	Seed pop.	References
			—— DOY ——		C		%		m^{-2}	
1988	NW and SW	DK-41Y	172	307	1504	MESA	50	E-W	15.9	Howell et al. (1997)
1997	NW and SW	PIO 8699	155–156	272	1556	na	0	E-W	13	
1998	NW	PIO 8699	175	277	1488	na	0	E-W	11.9	
1998	SW	PIO 8699	175	277	1488	na	0	E-W	8.6	
1999	NW	PIO 8699	179–180	287	1353	na	0	E-W	17	
1999	SW	PIO 8699	179–180	287	1353	na	0	E-W	10	
2007	NW and SW	DK-39Y	157	276	1537	na	0	E-W	9.6	
2014	NE and SE	CH NC+5c35	171	293	1470	SDI	100	E-W	21	Evett et al. (2016b)
2014	NW	CH NC+5c35	171	293	1470	MESA	100	E-W	21	Evett et al. (2016b)
2014	SW	CH NC+5c35	171	293	1470	MESA	75	E-W	21	Evett et al. (2016b)
2015	NE and SE	CH NC+5c35	174	284	1600	SDI	100	E-W	21	
2015†	NW	CH NC+5c35	173	284	1650	MESA	100	E-W	21	
2015†	SW	CH NC+5c35	173	284	1650	MESA	75	E-W	21	

† Calibration data not used to test model.

Table 4. Soybean year, cultivar, field, plant and harvest day of year (DOY), maximum cumulative growing degree days (CGDD), irrigation method, irrigation rate (% of full crop evapotranspiration), row orientation, seed population, and references.

Year	Field	Cultivar	Plant	Harvest (ormax. CGDD)	Max. CGDD	Irrig. method	Irrig. rate	Row orientation	Seed pop.	References
			—— DOY ——		C		%		m^{-2}	
1995	NW and SW	PIO 9461	137	277	1702	MESA	100	E-W	53	
2003	NE	PIO 94B73RR	139	275	1817	MESA	33	E-W	42	
2003	NE	PIO 94B73RR	139	275	1817	MESA	66	E-W	42	
2003	NE	PIO 94B73RR	139	275	1817	MESA	100	E-W	42	Howell et al. (2006)
2003	SE	PIO 94B73RR	139	273	1806	MESA	100	E-W	46	Howell et al. (2006)
2004†	NE	PIO 94B73RR	133	274	1759	MESA	33	E-W	23	
2004†	NE	PIO 94B73RR	133	274	1760	MESA	66	E-W	23	
2004†	NE	PIO 94B73RR	133	274	1761	MESA	100	E-W	46	Howell et al. (2006)
2004†	SE	PIO 94B73RR	133	274	1762	MESA	100	E-W	46	Howell et al. (2006)
2010	NW and SW	PIO 94B73RR	168	277	1665	na	0	E-W	20	

† Calibration data not used to test model.

A function $f(P_{x,\text{crop}}, \theta)$ is then sought that meets the following criteria: it is bell-shaped with a single peak; it maintains positive values for $0.0 \le \theta \le 1.0$; it trends to zero as θ trends to zero; it has four or less shape parameters; and the shape parameter values are physically meaningful. Archontoulis and Miguez (2015) present a systematic approach for selecting nonlinear models having specific, desired attributes. They provided numerous example models, with additional models in their supplement (Archontoulis and Miguez, 2013). Following their approach, we considered three models meeting all these criteria, including two forms of a β function (their Eq. [2.12] and [2.13]; Yin et al., 2003), and a three-parameter log normal function (their Eq. [5.6]). For all allometric model versions (Eq. [1] to [4]) and crops, the log normal function resulted in much less discrepancy with data compared with the β functions. In fact, the log normal function resulted in nearly the same discrepancies as a five-parameter Fourier series function used in an earlier analysis (Slack et al., 1996; data not shown). Therefore, the three-parameter log normal function was selected:

$$f(P_{(x,\text{crop})}, \theta) = Y_0 \exp\left[-0.5\left(\frac{\ln(\theta/\theta_0)^2}{\gamma}\right)\right] \qquad [6]$$

where Y_0 is the peak value of the function, q_0 is the value of θ at Y_0, and γ is a shape parameter ($0 < \gamma < 1$) where larger values result in a wider peak.

As previously stated, the three parameters (Y_0, q_0, and γ) will be specific for each allometric model (Eq. [1] to [4]) and each crop. The three parameters were determined using the MATLAB ‘fminsearch’ function that minimized the ordinary least squares cost function (MATLAB Release 2016b, MathWorks, 2016). The ‘fminsearch’ function included setting the options ‘MaxFunEvals’ to 50000 and ‘MaxIter’ to 10000. Initial values for all three parameters were 0.5. Using the optimized parameters, the coefficient of determination (r^2) and standard error of the estimate (SEE) were calculated in MATLAB for calculated $f(P_{x,\text{crop}}, \theta)$ (i.e., from Eq. [1] to [4]) vs. measured $f(P_{x,\text{crop}}, \theta)$ (i.e., from calibration data in Tables 1–4). The r^2 was calculated as the scalar matrix square of the correlation coefficient (i.e., row 1 and column 2), which was calculated by the MATLAB ‘corrcoef’ function. The SEE was calculated as:

$$\text{SEE} = \sqrt{\frac{\sum_{i=1}^{n}\left(f(P_{x,\text{crop}})_{i,\text{calc}} - f(P_{x,\text{crop}})_{i,\text{meas}}\right)^2}{n-3}} \qquad [7]$$

where calc and meas are calculated and measured values, respectively, n is the sample size of calibration data, and 3 is degrees of freedom.

CGDD Calculation

In the present study, CGDD was calculated as:

$$\text{CGDD} = \sum_{d=1}^{D} \text{GDD}_{b/p} \qquad [8]$$

where $\text{GDD}_{b/p}$ is growing degree days for a single day (°C) at crop-specific base (b) and peak (p) development temperatures, d is the number of days since planting, and D is the number of days at $\text{CGDD}_{\max}$, and

$$\text{GDD}_{b/p} = T_a - T_b \qquad [9]$$

where T_a is the mean daily air temperature, and T_b is the base temperature. Further, T_a is subject to the constraints:

$$T_a = \left(T_{\max} + T_{\min}\right)/2 \quad \text{for } T_{\max} \le T_p \text{ and } T_{\min} \ge T_b \qquad [10a]$$

$$T_a = \left(T_p + T_{\min}\right)/2 \quad \text{for } T_{\max} \ge T_p \text{ and } T_{\min} \ge T_b \qquad [10b]$$

$$T_a = \left(T_{\max} + T_b\right)/2 \quad \text{for } T_{\max} \le T_p \text{ and } T_{\min} \le T_b \qquad [10c]$$

$$T_a = T_b \quad \text{for } T_{\max} \le T_b \text{ and } T_{\min} \le T_b \qquad [10d]$$

$$T_a = \left(T_p + T_b\right)/2 \quad \text{for } T_{\max} > T_p \text{ and } T_{\min} < T_b \qquad [10e]$$

where T_{max} is the maximum daily air temperature, T_{min} is the minimum daily air temperature, T_p is the peak development temperatures, and all temperature variables have (°C) units. Although air temperature at hourly or similar time steps may result in more accurate GDD calculation compared with daily time steps (Snyder, 1985), daily time step data are more likely to be available, and GDD calculation based on Eq. [9] and [10] appear to be the most widely accepted method (McMaster and Wilhelm, 1997). Values of T_b and T_p for corn, cotton, sorghum, and soybean used in GDD calculations and relevant references are in Table 5.

Model Test Criteria

The allometric models were evaluated by calculating means, standard deviations, and various measures of discrepancies between measured and calculated LAI. Discrepancy measures included the coefficient of determination (r^2), intercept, slope, root mean square error (RMSE), mean absolute error (MAE), and mean bias error (MBE). The extent that RMSE is greater than MAE indicates the presence of outliers (Legates and McCabe, 1999). In addition, the model index of agreement (IOA) was calculated (Legates and McCabe, 1999), which is essentially a first-order version of the Nash-Sutcliffe coefficient of model efficiency (Nash and Sutcliffe, 1970). Values of IOA range from $-\infty$ to 1.0, where larger values indicate smaller discrepancy between measured and calculated variables, and IOA = 0 indicates the model gives no better calculations compared with the mean of all measurements (Legates and McCabe, 1999). All calculations used MATLAB Release 2016b; r^2 was calculated as described in Section 2.2 (Model Development), intercept and slope were calculated by dividing the calculated matrix by the measured matrix, and

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\mathrm{LAI}_{i,\mathrm{calc}} - \mathrm{LAI}_{i,\mathrm{meas}})^2}{n}} \quad [11]$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}\left|\mathrm{LAI}_{i,\mathrm{calc}} - \mathrm{LAI}_{i,\mathrm{meas}}\right|}{n} \quad [12]$$

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n}(\mathrm{LAI}_{i,\mathrm{calc}} - \mathrm{LAI}_{i,\mathrm{meas}})}{n} \quad [13]$$

$$\mathrm{IOA} = 1 - \frac{n \times \mathrm{MAE}}{\sum_{i=1}^{n}\left|\mathrm{LAI}_{i,\mathrm{calc}} - \overline{\mathrm{LAI}_{\mathrm{meas}}}\right| + \left|\mathrm{LAI}_{i,\mathrm{meas}} - \overline{\mathrm{LAI}_{\mathrm{meas}}}\right|} \quad [14]$$

where $\mathrm{LAI}_{i,\mathrm{calc}}$ and $\mathrm{LAI}_{i,\mathrm{meas}}$ are calculated and measured LAI values, respectively, n is the sample size, and the term with the overbar is the sample mean.

Table 5. Base (T_b) and peak (T_p) temperatures for crops used in the present study.

Crop	T_b	T_p	References
	——— °C ———		
Corn	10	30	Gilmore and Rogers (1958)
Cotton	15	50	Peng et al. (1989)
Sorghum	10	38	Gerik et al. (2003)
Soybean	8	30	Major et al. (1975)

RESULTS

Model Calibration

Each dataset used to calibrate the allometric models had mean LAI that would be expected over a full growing season for each crop at the study location (Table 6). Mean LAICH was less than mean LAI for corn (i.e., mean CH > 1.0 m), but greater than LAI for the other crops (i.e., mean CH < 1.0 m). This was also consistent for mean LAPP vs. mean LAPPCH. Convergence was obtained for each calibration of four allometric model versions (Eq. [1] to [4]) and each crop, with r^2 from 0.49 to 0.94 (all P < 0.001), and SEE were 15 to 40% of mean

Table 6. Allometric models fit to log normal function driven by normalized cumulative growing degree days (CGDD), with allometric variable mean, coefficient of determination (r^2), standard error of the estimate (SEE), and three fitted parameters (Y_0 = maximum value of allometric variable; q_0 = normalized CGDD at Y_0; γ = shape parameter).

Crop (n)	Allometric model	Units	Mean	r^2	SEE	Y_0	q_0	γ
Corn	LAI	$m^2\ m^{-2}$	2.88	0.91	0.57	5.00	0.611	0.395
(60)	LAICH	m^{-1}	1.83	0.70	0.40	2.47	0.450	0.532
	LAPP	m^2	0.38	0.94	0.062	0.658	0.618	0.410
	LAPPCH	m	0.25	0.73	0.049	0.330	0.444	0.542
Cotton	LAI	$m^2\ m^{-2}$	1.47	0.91	0.41	3.67	0.715	0.190
(48)	LAICH	m^{-1}	1.91	0.89	0.53	4.30	0.679	0.204
	LAPP	m^2	0.10	0.78	0.046	0.241	0.758	0.180
	LAPPCH	m	0.12	0.75	0.047	0.240	0.712	0.233
Sorghum	LAI	$m^2\ m^{-2}$	3.57	0.75	0.52	4.71	0.585	0.532
(84)	LAICH	m^{-1}	3.91	0.51	0.86	5.11	0.423	0.731
	LAPP	m^2	0.22	0.79	0.034	0.299	0.600	0.492
	LAPPCH	m	0.23	0.49	0.052	0.307	0.484	0.624
Soybean	LAI	$m^2\ m^{-2}$	2.64	0.69	1.11	4.77	0.629	0.258
(54)	LAICH	m^{-1}	3.69	0.53	1.20	5.24	0.537	0.402
	LAPP	m^2	0.071	0.85	0.019	0.131	0.640	0.250
	LAPPCH	m	0.10	0.72	0.024	0.143	0.565	0.363

allometric model values. Examples of measurements and resulting log normal models vs. normalized CGDD were plot for each crop for LAPPCH (Fig. 1). The log normal models were plot for 0 < normalized CGDD < 1 to show that their calculated values were physically plausible beyond the measured data. For corn and sorghum, the measured data and model increased and peaked when normalized CGDD was approximately 0.4, and then declined except for a small increase during 0.6 < normalized CGDD < 0.8. This occurred around anthesis for both crops, and was likely related to CH increasing due to tasseling or heading, while LA began to decrease (this small depression was not visible for LAPP; data not shown). This may be a weakness in the three-parameter log normal model used herein, which does not accommodate secondary peaks. For cotton, measured data increased during most of the season until normalized CGDD of ~0.85, then decreased sharply. The generally increasing scatter as the season progressed, and decline in scatter near the end of the season when normalized CGDD of ~0.98 (i.e., when leaves were mostly senesced) was consistent with LAI measurements for this season, which was discussed in Colaizzi et al. (2012) and Evett et al. (2012). However, the resulting model peaked somewhat earlier, when normalized CGDD of ~0.75. For soybean, measured data and the model increased up to normalized CGDD of ~0.65, followed by a decrease. Similar to cotton, scatter of soybean LAPPCH steadily increased as the season progressed, but did not decrease by the end of the season, which may have been related to the last leaf area measurements being obtained before senescence was complete. Overall, the timing of peak LAPPCH was earlier for the C_4 and determinate crops of corn and sorghum, but later for the C_3 and indeterminate crop of cotton and C_3 and less determinate crop of soybean.

Model Test

Measurements of LAI used to test the models were typical of crops over the growing season at the study location, and maximum measured LAI for each crop did not exceed 6 to 7 m^2 m^{-2} (Fig. 2). Measured and calculated means and standard deviations of LAI used to test the models were also as expected (Table 7).

For corn, discrepancies between measured and calculated LAI were smallest for the LAICH and LAPPCH models (for each discrepancy measure, smallest discrepancies are shown in bold in Table 7). Here, $r^2 > 0.84$, IOA were both 0.84, RMSE were <0.87 m^2 m^{-2} (<33% of measured mean), MAE was ≤0.60 m^2 m^{-2} (23% of measured mean), and |MBE| was ≤0.040 m^2 m^{-2} (1.5% of measured mean). Measured and calculated LAI discrepancies were larger for the LAPP model, and the largest discrepancy occurred for the LAI model. Therefore, corn LAI is related to both CGDD and CH, and these relationships are likely to depend on cultivar, biotic and abiotic stresses, and irrigation and agronomic management. Furthermore, CH should be included in allometric models used to estimate LAI for corn.

Cotton measured vs. calculated LAI discrepancies were larger for each model compared with those of corn (Table 7). The smallest discrepancies occurred for the LAPPCH model ($r^2 = 0.63$; IOA = 0.67; RMSE = 0.83 m^2 m^{-2} [60%]; MAE = 0.67 m^2 m^{-2} [48%]; however, MBE = −0.24 m^2 m^{-2} [−17%], which was slightly larger compared with the LAI model, where MBE = 0.048 m^2 m^{-2} [3.4%]). Discrepancies were larger for the LAICH, LAI (except for MBE), and LAPP models. These results also pointed to CH as being an important variable for developing allometric models to estimate cotton LAI, and inclusion of PP reduced discrepancies further compared with CH alone.

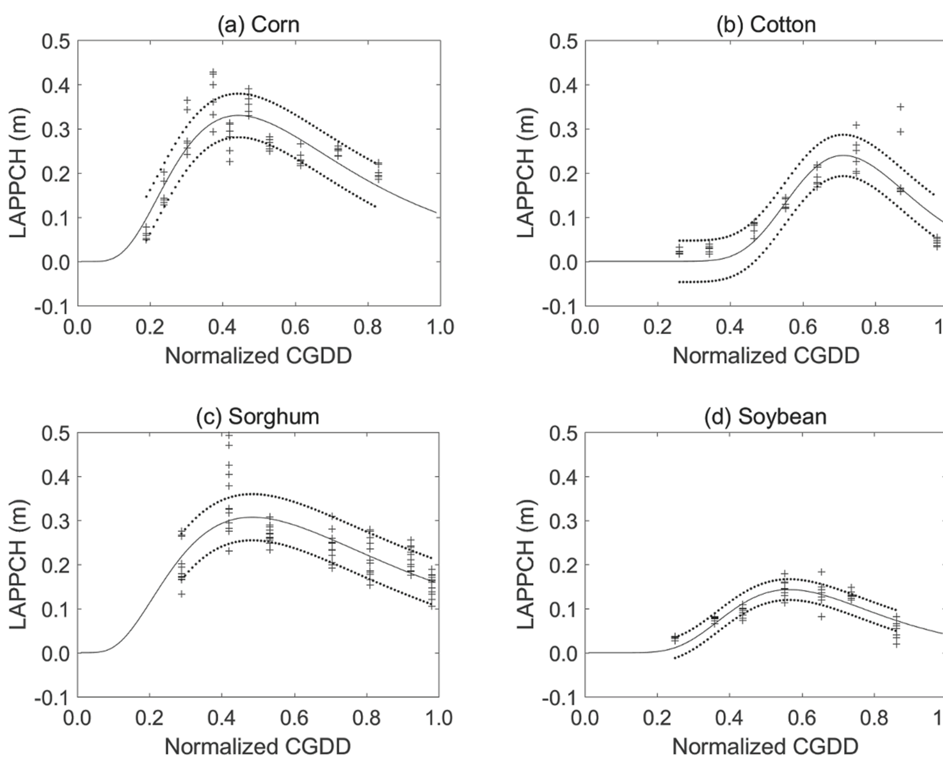

Fig. 1. Measured leaf area per plant per plant height (LAPPCH) (+ symbols), three parameter log normal model (solid line) with ± standard error (dotted lines) vs. normalized cumulative growing degree days (CGDD) for each crop. See Table 6 for fitted model parameters.

Sorghum appeared least sensitive to the choice of allometric model, with measured vs. calculated LAI discrepancies having greater similarity for each model compared with other crops (Table 7). The least discrepancy occurred for the LAPP model (r^2 = 0.74; IOA = 0.72; RMSE = 0.84 m^2 m^{-2} [30%]; MAE = 0.66 m^2 m^{-2} [24%]; however MBE = 0.42 m^2 m^{-2} [15%], but this was not much larger than MBE for the LAPPCH model at 0.34 m^2 m^{-2} [12%]). Other discrepancy measures (r^2, IOA, RMSE, and MAE) for the LAPPCH model were not much greater than the LAPP model, and discrepancies were only slightly larger for the LAICH and LAI models. These results implied that CH, LAI, and CGDD were strong covariates, so that inclusion of CH in a sorghum allometric model does not add much information beyond CGDD only. The same appeared to apply to PP. Previous studies have shown that planting sorghum in clumps reduced tillers and leaves per plant compared with uniform plant spacing (Bandaru et al., 2006; Krishnareddy et al., 2009), which implied that LAPP varied with planting geometry, but could conceivably have had a compensating effect on LAI (i.e., LAI and PP were weakly correlated). Nonetheless, inclusion of either CH or PP did reduce measured vs. calculated LAI discrepancies for sorghum.

Soybean model discrepancy measures (r^2, IOA, RMSE, and MAE) were consistent across models, where respective discrepancies increased for LAICH, LAPP, and LAI (Table 7). Discrepancies for the LAPPCH model were r^2 = 0.81, IOA = 0.79, RMSE = 0.80 m^2 m^{-2} (36%), and MAE = 0.62 m^2 m^{-2} (28%). However, MBE was −0.26 m^2 m^{-2} (−12%), which was substantially larger in magnitude than MBE for the LAI and LAPP models (≤|−0.078| m^2 m^{-2} [≤|−3.6%|]). Although inclusion of CH reduced discrepancies in terms of IOA, RMSE, and MAE compared with PP alone, inclusion of CH resulted in larger MBE in magnitude (i.e., more negative).

In summary, measured vs. calculated LAI discrepancies in terms of r^2, IOA, RMSE, and MAE were generally the smallest for the LAPPCH model for cotton and soybean, smallest for the LAICH model for corn, and smallest for the LAPP model for sorghum (Table 7). However, discrepancies for the LAPPCH model were the same or similar to LAICH for corn, and similar to LAPP for sorghum. For all crops and models, RMSE/MAE was ≤1.43, indicating discrepancies were relatively free of outliers (Legates and McCabe, 1999). Discrepancies in terms of the magnitude of MBE was smallest for the LAPPCH model for corn and sorghum, but not cotton and soybean. The LAPPCH allometric model nonetheless appeared the most robust for the different crops (both C_3 and C_4), cultivars, and wide range of management, growing, and climatic conditions.

The scatter of calculated vs. measured LAI were plot for each crop using the LAPPCH allometric model (Fig. 2). The scatter from the 1:1 line was similar for each crop, but differed relative to measured LAI. Scatter tended to be greater for the larger LAI measurements of corn and sorghum, and greater for the smaller LAI measurements for cotton and soybean.

DISCUSSION

The present study aimed to establish robust relationships for multiple crops between LAI and CH, PP, and normalized CGDD. These variables may be more widely available in crop production and other agro-ecological datasets compared with variables more typically used in previous allometric studies, such as leaf length or width, leaf dry mass, plastochron index, or stem node number (McKee, 1964; Wiersma and Bailey, 1975; Sinclair, 1984; Pengelly et al., 1999; Stewart and Dwyer, 1999; Soltani et al., 2006; Kathirvelan and Kalaiselvan, 2007;

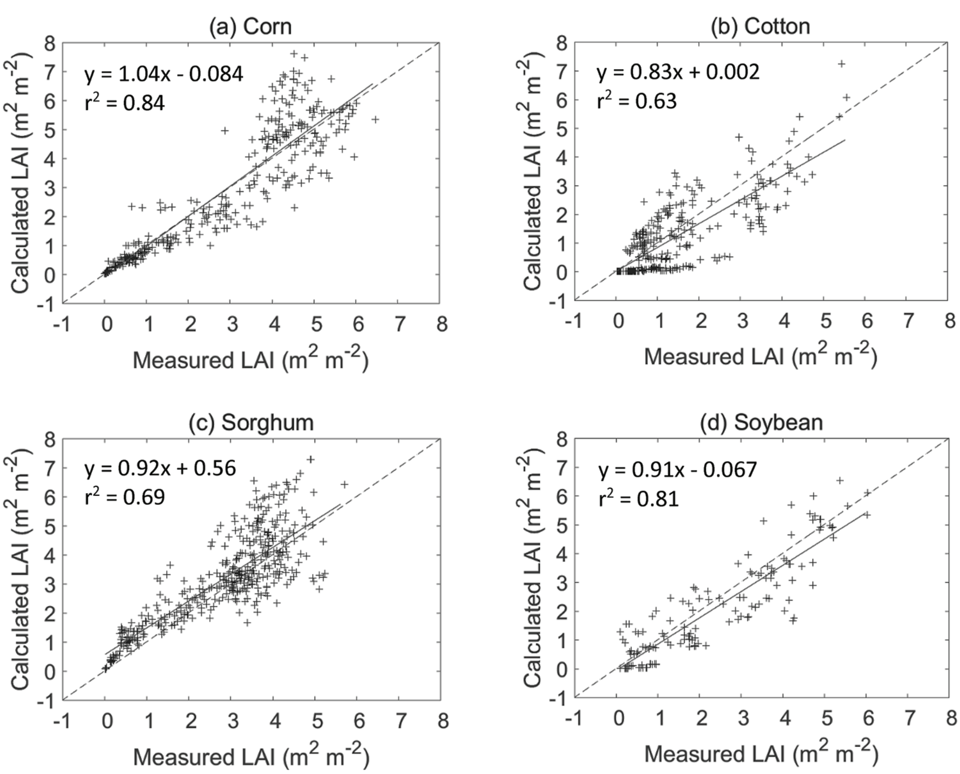

Fig. 2. Calculated vs. measured leaf area index (LAI) using the leaf area per plant per plant height (LAPPCH) allometric model (+ symbols), 1:1 line (dashed line), and linear regression (solid line) for each crop. See Table 7 for calculated vs. measured discrepancy parameters.

Rouphael et al., 2007; Vyas et al., 2010; Khosravi et al., 2012; Nehbandani et al., 2013). Previous studies usually reported allometric relationships in terms of r^2 only, and were typically >0.90. In the present study, r^2 for allometric relationships were 0.23 to 0.85, with most relationships having $r^2 \geq 0.50$ (Table 7). These were somewhat less compared with previous studies, but their relationships were often developed using more limited ground truth data. Allometric relationships in previous studies were usually linear, polynomial, or power functions. Several studies also estimated the plastochron index as a function of CGDD, which was used to estimate LA (Sinclair, 1984; Pengelly et al., 1999; Soltani et al., 2006), or estimated LAI as an exponential function of days since planting (Nehbandani et al., 2013). These contrasted with the present approach, where a log normal model as a function of normalized CGDD was used, which was selected because it met a greater range of physically realistic criteria (i.e., it was bell-shaped, it did not go negative over the exploratory variable range, it tended to zero as exploratory variable tended to zero, and required only three parameters that were physically meaningful).

Several previous studies went further and tested allometric relationships using independent datasets, where discrepancies between measured and calculated LA or LAI were reported (also usually in terms of r^2 only). These were mostly comparable to calculated vs. measured LAI discrepancies reported in the present study. Rouphael et al. (2007) calculated LA for sunflower using leaf length and width, and reported $r^2 = 0.97$ for calculated vs. measured LA. Blanco and Folegatti (2003) calculated LAI for cucumber and tomato using leaf height, width, and position (relative leaf height), and reported $r^2 = 0.98$ for calculated vs. measured LAI. Vyas et al. (2010) calculated LAI for teak and bamboo based on canopy width, and reported RMSE 0.38 to 1.15 $m^2\ m^{-2}$ for calculated vs. measured LAI. Carberry et al. (1993) calculated LAI for sorghum using main culm leaf number (as established by Hammer et al., 1993), resulting in $r^2 = 0.86$ and RMSE = 0.54 $m^2\ m^{-2}$. In the present study (Table 7), the LAPPCH model resulted in comparable r^2 (0.63–0.84) and RMSE (0.80–0.92 $m^2\ m^{-2}$). However, the present study differed in that datasets were usually larger and included a wider range of climatic and growing conditions (albeit only one location), and as stated before, used the log normal model in the allometric relations.

Retrieval of LAI has been demonstrated using remote sensing methods. Discrepancies with independent, ground-based estimates of LAI were reported, also usually in terms of r^2. Although these r^2 were comparable to the present study (Table 7), their independent, ground-based LAI were estimated indirectly. For example, Kross et al. (2015) retrieved LAI for corn and soybean using various reflectance-based indices and measurements from the RapidEye, Landsat, and SPOT satellites, resulting in $r^2 \geq 0.76$ and MAE ≤ 0.97 $m^2\ m^{-2}$ compared with LAI estimated by ground-based hemispherical photography. Mathews and Jensen (2013) compared LAI estimated by a digital camera aboard an unmanned aerial vehicle to indirect, ground-based estimates of LAI using a ceptometer for vineyards, and reported $r^2 = 0.57$. Kalisperakis et al. (2015) also estimated LAI of vineyards using an unmanned aerial vehicle, but they used both digital photography and hyperspectral sensors, and compared LAI estimated by remote sensing to

Table 7. Discrepancies between measured and calculated LAI for each allometric model tested. For each crop, the parameters indicating the smallest model discrepancies are shown in bold.

Crop (n)	Measured Mean	Measured SD	Allometric model	Units	Calculated Mean	Calculated SD	r^2	Int.	Slope	IOA	RMSE	%	MAE	%	MBE	%
Corn (339)	2.64	1.91	LAI	$m^2\ m^{-2}$	2.76	1.83	0.54	0.90	0.71	0.72	1.4	52%	0.95	36%	0.12	4.5%
			LAICH	m^{-1}	2.68	1.96	**0.85**	0.18	0.95	**0.84**	**0.76**	**29%**	**0.57**	**22%**	0.040	1.5%
			LAPP	m^2	2.59	1.87	0.74	0.37	0.84	0.77	1.0	38%	0.78	29%	−0.055	−2.1%
			LAPPCH	m	2.66	2.17	0.84	**−0.084**	**1.04**	**0.84**	0.87	33%	0.60	23%	**0.016**	**0.60%**
Cotton (306)	1.40	1.23	LAI	$m^2\ m^{-2}$	1.45	1.40	0.23	0.67	0.55	0.52	1.3	96%	1.1	76%	**0.048**	**3.4%**
			LAICH	m^{-1}	1.10	1.11	0.53	0.18	0.66	0.63	0.91	65%	0.72	51%	−0.30	−21%
			LAPP	m^2	1.48	1.67	0.30	0.45	0.74	0.54	1.4	103%	1.1	79%	0.086	6.2%
			LAPPCH	m	1.16	1.28	**0.63**	**0.002**	**0.83**	**0.67**	**0.83**	**60%**	**0.67**	**48%**	−0.24	−17%
Sorghum (400)	2.77	1.39	LAI	$m^2\ m^{-2}$	3.37	1.17	0.64	1.50	0.67	0.65	1.0	37%	0.81	29%	0.60	22%
			LAICH	m^{-1}	3.27	1.20	0.69	1.28	0.72	0.66	0.92	33%	0.75	27%	0.49	18%
			LAPP	m^2	3.19	1.40	**0.74**	0.78	0.87	**0.72**	**0.84**	**30%**	**0.66**	**24%**	0.42	15%
			LAPPCH	m	3.11	1.54	0.69	**0.56**	**0.92**	**0.72**	0.92	33%	0.69	25%	**0.34**	**12%**
Soybean (142)	2.20	1.69	LAI	$m^2\ m^{-2}$	2.12	1.68	0.40	0.74	0.63	0.60	1.4	65%	1.2	53%	−0.078	−3.6%
			LAICH	m^{-1}	1.74	1.22	0.78	0.33	0.64	0.70	0.95	43%	0.78	35%	−0.46	−21%
			LAPP	m^2	2.22	1.98	0.59	0.24	0.90	0.68	1.3	58%	1.0	46%	**0.020**	**0.91%**
			LAPPCH	m	1.94	1.71	**0.81**	**−0.067**	**0.91**	**0.79**	**0.80**	**36%**	**0.62**	**28%**	−0.26	−12%

LAI estimated by independent leaf counts of individual vines, resulting in $r^2 > 0.73$. Morsdorf et al. (2006) and Solberg et al. (2009) estimated LAI of forests using airborne laser scanning, and compared this to indirect, ground-based LAI estimates using hemispherical photography ($r^2 = 0.69$) or irradiance extinction ($r^2 \geq 0.73$), respectively.

The goal of developing a more robust allometric model using more readily available inputs compared with previous approaches nonetheless includes several limitations, which provides rationale for future studies. Specifically, greater model robustness often carries with it greater discrepancies between measured and calculated response variables (in this case, LAI) compared with previous studies. This was likely related to limiting the input variables to normalized CGDD and combinations of PP and CH, and perhaps using a relatively simple three-parameter model. Other variables impacting LAI might include biotic and abiotic stresses, such as soil water availability, soil temperature and microclimate, nutrients, pests, and competition from weeds (e.g., Evett et al., 2012; Yin et al., 2003). These may well induce spatial variability of LAI that is not captured in PP or CH measurements, along with measurement error of model inputs themselves. Reflectance-based remote sensing techniques such as those discussed here may provide a way to better quantify spatial variability of LAI beyond PP or CH; these could be extended to thermal remote sensing that has been long shown to detect shortages in soil water, which also impacts LAI (e.g., Howell et al., 2004).

CONCLUSION

Allometric models were developed and tested to estimate LAI for row crops, including corn, cotton, sorghum, and soybean, where LAI was measured directly by destructive sampling. The allometric models were based on four variants of a three-parameter log normal function driven by normalized CGDD. The four model variants included LAI calculated as a function of normalized CGDD only (LAI), normalized CGDD and CH (LAICH), normalized CGDD and PP (LAPP), or normalized CGDD, CH, and PP (LAPPCH). These variables are usually more widely available in crop production and other agro-ecological datasets compared with variables typically used in previous allometric studies, such as length and width of individual leaves, leaf dry mass, plastochron index, or stem node number. The three parameters used in the log normal function were specific to the allometric model version and crop. The resulting allometric relationships had r^2 that varied from 0.23 to 0.85, with most $r^2 \geq 0.50$, which were less than previous studies, where $r^2 > 0.90$ were typically reported, but often included smaller datasets that were subject to less variable crop management, growing, and climatic conditions.

Models were tested using independent data from several crop seasons, which included wide ranges of agronomic and irrigation management methods, and growing and climatic conditions. Discrepancies between calculated and measured LAI were calculated in terms of r^2, IOA, RMSE, MAE, and MBE. Discrepancies were mostly smallest for cotton and soybean using the LAPPCH model, for corn using the LAICH model, and for sorghum using the LAPP model. However, discrepancies using the LAPPCH model for corn and sorghum were very similar to the LAICH and LAPP models, respectively. Therefore, the LAPPCH model appeared robust for the four crops and wide ranges of conditions considered. A few previous studies tested allometric models to calculate LAI, and usually reported results in terms of r^2 (>0.86). These were comparable to r^2 for the LAPPCH model of the present study (0.63–0.84).

The allometric models developed herein were designed to address the paucity of LAI data relative to other, more common plant physical measurements typically included in agro-ecological datasets. Because LAI controls and interacts with virtually every aspect of the mass and energy balance of vegetated surfaces, this approach should encourage additional studies of LAI estimation for other crops and vegetation, and should also enhance the utility of datasets used in advancing the agricultural and natural sciences.

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