

Applications of georeferenced high-resolution images obtained with unmanned aerial vehicles. Part II: application to maize and onion crops of a semi-arid region in Spain

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Abstract Leaf area index (LAI) is involved in biological, environmental and physiological processes, which are related to photosynthesis, transpiration, interception of radiation and energy balance. Thus, most crop models use LAI as a key feature to characterize the growth and development of crops. However, direct measures of LAI are destructive and tedious so that samplings can seldom be repeated in time and in space. Green canopy cover (GCC) is directly involved in crop growth and development. GCC estimation can benefit from aerial observation, as it can be measured by using image analysis or estimated by obtaining different vegetation indices. The main purpose of the second part of this paper was to study the relationships between GCC and LAI by using aerial images from UAVs in order to characterize crop growth. Also, the relationships between GCC and a vegetation index based on the visible spectrum was calibrated and validated. Relationships between LAI and GCC, growing degree days (GDD) and GCC and GDD and LAI were calibrated and validated for maize and onion crops with proper fitting. Visible atmospherically resistant index also appears to be a sensitive indicator to different growing stages and could generally be applied to any field crop. To apply this methodology, GCC and LAI relationships must be calibrated for many other crops in different irrigable areas. In addition, the cost of the UAV is expected to decrease while autonomy increases through improved battery life and reductions in the weight of on-board sensors.

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Introduction

Monitoring crop development is an important tool as farming decision support, since it permits assessment of the most critical stages of growth. Phenological monitoring also improves the understanding of crop development and growth processes (Viña et al. 2004). Most crop models use leaf area index (LAI) as a key feature to characterize the growth and development of crops. LAI, is defined as one-sided area of leaf tissue per unit ground surface area (Watson 1947). Due to the applicability of LAI in modelling, there is a need for LAI estimation during a growing cycle. Also, LAI is involved in biological, environmental and physiological processes, which are related to photosynthesis, transpiration, interception of radiation and energy balance (Kucharik et al. 1998). Direct measures of LAI are destructive and time consuming so that samplings can seldom be repeated in time and in space. Several techniques of remote sensing have been developed to estimate LAI from easy indicators, such as vegetation indices. These studies have indicated the need for model calibration and validation and that high resolution images obtained with aerial vehicles at low altitude over experimental plots are an excellent resource (Chen et al. 2004).

Green canopy cover (GCC) is directly involved in crop growth and development. Many studies, such as Wright (1982), Allen et al. (1998) and Kato and Kamichika (2006), determined the growth intervals based on the different slope of the GCC curve throughout the progression of the crop cycle, considering GCC as the fraction of soil surface covered by the crop canopy (Steduto et al. 2009). Also, GCC is related to soil and erosion, with the atmosphere and transpiration, climate, plant stress agents and crop vegetation management (Pereira and Allen 1999). Recognised models, such as Aquacrop (Steduto et al. 2009) use GCC as the main parameter instead of LAI, developing an empirical relationship between GCC and LAI obtained by regression.

Unmanned aerial vehicle (UAV) platforms offer new possibilities to agriculture in order to obtain high spatial resolution imagery delivered in near-real time (Herwitz et al. 2004). Green canopy cover estimation can benefit from this aerial observation, as it can be measured by using image analysis. Spectral vegetation indices are widely used for temporal and spatial variations in vegetation structure and biophysical parameters. Normalized vegetation index (NDVI) is one of the most used in remote sensing applications related to land cover studies (Pettorelli et al. 2005). However, NDVI saturates as a function of LAI or GCC beyond a threshold value (Turner et al. 1999). Techniques that use only the visible range of the spectrum for quantitative estimation of GCC, such as green vegetation index (VI_{green}) and visible atmospherically resistant index ($VARI_{\text{green}}$) have been proposed (Gitelson et al. 2002; Stark et al. 2000). These indices have been applied to avoid the effect of saturation experienced with NDVI. Some studies, such as those developed by Asrar et al. (1989) and Baret and Guyot (1991) studied the correlations between different vegetation indices with LAI, green biomass and GCC.

The main purpose of the second part of this paper was to study the relationships between GCC and LAI by using aerial images from UAVs in order to characterize crop growth. Also, the relationship between GCC and a vegetation index based on the visible spectrum was calibrated and validated.

Materials and methods

Study area

The fields analysed were located in Tarazona de La Mancha (Albacete, Spain) in commercial plots for two seasons: 2010–2011 and 2011–2012. The main crop characteristics are shown in Table 1 for the two seasons. These maize and onion crops were both irrigated using permanent solid set systems. The cultivation techniques applied were the typical practices in this area for both crops. Sampling dates were selected according to the main phenological and vegetation closure changes (Allen et al. 1998), which will determine future crop biomass and yield rates.

Field work procedure

A procedure for field work for onion and maize was implemented (Fig. 1). Phenological observations were performed at the same plots and sampling events. After sampling area selection, the first step was to install targets for geo-referencing the final model (ortho-photo or 3D terrain model). A sampling area of 1 000 m² was selected from the total flight area for the different crop samples. For each flight event, three 1 m² plots (sampling plots) from the 1 000 m² sampling area were randomly selected using the Latin-hypercube method. Latin hypercube sampling procedure may be considered a particular case of stratified sampling. Stratified sampling provides better coverage of the sample space for the input factors. A 1 m² steel frame was used for delimiting each sample plot, which could be perfectly detected in the images due to very high resolution. After locating the frames, the flight was performed following the flight planning process described above. After the flight, plants from each sampling plot were collected and transported to the lab for measurements by separating plant components and measuring leaf area (LA) among other variables. In each sampling event, the LA for completely extended individual leaves was computed by using an automated infrared imaging system LI-COR-3100C (LI-COR Inc., Lincoln, Nebraska, USA). Six plants from each sampling plot were collected for both maize and onion, as stated by Córcoles et al. (2013), which means 50 and 38 % of the total number of plants in the sampling plot, respectively.

In each experimental plot, the total number of plants was counted in order to calculate the LAI using Eq. 1.

$$LAI = LA \cdot Np \quad (1)$$

where *LAI* is leaf area index (m² leaf m⁻² soil), *LA* is leaf area (m² plant⁻¹), *Np* is Number of plants per soil surface (number of plant m⁻² soil).

After field work, ortho-images were processed using the LAIC software in order to obtain the GCC in each experimental plot.

Modelling

Traditionally, GCC is one of the most utilized indices for quantifying crop growth and development because it is easy to determine with nadiral images taken with conventional cameras. This paper establishes the relationships between GCC and other key components of the crop growth and development, such as LAI, which are difficult to measure directly. Understanding temporal and spatial variation in LAI is therefore essential for climate,

Table 1 Plot location, sowing date, plant density, total amount of irrigation water, harvest date and yield for the analysed crop for 2010–2011 and 2011–2012 growing seasons (in brackets water content of grains for maize and bulbs for onion)

Season	Plot		Sowing date	Plant density (plants ha ⁻¹)	Irrigation (m ³ ha ⁻¹)	Harvest date	Yield (kg ha ⁻¹)
	Lat. (N)	Long. (W)					
Maize FAO-700 cycle	39.251	1.918	29th Apr.	120 000	4 918	28th Nov.	15 300 (18 %) ^a
Onion cv. "Ciclope"	39.251	1.918	26th Apr.	120 000	5 210	30th Nov.	13 900 (16 %) ^a
	39.244	1.923	09th Feb.	500 000	5 500	18th Aug.	68 100 (90 %) ^b
	39.251	1.926	10th Feb.	500 000	6 900	3rd Sept.	60 000 (88 %) ^b

^a Water content of grains for maize (%)

^b Water content of bulbs for onion (%)

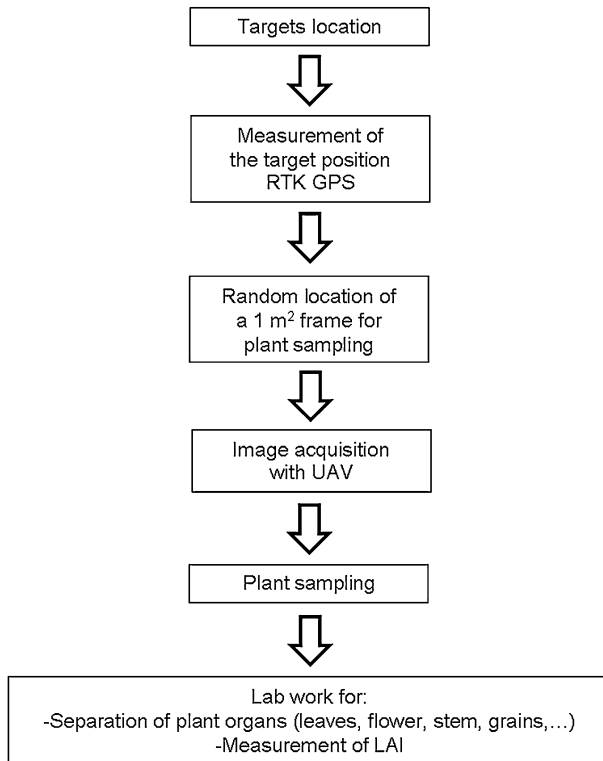


Fig. 1 Steps in field work data collection where GPS is global position system, UAV is unmanned aerial vehicle and LAI is leaf area

meteorological and hydrological modelling (Herbst et al. 2006). In mid-latitudes, crop growth and development tends to follow a well-defined temporal pattern (Viña et al. 2004). So, temporal profiles of GCC and LAI can be used to characterize crop phenology by evaluating their variability over time. In this study, in order to study inter-annual comparisons, different models based on growing degree days (GDD) were used to reproduce the behaviour of LAI and GCC (Table 2). To account for the climatic differences among years, the GCC and LAI was represented as a function of GDD, calculated with a base temperature of 8 °C for maize (Kiniry. 1991) and 5 °C for onion (Lancaster et al. 1996).

The studied models were linear, polynomial (second and third order), logarithmic and exponential-polynomial models. Exponential-polynomial models refer to polynomials generated by operating on exponential functions by differentiation, or by expanding the exponential into a power series in x (Bell 1934). All the proposed models were calibrated using collected and measured data from season 2011–2012. The model that best fits simulated with observed values is selected based on the highest coefficient of determination (R^2) and the lowest standard error. Then, the selected model was validated with the measured data in the previous season (2010–2011) which represent the third part of the total collected data.

Table 2 Models analysed for representing leaf area index (LAI), green canopy cover (GCC) and growing degree days (GDD) relationships and their references

Relationship	Expression	Reference
LAI-GCC	Linear $y = ax + b$	Gupta et al. (2000); Wang et al. (2004)
	Second order polynomial $y = ax^2 + bx + c$	Tei et al. (1996); Córcoles et al. (2013); de Medeiros et al. (2001)
	Logarithmic $y = (\ln(1-(x/a)^b))c^{-1}$	Nielsen et al. (2012)
GCC-GDD	Second order polynomial $y = ax^2 + bx + c$	López-Urrea et al. (2012); Nuarsa et al. (2011)
	Third order polynomial $y = (ax^3 + bx^2 + cx + d)$	de Medeiros et al. (2000); Jovanovic and Annandale (1999); López-Urrea et al. (2009)
	Exponential-polynomial $y = \exp(ax^2 + bx + x)$	Steduto et al. (2009); Lofton et al. (2012)
LAI-GDD	Second order polynomial $y = ax^2 + bx + c$	López (2004); Martín de Santa Olalla et al. (1994); Juskiw et al. (2001)
	Third order polynomial $y = (ax^3 + bx^2 + cx + d)$	Maturano (2002); Dutta et al. (2011); de Medeiros et al. (2000)
	Exponential-polynomial $y = \exp(ax^2 + bx + x)$	Tei et al. (1996); Srivastava et al. (2005)

Validation of the model

The validation of the model was done using independent data sets from the season 2010–2011, which were not used in the calibration process. In validating the model, observed and simulated values were compared. Model validation and performance was analysed with the root mean squared error (RMSE) (Eq. 2) and coefficient of efficiency (E) (Nash and Sutcliffe 1970; DeJonge et al. 2011) (Eq. 3) statistical indicators.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (O_i - S_i)^2} \quad (2)$$

where O_i are the observed values, S_i are simulated values, N is the number of observations. The units for RMSE were the same as that for O_i and S_i and the model fits improved when RMSE is approaching zero.

Coefficient of efficiency was calculated following Eq. 3.

$$E = 1 - \frac{\sum_{i=1}^N (O_i - S_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2} \quad (3)$$

where O_i are the observed values, S_i are simulated values, N is the number of observations, \bar{O} is the mean value of O_i . Coefficient of efficiency (E) expressed how much the overall deviation between observed and simulated values departs from the overall deviation between observed values (O_i) and their mean values \bar{O} : the best model simulations occurred when values are close to +1.

Vegetation indices in the visible spectrum

Normalized vegetation index is the vegetation index most frequently used. However, when the canopy is too sparse, the background spectral properties can affect significantly the NDVI value, thus when the canopy is too dense, NDVI can also saturate (Gilbert et al. 2010). Alternative indices have been proposed for remote estimation of LAI (Gitelson et al. 2003) and GCC (Gitelson et al. 2002). As described in part I of this paper, some of them are VI_{green} and $VARI_{\text{blue}}$ which only use bands in the visible region of the electromagnetic spectrum. The main difference between the VI_{green} and $VARI_{\text{green}}$ is that $VARI_{\text{green}}$ introduces an atmospheric self-correction. According to Gitelson et al. (2002), $VARI_{\text{green}}$ is more sensitive than VI_{green} to GCC estimation due to the introduction of the blue reflectance. In this study, the relationships $VARI_{\text{green}}$ versus GCC and $VARI_{\text{green}}$ versus LAI were evaluated.

Results

Several crop indices and relationships between indices and crop characteristics were established using the methodology and software developed for this study. These relationships can be used to calibrate satellite-based remote sensing crop measurements, to predict yield and to determine the crop stage variability in a plot, among many other applications. Some examples of the utility of the proposed methodology are described in this section.

Analysis of LAI and GCC values

Leaf area index and GCC observed values through 2010–2011 and 2011–2012 seasons are shown in Table 3 for maize. For 2011–2012 season (calibration season), LAI values showed high variability at the first sample date. This can be explained by different rates of leaf growth in the first phenological stage, where there were different sizes and numbers of leaves per plant. Green canopy cover exceeded average values at the second sampling event (12th July), when the third FAO-stage started and average LAI values were very high, reaching more than $4.3 \text{ m}^2 \text{ leaf m}^{-2} \text{ soil}$. At the third sampling event, 1 198 GDD, LAI and GCC reached maximum values after the period of maximum vegetative activity (start of fruit growth). The maximum LAI value ($4.6 \text{ m}^2 \text{ leaf m}^{-2} \text{ soil}$) represented a GCC of 95.4 %—common values for maize in this area (Maturano 2002). At this stage, the lowest coefficient of variation (CV) of the experiment was obtained because plants after flowering present similar growth rates meaning higher uniformity between sampling plots. Green canopy cover showed similar behaviour to LAI: both parameters reached maximum values after flowering and decreased quickly at maturity. However, although all leaves dried, GCC values were around 12.0 % at 1 911 GDD. This could be caused by other green portions, such as stems and bracts, supported by the crop during senescence.

Observed data at first sampling event for validation season, 2010–2011, did not show a high variability as in 2011–2012. It could be due to the highest crop uniformity of growth at the first phenological stages in this season. Maximum values of LAI and GCC, $5.31 \text{ m}^2 \text{ leaf m}^{-2} \text{ soil}$ and 89.2 % respectively, were observed at the second sampling event (1 244 GDD). From this sampling event, a decrease of LAI and GCC occurred coinciding with the beginning of the fourth FAO-stage. However, the highest variability was found at this moment, (from 1 412 GDD) due to the different rates of senescence along the sampling

Table 3 Measured values of plant density, leaf area index (LAI) and green canopy cover (GCC) for maize

	Density (plants/m ²)			Leaf area index (m ² leaf m ² soil)			Green canopy cover (%)		
	Individual sample	Mean	CV	Plot sampling	Mean	CV	Plot sampling	Mean	CV
<i>Season 2010–2011</i>									
Jun 22 (409) ^a	10	9.50	21.91	0.80	0.87	9.54	20.43	21.37	4.44
	9			0.95			22.31		
	13			0.81			21.60		
Aug 20 (1 244) ^a	11	12.00	9.62	5.44	5.31	5.87	89.60	89.24	1.96
	13			5.18			88.89		
	11			4.82			86.27		
Aug 30 (1 412)	13	13.50	7.41	4.83	5.32	19.85	79.17	87.51	19.95
	14			5.80			95.85		
	15			3.70			60.94		
<i>Season 2011–2012</i>									
Jun 21 (428) ^a	13	12.00	8.33	2.10	1.54	41.50	38.53	34.84	18.72
	12			1.67			38.69		
	11			0.84			27.31		
Jul 12 (698) ^a	11	11.67	4.95	4.34	4.36	8.39	74.21	75.32	16.75
	12			4.01			63.30		
	12			4.74			88.46		
Aug 14 (1 198) ^a	11	11.00	0.00	4.31	4.61	5.69	95.49	95.36	0.16
	11			4.73			95.38		
	11			4.78			95.19		
Aug 28 (1 455) ^a	10	11.00	15.75	4.17	3.84	18.90	61.58	58.56	6.38
	13			4.33			59.72		
	10			3.01			54.38		
Sep 10 (1 640) ^a	13	13.33	4.33	3.32	2.88	29.09	36.19	37.23	6.50
	13			3.41			39.99		
	14			1.91			35.50		
Oct 03 (1 911) ^a	13	12.00	8.33	0.00	0.00	0.00	13.88	11.58	19.16
	12			0.00			9.45		
	11			0.00			11.40		

CV Coefficient of variation

^a Growing degree days (GDD)

plot, which means that some plants reached their physiological maturity whereas the others were at early-dough stage. The high intra-plot variability in this stage was observed in the distribution of GCC obtained with the ortho-images and the LAIC software, as reported in part I of this paper.

Table 4 shows plot sampling events for onion for 2010–2011 and 2011–2012 seasons. In the first sample event of the calibration season (2011–2012), LAI values were 0.7 m² leaf m⁻² soil. For this season, LAI and GCC showed high variability, with CV values from 2.6 to 80.9 %. The highest variation was found at 966 GDD as ground closure and LAI

Table 4 Measured values of plant density, leaf area index (LAI) and green canopy cover (GCC) for onion

	Density (plants/m ²)			Leaf area index (m ² leaf m ² soil)			Green canopy cover (%)		
	Individual sample	Mean	CV	Plot sampling	Mean	CV	Plot sampling	Mean	CV
<i>Season 2010–2011</i>									
Jul 18 (1 303) ^a	58	58.33	4.31	3.45	2.61	28.00	45.01	40.96	8.77
	56			2.26			39.73		
	61			2.12			38.15		
Jul 29 (1 450) ^a	57	55.33	5.22	4.39	3.96	10.52	59.90	55.95	6.91
	52			3.92			55.76		
	57			3.56			52.18		
Aug 06 (1 561) ^a	59	59.00	0.00	5.21	4.86	10.34	69.90	64.86	11.00
	59			4.50			59.81		
<i>Season 2011–2012</i>									
Jun 20 (966) ^a	46	43.00	14.15	1.25	0.72	73.03	27.38	15.07	80.90
	47			0.73			14.82		
	36			0.19			3.00		
Jul 12 (1 268) ^a	38	38.67	1.49	2.92	2.47	18.02	40.57	33.48	23.34
	39			2.46			34.77		
	39			2.03			25.10		
Jul 23 (1 431) ^a	37	38.33	3.01	3.63	3.65	2.60	51.65	48.46	9.82
	39			3.75			50.74		
	39			3.56			42.99		
Aug 09 (1 685) ^a	30	32.33	6.44	3.16	3.59	10.40	44.69	50.62	11.78
	34			3.81			56.62		
	33			3.80			50.55		
Aug 23 (1 939) ^a	42	38.33	10.54	2.10	2.09	21.35	34.97	37.17	9.72
	39			2.53			35.21		
	34			1.64			41.34		

CV Coefficient of variation

^a Growing degree days (GDD)

depend on density, plant architecture and leaf posture. Due to different crop establishment rates, density values showed high variability. There were also significant differences between sampling plots caused by varying development states of the different sampling plots: different sizes of leaves appeared in each plot through the vegetative growth. According to LAI, there was higher heterogeneity in GCC for this first sampling event. These results agreed with other studies, such as Córcoles et al. 2013 that reported similar trends for onion crop. Physiological maturity is assumed to be at the time GCC decreases to zero. Extrapolated from LAI-GCC data, senescence start time is assumed to be the time when GCC decreases below a LAI = 3.6 m² leaf m⁻² soil. At this time, there was greater uniformity in LAI and GCC as there were no new leaf blades at the onset of bulbing (Jiménez 2008; Tei et al. 1996). After this stage, leaves continued to expand but then started to die and, as a consequence, there was a progressive decrease in LAI, reaching a final value of 2.1 m² leaf m⁻² soil (Jiménez 2008). At the end of the establishment stage,

GCC was around 15.1 %, similar to values reported in López-Urrea et al. (2009). Later in the development stage, GCC increased, rapidly, reaching the maximum value (50.6 %) when bulb growth and maximum LAI values occurred. After that, GCC decreased to 37.2 % during maturing of bulbs.

For the first sampling event of the validation season (2010–2011), average LAI values were $2.61 \text{ m}^2 \text{ leaf m}^{-2}$ soil and average GCC was 40.9 % without significant variability. Maximum values of LAI, $4.9 \text{ m}^2 \text{ leaf m}^{-2}$ soil were found at the third sampling event (1 561 GDD) when maximum GCC values were reached (64.9 %). However, GCC values were close to the maximum at the second sampling event after accumulating at 1 450 GDD (beginning of bulbing stage) which means that GCC remained for longer with maximum values than LAI. These values were a little higher than those collected during 2011–2012 season. Some problems with the third sampling event impeded acquisition of data from one of the three sampling plots, so data from two sampling plots were used.

Relationships between LAI and GCC

Different models were used to analyse the different relationships between LAI and GCC for maize (Table 5) and onion (Table 6), which had different model fit values.

The maize case study

The second order polynomial models had the best fit between GCC and LAI with an adjusted R^2 of 0.91 ($p < 0.001$) (Table 5; Fig. 2). The dispersion pattern of the residuals followed a normal distribution and displayed homoscedastic behaviour.

Exponential models were reported by Hsiao et al. (2009) with a high R^2 for three site-year experiments. However, no details were given on seeding and how GCC values were obtained. Nielsen et al. (2012) suggested low seeding rates used by Hsiao et al. (2009) as 70 % was the maximum GCC reached at $\text{LAI} = 3.0 \text{ m}^2 \text{ leaf m}^{-2}$ soil. So, this model was used for low plant densities and it would not be representative for LAI values greater than $3.0 \text{ m}^2 \text{ soil m}^{-2}$ leaf. It was also suggested using different relationships for higher seeding rates, which would involve higher GCC values. Exponential models were not appropriate for the results of this study, as $\text{LAI} = 4.6 \text{ m}^2 \text{ leaf m}^{-2}$ soil and $\text{GCC} = 95.4 \%$.

For maize, LAI did not increase much from $\text{GCC} = 75.3$ to 95.4% (Fig. 2). The same behaviour could be observed in other research (Nielsen et al. 2012), which reported that maximum values of LAI were obtained with different GCC values. This means that maximum LAI is maintained by the crop throughout maturity due to the changes in crop structure, as leaves became more horizontal and efficiency of solar radiation interception is increased (Lisazo et al. 2003). Thus, GCC is useful for determining the crop development status during the initial stages of the crop, but is difficult to differentiate when GCC is 70.0 % or higher. The effect is similar to the saturation of NDVI (Calera et al. 2001). The good agreement in the validation process between measured and simulated LAI using the second order polynomial model for 2010–2011 season is also shown in the statistical analysis given in Table 7, with high E obtained for these samples.

The onion case study

According to the models studied, linear equations presented the best fit ($R^2 = 0.85$, $p < 0.001$). In all models studied, the dispersion pattern of residuals followed a normal

Table 5 Calibration of the different studied models for maize

Expression	Adjusted R^2	p value	Standard error	a	b	c	d
LAI-GCC							
$y = ax + b$ (see Fig. 2)	0.822	***	0.755	5.5260×10^{-2}	-8.1800×10^{-3}		
$y = ax^2 + bx + c$ (see Fig. 2)	0.913	***	0.511	-7.0210×10^{-4}	1.3160×10^{-1}	-1.5040	
GCC-GDD							
$y = ax^2 + bx + c$ (see Fig. 4)	0.866	***	10.610	-1.1490×10^{-04}	2.4430×10^{-1}	-4.4040×10^1	
$y = (ax^3 + bx^2 + cx + d)$ (see Fig. 4)	0.932	***	7.590	8.4720×10^{-08}	-4.1940×10^{-4}	5.7140×10^{-1}	-1.4190×10^2
LAI-GDD							
$y = \exp(ax^2 + bx + c)$ (see Fig. 4)	0.963	***	5.679	-2.8940×10^{-06}	5.9660×10^{-3}	1.5770	
$y = ax^2 + bx + c$ (see Fig. 4)	0.899	***	0.558	-7.3310×10^{-06}	1.5920×10^{-2}	-3.6720×10^{-1}	
$y = (ax^3 + bx^2 + cx + d)$ (see Fig. 4)	0.907	***	0.534	1.8320×10^{-09}	-1.3910×10^{-5}	2.2990×10^{-2}	-5.7890
$y = \exp(ax^2 + bx + c)$ (see Fig. 4)	0.823	***	0.756	-2.5820×10^{-06}	5.4620×10^{-3}	-1.2020	

LAI leaf area index, GCC green canopy cover, GDD growing degree days, R^2 Coefficient of determination

*** $p < 0.001$

Table 6 Calibration of the different studied models for onion

Expression	Adjusted R^2	p value	Standard error	a	b	c	d
LAI-GCC							
$y = ax + b$ (see Fig. 3)	0.854	***	0.447	7.4340×10^{-2}	-2.4370×10^{-1}		
$y = ax^2 + bx + c$ (see Fig. 3)	0.846	***	0.441	2.8000×10^{-4}	5.7000×10^{-2}	-4.1200×10^{-2}	
GCC-GDD							
$y = ax^2 + bx + c$ (see Fig. 5)	0.747	***	7.355	-8.6690×10^{-5}	2.7790×10^{-1}	-1.7410×10^2	
$y = (ax^3 + bx^2 + cx + d)$ (see Fig. 5)	0.783	***	6.809	-1.1140×10^{-7}	3.9690×10^{-4}	-3.9870×10^{-1}	1.3000×10^2
LAI-GDD							
$y = \exp(ax^2 + bx + c)$ (see Fig. 5)	0.788	***	6.744	-3.1380×10^{-6}	1.0120×10^{-2}	-4.2190	
$y = ax^2 + bx + c$ (see Fig. 5)	0.860	***	0.437	-8.8130×10^{-6}	2.7626×10^{-2}	-1.7510×10^1	
$y = (ax^3 + bx^2 + cx + d)$ (see Fig. 5)	0.892	***	0.383	-8.3930×10^{-8}	2.7610×10^{-5}	-2.3710×10^{-2}	5.4020
$y = \exp(ax^2 + bx + c)$ (see Fig. 5)	0.904	***	0.362	-4.6670×10^{-6}	1.4650×10^{-2}	-1.0140×10^1	

LAI leaf area index, GCC green canopy cover, GDD growing degree days, R^2 Coefficient of determination

*** $p < 0.001$

Fig. 2 Relationship between leaf area index (LAI) and green canopy cover (GCC) for maize using linear model (solid line) and second order polynomial model (dashed line) according to the expressions described in Table 5

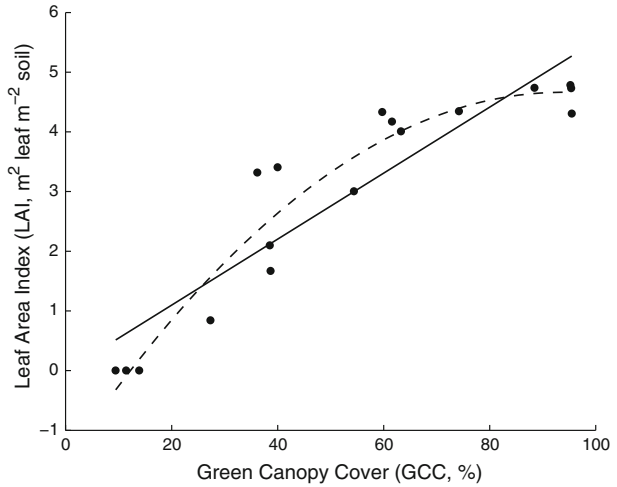


Table 7 The root mean squared error (RMSE) and coefficient of efficiency (E) obtained in the validation process for the selected green canopy cover (GCC)- leaf area index (LAI), GCC-growing degree days (GDD) and GDD-LAI relationships for 2010-2011 growing season data

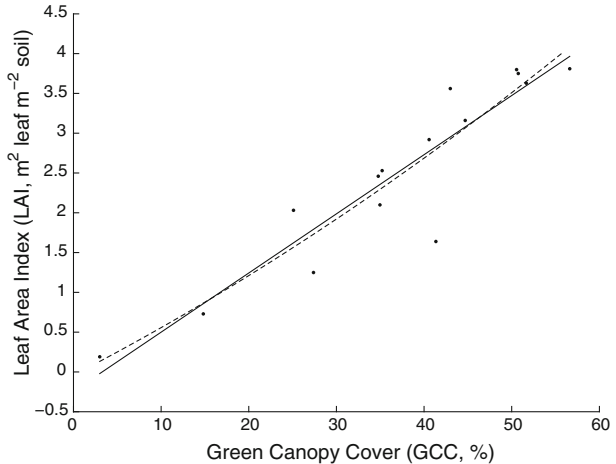
	RMSE (m ² leaf m ² soil) GCC-LAI	E	RMSE (%) GDD-GCC	E	RMSE (m ² leaf m ² soil) GDD-LAI	E
Maize	0.523	0.932	12.641	0.830	0.753	0.860
Onion	0.326	0.911	9.052	0.791	0.664	0.816

distribution and present homoscedastic behaviour. According to these results, a linear model can be considered the most suitable to describe the relationship between LAI and GCC (Fig. 3). Similar studies concluded also that linear models have a high significant fitting between LAI and GCC (Córcoles et al. 2013) with similar values of coefficient of determination ($R^2 = 0.84$) as that obtained in this paper for onion crops. Moreover, others authors, such as Gupta et al. (2000) and Calera et al. (2001) established a linear relationship between NDVI and LAI. Regarding the validation process, the linear model was able to properly simulate the 2010–2011 season. This is shown by the low RMSE and high E (close to 1.00) values (Table 7).

LAI and GCC patterns through the phenological cycle

Estimating and analysing the behaviour of LAI and GCC during the phenological cycle of the crops could supply useful information to decision makers about which cultivation techniques should be undertaken and at what time (Botella et al. 1997; Barker et al. 2010). A crop model can be described as a quantitative scheme for predicting the growth, development and yield of a crop, given a set of generic features and relevant environmental variables (Monteith 1996).

Fig. 3 Relationship between leaf area index (LAI) and green canopy cover (GCC) for onion using linear model (*solid line*) and second order polynomial model (*dashed line*) according to the expressions described in Table 6



Analysing GCC and LAI behaviour through the growing cycle using GDD, instead of days after emergence, allows the application of the obtained results to different growing seasons. Many models, such as AquaCrop (Steduto et al. 2009), not only are able to simulate crop development using GDD, but also have a key feature of simulating GCC instead of LA using canopy cover per seedling, canopy growth coefficient and maximum GCC as known variables. Temporal patterns of GCC for both crops (Fig. 4 for maize and Fig. 5 for onion) show phenological changes due to biomass accumulation, with a period of early leaf development, a period of maximum canopy expression and a period of senescence.

The case of maize crop

The relationships obtained between GCC and GDD showed that third order polynomial models were considered the best fit ($R^2 = 0.93$, $p < 0.001$) (Fig. 4). For all models studied, the dispersion pattern of residuals followed a normal distribution and homoscedastic behaviour.

Although an exponential-polynomial model showed the best statistical results ($R^2 = 0.96$; $p < 0.001$), using this model to represent GCC versus GDD involves an overestimation of maximum values of GCC. Exponential-polynomial models considered 104.77 % as maximum values of GCC at 1 031 GDD which is significantly higher than expected ones. According to third order polynomial model, maximum GCC (95.08 %) is reached at 961 GDD and lasts no longer than 179 GDD more (1 140 GDD in total) when canopy closure starts to decrease below 90.0 %. The second order polynomial model considers 85.82 % as the maximum value for GCC, which is much lower than values obtained in experimental plots. Thus, according to maximum GCC timing and length, third order polynomial models presented the best fit. Table 7 presents the statistics of the simulated results for the validation process during season 2010–2011. Coefficient of efficiency values of 0.83 and RMSE values of 12.64 % were due to the variability of GCC, as with the same amount of required GDD (1 412 GDD), the range of GCC values varied from 60.9 to 95.9 % in 2010–2011.

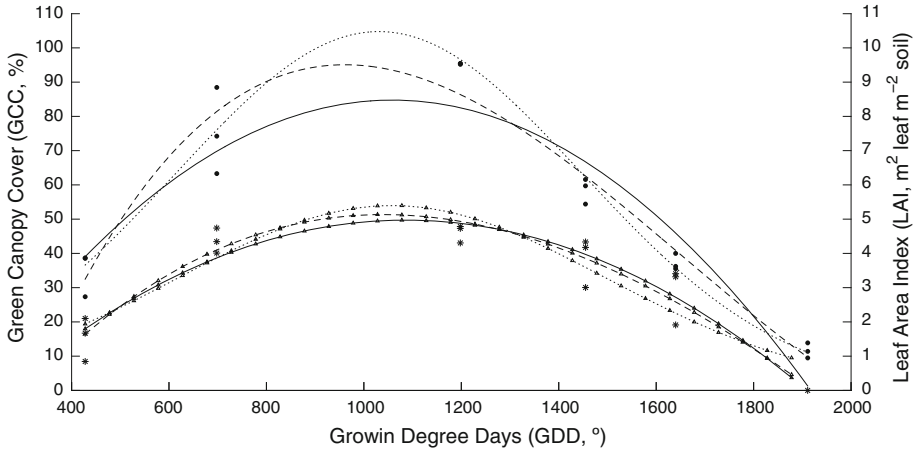


Fig. 4 Relationship between green canopy cover (GCC) and growing degree days (GDD) for maize using second order polynomial model (*solid line*), third order polynomial model (*dashed line*) and exponential-polynomial function (*dotted line*) and relationship between leaf area index (LAI) and GDD for maize using second order polynomial model (*solid line and triangles*), third order polynomial model (*dashed line and triangles*) and exponential-polynomial function (*dotted line and triangles*) according to the expressions described in Table 5

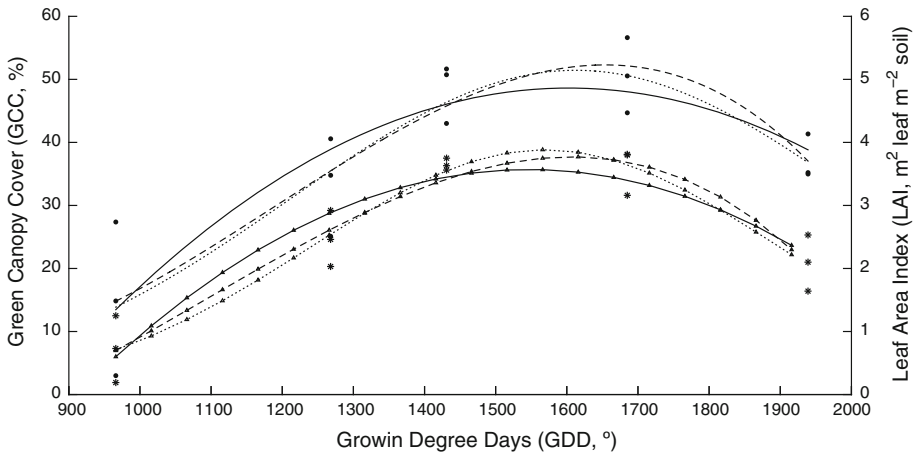


Fig. 5 Relationship between green canopy cover (GCC) and growing degree days (GDD) for onion using second order polynomial model (*solid line*), third order polynomial model (*dashed line*) and exponential-polynomial function (*dotted line*) and relationship between leaf area index (LAI) and GDD for onion using second order polynomial model (*solid line and triangles*), third order polynomial model (*dashed line and triangles*) and exponential-polynomial function (*dotted line and triangles*) according to the expressions described in Table 6

For the relationships between LAI and GDD combining all data, the second order or higher of polynomial models were considered the best fitting, with the highest R^2 in third order equations ($R^2 = 0.91$) (Fig. 4). Other studies, such as Maturano (2002) and López (2004), reported similar models (second order or higher) as best fitting due to their

accuracy according to maximum canopy length and declining start point. More complex models have been analysed but neither their statistical accuracy nor their agronomic meaning increased substantially. In all cases, the dispersion pattern of residuals followed a normal distribution and homoscedastic behaviour. Highest rates of LAI variability could be found at third sampling event during 2010–2011 validation season, resulting in low E values (Table 7). According to these results, it can be noted that LAI seems to be more sensitive to different rates of senescence than GCC.

Representing selected models for LAI-GDD and GCC-GDD relationships allowed observation of how the mentioned curves followed a similar trend (Fig. 4). Both parameters reached maximum values around 1 000 GDD, at the end of the reproductive stage. When maturity occurred, both parameters started their decrease. LAI decreased below $0.5 \text{ m}^2 \text{ leaf m}^{-2} \text{ soil}$ from 1 879 GDD, while GCC is over 13 %. This could be due to maintaining green structures after leaf senescence.

Although crop behaviour is properly represented by GCC, using LAI values may be more accurate at certain times. Some crop models use GCC, such as AquaCrop (Steduto et al. 2009), while others include the progression of LAI (Ritchie et al. 1989; Stöckle et al. 2003; DeJonge et al. 2011). Thus, it is very important to understand the relationships between the two variables and the moments where differences can appear. It is also important to report findings at different developmental stages, which can be established throughout the growing season using GCC.

The onion case study

In all models studied, the dispersion pattern of residuals followed a normal distribution and homoscedasticity for analyses of the relationships between GCC and GDD (Fig. 5). Adjustments obtained using third order polynomial and exponential-polynomial models offer very good results ($R^2 > 0.78$, $p < 0.001$ for both cases).

The other models (i.e. the second order polynomial) obtained lower values for maximum GCC (48.61 %) than those expected (>50 %). Jovanovic and Annandale (1999) defined third order models obtaining high statistical significance values. However, according to the results obtained in this paper, third order polynomial models established maximum values close to 52.3 %, which was higher than the values obtained. The exponential-polynomial model had similar statistical results but showed lower maximum values for GCC (51.0 %). Other authors, such as Tei et al. (1996), also reported exponential-polynomial models describing later stages: when leaves overlap with neighbouring plants, onion shows a small increase in ground cover with an increase in LAI. Thus, exponential-polynomial models have the best performance with these variables. The values of E and RMSE, 0.79 and 9.05 % respectively (Table 7), indicate an adequate performance of the selected expo-polynomial model in the validation process.

For all LAI-GDD models, the dispersion patterns of residuals followed a normal distribution and had homoscedastic behaviour. The exponential-polynomial model was considered the best fit ($R^2 = 0.90$, $p < 0.001$) (Fig. 5). The second order polynomial models underestimated maximum values of LAI; and the third order polynomial placed the maximum value over 1 605 GDD, while sampling events determined that maximum values were close to 1 500 GDD. Other studies that established the same relationships with similar indices (LA, specific leaf area), had also used exponential models with high statistical significance (Tei et al. 1996). For the validation process, E and RMSE values also showed adequate performance (Table 7) for LAI estimation (E = 0.79, RMSE = $9.05 \text{ m}^2 \text{ leaf m}^{-2} \text{ soil}$) during 2010–2011 season.

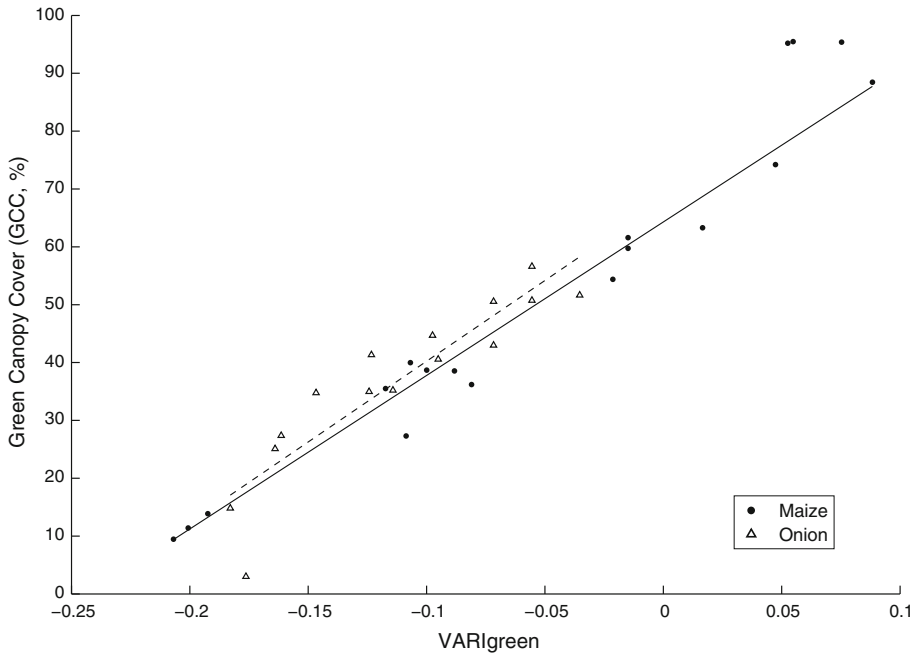


Fig. 6 Relationship between GCC and VARI_{green} for maize and onion according to Table 8

Table 8 Calibration of the different studied models for maize and onion

	Adjusted R ²	p value	Standard error
<i>Maize</i>			
GCC (%) = 293.8 × VARI _{green} + 67.13 (see Fig. 6)	0.946	***	6.714
LAI (m ² leaf m ⁻² soil) = -33.24 × VARI _{green} ² + 13.13 × VARI _{green} + 3.917	0.890	***	0.581
VARI _{green} = 2.715 × 10 ⁻¹⁰ × GDD ³ - 1.348 × 10 ⁻⁶ GDD ² + 1.82 × 10 ⁻³ GDD - 0.6534	0.972	***	0.016
<i>Onion</i>			
GCC (%) = 279.1 × VARI _{green} + 68.13 (see Fig. 6)	0.815	***	6.294
LAI (m ² leaf m ⁻² soil) = 22.62 × VARI _{green} + 5.03	0.838	***	0.470
VARI _{green} + 1 = exp(3.452 × 10 ⁻⁷ × GDD ² + 0.001083GDD - 0.9265)	0.661	***	0.028

LAI leaf area index, GCC green canopy cover, R² Coefficient of determination

*** p < 0.001

The progression of LAI and GCC values for the phenological cycle, using the models selected, showed that maximum values for both parameters were reached during bulb growth (third FAO-stage). In this stage, there was a high increase in absolute values from the first to the second sampling event (from the end of vegetative growth to the start of

Table 9 The root mean squared error (RMSE) and coefficient of efficiency (E) for the selected visible atmospheric resistant index (VARI_{green})-green canopy cover (GCC), VARI_{green}-leaf area index (LAI) and growing degree days (GDD)-VARI_{green} relationships validated for 2010–2011 growing season

	RMSE (%) VARI _{green} -GCC	E	RMSE (m ² leaf m ⁻² soil) VARI _{green} -LAI	E	RMSE GDD-VARI _{green}	E
Maize	14.197	0.849	0.897	0.796	0.040	0.765
Onion	4.38	0.874	0.728	0.705	0.046	0.879

bulbing). Maximum LAI was reached before maximum GCC value (1 570 GDD for LAI and 1 613 GDD for GCC), although GCC was located in the range of maximum values at this moment. Therefore, LAI remained constant to the following sampling event, meanwhile GCC continued increasing to 648 GDD, although this increased rate was not as high as the previous one (Fig. 5).

Relationships between spectral vegetation index and canopy parameters

Relationships between VARI_{green} versus LAI and GCC were studied for season 2011–2012 and validated for season 2010–2011. As expected and according to Viña et al. (2004), a linear model offered very good adjustments between VARI_{green} and GCC for both crops (Fig. 6): R² was 0.89 and 0.82 for maize and onion respectively (*p* value < 0.001) (Table 8). Similar results were reported by Gitelson et al. (2002) in both maize and wheat fields. From the results and Fig. 6, linear models can be used to characterise the VARI_{green}-GCC relationship accurately regardless of the crop type, which eases its application in remote sensing DSS.

Viña et al. (2004) reported that the VARI_{green} was sensitive to GCC and to the amount of chlorophyll present in leaves and thus pointed out the existing differences depending on growing cycle for VARI_{green} and GCC relationships: at the earliest stages, in which the soil is progressively covered by leaves and at senescence when leaves lose chlorophyll progressively. This pattern can be shown in this study with significant differences for GCC over 60 % during the leaf drying process (see part I). Thus, in this study, positive values of VARI_{green} are found for GCC values higher than 60 % for maize, also fitting with the results obtained by Rundquist et al. (2001) for two maize data sets collected during 1998 growing season. Maximum values of VARI_{green} (0.09) were reached at maximum GCC values which could be related with the appearance of the tassel and the beginning of reproductive stage, as from this moment VARI_{green} decreased progressively to -0.21 corresponding to the minimum values of GCC.

Just as for maize, the onion crop maximum VARI_{green} values (-0.05) were found at maximum GCC values (51.65 %) when the development of the harvestable vegetative plant parts has started. In none of the sampling events were positive VARI_{green} values found, and no GCC values higher than 60 % existed.

Then, the linear model was evaluated for 2010–2011 season to perform model validation (Table 9). The predicted and measured GCC for nine observations were compared for each crop. The results showed how the linear model was able to properly simulate the relationship VARI_{green} versus GCC for both crops. This is shown by the low RMSE and high E (higher than 0.80)

Second order polynomial and linear models were studied for $VARI_{green}$ versus LAI relationships for maize and onion respectively (Table 8). The results showed very good adjustments with R^2 values higher than 0.80. Also, the validation process with data obtained from for 2010–2011 season was analysed (Table 9). The results showed good relationships for the maize crop, although an under-prediction in the $VARI_{green}$ -LAI relationship for the onion crop ($RMSE = 0.73 \text{ m}^2 \text{ leaf m}^{-2}$ soil and $E = 0.71$) should be noted.

Growing degree days and $VARI_{green}$ relationships were of the same type as those obtained for GDD versus GCC for both crops (Table 8). Due to the characteristics of exponential-polynomial functions and the negative value of $VARI_{green}$ index, a mathematical transformation was required to represent this relationship. This transformation was that all $VARI_{green}$ values were transferred to the positive axis by adding the value 1. Thus, to obtain simulated values, the transformation should also be performed by subtracting 1 from the result of the model.

Conclusions

The use of high-resolution images obtained with UAVs together with proper treatment might be considered a useful tool for precision monitoring of crop growth and development, advising farmers on water requirements, yield prediction and weed and insect infestations, among others. This approach could also be used for climate, meteorological and hydrological modelling. It is necessary to couple the generated information with crop models such as AquaCrop to assist farmers with the decision making process.

For maize without growth and development restrictions, the second order polynomial models showed the best fit for relationships between LAI and GCC, while linear models best fit the onion data. The models that related GDD with LAI and GCC for maize are third order polynomial models. Maximum LAI values continue for maize throughout maturity, while GCC shows greater variation. For onion, the relationships for GCC and LAI throughout the growing cycle are represented by exponential-polynomial functions. This crop reaches the maximum GCC value shortly after the maximum LAI.

Visible atmospherically resistant index showed a linear relationship with GCC for both crops, maize and onion, with similar coefficients. Thus, the same model can be applied to other crops. Visible atmospherically resistant index also appears to be a sensitive indicator to different growing stages.

To apply this methodology, GCC and LAI relationships must be calibrated for many other crops in different irrigated areas. In addition, the cost of the UAV is expected to decrease while autonomy increases through improved battery life and reductions in the weight of on-board sensors.

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