# Vegetation indices combining the red and red-edge spectral information for leaf area index retrieval

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**Abstract**: Leaf Area Index (LAI) is a crucial biophysical variable for agroecosystems monitoring. Conventional Vegetation Indices (VIs) based on red and near infrared regions of the electromagnetic spectrum, such as the Normalized Difference Vegetation Index (NDVI), are commonly used to estimate Leaf Area Index (LAI). However, these indices commonly saturate at moderate-to-dense canopies (e.g. NDVI saturates when LAI exceeds 3). Modified VIs have then been proposed to replace the typical red/green spectral region with the red-edge spectral region. One significant and often ignored aspect of this modification is that, the reflectance in the red-edge spectral region is comparatively sensitive to chlorophyll content which is highly variable between different crops and different phenological states. In this study, three improved indices are proposed combining reflectance both in red and red-edge spectral regions into the NDVI, the modified simple ratio index (MSR) and the green chlorophyll index ($CI_{green}$) formula. These improved indices are termed $NDVI_{red\&RE}$ (red and red-edge normalized difference vegetation index), $MSR_{red\&RE}$ (red and red-edge modified simple ratio index) and $CI_{red\&RE}$ (red and red-edge chlorophyll index). The indices were tested using RapidEye images and in-situ data from campaigns at Maccarese Farm (Central Rome, Italy), in which four crop types at four different growth stages were measured. We investigated the predictive power of nine vegetation indices for crop LAI estimation, including NDVI, MSR, $CI_{green}$, the red-edge modified indices $NDVI_{Red\text{-}edge}$, $MSR_{Red\text{-}edge}$, $CI_{Red\text{-}edge}$ (generally represented by $VI_{Red\text{-}edge}$) and the newly improved indices $NDVI_{red\&RE}$, $MSR_{red\&RE}$, and $CI_{red\&RE}$ (generally represented by $VI_{red\&RE}$). The results show that $VI_{red\&RE}$ improves the coefficient of determination ($R^2$) for LAI estimation by 10% in comparison to $VI_{Red\text{-}edge}$. The newly improved indices prove to be powerful alternatives for LAI estimation of crops with wide chlorophyll range, and may provide valuable information for satellites equipped with red-edge channels (such as Sentinel-2) when applied to precision agriculture.

**Keywords:** Vegetation index; Remote sensing; RapidEye; Precision agriculture

## 1. Introduction

The explicit quantification of vegetation biophysical variables on large spatial scales is an important aspect in agricultural management and monitoring [1]. For instance, knowledge of the spatial distribution of leaf area index (LAI) and chlorophyll content can be used to improve the use of resources, such as fertilizer and water [2], leading to better yields and reduced costs [3-6]. Remotely sensed data from satellites and airborne sensors has great potential to provide information on vegetation biophysical variables over large spatial and temporal scales. Leaf area index (LAI), defined as one half the total leaf area per unit ground surface area [7, 8], is a biophysical key variable for estimating foliage cover and biomass production. The LAI can, therefore, be used to monitor and forecast crop growth and yield [1, 9, 10]. The LAI retrieval techniques from remote sensing data can be classified into three groups: (i) empirical retrieval methods, which typically relate the biophysical parameter of interest to spectral data [11, 12]; (ii) physical retrieval methods, which refers to inversion of radiative transfer models (RTM) from remote sensing observations [13]; (iii) hybrid methods, which aims to balance the strengths and weaknesses of empirical and physical based methods, e.g through a machine learning approach [14]. Amongst the three groups, the empirical retrieval methods typically use vegetation indices due to their simplicity, computational efficiency, and well-understood underlying mechanisms. The Normalized Difference Vegetation Index (NDVI)[15] is a widely used vegetation index to estimate vegetation biophysical variables, relying on chlorophyll absorption in the red spectral region, creating low reflectance, and high reflectance in the near infrared (NIR) spectral region due to the scattering of light from the intercellular volume of leaf mesophyll. Nevertheless, one unavoidable limitation of NDVI is that the relationship between NDVI and LAI approaches saturation asymptotically under the condition of moderate-to-dense canopy (e.g. LAI>3) due to the inherent drawback of NDVI [16].

The red-edge region is defined as the spectral region between 680nm and 750nm where there is a sharp change in vegetation reflectance [17]. This occurs due to the transition from chlorophyll absorption in the red region to cellular scattering in the NIR [18, 19]. The promise and potential of the red-edge spectral region for vegetation biophysical variable retrieval has motivated the design and also the launch of spaceborne imaging sensors involving red-edge bands, including hyperspectral satellites like Hyperion, HICO (The Hyperspectral Imager for the Coastal Ocean) and CHRIS (The Compact High Resolution Imaging Spectrometer), and multi-spectral satellites such as MERIS, RapidEye and recently, Sentinel-2 [19]. It has been demonstrated that in the red-edge spectral region the shape of the reflectance spectra is strongly influenced by LAI [20, 21]. The shift of red-edge position towards longer wavelengths is caused by an increase in leaf chlorophyll content [22]. Many studies have revealed that, within red and red-edge region, chlorophyll content and LAI contribute the most to PROSAIL simulated canopy reflectance [23, 24]. However, the effects of chlorophyll change on LAI retrieval is rarely discussed in studies using vegetation indices based on red-edge reflectance for LAI estimation. To note that, in those studies, the red-edge modified indices improve the LAI estimation when the indices are applied to crops with consistent chlorophyll content, e.g. datasets consisting of one type of crop at one growth stage [19, 25]. Therefore, how chlorophyll content affects spectral reflectance and leaf area index (LAI) when chlorophyll content and LAI vary simultaneously needs to be analysed, e.g. datasets with multi crop species and across multi growth stages. As such, the aims of this study are: (i) to analyse how variation in chlorophyll content and LAI contributes to red, red-edge and near infrared reflectance variability; and (ii) to apply three improved spectral indices for LAI estimation, and evaluate their advantages over other existing vegetation indices.

## 2. Experimental and Validation Data Collection

### *2.1. Test Site Description and LAI Measurements*

Ground LAI measurements were carried out *in situ* at the Maccarese farm (41°52′N, 12°13′E, alt. 8 m a.s.l.) near Rome, Central Italy (Fig. 1) in 2015 growing season. The site is within a plain coastal agricultural area comprising four dominant crops: winter wheat (Triticum aestivum L.), barley (Hordeum vulgare L.), alfalfa (Medicago sativa L.) and maize (Zea mays L.) (Table 1). Winter wheat was measured on 3 March, 20 March and 7 May, from its tillering stage to heading stage [26]; barley was measured on 3 March, 20 March and 7 May, from its tillering stage to earning stage

[27]; alfalfa was measured on 7 May, during its budding stage [28]; maize was measured on 7 July, during its jointing stage [29]. The soil is Cutanic Luvisol, with a prevailing sandy clay loam texture, becoming more clayey towards the north-east of the site. The climate is temperate Mediterranean with dry summers and wet autumns, with a yearly average temperature of 15.5 °C and annual rainfall of 734 mm. LAI Measurements were performed using an LAI-2200 Plant Canopy Analyzer (Li-Cor Biosciences Inc., Lincoln, Nebraska, USA), at 66 points each covering 1 m². To note that, LAI measurements taken by LAI-2200 are "effective LAI" [30].

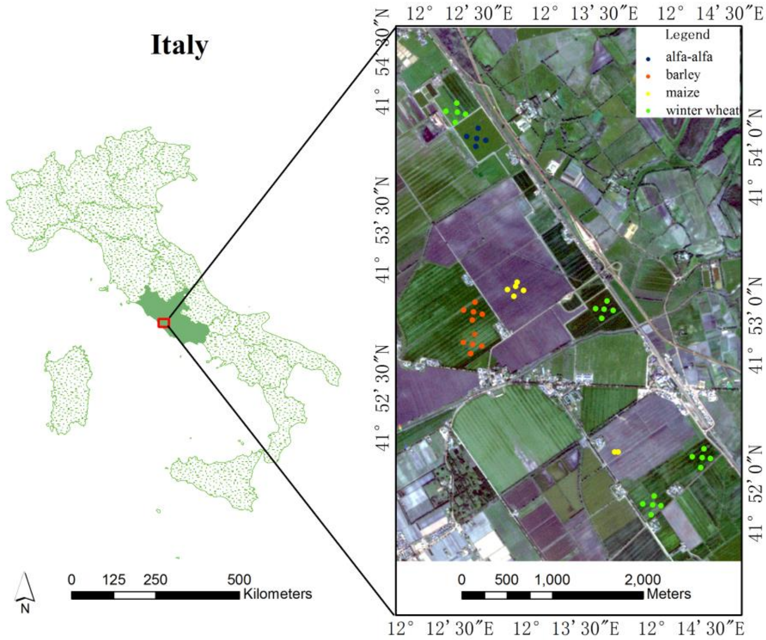


**Figure 1.** Location of the field test sites at Maccarese Farm, Rome, Italy. The locations of the field plots where non-destructive LAI measurements took place are also shown. The highlighted image is a false colour composite image from RapidEye collected on 18 March, 2015.

Because of the difficulties in collecting a large number of data in diffuse sunlight conditions, i.e. at sunset or dawn, which are considered optimal for LAI-2200 measurements, data were acquired during daytime in bright sunny days, within a maximum of four days since a satellite acquisition. A 45° view cap was employed and the operator shaded the sensor from direct radiation. The sequence suggested by the manufacturer for direct radiation scattering correction was followed and a post-processing correction was subsequently applied, using the FV2200 software (LI-COR Biosciences), as detailed in the equipment manual. Each LAI measurement was obtained, collecting 10 readings from below the canopy, from an area of about 10 m² of which the centre coordinates were recorded using a GPS with differential correction (accuracy in the order of 1-2 m).

*2.2. Satellite Data Acquisition and Processing*

Multispectral remote sensing images from the RapidEye sensor were obtained on 28 February, 18 March, 11 May and 5 July 2015, corresponding to field measurements on 3 March, 20 March, 7 May and 7 July (Table 1). This constellation of five identical EO satellites record radiance in five broad bands: blue (440nm - 510nm), green (520nm - 590nm), red (630nm - 685nm), red-edge (690nm - 730nm) and near infrared (760nm - 850nm), at a spatial resolution of 5m.

**Table 1.** Field measurements and corresponding satellite data obtained

| Data | Time | | | |
|---|---|---|---|---|
| Field measurements | March 3 (winter wheat, barley) | March 20 (winter wheat, barley) | May 7 (winter wheat, barley, alfalfa) | July 7 (maize) |
| RapidEye images | February 28 | March 18 | May 11 | July 5 |

The RapidEye images were delivered as level 3A Ortho Product, which offer the highest processing level with respect to radiometric, sensor, and geometric corrections. This means that the digital numbers (DNs) of the image pixels represent calibrated radiance values. A subsequent atmospheric correction was performed on RapidEye images by using ENVI's Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module, which is based on the radiative transfer model MODTRAN4 [31]. In this study, model parameters of a mid-latitude summer atmosphere and rural aerosols, as well as automatic aerosol retrieval, were used in FLAASH to correct the RapidEye images. The output of FLAASH assumed reflectance values rescaled to normal range of 0 to 1.

### *2.3. Reflectance Simulation with PROSPECT Model*

In order to analyse how variation in chlorophyll a+b content and leaf area index contribute to canopy spectral reflectance, the combined leaf (PROSPECT) and canopy (SAIL) reflectance model PROSAIL was used for a sensitivity analysis of the spectral vegetation indices. To investigate the effect of chlorophyll a+b content and LAI on canopy spectral reflectance, chlorophyll content values were set to change from 10 to 100 μg/cm$^2$ with a step of 5 μg/cm$^2$, and LAI values were set to change from 1 to 9 with a step of 0.5. The values of chlorophyll a+b content and LAI cover their plausible range respectively, based on our history field campaign data regarding the crop types investigated in this study. Equivalent water thickness (Cw) was fixed to an value of 0.01, because the absorption of leaf water does not influence significantly the canopy reflectance within the spectral range used in this study (< 0.9 μm) [32]. Other input variables were assigned with fixed reasonable values based on field measurements and previous studies [33, 34] (Table 2).

**Table 2.** Parameters used in simulating reflectance with PROSAIL model

| Parameter | Value | Units | Notes |
|---|---|---|---|
| Leaf parameters | | | |
| N | 1.5 | - | Leaf thickness parameters |
| Cw | 0.01 | g/cm$^2$ | Equivalent water thickness |
| Cm | 0.004 | g/cm$^2$ | Dry matter content |
| Cab | 10~100, step: 5 | μg/cm$^2$ | Chlorophyll a + b content |
| Canopy parameters | | | |
| LAI | 1~9, step: 0.5 | - | Leaf area index |
| LAD | Spherical | - | Leaf angle distribution |
| $\theta_s$ | 30 | degree | Solar zenith angle |
| $\theta_v$ | 0 | degree | View zenith angle |
| $\phi$ | 0 | degree | View azimuth angle |

## 3. Methods

### *3.1. Quantifying Sources of Variation in Simulated Reflectance Data*

A model sensitivity analysis was implemented to identify the significance of the leaf area index and chlorophyll content in explaining variance in the PROSAIL model output reflectance. The Extended Fourier Amplitude Sensitivity Test (EFAST) method was used [35], which is an extension of the classical Fourier Amplitude Sensitivity Test (FAST). The EFAST approach is a parametric transformation that enables reducing multidimensional integrals over the space of the input factors to one-dimensional quadratures, through a search curve that scans the whole input space. This approach allows the definition of a set of simulations in which all input parameters vary simultaneously. A Fourier decomposition is then conducted to obtain the fractional contribution of each input factor to the variance of the model output [36]. EFAST provides two sets of indices: first-order and total-order indices. The first-order indices give the additive effect of each input factor; while the total-order indices are overall measures of importance, accounting for the effects of the interactions of each factor with others.

Simulated spectral reflectance was analysed to understand the effect of chlorophyll content on relationships between the leaf area index (LAI) and the red, red-edge, near infrared (NIR) reflectance. In order to quantify the effect of chlorophyll content on spectral indices, $\Delta RED$, $\Delta RE$ and $\Delta NIR$ were formed (Eq. 1, 2, 3) as indicators to quantify the change of red, red-edge and NIR bands against near infrared spectral band under two different chlorophyll contents.

$$\Delta RED = \left| \frac{\rho_{RED1} - \rho_{RED2}}{\rho_{NIR2}} \times 100\% \right| \tag{1}$$

$$\Delta RE = \left| \frac{\rho_{RE1} - \rho_{RE2}}{\rho_{NIR2}} \times 100\% \right| \tag{2}$$

$$\Delta NIR = \left| \frac{\rho_{NIR1} - \rho_{NIR2}}{\rho_{NIR2}} \times 100\% \right| \tag{3}$$

Where $\rho_{RED1}$, $\rho_{RE1}$ and $\rho_{NIR1}$ are spectral reflectance at red, red-edge and near infrared regions respectively, under the one chlorophyll content, while $\rho_{RED2}$, $\rho_{RE2}$ and $\rho_{NIR2}$ are spectral reflectance under the other chlorophyll content. To set up the EFAST sensitivity analysis and to compute $\Delta RED$, $\Delta RE$ and $\Delta NIR$, the PROSAIL simulated spectral reflectance was spectrally re-sampled to the spectral response functions of RapidEye. (The spectral response functions of RapidEye were obtained from the RapidEye Science Archive website: https://resa.blackbridge.com/files/2014-06/Spectral_Response_Curves.pdf)

### *3.2. Existing and Improved Vegetation Indices*

Canopy spectral reflectance data derived from RapidEye was used to calculate the vegetation indices (Table 3) for subsequent LAI estimation. The existing vegetation indices tested include three red/green reflectance based indices: NDVI (normalized difference vegetation index), MSR (modified simple ratio index) and $CI_{green}$ (green chlorophyll index). NDVI is widely accepted as benchmark for comparing alternative inversion algorithms, it highlights the striking contrast between NIR and red spectral reflectance [37]. MSR was proposed to suppress the saturation problem of NDVI [38]. $CI_{green}$ shows a close relation to both chlorophyll content and LAI [39].

Additionally, three red-edge modified indices were tested, with red/green reflectance replaced by red-edge reflectance: $NDVI_{Red\text{-}edge}$ (red-edge normalized difference vegetation index), $MSR_{Red\text{-}edge}$ (red-edge modified simple ratio index), $CI_{Red\text{-}edge}$ (red-edge chlorophyll index). The red-edge modified indices ($NDVI_{Red\text{-}edge}$, $MSR_{Red\text{-}edge}$ and $CI_{Red\text{-}edge}$) have been shown to improve the LAI estimation compared to the red/green reflectance based indices, because the red-edge channel is sensitive to small changes in the canopy, gap fraction and senescence [40].

In this study, we established three newly improved vegetation indices combining red and red-edge spectral information: $NDVI_{red\&RE}$ (red and red-edge normalized difference vegetation index), $MSR_{red\&RE}$ (red and red-edge modified simple ratio index), $CI_{red\&RE}$ (red and red-edge chlorophyll index), in which a certain proportion of the red and the red-edge reflectance was used to replace the red/green reflectance in the formula of NDVI, MSR and $CI_{green}$. Following the principles of the original indices (NDVI, MSR, $CI_{green}$), the improved vegetation indices ($NDVI_{red\&RE}$, $MSR_{red\&RE}$ and $CI_{red\&RE}$) still utilise the strong contrast between the red and NIR reflectance sensitive to LAI. Furthermore, combining red and red-edge spectral information is a compensation strategy that neither puts heavy emphasis on the red reflectance, which will help to avoid saturation, nor put heavy emphasis on the red-edge reflectance, which will help avoid interruption from the change of chlorophyll content [24]. The definitions and formulas of the improved indices as well as six existing indices tested in this study are shown in Table 3.

**Table 3.** Descriptions and formulas of vegetation indices investigated in this study

| Index | Description | Formula | Reference |
|---|---|---|---|
| | Existing indices | | |
| NDVI | Normalized difference vegetation index | $\frac{\rho_{NIR}-\rho_{red}}{\rho_{NIR}+\rho_{red}}$ | [15] |
| $NDVI_{Red\text{-}edge}$ | Red-edge normalized difference vegetation index | $\frac{\rho_{NIR}-\rho_{RE}}{\rho_{NIR}+\rho_{RE}}$ | [41] |
| MSR | Modified simple ratio index | $\frac{\rho_{NIR}/\rho_{red}-1}{\sqrt{\rho_{NIR}/\rho_{red}+1}}$ | [38] |
| $MSR_{Red\text{-}edge}$ | Red-edge modified simple ratio index | $\frac{\rho_{NIR}/\rho_{RE}-1}{\sqrt{\rho_{NIR}/\rho_{RE}+1}}$ | [34] |
| $CI_{green}$ | Green chlorophyll index | $\frac{\rho_{NIR}}{\rho_{green}}-1$ | [42] |
| $CI_{Red\text{-}edge}$ | Red-edge chlorophyll index | $\frac{\rho_{NIR}}{\rho_{RE}}-1$ | [43] |
| | Improved indices | | |
| $NDVI_{red\&RE}$ | Red and red-edge normalized difference vegetation index | $\frac{\rho_{NIR}-(a*\rho_{red}+(1-a)*\rho_{RE})}{\rho_{NIR}+(a*\rho_{red}+(1-a)*\rho_{RE})}$ | - |
| $MSR_{red\&RE}$ | Red and red-edge modified simple ratio index | $\frac{\rho_{NIR}/(a*\rho_{red}+(1-a)*\rho_{RE})-1}{\sqrt{\rho_{NIR}/(a*\rho_{red}+(1-a)*\rho_{RE})+1}}$ | - |
| $CI_{red\&RE}$ | Red and red-edge modified chlorophyll index | $\frac{\rho_{NIR}}{a*\rho_{red}+(1-a)*\rho_{RE}}-1$ | - |

* NIR refers to near infrared; RE refers to red-edge; $a \in [0, 1]$

### *3.3. The Noise Equivalent (NE) ΔLAI*

The Noise Equivalent (NE) ΔLAI was used to test sensitivity of the different spectral vegetation indices against leaf area index (LAI) changes. The NE ΔLAI has been proved to be advantageous over the direct comparison between different vegetation indices, with different scales and dynamic ranges [44]. NE ΔLAI is calculated as:

$$NE\Delta LAI = \frac{RMSE\{VI\ vs.\ LAI\}}{d(VI)/d(LAI)} \quad (4)$$

Where RMSE and d(VI)/d(LAI) are respectively the root mean square error and the first derivative of the best-fit function in the “VI vs. LAI” relationship [2, 45]. The NE ΔLAI was calculated based on the “VI vs. LAI” relationship function. The LAI was obtained from ground measurements as introduced in Section 2.1 of this paper, and the VI was calculated with RapidEye data according to the formula in Table 3.

### *3.4. Validation Scheme*

Leave-one-out cross validation procedure was used to evaluate the performance of the improved vegetation indices to estimate LAI. This type of validation avoids the dependence on a single random partition into validation datasets. It also guarantees that all samples were used for both training and validation with each sample used for validation exactly once. The coefficient of determination ($R^2$) and root-mean-square error (RMSE) were selected as indicators of the accuracy of the statistical estimation models [46].

## 4. Results and Discussion

### *4.1. Sensitivity of Canopy Reflectance Against Leaf Area Index and Chlorophyll Content*

Table 4 shows the first-order and total-order indices, calculated by EFAST method introduced in Section 3.1 of this paper, for the study of how variation in chlorophyll a+b content (Cab) and leaf area index (LAI) contributes to red, red-edge and near infrared reflectance variability. Table 4 shows that, at red spectral region, the sum of Cab and LAI EFAST first-order indices (FOI) is about 85% (FOI of Cab=65.60%, FOI of LAI=19.30%). This means that approximately 85% of the uncertainty in the

PROSAIL model output red region reflectance is explained by the factors singularly, while the remaining 15% is explained by interactions between the two factors. Therefore, the EFAST total-order indices are provided (Table 4) to account for the additive effects of each input factor and their interactions with the others.

The EFAST indices also show that the first-order indices and total-order indices (TOI) of Cab at red and red-edge region (FOI at red/red-edge region: 65.60%/93.31%, TOI at red/red-edge region: 80.48%/98.92%) are vastly larger than corresponding indices of LAI at red and red-edge region (FOI at red/red-edge region: 19.30%/1.07%, TOI at red/red-edge region: 33.69%/6.59%), suggesting that variation in the reflectance measured at red and red-edge spectral region is mainly the result of variations in chlorophyll content. Compared to red spectral reflectance, the red-edge reflectance is more deeply controlled by chlorophyll content, given that the first-order and total-order indices of Cab at red-edge region (FOI: 93.31%, TOI: 98.92%) are larger than the indices at red region (FOI: 65.60%, TOI: 80.48%). In contrast, variation in the near infrared (NIR) spectral reflectance is mainly the result of variations in leaf area index, because the EFAST indices of LAI at NIR region (FOI: 97.64%, TOI: 99.66%) are vastly larger than corresponding indices of Cab (FOI: 0.41%, TOI: 2.35%). The EFAST sensitivity analysis confirms that the red-edge spectral reflectance is relatively easily affected by chlorophyll change than the red spectral reflectance, which means that the red-edge band will induce larger error for leaf area index retrieval when chlorophyll content varies simultaneously.

**Table 4.** First-order and total-order sensitivity indices for the study of how variation in chlorophyll a+b content (Cab) and leaf area index (LAI) contributes to red, red-edge (RE) and near infrared (NIR) reflectance variability.

| | | Red | RE | NIR |
|---|---|---|---|---|
| First-order Indices (%) | Cab | 65.60 | 93.31 | 0.41 |
| | LAI | 19.30 | 1.07 | 97.64 |
| Total-order Indices (%) | Cab | 80.48 | 98.92 | 2.35 |
| | LAI | 33.69 | 6.59 | 99.66 |

The PROSAIL simulated spectral reflectance was further analysed to understand the relationships between the leaf area index (LAI) and the red, red-edge, near infrared (NIR) reflectance (Fig. 2). Fig. 2 (a) shows that as LAI increases, the NIR reflectance increases, while the red reflectance decreases at early stage and then reached an asymptote when the LAI values exceeded 3. Thus, both red reflectance and NDVI approach a saturation level asymptotically when LAI > 3. The coefficient of determination ($R^2$) of the relationship between NDVI and LAI in Fig. 2 (a) is 0.81 for LAI<3, but drops to 0.04 for LAI>3. In addition, under visual comparison, the red-edge reflectance scatters most significantly due to chlorophyll content change, which is further supported by Fig. 2 (b), where reflectance in red-edge appears a sharp decrease when chlorophyll changes from 10 to 100 ug/cm$^2$. In order to quantify the effect of chlorophyll content on spectral indices formed by the combination of red/NIR or red-edge/NIR spectral bands, $\Delta RED$ , $\Delta RE$ and $\Delta NIR$ were defined as Eq. 1 through Eq.3 in Section 3.1 of this paper, to quantify the relative change of each band. Fig. 2 (c) demonstrates that, when chlorophyll content varies from 10 to 100 ug/cm$^2$, $\Delta RE$ is much greater than $\Delta RED$ and $\Delta NIR$ , which means that the relative change in red-edge spectral reflectance is larger than that in red and NIR. Therefore, vegetation indices combining red-edge and NIR bands are more sensitive to chlorophyll change than the indices combining by red and NIR bands. For example, for simulated samples of LAI=3 in Fig.2 (a), the NDVI value is increased by 26.4% when Cab increases from 10 μg/cm$^2$ (NDVI=0.72) to 100 μg/cm$^2$ (NDVI=0.91); in contrast, the $NDVI_{red-edge}$ value is increased by 159.3% when Cab increases from 10 μg/cm$^2$ ($NDVI_{red-edge}$=0.27) to 100 μg/cm$^2$ ($NDVI_{red-edge}$=0.70). The Cab variance would induce larger LAI retrieval error to $NDVI_{red-edge}$ model than to NDVI model. Therefore, replacing the red / green reflectance with the red-edge reflectance in NDVI, MSR and $CI_{green}$ [47, 48] does not necessarily improve the LAI estimation accuracy when applied to different crops at different growth stages in which the chlorophyll content and LAI vary together. Given that the red spectral reflectance saturates when LAI>3, while the red-edge region is easy to be affected by chlorophyll change, we recommend combining them into vegetation indices rather than abandoning one of the two regions.

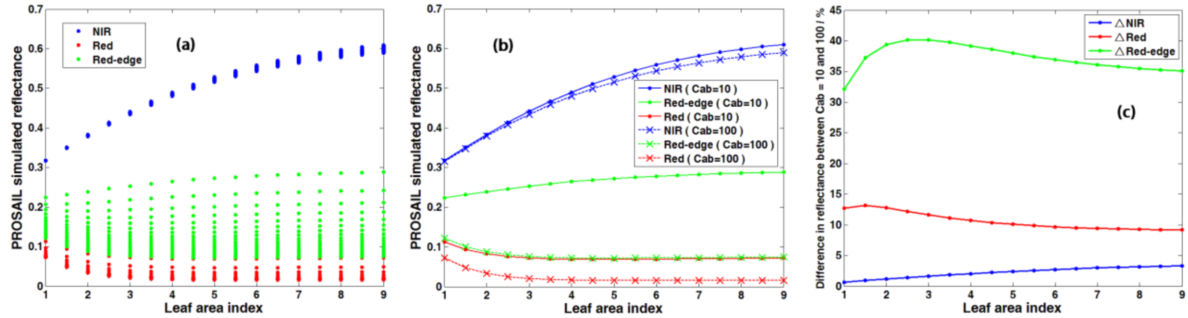


**Figure 2.** Red, red-edge and near infrared reflectance response to leaf area index: (a) when chlorophyll content varies from 10 ug/cm² to 100 ug/cm²; (b) extracted from subfigure (a), when chlorophyll content is 10 and 100 ug/cm²; (c) the change of red, red-edge and bands against near infrared spectral band under two different chlorophyll contents (Eq. 1~3).

*4.2. Relationship between Vegetation Indices and Leaf Area Index*

The analysis of the data in Table 4 and Fig. 2 provides a justification to combine red and red-edge spectrum to formulate ratio vegetation indices for leaf area index (LAI) retrieval when chlorophyll content and LAI vary simultaneously. The improved indices in Table 3 were calculated using RapidEye derived reflectance, with the parameter "a" ranges from 0 to 1, at a step of 0.1. The value of parameter "a" represents the proportion of red reflectance, and the value of (1-a) represents the proportion of red-edge reflectance. The coefficient of determination ($R^2$) of the calibration models based on improved indices ($NDVI_{red\&RE}$, $MSR_{red\&RE}$, $CI_{red\&RE}$) and in-situ measured LAI were calculated (Fig. 3). The $R^2$ of each improved index peaked at a=0.4 ($R^2$ of $NDVI_{red\&RE}$=0.62, $R^2$ of $MSR_{red\&RE}$=0.61, $R^2$ of $CI_{red\&RE}$=0.59), and the curve of each index followed the same trend: a small rise from a=0 ($R^2$ of $NDVI_{red\&RE}$=0.55, $R^2$ of $MSR_{red\&RE}$=0.53, $R^2$ of $CI_{red\&RE}$=0.50) to a=0.4, then a reduction until a=1 ($R^2$ of $NDVI_{red\&RE}$=0.48, $R^2$ of $MSR_{red\&RE}$=0.29, $R^2$ of $CI_{red\&RE}$=0.18). It is also noteworthy that each index achieved higher $R^2$ when a=0 compared to a=1, suggesting that replacing red/green reflectance with red-edge could enhance the relationship between LAI and vegetation indices (see VIs formula of Table 3), consistent with many researches [34, 41, 43, 47]. However, combining red and red-edge reflectance with selected proportion (in our case a=0.4, the percentage of red and red-edge reflectance were 40% and 60% respectively), further improves the correlation between LAI and vegetation indices. To note that, the optimal proportion found between red and red-edge reflectance in this study to maximize the LAI estimation may be varied for other types of agricultural systems, in which case we suggest to re-compute the optimal proportion for other datasets.

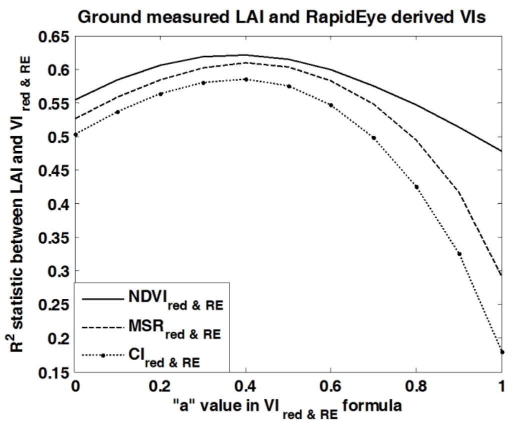


**Figure** 3. Coefficient of determination of the calibration models for different values of the parameter a (Table 3), based on in-situ measured

LAI and RapidEye derived reflectance. $VI_{red\&RE}$ represents $NDVI_{red\&RE}$, $MSR_{red\&RE}$, $CI_{red\&RE}$.

The NDVI, $NDVI_{Red\text{-}edge}$ and $NDVI_{red\&RE}$ exhibited logarithmic relationships with LAI, while MSR, $MSR_{Red\text{-}edge}$, $MSR_{red\&RE}$, $CI_{green}$, $CI_{Red\text{-}edge}$ and $CI_{red\&RE}$ exhibited exponential relationships with LAI (Fig. 4). The red/green reflectance based indices have weaker correlations with LAI, especially when LAI exceeded 3. NDVI saturated as LAI value increased while MSR and $CI_{green}$ showed considerable scatter against LAI. $VI_{Red\text{-}edge}$ (VI represents NDVI, MSR and CI) with red/green reflectance replaced by red-edge has a stronger relationship with LAI than red/green reflectance based indices; while $VI_{red\&RE}$ combining red and red-edge reflectance had the strongest relationship with LAI, with $R^2$ values increased by at least 10% compared to $VI_{Red\text{-}edge}$. Among the indices, $CI_{green}$, which consists of NIR and green reflectance, had the lowest coefficient of determination ($R^2$ = 0.063), suggesting that vegetation indices including green reflectance are not optimal for LAI estimation under various chlorophyll content. Although green-based indices can be highly accurate when applied to single species plant communities [49].

For the same LAI, all three red/green reflectance based indices (NDVI, MSR and $CI_{green}$) showed lower values for maize than other crops (Fig. 4 A, D, G), all $VI_{Red\text{-}edge}$ (Fig. 4 B, E, H) and $VI_{red\&RE}$ (Fig. 4 C, F, I) showed lower values for alfalfa than other crops. This is in agreement with the study of J. Delegido et al. [50], in which nine types of crops including maize, alfalfa and wheat were investigated based on field measurements in Spain, Germany and France. This could be explained by the effect of chlorophyll content. The in situ data we collected for this study does not include chlorophyll content, we have to refer the chlorophyll effects among these crops from other datasets and researches. According to other field measurements we have conducted and other research concerning these crops [50, 51], we can draw the conclusion that when at the same leaf area index value, usually the leaf chlorophyll content of maize is higher than that of wheat and barley, while the leaf chlorophyll content of alfalfa is lower than that of wheat and barley. As a result, the RapidEye reflectance in this study appears that the spectral reflectance of the red-edge is lower for maize than that in wheat and barley, while higher for alfalfa than that in wheat and barley, which is in accordance with the rule revealed by the simulated reflectance shown in Fig. 2: when the LAI value is fixed, the red-edge reflectance increases as the chlorophyll content decreases. In the red spectral region, the maize spectral reflectance is higher than that of other crops. Thus, the vegetation index (VI) values for crops with equivalent LAI values (moderate-to-dense canopies) show that the maize canopy has lower VI (NDVI, MSR, $CI_{green}$) values but higher $VI_{Red\text{-}edge}$ ($NDVI_{Red\text{-}edge}$, $MSR_{Red\text{-}edge}$, $CI_{Red\text{-}edge}$) than that of the other crops. In terms of alfalfa, the $VI_{Red\text{-}edge}$ values are lower than other crops with the same LAI.

Crop canopy reflectance is a complex signal affected by many factors, besides the chlorophyll content, there might be other factors affecting LAI retrieval such as leaf structures and canopy architectures of these crops. For example, the canopies of maize and alfalfa exhibit a planophile leaf angle distribution [49, 52], while the canopies of barley and wheat exhibit a more erectophile leaf angle distribution [53]. But these factors have much less impact than LAI and chlorophyll content on canopy reflectance as proved by other researchers [24]. According to our other field measurements and other researches concerning these crops [50, 51], within the RapidEye bands we investigated (red (630nm-685nm), red-edge (690nm-730nm), NIR (760nm-850nm)), the red and red-edge region are dominated by Cab and LAI where other factors do not need to be accounted for; the NIR region is impacted by multi factors, such as LAI, average leaf angle and dry matter content, but these factors do not affect the improvement of the vegetation indices proposed in our study. Because the NIR band remains unchanged during the improvement of VIs, in which the improvement relies on the combination of red and red-edge region. In this study, the newly improved VIs are focused on reducing the impact of chlorophyll content on LAI retrieval. Nevertheless, we suggest that the relationships between vegetation indices and LAI will potentially be further improved if the impact from other factors could be reduced as well.

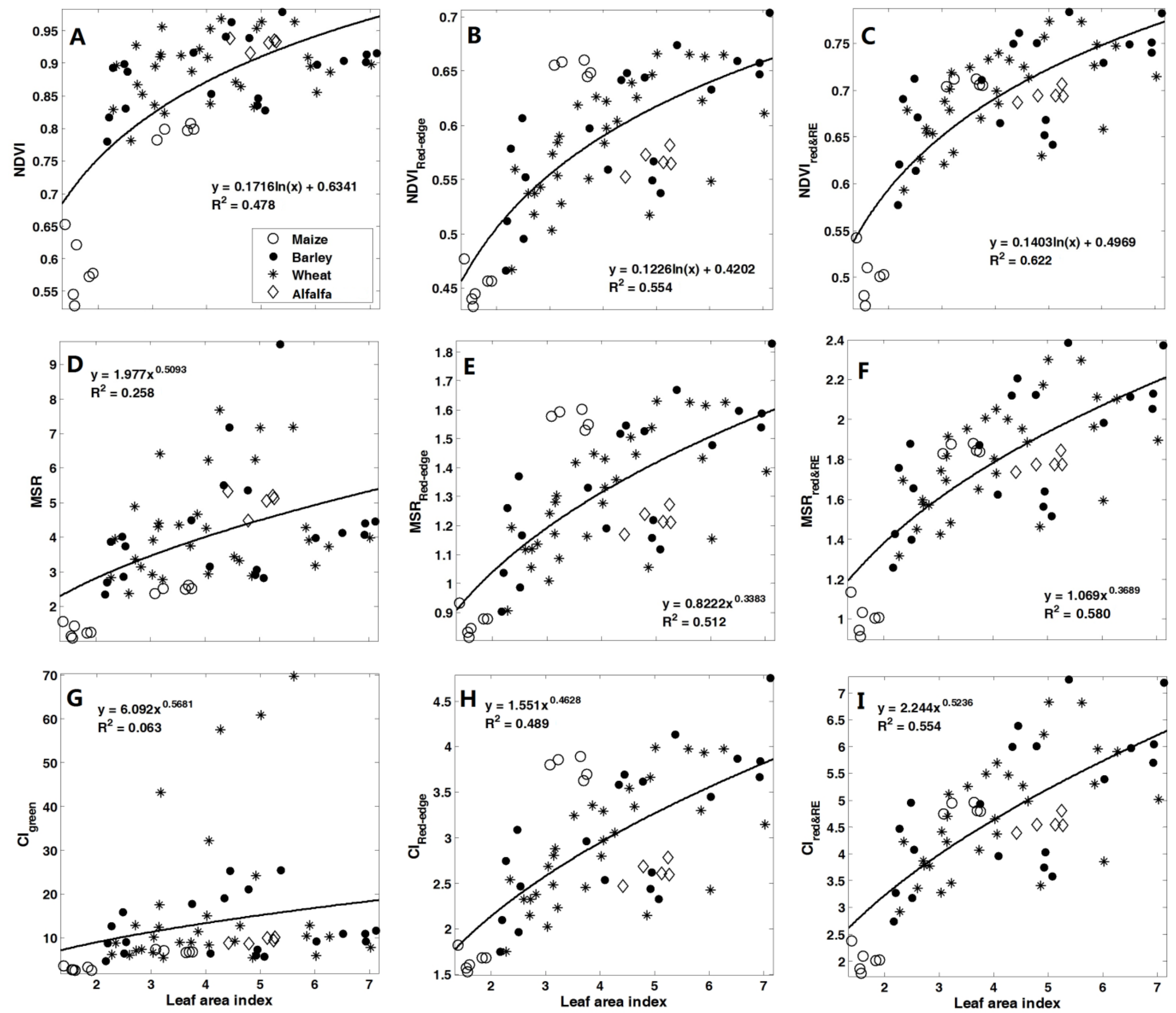


**Figure** 4. Relationships between vegetation indices (Subfigure A: NDVI, B: NDVI$_{\text{Red-edge}}$, C: NDVI$_{\text{red\&RE}}$, D: MSR, E: MSR$_{\text{Red-edge}}$, F: MSR$_{\text{red\&RE}}$, G: CI$_{\text{green}}$, H: CI$_{\text{Red-edge}}$, I: CI$_{\text{red\&RE}}$) and leaf area index, for maize, barley, wheat and alfalfa during the growing seasons of 2015.

The sensitivity analysis of the different spectral vegetation indices to leaf area index was performed by calculating the Noise Equivalent (NE) ΔLAI of the calibration models between each vegetation index (VI) and LAI, in order to compare the performance of the nine indices under the same criteria. This analysis (Fig. 5) shows that among vegetation indices of the same root (e.g. NDVI, NDVI$_{\text{Red-edge}}$ and NDVI$_{\text{red\&RE}}$), the NDVI exhibits the lowest NEΔLAI values (thus the highest sensitivity to LAI). In particular, the NDVI$_{\text{Red-edge}}$ (marked by blue markers) exhibits the highest NEΔLAI values (thus the lowest sensitivity to LAI), while the NDVI$_{\text{red\&RE}}$ shows moderate NE ΔLAI values (thus moderate sensitivity to LAI). MSR and CI$_{\text{green}}$, as well as their corresponding improved indices, show the same rule as NDVI series indices: original VI (marked by green markers) was the most sensitive to LAI, second by the VI$_{\text{red\&RE}}$, while the VI$_{\text{Red-edge}}$ was the least sensitive to LAI. The spectral analysis confirms that VI$_{\text{Red-edge}}$ is less sensitive to leaf area index than VI$_{\text{red\&RE}}$. Therefore, the improved vegetation indices VI$_{\text{red\&RE}}$ (NDVI$_{\text{red\&RE}}$, MSR$_{\text{red\&RE}}$, CI$_{\text{red\&RE}}$) have greater potential in leaf area index retrieval than corresponding VI$_{\text{Red-edge}}$ (NDVI$_{\text{Red-edge}}$, MSR$_{\text{Red-edge}}$ , CI$_{\text{Red-edge}}$).

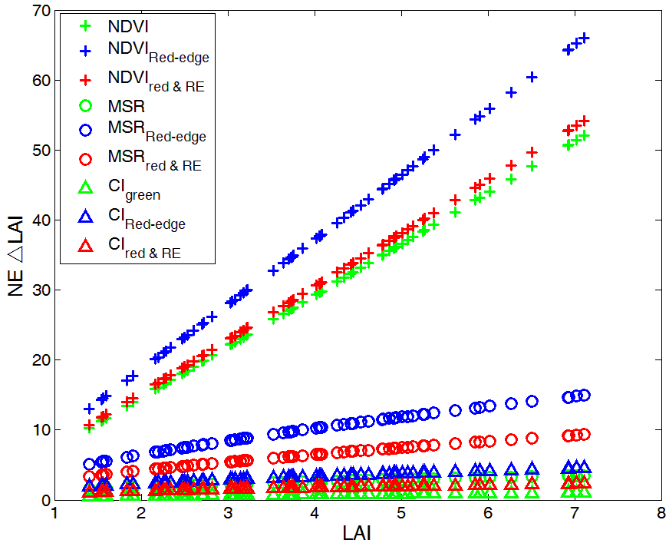


**Figure 5.** Sensitivity of the different vegetation indices tested to LAI using the NEΔLAI (Eq. 1).

### 4.3. Leaf Area Index Estimation Model Validation

Results of leave-one-out cross validation for LAI estimation are presented in Fig. 6, with coefficient of determination ($R^2$) and root mean square error (RMSE) computed and presented for each model. The estimated LAI values were compared with the ground measurements using least significant difference test performed using SPSS software [54]. Statistical analysis revealed that the estimates of $CI_{green}$ model reached 0.05 level of significance, and estimates of other eight models reached 0.01 level of significance. Among the examined indices, the red/green reflectance based vegetation indices (VIs) were the poorest at predicting LAI (Fig. 6 A, D, G), the $VI_{Red\text{-}edge}$ improved the LAI prediction (Fig. 6 B, E, H) on the basis of VIs, by including red-edge reflectance. This is agreed with other studies [19, 25], in which the red-edge modified indices improved the LAI estimation when the indices are applied to crops with consistent chlorophyll content, e.g. datasets consisting of one type of crop at one growth stage. However, the chlorophyll content varies across the crop growing season and varies among different crop types in our study, $VI_{red\&RE}$ resulted in the best prediction with the lowest RMSE (less than 1.07) and the highest $R^2$ (above 0.500) (Fig. 6 C, F, I), by combining the red spectral reflectance and the red-edge spectral reflectance into the vegetation indices. In comparison with the $VI_{Red\text{-}edge}$, the $VI_{red\&RE}$ improved the LAI estimation accuracy by at least 10% higher $R^2$ and 10% lower RMSE value. For instance, $NDVI_{red\&RE}$ exhibited an $R^2$ of 0.500 and RMSE of 1.068; $NDVI_{Red\text{-}edge}$ exhibited an $R^2$ of 0.438 and RMSE of 1.138, showing lower accuracy than $NDVI_{red\&RE}$; NDVI exhibited an $R^2$ of 0.314 and RMSE of 1.255, showing the lowest accuracy among NDVI, $NDVI_{Red\text{-}edge}$ and $NDVI_{red\&RE}$.

The red/green reflectance based indices (VIs) exhibited respective drawbacks; for instance, the NDVI saturated when LAI exceeds 3, MSR scattered when LAI exceeds 3, and the $CI_{green}$ overestimated LAI at low-to-moderate (LAI<3) canopy cover whilst significantly underestimated LAI when LAI > 3. The saturation of NDVI at LAI values higher than 3 was expected and is in agreement with the literature [16]. The red-edge based indices $VI_{Red\text{-}edge}$ improved the estimation by alleviating the underestimation of moderate-to-dense canopy, but did not improved much overestimation for low-to-moderate canopy, agreeing with the results in other researches using red-edge based indices [48, 50]. By accounting for the chlorophyll content effect, the improved vegetation indices we formed in this paper best yielded LAI with highest accuracy and robustness when applied to a wide range of crops across multi growth stages.

In addition, the effects of chlorophyll content difference among the four crop species on canopy spectra and vegetation indices, discussed in Section 4.2 of this paper, result in the different behaviour in LAI estimation. The maize and alfalfa LAI are better estimated by $VI_{Red\text{-}edge}$ (Fig. 6 B, E, H) than by the VI (Fig. 6 B, E, H), because the red-edge reflectance is significantly affected by the chlorophyll content: the red-edge reflectance of maize is lower than that of wheat and barley, while the red-edge reflectance of alfalfa is higher than that of wheat and barley. Hence replacing the red band with red-edge in vegetation indices (VIs) loose the robustness of VIs against chlorophyll change. Fig. 6 C, F and I demonstrate that $VI_{red\&RE}$ better retrieved maize and alfalfa LAI than $VI_{Red\text{-}edge}$, and $VI_{red\&RE}$ improved the underestimation and overestimation problems of VIs, confirming that combining red and red-edge reflectance in $VI_{red\&RE}$ could improve the underestimation and overestimation problems, whilst remain a certain capability of robustness against chlorophyll change. Our results agreed with many researchers who revealed that some indices using red-edge bands in their formulation, however, proved to be less sensitive to differences among species [43, 49]. As the performance of empirical methods are case depend, we suggest using our improved indices ($VI_{red\&RE}$) for the case of various chlorophyll content, e.g. various crop species and various growth stages. For complicated cases, a threshold method to choose among our improved indices, red-edge indices ($VI_{Red\text{-}edge}$) and original indices (VI) may yield higher LAI estimation accuracy. For example, on the choice between NDVI and red-edge NDVI, Nguy-Robertson et al selected NDVI = 0.7 as a threshold for their case of maize and soybean LAI estimation (NDVI saturates at 0.7) [55].

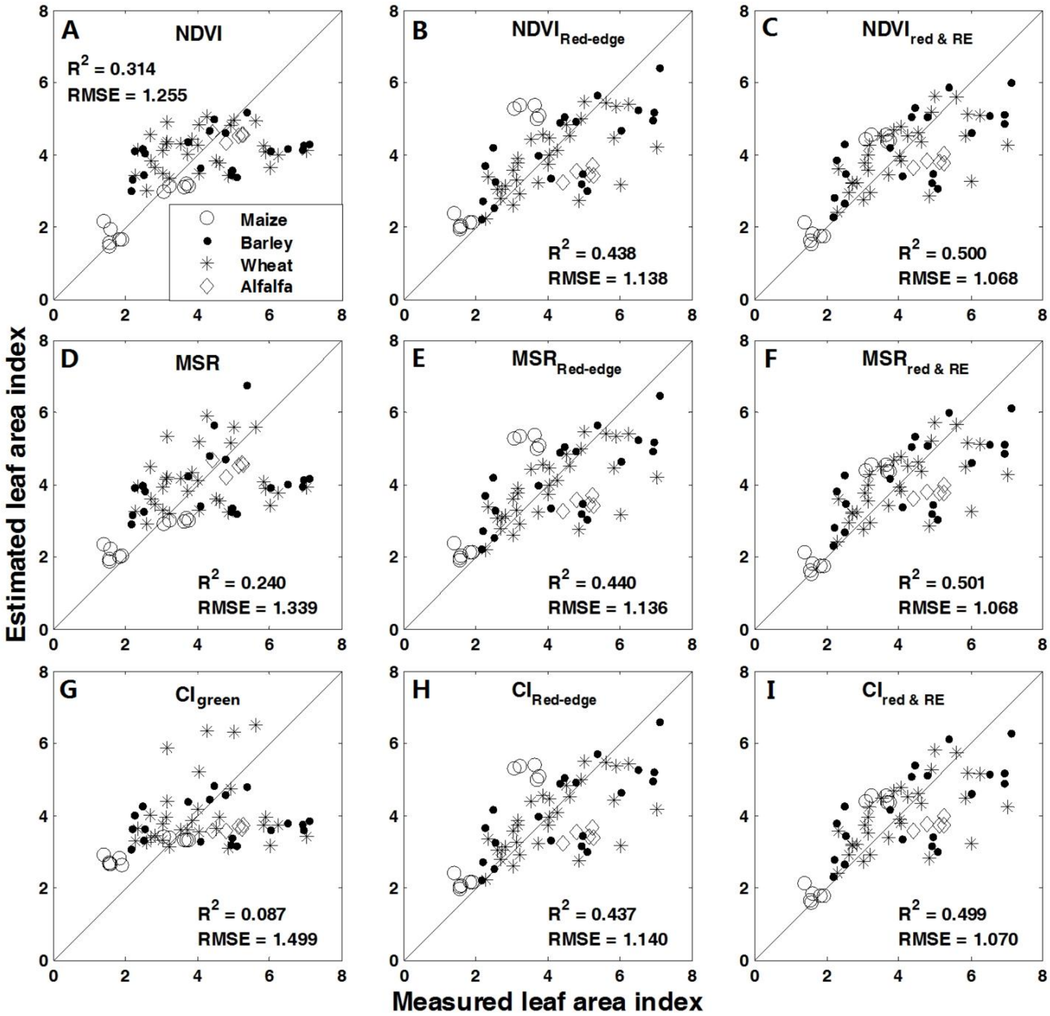


**Figure 6.** Measured leaf area index versus estimated LAI derived from RapidEye spectra; Subfigure A: NDVI, B: $NDVI_{Red\text{-}edge}$, C: $NDVI_{red\&RE}$, D: MSR, E: $MSR_{Red\text{-}edge}$, F: $MSR_{red\&RE}$, G: $CI_{green}$, H: $CI_{Red\text{-}edge}$, I: $CI_{red\&RE}$

## 5. Conclusion

In this paper, we have proposed three improved vegetation indices ($NDVI_{red\&RE}$,

MSR$_{red\&RE}$ and CI$_{red\&RE}$) combining red and red-edge spectral region and validated them with RapidEye satellite data and *in situ* data over four crops at four growth stages. The predictive power of the three improved vegetation indices and other six existing indices have been analysed, including three red/green reflectance based indices (NDVI, MSR and CI$_{green}$), three red-edge modified indices (NDVI$_{Red\text{-}edge}$, MSR$_{Red\text{-}edge}$ and CI$_{Red\text{-}edge}$), and three improved indices combining red and red-edge regions (NDVI$_{red\&RE}$, MSR$_{red\&RE}$ and CI$_{red\&RE}$). The proportion between red and red-edge reflectance that led to the best correlation between VI$_{red\&RE}$ (NDVI$_{Red\text{-}edge}$, MSR$_{Red\text{-}edge}$ and CI$_{Red\text{-}edge}$) and LAI was encountered at 0.4, which means using $0.4*\rho_{red}+0.6*\rho_{RE}$ to replace $\rho_{red}$ in the formula of red/green reflectance based indices (NDVI, MSR and CI$_{green}$). Under the comparison amongst the red/green reflectance based indices, the VI$_{Red\text{-}edge}$ and the VI$_{red\&RE}$, the VI$_{red\&RE}$ achieved the most accurate LAI estimation, improving at least 10% the coefficient of determination achieved by VI$_{Red\text{-}edge}$. The improved indices VI$_{red\&RE}$, combining red and red-edge reflectance, both of the spectral regions are strongly related to the physiological status of the plant, proved to be the most robust and stable for crop LAI estimation over a wide range of crop species and growth stages.

Such indices are of great potential for agricultural monitoring using sensors providing red-edge bands and high spatial resolution, such as RapidEye and the newly launched Sentinel-2. In view of delivering improved leaf area index products for environmental and agricultural applications, further research is planned in the directions of: (i) validation of the proposed vegetation indices over a broader range of crops with field collected both LAI and chlorophyll content, (ii) application and evaluation of more advanced plant parameter retrieval models.

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