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Green leaf area index estimation in maize and soybeans: combining vegetation indices to achieve maximal sensitivity

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Abstract

Vegetation indices (VIs), traditionally used for estimation of green leaf area index (gLAI), have different sensitivities along the range of gLAI variability. The goals of this study were to: (1) test twelve VIs for estimating maize and soybean gLAI; (2) estimate gLAI in both crops without the need to re-parameterize the model for different crops; and (3) devise a combined VI that is maximally sensitive to gLAI along its entire range of variability. The study was performed for eight growing seasons (2001-2008) in one irrigated and one rainfed field under a maize/soybean rotation and one irrigated field under continuous maize in eastern Nebraska, USA, for a total of 24 field-years. The gLAI ranged from 0 to 6.5 m^2/m^2 in maize and 0 to 5.5 m^2/m^2 in soybean. Normalized difference indices (e.g., NDVI) were most sensitive to gLAI below 2 m^2/m^2 while ratio indices, e.g., Simple Ratio (SR) and Chlorophyll Indices (CI), were most sensitive to gLAI above 2 m^2/m^2. For the crops evaluated, relationships between gLAI and VIs were species-specific with the exception of the Red Edge NDVI and the $CI_{red\ edge}$. In order to benefit from the different sensitivities of VIs along the entire gLAI range, we suggest combining VIs. For sensors with spectral bands in the red and NIR regions, the best combination was NDVI and SR (maize: coefficient of variation, CV = 20%; soybean: CV = 23%). However, this combined index is species-specific. For sensors with bands in the red edge and NIR regions, the best combination was Red Edge NDVI and $CI_{red\ edge}$, which was capable of accurately estimating gLAI in both crops (i.e., maize and soybean) with a CV below 20% and with no re-parameterization.

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Abbreviations: Leaf area index (LAI), green LAI (gLAI), vegetation index (VI), normalized difference vegetation index (NDVI), enhanced vegetation index 2 (EVI2), triangular vegetation index (TVI), modified TVI (MTVI), Chlorophyll Indices (CI), MERIS Terrestrial Chlorophyll Index (MTCI), Moderate Resolution Imaging Spectroradiometer (MODIS), Medium Resolution Imaging Spectroradiometer (MERIS), intensive measurement zones (IMZ), coefficients of determination (R^2), standard error (SE), coefficient of variation (CV), noise equivalent (NE), root mean square error (RMSE), combined vegetation index (CVI), near infrared (NIR).

The leaf area index (LAI), the ratio of leaf area per ground area, typically reported with the units m^2/m^2, is a commonly used biophysical characteristic of vegetation (Watson, 1947). LAI can be subdivided into photosynthetically active and photosynthetically inactive components. The former, termed green LAI (gLAI), is a metric commonly used in climate (e.g. Buermann et al., 2001), ecological (e.g. Bulcock and Jewitt, 2010), and crop yield (e.g. Fang et al., 2011) models. Because of its wide use and applicability to modeling, there is a need for a non-destructive remote estimation of gLAI over large geographic areas.

Various techniques based on remotely sensed data have been employed for assessing gLAI (see reviews in Pinter et al., 2003; Hatfield et al, 2004; 2008; Doraiswamy et al., 2003; Le Maire et al., 2008 and references within). Vegetation indices (VIs), particularly the normalized difference vegetation index, NDVI (Rouse et al., 1973) and the simple ratio, SR (Jordan, 1969) are the most widely used. However, NDVI is prone to saturation at moderate-to-high gLAI values (Kanemasu, 1974; Curran and Steven, 1983; Asrar et al., 1984; Huete et al., 2002; Gitelson, 2004; Wu et al., 2007; González-Sanpedro et al., 2008) and requires re-parameterization for different crops/species. The saturation of NDVI has been attributed to insensitivity of reflectance in the red region at moderate-to-high gLAI values due to the high absorption coefficient of chlorophyll. For gLAI below 3 m^2/m^2, total absorption by a canopy in the red range reaches 90-95% and further increases in gLAI do not bring additional changes in absorption and reflectance (Hatfield et al., 2008; Gitelson, 2011). Another reason for the decrease in sensitivity of NDVI to moderate-to-high gLAI values is the mathematical formulation of that index. At moderate-to-high gLAI, the NDVI is dominated by near infrared (NIR) reflectance. Because scattering by cellular/leaf structure causes the NIR reflectance to be high and the absorption by chlorophyll causes the red reflectance to be low, NIR reflectance is considerably greater than red reflectance: e.g., for gLAI = 3 m^2/m^2, NIR reflectance is around 40%, while red reflectance is below 5%. Thus, NDVI becomes insensitive to changes in both red and NIR reflectances.

Other commonly used VIs include the enhanced vegetation index, EVI (Huete et al., 1997; 2002), its alternative form, EVI2 (Jiang et al., 2008), and the triangular vegetation index, TVI (Broge and Leblanc, 2001). While the EVI is more sensitive to moderate-to-high LAI than NDVI, it was also found to be sensitive to canopy architecture (Gao et al., 2000), and it does not relate well to LAI during the senescence stages (Wang et al., 2005). The TVI relates the difference between reflectance in the NIR and red regions to the magnitude of reflectance in the green region, thus, defining a triangle in a three dimensional spectral space. While the TVI is less affected by atmospheric properties when compared to typical vegetation indices, it is sensitive to differences in canopy structure and soil background (Broge and Leblanc, 2001). To minimize the sensitivities of TVI, a soil adjustment factor has been introduced in a modified version of the TVI, MTVI (Haboudane et al., 2004). The same study found that a second modified version (MTVI2) was accurate in estimating gLAI in different canopy structures that were simulated through radiative transfer models. Another investigation, aimed at examining gLAI in wheat, found that MTVI2 was more sensitive than NDVI to gLAI at higher gLAI values; however, it was sensitive to heading (i.e. flowering), which is not a component of gLAI, but nevertheless affects the reflectance of crop canopies (Smith et al., 2008).

VIs that incorporate bands in the spectral transition zone between absorption by pigments and scattering by leaves/canopies, termed the “red edge region” (between 700 and 740 nm), were introduced to increase the sensitivity to moderate-to high vegetation densities and estimate total chlorophyll content and gLAI (Gitelson and Merzlyak, 1994; Gitelson et al., 2003; Dash and Curran, 2004). Radiation in the red edge region penetrates deeper into the leaves and canopies than radiation in the visible region due to a lower absorption coefficient in the former than in the latter. Thus, higher values of chlorophyll content and gLAI are required to decrease the sensitivity of red edge VIs to gLAI (Dash and Curran, 2004; Ciganda et al., 2008; Gitelson, 2011). Some of the red edge VIs constitute transformations of existing VIs, such as the red edge NDVI (Gitelson and Merzlyak, 1994), which replaces the red band with one in the red edge region. Others constitute semi-analytical procedures for estimating pigment content in diffuse

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media, such as the Chlorophyll Indices, CI (Gitelson et al., 2003a). While the CIs were developed for estimating chlorophyll content, they also relate closely with gLAI since total canopy chlorophyll content has been shown to relate closely with the gLAI (Ciganda et al., 2008; Peng et al., 2011). Therefore, CIs are suitable for estimating gLAI (Gitelson et al., 2003b; Brantley et al., 2011), but particularly for moderate-to-high gLAI values. For instance, it was found that VIs utilizing the red edge region (710-730 nm) were more accurate for estimating moderate-to-high gLAI in shrub canopies than normalized difference indices (Brantley et al., 2011). However, this study also found that at low-to-moderate gLAI values, normalized difference indices (e.g., NDVI) perform better than the $CI_{red\ edge}$. The MERIS Terrestrial Chlorophyll Index (MTCI) also contains a red-edge band, and was developed for the remote estimation of total canopy chlorophyll content (Dash and Curran, 2004; 2007). It has been shown that the MTCI closely relates with gLAI (Gitelson, 2011).

For gLAI estimation using VIs, it is ideal that the VI selected is not sensitive to canopy architecture (e.g. leaf angle distribution), leaf structure (e.g. foliar chlorophyll distribution), and heliotropism (e.g. sun-avoidance), so that the relationships gLAI vs. VI would be applicable to different vegetation types without requiring algorithm re-parameterization. The VIs selected should also be insensitive to soil background and atmospheric effects.

To minimize the effects of soil background and maximize the sensitivity to foliar chlorophyll, Daughtry et al. (2000) suggested combining two VIs by taking a ratio of a VI sensitive to chlorophyll and a VI insensitive to soil background, canopy architecture, and LAI variability. Thus, combination of indices based on the Transformed Chlorophyll Absorption Reflectance Index (TCARI), the MCARI, and the OSAVI, such as, TCARI/OSAVI and MCARI/OSAVI, were used to estimate leaf chlorophyll content in crops, minimizing the effects of the soil background and the green LAI variation (Daughtry et al., 2000; Haboudane et al., 2002). However, the goal of these studies was to remove the effect of LAI on the estimation of leaf chlorophyll content (Daughtry et al., 2000; Haboudane et al., 2002; Eitel et al., 2008; 2009), therefore, for this study, that particular set of VIs was not considered for estimating gLAI.

Viña et al., (2011) evaluated the potential effects of soil background on the remote estimation of gLAI. For this, they used reflectance spectra of spherical and planophile canopies with different gLAI values under two contrasting soil backgrounds (i.e., dark and bright), as simulated by the New Advanced Discrete Model (Gobron et al. 1997), and used them for calculating three vegetation indices - EVI, MTCI and $CI_{red\ edge}$. The EVI has been suggested to be less sensitive to background effects (Huete et al. 1997), however, the uncertainties of gLAI estimation due to soil background effects by all three indices were very similar. In the spherical canopy, the errors of EVI, MTCI and $CI_{red\ edge}$ were 0.25, 0.18, and 0.21 m^2/m^2, respectively, while in the planophile canopy they were 0.21, 0.20, 0.14 m^2/m^2, respectively.

Maize and soybean plants have contrasting canopy architectures (i.e., maize has a predominantly spherical leaf angle distribution while soybean has a predominantly planophile/heliotropic leaf angle distribution), and leaf structures (i.e., maize is a monocot while soybean is a dicot) that exhibit different chlorophyll distributions along the leaf depth (de Wit, 1965; Idso and de Wit, 1970; Ehleringer and Forseth, 1980). Additionally, these two species have different physiological pathways (C3 vs. C4). Based on contrasting anatomical and physiological traits, these crops are representative of many crops types, and most VIs have been shown to respond to them, thus are species- or crop-specific (Curran and Milton, 1983; Gao et al., 2000; González-Sanpedro et al., 2008). However, some indices that use red edge bands in their formulation have been shown to be less sensitive to differences among species (Gitelson et al., 2005; Gitelson, 2011; Brantley et al., 2011; Viña et al., 2011).

The objectives of this study were to: (1) test the performance of twelve VIs for estimating gLAI in maize (*Zea mays*) and soybean (*Glycine max*); (2) identify an algorithm that does not require re-parameterization for estimating gLAI in both maize and soybean (C3 vs C4 crops); and (3) devise a "combined vegetation index" that is maximally sensitive to gLAI along its entire range of variability (i.e. 0 to more than 6 m^2/m^2), and is applicable to current operational satellite-based sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS) on board the National Aeronautics and Space Administration (NASA) Terra and Aqua satellites, or the European Space Agency (ESA) Medium Resolution Imaging Spectroradiometer (MERIS).

Materials and Methods

The study area is located at the University of Nebraska-Lincoln (UNL) Agricultural Research and Development Center near Mead, Nebraska, U.S.A. It consists of three 65-ha fields under different management practices (Table 1). The soils are deep silty clay loams including Tomek, Yutan, Filbert, and Fillmore soil series (Suyker et al., 2004). During the years of study, field 1 was under continuous irrigated maize while fields 2 and 3 were under a maize/soybean rotation, with maize during odd years and soybean during even years. Field 2 was irrigated, while field 3 received only rainfall. Overall, there were nine maize hybrids and three soybean hybrids under different planting densities (Table 1). All crops were fertilized and treated with herbicide/pesticides following UNL's best management practices for eastern Nebraska.

It has been reported that 2003 and 2005 were especially dry years, with annual precipitation values of 650 and 607 mm, respectively, which were well below the 1026 mm of a "normal" year (Suyker and Verma, 2010). Thus, water stress occurred under low soil moisture conditions, which severely affected grain yield. For example, during dry periods in 2003, soil moisture at the 10 cm depth in the rainfed field dropped more than 40% compared to that in irrigated fields. The difference in daily gross primary production (GPP) between irrigated and rainfed fields increased during the dry periods and reached a peak value, which corresponded to 40% of the maximal daily GPP value (Suyker and Verma, 2010). As a result, the ratio of grain yield in the irrigated field to that in the rainfed field was above 1.8 in 2003, while in a "normal" year with higher precipitation (e.g., 2007), it was below 1.3 (Suyker and Verma, 2010).

Six small (20 x 20 m) plots (henceforth referred to as intensive measurement zones, IMZs) were established in each field for performing detailed plant measurements. The IMZs represented all major soil and crop production zones within each field (Verma et al., 2005). The IMZ results were aggregated to a field mean based on a weighted average of the relative area of the stratified zones represented by each IMZ. The gLAI was calculated from sampling a 1 m length of one or two rows (6 ± 2 plants), located within each IMZ, every 10-14 days starting at the initial growth stages (V1-V3), based on the scale by Abendroth et al., (2011), and ending at crop maturity (R5-R7) in both species. Collection rows were alternated between sampling dates to minimize edge effects. The plants collected were transported on ice (to reduce pheophytin formation) to the laboratory where they were visually divided into green leaves, dead leaves, stems, and reproductive organs. The leaf area was measured using an area meter (Model LI-3100, LI-COR, Inc., Lincoln, NE), which was subsequently used to determine gLAI (green leaf area in m^2 divided by ground area in m^2) by multiplying the green leaf area per plant by the plant population (number of plants per m^2) as counted in each IMZ (i.e. not based on planting density shown in Table 1). The values calculated from all six IMZs were averaged for each sampling date to provide a field-level gLAI. During the eight years of the study, the mean standard error of gLAI measurements was less than 0.15 m^2/m^{-2} (Guindin-Garcia et al., 2012). Cubic spline interpolation (in MATLAB®) was used to estimate values of gLAI corresponding to days of reflectance measurement when that parameter was not acquired concurrently with the destructive gLAI determination.

Canopy reflectance was collected using an all-terrain sensor platform, equipped with a dual-fiber system and two Ocean Optics USB2000 spectroradiometers, with a spectral range of 400-1100 nm and a spectral resolution of 1.5 nm (Rundquist et al., 2004). One fiber was fitted with a cosine diffuser to measure incoming downwelling irradiance, while the second one measured upwelling radiance. The field of view of the downward-pointing sensor was kept constant along the growing season (approximately 2.4 m in diameter) by placing the spectroradiometer at a height of 5.5 m above the top of the canopy. Radiometric data were collected close to solar noon (between 11:00 and 13:00 local time), when changes in solar zenith angle were minimal. Ten reflectance spectra were measured at each collection point along access roads into each of the fields, and computed average reflectance represented each collection point. Six randomly selected plots were established per field, each with six randomly selected sampling points. Thus, a total of 36 points within these areas were sampled per field at each data acquisition, and their median per date was used as the overall field reflectance. Measurements took about 5 minutes per plot and about 30 minutes per field. The two radiometers were inter-calibrated immediately before and immediately after measurement in each field. Reflectance measurements were carried out during the growing season each year over the eight-year period. This resulted in a total of 314 reflectance spectra for maize (47 in 2001, 30 in 2002, 92 in 2003, 30 in 2004, 53 in 2005, 13 in 2006, 40 in 2007 and 9 in 2008) and 145 spectra for soybean (54 in

2002, 49 in 2004, 26 in 2006 and 16 in 2008), which were representative of a wide range of gLAI variation found in maize and soybean cropping systems.

Using hyperspectral aerial imagery, acquired over the study site by an AISA Eagle hyperspectral imaging spectrometer, it was shown that the canopy reflectance in the fields were spatially homogeneous; thus, reflectance spectra taken along access roads were representative of the field (Viña et al., 2011). Therefore, the remotely estimated gLAI may be compared with measured field level gLAI.

The twelve VIs examined in this study (Table 2) were chosen as they are representative of VIs that are widely used (e.g., NDVI, SR), some of them minimize soil background effects (e.g., OSAVI, EVI). They were also selected because of their applicability to data collected by satellite sensors such as MODIS and MERIS. These two sensors are utilized much more frequently than hyperspectral sensors, which are expensive to operate and cover limited study areas. Since a goal of this study was to find VIs applicable to MODIS and MERIS, the collected field reflectance spectra were resampled by averaging the Ocean Optics data to simulate the spectral bands of MODIS (band 3/green: 545 - 565 nm, band 1/red: 620 - 670 nm, and band 2/NIR: 841 - 876 nm) and of MERIS (band 5/green: 555 - 565 nm, band 7/red: 660 - 670 nm, band 8/red: 677.5-685, band 9/red edge: 703.8 - 713.8 nm, band 10 NIR: 750 - 757.5 nm, and band 12/NIR: 771.3 - 786.3).

Best-fit relationships between VIs and gLAI were determined using Eureqa (Schmidt and Lipson, 2009; http://creativemachines.cornell.edu/eureqa), an algorithm search engine that identifies and ranks potential regression models that best correspond to the input data. Users input the desired relationship, e.g. VI = f(gLAI), along with potential operations (e.g. addition, subtraction, exponential, power, etc.) and an error metric (e.g. minimize absolute error, R^2, etc.).

In our case, the fitness metric used to rank the best-fit functions constituted the minimization of the root mean square error (RMSE). The inverse of these relationships (i.e., gLAI vs. VI) was utilized for gLAI estimation using VIs. After determining the best-fit relationships, a *k*-fold (*k* = 10) cross-validation procedure (Kohavi, 1995) was utilized to determine the estimates of model coefficients, coefficients of determination (R^2), standard error (SE), and coefficients of variation (CV) using the statistical package R (V. 2.12.2, R Development Core Team 2011). CV is the standard deviation of the gLAI vs. VI relationship divided by mean value of gLAI. The data or subgroups (i.e., different crops - maize or soybean) were randomly divided into ten sets using a random sequence generator (random.org), nine of which were used iteratively for calibration and the remaining set for validation.

It is important to note that the R^2 values, as well as SE and CV of gLAI estimation, represent the dispersion of the points from the best-fit regression lines. They constitute measures of how good the regression model (best-fit function) is in capturing the relationship between gLAI and VI. However, when the best-fit function is nonlinear, the R^2 as well as the SE values may be misleading. To determine the accuracy of gLAI estimation, we employed the noise equivalent (NE) of gLAI (Govaerts et al., 1999; Viña and Gitelson, 2005), that was calculated as:

$$\text{NE } \Delta\text{gLAI} = \text{RMSE(VI vs. gLAI)}/[\text{d(VI)}/\text{d(LAI)}] \qquad (1)$$

Where d(VI)/d(gLAI) is the first derivative of VI with respect to gLAI and RMSE(VI vs. LAI) is the root mean square error of the VI vs gLAI relationship. The NE ΔgLAI provides a measure of how well the VI responds to gLAI across its entire range of variation. NE ΔgLAI takes into account not only the RMSE of gLAI estimation but also accounts for the sensitivity of the VI to gLAI, thus providing a metric accounting for both scattering of the points from the best fit function and the slope of the best fit function.

To test the applicability of VIs to estimate the gLAI of different crops with no algorithm re-parameterization, we performed an analysis of variance (ANOVA) between the coefficients of the best-fit function for both species (maize and soybean) combined, versus the coefficients obtained for each individual crop (Ritz and Streibig, 2008).

Results and Discussion

While both maize and soybean undergo three major stages of development (green-up, reproductive, and senescence), the temporal dynamics of their gLAI are very different (Fig. 1). In maize, the green-up period was longer (~20 days) than in soybean. Maize remained in the vegetative stage as gLAI increased until it reached the maximum gLAI, which occurred when silking began. There was a decrease in gLAI of about 1 m^2/m^2 during the kernel development. Then, during the final stage before maturity (dent), gLAI dropped to nearly 0 m^2/m^2 (Fig. 1a). In contrast, soybean flowered before maximum gLAI was reached, which occurred during pod and seed development, and decreased once the plant reached full seed (Fig. 1b). The ranges of maize and soybean gLAI variability were also different. In irrigated maize, the maximum gLAI reached 6.5 m^2/m^2 while in soybean it did not exceed 5.5 m^2/m^2. For both crops, gLAI maxima in rainfed fields were typically lower than in irrigated fields (Fig. 1, Table 1). Thus, the maximum gLAI differed on per crop (i.e., maize vs. soybean) and water status (i.e. irrigated vs. rainfed) bases.

All best-fit functions established between gLAI and VI for either maize (Table 3) or soybean (Table 4) were non-linear, and the shapes of the relationships VI vs gLAI differed among VIs (Fig. 2). For example, NDVI reached an asymptote at around 0.7 when gLAI was between 2 and 3 m^2/m^2, and became almost invariant for gLAI > 4m^2/m^2 in both maize and soybean (Fig. 2b). This saturation of the NDVI (Fig. 2b) reduces its functionality for gLAI estimation at moderate-to-high gLAI values, since it generates large uncertainty in model inversions: almost the same value of VI corresponds to gLAI ranging from 4 to more than 6 m^2/m^2. Several other normalized difference indices (green NDVI, red edge NDVI, EVI2, and WDRVI with $\alpha = 0.2$), TVI and MTVI2 also showed different degrees of decreased sensitivity at moderate-to-high gLAI values (Figs 2c, d, e, h, j, k, l). SR had an exponential relationship with lower sensitivity to gLAI < 1 m^2/m^2 than to higher gLAI values (Fig. 2a). For gLAI > 1 m^2/m^2, the relationship between SR and gLAI was nearly linear. The relationships for CIs and the MTCI exhibited a similar shape, with an increase in slope at moderate to high gLAI (Figs. 2f, g, i).

In this study, we found that among the twelve VIs examined, only the red edge NDVI (ANOVA: $p = 0.36$, $n = 423$, $F = 1.09$) and the $CI_{red\ edge}$ (ANOVA: $p = 0.11$, $n = 423$, $F = 1.65$) can be applied for maize and soybean with no re-parameterization of the model. Best-fit functions of the relationships gLAI vs. red Edge NDVI and $CI_{red\ edge}$ for both maize and soybean are presented in Table 5. All other VIs were crop-specific (ANOVA: $p < 0.001$, $n = 423$, $F >$ 4.5).

As noted in the Materials and Methods section, R^2 and SE may be misleading when comparing non-linear and linear relationships. For example, although the relationship NDVI vs gLAI resulted in high R^2 values, the slope of the relationship decreased as gLAI exceeded 3 m^2/m^2 and became close to zero at gLAI values above 3.5 m^2/m^2 for soybean and above 4 m^2/m^2 for maize (Fig. 2b). With the decrease in sensitivity of VIs to gLAI (i.e., when gLAI exceeds 3 m^2/m^2), the scattering of the points from the best-fit functions drops, as can be seen for NDVI, green NDVI, red edge NDVI and OSAVI (Figs. 2b, 2c, 2d, and 2e, for soybean). Thus, most of the VIs had similar R^2 and SE (Tables 3 and 4) but very different shapes of the relationships VI vs gLAI (e.g., increasing exponential decay in NDVI vs. exponential growth in SR). Therefore, a different accuracy metric, specifically the NE ΔgLAI, was needed to compare the performance of VIs in estimating gLAI along its entire range of variation.

Fig. 3 displays values of NE ΔgLAI for normalized difference VIs, MTCI and ratio indices (SR, CIs). TVI and MTVI2 were not included in this analysis because their NE ΔgLAI values were always greater than those of normalized difference indices at low to moderate gLAI, and also were always greater than those of SR, CIs and MTCI at moderate to high gLAI. Therefore, TVI and MTVI2 did not meet the criteria for determining the best indices either for low-to-moderate, for moderate-to-high, or for the entire range of gLAI.

The normalized difference VIs had asymptotic relationships with gLAI (Figs. 2b, c, d, h, l); thus, the NE ΔgLAI was lowest at gLAI below 2.5 m^2/m^2 for maize and below 2 m^2/m^2 for soybean (Fig. 3). SR and CIs had exponential relationships with gLAI (Figs. 2a, f, g); thus, the lowest values of NE ΔgLAI were at gLAI exceeding 3 m^2/m^2 (Fig. 3). Therefore, the normalized difference VIs were more accurate in estimating low-to-moderate gLAI while the ratio indices, SR and CIs, were more accurate in estimating moderate-to-high gLAI.

While the relationship of MTCI with gLAI was asymptotic, the slope of the relationship was almost constant in a wide range of gLAI variation (Fig. 2i). Therefore, for MTCI, NE ΔgLAI varied little throughout the entire range of gLAI (Fig. 3). In the range of gLAI below 2.5 m^2/m^2, the MTCI had lower accuracy than normalized difference VIs and almost the same accuracy as SR and CI indices. However, in the range of gLAI > 2.5 m^2/m^2, it had lower accuracy than SR and CIs. Thus, it did not outperform normalized difference VIs or SR and CI indices in their respective regions of highest sensitivity to changes in gLAI.

At moderate to high gLAI, the noise equivalents of normalized difference indices in soybean were higher than those in maize. This may be explained by the very different canopy architectures and leaf structures of these crops. For the same amount of foliar chlorophyll content, the chlorophyll density on the adaxial side of soybean leaves is higher than that in maize leaves, causing a higher absorption in the red range and thus lower reflectance of soybean canopies: 2% for leaf chlorophyll above 500 mg/m^2 (Gitelson et al., 2005) compared to 3-5% of maize leaves. In addition, for the same gLAI, canopy reflectance of soybean in the NIR region was higher than that of maize: for gLAI around 5 m^2/m^2, NIR reflectance was 60% in soybean vs. 40% in maize (Peng and Gitelson, 2011). Thus, for the same gLAI, especially within the moderate-to-high range, a NIR to red reflectance ratio is higher in soybean than in maize. Therefore, the value of gLAI above which the normalized difference indices became insensitive to gLAI was lower in soybean than in maize.

Analysis of the NE ΔgLAI of VIs (Fig. 3) showed that for gLAI below 2.5 m^2/m^2, normalized difference VIs had the lowest NE ΔgLAI, and thus highest accuracy of gLAI estimation, while SR and CIs had the highest accuracy for gLAI > 3 m^2/m^2 and were the best suited for estimation of moderate-to-high gLAI. Therefore, there was no single index that had the lowest uncertainties of gLAI estimation along the entire range of gLAI variation. In order to obtain the highest possible accuracy (i.e., lowest NE ΔgLAI) across the entire range of gLAI, we suggest using more than one VI in combination, i.e., a combined vegetation index (CVI).

The CVI is comprised of two VIs that are the most accurate in gLAI estimation at different ranges of gLAI: the first index for low-to-moderate gLAI (below 2.5 m^2/m^2) and the second index for moderate-to-high gLAI (above 2.5 m^2/m^2). While it is possible to scale the VIs in CVI to create a linear relationship, any scaled algorithm will be data-set dependent and may result in a decrease in the sensitivity of the VI to gLAI. For both MODIS and MERIS data, containing the red and NIR bands, we suggest using NDVI as the first index and SR as the second index - CVI{NDVI, SR}. An NDVI value around 0.7 has been previously reported as a typical point where the NDVI vs. green LAI relationship becomes saturated (Myneni et al., 1995; Gitelson et al., 2003b). Therefore, we selected NDVI = 0.7 as a threshold for both maize and soybeans. In the range of NDVI from 0 to 0.7, the best fit functions of NDVI vs. gLAI for both crops were linear and, thus, NE ΔgLAI was constant and as low as 0.38 m^2/m^2 for maize (Fig. 4a) and 0.4 m^2/m^2 for soybean (Fig. 4b).

As gLAI exceeded 2.5 m^2/m^2, the NE ΔgLAI of SR decreased and the accuracy of gLAI estimation increased for both species (Figs. 4a and b). When SR was above 5.7 (corresponding to NDVI =0.7), the best-fit function of SR vs. gLAI was linear and, thus, NE ΔgLAI was constant and equal to 0.68 m^2/m^2 for maize (Fig. 4a) and 0.49 m^2/m^2 for soybean (Fig. 4b). A CVI comprised of two indices (NDVI and SR and, thus, using only red and NIR bands), was able to estimate gLAI ranging from 0 to more than 6 m^2/m^2 with a RMSE below 0.72 m^2/m^2 and a CV of 20% for maize, and a RMSE below 0.54 m^2/m^2 and a CV of 23% for soybean. However, the algorithms relating gLAI and CVI{NDVI, SR} for maize and soybean required different coefficients (Table 6) and, thus, were crop specific.

Alternatively, we suggest using the red edge NDVI as the first CVI index and the $CI_{red\ edge}$ as the second CVI index – i.e., CVI{red edge NDVI, $CI_{red\ edge}$} (Fig. 5) for data acquired by sensor systems containing red edge and NIR bands (e.g., MERIS, HYPERION). This combined index was not crop-specific at least for the species evaluated (i.e., maize and soybean), which have quite contrasting leaf and canopy structures. Therefore, this CVI does not require re-parameterization, since the same algorithm coefficients can be applied to estimate gLAI in both crops (Table 6). Based on the NE ΔgLAI results, presented in Fig. 5, we suggest using a threshold of red edge NDVI equal to 0.6. For the range of red edge NDVI of 0 to 0.6, the NE

ΔgLAI was 0.46 m^2/m^2 and for $CI_{red\ edge}$ above 3 (corresponding to the red edge NDVI value of 0.6) the NE ΔgLAI was 0.55 m^2/m^2 (Fig. 5). For both species, CVI{red edge NDVI, $CI_{red\ edge}$} was able to estimate gLAI along its entire range of variation (i.e., 0 to > 6 m^2/m^2), with a RMSE below 0.60 m^2/m^2 and a CV of 19%.

In applications where prior knowledge about crop type is available, using sensor systems containing red and NIR bands with spatial resolutions high enough to reduce the effects of mixed pixels, the CVI{NDVI,SR} is adequate. However, in many cases, there is uncertainty about the crop type present within a pixel (e.g., coarse spatial resolutions, mixed pixels, areas of crop rotation without prior knowledge of planted crops). Thus, the CVI{red edge NDVI, $CI_{red\ edge}$}, having a unified algorithm for crops with different leaf and canopy structures (e.g., maize and soybean), brings an objective estimation of total gLAI, even in the case of mixed pixels and crops at different phenological stages.

We acknowledge that further research is needed to evaluate the CVI{red edge NDVI, $CI_{red\ edge}$} in other crops. However, since in this study it was tested in crops that are very different (maize and soybean), it will likely be insensitive to leaf and canopy structure of crops that are not as different. It is also important to investigate the reliability of the CVIs developed when applied to estimating gLAI in other vegetation types, such as grasslands and forests. Additionally, the calibration equations for the CVIs built with simulated MODIS and MERIS bands obtained from close-range hyperspectral data should be tested against actual MODIS and MERIS data. However, it is likely that these equations are reliable since it has been shown that the coefficients of the relationships between gLAI and WDRVI, when taken at close range, remained the same as those applied to MODIS 250 m data, due to accurate atmospheric correction of the MODIS 250 m surface reflectance product (Gitelson et al., 2007; Guindin-Garcia et al., 2012).

The approach presented in this study is not limited to gLAI, as it may also be used for the remote estimation of other biophysical characteristics, such as vegetation cover, fraction of absorbed photosynthetically active radiation and gross primary production. Nevertheless, the CVIs presented in this study may not constitute the best vegetation index combinations for measuring these other vegetation characteristics. Therefore, future studies are needed to investigate which VI combinations are the most appropriate for assessing other biophysical characteristics of vegetation.

Conclusions

Twelve vegetation indices, calculated from simulated spectral bands of MODIS and MERIS satellite sensor systems, were evaluated for remotely assessing gLAI in two crop species with contrasting leaf structures and canopy architectures. All VIs investigated had essentially non-linear relationships with gLAI, although with different sensitivities along the range of gLAI variability evaluated. On this basis, we suggest combining vegetation that exhibit high sensitivity to changes in green LAI at particular ranges (i.e., low-to-moderate and moderate-to-high). When combined, these indices constitute suitable and accurate remotely sensed surrogates of gLAI along its entire range of variability. Specifically we suggest combining the NDVI and the SR, CVI{NDVI, SR} to be used in the case of sensors with spectral bands in the red and NIR (e.g., MODIS 250 m, Landsat TM and ETM+), although this combined index is crop-specific and requires re-parameterization of the algorithm for each crop. Alternatively, if a band in the red-edge region is available (e.g., MERIS, HYPERION), we suggest combining the red edge NDVI and the $CI_{red\ edge}$, CVI{red edge NDVI, $CI_{red\ edge}$}. Since it was not crop-specific, this combined index was capable of estimating gLAI with high accuracy, thus providing a suitable procedure for remotely estimating gLAI of crops with contrasting canopy architectures and leaf structures.

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Fig. 1: Temporal dynamics of gLAI in a) maize in 2007 and b) soybean in 2008, in both irrigated (solid line) and rainfed (dashed line) fields. Major crop growth stages (vegetative, reproductive, and senescence) are indicated. Bars represent one standard error of destructive gLAI determination at six intensive measurement zones in each field.

Fig. 2: Vegetation indices plotted versus green leaf area index, gLAI: a) Simple Ratio, b) Normalized Difference Vegetation Index (NDVI), c) green NDVI, d) red edge NDVI, e) Optimized Soil-Adjusted Vegetation Index (OSAVI), f) Chlorophyll Index Green (CI_{green}), g) $CI_{red\ edge}$, h) Triangular Vegetation Index (TVI), i) MERIS Terrestrial Chlorophyll Index (MTCI), j) Wide Dynamic Range Vegetation Index (WDRVI) α=0.2, k) Modified TVI 2 (MTVI2), and l) Enhanced Vegetation Index 2 (EVI2). In all panels – maize: open squares, solid line is best-fit function; soybean: closed triangles, dashed line is best fit function. The inverse of these relationships gLAI vs. VIs along with their summary statistics are shown in Tables 3 and 4.

Fig. 3: Minimal and maximal values of the noise equivalent NE ΔgLAI for a) maize and b) soybean for groupings of vegetation indices demonstrating increase of NE (decrease in accuracy) at moderate-to-high gLAI (NDVI, green NDVI, red edge NDVI, OSAVI, and WDRVI), high NE at low-to-moderate gLAI (SR, CI_{green} and $CI_{red\ edge}$) and almost invariant NE throughout the entire dynamic range (MTCI).

Fig. 4: Noise equivalent NE ΔgLAI of NDVI, SR and suggested combined vegetation index CVI{NDVI, SR} for (a) maize and (b) soybean. NDVI < 0.7 is the first index and SR is the second index.

Fig. 5: Noise equivalent NE ΔgLAI of red edge NDVI, $CI_{red\ edge}$ and suggested combined vegetation index CVI{red edge NDVI, $CI_{red\ edge}$} for maize and soybean combined. Red edge NDVI < 0.6 is the first index and $CI_{red\ edge}$ is the second index.

Table 1: Species, hybrid, planting density and maximum green leaf area index (gLAI) in the 24 year-fields evaluated.

Year	Site	Species	Hybrid	Planting Density (pl/ha)	Maximum gLAI (m^2/m^2)	Tillage operation	Applied N
	1	maize	Pioneer 33P67	82,000	6.1		196
2001	2	maize	Pioneer 33P67	83,314	6.1	intensive tillage	196
	3	maize	Pioneer 33B51	62,236	3.9		128
	1	maize	Pioneer 33P67	81,000	6.0		214
2002	2	soybean	Asgrow 2703	370,644	5.5	no-till	0
	3	soybean	Asgrow 2703	370,644	3.0		0
	1	maize	Pioneer 33B51	77,000	5.5		233
2003	2	maize	Pioneer 33B51	86,667	5.5	no-till	169
	3	maize	Pioneer 33B51	64,292	4.3		90
	1	maize	Pioneer 33B51	84,012	5.2		293
2004	2	soybean	Pioneer 93B09	370,644	4.4	no-till	0
	3	soybean	Pioneer 93B09	370,644	4.5		0
	1	maize	DeKalb 63-75	82,374	5.2		246
2005	2	maize	Pioneer 33B51	83,200	4.8	no-till	170
	3	maize	Pioneer 33G68	59,184	4.3		118
	1	maize	Pioneer 33B53	84,012	5.3	conservation-plow	210
2006	2	soybean	Pioneer 31N28	370,644	5.0	no-till	0
	3	soybean	Pioneer 93M11	370,644	4.5		0
	1	maize	Pioneer 31N30	80,697	6.3	conservation-plow	272
2007	2	maize	Pioneer 31N28	78,740	5.7	no-till	183
	3	maize	Pioneer 33H26	62,088	4.1		125
	1	maize	Pioneer 31N30	84,469	6.5	conservation-plow	123
2008	2	soybean	Pioneer 93M11	369,508	4.7	no-till	0
	3	soybean	Pioneer 93M11	369,508	3.6		0

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Table 2: List and formulation of the vegetation indices examined.

Index	Equation	Equation in Bands of MODIS or/and MERIS	Reference
Simple Ratio (SR)	NIR/Red	MODIS 2 / MODIS 1	Jordan, (1969)
Normalized Difference Vegetation Index (NDVI)	(NIR - Red) / (NIR + Red)	(MODIS 2 - MODIS 1) / (MODIS 2 + MODIS 1)	Rouse et al., (1973)
Green NDVI (green NDVI)	(NIR - Green) / (NIR + Green)	(MODIS 2 - MODIS 4) / (MODIS 2 + MODIS 4)	Gitelson and Merzlyak, (1994)
Red Edge NDVI (red edge NDVI)	(NIR - Red Edge) / (NIR + Red Edge)	(MERIS 12 - MERIS 9) / (MERIS 12 + MERIS 9)	Gitelson and Merzlyak, (1994)
Optimized Soil-Adjusted Vegetation Index (OSAVI)	(NIR-Red)/ (Red+NIR+0.16)	(MODIS 2 - MODIS 1)/ (MODIS1 + MODIS 2 + 0.16)	Rondeaux et al., (1996)
Green Chlorophyll Index (CI_{green})	(NIR / Green) - 1	(MODIS 2 / MODIS 4) - 1	Gitelson et al., (1996)
Red Edge Chlorophyll Index ($CI_{red\ edge}$)	(NIR / Red Edge) - 1	(MERIS 12 / MERIS 9) - 1	Gitelson et al., (1996)
Triangular Vegetation Index (TVI)	0.5*[120*(NIR - Green) - 200*(Red-Green)]	0.5*[120*(MERIS 10 - MERIS 5) - 200*(MERIS 7 -MERIS 5)	Broge and Leblanc, (2001)
MERIS Terrestrial Chlorophyll Index (MTCI)	(NIR-Red Edge) / (Red Edge - Red)	(MERIS 10 - MERIS 9) / (MERIS 9 + MERIS 8)	Dash and Curran, (2004)
Wide Dynamic Range Vegetation Index[#]	(α*NIR-Red)/(α*NIR + Red)	(α*MODIS 2 - MODIS 1) / (α*MODIS 2 + MODIS 1)	Gitelson, (2004)
Modified TVI 2 (MTVI2)	1.5*[1.2*(NIR - Green) - 2.5*(Red - Green)]/ sqrt{(2*NIR + 1)^2 – [6*NIR - 5*sqrt(Red)] - 0.5}	1.5*[1.2*(MODIS 2 - MODIS 4) - 2.5*(MODIS 1 - MODIS 4)]/ sqrt{(2*MODIS 2 + 1)^2 – [6*MODIS 2 - 5*sqrt(MODIS 1)] - 0.5}	Haboudane et al., (2004)
Enhanced Vegetation Index 2 (EVI2)	2.5*(NIR - Red) / (NIR + 2.4*Red + 1)	2.5*(MODIS 2 - MODIS 1) / (MODIS 2 + 2.4*MODIS 1 + 1)	(Jiang et al., (2008)

[#]This study utilized scaled WDRVI in the form (α*MODIS Band 2 - MODIS Band 1) /(α*MODIS Band 2 + MODIS Band 1) + (1- α)/(1+ α) (Peng et al. 2011).

Table 3: Best-fit functions of the relationships between green leaf area index (gLAI) and vegetation indices (VI) obtained using a cross-validation procedure for maize; x = VI, y = gLAI, R^2 is the coefficient of determination, and the SE is the standard error of the gLAI estimation, in m^2/m^2.

Index	Equation gLAI vs VI	R^2	SE
SR	$y = x^{0.654} - 1.24$	0.86	0.66
NDVI	$y = \log_{0.6}[-(x - 0.943) / 0.731]$	0.87	0.64
Green NDVI	$y = -\{[\ln(0.876 - x) + 0.66] / 0.409\}$	0.87	0.63
Red edge NDVI	$y = \log_{0.716}(0.88 - x) - 0.623$	0.90	0.54
OSAVI	$y = -[1.49*\ln(x)+2.71]/\ln(x)$	0.81	0.78
CI_{green}	$y = [(x - 0.931) / 1.44]^{0.971}$	0.89	0.59
$CI_{red\ edge}$	$y = [(x - 0.15) / 0.642]^{0.775}$	0.90	0.55
TVI	$y = (x / 8.85)^{1.73}$	0.65	1.05
MTCI	$y = (x - 1.49)^{0.926}$	0.85	0.69
WDRVI α=0.2	$y = \log_{0.775}(1.61 - x) + 1.61$	0.88	0.60
MTVI2	$y = \log_{0.81}(1.05 - x)$	0.67	1.01
EVI2	$y = (x + 0.863)^{4.08} - 0.863$	0.63	1.07

Table 4: Best-fit functions of the relationships between green leaf area index (gLAI) and vegetation indices (VI) obtained using a cross-validation procedure for soybean; x = VI, y = gLAI, R^2 is the coefficient of determination, and the SE is the standard error of gLAI estimation, in m^2/m^2.

Index	Equation gLAI vs VI	R^2	SE
SR	$y = [(x - 1.39)^{0.698}] / 2$	0.89	0.51
NDVI	$y = \log_{0.37}[x^{-0.526} - 1.03]$	0.90	0.48
Green NDVI	$y = \mathrm{sqrt}[(0.964 - x)^{-1.48} - 2.35]$	0.89	0.51
Red edge NDVI	$y = \ln[(0.805 - x)^{(1/-0.52)} - 0.82]$	0.91	0.46
OSAVI	$y = -[0.916*\ln(1/x) - 1.79]/\ln(1/x)$	0.84	0.60
CI_{green}	$y = [(x - 1.08) / 1.38]^{0.767}$	0.90	0.49
$CI_{red\ edge}$	$y = (x / 0.86)^{0.854}$	0.91	0.46
TVI	$y = \exp(x / 17.2) - 1.06$	0.60	0.95
MTCI	$y = (x - 1.03)^{0.981}$	0.80	0.67
WDRVI α=0.2	$y = -\{[\ln(1.79 - x) - 0.532] / 0.3\}$	0.90	0.47
MTVI2	$y = x^{1.61} / 0.172$	0.82	0.64
EVI2	$y = \exp(x / 0.472) - 1.3$	0.76	0.75

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Table 5: Best-fit functions of the relationships between green leaf area index (gLAI) and vegetation indices (VI) for both maize and soybean combined; x = VI, y = gLAI, R^2 is the coefficient of determination, and the SE is the standard error of the gLAI estimation, in m^2/m^2.

Index	**Equation gLAI vs VI**	**R^2**	**SE**
Red Edge NDVI	$y = (0.155 / x - 0.173)^{-0.542} - 0.739$	0.90	0.56
$CI_{red\ edge}$	$y = x^{0.898} / 0.904$	0.91	0.54

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Table 6: Best-fit functions for combined vegetation indices (CVI) as used to estimate gLAI. CVI represents the combination of two vegetation indices where the first index (i.e., NDVI or red edge NDVI) are most sensitive to low-to-moderate gLAI and the second index (i.e., SR or $CI_{red\ edge}$) are most sensitive to moderate-to-high gLAI. The threshold for NDVI was set at 0.7 and for red edge NDVI at 0.6. CV is coefficient of variation.

Index	**Crop**	**First index below threshold**	**Second index above threshold**	**CV (%)**
CVI{NDVI, SR}	Maize	(NDVI - 0.28)/0.18	(SR + 1.0)/3.5	20
CVI{NDVI, SR}	Soybean	(NDVI - 0.27)/0.22	(SR + 3.2)/6.2	23
CVI{Red Edge NDVI, $CI_{red\ edge}$}	Maize and Soybean	(red edge NDVI - 0.13)/0.14	($CI_{red\ edge}$ – 0.63)/0.95	20

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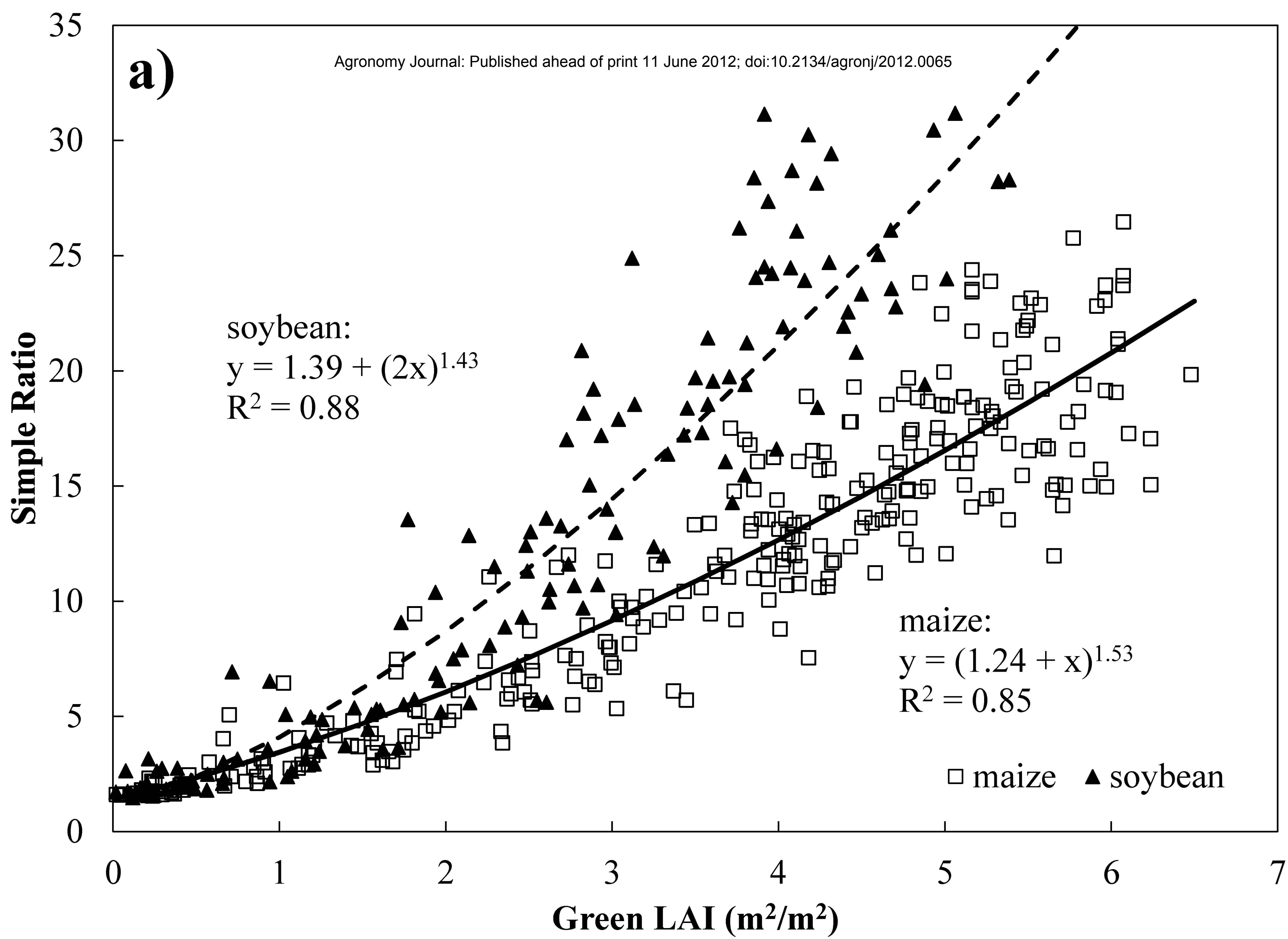

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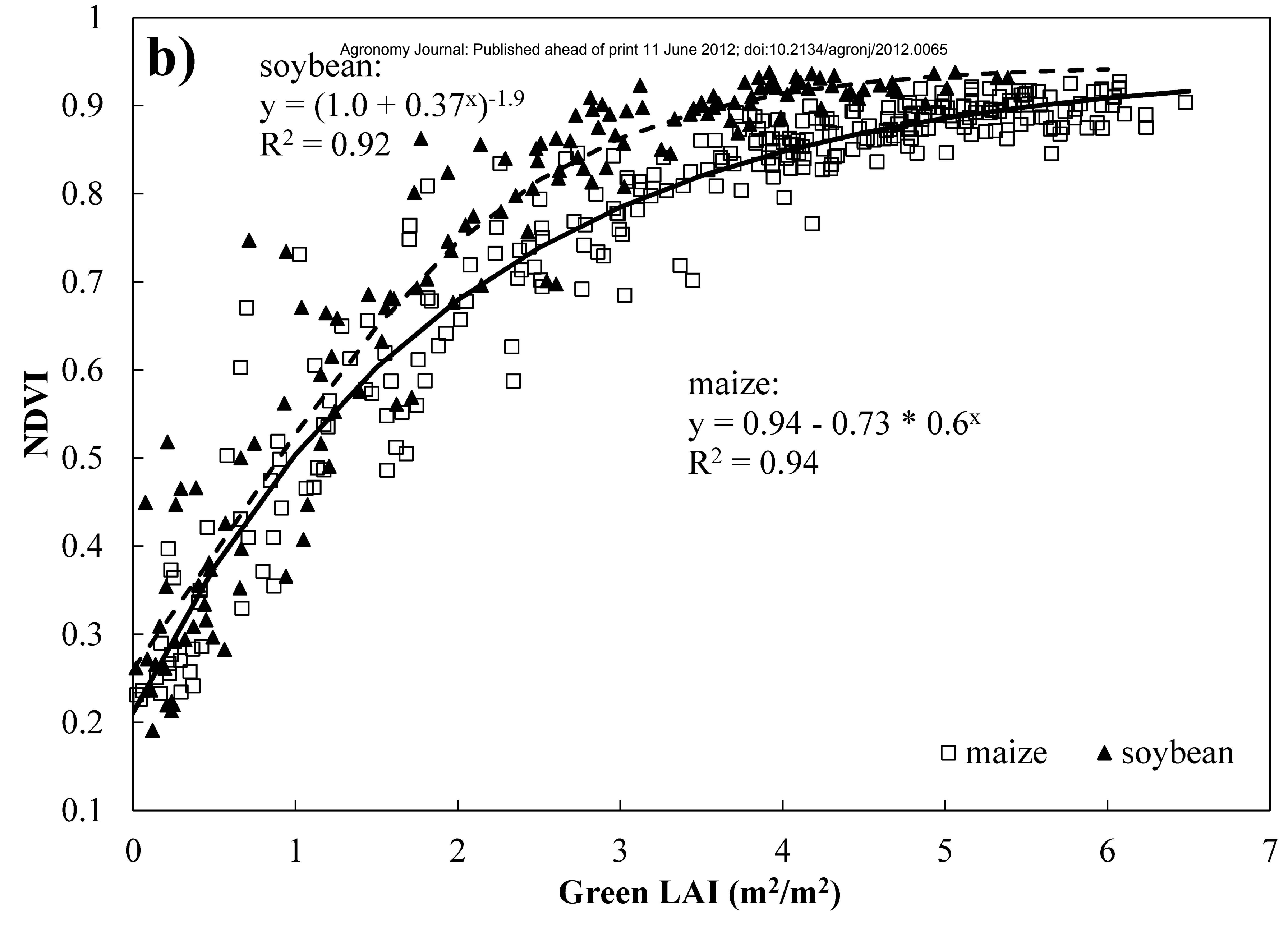

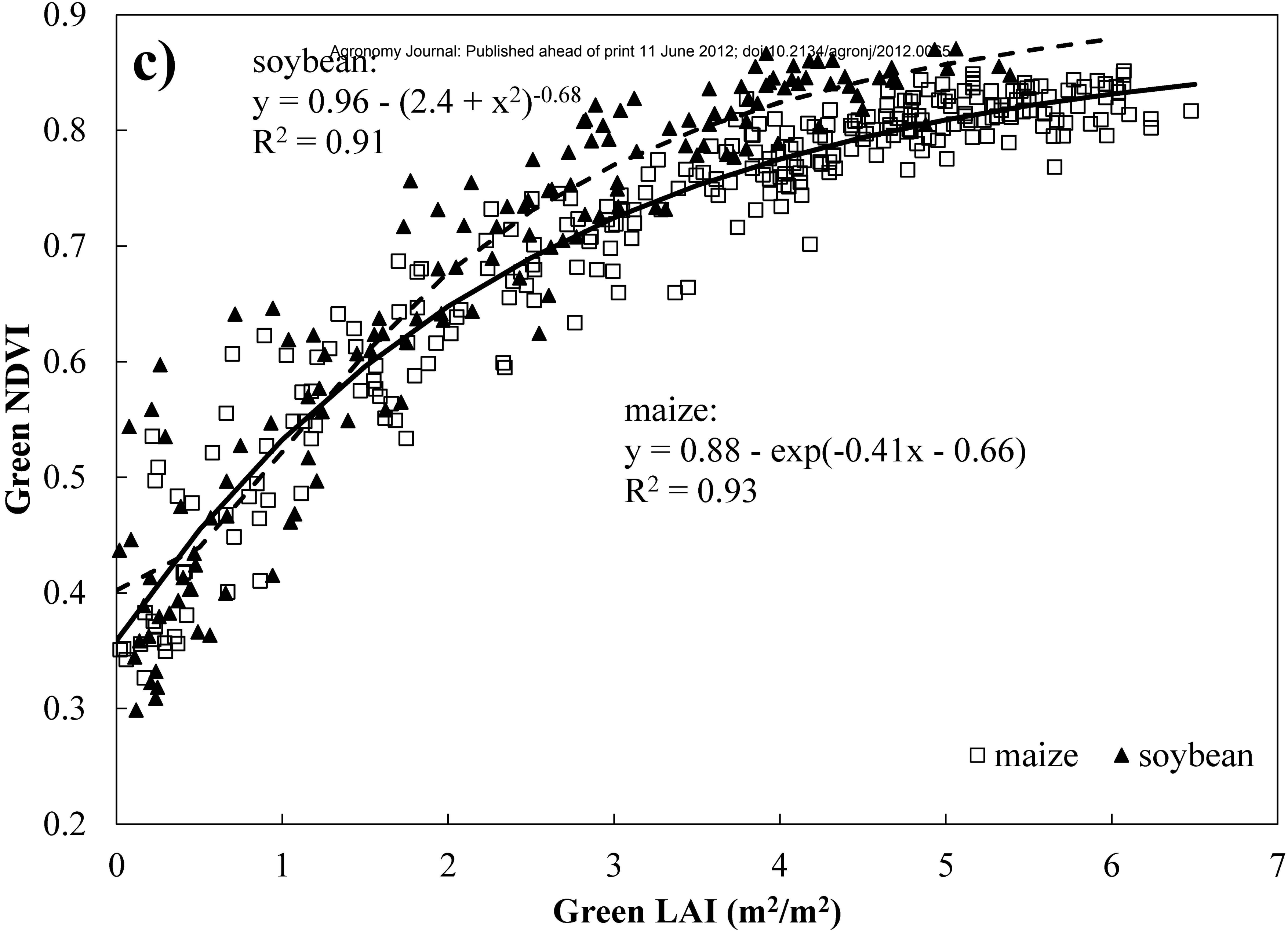
c)
soybean:
y = 0.96 - (2.4 + x²)^-0.68
R² = 0.91
maize:
y = 0.88 - exp(-0.41x - 0.66)
R² = 0.93
maize
soybean
Green NDVI
Green LAI (m²/m²)
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0
1
2
3
4
5
6
7

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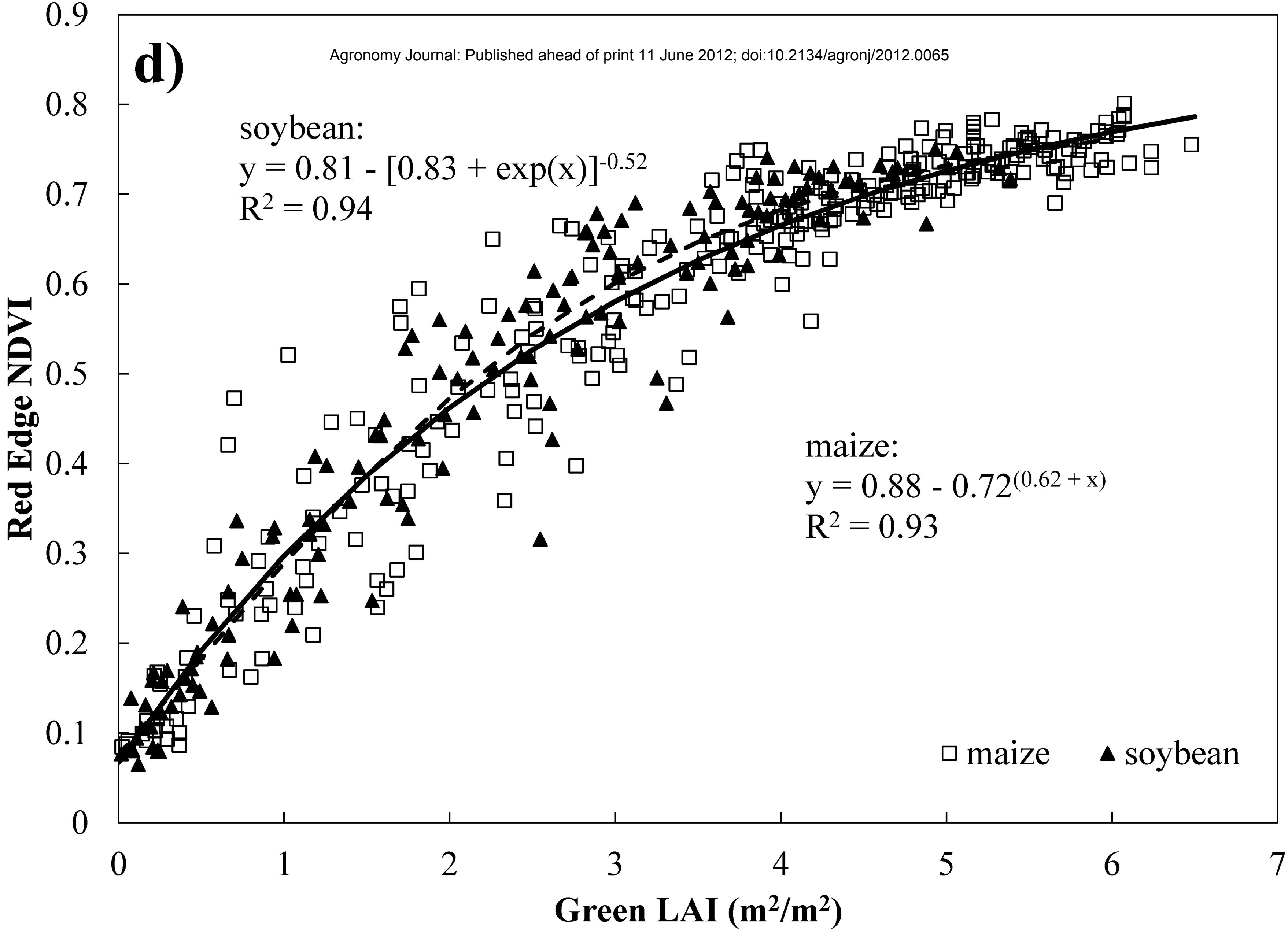

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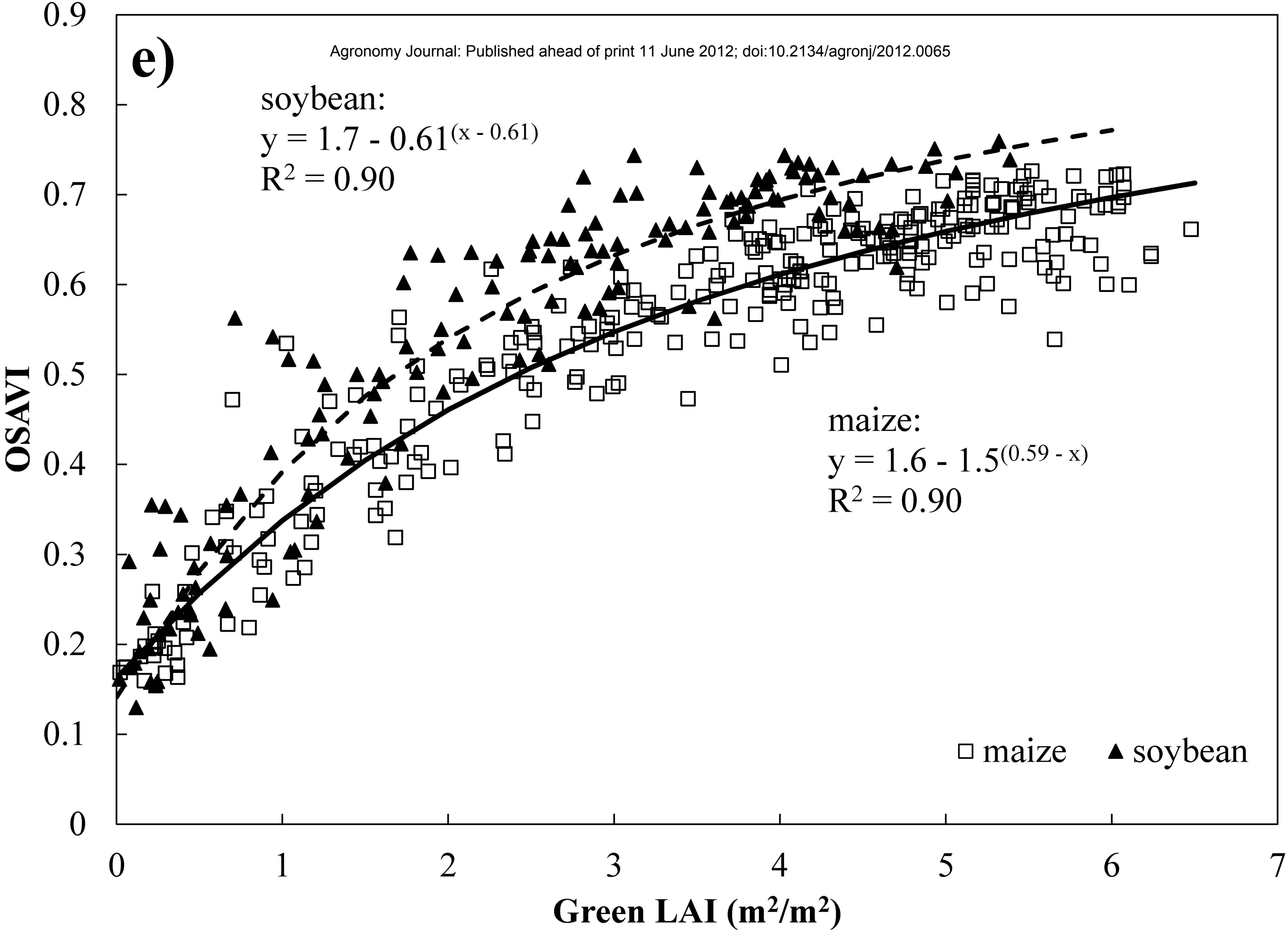

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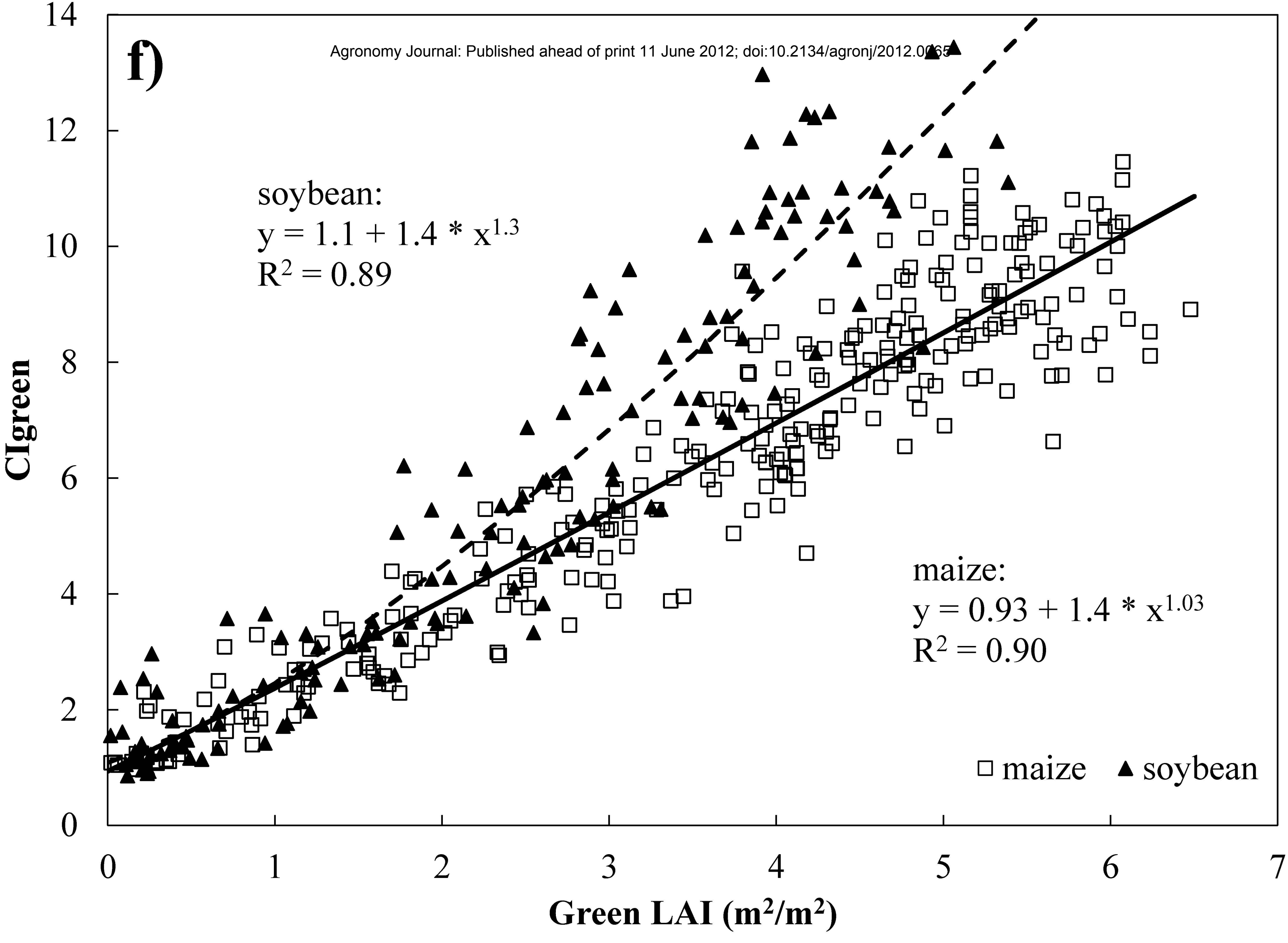

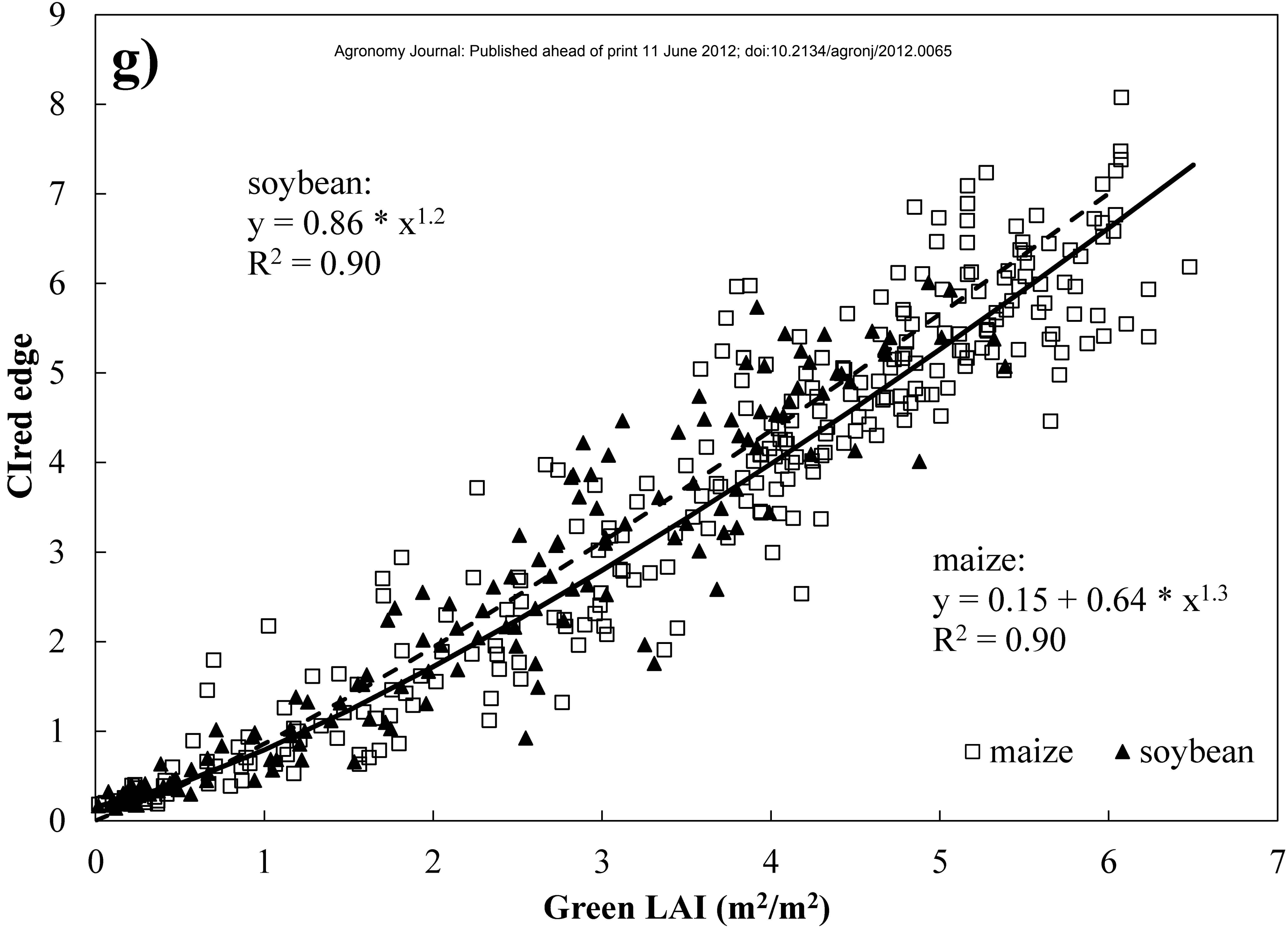
g)
soybean:
y = 0.86 * x^1.2
R^2 = 0.90
maize:
y = 0.15 + 0.64 * x^1.3
R^2 = 0.90
maize
soybean
CIred edge
Green LAI (m^2/m^2)
0
1
2
3
4
5
6
7
8
9

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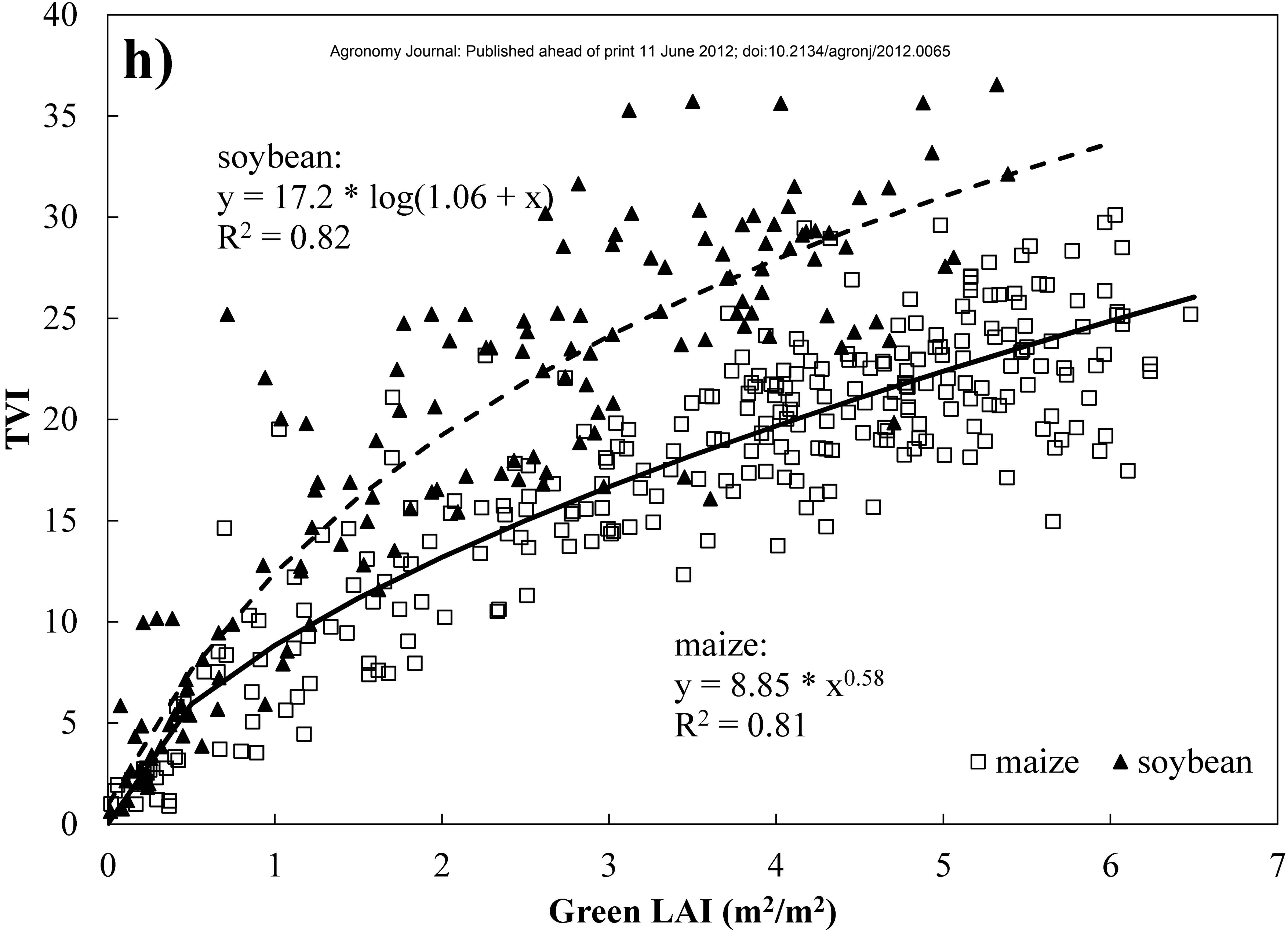

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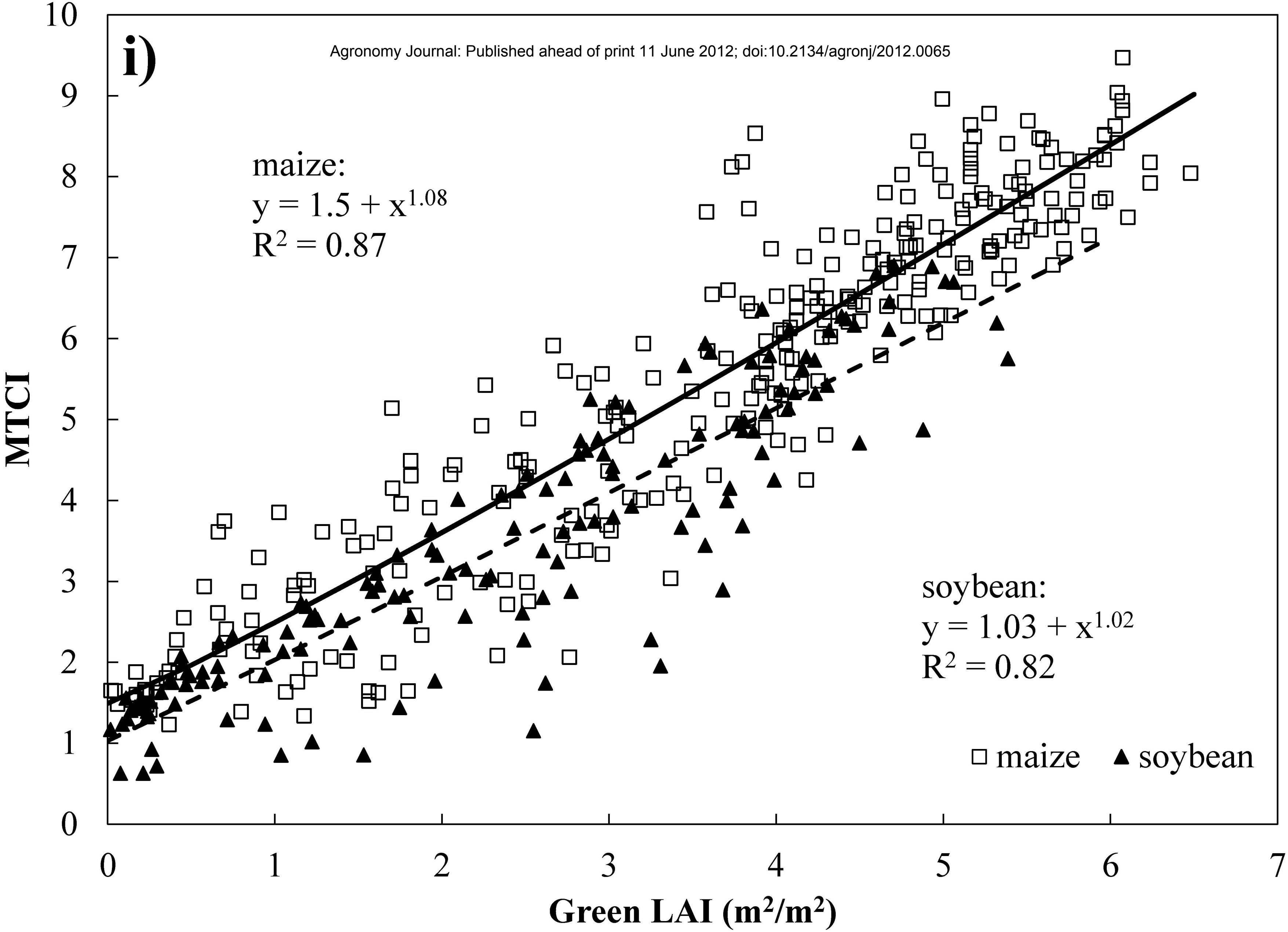

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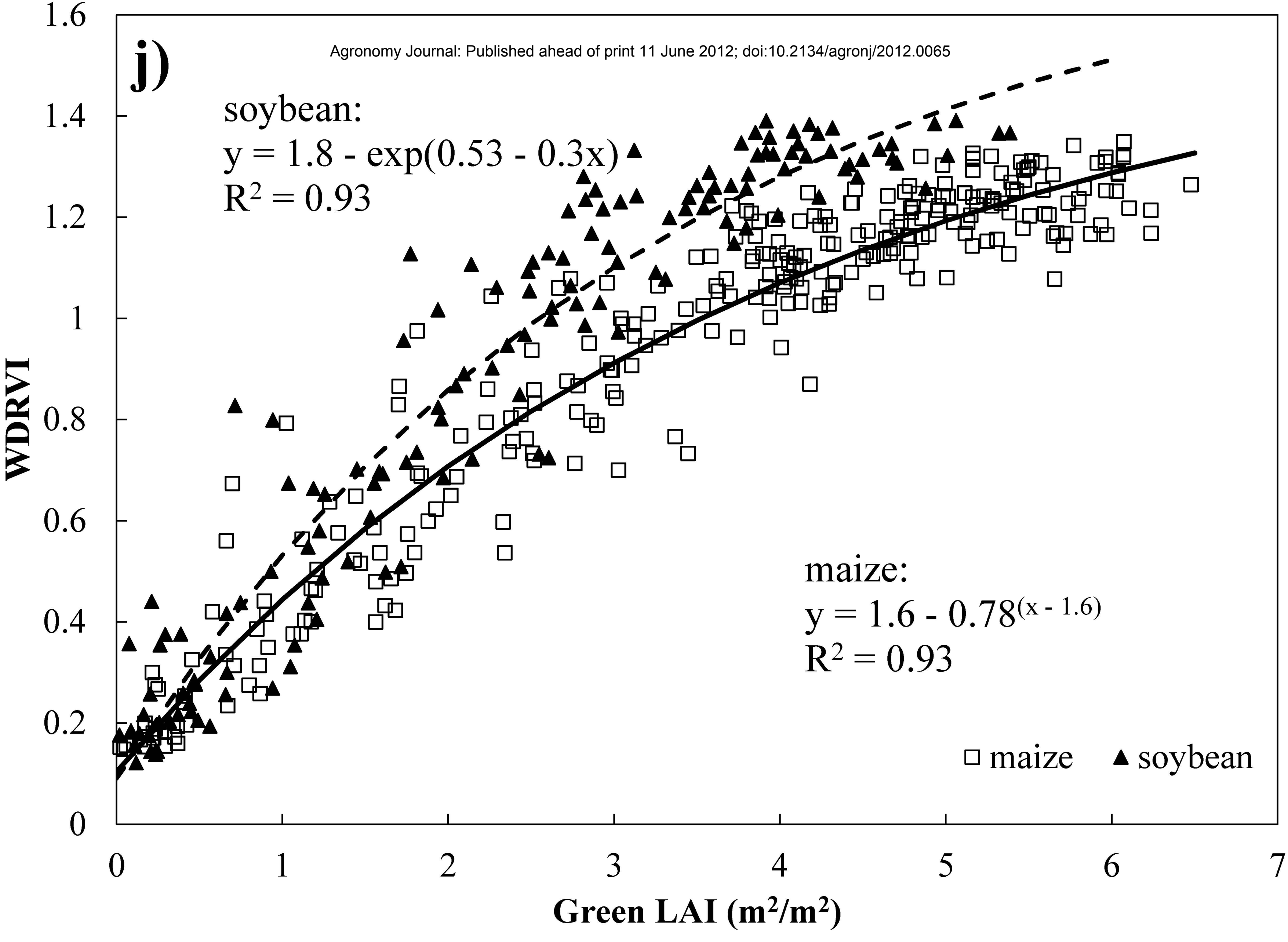

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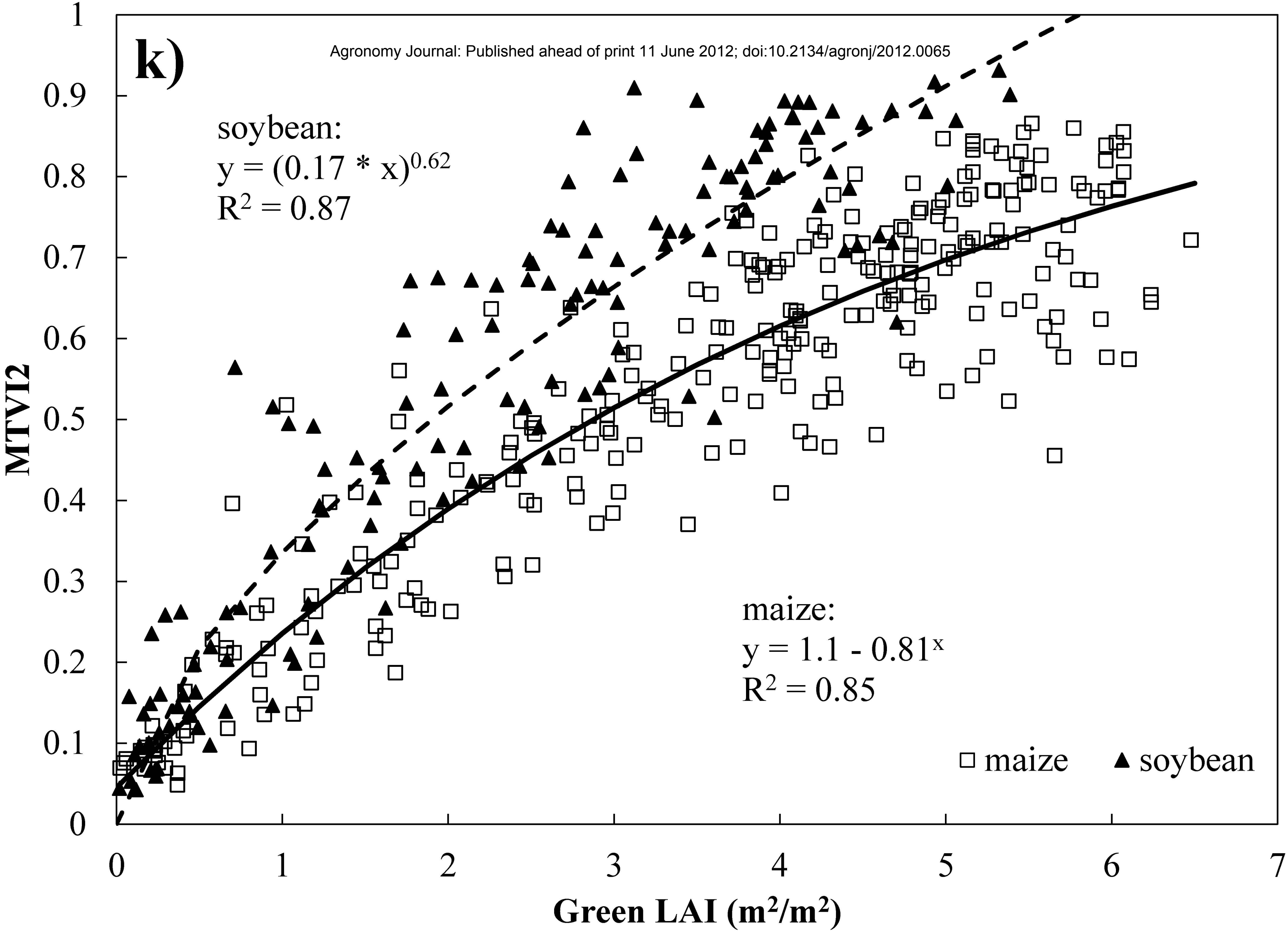

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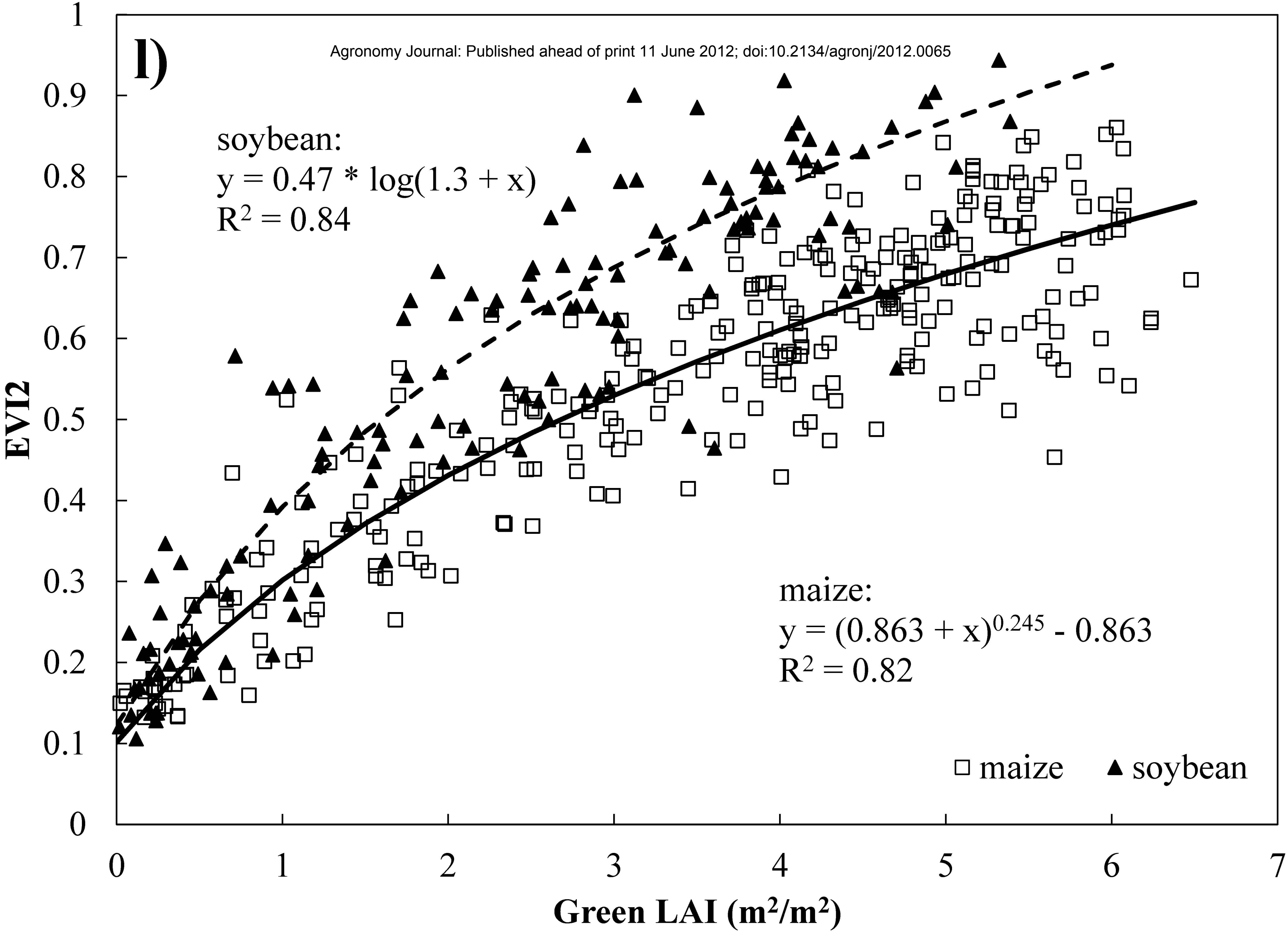

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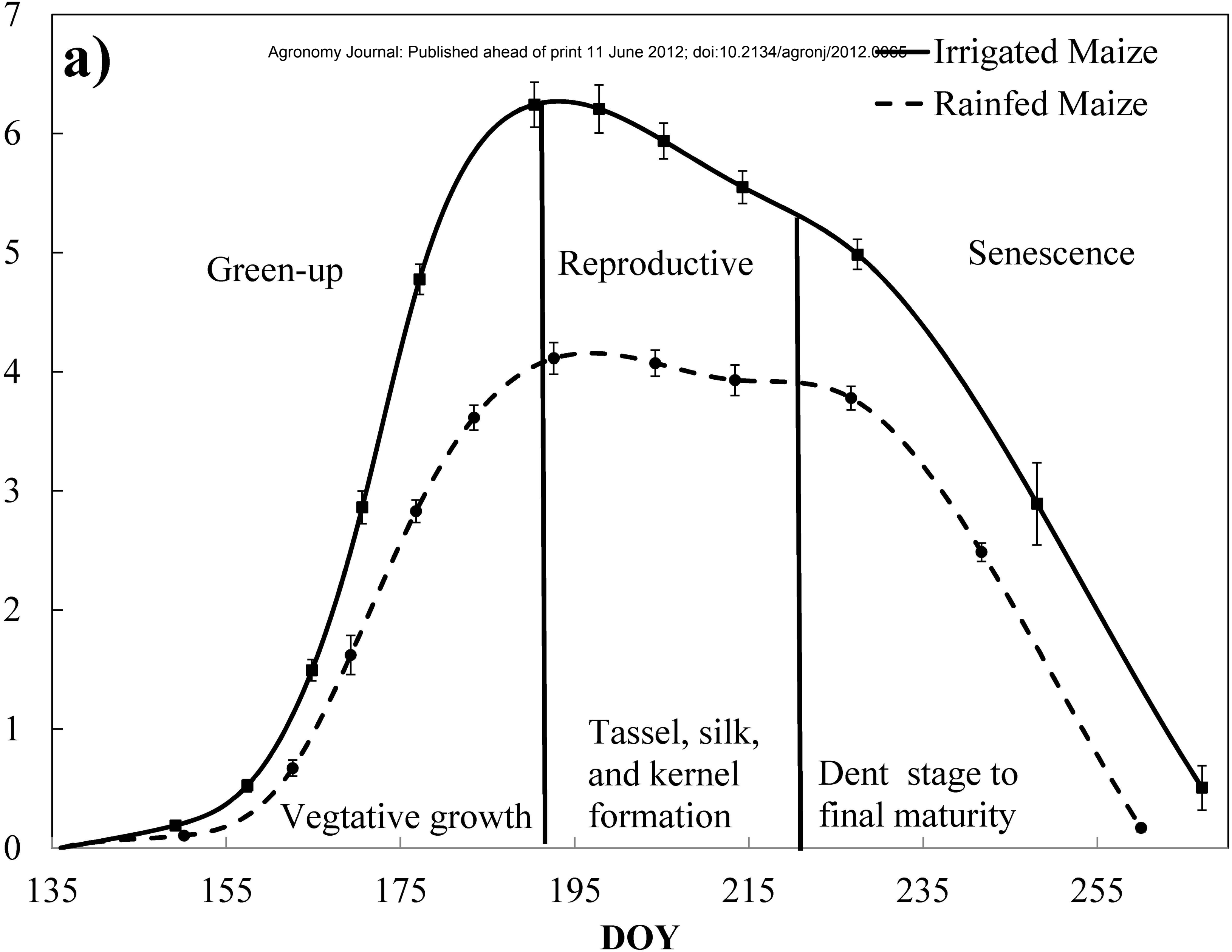

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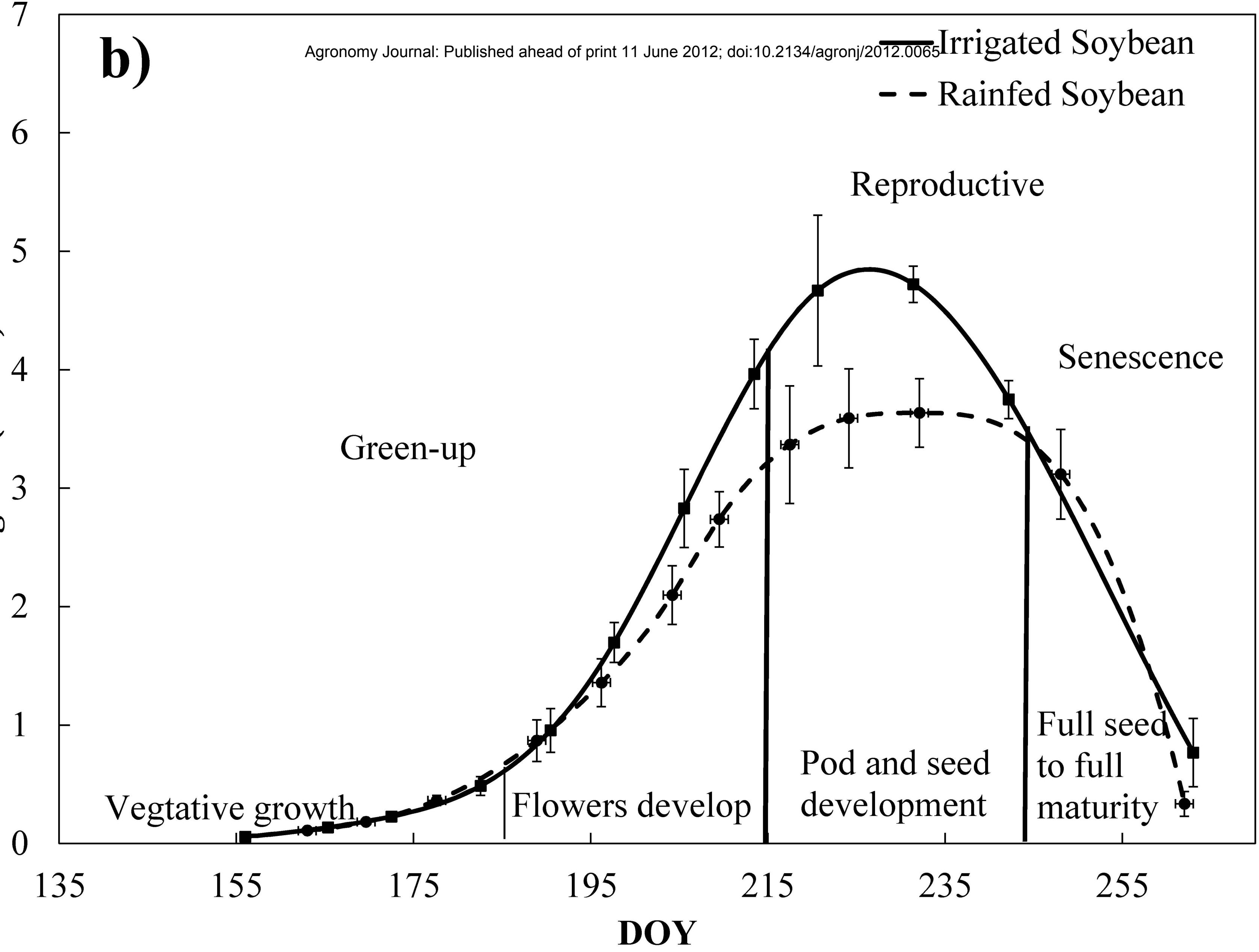

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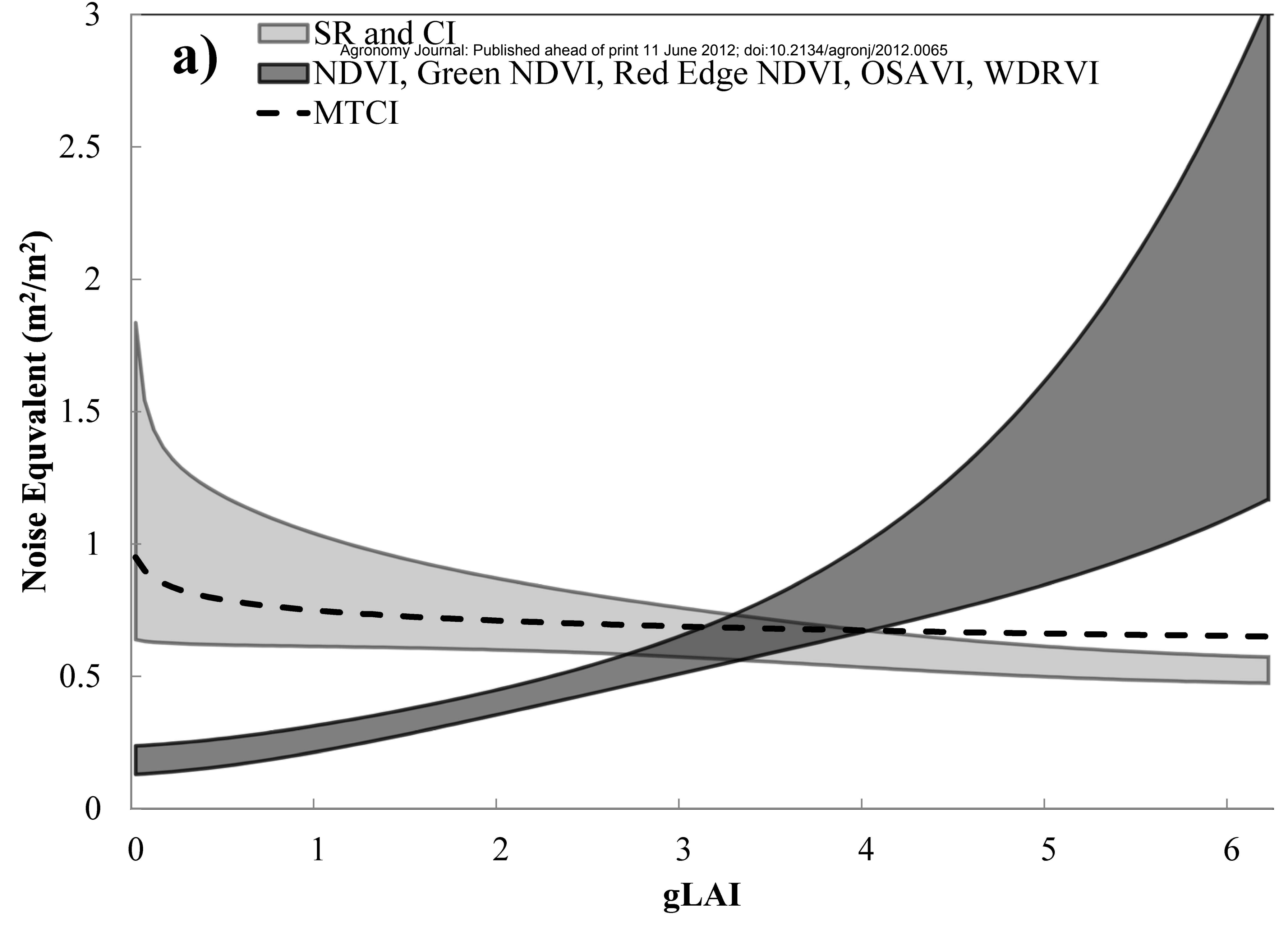

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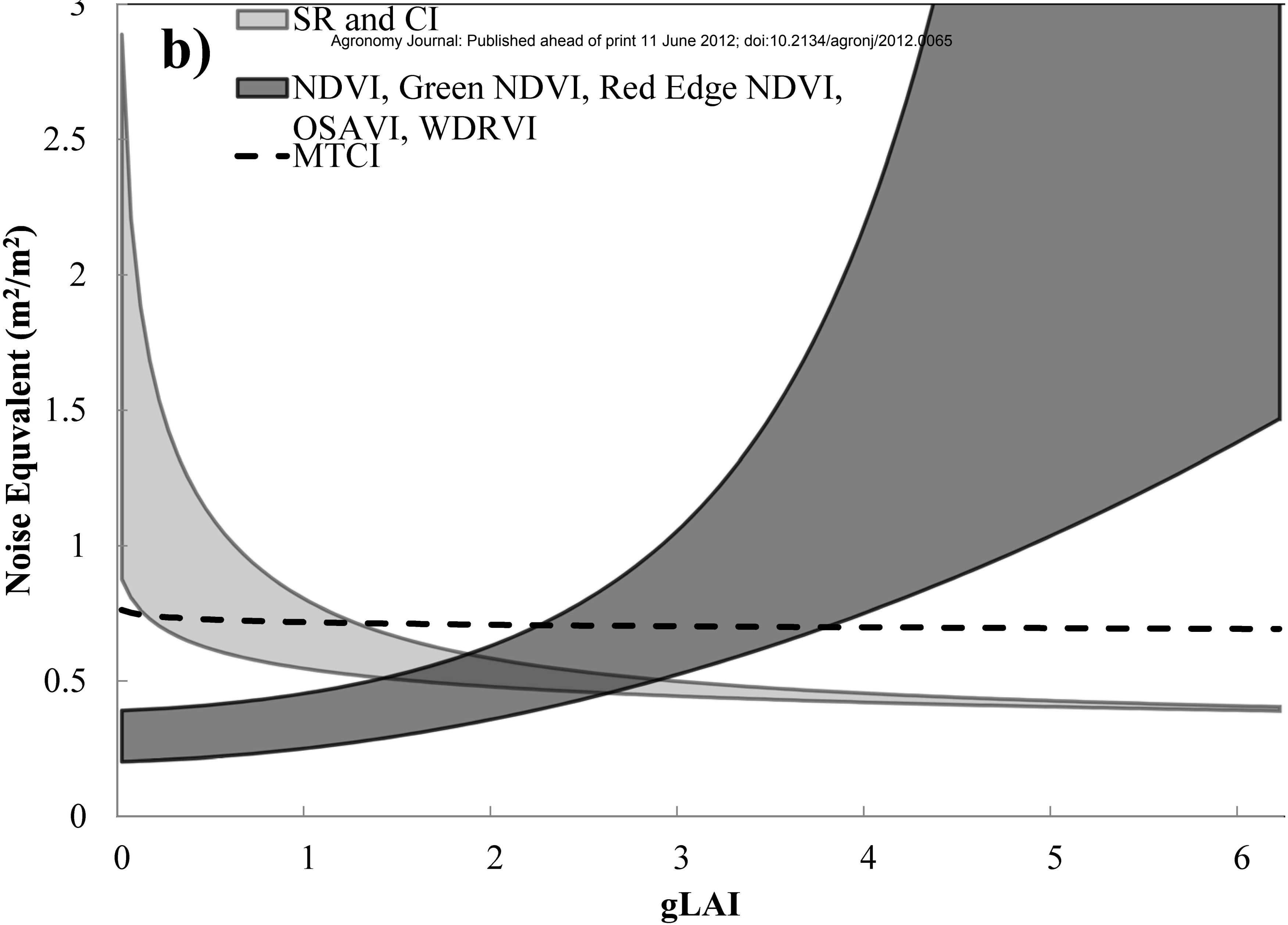

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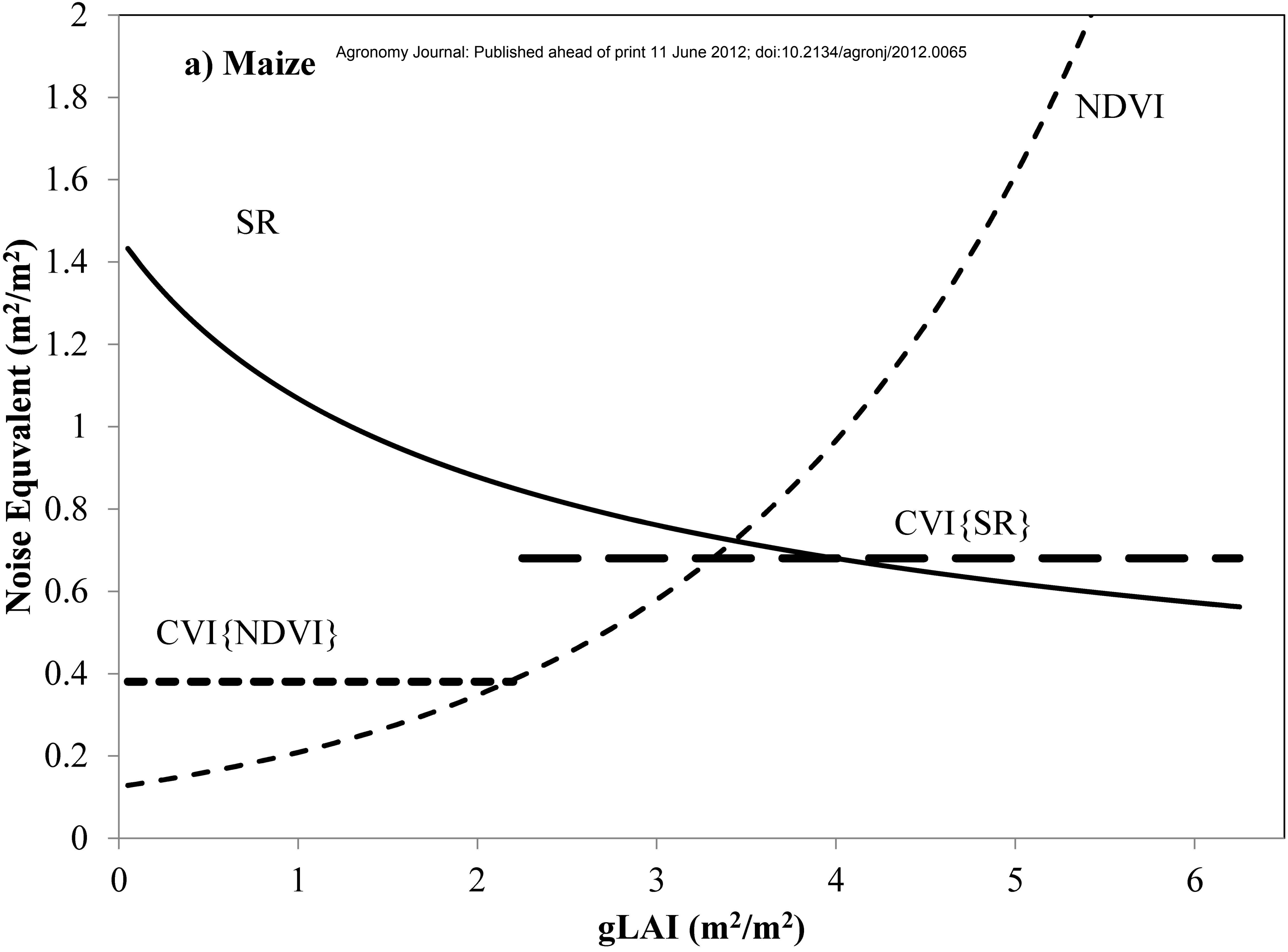

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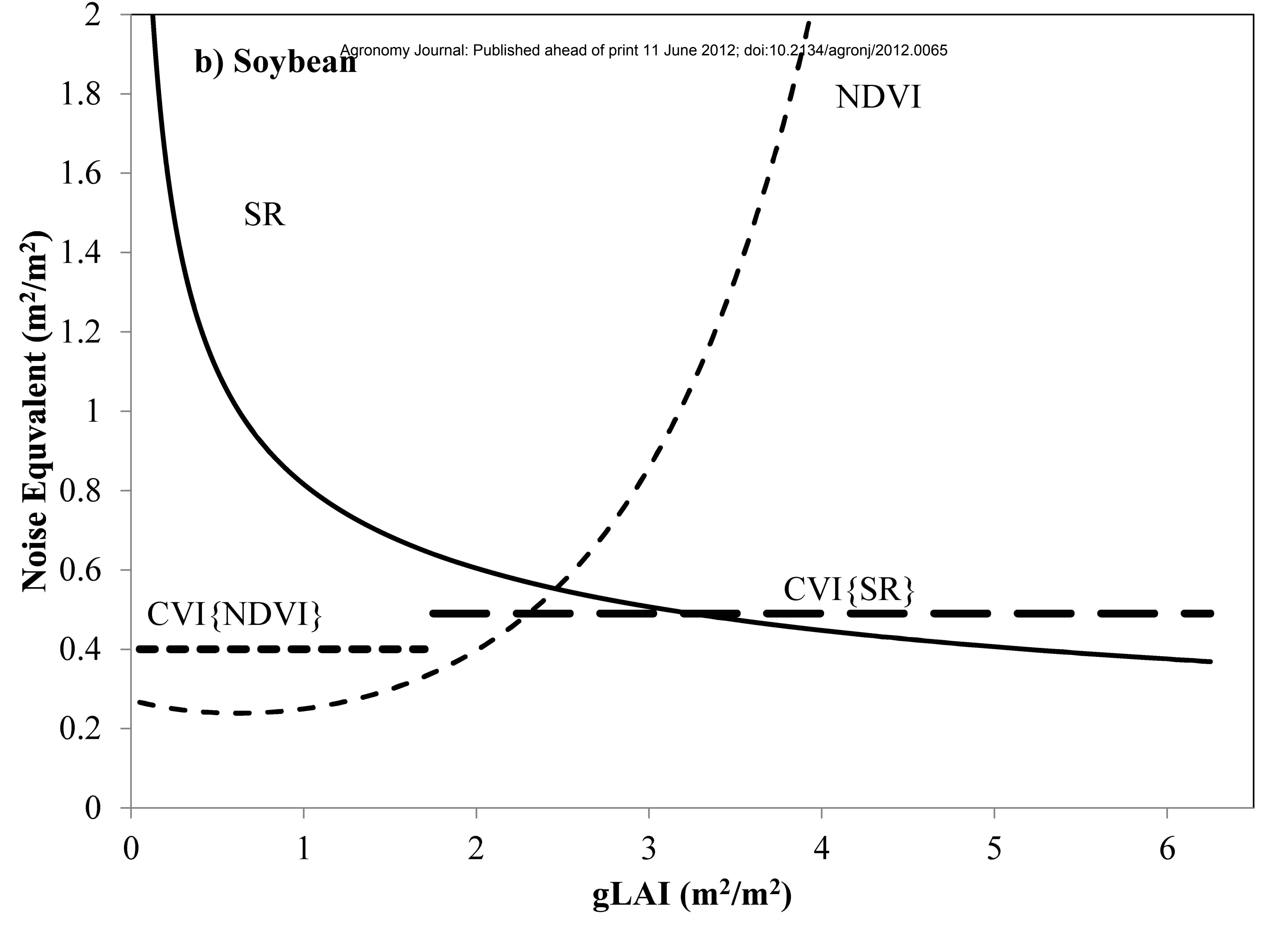

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