

Monitoring Landsat vegetation indices for different crop treatments and soil chemistry

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Abstract

The timing and quantity of fertilizer and herbicide applications in agricultural systems are critical where maximizing vigor and yield is the ultimate goal. While fertilizers are applied to the soil to promote plant growth, herbicides are commonly used to control weeds in order to reduce the weeds' competition for nutrients. Satellite imagery is frequently used to monitor agricultural activities and vegetation indices (VIs) are widely applied in temporal analysis of crop status. This study considers monitoring Landsat VIs for the period between 5 June and 27 October 2014 in agricultural systems under four different management treatments at the Kellogg Biological Station (KBS), in Michigan, USA. The results show that 1) fine-tuning conventional treatments by intense early herbicide applications in combination with no-tilled soil results in significantly higher VIs during the early growth stage, a more rapid maturity rate, and the highest crop yield; 2) nitrogen uptake from nitrate-based rather than from ammonium-based fertilizers might be more beneficial in terms of crop vigor and yield return; 3) organic treatments, with organic corn and no agricultural chemicals, keep higher VIs longer in the season at the cost of lower yield; and 4) genetically modified (GM) breeds under conventional or reduced-chemical treatments have synchronized early senescence. A positive correlation between VIs during the early growth stage and yield is observed for conventional no-till treatment (coefficient

of determination, $R^2 = 0.70$). The correlation becomes gradually weaker with each month from late June to October (29 June: $R^2 = 0.70$; 16 August: $R^2 = 0.61$; 17 September: $R^2 = 0.44$; 27 October: $R^2 = 0.01$). The analysis of variance (ANOVA) - Tukey-Kramer approach suggests significant differences in VIs between organic and GM corn (treated conventionally or with reduced chemicals) for the pre-harvest season (27 October 2014). The leave-out-one cross-validation analysis confirms the predictive accuracy of the model (mean square error, MSE = 0.0014). The rapid evolution of herbicide-resistant weeds requires constant refinement of chemical inputs to agricultural systems, thus making the monitoring of (Landsat) VIs important in the years to come.

Keywords

Landsat, corn, vegetation index, treatments, conventional

1. Introduction

There are different measures for estimating grain yield throughout the growing season. Some studies concentrate on environmental factors and extreme weather events, while others consider biological constraints due to agricultural chemicals such as fertilizers, pesticides, biomass, and weeds (Kruse and Smith 1994). High-dimensional spatial and temporal dynamics of weather and soil properties add to the complexity of agricultural systems and to model the interactions between the crop and nutrients is a challenge (Kruse and Smith 1994; Tremblay, Bouroubi, and Belec 2012; Ibrahim, Mohd, and Nizar 2014; Sandip 2014). In the early 1970s, Glenn, Daynard, and Watson (1974) designed an experiment to study the relationship between spring vigor and grain yield in corn, arguing that hybrids with a high early photosynthetic rate have the ability to emerge rapidly and grow quickly, leading to a longer grain-filling period and higher yield. Donald (1968) argued that the ability of crops to be tolerant to high plant density and resistant to crowding

is the driving factor behind higher efficiency of nutrient uptake and higher yield. Schepers and Holland (2012) emphasized the importance of application rates of nitrogen (N) fertilizer as well as residual N levels in soil from previous years for early-season crop vigor and yield. According to Raun, Solie, and Stone (2011), the demand for fertilizer and responsiveness of crop to N are closely related to crop yield level.

Quantification of fertilizer applications is time-sensitive and depends upon several factors including weather, soil moisture and texture, competition from weeds, as well as crop type and its nutrient uptake efficiency. Herbicide applications are commonly used to control weeds in order to reduce the weeds' competition for nutrients, thus making more nutrients available to crops. In addition to weed control, pre-harvest crop desiccation, i.e., the process of reducing green material in crops, involves the application of herbicides at maturity to speed up crop growth affecting yield (Guenther 2016). This is particularly important in northern climates where more even and synchronized ripening is needed for early harvest and earlier replanting due to unfavorable environmental conditions. Genetic modifications enhance a crop's capability to be insect resistant and herbicide tolerant, which further enhances yield (Green 2014). Genetic modification could also be done to shorten or prolong the maturity state of crops or to manipulate nitrogen uptake efficiency (Birger 2011). Certain genes' mechanisms may decrease while others may increase at different growth stages irrespective of nitrogen regime (Mushongi et al. 2013), which ultimately influences the interaction between the crop and soil nitrogen. Genetic control of the leaf chlorophyll may also play a role in accelerating the maturation process. For instance, in areas where corn genotypes are source-limited under harsh conditions, incorporating a specific trait in the corn genotypes would improve grain yields by accelerating grain-filling (maturation) duration (Banziger et al. 2000; Subedi and Ma 2005). Recent studies consider soil preparation as another important factor that influences the interaction between the crop and soil nutrients. Conservation tillage is a common

process of cultivating crops in which several tillage operations can take place during the growing season before, during, and after planting. The main purpose of these practices is to create conditions that would enhance good contact between seed and soil at the time of seed planting (Malhi, McAndrew, and Carter 1992).

As remote sensing technology advances, vegetation indices (VIs), expressed as reflectance band ratios, are increasingly used in empirical analysis to quantify crop parameters important for yield estimation (Bannari et al. 1995; Blackburn 1998; Haboudane et al. 2002; Sims and Gamon 2002; Almeida, De Souza Filho, and Ressetto 2006; Asner and Martin 2008; Jacquemoud et al. 2009; Ustin et al. 2009; Delegido et al. 2011; Simic et al. 2011; Obade, Lal, and Chen 2013; Zarco-Tejada et al. 2013; Simic et al. 2014; Yu et al. 2014; Rao et al. 2015). Due to their high spatial resolutions, very high resolution multispectral (e.g., WorldView or IKONOS), and Unmanned Aircraft System (UAS) technologies have been increasingly used to monitor agricultural systems (Zhang and Kovacs 2012). However, the multispectral technology of Landsat and Landsat-type sensors (e.g., Satellite Pour l'Observation de la Terre (SPOT)) is also important in precision farming applications due to their large synoptic view, large historical archived database, reasonably high resolution of 30 m or better, as well as their long history of understanding spectro-biophysical relationships using these sensors (Thenkabail 2003). The normalized Difference Vegetation Index (NDVI) and Simple Ratio (SR) are the two most commonly used VIs that characterize crop vigor (Blackburn 1998). VIs developed in such a way that they reduce the impact of soil background and canopy structure further increase their sensitivity to pigments (e.g., Optimized Soil Adjusted Vegetation Index (OSAVI), Transformed Chlorophyll Absorption Index (TCARI), Photochemical Reflectance Index (PRI)) (Gamon, Penuelas, and Field 1992; Rondeaux, Steven, Baret 1996; Haboudane et al. 2004; Motokha et al. 2010; Yu et al. 2014). In 2013, Lyle, Lewis, and Ostendorf (2013)

successfully used Landsat images to create a robust wheat yield prediction model over large areas for multiple seasons. Landsat near infrared (NIR) and mid infrared (MIR) reflectances are used to estimate crop water stress (Abduwasit et al. 2008; Lui et al. 2010) as well as chlorophyll and nitrogen content (Gitelson et al. 2008; Lui et al. 2010), and VIs early in the season (Yu et al. 2014).

The objectives of this study are to explore the capability of Landsat VIs to capture the subtle differences in agricultural systems that undergo four different treatments and to evaluate their temporal patterns in relation to different fertilizer and herbicide applications and soil practice. In particular, the relations between early VIs, nitrogen uptake from (a) nitrate-based and (b) ammonium-based fertilizers, yield and corn maturity based on pre-harvest VIs are explored.

2. Materials and methods

2.1 Study area and field data

The study site is situated within the Kellogg Biological Station (KBS) in Michigan, USA (42°24'46.77"N, 85°22'23.42"W) (Figure 1(a)). The KBS is a research area where factorial field experiments, which include different experimental treatments, ecological interactions, and agronomic performance, have been established. The KBS farmland is managed under the Main Cropping System Experiment (MCSE) of the Long Term Ecological Research (LTER) program, as part of a national network of LTER sites established by the National Science Foundation (Robertson et al. 2012; Robertson and Hamilton 2015). The 1-ha plots are replicated along a management intensity gradient and they include four annual cropping systems, three perennial crops, and from early- to late-successional unmanaged ecosystems (Robertson et al. 2012). The annual cropping systems are corn-soybean-winter wheat rotations ranging in management intensity from conventional to biologically based (Robertson et al. 2012; Gage, Doll, and Safir 2014). The parcels that undergo different

treatments are mixed and randomly spread over the study area and the same seed genetics are kept in all cropping systems from year to year. The climate at KBS is humid, continental, and temperate. Annual precipitation averages 1027 mm year⁻¹ and no crops are irrigated. The predominant soils at and around KBS are Alfisols, developed under upland forest vegetation. MCSE soils are well-drained Alfisol loams of the Kalamazoo series (fine-loamy, mixed, mesic Typic Hapludalfs) co-mingled with well-drained loams of the Oshtemo series (coarse-loamy, mixed, mesic Typic Hapludalfs), as summarized by Robertson et al. (2012).

[Figure 1]

In this study, 24 parcels of corn were considered (Figure 1(b)). Six parcels with the same management were assigned to each treatment (Michigan State University (MSU), 2016). There were two types of corn in the experiment:

1) genetically modified (GM) corn (Dekalb DKC52-59 Corn Hybrid) treated in three different ways: a) T1 - conventional plowed; b) T2 - conventional with no tilling; and c) T3 - biological with reduced chemical inputs (Table 1).

2) T4 - certified organic, non-genetically modified (non-GM) corn (Blue River Hybrid 25M75 Organic) with no chemical treatments (Table 1).

Corn has a rapid growing pattern. Once planted, corn commonly yields many leaves in a short time, having the reproductive structures initiated while leaves are still growing. It becomes completely dry before being harvested (Figures 2(a)-(c)).

[Figure 2]

[Table 1]

In-situ measurements included crop yield and soil chemistry during and after the growing season; all conducted under the LTER program. Agronomic yields were measured during

normal crop harvest at 15.5 % standardized moisture. Yields were determined by machine harvester as described in the Agronomic Protocol (MSU, 2016). Soil nitrate and ammonium concentrations were measured during the growing season. The protocol included triplicate subsamples (10 g fresh weight) extracted from the composite, sieved soil samples of each plot with 100 ml of 1 M KCl. Soil extracts were properly shaken and allowed to sit overnight before they were filtered with a syringe filter using a glass fiber filter. The analysis was performed on a Flow Injector Analyzer (Michigan State University, 2016). Soil phosphorus (P), potassium (K), calcium (Ca), and magnesium (Mg) were measured after the harvest (12 November 2014). Phosphorus was analyzed with a colorimeter using a dip probe; K and Ca were analyzed using a flame photometer; and Mg was analyzed with a colorimeter on a segmented flow analyzer. BrayP1 was used to extract the P and 1N Ammonium Acetate before extracting K, Ca, and Mg (MSU, 2016).

2.2 Satellite data and analyses

Two Landsat 8 and four Landsat 7 images (Path 21 and Row 31) acquired from 5 June to 27 October 2014 were used in this study (USGS, 2016) (Table 2). Although additional bands and better radiometric performance quantized over a 12 bit dynamic range are advantages of Landsat 8 over Landsat 7 (USGS, 2015), images from both sensors were used due to the low number of cloud-free images.

[Table 2]

ENVI FLAASH was used for the radiometric and atmospheric corrections of the images (Harris Geospatial Solutions, 2015). ENVI was used to extract spectral signature and to generate VIs. To avoid any edge effect, the final spectral signatures were extracted from the central pixel or a pixel closest to the center of each parcel. The common chlorophyll-

and leaf structure- related multispectral VIs and indices with the reduced impact of soil background were used in the analysis (Table 3). Temporal trends of VIs were examined and related to the in-situ soil chemistry and yield. In particular, the effects of the four treatments were assessed by examining the relations between early VIs, nitrogen uptake from (a) nitrate-based and (b) ammonium-based fertilizers, yield and corn maturity based on pre-harvest VIs. To evaluate the impact of early VIs, we consider data from 29 June when leaves were fully developed and soil exposure was minimal (Figure 2). The mean values of different treatments were compared using t-test statistics, the analysis of variance (ANOVA) and Tukey-Kramer method, a multiple comparison procedure to compare all the pairs of mean values at a significance level of 0.05. Given the small sample sizes, the leave-out-one cross-validation analysis was conducted to examine the predictive accuracy of the model. The analysis was done comparing two ANOVA models, with and without treatment effect. In the process of iterations, one observation was omitted at each step and each model was fitted for the remaining observations. The mean square errors (MSE) were recorded and compared.

[Table 3]

Due to differences in spectral resolution and the location of the bands between Landsat 7 and 8, some minimal uncertainty may be involved in our analysis. The uncertainties were expected to be minimized by using the reflectance ratios.

3. Results

3.1. Temporal trends of spectral reflectance for the different crop treatments

While the average spectral signals acquired on 5 June and 27 October consist of mixed soil and crop reflectances, the vegetation signals dominate from 29 June to 19 October (Figures 3(b)-(e)). Treatment T2 has significantly higher mid-infrared (MIR1) reflectance than other treatments in early June ($p \leq 0.008$ for 5 June) probably due to higher reflectance of no-till over tilled soil (Figure 3(a)). Significantly higher NIR reflectance ($p \leq 0.009$) for treatment T2 over other treatments is observed on 29 June (Figure 3(b)). The no-till soil, early herbicide applications, and increased amounts of herbicides are the only factors that may cause the differences between treatments T1 and T2 (Table 1).

In September, the reflectance in the red spectrum is lower for treatments T3 and T4 than for conventional treatments T1 and T2 (Figure 3(d)). While treatment T3 has a significantly lower NIR reflectance than treatments T1 and T2 in June, its values become significantly higher in September (Figures 3(b) and 3(d)). Treatment T4 has the lowest reflectance in all bands during early growth stage (Figures 3(a) and 3(b)). Interestingly, during the pre-harvest (senescence) stage (19 and 27 October), NIR reflectance for treatment T4 is significantly higher than for any other treatment ($p \leq 0.001$) (Figures 3(e) and 3(f)). The same trends are observed in all six replicates for each treatment and there is no significant difference between the parcels except for one T1 replicate that showed somewhat higher variability.

[Figure 3]

3.2. Comparison of Landsat vegetation indices between the different crop treatments

The performance of VIs used in this study (SR, NDVI, OSAVI, modified NDVI (mNDVI), Chlorophyll Index Green (CIgreen), and Green-Red Index (GRI)) is similar for all four

treatments (Figures 4(a)-(f)). For SR, OSAVI, and Clgreen, treatment T2 has significantly higher values on 29 June than any other treatment (Figures 4(a), 4(c), and 4(e)) based on the Tukey-Kramer test (see p values in Table 4). Treatment T3, with reduced chemical applications, and organic treatment T4 show significantly higher VIs than treatments T1 and T2 during September. This trend is observed for all VIs with some minor differences in their maximum values (Figures 4(a)-(f)). VIs for treatment T4 are significantly higher in October than for other treatments except for GRI (Figures 4(a)-(f)) (see p values in Table 4).

[Figure 4]

Out of all treatments, treatment T2 exhibits the most rapid decrease in the VI values during the season (Figures 4(a)-(f)). Differently, the VI values for treatment T1 are lower early in the season and decrease at a lower rate when compared to treatment T2. The prolonged high VI values for treatment T3 rapidly decrease after September and become insignificantly different from treatments T1 and T2 in October (Figures 4(a)-(f)). All three GM related treatments (T1, T2, and T3) exhibit synchronized decrease in VIs when compared with the control (organic) treatment T4.

SR, OSAVI, NDVI, Clgreen, and mNDVI are more consistent in their trends (Figures 4(a)-(e)). GRI, which does not include the NIR band, demonstrates more sudden changes from late June to October than other VIs (Figure 4(f)). Based on the variance-to-mean ratio (VMR), on 29 June the most variability is observed for treatment T4, particularly for VIs that involve NIR band (SR, NDVI, OSAVI, Clgreen, and mNDVI). Significantly smaller VMR as well as the lowest p value are observed for GRI on 29 June (see p values in Table

4). SR and OSAVI are most consistent (Figures 4(a)-(f)). OSAVI is used as a representative index in the next sections.

The leave-out-one cross-validation analysis, applied to the pre-harvest dataset (27 October), shows that the ANOVA model with treatment effect has significantly lower MSE (MSE = 0.0014) than the ANOVA model without treatment effect (MSE = 0.0037), suggesting the validity of the results shown in Table 4. A similar trend is observed for the early season (29 June) but the MSE value for the model with treatment effect is insignificantly lower (MSE = 0.0056) than for the model without treatment effect (MSE = 0.0060).

[Table 4]

3.3. Relationship between vegetation indices, yield, and soil chemistry

Based on the field measurements, treatment T4 has significantly lower yield when compared with other treatments (e.g., for OSAVI $p \leq 0.000$) (Figures 5(a) and 5(b)). Although the difference in yield between treatments T1, T2, and T3 is not significant, treatment T2 exhibits the highest yield of all treatments. We have found no correlation between early VIs and yield when all values from 29 June 2014 are considered (coefficient of determination $R^2 = 0.03$) (Figure 5(a)). There is a strong positive correlation between OSAVI and yield for treatment T2 ($R^2 = 0.70$); however, a larger sample size is needed to confirm the findings. The correlation for treatment T2 becomes gradually weaker with each month from late June to October (16 August 2014: $R^2 = 0.61$; 17 September 2014: $R^2 = 0.44$; 27 October 2014: $R^2 = 0.01$).

We have also explored the relationship between VIs and yield during the pre-harvest season. A relatively strong negative correlation between VIs and yield is observed on 27 October 2014 ($R^2 = 0.64$) (Figure 5 (b)) when all measurements are included in the analysis, which is different than in the study of Kross (2015). This is an important finding in our study because it reveals a connection between VIs, corn grain-filling period, yield, and corn maturity, to be discussed later. The linear discriminant analysis suggests clustering and strong separability between the organic treatment T4 and treatments T1-T3 with GM corn (Figure 5(b)). No correlation is observed for treatments T1-T3 with GM corn ($R^2 = 0.01$) (Figure 5(b)).

[Figure 5]

The average soil nitrate level rapidly decreases for treatment T2 in June and July, which may indicate a high initial uptake rate of nitrate-based nitrogen during the early growth stage while keeping the highest VI values (Figures 6(a) and 4(a)-(f)). Note that a nitrate-based fertilizer was applied to T1-T3 in May and that a larger quantity of Roundup agricultural herbicides was applied only to T2 earlier in the season just before planting (Table 1). Unlike treatment T2, the average soil nitrate level for treatment T1 is always greater relative to the control organic treatment T4 (Figure 6(a)), indicating low initial uptake of nitrate-based nitrogen. Treatment T3 shows a similar trend to treatment T2 at first, with a sudden decrease in uptake rate afterwards. Unlike T1 and T2, treatment T3 received Dual II Magnum agricultural herbicide (Table 1). Its VI values stay higher longer in the season, through August and September, meaning a potential longer grain-filling period than for treatments T1 and T2.

With respect to the relative concentration of soil ammonium, treatment T2 has a lower initial uptake rate during the early growth stage when compared with the control treatment

T4, but then it is followed by a sudden uptake in August (Figure 6(b)). Treatment T1 also exhibits a higher uptake of ammonium-based nitrogen in August. After August, treatments T1 and T2 behave similarly, both with low soil ammonium levels, while treatment T3 behaves similarly to the control treatment for most of the time. On 19 October, most likely due to some environmental conditions, all treatments show an increase in soil nitrate levels and a decrease in soil ammonium levels (Figures 6(a) and 6(b)).

[Figure 6]

Because P, K, Ca, and Mg, were collected after the harvest (12 November 2014), the correlation between their concentrations and VIs is unlikely to be strong (Figures 7(a)-(d)). An exception is phosphorus for which the correlation is strongly negative for treatment T4 ($R^2=0.67$) (Figure 7(a)). However, a larger sample size is needed to confirm the results. The linear discriminant analysis separates the data in two clusters: one cluster for the organic corn (T1) and another for the GM corn (T1-T3). In all cases, treatment T4 has higher OSAVI values for similar ranges of soil chemicals. No correlation is observed between OSAVI (or other VIs) and soil chemistry for the GM corn (T1-T3), indicating most likely its senescence stage (Figures 7(a) and 7(b)).

[Figure 7]

4. Discussion

4.1. The impact of soil tillage, early herbicide and reduced nutrient applications on VIs

The intense early herbicide applications of Roundup and ammonium sulfate in combination with no-till soil management produce 1) the highest early VIs, 2) high early

uptake of nitrate-based nitrogen, and 3) the highest grain yield (treatment T2). The trend is observed on 29 June when leaves were fully developed and the impact of soil on the overall reflectance signal was minimal (Figures 2 and 6(a)). There are several possible explanations for this trend. The herbicide management used for treatment T2 may have an earlier and a stronger effect on weeds, reducing the crop-weeds competition for nutrients (Green 2014). It is also possible that nutrients and water are leached less in no-till soils having better interactions with the roots at initial contact, which further may increase green leaf productivity and transpiration (Bender and van der Heijden 2015; Yu, Hui et al. 2016). Improved early vigor is an important trait for increasing water-use efficiency and thereby grain yield in rain-fed environments, which goes hand in hand with the probability of better preservation of soil moisture in no-till soils (Botwright et al. 2001; Lopez-Castaneda et al. 1996).

For opposite reasons, the soil tillage management as well as later and less intense herbicide application (Roundup, in particular) most likely inhibit the early nitrogen uptake for treatment T1. High uptake of ammonium-based nitrogen later in the season, during the grain-filling period, and the absence of high early uptake of nitrate-based nitrogen make this treatment less productive than the no-till treatment T2. Low VIs throughout the whole season result in significantly lower VIs and notably lower crop yield than treatment T2. While maximizing VIs during the grain-filling period may be important for high yield, maximizing the initial VIs by the high initial nitrate-based nitrogen uptake may be critical for high yield. Most likely the high nitrogen uptake from ammonium later in the season enhances already high VIs for treatment T2 triggered by the high initial nitrate-based nitrogen uptake making its grain-filling period shorter.

Literature sources suggest that nitrogen utilization is directly related to chlorophyll concentration and thus to corn vitality and maturity. Furthermore, urea-ammonium-nitrate fertilizers are considered main sources of nitrogen to the crop. Urea is decomposed by the enzyme urease or chemically hydrolyzed into ammonia and CO₂. In the process of ammonification, ammonia is converted to ammonium by ammonium-oxidizing bacteria, which is further changed into nitrate by nitrifying bacteria in the process of nitrification (PNA 2015). Unlike ammonium, which has to be converted to organic nitrogen in the roots, the conversion of nitrates to amino acid occurs in the leaf. The former requires additional energy at the expense of the plant leaf processes and yield (PNA 2015). Nitrates have higher mobility in soil and are readily absorbed by the crop without going through any further conversion (PNA 2015). As reported by PNA (2015), several studies suggest that high nitrate can be more beneficial over high ammonium in soil in terms of grower return.

Treatment T3, with the reduced amount of agricultural chemicals, also triggers high initial uptake of nitrate-based nitrogen keeping the VI values relatively high for a longer time. However, the reduced amount of nutrients, absence of the ammonium-based fertilizer, and different herbicide type (Dual II Magnum) and its later application may be the reason for lower yield. The starting point of nitrate uptake is lower, and VIs are high but not maximal longer in the season, suggesting a longer grain-filling period. The relatively high initial nitrate uptake for treatments T3 can also be due to nitrogen residuals, stored in soil from the previous year when red clover, a natural soil N fixer, was planted on treatment T3 parcels (MSU, 2016). These proposed underlying mechanisms are in agreement with the negative correlation between VIs and yields observed in Figure 5(b). The decreasing trend of VIs and the increasing trend of yields for T4, T3, T1, and T2, respectively seem to be directly related to the nitrogen uptake. The possibility remains that high initial (early)

uptake of nitrate-based nitrogen and high uptake of the ammonium-based nitrogen later in the season make the grain-filling period shorter, and maturity rate and yield higher.

4.2. The effects of corn type (GM vs. organic) on corn maturity and yield

At the end of the season, Landsat captures the synchronously low VIs for all GM treatments (T1-T3) when compared with the control (organic) treatment. The VIs are low over a wide range of soil chemistry, meaning that the crop is no longer productive. Early maturity is desirable in northern climates to avoid damage to the crop under harsh winter conditions as well as to be able to harvest the crop efficiently. The organic corn (T4), however, continues to keep its productivity longer in the growing season under minimal nutrient availability. The few days' delay in planting corn under treatment T4 is not considered a critical factor for the difference (Tables 1 and 3). The LTER program was carefully designed by Michigan State University so that it can compare the outcomes of all treatments.

Literature sources also suggest that the leaf chlorophyll concentration and vigor are associated with the physiological maturity of genotypes. The greater the time the genotype takes to reach maturity, the more chlorophyll is involved, whereas shorter maturing genotypes may lose chlorophyll earlier and faster under similar conditions. This means that in short-maturity scenarios, the high chlorophyll concentration would lead to high yield (Tollenaar and Daynard 1978; Mushongi et al. 2013). Using satellite images to predict crop yield from early vigor and crop maturity from the duration of the grain-filling period would give another dimension to remote sensing technology for precision agriculture applications.

Although some recent studies question whether organic and conventionally-treated corn exhibit differences in yield, a number of studies show that this is indeed the case (Mazzoncini et al. 2015). The ‘greener’ organic corn at pre-harvest season, despite its lower yield, could occur because of its high nutrient management efficiency. Organically treated corn most likely uses naturally-available nutrients in a slower development, while other treatments consume the nutrients at a higher rate, investing more in corn development (Rembialkowska 2007). The strong negative correlation between OSAVI and phosphorus for treatment T4 in our study should be further explored to confirm this conclusion. While in some studies nitrogen shortage explains the different composition of phenolic acid and the higher antioxidant power in the organic crops, many studies conclude that this effect is difficult to prove (Ceseviciene et al. 2012; Mazzoncini et al. 2015). Several reports introduce phosphate solubilizing bacteria (PSB) as being responsible for the increase in plant growth and P uptake (Liu et al., 2011; Pereira and Castro, 2014), while some authors report contradictory results (Yu et al. 2011). In the study of Xie, Pasternak, and Glick (1996) a positive correlation was observed between root biomass and root P concentration for corn growing in P-deficient soil due to bacterial inoculation. According to the “growth/differentiation balance” theory, plants always optimize the resources available by exploiting them in 1) growth or 2) primary and secondary metabolic processes, considering the particular needs at each growing stage (Mahdi et al. 2011; Rembialkowska 2007).

Overall, our findings show that Landsat VIs are capable of detecting subtle corn responses, in conjunction with soil preparation as well as type, timing, and quantity of nutrient and herbicide applications. Ground measurements of crops’ structural and biochemical properties are further required to validate our findings and hypothesis that monitoring Landsat VIs can be useful in refining the timing and quantity of chemical applications to

promote higher crop yield. Future genetic modification of GM corn along with the increase of herbicide-resistant weeds will require further and ongoing refinement of chemical inputs, thereby making the monitoring of (Landsat) vigor algorithms important in years to come.

5. Conclusion

This research explored the capabilities of Landsat Vegetation Indices (VIs) to capture subtle differences in corn status under different agricultural treatments and soil practices. In particular, the effects of four treatments were assessed by examining the relations between early VIs, nitrogen uptake from (a) nitrate-based and (b) ammonium-based fertilizers, yield, and corn maturity based on pre-harvest VIs. Four different agricultural systems, located at the Kellogg Biological Station (KBS), in Michigan, USA, were explored: 1) genetically modified (GM) corn (Dekalb DKC52-59 Corn Hybrid) treated in three different ways: a) T1 - conventional plowed; b) T2 - conventional with no tilling, and c) T3 - biological with reduced chemical inputs, and 2) T4 - certified organic, non-genetically modified (non-GM) corn (Blue River Hybrid 25M75 Organic) with no chemical treatments.

The results showed that Landsat was capable of capturing the following trends:

- 1) Intense early herbicide applications in combination with no-tilled soil resulted in significantly higher VI values early in the season, more rapid maturity rate, and the highest corn yield. Strong correlations were observed between VIs values early in the season and yield.
- 2) Nitrogen uptake from nitrate-based rather than from ammonium-based fertilizers might be more beneficial in terms of crop vigor and yield return.
- 3) Organically treated corn kept high VIs longer in the season than any other treatment.

- 4) The GM breeds under conventional or reduced-chemical treatments exhibited synchronized early senescence, a crop property desired in northern climates.

The findings are a technical confirmation that monitoring of multispectral Landsat vegetation algorithms could be used for fine-tuning agricultural treatments and soil practices to reach high yield and early senescence. With the increase of herbicide-resistant weeds and rapid development of new herbicides and new varieties of GM corn, monitoring satellite vegetation indices is becoming increasingly important in precision agriculture.

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Disclosure statement

The authors declare no conflict of interest.

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Figures:

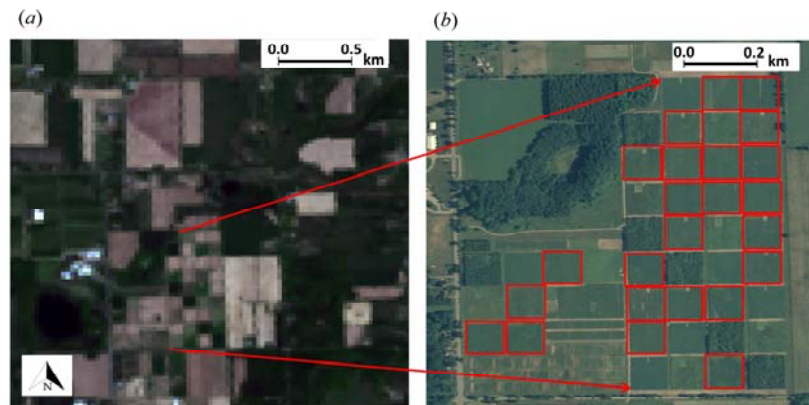


Figure 1. (a) Landsat image of the study area: W. K. Kellogg Biological Station, Michigan (42°24'46.77"N, 85°22'23.42"W), (b) Distribution of 24 parcels used in the study. Source: USGS and Google Earth.

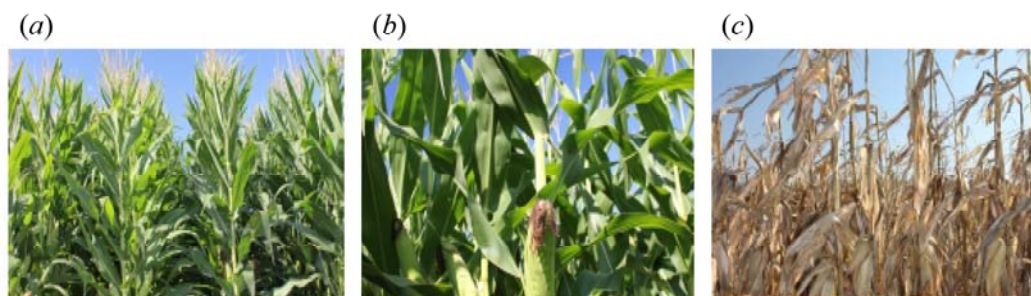
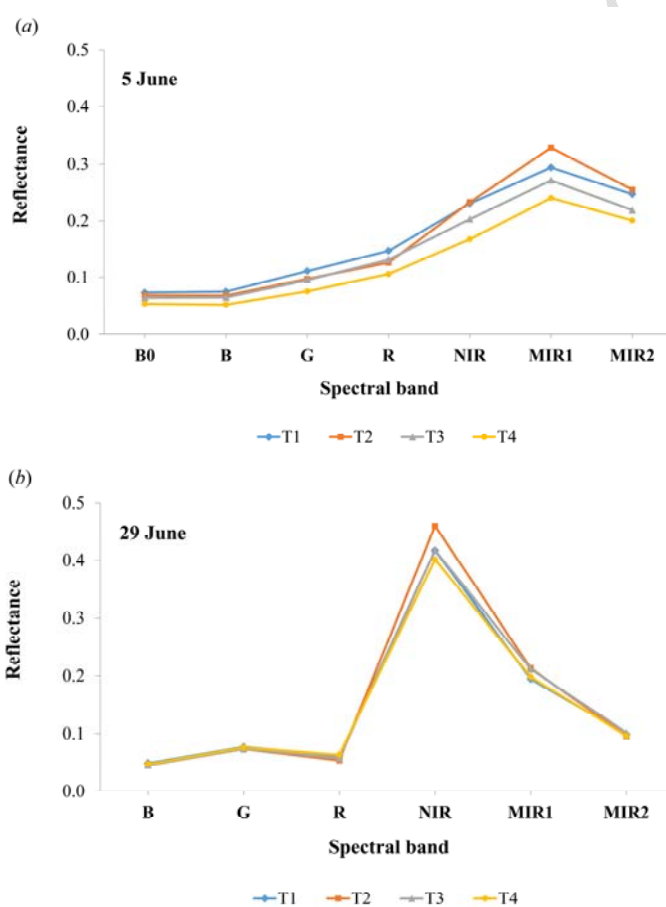
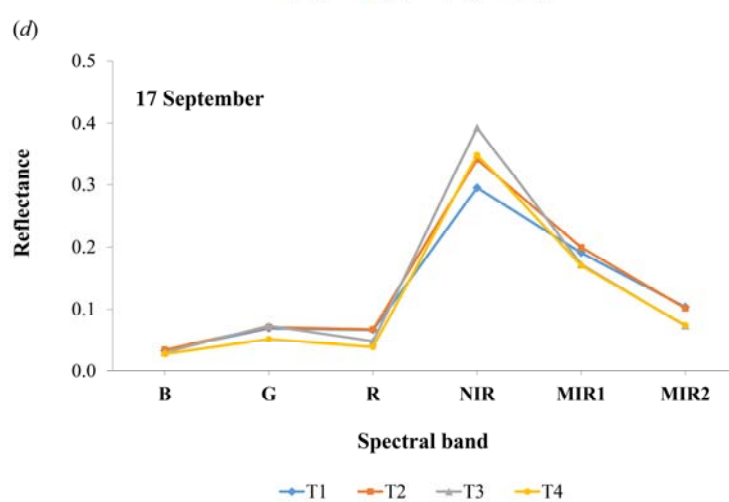
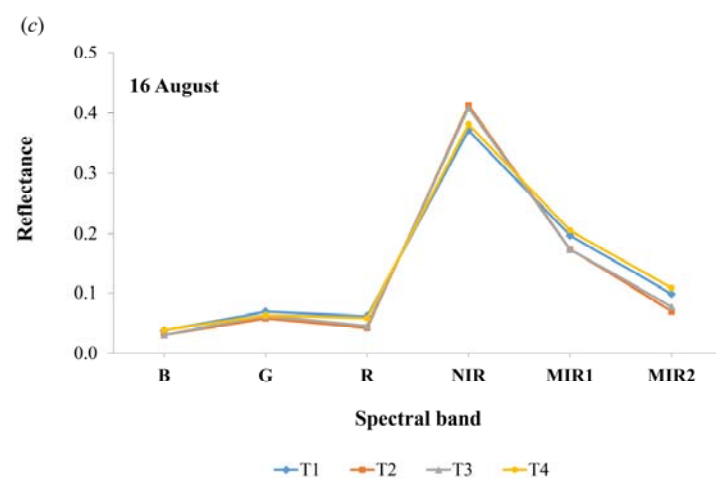


Figure 2. Corn growth stages at KBS: (a) Corn in late June (tassel initiation and growth); (b) Corn in mid-August (kernel growth and fill); (c) Corn in late October/November (corn to be harvested). Source: KBS LTER Photo Gallery (Michigan State University, 2016).





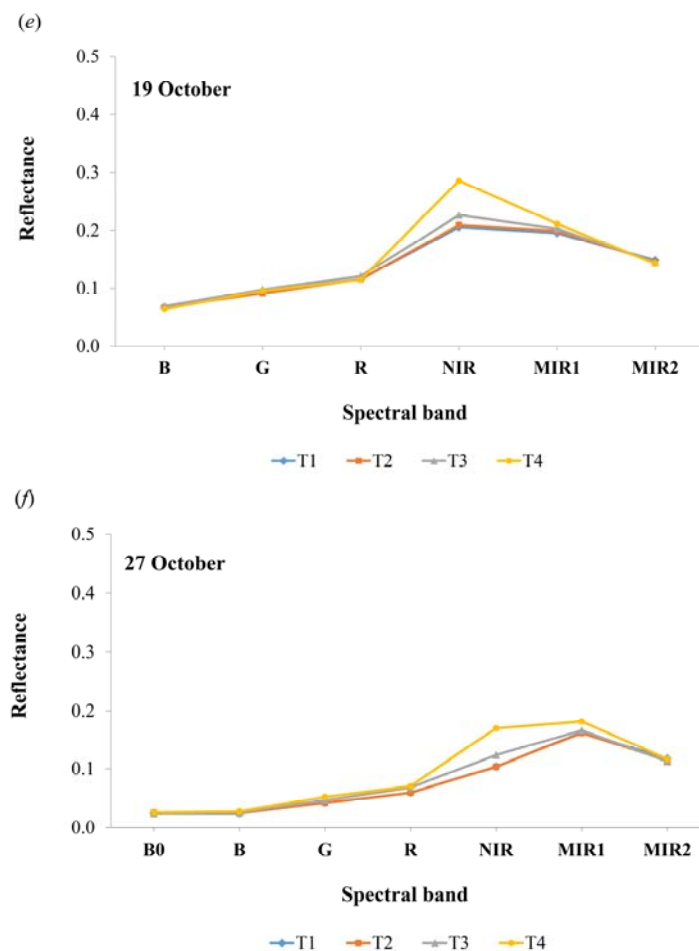
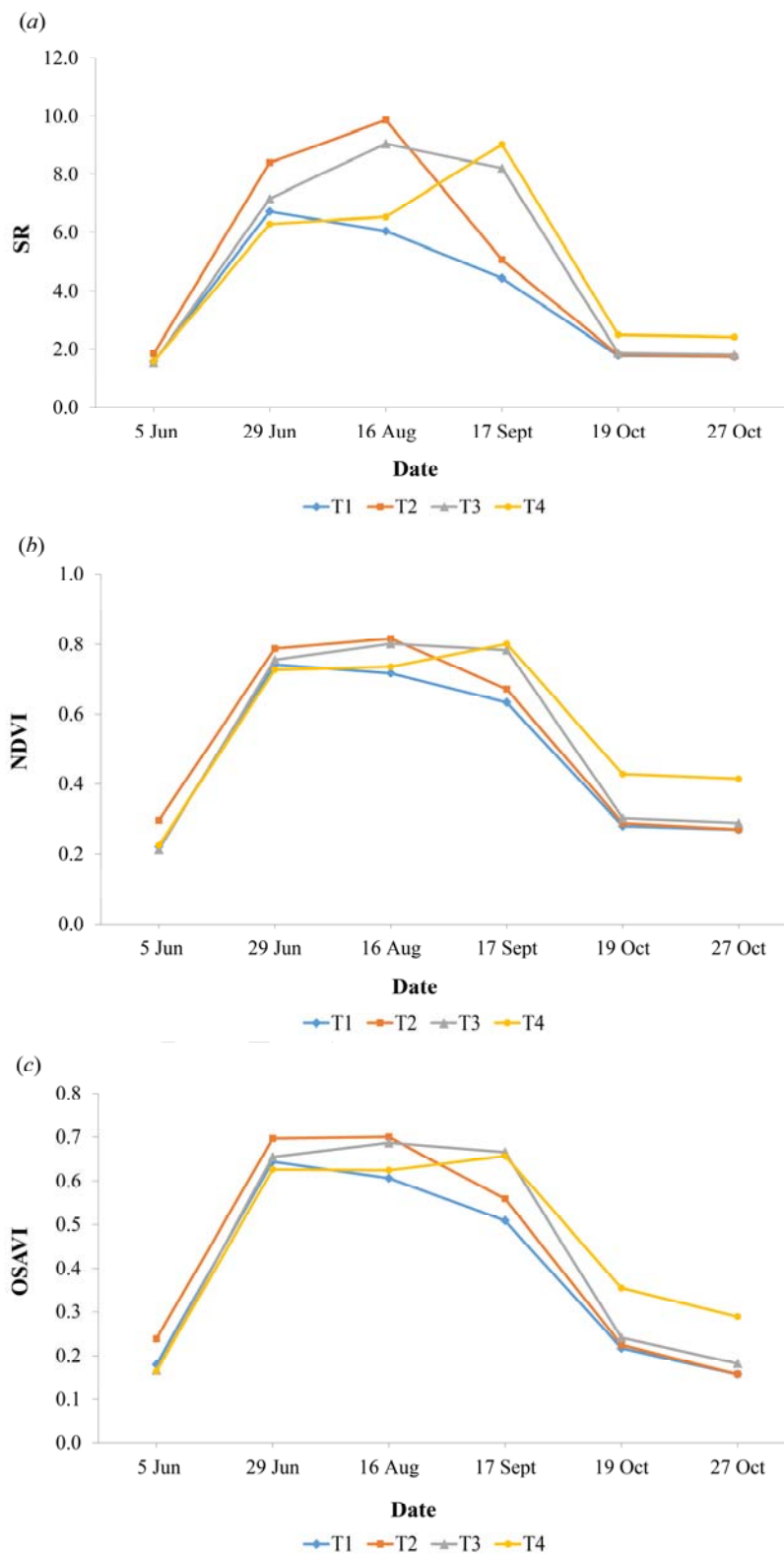


Figure 3. Averaged spectral signatures for the treatments collected on (a) 05 June 2014, (b) 29 June 2014, (c) 16 August 2014, (d) 17 September 2014, (e) 19 October 2014, and (f) 27 October 2014. Note: Conventionally-treated sites: T1 (plowed, GM), T2 (no-till, GM), T3 (biologically-treated, reduced input, GM), and T4 (certified organic, non-GM).



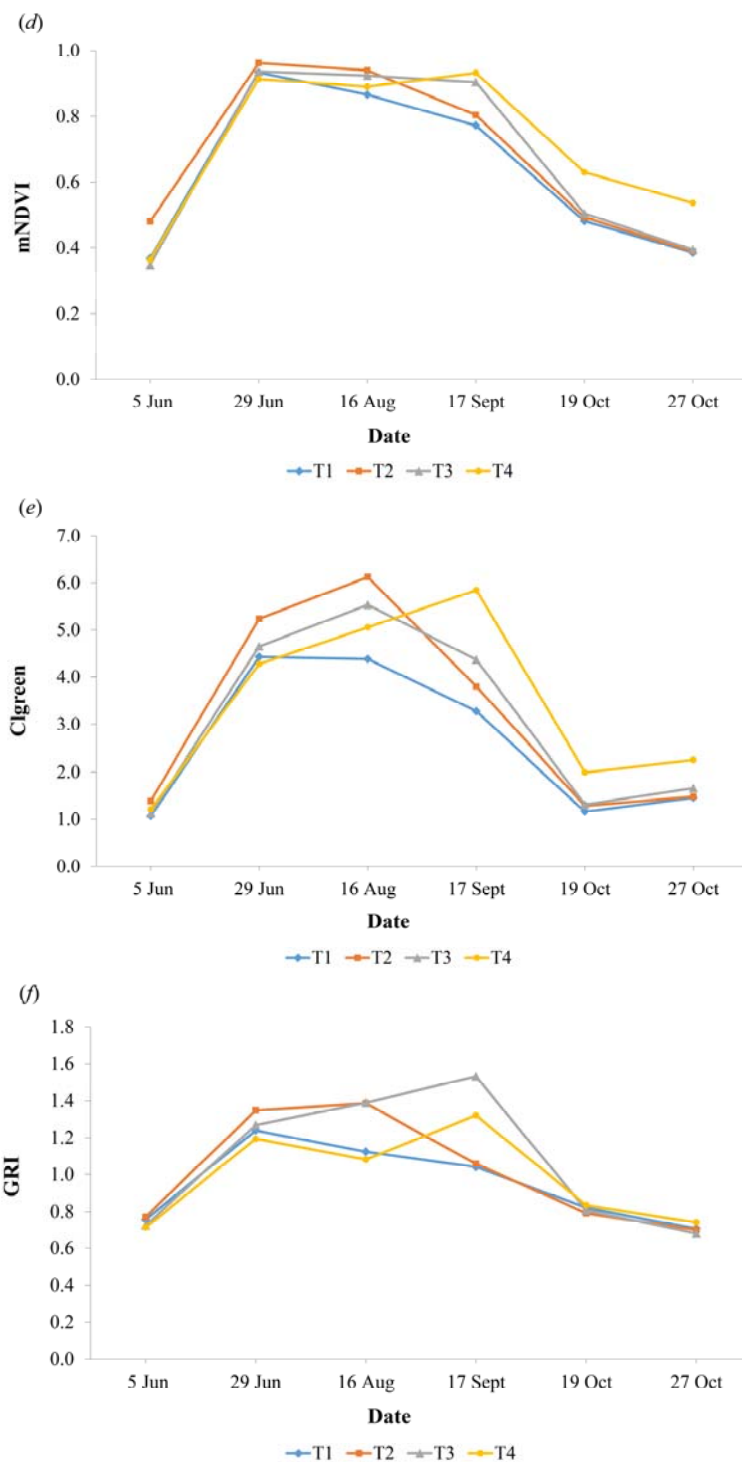


Figure 4. Vegetation indices for different treatments through the growing season based on Landsat 7 and 8: (a) SR, (b) NDVI, (c) OSAVI, (d) mNDVI, (e) CIgreen, and (f) GRI. Note: Conventionally-treated sites: T1 (plowed, GM), T2 (no-till, GM), T3 (biologically-treated, reduced input, GM), and T4 (certified organic, non-GM).

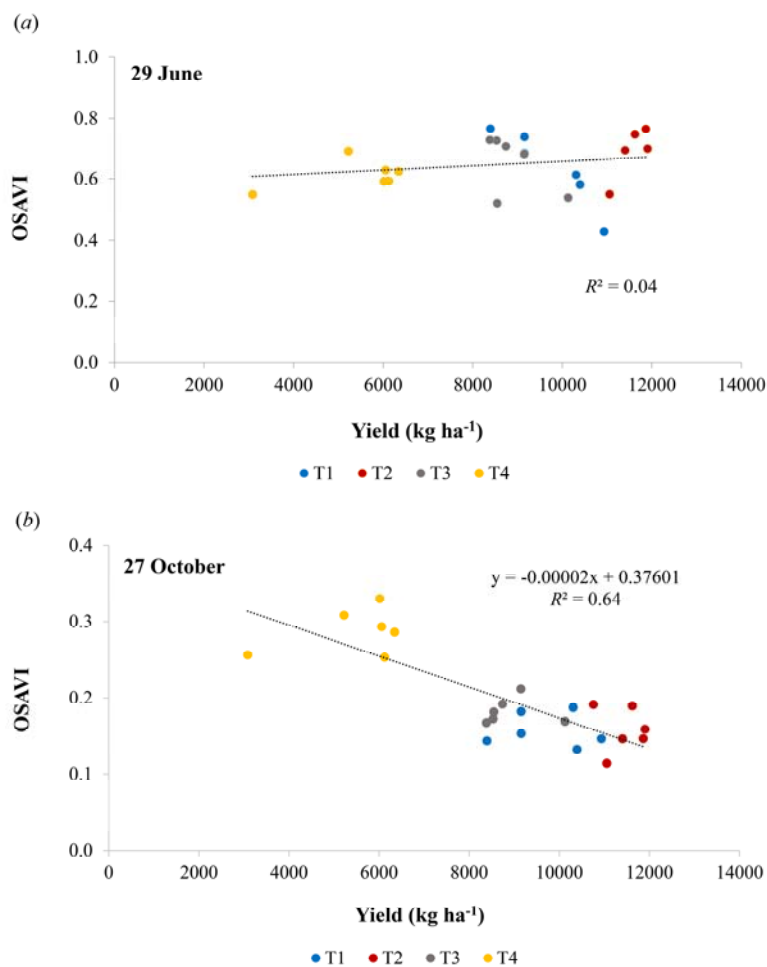


Figure 5. Relationship between OSAVI and yield measurements: (a) at the early growing stage (29 June), (b) at the pre-harvest stage (27 October). Note: Conventionally-treated sites: T1 (plowed, GM), T2 (no-till, GM), T3 (biologically-treated, reduced input, GM), and T4 (certified organic, non-GM).

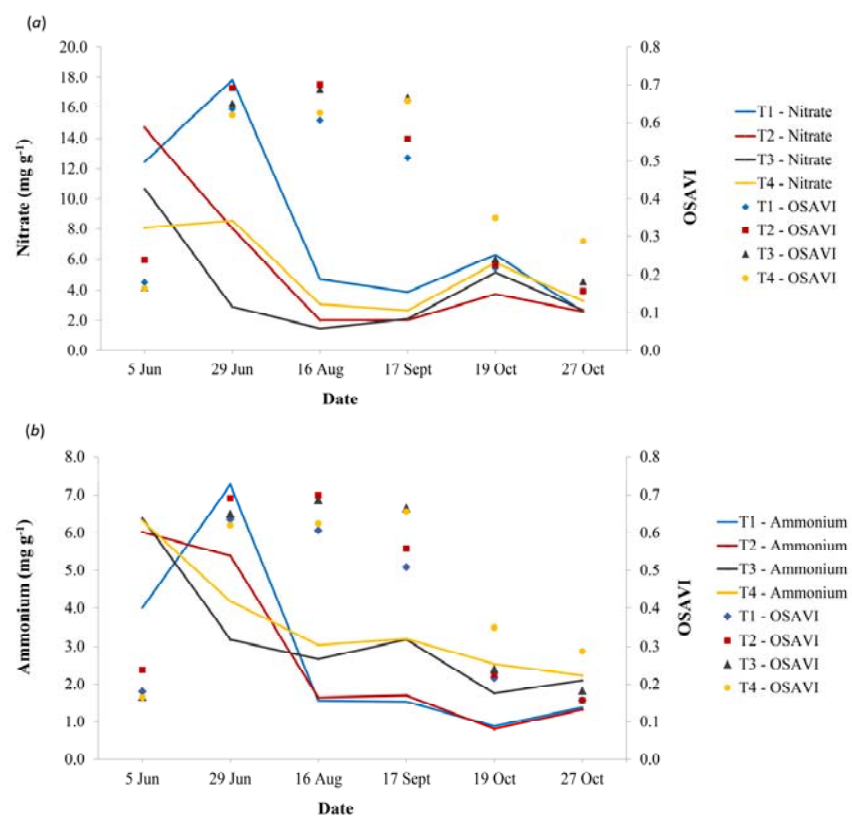


Figure 6. Temporal trends of soil nitrate (a) and soil ammonium (b) average levels, with OSAVI. Note: Conventionally-treated sites: T1 (plowed, GM), T2 (no-till, GM), T3 (biologically-treated, reduced input, GM), and T4 (certified organic, non-GM).

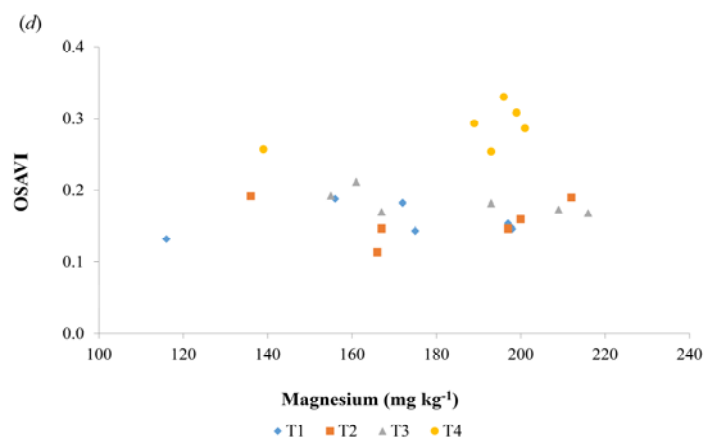
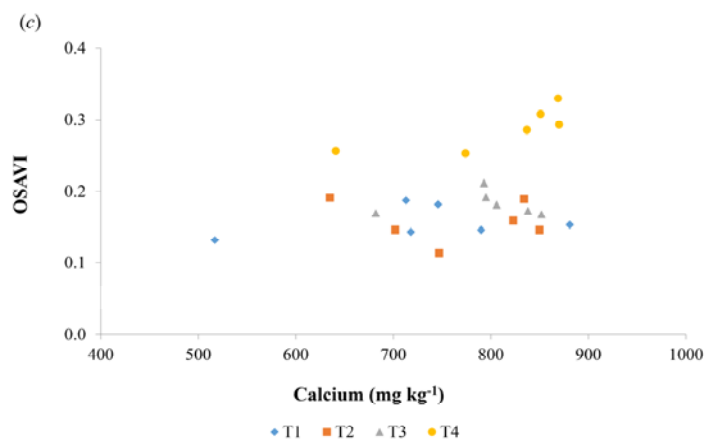
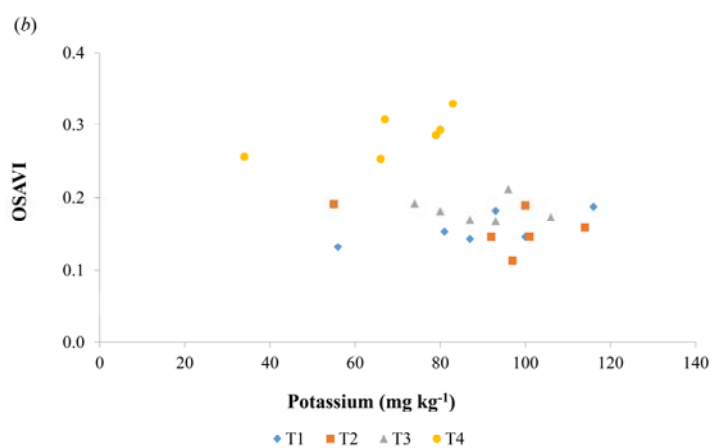
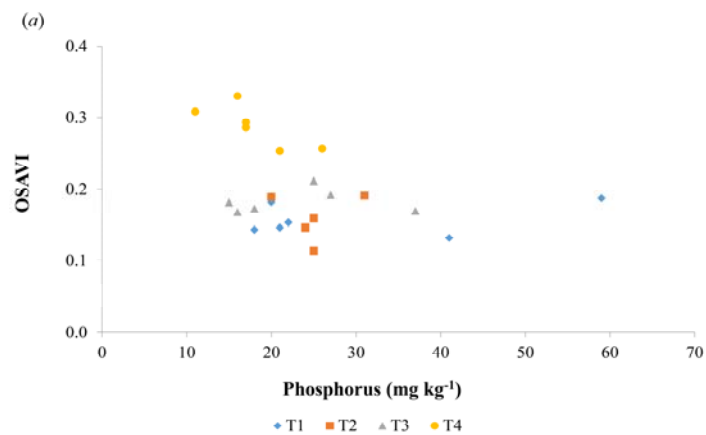


Figure 7. Relationship between OSAVI and soil chemical measurements (*a*) phosphorus, (*b*) potassium, (*c*) calcium, and (*d*) magnesium collected after harvest (12 November 2014). Note that each treatment type (T1-T4) has six replicates. Note: Conventionally-treated sites: T1 (plowed, GM), T2 (no-till, GM), T3 (biologically-treated, reduced input, GM), and T4 (certified organic, non-GM).