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A comprehensive assessment of the correlations between field crop yields and commonly used MODIS products

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ABSTRACT

An exploratory assessment was undertaken to determine the correlation strength and optimal timing of several commonly used Moderate Resolution Imaging Spectroradiometer (MODIS) composited imagery products against crop yields for 10 globally significant agricultural commodities. The crops analyzed included barley, canola, corn, cotton, potatoes, rice, sorghum, soybeans, sugarbeets, and wheat. The MODIS data investigated included the Normalized Difference Vegetation Index (NDVI), Fraction of Photosynthetically Active Radiation (FPAR), Leaf Area Index (LAI), and Gross Primary Production (GPP), in addition to daytime Land Surface Temperature (DLST) and nighttime LST (NLST). The imagery utilized all had 8-day time intervals, but NDVI had a 250 m spatial resolution while the other products were 1000 m. These MODIS datasets were also assessed from both the Terra and Aqua satellites, with their differing overpass times, to document any differences. A follow-on analysis, using the Terra 250 m NDVI data as a benchmark, looked at the yield prediction utility of NDVI at two spatial scales (250 m vs. 1000 m), two time precisions (8-day vs. 16-day), and also assessed the Enhanced Vegetation Index (EVI, at 250 m, 16-day). The analyses spanned the major farming areas of the United States (US) from the summers of 2008–2013 and used annual county-level average crop yield data from the US Department of Agriculture as a basis. All crops, except rice, showed at least some positive correlations to each of the vegetation related indices in the middle of the growing season, with NDVI performing slightly better than FPAR. LAI was somewhat less strongly correlated and GPP weak overall. Conversely, some of the crops, particularly canola, corn, and soybeans, also showed negative correlations to DLST mid-summer. NLST, however, was never correlated to crop yield, regardless of the crop or seasonal timing. Differences between the Terra and Aqua results were found to be minimal. The 1000 m resolution NDVI showed somewhat poorer performance than the 250 m and suggests spatial resolution is helpful but not a necessity. The 8-day versus 16-day NDVI relationships to yields were very similar other than for the temporal precision. Finally, the EVI often showed the very best performance of all the variables, all things considered.

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1. Introduction

The capability of society to closely monitor and estimate crop production from local- to global-scales cannot be understated. Food security, or one's ability to access the food supply, directly impacts livelihoods and is under constant pressure from increasing human population and environmental changes (Rosegrant et al., 2001; Bruinsma, 2003). Timely and accurate crop production statistics helps provide informed policy and decisions on how to best manage and distribute the food supply which reduces food security threats (World Bank, 2007). Furthermore, full and transparent understanding of the crop supply helps suppress market swings which tend to be most disruptive in regions where a large proportion of the economy is reliant on agriculture.

Collecting and disseminating national- or regional-level data about crop production through surveys and censuses is fairly common, particularly in developed countries, but they are of relatively high cost and still have associated uncertainties (Gallego et al., 2010). Being able to alternatively obtain this type of yield information from satellite imagery has been an operational promise but has unfortunately primarily remained in the research domain for decades from its initial foundings (Tucker et al., 1980; Barnett and Thompson, 1982; Hatfield, 1983). Wheat has been investigated the most through the years and there is a large body of work (e.g. Benedetti and Rossini, 1993; Labus et al., 2002; Reeves et al., 2005; Becker-Reshef et al., 2010; Kouadio et al., 2014). Corn has also been

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investigated extensively (e.g. Hays and Decker, 1996; Viña et al., 2004; Funk and Budde, 2009; Sakamoto et al., 2013; Gitelson et al., 2014) as well as with soybeans in combination (e.g. Doraiswamy et al., 2005; Prasad et al., 2006; Bolton and Friedl, 2013; Johnson, 2014; Shao et al., 2015). Rice has seen fewer studies (e.g. Patel et al., 1991; Tennakoon et al., 1992; Wang et al., 2010; Peng et al., 2014; Son et al., 2014) even though it is also a globally dominant agricultural commodity. Reasons for this are unknown but it could be a result of tending to be grown in more tropical, thus cloudy, regions make its monitoring from commonly used optical type sensors an increased challenge. Reinforcing this idea is that radar based research monitoring rice yields has indeed been undertaken (Shao et al., 2001; Li et al., 2003).

Remote sensing yield monitoring research on other commodities has been much less common. Tuber crops such as potatoes (Bala and Islam, 2009) and sugarbeets (Clevers, 1997) have seen some analysis, as has the fiber crop of cotton (Domenikiotis et al., 2004). Small grains like barley and spring planted wheat have also been studied individually or in combination with millet or canola (e.g. Quarmby et al., 1993; Rasmussen, 1997; Maselli and Rembold, 2001; Ferencz et al., 2004; Mkhabela et al., 2011). However, other globally common field crops like sorghum, cassava, sweet potatoes, or yams have been completely underrepresented.

Most of these studies have relied on freely available data from polar orbiting sensors like the Advanced Very High Resolution Radiometer (AVHRR) and the Moderate Resolution Imaging Spectroradiometer (MODIS). These types of platforms have shown a good tool for monitoring vegetation, and more specifically crops, because they have near daily revisit rates, are global in nature, and have spectral bands with reasonable spatial resolution useful for vegetation monitoring at landscape scales. There have been over a dozen AVHRR sensors aboard the long series of National Oceanic and Atmospheric Administration meteorological satellites operationally since the early 1980s. The more sophisticated MODIS sensor began collecting data in early 2000 aboard the earth science satellite Terra. A second MODIS was put into service similarly aboard the satellite Aqua in 2002.

These systems have the ability to collect radiances in the visible and near-infrared portions of the electromagnetic spectrum which are useful for vegetation monitoring (Tucker et al., 1980). Often the red and the near-infrared spectral bands are used in together to derive a dimensionless proxy of plant vigor and standing biomass known as the Normalized Difference Vegetation Index (NDVI). However, there are increasingly more vegetation indices being generated from the MODIS surface reflectance-based products (Vermote et al., 2011) and include the more sophisticated Enhanced Vegetation Index (EVI; Huete et al., 2002; Solano et al., 2010) alongside a variety of modeled biophysical products including Fractional Photosynthetically Active Radiation (FPAR) and Leaf Area Index (LAI; Myneni, 2012) and Gross Primary Production (GPP; Heinsch et al., 2003). In short, FPAR can be summarized as the fraction of incoming radiation absorbed by vegetation, LAI is an equivalent in biomass terms measuring the layers of leave relative to the ground area, and GPP is the amount of energy created as biomass. Each have biophysical process-based ties to crop yield accumulation and have been used to varying degrees and success in modeling efforts.

Additionally, thermal data is also being collected by these earth imaging satellites and is often translated into readings of surface temperature, particularly for MODIS (Wan, 2006). Surface temperature is also potentially useful for crop modeling given the known relationships of heat stress and the negative impacts on yield. Surprisingly, this type of data has been used only sparingly toward yield estimation work (Johnson, 2014). However, there have been more general studies linking vegetation health and stress to thermal data (Wan et al., 2004; Feddema and Egbert, 2005) so suggestive that it could be used for yields more broadly as well.

Some metadata analysis summarizing and assimilating much of the aforementioned remote sensing research toward yields has been undertaken and provides at least a partial summary of how various satellite products have been used (Funk and Budde, 2009), what crop types studied, and regional foci (Huang and Han, 2014). However, it is still a big challenge to optimize them all down to a few keys points that can be used concisely and ubiquitously. As such, *the goal of this research is to fully explore the wide range of the most common vegetation and temperature products that are available from a regional-scale remotely-sensed imaging systems and to consistently document their relationships to yields for a host of crop types*. It is purposely all encompassing yet sets out to provide a firm construct to identify which variables are most useful and at what time during the growing season they are most effective. In other words, this work is meant to rein in the bewildering array of remotely-sensed input choices available for possible inclusion into crop yield models. Note, it is beyond the scope being presented here to identify which modeling paradigms to consider and their resulting predictive utility.

Data from both MODIS sensors were used as a basis. The particular datasets that were investigated are relatively common in land-related remote sensing discipline activities (Justice et al., 2002) and included the abovementioned NDVI, FPAR, LAI, GPP, Daytime Land Surface Temperature (DLST), and Nighttime Land Surface Temperature (NLST). Differences between the MODIS data collected from the late morning orbit of Terra to that of the early afternoon orbit of Aqua were also sought. All the datasets examined were 8-day, clear-sky composites as developed and generated by the MODIS science community, but unique to the rest, the NDVI data had a native spatial resolution of 250 m while all the others were at 1000 m. Follow-on analyses was directed at the importance of pixel size (250 m vs. 1000 m), compositing length (8-day vs. 16-day), and utility of the increasingly popular EVI.

The analyses were undertaken across a broad variety of crops beyond just those most commonly studied (arguably wheat, corn, and soybeans). Nine food crops were investigated and included the cereals of barley, corn (maize), rice, sorghum, wheat (winter planted), the tubers of potatoes and sugarbeets, and the oilseeds of canola (rapeseed) and soybeans. Cotton, a fiber crop, was the tenth included. The examination was carried out in the United States (US) where each of these crops can be found in relative large areal proportion and have high quality annual county-level average yield statistics. The study was also cognizant of the importance these 10 particular crops globally and it is hoped that findings here can, at least in similar environmental regimes, be extrapolated beyond the US.

2. Data

Three publically available core datasets were integrated for this analysis comparing measured crop yields to information inferred from MODIS. The first, and foundation for all this work, were the NASS historical county-level average yields. Those are determined by NASS through a county-based mail survey which contacts as many farmers as possible after the growing season is fully complete. This county-level survey data is made most robust by reconciling with the already established state estimates which were derived prior during the season via the Agricultural and Objective Yield Surveys (USDA, 2012). This yield data, as well as any from NASS, is archived online in a central repository known as Quick Stats (USDA, 2015b). For this study county-level data were available and queried via Quick Stats in tabular format for all of the primary states for the 10 crops of interest from the years 2008–2013.

Table 1
Cropland Data Layer (CDL) average crop-specific errors over the years 2008–2013.

	Typical error rate%		Most commonly confused with
	Omission	Commission	(descending order)
Barley	32	18	Spring Wheat, Winter Wheat, Alfalfa, Grasslands, Fallow, Oats
Canola	7	6	Winter Wheat, Fallow, Spring Wheat, Grasslands
Corn	5	4	Soybeans
Cotton	11	11	Peanuts, Sorghum, Soybeans
Potatoes	8	7	Alfalfa, Dry Beans
Rice	6	5	Soybeans
Sorghum	27	21	Corn, Winter Wheat, Soybeans, Cotton, Grasslands, Fallow
Soybeans	5	5	Corn
Sugarbeets	8	4	Soybeans, Corn
Wheat	8	8	Fallow, Spring Wheat, Grasslands

NASS Cropland Data Layer (CDL) land cover information, available via the CropScape portal (Han et al., 2012; USDA, 2015a), was leveraged to identify which areas within a county were planted to each crop. US national-level CDLs exist from 2008 to present (Johnson and Mueller, 2010) and this history served to establish the six-year time frame for the study. The CDLs are supervised classifications derived from Landsat or Landsat-like data trained with administrative information from the USDA (Boryan et al., 2011). They are validated at the state-level and generally of high quality in the identification of dominant field crops as summarized by Table 1. Corn and soybean commission (i.e. over classification) and omission (i.e. under classification) error rates are typically excellent (less than or equal to 5%). Canola, potatoes, rice, sugarbeets, and wheat are very good (5–10% omission and commission errors) and cotton quite good as well (11% errors). Barley and sorghum accuracies are notably weaker overall but still reasonable for use in this context since they tend to omit more than commit and thus are conservatively mapping those crops. Table 1 also highlights in what ways crop type identification tend to be confused. The most common errors are for those crops which are predominantly grown in close proximity (e.g. corn with soybeans) or are structurally similar plant types (e.g. barley with wheat).

A large suite of MODIS data exists but only cloud-free "composited" products pragmatic for real-time vegetation monitoring, accessed from the Land Processes Distributed Active Archive Center (LP DAAC, 2013), were considered. The specific Terra and Aqua products obtained were the 8-day 250 m (232 m, more precisely) surface reflectance (technically known as MOD09Q1 and MYD09Q1, respectively) to be later converted to NDVI, the 8-day 1000 m (927 m) FPAR and LAI (both datasets contained within MOD15A2 and MYD15A2), the 8-day 1000 m GPP (MOD17A2 and MYD17A2), and the 8-day 1000 m daytime and nighttime LST (MOD11A2 and MYD11A2). Additionally, the 16-day NDVI and EVI 250 m products from MOD13Q1 (Terra only) were obtained for follow-on analysis. All data were version "Collect 5" which was the most state-of-the-art at time of analysis. These MODIS imagery are disseminated in "tiled" format and to cover the most important commodity growing regions of the US eight geographic tiles were needed (referenced as: h09v04, h09v05, h09v06, h10v04, h10v05, h10v06, h11v04, h11v05). The seasonal time period of interest fully captured the spring and summer ranging from the middle of February to late October. Thus, the 8-day composited time steps resulted in 32 periods to more than fully cover the growing season (USDA, 2010). 16 periods were needed for the MOD13Q1 16-day data to cover the same time span.

3. Methods

The MODIS imagery, CDL classifications, and county-level yield average data were all downloaded via the Internet. The preparation of the MODIS imagery first consisted of mosaicking each of the eight tiles for each time period, for each product, and for each satellite into a single mosaic. The MODIS Reproject Tool (MRT) version 4.0, also available from the LP DAAC, was used to perform the mosaicking. The second step involved extracting the relevant "layers" of interest from the Terra and Aqua MODIS datasets – namely LAI, FPAR, GPP, DLST and NLST. Because NDVI itself is not natively calculated within the 8-day MODIS products, it was derived from the raw red and near-infrared (NIR) bands (where NDVI = (NIR − red)/(NIR + red)) of the surface reflectance product. Subsequently, the 16-day NDVI and EVI were also extracted, but from Terra only as additional Aqua data was felt redundant for assessing time windowing impacts. This, and all the later imagery management, was performed in the commercial image processing software Erdas Imagine version 11.

The third step involved error checking of the data to look for outliers temporally. These are typically downside errors due to limitations of the 8-day compositing period sometimes having too short a dwell-time to obtain a clear sky maximum value. The most egregious example when by chance it is cloudy over the entire 8-day period. Ideally, the quality assessment bands MODIS provides in parallel with the composite imagery itself could used to guide the understanding of questionable pixels, but were often found too liberal in suggesting what error free. Furthermore, time-series smoothing algorithms were considered but they rely on having a full season's worth of data which is not possible for a within-season yield monitoring system. So in the end, a simple assessment and correction to a pixel that was likely erroneous was done by comparing it to the time-period before and after and if found to be lower than both, which is an unlikely real life scenario, averaged across the two. This error-checking was performed on all the MODIS imagery being evaluated with the exception of the 16-day NDVI and EVI since they are inherently less noisy due to the longer compositing period. All of the mosaicked and prepared data was ultimate stored and analyzed in the imagery's native grid cell size and sinusoidal projection.

Managed next were the CDLs. They come natively in an Albers conic equal area projection but, depending on the year and state, vary whether at 56 or 30 m resolution. Regardless, they were first reprojected to the MODIS sinusoidal projection to then be utilized in deriving pixel-level "masks" at the 250 m resolution. These masks were needed to isolate from the MODIS imagery those pixels which pertained to each crop. This was done for all 10 crops of interest over those states which the commodities existed in significant part, for each of the six years. The masks were derived by tabulating the area of the CDL contained within each 250 m grid cell and any greater than 90% were considered pure enough to be included in the crop mask. This 90% threshold was chosen as a balance of being stringent enough to only allow pixels with little cover type mixing, yet not too rigid as to end up with such a small number of MODIS pixels to be representative at a county level. Also, in combination any county that ultimately did not have at least 186 MODIS 250 m pixels (equivalent to 1000 ha) of a given crop type was excluded from later analysis because deemed too small a sample size to be representative.

With the variety of MODIS data and crop masks in a common spatial framework, an intersection was performed to produce a huge array of annual county-level average time series values for each MODIS product, crop, and year. This was crux of the data processing and effectively a vector 32 values long was created for each county, for each of the six years, for each of the MODIS variables, and for each of the crops. Hundreds of thousands of vectors were created through this process.

Next the county-level yield data from NASS was attached to each of the corresponding MODIS county-level annual vectors by crop type. The goal was to account for those counties that make up over 75% of the total production in the US and at the same time only include states that were contiguous. In combination, this was meant to reduce counties that were geographically spurious and less likely to represent the majority. Wheat was given an exception since it is grown in wide geographic scope across the US. The states that ultimately had counties considered for inclusion are shown in Fig. 1 along with the crop masks showing the distribution of the varying crop types. Many counties within those states still did not have published yield data so were naturally excluded. Other common commodities beyond the 10 chosen were also considered (such as oats, beans, peas, sunflowers and alfalfa) but lacked counties with yield data or sufficient area to in the CDL to build a reasonable sample size. Spring wheat had enough data to be chosen but it was excluded since it shared commonality with both barley and winter wheat which were already being addressed.

Finally, the vector and yield data were all assembled and read into the statistical software R version 3.0. Descriptive statistics showing average seasonal phenology were first generated to provide a basis as to the expected timing of yield relationships. Then Pearson's correlation statistics (using the R function "cor()") for the myriad of crop, date, and MODIS product combinations were calculated.

4. Results

Phenology summaries combining the years 2008–2013 for the 10 crops by Terra and Aqua satellite and MODIS composite product types of NDVI, FPAR, LAI, GPP, DLST and NLST are shown in Fig. 2. Technically these are averages of the county averages but can be thought representative of national-level means for the US. The number of county-level samples that resulted after the processing of the CDLs and finding an associated average yield value for each crop was: barley = 175, canola = 84, corn = 4067, cotton = 949, potatoes = 75, rice = 309, sorghum = 491, soybeans = 3999, sugarbeets = 101, and wheat = 1889. Again, the functional difference between the satellites is Terra's late-morning overpass time (10:30 AM) versus that of Aqua's in early-afternoon (1:30 PM). The exception in timing however is that for NLST which is 12 h opposite and thus Terra is late-evening (10:30 PM) and Aqua is early-night (1:30 AM).

From the charts there are obvious timing and amplitude differences for the variety of vegetation proxies from crop to crop. Starting with NDVI, wheat peaks mid-May which is the earliest of any of the crops and shows the lowest maximum value overall. Sorghum also has relatively low peaking NDVI but reaches it much later in middle of summer around early August. NDVI for soybeans show the highest peaking of all of crops with timing similar to sorghum and cotton. All of the other peaks are somewhere in between both in terms of amplitude and timing. For cumulative NDVI, or area under the curve, sugarbeets has both a relatively wide and high trajectory suggesting a long season of verdant biomass. Barley appears to have the narrowest profile although it peaks reasonably high. Finally, the differences between the data from Terra compared to Aqua are fairly minimal. Cotton and rice do appear to peak somewhat higher in the Aqua data, but otherwise there do not appear to be any systematic differences.

The time-series chart for FPAR is not radically different from NDVI other than to the degree at which each curve maximizes. Canola is the most different relatively speaking as it peaks higher in FPAR than in NDVI. Oppositely, but to a lesser degree, wheat is somewhat less peaked. Like with NDVI, there are only minimal differences between the Terra and Aqua data. Looking at the LAI graphic, it is similar to FPAR except the curves have a greater height to width ratio creating more relative difference between the lowest and highest values. There are three crops for LAI however that show more than a glancing difference between Terra and Aqua platforms. Namely, canola peaks higher in Terra's LAI profile and corn and soybeans are higher within Aqua's. Within the GPP phenology chart, it is similar to all of the others in a general sense, but the time-series curves do not appear as smooth temporally. Only barley and canola are consistent to the other charts throughout the growing season in that regard. Canola is the highest peaking crop for GPP, as it was for LAI. Sorghum GPP is the most different from the other charts in that it maximizes in the spring and not the summer. Differences between Terra and Aqua for GPP are again, like for the other indices, pretty minor and hard to concisely characterize.

The appearance of the time-series land surface temperature data at the bottom of Fig. 2 is radically different from that of the vegetation proxies. There are also notable differences between what the two satellites observed and radical differences between data collect at night versus day. Starting with DLST, the maximum temperature peak amplitudes and when they occur vary by crop type. The crops of canola, potatoes, and soybeans have lower temperatures throughout while wheat, sorghum, and cotton are higher. Potatoes, rice, and sorghum peak earlier in the growing season while wheat and canola are weeks later. Consistently different throughout the data are the Aqua temperatures always being greater by two or three degrees celsius, particularly in the middle of the growing season. The 12 h opposite in time NLST show a similar rise and fall over the growing season but overall average temperatures are notably cooler throughout by roughly 10–20°. There are also consistent differences between the Terra and Aqua NLST in that Aqua temperatures are always cooler, or the opposite for the DLST scenario. The timing of the peak nighttime temperatures also appears to be on average slightly earlier than that of the daytime temperatures. Furthermore, the timing of the peaks in the NLST data show less variance than DLST by hovering around early July on average.

Correlations of all the MODIS variables against yields, the crux of this study, are shown for each of the 10 crop types in Fig. 3. The results as discussed in alphabetical order by commodity in the following subsections. However, because the charts of Fig. 3 convey a lot of information only highlights are practical in the text.

4.1. Barley

NDVI, FPAR, and LAI yield correlations all peak late May with NDVI being the marginally highest giving a Pearson's coefficient of about 0.7. There is little difference between the Terra and Aqua signals. FPAR, LAI, and GPP also rise again late summer but NDVI does not. NDVI shows the smoothest appearance overall. In terms of the thermal data, both DLST and NLST bounce around noisily throughout the growing season and never show a real relationship and regardless of satellite. Those profiles also show little difference between Terra and Aqua.

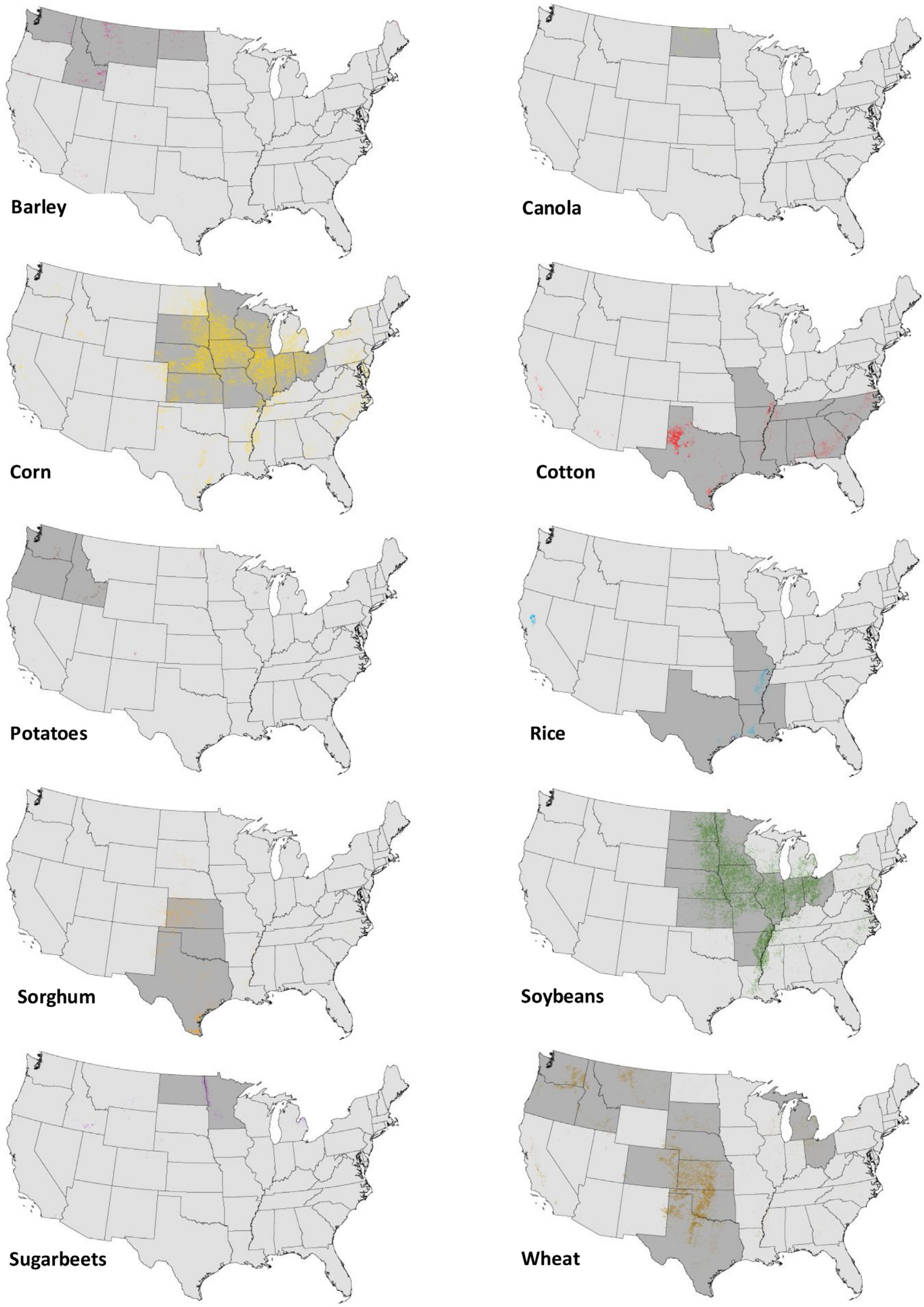

Fig. 1. Crop areas (colored) and states (dark-grayed) focused on for yield correlation analysis.

4.2. Canola

NDVI, FPAR, and LAI all show a positive and decent correlation of around 0.6 mid-summer for both satellites. FPAR is the very highest. GPP is much weaker throughout but does follow the same general timing. All of the vegetation variables show an inverse relationship of nearly −0.5 before the main growing season begins. The DLST is

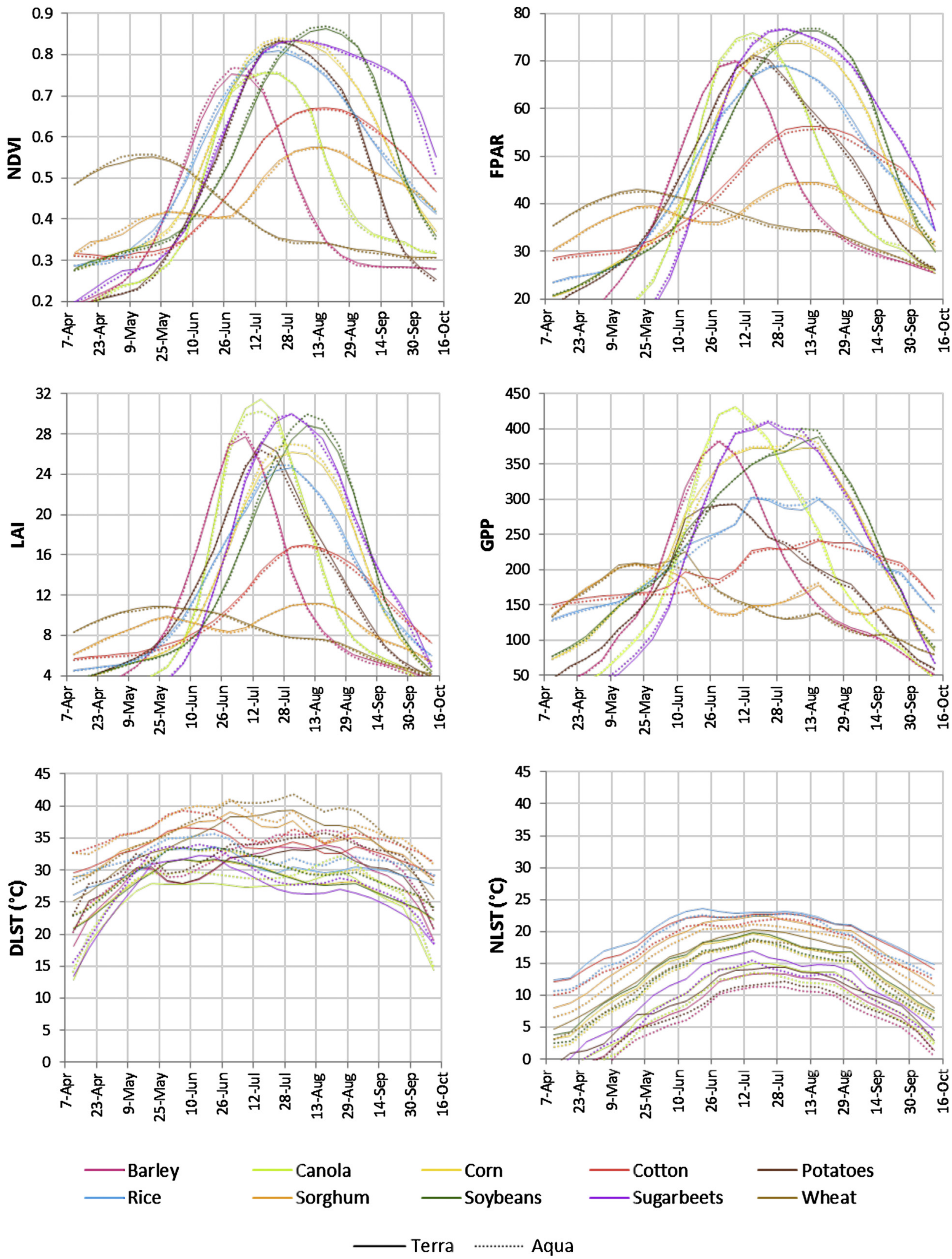

Fig. 2. Average 8-day crop phenologies through growing season by MODIS imagery products.

similar for both Terra and Aqua and is strongly negatively correlated early summer reaching nearly −0.8. NLST has some relationship as well but not to the same extreme as DLST.

4.3. Corn

All of the vegetation parameters rise smoothly and consistently peak mid-summer. NDVI has the strongest positive correlation

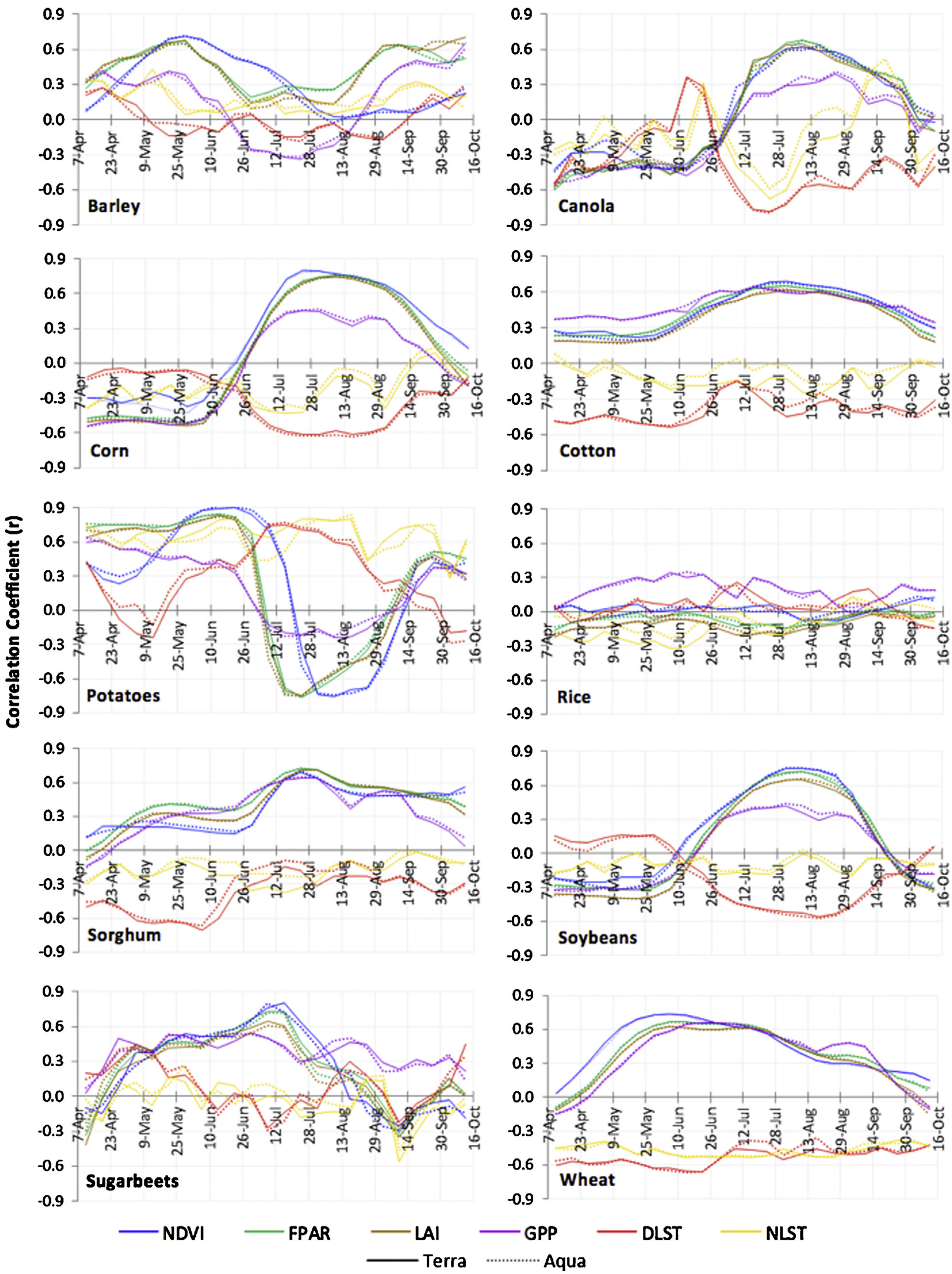

Fig. 3. Yield correlations through growing season for common MODIS products by crop type.

reaching nearly 0.8 and is clearly the earliest by a couple of weeks as well. GPP is consistently weaker regardless of timing. For FPAR and LAI there is a negative relationship of about −0.5 in the spring, while NDVI has a weaker negative correlation at this same time. In terms of surface temperature, the DLST show a consistent and long lasting inverse relationship of about −0.6 to crops yield. The NLST is weaker and inconsistent throughout. The curves for any of the best yield correlated variables are similar for Terra and Aqua.

4.4. Cotton

All of the vegetation products rise and fall together smoothly through the growing season. GPP is noisier and less peaked at the maximum but appears to be the best performer early on. NDVI, FPAR, and LAI are more similar to each other overall, and ultimately NDVI ranks the highest by providing a peak correlation coefficient of close to 0.7. The Terra and Aqua responses for these variables are quite similar. In terms of temperatures the DLSTs have a fairly consistent but weak inverse relationship to yields, regardless of the timing. Yield relationships to NLST are muddled and nonexistent throughout.

4.5. Potatoes

Here appear the most unique characterizations for any of the crops. NDVI is strongly positively correlated at over 0.9 in early summer and then swings negative at more than −0.7 late in the season. LAI and FPAR have a similar appearance but are not as strong on the positive side. Also, their negative response come a couple of periods earlier than that of NDVI. GPP loosely follows the same pattern of the other vegetation products but is much more dampened. Daytime temperatures have a positive correlation, early and mid-summer of over 0.7 which is converse to any other crops. Furthermore, nighttime temperatures are consistently positively correlated (above 0.6) at any time of the season. Both of the temperature profiles are fairly noisy. Any differences between Terra and Aqua are fairly minor.

4.6. Rice

The results for rice are simple to summarize. There are no relationships between any of the variables and crop yields. This is true any time during the growing season and from either Terra or Aqua.

4.7. Sorghum

All of the vegetation type variables are fairly consistent rising positively early summer and peaking near late July with correlations around 0.7. FPAR is marginal better through several periods but at the very peak NDVI and LAI are about equal to it. GPP is underperforming the rest throughout. NLST never shows any real correlations. DLST, however, appears negatively correlated to yields with a value of about −0.7 early in the season before transitioning to no relationship in the second half. There is suggestion that the daytime temperature data from Terra's late-morning collection is slightly better performing than that from Aqua's early-afternoon collection. All the temperature data profiles have a noisier appearance compared to the vegetative ones.

4.8. Soybeans

Smooth curves for all of the vegetation proxies result and they are similar to corn's appearance overall, albeit lagged a week or two later. NDVI's correlation peaks the very highest with a value above 0.7 and is also slightly earlier in optimal timing than the others. FPAR is just slightly less than NDVI at its peak, and LAI less than FPAR, throughout. GPP is much more dampened overall but follows a similar pattern to the others. NLST has no relationships at any time. However, DLST shows consistent negative correlations throughout the middle of the season peaking early August beyond −0.5. The Terra and Aqua signals are similar for all of the MODIS variables.

4.9. Sugarbeets

The signals for all the variables are quite noisy throughout the growing season. There is peaking of NDVI, FPAR, and LAI mid-July however. NDVI appears the strongest, reaching 0.8, but there are some differences in it because Aqua noticeably peaks a period earlier than Terra. None of the temperature products show any meaningful relationships to yield at any time.

4.10. Wheat

All of the vegetation curves are quite smooth and show meaningful relationships. NDVI rises earliest, and most positively, reaching a peak of 0.7 in early June. FPAR, LAI, and GPP are all less pronounced and peak slightly later. There are hardly any differences between Terra and Aqua for these four variables. In terms of surface temperatures, both DLST and NLST are consistently inversely related throughout the entire period. DLST is somewhat stronger negatively early on. The signals between the two satellites are, again however, very similar.

4.11. Varying spatial and time resolution and the inclusion of EVI

The above results were insightful but invoked questions of spatial control in regards to the strong performing NDVI being natively at 250 m while all the other products were 1000 m. Thus, follow-on analysis was performed to gain understanding of the impacts of the differing spatial resolutions. Only Terra data was used since it had been learned there is little difference between it and Aqua. To simulate an 8-day NDVI 1000 m product, the 250 m imagery were simply averaged over the shared 16 pixels and the time series extraction step rerun. Furthermore, it was decided to understand what differences yield correlations might also be appearing from the image compositing time span length. So, even though the 8-day composites are commonly used for MODIS temporal analysis, a few products, namely NDVI, are also produced at 16-day time intervals and thus prudent to compare them to the 8-day NDVI already examined here. And finally for completeness, the related 16-day EVI, which is generated alongside the 16-day NDVI, was also examined. Note, both the 16-day NDVI and EVI datasets were 250 m resolution.

Fig. 4 shows the average Terra phenologies for NDVI at 250 m and 1000 m resolutions at 8-day compositing intervals, and then 250 m NDVI and EVI at 16-day intervals. The curves for the 8-day, 250 m NDVI are the same as presented in portion of Fig. 2 but reshown to ease comparison and act as a benchmark. The 1000 m 8-day NDVI phenology curves are similar in appearance to the 250 m but dampened. Wheat is still the earliest and lowest to when it peaks and soybeans still has the latest and highest peak timing. The other crops sit rather similarly in between. Potatoes is the crop with the most notable difference as it is relatively lower in its peak ranking within the 1000 m data than for the 250 m. For all crops the 16-day 250 m NDVI curves neatly mimic the 8-day equivalent with the only difference being the jaggedness due to the doubling of the time step between samples. The 16-day EVI data has the similar jaggedness of the 16-day NDVI product. For EVI, given the nature of its calculation which allows for more dynamic range, all the values are lower relatively than for NDVI. However, most of the EVI curves rank in amplitude and peak in time similarly to the NDVI product with, again, the primary exception of potatoes. It is by far the top peaking crop in EVI and has an earlier rise there as well.

The correlation coefficients through the season for Terra's 250 m 8-day NDVI, 1000 m 8-day NDVI, 250 m 16-day NDVI and 250 m 16-day EVI are given in Fig. 5. In general, most of the curves are relatively similar by crop type, and all show at least a mild peak near the middle of the growing season. Rice, again, is the notable outlier

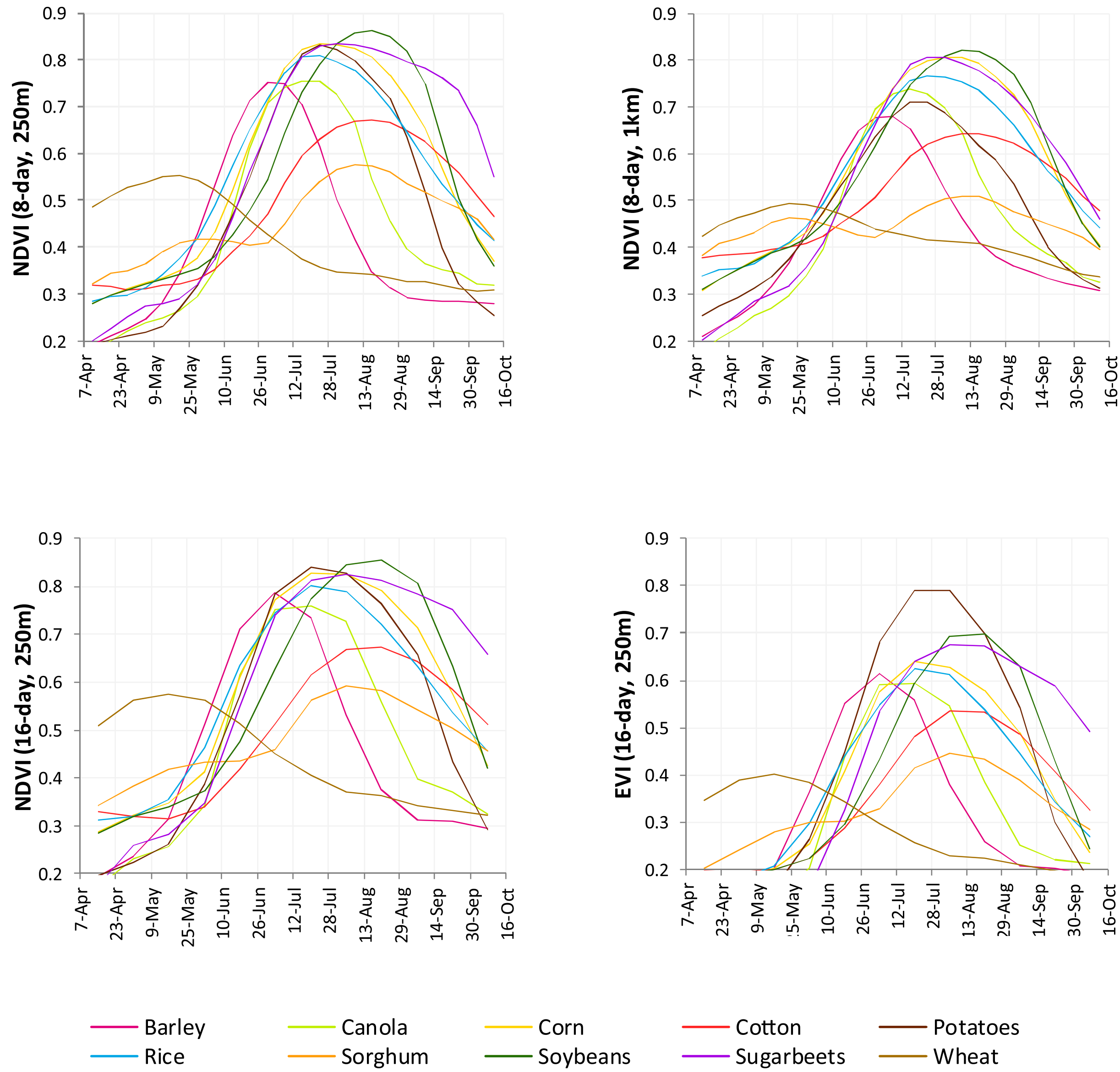

Fig. 4. Average crop phenologies through growing season of Terra NDVI variants and EVI.

Table 2
Optimal correlation coefficient timing and linear model performance of Terra MODIS NDVI variants and EVI.

	NDVI 8-day 250 m			NDVI 8-day 1000 m			NDVI 16-day 250 m			EVI 16-day 250 m		
	date	r	R^2	date	r	R^2	date	r	R^2	date	r	R^2
Barley	5/25–6/1	0.7156	0.5121	5/25–6/1	0.6365	0.4051	5/9–5/24	0.6364	0.4051	6/10–6/25	0.7266	0.5279
Canola	8/5–8/12	0.6202	0.3846	7/28–8/4	0.7117	0.5066	7/28–8/12	0.5798	0.3361	7/28–8/12	0.5941	0.3529
Corn	7/20–7/27	0.7982	0.6370	8/5–8/12	0.7093	0.5032	7/28–8/12	0.7851	0.6163	7/12–7/27	0.8222	0.6759
Cotton	7/28–8/4	0.6887	0.4744	7/20–7/27	0.6657	0.4432	7/28–8/12	0.6836	0.4673	7/28–8/12	0.6936	0.4811
Potatoes	6/18–6/25	0.9036	0.8164	6/2–6/9	0.8400	0.7056	6/10–6/25	0.9094	0.8271	6/10–6/25	0.9214	0.8489
Rice	7/20–7/27	0.0582	0.0034	7/20–7/27	−0.014	0.0002	7/12–7/27	0.0104	0.0001	7/12–7/27	0.0919	0.0084
Sorghum	7/20–7/27	0.6928	0.4800	7/20–7/27	0.7712	0.5947	7/12–7/27	0.6871	0.4721	7/12–7/27	0.6251	0.3908
Soybeans	7/28–8/4	0.7470	0.5579	7/28–8/4	0.7420	0.5506	7/28–8/12	0.7487	0.5606	7/28–8/12	0.7887	0.6220
Sugarbeets	7/12–7/19	0.8063	0.6501	7/4–7/11	0.7493	0.5615	7/12–7/27	0.6648	0.4419	7/12–7/27	0.7180	0.5155
Wheat	6/2–6/9	0.7392	0.5464	6/10–6/17	0.6883	0.4737	5/25–6/9	0.7141	0.5100	5/25–6/9	0.7706	0.5938

having no correlation any time of year. Table 2 lists when and how high the peak correlation occurs for each of the MODIS products by crop in order to provide a concise quantitative summary. Table 2 also provides r-squared values in order to better compare these all positive relationships if to be used in a simple linear modeling sense. Furthermore, Fig. 6 shows the raw scatterplot with the linear regression overlaid at each of the peak correlation times to provide deeper visual insight into the relationships.

For the crops of corn, soybeans, and wheat the 250 m EVI appears to drive the highest correlation versus crop yield with resulting values around 0.8. These quite strong correlation coefficients for the EVI are visually reinforced in the scatterplots which indeed show

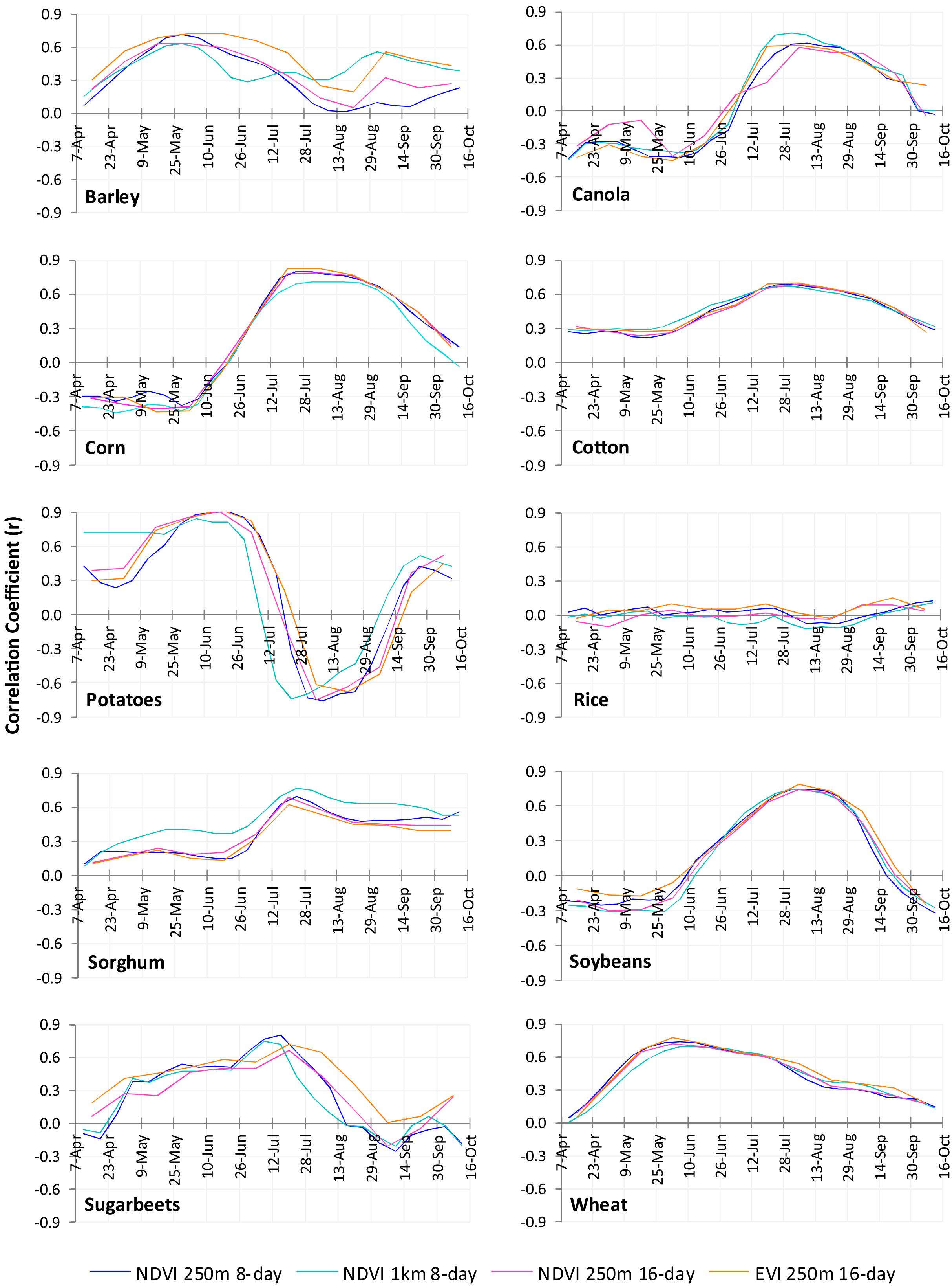

Fig. 5. Yield correlations through growing season of Terra NDI variants and EVI by crop type.

the relationships to be more linear in appearance than for any of the NDVI variations. Barley, cotton, and potatoes also show EVI to outperform, albeit modestly, anything NDVI related. In the case of cotton, the EVI clearly reduces the saturation that is evident in the NDVI scatters. Conversely however, for canola and sorghum it is the 1000 m NDVI that performs best while for sugarbeets it is the 250 m NDVI. For these three crops it is harder to find a discerning difference in pattern across the scatterplots, but they all do show

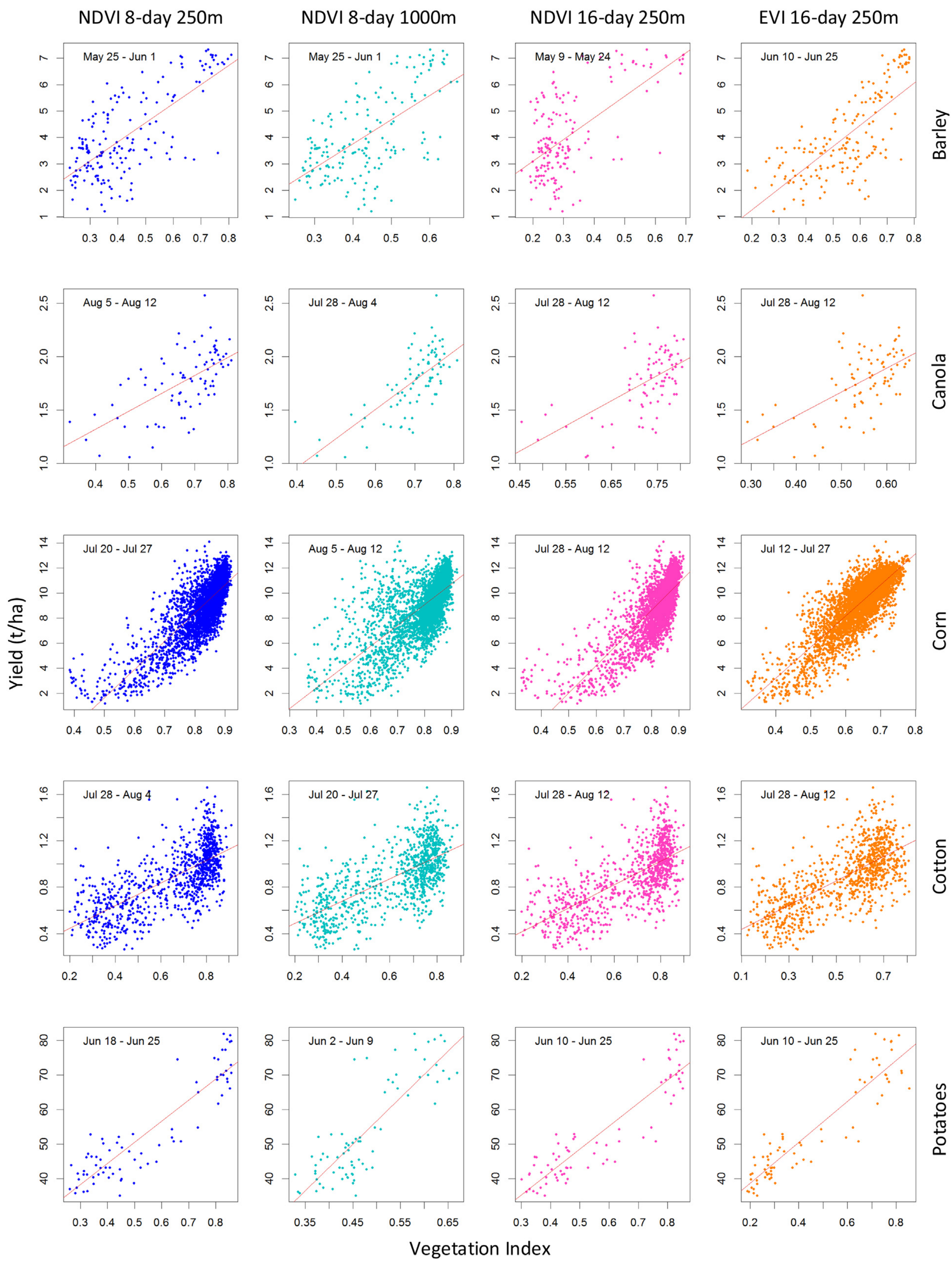

Fig. 6. Relationships of NDVI variants and EVI to yield at optiVmal time by crop type.

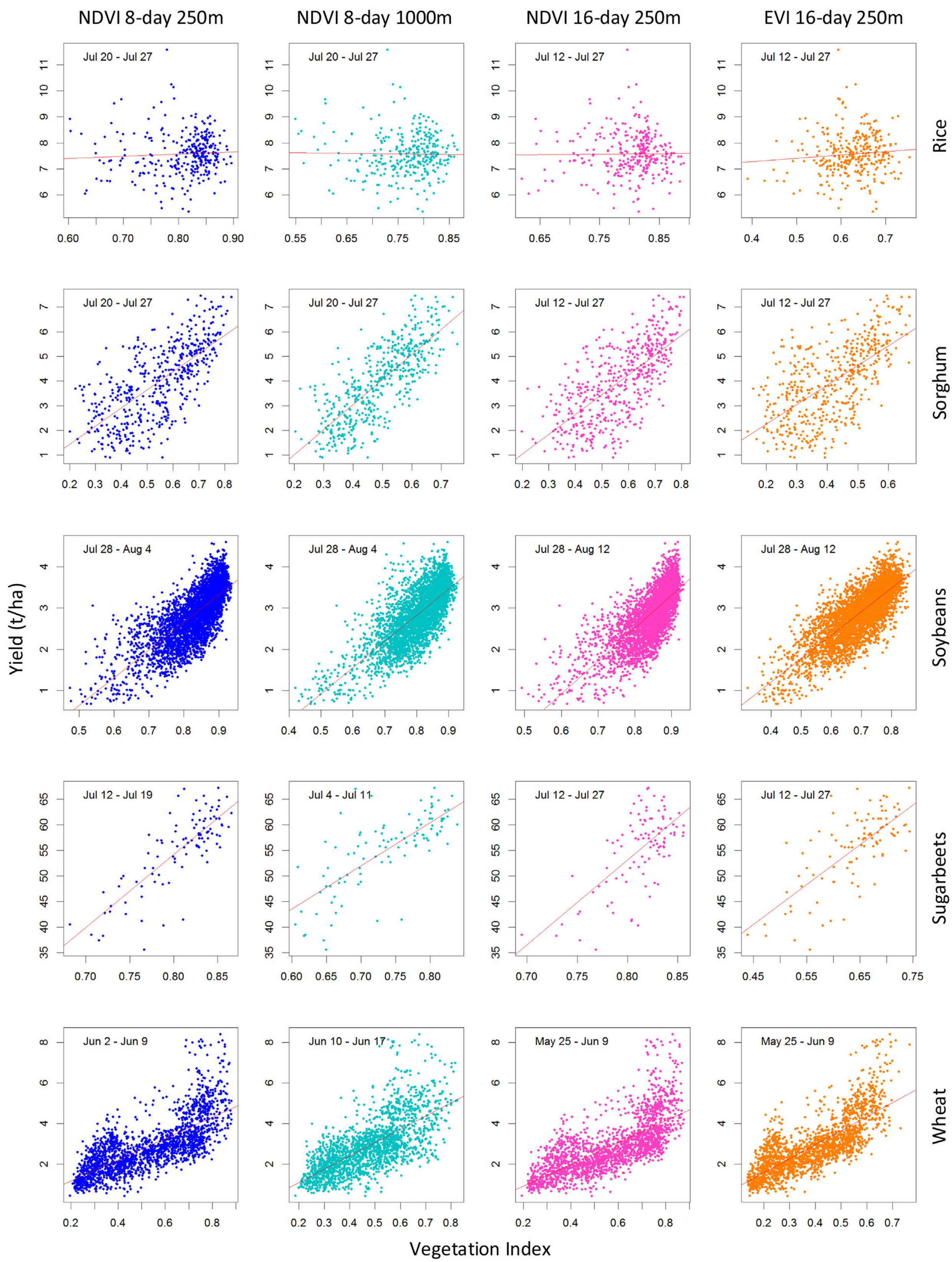

Fig. 6. (*Continued*)

at least some semblance of similar linear relationships supporting the statistics being away from zero. Rice, the final crop to mention, is still never providing a yield relationship and the random pattern of the scatterplots solidifies the results.

5. Discussion

The results provide some findings that are universal and others that are crop or data type specific. First and most general, there was little difference between the correlations as produced from Terra or Aqua. Not only was this consistence across all crops but also across all variables. It is useful and reassuring for a couple of reasons. First, if someone is utilizing Terra or Aqua MODIS data for crop yield estimation they can think of the data interchangeably which builds redundancy if one fails. Second, as future satellites are put into orbit they will not all have the same overpass time yet should be equally useful for yield monitoring. For example, land imaging satellites like Landsat have always been placed into a morning orbit to reduce increased afternoon cloud probabilities and that is unlikely to change with future missions. Conversely, satellites with sensors that have more atmospherically oriented missions, like the contemporary Visible Infrared Imaging Radiometer Suite (VIIRS), are likely to remain in an afternoon overpass type orbit. These results show it does not matter.

A second overall finding is that all of the vegetation parameters had at least some correlation with crop yields for all of the crops with the sole, albeit notable, exception of rice. Given that 9 of the 10 crops investigated showed correlations, it is likely that other annual crops would also display positive relationships regardless of the specific index used. NDVI, EVI, and FPAR competed for which was best and each could be argued most useful given a particular situation. Objectively however, EVI proved the very best overall in that it was the most correlated variable in five of the nine crops, excluding the outlier rice. Some may already have conviction about what parameter is best for their particular applications but the reality is they are all similar and each useful for crop yield monitoring and modeling situations. Better would be to choose the variable based which has the finest spatial resolution, which for MODIS means using the 250 m product of NDVI or EVI and not a 1000 m one such as is FPAR.

A third generalizable finding from this work was the complete lack of utility of MODIS NLST data in relating to crop yields. This reinforces what was found for corn and soybeans in previous research (Johnson, 2014) but expands to be shown consistent for any crop and from both the Terra and Aqua sensors (again, NLST being collected at 10:30 PM and 1:30 AM, respectively). There is some belief that high nighttime temperatures, particularly when occurring late in the diurnal cycle when things are typically coolest, are factors in limiting yields but this research does not support that. To be fair though, MODIS measures land surface temperature, and not the more commonly used air temperature, so the comparison is not direct. On the flip side, the MODIS DLST data is indeed related to yields for some crops and will be discussed crop specifically below. Perhaps most interesting, even though Aqua always acquires greater absolute DLST given its 1:30PM collection time allowing for three more hours of solar energy accumulation on the land compared to the 10:30 AM product from Terra, the yield relationships are quite similar.

Finally, there appeared to be little difference between yield relationships derived from the 8-day NDVI versus that of the 16-day product. None were necessarily expected but this should assure a user that one time-scale is not preferred over another. Given that 8-day can still often be compromised by cloud effects, and thus needs to be error checked more closely, the 16-day product might be preferable, particularly in a simple modeling scenario or when one can tolerate some added data latency.

A few caveats which could be confounding the comparison of results need to be included before concluding the broader discussion. First and foremost is the large variation in sample sizes between the crops. The 10 commodities were chosen given their relatively large footprint in the US but even so the degree between the largest (corn with 4067 samples) and the smallest (potatoes only 75) is pronounced. As a result it is natural to believe there is greater reliability to the results of the larger sample size crops like corn, soybeans, and wheat. And, this is suggestive in the charts because crops with larger sample counts appear to be smoother temporally.

Geography and year lack of independence could also be confounding some of the results. The county-level data in this study were combined both in space and time to boost the sample size, particularly for the lesser area crops, but could be causing bias in some situations. While a concerted effort was made to only use only geographically clustered counties in hopes of minimizing the heterogeneity of external environmental and anthropogenic factors, there are still known sharp spatial gradients such as irrigation/non-irrigation, soil types, planting/tilling practices etc. that could lead to different yield responses across the landscape. A more thorough analysis would include dissection of the results into smaller regions geographically or by year, but given the very large possible combinations of those variables it would be cumbersome so results capped at broad generalizations. However, ad hoc state- and year-level specific analysis was indeed undertaken when large enough sample size allowed usually showed the correlation results to be similar to, and in some cases better than, that overall.

Another confounding factor when comparing the results has to do with the possibility of land cover accuracy varying between counties that are not being captured in the state-level CDL accuracy metadata. This could be a function of crop type, region, or year. In general the CDLs are of high quality, particularly for corn, soybeans, and rice, and the masks derived from them for this work were purposely designed to be conservative to preserve only the purest of MODIS pixels. However, there may be some counties that did not have as clean of a time-series signal as hoped and thus marring the results.

A final consideration is the likely difference between the cover type purity of the pixels that were analyzed at 250 m versus those at 1000 m. Ideally, crop masks at 1000 m would have also been also developed to compliment those at 250 m, but very few areas can meet the basis constraint of having a 90% single cover type since the landscapes become more heterogeneous when upscaled. Thus, with 1000 m MODIS products one must grapple with signals that are at least partly a reflection of neighboring cover types. To better understand the type and percentage of pixel mixing occurring, adjacency averages were calculated from the multiple years of CDLs. Table 3 highlights those statistics for cover types that were neighboring at least 10 percent of the time. Grassland/pasture and low-density developed (which contains materials of roadways and additionally the herbaceous areas that often surround) are both commonly adjacent for many of the crops and thus one can expect it to be mixing in for much of the 1000 m analysis. However, those herbaceous areas are believed to be somewhat consistent and ubiquitous overall and thus likely just softening the overall time-series responses and yield relationships. Other cover type contrasts like alfalfa near potatoes or spring wheat near sugarbeets could be inferred to having increased impacts given their more differing plant structures and production practices. Ultimately, this caveat and those prior are not meant to undermine the conclusions but rather remind that some external factors may need to be considered when analyzing certain categories of the results. Detailed discussion by crop type follows.

5.1. Barley

The results show that NDVI, EVI, FPAR, and LAI could all be reasonably useful for barley yield estimation in late spring. While the sample size of 175 is relatively small, and thus could be of concern for drawing strong conclusions, the results are somewhat parallel to wheat, which is a similar crop type, and thus are reinforced. An interesting uniqueness to barley versus the other crops is a second rise in the correlations well after the season has ended. Reasons are unknown but could be hypothesized with the idea ver-

Table 3
Crop field adjacency statistics (10% and greater only) used to infer most likely pixel mixing scenarios when scaling from 250 m to 1000 m resolution.

	Adjacent land cover (%)
Barley	Spring wheat (33), Grassland/pasture (19), Winter wheat (10)
Canola	Spring wheat (25), Grassland/pasture (23), Low-density developed (13)
Corn	Grassland/pasture (27), Soybeans (25), Low-density developed (12)
Cotton	Grassland/pasture (15), Soybeans (15), Low-density developed (11)
Potatoes	Alfalfa (13), Grassland/pasture (13), Low-density developed (9)
Rice	Soybeans (37), Fallow/Idle (12)
Sorghum	Grassland/pasture (26), Winter wheat (12), Corn (12)
Soybeans	Corn (30), Grassland/pasture (23), Low-density developed (12)
Sugarbeets	Spring wheat (23), Soybeans (23), Low-density developed (19)
Wheat	Grassland/pasture (36), Idle/fallow (11), Low-density developed (10)

dant herbaceous cover appears in yield rich areas after harvest. It is not however believed to be due to cover type mixing because the similar crop of wheat is found adjacent abundantly. Finally, new knowledge gained is that MODIS DLST is not yield prediction helpful alongside the otherwise useful vegetative proxies.

5.2. Canola

The story for canola is similar to corn and soybeans both in terms of timing and amplitude of vegetation indices and surface temperatures. However, the sample size is nearly 20 times smaller so that aspect needs to be weighed before making any strong conclusions. Still it is believed that the results are likely valid, and are certainly reinforced again by similar research pertaining to the Canadian canola crop just north from the US (Chipanshi et al., 2015). The most compelling new information shown here from the canola work is the strong inverse relationship to DLST which is actually the best correlated variable of them all. In short, canola yields appear to be reduced by high heat.

5.3. Corn

The strong positive performance of NDVI and EVI, and to a slightly lesser extent FPAR and LAI, was expected and reinforces the large body of past research. Furthermore, the results for corn likely have the least degree of uncertainty based on the large sample size of 4067 and the homogenous nature of the crop across the Corn Belt. New knowledge gained from this study is the 0.2 drop in correlation going from a resolution of 250 m to 1000 m, alongside the peak timing shift being pushed back a couple of weeks to mid-August. Both factors should give pause to modeling scenarios that might be reliant on coarser data or where land cover masks are not as refined as they are in the US.

Why the 1000 m NDVI signal is softened and delayed is probably a result of mixing in of the signal from soybeans since in the US that is the most likely crop to be adjacent to corn. Bolstering this idea is the fact that soybeans are usually planted a couple of weeks later in than corn. This crop signal mixing is probably also a factor in creating lesser correlated results for FPAR and LAI. If those products were natively at 250 m it is thought they would match, or even better, the performance of NDVI and EVI. For variable use in modeling corn yields, EVI is probably the most compelling, particularly if being used in a simply linear fashion as its scatterplot does indeed appear straighter than that of NDVI. Else, if using NDVI a curved or piece-wise function is probably more prudent.

Also shown and reinforced from past work (Johnson, 2014) with the corn results is the reasonable utility of the DLST to predict yield. And while the absolute temperature profiles vary by satellite, the correlations are very similar so the data sources could be used interchangeably. This is new information and reassuring since current and future satellites are more likely to be in early afternoon collection orbits.

5.4. Cotton

The results for cotton are muted but believed solid nonetheless given the large, contiguous, and environmentally uniform area for which the crop spans across the southern US. All the vegetation indices show to be worthwhile through the season and come to a peak in late July. To be noted, however, from the scatterplots is the saturation at high values, even with EVI. This could make modeling efforts of cotton difficult in high yielding scenarios. The DLST signal shows a very mild inverse signal throughout the entire season but unlikely ever strong enough to add much useful information to a yield model. Unfortunately, there has been little other cotton research in which to help back or refute the findings here .

5.5. Potatoes

Results for potatoes are interesting and the most potentially confounded. Most notable is the fairly strong inverse relationships to the NDVI, EVI, FPAR, and LAI mid to late summer after being strongly positive earlier in the season. This is most true for NDVI which in itself is unique because lags in time, compared to say FPAR, during the positive to negative transition period. Explaining this rapid swing from positive to negative correlation could be the appearance of the scatterplot being not so much linear throughout but rather a clustering of points on the high and low ends. This look, which can amplify erroneous correlations, could have been from chance occurrence due to the low sample size of 75. Investigation through stratification thought showed it did not relate to a particular state. In response it was attempted to increase the samples by adding data from the next most significant potato states of Colorado, North Dakota, and Wisconsin. However, these states had very few county-level data points possible to add, and they would have been questionable for use anyway since from different growing regimes.

In terms of the land surface temperature, the results are also unique and perhaps somewhat suspect. NLST is uniquely always positively correlated regardless of seasonality suggesting warm temperature throughout are helpful for potato yields, but given its constant positive value it is also suggestive of bias. DLST, however, changes fairly smoothly through the growing season by going from no correlation, to that of positive, and then back to none again. It appears from DLST that warm summer temperatures help the crop but at other times it is insignificant.

Land cover mixing of the potato signal could be seeping through and skewing the results, but CDL accuracies for the category are actually quite good and thus those types of problems, at least with the 250 m NDVI and EVI should be minimal. Interestingly however, the 1000 m NDVI analysis does move in concert with the relationships of the other 1000 m products so cover type pixel blending is probably an issue at that scale. Crop mixing, when it does occur, is most likely to be with alfalfa which is a much different type of crop compared to potatoes. It is not sure how this crops' phenology would interplay, since not isolated in this work, but it assumed it is managed as an annual crop and as a result vegetation cover would be present all year long. Thus, it would be adding to any of the potato vegetation proxies before and after the potato growing season.

In the end, the results for potatoes should be interpreted cautiously and left to the reader to decide the utility. It is believed that the results are telling at least partial truth, particularly based on the clarity of all the other crops studied. However, more so than for any other crop here, an increased number of data points are likely needed to solidify the results.

5.6. Rice

Rice is the outlier investigated here since it showed no correlations to yields regardless of MODIS dataset. This is informative is at odds since all the other crops showed relationships and so at least some was expected for rice as well. More disconcerting in the lack of yield relationship is the contrarian aspect compared to research by others (Son et al., 2014; Peng et al., 2014). It is ultimately not known why the correlation results were nonexistent here but could have something to do with uniqueness to the local environment or the particularly heavily managed irrigation cropping practices in the Mississippi River alluvial plain for where US rice is so intensively produced. The irrigation could be nullifying the results knowing that indices like NDVI often are biased low in damp or flooded environments even if there is a decently sized plant canopy. Yet perplexingly, the observed rice vegetation profiles for all the vegetation products tested seemed quite verdant so it would seem at least some yield relationship would show through.

It should be also be noted that rice statistics within the US do not change much year to year thus there is less relatively variability to work with in those yields compared to the other crops. More pointedly, the coefficient of variation of the total rice yield samples is only 0.11 but for all the other crops is at least 0.17. What is not believed to be an issue though is the locational accuracy of the rice fields since the CDL accuracies are very high for that category. Regardless, the rice results show no ability to perform yield modeling in the US but are only taken as a cautionary tale in other parts of the world.

5.7. Sorghum

All vegetation indices show reasonable performance mid-season for sorghum which is promising for monitoring efforts. However, the sorghum results are interesting compared to the other crops because the 1000 m products, particularly for NDVI, tended to outperform the 250 m ones. Why this is happening is unclear but it is worth looking at the land covers adjacent to assess what crops are grown in concert with sorghum to help understand what else may be mixing into the signal. Ultimately, corn and wheat are the most common crops found in conjunction. So, it appears that those areas when embedded in sorghum actually improve the correlation results.

However, the temperature data for sorghum is unlike that of corn meaning there is no inverse relationship mid-summer. Prior to the season though there is indeed a relatively strong inverse relationship of DLST to yields. So, those cooler areas early seem to be a predictor for better sorghum yields later on. Reasons for this are hard to speculate, but early in the year the most likely crop mixed in based on the CDL with sorghum is wheat. Thus, wheat is also probably creeping into the early season sorghum signal as marked by the subtle correlation increase for the vegetation indices in May.

5.8. Soybeans

The soybean results are similar to corn, but to a slightly lesser degree, in terms of NDVI, EVI, FPAR, and LAI with them all showing positive predictive utility mid-season. This is backed by the past research as well. Also, like for corn, soybeans tend to appear saturated with NDVI whereas EVI creates a relationship that looks more linear. So, EVI is probably the best vegetation variable to use particularly if a simply linear model is being used. DLST is, again like for corn, is a negative predictor mid-season.

5.9. Sugarbeets

Correlations for sugarbeets are the noisiest looking overall and probably a testament to its small sample size of only 101. However, there is still a marked peaking mid-summer with the 250 m products performing best. Surface temperatures on the other hand never look useful. The results for sugarbeets suggest MODIS can indeed be used to predict it's yields, but there is little to no other research to confirm or deny so this should be used cautiously as a first reference point.

5.10. Wheat

The wheat results are generally easy to interpret and show reasonable positive correlations to all of the vegetation indices in late May. This conforms to the time of highest biomass the transition from vegetative stage to that of grain filling. These results also confirm what has been provided in the literature. New here though is the showing of the increased helpfulness of the 250 m data versus that of 1000 m. In these wheat areas the generated crop masks are likely being compromised by land cover mixing, most commonly with fallow barren fields, with the coarser resolution data having a softer signal which in turn decreases the positivity of the correlations. The scatterplots are interesting because they show the general linear trend but also highlight a saturation effect occurring in all scenarios. The plots additionally reveal a more scattered appearance in the lower values.

Surface temperatures are curious for wheat. DLST shows a reasonably strong inverse relationship early on and through June and then it decreases somewhat afterwards. NLST is similar to the post-season DLST values throughout. Because these values are relatively stable with little change throughout it suggests a confounding factor, like the wide geographic spread of wheat is in play.

In terms of controlling for the broad spatial range of wheat, there was effort put into stratifying and presenting the crop as more concise geographical regions or states to determine if there were potential differences. The simplest scenario, and that described here, involved splitting the data into three reasonably homogenous regions of the Southern Plains, Northwest, and Corn Belt. It was found that the Southern Plains (with 1389 samples) and Northwest (353 samples) were fairly similar in yield correlation appearance with the exception of the peak being a month later in the Northwest region versus the Southern Plains. That is consistent with the later maturing crop of the Northwest. For the Corn Belt region the vegetation index results ended up being very noisy and with no clear yield relationship to the MODIS data except mild response for the 250 m NDVI and EVI. The Corn Belt's sample size was only 146 however so it was likely more sensitive to noise. In terms of surface temperatures, neither the Northwest nor the Corn Belt showed any correlations, and the Southern Plains simply mimicked the full US results. So in conclusion, while wheat is found across much of the US and there is some variation, the full results here primarily reflect the majority of the crop which is centered in the Southern Plains.

6. Conclusions

The overarching purpose of this work is to provide well-rounded and objective guidance in deciding what remotely-sensed composited imagery datasets collected by MODIS, or potentially similar platforms, are truly useful for estimating crop yields. The inclusion here of many field crops beyond the previous research of primarily corn, soybean, and wheat expands the knowledge base. NDVI was used as a benchmark of sorts since much of the past research has used it. NASS county-level average yield data, which is considered of high quality and likely surpasses anything else found in the world in terms of robustness and breadth, were used a solid foundation to generate the results.

The conclusions can be generalized and are fairly straightforward to summarize. In terms of the vegetation indices inspected, NDVI showed to be consistently very good, albeit not always the best, in performance for all of crops (excluding rice which is summarized singularly below). This consistent NDVI finding is reassuring because much past research has promoted it and some people are indeed using it operationally (including by this author) as an input into crop yield models. FPAR is nearly as good or comparable to NDVI even considering it is probably hindered by its natively coarser pixel size (1000 m vs. 250 m). If the analysis being undertaken does not rely on finer scaled data then FPAR could be considered. Perhaps the best performer of the bunch though is EVI. It was shown most compelling for corn, soybeans, and wheat, given its most linear relationship to yields. And, unlike MODIS FPAR the EVI product is disseminated at 250 m instead of 1000 m so has much improved spatial resolution. However, there is a potential cost of using EVI operationally since it is only being provided at 16-day versus 8-day time steps which could bring a latency issue to those in a real-time monitoring environment. Finally, LAI and GPP were never consistently found to match or exceed the utility of the other indices so their use is not recommended in any situation.

In terms of seasonal timing, the optimal period for any of the vegetation indices tended to fall at the mid-point of the growing season which also coincided with when the vegetation was peaking. This was expected given plant physiologically of that point in the season of highest biomass and at the transitional point to the reproductive stage where plants are known to be putting energy into creating seed. But, it is reassuring to see it borne out here empirically for a variety of crop types and reinforcing what past research has shown. And, while there was found to be an optimal time for each of the indices, it is not to say the before or after periods are not useful. This is particularly the case if trying to estimate yield early in the season for which the peak point has not yet transpired yet there may already be enough information to drive a reasonable yield forecast model. EVI for corn, soybeans, and wheat shows an advantage in timing in that the correlation peaks a period or two early than for the other indices.

Differences in the results from the MODIS 10:30 AM overpass time data of Terra versus to that of the 1:30 PM of Aqua were quite small. This was both true in terms of the direct observations values themselves and how those measures correlated to yields. This is reassuring for several reasons including: (1) data interchangeability if one wants to integrate information from both sensors, (2) redundancy when one the MODIS platform fails, and (3) likely consistency with the future MODIS-like mission of VIIRS which are always slated for afternoon orbit. There has been concern that afternoon data for land monitoring data is compromised versus that of morning but for crop yield monitoring activities this appears to not to be the case.

Regarding the utility of land surface temperature, some of the cases indeed showed relationships to crop yields, albeit inversely related. Those relationships were never as strong as for the vegetative information though. DLST should certainly be considered for canola, corn, and soybeans and perhaps for sorghum and wheat too. The response from Aqua was somewhat stronger, and thus likely preferred, but Terra data could be used if needed. Nighttime temperatures were never found to be helpful regardless if from Terra or Aqua, and irrespective of crop type.

Finally, rice was the outlier crop since no relationships to yield was ever found. This was true regardless of the MODIS vegetation or temperature data used, whether the information was from the Terra or Aqua satellite, and for any time within the growing season. This finding contradicts previous research, granted which is limited, but in the context of this entire body of work presented here for the US is hard to refute. Further studies using optical data for yield estimation of rice, in the US or otherwise, should be welcomed, particularly since it is such a globally important crop.

Acknowledgments

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