Assessing Gross Primary Productivity of Cropland – an Index Perspective

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ABSTRACT

One critical tool used to monitor vegetation dynamics is the spectral vegetation index. Among many options, the Normalized Difference Vegetation Index (NDVI) has long been the most popular choice. However, numerous studies have suggested that NDVI becomes insensitive, or saturated, to growth of vegetation when biomass is dense. Here, with reflectance data collected in 2018 from an alfalfa and a corn field located in the Sacramento-San Joaquin River Delta, I examined the sensitivity of two alternatives: The Wide Dynamic Range Vegetation Index (WDRVI) and Enhanced Vegetation Index (EVI). I compared with sensitivity of each index to plant growth indicated by gross primary productivity (GPP). I found that WDRVI was more sensitive to growth once NDVI reached 0.4 in the corn site. For alfalfa, WDRVI was almost always at least as sensitive as NDVI throughout 2018. EVI, on the other hand, exhibited no improvements for alfalfa. Based on these results, WDRVI is a superior index because it does not become as saturated as NDVI at high biomass density. These findings are critical to further the use of vegetation index as a cost-effective way to estimate GPP of similar sites and even GPP on the global scale.

KEYWORDS

vegetation index, alfalfa, corn, saturation, GPP, NDVI, WDRVI, EVI

INTRODUCTION

One of the tools for assessing vegetation attributes such as distribution, biomass and phenology is vegetation index (VI) derived from spectral reflectance. Among many indices proposed throughout the years, Normalized Difference Vegetation Index (NDVI) is used most widely. NDVI can be derived from amounts of near-infrared (NIR) and red lights reflected by vegetation because chlorophyll absorbs red while the mesophyll leaf structure scatters NIR (Pettorelli et al. 2005).

Based on empirical results in natural non-stressed vegetation, NDVI yields consistent relationships with canopy structure and photosynthetic fluxes (Gamon et al. 1995). This relationship allows for monitoring spatial and temporal distribution of vegetation at various scales, differentiating vegetation types, estimating crop growth and assessing deforestation. Despite its extensive use, one critical issue with NDVI is saturation; NDVI becomes insensitive to growth in vegetation once the biomass reaches a certain density (Huete et al. 2002).

The saturation effect of NDVI leads to undesired consequences for monitoring vegetation dynamics (Gitelson 2004). For example, the degree of saturation largely depends on the spatial scale. This means that NDVI at different scales are not comparable, preventing the compilation of a global picture of NDVI as availability of datasets is not consistent in terms of spatial and temporal scales. To address the effects of the saturation effect, researchers have been investigating the possibility of adjusting existing definition of NDVI (J. O. Payero et al. 2004).

Gitelson (2004) introduced the Wide Dynamic Range Vegetation Index (WDRVI), a modified version of NDVI that includes a weighting factor for the NIR. According to Gitelson, this index is shown to be at least three times as sensitive to vegetation dynamics than NDVI. In addition to WDRVI, the Enhanced Vegetation Index (EVI), which also uses an additional blue waveband, has been reported to remain sensitive to vegetation growth throughout the growing season (Huete et al. 2002). Although various studies have shown EVI and WDRVI exhibit greater sensitivity, few studies have attempted to specifically compare the performance of these two indices with NDVI for assessing growth of croplands, a significant sector of carbon dynamics both globally and locally in California.

To fill this knowledge gap, I aimed to show if there is an improvement in WDRVI or EVI compared with NDVI for assessing growth of corn and alfalfa and how great the improvement is.

In this study, I used gross primary productivity (GPP) as an indicator of growth. Specifically, I explored these questions: 1) is reflectance-based vegetation index is an appropriate tool for estimating growth of corn and alfalfa in Northern California? 2) which vegetation index remains sensitive to growth and produces the strongest linear relationship with vegetation growth? 3) is there temporal variation in the performance of VIs in estimating growth. I hypothesized that WDRVI and EVI would generally produce stronger linear relationship with the growth of corn and alfalfa compared to NDVI in both study sites, but likely only for some parts of the year.

METHODS

Study site

The study sites of alfalfa (*Medicago sativa*, L.) and corn (*Zea mays*) fields are located on Bouldin Island in the Sacramento-San Joaquin River Delta, California, USA. The climate is typically Mediterranean with warm, dry summers and cool, wet winters. Alfalfa is perennial and mowed six times a year in the site. For corn, the growing season usually starts in June and ends in October (Knox et al. 2015).

Data collection

I collected spectral reflectance data for the entire year of 2018 with cost-effective sensors produced by Decagon Devices. The sensor measures spectral reflectance in the red and NIR wavebands, which are required for calculating the NDVI and WDRVI. To measure reflectance in blue waveband, which is required for deriving EVI, I deployed two sets of a recently developed meteorology system manufactured by Arable Labs. The Arable system is a solar-powered compact device that is capable of collecting various types of data, including spectral reflectance of blue, red and NIR. The system allows for real-time accessibility to the data collection via its cloud-based platform. The Arable systems were not installed until June and the Decagon sensors have been deployed to the study sites multiple years prior to this study. Besides reflectance measurements, I acquired estimates of GPP from flux towers that are part of the Ameriflux network. The towers are managed by the Biometeorology Lab of the University of California, Berkeley. Details about the tower setup for a similar neighboring site are reported in Knox et al. (2014). All of the above sensors except the Arable make continuous reflectance measurements and generate one measurement every 30 minutes. Arable is designed to make one measurement every 60 minutes.

Vegetation Indices

With reflectance measurements, I derived NDVI, WDRVI and EVI using the following equations:

$$NDVI = (\rho NIR - \rho red) / (\rho NIR + \rho red)$$

$$WDRVI = (a * \rho NIR - \rho red) / (a * \rho NIR + \rho red)$$

$$EVI = G * (\rho NIR - \rho red) / (\rho NIR + C1 * \rho red - C2 * \rho blue + L)$$

where ρNIR, ρred and ρblue stand for reflectance in near infrared, red and blue wavelength respectively. The *a* in the equation of WDRVI is a weighting factor to NIR in order to adjust for saturation effect. Typically, 0.2 is an appropriate value for *a* (Gitelson 2004). For EVI, L is the canopy background adjustment and C1, C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band. The commonly adopted values are L = 1, C1 =6, C2 = 7.5, and G (gain factor) = 2.5 (Huete et al. 2002).

Data analysis

Effect of the solar elevation angle on NDVI

Spectral reflectance could be potentially confounded by solar elevation angle (SEA). Sims et al. (2006) showed the NDVI is largely affected by SEA, which explains as much as 40% of the variation in NDVI according to the study even if there is no change in greenness. Ryu et al. (2010) attributed the dependence of NDVI on SEA to the land surface heterogeneity of the study site. Considering this possible effect, I evaluated its magnitude in my study sites by plotting daytime NDVI from five randomly selected days with respect to time in hour and looked for daily variations.

Comparing data from Decagon and Arable

I visually examined the time series of NDVI and EVI collected by both reflectance sensors and GPP estimates from the flux tower by looking for any irregularities that could indicate instrument malfunction. I removed data points only captured by one time series.

Comparing sensitivities of VIs to GPP

To compare the sensitivities of vegetation indices to daily GPP, I first conducted a linear regression analysis to see possible improvement in the strength of linearity represented by the correlation coefficients. Sensitivities were also compared quantitatively using an analysis with the following equation:

$$\mathrm{SR} = (dVI_1/dVI_2) \times (\Delta \mathrm{VI}_2/\Delta VI_1)$$

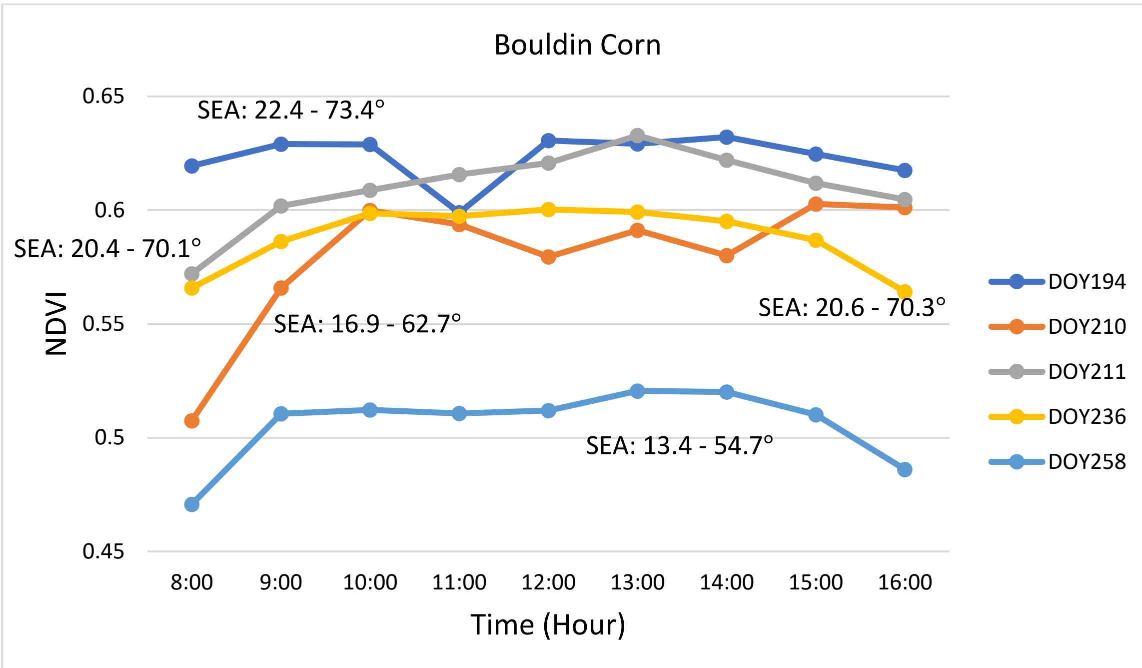
where $d\mathrm{VI}_1$ and dVI_2 are the first derivatives of the indices with respect to GPP and $\Delta\mathrm{VI}_1$ and $\Delta\mathrm{VI}_2$ are the range of each index. SR, which refers to relative sensitivity, is a value that represents sensitivity of VI_1 relative to that of VI_2. When SR < 1, it indicates that VI_1 is more sensitive to GPP than VI_2. Values of SR > 1 indicates VI_2 is more sensitive to GPP than VI_1. The sensitivity analysis also allowed me to see how relative sensitivity between two VIs varied over time (Gitelson 2004).

RESULTS & DISCUSSION

Effect of the solar elevation angle on NDVI

In both study sites, I found that NDVI showed very small diurnal variation. Despite variation over 50° in SEA during the course of some of the five randomly selected days, the maximum variation in NDVI was around 0.1 for corn and 0.06 for alfalfa (Figure 1). In contrast to Sims (2006), the effect of the SEA on NDVI was negligible. Yet this finding is in line with the presumption made by a previous study which asserted the surface heterogeneity of vegetation would explain the way NDVI responds to changes in SEA (Ryu et al. 2010). As the study sites were almost fully covered by vegetations, the surface was largely homogenous, suggesting that the use of VIs does not depend on SEA and is appropriate for use in the study sites.

(a)



(b)

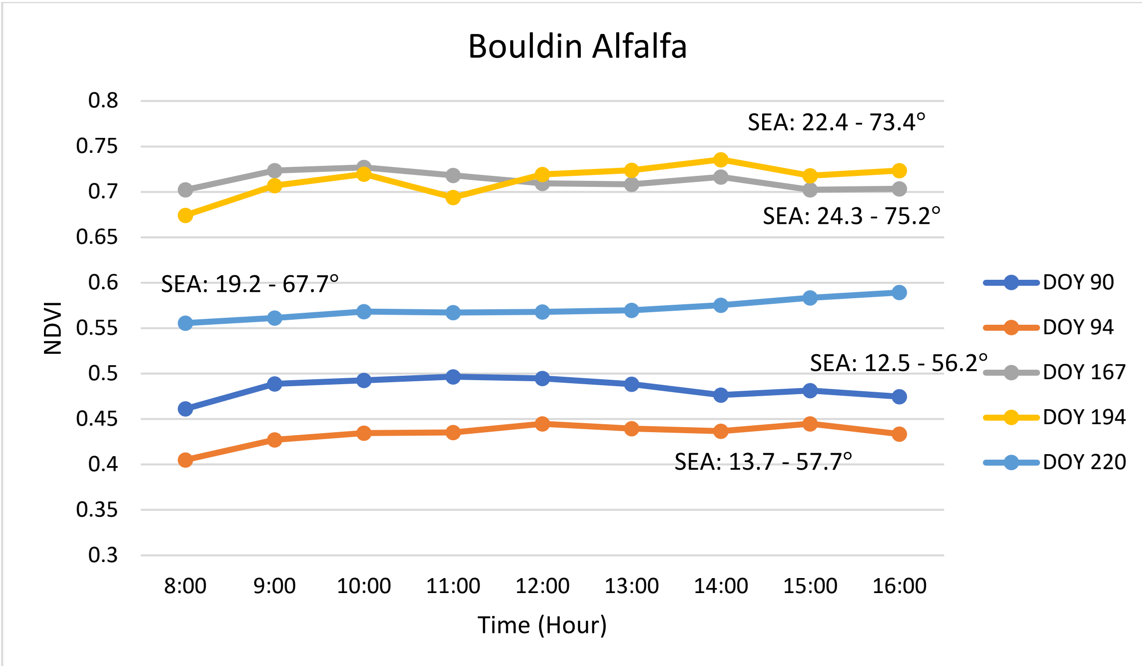
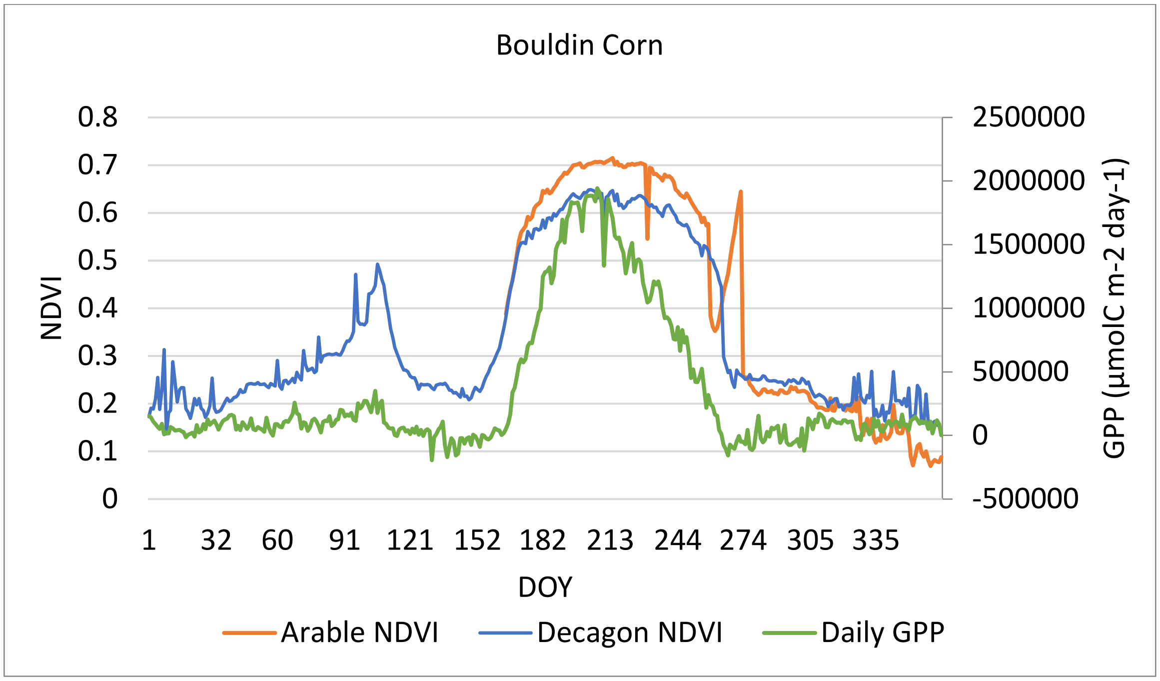


Figure 1. Hourly NDVI of five randomly selected days at the (a) corn and (b) alfalfa sites.

Irregularities in NDVI time series

I found that NDVI from Decagon and Arable sensors both captured the overall trend of GPP in both study sites. For the corn site, there are three major discrepancies between the two sensors. First, it appears that the numerical values of NDVI from Arable are higher than Decagon by up to 0.1 especially when given high level of GPP (Figure 2a). This is a possible result of mechanistic differences in the sensors' design and might play a role in the sensitivity of VIs. This difference also applies to the two indices for the alfalfa site (Figure 2b). Also, there was a sudden spike in the NDVI from Arable from DOY 262 to 273 in the corn site (Figure 2a). The spike was possibly a result of scratches found on the plastic cover of the Arable sensor. The scratches might have interfered with Arable's reflectance measurements from DOY 262 to 273 as the spike did not occur in neither GPP or the NDVI from Decagon. Interestingly, around the same time of the year a similar spike also showed in the NDVI of the alfalfa. In addition, Arable NDVI showed a sudden drop on DOY 230 but it was not shown by GPP and Decagon NDVI (Figure 2b). The cause of this drop is unknown. Including these rather obvious irregularities, there are multiple less noticeable deviations in the trend of Arable NDVI from that of GPP and Decagon NDVI. I removed these data points alongside invalid measurements from the dataset in order to conduct subsequent analyses. I applied the same procedures were applied to WDRVI and EVI.

(a)



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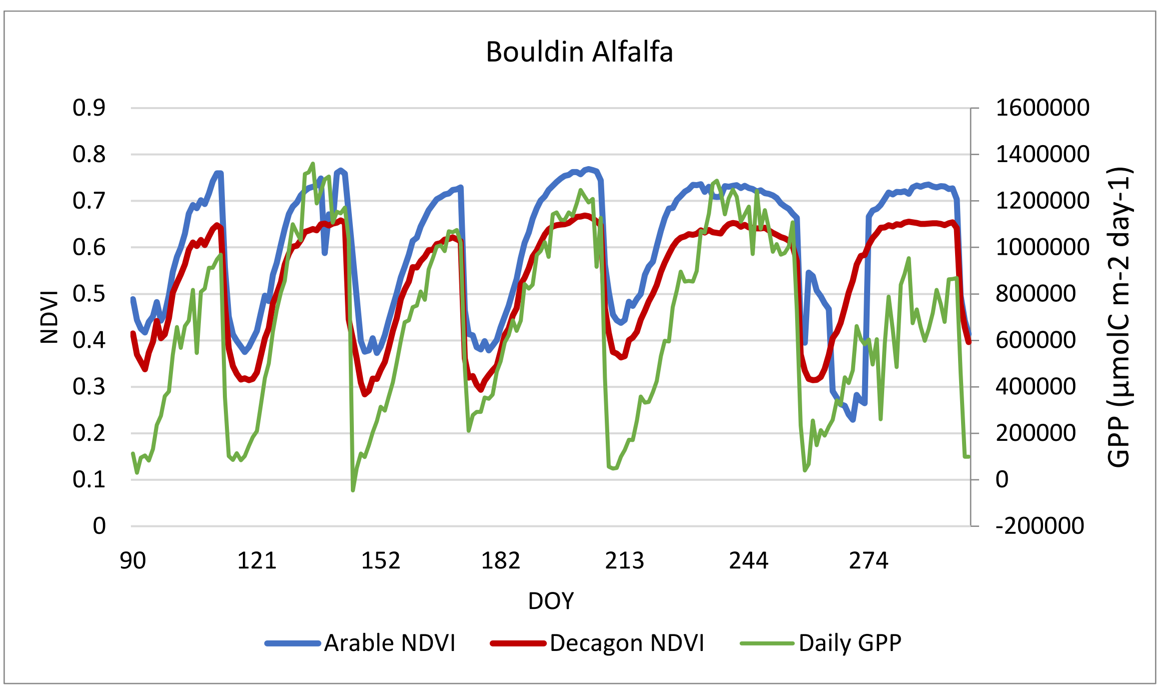
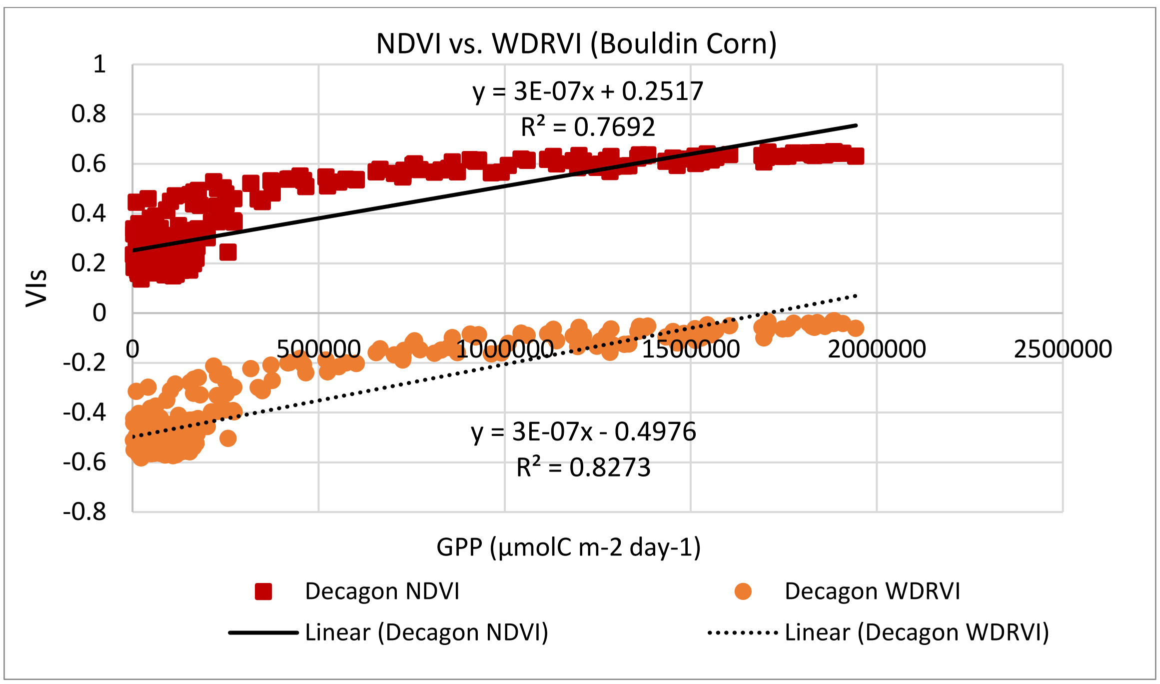


Figure 2. Time series of Decagon NDVI, Arable NDVI and daily GPP at the (a) corn and (b) alfalfa site.

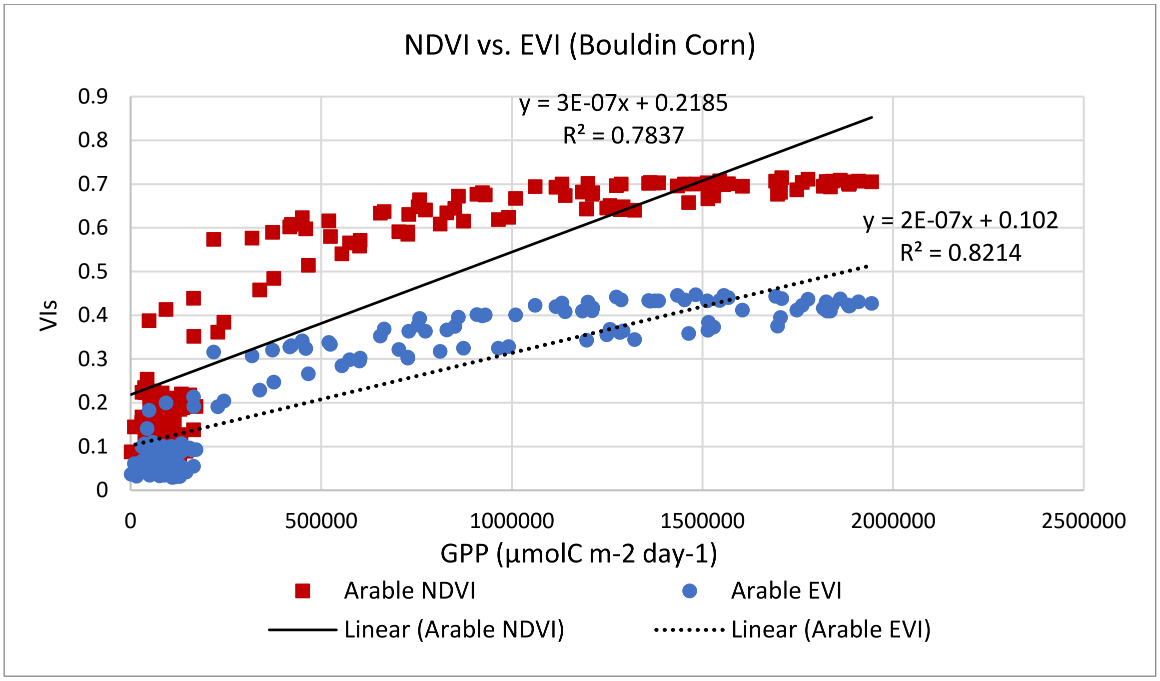
Comparing sensitivities of VIs to GPP

WDRVI exhibited less saturation than NDVI for corn and alfalfa whereas EVI was less saturated than NDVI only for corn (Figure 3). To compare the performance between each VI, I first examined the scatter plots between VIs and GPP and found that saturation was visually less pronounced for WDRVI (Figure 3a) and EVI (Figure 3b) compared to NDVI in the corn site. Linear correlation was slightly stronger as the correlation coefficient increased from 0.77 to 0.83 for WDRVI and 0.78 to 0.82 for EVI. In the meantime, the improvement by WDRVI was insignificant in the alfalfa site (Figure 3c) and EVI made the relationship even less linear (Figure 3d).

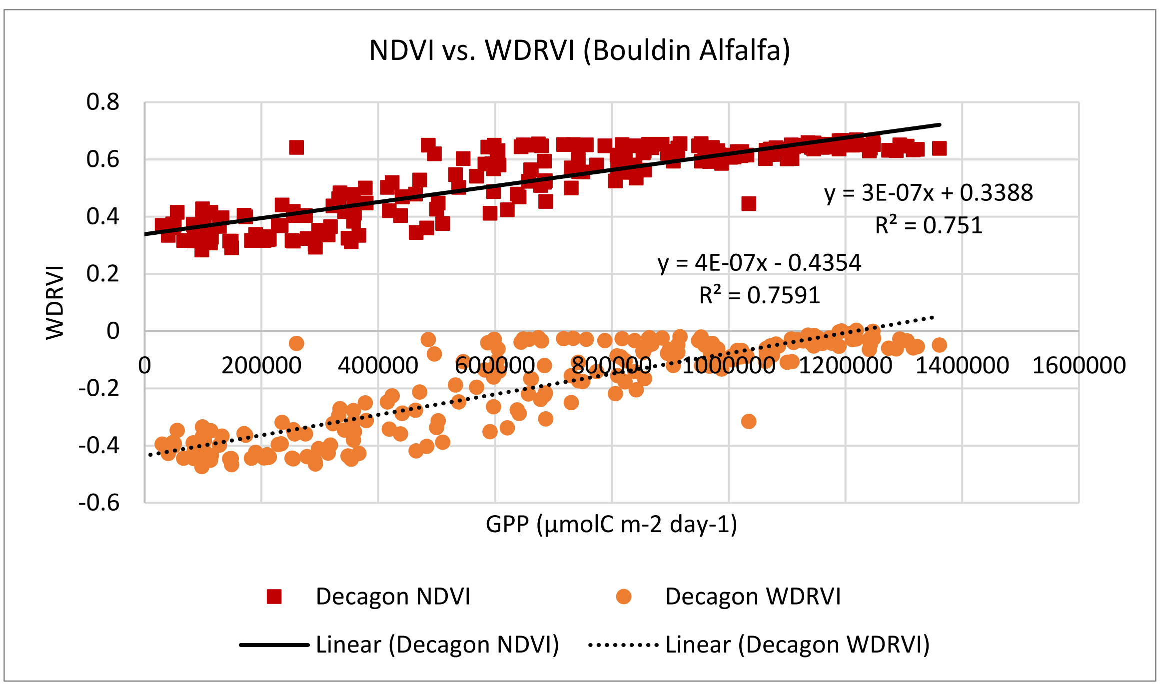
(a)



(b)


NDVI vs. EVI (Bouldin Corn)
y = 3E-07x + 0.2185
R² = 0.7837
y = 2E-07x + 0.102
R² = 0.8214
VIs
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
500000
1000000
1500000
2000000
2500000
GPP (µmolC m-2 day-1)
Arable NDVI
Arable EVI
Linear (Arable NDVI)
Linear (Arable EVI)

(c)


NDVI vs. WDRVI (Bouldin Alfalfa)
y = 3E-07x + 0.3388
R² = 0.751
y = 4E-07x - 0.4354
R² = 0.7591
WDRVI
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
0
200000
400000
600000
800000
1000000
1200000
1400000
1600000
GPP (µmolC m-2 day-1)
Decagon NDVI
Decagon WDRVI
Linear (Decagon NDVI)
Linear (Decagon WDRVI)

(d)

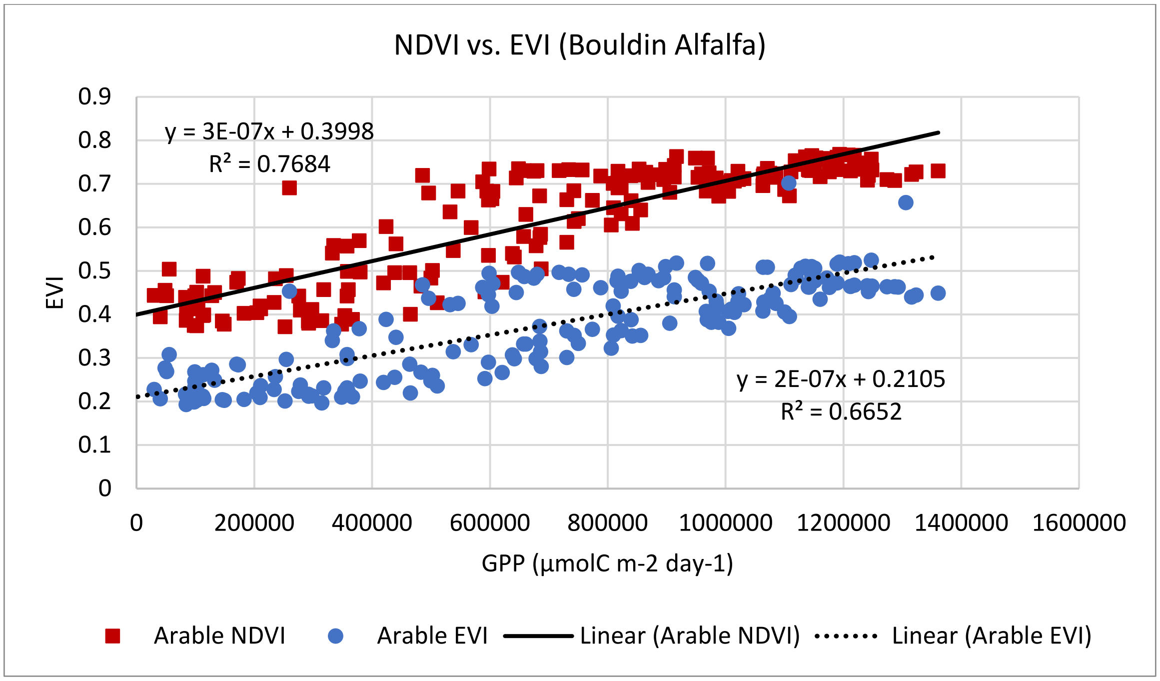
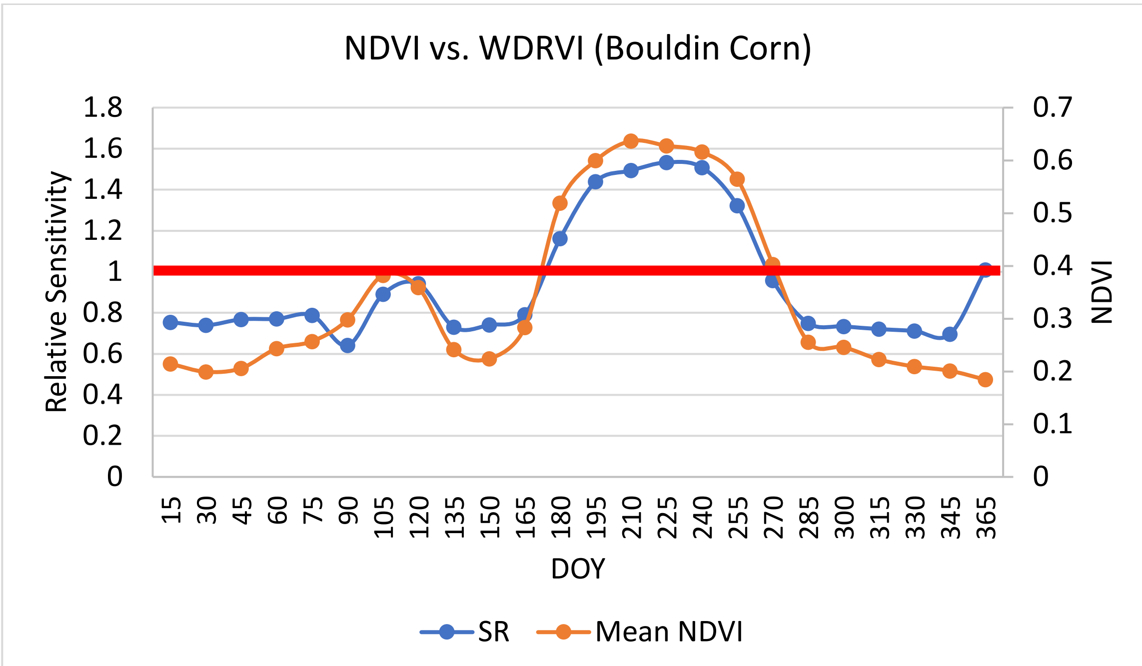


Figure 3. Scatter plots between VIs and GPP. The line of best fit correlation coefficient for each VI and GPP are displayed on the plots.

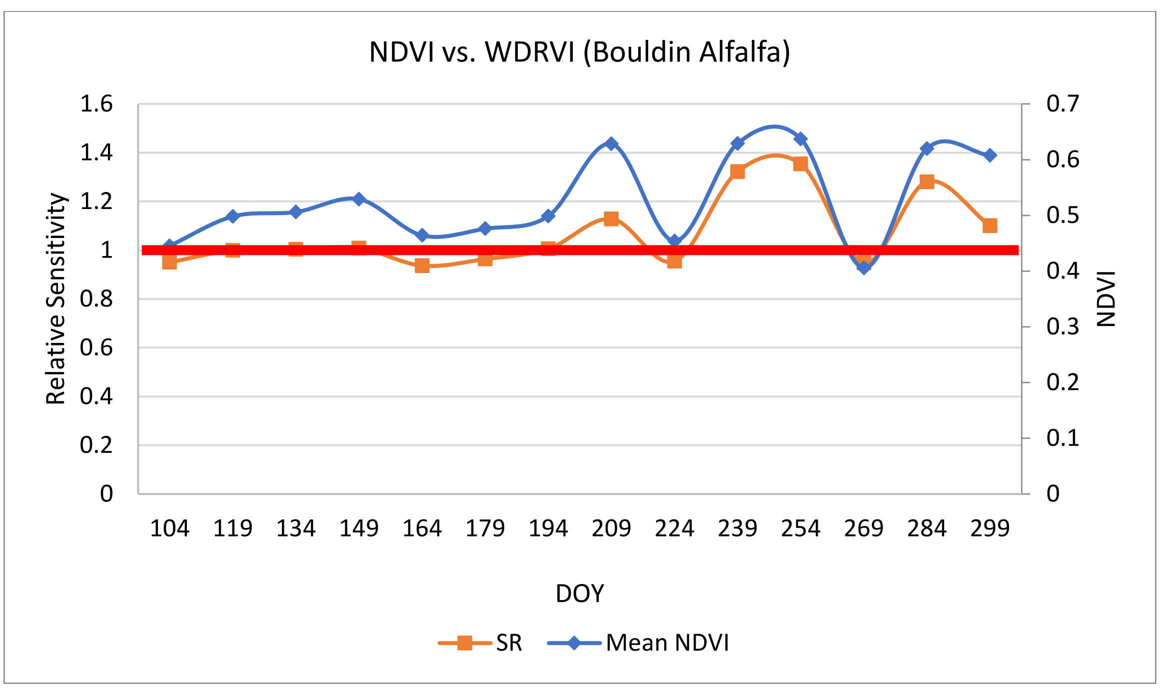
To compare the sensitivities of WDRVI, EVI and NDVI to GPP and analyze the temporal variations of improvements, I conducted a sensitivity analysis with the data. WDRVI displayed greater sensitivity to GPP of corn for some portion of the year. Specifically, once NDVI reached 0.4 around DOY 180, WDRVI remained less subject to saturation until NDVI decreased to 0.4 around DOY 285 (Figure 4a). NDVI at 0.4 approximately corresponded to daily GPP at 9 moles of carbon per square meter. This suggests that WDRIV is a better choice for estimating GPP of corn during the majority of the growing season. For alfalfa, the improvement in sensitivity between WDRVI and NDVI was more consistent but less significant. Except about one month of the growing season, the value of SR was greater than or close to 1, indicating the sensitivities of the two indices were comparable to GPP in the alfalfa site for most of the time (Figure 4b). Nonetheless, the consistent performance shown by WDRVI still makes it a preferable choice for characterizing corn and alfalfa, or possibly croplands in general (Viña et al. 2004). However, contrary to many studies that claimed EVI remained sensitive for dense biomass (Huete et al. 2002b), EVI was continuously insensitive to GPP of alfalfa than NDVI for the growing season

(Figure 4c). This could be explained by the fact that EVI was designed to optimize satellite-derived indices by correcting the effects of atmosphere on spectral reflectance (Testa et al. 2018), and in-situ measurements may be less prone to those effects.

(a)



(b)



(c)

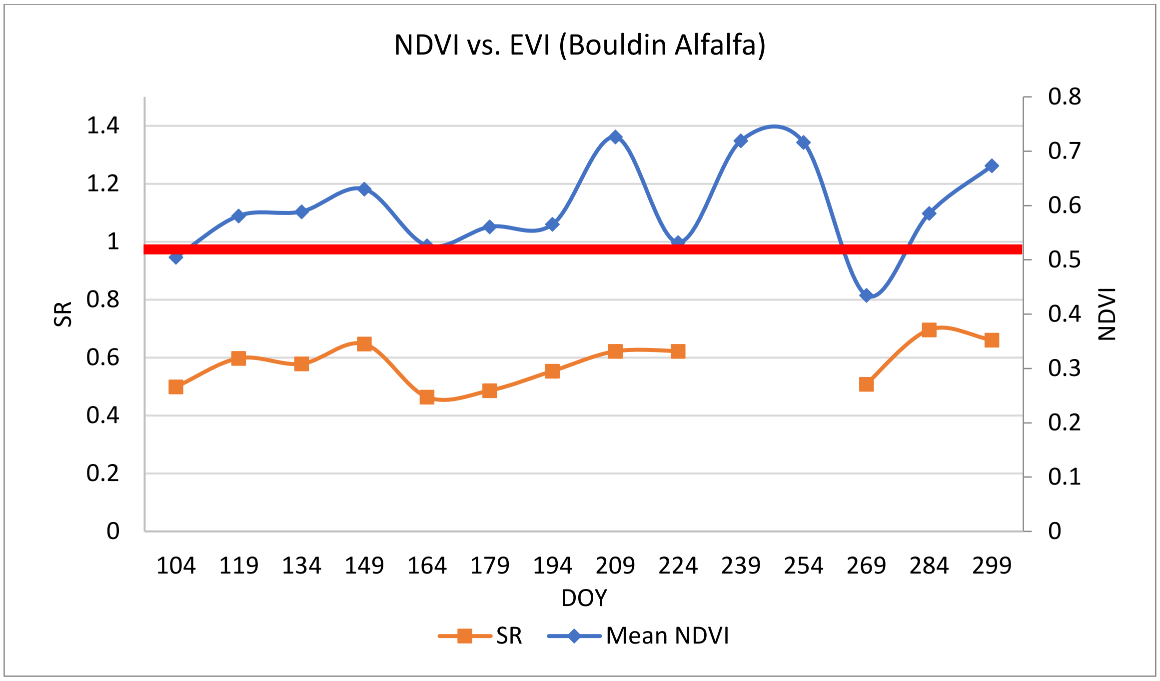


Figure 4. Temporal profiles of relative sensitivity and mean NDVI. The red horizontal line in each chart denotes SR = 1 where sensitivities of two VIs are equal. WDRVI was more sensitive than NDVI between around DOY 170 and 270 in the corn site (a). For the alfalfa, the sensitivities of NDVI and WDRVI were generally comparable throughout the growing season (b); EVI did not show greater sensitivity than NDVI (c). SR of NDVI and EVI for the corn site is not shown here due to too many gaps in the dataset after irregularities were removed.

Limitations

There are multiple limitations to the study design of this project. The project incorporates two types of sensors. One major shortcoming is the limited number of units deployed to the study sites. When some measurements from either sensor seem unexpected, the limited number of units prevented me from determining if the measurements were a result of one-time malfunction of a specific unit or a result of reproduceable issues with the instrument. Thus, certain parts of the design of the study might have been invalid in the first place.

Another limitation is the small size of dataset. The dataset collected by Arable only contained one year of measurements from the alfalfa site and around six months of measurements from the corn site. Meanwhile, because I was not able to determine the causes of some unexpected measurements, all these measurements had to be removed before any data analysis, shrinking the size of the dataset and creating gap. In other words, a larger dataset consisted of multiple years of data might have led to more definitive conclusions.

Future directions

The study identified the threshold values of NDVI and GPP at which WDRVI would be more sensitive to growth of corn. It is yet not clear if the threshold values also hold true for corn in general and also not clear if the threshold is primarily associated with NDVI or GPP, given that a specific value of NDVI does not always corresponds to the same GPP value. Further study may address this question by incorporating data from other corn sites experiencing similar or even different weather conditions. Similarly, further study could also attempt to find such a threshold value for an alfalfa field not being regularly harvested, since this study was only able to find comparable sensitives between NDVI and WDRVI and it might be linked to the harvesting operations.

The study found no improvements in sensitivity by EVI compared to NDVI. Because all measurements were made with in-situ sensors, it would be critical to explore whether the lack of improvement is site-specific or a result of EVI derived from ground-level measurements instead of satellite measurements, a more typical source of data for EVI calculations. One way to look into the issue is to compare ground-level and satellite-derived EVI for the same sites.

Broader implications

Besides the use of VI, there have been many other approaches for estimating GPP with ground, atmospheric and remote observations whereas a consensus on global GPP does not exist due to the fact that every approach relies on assumptions and none is based only on measurements (Anav et al. 2015). In fact, the GPP estimates used in this study are based on observations from flux tower and are a product of assumptions. Estimates from many models, often sophisticated, generally do not agree in either magnitude or trend. Therefore, as long as direct measurements of GPP still do not exist, it is important that we keep exploring more rigorous estimates by a variety of approaches. Deriving VI from reflectance measurements, a rather simple idea, is a cost-effective way for us to acquire an estimate based on data with great spatiotemporal resolutions and data on more types of vegetation species and ecosystems. This study provides a valuable initial investigation and indicates the potential for alternative indices to NDVI to capture more variation in vegetation. I believe further studies on other species or ecosystems using these alternatives will help us reach a more confident estimate of GPP at both local and global scales.

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