Quantifying Agricultural Intensification in the US

Trends in Yield & Microwave Remote Sensing in the Midwest

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Trends in Yield & Microwave Remote Sensing in the Midwest

by

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A thesis submitted to the Delft University of Technology in partial fulfillment of the requirements for the degree of

Master of Science in Civil Engineering

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Preface

For the past eight months I strived to become a remote sensing expert. I had the chance to couple the joy of code-tinkering with my admiration for the future of space technology applications. I learned the names of countless middle-of-nowhere counties, and I etched the outline of the Midwest into my brain for eternity. Writing a thesis during a global pandemic was both challenging and rewarding. I am so grateful for the flexibility, constant support, and enthusiasm of everyone who helped me along the way.

No part of this thesis would have been imaginable without the fantastic guidance of Susan, whose slack message notifications always gave me something to think about. Thank you, Susan, for bearing with me through all the video calls and time differences. Thank you for laughing with me and encouraging me during the chaotic hilarity that is life in 2020.

I want to thank Richard and everyone at VanderSat for being a critical part of my Master's Degree journey. My internship at the company last summer led me to to continue my quest in the Midwest, treading into the unknown territory of VOD. My unexpected passion for remote sensing is no doubt the result of inspiration from Richard and all the amazing employees VanderSat, who investigate the Earth with vigor. I also want to thank Edo and Bas for taking time out of their busy schedules to be a part my thesis committee.

I am incredibly thankful for the behind-the-scenes support I received during my two-plus years at TU Delft. Switching to the field of engineering and moving to a new country was exhilarating and exhausting, and I want to especially thank Fay, Sarah, and Sanne for their academic guidance and for helping me create unforgettable memories. Thank you to my wonderful housemates at BFM who supported me with chocolate deliveries, game nights, and always cheered me on. And finally, I am incredibly grateful to have an amazingly loving family who, although far away, have always supported me, encouraged me, and helped me reach my goals.

I am extremely proud to have studied Water Management at TU Delft, and I will carry the skills learned here with me for the rest of my life.

Vita Sandhu, November 2018

Abstract

Increases in crop production show increasing trends in agricultural intensification. These trends are predominant in the corn and soybean crop production of the United States' Midwest region. The increase of production and irrigation in the past 20 years is spatially diverse, with some regions in the Midwest intensifying agriculture at faster rates.

Measurement of vegetation through the use of satellite remote sensing methods has gained popularity in recent years, with the refinement of existing retrieval algorithms and the development of new ones. Many different indices can be used to study the vegetation, including optical products such as the Normalized Difference Vegetation Index (NDVI) and the Leaf Area Index (LAI). However, the use of microwave remote sensing has some advantages over near optical methods as it is unaffected by weather conditions and can therefore collect data more regularly. Microwave remote sensing methods can retrieve the vegetation optical depth (VOD), a parameter which is related to the intensity of microwave signal extinction by vegetation and can be derived through the use of both passive and active microwave observations.

In this study, these microwave remote sensing methods are used to look for evidence of agricultural intensification trends in the Midwest. The spatial distribution and intensity of trends is compared with trends in yield data and LAI. Trend analysis of soybean and corn yield in the Midwest show statistically significant increasing trends in the Western states of South Dakota, Nebraska, and parts of North Dakota. Similar spatial distributions were picked up in LAI and passive microwave data.

Contents

1 Introduction

The expansion and intensification of agriculture has resulted in a global increase in agricultural production (Estel et al., 2016; Tilman et al., 2011; Hatfield et al., 2013). These agricultural intensification trends are well known in the Midwest of the United States (Mueller et al., 2016; Hanberry and Abrams, 2018). To increase agricultural productivity and secure production in increasingly hot and arid conditions, irrigated areas in the Midwest have expanded in recent years (McGill et al., 2018). Studies of the effects of agricultural intensification in the past have considered both reported yield data and land use cover changes (Hatfield, 2012; Jelinski and Kucharik, 2009). However, in the past 30 years technological advancements allow us to visualize this intensification in vegetation using satellite data.

The estimation of vegetation water content, vegetation canopy biomass, and soil moisture via satellite remote sensing are increasingly popular as proxies for biomass and are commonly used by agricultural companies. Furthermore, the need for accurate and dependable estimates of these vegetation properties is important in creating numerical weather, climate and hydrologic predictions. Therefore, it is critical to continue to assess and improve these estimation methods.

Historically, analyses of vegetation using satellite data have focused mainly on the use of near optical remote sensing methods (i.e. visible and near infrared sensors). Specifically, the the Normalized Difference Vegetation Index (NDVI) is the most widely used index to analyze crop and vegetation trends (Atzberger and Rembold, 2013; Chen et al., 2019). The Leaf Area Index (LAI), which refers to the total area of leaves per unit ground area, can also be retrieved using a combination of surface reflection and canopy radiation models. Although the NDVI, LAI, and other such indices are commonly used to analyze changes in agriculture, they present several limitations. For instance, The availability and range of near optical methods are limited by clouds and aerosol cover. Furthermore, the NDVI monitors only the top of vegetation canopy, and measures photosynthetic activity, which does not always correlate highly with crop yields. (Liu et al., 2011, 2013)

Recent work with visual data has shown that NDVI can also be correlated with agricultural intensification, though with the aforementioned limitations (Wright et al., 2012; Carleton et al., 2008; Estel et al., 2016; Forecasting, 2001). However, the signal of intensification should be visible, and perhaps more comprehensive, through the use of microwave remote sensing methods.

Microwave remote sensing has gained popularity in recent years, primarily to measure soil moisture (Meesters et al., 2005). However, these sensors are also useful for measuring water content within vegetation. When compared with optical or infrared sensors, microwave sensors utilize longer wavelengths to measure deeper into the canopy. Microwave remote sensing can lead to retrieval of the so-called Vegetation Optical Depth (VOD). The potential application of microwave VOD in estimating vegetation properties is of increasing interest as it can provide uninterrupted, near real-time, measurements of vegetation.

In passive microwave systems, the measurement of natural emissions from earth's surface, which are sensitive to the dielectric properties of water, can be used to retrieve the VOD. In active microwave systems, the slope and curvature from radar backscattering can be used to retrieve VOD. (Konings et al., 2017; Friesen et al., 2007; Schroeder et al., 2016).It's important to note that not only are there different sensing modes in microwave remote sensing, but these microwave signals can also be acquired for different frequencies. Retrievals from these methods can result in different temporal dynamics, variability, and different spatial and regional differences.

The translation of back scattering (in the case of active) and emissivity (in the case of passive) into VOD requires a complex modeling, with many parameters and assumptions. As the retrieval algorithms of active and passive VOD as well as LAI and NDVI differ greatly, a comparison in the functioning of these methods is important to better understand vegetation patterns with respect to anthropogenic changes. In a recent review of VOD methods, Frappart et al. (2020) concluded that the disagreements between VOD observations from different frequencies and sensing modes (active and passive) need to be explored further. Therefore, analyzing and comparing signal changes in the Midwest using microwave remote sensing methods will provide insight into the sensitivity and performance of microwave remote sensing.

It is predicted that VOD should be able to visualize agricultural intensification in the US. To analyze the effectiveness of microwave VOD retrieval in picking up significant vegetation trends, VOD will be compared with trends in agricultural intensification of corn and soy in the Midwestern US.

To explore the validity of this hypothesis the following research questions will be investigated:

- Can VOD be used to quantify and/or measure agricultural intensification?
- To what extent are the VOD trends similar across different remote sensing methods?
- How well do these trends match with trends in crop yield?
- Are similar trends also reflected in optical data, i.e. LAI?

To answer these research questions, a trend analysis of various data sets was completed. This analysis involves a spatial comparison between microwave data trends and trends in LAI and crop yield within the study area. Each data set was run through a Mann-Kendall test to find the significance and intensity of trends. The results of this test were assessed to measure the spatial distribution of the trend intensities. Results from two microwave VOD datasets were compared with trends in soybean and corn yield as well as LAI, to analyze whether VOD can pick up significant agricultural intensification.

2 Methodology

In order to answer the research questions posed, several conditions were required. Firstly, to look for evidence of agricultural intensification in microwave VOD, the research area must also contain clear evidence of such intensification. Furthermore, metrics to measure the intensity should be readily available in the study area. This requires data over a long enough time period to see long term trends, not just yearly fluctuations. Additionally, microwave VOD retrievals should be available for the same time period and region as the measure of agricultural intensity. VOD trends should capture the changes only in the agricultural growing season. Trends in VOD and other datasets should be measured with consistent methods, while accounting for the inherent differences of each dataset.

2.1 Study Area

As mentioned, this analysis focuses on the Midwest of the United States. The Midwest is a prime area to look at VOD, as there is evidence of agricultural intensification in recent years, and there is a long time series of crop yield data available for analysis. Additionally, the Midwest is responsible for the production of about 60 % of the corn and soybeans in the US, with millions of acres of cropland as seen in Table 1. (USDA National Agricultural Statistics Service, 2014b). For the sake of this study, the Midwest is defined as twelve states, shown in Figure 1. Trend analyses will be considered on a county level, as this is the unit used by the United States Department of Agriculture (USDA). With more than 1055 counties, the Midwest is a sizable study area, covering a total of more than two million square kilometers.

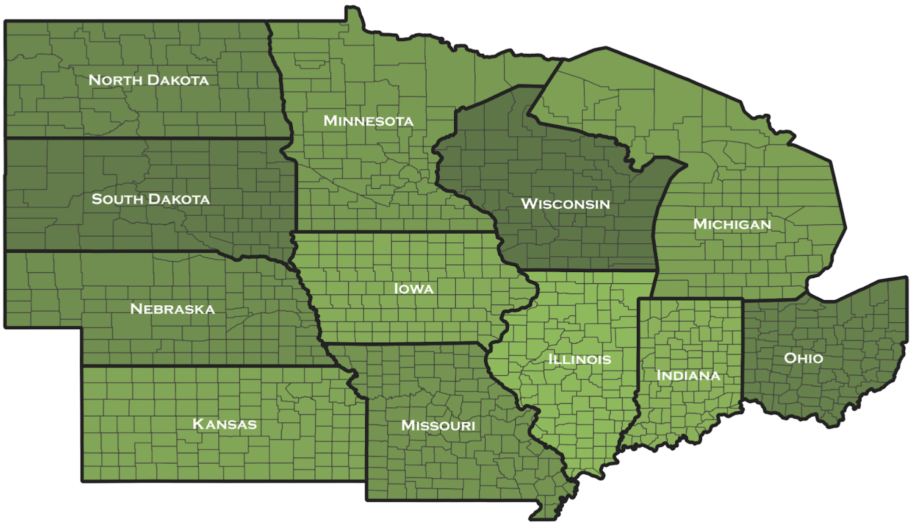


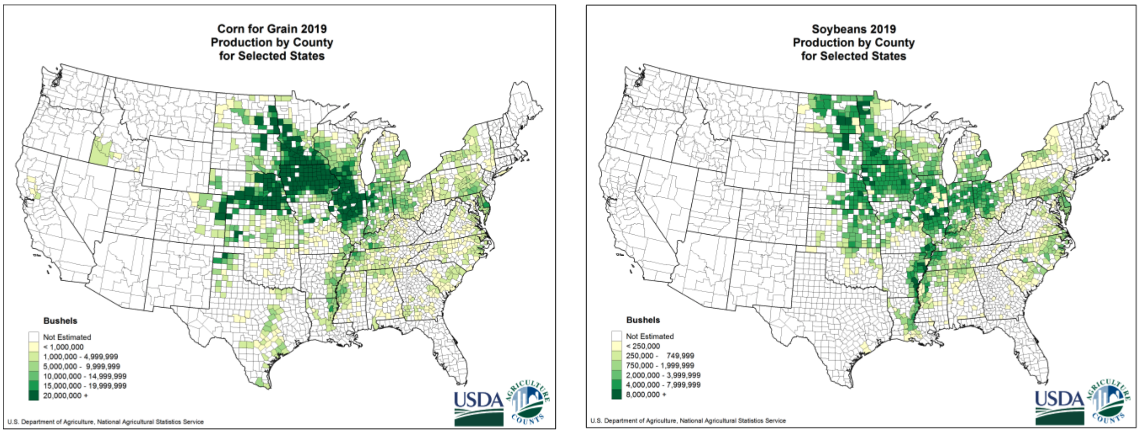
Figure 1

Year	Soybean Acres	Corn Acres
2007	46,033,291	69,658,161
2019	6,244,431	74,046,962

Table 1: Corn and Soybean Acres

2.2 Data

To evaluate the success of microwave data in representing agricultural intensification, several datasets are utilized. It is important to note that each of these datasets measures different signals. Even within the microwave sensing methods, these types (active & passive) measure different



(a) (b)

Figure 2

Dataset	Source	Type	Available Time Period	Resolution
Crop Yield	USDA National Agricultural Statistics Service	Yearly crop yield by county (Bushels per Acre)	1997-2018	County level (~1500 km²)
VODCA VOD	Moesinger et al. (2019), Land Parameter Retrieval Model	X-band Passive Microwave VOD	1997–2018	0.25 Degrees grid
ASCAT VOD	EUMETSAT Data Centre, TU Vienna Soil Moisture Retrieval	C-band Active Microwave VOD	2007-2020	12.5 km grid
MODIS LAI	MODIS Leaf Area Index/FPAR Combined Terra/Aqua, 4-day	Leaf Area Index	2002-2020	500 m pixel size

Table 2: Relevant datasets

frequencies, and utilize different retrieval mechanisms. This results in different absolute VOD values, different sensitivities, and different timing. An overview of the relevant datasets is given in Table 2.

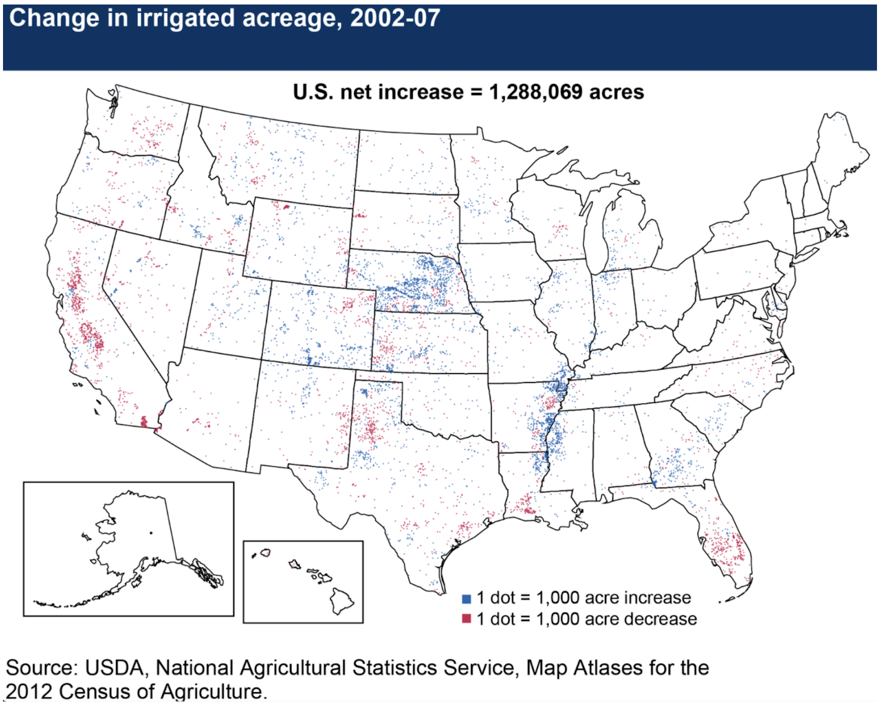


Figure 3: Nebraska shows major increase in irrigated areas.

2.2.1 USDA Data

Due to the high coverage of corn and soybeans in the Midwest, agricultural intensification in the region can be approximated with the yield data of these two crops. In order to quantify and map changes in agriculture, yield data from the United States Department of Agriculture (USDA) will be utilized. The USDA offers free access to historical, yearly, county level, crop specific yield data through their National Agricultural Statistics Service program.

However, it is important to note that the spatial and temporal coverage of irrigation data is not complete, and though it is useful to see areas of interest, it cannot be used to map trends in intensification. Crop specific yield data, on the other hand, has been widely available across the Midwest since 1997. Therefore, intensification will be considered by looking at yield as a proxy for intensification. However, additional irrigation information from the USDA can be used to supplement knowledge of intensification.

In addition to crop yield data, the USDA also reports the irrigated acres in several counties. Unfortunately, the spatial and temporal resolution of this data is not high enough for a complete trend analysis. However, Figure 3, which shows changes in irrigation, does give a preliminary glimpse into where intensification may be occurring.

2.2.2 Passive Microwaves

This research will utilize the recently presented series of long-term VOD products by Moesinger et al. (2020). The global long-term microwave Vegetation Optical Depth Climate Archive (VODCA) combines multiple VOD data sets derived from several sensors (SSM/I, TMI, AMSR-E, Windsat, and AMSR-2) using the Land Parameter Retrieval Model (Owe et al., 2008). The VODCA datasets presented by (Moesinger et al., 2020) are openly available, allowing for easy access to the data products produced. This research will focus on the VOD products using X-band, as studies have shown L-band is designed to penetrate through vegetation (better for soil mositure) (Liu et al., 2019).

The Advanced Microwave Scanning Radiometer (AMSR-E) retrieved passive microwave observations from 2002 to 2011 in six bands, however, as mentioned, only X-band will be considered. The spatial footprint of X-band AMSR-E is 51 km by 29 km. The satellite orbits in sun-synchronous circular orbit, passing the Equator at 13:30 when ascending and 01:30 when descending (Knowles et al., 2006; Kawanishi et al., 2003). The Advanced Microwave Scanning Radiometer 2 (AMSR2) continued AMSR-E's measurements beginning in 2012 with the same bands, orbit, and overpass times but with a marginally higher spatial resolution of 42km$\times$24 km.

Although the dataset spans from 1997-2018, the shift from the AMSR-E satellite to AMSR-2 in 2012 led to a discontinuity in the data. Due to the time-consuming nature of resolving this issue, the majority of the analysis was completed using only pre-2012 data from AMSR-E. A preliminary analysis with a corrected version of the X-band passive microwave data was also completed, with promising results. Additionally, the TRMM Microwave Imager (TMI), which was retrieved from 1997, has limited coverage in the Midwest, with only VOD from the most southern parts being retrieved for this time period. Therefore, this analysis is mainly a reflection of AMSR-E data (2002-2012).

The passive VOD in the VODCA dataset is retrieved using a radiative transfer model called The Land Parameter Retrieval Model (LPRM). Developed by Owe et al. (2008), this model retrieves soil moisture and VOD using vertically and horizontally polarized microwave data. The LPRM assumes that microwave radiation is dependent on surface temperature T_s and on emissivity e, a function of the dielectric constant k. The dielectric constant is also dependent on the soil moisture in the top layers of soil.

The microwave radiation from the soil is either absorbed or scattered, depending on the transitivity Γ and single-scattering albedo ω of the vegetation water content. However, vegetation also emits passive microwaves, with the radiation being dependent on vegetation temperature T_v. This can be translated into a brightness temperature T_b as seen in Equation 1 from Moesinger et al. (2020). The brightness temperature is a measurement of the upward microwave radiation from the top of the atmosphere to a satellite in the units of the temperature of an equivalent black body.

$$T_{b_p} = T_s e_p \Gamma + (1-\Gamma) T_v (1-\omega) + (1-e_p)(1-\omega) T_v (1-\Gamma)\Gamma \tag{1}$$

Note that subscript p denotes either horizontal or vertical polarization.

The transmissivity and incidence angle u can be translated to the VOD τ, as seen in Equation 2.

$$\Gamma = exp\left(\frac{-\tau}{cos(u)}\right) \tag{2}$$

2.2.3 Active Microwaves

ASCAT is a real aperture radar which offers C-band scatterometer data. Data from this radar is only available beginning 2007, which limits the ability to study long-term trends. ASCAT VOD data is of interest due to its recent success in correlating the backscatter data from its C-band scatterometry with the seasonal dynamics of vegetation (Steele-Dunne et al., 2019). However, the use of active microwaves is more common for soil moisture retrieval, and its application to VOD is relatively new.

The dataset used in this study utilizes Vienna University of Technology's (TU Wien) soil moisture retrieval algorithm. This algorithm can be used to retrieve soil moisture from scatterometers with multi incidence angle viewing capabilities, such as in the case of this study, EUMETSAT's MetOp-A Advanced Scatterometer (ASCAT), a real aperture radar operating in C-band. The TU Wien algorithm utilizes dependence of backscatter on the incidence angles. The slope and the curvature of this relationship are sensitive to changes in vegetation. The calculation of daily slope and curvature has paved the way to retrieve a time series of vegetation optical depth from backscatter observations (Vreugdenhil et al., 2017).

2.2.4 Leaf Area Index

Leaf area index (LAI) represents half the area of the green leaves per unit of ground surface area (Guindin-Garcia et al., 2012). LAI can be derived via the combination of surface reflectances with canopy radiation models. The algorithm used by MODIS to generate LAI utilizes spectral information from MODIS surface reflectances (MOD09). This algorithm also requires the input of a land cover classification, which comes from the MODIS Land Cover product (MOD12) (Guindin-Garcia et al., 2012).

The LAI dataset utilized for this study is the MODIS Level 4 500m Combined Fraction of Photosynthetically Active Radiation (FPAR), and Leaf Area Index (LAI). The algorithm for this dataset chooses the "best" pixel available from all the acquisitions of both NASA's Terra and Aqua satellites within the 4-day period. Available from 2002, this dataset is openly available via Google Earth engine.

2.3 Approach

To analyze the above mentioned datasets, the following approach is used:

- Select the peak of each signal for analysis to capture growing season
- Determine yield trends for corn and soybeans in US
- Analyze trends in passive and active microwave VOD
- Compare strength and spatial distribution of trends with LAI trends

From a passive perspective, changes in the VOD signal are of interest. Trends in VOD can then be compared to the signal shown in the active ASCAT data, the yield data, and the LAI. The comparison of these parameters will involve a time series analysis in python to look for trends.

2.4 Growing Season

When looking for trends in the microwave and LAI data, the growing season should be considered. Generally, May to October is considered the growing season in the Midwest. However, each signal has different sensitivities and thus peaks at different parts of the growing season. To capture the peak of each year, an averaged time series was made across the whole Midwest.

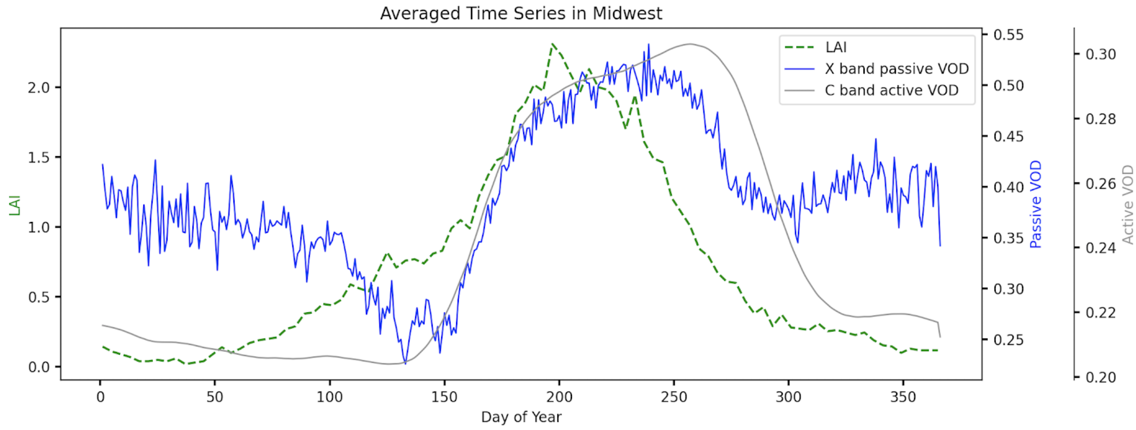


Figure 4

This involved finding the average value across all counties and then taking the mean for all years. As seen in Figure 4, LAI peaks before the other datasets, as it is more a measurement of greenness rather than true biomass. The maximum amplitude of each dataset was considered, and the half length of that maximum was taken to find the timing and length of the growing season. For the active microwave data this period was June through August. The LAI and passive microwave data had steeper peaks earlier, and thus only July and August were considered in the trend analysis.

2.5 Measuring Trends

The nonparametric Mann-Kendall trend test was used in this study to determine the significance of trends in each dataset. The advantage of using a nonparametric test is that it does not rely on the form of the underlying data distribution. This is beneficial when considering long term inter-annual vegetation signals, which have large seasonal shifts, and is therefore commonly used (Fensholt et al. 2012; Tushaus et al. 2014).

Mann-Kendall is calculated using the following equation:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \tag{3}$$

where n is the number of data points and x_i and x_j are adjacent values in the data series (Mann 1945; Kendall 1957; Gocic and Trajkovic 2013).

Furthermore, the variance can be calculated to test for statistical significance. Finally, the slope of the trend is also calculated using Sen's method as seen in Eq. 4.

$$d_k = \frac{x_j - x_i}{j - i} \tag{4}$$

where (1 ≤ i ¡ j ≤ n), d is the slope, x denotes the variable, n is the number of data, and i and j are consecutive values in the time series (Sen 1968).

The Mann-Kendall test is used significantly to determine both the existence of significant trends and the intensity of those trends. The exsistence statistically significant increasing trends indicates the presence of intensification. Furthermore, Sen's slope is used to measure the slope or intensity of different trends. A comparison of Mann-Kendall trends between VOD and yield can help to answer the central hypothesis. Furthermore, the matching and correlation of Sen's slope indicates the intensity of trends, since strong increasing trends should be picked up by VOD.

Thus there are two central metrics to measure the presence intensification. First if a statistically significant Mann-Kendall trend is shown in Yield, that is a strong indicator. Second the intensity of the trend can indicate where larger intensification has occurred. The first metric will be compared across datasets by looking for areas with increasing yield or LAI trends and checking if the same trend is reflected in the microwave data or optical data. Trends are compared both spatially by mapping, and numerically by calculating the percentage of total midwestern counties with increasing trends. Comparison of maps and percentages can inform the extent to which VOD is able to reflect agricultural intensification.

Secondly, intensity will be assessed by plotting the Sen's slope spatially, as well as looking at the Spearman's correlation coefficient to see if microwave data trends reflect the magnitude of intensification. The correlation coefficient ranges from positive to negative one. Positive one indicates that there is a perfect association of ranks, zero indicates no association between ranks and negative one indicates a perfect negative association of ranks. The Spearman correlation is useful as it doesn't require that either variable is normally distributed. The Spearman correlation coefficient has also been used in previous studies of VOD correlation such as Teubner et al. (2018)'s paper comparing it with Gross Primary Productivity, citing the absence of normal distribution in some VOD data.

3 Results

3.1 Signal Differences

To understand if VOD can visualize agricultural intensification, the trends of several different datasets were analyzed. However, when analyzing the similarities in trends, clear differences are seen in the magnitude and timing of different datasets. It is important to understand the observed differences in sensitivity and timing. To illustrate these differences a sample county with clear intensification was chosen. Full time series were plotted to underscore the differences in timing and magnitude of the signals.

As detailed in subsubsection 2.2.2, passive microwave data is available in different wavelengths and frequencies. The VODCA dataset used in this study offers high frequency measurements of C-band and X-band VOD. The active microwave data, however, is only available from a C-band scatterometer. Although it would seem logical to select C-band VOD from both passive and active microwave datasets, issues with Radio Frequency Interference (RFI) necessitated the selection of X-band passive VOD.

These measurements, which are are sensitive to vegetation, are also at risk of interference from artificial microwave emissions, which lead to unreliable VOD estimations. RFI is typically frequency-specific, and lower frequencies tend to be more susceptible. As C-band retrievals are slightly lower than X-band, they are more susceptible to RFI, with the measurements at 6.9 GHz and 10.7 GHz respectively. When looking at an area in the US where RFI is not an issue, the overall trend in C-band and X-band is essentially the same (see Figure 18). Therefore, although C and X band have slightly different values for VOD, the trend remains the same. Thus, the similarity between X and C-band, combined with the RFI issues of C-band, make X-Band passive VOD a better candidate for this analysis.

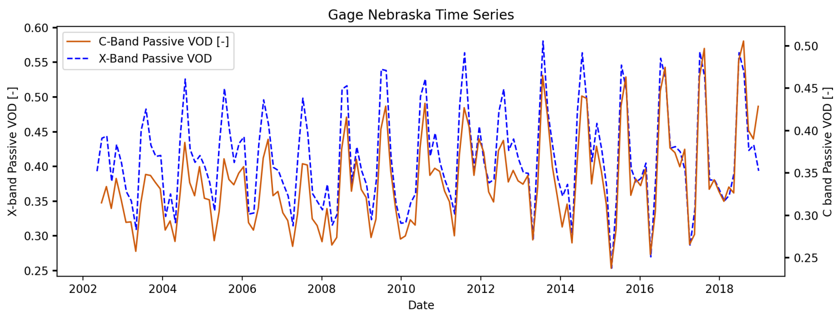


Figure 5: X-Band VOD vs C-band VOD passive microwave comparison for Gage county, Nebraska, a county with low RFI.

When comparing one county time series of LAI with the X-Band passive VOD, it is clear that the peak of the growing season in LAI is much sharper. This was also visible in Figure 4, which showed an "average year" for every county in the Midwest. This sharp peak is a result of the retrieval method for LAI. As discussed in subsubsection 2.2.4, LAI is based on surface reflection, whereas VOD is meant to reflect the vegetation water content. When the surface reluctance of a plant changes, due to sudden growth or browning, the LAI picks up the change quickly. Thus, the peak of the LAI occurs sooner and lasts shorter than that of VOD.

Finally, when considering the active C-band VOD data, the example county illustrates that the active dataset has a smaller range in VOD values, but that the peak is again clearer than in the X-band passive VOD. The smoothness of the graph is likely due to the kernel smoother utilized in the retrieval of VOD from slope and backscatter from ASCAT.

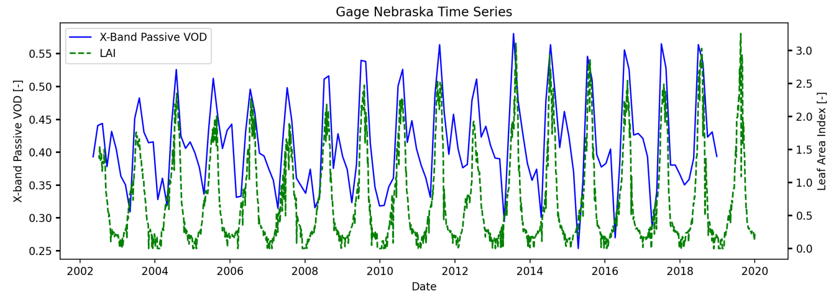


Figure 6: Passive X-Band VOD vs Leaf Area Index C-Band VOD in Gage County, Nebraska (1997-2018)

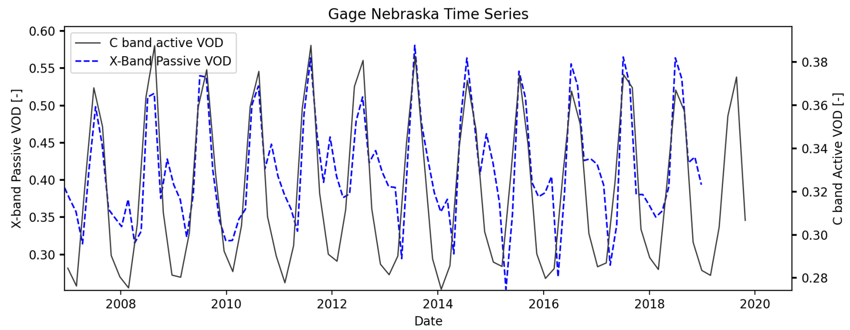


Figure 7: Passive X-Band VOD vs Active C-Band VOD in Gage County, Nebraska (2007-2020)

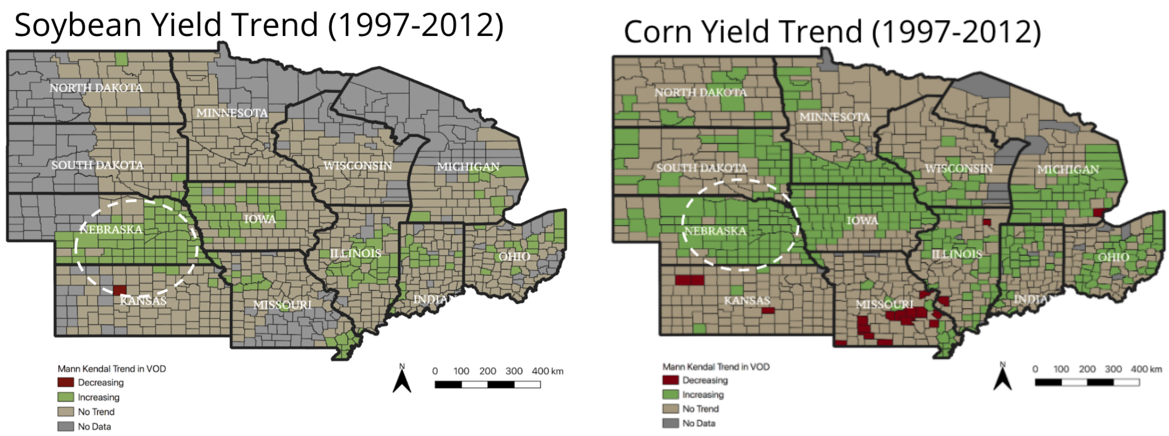
3.2 Yield Trends

3.2.1 Significant Trends

Yield trends were used as a proxy of agricultural intensification, thus it was critical to see the location and intensity of changes in yield. Mann-Kendall Trend tests for crop yield were run by county for the period of 1997-2012. Results for this period showed only a small number of statistically significant trends for soybean yield, with only 22 % of counties showing an increase. However, as seen in Figure 8a, there is a clear spatial pattern. The increasing trends in eastern Nebraska are also reflected in the USDA irrigation increases in Figure 3.

A seen in Figure 8b, corn yields showed more significant increasing trends across the entire Midwest, with 42% of counties having an increasing trend from 2002 - 2012.

Increasing trends for both crops cover more counties when the full time period of 1997-2018 is considered. See Figure 3.7 for preliminary comparisons of the full time series.



(a) (b)

Figure 8

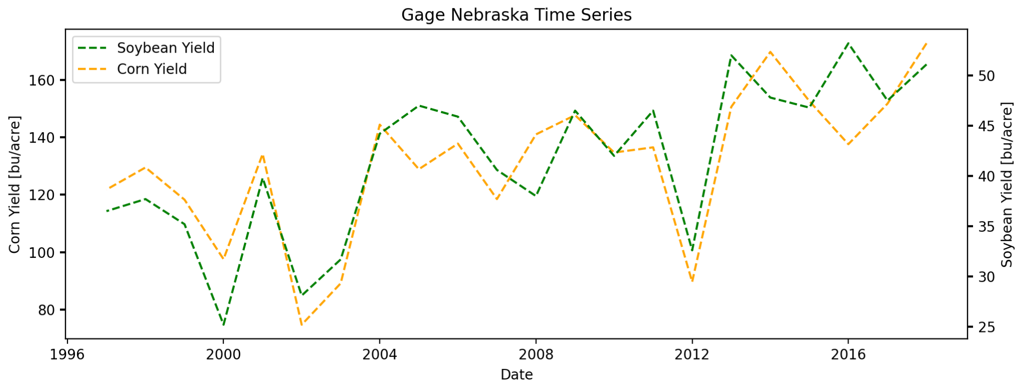
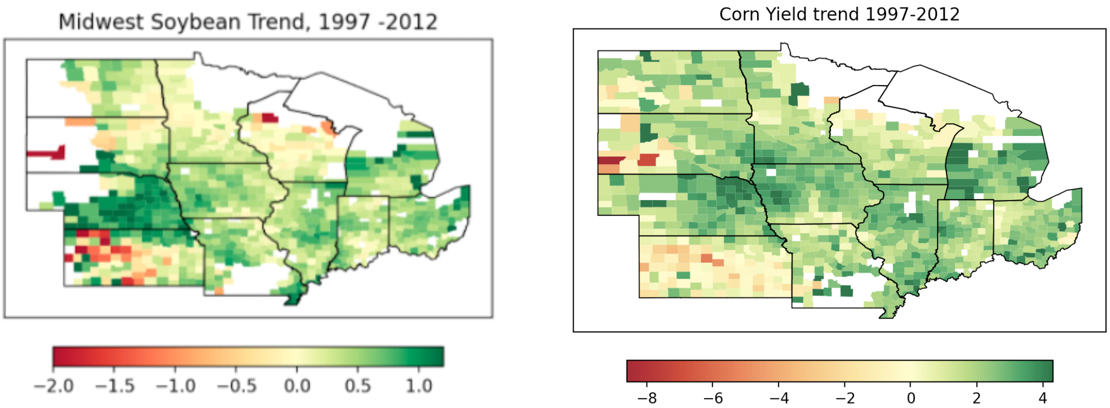


Figure 9: Corn vs Soybean trends in Gage Nebraska

3.2.2 Intensity of Trends

As explained in subsection 2.5, the intensity of these trends is also of interest. Some statistically significant trends are larger than others, and those are of interest when considering highly intensified areas. To get an idea of where corn and soybeans have increased the most, the Sen's Slope was calculated per county and visualized. As seen in Figure 8, the strongest trends in both corn yield and soybean yield lie in eastern Nebraska, which is in line with expectations from the irrigation maps. Furthermore, eastern Illinois and parts of Michigan show strong yield trends.



(a) Sen's slope for Soybean Yield, by county

(b) Sen's slope for Corn Yield, by county

Figure 10

3.3 Passive Microwave VOD Trends

The analysis of Mann-Kendall trends in the X-band passive microwave VOD showed a very similar spatial with yield. In other words, though only a small percentage of counties showed a significant increasing trend in VOD, 75% of counties have the same trend for both VOD and yield. Furthermore when the intensity of the trend, or slope, is considered, as seen in Figure 12, there is a strong trend shown in Nebraska and South Dakota. Major differences when compared with crop trends are seen in Eastern South Dakota and Central Iowa, where significant negative trends are found.

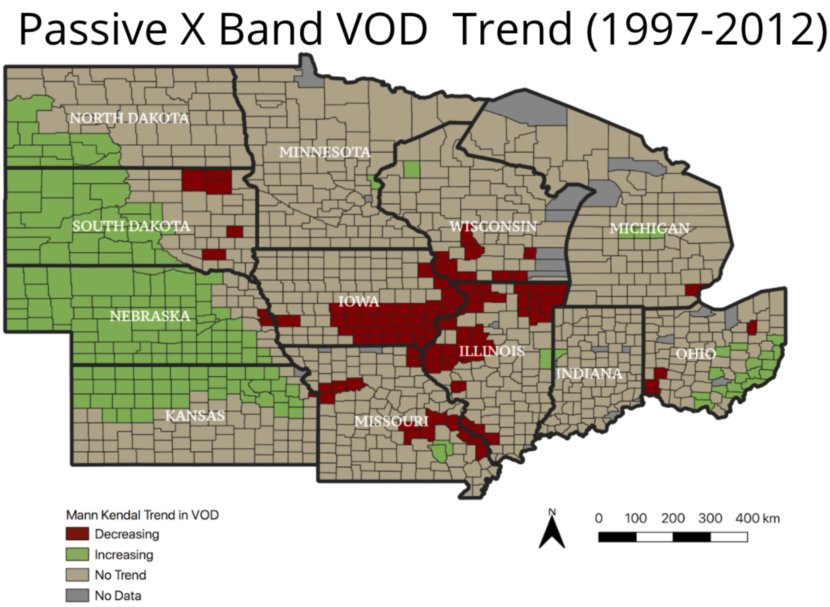


Figure 11: Significant Trends in X-band Passive VOD for 1997-2012

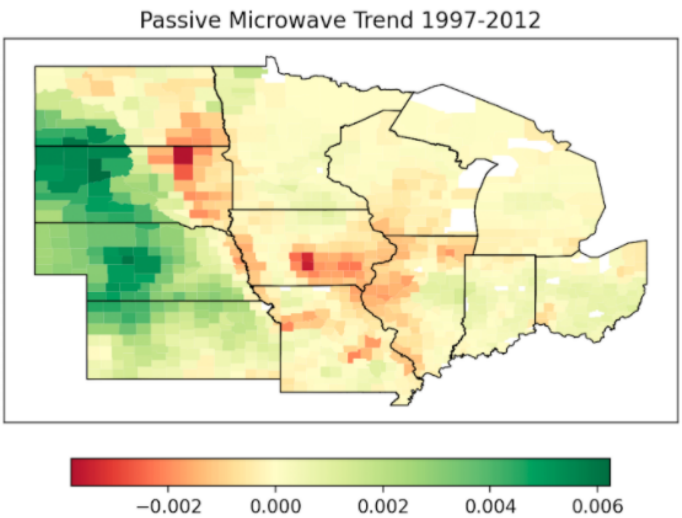


Figure 12: Sen's Slope for X-band passive microwaves (1997-2012).

3.4 LAI

Although not a microwave VOD product, LAI aims to measure plant activity. Therefore, the signal is of interest to compare with both the microwave VOD retrievals, as well as the crop yields to look for confirmation of intensification. When running a spatial trend analysis on LAI for the same time period as the X-band passive microwave VOD, a similar spatial pattern is clearly seen (Figure 14). The increasing trend in Nebraska and South Dakota seen in Figure 13 is consistent with previous findings in the passive, yield, and irrigation maps. Overall, there are more positive trends in LAI, which is likely due to the sensitivity of LAI to changes in greenness.

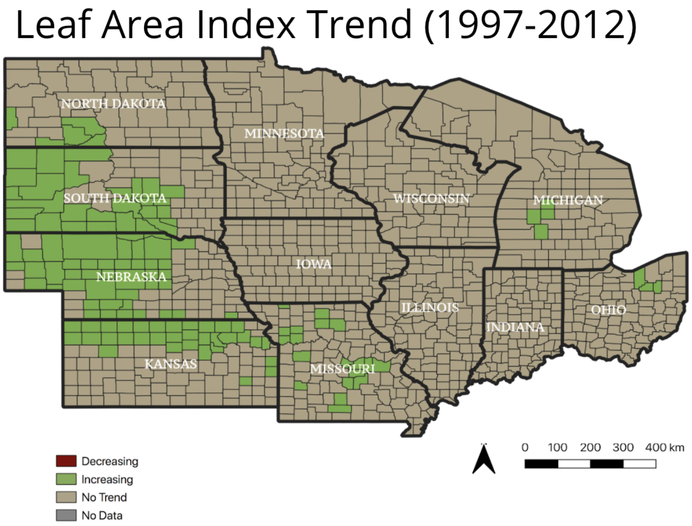


Figure 13: Spatial Map of Mann-Kendall Trends in LAI

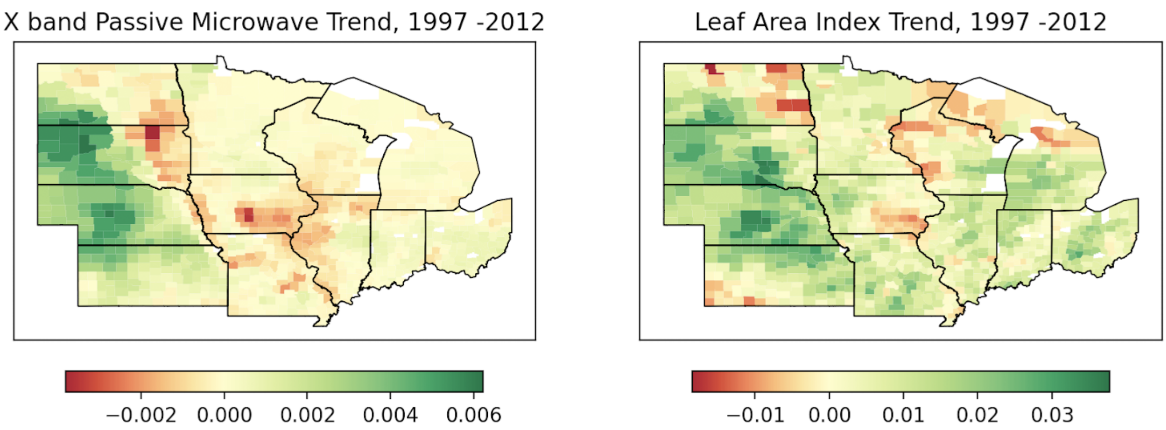


Figure 14

3.5 ASCAT Active trends

When looking for significant Mann-Kendall trends in the active VOD, nearly none of the counties had significant trends. The significant trends that were found were all negative, and mostly concentrated in the Northeastern Midwest, in Michigan, which may be due to the proximity to the Great Lakes or snow.

Upon investigation, it was found that the active data had very little inter-annual variability, as seen in Figure 16. Small differences can be seen in Figure 17, but the scale of these trends is incredibly small and essentially non-existent. Furthermore, the spatial pattern does not match the results in the other datasets, and no significant increasing trends were found, as seen in Figure 15.

3.6 Trend Comparisons Across Datasets

After looking at trends in each dataset and at the spatial similarities between datasets, additional metrics were used to analyze how well microwave VOD captured agricultural intensification. First, datasets were compared using significant trends from the Mann-Kendall test. Figure 20 compares the percentage of similarities across all counties, reporting the proportion of counties with the same

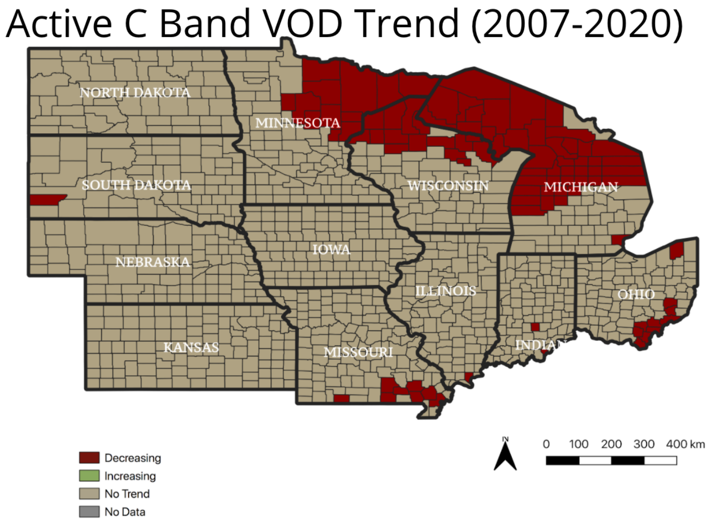


Figure 15

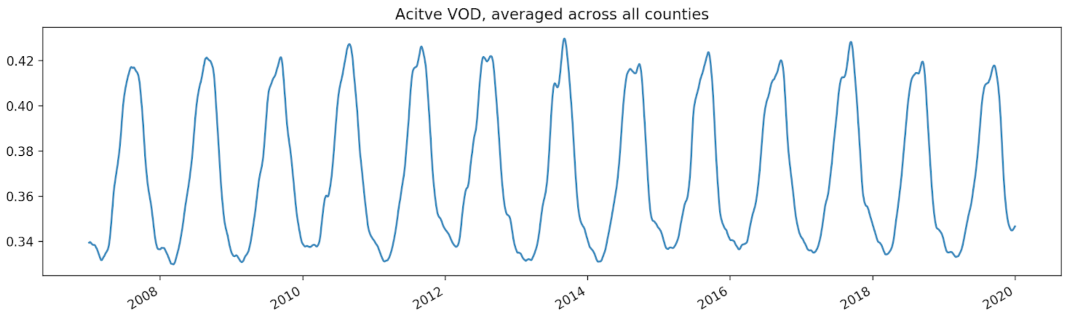


Figure 16

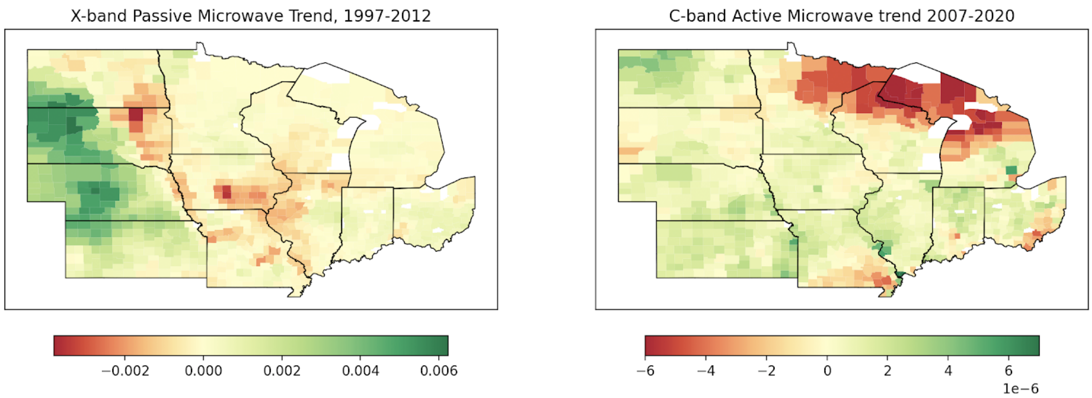


Figure 17

trend for both datasets. This means that counties where there was no significant trend in either dataset, of which there were many, were also considered matching. Though interesting to see that X-band passive VOD matches in more counties than C-band active VOD and LAI, this comparison is not very informative about the ability of datasets to capture increasing trends, which indicate intensification.

Figure 21 gives a better indicator of the performance of each dataset in capturing agricultural intensification. Counties where the corn yield, soybean yield, or Leaf Area Index show statistically significant increasing trends indicate intensification. Therefore, if an increasing Mann-Kendall trend is also found in VOD datasets or LAI, this indicates that the dataset shows intensification.

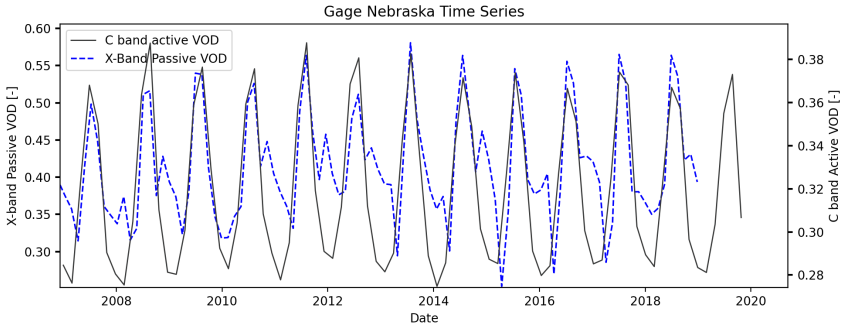


Figure 18: X-Band Passive vs C-Band Active VOD comparison in Gage County, Nebraska

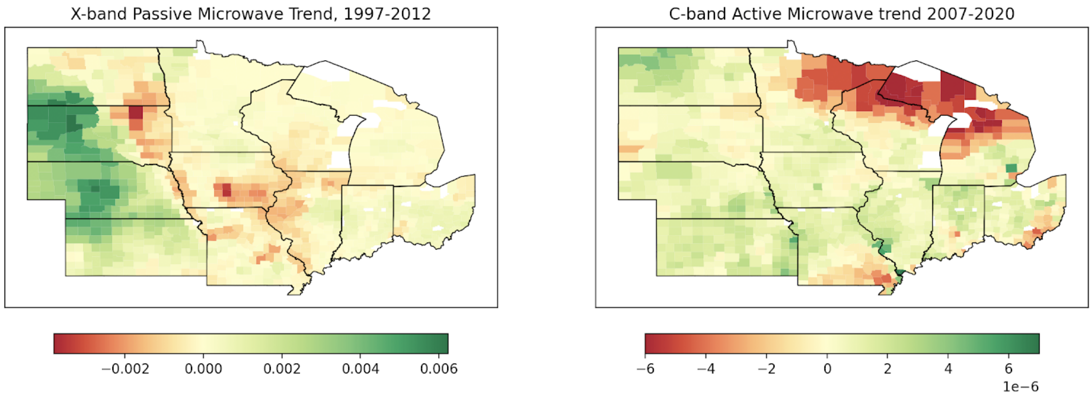


Figure 19: Sen's Slope for X-band Passive Microwave VOD vs C-Band Active Microwave VOD. Note that the date ranges are not the same due to the data discontinuity in X-band.

Since C-band active VOD showed no increasing trends, it is no surprise that the percentage of counties with matching increasing trends is zero.

Passive X-Band VOD, on the other hand, captures nearly 80 percent of corn yield increases and nearly 50 percent of soybean yield increases. Furthermore, 72% of counties which have an increasing trend in LAI also have an increasing trend in x-band VOD.

Leaf Area Index also shows intensification. Namely, it captures 73 % of counties with increasing soybean trends, and over 50 % of increasing corn yield trends. An analysis of the Spearman Correlation coefficient between datasets was completed to determine the intensity. As seen in **??**, postive correlations were seen in Soybean Yield trend with X-Band Passive VOD having a Spearman correlation coefficient of 0.143. Additionally, LAI had a strong correlation with the X-Band Passive VOD trend, with a correlation coefficient of 0.405. Mismatches between Corn and VOD however showed negative spearmann correlations, indicating that when corn yield had a high sen's slope, passive vod's slope was often low.

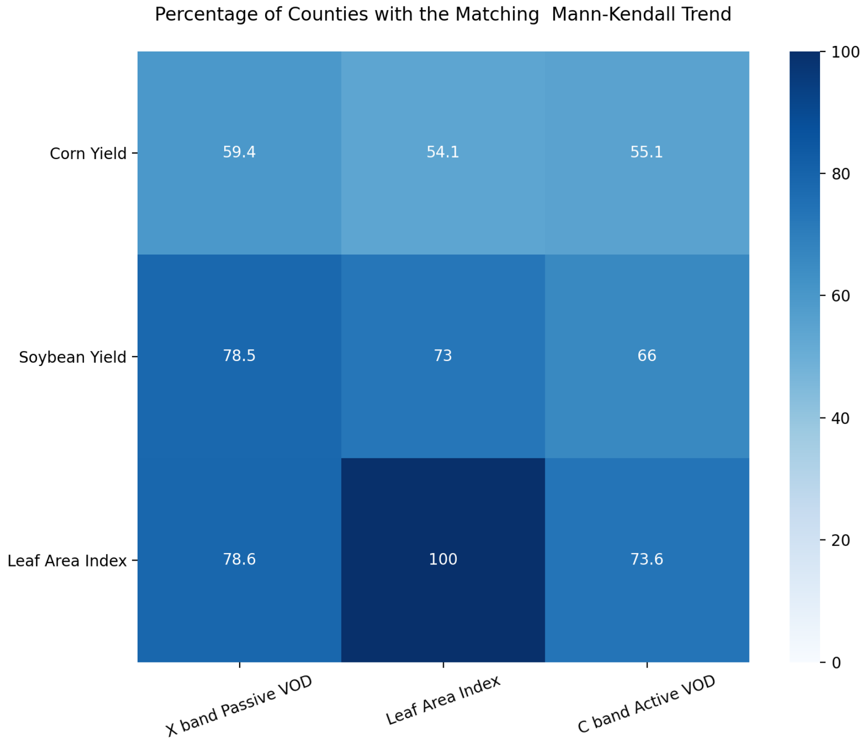


Figure 20: Percentage of counties where datasets on the X-axis share the same significant Mann-Kendall trend as the datasets on the Y-axis.

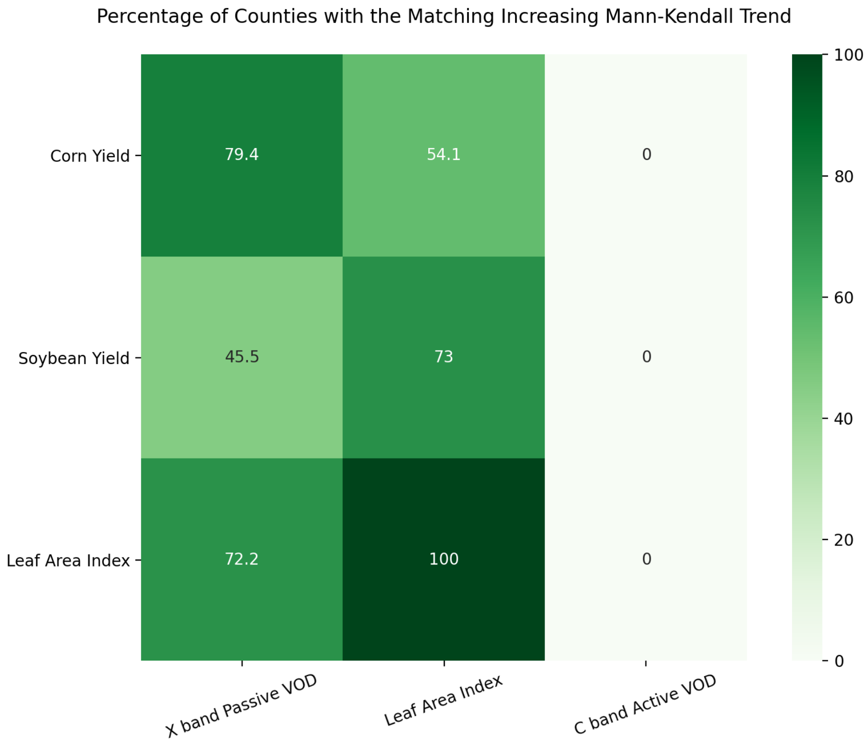


Figure 21: Percentage of counties where increasing significant Mann-Kendall trend from the datasets on the Y-axis are also reflected in the datasets on the X-axis.

3.7 Full Time Series, Fixed Passive VOD Dataset

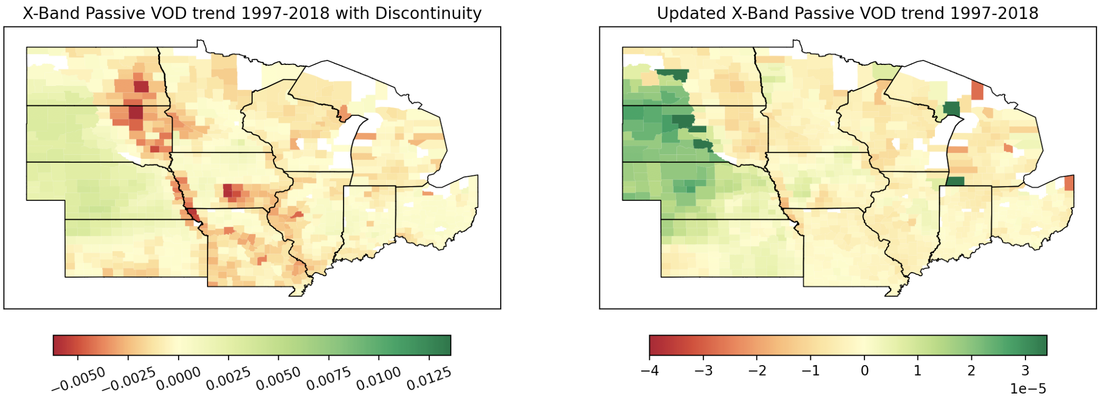


Figure 22: Comparison of VODCA X-band Passive Microwave VOD and the dataset updated with FENGYUN-3B data to fix discontinuity.

A recent effort to fix the discontinuity caused by the transition from AMSR-E to AMSR-2 has shown promising results. The data is a merger between AMSRE-AMSR2 and FENGYUN-3B. In some regions in the South of the Midwest, TRMM data is also included. Therefore the full time span of this dataset is 1997-2012. By fixing this discontinuity, trends can be visible for the full time period. As seein Figure 22, the negative trends seen in the dataset with the discontinuity have decreased, and there are strong increasing trends in the western US, which falls in line with previous findings. As seen in Figure 22, the spatial pattern of trends seen in the 1997-2012 dataset (**??** are still present, but with weaker intensity. This may be due to the slow of intensification in recent years. Unfortunately a full analysis comparing trends using this new dataset was not possible due to time constrains, see section 4 for more information.

4 Limitations & Uncertainties

In the course of answering the central research question, several uncertainties and limitations are important to consider. Firstly the input datasets themselves contain some uncertainty and have limitations. Variation in the time periods of each dataset can affect the trend. For instance, although the VODCA passive microwave data is available beginning in 1997, the spatial coverage of VOD from 1997-2002 is limited to only a small portion of the southern Midwest. However the two other datasets which begin in 1997 cover the majority of the Midwest. This may have lead to mismatches in certain counties between the X-band passive VOD and the LAI and Yield datasets. As seen in the time series plots in the results, the beginning the time period showed strong increasing trends. Therefore, though only a period of three years, this gap in data may lead to a decrease in similarity between trends. Though strong similarities between X-band passive VOD and LAI and yield were still found, results may have been even more similar if all datasets were more spatially complete for the time period considered.

Secondly the majority of the trend analysis relies on the choice of the Mann-Kendall trend test to reflect significant trends in datasets. By nature, this statistical test works best with more than ten measurements. With fewer data points, the test has a high probability of not finding a trend, even if with more points, a trend would be found. Thus the more data available in each county, the more likely the test will find a significant trend (Gocic and Trajkovic, 2013). Therefore, although a minimum number of points was set for the analysis, areas with limited data, either spatial or temporally, may falsely report no trend.

One major limitation of assessing the ability of different methods of VOD retrieval to capture agricultural intensification was the discontinuity in the VODCA Data. As mentioned, longer time series lead to more accurate recognition of significant trends. However as discussed in subsubsection 2.2.2, a discontinuity resulting from the switch between the AMSR-E and AMSR-2 retrieval resulted in an inability to measure trends for the full time period available. Although the initial VODCA dataset has since been improved through the use of another satellite, the new dataset is only a preliminary pilot and was therefore only recently available. Future studies using the full time series could provide a better analysis of the full time period.

Furthermore, although this study points to several possible reasons for mismatches in data, time constrains made investigating every county with a mismatched trend unfeasible. Although understanding that differences exist between datasets, it may be more interesting to investigate the precise cause of these incongruities. However, as the central question aims to find *if* microwave VOD can measure intensification and not *why* it does or does not, this was beyond the scope.

Lastly, it should be stressed that though promising, X-band Passive VOD is not retrievable globally, and using VOD products is always location specific. USing VOD as a metric for intensification in areas with issues from RFI,high amounts of snow/ice, or water bodies may be ineffective. Furthermore this study provided a unique area with relatively low coverage of forest/urban areas, and high coverage of cropland, when considering the size of the Midwest. Many areas of the world have more diverse crops, more densely populated urban areas fewer acres of cropland. The ability to use crop yield data as a proxy for intensification is not completely unique, but may be far more complicated in other regions. Therefore it's important to consider that though results from X-Band VOD seem to reflect yield and LAI trends, this could be a relatively unique case.

5 Conclusions

The central question of this research centered on the ability of microwave VOD products to quantify agricultural intensification. To investigate this ability, several trend comparisons were made using the Man-Kendall trend test. The trend comparisons relied on trends of soybean and corn yield data from the Midwest of the United States to represent intensification. The analyses relied on trend tests which were run on five different datasets, soybean yield, corn yield, X-band Passive VOD, C-band active VOD, and LAI. A small analysis of a recently improved version of the X-band passive VOD dataset was also briefly considered. Due to the different retrieval methods of each time series, the datasets indicated a clear difference in their signals with respect to timing and magnitude during the growing season. Therefore the growing season was separately selected and averaged to reflect the signal of each dataset. Spatial comparisons of statistically significant Mann-Kendall trends indicated strong intensification in Nebraska. This was clearly visible in supplementary irrigation data, as well as in the crop yield trends, specifically in soybeans. Passive X-band VOD trends where able to closely mirror the spatial pattern of the soybean trends, with nearly 80 percent of trends in soybean yield matching with the passive VOD trends. Furthermore X-band Passive VOD and LAI were very successful at showing increasing trends in counties with evidence of agricultural intensification (each catching approximately 60 percent of increasing trends). Furthermore X-band Passive VOD and LAI were very successful at showing increasing trends in counties with evidence of agricultural intensification (each catching approximately 60 percent of increasing trends). The comparison of C-Band active VOD, however, was far less successful at measuring agricultural intensification. Due to a lack of interannual variability in the active VOD, no increasing trends were found.

The lack of trends found in the Active VOD indicate a lack of sensitivity to interannual variability. A future investigation into the soil moisture product produced from a similar methodology to the ASCAT VOD,could provide answers to the lack of interannual variability in the VOD product. However, as the dataset exists currently the C-band ASCAT VOD product does not capture agricultural intensification in the Midwest of the US.

This study confirms previous findings that passive microwave VOD can capture vegetation dynamics. The results indicate that passive VOD can capture long term vegetation trends, and can specifically capture spatial trends of agricultural intensification. However not all trends were captured, and future research is needed to better understand and solve obstacles that prevent VOD from observing long term vegetation trends.

Since the spatial scope of this study was limited to the Midweset, future research could focus on using VOD to detect intensification in other climates, or in areas with diverse crop cover. By continuing to study the ability of VOD to reflect real vegetation parameters, better VOD retrieval and corrects can be made.

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6 Appendix

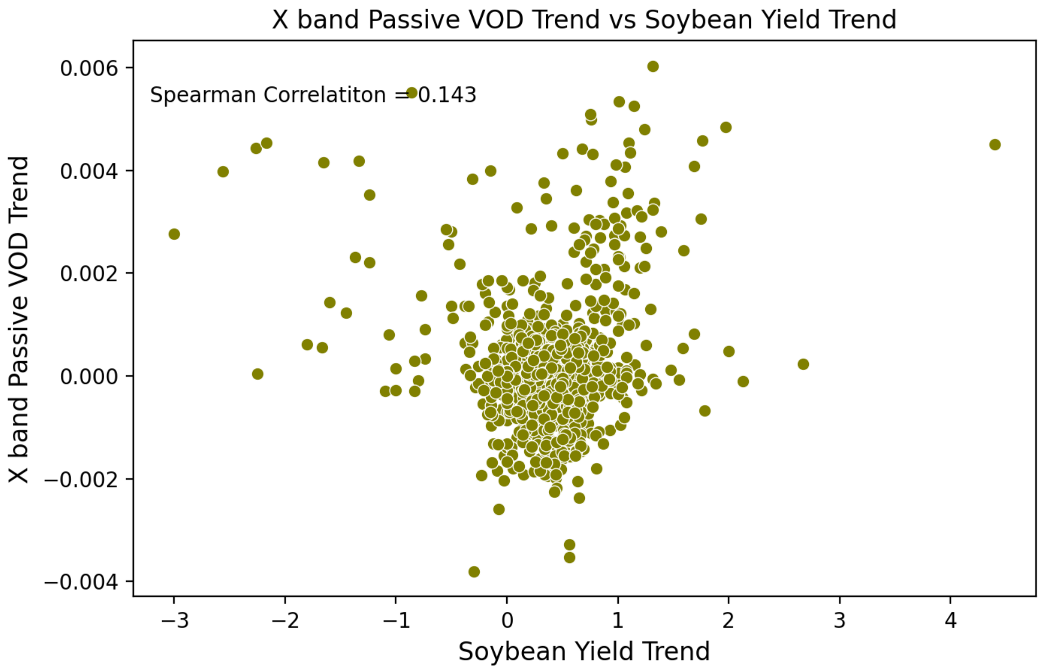

Figure 23: Comparison of Sen's Slope for X-Band Passive VOD and Soybean Yield. Spearman Correlation of 0.143.

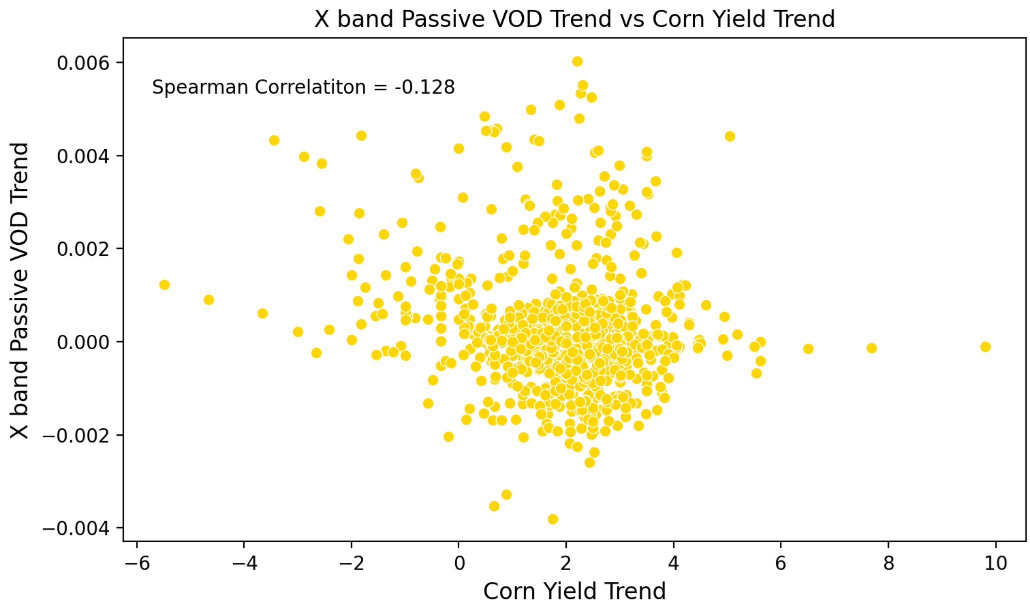

Figure 24: Comparison of Sen's Slope for X-Band Passive VOD and Corn Yield. Spearman Correlation of -0.128

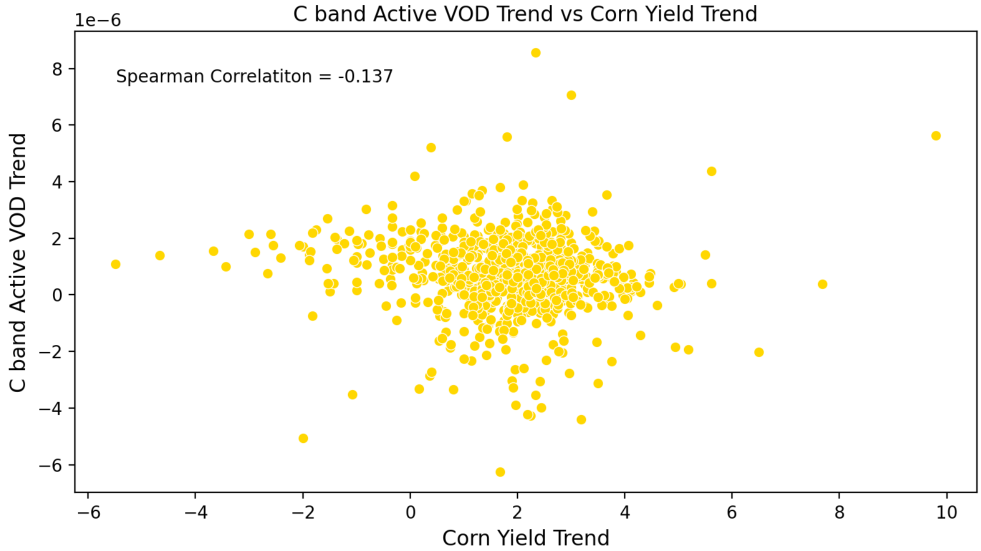

Figure 25: Comparison of Sen's Slope for C-Band Active VOD and Corn Yield. Spearman Correlation of -0.137.e

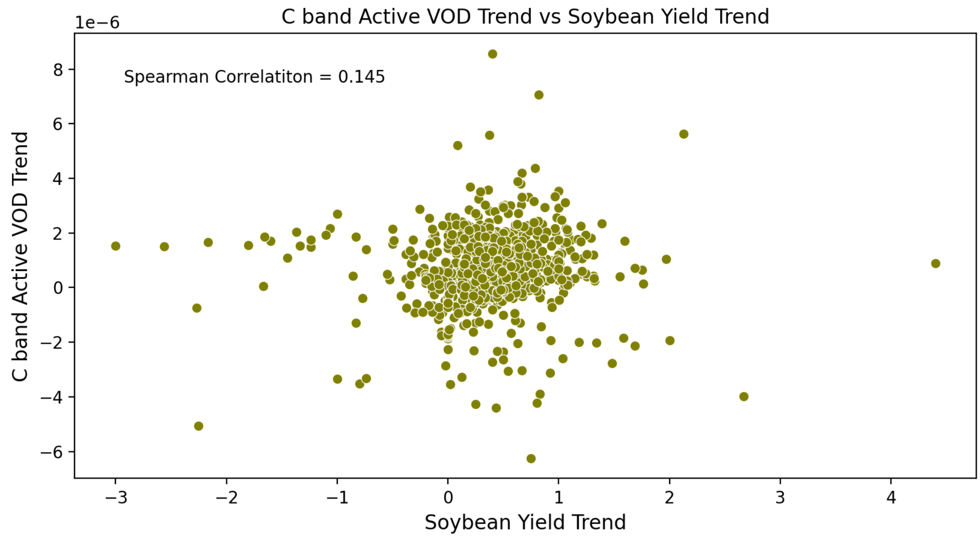

Figure 26: Comparison of Sen's Slope for C-Band Active VOD and Soybean Yield. Spearman Correlation of 0.145.

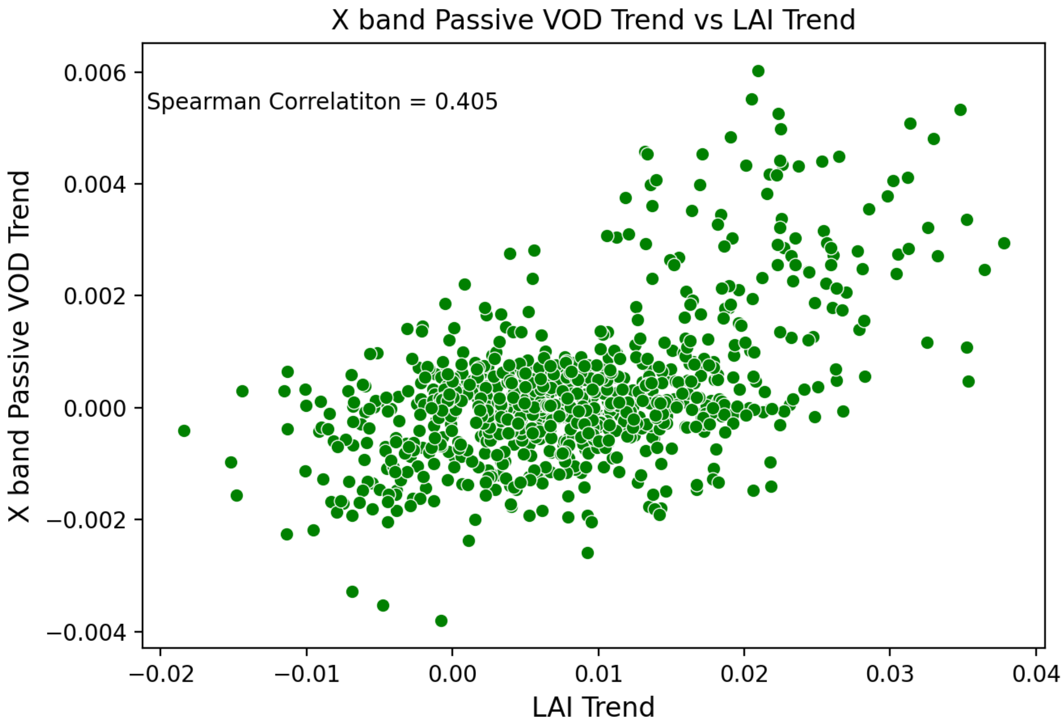

Figure 27: Comparison of Sen's Slope for X-Band Passive VOD and LAI. Spearman Correlation of 0.405.

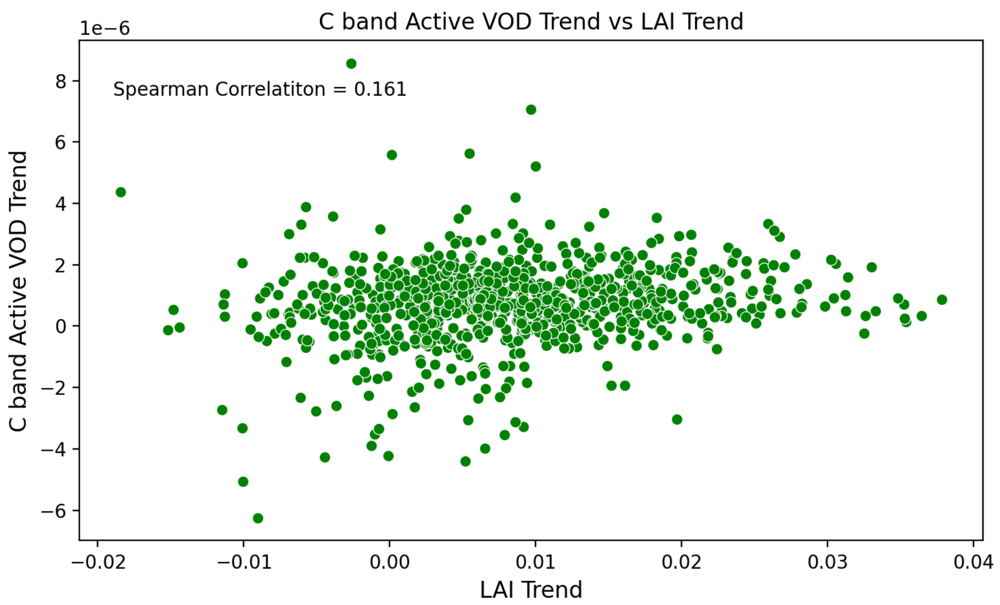

Figure 28: Comparison of Sen's Slope for X-Band Passive VOD and LAI. Spearman Correlation of 0.161