Crop Yield Estimation Using NDVI: A Comparison of Various NDVI Metrics

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ABSTRACT

The objective of this study is to examine and compare multiple Normalized Difference Vegetation Index (NDVI) metrics for estimating crop yield. There are several terms used to describe NDVI metrics including: process methods, aggregation techniques, phenological indices, and aggregation metrics. The various NDVI metrics included in this study are maximum NDVI (MaxNDVI), integrated-NDVI (INDVI), Minimum NDVI (MinNDVI), relative annual range of NDVI (RREL), days to maximum NDVI (DTM), and days from maximum NDVI (DFM). NDVI data was accessed from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) over a 13-year period (2006-2018). County level corn yield data was from the United States Department of Agriculture (USDA) National Agriculture Statistics Service (NASS) database. Temperature data was gathered from the Puget Sound Regional Synthesis Model (PRISM). Regression analysis was conducted to examine the performance of various NDVI metrics for estimating crop yield. The results indicate that MaxNDVI is best able to estimate county level corn yields. This research aids in understanding the ability of the various NDVI metrics to estimate crop yield. This information will assist those designing satellite-based crop yield forecasting and index-based crop insurance models.

Keywords: Crop Yield Estimation and Forecasting, Index-based Crop Insurance, Satellite, Remote Sensing, MODIS, Normalized Difference Vegetation Index (NDVI), NDVI Aggregation, NDVI Processing Methods, Maximum NDVI (MaxNDVI), Integrated-NDVI (INDVI).

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CHAPTER 1

INTRODUCTION AND BACKGROUND ON CROP MODELING

Introduction

Unexpected changes in the supply and demand of agricultural commodities around the world can lead to large movements in domestic and global market prices. Sustained volatility in prices can lead to significant, non-optimal reallocations of resources across the agricultural supply chain. In response to these kinds of market disruptions, many countries have developed government agencies with the aim to manage and minimize these risks. One of the most influential of these government agencies is the United States Department of Agriculture (USDA). The National Agricultural Statistics Services (NASS) of the USDA provides statistics on the US agricultural sector. Some of the most important statistics that NASS reports are the national production, demand, and stocks of the major crops grown in the US. To develop these statistics, NASS conducts a series of surveys throughout the year to assess farmer planting intentions, crop health, and production results. These surveys are used to make estimates and forecasts of production and stock amounts. NASS statistics underly government and private industry decisions and help improve market efficiency. The reliability of these reports is imperative in their usefulness to inform and stabilize the markets.

Background and Contribution

NASS production reports are published monthly throughout the growing season. They provide information on the seeded area and projected yields of US crops on a country, state, and county level. NASS applies a survey methodology that evolves over the growing season. Early in the season, farmers are quizzed about seeding intentions and trend yields are applied from historical data to make production forecasts. In the later part of the season, forecasts become more sophisticated, using a statistical combination of farmer surveys and field plot observations. The accuracy of the NASS reports depends on a high level of producer participation in these surveys. Since the early 1990s, response rates have been fallen below 60% (Schnepf, 2017). The low response rate is troubling for two reasons: it can lead to biased forecasts and can become quite costly. NASS surveys are initially conducted over the internet and mail which costs $2 and $4 per respondent, respectively. If the individual fails to reply, the survey is followed up with a telephone call that costs upwards of $12 per respondent or a personal interview which costs over $50 per respondent (Schnepf, 2017).

An alternative approach to using sampling and survey methods is to use satellite imagery and weather data to produce regional, in season, crop forecasts. There are several private companies using this method as well as some government agencies including Agriculture and Agri-Food Canada (AAFC). As technology has advanced, crop forecasting models based on remotely sensed imagery have become more promising as accurate, low cost, and timely methods for crop forecasting. Satellite-base crop forecasting models are expected to continue improving as technology progresses. These methods process satellite images into remote sensing indexes that are easier to use and have relationships with plant phenology. The Normalized Difference Vegetation Index (NDVI) is one of many indices that can be derived from remotely sensed imagery. NDVI has been found to have a relatively strong relationship with crop yield, making it one of the more popular indices to use for satellite-based crop estimation models, and for index-based crop insurance models.

NDVI data is collected on discrete intervals over a time period on a daily, weekly, or monthly basis. These discrete NDVI values need to be aggregated in a way that the data can be meaningfully related to crop production. NDVI data can be aggregated into several NDVI metrics. There are several terms use to describe NDVI metrics including: process methods, aggregation techniques, phenological indices, and aggregation metrics. This study will use the term NDVI metric. Two of the most common NDVI metrics are maximum NDVI (MaxNDVI) and integrated-NDVI (INDVI). These NDVI metrics have a close relationship to the overall biomass (productivity) of the crop (Paruelo and Lauenroth, 1998). MaxNDVI is a straightforward approach that uses the largest NDVI value in a growing season. INDVI is integrated on an approximate functional fit on all NDVI values within a growing season. Performing the integration for INDVI can be challenging as there are complications around defining the start and end of the INDVI integration which could impact model accuracy. This research will contribute to the development of satellite-based crop yield forecasting and index-based crop insurance by investigating various NDVI metrics for crop yield estimation.

Objective, Data, and Methodology

The objective of this research is to empirically examine multiple NDVI metrics for crop yield estimation including maximum NDVI and integrated-NDVI. The results of this analysis will aid in the development of satellite-base index crop yield estimation and forecasting models. For the integrated approach, crop progress reports and growing degree days are used to set the start and end dates of the integration period. For MaxNDVI the largest NDVI value over the growing season is used.

The following sections in this study contain background on NDVI and some of the current uses of NDVI. This is followed by the development of a novel process to derive INDVI, and a discussion of the results of the study and some of their implications.

The Normalized Difference Vegetation Index (NDVI)

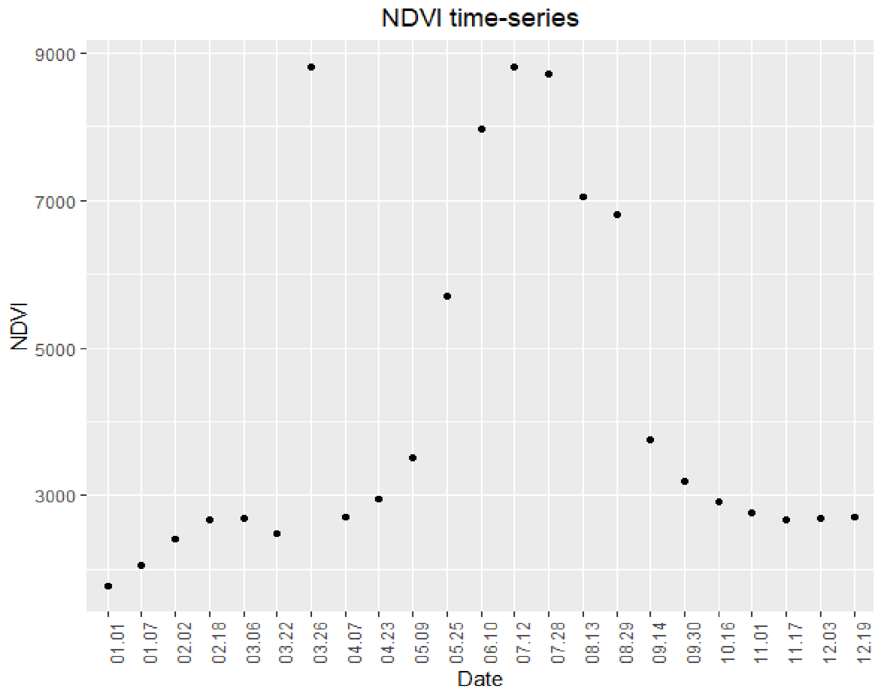
The Normalized Difference Vegetation Index (NDVI) is one of many indices that can be derived from remotely sensed imagery. NDVI is a means of evaluating crop productivity over a growing season and has been well documented in its ability to estimate and forecast various aspects of vegetation.

NDVI is a measure of the relative greenness of the crop. NDVI is derived from the red and near-infrared band reflectance ratio:

$$NDVI = (a_N - a_R)/(a_N + a_R) \qquad [1.1]$$

Where a_R is the red reflectance image band and a_N is the reflectance in the near infrared band. Green vegetation reflects more near infrared (a_N) and green light versus other wavelengths while absorbing more red and blue light. Equation [1.1] produces values ranging from -1 in the absence of vegetation (such as water surfaces) to 1 in areas of very dense vegetation (Lüdeke et al., 1996; Pettorelli et al., 2005). The range of NDVI values for crops during the growing season range from 0.2, which is considered soil reflectance, to 0.9 which signals dense vegetation. An example of an NDVI time-series is shown in Figure 1.

Figure 1 NDVI time-series for corn crops in Iroquois County Illinois for 2018



Notes: The above graph is an example of an NDVI time series over the course of a growing season. NDVI is low at the start of the year where there is little vegetation. NDVI increases rapidly from emergence to maximum phenological activity before decreasing again in the dry-down phase. Values for NDVI on the chart have been multiplied by a factor of 10,000 for interpretation.

The frequency, how often the satellite collects an image of discrete NDVI data, depends on the satellite that the sensor is mounted to and the resolution of the desired image. Depending on the satellite, an image of a geolocation could be taken multiple times in a given period, but there is a negative relationship between image frequency and resolution. More precise images are more prone to error, reducing the number of discrete data points.

Current Uses of NDVI

Moriondo et al. (2007), and Benedtti and Rossini (1993), found that NDVI could be used in regression analysis to make accurate estimations of wheat yields in Italy. Similarly, Mkhabela et al. (2011), performed regressions analysis on NDVI and yield data and found that NDVI could successfully estimate crop yields on the Canadian Prairies. In addition to being applied to agricultural crops, NDVI but has been used to measure phenological activity in ecosystems globally (Pettorelli et al., 2005). Forecasting and crop condition models are currently used by a number of private and government agencies. Government agencies using forecasting and crop condition models include: Agriculture and Agri-Food Canada (AAFC), National Agriculture Statistics Service (NASS), and Foreign Agriculture Service (FAS). Most government agencies and private companies use a combination of remotely sensed information (including NDVI) and expert opinion to forecast yields and estimate crop quality around the world (Schnepf, 2017; Johnson, 2014; Statistics Canada, 2020).

Forage insurance models using NDVI as the underlying index are currently being used in Canada, France, and Spain (Roznik, 2021). A version of NDVI based insurance was being used in the US but was dropped in 2016 because it was too complex for insurees to understand (Vroege et al., 2019).

CHAPTER 2

CROP YIELD ESTIMATION USING VARIOUS NDVI METRICS

Satellite Noise

Causes and Implications of Satellite Noise in NDVI Data

Conditions in the atmosphere such as clouds, water vapor, soil reflectance, shadows and smoke have a strong negative impact on NDVI (causing smaller NDVI values) (Viovy et al., 1992). Less-common cases such as sensor calibration error, sensor degradation, high solar levels and scan angles can cause NDVI values to be inflated (Pettorelli et al., 2005). These errors (or noise) can cause NDVI to inaccurately represent ground vegetation and impact model accuracy. Because of this, NDVI data is usually preprocessed to remove many of these errors (Pettorelli et al., 2005). It is often the practice during preprocessing that the largest discrete NDVI value (sometimes referred to as $NDVI_{max}$) within a timeframe (usually 5-16 days) is selected and the others are discarded. Because most of the error in NDVI data result in smaller NDVI, $NDVI_{max}$ is considered to have the least amount of error versus the other NDVI within a timeframe. Once $NDVI_{max}$ is selected, the remaining NDVI values are discarded and $NDVI_{max}$ is used to represent the entire timeframe (note: $NDVI_{max}$ is different than MaxNDVI, which is processed later).

NDVI Preprocessing

Some noise resulting in both false highs and lows will persist throughout preprocessing. These persisting errors result in the need for NDVI data to be smoothed. There are many ways to smooth NDVI including: cubic spline, maximum value compositing (MVC), curve fitting, stepwise logistic regression, best index slope extraction (BISE), weighted least-squares, and linear regression (Pettorelli et al., 2005). Once the data is smoothed, it can be processed using one of several related metrics.

NDVI metrics

Commonly Used NDVI Metrics

Various NDVI metrics have been developed from NDVI time-series to measure different aspects of the vegetative life cycle within a growing season. These metrics are often called NDVI metrics, process methods, aggregation techniques, phenological indices and aggregation methods. This study refers to them as NDVI metrics. Table 1 is an adaptation from Lloyd (1990), Reed et al (1994), and Pettorelli et al. (2005) and is a compilation of twelve commonly used NDVI metrics.

Each NDVI metric in Table 1 can be categorized into three general classes: temporal NDVI metrics, NDVI-value metrics, and derived metrics (Reed et al., 1994). Temporal NDVI metrics are the dates of significant events as derived from NDVI data (often described in Julian Days). NDVI-value metrics are the actual NDVI values at the time of significance. Derived NDVI metrics are those that use NDVI to compute a value that describes a specific phenological event.

Table 1 Twelve commonly used NDVI metrics

	Metric	Definition	Phenological Interpretation
Temporal NDVI metrics	Start of the growing season (SGS)	Emergence, or the day when the threshold signalling the start of the growing season is met	The day measurable photosynthetic activity starts
	End of the growing season (EGS)	Senescence, or the day when the threshold signalling the end of the growing season is met	The day measurable photosynthetic activity ends
	Date of the annual maximum NDVI (DMAX)	The day the largest NDVI value of the growing season is recorded	The day photosynthetic activity is at its highest
	Length of the growing season (LGS)	The number of days between the start (SGS) and end (EGS) of the growing season	The total time of crop growth
NDVI-Value Metrics	NDVI at the onset of greenness	The NDVI value at the start of the growing season (SGS)	The amount of photosynthetic activity at the start of the growing season
	NDVI at the end of greenness	The NDVI value at the end of the growing season (EGS)	The amount of photosynthetic activity at the end of the growing season
	Annual maximum NDVI (MaxNDVI)	The NDVI value on the date of the annual maximum NDVI (DMAX)	The maximum level of photosynthetic activity within the growing season
	Annual minimum NDVI (MinNDVI)	The NDVI value withing the growing season where NDVI is the lowest	The minimum level of photosynthetic activity
Derived NDVI Metrics	Integrated-NDVI (INDVI)	The integration of all positive NDVI values in a growing season	Measure of total photosynthetic activity in a growing season
	Relative annual range of NDVI (RREL)	(MaxNDVI-MinNDVI)/INDVI	Measures the variability of plant growth between growing seasons
	Rate of green up	The slope of NDVI between the start of the growing season (SGS) and the end of the green up period (usually DMAX)	Measures the acceleration of photosynthetic activity, or rate of plant growth
	Rate of senescence	The slope of NDVI during senescence (usually between DMAX and the end of the growing season (EGS)	Measures the deceleration of photosynthetic activity, or rate of plant senescence

Notes: Each NDVI metric can be placed into one of three categories: temporal NDVI metrics, NDVI-value metrics and derived NDVI metrics. Temporal metrics are the actual dates of a significant NDVI occurrence. NDVI-value metrics are the actual NDVI values of significant points in the growing season. Derived NDVI metrics use NDVI values to calculate values that represent significant events of a growing season. Adapted from Lloyd (1990), Reed et al (1994), and Pettorelli et al. (2005).

Some NDVI metrics measure seasonal characteristics of vegetation such as the start, end, and length of a growing season (Guerschman et al., 2003) as well as the rate of green up and senescence of a crop (Pettorelli et al., 2005). Metrics such as the relative annual range measure the variability of vegetation from year to year (Reed et al., 1994). Metrics such as integrated-NDVI (INDVI) and the annual maximum NDVI (MaxNDVI), are used to measure the overall biomass (productivity) of a crop (Paruelo and Lauenroth, 1998) and have been found to relate well will crop yields. The ability of MaxNDVI and INDVI to explain crop yield have made them two of the most common NDVI metrics used in NDVI forecasting and estimation models. The following sections take a closer look at the various NDVI metrics that will be examined in this study along with an introduction to growing degree days.

Temporal NDVI Metrics

Start of the Growing Season (SGS), End of the Growing Season (EGS), Length of the Growing Season (LGS)

Temporal NDVI metrics use NDVI data to determine important days or lengths of time within a growing season. Four common temporal NDVI metrics are: the start of the growing season (SGS), the end of the growing season (EGS), the date of the maximum NDVI (DMAX) and the length of the growing season (LGS). SGS, EGS and DMAX are metrics that correspond to the actual calendar day (often described in Julian days) of the event. For example, SGS is the day when the NDVI-value metric, NDVI at the onset of greenness, occurs (theoretically at emergence). Likewise, EGS is the day when NDVI at the end of greenness occurs. DMAX is the day when the annual maximum NDVI is reached in a growing season. Thus, DMAX is the day when photosynthetic activity is at it is highest. The length of the growing season (LGS) is the number of days between SGS and EGS.

$$LGS = EGS - SGS \quad [2.1]$$

LGS is a measure of the total number of days that photosynthesis is occurring.

In theory, SGS is the day when the plant emerges, EGS is the day the plant dies and LGS is the number of days from emergence to senescence. Satellite derived dates for SGS and EGS may not represent the exact dates of plant emergence and senescence due to satellite errors (often caused by soil reflectance), but they provide a way to measure these key parts of the growing season (Reed et al., 1994). Because of the difficulty in obtaining values for SGS and EGS, researchers such as Lloyd (1992) have made efforts to develop threshold NDVI values that signal these events. However, NDVI thresholds change depending on the crop being studied, the color of the soil, and the atmospheric conditions (Reed et al., 1994). For this reason, a popular way to estimate SGS and EGS is to identify the day when NDVI begins to rise rapidly (for SGS) and when the decline in NDVI starts to level off (for EGS) (Reed et al., 1994; Guerschman et al., 2003). The time period between these approximated SGS and EGS dates is sometimes referred to as the approximate growing season (AGS). For the purposes of this study, LGS will be used interchangeably for the actual length of the growing season and the approximate growing season. A more detailed discussion on the implications of defining SGS and EGS will follow in the integrated NDVI section.

Days to MaxNDVI (DTM), Days from MaxNDVI (DFM)

This study includes two additional temporal NDVI metrics including days to max NDVI (DTM) and days from max NDVI (DFM). DTM is the number of days between SGS and DMAX. DTM measures the length of the growing period from emergence to maximum phenological activity. DFM is the number of days from max phenological activity to senescence. DFM measures the length of the grain filling and dry down period.

NDVI-Value Metrics

Maximum and Minimum NDVI

Maximum NDVI (MaxNDVI) and minimum NDVI (MinNDVI) are NDVI value metrics. Maximum NDVI (MaxNDVI) occurs on DMAX as it is the maximum NDVI value in a given year (Paruelo and Lauenroth, 1998).

$$\mathrm{MaxNDVI} = \max(\mathrm{NDVI}) \quad [2.2]$$

MaxNDVI is used as a measure of overall productivity because it represents the highest level of photosynthetic activity of the crop before it begins to die. MaxNDVI occurs around the critical reproductive stages of a crop. MaxNDVI is a simple and straight forward NDVI metric because it only uses the largest NDVI value after preprocessing. As such, MaxNDVI works well to avoid false lows from shadow or cloud cover. Since it is the highest NDVI value in a season, it is sensitive to false highs (Pettorelli et al., 2005). Despite this, MaxNDVI has been shown to be related to crop yield (Lopresti et al., 2015; Becker-Reshef et al., 2010). The relatively strong relationship with crop yield has made MaxNDVI a popular NDVI metric to use in estimation and forecasting.

Minimum NDVI (MinNDVI) is the minimum NDVI value in a growing season. MinNDVI is rarely used on its own in estimation and forecasting models, but it is used to calculate derived NDVI metrics such as RREL.

Derived NDVI Metrics

Integrated NDVI (INDVI)

Integrated-NDVI (INDVI) is a derived NDVI metric. INDVI is the integration of all positive NDVI values over a given period.

$$\mathrm{INDVI} = \int_{b}^{a} \mathrm{NDVI} \qquad [2.3]$$

INDVI is an estimate the total amount of photosynthesis a plant canopy can achieve over a period of time (Guerschman et al., 2003). INDVI has been found to relate well with crop yield. Because of its usefulness in measuring crop yield, many crop modeling studies use INDVI to integrate NDVI values from time periods anywhere from 4 days to entire growing seasons. The period used depends on the goal of the study, the frequency of the satellite, and the climate of the area being studied. INDVI minimizes the effect of image errors that decrease NDVI values, but false high values can still impact INDVI.

INDVI Integration

In yield estimation models, INDVI is often integrated over the length of the growing season (LGS). INDVI has been found to outperform MaxNDVI in yield forecasting models (Ajith et al., 2017), but a major issue in the use of INDVI arises when identifying the start (SGS) and end of the growing season (EGS) over which NDVI will be integrated. The simplest approach is to use fixed dates for SGS and EGS when emergence would normally occur. However, using fixed dates does not allow the model to account for seasonal variability in weather conditions and crop growth (Labus et al., 2002). Lloyd (1990) studied the use of thresholds were an NDVI value is chosen that is expected to signal SGS. The weakness with this approach is that NDVI thresholds depend on several factors including crop type, soil color, and light (Reed et al., 1994). Most studies seek to approximate LGS using one of several techniques. One of the most common ways to approximate LGS is by using a moving average. When using the moving average approach, SGS is defined as the point when NDVI begins to rise rapidly. EGS is the point when the decline in NDVI levels off. (Labus et al., 2002; Reed et al., 1994). Using this approach, Reed et al. (1994) defined SGS as the time when the smoothed NDVI data intersected and stayed above the moving average. Labus et al. (2002) compared the moving average method of defining LGS with the fixed dates approach. Results showed that integrating over LGS as defined by the moving average showed stronger relationships with crop yield than when integrating between fixed dates. Another method of approximating LGS is to take the first derivative of the NDVI time-series. The start and end of the integration occurs when the first derivative equals a certain threshold (usually 0.4). INDVI does not have to be integrated over the entire growing season. Many studies have found that INDVI integrated around the time of the critical crop growth stages (flowering and grain filling) can be used to estimate crop yield (Labus et al., 2002, Benedetti and Rossini, 1993). INDVI integrated over critical growth stages only has been found to outperform models that integrate NDVI over other periods of the growing season (Mkhabela et al., 2011; Mkhabela et al., 2005; Rasmussen, 1992; Marti et al., 2007; Salazar et al., 2007; Arman, 2019). This study proposes a new method of defining SGS and EGS by applying information about the interaction of crop phenology and growing degree days (See heading: New Method of Using GDD to Aid the Definition of SGS and EGS).

Relative Annual Range (RREL)

The Relative Annual Range (RREL) of NDVI is a measure of the interannual variability in crop growth (Guerschman et al., 2003; Pettorelli et al., 2005).

$$\mathrm{RREL} = \frac{(\mathrm{MaxNDVI} - \mathrm{MinNDVI})}{\mathrm{INDVI}} \qquad [2.4]$$

RREL allows for comparison between different kinds of vegetation. RREL is sensitive to both false lows and false highs (Pettorelli et al., 2005). Guerschman et al. (2003) used DMAX, INDVI and RREL as three traits representing the seasonal dynamics of NDVI to compare native vegetation with regularly cropped areas. Results indicated RREL had stronger relationships with annual crops as opposed to perennial crops because annual crops have more distinct growing seasons.

Growing Degree Days

The concept of growing degree days (GDD) originated from observations that plant development is closely related to the accumulation of certain amounts of heat (Reamur, 1735). GDD is a method of assigning a heat value to each day. GDD has been found to be related to various stages of plant development. GDD for a given day is calculated by summing the maximum and minimum temperatures of the day and dividing by 2. This is then subtracted by a crop-specific base temperature that represents the temperature below which plant development stops.

$$\mathrm{GDD} = ([T_{max} + T_{min}]/2) - T_{base} \qquad [2.5]$$

Where T_{max} is the high temperature of the day, T_{min} is the low for the day and T_{base} is the low temperature where crop growth stops. It has been widely established that T_{base} for corn crops is 50°F.

Accumulated GDD for a specific timeframe is the summation of all the GDD within it:

$$\sum GDD = \sum([T_{max} + T_{min}]/2) - T_{base} \quad [2.6]$$

Gilmore and Rogers (1958) found that the addition of an upper temperature limit made corn models more precise. They found that temperatures more than 86°F began to negatively affect corn plant development. Gilmore and Rogers' (1958) study on corn gave birth to the 50/86 method; T_{base} is 50°F and any T_{max} that surpasses 86°F, is replaced with 86°F.

Data and Methodology Used in this Study

Data

NDVI Data

NDVI data at a 250-meter resolution (MOD13Q1) was accessed from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS). NDVI data was collected over a 13-year time frame spanning from 2006 to 2018, and multiplied (scaled) by a factor of 10,000. Images with vegetation types other than the ones of this study, for example, trees, grass, and crops other than corn, can add error (or noise) to NDVI models. Much of this error can now be avoided through the NASS Crop Data Layer (CDL). CDL is a 30 by 30-meter grid over the surface of the US that can identify over 100 different types of crops and non-crop land (USDA NASS). The CDL allows for the exclusion of areas of non-interest from the data which would otherwise add error (noise) (Roznik, 2021). NDVI time-series data for a given county for a given year are extracted from the CDL pixel locations which correspond to the location of a given crop. These pixels are then averaged over the county. The maximum of these NDVI values were selected on a 16-day basis which resulted in 23 NDVI data points for every year. NDVI data was collected on a county level for all states in the US (excluding Alaska and Hawaii). To avoid error, only counties with more than 1,000 acres planted to corn were kept for analysis. Excluding counties with less than 1,000 planted acres allowed the study to focus solely on the major corn producing areas. The primary region for corn production is the US Midwest.

Yield Data

Yield data in bushels per acre was collected from the USDA NASS database. The data was gathered on a by-county basis from 2006 to 2018 (13 years) for all of the main corn producing states in the US.

Growing Degree Day Data

Maximum and minimum temperature data (Tmax and Tmin) needed to calculate growing degree days (GDD) was gathered from the Puget Sound Regional Synthesis Model (PRISM) of the University of Washington. Tmax and Tmin were gathered on a state-level for all 50 states in the US.

Planting Progress Data

Planting data progress data was accessed from the USDA NASS database. During the planting season, NASS publishes weekly planting progress updates for the major corn producing states in the US.

NDVI, yield, GDD, and planting progress data was joined on a by-county basis. Data collected at the state level was distributed across the respective counties. While joining the data, states with missing data and counties with less than 1,000 acres were eliminated. This resulted in 18 states for analysis: Colorado, Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Carolina, North Dakota, Ohio, Pennsylvania, South Dakota, Tennessee, Texas, and Wisconsin. Each of the approximately 30 counties in this study have 1,000 or more planted acres. This allows the study to focus solely on the major corn producing areas.

Methodology

Design of Crop Yield Regression Models

The methodology of this study is divided into 4 steps. **Step 1** involves extracting the crop specific NDVI pixels from the CDL. For **step 2**, NDVI data is smoothed, and missing values are filled in using a cubic spline. In **step 3**, the various NDVI metrics: MaxNDVI, MinNDVI, RREL, LGS, DTM, DFM and the unique method of INDVI are created. In **step 4**, regression analysis is used to see if the unique INDVI method shows more accurate yield estimates than the other NDVI metrics, including MaxNDVI. R^2 is used to determine model fit (accuracy).

Extract NDVI Data from the Crop Locations Identified Using the CDL

NDVI vegetation data were gathered from the NASA MODIS sensor carried by the Terra satellite. The NDVI used was based on spectral radiation bands of 250m spatial resolution, the highest resolution available from MODIS. Errors can occur in NDVI data when areas of non-interest are included such as rocks, trees, grassland, and crops other than corn. Much of this error can be avoided through the CDL. CDL can identify and separate the various crops from the image at a 30 by 30m resolution. This way, only the specific crop of interest (corn) is included in the NDVI data.

NDVI was extracted on a by-county basis for corn crops in the US (except for Hawaii and Alaska). Counties with less than 1,000 acres of corn were excluded to allow the focus of the model to remain strictly on the main corn producing regions.

Preprocess NDVI

To avoid satellite errors that decrease NDVI such as cloud cover, smoke, and water vapor, the maximum NDVI in each time series was selected on a 16-day basis. This resulted in 23 NDVI data points for every year, for each county. Satellite errors can persist though this process. To deal with this, and to replace missing NDVI values within the time-series, the NDVI data was smoothed. This study uses the cubic spline smoothing method. The cubic spline method minimizes the squared errors between the data and the spline while minimizing the curvature. This results in a smooth fitted line to the data and allows for a representative data point for each day.

Establish NDVI Metrics

Once the NDVI data is processed and smoothed, it can be used to develop the relevant NDVI metrics: MaxNDVI, MinNDVI, INDVI, LGS, DTM, DFM and RREL. These metrics were chosen based on their popularity in previous research, their potential ability to estimate crop yield, and their ability to be understood by a crop producer. Selecting MaxNDVI is a simple process of choosing the annual maximum NDVI value for each county being studied. MaxNDVI occurs on DMAX. Selecting MinNDVI is a similar process, were the minimum NDVI value within the growing season was selected. For INDVI, NDVI data was aggregated over the entire length of the growing season (LGS). The process for defining the start of the growing season (SGS) and end of the growing season (EGS) is described in detail below. Once MaxNDVI, MinNDVI and INDVI were aggregated, RREL was created by taking the difference between MaxNDVI and MinNDVI and dividing by INDVI. DTM was calculated by taking the difference in days from SGS to DMAX. Similarly, DFM was calculated by taking the difference in days from DMAX to EGS. The result of each index is one data point per county per year.

New Method of Using GDD and Planting Data to Aid the Definition of SGS and EGS

NDVI integration conditions were set based on the general phenological behaviour of corn. SGS was defined as the time when planting progress for the respective state reached 70% complete plus the time for GDD to reach the threshold for the crop to emerge. EGS was defined as the point after SGS when enough GDD had accumulated for the corn crop to reach maturity. The conditions for the NDVI integration can be summarized as follows:

$$\mathrm{INDVI} = \int_{b}^{a} (\mathrm{NDVI_i}, \mathrm{NDVI_j}) \qquad [2.7]$$

Where $NDVI_i$ and $NDVI_j$ are the NDVI values at SGS and EGS. For example, corn crops generally take 125 GDD to emerge after being planted, thus $NDVI_i$ for each respective major corn growing state is the NDVI value that corresponds to the time when corn planting progress is 70% complete plus the time it takes for 125 GDD to accumulate. For 120-day corn varieties, the crop needs another 2,928 GDD after emergence to become mature, thus, $NDVI_j$ is the NDVI value that corresponds to the time after SGS when an additional 2,928 GDD have accumulated. Even though the NDVI data being used in this study is 16-day data with only 23 discrete NDVI annual values, the cubic spline method of smoothing produces a representative NDVI value for any given day. This allows for a representative data point each day that an integration condition is met. This new method of INDVI integration was examined with county level yield data and the results were compared to the other NDVI metrics.

Once SGS and EGS was derived, the remaining indices: LGS, DTM and DFM were calculated. LGS was calculated by taking the difference between EGS and SGS. DTM was calculated by taking the difference between DMAX and SGS. DFM was calculated by taking the difference between EGS and DMAX.

Adjusting Yield Data for Trend

Improving management practices and cropping technology has caused corn yields to increase in an upward trend over time. This gives rise to the dependency of the yield data over time. Linear approximation (an annual time trend variable) was used to adjust for the time dependency in the yield data.

Regression Estimates of Crop Yield Using Various NDVI Metrics

Regression analysis was conducted to examine the performance of various NDVI metrics for estimating crop yield. County level crop yields were estimated for corn using the metrics: MaxNDVI, INDVI, RREL, DTM, DFM, and LGS separately. For the DTM and DFM models, additional $DTM^{\wedge 2}$ and $DFM^{\wedge 2}$ variables were respectively added to capture the curvilinear relationship these variables are expected to have with yield. The relative fit of crop yield was compared for each NDVI metric. A better model fit (more accurate yield estimates) is indicated by a larger R^2. INDVI may have a better fit with crop yield through the incorporation of planting and GDD data. The use of planting and GDD data to define SGS and EGS should help INDVI better relate to crop phenology and improve the relationship with yield.

To see if there is an improvement in fit when multiple NDVI metrics are used in combination, MaxNDVI, RREL, DTM, and DTM$^{\wedge 2}$ were used together to estimate corn yield. These NDVI metrics were chosen to represent the most important aspects of the growing season.

Results

Descriptive Results for the Five Selected NDVI Metrics

Six models were tested to investigate the relationship of the five NDVI metrics with corn crop yields. First, MaxNDVI, INDVI, RREL, DTM, DFM, and LGS were tested independently, then specific NDVI metrics were selected and tested in combination. The fit of each model was determined by an examination of their R^2 values. A better model fit is indicated by a larger R^2. INDVI is expected to have a better fit with crop yield compared to MaxNDVI and the other NDVI metrics. The incorporation of planting and GDD data as conditions in determining SGS and EGS may allow INDVI to better account for seasonal variations in planting, emergence and growth rates which could improve its ability to relate to crop yield. The results of each model and their fit with corn and yields are discussed in detail below.

Regression Results

Regression Results Using the Five NDVI Metrics Independently

Tables 2 and 3 show the regression results of each NDVI metric used in separate models. For each model, county-level corn yield in bushels per acre was the dependent variable and one of the five NDVI metrics was the explanatory variable. The observations are the total number of county-level corn yield data points across the 18 states with a total planted area of 1,000 acres or more during the 13-year timeframe.

Table 2 shows that the coefficients for each of the NDVI metrics are positive. This indicates that as each metric for a specific county rises, corn yield in that county is expected to rise. For example, as MaxNDVI (multiplied by 10,000) rises by one unit, corn yield is expected to rise by 0.049 bushels per acre. INDVI was unable to outperform MaxNDVI when comparing the fit of the models. The INDVI model produced an adjusted R^2 of 0.190 while the MaxNDVI model showed an adjusted R^2 of 0.583. This means that INDVI produced less accurate corn yield estimates than MaxNDVI. The adjusted R^2 of 0.190 for the INDVI model indicates that just 19% of the variance in corn yield was explained. MaxNDVI outperformed all the other NDVI metrics in the study.

DTM is the number of days from emergence to peak photosynthetic activity while DFM is the number of days from peak photosynthetic activity to the end of photosynthetic activity. It is expected that both variables will have positive relationships with crop yield, but with decreasing effect. Thus, additional variables $DTM^{\wedge 2}$ and $DFM^{\wedge 2}$ were added to the respective DTM and DFM models on Table 3. Both models showed this to be true as both DTM and DFM variables have positive coefficients while the coefficients of the squared variables are negative. The coefficient for DTM indicates that as the time between SGS and DMAX increases by 1 day, corn yield will rise by 3.36 bushels per acre. Surprisingly, DTM (Table 3) showed the second highest model fit than all the other NDVI metrics with an adjusted R^2 of 0.235. This indicates that over 23% of the variance in corn yield can be explained by the number of days from emergence to max photosynthetic activity.

Table 2 Regression results for corn yield estimation in the US from 2006 to 2018 using NDVI metrics: MaxNDVI, INDVI, and RREL.

	MaxNDVI	INDVI	RREL
Time Trend	2.037***	3.447***	3.363***
	(0.089)	(0.122)	(0.121)
Coefficient	0.049***	0.002***	230.082***
	(0.001)	(0.0001)	(7.314)
Intercept	-259.687***	71.864***	103.295***
	(4.348)	(2.276)	(1.312)
Observations	7,084	7,084	7,084
R^2	0.583	0.191	0.200
Adjusted R^2	0.583	0.190	0.199
Residual Std. Error (df = 7081)	23.249	32.397	32.216
F Statistic (df = 2; 7081)	4,952.861***	833.553***	882.790***

Notes: Dependent variable is county-level corn yield in bushels per acre. Independent variables for each respective model are maximum NDVI (MaxNDVI), integrated-NDVI (INDVI), and relative annual range of NDVI (RREL). The coefficients for all 3 of the models are positive, indicating increases in each of the NDVI metrics relate to larger corn yields. For example, as MaxNDVI (multiplied by 10,000) rises by one unit, corn yield is expected to rise by 0.049 bushels per acre. The MaxNDVI model has an adjusted R^2 of 0.583, indicating that over 58% of the variance in corn yield can be explained by MaxNDVI. NDVI values have been multiplied by a factor of 10,000 for convenience. Standard errors are in parenthesis. Each regression was estimated by OLS.

***Significant at the 1 percent level.

**Significant at the 5 percent level

*Significant at the 10 percent level

Table 3 Regression results for corn yield estimation in the US from 2006 to 2018 using NDVI metrics: DTM and DFM.

	DTM	DFM
Time Trend	3.545*** (0.119)	3.488*** (0.120)
Variable	3.358*** (0.099)	7.088*** (0.231)
Variable^2	-0.023*** (0.001)	-0.033*** (0.001)
Intercept	19.655*** (3.252)	-236.115*** (12.839)
Observations	7,084	7,084
R^2	0.235	0.214
Adjusted R^2	0.235	0.214
Residual Std. Error (df = 7080)	31.497	31.390
F Statistic (df = 3; 7080)	725.081***	641.975***

Notes: Dependent variable for corn regressions is county-level corn yield in bushels per acre. Independent variables for the DTM model are days to maximum NDVI (DTM) and DTM^2. Independent variables for the DFM model are days from maximum NDVI (DFM) and DFM^2. The coefficient for DTM and DFM are both positive indicating that corn yield increases as the length of the growing season increases. For example, the coefficient for DTM indicates that as the time between SGS and DMAX increases by 1 day, corn yield in that will rise by 3.36 bushels per acre. For both models, the coefficient of the squared variable (DTM^2 and DFM^2) is negative, indicating a decreasing effect for both DTM and DFM. The DTM model has an adjusted R^2 of 0.235, indicating that over 23% of the variance in corn yield can be explained by DTM. Standard errors are in parenthesis. Each regression was estimated by OLS.
***Significant at the 1 percent level.
**Significant at the 5 percent level
*Significant at the 10 percent level

Regression Results Using Four of the NDVI Metrics in Combination

Table 4 shows the regression results for MaxNDVI, RREL, DTM, and DTM^2 used together to estimate county-level corn yield. These metrics were included to represent the most important aspects growing season. DTM-squared was included to account for the decreasing effect of DTM on crop yield. The combination of the NDVI metrics resulted in an adjusted R^2 of 0.644. This indicates that over 64% of the variance in corn yield was explained by the model. The increase in R^2 for the combination model indicates that the ability to estimate crop yield was enhanced by the additional information contained in the combination of metrics.

Table 4 Regression results for corn yield estimation in the US from 2006 to 2018 using a combination of NDVI metrics: MaxNDVI, RREL, and DTM.

	Combination Model
Time Trend	2.208***
	(0.082)
MaxNDVI	0.043***
	(0.001)
RREL	161.660***
	(5.057)
DTM	0.988***
	(0.074)
$DTM^{\wedge 2}$	-0.007***
	(0.001)
Observations	7,084
R^2	0.644
Adjusted R^2	0.644
Residual Std. Error (df = 7078)	21.487
F Statistic (df = 5; 7078)	2,561.821***

Notes: Dependant variable is county-level corn yield in bushels per acre. Independent variables are maximum NDVI (MaxNDVI), relative annual range (RREL), days to maximum (DTM), and days to maximum-squared ($DTM^{\wedge 2}$). The coefficients of MaxNDVI, RREL, and DTM are positive, indicating that corn yield is expected to rise as these NDVI metrics increase. $DTM^{\wedge 2}$ has a negative coefficient indicating a decreasing effect of DTM on yield. The adjusted R^2 of .644 indicates that over 64% of the variance in corn yield was explained by the model. NDVI values have been multiplied by a factor of 10,000 for convenience. Standard errors are in parenthesis. The regression was estimated by OLS.

***Significant at the 1 percent level.

**Significant at the 5 percent level

*Significant at the 10 percent level

CHAPTER 3

SUMMARY

Problem and Importance

Crop yield estimates and forecasts are used to help manage volatility in agricultural markets and aid in resource allocation along the supply chain. Government agencies around the world have traditionally relied on survey and sample methods of crop yield forecasting. Traditional crop yield forecasting methods are time consuming, expensive, and rely on a high level of producer participation. Producer participation has been declining which has been increasing the cost of the forecasts and could be causing biased results. Crop forecasting models based on remotely sensed imagery have become more promising as accurate, low cost, and timely methods for crop forecasting.

Objective

The objective of this research was to empirically examine various satellite based NDVI metrics for yield estimation, including maximum NDVI and integrated-NDVI. (NDVI metrics are often referred to as process methods, aggregation methods, phenological indices, and aggregation metrics). This study aids in the development and use of index-based crop estimation models by increasing the accuracy of NDVI crop yield estimation models. The addition of planting date and growing degree data was examined to see if it would enhance the ability of INDVI to relate to crop phenology and thereby improve NDVI based county crop yield estimates.

Data and Methodology

NDVI and corn-yield data was collected on a county-level basis from 2006 to 2018 (13 years) for all the counties (except for counties in Hawaii and Alaska) across the US with 1,000 or more planted acres. State-level GDD (temperature) data was collected for all the states in the US and planting progress information was collected for the major corn producing states. Once the states with missing data were eliminated, 18 of the top corn producing states and their respective counties (with 1,000 or more planted acers) were used for analysis. NDVI data was aggregated into several metrics including a unique method of aggregating INDVI using GDD and planting data. Regression analysis was conducted to examine the performance of the various NDVI metrics for estimating crop yield.

Results

The unique method of INDVI integration was unable to outperform the MaxNDVI approach for estimating crop yield. This was determined by evaluating the model fit of each NDVI metric with county-level yield by comparing the R^2 values each model. The MaxNDVI model produced an adjusted R^2 of 0.583 while the adjusted R^2 of the INDVI model was 0.190. The strong relationship that MaxNDVI had with corn yield is not unsurprising as several studies have shown the ability of MaxNDVI to relate to crop yield (Lopresti et al., 2015; Becker-Reshef et al., 2010). The decrease in model fit of INDVI verses MaxNDVI is likely because the increased ability of INDVI to relate to crop phenology was more than offset by the increase in satellite error in the model. There are larger amounts of soil reflectance error closer to SGS and EGS, and as data near to these points was added, there is a higher chance that persisting satellite noise will be included.

The ability of NDVI metrics to estimate crop yield was enhanced when used in combination. NDVI metrics, MaxNDVI, RREL, DTM, and DTM$^{\wedge 2}$, were chosen as the combination of these metrics reflect the most important aspects of the growing season. DTM-squared was included to account for the decreasing effect of the DTM. This combination model produced the strongest relationship to crop yield with an adjusted R^2 of 0.644.

The results of this study indicate that the addition of planting date and GDD data does not enhance the relationship between INDVI and crop yield compared to MaxNDVI. MaxNDVI can better account for seasonal variations in crop phenology while avoiding the additional measurement error of INDVI. This study also found that MaxNDVI is better able to relate to corn crop yield in estimation models than NDVI metrics: RREL DTM and DFM. This is important, as MaxNDVI is simple to use, straightforward, and easy to understand. The fact that no other NDVI metrics were able to outperform MaxNDVI further validates the many studies and crop estimation and forecasting models that use the MaxNDVI metric.

Days to max NDVI (DTM) was the metric with the second strongest relationship with county-level corn yield producing an adjusted R^2 of 0.235. DTM is a temporal NDVI metric that measures the days from emergence (SGS) to peak phenological activity (DMAX). This is an interesting result as it indicates that the amount of time between SGS and DMAX is better able to relate to county level corn yield than several other NDVI metrics, including NDVI integrated over the entire growing season (INDVI).

Future Research

The findings of this research draw several interesting implications and opportunities for further research. The fact that the unique method of INDVI integration was unable to outperform MaxNDVI not only validates the research that has been done using MaxNDVI, but also points to the notion that early and late season NDVI are not as important in crop forecasting models as NDVI during the critical reproductive stage (that occurs around MaxNDVI). Further research could include the following: using NDVI integrated over only the critical growth stages compared to MaxNDVI, comparing the various methods of defining SGS and EGS in INDVI integration, and doing similar research on a wider scope of crops. Research comparing NDVI integrated over the critical growth period to MaxNDVI could add further confidence to the superiority of MaxNDVI over the other metrics, or it could prompt an even more accurate method of NDVI integration. Comparing the various methods of defining SGS and EGS in INDVI integration would allow for a quantitative analysis on the best method of defining LGS in crop forecasting models. Similar research on other crops such as soybeans and wheat would help determine if MaxNDVI is superior across crop types or if the optimal NDVI metric changes with the type of crop in question.

The ongoing improvement of NDVI-based and other remote sensing models will continue to enhance the forecasting ability of government and private sector analysts. The timeliness and cost effectiveness of this satellite based remote sensing technology should aid market information of crop supply around the world, improving pricing efficiency, and facilitating more optimal allocation of resources throughout the agricultural supply chain.

APPENDIX

The Importance of Corn

The Importance of Corn in Global Agriculture

Corn is the second most widely used cereal grain for human consumption in the world and is a food staple in many cultures. The main use for corn in is livestock feed consumption, but corn is also used in a wide variety of food and non-food products from corn meal to ethanol. Corn is the largest component of the global coarse grain trade and changes to the supply and demand of corn tends to influence the prices of other grain commodities.

The Importance of Corn in US Agriculture

Corn is the most widely grown crop in the US and is most densely grown in the US Midwest. Corn area has grown from a low of 60.2 million acres in 1983 to a high of 97.3 million acres in 2012 (ERS, 2020). The rise in corn production largely came with the expansion of ethanol production. The Energy Policy Act (EPA) of 2005 and the Energy Independence and Security Act (EISA) of 2007 are two policies that increased the demand for corn ethanol production. The EPA established a renewable fuels standard which mandated the use of renewable fuels in gasoline. The EISA required the use of 4.7 billion gallons of renewable fuels in 2007 which will increase each year until total use reaches 36 billion gallons in 2022. Ethanol production accounts for as much as 40 percent of total corn use in the US. Corn accounts for approximately 95 percent of the total amount of feed grain grown in the US. The US is the largest corn producer and exporter in the world, accounting for roughly 30 percent of global production and exports. Because the US is a main producer, consumer, and exporter of corn, world corn prices are largely caused by supply and demand factors in the US.

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