Quality of Digital Aerial Imagery and Implications for Various Uses in Agriculture

Josh Pritsolas, remote sensing analyst, Laboratory for Applied Spatial Analysis, Southern Illinois University Edwardsville, Aaron Prestholt, data analyst, Iowa Soybean Association, Peter Kyveryga, director of analytics, Iowa Soybean Association, Randy Pearson, professor, Laboratory for Applied Spatial Analysis, Southern Illinois University Edwardsville

Introduction

Agriculture is seeing a significant surge in different digital imagery technologies. Compared with five years ago, satellite, aircraft and unmanned aerial vehicle (UAV) systems have shown dramatic advances. There have been significant improvements in turn-around time between imagery collection and imagery delivery, in imagery resolution and lower costs, as well as in imagery use for crop management. For these and other reasons, more farmers have started collecting their own imagery using UAVs.

Modern imagery uses the spectral signatures captured by digital sensors to provide more than a visual picture of soil and crop canopy (Hatfield et al., 2008; Mulla, 2013). These spectral signatures allow us to calculate different vegetation indices (VI) to provide more information about within-field differences than can be captured by the human eye (Hatfield and Prueger, 2010). In addition to field scouting, new imagery analytics enable us to process multiple imagery layers to: (1) predict yield; (2) estimate plant stand counts; (3) detect weed, insect and disease pressure; (4) identify water and nutrient stress; and (5) recognize equipment problems.

A recent trend in precision agriculture is to use digital imagery to develop different types of “vegetation crop health maps” to help farmers and agronomists better identify crop stress factors. Imagery is also being used in developing management or variability zones within their fields for target spraying or variable rate applications. In-season monitoring using “vegetation crop health maps” or site-specific zone management requires comparing crop canopy characteristics across time as well as from one field to another within a growing season and from year-to-year.

Unlike measuring temperature or yield (both of which have specific units of measurement), the digital data of imagery (in raw format) do not have a universal scale system. When these data, in raw format, are used to conduct analyses, the results are problematic. For example, if raw digital data are used to produce a “crop health map” from last August, it cannot be compared to an image of a different field taken last August, or the same field taken on a different day.

These temporal comparisons of crop canopy are often limited by a lack of uniform imagery radiometric calibration. Therefore, it is important to realize the difference between calibrated and uncalibrated imagery. Radiometrically calibrated imagery is expressed in a unit of measure, such as percentage reflectance. This process is achieved by using an internal calibration system for a given sensor or by using known reflectance values of ground targets. On the contrary, uncalibrated imagery is expressed in relative digital numbers, which the sensor collects in a unitless measurement of the intensity from reflected energy. Also issues with raw digital data arise when these data are post-processed by truncating, enhancing, or modifying the digital counts to reduce imagery volume and increase visual imagery appeal.

This paper emphasizes through several examples, the implications of various image related issues such as spatial accuracy, mosaicking (color balance and spatial stitching), and radiometric calibration quality. Ultimately, an understanding of these image quality differences will have an impact on imagery utility for visual assessment and quantitative measurements by crop scouts, farmers, and researchers alike.

What was done:

To evaluate the quality of different digital imagery systems, Iowa Soybean Association (ISA) and Southern Illinois University Edwardsville (SIUE) teamed up in 2015 to test digital aerial imagery quality. Since 2015, we partnered with 15 aerial and UAV imagery providers. Two farmers provided a 200-acre site located a few miles from Collins, Iowa, with multiple fields of both corn and soybean. Specifically, the ISA imagery calibration site was used to test (Pritsolas et al., 2016):

- Visual quality (e.g., accuracy of spatial registration, mosaicking issues, band inversion, and lack of clarity)
- Radiometric imagery calibration quality (e.g., linearity of imagery calibration equations, and reflectance changes of calibration tarps over time)
- Post-collection imagery processing and its potential to produce calibrated vegetation indices of crop canopy.

Calibration tarps (Figure 1) with known percentage reflectance values were deployed and images were collected every two weeks during the growing seasons from 2015 to 2019. Using on-the-ground tarps with known reflectance values, we produced calibrated imagery. Also, high-accuracy GPS control targets were placed at the corner of each field and around each calibration tarp. The locations of the control targets were recorded using a Topcon GR-5 GPS unit with sub-inch accuracy.

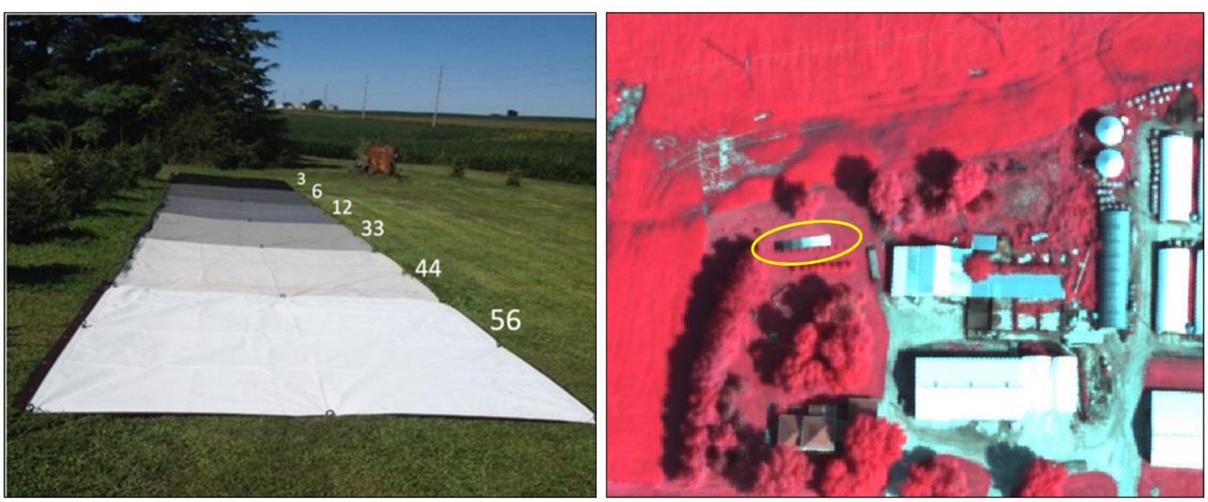

Figure 1. On-the-ground imagery calibration tarps with different percentage reflectance values (left). Tarps as seen in digital aerial imagery (right).

The calibrated imagery was used to generate different vegetation indices (VIs). Yield, soil, and crop scouting data were collected each growing season from both corn and soybean. Crop yield was aggregated using 25 x 25-meter grid cells to facilitate analyses of multiple factors over time.

Percentage reflectance from calibrated imagery was used to produce a dozen different VIs. For example, Normalized Difference Vegetation Index (NDVI) is the ratio of two quantities: (1) the difference between near-infrared and red and (2) the sum of near-infrared and red. NDVI ranges from -1 to +1 and correlates well with plant biomass and leaf health. Other indices such as GNDVI, MSAVI, CIG, TVI were also used.

A "Vegetation Index Time Series Interactive Tool" was developed to facilitate comparison of calibrated and uncalibrated times series of different vegetation indices of corn and soybean canopy from the ISA Imagery Calibration site. The tool is accessible at: http://analytics.iasoybeans.com/cool-apps/TimeSeries/.

Results

Figure 2 shows examples of possible imagery issues. Many of these problems often go unnoticed by the casual user; however, these issues cause problems for visual assessment, and more importantly, alter the quantitative value of these data. As the evolution of remote sensing transitions from a visual evaluation to a robust numeric analysis (VIs, yield modeling, etc.), these issues pose an even greater problem.

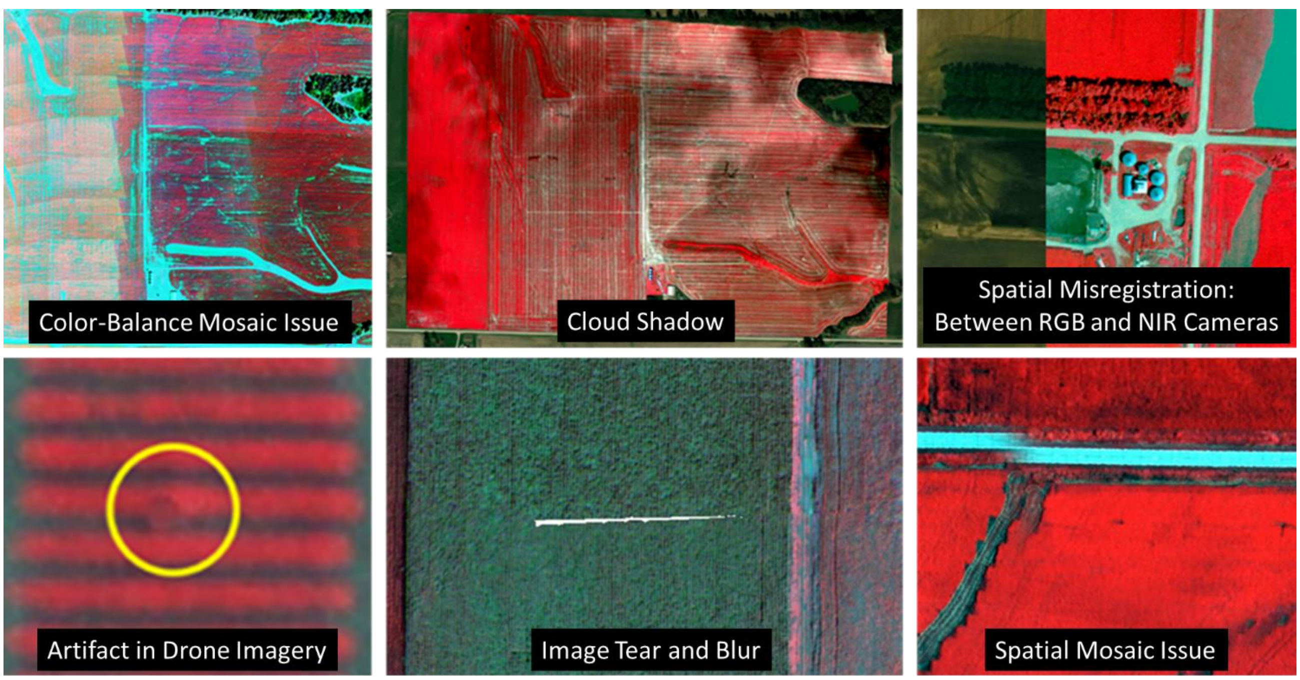

Figure 2. Examples of imagery problems that can be detected visually.

Spatial Accuracy of Aerial Imagery: Why it Matters

Aerial imagery collected by modern aircraft and UAV systems are georeferenced to project the objects in the imagery to relatively precise locations on the ground. However, several factors can affect the spatial accuracy of georeferenced imagery. Errors may occur during the stitching of individual images to form the final product, or the accuracy of the sensor-based GPS used during the image acquisition process may be inaccurate. Sometimes field topography will affect the registration accuracy, as will other factors such as camera-to-ground surface angle (image obliqueness) and pixel size.

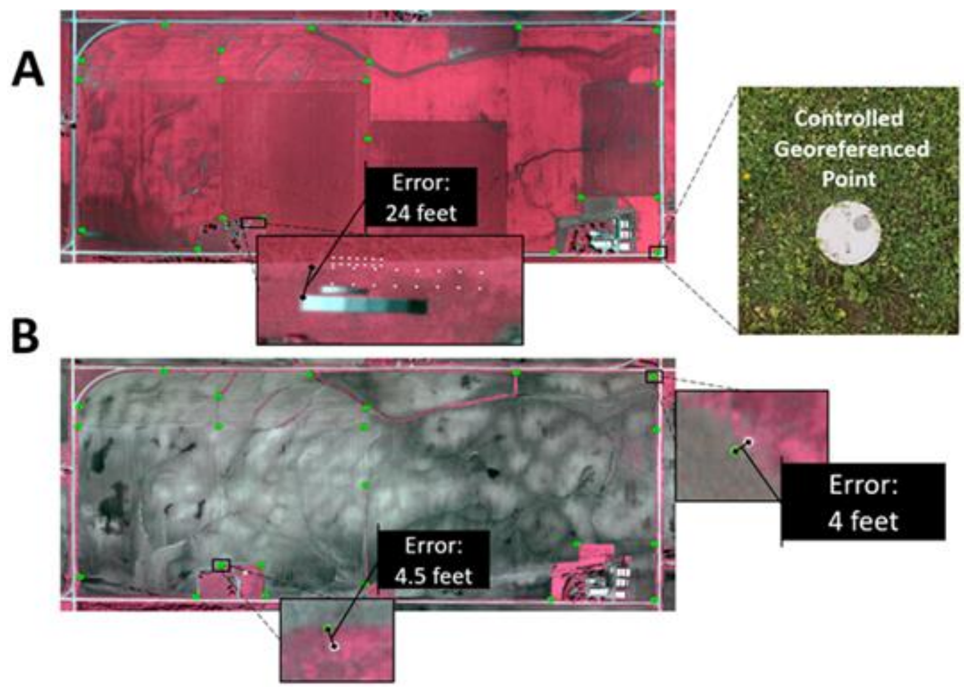

Figure 3. Example of testing imagery spatial registration using sub-inch accuracy GPS control targets. Image A taken in 2018 (by provider A) shows 24-foot spatial registration error. Image B taken in 2019 (by provider B) shows 4.5-foot spatial registration error.

Markers were located inside the 200-acre imagery calibration site as well as on the perimeter of the area. The ground truth locations of the markers were determined using a Topcon GR-5 GPS unit with sub-inch accuracy.

Figure 3A shows a 24-foot shift in the location of the imagery calibration tarps on the south part of the field in 2018 (imagery taken by Provider A) when compared to the GPS control targets. This is a relatively large error. The georeferenced error on the imagery collected in 2019 (from Provider B) was only about 4.5 feet (Figure 3B). These are approximate estimations because imagery resolution should also be considered. On average, we find imagery georegistration accuracy from different providers is about 10 feet.

Why does spatial accuracy matter? Spatial accuracy is important for developing accurate stand count maps, identifying weed, pest and disease-affected areas for targeting spraying, drainage tile locations, and things like compaction or high-traffic areas. Another method to check the spatial accuracy of aerial imagery is to overlay imagery with other spatial sources such as roads, topographic maps, satellite imagery, or historical imagery.

Temporal Patterns in Uncalibrated and Calibrated Imagery

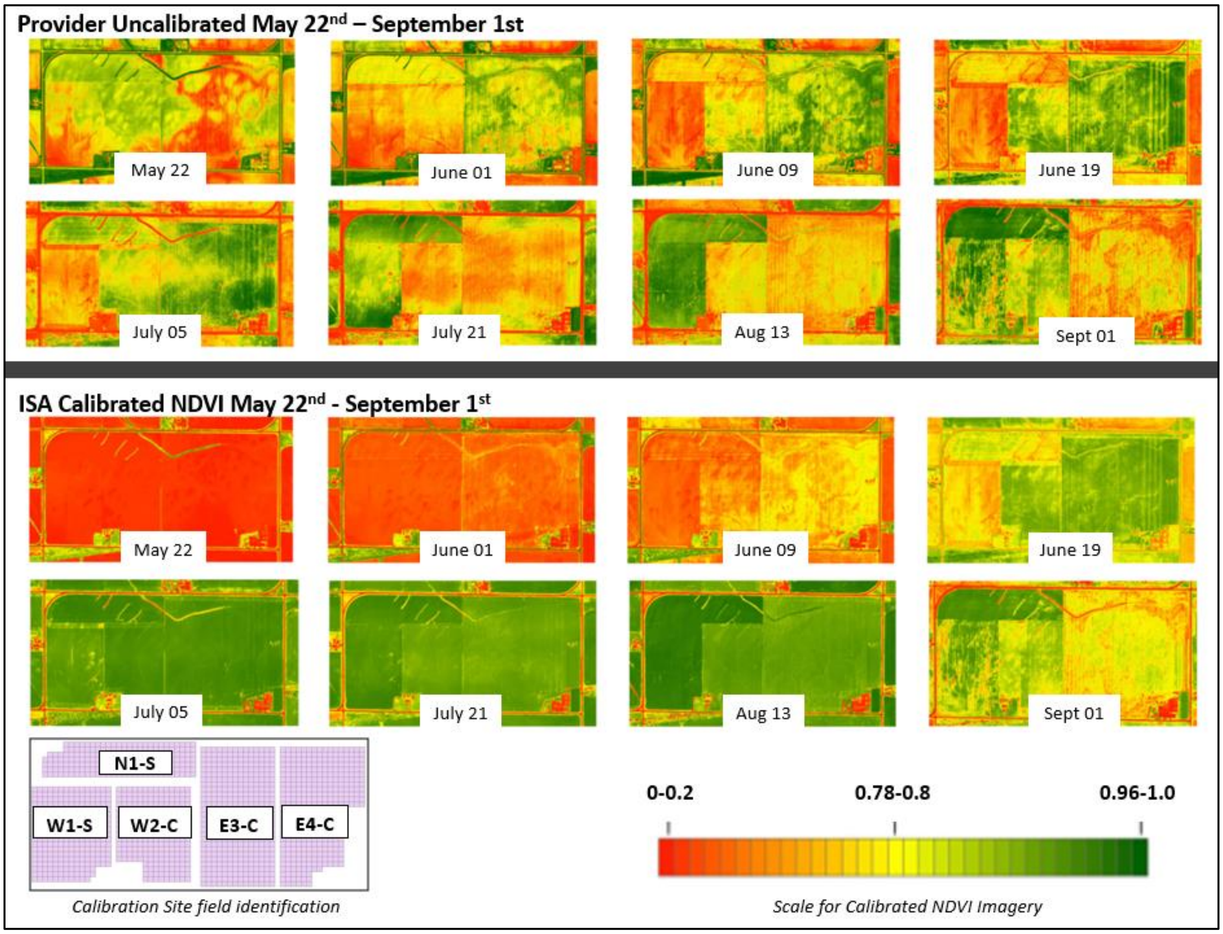

Figure 4. Temporal NDVI patterns from uncalibrated imagery (top two rows of images with no comparable scale across time) and calibrated imagery with absolute scale (bottom two rows). In 2016 (see schematic lower left), fields W1-S and N1-S were soybeans and W2-C, E3-C and E4-C were corn.

Temporal NDVI patterns from uncalibrated (top two rows) and calibrated imagery (bottom two rows) are shown in Figure 4. The uncalibrated imagery shows the maximum within-field contrast of NDVI differences for each date. It does not have an absolute or consistent NDVI scale across dates. Therefore, the uncalibrated imagery cannot be used to compare within-field NDVI patterns over time and between fields from different dates. However, this imagery is well suited for scouting and problem detection at each date.

The calibrated NDVI imagery has the same NDVI scale over time and between locations. This enables the end-user to compare crop canopy changes, crop development, crop stresses, and other crop characteristics over time. Unlike uncalibrated data, the calibrated image on May 22 shows very little within-field NDVI variation because it is of bare soil. We can see similar patterns on July 5 calibrated imagery where the NDVI variation is between crop types, corn vs soybean, but not within the fields.

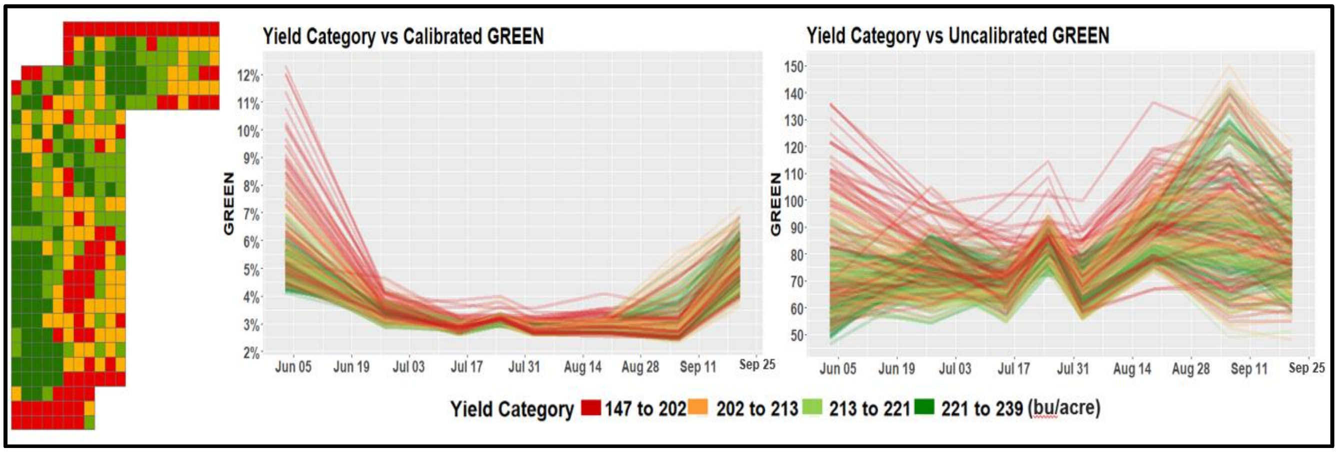

Figure 5. Yield grid 25 x 25-meter (left), time series of calibrated Green band – in percentage reflectance (center), and uncalibrated Green band – in relative digital numbers (right) of corn field in 2017. Each line in the time series refers to a grid cell in the yield map. Colors/shades represent four different yield categories, from lowest to highest.

Deployment of imagery calibration tarps before each flight enables expression of crop canopy reflectance values in absolute terms: percentage reflectance. Figure 5 shows the difference between calibrated (center) and uncalibrated Green band (right) reflectance of a corn canopy from 2017. Unlike "crop health maps" that are usually based on NDVI, lighter color of the corn Green band in Figure 5 indicates less chlorophyll content and greater light reflectance. The uncalibrated Green time series lines look more random while the calibrated times series lines show specific patterns. The lines that show low yielding grids tend to cluster on the top of the calibrated time series while the lines that show high yield areas tend to cluster on the bottom. These patterns are not as easy to detect on the uncalibrated imagery.

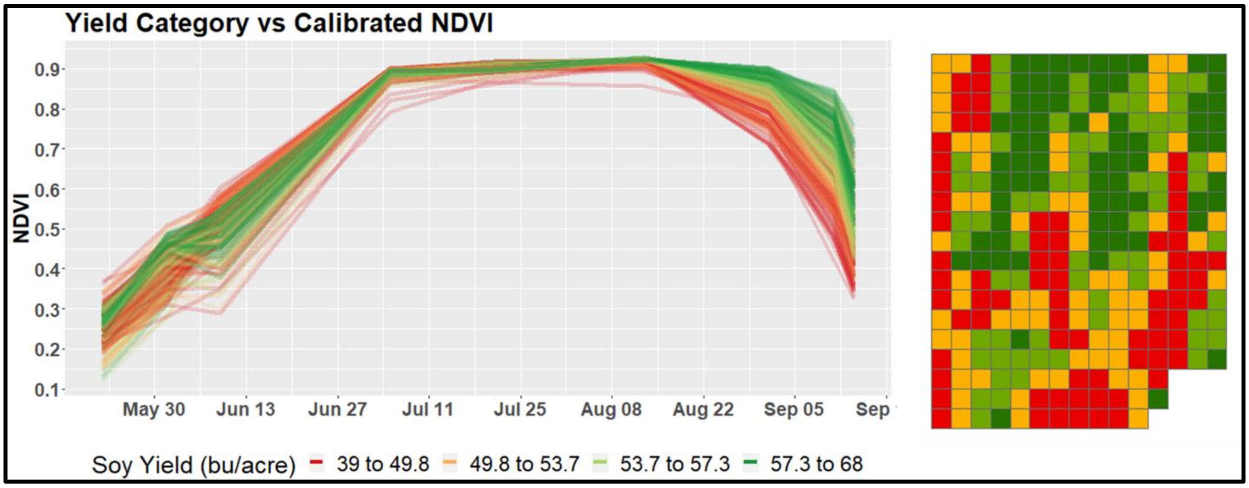

Figure 6. Calibrated NDVI time series for a soybean field in 2016 (left), and yield grid for the corresponding field in same year (right). Colors/shades represent four different yield categories.

Higher soybean yielding lines are on the top of the calibrated NDVI series in Figure 6. Please note that a time series NDVI (and other VIs) should only be produced from calibrated data. The separation between different yield categories or magnitude of correlation (not shown here) is highest in the beginning and at the end of the growing season in Figure 6. Also, the NDVI values reached their maximum, or saturation, for this soybean field at the end of June. The NDVI yield categories diverge again in mid-August. The shape of the NDVI time series is determined by the number of flights and the timing of NDVI saturation.

Factors that Impact Imagery Calibration Quality

Because of cost, time, and logistical constraints in managing calibration tarps, the shape of calibration equations is critical (Figure 7). Compared with non-linear, linear calibration equations require the use of fewer reflectance tarps, with the potential to extrapolate calibration equations from one field to another.

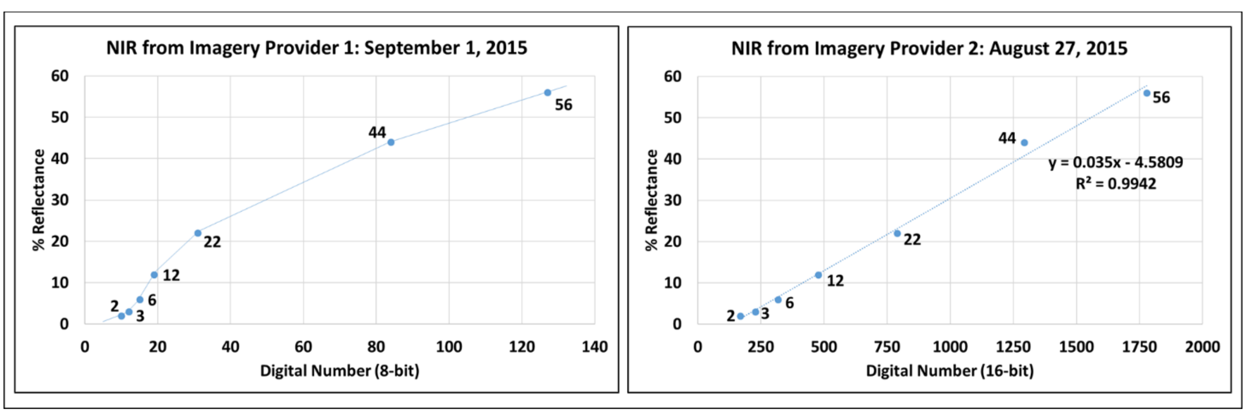

Figure 7. Shapes of imagery calibration equations produced using on-the-ground calibration tarps to calibrate imagery for absolute percentage canopy reflectance values.

The shape of the calibration equation is affected by the process of rescaling when converting from a high-to-low bit level. For example, 16-bit imagery in Figure 7 shows more linearity than 8-bit imagery. To reduce the size of the imagery files, the digital information is often converted to 8-bit or is truncated to the most significant portion of the data histogram. This increases the complexity of the calibration process and reduces the transferability of the calibration equations to other field locations because data compression is often on a field-by-field basis.

An interesting aspect of the calibration process occurs in the low-end of the visible spectrum. Since the vegetation canopy absorbs most of the visible light for photosynthesis, the reflectance in vigorous and healthy vegetation in these wavebands is very low (sometimes as low as 1-2% in the red waveband). Moreover, errors in calibration of the low percentage visible wavebands can have an impact on the overall calibration process and the subsequent VI calculation. For example, empirical testing of hypothetical changes in the near-infrared and red wavebands indicate that minor changes in the red waveband outweigh moderate-to-high changes in the near-infrared waveband.

As Table 1 shows, when the near-infrared waveband reflectance changes by 10%, the resulting difference between the NDVI values is 0.026. However, a minimal change of 2% reflectance in the red waveband changes the NDVI value by 0.056. This indicates that NDVI is more sensitive to changes in the visible red waveband than in near-infrared. Many VIs, which utilize visible and near-infrared wavebands, are susceptible to this sensitivity problem. This phenomenon is important to understand when calibrating digital imagery because minor calibration errors in the visible wavebands can alter VI values and any subsequent analysis.

Table 1. Impact of hypothetical percentage changes of red in the lower end and near-infrared in the upper end wavebands on NDVI calculations. NDVI is more sensitive to changes in the visible red waveband than in near-infrared.

Changes in Near-Infrared Waveband			
NIR (%)	75	65	55
Red (%)	3	3	3
NDVI	0.923	0.912	0.897
Changes in Red Waveband			
NIR (%)	65	65	65
Red (%)	2	3	4
NDVI	0.940	0.912	0.884

Both calibrated and uncalibrated NDVI images can be used by agronomists. The uncalibrated NDVIs are excellent at identifying areas of potential stress, while the calibrated NDVI gives some sense of scale or magnitude to the stressed areas. Finally, it is important to emphasize that one can only use calibrated NDVI values to compare one point in a field to another point in a different field, or from one point in time to another point in time.

Vegetation Index Time Series Interactive Tool

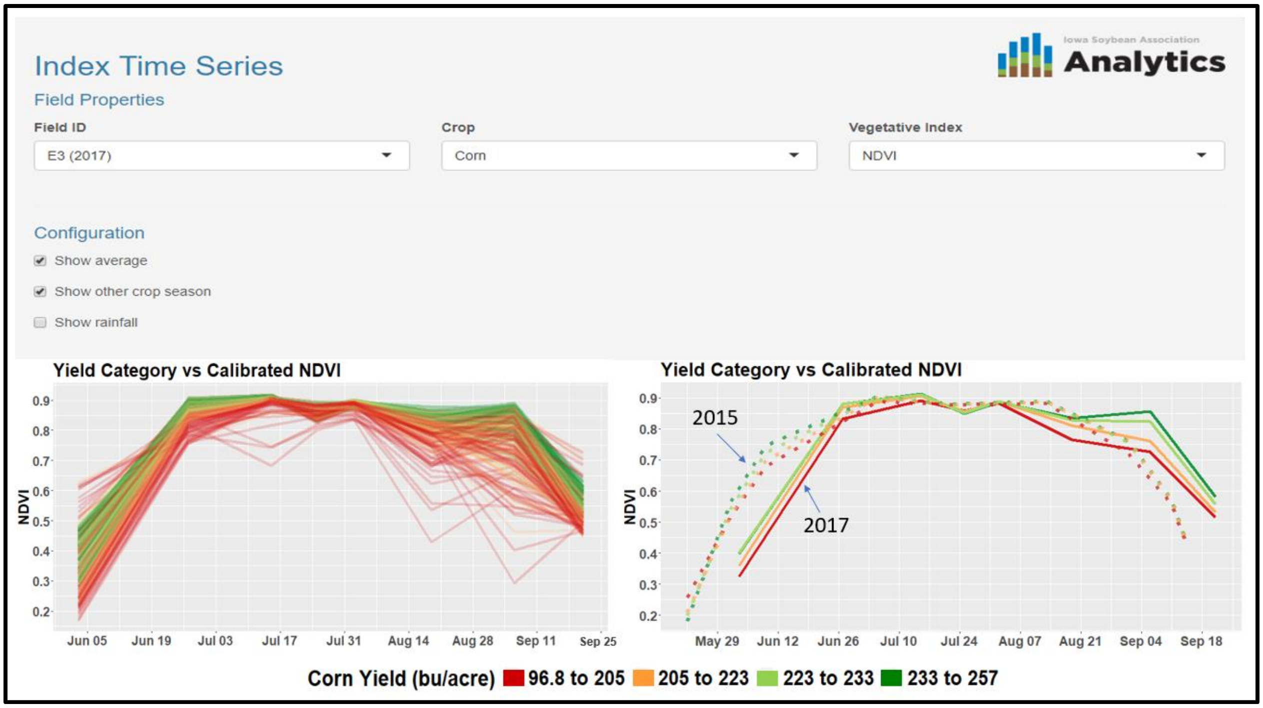

Figure 8. User interface for the Vegetation Index Time Series Interactive Tool that show NDVI temporal patterns by yield grid cells and by averages for 2017 and 2015 year with the same crop.

As shown in Figure 6, NDVI saturated for a period of about 6 weeks in the middle of the growing season. Calibrated imagery enabled the production of a dozen or more different vegetation indices. The online "Vegetation Index Time Series Interactive Tool" (https://analytics.iasoybeans.com/cool-apps/TimeSeries/) allows users to select a crop and a field to produce time series graphs of different vegetation indices (Figure 8). The tool shows averages for yield categories and shows the time series for a previous growing season with the same crop. The tool also plots daily rainfall and crop growth stage Figure 9. In contrast to the NDVI time series in Figure 8, Chlorophyll Index Green (CIG) time series does not saturate in Figure 9. The high and low yield areas are easily distinguishable in the 2017 data. The CIG time series shows peaks and valleys in middle of the growing season in both years, which can coincide with time of corn tasseling. For this specific year, using different indices from calibrated imagery can help spot crop stresses before they are visually detected on the ground.

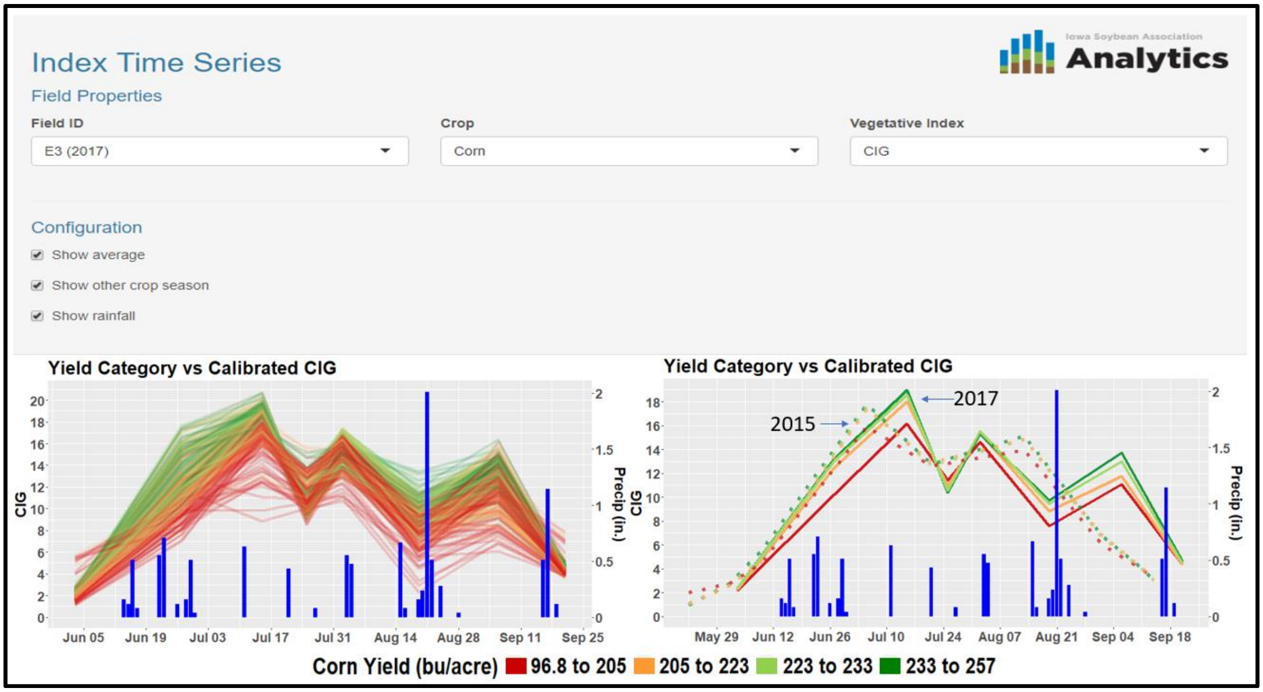

Figure 9. Chlorophyll Index Green (CIG) time series by yield grid cells and by average CIG for 2017 and 2015 with daily rainfall from 2017. The image on August 19, 2017 was taken without the calibration tarps, likely contributing to a sharp decrease in calibrated CIG.

Potential Economic Benefits of Imagery in Crop Management

There are many ways digital imagery can be used in crop production. Table 2 lists examples of corn and soybean management practices and problems that can be detected by imagery. Detecting some of these problems requires calibrated imagery with different resolution and timing of collection. Problems that require imagery to be taken more than one time during the growing season or across years usually will benefit from calibrated imagery.

Potential economic benefits of using imagery depends whether the problems exist and can be corrected timely and cost effectively. For example, detection of weed areas early in the season can help timely and targeted spraying, reducing the negative impact of weeds on crops, thereby reducing the volume and cost of chemicals.

Table 2. Examples of Crop Management Problems and Economic Benefits from Using Imagery.

Crop Management Practices or Problems	Imagery Source	Maximum resolution	Number of flights during the season	Potential economic benefits from using imagery	Radiometric calibration
Identifying zones of yield variability or management/decision zones	Satellite UAV Aerial	Up to 5m	Multiple images within and across years	Medium (depends on whether decisions about input use by zones is consistant)	**Calibration Required**
Early detection of diseased areas before disease is visible	Satellite UAV Aerial	Up to 5m, 1m optimum	Multiple images during the season	High to medium (depends on whether decisions to use fungicide are economical)	
Yield Modeling/Predictions	Satellite UAV Aerial	Up to 10 m	Multiple images within season at critical crop stages	Medium (excluding extreme weather events)	
Early detection of water stress	Thermal	Not critical	Multiple images within season at critical crop stages	High to medium (assuming irrigation is used or controlled drainage)	
Detecting damaged areas due to extreme weather	Satellite UAV Aerial	Up to 5m, 1m optimum	Mefore and after damage	High (if problems exist and can be addressed economically)	**Calibration Preferred**
Detecting weeds	UAV Aerial	5-10 cm	Multiple images during the season	High to medium (if accurate spatial registration)	
Detecting and Quantifying Soybean Iron Chlorosis Areas	UAV Aerial	1m optimum	Two images during the season or historical imagery	Medium/low (if decisions are economical)	
Quantifying cover crop stand and biomass variation	Satellite UAV Aerial	Up to 5m, 1m optimum	One later in the fall and another in spring before cover crop termination	Medium (reduces scouting time and cost)	
Quantifying crop residue distribution	Satellite UAV Aerial	Up to 5m	Historical image of bare soil the late fall and early spring	Medium to low (if problems can be economically corrected)	
General scouting for detecting pest, disease and insects and equipment problems	Satellite UAV Aerial	Up to 5m, 1m optimum	As needed	High if problems exist and can be addressed	**Calibration Not Required**
Quantifying plant stand problems	UAV Aerial	5-10 cm	One-early season	High if problems exist and can be addressed	
Guiding soil and plant tissue collection	Satellite UAV Aerial	Up to 5m, 1m optimum	As needed	High to medium (if sample size can be reduced or problems can ecomonomically be addressed)	
Detecting tile drainage problems	UAV Aerial	1m optimum	Historical bare soil imagery and bare soil image after rainfall	High	
Herbicide and planting overlapped detection	UAV Aerial	1m optimum	Early season	High (if equipment problems exist and can be addressed economically)	

Conclusions

Agriculture is seeing a significant surge in different digital aerial and drone imagery technologies. For the last 4 years, we worked with more than 15 imagery providers to evaluate the quality of different imagery platforms. This study emphasized the negative implications of various image related issues such as georegistration accuracy, mosaicking (color balance and spatial stitching), and specifically radiometric calibration quality. While radiometric calibration is not always needed, calibrated imagery is critical for field-to-field comparisons and temporal monitoring using different vegetation indices of crop canopy for more accurate diagnoses and reliable predictions in crop production.

Ultimately, an understanding of these image quality differences will have an impact on the utility for visual and digital assessments and quantitative measurements by crop scouts and agricultural researchers. Development of tools like the Vegetation Index Time Series Interactive Tool combines visual and digital assessments of calibrated and uncalibrated imagery to help farmers, agronomists, researchers, and industry recognize the difference, utility, and economic value of each imagery source.

Acknowledgments

Studies described here were partially funded by the Iowa Soybean Association Checkoff dollars, Integrated Farm Livestock Management Project from the Soil Conservation Division of the Iowa Department of Agriculture and Land Stewardship. The imagery for this summary was provided primarily by Aeroptics, IntelinAir, and Mavrx Inc providers. We are very thankful to all farmers, agronomists, technical providers, industry professionals, and partner university scientists who participated and contributed to the on-farm studies described in this publication.

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