

A NOVICE EXPERIMENT WITH SATELLITE-BASED CLASSIFICATION OF AGRICULTURAL CROPS AND BMPs

By David G. Burke and John Dawes

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A Novice Experiment with Satellite-Based Classification of Agricultural Crops and BMPs

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Executive Summary

In 2013 Burke Environmental Associates received funding from the Keith Campbell Foundation for the Environment to work in collaboration with Chesapeake Commons and the Environmental Working Group to investigate how satellite-based classification of agricultural crops and best management practices (BMPs), could potentially be used by GIS analysts, who are not remote sensing specialists.

Key objectives of this study included: (1) documentation of field reconnaissance and data collection methods; (2) documentation of basic GIS analysis and satellite image processing work flows; (3) documentation of data resources and Normalized Difference Indices (NDIs) needed for image processing; (4) classification of the principal agricultural crops found in the study area; and (4) conducting a rudimentary assessment of the use of cover crops and conservation tillage practices in a localized area. Cover crops and conservation tillage are two of the most important agricultural BMPs in the Chesapeake Bay watershed to maintain soil health and water quality. However, spatially specific, quantitative and qualitative information about these practices are not available to the general public, making verification of publically funded practices difficult.

The authors' results *demonstrated*:

1. A non-expert GIS analyst, supported by a two-person field observation team, can produce useful satellite-based interpretive maps and data through the use of NDVI and NDTI indices.
2. The successful classification of principal agricultural crop types using the NDVI and a ground controlled set of fields. A county-wide map was produced through the use of an NDVI index that matched conditions observed during site visits.
3. Maps derived from the image processing steps outlined in this report can identify potential field locations where cover crops may be lacking and/or conservation tillage appears excessive.
4. The methods used by the study team provide a coarse landscape level indicator tool that can be adjusted by the analyst to set threshold reflectance values for target BMPs. Processed satellite data can then be visualized on maps using choropleths to indicate more clearly where threshold values are exceeded. In turn, these areas can be observed in the field to validate or dismiss concerns about particular areas.

The authors *concluded*:

1. Small watershed and/or conservation groups who are willing to explore and learn more about how remote sensing applications can benefit their organizations will be well rewarded for their efforts.
2. These small organizations can upgrade and expand their abilities to track and verify a variety of BMPs and detect hot spots where improved field conservation practices are needed.
3. Current leaders in satellite-based conservation applications can and should make a greater effort to sponsor training sessions to those who are interested in upgrading their skills while learning practical applications to enhance conservation and restoration activities of all kinds.
4. A community of practice could emerge to make remote sensing applications a more ubiquitous and valuable toolset that can extend beyond the exclusive domain of high-end government and research practitioners.

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Introduction

In the Spring of 2013 Keith Campbell Foundation provided grant funds to Burke Environmental Associates to investigate how satellite-based classification of agricultural crops and best management practices (BMPs), could potentially be used by GIS analysts, who are not remote sensing specialists, to help the conservation community track two commonly used agricultural BMPs in the Chesapeake Bay watershed.

While there are many technical reports, watershed report cards and other water quality-based studies about the state of the Bay's health, there are few published reports available that track the current status of BMPs at the farm field level in specific geographic locations. Conducting such investigations is generally beyond the scope or capacity of local watershed groups or conservation organizations. Yet this information could be highly useful to these groups to facilitate their understanding of where local resources could best be directed to support improved agricultural conservation practices.

The goal of this initial investigation was to determine if a conservation organization with in-house geographic information systems expertise could successfully use satellite-based classification techniques to track the use of cover crops and conservation tillage—two of the most important agricultural BMPs in the Bay watershed. Burke Environmental Associates (BEA) teamed with Environmental Working Group's (EWG) Agriculture and Natural Resources program and Chesapeake Commons to build and conduct the basic work flow processes and obtain the appropriate data sources needed to accomplish the goal. Without the help of the report collaborators--EWG's Soren Rundquist, Landscape and Remote Sensing Analyst, and John Dawes, Systems Administrator of Chesapeake Commons, this report could not have been compiled.

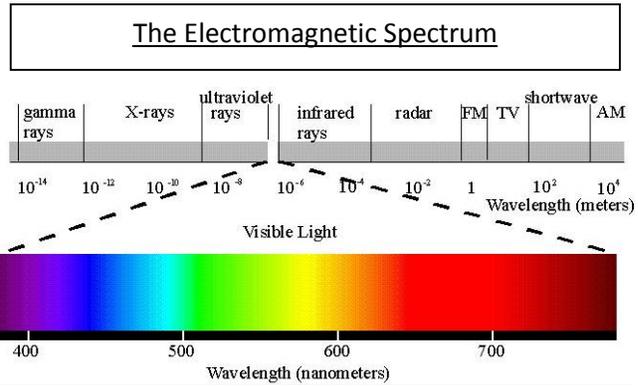
LANDSAT view of the Chesapeake Bay



The documentation presented in this report is by no means a substitute for acquiring the professional knowledge and expertise required to thoroughly understand the principles and techniques associated with complex satellite-based classification methods. It does represent an earnest attempt to document the basic work flow processes and data resources an average GIS analyst would require to conduct a rudimentary assessment of the use of cover crops and conservation tillage practices in a localized area.

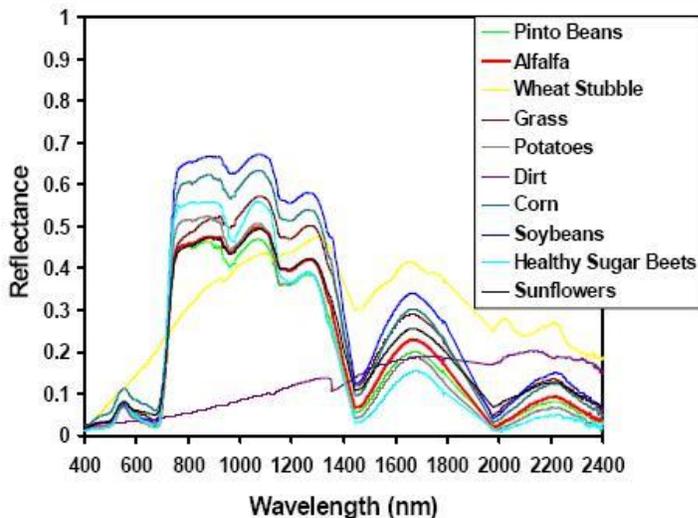
Overview of Satellite and Agricultural Data Sources Used

To detect crop and BMP presence during the 2013 growing season, the study team used remote sensing data from Landsat 8 and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) to process images of various crops in different stages of growth and post-harvest. Earlier Landsat imagery was used to test and improve our methods when Landsat 7/8 data was unavailable due to cloud cover. Landsat 8, the newest U.S. government satellite, was launched in February 2013 with data availability beginning in May 2013. Landsat 7 ETM+, was launched in April 1999 and is still functioning, but with a faulty scan line corrector occurring since May 2003. The faulty corrector creates gaps in the data that requires compositing of multiple images to fill the gaps using data acquired from different time periods. This creates temporal inconsistencies which will be more noticeable in cases, for example, where a major change in crop conditions or crop harvesting occurs.



The Landsat satellites are equipped with passive multispectral sensors that measure energy, in the form of light waves from the sun. Energy from sunlight is measured along the electromagnetic spectrum. Landsat 8 sensors organize data in 8 different band arrays which are capable of recording data by the emitted wavelength. When this energy strikes plants it is reflected, absorbed or transmitted through the plants in various ways depending upon the wavelengths, plant type and condition. These interactions give rise to different spectral signatures for plant species throughout the life stage of the plant and the growing season. Thus, in the case of agricultural crops, crop signatures vary between a range of spectral

Spectral Signatures for Various Agricultural Crops



reflectance values from the time seedlings emerge, through the maturing and finally, the post-harvest plant residuals that remain on the ground.

The field data analyst uses several clues about the life stage of the plant, spectral reflectance values, typical planting and harvesting dates, climatic conditions during the growing season (i.e. average/abnormal temperature swings, normal precipitation, drought conditions, hail storm damage etc.) to validate what the satellite sees. This permits extrapolations to a larger area of interest.

Satellite Data Sources

The study team obtained satellite data from various locations including the U.S. Geological Survey's Earth Resources and Observation Science Center (EROS) webpage (<http://glovis.usgs.gov/>). This site uses a global visualization viewer that allows users to sort through and download a wide variety of satellite image data sets. The visualization tool has a quick start guide and a more detailed guide to assist users in finding their way through the data and using the map layers and tools. For example, the Map Layers tab on the viewer helps the user locate the area of interest for a particular investigation through the use of jurisdictional boundary files, an address query function, showing major cities and other helpful reference points.

U.S. Geological Survey's Earth Resources and Observation Science Center (EROS) Webpage

The screenshot displays the USGS Global Visualization Viewer interface. The browser address bar shows glovis.usgs.gov. The page title is "USGS Global Visualization Viewer" with a "System Notices (1) (New)" button. The main interface includes a menu bar with "Collection", "Resolution", "Map Layers", "Tools", "File", and "Help". The central map shows a satellite image of the Chesapeake Bay region, with a yellow rectangular box highlighting a specific area of interest. Various cities are labeled on the map, including New York, Lock Haven, Harrisburg, Trenton, Philadelphia, Pittsburgh, Baltimore, Annapolis, Washington, Dover, Chincoteague, Richmond, Virginia Beach, South Hill, Nags Head, Roanoke, Charlottesville, Winchester, Fairmont, and Marlinton. The USGS logo is visible in the bottom left corner of the map area. On the left side, there is a control panel with fields for "WRS-2 Path / Row" (15 / 33), "Lat / Long" (38.9 / -76.9), and "Max Cloud" (100%). Below these are "Scene Information" details: ID: LC80150332013111LGN01, CC: 3%, Date: 2013/4/21, Qlty: 9, Product: OLI_TIRS_L1T, and a date selector set to "Apr 2013". At the bottom of the interface, there are three columns of navigation links: "Quick Start Guide", "User Guide", and "What's New!".

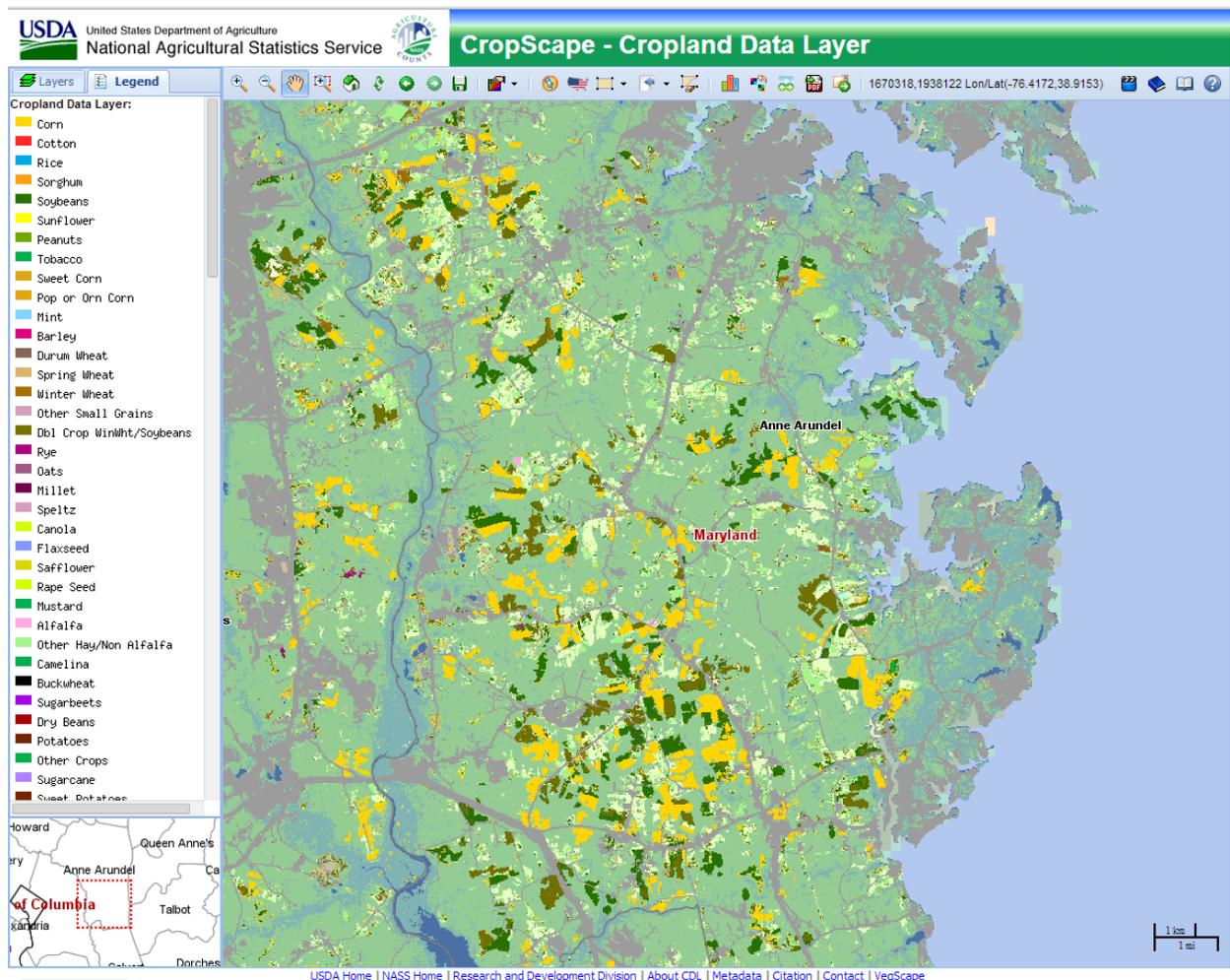
Quick Start Guide	User Guide	What's New!
Browser Requirements	Download Source Code	About Browse Images

This screen capture of the EROS website shows a Landsat 8 scene of the Chesapeake Bay with additional map layers selected to show major cities and protected lands polygons to facilitate finding the data scene of interest to the user.

Agricultural Data Sources

Two primary data sets were used to help classify crops and detect BMPs. The first data set is called the Cropland Data Layer (CDL). The CDL is created by the U.S. Department of Agriculture's National Agricultural Statistics Service and is hosted on CropScope (<http://nassgeodata.gmu.edu/CropScope/>). According to USDA, the CDL is a raster, geo-referenced, crop-specific land cover data layer created annually for the continental United States using moderate resolution satellite imagery and extensive agricultural ground truth. The purpose of the Cropland Data Layer Program is to use satellite imagery to provide acreage estimates to the Agricultural Statistics Board for the state's major commodities and to produce digital, crop-specific, categorized geo-referenced output products. All historical CDL products are available for use and free for download through CropScope. To access the particular information needed to construct the CDL for a given state and year, users can visit <http://www.nass.usda.gov/research/Cropland/metadata/meta.htm>.

U.S. Department of Agriculture's CropScope Cropland Data Layer Webpage



CropScope allows users to readily define an area of interest and download data for the area, conduct statistical and change analyses, run information queries and other functions. The area shown here is located in Anne Arundel County, Maryland—where the authors conducted their crop and BMP detection demonstration.

The analyst should note that the Cropland Data Layer for a given year is not released until the end of January, the year thereafter. CropScape allows users to access, visualize, retrieve, and analyze on-demand CDL data at any geographic level in the continental United States through an intuitive graphical user interface. The primary focus of the CDL is on large area summer crops. Farm Service Agency Common Land Unit (CLU) data, reported by farmers, is the primary source of agricultural information used for the CDL classification. The CDL crop legend shows whether a single or double crop was planted in a particular field. For example, a winter wheat field planted in the fall of 2009 will be identified in the 2010 CDL, as the protocol used considers the time of harvest as the current year of production. If the field is in multi-use, for example winter wheat (ww) followed by soybeans (sb), then a double cropping situation exists and the legend notation for that field will be ww/sb. If a field is only soybeans during that year, then it will be identified as sb only. All major crop rotations/patterns are captured using this method and are considered mutually exclusive for a given data pixel or farm field.

The second key data set used in the demonstration is the USDA Farm Service Agency Common Land Unit file. A Common Land Unit (CLU) is the smallest agricultural unit of land that has a permanent, contiguous boundary, a common land cover and land management, a common owner and a common producer association. FSA maintains a wide array of information related to these land units. Information that was formerly fragmented among paper documents and computer systems that relates to CLU's is now consolidated to facilitate reporting acreage calculations and boundary information by

tracts and fields. Unfortunately, privacy laws set forth in section 1619 of the farm bill prevent any non USDA affiliate to access crop, BMP, field boundaries or any information at a field scale.

Common Land Unit Boundaries Map



This graphic shows Common Land Units (tan shaded polygons) which are superimposed over a Google Earth image. The composite map helps to distinguish farm field boundaries during the ground truthing process.

Normalized Difference Vegetation Index (NDVI)

The primary means of detecting crop types and BMPs is through the use of a Normalized Difference Vegetation Index (NDVI)—a ratio that takes into account the amount of infrared reflected by healthy growing plants. NDVI is related to vegetation because growing vegetation has peak reflectance in the near-infrared portion of the electromagnetic spectrum. Specifically, green leaves have a reflectance in the 0.5 to 0.7 micron range (green to red) and 0.7 to 1.3 micron range (near-infrared). These reflectance values are ratios taking on values between 0.0 and 1.0. Thus, NDVI varies between -1.0 and +1.0 (ESRI. 2013).

Negative values of NDVI equate to deep water. Values approaching 0 (-0.1 to 0.1) correspond to barren areas of rock, sand, or snow. Low, positive values denote shrub and grassland (approximately 0.2 to 0.4), and high values indicate temperate and tropical areas (values approaching 1) (ESRI. 2013). Depending on region the standard range in NDVI is -0.1 (for a not very green) to 0.6 (very green area).

NDVI serves as an estimate of vegetation health and can be used to sense changes in vegetation over time. It is one of the most widely adopted indexes to detect live green plant canopies in multispectral imagery. NDVI is calculated by dividing the difference in the near-infrared (NIR) and red color bands by the sum of the NIR and red colors bands for each pixel in an image (ESRI. 2013). The NDVI index is expressed as follows: $NDVI = (NIR - Red) / (NIR + Red)$.

Just as the NDVI is optimized to detect plant signatures during the growing season, there are two additional indices the authors were informed of by Environmental Working Group that are commonly used to identify crop residue, or the portion of a crop that is left in the field after harvest. Determining the degree of crop residue remaining on farm fields is important to maintaining productive soils and water quality. As the intensity of tillage increases the rate of crop residue decomposition accelerates, soil cover is lessened and there is a greater chance of soil erosion and pollution of nearby waters. The two indices used for residue detection are the NDRI Residue Index: $NDRI = (RED - SWIR2)/(RED + SWIR2)$; and the NDTI Tillage Index: $NDTI = (SWIR1 - SWIR2)/(SWIR1 + SWIR2)$. Gelder, Kaleita and Cruse, 2009, evaluated the effectiveness of these indices and found the following:

The NDRI, using Landsat Bands 3 and 7, performed best overall, explaining 81% of the residue cover differences overall, 78% before emergence, and 9% after emergence. The normalized difference tillage index (NDTI), using Landsat Bands 5 and 7, also performed well explaining 68% of the variation overall, 86% before emergence, and 6% after emergence. Introduction of an empirical correction of the influence of green vegetation improved index performance. The NDTI outperformed the NDRI after green vegetation correction, explaining 67% of the variation versus 63%. The NDTI also returned the best RMSE (0.11) under preemergence conditions and 0.15 after green vegetation correction. Generally, indices utilizing Landsat Band 7, which contain lignin and cellulose absorption bands absent in soil, returned the best residue detection results. Indices utilizing Landsat Band 4, where the reflectance of green vegetation is high, had difficulty detecting residue cover, especially after plant emergence.

For the purpose of running NDVI, Landsat 4, 5, 7, and 8 imagery was used to create new GIS raster surfaces. Landsat 8, launched in February 2013, has an Operational Land Imager (OLI) with nine spectral bands, a spatial resolution of 30 meters for Bands 1 through 7 and Band 9. The resolution of Band 8 (panchromatic, or pan--used to sharpen images) is 15 meters (USGS EROS. 2013). A QA band is included

in free processed downloads that can be used to correct artifacts such as hill shade and clouds. It's important to note that based on the Landsat mission, bands carrying reflectance values change based on the electromagnetic spectrum. Band wavelengths based on Landsat mission are outlined below:

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) (USGS EROS. 2013)

Band	Wavelength	Useful for mapping
Band 1 – coastal aerosol	0.43-0.45	coastal and aerosol studies
Band 2 – blue	0.45-0.51	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation
Band 3 - green	0.53-0.59	Emphasizes peak vegetation, which is useful for assessing plant vigor
Band 4 - red	0.64-0.67	Discriminates vegetation slopes
Band 5 - Near Infrared (NIR)	0.85-0.88	Emphasizes biomass content and shorelines
Band 6 - Short-wave Infrared (SWIR) 1	1.57-1.65	Discriminates moisture content of soil and vegetation; penetrates thin clouds
Band 7 - Short-wave Infrared (SWIR) 2	2.11-2.29	Improved moisture content of soil and vegetation and thin cloud penetration
Band 8 - Panchromatic	.50-.68	15 meter resolution, sharper image definition
Band 9 – Cirrus	1.36 -1.38	Improved detection of cirrus cloud contamination
Band 10 – TIRS 1	10.60 – 11.19	100 meter resolution, thermal mapping and estimated soil moisture
Band 11 – TIRS 2	11.5-12.51	100 meter resolution, Improved thermal mapping and estimated soil moisture

Landsat 4-5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+)

Band	Wavelength	Useful for mapping
Band 1 - blue	0.45-0.52	Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation
Band 2 - green	0.52-0.60	Emphasizes peak vegetation, which is useful for assessing plant vigor
Band 3 - red	0.63-0.69	Discriminates vegetation slopes
Band 4 - Near Infrared	0.77-0.90	Emphasizes biomass content and shorelines
Band 5 - Short-wave Infrared	1.55-1.75	Discriminates moisture content of soil and vegetation; penetrates thin clouds
Band 6 - Thermal Infrared	10.40-12.50	Thermal mapping and estimated soil moisture
Band 7 - Short-wave Infrared	2.09-2.35	Hydrothermally altered rocks associated with mineral deposits
Band 8 - Panchromatic (Landsat 7 only)	.52-.90	15 meter resolution, sharper image definition

Landsat Multi Spectral Scanner (MSS)

Landsat MSS 1, 2,3 Spectral Bands	Landsat MSS 4,5 Spectral Bands	Wavelength	Useful for mapping
Band 4 - green	Band 1 - green	0.5-0.6	Sediment-laden water, delineates areas of shallow water
Band 5 - red	Band 2 - red	0.6-0.7	Cultural features
Band 6 - Near Infrared	Band 3 - Near Infrared	0.7-0.8	Vegetation boundary between land and water, and landforms
Band 7 - Near Infrared	Band 4 - Near Infrared	0.8-1.1	Penetrates atmospheric haze best, emphasizes vegetation, boundary between land and water, and landforms

The NDI indices and Landsat bands used in this study are summarized in the table below.

<u>NDVI, NDTI and NDRI Indices and Corresponding Bands Used</u>
NDVI Vegetation Index
$NDVI = (NIR - RED)/(NIR + RED)$ LANDSAT 8: $NDVI = (band5 - band4)/(band5 + band4)$ LANDSAT 5: $NDVI = (band4 - band3)/(band4 + band3)$ LANDSAT 7: $NDVI = ((band4*1.5) - band3)/((band4*1.5) + band3)$
NDTI Tillage Index
$NDTI = (SWIR1 - SWIR2)/(SWIR1 + SWIR2)$ LANDSAT 8: $NDTI = (band6 - band7)/(band6 + band7)$ LANDSAT 5 and 7: $NDTI = (band5 - band7)/(band5 + band7)$
NDRI Residue Index
$NDRI = (RED - SWIR2)/(RED + SWIR2)$ LANDSAT 8: $NDRI = (band4 - band7)/(band4 + band7)$ LANDSAT 5 and 7: $NDRI = (band3 - band7)/(band3 + band7)$

Late in the study process the authors learned that there are several factors that make it difficult to detect differences in crop residue level and bare soil. Chief among these are:

1. soils and residues are spectrally similar in visible and near infrared
2. spectral reflectance of crop residue is determined by moisture content, age and crop type
3. spectral reflectance of soils is determined by moisture, iron oxide, and organic content, and mineralogy, particle size distribution, and soil structure. Further, the resolution of Landsat imagery poses additional classification issues. Taken together, these and other variables exceeded the level of expertise and resources the novice authors had at their disposal to feel totally confident about our results. Nonetheless, the authors were able to observe apparent distinctions between bare soils and high levels of crop residue (discussed further below).

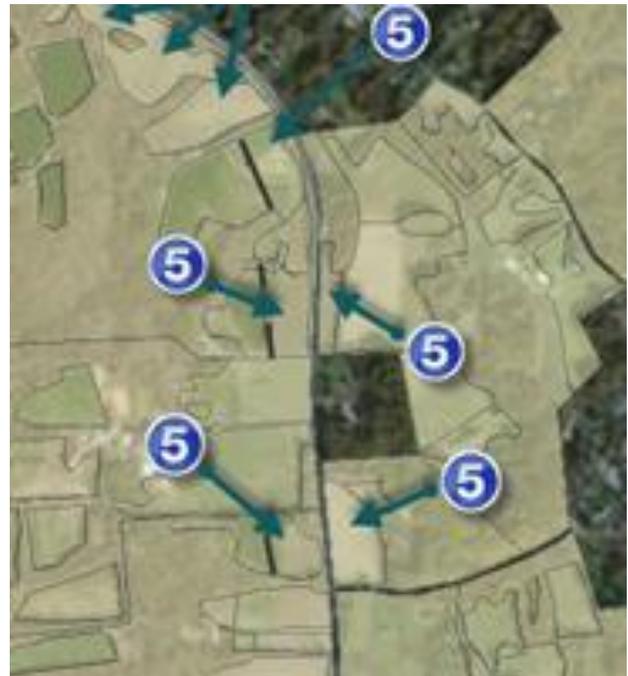
Field Data Collection Methods

During the course of this study, the authors changed their methods of field data collection several times until the most efficient combination of procedures was identified. If the study had continued on, we suspect our methods would further evolve. We used a combination of high and low tech approaches to record field observations. Under each heading below, we provide a brief accounting and commentary of what proved to be the most effective work flow for this study. Hopefully, this information will help others save time and organize their data in a useful way that can be readily transferred.

1. Selecting an Area of Interest (AOI). Aside from the fundamental decision of where an analyst wants to evaluate crop types and BMPs, there are other factors to consider when selecting an AOI and specific “training sites” or those that will be used to calibrate final output maps. Here are a few things to keep in mind:

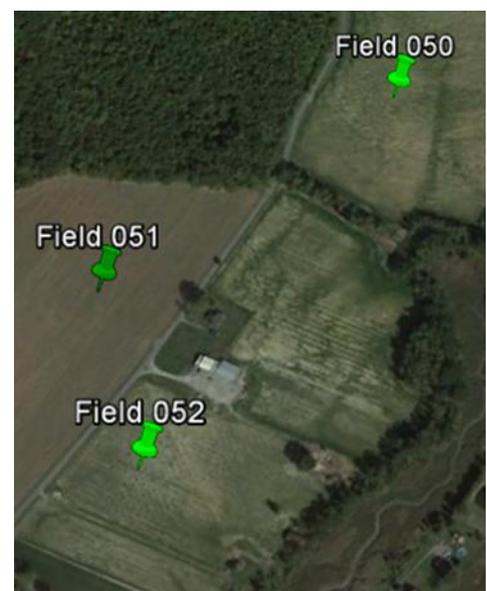
- a. *Field size and “line of sight”*—

Selecting larger, homogeneous fields that can easily be seen from a public roadway works best. Trees bordering farm fields or even modest elevation differentials between the roadway and farm field can obstruct some of or the entire field from view—leaving the field technician in doubt of what to record. We drew dark lines on our field maps to indicate the extent of



what we could see from the roadway (see the left half of the photo to the right). If the field was too small to use for training purposes, we eliminated it from our data sheets.

- b. *Safe “pull-off” areas*—On well-traveled roads, we needed an adequate area of space to pull off and make notes or to shoot a quick photo for reference purposes. Without this, we found it could be dangerous and time consuming to make u-turns to re-visit and confirm our observations. In very rural areas, this is definitely not a problem, but our sites were located in high traffic areas, often with curvy roads.
- c. *Reviewing and marking candidate field sites ahead of time*—Before we hit the road, we used Google Earth to examine “line of sight” conditions, field size and other information about where we intended to go and then located a digital push pin at that point. We also assigned a field number that indicated the order in which we intended to



drive by the site. While this may seem intuitive, the actual roadway and traffic patterns will dictate how you get there and the most effective driving route (see graphic at right).

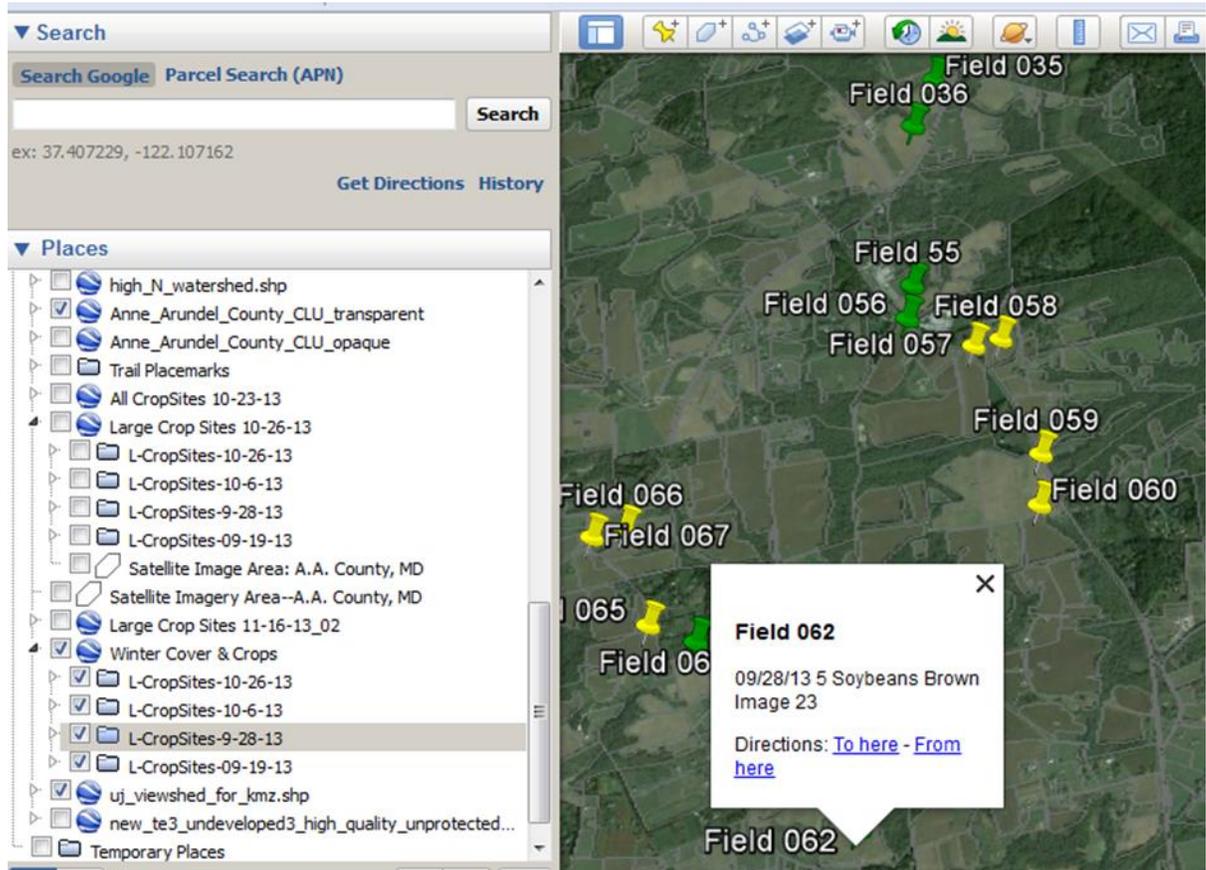
2. Maps to use in the field. To help us navigate in the field and quickly note information about the sites we were observing (e.g. “line of sight” limitations, questions we had, sites to eliminate etc.) we made 17”x22” map panels from Google Earth screen captures. This old fashioned use of paper replaced our former practice of using an Ipad with cellular connections to Google Earth and ArcGIS online. We found that we had too many issues with the speed at which we could readjust our map coverage to reflect our current location. But we did bring the Ipad to check, from time to time, Google Earth to zoom-in to a high resolution view of sites that we wanted a closer look at than what could be seen from our paper maps. We would also, occasionally, activate our Common Land Unit boundary map overlay on Google earth to make sure which field unit we were observing.

10/6/2013				
Field Verification of Cover Crops				
Field ID	CDL ID	Crop Type	Notes	Image 1
Field_1	62	Pasture/Grass	Bare Dirt in the Back	5
Field_2	62	Pasture/Grass		4
Field_3	62	Pasture/Grass	Moderately Tall Grass	7
Field_4	1	Corn	Cut, Short Standing Stalks, Good residual	6
Field_5	61	Fallow/Idle Cropland		1
Field_6	61	Fallow/Idle Cropland	Grass in the Back	2
Field_7	61	Fallow/Idle Cropland		3
Field_8	1	Corn	No Standing Stalks/Good Residual	8
Field_9	62	Pasture/Grass		
Field_10	61	Fallow/Idle Cropland		11
Field_11	61	Fallow/Idle Cropland	Bare Dirt/Emerging Cover Crop	10-Jan
Field_12	62	Pasture/Grass		
Field_13	61	Fallow/Idle Cropland	Grass in the Back	12
Field_14	62	Pasture/Grass		
Field_15	62	Pasture/Grass		13
Field_16	62	Pasture/Grass	Mixed Trees/Weeds	14
Field_17	62	Pasture/Grass		
Field_18	1	Corn	Standing/Brown	15
Field_19	62	Pasture/Grass	Sod Farm	16
Field_20	62	Pasture/Grass	Sod Farm	
Field_21	5	Soybeans	Green	17
Field_22	62	Pasture/Grass	Sod Farm	
Field_23	5	Soybeans	Green	18
Field_24	1	Corn	Standing/Brown	18
Field_25	5	Soybeans	Green in rows with bare dirt	19
Field_26	1	Corn	Standing/Brown	20
Field_27	1	Corn	Standing/Brown	21
Field_28	1	Corn	High Residual mixed with dead grass	22
Field_29	1	Corn	High Residual mixed with dead grass	

3. Field data sheets. In advance of each trip, we also prepared data sheets that contained a pre-entered list of the numbered field sites we planned to visit, and columns to enter the Cropland Data Layer identification code for each site, the crop type, observation notes, and a column to record the image number of any photo(s) taken. Once the data sheets were completed, the Excel spreadsheet file was used to populate the ArcGIS database file used in conjunction with this project (see discussion under GIS Analysis).

4. Google Earth Post Field Data Recording. After completing the field data sheets, we used Google Earth to record each field trip as a separate dated event. All sites were assigned a new sequential number generally proceeding from the north to the south of the study area. New numbers were assigned since several sites that had recorded observations were dropped. These sites were determined to be poor “training sites” for classification purposes due to a variety of limitations(e.g. too small, not fully observable, mixed cropping patterns, etc.) Since some sites were visited post-harvest, the data files on Google Earth are organized to reflect that they were

viewed during the growing season unless they appear under “Winter Cover & Crops” (left side of image below).



Also note, that we recorded essential information in the Properties function of Google Earth as shown on the pop-up for Field 062. The pop-up shows the crop was soybeans, that it was still standing on 9-28-13, that it was brown in appearance, and that a photo—image 23 in the pop-up (below), is available for viewing. To easily see what crop was grown in each field, we color coded the push pins to help visualize their distribution.

In this example, yellow indicates corn and green is soybeans. The Common Land Unit layer is activated in this view and made semi-transparent (light white outlines), as shown by the check marked box on the upper left portion of the Google Places bar.



GIS Analysis

Materials and Methods

By using remote sensing techniques, normalized difference indices (NDI), and localized ground truthing, the GIS analyst can identify: various types of crops in agricultural areas, where the greatest areas of biomass occur during normal planting seasons, where cover crops have been planted and roughly determine conservation tillage practices. It's important to note that the development of localized NDIs depends heavily on accurate and geospatially explicit data. Ideally teams performing this work would have access to data identifying dates, fields, and types of cover crop planting on a farm by farm basis. Unfortunately this data, maintained by NRCS, is unavailable to the public and is protected under a privacy clause under section 1619 of the farm bill.

Throughout Maryland, the use and adoption of winter cover crops has been a cost effective BMP in curbing agricultural related nitrogen runoff. In Maryland, both Federal and state cost-share funds are being provided to farmers (MDA 2005b) to compensate for the costs of planting winter cover crops such as wheat (*Triticum aestivum* L.), rye (*Secale cereale* L.), and barley (*Hordeum vulgare* L.). If properly implemented during regional planting seasons, wheat, rye, and barley fix nutrients from nitrogen saturated fields until springtime where they are returned to the soil during Maryland's summer growing season. Specifically on Maryland's Eastern shore, rye is a commonly planted cover crop that has been found to reduce the leaching of soil nitrogen by up to 80% at a cost of roughly \$5.49 kg⁻¹ N (W.D. Hively, M. Lang 2009).

Building NDI Surfaces for Analysis

The study relied on 3 different indices for analysis, Normalized Difference Vegetation Index (NDVI), Normalized Difference Tillage Index (NDTI), and Normalized Difference Residue Index (NDRI). Methods for building these raster surfaces vary slightly however, the type of multispectral imagery data used in the analysis remains the same. With a combination of publically available Landsat data and ESRI's Spatial Analyst extension, BEA created topographic derivatives that were related to real world field observations over cover crop type.

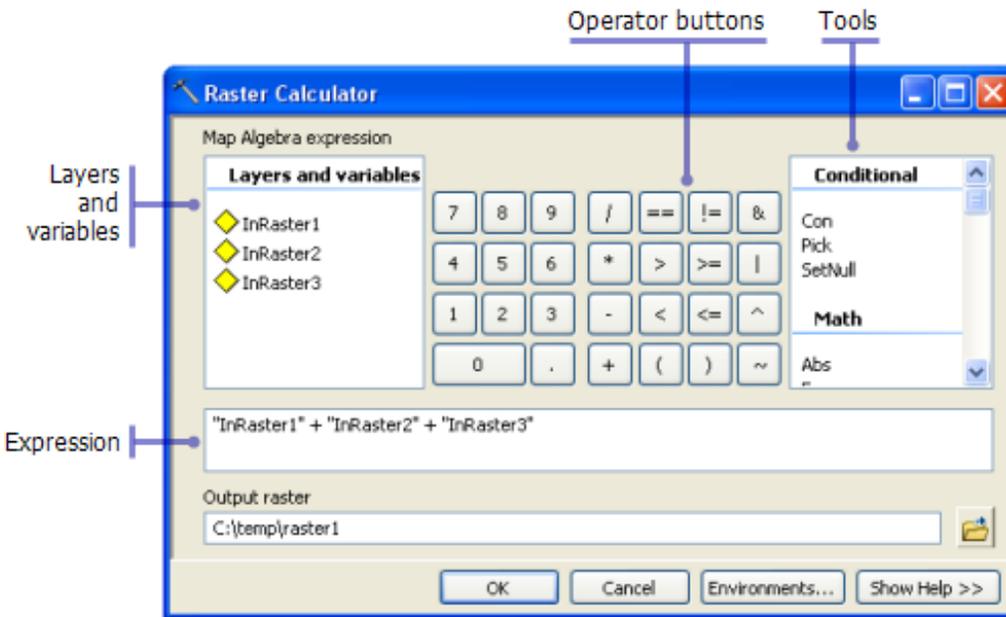
1. Data acquisition. BEA obtained multispectral aerial imagery for use in the crop classification of corn, soybeans, pasture/grass, and winter wheat. Time and date stamped imagery scenes were obtained for the Anne Arundel county study area during growing season dates as follows:

Date	Corn	Winter Wheat	Soybeans	Grass/Pasture
March, 2013			x	x
July, 2013	x			x
August, 2013	x	x		x
September, 2013		x		x
December, 2013			x	x

Working with USGS' Glovis application, a user can very easily query and extract multispectral scenes from publically available Landsat archives. Scenes were selected based on specified

date, area of interest, and cloud cover. The methodology used to generate NDVI, NDTI, and NDRI rely heavily on the spectral reflectance values obtained by the onboard Landsat sensors. The values and sensors do not account for or negate data artifacts such as haze and light (Mie) scattering. Atmospheric haze and cloud cover can obfuscate reflectance values leading to improperly built NDVI, NDTI, and NDRI surfaces. It is the best practice to select images that are free of haze/cloud cover and if resources and expertise allows, to use USGS's Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) to correct for haze.

2. Surface generation. Using ArcGIS Spatial Analyst, BEA built and analyzed complex surfaces for NDVI, NDTI, and NDRI for the development of local indices for cover crop type, tillage, and residue. NDVI, NDTI, and NDRI surfaces can be generated using the Raster Calculator in Spatial Analyst. ESRI's Raster Calculator allows a user to build and execute a single Map Algebra expression using Python syntax. The output is a newly generated raster surface that can be used for further analysis.



Raster Calculator's interface allowed BEA to construct the following equations for NDVI, NDTI, and NDRI that result in a newly built raster surface for the area of interest:

$$\text{NDVI} = (\text{Near Infrared} - \text{Red}) / (\text{Near Infrared} + \text{Red})$$

$$\text{NDTI} = (\text{Shortwave Infrared 1} - \text{Shortwave Infrared 2}) / (\text{Shortwave Infrared 1} + \text{Shortwave Infrared 2})$$

$$\text{NDRI} = (\text{Red} - \text{Shortwave Infrared 2}) / (\text{Red} + \text{Shortwave Infrared 2})$$

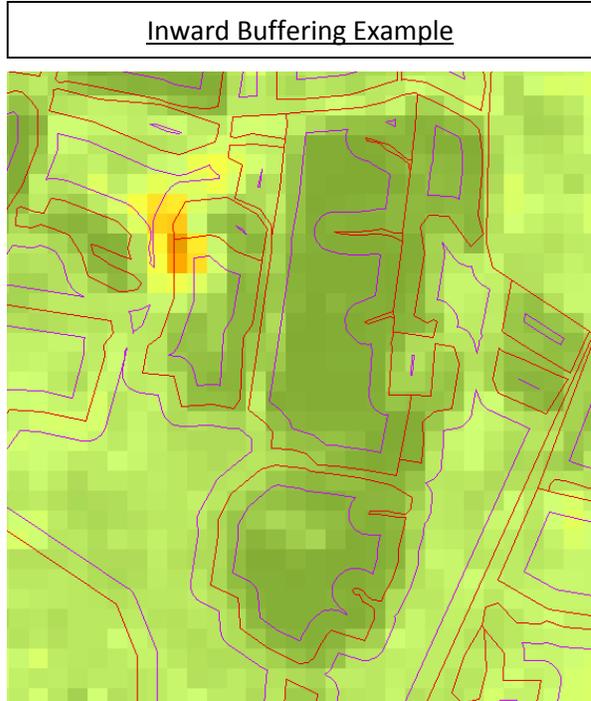
Running all three NDIs resulted in date stamped raster surfaces that are used for correlation to both the Cropland Data Layer and in field ground truthing.

3. Correlation of NDIs to field observations. Using the newly date stamped raster surfaces an average value of each NDVI, NDRI, and NDTI was calculated for a given field observed CLU. BEA verified cover crops on a total of 94 ground truthed fields that served as control for index association. Field sampled CLU's were placed over top one of three newly created raster surface

types. Inwardly buffered CLU polygons were generated to account for NDVI, NDRI, or NDTI mixed pixel errors. An inward buffer of 100 feet eliminated any mischaracterized pixels and ensured that average index values were indicative of the ground truthed field.

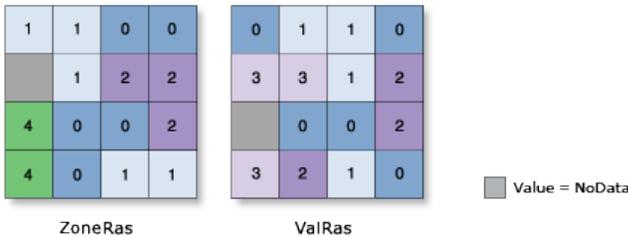
When analyzing rasters within a vector boundary, best practices dictate that users create a buffer within the initial CLU boundary (Thenkabail, P.S., R.B. Smith 2000). This eliminates the mixed pixel problem and accounts for pixels occurring at the edge of features whose digital number represents the average of several spectral classes.

Keppler and Hively create an inward buffer to account for irregular field conditions that were not indicative of cover crop performance traits. Specifically, inwardly buffered CLU layers in Hively’s analysis work to eliminate hedgerow shadows, vegetated drainage ditches, and inundated areas (W.D. Hively, M. Lang 2009). Inward buffers are most easily created using ESRI’s ArcGIS for Desktop 10.2 software and the buffer tool in ArcToolbox. Users can easily specify the polygonal vector layer they wish to perform the analysis on as well as enter the size, unit, and direction of the buffer from the original vector layer. With a newly constructed inward buffer that eliminates mixed pixels occurring near feature edges, the average NDVI is calculated for representative cover crops within the CLU.



Lastly BEA used ESRI’s Zonal Statistics as Table tool to associate an average NDVI, NDTI and NDRI with a particular field observation. Zonal Statistics as a Table summarizes the values of a raster within the zones of another dataset and reports the results to a table. So in this case the NDVI surface was used as a raster input to be summarized by the geo spatial boundaries of the buffered field observed CLUs.

Zonal Statistics as a Table (ZoneRas, "Value", ValRas, OutTable, "ALL")



Rowid	VALUE	COUNT	AREA	MIN	MAX	RANGE	MEAN	STD	SUM	VARIETY	MAJORITY	MINORITY	MEDIAN
1	0	5	5	0	2	2	0.6	0.8	3	3	0	1	0
2	1	5	5	0	3	3	1	1.095	5	3	0	3	1
3	2	3	3	1	2	1	1.667	0.471	5	2	2	1	2
4	4	1	1	3	3	0	3	0	3	1	3	3	3

Summary statistics consisting of a mean, max, min, range, and standard deviation were generated for each crop type observed in the CLU. This is an extremely valuable part of the analysis because it allows a user to generate one of the three raster surfaces for a given month and confidently associate the index value with a type of crop.

NDVI Results

After successfully generating mean NDVI values for each field observed cover crop, NDVI indices were created for August and December. At a county wide scale, August NDVI shows that the greatest areas of biomass occur in the southern most regions of Anne Arundel County and northeast. Areas of the map showing significant gaps in data exist due to significant cloud coverage for the month and day the multispectral data was obtained.

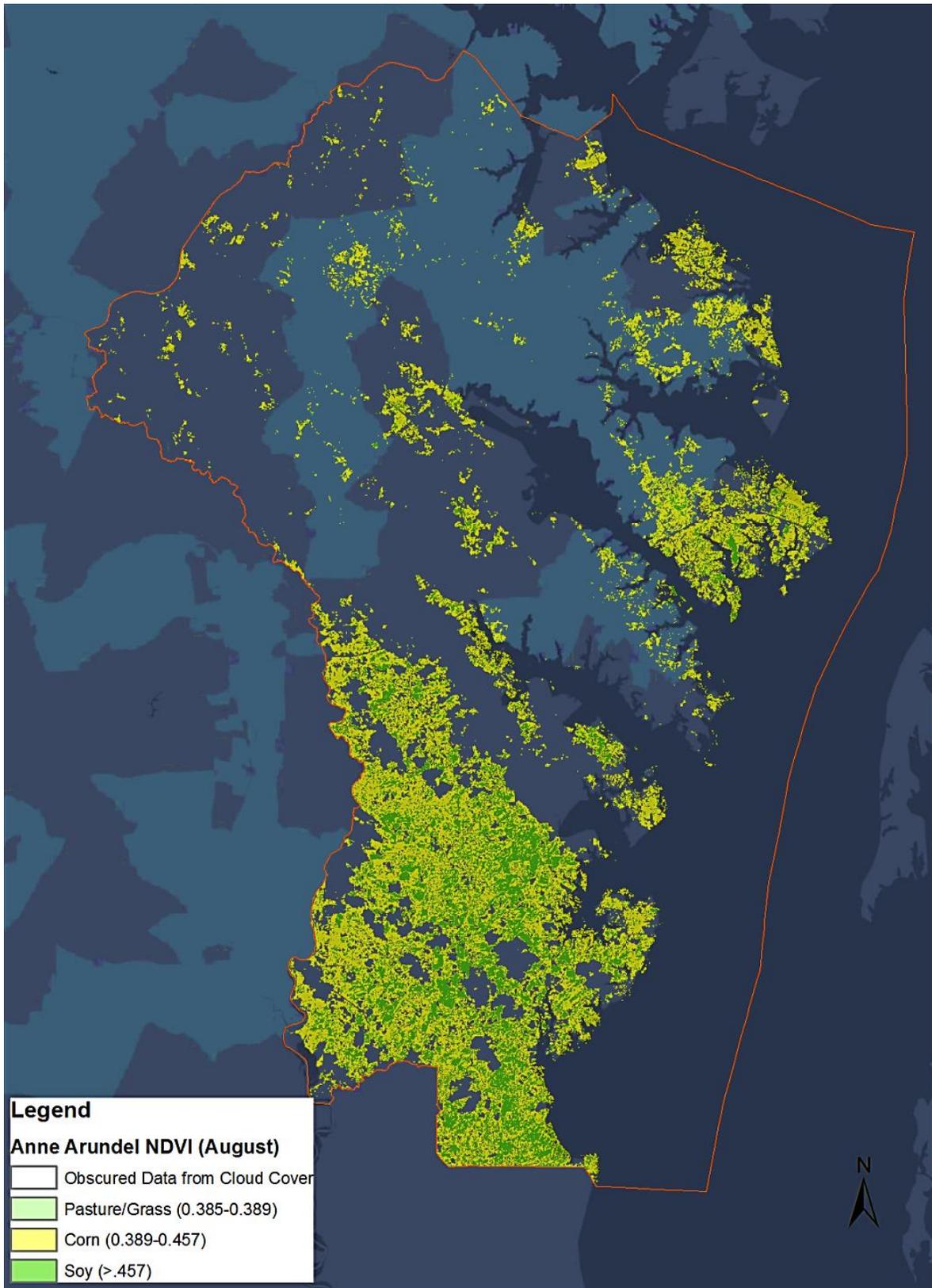
As work on this project progressed it became apparent that cloud coverage and Mie scattering had significant impact on the quality of images obtained by Landsat 8. Further, satellite passes occur on a 16 day cycle leaving only two opportunities to obtain clear imagery for a given month. A workaround using Landsat 7 is possible, but time intensive. While August imagery exhibited large gaps at the county scale, BEA field assessment areas remained fairly clear.

A majority of the field observations performed by BEA occurred in the southern portion of Anne Arundel County. Localized observations combined with NDVI values tended to be more accurate on fields with a larger acreage.

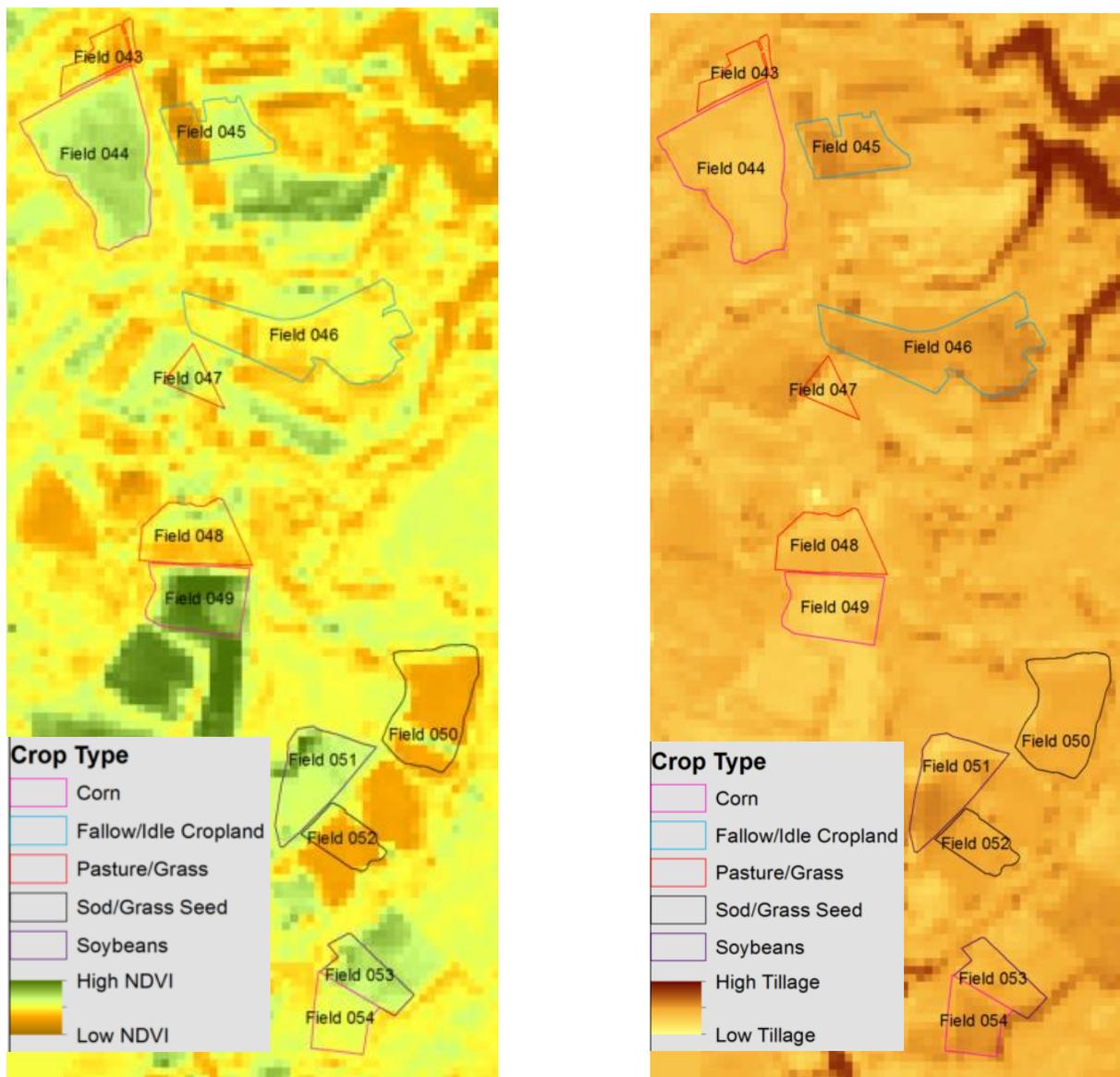
Smaller fields tended to have a greater number of instances where less NDVI pixels were present. This is due to the fact that Landsat 8's resolution is 30m. This results in a smaller sample size of pixels making it difficult to generate accurate zonal statistics. However a majority of BEA sampled sites retained accuracy and NDVI was an appropriate index for cover crop classification.

The localized map below demonstrates successful crop type classification using the NDVI index and a ground controlled set of fields. All fields in the map fall under the NDVI index generated at the county scale and match what was observed during site visits.





Side by Side Comparison of NDVI and NDTI Processed Images for Selected Ground Control Sites



The side by side NDVI (left) and NDTI (right) maps were created using a December 1, 2013 Landsat8 image of selected ground control sites to test our ability to interpret the presence of cover crops and levels of conservation tillage. Our chief aim was to see if the ground truth data obtained in October/2013 and February/2014 could be explained by the reflectance values and visual observations derived from the NDI maps. Below is a table that presents our interpretation of the maps and their degree of alignment with the field reconnaissance *data we had to work with*. It is important to note that our interpretation necessarily relies on assumptions which may or may not be correct since *the dates of the field observations are not the same as the Landsat8 image date*. Further, not all fields were observed during the reconnaissance missions due to accessibility and observation constraints. These kinds of limitations are not surprising since no formal arrangements were made with landowners to collaborate in this demonstration.

Data Table: Side by Side Comparison of NDVI & NDTI Processed Images of Selected Ground Control Sites

Crop Type/Field	Condition During:		NDI 12/1/13 Visual Evaluation & Mean Reflectance Values		Interpretation	Validation
	10/6/13	2/23/14	NDVI	NDTI		
Corn/44	cut, good residual	light cover crop	medium high 0.011	medium tillage -0.045	assume: less residual due to planting	Both NDI values align very well with assumptions & field notes
Corn/49	standing, brown	no cover crop, good residual	high 0.032	low tillage -0.065	assume: corn not harvested, left cut in place, no tillage	
Corn/54	standing	unknown	medium -0.002	medium high tillage 0.017	assume: no cover crop based on NDI values	
Soybeans/51	green	low residual, mostly tilled	medium 0.010	medium high tillage -0.004	assume: crop still standing in Dec.	NDTI values support the conclusion these fields have no cover crops
Soybeans/53	green	unknown	medium high 0.011	medium tillage -0.010	assume: crop still standing in Dec.	
Pasture/grass/43	tall grass	dormant appearance	medium low -0.017	medium low tillage -0.031	N/A	NDVI visual eval. & values align; NDTI visual eval. not supported by values
Pasture/grass/47	normal	dormant appearance	medium 0.002	medium tillage -0.034	N/A	
Pasture/grass/48	normal to short	dormant, grazed, geese	medium low -0.014	medium low tillage -0.030	N/A	
Sod/grass/50	sod farm	good grass cover	low -0.023	medium low tillage -0.006	NDVI/NDTI Mean NDI values for the entire CLU of fields 45/46 are not useful.	NDI values detecting observed shifts in sod farm cycles: moving from bare earth, to newly seeded areas; then on to stages of more mature growth.
Sod/grass/52	sod farm	unknown	low -0.022	medium low tillage 0.010		
Sod/grass/45	sod farm	left field grass cover; right field not visible	left field low: -0.034 right field medium: 0.003	left field medium high: 0.024; right field medium: 0.008	Values for left and right field portions were generated to support the validation comments	
Sod/grass/46	sod farm	left field light cover crop; right field spotty cover crop & wet spots	left field medium low: -0.014 right field medium: -0.007	left field high: 0.019; right field high: 0.022		

Results and Conclusions

Results

As stated previously, the goal of this “novice” investigation was to determine if a conservation organization with in-house geographic information systems expertise could successfully use satellite-based classification techniques to track the use of cover crops and conservation tillage—two of the most important agricultural BMPs in the Bay watershed. To summarize our results as succinctly as possible we found that:

1. It is possible for a non-expert GIS analyst, supported by a two-person field observation team, to produce satellite-based interpretive maps and data through the use of NDVI and NDTI indices. Maps derived from the image processing steps outlined in this report can identify *potential* field locations where cover crops may be lacking and/or conservation tillage appears excessive.
2. The methods used by the study team provide a coarse landscape level indicator tool that can be adjusted by the analyst to set threshold reflectance values for target BMPs. Processed satellite data can then be visualized on maps using color coded map legend ramps to indicate more clearly where threshold values are exceeded. In turn, these areas can be observed in the field to validate or dismiss concerns about particular areas.
3. To better assess where conservation problem areas might be, we found that multi-colored map legend ramps are much easier to visually interpret than monochromatic color ramps, as can be seen in the side by side NDVI (multi-colored ramp) and NDTI (monochromatic colored ramp) images shown above. We found that assigning categories to visual observations of the maps (e.g. medium, low, medium high) is more useful in the extremes (i.e. high, low) and is less reliable and consistent both within crop types and across crop types—particularly when using a monochromatic color ramp.
4. Use of the NDVI was very successful for classifying typical agricultural crops and pasture lands. Our field observations validated this conclusion.
5. The NDTI versus the NDRI proved to be a better image processing tool for the study team to interpret and validate our mapping and field observations.
6. Methods documented by the team for the target BMPs were not statistically defensible in this pilot project due to time constraints, but this standard could be readily achieved by including more ground truthed sites over a wider study area.
7. Limitations were encountered that reduced the utility of conducting a single growing season assessment of the two target conservation practices. These limitations included:
 - a. Frequent cloud cover on Landsat images that made it impossible to synchronize field observations with the 16 day Landsat 8 image capture interval. Extended snow cover also reduced our ability to conduct timely field observations.
 - b. A narrow window exists to document cover crops that are planted before the deadline specified by the State of Maryland. This is useful information to know as cover crops are most effective when planted before this date.
 - c. A combination of hilly terrain and tree-lined field edges prevented us from observing the full extent of many sites. This resulted in our inability to use several larger fields that would have made our data more robust.

Conclusions

The investment in time and effort to conduct satellite-based assessments relating to the presence or absence of target BMPs in an area conservation interest has primarily been limited to sophisticated researchers and high-end GIS analysts with formal training or extensive experience in remote sensing applications. Professional journals that feature the results of breakthrough remote sensing research and new techniques are written for experts and are likely to be less comprehensible to most small conservation organization personnel that could directly benefit from this technology.

The study team was encouraged by the results of this investigation and concludes that some small watershed and/or conservation groups who are willing to explore and learn more about how remote sensing applications can benefit their organizations will be well rewarded for their efforts. The incredible amount of data continually collected by Landsat 8 and other government satellites is freely available to the conservation community and offers opportunities to create practical conservation applications. This simple investigation suggests that even small organizations can upgrade and expand their abilities to track and verify a variety of BMPs and detect hot spots where improved field conservation practices are needed. Current leaders in satellite –based conservation applications can and should make a greater effort to sponsor training sessions to those who are interested in upgrading their skills while learning practical applications to enhance conservation and restoration activities of all kinds. In this way, a community of practice could emerge to make remote sensing applications a more ubiquitous and valuable toolset that can extend beyond the exclusive domain of high-end government and research practitioners.

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