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The state of tobacco : a remote sensing approach to understanding tobacco crop production in Kentucky.

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The State of Tobacco: A Remote Sensing Approach to Understanding Tobacco Crop Production in Kentucky

By

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ABSTRACT

Agricultural policy allows for governing bodies to better control the landscape, economy, and security of resources. Because of this power, it is essential for policy and its effects to be thoroughly understood. This study examines the Tobacco Transition Payment Program (TTPP, “tobacco buyout”), in effect from 2005 to 2014, using a mixed methods approach. The TTPP lifted the existing geographic restrictions of tobacco production and deregulated market prices formerly controlled by the government. Kentucky’s economic, social, and agricultural landscapes changed significantly in the wake of this legislation. To explore these changes, this study employs semi-structured interviews and remote sensing analyses for a full understanding of the tobacco buyout in Kentucky. Remote sensing, and specifically multispectral imagery, offer an effective and economical way to classify crops, which is important in understanding what exists on the physical landscape. Using Landsat imagery from 2015, I employed a supervised classification of data to quantify the extent of tobacco production. I then integrate the classified landscape with survey and interview data regarding trends among tobacco farmers. This research will not only provide an extension of the existing narrative for the buyout, and further explore TTPP policy’s influence on the Kentucky agricultural landscape, but also exemplify remote sensing as a tool for policy assessment.

INTRODUCTION

Agriculture, as a vulnerable system, has long required government attention and intervention. Because agricultural products play a critical role in the survival of human societies, and because of the sensitive nature of growing crops, policy will remain integral in securing basic needs provided by agricultural products, such as food. Policy implementation in the realm of agriculture varies widely, and does not result in uniform responses from agriculturalists in terms of how they influence the landscape (Raymond et. al. 2015). Because agricultural decision-making manifests differently via perceptions at a local level (Raymond et. al. 2015), this variability may impede the reaches of political influence on land-cover across space.

Developing a better understanding for how government can influence ground cover requires understanding how legislated policy affects farmers, and subsequently the landscape. The goals of government-produced agricultural policy are mainly: efficiency, equitable distribution, and security (Monke and Pearson 1989). According to Monke and Pearson (1989), efficiency refers to the distribution of resources in order to maximize yield; equitable distribution refers to equal opportunities to benefit from agricultural production; security refers to stable production, prices, and sources of nutritional sustenance.

Often trade-offs against one or more of these factors must be made in favor of another. For instance, in the face of unstable prices, saturated markets, or other threats to equitable distribution, governing bodies often institute a “quota” system (Monke and Pearson 1989). When domestic supply and demand, or other economic and environmental elements fail to support a commodity crop, governments regularly institute a policy known as a "buyout," (Dohlman et. al. 2009). Both types of policy aim to facilitate change in the current trends of specific agricultural production. Exploring outcomes and impacts of policy, in relation to their respective goals, allows for improvement of policy implementation in the future. Therefore, as buyout policy becomes relevant, knowing the intricate effects of a policy on a particular population or landscape should prompt constructive change to legislative structure, implementation, target populations, etc.

Most recently, the Tobacco Transition Payment Program (TTPP), known commonly as the "tobacco buyout," has enacted substantial change on Kentucky's agricultural landscape and economy (Dohlman et. al. 2009, Stull 2009, Snell 2005). Kentucky, the second largest national producer of tobacco, and representing the most tobacco farmers, experienced the loss of tens of thousands of tobacco farmers and farms. Reviews of the federal tobacco buyout have been limited in temporal and spatial scope, due the patterns of census collection.

In studying this policy, much of the economic impacts of the TTPP have been tracked and understood by the United States Department of Agriculture (USDA). Although there is information regarding the policy's economic impact (Dohlman et. al. 2009, Snell 2005, United States 2011), this type of legislation influences other aspects of society such as culture and the physical environment. Several papers offer insight into the social impacts of the tobacco buyout between 2005 and 2014 (Stull 2009, Dohlman et. al. 2009). The government report, "The Post Buyout Experience," published in 2009 by the USDA, aimed to characterize the TTPP for the most relevant areas affected by the policy. However, since the tobacco buyout expired, there has yet to be exploration of the TTPP longer-term impacts. This research aims to inform the existing narrative of social impacts of the tobacco buyout, and the resulting environmental impacts.

Research Objectives

Investigating the pattern of tobacco production through the use of remote sensing, in tandem with qualitative assessment, offers an opportunity to better understand the outcomes of legislation. The objective of this study is to better understand and characterize the changes in Kentucky after the TTPP. The study will explore two questions: how did Kentucky farmers respond to the Tobacco Transition Payment Plan, and more specifically, are Kentucky farmers' responses to the Tobacco Transition Payment Plan detectable on the landscape measured by remote sensing classification techniques? My hypotheses for this study are that farmers agree that the tobacco buyout was successful, and that the buyout money contributed to changes in farming practices. I also hypothesize that tobacco can be differentiated from other agricultural products using Landsat-derived, thirty-meter, multispectral imagery in two Kentucky counties.

My research questions aim to provide a more thorough perspective of human-environment interaction in the context of major policy shift that influenced not only socio-economic agendas, but also the landscape on which those decisions played out. The purpose of my study is to explore the reactions of farmers to the TTPP, with a focus on how government aid was utilized in transitioning away from tobacco farming. Another goal of my research is to successfully identify production of tobacco on the landscape among other agricultural products. This is with the intention of forming a better understanding of land-use decisions made by Kentucky farmers over the past decade. By integrating qualitative and quantitative data, insight is provided into not only tobacco buyout legislation, but also how future agricultural policies will affect the landscape and culture relating to specific crops.

BACKGROUND OVERVIEW

The Tobacco Buyout

Because of financial instability and unrest among tobacco farmers during the early 20th century, the USDA established the Agricultural Adjustment Act of 1938 (Mathis and Snell 2007). This modified the Agricultural Act of 1933 which was put in place during the New Deal in order to curb production and raise the prices of agricultural products across the board (Mathis and Snell 2007). A quota system regulated the amount of tobacco that growers could raise on a certain parcel of land in a specific region. Quotas ensured that the market could support tobacco growers' output. Until 2004, a government appointee graded tobacco crops that were brought to market. Tobacco producers distributed their product through contracts with tobacco companies, or, more commonly, at auctions at the county level. Tobacco companies bought different grades of tobacco for smoking or chewing products. Unsold product was bought by the government, and auctioned to the companies for cheaper than the set price, or sold the next year.

Quotas and their geographic restrictions meant that many growers grew tobacco on several parcels of land, or rented tobacco quota from neighboring landowners. Along with quotas, price floors established by the USDA regulated the price of tobacco. Federal policy deregulating tobacco had been in consideration since the mid-1990s (Snell, personal communication, October 8, 2015). Market conditions for tobacco were in decline, and loss of farms and farmers were beginning to emerge in census data (U.S. Census 1997, 2002, 2007). Along with an increase in imported tobacco, of similar quality to that grown in the U.S., the market dynamic in supply and demand changed for the crop as well (Snell, personal communication, October 8, 2015). A third motivation for the tobacco buyout was pressure from health organizations, as data in the early nineties continued to confirm the negative health effects of tobacco products (Snell 2005). The guaranteed price for tobacco crops, enforced and supported by the federal government, became impractical.

In 2004, the Fair and Equitable Reform Act was passed, aiming to regulate advertisements related to tobacco products (Stull 2009). The component of this Act that enacted the tobacco buyout revoked the quota system and price supports for farmers at a federal level. The legislation provided funding for tobacco growers to sell off their quota between January 2005 and December 2014. Alternatively, farmers were allowed to keep growing tobacco but without any restrictions or stability of government support.

In the years before the tobacco buyout, demand for the crop had been diminishing. Census data from as far back as the 1990s shows a decreasing number of farms, acres, and quantity. The rate of decrease increased tremendously after the TTPP. Since the tobacco buyout, census data confirms the loss of many farmers and farms (U.S. Census 2002, 2007, 2012). The quantity of tobacco grown also decreased across census years. While numbers of tobacco growers in Kentucky plummeted (U.S. Census 2002, 2007, 2012), the TTPP resulted in fewer, larger farms in the western region of the state (Figure 1; Dohlman et. al. 2009). Despite the drop in acres under tobacco production, the statewide acreage of tobacco between the years of 2007 and 2012 stabilized. This pattern, compared to the number of farms, indicates that farms are fewer but larger after the tobacco buyout.

Year	Number of Farms	Acres in Tobacco	Quantity
1997	46,850	250,885	497,856,262
2002	29,237	110,734	219,978,920
2007	8,113	87,641	196,259,377
2012	4,537	87,931	183,904,938

Table 1. Census years and data from the USDA Agricultural Census, demonstrating the loss of tobacco farms and products across time. Data: USDA, U.S. Census.

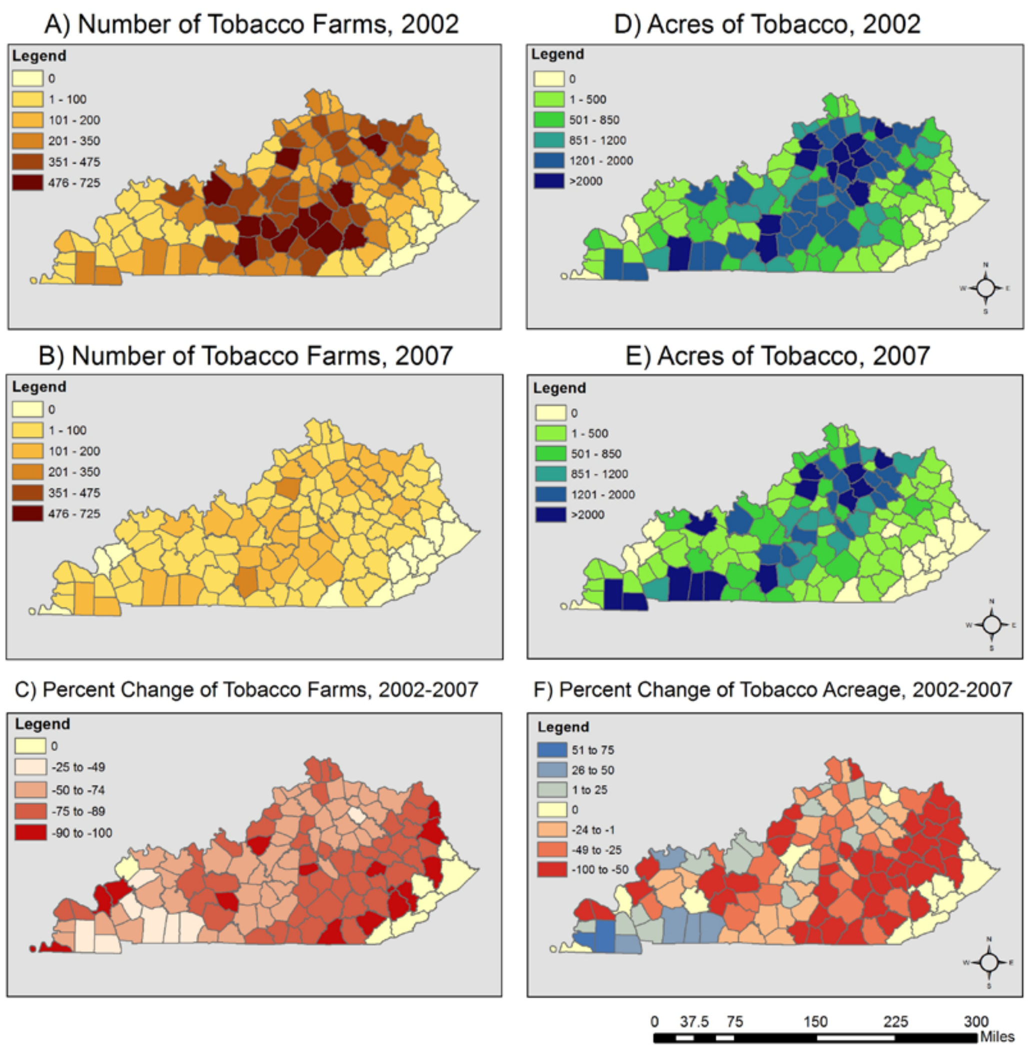

Figure 1. Quantity and percent change in Kentucky counties between the census years around the time of the buyout. Data: USDA, KYGeoportal.

Agriculture and Remote Sensing

Policies like the TTPP result in changes on the landscape that follow specific and unique spatial patterns. Geospatial tools like remote sensing offer an opportunity to gain new perspective on these by directly monitoring landscape changes. With increasing applicability of spatiotemporal considerations in remote sensing, as well as advancing technology, more nuanced techniques of understanding crop productivity have emerged. Previously, crop inventory and classification was constrained to less geographic-specific mapping methods such as: choropleth mapping, census data, and intensive agricultural record-keeping (Nellis, Price, and Rundquist 2009). Many approaches have been tested in classifying crop type and farming patterns since the introduction of remote sensing technology within agricultural applications (Nellis, Price, and Rundquist 2009). Answering questions about land cover requires decisions around spatial and temporal scale, and remote sensing tools have demonstrated the range necessary to address fine, medium, and coarse scale study areas.

As the spectral and spatial capacity for imaging technology has widened, applications such as “precision agriculture” have emerged as critical tools in quantifying agricultural yields each year, and in close supervision of crop health before harvest (Mulla 2013). Hyperspectral data is especially useful when looking at spectral information of different agricultural components of a scene, i.e. robust corn differs from bare ground, nitrogen-deficient soils, and pest damaged crops, etc. (Apan et. al. 2002). Seelan et. al. (2003) explore different techniques for examining crop stress, pest invasion, poor soil conditions, and flooding using different types of fine-scale imagery. Precision agriculture has led to the use of highly controlled crop management practices, both within season and over time, for specific study areas with increasing access to remote sensing tools (Seelan et. al. 2003).

Because precision agriculture is often highly specified, it limits the use of remote sensing to small geographic areas. Expanding land-cover observation from a smaller area to a regional scale, coarse imagery has proved to be important in describing trends of crop health and extent, agricultural yields, and landscape variability (Vrieling, Beurs, and Brown 2011; Zhang et. al. 2005). Regarding crop extent, Misra et. al. (2012) successfully performed a classification of sugarcane ratoon using ~60-m spatial resolution imagery in the state of Utar Pradesh, India. Chen et. al. (2006) employed several derived products to identify areas under corn production in western Mexico. The study aimed to compare different temporal composites of vegetation indices for the TERRA-Moderate Resolution Imaging Spectroradiometer (MODIS) at 250-m, 500-m, and 1000-m spatial resolution. This study resulted in the conclusion that 250-m resolution MODIS data did not improve accuracy in understanding the quantity of corn, in comparison to 500-m and 1000-m resolution MODIS data (Chen et. al. 2006). This study helps to demonstrate that spatial resolution is one of many factors that facilitate accurate classification for coarse spatial scale data, and that often transformations, such as vegetation indices, contribute to more accurate classification attempts (Liu et. al. 2003).

Multispectral, medium spatial scale imagery provides a cost-effective, and sufficient method for classification of crops (Misra et. al. 2012; Meroni et. al. 2013). For example, Apan et. al. (2013) utilized Advanced Spaceborne Thermal Emission and Reflectance Radiometer (ASTER) data for two study scenes in Australia. Evaluating the utility of fifteen-meter spatial resolution imagery in defining agricultural crops and soils, Apan et. al. (2013) employed a supervised classification of chickpeas, wheat, and barley. The study concluded that ASTER data provided sufficient spectral separability among the designated classes, as well as sufficient spatial resolution to perform a highly accurate classification (Apan et. al. 2013). Akbari et. al. (2005) used Landsat 7 imagery to classify agricultural management systems associated with irrigation in Iran. The researchers used minimum distance classification to target crop types and irrigation practices. The results of that classification were compared to agricultural statistics (Akbari et. al. 2005).

The Landsat platform offers regular revisit time, historical satellite information, and open-source data at a medium spatial scale, making Landsat an ideal vehicle for this research. Using multispectral imagery at a medium spatial resolution, this study can examine the spectral separability among crops, while also gaining understanding about regional patterns of production.

DATA AND METHODS

Study Area

In Kentucky, Christian County (724 square-miles) and Trigg County (481 square-miles) both experienced an increase in tobacco production after the TTPP. This was uncharacteristic of most Kentucky counties. Because tobacco continues to be a relevant and common crop in these two counties, this area was ideal for collection of reference data and classification potential. They are adjacent, and fall within the same Landsat Worldwide Reference System scene (WRS-2, row 34, path 141).

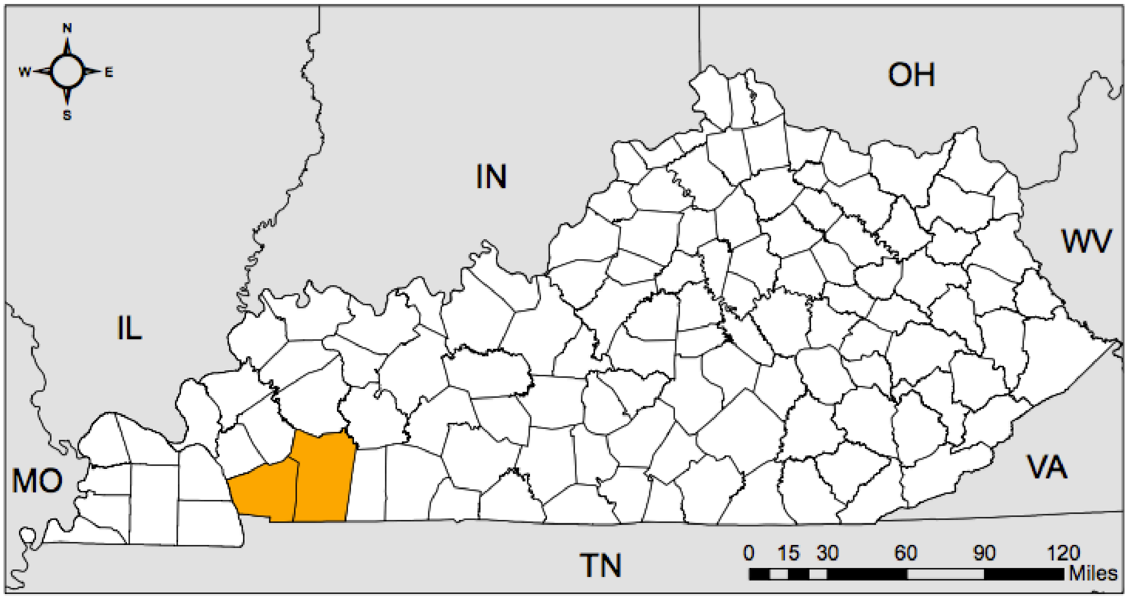

Figure 2. Kentucky study area highlighting Trigg County and Christian County, which are investigated using remote sensing analysis. Data: KYGeoportal.

Data

Local Policy Perceptions

For understanding local policy perceptions, I conducted semi-structured interviews with people involved with the TTPP including tobacco farmers and an agroeconomist. A survey instrument (Appendix A), designed to gather data on individual perceptions of the buyout, builds knowledge about shifts of tobacco production.

Remote Sensing Analysis

A Landsat 8 image, from 2 August 2015, with thirty-meter spatial resolution for the visible and infrared bands was used for remote sensing analysis. This time period is peak productivity for many agricultural plants, and burley tobacco has begun the senescing process. Data was downloaded from GLOVIS (USGS) (http://glovis.usgs.gov). The Landsat Program is a series of earth-observing satellites launched in the early 1970s that provide continuous, multispectral imagery. Landsat 8 spectral resolution includes eleven bands collecting in the visual, near to mid-infrared, and thermal portions of the electromagnetic spectrum. The thermal bands ten and eleven were collected at 100 meter spatial resolution, but were then resampled to thirty-meter resolution. These data, represented in Table 2, are free for use and provide georeferenced-as-terrain and sensor corrected (Level 1T) products. While using imagery with higher spectral and spatial resolution would allow for a more precise distinction among crops, the use of multispectral data takes less time to process, is more freely available, and often provides continuous data at larger swath widths.

Band	Name	Wavelength (μm)	Spatial resolution
1	Coastal/Aersol	0.435-0.451	30 meter
2	Blue	0.452-0.512	
3	Green	0.533-0.590	
4	Red	0.636-0.673	
5	NIR	0.851-0.879	
6	SWIR-1	1.566-1.651	
7	SWIR-2	2.107-2.294	
8	Pan	0.503-0.676	15 meter
9	Cirrus	1.363-1.384	30 meter
10	TIR-1	10.60-11.19	100 meter
11	TIR-2	11.50-12.51	

Table 2. A representation of the Landsat 8 bands with spectral range and spatial resolution listed. Those in bold were included in the classification. Data: USGS.

In addition, the National Land Cover Database (NLCD) 2011 product, developed by land the Multi-Resolution Land Characteristics (MRLC) Consortium, was used to derive a mask of non-agricultural areas. The NLCD 2011 offers land cover classification of the United States using a sixteen-class scheme, applied at a spatial resolution of thirty meters, which is compatible with that of this study. This data set is largely based on a decision-tree classification of 2011 Landsat satellite data. Masking allowed for the exclusion of areas built-up, forested, or protected by government agencies, leaving land cover categories: Grassland/Herbaceous, Pasture/Hay, and Cultivated Crops.

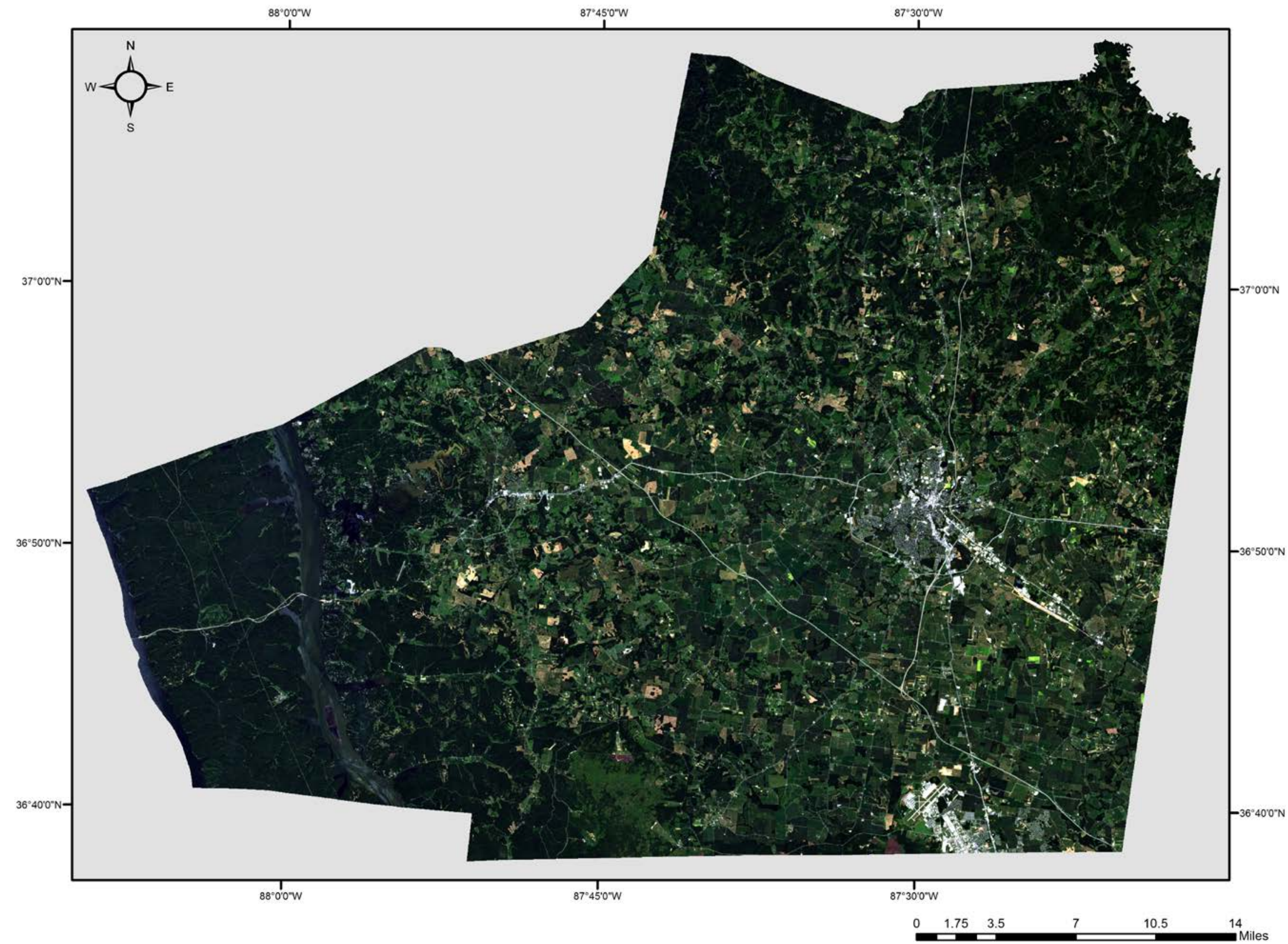

Figure 3. Landsat 8-OLI 4,3,2 composite of the subsetted study region. Data: Landsat.

Methods

Policy Context

To collect surveys, a snowball sampling method was applied. Snowball sampling allows for hard-to-reach populations to be contacted through initial contacts (Raymond et. al. 2015). In this study, the Community Farm Alliance, the Burley Cooperative of Kentucky, and Will Snell were initial contacts. Spatial bias from survey response is likely due to the snowball sampling method, which relied heavily on these Central Kentucky-based contacts.

The surveys were collected utilizing the website SurveyMonkey, an online interface, allowed the survey to reach people at minimal cost. The survey was adapted to fit the format of the website; however, each question remains in the style in which it was initially developed. Descriptive statistics, along with general trends in survey response data were organized into figures, and placed in the context of previously collected data on the social and economic impact of the TTPP. Further analysis was not applied due to the time frame for data collection combined with the survey response rate.

Classification of Imagery

The Landsat image was subsetted to Trigg and Christian counties. The image was then radiometrically converted to top-of-atmosphere reflectance and corrected for atmospheric effects using the FLAASH algorithm (Cooley, et al. 2002) as implemented in ENVI 5.1.

In identifying tobacco for a supervised classification, a purposive sampling method was executed across these counties to collect representative sample sites of dark tobacco and burley tobacco, corn, and soy using a Trimble Juno GPS unit. This unit provides three-to-five meter accuracy. Regions of tobacco larger than thirty by thirty meters were chosen as ground reference sites. Because research contacts for tobacco locations were limited, and due to the scale on which tobacco is grown, a sufficient number of larger regions of tobacco (90 by 90-m, to minimize spatial errors and "mixed pixel" issues) were difficult to find. Regions of other crops were at least ninety by ninety meters in dimension, to ensure pure Landsat pixel values.

Points of known land cover for tobacco, corn/wheat, and soy were chosen from a randomly generated set of 200 points imported into Google Earth, compared to high-resolution satellite imagery from October 2015. Areas of tobacco were purposively sampled from field reference data.

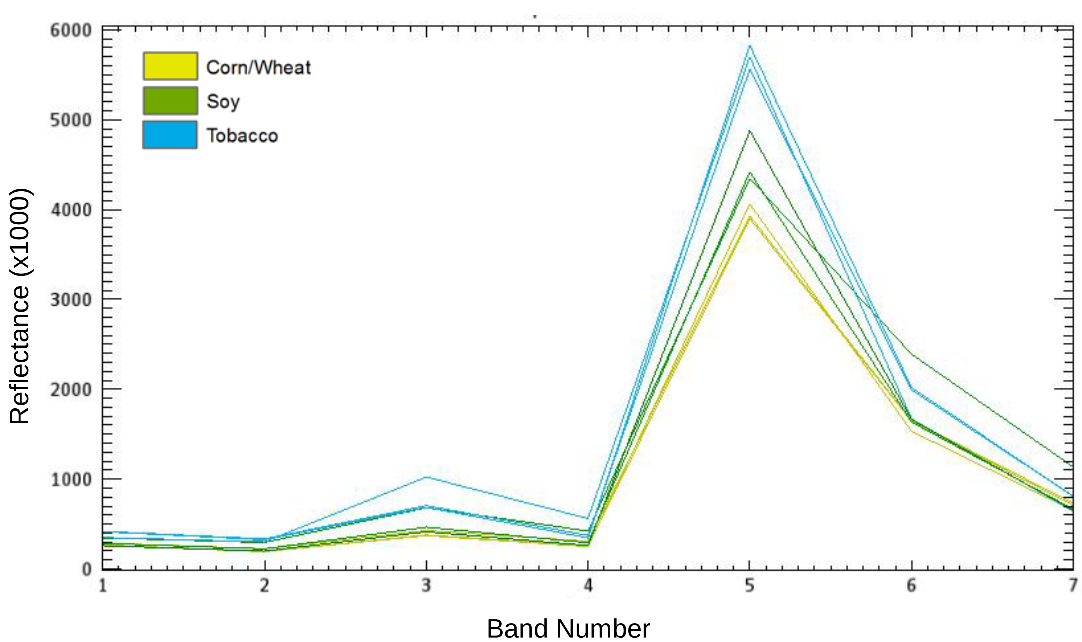

Figure 4. A spectral plot (ENVI 5.1) highlighting the different spectral responses for training data in each of the Landsat bands for the 2 August 2015 image .Reference Table 2 for spectral ranges recorded in each band.

Training data for the classification were grouped into corn/wheat, soy, and tobacco classes. Each class consisted of twelve to sixteen field-validated areas from the 2015 growing season, and of ten Google Earth-validated training areas. A mask derived from the NLCD 2011 data was applied before the classification of the image to isolate only agricultural land cover. In order to best highlight areas of tobacco, the data to be classified was a layer stacked image of spectral information and vegetation indices. Spectral bands included the blue, green, red, and near-infrared portions of the electromagnetic spectrum. The study took consideration of the phenological differences among tobacco types and stages of growth. Training data included yellowing tobacco.

The stack of spectral and derived data also included several vegetation indices: tassel-cap transformation and Normalized Difference Vegetation Index (NDVI). Tassel-cap transformation compresses spectral data into a few useful bands of data: brightness, greenness, wetness, and other uncorrelated data. The band of uncorrelated data was not included in the classification. These bands are built multiplying the sum of each band by a constant that is specific to each sensor. The transformation was originally developed from Landsat Thematic Mapper data to highlight agricultural products and their development (Krauth and Thomas 1976). NDVI is a transformation that is a proxy for the "greenness" of a pixel, and enhances spectral differences on the basis of absorption and reflectance in the red and near-infrared bands. It is calculated using the equation:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

A supervised classification technique known as minimum distance classification was implemented across the subsetted, stacked image (Jensen 2000). Minimum distance classification uses the central values of the spectral data that form the training locations to assign pixels to informational categories. The spectral data is clustered according to similarity across input bands to determine the positions of each pixel within the cluster. I defined these clusters using reference data collected for corn/wheat, soy, and tobacco, each representing unique spectral responses, and resulting in classes represented by their spectral mean. The distance between this mean and an unassigned pixel are compared in order to sort that unassigned pixel into a cluster. So, the "minimum distance" between a pixel and a cluster's mean value determines the class into which a pixel is sorted.

Accuracy Assessment

For validation of the 2015 classification, Google Earth imagery from October 2015 was used. Within the study region 400 random points were generated in ArcGIS (Version 10.2.2, 2014, ESRI, Inc.), which were then imported into Google Earth. Based on expert knowledge and visible cropping clues in the high resolution imagery, each random point was assigned to soy, corn/wheat, or tobacco, or was excluded because land cover was unclear or masked. Since tobacco is a more rare land cover and of significant importance, tobacco reference points were purposively oversampled from known tobacco fields. From these randomly selected and oversampled points, forty reference points from each class were withheld from training the classification for accuracy assessment.

I produced a confusion matrix to derive overall accuracy, producer and user accuracy, and Cohen's Kappa statistic. Overall accuracy is found by adding all pixels classified correctly and dividing by the total number of pixels. Producer accuracy is a measure of exclusion (how often the classification misclassifies or omits any one class) while user accuracy is a measure of inclusion (how often within a class a pixel from some other reference class is misclassified/committed) (Jensen 2000). Cohen's Kappa statistic is a measure of agreement between classified and reference samples. A Kappa value of 1 represents perfect agreement, while a Kappa value of 0 or less represents agreement at levels less than what we might expect by chance.

RESULTS

Policy Context

The survey was released 1 December 2015, and closed 25 January 2016. Comprised of thirty-three questions, the estimated time necessary for the survey was twenty minutes. Fifteen surveys were collected in total, but one is likely a repeat participant. In summarizing the responses to the survey, it is necessary to recognize that participants skipped some questions. The average age of respondents was 50.1 years old, all had some college education, and all recorded yearly incomes of above $40,000 a year (N=11). Nine of the respondents were male, while two were female. Five confirmed that they work on their land or in their homes full-time (N=11). Thirteen are residents of Kentucky, and actively farm in Kentucky (N=14). Respondents' locations were mapped by zip code in Figure 5. The majority of eleven survey participants own land. In comparison, two respondents lease land. Six respondents took legal control of the land on which they farm after the TTPP was put in place (N=14).

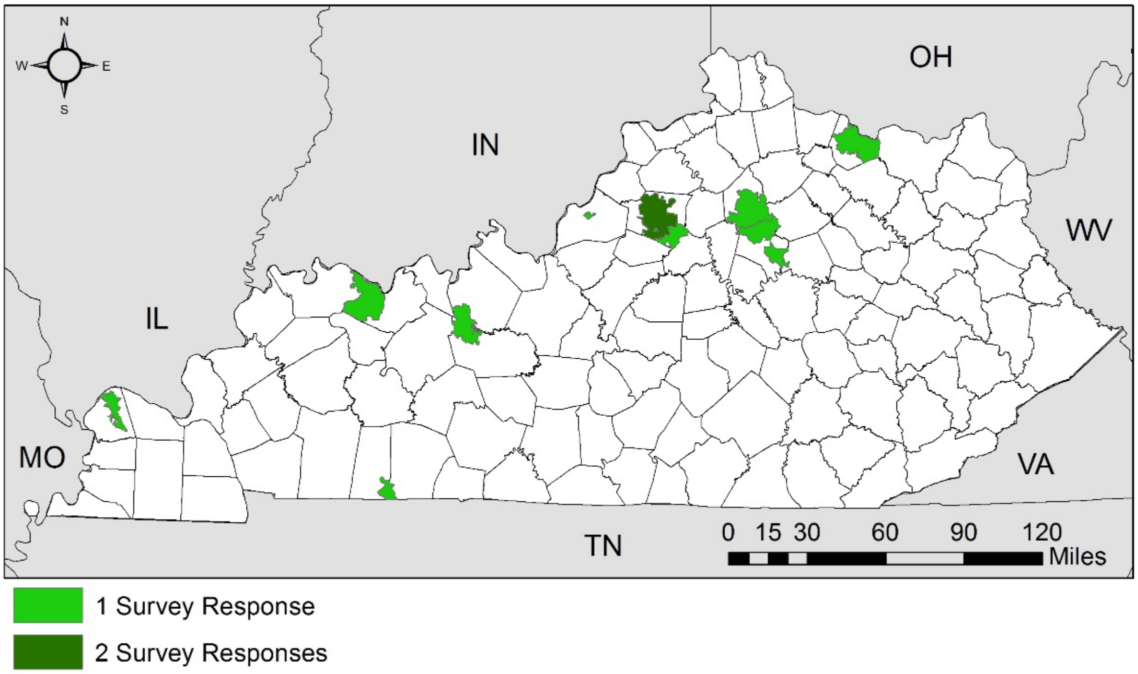

Figure 5. Study area: Kentucky. Survey response by zipcode. Data: KYGeoportal.

All respondents transitioned to entirely burley tobacco production, and farm size decreased (N=9). Before the policy implementation, eight respondents recorded a tobacco production size between twenty five and ninety nine acres (N=12), while after, one reported a farm size larger than twenty five acres (N=11). All agreed that the TTPP was, “Successful,” or, “Somewhat successful,” (N=12). In terms of its impact on individual households and communities, survey responders included comments such as “substantial investment in land and infrastructure improvements” were provided by the tobacco buyout. However, another commented that, “the price of tobacco has stayed profitable, but the power it placed in the hands of the tobacco buyers has been negative for the producers.” Though, each respondent confirmed that the TTPP was a success.

Classification of Imagery

Land cover classification for the 2015 image resulted in estimates of is 8.6% soy, 23.4% corn/wheat, and 9.1% tobacco across all, unmasked agricultural lands (Figure 6).

This means 58.9% of the counties are made up of non-agricultural land cover. The results from the accuracy assessment for the 2015 image of Trigg and Christian counties are shown in Table 2. An overall accuracy of 79.2%, was measured with a Kappa statistic of 68.8%. These were derived from the forty points in each class validated by October 2015 imagery on Google Earth. The lowest user and producer accuracy was observed for tobacco because of difficulty distinguishing between tobacco and soy crops.

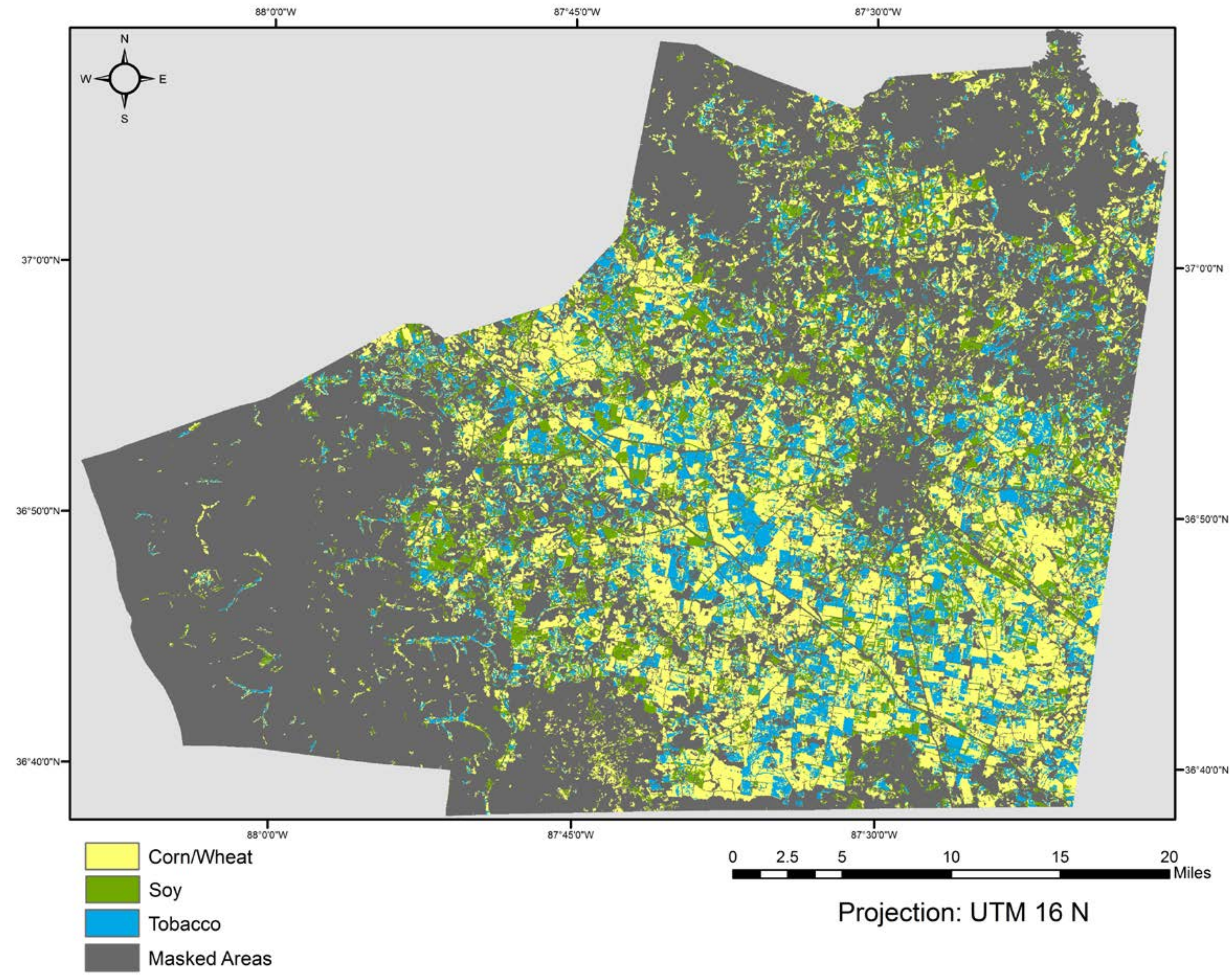

Figure 6. Classification of masked, cropped areas using Landsat-derived data for 2015 in Trigg and Christian counties in Kentucky.

Reference	Landsat Classification 2015					
	Soy	Corn/Wheat	Tobacco	Total		
Soy	32	0	10	42		
Corn/Wheat	3	33	0	36		
Tobacco	5	7	30	42		
Total	40	40	40	120		
User's	80%	82.5%	75%		Kappa Statistic =	68.80%
Producer's	76.2%	91.7%	71.4%		Overall Statistic =	79.17%

Table 2. Error Matrix for Trigg and Christian County 2015 from Google Earth reference data, compared with Landsat-derived classification (Figure 6).

DISCUSSION

Policy Context

Survey data and three semi-structured interviews shed light on the dynamics of regional landscape and agricultural shift. Much of the literature (Stull 2009, Dohlman et. al. 2009) suggests that most people took buyout money upfront, and likely retired, which is not reflected in the survey results of this study. Instead, many of the participants used money to improve other farming initiatives. One participant commented that there were "many farm improvements in the community." Another noted the, "…huge impact in Shelby County as [they] were a big tobacco county. Most producers used the money to either reduce debt or grow another enterprise." These responses were synthesized by another surveyed,

> "Tobacco was in a slow decline that continues today. Without the buyout…that would not have changed. This money did allow most to make improvement in other production. All of that improvement was in food production. Buyout money has provided for local food production and local food markets in many areas. The consumer has benefited along with the [agricultural] community."

While not “all” of the improvement was in food production, these survey responses substantiate a different narrative of the tobacco buyout than previously recorded. Tobacco buyout funding was recycled into agricultural endeavors.

It is generally accepted that farmers moved out of tobacco production in response to the tobacco buyout. As one respondent explained, “[The TTPP] allowed the opportunity for long time quota owners to get out of the system.” However, the TTPP represented opportunity for some farmers to enter tobacco production without the barrier of a quota expense (Snell, personal communication, 8 October 2015). “A lot of farmers started tobacco after the buyout, including [a survey respondent].” Along with intensification of tobacco in some regions, there were also new opportunities to grow tobacco outside of geographic restriction and economic regulation (Snell, personal communication, October 8, 2015). This development led a group of young tobacco farmers to enter tobacco production, according to one informant who farms outside of Lexington.

The rapidly dropping census numbers (Table 1) indicate that most people farming tobacco in 2002 have transitioned to other enterprise, or stopped farming altogether. Outside factors, such as increased corn prices, encouraged tobacco farmers to shift their production energy elsewhere (Snell, personal communication, October 8, 2015). It has also been noted in former research that flue-cured (dark) tobacco producers were more likely to increase tobacco production, and at a faster rate, in response to the TTPP (Foreman and McBride 2011). Because most of the dark tobacco producers are in Western Kentucky, a spatial bias relating to who continued growing versus who discontinued growing exists. It is clear from these personal communications that there are regional differences, even within the state of Kentucky, in terms of how the buyout changed land cover and farming practices. Further research should consider the different agroeconomic climates that have emerged within the state between central and western regions.

Remote Sensing

The classification using minimum distance was successful, though several features should be noted. First, the final classification of Trigg and Christian counties did not include agricultural products outside of soy, corn/wheat, or tobacco. Future classification attempts will benefit from another class of "pasture" or other, less common agricultural products, accounting for variation in agricultural pursuits. From an on-the-ground perspective, the final classification overestimated tobacco and underestimated soy. To improve these results, especially among hard to separate crops like these, unsupervised classification could be applied, eliminating the need for specific training data from many crop types. This could result in separate classes for dark and burley tobacco, but also soy and tobacco. More ground-verified data should also be used to refine classification efforts and serve as an accuracy assessment, the lack of which this study recognizes as a limitation of the time and resources required to collect such data.

Misclassifications are derived from several potential problems: soy and dark tobacco stay greener on the landscape for longer than burley tobacco, corn, or wheat; field size and spatial resolution may be conflicting. Including imagery from different parts of the growing season in the final layer stacked image could potentially improve separability between soy and dark tobacco. In addition, more ground-verified training data might improve distinguishing between tobacco and soy.

Problems of spatial resolution are more difficult to solve. Tobacco requires intensive management, specifically around harvest (Snell, personal communication, 8 October 2015), so growing is limited to smaller areas of production, especially for dark tobacco. Figure 7 shows an area of tobacco and soy that is accurately classified but does not exhibit the differences between the crop classes at the point where land cover changes. Other classification techniques such as object-based image analysis (OBIA) may improve the current approach (Burnett and Blaschke 2003). The segmentation process, a part of OBIA that identifies configurations of similar pixels, could possibly identify field extents. After the image has been segmented, it could then be classified based on field size *and* spectral similarity. Addressing the close proximity of tobacco and other fields, a spectral unmixing technique, such as spectral mixture analysis, could also be used (Adams, Smith, and Johnston 1986). In this process, pure pixels are used to represent different classes, resulting in a classifier that can project percentages of certain land covers within a pixel.

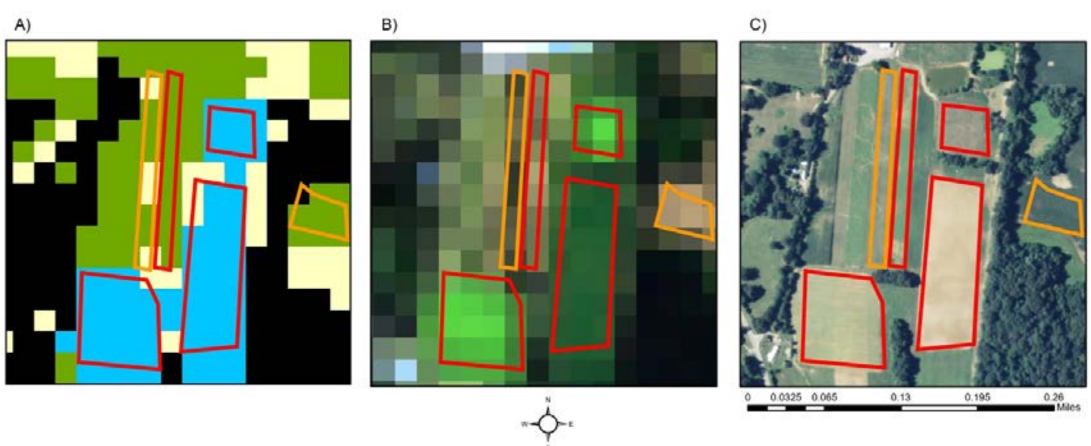

Figure 7. The area represented in each panel contains areas of known corn/wheat, soy, and tobacco. The first panel is the classification (2015) attempt. The second image is that area in true-color composite, and the third image is a high resolution image from GoogleEarth (October, 2015). True areas of tobacco are in red, areas of soy are in orange.

More accurate classification would expand the ability to connect policy to land cover change. Spectral response varies among crops and according to season-specific elements such as environmental conditions, soil quality, and factors like rainfall (Apan, et. al. 2013). Yet other remote sensing techniques hold potentential to improve the results of these findings; though, the current effort has promise to answer questions about agricultural landscapes. Using Landsat imagery in this pursuit has foundations and promise validated by literature (Lyle, Lewis, and Ostendorf 2013; Edlinger et. al. 2012; Cordero-Sancho and Sader 2007).

Increasing the accuracy and information derived from remote sensing analyses can intersect with increased understanding of the human elements of tobacco production. For instance, dark tobacco production is more prevalent in the study area because of the available resources, as well as the nuanced skill set involved in producing dark tobacco (Snell, personal communication, 8 October 2015). A change trajectory that quantifies change on the landscape could link the growing field size of tobacco with the individual farmers who are freed up to increase production within specific geographic areas. This study, with improved confidence in a classification system applied across time, could expand policy assessment greatly by measuring changes in tobacco cropping patterns across time.

For agriculturalists and beyond, policy does not evoke uniform change, as unintended consequences arise. Accordingly, recognizing the limitations of policy implementation allows for more accurate assessments of a specific policy’s impact. Changes that occur on the landscape are directly related to those who are both in control of the land and subject to governing structure. Evaluation of agricultural policy and resultant land changes are only complete if they consider the diversity of the reacting population and their land use decisions.

As such, the conclusions drawn from only a classified image mean very little without considering the mechanisms that drive agricultural organization and change. Informing future policy should be rooted in the understanding that policy does not manifest in each state, county, or farm the same way because people are involved. When looking at land cover, remote sensing analysts can only correlate the timing of certain events with patterns on the landscape. The people making land use decisions, and their individual human experiences and opinions, are crucial to linking true causal events of land cover. Agriculture, as an unstable and vital land use, demands this sort of attention from policy-makers.

CONCLUSIONS

The survey data supported findings previously discussed by literature on the TTPP, and provide a narrative for continuing tobacco farmers and other agriculturalists. These farmers utilized money to expand other agricultural enterprises, proving that the money provided by the buyout became integral in a transitioning economic environment. The accuracy of the 2015 classification of Trigg and Christian counties supports that Landsat 8 imagery and minimum distance classification produces accurate representations of land cover. Though, further considerations of spatial and spectral resolution, amount of training data, and seasonality could better refine these results and be used to directly estimate changes through time.

The use of remote sensing tools accesses a unique perspective on the ever-crucial understanding of land cover, and can be used to successfully distinguish among crop extent, depending on spatial and spectral resolution. Refining the ability to track different agricultural pursuits, in tandem with ancillary data on land use decision-making, could help assess agricultural policy. Policy, as one major influence on land cover, results in differing interpretations and responses from agriculturalists. Because each farmer responds to policy in a unique way, finding trends in land cover change in response to past policy implementation allows for better planning. Human society depends on healthy and secure agriculture, and this study illuminates the monitoring tools, and critical supplementary data, that offer a better understanding of how agriculture influences the landscape.

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APPENDIX A

Survey Questions

The Tobacco Transition Payment Program
Survey 2015

I. General Questions About Your Residence

1. Where is your current, permanent residence? ____
(County/State/Zip)

2. Do you own or lease land? _________Own __________Lease

The questions in the next section refer to your experience as a tobacco producer in the State of Kentucky, which had the largest number of tobacco farms prior to Tobacco Transition Payment Program. This location will only be used to correlate your responses with other geographically relevant information; **your responses will never be presented in a way that personally identifies you.**

3. Is your primary residence on the parcel you marked on the map? 1____ No 2____ Yes

4. In what year did you purchase (or assume legal control over) this parcel? ___________________

5. When did you start farming? ____

6. Is farming your primary source of income? 1____ No 2____ Yes

6a. If not, how much of your income does it account for? ______________________________________

7. What has the parcel been used for in the past? ____

8. How much of it is in farm production today? ____

9. What type of crops are you currently growing?

___Corn ___Soybeans ___Tobacco ___Grains ___Hay ___Other: ________________________

9a. Do you also keep livestock, poultry, or other animals on your farm?

___Cattle ___Hogs ___Poultry ___Horses ___Sheep ___Other: ________________________

10. What are your predominant crops by gross net income? (Check all that apply).

___Corn ___Soybeans ___Tobacco ___Grains ___Hay ___Livestock
___Other: ________________________

II. Program Questions Regarding the Tobacco Transition Payment Program

11. Did you participate in the Tobacco Transition Payment Program? ____

12. How did you receive your money? ______Lump Sum ______Installments

13. What type of tobacco do you grow before the TTPP? ______Burley ______Dark

13a.What type of tobacco do you grow since the TTPP? ______Burley ______Dark

14. Where do you currently get your information to manage your land? Circle those that most closely apply

	None	Some	Most
Cooperative Extension	1	2	3
Internet Search	1	2	3
Tours	1	2	3
Workshops, Meetings	1	2	3
Online Classes	1	2	3
Newsletters, Publications	1	2	3
Short Videos	1	2	3
Site Visits	1	2	3

15. Prior to your participation, how many acres of tobacco did you grow in 2004

- ☐ Less than 2 Acres
- ☐ 2.0 to 4.9 Acres
- ☐ 5.0 to 9.9 Acres
- ☐ 10.0 to 24.9 Acres
- ☐ 25.0 to 49.8 Acres
- ☐ 50.0 to 99.9 Acres
- ☐ More than 100 Acres

16. How much tobacco did you grow in 2015?

- ☐ Less than 2 Acres
- ☐ 2.0 to 4.9 Acres
- ☐ 5.0 to 9.9 Acres
- ☐ 10.0 to 24.9 Acres
- ☐ 25.0 to 49.8 Acres
- ☐ 50.0 to 99.9 Acres
- ☐ More than 100 Acres

17. How did you spend your TTPP income? Check all that apply.

___Alternative Crops ___Retirement ___Additional land ___Expansion of tobacco ___Debt Reduction
___New business ___Other: __________________________

18. What percentage of your total household income came from tobacco before the buyout? __________________________

18a. What percentage of your total household income is now from tobacco?________________________________

19. Did you support the TTPP?
______Yes _____Somewhat ________No

20. What impacts in your household/community did the TTPP have? Are there any notable changes?

____
____
____

III. Questions About You

21. As of your last birthday, how old are you? ___________ years

22. Are you male or female? 1___ Male 2___ Female

23. What is the highest grade in school, or level of education that you've completed and received credit for?

1_____	Eighth grade or less	2_____	Some high school	3_____	High school graduate (incl. GED)
4_____	Technical school	5_____	Some college	6_____	College graduate
7_____	Postgraduate degree (MD, MS, MA, Ph.D.)				

24. Please choose the item that most closely describes your political identification:

1_____	Strong Democrat	2_____	Independent	3_____	Strong Republican
4_____	Not Very Strong Democrat	5_____	Other Party	6_____	Not Very Strong Republican

Comment:

25. What was your total household income (including all wages, public assistance and child support) for 2015, before taxes? Counting all members living in your household, would you say that it was:

1_____	<$20,000	2_____	$40,001-$60,000	3_____	$90,001-$160,000
4_____	$20,001-$40,000	5_____	$60,001-$90,000	6_____	>$160,000

26. Do you work on your land or in your home full-time? 1___ No 2___ Yes

27. Which of the following best describes your employment status during the PAST YEAR?

1_____	Employed full time	2_____	Employed part-time, or part of the year
3_____	Retired and not working	4_____	Not employed

Any additional information you would like to include:

THANK YOU very much for completing this survey!