Incorporating New Crops into Traditional Crop Rotation and the Environmental Implication

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Selected Paper prepared for presentation at the Southern Agricultural Economics Association's 2017 Annual Meeting, Mobile, Alabama, February, 4-7 2017

The authors acknowledge primary funding support from NSF EPSCoR Project #1355438

Introduction

In 2014, the state of Kentucky began a project to explore the potential of developing a statewide sustainable BioEconomy. This does not mean the production of biofuels but is more focused on the production of high-value biobased products, such as, lignin-derived membranes to be used in batteries and solar panels. For over 200 years the coal industry in Eastern Kentucky has shaped the economy. However, between 2011-2013 over 7,000 miners have been laid off and created the need to reenvision the state economy. One consideration is the production of biomass to be utilized in a Bioeconomy. Kentucky is the largest cow/calf state east of the Mississippi River and one of the reasons for this is it ability to produce forages or biomass. In the period between 2010 and 2014 a large number of acres in the state switched from pastureland to crop production to take advantage of record prices. Figure 1 shows where the majority of these changes took place. Now that crop prices are trending down many of these producers are searching for alternative viable feedstocks.

The identification of viable feedstocks and locations that these feedstocks can be produced is one of the first steps in the development of the Kentucky Bioeconomy. Kentucky has long been known for its ability to produce forages for the livestock industry. Furthermore, its subtropical climate makes it an ideal location for a wide variety of potential feedstocks. Some of these potential feedstocks include but are not limited to switchgrass, miscanthus, sweet sorghum, hemp, big blue stem, and corn stover. However, for any of these feedstocks to be adopted and purchase acres from the traditional commodities grown, such as corn, soybeans, wheat, tobacco, etc. they must provide producers with at least the same profit per acre as the current commodities being produced. In recent years, this would have been a very difficult task, but falling commodity prices have made this a more realistic situation.

Specifically, the eastern half of the state that is not traditionally known as a grain producing area, although may be one of the first places where these alternative feedstocks could be adopted. The objective of this study is to assess at the field level where the production of these crops might be grown. This manuscript focuses on estimating the transition probabilities for the five primary row crops produced in the state. Then we employ a simulation technique to generate the distribution of each crop based on the transition probabilities. To our knowledge this is the first such study that does this for the state of Kentucky.

Conceptual Framework

Random Utility Model (RUM)

The discrete choice (also called qualitative choice) model in economics explains choices between two or more discrete alternatives. The multiple choice models are motivated by a random utility model (RUM), and following the discussion of RUM is based on McFadden (1973) and Croissant (2012). Suppose individual chooses at least one alternative from J different alternatives. For each alternative, the utility function of the individual could be

$$\begin{cases} U_1 = \beta_1' x_1 + \varepsilon_1 = V_1 + \varepsilon_1 \\ U_2 = \beta_2' x_2 + \varepsilon_2 = V_2 + \varepsilon_2 \\ \vdots \\ U_J = \beta_J' x_J + \varepsilon_J = V_J + \varepsilon_J \end{cases}$$

where $V_j = \beta_J' x_J$ is a function of different observed variables x_j, ε_j is an unobserved component (i.e., error terms, and alternative *l* is chosen if and only if $\forall\ j \neq l\ U_l > U_j$ to lead $J - 1$ conditions:

$$\begin{cases} U_l - U_1 = (V_l - V_1) + (\varepsilon_l - \varepsilon_1) > 0 \\ U_l - U_2 = (V_l - V_2) + (\varepsilon_l - \varepsilon_2) > 0 \\ \vdots \\ U_l - U_J = (V_l - V_J) + (\varepsilon_l - \varepsilon_J) > 0 \end{cases}$$

The choices can be modeled regarding probabilities since ε_j are not observed, and the $J - 1$ condition for the $J - 1$ remaining error terms can be written as

$$\begin{cases} \varepsilon_1 < (V_l - V_1) + \varepsilon_l \\ \varepsilon_2 < (V_l - V_2) + \varepsilon_l \\ \vdots \\ \varepsilon_J < (V_l - V_J) + \varepsilon_l \end{cases}$$

Then, the probability of choosing alternative *l* is expressed as

$$(P_l|\varepsilon_l) = P\big(U_l > U_1, \dots, U_l > U_J\big)$$

$$(P_l|\varepsilon_l) = F_{-l}(\varepsilon_l < (V_l - V_1) + \varepsilon_l, \dots, \varepsilon_J < \big(V_l - V_J\big) + \varepsilon_l)$$

where F_{-l} is the multivariate distribution of $J - 1$ error terms (i.e., all the ε's except ε_l), and this probability is conditional on the value of ε_l. This probability both on β and the value of the observed explanatory variable can be rewritten as the unconditional probability as following:

$$P_l = \int (P_l|\varepsilon_l) f_l(\,\varepsilon_l) d\varepsilon_l$$

$$P_l = \int F_{-l}((V_l - V_1) + \varepsilon_l, \dots, \big(V_l - V_J\big) + \varepsilon_l) f_l(\,\varepsilon_l) d\varepsilon_l$$

where f_l is the marginal density function of ε_l.

Data

Data utilized to conduct the empirical analysis is collected from a wide range of sources. The primary source of information for crop data is the Cropland Data Layer. CDL is produced by the National Agricultural Statistics Service (NASS) of the United States Department of Agricultural (USDA). The CDL program was initiated in early 1997 to provide annual geospatial content to customers who were interested in annual cropland cover updates. The CDL product is comprehensive, raster-formatted, and geo-referenced imagery for crop-specific land cover classification to identify field crop types accurately and geospatially (Boryan et al., 2011). The CDL includes an entire state in the U.S. with a crop or land use classification code by assigning to each pixel, which is classified and completed by NASS using data from satellite sensor and validation exercise (Hendricks et al., 2014). This paper employs crop data in Kentucky with five crop classifications: corn, soybean, tobacco, wheat, and alfalfa. It is due to the fact that those crops are classified as major crops in Kentucky. According to the NASS, the CDL data for Kentucky is available from 2008; however, this study uses the crop data for the period 2010-2010 due to different resolutions.[1] The CDL has been widely used in a variety of research especially for the crop rotation such as Stern et al., (2012), Plourde et al., (2013), Hendricks et al., (2014[a], 2014[b]), Long et al., (2014), and Yost et al., (2014).

[1] The CDL pixel size for the period 2008-2009 is 56 meter by 56 meter whereas the pixel size for the period 2010-2015 is 30 meter by 30 meter.

This study also employs Common Land Unit (CLU) boundaries obtained from the website GeoCommunity (http://www.geocomm.com).[2] Based on Farm Service Agency (FSA) of the USDA, the CLU is defined as the smallest unit of land and individual contiguous farming parcel. The CLU includes a permanent, contiguous boundary, common land cover, and land management (FSA, 2016). To construct crop data, we first overlay the CLU with the National Land Cover Dataset 2011, which is the most recent national land cover product, produced by the Multi-Resolution Land Characteristics (MRLC) to remove non-agricultural fields.[3] Second, we overlay the CLU with the CDL to identify changes in rotations on a field by field basis instead of pixel or county basis. Third, we apply a moving window filter, which replaces each cell in raster based on the majority of adjacent cells, using Geographic Information System (ArcGIS) not only to remove misspecified (i.e., spurious) cells but also to smooth rasters. Finally, we employ a zonal statistics, which calculate the values of a raster within the zones of another dataset, to identify how may pixels are located in each field. Table 1 and 2 show the total observation and percent of observations by crop class by year respectively. Based on Table 1 and 2, corn, soybean, tobacco, wheat, and alfalfa is planted 36%, 42%, 0.6%, 0.4%, and 1% in Kentucky, 2015 respectively. Figure 1 represents how those major crops are distributed in Kentucky, and it shows that the majority of corn and soybean are planted in western Kentucky.

<Insert Table 1 Here>

<Insert Table 2 Here>

[2] The CLU data was publically available on FSA before 2008. However, FSA no longer provides the geospatial data including the CLU due to the Food, Conservation, and Energy Act of 2008.
[3] There are 16 different classifications of the NLCD, and this study only focuses on pasture/Hay and row crops as agricultural lands definded by the MRLC.

<Insert Figure 1 Here>

Crop production is heavily dependent on the precipitation and temperatures experienced of the the growing season. This data is obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM), which is official climatological data from the USDA.[4] This study employs monthly data in April, May, and June for the precipitation and June, July, and August for the temperature. We also use Major Land Resource Areas (MLRAs) from the Natural Resources Conservation Service (NRCS) to identify different groups of fields in Kentucky. There are eight MLRAs in the Kentucky, and different characteristics of MLRAs are listed in table 3.

<Insert Table 3 Here>

Data on soil textures such as percent clay, percent silt, and percent sand are obtained from Gridded Soil Survey Geographic (gSSURGO) database provided by USDA NRCS. The sSSURGO database has greater spatial extents than the traditional SSURGO.[5] Finally, we obtain National Elevation data (30 meters) from the Geospatial Data Gateway provided by USDA-NRCS to calculate the elevation and slope. All of the data, which are precipitation, temperature, slope, elevation, soil textures, and MLRAs are spatially joined into the unique field ID, and Table 4 shows the summary statistics of the data.

<Insert Table 4 Here>

[4] For more detail information about the PRISM dataset, see http://www.prism.oregonstate.edu/documents/PRISM_datasets.pdf
[5] For more detail information about the gSSURGO, see https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/nrcs142p2_052164.pdf

Empirical Model

This study employs the multinomial logit (ML) model to develop Markov transition probabilities for the five primary crops in Kentucky: corn, soybean, tobacco, wheat, and alfalfa. The multinomial logit (ML) model is a generalization of the binary logit model. The difference between ML and logit model is the different number of choices. If an individual faces with only two (i.e., binary) choices, then logit model is used. Based on Croissant (2012), if the alternative *l* is better than other alternative *j*, then the probability of the alternative *l* can be defined as

$$P\left(\varepsilon_j < V_l - V_j + \varepsilon_l\right) = e^{-e^{-(V_l - V_j + \varepsilon_l)}}$$

Then, the probability of choosing *l* is the product of probabilities for all other alternatives except *l* based on the assumption of independence of errors:

$$(P_l|\varepsilon_l) = \prod_{j \neq l} e^{-e^{-(V_l - V_j + \varepsilon_l)}}$$

By taking expected value with respect to ε_l, the unconditional probability can be defined as

$$P_l = \int_{-\infty}^{+\infty} (P_l|\varepsilon_l) e^{-\varepsilon_l} e^{-e^{-\varepsilon_l}} d\varepsilon_l = \int_{-\infty}^{+\infty} \left(\prod_{j \neq l} e^{-e^{-(V_l - V_j + \varepsilon_l)}} \right) e^{-\varepsilon_l} e^{-e^{-\varepsilon_l}} d\varepsilon_l$$

For all alternatives by including the *l* alternative, the unconditional probability can be rewritten as

$$P_l = \int_{-\infty}^{+\infty} \left(\prod_{j \neq l} e^{-e^{-(V_l - V_j + \varepsilon_l)}} \right) e^{-\varepsilon_l} \, d\varepsilon_l$$

$$P_l = \int_{-\infty}^{+\infty} e^{-\sum_j e^{-(V_l - V_j + \varepsilon_l)}} e^{-\varepsilon_l} d\,\varepsilon_l = \int_{-\infty}^{+\infty} e^{-e^{-\varepsilon_l} \sum_j e^{-(V_l - V_j)}} e^{-\varepsilon_l} d\,\varepsilon_l$$

Let $A = e^{-\varepsilon_l} \Rightarrow dt = -e^{-\varepsilon_l} d\varepsilon_l$, then unconditional probability as a closed from is

$$P_l = \left[-\frac{e^{-A} \sum_j e^{-(V_l - V_j)}}{\sum_j e^{-(V_l - V_j)}} \right]_{-\infty}^{+\infty} = \frac{1}{\sum_j e^{-(V_l - V_j)}}$$

As the general logit probability, this probability of choosing alternative *l* can be rewritten as

$$P_l = \frac{e^{V_l}}{\sum_j e^{V_j}} = \frac{e^{\beta_l' x_l}}{\sum_j e^{\beta_j' x_j}}$$

This study estimates two ML models: ML model using only lagged dependent variable as an explanatory variable and ML model using lagged dependent with other explanatory variables such as precipitation, temperature, soil texture, slope, and elevation. This study also considers fallow fields. In other words, farmers do not plant any crops in this field. There are a variety of reasons a producer may choose to leave a field fallow. Therefore, we incorporate an additional alternative namely on production choice. In the ML model, one set of coefficients is necessary to be normalized to zero because there is more than one solution to set of coefficients provide the identical set of probabilities for all alternative (Green, 2012). By setting $\beta_1 = 0$, the set of coefficients corresponding to each outcome are estimated as following:[6]

$$Pr(y = 1) = \frac{1}{1 + \sum_{j=1}^{6} e^{\beta_j' x_j}}$$

[6] We record outcomes 1, 2, 3, 4, 5, and 6 for no production, corn, soybean, tobacco, wheat, and alfalfa respectively. Since the recorded numerical values are arbitrary, greater number does not imply better outcome compared to the smaller number. In addition, outcome of no production is our base outcome since we set $\beta_1 = 0$.

$$Pr(y = 2) = \frac{e^{\beta_2' x_2}}{1 + \sum_{j=1}^{6} e^{\beta_j' x_j}}$$

$$Pr(y = 3) = \frac{e^{\beta_3' x_3}}{1 + \sum_{j=1}^{6} e^{\beta_3' x_3}}$$

$$\vdots$$

$$Pr(y = 6) = \frac{e^{\beta_6' x_6}}{1 + \sum_{j=1}^{6} e^{\beta_6' x_6}}$$

Empirical Results

ML Results and Transition Probabilities

Table 5 represents the estimated results from the ML model using only lagged dependent variable, we call "*conditional ML model*". Based on the likelihood ratio chi-square of 348,122.68 with a p-value of 0.0000 indicates that the model as a whole significantly fit better compared to an empty model. The general interpretation of the ML model is not the same as the parameter estimates of the linear model. In other words, we cannot interpret a one unit change in the dependent variable as the partial derivative. For the corn in table 5 as an example, an estimated coefficient of 0.127 refers that the relative log odds of planting corn compared to the no planting will increase by 0.127 if corn was planted rather than no planting in the previous year. Consequently, the direct results from the ML model do not provide quantitative economic meaning.

<Insert Table 5 Here>

Based on the results from the ML model, we generate a set of average conditional, which refers to the predicted probabilities, Markov transition probabilities. Table 6 shows the calculated as the average number of observed transition between 2010 and 2015. Based on table 6, this study finds that the probability of planting corn next year is 0.327 if corn is planted in current year. Crop rotation probabilities between corn to soybean and soybean to corn from current year to the next year are 0.462 and 0.587 respectively. Table 7 represents the results from the ML model by incorporating all other explanatory variables, called "*unconditional ML model*", and table 8 shows the calculated Markov transition probabilities based on table 7.

<Insert Table 6 Here>

<Insert Table 7 Here>

<Insert Table 8 Here>

Concluding Remarks

This study finds from the conditional ML model that the probability to plant corn, soybean , and tobacco are positively realted with those crops planted in previous year compare to the no production choice. Alfalfa, however, has negatively impact on probability of those crops in current year if alfafa was planed in the previous year. Based on the unconditional ML model by incorporate other covariates such as soil texture, precipitation, temperature, slope, and elevation, we find different impacts of those factors across different crop choice.

Based on the results from the ML model, we generate the Markov transition probabilities. We find that no transition probabilities under the conditional model are less stable to those of probabilities under the unconditional model except corn to corn rotation. Based on the results from the unconditional transition probabilities, we find that transition probabilities for corn to corn, corn to soybean, soybean to soybean, and soybean to corn rotations are approximately 0.22, 0.49, 0.57, and 0.31 respectively.

Future work includes using the results of the transition probabilities to simulate and forecast future distribution of the main crops in Kentucky. Base on the simulation, we are able to find what percentage of crop will be placed on average in future by given acreage. Later, we can incorporate the information on nitrogen usage and runoff to generate a distribution of the nitrogen runoff and forecast the percentage of the nitrogen runoff in the future. Furthermore, we will add additional crops to the transition matrix that are being consider for production and usage by the Kentucky Bioeconomy. The two feedstocks currently being considered are hemp and sweet sorghum. The lignin structures of these two crops are appealing to the engineers working to develop high value products from these crops.

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Table 1: Observations by Crop Class by Year

	2010	2011	2012	2013	2014	2015	Sum
Corn	105266	100060	123638	112930	113079	113662	668635
Soybean	98311	79480	76268	79492	99343	129684	562578
Tobacco	456	298	734	1056	1317	1730	5591
Wheat	276	254	267	344	203	1232	2576
Alfalfa	1742	2936	1593	1537	2168	3136	13112
No Cultivation	106313	129336	109864	117005	96254	62920	621692
Sum	312364	312364	312364	312364	312364	312364	1874184

Table 2: Percent of Observations by Crop Class by Year

	2010	2011	2012	2013	2014	2015
Corn	0.337	0.320	0.396	0.362	0.362	0.364
Soybean	0.315	0.254	0.244	0.254	0.318	0.415
Tobacco	0.001	0.001	0.002	0.003	0.004	0.006
Wheat	0.001	0.001	0.001	0.001	0.001	0.004
Alfalfa	0.006	0.009	0.005	0.005	0.007	0.010
No Cultivation	0.340	0.414	0.352	0.375	0.308	0.201
Sum	1.000	1.000	1.000	1.000	1.000	1.000

Table 3: MLRA Characteristics in Kentucky

MLRA Name	Freq.	Percent	Cum.
Central Allegheny Plateau	6	0	0
Cumberland Plateau and Mountains	6,030	0.32	0.32
Highland Rim and Pennyroyal	608,052	32.44	32.8
Kentucky Bluegrass	205,686	10.97	43.7
Kentucky and Indiana Sandstone	604,980	32.28	76
Southern Mississippi River Alluvium	9,528	0.51	76.5
Southern Mississippi Valley Loess	422,166	22.53	99.1
Western Allegheny Plateau	17,736	0.95	100
Total	1,874,184	100	

Table 4: Descriptive Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Acres	5.97	15.92	0.00	934.28
Percent Silt	66.25	13.27	0.00	82.00
Percent Clay	20.59	7.00	0.00	58.00
Percent Sand	11.83	8.75	0.00	93.90
Slope	2.51	1.95	0.00	35.07
Elevation	174.79	60.56	0.00	423.09
Temperature	24.94	1.27	20.78	28.13
Precipitation	143.68	55.25	0.00	308.89

Table 5: Results from Conditional Multinomial Logit Regression

Choice	Variables	Coef.	Std.	P-value	[95% Conf	Interval]
Corn	Corn	0.127	0.005	0.000	0.118	0.137
	Soybean	2.017	0.006	0.000	2.006	2.028
	Tobacco	0.138	0.044	0.002	0.052	0.223
	Wheat	0.993	0.064	0.000	0.867	1.119
	Alfalfa	-1.249	0.037	0.000	-1.322	-1.175
	Constant	-0.446	0.003	0.000	-0.452	-0.440
Soybean	Corn	1.649	0.005	0.000	1.639	1.658
	Soybean	2.098	0.007	0.000	2.085	2.111
	Tobacco	0.942	0.044	0.000	0.856	1.028
	Wheat	0.732	0.084	0.000	0.568	0.896
	Alfalfa	-0.831	0.044	0.000	-0.917	-0.744
	Constant	-1.244	0.004	0.000	-1.252	-1.236
Tobacco	Corn	0.075	0.035	0.032	0.007	0.143
	Soybean	0.820	0.040	0.000	0.741	0.899
	Tobacco	4.399	0.051	0.000	4.299	4.500
	Wheat	1.360	0.307	0.000	0.759	1.961
	Alfalfa	-0.493	0.220	0.025	-0.923	-0.062
	Constant	-4.907	0.022	0.000	-4.950	-4.865
Wheat	Corn	1.631	0.055	0.000	1.523	1.739
	Soybean	1.734	0.067	0.000	1.603	1.864
	Tobacco	2.528	0.212	0.000	2.113	2.942
	Wheat	2.925	0.310	0.000	2.318	3.532
	Alfalfa	0.513	0.293	0.080	-0.061	1.087
	Constant	-6.472	0.048	0.000	-6.566	-6.379
Alfalfa	Corn	-1.533	0.038	0.000	-1.609	-1.458
	Soybean	-0.445	0.040	0.000	-0.524	-0.367
	Tobacco	-0.119	0.211	0.572	-0.533	0.294
	Wheat	1.855	0.150	0.000	1.561	2.148
	Alfalfa	3.681	0.025	0.000	3.631	3.730
	Constant	-3.868	0.013	0.000	-3.894	-3.842

Table 6: Conditional Transition Probabilities

	No_Prod	Corn	Soybean	Tobacco	Wheat	Alfalfa
No_Prod	0.511	0.327	0.147	0.004	0.001	0.011
Corn	0.308	0.224	0.462	0.003	0.002	0.001
Soybean	0.122	0.587	0.287	0.002	0.001	0.002
Tobacco	0.321	0.236	0.238	0.193	0.006	0.006
Wheat	0.284	0.491	0.170	0.008	0.008	0.038
Alfalfa	0.466	0.086	0.059	0.002	0.001	0.386

Table 7: Results from Unconditional Multinomial Logit Regression

Crop Choice	Variables	Coeff	Std.Err	P-value	[95% Conf	Interval]
Corn	Corn	-0.552	0.006	0.000	-0.563	-0.542
	Soybean	1.188	0.006	0.000	1.176	1.200
	Tobacco	-3.181	0.202	0.000	-3.576	-2.785
	Wheat	0.015	0.084	0.855	-0.149	0.180
	Alfalfa	-1.786	0.044	0.000	-1.871	-1.700
	Crop_Acre	0.765	0.002	0.000	0.761	0.770
	Silt	0.000	0.000	0.036	0.000	0.001
	Slay	-0.008	0.000	0.000	-0.008	-0.007
	Sand	-0.006	0.000	0.000	-0.007	-0.005
	Slope	-0.025	0.001	0.000	-0.027	-0.022
	Elevation	-0.005	0.000	0.000	-0.005	-0.004
	Temperature	-0.021	0.002	0.000	-0.025	-0.016
	Precipitation	-0.002	0.000	0.000	-0.002	-0.002
	Constant	0.921	0.068	0.000	0.789	1.053
Soybean	Corn	1.070	0.006	0.000	1.059	1.081
	Soybean	1.323	0.007	0.000	1.309	1.337
	Tobacco	0.633	0.062	0.000	0.513	0.754
	Wheat	-0.211	0.099	0.033	-0.405	-0.017
	Alfalfa	-1.403	0.049	0.000	-1.499	-1.307
	Crop_Acre	0.760	0.002	0.000	0.755	0.765
	Silt	-0.001	0.000	0.000	-0.002	-0.001
	Slay	-0.003	0.000	0.000	-0.004	-0.003
	Sand	0.002	0.000	0.000	0.001	0.003
	Slope	-0.005	0.001	0.000	-0.007	-0.002
	Elevation	-0.006	0.000	0.000	-0.006	-0.006
	Temperature	-0.236	0.003	0.000	-0.241	-0.230
	Precipitation	0.000	0.000	0.000	-0.001	0.000
	Constant	5.302	0.070	0.000	5.164	5.439
Tobacco	Corn	-0.329	0.036	0.000	-0.400	-0.259
	Soybean	0.200	0.041	0.000	0.120	0.281
	Tobacco	5.849	0.052	0.000	5.747	5.951
	Wheat	0.320	0.309	0.299	-0.285	0.926
	Alfalfa	-1.352	0.220	0.000	-1.784	-0.920
	Crop_Acre	0.760	0.003	0.000	0.754	0.765
	Silt	0.005	0.002	0.005	0.001	0.009
	Slay	-0.002	0.003	0.519	-0.007	0.003
	Sand	0.014	0.002	0.000	0.010	0.018
	Slope	-0.084	0.008	0.000	-0.101	-0.068

	Elevation	0.002	0.000	0.000	0.001	0.002
	Temperature	-0.253	0.017	0.000	-0.286	-0.220
	Precipitation	-0.003	0.000	0.000	-0.004	-0.003
	Constant	0.466	0.476	0.328	-0.468	1.399
Wheat	Corn	1.266	0.057	0.000	1.154	1.378
	Soybean	1.127	0.068	0.000	0.993	1.261
	Tobacco	-0.920	1.283	0.473	-3.435	1.595
	Wheat	1.868	0.318	0.000	1.246	2.491
	Alfalfa	-0.361	0.297	0.224	-0.944	0.221
	Crop_Acre	0.758	0.003	0.000	0.753	0.764
	Silt	-0.006	0.002	0.006	-0.010	-0.002
	Slay	0.010	0.003	0.001	0.004	0.016
	Sand	-0.007	0.003	0.028	-0.013	-0.001
	Slope	-0.071	0.013	0.000	-0.096	-0.045
	Elevation	0.003	0.000	0.000	0.002	0.003
	Temperature	-0.258	0.025	0.000	-0.307	-0.209
	Precipitation	0.000	0.000	0.660	-0.001	0.001
	Constant	-0.889	0.677	0.189	-2.215	0.437
Alfalfa	Corn	-1.673	0.039	0.000	-1.750	-1.595
	Soybean	-0.975	0.041	0.000	-1.055	-0.895
	Tobacco	-3.592	1.380	0.009	-6.297	-0.887
	Wheat	0.756	0.161	0.000	0.440	1.073
	Alfalfa	2.610	0.031	0.000	2.550	2.671
	Crop_Acre	0.752	0.003	0.000	0.747	0.758
	Silt	-0.002	0.001	0.129	-0.004	0.001
	Slay	0.027	0.002	0.000	0.023	0.030
	Sand	-0.016	0.002	0.000	-0.019	-0.012
	Slope	0.002	0.005	0.647	-0.007	0.012
	Elevation	0.006	0.000	0.000	0.006	0.007
	Temperature	-0.650	0.015	0.000	-0.679	-0.621
	Precipitation	0.009	0.000	0.000	0.009	0.010
	Constant	8.131	0.381	0.000	7.385	8.876

Table 8: Unconditional Transition Probabilities

	No_Prod	Corn	Soybean	Tobacco	Wheat	Alfalfa
No_Prod	0.4732	0.3461	0.1621	0.0040	0.0009	0.0138
Corn	0.2833	0.2196	0.4900	0.0026	0.0027	0.0018
Soybean	0.1142	0.5741	0.3058	0.0023	0.0012	0.0024
Tobacco	0.1421	0.0072	0.1476	0.7028	0.0002	0.0001
Wheat	0.2799	0.4592	0.1687	0.0096	0.0102	0.0725
Alfalfa	0.3734	0.0704	0.0556	0.0019	0.0012	0.4974

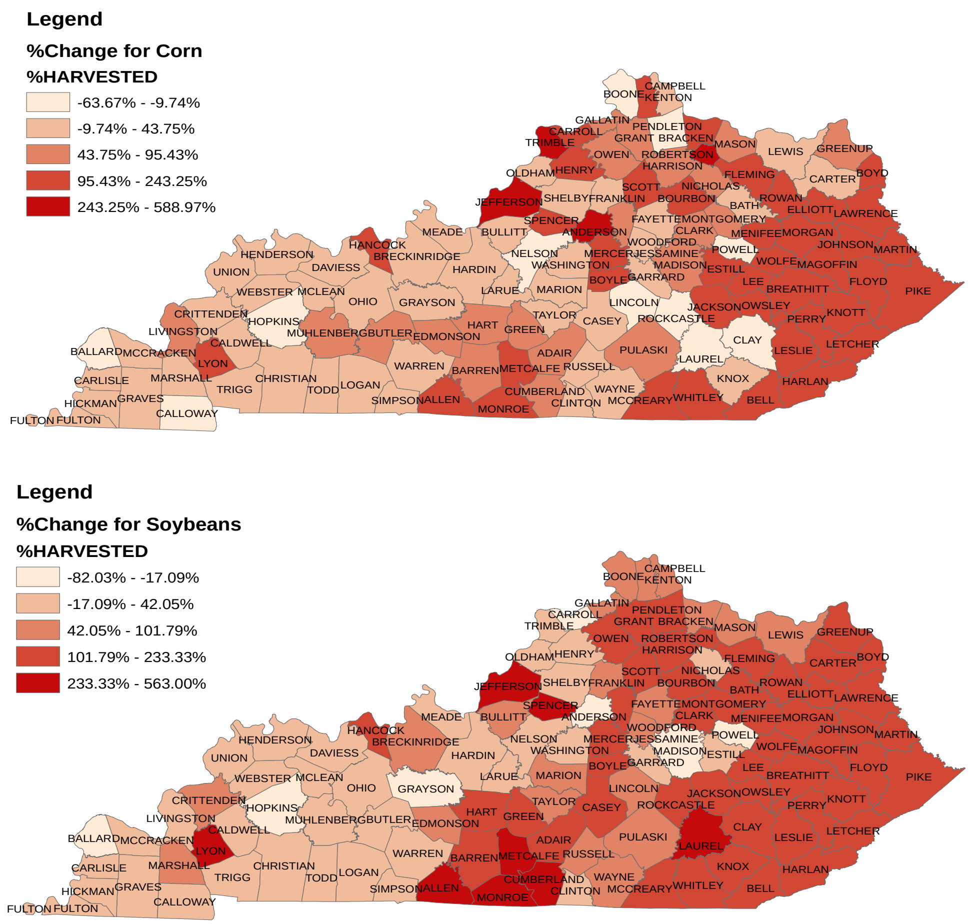

Figure 1: Percentage Change in Corn (Top) and Soybean (Bottom) in Kentucky from 2010 to 2014

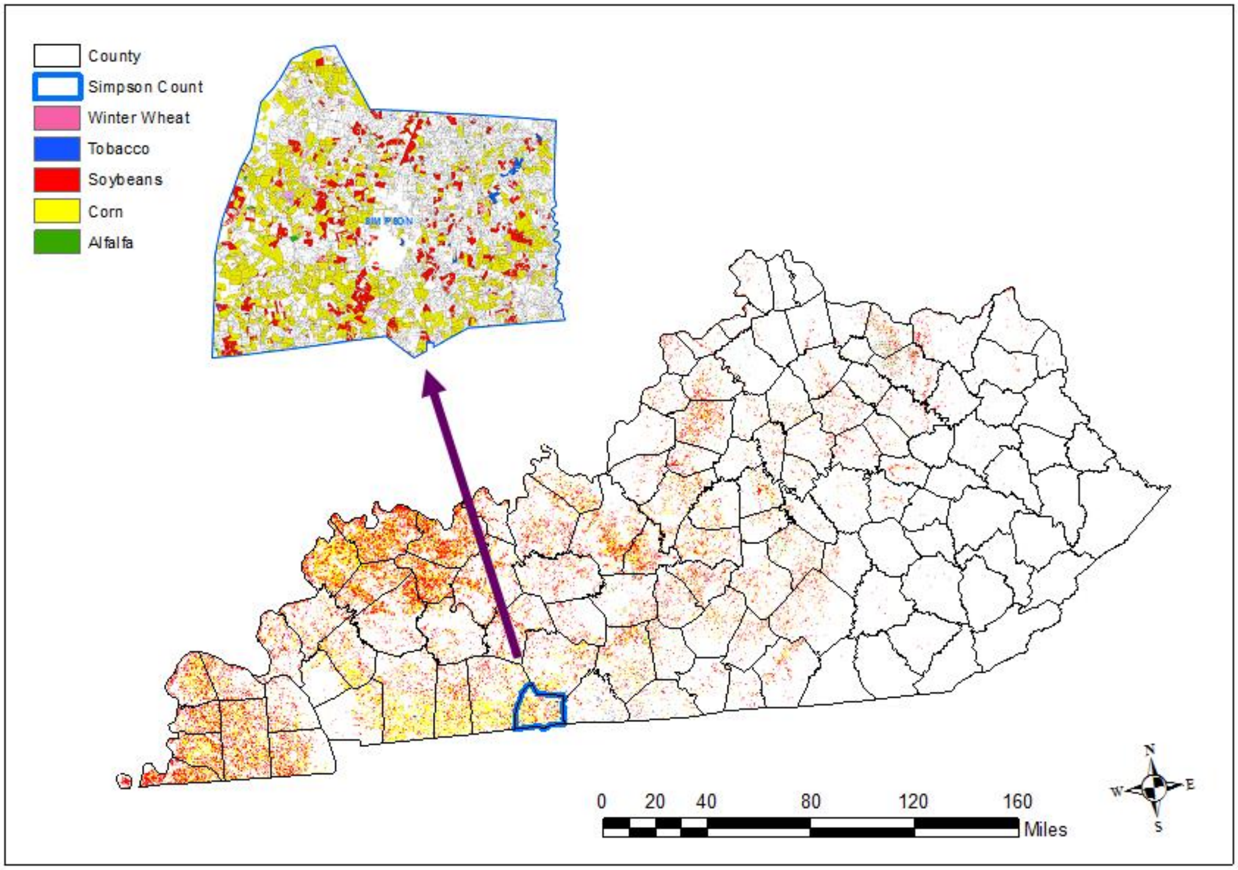

Figure 1. Major five crops in Kentucky, 2015