Adoption of Precision Agriculture Technology Bundles on Kansas Farms

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Abstract: The Kansas Farm Management Association (KFMA) is an organization affiliated with Kansas State University that maintains a database of annual production and financial data on Kansas farms stretching back to 1973. The KFMA surveyed farms, beginning in fall of 2015, on the adoption, utilization, and abandonment of ten precision agriculture technologies. The technologies examined in the survey included yield monitor (with and without GPS), lightbar guidance, automated guidance system, automated section control, variable rate application (fertilizer and seed), and precision soil sampling. Given the advancements in precision agriculture technology it is important to identify how older, obsolete technologies have been abandoned and/or replaced by newer ones. This study uses a sample of 348 farm-level observations to identify patterns of adoption, upgrading, and abandonment of precision agriculture technology on Kansas farms. This study identifies a farm's conditional probability of adopting technology given previous adoption of other technologies. Additionally, sequential probabilities were estimated to provide insight on the order, or sequence, of adoption.

Keywords: technology adoption, transition probabilities, Markov process, precision agriculture

Introduction

Precision agriculture (PA) technologies have been available for several decades, however only specific technologies have been readily adopted. Of available technologies, farms have focused on the adoption of ‘embodied knowledge’ technologies – that is, the adoption of technologies where no additional skills are needed by the individual to enhance the value embodied in the technology (e.g. hybrid seed varieties) (Griffin et al. 2004). The past fifteen years have seen the rise in adoption of ‘information intensive’ technologies. Unlike ‘embodied technologies’, ‘information intensive’ technologies provide additional information that can be useful in decision making, but in order to fully capitalize on these technologies they require specialized skills and an additional time investment by the farm (e.g. variable rate application of seed).

Farm-level utilization of individual or combinations of ‘information intensive’ technologies is still not well understood. Kansas Farm Management Association (KFMA) members provided information regarding their utilization of precision agriculture technologies. KFMA data was analyzed to describe the adoption path of three information-intensive precision agriculture technologies (yield monitor, precision soil sampling, and variable rate). Specific objectives included 1) determining the bundles of technologies that farmers adopt and 2) estimating the probability of transitioning from one bundle to another. To meet the first objective, farms were classified as having adopted one of eight possible technology “bundles” (i.e. states of the world) - eight combinations of one or more the three technologies in addition to a possible “no technology adopted” category. Markov chain transition probabilities were then estimated to show the probability or likelihood of transitioning from one bundle of technology to another.

Background and Literature Review

Olson and Elisabeth (2003) reported inconclusive results regarding whole-farm profitability impacts of precision agriculture adoption in Minnesota during the infancy of these technologies. They reported 59 of 212 farms used at least some precision technology in their operation and that the relatively small sample size was not sufficient to discern differences between adopters and non-adopters during the time when even the most innovative farmers were still trying to find the best use of the technology.

Previous studies on technology adoption and profitability have been disjointed, focusing on either farm-level adoption or the profitability of technology. Schimmelpfennig and Ebel (2016) reported sequential adoption of combine yield monitors (YM) with and without GPS along with variable rate (VR) application technologies. They examined the cost differences between adopters and non-adopters of precision technology, reporting small but significant advantage to adopters. Lambert et al. (2015) evaluated cotton farmers' adoption of precision technology and reported that farmers have adopted technologies both individually and in bundles. Erickson and Widmar (2015) reported the proportion of service providers using many of the same technologies examined in farm-level studies. They reported that automated technologies such as automated guidance (AG) and lightbar (LB) had substantially higher adoption rates than information intensive data technology such as YM or VR.

Data and Methods

Beginning in the fall of 2015, the Kansas Farm Management Association (KFMA) dataset was appended with farmers' adoption of precision agricultural technologies. The electronic KFMA databank includes detailed farm-level agronomic and financial information from 1973 to 2015. By August 2016, 348 farms reported their respective adoption of precision agricultural technologies including the year of adoption and abandonment if no longer in use. Of the 348 responses, 299 farms reported adopting at least one precision agriculture technology. The data was analyzed to estimate conditional and transition probabilities.

Conditional probabilities were estimated for all ten technologies. The conditional probability of an event (in this case the adoption of technology) is the probability that the event will occur given that another event has already occurred. The probability of event A given event B is P(A|B) and can be calculated by dividing the joint probability of A and B by the probability that B has occurred, or

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \quad (1)$$

Transition probabilities were estimated for bundles comprised of three information-intensive technologies including 1) YM with or without GPS 2) VR, and 3) precision soil sampling (PSS). Markov chain transition probabilities (Eddy 1998) have in the past been applied to 1) soil erosion classification (Skaggs and Ghosh 1999), 2) livestock farm size (Gillespie and Fulton 2001), 3) health and medicine (Jung 2006), 4) land use changes (Muller and Middleton 1994), and 5) financial vulnerability (Stabel et al. 2016).

The probability of transitioning from one bundle of technology to any other bundle was estimated over a 17-year time period from 2000 to 2016 (with a total of 16 observations of transitions (*t-1*)). Transition probabilities were estimated to indicate the likelihood that a farmer would stay with the same bundle of technologies or transition to a different bundle in a given year. The probability of transitioning from one state of the world to any other state can be estimated with a one-step Markov chain (i.e. one year of memory). The probability indicates the likelihood that an individual would persist in their respective state or transition to a different state by the next time period. The transition probability matrix, P, is the matrix consisting of one-step transition probabilities, p_{ij}, defined as,

$$p_{ij} = Pr\{X_t = j | X_{t-1} = i\} \tag{2}$$

where p_{ij} is a one-step transition probability equal to the probability of being in technology bundle state *j* given the individual farm was in technology bundle state *i* in the previous year, *t-1*. The underlying assumption is that the state of the world in time *t* is only a function of the previous time period, time *t-1*. The probability of transitioning from one bundle to another bundle was an estimated subset of the historical period, 2000 to 2015 (Table 1).

Results

Some precision agriculture technologies have had higher adoption rates than others. Figure 1 shows the proportion of KFMA farms that have adopted technologies over time. In 2008, the number of farms using AG surpassed the number of farms using LB (Figure 1). By 2011, the utilization of LB had leveled off while AG continued to be adopted (Figure 1). Given that these technologies have been available for several years and often installed on new equipment by the manufacturer, farms that only purchase used equipment may have this technology even if they had not actively sought it.

Historically, the adoption of YM has been the yardstick that precision agriculture was measured by. Today nearly all new combines come equipped with YM although this does not imply utilization at the farm level. Even for farms purchasing used combines, there is a substantial likelihood that a YM is already installed. Less than half of KFMA farms have adopted YM (Figure 1) which is consistent with USDA ARMS estimates (Schimmelpfennig, 2016). Unlike USDA ARMS surveys, the KFMA data suggests relatively more YM being associated with a GPS than without a GPS (Figure 1). Although adoption rates are still less than half of all farmers reporting to the KFMA study, Kansas farms make use of PSS (Figure 1). Roughly one in four and one in five farms make use of VRF and VRS, respectively (Figure 1). These results are consistent with USDA ARMS reports.

Figure 1. Kansas Farms' Use of Precision Agriculture over Time

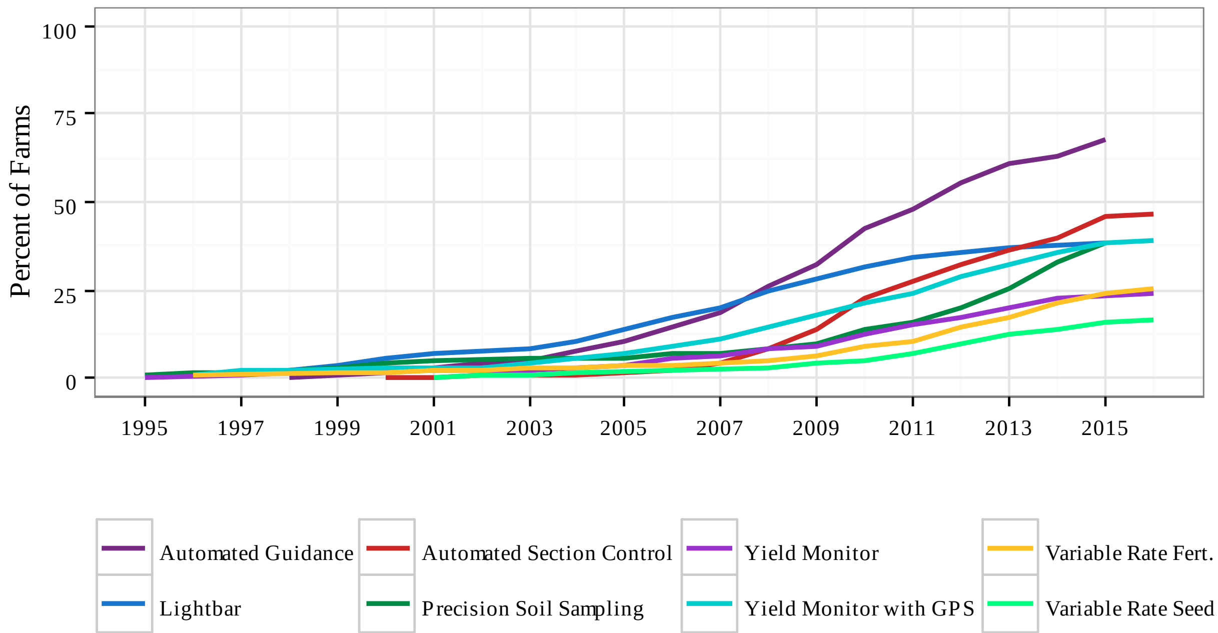

Table 1 presents the number of farms adopting each technology. For instance, 228 farms (66% of the sample) have adopted AG (Table 1). Nearly half (47%) of Kansas farms utilize automated section control (ASC) (Table 1). Only 17% of Kansas farms use variable rate technology to apply seeds at site-specific rates (Table 1). To get a better idea of how farms utilize precision agriculture technologies in bundles, the proportion of farms using one technology given another technology being used is presented in the next section. These conditional probabilities provide insights into how a farm uses a specific technology given that other technologies are already being utilized.

Table 1. Number of Farms Currently using Precision Agriculture Technology

Technology	*Farms*	*% of total (N=348)*
Automated Guidance (AG)	237	66
Automated Section Control (ASC)	169	47
Lightbar (LB)	148	41
Precision Soil Sampling (PSS)	143	40
Yield Monitor (YM w/ GPS)	140	39
Variable Rate Fertility (VRF)	91	25
Yield Monitor (YM w/out GPS)	88	25
Variable Rate Seeding (VRS)	59	16

Conditional Probabilities

The KFMA data provides useful information on the likelihood of farm adoption of technology given other technologies are being used. The figures presented in Table 2 and Table 3 show a farm's conditional probability of adopting one technology given that another technology is being used on the farm in the same year. These technologies include PSS, VRF, VRS, YM without GPS, YM with GPS, AG, LB, and ASC. Specifically, Table 2 presents the conditional probabilities for the two yield monitor technologies (with and without GPS) and the three GPS guidance technologies (LB, AG, and ASC). Table 3 presents the conditional probabilities for PSS and the two variable rate application technologies (VRF and VRS), AG, and YM with GPS.

The probability that a farm with YM with GPS uses AG is 97% (both Table 2 and Table 3 present this information). Farmers who use YM without GPS are less likely to use ASC and AG than farmers who have GPS on their yield monitors (Table 2). Farms that use VRF have a 92% likelihood of using PSS while the probability of using VRS is 37% (Table 3). In other words, farms that use VRF are more likely to use PSS than VRS. For farms that have YM with GPS, the probability of using VRS is 36%, while the probability of using AG is 97%. Farms that have adopted YM with GPS are therefore more likely to use AG than VRS.

Table 2. Farms' Probability of Technology Adoption Given Prior Adoption of a Different Technology, (N=348)

	Probability of Adopting…				
Given …	YM w/out GPS	YM w/ GPS	LB	AG	ASC
YM w/out GPS	-	55%	71%	86%	65%
YM w/ GPS	58%	-	69%	97%	87%
LB	51%	48%	-	80%	58%
AG	54%	59%	69%	-	69%
ASC	57%	74%	70%	97%	-

Note: Diagonal values are blank since statistics on a technology given the same technology does not provide useful information.

Some technologies are clearly preferred to others. The proportion of farms adopting AG was highest, ranging from 87% (for farms that had previously adopted PSS) to 98% (for farms that had previously adopted VRS) (Table 3). Automated guidance technologies have higher adoption rates than information intensive technologies such as YM, PSS, VRF, or VRS. Since most KFMA farms utilize AG while less than half utilize YM or variable rate applications, it logically follows that the proportion of farms adopting AG, given any other technology, would be the highest values in the table. In addition, some sort of GPS is required to be utilized on the farm to make controller-driven variable rate applications and to collect site specific yield monitor data (i.e. GPS yield monitor). As opposed to AG, VRS had much lower adoption rates, ranging from 24% (for farms that had adopted AG) to 37% (for farms that had adopted VRF) (Table 3). It seems intuitive that if a farm utilizes VRF, then adopting VRS would be a relatively seamless matter.

Table 3. Conditional Probabilities of Farms' Adoption of Precision Agriculture Technologies+*--

	Probability of Adopting…				
Given…	PSS	VRF	VRS	YM w/ GPS	AG
PSS	-	59%	30%	65%	87%
VRF	92%	-	37%	68%	92%
VRS	75%	60%	-	86%	98%
YM w/ GPS	69%	46%	36%	-	97%
AG	55%	37%	24%	58%	-

To make decisions on VRF, some sort of site-specific information is needed. Three of the leading methods to obtain data sufficient for variable rate applications are 1) on-the-go sensor based, 2) map based from yield monitors (for nutrient replenishment based on grain nutrient removal), and 3) PSS (for sufficiency, buildup, and maintenance) (see Ess et al. 2001 for an overview of sensor-based versus map-based variable rate application systems). Therefore, it is expected that farms using VRF either also use a YM with GPS (69%) or PSS (92%) to make prescription applications. Since the highest proportion of respondents adopt PSS given that VRF is already being used, it can be concluded that farms rely mostly on chemical analysis of soil samples rather than yield data as a proxy for nutrient removal especially when applying phosphorus and potassium.

Obsolescence and Sequential Adoption of Precision Agricultural Technologies

Detailed KFMA data from 348 farms indicates how some of the technologies were abandoned after having been used for several years. Of the precision agriculture technologies examined, six were abandoned by at least one farm that had used the technology (Table 4). Four technologies had relatively low abandonment rates (Imagery, YM with GPS, VRF, and PSS) while two had higher rates (LB and YM without GPS). While YM without GPS and LB had relatively larger proportions of farmers ceasing to use the technology at 41% and 28%, respectively, these technologies were also the two that were considered obsolete once more advanced technology became available (with YM with GPS replacing YM without GPS and AG replacing LB). Given the scientific advancement made with these technologies, it seems intuitive that some farms abandoning YM without GPS or LB may have upgraded to YM with GPS and AG.

The expectation is that farms that abandoned YM without GPS would adopt YM with GPS the following season. The same expectation is assumed for LB and AG.

Table 4. KFMA Farms' Adoption, Upgrading, and Abandonment of Precision Agriculture Technology

	Number of Farms…				
Technology	Adopted	Abandoned	Upgraded	Abandoned (Adjusted)**	% Abandoned (Adjusted)
YM w/out GPS	147	60	54	6	4
LB	202	57	45	12	6
PSS	149	6	NA	6	4
VRF	94	3	NA	3	3
YM w/ GPS	142	2	NA	2	1
Imagery	46	1	NA	1	2

Kansas Farm Management Association, Sample size = 38.
*NA = Not applicable to upgrade
**Adjusted accounts for farms that upgraded immediately to more advanced technology

These two technologies are representative of the major types of precision agriculture technology; embodied-knowledge and information-intensive technology. Embodied knowledge technologies describe those that require limited additional skills to fully make use of the technology. LB represents a classic example of embodied-knowledge technology in that the user can use this technology without investing a significant amount of human capital. Yield monitors are the classic example of the other type of technology - information-intensive technologies.

Information-intensive technologies provide data but they also require additional management ability.

Of the 60 farms that ceased to use YM without GPS, only six farms abandoned or disadopted YM without GPS without adopting YM with GPS by the next harvest. Of these six farms, three never adopted another yield monitor, and the other three adopted YM with GPS within six years after ceasing to use YM without GPS. Fifty-four farms adopted YM with GPS by the next harvest season (i.e. within one year). Taking into consideration the number of farms that upgraded, a net 4% abandoned YM without GPS.

Of the 57 farms that abandoned LB, 79% either already had AG or adopted it by the next growing season. When the farms that upgraded from LB to AG was taken into account, a net of only 6% of farms that adopted LB disadopted. Of the farms that ceased to use LB, 12 were already using AG on other equipment. Eight farms that ceased to use LB adopted AG after at least a gap of two years. Thirty-three farms adopted AG immediately after ceasing to use LB. Two farms that ceased using LB abandoned guidance technology altogether.

Transition Probabilities

Table 5. Transition probabilities between information-intensive technology bundles, 2000-2016

	None	PSS	PSS VR	VR	YM	YM PSS	YM VR	YM PSS VR
None	0.942	0.008	0.003	0.002	0.038	0.001	0.003	0.003
PSS	0.014	0.822	0.041	0	0	0.116	0	0.007
PSS VR	0.011	0	0.935	0	0	0	0	0.054
VR	0	0	0	0.533	0	0	0.467	0
YM	0.008	0	0	0	0.903	0.037	0.026	0.025
YM PSS	0	0	0.004	0	0.004	0.886	0	0.105
YM VR	0.119	0	0	0	0.008	0	0.771	0.102
YM PSS VR	0	0	0	0	0	0.003	0.003	0.993

N=348

The Markov transition probabilities indicate that farmers tend to remain in the same bundle of technology, however transitions between bundles were observed (Table 5). Consider the bundle of yield monitors (with and without GPS) (YM) and PSS (row 6 of Table 5). The likelihood that farms keep using YM and PSS from year to year is approximately 89%; while the likelihood of farms adding variable rate fertility or variable rate seed (VR) (i.e. moving to the YM, PSS, and VR bundle) to this bundle of PA technologies is approximately 11%. Where the probabilities along the principle diagonal of Table 5 are the highest value in each row, it is said that persistence occurs (i.e. farms are likely to remain in their current state the following year). Table 5 indicates that persistence is observed for all eight possible bundles. When a farm had only YM in the previous year there was a 90% likelihood that the farm would only have YM in the current year. However, when a farm with only YM in the previous year added another technology, then most often they adopted PSS followed by VR or a combination of VR and PSS. This suggests that adoption of these new technologies is a longer process than some may anticipate, given the relative dominance of persistence.

Conclusions and Future Work

The KFMA dataset accounted for farms that abandoned technology use so that current technology use could be reported. This data also provided the ability to determine how Kansas farms replaced or upgraded obsolete technology for more advanced capabilities. The proportion of farms that truly abandoned technology was similar (and quite low) across all technologies once upgrades were accounted for. The data suggests that less than 6% of Kansas farmers who adopt precision agriculture technologies ever truly abandoned the technology.

In addition to understanding what technologies exist on the farm at the same time, it is important to understand the order, or sequence, that technologies are adopted. The results suggest that farms inhabiting either end of the adoption spectrum (i.e. those with no technology and those with a complete bundle of all three information-intensive technologies) behave differently than farms that had only adopted one or two technologies. Farms that adopted all three technologies were likely to remain with that bundle in the next year, thus indicating some type of optimal combination of technology. Firms in the agricultural industry vying to become 'big data' service providers are likely to avoid working with farms that only have individual technologies such as 'only YM or 'only VR'. These big data companies are more apt to work with a farm that use all three technologies to ensure that the farm is likely to continue providing site specific data. Results provide useful information for policymakers trying to promote adoption of precision agriculture technologies. For example, adoption of precision agriculture technologies has been promoted using financial incentives in USDA, Natural Resource Conservation Service programs, such as the Environmental Quality Incentives Program (NRCS-USDA, 2016). Policymakers wishing to promote adoption need to be aware of the slow length of adoption of PA technologies and allow programs to be available long enough to achieve desired adoption rates and conservation goals. Further insights into farm decision-making regarding technology adoption can be explored from a deeper analysis of the current database.

The characteristics of technology adopters will continue to be compared and contrasted to non-adopters. Given the breadth of the KFMA databank, the characteristics of adopters immediately prior to adoption should be examined to determine which farms are likely to be the next users of spatial technologies. One goal of such a study would be to evaluate the agronomic and financial impact of technology adoption on Kansas farms. Future research includes appending adoption data to agronomic and financial characteristics to KFMA farms. Results from future analyses are expected to reveal the financial characteristics of adopters and how those adopters make use of PA technology such that they profit more than their non-adopter peers.

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