The Impact of Precision Agriculture Techniques on Kentucky Grain Farmers' Carbon Footprint

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Abstract

This study estimates the carbon footprint of a Henderson County, Kentucky grain farmer under different production strategies; traditional farming and precision agriculture technologies**.** Four constrained optimization, whole farm analysis models were formulated under no-till conditions. One of the models was optimized without utilizing any precision agriculture techniques and was used as a base model to compare the other three models which incorporated precision agriculture technologies (PAT). The three technologies investigated include sub-meter auto-steer, RTK auto-steer and automatic section control (ASC). These models are used to analyze the different production systems to determine if said technologies increase expected net returns and enhance the carbon input:output ratio. Given the levels of anthropogenic greenhouse gases released by the agricultural sector, quantifying the potential reduction in these gases due to the adoption of PAT is essential in seeing exactly how PAT can alter the impacts to the environment. The results show that all precision agriculture techniques produce a Pareto improvement over the base model. Specifically, automatic section control gave the greatest improvement with a mean net return that was 0.59% over the base. RTK provided the most significant enhancement in the carbon ratio with an improvement of 2.42% over the base model. All of these improvements over the base scenario can to the adoption of precision agriculture technology.

Keywords: Resource and Environmental Economics, Production Economics, Precision Agriculture, Farm Management, Policy

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Precision agriculture is the application of technologies and principles to help manage the spatial variability associated with all aspects of agricultural production. The potential benefits of these systems include the reduction of overlaps and skips, the lengthening of operator's workday, accurate placement of inputs and reduced machinery costs resulting from an increase in machinery field capacity. The increase in machinery field capacity not only could reduce direct costs, but permit more land area to be planted closer to the optimal date. These advantages provide an incentive for producers to evaluate the potential benefits of these technologies in their farm operations (Shockley et al., 2011). The potential benefits of PAT directly impact crop performance and environmental quality, including the reduction of gases released into the atmosphere by the agriculture sector.

The continued increase in the atmospheric concentration of carbon dioxide due to anthropogenic emissions is predicted to lead to significant changes in the climate during the middle years of the 21st century if conditions continue with "business as usual." (Cox et al., 2000) In 2007, the agricultural sector was responsible for 413.1 teragrams of Carbon Dioxide (CO_2) emissions. This represented approximately 6% of the total US greenhouse gas emissions (USEPA, 2009). The primary gases released into the atmosphere by agriculture practices are methane (CH_4) and nitrous oxide (N_2O) (USEPA, 2009). The agriculture sector contributed 50% of the total anthropogenic CH_4 emissions (Cole et al., 1997), which are 21 times more potent than CO_2 (Rodhe, 1009; IPCC, 2007), and 75% of the total anthropogenic N_2O emissions (Cole et al., 1997), which are 310 times more potent than CO_2 (Cole et al., 1997).

The three applications of PAT technology reviewed in this paper are examples of embodied-knowledge technology. Embodied-knowledge technologies are technologies that increase efficiency without the requirement of additional management skills. On the other end of the spectrum there are information-intensive technologies such as variable rate applications and yield monitors (Griffin, 2009). An introduction to the three types of PAT is as follows:

- Sub-meter: Auto-steering is accomplished with a device mounted to the steering column or through the electro-hydraulic steering system. This bolt-on auto-steer system is equipped with a sub-meter receiver (Shockley, et al., 2011).
- RTK: integral valve system with a real time kinematic (RTK) GPS receiver on a tractor (Shockley, et al., 2011). RTK differential correction is accurate within one inch. Vehicles equipped with RTK equipment can be used to conduct strip tilling, drip-tape placement, land leveling and other operations requiring superior performance; as well as virtually any other task. In addition to the ability to accurately determine geographic location, auto-guidance systems usually measure vehicle orientation in space and compensate for unusual attitude, including roll, pitch and yaw.
- Automatic section control (ASC): a horizontal series of light emitting diodes (LEDs) in a plastic case 12 inches to 18 inches long. This system is linked to a GPS receiver and a microprocessor. The lightbar is usually positioned in front of the operator, so he or she can see the accuracy indicator display without taking their eyes off the field. Software allows the operator to specify the sensitivity to and distance between the swaths (Grisso, et al., 2009).

These capabilities reduce the over and under application on irregular shaped fields that is prevalent in standard machinery technologies (Shockley, et al., 2008). With the increased accuracy, less time is actually spent with the machine in use. It is thought that the reduction in the use of the inputs, combined with the reduction in the use of the machinery will total a reduction in the carbon footprint of the farm itself.

While some studies have demonstrated potential increases in profitability from PAT (Shockley et al., 2009; Griffin et al., 2008), there is also the potential for enhanced environmental benefits due to the reduction in input usage given the improved performance rates. This has previously been discussed but no empirical studies have been performed. This study aims to look at the potential reduction in the carbon footprint of the farmer using the PAT against a base model.

Literature Review

There have been many articles emphasizing the potential beneficial effects that using PAT can have versus conventional farming methods (Ancev et al., 2004, Bergtold, 2007, Bongiovanni et. al, 2004). However, little empirical research has been conducted to document the actual changes in the environmental impacts that PAT could have and the possible policy implications of those changes.

PAT can help manage crops in an environmentally friendly way. PAT can contribute in many ways to long-term sustainability of production agriculture, confirming the intuitive idea that PA should reduce environmental loading by applying fertilizers and pesticides only where they are needed, and when they are needed (Bongiovanni et. al, 2004). This article by Bongiovanni is an excellent reference that clearly lays out how PAT could be more environmentally friends than conventional agriculture. According to the USDA, precision agriculture can possibly reduce soil erosion, protect water quality, improve soil health and productivity and improve the wildlife and landscape (Bergtold, 2007).

Ancev looks at the environmental aspect of PAT from an "environmental damage cost." He uses this cost function to look at how PAT affect the environment that it engages with. By separating the cost function into two parts, he is able to look at both the pollutant emission function and the damages caused by emissions. He concludes that the use of PAT could improve the environment it interacts with if the PATs are used on a regular basis and not once or twice (Ancev et al., 2004).

Many studies have analyzed the factors that farmers take into account when making the decision to adopt certain PAT (Pandit, et al., 2011, Daberkow and McBride, 2003; Larkin et al., 2005; Roberts et al., 2004). Farmers who are environmentally conscious focus on the adoption of PAT and other technologies that could help mitigate environmental hazards. For example, 23% of cotton producers in the South East United States answered in a survey about the adoption of PAT that they consider the environmental benefits associated with the precision agriculture machinery a part of their decision making process while 14% viewed it as unimportant (Pandit et al, 2011). In another study looking at the impacts of PAT on the environment, 36.2% of the PAT adopters saw an environmental improvement following the use of PATs (Larkin et al., 2005).

Methods, Data and Procedures

A whole farm analysis using a resource allocation model was conducted on a hypothetical grain farmer producing corn and soybeans in Henderson County, Kentucky. This modeling process is a modification of previous mathematical programming models (Shockley, et al., 2011). The structure of these models includes both production and economic environments. These models will be used to analyze and determine if the various PAT increase mean net returns above specified costs and enhance the carbon input:output ratio. The carbon input:output ratio is defined as the ratio of the carbon equivalents of the inputs used for the different production practices to the carbon equivalent of the biomass produced from the production of corn and soybeans (Lal, 2004).

The reduction in energy and inputs due to various PAT will come from pertinent literature and expert opinion. Relevant literature will also be utilized in determining the appropriate carbon equivalent for each production strategy in order to calculate a representative input:output ratio for comparison. The inputs used for this ratio will include fertilizer, herbicides, insecticides and fossil fuel combustion for each machine. Outputs used will include total biomass.

The four different scenarios are as follows:

1. Grain farmer under no-till conditions. (Base Model)
2. Utilization of the sub-meter auto-steer technology on a tractor. (Sub-meter)
3. Utilization of RTK auto-steer technology on a tractor. (RTK)
4. Utilization of automatic section control equipped with lightbar navigation technology on a self-propelled sprayer. (ASC)

The Production Environment

Expected production estimates were obtained using Decision Support System for Agrotechnology Transfer (DSSAT v4) which is a biophysical simulation modeling tool. This biophysical simulation will be used to estimate the underlying crop yield for a Kentucky grain farmer by altering production and management practices. The requirements to develop said yield estimates in DSSAT include weather data for the entire growing season, soil data and the designation of production practices. Historical weather data for Henderson County, Kentucky for the previous 30 years was obtained from the University of Kentucky Agricultural Weather Center (2008). Following the identification of the soil series in Henderson County, Kentucky, data was obtained from a National Cooperative Soil Survey of Henderson County, Kentucky from the USDA NRCS (2008) and the NRCS Official Soil Series Description (Shockley, 2011). The four representative soils utilized in DSSAT are deep silty loam, deep silty clay, shallow silty loam and shallow silty clay.

The definition of production practices for both corn and full season soybeans were identified in order to meet the minimum requirements for the DSSAT simulation; this information was established in accordance with the University of Kentucky Cooperative Extension Service Bulletins (2008). Production practices utilized in this study included planting date, crop variety, plant density, row spacing, and fertilizer practices (Shockley, 2011). Other data required for this study includes land available and the carbon equivalent for each production activity. By utilizing 30 years of data and varying production practices, the model is given strength and is able to model for an extensive number of scenarios.

The Economic Environment

The objective of these models was to maximize mean net returns above specified costs while looking at the carbon footprint of each model. The costs included in the models consist of input variable costs, operating costs and the cost of ownership of the PAT in applicable models. Decision variables in the model include corn and soybean production as well as optimal production strategies for which mean net returns and the estimated carbon equivalents are determined. Based on the decision variables, the models produced results including expected yields and expected net returns. A carbon footprint accounting variable was utilized to estimate the carbon emissions, carbon output and carbon ratio for each model. The mathematical representation of the carbon footprint equation utilized in this model can be found in the appendix.

Constraints include land, labor, crop rotation and variable rate feasibility. The land constraint guaranteed that the production of both corn and soybeans aggregated did not exceed the land available. Labor constraints include sowing, spraying, fertilizing and harvesting. This was constrained by suitable field days and labor available. Labor hours were determined based on the field capabilities of the operating machinery. In addition, prices are necessary for calculating the expected net returns. Prices for the commodities produced were determined by means of the World Agricultural Outlook Board (2008). "Prices used were the 2009 median estimates less Kentucky's basis, which resulted in $9.75/bu and $4.25/bu for soybeans and corn, respectively" (Shockley, 2011).

Nitrogen Price Risk Modeling

A mean-variance (E-V) analysis was conducted each model to test the sensitivity of a farm to nitrogen price risk. This was done to determine if the farmer is sensitive to nitrogen prices and if it is reasonable for the farmer to try and mitigate nitrogen price risk. 12 years of historical nitrogen prices were collected from the USDA Economic Research Service (1997-2008) and a regression analysis was utilized to determine the residuals. Using the base model before testing for nitrogen price risk, the standard deviation was collected and nine risk aversion parameters were calculated. Using these risk aversion parameters and the residuals from the data, the models are able to provide information as to how farmers may react to variation in nitrogen prices.

Results and Findings

The results from the four models are presented in Table 1; the figures reported are mean net returns above specified costs (NR), carbon emissions, carbon output and carbon ratio.

Table 1. Results from the execution of the four models[1]

	Base	Sub-Meter	% change from base	RTK	% change from base	ASC	% change from base
Net Returns	$868,468.00	$873,314.00	0.56%	$871,018.00	0.29%	$873,615.00	0.59%
Carbon Emissions	173488	171415	-1.19%	169430	-2.34%	170521	-1.71%
Carbon Output	5584615	5586140	0.03%	5586838	0.04%	5586140	0.03%
Carbon Ratio	32.19	32.59	1.24%	32.97	2.42%	32.76	1.77%

[1] Carbon emissions and carbon ratio are reported using teragrams as units.

ASC has the greatest benefit to the farmer with a net return of .59% over the base model. While not seemingly substantial, it should be noted that the mean net returns of the base scenario is $868.468.00 and therefore this represents an increase of $5,147.00. Automatic section control has the lowest input costs associated with pre-herbicide variable costs, post-herbicide variable costs and spray fuel being 11% less than the other models and insecticide variable costs being 16% less than that other models. Sub-meter offers the next best improvement to net returns; ASC has an annual cost of $2161.50 greater than that of the sub-meter, but the amount saved by reducing the costs of inputs with ASC has allowed that to be a better production practice for the farmer.

Table 2. Carbon footprint by input[1]

	Base	Sub-Meter	ASC	RTK
Pre-Plant	8620.50	8021.86	7711.41	8620.50
Post-Plant	14374.50	13376.28	12858.61	14374.50
Tractor Fuel	12558.00	12558.00	12558.00	11247.64
Sprayer Fuel	2247.00	1896.82	1896.82	2247.00
Insecticide	1816.50	1690.35	1624.94	1816.50
Seed	18637.50	18637.50	18637.50	18199.43
Other Fuel	11949.00	11949.00	11949.00	11949.00

[1] All figures are reported using teragrams as units.

While automatic section control is most profitable for the farmer, from the carbon footprint standpoint, RTK is the most beneficial. RTK reduces the carbon emissions by 2.34% and improves the carbon ratio bringing it to 2.43% over the base model. This can be primarily attributed to two inputs: seeds and tractor fuel. When modeling the carbon aspect a carbon number was associated with each unit of input reported on the table. For seeds, the carbon number indicated the amount of carbon related to the production and sales of each individual seed. RTK uses 2% less seed than the other production practice modeled. While the amount of seed used and the reduction of 2% may not seem substantial, that resulted in a decrease of 438.07 tergrams of carbon from all other models. The reduction in the amount of seed used can be attributed to the more precise seeding when using RTK, this providing improved results over the other production practices. For tractor fuel, the carbon number indicates the amount of carbon related to the production and combustion of each kilogram of tractor fuel used. RTK uses 10% less fuel than the other production practices modeled; again this can be attributed to the precision of RTK over the other production practices modeled.

Pre-herbicide, post-herbicide, insecticide and sprayer fuel were most carbon efficient with automatic section control. Pre-herbicide, post-herbicide and insecticide all had a reduction of 11% from the base model and a 4% reduction from the next best production practice. This coupled with the 16% reduction from the base model in sprayer fuel can be primarily attributed to the fact that ASC can spray more effectively by controlling specific sections of the boom. This resulted in the highest increase in mean net returns to the farmer.

The optimal production practices for the base scenario were altered when modeling for the three PAT. All modifications to the production practices occurred exclusively to soybeans; results are presented in Table 3.

Table 3. Selected results of soybean sowing and harvesting[1]

Aggregation by harvest week separated by production practice

	Base	Sub-Meter	ABSC	RTK
Harvest Week 1	831.98	447.51	420.24	590.92
Harvest Week 2	217.41	602.49	629.78	459.08
H1/H2 Ratio	3.83	0.74	0.67	1.29

Acres planted by sowing date and production practice

	Base	Sub-Meter	ASC	RTK
April 22	808.33	967.04	967.06	1050.00
April 29	13.03	13.64	13.64	-
May 6	228.03	69.32	69.32	-

[1] Soybeans planted are reported in acres planted.

It is noteworthy to point out that plant population and row spacing were unvarying throughout all models for both corn and soybean production. For the base model during harvest week one (H1), sowing dates of 4/22, 4/29 and 5/6 are utilized while during harvest week two (H2) only sowing date 4/22 is utilized. The sowing dates for the sub-meter model are identical, but there is a shift in the acres sowed per harvest week. This is most likely attributed to the fact that with the ability to spray more effectively with sub-meter, more suitable field hours were available for planting allowing for the most optimal combination of the soybean sowing dates available. The largest change that occurred in consideration of the planting of soybeans was with the use of automatic section control. During H1, sowing dates of 4/22 and 5/6 were utilized while during H2, sowing dates of 4/22 and 4/29. This allowed for a more even distribution of the amount of soybeans planted during each harvest week. Perhaps the most substantial change was with the use of RTK. For both harvest periods the only planting date that was utilized was 4/22. RTK increases the efficiency of tractor operations which allowed for the optimal number of acres of soybeans to be planted on April 29. Since all of the soybeans were able to be planted on this date, the other available planting dates are essentially obsolete. These differences demonstrate the importance of the whole-farm model and the need to adjust practices to take full advantage of the technologies available.

It is interesting to take a look at the ratio of acres planted during H1 and H2 with respect to the different production practices. For the base model, the ratio is 3.83, meaning that for each acre planted during H2, 3.82 acres were planted during H1. Even though sub-meter had identical sowing dates, the amount planted in each harvest period shifted drastically causing a ratio of 0.74. For every 1 acre of soybeans planted in H1, 0.74 acres were planted in H2. Again, this can be attributed to suitable field hours and the ability to spray more effectively. Automatic section control also planted more acres in H2 than H1 allowing for a ratio of 0.67. With the use of RTK, the number of acres planted in H1 surpassed the number of acres planted in H2, but is not nearly as asymmetrical as the base model, with a ratio of 1.29.

While it was not optimal to vary the acres of corn produced from model to model, it is interesting to note that corn production utilized two plant varieties while soybean production only utilized one plant variety. During harvest week one, plant varieties 2650 and 2700 were utilized with fertilizer rate 168 and 196, respectively. During harvest week two, only plant variety 2700 was utilized with a fertilizer rate of 196.

The findings for determining nitrogen price risk using E-V analysis suggest that nitrogen price is not a significant enough factor on its own to account for the management of its risk. The models were responsive at two risk aversion parameters; one at moderate risk and one at high risk. Even then, the mean net returns only decreased by 0.22% and 0.74% respectively. The responsiveness and level thereof was identical for all models. While nitrogen is important in the production of corn, and it is possible for a farmer to mitigate for nitrogen price risk, it is not a substantial enough percentage of the inputs used to warrant the mitigation of its risk.

Discussion

It is clear from the results that with the use of the three PAT investigated there is a Pareto improvement in each model over the base model. The farmer receives a higher net return than the base model and the carbon input:output ratio is enhanced. These results are significant because there have been no previous studies to offer empirical results to verify previous thoughts on the subject. If this is truly a Pareto improvement over the base scenario, this begs the questions as to what the adoption rate is for corn and soybean producers.

According to an ERS study conducted, corn and soybean farmers are among the first adopters when a new PAT emerges. In 2001, approximately 30% of corn producers and 25% of soybean producers were using some form of yield monitors (a precision agriculture technology). The adoption of PAT is expected to increase based on the previous trend of adoption. One of the main factors in determining if a PAT is suitable for farm operations is the farm size. Innovations with large fixed acquisition or information costs are typically less likely to be adopted by smaller farms since there are fewer acres over which to spread these costs. With a larger farm, the cost per acre of the PAT is more manageable for the farmer, therefore the larger farms are more likely to adopt these technologies. There is also regional variability in the adoption of PAT. There is a high concentration of yield monitor use in the Heartland and Northern Crescent regions. This can be attributed to the fact that this is where yield monitors were first introduced; specifically for corn and soybean production. These regions are major corn and soybean producers, and a sizeable PAT service sector has become established there (Daberkow, 2001).

If the larger farms are able to purchase this equipment and the smaller farms are not afforded an opportunity to receive the benefits of these technologies, then at some point the smaller farms will collapse. The USDA NRCS has enacted two programs to help both the large and small farmers acquire the machinery necessary to keep them competitive; Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP). The first program, EQIP, is a voluntary program that provides financial and technical assistance to agricultural producers through the use of contracts. In 2011, the EQIP program has contract obligations totaling $514,060,894.37, with an average of $20,673.24 per contract and $68.25 per acre. The contracts provide financial assistance to help plan and implement conservation practices that address natural resource concerns and for opportunities to improve soil, water, plant, animal, air and related resources on agricultural land and non-industrial private forestland. In addition, a purpose of EQIP is to help producers meet Federal, State, Tribal and local environmental regulations. EQIP provides financial assistance payments to eligible producers based on a portion of the average cost associated with practice implementation. (NRCS, 2011) While this program is not directed toward PAT practices, is does not exclude them either.

The second program, CSP, is very similar to the EQIP program as it is also a voluntary program that encourages agriculture and forestry producers to address resource concerns through two directions. One, by undertaking additional conservation activities, and two, improving and maintaining existing conservation practices. CSP is open to all producers, regardless of operation size or crop produced. It rewards producers by the higher the performance, the higher the payment to the producer. The contracts can run five years in length and have a maximum payment of $40,000 per annum. (Conservation Stewardship Program, 2011) The advantage that CSP has over EQIP is that is specifically targets farmers who utilize PAT as a conservation practice. Of the many activities outlined on the CSP program, PAT is specifically targeted by highlighting three activities that a producer can take advantage of: 1) GPS, target spray application, or other chemical application electronic control system, 2) fuel use reduction for field operations and 3) precision application technology to apply nutrients (Conservation Stewardship Program Conservation Activity List, 2011).

Summary and Conclusions

Precision agriculture is both economically viable and more environmentally beneficial, due to the reduction of the carbon footprint, than conventional farming. The reduction in the carbon footprint with the use of precision agriculture can be attributed to several factors. Because precision agriculture is more precise with the application of fertilizers and seeds, fewer inputs are used thereby reducing the carbon footprint of the operation. With the reduction of inputs there is a reduction in the carbon footprint from two directions. First, the production of the inputs carries a carbon footprint while, second, the use on the farm carries a carbon footprint.

This study aimed to look at three precision agriculture techniques versus a base model of conventional farming and compare the four models against one another. The results show that all precision agriculture techniques produce a Pareto improvement over the base model.

Specifically, automatic section control gave the greatest improvement with a mean net return that was 0.59% over the base. RTK provided the most significant enhancement in the carbon ratio with an improvement of 2.42% over the base model. All of these improvements over the base scenario can to the adoption of precision agriculture technology. These results are significant because there have been no studies conducted to offer empirical results to verify previous thoughts on the subject.

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Appendix: Mathematical Representation of the Carbon Footprint Equation

The carbon footprint accounting equation described in the model is depicted mathematically as follows:

$$\sum_{H}\sum_{VS}\sum_{ST}\sum_{PS}\sum_{RS}\sum_{SS} CFACT * SCARB_{I,PS,RS} * XS_{H,VS,ST,PS,RS,SS}$$
$$+ \sum_{H}\sum_{SC}\sum_{VC}\sum_{ST}\sum_{PC}\sum_{FR} CFACT * CCARB_{I,PF,FR} * XC_{H,VC,ST,PC,FR,SC}$$
$$- \; CARBFP_{I} \qquad \leq 0 \;\; \forall \, I$$

<u>Activities include:</u>

$XS_{H,VS,ST,PS,RS,SS}$ = production of soybeans harvested during period *H* in acres of variety *VS* for soil type *ST* with plant population *PS* with row spacing *RS* under sowing date *SS*.

$XC_{H,VC,ST,PC,FR,SC}$ = production of corn harvested during period *H* in acres of variety *VC* for soil type *ST* with plant population *PC* with fertilizer rate *FR* under sowing date *SC*.

<u>Coefficients include:</u>

$SCARB_{I,PS,RS}$ = Soybean production requirements for input *I* for plant population *PS* with row spacing *RS*.

$CCARB_{I,PF,FR}$ = Corn production requirements for input *I* for plant population *PF* with fertilizer rate *FR*.

CFACT = carbon emissions for each input used

$CARBFP_{I}$ = carbon footprint by input used

<u>Indices include:</u>

SS – sowing date soybeans
SC – sowing date corn
VS – plant variety soybeans
VC – plant variety corn
PS – plant population soybeans
PC – plant population corn
FR – fertilizer rate corn
RS – row spacing soybeans
ST – soil type
I – inputs
H – harvest week