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Economic Optimization and Precision Agriculture: A Carbon Footprint Story

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ECONOMIC OPTIMIZATION AND PRECISION AGRICULTURE:
A CARBON FOOTPRINT STORY

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in the
College of Agriculture
at the University of Kentucky.

By

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Lexington, Kentucky

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Lexington, Kentucky

2013

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ABSTRACT OF THESIS

ECONOMIC OPTIMIZATION AND PRECISION AGRICULTURE: A CARBON FOOTPRINT STORY

This thesis examines the economic and environmental impacts that precision agriculture technologies (PATs) can have on the carbon footprint of a grain farm. An analysis is offered using two manuscripts. The first examines the impacts of three PATs and compares the findings to a conventional farming method. It was found that all three PATs investigated showed a potential Pareto improvement over conventional farming. The second manuscript expanded the model used previously to in order to develop a process to construct a carbon efficient frontier (CEF). The model employed examined uniform and variable rate technologies. In addition to the CEF, a marginal abatement cost curve was constructed. Using these curves in a complementary fashion, more accurate information on the adaptive behavior of farmer technology adoption can be gleaned. The information gleaned for the two manuscripts can give both producers and policy makers the analytical tools needed to make more information decisions with regard to economic and environmental feasibility of PATs.

KEYWORDS: Precision Agriculture, Mathematical Programming, Carbon Footprint, Production Agriculture, Environmental Economics

Rachael Martha Brown

May 30, 2013

ECONOMIC OPTIMIZATION AND PRECISION AGRICULTURE:
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There are three women in my life of whom I admire for their strength, perseverance and love: my mother, Joy, my aunt, Bonnie, and my grandmother, Roz. My mother has shown me that love is possible in even the most difficult of situations. My aunt Bonnie has encouraged me to be the best woman I can be and to always go forth and conquer. My grandmother has shown me how to hold your head high, even when the odds seem insurmountable, and that afternoon naps are one of life's simple pleasures. My brother, Adam, has been a rock that I have been able to count on every step of this journey. For all these reasons and more, I humbly thank and acknowledge everyone that has touched my life in even the slightest of graces.

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Chapter One

Introduction

Currently, there is amplified interest in the effects that the continually increasing concentration of anthropogenic greenhouse gases (GHGs) emissions has on climate change. This increase in gases is dominated by human activities such as the burning of fossil fuels and methane (CH₄) and nitrous oxide (N₂O) emissions from various activities (Karl and Trenberth, 2003). In 2008 the United States was responsible for 19% of the world's GHG emissions, with the agricultural sector in the U.S. accounting for more than 6% of carbon dioxide (CO₂), 50% of CH₄ and 75% of N₂O emissions (Cole et al., 1997; IPCC, 2007; Olmstead and Stavins, 2012; Rodhe, 1990). Concerns over environmental quality due to the consequences of climate change are likely to escalate as resource scarcity increases.

In agriculture, there are varied sources of pollution where abatement practices are nearly unobservable. This difficulty leads to inefficient control mechanisms as there is no one best solution for all pollution sources in agriculture. One way to combat this problem is to focus on technological innovations and business-led solutions instead of economic based incentives (Weersink et al., 1998). Methods to secure an agricultural sector that promotes economic gains and environmental quality will require research and policy measures that focus on farm-level technological innovations.

The overriding goal of this research was to explore production strategies that could be both environmentally and economically preferable to conventional farming techniques. The technologies investigated in this study were types of precision agriculture technologies (PATs), which are defined as the application of technologies and principles

that help manage the spatial variability associated with certain aspects of agricultural production. The PATs investigated were sub-meter auto steer, automatic section control with lightbar, a real time kinematic system with an integral valve system and variable rate technology. While several studies have shown an economic enhancement with the use of PAT and have postulated environmental benefits, empirical testing that aims to sustain this notion has been lacking. This study aims to help fill the void in knowledge to determine whether select PATs are in fact economically and environmentally superior to conventional farming methods.

This thesis uses a two essay approach wherein the essays are distinctly different yet clearly related. Both essays examine carbon footprint aspects of a grain farm in Kentucky in a general sense while adding specificity. The first essay (Chapter Two) investigates economic and environmental differences seen with the use of PATs against a base, no PAT scenario. The second essay (Chapter Three) expands upon this model to develop a carbon efficient frontier under uniform and variable rate technology.

A whole-farm analysis using a resource allocation model was conducted representing a hypothetical grain farmer producing corn and soybeans in Henderson County, Kentucky. The modeling process for both Chapter Two and Three is a modification of a previous mathematical programming model (Shockley, Dillon and Stombaugh, 2011). The models include production and economic environments as well as the opportunity for strategic and tactical decisions to be made. Based on the decision variables, the models produced results including optimal expected yields and mean net returns. A carbon footprint accounting variable was utilized to estimate the carbon emissions (inputs), carbon output (biomass) and carbon ratio for each model. Each

production input and output is assigned a carbon equivalent according to pertinent research and literature. The reduction in energy and inputs due to various PATs will come from relevant literature as well (Lal, 2004).

In Chapter Two, three PATs are investigated to 1) determine what, if any, effects precision agriculture strategies could have on the carbon footprint of a grain farm, 2) compare the environmental and economic performances of the different production strategies and 3) examine the changes in optimal production practices with the use of PAT. The objectives of this study perfectly align with the demand for increased knowledge about underpinnings of the agricultural sector's carbon footprint.

It was determined that all of the PATs produced both economic and environmental improvements over the base model. Specifically, automatic section control with lightbar provided the greatest economic enhancement while the real time kinematic system with integral valve control had the greatest environmental benefit. The increase in profitability and decrease in carbon emissions can be attributed to several factors. With the increased precision of the PATs, the application of fertilizer and seed is more efficient, leading to the use of fewer inputs which ultimately reduces the carbon footprint of the farm operation. With the decrease in input requirements there is a reduction in the carbon footprint both directly and indirectly. The production of the inputs carries a direct carbon footprint while the application of inputs on the farm carries a carbon footprint attributed to the fuel consumption.

In Chapter Three, a further progression on the carbon footprint concept is pursued. The focus was to develop a modeling process that could be used to construct a carbon efficient frontier (CEF). Using uniform rate (conventional farming) and variable

rate technology, through the imposition of carbon emission constraints on the model, the CEF was developed. In addition to the CEF, a marginal abatement cost curve (MACC) was estimated. By using the two curves in a complementary fashion, the empirical results highlight the factors that drive production changes with the restriction of the carbon footprint.

The results show that VRT is an economically and environmentally superior production strategy at all but the very highest restriction levels. It was found that there were management opportunities for carbon reduction through the application of nitrogen fertilizer and seed rates. While planting date changes are not accompanied by carbon reductions, the interactive effects embodied across production practices are influential. Specifically, impacts on profitability from reduced fertilizer and seeding rates are diminished by employing earlier planting dates. The CEF is employed as a tool with focus on technology adoption while the MACC is utilized to examine incremental costs associated with carbon footprint restrictions. When the two tools are employed simultaneously, a clearer picture of the impacts that a carbon footprint restriction would have on a grain producer is conveyed.

This study explored the economic and environmental impacts that PATs could have, which until now has been an information void in the applicable literature. The empirical results presented could be extremely useful when used in appropriate circumstances. Chapter Two shows how the use of different PATs can produce different optimal results. The CEF developed in Chapter Three can be an extremely useful tool in analyzing site specific carbon emissions management decisions. Both of the models exemplify how, with the use of increased knowledge of production practices, the carbon

footprint of a grain farm can be altered and managed. Depending on the outcome desired, policy makers could use this information to make more informed decisions when enacting agricultural policies while producers will be able to make more informed decisions regarding the adoption of PATs based upon their operation.

Chapter Two

The Carbon Footprint and Economic Impact due to Precision Agriculture Strategies on a Grain Farm

Currently, there is heightened interest in the role that the agricultural sector plays within climate change generally and more specifically upon the individual farm's carbon footprint. The purpose of this study is to inform farm managers, agribusiness decision makers and policy makers concerned with related aspects throughout the agro-environmental sector, such as agricultural production and environmental efficiency, about the effect of precision agriculture technology (PAT) on the farm level carbon footprint. Armed with this information, producers are empowered to determine whether employing certain PATs could make their land more profitable and increase their environmental stewardship. Policy makers can utilize this information to make policy determinations that incentivize producers to adopt these preferred technologies. This holds value for those policy makers concerned with mitigating greenhouse gas (GHG) emissions vis-à-vis climate change policy.

The objective of this study was trifold: 1) to expand a previous model to incorporate the effects that precision agriculture strategies could have on the carbon footprint of grain farms, 2) to evaluate and compare the economic and environmental performance of PATs against a base model and 3) to investigate the changes in optimal production practices with the use of PATs. The model employed four scenarios across three PATs and was successful at gaining insight into the potential benefits these technologies might have, both economically and environmentally. The potential for scientific advancements in this regard raises the question of whether PATs are a promising possibility for GHG emissions mitigation while simultaneously being a

lucrative production opportunity for farmers. Prior to the completion of this study, no other study (that the author is aware of) that provided empirical results of PAT's impact on carbon footprints had been published in the available literature. Part of this study's contribution to the literature is to help fill that information void as well as provide specific empirical results that could be highlighted for policy decisions.

If conditions proceed with "business as usual," then the continual increase in the atmospheric concentration of carbon dioxide (CO₂) due to anthropogenic emissions is predicted to lead to significant changes in the climate during the middle years of the 21st century (Cox et al., 2000). In 2007, the agricultural sector was responsible for 413.1 teragrams of CO₂ emissions. This represented approximately 6% of the total US GHG emissions (USEPA, 2009). While CO₂ is the most important GHG due to the sheer volume produced, the primary gases released into the atmosphere by agricultural practices are methane (CH₄) and nitrous oxide (N₂O) (USEPA, 2009). The agricultural sector contributed 50% of the total anthropogenic CH₄ emissions which are 21 times more potent than CO₂ and 75% of the total anthropogenic N₂O emissions which are 310 times more potent than CO₂ (Cole et al., 1997; IPCC, 2007; Rodhe, 1990).

The Intergovernmental Panel on Climate Change (IPCC) clearly states that the change in climate observed over the last 50 years can very likely be attributed to an increase in anthropogenic GHG concentrations due to human influences. The IPCC does not stand alone on this issue; all major scientific bodies in the United States have made similar statements (Oreskes, 2005). These gases are accumulating in the Earth's atmosphere, causing a trapping of outgoing radiation, which is ultimately causing a warming of the planet and influencing the global climate. This increase in gases is

dominated by human activities such as the burning of fossil fuels and CH₄ and N₂O emissions from various activities (Karl and Trenberth, 2003).

Each greenhouse gas has a different warming influence on the climate due to differing radioactive properties and life spans in the atmosphere. In this study, these differing warming influences are converted to a carbon emissions equivalent using a metric based on the radioactive forcing of carbon. This emissions equivalent is a useful tool for comparing emissions of different anthropogenic GHG, but does not imply the same climate change responses for each gas (IPCC, 2007).

For this study, precision agriculture is defined as the application of technologies and principles to help manage the spatial variability associated with certain aspects of agricultural production. The potential benefits of these technologies include the reduction of overlaps and skips, the lengthening of the operator's workday, increased accuracy with the placement of inputs and reduced machinery costs resulting from an increase in machinery field capacity. While some studies have demonstrated potential increases in profitability from PAT (Griffin, 2009; Shockley, 2010; Shockley, Dillon and Stombaugh, 2011), there is also the potential for enhanced environmental benefits from reduced GHG emissions due to the reduction in input usage given the improved performance rates. This has been discussed in literature, but no empirical studies have been performed. This study aims to look at the potential reduction in the carbon footprint of the farmer using PATs against a base model.

Literature Review

There have been several articles emphasizing the potential environmental benefits that using PAT can have compared to conventional farming methods (Ancev, Whelan and McBratney, 2004; Bergtold, 2007; Bongiovanni and Lowenberg-DeBoer, 2004). However, little empirical research has been conducted to document the actual changes in the environmental impacts that PAT could have.

PAT can contribute in many ways to long-term sustainability of production agriculture, confirming the intuitive idea that PAT should reduce environmental damages by applying fertilizers and pesticides only *where* they are needed and *when* they are needed (Bongiovanni and Lowenberg-DeBoer, 2004). Using this intuition, one can logically draw the conclusion that PAT can help manage crops in an environmentally friendly way. Bongiovanni clearly defines how PAT could be more environmentally friendly than conventional agriculture. According to the United States Department of Agriculture (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 *et al.* (2004) look at the environmental aspect of PAT from an “environmental damage cost” angle. Their study uses a cost function to look at how PAT affects the environment that it interacts with. By separating the cost function into two parts, they are able to look at both the pollutant emission function and the damages caused by emissions. The results indicate that the use of PAT could improve the environment it interacts with if the PATs are used on a regular basis, not only once or twice or irregularly (Ancev, Whelan and McBratney, 2004).

Additionally, prior studies have analyzed the factors that farmers take into account when making the decision to adopt certain PATs (Daberkow, Fernandez-Cornejo and Padgitt, 2002; Larkin et al., 2005; Pandit et al., 2001; 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, in a survey about the adoption of PAT, 23% of cotton producers in the Southeastern United States said that they consider the environmental benefits associated with the use of precision agriculture machinery a part of their decision-making process while 14% viewed it as unimportant (Pandit et al., 2001). In a separate study examining the impacts that PAT may have on the environment, 36.2% of the PAT adopters saw an environmental improvement following the implementation of PAT (Larkin et al., 2005).

In the 2010 ARMS Farm Financial & Crop Production Practice study conducted by the USDA Economic Research Service (ERS), corn and soybean producers in Kentucky had a greater average adoption rate of PAT over the average of the states in the study. Kentucky corn producers had an adoption rate of 84% while the other states in the study had an adoption rate of 72%. The 2006 ARMS Farm Financial & Crop Production Practice data indicate that Kentucky soybean producers had an adoption rate of 37% while the other states in the study had an adoption rate of 45%. This could be attributed to the fact that it may be especially economically viable for Kentucky producers to strategically apply nitrogen, which is the key fertilizer in corn production.

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 a previous mathematical programming model (Shockley, Dillon and Stombaugh, 2011). The structure of the models used in this study includes production and economic environments, as well as strategic and tactical decisions. Strategic, or long term, decisions include the use of PATs, while tactical, or short term, decisions include planting date or fertilizer rate.

The results from the models were used to determine whether the various PATs simultaneously increase mean net returns above specified costs and enhance the carbon input-output ratio (carbon ratio). The carbon ratio is defined as the ratio of carbon equivalents (CE):

$$\frac{\text{CE of the inputs used for the different practices}}{\text{CE of the biomass in production}} \text{ (Lal, 2004).}$$

To determine the carbon ratio, each production input and output is assigned a carbon equivalent according to pertinent research and literature. The reduction in energy and inputs due to various PAT will come from relevant literature as well. The inputs used for this ratio will include fertilizer, herbicides, insecticides and fossil fuel combustion for each machine. Outputs used will include total biomass which is directly related to yields. A higher carbon ratio is indicative of a production technology being more environmentally friendly.

The Production Environment

The three applications of PATs 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 are information-intensive technologies such as variable rate applications and

yield monitors (Winstead et al., 2010). An introduction to the three types of PAT used in this study are as follows:

- Sub-meter auto-steer (SUB): 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). The annualized cost of ownership for SUB was \$980.00.
- Automatic section control with lightbar (ASC-L): Automatic section control technology allows the machinery to automatically turn on or off depending on the tractor's location in the field and if it is about to pass over a previously applied field. Lightbar is a horizontal series of light emitting diodes in a plastic case 12" - 18" long and is usually positioned in front of the operator. This allows the operator to see the accuracy indicator display without taking their eyes off the field. This system is linked to a GPS receiver and a microprocessor with software that allows the operator to specify the sensitivity to and distance between the swaths (Grisso, Alley and Groover, 2009). The annualized cost of ownership for ASC-L was \$3,141.50.
- RTK: An integral valve system with a real time kinematic (RTK) GPS receiver mounted onto a tractor (Shockley, Dillon and Stombaugh, 2011). 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 determining geographic location, auto-guidance systems usually measure vehicle orientation in space and compensate for unusual altitude, including roll, pitch and yaw. RTK

allows for increased precision with seeding, harvesting and nitrogen application. It does not increase the precision of sprayer functions. RTK differential correction is accurate within one inch. The annualized cost of ownership for RTK was \$4,900.00.

In addition to examining the economic implications of SUB, ASC-L and RTK, the study herein contributes to the body of research by examining the environmental observations for all three technologies. The four production strategies used in this study are as follows:

1. Grain farm under no-till conditions without the use of PATs (Base),
2. Utilization of the sub-meter auto-steer technology on a tractor (SUB),
3. Utilization of automatic section control equipped with lightbar navigation technology on a self-propelled sprayer (ASC-L) and
4. Utilization of RTK auto-steer technology on a tractor (RTK).

These PAT machinery complements have the capability to reduce the over and under application of agrochemicals, nitrogen and seed, on irregularly shaped fields which are prevalent with the use of standard machinery technologies (Shockley, Dillon and Shearer, 2008). The use of some PATs reduces time requirement and improves accuracy with regards to the application of farm inputs. It is thought that the reduction in the use of the inputs, combined with the reduction in the fuel consumption of the machinery, will total a reduction in the carbon footprint of the farm itself.

Expected production estimates were obtained using the Decision Support System for Agrotechnology Transfer (DSSAT v4), a biophysical simulation modeling tool. 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 from the previous 30 years for Henderson County were obtained from the University of Kentucky Agricultural Weather Center (2008). Identification of the soil series data in Henderson County were obtained from a National Cooperative Soil Survey of Henderson County, Kentucky from the USDA Natural Resource Conservation Service (NRCS) (2008) and the NRCS Official Soil Series Description (Shockley, Dillon and Stombaugh, 2011).

The four representative soils utilized in DSSAT are deep silty loam (DSL), deep silty clay (DSC), shallow silty loam (SSL) and shallow silty clay (SSC). 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). By utilizing 30 years of weather data and varying production practices, the model is given strength and is able to be employed for an extensive number of scenarios.

The Economic Environment

The objective of these models is 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 and the cost of the ownership of the PATs in applicable models. Decision variables in the models include corn and soybean production acreage under alternative production practices for which mean net returns above specified costs and the estimated carbon equivalents are determined. The cost of ownership for the PATs included the annualized depreciation and the opportunity cost of capital invested

for the different machinery components across production strategies. However, it did not include costs for machinery which remained the same for each scenario, such as the combine.

Production practices for soybeans included nine available planting dates ranging weekly from April 22nd through June 17th, three plant variety options and three population density options as well as two row spacing options. Production practices for corn included nine available planting dates ranging weekly from March 25th through May 30th, three plant variety options, three plant population density options and five nitrogen fertilizer rate options. Both corn and soybeans had the option of early (H1) and late (H2) harvest (Shockley, Dillon and Stombaugh, 2011). For specific production practice information see Tables 2.1 and 2.2. Based on the decision variables, the models produced results including optimal expected yields and mean 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 appendix 2A.

Constraints include land, crop rotation, labor and soil constraints when PATs are employed. The land area chosen for this study corresponds to a typical Henderson County, Kentucky corn and soybean farmer. According to Kentucky Farm Business Management (KFBM), Kentucky grain farm size averaged 2,350 acres in 2010; that acreage level was determined to be appropriate and was assumed for this study. Additionally, the crop rotation constraint required that no more than 50% of the land available is used to produce corn and no greater than 50% is allocated to produce

soybeans; a 2-year crop rotation represents a typical Kentucky grain producer (Shockley, Dillon and Stombaugh, 2011).

Required labor hours were determined based on the field capabilities of the operating machinery. Labor constraints include planting, spraying, fertilizing, harvesting, suitable field days and labor available. Suitable field days were calculated based on the probabilities of it not raining 0.15” or more per day over a period of a month¹. The probabilities were then multiplied by the hours worked in a day and days worked in a week to determine the expected suitable field days per week (Shockley, Dillon and Stombaugh, 2011). The average number of suitable field days available per week was 4.76 with a standard deviation of 0.79.

Price expectations for each commodity were necessary for calculating the expected net returns. The price expectations for both corn and soybeans were calculated using

$$PE_c = \left[.5 \left(\frac{\sum P_{cwy}}{\sum T_{cy}} \right) + .33 \left(\frac{\sum P_{cwy}}{\sum T_{cy}} \right) + .17 \left(\frac{\sum P_{cwy}}{\sum T_{cy}} \right) \right] - 0.26 ,$$

where PE_c is the price expectation for crop c , P_{cwy} is the realized price for crop c in week w during year y and T_{cy} is the number of weekly realized price observations for crop c during year y (Chavas and Holt, 1990). Cash price observations were collected from the Kentucky Green River grain elevator from January 1, 2009 to December 31, 2011. A \$0.26 haul fee was subtracted from the weighted average price to account for the transportation cost of taking the commodity to market.

Several calculation methods were considered while conducting this research. Three years’ price data was determined to be an acceptable blend between reflecting

¹ This was determined from the 30-year historical weather dataset previously mentioned.

more observations while emphasizing recent rises in grain prices. Ultimately, the three year weighted average less the haul fee based upon Chavas's work on corn and soybean prices was determined to be the most reliable method for calculating these price expectations. The prices used for this study were \$11.59/bu and \$5.16/bu for soybeans and corn, respectively.

Results

Under the four production strategies there are three separate areas where changes due to the adoption of PAT can be individually observed: economic, environmental and production.

Economic Observations

The modeling of PAT strategies resulted in increased mean net returns for all PAT scenarios over the Base model. ASC-L proved to be the most profitable of the four production strategies, exhibiting mean net returns of \$1,279,814, an increase of 0.47% over the base model (without PAT). SUB is economically the second best alternative providing a 0.42% increase in mean net returns while RTK produces a 0.36% increase in mean net returns over the base model (Table 2.3). The 0.05% difference in net returns between SUB and ASC-L can be attributed to the varying levels of input use reduction, further explored below. The level of economic favorability is determined by the level of precision of the equipment, cost of ownership and the benefits accrued from efficiency gains such as cost savings and, to a lesser degree, yield improvements.

The increase in mean net returns with the use of ASC-L can be attributed to the fact that it has the ability to spray herbicide and insecticide more effectively by controlling specific sections of the boom. With the ability to precisely control sections of

the boom, overlap is reduced which is not possible without the use of PAT. The reduction in overlap produces a decreased use of pre- and post-plant herbicides (10.55%), sprayer fuel (15.58%), insecticide (10.55%) and nitrogen (0.14%) (Table 2.4). Together, the reduction in the use of these inputs totals a 1.1% decrease in variable costs from the base model. The profit increase can largely be attributed to both a cost decrease and an increase in yields from shifting production practices, as discussed in the production results section.

SUB decreased the use of pre-plant and post-plant herbicide (6.94%), sprayer fuel (15.58%), insecticide (6.94%) and nitrogen (0.14%). SUB and ASC-L are closely related PATs, as evidenced by the reduced use of the same inputs (of varying levels) and the nearly identical economic results. While ASC-L has an annual ownership cost of \$2,161.50 greater than that of SUB, the increased reduction in specific input costs with the use of ASC-L has allowed it to be a more economically lucrative production strategy for the farmer.

While it was not an objective of this study to determine production risk management options associated with the adoption of the PATs investigated, the coefficient of variation (CV) can be used as a measure of risk. As the mean net returns for each PAT decreased, the CV simultaneously increased, with ASC-L having the lowest CV and RTK the highest. Both SUB and ASC-L had a standard deviation of \$200,222 and a net returns range of \$816,498, with the minimum net returns exceeding the minimum base net returns. However, RTK has a larger net returns range (\$825,721) with a minimum net returns less than Base and a standard deviation of \$201,955 (Table 2.3). From this it can be surmised that minimal alterations in risk is experienced with these

PATs as compared to Base. However, if a producer were solely concerned with increasing profits, any of the three PATs examined here would provide the farmer with those desired results as compared to a conventional farming strategy (Base).

Environmental Observations

While all of the precision agriculture technologies investigated in this study produced an enhanced environmental result, RTK is the most rewarding. In this study, RTK is the most precise applicator of nitrogen and seed, allowing for reduced over and under application (overlap) of those inputs. With this reduction in overlap, it takes fewer passes with the PAT machinery over the field at the optimal time to produce the optimal results, thereby also reducing tractor fuel needs. The reductions in overlap and tractor fuel combined with the use of RTK decrease the carbon emissions by 2.60% and improve the carbon ratio by 2.74% over the base model (Table 2.4). RTK is the only technology investigated that reduced the carbon emissions associated with nitrogen fertilizer, seed and tractor fuel.

When modeling the carbon aspect, a carbon number was associated with each unit of input reported on the table. Nitrogen is a carbon intensive input with an estimated carbon equivalent mean of 1.3, meaning that nitrogen fertilizer is 1.3 times more carbon intensive than carbon alone which has a carbon equivalent of 1 (Lal, 2004). The use of nitrogen fertilizer for corn production is a major source of CO₂ and N₂O emissions, two of the most harmful GHG produced. Furthermore, nitrogen is the largest contributor to the carbon footprint in this study, accounting for between 63.3% - 64.4% of the total carbon footprint depending on the model. RTK has the ability to directly reduce nitrogen emissions by applying the fertilizer more precisely on the field, resulting in a 2.67%

(3,618 teragrams) reduction in nitrogen use. Enhancing nitrogen use efficiency is an important step to reducing the agricultural sector's emissions of greenhouse gases.

The substantial nitrogen reduction with the use of RTK is due to the precision application associated with the technical specifications of this machinery component. However, rather than a technical efficiency, ASC-L and SUB offer an indirect 0.14% reduction in nitrogen use due to a redistribution of corn planted acreage. The redistribution occurred because, with SUB and ASC-L, soybean burndown was accomplished earlier allowing for more corn acres to be planted at the optimal time and with a lower profit maximizing nitrogen rate associated with that planting date.

With regards to seed, the carbon equivalent number indicates the amount of carbon related to the production and sales of each individual seed. With RTK, a 2.35% reduction in seed use was realized, and while this may not seem substantial, seed accounts for almost 10% of the total carbon footprint and is the second largest contributor to the carbon footprint in this model (Table 2.5). The reduction in the amount of seed used can be attributed to the reduction in overlap with the use of RTK, thus providing improved results over the other production strategies. RTK is the only production strategy investigation in this study with the ability to more accurately place seeds in the field.

The carbon equivalent for tractor fuels indicates the amount of carbon related to the production and combustion of tractor fuel used. RTK uses 10.43% less fuel than the other production practices modeled which accounts for approximately 6% of the total carbon footprint. With the increased precision of RTK, the farmer is able to reduce overlap which directly corresponds to the realized reduction in tractor fuel.

Of course, SUB and ASC-L both provide environmental enhancements with reductions in their carbon footprint of 1.17% and 1.64%, respectively, from Base (Table 2.4). Both SUB and ASC-L are capable of applying agrochemicals more precisely than the Base and RTK models. As such SUB reduces the carbon emissions by 6.94% and for pre-plant herbicide, post-plant herbicide and insecticide and ASC-L reduces the carbon emissions by 10.55% for pre-plant herbicide, post-plant herbicide and insecticide. This increased precision of spraying corresponds to a reduction in overlap leading to a reduction in the time the machinery will be in use, ultimately leading to a 15.58% decrease in sprayer fuel used. The economic and environmental results illustrate a potential tradeoff between optimal economic efficiency and optimal environmental stewardship.

Production Observations

Differing optimal production practices by technology are exhibited for both corn and soybeans. For example, optimal soybean planting with the use of RTK is done on April 22nd and 29th while SUB and ASC-L utilize April 22nd and May 6th. This occurs due to the competition for suitable field hours for either applying nitrogen fertilizer to corn or planting soybeans, which can happen in the same week. The marginal value product (MVP), or shadow price, for labor jumps from \$102.15 for Base, SUB and ASC-L in week 17 (April 22nd) to between \$494.36 and \$531.13 in week 18 (April 29th) while RTK's MVP of labor is zero or \$30.59 for those same weeks respectively (Table 2.6). It is not optimal for Base, SUB and ASC-L to plant soybeans on April 29th, however it is optimal the week before and the week after, implying that it is more important for the

nitrogen application on corn and that there is a desire to simultaneously plant soybeans and fertilize corn on April 29th (Tables 2.7 and 2.8).

The difference in PAT capabilities plays into this shifting as well, whereas SUB and ASC-L increase the efficiency of spraying while RTK increases the efficiency of planting. Given that, the changes in production practices are directly related to the reduction in overlap seen with the use of RTK. With the enhanced performance of field operations and the reduced field time requirements, RTK enhances the efficiency of planting and nitrogen application. The observed increase in optimal production practices, including plant population, planting date and fertilizer application, resulted in token yield increases across all PATs (Table 2.3).

Corn production is directly affected by the adoption of PATs in several ways. While soybeans only utilize one maturity group, corn utilizes two maturity groups (Table 2.9). Different maturity groups have different lengths of growing time which can lead to different harvest times for corn that was planted at the same time. By utilizing more than one maturity group harvest time is managed by redistributing acres to an optimal production schedule (Table 2.9). For the April 1st corn planting date, there is a shift from early to late harvest and a subsequent shift in acres produced. This is due to the competition for planting soybeans and the last post-plant fertilizer for corn occurring simultaneously. There is a desire to plant soybeans as early as possible and, with the increase in post-plant capabilities, soybean planting is shifted earlier as well as corn planting. These alterations in production practices exemplify the importance of whole farm analysis models and the need to modify production practices to extract the most gains possible from the technologies at hand (Shockley, 2010).

Discussion

It is clear from the results that with the use of the three PATs investigated there is a potential Pareto improvement associated with each technology over the base model. The farmer receives a higher net return and the carbon footprint is reduced. These results are substantial because no other study was found to provide empirical results of PAT's impact on the carbon footprint. The results show that there is both an economic and environmental gain to be realized with the use of PATs, which implies that each PAT can produce a potential Pareto improvement for the farmer and society. If this is truly a potential Pareto improvement over the base model, it raises the question as to what the adoption rate is for corn and soybean producers. If not 100%, then why have they not adopted said technologies?

There have been several studies looking at factors affecting the adoption decisions of PATs and numerous factors were found to influence a farmer's decision to adopt or not. Rather than general education level, results indicated that farmers were more likely to adopt a GPS guidance system if they had previous experience with PATs or if they used a computer for some type of farm management activity. In addition, younger farmers, more affluent farmers and farmers with larger farms were found to have a higher adoption rate than their counterparts. Also, farmers specializing in grains or oilseeds were more likely to adopt than livestock farmers. This would suggest that targeted extension programs, possibly to older farmers or medium sized farms, could be beneficial in increasing the adoption rate of PAT, which would in turn possibly lower the carbon footprint of the agricultural sector in that area (Banerjee et al., 2008; Daberkow and McBride, 2003).

According to an ERS study (Daberkow and McBride, 2003), 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 acreage associated with the farm and the crops in production. 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 technology, mechanical or informational, 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 Corn Belt regions. This can be attributed at least partially to the fact that this is where yield monitors were first introduced and developed specifically for corn and soybean production. These regions are major corn and soybean producers, and a sizeable PAT service sector has been established there (Daberkow, Fernandez-Cornejo and Padgitt, 2002). 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 succumb to the pressures put on the market by the larger farms and might either dissolve or be liquidated into the surrounding larger farms.

To help both the large and small farmers acquire the machinery necessary to keep them competitive, the USDA Natural Resource Conservation Service (NRCS) has enacted two programs: 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. The contracts provide financial assistance to help plan and implement conservation practices that address natural resource concerns and for opportunities to improve soil, water, air and related resources on agricultural land and non-industrial private forestland. EQIP provides financial assistance payments to eligible producers based on a portion of the average cost associated with practice implementation. In 2011, the EQIP program had contract obligations averaging \$68.25 per acre (“EQIP Data”, 2011). While this program is not specifically directed toward PAT practices, it does not exclude them either. For the 2,350 acre farm and given the cost of ownership of PATs used in this study, the cost of ownership per acre would be \$0.42, \$1.37 and \$2.09 for SUB, ASC-L and RTK, respectively. If this farmer applied and was accepted into the EQIP program for half of the average cost of implementation, the payments they could receive would substantially offset their costs of adopting an economically and environmentally optimal technology.

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. The contracts can run five years in length and have a maximum payment of \$40,000 per annum. (“Fact Sheet: Conservation Stewardship Program”, 2011) The advantage that CSP has over EQIP is that it specifically targets farmers who utilize PATs as a conservation practice. Of the

many activities outlined on the CSP program, PATs are 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 Activity List”, 2011). All three of these specified activities are included in the PATs investigated in this study.

With the potential Pareto improvement shown in this model, it is demonstrated that the farmers who adopt these PATs could enjoy a competitive advantage. Porter stated in his 1995 paper that there is a battle between economic gains, or industrial competitiveness, and environmental goals due to the notion that the nature of decisions is static on the part of the producer. However, part of Porter’s hypothesis theorized that with regulation, innovation will occur, ultimately leading to a more efficient process and product. Therefore “competitive advantage ... rests not on static efficiency nor on optimizing within fixed constraints, but on the capacity for innovation and improvement that shift the constraints.” (Porter and Vanderlinde, 1995, p. 98) It can be surmised that this chain of events would then encourage innovative competitiveness within the producers of a given sector. As applied to this study, the producers that adopt PATs are at a competitive advantage due to the increased profitability associated with PATs. In addition, if more strict environmental regulations were placed on the agricultural sector, those already employing PATs would also have a first mover advantage (Porter and Vanderlinde, 1995; Wanger, 2003).

Summary and Conclusions

Precision agriculture is both economically viable and more environmentally beneficial than conventional farming for the conditions examined due to the alterations in production practices and the reduction of the carbon footprint associated with the use of PAT. The reduction in the carbon footprint with the use of precision agriculture can be attributed to several factors. Due to the increased precision of these technologies, the application of fertilizers and seeds is more efficient, leading to fewer inputs being used thereby reducing the carbon footprint of the operation. With the decrease in input requirements there is a reduction in the carbon footprint both directly and indirectly. First, the production of the inputs carries a direct carbon footprint while, secondly, the application of inputs on the farm carries a carbon footprint attributed to the fuel consumption.

This study compares economic, environmental and optimal production results of three PATs to a base model of conventional farming. The findings demonstrate that all of the PATs used in this study produce a potential economic and environmental Pareto improvement over the base model. Specifically, ASC-L gave the greatest improvement with a mean net return that was 0.47% over the base. This is attributed to the fact that ASC-L has the ability to spray more precisely thereby reducing the over and under application of certain inputs. RTK provided the most significant enhancement to the carbon ratio with an improvement of 2.74% over the base model. This is attributed to RTK's increased technical efficiency with the ability to apply nitrogen and seed more accurately than the other PATs investigated. With the increased accuracy labor was able

to be allocated more efficiency allowing for more optimal production practices to be employed. All of these improvements over the base scenario can be attributed to the reduced use of inputs and the alternative optimal production practices associated with the adoption of PAT.

This study aimed to explore the environmental implications of PATs which until now has been an information void in the applicable literature. The empirical results presented could be extremely useful when used in the appropriate settings. Using this information, policy makers will have a better understanding of the potential benefits associated with PATs. Additionally, this information can be used to help regulators make choices between such measures as environmental restrictions or minimum technology requirements. Producers will have more access to information that could help in determining if PATs are a fit for their farm. Using this information could help them in getting over the technological hump that so often discourages farmers from adopting PATs. Researchers could use this study as a baseline for further research, including research into PATs not investigated in this study or by using this modeling process to apply it to different commodities and/or different farming communities.

Table 2.1 – Summary of Corn Production Practices

Planting Date	March 25, April 1, April 8, April 15, April 22, April 29, May 6, May 13, May 20
Maturity Group (growing degree days)	2600, 2650, 2700
Plant Population (plants/acre)	24,000, 28,000, 32,000
Fertilizer Rate (nitrogen lbs/acre)	100, 150, 175, 200, 225
Harvest Week ¹	H1, H2
Row Spacing	30"
Plant Depth	1.5"

¹H1 indicates an early harvest time and H2 indicates a late harvest time.

Table 2.2 – Summary of Soybean Production Practices

Planting Date	April 22, April 29, May 6, May 13, May 20, May 27, June 3, June 10, June 17
Plant Variety (maturity group)	MG2, MG3, MG4
Plant Population (plants/acre)	111,000; 139,000; 167,000
Harvest Week ¹	H1, H2
Row Spacing	38", 76"
Plant Depth	1.25"

¹ H1 indicates an early harvest time and H2 indicates a late harvest time.

Table 2.3 – Economic Results by Production Strategy

	BASE	SUB	ASC-L	RTK
Mean Net Returns	\$1,273,812	\$1,279,220	\$1,279,814	\$1,278,399
% from base		0.42%	0.47%	0.36%
Minimum Net Returns	\$830,981	\$832,882	\$833,476	\$824,494
% from base		0.23%	0.30%	-0.78%
Maximum Net Returns	\$1,643,176	\$1,649,380	\$1,649,974	\$1,650,215
% from base		0.38%	0.41%	0.43%
Standard Deviation	\$199,463	\$200,222	\$200,222	\$201,955
% from base		0.38%	0.38%	1.25%
Coefficient of Variation	15.66	15.65	15.64	15.80
% from base		-0.06%	-0.13%	0.89%
Total Specified Cost	\$580,983	\$575,987	\$575,393	\$577,869
% from base		-0.86%	-0.96%	-0.54%
Average Soybean Yield (Bu/Acre)	62.18	62.20	62.20	62.27
% from base		0.03%	0.03%	0.14%
Average Corn Yield (Bu/Acre)	166.25	166.27	166.27	166.31
% from base		0.01%	0.01%	0.04%

¹ BASE refers to operating without any precision agriculture technology.

² SUB refers to the adoption of a bolt-on auto-steer system equipped with a sub-meter receiver.

³ ASC-L refers to the adoption of automatic section control with lightbar technology.

⁴ RTK refers to the adoption of an integral valve system with a real time kinematic GPS receiver mounted onto a tractor.

Table 2.4 – Carbon Footprint by Input and Production Strategy^{1 2}

	BASE	SUB	ASC-L	RTK
Pre-Plant Herbicide	9647	8977	8629	9647
% from base		-6.94%	-10.55%	0.00%
Post-Plant Herbicide	16086	14969	14389	16086
% from base		-6.94%	-10.55%	0.00%
Tractor Fuel	14053	14053	14053	12587
% from base		0.00%	0.00%	-10.43%
Sprayer Fuel	2515	2123	2123	2515
% from base		-15.58%	-15.58%	0.00%
Insecticide	2033	1892	1818	2033
% from base		-6.94%	-10.55%	0.00%
Nitrogen	135576	135383	135383	131958
% from base		-0.14%	-0.14%	-2.67%
Seed	20856	20856	20856	20366
% from base		0.00%	0.00%	-2.35%
Other Fuel	13372	13372	13372	13372
% from base		0.00%	0.00%	0.00%
Total Carbon Footprint	214137	211623	210623	208562
% from base		-1.17%	-1.64%	-2.60%
Total Carbon Output	6275227	6276363	6276363	6279165
Carbon Ratio	29.30	29.66	29.80	30.11
% from base		1.21%	1.69%	2.74%

¹ All figures are reported using teragrams as units.

² Refer to Table 2.3 for an explanation of BASE, SUB, ASC-L and RTK.

³ Carbon output refers to biomass produced which is directly linked to yields.

Table 2.5 – Carbon Footprint by Input and Production Strategy as a Percentage of Total Carbon Footprint¹

	BASE	SUB	ASC-L	RTK
Pre-Plant Herbicide	4.50%	4.24%	4.10%	4.63%
Post-Plant Herbicide	7.51%	7.07%	6.83%	7.71%
Tractor Fuel	6.56%	6.64%	6.67%	6.03%
Sprayer Fuel	1.17%	1.00%	1.01%	1.21%
Insecticide	0.95%	0.89%	0.86%	0.97%
Nitrogen	63.31%	63.97%	64.28%	63.27%
Seed	9.74%	9.86%	9.90%	9.76%
Other Fuel	6.24%	6.32%	6.35%	6.41%

¹ Refer to Table 2.3 for an explanation of BASE, SUB, ASC-L and RTK.

Table 2.6 – Labor Marginal Value Product by Production Week^{1 2}

Week	BASE	SUB	ASC-L	RTK
17	102.15	102.15	102.15	30.59
18	531.13	494.36	494.36	-
35	171.55	171.55	171.55	251.28
36	239.41	239.41	239.41	320.04
37	239.41	239.41	239.41	320.04

¹ Figures are reported in dollars/unit of labor.

² Refer to Table 2.3 for an explanation of BASE, SUB, ASC-L and RTK.

³ Week refers to the Julian calendar week.

Table 2.7 – Production Schedule for Corn and Soybeans by week^{1 2}

	Corn	Soybeans
Week 9	Burndown	
Week 13	Plant	Burndown
Week 15	Post-plant herbicide	
Week 17	Post-plant herbicide	Plant
Week 18	Nitrogen application	
Week 21		Post-plant herbicide
Week 32		Post-plant herbicide
Week 35	Harvest	Harvest

¹ This is an example schedule for one planting date (corn on 25-Mar, soybeans on 22-Apr). This schedule will fluctuate based upon differing production practices.

² Week refers to the Julian calendar week.

Table 2.8 – Optimal Soybean Production by Date, Harvest Period and Production Strategy^{1 2}

Planting Date	Harvest Period ³	BASE	SUB	ASC-L	RTK
22-Apr	H1	217.66	489.55	489.55	404.80
	H2	685.45	480.57	480.57	685.45
29-Apr	H1	-	-	-	-
	H2	-	-	-	84.74
6-May	H1	-	204.88	204.88	-
	H2	271.86	-	-	-

¹ Figures reported are in acres per planting date and harvest period.

² Refer to Table 2.3 for an explanation of BASE, SUB, ASC-L and RTK.

³ H1 indicates an early harvest time and H2 indicates a late harvest time.

Table 2.9 – Optimal Corn Production by Planting Date, Harvest Period, Maturity Group and Production Strategy^{1 2}

Planting Date	Harvest Period ³	Maturity Group ⁴	BASE	SUB	ASC-L	RTK
25-Mar	H1	2650	356.16	356.16	356.16	356.16
25-Mar	H1	2700	303.61	344.29	344.29	344.29
	H2	2700	362.11	334.55	334.55	362.11
1-Apr	H1	2700	40.68	-	-	-
	H2	2700	-	27.55	27.55	-
15-Apr	H2	2700	112.45	106.53	106.53	112.45

¹ Figures reported are in acres per planting date, harvest period and maturity group.

² Refer to Table 2.3 for an explanation of BASE, SUB, ASC-L and RTK.

³ H1 indicates an early harvest time and H2 indicates a late harvest time.

⁴ Growing degree days.

Chapter Three

Developing a Carbon Efficient Frontier: Examinations of Variable Rate Technology

With the heightened interest in the role that the agricultural sector plays in carbon emissions specifically, and climate change in general, it is imperative to find new ways to see through the looking glass. An innovative modeling technique is designed in this study wherein, using Kentucky farm-level data for corn and soybean production in Henderson County, a carbon efficient frontier is developed. The objective of this study was trifold: 1) to develop a new modeling process that will be used to determine a carbon efficient frontier (CEF), 2) to use empirical results to develop a marginal abatement cost curve (MACC) and 3) to understand through the empirical results what factors drive production changes with the restriction of the carbon footprint.

The development of this model has two components. First, the model employs two production techniques: conventional uniform rate farming and variable rate technology. Second, a carbon footprint restriction is placed upon the model in order to obtain optimal results required to trace out the frontier. Methodologically, the development of a carbon efficient frontier has not been done previously nor have farm-level carbon footprint restrictions been explored; however, there have been several studies that have developed a MACC. A MACC is a tool that can be used to help producers make short-run, within-season decisions, such as plant population, fertilizer rate or planting date. A CEF is a tool for strategic, long-run evaluation that can help farmers make adoption decisions. A further contribution of this study is to identify potential policy actions that could lead to reduced GHG emission from the agricultural sector.

The mathematical programming model used to develop the CEF will incorporate a type of precision agriculture technology (PAT): variable rate technology (VRT). VRT is defined as any technology that allows producers to vary the rate of crop inputs. VRT allows for the application of fertilizer, lime, seed and pesticide at different rates as the machinery moves across the field ultimately achieving site-specific results (Schimmelpfennig and Ebel, 2011). Site-specific management allows one to recognize the inherent spatial variability recognized in most fields under crop production (Koch et al., 2004). With VRT, producers are able to enhance management decisions by varying the locations of inputs applied within the field and applying them at the optimal levels according to the unique properties of a specified location. This technology has the potential to reduce input and labor costs, increase productivity and reduce the over/under application of inputs thereby increasing environmental efficiency as well. The overuse of fertilizer can lead not only to higher costs but nutrient leaching from farms into wells and waterways. Nitrogen, the main fertilizer for corn production, when not incorporated into the soil, can oxidize into nitrous oxide (N_2O) and be released into the atmosphere as a GHG. The IPCC stated that the reduction of N_2O emissions by improving fertilizer application processes from the agricultural sector is a key component to reducing GHG emissions (IPCC, 2007; Schimmelpfennig and Ebel, 2011).

In 2007, the agricultural sector was responsible for 413.1 teragrams of carbon dioxide (CO_2) emissions (approximately 6%) (USEPA, 2009), 50% of the total anthropogenic methane (CH_4) emissions and 75% of the total anthropogenic N_2O emissions (Cole et al., 1997; Rodhe, 1990). Each GHG has a different warming influence on the climate due to differing radioactive properties and life spans in the atmosphere. In

this study, these differing warming influences are converted to a CO₂ emissions equivalent using a metric based on the radioactive forcing of CO₂. This emissions equivalent is a useful tool for comparing emissions of different anthropogenic GHGs, but does not imply the same climate change responses for each gas (IPCC, 2007).

The United States Department of Agriculture (USDA) Natural Resource Conservation Service (NRCS) assists farmers in adopting and implementing precision agriculture techniques through two current programs: the Environmental Quality Incentives Program (EQIP) and the Conservation Stewardship Program (CSP). Both of these programs are voluntary, offering financial and technical assistance to agricultural producers through the use of contracts with the land owners. The assistance is offered with the intent to help plan and implement conservation practices that address natural resource concerns.

One issue plaguing policy makers is how to determine the level of assistance needed by the farmers in order for them to implement the practices necessary for the reduction of environmental impacts. A contribution of this study is to introduce the new concept of a carbon efficient frontier as an evaluative mechanism to complement the commonly used marginal abatement cost curve, herein associated with VRT, to shed some light on this issue. With this information, policy-makers can more accurately identify the cost of a given level of carbon reduction and offer appropriate contracts to meet the needs of producers. Producers will also be able to make a more informed decision as to the practices they can choose in order to reduce their environmental impact according to the contracts set forth.

Literature Review

There have been several studies that utilize a biophysical simulation model with an economic optimization model to determine pollution levels from agricultural sources. These studies use both the biophysical simulation and a mathematical programming model that forces management decisions from a discrete set of choices: such as fertilizer rate, tillage or rotations (Weersink, Dutka and Goss, 1998). The pollution limits are set by the biophysical model and act as the constraint on the mathematical programming (economic) model. This type of constraint enforcement causes a reduction in profits from the unconstrained model, then using the reduction in profits one is able to measure the abatement cost of the pollution limit (Helfand and House, 1995; Johnson, Adams and Perry, 1991; Taylor, Adams and Miller, 1992).

Yiridoe takes this principle and conducts a study that characterizes the MACC in order to evaluate the cost effectiveness of meeting specific environmental standards. The model in Yiridoe's study evaluates the optimal level of nitrogen fertilizer rates and on-farm abatement costs for alternative farming systems as continuous choice variables while meeting environmental quality standards. The study specifically looks at groundwater nitrogen pollution and groundwater nitrogen leaching (Yiridoe and Weersink, 1998). The MACC used was a stepwise function with a discrete set of management choices; other studies that have used such an approach to estimate abatement costs include Randhir and Lee (1997) and Weersink, Dutka and Goss (1998).

MACCs have been developed for emissions using qualitative methods (Boyd, 1996; De Cara, Houze and Jayet, 2005; EPA, 2006; McCarl and Schneider, 2001; Perez, 2005; Smith et al., 2007; Weiske, 2005; Weiske and Michel, 2007). MACCs have been

used as a convenient tool for environmentally related policy analysis as several studies argue that environmental innovation shifts the MACC downward (Fischer and Sterner, 2012; Jaffe, Newell and Stavins, 2002, 2005; Montero, 2002; Porter and Vanderlinde, 1995). While these models are generally theoretical, there are empirical studies that dispute this fact and argue that the true response to technological innovation is an upward shift in the MACC (Amir, Germain and van Steenberghe, 2008; Brechet and Jouvét, 2008). Moran uses a bottom-up exercise to determine one MACC for an economically efficient greenhouse gas emissions budget for the whole of United Kingdom's agricultural sector. However, the aggregation of the data highlights weak points within the bottom-up approach (Moran et al., 2011).

Technology and innovation also have a role to play in pollution abatement. Many studies look at aggregated totals of technological innovation, meaning the abatement that could be achieved if all producers adopted certain technologies regardless of cost. This is considered the upper limit on abatement and since it will most likely never be realized, a lower level of adoption or abatement is normally chosen for modeling (Amir, Germain and van Steenberghe, 2008; Brechet and Jouvét, 2008; Fischer and Sterner, 2012; Montero, 2002; Moran et al., 2011). Moreover, there have been several studies have examined specifically VRT and its potential environmental impact. These studies have found that VRT are economically superior in most scenarios and to be more environmentally beneficial than conventional farming (Feiez, 1994; Intrapapong, 2002; Thrikawala, 1999).

Methods, Data and Procedures

A whole-farm analysis using a resource allocation model was conducted representing a hypothetical grain farmer producing corn and soybeans in Henderson County, Kentucky. This modeling process is a modification of a previous mathematical programming model (Shockley, Dillon and Stombaugh, 2011). The structure of the model used in this study includes production and economic environments as well as strategic and tactical decisions. Strategic, or long term decisions, include the adoption of VRT while tactical, or short term decisions, include planting date or fertilizer level, possibly using variable rate management.

The results from the model were used to construct a carbon efficient frontier CEF and a marginal abatement cost curve MACC. To construct the CEF, both mean net returns and the carbon footprint each restriction level was determined. To calculate carbon footprint, each production input and output is assigned a carbon equivalent according to pertinent research and literature (Lal, 2004). The reduction in energy and inputs due to the use of VRT will come from relevant literature as well (Lal, 2004). The inputs used to calculate the carbon footprint will include fertilizer, seed, herbicides, insecticides and fossil fuel combustion for each machine. Outputs used will include total biomass which is directly related to yields. To construct the MACC, both mean net returns and the carbon footprint for each restriction level was determined and using that information the marginal abatement costs for each level of restriction was calculated.

The Production Environment

VRT, a type of PAT, is an example of an information-intensive technology. An information-intensive technology is one that provides more information but also requires

additional management skills to make practical use of the technology (Winstead et al., 2010). The VRT applicators examined in this study have the ability to apply specify seed and nitrogen fertilizer applications to suit different sections of the field depending on soil type, nutrient needs and a variety of other conditions thereby reducing input costs without unnecessarily sacrificing yields thus leading to a higher profit for the producer.

Expected production estimates were obtained using the Decision Support System for Agrotechnology Transfer (DSSAT v4), a biophysical simulation modeling tool. 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. Data for the simulation was collected from the University of Kentucky Agricultural Weather Center (2008), the USDA Natural Resource Conservation Service (NRCS) (2008) and the NRCS Official Soil Series Description (Shockley et al., 2011). 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). Varying levels of nitrogen application for corn and seeding rate for both corn and soybean production is incorporated. Notably, there are especially important factors of production to consider from the carbon emissions perspective as demonstrated later. While alternative levels of other inputs (e.g. pesticides and fuel) would ideally be investigated, their impact on yield is not reflected in the biophysical simulation model and therefore beyond the scope of this study. For more information regarding the production requirements for the simulation please see Chapter Two.

The mathematical programming model contained two production strategies: uniform rate and variable rate. Uniform rate, or conventional farming, required the same amount of agrochemicals, fertilizer and seed to be applied to all areas of the field. VRT allowed for the economically optimal spatial allocation of nitrogen fertilizer on corn as well as corn and soybean seeding rate by soil type. A carbon footprint restriction was then imposed upon the model, allowing for a set of results for each level of carbon regulation. The mathematical representation of the carbon footprint equation can be found in Appendix 2A and the variable rate and uniform rate equations can be found in Appendix 3A.

The Economic Environment

The objective of the economic model was to maximize mean net returns above specified costs under varying allowable carbon footprint levels. The costs included in the models consist of input variable costs and VRT ownership costs. Decision variables in the model include corn and soybean production variables as well as production practices for which mean net returns above specified costs and the estimated carbon equivalents are determined. Based on the decision variables, the model produced results including economically optimal expected yields and mean net returns. A carbon footprint accounting variable was utilized to estimate the carbon emissions and carbon output from which the carbon ratio could also be determined. The cost of ownership for the VRT included the annualized depreciation as well as opportunity cost of investment for the different machinery components. However, it did not include costs for machinery used for both uniform and variable rate, such as the combine.

Production practices for soybeans included planting dates, plant variety, population density and row spacing options. Production practices for corn included planting dates, plant variety, plant population and nitrogen fertilizer rate options. Both corn and soybeans had the choice between early (H1) and late (H2) harvest options (Shockley, Dillon and Stombaugh, 2011). For specific production practice information see Tables 2.1 and 2.2 in Chapter Two. For information regarding land, labor, crop rotation, soil constraints and suitable field days, refer to Chapter Two.

In addition to the constraints and decision variables discussed, price expectations were also required. Using Chavas and Holt's (1990) formulation, a weighted average price for both corn and soybeans was calculated. The formula utilized was:

$$PE_c = \left[.5 \left(\frac{\sum P_{cwy}}{\sum T_{cy}} \right) + .33 \left(\frac{\sum P_{cwy}}{\sum T_{cy}} \right) + .17 \left(\frac{\sum P_{cwy}}{\sum T_{cy}} \right) \right] - 0.26 ,$$

where PE_c is the price expectation for crop c , P_{cwy} is the realized price for crop c in week w during year y and T_{cy} is the number of weekly realized price observations for crop c during year y (Chavas and Holt, 1990). Cash price observations were collected from the Kentucky Green River grain elevator from January 1, 2009 to December 31, 2011. A \$0.26 haul fee was subtracted from the weighted average price to account for the transportation cost of taking the commodity to market. The prices used for this study were \$11.59/bu and \$5.16/bu for soybeans and corn, respectively. Further details on the price expectation calculation method may be found in Chapter Two.

Results

The results from the model were used to develop a CEF, a new technique that has not previously been used before, and a MACC. The CEF can be likened to a mean

variance (E-V) frontier. An E-V frontier considers efficient tradeoffs between profitability (expected value of net returns) and risk (variance of net returns) while the CEF examines the tradeoff between profitability and environmental stewardship. With an E-V frontier, a decision-maker's risk attitude determines where a producer should operate on the frontier. In parallel fashion, the CEF focuses upon the efficient tradeoff between profitability and environmental outcome. Consequentially, the CEF depicts the greatest mean net returns that a farmer could be expected to achieve given a specific carbon restriction under a given production strategy selection (uniform rate and variable rate).

Given the complementary advantage of both a CEF and a MACC, and the fact that they are not mutually exclusive, the two techniques may be jointly considered to strengthen comprehension of the economic consequences of adoption to enhanced environmental stewardship. The CEF arguably provides a direct focus on evaluating technology adoption in that the consideration of expected net returns with corresponding costs of ownership allows for direct comparison between strategic choices. Thus it serves as an appropriate decision-making tool for farm managers considering the most profitable technology to adopt under varying levels of economic performance. Furthermore, it reflects the adaptive behavior of decision makers regarding technology choice changes providing valuable information regarding proportions of farm operations using the different production technologies. As such, it can provide needed information to policy makers. Meanwhile, the more familiar MACC offers a means of focusing upon incremental costs associated with achieving environmental well being as a product. Specifically, concentration upon tactical alterations in management highlight the opportunity costs of varying environmental performance levels for a given technology

adoption strategy. Thus, jointly considering the two tools can provide synergism in guiding environmental policy making and farm management decisions.

Results for the CEF are displayed in Figure 3.1. For almost all levels of carbon restriction, it can be seen on the frontier that VRT is an economically and environmentally superior option to uniform rate. The notable exceptions are the case of no environmental constraint or extreme levels of carbon emissions restriction. Therefore, one would surmise that there would be strong preference among producers for the adoption of VRT under the preponderance of carbon emission goals.

The superior potential for managers using VRT in environmental stewardship in an economically efficient manner is evident in the curvature of the VRT CEF as compared to the uniform rate CEF. The few opportunities for economically managing carbon emissions under uniform rate are soon depleted. The lack of options for effectively manipulating interactive effects across production practices is reflected in the linear form of the uniform rate CEF. The varied opportunity to engage in profit maximizing production practice substitution is exhausted in the nonlinearity of the VRT CEF. This adaptive behavior permits dramatically lower impacts from heightened environmental stewardship. Spatial management opportunities therefore afford adjustment to select areas of the field. As production practices on the preferred areas are modified, existing opportunities on less preferable areas of the field reflect profitability decreasing at an increasing rate. In the extreme carbon emissions standards case, VRT will optimally operate under uniform application levels but still bear ownership cost burdens of the technology leading to greater profitability of uniform rate at these extreme restriction levels.

The MACC developed can lend insight into the ability to exploit the interactive effects of tactical decisions including seed, nitrogen and planting date. The interactive effects can reduce the economic consequences of environmental stewardship. These effects are identified with both uniform rate and VRT; however, the production changes vary by technology. Interestingly, note that a lower marginal abatement cost does not imply greater profitability of the technology.

For all levels of carbon footprint restriction, direct changes were experienced with regard to nitrogen and seed rate (plant population) for both uniform rate and variable rate. This is because nitrogen and seed are the only two inputs used modeled herein under varying levels that are directly able affect the carbon footprint. With uniform rate, the most effective direct compensating factor was the reduction in the use of nitrogen fertilizer. The amount of nitrogen applied consistently decreased with each increase in carbon footprint restriction with the exception of a large initial decrease in response to the first constraint. The same nitrogen rate was applied to each soil type due to the fact that uniform rate does not have the ability to specify nitrogen application by soil type. VRT is able to manage carbon footprint restrictions through optimal application of nitrogen fertilizer based on a soil type's responsiveness to said fertilizer. As the economic opportunity of carbon reduction is exhausted, the lowest modeled nitrogen rate is applied and the fertility for the next best soil type is reduced until all soil types have been exploited (Figure 3.3). Specifically, the least profit reducing mechanism is exploited to cope with enhanced environmental performance. The marginal physical products of silty clay soils dictate that their yields suffer least from nitrogen decreases and consequentially face the greatest alterations in fertilization. This is especially true for shallow silty clay

soils. Notably, deep silty loam is the last soil type to experience nitrogen reductions reflective of the fact that it is the most productive soil in the model. This implies that the optimal application of nitrogen depends upon the soil fertility; a similar result was found in Koch, et al. (2004).

Seeding rate (plant population) is the second method modeled allowing direct management of the carbon footprint. With uniform rate, soybean plant population is constant throughout all levels of restriction. Soybean seed, in the unrestricted model, is at the lowest allowable plant population initially. With the addition of the carbon footprint constraint, there are no available alterations to the soybean seeding rate. With uniform rate, the same amount of seed has to be applied to all soil types; therefore there is no opportunity for specificity or increased accuracy with regards to seeding rates (Figure 3.4). However, unlike soybean plant population, corn plant population provides some measure of carbon footprint abatement management under the uniform rate application. Corn plant population, under uniform rate, consistently decreases with every level of carbon restriction imposed except for the lowest levels of the carbon footprint constraint (Figure 3.5). This is not surprising as reduction of nitrogen and seeding rate for corn are the only remaining avenues to lower carbon emissions and uniform rate affords no spatial management opportunities. Thus, a steady and uniform input reduction is required.

Initially, soybean plant population with the use of VRT is higher than with uniform rate. This is due to the fact that VRT allows for the optimal allocation of seed based on soil type. VRT is able to take advantage of the differences in soil productivity up until a restriction level of 172,000 teragrams (Figure 3.4). In part, this allows for a less severe decrease in nitrogen, limiting the impact on corn yields and profitability.

Specifically, spatial management alterations in corn population levels parallel nitrogen fertilizer results in that silty clay soils are reduced first followed by silty loam, with shallow preceding deep. As with uniform rate, corn plant population experiences generally consistent decreases with every level of restriction imposed (Figure 3.5). Corn plant population is more exploitable for both models, as there is a largely steady and predictable decrease in corn plant population seen throughout the experiment. However, VRT corn plant population is at a higher level throughout which in part leads to higher average yields and profitability of VRT.

In addition to the direct changes described, indirect changes were seen in the planting date due to interactive effects of production decisions. As the model seeks to maximize profitability there is a simultaneous desire to seek the least economical impact under carbon emission restrictions. Accompanying the alterations in production practices (seed and nitrogen which directly permit carbon reduction), an indirect effect is seen in the movement of optimal planting dates for both commodities. With uniform rate, there is an initial shift to later corn and soybean planting immediately followed by a return to the original early planting date. This is attributable to the later planting date's yield reduction congruent with lower nitrogen rates relative to the underlying marginal physical product for nitrogen on earlier planted corn. The initial substitution opportunities of changing planting date to lessen economic impacts of lowering carbon emissions under uniform rate were quickly exhausted under greater reductions. Subsequent carbon emissions reductions therefore are only possible with consistent decreases in nitrogen and corn seed with correspondingly substantial yield and expected net returns loss.

With the use of VRT, there was a change to a later planting date observed with moderate restriction levels for both corn and soybeans. However, with increased carbon footprint constraint, the option for interactive effects with regards to planting date is exhausted. The change in planting date is due to the fact that, like with uniform rate, the value of the marginal physical product is greater for later planting dates given the nitrogen level required to reach the required carbon footprint restriction.

The results indicate that at every abatement level of carbon footprint restriction VRT is an economically and environmentally superior option than uniform rate. This is due to direct consequences on the nitrogen rate and plant population and indirect consequences with regards to the planting date. The results exemplify the need for whole-farm modeling and to consider adaptive behavior and the simultaneity of production practices.

Discussion

The desire to regulate pollution may follow from a market failure within the agricultural sector which could result from either producers not having the right incentives to concern themselves with farm pollution, or a lack of information, meaning that farmers are unaware of the environmental consequences of their production (Weersink et al., 1998). The results of the present study indicate that at most levels of carbon footprint restriction, VRT is economically and environmentally superior to uniform rate. These findings compel two questions: 1) what information is gained from using the CEF and the MACC and 2) using the information gained, what policy measures are available and employable to achieve the goal of reducing the agricultural sectors environmental impact.

The MACC can be a useful tool for policy makers as it shows the cost of improving environmental quality. Within the scope of this study, the MACC shows the ability to exploit the interactive effects of tactical decisions including seed, nitrogen and planting date. The CEF focuses upon the efficient tradeoffs between profitability and environmental outcome given certain PATs. The CEF provides a convenient means of summarizing information on the tradeoff between economic and environmental benefits for alternative production strategies. CEF is especially useful for farmers when making technology adoption decisions. It can also provide insight into changes in producers' adoption of various technologies and in turn be used to develop an aggregate MACC that could help with policy decisions. The CEF identifies adaptive behavior of technology adoption by farmers, and, using a weighted average based on the percentage of technology adoption, a more accurate representation of adoption behavior is understood. By having more complete information on technology adoption, more accurate policy decisions can be made.

In order to achieve environmental goals, policy devices can be classified into two categories: command and control or incentive-based mechanisms. Command and control has been the dominant instrument for environmental policy regulation. Such regulations can direct polluters to conform in a number of ways, either by implementing a level of allowable pollution, types of activities that may be practiced or by enforcing minimum technology standards (Weersink et al., 1998). Minimum technology standards are common practice nowadays such as the bag leak detection systemⁱⁱ for hazardous waste

ⁱⁱ The bag leak detection system (BLDS) is a requirement for incinerators, cement kilns and lightweight aggregate kilns included in the national emission standards for hazardous air pollutants for sources that burn hazardous waste, enacted in October of 2005. The BLDS is an instrument that can monitor the

or the required use of scrubbersⁱⁱⁱ in coal-fired power generation facilities. The CEF is especially useful for minimum technology standard policies due to the fact that it considers net returns that are directly affected by the adoption of minimum technology standards.

Incentive-based designs are categorized as economic incentives, such as subsidies, taxes and tradable permits (Weersink et al., 1998). Hurwicz, Maskin and Myerson's (2007) theory of mechanism design can be employed as a tool for understanding the producer/regulator relationship (The Royal Swedish Academy of Sciences, 2007). Mechanism design proposes that for a policy to work effectively it should 1) take into account the incentives of self-interested agents and 2) that those agents must find it in their best interest to reveal that information (Cantillon and Legros, 2001). For this study, the information gained from the CEF and MACC provide insight into the incentives needed by the producers to implement a PAT. For instance, CEF might be especially germane in considering technology investment subsidies while when used in conjunction with MACC it might appropriately meld consideration of both technology adoption and tactical response to marginal abatement under tradable permits.

The use of a tradable permit system, or cap and trade system, has been used in the United States with varying degrees of success. In the 1980's this type of mechanism was used to eliminate lead in gasoline, saving the U.S. more than \$250 million per year. A caps and trade system was also used to reduce sulfur dioxide emission from power plants

changes in particulate matter emissions for the purpose of detecting fabric filter bag leaks or similar failures, which can release hazardous air pollutants. Source: US EPA

ⁱⁱⁱ All coal fire power generation facilities built after 1978 are required to have special devices installed that clean the sulfur from the coal's combustion gases before the gases go up the smokestack. The technical term for the device is "flue gas desulfurization units" but in layman's terms they are called "scrubbers". Source: US EPS

from 1990-2010, saving the U.S. upwards of \$1 billion dollars per year (Olmstead and Stavins, 2012). In addition to the two examples given, the European Union has a successful carbon permit program and more recently California created a carbon permit market as well. A cap and trade system focused on carbon emission reduction would be a more cost-effective way to reduce said emission than command and control mechanisms. This study provides a representative example of a farm located in the Corn Belt, and with this information, regulators could make more informed decisions when determining the optimal number of permits to be made available if a carbon permitting system were put in place for the agricultural sector.

A tax on pollution is another incentive-based design. With the MACC function, policy makers can determine what tax level would be needed to achieve a specific level of abatement. Alternatively, if policy makers choose to follow the Pigouvian strategy of setting the tax equal to marginal damages, the MACC function can predict the costs that producers will incur, and ultimately the effects on output levels and production choices. This type of mechanism design has been popular recently in academic circles, however it has received a cold welcome from policy makers (Olmstead and Stavins, 2012). With the CEF's ability to shed increased light on adaptive behavior shifts with regards to technology adoption, more accurate estimation of a tax mechanism can be achieved. Specifically, by using an aggregate measure of marginal abatement costs in conjunction with the CEF, when a tax aimed at carbon emissions is imposed upon the agricultural sector, a truer level of carbon emissions based upon the tax will be revealed.

One key issue in policy development is how uncertainty about the marginal abatement cost curve affects the ex post efficiency of price instruments (taxes) and

quantity instruments (tradable permits) (Weitzman, 1974). This study uses the mean outcomes, but future research could look at the variability of those outcomes in terms of analyzing the differences between these two types of policy instruments.

Given the issues facing regulators, such as what types of policies are available, such as the tradable permitting system or a tax, what the goals of the policies are and what effects on commodity productivity these regulations would have, both individual agents and entities concerned with carbon emissions can use the CEF and MACC in conjunction to help make more informed decisions. Regulators can use the information to help determine what type of policy would best suit their goals while producers can likewise use the information to determine strategic and tactical decisions. However, the CEF is a new and unfamiliar analytical tool and it will take further research in order to truly capture all of the benefits that the modeling process has to offer.

The CEF and MACC are tools that policy makers can use when determining what type of policy is best suited for the goals of the restriction. The MACC is a tool to help in policies that aim to place a direct restriction on the carbon footprint allowable from producers. The CEF is a tool to help with minimum technology standards in the aim of reducing the carbon emissions of agricultural producers. While the CEF and MACC are different tools, they are very complementary and, used in conjunction, could provide optimal results based upon the objectives of the decision makers, whether they be agricultural producers or policy makers.

Summary and Conclusions

In this model a carbon efficient frontier was developed as well as a marginal abatement cost curve, and in using those tools in a complementary fashion, insights into

what factors drive production changes when a restriction of the carbon footprint is enforced. The CEF allows for insights into strategic decisions while the MACC provides insights into tactical decisions. Seed and nitrogen rates are directly affected by the optimal production strategy while planting date is indirectly affected through interactive effects. These interactive effects ultimately tell the story of how producers will manage carbon emissions in the most economically efficient manner. The results show that VRT is an economically and environmentally superior production strategy at all restriction levels, with the exception of no restriction or very high restriction levels.

This new concept of a CEF will allow producers and policy makers to acquire more complete information with regards to farm level carbon emissions abatement techniques as well as more direct profitability and environmental tradeoff assessments. Used in conjunction with a MACC, regulations will more appropriately reflect changes in proportions of numbers of farmers engaged in abatement techniques for better aggregation of MACC results. Given this is a farm-level model of a typical Corn Belt type farm, further research could be conducted to look at similar operations in different parts of the country and corn and soybean producing states. Given the reliance on soil type for optimality with VRT, it can be inferred that differences in other production technologies, including other PATs, would be seen in varying parts of the country as well as changes in additional inputs (e.g. – pesticide, herbicide, etc.) and is a topic for future research.

Table 3.1 – Selected Economic, Environmental and Production Results Under Selected Carbon Footprint Restrictions

<u>Uniform Rate</u>				
Mean Net Returns	\$1,209,987	\$1,203,916	\$1,177,880	\$1,111,614
Carbon Ratio	33.16	33.97	35.27	39.27
Total Carbon Footprint ¹	185,625	180,000	170,000	145,000
Carbon Output ²	6,155,334	6,114,600	5,995,900	5,694,150
Marginal Abatement Cost		\$1.08	\$2.63	\$2.67
Corn Planting Date ³	88.62	88.73	88.62	88.62
Corn Plant Population ⁴	31.62	31.48	29.40	24.19
Corn Nitrogen Rate ⁵	154.76	146.76	133.73	101.17
Soybean Planting Date ⁶	117.46	117.57	117.46	117.46
Soybean Plant Population ⁷	111	111	111	111
<u>Variable Rate</u>				
Net Returns	\$1,209,794	\$1,204,589	\$1,187,353	\$1,108,659
Carbon Ratio	33.20	34.17	35.67	39.18
Total Carbon Footprint	185,878	180,000	170,000	145,000
Carbon Output	6,171,137	6,150,600	6,063,900	5,681,100
Marginal Abatement Cost		\$0.89	\$2.39	\$3.34
Corn Planting Date	88.62	88.62	88.83	88.30
Corn Plant Population	31.71	30.96	29.54	24.72
Corn Nitrogen Rate	153.59	146.63	133.37	103.38
Soybean Planting Date	117.46	117.46	118.29	117.46
Soybean Plant Population	127.80	116.35	111	111

¹ Carbon units are reported using teragrams.

² Carbon units are reported using teragrams.

³ Planting date refers to the Julian calendar date.

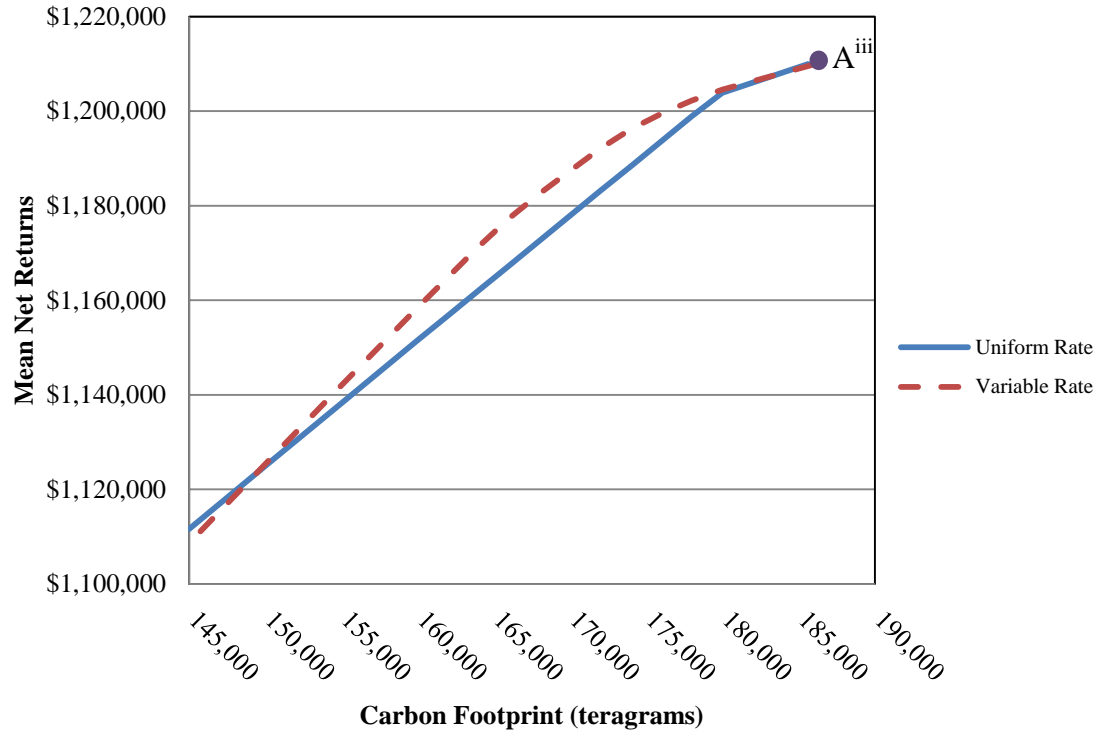
⁴ Corn plant population refers to 1,000 plants/acre.

⁵ Nitrogen rate is in lbs/acre.

⁶ Planting date refers to the Julian calendar date.

⁷ Soybean plant population refers to 1,000 plants/acre.

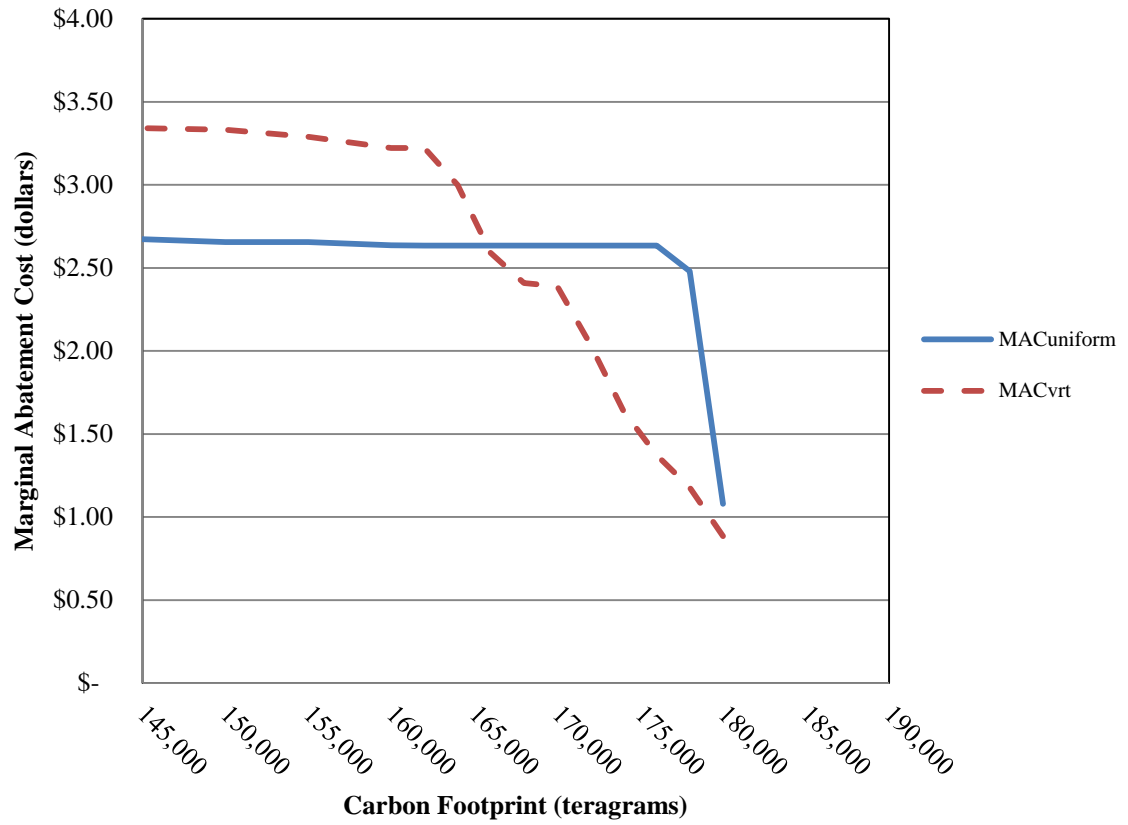
Figure 3.1 – Carbon Efficient Frontier (CEF) ^{iv}



^{iv} All points that lie directly on the uniform and variable rate curves are efficient and optimal points. All points that lie within the curves are inefficient but still within the feasible region. All points that lie outside of the curves are infeasible.

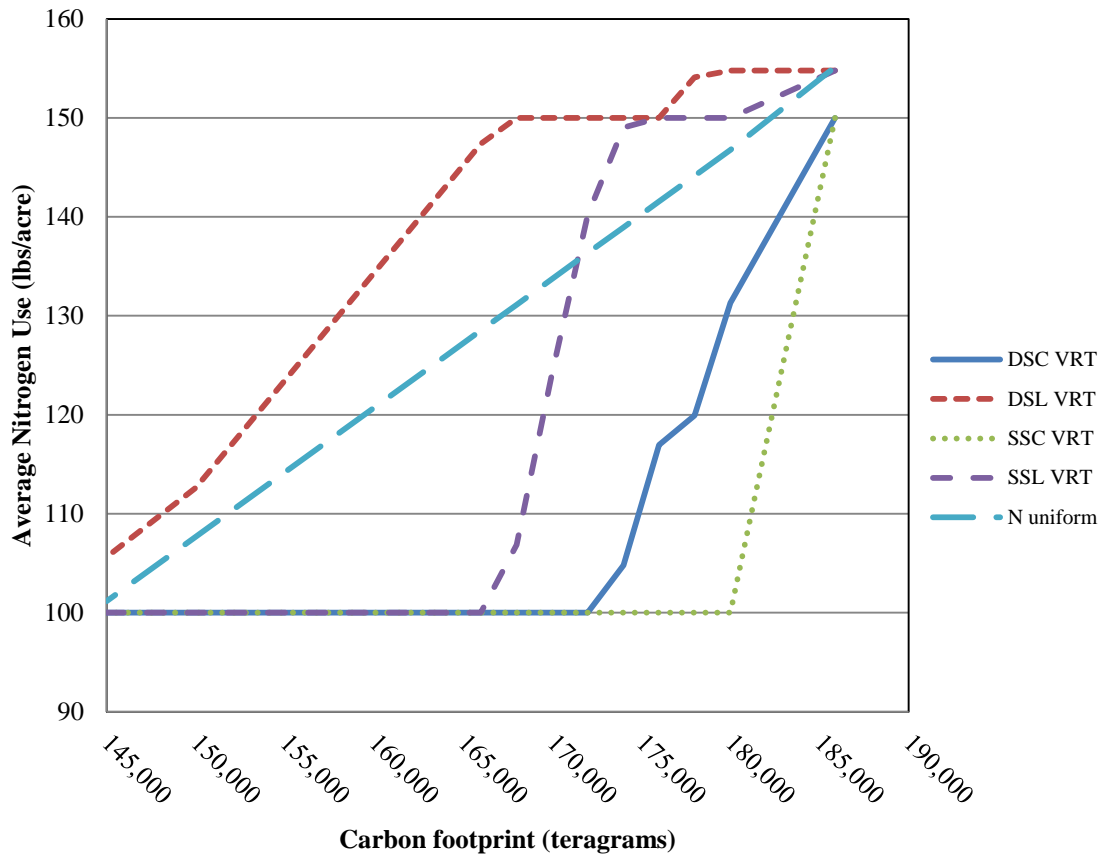
ⁱⁱⁱ Point A refers to the unrestricted case.

Figure 3.2 – Marginal Abatement Cost Curve (MACC)¹



¹ For carbon footprint restriction levels below 145,000 teragrams, acreage used for production began to suffer.

Figure 3.3 – Average Nitrogen Use by Production Practice and Soil Type¹



¹ Soil type refers to deep silty clay (DSC), deep silty loam (DSL), shallow silty clay (SSC) and shallow silty loam (SSL).

Figure 3.4 – Soybeans Plant Population

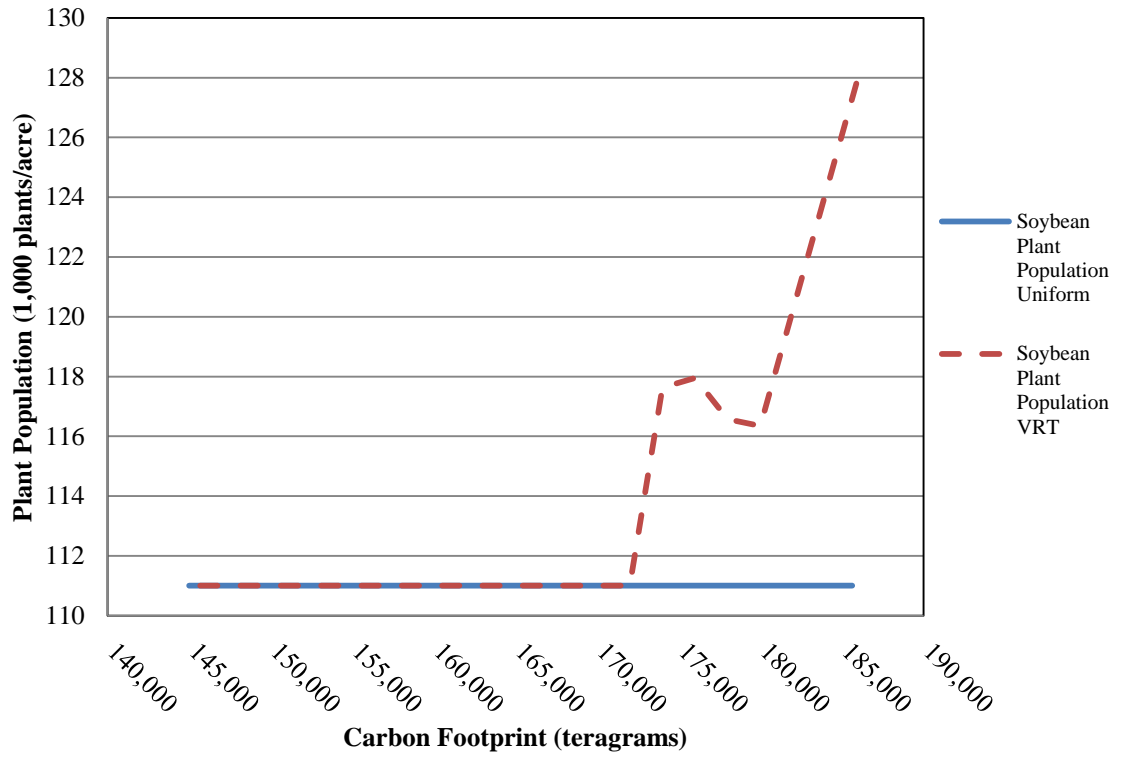
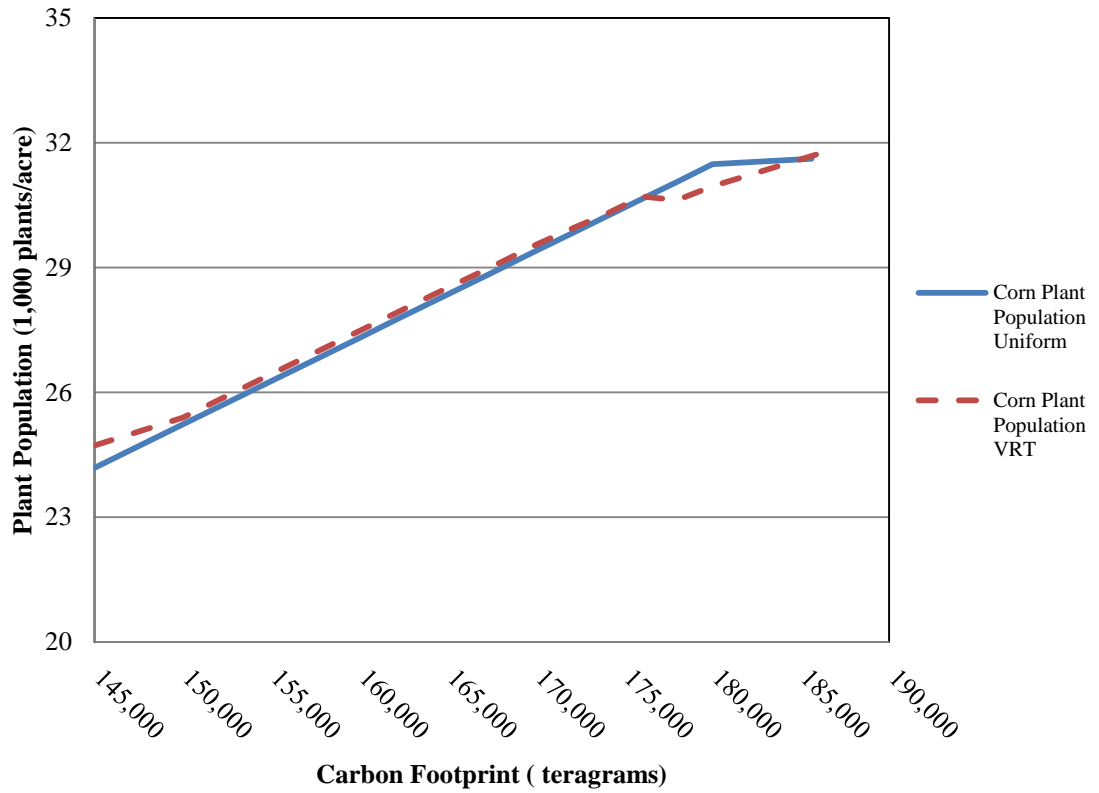


Figure 3.5 – Corn Plant Population



Chapter Four

Concluding Remarks

This thesis explored the economic and environmental impacts that the adoption of precision agriculture technologies (PATs) can have over conventional farming when used in the appropriate setting. The research was motivated by the heightened interest in the role that the agricultural sector plays in climate change by way of its pollution of greenhouse gases. It has done so with two separate yet complementary manuscripts.

The first manuscript (Chapter Two) considers the economic and environmental differences realized with the use of PATs against a base, no PAT scenario. A whole-farm analysis using a resource allocation model was conducted using biophysical simulation for a grain farm that produces corn and soybeans in Henderson County, Kentucky. The structure of the models used in this study included production and economic environments, as well as strategic and tactical decisions. Based on the decision variables in the model, the results included optimal expected yields, mean net returns and carbon footprint information.

It was realized that all of the PATs investigated in this study proved to be economically and environmentally superior to the base model resulting in a potential Pareto improvement. While all of PATs investigated were potential Pareto improvements, the real time kinematic system with integral valve system (RTK) was the most environmentally rewarding while automatic section control with lightbar (ASC-L) was the most economically beneficial. The increase in profitability and decrease in carbon emissions was due to the increased accuracy of the PATs. The increased precision allowed for less overlap which in turn reduced inputs and ultimately carbon emissions.

With a decrease in inputs, there is a direct and indirect reduction in the carbon footprint of the farm operation. The production of the inputs carries a direct carbon footprint while the application of the inputs at the farm carries an indirect carbon footprint which is attributed to the fuel consumption for the usage of said inputs.

The empirical results presented served two purposes: 1) to fill an information void and 2) to provide information to producers and policy makers. Using the results from this study, policy makers will have a better understanding of the potential benefits associated with PATs. Additionally, this information can be used to help regulators make choices between such measures as environmental restrictions or minimum technology requirements. Moreover, producers will have more access to information that could help in determining if PATs are a fit for their farm.

The second manuscript (Chapter Three), focused on expanding the economic model used in Chapter Two to develop a process to construct a carbon efficient frontier (CEF). The process included the use of uniform rate (conventional farming) and variable rate technology (VRT) with the application of strategic carbon emissions reductions forced upon the model. In addition to the CEF, a marginal abatement cost curve (MACC) was constructed to be used in a complementary fashion with the CEF. Using the two curves, the results indicate what factors of production are altered in order to accommodate the carbon emissions restriction.

The results showed that through the strategic application of nitrogen fertilizer and seed, VRT is economically and environmentally superior to conventional farming at all constrained emissions levels, with the exception of the very high restriction levels. While planting date changes did not directly affect the carbon footprint, through a series of

interactive effects the planting date was influenced. This was due to the fact that the total physical product for later planting dates under initial reductions in nitrogen and seed was higher than for earlier planting dates. In addition, soil productivity dictated the strategic placement of both fertilizer and seed in that levels of application for silty clay soils are reduced first followed by silty loam, with shallow preceding deep. The interactive effects of nitrogen, seed and planting date ultimately tell the story of how producers will manage carbon emissions in the most economically efficient manner

The CEF, as modeled in this study, is an analytical tool that focuses on technology adoption while the MACC examines incremental costs associated with the carbon emissions restrictions imposed. Given the issues facing regulators, such as what types of policies are best suited for given desired outcomes, and what effects on commodity productivity would these regulations have, both individual agents and entities concerned with carbon emissions can use the CEF and MACC in conjunction to help make more informed decisions. When used in a complementary fashion, the two analytical tools will allow producers and policy makers to acquire more complete information with regards to farm level carbon emissions abatement techniques as well as more direct profitability and environmental tradeoff assessments.

This research has made many contributions to this area of research. The primary contribution was the development of a model that determined both economic and environmental results for PATs. It had been postulated in previous studies that PATs are environmentally superior to conventional farming; however no empirical results were available to verify such a theory. The results presented in this thesis verify that PATs do indeed provide economic and environmental superiority over conventional farming. The

second focus of this thesis was to develop a process to construct a CEF. This new technique for looking at strategic decision opportunities, when used in conjunction with a MACC, will assist decision makers along the agricultural-environmental spectrum.

There are certainly areas for further research, such as inquisition into other PATs and their economic/environmental relationships, the ability of the second model to specify other inputs for precision application, such as insecticides or herbicides or the alterations of information for the CEF to allow it to be of value for other areas of production agriculture. The information contained in this thesis can give famers and policy makers the tools they need to make more informed decisions with regards to the economic and environmental feasibility of PATs.

Appendix 2A:

Mathematical Representation of the Carbon Footprint Equation

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

$$\begin{aligned} & \sum_H \sum_{PS} \sum_{RS} \sum_{SS} \sum_{ST} \sum_{VS} CFACT_I * SCAR_{BI,PS,RS} * X_{SH,PS,RS,SS,ST,VS} \\ + & \sum_H \sum_{FR} \sum_{PC} \sum_{SC} \sum_{ST} \sum_{VC} CFACT_I * CCAR_{BI,PC,FR} * X_{CH,FR,PC,SC,ST,VC} \\ - & CARBFP_I \end{aligned} \leq 0 \quad \forall I$$

Activities include:

$X_{SH,PS,RS,SS,ST,VS}$ = 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 planting date SS .

$X_{CH,FR,PC,SC,ST,VC}$ = 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 planting date SC .

$CARBFP_I$ = carbon footprint accounting variable by input used

Coefficients include:

$SCAR_{BI,PS,RS}$ = Carbon associated with soybean production for input I for plant population PS with row spacing RS .

$CCAR_{BI,PC,FR}$ = Carbon associated with corn production for input I for plant population PC with fertilizer rate FR .

$CFACT_I$ = carbon emissions factor for each input used

Indices include:

FR – fertilizer rate corn

H – harvest week

I – inputs

PC – plant population corn

PS – plant population soybeans

RS – row spacing soybeans

SC – planting date corn

SS – planting date soybeans

ST – soil type

VC – plant variety corn

VS – plant variety soybeans

**Appendix 3A:
Mathematical Representation of the Uniform Rate and Variable Rate Equations**

The uniform rate soil ratio equations described in the model is depicted mathematically as follows:

Soybeans

$$\begin{aligned} SR_{ST1} * X_{SH,VS,PS,ST2,RS,SS} - SR_{ST2} * X_{SH,VS,PS,ST1,RS,SS} \\ = 0 \quad \forall H,VS,PS,RS,SS,ST1,ST2 \mid ST1 \neq ST2 \end{aligned}$$

Corn

$$\begin{aligned} SR_{ST1} * X_{CH,SC,VC,ST2,PC,FR} - SR_{ST2} * X_{CH,SC,VC,ST1,PC,FR} \\ = 0 \quad \forall H,SC,VC,PC,FR,ST1,ST2 \mid ST1 \neq ST2 \end{aligned}$$

The variable rate soil ratio equations described in the model is depicted mathematically as follows:

Soybeans

$$\begin{aligned} \sum_{PS} SR_{ST1} * X_{SH,VS,PS,ST2,RS,SS} - SR_{ST2} * X_{SH,VS,PS,ST1,RS,SS} \\ = 0 \quad \forall H,VS,RS,SS,ST1,ST2 \mid ST1 \neq ST2 \end{aligned}$$

Corn

$$\begin{aligned} \sum_{PC} \sum_{FR} SR_{ST1} * X_{CH,SC,VC,ST2,PC,FR} - SR_{ST2} * X_{CH,SC,VC,ST1,PC,FR} \\ = 0 \quad \forall H,SC,VC,ST1,ST2 \mid ST1 \neq ST2 \end{aligned}$$

Activities include:

$X_{SH,VS,PS,ST1,RS,SS}$ = production of soybeans harvested during period H in acres of variety VS for soil type $ST1$ with plant population PS with row spacing RS under planting date SS .

$X_{SH,VS,PS,ST2,RS,SS}$ = production of soybeans harvested during period H in acres of variety VS for soil type $ST2$ with plant population PS with row spacing RS under planting date SS .

$X_{CH,SC,VC,ST1,PC,FR}$ = 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 planting date SC .

$X_{CH,SC,VC,ST2,PC,FR}$ = production of corn harvested during period H in acres of variety VC for soil type $ST2$ with plant population PC with fertilizer rate FR under planting date SC .

Coefficients include:

SR = soil proportion for each soil type.

Indices include:

ST1 – soil type; DSC, DSL, SSC, SSL

ST2 – soil type; DSC, DSL, SSC, SSL

SS – planting date soybeans

SC – planting 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

I – inputs

H – harvest week

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Vita

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EDUCATION

- Anticipated 05/2013 **Master of Science**, Agricultural Economics
University of Kentucky
- 05/2011 **Bachelor of Science**, Food and Resource Economics
University of Florida
- 12/2008 **Associate of Arts**, Business Administration
Santa Fe College

PROFESSIONAL EXPERIENCE

- 05/2013 – 08/2013 **Agricultural Economist**
United States Department of Agriculture
Economic Research Service
- 05/2011 – 05/2013 **Research Assistant**
University of Kentucky
Department of Agricultural Economics

TEACHING EXPERIENCE

- Spring 2013 **Teaching Assistant**, University of Kentucky.
- Fall 2012 **Teaching Assistant**, University of Kentucky.
- Fall 2010, Spring 2011 **Teaching Assistant**, University of Florida.

RESEARCH

Master's Thesis

Economic Optimization and Precision Agriculture: A Carbon Footprint Story

This research examined the economic and environmental impacts that precision agriculture technologies can have on the carbon footprint of a grain farm in Kentucky.

ERS Internship 2013

The main focus of the research was to investigate the profitability of US biofuel production. Using this information, I helped develop a linear programming model that added a bioenergy component to the Regional Environment and Agriculture Programming Model. Additionally, I provided consultation on a precision agriculture study that investigated the profitability of different technologies.

ERS Internship 2012

My main responsibilities involved updating commodity elasticities and developing a linear programming model that revamped the livestock feed rations portion of the Regional Environment and Agriculture Programming Model.

PROFESSIONAL PRESENTATIONS

Brown, R. and S. Enlow. "ERS Internships and Government Data Accessibility." Agricultural Economics Department, University of Kentucky, October 19, 2012.

Brown, R., C. Dillon, J. Schieffer and J. Shockley. "The Impact of Precision Agriculture Techniques on Kentucky Grain Farmers' Carbon Footprint." Selected paper prepared for presentation at the Southern Agricultural Economics Association annual meeting, Birmingham, Alabama. February 4-7, 2012.

Brown, R., C. Dillon and J. Schieffer. "Using Mathematical Programming to Determine a Carbon Efficient Frontier." Poster prepared for presentation at the Agricultural and Applied Economics Association annual meeting, Seattle, Washington, August 12-14, 2012.

ADDITIONAL WORK EXPERIENCE

- 05/2009 – 05/2011 Clerical Student Assistant, University of Florida, Student Financial Affairs, Administrative Office.
- 05/2009 – 05/2011 Legal Assistant, Attorney Christian A. Straile, LLC.
- 10/2006 – 10/2009 Legal Assistant, Law Offices of DeCarlis and Sawyer.

PROFESSIONAL SERVICE

- 01/2012 – 03/2013 President, UK Agricultural Economics Graduate Student Organization.
- 05/2012 – 04/2013 Executive Member of the Board, Graduate Student Officer, Kentucky Hillel.
- 03/2010 – 03/2011 Treasurer, University of Florida Collegiate Veterans Society.

PROFESSIONAL MEMBERSHIPS

- Agricultural and Applied Economics Association
- Southern Agricultural Economics Association