ANALYZING THE EFFECTS OF AUTONOMOUS NAVIGATION ON ROW CROP FARMING

by

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To my wonderful family and friends. I would not be where I am today without the support of my parents, and the friends I made along the way. Life is better when you can share it with the people you love. I enjoyed my stay.

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ABSTRACT

As the global population rises, so does the demand for food, feed, fiber, and fuel. Meeting this demand has become increasingly difficult due to the decline in farm labor and challenges associated with the economic viability of agricultural systems. Autonomous agricultural machinery has the potential to mitigate some of major challenges that crop production systems will face. Widespread adoption of autonomous machinery is dependent on two key factors, the cost and environmental impact. The development and adoption of autonomous vehicles will only occur if it is profitable for equipment manufacturers and farmers. As distillate fuel use for crop production increases, fuel efficient operations that minimize greenhouse gas emissions will mitigate the environmental impact of farming.

The objective of this research was to develop a model to quantify the cost, energy use, and emissions associated with the use of agricultural machinery used for row crop farming. The model calculates the cost of different sized machinery fleets for planting and harvest. Autonomy facilitates swarm farming, and the model can quantify and compare these to human-operated machinery systems.

For an 800-hectare case study farm in the Midwest, with the acreage split evenly between corn and soybeans, the most cost-effective planting machinery fleet was comprised of two autonomous, 56-kW JD 5075E tractors pulling 4-row planters ($40/ha/yr). The most cost-effective fleet used the most fuel (4,327 liters) and produced the most emissions (219,735 grams). For a similar conventional system to complete planting during the same working window, it would require 4 tractors and cost $75/ha/yr. The $35/ha/yr difference between the similar fleets was the value added by autonomy. Current row crop farming trends have shifted towards fewer operators with larger machines and implements. The most cost-effective, single operator machinery set from the database (Case Magnum 200 with a 16-row planter) costs $43/ha/yr more than overall most cost-effective fleet. Total fuel used to complete the planting operation was minimized by using a single John Deere 8320R pulling a 36-row planter. To plant all 800-hectares, the 8320R used 2,528 liters of diesel fuel and produced a combined 44,002 grams of emissions. The JD 5075E was able to minimize cost, but it used the most fuel and produced the most greenhouse gas.

CHAPTER 1. COST ANALYSIS

1.1 Introduction

One of the major challenges that agriculture will face in the coming years is population growth (United Nations, Department of Economic and Social Affairs, & Population Division, 2019). The United Nations Department of Economic and Social Affairs expects the world population to reach 9.7 billion in 2050. Their projections show that the population could reach 11 billion near the end of the current century. The following nine countries are expected to account for more than half the projected growth between now and 2050: India, Nigeria, Pakistan, the Democratic Republic of the Congo, Ethiopia, the United Republic of Tanzania, Indonesia, Egypt, and the United States. The order of the list correlates to magnitude of growth (high to low). During this time, it is estimated that the population sub-Saharan Africa will increase 99%, while North America is only expected to increase 2%. Food production will have to increase to meet the demands of a larger population.

Based on projections from the Food and Agriculture Organization (FAO) in 2009, feeding a global population of 9.1 billion would require total food production to increase by approximately 70% between the years 2005 and 2050. In 2009, the demand for cereals for human and animal consumption was 2.1 billion tonnes. This demand is expected to reach 3 billion tonnes by 2050. As incomes increase in developing countries, so does the need for food products such as livestock, dairy, and vegetable oils. Production of these products will need to rise significantly faster than cereal production to meet the large, expected increase in demand. The meat production industry will need to grow to meet the expected demand of 470 million tonnes in 2050 (Food and Agriculture Organization, 2009).

As the demand for food increases, so will the need for farm labor. According to data from the National Agricultural Statistical Service's Farm Labor Survey, a 74% decrease in self-employed and family farmworkers occurred from 1950 to 2000 in the US. During that time, there was also a 51% decrease in hired farm labor. The Quarterly Census of Employment and Wages reports that metrics in agriculture employment stabilized during the 2000s and have increasing since 2010. Between 2010 and 2019, the number of hired farmworkers increased from 1.07 million to 1.18 million. Of the 1.18 million hired farmworkers, only 16% are classified as agricultural equipment operators. This value does not include contracted agricultural service workers. The H-2A Temporary Agricultural Program (H2-A visa) allows farmers to bring foreign-born workers into the United States for temporary employment. To be part of H2-A program, farmers must show that their attempt to hire workers from the United States was not successful, and this must be certified by the U.S. Department of Labor. The increase and approval of more H-2A positions is a clear sign of a farm labor shortage. In fiscal year (FY) 2005, there was 48,300 employed through the H2-A visa program. The number of H2-A visa employees has increased to 257,700 in FY 2019 (Castillo & Simnitt, 2020). Some farmers have even started addressing this issue with a different approach, technology. The American Farm Bureau Federation states that 56% of farms in the United States have adopted the use of agricultural technology. Of that 56%, more than half made this change because of labor shortages (Ag America Lending, 2020).

Chemical fertilizers and animal manures are applied to fields to provide crops with nitrogen and phosphorous. The nitrogen and phosphorus that is not utilized by the plants can be washed away by precipitation and negatively impact water that is downstream. These nutrients can also reach groundwater sources by leaching through the soil. When high levels of nitrogen and phosphorous contaminate bodies of water, eutrophication and algal blooms occur. Eutrophication can cause hypoxia; this is when the oxygen level in the water is too low. The decreased oxygen leads to dead zones where aquatic life is no longer able to live. Algal blooms can disrupt the current wildlife and product toxins that are harmful to humans. Nitrogen-based fertilizers are susceptible to volatilization. This can cause ammonia and nitrogen oxide, a greenhouse gas, to enter the atmosphere. Ammonia is harmful to aquatic life when large amounts are deposited into the water (United States Environmental Protection Agency, 2020a).

Increased land use for crop production will result in the rise of energy and fuel consumption. More agricultural machinery will need to be used to keep up with production demands. Based on reports of the energy used by the United States agricultural industry in 2012, distillate fuel makes up most of the energy consumption for both crop and livestock operations (Hicks, 2014). Distillate fuels are petroleum based and used to power heavy machinery on farms. Of the approximately 528 billion megajoules that were used for crop production, 274 billion came from distillate fuel use, and electricity accounted for 95 billion. With fossil fuel supplies depleting, it would be beneficial to minimize fuel use, As farm sizes and the need for agricultural products grow, another environmental concern is greenhouse gas emissions. The agricultural sector accounted for 9.9% of the United States' total greenhouse gas emission in 2018 (6,677 million metric tons of CO_2 equivalent). Beyond the emissions of agricultural operations, it is important to account for the energy expenditures needed to maintain current practices (United States Environmental Protection Agency, 2020b).

The National Institute of Food and Agriculture, a federal agency of the USDA, outlines the importance of sustainable agriculture. A rising population will need sufficient food, feed, fiber, and fuel to meet demands. An increase in agricultural production will negatively impact the environment if plans are not established to protect it. There is a need to expand the global natural resource supply and sustain the economic viability of agricultural systems (USDA National Institute of Food and Agriculture, n.d.).

One goal of sustainable agriculture is to satisfy the growing need for human food and fiber while also increasing farm profits. An important aspect of feasible agricultural operations, especially for the farmer, is the economic viability. Like any business, farms will not be able to support themselves if they are not able to profit from the time and money that is invested. Farm systems model have been developed to understand the finances of existing and proposed crop production systems. The ability to quantify the costs of real and hypothetical systems allows these models to be used for research and decision-making.

1.1.1 Research Objectives

This research has two primary objectives:

1. **Agricultural Machinery Cost Modeling:** The first objective was to create a model to calculate the cost of agricultural machinery and associated operational costs for planting and harvest of row crops.
2. **Quantify Impact of Autonomous Navigation:** The second objective was to use the model created in objective one to compare the economics of autonomous navigation and swarm farming to human-operated systems.

1.2 Background

1.2.1 General Analysis

To better understand and the costs of in-field and transportation operations for a multi-field, multi-crop production system, a predictive model was developed by Sopegno et al. (2016). The model stores coefficients from ASABE standards and application rates in a SQL server to prevent the user from editing them. Scenario-specific data is entered into a GUI by the user so MATLAB can perform the calculations and return the outputs. Analysis was performed on a multi-field, corn and wheat operation to demonstrate the model's capability. For this operation, corn had higher input costs and a lower out/input ratio, both in terms of cost per hectare. A sensitivity analysis was performed to determine how transport cost, operational cost, and profit change as the yield for the crops vary. Days suitable for work or as time constraint was not accounted for by this research. The machinery database is limited and the objective of this research was not focusing on how machinery sizing and selection affects the crop production system.

Tieppo et al. (2019) developed a model to calculate the cost associated with sowing, spraying, and harvesting of no-till corn and soybeans. The following three tractor and planter pairs were used for the planting operation (power and capacity): 89-kW and 1.76 ha hr^{-1}, 125-kW and 2.63 ha hr^{-1}, 162 kW and 3.73 ha hr^{-1}. The three sprayer's power (kW) and capacity (ha hr^{-1}) were: 89 and 12.29, 96 and 28.08, 136 and 31.59, respectively. The self-propelled combines were rated at 132-kW and 2.55 ha hr^{-1}, 177-kW and 3.38 ha hr^{-1}, 261-kW and 5.41 ha hr^{-1}. Results show the lowest operational cost for the three operations, across a range of field sizes, for a variety of machine combinations. Time available for an operation was set by gathering data from a local farm. The goal of the model was to determine the influence of machinery sizing on cost. The size of the machinery and implements used in the research was limited and relatively small. The model does not perform any analysis on how autonomy could potentially change the cost operational costs.

A model was developed by Beard, McClendon, and Manor (1995) to compare costs and returns for a simulated soybean farm that used five different machinery setups. A single tractor system, three two-tractor systems, and a system that uses one wide-span, controlled-traffic vehicle. Operations performed by the machinery included tillage, planting, cultivation, and harvesting. The size of the case study farm varied from 200 to 1100 ha, in steps of 100, for the simulations. The only systems to make a profit were the wide-span vehicle and the two, 130-hp tractor operations. Net returns were affected by machinery set capacity, field size, working windows, soybean market prices, and operational expenses. This research was limited to a small collection of machinery setups and does not have any analysis for autonomous machinery.

1.2.2 Automation

A systematic review paper by Lowenberg-DeBoer et al. (2020) looked at research published after 1990 on the economics of agricultural automation and robotics. The following databases were used to obtain search results: AgEcon Search, EbscoHost (including Business Source Complete, CAB Abstract, Greenfile, Food Science Source), Emerald, ScienceDirect and Wiley Online. The initial pool of 5,119 papers was parsed to 18 after screening and eligibility checks. Most studies used partial budgeting, which only considered the cost and revenue changes associated with the introduction of robotics; other factors remained constant. A majority of the papers found where based on the economics of specialty fruits and vegetables. All of the studies found scenarios where automation or robotics would be profitable. A couple of the papers found the systematic review will be discussed below.

Early research from Have (2004) and Goense (2005) attempted to quantify the effects that automation would have on the economics and operation of row crop farming. Have assumed the following for the autonomous tractor: 1.2 times the purchase price, 0.2 times the labor requirement, and 2 times more daily working hours of a tractor that requires an operator. The assumptions were used to calculate the annual average cost of the tractor, the least cost width, and the least cost power. The objective of Goense's research was to determine the effect that the size of autonomous has on cost. Three different row crop cultivator systems were compared: a tractor mounted cultivator with an operator, a self-propelled (SP) cultivator with an operator, and an autonomous machine. The autonomous system was assumed to work 23 hours per day and the working time was 12 hours for the operated equipment. It also assumed that the autonomous equipment travels at slow speeds and turns at a slower rate. Results for the research report on the machine capacity, yearly use, and operation cost. The results from the early research were heavily influenced by the assumptions made, and the machinery used in the analysis was limited. The model was not capable of comparing how multiple, smaller machines would affect cost.

A methodology was developed by Lampridi et al. (2019) to analyze the economics associated with the use of robotic systems for farming. For the case study, a robotic and conventional system were used on a 10- and 100-hectare farm. The chosen operation used in the case study was row crop cultivation. It was assumed that the robotic and conventional had the same working hours per day. Three different fleets were selected. The robotic system consists of an electric, 4WD machine with a working width of 1.2 meters and operating at 4 kilometer per hour. The first conventional machine was a diesel-powered 40-kW tractor, with a 2.6-meter cultivator, working at 8 kilometers per hour. The larger conventional machine has 80-kW of power, travels at the same speed as the smaller conventional system, and a 6-meter working width. The total cost of the robotic system was larger than the conventional system for both farm sizes. This economic analysis is hindered by the technical specs of the autonomous platform. There is no system used in the case study that assumes that autonomous machinery could be operating at the same capacity of a similar, conventional system.

Research by de Witte (2019) also analyzed the economics of autonomous machines, specifically the use of small machinery. For this study, a small and large machinery set was analyzed for harvesting and cultivation. The power and width of the small harvester was 44 kW and 1.2 meters. The power and width of the large harvester was 400 and 10.7, respectively. The small tractor and cultivator were assumed to be 60-kW and 1.5 meters in width. The power and width of the large cultivator was 320-kW and 8 meters. To finish the harvesting and cultivation, use of the small machinery resulted in a higher cost. When wages are factored in, the cost per hectare to complete the cultivation operation using the smaller machinery becomes the more cost-effective option. While this work does attempt to quantify the use of smaller machinery, the range of equipment in the research is limited. A large database of commercially available machines and implements was not used in the analysis.

Lowenberg-DeBoer et al. (2020) performed an economic feasibility analysis on autonomous equipment that would be used for biopesticide application. The research adapted the Hands Free Hectare (HFH) model to be accomplish the objective of the study, which is to determine the use cases where autonomous biopesticide application equipment is profitable. The initial results from the research show that low-cost biopesticide maybe be profitable when using either autonomous or conventional machinery. This economic analysis was limited to biopesticide application. The research does not focus on machinery selection and how equipment size affects operating cost.

Research has also been conducted to determine the impact that global navigation satellite system (GNSS) automated guidance would have on mechanical weeding (Griffin & Lowenberg-DeBoer, 2017). The study wanted to evaluate the economic feasibility of mechanical weed control to eliminate herbicide-resistant weeds. The case study was analyzed using the Purdue Crop/Livestock Linear Programming software. Linear programming is an optimization tool that calculates the scenario with the highest return. Results show that mechanical weeding and herbicide application was feasible for a range of speeds. Row cultivation was considered optimal when herbicide costs are high. This is because the cultivation offsets the high agrochemical cost. The scope of this research was limited to weeding, and implement inventory used in the analysis is limited. Only size of implement is analyzed for the various implement types.

Lowenberg-DeBoer et al. (2019) studied the impact of swarm robotics for wheat and oilseed rape planting. Four equipment sets were used: a 38-hp tractor with an operator, an autonomous 38-hp tractor, a conventional 150-hp tractor, and a conventional 300-hp tractor. It was assumed that the autonomous tractors can work 22 hours per day and conventional machinery could work on average about 10 hours per day. For the wheat production operation, the cost per ton was lower for all autonomous machinery. This holds true for a range of farm sizes. The model used in the research was the HFH farm-level linear programming model. A large range of tractor sizes was not studied, and only one autonomous system was included in the analysis.

To determine the economic feasibility of using autonomous machinery, it was compared to conventional machinery in three systems. The first one was robotic weeding in sugar beet. The latter two are the use of autonomous machines in cereal crop scouting, and golf course grass cutting. It is stated that the dimensions, capacities, speed, and all other technical data were based on recommendations from other research groups and experts. This research references the Danish Institute of Agricultural Sciences (DIAS) and the lead scientist there at the time, Ivar Lund. Manual weed detection cost was based on DIAS estimates, the conventional weeding costs were based on the average price when the operation was contracted, and cost labor for manual grass cutting was estimated using hours per year for certain golf course areas. Results show that autonomous machinery can reduce costs by 12%, 20%, and 52% in weeding, scouting, and cutting, respectively (Pedersen, Fountas, Have, & Blackmore, 2006). While three different scenarios were analyzed, only one autonomous system was included in each scenario. The research was not able to quantify how different machinery sizes affects the operations costs.

Additional work by Pedersen et al. (2008) analyzed robotic weeding in sugar beet and crop scouting in cereals. An economic study, based on partial budgeting, was performed on the two different operations to determine how the robotic vehicles compared to conventional operations. The analysis accounted for factors such as the initial investment, labor cost, and daily working hours. The conventional system used for comparison was based on economic statistics from Danish farm management standards. The autonomous data was based on an autonomous platform developed by the Danish Institute of Agricultural Sciences. The assumed commercial cost of the autonomous weed detection platform was greater than the costs associated with manual scouting. For the sugar beet weeding, an autonomous vehicle using a micro sprayer was compared to a conventional sugar beet sprayer. The autonomous sprayer was assumed to reduce herbicide application by 90%, when compared to standard application amounts. The two systems were applied to case study farms in Denmark, Greece, the United Kingdom, and the United States. The technical specs of the conventional system were not stated. Like Pedersen's earlier work, the range of machines studied in the research was limited. This does not allow conclusions to be drawn about how machinery size and selection affects cost.

In order to quantify the effects of autonomous vehicles on row crop farming, Wilfong (2019) created an Excel-based model to calculate the costs associated with various machinery used for fertilizer application, herbicide spraying, planting, and harvest. This model accounts for the price of inputs such as seeds, fertilizer, and pesticide. If these inputs cost are kept constant across all machinery systems, that will not affect the total cost. Fertilizer and herbicide application rates were assumed to be different for the conventional and autonomous systems. This affects the total cost significantly. It was assumed that autonomous machines can only work 12 hours a day, while conventional machines that require an operator can be used 16 hours a day. A limitation of Wilfong (2019) is the machinery width and the number of machines are user inputs. Another factor that was not accounted for is the operations working window. This type of data could be used to determine the number of machines needed to complete an operation during a specific time frame.

A model developed by Shockley et al. (2019) to compare autonomous and conventional machinery used for grain crop production in terms of economic feasibility. For this comparison to be made, the optimal conventional machine complement, and number of autonomous vehicles had to be determined. A conventional complement consists of a tractor, planter, sprayer, and fertilizer applicator. The finances of the different production methods were used to calculate the break-even investment price for autonomous controls, since the cost for autonomous controls was not included in the investment cost. A mixed integer mathematical formula was developed and utilized three optimization models: machinery selection, resource allocation, and sequencing. The objective of the model was to maximize average net return over a case study period of 30 years. Net returns per year were calculated by subtracting total costs from total sales. Costs were defined by the following categories: machinery operating cost, machine ownership cost, and all other variable costs. The model is limited by the following constraints to determine the output: machinery selection, land use, yield/soil data, sequence of activities, and time.

The case study farm is a no-till, 850-hectare corn and soybean rotation. The application of phosphorous, potassium, and lime were outsourced. Harvest was also assumed to be a custom hired operation. For the conventional machinery options, 5 tractor sizes, 6 sprayers, 6 planters, and 3 liquid fertilizer applicators were considered. Since autonomous vehicles are still in development, this model only uses machine and implement data from a prototype developed by the University of Kentucky. The total cost of the autonomous prototype did not include the cost of a control system.

Results for the case study simulation only showed the optimal conventional machinery fleet and the number of autonomous vehicles in four scenarios. The first scenario did not reduce input cost and increase yield. The second scenario only reduced inputs costs, and the third only increased yield. The final scenario assumed that autonomy positively impacts input cost and yield. Under the base assumption, the autonomous fleet increased average net returns by $5,993. This value is considered the maximum price that farmers are willing to pay annually for autonomous controls. The cost for autonomous control, when added to the base costs of the tractor, is considered the break-even investment price. The break-even price is the maximum price that a tractor with autonomous controls can be purchased for, without noticing a financial difference when being compared to conventional machinery.

Sensitivity analyses were performed to see the impact of farm size, suitable workdays, and grain prices. The net returns for smaller farms with autonomous machinery was drastically higher. The farm size sensitivity analysis performed on the four different autonomous systems, each using a different assumption, shows that the break-even cost for autonomous controls increased as farm size increased. When the days suitable for field work decreased, average net returns for the autonomous machinery scenarios decreased. As grain prices increased, the net returns for all scenarios using autonomous machinery decreased (Shockley et al., 2019). This research was limited because it only includes one autonomous system in the analysis. It also lacks comparison between different sized, conventional machinery. If the research compared a large range of possible autonomous and conventional equipment pairs, conclusions could be drawn on how the adoption of automation and fleet sizing affects cost.

1.2.3 Whole Farm

The Integrated Farm System Model (Rotz & Corson, 2012) and the Farm Assessment Tool (Jacobsen et al., 2013) are both whole farm models that are capable of economic analysis. IFSM requires the users to input the machines being used and simulation results are limited to one system per run. Since the number of machines and the size of the implements is an input from the user, the model is not performing a calculation to determine the machinery fleet that is necessary to complete an operation in a specific working window. The goal of the FASSET model is to determine nitrogen leaching and farm economics during climate change. To determine the effect of machinery sizing and selection, multiple runs using different assumptions would need to be analyzed. **Table 1.1** shows all the research discussed in **Background** and breaks down their capability in four areas.

Table 1.1: Crop production economic analysis literature comparison for five areas

	A Cost Prediction Model for Machine Operation in Multi-Field Production Systems	Modeling Cost and Energy Demand in Agricultural Machinery Fleets for Soybean and Maize Cultivated Using a No-Tillage System	Comparing Widespan Equipment with Conventional Machinery Systems for Soybean Production	Effects of Automation on Sizes and Costs of Tractor and Machinery	The Economics of Autonomous Vehicles in Agriculture	A Case-Based Economic Assessment of Robotics Employment in Precision Arable Farming	Economic Perspectives of Small Autonomous Machines in Arable Farming	The Economic Feasibility of Autonomous Equipment for Biopesticide Application
Cost Analysis	✓	✓	✓	✓	✓	✓	✓	✓
Machinery Analysis	✓	✓	✓	✓	✓	✓	✓	✓
Autonomy						✓		
Working Window		✓	✓					

	Impact of Automated Guidance for Mechanical Control of Herbicide Resistant Weeds in Corn	The Impact of Swarm Robotics on Arable Farm Size and Structure in the UK	Agricultural Robots - System Analysis and Economic Feasibility	Agricultural Robots - Applications and Economic Perspectives	Modeling and Analysis of Ground-Based Autonomous Agricultural Vehicles	An Economic Feasibility Assessment of Autonomous Field Machinery in Grain Crop Production	Integrated Farm System Model	Farm Assessment Tool
Cost Analysis	✓	✓	✓	✓	✓	✓	✓	✓
Machinery Analysis	✓	✓	✓	✓	✓	✓	✓	✓
Autonomy		✓	✓	✓	✓	✓		
Working Window						✓		

1.2.4 Machinery Sizing and Automation

Based on the research presented in the background, there is a gap in currently available studies and models. None of the work covered in the literature review is able to calculate the cost associated with a large range of commercially available agricultural equipment that is used for row crop farming. Assumptions are also made on the possible configurations of these new autonomous systems. These assumptions result in the autonomous system being analyzed to lack similarities and operational capacities that are currently available with equipment on the market. Some previous work does not factor in that farming operations are time sensitive, so variable working windows are not included in the analyses. Some research is trying to determine the economic impact of autonomous machinery adoption. The assumed change in cost and technical capability for the autonomous equipment heavily affects the results. There is an opportunity for novel research on the value add that autonomy and machinery fleet sizing has on row crop farming systems under current economic conditions.

1.3 Model Development

The cost and energy/emissions model were created with Microsoft Excel and Visual Basics for Applications (VBA). The energy and emissions aspect of the agricultural machinery is discussed in **CHAPTER 2**. The flow chart below, **Figure 1.1**, shows the major sections of the cost model.

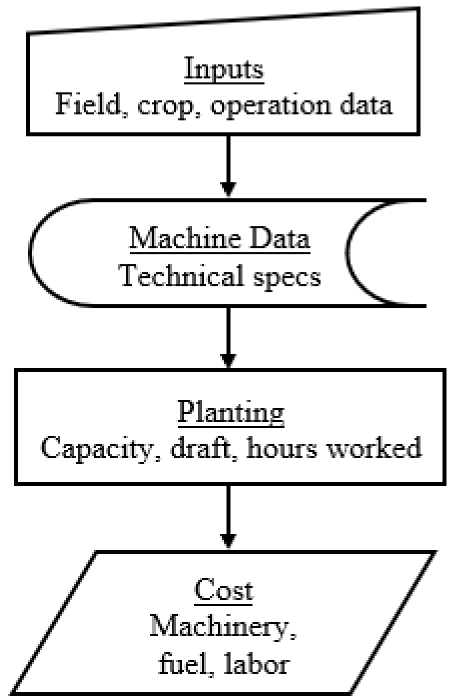

Figure 1.1: Structure of the cost model

The Excel workbook was designed to be simple for the user. Setting parameters and case study data is mostly limited to the Inputs worksheet. Operating speeds for planting and harvest can be adjusted in their respective module, which are organized as workbook sheets in the model. The calculations performed by the traction machine and planting model do not require user interaction. Outputs regarding cost, energy consumption, and emissions are generated by the model. The following sections describe the model, its capabilities, and limitations. Rather than speculate the potential cost differences and configuration changes of autonomous vehicles, this work sets out to ascertain the potential value add of fully autonomous navigation by comparing it to conventional machines.

1.3.1 Inputs

Model inputs are in categorizes of field, planting, harvest, and variable factors data. Field data is used to set parameters such as field size, staff limiter, and percent of land dedicated to each crop. The staff limiter is used to analyze a farming system that has a limited number of operators.

For this research, a corn/soybean rotation is assumed. Planting data includes: the working window for planting, soil conditions, hours worked per day, and planter field efficiency. Key harvesting input data points are the working window, hours worked per day, harvester field efficiency, and grain cart variables.

1.3.2 Assumptions

The following list details some of the major assumptions used when developing the model:

- 30-inch crop row width
- Only one machine type and size per fleet
- Input costs for seed and agrochemicals are not impacted by machinery selection
- No-till operation
- Spraying is not considered
- Field shape and grade are not considered
- Autonomous machinery can work longer hours per day and require no labor

Previous models from research such as Wilfong (2019), Shockley et al. (2019), and Lampridi et al. (2019) have speculated that potential configurations changes and cost premiums between conventional and autonomous agricultural vehicles. Wilfong assumed the following for autonomous machinery: a 10% weight reduction, 50% fertilizer application reduction, 65% pesticide application reduction, and a 10% price increase. Shockley et al. based their cost (repair and maintenance, total ownership cost) and performance data (speed, field capacity) on an autonomous prototype. Lampridi selected a 4WD, electric platform for their autonomous system. The working width of the implement was smaller than the conventional machinery, and the field speed was also slower. These assumptions had substantial impacts on model outcomes, but with no current market offerings, they were difficult to quantify.

For the model in this research, no assumptions were made that would change the technical specifications of the autonomous vehicles. The weight of the tractor was not reduced for the autonomous vehicles even though a cab-less vehicle would not have to accommodate an operator. No cost or fuel consumption savings or increase were assumed for the autonomous system. The main assumption that differentiated conventional and autonomous machines were the reduction in labor and the hours the machines could operate in a day which are widely accepted as potential benefits of autonomous machines.

1.3.3 Traction Machines

The traction machines module calculates vehicle specific parameters such as the motion resistance, fuel consumption, emissions, and technical capability. The tractor database used in the model was developed by determining popular make and models using https://www.fastline.com/. The method of locating tractors from 25 to 625 horsepower (18.6 to 466.1 kW), in steps of 25 horsepower, was used so that the model would be able to quantify the impact of machinery size. The final database was composed of 28 tractors, with some using tracks instead of tires. Using commercially available tractor in the model allowed for accurate pricing and tractor-specific fuel consumption calculations. **Table 1.2** details the make, model, rated engine power, price, and mass of the tractors in the database.

The price of tractors was gathered from manufacturers online listings. For tractors with less than 200 horsepower, 149 kW, it was assumed that guidance technology was not included in the base list price, so $10,000 was added to the price to account for this. The additional cost would account for the software subscription, auto steer, receiver, and display for the life of tractor. For base list price tractors that came with an open operator station, an additional $8,143 was added to the price. This cost would account for the operator station's cab. The inclusion of these features and costs would allow for a more accurate comparison between equally capable tractors. A cost of autonomy was not assumed. The goal of the research was to determine the value-add that autonomous navigation and swarm farming will have on row crop farming operations.

Table 1.2: Tractor database

Make and Model	Rated Engine Power (kW)	Price (USD)	Mass (kg)
John Deere 3025E	19	$37,022	1007
Massey Ferguson 2850M	37	$50,308	1830
John Deere 5075E	56	$47,947	2563
John Deere 5090EL	67	$74,590	3200
John Deere 5100E	75	$74,641	3602
Case Maxxum 125	93	$140,951	6165
John Deere 6150R	112	$169,249	6872
John Deere 6175R	130	$200,807	8466
Case Magnum 200	149	$210,553	9471
Case Magnum 220	164	$220,020	9945
New Holland T8.320	186	$334,214	11049
John Deere 8270R	201	$347,928	11437
John Deere 8295R	220	$380,726	11491
John Deere 8320R	239	$425,743	11741
Case Magnum 340	254	$441,121	12104
John Deere 8370R	276	$411,456	12608
John Deere 8400R	294	$428,250	13515
John Deere 9420R	313	$424,548	19568
John Deere 9470R	350	$454,282	20770
Case Steiger 500*	373	$498,478 & $613,209	21806 & 26147
John Deere 9520R	388	$492,189	21570
Case Steiger 540*	399	$530,581 & $652,767	22423 & 26249
Case Steiger 580*	433	$560,543 & $679,257	24514 & 27361
Case Steiger 620*	462	$583,266 & $720,969	24514 & 27261
https://www.deere.com/en/tractors/ https://www.masseyferguson.us/products/tractors/ https://www.caseih.com/northamerica/en-us/products/tractors/ https://agriculture.newholland.com/nar/en-us/equipment/products/tractors-telehandlers/			

**Wheel and track version*

1.3.3.1 Motion Resistance

The motion resistance (MR) of the traction machine is the resistive force experienced by the vehicle as it travels along a surface. The power needed to overcome motion resistance affects the fuel consumption. There was a detailed database of technical specification for tractors, provided by NTTL tests, that allowed for the motion resistance to be calculated. For combines, the motion resistance experienced was part of the 0.8 rated power demand ratio assumed for harvesting. The MR varies depending on the tractor's drive type, tire type, and the soil condition. **Eq. 1.1** and **Eq. 1.2** are the motion resistance ratio, ρ (decimal), of different tire types:

Bias-ply tires

$$\rho = \frac{1}{B_n} + 0.04 + \frac{0.5(slip)}{\sqrt{B_n}} \qquad \text{Eq. 1.1}$$

Radial-ply tires

$$\rho = \frac{0.9}{B_n} + 0.0325 + \frac{0.5(slip)}{\sqrt{B_n}} \qquad \text{Eq. 1.2}$$

B_n is the mobility number (dimensionless) and $slip$ is slip the tire experiences (decimal). If the vehicle drive type is 2WD, slip is zero for nondriving tires. The mobility number calculation for radial and bias-ply tires is shown below in **Eq. 1.3**:

$$B_n = \frac{CI * b * d}{W} * \frac{1 + 5\frac{\delta}{h}}{1 + 3\frac{b}{d}} \qquad \text{Eq. 1.3}$$

CI is the cone index of the soil (kPa), b is the unloaded tire section width (m), d is the overall tire diameter when unloaded (m), W is dynamic wheel load (kN), δ is the tire deflection (m), and h is the tire section height (m). To calculate the mobility number for an axle (front or rear), W becomes the weight at the axle divided by the number of tires, since the load is spread across all the tires. The motion resistance ratio for vehicles using rubber tracks is calculated using **Eq. 1.4**, defined by Grisso et al. (2006):

$$\rho = \frac{1.75}{B_n(0.7 * DWI)} + \frac{0.03}{DWI} + \frac{0.5(slip)}{\sqrt{B_n}} \qquad \text{Eq. 1.4}$$

The dynamic weight index, DWI, is given by **Eq. 1.5**:

$$DWI = 1 - \left|\frac{0.7(DWR - 1)}{DWR - 1}\right| \qquad \text{Eq. 1.5}$$

DWR, the dynamic weight ratio, is the ratio between the dynamic load on the rear and front. For vehicles using tracks, tractive efficiency is maximized when the DWR is one. For tracked vehicles in the model, the dynamic weight ratio is assumed to be one.

The mobility number calculation for tracks is different than the calculation for tires. **Eq. 1.6** is the mobility number calculation for radial tracks:

$$B_n = \frac{CI * TW * TL}{W(1 - e^{-CI/_{0.698}})} * \frac{5}{1 + 6\left(\frac{TW}{TL}\right)} \qquad \text{Eq. 1.6}$$

TW is the track width (m) and TL is the track length (m). For an entire axle, W becomes the weight at the axle divided by the number of track sets, since the load is spread across the tracks. The technical specifications used in the calculation of motion resistance were retrieved from Nebraska Tractor Test Lab (NTTL) data.

Slip, also known as travel reduction, is the percent difference between the vehicle's theoretical and actual speed. This is due to the power loss experienced between the drive tire and surface/soil interaction. **Table 1.3** shows slip, for a variety of surfaces, assuming maximum tractive efficiency.

Table 1.3: Optimum slip ranges for different surfaces

Surface	**Slip (%)**
Concrete	4-8
Firm soil	8-10
Tilled soil	11-13
Soft soil	14-16

Eq. 1.7 is used to determine the total draft force caused by the vehicle's resistance to motion (kN):

$$Draft_{TM} = (\rho * W)_{front} + (\rho * W)_{rear} \qquad \text{Eq. 1.7}$$

where ρ is the motion resistance ratio (decimal) and W is dynamic wheel load (kN).
The calculation to determine the power needed to overcome $Draft_{TM}$ (kW) is shown in the below in **Eq. 1.8**:

$$P_{TM} = Draft_{TM} * s \qquad \text{Eq. 1.8}$$

where s is the vehicle speed (m s^{-1}).

1.3.3.2 Fuel Consumption

Eq. 1.9 to **Eq. 1.12** were develop by (Grisso, Vaughan, & Roberson, 2008) and are used to calculate the fuel consumption for specific tractor models (L hr^{-1}):

$$Q = (a * X + b) * [1 + (c * X * N_{red} - d * N_{red})] * P_{pto} \qquad \text{Eq. 1.9}$$

Coefficients a, b, c, and d are tractor-specific parameters that are calculated from Nebraska Tractor Test Lab (NTTL) data. The coefficients for the tractors in the database can be found in **A.4**. Variable X is the ratio of equivalent PTO power to rated PTO power (decimal). The engine speed reduction for a partial load, from full throttle, is denoted as N_{red} (%). If no engine speed decreased is experienced, N_{red} is equal to zero. P_{pto} is the rated PTO power of the tractor (kW). This allows for a more accurate estimate of fuel consumption since the data points are for a single vehicle, rather than the average of a large population.

The ratio of rated power used by a tractor for a field operation, **Eq. 1.10**, is calculated as follows:

$$X = \frac{HI - FES}{HI - Rated} \qquad \text{Eq. 1.10}$$

where HI is engine speed at high-idle (RPM), FES is the engine speed during the field operation (RPM), and $Rated$ is the rated engine speed of the tractor (RPM). The ratio can also be calculated using **Eq. 1.11**:

$$X = \frac{P_{eq}}{P_{pto}} \qquad \text{Eq. 1.11}$$

where P_{eq} is the equivalent PTO power required by the operation and P_{pto} is the rated PTO power of the tractor (kW). This method was used to calculate X in the model for planting.

Eq. 1.12 is the reduced engine speed, from full throttle, for a partial load calculation. N_{red} at full throttle is equal to zero.

$$N_{red} = \left(\frac{RPM_F - RPM_R}{RPM_F}\right) * 100 \quad \text{Eq. 1.12}$$

The fuel consumption of smaller tractors that have not been tested by the NTTL are also calculated using **Eq. 1.9**, but coefficients a, b, c, and d cannot be calculated since NTTL data is not available for them. The general version of a, b, c, and d, found in **Table 1.4**, are used instead.

Table 1.4: Values for the generalized fuel consumption equation (SI units)

Coefficient	**Value**
a	0.22
b	0.096
c	0.0045
d	0.00877

1.3.3.3 Technical Capability

The tractor's implement capacity was determined from manufacturer recommendations (John Deere, 2021). Required tractor power data was gathered from John Deere's recommendation for their drawn and DB planters. A plot of the data can be seen below in **Figure 1.2**.

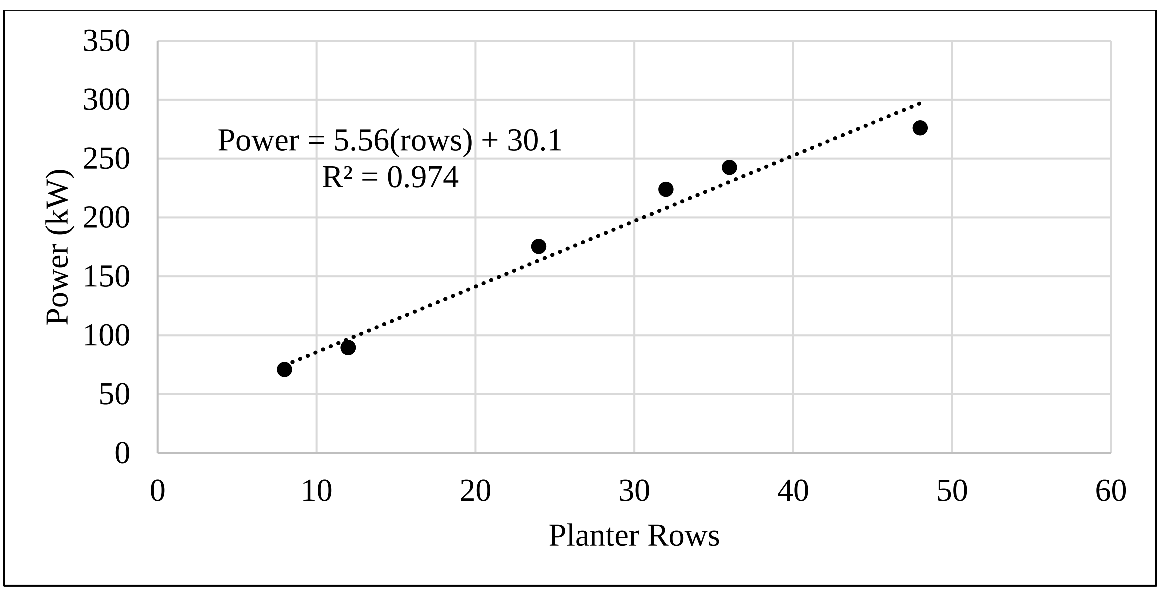

Figure 1.2: Minimum recommended tractor power based on 30-inch row crop planter width with no-till assumed (John Deere, 2021)

Recommended tractor power was not provided by John Deere for four and six-row planters, so the regression equation was extrapolated. In the model, all tractors use the largest possible planter they can feasibly power.

Pairing tractors to grain carts was set using recommendations from Brent Grain Handling (Brent, 2021). The **Table 1.5** shows the minimum tractor power required to pull grain carts of varied capacity.

Table 1.5: Maximum grain cart capacity based on tractor power

Grain Cart Capacity (bushels)	Minimum Tractor Power (kW)
550[1]	97
630[1]	104
750[2]	112
850[2]	134
1000[2]	149
1100[2]	168
1300[2]	186
1500[3]	224
2000[3]	298
2500[3]	373

[1]https://www.brentequip.com/grain-carts/corner-auger/
[2]https://www.brentequip.com/grain-carts/v-series/
[3]https://www.brentequip.com/grain-carts/avalanche/

Like the tractor and planter pairing, tractors are assumed to operate with the largest grain cart that they could pull based on the manufacturer's recommendation.

1.3.4 Timeliness

1.3.4.1 Days Suitable for Work

Both yield loss and the days suitable for fieldwork (DSFW) is dependent on geographic location and weather. The United States Department of Agriculture (USDA) National Agriculture Statistics Service (NASS) allows users to export data on DSFW for different states and a range of years. The DSFW data used in the model, measured in days per week, is from Indiana and is an average of the 2013 to 2020 values. The averaged values can be seen in **A.3**. The NASS data is used to define possible working windows for planting and harvest in the model. Due to the annual calendar changes, the weeks of the year for the historical data were adjusted to match the 2021 calendar (USDA NASS, 2017).

1.3.4.2 Yield Loss

Irwin and Hubbs compiled data from Professor Emerson Nafziger to report corn and soybean yield loss for central and northern Illinois (Irwin & Hubbs, 2019). The data is reported as percent yield loss, relative to maximum yield. The yield of corn and soybeans is dependent on the date that it is planted and the weather during that time. The plotted can be found in **Figure 1.3** and **Figure 1.4** respectively. Due to the variance in geographic location, there is no established and agreed upon optimum planting window and cutoff date. The cutoff date is when late planting starts to significantly impact crop yield. To help account for the yearly variance, the presented data is based on an 11-year average for corn and 8-year average for soybeans.

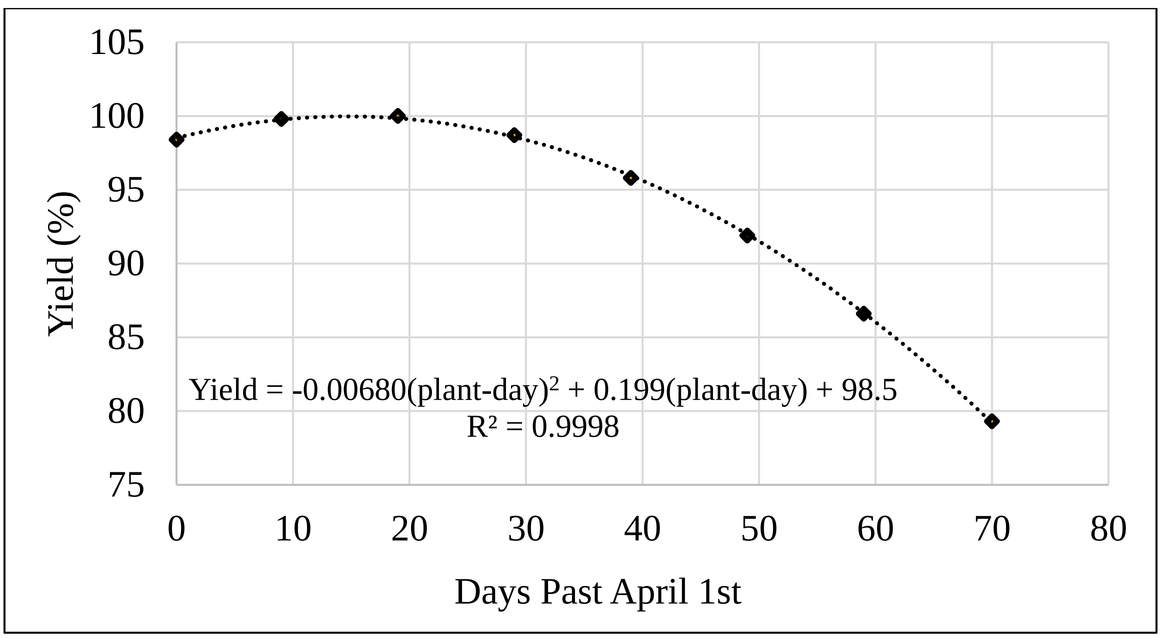

Figure 1.3: Corn yield drop vs. planting date for Central and Northern IL (Irwin & Hubbs, 2019)

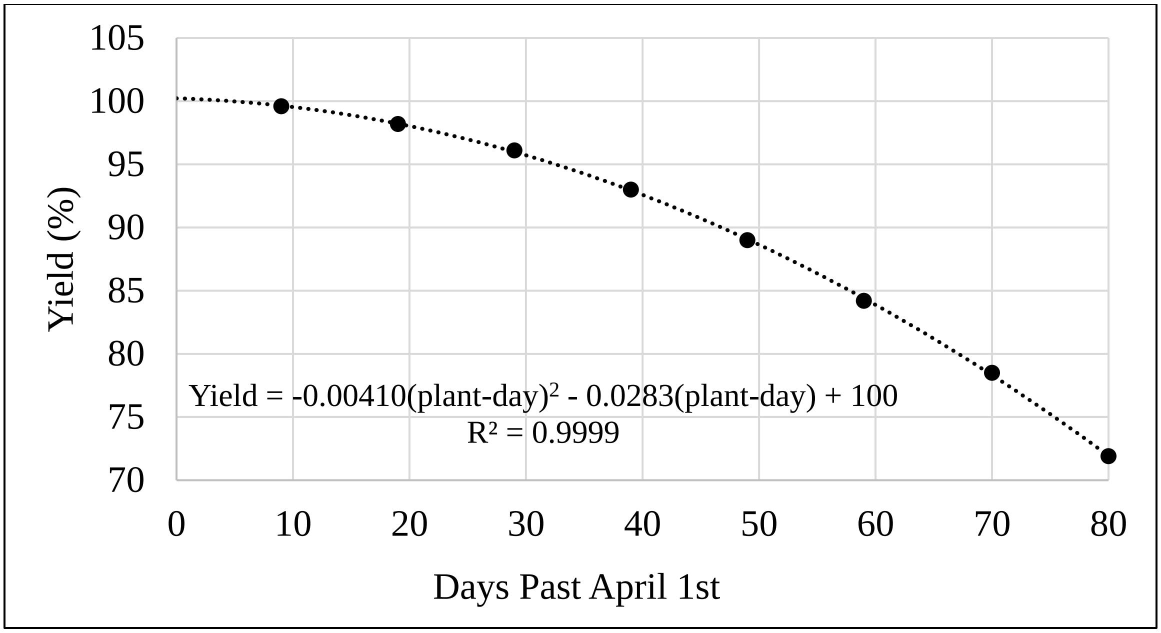

Figure 1.4: Soybean yield drop vs. planting date for Central and Northern IL (Irwin & Hubbs, 2019)

A linear regression was not sufficient for modeling the corn yield data, $R^2 = 0.8$, so a polynomial was used for both sets of data. The equations are incorporated into the model to quantify yield loss due to timeliness. Since different machinery fleets are planting at different rates, being able to identify how the fleet's capacity affects crop yield is vital.

The VBA script used to calculate the yield for the planting systems accounts for the days suitable for planting, discussed in **Days Suitable for Work**. After a planting window is defined by user inputs, the USDA NASS data defines the number of days within that window that are suitable for fieldwork. It was assumed that the suitable working days in were distributed evenly throughout the working window. **Eq. 1.13** was used to calculate the days between suitable working days.

$$Days_{BTWN} = \frac{WIN_{planting}}{DSWF_{planting}} \qquad \text{Eq. 1.13}$$

$Days_{BTWN}$ is the number of days between working days (day integer), $WIN_{planting}$ is the planting window defined by user, and $DSWF_{planting}$ (days) is the number of days within the defined window that are suitable for planting.

The total number of days needed to plant a crop is calculated using **Eq. 1.14**:

$$Day_x = \left(\frac{Field\ Size}{C_{total}}\right) * \ Crop\ \% \qquad \text{Eq. 1.14}$$

$Field\ Size$ is the farms area (ha), C_{total} is the field capacity of all the planters (ha day^{-1}), and $Crop$ % is the percent of land dedicated to that particular crop. The field capacity of one planter is calculated using **Eq. 1.24** and the number of tractors need is found using **Eq. 1.27**.

Eq. 1.15 is used to calculate the number of days between when the planting of corn is finished, and the planting of soybeans is started:

$$Day_{offset} = Days_{BTWN} * \ Day_{corn} \qquad \text{Eq. 1.15}$$

$Days_{BTWN}$ is defined in **Eq. 1.13** and Day_{corn} is the number of days needed to plant all corn. For this model, it is assumed that all corn is planted before soybean planting starts.

The resulting, final yield equations for the VBA calculation is shown below in **Eq. 1.16** and **Eq. 1.17**:

$$\begin{aligned} array\_corn(i) &= -0.0068 * (((i \\ &* days\_btwn\_workingdays) \\ &+ days\_after\_first) \text{ ^ } 2) + 0.1992 * ((i \\ &* days\_btwn\_workingdays) \\ &+ days\_after\_first) + 98.513 \end{aligned} \qquad \text{Eq. 1.16}$$

$$\begin{aligned} array\_soy(m) &= -0.0041 * (((m \\ &* days\_btwn\_workingdays) + days\_offset \\ &+ days\_after\_first) \text{ ^ } 2) - 0.0283 * ((m \\ &* days\_btwn\_workingdays) + days\_offset \\ &+ days\_after\_first) + 100.22 \end{aligned} \qquad \text{Eq. 1.17}$$

i and m are indexing values in the for loop and represent Day_x. These are necessary because the yield changes every day, so the yield for all planting days needs to be calculated before they are averaged. In **Eq. 1.18** and **Eq. 1.19**, $days\_after\_first$ is used to determine the numbers of days after April 1st. The timeliness data in **Figure 1.3** and **Figure 1.4** begins after April 1st, so the VBA must be able to account for a planting start date that is not April 1st.

1.3.5 Planting

The planting module is used to calculate major parameters such as the number of machines, fuel consumption, yield, emissions, and energy used during the planting operation. The tractor database, **Table 1.2**, used for planting analysis consists of 28 vehicles. Based on the linear regression for planter sizes in **Figure 1.2**, the **Table 1.6** shows the maximum planter size the vehicles in the database can pull based on tractor power.

Table 1.6: Tractor and planter pair based on manufacturer recommendation

Make and Model	**Planter Size (rows)**
John Deere 5075E	4
John Deere 5090EL	6
John Deere 5100E	8
Case Maxxum 125	8
John Deere 6150R	12
John Deere 6175R	16
Case Magnum 200	16
Case Magnum 220	24
New Holland T8.320	24
John Deere 8270R	24
John Deere 8295R	32
John Deere 8320R	36
Case Magnum 340	36
John Deere 8370R	36
John Deere 8400R	36
John Deere 9420R	48
John Deere 9470R	48
Case Steiger 500 (wheel & tracked)	48
John Deere 9520R	48
Case Steiger 540 (wheel & tracked)	48
Case Steiger 580 (wheel & tracked)	48
Case Steiger 620 (wheel & tracked)	48

The two smallest tractors in the database, the John Deere 3025E and Massey Ferguson 2850M, are not capable of operating the smallest planter. Only common, commercially available planter sizes were used in this model. Planter selection was limited to those with a 0.762-meter or 30-inch row spacing. The following John Deere planter models, shown in **Table 1.7**, were used in the database.

Table 1.7: Planter database

Model	Size (rows)	Mass (kg)	Price (USD)
1755	4	2966*	$21,877
1755	6	3859*	$46,343
1745	8	4410	$70,809
1775NT	12	5398	$119,741
1775NT	16	8326*	$168,673
DB60	24	13990	$266,537
DB80	32	16066	$364,401
DB90	36	16851	$413,333
DB120	48	21827	$560,129
https://www.deere.com/en/planting-equipment/			

**Estimated*

The smaller planters may not have the same level technology as the larger ones, but the base list price was the fairest comparison. John Deere's planter specifications were used to get mass data for various planter sizes. Mass data for the 4, 6, and 16 row planters was not available through the manufacturer's website so a trendline was developed using accessible data and applied to the planters that were missing mass data. The r-squared for the trendline was 0.9704.

1.3.5.1 Total Power

The total power required to operate an implement (kW) is the sum of the individual power terms shown in **Eq. 1.18**:

$$P_{imp} = \frac{P_{db}}{E_m E_t} + P_{pto} + P_{hyd} + P_{el} \qquad \text{Eq. 1.18}$$

P_{db} (kW) is the required drawbar power, E_m (decimal) is the mechanical efficiency of the tractor's powertrain/transmission, E_t (decimal) is the tractive efficiency of the tractor, P_{pto} (kW) is the power that needs to be produced by the power-takeoff of the tractor, P_{hyd} (kW) is the needed hydraulic power, and P_{el} (kW) is electrical power used to run the implement.

The total power required to power the planter is used in the fuel consumption calculation, **Eq. 1.9**. In **Eq. 1.9**, X is the ratio of equivalent PTO power to rated PTO power, the equivalent PTO power is the power needed to complete the operation. The power required to plant is a sum of the power required by the planter and the power to overcome the rolling resistance of the tractor.

The mechanical efficiency of tractors with gear transmission is typically 0.96. The tractive efficiency, provided by ASABE D497.7, is dependent on the tractor's drive type and the tractive condition.

1.3.5.2 Drawbar Power

Eq. 1.19 shows the functional draft force caused by the planting implement's resistance to crop and soil in the direction of travel, $Draft_{imp}$ (N):

$$Draft_{imp} = F_i[A + B(s) + C(s)^2]w * T \quad \text{Eq. 1.19}$$

where F_i is a soil texture adjustment parameter (dimensionless) that varies with implement type and soil. Variables A, B, and C are implement-specific parameters. The values for these parameters can be found in Table 1 of ASABE standard D497.7. Field speed is represented by s (km hr^{-1}), w is the implement width (m, rows, or tools), and T is the tillage depth (cm). Implements are classified as major tillage, minor tillage, or seeding implements in Table 1 of D497.7. For minor tillage and seeding implements, the tillage is depth is one. The drawbar power required to pull tractor-drawn implements (kW) is calculated using **Eq. 1.20**:

$$P_{db} = \frac{Draft_{imp} * s}{3.6} \quad \text{Eq. 1.20}$$

$Draft_{imp}$ is the implement draft (kN) and s is the travel speed (km hr^{-1}).

1.3.5.3 PTO Power

Eq. 1.21 is the power used by the PTO during operations such as mowing, baling, and raking:

$$P_{pto} = a + (b * w) + (c * F) \quad \text{Eq. 1.21}$$

Coefficients a, b, and c are machine specific parameters from Table 2 of ASABE Standard D497.7. Variable w is the width of the implement (m), and F is the material feed rate (t hr^{-1}). Since planters do not require rotary power, P_{pto} is ignored.

1.3.5.4 Hydraulic Power

The power required (kW) to operate the implement's hydraulic system is calculated using **Eq. 1.22**:

$$P_{hyd} = \frac{p * Q}{1000} \qquad \text{Eq. 1.22}$$

where p is the fluid pressure (kPa) and Q is the fluid flow rate (L s^{-1}).

1.3.5.5 Electrical Power

The electrical power used to operate the planter is shown in **Eq. 1.23**:

$$P_{el} = \frac{I * E}{1000} \qquad \text{Eq. 1.23}$$

I is the current (amps) and E is the potential (volts). Electrical power is minimal compared to drawbar and hydraulic power, so it was not accounted for in the total power required to operate the planter.

1.3.5.6 Field Capacity

After tractors are paired with planters, the field capacity must be calculated to determine the number of planters needed to complete the operation during the working window.

The effective field capacity of a single tractor pulling an implement (ha hr^{-1}) is determined using **Eq. 1.24**:

$$C_a = \frac{s * w * E_f}{10} \qquad \text{Eq. 1.24}$$

with s representing the travel speed (km hr^{-1}), w is the implement width (m), and E_f (decimal) is the field efficiency. ASABE D497.7 Table 1 has typical field efficiencies and speeds for various implements. For this model, a planter field efficiency of 0.65 was used. The speed of the tractor during planting was 10 km hr^{-1}.

Eq. 1.25 is the minimum field capacity (ha hr^{-1}) required to complete planting within a specified working window calculation:

$$C_{min} = \frac{Field\ Size}{HSFW_{plant}} \qquad \text{Eq. 1.25}$$

$Field\ Size$ (ha) is defined by the user in the inputs section of the model and the hours suitable for work, $HSFW_{plant}$, is calculated from the NASS data and shown in **Eq. 1.26**.

$$HSFW_{plant} = DSWF_{plant} * T_{plant} \qquad \text{Eq. 1.26}$$

$DSWF_{plant}$ is the days suitable by planting within a defined window and T_{plant} is the hours worked per day during planting.

The number of tractor, planter pairs is calculated using **Eq. 1.27**:

$$N_{plant} = \frac{C_{min}}{C_a} \qquad \text{Eq. 1.27}$$

The result of the calculation is rounded up to the nearest whole number.

Eq. 1.28 is used to quantify the number of hours that a single planter and tractor pair is used a year:

$$Hr_{plant} = \frac{C_{plant}}{C_a} \qquad \text{Eq. 1.28}$$

where $C_{planted}$ is the area planter by that single pair (ha), and C_a is the field capacity (ha hr^{-1}) of the corresponding pair.

The area planted by a single tractor and planter pair, **Eq. 1.29**, is as follows:

$$C_{plant} = \frac{Field\ Size}{N_{plant}} \qquad \text{Eq. 1.29}$$

1.3.6 Harvest

The harvesting module analyzes four different harvesting systems. A detailed list of the different system is shown below in **Table 1.8**.

Table 1.8: Combine and header pairing

System	Corn Header Width (rows)	Soybean Header Width (m)
Class 6 – 249kW	6	6.1
Class 7 – 292kW	8	9.1
Class 8 – 353kW	12	10.7
Class 9 – 405kW	16	12.2

1.3.6.1 Fuel Consumption

The harvester's specific fuel consumption volume (L kW-hr^{-1}) is calculated using the following equations. **Eq. 1.30** is the specific fuel consumption for a combine diesel engine operating at or below maximum load and set to full and partial throttle (ASABE, 2015b).

$$SFC_V = \left(0.22 + \frac{0.096}{X}\right) * PTM \qquad \text{Eq. 1.30}$$

X is the fraction of equivalent PTO power available, refer to **Eq. 1.11** in **Fuel Consumption**. PTM is the partial throttle multiplier, calculation shown in **Eq. 1.31**.

$$PTM = 1 - [(N-1)(0.45 * X - 0.877)] \qquad \text{Eq. 1.31}$$

N, determined using **Eq. 1.32**, is the ratio of partial throttle engine speed to full throttle engine speed at the operating load.

$$N = \frac{n_{PT}}{n_{FT}} \qquad \text{Eq. 1.32}$$

where n_{PT} is the partial throttle engine speed (RPM) and n_{FT} is the full throttle engine speed (RPM).

Fuel consumption (L hr^{-1}) is calculated in **Eq. 1.33** by multiplying the specific fuel consumption volume with the PTO power used during harvest (kW).

$$Q_{harvest} = SFC_V * PTO_{harvest} \qquad \text{Eq. 1.33}$$

For harvest the harvest of corn and soybeans, it is assumed that engine speed is not reduced, and the fraction of equivalent PTO power available is 0.8.

1.3.6.2 Material Capacity

The material capacity of the harvester (bu hr^{-1}) is based on the field capacity of the harvester, header pair and the yield of the crop. The two crops being analyzed for this research are corn and soybeans. The capacity is calculated in **Eq. 1.34**:

$$MC = FC * Yield \qquad \text{Eq. 1.34}$$

where FC is the field capacity of the harvester (ha hr^{-1}) and $Yield$ is the yield of the crop (bu ha^{-1}). The field capacity of the harvester is determined using the same equation used to calculate planter field capacity, **Eq. 1.24**. The combine speed during corn harvesting is 9 (km hr^{-1}) and 5 (km hr^{-1}) during soybean harvest.

Eq. 1.35 is the minimum material capacity required by the combine to complete the harvesting operation within the specific working window:

$$MC_{min} = FC_{min} * Yield \qquad \text{Eq. 1.35}$$

FC_{min}, calculated in **Eq. 1.36**, is the minimum field capacity (ha hr^{-1}) required to complete the operation within the defined working window. The minimum field capacity is result of dividing the field size by the hours suitable for work.

$$FC_{min} = \frac{Field\ Size}{HSFW_{harvest}} \qquad \text{Eq. 1.36}$$

$Field\ Size$ (ha) is specified by the user and the hours suitable for work is calculated using **Eq. 1.37**.

$$HSFW_{harvest} = DSWF_{harvest} * T_{harvest} \qquad \text{Eq. 1.37}$$

$DSWF_{harvest}$ are the days suitable for harvest work, defined by USDA NASS data, and $T_{harvest}$ (hr day^{-1}) is the time per day that the combine is capable of working.

After the minimum material capacity required and the combine's actual material capacity are calculated, then the number of combine and header pairs needed can be determined with **Eq. 1.38**. The number of combines needed varies between the corn and soybeans because field capacity changes based on the working width of the header and the combine speed.

$$N_{harvest} = \frac{MC_{min}}{MC} \qquad \text{Eq. 1.38}$$

The final number of combines and headers is determined by comparing the number needed for both crops and selecting the larger of the two. A result of this choice is that the cropping system that needed fewer harvesters might have an additional unit working.

Eq. 1.39 is used to determine the time required to complete the harvest of a particular crop:

$$Hr_{HVX} = \frac{Field\ Size * Crop\ \%}{TFC_{HVX}} \qquad \text{Eq. 1.39}$$

The HVX subscript represents the harvest operation of a particular crop, corn and soybean for this research. $Field\ Size$ is the total field size (ha) and $Crop$ % (decimal percent) is the percent of land dedicated to that particular crop. TFC_{HVX} is the total field capacity (ha hr^{-1}) of all the combines used in the harvest of that crop.

1.3.7 Grain Carting

The grain cart module is dependent on the harvesting module. The grain cart module has two systems. The first system limits the number of tractors and grain carts available equal to the number of planter tractors. The second system sets the number of tractors and grain carts equal to the material capacity of the corn harvesting operation. This system uses the yield values provided by the user for a specific case study and does not account for the timeliness associated the individual planting fleets. **Table 1.9** shows the tractor and grain cart pairings based on the minimum tractor power outlined in **Technical Capability**.

Table 1.9: Tractor and grain cart pair

Make and Model	**Grain Cart Size (bushels)**
John Deere 6150R	630
John Deere 6175R	750
Case Magnum 200	1000
Case Magnum 220	1000
New Holland T8.320	1300
John Deere 8270R	1300
John Deere 8295R	1300
John Deere 8320R	1500
Case Magnum 340	1500
John Deere 8370R	1500
John Deere 8400R	1500
John Deere 9420R	2000
John Deere 9470R	2000
Case Steiger 500 (wheel & tracked)	2000
John Deere 9520R	2000
Case Steiger 540 (wheel & tracked)	2500
Case Steiger 580 (wheel & tracked)	2500
Case Steiger 620 (wheel & tracked)	2500

The Brent Grain Carts used in the machinery database are shown below in **Table 1.10**.

Table 1.10: Grain cart database

Model	Size (bushels)	Mass (kg)
576	550	6500
678	630	8100
V700	750	11360
V800	850	12160
V1000	1000	14000
V1100	1100	15645
V1300	1300	19050
1596	1500	26840
2096	2000	36640
2596	2500	37680

The empty mass of the grain carts was obtained from Brent Grain Cart product data that was listed on their website. The first six tractors in the vehicle database, **Table 1.2**, are not capable of pulling the smallest grain cart used in the model. The recommended tractor power to pull the 550-bushel grain cart is 97 kW and no tractor in the database met that requirement or met it without exceeding it. Like the planting system, tractors are paired with the largest grain cart that they are recommended to be used with. After pairing capable tractors with carts based on rated engine power, the 850- and 1100-bushel carts were not used. This is because none of the tractors in the database fell within the power ranges for those cart sizes.

1.3.7.1 Material Capacity

The user can set the estimated trips per hour that a tractor and grain cart can make. This input establishes a material capacity, calculation shown in **Eq. 1.40**:

$$MC_{GC} = SZ_{GC} * CAP_{mod} \qquad \text{Eq. 1.40}$$

MC_{GC} is the material capacity of the grain cart (bu hr^{-1}), SZ_{GC} is the size of cart (bu), and CAP_{mod} is the number of unload trips it can make (trips hr^{-1}).
The total hours that the tractor and grain cart are used per year is calculated using **Eq. 1.41**:

$$Hr_{GC} = Hr_{HVC}\left(\frac{MC_{HVC}}{MC_{GC} * N_{GC}}\right) + Hr_{HVS}\left(\frac{MC_{HVS}}{MC_{GC} * N_{GC}}\right) \qquad \text{Eq. 1.41}$$

where Hr_{HVC} is the hours needed to complete the corn harvesting, MC_{HVC} is the material capacity (bu hr^{-1}) of the corn harvesting, MC_{GC} is the material capacity of a single grain cart (bu hr^{-1}), and N_{GC} is the number of grain carts. The latter half of **Eq. 1.41** refers to the same calculations, but for the soybean harvest.

1.3.8 Cost

1.3.8.1 Machine Prices

The cost of planters was determined by plotting the list price of 30-inch planters from John Deere's drawn and DB series. A plot of the data can be seen below in **Figure 1.5**.

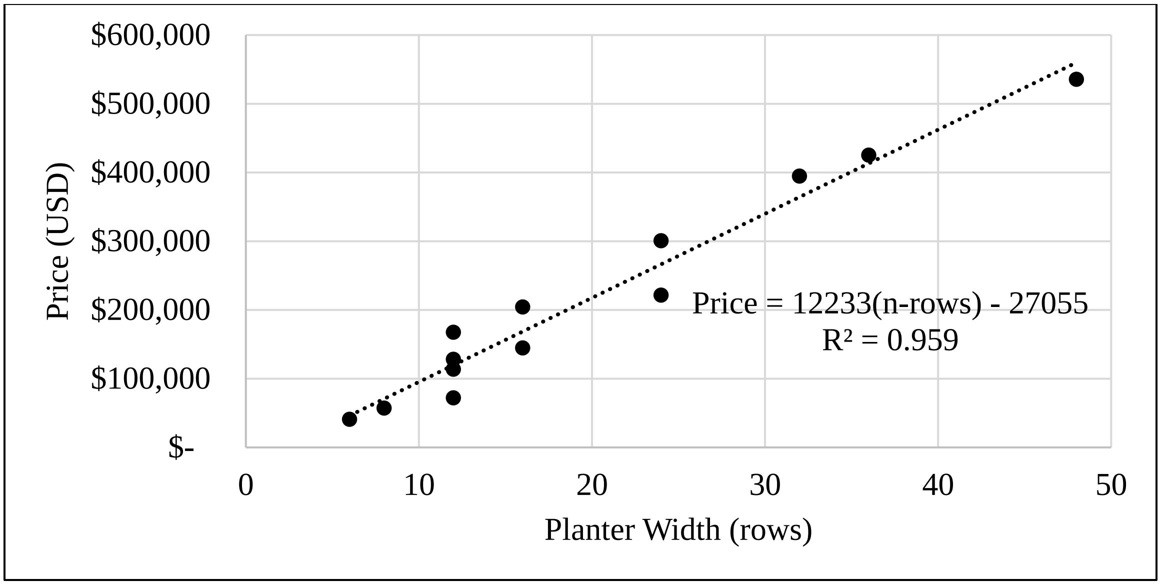

Figure 1.5: 30-inch row crop planter price depending on planter width

The r-squared value of 0.9597 shows a strong correlation in the data and fitted line. The regression line was then used to determine the cost of common planter sizes (4, 6, 8, 12, 16, 24, 32, 36, and 48). The regression was extrapolated by using it to determine the cost of a 4-row planter, which was not listed on the John Deere website.

Price data for grain carts were retrieved from Brent Grain Handling and plotted to obtain a fitted line. **Figure 1.6** shows the price depending on the size.

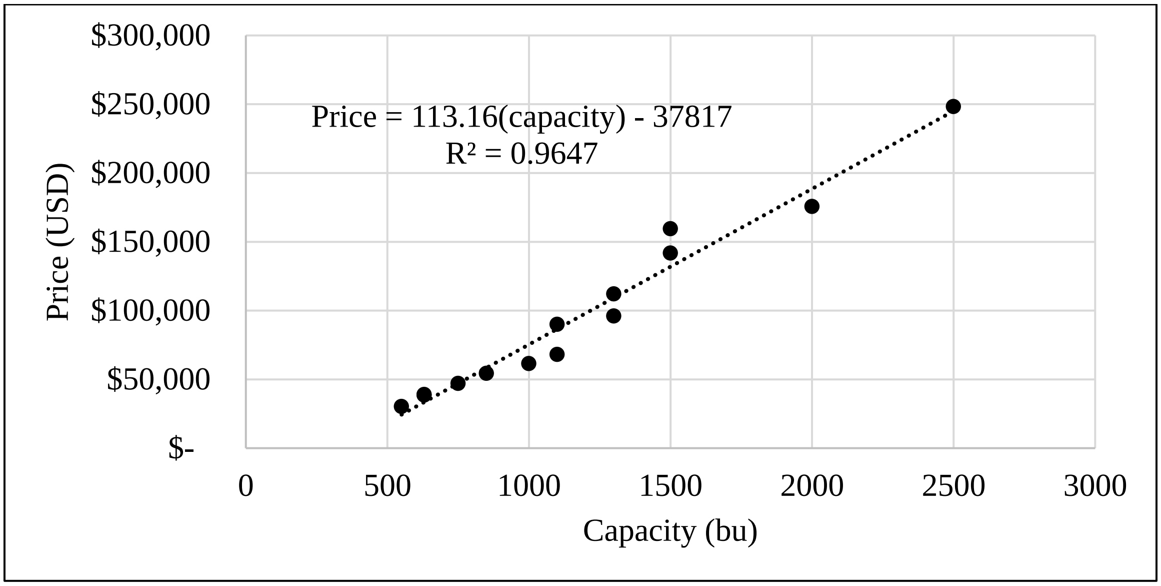

Figure 1.6: Grain cart price depending on cart capacity

The most cost-effective configuration of the Brent grain carts, **Table 1.10**, was used in this analysis. The high r-squared value shows that the fitted line is a good model for explaining the variability in the empirical data.

Corn header prices are based on the starting list price for John Deere's CXR Rigid Corn Heads. An itemized cost and mass based on the width of the head can be seen below in **Table 1.11**.

Table 1.11: Corn head database

Model	Width (rows)	Price (USD)	Mass (kg)
C6R	6	$63,818	2064
C8R	8	$82,955	6431
C12R	12	$127,135	7694
C16R	16	$167,561	10798
https://www.deere.com/en/harvesting/corn-heads/			

Like the corn headers, the cost of soybean heads is based on the starting list price provided by John Deere. The pricing and technical data is listed in **Table 1.12**.

Table 1.12: Soybean head database

Model	Width (m)	Price (USD)	Mass (kg)
620F	6.1	$40,355	3942
630F	9.1	$51,353	5641
635F	10.7	$58,479	6620
740D	12.2	$97,443	7600
https://www.deere.com/en/harvesting/auger-platforms/ https://www.deere.com/en/harvesting/draper-platforms/			

The large increase in between the two largest option is because John Deere does not make a 12.2-meter auger platform, so a 12.2m draper platform was selected. The first three option are classified as rigid frame cutting platforms, while the fourth is a rigid draper.

Combine price (USD) was retrieved from John Deere. The data in **Table 1.13** is based on the starting list price for S-Series combines.

Table 1.13: Combine database

Model	Power (kW)	Price (USD)	Mass (kg)
S760	249	$469,273	18400
S770	292	$514,104	18950
S780	353	$560,668	20750
S790	405	$586,700	20750
https://www.deere.com/en/harvesting/			

1.3.8.2 Fixed Costs

The total machinery cost (USD) equation is determined using **Eq. 1.42**:

$$C_{machine} = N_{machine} * Pr_{machine} \quad \text{Eq. 1.42}$$

where $N_{machine}$ is the number of machines and $Pr_{machine}$ (USD) is the price per machine. This equation is used to determine the initial value of the tractors, planter implements, headers, grain carts, and harvesters.

The annual payment equation (**Eq. 1.43**), as known as the capital-recovery factor, was used to calculate the annual payment (USD) for the various machinery.

$$AP_{machine} = C_{machine} * \left[\frac{i * (1+i)^n}{((1+i)^n - 1)}\right] \quad \text{Eq. 1.43}$$

where $C_{machine}$ (USD) is initial value of the assets, i (decimal) is the interest rate, and n (yrs) is the loan term.

The salvage value of the machinery (USD) is calculated in **Eq. 1.44**:

$$SVG_{machine} = C_{machine} * SVG \quad \text{Eq. 1.44}$$

where SVG (decimal) is the machine's salvage value factor at the end of its life.

The machinery's annual depreciation (USD yr^{-1}), shown in **Eq. 1.45**, was determined using the straight-line depreciation method.

$$DPR_{machine} = \frac{C_{machine} - SVG_{machine}}{n} \quad \text{Eq. 1.45}$$

where $C_{machine}$ (USD) is the cost of all machinery, $SVG_{machine}$ (USD) is the salvage value of all machines, and n (yrs) is the loan term.

The other ownership costs (USD yr^{-1}) are taxes, housing, and insurance. They are 1%, 0.75%, and 0.25% respectively. **Eq. 1.46** is used to calculate the other ownership costs.

$$OWN_{machine} = C_{machine} * (TX + HS + IN) \qquad \text{Eq. 1.46}$$

Variable TX is used to denote taxes, HS is housing, and IN is insurance. All other ownership costs in **Eq. 1.46** are reported in decimal percent.

The calculation for the fixed cost per year associated with the tractor is different than other machines because the tractor is used for multiple operations. This means that the fixed cost of the tractor is divided amongst the hours it is used, shown in **Eq. 1.47**.

$$ADJ = \frac{DPR_{tractor} + AP_{tractor} + OWN_{tractor}}{ADD_{work} + Hr_{plant} + HR_{GC}} \qquad \text{Eq. 1.47}$$

ADJ is used to represent the adjusted fixed cost of a single tractor (USD hr^{-1}), $DPR_{tractor}$ is the depreciation (USD yr^{-1}), $AP_{tractor}$ is the annual payment (USD yr^{-1}), and $OWN_{tractor}$ is the other ownership costs (USD yr^{-1}). Hr_{plant} and HR_{GC} are the time spent planting and carting (hr yr^{-1}), and ADD_{work} is the additional time that the tractor is used during the year for other work (hr yr^{-1}). All variables used to calculate ADJ are based on the payments, loss, and hours used for a single unit. **Eq. 1.48** is the final fixed cost for all tractors (USD yr^{-1}) used in a given operation:

$$FF = ADJ * Hr_x * N_{tractors} \qquad \text{Eq. 1.48}$$

where ADJ is the adjusted fixed cost of a single tractor (USD hr^{-1}), Hr_x (hr yr^{-1}) is the hours that the tractor was used for during an operation such as planting or carting, and $N_{tractors}$ is the number of tractors.

1.3.8.3 Variable Costs

The cost of fuel (USD yr^{-1}) is the product of multiple values. The calculation is determined using **Eq. 1.49**:

$$C_{fuel} = Q_{machine} * Hr_{machine} * N_{machine} * Pr_{fuel} \qquad \text{Eq. 1.49}$$

where $Q_{machine}$ (L hr^{-1}) is the fuel consumption of one machine, $Hr_{machine}$ (hr yr^{-1}) is the number of hours one machine is used per year, $N_{machine}$ is the number of machines, and Pr_{fuel} is the price of diesel (USD L^{-1}). This calculation was used to determine the cost of fuel for the planting, harvesting, and grain carting operation. For this research, the price of diesel fuel was set to 1 USD L^{-1}.

The cost of labor for the conventional fleets (**Eq. 1.50**) is calculated as follows:

$$C_{labor} = Hr_{machine} * N_{machine} * Pr_{labor} \qquad \text{Eq. 1.50}$$

where $Hr_{machine}$ (hr yr^{-1}) is the number of hours one machine is used per year, $N_{machine}$ is the number of machines, and Pr_{labor} is the price of labor (USD hr^{-1}). The number of hours and machines is dependent on the operation being evaluated.

The accumulated cost of repair and maintenance was calculated using **Eq. 1.51**, retrieved from ASABE Standard EP496.3.

$$C_{RM} = RF1 * C_{machine} * \left(\frac{Hr_{machine}}{1000}\right)^{RF2} \qquad \text{Eq. 1.51}$$

where $RF1$ and $RF2$ (dimensionless) is the machine repair factors, $C_{machine}$ (USD) is the cost of all machinery, and $Hr_{machine}$ (hr yr^{-1}) is the accumulated hours one machine is used. The repair factor coefficients are based on machinery type and can be found in Table 3 of ASABE Standard D497.7.

Oil consumption for diesel engines (L hr^{-1}) is determined using **Eq. 1.52**:

$$C_{oil} = [(0.00059 * P_{rated}) + 0.02169] * Hr_{machine} * N_{machine} * Pr_{oil} \qquad \text{Eq. 1.52}$$

The portion of the equation within the brackets is provided by ASABE D497.7 Section 3.4 and is defined as the rate of engine crankcase oil being replaced at the change interval recommended by the manufacturer. P_{rated} (kW) is the rated engine power of the vehicle and Pr_{oil} (USD L^{-1}) is the price of oil. The assumed price of oil for this model is 6.35 USD per liter. This calculation applies to the tractors and harvesters.

1.3.9 Limitations

The model presented in this chapter can calculate machinery costs and associated operational costs. A partial budgeting methodology was used to analyze the autonomous and conventional systems. While the model can quantify the impact of machinery selection and autonomous machinery, some limitations of the model need to be discussed.

Seeding rate and agrochemical application rate was assumed to not be impacted by machinery selection, so they remained constant. This means that the model is not capable of calculating the change in cost associated with different seeding and chemical application rates.

The model is only capable of analyzing planting and harvesting. It cannot calculate costs associated with operations such as spraying and tillage.

Machinery costs were gathered from manufacturers, but there is a difference in the available technology across the range of machines. The starting list price was used as a baseline comparison, but the model that was developed and prices used in the database are not capable of reflecting the difference in available technology and features that come standard with a machine. An example of this technology difference is section control in planters. That is not a feature that is available with smaller planters.

Finally, the days suitable for work data and crop yield due to timeliness are limited to the Midwestern region. The crops analyzed in the model are corn and soybeans. This limits the model’s applicability to other regions that farm other crops and have differing days suitable for work for a given week.

1.4 Case Study

A case study farming operation was analyzed with the model to determine the effect that different machinery and operating times would have on the system. A larger farm size, 800 hectares, was chosen to see the costs associated with needing to use multiple, smaller vehicles to complete the operation during the working windows. This also allowed for the full utilization of the large, high-capacity machinery. It is not viable for small farms to purchase high-capacity machinery due to the return on investment. The revenue from a small farm cannot sustain the large payments required by the machinery.

For each major operation (planting and harvesting), three systems were analyzed. The three systems are titled: conventional, limited, and autonomous. The conventional and limited system are both set to work a maximum of 11 hours per day. The difference is that the limited system uses an input in the model (Staff limiter) to limit the number of workers for an operation, which limits the numbers of machines available per operation. If the limit input is set to two, the model will constrain the number of tractors/planters, harvesters, and tractor/grain carts to two. Then the analysis will return results for economic analysis in two of each machine and implement were used. This feature of the model allows the user to analyze the cost and capacity of a system not bound by required, minimum field or material capacity. Results for the limited system can be seen in **A.1**. Since the limited system may or may not complete the operation within the specific time window, plots for hectares not planted and the number of hectares actually harvested are provided. The inputs used for the case study can be seen in **Table 1.14**.

Table 1.14: Case study operational constraints

Variable Name	Value
Total Farm Size	800 hectares
Percentage Corn and Soybeans	50%, 50%
Staff Limiter	1
Planting Window	4/18 – 5/16
Harvest Window	9/26 – 10/31
Conventional and limited time worked per day (planting and harvest)	11 hours
Autonomous time worked per day (planting and harvest)	20 hours
Implement Soil Parameter	Medium texture
Planter Type	Row crop planter, no-till (Seed, fertilizer, herbicide) and 1 fluted coulter/row
Soil Condition	Firm
Planting Field Efficiency	0.65
Harvesting Field Efficiency	0.7
Grain Cart Rate	4 trips per hour
Grain Cart System	# of carts meets harvesting material capacity
Harvesting System	Class 9 – 16 row corn, 12.2m wide soybean

1.4.1 Planting

The planting window was set using crop insurance dates and the first, frost-free day in West Lafayette, Indiana. The early planting date for corn and soybean is 4/5 and 4/20 respectively. This is the earliest date that the crop can be planted and still fall under the crop insurance plan (USDA RMA, 2018a, 2018b). Based on data from the National Weather Service, the normal last day for the final spring freeze in West Lafayette is April 25. This is based on historical records that date back to 1901 (US Department of Commerce, n.d.).

There is also a final planting date. If corn and soybean are planted after this date, the insurance guarantee is reduced by one percent for each day after the final planting date. The final planting date is 6/5 for corn and 6/20 for soybeans. For corn, after 20 days past the final planting date, the guarantee is 55%. The guarantee for soybeans is 60% after 25 days. These dates are established by the USDA Risk Management Agency (USDA RMA, 2018a, 2018b). Yield starts to decrease substantially 30 days after April 1st, **Figure 1.3** and **Figure 1.4**, so the planting window was constrained to 28 days.

The implement soil parameter and planter type define how much draft force is experienced during the planting operation. The soil condition affects the tractive efficiency and the drawbar power. Planter and harvester efficiency values are based on typical field efficiencies for the machines, found ASABE D497.7 Table 3 (ASABE, 2015a).

1.4.2 Costs and Harvest

The grain cart module of the model is only capable of analyzing the material capacity of one harvesting system at a time. For this simulation, that is not a major factor since the number of grain carts is equal to the number tractors. The last variable in **Table 1.14** would affect the grain cart system if the grain cart system were set to have the number of carts and the corresponding capacity equal to the material capacity of the corn harvesting operation. **Table 1.15** lists the values used for variable factors that influence the cost calculations and harvesting of the case study.

Table 1.15: Case study variable factor values

Variable Name	Value
Corn Yield Before Timeliness	469 Bushels/hectare
Soybean Yield Before Timeliness	148 Bushels/hectare
Labor Cost	15 USD/hour
Fuel Cost	1 USD/liter
Oil Cost	6.35 USD/liter
Salvage Value	10 % of purchase price
Interest Rate	3%
Loan Term	10 years
Other Ownership Costs (taxes, housing, insurance)	2% of purchase price
Time Tractor is Used for Other Work	50 hours

Corn and soybean yield is based on the state average yield for Indiana in 2020, reported by the USDA.

1.5 Results and Discussion

1.5.1 Planting Results

Figure 1.7 shows the number of tractors needed to complete the 800-hectare planting within the working window.

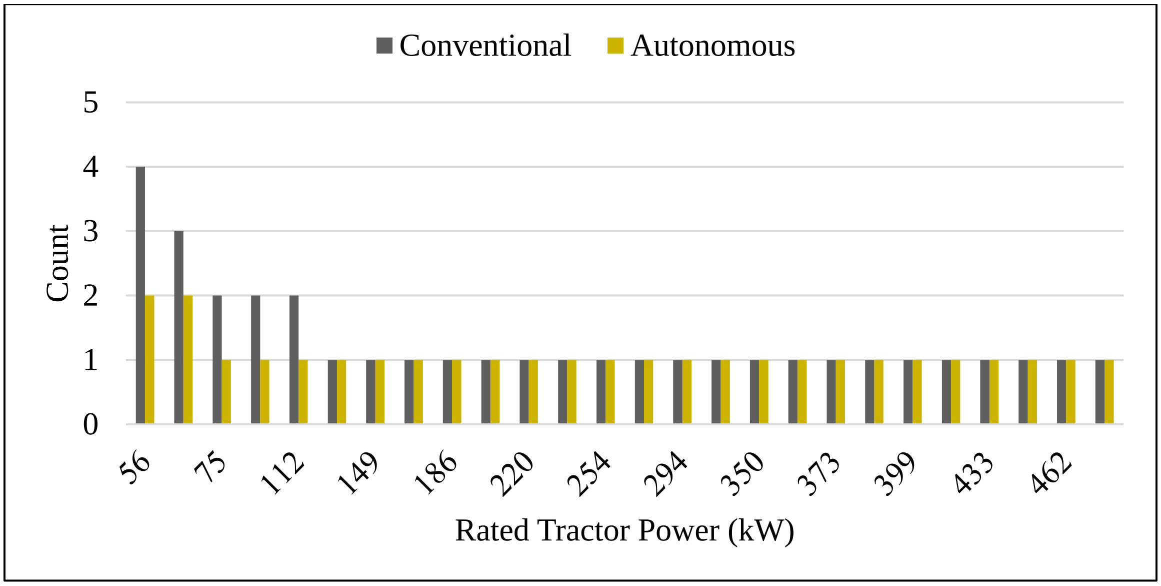

Figure 1.7: Numbers of tractors needed for the planting operation

Since the field capacity of the smaller tractor and planter is low, more pairs are needed to meet the minimum, required field capacity per day. Since the autonomous machinery is able to work more hours per day, it is able to achieve the minimum field capacity with less tractors and planters.

The cost per year for the planting operations is the sum of fixed and variable cost for the tractor and planter implement. For the conventional and autonomous machinery, the total cost can be seen below in **Figure 1.8**.

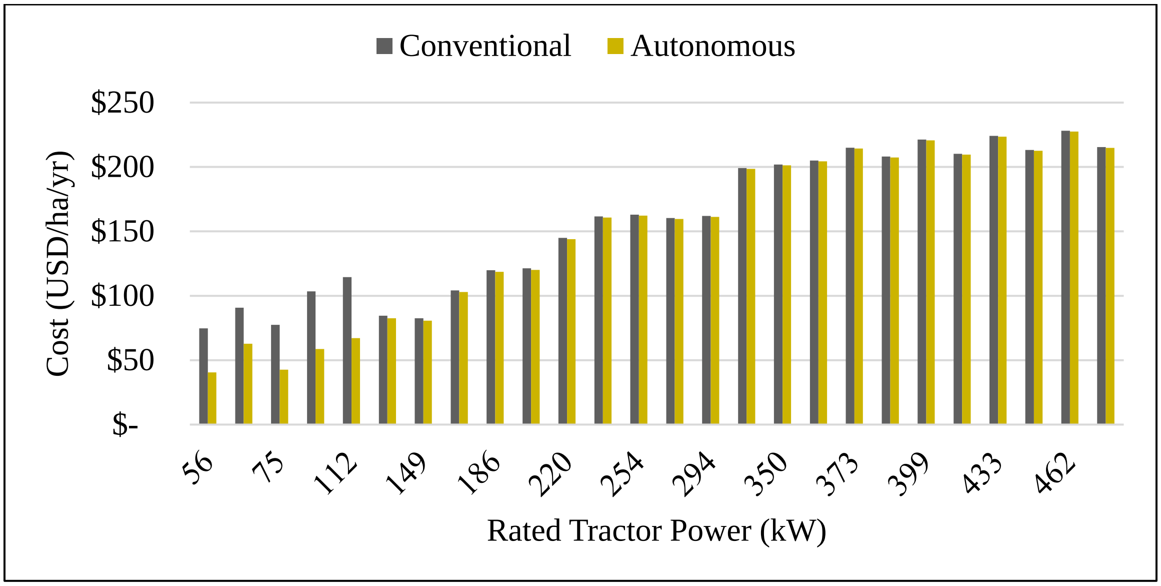

Figure 1.8: Total cost for planting 800-ha for varied tractor power ratings

All machinery in the conventional system accounts for the cost of labor associated with the operation of the individual units. A linear increase can be seen. This was due to the increasing machinery cost as tractor power increases. The dips in the cost are when the number of units needed to complete the operation decreases and the required system capacity was closer to machinery capacity. The most cost-effective option was the autonomous systems consisting of two, 4-row planters since less units are required, and capital does not need to be spent on labor. When there was not a difference between the number of units required, the percent difference in cost is minimal. That small difference was due to the cost of labor. The cost results show the value add of autonomous navigation. They do not represent the actual cost since the price of technology or logistics was not accounted for. Those additional costs could make the autonomous system a less economically feasible option.

Figure 1.9 shows the expenses that contribute to the planting cost of the most cost-effective, conventional planting fleet.

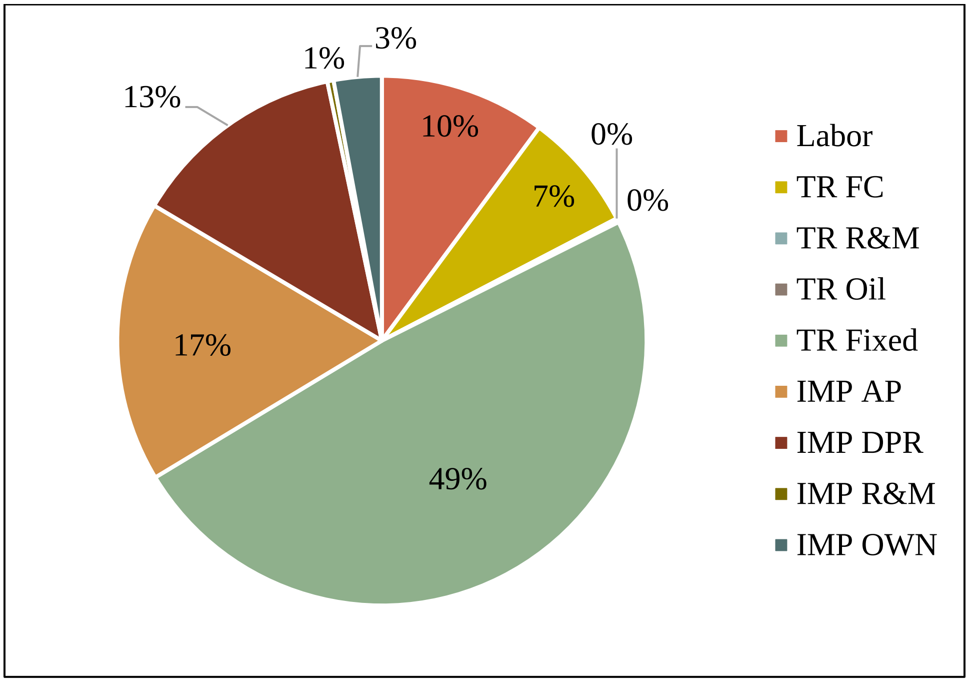

Figure 1.9: Breakdown of expenses contributing to the planting cost of the conventional 56-kW fleet

The three major categories are labor, tractor costs (TR), and implement costs (IMP). The largest contributor is the fixed cost of the tractor. It accounts for 49% of the cost to plant for this fleet. Labor makes up 10% of the total cost, the annual payment (AP) on the implements is 17%, and 13% is the implements yearly depreciation.

The hours used per tractor and planter pair was calculated to in order to determine the costs for all hourly based costs. The results in **Figure 1.10** are for the conventional and autonomous system.

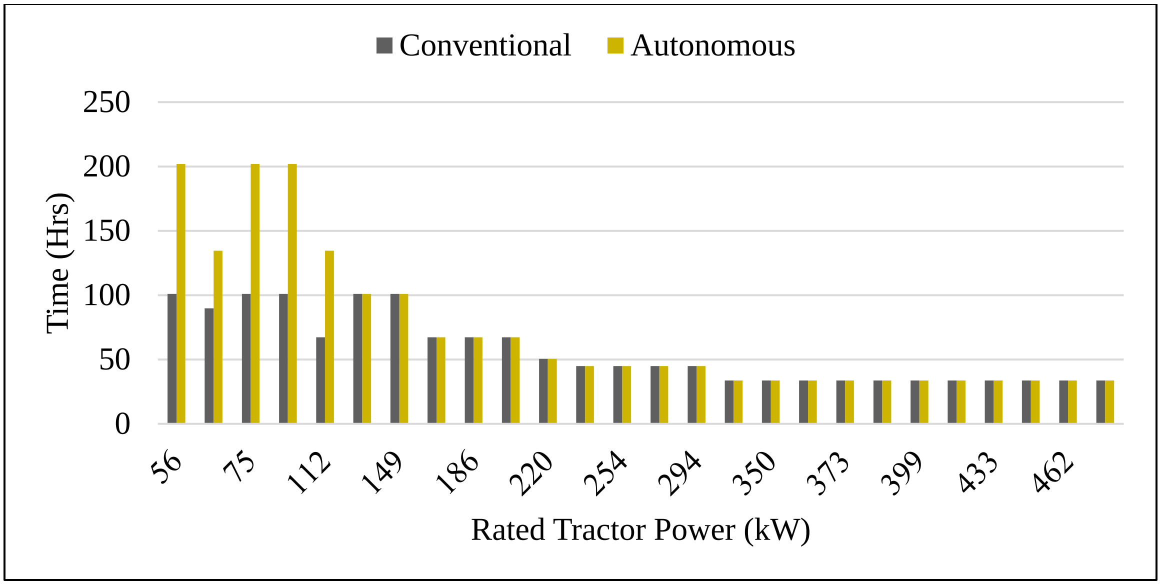

Figure 1.10: Planter hours to plant 800-ha with varied tractor power rating

The hours used per year for the pairs with a lower field capacity is higher because less work is completed at an hourly / daily rate. This means more days of the allotted planting window are used to complete the planting operation. The hours used per autonomous unit increases because they need to complete the same amount of work with less units.

Since the field capacity of the autonomous and conventional planting is different, the crop yield will vary due to the planting date. The percent change for soybean yield can be seen in **Figure 1.11**.

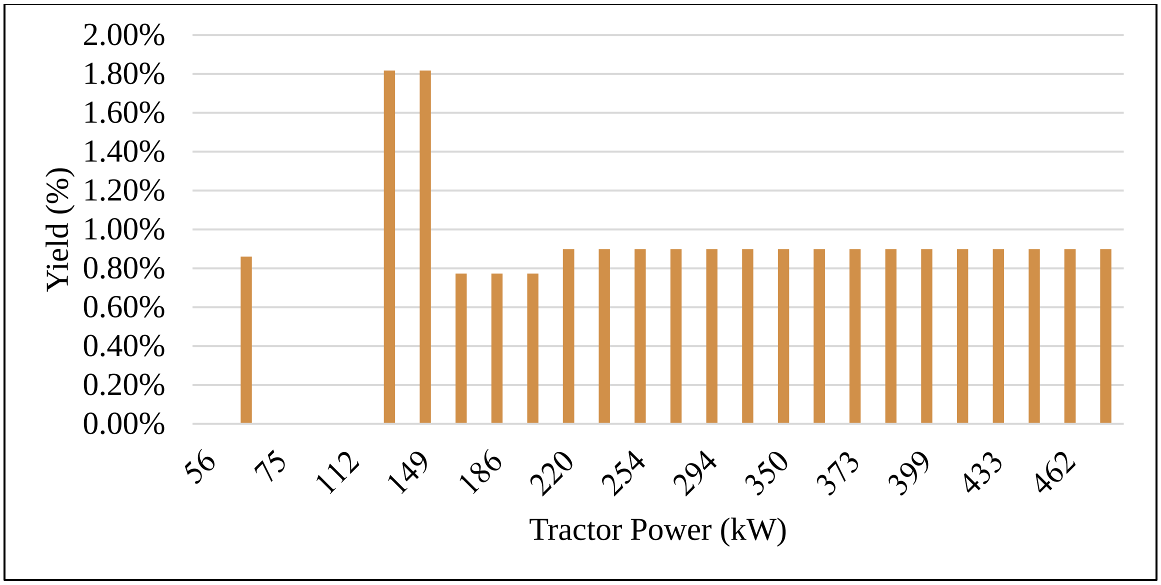

Figure 1.11: Percent difference in soybean yield for the autonomous and conventional system for varied tractor power ratings

The percent change in the yield between the two systems for corn was minimal because this model assumes that corn is planted first. The yield of some autonomous systems is higher than conventional because it can plant more hectares a day. The positive percent change shown means that the yield of the autonomous system was higher than the similar, conventional fleet. For other systems, the increase in working hours per day did not have an effect.

1.5.2 Harvesting Results

Table 1.16 shows the number of combines needed to complete the 800-hectare harvesting operation within the case study defined working window. The power of the harvester is based on S-series John Deere combines.

Table 1.16: Number of combines need to complete harvest

Harvester Power (kW)	249	292	353	405
Conventional	2	1	1	1
Autonomous	1	1	1	1

The autonomous system needs one less combine for the 249-kW configuration. A single, conventional 249-kW is not able to meet the minimum material capacity requirement when operating 11 hours per day, so a second machine is required. Due to the capacity of the harvesters, only one is typically needed to complete harvest in the specific window, September 26th to October 31st.

The total cost of the different harvesting configurations based on the numbers in **Table 1.16** can be seen below in **Table 1.17**.

Table 1.17: Cost of all harvesting configurations

Harvester Power (kW)	249	292	353	405
Header Sizes	6 row corn, 6.1m wide soybean	8 row corn, 9.1m wide soybean	12 row corn, 10.7m wide soybean	16 row corn, 12.2m wide soybean
Conventional Cost (USD/ha/yr)	$358	$206	$234	$264
Autonomous Cost (USD/ha/yr)	$191	$203	$231	$261

The difference in cost between the first fleet is because the autonomous system needs one less harvester to complete harvesting within the specified window. The cost difference between the latter three is due to the labor cost. The conventional, 292-kW combine can finish harvest in the time frame and the total cost is lower than the two larger combines. The lower cost shows that the machine capacity is closer to the required, minimum capacity.

Due to the large number of tractor and grain cart pairs that were analyzed, the total cost data for the grain carting systems is separated into three tables: **Table 1.18**, **Table 1.19**, and **Table 1.20**.

Table 1.18: Cost of grain cart systems for varied tractor power ratings – Part 1

Rated Tractor Power (kW)	112	130	149	164	186	201	220
Cart Size (bu)	630	750	1000	1000	1300	1300	1300
Conventional Cost (USD/ha/yr)	$51	$55	**$42**	$46	$61	$62	$69
Autonomous Cost (USD/ha/yr)	$41	$53	**$40**	$45	$60	$61	$68

Table 1.19: Cost of grain cart systems for varied tractor power ratings – Part 2

Rated Tractor Power (kW)	239	254	276	294	313	350	373
Cart Size (bu)	1500	1500	1500	1500	2000	2000	2000
Conventional Cost (USD/ha/yr)	$77	$78	$76	$77	$89	$91	$94
Autonomous Cost (USD/ha/yr)	$76	$77	$75	$76	$88	$90	$94

Table 1.20: Cost of grain cart systems for varied tractor power ratings – Part 3

Rated Tractor Power (kW)	373	388	399	399	433	433	462	462
Cart Size (bu)	2000	2500	2500	2500	2500	2500	2500	2500
Conventional Cost (USD/ha/yr)	$103	$104	$114	$106	$116	$108	$119	$110
Autonomous Cost (USD/ha/yr)	$103	$103	$114	$106	$116	$108	$118	$109

Cost differences between the conventional and autonomous are due to labor cost. The most cost-effective option for grain carting, based on this model and case study, is the 149-kW tractor pulling a 1000-bushel grain cart. It is most cost-effective for both systems. As tractor power and grain cart size increases, so does the cost of the fleet.

1.5.3 Scenario Analysis

The major assumptions driving the autonomous system is that there is no operator needed, and the working hours per day. For the scenario analysis, two workers were included in the autonomous system to see the effect of supervisors managing the planting operation. A separate analysis was performed using the assumption that autonomous machinery can work 16 hours days during the planting operation, instead of the 20 hours that was used in the case study. The planting operation was selected because the large range of vehicles and field capacities shows input adjustments better than harvesting. All other inputs such as the field size and working window were not changed. The numbers of tractors need to complete planting, for the case study inputs and scenario analysis example can be seen in **Figure 1.12**.

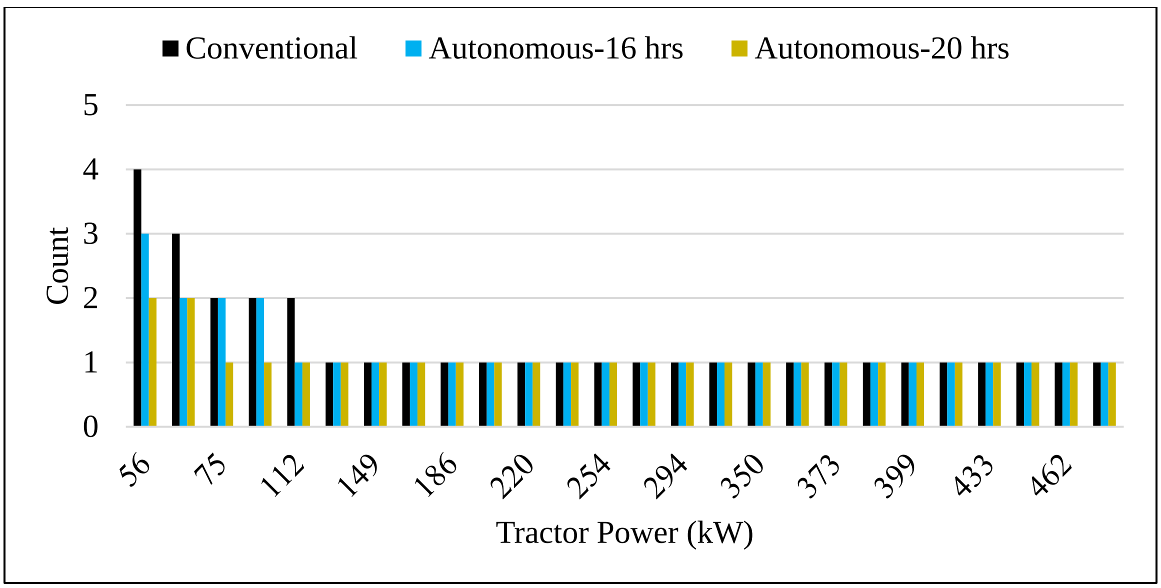

Figure 1.12: Scenario analysis - tractors of varying rated power needed to plant 800-ha

A difference can be seen in the first, third, and fourth autonomous planting fleets. When the working hours per day were decreased from 20 hours to 16, those fleets needed to increase their daily field capacity to meet the minimum, required field capacity needed to complete the 800-hectacre planting in time. The change in cost per year due to this change can be seen in **Figure 1.13**.

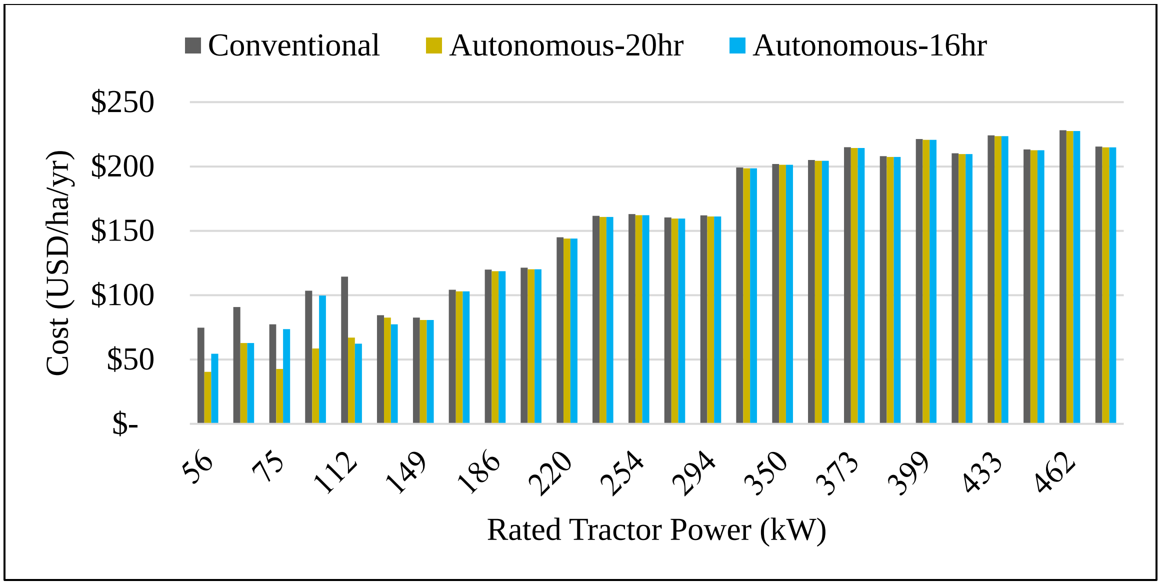

Figure 1.13: Scenario analysis – planting cost

The subtle difference for fleets that only require one vehicle is due to the labor cost needed for conventional machines. A substantial difference can be seen in the first (John Deere 5075E), third (John Deere 5100E), and fourth (Case Maxxum 125) autonomous fleets. **Table 1.21** shows the difference in cost between those fleets and systems. "C" will be used to abbreviate the conventional system, "A16" and "A20" will represent the 16-hour and 20-hour autonomous systems, respectively.

Table 1.21: Scenario analysis – fleet planting cost

System and Fleet	Cost (USD/ha/yr)
C - John Deere 5075E	$75
A16 - John Deere 5075E	$54
A20 - John Deere 5075E	$40
C - John Deere 5100E	$77
A16 - John Deere 5100E	$74
A20 - John Deere 5100E	$43
C - Case Maxxum 125	$103
A16 - Case Maxxum 125	$100
A20 - Case Maxxum 125	$59

When comparing the difference between the conventional system and the two autonomous systems, the largest value-add of autonomy between "C" and "A16" is the John Deere 5075E. Between "C" and "C20" is the Case Maxxum 125. If the cost of autonomous technology and the logistics/subscription is not larger than the difference between the conventional and autonomous system, there is value in having an autonomous system. When more, low-capacity machines are used to complete an operation, there is a larger difference in cost between the conventional and autonomous systems. This means that autonomy has a potential for a higher value-add when a swarm is used.

For the 20-hour autonomous scenario that requires supervisors, the hours worked by the supervisors are equal to the hours that a planter is used per year. The cost of labor for the analysis is 15 USD per hour.

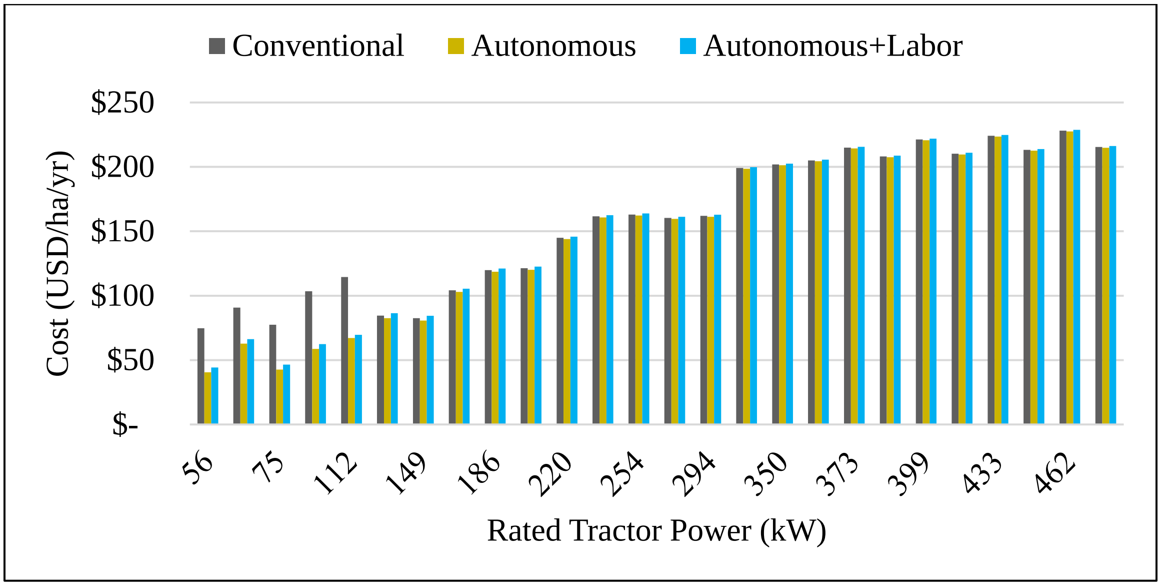

Figure 1.14: Scenario analysis – supervised autonomy

The additional labor cost, when added to the autonomous systems with only one vehicle, is greater than the cost of the conventional system. For fleets that require more than one machine, the cost of the autonomous+labor system and the conventional can be seen below.

Table 1.22: Scenario analysis – supervised autonomy cost

Machine	**JD 5075E**	**JD 5090EL**	**JD100E**	**Case Maxxum 125**	**JD 6150R**
Autonomous+Labor Cost (USD/ha/yr)	$44	$66	$46	$62	$70
Conventional Cost (USD/ha/yr)	$75	$91	$77	$103	$114

When an operator is required for every vehicle, the total cost to complete the planting increases a non-trivial amount.

1.6 Conclusion

A partial budget model was developed to calculate the economics associated with conventional and autonomous machinery selection. The cost model was designed to calculate fixed and variable costs such as the annual payment, depreciation, labor, and fuel consumption. The cost of equipment for the database and model were retrieved from the online list price of manufacturers. Factors that are not associated with machinery selection were assumed constant for all scenarios and therefore neglected. To get a better estimate on tractor fuel consumption, NTTL data was used to calculate fuel use coefficients for the various tractors used in the database. Tractors were also paired with planters and grain carts based on the implement manufacturer's recommendation.

An 800-hectare case study farm was analyzed using the model to calculate the costs associated with machinery fleets that can meet the minimum planting and harvesting capacity. The case study farm was a no-till, corn and soybean operation in the Midwest United States. There was a larger value add when more machines are required. The large difference in cost for the multi-machine, lower field capacity conventional and autonomous planting fleets was because the autonomous system needed fewer machines. Small cost differences in the large field capacity planting fleets are due to the labor cost. For harvesting, four different fleets were analyzed. Each fleet used a different sized corn and soybean head to show the variance in field capacity. There was a large cost difference when the power and capacity of the fleets varied greatly. Small, multi-unit planting operations were able to drastically decrease planting cost. But there was little cost difference when the machine became bigger. The cost variance between the different large, high field capacity harvesters was minimal.

The sensitivity analysis looked at two different scenarios and compared them to the case study's conventional and autonomous fleets. The first scenario looked at 16-hour workdays instead of 20-hour days for the autonomous machinery. Shorter workdays require some low-capacity planting systems to use another vehicle to complete the operation on time. The other scenario analysis looked at the labor cost associated with autonomous fleet supervisors. For conventional fleets that require multiple tractors, high labor and machinery costs allow for a larger value add if autonomy was implemented. For single unit autonomous systems, the labor cost became greater than the comparable conventional system.

Based on the case study results, the adoption of autonomous navigation has the potential to greatly reduce the cost of planting by enabling the use of small, more cost-effective machines. The total cost reduction will depend on the cost of the autonomous technology. The magnitude of the value add would likely be greater than the technology cost for the smaller fleets.

1.7 Future Work

Future work on the cost section of the model should increase the accuracy of the economic analysis. Currently, the model does not account for the downtime due to breakdowns, equipment maintenance, and the set up before/after operations. These events effect the time worked and time available for field work. The model is currently restricted to one machine type and implement size per fleet. The cost analysis and decision making will vary drastically if a pair with a large and small field capacity could work together. Current fleets have multiple of the same equipment to complete a task. A combination fleet could potentially be more cost-effective. The inclusion of more suitable working days data and the ability to determine the cost of other operations would increase the utility of the model. The case study assumed a no-till operation. Tillage is a high draft operation and that would decrease the number of tractors in the database that could perform all operations. A final aspect that would improve the model is the ability to contract / outsource operations such as spraying.

A.1 Simulation Results

A.1.1 Limit Planting

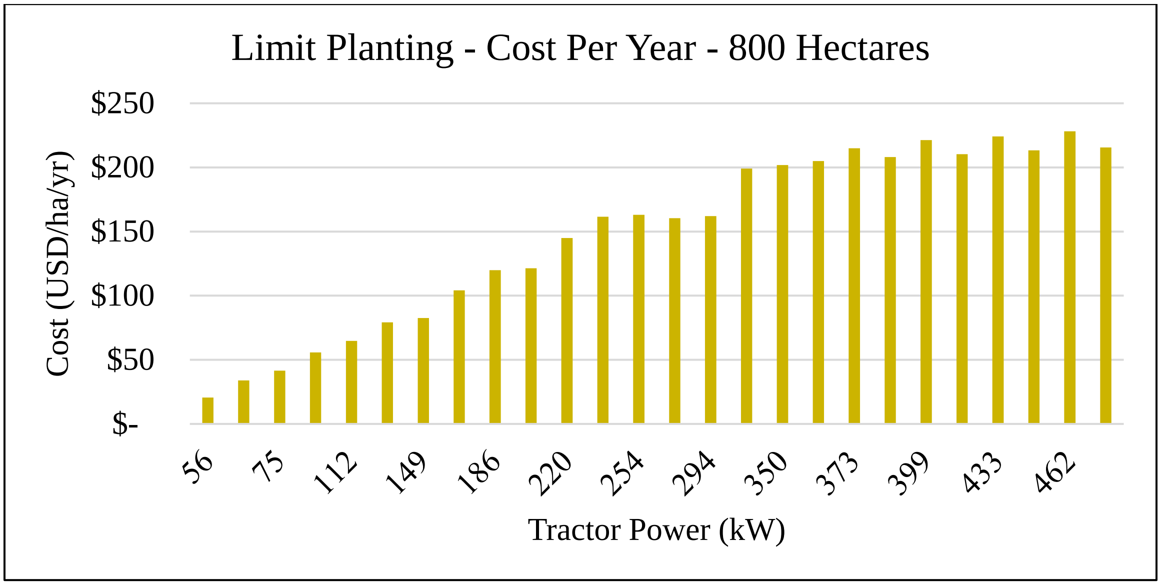

Figure 1.15: Total cost for planting 800-ha with one operator for varied tractor power ratings

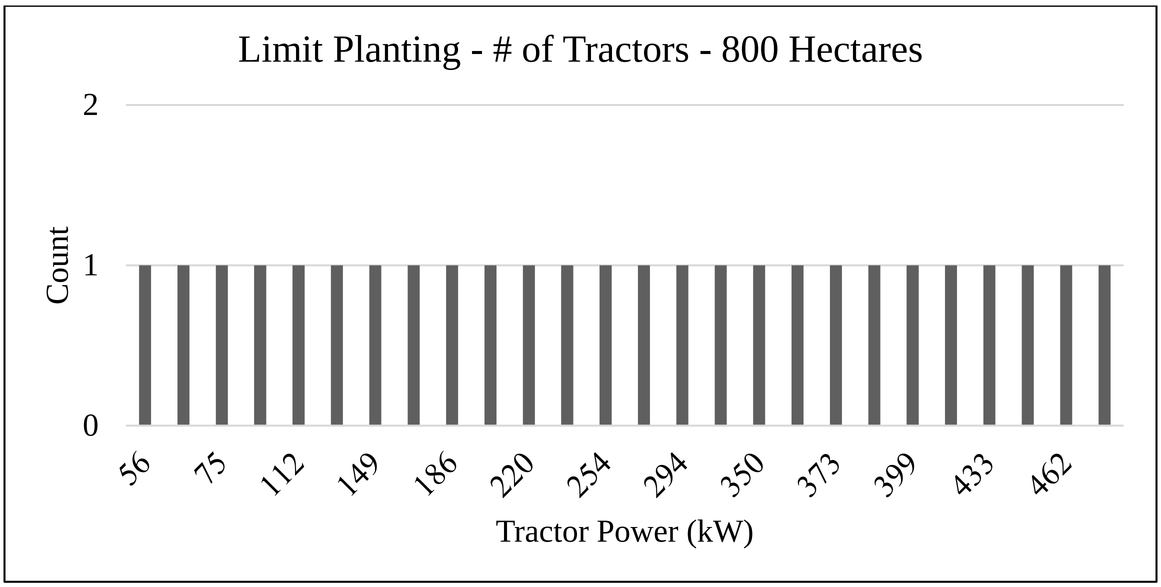

Figure 1.16: Numbers of tractors set by the staff limiter option

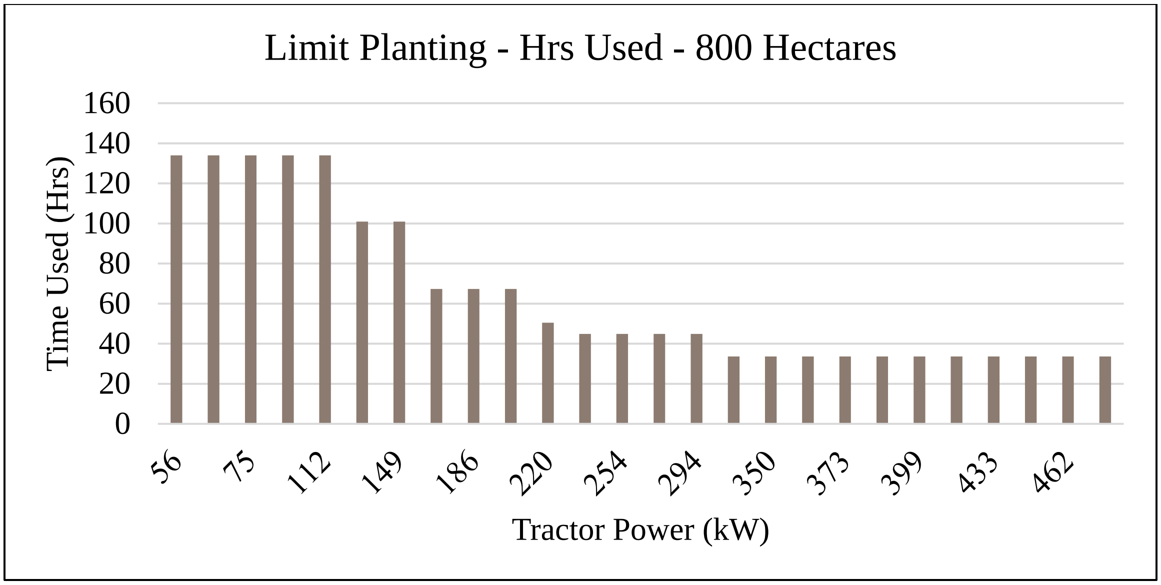

Figure 1.17: Hours worked by the planting tractors in the staff limited analysis

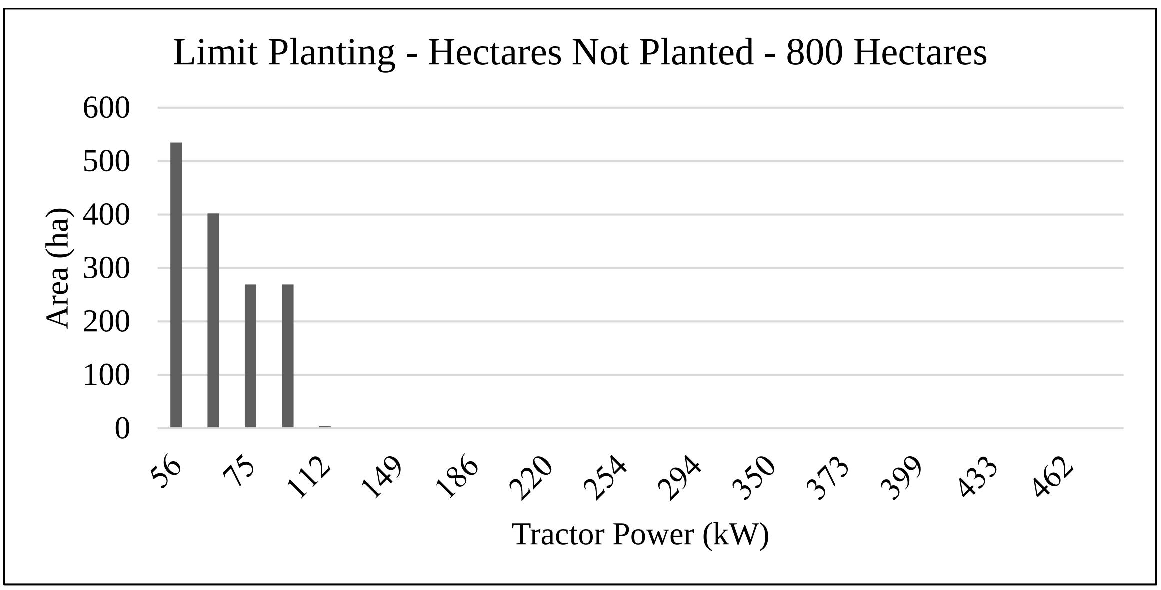

Figure 1.18: Numbers of hectares not planted by a single operator in the staff limited analysis

A.1.2 Conventional Harvest

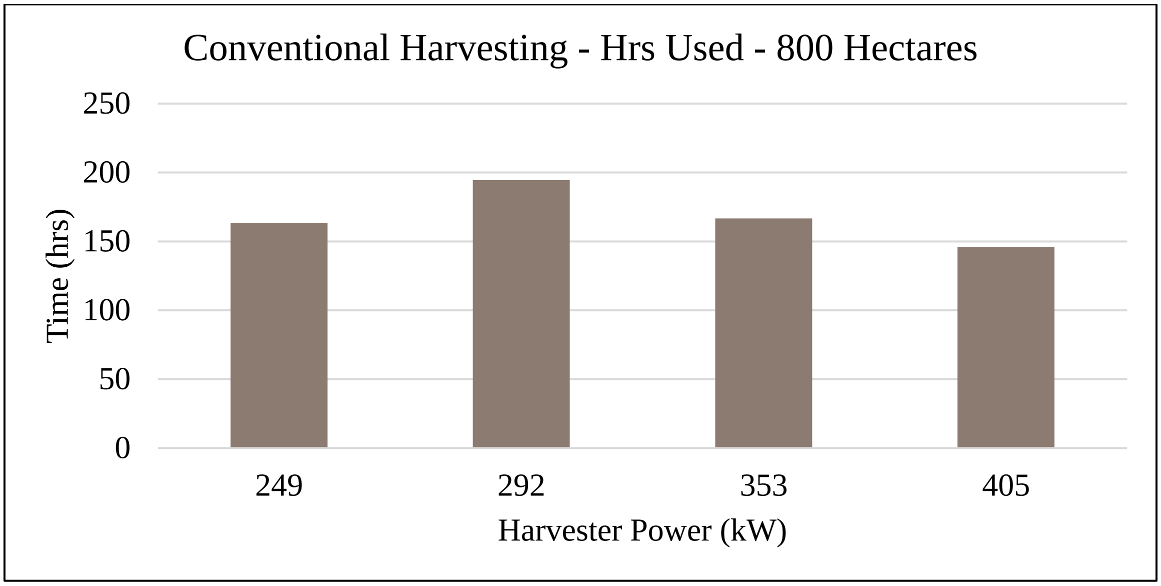

Figure 1.19: Number of hours that a single combine is used for the 800-ha conventional harvesting operation

A.1.3 Limit Harvest

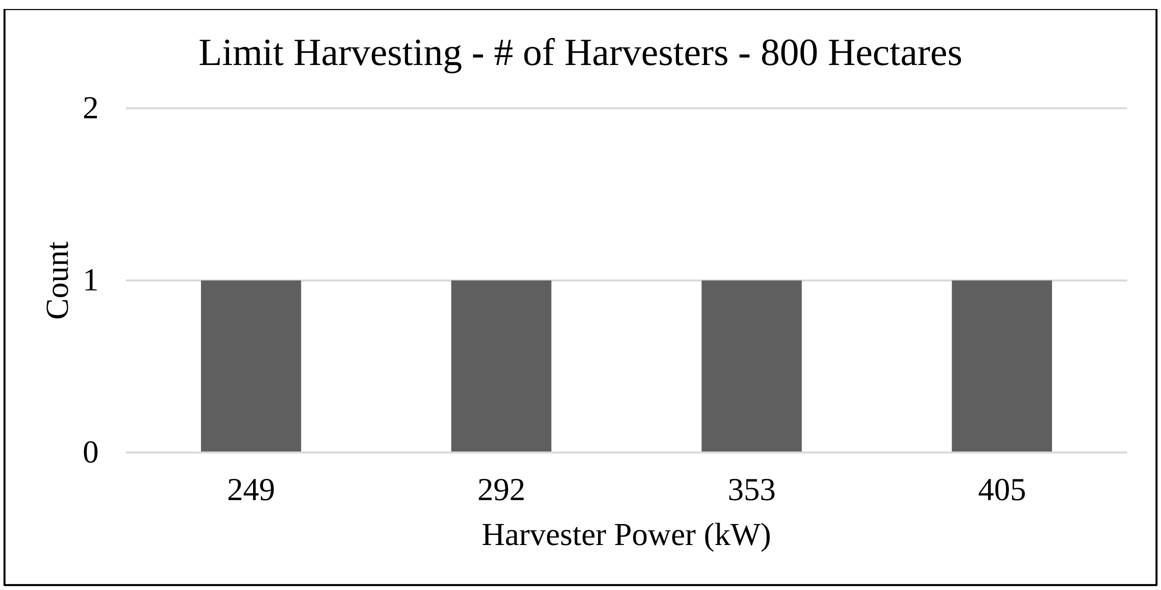

Figure 1.20: Numbers of combines set by the staff limiter option

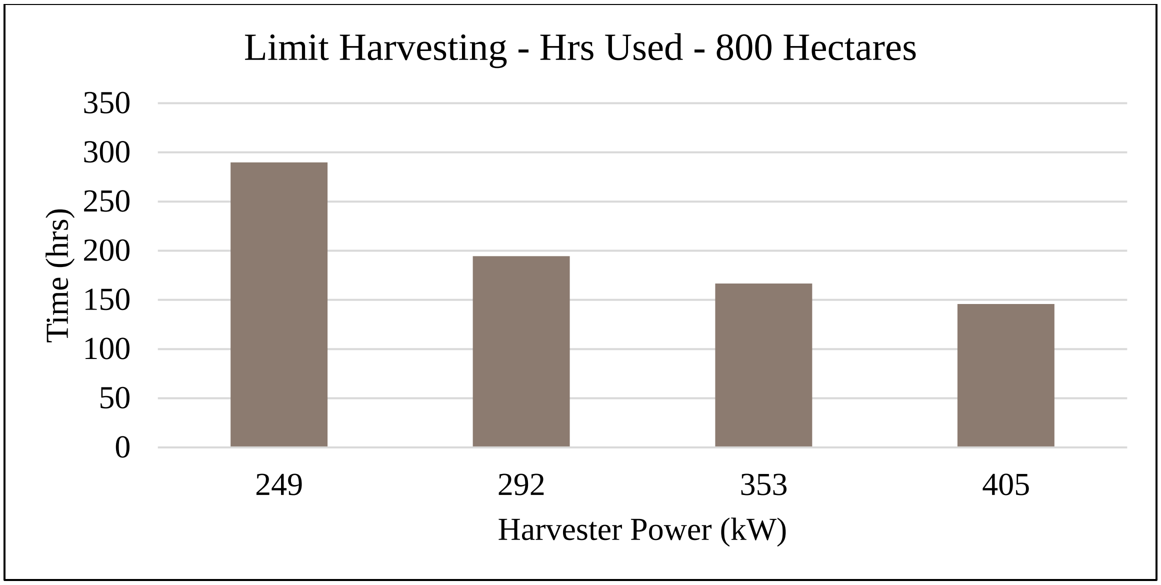

Figure 1.21: Number of hours that a single combine is used for the 800-ha staff limited harvesting operation

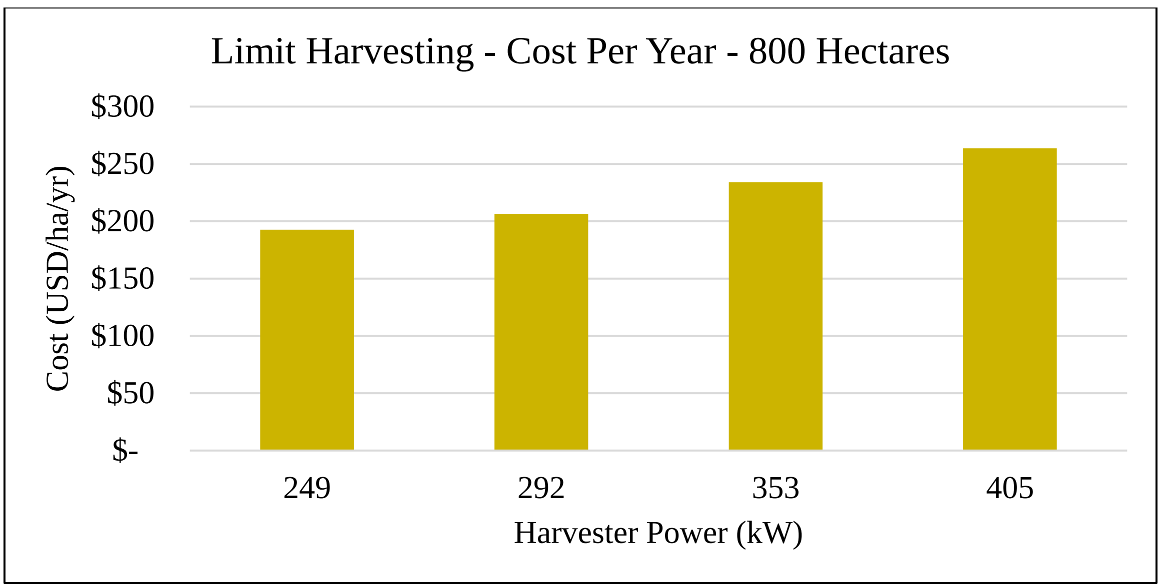

Figure 1.22: Cost per year, for varied combine powers, to harvest with one combine

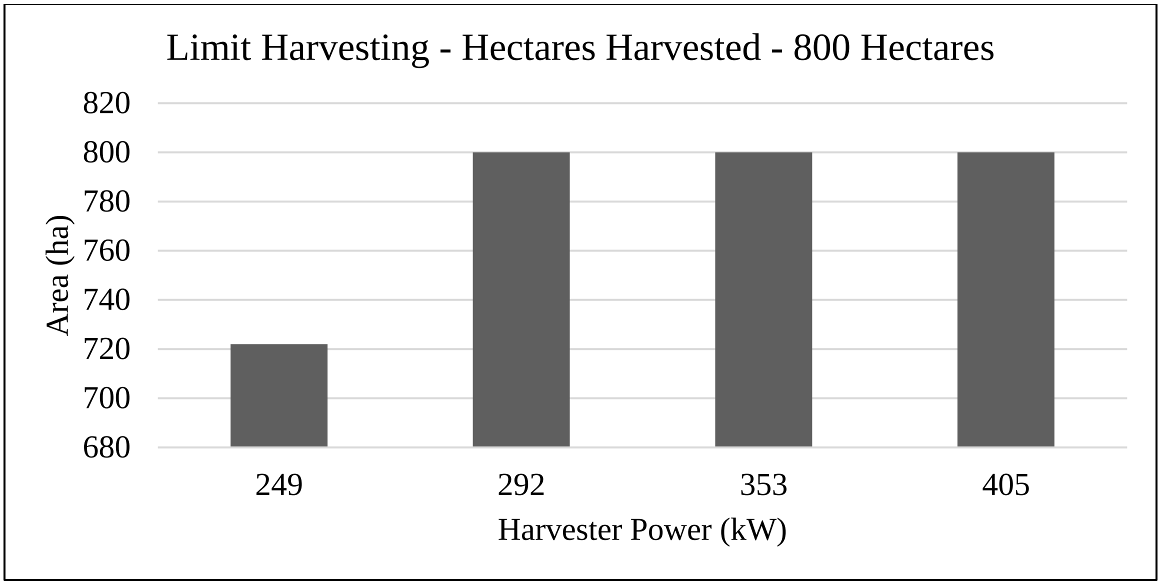

Figure 1.23: Numbers of hectares actually harvested a the single operator in the staff limited analysis

A.1.4 Autonomous Harvest

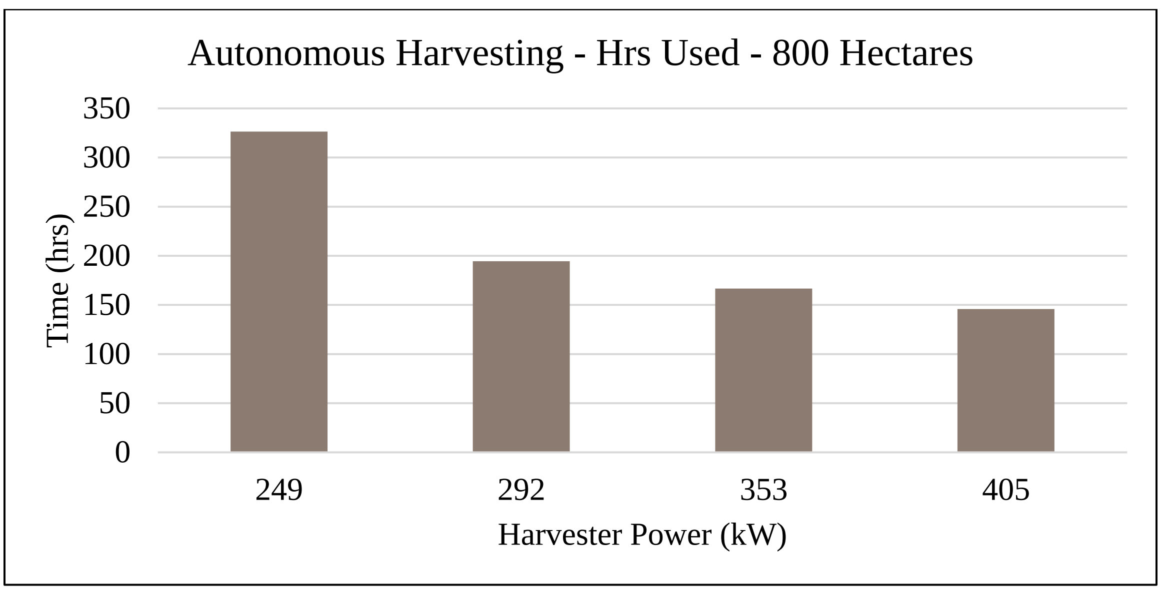

Figure 1.24: Number of hours that a single combine is used for the 800-ha autonomous harvesting operation

A.1.5 Conventional Carting

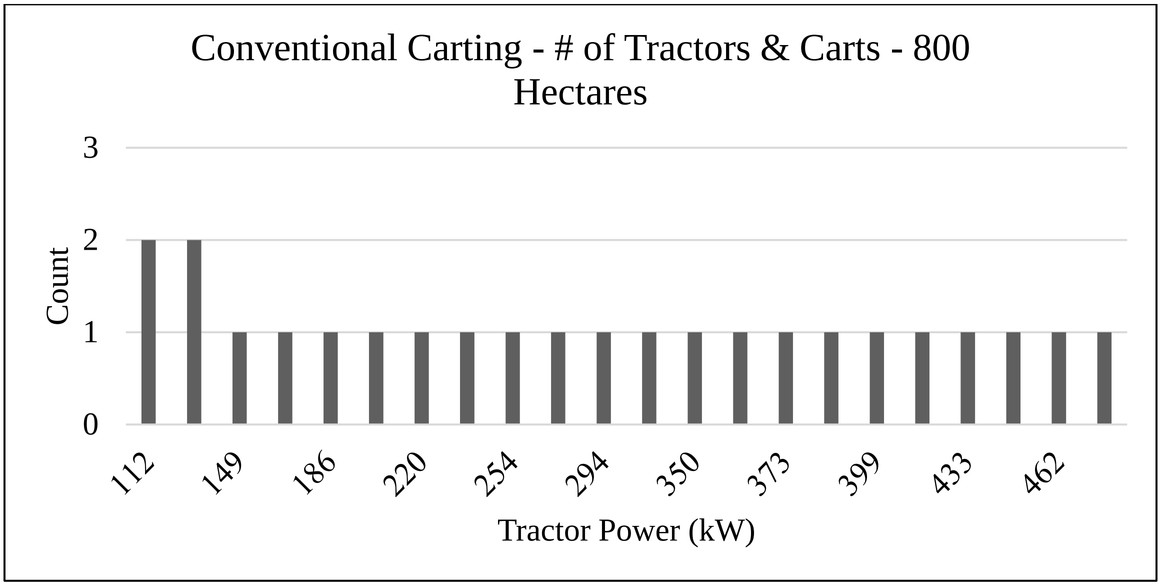

Figure 1.25: Number of tractors and grain carts needed meet the material capacity demand of the conventional harvesting system

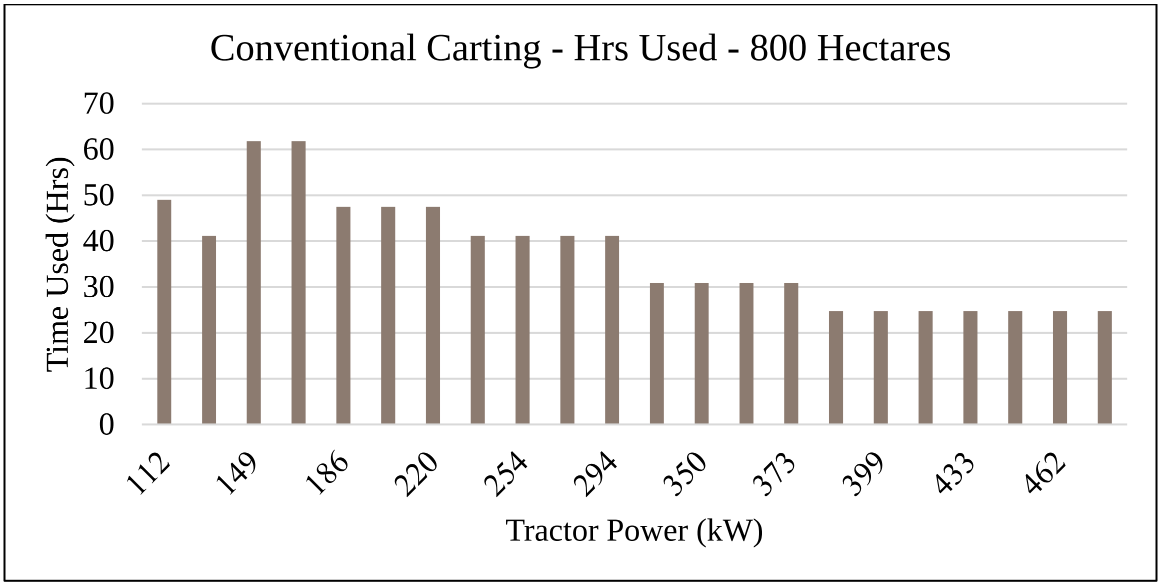

Figure 1.26: Hours used per grain cart for the 800-ha conventional harvesting operation

A.1.6 Limit Carting

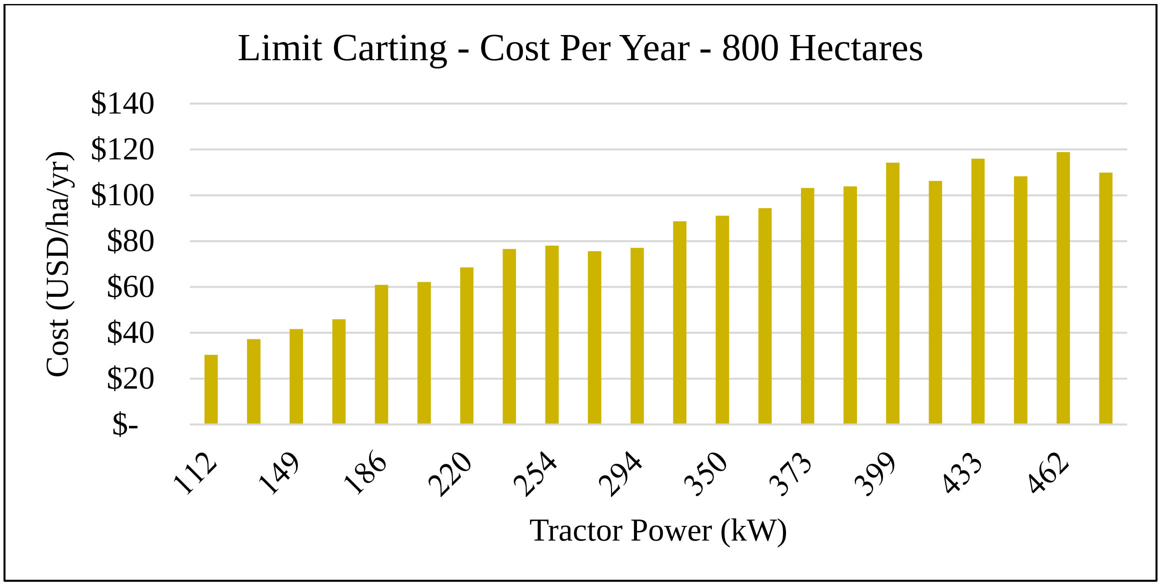

Figure 1.27: Hours used per grain cart for the 800-ha staff limited harvesting operation

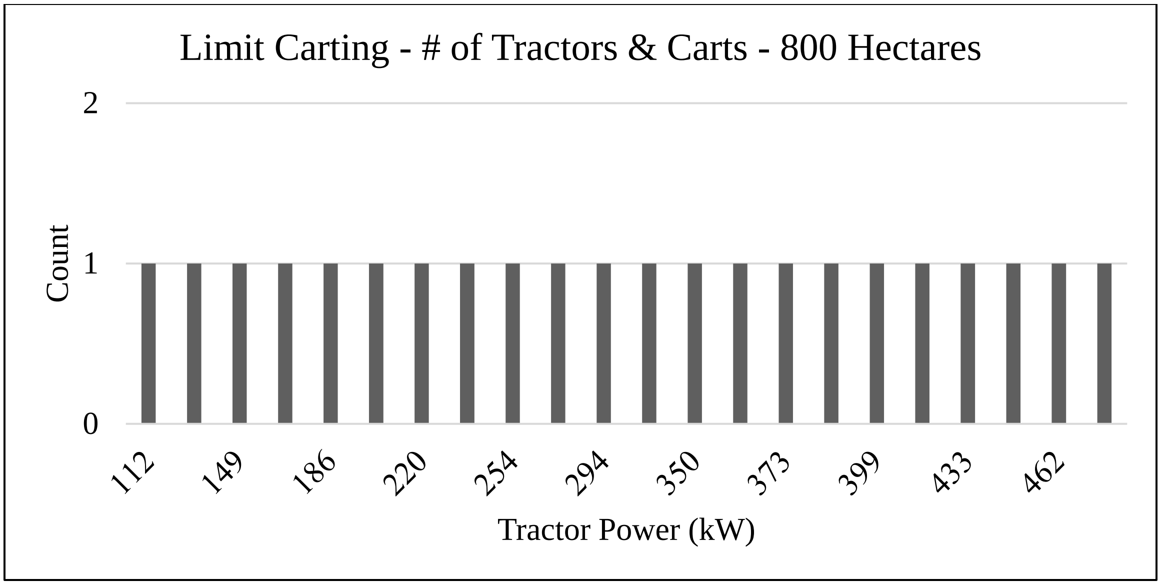

Figure 1.28: Number of carts set by the staff limiter option

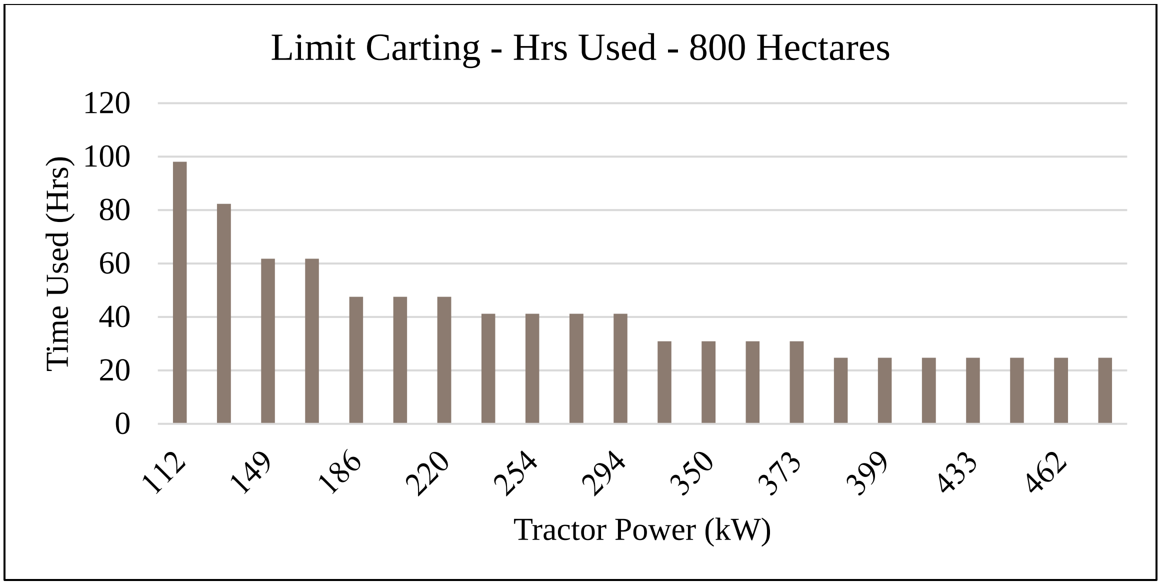

Figure 1.29: Hours worked by the grain cart tractors in the staff limited analysis

A.1.7 Autonomous Carting

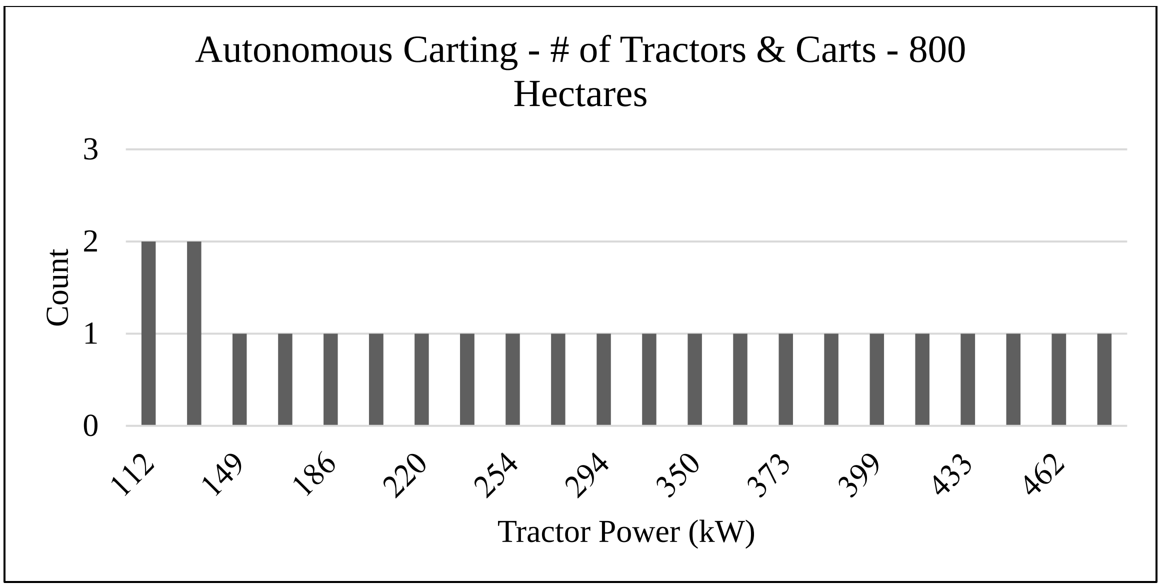

Figure 1.30: Number of tractors and grain carts needed meet the material capacity demand of the autonomous harvesting system

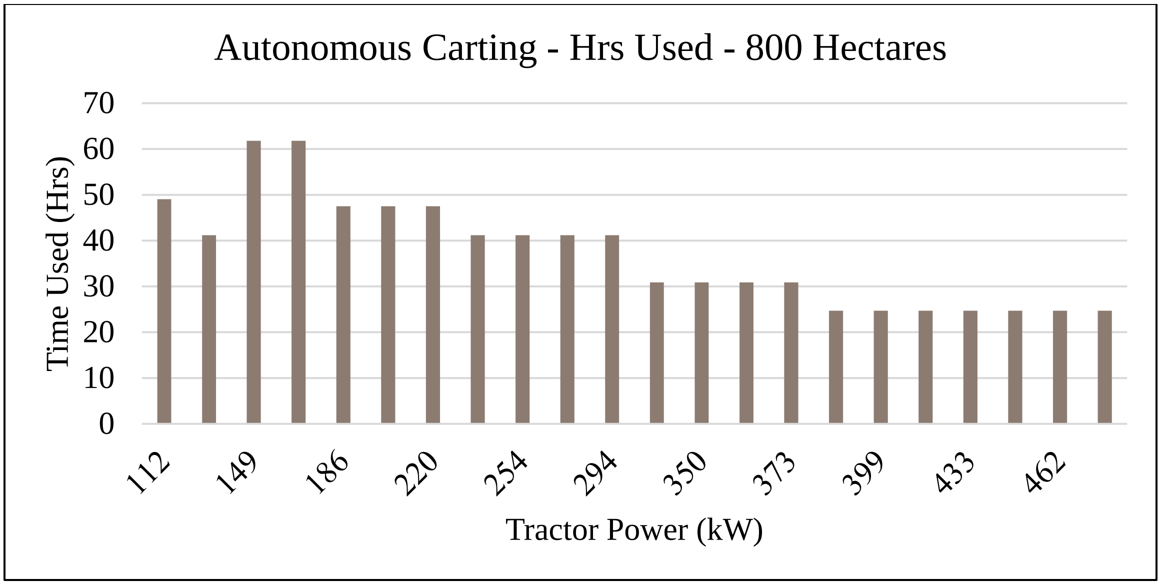

Figure 1.31: Hours used per grain cart for the 800-ha autonomous harvesting operation

A.2 VBA Code

A.2.1 Conventional Yield Calculation

```
Option Explicit

Sub conventional()

'initialize sheet and book
Dim wb As Workbook
Dim ws0 As Worksheet
Dim ws1 As Worksheet
Set wb = ActiveWorkbook
Set ws0 = wb.Sheets("Inputs")
Set ws1 = wb.Sheets("Planting")

'initialize
Dim days_btwn_workingdays As Double
Dim days_after_first As Double
days_btwn_workingdays = ws0.Cells(11, "E").Value     'grab single value
days_after_first = ws0.Cells(7, "E").Value     'grab single value
days_btwn_workingdays = Round(days_btwn_workingdays, 0)

Dim DaysToFinish_corn As Long
Dim DaysToFinish_soy As Long
Dim array_corn As Variant
Dim array_soy As Variant
Dim AVGyield_corn As Double
Dim AVGyield_soy As Double

Dim start_corn As Range
Set start_corn = ws1.Range("I33")       'to start corn timeliness calc

Dim start_soy As Range
Set start_soy = ws1.Range("I31")       ' to start soy timeliness calc

Dim print_corn As Range
Set print_corn = ws1.Range("I37")       ' to print corn timeliness output

Dim print_soy As Range
Set print_soy = ws1.Range("I36")       ' E36 to print soy timeliness output

'increment for corn calculation
Dim j As Long
Dim i As Long
'increment for soybeans
Dim k As Long
Dim m As Long

'the total days worked to complete the corn operation, changes across columns
Dim days_offset As Range
Set days_offset = ws1.Range("I35")

'days offset element increment
```

```
Dim c As Integer
c = 0

' equations based on data from https://farmdocdaily.illinois.edu/2019/06/late-planting-and-projections-of-the-2019-u-s-soybean-yield.html
'Loop for Corn calc
For j = 1 To 26 Step 1

  DaysToFinish_corn = start_corn.Value               'days to finish is equal to those cell values
  ReDim array_corn(1 To DaysToFinish_corn) As Double

    For i = 1 To DaysToFinish_corn Step 1                        'For all DaysToFinish values, make array_corn
        array_corn(i) = -0.0068 * (((i * days_btwn_workingdays) + days_after_first) ^ 2) + 0.1992 * ((i * days_btwn_workingdays) + days_after_first) + 98.513
    Next i

  AVGyield_corn = Application.WorksheetFunction.Average(array_corn)

  'set those cells = to the calculated yield value
  print_corn = AVGyield_corn

  'move through each column, calculating and printing along the way
  Set print_corn = print_corn.Offset(0, 1)
  Set start_corn = start_corn.Offset(0, 1)

Next j

'Loop for Soy calc
For k = 1 To 26 Step 1

  DaysToFinish_soy = start_soy.Value                             'days to finish is equal to those cell values
  ReDim array_soy(1 To DaysToFinish_soy) As Double

    For m = 1 To DaysToFinish_soy Step 1                         'For all DaysToFinish values, make array_corn
        array_soy(m) = -0.0041 * (((m * days_btwn_workingdays) + days_offset + days_after_first) ^ 2) - 0.0283 * ((m * days_btwn_workingdays) + days_offset + days_after_first) + 100.22
    Next m

  AVGyield_soy = Application.WorksheetFunction.Average(array_soy)

  'set those cells = to the calculated yield value
  print_soy = AVGyield_soy

  'move through each column, calculating and printing along the way
  Set days_offset = days_offset.Offset(0, 1)
  Set print_soy = print_soy.Offset(0, 1)
  Set start_soy = start_soy.Offset(0, 1)

Next k

End Sub
```

Figure 1.32: VBA corn and soybean yield calculation for the conventional planting operation

A.2.2 Autonomous Yield Calculation

```
Sub autonomous()

'initialize sheet and book
Dim wb As Workbook
Dim ws0 As Worksheet
Dim ws1 As Worksheet
Set wb = ActiveWorkbook
Set ws0 = wb.Sheets("Inputs")
Set ws1 = wb.Sheets("Planting")

'initialize
Dim days_btwn_workingdays As Double
Dim days_after_first As Double
days_btwn_workingdays = ws0.Cells(11, "E").Value     'grab single value
days_after_first = ws0.Cells(7, "E").Value     'grab single value
days_btwn_workingdays = Round(days_btwn_workingdays, 0)


Dim DaysToFinish_corn As Long
Dim DaysToFinish_soy As Long
Dim array_corn As Variant
Dim array_soy As Variant
Dim AVGyield_corn As Double
Dim AVGyield_soy As Double

Dim start_corn As Range
Set start_corn = ws1.Range("I118")       'to start corn timeliness calc

Dim start_soy As Range
Set start_soy = ws1.Range("I116")       'to start soy timeliness calc

Dim print_corn As Range
Set print_corn = ws1.Range("I122")       'to print corn timeliness output

Dim print_soy As Range
Set print_soy = ws1.Range("I121")       'to print soy timeliness output

'increment for corn calculation
Dim j As Long
Dim i As Long
'increment for soybeans
Dim k As Long
Dim m As Long

'the total days worked to complete the corn operation, changes across columns
Dim days_offset As Range
Set days_offset = ws1.Range("I120")

'days offset element increment
Dim c As Integer
```

```vba
c = 0

' equations based on data from https://farmdocdaily.illinois.edu/2019/06/late-planting-and-projections-of-the-2019-u-s-soybean-yield.html
'Loop for Corn calc
For j = 1 To 26 Step 1

  DaysToFinish_corn = start_corn.Value                   'days to finish is equal to those cell values
  ReDim array_corn(1 To DaysToFinish_corn) As Double

    For i = 1 To DaysToFinish_corn Step 1                        'For all DaysToFinish values, make array_corn
        array_corn(i) = -0.0068 * (((i * days_btwn_workingdays) + days_after_first) ^ 2) + 0.1992 * ((i * days_btwn_workingdays) + days_after_first) + 98.513
    Next i

  AVGyield_corn = Application.WorksheetFunction.Average(array_corn)

  'set those cells = to the calculated yield value
  print_corn = AVGyield_corn

  'move through each column, calculating and printing along the way
  Set print_corn = print_corn.Offset(0, 1)
  Set start_corn = start_corn.Offset(0, 1)

Next j

'Loop for Soy calc
For k = 1 To 26 Step 1

  DaysToFinish_soy = start_soy.Value                              'days to finish is equal to those cell values
  ReDim array_soy(1 To DaysToFinish_soy) As Double

    For m = 1 To DaysToFinish_soy Step 1                         'For all DaysToFinish values, make array_corn
        array_soy(m) = -0.0041 * (((m * days_btwn_workingdays) + days_offset + days_after_first) ^ 2) - 0.0283 * ((m * days_btwn_workingdays) + days_offset + days_after_first) + 100.22
    Next m

  AVGyield_soy = Application.WorksheetFunction.Average(array_soy)

  'set those cells = to the calculated yield value
  print_soy = AVGyield_soy

  'move through each column, calculating and printing along the way
  Set days_offset = days_offset.Offset(0, 1)
  Set print_soy = print_soy.Offset(0, 1)
  Set start_soy = start_soy.Offset(0, 1)

Next k

End Sub
```

Figure 1.33: VBA corn and soybean yield calculation for the autonomous planting operation

A.2.3 Limit Yield Calculation

```
Sub limited()

'initialize sheet and book
Dim wb As Workbook
Dim ws0 As Worksheet
Dim ws1 As Worksheet
Set wb = ActiveWorkbook
Set ws0 = wb.Sheets("Inputs")
Set ws1 = wb.Sheets("Planting")

'initialize
Dim days_btwn_workingdays As Double
Dim days_after_first As Double
days_btwn_workingdays = ws0.Cells(11, "E").Value     'grab single value
days_after_first = ws0.Cells(7, "E").Value     'grab single value
days_btwn_workingdays = Round(days_btwn_workingdays, 0)

Dim DaysToFinish_corn As Long
Dim DaysToFinish_soy As Long
Dim array_corn As Variant
Dim array_soy As Variant
Dim AVGyield_corn As Double
Dim AVGyield_soy As Double

Dim start_corn As Range
Set start_corn = ws1.Range("I77")       'to start corn timeliness calc

Dim start_soy As Range
Set start_soy = ws1.Range("I75")       'to start soy timeliness calc

Dim print_corn As Range
Set print_corn = ws1.Range("I82")       'to print corn timeliness output

Dim print_soy As Range
Set print_soy = ws1.Range("I81")       'to print soy timeliness output

'increment for corn calculation
Dim j As Long
Dim i As Long
'increment for soybeans
Dim k As Long
Dim m As Long

'the total days worked to complete the corn operation, changes across columns
Dim days_offset As Range
Set days_offset = ws1.Range("I80")

'days offset element increment
Dim c As Integer
c = 0
```

```
' equations based on data from https://farmdocdaily.illinois.edu/2019/06/late-planting-and-projections-of-the-2019-u-s-soybean-yield.html
'Loop for Corn calc
For j = 1 To 26 Step 1

  DaysToFinish_corn = start_corn.Value                            'days to finish is equal to those cell values
  ReDim array_corn(1 To DaysToFinish_corn) As Double

    For i = 1 To DaysToFinish_corn Step 1                        'For all DaysToFinish values, make array_corn
        array_corn(i) = -0.0068 * (((i * days_btwn_workingdays) + days_after_first) ^ 2) + 0.1992 * ((i * days_btwn_workingdays) + days_after_first) + 98.513
    Next i

  AVGyield_corn = Application.WorksheetFunction.Average(array_corn)

  'set those cells = to the calculated yield value
  print_corn = AVGyield_corn

  'move through each column, calculating and printing along the way
  Set print_corn = print_corn.Offset(0, 1)
  Set start_corn = start_corn.Offset(0, 1)

Next j

'Loop for Soy calc
For k = 1 To 26 Step 1

  DaysToFinish_soy = start_soy.Value                              'days to finish is equal to those cell values
  ReDim array_soy(1 To DaysToFinish_soy) As Double

    For m = 1 To DaysToFinish_soy Step 1                         'For all DaysToFinish values, make array_corn
        array_soy(m) = -0.0041 * (((m * days_btwn_workingdays) + days_offset + days_after_first) ^ 2) - 0.0283 * ((m * days_btwn_workingdays) + days_offset + days_after_first) + 100.22
    Next m

  AVGyield_soy = Application.WorksheetFunction.Average(array_soy)

  'set those cells = to the calculated yield value
  print_soy = AVGyield_soy

  'move through each column, calculating and printing along the way
  Set days_offset = days_offset.Offset(0, 1)
  Set print_soy = print_soy.Offset(0, 1)
  Set start_soy = start_soy.Offset(0, 1)

Next k

End Sub
```

Figure 1.34: VBA corn and soybean yield calculation for the staff limited planting operation

A.3 Days Suitable for Work

Table 1.23: USDA NASS days suitable for work data based on Indiana's average from 2013 to 2020

USDA NASS: Indiana Average 2013 - 2020		
Week	**Week Ending Date (Sunday)**	**Days Suitable for Work (days/week)**
14	4/4	1.52
15	4/11	1.85
16	4/18	2.50
17	4/25	2.78
18	5/2	3.03
19	5/9	2.85
20	5/16	3.52
21	5/23	3.63
22	5/30	3.87
23	6/6	4.28
24	6/13	5.06
25	6/20	4.34
26	6/27	3.85
27	7/4	4.00
28	7/11	4.41
29	7/18	4.77
30	7/25	4.98
31	8/1	5.52
32	8/8	5.60
33	8/15	5.78
34	8/22	5.31
35	8/29	5.20
36	9/5	5.66
37	9/12	5.52
38	9/19	5.48
39	9/26	5.85
40	10/3	5.89
41	10/10	5.33
42	10/17	5.02
43	10/24	5.20
44	10/31	4.91
45	11/7	3.94
46	11/14	4.81
47	11/21	4.53
48	11/28	4.18

https://quickstats.nass.usda.gov/ (USDA NASS, 2017)

A.4 Tractor Fuel Consumption Coefficients

Table 1.24: Specific fuel consumption coefficients of the tractors used in the database

NAME	MODEL	a	b	c	d
CASE-IH	MAXXUM 125, 16 SP	0.030	0.030	0.030	0.032
JOHN DEERE	6150R, AUTOQUAD+, 20	0.044	0.021	0.007	0.010
JOHN DEERE	6175R, AUTOQUAD+, 20	0.042	0.019	0.006	0.009
CASE IH	MAGNUM 200, 19-SP	0.040	0.013	0.005	0.007
CASE IH	MAGNUM 220, 19-SP	0.043	0.010	0.002	0.005
NEW HOLLAND	T8.320, 18-SP	0.042	0.014	0.006	0.008
JOHN DEERE	8270R, 16-SP	0.039	0.014	0.007	0.009
JOHN DEERE	8295R, 16-SP	0.041	0.012	0.006	0.007
JOHN DEERE	8320R, 16-SP	0.041	0.011	0.006	0.008
CASE IH	MAGNUM 340, 19-SP	0.041	0.011	0.006	0.007
JOHN DEERE	8370R, IVT	0.045	0.009	0.002	0.004
JOHN DEERE	8400R, E23-SP	0.048	0.006	0.002	0.003
JOHN DEERE	9420R, 18-SP	0.044	0.020	0.001	0.008
JOHN DEERE	9470R, 18-SP	0.046	0.023	0.003	0.008
CASE IH	STEIGER 500, 16-SP	0.044	0.011	0.003	0.007
CASE IH	STEIGER 500 QUADTRAC	0.044	0.011	0.003	0.007
JOHN DEERE	9520R, 18-SP	0.058	0.021	0.003	0.008
CASE IH	STEIGER 540 QUADTRAC	0.036	0.017	0.008	0.011
CASE IH	STEIGER 540, 16-SP	0.045	0.010	0.005	0.008
CASE IH	STEIGER 580, QUADTRA	0.049	0.010	0.004	0.007
CASE IH	STEIGER 580, 16-SP	0.052	0.009	0.004	0.007
CASE IH	STEIGER 620, QUADTRA	0.052	0.011	0.005	0.007
CASE IH	STEIGER 620, 16-SP	0.055	0.010	0.005	0.007

A.5 Model Screenshot

	Name	Units	Symbol		
Field	Total farm size	[ha]	ha	800	
	Fraction of farm for corn	-	CNT_{corn}	0.5	
	Fraction of farm for soybean	-	CNT_{soy}	0.5	
	Staff limiter	-		1	Set the amount of labor for the limited system analysis
Planting	Planting Start Date			04/18	All corn is planted before soybeans. Both crops are planted during the defined window
	Days past April 1st			17	For timeliness/yield calculation
	Planting End Date			05/16	Corn and soybean planting must be completed by end date
	Planting Window Duration	[days]	WIN_{plant}	28	Days between start and end date
	Days suitable for planting in the window	[days]	$DSFW_{plant}$	12.18	Based on USDA NASS data
	Days between working days	[days]	Day_{btwn}	2.30	Used to space working days across the duration of the window
	Planting time worked per day	[hr/day]	$T_{plant,conv}$	11	Conventional
	Planting time worked per day	[hr/day]	$T_{plant,auto}$	20	Autonomous
	Implement Soil Parameter	-	F_i	Medium texture	Soil texture for planter draft calculation
	Planter Type	-		2	Row crop planter - No-till, SFH - 1 fluted coulter/row
	Soil Condition for Slip	-	$Soil_{slip}$	Firm	Tractive condition to determine tractive efficiency
	Soil Condition for Motion Resistance	-		Firm	Defines cone index of soil
	Planter Field Efficiency		E_f	0.65	Field efficiency for effective field capacity calculation (D497.7 Table 3)
	Row spacing	m	SPC	0.762	30 inch rows for corn and soybeans
	Minimum field capacity to complete planting	[ha/day]	FC_{min}	65.7	Accounting for probability of a good working day
Harvesting	Harvest Start Date			09/26	Both crops are harvested during the defined window
	Harvest End Date			10/31	Corn and soybean harvesting must be completed by end date
	Harvest Window Duration	[days]	WIN_{HV}	35	Days between start and end date
	Days suitable for harvesting in the window	[days]	$DSFW_{HV}$	26.34	Based on USDA NASS data
	Harvesting time worked per day	[hrs/day]	$T_{HV,conv}$	11	Conventional system
	Harvesting time worked per day	[hrs/day]	$T_{HV,auto}$	20	Autonomous system
	Harvester Field Efficiency	[--]	$E_{HV,f}$	0.7	Field efficiency for effective field capacity calculation (D497.7 Table 3)
	Required field capacity for harvest	[ha/day]	$FC_{HV,min}$	30.37	Required field capacity per day to complete harvest operation
	Estimated trips per hour	[1/hr]	CAP_{mod}	4	Convert bushels to bushel/hour (trips per hour)
	Grain cart system			2	# of carts meets harvesting material capacity
	Harvesting system selector - determines carting			3	Class 8 - 12 row corn, 10.7m wide soybean
Variable Factors	Corn yield before timeliness	bu/ac	YLD_{corn}	190	Yield used to define harvest material capacity
	Soybean yield before timeliness	bu/ac	YLD_{soy}	60	Yield used to define harvest material capacity
	Labor cost	$/hr	LBR	$15.00	
	Fuel cost	$/L	Pr_{fuel}	$ 1.00	
	Oil cost	$/L	Pr_{oil}	$ 6.35	
	Salvage value	-	SVG	0.1	Fraction of purchase price
	Interest rate	decimal %	INT	0.03	Interest rate in annual payment calculation
	Loan term	yrs	LT	10	Loan term used in annual payment calculation
	Taxes	-	TX	0.01	Fraction of purchase price
	Housing	-	HS	0.0075	Fraction of purchase price
	Insurance	-	IN	0.0025	Fraction of purchase price
	Other ownership costs	-	OWN	0.02	Taxes, housing, insurance summed
	Time tractor is used for other work (applied to all tractors)	hr	ADD_{work}	50	Tractor is used for work besides planting and/or carting. Reducing fixed cost

Figure 1.35: Screenshot of the inputs and variable factor values used in the cost case study

CHAPTER 2. ENERGY AND EMISSIONS ANALYSIS

2.1 Introduction

To mitigate the impacts that come with population growth, farm labor shortages, agrochemical use, and emissions, agricultural operations will need to become more efficient. Mechanistic, process level, models have been developed to estimate the energy consumption and emissions of crop production systems. Mechanistic energy models rely on mathematics to quantify the behavior of the system and individual operations. These models can be used to design efficient farm systems and determine the impact of current practices. The objective of this chapter is to utilize and expand the model of **CHAPTER 1** to enable analysis of energy consumption and vehicle emissions.

2.1.1 Research Objectives

This chapter of research has two primary objectives:

1. **Energy and Emissions Modeling:** The first objective is to create a model to calculate the energy use and emissions of agricultural machinery. The model will use vehicle data, EPA emissions standards, and embodied energy coefficients to determine the environmental impact associated with the same planting and harvest operation analyzed in **CHAPTER 1**.
2. **Environmental Impact of Autonomous Navigation:** The second objective is to quantify the environmental impact of autonomous navigation and swarm farming. The energy use and emissions from conventional and autonomous farming systems need to be calculated to see the advantages or disadvantages of adopting new machinery and the operational changes that come with it. As distillate fuel use for farming increases, so does the emissions. Sustainable agriculture aims to keep agricultural systems economically viable and protect natural resources. Being able to understand the cost, as well as the energy and emissions of row crop machinery will provide a strong basis for machinery selection.

2.2 Background

2.2.1 Row Crop

Research to quantifying greenhouse gas (GHG) emissions and energy use in different crop production systems using the Farm Energy Analysis Tool (FEAT) has been completed by Hoffman et al. (2018). FEAT is an open-source, data-base model developed by Penn State University. It is intended to be used as an educational tool for farmers and students. The parameters: herbicide application rate, seeding rate, yields, insecticide application rate, crop moisture, fertilizer application rate, embodied energy (EE) estimations, GHG parameters, and fuel consumption used in FEAT are all from prior research and literature. Fuel consumption rates are based on the crop and vary depending on the tillage method and field operations performed. The model was used to determine the environmental impact of five, real cropping systems that were part of a United States Department of Agriculture (USDA) research project. The underlying coefficients used in the FEAT model for parameters such as application rates and consumption are calculated by taking the average of values from prior research. The compiled coefficients can vary drastically due to the different use cases, machinery, and field conditions. The model calculates results for emissions and energy by multiplying coefficients in the database with user defined values for crop yield and field size. The Farm Energy Analysis Tool is not capable of accounting for and analyzing agricultural machinery choice.

The Fieldprint Calculator by Field to Market (2021) is a tool for farmers to calculate their environmental impact by allowing them to input their field information, crop rotation system, residue practice, management data, and operations . The goals of the calculator are to quantify management choices and serve as a tool for continuous improvement opportunities. The model's output metrics are land use, soil conservation, soil carbon, energy use, greenhouse gas, water quality, and biodiversity. The farmer can compare the results from their simulated farm to state and national benchmarks, based on the averages of USDA statistical data, for most metrics. Energy use is classified as all the energy consumed in the production of the crop. The calculations and coefficients used to determine the metrics are not disclosed. The only resource that is referenced is the USDA NRCS. The Field Calculator does not allow the user to input data about the machinery used on the operation.

The cost and energy associated with sowing, spraying, and harvesting of no-till corn and soybeans was calculated using a model developed by Tieppo et al. (2019). Three sizes of commercially available machinery (small, medium, and large) and seven different field sizes (500, 1000, 2000, 4000, 6000, 8000, and 10,000 ha) were evaluated during this simulated study. The size of the machinery is related to the field capacity (ha hr^{-1})and that varied for the different field operations. The capacities of the tractor and planter used for the sowing operation are: 1.76, 2.63, and 3.73 ha/hr. The lowest capacity sprayer, pulled by a tractor, could work 12.29 ha hr^{-1}. The medium and large self-propelled sprayers were capable of 28.08 and 31.59 ha hr^{-1}. The different sized combines were able to complete 2.55, 3.38, and 5.41 ha hr^{-1}. For the model, data is inputted into three modules: sizing, machinery costs, and energy demand. Timeliness is accounted for by establishing a time window for each operation. The outputs of the model include energy demand and cost. The case study for the model was a no-till soybean production system in Brazil. To determine the validity of the fuel consumption and hourly cost estimation methods, predicted values were compared to field data to determine the difference.

The results of the case study combinations report the number of machines, size of machines, and equipment hours/time required per operation for seven different field sizes. For most of the field sizes, five vehicle combinations were assessed to determine the operational cost and energy demand for different machinery fleets. Valid vehicles combinations were determined using field capacity, the time available per operation, and field size. Conclusions drawn from the results show that there is no uniform correlation between cost and energy demand. The research does not disclose the vehicle speed, width, and efficiency that resulted in the different machinery field capacities used for the input values. Energy demand was solely based on fuel consumption. The model is not capable of recommending an optimal machinery fleet and uses equations to estimate parameters such as fuel consumption instead of empirical data (Tieppo et al., 2019).

The Integrated Farm System Model (Rotz & Corson, 2012) is a process level simulation of crop, beef, and dairy production. The model is used to estimate environmental impact and economic performance. Inputs to the model are defined by three types of text files: farm, machinery, and weather. The farm file includes general data about the acreage, soil, animals, costs, and equipment. The machine file contains information about machine type, technical specifications, cost, and repair & maintenance. This model is not able to determine the optimal machinery fleet because it requires the user to input the size and number of vehicles and implements being used.

This also means that the model is not capable of determining the optimal farming scenario to maximize profits. Energy use is calculated by tracking fuel, embodied energy, and electricity use.

A Microsoft Excel-based model was developed by Wilfong (2019) to understand and compare the energy use of conventional farms against operations that implemented ground-based autonomous agricultural vehicles (GAAVs). The embodied energy of the machines, embodied energy of the agricultural inputs, energy consumed during vehicle operation, labor energy, and the time spent working were used to calculate the total energy consumed. The case study used for the simulation was a 300-hectare Midwestern corn production system. A whole farm (fertilizing, spraying, planting, harvesting) was analyzed with three different machine configurations, all using one machine per operation, to see the capabilities of the model. During the analysis, a conventional operation was compared to two GAAV operations. The individual tasks of the farming operation were then analyzed separately to get a better perspective of the impact that different machinery had. This allowed for the investigation of swarm farming with smaller machinery. Production efficiency metrics were calculated for fertilizing and herbicide application to compare fleets. For almost all GAAV fleets that matched the machinery cost of the single conventional vehicle, they were able to perform better in terms of cost and energy. Timeliness was not accounted for in this work. This means that the working window, the allotted time to complete an operation, does not affect the number and size of the machines being used. Farming has lots of critical dates, and that should be considered with the field capacity of the vehicles and fleets being analyzed. Since GAAVs are not widely available on the market, parameters such as cost, agrochemical use, vehicle weight, and energy use must be assumed. With 70 inputs per vehicle required to determine the energy use and cost of a single farming operation a more streamlined data entry process for the inputs could benefit the users of this model.

Berruto and Busato (2006) developed a website that allows the user to compare and evaluate crop production operations based on finances and energy. The first step in the model is inputting farm data such the crops and production operations. The second input phase focuses on the farm machinery. Calculations are then performed to output results such as an energy balance, cost, revenue, and equipment use. Two case studies on corn cultivation were used to test the EnergyFarm application: a traditional method with high mechanical and chemical input, and a minimum tillage and chemical input method that focuses on conservation. Less energy, in terms of MJ/ha, was input into the minimum cultivation method and resulted in a higher output/input energy ratio. Results show that the high yield from the traditional method increases total energy output.

To determine the energy that is consumed to produce one kilogram of wheat in the United States, Piringer and Steinberg (2006) utilized a life-cycle analysis to estimate the total energy input. Prior work regarding energy inputs in wheat production has been published, but this research aims to provide updated values using recent data. A literature review was used to compile nationwide, average input rates and energy coefficients. High and low values for energy coefficients were recorded to establish a “best” estimate by selecting from the two values. The data’s source was used to help determine the “best” estimate. Values from more recent studies or data from the United States were favored. To calculate the total energy used, input rates were multiplied by the three categories of energy coefficient data (high, low, best) to determine a range of values. The results report that it takes 3.1 to 4.9 MJ kg^{-1} to produce one kilogram of wheat in the United States, with the best estimate being 3.9 MJ kg^{-1}. This estimate will not apply to all wheat production systems because energy use varies with management, location, and the type of wheat.

Research was conducted by Safa and Samarasinghe (2011) to quantify the energy used in wheat production systems. A survey and interview of 40 farmers in the Canterbury province was utilized to gather data for the direct and indirect input factors. Energy input is calculated by multiplying the input factors and their corresponding energy coefficient, then summing all the products. Additionally, an artificial neural network and multiple linear regression model was developed to predict energy consumption based on five parameters: crop area, farmer’s education level, nitrogen use, phosphorous use, and irrigation frequency. The regression model was able to account for 74% of the variance in the validation data set, and for 68% of the variance in the training data. The R-squared for the ANN was 0.81 for the training data, and 0.91 for the validation data.

The Farm Assessment Tool, FASSET, is a model that was developed by Jacobsen et al. (2013) to determine the impact of different environmental policies on farms. The goal of this research is to quantify nitrogen leaching and farm economics with a changing environment. Within the model, there is a labor and machinery section to calculate the energy requirements and energy inputs for the operation. A machinery selection optimization model was produced after simulations were run on four case study farms in FASSET. This means that the machinery fleet for the case study farms were based on equipment from real farms that were similar to the corresponding case study farms. The machinery selection model uses least cost optimization to select the machinery set and is constrained by the following rules: the set must be capable of completing each operation, the power of the tractor is selected based on the implement that requires the most power, and the tractors will be working on the same operation simultaneously. The researchers plan to incorporate the optimization model into FASSET. The Farm Assessment Tool is not capable of accounting for embodied energy of agricultural inputs such as seed, fertilizer, and pesticides. The machinery selection model, paired with FASSET, can only report the economics and energy use of one machinery set. This eliminates the possibility of comparing different equipment fleets based on their financial or environmental impact.

The Cool Farm Tool is a software, developed in Microsoft Excel, for farmers to determine the GHG emissions and energy use of crop and livestock production systems. The purpose of the Cool Farm Tool is to provide farmers with the information that they would need to make informed decisions regarding their farm and management practices. The model requires the user to data into the following categories: general, crops, sequestration, livestock, energy use, processing, and transport. The energy use calculations performed by this model are very basic. Annual energy requires the user to input the kilowatt-hours of electricity use, and the volume of various fossil fuels consumed by the farm. Outputs for energy consumption are report in megajoules (Hillier et al., 2011).

2.2.2 Biomass Crop

A model was developed by Sopegno et al. (2016) to estimate the energy requirements for miscanthus production. The three main components of the production system are: inputs, field operations, and storage (which was not analyzed during this research). Field information, agricultural inputs, and machinery inputs were used to determine the total energy input. The energy used by field operations is impacted by three processes: neutral, input, or output material flow. To account for the processes, the module that calculates energy use for field operations is divided into sub-modules. The modules that feed the field operations component are in-field operations, farm-field transport, and biomass transport. To test the model, miscanthus farmers were interviewed to determine realistic input data. The test scenario was used to estimate a production period of 10 years. Various graphical analyses were performed to visualize the input energy, fuel consumption, and embodied energy relating to operations. Machinery used for the simulation was not optimized based on least cost or lowest energy use.

Research by Rodias et al. (2017) utilized a tool, an extension of model described in the previous paragraph, to calculate the energy use of biofuel production systems to compare the farming of miscanthus, giant reed, and switchgrass. The computational model categorized inputs parameters into four categories: general production, field and transport, field machinery, and material specific. All three case study fields were assumed to be one-hectare large, five kilometers (km) from the farm, and ten km from the biomass storage facility. Input values for the field machinery, transportation, and irrigation were established using ASABE standards and prior research from other authors. The production simulation was for a ten-year period, with farm operations varying between year and biofuel crop. Consumption results (MJ/ha) for the different crop production scenarios report fuel use, embodied energy, and material energy for the field operations performed. Final values report the energy input, output, and efficiency of the three systems.

Biomass operations have multiple crops, a variety of machines, an array of farming practices, and differing transport times. This multi-crop production model developed by Busato et al. (2017) is a continuation of previous work that developed a tool to estimate the cost of biomass production systems. A variety of resources were used to determine the energy coefficients of the fuels, oil, machinery, agrochemicals, seeds, and products. User-defined inputs are combined with energy and operational coefficients in the processing model to determine outputs. The model calculates energy use from the planting operation up to transportation to the processing facilities. Results can be used to compare how the different crops and their corresponding operations compare in terms of energy input and output. For the case study, a biomass production with ten different field with varying amounts of corn silage, wheat, and rapeseed was selected. The model is not able to account for how yield changes with inputs, and the effects of weather.

The objective of this research by Rodias et al. (2019) is to maximize the energy gained by a biomass operation by using binary and linear programming in MATLAB to determine allocation of resources. With binary programming, only one energy crop is allowed per field. Linear programming allows for a combination of crops on a single field. A constraint is applied to ensure that the area allocated for a crop is larger than a minimum area. The difference in the energy balance, energy output minus energy input, for the different optimization techniques and alternative production scenarios is approximately between 1,000 to 5,000 GJ.

2.2.3 Individual Operations

The objective of research from Sørensen et al. (2014) was to determine the energy efficiency and GHG emissions of optimized machinery sets used for three, main different tillage scenarios: conventional, reduced, and no-till. Four subsets of scenarios were then developed for each tillage method. The subsets used the same equipment, but the field size, implement width, and capacity varied. The model accounted for both direct energy, fuel use, and indirect energy, estimations of embodied energy. Optimal machinery selection for this research was based on Sørensen & Søgaard's (2004) publication, *A Model for Optimal Selection of Machinery Sizes within the Farm Machinery System*, which defined the optimal machinery as being the least cost option that could meet the required field capacity. The individual operations analyzed within the different tillage scenarios included: ploughing, cultivating, seeding, spraying, fertilizing, and harvesting. Results show that energy input was reduced by 26% for a reduced tillage operation, and by 41% for a no-till operation. Total GHG emissions varied depending on the crop and decreased as tillage was reduced. This research does not evaluate the possible impact of autonomous agricultural vehicles or compare the effects of having different sized fleets complete the same tillage operation.

A model was created by Lampridi et al. (2020) to calculate the energy used while performing an agricultural operation. Total energy is divided into direct energy such as fuel and labor, and the indirect energy associated with embodied energy. Machinery selection is calculated with two methods: a continuous model that outputs machinery that does not follow standard sizing, and a discrete model that considers commercially available sizes. The capability of the model was testing using two tillage operations. Operating width, number of machines, machine power, and energy consumption was calculated for various available time windows. These outputs were also calculated using a fixed time window and different field sizes. The results of the continuous model were typically lower than the discrete model in all categories: operating width (m), machine power (kW), and energy consumption (MJ ha^{-1}). For both models, machine power and operating width increased when the available time was fixed, and the field size was raised. The opposite effect happened when field size was fixed, and available time was increased. Energy consumption calculations from the discrete model fluctuated with operating width. Energy use remained constant when calculated by the continuous model. The model was not used to determine the energy use of other agricultural operations. If the case study applied to the model was an entire farming operation and the research was expanded on, an optimal machinery recommendation could be made. This would allow farmers to determine the number and size of vehicles and implements that are needed to complete the operations of a farming operation that is constrained by the available time and acreage based on minimized energy use.

Optimized routes for agricultural operations can reduce non-working distances, increase area capacity, and decrease total operation time. The objective of the research Rodias et al. (2017) was to quantify the energy savings that would occur with the implementation of optimized field route planning. To compare the difference between optimized and non-optimized (AB pattern) operations, two cropping systems (Miscanthus and Switchgrass) and five field shapes were selected. Since the analysis is limited to operations that do not require coupled machinery (i.e harvesting with a combine, tractor, and grain cart), it is assumed that the harvesting unit has an on-board wagon. For the two different cropping systems, the implement operating width, tractor minimum turning radius, tractor power, and operating speed were established for all operations. The model and parameters were used to calculate the time need for operations, fuel consumption savings, embodied energy savings, and total energy savings. The tractor and implement size combinations were considered optimum for this section of the analysis. The optimized routes can reduce fuel energy consumption by up to 8%, embodied energy up to 7%, and total energy consumption up to 8%. Analysis was also performed to see the effect of machinery size on total energy savings due to path optimization, while keeping the implement size the same. **Table 2.1** shows all research discussed in the background and breaks down their capability in five areas.

Table 2.1: Crop production energy and emission literature comparison for five areas

	Farm Energy Analysis Tool	Fieldprint Calculator	Modeling Cost and Energy Demand in Agricultural Machinery Fleets for Soybean and Maize Cultivated Using a No-Tillage System	Integrated Farm System Model	Modeling and Analysis of Ground-Based Autonomous Agricultural Vehicles	EnergyFarm: Web Application to Compare Crop Systems Under Technical, Economic and Energy Aspects	Reevaluation of Energy Use in Wheat Production in the United States	Determination and Modelling of Energy Consumption in Wheat Production Using Neural Networks: “A Case Study in Canterbury Province, New Zealand"	Farm Assessment Tool
Energy Analysis	✓	✓	✓	✓	✓	✓	✓	✓	✓
Emissions Analysis	✓	✓		✓					
Machinery Analysis			✓	✓	✓	✓			✓
Autonomy					✓				
Working Window			✓						

	Cool Farm Tool	Model for Energy Analysis of Miscanthus Production and Transportation	A Computational Tool for Comparative Energy Cost Analysis of Multiple-Crop Production Systems	A Web-Based Tool for Energy Balance Estimation in Multiple-Crops Production Systems	Optimal Energy Performance on Allocating Energy Crops	Energy Inputs and GHG Emissions of Tillage Systems	Energy Footprint of Mechanized Agricultural Operations	Energy Savings from Optimised In-Field Route Planning for Agricultural Machinery
Energy Analysis	✓	✓	✓	✓	✓	✓	✓	✓
Emissions Analysis	✓					✓		
Machinery Analysis		✓	✓	✓		✓	✓	✓
Autonomy								
Working Window							✓	

2.2.4 Agricultural Machinery Analysis

Future crop production systems will need to be more efficient in order to address challenges such as a growing population, an increasing demand for agricultural products, labor shortages, and mitigating environmental impact. The background discusses the objectives and significance of multiple farm models that can determine the energy use of crop production systems. The scope of the analysis performed and the intended user for the models vary. A majority of the research presented in paper focuses on whole farm analysis. The models that are intended to be used for decision-making support and teaching, FEAT, IFSM, Cool, and the Fieldprint Calculator are available online. All the models attempt to quantify the energy consumption of crop production systems. Some require the user to select the machinery that is used on the farm, while others attempt to determine an optimal machinery set for the farm. Timeliness is a very important factor, and it is neglected by some of the models. Based on the presented research, none of the models can calculate and report the total energy used by a farm, for a variety of machinery fleets (autonomous or conventional) that meet the capacity demands of a time limited planting and harvest operation.

There is an opportunity to develop a whole farm model that quantifies the energy use and emissions of different machinery fleets. Unlike many of the models discussed in the literature review, this proposed model will calculate the energy consumption and emissions for a variety of machinery complements that are capable of complete the operation within a time window, rather than asking the user to input a single agricultural machinery fleet or only providing the results for an optimized fleet. This will allow for the comparison between all capable machinery. Another key aspect of this model is the ability to account for the potential impact that autonomous machinery will have on row crop farming operations. Technological advances across all industries have helped spark the research and development of autonomous agricultural vehicles. AAVs have the potential to address some of the problems that agriculture will be facing soon.

2.3 Model Development

The model that was developed for this research calculates the cost, energy consumption, and emissions in the same Excel worksheet. **CHAPTER 1** details the cost section of the model. The architecture of the energy and emissions portion of the can be seen below in **Figure 2.1**.

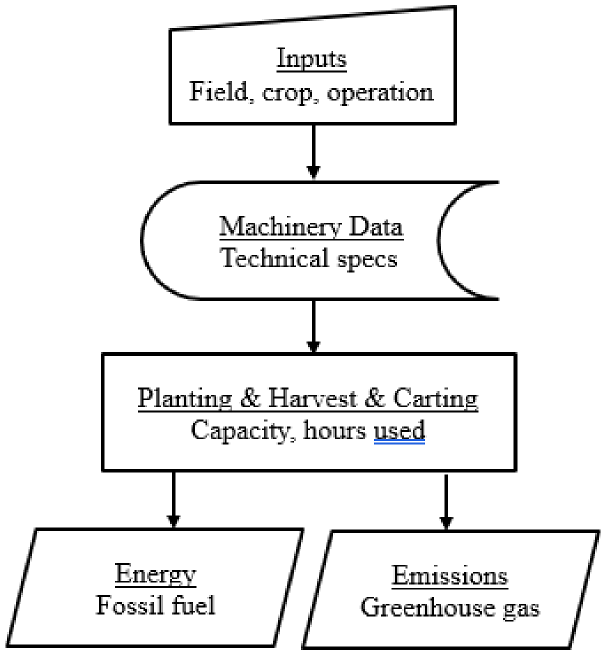

Figure 2.1: Structure of the energy and emissions model

This section of the model relies on the same inputs, machinery, and operational calculations that was defined in the previous chapter. The new outputs rely on embodied energy data, diesel energy density, and EPA vehicle emissions standards to quantify the environmental impact of the possible machinery fleets that can be used for the 800-hectare, no-till, corn and soybean operation.

2.3.1 Inputs

The inputs used for the energy and emissions portion of the model are shared with the cost analysis section. Inputs such as crop seeding rate and agrochemical use were assumed to be constant for all machinery fleets, so they were neglected during the embodied energy analysis.

2.3.2 Assumptions

The cost and energy/emissions model utilized the same assumptions when being developed. A list of the key assumptions can be seen below:

- 30-inch crop row width
- Only one machine type and size per fleet
- Input costs for seed and agrochemicals are not impacted by machinery selection
- No-till operation
- Spraying is not considered
- Field shape and grade is not accounted for
- Autonomous machinery can work longer hours per day and require no labor cost

The objective of the research is to determine the impact of machinery selection, sizing, and autonomation. A partial budgeting approach was taken, so factors not pertaining to the machinery were assumed to be constant. This results in inputs such as agrochemical application and seeding rates to remain unchanged for all fleets and systems. Since tillage and spraying are not analyzed, the model is limited to planting and harvest calculations.

In a previous energy analysis model, *Modeling and Analysis of Ground-Based Autonomous Agricultural Vehicles* (Wilfong, 2019), it was assumed that autonomous could apply less pesticides and fertilizer. The assumption that automation allows for more efficient agrochemical use heavily affected the total embodied energy of the system. The goal is not to speculate the efficiency increases in factors such as fuel consumption and application rates. The purpose of the model is to determine the fuel use, emissions, and embodied of different machinery fleets and systems.

2.3.3 Tractor Fuel Consumption

Tractor fuel consumption rate and the hours used are needed to calculate the direct energy use associated with the diesel fuel required to power the machines. The tractor-specific fuel consumption calculation can be found in the **Fuel Consumption** section of **CHAPTER 1**. For smaller tractors that have not been tested by the NTTL, a generalized version of the fuel consumption equation was used. The general coefficients are found in **Table 1.4** and were applied to the following tractors: JD 3025E, Massey Ferguson 2850M, John Deere 5075E, John Deere 5090EL, John Deere 5100E.

The hours worked by the tractor for the planting operation was calculated using the equations outlined in **Field Capacity**. The time that the tractor is used for the grain cart operation is calculated using **Eq. 1.40** and **Eq. 1.41**.

The resulting volume of fuel used (L) for a particular operation can be defined **using Eq. 2.1**:

$$V_{tractor} = Q_{tractor} * Hr_x * N_{tractor} \qquad \text{Eq. 2.1}$$

$Q_{machine}$ (L hr^{-1}) is the fuel consumption of the tractor, Hr_x is the number of hours that a single tractor is used for an operation (planting or grain carting), and $N_{tractor}$ is the number of tractors used. Fuel consumption for planting and grain carting is different because the hours needed to complete the operation, the rated power ratio, and engine speed is different.

2.3.4 Combine Fuel Consumption

Like tractor fuel consumption, the combine fuel consumption calculation (**Eq. 2.2**) requires the rate at which fuel is consumed, the number of hours that the combine was used during harvest, and the number of combines.

$$V_{harvest} = Q_{harvest} * Hr_{harvest} * N_{harvest} \qquad \text{Eq. 2.2}$$

where $Q_{harvest}$ is the fuel consumption rate of the combine (L hr^{-1}), $Hr_{harvest}$ is the hours used to complete the harvesting of corn and soybeans, and $N_{harvest}$ is the number of combines. The fuel consumption rate can be found in **Eq. 1.33**. The time that the combine was used (hr) is calculated using **Eq. 1.39**, and $N_{harvest}$ is determined using **Eq. 1.38**.

2.3.5 Direct Energy

The direct energy that was consumed by the machines used for planting, harvesting, and grain carting is dependent on the volume of diesel used. The machinery analyzed in the model did not use other forms of energy for propulsion, such as electricity. Fuel energy use (kW-hr) is calculated using **Eq. 2.3**:

$$NRG_x = Q_{machine} * \rho_{diesel} \qquad \text{Eq. 2.3}$$

where $Q_{machine}$ is the fuel consumption rate of the machine (L hr^{-1}) and ρ_{diesel} is the energy density of diesel fuel. The energy density of diesel was set at 38.6 MJ per liter, which is 10.72 kW-hr. The fuel consumption rate varies depending on the machine and operation.

2.3.6 Indirect Energy

The embodied energy, also known as the sequestered energy, is an estimation of the energy associated with the raw material, manufacturing, and distribution. The values used for this research were retrieved from *CIGR Handbook of Agricultural Engineering – Volume V* and can be seen in **Table 2.2** (Kitani, Jungbluth, Peart, & Ramdani, 1999).

Table 2.2: Embodied energy of various agricultural machinery

Machine	**Embodied Energy (MJ/kg)**
Tractor	138
Plow	180
Disc Harrow	149
Planter	133
Fertilizer	129
Rotary Hoe	148
Combine	116
Average	142

Embodied energy data was not available for grain carts and combine headers so an average of the values from **Table 2.2** was used.

Mass data from **Table 1.2**, **Table 1.7**, **Table 1.10**, **Table 1.11**, **Table 1.12**, and **Table 1.13** was used to calculate the embodied energy (MJ) of the various equipment. The equation (**Eq. 2.4**) used is shown below:

$$EE_x = m_x * EMB_x \qquad \text{Eq. 2.4}$$

m_x is the mass of the equipment (kg) and EMB_x is the embodied energy of the equipment (MJ kg^{-1}).

2.3.7 Emissions

The United States Environmental Protection Agency has established exhaust emissions standards for non-road, compression-ignition engines. Diesel-powered tractors that are used for agriculture fall under this classification. The latest version of this standard, Tier 4 Final, outlines the maximum emissions these engines can produce. The allowable emissions for different rated engine powers are shown below in **Table 2.3**.

Table 2.3: Allowable emissions from non-road, compression-ignition engines based on power rating

Power (kw)	**Tier**	**Year**	**NMHC[1] (g/kW-hr)**	**NMHC[1] + NOx[2] (g/kW-hr)**	**NOx[2] (g/kW-hr)**	**PM[3] (g/kW-hr)**	**CO[4] (g/kW-hr)**
<8	4	2008+		7.5		0.4	8
8 ≤ kW < 19	4	2008+		7.5		0.4	6.6
19 ≤ kW < 37	4	2013+		4.7		0.03	5.5
37 ≤ kW < 56	4	2013+		4.7		0.03	5
56 ≤ kW < 75	4	2014+	0.19		0.4	0.02	5
75 ≤ kW < 130	4	2014+	0.19		0.4	0.02	5
130 ≤ kW < 225	4	2014+	0.19		0.4	0.02	3.5
225 ≤ kW < 450	4	2014+	0.19		0.4	0.02	3.5
450 ≤ kW < 560	4	2014+	0.19		0.4	0.02	3.5
560 ≤ kW < 900	4	2015+	0.19		3.5	0.04	3.5
kW > 900	4	2015+	0.19		3.5	0.04	3.5

[1] Non-methane hydrocarbon
[2] Nitrogen oxides
[3] Particulate matter
[4] Carbon monoxide

Emissions standards for more powerful engines are stricter. These values will be used to determine the amount of emissions produced by the tractors while operating.

In order to determine the upper limit of emissions that a vehicle is allowed to emit under EPA standards, **Eq. 2.5** was used:

$$EM_{x,total} = EM_x * N_{machine} * Hr_{operation} * P_{rated} \qquad \text{Eq. 2.5}$$

$EM_{x,total}$ (g) is the mass of the emission and EM_x is the allowable emission rate for a particular power rating (g kW-hr^{-1}). EM_x is a general term for NMHC, NOx, PM, and CO. Variable $N_{machine}$

is the number of machines used during the operation, $Hr_{operation}$ is the number of hours each machine is used, and P_{rated} is the rated engine power of the machine.

2.3.8 Limitations

The energy and emissions model expands on the work presented in **CHAPTER 1**. The limitations of the environmental impact analysis are the same as the limitations detailed in **1.3.9**.

2.4 Case Study Description

The case study used for this chapter is the same as the case study outlined in **CHAPTER 1**.

2.5 Results and Discussion

The main difference in energy usage between autonomous and conventional machinery configurations came from the embodied energy. There was no difference in the fuel energy and emissions when comparing the conventional system to the autonomous system because the same amount of work was still being completed, just with less vehicles. For example, with a 56-kW tractor fleet the autonomous system requires two less tractors and planters to complete the planting operation on time. The percent change calculation compares the autonomous 56 kW tractor fleet to the conventional version of the same fleet. Since the area to be covered was the same, fuel consumption and emissions rate do not change between the systems only the time to complete the operation.

Like the outputs from **Results and Discussion** of the first chapter, **COST ANALYSIS**, the energy and emissions of the limited system were calculated but will not be discussed in order to keep the number of graphical outputs and text to a reasonable amount. A recap of the planting, harvesting, and grain cart machinery pairs can be seen by referring to **Table 1.6**, **Table 1.8**, and **Table 1.9** respectively.

2.5.1 Indirect Energy

The number of tractor and planter pairs can be seen in **Figure 1.7**. This is directly related to the embodied energy of the machinery, shown in **Figure 2.2**.

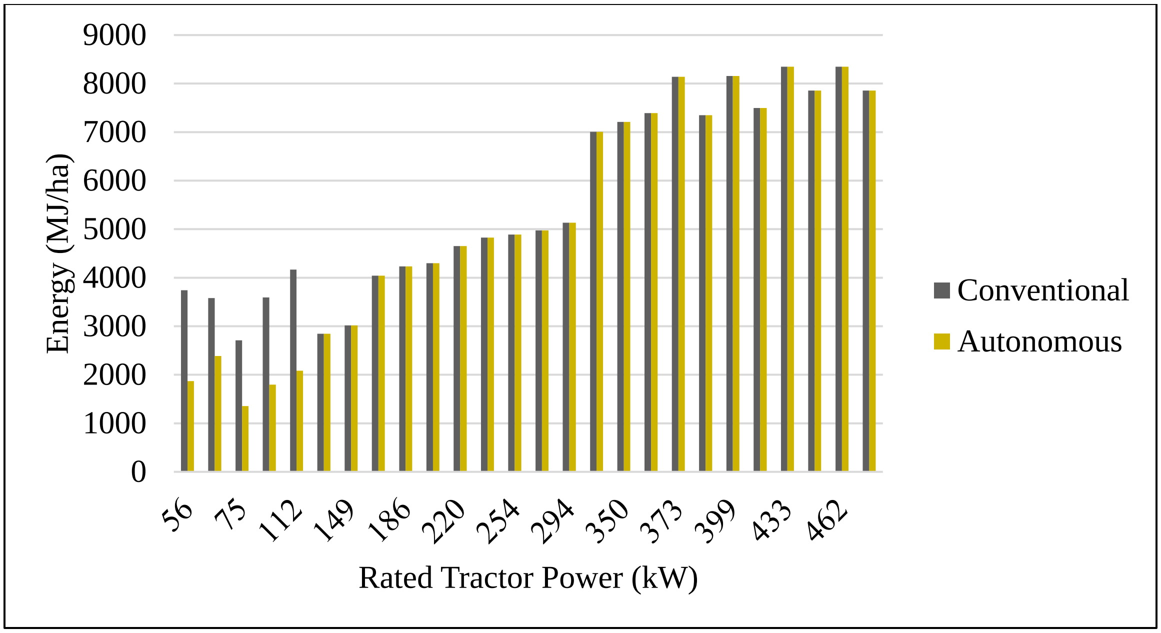

Figure 2.2: Embodied energy of machinery used to complete planting

The difference at 56-kW is because the autonomous system at this power rating needs two less tractors and planters. The difference between the 67-kW to 112-kW systems is because one less pair is needed. For the remaining fleets where there is not a difference in machines needed, the increase in embodied energy is due to the increase in mass. As tractor power increases, so does the vehicle and implement mass.

The number of combines and headers needed to complete the 800-hectare harvesting, comparing the autonomous system to the conventional system, is shown in **Table 1.16**. The resulting EE calculation is shown in **Figure 2.3**.

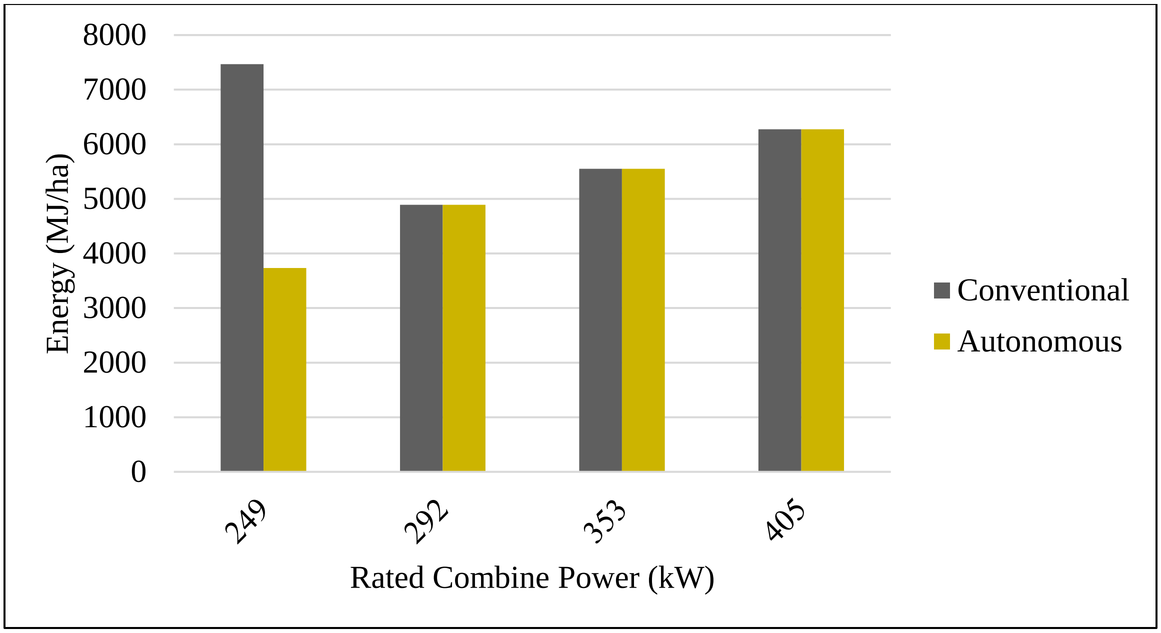

Figure 2.3: Embodied energy of machinery used to complete harvesting

Since the autonomous, 249-kW combine is able to complete the harvesting operation with one combine, the EE is much is lower than the conventional counterpart. For the larger capacity combines, only one combine is needed in the case of both systems.

The selected grain cart system sets the number of tractor and cart pairs to the amount needed to meet the material capacity of the harvesting operation. There is a difference between the tractors that are capable of pulling a row crop planter and the ones that can pull a grain cart. The JD 3025E and MF 2850M do not have enough power to operate the smallest planter and grain cart. The JD 5075, JD 5090EL, JD100E, and Case Maxxum 125 are also not capable of pulling a grain cart, based on Brent Grain Handling's recommendation. The legitimate tractor and grain cart pairs can be seen in **Table 1.9**. **Figure 2.4** shows that there is no grain cart fleet that has a difference in embodied energy between the autonomous and conventional system.

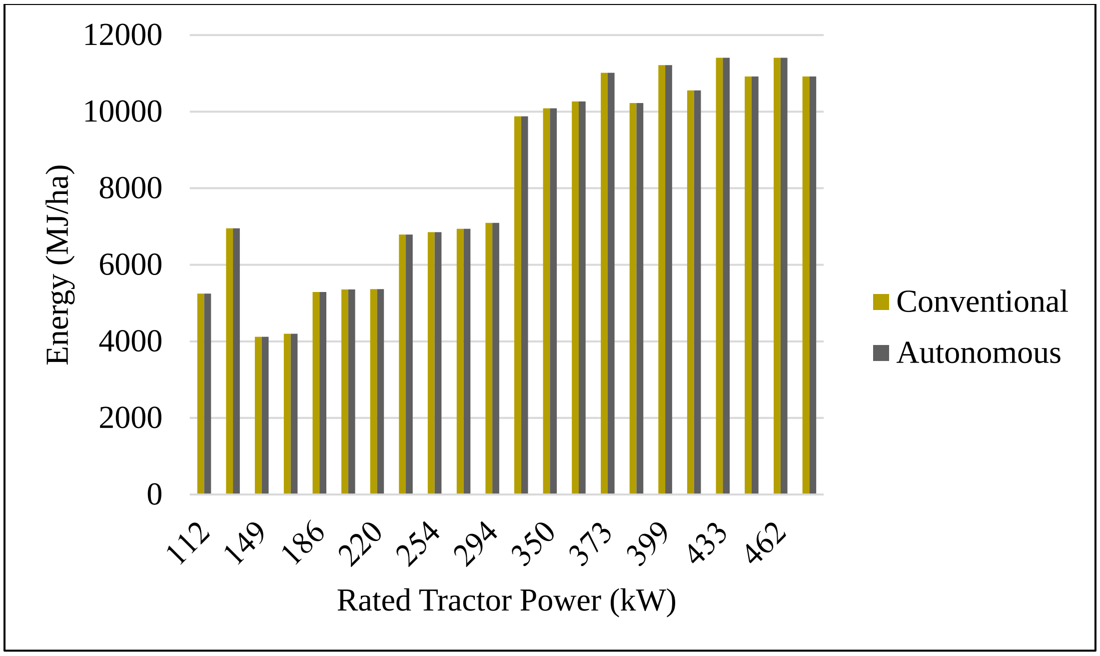

Figure 2.4: Embodied energy of machinery used to transport harvested crops

2.5.2 Direct Energy

2.5.2.1 Planting

The direct energy results will focus on the fuel energy of the different machinery fleets. This is because the fuel energy consumption between the conventional machinery and autonomous versions is the same (see **Section 1.5)**. **Figure 2.5** shows the fuel energy used by the different conventional machinery fleets to complete the 800-hectare planting operation.

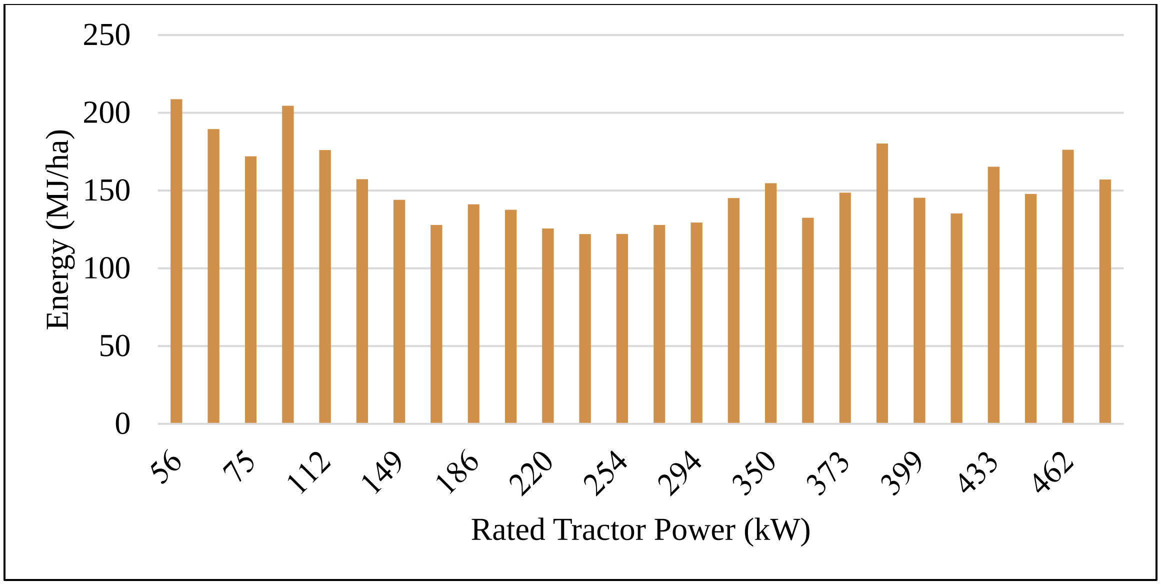

Figure 2.5: Fuel energy consumed during the planting operation for varied power ratings of tractors

The volumetric fuel consumption for the tractors is based on tractor-specific fuel consumption, rather than a general formula. The process used to calculate the fuel used is outlined in **1.3.3.2**. The least amount of fuel was used by the 239-kW tractor, the John Deere 8320R, to plant the 800-hectare case study farm. There is a noticeable valley in the bar chart at the center, near the 200- to 300-kW rated tractor power. The 8320R used 2528 liters of diesel, which equates to 122 MJ of fuel energy per hectare. The smallest tractor, the John Deere 5075E, used the most fuel. To complete the planting operation, the tractors used 4327 liters of diesel and 209 MJ of energy per hectare.

2.5.2.2 Harvest

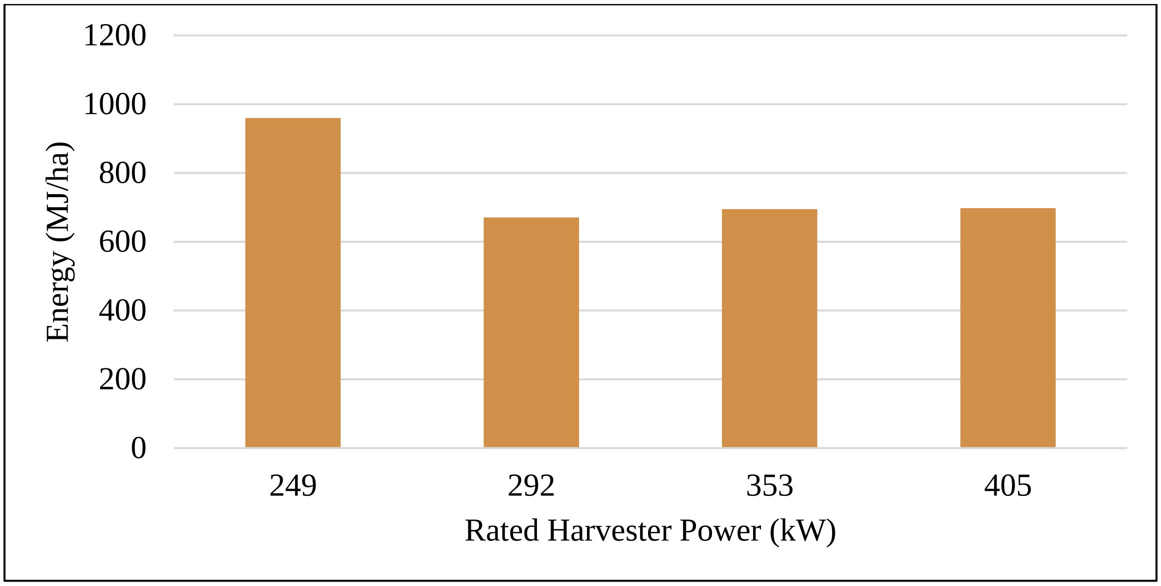

Figure 2.6: Fuel energy consumed during the harvesting operation for varied power ratings of harvesters

The 292-kW harvester used the least amount of fuel to complete the harvesting operation, 13,897 liters or 671 MJ per hectare of fuel energy. A significant difference in fuel use can be seen between the most and least fuel-efficient systems. The 249-kW harvester used 19,893 liters of diesel, which is equal to 960 MJ per hectare of energy.

2.5.2.3 Carting

The tractors in the database were used to analyze the planting and grain carting operation. Since the tractors would be operating at a different engine speed, rated power ratio, and for a different period of time when pulling grain carts, the fuel consumption between the two operations is different.

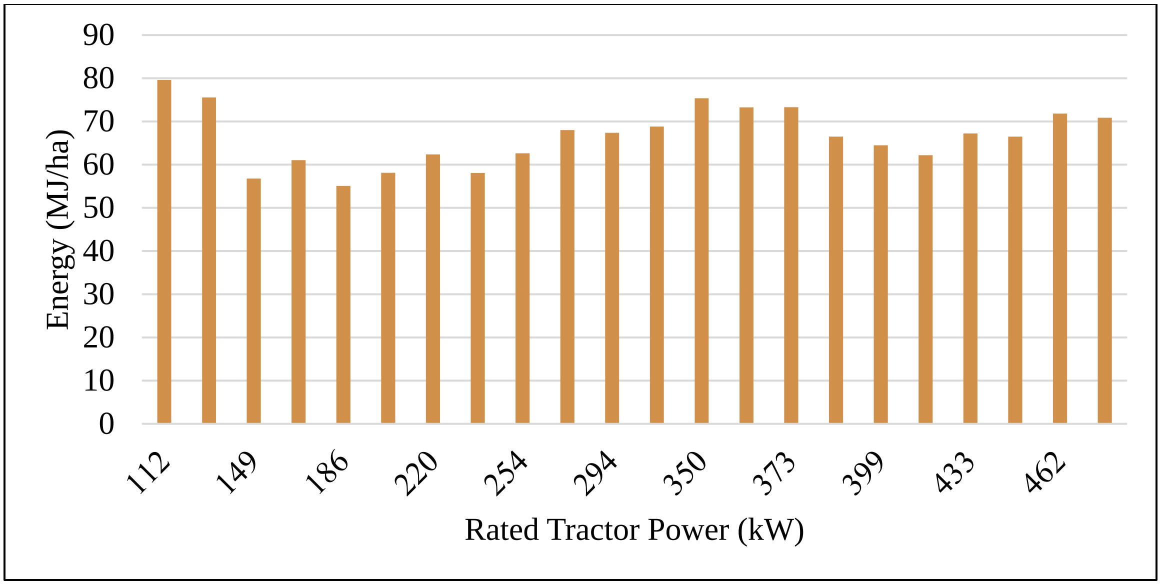

Figure 2.7: Fuel energy consumed during the grain cart operation for varied power ratings of tractors

The least amount of fuel was used by the 186-kW tractor, the New Holland T8.320. It consumed 1,142 liters of fuel, which totals to 55 MJ per hectare of energy. The most fuel was used by the 112-kW John Deere 6150R, 1,650 liters or 80 MJ per hectare of energy.

2.5.3 Emissions

2.5.3.1 Planting

Figure 2.8 reports the upper limit or legal amount of emissions that can be expelled by the planting tractors. The emissions rates are based on values in **Table 2.3**.

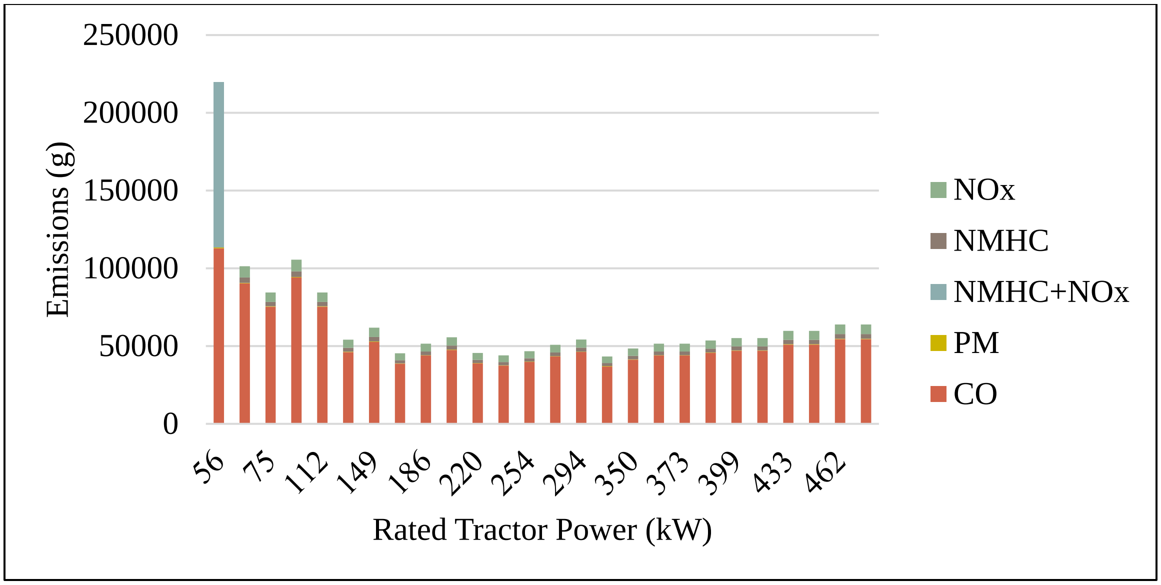

Figure 2.8: Allowable emissions from varied power ratings of tractors during planting

The smallest tractor that can pull a planter emits a substantially larger amount of NMHC and NOx. This is because it falls under the greater than or equal to 37 kW and less 56 kW engine power category. The total sum of all emissions for the smallest tractor, the John Deere 5075E with a 4-row planter, is 219,735 grams. That is 176,420 more grams than the tractor with the lowest emissions output, the 239-kW John Deere 9420R pulling a 48-row planter.

2.5.3.2 Harvest

The emissions results in the **Figure 2.9** are from the combines used for the harvest of the corn and soybeans.

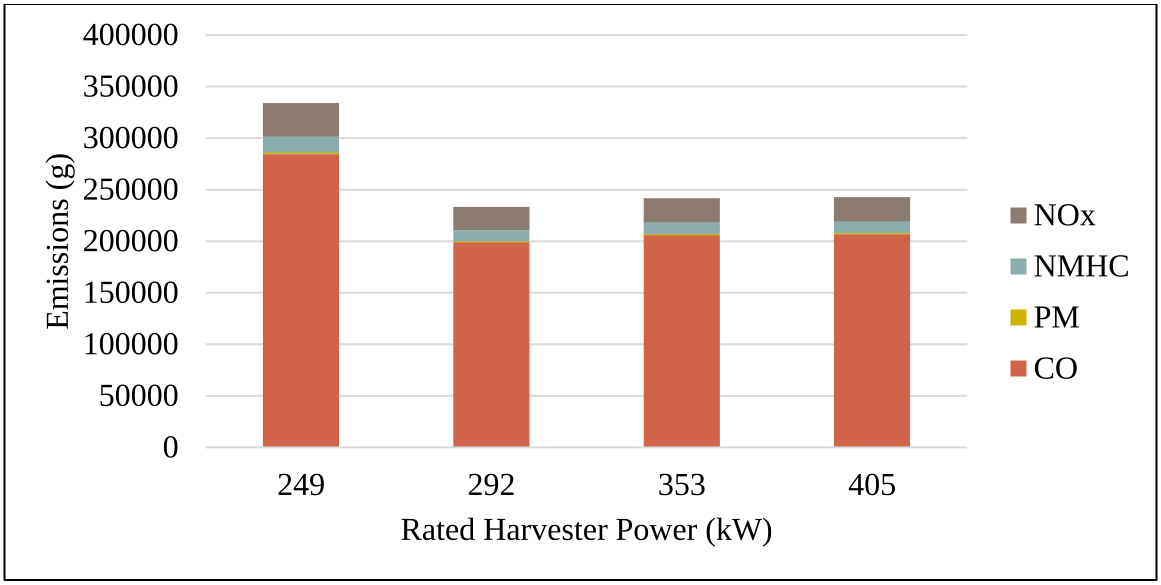

Figure 2.9: Allowable emissions from varied power ratings of combines during harvesting

The difference in the upper bound of total emissions is due to two factors: 1. the field capacity of the harvester and 2. the fuel consumption. Based on EPA emissions standards, the allowable emissions rate for all the combines that were analyzed is the same. The combines fell under the same rated power category, greater than or equal to 225-kW and less than 450-kW (**Table 2.3**). The field capacity of the system determines the number of hours that the header and combine are used. The fuel consumption of the combines varies due to the power of the vehicle. The harvester system with the lowest total allowable emissions was the 292-kW combine (233,998 grams). The result of the 249-kW combine was 333,981 grams. There is a large difference when the size and capacity of a machine is small, but there is little difference when it becomes bigger.

2.5.3.3 Carting

Figure 2.10 shows the emissions from the tractors used for grain carting. The smallest tractor that is capable of pulling a grain cart, the 112-kW John Deere 6150R, emits much more than the other tractors.

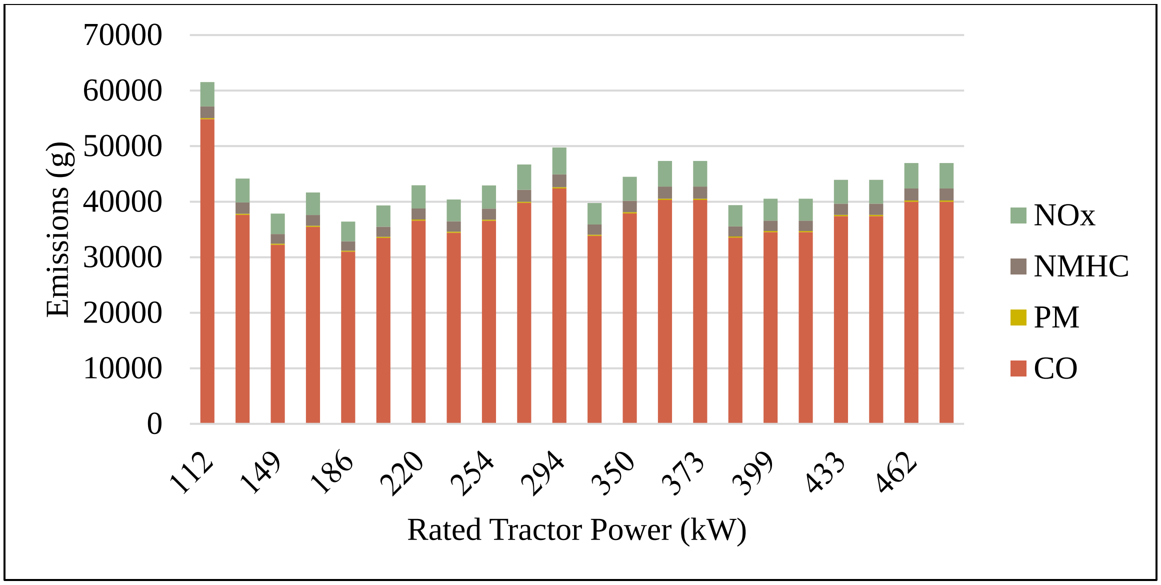

Figure 2.10: Allowable emissions from varied power ratings of tractors during the grain carting operation

All tractors greater than, or equal to 56-kW and less than 560-kW are allowed to emit the same amount of NMHC, NOx, and PM. The difference is that the tractors that have greater than, or equal to 56-kW and less than 130-kW can emit 5 grams of CO for every hour that the engine is used at a certain power. Tractors that are greater than, or equal to 130-kW are limited to 3.5 grams of CO. The 186-kW New Holland T8.320 released the least amount of emissions, 36,410 total grams. The 112-kW John Deere 6150R released a total of 61,531 grams.

2.5.4 Scenario Analysis

The analysis used in the energy and emissions model is the same as the analysis performed in Section **1.5.3**. Adding an operator to supervise the autonomous fleet does not affect the amount of vehicle emissions or fuel energy consumed. To reiterate the statement in **2.5**, changing the hours worked will not influence the fuel used or emissions from the machinery. In the end, the same amount of work gets completed with a different number of vehicles in a fleet. And vehicles within a fleet have the same fuel consumption coefficients and emissions rates. The change in the number of tractors is shown in **Figure 1.12**. The results below, shown in **Figure 2.11**, is the change in embodied energy when a 16-hour planting workday is assumed.

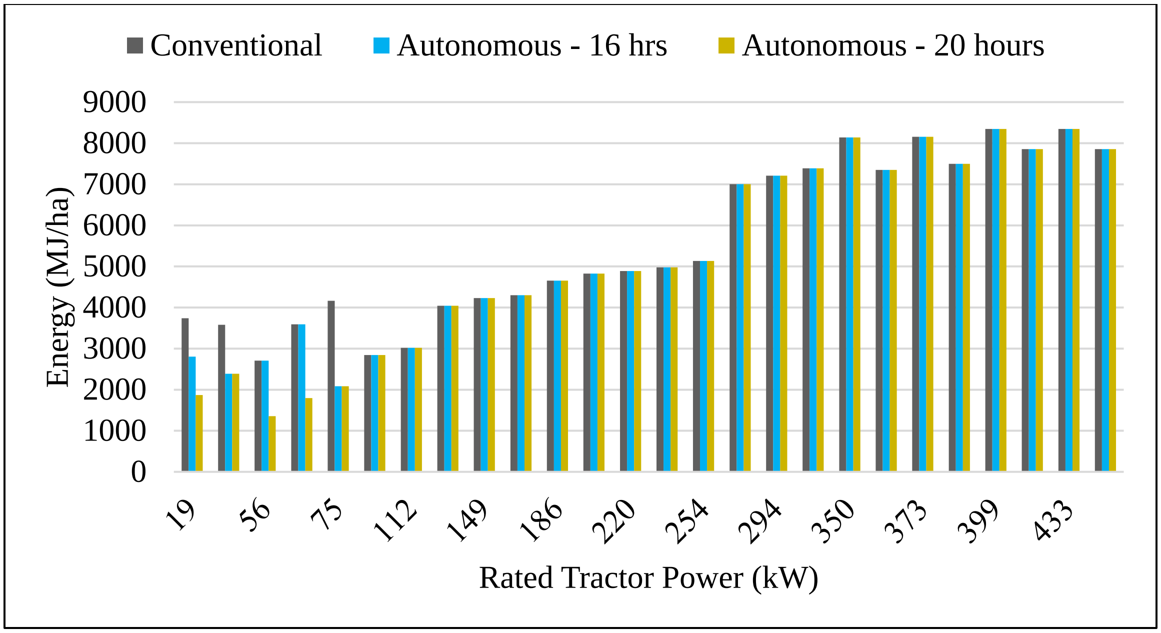

Figure 2.11: Scenario analysis – planting machinery embodied energy

There is a difference of one less tractor and planter pair for the 56-, 75-, and 93-kW autonomous fleets. For the 800-hectare planting operation, tractors with equal to and greater than 112-kW operating for 16 hours can fulfill the field capacity requirement without needing another unit. There is no change in EE between the 16-hour and 20-hour 67-kW tractor using a 6-row planter.

2.6 Conclusion

A model was developed to quantify the energy consumption and emissions of autonomous and conventional machinery in row crop planting and harvest operations. The model was used to determine the effects of swarm farming and autonomous navigation compared to conventional systems. The model calculated the embodied energy, fuel energy use, and emissions from agricultural machinery used in row crop production. A case study farm was applied to the model to determine the embodied energy, how much fuel was used, and the vehicle emissions. The case study farm was an 800-hectare, no-till, corn and soybean operation in the Midwest region of the United States.

The case study showed a large difference in the embodied energy of the autonomous and conventional planting fleets using tractors 122-kW and smaller. The autonomous fleets that required multiple machines needed less tractor and planter pairs than the conventional counterpart because they can work more hours per day. Since the grain cart system that matches the material capacity of the carts to the material capacity of the harvester was selected for the case study, there was no differences in the number of tractors and carts needed when comparing the autonomous and conventional system.

The amount of fuel consumed by the smaller machinery during the planting and harvest operation was typically greater than or comparable to the largest machines. Fuel use was minimized when the rated vehicle power was near the average of the upper and lower bound of the different vehicles used in an operation. Allowable emissions rates for the machines with a lower rated power were drastically higher than the larger machines. At the higher rated engine powers, emissions standards were almost identical and variance between vehicles was minimal.

Based on the results, the adoption of autonomous navigation has the potential to increase greenhouse gas emissions and fuel use by enabling the use of small, low field capacity machines. Smaller planting fleets decreased the embodied energy associated with the agricultural machinery by reducing mass.

2.7 Future Work

Future work on the model should aim to increase the applicability of the model. The current model can analyze planting, harvest, and grain carting, but it is not capable of determining the energy use and emissions associated with tillage or spraying. Another area that could be improved is allowing for different machine sizes to be within the same fleet. Currently, the model limits the vehicle and equipment size per fleet to one. This means that the model is not capable of determining the environmental impact of mixed machinery fleets, i.e., a 75-kW tractor with an 8-row planter working simultaneously with a 462-kW tractor pulling a 48-planter to finish the same 800-hectare farm. Additional timeliness and days suitable for work data should be incorporated to allow users in other states / regions to utilize the model. Yield timeliness data and the days per week that are suitable for fieldwork vary spatially and temporally. This must be accounted for when developing a decision-making tool for others. The final facet of the model that could be improved upon is the interpretation of the results. With the volume of results from the model, an optimization methodology could be applied to determine the most efficient fleet per operation.

A.6 Appendix - Simulation Results

A.6.1 Limit Planting

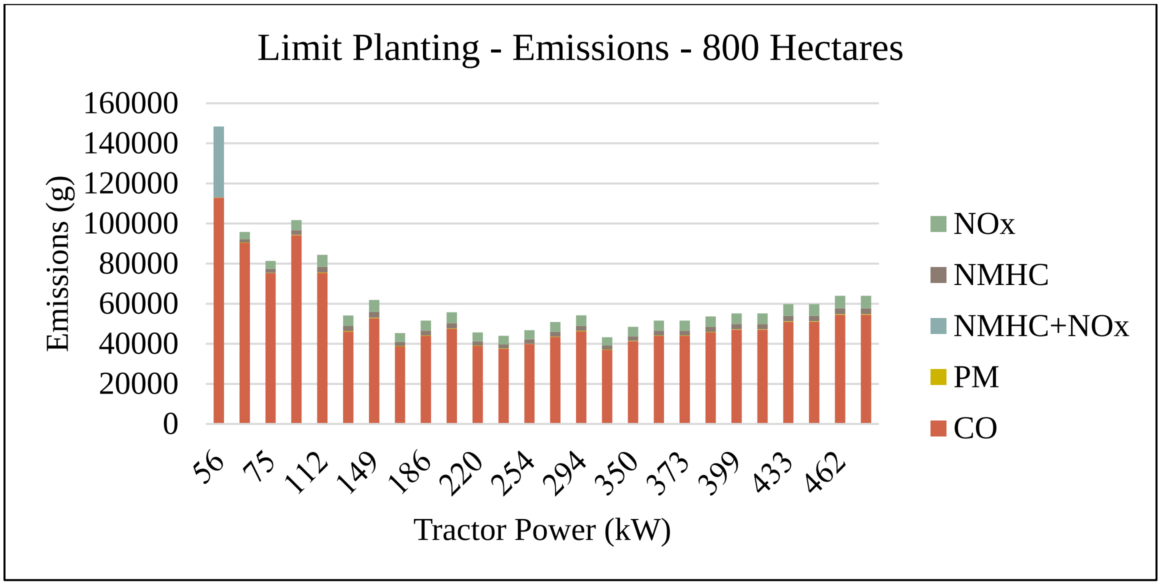

Figure 2.12: Allowable emissions from varied power ratings of tractors during staff limited planting

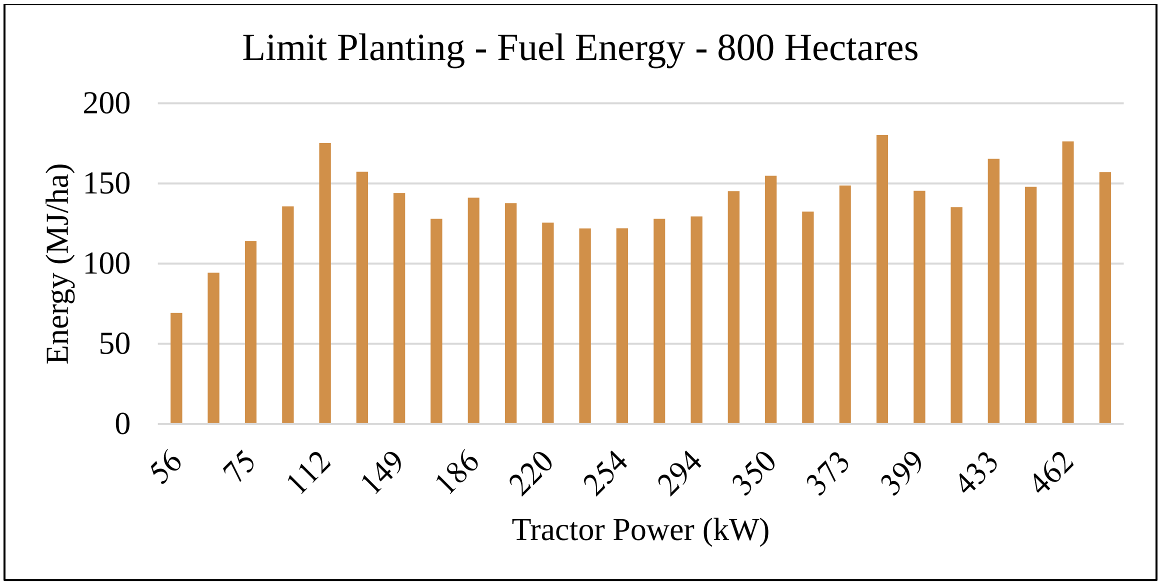

Figure 2.13: Fuel energy consumed during the staff limited planting operation for varied power ratings of tractors

A.6.2 Limit Harvesting

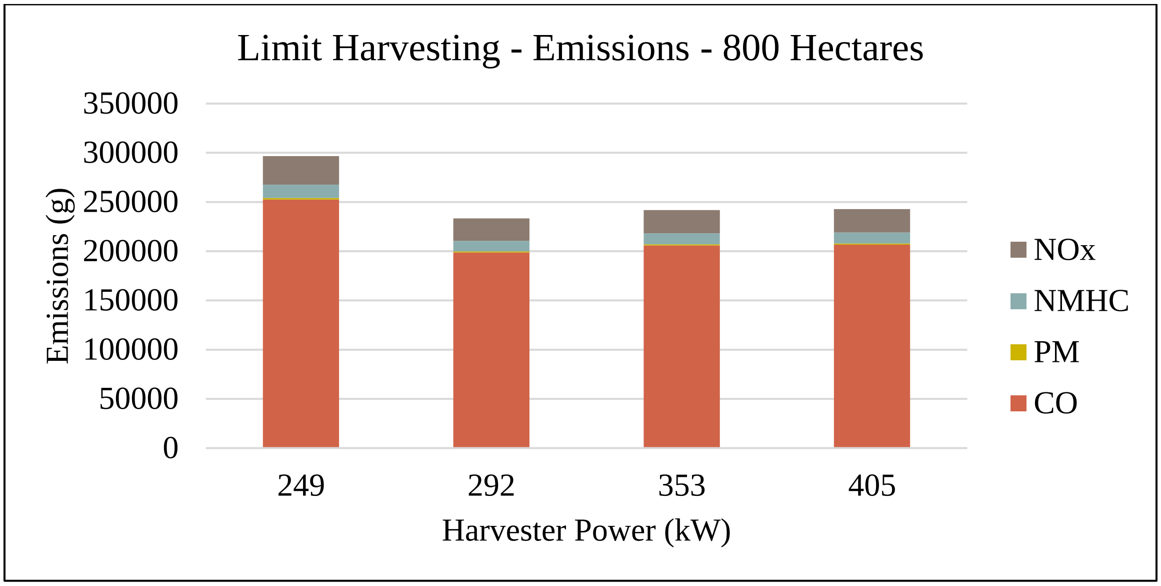

Figure 2.14: Allowable emissions from varied power ratings of combines during staff limited harvesting

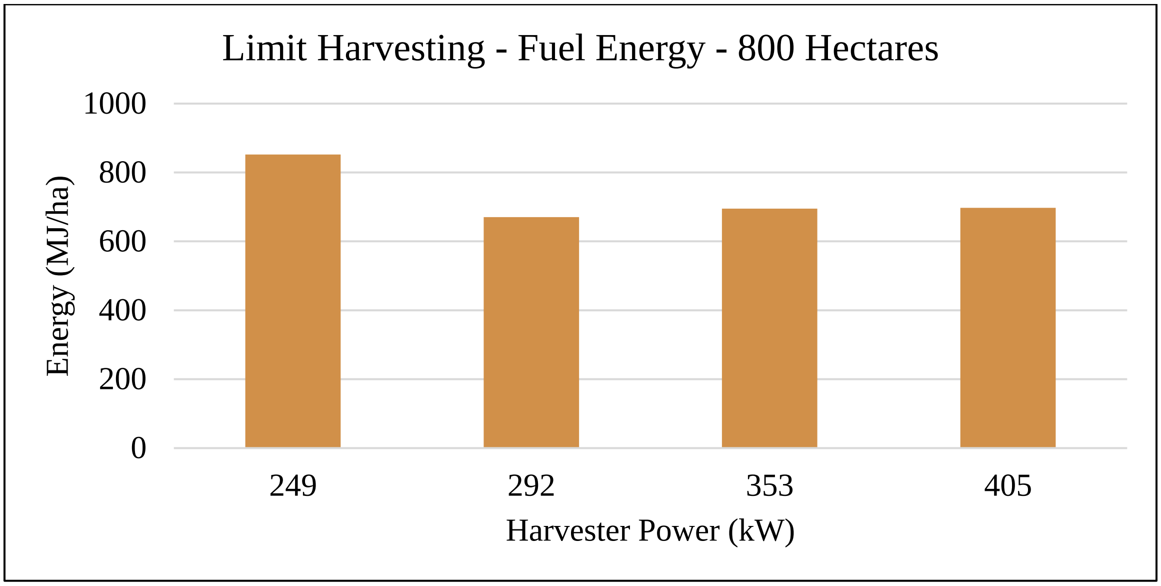

Figure 2.15: Fuel energy consumed during the staff limited harvesting operation for varied power ratings of harvesters

A.6.3 Limit Carting

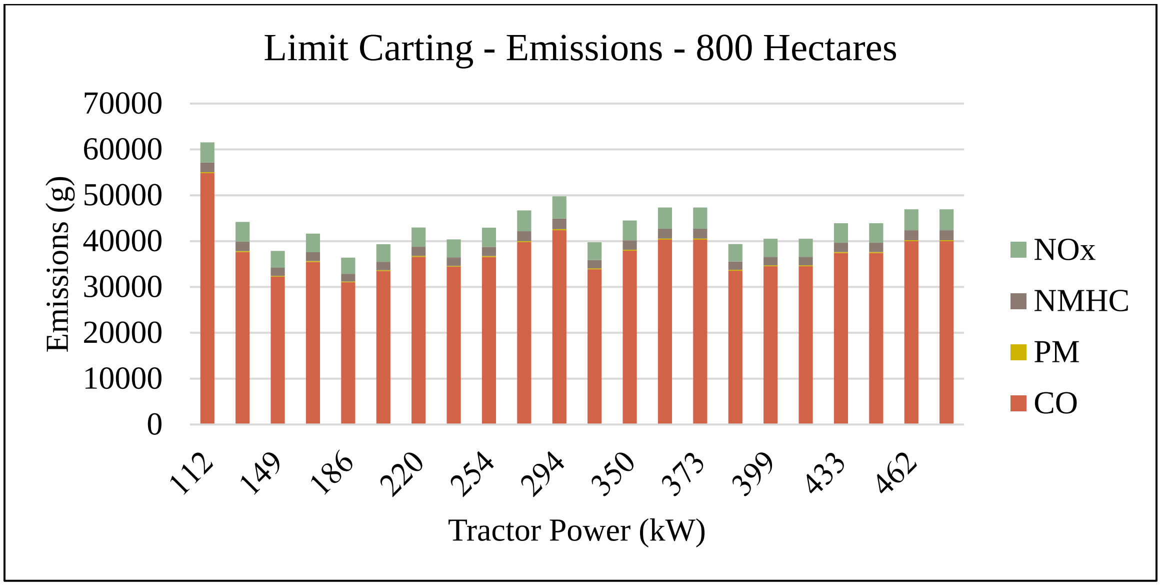

Figure 2.16: Allowable emissions from varied power ratings of tractors during the staff limited grain carting operation

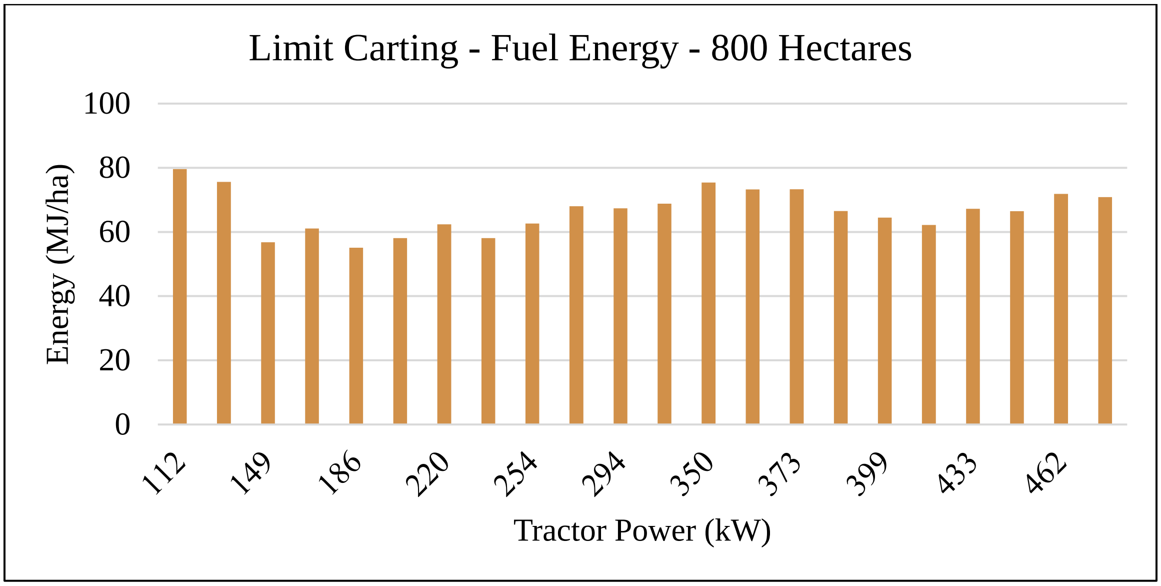

Figure 2.17: Fuel energy consumed during the staff limited grain cart operation for varied power ratings of tractors

A.7 Model Screenshot

	Name	Units	Symbol		
Field	Total farm size	[ha]	ha	800	
	Fraction of farm for corn	-	CNT_{corn}	0.5	
	Fraction of farm for soybean	-	CNT_{soy}	0.5	
	Staff limiter	-		1	Set the amount of labor for the limited system analysis
Planting	Planting Start Date			04/18	All corn is planted before soybeans. Both crops are planted during the defined window
	Days past April 1st			17	For timeliness/yield calculation
	Planting End Date			05/16	Corn and soybean planting must be completed by end date
	Planting Window Duration	[days]	WIN_{plant}	28	Days between start and end date
	Days suitable for planting in the window	[days]	$DSFW_{plant}$	12.18	Based on USDA NASS data
	Days between working days	[days]	Day_{btwn}	2.30	Used to space working days across the duration of the window
	Planting time worked per day	[hr/day]	$T_{plant,conv}$	11	Conventional
	Planting time worked per day	[hr/day]	$T_{plant,auto}$	20	Autonomous
	Implement Soil Parameter	-	F_i	Medium texture	Soil texture for planter draft calculation
	Planter Type	-		2	Row crop planter - No-till, SFH - 1 fluted coulter/row
	Soil Condition for Slip	-	$Soil_{slip}$	Firm	Tractive condition to determine tractive efficiency
	Soil Condition for Motion Resistance	-		Firm	Defines cone index of soil
	Planter Field Efficiency		E_f	0.65	Field efficiency for effective field capacity calculation (D497.7 Table 3)
	Row spacing	m	SPC	0.762	30 inch rows for corn and soybeans
	Minimum field capacity to complete planting	[ha/day]	FC_{min}	65.7	Accounting for probability of a good working day
Harvesting	Harvest Start Date			09/26	Both crops are harvested during the defined window
	Harvest End Date			10/31	Corn and soybean harvesting must be completed by end date
	Harvest Window Duration	[days]	WIN_{HV}	35	Days between start and end date
	Days suitable for harvesting in the window	[days]	$DSFW_{HV}$	26.34	Based on USDA NASS data
	Harvesting time worked per day	[hrs/day]	$T_{HV,conv}$	11	Conventional system
	Harvesting time worked per day	[hrs/day]	$T_{HV,auto}$	20	Autonomous system
	Harvester Field Efficiency	[--]	$E_{HV,f}$	0.7	Field efficiency for effective field capacity calculation (D497.7 Table 3)
	Required field capacity for harvest	[ha/day]	$FC_{HV,min}$	30.37	Required field capacity per day to complete harvest operation
	Estimated trips per hour	[1/hr]	CAP_{mod}	4	Convert bushels to bushel/hour (trips per hour)
	Grain cart system			2	# of carts meets harvesting material capacity
	Harvesting system selector - determines carting			3	Class 8 - 12 row corn, 10.7m wide soybean
Variable Factors	Corn yield before timeliness	bu/ac	YLD_{corn}	190	Yield used to define harvest material capacity
	Soybean yield before timeliness	bu/ac	YLD_{soy}	60	Yield used to define harvest material capacity
	Labor cost	$/hr	LBR	$15.00	
	Fuel cost	$/L	Pr_{fuel}	$ 1.00	
	Oil cost	$/L	Pr_{oil}	$ 6.35	
	Salvage value	-	SVG	0.1	Fraction of purchase price
	Interest rate	decimal %	INT	0.03	Interest rate in annual payment calculation
	Loan term	yrs	LT	10	Loan term used in annual payment calculation
	Taxes	-	TX	0.01	Fraction of purchase price
	Housing	-	HS	0.0075	Fraction of purchase price
	Insurance	-	IN	0.0025	Fraction of purchase price
	Other ownership costs	-	OWN	0.02	Taxes, housing, insurance summed
	Time tractor is used for other work (applied to all tractors)	hr	ADD_{work}	50	Tractor is used for work besides planting and/or carting. Reducing fixed cost

Figure 2.18: Screenshot of the inputs and variable factor values used in the energy and emissions case study

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VITA

Eric Kong

EDUCATION

Purdue University – West Lafayette, IN August 2019 – Present

Master of Science in Agricultural & Biological Engineering

- Specialization: Agricultural systems modeling and simulation
- GPA: 3.9/4.00

Purdue University – West Lafayette, IN August 2015 – May 2019

Bachelor of Science in Agricultural & Biological Engineering

- Specialization: Machine systems engineering
- GPA: 3.17/4.00

TEACHING EXPERIENCE

Tech Liaison – Education Technology Support January 2021 – Present

Purdue University, College of Engineering

- Developed teaching assistant training material
- Assisted professors with Brightspace related issues

Teaching Assistant – AE and ASM Senior Design May 2020 – Present

Purdue University, Agricultural & Biological Engineering

- Developed course material for synchronous and asynchronous delivery
- Implemented Microsoft Teams to facilitate collaboration and communication
- Created content with Brightspace learning management software

Teaching Assistant – AE and ASM Senior Design August 2019 – April 2020

Purdue University, Agricultural & Biological Engineering

- Supervised and assisted students working in the machine shop
- Assessed team presentations and provided feedback
- Taught a sheet metal modeling and electrical hardware development activity

UNIVERSITY INVOLVEMENT

Graduate Student Association – President May 2020 – Present

Purdue University, Agricultural & Biological Engineering

- Presided over executive board meetings
- Created a funding proposal
- Planned the research symposium

Graduate Student Advisory Committee – Board Member June 2020 – Present

Purdue University, College of Engineering

- Discuss initiatives to promote diversity and cultural change
- Serve as a liaison between the College of Engineering and the ABE department

Quarter Scale Tractor Team – Technical Mentor August 2019 – Present

Purdue University, Agricultural & Biological Engineering

- Provide feedback on technical decisions
- Assist team members with planning

Summer Undergraduate Research Fellowship (SURF) – Mentor June 2020 – August 2020

Purdue University, Agricultural & Biological Engineering

- Evaluated projects during the virtual research symposium
- Provided technical presentation and writing feedback to my mentee

Graduate Student Association – Recruitment Chair October 2019 – May 2020

Purdue University, Agricultural & Biological Engineering

- Helped organize the Graduate Industrial Research Symposium
- Interacted with and hosted prospective graduate students

Quarter Scale Tractor Team – Captain August 2018 – June 2019

Purdue University, Agricultural & Biological Engineering

- Tractor design and fabrication (3D modeling, component selection)
- Prepared technical documents (cost report, design report, team presentation)
- Planned team meetings

INDUSTRY EXPERIENCE

Continuous Improvement Engineering Intern May 2018 – August 2018

Wabash National, Lafayette, IN

- Optimized build areas
- Performed cycle time studies
- Implemented a daily improvement board
- Designed part racks

Asset Management Intern July 2017 – January 2018

Naval Facilities Engineering Command, Crane, IN

- Produced basic facility requirement spreadsheets
- Prepared report of excess documents
- Organized explosive safety site approvals

AWARDS AND CERTIFICATES

Estus H. and Vashti L. Magoon Award for Excellence in Teaching March 2021

Purdue University, College of Engineering

- Recognition for outstanding teaching assistants and instructors

SURF Mentoring Certificate June 2020

CISTAR NSF Engineering Research Center

- Completion of the Summer Undergraduate Research Fellowship training