DISSERTATION

ESSAYS ON FERAL SWINE: PRODUCER WELFARE EFFECTS AND SPATIOTEMPORAL MANAGEMENT OF FERAL SWINE.

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ABSTRACT

ESSAYS ON FERAL SWINE: PRODUCER WELFARE EFFECTS AND SPATIOTEMPORAL MANAGEMENT OF FERAL SWINE.

Feral swine are known to cause damage to crops among other types of property damage. With a lack of economic welfare estimates of feral swine crop damages, the first essay of this dissertation addresses this gap in the literature by estimating the value of feral swine removal with respect to five crops in nine southern states. An equilibrium displacement model was used to assess the changes in price and quantity that would result from eliminating damage to corn, soybeans, wheat, rice, and peanuts in these nine states. Changes in price and quantity are then used to calculate the changes in producer and consumer welfare in both the short and long-run. Respectively, those net surplus gains are $142 million and $89 million.

The second essay addresses the need for analysis in complex management questions. The essay serves as an advance in building an agent-based model for use in feral swine management and extending it by developing a method for passing optimal management information to the agent-based decision maker. This essay constructs an agent-based model for use in examining different imperfect, but reasonable, ways that decision makers could implement a marginal benefit to the removal of feral swine and a marginal cost of removal. This essay finds that the implementation of the marginal benefit to removal matters for the land managers. Further, the essay finds that the dynamics of the sounder and movements related to sounders matter to the land managers and society at large and encourages further research into that area.

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DEDICATION

To Mandi, and all the other people who helped me through this.

Thank you.

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1. INTRODUCTION

In the continental United States, feral swine were originally introduced into the Southeast and California by Desoto's and subsequent expeditions (Mann 2006). The population and range remained constant into the 1990s (Keiter et al. 2016). Over the past thirty years, with the help of hunters, feral swine have expanded their range from 17 to 38 states (Bevins et al. 2014). Figure 1.1 shows the counties with known feral swine presence in 2012, represented by light grey. The land area of counties that gained feral swine presence in the years between 1982 and 2012 was 1.9 million square kilometers. The nationwide feral swine population is unknown, but the population in Texas has been estimated at 2.6 million head (Timmons et al. 2012).

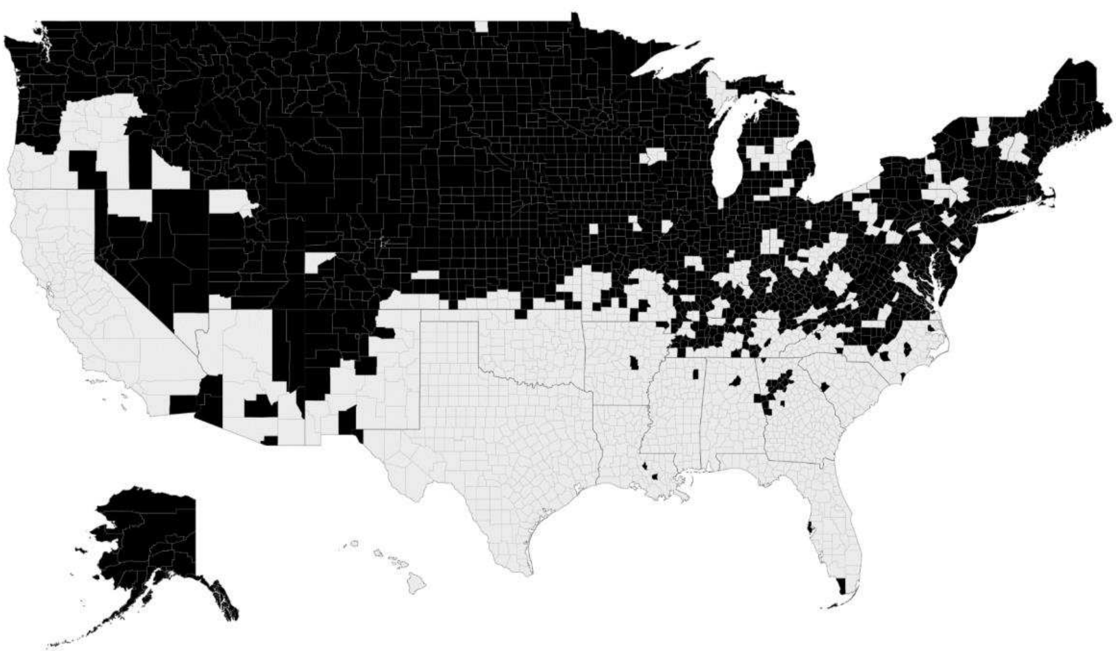

Figure 1.1 Counties With Known Feral Swine Presence in 2012 (light grey). Data Source: Lutman (2013).

A Roman proverb fits the problem of feral swine as time progresses, *'tandem aliquando invasores fiunt vernaculi'* which translates to 'in time invaders become the natives' (Shrader-Frechette 2001, p. 511). As feral swine spread, they cause damage and pose a threat to the economy on many fronts. However, as they become established they are more difficult to remove and in some areas, the local populace has become an advocate for feral swine, regarding them as native and an essential part of the community. Feral swine increasing their range would not be an issue if they did not cause damage. They cause damage to property with estimates ranging from area estimates based on surveys (Mengak 2012; Higginbotham et al. 2008; Adams et al. 2005) to national estimates based on experts opinions (Pimentel et al. 2005). Recently, Anderson et al. (2016) surveyed producers in 11 states to estimate the crop damage in those states and this dissertation will build off of those results.

In addition to crop damage, they also can act as a vector for diseases that pose a threat to human and animal health as well as trade (Miller, et al. 2013; Pineda-Krch et al. 2010; Ward et al. 2009; Hall et al. 2008; Ward et al. 2007; Kreith 2007). Furthermore, feral swine pose a threat as predators to livestock, pets, native species, and even humans (Mayer 2013; Love 2013; Seward et al. 2004; Engeman et al. 2003; Beck 1999; Barrett and Birmingham 1994).

Broadly speaking, a survey of the literature revealed two areas for focusing future research that were of interest to the author to address. First, the literature was missing an estimate of the welfare impacts of feral swine crop damage. Estimates of the missing commodities were available, but not how that affected the U.S. agricultural economy. The second chapter addresses that gap. The second gap was a lack of understanding about how land managers and feral swine interact. Many of the smaller relationships had been defined, but a framework to analyze the situation on the scale of a local community was lacking. The third chapter addresses that need by modeling a community of land managers and feral swine in the smallest rural political unit in the United States – the township.

The first chapter of this dissertation reviews the steps that have been taken to quantify the costs and benefits of feral swine. Surveys and estimates of varying levels of detail and scope were available as a starting point (Anderson et al. 2016). Numerous crop damage, property damage, and environmental damage estimates have been published. Overall, either these estimates were so general that it was not clear how the estimate was developed, or they addressed a very specific case of damage. Those estimates are extremely useful for developing an intuition for the size and impact of feral swine damage to crops and property. However, it is not exactly clear how damage reported in a given region affects the country as a whole. As federal resources are being mobilized, an assessment of the damage inflicted by feral swine with a national view of the economy is warranted.

The second chapter of this volume builds a piece for that national assessment. Chapter Two begins with the survey results reported by Anderson et al. (2016) and constructs an equilibrium displacement model to find the net impact to the United States of the damage to corn, soybeans, wheat, rice, and peanuts inflicted by feral swine in nine Southeastern states. The commodities that are currently missing from the market are replaced, and the changes in price and quantity are used to calculate the change in producer and consumer welfare. A welfare improvement for consumers is expected, while the producers who are not in the feral swine region (i.e., no reduction in crop damage) will be worse off. However, the outcome for producers who are in the feral swine impacted region is unknown.

The third chapter addresses the need to assess and explore complex feral swine management questions. Feral swine are prolific and damaging, yet popular among hunters and people who simply enjoy their presence. Feral swine are mobile and responsive to the actions of land managers. The actions of one land manager will affect other land managers. Analysis of interactive environments such as this can be analyzed in an agent-based framework. In this context, purposeful representations of individuals are simulated in some time and space. Numerous types of questions can be answered with agent-based models, but this dissertation will focus on management decisions.

An agent-based model for feral swine management was built and tested. It was further expanded to introduce information from optimal management strategies into a simple linear programming framework. Ideally, decision makers would apply control as an input to the point where the marginal value product is equal to its marginal cost. It is not clear what either the marginal value product or the marginal cost of removal entails for a mobile, persistent, damaging species with value as a game species. Furthermore, it is not clear how decision makers should be informed of those values.

The third chapter addresses this gap in the literature. An agent-based model is used to characterize differences in land manager accumulated profit resulting from different implementations of the marginal value product of control and the marginal cost of control. In this chapter, the agent-based model is used to consider both direct and indirect interactions between land managers and feral swine as they choose to control or not to control feral swine, and as feral swine attempt to evade applied control. The primary contribution of the third chapter is the application of agent-based modeling to feral swine management and the extension of including information from optimal management in a myopic land manager’s decision.

The focus for the two chapters has been primarily on agricultural commodities, however at two very different scales. The second chapter assesses the U.S. agricultural economy at a very broad scale. A study at that scale is of interest to policy makers who are tasked with evaluating actions against feral swine or other intervention programs. The third chapter examines interactions at a local scale. This chapter is of interest to individuals who want to know what to expect from a given action in a location. The third chapter is an important step forward in invasive species management and agent-based modeling to build upon methods employed. This is the first application of agent-based modeling to feral swine management with land managers modeled as making production decisions with a linear programming model. Chapter 3 also extends this decision framework to incorporate information from an optimal management framework separate from the agent-based model.

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2. VALUING THE ABSENCE OF FERAL SWINE: A PARTIAL EQUILIBRIUM APPROACH.

2.1. Introduction

Conflicts between humans and wildlife arise due to diverging interests between species. Those conflicts can range from property damage to threatening and predatory behavior (USDA APHIS 2015). The United States devotes considerable financial resources to managing human-wildlife conflicts. In 2014, the USDA allocated $106 million to the Wildlife Services division of the Animal and Plant Health Inspection Service for a portion of the federally-funded human-wildlife conflict mitigation efforts (USDA 2015). Among policy makers and researchers interested in human-wildlife conflicts, one species of particular recent interest is feral swine. The USDA has dedicated $20 million to support the goal to "eliminate feral swine from two States [sic] every three to five years and stabilize feral swine damage within 10 [sic] years" (Bannerman and Cole 2014, p1).

Feral swine were introduced by Spanish Conquistadors to the southeastern United States and California in the sixteenth century as well as by Polynesians to Hawaii in the fourth or fifth century (Kirch 1982; Mayer and Brisbin 2008; Mann 2006). By 1982, feral swine were present in 699 counties in 19 states, primarily in the southeastern United States (Mayer and Brisbin 2008). Over the next 30 years, feral swine spread at an accelerated rate across the United States, affecting 1,323 counties in 39 states (Lutman 2013; Bevins et al. 2014). The 624 counties into which feral swine moved between 1982 and 2012 comprised a land area of approximately 1.9 million square kilometers, which is more than the combined land area of Texas, California, Montana, and New Mexico.

Feral swine are known to cause damage to crops and other types of property. A recent survey reported by Anderson et al. (2016) found a production loss of nearly $190 million in eleven states from just six of the crops grown in those states. This survey result is important, as it demonstrates the size of the crop that feral swine have prevented reaching the market.

The production losses are only part of the impact of feral swine. Preventing commodities from reaching the market restricts supply and results in higher equilibrium prices for consumers . In the absence of feral swine damage, market supply would increase resulting in a downward push on prices. Unequivocally consumers would be better off, as they would enjoy more of these commodities at a lower price, however, the outcome for producers is less obvious. Producers enjoying the reduction in damage would be better off only if the increase in quantity made up for the decrease in price. Producers who would not increase production would be worse off. These changes in the wellbeing of consumers and producers are known as welfare changes. To date, the authors are unaware of any studies that assess the welfare implications of feral swine crop damage.

To address this gap in the literature, this study estimates the economic impact of feral swine on crop producers and consumers. Specifically, this research estimates changes in producer and consumer welfare by calculating the changes in price and quantity implied by assuming the missing commodities now enter into the market. Price and quantity changes are used to calculate the change in welfare. Our study will find the value of feral swine removal with respect to corn, soybean, wheat, rice, and peanut damages in nine Southeastern states. Grain sorghum is not included, as it was only reported by Anderson et al. (2016) for one state, and Missouri and California were not included as they did not have sufficient responses in the five commodities of interest to report damages.

After reviewing previous literature, a partial equilibrium model is presented in the next section based on historical U.S. production data from USDA NASS and feral swine presence data and damage estimates from Anderson et al. (2016). The result of this model depicts a reality free of feral swine damage to contrast with the current reality of feral swine damage. It stands to reason that the difference in welfare measures between the model result and the current reality of damage is the value of removal with respect to these five crops in these nine states.

2.2. Literature Review

Feral swine have been present for centuries in some states, and in the past 30 years, they have expanded their range dramatically. With this range expansion has come the realization that feral swine can be both a problem and an opportunity. This section details the literature's previous efforts of quantifying the costs and benefits of feral swine, and then explores the literature related to a promising technique previously unused in this application.

Feral swine damage crops and property (Mengak 2012; Adams et al. 2005; Higginbotham et al. 2008; Mayer and Johns 2011) as well as prey on native species (Engeman et al. 2003; Seward et al. 2004), livestock (Barrett and Birmingham 1994; Beck 1999; Seward et al. 2004), and humans (Mayer 2013; Love 2013), and act as a vector for foreign animal diseases and other pathogens (Ward et al. 2009; Ward et al. 2007; Miller, Farnsworth and Malmberg 2013; Pineda-Krch et al. 2010; Hall et al. 2008; Kreith 2007). Crop damage is a visible effect of feral swine presence. Consequently, policymakers and researchers have been addressing the topic of feral swine damage to crops as a first step of the debate surrounding feral swine management.

Previous feral swine damage estimates have typically focused on the value of the destroyed property. A variety of methods have been used to find the value of the destroyed property. Pimentel et al. (2005) used a method that relied on the expert opinion, to determine that an individual feral swine caused approximately $200/hog in property damage. Assuming that there are four million feral swine in the United States, the average damage estimate is over $800 million in crop, environmental, and property damage in 2005. Higginbotham et al. (2008) elicited producer responses during a workshop series held during 2006 and 2007 at three locations in Texas, where agricultural producers reported destruction to crops and property as a dollar estimate based on their opinion. The damages and expenditures reported in 2005 were more than $2 million for the three pilot locations. In 2011, Mengak (2012) implemented a producer-level mail survey and obtained producer-defined estimates of crop and property destruction in monetary terms for part of Georgia, finding damages to crops and crop-related damage in excess of $57 million.

Ober et al.(2011) advanced feral swine damage estimates by finding the impact on crop-yields imposed by feral swine. Ober et al.(2011) surveyed producers in northeastern Florida regarding yield changes and destroyed acres attributed to feral swine. Damage estimates derived by Ober et al.(2011) were based on an extrapolation of survey responses to determine destroyed acres, and then valued at the current market price in 2009. Recently, the USDA surveyed producers concerning crop damage by feral swine in Alabama, Arkansas, California, Florida, Georgia, Louisiana, Mississippi, Missouri, North Carolina, South Carolina, and Texas (Anderson et al. 2016). Information was obtained so that damages could be reported in such a way as to describe the amount of increased production that would result from an absence of feral swine. A selection of results from this study has been presented in Table 2.1. Anderson et al. (2016) detail how these percentage losses measure the increase in what would exist in the absence of feral swine.

It is still not clear, based on damage estimates from these studies, how much worse off farmers or consumers are due to feral swine, or how much they would be willing to pay to avoid suffering these damages. An objective metric is needed to consider the costs and benefits of a policy at a societal level, such as social welfare. Welfare measures are extensively used to determine the effects of agricultural policy actions. Two commonly used social welfare measures are producer and consumer surplus.

One commonly used framework for measuring the quantity and price effects due to an exogenous supply or demand shock, such as feral swine crop damage, is an equilibrium displacement model (EDM). The EDM is a linear abstraction of supply and demand functions that describe the transition from one equilibrium to another without defining an exact functional form (Wohlgenant 1993; Wohlgenant 2011). The versatility of the EDM has allowed it to be used in multiple settings from examining the effects of export demand on grain, feed products, and livestock using genetically modified organisms (Preckel et al. 2002). Additionally, EDMs have been used to estimate the returns on public research (Alston, Norton and Pardey 1995), welfare effects of a university wheat breeding program (Nogueira et al. 2015), country of origin labeling (Brester et al. 2004), animal disease outbreaks (Pendell et al. 2007), and distributional impacts of crop insurance subsidies (Lusk 2016).

The simplest EDM describes the change in the equilibrium of a single good in a single market. Relative change in supply and demand is used to motivate movement from one equilibrium to a new one while considering relative own price demand and supply elasticities (Wohlgenant 2011). Parallel shifts of linear functions can be interpreted geometrically (Wohlgenant 2011).

The accuracy of the EDM approach depends on the degree of non-linearity of the true supply and demand functions and the magnitude of the exogenous changes being modeled (Wohlgenant 1993). Total surplus measured from linear approximations will likely include error, but changes in surplus should be relatively close to true values provided that exogenous changes are small. For the case of feral swine, it is likely that changes will be quite small relative to the quantities of commodities clearing the market, allowing the linear approximation to be appropriate.

Wohlgenant (2011) shows that the framework can be expanded beyond a single market. Perrin and Scobie (1981) used an EDM with multiple markets and price wedges to study the options for increasing nutrient consumption among Colombia's poor. Nogueira et al. (2015) developed a model that incorporated both multiple commodities and multiple markets. Lusk (2016) presented an EDM that simulated the links from farmer to end user to show the distributional effects of crop insurance subsidies. Each of these models took a slightly different approach to measuring welfare changes. The EDM in this study is similar to Nogueira et al. (2015) in that we evaluate more than one commodity in more than one location.

2.3. Methods

Building on previous feral swine damage literature, this analysis constructs an exogenous shock of hypothetically removing feral swine; thus, eliminating feral swine crop damage affects market linkages. At the farm gate, the end use of the crop is indistinguishable, and damage from feral swine is primarily incurred at the farm level; thus, the primary market of concern is that of the producer selling output. First, supply and demand functions are derived for the EDM. Second, the exogenous production shocks are incorporated into the EDM, and changes in price and quantity are obtained. Third, producer and consumer welfare are calculated and used to evaluate the changes in welfare resulting from a reduction in feral swine damage.

2.3.1. The Model

For this analysis, the exogenous production shock is the removal of feral swine damage from a targeted area. For illustration purposes, we will assume the market discussed herein is for commodity k at the farm gate. The commodities denoted by k are corn, soybeans, wheat, rice, and peanuts. At the core of this relationship is the idea that there is a market where conditions of perfect competition for both buyers and sellers holds. A single national market demands each crop k. Derived demand for commodity k is defined as:

$$Q_k^d = D_k(P_k, C_k) \tag{1}$$

where Q_k^d is the quantity demanded of product k and is a function of its own price (P_k) and an exogenous demand shock (C_k). Supply is defined for product k in two regions (ω): states where feral swine removal occurs (FRS) and all other states (AOS). Equation 2 describes the structural relationship for quantity supplied for the various crops:

$$\mathrm{Q}_{k,\omega}^f = f_{k,\omega}(P_{corn}, P_{soy}, P_{wheat}, P_{rice}, P_{peanuts}, B_{k,\omega}). \tag{2}$$

$Q_{k,\omega}^f$ is the quantity supplied of product k in region ω. $B_{k,\omega}$ is the exogenous shock to supply.

Two additional considerations for the destinations of these crops are the export market and storage. Dhoubhadel (2015) included a corn export market in his analysis of the effects of the renewable fuels standard during the 2012 U.S. drought. However, Dhoubhadel (2015) assumed that the world price and the U.S. price were equal. Among other factors, producer storage is motivated as both a risk mitigation technique and a method of speculation (Womack 1976). Market response to releases of information demonstrate the effectiveness of the market in knowing how much of a given crop is available at what price, even providing the signal of a negative price in storage to draw product out of storage in times of shortage. Given the question at hand, imports and exports are included in this analysis; however, storage is only implicitly included as part of the price.

Export and import functions are similar to the implementation of those categories by Nogueira et al. (2015). Exports (*X*) and imports (*I*) are modeled as functions of the world price (P_k^W) for the respective commodities:

$$Q_k^I = I_k(P_k^W) \tag{3}$$

$$Q_k^X = X_k(P_k^W) \tag{4}$$

$$P_k^W = P_k. \tag{5}$$

A single price for all regions of the United States and the world is assumed. Market clearing conditions are found with the following equations:

$$Q_k^d + Q_k^X - Q_k^I = Q_{k,FRS}^f + Q_{k,AOS}^f \tag{6}$$

$$P_{k,\omega}^f = P_k^D = P_k \; \forall \; k \; and \; \omega. \tag{7}$$

These relationships in equations (1) through (6) are logged and totally differentiated to find linear change functions. The E operator is used to denote relative change, $s_{k,\omega}^{market}$denotes the weight of each subset's contribution to supply or demand in the larger market, and η, ϵ, and ε are used to denote demand, supply, and import/export elasticities, respectively. In a condensed form, the EDM is stated as:

$$EQ_k^d = \eta_{kk} \times EP_k + EC_k \tag{8}$$

$$EQ_{k,\omega}^f = \epsilon_{kk,\omega} \times EP_k + \sum_k \epsilon_{kj,\omega} \times EP_j + EB_{k,\omega} \text{ where product } j \neq k \tag{9}$$

$$EQ_k^I = \varepsilon_k^I \times EP_k^W \tag{10}$$

$$EQ_k^X = \varepsilon_k^X \times EP_k^W \tag{11}$$

$$EQ_k^d + s_k^X \times EQ_k^X - s_k^I \times EQ_k^I = s_{k,FRS}^f \times EQ_{k,FRS}^f + s_{k,AOS}^f \times EQ_{k,AOS}^f. \tag{12}$$

2.3.2. Elasticities

Elasticities are established for substitution. Elasticities can be obtained from past literature, “guestimated,” or estimated (James and Alston 2002). “Guestimated” elasticities often take the form of unit elasticities (Sumner 2007; Harrington and Dubman 2008). For this study, a mixed strategy is employed. Supply, import, and export elasticities come from previously published studies or are set to a value consistent with previous literature. Demand elasticities are estimated using the Almost Ideal Demand System (AIDS) developed by Deaton and Muellbauer (1980). These elasticities are estimated because a single source for all the demand elasticities in the system was not available. The set of elasticities used in this study is presented in Table 2.2 and Table 2.3 along with their sources.

2.3.3. Weighted Shares

Equilibrium conditions in equation 12 use shares (s) for production, exports, and imports. The production shares are calculated using 2014 production values data from USDA NASS (2015). Import and export weights are calculated with ERS data sources for 2014. Corn import, export, and consumption data are gathered from Table 4 of USDA ERS (2016), soybean data are gathered from Table 6 of USDA ERS (2016), wheat data are gathered from Table 5 of USDA ERS (2016), rice data from Table 8 of USDA ERS (2016b), and peanut data from Table 11 of USDA ERS (2016a).

2.3.4. Scenario

Exogenous production shocks ($EB_{k,\omega}$) are derived from estimates of damage for each of the nine U.S. states (State) as reported by Anderson et al. (2016). Anderson et al. (2016) presents the amount of each crop that would be present in the absence of feral swine ($Damage_k^{State}$). Pre-shock production ($Production_k^{State}$) is total reported production in each state by USDA NASS (2015). The shock is calculated as follows:

$$EB_{k,\omega} = \frac{\sum_{States}(Damage_k^{State} * Production_k^{State})}{\sum_{States} Production_k^{State}} \times 100. \tag{13}$$

In this scenario, we assume that feral swine are instantly and permanently removed from nine Southeastern U.S. states. As shown in Figure 2.1, the feral swine removal states are Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, and Texas. California and Missouri are omitted from this study due to low survey coverage in Anderson et al. (2016). This scenario is used to find a value of removal in these nine states with respect to these five crops. The calculated production shocks represent a 1.5%, 0.5%, 1.7%, 0.5%, and 1.8% increase in corn, soybeans, wheat, rice, and peanuts, respectively, in the FRS region.

2.3.5. Consumer and Producer Welfare

As illustrated in Figure 2.2, producer surplus is represented as the area below the price line and above the supply function, while consumer surplus is the area above the price line and below the demand function. Simply stated, the area above the marginal cost curve and below the price line is estimated for the short- and long-run and compared to the pre-exogenous shock levels to find the change in producer surplus. The change in consumer surplus is found by estimating the area above the price line and below the demand curve for the short- and long-run, and comparing these to their respective pre-exogenous shock levels. It is generally accepted that producers and consumers are more responsive in the long-run than in the short-run. Because producers and consumers are more responsive over time, we use short-run elasticities to calculate immediate results and long-run elasticities to calculate impact in the long-run.

2.4. Results

Using the exogenous damage estimates from Anderson et al. (2016), an EDM was used to estimate the changes in prices and quantities for the commodities. The changes in prices and quantities were used to estimate the consumer and producer welfare of an instant hypothetical feral swine removal. A short-run change in welfare demonstrates the change in wellbeing from the pre-removal equilibrium to the equilibrium that results from the exogenous shock in an undetermined, but short, period of time. The long-run change in welfare also demonstrates the change in wellbeing between two equilibriums; however, this is over a longer, but still undetermined, period of time. The two are not necessarily additive in nature, as the model does not calculate any intermediate values. This lack of damage would be realized in an increased quantity of each of the five crops. An outward shift of the supply curve with no change in demand implies that the market clearing prices decrease. For consumers, lower prices translate to increases in consumer surplus. For producers in the AOS region, where feral swine damage is not eliminated, lower prices imply that producers are worse off. Producer welfare in the FRS region is unknown *a priori*. Producer welfare will depend on whether or not the increase in quantity offsets the lower price, and that is a function of relative elasticities. Long-run responses are expected to be smaller than the short-run movements, as producers and consumers will adjust with smaller impacts.

The instantaneous removal of feral swine results in the additional supply of each commodity available on the market; thus, most short-run commodity prices decreased by a small amount (Table 2.4). The one exception is the change in the price of peanuts, which fell by 2.11%. This is because 97.2% of peanuts are grown in the FRS region, and peanuts usually experienced the most intense damage among states reporting damage. As expected, long-run changes in prices were smaller when compared to the short-run, because producers and consumers are able to shift to other commodities for production and consumption purposes.

Lower commodity prices lead to a small increase in the quantity demanded of each of the commodities. In the FRS region, supply increases for all the commodities as we remove feral swine. The increase in quantity was slightly smaller than the exogenous shock, as producers are reacting to the lower price as well as experiencing higher production with the absence of feral swine. In the AOS region, supply of corn, wheat, and rice all decreased by 0.01% in the short-run, and 0.04%, 0.01%, and 0.02%, respectively, in the long-run. Peanuts decreased by 0.74% and 0.79% in the short- and long-run, respectively. Soybean production increased by 0.01% and 0.008% in the short- and long-run, respectively, as producers substituted commodities with smaller impacts. Long-run changes are not simply linear adjustments to short-run changes, because the relationship between each commodity varies between the short- and long-run. In both the short- and long-run, producers substitute commodities with less extreme price movement for commodities with more extreme price movement.

The key difference between the short- and long-run is that producers and consumers are able to react in the long-run because no factors of production or consumption are fixed. The clear majority of corn, soybeans, and wheat in the United States are not grown in the removal region. Net welfare changes in corn were the largest ($50 and $21 million, in the short- and long-run, respectively), even though most corn production takes place outside of the removal region (Table 2.5). Corn is a major crop in the United States, and as such, a very small change in price has very large welfare effects. Soybeans are also a major U.S. crop with substantial welfare effects ($37 and $38 million in the short- and long-run, respectively) from a very small price change. Net effects of wheat are $23 and $14 million in the short- and long-run, respectively. Over 75% of rice is grown in the FRS region; however, the exogenous shock is only 0.46%. The resulting price changes to rice only change welfare by $12 and $5 million in the short- and long-run, respectively. Over 97% of peanuts are grown in the FRS region, and the exogenous shock was calculated at 1.8%, leading to welfare effects rivaling wheat at $21 and $11 million, in the short- and long-run, respectively.

Short- and long-run changes in consumer surplus were positive by $109 and $39 million, respectively. Producer surplus in the AOS region was a net loss of $65.06 million and $13.17 million, in the short- and long-run, respectively. Producer surplus in the FRS region was a net gain of $98.29 million and $63.59 million, in the short- and long-run, respectively. An eradication of feral swine in these nine states will result in a net surplus gain of approximately $142 million immediately and $89 million in the long-run.

This result is lower than might be expected given the work of Pimentel et al. (2005), Higginbotham et al. (2008) and Mengak (2012). However, the scope of Pimentel et al. (2005) was much wider as an estimate of nationwide damage across substantially more types of property. Both Higginbotham et al. (2008) and Mengak (2012) covered more types of losses (e.g. fixed assets, timber, and crops excluded from this analysis) in a more limited area. Anderson et al. (2016) covered more crops and states, but did not address the market component of feral swine impact. As estimates at a point in time, these studies do not consider the market responses and kinds of adaptations that producers will take due to changes in market prices. It is important to note the substantial surplus losses for producers outside of the removal region, and this is the first analysis to cover that impact in this context.

2.5. Conclusions

Feral swine inflict destruction in terms of damage, predatory behavior, and disease transmission. For this paper, we are particularly concerned about the destruction feral swine cause to crops. Simply valuing the crops that are destroyed is an inadequate measure of impact, because it does not take into account market impacts due the reduction in supply of those crops. To estimate the value of the absence of feral swine with respect to crop damage, estimates of the crop damage are used in an equilibrium displacement model (EDM) to calculate the changes in price and quantity that would result from a removal of feral swine in nine Southeastern U.S. states.

A net surplus gain in both the short and long-run of $142 million and $89 million, respectively, show that feral swine inflict significant damage on producers and consumers of corn, soybeans, wheat, rice, and peanuts. Long-run welfare effects are smaller due to the ability of producers and consumers to adapt to price changes of commodities in the long-run. Producers and consumers will enjoy the benefits of feral swine removal perpetually at a rate of between $142 million and $89 million per year, with the welfare effects decreasing across time. It is also important to consider the distribution of the losses. Most of the short-run welfare losses to the states not benefiting from feral swine removal would be borne by corn producers, and that loss would amount to nearly 1/3 cent per bushel in 2014 production.

There are three primary limitations to the current results to be addressed in future research. First, there are other potential and actual costs imposed by feral swine that are not covered in the analysis, such as removal costs, possible losses from a disease event, crops not covered in this analysis. Second, the short-run changes represent the within-season benefits and costs of immediately reducing damage. The long-run changes represent the impact on a timescale when producers and consumers are able to fully adapt to the change in price expected from the restoration of the damaged goods to market. The exact duration of the transition from short- to long-run is unknown, but is generally understood to be less than ten years. The periods between each equilibrium, and how those benefits and costs are distributed, may be of interest to policy analysis. The uncertainty about short-run to long-run transitions is why the welfare effects are stated in a range. Third, the instant reduction in damage is not realistic. The nature of damage reduction and population reduction over an area this large is unknown.

2.6. Tables and Figures

Table 2.1 Percent of Crop Lost to Feral Swine by State (%)

State	Corn	Soybeans	Wheat	Rice	Peanuts
Alabama	0.93	1.38	0.62	NA	6.17
Arkansas	1.09	0.27	0.75	0.27	NA
Florida	4.41	3.43	NA	NA	1.84
Georgia	4.73	1.07	4.39	NA	NA
Louisiana	0.83	0.74	0.94	1.26	NA
Mississippi	1.34	0.4	0.7	0.12	NA
North Carolina	0.38	0.09	0.15	NA	0.49
South Carolina	1.59	1.52	1.71	NA	NA
Texas	1.65	1.1	3.05	2.46	9.28

Source: Anderson et al. (2016)
NA is not applicable.

Table 2.2 Short and Long-Run Price Elasticities of Supply by Region

		Corn	Soybeans	Wheat	Rice	Peanuts
		AOS Region / Short Run (A) — Price of:				
Quantity of:	Corn	0.201	-0.108	-0.004	0	0
	Soybeans	-0.167	0.153	-0.005	-0.001	0
	Wheat	-0.155	-0.110	0.201	-0.001	0
	Rice	-0.164	-0.117	-0.006	0.238	0
	Peanuts	0	0	0	0	0.350
		AOS Region / Long Run (B) — Price of:				
Quantity of:	Corn	2.010	-1.080	-0.040	0	0
	Soybeans	-0.501	0.459	-0.015	-0.003	0
	Wheat	-0.952	-0.676	1.235	-0.006	0
	Rice	-0.843	-0.602	-0.031	1.224	0
	Peanuts	0	0	0	0	1.883
		FRS Region / Short Run (C) — Price of:				
Quantity of:	Corn	0.326	-0.036	-0.003	-0.034	0
	Soybeans	-0.031	0.191	-0.008	-0.095	0
	Wheat	-0.016	-0.047	0.331	-0.045	0
	Rice	-0.015	-0.050	-0.004	0.473	0
	Peanuts	0	0	0	0	0.35
		FRS Region / Long Run (B) — Price of:				
Quantity of:	Corn	3.260	-0.360	-0.030	-0.340	0
	Soybeans	-0.093	0.573	-0.024	-0.285	0
	Wheat	-0.098	-0.289	2.033	-0.276	0
	Rice	-0.077	-0.257	-0.021	2.432	0
	Peanuts	0	0	0	0	1.883

Sources: (A) FAPRI-MU (2004) corn belt and Peanuts: Beghin and Matthey (2003), (B) Authors best estimate, (C) FAPRI-MU (2004) Delta States and Peanuts: Beghin and Matthey (2003).

Table 2.3 Short and Long-Run Price Elasticity of Demand, Exports, and Imports.

	Price Elasticity of Demand		Price Elasticity of Exports		Price Elasticity of Imports	
Commodity	SR	LR	SR	LR	SR	LR
Corn	-0.696 (A)	-0.915 (A)	-1.200 (B)	-1.773 (D)	0.500 (E)	12.750 (A)
Soybeans	-0.536 (A)	-0.701 (A)	-2.500 (B)	-4.028 (D)	0.500 (E)	1.333 (A)
Wheat	-0.235 (A)	-1.066 (A)	-0.850 (B)	-2.361 (D)	0.500 (E)	4.300 (A)
Rice	-0.157 (A)	-0.668 (A)	-2.620 (B)	-4.658 (C)	0.400 (E)	3.040 (A)
Peanuts	-0.202 (A)	-0.935 (A)	-1.000 (C)	-5.143 (A)	0.500 (C)	5.628 (A)

Sources: (A) Author Estimation, (B) Lusk (2016), (C) Authors Best Estimate, (D) Reimer et al. (2012), (E) Sumner (2007).

Table 2.4 Relative Price and Quantity Changes Induced by Feral Swine Removal (%)

	Short-Run	Long-Run
Relative Price Changes		
Corn	-0.080	-0.032
Soybeans	-0.027	-0.017
Wheat	-0.150	-0.046
Rice	-0.130	-0.053
Peanuts	-2.110	-0.430
Relative Change in Quantity Supplied From the AOS Region		
Corn	-0.013	-0.043
Soybeans	0.010	0.009
Wheat	-0.015	-0.015
Rice	-0.013	-0.027
Peanuts	-0.740	-0.820
Relative Change in Quantity Supplied From the FRS Region		
Corn	1.450	1.390
Soybeans	0.510	0.510
Wheat	1.620	1.590
Rice	0.400	0.340
Peanuts	1.060	0.980
Relative Change in Quantity Demanded		
Corn	0.056	0.029
Soybeans	0.014	0.012
Wheat	0.031	0.049
Rice	0.020	0.036
Peanuts	0.500	0.410

Table 2.5 Changes in Producer and Consumer Surplus Due to Feral Swine Removal (million $)

Short-run change in:	Consumer Surplus	Producer Surplus (AOS Region)	Producer Surplus (FRS Region)
Corn	46.571	-42.044	45.509
Soybeans	13.231	-5.498	28.882
Wheat	19.650	-15.926	18.938
Rice	4.372	-0.893	8.907
Peanuts	25.182	-0.698	-3.944
Total	109.005	-65.058	98.293
		Net change in surplus	**142.239**

Long-run change in:	Consumer Surplus	Producer Surplus (AOS Region)	Producer Surplus (FRS Region)
Corn	18.060	-11.558	14.048
Soybeans	8.314	-0.297	29.631
Wheat	5.415	-1.012	9.906
Rice	1.754	-0.163	3.755
Peanuts	5.018	-0.139	6.252
Total	38.560	-13.169	63.592
		Net change in surplus	**88.983**

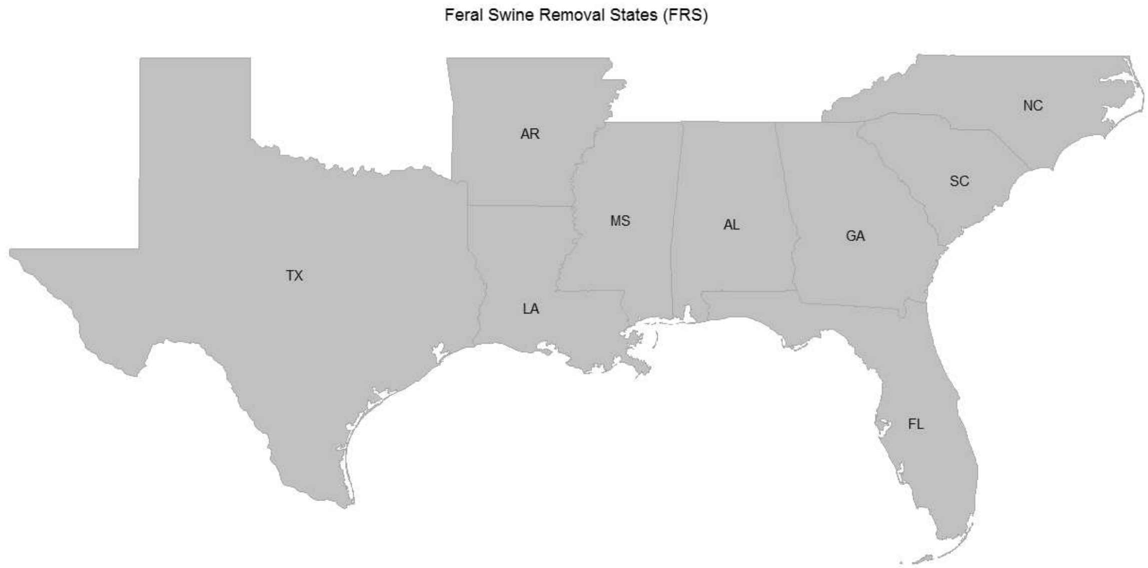

Figure 2.1 Map of Feral Swine Removal States (FRS).

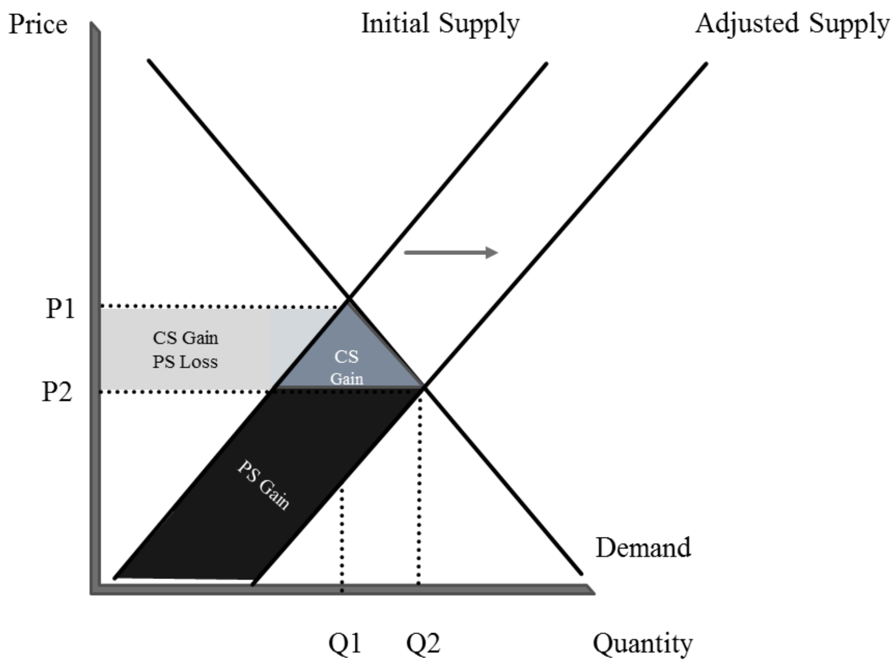

Figure 2.2 Surplus Change and a Parallel Supply Shift

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3. PIGS ON THE WRONG SIDE OF THE FENCE: AN AGENT-BASED APPROACH TO EVALUATING THE COMMUNICATION OF MARGINAL VALUES.

3.1. Introduction

Agriculture is a major component of the U.S. economy, generating $395 billion in market value of agricultural products in 2012 (USDA NASS 2014). Invasive species have been shown to cause broad agricultural and environmental damages (Shwiff et al. 2017). Feral swine are a particularly problematic species to agriculture. In the United States, feral swine are responsible for over $800 million in crop and environmental damages and control costs per year (Pimentel et al. 2005). These damages are primarily due to rooting and trampling.

In response to damage, land managers often carry out control actions. Compounding the damage inflicted on crops is the difficulty with which feral swine are removed. Feral swine are mobile and intelligent. They are intelligent enough that they are known to learn to avoid repeated control measures. In response to control measures, feral swine will change locations and learn to recognize signs of impending control to evade the measure employed. Land managers decisions regarding their property will affect other land managers and feral swine. Even indirectly, land managers may affect each other by providing safe harbor for populations to damage neighboring property, push populations onto other property, or make the animals more difficult to remove by unsuccessfully attempting to control them.

Characterizing interactions, such as those described above, in a tractable manner is the forte of agent-based models (Bonabeau 2002; Epstein 1999). This paper develops an agent-based model of feral swine management in a synthetic environment reflective of a township in the Southeastern United States with individual land managers and crop damage. The model is extended to include information about decision-making over time. This study demonstrates the model's potential for policy analysis.

3.2. Literature Review

Feral swine (*S. scrofa*), commonly referred to as wild pigs in the United States, are the wild-living descendants of domestic swine (*S. s. domesticus*), Eurasian wild boar, and hybrids of the two (Keiter et al. 2016). These animals are unique among invasive species due to their intelligence and opportunistic nature (Mayer 2009d). The intelligence is seen in their adaptability and social structure. Feral swine are known to be social animals, interacting directly within groups and between groups and individuals. They are also known to respond to human actions and learn to avoid control (Campbell and Long 2009). Their opportunism is seen in the variety of their diet and the habitats they occupy. Over the past 30 years, they have expanded their range from 17 to 38 states (Bevins et al. 2014).

3.2.1. Feral Swine Behavior and Biology

Feral swine intelligence is observed by their ability to adapt to control efforts as demonstrated by the fact that any given control measure cannot be exclusively employed as the animals learn to avoid repeated control treatments (Campbell and Long 2009). One could describe their behavior as "cagey" as they are marked by cleverness and wary of possible threats. In addition to intelligent, they have a social structure (Mayer 2009d).

Sows (female swine) and juvenile offspring generally congregate in groups called sounders. Sounders can contain three generations of related individuals. The size of the group varies, depending on season, habitat, and predation (Mayer 2009d) and membership of the group can change over the course of the year (Mayer 2017). Sounders do seem to maintain a territory with some level of exclusion, but this herd dynamic is not completely understood. Boars (uncastrated male swine) are generally solitary and only interact with groups and females for breeding (Mayer 2009d).

Feral swine have a home range or territory. Sounders have a core territory and peripheral territory surrounding the core (Mayer 2009d). Sounder territory is manifested in that sounders and boars generally do not coexist in the same space (Mayer 2017). Over a period of time, sounders and individual males may be present on the same territory, but generally only in the absence of other sounders. The territory claim also manifests itself in signs of presence, including damage.

Schlichting et al. (2016) documented the sizes of territories and examined factors that determine the size of the territory claimed. They report the variety of territory sizes, with island populations showing less than one square kilometer to large territories in Texas of 34 square kilometers. Seventeen of the 32 reported territory sizes were less than five square kilometers and 27 were less than 10 square kilometers. Two notable territory sizes are that of the Savannah River Plant, South Carolina with 2.5 square kilometers and Fort Benning, Georgia with three square kilometers. Population density, food availability, and hunting pressure affect the size and location of swine home ranges (Mayer 2009d). Campbell et al. (2010) report the mean core territory in Kleberg County, Texas under aerial gunning removal pressure of 2.2 square kilometers.

Campbell et al. (2010) were unable to show a statistically significant difference in home ranges of feral swine under helicopter pressure versus not under helicopter pressure. They report a large difference in home ranges, but also report very high variance in estimates when compared to the means. In other studies, human activity and hunting pressure have been shown to affect size and location of feral swine home ranges (Mayer 2009d).

Choice of territory is a function of food attractiveness and availability, crowding, and removal pressure. As these factors change, feral swine will respond by moving to a new territory. Described as the "ultimate opportunistic omnivore" (Mayer 2017), they eat everything that will not eat them first, but do have preferences for some food types over others (Mayer 2009b; Mayer 2017). Damages to crops inflicted by swine are often the result of rooting and trampling. Feral swine are generally sedentary, but are occasionally known to travel long distances (Mayer 2009d). Anecdotally, they have been known to travel ten miles to feed on maturing corn crops (Mayer 2017) and documented to travel hundreds of kilometers for breeding (Mayer 2009d).

Feral swine reproduction is high enough and their natural mortality low enough that to keep the population from growing, between 50 and 70 percent of a given population would have to be removed each year (Carson 2013; Mayer 2009c; Bevins et al. 2014; Hone and Pedersen 1980). Land characteristics such as fertility and available cover will impact the number of offspring that survive to sexual maturity (Bieber and Ruf 2005; Geisser and Reyer 2005). However, the magnitude of the effect depends on the landscape in question. Removal pressure also impacts the ability of sows to produce viable adult swine.

3.2.2. Feral Swine-Human Interaction

The damage inflicted by feral swine and the difficulty in their removal is the impetus for the policy attention they have attracted. The policy focus for invasive species in general is mitigating damages, or direct costs, caused by the invasive: destruction, depredation, and disease (Shwiff et al. 2017). In addition to these direct costs, indirect costs are incurred, such as land uses change and individuals and organizations choose to control them. Feral swine are known to inflict damages in all three classes, but this study focuses on damages to agricultural crops (destruction). Damage to agricultural crops is primarily inflicted as feral swine root for food.

Pimentel et al. (2005) report U.S. feral swine damage, estimating $800 million of crop and environmental damages per year. Crop damage has been found to be substantial in a number of studies (Mengak 2012; Higginbotham 2013; Tanger et al. 2015; Ober et al. 2011; Adams et al. 2005; Tolleson et al. 1995; Sweitzer and McCann 2007). However, as interest in feral swine continually increases, the methods used to assess damages are improving. Most recently, Anderson et al. (2016) found $190 million in crop damage in a ten-state area.

Zivin et al. (2000) used a linear parameter as a function of the population to model damage. However, a non-linear damage function would better fit the known behavior of feral swine. At a population of zero, there should be no damage and a damage function should reflect a maximum level of damage once some population threshold has been attained. At most, all of the crop would be removed. Hone (1995) found that a non-linear change in damage function fits a change in damage measure and found a curvilinear relationship between the extent of rooting and frequency of rooting and feral swine density.

In response to the losses imposed by feral swine, considerable effort and resources have been devoted to the control and management of feral swine populations. Few feral swine eradication efforts are documented in the literature. Two efforts carried out in the United States by government officials are reported. Eradication and fencing efforts at Pinnacles National Monument in California cost over $2 million across an 18-year period and approximately $55,000 per year to maintain the 14,500 acre monument as swine free. Another example in California is the eradication of Santa Cruz Island feral swine, which cost approximately $5 million for a 62,000-acre island (Kreith 2007).

Individual land managers do not typically engage in eradication efforts. Frequently attempts at control are undertaken as opportunistic shooting, hunting, and trapping (Anderson et al. 2016). Infrequently do land-managers attempt to fence feral swine out (Anderson et al. 2016). There are professional removal services that could be employed by private land managers to reduce a population of feral swine.

3.2.3. Land Manager Decisions

The profit maximization motive of agricultural producers is one of the core principles of production economics. Profit maximization is generally found to be a consistent motivator of land managers; thus, land managers are typically modeled as profit maximizing. Land managers are motivated by private gain and private costs.

Land management using mathematical programming to model profit maximization for a single period remains an important tool in use in agricultural economics. Even recent work modeling crop mixes over time considering biofuel policy did not consider multiple periods in their optimization (Chen and Önal 2012). Chavas et al. (2010) reviewed the progress of contributions over the prior century of production economics and farm management, and concluded that land manager level decision-making over time is still not fully understood. They specifically call out the "difficulties in dealing with heterogeneous managerial abilities" as a limiting factor (Chavas et al., 2010; p. 370).

There are approaches for modeling landowner decisions over time. In the specific case of feral swine management, the land manager portrayed by Zivin et al. (2000) maximized profit across multiple periods by balancing rangeland activities under damage and hunting revenues. They found that the steady state of a single feral swine population is higher when recreation benefits are included in their model. However, their framework was unable to account for externalities such as increased damage on neighboring property due to higher feral swine populations (Zivin et al. 2000).

Research prescribing minimum cost management strategies over time has used optimal control and dynamic programming methods. Often these models use a single decision maker over a single population, though some have represented a single decision maker over multiple populations. In feral swine management, Melstrom (2014) compared eradication and perpetual control of feral swine in an optimal control framework, demonstrating the importance of the discount rate in determining which strategy is optimal. In invasive species management, Epanchin-Niell and Wilen (2012) use an optimal control model focusing on the characteristics of a new invasion in a spatially explicit manner. Epanchin-Niell and Wilen (2012) were able to prescribe optimal management over a large discrete map, but only had a single decision maker. Focusing on a generic invasion, Chalak (2014) used an optimal control framework in a smaller, two-cell environment to look at relationships between control levels, competition, dispersal, and steady states. Chalak (2014) concludes with the need to study more complex systems, specifically calling for interactions between different species.

The reasons most decisions are often simplified to a single decision maker over a limited set of populations are threefold. First, problems quickly become unsolvable as closed form solutions as the dimensions of the problem grow. Closed form solutions are attractive because they allow the analyst to describe the essence of the relationship.

Second, as the dimensionality increases, numerical solutions become more computationally demanding. This is not a trivial concern and has attracted research on better solution algorithms in operations research and computer science (Spampinato and Elstery 2009; Tomov et al. 2010). An economic application of a genetic algorithm can be found in the treatment of the management of multiple invasive species from a common budget carried out by Carrasco et al. (2010).[1]

Third, as Chavas et al. (2010) concluded this kind of complex decision-making is not well understood. Conventional tools are deficient; however, lessons can be drawn from their application. For example, in the case of feral swine management with multiple land managers each able to manage a parcel, each land manager would need to understand not only the state of feral swine populations, but also the response of each individual land manager to their population in space and time. A managed property with feral swine presence scenario, has elements of both an open access property and private property. The land is privately held or managed, but the feral swine are free to move across property lines. The lack of an ability to effectively protect one's property will likely result in an outcome where decision makers do not effectively control feral swine because they will be unable to capture the full benefit of doing so.

3.2.4. Agent-Based Modeling

A promising modeling technique for modeling interactions between decision makers is agent-based modeling. Agent-based models are purposeful representations of interactions between organisms of interest. Agent-based modeling is differentiated from other modeling constructs in that the agent-based model is built to represent the individual components making up a system (Railsback and Grimm 2011). Space and time can be represented in simple terms, but the key to agent-based modeling is the system is constructed by defining the interactions and actions of the parts of the system. Individuals within the system are known as agents and

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[1] Genetic algorithms are a class of algorithms used to solve optimization problems not well suited for other standard optimization algorithms by solving a problem many times and finding a solution by evolving a population of solutions to optimal (Mathworks 2017)

experiments can be conducted to examine the impact of a policy or condition on either the agents or the system as a whole.

Bonabeau (2002) points out that some of the phenomena modeled in agent-based models could alternately be modeled using game theory. Bonabeau goes on to claim that the game theoretic requirement to prove theorems places a substantial burden on the analyst, preventing him or her from effectively examining complex systems. The agent-based construct can simulate systems and generate results without requiring that the solution be represented as a proven theorem.

Researchers have used agent-based models in established areas of interest in the agricultural economics literature. Of particular interest for feral swine management, farm management topics have been explored using agent-based modeling.

Freeman et al. (2009) used an agent-based model to model land acquisition, land manager growth, and land manager exit. They used a population of synthetic profit maximizing farmers with a single year planning horizon who developed expectations about the profitability of the enterprises in their choice set by using a weighted average of prior expectations and outcomes. The importance of management styles with risk attitudes, factor endowments, and government transfer payments were evaluated. Management styles were not determined as important, while endowment and government payments were important for modeling land ownership and leasing.

Berger and Troost (2014) used a representative population of Chilean producers to model their adaptation to climate change using mathematical programming methods integrating information from prior periods to form expectations for planning. They were able to use the model to provide strategies for response to climate change.

Troost and Berger (2015) developed a detailed agent-based model of production decisions using a mathematical programming approach within the agent-based model on climate change adaptation. The agents maximize profit over a single period based on expectations about prices and yields derived from previous experience. The results were able demonstrate several results including the importance of interactions such as machinery sharing and the importance of climate change analysis going beyond incorporation of yield changes into aggregate sector models.

3.2.5. Modeling the Formation of Expectations

The review of agent-based approaches in land management demonstrates the importance of interactions and the ability of agent-based models to account for the interactions. It also demonstrates the ability of agent-based models to build off of traditional representative farmer management approaches using familiar tools such as mathematical programming. Each of the cited studies demonstrate integration of expectations of future prices and yields. These expectations are formed through evaluation of historical outcomes. No forward-looking expectations mechanisms were found to be used in agent-based modeling.

It seems intuitive that individuals perceive their futures and plan for more than the current season. Producers have opinions on the effectiveness of feral swine control and the causes of the spread of feral swine (Anderson et al. 2016). At one end of the spectrum is the dynamic decision maker who makes decisions perfectly through time, considering the acts and reactions of others, and successfully balancing costs and benefits against his or her individual objective function. At the other end is the myopic decision maker, planning only for a single season and only considering his or her own actions. The myopic decision maker makes decisions based on the information available, but does not consider the consequences of the current decision on future periods.

Previous discussion of forming expectations in agent-based models demonstrate past research with backward-looking informed expectations (Freeman et al. 2009; Berger and Troost 2014; Troost and Berger 2015). In other strands of literature, approaches include static and rational expectations. For static expectations, the decision maker forms expectations of prices in a production decision based on current prices and does not alter them for future periods in the current production decision, but does update with experience (Thijssen 1996). For rational expectations, the decision maker is able to form conditional expectations for prices for a production decision based on the information available (Thijssen 1996). Shi and Irwin (2005) were able to integrate a decision maker's subjective beliefs into an optimal hedging portfolio. They developed an approach to integrate these beliefs using a Bayesian updating framework. The approach blends information from prior periods with the decision maker's beliefs.

Price expectations are important, but developing expectations about future populations of feral swine and their impact conditioned on the known current populations is more complex. Feral swine move, reproduce, die, and cause damage according to stochastic non-linear functions, and as the population decreases to zero, they are increasingly expensive to remove. A growing perpetuity calculation would be a viable option only if damage were a linear function of population and one could arrive at an expectation of population growth and the actions of neighboring managers. A net present value calculation values future cash flows in present value terms (see Moss 2013, ch. 5). A method of integrating a present value of a biologically informed stream of future cash flows conditioned on management decisions that consider future periods about feral swine is needed.

The economics literature has developed a concept of "user cost" to express a similar idea with respect to a natural resource stock (see Berck and Helfand 2011, ch. 16; Field (2001), ch. 10). In this literature, the concept of user cost is used to describe the opportunity cost for a multi-period profit maximizing firm of leaving a resource unextracted, conditioned on optimal removal of the resource for maximum total discounted profit over time. That concept can be applied within the context of the agent-based model of feral swine management in that the best course of action, based on the agent's objective function, may be to leave a feral swine population on the landscape due to the cost of control today being greater than the stream of current and future benefits from removal. User cost provides a starting point for developing forward-looking expectations.

3.2.6. An Agent-Based Model with Forward-looking Expectations

This research extends previous literature to construct a comprehensive model to investigate feral swine management. This paper details the development of a model based on what is known about individual decision-making by integrating mathematical programming with an agent-based approach to feral swine to characterize outcomes in complex economic and social settings.

The remaining sections will document the development of an agent-based model for feral swine management in the context of agricultural crop damage. As demonstrated early in the literature review, feral swine respond to the actions of land managers and the actions of individual land managers will affect others and those linkages are substantial. The agent-based model framework is the modeling construct best able to model these interactions. A mechanism for developing forward-looking expectations is developed and implemented.

3.3. Analytic Framework

Interactions amongst land managers, feral swine, and between the two groups are important and the agent-based modeling framework provides a framework for analysis. This section describes the model, the background leading to the design choices, and the mechanism for informing decisions using forward-looking expectations. The model is described in terms of first, representation of agents; second, the simulation environment; and third, the core actions taken by agents within the defined environment.

3.3.1. Representation of Agents

Relevant agents for this question are land managers and feral swine. Land managers describe any individual who has control and use of a parcel of land. Land managers interact with their land environment and the feral swine who are also modeled as agents. Land managers do not explicitly communicate or interact with each other, but their actions affect one another indirectly through the feral swine population. They are profit maximizers, choosing from a choice set of production and swine control activities. The model records the accumulated profit of land managers.

Three agent classes represent feral swine: boars, sows, and sounders. The age and location are tracked for all feral swine agents by the model. Sows are the principal reproductive agents within the model. The sounder agents determine sow movement and grouping. This modeling strategy was adopted to reflect the necessary behavior in a much more tractable manner and to save substantial computing time.[2]

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[2] Generating the same behavior with only sows required much more complex movement functions and required the sows to iteratively solve equations for land desirability, land claim, and sounder membership.

3.3.2. Simulation Environment

The setting for the model is a synthetic environment reflective of locations in Georgia and the greater Southeastern United States with adequate food, water, and cover to support a large population of feral swine, and suitable growing conditions for corn and soybeans. The model consists of agents placed on a landscape that is set to approximate a Public Land Survey System (PLSS) township. The township is subdivided into 2,401 four-hectare patches. Each edge of the township is 49 patches long with each patch 1/5 kilometer on each edge.

The land is under the exclusive control of a land manager. The land manager is able to choose the use and management actions of their assigned collections of patches. Each patch has a differential productivity attribute. Productivity is a scalar that describes the relative productivity of the land with respect to a mean expected crop yield. The productivity measure is a factor in choice of and profitability of productive uses of the property, feral swine breeding, and feral swine choice of location.

3.3.3. Actions taken by agents

This section describes the actions that agents take in the model. A brief introduction of the sequence of actions is followed by subsections that describe these actions in detail. Time is defined in year intervals (Figure 3.1) starting in January and ending in December and simulations are carried out over five years. Initial conditions are set outside of the time-loop and are discussed in the section 3.3.4.

In the Inventory Phase, a January census of all agents is carried out in each iteration. Land managers then update their expectations of the gross margins that each patch will produce, conditioned on feral swine populations and the productive capability of the land. In the Planning

Phase, the J land managers then optimize production and control activities using a mathematical programming model to create a plan.

In the Execution Phase, land managers implement their plan and most of the feral swine actions are taken. The biology has been represented as an annual cycle to mirror the year intervals of the model. Key actions undertaken by feral swine are reproduction, movement, sounder group changes, removal or avoidance of removal, update sensitivity to control, and damage crops.

In the Realization Phase, land managers harvest crops and damage is determined based on the feral swine population left after management actions are taken in the Execution Phase. After damage and income are calculated for each land manager, the land managers update their accumulated profit with the income from that year.

Planning Phase

Each year land managers choose the course of action from a suite of options that best fits their situation. The land managers have adequate resources to do anything within the stated choice set. The land managers' goal is to maximize profit each year. The accumulated profit of land managers is the primary point of comparison between simulations, as it represents a cumulative effect on the land manager's profit function.

Each land manager's objective function is:

$$\max \ \Pi = \sum_{i=1}^{I} \sum_{k=1}^{K} \left(P_k Y_k \alpha_i \times \left(1 - \delta_{i,k}\right) - VC_k - CC_{i,k}\right) \times ACRES_{i,k} \tag{1}$$

subject to land availability:

$$\sum_k ACRES_{i,k} \leq \text{PatchSize} \ \forall \ \text{i}. \tag{2}$$

Each land manager has control over I patches of land and can choose from among K activities on each of those patches. For this study, there are nine activities in set K, three cropping choices (corn, soybeans, and conservation use) and three control choices (no control measures, light (25%) control measures, and heavy (90%) control measures).

The agent faces an expected gross margin contribution for each of those nine activities on each patch of land they control, considering the feral swine population resulting from each combination of crop choice and removal effort. $ACRES_{i,k}$ represents the land in patch i dedicated to activity k. By using discrete choices of control, a linear model can represent a non-linear relationship at the cost of granularity in the control decision. For each land use activity k, P_k is the price received for the crop planted, Y_k is the mean expected yield for the chosen crop, α_i is a scalar parameter that reflects the land's ability to produce crops relative to the mean yield, and VC_k are the variable costs of production for crop k. The proportion of the crop k lost to damage ($\delta_{i,k}$) on the i^{th} patch is a function of the expected number of feral swine remaining after the chosen control action. The cost of the removal ($CC_{i,k}$) implied by choice k on patch i is a function of the choice of the number of animals removed. Both damage ($\delta_{i,k}$) and removal cost ($CC_{i,k}$) are calculated each period outside of the mathematical programming model. Baseline and sensitivity levels of parameters are available in Table 3.1.

The literature established a need for a mechanism to form forward-looking expectations about feral swine. The following develops management decisions informed by a forward-looking expectation coined here as "Opportunity Cost of Swine Control" (OCSC). Similar to user cost, OCSC is a representation of the future costs imposed by leaving a feral swine alive on the landscape at the end of a planning period.

OCSC is calculated in a multistep process. First, an auxiliary model is used to find optimal management of feral swine under dynamic decision-making. The marginal effect of feral swine is recovered from the auxiliary model. The agent-based linear programming framework already considers current period damage, so the first derivative of the damage function introduced in damage section is evaluated and subtracted from the recovered marginal effect of a feral swine. This subsection describes the limited model, the process of recovery, and the final calculation of OCSC.

A non-linear programming (NLP) routine is used to solve for dynamic management of a problem smaller than the agent-based problem. The agent-based linear programming framework cannot optimize accounting for future periods because the information demands are too high. As in reality, the agent would need to be able to understand the movement of the swine and all of the other relevant agents. Again, as in reality, a simplified modeling framework can provide information to augment an information deficient decision-making process.

In an auxiliary dynamic model, the marginal cost of a single pig in the context of a properly managed feral swine population across time can be recovered by reducing dimensionality of space and decision makers. The population of swine on the landscape can be represented as a state variable that is managed through a net population growth function. The first-order necessary conditions of the dynamic optimization problem require that the partial derivative of the objective with respect to the state variable is the shadow price of that resource stock (McCarl & Spreen 1997). McCarl & Spreen present Hadley's (1964) proof that this partial derivative is the Lagrange multiplier of constrained optimization and demonstrate the usefulness of the shadow price construct as it is the impact on the objective of an additional unit of the constrained resource and can be recovered from the solution of the auxiliary dynamic model.

This auxiliary dynamic model is configured as a single decision maker that maximizes gross margin for a subset of the larger agent-based township. The size of the reduced map is the home range of an animal, approximately two square kilometers. The approximately two square kilometers of this map are managed as one unit, with no movement into or out of the area. Treating the management area as a single unit implies that damage is uniform over the management area. This closed-world approach implicitly assumes that neighbors will engage in the same actions. The model is estimated for a 75-year planning horizon, which is sufficiently long to make terminal conditions irrelevant with a 5% discount rate. Crop prices, yields, and variable costs used are the same as those employed in the agent-based framework. Productivity is the average for the subset of patches included.

The objective function from the agent-based framework has been adapted to reflect additional planning periods and a single decision maker and parcel of property.

$$\Pi = \sum_{k=1}^{K} \sum_{t=1}^{T} (1+r)^{-t} \times [(P_k Y_k \alpha \times (1-\delta_t) - VC_k) \times ACRES_{k,t} - \omega_t \times REMOVED_t] \quad (3)$$

The objective (Π) is the total discounted profit for the management unit over time. Price (P_k), yield (Y_k), α, variable costs (VC_k), and damage (δ_t) are all the same as previously introduced in equation 1, although some indices have been dropped because of the simplification of the dimensions of the problem. New to this optimization is the implementation of the price of removal (ω_t) and a new decision variable representing the number removed ($REMOVED_t$). The short-run profit each period is discounted back to the present.

Results from the non-linear optimization show a typical response to a species that inflicts damage and is costly to remove. Removal effort is characterized by strong, but incomplete, removal effort to an approximately steady state population that is above zero and ends with a relaxation of removal effort. Figure 3.2 shows that regardless of initial population, removal efforts and population converged to a near-same path within approximately ten years.

The purpose of this dynamic model is to approximate the cost of leaving an animal on the landscape. Transformations of the result from the dynamic optimization are required to meet this end. In the dynamic model, the population control equation reconciles the population after reproduction, after removal efforts, and before damage, i.e. the same schedule as the agent-based model. As a constraint in the optimization, the shadow price associated with this stock of feral swine is the target for recovery. The agent-based decision maker already considers damage in the present. Subtracting current damage from the non-linear model's accounting of future costs avoids double counting the current period's damage, which is already accounted for in the myopic model. The future period's damage is found by subtracting the evaluated derivative of the damage function from the shadow price of the feral swine population for the first period recovered from the dynamic model.

The marginal damage functions of corn and soybeans are combined. The two functions are very close at the tails and fairly close at the functions' maximum. R's spline interpolation functionality was used to develop a function ($OCSCf$) that would find the marginal future cost imposed by an additional animal left alive after the first period. Figure 3.3 plots both functions. The difference evaluated between zero and 50 head is the OCSCf function.

The agents make land use choices in a linear programming framework. The agent-based framework developed here gives substantially more granularity to spatial decisions and individual personalities in exchange for less granularity in the selection of actions available in the non-linear framework. The key difference between the different implementations of OCSC is in the construction of the objective function.

The agents will evaluate $OCSCf$ for each of the nine choices in their objective function as part of the calculation of gross margin. The two population levels evaluated are: no action (Pop), and the remaining population implied by the action proposed by the choice of activity k (Pop'). No action is simply the current population of the patch. The population implied by activity k is calculated prior to evaluation by multiplying the current population by one minus the proportion planned to be removed by choice k.

The first implementation of OCSC is to ignore OCSC as a BASELINE scenario and will be referred to as “myopic.”

$$OCSC = 0 \tag{4}$$

The first treatment framework (Treatment 1) evaluates $OCSCf$ at the choice population, and multiplies that result by the difference between no action and the choice population levels.

$$OCSC = -OCSCf(Pop') \times (Pop - Pop') \tag{5}$$

The second treatment framework (Treatment 2) decision maker evaluates the $OCSCf$ function at current and proposed population levels and multiplies the difference by the proposed population change, and views this value as a revenue by addition to the objective function.

$$OCSC = \left(OCSCf(Pop') - OCSCf(Pop)\right) \times (Pop - Pop') \tag{6}$$

Of the two treatments, the first is the most consistent with the true application of $OCSCf$ as a continuous variable.

Execution Phase

In the Execution Phase most feral swine activities are represented. The feral swine reproduce, move, update their caginess, and are either controlled or avoid control. Sounders are reconfigured and crops are damaged.

Consistent with the annual cycle, the reproduction function is a net population growth function. Representing swine as having three litters of ten piglets every fourteen months would necessitate in-and-out migration and natural mortality functions. The model achieves substantial decreases in computational demands by simplifying to a net reproduction function that accounts for migration and natural mortality. This approach would not support the analysis of targeted removal or models with very small populations where the age of the animal may be significant. To find the number of progeny ($PROGENY$) for each sow, the base expectation of progeny is adjusted for land productivity and for the previous year's control activities on the patch where the sow is currently living. Each period the number of progeny for each sow in the township is found by evaluating:

$$PROGENY = (1 - \frac{n_i}{\phi_{COUNT}}) \times \gamma \times (\alpha_i - \Psi_{i,t-1}). \tag{7}$$

The number of expected offspring will decrease to zero as the total township population (n_t) nears capacity (ϕ_{COUNT}). The default litter (γ) was set at 0.80.[3] The scaled effect of the productivity of the land is embedded in the parameter, α_i. The prior year's removal pressure ($\Psi_{i,t-1}$) reduces the number of progeny that a sow will have.

The individualized number if progeny is then split according to the expected sex ratio and rounded up to the nearest integer. Sex ratio is a point of uncertainty. The litters are approximately equal between the sexes at the fetal stage, but significantly fewer newly born males (neonates) were found (Comer and Mayer 2009) and there is mixed evidence about the sex ratio of adult feral swine (Mayer 2009c). This uncertainty is explored through sensitivity analysis.

Movement of feral swine is reflected by updating the territory claimed by individual boars and sounders. The size claimed territory for both individual boars and sounders is constant

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[3] If it is known that between 60% and 80% of feral swine must be killed per year to keep the stable, the net population growth can be verified by the following exercise. Population in period t ($\mathbb{P}_t$) is the previous period's population plus the previous period's population ($\mathbb{P}_{t-1}$) times an effective birthrate (γ) minus the previous year's population times a removal rate (ψ_t). $\mathbb{P}_t = \mathbb{P}_{t-1} + \mathbb{P}_{t-1} \times \gamma - \mathbb{P}_{t-1} \times \psi_t$ If . $\mathbb{P}_t = \mathbb{P}_{t-1}$ then, solving for γ finds $1 = 1 + \gamma - \psi_t$. Which means that if, $\mathbb{P}_t = \mathbb{P}_{t-1}$then $\gamma = \psi_t$. Since only females reproduce the result can be solved again to find $\frac{\psi_t}{\mathbb{F}} = \gamma$. So if 75% of feral swine are female ($\mathbb{F}$) and removal of 60% of the population is required to maintain a stable population, the net birth rate is 60/75=0.80 per year.

at approximately two square kilometers in the auxiliary dynamic model due to the implied assumption of constant damage over the management area. Two square kilometers is relatively small in light of what is reported by Schlichting et al. (2016). With corn and soybeans as the primary options for land use, it is a more hospitable setting than Kleberg County, Texas, where Campbell, Long, and Leland (2010) report an approximately 2.21 square kilometer home range for swine under removal pressure. The agent-based model is configured to represent damage dissipating from a center patch so a larger territory of approximately five square kilometers is used in the agent-based model.

Each period all of the patches are evaluated to determine their attractiveness to feral swine which will influence movement to a particular patch. Attractiveness of patch i is found:

$$ATTRACTIVENESS_i = \left(\frac{\phi_{PATCH}}{c_{\mathrm{i,t}}} + \alpha_i + \frac{1}{\Psi_{\mathrm{i,t-1}}}\right). \tag{8}$$

Patch i's $ATTRACTIVENESS_i$ is based on productivity of the patch (α_i), last year's removal pressure on the patch ($\Psi_{i,t-1}$)[4], and the population of the patch ($c_{i,t}$) relative to the maximum patch population (ϕ_{PATCH}).

Each year, boars move to the most attractive patch within a defined range. Compared to boars, sow movements are much more complicated. The sounder agent was created to coordinate movement and grouping of sows. The sounder prefers to live on land not claimed by another sounder. The basic function governing attractiveness of patches for sounders is the same as that used to move boars. The sounders are moved by evaluating the attractiveness function and multiplying it by a term that considers land claims by other sounders. The sounder will then

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[4] The impact of removal pressure on attractiveness is stated as an inverse because removal pressure is stated as a proportion. Therefore, since the two removal strength choices are 0.25 and 0.90, their respective impact on attractiveness of the patch is 4.00 and 1.11. The lower pressure leads to a higher level of attractiveness.

attempt to find attractive, unclaimed land within a defined radius. If unable to do so, the sounder will choose a patch at random to call home. Once the sounders establish a land claim, the sows simply move to that location for the next year.

The sounder agent was created to coordinate the herd dynamic. Sows pass on sounder membership to their female offspring. Sounder group dynamics are relatively fluid, with sounders merging and breaking up multiple times in a given year.

When examined on a year scale, the likelihood of a split or merge is dependent upon the number of individuals within a sounder. Sounder splits occur when the population of a sounder is above a maximum threshold ($\phi_{SOUNDER} = 50$). Sounders are combined when the sounder has fewer individuals than a minimum threshold ($\zeta_{SOUNDER} = 4$). The animals in the small sounder are reassigned to the nearest sounder.

Crop damage ($\delta_{i,k}$) is a function of the presence of the feral swine remaining at the end of a period. To integrate what is known from Zivin et al. (2000) and Hone (1995) without using logarithmic functions, a symmetric sigmoidal curve is defined and parameterized as:

$$\delta_{i,k} = 0.9 + (-0.899)/(1 + (PRESENCE_i/14.21)^5). \quad (9)$$

This curve is defined to produce a maximum level of 90% damage at a full population of 30 head and near zero at a population of zero, which is consistent with Zivin et al. (2000).

Presence ($PRESENCE_i$) is essentially a representation of the impact of swine presence, with impact decaying as distance between the outer patch and the home patch increases. For example, say a patch has ν feral swine who claim that patch as home. The home patch has a presence of $\nu \times 1$. The patches on the four edges of the home patch have a presence of $\nu \times \frac{1}{4}$. The eight patches on the outer edges of those four patches have a presence of $\nu \times \frac{1}{8}$. This process repeats for the next sixteen, thirty-two, and sixty-four patches for a territory of approximately five square kilometers.

Saunders and Bryant (1988) found that the effort required to reduce feral swine populations increases as the population nears zero. This implies a non-linear removal cost function. Wildlife managers understand the increasing cost of removal, but costs in the United States are often reported as averages. Recall that close to 20–30% of the feral swine in Texas are being removed (Carson 2013), and that mixed removal actions in Texas cost approximately $65/head (Bodenchuk 2014). Building upon these reported average removal costs an appropriate cost function was derived.

The marginal cost function of an individual removal ($w_{control}$) should retain the shape of Saunders and Bryant's (1988) result, and should be a function of the population following control ($\widehat{pop}$). Calibrated to approximate 20% removal at approximately $65/head, with elimination of the last animal at roughly $1,500, the resulting derivation is given by:

$$w_{control} = 35.404 + \frac{1464}{1+(\frac{\widehat{pop}}{3.299004})^{1.843566}}. \quad (10)$$

Removal cost is then applied to a set of possible populations to find the per patch cost of removal:

$$RC_{i,k} = \sum_{\widehat{pop}=pop}^{pop'} \mathrm{w}_{\mathrm{control}}(\widehat{pop}). \quad (11)$$

$RC_{i,k}$ is the calculated per patch cost of removal under the chosen cropping and control measures. The cost function is evaluated for each animal removed and summed. For example, the land manager chooses to remove the tenth animal, re-evaluates for the ninth, and so on and then sums the evaluated prices from the population if no action is taken (pop) to the population implied by activity k (pop').

The number of pigs removed is governed by a function that determines if individual animals are removed. The probability of an individual swine being removed ($pr(REMOVAL)$) is a function of the level of control applied to on the patch it calls home ($\Psi_{i,t}$), the swine's caginess ($CAGINESS_t$), and the degree of uncertainty in effect (ρ). This uncertainty means that land managers may not meet planned removal objectives or, with movement, may exceed the planned number of swine removed on a given patch. The removal function is specified as:

$$REMOVAL() = \begin{cases} Removed, & \text{if } \rho < (\Psi_{i,t} - \Psi_{i,t} \times CAGINESS_t) \\ Not\ Removed, & \text{otherwise.} \end{cases} \tag{12}$$

Removal is not certain for any individual animal. Individual swine, in turn, are evaluated against the function after a draw from a uniform distribution ($\rho = U(0,1)$).

Each year each feral swine updates their caginess (i.e. the level of sensitivity to control measures) in response to the previous period's control actions for their home patch. The variable $CAGINESS_t$ is the representation of an individual swine's learning to resist removal methods and is calculated in Equation 13.

$$CAGINESS_t = \frac{1}{\chi} \times CAGINESS_{t-1} + \frac{1}{2} \times \psi \tag{13}$$

This variable captures the learning process and the state of the swine's learned suspicion of control efforts. The caginess decays (χ) in the base model each year.[5] This year's caginess incorporates the remainder and half of last year's individual removal pressure experience (ψ). Because this is a point of uncertainty, the variable χ will be the subject of sensitivity analysis.[6]

[5] In the case of the base model, only 25% of last year's caginess will carry into this year.

[6] The case could be made that feral swine continually harden and their resistance will not decay. A consequence of that modeling construct would be immortal swine and given that some eradication efforts are successful, no individual is immortal.

Realization Phase

At the end of the year, the production on each patch is evaluated considering damage. The accumulated profit operation is independent of the planning operation in order to allow the land manager to suffer damage imposed by the actions of the others as well as to enjoy the benefits of the actions of others. Accumulated profit is the central point of comparison between outcomes of the model. The realization phase outcomes are saved and serve as the initial conditions for the following period.

3.3.4. Initial Conditions of the Agent-Based Model

Lacking direction of a given reality, the model described herein has been parameterized to represent a synthetic setting. A random process is used to initialize several functions and placements to avoid biases that could arise from land ownership assignment or order of movement.

Land productivity is one of the randomly assigned parameters. The patch-specific productivity is drawn randomly from a uniform distribution, $\alpha_i = U(0.5,1.5)$. There is no serial correlation or relationship between the quality of different patches and once assigned, the productivity coefficients remain constant for the duration of the simulation. Land ownership is randomly assigned. Land managers are assigned a home patch and then an iterative process is applied to select unclaimed patches until all patches are claimed. Ownership of patches remains constant. Initial placement of feral swine is random, but the animals move across time as described.

3.4. Results

The agent-based model was built and executed in R (R Core Team 2017) and NetLogo (Wilensky 1999). R served as the primary scripting language, NetLogo conducted most of the biological operations, the link between R and NetLogo was provided by the RNetLogo package (Thiele 2014; Thiele et al. 2012), and the solver functionality was provided by Rglpk (Theussl 2016). The auxiliary non-linear model was calculated in GAMS (GAMS Development Corporation 2007). More information and the model are available for download and browsing in "Public Agent-Based Model—Accounting for interactions and heterogeneity in feral swine policy analysis," (Holderieath 2017).

As the scenario that has all the common actions and components between the tested scenarios, the myopic simulation serves as the BASELINE scenario. Extension of the BASELINE with the Opportunity Cost of Swine Control "OCSC" and sensitivity analyses are compared against the BASELINE.

In each scenario, land managers maximize profit and encounter a feral swine population. The land managers choose control activities along with productive uses of the land in the context of feral swine presence. The land managers choose a combination of cropping and control choices. For example, the costs of producing corn are substantially higher than either of the other two productive uses of soybeans and conservation use. As a result of feral swine presence, production shifts out of corn to one of the other productive uses. In some cases, the presence is such that production is shifted to conservation use, which has no costs and no damage, but low comparative profit in the absence of damage.

In response to damage, land managers will choose to control feral swine. Control is reflected in both movement of swine populations and in the number of swine present. The decision maker can be informed of the costs imposed by swine (with the OCSC mechanism) present on conservation use prompting control efforts on conservation use property when it would otherwise be unprofitable to do so.

Accumulated profit of the land managers is the measure of profit across time considering the yearly outcomes of a given scenario. Accumulated profit provides a convenient measure of the impact of a policy or condition against the BASELINE outcome for land managers. In addition to accumulated profit distribution, removal and population numbers and location are used to inform analysis of the accumulated profit distributions. Movement of feral swine over the simulation is also used for informing the analysis.

The ending accumulated profit distribution across all land managers for the BASELINE scenario is plotted in Figure 3.4. The empirical cumulative density function (CDF) plots the proportion of land managers that have achieved the given level of accumulated profit or less. The CDF allows one to compactly demonstrate the outcome for all agents in a single plot. The mean and median accumulated profit are \$502,686.2 and \$400,263.5, respectively. The result is right skewed, disproportionately above the median, at a skewness value of 0.73.

Figure 3.5 shows that the number removed grows steadily and the number of boars and sows changes each period. One may notice that in period two the population grows substantially before decreasing in subsequent periods. This is due to the initial number of feral swine starting so low in the BASELINE model. In simulations started with 1000 feral swine, this bump is not observed and the population decreases until the last period when the population is allowed to rebound. The removal path indicated by the line representing “Feral Swine Removed Through Control” shows generally decreased effort after the second period with intermediate pulses of higher effort. Simulations run over twenty years instead of five years show this pattern for the myopic decision maker. In the longer simulations, it appears that a target population exists and the decision makers pulse effort to achieve this goal. This could be an emergent management strategy, or it could be due to the coarse decision space the land managers face with respect to control. The coarse choice set should be examined in future research.

Movement can be seen in Figure 3.6. Each period is plotted under the year and the swine are plotted in their position in the township at the end of the period. White represents no or low presence and black is high presence. In period two, the population grows substantially. This is visible in the sounder locations becoming much darker grey and black. The dispersed nature of boars means that they are likely not in the higher density areas. Sows are all present in the patch with their sounder, meaning that those patches will have a higher density as the population of sows in the sounder increases. In subsequent periods, the intensity of presence decreases. This is a function of fewer swine on the landscape and of dispersion. In periods three, four, and five, the swine are dispersing across the map. More patches in the township have a presence, but the presence is less intense compared to the second period. Figure 3.6 demonstrates the proper functioning of the model as defined; population grew, control actions were undertaken, and the population was decreased and dispersed. This behavior is necessary to fully account for the externality feral swine represent. Not only can a land manager give safe harbor by failing to control and inflict damage on neighboring property, the land manager can manage his or her population and disperse the swine to neighboring property.

3.4.1. OCSC Impact on Outcomes

The results illustrate the difference decision maker implementation of information can make on outcomes for those decision makers. This section of results includes simulation results that characterize the differences between the three OCSC methods over five years. Treatment 1 refers to the implementation that imposes a cost on the decision maker for leaving swine and Treatment 2 provides a reward for removal.

Figure 3.7 shows the empirical cumulative density function of ending accumulated profit for each of the three methods. If one were comparing plots, the rightmost distribution would be preferred to distributions to the left. This is because distributions to the right have a higher accumulated profit at any percentile of the population. When the distributions are not clearly ordered one must weigh the differences. Generally, the area under each distribution is compared with lower areas preferred because they indicate better accumulated profit outcomes for most individuals. Preferred distributions are said to dominate inferior distributions. Table 3.2 reports the means and median values for the land manager accumulated profit result to support interpretation of the CDFs.

Most individuals are worse off in the Treatment 2 scenario, and by most criteria, Treatment 2 would be dominated by both Treatment 1 and the BASELINE. The ordering of Treatment 1 and the BASELINE is not as clear, however, under most criteria Treatment 1 would dominate the BASELINE. Very few land managers are worse off with Treatment 1. The accumulated profit outcomes for Treatment 1 are superior from the origin to approximately the seventy-fifth percentile. Treatment 1 and BASELINE are very close from there to approximately the eighty-seventh percentile, where Treatment 1 is superior to approximately the ninety-third percentile where both the BASELINE and Treatment 2 are superior to the end of the distribution.

In the Treatment 2 results (Figure 3.8), more animals are removed, but the sow count at the end is higher than in the other two scenarios. The difference in the population paths of the two methods with forward-looking planning appear to be less pulsed in their efforts than in the myopic scenario. Treatment 2 clearly provides the wrong incentive for removal (given that profit maximization is the objective). Initial period effort is very low, period two is much higher than either of the other methods. Even with this extra effort, the ending populations were higher.

These counts are likely why the accumulated profit outcomes under Treatment 2 were inferior. Treatment 1 appears to provide a more appropriate incentive for removal.

Compared to the auxiliary non-linear result in Figure 3.2 of the scaled down problem agent based initial control is much lower, but ending control is higher. In the dynamic result, management paths converged to approximately 2.5 head removed per period at approximately the five-year mark. The reduced scenario is approximately 2% of the land area of the agent-based model. This would mean that for every 100 animals removed in the agent-based model, approximately two were removed in the dynamic model if scaling were the only difference. Last period removal for the myopic was 226 head, Treatment 1: 277 head, and Treatment 2: 258 head. Those removal numbers scaled to the smaller problem would be: 4.52, 5.54, and 5.16 head, respectively. However, auxiliary non-linear removal in the optimal framework was much higher. Figure 3.9 plots the scaled removal values for each of the simulations for comparison to the optimal result from the dynamic auxiliary model.

None of the methods effectively convey all of the needed information to the agent-based model. However, the results do demonstrate promise. Accumulated profit outcomes are improved by the use of Treatment 1 over myopic planning. The substantially worse result for Treatment 2 demonstrates how improper signaling can make the outcome worse.

3.4.2. Tests for Sensitivity and Interactions

This study has shown that the method of implementation of the OCSC matters. There are numerous parameters and functional forms for sensitivity analysis and many more parameters and functional forms were tested than were fully presented here. Untested parameters include, yield, land productivity, and the base number of progeny.

Tested, but not presented, include prices (which was believed to have covered the profitability that would be addressed through yield sensitivity), functional form of the removal cost function, initial number of feral swine, and duration of the simulation. Additional methods of evaluating the cost of removal were available in additional simulations not described here; however, systematic differences were not found. The following two sets of sensitivity analysis were carried out with land managers randomly assigned a removal cost function. The conducted, but not presented, sensitivity analyses demonstrated unsurprising results and indicated that the model was working as intended. The two presented sensitivity analyses demonstrate potential biological questions of sex ratio and decay of caginess.

As discussed in the model implementation, the sex ratio was a point of uncertainty. Feral swine are born at a rate of roughly 50 male pigs to 50 female pigs. Fewer males, but how many is unknown, make it to sexual maturity than do female pigs. The base model used 25 boars to 75 sows. The sex ratio (proportion boars) sensitivity tested the base ($sexRatio = 0.25$), 50:50 ($sexRatio = 0.5$), and 75:25 ($sexRatio = 0.75$).

Caginess is a known phenomenon. However, the choice of implementation parameters was not completely clear. No quantitative study was found to parameterize the function. The variable χ was varied to half (two) and double (eight) of the base value (four). The effect of decay is not visible in this set of results. There is variation between the simulations, but no systematic differences are apparent. This does not mean that the variable is meaningless. It could be that more extreme values are needed or that systematic differences will not be apparent at this coarse cut at the results. Reducing dimensionality can clarify results so plots will not include the sensitivity for χ.

The next set of plots (Figure 3.10 and Figure 3.11) include simulations with $decay = 4$. Ending accumulated profit distributions are sensitive to this variable. This is somewhat obvious, but the sensitivity indicates that the model is responsive to its inputs.

There is likely a need for better understanding of feral swine movements. The two forward-looking treatments had similar results in that the two higher sex ratios were worse than the BASELINE. One would expect that the reduced reproductive capacity of the population with a higher number of boars would be beneficial to land manager accumulated profit outcomes. In the current inception of the model, boars are more spread across the map than are sows. It is likely that the damage implied by the dispersion of boars across the map is more detrimental than is the concentrated damage of the sows. The removal efforts, though fewer in quantity, would be more expensive in the higher sex ratio scenarios as well. Figure 3.11 shows a much smaller feral swine population and a lack of the characteristic Period 2 increase in population.

This is an example of the analysis that a fully calibrated model could inform. Questions about the value of knowing the sex ratio, the impact of using proactive management to alter the sex ratio, or the impact of selected removal are all areas that variation of this sex ratio variable could address with proper framing.

3.5. Conclusions

Feral swine have a non-trivial impact on the U.S. economy. One of the most critical, and least addressed, component of feral swine management, however, is how feral swine and land managers interact. The actions of land managers will affect surrounding land managers. The externality effect of feral swine, the uncertainty of efficacy of management actions, and the long payback period of successful control efforts are all deterrents to removal action.

Feral swine management needs to be informed by models that can capture interactions between land managers and feral swine, as well as any other relevant actors. This research is a first step in that direction. This paper presented the development of an agent-based model to characterize the relationships between feral swine and land managers, including the interactions in the context of the private management of property. The agent-based framework was used because of its ability to demonstrate important interactions. The agent-based linear programming decision framework had a deficiency seen in real world decision-making in that it could not effectively incorporate all the information needed to make a decision about feral swine considering future periods. This paper serves as a methodological improvement in the agent-based modeling literature and feral swine management literature by augmenting the agent-based myopic decision-making process with information from a forward-looking expectation of feral swine generated through a process incorporating information from a dynamic optimization model. The results show that how this information is integrated matters. Small improvements on myopia can be made, however if done incorrectly, can make land managers substantially worse off.

The model provides a framework for future feral swine management analysis. As advances in the biology are made, they can be incorporated into the model. The field of feral swine research is expanding quickly, and new research has become available that may be able to address some shortcomings of this model. This process of updating and evaluating is one of the benefits of a model constructed modularly. As new research becomes available, it can be incorporated and evaluated for its impact on land managers. As part of the same process, if a setting is determined of interest, this version is capable of characterizing potential outcomes. The model can also be used to characterize differences of outcomes due to unknown parameters to motivate research on those parameters.

The sex ratio sensitivity demonstrates the type of analysis that can be conducted. The model could characterize the benefit to knowing the sex ratio if the sensitivity analysis had instead been prompted by a question about the parameter. There are potentially counter-intuitive costs imposed by the variation of sex ratios in that analysis. This research is a step in the direction of improved policy analysis in feral swine management.

Policymakers need a tool to understand the potential outcomes of recommendations in this interactive environment. The end goal would be to provide policymakers the probabilities of potential outcomes of an action given the setting they specify. There are numerous advances that are needed prior to that level of output.

The model and all documentation are available under a permissive license. The model is available under these terms in the hope that Perkel's (2016) vision for "democratic data" will be true. In Perkel's vision, researchers (of all disciplines) post their data and models so that other researchers can build off and extend their work. The detail contained in this paper is sufficient to build a similar model. However, this model was built at great expense of time and the pace of discovery will increase if other researchers do not have to replicate this model. The license is important, as no experienced researcher would integrate my code into their model due to the risk that I invoke my implied copyright once their model is in use.

As one might note in the analytic framework, there are numerous relationships and this has required the use of several different software packages. Each of the handoffs between software packages is expensive in terms of computational time. The linear solver program iterating through all the land managers is very computationally expensive. As these needed computational advances are addressed, the speed of the simulations will decrease to a point where Monte Carlo analysis is feasible. At that point, once parameterized and validated for a setting, the end goal of being able to characterize the probability of different possibilities is within reach. This incorporation of agent-based modeling, linear programming, and dynamic management in a setting of feral swine damage to privately managed property was a necessary step in that direction. In the interim, the work stands as an improvement in mechanisms to develop forward-looking expectations for agent-based modeling in the context of a damaging invasive species.

3.6. Tables and Figures

Table 3.1 BASELINE and Sensitivity Parameter Values

Description	Parameter	Value(s)	Units
Decay parameter for caginess function.	χ	2,4,8	N/A
Default number of expected offspring in litter.	γ	0.8	Head
Discount rate.	r	5	Percent
Maximum number of feral swine in the township.	ϕ_{COUNT}	1440	Head
Maximum number of sows in a sounder.	$\phi_{SOUNDER}$	100	Head
Maximum number of feral swine on a patch	ϕ_{PATCH}	10.60	Head
Minimum number of sows in a sounder.	$\zeta_{SOUNDER}$	4	Head
Price of corn.	P_{corn}	3.71	$/Bu.
Revenue from conservation use of property.	P_{CRP}	50	$/Ac.
Price of soybeans.	P_{soy}	9.15	$/Bu.
Number of acres in a patch.	$PatchSize$	10	Acres
Proportion of boars to total number of head.	$sexRatio$	0.25,0.50,0.75	Proportion
Base yield for corn.	Y_{corn}	1350	Bu./Patch
Base yield for soybeans.	Y_{soy}	450	Bu./Patch
Variable costs for corn production.	VC_{corn}	3740	$/Patch
Variable costs for soybean production.	$VC_{soybeans}$	2360	$/Patch

Table 3.2 Last Period Mean and Median Land Manager Accumulated Profit By Simulation ($)

	Mean	Median
Opportunity Cost of Swine Control		
	Mean	Median
BASELINE	502,686.2	400,263.5
Treatment 1	455,785.2	407,305.1
Treatment 2	295,898.7	175,392.0
Sensitivity: sexRatio=0.25		
BASELINE	418,720.8	347,382.1
Treatment 1	464,986.3	341,816.3
Treatment 2	357,054.7	239,269.4
Sensitivity: sexRatio = 0.50		
BASELINE	308,636.1	251,585.9
Treatment 1	345,613.7	320,542.5
Treatment 2	223,877.1	201,702.7
Sensitivity: sexRatio = 0.75		
BASELINE	360,886.8	273,926.7
Treatment 1	385,563.0	418,580.9
Treatment 2	189,815.4	133,865.3

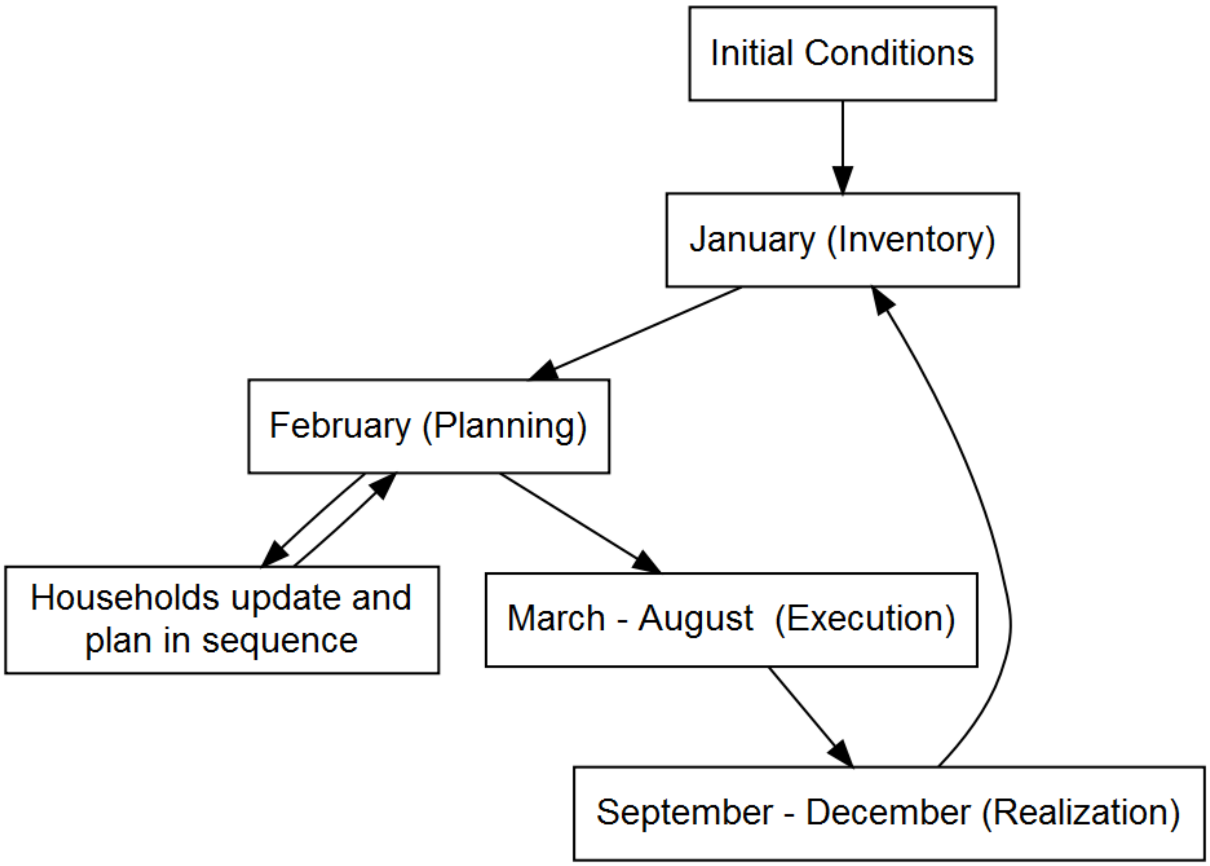

Figure 3.1 Flow chart of major operations for the agent-based feral swine management model.

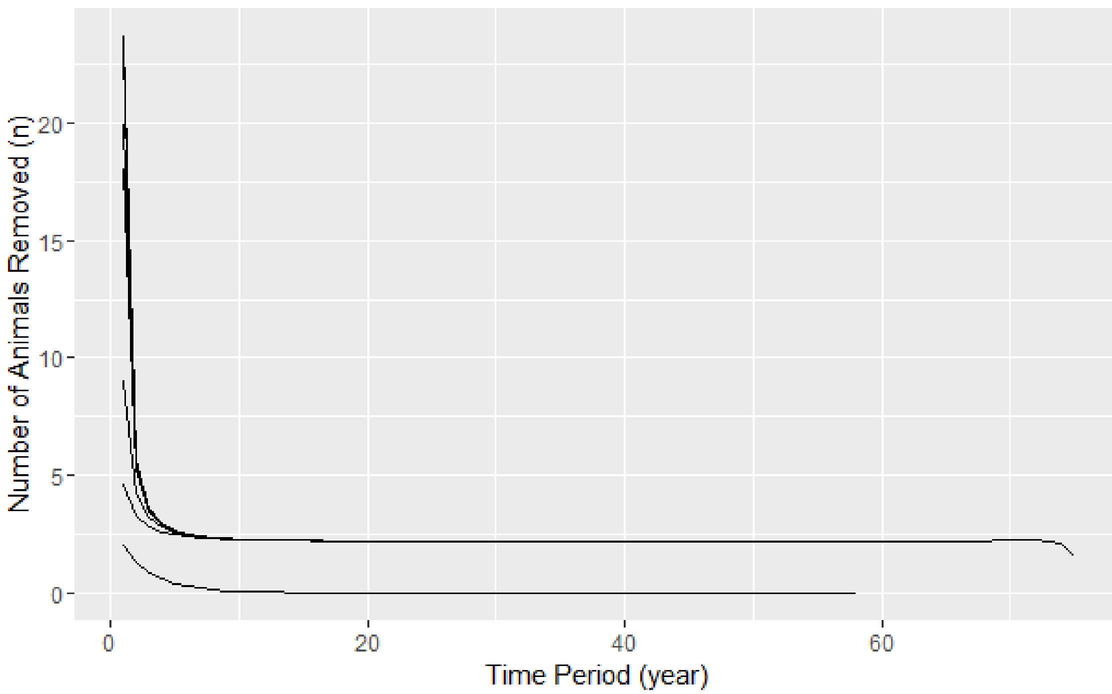

Figure 3.2 Optimal number of feral swine removed in each period by initial number of swine from the auxiliary dynamic model.

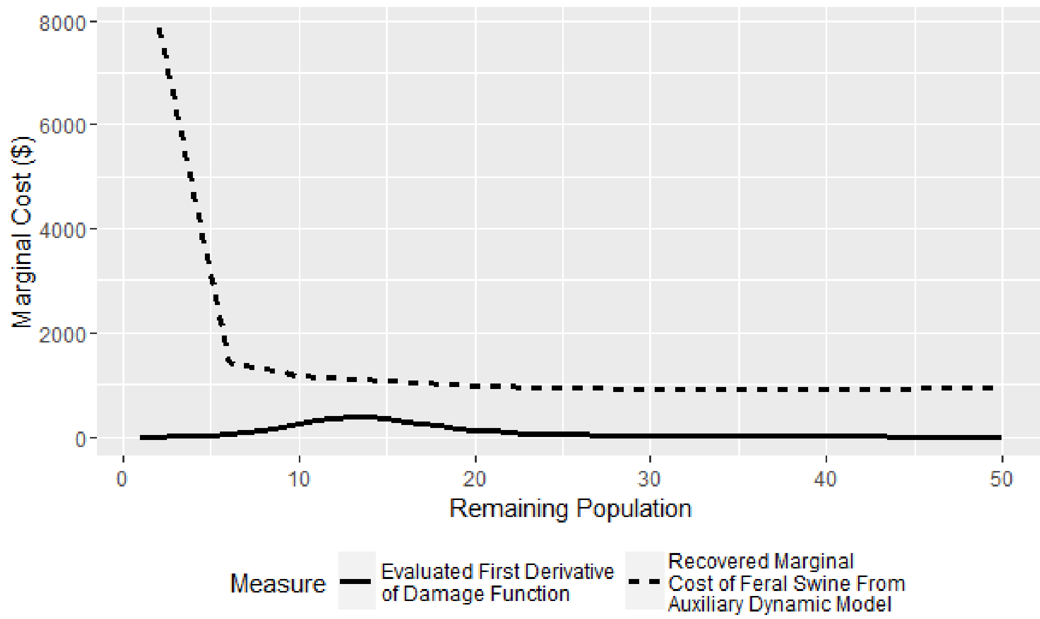

Figure 3.3 Recovered marginal value of feral swine for initial populations between two and fifty head and the first derivative of the marginal damage function evaluated over the same range of populations. The difference is the opportunity cost of swine control (OCSC).

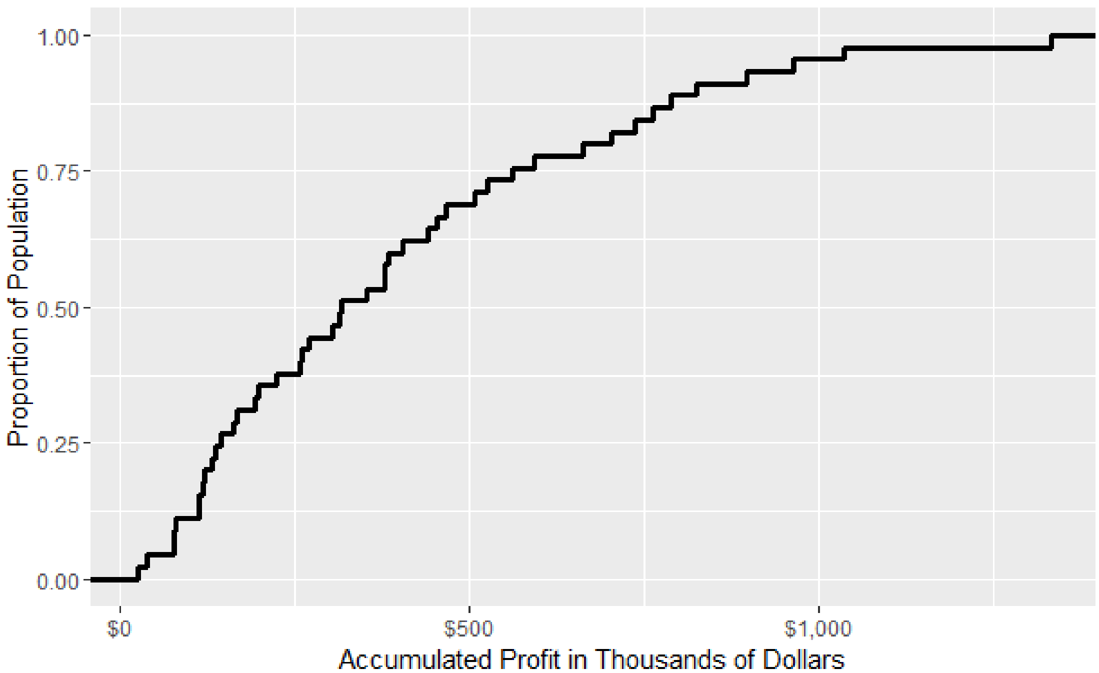

Figure 3.4 Empirical cumulative density function of accumulated land manger profit, BASELINE simulation.

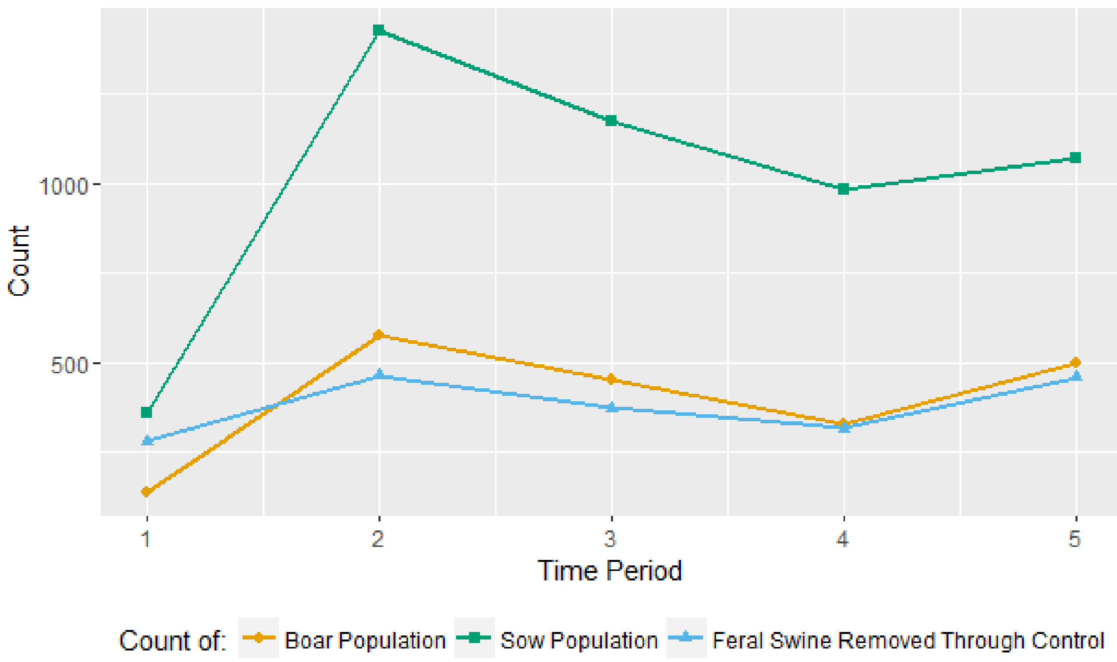

Figure 3.5 Population of sows, boars, and removed by time period, BASELINE simulation.

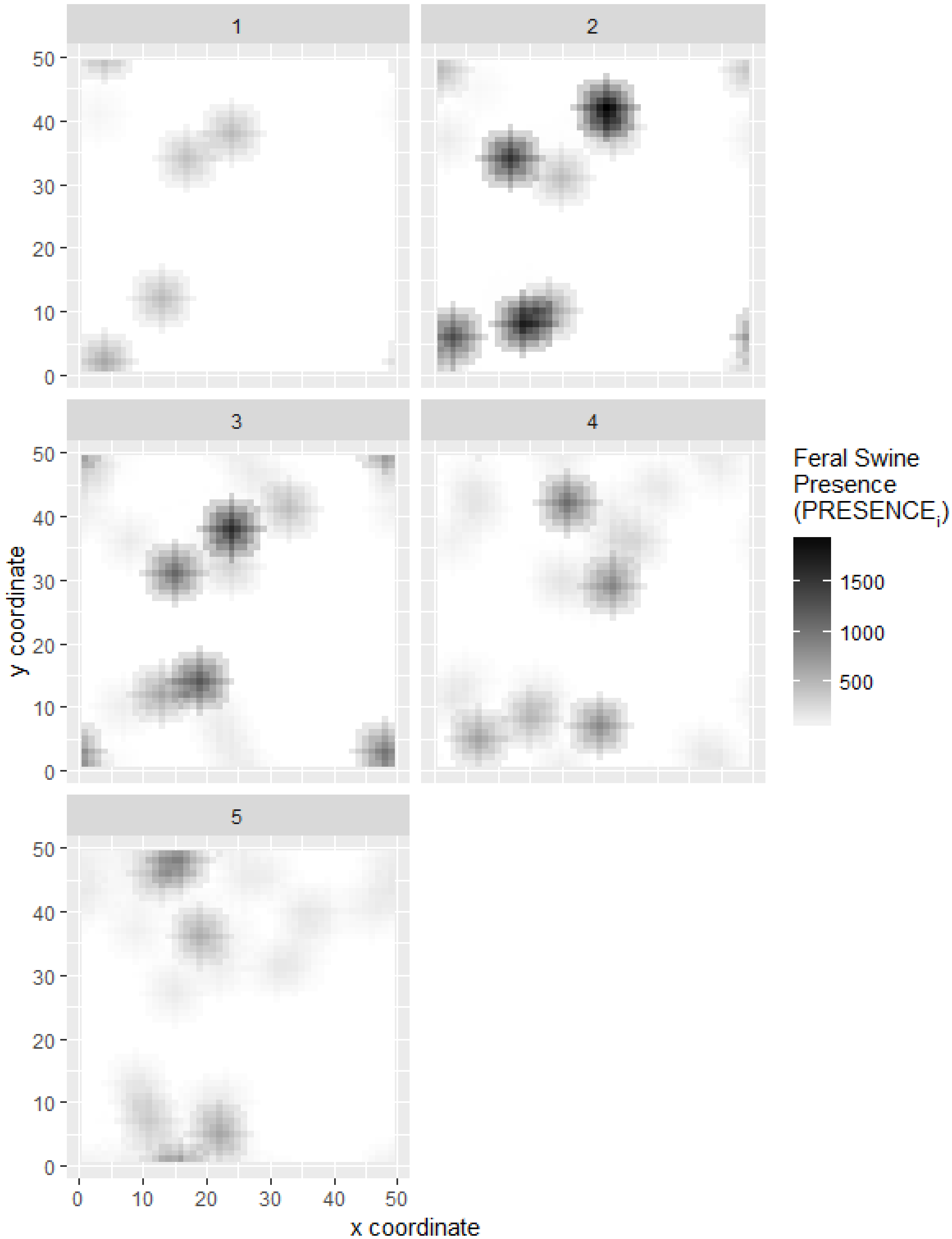

Figure 3.6 Feral swine presence by period, BASELINE simulation.

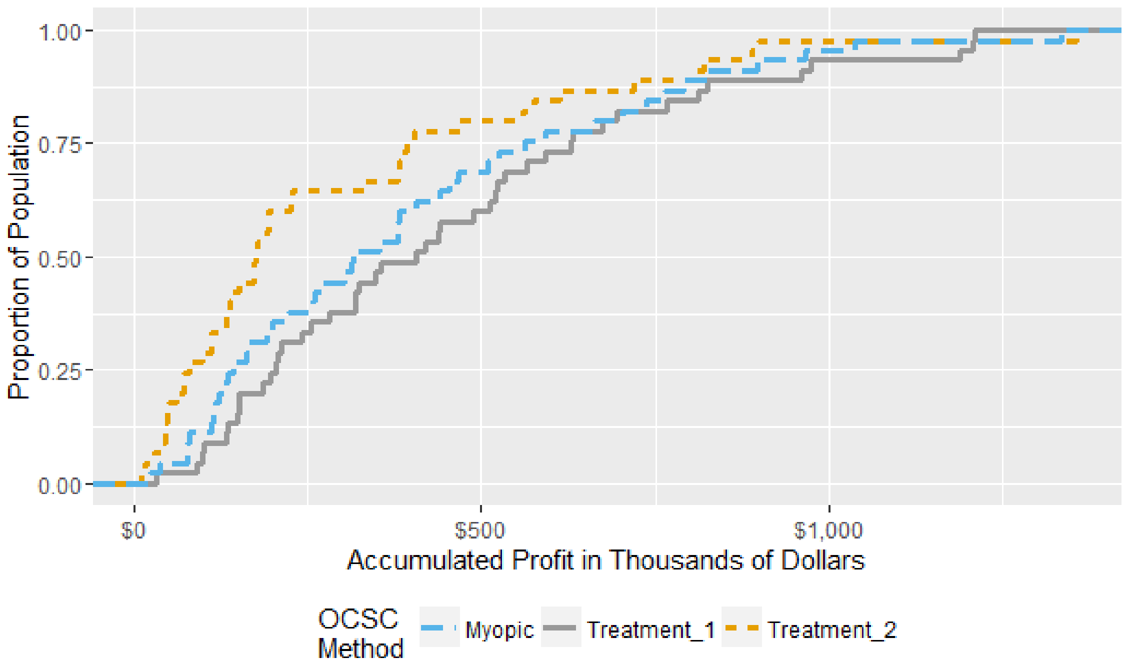

Figure 3.7 Ending land manager accumulated profit distributions for simulations characterizing differences the of opportunity cost of swine control approaches (OCSC).

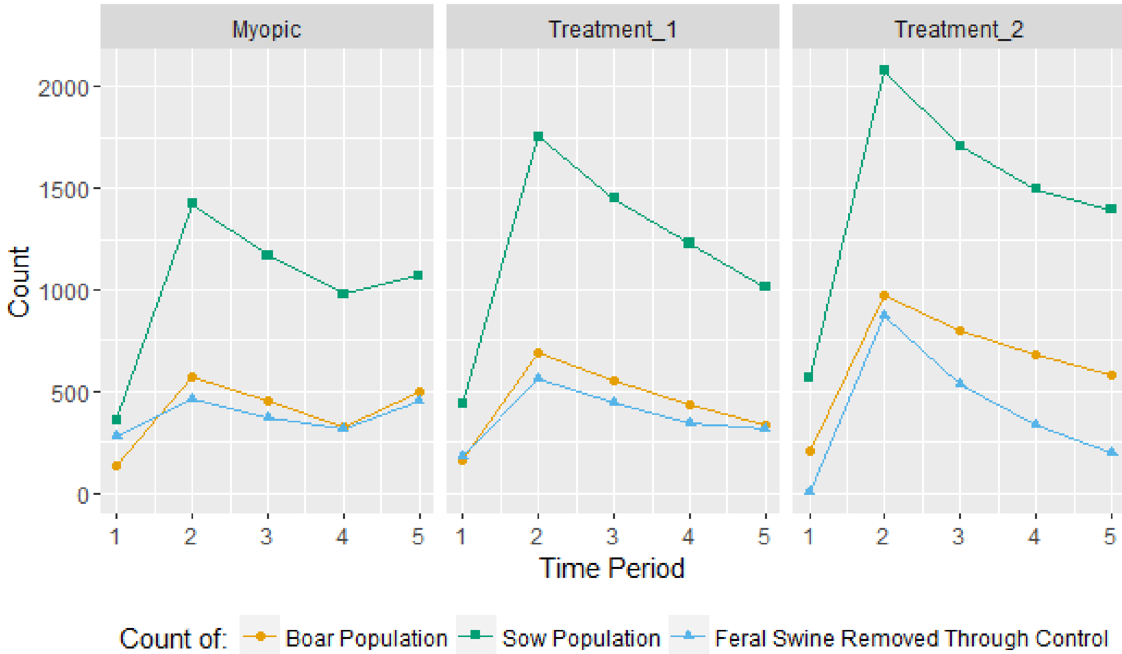

Figure 3.8 Population of sows, boars, and removed by time period for simulations characterizing differences the of opportunity cost of swine control approaches (OCSC).

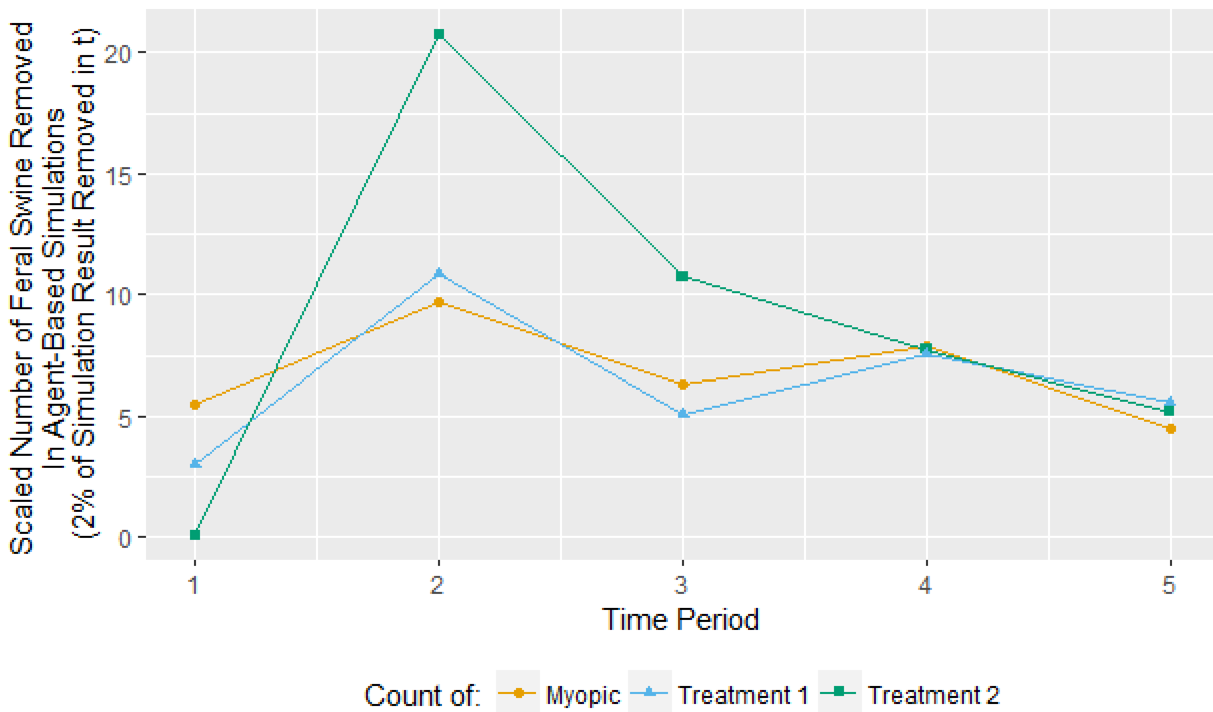

Figure 3.9 Removal results from agent-based simulations scaled for comparison to dynamic removal from the auxiliary model.

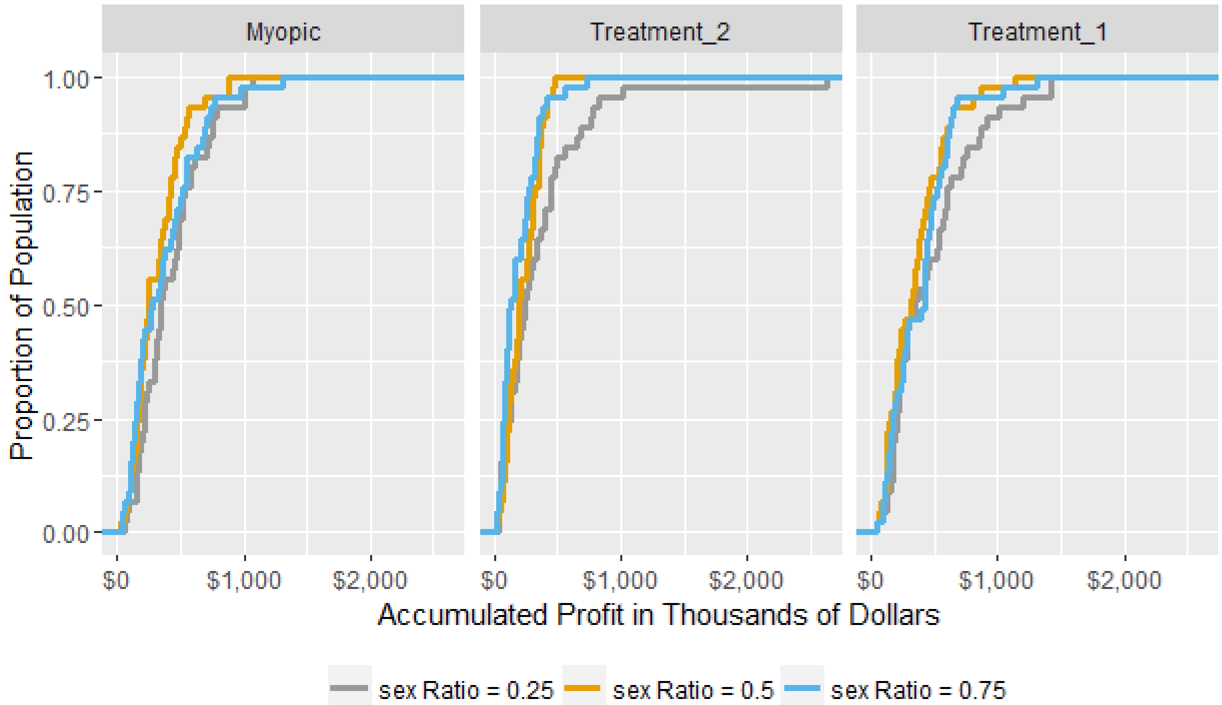

Figure 3.10 Ending land manager accumulated profit distributions for simulations characterizing differences from sensitivity analysis of sex ratio (proportion male to total) and opportunity cost of swine control approaches.

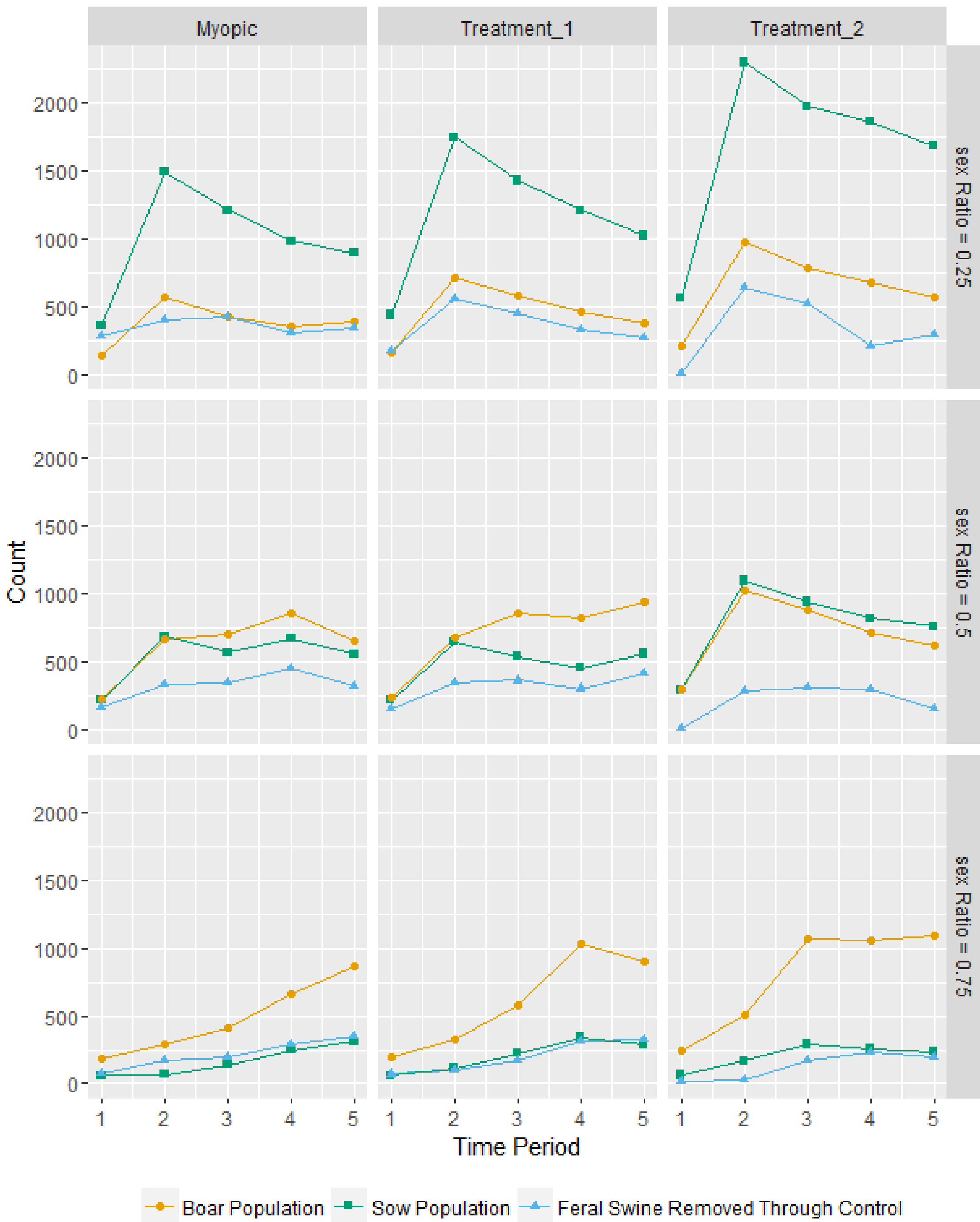

Figure 3.11 Population of sows, boars, and removed by time period for simulations characterizing differences from sensitivity analysis of sex ratio (males to total population) and opportunity cost of swine control approaches.

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4. CONCLUSION

A review of the literature revealed two major gaps in the literature, integrating market impacts into feral swine damage assessments and a lack of consideration of the importance of interactions between and among land managers and feral swine. The first gap is demonstrated in the numerous estimates of the missing commodities due to feral swine damage. Those estimates are an essential piece of information but lack a key piece of information for policymakers. The previous estimates lack the benefits and costs imposed by feral swine damage through the market. An equilibrium displacement model (EDM) was used to address the lack of market impact analysis while an agent based model was used to address the need for analysis considering the relevant interactions of feral swine management. This research used an agent-based model to capture the interactions and builds on agent-based modeling literature by developing and implementing a mechanism for informing agents within a simulation about future values of removal informed by an auxiliary dynamic model.

In Chapter Two, an equilibrium displacement model (EDM) was constructed to assess the value to the United States of damage inflicted by feral swine on corn, soybeans, wheat, rice, and peanuts in nine Southeastern states. Most previous work valued the physical product missing from the market without considering the market effects of the missing product. This work fills a critical gap by considering the market effects of the missing commodities. Specifically, the equilibrium displacement framework used in this chapter assumes that there is an initial equilibrium, then an exogenous shock, and finally the markets revert back to equilibrium. The end result is the impact on price and quantity due to the exogenous shock. The shock used in this valuation of feral swine damage was the instant removal of this damage. The model has three categories of participants: producers in the damaged region, producers outside the damaged region, and consumers. Change in producer surplus and consumer surplus, which are derived from the change in price and quantity solution from the EDM, are the measures of wellbeing used in Chapter Two.

Change in producer surplus in the damage affected region (FRS) is the cumulative effect of adding that product back into the market (i.e. the value of the missing product) and a market effect as producers adjust to the change in price. The change in producer surplus of the other region (AOS) is the impact that placing the missing product into the market has on producers not directly affected by the removal of damage from their region. The re-introduction of that product leads to price and quantity changes and those price and quantity changes impact the wellbeing of producers in the AOS region. Like producers in the AOS region, consumers are impacted by the price and quantity adjustment, and this is measured through the change in consumer surplus.

Chapter Two shows that, as one should expect, consumers are better off and producers in the AOS region are worse off from an elimination of feral swine damage in the removal states. The uncertain change was the producers in the FRS region. Although producers in the FRS region are better off, this is not true for all commodities as peanut producers are worse off. This is because the downward price change of peanuts was not offset by the increase in quantity due to relative elasticities and the relative size of the exogenous shock. The net change in welfare for the short- and long-run is \$142 million and \$89 million per year, respectively. This assessment is the first of its kind for feral swine, but not in wildlife management. Future work will extend these estimates to consider the impact to producers and consumers over time in addition to the two snapshots.

The third chapter compared methods of implementing an approximation of the value of removal in an agent-based model developed for analysis of feral swine management questions. Agent-based models are particularly adept at modeling interactive systems, which is important because feral swine management is an interactive activity. The actions of a land manager can impact his or her neighbors across space and time, and feral swine will spread, reproduce, and evade control efforts. These interactions and their importance are the impetus for the use of an agent-based model.

Chapter Three advances a framework for developing forward-looking expectations about the costs imposed by feral swine and incorporating that information into a myopic agent-based linear programming decision model. The forward-looking expectations are developed through the use of an auxiliary dynamic model that optimizes management of feral swine over time. The results demonstrate the potential for improvement of land manager outcomes by incorporating this information, but also the potential for much worse outcomes if improperly implemented. Sensitivity analysis of feral swine biological parameters representing the ratio of males to total population and the decay of feral swine sensitivity to control measures illustrates the need for further research on feral swine movement and herd dynamics with some unexpected, but explainable results surrounding those parameters.

The model developed in Chapter Three is very flexible and can be applied to nearly any situation where a species is impacted by management decisions, and those impacts spill over property boundaries. One needs to be able to define the interactions, but the potential for applications is extensive. Future work will expand computational capabilities and integrate new information about feral swine biology and behavior. When the model is at its end goal, the analyst will be able to characterize potential outcomes from a management or policy decision.

The volume as a whole demonstrates the importance of feral swine management. Damage is a consequence of presence, and communication about damage and the impacts of management is complicated. Further research on damage functions and management costs could advance both chapters. However, both essays contribute to the literature on feral swine and the second contributes to the literature on human-wildlife interactions in general as well. This work makes a significant contribution to the literature on both feral swine and human-wildlife interactions in general, and future literature will find its focus on interactions and agent-based models a useful starting point for further research.

APPENDICES

A.1 THE ALMOST IDEAL DEMAND SYSTEM

The Almost Ideal Demand System (AIDS) proposed by Deaton and Muellbauer (1980) provides a mechanism to estimate demand elasticities to use as inputs to the EDM model. The AIDS model is a robust and well-tested method of estimating elasticities. In general terms, estimation is carried out by estimating budget shares (w_i) as a function of prices (p_k, p_j) and total expenditure (x) using Stone's geometric price index (P*).

$$w_i = \alpha_i + \sum_j \gamma_{ij} \ln(p_j) + \beta_i \ln\left(\frac{m}{P}\right) \tag{a1}$$

P is a price index:

$$\ln P \approx \ln P^* = \sum_k w_k \ln p_k \tag{a2}$$

In order for this to represent a valid demand system, the system must exhibit homogeneity and symmetry. Each of these can be tested and, if necessary, imposed. Income effects sum to zero:

$$\sum_j \beta_j = 0. \tag{a3}$$

Cournot aggregation holds (implying that price changes will be absorbed within the system):

$$\sum_j \gamma_{jk} = 0. \tag{a4}$$

Homogeneity holds:

$$\sum_j \gamma_{kj} = 0. \tag{a5}$$

Symmetry holds (pure substitution effects are equivalent):

$$\gamma_{ij} = \gamma_{ji}. \tag{a6}$$

The results of the regression can be used to find the relevant elasticities. Income elasticity is found $\eta_{i,m} = 1 + \frac{\beta_i}{w_i}$, own price elasticity of demand is found $\eta_{ii} = -1 + \frac{\gamma_{ij}}{w_j} - \beta_i$, and cross price elasticity of demand is found $\eta_{ij} = \frac{\gamma_{ij}}{w_i} - \beta_i * \frac{w_j}{w_i}$.

The seemingly unrelated regression (SUR) method of estimation was used to estimate the system of equations. More than just the five commodities in the EDM are used in estimation in order to build the most complete farm-gate demand system possible. An attempt was made to include all grains and oilseeds in the demand system. Total expenditure is equal to $x = \sum_i p_i \times q_i$,where the set of commodities is Corn, Barley, Oats, Soy, Peanut, Cotton Seed, Sunflower Seed, Rice, and Wheat. One grain, oats, and one oilseed, sunflower seed, were excluded from estimation to prevent a problematic perfectly linear combination of variables from being present in the regression. The short-run system was estimated using data from USDA ERS Commodity Yearbooks for each of the crops. The prices used were farm-level prices and the quantities were the total domestic commodity use between the 1980/1981 crop year and the 2015/2016 crop year. The same model was used, except prices were lagged ten years, leaving 1990/1991 to 2015/2016 expenditure shares in the estimation. Tables A1 and A2 report the calculated compensated and uncompensated price elasticities of demand for the short- and long-run, respectively.

Standard errors and significance were calculated with a bootstrap method documented in detail in Holderieath (2016). The estimation process was repeated 1,000 times with subsamples of the original data used in estimation. Standard errors and elasticities (reported in Tables A1 and A2) were used to calculate the *t* statistic and the *t* statistic was compared to critical values at the 10%, 5%, and 1% significance levels.

Table A1. Short-run Calculated Elasticities of Demand

	Corn	Barley	Soybeans	Peanuts	Cotton Seed	Rice	Wheat
Corn	-0.696***	-0.012	-0.289***	-0.094***	-0.021	-0.024	-0.172***
	(0.05)	(0.019)	(0.044)	(0.017)	(0.017)	(0.016)	(0.032)
Barley	0.79**	-0.324	0.438	0.211**	-0.288**	0.017	-0.141
	(0.401)	(0.217)	(0.398)	(0.102)	(0.134)	(0.1)	(0.278)
Soybeans	-0.382***	-0.001	-0.536***	0.031	-0.01	-0.021	-0.046
	(0.081)	(0.033)	(0.093)	(0.026)	(0.024)	(0.026)	(0.064)
Peanuts	-1.665***	0.186*	0.498	-0.202	0.09	0.056	0.591**
	(0.42)	(0.108)	(0.326)	(0.13)	(0.115)	(0.069)	(0.295)
Cotton Seed	-0.18	-0.405**	-0.027	0.114	-0.429**	-0.065	0.477
	(0.505)	(0.174)	(0.373)	(0.141)	(0.181)	(0.142)	(0.314)
Rice	-0.511	-0.027	-0.323	0.04	-0.065	-0.157	-0.159
	(0.373)	(0.106)	(0.328)	(0.069)	(0.114)	(0.107)	(0.204)
Wheat	-0.191	-0.05	0.108	0.127**	0.082	-0.008	-0.235
	(0.17)	(0.056)	(0.164)	(0.057)	(0.05)	(0.04)	(0.153)

Notes: *, **, ***, denote statistical significance at 10%, 5%, and 1% significance levels, respectively. Demand elasticity of row *i* with respect to the price of column *j*. Standard errors in parentheses.

Table A2. Long-run Calculated Elasticities of Demand

	Corn	Barley	Soybeans	Peanuts	Cotton Seed	Rice	Wheat
Corn	-0.915***	0.002	-0.231***	-0.022	0.008	-0.011	0
	(0.135)	(0.032)	(0.072)	(0.034)	(0.029)	(0.035)	(0.082)
Barley	0.366	-0.662	0.124	0.065	-0.23	0.213	-0.495
	(0.888)	(1.064)	(1.127)	(0.317)	(0.404)	(0.335)	(0.632)
Soybeans	-0.305**	0.004	-0.7***	0.02	0.015	0.012	0.076
	(0.139)	(0.082)	(0.178)	(0.037)	(0.032)	(0.044)	(0.104)
Peanuts	-0.122	0.066	0.424	-0.935***	0.099	-0.019	0.178
	(0.878)	(0.298)	(0.489)	(0.248)	(0.171)	(0.192)	(0.515)
Cotton Seed	0.514	-0.244	0.287	0.106	-1.046***	-0.169	-0.089
	(0.839)	(0.426)	(0.48)	(0.192)	(0.289)	(0.267)	(0.538)
Rice	-0.122	0.168	0.122	-0.03	-0.136	-0.668*	-0.271
	(0.761)	(0.272)	(0.52)	(0.166)	(0.205)	(0.368)	(0.471)
Wheat	0.235	-0.088	0.227	0.025	-0.016	-0.053	-1.066***
	(0.395)	(0.11)	(0.255)	(0.092)	(0.088)	(0.098)	(0.26)

Notes: *, **, ***, denote statistical significance at 10%, 5%, and 1% significance levels, respectively. Demand elasticity of row *i* with respect to the price of column *j*. Standard errors in parentheses.