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Agrobiodiversity For Pest Management: An Integrated Bioeconomic Simulation and Machine Learning Approach

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AGROBIODIVERSITY FOR PEST MANAGEMENT: AN INTEGRATED BIOECONOMIC SIMULATION AND MACHINE LEARNING APPROACH

BY

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THESIS

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Original approval signatures are on file with the University of New Hampshire Graduate School.

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ABSTRACT

Agrobiodiversity For Pest Management: An Integrated Bioeconomic Simulation and Machine Learning Approach

By
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A pressing challenge of modern agriculture is to develop means of decreasing the negative impacts of pesticides while maintaining low pest pressure and high crop yield. Certain crop varieties, especially wild relatives of domesticated crops, provide pest regulation ecosystem services through chemical defense mechanisms. Benefits from these ecosystem service can be realized by intercropping cash crops with repellent wild varieties to reduce pest pressure. An opportunity cost exists, however, which consists of lower yield and market value. Such is the case of heirloom apple varieties that are more resistant to the codling moth but have a lower market value compared to commercial apples such as Red Delicious and Gala. In this thesis, I first develop a model to identify the bioeconomically optimal intercropping level of commercial and wild varieties with the purpose of pest management in the specific case of the codling moth. Second, I develop a model that uses a machine learning technique to determine pesticide application policies for the multi-variety orchard, where the solution is robust to model and data uncertainty.

Model 1 is a tree-level, spatially-explicit, bioeconomic simulation model. In the baseline case, we find that the bioeconomically optimal variety mix consists of 20% cider variety and 80% commercial variety. We analyze the sensitivity of the optimal mix to the market price difference of the two apple varieties and find that the optimal proportion of cider decreases linearly and that 100% commercial variety is optimal if the price difference is greater than \$0.3/lb. We consider eight different spatial configurations for the intercropping, in addition to the baseline random spatial intercropping and find that the diagonal configuration yields the highest net present value and requires the lowest amount of cider intercropping (4%). Random spatial intercropping, in contrast, ranks seventh and has the second-highest optimal proportion of cider (30%). We use the certainty equivalent measure to determine how the optimal mix changes for a grower who has a moderate level of risk aversion, where production risk is driven by the effect of temperature on codling moth infestation over the years. The optimal cider variety percentage for a moderately risk-averse grower increases to 38% compared to the baseline case of 20% of a risk-neutral grower. We also document the risk-reducing effect of apple agrobiodiversity by characterizing how the risk premium decreases with increasing proportions of cider.

In Model 2, we determine the robust optimal pesticide application threshold, given an infested multi-variety orchard consisting of the optimal proportion of cider varieties, arranged in a random spatial configuration. We use historical degree-day (DD) data and associated established DD threshold-based spray recommendations to add pesticide application features to our Model 1 and then use it as a simulator to generate data on infestation and damage level over time. We then use Reinforcement Learning (RL) to find the robust optimal pesticide application threshold around 1,000 insects over the entire orchard. The model solution shows a greater degree of sensitivity to pesticide application costs compared to the pest growth rate, indicating the importance of addressing the data uncertainty of these parameters.

CHAPTER 1

INTRODUCTION

Agricultural production currently predominantly depends on chemical pesticides to control pest pressure. Chemical pest management allows growers to obtain high agricultural yields. However, the yield benefits of such chemical pesticides come at financial costs to growers, in addition to costs to human health and the environment. Chemical pest control methods lead to numerous long-term and short-term health issues (Wilson and Tisdell, 2001). In addition to the adverse effects on human health, agrochemicals disrupt the flow of ecosystem services provided by beneficial pest predators (Pimental et al., 1993). The termination of these natural enemies causes an increase in the pest population. Increased use of pesticides also leads to the development of resistance in pests, which occurs over time and may lead to the loss of pesticide effectiveness and crop failure (Pimental et al., 1993). Nevertheless, despite all the negative impacts of chemical pesticides, they are still widely used due to the lack of reliable and practical alternatives. Therefore, a pressing challenge of modern agriculture is to develop means of decreasing the negative impacts of pesticides while maintaining low pest pressure and high crop yield.

Most domesticated crops have been selected to increase their yields relative to their wild ancestors, often at the expense of reduced plant defenses to pests. For example, Whitehead and Poveda (2019) found that wild apples have a higher diversity of metabolites than domesticated apples in the skin, pulp, and seeds, and that codling moth resistance was positively correlated with higher phenolic diversity. Other pests in other crops also respond to metabolites and other chemical signals; examples include grapevine moths in grapes and oriental fruit moths in pomp fruits (Witzgall et al. 2008). The pest regulation ecosystem service benefits provided by wild relatives of domesticated crops can be capitalized on by designing orchards where such varieties are optimally intercropped with cash crops to reduce pest pressure. However, an opportunity cost exists, which consists of lower yields and market values for such wilder varieties, as is the case for cider apples and commercial apples for fresh consumption. In addition, based on this tradeoff between pest regulation and yields, it is unclear what the optimal amount of intercropping is and whether different spatial configurations perform better than others. The ecological literature and the agricultural and resource economics literature lack models of pest spread and control that can assess the economic and ecological trade-offs of using pest-resistant varieties in perennial crops, both in terms of amount and spatial configuration of the intercropping. Also, existing related computational economic models that are used to solve for optimal pesticide application policies are very sensitive to data and model parameter uncertainty (Kotani et al. 2011; Garcia and Fernandez 2015). Consequently, the solutions predicted by these models have a high risk of failure in a real-world deployment.

In this thesis, to address these two needs in the literature, we first consider how a commercial and an heirloom variety of apple can be intercropped in an orchard to reduce pest pressure and year-to-year production risk. We focus on the case of a codling moth infestation and set out to solve for the optimal intercropping level and compare the pest regulation and economic performance for different spatial configurations of intercropping. Second, we consider how machine learning techniques can be utilized to determine pesticide application policies for the multi-variety orchard. We examine whether uncertainty in growth rate and pesticide cost parameters affect the solution (i.e., the threshold-based spraying policies) and proceed to solve for policies that have a lower risk of failure in real-world deployment due to such uncertainties.

We develop two models to address these two research questions (See Fig 1.1). Model 1 is a tree-level, spatially-explicit, bioeconomic simulation model. We use Model 1 to find the optimal level of intercropping (i.e., variety mix) that maximize profits and show that increasing intercropping levels decrease production risk by minimizing profit fluctuations over multiple years due to the changes in infestation caused by temperature fluctuation. We analyze the sensitivity of the optimal mix to different spatial configurations of intercropping. Finally, we evaluate and estimate the risk-reducing effects of using agrobiodiversity as a pest regulation method.

For Model 2, we consider the optimal level of cider apple intercropping in our baseline spatial arrangement from Model 1, and search for the optimal threshold of pest population at which pesticide application should be triggered in order to maximize the net revenue of the orchard over a finite time horizon. We formulate the management problem by combining Bayesian inference with a machine learning methodology called Reinforcement Learning (RL). To generate data on infestation overtime for the RL, we add a pesticide application feature to Model 1. The model solves for optimal pesticide application policies that are robust, that is, immune to uncertainty posed by data (i.e., parameter values in our model). We further evaluate whether uncertainty in the growth rate parameter or pesticide costs impact the robustness of our solution the most.

The key contribution of this research to sustainable agriculture is the development of novel approaches that can guide growers to cost-effectively use agrobiodiversity-based integrated pest management practices that are environmentally friendly in that they rely solely on variety intercropping (model 1), or they minimize sprays by using threshold-based policies while also reducing solution sensitivity to data uncertainty (model 2) and, therefore, lowering the risk of crop failure due to data uncertainty in a future real-world deployment.

The remainder of the thesis is arranged as follows. Chapter 2 and Chapter 3 include the literature, methodology, and results related to Model 1 and Model 2, respectively. Chapter 4 concludes the thesis.

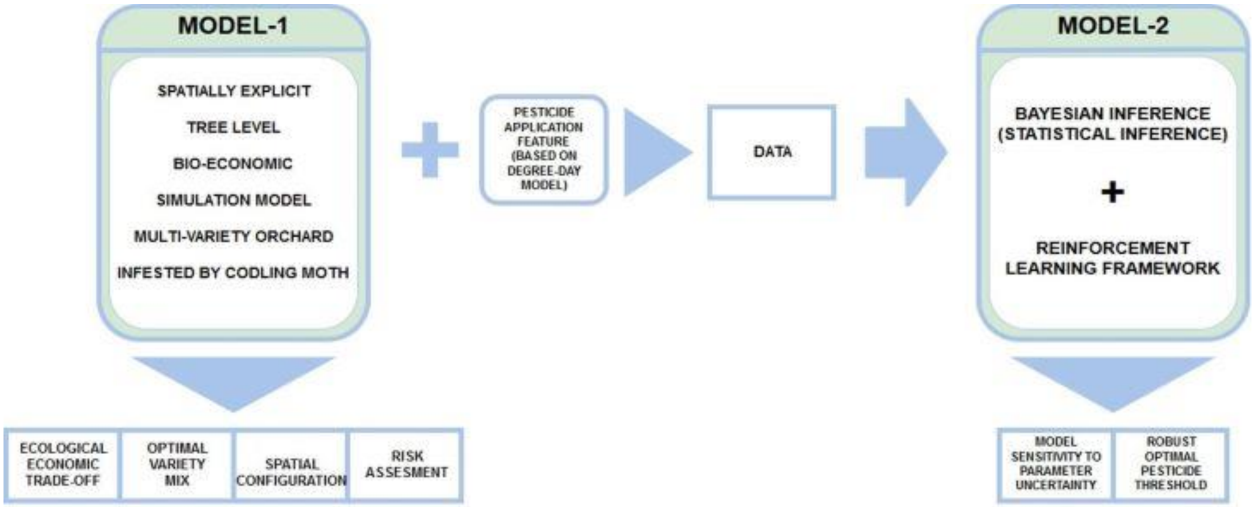

Fig 1.1: Conceptual Framework for Models 1 and 2.

CHAPTER-2

A SIMULATION MODEL FOR THE CODLING MOTH GROWTH AND CONTROL IN AN APPLE ORCHARD

2.1 Literature Review

2.1.1 The apple industry and the codling moth

Apple industry

Apple is the most consumed fruit in the United States (U.S.). In 2015, the average person in the U.S. consumed about 115.4 pounds of fresh and processed fruits and 24.7 pounds of apple in other forms such as juice, canned, or frozen (USDA ERS, 2015). There are 32 states across the U.S. that produce apples commercially. The U.S. has 7,500 apple producers who grow, on average, 240 million bushels of apples each year. These producers grow the apples on approximately 322 thousand acres of land (U.S. Apple Association, 2018). In the state of New Hampshire (N.H.), 1,400 to 1,600 acres of land are used to grow apples over 146 farms, and it has a farm gate value fluctuating between $7 and 10 million, making it the second most valuable agricultural product in the state after dairy products (USDA ERS, 2015). The U.S. is the second-largest producer of apple, surpassed only by China. Approximately one of every four apples that are grown in the U.S. is exported. Exports from the U.S. are expected to rise in 2018 by 15 percent to 995,000 tons (U.S. Apple Association, 2018). The U.S. grows approximately 200 unique apple varieties. The top 10 varieties in the U.S. are Red Delicious, Gala, Granny Smith, Fuji, Golden Delicious, Honey Crisp, McIntosh, Rome, Cripps, Pink/Pink Lady and Empire (U.S. Apple Association, 2018).

The codling moth

One of the most damaging apple pests is the codling moth (*Cydia pomonella*). If left unchecked, it can claim up to 95 percent of apple crop yield (Peck and Merwin, 2010). The insect's phenology and the number of generations are temperature-driven and therefore varies over geographic regions. In New Hampshire, U.S., the moth generally has two generations, which are primarily spread through aerial dispersal. In addition, a partial third generation develops during the extra hot summers. The first adult flight starts approximately during the full bloom of the apple trees (late April or early May), and the peak flight does not occur until after petal fall. Eggs are laid on leaves near fruits, and incubation takes 7-8 days. The larvae usually enter into the fruit around late bloom. The second generation of flight begins around late July to early August. The second period of larval feeding is during August and September. There is an overlap between the first and second generation, which usually takes a higher toll on fruits than does the first generation. From the middle of September to early October, the fully-grown larvae form silken cocoons (hibernacula) and enters diapause or a state of inactivity to pass the winter (Eaton, 2016). Managing the population level of this pest is essential due to a low tolerance for damaged fruits in both domestic and international markets (USDA ERS, 2015). The conventional means of control is mostly dependent on chemical pesticides. Chemical pesticide applications are made based on the biofix date. The biofix date is determined by extension agents and defined as the first sustained moth catch for two consecutive weeks. It is a biological reference point used for the prediction of key events of a codling moth's phenology, e.g. first or peak egg hatch of each generation (Riedl et al. 1976). This initiates the beginning of growing-degree-day (GDD) calculations. GDD is heat-time units used to track temperature-dependent biological processes over time (Reidl et al. 1976; McMaster 1997). To identify the biofix date, pheromone traps are used. The corresponding temperature data is noted in degree days (DD). Spray timing for the pest is directed at newly hatched larvae since most insecticides are not effective at controlling adults. The first spray is recommended at first egg hatch, which occurs 220-250 DD (base 50°F) after biofix. The spraying threshold for the second generation of codling moth is around 1260 DD. High moth pressure requires 2-3 sprays for each generation (Breth 2013).

2.1.2. Natural capital, agrobiodiversity, production risk, and pest regulation ecosystem services

In addition to controlling the codling moth through market inputs such as insecticides, the diversity of crops in an agricultural system can provide a non-marketed input in the form of pest regulation ecosystem services. Ecosystem services (ES) consist of flows of energy, materials, and information from natural capitals which, combined with human-made capital such as financial, human, and social capital, produces welfare for the society (Costanza et al. 1997; Wainger et al. 2010; Jones et al.2016). The ES and the natural capital which produces them represents part of the total economic value which is often not adequately captured in the commercial market and therefore neglected during decision or policymaking.

Agrobiodiversity is defined as the many ways in which growers use the natural diversity of the environment for production, including not only their choice of crops and crop varieties but also their management of land, water, and other resources (Brookfield and Padoch 1994). Agrobiodiversity is a part of natural capital, and the flow of ES can be compared to the interest on that capital (Kontoleon et al. 2009). Growers and breeders can use agrobiodiversity to increase the resilience of crops to changing production environments such as increased pest pressure and risk due to a changing climate. This makes agrobiodiversity such as multi-variety agricultural production systems essential for the functioning of ecological systems and the generation of a vast array of ecosystem services.

Agrobiodiversity and risk reduction

Empirical evidence suggests there are sizable effects of agrobiodiversity on agricultural yield and production risks. Smale et al. (1998) studied the relationship between crop genetic diversity and the mean and variance of wheat yields. They concluded that genetic diversity is positively correlated with the mean yields and negatively correlated with the variance of the yields, suggesting a risk-reduction effect. This was further affirmed by the findings of DiFalco et al. (2007), where authors investigated the effects of wheat genetic diversity on agricultural productivity and cost of risk. Their econometric analysis showed that diversity in crop variety increases farm productivity and improves the grower's profits. They further concluded that moderate to high levels of agrobiodiversity contribute to a reduction in the cost of risk. Clasen et al. (2011) simulated forest growth to obtain the probability density function (PDF) of forest damage. They concluded that mixed forests have a higher ability to withstand damage and financial risk. From here onwards, we use the simplified definition of agrobiodiversity that refers to the use of multiple cultivated varieties (i.e., cultivars) in a production system, which is consistent with the definition used in much of the empirical literature aforementioned.

Agrobiodiversity to control pest and disease spread

Certain crop varieties produce chemical phenolics and volatiles, which makes them naturally resistant to pest infestation (Whitehead and Poveda, 2019). There is evidence of the success of using such varieties with cash crops to control diseases and insect pests. Altieri (1999) reviewed the role of biodiversity in securing crop protection and reported that agricultural systems consisting of monocultures tend to have a higher abundance of specialized herbivore species compared to polycultures. The authors further described the characteristics of agricultural systems where low pest pressure can be expected. Such characteristics include high crop diversity through mixing crops in time and space; the high presence of tolerable levels of specific weed species and high genetic diversity resulting from the use of a variety of mixtures. Bianchi et al. (2006) tested the hypothesis that natural pest control is enhanced in complex patchy landscapes with a high proportion of non-crop habitats as compared to simple large-scale landscapes with little associated non-crop habitat. Natural enemy populations were higher and pest pressure lower in complex landscapes versus simple landscapes, in 74% and 45% of the studies reviewed, respectively. They concluded that diversified landscapes hold the most potential for sustaining the pest control function of biodiversity. Landscape ecology allows a comprehensive management approach for farming systems (Garcia et al. 2014). Garcia et al. (2014) found that, under laboratory conditions, host plants with the greatest dissimilarities in the parameter values (oviposition rate; larval mortality rate; larva-to-adult development rate; and adult mortality rate) can be intercropped to manipulate the habitat of pests and protect the cash crops. Rodriguez-Saona et al. (2008) found that host plant volatiles can be used alone or in combination with other stimuli in control strategies such as mass trapping, attract-and-kill, push-pull, and disruption of host finding. There is evidence of pests either being repelled from the cash crop by “repellent” or attracted away from the cash crop by a “more attractive” stimuli, either of which can be obtained by intercropping a crop with nonhost plants of repellent characteristics or other host plants of relatively more attractive characteristics (trap cropping), that are appropriate for the target pest (Ratnadas et al. 2011). Examples of the “repellent” strategy include intercropping carrots with onions where volatiles in onion plants reduce the pressure of carrot flies (Uvah and Coaker 1984). Planting trap crops is another strategy to use agrobiodiversity for pest control. According to Shelton and Badenes-Perez (2006), trap crops are plant stands that attract, divert, intercept or retain targeted pests or the diseases they spread, to reduce damage to the cash crop. Vilich-Meller (1992) found that intercropping wheat with barley leads to a greater degree of disease reduction compared to when only fungicides are applied. Another strategy is the “push-pull” strategy, which uses the characteristics of both trap and repellent plants (Pyke et al. 1987; Miller and Cowles 1990). The idea is to repel the insect pest from the cash crop using repellent (“push”) crops and attracting it to the border of the agricultural system using trap (“pull”) plants (Hokkanen 1991; Shelton and Badenes-Perez 2006; Cook et al. 2007). Khan et al. (1997) successfully demonstrated the “push-pull” principle by intercropping maize (the cash crop) with molasses grass (the repellent) and Napier or Sudan grass (the trap crop). Stem borers were repelled from the maize and were simultaneously attracted to the trap crop.

Agrobiodiversity in apple orchards

Pest-regulating agrobiodiversity in the case of apples could consist of intercropping commercial apple trees with less domesticated, heirloom (e.g., cider) varieties that still have natural pest defense mechanisms that are diminished or lost in domesticated, commercial trees. According to Stamp (2003), chemical defenses are physiologically costly for a plant as the production of natural defenses requires the use of their carbon- and nitrogen-based resources that may otherwise be allocated to growth and reproduction. In the context of plant domestication, the existence of such allocation-based trade-offs within plants would indicate that domestication may indirectly reduce plant defenses due to the preference for increased yield (Rosenthal and Dirzo, 1997; Chaudhary, 2013). In the case of apples, the fruit pulp and skin are rich in phenylpropanoid-derived phenolic compounds (Escarpa and Gonzalez, 1998). The production of such compounds by plants has a negative correlation with the plant’s growth (Koricheva, 2002). The loss of phenolic compounds in apples would negatively affect its natural defense against pests. Whitehead and Poveda (2019) tested the hypothesis of whether the increased allocation of resources by apples to yield through domestication has reduced its natural defense to pests. The study analyzed apple fruit chemical defense traits and pest resistance across 52 wild and 56 domesticated genotypes of apples that vary in fruit size. Different phenolic metabolites were quantified from apple skin, pulp, and seeds. The results verified that wild apples have higher total phenolic concentrations and a higher diversity of metabolites than domesticated apples in the skin, pulp, and seeds. The study further confirmed the negative relationship between fruit size and natural phenolics produced by the apples, indicating that amongst other reasons, this could be due to the allocation of resources and the trade-off that exists between yield and defense. Most importantly, the results showed that wild apples have a higher diversity of metabolites than domesticated apples and that codling moth resistance was higher in apples with higher phenolic diversity.

2.1.3. Review of Bioeconomic models for pest and disease control

Accounting for the benefits and opportunity costs of variety intercropping in the case of pest infestations require integrated ecological-economic modeling frameworks that can be sued to guide grower decision-making. Bioeconomic models are a class of such integrated models and have emerged as a preferred framework for evaluating the economics of pest and disease control strategies in agricultural contexts. They range from non-spatial to spatially explicit and from purely mathematical to fully computational.

Non-spatially explicit bioeconomic models using Differential Equation

The study of the economics of agricultural pest and disease control has focused on pest threshold models where the economic component of the model consists of taking a costly action at a certain population threshold (Hall and Norgaard 1973). More recently, researchers have achieved a greater level of integration between the ecological and economic sub-models to allow for feedbacks among them so that the target population threshold is not fixed but a function of ecological and economic parameters (Fenichel and Horan 2008; Horan and Wolf 2005). These models integrate ecological-economic sub-models where the ecological sub-model represents the pest population by aggregating individuals into state compartments based on their infestation or infection level. The transitions between different states (e.g., healthy to infested tree) are modeled using differential equations (DEs). One limitation of using DEs is that they assume within-compartment homogeneity and population perfect mixing (Brauer and Castillo-Chavez 2001). In the case of modeling agrobiodiversity as a pest regulation strategy, the homogeneity and perfect spatial mixing assumptions that characterize DEs do not hold: the strategy consists of disrupting the perfect homogeneity of apple trees and codling moth over space by intercropping commercial trees with cider trees in a way that alters pest infestation over space through the impacts of volatiles and phenolics. In practice, reduction in pest infestation occurs through a lower preference (attractiveness) to and performance (ability to lay eggs) on cider varieties. Therefore, the homogeneity assumption of population-level models acts as a hindrance in analyzing spatial patterns where different tree varieties are not necessarily perfectly mixed over space.

Spatially explicit bioeconomic models using Partial Differential Equation

According to Sanchirico and Wilen (1999, 2005), ignoring the spatial aspect can lead to suboptimal resource management policies. Ratnadas et al. (2012) found that the ratio of the cash crop to the trap crop and its spatial arrangement (i.e., intercropped with a trap crop) is crucial for the success of pest management strategy using agrobiodiversity. The spatial aspect can be incorporated in bioeconomic models of pest spread and diseases by specifying location-dependent, state-transition probabilities, or by using partial differential equations (PDE). In such models, spatial heterogeneity is exogenous and fixed over time (Smith, Sanchirico and Wilen 2009). However, in the case of an apple orchard, spatial heterogeneity is based on the variety of crops planted across the farm and also on the spatial diffusion of the pest or disease. The spatial heterogeneity is further affected by the implementation of control strategies such as the spatial arrangement of trap or repellent crops. Relaxing such assumptions in PDE models makes obtaining analytical solutions computationally expensive (Wilen 2007).

Spatially-explicit, tree-level bioeconomic models using cellular automata

There are dynamic models called cellular automata that can incorporate both the dynamic and spatial features in bio-economic models. They operate in discrete space and time over a lattice of cells, where each cell is in one of a finite number of states. The state transition rules are set using mathematical functions and algorithms. The new state of a cell depends on its previous state as well as the state of its neighboring cells (Tesfatsion and Judd 2006; Wolfram 1986). The main advantage of cellular automata models is that they do not aggregate individuals into compartments, thus allowing each modeling unit to be heterogeneous based on certain attributes (Rahmandad and Sterman 2008). This is ideal for modeling the case of a multi-variety agricultural system where each variety has a different infestation or infection probability. Cellular automata models have been used to model the spatial dynamics of disease epidemics (e.g., Sun et al. 2010) and pest infestations (Garcia et al. 2014). They have also been used to construct bioeconomic models to identify profit-maximizing, spatially-explicit disease control strategies (e.g., Atallah et al. 2014). The spatial explicitness of cellular automata makes them ideal to model the spatial management of agricultural systems such as the use of physical boundaries and the alteration of geometric configurations of fields or orchards to maximize ecosystem service provision such as increasing habitat connectivity or altering pest abundance (Garcia et al. 2014).

2.1.4 Review of risk assessment methods

In addition to maximizing net revenues through pest control, increasing agrobiodiversity on the farm can reduce year-to-year fluctuations in net revenues by attenuating temperature-dependent infestation fluctuations. For instance, Gao (2018) showed that intercropping coffee shrubs with shade trees reduces year-to-year profit fluctuations, in addition to increasing net revenues in the case of coffee berry borer infestations.

There are two classes of methods used in the literature to model and estimate agricultural risk in production: (1) Survey-based econometric models, which are used to provide an empirical estimate of the effect of inputs (e.g., crop diversity) on production risks (e.g., variance and/or skewness of yields); (2) Simulation models, which are used to simulate the effects of inputs on output or profits, and to generate the distributions of yields or profits (Gao 2018). Financial risk assessment measures (e.g., VaR, CVaR) are then used to rank risks based on these distributions (Abadie et al. 2016; Gloy and Baker 2001).

Di Falco et al. (2007, 2009) used household survey data to estimate a production econometric model where crop genetic diversity is a production input and established the relationship between yields and agrobiodiversity as an input. In the study, production risk was defined as the variance and skewness of yields. Similar moment-based approaches were used by Smale et al. (1998) and Di Falco and Perrings (2003, 2005).

In the case of simulation models, crop growth models are used to assess the risk effects of a production practice or that of climate on crop production. Luo et al. (2007) used the Agricultural Production System Simulator (APSIM) to assess the production risks faced by wheat growers due to different future climate change scenarios. They examined the sensitivity of wheat production systems to future climate change. Similarly, Clasen et al. (2011) simulated forest growth using the growth simulation model Silva to assess the ability of the mixed forest to withstand the risk of damage. Finger (2012) used a cropping system simulation model called CropSyst to simulate maize yields for different levels of water nitrogen application under different climate scenarios in order to generate yield data. Using the mean and variance of crop yields, they calculated the risk premium, which they defined as the amount they a grower is willing to pay to eliminate risk exposure due to changes in crop market prices.

Various risk assessment methods exist which can be used to conduct risk analyses on distributions of yields or profits obtained under different management scenarios through simulations. Ramirez and Sosa (2000) and Luo et al. (2007) assessed risk using conditional probability where the conditional probability was that of not exceeding a certain yield or profit level. Financial risk metrics such as Value at Risk (VaR) and the Conditional Value at Risk (CVaR) have also been used in resource economics literature to assess risk (Yemshanov et al. 2019; Abadie et al. 2016). Yemshanov et al. (2019) evaluated the expected worst-case time to detect invasive species for the case of both risk-averse and risk-neutral resource managers. Their results suggested that minimizing mitigation cost or detection time of invasive species is more relevant in the case of risk-averse managers over risk-neutral manages.

The drawback of an econometric model approach to model risk is that they require large amounts of survey data and can only provide empirical results for the effects of risk from a context with no ability to make recommendations for growers. However, simulation models if properly calibrated and parameterized can generate observations and results under different scenarios. Simulation models can further be incorporated with optimization models to determine the optimal management policies for different environmental, ecological, economic and risk preference parameters.

2.1.5 Motivation behind the proposed model

The literature on pest management lacks models of pest spread and control that test economic and ecological trade-offs of using pest-resistant varieties in perennial crops, while simultaneously being able to consider different spatial configurations and assess the risk reduction benefits involved. Such models should incorporate trade-offs between yield and pest regulation and be spatially explicit. To address this gap, we develop a spatially explicit, tree-level, bio-economic simulation model of codling moth infestation in an apple orchard, which consists of multiple tree varieties. The apple varieties differ in their market value, yield and their susceptibility to codling moth infestation. We further use the simulation model to generate the Expected Net Present Value (ENPV) over 25 apple-growing seasons and different orchard spatial configurations, to identify the profit-maximizing mix of apple varieties for each configuration, for a risk-neutral grower. We then use the certainty equivalent method to solve and find the optimal level of apple varieties for a risk-averse grower. We re-write the objective function as the maximization of the certainty equivalent where the variance of ENPVs is the year-to-year NPV variance is driven by historical temperature, and therefore infestations, changing from year to year over a time horizon of 25 years. The model is created using AnyLogic, a Java-based simulation software.

The remainder of the chapter is as follows, Section 2.2 gives an overview of the methodology: bioeconomic model initialization, calibration and parameterization, and the risk assessment method used. Section 2.3 presents the results and discusses them.

2.2 Methodology

2.2.1 Bioeconomic Model

Model Overview

The apple orchard is represented by a two-dimensional grid G. G is the set of $I \times J$ cells where I and J are the number of rows and columns, respectively. In our model, there are 500 cells $(i, j) \in G$, each representing one apple tree. Apple orchard rows are oriented north to south with $I = 25$ trees per grid row and $J = 20$ trees per grid column, resulting in an orchard area of approximately one acre. Each cell (i, j) has a state describing the apple variety $v_{i,j}$ and an infestation state at time t, S_{ijt}. The variety state v_{ij} , represents whether the cell is a commercial variety or a hard cider variety. For the infestation state S_{ijt}, a cell can be in *Susceptible*, *Low Infestation* or *High Infestation* state (see Fig 2.1). The distinct infestation levels are based on the different grades of apple quality in the market that are partially determined by the extent of pest damage on the fruit (e.g., Extra fancy, fancy). The higher the infestation state, the lower the market grade and the economic value of the apples. This set up also implicitly represents the discrete moth population levels in a tree. Time t progresses in discrete daily steps up to 168 days per apple growing season, and the model runs for a total of 25 consecutive seasons (or years).

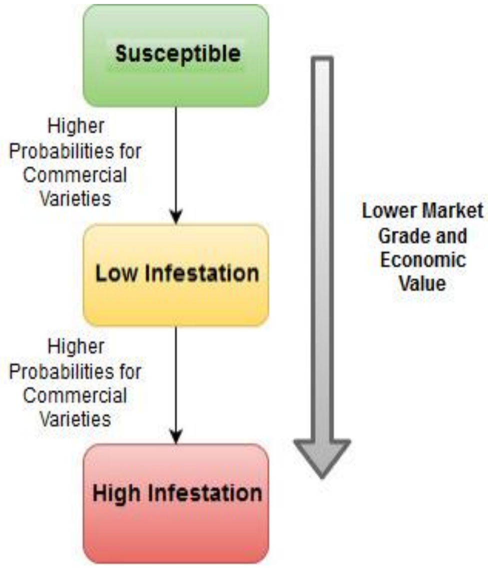

Fig 2.1: Discrete infestation levels or states of an apple tree (cell)

Rather than being deterministic, the number of apples produced by a tree is drawn from a triangular distribution with known minimum, most common, and maximum values. The values of the moments of the distribution depend on the variety state of the cell and were derived using survey data produced by the USDA National Agricultural Statistics Service (NASS) (2007-2015). All baseline parameter values are reported in Table 2.1.

Table 2.1: Model Parameters

Parameter	Description	Values	Units	Reference
A	Exponent of the infestation rates $r_1$and r_2.	0.3252 Value calibrated using moth flight distance data from Trematerra et al. (2004).	n/a	Author' calibration.
p_{ij}	Price per lb. of apple.	Commercial: 0.463	$/lb.	Apple price received, measured in $/lb,

		Cider: 0.076		NH, USDA NASS (1980-2010) US Apples utilized for juice and cider, NY, USDA NASS (1980-2010)
q_{ij}	Apple yield (minimum, mode, maximum). Moments derived using past data on yield.	Commercial: (22.2, 29.84, 36.6) Cider: (18.02, 30.86, 35.56)	lb/tree	Apple-Yield measured in lb/acre, NH, USDA NASS (2007-2015) Apples Processing-Production, measured in lb, NY, USDA NASS (2007-2015)
f_v	Scaling factor for infestation probability function. Used to provide different infestation probability for the two apple varieties.	$f_{commercial} = 1$ $f_{cider} = 0.2$		Apples acres bearing, NY, USDA NASS (2007-2015) Assumed
c_{ij}	Cost incurred per tree excluding harvest cost.	Commercial: 0.082 Cider: 0.14	$/tree	Galianto et al. (2014), Cost Estimates of Establishing, Producing, and Packing Gala Apples in Washington State Galianto et al.(2016), Hand Harvested Cider Apple

Infestation occurs throughout the grid G according to a pest dispersal mechanism that drives the transition of a cell from the *Susceptible* state to the *Low Infestation* state. The dispersal occurs when *Susceptible* cell (*i,j*), gets infested by an infested neighbor (i.e., a neighbor in state $Low\ Infestation$ or $High\ Infestation$), at the following daily rate, r_1:

$$r_1 = \frac{Total\ number\ of\ infested\ plants\ in\ the\ orchard \times Infestation\ rate}{(Minimum\ euclidean\ distance\ from\ an\ infested\ neighbor)^{\alpha}}$$

The $Infestation\ rate$ in r_1 depends on the season-dependent infestation probability b:

$$b_{spring} = Pr\left(S_{i,j,t+1} = \ Low\ Infestation \mid v_{i,j}, S_{i,j,t} = \ Susceptible\right) = \frac{95.75 f_v}{1 + \ e^{\frac{(280.04 - x)}{78.40}}}$$

$$b_{summer} = Pr\left(S_{i,j,t+1} = \ Low\ Infestation \mid v_{i,j}, S_{i,j,t} = \ Susceptible\right) = \frac{95.75 f_v}{1 + \ e^{\frac{(1186.15 - x)}{68.40}}}$$

These infestation probabilities depend on past degree-day temperature data (Riedl et al. 1976) and the variety of the apple tree– commercial varieties have a higher infestation probability compared to the cider varieties. Here x is the number of degree-days after the biofix date and f_v is a scaling factor that depends on the variety of the apple tree. The infestation probability represents the probability of a tree variety getting infested based on degree-day temperature. We describe in the *Model calibration and Parameterization* section how we obtain the parameter values of all the probability functions.

The infestation probability functions are different for spring and summer seasons, as codling moth infestation tends to reach a peak during summer. The probability function denotes the probability of a *Susceptible* apple tree getting infested by an immediate neighboring infested tree. This probability specification allows the simulation of the agrobiodiversity-mediated pest regulation services that consist of a lower probability of infestation for cider varieties compared to commercial varieties. Given an infestation probability b, the corresponding infestation rate is as follows[1]:

$$Infestation\ rate = - ln[1-b]$$

Once a cell (*i,j*) is in the *Low Infestation* state, it transitions to a *High Infestation* state at the rate r_2:

$$r_2 = \frac{Infestation\ rate}{(2.84)^{\alpha}}$$

Here, r_2 denotes the daily rate at which the pests colonize the cell or tree where it is already residing. As opposed to r_1, r_2 is therefore not density-dependent the denominator of r_2 denotes the length of a branch of a tree in meters.[2] We describe in the *Model calibration and Parameterization* section how we obtain the parameter values of all the probability functions.

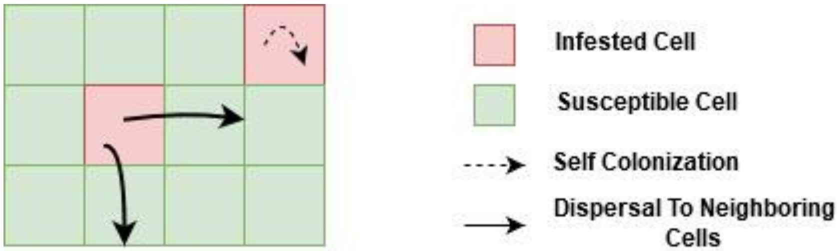

Fig 2.2: Dispersal Mechanism

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The simulation of different spatial configurations of the multi-variety orchards in the model is based on comparing standard candidate configurations typically evaluated in the landscape ecology literature, along with some spatial configurations we propose (Vacher et al.

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[1] This definition assumes that the time *X* until the transition from *Susceptible* to *Infested* occurs is exponentially distributed and that b= Pr (X<1) =1-exp (-infestation rate).

[2] Since 500 square units of cells in the model represents 4046.86 square meters (1 acre), therefore 1 square unit of area of a cell represent 8.09 square meters, which in turn means 1 unit of cell length represents 2.84 meters.

2003; Garcia et al. 2014). These are: random,; alternate rows or columns of cider or commercial variety; a vertical line of cider variety in the middle; planting the cider trees so that they form four separate quadrants for commercial trees; planting the cider trees along a diagonal or cross-diagonal across the orchard; planting the outer boundary of the orchard with cider trees; or planting the cider varieties in the form of concentric rectangles (see Fig. 3). In the model, the variety of each cell (*i*,*j*) is set in accordance with the spatial configuration being modeled.

The net revenues of the orchard at time *t* are known by the grower but only in expected value terms due to the stochastic nature of the infestation process. We compute the orchard expected net present value (ENPV) over 25 years. Let *P* and *Q* be the set of market prices and the number of apples produced by a tree, respectively. Then, $p_{ij} \epsilon P$ is the price per bushels of apple produced in the cell (*i*,*j*). *P* depends on the variety and infestation state of the cell (i.e., lower prices are paid for lower grade apples). The yield of apple produced by cell (*i*,*j*), q_{ij} (in bushels) also depends on both the variety and infestation states of the cell. This yield specification captures the tradeoffs between pest susceptibility and commercial value: while cider varieties can reduce orchard-level pest pressure, they present an opportunity cost in terms of their lower commercial value. The revenue and total costs from a tree in cell (*i*,*j*) are given by r (p_{ij} , q_{ij}) and *C*, respectively. Harvest cost is the labor cost associated with picking the fruits for harvest in a multi-variety orchard. Total costs, excluding harvest costs, are linear in the output ($C=c(q_{ij})$). The harvest costs, however, are a non-linear function of output: the greater the heterogeneity of the orchard in terms of the cell variety, the higher the harvest cost because different apple varieties mature at different times, which necessitates more harvest trips. We propose and use a harvest cost that has the following sigmoid functional form:

$$h(n,s) = \left(\frac{n}{1+e^{-s}}\right)$$

Here *n* is the total number of cells in the cider variety state in *G* and *s* is the spatial index cost representing the inconvenience cost of having different varieties mature at different times and defined as the number of instances in a spatial configuration where an apple tree has a neighboring tree from the other type. This cost term represents another source of tradeoff that a grower faces when increasing agrobiodiversity on their orchard to increase resilience to pests.

If E is the expectation operator, then the expected net present value of the orchard (ENPV) is as follows:

$$ENPV = E \sum_{t \,\epsilon\, \mathrm{T}} \mu^t \sum_{(i,j) \epsilon\, \mathrm{G}} r\left(p_{ij}, q_{ij}\right) - C - h(n, s)$$

Model Initialization

At the beginning of each simulation, the variety state of each cell (*i*,*j*) is defined so as to replicate the spatial configuration under consideration. Depending on the spatial configuration, the spatial index cost, *s*, is calculated. If two adjacent cells are of different varieties, then s is incremented. This process is repeated throughout the grid in order to determine the cumulative s for the specific spatial configuration of *G*. Once the spatial configuration is simulated, an infestation is initialized by randomly selecting a commercial variety cell in *Susceptible* state to transition to the *Low Infestation* state. The dispersal mechanism causes pest dispersal to take place and a tree in the *Low Infestation* state transitions to a *High Infestation* state at the rate r_2. The dispersal process is repeated throughout the grid over time.

Model calibration and parameterization

To determine the exponent of the dispersal rates, α, we first define a calibration objective function that minimizes the difference of the distance between infested cells over time obtained from our computational model (when no cider varieties are present) and the distance travelled by the moth over time from temporal moth dispersion data in Trematerra et al. (2004). Next, we use an optimization engine (OpQuest) that varies the value of α in each of the Monte Carlo simulations to find the optimal parameter value. The value of α is determined to be 0.3252.

The price per pound of apple varieties, depending on the infestation level or grade is parameterized from yearly price reports (1980-2010), published by USDA NASS (Table 2.1). The infestation probability distribution of each variety is determined using past degree days data collected from Network for Environment and Weather Applications (NEWA). The functional form of the infestation probability functions is derived by using the data from the graph of "Cumulative Percent of moth emergence/oviposition versus degree-day" from Reidl et al. (1976). The data was obtained from the graphs using a software called "GetData Graph Digitizer" which is commonly used to get original x and y coordinates from a scanned scientific plot. There were separate graphs for emergence and oviposition. Given the logistic shape of each graph, we used the data from the emergence graph to fit the logistic function which determines the infestation probability *b* for the dispersal.

2.2.2 The case of risk-averse growers and the insurance value of agrobiodiversity

The ENPV objective function used above assumes that the apple grower is risk neutral. In this section, we use the expected utility theory to consider the case of risk-averse growers. Following Finger (2012) and Lehmann et al. (2013), we assume that a risk-averse grower maximizes the certainty equivalent (CE). The CE is the sure sum of money that has the same utility as the expected utility of a risky alternative (Keeney and Raiffa 1976). The CE is defined as follows:

$$CE = E(NPV) - \pi$$

where $E(NPV)$ is the expected net present value and π is the risk premium. In the case of a risk-averse grower, $\pi > 0$.

According to Pratt (1964), a risk premium is the amount of money the grower is willing to pay to eliminate risk exposure and can be approximated as follows:

$$\pi = \frac{\gamma\ .\ \sigma_{NPV}^{2}}{2\ \mathrm{E(NPV)}}$$

Here, γ is the coefficient of relative risk aversion, and σ_{NPV}^{2} is the year-to-year variance of the NPV over a time horizon of 25 years. The NPV variance over the years is due to the variation in orchard temperature, and therefore infestation dynamics, over the years. Combining the two equations, we get the following expression for CE, where E(NPV) and σ_{NPV}^{2} is the mean and the variance respectively, of the NPVs observed over 25 years for a given proportion of cider:

$$CE = \mathrm{E(NPV)} - \frac{\gamma\ .\ \sigma_{NPV}^{2}}{2\ \mathrm{E(NPV)}}$$

For a given spatial configuration of the orchard, we carry out a single simulation over 25 years, for each proportion of cider in the apple orchard and collect data on the corresponding NPVs and compute the mean and variance across years. We then get the CE value for a moderately risk-averse grower ($\gamma = 2$).

2.3 Results and Discussion

In this section, we use our bioeconomic model to analyze the ecological and economic trade-off of adopting a pest management strategy that consists of increasing agrobiodiversity and that is based on the chemical ecology of plant defenses. The policy variable of our model is the proportion of cider. Its optimal value is the one that maximizes the ENPV of an apple orchard managed by a risk-neutral grower when the orchard has a random spatial configuration. We further carry out a sensitivity analysis in order to determine the effect the differences in the prices of the two apple varieties have on the optimal proportion of cider that needs to be planted in the orchard.

In order to verify the sensitivity of our optimal policy variable to more structured inter-cropping spatial strategies compared to a random strategy, we solve for the optimal proportion of cider for different intercropping spatial configurations.

Finally, we solve the problem again from the point of view of a risk-averse grower to analyze the risk-reducing effects and highlight the insurance value of using agrobiodiversity as a pest regulation service.

2.3.1 Ecological-Economic Trade-off and Optimal Proportions of Cider

The desired ecological outcome of pest suppression can be measured through the half-life measure, where the half-life is the average number of days it takes for half of the orchard to get infested over 25 apple-growing seasons. We quantify the economic return using the ENPV of the orchard over the same time period. In order to test the ecological and economic trade-off, we analyze the effects of increasing values of the policy variable, the proportions of cider in the orchard, on the half-life (Fig. 2.3) and the ENPV (Fig. 2.4) of the orchard, respectively. From an ecological standpoint, the objective is infestation minimization or half-life maximization. Unsurprisingly, the maximum half-life is obtained when the proportion of cider is 100%. As shown in Fig 2.3, there is a convex relationship between the orchard half-life and the proportion of cider varieties, with pest control benefits increasing at an increasing rate.

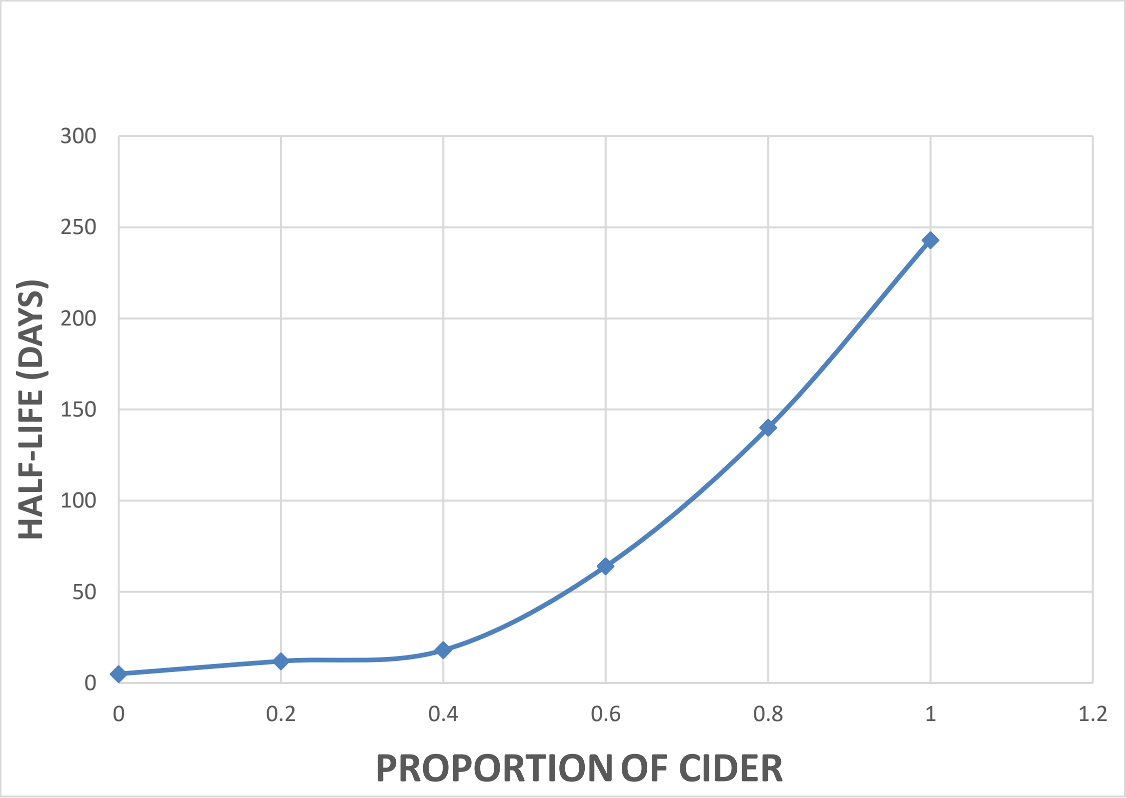

Fig 2.3: Half-Life (Days) vs. Proportion of Cider (each data point is obtained from 50 simulation runs)

However, from an economic standpoint, the objective is to maximize the orchard ENPV. As shown in Fig 2.4, the economically optimal mix of cider varieties is 20%.

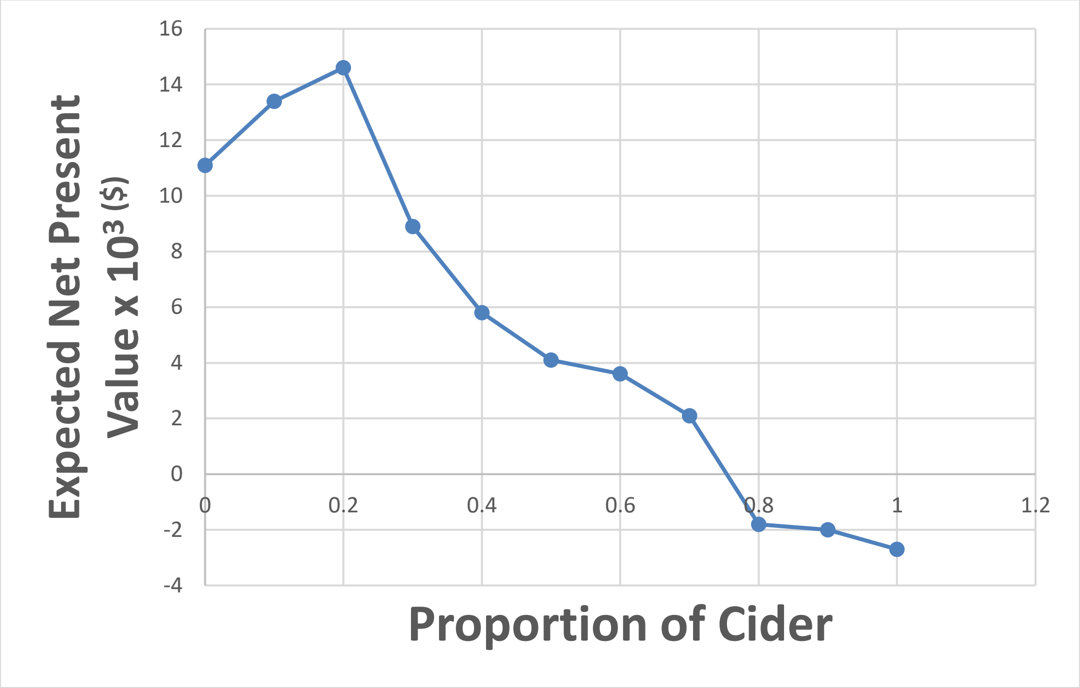

Fig 2.4: ENPV($) vs. Proportion of Cider (each data point is obtained from 50 simulation runs)

The divergence between the ecological and the economic optimal levels of cider is driven by the opportunity cost presented by the difference in market values between commercial, vulnerable varieties and cider, resistant varieties. We next determine the sensitivity of our optimal policy variable to the difference in market prices between the two apple varieties. We find that the optimal proportion of cider decreases at a decreasing rate. When the price difference is zero, there is no ecological and economic trade-off, and the ecological optimum becomes the economic optimum, and therefore, the optimal proportion of cider becomes 100% (Fig 2.5).

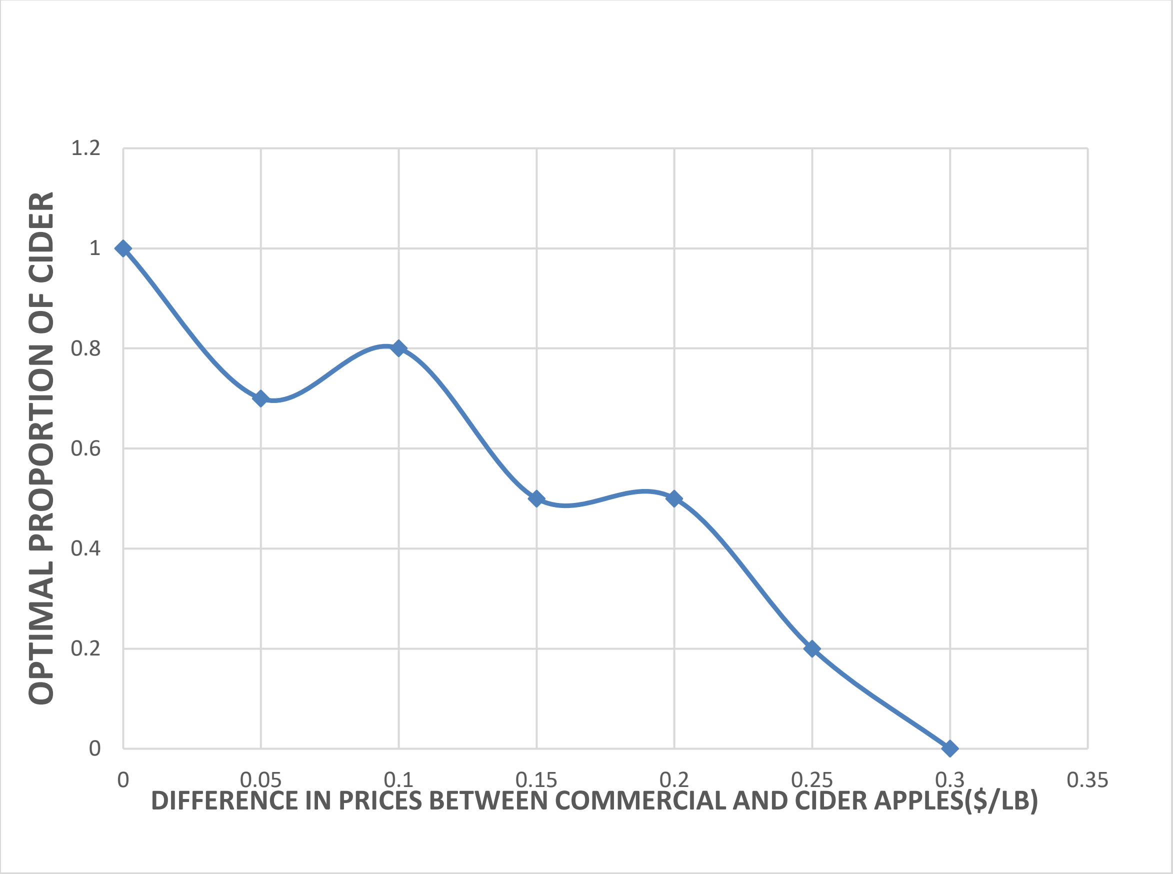

Fig 2.5: Optimal Proportion of Cider Apple vs. Commercial and Cider Price Difference ($/lb)

2.3.2 Sensitivity of optimal policy variable to the different spatial configurations

It has been noted in past literature that, when dispersal of spatially explicit, ignoring the spatial aspect of management can lead to suboptimal management policies (Sanchirico and Wilen 1999,2005; Ratnadas et al. 2012). To determine the sensitivity of the optimal proportion of cider to different spatial configurations, we collected data on the half-life and ENPVs for each of the nine configurations illustrated in Fig 2.6. The results for the different spatial strategies are summarized in Table 2.2. The ‘boundary’ (#8) and ‘concentric rectangular’ (#9) configurations maximize the orchard’s half-life (132 and 145 days, respectively) by using the highest proportion of cider (30%). However, this desired pest control outcome is achieved at a high opportunity cost, which leads these configurations to generate the lowest ENPVs ($12600/acre and $12900/acre, respectively, over 25 years). In contrast, the diagonal configuration (#6) maximizes the ENPV measure ($20100/acre over 25 years) by requiring the lowest proportion of cider (4%). Our baseline random spatial configuration (#3) has an intermediary economic performance ($14600/acre over 25 years) and requires an intermediary optimal amount of cider (20%). In general, we find that spatial configurations that yield higher ENPVs employ lower proportions of cider, which leads to lower half-life measures, which is a direct result of the tradeoff between market value and resilience to the pest.

Table 2.2: Summary of the sensitivity of the optimal proportion of cider to different spatial configurations

Spatial configuration	**Half-life (days)**	**Net present value (over 25 years, x 10^3 USD)**	**Optimal proportion of cider**
Random	55	14.6	20%
Alternate rows	42	15.2	19%
Alternate columns	41	15.4	20%
Middle column	32	19.3	4.6%
Cross in middle	15	18.1	8.6%
Diagonal	14	20.1	4%
Cross diagonal	14	18.5	7.8%
Boundary	132	12.6	17.2%
Concentric rectangles	145	12.9	29.6%

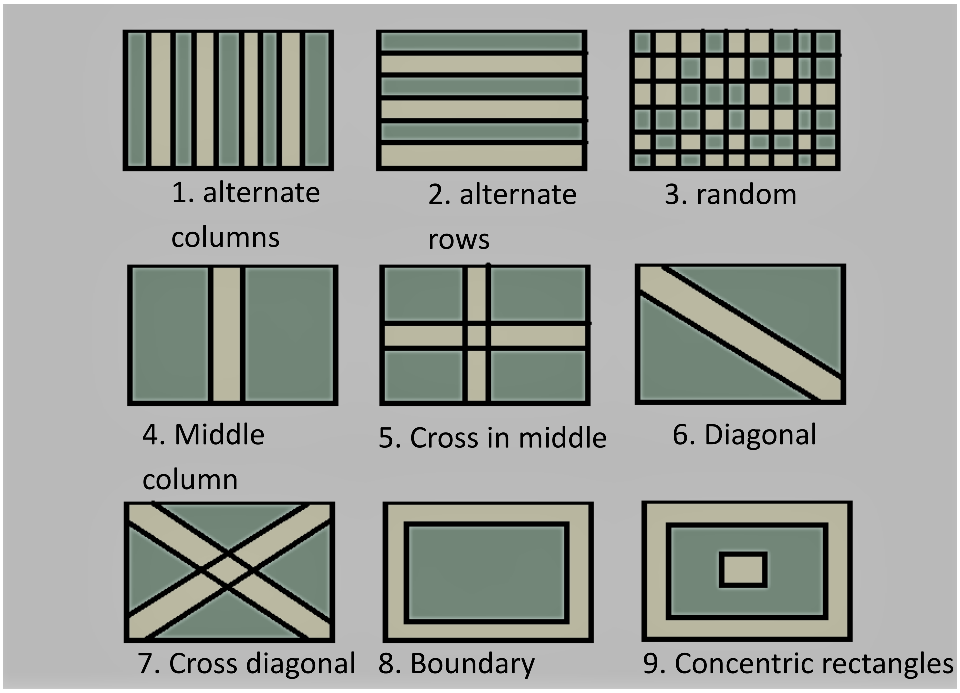

Fig 2.6: Different spatial configurations used in Table 2.2. Starting from left to right- (1) alternate columns; (2) alternate rows; (3) random configuration; (4) one middle column; (5) Cross in middle; (6) diagonal; (7) cross-diagonal; (8) boundary; (9) concentric rectangles

2.3.3 Risk-reducing effects and insurance value of agrobiodiversity as pest regulation service

In order to resolve the optimal configuration problem from the point of view of a risk-averse grower, we re-write the objective function as the maximization of the certainty equivalent where the variance of ENPVs is the year-to-year ENPV variance is driven by historical temperature, and therefore infestations, changing from year to year over a time horizon of 25 years. (See Fig 2.7). We assume a moderate level of relative risk aversion, where the coefficient of relative risk, $\gamma = 2$ (Finger 2012). Our results show that for a moderate level of risk-aversion, the optimal proportion of cider apple is 38% compared to the optimal of 20% for risk-neutral growers, suggesting that more risk-averse growers would select higher levels of cider to insure themselves from pest-related profit fluctuations. Consistently with this explanation, we find that the risk premium (π) for risk-averse growers decreases with increasing proportions of cider (See Fig 2.8), highlight the risk-reducing effect of increased cider proportions in the orchard: Cider trees reduce the pest pressure through their volatiles and phenolics which reduces temperature-related production risk due to codling moth infestation over time. This optimum remains roughly constant for higher levels of risk-aversion ($\gamma > 2$) (See Table 2.2).

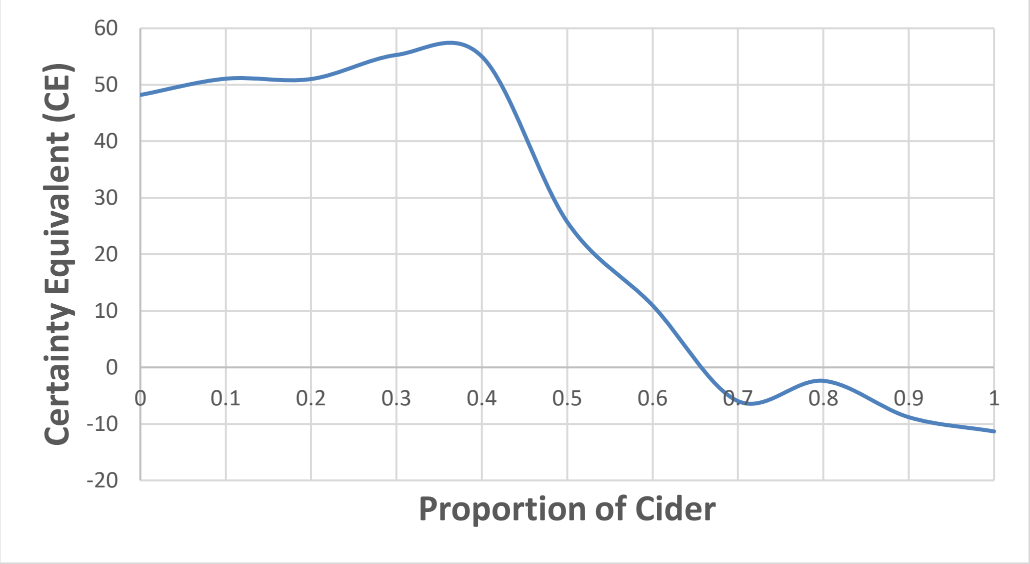

Fig 2.7: Certainty Equivalent (CE) vs. Proportion of Cider

Table 2.3: Summary of Effect of Risk Aversion on Optimal Proportion of Cider

Risk Aversion Coefficient (γ)	1	2	2.5	3
Optimal Proportion of Cider	20%	38%	38%	38%

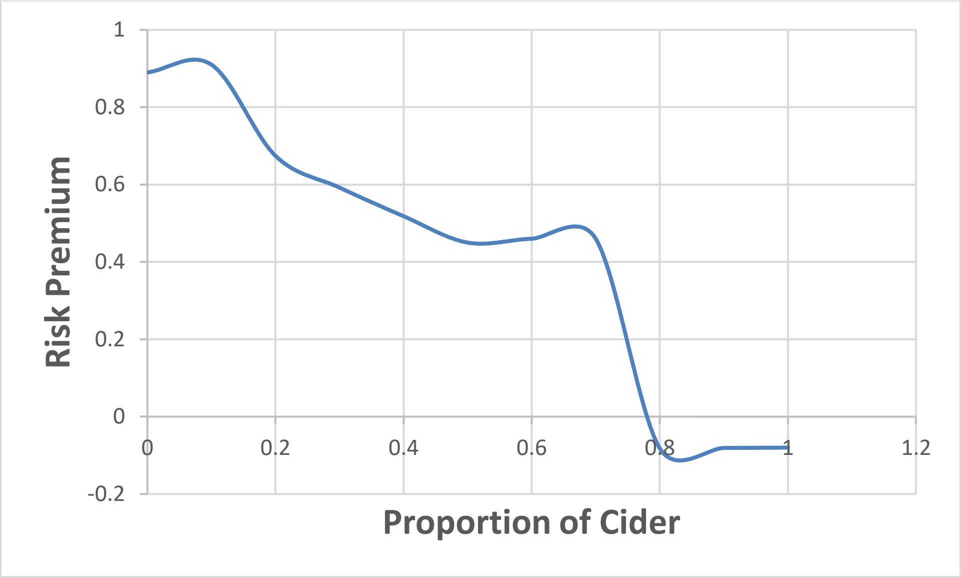

Fig 2.8: Risk Premium vs. Proportion of Cider

CHAPTER-3

A SIMULATION BASED MACHINE LEARNING FRAMEWORK FOR ROBUST PEST MANAGEMENT

3.1 Literature Review

In this chapter, we use a machine learning technique called robust reinforcement learning (RL) that can compute robust solutions even when certain parameters of the model are not known precisely. We build on Chapter 2's model of a multi-variety apple orchard infested by codling moths: Whereas the model in Chapter 2 was focused on the optimal level and spatial arrangement of apple varieties in an orchard, in this chapter, given the optimal level of cider apple and a random spatial arrangement, the grower must decide at what threshold of pest incidence to apply pesticides, in order to maximize the net revenue of the orchard over a finite time horizon. We formulate the management problem using the RL methodology. To generate data on infestation overtime for the RL, we add a pesticide application feature to our cellular automata simulation model from Chapter 2. Based on the historical degree-day (DD) data, pesticide application for a single season is simulated in the model by letting apple trees transition to a lower level of infestation state from their current state, without affecting the level of fruit damage in a tree (i.e., damage is irreversible, but the pest population level is reversible). Historical degree days (DD) data were collected from the Network for Environment and Weather Applications (NEWA). We estimate the pest's intrinsic growth rate from the data generated in Chapter 2 using Bayesian inference. Bayesian inference incorporates prior knowledge of a domain (in this case knowledge about the prior distribution of a model parameter) to gain new knowledge (posterior distribution of model parameter). Our main contribution is that we evaluate which model parameter uncertainties have the greatest impact on solution quality, that is, how susceptible the solution is to the risk of failure.

3.1.1 Scientific Evidence-Based Environmental Management and Decision Support Tools (DSTs)

Over the years, due to the low availability of appropriate scientific evidence, the traditional approach for environmental management has been mostly experience-based (Pullin et al. 2003). For example, in the agricultural sector, common pest management actions are mostly dependent on chemical pesticides, and the manager depends on first-hand observation and experience to decide when to apply the pesticides. Avoiding the use of a pesticide decreases costs and can increase revenues by improving the quality of an apple crop, but waiting too long after the pest is detected can lead to crop failure (Artzner et al. 1999; Nemirovski et al. 2009; Ben-Tal and Nemirovski 2009). Farm managers rarely have data or capability to verify whether such experience-based management practices are optimal (Pullin et al. 2003).

In recent years, a growing body of literature has made a case for evidence-based environmental management practices (Pullin et al. 2001, 2003; Sutherland et al. 2004; Adams et al. 2013; Segan et al. 2010). Adams et al. (2013) define evidence-based environmental management practices as those that are primarily based on quantitative data and analytical models. Dicks et al. (2014) described a hierarchical framework for organizing relevant scientific knowledge to make informed environmental management policies and decisions. They further identified decision support tools as the final step in the hierarchical model, which links the full body of evidence. Decision support tools (DSTs) are software-based tools that provide possible outcomes as output, either quantitatively or visually, or guides the user through possible management steps (Dicks et al. 2014; Rose et al. 2016). DSTs usually use a selected subset of research studies and data sets along with conceptual models to represent the environmental management problem at hand (Packalen et al. 2013). Some argue that effective environmental management is only possible with the aid of DSTs (Walker et al. 2002).

3.1.2 The Use of Machine Learning (ML) in Decision Support Tools (DSTs)

Machine learning (ML) along with big data technologies and high-performance computing has emerged as the preferred choice for creating DSTs for agricultural management (Liakos et al. 2018). ML is a branch of artificial intelligence (AI) which is based on the idea that computer systems can learn from data by identifying patterns and then carry out classifications or predictions with the purpose of aiding humans in decision making (Liakos et al. 2018). At its core, machine learning consists of computational methods or techniques which can be used to solve analytical problems. In the context of agriculture, different ML techniques have been used to achieve various objectives, e.g., crop yield prediction; pest and disease control policies, etc. (Ali et al. 2016) used an ML model called Artificial Neural Networks (ANN) along with multitemporal data to estimate grassland biomass (kg dry matter/ha/day). Models such as Support Vector Machines (SVM) in conjunction with geographic data from weather stations have been used to predict the development stage of rice (Su et al. 2017). In the case of pest and disease control in agriculture, the traditional approach is to uniformly spray chemical either prophylactically or as a treatment. Although this is effective, there is increased concern over the financial, environmental, and health externalities posed by such practices. Therefore, precision agricultural management techniques have been developed using ML models that treat chemical control measures as inputs that need to be applied non-uniformly over time and/or location. Pantazi et al. (2017) used an ML tool for the detection of healthy and unhealthy *Silybum marianum* plants. Chung et al. (2016) used a method to accurately detect the pathogen *Fusarium fujikuroi* for rice cultivars. The automation of this infection detection process increased crop yields. Meisner et al. (2016) used a dataset consisting of information about pest, pest management and yield of commercial cotton crops in California to create a model where they applied an ML technique called reinforcement learning, with the objective of finding the optimal pesticide application policy for the pest *Lygus hesperus*.

3.1.3 The Use of Reinforcement Learning (RL) Techniques in Decision Support Tools (DSTs)

While using ML, in certain cases, inputs and outputs are only partially observable and given as feedback to the actions in a dynamic environment. To solve a certain objective in such dynamic environments, Reinforcement Learning (RL) is a preferred technique (Liakos et al. 2018). RL is a class of ML techniques where a software agent takes a form of action on its environment. The agent's selection of actions represents the policy it is following. The goal of the agent is to maximize a reward or minimize a cost based on its actions, that is, to find the optimal policy. AI problems usually consist of a software agent residing in an environment. In order to apply an ML technique to solve such a problem, the problem in focus needs to be represented using a mathematical framework. In the case of RL, Markov Decision Process (MDP) is the mathematical framework of choice. An MDP is a discrete-time model and comprises the following elements:

- S is the set of states the environment can be in at time t.
- A is the set of actions that the agent can take on the environment at time t.
- P is the transition probability matrix where each element of the matrix represents the probability of transitioning from state s to s' due to the action a (where $a \epsilon A$), taken by the agent at time t, on the environment.
- R is the reward matrix where each element denotes the reward for taking action in state s at time t.

- γ is the discount factor.

Reinforcement learning usually solves an MDP by computing (approximately) the optimal value function $V(s)$, which has the following mathematical form:

$$V(s) = max_{a\epsilon A}\,\{p_{s,a,s'}^{T}\left(r_{s,a,s'} + \gamma V(s')\right)\}$$

Here, $V(s)$ is the value of the state s, at time *t*; $r_{s,a,s'}$ is the reward that the agent gets when it takes action *a* in state s and it is an element from the reward matrix *R*; $p_{s,a,s'}$ is the probability of transitioning from state s to s' for taking the action *a* at time *t* and it is an element of the transition probability matrix T; $V(s')$ is the maximum value when the environment is in state s'at time *t+1*, when action *a* is taken. In recent years, reinforcement learning has been used with great success to model complex environmental systems such as e.g. optimal management of invasive plant species in river systems; predicting optimal pesticide application policies for cotton pests (Dietterich et al. 2013; Meisner et al. 2016). There is a subset of RL problems called batch RL where policies are computed from a logged dataset (Lange et al. 2012). Such settings are common in areas where experimentation is either too expensive or time-consuming, such as in the case of the agricultural sector.

3.1.4 Lack of Reliability in DST Solutions and Need for Robust Solutions

From the viewpoint of a user, in addition to a DST's usability, the completeness and reliability of the policies provided by DSTs are equally important (Diez et al. 2011). Although there is literature concerned with improving the usability of DSTs on environmental systems, however, there is very little work on how reliable these systems are in representing scientific knowledge. Developing cheap and effective strategies can be challenging because natural systems are complex, difficult to model, expensive to observe, or only partially observable (Asmuth et al. 2009).

The drawback of using such systems is that they require data sets of appropriate size and accuracy. For example, in the context of invasive species management, even though thousands of samples can be generated using domain simulators, any form of available data sets on the distribution of pests tend to suffer from biases and inaccuracy (Davidson et al. 2015). In the context of RL, a limitation of MDPs is that they assume that the transition probabilities are known. This is hardly the case, as the transition probabilities are derived from data and limited data sets, modeling errors, value function approximation, and noisy data are common reasons for errors in transition probabilities (Iyengar 2005; Wiesemann et al. 2013; Petrik and Subramanian 2014). For example, a common problem in batch RL is that the size of the data set is often insufficient to compute a good policy (Petrik et al. 2016; Thomas et al. 2015; Li et al. 2015). Also, the uncertainty in data make it difficult to identify the states correctly and as full observability of states is an assumption made by MDP, the solution quality is further compromised (Petrik 2012). This results in policies that have a high risk of failure in real-world deployments. To make more effective and timely decisions, there is a need for DSTs that recommend safe actions in the face of limited and flawed data (Abrol 2014).

For solutions to be insensitive to such data and parameter uncertainties, there is a need for our solution method to be robust. A robust method will compute solutions that trade-off optimality for increased confidence. Lydakis et al. (2018) proposed a method for data-driven DSTs that are risk-averse to data and parameter uncertainty.[3] They used a distributionally robust

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[3] Note that their concept of risk aversion is defined with respect to model error, which is different from the traditional approach to risk aversion in economics, in which risk is taken by an agent with respect to a probabilistic outcome.

optimization to compute robust optimal management strategies for an invasive shrub called glossy buckthorn.

3.2 Methodology

3.2.1 Model Overview

We represent our problem as a Markov Decision Process (MDP) (See Fig 3.1 for illustration), consisting of a set of states S, where $s_i \epsilon S$, represents a range of pest population level in the orchard at time t. At each time step t, the grower can choose an action from the set A, where $A = \{a, a'\}$, where a represents the action of applying pesticides and a' represents the action of not applying pesticides. P is the transition probability matrix where each element denotes the probability of transitioning from state s_t to s_{t+1} for taking an action from set A, for pest growth rate (λ_j), where $\lambda_j \epsilon r$. The reward matrix R denotes the respective cost of applying pesticides, as well as the cost incurred due to pest damage of the crops, on each state. The time horizon T represents the total number of weeks in an apple growing season. The grower follows a pesticide application threshold policy which is the pest population level at which the grower needs to apply pesticides. When the pesticide threshold policy π_i is followed, where $\pi_i \epsilon \pi$, and pest growth rate is λ, and the sales revenue after harvest is H, we get the following net revenue as a return:

$$p(\pi_i, \lambda_j) = H + ((S^{\mathrm{T}}P)^{\mathrm{T}})^{\mathrm{T}}R$$

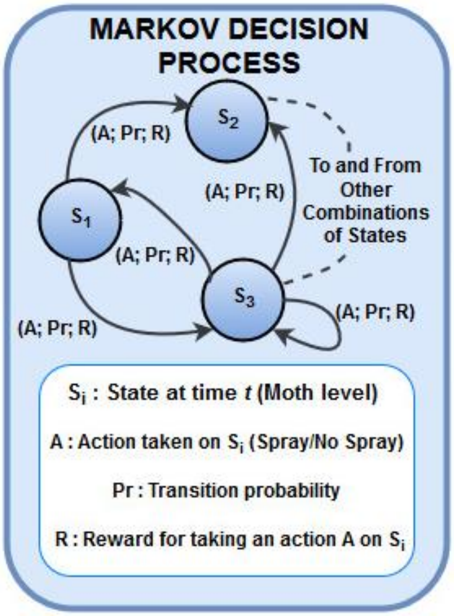

Fig 3.1: Illustration of MDP

The pest growth rate λ_j is typically estimated from the pest population data. To generate data on infestation overtime for the RL, we combine a degree day (DD) model for codling moth (Riedl, Croft and Howitt, 1976; currently used by the Network for Environment and Weather Applications (NEWA) repository to provide spraying recommendations for growers) with the cellular automata simulation model in Chapter 2. Our initial data consist of codling moth infestation in an orchard made of 500 apple trees over 25 seasons of an average of 23 weeks each. Each apple tree has one out of three possible infestation levels (*Susceptible*, *Low Infestation*, and *High Infestation*). The data set D consists of observations in the following format: at each time step t, we have the total number of trees in three distinct categories based on the number of fruits infested in each tree: no pest infestation (I_N), a low infestation (I_L), or a high infestation (I_H). It also consists of three similar categories of tree damage based on the number of fruits injured by the pest in each tree: no damage (d_N); low damage (d_L) or high damage (d_H). We also know whether pesticide was applied during each time step based on the DD model recommendation. Where n is the average number of moths in a tree of a particular infestation category and using observations from the infestation categories, we determine the pest population level at each time step t, N_t, as follows:

$$N_t = (I_N \times n_{\mathrm{N}}) + (I_L \times n_L) + (I_H \times n_H)$$

Here, n_{N} is 0, n_L is 1 and n_H is 10. We converted the infestation level to moth level with a ratio 0:1:10 (each susceptible apple tree has 0 infested fruit; each low infestation apple tree is assumed to have 1 infested fruit, and each high infestation apple tree has 10 infested fruits). We use the same ratio to derive the damage level of fruits.

To determine the set of growth rates r, we use an exponential growth model in order to project the pest population level over time. The exponential model has the following form:

$$N_{t+1} \sim Normal\ (\lambda N_t\ , \sigma^2\ )$$

Here, λ is the growth rate parameter we need to estimate. The data set D consists of two subsets, D_a and $D_{a'}$, where D_a is the dataset when the pesticide was applied and $D_{a'}$ is the dataset when no pesticide was applied. Therefore, we will need to estimate the growth rate parameter spraying, λ^a and growth rate parameter of not spraying $\lambda^{a'}$, based on the datasets D_a and $D_{a'}$, respectively. The distribution for the growth rate parameters in each case λ_j, where λ_j = $(\lambda_j^a, \lambda_j^{a'})$ is generated using Bayesian inference as follows:

$$P(\lambda_j|D) = \frac{P(D|\lambda_j)P(\lambda_j)}{P(D)}$$

Here, $P(\lambda_j)$ is the prior distribution of growth rates; $P(D|\lambda_j)$ is the likelihood distribution and $P(D|\lambda_j)$ is the posterior distribution of growth rates. The Bayesian inference is carried out by creating a Bayesian inference model via MCMC using Stan, a probabilistic programming language. We select an arbitrary subset r from the posterior distribution $P(\lambda_j|D)$.

We create the state space S based on N_t, where $s_i \epsilon S$ has L distinct state space. We divide the sorted data of N_t into L equal segments. For example, a range of 0 to 1/L of N_t will represent s_1; s_2 has a range of 1/L to 2/L of N_t and so on.

We obtain the transition probability matrix P_{ij}, which is the transition matrix we get when we apply policy π_i for the case of growth rates λ_j^a and $\lambda_j^{a'}$, where $(\lambda_j^a, \lambda_j^{a'}) = \lambda_j \epsilon r$. In order to find the transition probability P_{ij} for threshold policy π_i and growth rate λ_j, we first determine the transition probability matrix P_j^a and $P_j^{a'}$. For each threshold policy π_i, we spray when the infestation state is greater than the threshold (s_i> threshold), the transition probability P_{ij} is constructed as follows- if $\pi_i < s_i$, we will get P_{ij} by merging all the rows above state s_i in the matrix P_j^a with all rows below from state s_i from the matrix $P_j^{a'}$.

The elements of the reward matrix R consist of the cost incurred for taking action on a particular state. It is a sum of two values: 1) the cost of applying pesticides (market price of pesticides); 2) the cost due to irreversible damage of the apple fruits due to the infestation cost (damage cost). We create a distribution for the pesticide application cost with hypothesized market prices ranging from \$0 to \$500 per acre. We create a second distribution for the damage cost. This distribution is created using the damage data from dataset D. Similar to how the distribution of N_t was divided into L segments to create the state space S, the damage cost distribution is also divided into L segments to be able to assign an appropriate damage cost corresponding to each state. Suppose an action was taken on state s_i, then the corresponding damage cost is a random draw from the segment (i-1)/L to i/L of the damage cost distribution and the pesticide application cost is a random draw from the entire pesticide cost distribution. The total cost taking an action on state s_i is the sum of these two random draws. The reward matrix R is then populated accordingly.

The revenue from the sale of apples, H is calculated using apple harvest data from dataset D. In order to determine the prices received by the growers for the apple varieties, we took the average of the historic prices from the years 1980-2010. The historic prices were collected from price reports by USDA NASS. In our formulation, the commercial apple is sold at an average price of $0.46/lb and for cider varieties, they had an average price of $0.076/lb.

3.2.2 Objective Overview

Given our model, we will first analyze whether robustness matters for the economic bottom line of a grower comparing the performance of different pesticide application threshold policies. For a set of different pesticide application threshold policies (π), we determine the worst case and average case scenario net revenue, based on its application on a set of pest growth rates (r). The optimal threshold of the average-case scenario is the optimal solution that we obtain if a traditional optimization method was used, where traditional optimization methods do not consider the notion of robustness. The robust optimal policy is the optimal policy of the worst-case scenario. If the optimal pesticide application threshold of the worst-case scenario is different from the optimal threshold for the average-case scenario, then it would indicate that the model solution is sensitive to parameter uncertainty and therefore robustness matters. Following are the mathematical definitions of the two scenarios we consider:

$$Average\ Case\ Scenario\ Net\ Revenue\colon E_{\lambda\epsilon r}[p(\pi_i,\lambda) \vee D]$$

$$Worst\ Case\ Scenario\ Net\ Revenue\colon min_{\lambda\epsilon r}p(\pi_i,\lambda)$$

Then, we proceed to determine the robust policy given our set of threshold policies (π) and our set of pest growth rates (r). Following is the mathematical definitions of robust return:

$$Robust\ Return: max_{\pi} min_{\lambda \epsilon r} p(\pi, \lambda)$$

To this end, we create the "threshold policy performance" matrix M. The column number of the matrix, i, corresponds to the pesticide threshold policy π_i and $\pi_i \epsilon S$. The row number of M, j, corresponds to the growth rate λ_j and $\lambda_j \epsilon r$. Each element in the matrix is the return value $p(\pi_i, \lambda_j)$.

3.3 Results and Discussions

To evaluate our framework, we identify the key parameters whose uncertainty affects the pesticide application policies and therefore whether robustness matters in such a problem setting. We further determine the robust optimal policy for the pesticide application which the grower can follow.

We consider three different settings for our evaluation: 1) given a known cost for pesticide application, we study the effect of uncertainty of growth rate parameter on the threshold policy; 2) given a known growth rate parameter, we study the effect of uncertainty of the pesticide application cost on the threshold policy. Uncertainty in pesticide costs includes uncertainty in the market price of the pesticide, as well as the infestation damages; 3) we simultaneously consider the uncertainty in both the growth rate parameter and the cost of the pesticide application.

For each setting, we plot a graph of "Net Revenue" against "Pesticide Application Threshold" to compare the results of both the average-case scenario and worst-case scenario.

Robustness in terms of data and parameter uncertainty matters if the optimal threshold of the worst-case scenario is different from that of the average-case scenario.

3.3.1 Growth rate uncertainty and fixed cost of pesticide application

Initially, we focus on the uncertainty of the pest growth rate parameter λ only. We keep the cost incurred for the action of either applying or not applying pesticides constant (i.e. -*c* and 0, respectively). Given this set up (See Fig 3.2), we observe that the optimal threshold of the average-case scenario and the optimal threshold of the worst-case scenario are different, suggesting that robustness in terms of growth rate parameter uncertainty does matter. The optimal threshold policy of the average-case scenario suggests applying pesticides at the very beginning when the pest population level is around zero. The intuition behind the observed policy is, if a grower always applies a pesticide at a lower population level, the pest population level will be relatively low going forward, which in turn means they are more likely to end up with good quality apple during harvest and obtain a high net revenue. However, conditional on the initial pest population level, lengthening the preharvest pesticide application interval increases the mean and variance of the insect population at harvest, leading to more pesticide application (Sunding et al. 2000).

This set up also has certain limitations. It is not realistic to apply pesticides frequently at lower pest population levels, as it does not consider the costs associated with externalities posed by applying pesticides, as well as the negative financial loss incurred due to the fruit damage that occurs for not applying the pesticides. This financial loss occurs because, when an apple tree is infested, the damage that the fruit incurs is not reversible. This is because applying the pesticides can only reduce the pest pressure, but the fruits will remain damaged. Rossing et al. (1994)

concluded that it is necessary to take into consideration the uncertainty related to predicted costs, even without reference to the level of risk aversion of the decision-maker.

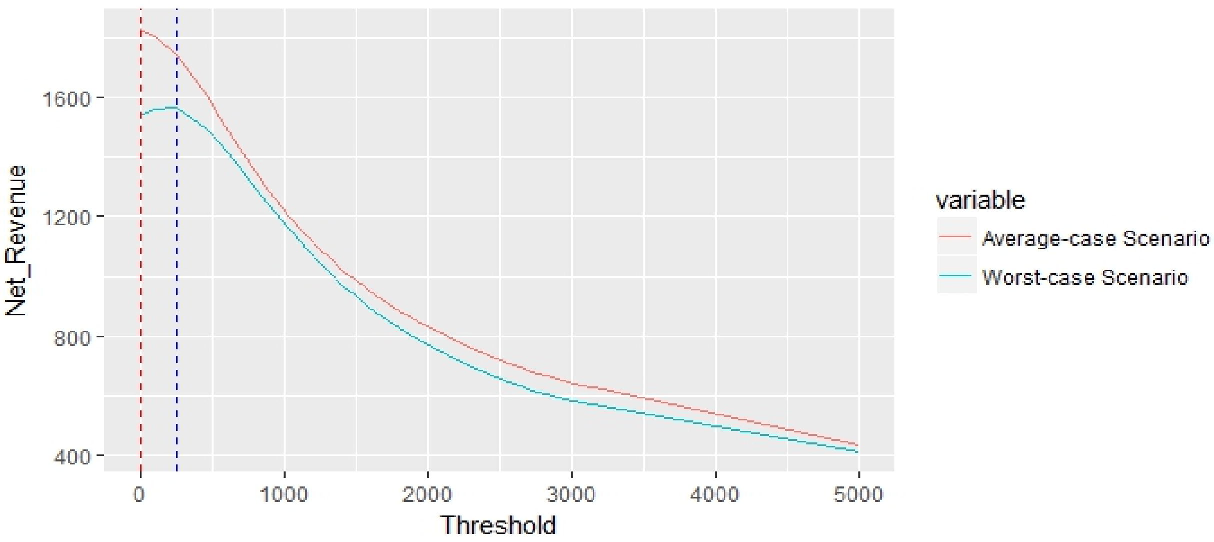

Fig 3.2: Uncertainty of cost, fixed growth rate

3.3.2 Uncertainty of pesticide application cost and fixed growth rate

To address the limitations of the previous set up, we first evaluate whether the model is sensitive to the cost of the pesticide application. We kept the growth rate fixed and updated the cost function with values from two distributions: (i) cost of applying pesticides (hypothetical market price of pesticides) and (ii) irreversible cost due to fruit damage (damage cost). The distributions and the respective values for costs are determined using the procedure described in Section 3.2.1. We observe (See Fig 3.3) that the model is sensitive to the uncertainty of pesticide costs. The optimal threshold for both the average-case and worst-case scenarios has increased to a pest population level roughly around 250 and 500, respectively. This observation is consistent with findings in the literature where pest economic threshold models were observed to be sensitive to their cost parameters (Talpaz et al. 1974; Sunding et al. 2000). This is because the worst-case scenario captures both higher levels of cost and growth rate. Our results are also consistent with the findings of Sunding et al. (2000) where the authors carried out a comparative statistics exercise on a conceptual economic threshold model and observed that an increase in pesticide cost increases the level of optimal economic threshold, which in turn confirmed that increased cost leads to a decrease in the use of pesticides.

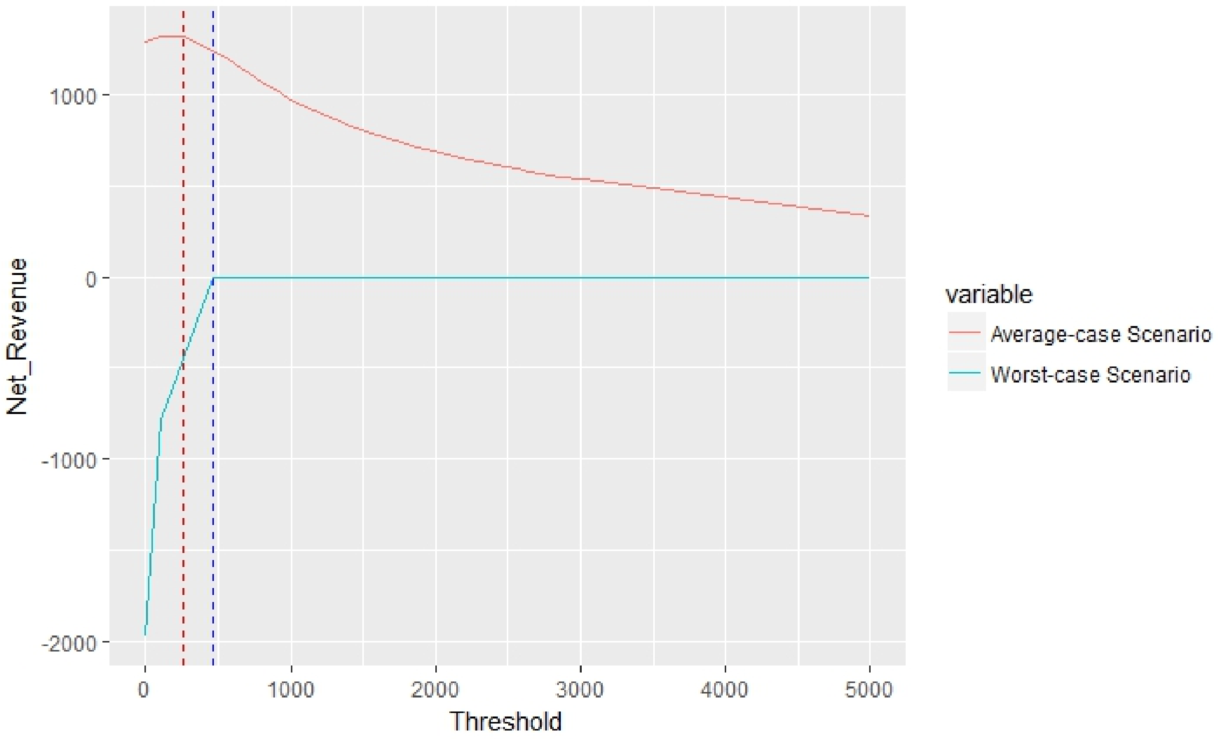

Fig 3.3: Uncertainty of growth rate, fixed cost

3.3.3 Uncertainty of growth rate and pesticide application cost

Since the model is sensitive to the uncertainty of both the growth rate as well as the cost of pesticide application, we simultaneously considered the uncertainty of both in order to determine the robust optimal policy. In Fig 3.4, the robust optimal threshold is the optimal threshold for the worst-case scenario. The robust optimal threshold is around 1,000 and the optimal threshold for the average-case scenario is 250. The net revenue for the robust optimal policy is lower than that of the average-case optimal policy. This is because the robust policy acts as a high-confidence lower bound in terms of return. A lower bound on the return can prevent the application of bad policies (Petrik et al. 2016; Lim et al. 2013; Hanasusanto and Kuhn 2013). Risk-averse growers prefer the high-confidence lower bound return policies over the conventional low confidence policies with a relatively higher return (Menapace et al. 2012).

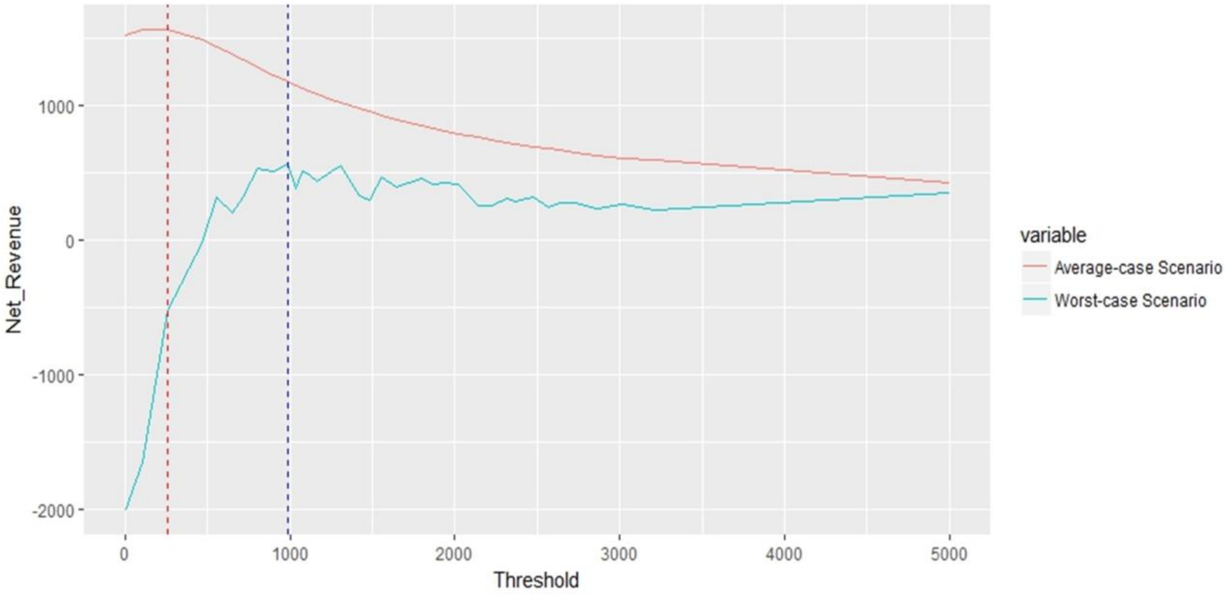

Fig 3.4: Uncertainty of both growth rate and cost

CHAPTER 4

CONCLUSION

In this thesis, we developed two models to evaluate how agrobiodiversity and threshold-based pest management can be used to reduce pest pressure and risk in an apple orchard infested by codling moths. Model 1 represents a multi-variety apple orchard consisting of hard cider variety and commercial variety. Due to the impacts of volatiles and phenolics, the hard cider variety is naturally more resistant to pest infestation but has a lower market value compared to the commercial variety. It is a tree-level, spatially explicit, bioeconomic simulation model represented using cellular automata. It determines the optimal mix of the two apple varieties over 25 apple-growing seasons, for different spatial configurations of the intercropping. We had a random spatial configuration in our baseline model, and we evaluated the ecological and economic trade-off which exists for our management practice. The ecological and economic objective was represented using the maximization of half-life and ENPVs, respectively. The bio-economically optimal proportion of cider was 20%. We analyzed the sensitivity of our policy variable, the proportion of cider variety in the orchard, to the market price difference of the two apple varieties (i.e., the opportunity cost of agrobiodiversity in the case of cider varieties). The optimal proportion of cider decreases at a decreasing rate as the price difference increases. To determine the sensitivity of the optimal proportion of cider to different spatial configurations, we compared the optimal half-life and ENPV of a random strategy against that of well-known spatial configurations suggested in the landscape ecology literature. The optimal policy variable value is sensitive to different spatial configurations and out of the nine spatial configurations, the diagonal configuration maximizes the ENPVs while the random configuration ranked seventh in terms of ENPV. Finally, we used the certainty equivalent measure to determine the optimal mix for a grower who has a moderate level of risk aversion to production risk posed by changing orchard temperature, and therefore infestations, over the years. We found that the optimal cider variety increases to 38% compared to the baseline case of 20% of a risk-neutral grower. We also documented the risk-reducing effect of apple agrobiodiversity by characterizing how the risk premium decreases with increasing proportions of cider.

Using Model 2, we determined the robust optimal pesticide application threshold, given an infested multi-variety orchard consisting of the optimal proportion of cider varieties, arranged in a random spatial configuration. The robustness of the solution ensures that it does not fail in the presence of data uncertainty. We built on our Model 1, by using historical degree-day data to add pesticide application features to our cellular automata and then used it as a simulator to generate data on infestation and damage level over time. We used Bayesian inference on our data set to determine the intrinsic pest growth rate and we modeled our problem as an MDP. We used RL technique on our MDP to find the optimal pesticide application threshold for both an average-case scenario and worst-case scenario. We found that the robust optimal threshold (worst-case optimal) is around 1,000 insects whereas the average-case optimal is around 250. Having obtained a different optimal policy for each case verifies the notion that robustness matters for the economic bottom line of a grower and a robust policy acts as high-confidence lower bound in terms of return. In order to identify the key parameters whose uncertainty impacts the model solution the most, we carried out a sensitivity analysis of the model solution to the uncertainty of the pest growth rate and the pesticide application cost. The model solution was sensitive to both, but the solution had a greater degree of sensitivity to pesticide application cost compared to the pest growth rate. This result indicated the importance of addressing the uncertainty of these parameters for such problem settings with a higher priority for addressing cost uncertainty.

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