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THE BIOECONOMICS OF SHADE-GROWN COFFEE PRODUCTION UNDER CLIMATE AND PRICE RISKS IN PUERTO RICO

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

The bioeconomics of shade-grown coffee production under climate and price risks
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Coffee production is severely affected by global climate change. One of the important impacts comes from the increasing infestation and distribution of coffee berry borer (CBB), the most damaging coffee pest worldwide. Shade-grown coffee (SGC) systems can alleviate the impacts and increase the resilience of coffee farms by providing non-market and market ecosystem services.

From an ecological perspective, SGC systems can provide many non-market ecosystem services such as pest risk mitigation, soil water retention, soil fertility, and pollination, which are all critical factors affecting coffee yields. From a financial perspective, SGC systems can benefit farmers by increasing the prices through shade-grown certification price premiums or quality price premiums, reducing price risks faced by farmers by providing alternative sources of income such as shade, and reducing the production risks by allowing more steady year-to-year coffee production. However, SGC systems can be more labor-intensive and often produce lower yields either due to lower per-shrub yields or due to lower coffee shrub density, or both, which can decrease farmers' profits.

Although farmers might agree that environmental conservation is an important goal of SGC systems, planting decisions are likely to be driven by farm production costs and revenues. The existence of trade-offs between ecosystem service provision and coffee production calls for an integrated bioeconomic analysis of SGC systems before recommendations can be made to

farmers, with the net value of ecosystem service provision and the risk effects taken into consideration.

In this thesis, we construct an integrated bioeconomic model, including a cellular automata model, a coffee yield model, and an economic model, to incorporate the ecosystem services and risk preferences into a farmer's decision-making and find the optimal amount of shade on a coffee farm for risk-neutral and risk-averse farmers.

Results show that, for risk-neutral farmers, the shade-grown systems generate higher net present values (NPVs) than sun-grown systems within shading levels of 12% - 37%. The optimal shading level is 24% and the optimal NPV is about $24,593 /0.5ha over 25 years. For moderately risk-averse farmers, shade-grown systems generate higher utility than a sun-grown system at any shading level, and the optimal shading level is 30%. Higher risk aversion leads to higher shading level selection.

In the United States, the CBB is a new threat to the domestic production in Puerto Rico and Hawaii. Results of this thesis can inform policy discussions on the economic argument for shade-grown coffee systems that, under optimal shade levels, can maximize farm profits while to protecting farmers from temperature and price risks.

CHAPTER I. INTRODUCTION

Impacts of climate change on agricultural production

The agricultural sector is highly sensitive to climate change (Gay et al., 2006; Schlenker and Lobell, 2010). It can be affected directly by the temperature, precipitation, and radiation and indirectly by the incidence and distribution of pests, soil erosion and degradation, increased tropospheric ozone levels and extreme events such as floods, droughts, and wind storms. Current research shows that while the increasing atmospheric CO2 concentrations, without associated climate change effects, would be beneficial for agricultural systems by enhancing plant productivity and increasing resource use efficiencies (Adams et al., 1998; Olesen and Bindi, 2002; Lehmann et al., 2013), in aggregate the climate change is expected to have negative influences on global crop production even if taking the plant adaptation strategies into consideration (Parry et al., 2004).

Temperature and precipitation are the two main factors that affect crop production. Schroth et al. (2016) concluded that the increasing maximum dry season temperature with climate change is the major limit for cocoa production in West Africa. Lobell and Field (2007) showed that the simple measures of growing season temperatures and precipitation explain approximately 30% or more of year-to-year variations in global average yields for wheat, rice, maize, soybeans, barley and sorghum. Schlenker and Lobell (2010) explored the relationship between crop yields and temperature and precipitation and projected that by mid-century, the aggregate production of maize, sorghum, millet, groundnut, and cassava in Sub-Saharan Africa would be decreased by 22, 17, 17, 18, and 8%, respectively, due to climate change. Based on the yields of corn, soybean and cotton and weather data in the U.S., Schlenker and Roberts (2009) found that the yields increase modestly up to a critical temperature and then decrease sharply: the critical threshold is 29° C for corn, 30 ° C for soybeans and 32 ° C for cotton. Machovina and Feeley (2013) predicted the global changes of areas suitable for banana production based on the projected temperature and precipitation and found that these areas will decrease by 19% by 2060.

Besides temperature and precipitation, other factors like radiation and humidity also have severe impacts on crop yields. With the consideration of the impacts of solar radiation, Chen et al. (2016) found nonlinear and inverted U-shaped relationships between corn and soybean yields and weather variables and projected that corn and soybean yields would decline by 3–12% and 7–19%, respectively, by 2100 in China. By considering not only temperature and precipitation, but also humidity, wind speed, sunshine duration, and evaporation, Zhang et al. (2017) concluded that those additional climatic variables, especially humidity and wind speed, are critical for crop growth and indicated that climate change is likely to decrease the yields of rice, wheat, and corn in China by 36.25%, 18.26%, and 45.10%, respectively, by the end of this century.

In addition, extreme weather events, such as floods, droughts, and windstorms, can cause unpredictable and severe impacts on agricultural production. For example, the severe drought of 1988 in the U.S. Midwest caused a drop of approximately 37% in crop yields and required a $3-billion Congressional bailout for farmers, while the Mississippi River Flood of 1993 damaged over 11 million acres of crops and lead to losses of over $3 billion (Rosenzweig et al., 2001). Most scientists believe that climate change would increase the frequency and severity of extreme weather events (Reddy, 2015). Strzepek et al. (2010) concluded that almost all parts of the U.S. would experience increases in drought risk by 2050. Cai et al. (2014) projected that the occurrences of EI Niño, which is associated with several severe weather events, will double in the future in response to greenhouse warming.

Pests and diseases are also climate-related severe threats to agriculture production. Climate change can affect the development, infestation severity, and distribution of pests and diseases by changing precipitation intensity and temperature. Because the specific nature of different pests and diseases, climate change's impacts could be positive, negative, or neutral (Coakley et al., 1999). However, in general, temperature increases can benefit pests and diseases by facilitating the fertility rate, development rate, distribution and the winter survival rate (Rosenzweig et al., 2001; Reddy, 2015). For example, Jaramillo et al. (2011) reported that temperature rise in East Africa increased the number of generations of coffee berry borer (CBB) per year, the most serious pest of coffee, and expanded its distribution range, which increased the damage to coffee crops in regions where the pest had limited presence. Deutsch et al. (2008) concluded that the impacts of temperature increases may have the most severe impacts on the tropical insects, which are relatively sensitive to temperature change.

Overall, climate change can affect agricultural production through multiple ways that are interacted, complex, and uncertain. To assess the impact of climate change accurately, it is essential to consider the value of adaptation (Guo and Costello, 2013) and how this value is produced through the adoption of adaptation strategies that regulate these multiple, interacted, complex, and uncertain processes through which climate change affects production.

In this thesis, we focus on the impact of climate change on coffee production through the temperature-mediated pest infestation channel and consider the value of adaptation provided by shade-grown systems through interacting, shade-induced yield-enhancing and pest-regulating ecosystem services.

Coffee production under changing climate

Coffee is the world's second-largest export commodity just after oil (Sorby, 2002), which supports the livelihoods of approximately 4.3 million coffee producers worldwide (Rahn et al., 2014), most of whom are smallholder farmers. Arabica coffee (*Coffea arabica*) and Robusta coffee (*Coffea canephora*) are the two main coffee species, which are responsible for 99% of world bean production (DaMatta et al., 2006). Arabica coffee is regarded as having higher beverage quality and accounts for about 62% of coffee consumed (DaMatta et al., 2006). But it grows in a narrower range of climatic conditions than Robusta coffee. For example, the suitable temperature range is 15-24 °C for Arabica coffee, with the best production achieved at 18 to 22°C, while the range is15-30 °C for Robusta coffee, with optimum production between 22 and 28 °C (Magrach and Ghazoul, 2015).

Coffee production is extremely vulnerable to climate change (Davis 2012; Baca et al. 2014). The projected climate change would have great effects on coffee production, especially the main Arabica coffee species, which has higher cup quality and higher climatic requirements. Gay et al. (2006) showed that temperature is the most relevant climatic factor for coffee production and the projected climate change conditions for the year 2020 indicate a reduction of 34% of the current production in Veracruz, Mexico. Bertrand et al. (2012) showed that the quality of coffee beverage is greatly affected by the mean temperature during seed development and concluded that the increase in temperature with climate change is expected to have a negative impact on coffee quality.

Further, climate change will lead to the loss of areas that are climatically suitable for coffee production: the optimal coffee-growing elevation will shift to higher latitudes and higher altitudes with climate change. Baca et al. (2014) predicted that land affected by decreases in suitability is 40% or greater in El Salvador and Nicaragua in 2050 and optimal coffee-growing elevation will shift from 1,200 m.a.s.l currently to 1,600 m.a.s.l by 2050 in Central America as a whole. Bunn et al. (2015) concluded that climate change would reduce the global area suitable for coffee production by 50% by 2050 across emission scenarios. Schroth et al. (2015) projected that changes in climatic conditions would affect 84% of current coffee production zones in Indonesia by 2050 and might become a major driver of deforestation in the highlands. Magrach and Ghazoul (2015) had the same conclusion that, although there is enough suitable area to meet future coffee demands, 49% of the future area suitable for Arabica cultivation, and 65% of that for Robusta are currently under forest cover.

Further, the higher temperature in the tropics due to climate change increases the fecundity and geographic distribution of coffee berry borer (CBB). CBB is the most devastating pest of coffee worldwide, and it can cause up to 70% reduction in yield (Duque and Baker, 2003). According to Magrach and Ghazoul (2015), CBB has infested about 57% of Arabica and 50% of Robusta coffee plantations currently. According to their scenarios, CBB is projected to expand its distribution and will affect approximate 77.8% and up to 93.02% of future suitable areas for Arabica and Robusta respectively. Jaramillo et al. (2009) showed that higher temperature can increase the population per generation and generations per coffee season of CBB.

Economics of climate change adaptation in agriculture

To abate the vulnerability of agricultural systems, adaptation strategies will play a decisive role (Guo and Costello, 2013). According to the Intergovernmental Panel on Climate Change (IPCC, 2014), adaptation is defined as the process of adjustment to actual or expected climate and its effects, seeking to moderate or avoid harm or exploit beneficial opportunities. Based on the decision environments, adaptation strategies can be diversified as local-, regional-, national-, and international-levels (Smit and Wandel, 2006; Howden et al., 2007).

In the agriculture sector, since the actual impacts of climate change are largely affected by farm characteristics, including intensity, size, land use and other factors, the farm-level (local-level) responses are extremely important to the adaptive process (Reidsma et al., 2010). In general, most farmers have the perception that climatic conditions have changed over the past several decades. Harvey et al. (2014) conducted surveys of 600 households in Madagascar and showed that smallholder farmers have a good awareness of the changes in temperature and precipitation over the past ten years. Thomas et al. (2007) concluded that most of the respondents had noticed the changing climate trends, such as hotter dry season, through conducting semi-structured interviews with 50 groups in South Africa.

However, knowing the existence of climate change doesn't necessarily mean that farmers are willing or able to adopt the adaptation strategies. Harvey et al. (2014) showed that only a small subgroup of people had made changes in their farming practices to reduce their current and/or possible losses due to more severe droughts, floods, or climate change in general. Based on the survey data from 5000 corn farmers across 22 Midwestern U.S. Watersheds, Mase et al. (2017) found that in-field conservation practices and crop insurance are the two strategies that most farmers may take to manage climate risks, while for other strategies, such as adopting new technology and implementing edge-of-field conservation practices, most farmers' response was "Not doing and don't plan to do". Many studies have examined the driving forces behind farm households' decisions to adapt to climate change and found that the level of education, gender, age, and wealth of the head of household; information on climate; access to extension and credit;

technology and farm assets (labor, land, and capital) are the main drivers behind farmers' adaptation (Hassan and Nhemachena, 2008; Deressa et al., 2009; Di Falco et al., 2011; Waha et al. 2013; Meijer et al., 2015).

Climate adaptation strategies include the use of different crop varieties, changes in sowing time, irrigation, pesticide, tree planting, soil conservation among others (Smit and Skinner, 2002; Deressa et al., 2009; Mertz et al., 2009). Usually farmers can make small adjustments to their farming practices, such as changes in planting date, planting densities, and crop varieties, but they lack the capability to adopt costlier strategies, such as irrigation or agroforestry, due to technical, financial and other barriers (Bryan et al., 2013).

Government policies can play an important role in facilitating farm-level adaptation, especially when investments are unaffordable by smallholders, by providing information, technical support and access to credits (Berry et al., 2006; Hassan and Nhemachena, 2008). Before the implementation of a potential adaptive strategy, it is essential to identify the economically optimal amount of adaptation for different scenarios. However, most studies have focused on farmer's perception of climate change and willingness and ability to adapt, or on empirical evidence of climate adaptation (e.g., Harvey et al., 2014 and Deressa et al., 2009) but less attention has been paid to the optimal amount of adaptation, which is necessary for farmers who face ecological-economic trade-offs when adopting a climate-resilient strategy and for organizations and policymakers formulating recommendations for farmers. One exception is Lehmann et al. (2013) that uses a bioeconomic modeling system to find the optimal adaptation options, including irrigation and the amount, timing, allocation of nitrogen fertilization.

Agroforestry as an ecosystem-based mitigation and adaptation strategy

Ecosystem-based adaptation (EbA) strategies aims to help farmers to change farm management practices to maximize the provision of ecosystem services that directly or indirectly benefit smallholder farmers (Vignola et al., 2015). Recently, agroforestry was proposed as a promising ecosystem-based adaptation strategy to climate change for coffee farmers (Verchot et al., 2007; Schroth et al., 2009; Tscharntke et al., 2011). Agroforestry is an integration system that includes woody perennials, crops, and/or animals (Zomer et al., 2009). Based on the system's structure (composition and arrangement of components), the system can be grouped as agro-silviculture (crops and trees), silvo-pastoral (trees and pasture/animals), and agri-silvo-pastoral (crops, pasture/animals, and trees) (Nair, 1985). In this thesis, we focus on the agri-silvicultural systems, specifically, shade-grown coffee systems.

From the ecological perspective, agroforestry can provide many non-market ecosystem services, such as soil water retention (Lin, 2010), soil fertility (Beer, 1987; Martius et al., 2004; Dossa et al., 2008; De Souza et al., 2012), carbon sequestration (Dixon, 1995; Nair et al., 2009; Soto-Pinto et al., 2010), pest regulation (Jaramillo et al., 2011; FAO-PAR, 2011), and pollination (Jha and Vandermeer, 2009; Klein et al., 2002). Some of the ecosystems services produced in an agroforestry system increase the ability of coffee production systems to adapt to climate extremes (e.g., temperature regulation, pest regulation, soil water retention), others give such systems the ability to contribute to climate mitigation (C sequestration). Researchers have explored the synergies between adaptation and mitigation effects of agroforestry and concluded that agroforestry systems have compelling potential for both adaptation and mitigation (Verchot et al., 2007; Lasco et al., 2014; Rahn et al., 2014). Lin (2010) examined the ability of shade trees to maintain water availability for the coffee shrubs in a shade agroforestry system in Southern

Mexico (Chiapas, Mexico). By comparing the soil evaporation and evaporative demand for crop transpiration in coffee systems under different levels of shade canopy, Lin found that the higher shade cover is capable of reducing overall evaporative demand from soil evaporation and coffee transpiration. Hailu et al. (2000) found that using *Millettia ferruginea*, an endemic tree in Ethiopia, as the shade tree for maize production in southern Ethiopia, can increase the level of surface soil P, organic C, exchangeable base-forming cations, and cation exchange capacity and lead to significantly higher maize yields. Albrecht and Kandji (2003) estimated the C sequestration potential of agroforestry systems and argued that soil C sequestration constitutes a realistic option that is achievable in many agroforestry systems.

Agroforestry can provide pest regulation ecosystem services by (1) regulating temperature and humidity around the crop, and (2) by providing habitat to birds, bats, spiders and other animals that are predators of crop pests. Williams-Guillén et al. (2008) proved that the presence of bats and birds enhances the efficacy of arthropod reduction in an agroforestry system. Van Bael et al. (2008) showed that insectivorous birds reduce arthropod abundances and their damage to plants.

From the economic perspective, agroforestry provides farmers an additional source of income from shade trees, which diversifies farmers' sources of income generation and lowers their income risks. Current et al. (1995) showed that most agroforestry practices are cost-effective. However, Gobbi (2000) showed that monoculture systems such as sun-grown coffee are more profitable than agroforestry systems but riskier. Comparing agroforestry systems (e.g. SGC) with a farmer's baseline system (e.g., sun-grown coffee) is important because most smallholder farmers will consider profits when deciding to adopt a new system, regardless of its intrinsic cost-effectiveness. In this thesis, we are interested in SGC as a climate adaptation strategy, and particularly in the pest regulation ecosystem benefit of this system. In addition, rather than a decision on the extensive margin only (whether to transition from sun to shade), we are also interested in a farmer's adjustment at the intensive margin (how much shade).

Shade-grown coffee as an ecosystem-based adaptation strategy

In Fig. 1, we enumerate the non-market ecosystem services that can be produced in SGC systems. Pest control services are produced through decreasing temperature around coffee shrubs (Jaramillo et al., 2011; FAO-PAR, 2011). This ecosystem service provides farmers with protection from CBB risk by protecting against yield damages that might occur in the case of higher temperature and ensuing CBB infestations. SGC systems can also provide many other yield-enhancing ecosystem services such as soil water retention (Lin, 2010), and soil fertility (Dossa et al., 2008). Soto-Pinto et al. (2000) find that there is a per-shrub yield-maximizing shading level below which shade trees increase per-shrub coffee yields arguably through soil water retention and soil fertility ecosystems services and beyond which yields decrease due to competition for light, water, and other resources.

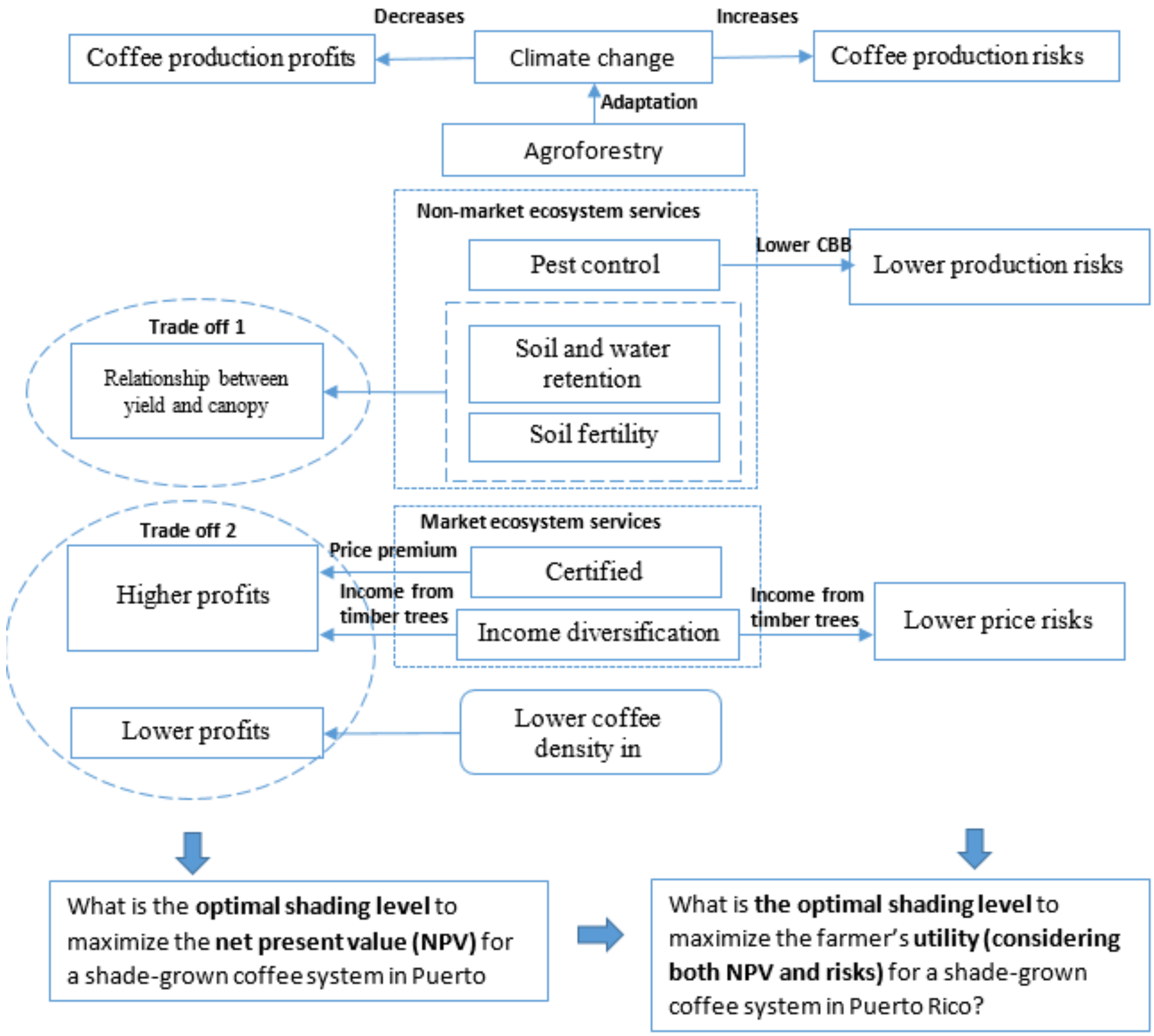

Figure 1. Conceptual Framework

From the financial and risk perspective, agroforestry systems benefit farmers by possibly increasing the prices received, reducing the production risks faced by farmers and providing an additional source of income. First, SGC might command higher prices than sun-grown coffee either because buyers value the sustainability of a production system (e.g., bird-friendly coffee) or because it has a higher quality (e.g., more complex or nuanced aromas). Some industry and conservation organizations have certification programs for shade-grown coffee (Bentley and

Baker, 2000) that provide a price premium for “bird-friendly” or higher-quality coffee produced under shade, which presumably can lead to higher profits received by farmers. Second, because of its higher protection from pest risk, a SGC might benefit from lower year-to-year fluctuations in yields, which is a production risk reduction feature that might be attractive to a risk-averse farmer (Barradas and Fanjul, 1986; DaMatta et al., 2006). Third, SGC system provides farmers alternative sources of income, such as income from shade trees or fruits. This diversification of income serves as a buffer against coffee price volatility (Castro et al., 2013), which increases farmers’ ability to cope with coffee price risks. However, SGC system might produce lower yields either due to lower per-shrub yields or due to lower coffee shrub density, or both. Additionally, SGC systems are more labor-intensive. Farmers may not be willing to make the conversion from sun-grown to SGC in the absence of internal (e.g., pest regulation) or external (e.g., price premium or conversion subsidy) economic incentives or strong environmental preferences (Borkhataria et al., 2012).

In Puerto Rico, most coffee plantations were traditional shade-grown systems before the 1960s (Borkhataria et al., 2012). Sun-grown coffee was encouraged in the late 1960s because the intensive coffee management had the potential to increase per-acre yields and profits. In the latter half of the 1980s, there was a widespread conversion from SGC to sun-grown systems (Borkhataria et al., 2012). Since 2007, the SGC system has been recommended by the government to provide habitat to biodiversity, conserve soil and water, and sustain the wellbeing of coffee farmers (Ríos and Ferguson, 2015; USDA, 2016). CBB was first found in Puerto Rico in 2007, which is a new threat to the U.S. domestic coffee production and makes the SGC more attractive.

The existence of the ecological-agronomic trade-offs between ecosystem service provision and coffee yields on the one hand and ecological-economic tradeoffs between ecological benefits and economic costs of transitioning to SGC on the other hand calls for a financial analysis of SGC systems that takes these tradeoffs into consideration, especially the value of ecosystem services and the value of risk reduction.

This thesis aims to construct an integrated bioeconomic model, including a cellular automata model, a yield model, and an economic model, to incorporate the ecosystem service values and the risk effects into a representative farmers' decision-making and find the optimal amount of the adaptation.

Research questions

We assess the net economic returns, including risk reduction, in a sun-grown coffee vs. SGC system. We first find the optimal shading level under farmer risk neutrality and then analyze how farmer risk preferences might affect the optimal shading level under climate and price risks.

While many papers have explored the farmers' willingness to adapt (Deressa et al., 2009; Meijer et al., 2015) and the cost and benefit of agroforestry adaptation (Rahman et al., 2011; Thorlakson and Neufeldt, 2012; Lasco et al., 2014), there is limited research focusing on the optimal amount of adaptation (e.g., the optimal ratio between shade trees and crops). Furthermore, most studies consider only the economic costs and benefits and neglect the value of non-market ecosystem services and the risk reduction effects. According to Daily et al. (2009), it is very hard to incorporate the ecosystem services provision into farmers' decision-making, but it is also a vital factor to the optimal amount of adaptation. One exception includes Atallah, Gomez, and Jaramillo (2018) where the optimal shading strategy is solved, and non-market ecosystem services are accounted for. However, this study does not consider the effect of temperature and price fluctuations and their effects of the optimal shading strategy for a range of farmer risk preferences. In addition, while many economic studies rely on mostly secondary data from various locations, in this thesis, we use primary ecological data to characterize the agronomic-ecological tradeoffs between shade level and coffee yields.

By constructing a bioeconomic model to incorporate the ecosystem service values and the risk preferences in a farmers' decision-making, this thesis aims to answer the following questions:

(1) What are the agronomic-ecological tradeoffs of increased levels of shade in Puerto Rico? In other words, what is the relationship between coffee yield and the shading level in an SGC system? Is it positive (i.e., increased shade and pest regulation ecosystem services are complementary), negative (i.e., competitive), or non-linear (both, depending on the range)?

(2) What is the optimal shading level that maximizes the net present value (NPV) for a shade-grown coffee system in Puerto Rico with the value of pest regulation ecosystem services considered?

(3) What is the optimal shading level that maximizes the farm's resilience -- defined as utility maximization considering both NPV and risks-- for a shade-grown coffee system in Puerto Rico with the value of ecosystem services considered? How does this optimum change under different risk preferences and for different price premium incentives?

CHAPTER II. LITERATURE REVIEW

Relationship between shade and coffee yield

Shade tree covers in an SGC system regulate the microclimate for coffee shrubs, including reduce temperature and radiation, increase soil fertility and water availability, and regulate pests, among other services. However, due to the possible competition between shade trees and coffee shrubs for water, sunlight, and nutrients, there is no agreement on the relationship between shade and coffee yield. Lin (2009) compared coffee yields per hectare[1] between a high-shade (60%-80%) and a medium-shade site (30%-50%) and found that they had similar yields. Siles et al. (2010) found that coffee yields per hectare[2] in SGC and sun-grown systems are similar during shade trees establishment period. However, the yield per hectare in SGC is 30% lower than that in a sun-grown system during the latter years in the absence of an adequate shade tree pruning. Haggar et al. (2011) revealed that yields in full sun coffee production systems were greater than in shaded coffee systems in Costa Rica, while they were similar in another site in Nicaragua. Results differ in part because the studies were carried out in different locations, with different environmental factors and coffee varieties (Lin, 2009). The disagreement in the results might also be due to the different levels of shade and shade management in the different sites. Using data from 63 farms ranging in their shade level from 23% to 70%, Soto-Pinto et al. (2000) showed that shade tree cover had a positive effect on per-

[1] The two sites have the same coffee planting density: the coffee shrub spacing is 2m × 1.5m for both sites.

[2] The density is 5000 coffee plants per hectare for sun-grown system and 4722 coffee plants per hectare for SGC.

shrub coffee yields between 23 and 38% shade cover. Yields remained constant up to 48% shade and decreased for shade covers values exceeding 50%.

In this research, we use primary data from 33 farms in Puerto Rico and follow the estimation procedure in Soto-Pinto et al. (2000) to estimate the relationship between shade and per-shrub yield.

Financial analysis of shade-grown coffee

While the ecological services of SGC have been widely discussed, the economic analysis of SGC has been studied to a lesser extent. Gobbi (2000) used a cost-benefit analysis model to estimate the net present values and risks associated with the investment in five hypothetical, but typical, coffee farms, i.e., traditional polyculture, commercial polyculture, technified shade less than 1200 m elevations, technified shade greater than 1200 m elevation, and unshaded monoculture. Results showed that the unshaded monoculture farm type was the most profitable and the farm under traditional polyculture was the only risk-free investment. Current et al. (1995) employed a cost-benefit analysis to twenty-one agroforestry projects of coffee in six Central American and two Caribbean countries and found that most of the agroforestry practices are profitable under a broad range of conditions. While traditional cost-benefit analyses are useful to make recommendations based on financial costs and benefits, they do not account for non-market ecosystem service values, which might be a major driver of the cost-effectiveness, especially when studying ecosystem-based adaptations. In addition, most cost-benefit analysis model assumes risk neutrality while the farmers are risk-averse.

As for the risks, previous research has shown that agrobiodiversity (including gene diversity, crop diversity, and forest diversity), defined as either an intermingled mixture (i.e., land sharing) or separated areas of various plants within the same farm (i.e., land sparing), have a risk reduction effect. Castro et al. (2013) showed that an SGC system carries less risk than a maize monoculture although intensively-grown maize is more profitable in the case of small-scale land-users in southern Ecuador. Di Falco and Chavas (2006, 2009) estimated the impact crop genetic diversity had on the mean, variance and skewness of yield based on farm-level empirical data and found that crop diversity increased the mean yield and lowered risk exposure. Ramirez and Sosa (2000) estimated the net profit probability distribution function and cumulative distribution function for three different agroforestry SGC production and found that the more diversified system provided more risk protection, especially during low price cycles. Clasen et al. (2011) found that a mixture of tree species (spruce and beech) led to less financial risks compared to a monoculture.

We build on these findings to incorporate risk preferences into the representative farmer's decision-making framework. Currently, coffee farmers tend to choose sun-grown systems because of higher profits received per hectare (Gobbi, 2000; Borkhataria et al., 2012), but a farmer might prefer a SGC system, once non-market ecosystem values are accounted for services and the risk reduction effects are considered

Risk assessment methods review

There are two generally-defined methods used in the agricultural and resource economics literature to model agricultural risk in production: (1) Survey-based econometric models are used to estimate the effect of inputs (e.g., crop diversity) on production risks (e.g., variance and/or skewness of yields); (2) Simulation methods are used to simulate the effects of inputs on output (yield) or profits, and to generate the distributions of yields or profits. Financial risk assessment methods are then used to rank risks based on these distributions.

Di Falco & Chavas (2006, 2009) used household survey data to estimate the relationship between crop genetic diversity and farmers' risk exposure using an econometric, moment-based model. The theoretical framework behind their econometric model is to treat genetic diversity as an input, similarly to other inputs such as fertilizer, pesticide, and weather, and then use a production function estimation to identify the relationship between yields and inputs. The variance and skewness of yields denote the risk exposure of farmers. They then estimated the relationship between genetic diversity and the mean, variance and skewness of yields and found that crop diversity is positively related to mean yields and negatively related to variance and skewness of yields. Smale et al. (1998) and Di Falco and Perrings (2003, 2005) used a similar method to estimate the impact of diversity on mean and variance of yields and found similar results. Widawsky & Rozelle (1998) used the same moment-based model and found that crop diversity reduced both the mean and the variance of rice yields.

The economic literature employing simulation methods usually uses crop growth models, such as the CropSyst and Agricultural Production System sIMulator (APSIM) model, to simulate the impact of various factors on the production of crops. Luo et al. (2007) used the APSIM-Wheat model to examine the sensitivity of wheat production systems to future climate change. In their model, risk is assessed using the conditional probability of not exceeding the critical yield thresholds. They found that under the most likely climate change scenario, wheat production risks increased in all locations. Clasen et al. (2011) simulated forest growth using the growth simulation model Silva 2.2. The risk factor is added as an input using a binomial distribution function, and the output of the model is the probability density function (PDF) of forest damage.

Based on the Sharpe Ratio, they concluded that mixed forests have a higher ability to withstand risk. Finger (2012) used the deterministic crop yield simulation model CropSyst to simulate maize yields for different levels of water nitrogen application under different climate scenarios. After generating yield data, they estimated the non-linear production function as a function of water and nitrogen and calculated the risk premium using the mean and variance of crop yields. By maximizing the certainty equivalent, they solve for the optimal nitrogen and water uses and find their optimal levels decrease with increasing price variability and increase with increased temperature and reduced precipitation.

There are various risk assessment methods that authors use to conduct risk analyses based on simulated distributions of yields or profits obtained under different climatic or management scenarios. Ramirez and Sosa (2000) and Luo et al. (2007) used conditional probability to assess risks, i.e., the conditional probability of not exceeding a certain yield or profit level. Clasen et al. (2011) used Sharpe Ratio (SR), which is defined as the difference in returns between one asset and the risk-free asset over the standard deviation, to value the risks. Castro et al. (2013) ranked different strategies using Second Order Stochastic Dominance (SOSD) tests. Abadie et al. (2016) used Value at Risk (VaR) and the Conditional Value at Risk (CVaR) to assess the risks. Finger (2012) and Lehmann et al. (2013) used risk premium measures to assess risks and used Certainty Equivalent (CE), which is the difference between the expected profit and risk premium, to represent the decision makers' utility. VaR, CVaR, and SOSD methods focus on a region of the cumulative distribution function. SR and Risk Premium are both a function of mean and variance. The conditional probability can be considered as a converse process of CVaR. Gloy and Baker (2001) showed that when producers evaluate risk management strategies, the SR, SOSD, and VaR are likely to produce similar results if the agents are very risk-averse. One advantage of the CE method is that it is expressed as an explicit function of a farmer risk aversion parameter.

The econometric models used mentioned above require large amounts of household or farm survey data, e.g. DiFalco et al. (2010) uses almost 1,800 surveys and are suited to provide empirical evidence of risk reduction effects from a particular context, while simulation models offer the flexibility to provide insights and recommendations under different scenarios. This advantage of simulation models is related to their ability to be linked to optimization models to identify the optimal amount of adaptation under different environmental, ecological, economic, and risk preference parameters.

In this thesis, we use a simulation model to represent CBB infestations in SGC and sun-grown coffee systems, generate the yearly profits received by farmers and identify the profit maximizing shading levels. Then, use the certainty equivalent method to solve for the utility-maximizing shading levels for risk-averse farmers. We estimate year-to-year temperature and price risks using the risk premium measure to estimate the risk-reduction effects of increasing shading levels

CHAPTER III. COFFEE PRODUCTION IN PUERTO RICO

Historical development

Coffee was first planted in Puerto Rico as an agricultural commodity in 1736, and it was a major commercial crop by the early 1800s (Borkhataria et al., 2012). Coffee was grown under a canopy of shade trees, in a production system referred to as traditional or shade-grown coffee. Hurricanes are main threats to coffee production in Puerto Rico, which typically lead to the abandonment of coffee plantations. Hurricane Hugo (September, 1989), coupled with a fall in coffee prices, labor shortages and low average yields per hectare, led to a sudden decline in coffee production in the latter part of 20th century (Zimmerman et al., 1995; Borkhataria et al., 2012). In the 20th century, to re-invigorate the coffee industry, researchers and governments recommended sun-grown coffee systems and the government subsidized inputs for such systems, which have higher intensity and thus higher yield per hectare (Borkhataria et al., 2012). The widespread conversion from traditional plantation to sun-grown systems occurred at the end of the 1980s. According to U.S. Department of Commerce (1980, 1994), the proportion of shade-grown coffee area declined from 95% in 1978 to 48% in 1992. However, the consequences of this practice caused soil erosion, loss of soil fertility, and loss of habitat and biodiversity (Ríos and Ferguson, 2015).

In recent decades, governmental and non-governmental organizations (NGOs) turned their attention to the benefits of shade-grown coffee, such as the conservation of wildlife habitat, reduction of soil erosion and other environmental benefits. For example, the Natural Resources Conservation Service (NRCS), U.S. Department of Agriculture (USDA), launched the Shade-

Grown Coffee Initiative in 2007, which helps farmers convert their sun-grown coffee to shade-grown plantations in Puerto Rico. Through this initiative, farmers have planted about 83,000 shade trees since 2007. The Shade Coffee Roundtable Initiative was instigated in March 2011, aiming to develop criteria for shade coffee certification in Puerto Rico and identify incentives for planting shade-grown coffee (Ríos and Ferguson, 2015).

Table 1. The history of coffee production in Puerto Rico

Year	History
1736	Coffee was introduced to Puerto Rico
The 1800s	Coffee was a major commercial crop by the early 1800s
The 1900s	Coffee had replaced sugar as PR's leading agricultural commodity
The late 1960s	Sun-grown coffee has been encouraged because the intensive coffee management had the potential to increase yields
The 1980s	Widespread conversion to sun coffee
The 21st Century	Policies to encourage shade-grown coffee

Source: Borkhataria et al. (2012)

Trends of coffee production and market value in Puerto Rico

As shown in Figure 2, coffee outputs peaked in 1992 at about 17.3 million kg in Puerto Rico. From 1978 to 1992, coffee outputs almost doubled from 9.0 million kg to 17.3 million kg. However, probably due to the devastating Hurricane Georges in 1998 and other economic factors, such as high labor costs and low coffee prices, coffee production showed a steady decline from 17.3 million kg in 1992 to 6.5 million kg in 2012. There's a similar trend for the share of coffee's market value in the total crop products, which peaked in the 1980s. Coffee accounted for about 16.1% of total market value in 1978, and this share increased to 30.3% in 1982 and had small fluctuations around 30% in the 1980s. Coffee was the dominant crop in terms of market value from 1982 to 1998 in Puerto Rico. In 2002, plantain surpassed coffee as the dominant crop, with a share of 20%, compared to 17% for coffee. Coffee's share declined to

10.8% in 2012, following behind plantain (29.7%) (USDC, 1980, 1984, 1989, 1994; USDA, 2004, 2009, 2014; similarly hereinafter unless otherwise indicated)[3].

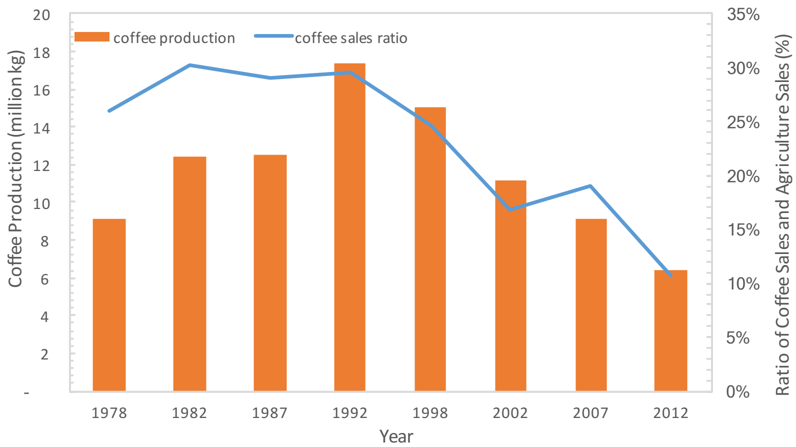

Figure 2. Coffee production and the ratio of market value (1978-2012)
Data source: (USDC, 1980, 1984, 1989, 1994; USDA, 2004, 2009, 2014).

Trends of numbers and sizes of coffee farms

As shown in Fig. 3, from 1978 to 1992, the total number of coffee farms increased from 8,890 to 11,263, but a considerable decline followed. In 2012, Puerto Rico had only 4,478 coffee farms left, which is 40% of the number in 1992. At the same time, along with the decreases in the farm numbers, the farm sizes also have shrunk over the years (see Fig. 4). The share of farms which were less than ten cuerdas - around 3.9 hectares - increased dramatically from about 20% in 1982 to 47% in 2012. The shares of farms that were in other intervals all decreased. The share of farms of sizes 50-99 cuerdas decreased from 11% to 3.1%. The farms which were higher than (and equal to) 100 cuerdas accounted for only 2.2% which that share was 10.2% in 1978. Given the fact that 43% of coffee farmers were over 65 years old and only 7% farmers are less than 45

[3] The data used in this chapter are from Census of Agriculture conducted by the U.S. Department of Commerce (USDC) and U.S. Department of Agriculture (USDA). The data sources are USDC (1980, 1984, 1989, 1994) and USDA (2004, 2009, 2014).

years old in 2012, we can project that the numbers and sizes of coffee farms would shrink in the following years if there are no encouraging incentives.

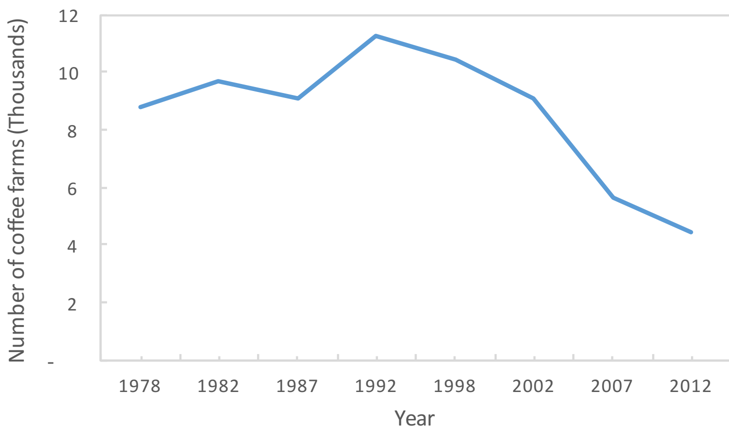

Figure 3. Number of coffee farms in Puerto Rico (1978-2012)
Data source: (USDC, 1980, 1984, 1989, 1994; USDA, 2004, 2009, 2014).

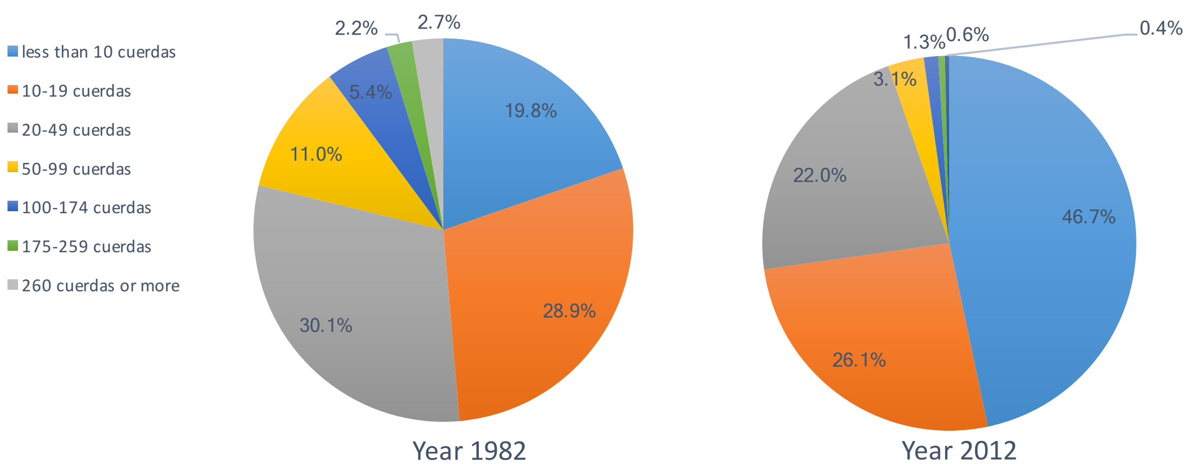

Figure 4. Sizes of coffee farms in Puerto Rico (1982 and 2012)
Note: 1 cuerdas = 0.393 hectare (Borkhataria et al., 2012). Data source: (USDC, 1984; USDA, 2014).

Trends of shade-grown coffee

As Figure 5 shows, shade-grown coffee covered the vast majority of coffee planting area (95%) and produced most coffee yields (89%) in Puerto Rico in 1978. In that year, 30,032 hectares of land was devoted to shade-grown farming while only 1,716 hectares were in sun-grown farming. However, the ratio of shade-grown coffee land area showed a steady decline from 1978 to 2012, while the ratio of shade-grown coffee yield decreased from 1978 to 2007 and had a slight increase from 24% in 2007 to 25% in 2012. The sun-grown farming has dominated since 1992. In 2012, the land area devoted to shade-grown farming accounted for only 28%.

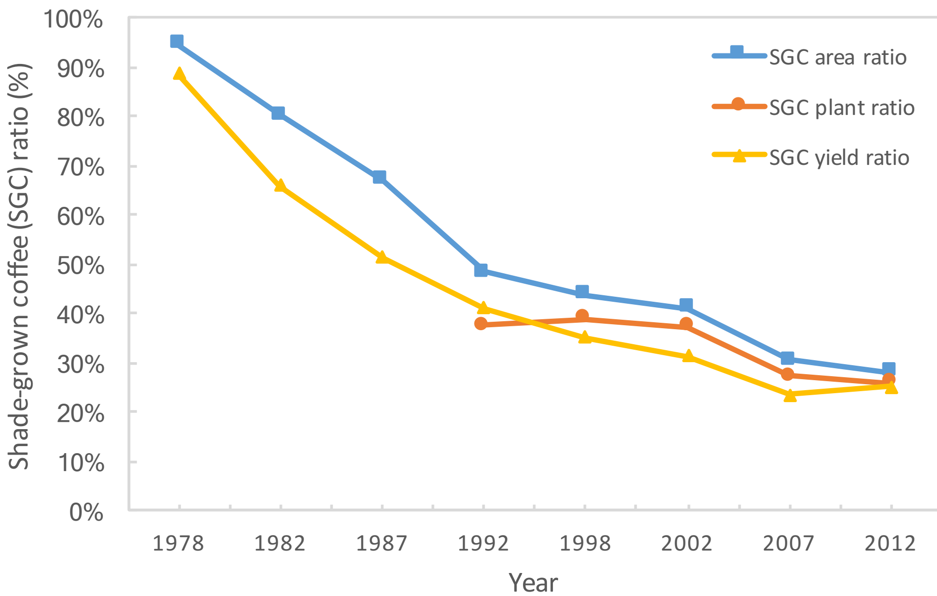

Figure 5. Trends of shade-grown coffee share in Puerto Rico in terms of area planted, number of coffee plants, and farm yields (1978-2012)
Data source: (USDC, 1980, 1984, 1989, 1994; USDA, 2004, 2009, 2014).

CHAPTER IV. THE YIELD AS A FUNCTION OF SHADE CANOPY

Shade tree covers in an SGC system can retain soil water and increase soil fertility. However, at high shading levels, shade trees may compete with coffee shrubs for water, sunlight, and other resources. Following the shade-yield estimation in Soto-Pinto et al. (2000), we use farm survey data (Iverson, 2015) to estimate the relationship between per-shrub coffee yield per plant and the canopy using ordinary least squares. The yield function estimated here serves as the pest-free yield in the CBB infestation simulation model in Chapter V. In the simulation model, we used it to model the shade-induced soil water retention and soil fertility ecosystem services.

Data and methods

The field survey was conducted in five areas, including Utuado, Jayuya, Lares, Adjuntas, and Ciales, in Puerto Rico in 2012 (Iverson, 2015). Data on coffee farming costs, yields, shrub densities, and shade tree percentages and species was collected from 33 coffee farm owners. Farm sizes are between 0.6 and 40 hectares. The range of shade tree cover is from 0.6% to 83.6%. The range of green coffee yield per hectare is from 180.7kg to 5855.2kg. The average green coffee yield per plant is between 0.1kg and 16.8kg.

Table 2.Summary statistics of primary data

Variable	Observations	Mean	Std. Dev.	Min	Max
Land area	33	5.2	7.4	0.6	39.4
Yield per plant (grams)	33	76.0	44.7	5.7	179.3
Shading richness	33	4.6	1.8	1.0	10.0
Canopy	33	36.5	29.1	0.6	83.6

Consistently with Soto-Pinto et al. (2000) where the estimation is done for shading levels between 20-70%, we estimate the yield model for shading levels between 15 and 80% (Table 3).

Table 3.Summary statistics for farms with 15% shade or more.

Variable	Observations	Mean	Std. Dev.	Min	Max
Land area	22	3.6	3.4	1.0	15.7
Yield per plant (grams)	22	65.4	46.3	5.7	179.3
Shading richness	22	5.0	1.8	2.0	10.0
Canopy	22	50.5	25.7	15.1	83.6

The assumed relationship between yield and shade canopy is:

$$Y = \beta_0 + \beta_1 Canopy + \beta_2 Canopy^2$$

where Y denotes log yields per plant (grams of dry coffee), $Canopy$ is the percentage of shade cover (%).

Following Soto-Pinto et al. (2000), we expect that there is a shading threshold below which benefits from shade-induced soil fertility and soil water retention increase per-plant yields and beyond which, per-plant yields decrease due to the competition between shade trees and coffee shrubs. Thus, we expect that $\beta_1 > 0$, $\beta_2 < 0$.

Results

Using ordinary least squares estimation in Stata, we obtain the following estimated model where values in parentheses are standard errors:

$$\underset{(0.907)}{Y = 2.217} + \underset{(4.402)}{8.046} * Canopy - \underset{(4.340)}{7.489} * Canopy^2$$

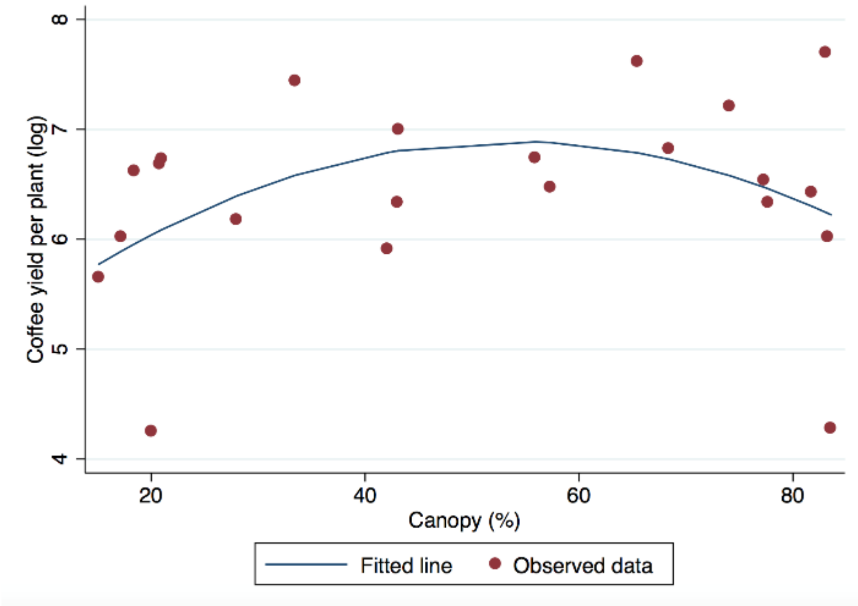

Figure 6.Effect of shading level on coffee yield per plant (R^2 = 16%)

As shown in Fig. 6, the canopy has a positive effect on the coffee yield per plant if the canopy is between 15% and 54%. When the canopy exceeds 54%, the canopy has negative effect on the per-plant coffee yield. The maximized yield occurs at the 54% canopy level.

The results are qualitatively similar as those in Soto-Pinto et al. (2000), i.e., shade canopy is beneficial to coffee yield within a certain range, likely due to soil water retention and soil fertility ecosystem services provided by the shade trees. When the canopy exceeds the threshold, increasing canopy may decrease decreases the per-plant coffee yield due to the competition between shade trees and coffee shrubs. The difference in the yield-maximizing shade level here (54%) and the one in Soto-Pinto et al. (2000) (40%) is likely due to the shade tree species and their marginal contribution to yield (i.e., parameter β_1).

Although this estimated model is theoretically consistent with a non-linear relationship between shade and yields, its statistical explanatory power is not strong (R^2 = 16%). This model only includes the canopy level as the explanatory variable, but there are other variables that affect coffee production, such as fertilizer use, soil fertility and farmer characteristics, that are highly heterogeneous across farms. Given the small sample size, it was not possible to include such explanatory variables.

CHAPTER V. THE OPTIMAL SHADING LEVELS

This chapter aims to construct an integrated bioeconomic model that incorporates the ecosystem service values and the risk preferences into a representative farmers' decision-making process to find the optimal amount of the adaptation. Figure 8 presents a graphical overview of the methodological framework (models and required data).

This bioeconomic model is basically composed of a cellular automata model and an economic model. The cellular automata model is used to simulate the infestation of CBB given different shading strategies, with the effects of temperature fluctuations considered and shade-induced local temperature reduction on pest dynamics over space and time, and to construct the resulting yield damage function. The economic model, which includes the yield damage function, the production function, distribution of prices, costs, and a discount factor, computes the yearly profits and the total net present values (NPVs) over 25 years, and generates distributions of NPVs through Monte-Carlo simulations. The ecosystem production function in the model is based on the empirical estimation in Chapter 4 used to characterize the relationship between canopy and coffee yield. Finally, we use the yearly profits and the distribution of NPVs, to compute the expected net present value (ENPV), several risk measures, and farmer utility with increasing risk aversion coefficients.

Methods

The cellular automata model

Following Atallah, Gomez, and Jaramillo (2018), we use a cellular automata model to simulate the infestation of CBB in a half-hectare coffee farm. In this model, the farm is represented by a two-dimensional grid G, which includes I rows and J columns, i.e., $I \times J$ cells where each cell (i, j) denotes either a coffee shrub or a shade tree. In a sun-grown coffee system, there are 1,444 unshaded shrubs on the farm, i.e., $I = 38$ and $J = 38$[4]. In a shade-grown system, a cell (i, j) is either occupied by a coffee shrub or a shade tree, depending on the level of shade adopted by the farmer. A cell cannot be occupied by both simultaneously because of space competition between coffee shrubs and shade trees. The location of shade trees is chosen at random. The total number of cells, including both those occupied by coffee shrubs and shade trees, in a shade-grown system is 1,296, with $I = 36$ and $J = 36$. The number of coffee shrubs depends on the shading level, which is the decision variable in the bioeconomic model. The shading level is defined as the percentage of the shade trees in a farm.

$$Shading\ level = \frac{N_{shade}}{N_{shade} + N_{coffee}} \tag{1}$$

where N_{shade} denotes the number of shade trees, and N_{coffee} denotes the number of coffee shrubs.

[4] The densities of the sun-grown system and shade-grown system are sourced from USDA Census data. Include the citation incl. year.

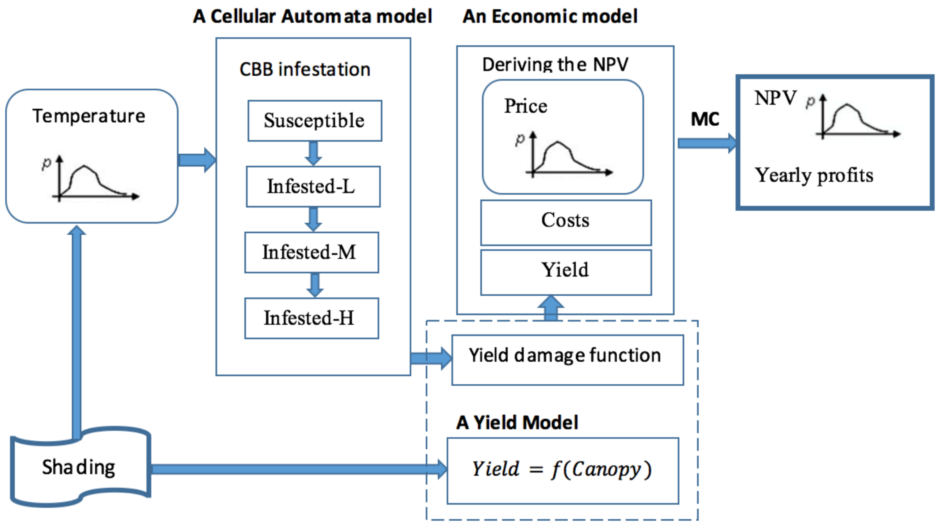

Figure 7. Method Framework

We use a Moore neighborhood for each cell, i.e., each cell (i, j) in the grid G has eight neighbors. Each cell can only interact (e.g., through pest dispersal, temperature reduction from shade) with its immediate neighbors. We define a coffee shrub as being shade-grown if it has at least one shade tree neighbor and shade-grown coffee shrubs will have a temperature reduction due to the shade. For example, when a cell (i, j) represents a shade tree, the coffee shrubs in its eight neighboring cells are all shade-grown coffee shrubs. According to Soto-Pinto et al. (2000), the amount of shade provided by shade trees is defined as the canopy of the coffee shrubs. Following Atallah, Gomez, and Jaramillo (2018), we assume that a shade tree provides 30% canopy for each of its neighboring cells and the maximal canopy for a coffee shrub is 100%. The canopy for a coffee shrub is defined as:

$$canopy = \begin{cases} 30\% \times N_{Shade} & if\ 30\% \times N_{Shade} < 1 \\ 1 & otherwise \end{cases} \quad (2)$$

where N_{Shade} is the number of shade tree neighbors.

Since a cell can represent either a coffee shrub or a shade tree, we define a tree type state variable $\tau_{i,j}$ that equals to 1 if the cell (i,j) represents a coffee shrub and equals to 0 if the cell (i,j) represents a shade tree.

$$\tau_{i,j} = \begin{cases} 1 & if\ a\ coffee\ shrub \\ 0 & if\ a\ shade\ tree \end{cases} \tag{3}$$

In addition to the tree type states, each cell has various different age states, $a_{i,j,t}$,and four different infestation states, $s_{i,j,t}$, , which are changing over time t. Assuming the lifetime of a coffee shrub is 25 years, then the time dimension of the model is 9,130 days (25 years), and each model step is one day. The age state $a_{i,j,t}$, for each cell (i,j) updates daily and has 9,130 different states. Similarly, the infestation state $s_{i,j,t}$ for each cell (i,j) updates every day. Each cell has four infestation states: healthy (H), infested-low (I_L), and infested-moderate (I_M), and infested-high (I_H). We define $s_{i,j,t}$ is a 4×1 dimension vector that represents the infestation states of each cell (i,j).

$$s_{i,j,t} = \begin{cases} (1,0,0,0)' & if\ healthy \\ (0,1,0,0)' & if\ infested - low \\ (0,0,1,0)' & if\ infested - moderate \\ (0,0,0,1)' & if\ infested - high \end{cases} \tag{4}$$

The transition from state healthy to infested-low for a cell is defined by the infestation states of its neighbors and its net temperature. If a coffee shrub, which is in the healthy state, has no infested neighbors, its infestation rate is zero. If it has at least one infested neighbor, it will get infested after a certain amount of time. The period, or waiting time, is a function of temperature.

$$L1\left(s_{i,j} = I_L \middle| s_{i,j} = H\right) = \begin{cases} \alpha_1 + \alpha_2(T_t - \Delta T) & if\ NN_{i,j} \geq 1 \\ \infty & if\ NN_{i,j} = 0 \end{cases} \tag{5}$$

where T is the farm temperature, ΔT is the cell-level temperature reduced by the shade, $NN_{i,j}$ is the number of infested neighbors for the cell (i, j), α_1 and α_2 are parameters and $\alpha_1 > 0$, $\alpha_2 < 0$. For the coffee shrubs without shade, $\Delta T = 0$. For the shrubs with shade, we assume shade cover reduces the temperature around the berries (i.e., cell-level temperature) by a percentage reduction σ, i.e., $\Delta T = \sigma T$. According to Barradas and Fanjul (1986), $\sigma = 15\%$ is applied in our model. According to Eq. (5), it will take longer for a shaded coffee to get infested, compared an unshaded one.

The transition time from state infested-low to infested-moderate is a function of net temperature.

$$L2\left(s_{i,j} = I_M \middle| s_{i,j} = I_L\right) = \alpha_3 + \alpha_4(T - \Delta T) \tag{6}$$

We assume that if a coffee shrub is shaded, it will never reach the infested-high state. For the unshaded shrub, it will take about 60 days to be infested-high (Johnson et al., 2009). The waiting time from infested-moderate to infested-high is

$$L3\left(s_{i,j} = I_M \middle| s_{i,j} = I_L\right) = \begin{cases} 60 & if\ it\ has\ no\ shade \\ \infty & if\ it\ is\ shaded \end{cases} \tag{7}$$

The infestation states, tree type states and canopy levels simulated in this cellular automata model will enter the subsequent economic model and be used to calculate the NPVs.

The economic model

The before described infestation states will decide a yield damage function, which, together with the yield function for healthy shaded coffee estimated in Chapter IV, can be used to calculate the total yields of a coffee farm. We will introduce the costs of coffee and shade tree production, the prices for shade-grown and sun-grown coffee, and the discounting factor in this section. Based on the historical temperature and price data, the yearly profits of 25 years will be received and can be used to calculate the year-to-year risks faced by farmers. In addition, the distribution of NPVs over 25 years will be generated using the Monte-Carlo simulation and used to calculate the risks due to the variability of prices and temperatures.

(1) The yield damage function

At each time t, each cell has a tree type state $\tau_{i,j,t}$ and an infestation state $s_{i,j,t}$, we can map the states to a yield damage function $\tilde{y}_{s_{i,j,t}}$. We use a percentage to represent the damages due to CBB infestation. Based on Duque and Baker (2003), coffee yields are reduced by 2%, 6%, and 20% if the coffee shrub is in the infestation state of infested-low, infested-moderate, and infested-high respectively. In a shade-grown coffee system, shade trees decrease the temperature around coffee shrubs, and therefore delay the infestation stages, so that the shade-grown coffee system benefits from pest regulation ecosystem services (Johnson et al., 2009; Atallah, Gomez, and Jaramillo, 2018).

(2) The NPV function

We use the historical prices for the unshaded coffee. For certified SGC, we consider price premiums. The objective function of a farmer can be represented by:

$$NPV = \sum_{t=1}^{9125} \rho^t \cdot \sum\nolimits_{(i,j)} \left(r\left(\tau_{i,j}, s_{i,j,t}, a_{i,j,t}\right) - c_{1\ i,j,t} - c_{2\ i,j,t} \right) - u_{i,j,0} \left(r\left(\tau_{i,j}, a_{i,j,t}\right) - c_{u_{i,j,0}} - c_{u_{i,j,t}} \right)) \quad (8)$$

where NPV denotes the net present value for farmers; (i, j) denotes a cell in farm $I \times J$, t denotes time, $s_{i,j,t}$ denotes the state in cell (i, j) in time t; ρ is the discount factor per day; $r\left(\tau_{i,j}, s_{i,j,t}, a_{i,j,t}\right)$ is the revenue from a coffee shrub, which is a function of tree type states, infection state and age states; $c_{1\ i,j,t}$ is the unit cost of coffee production; $c_{1\ i,j,t}$ is the unit cost of replanting sun-grown coffee shrubs, which occurs every five years; $u_{i,j,o}$ is a binary variable that equals 1, if a cell has a shade tree and 0 otherwise; $r\left(\tau_{i,j}, a_{i,j,t}\right)$ is the revenue from a shade tree, which is a function of tree type and age state; $c_{u_{i,j,o}}$ is the unit cost of planting a shade tree; $c_{u_{i,j,t}}$ is the unit cost of maintaining a shade tree. All total costs are assumed to be linear (i.e., calculated by multiplying unit costs with quantity).

For a coffee shrub in cell (i, j) in time t, revenue equals to:

$$r\left(\tau_{i,j}, s_{i,j,t}, a_{i,j,t}\right) = p \cdot yield_{shade} \cdot (1 - \tilde{y}_{s_{i,j,t}}) \quad (9)$$

where p is the coffee price, $\tilde{y}_{s_{i,j,t}}$ is the yield reduction percentage due to CBB, and

$$yield_{shade} = yield_{sun} + \beta_1 \cdot (canopy) + \beta_2 \cdot (canopy)^2 \quad (10)$$

where $yield_{sun}$ is the sun-grown coffee yield per plant per day and $canopy$ is the shading level for a certain coffee shrub.

Farmers' utility function

We follow Finger (2012) and Lehmann et al. (2013) in using the certainty equivalent (CE) to represent the utility function of farmers with risk preferences. The CE is defined as the sure sum of money that has the same utility as the expected utility of a risky alternative (Keeney and Raiffa, 1976) and is defined as follows:

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

where NPV is the net present value, π is risk premium; for a risk aversion farmer, $\pi > 0$.

Risk premium is the amount of money the farmer is willing to pay to eliminate risk exposure. According to Pratt (1964), the risk premium can be approximated by

$$\pi \approx \frac{1}{2} \cdot \frac{\gamma}{E(NPV)} \cdot \sigma_{NPV}^2$$

where γ is the coefficient of relative risk aversion, and σ_{NPV}^2 is the variance.

Thus, we get the following expression for CE:

$$CE = E(NPV) - \frac{1}{2} \cdot \frac{\gamma}{E(NPV)} \cdot \sigma_{NPV}^2 \tag{11}$$

Model Initialization and Parameterization

Model Initialization

Depending on the shading level assigned, a certain percentage of cells are initialized as shade trees. All remaining cells are initialized as coffee shrubs in health state *Healthy*. In every September, when berries are ripe, 0.5% of the coffee trees are chosen randomly to transit from *Healthy* (H) to *Infected-low* (I_L). Every December, when berries are harvested, all the coffee shrubs transit to *Healthy* (H) state. We assume that the model starts at the time of planting and coffee shrubs do not bear fruits until year 4. The baseline scenario assumes that farmers receive an 8% price premium for shade grown coffee. For example, the price of shade grown coffee is \$3.41/kg if the price of sun grown coffee is \$3.16/kg.

Model Parameterization

Temperature T_t in Eq. (5) and (6) is the historical daily daytime temperature from 1990 to 2014 in Adjuntas, Puerto Rico (NOAA 2018). Based on data in Johnson et al. (2009) and the model in Atallah, Gomez, and Jaramillo (2018), parameters α_1 and α_2 in Eq. (5) are equal to 285 and 10 respectively and parameters α_3 and α_4 in Eq. (6) are equal to 285 and 10 respectively.

Table 4 shows the values for economic parameters in Eq. (8) - (10). The prices p_t for sun-grown coffee are historical international coffee prices sourced from Macrotrends (2018). For shade-grown coffee, we consider three price premium scenarios, i.e. no price premium, high price premium (16%), and moderate price premium (8%), which is the baseline scenario.

Table 4. Economic parameters

Parameter	Description	Unit	Coffee production system	
			Sun	Shade
			Value	
Coffee				
$\boldsymbol{y_{sun}}$	Yield-sun[b]	Kg/tree/year	2.2	n/a
$\boldsymbol{\beta_1}$	Yield-shade[b]		n/a	0.0248
$\boldsymbol{\beta_2}$	parameters[b]		n/a	-0.0259
$\boldsymbol{c_{1\ i,j,t}}$	Production cost[a]	USD/tree/year	1.28	1.28
$\boldsymbol{c_{2\ i,j,t}}$	Replanting cost	USD/tree/year	1.28	n/a
Shade				
$\boldsymbol{y_{shade}}$	Yield	Inches/tree/year	n/a	0.0099295
$\boldsymbol{p_{shade}}$	Price	USD/inch	n/a	537
$\boldsymbol{c_{u_{i,j,o}}}$	Planting cost	USD/tree	n/a	0.12
$\boldsymbol{c_{u_{i,j,t}}}$	Maintenance cost	USD/tree	n/a	0.01
$\boldsymbol{\rho}$	Discount rate	year^{-1}	10%	10%

[a] Parameter values are from Atallah, Gomez, and Jaramillo (2018), unless otherwise noted.
[b] Estimated in Ch. 4

Data generation process

The distribution of NPVs over 25 years and the yearly profits are generated from the bioeconomic model, which combines the cellular automata model and the economic model.

Initially, stochasticity is introduced to the model by the random locations of initial infestation of CBB and the random selection of shade tree position. We generate NPVs over 25 years and yearly profits for different shading levels. There are two types of randomness sources in the model. The variability capture in the expected NPV includes only the variability among simulation runs generated by the random spatial allocation of initial infestation and shade trees and excludes the effect of variability in temperatures and prices from year to year. The second source of variability is captured in yearly profits of 25 years and represent the risks caused to the farmer by year-to-year changes in temperature and price.

In each simulation, the shading level is the decision variable. The shading levels range from 5% to 80%. Decisions are made at the beginning of the model (the day zero of the 25 years). We account for farmers' preferences over risk as defined by NPV variability from year to year generated by temperature and price variability and affected by a farmer's decision over the shading level.

Results

Farmer risk neutrality case

In Fig. 8, we report the effect of increasing shading levels on the NPV of a half-hectare coffee farm with CBB infestation under all the baseline assumptions. Shade-grown systems have higher NPVs than sun-grown systems when the shading level is between 12% and 37%. The highest NPV occurs at 24% shading level and the NPV at this optimal shading level is about $24,593 /0.5ha over 25 years.

When the shading level is lower than the optimal point, 24%, the NPVs are increasing with increasing shade, which indicates increasing net benefits from shade-induced ecosystem services, namely CBB control, water provision, soil health, and increased coffee quality rewarded by a price premium for shade-grown coffee. Although there are shade-induced costs associated with increasing shade levels, such as lower coffee density and increased labor costs, the benefits exceed these costs within this shading range. However, for shading levels higher than 24%, the competition between shade trees and coffee shrubs increases and causes the overall costs to increase relative to the benefits, including the CBB control and price premiums provided by the shade. For shading levels beyond 70%, shade-related costs outweigh shade-induced benefits, under the baseline model parameters.

Fig. 9 represents the situation where there are no CBB infestations. Although a farm is unlikely not to have any CBB infestation, this scenario allows us to test the relative importance of pest control ecosystem service benefits to the total benefits from soil water retention services, soil fertility services, timber, and the price premium. Results show that sun-grown systems have higher NPVs than shade-grown systems for all shading levels, which means that the benefits of shading, including the ecosystem services and price premiums, are lower than shade-related costs if there are no benefits of CBB control. In comparison to Fig. 8, there is no benefit to increasing shading level in Fig. 9: the relationship between NPV and shading level is negative and linear instead of concave, from which we can conclude that the benefits of shading never exceed the cost of shading, when there are no CBB control benefits. We conclude that the CBB control service is the main component of the benefits in Fig. 8.

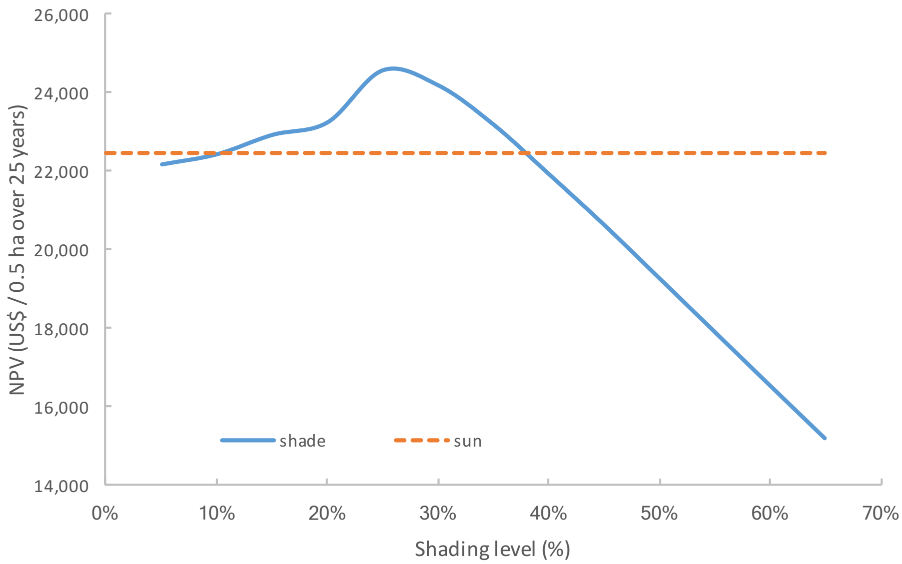

Figure 8. Effect of shading on the NPV of a half-hectare coffee farm with CBB infestation

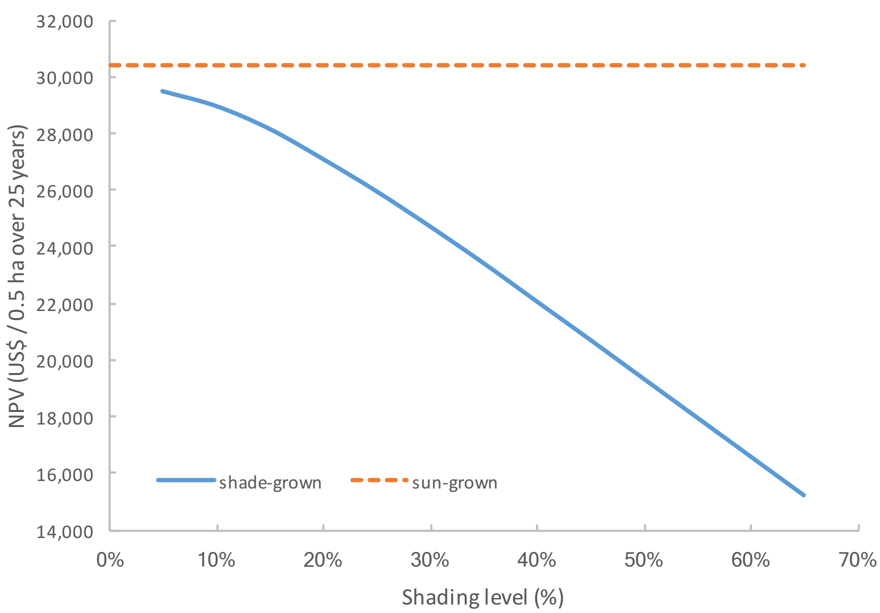

Figure 9. Effect of shading on the NPV of a half-hectare coffee farm without CBB infestation

Case where a farmer is averse to year-to-year risk

Results of the certainty equivalent maximization for risk-averse farmers are shown in Fig. 10 and Fig. 11. We assume a moderate level of relative risk aversion, i.e., $\gamma = 2$, as in

Gardebroek (2006) and Finger (2012). In comparison to risk-neutral farmers, risk-averse farmers tend to choose higher shading levels. The shade-grown systems have higher utility than sun-grown at any shading level, and the optimal shading level is 30% for moderately risk-averse farmers. Similarly, for the scenario with no CBB infestations, a relatively risk-averse farmer derives higher utility from shade-grown systems with shading levels between 5% and 55%, relative to a sun-grown farm. The optimal shading level is 10%, compared to 0% in the case of a risk-neutral farmer with CBB.

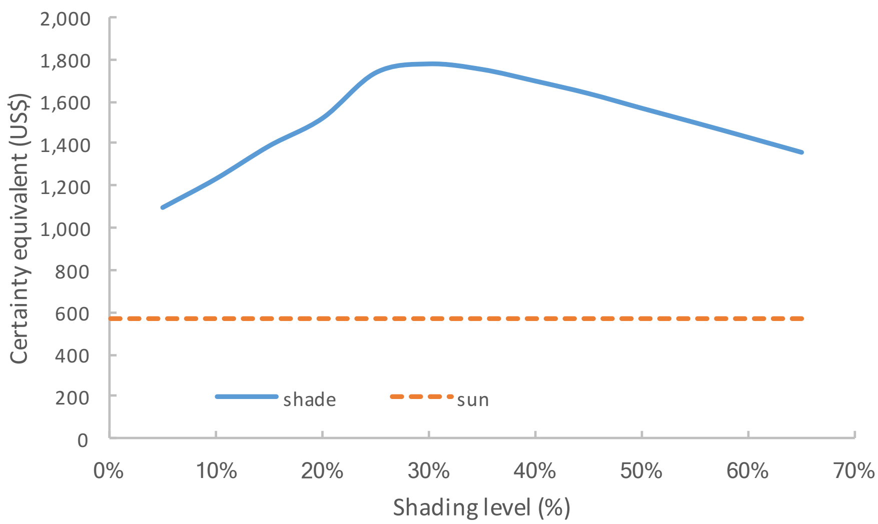

Figure 10. Effect of shading on the CE of risk-averse farmers with CBB
Note: Risk aversion coefficient is 2, i.e. moderate risk aversion according to Gardebroek (2006) and Finger (2012).

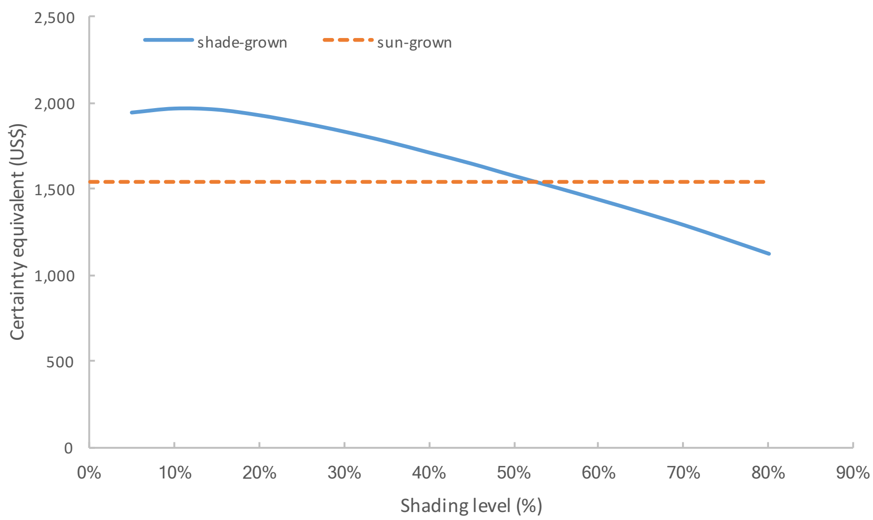

Figure 11. Effect of shading on the CE of risk-averse farmers without CBB
Note: Risk aversion coefficient is 2, i.e. moderate risk aversion according to Gardebroek (2006) and Finger (2012).

The shade-grown systems have risk-reduction effects: As shown in Fig. 12, the risk premium for risk-averse farmers decreases with increasing shading levels. One reason is that shade trees reduce temperature around coffee shrubs and control the infestation of CBB, which lowers the year-to-year production risks due to CBB. Secondly, the profits from shade trees provide farmers with an additional source of income, which can reduce the coffee income risks due to both production risk and price risk.

A related finding is that higher risk aversion leads to higher shading level selection (Table 5). For low risk-averse farmers, the optimal shading level is 24%, while for extremely high risk-averse farmers, it increases to 70%. The optimal shading level increment is from 24% to 30% when risk aversion coefficient changes from 1 to 2, while the increment is from 30% to 70% when risk aversion coefficient changes from 2 to 3.

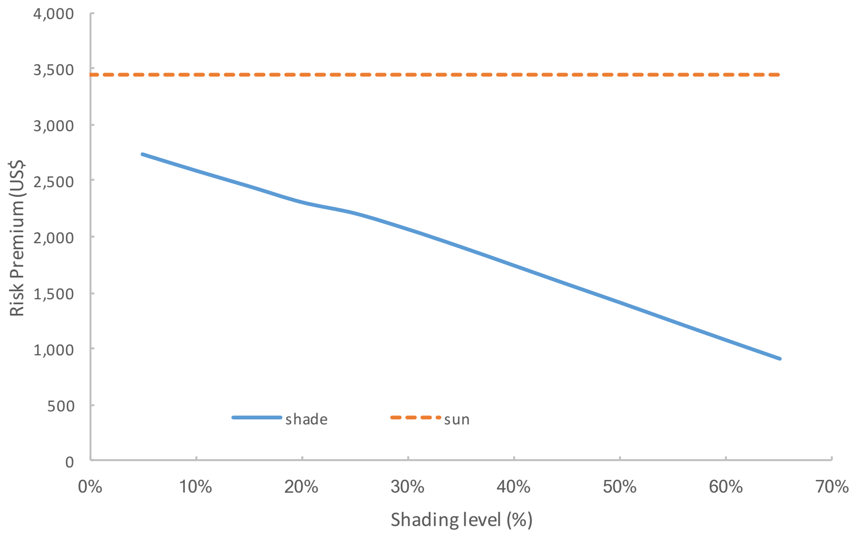

Figure 12. Changes of risk premiums with shading levels
Note: Risk aversion coefficient is 2, i.e. moderate risk aversion according to Gardebroek (2006) and Finger (2012).

Table 5. The effect of risk aversion on the optimal shading level

Risk aversion coefficient		1	2	2.25	2.5	2.75	3
Optimal shading level	CBB	24%	30%	30%	35%	45%	70%
	no CBB	sun[a]	10%	15%	20%	45%	70%

Note: [a] sun means sun-grown coffee.

Sensitivity analysis

Three price premiums

The price premium in the baseline scenario is moderate (8%). In this section, we test the model sensitivity to two other values of the price premium: no price premium and a high price premium of 16%. When there is no price premium for shade-grown coffee, the optimal shading level is still 24% for risk-neutral farmers and the optimal NPV is \$22,600 /0.5ha over 25 years, which is 8.1% lower than that in the baseline scenario (Fig. 13). When farmers receive a high price premium of 16%, the optimal shading level is 25%, slightly above the baseline optimum. The optimal NPV is 8.3% higher (\$26,633 /0.5ha over 25 years) compared with the baseline.

High price premiums may lead to higher optimal shading levels but the increase is not meaningful.

In addition, Fig. 13 shows that the rate of increase in the NPV function is larger for higher price premiums. The price premium for shade-grown coffee constitutes therefore an important component of the shade-related benefits.

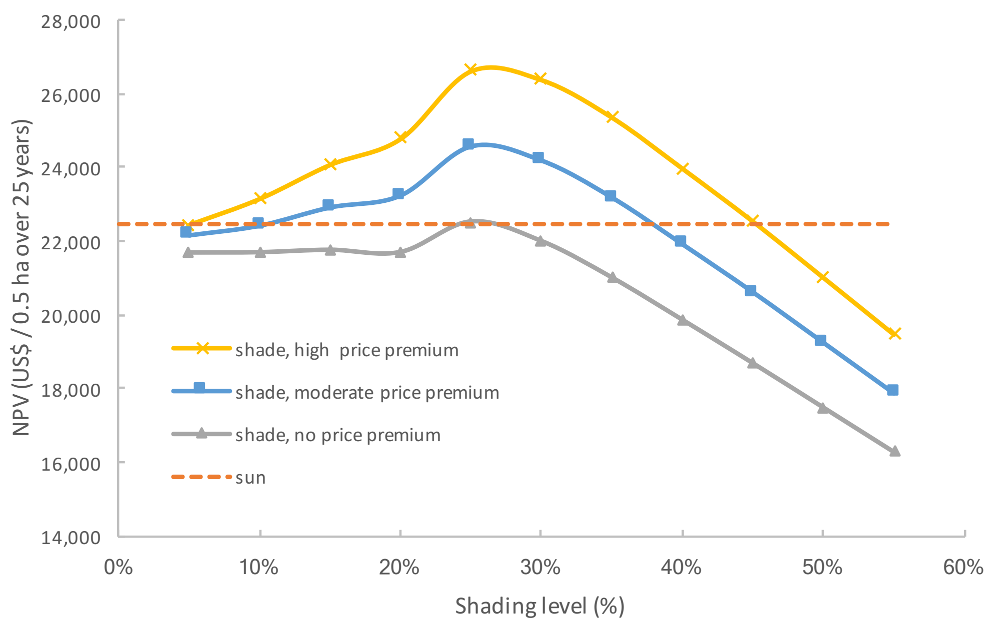

Figure 13. Effect of shading on the NPV of a half-hectare coffee farm under different price premiums
Note: Moderate price premium: 8% (baseline); High price premium: 16%.

Fig. 14 shows the results for risk-averse farmers under the same three price premiums. When there is no price premium, the optimal shading level is 40%, compared to 30% for the baseline case of a moderate price premium. The main reason is that lower price premiums dramatically reduce the slope of the CE functions, more than the reduction in the slope of the NPV function in Fig. 13, which increases the shading level at which the maximum is reached. When farmers receive a high price premium, the optimal shading level for risk-averse farmers is unchanged (30%) with respect to the baseline case of a moderate price premium These results suggest a complex relationship between price premiums and shading levels in the case of risk-averse farmers that did not exist for risk-neutral farmers. While increasing price premiums can be used as an incentive for risk-neutral farmers to increase their shading levels, the same cannot be said for risk-averse farmers for whom it might be optimal to reduce the shade level (e.g., from 40% to 30%) as a response to receiving a moderate price premium (e.g., 0% to 8% price premium). With higher price premiums, a risk-averse farmer can maximize their CE at lower shading levels.

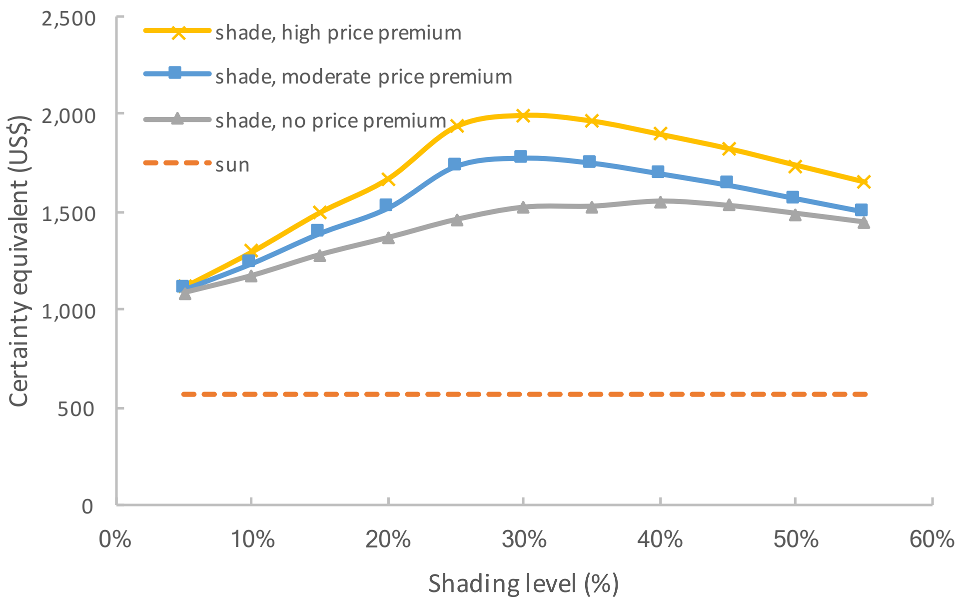

Figure 14. Effect of shading on the CE of risk-averse farmers under different price premiums
Note: Risk aversion coefficient is 2, i.e. moderate risk aversion according to Gardebroek (2006) and Finger (2012). Moderate price premium: 8% (baseline); High price premium: 16%.

Sensitivity analysis to ecological parameters

Firstly, we conduct the sensitivity analysis to the initial infestation level, i.e., the percentage of coffee trees that are chosen to transit from *Healthy* (H) to *Infected-low* (I_L) every September. The optimal shading level is 25% for risk-neutral farmers when the initial infestation level increases from 0.5% to 1%, and the new optimal NPV is $23,807/0.5ha, 3.2% lower than the baseline ($24,593). When we increase the initial infestation level from 1% to 5%, the optimal shading level is 25% while the optimal NPV is 7.7% lower than the baseline. If we decrease the initial infestation level from 0.5% to 0.1%, the optimal shading level is still 24% while the optimal NPV increases by 4.9%. These results show that the optimal shading level is mildly sensitive to the initial infestation level, and higher initial infestation leads to lower optimal NPV, as expected.

We also test the model's sensitivity to the parameters related to infestation states transition, i.e., the parameter of waiting time between *Healthy* (H) and *Infected-low* (I_L) (α_1), parameter of waiting time between *Infected-low* (I_L) and *Infected-moderate* (I_M) (α_3), waiting time between *Infected-moderate* (I_M) and *Infected-high* (I_H) ($L3$). When we decreases α_1 from the baseline of 285 days to 280 days, the optimal shading level increases as expected, from 24% to 25%, and the optimal NPV decreases by 1.1%. If we increase α_1 from 285 days to 290 days, the optimal shading level remains 24% while the optimal NPV increases slightly by 2.14%. When we decrease α_1 to 275 days, the resulting optimal shading level is 27% and the NPV is 2.3% lower than the baseline. We can conclude that the optimal shading level is most sensitive to α_1, but the resulting changes in optimal shading level are not large-enough to practically change recommendations and the optimal NPVs are relatively stable to small changes in α_1.

As for the parameter α_3 in the waiting time function from *Infected-low* (I_L) and *Infected-moderate* (I_M), results show that a lower (280 days) or a higher (290 days) value of this parameter do not change the optimal shading level and have little effects on the optimal shading level (about 0.1%). For the waiting time between *Infected-moderate* ($\mathrm{I_M}$) and *Infected-high* ($\mathrm{I_H}$) , L3, when we decrease it from 60 days to 45 days, the optimal shading level remains at 24% and the optimal NPV is just 0.2% lower than the baseline. Similarly, if we increase L3 from 60 days to 120 days, the optimal shading level remains at 24% and the optimal NPV is 1.5% higher than its baseline value. These results show that the optimal shading level and optimal NPV are mildly sensitive to the parameter α_3 and L3.

In the baseline, we assume shade covers can reduce the temperature around coffee berries by 15% based on Barradas and Fanjul (1986). Here we test the model sensitivity to the temperature reduction percentage σ provided by shade covers. When we assume a lower temperature reduction (10%), the optimal shading level increases from 24% to 25%, and the optimal NPV reduces by 1.6%. When we assume a higher reduction percentage (30%), the optimal shading level remains at 24% while the optimal NPV increases by 2.0%. The optimum is mildly sensitive to the shade cover's temperature reduction percentage (σ).

Finally, we test whether the model is sensitive to yield reduction parameters for different infestation levels, i.e. 2% reduction for low infestation states, 6% for moderate, and 20% for high. When the yield reduction parameters are lower, i.e. 1%, 4%, 13% for low, moderate, and high infestation states respectively, the optimal shading level remains at 24%, while the optimal NPV has a small increase (1.8%). If the yield reduction parameters are higher, i.e. 3%, 9%, 30% for low, moderate, and high infestation states respectively, the optimal shading level changes to 25% and the optimal NPV is 2.3% lower than the baseline value. Results show that higher yield reduction parameters lead to higher optimal shading levels, as expected, and the optimal shading level and NPV are mildly sensitive to the yield reduction parameters.

In conclusion, among the ecological parameters, the optimal shading level is most sensitive to α_1, the parameter in the function of waiting time between *Healthy* (H) and *Infected-low* (I_L), followed by the initial infestation level. The optimal NPV is most sensitive to the initial infestation level. However, in summary, small changes in these ecological parameters do not change the basic recommendations we made based on the baseline and we can conclude that the model is mildly sensitive to all ecological parameters.

Table 6. Sensitivity analysis to ecological parameters

Parameter	Optimal shading level (% shade trees)	NPV ($1000/0.5ha)	Difference	Optimal shading level for risk averse farmers
Initial infestation (%)				
0.1	24%	25.794	4.9%	30%
0.5	24%	24.594	-	30%
1	25%	23.807	-3.2%	30%
5	25%	22.692	-7.7%	30%
Parameter of waiting time between *Healthy* (H) and *Infected-low* (I_L), α_1				
275	27%	24.029	-2.3%	35%
280	25%	24.323	-1.1%	30%
285	24%	24.594	-	30%
290	24%	25.120	2.1%	30%
Parameter of waiting time between *Infected-low* (I_L) and *Infected-moderate* (I_M), α_3				
280	24%	24.569	-0.1%	30%
285	24%	24.594	-	30%
290	24%	24.619	0.1%	30%
Waiting time between *Infected-moderate* (I_M) and *Infected-high* (I_H), $L3$				
45	24%	24.545	-0.2%	30%
60	24%	24.594	-	30%
120	24%	24.966	1.5%	30%
Temperature reduction (%), σ				
10	25%	24.208	-1.6%	30%
15	24%	24.594	-	30%
30	24%	25.073	2.0%	30%
Yield reduction parameters, $\tilde{y}_{s_{i,j,t}}$				
1;4;13	24%	25.037	1.8%	30%
2;6;20	24%	24.594	-	30%
3;9;30	25%	24.033	-2.3%	30%

Sensitivity analysis for economic parameters

In this section, we test the model sensitivity to discount rate (ρ), and the shade tree maintenance cost $(c_{u_{i,j,t}})$.

We generated new results for a lower (4%) and a higher (10%) discount rate. If the discount rate is 4% instead of 10%, the optimal shading level remains at 24%, while the optimal NPV has a large increase (120.5%). When the discount rate is 15%, the optimal shading level changes to 25%, and the optimal NPV decreases by 44.1%. When the discount rate is 30%, the optimal shading increases to 34% and the optimal NPV is substantially lower (88.2%). These large changes in the optimal NPV caused by changes in the discount rate values are expected because a higher discount rate lowers the present value of the future income and a lower discount rate means a higher present value of future income flow. The selection of a discount rate depends on the market interest rate and producers' attitudes toward uncertainties. The results show that our optimal shading recommendations are robust to the discount rate.

Table 7. Sensitivity analysis to economic parameters

Parameter	Optimal shading level (% shade trees)	NPV ($1000/0.5ha)	Difference	Optimal shading level for risk averse farmers
Discount rate (%)				
4	24%	54.244	120.5%	30%
10	24%	24.594	-	30%
15	25%	13.739	-44.1%	30%
30	34%	2.898	-88.2%	30%
Tree Maintenance cost ($)				
0.008	29%	26.955	9.6%	40%
0.01	24%	24.594	-	30%
0.012	24%	22.508	-8.5%	

Then, we test the model's sensitivity to the tree maintenance cost, which include the shade tree fertilization and pruning costs. When the maintenance cost decrease from $0.01 to $0.008, the optimal shading level increases to 29%, and the optimal NPV increases by 9.6%. When the maintenance cost increases to $0.012, the optimal shading level remains at 24%, while the optimal NPV decreases by 8.5%. The optimal results are relatively sensitive to the shade tree maintenance cost. This indicates that shade tree maintenance might be a barrier for adopting higher shading levels. Given that different types of shade trees have different levels of labor intensity, shade tree type selection is critical when making shading level recommendations.

CHAPTER VI. CONCLUSION

In this thesis, we constructed an integrated bioeconomic model that includes a coffee yield model that we estimated using farm-level survey data in Puerto Rico, a cellular automata coffee berry borer infestation model, and an economic model. The resulting model incorporates the values and costs of shade-induced ecosystem services into a farmer's decision-making and solves for the optimal amount of shade on a coffee farm for risk-neutral and risk-averse farmers.

We find that the shade canopy has a positive effect on the coffee yield per plant if the canopy is between 15% and 54%. When the canopy exceeds 54%, the canopy has negative effect on the per-plant coffee yield. The maximized yield occurs at the 54% canopy level.

By constructing a bioeconomic model to simulate the CBB infestation in shade-grown and sun-grown coffee systems, we reach the following findings:

For risk-neutral farmers, shade-grown systems have higher NPVs than sun-grown systems within a range of 12% - 37% shading levels. The optimal shading level is 24% and the optimal NPV is about $24,593 /0.5ha over 25 years. If we exclude the benefits from CBB control services, sun-grown systems have higher NPVs than shade-grown systems for all shading levels. CBB control service is the main component of the economic benefits from shading.

For risk-averse farmers, assuming a moderate level of relative risk aversion, shade-grown systems generate higher utility than sun-grown at any shading level, and the optimal shading level is 30%. For any level of price premium, higher risk aversion leads to higher shading level selection.

Finally, we find that model results are mildly sensitive to ecological and economic parameters. Among the ecological parameters, the optimal shading level is most sensitive to the

CBB infestation parameter α_1 in the function of waiting time between *Healthy* (H) and *Infected-low* (I_L). Among the economic parameters, the optimal shading level is most sensitive to the shade tree maintenance cost. However, small changes in the values of these parameters variables do not cause large-enough-results to change shading recommendations based on this model.

Besides the ecosystem services we considered in this thesis, i.e., yield-enhancing ecosystem services (i.e., soil water retention and soil fertility services), pest regulation services (i.e., CBB control), quality-enhancing ecosystem services (as proxied by a price premium), and timber, shade trees provide many other services, such as wildlife habitat conservation, water provision, and pollination, among others. Including such other shade-induced ecosystem services into the model is one of the possible extensions of this model. We expect that adding these ecosystem services to the model will increase the optimal shading level, in which case the optimal shading level suggested here is an underestimate.

In this model, we have assumed that coffee shrubs under grown under shade and under sun have the same productive lifespan. In practice, the lifespan of a coffee shrub grown under sun is likely shorter than that grown under shade. This model does not account for the additional replanting costs and lost productivity after planting and before fruit bearing that a sun grown farmer incurs. Accounting for these costs would increase the difference between sun-grown and SGC NPVs.

While shade provides pest control benefits, an optimal shading level for CBB control might provide micro-environmental conditions, chiefly higher humidity, that increases the risk of coffee rust infections. If this model were to include coffee rust infestations, the optimal shading level might be lower than suggested here. Farms in different locations may be at higher risks of droughts and CBB or heavy rain and coffee rust. Our results provide implications for coffee farms at a high risk of CBB infestations and low risk of coffee rust.

Finally, we assumed in this model that a farmer plants laurel trees. One possible extension of this model is to include other shade trees and find the optimal mix of timber and fruit trees that maximize the net benefits from shade while reducing risks to farmers.

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