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How do the risk preferences of smallholder farmers affect the attractiveness of restoration activities? Evidence from forest and agricultural land in Rwanda

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In 2011, the country of Rwanda made a commitment to restore the productivity of 2 million hectares of degraded forest and agricultural land. Agroforestry and improved woodlot management activities were proposed to restore the ecological and economic productivity of agricultural and forestland in Rwanda, but the activities have not been evaluated in terms of their financial profitability, profitability risk, or ecological impacts despite being significant factors that influence the adoption decisions of smallholder landowners who occupy the majority of land in the country. This paper evaluates the two activities from the perspective of risk-averse smallholders to show whether or not the activities are likely to be adopted. The paper presents a methodology that combines enterprise budgets, biological production functions and Monte Carlo analysis in an expected utility framework to investigate the financial profitability, financial risk and ecological impacts of the activities in a smallholder context in four provinces of Rwanda. Risk is accounted for by charactering the variability of financial and ecological outcomes, including profitability, crop and timber yields, erosion and carbon storage. The distributions of net present values of each activity are estimated and compared using stochastic dominance and certainty equivalence criteria in order to rank the activities. The results show that both activities are too risky from the perspective of smallholders. Internalizing the value of public ecosystem services does not change the results.

Key words: Forest landscape restoration, ecosystem services, land use, risk, stochastic dominance, international environmental policy, Monte Carlo analysis.

INTRODUCTION

In 2011, the country of Rwanda made a commitment to begin restoration of the economic and ecological productivity of 2 million hectares of degraded land by 2020 as part of a broad development strategy designed to secure livelihoods, reduce poverty and promote economic development (IUCN, 2015). Improving the

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productivity of the country's land base is important in achieving its development goals as an estimated 90% of the population and 70% of the country's land area are devoted to subsistence agricultural production. A further 16% of land area is allocated to fuelwood and timber production to meet the country's energy needs (Habiyambere et al., 2009).

Government ministries, non-governmental organizations (NGOs) and development agencies have proposed several activities to improve the productivity of smallholder-owned agricultural and woodlot land in the country (Belgian Development Agency, 2012; WVI, 2015). The activities are generally designed to improve the productivity of agricultural land and woodland by increasing crop and timber yields, reducing soil erosion, increasing forest cover and conserving biodiversity. Most recently, the Rwandan Natural Resource Authority in partnership with the International Union for the Conservation of Nature (IUCN) and the World Resources Institute (WRI) led a stakeholder centered process to identify 'restoration' activities that would be suitable on smallholder owned land in Rwanda. At the conclusion of the process, two land-use activities were recommended to improve the production of different services on agricultural and woodlands. The Rwandan Natural Resource Authority is considering promoting the technologies to smallholders through extension and outreach campaigns.

To date, the activities have not been evaluated in terms of their financial profitability, financial risk, or ecological impacts despite being significant factors that influence the adoption decisions of smallholders who occupy the majority of land in the country (Clay et al., 1998; Jacobson and Petrie, 2009; Bidogeza et al., 2015). Smallholders in Rwanda have been shown to be risk averse, meaning that they consider both the mean financial return and its variation in their land use decision making (Bidogeza et al., 2015). Risk-averse smallholders could prefer activities with lower average returns if the variation of the returns was smaller than alternative land uses (Jacobson and Petrie, 2009; Bidogeza et al., 2015). Clay et al. (1998) support this view and suggest that household adoption decisions in Rwanda are a function of four primary factors: 1. Financial returns; 2. riskiness of financial returns; 3. physical returns to investment; and 4. capacity to invest. It is important to evaluate new activities in terms of these factors because failing to do so can lead to the promotion of risky activities that have low probabilities of adoption or lead to poor ecological and financial outcomes for risk-averse smallholders (Rosenstock et al., 2014).

Historically, restoration activities have not been evaluated along these dimensions because there is a lack of financial and environmental data to support such an effort. Previous authors have incorrectly concluded that if the discounted net present value (\$ ha^{-1}) of a restoration activity were higher than those from current land management practices then smallholders would adopt the restoration activity (Guto et al., 2011). However, these types of arguments only reflect the central tendency of the payoff distribution, which is one dimension of risk. Only risk neutral or risk seeking smallholders would strictly prefer restoration activities with larger average financial returns as compared to current land uses. Risk-averse smallholders, in contrast, would consider both the mean and variance of financial returns of restoration activities (Mas-Colell et al., 1995).

In response to these shortcomings, recent studies have characterized the financial risk of restoration activities by using Monte Carlo simulations of enterprise budgets to characterize both the central tendencies of profit distributions as well as their variance (Rosenstock et al., 2014; Crookes et al., 2013; Djanibekov and Villamor, 2014). While these improvements account for risk that are valuable contributions to the literature on the economics of restoration; there is still a need for a framework for evaluating the risk of restoration activities from the perspective of risk-averse smallholders.

To address this problem rapid, rigorous, and objective approaches need to be developed. The methodologies should be able to evaluate activities in terms of their financial profitability, financial risk, and ecological impacts from the perspective of risk-averse smallholders without the need for large data collecting exercises. Combining enterprise budgets, biological modeling, and Monte Carlo analysis in an expected utility framework, is one way to address this challenge. This approach characterizes both the likely and extreme financial and ecological outcomes of adopting the activities. As a result, this approach allows restoration activities to be evaluated across a range of potential outcomes and also to ask whether risk-averse smallholders would be likely to adopt the activities given the outcomes that would be expected.

The remaining part of this paper contributes to the literature on the economics of restoration in the following ways. This paper advances previous work by accounting for a broader set of ecological outcomes, including erosion, carbon sequestration and timber production (Rosenstock et al., 2014). Additionally, while previous studies have accounted for risk created by variability in market prices, this paper accounts for the risk created by the variation of climactic, ecological and market price variables associated with each restoration activity. As a final contribution, this paper demonstrates how expected utility theory can be used to evaluate the variability in key parameters in a way that allows the activities to be ranked from the perspective of a risk-averse smallholder.

METHODS

Identifying restoration activities in Rwanda

Beginning in June 2013, the Rwandan Natural Resource Authority (RNRA), in partnership with the International Union for the Conservation of Nature (IUCN) and the World Resources Institute (WRI), led a stakeholder-centered process to identify restoration activities that would be suitable on smallholder owned land in Rwanda (RNRA, 2014). The process followed the Restoration Opportunity Assessment Methodology (ROAM) developed by IUCN and WRI to identify areas of restoration potential through collaborative, stakeholder focused processes at multiple geographic scales (IUCN and WRI, 2014). Stakeholders from communities, NGOs and government were convened at four regional workshops held in the northern, southern, eastern and western parts of the country to discuss what they hoped to achieve through the restoration process. Workshops were held in October 2013 in Kibuye (Western Province), Nyanza (Southern Province), Kigali (Kigali Province) and Ruhegeri (Northern Province). Approximately 30 – 50 officials from local government and local farmers and foresters participated in each workshop.

During the workshops stakeholders worked together to create a short list of the most relevant and feasible restoration activities for agriculture land and woodlots. Stakeholders described restoration activities by defining which tree species could be used, what their planting density would be, which crops would be used in agroforestry, and which management practices would be used on both agroforestry and improved woodlot sites. Additionally, stakeholders reported the most pressing environmental issues they hoped to address through restoration activities. The issues reported by stakeholders included improve crop and fuelwood yields, reducing erosion on cultivated fields located on hillsides, and creating additional sources of revenue through, for example, carbon sequestration.

Government ministries, including the Rwandan Natural Resource Authority, the Ministry of Agriculture, the Rwandan Environmental Management Authority, the Rwandan Development Board, and the Rwandan Ministry of Finance and Economic planning, helped to characterize the current land use management practices to establish baselines against which to compare the restoration activities.

In total, the stakeholder process identified two degraded land uses that would benefit from restoration:

1. Degraded maize agriculture
2. Poorly managed eucalyptus woodlots and plantations

Stakeholders also identified two restoration activities that could be used to improve the ecological and economic productivity of the above degraded land uses:

1. Agroforestry with maize
2. Improved management of existing woodlots for fuel wood and structural wood with spacing and erosion and fire-prevention best practices

Based on the current land uses and restoration technologies, the following restoration transitions were identified:

1. Degraded maize agriculture → Agroforestry with maize
2. Poorly managed eucalyptus woodlots and plantations → Improved management of existing woodlots with spacing and erosion and fire-prevention best practices

The financial and ecological effects of each restoration transition were modeled by creating enterprise budgets and biophysical models of crop and timber production, carbon sequestration and erosion based on the stakeholder characterizations of the land use practices discussed below.

Data collection

Data for the biological production functions were taken from a number of sources. Estimates of the mean annual increment of timber growth for *Grevillea robusta*, a common tree species used in agroforestry systems, were taken from Kalinganire (1996), while estimates for *Eucalyptus tereticornis*, the most common tree species used in fuelwood plantations, were taken from the Belgian Development Agency (2012). Provincial level monthly precipitation data from 2007 to 2009 was sourced from Meteo Rwanda. Provincial level soil erodibility and soil cover values were retrieved from a GIS database provided by the Rwandan Natural Resources Authority (RNRA). Provincial level slope estimates were taken from the 2008 Rwandan Agricultural Survey. Provincial level crop yield data for maize and beans for 2007 to 2009 were sourced from RNRA.

Financial data for the enterprise budgets were taken from a number of sources. During the regional workshops, stakeholders reported the most likely tree species, stocking densities, crop types and management practices associated with each degraded land use and restoration activity. Officials at the Rwanda Ministry of Agriculture and Animal Resources and the Rwanda Natural Resource Authority reported the average market prices for maize and fuelwood. The price of carbon was taken from the 2015 report on the state of the voluntary carbon market (Hamrick, 2015).

Biological production functions

This paper uses biological production functions to account for the ecosystem service effects of each degraded land use and restoration activity.

Timber

The mean annual increment of timber growth for 1-hectare of agroforestry and woodlots was estimated with growth data for two representative tree species. Growth data for the agroforestry species, *G. robusta*, was taken from Kalinganire (1996). Growth data for the most common woodlot species, *E. tereticornis*, was taken from Belgian Development Agency (2012). Stakeholders reported that *G. robusta* is the most common agroforestry species adopted by farmers and eucalyptus species are the most commonly grown species on fuelwood plantations (Belgian Development Agency, 2012).

Annual timber yields were estimated by multiplying the mean annual increment for a single tree of each tree species by the stocking density of trees for each current land use and restoration activity following Table 1.

Carbon sequestration

The annual rate of carbon sequestration is calculated for each current land use and restoration activity following Equation 1 from the Intergovernmental Panel on Climate Change's (IPCC) Good Practice Guidelines (IPCC, 2003):

$$CO_2e\ (tonnes) = (AGB + RBDM)\ x\ 0.49 \times 3.67 \quad (1)$$

$$RBDM = e^{(-1.805+0.9256 \cdot \ln(AGB_i))} \quad (2)$$

Where 0.49 is the factor used to convert short tons of dry matter to carbon and 3.67 is the factor used to convert carbon to CO_2 equivalent (IPCC, 2003). The variable AGB refers to above ground biomass and it is calculated by multiplying the timber volume estimates from Table 1 by biomass conversion expansion factors reported by the IPCC for each climate zone and forest type (IPCC, 2003).

The variable RBDM represents root biomass dry matter or below ground biomass and it is calculated using Equation 2, which is a function of AGB reported in Table 1 (IPCC, 2003).

Table 1. Mean annual increments (MAI) for Grevillea Robusta and Eucalyptus Tereticornis for Representative Stocking Densities.

Species	Single tree	300 trees (ha^{-1} yr^{-1})	1100 trees (ha^{-1} yr^{-1})	1600 trees (ha^{-1} yr^{-1})	Source
Grevillea robusta	0.0048 (0.002)	1.44 (0.6)	-	-	Kalinganire, 1996
Eucalyptus tereticornis	0.0065 (0.001)	-	7.15 (1.1)	10.4 (1.6)	Belgian Development Agency, 2012

Standard Errors are in parentheses. Grevillea robusta was only considered in an agroforestry context with 300 trees ha^{-1}.

Table 2. Parameter values used to estimate erosion.

Land Use	USLE parameter					Estimated annual erosion short tons (ha^{-1} yr^{-1})
	R	K	LS	C	P	
Degraded maize agriculture	332	0.12	1.5	0.3	1	18
Agroforestry with maize	332	0.12	1.5	0.1	1	6
Poorly managed woodlots	431	0.15	1.5	0.15	1	19
Well managed woodlots	431	0.15	1.5	0.1	1	15

Annual precipitation data was converted into an estimate of energy intensity, R, by dividing total precipitation by the average number of annual precipitation events and assuming each event lasts an average of 3 h. The soil erodibility index, K, and soil cover factor, C, were queried from a GIS database provided by the Rwandan Natural Resources Authority for each land use and restoration intervention. Plot lengths were estimated from the 2008 Rwandan Agricultural Survey by taking the square root of the average plot size for each province. The support practice factor, P, reflects the effects of practices that would reduce the amount and rate of the water runoff thereby reducing erosion. However, P is often assigned a value of 1 unless specific management practice information is available (Renard et al., 2011).

Erosion

Annual rates of erosion are calculated using the Universal Soil Loss Equation (USLE) following Equation 3 (Renard et al., 2011):

$$Erosion = R * K * LS * C * P \tag{3}$$

Where, R = Rainfall erosivity factor, K = soil erodibility factor, LS = plot length and slope factor, C = soil cover factor, P = support practice factor.

Table 2 shows the information used to estimate the annual rate of erosion for each degraded land use and restoration activity.

Crop yields

Production risk is one of the defining features of smallholder agricultural systems in SSA (Di Falco and Chavas, 2009). Crop production in Rwanda is largely rain-fed, with more than 1 million hectares relying solely on rain (Habiyambere et al., 2009). Variation in precipitation, specifically a lack of rain, can severely reduce crop yields and cause significant negative impacts on the livelihoods of smallholders. In order to account for this risk, the relationship between annual precipitation and the average annual per hectare crop yields have to be estimated. A district-level panel data set of crop production, seasonal precipitation and annual total planted area from 2007 to 2009 is used to estimate crop production functions that account for the relationship between crop yields and precipitation.

Following previous literature, the annual per hectare regional crop production (in tons) for maize in region i during time period t is defined as a deterministic Cobb-Douglas production function (Bravo-Ureta and Pinheiro, 1993; Bravo-Ureta and Evenson, 1994; Battese and Coelli, 1995). The functional form is estimated as:

$$\ln(\text{average per hectare yield}_{it}) = \left\{ \begin{matrix} \beta_1 \ln(\text{planted land area}_{it}) + \\ \beta_2 \ln(\text{annual precipitation}_{it}) + \beta_i Z_i + \varepsilon_{it} \end{matrix} \right\} \tag{4}$$

Where Z_i is a vector of region specific dummy variables that account for region-specific time-invariant unobservable variables that influence the average per hectare maize yields in each region. ε_{it} is the deviation from the conditional mean for region at i at time t. Equation 4 is linear in the parameters and can be estimated with OLS if the potential simultaneity bias is overlooked. Table 3 shows the results from the regression analysis.

Table 3. Crop yield regression results.

Variable	Maize
Precipitation (mm Yr^{-1})	0.49** (0.14)
Land Area Planted (Ha^{-1} Yr^{-1})	-0.46*** (0.11)
Sample size (N)	108
R^2	0.42
F-Value	2.95

Standard errors in parenthesis. *** = P < 0.001.

The results of the regression equation reported in Table 3 are used to estimate the crop yields that could be achieved with agroforestry by combining them with data from Dreschel et al. (1996). The authors reported the impacts of agroforestry systems on maize yields in Rwanda as a percentage of degraded agricultural yields. The authors found that the yield response could

Table 4. Enterprise budget for degraded agriculture and agroforestry in Rwanda.

Variables	Unit	Degraded agriculture (maize)			Agroforestry	
		Price (RwF)	Quantity	Value (RwF)	Quantity	Value (RwF)
Variable costs						
Crop Seed	Kg	90	40	3,600	40	3,600
Labor (crops)	Days	660	221	145,860	199	131,340
Labor (trees)	Days	660	-	-	44	29,040
Organic fertilizer	Kg	2	3,000	6,000	-	-
Capital costs	-	660	-	660	-	660
Fixed costs						
Tree seedlings	Seedlings	1,000	-	-	300	300,000
Small agricultural equipment	-	-	-	1,900	-	1,900s
Revenue						
Crop yields	Kg	350 - 515	910	318,500	578 - 2260	202,300 – 1,163,900
Timber yields (Year 30)	m^3	10,900	-	-	98	1,068,200
Ecosystem Services						
Carbon	Short Tons $Ha^{-1}Yr^{-1}$	2,500	-	-	0.9 - 2.7	2,250 – 6,750
Erosion	Short Tons $Ha^{-1}Yr^{-1}$	1,350	18		6	

range from -35 to 65% as compared to degraded maize yields (Dreschel et al., 1996). To estimate the yield of agroforestry, this paper first calculates the yield of degraded agriculture using Equation 4 and the estimated coefficients in Table 3 and multiplies that value by the expected crop yield response.

Enterprise budgets

Enterprise budgets were created for each degraded land use and restoration activity based on the information provided by stakeholders during the four regional workshops. Stakeholders validated the final versions of the enterprise budgets during a fifth workshop held in Kigali in March, 2014. Tables 4 and 5 display the enterprise budgets for degraded agriculture, agroforestry, poorly managed woodlots and well-managed woodlots, respectively.

Table 4 shows the cost and revenue structure for degraded agriculture and agroforestry operations. Agriculture in Rwanda is a low-input activity that uses no mechanization and relies on very few inputs because most farmers cannot afford to make investments (Habiyamere et al., 2009). Labor and farm equipment, like hoes and shovels, are the most costly farming inputs. Degraded agricultural systems use approximately 3000 kg of organic fertilizer, but one of the advantages of agroforestry systems is that they do not use organic fertilizer because the tree roots bring soil nutrients from deep below ground closer to the surface where crops can take advantage of them (Sanchez and Palm, 1996).

The fixed costs of agricultural systems are very low because only basic materials like a hoe and shovel are required. The fixed costs associated with agroforestry are higher because tree seedlings have to be purchased. Both systems generate revenue from crop yields, but agroforestry systems generate additional revenue from the sale of timber at the end of a twenty-year rotation interval.

Table 5 shows the cost and revenue structure for poorly managed woodlots and well managed woodlots with best practices observed. The productivity of most woodlots in the country is low because they are established on marginal land, and landowners use poor management practices during planting, thinning and harvesting (AFF, 2011). Planting material is the largest cost of establishing a woodlot whether it is poorly managed or well managed.

In both cases, the site is prepared before planting by clearing bush. In well-managed woodlots, the site is also prepared in a number of other ways. The stumps of old eucalyptus trees are removed to maximize the plantable area for the new seedlings. Stakeholders reported that trenches and fire lanes were also needed to limit erosion and reduce the risk stand-destroying wildfires. Trenches and fire lanes also require annual maintenance. After the first year, seedlings that did not survive are replaces through a process known as ‘beating up.’ In poorly managed woodlots, the average seedling replacement rate is 30% while it is 15% for well-managed woodlots (Belgian Development Agency, 2012). At the end of the fourth year, the stand is thinned by removing approximately 250 trees, which are sold as poles. Every seven years, the stand is coppiced and the timber is sold as fuelwood.

Repeated random sampling (Monte Carlo simulations)

This paper uses repeated random sampling (Monte Carlo simulations) to account for the variability of financial revenue and ecosystem service values. The simulations draw parameter values from their probability distributions to determine the variability of the associated outcomes. Variability is characterized for the market prices of crops and fuelwood, precipitation, tree growth rates and the impact of agroforestry tree species on crop yields. Table 6 lists the assumptions and data sources used to characterize the distributions of each variable included in the Monte Carlo simulations.

The studies reported in the Table 6 did not characterize the distributions of the data. To overcome this limitation, the data was used to parameterize the most likely probability distribution functions associated with the processes that generated the data.

Table 5. Enterprise Budget for Poorly Managed and Well Managed Woodlots in Rwanda.

Items	Unit	Price (Rwf)	Poorly managed woodlots		Well managed woodlots	
			Quantity	Total cost (RWf)	Quantity	Total cost (RWf)
Variable costs						
Digging	Hole	10	1,100	11,000	1,600	16,000
Planting material	Seedling	100	1,100	110,000	1,600	160,000
Seedling transport	Seedling	10	1,100	11,000	1,600	16,000
Planting	Seedling	5	1,100	55,000	1,600	8,000
Beating up (15% - 30%)	Seedling	50	330	16,500	240	12,000
Pruning	Tree	25	1,100	25,250	1,600	40,000
Thinning (after 4th year)	Tree	30	250	7,500	250	7,500
Coppicing (every 7 years)	Tree	25	1,100	27,500	1,600	40,000
Fixed costs						
Bush clearing	Days	660	20	13,200	20	13,200
Trench establishment	Meter	125	-	-	300	37,500
Fire lane creation	Meter	125	-	-	300	37,500
Fire lane maintenance	Year	5,000	-	-	-	5,000
Trench maintenance	Meter	50	-	-	300	15,000
Remove old stumps	Ha	100,000	-	-	1	100,000
Revenue						
Poles	Pole	1500	250	256,130	250	256,130
Fuelwood	Stere	2400	52	124,800	73	171,865
Ecosystem Services						
Carbon	Short Tons $Ha^{-1}Yr^{-1}$	2,500	11	-	16.32	13,300
Erosion	Short Tons $Ha^{-1}Yr^{-1}$	1,350	19		15	

Table 6. Distributional assumptions for economic and biological variables used in the Monte Carlo analysis.

Variables	Distribution assumptions	Draws	Source
Grevillea robusta MAI	MAI~N(1.44,0.6)	N=1,000	Kalinganire, 1996
Eucalyptus tereticornis MAI	MAI~N(7.15,1.1); MAI~N(10.4,1.6)	N=1,000	Belgian Development Agency, 2012
Impact of agroforestry tree species on crop yields	Impact~Tri(-0.35, 0.3, 0.6)	N=1,000	Dreschel et al., 1996
Market prices	Fuelwood~Tri(380,2400,4700) Maize~Tri(160,250,450)	N=1,000	Rwanda Ministry of Agriculture and Animal Resource
Growing season precipitation	Precip~ Bootstrapped	N=1,000	Meteo Rwanda

Previous studies of tree growth rates used normal distributions to approximate the distribution of mean annual increments when both the mean and standard errors were observable (Moore et al., 2012).

The effect that agroforestry trees would have on crop yields is only reported for Rwanda in terms of the maximum, minimum and mean impacts as a percentage of average yield so a triangular distribution is used to approximate the data generating process. Data on market prices for fuelwood and maize were only reported as maximum, minimum and means without standard errors so their distributions were characterized as triangular distributions. Histograms of annual precipitation revealed that the distributions of the data did not fit any known distributions. The distributions of that data were approximated with repeated random sampling with replacement (bootstrapping). While this method approximates the empirical distributions of the data, its major limitation is that it does not draw values that have not already been observed in the sample. As a result, extreme precipitation values may be absent from the simulation.

Exactly 1,000 random samples of each variable were drawn from the distributions presented in Table 6. Each draw was composed of 30 annual observations that were used to calculate the NPV of the land use enterprise. In total, the data set contained 1,000 observations of NPVs calculated over a thirty-year period. The data were used to estimate the distribution of NPVs for each current land use and restoration activity.

NPV decision metric

This paper uses the Net Present Value (NPV) metric to compare the financial attractiveness of current land uses and restoration activities. The net present value metric is calculated by subtracting the summed and discounted stream of costs from the summed and discounted stream of benefits for each enterprise over a thirty-year time horizon as shown in Equation 5:

$$NPV = \sum_{t=0}^{30} \delta^t (B_t - C_t) \quad (5)$$

Where B_t are the financial benefits and costs at time t, respectively, and δ^t is the discount factor. Enterprises with larger NPVs are considered to be more efficient than alternatives with smaller NPVs as long as the benefits and costs can be distributed amongst stakeholders in a way that improves the welfare of some without reducing the welfare of others. The enterprises budgets from Tables 4 and 5 are used with the data from the Monte Carlo simulations to estimate the NPV of agriculture, agroforestry, poorly managed woodlots and well managed woodlots. This analysis follows previous studies of farm profitability in Rwanda, which have discounted the costs and benefits of farm enterprises using a 16% rate of discount, which is the average rate of interest charged to farmers by the National Bank of Rwanda (Maniriho and Bizoza, 2013).

Theory of decision making under risk and expected utility

The theory of decision-making under uncertainty assumes smallholder agriculturists face choices among risky agricultural activities. The goal of decision-making under uncertainty is to find activities that risk-averse smallholders would prefer to alternative activities. The expected utility framework therefore attempts to understand how smallholders make trade-offs among risky alternatives (Anderson, 1974). Risky agricultural activities can produce a number of financial outcomes. From the perspective of the smallholder, it is uncertain which outcome will occur at the time they decide on which activity they will adopt. Such risky activities are often thought of as lotteries (Mas-Colell, 1995).

Comparing the expected utility functions of smallholders under different agricultural and restoration activities is data and or assumption intensive. Expected utilities reflect individual preferences for income and risk that have to be characterized through elicitation of risk-preferences or through assumptions. This is problematic because operationalizing expected utility theory depends on either 1. Collecting information on smallholder's preferences, or 2. Making assumptions about smallholder preferences (Andersen, 1974).

One way to navigate this challenge without information on individual risk-preferences and with minimal assumptions about the shape of individual utility functions is to compare the distributions of payoffs from different activities rather than comparing the expected utilities that would be achieved under those distributions (Mas-Colell, 1995). The pay offs of different distributions can be compared in two ways that are consistent with expected utility theory. First, the distributions can be compared by their expected returns. Second, they can be compared by the dispersion of those returns. The goal is to be able to look at two distributions from different activities and unambiguously say that $F(\cdot)$ has higher returns than $G(\cdot)$ and that $F(\cdot)$ is less risky than $G(\cdot)$. These ideas are known as first and second order stochastic dominance, respectively.

First order stochastic dominance

Smallholders with a non-decreasing expected utility functions prefer more to less. First Order Stochastic Dominance (FOSD) compares distributions of payoffs in a way that makes it possible to say that every utility maximizer who prefers more to less would prefer $F(\cdot)$ to $G(\cdot)$. A distribution is said to display First Order Stochastic Dominance over another distribution if for every non-decreasing function $u: \Re \to \Re$ that $\int u(x)dF(x) \geqslant \int u(x)dG(x)$. It can be shown that this is true if and only if $F(x) \leq G(x)$ for all x (Mas-Colell, 1995). That is, smallholders with a utility function, U(x), such that U(x)>0 will prefer a FOSD distribution to one that is dominated.

Second order stochastic dominance

Second Order Stochastic Dominance (SOSD) captures the idea that risk-averse smallholders receive diminishing marginal utility from increasing amounts of income. If a distribution demonstrates Second Order Stochastic Dominance over another distribution, then every risk-averse individual would prefer that distribution to the distribution that is dominated. A distribution can be said to display SOSD over another distribution if and only if:

$$\int_{-\infty}^{x} [G(\cdot) - F(\cdot)]dt \geq 0 \; for \; all \; x \quad (6)$$

Foster and Sen (1997 cited by Formby et al. (1999) have proposed an alternative approach to assess SOSD for distributions with different means. This approach, known as Normalized Stochastic Dominance (NSD) compares the CDFs of normalized distributions. For a probability distribution function of NPV $f(\cdot)$ with mean u_f its normalized PDF, $f(x^n)$, is defined as the PDF of the normalized NPV, $x^n = x/u_f$. The corresponding normal CDF is $F(x^n)$. The distribution $F(x^n)$ dominates the distribution $G(x^n)$ if and only if:

$$F(x^n) \leq G(x^n) \text{ for all } x^n \quad (7)$$

That is, $F(x)$ SOSD $G(x)$ if and only if $\int_{-\infty}^{x} U(x^n)dF(x^n) \geq \int_{-\infty}^{x} U(x^n)dG(x^n)$ for all x^n.

Certainty equivalence

In theory, Stochastic Dominance is a good way to rank and compare distributions in an expected utility framework because it requires making minimal assumptions about the shape of individual utility functions. However, in practice it is not always useful because a large number of empirical distributions cannot be ordered (Meyer, 1977). One way around this obstacle is to estimate the Certainty Equivalents (CE) of each distribution. The CE of a lottery is the amount of money an individual would have to be paid with certainty to be indifferent between the payment and participating in the lottery. For risk-averse smallholders, CEs are always less than the expected monetary payoff of a lottery. When comparing several different activities a risk-averse smallholder would always prefer the alternative with the largest CE (Mas-Colell, 1995). One drawback to this approach is that it requires specifying a utility function for smallholders. However, the benefit is that it allows for definitive rankings of different activities under specific risk-aversion parameters.

Smallholder preferences over uncertainty are often analyzed by specifying twice differentiable functions like the negative

exponential or constant relative risk aversion (CRRA) utility functions (Di Falco et al., 2007). Previous studies from SSA have shown that smallholder behavior is best represented by CRRA utility functions with relative risk aversion coefficients between 1 and 5. A relative risk aversion of 3 is considered to be moderately risk averse (Binswanger, 1981; Chavas and Holt, 1996; Gollier, 2001). CRRAs are also attractive because they imply that absolute risk aversion is decreasing with wealth. This suggests that relatively poor subsistence smallholders would be much more sensitive to downside risk than relatively wealthier smallholders.
The CRRA utility function is represented by:

$$U(X) = X^{1-\gamma}/(1-\gamma) \quad (8)$$

Where γ is the measure of relative risk aversion and is assumed to be $\gamma \geq 1$. A value of $\gamma = 0$ reduces Equation 8 to $U(X) = X$, which would reflect a risk-neutral smallholder. If $\gamma = 1$ then Equation 8 becomes $U(X) = \ln(X)$. Higher values of γ correspond to smallholders with more aversion to risk.

Under a CRRA utility function, the CE of a given lottery can be determined by finding the value of CE that solves the following equation:

$$U(CE;\gamma) = \sum_i \pi_i (X_i^{1-\gamma}/(1-\gamma)) \quad (9)$$

Where π_i is the probability weight associated with observing payoff X_i. In this study, the values of π_i for each realization of NPV (X_i in 2.12) were calculated using Proc Freq in SAS 9.2, which returned an empirical probability distribution of the NPV realizations and their corresponding frequencies. The frequencies were used as estimates of the probabilities. As the value of γ increases (the smallholder becomes more risk-averse), the value of the CE decreases relative to the expected value of the lottery. The difference between the CE and the expected value is known as the 'risk premium.' It reflects the amount of money a smallholder would be willing to give up to avoid the risk of the lottery. In a study of smallholder risk in the Ethiopian Highlands, Di Falco et al. (2007) assumed the smallholders had a relative risk aversion equal to 3. The CE for each activity in this study are solved for values of γ from 0 to 9, reflecting smallholders with no, low, moderate and high levels of risk aversion, respectively (Di Falco et al., 2007).

RESULTS

Stochastic dominance

The results for the Stochastic Dominance analysis are shown in Figures 1 to 4. The analysis considered the CDFs for the transitions from degraded maize agriculture to agroforestry with maize and from poorly managed to well-managed woodlots for all four provinces considered in this study. The Stochastic Dominance analysis was also carried out by including the values of ecosystem services in the partial enterprise budgets to see if internalizing their value would alter the preferences of smallholders. The results showed that including the values did not change the preferences of smallholders.

Neither degraded maize agriculture or agroforestry with maize displays First Order Stochastic Dominance (FOSD) over the other activity. The CDFs of NPV show that the financial returns from agroforestry are more likely to be smaller than the returns from maize, but they are also more likely to be larger. This can be seen in Figure 1 where the CDFs of the NPV for both activities cross each other in every province. The definition of FOSD is that one distribution dominates another if and only if $F(x) \leq G(x)$ for all x (Mas-Colell, 1995). As shown in Figure 1, neither activity dominates the other and this suggests that there is not an unambiguously dominant activity for smallholders who strictly prefer higher financial returns.

The test for SOSD is designed to find activities that unambiguously result in lower variability of net financial returns than alternative or competing activities. Risk-averse smallholders would strictly prefer an activity that demonstrates SOSD over its alternatives. The seen in Figure 2, there was neither degraded maize agriculture or agroforestry with maize dominatingeach other. First Order Stochastic Dominance is a necessary condition for a CDF to SOSD another distribution. This suggests that there is no unambiguously dominant activity for smallholders who strictly prefer low variability to high returns or for those who prefer higher returns as well as low variability.

Figure 3 show that poorly managed woodlots display FOSD over well-managed woodlots. In other words, a smallholder with a utility function that strictly prefers more to less will always choose to invest in poorly managed woodlot practices rather than well managed woodlot practices. The CDFs show that poorly managed woodlots unambiguously lead to smaller financial losses than well-managed woodlots. The definition of FOSD is that one distribution of FOSD and another if and only if $F(x) \leq G(x)$ for all x (Mas-Colell, 1995). As shown in Figure 3, it is clear that poorly managed woodlots FOSD are well-managed woodlots. Figure 4 shows that neither poorly managed woodlots or well-managed woodlots display Second Order Stochastic Dominance. This suggests that there is no unambiguously dominant woodlot activity for smallholders who strictly prefer low variability to high returns or for those who prefer higher returns as well as low variability.

Certainty equivalence[1]

Unlike the Stochastic Dominance analysis, the results from the Certainty Equivalence analysis allow precise preference orderings to be made between agriculture with maize and agroforestry with maize. Figure 5 shows smallholders with CRRA utility functions prefer agriculture to agroforestry in each province across all values of relative risk aversion coefficients.

For Kigali Province, the CE for agriculture under a relative risk aversion coefficient of 3 is 485,965 RwF and

[1] A CE analysis was not done for the woodlot activities because the Stochastic Dominance analysis definitively showed that any risk-averse smallholder would prefer current woodlot management practices to the best practices being proposed.

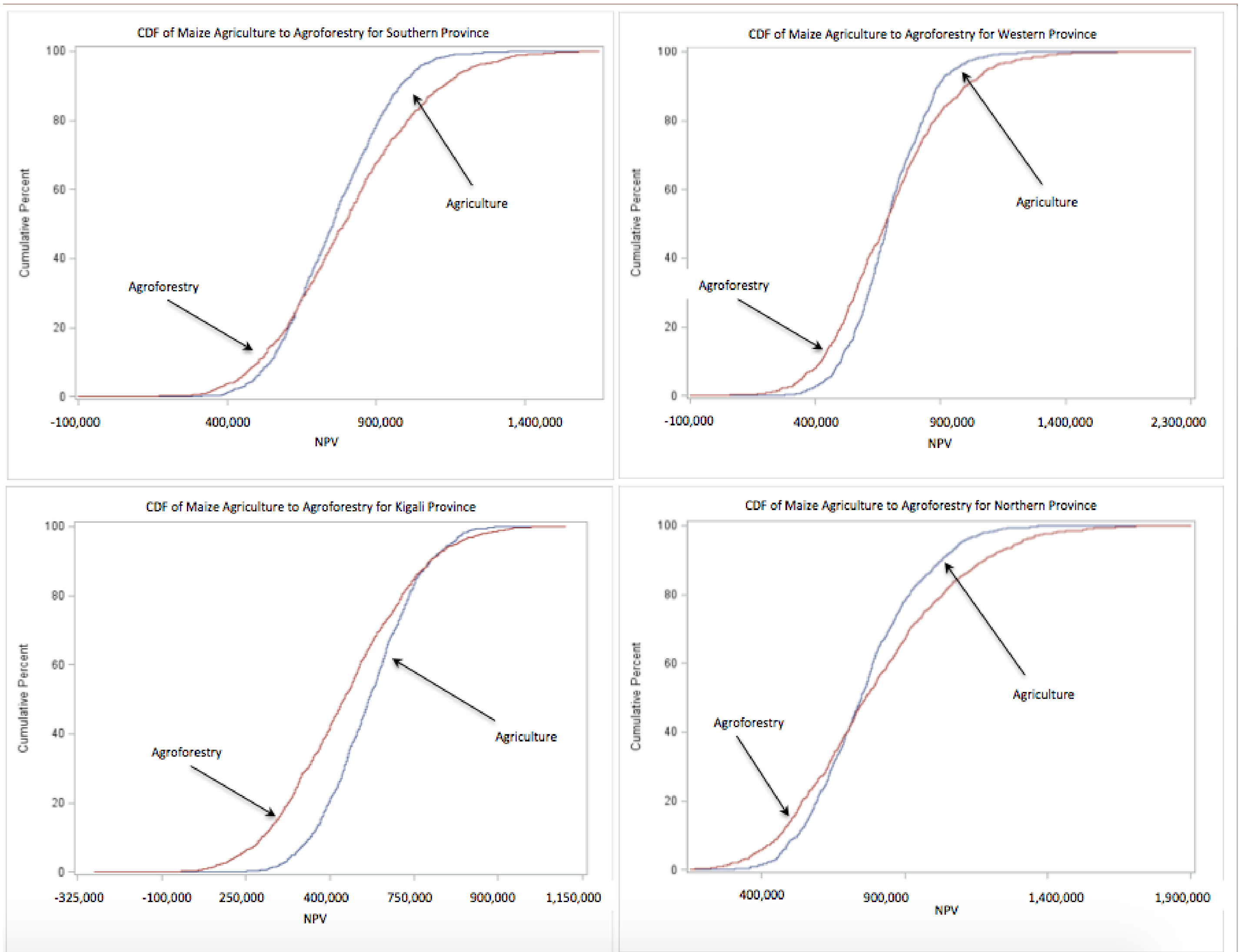

Figure 1. The CDFs of NPV for degraded maize agriculture to agroforestry with maize for four provinces in Rwanda. A non-overlapping CDF to the right of an alternative CDF is said to demonstrate First Order Stochastic Dominance over the alternative. Smallholders who prefer more to less will always choose an activity with a CDF that strictly dominates another CDF. In the example above, none of the CDFs dominate the others as shown by the crossing graphs of the CDFs in every province.

for agroforestry it is 316,401 RwF. The results suggest smallholders with moderate risk aversion will prefer agriculture to agroforestry. When smallholders are more risk averse (relative risk aversion coefficient of 5), the CEof agriculture in Kigali province is 459,369 and 261,969 RwF for agroforestry meaning agriculture is the preferred activity of highly risk-averse smallholders as well. These results are supported by the Stochastic Dominance analysis, which showed that the CDF of agriculture was almost exclusive to the right of the CDF for agroforestry.

In the Northern Province, the CE for agriculture under a relative risk aversion coefficient of 3 is 711,307 RwF and for agroforestry it is 618,765 RwF. This suggests smallholders with moderate risk aversion will prefer agriculture to agroforestry. When smallholders are more risk averse (relative risk aversion coefficient of 5), the CE of agriculture in Northern Province is 672,020 and 529,703 RwF for agroforestry, meaning agriculture remains the preferred activity of highly risk-averse smallholders. This same pattern is observed in the Southern and Western provinces as well. In both provinces, smallholders prefer agriculture because it has lower probabilities of large losses as shown in the Stochastic Dominance analysis.

Policy makers could offer upfront one-time payments to risk-averse smallholders to incentivize them to adopt restoration activities that are otherwise deemed too risky.

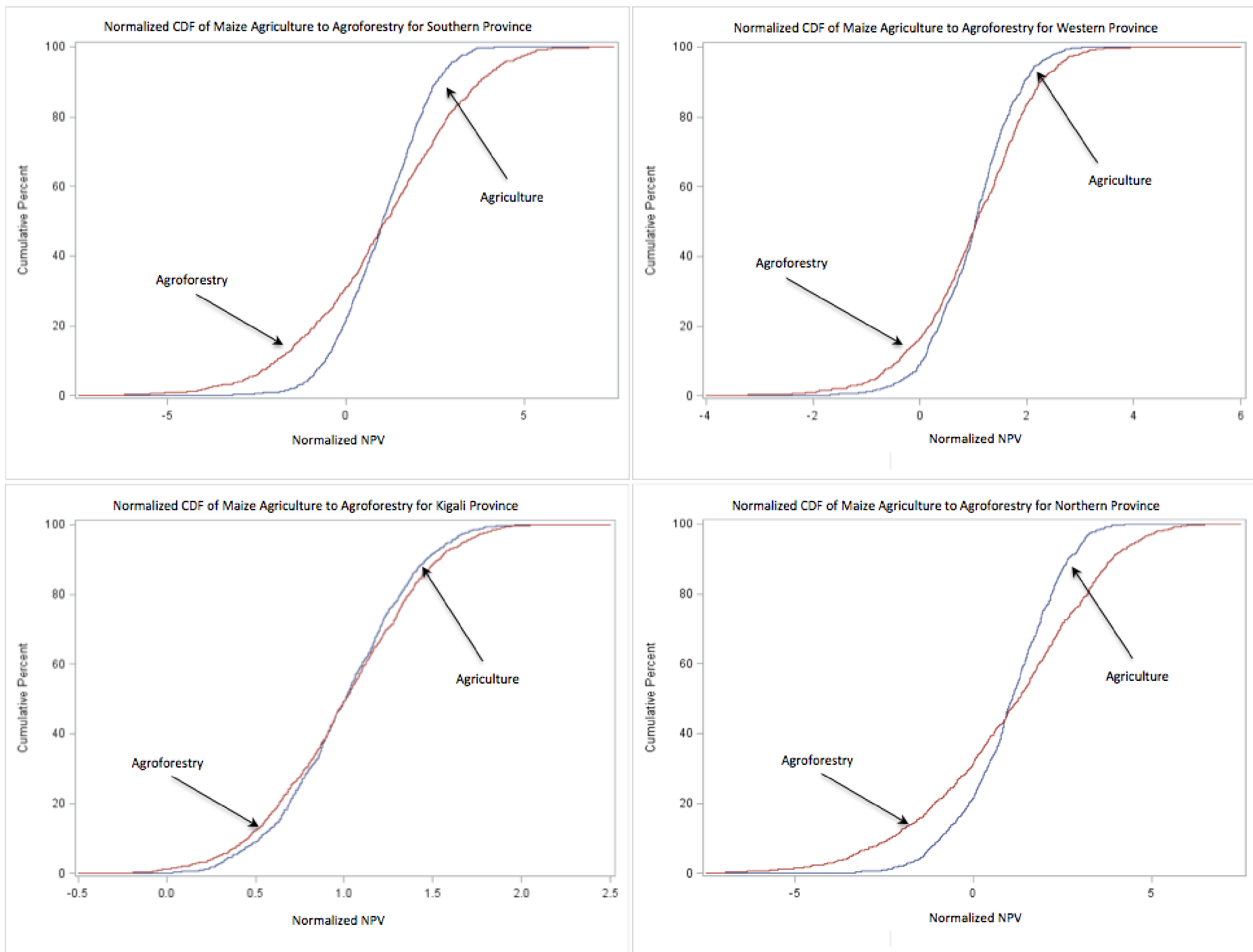

Figure 2. The normalized CDFs of NPV for degraded maize agriculture to agroforestry with maize for four provinces in Rwanda. A non-overlapping normalized CDF to the right of an alternative normalized CDF is said to demonstrate Second Order Stochastic Dominance over the alternative. Smallholders who are risk averse will always choose the activity with a normalized CDF that demonstrates Second Order Stochastic Dominance. In the example above, none of the normalized CDFs dominate the others as shown by the crossing graphs of the normalized CDFs in every province.

The difference between the curves in Figure 5 represents the one-time payments that would be necessary to equate the CE values of agroforestry with agriculture. For moderately risk averse smallholders in Kigali (relative risk aversion coefficient of 3), a one-time payment of 169,563RwF Ha^{-1} (\$257 Ha^{-1}) would equate the CE values of agriculture and agroforestry. Small holders in Kigali province with a relative risk aversion coefficient of 5 would require a one-time payment of 197,400 RwF Ha^{-1} (\$300 Ha^{-1}) to equate the CE values. Smallholders in northern, southern and western provinces with a relative risk aversion coefficient of 5 would require 142,317, 111,127 and 168,945 RwF in one-time payments, respectively, to equate the CE values of agriculture with agroforestry. These payments could be justified if the present value of public ecosystem goods and services or other external impacts from agroforestry were less than or equal to the payments that would be necessary to equate the CE values of the two activities.

DISCUSSION

This study analyzed the financial profitability, financial risk and ecological impacts of two proposed restoration activities in Rwanda. The study developed a methodology combining enterprise budgets, ecosystem service modeling and Monte Carlo analysis in an expected utility

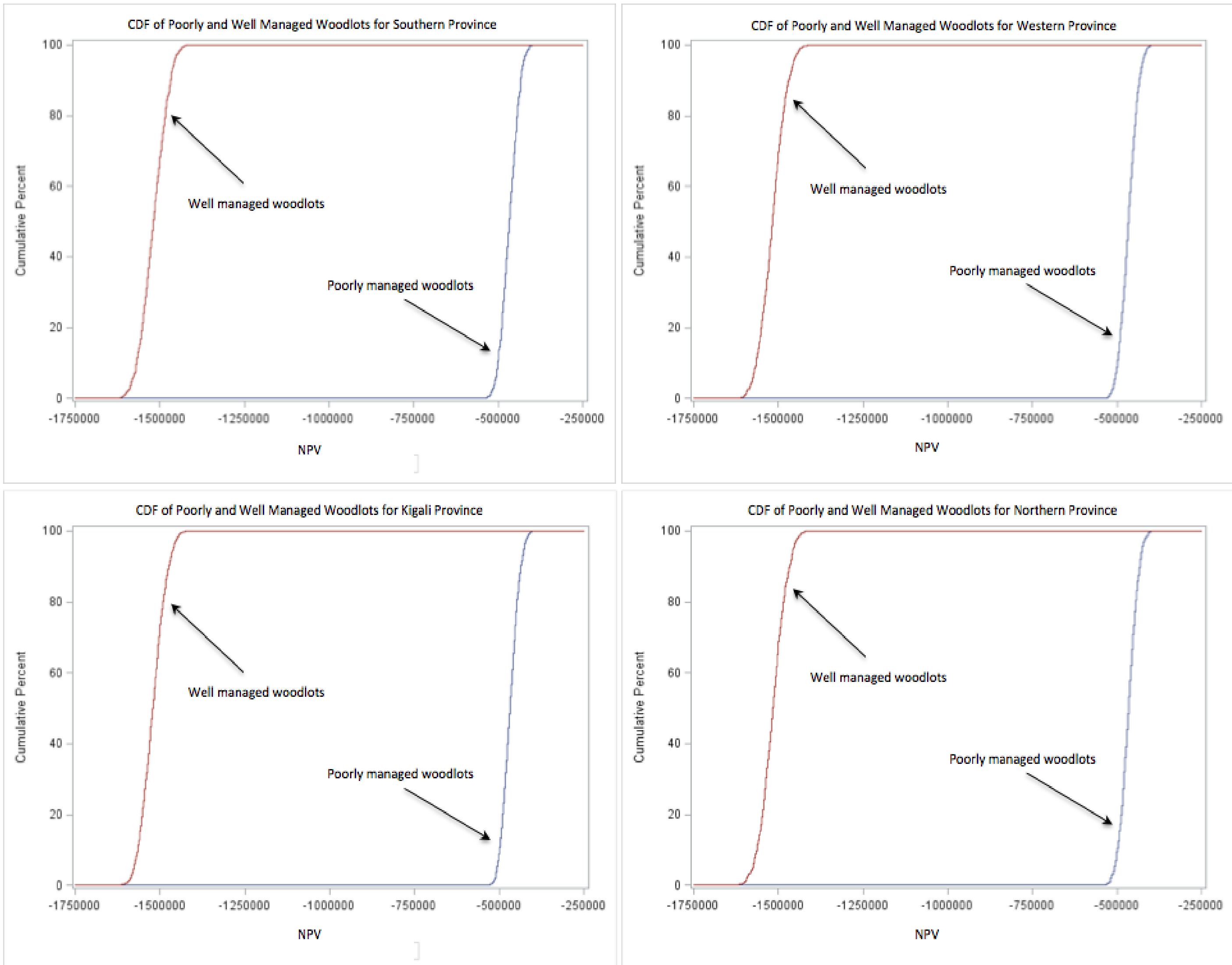

Figure 3. The CDFs of NPV for poorly managed woodlots and well managed woodlots for four provinces in Rwanda. A non-overlapping CDF to the right of an alternative CDF is said to display First Order Stochastic Dominance over the alternative. Smallholders who prefer more to less will always choose an activity with a CDF that dominates another CDF. In the example above, poorly managed woodlots display First Order Stochastic Dominance over well-managed woodlots in each province.

framework. Employing this type of mixed methodology to analyze the factors that influence smallholder adoption is important because failing to account for these factors can lead to the promotion of risky technologies that have low probabilities of adoption or lead to poor ecological and economic outcomes. Additionally, accounting for both the financial and ecological impacts of land use transitions can provide information to policy makers that could make transitions more profitable and thus increase the rate of adoption.

Increasing the adoptability of best management practices for woodlots will require reducing the costs. The results of the Stochastic Dominance analysis of woodlot management practices show that current practices, which are said to be poor by environmental authorities in the country, display First Order Stochastic Dominance over well-managed woodlot practices. This analysis showed that best practices are very costly relative to the marginal gains in timber yields they achieve. Smallholders with utility functions that value more over less will strictly prefer to continue with the current woodlot management practices. The second order Stochastic Dominance analysis showed that the best practices also did not lower variability of woodlot returns enough for risk-averse smallholders to prefer this management style over current practices. The results of this analysis suggest that higher stocking densities can improve the productivity of woodlots. However, the suite of best management

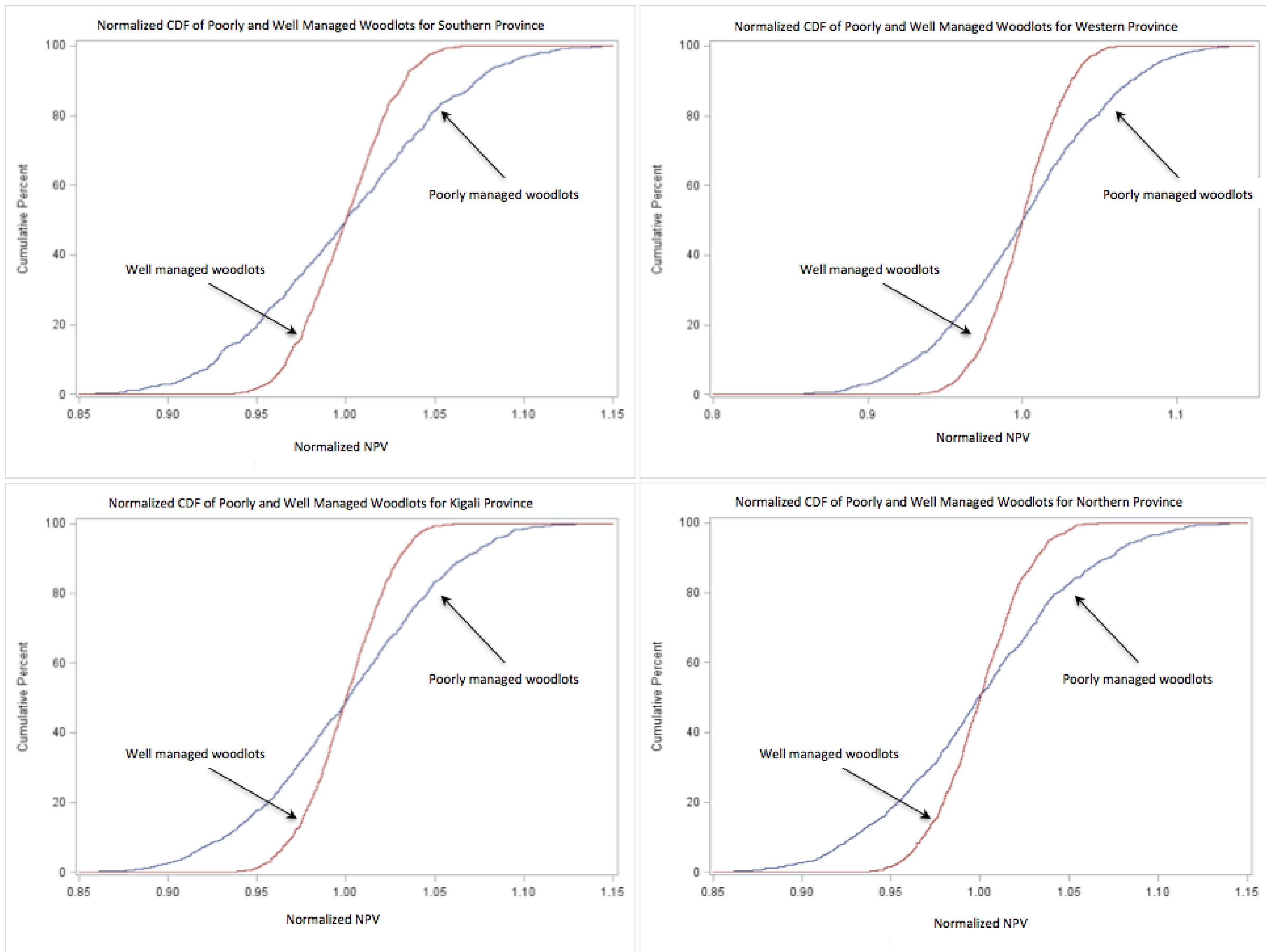

Figure 4. The normalized CDFs of NPV for poorly managed woodlots and well managed woodlots for four provinces in Rwanda. A non-overlapping normalized CDF to the right of an alternative normalized CDF is said to display Second Order Stochastic Dominance over the alternative. Smallholders who are risk averse will always choose activities with a normalized CDF that displays Second Order Stochastic Dominance.

practices that are also being recommended will not be adopted. Even including the values of ecosystem services does not change the profitability enough for smallholders to adopt best management practices. This suggests that policies designed to incentivize good woodlot management may not be justified from a social benefit perspective. The results of the Stochastic Dominance analysis suggest that smallholder households do not have well defined preference for degraded maize agriculture and agroforestry. Even when the values of ecosystem services were internalized from the perspective of the smallholder, the results of the Stochastic Dominance analysis were still inconclusive. This result suggests that privatizing the public benefits of ecosystem services associated with agroforestry will not change the adoption decisions of most smallholders on its own.

The Certainty Equivalent analysis extended the Stochastic Dominance analysis by representing the preferences of smallholders under varying degrees of risk-aversion. The results from this analysis showed that maize agriculture was the preferred activity across all risk preferences. This is particularly problematic because the current agricultural practices are leading to the long-term decline of crop yields and many experts believe wide-scale smallholder adoption of agroforestry is necessary in order to maintain or enhance food security in the country.

Policy makers can take several actions to decrease the risk and thus increase the adoptability of agroforestry. In many cases, agroforestry is proposed to smallholders without investing in extension services that would introduce the skills farmer's need to properly manage

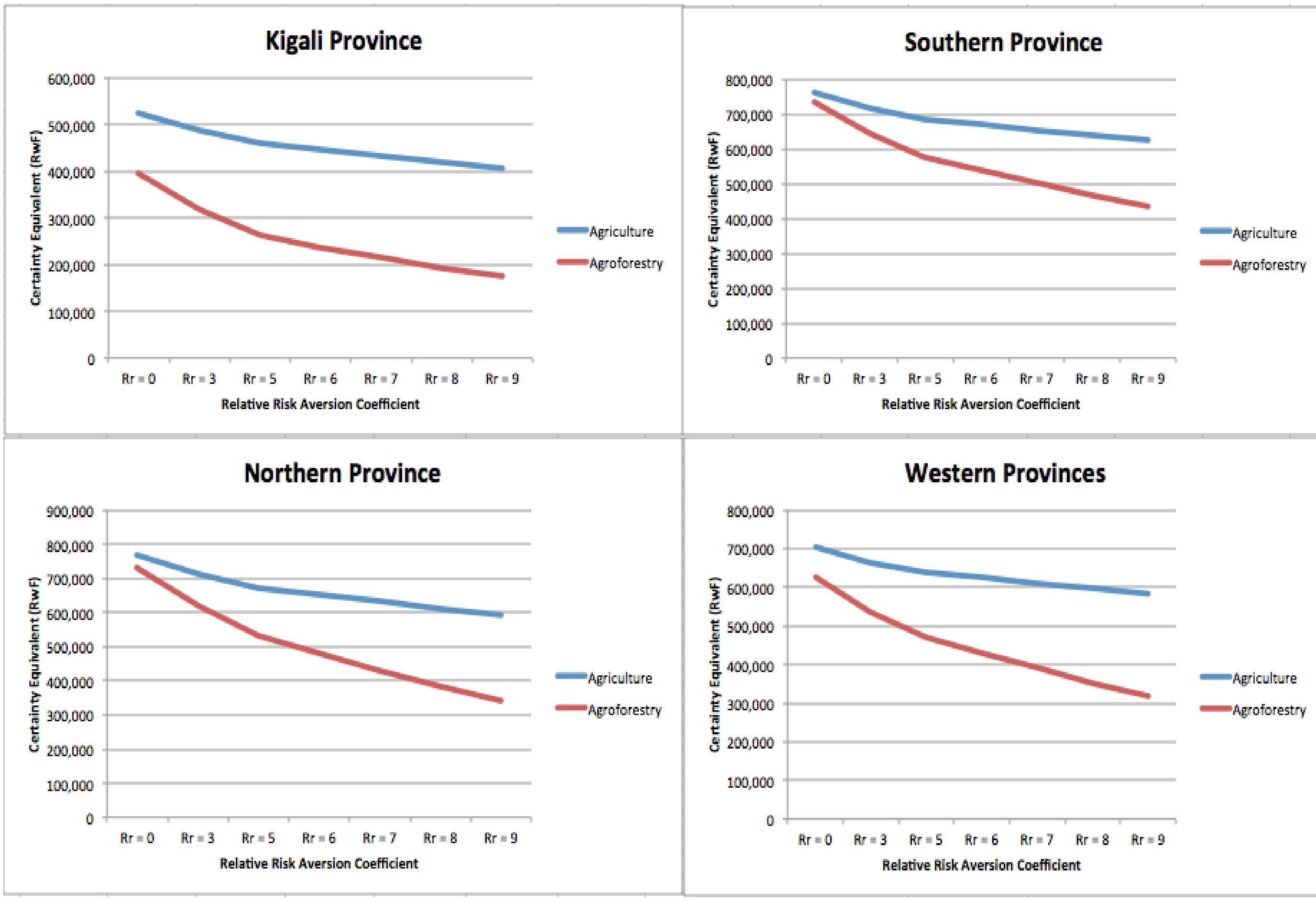

Figure 5. Certainty Equivalence Under Different Risk Aversion Coefficients for Agriculture and Agroforestry.

agroforestry system. Farmers also commonly lack quality agroforestry seedlings, access to on-farm research and development, access to crop insurance with premium subsidies for agroforestry, agroforestry specific market information and price guarantees, and value-adding activities that would all go a long way towards reducing the risks of adopting agroforestry (Rahman et al., 2008).One source of risk in this study was the wide-ranging effect agroforestry has been observed to have on crop and tree yields. Following a set of best practices can systematically reduce this variation. Instead of making agroforestry extension part of small-scale projects, the government should promote knowledge about the activity through national-level extension campaigns that are designed to reduce risk across multiple dimensions of agroforestry activities. Extension efforts should focus on developing and distributing training materials promoting best practices. In countries like Rwanda, where funds to support in-person extension efforts are limited, technologies like farm radio may present better options for disseminating knowledge to a large number of people in rural areas. Extension services can also lower the variability and associated risk of integrating trees in cropping systems by providing smallholders with knowledge and support to produce improved planting materials. This would improve tree growth rates and potentially lower their variability, all of which would lower the risk of the agroforestry enterprise.

If national extension campaigns are not possible there are still other alternatives to disseminate knowledge about agroforestry practices to smallholders in rural areas. Projects like the Community Vitalization and Afforestation of the Middle Shire (COVAMS) in Malawi have adopted an extension approach that gives so-called ‘lead farmers’ access to on-farm research and development so they can disseminate knowledge to other farmers afterwards. These types of extension approaches have only recently been introduced in East Africa, but they have the potential to promote wide-scale adoption of agroforestry because they are low cost and promote practices that smallholders can implement with the resources they have available.

Risk-sharing markets can also improve the adoption rate of restoration activities. As the CE analysis showed, Rwandan smallholders are willing to pay risk premiums to reduce their exposure to climactic risk and a nascent agricultural insurance industry is emerging to meet this demand. However, insurance cannot increase the attractiveness of agroforestry on its own because smallholders can also buy crop insurance for more common agricultural activities, although the cost of premiums will determine whether or not purchasing insurance for a particular activity is worthwhile. However, the results from this study suggest that agroforestry is inherently more risky than agriculture because there are more sources of risk. This suggests agroforestry risk premiums would be higher than those for other agricultural activities. Policy makers could subsidize agroforestry premiums to increase the attractiveness of the activity as long as the social costs of the market distorting effects of the subsidy were less than the social benefits of increased agroforestry adoption. Yet, current research suggests that funds to subsidize crop insurance premiums would provide even more incentives for smallholders to adopt agroforestry if they were used as cash payments, especially when farmers are more risk averse (Marenya et al., 2014)

As the result from the Certainty Equivalence analysis showed, upfront payments would also improve adoption. Payments could be made in cash or in kind. One potential solution would be to offer smallholders vouchers of a certain value that are redeemable at local tree nurseries for a certain number of trees of the smallholders choosing. Similar voucher programs have been put in place to encourage the use of artificial fertilizers and results from Rwanda suggesting that smallholders are willing to adopt agroforestry practices if they can choose tree species tailored to their individual household needs (Bucagu et al., 2012).

Another option is to offer safety nets to farmers who adopt agroforestry. A safety net works by providing some sort of assistance, either food or cash, to smallholders in times of adverse weather shocks. If the safety net available is contingent on the adoption of agroforestry it would reduce the risk found in the tail of the distribution of payoffs. This would change the risk profile of the activity to make it more competitive with agriculture. This would primarily influence the land use decision of very risk-averse smallholders who are the most sensitive to the risk found in the left hand tail of the pay-off distribution.

Previous research has shown that smallholders have clear preferences over the types of policy-based incentives that they respond to and also these preferences are defined by the smallholder’s level of risk aversion (Marenya et al., 2014). Additionally, the incentive that offers the largest financial benefits may not be the one preferred by smallholders. As a result, it is difficult to say which of the policy interventions mentioned above are the best suited to expand the adoption of agroforestry in Rwanda. Future research should focus on consulting with smallholders to determine the activities and incentives that are most likely to result in the adoption of agroforestry activities.

Conflict of Interests

The authors have not declared any conflict of interests.

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