Agroforest Syst (2012) 84:59–72
DOI 10.1007/s10457-011-9426-z

Jatropha adoption: a statistical observational study of factors influencing Malian farmers' decision to grow Jatropha

M. Basinger · J. Chen · F. Jeffrey-Coker · F. S. Rodriguez-Sanchez · T. Singer · V. Modi

Received: 10 August 2010 / Accepted: 6 August 2011 / Published online: 20 August 2011

Abstract An accurate understanding of the factors that influence farmers' adoption of a crop is critical for effective policy promotion and technical support. Agroforestry crop adoption is a complex topic involving many factors not often addressed by tradition crop adoption models. This complexity, when applied to Jatropha (*Jatropha curcas* L.), an often widely promoted yet poorly understood biofuel feedstock crop, requires a detailed analysis across diverse topics. Such an analysis was carried out through applying rigorous statistical tools to the data acquired from an interview-based household survey among Malian farmers and was combined with relevant geospatial datasets. The results showed that though farmers' adoption is based on a wide variety of factors from household preferences, resource endowments, bio-physical factors, and market incentives, factors related to risk and uncertainty appear to provide the strongest correlation. Specifically, the number of visits that an agriculture extension agent makes with a farmer was found to be the most significant factor influencing adoption.

M. Basinger (✉) · J. Chen · F. Jeffrey-Coker · V. Modi
Columbia University, 500 W. 120th Street, Mudd 220, MC4703, New York, NY 10027, USA
e-mail: mlb2133@columbia.edu

F. S. Rodriguez-Sanchez · T. Singer
Mali Biocarburant, Bamako, Mali

Keywords Jatropha · Adoption · Mali · Biodiesel · Agroforestry

Introduction

Jatropha

Jatropha (*Jatropha curcas* L.) is a small tree that over the last decade and a half has received a great deal of attention for its potential to provide energy inputs for both the local tropical contexts where it is suitable to grow, as well as more temperate areas seeking to import biodiesel feedstock. As a non-edible oil-seed able to grow on marginal land, Jatropha arguably avoids food versus fuel debates. Jatropha grows wild throughout much of the world, including Mali where it is widely used as a living fence. Heralded for its capabilities to contribute in wasteland reclamation and erosion control, surviving extreme drought conditions, as well as producing oil rich seeds at a high yield, Jatropha has been hyped in gray literature.

Several peer-reviewed articles have been published in academic journals summarizing ongoing research efforts with regard to Jatropha and energy applications (Banerji et al. 1985; Gubitz et al. 1999; Openshaw 2000; Achten et al. 2008; Kumar and Sharma 2008). One of the more recent articles, Achten et al.'s *Jatropha Bio-diesel Production and*

Table 1 Meta-analysis comparison of variable inclusion and significance in agroforestry adoption studies (from Pattanayak et al. 2003)

Factor type	Included in studies (%)	Significance in included studies (%)
Preferences proxies (education, age, gender, social status)	48	48
Resource endowments (income, assets, labor, livestock, credit/savings)	41	65
Market incentives (potential income gain, distance to market, price)	34	58
Bio-physical factors (soil, slope, plot size, irrigation)	37	80
Risk and uncertainty (tenure, experience, extension, membership)	43	72

Use, provided an updated, even-handed accounting of several controversial issues surrounding Jatropha (Achten et al. 2008). Achten et al. highlighted the complex, and still partially unknown relationships that tree spacing, precipitation, maturity, and other factors have on annual oil yield. Literature varied widely with regard to the treatment of these factors. Climatic and genetic influences aside, Jatropha is regularly promoted by international institutions, governments, NGOs, and others for its benefits to small-holder farmers for its multipurpose, agroforestry uses, including erosion control, income generation from seeds sold into biodiesel and soap markets, and the production of fertilizer from oil extraction processes (Openshaw 2000; Kumar and Sharma 2008). But even with all of this ongoing agronomic research and heavy promotion, the adoption of Jatropha seems to be trailing far behind the knowledge base which promotes it. Even in biodiesel circles, it is difficult to find companies with a large-scale production of biodiesel from Jatropha, due to the low availability of the feedstock. For this reason there is particular interest in better understanding the factors that influence a farmer's decision to grow Jatropha: the adoption of Jatropha.

Mercer (2004) provides a meaningful review of agroforestry adoption, specifically in the tropics. In the review Mercer traces the history of adoption studies related to more traditional agricultural innovations from the 1950s to the present. He provides a detailed account of the use of various models in both traditional agricultural innovation adoption studies over the last half century and agroforestry adoption studies during the last decade and a half. The approaches included hierarchical decision tree models, epidemic or logistic models, participatory approaches, decision-theoretical models, spatial-diffusion models, ex-ante studies, and ex-post studies. Regardless of the approach, agroforestry crop adoption should be differentiated from traditional crop adoption due to the inherent complexity of agroforestry systems. For example, farmer education seems to be more important to agroforestry crop adoption than in conventional agriculture (Barrett et al. 2002). Conventional agricultural development packages tend to be based on improved seed, chemical, and/or mechanical inputs, but agroforestry systems require more complexity through the new input-out mixes of annuals, perennials, green manure, fodder and other components, combined with new techniques such as hedgerows, etc. (Mercer 2004).

A far-reaching survey of agroforestry adoption studies has been undertaken by Pattanayak et al. (2003). The study reviewed 120 articles on agroforestry adoption by smallholder farmers and concluded that there were five categories of factors influencing adoption: household preferences, resource endowments, market incentives, bio-physical factors, and risk and uncertainty as shown in Table 1. Thirty-two empirical, regression-based studies were further compared through a statistical meta-analysis. Though most studies included more easily measured factors like household preferences and resource endowments, these tended to be less important than harder to measure factors such as risk and uncertainty, bio-physical considerations, and market incentives.

The adoption study carried out in this paper involved the collaboration of Columbia University researchers with a local Malian company—Mali Biocarburant (MBSA). The involvement of MBSA was critical in order to take into account the special cultural and social context of Mali and MBSA's business model. MBSA is a biodiesel company, located in Mali, utilizing Jatropha oil as a feed-stock for biodiesel production, which is then sold and consumed in local Mali markets. MBSA runs an agriculture extension network to educate and support farmers in the growing of Jatropha, which is then sold to MBSA. Jatropha farmers are included as shareholders in MBSA via a system of registered farmer associations. MBSA's business model seeks to operate at all levels of the Jatropha value chain, coordinating various actors to create mutually beneficial relationships (Rodriguez-Sanchez 2010). In 2007 Mali Biocarburant (MBSA) began an agriculture extension program for local farmers in Koulikoro focused on cultivation of Jatropha for use as a biofuel feedstock. By 2009 MBSA had expanded its efforts to include the recruitment of over 2,800 farmers in the *cercles* of Koulikoro, Kita, and Kati to produce a combined targeted total of 12,000,000 kg of Jatropha seeds needed to reach the goal of 750,000 l of annual biodiesel production.

MBSA's agriculture extension model was based on recruiting and training farmers through a Farmer Business School outreach network. The business schools used a network of 25 agricultural extension agents who lived in the rural villages where they recruited and trained farmers in Jatropha production. Each agent worked with 3–5 schools across 4 or more villages. Each school was targeted to have at least 25 members (farmers), and each farmer was encouraged to plant at least 1,500 Jatropha trees, totaling approximately 4,000,000 trees across the entire network. Therefore this study paid particular attention to the interventions of MBSA, specifically the influence that extension agents' visits with farmers had on Jatropha adoption.

Regional overview

The study utilized a cluster sampling approach based on MBSA's agriculture extension operation locations in the *cercles* of Koulikoro, Kita, and Kati, shown in Fig. 1. Of the three *cercles* MBSA operated in, Koulikoro contained the largest economic hub, benefiting both from its proximity to the capital city of Bamako and from being a thoroughfare for the transnational trade route that stretched eastward up the Niger River toward Mopti and northward up National Route 27 toward Mauritania. These factors combined with Koulikoro's more arid climate compared with Kita and Kati, may have reduced the central role that farming played among Koulikoro's population, compared to populations in the other two *cercles*. Though Koulikoro was noticeably better equipped in terms of energy, health, and education in its major population hubs, both Kati and Kita possessed better climatic conditions for agricultural activity. The Kati operations were nearer to Bamako than the more remote Kita villages. Recent activities in the cotton industry, combined with the more pervasive presence of the PTFM program (the national program enabling village scale agroprocessing) may have contributed to Kati farmer's receptivity to Jatropha. Though remote, the Kita operations benefit from the most verdant ecologically and climatically viable conditions for agriculture

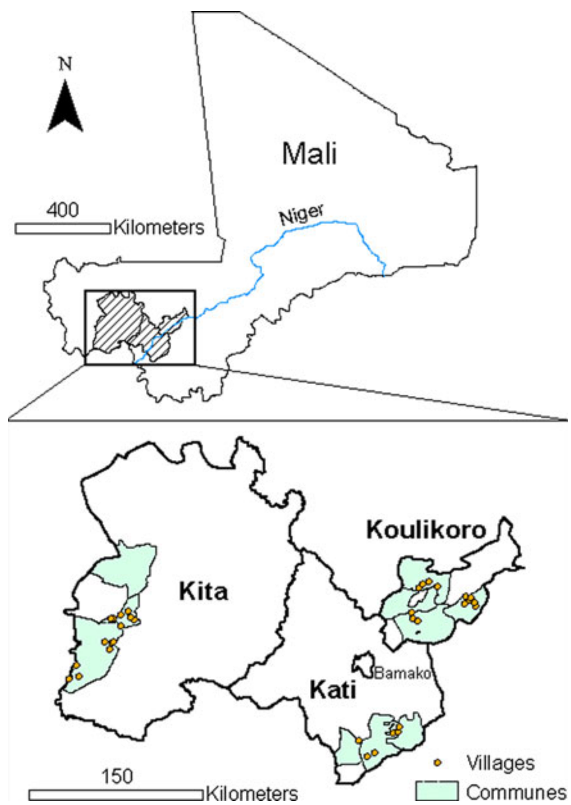

Fig. 1 Map of Kita *cercle*, Kati *cercle*, and Koulikoro *cercle* with highlighted communes and villages where the adoption study occurred

production (having the best rain and river access) of the three areas where MBSA operates.

Methods and approach

Study design

As no known previous study had been carried out on Jatropha adoption explicitly, this study was designed to be an exploratory, retrospective, observational study providing a starting point for further investigations. Prior to data collection there was not a specific model that was designed for testing, with defined parameters having been previously hypothesized before the study was undertaken. Instead, the focus of this study was to measure a diverse set of factors and to compare the correlation of these different factors with the occurrence of Jatropha adoption. This correlation was looked at on an individual variable basis, as well as through a multi-variable model. The full list of major and minor category factor types, shown in Table 1, covered in the Pattanayak et al.'s (2003) meta-analysis of agroforestry studies, was included in this investigation.

Per Pattanayak et al.'s categorization scheme, a lengthy list of almost 200 variables were targeted (factors were approached through measuring variables; all factors were associated with multiple variables to provide a robust redundancy). A few additional factor sub-categories were added to those described by Pattanayak et al. These additional sub-categories were:

- methods, pests, and temperature (bio-physical factors)
- remoteness/accessibility (market incentives)
- priorities and social life (preference proxies)
- crops (resources endowments)

The primary mechanism for measuring each variable was through a questionnaire delivered by MBSA field agents during in-person interviews. Agents asked farmers a series of more than 100 questions and collected GPS (Global Positioning System) points at farmer's homes and fields. These GPS points were then used later to calculate further geospatially related variables, as described below. Due to instances of missing questions and a lack of meaningful variance in some variables, the list of 195 variables was reduced before analysis. This reduced list of variables, by category, sub-category, and type is shown in Table 2.

The sample frame of the study included the entire informed population of farmers with which MBSA was working, or had tried to work. The informed population included more than 2,300 adopting farmers who had registered with MBSA in 2009; adopters had chosen to attempt to grow at least 1,500 trees during the year. Non-adopters were farmers who had been approached by MBSA, but had chosen not to attempt to grow 1,500 trees in 2009. In this way the study was specific to only the informed population not the entire farmer population.

Sampling process

400 random samples were taken to achieve a reasonable significance level and statistical power (5% two sided alpha, 80% power) based on estimated results from a pilot study. 33% oversampling was employed to account for anticipated non-response (estimated results from the pilot study required a sample size of only 300). Simple random sampling (SRS) across the entire sampling frame was not practical; instead, stratified, proportional cluster sampling was employed. There were primarily three reasons for this sampling approach.

1. From the pilot, it appeared there were likely some differences among the three *cercles*, as well as differences among the field agents. Stratifying the sample proportionally among the three *cercles* was assumed to likely decrease variance and improve the analysis.
2. An SRS over the entire frame was assumed to likely result in a small number of samples per village across a large number of villages. Logistically this would have been too expensive. Instead, per region, a proportional number of extension agents were randomly sampled. From these extension agents a number of villages were sampled. This provided a balance between an adequately limited yet still diverse geographic scope.
3. A complete list of all farmers from the frame was not easily accessible. A total count of adopters per village, per extension agent, per region was available. But only each extension agent had the

Table 2 Number of measured variables per factor category, sub category, and type

	Binary	Categorical	Continuous	Count	Grand total
Bio-physical factors	9	10	5		24
Irrigation	1	3	1		5
Land cover		1			1
Methods		1			1
Pests	3	2			5
Plot size		1	3		4
Soil	5	2			7
Temperature			1		1
Market incentives		16	7	1	24
Distance to market		1			1
Potential income gain		2			2
Price		1	1		2
Remoteness/accessibility		12	6	1	19
Preference proxies	5	12	3	3	23
Age			2		2
Education	1	4			5
Gender	1				1
Priorities	1	4	1		6
Social life		2		3	5
Social status	2	2			4
Resource endowments	18	15	29	22	84
Assets	2	4		15	21
Credit/savings	6				6
Crops	10	9	28	1	48
Income		1			1
Labor		1	1	3	5
Livestock				3	3
Risk and uncertainty	4	4		2	10
Experience	3	2		1	6
Extension		1		1	2
Membership	1				1
Tenure		1			1
Grand total	36	57	44	28	165

list of non-adopters. For this reason, only once the specific villages had been sampled, was the list of corresponding adopters and non-adopters easily obtained from this subset of villages. From these villages (the clusters) the specific farmer sampling took place.

The number of adopters from within the sample frame was known to be 2,312 farmers previous to the study. These adopters were spread across the three *cercles* MBSA operated as shown in Fig. 2. A random sample of 40% of the extension agents was determined to be the highest number logistically manageable. This resulted in 4 agents being randomly selected from Kita, 4 from Koulikoro, and 2 from Kati. Once these agents were identified, a proportional number of villages were randomly sampled from each animator resulting in 13, 13, and 6 villages from the three *cercles* as shown in Table 3. Once these villages were chosen, a complete count of each of their adopter and non-adopter populations was obtained. Proportional random sampling was carried out across these villages: the number of farmers

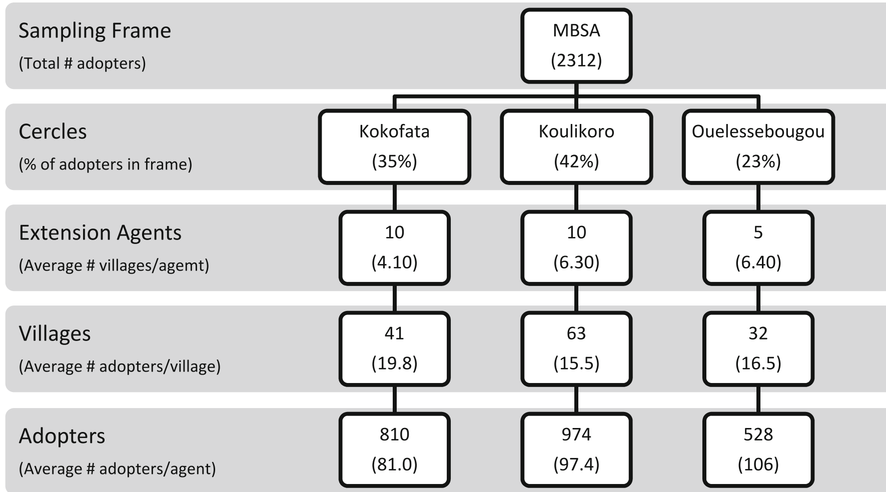

Fig. 2 Distribution of extension workers, villages, and adopters across the sampling frame

Table 3 Sample distribution

Cercle	Target % of total sample	Agents sampled	Villages sampled	Adopters sampled	Non-adopters sampled
Kita	40	4 of 10	13 of 68	81 of 175	74 of 108
Koulikoro	40	4 of 10	13 of 84	87 of 184	89 of 144
Kati	20	2 of 4	6 of 39	32 of 68	37 of 54

sampled from each village was based on the proportion of the overall adopter (or non-adopter) population residing in that village. For example, in one village there were 16 adopters which was 4% of the total number of adopters across the 32 sampled villages, 7 of these 16 adopters were randomly selected, to maintain the proportion (7 was approximately 4% of the 200 sampled adopters).

Mobile telephony was used to collect data from the interviews using the household questionnaires as well as geospatial data. The University of Washington's Open Data Kit (ODK) platform was used with G1 smart phones running the Android operating system (Jeffrey-Coker and Basinger 2010). The use of these survey tools provided quick feedback, allowing for real-time enumerator error checking during survey training and actual data collection.

Results

Calculated geospatial variables

GPS points (longitude and latitude) were acquired at each farmer's home. (Farmer field and water source points were also collected, but due to a large amount of incompleteness in these data points, they were not included in the analysis.) The farmer home positions were utilized to calculate several geospatial related variables as listed in Table 4.

The GIS software platform ArcGIS was used for all geospatial analysis. Calculations were undertaken using applicable UTM projections. From the GPS data points and political boundary shapefiles from GADM (Hijmans et al. 2010a), the name of the *cercle*, *arrondissement*, and commune were identified for each farmer. The total arrondissement and commune land area (number of square kilometers) was calculated for each farmer and tabulated. The nearest road and river to each farmer's home was calculated using the ESRI's Digital Map of the World data set (Environmental Systems Research Institute 1993). The road type (Primary Route, Secondary Route, or Unknown) and the river type (Perennial–Permanent or Non-Perennial–Intermittent–Fluctuating) were also identified. The type of land cover occurring at each home was identified using the GlobCover Land Cover data set (European Space Agency 2008). Of the 22 different categories of land cover, six were encountered across the 285 homes:

Table 4 List of geospatial variables calculated using GPS points of farmer's home

Variable	Description (relative to farmer's home)	Data set
Arrondissement area	km^2 of the arrondissement	GADM
Arrondissement	Name of the arrondissement	GADM
Cercle	Name of the *cercle*	GADM
Commune area	km^2 of the commune	GADM
Commune	Name of the circle	GADM
Commune population	Total population of the commune	IPUMSI, GADM
Commune population density	People/km^2 in the commune	IPUMSI, GADM
Distance to river	Number of meters to the nearest river	ESRI
Distance to road	Number of meters to the nearest road	ESRI
Land cover	Type of land cover	GlobCover
Precipitation	Average number of mm of annual rainfall	WorldClim
Nearest river type	Type of river that was closest	ESRI
Nearest road type	Type of road that was closest	ESRI
Temperature	Average annual temperature (C)	WorldClim

closed to open shrub-land, mosaic croplands vegetation, mosaic forest shrub-land grassland, mosaic vegetation croplands, open broadleaved deciduous forest, and rain-fed croplands. Annual precipitation (compiled and interpolated from 1950 to 2000) via the WorldClim data set was used to identify the number of annual millimeters of rainfall encountered at each home (Hijmans et al. 2010b). Average annual temperature, from the GlobClim data set was obtained for each home (Hijmans et al. 2010b). The University of Minnesota's Integrated Public Use Microdata Series International (IPUMSI) data set was used to estimate populations of communes in Mali (Minnesota Population Center 2009).

Model construction

The responses of the model are the binary choice of whether a farmer adopted Jatropha or not. The study's questionnaire utilized a great deal of question redundancy, requiring the use of three approaches for the construction of a reasonable statistical model: (1) a model selection procedure, (2) expert knowledge, and (3) variable transformations. The *Group Lasso Method* by Meier et al. (2008) was utilized for the model selection process because of its ability to select categorical variables. Meta-analysis results from Pattanayak et al. (2003) were utilized for expert knowledge. As described above, Pattanayak et al. classified five categories of adoption variables: biophysical factors, market incentives, preference proxies, resource endowments, and risk and uncertainty. Variable transformation was also required for a set of questions involving the farmer's ownership of various household items including TVs, Radios, Solar Panels, Roofing Materials, Motorcycles, Cell phones, Batteries, and Bikes. A principle component analysis was carried out, per Filmer and Pritchett (2001), to construct an asset index for the aggregation of these asset variables.

Missing data problems

There were two kinds of missing data issues in the dataset: (1) missing questionnaires (the whole questionnaire was missing), or (2) missing questions (some variables were missing). The first case (missing questionnaires) was due to noncontact or refusal. Weighting adjustment for non-response was used to handle the first case, and multiple imputation was implemented to impute the missing variables for the second case (missing questions).

Response weighting

Response weights were calculated to adjust for the non-responses (Lohr 2009). The weighting class was defined as the responses in the same animator areas, since this information was known for every sampled response.

$$r_j = \frac{\text{number of samples sampled for agent } j}{\text{number of responses for agent } j} \quad (1)$$

In this way it was assumed that in each agent's area, the response probability did not depend on the outcome. Table 5 compares response rates for adopters and non-adopters for each agent using log odds ratios. None of the log odds ratios are significantly different from zero, which supports the assumption for using the weighting described method

Multiple imputation

The multiple imputation was implemented through the utilization of the *mi* package in R, as detailed by Su (in review). After running the *mi* procedure for 200 iterations, it converged, and three imputed datasets were generated. The results for analyzing the three imputed datasets were similar; so only one set of results has been presented.

Survey weights

Besides response weights, there were also unequal sampling weights for different sampled responses. Samples in the survey were sampled using a multi-stage sampling procedure: for each of the three *cercles*, 40% of the agents were randomly selected; among each selected agent, a subset of villages was randomly selected with slightly different probabilities for villages of different agents (some agents were responsible for more villages then others); among each selected village, certain numbers of Jatropha adopters and nonadopters were randomly selected based on the known ratio of adopters to nonadopters. In the last sampling step, the selection probabilities depended on the farmers' adoption status. All of these sampling weights were known.

Survey weighted estimate studies have a rich body of literature, including Korn and Graubard (1995a) which compared the difference between weighted and unweighted estimates, and showed examples where they can differ greatly. As is well known, weighted estimates reduce estimation bias, but might increase estimation variances compared to unweighted estimates. As recommended by Korn and Graubard (1995b), both weighted and unweighted estimates were studied, since it is not clear that it is always better to use weighted estimates.

Weighted multilevel modeling

Multilevel modeling is a natural fit for multistage sampling, and is thus applicable to this study. Pfeffermann et al. (1998) thoroughly discussed multilevel modeling with unequal survey weights. Rabe-Hesketh and Skrondal (2006) provided an even more practical discussion as well as a STATA function implementing weighted Pseudo-multilevel modeling with a Sandwich estimator of the standard errors. This function was used for the study at hand, with the following three levels: agent, village, and households. Only two levels: agent and households were considered for the model, since there were not enough data points for each village to estimate the

Table 5 Response rates for agents

AGENT	Response non-adopters	Response adopters	Non-response non-adopter	Non-response adopter	Log odd ratio	SE of log odd ratio
Agent 1	0	3	14	15	–	–
Agent 2	11	25	3	3	−1.44	0.89
Agent 3	10	12	3	1	−0.94	1.23
Agent 4	0	19	0	13	–	–
Agent 5	5	9	1	6	−1.40	1.22
Agent 6	23	13	2	1	−1.01	1.27
Agent 7	10	18	2	0	–	–
Agent 8	17	9	15	3	0.04	0.75
Agent 9	42	15	27	7	0.12	0.52
Agent 10	14	25	1	3	−1.84	1.20

The log odds ratios for cells with "–" are not available intra and inter village variations thoroughly. For the agent level, the weights are shown in Eq. 2

$$w_j = 1/0.4 = 2.5 \tag{2}$$

and these weights are the same for every agent. For the households level, the weights are provided in Eq. 3

$$H_{kij} = w_{k|i} w_{i|j} r_j \tag{3}$$

where $w_{k|i}$ is the survey weight for adopter ($k = 1$) or nonadopter ($k = 0$), when the ith village is selected, $w_{i|j}$ is the survey weight for the ith village, when the jth animator is selected, and r_j is the adjusted response weight for the jth animator as defined in Eq. 1.

As Pfeffermann et al. (1998) noted, the scaling of H_{kij} affects the estimates of the variances. For this reason, the suggestions from Carle (2009) were followed, results for models without weight scaling have been presented, together with results for two different scaling methods. These two scale methods (s1 and s2) were suggested by Pfeffermann et al. (1998), and are defined as follows:

$$\text{Scaling method (1)}: \quad H_{kij}^{s1} = \frac{H_{kij} H_j}{\sum_{kj} H_{kij}^2}, \qquad H_j = \sum_{ki} H_{kij} \tag{4}$$

$$\text{Scaling method (2)}: \quad H_{kij}^{s2} = \frac{H_{kij} n_j}{\sum_{kj} H_j}, \quad n_j = \sum_{ki} n_{kij} \tag{5}$$

As is clearly seen, after scaling, the response weight defined in (1) does not affect the scaled version of weights (Table 7).

Multilevel model estimate results

What follows is the presentation of the estimate results for the logistic multilevel models without weights, and with weights by scaling method (1), using the *gllamm* function developed by Rabe-Hesketh and Skrondal in STATA (Rabe-Hesketh and Skrondal 2006). Since the results using weights scaled by scaling method (2) are very similar to the results from scaling method (1), only one set of weighted results are presented. All the continuous variables are standardized, and all the binary variables are standardized by two standard deviations, as suggested by Gelman (2008).

For robustness checking and model selection, different model specifications were tested where other variables were added or some variables were deleted. The model presented achieved the highest Akaike Information Criterion (AIC) and interpretability.

Discussion

The multilevel model results can be used as a tool for practitioners, providing a quantitative mechanism for making initial, high level agriculture extension policy decisions. These estimated coefficients from the model point toward what type of interventions may more readily lead toward adoption, and which types of farmers are more likely to adopt. What follows is a discussion of these results through an unpacking of several of the more important variables (A description of all the variables used in the model can be found in Table 6).

Biophysical factors

Precipitation, type of land cover, amount of total and fallow land a farmer has access to, and the average temperature all show strong associations with adoption status. Land cover was coded to be 1 if it was a "Rainfed cropland", which was assumed to be the most suitable land type for growing Jatropha. The positive sign for the estimated coefficient for the land cover type shows that farmers are more likely to choose to adopt Jatropha if their land is more suitable for growing. Similarly, the estimated coefficient for the amount of land available to a farmer shows that greater land access relates to greater tendency to adopt.

With all the other variables being the same, the farmers with smaller fallow land tend to have larger probabilities of adoption. This could be explained by assuming that a) either a farmer used their fallow land to plant Jatropha, in effect reducing the amount of fallow land they had, or b) farmers who were more likely to adopt had less fallow land all along. In either case, there appears to be a relationship between access to fallow land and adoption.

This could also imply another type of relationship between land availability and adoption: land

Table 6 Description of variables used in model

	Description
Biophysical factors	
Precipitation	Yearly rainfall total at farmer's home
Land cover type	Type of land cover at farmer's home
Pesticide	Does the farmer use pesticide
Fallow land	Number of hectares of fallow land
Chemical fertilizer	Does the farmer use chemical fertilizer
Land	Number of hectares of total land
Average temperature	Average ambient temperature at farmer's home
Market incentives	
Price	Price per kg of Jatropha seed that the farmer perceives
Community population	Population of the village where the farmer lives
Nearest river type	Type of river (permanent, seasonal) closest to farmer
Distance to permanent river	Distance from closest permanent river to farmer
Nearest river type * Distance to permanent river	Combination of nearest river type and distance to permanent river
Distance to mali road	Distance from closest road to farmer
Land * Distance to permanent river	Combination of Land and Distance to permanent river
Preference proxies	
Age	Age of the farmer
Education of man	Education of the most educated man in the farmer's household
Waiting	Number of years farmer is willing to wait for Jatropha income
Resource endowments	
Asset index	Principal component analysis of several household items
Total tools	Number of different farming tools farmer has
MFP	Access to an agro-processing center in their village or nearby
MFP * Land	Combination of MFP and Land
Distance to the closest permanent river * MFP	Combination of MFP and distance to closest permanent river
Millet	Does the farmer grow millet
Peanuts sacks Ha	Number of sacks of peanuts produced per hectares planted
Rice sacks Ha	Number of sacks of rice produced per hectares planted
Sesame Ha	Number of hectares of sesame planted
Cotton Ha	Number of hectares of cotton planted
Food crops	Total number of different food crops grown
Total crops	Total number of all crops grown
Credit yes	Does the farmer has access to credit
Total labor	Total number of laborers the farmer utilizes
Bee	Does the farmer own bee hives
Risk and uncertainty	
Knowledge	Has the farmer planted something similar to Jatropha in the past
Union	Is the farmer a member of a farmers' union
MBSA visits	How many visits per year an MBSA agent makes to farmer
MBSA visits^2	MBSA visits squared
MFP * MBSA visits	Combination of MFP and MBSA visits
Total threat	Total number of types of agricultural threats

ownership or designation may change with the growing of a perennial crop. Singer's Socio-Economic Baseline Study of Jatropha farmers across 12 villages in Koulikoro Mali (Singer 2008) found land ownership implications with regard to Jatropha adoption: 94% of land, among interviewed Jatropha farmers, was family owned before Jatropha was adopted and just 36% was family owned after adoption where as individual ownership rose to 60%. Singer's study utilized individual interviews with farmers and provided evidence that the planting of Jatropha contributed to a rise in individual land ownership. This was not to say that families weren't working fields collectively after adoption, but rather the planting of Jatropha (a perennial crop) may have designated a farmer as responsible for that specific field; a perceived "specialization" in the production of certain fields may have communicated investment in the long-term productivity of those fields. Along this reasoning, the intensification of farming on certain plots could lead to an adopter's response that they had little fallow land. Theses farmers may simply have been designating a parcel of their family plot for themselves and farming it very actively. It is likely that families may own large portions of land, but with no specific individual as the point person for that plot. Singer's study also found that large tracts of land, particularly in very rural areas, may often remain fallow for long periods of time. Land ownership and designation in the developing world is a highly complex, politically charged issued. A full treatment of the land ownership implications of Jatropha and its political interpretation is beyond the scope of this study.

For the case of rainfall and temperature's influence on adoption, higher precipitation and higher temperature were both associated with higher adoption rates. The range of the temperature variable was very small, but even so, the significance might reflect the importance of certain geographic characteristics for Jatropha adoption.

Market incentive

The distance a farmer lived from a road was found to be negatively significant, which follows the results reviewed in Pattanayak et al. (2003) where 8 of 8 studies which included distance to market variables found significantly negative results. These results show that, with all the other characteristics being the same, the farmers who are closer to the road have more incentive to adopt Jatropha.

Geographic variables come in many forms. The distance a farmer lived from a river was also measured. The farther away from a river a farmer was, the more likely they were to adopt Jatropha, and this negative association was stronger for farmers whose closest river was a permanent river. However the increased adoption probability from being farther away from the permanent rivers shrinks if the farmer had more land. The results conform to the local observation that most of the farmers who are close to the permanent rivers emphasize vegetable gardens as a main agricultural focus, or primarily fishermen. Their proximity to the river may indicate an increased emphasis on other high value crops (vegetables) or fishing and decreased emphasis on farming, reducing the likelihood of adopting Jatropha.

Preference proxies

The age and education of men in the household showed weak significance with regard to adoption, yet the sign of estimated coefficients for education did show that higher education increased Jatropha adoption.

The preference proxy with the greatest significance was the variable "Waiting." This variable was measured by asking the farmers about the number of years that they would wait for one hectare of Jatropha to start earning a revenue of 65,000 fCFA before deciding that it was not worth it to have planted. This variable represented a farmers' patience with adopting Jatropha. The estimation results showed that the longer that the farmers were willing to wait, the more likely they were to adopt Jatropha.

Resource endowments

The asset index and the total number of tools variables did not show significant results. However, the existence of a local agroprocessing system (a Multifunction Platform, or MFP for short) in a farmer's village or nearby village was influential: when a farmer had easy access to agroprocessing (an MFP) and enough land, they had a high probability to adopt Jatropha.

The results also show that when farmers already planted a lot of cash crops, like millet, peanut,

Table 7 Multilevel model results

	No weighting		Scaling method (1)	
	Estimates	SE	Estimates	SE
Biophysical factors				
Precipitation	3.13	(1.63)*	2.93	(1.59)*
Land cover type	1.99	(0.79)**	2.19	(0.89)**
Pesticide	−0.31	−0.87	−0.12	−0.71
Fallow land	−1.6	(0.80)***	−1.72	(0.68)**
Chemical fertilizer	−0.13	−0.89	0.12	−0.59
Land	1.27	(0.67)*	1.46	(0.38)***
Average temperature	2.45	(0.89)***	2.67	(1.33)**
Market incentives				
Price	0.4	−0.8	0.43	−0.92
Community population	1.69	(0.86)*	1.64	(0.92)*
Nearest river type	−1.25	−1.27	−0.57	−1.12
Distance to permanent river	1.09	−1.07	1.56	−1.31
Nearest river type * Distance to permanent river	2.05	(1.24)*	2.84	(1.19)**
Distance to mali road	−1.9	(1.12)**	−1.77	(0.88)**
Land * Distance to permanent river	−1.77	(0.86)**	−1.94	(0.88)**
Preference proxies				
Age	0	−0.28	0.06	−0.31
Education of man	0.11	−0.53	0.14	−0.54
Waiting	4.46	(0.99)***	4.89	(1.52)***
Resource endowments				
Asset index	0.1	−0.5	−0.02	−0.45
Total tools	0.09	−0.53	0.41	−0.68
MFP	1.49	−1.79	1.61	−1.12
MFP * land	4.14	(1.93)**	4.56	(1.91)**
Distance to the closest permanent river * MFP	−2.88	−1.89	−1.82	−1.79
Millet	−1.38	(0.78)*	−1.6	(0.71)**
Peanuts sacks Ha	−0.28	−0.35	−0.3	−0.39
Rice sacks Ha	0.17	−0.51	0.15	−0.23
Sesame Ha	−1.45	(0.40)**	−1.65	(0.79)**
Cotton Ha	−0.45	−0.4	−0.58	−0.54
Food crops	−2.84	(0.68)***	−2.94	(1.01)***
Total crops	3.75	(0.79)***	3.83	(1.17)***
Credit yes	−0.08	−0.6	−0.03	−0.45
Total labor	−0.42	−0.77	−0.83	−0.7
Bee	0.69	(0.34)***	0.76	(0.28)***
Risk and uncertainty				
Knowledge	1.35	−0.87	1.42	(0.36)***
Union	1.7	(0.73)**	1.8	(0.83)**
MBSA visits	11.43	(2.67)***	11.16	(2.39)***
MBSA visits^2	−6.04	(1.80)***	−5.86	(1.40)***
Total Threat	−0.59	−0.5	−0.61	(0.37)*

*$P < 0.1$; **$P < 0.05$; ***$P < 0.01$

sesame, and cotton, they were less likely to start planting another cash crop: Jatropha. The variable "Total Crops" was the number of different kinds of crops that were planted, including both cash crops and food crops (but not including Jatropha). The greater the number of different kinds of crops overall (total crops) that a farmer planted, the more likely that they were a Jatropha adopter. While the more food crops that they planted, the less likely they were to adopt. This may indicate that greater food crop diversity alone shows an indication of an emphasis on subsistence farming and a lack of capacity for cash crops, where as a greater diversity of overall crops (total crops) shows a capacity for expanding to new cash crops (i.e., Jatropha). These findings show that when resources (land, water, etc.) are fixed, farmers may be practicing wise allocation.

Risk and uncertainty

If a farmer had experience with crops that they believed were similar to Jatropha, they were more likely to adopt (per the estimate results for the variable "knowledge": the variable "Knowledge" was coded as a "1" if a farmer said they had previous experience growing a crop that they thought was similar to Jatropha.). It is likely that if a farmer has experience, the risk that they view for adopting it will be smaller. Similar conclusions can also be found from the analysis of the variable "MBSA visits" and "union". "MBSA visits" was a continuous variable transformation of the mutually exclusive choice, categorical question asking the farmer to describe how often during 2009 they received visits from an MBSA agent. The options for responses were: never, once a year, once a month, 2–4 times per month, once a week, 2–6 times per week, every day. Each farmer's response was transformed into a numeric value based on their categorical response. 153 farmers responded that an agent visited 2–4 times per month or less, 23 responded that an agent visited weekly, and 57 responded that an agent visited daily. By adding a quadratic term of "MBSA visits," the result suggests that agents visiting daily did not increase the adoption further, while visiting weekly seems to be the most cost-effective visiting frequency.

Farmers were asked about several perceived threats including erosion, insects, rain shortage, poor soil, etc. The sum total of all of these threats that the farmer identified was captured in the variable "total threats." Though this estimate coefficient was negative (more threats meant less likelihood of adoption), it was not highly significant.

Conclusion

The factors influencing adoption of agroforestry crops are complex. As no previously known adoption studies had been carried out for Jatropha, the results from this study provide a critical starting point, helping to narrow down the hundreds of possible options to a few core, highlighted factors. The results from Table 7 show that all five characteristics (biophysical factors, market incentives, preference proxies, resource endowments, and risk and uncertainty) play important roles in Jatropha adoption, and farmers' decisions are rather rational. The decision to adopt Jatropha is more likely when a farmer has enough land, more incentive and information. Among these factors, the role that information plays (as indicated by the variables MBSA visits, knowledge, and union) is important and is especially interesting. Giving farmers enough information to booster the adoption agrees with other studies such as Duflo's work on fertilizer adoption in west Kenya which found that giving farmers more information about the benefits of fertilizer increased their fertilizer adoption (Duflo et al. 2005). Further work should be carried out to test these particular results regarding Jatropha adoption: a random experiment should be devised to test the causal effects that information may have for increasing Jatropha adoption. Such follow-up work could further help to quantify adoption mechanics, further unlocking decision making tools toward appropriate agroforestry practices.

References

Achten WMJ, Verchot L et al (2008) Jatropha bio-diesel production and use. Biomass Bioenergy 32(12):1063–1084

Banerji R, Chowdhury AR et al (1985) Jatropha seed oils for energy. Biomass 8(4):277–282

Barrett CB, Place F et al (2002) The challenge of stimulating adoption of improved natural resource management practices in African agriculture. In: Barrett CB, Place F, Aboud A (eds) Natural resources management in African agriculture: understanding and improving current practices. CABI Publishing, Wallingford, pp 1–22

Carle AC (2009) Fitting multilevel models in complex survey data with design weights: recommendations. BMC Med Res Methodol 9:49

Duflo E, Kremer M, Robinson J (2005) Understanding fertilizer adoption: evidence from field experiments. Mimeo, MIT

Environmental Systems Research Institute (1993) Digital chart of the world

European Space Agency (2008) GlobCover land cover (v2.2)

Filmer D, Pritchett LH (2001) Estimating wealth effects without expenditure data—or tears: an application to educational enrollments in states of India. Demography 38(1):115–132

Gelman A (2008) Scaling regression inputs by dividing by two standard deviations. Stat Med 27:2865–2873

Gubitz GM, Mittelbach M et al (1999) Exploitation of the tropical oil seed plant *Jatropha curcas* L. Bioresour Technol 67(1):73–82

Hijmans R, Garcia N et al (2010a) GADM: database of global administrative areas

Hijmans RJ, Cameron S et al (2010b) WorldClim global climate data

Jeffrey-Coker F, Basinger M (2010) Open Data Kit—technology review. http://modi.mech.columbia.edu/2010/04/open-data-kit/

Korn EL, Graubard BI (1995a) Examples of differing weighted and unweighted estimates from a sample survey. Am Stat 49:291–295

Korn EL, Graubard BI (1995b) Analysis of large health surveys: accounting for the sampling design. J R Stat Soc A 158:263–295

Kumar A, Sharma S (2008) An evaluation of multipurpose oil seed crop for industrial uses (*Jatropha curcas* L.): a review. Ind Crop Prod 28(1):1–10

Lohr SL (2009) Sampling: design and analysis. Brooks/Cole Cengage Learning, Boston, MA

Meier L, van de Geer S et al (2008) The group lasso for logistic regression. J R Stat Soc B 70(1):53–71

Mercer DE (2004) Adoption of agroforestry innovations in the tropics: a review. Agrofor Syst 61–62:311–328

Minnesota Population Center (2009) Integrated public use microdata series, international: version 5.0 [machine-readable database]. University of Minnesota, Minneapolis

Openshaw K (2000) A review of *Jatropha curcas*: an oil plant of unfulfilled promise. Biomass Bioenergy 19(1):1–15

Pattanayak SK, Mercer DE et al (2003) Taking stock of agroforestry adoption studies. Agrofor Syst 57(1):173–186

Pfeffermann D, Skinner CJ, Holmes DJ, Goldstein H, Rasbash J (1998) Weighting for unequal selection probabilities in multilevel models. J R Stat Soc B 60:23–40

Rabe-Hesketh S, Skrondal A (2006) Multilevel modeling of complex survey data. J R Stat Soc A 169:805–827

Rodriguez-Sanchez FS (2010) Development and testing of business models for Jatropha powered multifunctional platforms (MFPs) for energy access services. Internal Report for cooperation agreement between Mali Biocarburant SA and ETC Foundation Agreement Number 079265-2009-033

Singer T (2008) Socio-economic baseline study. Mali Biocarburantm, Bamako

Su Y-S, Gelman A, Hill J, Yajima M (in review) Multiple imputation with diagnostics (mi) in R: opening windows into the black box. J Stat Softw