Agroforestry Systems **57**: 173–186, 2003.
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Taking stock of agroforestry adoption studies

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Received 23 April 2002; accepted in revised form 13 February 2003

Key words: Contour hedgerows, Meta-analysis, Soil and water conservation, Tree planting, Vote-counting

Abstract

In light of the large number of empirical studies of agroforestry adoption published during the last decade, we believe it is time to take stock and identify general determinants of agroforestry adoption. In reviewing 120 articles on adoption of agricultural and forestry technology by small holders, we find five categories of factors that explain technology adoption within an economic framework: *preferences, resource endowments, market incentives, biophysical factors*, and *risk and uncertainty*. By selecting only empirical analyses that focus on agroforestry and related investments, we narrow our list down to 32 studies primarily from tropical areas. We apply vote-counting based meta-analysis to these studies and evaluate the inclusion and significance of the five adoption factors. Our analysis shows that preferences and resource endowments are the factors most often included in studies. However, adoption behavior is most likely to be significantly influenced by risk, biophysical, and resource factors. In our conclusion, we discuss specific recommendations for the next generation of adoption studies and meta-analyses that include considering a fuller menu of variables, reporting key statistics and marginal probabilities, and conducting weighted meta-regressions.

A growing interest in adoption behavior

Despite some impressive scientific and technological advances over the last three decades, agroforestry rural development projects have experienced uneven success rates in many parts of the world due to inadequate adoption rates and/or abandonment soon after adoption. Faced with this situation, Sanchez (1995) highlighted 'the need to develop a predictive understanding of how farm households make decisions regarding land use,' as others argued for more socioeconomic research on agroforestry (Current et al. 1995a; Mercer and Miller 1998). Soon thereafter, *Agroforestry Systems, Agricultural Economics* and other academic journals began to publish empirical adoption studies at a rapid rate, reflecting researchers' efforts to better understand the behavioral components of agroforestry adoption. Seven years after Sanchez's call to action, we believe that it is time to step back and take stock of what we have learned from the numerous empirical studies on agroforestry adoption. Specifically, we compare and combine the specific cases described and modeled in the published literature to find general patterns in agroforestry adoption. Such a review also responds to Scherr's (1992, p. 807) call 'to improve our skill in collecting and analyzing existing information' in order to understand agroforestry adoption.

Most of the recent adoption studies explain how various farmer, farm, and project characteristics are correlated with past adoption behavior, based on binary choice regression models estimated from household surveys that represent a single snapshot in time. Because many of the studies fail to link the empirical analysis to underlying theory and use only a few factors in regression models of adoption in limited geographic areas, they cannot offer a general predictive understanding of farmers' adoption decisions. In general, it is difficult, if not inappropriate, to generalize from these adoption studies due to limitations of (a) populations sampled, (b) time dimension considered, (c) factors and variables included, and (d) variation

in technology or policy variables. Therefore, in this paper we: (1) review the general adoption literature to identify the major determinants of technology adoption and (2) combine information from 32 agroforestry adoption studies in a simple meta-analysis to evaluate the influence of general factors on agroforestry adoption. To our knowledge, this represents the first meta-analysis of agroforestry adoption studies.

Simple meta-analysis: a systematic way to learn about agroforestry adoption

Good literature reviews or surveys are useful because they provide (a) an immediate access point to the literature for those new to an area, and (b) a useful way to update material for practicing researchers. However, even the most thoughtful review of large collections of empirical studies offers limited benefits due to the heterogeneity of the literature (Cook et al. 1992). In the context of agroforestry adoption, we can improve on conventional reviews of quantitative, empirical literature by asking whether a group of studies can collectively provide a richer picture of the determinants of agroforestry adoption than can be developed from a qualitative comparison of the individual study features and results.

Meta-analysis includes several quantitative methods for synthesizing results and generalizing from a variety of research methods, including opinion surveys, correlation studies, experimental and quasi-experimental studies, and regression analyses (Cook et al. 1992).[1] As Stanley (2001, p. 131) describes it, '[meta-analyses] act as intelligent agents searching through mountains of potentially contradictory research to uncover the nuggets of knowledge that lie buried underneath.' For most intents and purposes, study level summaries are analyzed like any other data, permitting a wide variety of quantitative methods.[2] If study characteristics differ in a systematic manner, meta-analysts construct indicator (moderator) variables of the differences between study characteristics and test whether those explain differences in the main results of the individual studies. Examples of moderator variables include characteristics of research design, sample, resource quality, and policies.

In the simplest type of meta-analysis, called the vote-counting method, the analyst counts the number of studies that found a statistically significant result, for example a positive correlation between tenure and agroforestry adoption. For each variable, the number of votes can be used to identify a 'winner' or a general relationship that is consistent across studies. Continuing our previous example, if 9 out of 12 empirical studies found a positive correlation between tenure and agroforestry adoption, we can be fairly confident of the general correlation between tenure and agroforestry adoption. As such, vote-counting provides a useful starting point for a systematic assessment of multiple studies.

More rigorous meta-analysis techniques use regression analysis that includes study characteristics as moderator variables (unique to the method, site, sample, etc.) to test for statistical significance, measure experimental effects, and explain heterogeneity of effects and significance. We could not conduct meta-regressions because of data constraints in the agroforestry adoption studies. Specifically, we are restricted by (a) the discrete choice nature of the dependent variable (adopt or not adopt), (b) insufficient summary statistics on explanatory variables, and (c) missing data on marginal probabilities of adoption (effect sizes).

[1]See Smith and Pattanayak (2002) for a recent review of the applications of meta-analysis in environmental and resource economics.

[2]There are a few cautions in the practice of meta-analysis. First, meta-analysis can reduce but not remove subjectivity, because the technique brings together a number of studies and the analyst is obviously still instrumental in their selection. Selection may be based on arbitrary criteria such as statistical cut-off points and the compatibility of data used. Second, a big assumption of meta-analysis concerns the separability of studies, and the fact that each study examined should be clearly distinct from others. However, studies draw on each other – particularly those that are in a meta-analysis by virtue of being in the relevant published literature. Consequently, error correlation may be problematic in the more sophisticated meta-regression approaches. Third, a number of professional studies may not be available for analyses because of confidentiality concerns and/or lack of interest in publication. Fourth and perhaps the most limiting for economic studies, is that microeconomic empirical methods are typically quasi- rather than strict experiments. Unlike strict experimental settings, the reporting of assumptions, error distributions, and data idiosyncrasies are not standardized.

What influences technology adoption?

Scherr (1992) has argued that the uniqueness and complexity of agroforestry technology in the form of (a) multiple interacting outputs, (b) temporal variability, (c) multiple economic contributions, and (d) off-farm impacts has hampered both conceptual and empirical economic analysis. Nevertheless, she concurs with Anderson (1992) that insights from the application of investment theory to agriculture, soil fertility, forestry, and pasture, all of which deal with complex durable assets, are transferable to 'agroforestry economics'. Indeed, as shown by Amacher et al. (1993) and Mercer and Pattanayak (2003), key features of investment theory are readily applied to construct a skeletal model of (and compound hypotheses regarding) agroforestry adoption.

Consequently, we review the agroforestry adoption studies within the general framework of agriculture and forestry technology adoption. First, we discuss our findings from a systematic review of the larger literature on agriculture, forestry and agroforestry technology adoption based on 120 empirical studies of technology adoption, paying particular attention to the seminal survey by Feder et al. (1985) and a recent study of sustainable agricultural intensification by Clay et al. (1998).[3] Then, we review the empirical agroforestry adoption literature to catalog specific explanatory variables that correspond to the categories of determinants described in the general literature. Table 1 presents a list of the 32 agroforestry adoption studies used for the analysis.

Before we turn to the categories and their constituent variables, consider two caveats regarding the categorization. First, these are not mutually exclusive categories because of complementarity and/or correlation between categories. To some extent, these interrelationships arise because we are using 'economic lenses' (or an economic framework), which categorize all non-economic elements (physical, institutional, etc.) in terms of economic incentives, constraints, or expectations and integrate them within one framework.[4] That is, we can view all non-economic drivers as implicit economic determinants of adoption. Second, in a world of limited research resources and less than exhaustive lists of explanatory variables, investigators may have employed the same variable to proxy for different underlying pressures. Thus, we can always debate whether a specific variable accurately proxies specific relationships and pressures, and the reader may interpret these proxies differently.

Our review of the broad literature on agriculture and forestry technology adoption produced the following five general categories of determinants: *farmer preferences, resource endowments, market incentives, bio-physical factors*, and *risk and uncertainty*.[5] Each is briefly described below.

1. *Preferences* are placeholders for the broad category of farmer specific influences such as risk tolerance, conservation attitude and intra-household homogeneity. Because farmer preference effects are difficult to measure explicitly, socio-demographic proxies such as age, gender, education, and social status are used instead. There may be some issues with whether these variables are good preference proxies. For example, education levels may also measure the opportunity cost of labor investments in agroforestry technology. Gender or the percentage of males may reflect the resource capacity of the household. Based on the signs of association we found in the literature (as seen in Table 2), we believe that these are best interpreted as preference proxies. However, we also mention alternative interpretations when they are discernible. It is impossible to determine *a priori* the direction of the influence on adoption of this broad category.

2. *Resource endowments* measure the resources available to the technology adopter for implementing the new technology. Examples of resource endowments include asset holdings such as land, labor, livestock and savings. Generally, resource endowments are likely to be positively correlated with the probability of adoption. However, it is likely that different endowments will encourage different types of agroforestry practices.

3. *Market incentives* include factors related to explicitly lower costs and/or higher benefits from technology adoption. This factor focuses on the explicitly economic determinants of adoption such as prices, availability of markets, transportation, and potential

[3]Contact the authors for a full list of the 120 empirical studies.

[4]For example, a bio-geo-chemical or physical feature can be treated as part of a technical constraint to the objective maximization process. Consequently, the non-economic feature will have a shadow price or value with economic interpretations. A cynic might view these as semantic categories. In contrast, a purist might be able to identify further sub-categories or other categories. Recognizing that it will be impossible to please all readers, we present the set with which we are most comfortable.

[5]In previous reviews of the literature on smallholder tree cultivation and agroforestry, Godoy (1992) and Reardon (1992) identified several variables (e.g. prices, tenure, information, credit, government policies, and labor) that fall within our general categories of key determinants of adoption.

Table 1. Empirical studies of agroforestry and related technology adoption

Author (s)	Year	Country	Model	Type of investment
Adesina and Chinau	2001	Nigeria	logit	alley farming
Adesina et al.	2000	Cameroon	logit	alley farming
Ayuk	1996	Africa	logit	live hedges
Caviglia and Kahn	2001	Brazil	probit	inter-cropping perennials
Lapar and Pandey	1999	Philippines	probit	contour hedgerows
Pattanayak and Mercer	1998	Philippines	probit	contour hedgerows
Shively	1999	Philippines	probit	contour hedgerows
Shively	1997	Philippines	probit	contour hedgerows
Alavalapati et al.	1995	India	logit	homegardens
Allen	1990	Swaziland	t-tests	tree planting
Amacher et al.	1990	Pakistan	t-tests	tree planting
Besley	1995	Ghana	linear probability	tree planting
Glendinning et al.	2001	India	logit	tree planting
Lucas and Nwonwu	2000	Kenya	logit	tree planting
Linde-Rahr	1999	Vietnam	probit	tree planting
Mercer and Snook	2000	Mexico	logit	tree planting
Otsuka et al.	2001	Indonesia	logit	tree planting
Owubah et al.	2001	Ghana	logit	tree planting
Pisaneli et al.	2001	Kenya	logit	tree planting
Salam et al.	2000	Bangladesh	logit	tree planting
Thacher et al.	1997	Costa Rica	logit	tree planting
Pomp and Burger	1995	Indonesia	probit	cocoa planting
Anderson et al.	1999	USA	logit	laser leveling of fields and basins
Baidu-Forson	1999	Niger	tobit	tassa' (water harvesting and nutrient concentration)
Caveness and Kurtz	1993	Senegal	linear probability	live fences, windbreaks and homegardens
Clay et al.	1998	Rwanda	gls	hedgerows, grass strips, anti-erosion ditches, terraces
Feather and Amacher	1994	USA	probit	manure, legumes, split N2, irrigation scheduling, deep soil nitrate testing
Pattanayak	2000	Indonesia	probit	contour farming
Pattanayak	2000	Indonesia	probit	erosion control
Pender and Kerr	1998	India	tobit	bunds, drains, waterways, gully checks, grass strips
Shiferaw and Holden	1998	Ethiopia	logit	earth & stone bunds, level bunds, graded fanya-juu
Traore et al.	1998	Canada	logit	chisel plow, shallow sweep, minimum or no-till

income losses or gains. Clearly, a factor that is expected to increase the net benefits associated with the technology is likely to be a positive influence on adoption.

4. *Bio-physical factors* relate to influences on the physical production process associated with farming and/or forestry. Examples include soil quality, slope of farmland, and plot size. In general, poorer biophysical production conditions (e.g., greater slope or potential for high erosion) create a positive incentive to adopt technologies that will alleviate these situations. However, it is also possible that some farms are of a quality that is below the threshold of useful investment.

5. *Risk and uncertainty* reflect the unknowns in the market and institutional environment under which decisions are made. Examples of short-term risk and uncertainty include fluctuations in commodity prices, projected output and rainfall. To some degree, uncertainties of the new technologies are mitigated by public inputs such as extension and training, and their private complements such as household familiarity or related experience. Tenure insecurity is an example of long-term risk and uncertainty. Given the long gestation period of investments in farming and forestry, lower risk and uncertainty will in general foster technological adoption. The multiple-output, multiple-input, multi-seasonal character of agroforestry makes it a potential mechanism for reducing risk and uncer-

tainty by diversifying the farmer's portfolio and therefore a good candidate for adoption by small holders (Scherr 2000; Franzel and Scherr 2002).

Preferences, resources, market incentives, bio-physical factors and uncertainty, thus, constitute the five factor clusters influencing the adoption of technologies such as agroforestry (see Amacher et al. (1993) and Mercer and Pattanayak (2003) for a formal integration of these factors). Preferences define the objectives and motivations of the economic agents choosing technologies. Resource endowments enable their technology choices. Market incentives and bio-physical factors condition the extent, timing and nature of the technology choices. Finally, risk and uncertainty can seriously undermine investments that pay dividends only in the long run.

Data collection for vote-counting meta-analysis

Our review of adoption studies is restricted to either peer-reviewed publications or draft manuscripts in the review process. Even though a meta-analysis seeks to synthesize results from a variety of research methods, including opinion surveys, correlation studies, experimental and quasi-experimental studies, and regression analyses, the central task is to compare comparables (Smith and Pattanayak 2002). Consequently, although we started with a set of 120 articles on adoption of agricultural and forestry technology by small holders, ultimately, based on the criteria of (a) multivariate empirical analysis and (b) focus on agroforestry and related technology investments, we narrowed our list to 32 studies. Twenty two of the thirty two studies investigate planting trees or hedgerows on farms. The remaining nine studies examine various soil and water conservation investments by small farmers, including contour farming. For the remainder of this paper, we refer to these two sets as the partial (22 agroforestry studies) and expanded (32 studies of agroforestry and related technology investments) sample. We defined empirical analysis as micro-economic studies that (a) used household survey data, (b) reported descriptive statistics, and (c) presented empirical results of multivariate analysis of technology adoption.[6]

Our analysis excludes a set of studies in Current et al. (1995b) and Franzel and Scherr (2002) because they do not satisfy these criteria.[7] The studies in Current et al. (1995b) apply informal surveys, in-depth interviews, and focus groups with participating farmers to measure costs and benefits of agroforestry projects. They also offer informal observations on the differences between adopters/participants and non-adopters/non-participants. Franzel and Scherr (2002) include five case studies from Africa on participatory on-farm trials using farming systems methods and drawing on an eclectic set of methods including formal surveys by economists, research trials by bio-physical scientists, participatory methods by anthropologists, and informal experiments by farmers. Collectively, these studies help us measure agroforestry returns and understand *what a farmer would get from agroforestry*, rather than *who adopts agroforestry*. Although these are related questions, their focuses and findings are not comparable to the studies considered in our meta-analysis. Specifically, they do not (a) have samples including adopters and non-adopters, (b) therefore do not statistically analyze the relationship between observable characteristics and the probability of adopting agroforestry, and (c) do not evaluate multiple determinants of adoption. Certainly, both types of studies are valuable, but the purpose of our paper is to compare studies that use similar enough methodologies to make the comparison meaningful. We focus on the statistical models of adoption using survey data, not because they can answer all of our questions about agroforestry, but because they are an important and common part of the literature that we believe can be advanced by a systematic and quantitative comparison of results.

In Table 1, we describe the studies included in our analysis in terms of agricultural and/or forestry investment, analytical method, location, author(s), and year. The studies are predominantly from tropical settings in Asia or Africa, with Indonesia, Philippines, and India being the countries most represented in these empirical assessments. A majority of these studies (23) have been published, submitted for publication, or made publicly available within the last 5 years.

For each study, we reviewed the text and the tables to identify variables that fit our five categories of adoption influences – *preferences, resource endowments, market incentives, bio-physical factors, and risk and uncertainty*. We identified several variables within each of these broad categories and applied the

[6]In addition, we reviewed 20 other empirical adoption studies on related topics: 12 on high yielding variety seeds and 8 on pesticides and fertilizers. These are not included in the paper.

[7]We thank a reviewer for pointing us to this literature.

Table 2. Votes on the determinants of agroforestry adoption – partial sample*

	Included	Significant		Insignificant	Included %	Significant %	Significant %
		Pos.	Neg.			(included studies)	(all studies)
Preference Proxies					**47%**	**41%**	**16%**
Education	17	3	1	13	77%	24%	18%
Age	14	4	0	10	64%	29%	19%
Gender	8	5	0	3	36%	63%	23%
Social Status	2	1	0	1	9%	50%	4.5%
Resource Endowments					**38%**	**60%**	**19%**
Income	12	6	0	6	55%	50%	27%
Assets	8	8	0	0	36%	100%	36%
Labor	15	5	0	10	68%	33%	22%
Livestock	6	1	0	5	27%	17%	4.6%
Credit/Savings	1	1	0	0	5%	100%	5%
Market Incentives					**33%**	**73%**	**20%**
Potential Income Gain	13	5	1	7	59%	46%	27%
Distance to Market	7	0	5	2	32%	71%	23%
Price	2	1	1	0	9%	100%	9%
Bio-physical Factors					**27%**	**64%**	**24%**
Soil	5	3	0	2	23%	60%	14%
Slope	5	2	1	2	23%	60%	14%
Plot Size	14	7	3	4	64%	71%	45%
Irrigation	0	0	0	0	0%	0%	0%
Risk and Uncertainty					**39%**	**78%**	**30%**
Tenure	11	6	1	4	50%	64%	32%
Experience	10	7	2	1	45%	90%	40%
Extension	6	6	0	0	27%	100%	27%
Membership	7	4	0	3	32%	57%	18%

*This sample comprises 23 empirical studies that investigate planting trees or hedgerows on farms. Details on the included studies such as author(s), year, location, are provided in Table 1

vote-counting method to each. That is, for each study, category and variable, we determined whether there was a statistically positive or negative relationship with the adoption decision. Variables with statistically insignificant correlation were assigned a '0' label. If a study did not report results for a particular variable, we left the cell as a blank.

Vote-counting results

Overview

The results of the vote-count meta-analysis are presented in Table 2 (partial sample) and Table 3 (expanded sample). First, examine the second column in Tables 2 and 3, which shows the total number of studies that included each variable, and the sixth column (Included %) which shows the percentage of studies including each variable. Although all five categories of variables are about equally likely (30–40% of the time) to be included in models of agroforestry adoption, preference proxy variables are most often included while bio-physical variables are least often included. Looking at individual variables, education, labor, plot size and age are the most common variables, present in approximately 65% of the empirical models. In contrast, price incentives, social status, savings and credit are the least common variables, being present in only about 5–15% of the models.

Inclusion of these categories and/or variables in the model, however, does not necessarily mean that they influence the adoption decision. For a better assessment, consider the percentage of the studies that found a *significant* effect for a variable or factor out of all the studies that *included* the variable or factor (column 7, 'Significant Percent (included studies)'). On this count, risk and uncertainty (78%), market in-

Table 3. Votes on the determinants of agroforestry adoption – expanded sample**

	Included	Significant		Insignificant	Included %	Significant %	Significant %
		Pos.	Neg.			(included studies)	(all studies)
Preference Proxies					**48%**	**48%**	**19%**
Education	25	8	2	15	81%	40%	32%
Age	21	5	0	16	68%	24%	16%
Gender	10	5	1	4	32%	60%	19%
Social Status	3	2	0	1	10%	67%	6.7%
Resource Endowments					**41%**	**65%**	**23%**
Income	18	9	2	7	58%	61%	35%
Assets	12	11	0	1	39%	92%	36%
Labor	23	8	1	14	74%	39%	29%
Livestock	9	2	1	6	29%	33%	9.6%
Credit/Savings	2	2	0	0	6%	100%	6%
Market Incentives					**34%**	**58%**	**20%**
Potential Income Gain	19	9	2	8	61%	58%	35%
Distance to Market	8	0	6	2	26%	75%	19%
Price	5	1	1	3	16%	40%	6.4%
Bio-physical Factors					**37%**	**80%**	**27%**
Soil	12	8	2	2	39%	83%	32%
Slope	10	6	1	3	32%	70%	22%
Plot Size	21	9	5	7	68%	67%	46%
Irrigation	3	2	1	0	10%	100%	10%
Risk and Uncertainty					**43%**	**72%**	**31%**
Tenure	18	12	1	5	58%	72%	42%
Experience	16	11	2	3	52%	81%	42%
Extension	10	9	0	1	32%	90%	29%
Membership	9	4	0	5	29%	44%	13%

**This sample comprises 32 empirical studies that investigate tree planting, hedgerows and various soil & water conservation technologies. Details on the included studies such as author(s), year, location, are provided in Table 1

centives (73%), bio-physical factors (64%), and resource endowments (60%) are most likely to impart a statistically significant effect. In contrast, at 41%, the preference proxies are least likely to show a statistical influence. Turning to individual variables, assets, savings-credit, price, and extension are statistically significant in 100% of the models that include these variables. At the other end, 'livestock' is statistically significant in only 17% of the models. These patterns are generally consistent (except 'irrigation') for the expanded sample of cases that include the 'soil and water conservation' studies in Table 3.

It is important to recognize three caveats regarding statistical significance (McCloksey and Ziliak 1996). First, statistical significance is only part of the story; it says nothing about the size of the influence on adoption. Unfortunately, the studies either do not report or do not provide enough detail to calculate the marginal probability of adoption, which is required for comparing the size of the variables' influence. Second, given the predisposition towards 'significance' in the literature, investigators tend to focus on finding significance in their analyses and to include only variables with significant coefficients in their reported models. That is, the probability that the studies report a significant result is conditional upon the study including the variable in the analysis. The final row in Tables 2 and 3, 'Significant Percent (all studies)', shows the percent of all the studies in the sample that found significant results.[8] Finally, the statistical significance measure simply records whether the variable was significant and not whether the direction of its influence is consistent across studies. As in the case of plot or farm size, the correlation with adop-

[8]This is simply the product of the number in the 5th column and the number in the 6th column, and is therefore smaller than the numbers in 6th column. That is, if we account for the possibility that insignificant results are not reported, it is harder to find 'significant' factors.

tion is split between being positive and negative. We discuss these issues in more detail for each category and variable below.

Preferences

Preference proxies such as education, age, and gender are included in 47% and 48% of the partial and expanded samples. Preference proxies are included in adoption studies more than other categories, and tend to have reasonable statistical power – they are significant in 41% and 48% of the cases, when included.

Education: To proxy education levels, most studies measured the average level of education of all household members or simply the education level of the household head. This variable is included in 77% and 81% of the partial and expanded samples, a clear indication of the popularity of this variable as a potential determinant of adoption. However, when included in a study, education is statistically correlated with adoption in only about 24% (40%) of the partial (expanded) sample. As suggested in the previous section, one possible explanation for this poor statistical performance is that education might be proxying for opportunity costs of labor investment required to implement new technology as well as the willingness and ability to experiment.

Age: The age variable is measured, as in the case of education, as the average age of all household members or the age of the household head. It has been included in 64% and 68% of the partial and expanded samples. It performs poorly in statistical terms with a significant coefficient in only 29% (24%) of the studies that include it in the partial (expanded) sample. When significant, it is positively correlated with the adoption decision.

Gender: The gender variable is measured by proportion of males in the household and included in 36% and 32% of the partial and expanded samples. Among the preference proxies, it is the one with the highest explanatory power and is significant in around 60% of the models that included it. Households with a higher proportion of males are more likely to adopt agroforestry technologies. As suggested earlier, in addition to a preference effect, this may also reflect the resources of the adopting households.

Socio-cultural status: Only about 10% of the partial and expanded samples have included any measures of socio-cultural status to explain adoption behavior. Two measures considered are ethnicity and caste. The authors argue that attributes such as caste and ethnicity proxy for the risk-taking characteristics of farm households.

Resource endowments

Measures of resource endowment, such as income, assets, labor, etc. are included in 38% of the partial sample and 41% of the expanded sample. Collectively they do a good job of explaining the statistical variation in adoption patterns with resource variables achieving significance in approximately 60%–65% of the models when included. The sign of the correlation is consistently positive across different measures of endowments.

Income: Measures of income are based on a variety of income sources (including, but not limited to, agriculture, wage, off-farm, and total) and are included in 55% and 58% of the partial and expanded samples. Income variables are statistically correlated with adoption in 50% and 61% of models that include them in the partial and expanded samples. The association is typically positive, although not always. It is possible that a smallholder who relies on farming as the dominant source of income may not risk investing in an unknown technology. At the other extreme, if non-farm sources dominate income earnings, the small holder may have no interest in farming technology. These may explain the few exceptions to the generally positive relationship between income and adoption.

Assets: This category includes several different variables including land holdings, condition of land (irrigated), house type, value of durables, and motor vehicle. Assets have been included in 36% and 39% of the partial and expanded samples and are statistically correlated with adoption in 100% and 92% of the models that include them in the expanded and partial samples. Overall, we find a consistent and unambiguous positive influence of assets on agroforestry adoption.

Labor: The labor variable is typically based on either the size of the family or the number of adults and/or males in the family. Measures of labor endowments have been included in 68% and 74% of the partial and expanded samples and are statistically significant in 33% and 39% of the models that include them in the partial and expanded samples. The sign of the correlation is found to be quite consistently positive across the cases.

Livestock: Although livestock, typically measured as a count, could be rolled in with other assets to

proxy household wealth, we have separated it out because it is a key element of certain agroforestry systems. Livestock is included in 27% and 29% of the partial and expanded samples but is statistically significant in only 17% and 33% of the models that include it in the partial and expanded samples, with the expected positive correlation. The low statistical power could be due to the fact that most studies do not consider livestock-based agroforestry systems in which fodder is a key output. Moreover, as pointed out by a reviewer, many fodder based agroforestry programs are focused on selling fodder in the market. Therefore, the farmer may not own any livestock, but might still be interested in agroforestry that generates fodder.

Credit/Savings: Availability of credit or savings is included in only 5% and 6% of the partial and expanded samples. This is not surprising, given that formal credit is rarely available in rural areas in tropical countries. However, when included it has the expected positive and statistically significant influence in 100% of the cases. It is possible that credit was included in the analysis only when it was found to be statistically significant.

Market incentives

Adoption studies generally do not include direct measures of market incentives in the empirical models, except for some subjective or objective measure of potential income gains (included in 59% of the partial sample and 61% of the expanded sample). On average, market factors are included in about 33% of the studies in the partial sample and 34% of the expanded sample. With regard to statistical significance, the market/economic variables perform quite well, being statistically significant in over 55% of the studies that include them. Typically, market incentives are positively correlated with the adoption choice.

Potential Income Gain: Among the market incentive variables, potential income gain is by the far the most likely variable to be included in models of adoption. Measures of potential gain range from direct 'subjective estimates of yield' to indirect measures such as the current levels of activities likely to be affected, e.g. farm income. As a consequence of these indirect attributions, it is not surprising that the statistical significance of the variable is somewhat tenuous. A significant positive influence is evident in only about 46% and 58% of the models including this variable in the partial and expanded samples.

Distance to market: Probably because of the limited by the availability of geographical detail in the data, only 32% of our partial sample and 26% of the expanded sample include this variable. However, distance to market is statistically significant in over 70% of these cases, with the expected negative correlation. In many ways, the distance variable is capturing a price effect and may, therefore, be directly correlated with our next variable in this set.

Price effect: Only 9% of the partial sample and 16% of the expanded sample include prices in their analyses. The typical limitations on this variable include lack of geographical detail and insufficient statistical variation in studies using cross-sectional data (which encompasses all our studies). When included, price is statistically correlated with the adoption choices in 100% and 40% of the partial and expanded samples, presumably due to insufficient statistical variability. Note, in the two cases of statistical significance the sign of the effect is positive in one case and negative in the other case. This can be explained by the fact that the price in the first case is for fuelwood – an output of agroforestry, and the price in the second case is for capital (interest rate) – a potential cost of conservation investments.

Bio-physical factors

Bio-physical factors have been included in only 27% of the partial sample and only 37% of the expanded sample. The exception is the 'plot size' variable, included in about two-thirds of the studies. When included, bio-physical factors are statistically significant in about 64% (80%) of the partial (expanded) sample on average; the sign of the correlation with adoption, however, is inconsistent across studies.

Soil quality: This variable is notoriously hard to measure, and consequently, it is included in only 23% and 39% of the partial and expanded samples. Investigators have employed a battery of subjective and objective criteria to measure soil quality and found it to be statistically correlated with adoption in 83% of the studies. Typically, poorer soil quality and severe threat of soil degradation are positively correlated with adoption. In the partial sample, the lack of a negative correlation with adoption suggests that, in some cases, soil quality may be so poor as to make investments in soil conservation futile. However, we find two such negative associations in the 'soil and water conservation' studies.

Slope: The slope of the farmland, usually measured in percentage terms, has been included in 23% of the partial sample and 32% of the expanded sample. When included, it is statistically significant in 60% (70%) of the partial (expanded) sample. As expected, farmers owning steeper plots of land are generally more likely to adopt agroforestry technologies.

Plot size: With an inclusion rate of 64% and 68% for the partial and expanded sample, plot size is a common variable in adoption studies and is found to be statistically correlated with adoption in approximately 66% of the cases. However, the sign of the correlation is inconsistent across the studies, with about 50% (43%) of the partial (expanded) sample finding a positive association and 28% (24%) finding a negative correlation. This calls into question the 'economies of scale' explanation of adoption; that is, a farmer with more land is more able and/or willing to experiment with a new technology. Perhaps, a key issue is the extent to which other important variables have been omitted (due to data constraints), as a consequence of which plot size becomes a proxy for other features such as risk tolerance or economic compulsion. In other cases, plot size may be acting as a proxy for assets or wealth.

Irrigation: This variable is included in 0% and 10% of the partial and expanded samples of studies but is found to be significantly correlated with adoption in 100% of the expanded sample. Typically, the correlation is positive – suggesting that irrigated lands are more valuable and therefore worth the conservation investment. The sole exception to this finding is a study by Pattanayak (2000) in which the negative correlation between irrigation and the adoption of erosion control is probably because of substitution possibilities between different types of conservation investments. That is, as an alternative to erosion control, farmers might choose to invest in contour farming, which is positively correlated with irrigation.

Risk and uncertainty

Variables measuring risk and uncertainty such as tenure, experience, and training, are included in 39% and 43% of the partial and expanded samples. Typically, these variables exert considerable statistical power in the estimated models, being significant in over 70% of the cases when included. In general, greater uncertainty and risk are negatively correlated with the adoption choice.

Tenure: Tenure is usually measured as whether the farmer is an owner (has tenure) or a renter (doesn't have tenure). Binary variables of this type have been included in 50% and 58% of the partial and expanded samples. Our review shows an unambiguous and consistent result for the tenure variable; landowners are more likely than tenants to adopt agroforestry and other conservation technologies. When included, the tenure variable is significant in 64–72% of the cases considered.

Experience: We construct this measure based on an array of variables reported by investigators that range from previous experience with farm-forestry and tree planting, to years of farming experience, to familiarity with the technology under consideration. The basic argument is that familiarity decreases the uncertainty associated with an investment with unpredictable returns. These types of experience based measures have been included in 45% (52%) of the partial (expanded) sample and exert considerable statistical power – significant in 90% and 81% of the models that include them in the partial and expanded samples. As expected, the sign on these variables is typically positive.

Extension and Training: Investigators typically report binary variables on whether the household or farmer has received any training in the technology under consideration or has any access to extension services. Such measures of 'extension and training' are found in 27% and 32% of the partial and expanded samples. They generate the expected positive correlation with adoption in 100% (90%) of the partial (expanded) sample, when included.

Membership: This variable measures whether the farmer or household is part of a community organization or cooperative. We can expect participation through groups and the support of a community network to mitigate some of the uncertainties associated with new technology. The groups and networks could also provide extension and training. Proxies of community membership have been included in 32% and 29% of the partial and expanded samples. The variable is significant in over 40% of the models with the expected positive correlation with adoption.

Overall determinants of agroforestry adoption

We review 32 agroforestry and related technology adoption studies to develop a meta-data set of specific variables within the five classes of technology adop-

tion factors. By applying vote-counting based meta-analysis to this data set, we provide a richer picture of agroforestry adoption than can be developed from a qualitative comparison of the individual study features and results. In this regard, the review highlights two kinds of meta-statistics on the empirical literature on agroforestry adoption: *inclusion* and *influence* of factors. We find that 'preference proxies' and 'resource endowments' are most likely to be included in analyses of adoption, while 'bio-physical factors' are least likely to be included.[9] Specifically, over 60% of the studies include 'education', 'labor endowment', 'plot size', and 'age'. Investigators either see them as critical determinants or (and) find them easier to measure.

Using the influence (significance) criteria, we find that adoption is most often statistically correlated with the risk, bio-physical factors, and resource endowments categories. This result would be somewhat different if we measured significance conditional on whether the investigators included these factors in their regression models. Considering specific variables, soil quality, plot size, extension and training, tenure, and assets exert the greatest statistical power; that is, when included they are statistically significant in the greatest number of cases.

When we compare the general determinants and specific variables in the 'included' and 'statistically influential' sets, we find a far from perfect overlap. Before we jump to conclusions regarding the mismatch of attention and significance, consider some important caveats. First, as argued elsewhere (most poignantly by McCloksey and Ziliak (1996)), results reported in the published literature are heavily influenced by the bias against insignificance in scientific literature. In effect, investigators try very hard to find significance in their analyses and voluntarily or because of convention often include only significant results in their published papers. Second, we cannot claim that our set of adoption studies represents a random and, therefore, unbiased set. Our set may not represent the true population of studies in part because we engaged in a purposive search of the published and gray literature to find studies that satisfy predetermined compatibility criteria of topical content, empirical methods, analysis units, and variable measures. It also may not be random because the scientific literature is an evolving and organic phenomenon, in which investigators are constantly building off previously published work that may have been published by their colleagues or by themselves. Third, while we found that the direction of the correlation is unambiguous in most cases, statistical significance *per se* may not be a very useful criteria for variables such as plot size that have an equal number of positive and negative influences. Finally, statistical significance tells only a part of the story. We could not estimate the magnitude of the effects because of insufficient details on the marginal probabilities of adoption.

[9]As one reviewer pointed out, climatic zones and severity of resource degradation are rarely included in agroforestry studies. In general, climatic zones and widespread resource degradation could affect any one of the five determinants of agroforestry adoption – *preferences, resource endowments, market incentives, biophysical factors*, and *risk and uncertainty*. Unfortunately, it will be difficult for adoption studies of the types described and analyzed in this paper to evaluate such factors in the sense of including them in regression models because these factors typically will not vary within the study region. However, we believe it would be useful to have some standardized report of these factors (because then they could potentially be included in future meta-analyses and or considered in the design of future studies.

Conclusions

The policy and academic world has sustained a keen interest in technological change because of promises of economic growth and prosperity, particularly for parts of the developing world. We review approximately 120 empirical studies (32 of which are studies on adoption of agroforestry and related technologies), with particular attention to the survey by Feder et al. (1985) to identify five key determinants of technology adoption: *preferences, resource endowments, market incentives, bio-physical factors* and *risk and uncertainty*. These five determinants provide a useful organizing framework for conceptual and empirical evaluations of agroforestry adoption. We find that preferences and resource endowments are the most common factors studied while market incentives, risk and uncertainty and bio-physical factors are examined less frequently. However, adoption behavior is most likely to be influenced by risk, bio-physical, and resource factors. Specifically, our review suggests that credit, savings, prices, market constraints, and plot characteristics are potentially important determinants of adoption behavior that have not been studied adequately. We hope researchers will take on the challenge of measuring these factors and variables to include in future studies.

In reviewing these results, we recognize that some aspects of these studies *must* be technology specific. Clearly there will be something unique about each

study that can only be uncovered by reviewing that particular study. However, as discussed in the introduction to this paper, individual studies have their own limitations. The goal of a literature synthesis, such as the meta-analysis in this paper, is to find explanations that hold across a range of agroforestry adoption studies and to offer general conclusions. With this purpose in mind, we have culled our sample to look only at tree-planting and contour hedgerow technologies, and to consider an expanded set of related soil and water conservation technologies. That is one reason why we report partial and expanded sample results throughout the study so that we can compare 'comparables' and make general statements.

Nevertheless, some of the limitations discussed in the previous section also provide lessons for future research using more sophisticated types of meta-analyses. First, we assigned equal weights to all studies with no quality adjustments. It may be possible to conduct more discriminating analyses by developing quality-differentiated weights, based on publication source, sampling methods and size, and scientific rigor. Second, by collecting additional data, investigators could apply combined tests of significance and effect sizes. Finally, future work could include moderator variables and attempt meta-regressions with corrections for heteroskedasticity.

All sophisticated meta-analyses rely, however, on even more purposive data collection exercises that pay attention to information on marginal probabilities of adoption (i.e., how a specific variable changes the probability of adoption). Because this will require contacting the authors directly for information beyond what is typically provided in the publications, our experience with collecting the simpler data set for this study suggests that such a venture will have significant time and resource costs. The effort may well be worth the costs, however, because meta-regressions can generate at least three types of results. First, the sign and significance of coefficients in the meta-regression provide statistically defendable criteria by which to judge the influence of the variable in question – that is, not just the number of positive or negative votes. Second, the analyst can exploit the variation of marginal probabilities across studies to develop a generalized equation of marginal probability of adoption. This could explain how the influence of adoption factors changes in response to farmer, farm and project characteristics. Finally, sufficient variation in factors across all or most studies could be used to develop a generalized model of adoption. Such a model could be used by project administrators to predict adoption in new areas.

Collectively these ideas suggest that statistical analysis of agroforestry adoption using household survey data comprise a narrow but potentially insightful subset of the empirical literature on agroforestry adoption. Based on the ideas discussed in the previous paragraphs and the growth in numbers of such studies in the published literature, we believe that journals should consider standardizing the reporting requirements for this literature. In the best scenario, authors of such studies could be encouraged to consider the full range of factors discussed in this paper and report basic descriptive statistics and marginal probabilities. By standardizing the reported results, journals and editors would facilitate more sophisticated meta-analyses to learn from the growing body of agroforestry adoption research in a scientifically rigorous manner. In evaluating this suggestion, we clarify that agroforestry adoption is a complex process that can only be truly understood and explained by using multiple methods and data (quantitative and qualitative), not just statistical models of household survey data. Thus, journals such as *Agroforestry Systems* and *Agricultural Economics* must certainly be open to publishing studies using different methods and data.

Several studies in Current et al. (1995b) and Franzel and Scherr (2002) illustrate alternative methods and data and offer vital insights on agroforestry. Particularly, they can help us understand the farmers' preferred way to learn about agroforestry, who within the farming household makes the decision about agroforestry adoption, the perceived benefits of agroforestry and stated motivations for adopting the technology, the extent and particular technologies adopted, and efficient design and dissemination of agroforestry technology. Their approach is perhaps best for addressing issues such as the viability of particular technologies in different environments. Their approach also allows greater attention to the extent of adoption, which is defined differently across studies and therefore less amenable to comparison than the binary adoption decision that we consider. However, their approach cannot pinpoint the differences between adopters and non-adopters, due to lack of information on non-adopters. Non-adopters may have had some of the same reasons to adopt agroforestry but still not have adopted due to socioeconomic constraints. The contribution of the studies evaluated in this meta-analysis is to advance understanding of the character-

istics of farmers and their farms that affect adoption of agroforestry.

Acknowledgements

The authors are grateful to Kirsten Cassingham and Brooks Depro for research assistance, Sara Scherr and Bill Hyde for comments, and the USDA Forest Service for financial support. The authors alone, however, are responsible for the opinions reflected in this paper.

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