Taking Stock of Agroforestry Adoption Studies

Subhrendu K. Pattanayak
D. Evan Mercer (US Forest Service)
Erin O. Sills (North Carolina State University)
Jui-Chen Yang
Kirsten Cassingham (US Geological Survey)

Working Paper 02_04 April 2002

RTI International's* Environment and Natural Resource Economics Program circulates these working papers to convey information and entertain discussion. The papers may not have undergone formal peer review. Contact Subhrendu Pattanayak (subrendu@rti.org) if you have any questions or concerns. <www.rti.org/enrepaper/>

*RTI International is a trade name of Research Triangle Institute.

Taking Stock of Agroforestry Adoption Studies

Subhrendu K. Pattanayak
D. Evan Mercer (US Forest Service)
Erin O. Sills (North Carolina State University)
Jui-Chen Yang
Kirsten Cassingham (US Geological Survey)

JEL Classification:
Q1, Q2, O1, O2
Keywords:
contour hedgerows, tree planting, soil and water conservation, meta-analysis, 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 from 21 countries. 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, bio-physical, and resource factors. In our conclusion, we discuss the potential gains and challenges of more rigorous analyses such as meta-regressions.

A GROWING INTEREST IN ADOPTION BEHAVIOR

Despite some impressive scientific and technological advances over the last three decades, agroforestry projects commonly suffered from inadequate rates of adoption 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 socio-economic research on agroforestry (Current et al. 1995; 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.

Most of the recent adoption studies explain how various farmers, farms, and projects 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 have done little to promote 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.

After briefly discussing meta-analytic methods, we review the agricultural and forestry technology adoption literature to identify the key determinants of adoption across a variety of technologies. Next, we focus on adoption of agroforestry and related technologies and identify explanatory variables within five general determinants of adoption. We report the results of a vote-count based meta-analysis of the inclusion and significance of explanatory variables. Finally, we conclude by qualifying our findings and discussing some extensions to the methods used in this paper.

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, (b) a useful way to update material for practicing researchers, and (c) a critical reference point. However, even the most thoughtful review of large collections of empirical studies offers limited benefits due to the heterogeneity of treatment effect sizes, quality weights, sample sizes (and associated statistical power) and variations in moderator/probing variables (Cook et al 1992). We can improve on conventional reviews of quantitative, empirical literature by asking whether it is possible to combine quantitative information from many studies to produce more general knowledge, including knowledge about causal explanation. In the context of agroforestry adoption, the question becomes 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: pp 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." Thus, meta-analyses seek to summarize results or explain the differences in results from several analyses. 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 this paper, we use meta-analysis techniques to investigate whether different agroforestry adoption studies have collectively provided clear signals, rather than random noise, regarding the determinants of adoption.

In the simplest type of the 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

---

[1] See Smith and Pattanayak (forthcoming) 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 micro-economic empirical methods are typical quasi- rather than strict experimentation. Unlike strict experimental settings, the reporting of assumptions, error distributions, and data idiosyncrasies are not standardized.

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 probability of adoption (effect sizes). Therefore, in this paper we present results of a vote-counting based meta-analysis. In our concluding discussion, we qualify our findings by recognizing the limitations of vote-counting and suggest strategies for regression based meta-analyses.

WHAT INFLUENCES TECHNOLOGY ADOPTION?

Although there has been some debate in the literature regarding the uniqueness and complexity of agroforestry technology (Scherr, 1994), we believe that the key features relevant to agroforestry adoption are common to agriculture and forestry technology adoption. Consequently, we review the agroforestry adoption studies within the general framework of agriculture and forestry technological 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

[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 this 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.

resources and less than exhaustive lists of explanatory variables, we can see how 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 a *priori* determine 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.

(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 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 bio-physical 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 also possible that some farms are of a quality that is below the threshold of useful investment.

---

[5] In his review of the literature on smallholder tree cultivation, Godoy (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.

(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, some 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. Examples of long-term risk and uncertainty include tenure insecurity. Given the long gestation period of investments in farming and forestry, lower risk and uncertainty will in general foster technological adoption.

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 [forthcoming] 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. 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) 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 full (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 technology adoption.[6]

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 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

[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.

categories and applied the 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 (full 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 Percent) which shows the percentage of studies containing 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 <u>significant</u> effect for a variable or factor out of all the studies that <u>included</u> the variable or factor (column 7, "Significant Percent (included studies)"). On this count, risk and uncertainty (78%), market incentives (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 full sample of cases that include the 'soil and water conservation' studies in Table 3.

It is important to recognize three caveats regarding statistical significance (McCloskey 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 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.[7] 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 adoption is split between being positive and negative. We discuss these issues in more detail for each category and variable below.

Preference Proxies

Preference proxies such as education, age, and gender are included in 47% and 48% of the partial and full sample. 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 full 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 (full) 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 full samples. It performs poorly in statistical terms with a significant coefficient in only 29% (24%) of the studies that include it in the partial (full) 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 full 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 full 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.

---

[7] 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.

Resource Endownment

Measures of resource endowment such as income, assets, labor etc. are included in 38% of the partial sample and 41% of the full 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 full sample. Income variables are statistically correlated with adoption in 50% and 61% of models that include them in the partial and full sample. 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 full sample and are statistically correlated with adoption in 100% and 92% of the models that include them in the full 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 full sample and are statistically significant on 33% and 39% of the models that include them in the partial and full 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 full samples but are statistically significant in only 17% and 33% of the models that include it in the partial and full 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.

Credit/Savings: Availability of credit or savings is included in only 5% and 6% of the partial and full sample. However, when included it has the expected positive and statistically significant influence in 100% of the cases. It is entirely 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 full sample). On average, market factors are included in about 33% of the studies in the partial sample and 34% of the full 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 estimate 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 full samples.

Distance to market: Including this variable is typically limited by the availability of geographical detail in the data so that only 32% of our partial sample and 26% of the full 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 full 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 full sample, 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 full sample. The exception is the 'plot size' variable, included in about 64% of the studies. When included, bio-physical factors are statistically significant in about 64% (80%) of the partial (full) sample on average; the sign of the correlation with adoption, however, is often 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 full 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 full sample. When included, it is statistically significant in 60% (70%) of the partial (full) sample. As expected, farmers owning steeper plots of land are generally more likely to adopt agro-forestry technologies.

Plot size: With an inclusion rate of 64% and 68% for the partial and full 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 (full) 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 only 0% and 10% of the partial and full sample of studies but is found to be significantly correlated with adoption in 100% of the full 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 effects such as tenure, experience, and training, are included in 39% and 43% of the partial and full 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 full sample. 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 (full) sample and exert considerable statistical power – significant in 90% and 81% of the models that include them in the partial and full 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 have any access to extension services. Such measures of 'extension and training' are found in 27% and 32% of the partial and full sample. They generate the expected positive correlation with adoption in 100% (90%) of the partial (full) 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 full sample. The variable is significant in over 40% of the models with the expected positive correlation with adoption.

GENERAL PATTERNS OF AGROFORESTRY ADOPTION

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, resources, 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 review 32 agroforestry and related technology adoption studies to develop a meta-data set of specific variables within the five classes of technology adoption 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. 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 to begin with. 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 McCloskey 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 include only significant results in the 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.

The limitations discussed above provide lessons for future research using more sophisticated types of meta-analyses. Consider a few additional issues. 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. Further, 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 in 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 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 journals such as *Agroforestry Systems* and *Agricultural Economics* should consider standardizing the reporting requirements for results published in their journal. In the best scenario, authors would be required to consider as a minimum the full range of factors affecting adoption and describe how these factors affected the statistical models of adoption. While this would clearly limit the ability to work with convenient but incomplete data sets, the resulting analysis would be based on a model that is conceptually sound and empirically complete. In general, it would force researchers to expend more effort in research design. At the very least, editors could require authors to report a basic number of 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.

To sum, given the recent surge in interest and empirical research on agroforestry adoption, it is time to examine this growing literature and take stock of what we have learned. We take the first step by reviewing 120 general technology adoption studies and conducting a simple meta-analysis of 32 agroforestry and related technology adoption studies. 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.

ACKNOWLEDGEMENTS

Financial support from the USDA Forest Service and research support from Brooks Depro are gratefully acknowledged. The authors alone, however, are responsible for the opinions reflected in this paper.

REFERENCES

Adesina, A., and J. Chianu. 2001. "Alternatives to Slash-and-Burn: Determinants of Adoption of Alley Farming and Variants by Farmers in Nigeria." Unpublished Manuscript.

Adesina, A.A., D. Mbila, G.B. Nkamleu, and D. Endamana. 2000. "Econometric analysis of the determinants of adoption of alley farming by farmers in the forest zone of southwest Cameroon." *Agriculture, Ecosystems & Environment* 80(3):255-265.

Alavalapati, J., M. Luckert, and D. Gill. 1995. "Adoption of agroforestry practices: a case study from Andhra Pradesh, India." *Agroforestry Systems* 32: 1-14.

Allen, J. 1990. "Homestead tree planting in two rural Swazi communities." *Agroforestry Systems* 11: 11-22.

Amacher, G., W. Hyde, and M. Rafiq. 1993. "Local Adoption of New Forestry Technologies: An Example from Pakistan's NW Frontier Province." *World Development* 21(3):445-453.

Anderson, D., P. Wilson, and G. Thompson. 1999. "The Adoption and Diffusion of Level Fields and Basins." *Journal of Agricultural and Resource Economics* 24(1):186-203.

Ayuk, E. 1997. "Adoption of Agroforestry Technology: The Case of Live Hedges in the Central Plateau of Burkina Faso." *Agricultural Systems* 54(2):189-206.

Baidu-Forson, J. 1999. "Factors Influencing Adoption of Land-Enhancing Technology in the Sahel: Lessons from a Case Study in Niger." *Agricultural Economics* 20: 231-239.

Besley, T. 1995. "Property Rights and Investment Incentives: Theory and Evidence from Ghana." *Journal of Political Economy* 103(5):902-937.

Caveness, F.A., and W.B. Kurtz. 1993. "Agroforestry adoption and risk perception by farmers in Senegal." *Agroforestry Systems* 21: 11-25.

Caviglia, J., and J. Kahn (2001). "Diffusion of Sustainable Agriculture in the Brazilian Tropical Rain Forest: A Discrete Choice Analysis." *Economic Development and Cultural Change* 49 (2):311-334.

Clay, D., T. Reardon, and J. Kangasniemi. 1998. "Sustainable Intensification in the Highland Tropics: Rwadan Farmers' Investments in Land Conservation and Soil Fertility. *Economic Development and Cultural Change* 46 (2):351-378.

Cook, T., H. Cooper, D. Corday, H. Hartmann, L. Hedges, R. Light, T. Louis, and F. Mosteller. 1992. *Meta-Analysis for Explanation: A Casebook*. Russell Sage Foundation, New York.

Current, D., E. Lutz, and S. Scherr. 1995. "The costs and benefits of Agroforestry to farmers." *The World Bank Research Observer* 10(2):151-180.

Feather, P., and G. Amacher. 1994. "Role of information in the adoption of best management practices for water quality improvement." *Agricultural Economics* 11: 159-170.

Feder, G., R. Just, and D. Zilberman. 1985. "Adoption of agricultural innovations in developing countries: A survey." *Economic Development and Cultural Change*: 255-297.

Garrett, H.E., W.B. Kurtz, L.E. Buck, J.P. Lassoie, M.A. Gold, H.A. Pearson, L.H. Hardesty, and J.P. Slusher. 1994. "Agroforestry: An integrated land management system for the production and farmland conservation." Final Report for the USDA Soil Conservation Service Project. USDA SCS 68-3A75-3-134: Resource Conservation Act Appraisal, Soil Conservation Service, Washington, D.C. 58 pp.

Glendinning, A., A. Mahapatra, and C.P. Mitchell. 2001. "Modes of communication and effectiveness of agroforestry extension in eastern India." *Human Ecology* 29(3):283-305.

Godoy, R. 1992. "Determinants of Smallholder Commercial Tree Cultivation." *World Development* 20(5):713-725.

Lapar, M.L., and S. Pandey. 1999. "Adoption of soil conservation: the case of the Philippines uplands." *Agricultural Economics* 21: 241-256.

Linde-Rahr, M. 1999. "Rural Reforestation: Gender Effects on Private Investments in Viet Nam." Unpublished Manuscript.

Lucas, D., and F. Nwonwu. 2000. "A study of socio-economic factors that affect adoption of farm forestry in Busia Districts, Kenya." Unpublished Manuscript.

McCloksey, D., and S. Ziliak. 1996. "The Standard Error of Regressions." *Journal of Economic Literature* 35: 97-114.

Mercer, E., and S.K. Pattanayak (forthcoming). "Agroforestry Technology: A Socio-Economic Model of Adoption by Filipino and Mexican Farmers." In *Forests in a Market Economy*, E. Sills and K. Abt (eds.). Forestry Sciences Series by Kluwer Academic Publishers, Dordrecht.

Mercer, E., and A. Snook. 2000. "A stated and revealed preference analysis of adoption of tree planting by farmers in the Calakmul Biosphere Reserve, Campeche, Mexico." Paper presented at Conference of Latin American Geopgraphers 2000. Jan 6-8, 2000. University of Texas at Austin.

Mercer, D.E., and R.P. Miller. 1998. "Socioeconomic research in agroforestry: progress, prospects, priorities." *Agroforestry Systems* 38: 177-193.

Nair, P.K.R. 1998. "Directions in tropical agroforestry research: past, present, future." *Agroforestry Systems* 38: 223-245.

Otsuka, K., S. Suyanto, T. Sonobe, and T. Tomich. 2001. "Evolution of Land Tenure Institutions and Development of Agroforestry: Evidence from Customary Land Areas of Sumatra." *Agricultural Economics* 25: 85-101.

Owubah, C.E., D.C. Le Master, J.M. Bowker, and J.G. Lee. 2001. "Forest tenure systems and sustainable forest management: the case of Ghana." *Forest Ecology and Management* 149 (1-3):253-264.

Pattanayak, S. 2000. "Conservation Investments in Flores." Unpublished Manuscript.

Pattanayak, S., and Mercer D.E. 1998. "Valuing soil conservation benefits of agroforestry: contour hedgerows in the Eastern Visayas, Philippines." *Agricultural Economics* 18: 31-46.

Pender, J., and J. Kerr. 1998. "Determinants of farmers' indigenous soil and water conservation investments in semi-arid India." *Agricultural Economics* 19: 113-125.

Pisaneli, A., S. Franzel, J. De Wolf, R. Rommelse, and J. Poole. 2001. "The adoption of improved tree fallows in western Kenya: farmer practices, knowledge and perception." Unpublished Manuscript.

Pomp, M., and K. Burger. 1995. "Innovation and Imitation: Adoption of Cocoa by Indonesian Smallholders." *World Development* 23(3):423-431.

Salam, M., T. Noguchi, and M. Koike. 2000. "Understanding why farmers plant trees in the homestead agroforestry in Bangladesh." *Agroforestry Systems* 50(1):77-93.

Sanchez, P.A. 1995. "Science in Agroforestry." *Agroforestry Systems* 30:5-55.

Scherr, S. 1994. "Not out of the woods yet: challenges for economics research on agroforestry." *American Journal of Agricultural Economics* 74(3):802-808.

Shiferaw, B., and S. Holden. 1998. "Resource degradation and adoption of land conservation technologies in the Ethiopian Highlands: A case study in Andit Tid, North Shewa." *Agricultural Economics* 18: 233-247.

Shively, G. 1997. "Consumption risk, farm characteristics, and soil conservation adoption among low-income farmers in the Philippines." *Agricultural Economics* 17: 165-177.

Shively, G. 1999. "Risks and returns from soil conservation: evidence from low-income farms in the Philippines." *Agricultural Economics* 21: 53-67.

Smith, V.K., and S.K. Pattanayak (forthcoming). "Is Meta-Analysis the Noah's Ark for Non Market Valuation?" *Environmental and Resource Economics*.

Stanley, T.D. 2001. "Wheat from Chaff: Meta-Analysis as Quantitative Literature Review." *The Journal of Economic Perspectives* 15 (Summer):131-150.

Thacher, T., D. Lee, and J. Schellas. 1997. "Farmer Participation in reforestation incentive programs in Costa Rica." *Agroforestry Systems* 35(3):269-289.

Traore, N., R. Landry, and N. Amara. 1998. "On farm adoption of conservation practices: the role of farm and farmer characteristics, perceptions, and health hazards." *Land Economics* 74(1):114-27.

Table 1. Empirical Studies of Agroforestry and Related Technology Adoption

Author (s)	Year	Country		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	1997	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	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	Banglades	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	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
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

Table 2. Results of Vote-Counting Meta-Analysis of Determinants of Agroforestry Adoption (Partial Sample, 22 studies)

	Included	Significant		Insignificant	Included %	Significant % (Included Studies)	Significant % (All Studies)
		Pos.	Neg.				
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%
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%
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%

Table 3. Results of Vote-Counting Meta-Analysis of Determinants of Agroforestry Adoption (Full Sample, 32 studies)

	Included	Significant		Insignificant	Included %	Significant % (included studies)	Significant % (all studies)
		Pos.	Neg.				
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%
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%
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%