ADOPTING AGROFORESTRY

Subhrendu K. Pattanayak, D. Evan Mercer, Erin O. Sills & Kirsten Cassingham[1]

ABSTRACT There is growing interest in the study of agroforestry adoption because it is promoted as a technology that can generate a sustainable version of development in which economic growth occurs in tandem with 'sustenance' or protection of ecological capital. Conventional wisdom suggests that agroforestry provides substantial economic and ecological benefits to communities and households and, therefore, should be readily adopted by farmers. Yet, many attempts to promote agroforestry systems have resulted in inadequate rates of adoption. We review the literature on technological innovations in general to identify the determinants of adoption within an economic framework. We find five categories of determinants of technology adoption: *preferences*, *resource endowments*, *economic incentives*, *biophysical factors*, and *risk and uncertainty*. We then analyze 56 articles on adoption of agricultural and forestry technology by small holders to evaluate these factor-clusters. Ultimately, based on the criteria of (a) empirical analysis and (b) focus on agroforestry and soil-water conservation investments, we narrow our list down to 26 studies from 17 countries. We discuss in detail the direction of influence of variables in each category.

Agroforestry technology is sold on the promise of a sustainable version of development in which economic growth occurs in tandem with 'sustenance' or protection of ecological capital. Given these potential benefits to target communities, conventional wisdom suggests that agroforestry should be readily adopted. Nevertheless, attempts to promote agroforestry systems have often resulted in inadequate rates of adoption. Although a variety of reasons contribute to low adoption rates, they often result from inadequate assessments of farmer preferences, priorities, and constraints prior to designing new agroforestry systems (Current et al. 1995; Mercer and Miller 1998). In the mid-1990's, agroforestry leaders began to plead for increased emphasis on research to understand the agroforestry adoption decision process (Sanchez 1995, Mercer and Miller 1998). As a result, a plethora of agroforestry adoption studies have emerged recently (see reference list in Pattanayak et al. 2001). Our goal is to see if it is possible to combine information from many studies in a simple meta-analysis so as to produce more general knowledge.

SIMPLE META-ANALYSIS: A SYSTEMATIC WAY TO LEARN ABOUT AGROFORESTRY ADOPTION?

In its most general form, meta-analysis offers a set of quantitative techniques for synthesizing results of many types of research, including opinion surveys, correlation studies, experimental and quasi-experimental studies, and regression analyses probing causal models. In our context, we investigate consistency across different adoption studies to evaluate whether the studies are generating more than random noise regarding the determinants of adoption. In this method, the investigator gathers together all the studies relevant to an issue and constructs at least one indicator of the relationships under investigation from each study. For most intents and purposes, study level data can be analyzed like any other data, permitting a wide variety of quantitative methods.

The simplest of the meta-analytical methods is called vote-counting. In this method, the analyst counts all the studies that have a statistically significant result. We use a vote-counting meta-analysis of agroforestry adoption because of some severe data constraints. Specifically, we are restricted by the discrete choice nature of our dependent variable (probability of adoption) and the lack of detail on marginal probability of adoption (effects size) provided in our set of studies. In our concluding discussions, we offer some qualifications to our research findings, given the limitations of the vote-counting method employed and the studies reviewed. This does, however, position us to make specific recommendations for more sophisticated meta-analyses of agroforestry adoption.

WHAT INFLUENCES ADOPTION OF AGRICULTURAL AND FORESTRY TECHNOLOGY?

There is a large and growing literature on issues surrounding adoption of technologies, because technology is an engine for economic growth. We drew on approximately 60 empirical studies to identify the key determinants of technology adoption,

[1]Pattanayak is with the Research Triangle Institute, Mercer is with the US Forest Service, Sills and Cassingham are with North Carolina State University. Direct all correspondence to: Subhrendu K. Pattanayak, Center for Regulatory Economics and Policy Research, Research Triangle Institute, RTP, NC 27709-2194. Email: subrendu@rti.org.

paying particular attention to the seminal survey by Feder et al. (1986) and a recent study of sustainable agricultural intensification by Clay et al. (1998). Although there has been some debate in the literature regarding the uniqueness and complexity of agroforestry technology (Scherr, 1994), we believe that its basic features are common with farming and forestry technology. Consequently, we reviewed the agroforestry adoption studies within the general framework of agricultural and forestry technology adoption. That is, we viewed the explanatory variables in the agroforestry and soil and water conservation studies as elements of the factor clusters or categories described in the general literature.

Our literature review revealed five categories of determinants of technology adoption. Preferences, resources, incentives, bio-physical factors, and risk and uncertainty constitute the 5 factor clusters. In discussing the results, we present specific examples of variables in these factor clusters. Preferences define the objectives and motivations of the economic agents choosing technologies. Resource endowments enable their technology choices. Economic and bio-physical incentives condition the extent, timing and nature of the technology choices. Finally, the degree of risk and uncertainty can seriously undermine investment initiatives that pay dividends only in the long run. Caveats regarding this categorization are in Pattanayak et al. (2001).

DATA COLLECTION

Our review of adoption studies was restricted to either peer-reviewed publications or draft manuscripts in the review process. We started with a set of 56 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 soil-water conservation investments, we narrowed our list down to 26 studies. 17 of the 26 studies are on planting trees or hedgerows on farms. The remaining 9 are on various soil and water conservation investments, including contour farming. It is important to clarify what criteria we used to identify elements of the empirical analysis. Our criteria included micro-economic studies that (a) used household survey data, (b) reported descriptive statistics, and (c) presented empirical results of technology adoption. In addition, we reviewed 8 other empirical adoption studies on related topics: 3 on high yielding variety seeds and 5 on pesticides and fertilizers. For the remainder of this paper, we will refer to these two sets as the partial (26) and full (34) sample.

For each study, we reviewed the text and tables to identify variables in our five categories of adoption influences – preferences, resource endowments, economic incentives, bio-physical factors, and risk and uncertainty. We identified several variables within these broad 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 labeled "0". If a study did not report the results for a particular variable, we left the cell as a blank. We will return to some of the limitations of this vote counting method.

RESULTS

We find that on the average all 5 categories are equally likely to be represented in models of agroforestry adoption, perhaps with marginally higher inclusion of our ‘preference proxies’ category represented by variables such as ‘education’, ‘age’ etc. In terms of individual variables, ‘education’, ‘farmsize’ and ‘labor endowment’ are the most common, present in approximately 70% of the empirical models. In comparison, prices and availability of ‘training’ and ‘savings-credit’ are the least common variables, being present in only about 10% of the models. These patterns are more or less consistent when we look at the full sample of cases, that is including the ‘hyv’ and ‘ipm’ adoption studies.

Inclusion of these categories and/or variables in the model, however, tells us very little about the influence of these variables on the adoption decision. For a better assessment of that, we consider the number of times the variable is significant as a percentage of the number of times it is included. On this count we see that bio-physical factors (86%), risk & uncertainty (74%), and resource endowments (74%), are most likely to impart a statistical effect. In contrast, at 40%, the preference proxies are least likely to show a statistical influence. Turning to individual variables, soil quality, and savings-credit are statistically significant in 100% of the models. At the other end, ‘age’ is statistically significant in only 19% of the models. As above, these patterns are consistent when we look at the full sample of cases by including the ‘hyv’ and ‘ipm’ studies.

It is important to recognize three caveats to the results regarding statistical significance. First, statistical significance is only part of the story; it does not tell us the size of the influence on adoption. As in many meta-analyses resorting to vote-counting, we find that unfortunately the studies do not provide enough detail to calculate the marginal probability of adoption. We

return to this issue when we discuss future extensions. Second, it is likely that investigators voluntarily or otherwise include only significant results or try very hard to find significance in their analysis, given the predisposition towards 'significance' in the literature. Finally, statistical significance 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 is sometimes positive and sometimes negative.

Preference Proxies

Preference proxies such as 'education', 'age', and 'gender' are included in 46% and 43% of the partial and full sample. We see that this is the 'most included' category. These variables have reasonable statistical power – on average, they are significant in 55% - 59% of the cases, when included.

Education: The education variable is normally measured as the average level of education of all household members or of the household head. It is included in 77% and 79% of the partial and full samples. This is a clear indication of the popularity of this variable as a potential explanator of adoption behavior. However, we find that when included it is statistically correlated with adoption in only about 40% (48%) of the partial (full) sample. One possible explanation for its poor statistical performance is that it might proxy for both opportunity costs of labor investment and 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 age of household head. It has been included in 62% and 53% of the partial and full samples. It performs poorly in statistical models and is significant in only 19% and 28% of the partial and full samples. 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 38% and 35% of the partial and full samples. Among the preference proxies, it is the one with the highest explanatory power and is significant in 60% of the models, when included. We find that households with a higher proportion of males are more likely to adopt agroforestry technologies. As suggested earlier, in addition to a preference effect, this probably reflects resource capacity of the households.

Socio-cultural status: Only 8% and 6% 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; both of these have been positively correlated with adoption. The authors argue that attributes such as caste and ethnicity proxy for risk preferences.

Resource endowment

Measures of resource endowment such as *income*, *assets*, and *labor* are included in 41% of the partial sample and 42% of the full sample. Collectively they do a good job of explaining the statistical variation in adoption patterns. We find that resource variables are significant in 63% - 69% of the models when included. The sign of the correlation is consistently positive across different measures of endowments.

Income: Measures of income have been based on a variety of income sources (including, but not limited to, agriculture, wage, off-farm, and total). We find that such measures are included in 62% and 65% of the partial and full sample. These variables are statistically correlated with adoption in 69% and 73% of the partial and full sample. The association is typically positive. It is possible, however, that if a household's dominant source of income is farming, it may not want to risk investing in an unknown technology. At the other extreme, if non-farm sources dominate income earnings, the household may have no interest in farming technology. These may explain the few exceptions to the otherwise positive relationship between income and adoption.

Assets: We proxy asset holdings by several different variables reported in the studies, including land holdings, condition of land (irrigated), house type, value of durables, motor vehicle, and total income. On this count, assets have been included in 38% and 47% of the partial and full samples. They are statistically correlated with adoption in 90% and 69% of the full and partial sample. Overall, we find a consistent and unambiguous positive influence of assets on agroforestry adoption.

Labor: The labor variable is based on the size of the family or the number of adults or males in the family. Measures of labor endowment have been included in 65% and 56% of the partial and full sample. They are statistically significant in 47% and 42% of the partial and full sample. The sign of the correlation is 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 they can be a key element in certain agroforestry systems. We find that livestock have been included in 31% (29%) of the partial (full) sample. When included, they are statistically significant only in 38% (30%) of the partial (full) sample, with the expected

positive correlation. The low statistical power could be due to the fact that most of our cases do not consider livestock-based agroforestry systems in which fodder is a key output.

Credit/Savings: Availability of credit or savings has been included in only 8% and 12% of the partial and full sample. However, when included, it has the expected positive and statistically significant influence in 100% of the cases.

Economic incentives

The adoption studies have not done a good job of including direct measures of economic incentives in the empirical models, barring the use of some subjective or objective measure of potential income gains (included in 58% of the cases). On the average, economic factors have been included in 35% of the studies. If we look at the full sample, the average is 32% and again 'potential income gains' has been included in 62% of the studies. When we turn to statistical significance, however, we find that economic variables perform quite well; they are statistically significant in over 55% of the studies.

Potential Income Gain: Among the economic variables, at 58% this is by the far the most likely to be included in models of adoption. The directness of the measure of potential gain ranges from 'subjective estimate of yield' to indirect effects attributed to the current levels of related activities such as farm income. As a consequence of these indirect attributions, it is not surprising that the statistical significance of the variable is somewhat tenuous. We see a significant positive influence in only 53% and 62% of the partial and full sample.

Distance to market: The inclusion of this variable is typically limited by the availability of geographical detail in the data. We find 27% of our partial sample and 21% of the full sample include this variable. The variable is statistically significant in 71% the cases, with the expected negative correlation. In many ways, the distance variable is capturing a price effect directly correlated the next variable.

Price effect: Only 19% of the partial sample and 15% of the full sample include this variable. The typical limitations on this variable include lack of geographical detail and insufficient statistical variation in studies using cross-sectional data (all our studies). When included, we find that it is statistically correlated with the adoption choices in only 40% of the cases, presumably due to insufficient statistical variability. In one case of statistical significance, the sign of the effect is positive, while in the other, it is negative. 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 on average in 38% of the partial sample and only 34% of the full sample. The exception is the 'plotsize' variable, included in about 70% of the studies. When included, however, we find that they are statistically significant in 86% of the cases on the average. A qualification on this finding is the fact that the sign of the correlation is often inconsistent across studies.

Soil quality: This variable is notoriously hard to measure and consequently we see it included in only 35% 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 100% of agroforestry and soil-water conservation case studies, when included. Typically, poorer soil quality or severe threat of soil degradation is positively correlated with adoption. In two studies, we find a negative relation, which suggests that in some cases soil quality may be so poor that investments in soil conservation are a futile exercise. We also find two negative associations in the 'hyv' and 'ipm' studies.

Slope: The slope of the farmland, usually measured in percentage terms, has been included in 38% of the partial sample and 29% of the full sample. When included, we see that it is statistically significant in 70% of the cases. As expected, farmers owning steeper plots of land are more likely to adopt agro-forestry technology.

Plot size: With an inclusion rate of 69% and 59% for the partial and full sample, we see that plot size is a common variable in many of the adoption cases. It is found to be statistically correlated with adoption in approximately 70% of the cases. However, the sign of the correlation is inconsistent across the studies, with about 45% of the sample finding a positive association and 33% finding a negative correlation. This weakens the 'economies of scale' justification for adoption; that is, farmers with more land are more able and/or willing to experiment with a new technology. Perhaps the 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 risky behavior or economic compulsion.

Irrigation: This variable is included in only 12% (21%) of the partial (full) sample of studies, but is

found to be significantly correlated with adoption 100% (71%) of the times that it is included. Typically, the correlation is positive – suggesting that irrigated lands are more valuable and therefore worth the conservation investment. The one exception to this finding is a study 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, the farmers could choose to invest in contour farming, which is positively correlated with irrigation.

Risk and uncertainty

Finally, the variables measuring risk and uncertainty effects such as 'tenure', 'experience', and 'training' are included in 36% and 34% of the partial and full sample. Typically, these variables exert considerable statistical power in the estimated models, being significant in 74% of the cases when included. In general, greater uncertainty and risk is negatively correlated with the adoption choice. Details on specific variables are as follows.

Tenure: Typically, tenure is measured as whether the farmer is an owner (has tenure) or a renter (does not have tenure). Binary variables of this type have been included in 58% and 50% 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 71-73% of the cases.

Experience: We construct this measure based on an array of variables reported by investigators, ranging 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 54% of the studies. They exert considerable statistical power – significant in 71% and 78% of the partial and full samples. As expected, the sign on these variables is typically positive.

Extension and Training: Investigators typically report binary variables for whether a household received any training in the technology under consideration or has any access to extension services. Such measures of 'extension and training' are found in 35% of the partial and full sample. They generate the expected positive correlation with adoption in 89% (67%) 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 expect participation in groups and support of a community network to mitigate some of the uncertainties associated with new technology. It is also possible that such groups provide extension and training. Proxies for community membership are included in 31% (24%) of the partial (full) sample. The variable is significant in 38% of the models with the expected positive correlation with adoption.

DISCUSSION

By conducting a simple meta-analysis of 34 agroforestry and related technology adoption studies, we can 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 detailed in the previous section highlights two kinds of information on the adoption of agroforestry technologies: *inclusion* and *significance* of factors. We find that 'preference proxies' and 'resource endowments' are more likely to be included in analysis of adoption. Specifically, 'education', 'plot size', 'labor', 'income', and 'age' are included in over 50% of the studies. In sum, investigators tend to pay attention to these variables.

Using the significance criteria, we find that the categories of 'bio-physical factors', 'risk and uncertainty' and 'resource endowments' are statistically most likely to be correlated with the adoption decision, when included in the analysis. Specifically, we see that 'soil quality', 'irrigation', 'plot size', 'extension and training', 'tenure', 'savings', and 'assets' exert the greatest statistical power – that is, they are statistically significant in the highest number of cases. We will not attempt to summarize all the information here. Instead, we draw attention to the finding that these are the main categories and variables that deserve the attention of investigators interested in agroforestry adoption.

When we compare the two sets of categories and variables –those in the 'included' set and those in the 'statistically influential' set - we find imperfect overlap. Before we jump to conclusions regarding the extent of the mismatch of attention and significance, it is best to review some important caveats related to the data and the methods employed. First, as argued elsewhere, there is a bias against insignificance in scientific ventures that can influence the reported results or the analysis that underlies the results in scientific literature. So it is likely that investigators will voluntarily or because of

convention include only significant results or try very hard to find significance in their analysis. Second, we cannot claim that our sampling of adoption studies is random and therefore unbiased. It is not random in part because we engaged in a purposive search of the published and gray literature to find studies that satisfied a predetermined compatibility criteria of topical content, empirical methods, units of analysis, and variable measures. It also may not be representative because of an 'error-correlation', that is, the scientific literature is an evolving and organic phenomenon, in which investigators are constantly building off previously published work, which may have been published by their colleagues or by themselves. Finally, statistical significance is only part of the story. Perhaps a bigger part of the story is the 'economic significance' of the categories and variables. Lack of details on the marginal probabilities of adoption prevented us from investigating the magnitude of the significance. On a related note, while we found that the direction of the correlation was unambiguous in most cases, statistical significance *per se* is not a very useful criteria for variables such as plot size that had an equal number of positive and negative influences.

The limitations discussed above provide lessons for future research that might rely on more sophisticated types of meta-analyses. Combined tests of significance and effect sizes are the next step. In addition, we assigned equal weights to all studies with no quality adjustments. When possible, quality-differentiated weights derived from criteria such as publication source, sampling methods and size, and scientific rigor should be used for more discriminating analysis. Finally, future work could also attempt meta-regression analysis with corrections for heteroskedasticity (see van den Bergh et al. [1997] and Cook et al. [1992] for details).

REFERENCES

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. *World Bank Research Observer* **10**(2):151-80.

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

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

Pattanayak, S. K., D. E. Mercer, E. Sills and K. Cassingham, 2001. "Why do farmers adopt agroforestry? A simple meta-analysis." Discussion Paper. Research Triangle Institute.

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

Scherr S. (1994) Agroforestry. *National Geographic Research and Exploration* **10**(2): 144-157.

Van den Bergh, J., K. Button, P. Nijkamp, and G. Pepping, 1997. *Meta-Analysis in Environmental Economics*. Kluwer Academic Publishers, Dordrecht, Netherlands.