Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature

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Journal of Environmental Management 96 (2012) 17–25

Contents lists available at SciVerse ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

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ARTICLE INFO

Article history:
Received 14 March 2009
Received in revised form
28 September 2011
Accepted 9 October 2011
Available online 25 November 2011

Keywords:
Adoption
Diffusion
Agricultural BMPs
Meta-analysis
Water quality

ABSTRACT

This meta-analysis of both published and unpublished studies assesses factors believed to influence adoption of agricultural Best Management Practices in the United States. Using an established statistical technique to summarize the adoption literature in the United States, we identified the following variables as having the largest impact on adoption: access to and quality of information, financial capacity, and being connected to agency or local networks of farmers or watershed groups. This study shows that various approaches to data collection affect the results and comparability of adoption studies. In particular, environmental awareness and farmer attitudes have been inconsistently used and measured across the literature. This meta-analysis concludes with suggestions regarding the future direction of adoption studies, along with guidelines for how data should be presented to enhance the adoption of conservation practices and guide research.

Published by Elsevier Ltd.

1. Introduction

This study provides a quantitative summary of 46 studies from 1982 to 2007 addressing the adoption of agricultural Best Management Practices (BMPs) in the United States. Some results from these studies are complementary, but as demonstrated in Prokopy et al. (2008), subsequent studies often contradict earlier ones. These conflicting findings make it difficult to comprehend this body of research. Understanding this literature, however, is essential to maximize BMP adoption. Given that the US federal government spends billions of dollars each year on conservation practices (Claassen and Ribaudo, 2006) it is crucial that we have a better understanding of what leads to farmer adoption.

Previous reviews of the adoption literature have been conducted. Pannell et al. (2006) conducted a qualitative review of primarily Australian literature which found that characteristics of the practice are important in the adoption decision. There have also been previous attempts to summarize adoption literature using the vote-count methodology. This approach produces intuitive results by tallying the number of times a variable is positively significant, negatively significant, and insignificant. Whichever results occurs most frequently "wins". The major limitations with the vote count are that it does not consider sample size, has relatively low statistical power, or provide a measure of effect size to quantify the strength of relationship between two variables, such as a regression coefficient.

Knowler and Bradshaw (2007) summarized conservation tillage across the world. This broad topic produced no variables that could universally explain adoption. Kabii and Horwitz (2006) looked at conservation easements across the world and found that age, tenure, and knowledge of and attitudes towards these programs were significant. These findings emphasized the importance of the perceived BMP benefit. Prokopy et al. (2008) summarized the adoption literature in the US between 1980 and 2005. This vote count found that all commonly-used social factors (such as attitudes, awareness, and demographic variables), were insignificant in a majority of the studies that used them. While a useful tool to summarize a body of literature, the vote count methodology does not have adequate power to distinguish variables with small effect size from those that are insignificant. Given that Prokopy et al. (2008) found most variables insignificant, it is worth using a statistical meta-analysis for a more in-depth examination of these variables to determine which variables have small sizes, from those that are insignificant.

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0301-4797/$ – see front matter Published by Elsevier Ltd.
doi:10.1016/j.jenvman.2011.10.006

We use the variable categorization framework developed by Prokopy et al. (2008) along with a statistical meta-analysis to overcome the limitations of the vote count. The primary purpose of this study is to provide a quantitative summary of the adoption literature. To this end we provide an effect size and confidence interval for the commonly examined social factors of adoption research. We use this approach to answer two questions. First, which constructs are positively or negatively related to BMP adoption? Second, can we identify methodological issues that reduce the reliability of adoption research? Through these analyses we provide a clear summarization of the adoption literature to guide both policy and research.

2. Materials and methods

Through an intensive search process, we found a total of 46 studies that met the following criteria: 1) focused on the adoption of BMPs – as opposed to willingness to adopt or likeliness to adopt; 2) were conducted within the United States; and 3) had enough information to calculate an effect size. Summary information about the included studies is presented in Table 1. The region column of Table 1 was determined based on the USDA Farm Productions Regions map (USDA, 2000). Some regions were combined due to the large volume of overlapping studies and similar farming practices within regions. These regions can be seen in Fig. 1. Some studies cover the entire U.S. and are noted as "U.S." in the table.

2.1. Meta-analysis

A meta-analysis is a quantitative summary of a body of literature. When properly done, it controls for important exogenous factors to provide an effect size and confidence interval, as well as a measure of heterogeneity for variables of interest. The importance of heterogeneity is explained in greater detail in Section 2.2. This approach treats each study as a stochastic event in a larger trend, with each study being a single observation. A statistical meta-analysis increases power by pooling all studies into a single data-set. Because there are potentially hundreds of variables in our study, some data reduction was necessary before performing this analysis. To this end variables are grouped into overall categories and subcategories (Cooper and Hedges, 1994). It is these categories and subcategories that we analyzed. This grouping of variables is discussed in a later subsection after we first introduce some important concepts related to meta-analysis. The meta-analysis in this paper was performed using MetaWin 2.0 (Rosenberg et al., 2000)

2.1.1. Creating effect sizes

Our approach utilizes the Hedges d, which provides a measure of effect size and a confidence interval (Lipsey and Wilson, 2001). In the general form, a d-effect size represents the standardized mean difference between two groups. It is similar to a *t*-test, but independent of sample size (Hunter and Schmidt, 2004). Other measures of effect size are readily converted to a d effect size. Table 2 provides the necessary equations to calculate both effect size and variance for this analysis. Further detail on this process can be found in Cooper and Hedges (1994).

The basic meta-analysis uses an unbalanced ANOVA, which does not assume equal group size. This allows us to compare groups with different sample sizes. Failure to account for uneven group size can produce misleading results (Shaw and Mitchell-Olds, 1993). A meta-analysis can use a fixed effects, random effects, or mixed model. It is important to note that the terms fixed effect and random effect have different meaning for a meta-analysis than the usual statistical definition (Borenstein et al., 2009). A fixed effects model assumes a normal distribution, a single true effect size in the population, and variation across studies due to sampling error only. This third assumption, which would not allow for variance in BMP adoption due to farm type, geographical differences, or BMP type, is unreasonable considering we are summarizing a body of literature spanning 25 years.

The random effects model assumes that effect size varies across studies and provides a method to estimate the average effect size (Borenstein et al., 2009). In our study this would be akin to assuming that factors of BMP adoption vary from region to region across the United States, or may have changed over time. A major

Table 1
Overview of studies included in meta-analysis.

Author(s) (Year)	Region	Sample size	Types of BMPs
Alonge and Martin (1995)	3	115	Sustainable practices
Belknap and Saupe (1988)	3	517	No-plow tillage
Bosch et al. (1995)	3	449	Nutrient management
Daberkow and McBride (2003)	U.S.	8429	Precision agriculture
Dorfman (1996)	U.S.	625	IPM, IRR, improved irrigation
Drost et al. (1998)	2	23/24	IPM, field operation, nut. mgmt
Ervin and Ervin (1982)	3	92	Many
Esseks and Kraft (1988)	3	99–160	CRP participation
Featherstone and Goodwin (1993)	3	541	Long-term conservation investment
Fernandez-Cornejo et al. (2001)	U.S.	4040	Precision agriculture
Friedrichsen (2003)	3	67	Precision agriculture
Fuglie (1999)	3	1425	Soil management
Fuglie and Kascak (2001)	U.S.	2373/2456	IPM, conservation tillage
Gould et al. (1989)	3	517	Conservation tillage
Habron (2004)	1	297	Many
Harper et al. (1990)	5	117	IPM (sweep net adoption)
Hindsley (2002)	4	389	Many
Khanna (2001)	3	650	Variable rate technology
Khanna et al. (1999)	3	754	Precision agriculture
Korsching et al. (1983)	3	117	Minimum tillage adoption
Lambert et al. (2007)	U.S.	1580	Conservation program participation
Lasley et al. (1990)	3	2016	Fertilizer and pesticide management
Lee and Stewart (1983)	U.S.	7649	Minimum tillage adoption
Lynne et al. (1995)	5	40	Water conservation technology
Lynne et al. (1988)	5	103	Conservation practices
McBride and Daberkow (2003)	U.S.	3193	Precision agriculture
McNamara et al. (1991)	U.S.	220	IPM
Moreno and Sunding (2005)	1	4433	Water conservation technology
Napier et al. (1984)	3	918	Many
Norris and Batie (1987)	4	74	Soil management
Nowak (1987)	3	89	Soil management
Park and Lohr (2005)	U.S.	1001	IPM, weed mgmt, crop disease
Pautsch et al. (2001)	U.S.	1343	Conservation tillage
Rahm and Huffman (1984)	3	797/869	Conservation tillage
Rahelizatavo (2002)	5	124	Many
Rahelizatovo and Gillespie (2004)	5	124	Many
Saltiel et al. (1994)	2	358–457	Many
Saliba and Bromley (1986)	3	168	P-factor, conservation support practice
Shortle and Miranowski (1986)	3	338	Conservation tillage
Soule et al. (2000)	U.S.	941	Conservation tillage
Uri (1997)	U.S.	825	No till, mulch till
Weaver (1996)	U.S.	246	Number of practices
Westra and Olson (1997)	3	688	Conservation tillage
Wu et al. (2004)	3	27,337	Minimum tillage
Wu and Babcock (1998)	3	539	Conservation tillage, crop rotation
Zhong (2003)	5	235–247	Many

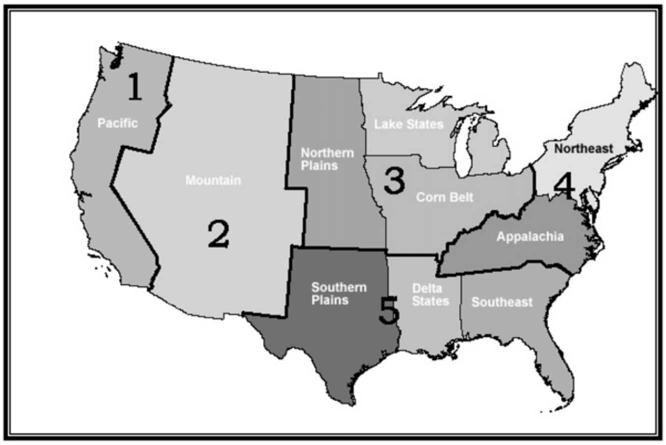

Fig. 1. Study regions and USDA Farm Production Regions (USDA, 2000).

drawback of this model, however, is that there is no way to control for heterogeneity. By using a mixed model (both fixed and random effects), we get the advantages of the random-effects model, but also gain a method for controlling heterogeneity (Cooper and Hedges, 1994; Rosenberg et al., 2000; Borenstein et al., 2009).

Once the effect sizes from the various studies are converted to a standard metric, the cumulative effect size for each category, $\overline{E}_j$, is calculated as follows:

$$\overline{E}_j = \frac{\sum_{i=1}^{k_j} \omega_{ij} E_{ij}}{\omega_{ij}}$$

ω_{ij} is the weight for ith study of the jth group. The weight is calculated:

$$\omega_i = \frac{1}{\nu_i + \sigma^2_{\text{pooled}}}$$

Variance is, ν, is calculated using Table 2. For categorical variables σ^2_{pooled} is defined as:

$$\sigma^2_{\text{pooled catergorical}} = \frac{Q_E - (n - m)}{\sum_{j=1}^{m}\left(\sum_{i=1}^{k_j} - \frac{\sum_{i=1}^{k_j}\omega_{ij}^2}{\sum_{i=1}^{k_j}\omega_{ij}}\right)}$$

and for continuous variables σ^2_{pooled} is calculated by:

$$\sigma^2_{\text{pooled continuous}} = \frac{Q_T - (n - 1)}{\sum_{i=1}^{n}\omega_i - \frac{\sum_{i=1}^{n}\omega_i^2}{\sum_{i=1}^{n}\omega_i}}$$

where n is the number of studies, m is the number of groups, k_j is the number of studies in the jth group, Q_E is the residual error heterogeneity and Q_T is total heterogeneity.

$$Q_T = Q_M + Q_E$$

$$Q_M = \sum_{j=1}^{m}\sum_{i=1}^{k_j}\omega_{ij}\left(\overline{E}_j - \overline{\overline{E}}\right)^2$$

$$Q_E = \sum_{j=1}^{m}\sum_{i=1}^{k_j}\omega_{ij}\left(E_{ij} - \overline{E}_j\right)^2$$

where $\overline{\overline{E}}$ is the overall cumulative effect size.

2.1.2. Heterogeneity

In a meta-analysis heterogeneity refers to the variance introduced by using multiple studies. The I^2 is effectively the percentage of variance explained by heterogeneity, and measures whether the observed variance is greater than would be expected by chance. An I^2 greater than 50 is a substantial amount of heterogeneity (Higgins and Green, 2011). Higgins et al. (2003) mention that these cutoff values have been established in the medical literature. In other fields the I^2 values of up to 75 may be acceptable (Higgins et al., 2003; Higgins and Green, 2011). Our general interpretation of heterogeneity is that I^2 of 50 or less is desirable. An I^2 value between 50 and 75 is interpreted as likely measuring a single latent variable, but needs to be standardized. I^2 values over 75 are addressed individually.

Sometimes it is possible to reduce the effects of heterogeneity by including a control variable (Higgins and Green, 2011). When a variable had an I^2 above 50, the following variables were incorporated in an attempt to reduce heterogeneity: model type, region of the country, year of study (measured by when it was published), and BMP type. Several authors discuss how different statistical models can influence findings of farmer adoption, thus model type is a potential control for heterogeneity (see e.g., Feder et al., 1985; Knowler and Bradshaw, 2007; Moreno and Sunding, 2005). We include ‘year of study’ as a control because methods, and even how some variables are interpreted, have changed over time. To account for geographical differences we used regions as a control variable (Fig. 1). We also grouped BMPs according to the BMP categories presented in Schenpf and Cox (2007) to see if this influenced heterogeneity (Appendix A). If results for a particular subcategory displayed elevated heterogeneity, we utilized each of the control variables described above. The results with the lowest amount of heterogeneity are presented.

Table 2
Converting standard significance measures to Hedges d.

Descriptive statistic or measure of effect	Equation to convert to d-statistic	Equation to calculate variance, ν, for d-statistic
Probit model	Probit coefficient	Probit Coefficient se
Logit model	$\frac{\sqrt{3}}{\pi}$ logit coefficient	$\frac{\sqrt{3}}{\pi}$ logit coefficient se
Odds ratio	$\frac{\sqrt{3}}{\pi}\log\text{OR}$	$\frac{\sqrt{3}}{\pi}\log\text{se}_{\text{OR}}$
t-test	$\frac{2t}{\sqrt{\text{df}}}$	$\left(\frac{n_1+n_2}{n_1 n_2} + \frac{d^2}{2(n_1-n_2-2)}\right)\left(\frac{n_1+n_2}{n_1-n_2-2}\right)$
F	$\frac{2\sqrt{F}^*}{\sqrt{\text{df}}}$	$\left(\frac{n_1+n_2}{n_1 n_2} + \frac{d^2}{2(n_1-n_2-2)}\right)\left(\frac{n_1+n_2}{n_1-n_2-2}\right)$
R	$\frac{2r}{\sqrt{1-r^2}}$	$\left(\frac{n_1+n_2}{n_1 n_2} + \frac{d^2}{2(n_1-n_2-2)}\right)\left(\frac{n_1+n_2}{n_1-n_2-2}\right)$

Note: F-test assumes one degree of freedom. For the above equations, d is the d-family effect size, n_1 is the control sample size, and n_2 is the treatment sample size. When these were not provided, we assumed equal sample sizes between treatment and control.

2.1.3. Interpreting cumulative effect sizes

An effect size is independent of sample size and is used to quantify the strength of the relationship between two variables, or strength of relationship between a response and explanatory variables. The d-family of effect sizes is a useful tool for a quantitative literature review that converts effect sizes of multiple studies into a single effect size, accounts for the variance of different studies, and can be pooled for a single analysis of all pertinent studies. The d-family effect size, however, does not have a simple interpretation. Cohen's "Rule-of-Thumb" is often used in the social sciences (Higgins and Green, 2011). Variables with an effect size of 0.2 are considered to have a small impact, of 0.5 a medium effect, and of 0.8 a large effect (Cohen, 1988). While this rule is useful, it is important to recognize that the individual variables measured in this analysis are often small components of a larger effort to influence adoption. Additionally, since we would expect social factors individually to have small effect sizes, simply noting that a variable has a small but significant impact on adoption is not very revealing. Rather, observing which constructs have large or small effect sizes compared to others is a more useful interpretation. In terms of program assessment, noting which factors are complementary and could be combined to create a more comprehensive approach to BMP adoption.

2.2. Categorizing variables

To conduct a successful meta-analysis, it is essential that the researcher read and understand each study included. A common critique of meta-analyses is that the researcher can compare "apples to oranges" (Borenstein et al., 2009). This refers to the mathematical ability to combine effect sizes that are conceptually incompatible. To avoid such comparisons, a reliable coding procedure is vital. Methods for categorizing variables are quite similar to a coding for a content analysis: a coding procedure is developed according to theoretical and empirical works which clearly directs coders (Lipsey and Wilson, 2001). In this research, we used the framework developed by Prokopy et al. (2008), and which was based upon theoretical considerations as explained for individual categories below. All four authors read each paper and categorized variables according to the definitions in Table 3. In cases where variables were coded differently by different researchers, all researchers discussed the most appropriate category and came to consensus on the variable based on the original author's explanation. If no explanation was given, decisions were based upon the literature. This method is at least as effective, if not more so, than the accepted method of calculating inter-coder reliability scores which assess how often independent coders were in agreement on a subsample of document codes.

The statistical meta-analysis requires the calculation of specific effect sizes (Table 2). Ten studies were omitted due to the more stringent data requirements of the meta-analysis. Sub-categories with too few studies were excluded from our analysis, as this information was not able to be aggregated for comparison (Lipsey and Wilson, 2001). The grouping of these variables is described below; greater detail can be found in Prokopy et al. (2008).

2.2.1. Capacity

Through the years, human and institutional capacity variables have been considered important influences on a farmer's decision to adopt a BMP. *Acres* is a measure of farm size and has been used as a measure of capital (Norris and Batie, 1987), or scale of economy (see e.g., Belknap and Saupe, 1988; Caswel et al., 2001; Daberkow and McBride, 2003: Khanna, 2001). *Age* has been included in many models as a barrier to adoption. It has been used as a proxy for environmental awareness, hypothesizing that younger farmers were more aware of the benefits of BMPs (Gould et al., 1989). Ervin and Ervin (1982) proposed that older farmers have a shorter planning window and are thus less likely to adopt BMPs. *Education*

Table 3
Categorization of independent variables.

Category	Sub-category	Brief explanation
Capacity	Farm size	Number of Acres farmed
	Age	Farmer age
	Capital	Measure of investment into farm (excluding acres)
	Education	Farmer education
	Extension Training	Subgroup of EDUCATION includes only extension training
	Formal education	Subgroup of EDUCATION- includes only formal education
	Farming exp	Years farming
	Income	Measures of wealth such as income, crop value, etc
	Information	Access to and quality of information
	Institutional	Measures used in original studies to capture farm structure or organization
	Networking	Overall measure of networking capacity
	Agency	Subgroup of NETWORKING- Connectivity to and familiarity with agency personnel and procedures
	Business	Subgroup of NETWORKING- Measures of networking capacity in the agribusiness sector
	Local	Subgroup of NETWORKING- Interacts with neighboring farms as well as any grass roots organization
	University Extension	Subgroup of NETWORKING- Exposure to a university extension office
	Tenure	Whether operator owns farmland
Attitude	Environmental	Importance individual places on environmental quality
	Profitability of practice	Farmer places financial gain as primary purpose of farm
	Heritage	Farm will be taken over by a family member
	Quality of Env	Farmer's perception of the current quality of the environment
	Regulatory	Farmer feels government can/should regulate agriculture
	Risk	A measure of risk averseness
	Scientific	Values scientific research
	Adoption payments	Farmer receiving payments for participating in conservation programs
Environmental awareness	Awareness	The environmental awareness category as a whole
	Cause	Understanding how agriculture can impact environmental quality
	Consequences	Understanding the consequences of a degraded system
	Knowledge	Knowledge of general terms or facts related to environmental quality
	Program	Knowledge of NPS programs or efforts

Note: In some cases, we needed to reverse the sign of a variable to make it fit within a sub-category. For example, the sub-category RISK measures risk aversion; variables measuring "willing to take risks" would have its sign reversed to be consistent with variables measuring risk averseness.

is discussed in almost every study included in this analysis as a positive measure of individual capacity. As used in several studies, *education* is a general variable that includes educational attainment, years of school, if the individual has graduated high school, and whether or not the farmer has a college education. Additionally this category includes variables that capture whether or not an individual participated in an extension program or field day. Other studies treated formal education and extension training as separate variables. To be consistent with the literature we examine *education* as a category, but also break it into two subcategories, formal education and extension training (Table 3). Higher *income* is hypothesized to ease the burden of investing in BMPs, and increase tax incentives of certain BMPs; in the various studies that use income it is measured by a combination of on and off farm income (including investments and other non-farm household income). (see e.g., Gould et al., 1989; Norris and Batie, 1987).

Norris and Batie (1987) began discussing the importance of access to, and quality of *information* about BMPs. Subsequent studies on BMP adoption began to incorporate this. Access to and participation in various *networks* comes from the diffusion literature. We examine connectivity with four different types of networks in this paper: agency, business, local and university. *Tenure* has been measured in various ways in the literature. In some studies, *tenure* is the portion of farmed acres owned (Rahm and Huffman, 1984; Belknap and Saupe, 1988; Featherstone and Goodwin, 1993), others use dummy variables to identify the different types of ownership (Lynne et al., 1995, 1988), while Fuglie and Bosch (1995) examined owner-operated fields. Ownership type captures whether the farm is individually owned vs. a corporate farm.

2.2.2. Environmental attitudes and awareness

Ajzen (1985) Theory of Planned Behavior (TPB) examines the relationship between an individual's attitudes and their actions. This framework has been one of the theoretical driving to integrate attitudes in the adoption literature. The TPB defines an attitude towards a behavior as "the degree to which performance of the behavior is positively or negatively valued." Awareness variables are important precursor to forming an attitude regarding a specific topic (Forsyth et al., 2004). Knowing how to enact a behavior is more relevant to an outcome like BMP adoption (Kaiser et al., 1999). When examining attitudes and awareness through the lens of BMP adoption, specific attitudes towards and awareness of BMPs should be examined, rather than general environmental awareness or attitudes (e.g., see the TPB Ajzen, 1985).

Many studies include measures of attitudes without strict adherence to theory. Lynne et al. (1988) presents a detailed discussion of how to apply several social theories to BMP adoption. When creating the subcategories, we made every effort to balance behavioral theories with the manner in which the constructs were actually used in the BMP studies. Utilizing the TBP, taking *payments* from the government reflects a positive attitude towards governmental programs because it results in a government subsidized BMP (Prokopy et al., 2008). The *environmental* subcategory reflects the importance of water quality to an individual, and is expected to be a positive predictor of adoption. *Profitability of practice* reflects farmers' perceived economic impact of a given BMP, and is believed to have a positive impact on adoption (see e.g. Napier et al., 2000). *Heritage* was introduced to explore the relationship between multigenerational family farms and BMP adoption. Ervin and Ervin (1982) found that farms maintained within a family would have greater incentive to conserve soil fertility. *Quality of environment* measures a farmer's perception of local water quality (Hindsley, 2002). *Risk* measures a famer's willingness to take risks, which is hypothesized to have a positive impact on adoption (Ervin and Ervin, 1982; Lynne et al., 1988).

A measure of overall *awareness* was included to be consistent with the adoption literature. *Cause* reflects an individual's understanding of how non-point source (NPS) pollution runoff degrades an aquatic system (Ervin and Ervin, 1982; Esseks and Kraft, 1988), and *consequences* captures if an individual is aware of the consequences of poor water quality (Saliba and Bromley, 1986; McNamara et al., 1991). *Knowledge* reflects retention of facts pertaining to environmental quality (Belknap and Saupe, 1988; Saltiel et al., 1994). Knowledge of specific NPS efforts is measured by program (Norris and Batie, 1987; Saltiel et al., 1994).

2.3. Reliability tests

One limitation of the vote count methodology is that there is no quantitative test to check the sorting. In order to maximize reliability, however, it is important to see if studies are consistently using constructs. Since the statistical meta-analysis allows us to do so, we examined if constructs had been appropriately conceptualized in studies of adoption. The first construct we examine is whether university extension networks are distinct from state or federal agency networks. The second tests if formal education and extension training belong together. The third explores if there is a significant difference between an environmental attitude addressing local ecosystems, as opposed to the New Environmental Paradigm (NEP), which measures general attitudes about the environment. Attitudes about a local area will influence actions an individual takes regarding that ecosystem. Attitudes regarding the earth as a whole are unlikely to sway decisions that affect a single stream (Kaiser et al., 1999).

During the grouping, we hypothesized about what might cause excessive heterogeneity. In several instances we noted the inconsistencies in data collection across studies, and felt this was a potential source of heterogeneity. We tested this hypothesis with *education* (excluding extension training) because it is used 77 times with a good distribution of the different data types. *Education* was recorded as a multi-categorical measure of educational attainment as follows: years of education, educational attainment, if a farmer received a high school diploma, and college degree. We examined if data type (continuous, binary, and ordinal) was a significant source of heterogeneity with the formal education sub-category.

Finally, we observed farmers' attitudes towards risk were significant more often in earlier studies than in recent adoption papers. *Risk* was first included by Ervin and Ervin (1982) because BMPs were an investment, and farmers didn't know if it would pay off. Individuals who were less averse to risk would be more willing to adopt. Over time, however, BMPs have become more common. Our hypothesis is that the perceived risk of adoption has diminished as BMPs have become more widely used. The various tests of reliability are highlighted in Table 4.

Table 4
Tests of reliability.

Broad category of reliability	Specific research question
Testing groups of variables	• Is university extension distinct from agency extension? • Are formal education and extension training different types of capacity? • Is the NEP a different attitudinal construct than "local" environmental attitudes?
Testing heterogeneity introduced through data collection and analysis tools	• Do various data types create heterogeneity within a sub-category?
Testing whether social construct changing over time	• Has the impact of risk changed as a function time over 25 years of adoption research?

Table 5
Results from different data types.

Class	#Studies	Effect size	df	95% CI
Formal (binary)	42	0.057	41	−0.0542 to 0.1682
Formal (cont)	26	−0.1148	25	−0.2293 to −0.0002
Formal (ordinal)	9	0.2329	8	−0.024 to 0.4898

2.4. Limitations

The file drawer effect refers to a potential bias of the literature to publish studies with significant findings only (Rosenthal, 1979, Higgins and Green, 2011). A lot of effort went into finding unpublished studies. However, it is unlikely we uncovered every report. Furthermore, many studies reported only significant variables, which may aggravate this issue.

As pointed out by Wilkinson (2011), the concept of "adoption" is not as simple as it is frequently portrayed in the literature. Many of the reviewed studies use a simple binary assessment of adoption; however, it should be noted the adoption process is much more complex. Finally, not enough of the reviewed studies looked at characteristics of the practice being adopted for us to include this as a variable; this has been found in other studies to be a determinant of BMP adoption (Pannell et al., 2006).

3. Results and discussion

In the methods section we raised a few questions about how data are collected, used, and presented in the adoption literature. Before discussing our general findings, the results for data type are presented, as they have implications for many variables included in this study.

3.1. Data type

We found that data type can influence the relationship between the dependent variable and independent variable. For example, data type is significant at a *p*-value of 0.0078, and explains 63% of the heterogeneity of *formal education*. The results for the individual data types are presented in Table 5. Years of education (continuous) has a negative impact on adoption, while the binary and ordinal forms are insignificant but positive.

Exploring the impacts of different data types for a variable is intended to highlight how survey results are susceptible to apparently minor changes, such as data type (Table 5). When using a variable from the literature, changing the data collection tool may introduce this type of error. If changes are made, pre-testing should be done to note how the various options influence results. While researchers must fit the survey to their target audience, it should be acknowledged that these differences may affect the results.

3.2. General findings

The tables throughout this section include many columns. These include the variable name, which is explained previously in Table 1, the effect size, the 95% confidence interval for that effect size, and a column for whether the effect size is significant at a .05 level. We also measure heterogeneity with the I^2 statistic. We include the degrees of freedom so that the reader understands the number of studies included in the analysis for the particular variable. To deal with heterogeneity issues, we often needed to include a control variable. As mentioned earlier, the model chosen only allows for a single control variable. The control variables were identified *a priori*, and the one that led to the best results (as measured by the lowest I^2 statistic) is included in the table.

3.3. Capacity

The results of our analysis are presented in Table 6. *Farm size* has a relatively large impact and high heterogeneity. Data collection for this construct varies widely across the literature. Additionally, what is considered a large farm is geographically dependent, so a high heterogeneity may be, at least in part, inherent. *Age* has a significant and negative impact on BMP adoption, suggesting that older farmers may have a shorter planning horizon than younger farmers. We used the BMP categories to control for heterogeneity. Like many variables, *age* is composed of various data types. In some studies the variable was continuous, while others used ordinal data, and still others collected it as a dichotomous variable. We attempted to control for this variability, but this resulted in too few variables in each subcategory for any meaningful analysis.

While the overall *education* category and *formal education* are insignificant, *extension training* has a positive impact on farmer adoption. *Formal education* is insignificant with a relative large *n* (77), suggesting it is not relevant for adoption studies. *Extension training*, however, has a positive influence on adoption. BMP

Table 6
Results for variables in the capacity category.

Variable	Effect size	95% CI	*P*-value	*I*-sq	df	Control
Farm size	0.2508	0.0476 to 0.4539	0.0149	75.2	89	Acre/acre sq
Age	0.0498	−0.0764 to −0.0233	0.0006	51.6	48	BMP categories
Education	0.0308	−0.0118 to 0.0733	0.1589	70	106	BMP categories
Extension	0.0844	0.0371 to 0.1318	0.0016	58.6	28	BMP categories
Formal education	0.002	−0.766 to 0.0806	0.9926	63.3	76	Region
Income	0.0786	0.0469 to 0.1103	<0.0001	74.6	83	BMP categories
Capital	0.1192	0.0688 to 0.1696	<0.0001	52.9	53	None
Information	0.186	0.0529 to 0.3191	0.0088	18.9	45	None
Institutional	0.568	−6.4718 to 7.6079	0.8746	−5303	108	None
Labor	1.4388	−10.5019 to 13.3795	0.8146	−1818	38	None
% Income from farm	0.1615	0.017 to 0.306	0.0352	44	35	None
Ownership	−0.0247	−0.134 to 0.0846	0.4278	−10.5	33	None
Networking	0.0343	0.0258 to 0.0428	<0.0001	95.2	61	BMP categories
Agency	0.3178	0.1212 to 0.5145	0.006	25.5	16	None
University	0.0002	−0.0005 to 0.0009	0.5843	−68.8	14	None
Local	0.334	0.1815 to 0.4865	0.0003	46.3	22	BMP categories
Business	0.2759	0.1043 to 0.4475	0.0253	74.2	5	None
Tenure	0.0239	0.0112 to 0.0366	0.0006	90.8	50	BMP categories
Farming exp	−0.0046	−0.0922 to 0.083	0.9185	12.5	42	None

categories control heterogeneity reasonably well. The remaining heterogeneity is likely due to different types, quality, and duration of extension training across the US, as well as different data types to record this information in the various studies. The effect size of 0.0844 is relatively large considering most reported extension events were 1-day training efforts. Farming experience is insignificant with minimal heterogeneity.

Capital is the best financial predictor of adoption. *Information* also has a relatively high impact, with low heterogeneity considering the variety of information sources used across studies. The *% income from farming* has a significant impact on adoption. Since this variable was generally included as a measure of the farmer's financial commitment to farming, the sign and significance of this variable makes sense.

The overall *networking* category is a significant predictor of BMP adoption. Heterogeneity, however, is over 95%. Both *agency* and *local networks* have relatively large impacts (0.3178 and 0.334 respectively) and heterogeneity below 50%. While *business networks* is significant, the small sample size (6 studies) and high heterogeneity prevent any conclusion. The results for *business networks*, along with theoretical considerations, suggest further investigation is warranted. *Tenure* is a positive predictor of BMP adoption, but heterogeneity accounts for 90.8% of the variation in this variable, preventing any meaningful interpretation. Like *education*, some standardization in how this variable is collected and interpreted is needed. The significance of *tenure* is consistent with theories that different ownership types may still be pertinent for specific BMPs. Soule et al. (2000) present an in-depth discussion of the effects of ownership type on the adoption of large investment BMPs, as well as BMPs with short-, medium-, and long-term benefits.

3.4. Farmer attitudes

Table 7 displays the results from the attitudes category. The overall *attitudes* variable is insignificant with high amounts of heterogeneity. Farmers' attitude towards *risk* is insignificant, with minimal heterogeneity. We tested our hypothesis that the influence of *risk* lessened over time and found it did diminish, with an effect size of −0.0039. This suggests that, over time, BMPs are perceived as less of a risk and casts doubt on the continued utility of this variable in adoption studies. *Adoption payments* is insignificant, and heterogeneity comprises almost 98% of the variance of this variable. This is unexpected and deserves further investigation. The perceived *quality* of a local ecosystem is insignificant, but theoretical consideration, *p*-value (0.0834), and limited degrees of freedom (9), make this variable worth further investigation (Table 7).

3.5. Environmental awareness

Awareness results are shown in Table 8. Many studies discussed environmental awareness as a whole. Since the overall category has been used in several adoption studies, we included it as a variable in this analysis. When examined as a category, *environmental awareness* was significant. However, the I^2 is over 98%, despite all efforts to control this. This supports our hypothesis that *environmental awareness* consists of distinct sub-categories.

Of the environmental awareness sub-categories, *cause* and *consequences* were insignificant, while *program* and *knowledge* were positive significant predictors of adoption. This suggests that rather than addressing how agriculture, in general, can degrade water bodies, efforts should focus on how the actions of individuals on their farm impact water quality (*knowledge*). Having specific familiarity of program goals and efforts has the largest impact and is an important step preceding BMP adoption. We see that variables with a direct connection to action, *program* and *knowledge*, are significant, while more general variables are not.

4. Summary and conclusions

This study summarized the influence of 31 social factors assessed over 25 years of BMP adoption. The results show that many of these constructs have a small influence on BMP adoption when examined individually. This does not mean that social factors are not relevant. Rather, effective BMP adoption efforts should combine complementary social factors to increase their impact overall. Indeed, many of these elements fit together naturally. For example, using networks to implement extension efforts and disseminating information presents a logical way to combine and extend the reach of factors found to have a significant effect on BMP adoption.

Both environmental awareness and attitudes are positive influences of BMP adoption, but these indicators must be used carefully. There should be a clear link between these variables and BMP adoption. Too often attitudinal and awareness indicators have been included in studies without defining a clear connection to BMP adoption. Awareness questions regarding general causes and consequences of NPS are not specific enough. Instead they should focus on how an individual's actions relate to NPS pollution. Similarly, attitudinal questions must be behavior-specific rather than universal attitudes.

The findings in this paper suggest policy makers can use this finding to create a two-tiered approach to BMP installation. The first tier would have an implementation focus, targeting farmers most likely to adopt (an idea also suggested by Llewelyn, 2011). The second tier would continue to increase individual capacity and awareness by using networks to inform other farmers about the benefits of adoption.

Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

Table 7
Results for variables in the attitude category.

Variable	Effect size	95% CI	*P*-value	*I*-sq	df	Control
Overall attitudes	0.0012	−0.0003 to 0.0026	0.1066	88.55	173	None
Risk	0	−0.0004 to 0.0003	1	14.32	36	None
Environment	0.2788	0.1858 to 0.3718	<0.0001	58.73	26	BMP categories
New environmental paradigm	0.0001	−0.0015 to 0.0017	0.7976	−33.45	12	None
Innovation	0.0425	−0.004 to 0.0889	0.0907	27.71	17	None
Heritage	−0.0002	−0.0011 to 0.0008	0.6842	8.016	20	None
Financial	−0.2488	−1.1028 to 0.6052	0.582	16.29	9	BMP categories
Regulatory	−0.02	−0.2883 to 0.2482	0.8847	7.094	33	None
Quality	0.4455	−0.003 to 0.8941	0.0834	−12.47	9	None
Adoption payments	0.001	−0.0003 to 0.0022	0.127	97.6	31	Region

Table 8
Results for variables in the environmental awareness category.

Variable	Effect size	95% CI	*P*-value	*I*-sq	df	Control
Env awareness	0.0323	0.0238 to 0.0408	<0.0001	98.8	138	BMP categories
Cause	0.0006	−0.0003 to 0.0014	0.1787	49.8	25	None
Consequences	0.202	−0.0617 to 0.4657	0.1591	15.2	12	None
Program	0.3066	0.1854 to 0.4277	<0.0001	92.7	51	BMP categories
Knowledge	0.106	0.0602 to 0.1517	<0.0001	89.9	46	BMP categories

Appendix A. BMP categories

This appendix is intended to clarify the various types of BMPs included in this analysis. Based on Schenpf and Cox (2007), Table A-1 provides examples of the various types of BMPs included in this analysis, and how BMP types were categoriezed.

Table A-1
BMP categories (Schenpf and Cox, 2007).

BMP category name	Example BMPs
Soil management	No-till, mulch-till, cover crop, contour farming, field border, critical area planting
Water management (irrigation)	Irrigation storage reservoir, irrigation conveyance lining, irrigation land leveling, micro-irrigation
Nutrient management	Site-specific management, manure storage, precision agriculture, method of nutrient application
Integrated pest management	Sweep nets, hormone traps, crop rotation
Landscape management	Riparian buffers, streambank stabilization

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