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A meta-analysis of factors driving the adoption of precision agriculture

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Abstract
Using a literature pool spanning 23 years, this meta-analysis quantifies the effect of factors underlying the adoption of precision agriculture. Unlike statistical significance, which demonstrates how likely adoption is due to chance, effect size indicates the importance of a factor to adoption. This meta-analysis finds that *perceived profitability*, *consultants* and *use of a computer* factors have a moderate effect. However, the findings should not be regarded as definitive because of issues of sample size and heterogeneity embedded in a number of the reference studies. This latter point is re-enforced by observation of other factors that had a negligible effect on adoption. Whether future studies will provide meaningful policy implications depend on a careful understanding and selection of factors, models, and statistical treatment in relation to decision-making paths and their context.

Keywords Review · Meta-analysis · Adoption · Precision agriculture · Drivers

Introduction

Given growing investment in research, development and the importance of precision agriculture, a pool of learned investigations has been published since the late 1990s. This paper conducts a meta-analysis to identify the drivers underlying the adoption of precision agriculture. Previous narrative reviews in this research area are traced; highlighting their methodological merits and limitations. In doing so, a knowledge gap remains: to understand the overall effect of the determinants of technological adoption (as identified by separate studies undertaken in the precision agriculture realm). In innovation diffusion studies, effect size quantifies the influence of factors leading to adoptive decisions. Based on such quantitative understanding, policy interventions can be targeted towards influential factors. Baumgart-Getz et al.'s (2012) meta-analysis of the adoption literature on best management practices in the United States provides a useful example. Their meta-analysis identifies 'labor' as having a large impact, but its high variability dampens any recommendation for expansion in the farm labor market. In exploring policy options, such a combination of

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effect size with its variance band allows scientists and policymakers to move from the 'Is this factor important?' question to the more insightful question 'How critical is this factor within a range of possibilities?'. Answering that question is more useful to augment the implementation of precision agriculture.

The emergence of precision agriculture over the last two decades has been documented (Lee et al., 2021). The overall goal of precision agriculture is to help farm operators optimize input management according to agronomic need. Such need increases with world's growing demand for agricultural products. At the same time, supply challenges loom, in terms of reduced arable land, higher input costs, and climate change. According to Nowak's (2021) review, intra-field diagnosis tools (crop sensing, soil mapping, yield monitoring, and geo-referenced field scouting), automatic variable-rate treatments (for fertilizer application, crop protection, and other purposes), and Global Navigation Satellite Systems (GNSS) (guidance system and automatic section control) have emerged for meeting both production and environmental goals.

A new branch of the technological developments related to precision agriculture aims to support farmers to cope with the declining availability of labor. Drones are one example. Their use began as a labor input reduction innovation, but they are now increasingly used for mapping, monitoring, analytics, and precise application purposes. Similarly, smartphone applications simplify data collection and the data processing required to guide targeted agricultural practices. Attempts are underway to integrate precision agriculture with artificial intelligence and predictive analytics (e.g., Lee et al., 2020). While these developments suggest that precision agriculture is not strictly confined to any pre-definable suite of technologies, they are conceptualized as offering a means for an agri-tech revolution known as 'Agriculture 4.0', 'Smart Agriculture', and 'Digital Farming' (Santos Valle & Kienzle, 2020).

Some precision agricultural technologies have achieved greater adoption rates than others. Robertson et al. (2016) report that 90% of Australian grain farms utilize auto-steer and guidance. Steele's (2017) producer survey in western Canada finds that over 80% of respondents self-managed farm data and had yield monitoring, more than 75% used guidance systems, and nearly half used variable-rate applications. In the USA, USDA (2019) reports that, among its field crops, corn farms recorded the greatest jump in agricultural technology usage: yield mapping, guidance systems, and variable-rate technology grew from less than 10% of corn farms in 2001–2002 to over 40% by 2016. European countries had lower adoption rates, e.g., the European Parliament (2016) determines a technologies usage rate of 25% (including those under the umbrella of precision agriculture). The adoption rates of precision agricultural practices in developing countries remain undocumented.

A mix of socio-economic, economic, institutional, and technical barriers has limited the adoption of precision agriculture. A lack of skills necessary to operate precision agricultural technologies represents a fundamental barrier (Robert, 2002). While learning is possible, farm operators, with pressure to generate farm incomes and to meet their financial obligations, are pressured to prioritize their efforts (Mitchell et al., 2020). The time and effort required at both the implementation and maintenance levels for precision agriculture is relatively complex and these are also important considerations. 'Know-how' support is scarce (Pedersen & Lind, 2017). Another consideration stems from the uncertainty of benefits vis-à-vis the capital outlays and the alteration of existing agricultural practices (Thompson et al., 2019). Fragmented organizational structures in agriculture also slow diffusion (Balogh et al., 2021). Other barriers are discussed in Wiebold et al. (1998).

Mixed attainment achievements and barriers have kindled dialogue over (1) how adopters differ from the non-adopters; and (2) based on their differences, how to facilitate advocacy policies that accelerate adoption. It becomes important to ensure that policymaking is evidence based and represents the best option in any circumstance. Meta-analysis aids policymaking through enabling both an aggregation of disparate studies and quantification of the influence of factors that appear to affect a farmer's decision to adopt a particular technology. In this study, following the National Research Council's (1997) definition, the term 'precision agriculture' is conceptualized as a unifying label for several related technologies whose implementation involves data collection, data analysis and decision making, and/or variable rate control. As suggested by Knowler and Bradshaw (2007), such an aggregation of both scope and findings can help quantify the state of existing knowledge and improve its advocacy as a package of practices.

Conceptual framework

Agricultural innovation literature posits that the binary choice—to adopt or not to adopt—is based on the perceived utility that may be derived from the innovation. Following the seminal work of Rahm and Huffman (1984), it has been established that profit is not the only form of utility. Since farmers and enterprises choose according to their own preferences, adoption is undertaken when a farm enterprise forms the expectation that its utility exceeds its opportunity costs. This is categorized as "random utility maximization behavior". A central component of this approach is the identification of the factors directing a decision, based on the aspects of investigation, i.e., how the attributes of a technology are perceived, and the identification of their relationship with its adoption (Adesina & Zinnah, 1993).

Hence, the random utility maximization approach is a relevant framework for understanding the desired action, which is an indication that precision agriculture satisfies the expected utility of users within their respective constraints. It can, therefore, facilitate an understanding of the drivers underlying the adoption of precision agriculture, i.e., what factors are important in driving its adoption. Such significant factors explain adoption and carry policy implications since they can help to facilitate reaching the desired target. Accordingly, a branch of research has applied this approach to understanding the direction and the strength of the correlation between explanatory factors and the adoption of precision agriculture.

There are at least three ways through which a review can be conducted for the purpose of synthesis. Recent review studies have employed two of them. Pierpaoli et al. (2013), Antolini et al. (2015), and Pathak et al. (2019) perform literature reviews, then summarize the results. They indicate that the adoption of precision agriculture is affected by a wide range of factors. Tey and Brindal's (2012) vote count review find that no single variable could universally explain the adoption of precision agriculture. The synthesis approach analyses the frequency at which a variable is positively and negatively significant. The output summary may be useful to hypothesize the likelihood of any association between the two variables.

While narrative review approaches have their own merits, the absence of objective and systematic selection criteria culminates in methodological shortcomings that skew results and policy implications (Pae, 2015). For example, previous narrative reviews engage in unit-of-analysis error by accounting multiple investigations that employed the same dataset as separate studies. Furthermore, the interpretation of significant findings in narrative reviews is based on equal weight (irrespective of the sample size) included across statistical analyses (Popay et al., 2006). Narrative studies, thus, have low inference power. Against the limitations of these narrative review approaches, a third approach involves a systematic selection and quantification of the impact of influential variables via meta-analysis.

In meta-analysis, the quantification of effect size enhances researchers' understanding of factors underlying the uptake of precision agriculture. In medical science, effect size helps to identify the effectiveness of an intervention. Effect size is pivotal in providing a standard measure for different studies; through combining their findings into an overall summary, with consideration given to their sample sizes (Sullivan & Feinn, 2012). The magnitude of an effect size indicates the strength of a factor in association with the desired action. Resource allocation is undermined when policy consideration is limited to knowing whether a factor affects adoption (Kline, 2004). Policymakers would have difficulty in differentiating interventions and thereby split their scarce resources across every statistically significant factor. Conversely, effect size enables policymakers to consider how much factors affect adoption and concentrate on the influential ones, thus increasing the odds of success.

The drivers synthesized in this study can be discussed in relation to the characteristics distinguishing precision agriculture from other agricultural innovations. In America, Baumgart-Getz et al. (2012) identify three groups of factors: capacity, attitude, and environmental awareness as leading to the adoption of best management practices. Effect size, as estimated by Guo et al. (2020) for research undertaken in Southern Africa, points to the importance of socio-economic and institutional factors in driving the use of sustainable intensification practices. Xie and Huang's (2021) find that the positive effect of farm income, policy awareness, and land transfer on the adoption of pro-environmental agricultural technologies is noteworthy in China. Importantly, Ruzzante et al.'s (2021) wider scope meta-analysis uncovered varying effects with no variable being a universal predictor for the adoption of all agricultural innovations. Given such heterogeneous meta-analytic findings across agricultural innovations, this study is compelled to focus on those influential factors that guide the diffusion of precision agriculture.

Methodology

This study used Shamseer et al.'s (2015) preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) to prepare a dataset. Meta-analysis was conducted to estimate effect size of factors.

Materials

From the outset, this study considered only peer-reviewed journal articles that quantitatively investigate the drivers of the adoption of precision agriculture. Studies reporting insufficient data for computing effect size were excluded. Qualitative studies were also excluded. Studies that focused on ex-ante scenarios such as 'willingness or likeliness to adopt' were deemed ineligible.

Searches were performed using the Google Scholar, SCOPUS, and Web of Science databases. Reverse citation searches were also conducted. Such a combination of databases and search strategies ensures adequate and efficient coverage (Bramer et al., 2017). The searches used the following keywords:

- ‘drivers’, ‘determinants’, ‘factors’, ‘enablers’, and ‘motivations’;
- ‘adoption’, ‘use’, ‘uptake’, and ‘implementation’;
- ‘precision agriculture’, ‘remote sensing’, ‘imagery’, ‘georeferenced soil sampling’, ‘yield monitoring’, ‘soil mapping’, ‘variable-rate’, ‘guidance system’, ‘autosteer system’, ‘drone’, and ‘smartphone’.

Figure 1 presents the PRISMA-P flow diagram used for preparing the dataset in this study. It began with searches that returned a total of 1,367 articles in the literature. Because multiple databases were used, 627 articles were identified as duplicates and they were excluded. Subsequently, the title and the abstract of each of the remaining 740 articles were read. This led to the exclusion of 663 articles and the shortlisting of 77 articles.

The shortlisted articles then underwent an evaluation against the eligibility criteria (as previously defined). Skimming that focused on the main contents identified 37 irrelevant articles (including ex-ante articles and articles investigating intensity, and the time of adoption) and 11 qualitative articles. These articles were excluded.

As a result, a total of 29 articles qualified for qualitative synthesis in this study. Among these, six articles did not report sufficient information for effect size estimation. E-mails seeking more information were not replied to. Consequently, six further articles were excluded. The dataset of this study thus comprises 23 articles.

Qualitative synthesis

When conducting the in-depth analysis for qualitative synthesis, as mentioned, six articles were identified as failing to provide sufficient information to enable meta-analysis: Roberts et al. (2004); Aubert et al. (2012), Robertson et al. (2012), Lambert et al. (2014), Lambert et al. (2015), and Barnes et al. (2019) were, therefore, omitted.

Table 1 provides basic information about the 23 eligible articles. Two-third of the articles were conducted in the United States, and focused, largely, on cotton and corn farming. About one-third were in European countries, covering various agricultural crops. Only one article examined the adoption of precision agriculture in Brazil. Their investigation encompasses the field from general precision agriculture to specific

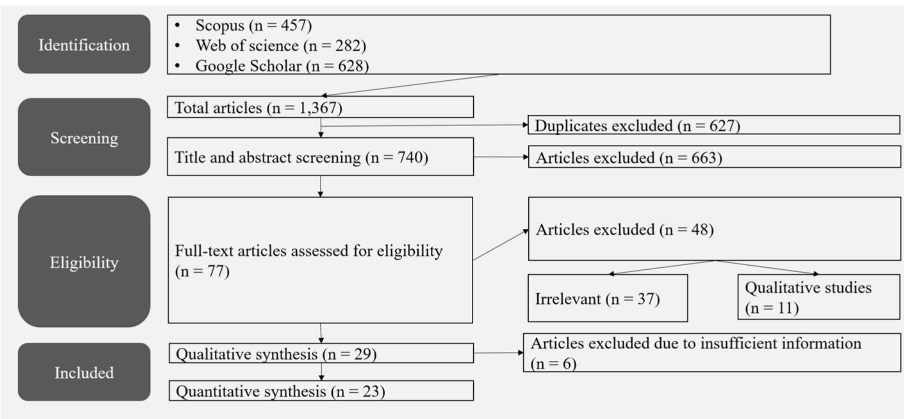

Fig. 1 PRISMA-P flow diagram towards preparing the dataset of this study

Table 1 Overview of 23 eligible articles in this review

No	Author(s) (Year)	Country	Sector	Types of precision agriculture (adoption rate)	Sample
1	Asare and Segarra (2018)	United States	Cotton	Georeferenced grid soil sampling	1344
2	Banerjee et al. (2008)^	United States	Cotton	Global positioning guidance system (25.8%)	879
3	D'Antoni et al. (2012)^^, **	United States	Cotton	Autosteer technology (44.7%) and lightbar GPS technology (21.1%)	1692
4	Daberkow and McBride (1998)	United States	Corn	Precision agriculture	950
5	Daberkow and McBride (2003)	United States	Cotton	Precision agriculture (20.2%)	3883
6	Gardezi and Bronson (2019)	United States	Corn	Precision agriculture (56%)	3574
7	Groher et al. (2020)*, **	Switzerland	Arable crops, fodder crops, vegetables, grapes, fruits, and strawberries	Precision agriculture (41;8%), driver assistance system (36.5%), and electronic measuring system (16.8%)	827
8	Isgin et al. (2008)*	United States	Corn	Precision agriculture (36.0%)	491
9	Khanna (2001)**	United States	Corn	Soil test (14.2%) and variable-rate application technology (42.7%)	569
10	Kolady et al. (2021) *, **	United States	Corn, soybeans, and other crops	Embodied-knowledge (72%) and information-intensive (66%) precision agricultural technologies	198
11	Larson et al. (2008)^	United States	Cotton	Remote sensed imaginary for site-specific management (8%)	941
12	Michels et al. (2020a)^^^	Germany	Arable crops	Smartphone applications for crop protection (71%)	207
13	Michels et al. (2020b)^^^	Germany	Arable crops	Smartphone for agricultural purposes (50.2%)	817
14	Michels et al. (2021)	Germany	Agriculture	Drones (22%)	167
15	Nair et al. (2011)^^, *, **	United States	Cotton	Plant and soil-based variable detection technology (24.6%) and variable rate application technology (67.6%)	1472
16	Paustian and Theuvsen (2017)	Germany	Wheat, barley, rye, oilseed rape/canola, sugar beet, corn, potato, and feeding crops	Precision agriculture (30.0%)	227

Table 1 (continued)

No	Author(s) (Year)	Country	Sector	Types of precision agriculture (adoption rate)	Sample
17	Pivoto et al. (2019)**	Brazil	Soybean, wheat, corn, rice, and oat	Soil georeferenced sampling (64.9%), variable-rate fertilizer and corrective applications (56.3%), auto-pilot spraying (56.8%), and management spraying (50.8%)	119
18	Roberts et al. (2002)**	United States	High valued crops, i.e., tobacco, nursery crops, fruits and, vegetables	Yield monitor with GPS (22%) and without GPS (25%), grid soil sampling (29%), variable-rate application technology (19%), and any precision agricultural technology (39%)	1027
19	Schimmelpfennig and Ebel (2016) **	United States	Corn	Yield monitor (43.0%), yield mapping (22.0%), variable-rate application technology (19.0%), GPS (17.0%)	1507
20	Tamirat et al. (2018)	Denmark and Germany	Not specified	Precision agriculture	260
21	Vecchio et al. (2020)	Italy	Not specified	Precision agriculture (28.7%)	174
22	Walton et al. (2008)^, *	United States	Cotton	Precision soil sampling (40.5%)	827
23	Walton et al. (2010)^	United States	Cotton	Portable/handheld GPS device (11.4%)	765

^, ^^, and ^^^ multiple articles that used the same respective dataset. Each group (e.g., ^) was considered as a study; * only the best model (among multiple statistical analyses) is reviewed; ** separate statistical analyses concerning different types/combinations of precision agriculture were considered as a study technologies (e.g., smartphone applications and drones recently). They report variable adoption rates, and that can be attributed to differed sampling designs (e.g., random and convenient samplings; regional and small-scale surveys; face-to-face and mail interviews), varying years of data collection, and the data cleaning procedures across investigations. The latter occurs in articles (e.g., D'Antoni et al., 2012; Nair et al., 2011) that utilized the same dataset (e.g., the 2009 Southern Cotton Precision Farming Survey in the United States).

This study follows Higgins et al.'s (2019) Cochrane handbook that recommends handling multiple groups from one study. Multiple articles that used the same dataset were combined as one study. The same approach was taken for separate statistical analyses concerning different types/combinations of precision agriculture that were reported in an article. Where multiple statistical models were analyzed for a type/combination of precision agriculture, only the best model was considered as the unit of study. As a result, the dataset for this study consists of 18 studies.

Based on those 18 studies, factors that are conceptually compatible were grouped through a coding-and-counting procedure. This coding exercise was guided by categories identified in the previous review of Tey and Brindal (2012) (which are also applied by Antolini et al. (2015)). Agreement for common factor parameters was reached through discussion and consensus. The coding and counting outcomes were then compared to seek inter-coder reliability. In cases where a different outcome was obtained for a factor, the corresponding literature was referred to. The 13 common factors revealed in the 18 studies are summarized in Table 2.

Traits involving human capital have long been considered an important condition in adopting the technologies of precision agriculture. *Age* was included in 7 studies, hypothesized on the supposition that younger farm operators have a longer career horizon and, therefore, an aptitude to learn new technologies (Roberts et al., 2004). *Education* was common to 13 of the studies. Larson et al. (2008) propose that higher education level attainment enables a greater capacity for meeting the analytical requirements of precision technology. *Farming experience* was investigated by four studies. Greater experience in agriculture, it was considered, may reduce the need for supplementary input (Isgin et al., 2008). *Full-time farmer* is used as a measure distinguishing the employment status of farm operators. Full-time operators are posited to be more inclined to advance farm operations through innovation adoption. Four studies used higher *farm income;* hypothesizing that it enables greater financial capacity that farmers purchase and use precision agricultural technologies.

Farm endowments are considered important influences on a farm operator's decision to adopt precision agriculture. *Cropped farm size* was explored in 13 studies. While it is typically regarded as a proxy for capital, land size has also been used as a measure for economies of scale from both the cost and risk distribution perspectives. Larger farms also exhibit greater capacity and should, therefore, have a greater tendency to adopt precision agriculture (Robertson et al., 2012). *Land tenure* is used to distinguish ownership types in respect to farmland. Because owner-operators directly benefit from their farm's performance, they have a greater incentive to improve farm management practices through adoption (Tey & Brindal, 2012). *Yield* is used as a proxy for soil and environmental quality.

Extension services are the institutional support of government and/or macro groupings such as universities and industry bodies provide to farm operators. They are measured according to the frequency with which farm operators have access to extension service and the number of occasions on which an operator received extension visits/training. Extension services are hypothesized as elevating the capacity of farm operators to adopt precision agriculture (Larson et al., 2008).

Table 2 Categories of 13 factors examined in the 18 included studies

Category	Factor	Description	No. of studies
Socio-economic	Age	Age of operator (in years)	7
	Education	Years/level of education of operator (after kindergarten)	13
	Farming experience	Years of farming experience	4
	Full-time farmer	Farming as the full-time employment	4
	Farm income	Total or percentage of farm income	4
Farm and agro-ecological	Cropped farm size	Farm size measures in hectares/by category	14
	Land tenure	Whether and extent operator owns farmland	7
	Yield	Average output per hectare	5
Institutional	Extension services	Access and attendance to extension services	4
Informational	Input suppliers/dealers	Received and used information obtained from input suppliers/dealers	5
	Consultants	Received and used information obtained from consultants	4
Technological	Use a computer	A computer or laptop is used in farm operation	6
	Perceived profitability	Profitability of precision agriculture perceived by farmers	4

Study as the unit of analysis. Factors analyzed by less than four (4) studies were excluded in this study

Input suppliers/dealers and *consultants* provide additional support. Their complementary/paid inputs may come in the forms of information dissemination and/or technical assistance. The latter is particularly helpful in overcoming the technical barriers to data collection, analysis, interpretation, and recommendations (Robertson et al., 2012). Farm operators who engage input suppliers/dealers and consultants are hence more likely to adopt the technologies of precision agriculture.

Technological literacy has been specifically emphasized as an important precursor to encouraging the implementation of precision agricultural practices. Knowing how to *use a computer* is thought to demonstrate an ability to handle the complexities of the innovation (Banerjee et al., 2008). Therefore, experience in using a computer (required for precision agriculture in farm management) is believed to lead to the adoption of new and/or other types of precision technology.

Perceived profitability has been explored since it is thought to reflect farm operators' perception towards the economic benefits of precision agriculture. Favorable perceptions mean that the innovation in question is believed to generate desirable change (Tamirat et al., 2018).

Quantitative synthesis

The meta-analysis in this study began with the estimation of Hedge's *d* (a measure of effect size). Baumgart-Getz et al.'s (2012) specifications of *d*-effect size and variance are summarized in Table 3. A *d*-effect size is the standardized mean difference, assuming that the standard deviations of the two groups (e.g., adopters and adopters in this study) are similar.

However, as noted by adoption rates in Table 1, the groups included in the 18 eligible studies are dissimilar in size. Pooling two such differing groups violates the homogeneity of the variance assumption (Ellis, 2010). Hedges (1981) recommends that each group's standard deviation be weighted by its sample size in the calculation of Hedges' *g*. In the same seminal work, the *g*-effect size is also recommended through a correction factor, *J*, to correct the upward bias inherent when a small sample size (i.e., below 20 studies) is used for meta-analysis.

As this meta-analysis involved a small sample (18 studies), an approximation of *J* that is commonly used by researchers, and as expressed by Borenstein et al. (2009), was estimated:

Table 3 Formulas converting statistical measures to Hedges' *d*

Statistical method	To *d*-effect size	To variance of *d*-effect size
Independent groups	$\frac{\overline{Y_1}-\overline{Y_2}}{\sqrt{\frac{(n_1-1)S_1^2+(n_2-1)S_2^2}{n_1+n_2-2}}}$	$\frac{n_1+n_2}{n_1 n_2}+\frac{d^2}{2(n_1+n_2)}$
t-test	$\frac{2t}{\sqrt{df}}$	$\frac{n_1+n_2}{n_1 n_2}+\frac{d^2}{2(n_1-n_2-2)}$
Probit model	Probit coefficient	Probit coefficient *se*
Logit model	$\frac{\sqrt{3}}{\pi}$ logit coefficient	$\frac{\sqrt{3}}{\pi}$ logit coefficient *se*

n_1 is the sample size of the control group, n_2 is the sample size of the treatment group, $\overline{Y_1}$ and $\overline{Y_2}$ are the sample means in the two groups, S_1 and S_2 are the standard deviations in the two groups, *d* is the *d*-effect size, *t* is *t*-value, *df* is the degree of freedom, and *se* is the standard error

$$J = 1 - \frac{3}{4df - 1} \tag{1}$$

where df is the degree of freedom. Then Hedges' (1981) g was calculated through:

$$g = J \times d \tag{2}$$

where J is the correction factor and d is the Hedges' d effect size. The variance of Hedges' g (V_g) was estimated through:

$$V_g = J^2 \times V_d \tag{3}$$

where J is the correction factor and V_d is the variance of Hedges' d. Standard error of Hedges' g (SE_g) was obtained through:

$$SE_g = \sqrt{V_d} \tag{4}$$

After converting all statistical measures to the Hedges' g effect size, a random-effects model was implemented. This is because the 18 studies involve a mixture of farm operators producing various agricultural products. They also differed both in terms of the types of precision agriculture adopted and the study areas. Nevertheless, they shared sufficient commonality in their adoption of precision agriculture for a plausible synthesis to be undertaken. Such is the assumption of the random-effects meta-analysis model and Borenstein et al. (2010) reason that "there is generally no reason to assume that they (past studies) are 'identical' in the sense that all studies share the same true effect size."

The cumulative effect size for each factor, $\overline{E_j}$, was estimated as follows:

$$\overline{E_j}, = \frac{\sum_{i=1}^{k_j} w_{ij} E_{ij}}{w_{ij}} \tag{5}$$

where w_{ij} is the weight of ith study in the ith group. The weight was estimated using:

$$w_{ij} = 1/v_i + \sigma^2_{pooled} \tag{6}$$

where v is the variance as defined in Table 3 and σ^2_{pooled} for categorical variables was defined as:

$$\sigma^2_{pooledcategorical} = \frac{Q_E - (n - m)}{\sum_{j=1}^{m} \left(\sum_{i=1}^{k_j} - \frac{\sum_{i=1}^{k_j} w_{ij}^2}{\sum_{i=1}^{k_j} w_{ij}} \right)} \tag{7}$$

and σ^2_{pooled} for continuous variables was defined as:

$$\sigma^2_{pooledcontinuous} = \frac{Q_T - (n - 1)}{\sum_{i=1}^{n} w_i - \frac{\sum_{i=1}^{n} w_i^2}{\sum_{i=1}^{n} w_i}} \tag{8}$$

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

The cumulative effect size for each factor ($\overline{E_j}$) quantifies the strength of the relationship between that factor and the adoption of precision agriculture. According to Ellis

(2010), an effect size of 0.2 indicates a weak effect, 0.5 a medium effect, and 0.8 a large effect. As innovation adoption is a social issue, the absolute effect of most factors is likely to be small. The sign of an effect size indicates the direction of the effect. In this study, a positive (negative) effect size shows a positive (negative) impact on adoption.

Understanding of the overall effect size needs to assess the consistency of results across studies. The I^2 measure describes the percentage of variance that is due to heterogeneity rather than chance. Higgins et al. (2003) suggest that an I^2 of 0%, 25%, 50%, or 75% generally reflects zero, low, moderate, or high heterogeneity whilst the acceptable threshold is higher (up to 75%) in certain fields. A reasonable rule is that a smaller I^2 value is always desirable. For avoiding a potential bias of I^2 that may arise from a small meta-analysis, the confidence intervals of effect size are also considered (von Hippel, 2015).

As recommended by Higgins and Green (2011), this review attempts to reduce the effects of heterogeneity by including a control variable. Following Baumgart-Getz et al. (2012), attempted control variables were *region* (North America, Europe, and South America), *crop type* (corn, cotton, and others), *category of precision agricultural technologies* (intra-field diagnosis tools, automatic variable-rate treatments, and GNSS), and *statistical models* (logit, probit, *t*-test, and independent groups). Amongst these, *region* control variable resulted in the lowest estimate of heterogeneity for *land tenure*, *consultants*, and *use a computer* factors.

Given there is heterogeneity between studies, statistical power for the random effects overall effect was estimated to assess the probability that an effect is detected. In other words, it informs the reliability of an effect size. In this review, the power test followed that of Valentine et al. (2010). It begins with the estimation of the variance of the overall effect size, v:

$$v = \left(\frac{n_T + n_C}{n_T n_C}\right) + \frac{\overline{E}^2}{2(n_T + n_C)}) + \tau^2 \tag{9}$$

where $n_T + n_C$ is the average sample size of respondents across studies and $\overline{E}$ is the effect size. The τ^2 is represented by 0, 0.33, 1.0, and 3.0 values for zero, small, moderate, and large degrees of heterogeneity (as defined by I^2), respectively. When the overall effect is statistically significant different from zero, the Z-statistic has a normal distribution with a mean (γ) equal to:

$$\gamma = \frac{(\overline{E} - 0)}{\sqrt{\frac{v}{k}}} \tag{10}$$

where $\overline{E}$ is the effect size, v is the effect size variance, and k is the number of studies. The random effects power of an overall effect size is estimated through:

$$p = 1 - \varnothing(c_a - \gamma) \tag{11}$$

where $\varnothing(x)$ is the standard normal cumulative distribution function and c_a is the critical value for the standard normal distribution ($c_a = 1.96$ at $a = 0.05$ for a two-tailed test). Generally, power decreases if there is high heterogeneity between studies. This is indicative that more studies are needed to reliably detect an effect.

Findings

The statistical outcomes of the meta-analysis for the previously identified factors are presented in Table 4. The effect size, the significance of that effect size, and the 95% confidence interval for that effect size, and the estimate of heterogeneity (I^2) between studies are reported. Additionally, the random effects power of an overall effect size is also reported in the final column.

All socio-economic factors had a negligible effect size (<0.1) and high heterogeneity (>85%). *Age*, *full-time farmer*, and *farming experience* had a variance of effect size that ranged from negative to positive. A low statistical power was also found for these factors. Consequently, interpretation of their effect on the adoption of precision agriculture is fallacious.

Education and *farm income* were two significant factors. However, only the effect size of *education* was found to possess a reasonable statistical power. While this suggests an association between formal education and the capacity of farm operators, its high variance (that is underpinned by a relatively large sample size) necessitated a sensitivity analysis to explore the impact of variable definition on results (which will be discussed in Sect. 4.2). For example, higher education may imply that farm operators have a greater capacity to manage data and to understand the resultant insights generated by precision agriculture adoption (e.g., McBride and Daberkow, 2003).

In the farm and agro-ecological aspect, all factors had a negligible effect size (<0.1) and high heterogeneity (>99%). This remained the case when their respective variance in effect size was considered. Coupled with low statistical power (<10%), the effect size of statistically significant *cropped farm size* and *yield* is not interpreted.

The effect size of external supports to farm operators was variable. *Extension services* and *input suppliers/dealers* had high heterogeneity (>95%) and low statistical

Table 4 Meta-analytical results of factors underlying the adoption of precision agriculture

Category	Factor	Control	Effect size	95% CI	I^2	Df	Asf	Power
Socio-economic	Age	None	– 0.006	– 0.016 to 0.003	99.98	6	633	1.74
	Education	None	0.080***	0.010 to 0.061	99.91	12	617	74.76
	Farming experience	None	0.005	– 0.020 to 0.03	99.96	3	282	2.86
	Full-time farmer	None	– 0.006	– 0.168 to 0.156	85.62	3	239	2.12
	Farm income	None	0.005***	0.004 to 0.006	99.99	3	862	3.20
Farm and agro-ecological	Cropped farm size	None	0.008***	0.008 to 0.009	99.99	13	429	4.18
	Land tenure	Region	– 0.044	– 0.143 to 0.059	99.86	6	828	0.10
	Yield	None	0.026**	0.012 to 0.040	99.99	4	272	5.21
Institutional	Extension services	None	– 0.028	– 0.135 to 0.080	97.46	3	577	0.75
Informational	Input suppliers/dealers	None	0.072	– 0.183 to 0.326	95.35	4	426	21.37
	Consultants	Region	0.440***	0.282 to 0.599	68.39	3	500	99.99
Technological	Use a computer	Region	0.379***	0.284 to 0.473	67.32	5	685	99.99
	Perceived profitability	None	0.559***	0.264 to 0.855	82.24	3	329	99.99

CI confidence interval, I^2 *I*-square, *df* degree of freedom, *asf* the average sample size of studies

***, **Significance at 1% level and 5% level respectively power (< 25%), with a range of individual effect sizes spanning from a negative to a positive value. Consequently, interpretation of their individual overall effect size is inhibited.

In contrast, *consultants* engagement had a marginally medium effect (0.44) on the adoption of precision agriculture. Its positive effect was statistically significant, and it had an acceptable heterogeneity measure (68%) and a high statistical power (99.99%). This finding suggests that consultancies facilitate adoption through targeted support. For example, the users of precision agriculture studied by Larson et al. (2008) employed a crop consultant to help them generate map-based input prescription. External assistance like this helps farm operators to overcome their personal limitations and aids their utilization of precision agriculture.

The *use of a computer* had a marginally medium effect (0.38), with an acceptable heterogeneity level (67%) and a high statistical power (99.99%). It was statistically significant. Irrespective of whether a desktop or a laptop is used, computer literacy is essential to make productive use of the complex information collected for and analyzed by the technology. Computers are also an integral component of certain precision agricultural technologies. They are essential in generating evidence-based prescriptions for input applications and machine automation.

The *perceived profitability* of precision agriculture was a significant predictor, with a medium effect (0.56) on adoption. Its heterogeneity was approximately 82% and statistical power was 99.99%. This finding suggests that the degree to which precision agriculture is perceived as more economically advantageous by potential users than its alternatives profoundly influence their decisions.

Towards this point, as per Table 4, the overall effects that constrained by high heterogeneity and low statistical power raised some issues concerning the robustness of the results. Interpretation of variance from negative into positive territory and low statistical power can lack efficacy when synthesized. Those factors (*consultants*, *use of a computer*, and *perceived profitability*) that exhibited a significant moderate effect were based on a small number of studies. Such results should not, then, be overinterpreted.

Publication bias

Borenstein (2005) suggests the use of funnel plots to look for evidence of publication bias. Publication bias arises since studies with statistically significant or positive results are more likely to be published than those reporting statistically insignificant or negative results. The two common statistical alternatives (rank correlation test and Egger's regression) require a range of study sizes (Sterne & Egger, 2005). Given the small sample size in this study, funnel plots were used. Sterne et al. (2005) recommend the use of the standard error to facilitate bias detection.

Figure 2 presents funnel plots with standard error on the vertical axis as a function of effect size on the horizontal axis. In general, large studies appear toward the top of the plots, and they are clustered near the mean effect size; smaller studies are positioned toward the bottom of the plot and dispersed further from the mean effect size. Because no concentration of small studies was detected on one side of the mean, an absence of publication bias is indicated.

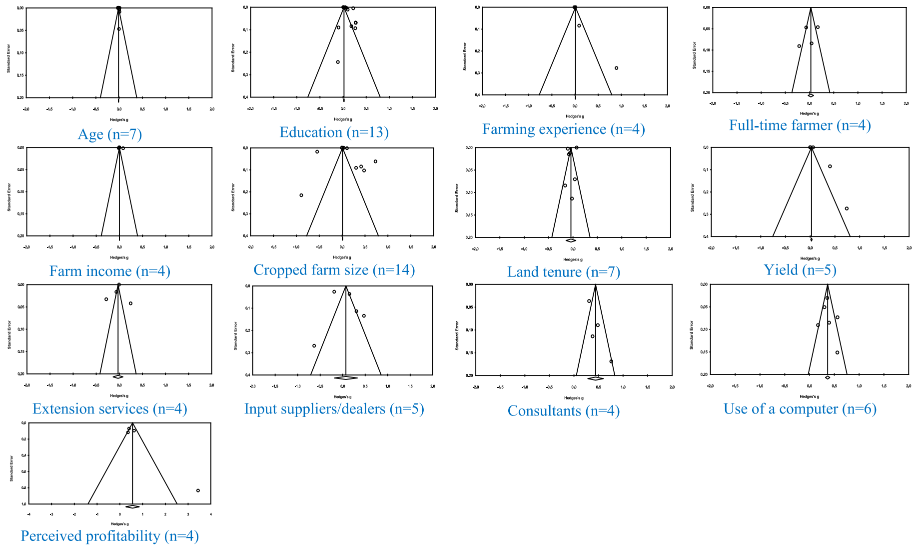

Fig. 2 Funnel plot (standard error by Hedges' *g*) of 13 factors investigated in this review

Sensitivity analysis

While there was no evidence of publication bias, it is apparent that heterogeneity rises with sample size. As this may influence the decisions concerning categorization, a sensitivity analysis was conducted to explore the impact of different decisions on the effect size of *education* and *cropped farm size*. These factors appear within at least half of the samples and are shared by a variety of data type. *Education* was captured as *years of education* (a continuous variable) and *received at least college education* (a categorical variable); *cropped farm size* as *planted hectarage* (a continuous variable) and *large farm size* (a categorical variable).

When compared with the aggregated analysis, the sensitivity analysis presented in Table 5 gives two important insights. First, nearly all disaggregated factors (except *planted hectarage*) had inconsistent results in relation to their corresponding aggregator. Secondly, nearly all disaggregated factors (except *years of education*) had higher statistical power.

Table 5 Disaggregated results of two commonly assessed factors, controlling for data type

Factor	Data type	Effect size	95% CI	I^2	Df	Power
Education	As a group	0.0803***	0.0098 to 0.0611	99.91	12	74.76
Years of education	Continuous	0.0453***	0.0239 to 0.0667	99.95	6	40.90
> College education	Categorical	0.1434***	0.0564 to 0.2304	96.61	5	91.72
Cropped farm size	As a group	0.0086***	0.0082 to 0.0089	99.99	13	4.18
Planted hectarage	Continuous	0.0086***	0.0083 to 0.0090	99.99	9	4.89
Large farm size	Categorical	0.0259	–0.3620 to 0.4138	99.64	3	8.39

CI confidence interval, I^2 *I*-square, *df* degree of freedom

***Significances at 1% level

These are indicators that the overall results of this meta-analysis need to be interpreted with care.

Discussion

The 18 studies included in this meta-analysis pay little attention to the importance of transition paths from short-run to long-run equilibria. While *perceived profitability* has a moderate effect on the adoption of precision agriculture, Lowenberg-DeBoer (1996) points that the initial investment costs are often underestimated to a level that poses a hurdle to generating short-term profits. Economies of scale can accelerate the payback period (Shockley et al., 2011). Importantly, continued improvement in management capacity is a necessary condition for precision agriculture to be perceived as profitable in the longer term. *Consultants* and the *use of a computer* are factors that revealed a moderate effect. This leads to the obvious conclusion that targeted external support and computer literacy are important consideration in enabling farmers to handle the complexities of precision agriculture.

However, the above conclusions should be treated with care given that the three factors were based on a small sample size and that heterogeneity generally rises with the number of studies. First, in common with most factors, each of the three was examined by less than half of the 18 eligible studies. Such representation is an inadequate base to deduce robust understanding. Secondly, heterogeneity implies that there is a unique context to be considered in every adoption issue. Contextual differences span socio-geography to generic/specific technologies, and they are blended within the various studies. In particular, the varied selection of factors across studies may have contributed to the lack of convergence. Differing data types/definitions compound this issue. Under these circumstances, the factors may have been poorly defined or understood. Any attempt to identify a universally facilitative opportunity in respect to adopting precision agriculture remains challenging. Such qualifications point to a need for further studies to be undertaken.

Even if there are more future studies, statistical powers found in this review suggest that there is little likelihood of obtaining a more reliable result. Smaller average sample sizes across studies and a low number of studies had power to detect only medium effect sizes. Weak effect sizes were undetected even when more studies and greater sample sizes were included. These findings imply that greater attention is required to improve study designs of primary research.

In future studies, statistical models should strive to represent the reality in at least two aspects. Firstly, the consideration of innovation adoption is not limited to a dichotomous choice (use or do not use). De Oca Munguia et al. (2021) show that adoption involves heterogenous flows, with individual farmers following different pathways ((non-)awareness, no adoption, trial, use, increased/constant/decreased use, and/or dis-adoption) in the adoption process over time. While future research is encouraged to address such complexities, Glover et al. (2019) propose an alternative framework to view the process of adoption as propositions, encounters, dispositions, and responses. Secondly, models attempting to explain the one-way relationships between factors and a single desired behavior (i.e., adoption), which, in turn, are likely to influence their antecedent predictors, face methodological limitations (Cary & Wilkinson, 1997). For example, perceptions of profitability and the capacity of farm operators are modified by experience. Fountas et al. (2005) note a change in farm management practices due to precision agriculture. The complementary nature of precision agricultural technologies and prior education in their use enable their sequential adoption (DeLay et al., 2020). Lowenberg-DeBoer (2021) recently finds that the economic outcome of certain technologies changes with public rules and regulations.

Self-selection bias presents another potential modelling challenge. Because new precision agricultural technologies continue to be developed, adopters may not be a random representation of farm operators. Those who volunteer to adopt may share characteristics (i.e., awareness of that innovation) that differentiates them from non-adopters. Daberkow and McBride (1998), whose study is the earliest adoption study in this review, have noted the need to minimize self-selection bias. However, most studies covered in this review did not address the issue. Consequently, their research may thus have influenced the reliability of the findings of this meta-analysis.

Conclusion

Scientific attempts have been made to identify factors that can lead to the adoption of precision agriculture. Complementing previous narrative reviews, the novelty of this meta-analytical paper involves quantification of the effect of the drivers underlying that desired behavior. The findings suggest that *perceived profitability*, *consultants*, and the *use of a computer* factors had a moderate effect. However, the efficacy of their conclusions is constrained by the small sample size and with the heterogeneity issues that arose with a number of the studies. This latter point is supported by other factors that had a negligible effect size. Instead, this review identifies study designs and statistical methodologies as areas of concern. To produce results that are meaningful and of practical use to local management, further investigation into the influence of (an expanded list of) drivers on the motivation for the adoption of precision agriculture is encouraged.

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