RESEARCH ARTICLE

Farmers' willingness to adopt sustainable agricultural practices: A meta-analysis

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Abstract

This research is a meta-analysis that focuses on farmers' willingness to accept adopting sustainable practices. We use a set of meta-regressions and statistical tests to analyze 59 studies providing 286 WTA estimates. Our aim is to examine gaps in the literature of sustainable agriculture adoption and highlight the major findings of peer-reviewed works. We found evidence for significant methodological factors affecting WTA values, and the presence of unique Willingness to Accept mean value that would be the true proxy for how much farmers' must be compensated to adopt sustainable agriculture practices.

Author summary

The increasing growth of consumption needs puts pressure on the natural system, harming climate, biodiversity, water, and environment which has induced a recognition that action should be taken to mitigate irreversible damage to the environment. Sustainability is believed to be obtainable through a change in consumer's and producer's behavior, which can be primarily done through the transformation of our agricultural system using alternative farming approaches that are based on ecological principles [1]. The literature is very expansive on analyzing farmers' willingness to adopt sustainability but it is limited in providing WTA values. Thus, in our meta-analysis we focus on quantitative WTA studies to investigate the presence of a proxy for a true mean WTA for sustainable agriculture and detect the methodological variables that might affect the WTA value. We found a proxy for the mean WTA for sustainable farming ranging between 567 USD/ha/year and 709 USD/ha/year, as well as a proxy for WTA producing biomass crops ranging from 2054 USD/ha/year to 2766 USD/ha/year. Also, among the significant methodological variables that affect WTA values are the use of a non-random sampling method, and contingent valuation. The two methods are found to lead to higher WTA values than when random and conjoint valuation methods are used.

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1. Introduction

Scientists assert that producers need to change their conventional practices in favor of practices that promote environmental sustainability. As a concept, sustainability in agriculture has been defined by many entities but was knowledgeably introduced in late 1980 in the report of the World Commission on Environment and Development [2,3]. Since then, the concept has evolved and attained attention in agricultural policy debates [3]. The USDA defines sustainable agriculture as an integrated system of plant and animal production practices that aim to 1) satisfy human food and fiber needs, 2) enhance environmental quality and the resource base, 3) sustain the economic viability of agriculture, 4) use efficiently nonrenewable resources and integrate where appropriate biological cycles and controls, and 5) enhance the quality of life for farmers, farmworkers, and society as a whole [4].

Were sustainability practices generally profitable, we would expect farmers to have adopted them. Because they have not been widely adopted, researchers have investigated what compensation is required for adoption. There are a large number of practices that can enhance sustainability. Producer adoption of those practices is a key area of study resulting in a very broad literature. This abundance of literature has also encouraged the production of numerous qualitative and quantitative literature reviews summarizing past works on farmers' preferences and adoption for sustainable agricultural practices. However, most of these reviews focused on either revealing the determinant factors of the adoption decision [e.g. Lastra-Bravo et al. [5]], and methodological approach affecting the Willingness to Accept (WTA) estimation, while being either limited to specific sustainable practices [e.g. Lesch and Wachenheim [6]; Loomis and White [7]; Van Houtven et al. [8]], or specific elicitation methods [e.g. Mamine et al. [9]; Barrio and Loureiro [10]].

This study aims to present a more expansive work by exploring past studies that focus on the elicitation of farmers' willingness to produce bioenergy crops, to adopt practices that reduce pollution levels as well as their willingness to adopt water and soil conservation practices from all continents. We target studies with hypothetical settings using either conjoint analysis or contingent valuation, and that provide a quantitative estimate for the WTA. This paper elicits gaps in the literature and highlights the major findings of peer-reviewed works to estimate a unique WTA value that can be used as a proxy for how much farmers require in incentives to adopt sustainability practices in their farming, and identifies the methodological factors that a scholar should take into account while designing research on farmers' preferences for sustainable practices.

2. Methods and procedures

Meta-analysis is a body of statistical methods that are useful in reviewing and evaluating empirical research results [11]. It integrates the finding of separate studies to determine the overall size of an effect and to determine the impact of moderating variables on the effect size. To do this, the meta-analysis needs to be reliable and valid allowing for the detection of the effect size and the impact of moderator variables [12]. To conduct our meta-analysis, several steps were followed to search, collect, and analyze the meta-sample. For convenience, the process is divided into two phases: (1) the search of the literature that will constitute the meta-sample, and (2) the estimation of the meta-regression.

Phase 1: Literature search

The objective of our investigation is to explore studies that focused on farmers' WTA to adopt or to convert to sustainable farming practices; thus, it is important to set a definite list of

Table 1. SPIDER Search Technique.

SPIDER Tool	Search terms
S- Subject	"Farming methods"; "Farming practices", "Agriculture"
PI- Phenomenon of Interest	"Sustainable", "Environmentally friendly"; "Ecological"; "Green"; "Organic", "Conservation", "Bioenergy", "Climate-smart", "BMP", "Biodiversity"
D-Design	"Questionnaire"; "Survey"; "Interview", "Experiment"
E-Evaluation	"WTA"; "Premium"; "Reward"
R-Research Type	"Quantitative"

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keywords that represent our subject of interest and to set the correct search strategy that will be followed to collect the meta-data.

The first step is to search for the works corresponding to our topic of interest. Following the approach adopted by Tey et al. [13], we use the SPIDER search tool to target the studies that compose our meta-sample. This technique consists of finding keywords that best identify our topic during searches on electronic databases. Table 1 reports the keywords that have been employed to identify published works focusing on the WTA to adopt or convert to sustainable farming.

As reported in Table 1, our research includes only quantitative studies, which means that our sample choice is limited to research works that report estimated values of the WTA excluding all other studies that present a qualitative analysis of producers' WTA, as well as studies that express WTA premium per other metrics than a unit of area (e.g., some studies expressed WTA per household) or other than an monetary value (e.g., some studies report WTA in percentages). Also, the keywords reported in the section "Phenomenon of Interest" include practices that are considered sustainable farming practices based on the USDA's definition of sustainable farming [14]. The search is conducted in the electronic databases reported in Table 2 and targeted published studies in English and French without a time-frame limit.

Table 3 illustrates our literature search process for preparing the metadata. The preliminary search resulted in 557 eligible articles where 103 articles were removed as duplicates (this is because we are using different databases for the same keywords). For the remaining 454 articles, the title, abstract, and keywords were read, resulting in 166 eligible articles. These shortlisted articles were then examined individually to verify their eligibility to our criteria, which allowed us to identify the final 59 articles that constitute our metadata.

Note that each keyword or set of keywords was individually used in the search in combination with the terms "Farmers", "Adoption", and "WTA". Also, using our keywords, none of the published works in the French language were found to be eligible to our search criteria. In sum, these articles were either focusing on other aspects of sustainability adoption or were qualitative studies [i.e. Carvin and Said [15]; Plumecocq et al. [16]].

The choice of the 59 papers was based on their relevance by examining their abstracts, results, and methods and procedures sections. Once collected, we examined how WTA values are expressed in each study and brought to consistent terms when necessary. The sample studies include various type of producers, and various production environments. Values expressed in a foreign currency were converted to USD as well as values that were expressed in other metric measures converted to USD/hectare. Our meta-data comprises 59 studies and 286 WTA estimates.

Table 2. List of Databases.

Databases in English	Databases in French
AgEcon Search, Web of Science, Google Scholar, Scopus	CAIRN, Tel-Archives, Persee

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Table 3. Search Synthesis.

Database	Screening			Eligibility		
	Keywords 1	Keywords 2	Keywords 3	Keywords 1	Keywords 2	Keywords 3
SCOPUS	640	120	450	80	37	23
Google Scholar	3250	2524	3640	120	54	36
AgEcon Search	18	118	286	12	45	19
Web of Science	55	71	90	95	21	15
Tel-Archives	12	33	0	0	0	0
CAIRN.info	270	46	4	0	0	0
PERSEE	37	19	0	0	0	0
Total Articles by KeyWords Group				307	157	93
Articles excluded - Irrelevant - Qualitative Studies				204 118 86	128 52 76	63 47 16
Duplicates excluded				71	12	20
Total Eligible Articles by KeyWords Group				32	17	10
Total Eligible Articles for the Metadata				59		

NB: For convenience, we displayed the search results in Table 3 by keywords groups

- Keywords 1: sustainable, environmentally friendly, ecological, and green
- Keywords 2: BMP, bioenergy, and organic
- Keywords 3: conservation and climate-smart

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Phase 2: The meta-regression analysis

Meta-regression analysis (MRA) is a form of meta-analysis especially designed to investigate empirical research [17,18]. Meta-regression seeks to provide a scientific approach to research synthesis [19], and to go beyond estimates that are obtained from individual studies [20].

In a meta-regression analysis, the dependent variable could be a summary statistic, or a regression parameter drawn from each study, while the independent variables may include characteristics of the method, design, and data used in these studies [11].

a. The MRA model. The meta-analysis function in the present study has a panel structure. Because some original studies report multiple WTA estimates and an unbalanced structure exists as the number of reported estimates differs between studies, our meta-regressions are primarily based on the following model presented by Stanley [11], and Lagerkvist and Hess [21]:

$$WTA_{mn} = \alpha + \sum\nolimits_{k=1}^{k} \beta_k X_{k,mn} + \varepsilon_m + \mu_n \tag{1}$$

WTA_{mn} stands for the dependent variable, the subscript "*m*" denotes the sampled study from which the WTA estimate comes ($m = 1, \ldots M$), and "*n*" denotes the WTA estimate reported in that study (n = 1,. . .., N_m). If each study "m" provides a single estimate "n", then $N_m = 1$, and the error terms ε_m collapse into μ_n. Alternatively, if study "m" provides more than one estimate, then it is necessary to account for the common error across estimates (μ_n), and the group-specific panel error in a study (ε_m). The total number of WTA estimates is $N = \sum\nolimits_{m=1}^{M} N_m$. The variations in WTA_{mn} are explained by a vector of explanatory variables, i.e. $k = 1, \ldots, K$, denoted $x_{k,mn}$ [21]. The parameter α represents the intercept term of our regression and β_k is a vector of slope parameters to be estimated.

However, given that the intuition behind the meta-regression analysis is that the variation in reported WTA estimates can be explained by the study design characteristics (Table 4), the

Table 4. Summary statistics of the overall data and the four subsets.

	Overall Data		Soil Data		Water Data		Energy Data		Pollution Data	
VARIABLE	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
WTA	403.16	818.41	151.14	323.79	297.79	487.62	1347.89	1383.99	279.9	592.11
Elicitation Method	0.188	0.391	0.015	0.12	0.613	0.495	0.122	0.331	0.11	0.32
Random Sampling	0.62	0.487	0.478	0.50	0.581	0.501	0.776	0.422	0.2	0.401
Europe	0.582	0.494	0.073	0.262	0.032	0.180	0.755	0.434	0.394	0.492
Africa	0.226	0.419	0.072	0.45	0.774	0.425	0	0	0.437	0.500
America	0.181	0.386	0.206	0.406	0	0	0.204	0.407	0.141	0.35
Asia	0.063	0.243	0.015	0.121	0.194	0.402	0.041	0.200	0.099	0.300
Soil	0.474	0.500	-	-	-	-	-	-	-	-
Water	0.108	0.311	-	-	-	-	-	-	-	-
Energy	0.171	0.377	-	-	-	-	-	-	-	-
Pollution	0.247	0.432	-	-	-	-	-	-	-	-
Trend	8.08	2.57	8.26	2.87	7.52	2.51	7.84	1.98	8.13	2.33
Sample Size (n)	740	886.05	479	672.15	210	58.19	328	246.55	344	26.458
Grassy crops	-	-	-	-	-	-	0.184	0.391	-	-
Woody crops	-	-	-	-	-	-	0.571	0.5	-	-
Cereal crops	-	-	-	-	-	-	0.245	0.434	-	-
Agroforestry	-	-	0.213	0.411	-	-	-	-	-	-
BMPs	-	-	0.787	0.411	-	-	-	-	-	-
Watershed	-	-	-	-	0.742	0.445	-	-	-	-
Riparian	-	-	-	-	0.258	0.445	-	-	-	-
Chemical	-	-	-	-	-	-	-	-	0.437	0.500
Biodiversity	-	-	-	-	-	-	-	-	0.268	0.460
Other	-	-	-	-	-	-	-	-	0.268	0.446

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estimation of Eq (1) requires to consider two possible problems. First, due to heterogeneous variances in WTA estimation -non-homogeneous variances result from the different sample sizes, sample observations, and different estimation procedures of the sampled studies [20], a potential heteroskedasticity in the error terms can occur. Second, since we have 286 WTA estimates from 59 cluster studies, intra-cluster error correlations may affect WTA observations, which would result in biased standard error estimates [20,22,23].

To solve these potential issues and generate efficient estimates of (1) with corrected standard errors, we use two regressions where the square root of sample size is used as weight: a weighted least squares (WLS) regression with robust standard errors [24–26] that serves as the base specification, and the weighted least squares with cluster robust standard errors that we consider to be the main model to which we are referring while interpreting our findings. Following previous meta-analyses literature in Agricultural Economics [e.g., Printezis et al. [23]; Lagerkvist and Hess [21]; and Lusk et al. [27]], this model is justified because it takes into account the 59 cluster studies and addresses potential heteroskedasticity [28].

The meta-regressions that are estimated in this study share the same objective which is estimating the WTA, but differ partly or completely from the chosen explanatory variables. Thus, the estimates might not be independent in a given sample study and we need to assume the decomposed error variance at the study level, ε_m, and error at the estimation level, μ_n to be normally distributed with zero mean and constant variances, σ_ε^2 and σ_μ^2, respectively [12].

b. Publication selection bias and precision effect. Besides the two potential econometric problems mentioned in the previous section, a meta-analysis also presents the risk of publication selection bias. Publication selection bias refers to a tendency of having a greater preference for estimation and publishing statistically significant results compared to results that do not reveal statistical significance [22]. Stanley [25,29] shows that the relationship between analyzed estimates and their precision (e.g., standard errors or sample size) can serve as an indicator for publication selection bias. Therefore, we chose to use the square root of the sample size (labeled "sqrt(n)") which can also serve as an adequate precision measure because it is proportional to the inverse of the standard error [25,30–33].

Combining information from independent but similar research, meta-analysis has the capacity to improve parameter estimates that are obtained from a single study [23,34], and this allows the estimation of a proxy for the "true" effect of the variable of interest. Thus, Eq (2), which is a simplified version of Eq (1), is used to obtain a proxy of the true WTA proxy:

$$WTA_i = \beta_0 + \beta_1 sqrt(n_i) + \varepsilon_i, \tag{2}$$

where WTA_i is the explained variable which is the WTA estimates collected from the 62 studies, and $sqrt(n_i)$ is the squared root of the sample size variable, the precision measure variable. Using the same models as for Eq 1, the "true" WTA is obtained by the estimated constant, such as *True* WTA_i *effect* = $WTA_i = \beta_0$. To confirm the presence of a significant WTA for sustainable farming, we perform the precision effect test (PET) which is a t-test for the constant. Rejecting H_0: $\beta_0 = 0$ means that a significant WTA exists [25].

If the publication selection bias is not verified, then the observed WTA effects should vary randomly around this "true" effect, independently of their precision (sqrt (n)) [23,25,31]. Therefore, to test for the presence of publication selection bias, we use the funnel asymmetry test (FAT), which is also a t-test performed for the slope β_1 that is estimated using Eq 2. Rejecting H_0; $\beta_1 = 0$, would indicate the presence of publication bias [25]. Note that it is mandatory to have at least 10 studies in a meta-data, and sampled studies should not have similar standard errors to perform this test, conditions that are fulfilled for our case. Also, to affirm the findings, it is recommended to provide a visual representation of the result by a plot of the dependent variable (WTA), and the precision measure variable (sqrt(n)) [23]. Following the recommendation of Nelson and Kennedy [20], we perform a robustness check, by estimating Eq (2) using the sample size "n" as the precision measure as well as presenting two regression models (WLS with robust errors and WLS with cluster robust errors) for all of our meta-regressions.

c. The variables

The dependent variable. In the meta-regression models, the WTA estimates reported by the 59 articles are used as the dependent variable. As explained above, we converted the WTA values to USD/Ha/year to keep the common metric across studies consistent. The final total number of WTA estimates (n = 286) is larger than the number of studies included in the meta-regression (n = 59) because some studies report multiple WTA estimates due to multiple programs/schemes, or products or samples per each study.

The independent variables. *Year of study/Trend*. identifies the year when each study was published. We choose the year of the study because many of the sampled studies do not provide the year in which the data was collected. We used a trend variable for each study since one study can have more than one WTA estimate. This variable allows testing if there is a trend over time in WTA for sustainable practices' estimates [23]. For our MRA, a trend variable is created to assess the evolution of WTA elicitation through time.

The continent of study. the meta-data has studies that have been conducted in numerous countries. The continent to which each article belongs is controlled as a dummy variable. We created three dummy variables for Europe, Africa, America, and one for both Australia and

Asia (Australasia), which serves as the base. This variable permits the identification of differences in the reported WTA estimates among the continents.

Sample size. the sample size used in each study is included to have an insight into how much sample size magnitude can influence the WTA estimation. The sampled individuals in all studies are individual farmers so that the sample size represents the number of sampled farmers.

The square root of the sample size. this precision estimate is included as an independent variable to explain the variance in reported WTA estimates because although it is highly correlated with $^1/_S E$, the square root of the sample size is free of estimation error [25].

Sampling method. the sampling method used in each study is also included as an explanatory variable to test if the manner of choosing the sample affects the WTA estimation. Random and non-random sampling methods were identified across our meta-data: random sampling, stratified sampling, quota sampling, cluster sampling, and convenience sampling. Thus, we created a dummy variable that takes the value one if the study uses a random sampling method and takes the value zero if a non-random sampling is used.

Elicitation method. several methods have been employed across the literature to analyze preferences and most of the studies used choice experiments. Because all the sampled research used hypothetical methods, two elicitation methods were identified across the metadata: conjoint (or choice-based) analysis and the contingent valuation method. A dummy variable was created taking the value of 1 if the study uses a "contingent valuation method" and the value of zero if it is using the "conjoint analysis".

Energy. refers to the planting of biomass crops for energy production. In our data, we observe studies focusing on farmers' willingness to plant biomass woody (e.g., pine hoak), grassy (e.g., switchgrass), and cereal (e.g., corn) crops. This variable takes the value of one when the article discusses the willingness to grow one of these biomass crops and takes the value of zero otherwise.

Soil. refers to all agricultural practices that aim to enhance/preserve soil health. Based on our data, included practices are agroforestry, cover crops, conservation tillage, rotational grazing, and organic farming. Thus, the variable takes the value of one if one of these practices is identified in the sample article and takes the value of zero otherwise.

Water. refers to practices that aim to conserve water resources like the conservation of wetlands, watersheds, water reservoirs, and riparian lands. Thus, it takes the value of one when the study sample focuses on one of these and the value of zero otherwise.

Pollution. refers to practices that aim to reduce pollution levels and those that preserve ecosystem biodiversity. The specific practices found in our data are reduction of chemical use, "climate-smart" agricultural practices, and biodiversity conservation. The variable takes one if one of these practices are identified and zero otherwise.

d. Subsets

In addition to a model that includes all the WTA estimates and variables described above, we subdivided the metadata into four subsets based on the sustainable practice category and estimated separate models for each data subset. The categorization of these subsets is based on the last four dummies previously described (soil, water, energy, and pollution), such as (1) soil data for the sub-dataset that gathers studies focusing on soil health-related practices, (2) water data for the one combining studies on WTA adopt riparian lands, watersheds, and wetlands conservation practices, (3) energy data including studies on biomass crops production, and (4) Pollution data including studies on climate-smart agriculture, practices reducing pollution levels and preserving biodiversity.

Soil-health dataset. For this subset, we have 136 WTA estimates derived from 17 studies. We identified two categories of sustainable practices: one related to agroforestry practices (forest), and another one referring to agricultural practices that are qualified as Best Management Practices (BMPs) such as organic farming, crop rotation, grazing rotation, cover crops, grassland conservation, and conservation tillage. We created an additional explanatory dummy variable for each of the two categories-agroforestry and BMPs—that is equal to one if the practice in the study sample is related to agroforestry and takes zero if the discussed practice belongs to the BMPs category, with the dummy BMP being the base category.

Biomass crops production dataset. This subset contains 48 WTA estimates from 13 studies. We created three additional explanatory dummy variables corresponding to the biomass crop type: grassy crops (switchgrass & hay), cereal crops (corn & wheat), and woody crops (pine & hoak) that are the base variable for the analysis of this subset. Thus, the variables take the value of one when the respective biomass crop is identified in the sampled study and take the value of zero otherwise.

Water conservation dataset. For this subset, we have 31 WTA estimates from 10 studies that focus on either farmers' willingness to accept to adopt watersheds/wetlands conservation or riparian lands conservation. A. additional dummy explanatory variable was created to equal one for riparian lands and zero otherwise (watersheds/wetlands).

Pollution reduction dataset. This dataset includes 69 WTA estimates from 19 studies and gathers studies investigating farmers' willingness to adopt practices that aim to reduce pollution levels and preserve natural biodiversity. We created three additional explanatory dummies: one for practices that aim to reduce chemical use (chemical), one for practices that aim to preserve biodiversity (biodiversity) which is also the base for the analysis of this subset, and the last one for climate-smart agriculture practices (pollute). These variables take the value of one when the specific practice is observed and take the value of zero otherwise.

3. Results

a. Summary statistics

The summary statistics table reveals that the average reported WTA to adopt sustainable practices in farming across the included studies is estimated to $403/Ha/year. The mean number of farmers participating in each study is 740 individuals, which forms the basis of the precision measure used in the publication bias analysis.

For the variables related to the study design, the data shows that 19% of the included studies used a contingent valuation method to elicit farmers' WTA for sustainable practices in their farming, which implies that 81% of the meta-data used studies utilizing conjoint (choice-based) surveys. Data also shows that 59% of the meta-data studies were carried out in Europe, 18% were conducted in America, 23% in Africa, and only 6% in Asia and Australia. On average, 62% of the studies used random sampling methods to draw their samples.

Regarding the sustainable practices investigated in the sampled studies, 47% of the studies focused on farmers' WTA for a practice that would enhance/conserve soil health, and 25% to preserve biodiversity and reduce pollution levels, while water conservation practices and biomass crops planting represented only 11% and 17% respectively, of the sampled studies.

At the subset level, descriptives show that practices related to BMPs and conservation of watersheds and wetlands are the most investigated practices (respectively, 79% and 74%) within their categories: "soil-health" and "water conservation" datasets, respectively. Also, 57% of the "biomass crops production" subset combines articles analyzing WTA to plant biomass woody crops, and 44% of the "pollution reduction dataset" is relative to studies valuing farmers' WTA to adopt practices that aim to reduce chemical use.

Table 5. PET and FAT analyses (using WTA in $/ha).

	WLS robust				WLS cluster Robust SE			
	(1)		(2)		(3)		(4)	
	Coef.	CI	Coef.	CI	Coef.	CI	Coef.	CI
Constant	680.72*** (*91.067*)	(501.47; 859.96)	546.06*** (*68.47*)	(411.29; 680.84)	709.45* (*362.46*)	(-15.31 1434.24)	566.68* (*271.88*)	(23.02;1110.34)
sqrt(n)	-11.73*** (*1.99*)	(-15.67; -7.80)	-	-	-12.24 (*7.49*)	(-27.22; 2.73)	-	-
n	-	-	-0.18*** (*0.031*)	(-0.24; -0.12)	-	-	-0.19 (*0.12*)	(-0.43; 0.04)
Obs	287		287		287		287	
F	34.44		35.40		2.67		2.80	
Pr > F	0.000		0.000		0.1072		0.0996	
R^2	0.1064		0.1111		0.0790		0.0824	

Standard errors are in parentheses

*** and * indicate significance at the 1%, and 10% levels

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b. FAT and PET analyses

Following Printezis et al. [23], we employ two approaches to correct the intra-study error correlations and publication bias using the square root of the sample size "sqrt(n)" and the sample size "n" as precision measures: the funnel asymmetry test (FAT) and the precision effect test (PET). Table 5 presents WLS regressions results for the simple model without additional study design covariates (Eq 2). We base our interpretation on results obtained from the WLS cluster robust standard errors as it is the main model of our study.

The Funnel Plot is used as an initial check for the presence of publication bias. It is a scatter diagram that plots the precision measure against the variable of interest, which are in our case: the square root of the sample size (sqrt(n)), and the WTA for sustainable farming practices (WTA $/ha). Publication bias is detected when the scatter is overweighed on one side [25]. Fig 1 displays a concentration to the right of the plot which might be an indication of publication bias.

Because the funnel plot is a visual inspection and is subject to a subjective interpretation [25], there is a need to check this publication bias suspicion by a more objective test: the funnel asymmetry test (FAT). From the t-test obtained from the simplified MRA (Eq 2), we found that the coefficient of the precision variable "sqrt(n)" in (3) of table (5), as well as the coefficient of "n" in (4) of table (5), are not significant which reject the null hypothesis, and thus, we conclude that in contrast to the funnel plot, there is no presence of publication bias in our metadata.

In his paper on publication bias, Stanley [25] explains highly skewed funnel plots in meta-analyses might result from the different econometric modeling choices supported by the sampled studies. However, because funnel plot analysis is a subjective method, we will limit our analysis of the subsets data's publication bias to a more objective analysis using the funnel asymmetric test (FAT).

For the precision analysis test (PET), we observe that the estimated constant which serves as a proxy for the "true" mean WTA for sustainable agricultural practices, presented in Table 5 indicates the presence of a WTA for sustainable agriculture. That is, the constant estimate is significant in our two models implying that the weighted average of WTA for adopting sustainability in farming across the included studies ranges between $567/ha/year and $709/ha/year. The following sections will present the MRA results obtained from the overall metadata as well as from the four sub-metadata sets.

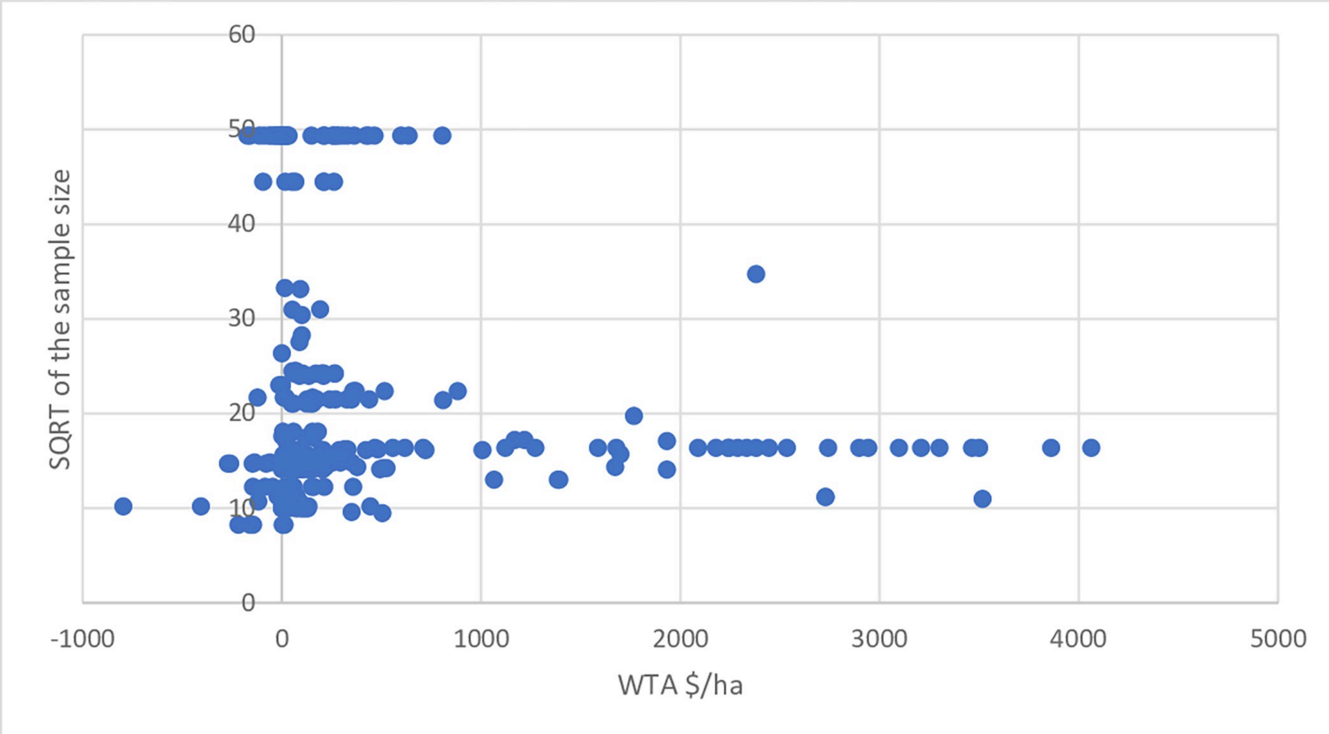

Fig 1. Funnel plot for WTA ($/ha) for sustainable practices estimates.

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c. Meta-regressions analysis

c.1. Overall data MRA. Table 6 presents the results of the full MRA models that consider methodological differences and other characteristics (e.g., location, agricultural practice) across the studies included in our analysis. Model diagnostics show that the two models are in overall significant based on the F-test.

As previously demonstrated through the PET analysis, the result confirms the presence of a proxy of the true mean "WTA" because it shows a positive and significant constant. The result also shows significant covariates at the 10% level: time trend, Africa, soil, elicitation method, and random sampling. The overall model, however, likely suffers from significant heterogeneity of motivations across sustainability practices thus masking overall effects. Therefore, we estimated the MRA models on the data subsets and focus interpretations on those model results.

c.2. Soil-health data. The subset "soil-health" includes studies focusing on eliciting farmers' WTA for Best Management Practices (BMPs) and agroforestry practices. Those results, which include 137 estimates from 19 studies, are shown in Table 7.

The regression displays no evidence that farmers have a significant average WTA for soil-health practices (constant is not statistically significant) nor is there evidence that farmers treat agroforestry or other BMPs significantly differently ("agroforestry" is not statistically different from zero). However, regarding research methods for soil-health practices, it seems that contingent valuation leads to higher WTA premiums compared to studies using the conjoint valuation method. This result is not unexpected as some literature criticizes contingent valuation for generating more hypothetical bias than conjoint methods [e.g. Halvorsen et al. [35]; Stevens et al. [36]]. Also, the regression shows that, in contrast to findings from studies carried in Europe, Asia, and Australia, American farmers have a higher WTA value. The higher WTA

Table 6. Meta-regression of the overall data (using WTA in $/ha).

	WLS Robust SE		WLS Cluster Robust SE	
	(1)		(2)	
	Coef.	P>|t|	Coef.	P>|t|
Constant	762.969 (195.228)	0.000***	793.536 (351.638)	0.028*
Elicitation Method	305.626 (115.927)	0.009**	290.004 (144.799)	0.050*
Random Sampling	309.697 (113.583)	0.007**	318.848 (146.455)	0.033*
Europe	174.300 (145.216)	0.231	211.096 (238.833)	0.380
Africa	-343.285 (126.774)	0.007**	-325.541 (181.836)	0.078*
America	-72.474 (177.608)	0.684	-88.553 (214.314)	0.681
Soil health related ag. practices	-903.044 (174.820)	0.000***	-908.287 (424.569)	0.036*
Water related ag. practices	-750.992 (234.312)	0.002**	-769.416 (460.411)	0.100
Pollution related ag. practices	-704.007 (200.281)	0.001**	-711.006 (447.512)	0.117
Trend	53.373 (14.939)	0.000***	53.829 (25.826)	0.041*
Sqrt(n)	-15.602 (2.973)	0.017*	-16.982 (6.448)	0.011*
Obs	287		287	
F	7.81		2.53	
Pr>F	0.000		0.0127	
R^2	0.3855		0.4030	
Adj. R^2				

***, **, * indicate significance at the 1%, 5%, and 10% levels, sqrt(n) is used as weight

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values may reflect higher opportunity costs for American producers switching production practices. Finally, although only significant at the p = 0.116 level, the negative sign on the trend signals lower WTA values (or more willingness to adopt at lower payment rates) through time for soil health practices. This result could reflect the impact of education and demonstration projects on soil health practices that are leading producers to value those more on their own operations (require smaller payments to induce them to adopt). This result could also be a

Table 7. Meta-regression results for soil-health related ag. practices data.

	WLS Robust SE		WLS Cluster Robust SE	
	(1)		(2)	
	Coef.	P>|t|	Coef.	P>|t|
Constant	4.333 (87.448)	0.961	15.815 (143.84)	0.914
Elicitation Method	470.122 (60.293)	0.000***	506.582 (97.851)	0.000***
Random Sampling	116.423 (142.017)	0.414	107.790 (148.688)	0.478
America	542.742 (265.457)	0.043*	711.401 (335.697)	0.048*
Africa	166.563 (109.595)	0.131	219.442 (174.888)	0.226
Agroforestry	113.231 (150.437)	0.453	193.909 (217.388)	0.384
Trend	-36.536 (27.269)	0.183	-59.419 (35.997)	0.116
Sqrt(n)	4.291 (2.940)	0.147	7.602 (7.106)	0.299
Obs	136		136	
F	24.47		12.64	
Pr>F	0.000		0.000	
R^2	0.1587		0.2148	
Adj. R^2	0.2328		0.3029	

***, **, * indicate significance at the 1%, 5%, and 10% levels, sqrt(n) is used as weight

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dummy study effect since studies using contingent valuation method represent only 1.5% of the observations.

c.3. Water conservation data. The subset "water conservation" is limited to research works related to water conservation practices' adoption, more specifically: riparian lands, wetlands, and watersheds conservation practices. This data includes 32 WTA estimates obtained from 8 studies.

The estimates resulting from the two regressions (WLS with Robust SE, and WLS with Clusters Robust SE) are all significant, except for the time trend variable trend in the clustered regression. Farmers demand higher WTA for adopting watersheds and wetlands conservation-related practices than for riparian lands conservation practices. Regarding the geographic area, we observe that in contrast to Australasia, higher incentives are required in Europe while in Africa, farmers require lower incentives. This later result does not support previous findings that demonstrate a low adoption of water conservation technologies by African farmers [e.g. Perret and Stenvens, [37]; Mango et al. [38]; Jha et al. [39]], which is a complex hurdle given the problem of water scarcity in Africa. Perret and Stenvens [37] relate this reluctance to a range of factors related to African farmers' circumstances and needs. In their paper, they argue that resource-conserving technologies are mainly developed ignoring the farmers' agenda of short-term production for survival, that most research is done in areas with favorable soil and climatic conditions which is not typical of farmers' conditions, and that the adoption doesn't depend upon only the farmers' willingness but also upon the role of property rights to resources and collective action at the community level.

From Table 8, and regarding the methodological covariates, the result shows that on average, studies carrying a random sampling method provide higher WTA which is in line with the result of the MRA model suing the overall data, while for the elicitation method, this dataset shows that using a contingent valuation method provides lower WTA than studies using conjoint valuation which is in contrast with the overall data MR result.

Also, the negative sign and the significance of the constant's estimate mean that if setting all other covariates equal to zero, there would be, on average, no evidence for a true mean WTA estimate for water conservation practices.

Table 8. Meta-regression results for water conservation-related ag. practices data.

	WLS Robust SE		WLS Cluster Robust SE	
	(1)		(2)	
	Coef.	P>|t|	Coef.	P>|t|
Constant	-1653.578 (392.398)	0.000***	-1607.772 (569.424)	0.022**
Elicitation Method	-806.897 (157.069)	0.000***	-826.823 (231.683)	0.007**
Random Sampling	624.226 (133.143)	0.000***	639.080 (204.685)	0.014**
Europe	1110.148 (125.100)	0.000***	1098.95 (184.180)	0.000***
Africa	-763.009 (108.981)	0.000***	-781.822 (163.539)	0.001
Watershed	318.120 (88.522)	0.002**	319.431 (121.266)	0.030**
Trend	39.223 (16.002)	0.022**	39.008 (21.268)	0.104
Sqrt(n)	146.838 (19.956)	0.000***	145.001 (26.961)	0.001***
Obs	31		31	
R^2	0.9356		0.9424	
Adj. R^2	0.7005		0.9637	

***, **, * indicate significance at the 1%, 5%, and 10% levels, sqrt(n) is used as weight

NB: the variable America was removed from this dataset since none of the sample studies was carried in this geographic area.

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c.4. Pollution reduction data. This third subset combines 73 estimates from 19 studies investigating farmers' willingness to reduce chemicals' use, conserve biodiversity, and adopt climate-smart agriculture practices.

The WLS Cluster Robust SE model result in Table 9 displays only three significant coefficients. The variable elicitation method is positive and highly significant meaning that on average, studies using contingent valuation reported a significantly higher WTA than those using conjoint analysis. In contrast with the previous results, the MRA result for the pollution-reduction practices dataset shows that studies that used random sampling reported lower WTA than those having used a non-random sampling method.

Also, as this dataset provides a positive and significant estimate for the constant, it means that there might be a true proxy for the mean WTA for practices that aim to reduce pollution. To test for that, a PET is performed using Eq 2 (Table 10).

Table 10 shows different results. Using the squared root as a precision measure doesn't provide significant estimates while using the sample size instead displays a significant estimate for the constant but not for the variable sample size. We can conclude that the hypothesis of the existence of a true proxy mean for the WTA for this category of practices is rejected.

c.5. Biomass crops production data. This last subset includes studies on farmers' willingness to grow/produce: grassy, woody, and cereal biomass crops. From the 15 studies, 50 estimates were collected.

All the covariates related to study design are significant (Table 11). For the variables "crop" and "grass" (corresponding to cereal and grassy biomass crops, respectively), the estimates are highly significant and negative, which means that in contrast to woody biomass crops, studies focusing on grassy and cereal biomass crops reported WTPs. We also found that studies carried in America display higher WTA premiums compared to studies conducted in the other continents.

Also, and in contrast with the other subsets results, this output shows the presence of a proxy for a true value of WTA for biomass crops production based on the positive and

Table 9. Meta-regression results for pollution reduction-related ag. practices data.

	WLS Robust SE		WLS cluster Robust SE	
	(1)		(2)	
	Coef.	P>|t|	Coef.	P>|t|
Constant	982.804 (378.582)	0.388	1016.144 (547.237)	0.079*
Elicitation Method	1192.987 (232.071)	0.000	1223.05 (253.121)	0.000***
Random Sampling	-221.256 (97.218)	0.048	-209.549 (103.643)	0.058*
America	331.120 (286.462)	0.280	334.242 (323.105)	0.314
Africa	-100.881 (114.063)	0.554	-87.573 (186.109)	0.643
Chemicals	-292.850 (224.036)	0.087	-300.259 (273.446)	0.286
Pollute	377.342 (159.453)	0.316	358.055 (220.199)	0.120
Trend	-25.925 (22.532)	0.382	-30.176 (34.864)	0.398
Sqrt(n)	31.901 (13.620)	0.382	31.570 (16.860)	0.077*
Obs	71		71	
F	47.88		26.60	
Pr>F	0.000		0.000	
R^2	0.5639		0.6569	
Adj. R^2	0.5814		0.6063	

***, **, * indicate significance at the 1%, 5%, and 10% levels, sqrt(n) is used as weight

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Table 10. PET analysis for pollution reduction data (using WTA in $/ha/year).

	Model 1		Model 2	
	Coef.	**P-Value**	**Coef.**	**P-Value**
Constant	560.684 (*365.084*)	0.141	462.102* (242.569)	0.072
sqrt(n)	-15.173 (*15.240*)	0.332	-	-
n	-	-	-0.474 (0.413)	0.265
Obs	71			
F(1;19)	0.99		1.32	
Pr > F	0.3320		0.2649	
R^2	0.0302		0.0386	

Standard errors are in parentheses

*** and * indicate significance at the 1%, and 10% levels

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significant constant. Given this finding, we performed a robustness check using the simplified MR's Eq (2) (PET analysis) to test for the presence of a proxy (Table 12).

Thus, based on the result, the proxy of the true mean WTA for biomass crops production ranges between 2054.4 USD/ha to 2765 USD/ha.

4. Conclusion and discussion

The literature on sustainable agriculture is extensive, with many studies investigating questions around producers' willingness to adopt sustainable agricultural practices. A more limited literature estimates farmers' economic valuation of sustainability. Thus, our interest in this review was limited to studies providing quantitative WTA values. Our metadata shows results from different research works offering a range of estimates that appears to vary significantly based on the region, the sustainable practice of interest, the elicitation method, and the sampling method.

Table 11. Meta-regression results for biomass crops production-related ag. practices data.

	WLS Robust SE		WLS cluster Robust SE	
	(1)		(2)	
	Coef.	**P>|t|**	**Coef.**	**P>|t|**
Constant	2305.446 (218.094)	0.000***	2294.758 (45.923)	0.000***
Elicitation Method	48.535 (25.108)	0.060*	42.677 (21.689)	0.071*
Random Sampling	-15.089 (10.878)	0.173	-15.109 (10.741)	0.183
America	1179.561 (213.822)	0.000***	1187.994 (32.040)	0.000***
Crop	-2290.097 (210.934)	0.000***	-2287.439 (12.454)	0.000***
Grass	-3452.359 (28.902)	0.000***	-3455.401 (31.995)	0.000***
Trend	-2.010 (5.684)	0.725	-1.025 (3.640)	0.783
Sqrt(n)	1.061 (1.312)	0.423	1.173 (1.487)	0.444
Obs	49		49	
F				
Pr>F				
R^2	0.7296		0.7134	
Adj. R^2	0.6752		0.6546	

***, **, * indicate significance at the 1%, 5%, and 10% levels, sqrt(n) is used as weight

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Table 12. PET analysis for biomass crops production data (using WTA in $/ha/year).

	Model 1		Model 2	
	Coef.	**P-Value**	**Coef.**	**P-Value**
Constant	2765.586* (*1375.792*)	0.066	2054.385* (828.343)	0.028
sqrt(n)	-78.644 (*48.989*)	0.132	-	-
n	-	-	-1.936* (0.933)	0.058
Obs	49			
F(1;13)	2.58		4.30	
Pr > F	0.1324		0.0585	
R^2	0.1476		0.1826	

Standard errors are in parentheses

*** and * indicate significance at the 1%, and 10% levels

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Through this research, we looked forward to estimating a proxy for the "true" WTA for sustainable agriculture adoption and providing a comprehensive and quantitative analysis of previous works on the topic. To do so, five meta-regression analyses were estimated to analyze the effect of practice-category variables and study-specific characteristics on published empirical results, in addition to four simplified MRAs that were used to depict the proxy for the WTA.

The contribution of our work in the broad literature is that from the 59 collected studies and the 286 WTA estimates, that form our overall meta-data, we found that there is a significant mean estimate for sustainable farming practices. By using the precision measures square root of the sample size (sqrt (n)) and the sample size (n), we found that a proxy for the true mean WTA exists ranging, on average between 567 USD /ha/year and 709 USD/ha/year. A proxy for mean WTA for biomass crops production was also found following the same method, ranging between 2054 USD and 2766 USD per hectare and per year. Estimating a proxy for farmers' WTA demonstrates the presence of a willingness to adopt sustainability and growing biomass crops by farmers worldwide which should reflect a positive general average response to the numerous environmental policies and programs encouraging sustainability. However, the ranging values should be taken very carefully because even if the metadata WTA values were carefully converted to a common metric and currency (WTA in USD per 1 ha per year), the conversion did not take into account inflation nor has been calculated in the same day for all observations, which means that if reevaluated to today's currency exchange rate, for example, the ranging values would variate following currency rates' fluctuation.

Using our analysis, we also provide results on the effect that practice-category and methodological variables have on the WTA estimates. Starting with the methodological variables, it seems that the effect of using a random sampling method depends on one the practice used. On average, a researcher who examines farmers' willingness to adopt water conservation programs (based on water conservation dataset analysis result), or sustainability without specifying the practice type (based on the overall metadata analysis result), would get a higher WTA than if he uses a non-random sampling method. While, if the research is oriented towards sustainable practices that are for biodiversity preservation, chemicals reduction, and climate-smart agriculture, the WTA values would likely be lower than if non-random methods were used. For soil-health practices and biomass crops growing, our results didn't provide evidence of an effect of the sampling method on the WTA.

By analyzing literature, it was found that using either method random or non-random sampling gives the same result as long as the attribute being sampled is randomly distributed among the population [40]. However, if the relevance of this statement is true for conventional analyses, it is not verified yet for meta-analyses and should be an interesting research opportunity.

Regarding the elicitation method, four out of the five MRs display a highly significant and positive estimate for the variable elicitation method showing that the methodology of elicitation has a direct effect on the magnitude of the WTA value. The MRs result of the three subsets "biomass crops production", "soil-health" and "pollution reduction" shows that using a contingent valuation method when eliciting farmers' preferences for pollution reduction, biomass crops growing, and soil conservation practices lead on average to higher WTAs than if using conjoint analysis. While for water conservation practices, on average, using contingent valuation leads to lower WTA values. This result is interesting because it highlights a difference in outcomes that could reflect a difference in the suitability of an elicitation method over another based on the nature of the practice being valued.

Though the two methods are widely used in agricultural and environmental economics to estimate valuations, the two approaches are different in their settings: the contingent valuation (CVM) is generally designed to examine changes in a single attribute while the conjoint analysis is designed to examine multi-attribute goods [41]. Only few studies tried to compare the two approaches and determine if they provide different results [35,36,42], and the findings are controversial. For example, in a study that compares the two methods for WTA elicitation to value environmental amenities, Harper [41] found no statistical difference can be determined between contingent and conjoint analyses in environmental studies, while other studies estimating WTP found that using the conjoint valuation method provides higher WTP than the contingent valuation [e.g. Halvorsen et al. [35]; Printezis et al. [23]; Carlsson and Martinsson [43]; Lusk and Schroeder [44]; List et al. [45]]. Given our findings and the limited literature supporting (or not) these differences, we cannot draw a firm conclusion on the effect of contingent valuation use versus conjoint valuation use on WTA values. Therefore, it is clear that there is still a need to jointly investigate and test the reliability and suitability of these two methods based on the type of agricultural practice of interest.

The findings obtained from the four subsets' MRAs show WTA measurement vary depending on practice category-type and/or the continent of the study, except for the subset "pollution reduction". The result of our meta-analysis shows that American farmers require higher incentives to engage in biomass crops production in contrast to Australasian and European farmers, which is supported by the literature that identifies hesitation and skepticism among farmers as important barriers to the development of renewable energy industries in the United States [46,47]. At the same time, the coefficients of the variables regarding cereal and grassy biomass crops, are negative and significant which indicates that on average, farmers, in all regions, are require lower payments to grow/supply biomass cereal and grassy crops than for growing/supplying woody biomass crops.

Several studies have found reluctance among farmers to produce biomass crops in general, and woody crops specifically [e.g.: Signorini et al. [48]; Nepal et al. [49]; Jensen et al. [50]; Khanna et al. [51]; Jiang et al. [52]]. If grassy crops like switchgrass are seen as low-intensity cropping systems, woody and cereal crops are perceived as high-intensity cropping production systems [48]. Woody energy crops require different crop establishment, cultivation harvesting, and transportation processes [53] which involve additional costs to the farmer. In addition to that, grassy crops are found to have a greater probability of making profits than woody crops [54]. Similarly, cereal biomass crops are found to present other advantages. For example, cereal straws have the advantage to use on-farm technology for their production system [55], their storage and transportation are economically feasible, and are a potential source of additional income for farmers [56] as they can be transformed into fiber and used for isolation, in the textile industry, and more. These low production costs, as well as the profitability, may explain the low WTA for grassy and cereal biomass crops in comparison to WTA for woody biomass crops.

However, this result does not reflect all the existing literature as numerous studies discuss a low WTA to grow biomass crops. These studies explain this low interest by factors linked to farmer and farm characteristics like risk aversion, age, education, farm size, logistics, etc. [57–59], as well as factors linked to a lack of knowledge regarding biomass systems [59], and free technical assistance availability [59–61]. In sum, from this result we can provide some suggestions that would benefit researchers and farmers in the future. Based on the factors determining the low interest in supplying biomass crops, it is noteworthy to suggest that larger efforts need to be made in extension activities to elevate and ameliorate knowledge about biomass crops production among farmers. Also, this finding shows a gap that needs to be filled on the research on the feasibility and consequences of biomass crop planting, because there are still unanswered questions regarding biomass crops characteristics, storage, and transportation issues that affect farmers' growing decisions, in addition to their risk aversion that should be also a research focus since it was mentioned more than once in the literature as one of the farmers' determinant factors of non-adoption [e.g. Fewell et al. [58], Hand et al. [59]].

Another interesting finding of our research is the negative and significant coefficients for the variable Africa for MRAs of the overall data and the water conservation subset. Compared to farmers from Australasian and American farmers, African farmers require on average lower incentives for water conservation and biomass crops production practices. This result might mean that the efforts of the international and national programs and policies to implement sustainable practices in African agriculture [e.g. The Plan Maroc Vert [62], the Comprehensive Africa Agriculture Development Program -CAADP- [63], and ECOWAS Agricultural Policy-ECOWAP-[64,65]] were productive and could encouraged farmers to embrace sustainability. However, the literature provides strong evidence on African farmers' low willingness to adopt sustainability [e.g., Perret and Stevens [37]; Mango et al. [38]; Jha et al. [39]], and our result is not in line with previous findings. Therefore, as most of the 22.6% sampled studies that were carried in Africa, have their WTA values expressed in local currencies (see S6 Table) that were converted in $USD for uniformization purposes, we suggest that this controversial result is due to the lower value of African currencies compared to $USD since their currencies' units trade under one $USD, this might explain the disparity between our result and the literature on sustainability adoption in Africa.

Many studies that focused on the barriers of sustainability adoption in Africa presented a wide range of factors that explain this behavior such as knowledge, labor, profit, [66–72], lack of infrastructure [73], corruption [74], gender bias in agriculture [75], and unstable governments [76].

Though there is a wide Agricultural Economics research focusing on Africa, based on my review, most studies investigating African farmers' behavior and drivers for adoption or non-adoption of sustainability, follow the same research approach as studies conducted elsewhere. Consequently, since Africa overlaps many different issues that make its case complicated, researchers need to use more complex models and techniques (e.g. spatial models, dynamic models, general equilibrium models, etc.) [72], and give more importance to local political and social issues while analyzing African farmers' behavior.

As a response to sustainable agriculture, an abundance of empirical studies has attempted its promotion by investigating and estimating consumers' WTP for sustainable products [77]. These various studies showed that there is a very strong responsiveness and consumers were willing to pay a premium price for sustainability [78]. Premiums were found for biomass energy [79], organic fiber [80], supporting farmers' adoption of BMPs that enhance water quality [81,82], for policies supporting agricultural practices reducing pollution [83]. . .etc.

However, this research is not without limits. First, since our meta-sample was randomly built, the subset regarding water conservation practices doesn't contain studies carried in America, and similarly for Africa regarding the subset for bioenergy crops production. Thus, it would be better if we could find more studies about these practices in these regions.

Also, it would be ideal if the conversion of all WTA values were estimated at the same time using the same daily currency exchange rate. Also, since the meta-data is compiling values that were obtained from different econometric estimation procedures, future work should consider including variables to indicate the used econometric models.

Needless to say, that the sustainability of some practices is seriously questionable if we refer to all the energy and resources it consumes through the technology or/and the production systems used. Accordingly, this should be another concern to take care of in future research as it would be interesting to investigate within each practice category what would be the perfect sustainable practice. In other words, does a "fully" agricultural sustainable practice even exist?

Though these limits, we tried to avoid methodological mistakes of past meta-analyses in the environmental and natural resource economics, following the "best practices" guidelines for meta-analyses in the field [20].

In sum, our review shows that on average, farmers are only willing to adopt practices if paid. Moreover, this analysis leads us to state that there are still gaps in the literature regarding the analysis of farmers' behavior regarding sustainable agriculture which calls for more research (see S1 Fig). To conclude, this study provides valuable information about farmers' valuation of sustainable agriculture, which should be taken into consideration by future research focusing on farmers' WTA for sustainability. Also, knowing a more precise proxy for the value that producers are ready to forgo to adopt green farming, can help industrials and policy-makers to understand both the average effect across studies and its variability which should lead to more informed decisions, regarding sustainability programs' design and how to promote sustainability.

Supporting information

S1 Fig. The trend of WTA adopting sustainable farming studies based on Science-Direct publications.
(TIFF)

S1 Table. Number of sample studies and WTA estimates per continent.
(DOCX)

S2 Table. WTA estimates proxy in USD/Ha/Year per continent.
(DOCX)

S3 Table. Simplified meta-regression results for biomass crops production-related ag. practices data.
(DOCX)

S4 Table. Energy data summary statistics.
(DOCX)

S5 Table. Soil data summary statistics.
(DOCX)

S6 Table. Pollution data summary statistics.
(DOCX)

S7 Table. Water data summary statistics.
(DOCX)

S8 Table. List of articles included in the metadata.
(DOCX)

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