RESEARCH ARTICLE

A meta-analysis of the adoption of agricultural technology in Sub-Saharan Africa

Aslihan Arslan[1]*, Kristin Floress[2], Christine Lamanna[3], Leslie Lipper[4], Todd S. Rosenstock[3,5]

1 International Fund for Agricultural Development (IFAD), Via Paolo di Dono, 44, Rome, Italy, **2** United States Department of Agriculture-United States Forest Service, Northern Research Station, 1033 University Place, Suite 360, Evanston, Illinois, United States of America, **3** Center for International Forestry Research-World Agroforestry (CIFOR-ICRAF), PO Box 30677–00100, Nairobi, Kenya, **4** Cornell University, Department of Global Development, Ithaca, New York, United States of America, **5** The Alliance of Bioversity International and the International Center for Tropical Agriculture (Bioversity-CIAT), 1990 Bd de la Lironde, Montpellier, France

* a.arslan@ifad.org

Citation: Arslan A, Floress K, Lamanna C, Lipper L, Rosenstock TS (2022) A meta-analysis of the adoption of agricultural technology in Sub-Saharan Africa. PLOS Sustain Transform 1(7): e0000018. https://doi.org/10.1371/journal.pstr.0000018

Editor: Juan Uribe Toril, Universidad de Almeria, SPAIN

Received: November 2, 2021

Accepted: May 27, 2022

Published: July 1, 2022

Peer Review History: PLOS recognizes the benefits of transparency in the peer review process; therefore, we enable the publication of all of the content of peer review and author responses alongside final, published articles. The editorial history of this article is available here: https://doi.org/10.1371/journal.pstr.0000018

Data Availability Statement: Relevant data underlying the study are available at doi.org/10.7910/DVN/73LEVJ.

Funding: Food and Agriculture Organisation paid the salary of A.A. in 2016 and seed funding for the

Abstract

Both global poverty and hunger have increased in recent years, endangering progress towards accomplishing Sustainable Development Goals (SDGs) 1 and 2. The regression has been most pronounced in Sub-Saharan Africa (SSA). Meeting the SDG targets requires achieving resilient farm productivity. Although many farm management technologies exist to improve yields, farmers in SSA largely have not adopted these approaches. A long-standing literature about technology adoption identifies multiple hypotheses as to why farmers may or may not adopt new agricultural technologies, culminating in numerous micro-econometric studies. We analyse a metadata set capturing the findings of 164 published studies specifically focusing on SSA and show that 20 out of 38, or 53%, of the determinants commonly believed to influence technology adoption lack empirical support. Eighteen determinants—primarily related to information access, wealth, group membership and social capital, and land tenure—consistently influence adoption across studies. Wealth remains a significant determinant of fertilizer adoption, despite long-running subsidies in most countries, although it is decoupled from the adoption of improved seeds and alternative crop and nutrient management technologies. We highlight the foundational determinants of adoption and offer guidance to design effective interventions that can decrease poverty and hunger towards 2030.

Author summary

Achieving SDG1&2 requires improved farm productivity in Sub-Saharan Africa (SSA). Although many agricultural technologies exist to improve yields, adoption remains low. We analyse a metadata set capturing the findings of 164 published studies focused on SSA that span nearly 30 years. We present the complexity of determinant-technology interactions for 3 technology groups using vote-count methodology, which can be subject to publication bias. We address this using sign-tests and establish that more than half of the

first round of literature search. International Fund for Agricultural Development paid the salary of A.A. during 2017-2022 and funding for the second round of literature search in 2018. USDA Forest Service paid the salary of K.F. since the start of the project in 2016. CGIAR Research Program on Climate Change, Agriculture and Food Security paid the salaries of T.S.R. and C.L., and provided seed funding for first round of literature search. International Development Association (IDA) of the World Bank to the Accelerating Impact of CGIAR Climate Research for Africa (AICCRA) project provided support to T.S.R. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing interests: The authors have declared that no competing interests exist.

determinants commonly believed to influence technology adoption lack empirical support. Access to general information (as opposed to narrowly focused practice specific information), wealth, and land tenure consistently influence adoption. Context specificity of technologies and determinants is illustrated by focusing on selected combinations with enough number of studies and important policy implications. Wealth remains a significant determinant of fertilizer adoption, despite long-running subsidies in most SSA countries, although it is decoupled from improved seed and alternative crop and nutrient management technology adoption. We highlight methodological recommendations to facilitate more rigorous meta-analyses in this increasingly complex literature to better guide effective intervention design to decrease poverty and hunger.

Introduction

The Sustainable Development Goals (SDGs) aim globally to eliminate poverty (SDG 1) and hunger (SDG 2) by doubling smallholder productivity and incomes, while simultaneously ensuring sustainable food systems. This objective represents a staggering challenge in Africa, where, as of 2019, 239 million people—17.8% of the total African population—were undernourished and another 399 million—29.7%—were moderately food insecure [1]. The COVID-19 pandemic has further exacerbated hunger; the economic consequences of the pandemic may increase the number of rural poor by 15% and the number of urban poor by 44% [2]. Radical gains in agricultural productivity to combat hunger and poverty are possible, however. The average agricultural productivity of countries in Sub-Saharan Africa (SSA) is currently about 50% that of other low- and middle-income countries worldwide [3], and average yields reach less than 20% of their biological potential (www.yieldgap.org) [4].

Adoption of fertilizers and high-yielding crop varieties at scale in Asia has helped to quadruple yields per unit of land over the past 60 years [3]. In SSA, adoption rates of modern inputs or other agricultural technologies, including some that are traditional such as agroforestry, crop rotations, and manure use, remain stubbornly low [5]. Yields per unit of land have only doubled over the same period [3]. Gains in productivity in SSA have occurred primarily through expansion into natural spaces rather than through enlarging the yield per land area [6]. Current farming techniques, including farming at the extensive margin, fail to deliver sufficient calories and nutrition. Further, they degrade natural resources and exacerbate the region's vulnerability to climate change [7]. Adopting improved agricultural technologies, on the other hand, can help build resilient systems and double productivity and incomes as targeted by SDG 2, and will have cascading impacts on poverty (SDG 1), climate change (SDG 13), and land degradation (SDG 15), among other SDGs.

Scientists, often and increasingly together with farmers, have developed and tested myriad ways to enhance crop, livestock, and tree production in SSA [8]. New or improved agroforestry, chemical inputs, crop varieties, intercropping, and protein-rich livestock diets, among many other approaches, have been shown to increase productivity compared to farmers' standard technologies [9–11]. Although chemical inputs like nitrogen fertilizers and pesticides may have negative environmental or health effects if overused or misused, they remain underused in Africa, which leaves room for sustainably scaling up best management practices [12, 13]. Despite this scientific evidence, relatively few farmers adopt new or improved approaches [5], especially among smallholders in SSA [14,15].

Theory suggests that farmer technology adoption decisions depend on complex interactions among a large set of factors including demographics, wealth, agroecology, markets, information, social networks, risk, and uncertainty [16–20]. Partly due to this complexity, empirical results fail to converge around the key determinants of adoption. Most individual studies tend to offer idiosyncratic results presented as specific to a particular farmer group, technology, or location [21,22].

The increasing demand for evidence-based policymaking in this realm has led to burgeoning review and synthesis papers [21–28]. Earlier efforts largely employ "vote-counting" approaches to tally the significance or non-significance of findings describing a determinant's influence on binary adoption decisions (S1 Table). Only the most recent such publication uses a quantitative meta-analysis framework [28], and none of these studies focus specifically on Africa. We synthesize evidence about what determines the adoption of 97 agricultural technologies in SSA from approximately 30 years of published research. Our goal is to provide guiding principles of adoption that could inform effective policy and programming critical to the well-being of more than 10% of the global population.

Materials and methods

We provide a broad overview of the influence of determinants commonly used to predict adoption in econometric studies of improved agricultural technologies in SSA. Our methods are consistent with best practices for evidence syntheses [29,30] in cases where most publications do not report sufficient data to enable meta-regressions [28].

Search protocol and screening

A protocol to search for applied agricultural economics literature about technology adoption in SSA was developed by building on Rosenstock et al. [31]. We use the same search strings to identify improved agricultural technologies that were created to search the literature about the effects of crop, livestock, and tree management technologies on productivity, resilience, and greenhouse gas emissions. We created new search strings to include keywords for determinants of adoption commonly used in applied economics literature (S2 Table). All searches were conducted in Web of Science and Scopus, accessed at the headquarters of the Food and Agriculture Organization of the United Nations (FAO) and the International Fund for Agricultural Development in Rome. The original search was conducted in 2016 and updated in 2018. Inclusion and exclusion criteria were created to cover the relevance of technologies, determinants, the location (Africa), the type of econometric analysis, and the quality of reporting (S3 Table). To exclude studies with a strong likelihood of bias, we screened for econometric analyses that (i) targeted at least one of the pre-selected agricultural technologies, (ii) reported primary data about adoption, (iii) reported coefficients for all variables used as determinants in the model, and (iv) had a sufficient sample size. The resulting list of articles was complemented with a recursive search using the reference lists of articles identified during both rounds of searching.

The searches yielded 1,113 studies investigating agricultural technology adoption by African farmers. All papers were screened in two stages. First, the titles and abstracts were screened against inclusion criteria. Then, full texts were screened both for inclusion and a recursive search. The 164 articles that met the criteria were included in the final meta-database (Fig 1 and S1 Text). References were stored and managed in EndNote (version X7, Clarivate Analytics).

Coding

The information extracted from each study included locations, sample sizes, technologies, econometric specifications, adoption determinants, regression coefficients, and the level of

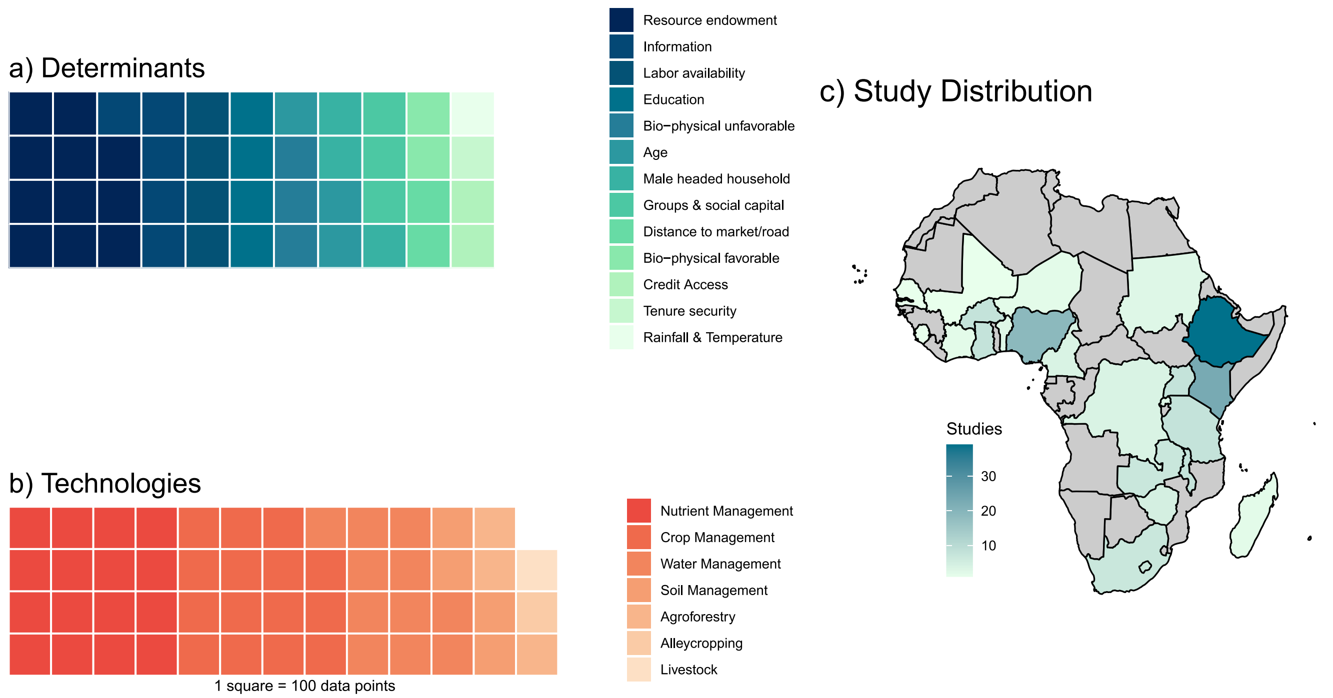

Fig 1. Geographic and topical distribution of the technology adoption evidence. Panel a shows the distribution of determinants and panel b that of technologies in our data. Panel c shows the number of studies in each country for which there is at least one included study (gray shaded areas indicate countries where no study satisfied inclusion criteria). The vast majority of studies investigate agronomic practices and have been conducted in Ethiopia, Kenya, and Nigeria. The base layer of the map is imported from the Natural Earth project (the 1:50m resolution version, https://www.naturalearthdata.com/).

https://doi.org/10.1371/journal.pstr.0000018.g001

significance. An extraction guide was created to establish codes for reference, and all coding was reviewed to ensure consistency across enumerators.

The final meta-database includes information from 164 articles—5,427 data points—that analyse the determinants of adoption of 97 technologies in 23 countries in Africa. The data points refer to the estimated coefficients of the determinants of adoption reported in each paper. If multiple technologies were studied, we captured the coefficients from each, and if multiple specifications were presented for one technology, as is common in the literature, we captured the coefficients from the most robust specification.

Information about technologies and adoption determinants was standardized. The aggregation of the 97 technologies follows the hierarchical taxonomy set out in Rosenstock et al. [31] to categorize them into agronomic, agroforestry, or livestock practices (S4 Table). The 384 unique adoption factors, or independent variables, were harmonized and aggregated to three levels: determinant categories, determinant subcategories, and factors (Box 1).

Box 1. Hierarchical taxonomy of adoption determinants

Study authors use different terminology to describe adoption factors—that is, the independent variables in regression models. To deal with the large variation observed in the definitions of determinants within the included studies, we aggregated factors for analysis. First, we standardized terms to reduce the 384 unique factors to 43 subcategories. Second, these subcategories were aggregated to form 12 determinant categories that match key hypotheses about adoption (S5 Table). For example, the determinant category called "information" includes the following factors: access to information specific to improved agricultural technologies, access to extension, access to general information, farming experience, and previous use of the technologies analysed. The category called “socio-demographics” includes the age, education, and gender of the household head, as well as other household characteristics.

Data analysis

Vote count. Simple vote-count analyses are used to understand how often an independent variable has a significant positive, significant negative, or non-significant relationship with a dependent variable. Each observation is a coefficient from a multi-variate analysis of the adoption of one of the practices included in the metadata; therefore, reported results control for a set of livelihood characteristics of households. Vote counts are a commonly used and easily interpretable method [25,26]. We present the full vote count results for 43 subcategories of determinants (S6–S8 Tables).

Sign test. Simple vote count analyses give all observations the same weight regardless of the sample size and may be particularly subject to publication bias [32]. Because statistical significance within individual studies is sensitive to sample size and the population from which the sample is drawn, we complemented the vote-count meta-analysis with an analysis using the sign test methodology described by Bushman and Wang [22] and used in similar research about the adoption of conservation practices in the United States [19,25]. The sign test examines whether determinants have hypothesized positive or negative relationships with a given behaviour across multiple studies, thus eliminating the shortcomings of focusing only on significant results, which is a common approach in vote counting.

The sign test was employed by creating binary variables to indicate whether a given determinant coefficient was consistent with its hypothesized relationship to the dependent variable. Binomial confidence intervals for proportions were then estimated. These confidence intervals were used to gauge the overall positive or negative effect of a determinant on the adoption of practices analysed, where a lower-bound estimate at or below 0.50 indicates the absence of a statistically significant correlation. We present the minimum, maximum, and mean sample sizes along with the number of observations from studies within each determinant category to provide additional information for readers to understand the applicability of results (S9 Table).

Meta-analysis methods are different from those of primary data analyses in important ways. With primary social science data, the unit of analysis is often individual, and the sample is used to estimate population proportions. In the case of meta-analysis, the unit of analysis is a published study, the sample is the entire set of included studies, and the estimates pertain to the sample. This implies that the confidence interval range represents the proportion of studies finding a positive or negative relationship, not a proportion of agricultural producers.

Based on literature, we developed hypotheses about the direction in which each determinant in our data would drive the adoption of improved agricultural technologies [17 and S1 Table]. We first tested these hypotheses using positive and negative sign tests for all the improved agricultural technologies in our dataset. For more specific policy insights, we also apply the sign tests to a selected set of determinant-technology combinations to unpack technology-specific and potentially opposing impacts. Given the importance of understanding the determinants of modern input use in SSA, we focus on the potentially opposing relationships between wealth and income indicators on one hand, and the adoption of modern inputs versus alternative nutrient and crop management technologies on the other. We select these technologies because the use of modern inputs like seeds and fertilizers remains low in SSA (despite subsidy programmes in many countries), and alternative land management practices have been promoted with mixed results. We emphasize wealth-signalling determinants because they are positively correlated with adoption in many studies [18,26], and they can act as proxies of other behavioural characteristics like risk aversion that can help with targeting [17,33].

We test the following two hypotheses using positive and negative sign tests. Firstly, we examine whether indicators of wealth and overall income, such as credit, land size, livestock, off-farm income, overall income, and wealth indices, would positively affect the adoption of improved seeds and fertilizers that require upfront cash investments [15]. Secondly, we explore the corollary to this expectation that is whether these factors would negatively affect the adoption of commonly promoted sustainable practices with negligible cash outlay needs including the use of traditional crop varieties, organic manure, and intercropping.

Results

The dataset

Of the 164 studies in the final meta-database, about 50% used statistically representative sampling designs. The median sample size across all studies was 591 households. The studies spanned 23 countries; however, the bulk of them—47%—were conducted in either Ethiopia (39), Kenya (23), or Nigeria (19). No other country had more than 10 studies. With the exceptions of Burkina Faso (8) and Ghana (8), each West African country was the subject of five or fewer studies (Fig 1, panel c).

The resource endowments and information categories together contribute more than one third of the total data points, or 35% (Fig 1, panel a). Other determinant categories most frequently included in the dataset are labour availability at 9%; socio-demographic variables such as education (9%), age (7%), and gender (6%); group membership/social capital at 6%; biophysical factors at 11% total, divided into 7% unfavourable and 4% favourable factors and market access, also at 6%. Least frequently used determinants are related to rainfall and temperature, which are increasingly incorporated in this literature given the improved understanding of the importance of the effects of climate change on smallholder agriculture.

Regarding technologies, the vast majority of the adoption analyses included, or 89%, focused on agronomic technologies, including water, soil, nutrient, and crop management (Fig 1, panel b). Agroforestry was addressed in 8.5% and livestock management in just 2.5% of analyses (S4 Table). Among the agronomy group, 64% of studies focus on the adoption of technologies for grains (including all grains such as maize, wheat, rice, barley, millet, sorghum and teff), and 52% on maize alone. This skewed distribution reflects the importance of staple crops such as maize, rice, and wheat to SSA food security, as well as the historical scientific emphasis on technologies such as improved seeds, fertilizers, and irrigation focusing on a selected number of grains.

Vote counting illustrates the importance of context

Although vote-count methods are driven by statistical significance and sensitive to sample size, they are easily interpretable and widely used in this literature [25,26]. We unpack the socioeconomic determinants category to present vote counts separately for age, education, and gender for easier interpretation. The determinants were positive and significant 26–38% of the time on average across the 15 categories (Fig 2). The information access category is the most consistently important; it is positively associated with adoption at least 36% of the time for each of the technology categories. Resource endowments are also consistently positive and

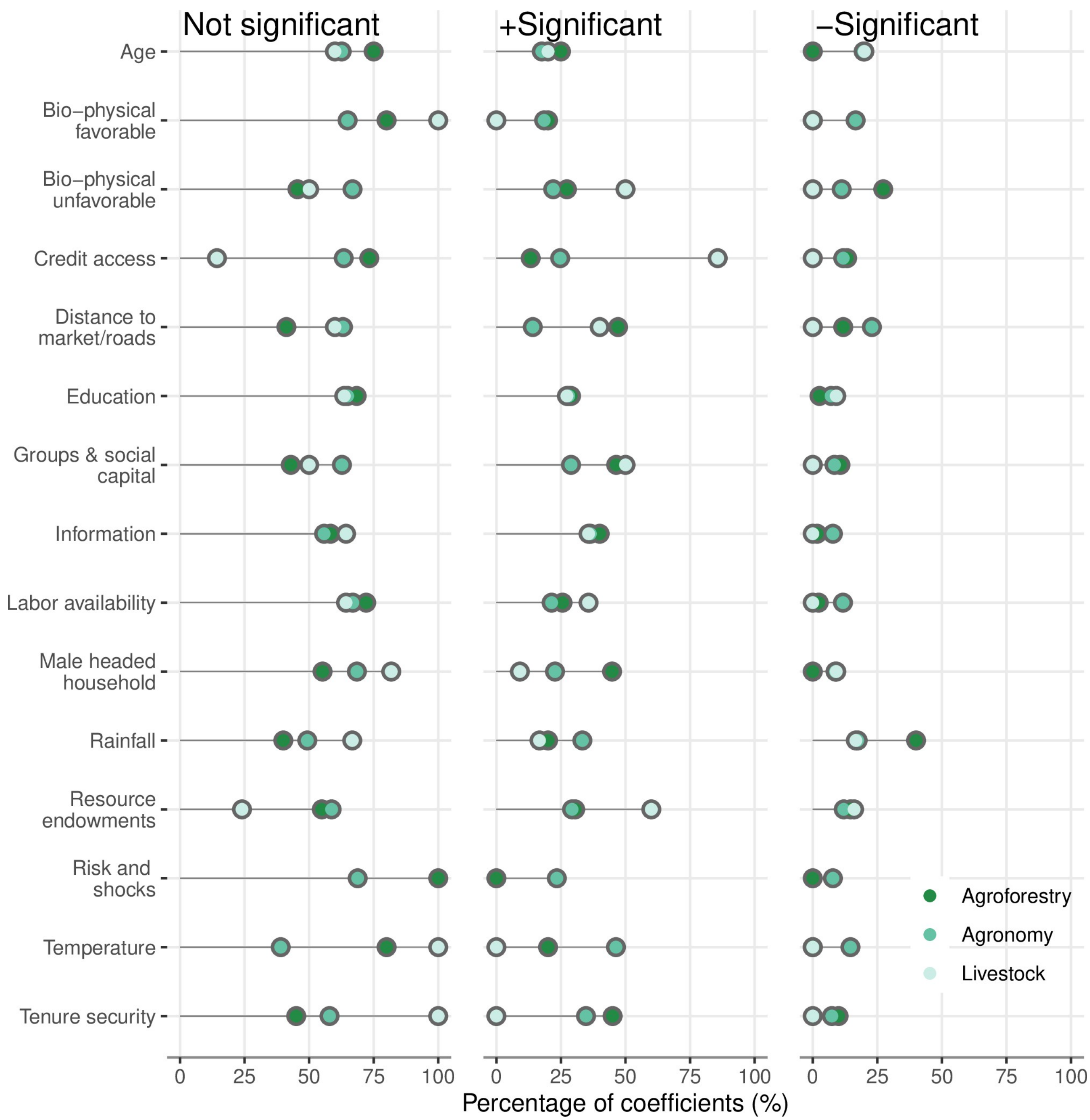

Fig 2. The determinants of SSA technology adoption. The percentage of regression coefficients that are not significantly, significantly positively, and significantly negatively associated with adoption of 3 technology groups and for 15 determinant categories, including the expanded socio-demographics category. The number of factors included in each category and the frequency with which each is included in the 164 studies vary by an order of magnitude (S6–S8 Tables).

https://doi.org/10.1371/journal.pstr.0000018.g002

significant in driving adoption at least 30% of the time for all three technologies. No other determinant category is consistently affects adoption more than 30% of the time for all technology groups, highlighting the importance of context [21]. Negative correlations between the 15 determinant categories and adoption occurred just 11% of the time on average.

The influence of most determinants on adoption is practice-specific. For example, resource endowments (including wealth and off-farm income) and credit access stand out for the adoption of livestock-related practices: they are significantly associated with adoption in more than 60% and 85% of the time, respectively. Credit access is considerably less important outside of livestock management, with only 13% and 25% significant associations with the adoption of agroforestry and agronomy practices, respectively. Similarly, tenure security is never correlated with the adoption of livestock practices but is a significant predictor of the adoption of agroforestry and agronomy practices about 45% and 35% of the time, respectively. Notably, the social capital category (including membership in farmer groups/cooperatives) is equally or more important than education, and is significantly correlated around 50% of the time with the adoption of agroforestry and livestock practices, but to a much smaller extent for agronomy practices.

Weather variables, such as current or past rainfall and temperature, are mostly included in the agronomy group, where they were positively associated with adoption 33% and 46% of the time, respectively. The role of rainfall in agroforestry adoption seems to stand out with positive correlations 40% of the time, implying agroforestry is mostly adopted in environments with lower rainfall. Though this information is based on 5 studies only and an equal share of studies found rainfall to be not correlated with agroforestry adoption.

Published empirical studies tend to report the direction of impact of a determinant as if it is always positive, negative, or non-significant, primarily because most studies cover one practice in one setting at a time. Equally importantly, however, a determinant can have both positive and negative correlations in different settings, which can only be assessed in meta-analyses and is the most common trend we observe (Fig 2). The distance from a household to markets or roads, for example, is most frequently significantly positively correlated with the adoption of improved agroforestry and livestock practices. In the case of improved agronomic practices, however, 23% of the data points show a significant negative correlation with distance, 14% show a significant positive correlation, and 63% show a non-significant correlation. These seemingly conflicting results among studies stem from the highly context-specific nature of some adoption determinants.

This trend holds when considering the more disaggregated determinant subcategories. If a significant association with agronomic practice adoption was found at all, only 4 of 43 subcategories were always positive or negative. Access to information and land pressure always showed a positive association, and distance to water and being single always had a negative association (S7 Table)–though the latter two were included only in 2 studies each. The direction of significant associations for most determinant subcategories includes both positive and negative ones with significant variation across technology groups. Overall, only 38% of all the factors were statistically significant (12% negative and 26% positive). Some of the most widely studied, including age, education, gender, and marital status, had no effect on adoption at least 60% of time.

For agroforestry, 6 out of 38 subcategories included had no significant association with adoption at all, while 13 had always positive associations. Notably access to extension, farmer group participation and male household head are included in at least 50% of studies and are positively associated with adoption for more than 40% of the time.

Hypothesis testing shows expectations would only be accurate about 50% of the time

To address the methodological shortcomings of vote counts, we also used sign tests to evaluate whether the data supported the generally hypothesized direction of associations between

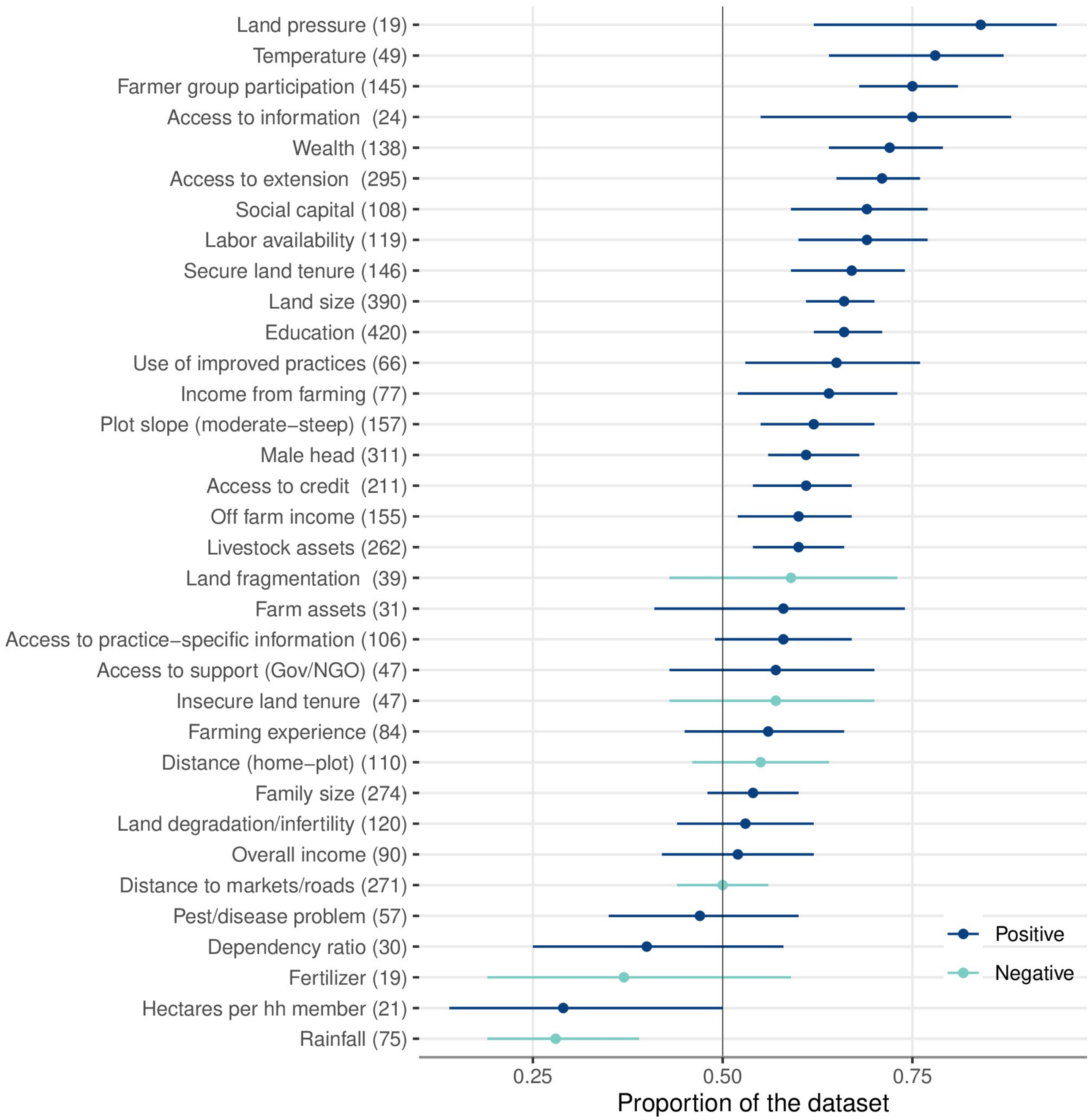

Fig 3. The influence of select determinant subcategories on the adoption of improved agriculture technologies. The colours indicate the directional hypotheses of influence: dark blue is positively related, light blue is negatively related. Points indicate the percentage of the data points that match the hypothesized direction of influence. Lines indicate the confidence interval across studies. The values in parentheses show the number of times the determinant was included in the dataset. For disaggregated results, see S9 Table.

https://doi.org/10.1371/journal.pstr.0000018.g003

determinants and adoption regardless of significance [21,24]. Of the 30 determinants hypothesized to have positive relationships with adoption, only 18 or 60% exhibited this relationship in a statistically significant way (Fig 3, S9 Table).

Confidence intervals highlight the benefit of using sign tests: although the share of positive results exceeds 50% for all but one determinant, potentially reflecting publication bias, confidence intervals show that not all are positively related to adoption in a statistically significant way. Significant positive drivers of adoption that can guide policies include both direct policy levers and factors that can be used for targeting interventions. The former include access to credit, general information and extension, farmer group participation, education, tenure security and labour availability, while the latter include wealth indicators (such as land size, livestock assets, off-farm income, and composite wealth indices), shock exposure, and temperature. One factor that stands out among those that were not significantly positively related to adoption is access to practice-specific information, indicating that broader access to information matters more for technology adoption than narrowly focused information about specific practices. None of the determinants typically expected to negatively affect adoption exhibited this relationship in our analysis.

Technology-specific analyses shed additional light on policy-relevant factors

Meta-analyses, by definition, group a large set of agricultural practices—97 in our case—as "improved technology," although some determinants may have opposing impacts on different practices. Unpacking these implications can better guide policy. We explore "mixed effects" focusing on the impacts of wealth on the use of modern inputs like seeds and fertilizers versus alternative nutrient and crop management technologies. Wealth is positively correlated with adoption of new agricultural technologies in many studies [20], and modern input use remains low on the continent (despite subsidy programmes in many countries), especially in marginal environments [34,35]. The hypothesized positive relationships between four of the wealth-signalling factors—credit, land size, livestock assets, and the asset-based wealth index—and inorganic fertilizer use were supported by sign tests. Regarding the use of improved seeds, however, only the composite wealth index and livestock assets showed the expected positive relationship (Fig 4). None of the hypothesized negative relationships between wealth-signalling factors and other, mostly adaptive and sustainable crop and nutrient management practices occurred more than chance would indicate (S9 Table).

Discussion

The transformation of SSA agriculture to achieve SDGs 1 and 2 will require hundreds of millions of farmers to adopt improved technologies. History would suggest that catalysing such a change in short order is a daunting challenge [8,36,37]. Our meta-analysis shows that a set of 18 broad determinants generally influence technology adoption. Four relate to policy tools that enable access to extension, information, farmer group participation, and credit. Of those tools, access to general information, as opposed to narrowly focused practice-specific information, and farmer group participation increase adoption most consistently across a range of farming technologies and contexts. Policy and programming that build on these factors, such as digital connectivity and extension, village savings programs, and cash transfers, are therefore likely to effectively increase adoption of improved agricultural technologies. The importance of these factors has also been attested in reviews and randomized control trials [38–41].

The influence of most determinants does not follow a consistent pattern, however. Diverse determinants affect adoption decisions in different ways across varying contexts, creating highly technology-, site-, and adopter-specific circumstances. Nevertheless, broad themes emerge across these idiosyncrasies, allowing the identification of specific determinant-practice combinations that obstruct or enable adoption. For example; tenure was often associated with the adoption of improved agronomy and agroforestry practices. In contrast, no study in our data found land tenure to be significantly associated with the adoption of improved livestock

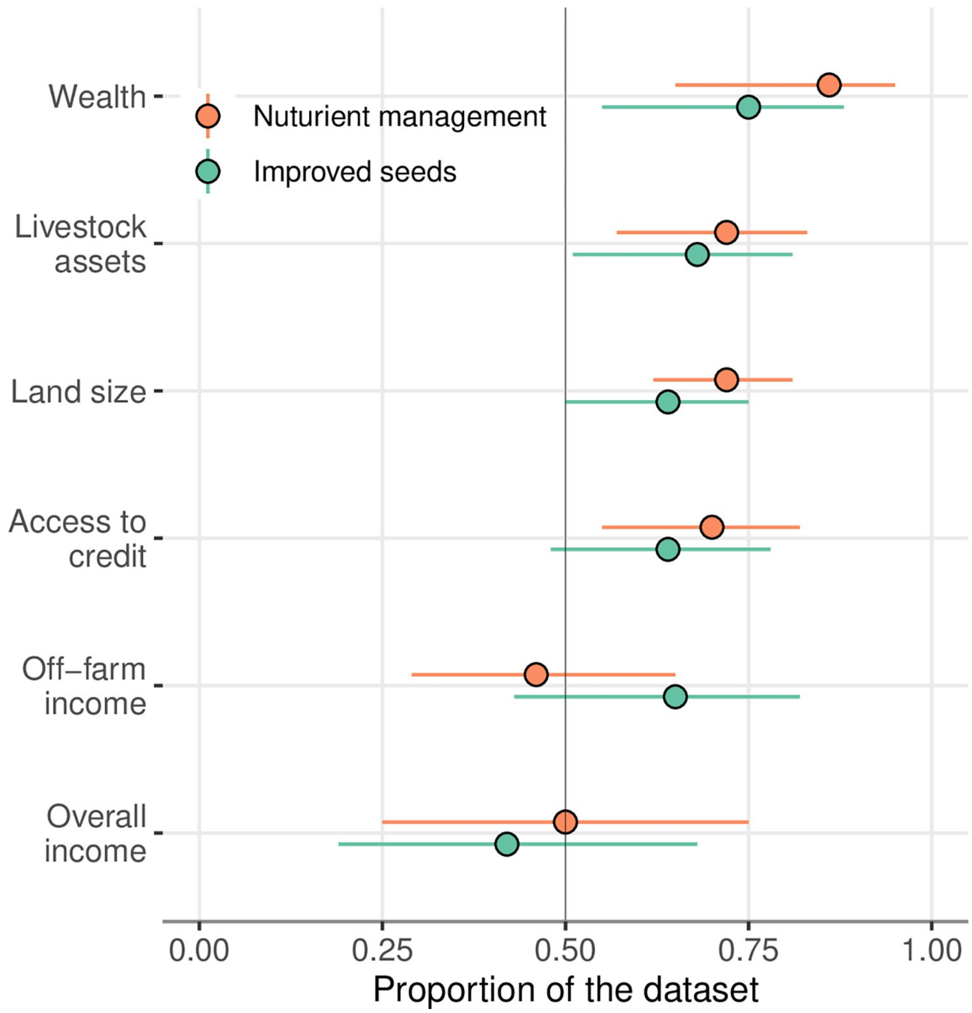

Fig 4. The influence of wealth-signalling determinants on the adoption of improved seeds and fertilizers. Only the wealth index and livestock assets are consistent predictors of adoption of both technologies. Wealth, by contrast, had an inconsistent influence on the adoption of alternative soil management technologies (S9 Table).

https://doi.org/10.1371/journal.pstr.0000018.g004

practices. Livestock do not necessarily require private land holdings and may be grazed on communal lands or fed in stalls. Notwithstanding the complexities of conflict between herders and farmers in Africa [42,43], only 8 studies analyse livestock related practices, most of which relate to nutrient management (e.g. improved diet supplements) not directly linked to land tenure. In contrast, agroforestry and agronomy practices necessarily relate to land, and returns on investments come months and/or years later. Informal and insecure land tenure systems are pervasive in Africa, and previous systematic reviews analysing the effects of land tenure on productivity and incomes on the continent were inconclusive [44,28]. Our finding that tenure security positively influences agronomic and agroforestry technology adoption builds on this literature to suggest that greater tenure security can help improve the adoption particularly of sustainable technologies with long time horizons.

Technology adoption typically requires up-front investments, and in many cases, meaningful benefits accrue only over extended time horizons. In such cases, exposure to shocks and risk can constrain adoption [45,46]. This negative association is reported in only 8% of agronomic practice adoption studies, while 33% report a positive association suggesting that the improved practices captured in included agronomy studies are likely perceived as ex-ante risk management strategies by farmers [16,17]. Though livestock is considered as a mobile asset that helps households deal with shocks [47] none of the included studies included this as a determinant. Social networks positively influence adoption of most technology categories (at least in around 30% of cases), this association is most prominent for technologies with high upfront investments and relatively long time horizons–as in agroforestry. This insight reflects growing recognition of the importance of social contexts for adoption decisions and underlines the need to account for them in programming [19,20,51].

Previous work has also suggested that environmental conditions influence adoption [20–23,48]. For example, lower rainfall and higher temperatures have generally been expected to drive adoption of soil-water conservation practices or stress-tolerant crops. We found that higher temperatures—including annual, seasonal, or long-term averages—are more likely to significantly increase adoption, suggesting that improved technologies are perceived as strategies to cope with increased temperature. In contrast, rainfall affects adoption both positively and negatively in all technology groups. The variation in rainfall measurements in included studies—such as annual, seasonal, or lagged totals and long-term averages—and the potentially nonlinear effect of rainfall might explain this finding; though these realities are not captured in most published studies. Farmers' adoption decisions may also be sensitive to crop-specific conditions during the growing season and to historical beliefs [49,50], which need to be properly captured by well-defined rainfall variables in adoption studies.

The use of synthetic fertilizers and improved seeds has historically been heavily emphasized in SSA agricultural development; nevertheless, the use of both remains low on the continent. We therefore zoomed in on wealth-related determinants of their adoption with additional sign tests to identify relevant policy implications. We found a clear difference in how wealth affects the adoption of these two technologies. Most wealth indicators significantly increase the adoption of inorganic fertilizers, suggesting that long-standing subsidies in many countries in Africa do not seem to be effective in increasing adoption for those least able to afford these fertilizers. No amount of promotion will be effective without good access to financial services or other incentives. The correlation is much weaker for improved seeds; only the composite wealth index and livestock assets increase the adoption of improved seeds. This distinction suggests that asset-based wealth rather than liquid income is the driver of improved seed adoption. In contrast, wealth indicators do not influence the adoption of alternative soil nutrient and seed management practices, indicating that promotion of sustainable land management practices can make a difference even in low-income settings.

Unfortunately, most studies do not capture the intensity of technology adoption nor adoption of multiple technologies at a time; hence this analysis cannot establish whether wealthier households adopt improved inputs at the expense of alternative soil nutrient management approaches. Agricultural households adopt numerous technologies to balance manifold risks across their crop and livelihood portfolios. Methodological innovations to address the endogeneity issues and data requirements associated with analysing the adoption of multiple technologies would drastically increase the relevance of these studies for interventions on the ground.

Methodologically, by statistically evaluating hypotheses using sign tests and comparing the synthesized results with previous studies that used vote counting alone, we revealed new insights [20,23]. The sign tests show that the positive association of many determinants with adoption more than 50% of the time in vote-counting approaches is not statistically significant. Of the 30 determinants hypothesized to be significantly positively correlated with the adoption of improved agricultural practices, 18 or 60% exhibited this relationship. The hypotheses for 20 of the 38 categories were not supported by quantitative evaluation, meaning that about 50%

of the results defy expectations. Going beyond overall improved technology adoption by using sign tests for specific determinant-technology combinations provided evidence that can support the promotion of improved input use as well as alternative soil and crop management technologies. Similar uses of sign tests may in the future help address some of the critiques of meta-analyses and syntheses in this domain.

Simple changes to study methodologies would bring greater insights in future meta-analyses. More sophisticated meta-analyses of large samples are often challenging because key information is rarely reported, such as the number of adopting and non-adopting households as well as the averages and standard deviations of all variables by group. Additionally, the factors driving adoption are not standardized across studies. We aggregated 384 unique factors into 43 broader subcategories with the same direction of influence, although 84 unique factors did not fit into any subcategory because they were too location-specific to be useful beyond the study that included them. The development and use of a standard ontology for determinants could help ensure comparability across studies. This meta-analysis illustrates both the power of and the need for a data revolution to standardize reporting. Movements toward standardization currently occurring in other fields of study may serve as apt examples [51]. The results would be enhanced value of adoption case studies to facilitate more rigorous and revealing meta-analyses that support policy.

Conclusion

Our results set the benchmark for understanding agricultural technology adoption in SSA. They support several entrenched beliefs about some adoption determinants while challenging others. We arrived at these conclusions by complementing common vote-counting methods with examination of directional hypotheses. In addition, this meta-analysis highlighted opportunities to help bring order to currently disparate adoption studies in order to generate information that matches realities on the ground. Future studies could focus on the characteristics of interventions and how they interact when multiple technologies are adopted together. Herein we have only considered studies within a quantitative, deterministic framework; this perspective reinforces the importance of context. Employing mixed methods or complex systems approaches could help disentangle the seemingly contradictory influences of factors in econometric studies. Increasing use of behavioural models in agricultural technology adoption studies also have the potential to improve our understanding of farmer adoption in complex and embedded systems [52]. These conclusions complement the literature on leverage points perspectives in sustainability science from a developing country point of view [53]. Meta-analyses of such complex systems embody a quest to simplify behaviour and require a balancing act between site-specific detailed knowledge of a complex system and standardized generalizable conclusions at larger (geographic and time) scales to guide policy. The increase in causal modelling would support greater external validity by revealing new insights about the interactions between social and environmental factors and technology characteristics. If the above methodological recommendations are heeded, such studies would better facilitate policy and programming to meet the herculean challenge of defeating poverty and hunger in SSA.

Supporting information

S1 Table. Selected technology adoption meta-analyses. There has been increased use of quantitative synthesis in the adoption literature, though still rare. No previous quantitative synthesis targets SSA smallholder farmers.
(DOCX)

S2 Table. Search strings.
(DOCX)

S3 Table. Inclusion and exclusion criteria for identifying publications in the literature.
(DOCX)

S4 Table. The number of observations by technology categories.
(DOCX)

S5 Table. The frequency of factors grouped under each of the 12 determinant categories.
(DOCX)

S6 Table. Vote-count results for determinant subcategories in agroforestry studies ($N = 31$).
(DOCX)

S7 Table. Vote-count results for determinant subcategories in agronomy studies ($N = 144$).
(DOCX)

S8 Table. Vote-count results for determinant subcategories in livestock studies ($N = 8$).
(DOCX)

S9 Table. Full results for the influence of determinants on adoption sign tests.
(DOCX)

S1 Text. List of included studies.
(DOCX)

Acknowledgments

We thank A. Poultouchidou, M. Ravina da Silva, Zhou Cheng, S. Rayess, Gloria di Caprera, and Margherita Squarcina, who conducted literature search and coded the studies, and M. Mayzelle for comments on an early version. Thanks to Solomon Asfaw, for facilitating access to a research assistant for the latest update to the literature search. The findings and conclusions in this publication are those of the authors and should not be construed to represent any official FAO, IFAD, CGIAR, IDA, United States Department of Agriculture, U.S. Government, or other institutional determination or policy.

Author Contributions

Conceptualization: Aslihan Arslan, Leslie Lipper, Todd S. Rosenstock.

Data curation: Aslihan Arslan.

Formal analysis: Aslihan Arslan, Kristin Floress.

Funding acquisition: Aslihan Arslan, Leslie Lipper, Todd S. Rosenstock.

Investigation: Aslihan Arslan, Kristin Floress.

Methodology: Aslihan Arslan, Kristin Floress, Leslie Lipper.

Project administration: Aslihan Arslan.

Software: Christine Lamanna.

Supervision: Aslihan Arslan, Todd S. Rosenstock.

Validation: Aslihan Arslan, Leslie Lipper.

Visualization: Christine Lamanna, Todd S. Rosenstock.

Writing – original draft: Aslihan Arslan, Leslie Lipper, Todd S. Rosenstock.

Writing – review & editing: Aslihan Arslan, Kristin Floress, Christine Lamanna, Leslie Lipper, Todd S. Rosenstock.

References

1. FAO. Africa regional overview of food security and nutrition 2016 –Key messages. FAO–Food Agric. Organ. United Nations. 2019.
2. Laborde D., Martin W. J., Vos R. Estimating the poverty impact of COVID-19. 2020. Available from: https://doi.org/10.13140/RG.2.2.36562.58560
3. FAOSTAT. FAOSTAT. Accessed 11 November 2020 (2020).
4. van Ittersum M. K., van Bussel L.G.J., Wolf J., Grassini P., van Wart J., Guilpart N. et al. Can sub-Saharan Africa feed itself? PNAS. 2016, 113 (52), 14964–14969. https://doi.org/10.1073/pnas.1610359113 PMID: 27956604
5. Stevenson J. et al. Farmer adoption of plot- and farm-level natural resource management practices: Between rhetoric and reality. Glob. Food Sec. 2019, 20, 101–104.
6. Tilman D., Balzer C., Hill J. E., Befort B. L. Global food demand and the sustainable intensification of agriculture. Proc. Natl. Acad. Sci. 2011, 108, 20260–20264. https://doi.org/10.1073/pnas.1116437108 PMID: 22106295
7. IPCC. IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems (SR2). Background report for the Scoping Meeting. 2017.
8. Lipper L., Defries R. Bizikova L. Shedding light on the evidence blind spots confounding the multiple objectives of SDG 2. Nat. Plants 6. 2020, 1203–1210. https://doi.org/10.1038/s41477-020-00792-y PMID: 33051617
9. Corbeels M., Naudin K., Whitbread A. M., Kühne R. Letourmy P. Limits of conservation agriculture to overcome low crop yields in sub-Saharan Africa. Nat. Food. 2020, 1, 447–454. https://doi.org/10.34067/KID.0000092020 PMID: 35368589
10. Kuyah S., Whitney C. W., Jonsson M., Sileshi G. W., Öborn I., Muthuri C. W. et al. Agroforestry delivers a win-win solution for ecosystem services in sub-Saharan Africa. A meta-analysis. Agron. Sustain. Dev. 2019, 8, 39–47.
11. Gram G. Roobroeck D., Pypers P., Six J., Merckx R., Vanlauwe B. Combining organic and mineral fertilizers as a climate-smart integrated soil fertility management practice in sub-Saharan Africa: A meta-analysis. PLoS One 15. 2020, e0239552. https://doi.org/10.1371/journal.pone.0239552 PMID: 32970779
12. Good A. G., Beatty P. H. Fertilizing nature: A tragedy of excess in the commons. PLoS Biol. 2011, 9(8). https://doi.org/10.1371/journal.pbio.1001124 PMID: 21857803
13. Lotter D. Facing food insecurity in Africa: Why, after 30 years of work in organic agriculture, I am promoting the use of synthetic fertilizers and herbicides in small-scale staple crop production. Agric. Hum. Values. 2015, 32, 111–118.
14. Acevedo M., Pixley K., Zinyengere N., Meng S., Tufan H., Cichy K. et al. A scoping review of adoption of climate-resilient crops by small-scale producers in low- and middle-income countries. Nat. Plants, 2020, 6, 1231–1241. https://doi.org/10.1038/s41477-020-00783-z PMID: 33051616
15. Editors. Evidence synthesis for sustainability. Nat. Sustain. 2020, 3, 41893.
16. Zilberman D., Zhao J., Heiman A. Adoption versus adaptation, with emphasis on climate change. Annu. Rev. Resour. Econ. 2012, 4, 27–53.
17. Feder G., Just R. E., Zilberman D. Adoption of agricultural innovations in developing countries: A survey. Econ. Dev. Cult. Chang. 1985, 33, 255–298.
18. Sunding D., Zilberman D. The agricultural innovation process. In Handbook of Agricultural Economics vol. 1, 2001, 207–261.
19. Foster A. D., Rosenzweig M. R. Microeconomics of technology adoption. 2010. Available from: http://www.econ.yale.edu/growth_pdf/cdp984.pdf
20. Pannell D., Zilberman D. Understanding adoption of innovations and behavior change to improve agricultural policy. Appl. Econ. Perspect. Policy, 2020, 42, 3–7.

21. Oca Munguia O. M., Llewellyn R. The adopters versus the technology: Which matters more when predicting or explaining adoption? Appl. Econ. Perspect. Policy, 2020, 42, 80–91.
22. Prokopy L. S., Floress K., Arbuckle J.G., Church S.P., Eanes F.R., Gao Y. et al. Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. J. Soil Water Conserv. 2019, 74, 520–534.
23. Pattanayak S. K., Mercer D. E., Sills E., Yang J. Taking stock of agroforestry adoption studies. Agric. Econ. 2003, 57, 173–186.
24. Bushman B. J., Wang M. Vote-counting procedures in meta-analysis. In The Handbook of Research Synthesis and Meta-Analysis (eds. Cooper, H., Hedges, L. & Valentine, J. C.) 632. Russell Sage Foundation. 2009.
25. Knowler D., Bradshaw B. Farmers' adoption of conservation agriculture: A review and synthesis of recent research. Food Policy, 2007, 32, 25–48.
26. Prokopy L. S., Floress K., Klotthor-Weinkauf D., Baumgart-Getz A. Determinants of agricultural best management practice adoption: Evidence from the literature. J. Soil Water Conserv. 2008, 63, 300–311.
27. Floress K. M., Gao Y., Gramig, Benjamin M., Arbuckle J. G.; Church S. P. et al. Meta-analytic data from agricultural conservation practice adoption research in the United States 1982–2018. 2019. Available from: https://doi.org/10.2737/RDS-2019-0011
28. Ruzzante S., Labarta R., Bilton A. Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. World Development, 2021, 146, 105599. https://doi.org/10.1016/j.dib.2021.107384 PMID: 34621923
29. Woodcock P., Pullin A. S., Kaiser M. J. Collaboration for Environmental Evidence Synthesis Assessment Tool (CEESAT) criteria and scoring guidelines for reliability of evidence reviews. 2014. Available from: https://www.environmentalevidence.org/wp-content/uploads/2014/09/CEESAT-Guidelines-1.pdf
30. Haddaway N. R., Bethel A., Dicks L. V., Koricheva J., Macura B., Petrokofsky G. et al. Eight problems with literature reviews and how to fix them. Nat. Ecol. Evol. 2020. Available from: https://doi.org/10.1038/s41559-020-01295-x
31. Rosenstock T. S., Lamanna C., Chesterman S., Bell P., Arslan A., Richards M. et al. The scientific basis of climate-smart agriculture: A systematic review protocol. CCAFS, Copenhagen. 2015. Available from: https://cgspace.cgiar.org/bitstream/handle/10568/70967/CCAFSWP138.pdf
32. Hedges L.V., Olkin I. Chapter 4—Vote-Counting Methods, Editor(s): Larry V. Hedges, Ingram Olkin, Statistical Methods for Meta-Analysis, Academic Press, 1985, 47–74, 1985.
33. Eswaran M., Kotwal A. Credit as insurance in agrarian economies, Journal of Development Economics, 1989, 31 (1), 37–53.
34. Vanlauwe B., AbdelGadir A. H., Adewopo J., Adjei-Nsiah S., Ampadu-Boakye T., Asare R. et al. Looking back and moving forward: 50 years of soil and soil fertility management research in sub-Saharan Africa. Int. J. Agric. Sustain. 2017, 15, 613–631. https://doi.org/10.1080/14735903.2017.1393038 PMID: 30636968
35. Pingali P. Green Revolution: Impacts, limits, and the path ahead. PNAS, 2012, 109 (31), 12302–12308. https://doi.org/10.1073/pnas.0912953109 PMID: 22826253
36. Piñeiro V., Arias J., Dürr J., Elverdin P., Ibáñez A. M., Kinengyere A. et al. A scoping review on incentives for adoption of sustainable agricultural practices and their outcomes. Nat. Sustain. 2020, 3, 809–820.
37. Baltenweck I., Cherney D., Duncan A., Eldermire E., Lwoga E. T., Labarta R. et al. A scoping review of feed interventions and livelihoods of small-scale livestock keepers. Nat. Plants. 2020, 6.
38. Fabregas R., Kremer M., Schilbach F. Realizing the potential of digital development: The case of agricultural advice. Science, 2019, 1328. https://doi.org/10.1126/science.aay3038 PMID: 31831641
39. Suri T., Jack W. The long-run poverty and gender impacts of mobile money. Science, 2016, 354 (6317), 4–9. https://doi.org/10.1126/science.aah5309 PMID: 27940873
40. Waddington H., Snilstveit B., Hombrados J., Vojtkova M., Phillips D., Davies P. et al. Farmer field schools for improving farming practices and farmer outcomes: A systematic review. Campbell Syst. Rev. 10. 2014.
41. Iiyama M., Neufeldt H., Dobie P., Njenga M., Ndegwa G., Jamnadass R. The potential of agroforestry in the provision of sustainable woodfuel in sub-Saharan Africa. Curr. Opin. Environ. Sustain. 2014, 6, 138–147.
42. Hussein K., Sumberg J., Seddon D. Increasing Violent Conflict between Herders and Farmers in Africa: Claims and Evidence. Development Policy Review, 1999, 17(4), 397–418.

43. Turner M.D., Ayantunde A.A., Patterson K.P., Patterson E.D. III Livelihood transitions and the changing nature of farmer-herder conflict in Sahelian West Africa. J Dev Stud. 2011, 47(2), 183–206. https://doi.org/10.1080/00220381003599352 PMID: 21495287

44. Higgins D., Balint T., Liversage H., Winters P. Investigating the impacts of increased rural land tenure security: A systematic review of the evidence. J. Rural Stud. 2018, 61, 34–62.

45. Ngwira A. R., Thierfelder C., Lambert D. M. Conservation agriculture systems for Malawian smallholder farmers: Long-term effects on crop productivity, profitability and soil quality. Renew. Agric. Food Syst. 2013, 28, 350–363.

46. Fox P., Rockström J., Barron J. Risk analysis and economic viability of water harvesting for supplemental irrigation in semi-arid Burkina Faso and Kenya. Agric. Syst. 2005, 83, 231–250.

47. Mehrabi Z., Gill M., van Wijk M., Herrero M., Ramankutty N. Livestock policy for sustainable development. Nat. Food. 2020, 1, 160–165.

48. Niles M. T., Brown M. E. A multi-country assessment of factors related to smallholder food security in varying rainfall conditions. Sci. Rep. 2017, 7, 1–11. https://doi.org/10.1038/s41598-016-0028-x PMID: 28127051

49. Wood S. A., Jina A. S., Jain M., Kristjanson P., DeFries R. S. Smallholder farmer cropping decisions related to climate variability across multiple regions. Glob. Environ. Chang. 2014, 25, 163–172.

50. Guido Z., Zimmer A., Lopus S., Hannah C., Gower, Waldman K. et al. Farmer forecasts: Impacts of seasonal rainfall expectations on agricultural decision-making in Sub-Saharan Africa. Clim. Risk Manag., 2020, 30, 100247.

51. Arnaud E., Laporte M.A., Kim S., Aubert C., Leonelli S., Miro B. et al. The ontologies community of practice: a CGIAR initiative for big data in agrifood systems, Patterns, 2020, 1.

52. Streletskaya N.A., Bell S.D., Kecinski M., Li T., Banerjee S., Palm-Forster L.H., Pannell D. Agricultural Adoption and Behavioral Economics: Bridging the Gap. Applied Economic Perspectives and Policy, 2020, 42: 54–66.

53. Leventon J., Abson D.J., Lang D.J. Leverage points for sustainability transformations: nine guiding questions for sustainability science and practice. Sustain Sci. 2021, 16, 721–726.