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Abstract

A major challenge for countries dealing with conflict and instability is encouraging the use of farming technologies and natural resource management practices that are climate-smart. These practices boost productivity, build resilience to climate challenges and thus contribute to other dimensions of resilience such as those associated with conflict. In this review and meta-analysis, we assess factors associated with farmers' adoption decisions for such technologies and practices. We use advanced machine learning tools to analyze over 42,000 published papers. Focusing on countries identified as fragile due to either climate shocks or conflict, we select 109 papers and extract 1330 coefficients and implement partial correlation coefficient analysis. Our findings show that most of the research comes from two countries; Ethiopia and Nigeria and we do not find any studies from Small Island States. We categorized the technologies into five technology groups, including soil health, erosion management, mechanization, input use and risk reduction technologies. Analysis reveals that factors such as farmer training, access to information, subsidies, and past experiences of using technologies predicts further technology adoption. However, there are significant differences across various technology groups and most especially, a very low coverage of risk-reduction technologies such as insurance.

JEL-Codes: Q12, Q16, Q20

Keywords: Agriculture technology adoption, climate change, fragility, determinants

November 2024

** Emmanuel Nshakira-Rukundo, RWI, Apata Insights, and ILR Bonn; Martin P. Jr. Tabe-Ojong, World Bank and DiMTEC; Bisrat H. Gebrekidan, CIMMYT, Apata Insights, and ILR Bonn; Monica Agaba, KU Leuven; Subash Surendran-Padmaja, ZEF; Boubaker Dhehibi, ICARDA.* *– This work was undertaken as part of the CGIAR Research Initiative on Fragility to Resilience in Central and West Asia and North Africa. The CGIAR Initiative on Fragility to Resilience in Central and West Asia and North Africa (F2R-CWANA) is building resilient agrifood systems that can withstand the impact of climate change, generate economic opportunities, and deliver better incomes and livelihoods for rural communities in the region. Other CGIAR centres participating in initiative include the International Center for Agricultural Research in the Dry Areas (ICARDA), Alliance of Bioversity and CIAT and the International Water Management Institute (IWMI). We would like to thank all funders who supported this research through their contributions to the CGIAR Trust Fund: https://www.cgiar.org/funders/. All usual caveats apply.* *– All correspondence to: Emmanuel Nshakira-Rukundo, RWI, Hohenzollernstraße 1–3, 45128 Essen, Germany, e-mail: erukundo@rwi-essen.de*

1. Introduction

Increasing agricultural productivity and maintaining environmental sustainability are two important and seemingly complementary sustainable development goals[1,2]. The adoption of natural resource management practices (including for instance various climate-smart agriculture, sustainable intensification, conservation agriculture, agroforestry, and carbon farming among others) influences both agricultural productivity and environmental sustainability[3–5]. However, the adoption of practices has been extremely low and varying in many developing countries[6–8] and more so in those countries under different dimensions of fragility. Missing markets, market imperfections, productivity, and supply-side constraints have been identified as some of the constraints limiting the adoption of some of these CSA practices[9–11]. Lack of profitability including heterogeneous profits with some farmers benefiting more than others also matters[11]. Also, poor rural infrastructure may lead to high transaction costs, lowering adoption[11]. Lack of adequate and timely information, education, and training[12] are some of the factors constraining the adoption of these practices among smallholder farmers. Some reviews have been undertaken to synthesise the evidence of these practices and their impacts as a way of improving learning on the adoption[13–15]. While these reviews are extensive and improve our understanding of technology adoption, there remain knowledge gaps regarding geographical coverage and more importantly issues of external validity and conceptual understanding. Moreover, none of the existing reviews examine the context of conflict and fragile settings regarding their adoption experiences. We apply state-of-the-art machine learning to support our literature selection and conduct descriptive and meta-analysis on the determinants of the adoption of a range of agricultural technologies and sustainable natural resource management practices in fragile and conflict-affected settings. Our definition of agricultural technologies follows from Rosenstock et al [16] who defined agricultural technology as agriculture and food systems that sustainably increase food production, improve the resilience (or adaptive capacity) of farming systems, and mitigate climate change. These are new methods and practices that are introduced to farmers either externally (from an external source/ provider) or internally (from farmers' local expertise and processes), aimed at improving agricultural outcomes and retaining objectives of sustainable agricultural production systems. We categorise these technologies into five categories, namely: (1) soil fertility improvement, (2) erosion management, (3) mechanisation, (4) inputs and (5) risk reduction technologies.

Our work builds on a few existing reviews[13,14,17,18](See Supplementary Table 1 for a list of other related reviews), and also makes a key contribution of focusing primarily on fragile and conflict-affected settings around the world, which none of the other reviews tackle. Fragility is defined as a systemic condition or situation characterized by an extremely low level of institutional and governance capacity which significantly impedes the state's ability to function effectively, maintain peace, and foster economic and social development [19]. To this end, fragility might emanate from political and non-political situations including climate stress. Thus, several Small Island States are some of the most vulnerable to fragility [20]. Conflict and climate-induced fragility might co-exist as it is in several Sahelian/West African countries [21,22]. Therefore, focusing on these geographical areas is important as these countries are likely more exposed to the adverse effects of climate change such as higher risk of food insecurity and other adverse welfare conditions [23,24]. Of note, none of the previous reviews (see Table S1 in the Appendix) have studied this specific group of countries and only one [25] focuses on sub-Saharan

Africa. Indeed, there can be a potential black hole scenario of technology adoption and impact regarding "farmers in crises", where household welfare and poverty are affected by conflicts, climate shocks, or both [24,26]. Moreover, apart from Ruzzante et al[18], none of the reviews implement a meta-analysis and therefore do not show how different determinants might influence technology adoption differently.

2. Methodology

2.1. Thematic scope of the review.

Our classification of agricultural technologies largely relies on Rosenstock et al[16]. We create five categories, namely; (1) inputs, which include improved seeds (such as climate-resilient seeds, pest-resistant seeds, drought-resistant seeds, and genetically modified seeds) and pesticides and herbicides; (2) soil fertility management technologies. Technologies assessed here include those that organically replenish soil fertility such as mulching, organic fertiliser use, crop residue use, inter-cropping, and agroforestry as well as chemical fertilisers. The third type of technologies include erosion management techniques including conservation farming, soil bunds, contour ploughing, rock bunds and tillage. These technologies and practices broadly include those aimed at controlling the flow of water, maintaining soil stability, controlling sedimentation as well as managing and maintaining optimal watersheds [46]. The fourth category is mechanisation technologies which include the introduction of new and advanced equipment in farm activities such as tractor use, irrigation, treadle pumps, precision farming, water storage and water harvesting, and improved grain drying techniques, among others. The fifth category includes risk reduction technologies mainly agricultural insurance and risk contingent credit.

2.2. Geographical scope

Our scope is limited to countries which are categorised as in fragile and conflict-affected settings. The definition of FCA countries is based on the World Bank's classification [19,47], which categorises FCA countries as (1) facing high-intensity conflicts (>10 per 100,000 individual conflict deaths) (2) medium-intensity conflicts, or (3) those with a minimum Country Policy and Institutional Assessment (CPIA) score of 3 or the presence of non-international UN peacekeeping operation or countries from which more than 2000 per 100,000 individuals are refugees. Conflict deaths are measured by the ACLED and UCDP Uppsala criteria and datasets. We used the World Bank list of FCA countries covering 2006 to 2022, excluding Ukraine. We considered papers published between 2000 and 2023 in the English language.

2.3. Types of studies

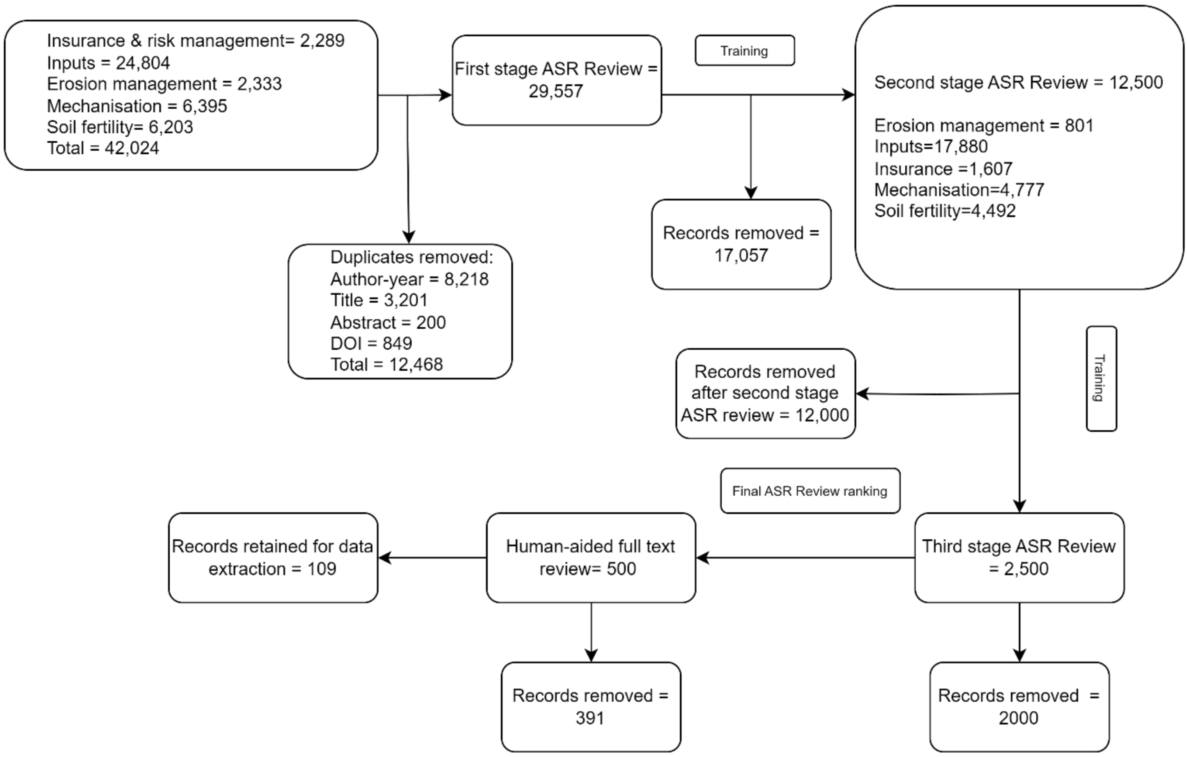
We include quantitative studies that address and examine the determinants of technology adoption and natural resource management. The selected studies include both cross-sectional and panel studies that conduct predictive analysis of determinants of technology adoption.

2.4. Literature search and selection

We conducted an initial search of Web of Science and Scopus, from which we extracted 42,024 records. To process all these data, we employed a machine learning-driven process to improve our efficiency in the literature selection process. Specifically, we used ASReview [48], a Python-based open-source and transparent algorithm for literature selection. Our machine learning data selection process was in two stages. First, we combined Scopus and Web of Science results into one sheet. We then run an R-script to remove duplicates. Duplicates include a combination of author-year-title, title, abstract, and digital object identifier (doi). We also removed studies that did not have an abstract. At this stage, we were able to remove 30% of records in adoption and about 36% of the studies on impact.

The second stage machine learning strategy includes training and running the ASReview model. For each of the groups of the studies, we hand-selected (after reading their abstracts) between 20 and 30 studies that met the inclusion criteria. We then use them as the training dataset such that the ASR Review model ranks papers according to how best they meet the preference of the training dataset. Four reviewers (BHG, ENR, MA, CA) conducted this selection of the training dataset and agreed on all the inputs therein. Where there was some disagreement, we used majority voting to decide if the paper was included in the training dataset or not. Using the training data, we re-run a second-stage ASReview which helps us to further drop 12,000 records and retain only the top 500 records in each category – altogether 2500 records. Using this dataset, we conduct another training and selection procedure similar to the one before. Re-running the selection script, we select only the top 100 ranked records in each technology category, altogether 500 records for full-text review. Figure 1 below shows the PRISMA flow chart of the literature search and selection process. Throughout the process, two researchers (BHG and EN-R) conducted the ASR screening and two researchers (EN-R and MT-O) did quality assurance through code review. MA and SS entered data into SurveyCTO, EN-R, SS and BHG conducted the initial analysis, and MT-O and DB supervised the whole project.

Figure 1: PRISMA for Adoption of Climate Smart Agricultural Technologies



Data from the 109 studies were extracted and aggregated using a questionnaire (see Supplementary Materials) designed on SurveyCTO, a data collection platform. The questionnaire captured the following study characteristics: year of publication, number of authors, and the study country. Where the study covered multiple countries, each country was entered as an individual study. We further collected the sample size of the studies, whether the study was nationally representative or not. We list the technology under study and its adoption rate. Technologies are categorised into groups as described above. For the adoption dimension of this review, we assessed the results of the studies and extracted all determinants of the technology adoption. For each of the determinants of technology adoption, we extract coefficients, standard errors, and p-values. Altogether, we collected 1330 coefficients were extracted.

2.5.Data Analysis

To assess the determinants of technology adoption, first, we explored various dimensions of descriptive analysis. As mentioned in the data extraction section, we recode all coefficients that were statistically significant predictors for adoption – whether in the positive or negative dimension. We categorise all the coefficients into 21 groups and summarise their mean effect to assess their contribution to adoption. We use Sankey diagrams to visualise the relationships and the strength of the relationship between each of the predictors with the five pre-specified technology groups.

We then used meta-regression, a weighted least-square regression that accounts for within-study sampling variance. Following recent studies [18,49], we estimate the partial correlation coefficients of the characteristics for overall technology adoption and each of the five technology categories. We then used a mixed-effect meta-regression with characteristics determining adoption as a fixed-effect model with a hierarchical structure accounting for with-in-study variations. The mixed effect meta-regression allows us to estimate the true effects due to variability in the observed characteristics and type of technology. The predicted values of the mixed-effect meta-regression can be interpreted as the mean effect size across studies. The empirical form of meta-regression is given as follows:

$$Y_{ij}^{*} = \gamma_{ij} M_{ij} + \varepsilon_{ij}$$

where Y_{ij}^{*} is the estimated expected value of i^{th}predictor variable for the j^{th} technology type, Mij is the vector of moderators (characteristics) and γ_{ij} is the vector of the coefficients and ε_{ij} is the error term. For Y_{ij}^{*}, we estimated the partial correlation coefficient (PCC) using the formula:

$$PCC_i = \frac{t_i}{\sqrt{t_i^2 + df_i}}$$

The standard error of the PCC is calculated as follows:

$$SE_i = \sqrt{(1 - PCC_i^2) / df_i}$$

The advantage of using the standard error of the PCC instead of a coefficient estimate is that it standardizes the coefficient across studies. In case of this lack of uniformity in the metadata extracted, the partial correlation coefficient is the preferred method that allows to relative comparison of the strength between variables and an outcome given the presence of other variables (other determinants) [18,49]. There are several benefits of using PCCs. First, PCCs are unitless measures and therefore allow partial correlations from multiple different studies to be compared to each other [50]. Moreover, partial correlations can be computed from a larger set of estimates and studies than other effect size measures, and yet the interpretations remain straightforward to understand [50]. For its advantages, PCC has been the preferred method for meta-analysis in technology adoption studies [18,49] and overall in other applied disciplines. We used the R package *metafor* [51] to estimate the mean effect size by the characteristics. The weights for the regression are estimated using the formula:

$$W_j = \frac{1}{\left(\hat{\tau}^2 + s_j^2\right)}$$

where s_j^2 is the estimate of the sampling variance σ_j^2 of the j^{th} study and $\hat{\tau}^2$ is an estimate of the inter-study heterogeneity τ^2. Several studies did not record standard errors and instead reported t-statistics or z-statistics. In such cases, these statistics were recorded and standard errors were computed using standard conversion formulas.

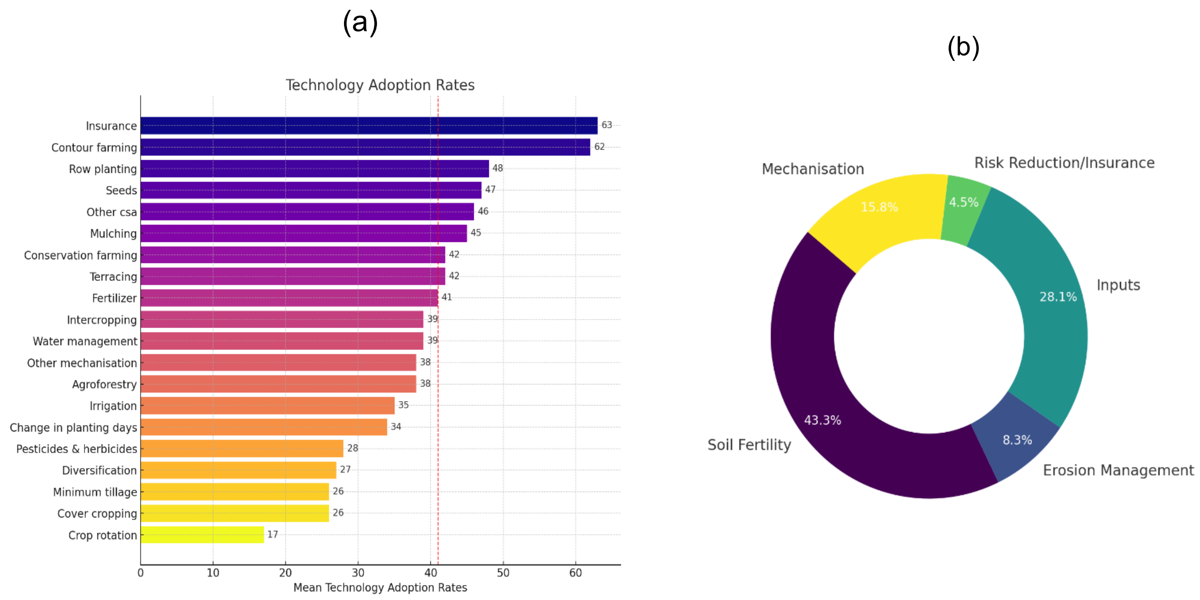
3. Results

3.1. Literature Description

The number of studies reviewed increased from 2 studies in 2001 to about 50 studies in 2022 (Supplementary Figure 1). About 90% of studies reviewed were published after 2017. The geographical coverage of the studies was not diverse. Of all the studies included in the review, 61% (67 studies) are from Ethiopia and an additional 20% (22 studies) are from Nigeria implying that about 82% of all the studies reviewed are from only 2 countries (Supplementary Figure 2). From 109 studies, 20 unique technologies were recorded. The most common technology was the use of improved seeds and fertilizers. We combine all types of improved seeds including hybrid and drought-resistant varieties and high-yielding varieties among others. The least common technologies were cover cropping recorded only once, contour farming, mulching, and row planting each recorded in only two studies.

The average adoption rate for all technologies was about 41.2%. Figure 2 (a) shows the mean rates per technology category. The technology with the highest adoption levels was insurance with a 63% adoption rate. However, as we observe further, insurance was one of the least observed technologies, found in only 9 of the 109 studies. Other highly adopted technologies were contour farming, row planting, and the adoption of improved seeds. On the lower end of the adoption spectrum, crop rotation had an adoption level of only 17%, and crop covering and minimum tillage both had adoption levels of only 26%. Figure 2 (b) shows the proportion of coefficients by technology type. About 43% were associated with the adoption of soil fertility-improving technologies. An additional 28% of the coefficients were associated with inputs, 16% with mechanisation technologies, and slightly more than 8% of the coefficients were associated with erosion management technologies. Risk reduction and insurance technologies had the smallest proportion of determinants, about 4.5%.

Figure 2: (a) Technology adoption rates for 20 unique technologies. (b) Proportion of coefficients by technology type



We categorised all the 1330 coefficients into 35 determinants/dimensions/ characteristics. Figure 3 shows the number of coefficients for each determinant by technology type. Overall, extension services, land size, social capital, and education were the most prevalent characteristics extracted from the literature. Contract type, seasonal difference, health status, and marital status had the fewest coefficients from the literature.

To further explore descriptive associations of each determinant with various technologies, we employ Sankey graphs. Figure 4 shows the relationship between all the 35 determinants/ characteristics and the various technology types mediated by the direction of the relationship. The most prevalent determinants were extension services and land size, social capital, education, and age. Others include distance to markets (thus the importance of spatial access to technologies), gender, and household size. Households with more individuals are more likely to have higher adoption levels due to the labour availability. Credit access savings and income were also found to be important predictors. Overall, credit, costs and income all relate to households' affordability and capacity to demand. On the other end of the spectrum, we observed that some characteristics that would otherwise be thought to be major predictors were instead not as much as would be predicted. Subsidies, other employment, previous and existing experience of inputs farm management practices, and the presence of markets were some of the characteristics with low representation in our sample. Of the characteristics that are particularly surprising in how less they show up in our sample are subsidies, which were recorded in only nine studies. The literature on the importance of subsidies in low-income countries especially for poor farm households is well established [27–29]. However, what seems to be vivid here is the capacity of poor, conflict-affected countries to provide subsidies to their farmers. Similarly, mechanisation appeared in only 13 studies with only 24 coefficients.

Figure 3: Number of coefficients by technology type

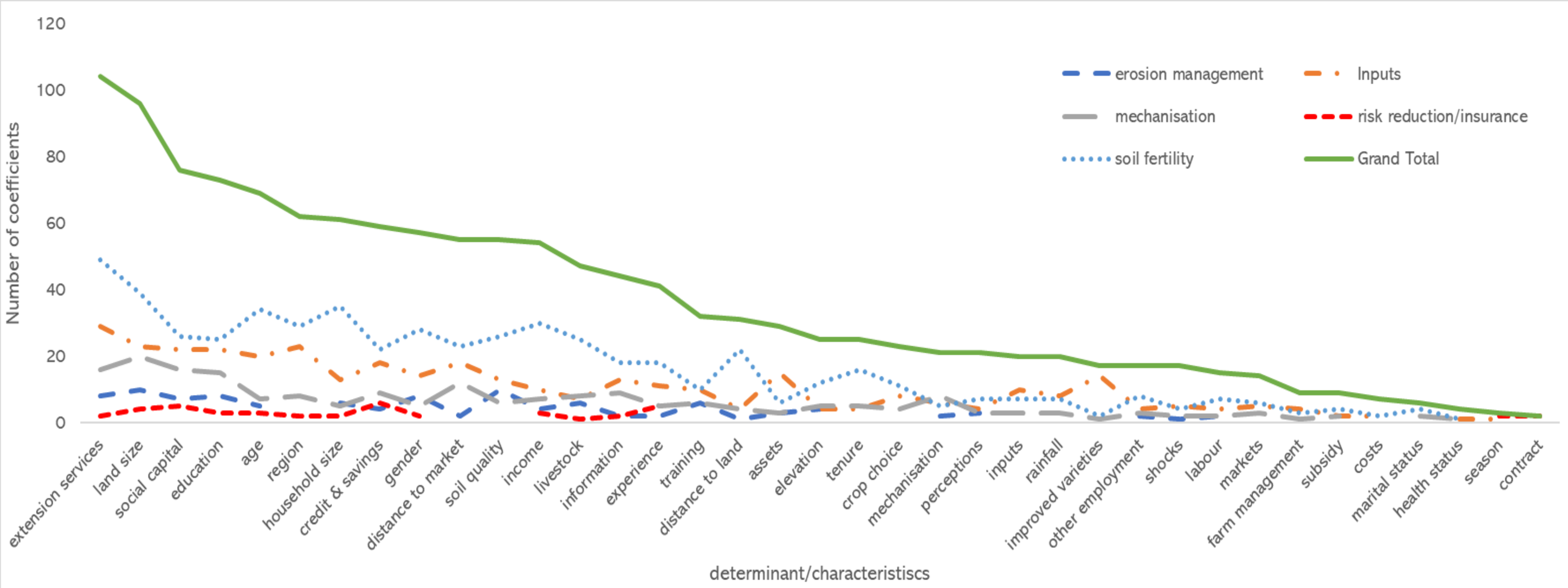
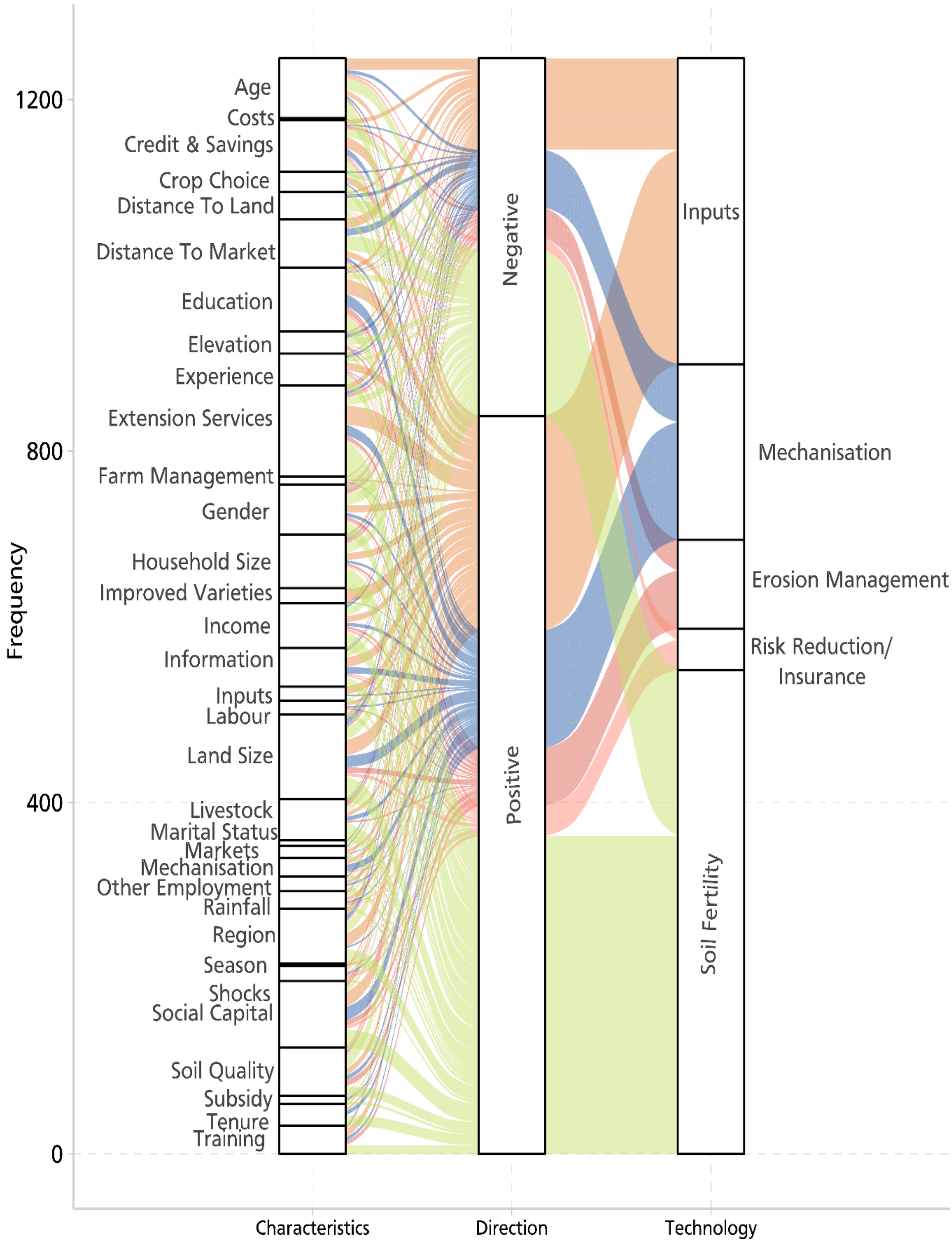


Figure 4: Sankey diagram of relationships and weight/strength of relationships between determinants and technology types



3.2. Univariate Partial Correlation Coefficients of Technology Adoption

Figure 5 shows divergent bar plots emanating from univariate partial correlation coefficient analysis to visualize the partial correlation for the association of each of the 32 determinants across the technology types. Sub-figure (a) is for overall correlations and (a-f) corresponds to technology adoption for each of the 5 technology categories. All the coefficients are standardised by their standard errors and weighted by the sample size of the study from which they are extracted. From sub-figure a, almost all determinants have both negative and positive correlations, implying that a more refined look into how each determinant might influence technology adoption is important. Secondly, it could also imply that increasing the availability of a given characteristic does not necessarily increase adoption levels considering how other characteristics behave. Our findings here are similar to those of Arslan et al[30] who also found positive and negative correlations for almost all characteristics. However, ours on average are of a greater magnitude, which underscores the special situations of countries with violence and climate fragility. In the overall correlation, (Figure 5 (a)), the characteristics with the greatest negative correlation with adoption were other employment and availability of markets. For these two, their negative Partial Correlation Coefficients (PCCs) were larger than their positive PCCs.

Other characteristics with negative correlations were mechanisation, labour availability, training, subsidy, education, and income. However, these characteristics also have generally higher positive PCCs. Indeed, from the positive side of the scale, labour availability had the largest PCC (0.21) overall. Other determinants with higher positive partial correlations were inputs, improved varieties, soil quality, farm management experience, training, and provision of subsidies. Inputs and improved varieties are generally path-dependent. Households/ farmers who have used improved technologies are more likely to use them in the future. In addition, farmers evaluate ecological and other physical conditions to support adoption. Among these, soil quality had the highest PCC though elevation, rainfall and season also featured. Next, we look into the five technology categories separately and show the results in Figure 5 (B-F).

Soil fertility management technologies

Figure 5 (b) shows the PCC coefficients for soil fertility management technologies. Having other employment, presence of markets, farmer experience, presence of other mechanisation technologies, and farmer education all have a negative PCC greater than 0.2. In each of these determinants, the positive PCC was always lower than the negative PCC implying that a bulk of their contribution to soil fertility technology adoption was more negative than positive. Farm management and provision of subsidies, inputs, labour, and rainfall had relatively higher PCCs with farm management and subsidies having PCCs greater than 0.2.

Information availability and provision, training (different from extension services), inputs, and shocks had only positive PCCs. One of these – shocks, potentially requires additional context. While shocks are a negative input into farmer welfare, they might spur the adoption of shock mitigation technologies. For instance, the emergency of ecological shocks like crop pests and diseases was associated with the increase of fertiliser use in Ethiopia[31]. Shocks such as droughts might also be associated with increased fertiliser use with farmers attempting to recover lost production.

Erosion management technologies

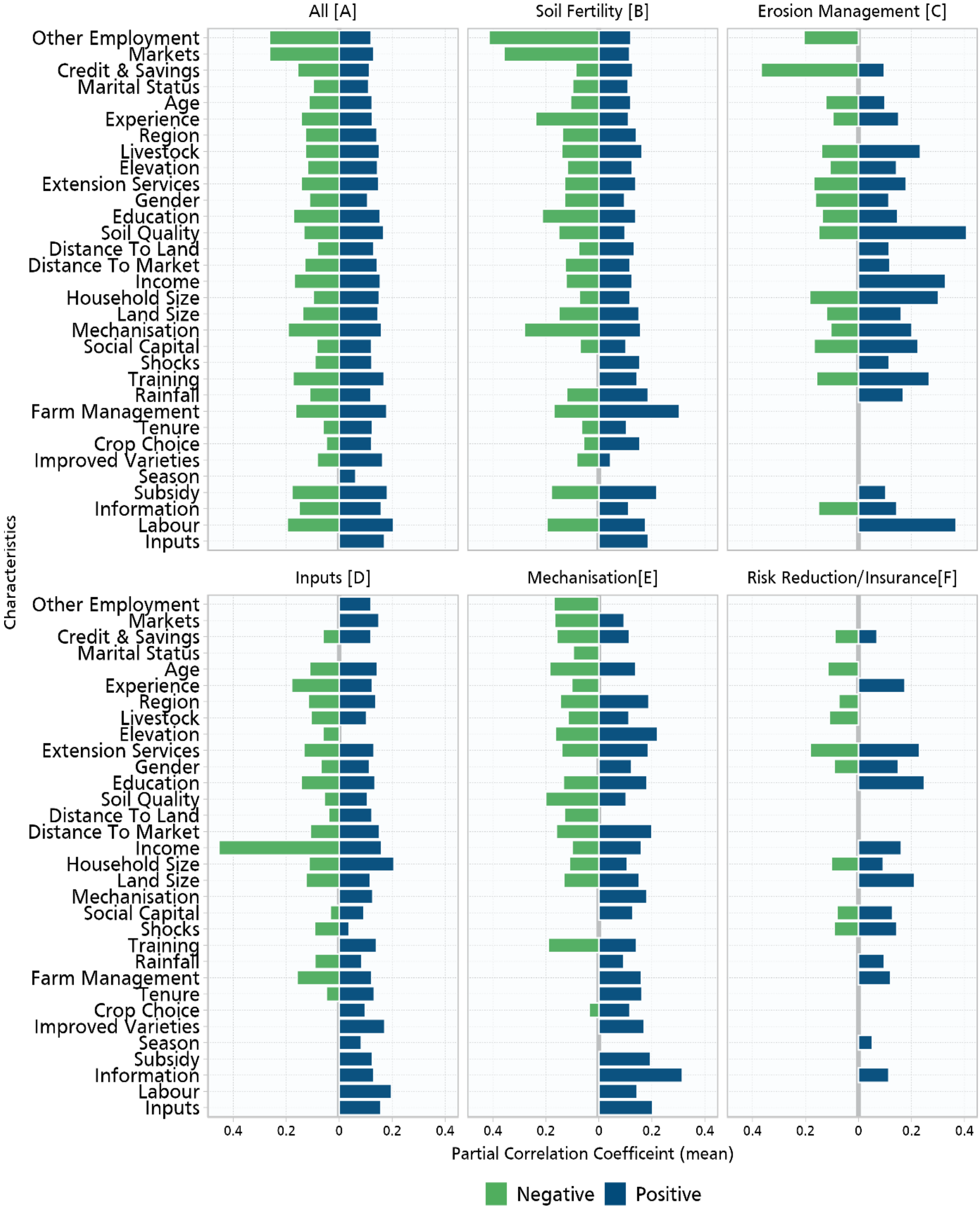
Figure 5 (c) shows the determinants of erosion management technologies. Compared to how the same characteristics are associated with soil fertility technologies, we find that correlations with erosion management are of a smaller magnitude overall, with only one characteristic having a larger negative PCC. Credit and savings had a PCC of about 0.38 while having other employment had a negative PCC of about 0.2. All the other characteristics have either positive PCCs only or their positive PCCs were larger than their negative correlations. Labour availability, income, rainfall, distance to markets, shocks, distance to agricultural land, and subsidies all had positive correlations only. However, the largest positive associations are from soil quality (0.41), labour (0.37), income (0.35), and household size (0.34). Training, mechanisation, livestock ownership, and social capital also have partial correlation coefficients higher than 0.2.

Input technologies

Figure 5 (d) depicts the PCCs for input technologies, specifically chemical fertilisers and pesticides. Compared to the overall correlations (Sub-figure (a)) or Sub-figures (b) and (c), we observe that more characteristics have only PCCs and the majority of the characteristics have larger positive PCCs than their negative dimensions. Improved varieties, availability of labour, other inputs, availability of markets, training, information provision, mechanisation, subsidies, other employment, crop choices, and season of growing all had positive PCCs only. The coefficients for labour and household size are particularly high (at about 0.2) and likely correlated in that they both give an idea about the amount of labour at the households' disposal either for hire or unpaid family and exchange labour. Overall, income has the largest PCC which enters mainly in a negative dimension (0.45). Increasing household income might likely offer households more economic options, which might include moving out of the agricultural sector – hence reducing technology adoption. However, income, on the other hand, had a high positive PCC (about 0.17). The importance of income cannot be understated in enabling farmers to purchase/ adopt inputs or potentially leading them out of the sector.

Finally, we highlight experience, extension services, education, and land size from a negative dimension. Increasing adoption of technologies implies somewhat complex resource optimisation for poor households. In some dimensions, therefore, accumulation (or any increase) of one characteristic/attribute might reduce the propensity to adopt the technology if the attribute provides some substitutionary value. Experience, income, household size, farm management, and extension services are attributes that might increase productivity potentially in a similar way as inputs would or when the cost of inputs is high. Land size fits into the category of an attribute that might increase the costs of technology adoption and hence increasing it can be negatively correlated to the adoption of input technologies.

Figure 5: Average association of composite determinants of adoption



Mechanisation technologies

Figure 5 (e) shows the PCCs for mechanisation technologies, specifically irrigation and the use of heavy equipment such as tractors. Regarding mechanisation technologies, we observe fewer characteristics that are negatively associated with other technologies. Of the 31 characteristics correlated with the adoption of mechanisation technologies, about 35% (11/31) had correlations of only positive PCCs. This was the highest proportion among the five technology categories studied. Of these, access to information stands out with a PCC> 0.3. This was the highest correlation among all the determinants of mechanisation technology adoption, whether from a positive or negative dimension. Using other inputs also had a high PCC (0.2). About 48% of the characteristics (15/31) had PCC correlations of both a negative and positive dimension. Farmers must evaluate the suitability of their land for the adoption of mechanisation. Where the land is not suitable, for instance, elevation of soil stability, farmers are unlikely to make substantial investments. Marital status had only a negative PCC. Individual studies might find opposing results on marital status and the more succinct characteristics might be the level of level of empowerment and decision-making power between partners in a household. The long-standing evidence is that women with less decision-making power in their households and yet engaging more in agricultural activities are less likely to make key agricultural investment decisions[32,33] and these might include those related to climate-adaptive strategies [34].

Insurance and risk management technologies

Finally, insurance and risk management technologies (Figure 5 (f)) had the least presentation in our review with only 4.3% coefficients featured in our dataset. This already shows how underrepresented and underutilised these technologies are. The main technology under this category is agricultural insurance (livestock and crop insurance) and related technologies such as risk contingent credit. Only three countries (Ethiopia, Myanmar, and Nepal) are represented in our sample, altogether contributing only 9 out of the 109 studies. Figure 5 (F) shows the results for the univariate PCC for insurance technologies. Education, extension services, and land size had the largest positive PCCs (>0.2). In general, agricultural insurance, despite its promise and sometimes proven usefulness, has not received commensurate demand in low-income countries[35]. Low education and lower literacy are some of the reasons for the low uptake of insurance because insurance contracts are often complicated to explain and understand. Therefore, where these technologies are available but are not correctly understood by the target market, demand remains low. The correlation here therefore aligns with others who observe how much education improves potential demand. Holding affordability constant (income PCC +0.16), farmers with larger land sizes are likely to demand insurance (PCC 0.21). Farmers with more land are likely to extensively use it and therefore expose themselves to higher losses in case of a climate shock. For these farmers, insurance demand is high. Considering the income limitations of rural farmers, and later on rural farmers in conflict settings, subsidies would increase demand substantially. However, we do not observe any coefficients on subsidies for insurance adoption. In a non-FCA setting, premium discounts have been used to increase demand [36].

3.3. Multivariate Partial Correlation Coefficients Meta-Regression for Technology Adoption

Next, we conduct multivariate PCC analysis to explain how each aggregate characteristic was associated with the adoption of technologies holding the contribution of other characteristics constant. In this analysis, about 246 coefficients were dropped from the regressions due to missing standard errors, p-values, or t-values. Figure 6, shows PCC regression results of all combined technology adoption (Sub-Figure (a)) and the five technology types with five other sub-figures corresponding to the various technologies. In each of the sub-figures, the colour coding is for characteristic dimensions (i.e. (a) demographics, (b) institutional factors, (c) inputs, (d) spatial, (e) biophysical and (f) institutional factors) (See Supplementary Figure 4). The numbers in the coefficient plots are the number of observations per characteristic. Where the number of observations is low it is advisable to interpret the findings with some caution as the result might be driven by insufficient data. The PCC meta-regression controls for a dummy for Ethiopia, and four dummies for the years 2000-2010, 2011-2015, 2016-2020, and 2021 – 2022, number of authors, sample size, dummy for land, and the type of analytical method used in the paper as well as age of the farmer (usually household head) which is the base variable.

Socioeconomic determinants: Socioeconomic determinants cover a wide range of characteristics that measure a household's socioeconomic standing. We include household wealth (assets), livestock, land size, income, subsidy and other employment in this category. Overall, these characteristics are positively correlated with adoption. Figure 6 (a) shows the results. Receiving a subsidy was positively correlated with overall adoption, (PCC 0.12; 95% CI: 0.019 - 0.225); having livestock (PCC 0.075; 95% CI: 0.019 - 0.131) and income (PCC 0.05; 95% CI: -0.006 - 0.109) were positively correlated with adoption. However, for the various technology types, subsidies are not statistically significantly correlated with any adoption. This is partly because there are only a few observations in each technology category. For livestock ownership, we observe significant associations with soil fertility-improving technologies (PCC 0.077; 95% CI 0.002 - 0.153) and inputs (PCC 0.139, 95% CI 0.013 - 0.267). Livestock can be complementary and a source of soil fertility-improving technologies such as manure/ organic fertilizer. In addition, livestock ownership is a proxy for household wealth and capacity to demand, which also might increase input use. Income was positively correlated with erosion management (PCC 0.345; 95% CI 0.087 - 0.604) and insurance (PCC 0.344; 95% CI 0.066 - 0.622).

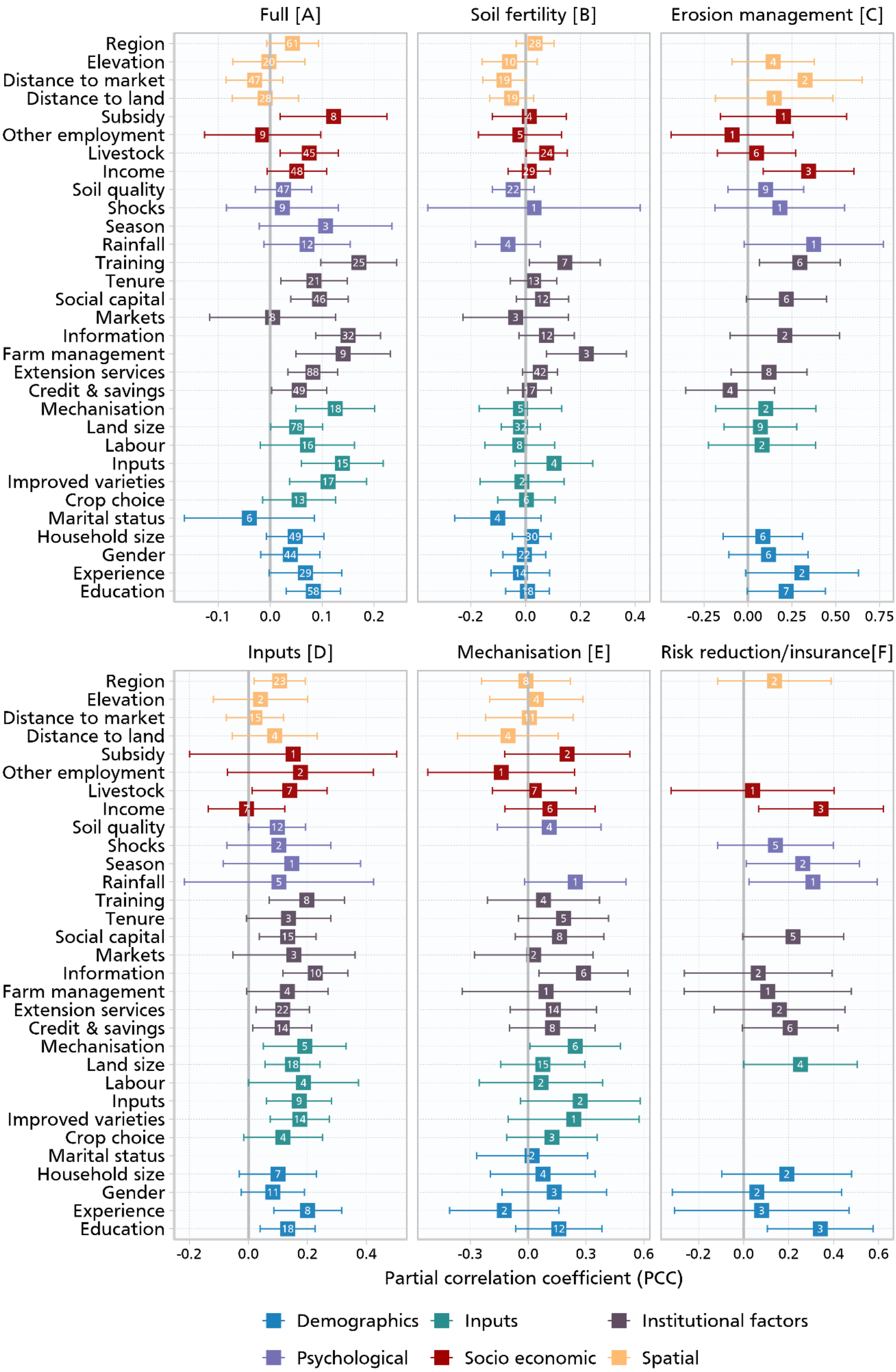
Demographic determinants: Age, education, gender, marital status, and household size were the determinants categorised as demographic. The age of the farmer (usually the household head) is the base variable therefore it does not show up in the results. Education was significantly correlated (PCC 0.083, 95% CI 0.031 - 0.136) with overall adoption and remained significantly correlated with erosion management technologies (PCC 0218, 95% CI -0.005 0.442), inputs (PCC 0.133 95 % CI 0.039 - 0.226) and insurance (PCC 0.341 95 % CI 0.105 - 0.576). It is therefore one of the major predictors across most technologies. Farmer's experience was also strongly associated with overall adoption (PCC 0.068; 95% CI -0.002 - 0.138), and with erosion management (PCC 0.301, 95% CI -0.014 - 0.630), and inputs (PCC 0.201; 95% CI 0.086 - 0.316). To some extent, experience and education are connected through the capacity of the farmer to learn and apply new information and knowledge in their farming practices.

Biophysical determinants: We categorised weather shocks, rainfall, soil quality, and season of planting as the biophysical determinants. Of these, while soil quality has the largest number of observations entering the model (n=47), it was not a strong correlate in the overall analysis (Figure 6 (a)) but was significantly correlated with inputs (PCC 0.098, 95% CI 0.001 - 0.194). This is of course not surprising. Farmers are likely to adopt inputs considering their soil quality. Elsewhere, seasons (PCC 0.263; 95% CI 0.011 - 0.515) and rainfall (PCC 0.309; 95% CI 0.024 - 0.594) were strong predictors of risk insurance technologies. Rainfall was also significantly correlated with mechanisation (PCC 0.244, 95% CI -0.019 - 0.508).

Spatial determinants. Biophysical factors can have strong perceivable relationships with spatial factors such as elevation and regional variation. Other spatial determinants included distance between households and plots of land and distance to markets. Apart from regional differences (PCC 0.043, 95% CI -0.007 - 0.093), all the other factors were not significantly associated with overall adoption. Regional differences were also correlated with input technologies (PCC 0.106 95% CI 0.019 - 0.193). Distance to markets was negatively correlated with soil fertility technologies (PCC -0.080, 95% CI -0.157 -0.003) but positively correlated with erosion management technologies (PCC 0.323; 95% CI 0.001 - 0.651). The finding here implies that there is a financial cost to soil fertility technologies (e.g., buying fertilizers) and greater distances in accessing markets reduced adoption. On the other hand, farmers are likely to invest in less costly erosion management technologies (e.g., mulching, cover cropping etc) when access to markets is curtailed.

Institutional determinants: Institutional determinants enhance a household's capacity to respond, especially using institutionally acquired information/ knowledge or 'out of the household' support. In these, we include access to information, potentially learned farm management methods, availability and access to markets, social capital, land tenure, availability of credit & savings, extension services, training, and contract structure especially for insurance technologies. Availability of credit and savings (PCC 0.056 95% CI 0.003 - 0.109, extension services (PCC 0.082, 95% CI 0.034 - 0.130), farm management (PCC 0.141 95% CI 0.050 - 0.231), access to information (PCC 0.150, 95% CI 0.088 - 0.212), social capital (PCC 0.095 95% CI 0.039 - 0.150), land tenure (PCC 0.084, 95% CI 0.020 - 0.149) and training (PCC 0.171, 95% CI 0.098 - 0.244) all were correlated with technology adoption.

Figure 6: Partial Correlation Coefficients for the Effect of Characteristics on Technology Adoption



Training and access to information had the largest correlations not only among institutional factors but also across all the characteristics, further underlining their usefulness. Farm management (PCC 0.223, 95% CI 0.077 - 0.368) and training (PCC 0.143, 95% CI 0.013 - 0.273) were significant correlates of soil fertility technologies. For erosion management technologies, social capital (PCC 0.219 95% CI -0.010 - 0.448) and training (PCC 0.296 95% CI 0.066 - 0.526) were significant correlates. Institutional factors were important determinants of input technologies. Apart from access to markets, all characteristics in the model were significant determinants of input technology adoption. Credit and savings (PCC 0.115; 95% CI 0.014 - 0.215), extension services (PCC 0.116; 95% CI 0.025 - 0.207), farm management practices (PCC 0.132, 95% CI 0.006 - 0.270), access to information (PCC 0.227; 95% CI 0.117 - 0.337), social capital (PCC 0.133; 95% CI 0.037 - 0.229), land tenure (PCC 0.135; 95% CI -0.007 - 0.279) and training (PCC 0.198; 95% CI 0.071 -0.325) were all positively correlated with input technology adoption. The finding that markets were not statistically significantly correlated with adoption is perhaps surprising but could be explained by the limited number of studies entering the model. Information access (PCC 0.289; 95% CI 0.057 - 0.518) was the only institutional determinant statistically significantly correlated with mechanisation technologies. Regarding risk reduction technologies, credit and savings (PCC 0.207; 95% CI -0.006 - 0.419) and social capital (PCC 0.220; 95% CI -0.004 - 0.444) were the significant correlates. Overall, we find social capital one of the most important institutional factors as it was significantly correlated with adoption in 5 of the 6 PCC regressions. Social capital underlines that farmers learn from their networks [37–39] and technologies targeted through centralised networks are likely to attain higher adoption.

Inputs: Input technologies include land size, labour, seeds and fertilizers (inputs) improved crop varieties, and crop choice. For clarity, the difference between inputs as a technology category and inputs as a determinant characteristic is that inputs as technology include only seeds and pesticides or herbicides. Chemical and organic fertilizers are included in soil fertility-improving technologies. Improved crop varieties (PCC 0.112, 95% CI 0.037 - 0.186), inputs (in other words seeds and pesticides) (PCC 0.139; 95% CI 0.060 - 0.212), land size (PCC 0.051; 95% CI 0.001 - 0.101) and mechanisation (PCC 0.125; 95% CI 0.049 - 0.201) were significant predictors of technology adoption. In general, these correlates reflect a kind of path dependence. Farmers who have used inputs before are likely to continue to use them in the future. This is clearer when we look at the results of the different technology categories Figure 7, Sub-figures B-F. Looking at input technologies, we find that all the characteristics under inputs were significantly correlated by significant PCCs between 0.12 to 0.19. Crop choice (PCC 0.117; 95% CI -0.016 - 0.251), improved crop varieties (PCC 0.174; 95% CI 0.074 - 0.274), inputs (PCC 0.173; 95% CI 0.062 - 0.283), labour (PCC 0.186; 95% CI -0.000 - 0.373), land size (PCC 0.149; 95% CI 0.056 - 0.243) and mechanisation (PCC 0.191; 95% CI 0.050 - 0.331) were all significant correlates of input technology adoption. Regarding mechanisation, inputs (PCC 0.271; 95% CI -0.041 - 0.581) and mechanisation (PCC 0.244; 95% CI 0.008 - 0.479) were significant predictors. Finally, land size was the only institutional predictor of insurance technologies with a PCC of 0.252 (95% CI 0.000 - 0.505).

4. Discussion and Conclusion

Several reviews have recently assessed the adoption of climate-smart agricultural technologies and natural resource management practices in various dimensions [13,14,18,30]. However, none of them have so far been done with a focus on countries that are conflict-stressed or facing climate change-induced fragility. This review fills this gap but also reveals some areas of further enquiry. From a literature search of over 42,000 records, 109 were selected using a machine learning-aided literature selection. A large proportion (86%) of the studies are from two countries, namely Ethiopia and Nigeria and not a single paper from any of the countries listed as fragile due to climate change – typically Small Island States such as Comoros, Kiribati, Marshall Islands, Federated States of Micronesia, Solomon Islands, Tuvalu and Papua New Guinea.

Adoption of improved seeds, use of organic fertilizers, and use of inorganic fertilizers were the most frequent technologies, and the least frequent technologies were contour farming, row planting, cover crop and mechanisation, and irrigation. The most adopted technologies were timely weeding (77%) and contour farming (67%) while the least adopted was a cover crop with an average adoption rate of only 11%. The mean adoption rate for all technologies was 50%. The technologies were categorised into soil fertility improvement, erosion management, mechanisation, inputs and insurance/ risk reduction technologies, broadly following previous categorisations [16].

We collected 1330 coefficients and categorised them into seven groups, namely household demographics, socioeconomic factors, institutional factors, spatial factors, inputs, psychological factors, and biophysical factors. We descriptively assess univariate partial correlations and also implement multivariate partial correlation regressions. Descriptively, almost all the characteristics identified had a bidirectional relationship with adoption. Multivariate partial correlation meta-regressions show on average, which characteristics influence adoption. Overall receiving training, providing information, subsidies, and providing inputs are the strongest correlates of technology adoption in conflict-affected and fragile countries.

In general, our analysis offers two insights. The first one is that for policymakers interested in increasing adoption rates of agricultural and natural resource management technologies in conflict and fragile countries, with some level of caution, this analysis can guide them in targeting the characteristics that can increase adoption such as training, subsidies and information. There might be some cross-country heterogeneity unfortunately, our analysis is highly dominated by one country (Ethiopia) so it is not possible to assess these characteristics by country or region. However, players in this space might conduct smaller feasibility studies assessing which characteristics are likely to deliver higher adoption rates. The second is that risk management technologies such as insurance or risk contingent credit and other related issues remain poorly explained because of a dearth of relevant literature in this group of countries. Risk reduction technologies were the least prevalent with only about 9 out of 109 papers studying these technologies and only from 3 countries. Only 16 of the 32 characteristics enter the PCC model and only about six of the characteristics were statistically significant predictors. Risk management technologies such as agriculture insurance have faced extensive barriers and take-up has remained very low across many low-income countries [35,40]. It is therefore important to continue exploring these technologies, the possibility of even newer and potentially more trusted delivery channels and product structuring such as picture-based insurance [41] or multi-trigger insurance policies[42] or risk contingent credit[43,44]. These products might offer farmers in conflict and fragile situations with more options and thus potential uptake. Moreover, emerging research suggests that providing risk mitigation options such as insurance in conflict-affected countries can reduce the potential of conflict[45]. More research is critically needed especially as policymakers increase their interest in agricultural insurance as a pathway for reducing climate and conflict-related vulnerability.

The systematic review and meta-analysis were guided by a pre-registered protocol (available at https://osf.io/zbxhk). However, we implemented some minor deviations from the registered protocol. We do not think that these deviations affect the result and have transparently discussed them in the appendix.

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Appendix 1: Additional Results

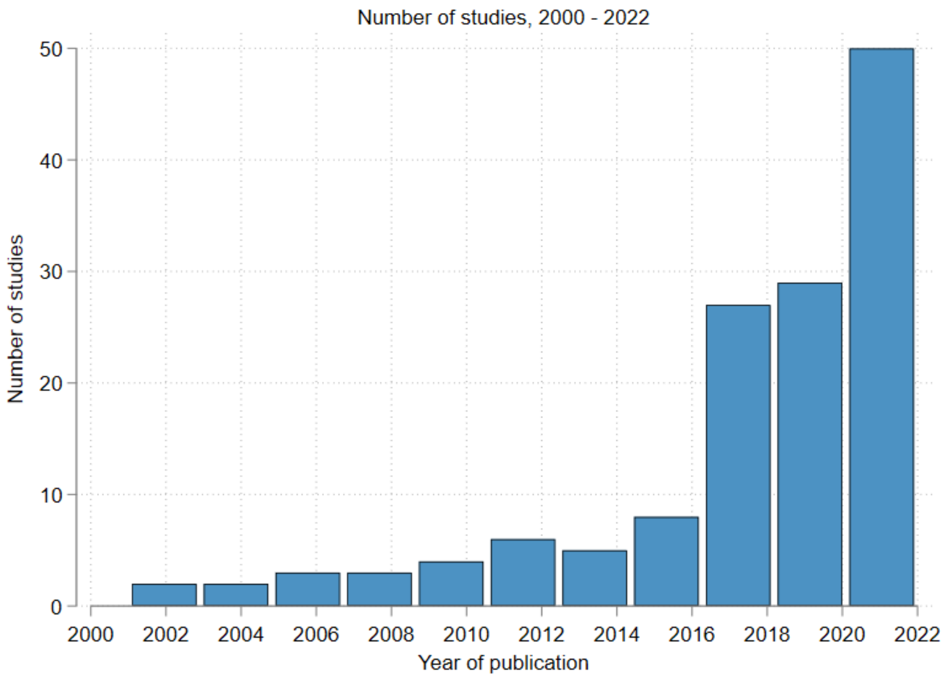
Additional Descriptive Results

Table S1: Overview of existing reviews

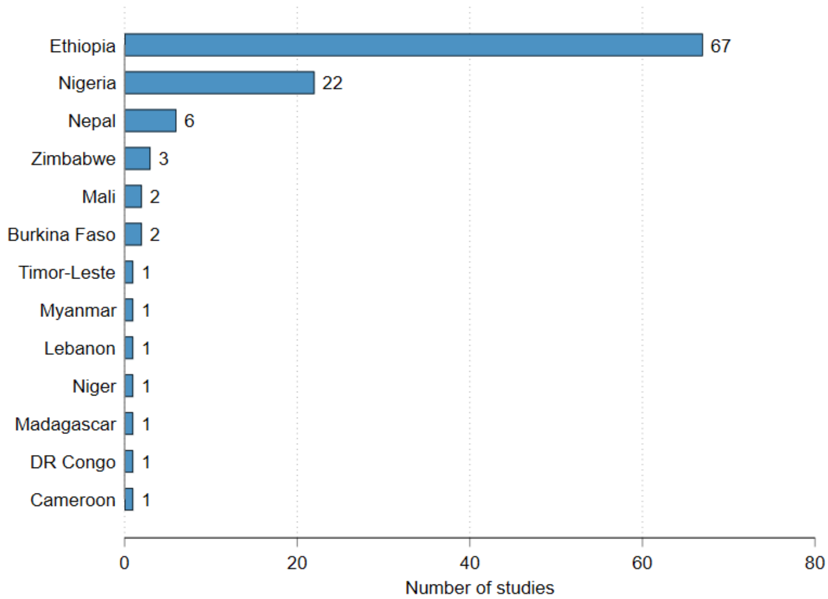
	Systematic literature selection	Thematic coverage	Methodological focus	Outcome focus	Geographical focus
Piñeiro et al. (2020)	Yes	General	Descriptive	Determinants	General
Acevedo et al. (2020)	Yes	Climate-resilient crops	Descriptive	Determinants	General/low- and middle-income countries
Ahmad et al. (2020)	Yes	Erosion control practices	Descriptive	Determinants	Asia
Stathers et al. (2020)	Yes	Post-harvest loss reduction	Meta analysis	Determinants	Sub-Saharan Africa and Asia
Takahashi et al. (2020)	No	General	Descriptive	Determinants and impacts	Sub-Saharan Africa
Ruzzante et al. (2021)	No	General	Meta analysis	Determinants	General
Arslan et al. (2022)	Yes	General	Meta analysis	Determinants	Sub-Saharan Africa
Oyetunde-Usman (2022)	No	General	Descriptive	Determinants	East and West Africa
Suri & Udry (2022)	No	General	Descriptive	Determinants	Africa
Schulz & Börner (2023)	Yes	General	Meta analysis	Determinants	General

Additional Descriptive Results

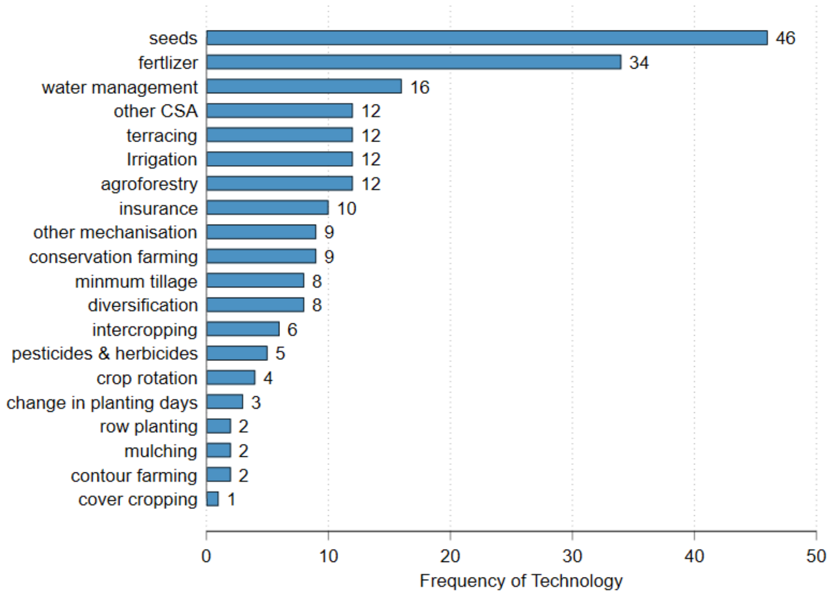
Supplementary Figure 1: Number of studies per year (2000 - 2022)



Supplementary Figure 2: Studies by country



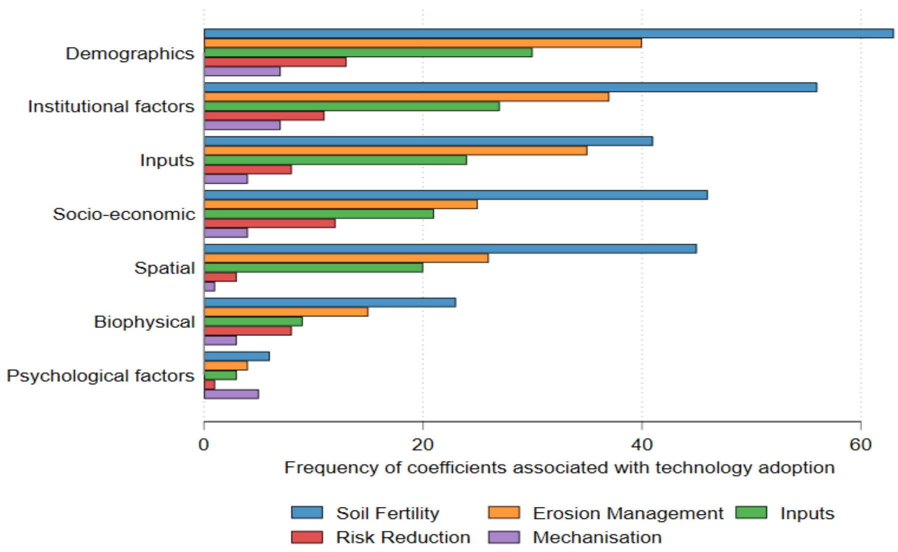
Supplementary Figure 3: Frequency of technologies



Frequency of studies by category of determinants

Determinants of mechanisation technologies are more likely to be institutional factors and household demographics. Overall, demographics and institutional factors account for a large proportion of determinants while psychological factors were the least observed in the literature. Psychological factors were only observed in insurance adoption and not in other technologies.

Supplementary Figure 4: Frequency of the determinants of adoption by technology type and the dimension of the determinants



Some minor deviations from the pre-registered protocol

Two deviations from the pre-registered protocol were implemented. The first is the level of coverage we achieve in our literature search. This is as much a problem of deviation from the protocol but rather what was not captured by our protocol. In particular, we intended to assess both dimensions of fragility emanating from conflict and climate change as defined by the World Bank categorisation of conflict or institutional and social fragility (World Bank, 2022). However, our search process did not yield enough studies to aid social fragility related to climate change. More than 85% of the studies in this review were from Nigeria and Ethiopia, both facing medium to high conflict situations and we did not find any studies from Small Island States facing increased climate fragility. The current analysis is therefore more representative of countries in conflict and fails to represent the situation in countries with climate-fragility. This is less of the failure of the protocol but rather the unavailability of literature from climate-fragile countries. This group of countries needs more research attention.

Finally, in our protocol, we intended to conduct an extensive meta-analysis of both determinants and impacts. We achieved this in an earlier version (Nshakira-Rukundo et al., 2023). However, in this paper, we only present the determinants of adoption and not the impacts of adoption. This is mainly due to word count requirements for journal publications. Another paper focusing only on the impacts of agricultural technologies is underway and will follow the process detailed in the pre-registered protocol.

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List of papers included in the review

Author	Country	Sample size	Technology	Technology type
Tadesse & Belay (2004)	Ethiopia	120	terracing	erosion management
Teklewold et al. (2017)	Ethiopia	926	seeds	Inputs
			fertilizer	soil fertility
			water management	mechanisation
Hailu & Mezegebo (2021)	Ethiopia	393	fertilizer	soil fertility
Umeh & Igwe (2019)	Nigeria	160	other CSA	soil fertility
Tolassa & Jara (2022)	Ethiopia	138	seeds	Inputs
			conservation farming	soil fertility
Bishu et al. (2018)	Ethiopia	336	insurance	risk reduction/insurance
Razafimahatratra et al. (2021)	Madagascar	240	conservation farming	soil fertility
Waktola & Fekadu (2021)	Ethiopia	120	agroforestry	soil fertility
Wodaju et al. (2023)	Ethiopia	261	insurance	risk reduction/insurance
Muluneh et al. (2022)	Ethiopia	174	fertilizer	soil fertility
Belissa et al. (2019)	Ethiopia	8579	insurance	risk reduction/insurance
Jaleta et al. (2018)	Ethiopia	2327	seeds	Inputs
Assaye et al. (2022)	Ethiopia	594	seeds	Inputs
Adeniji et al. (2007)	Nigeria	250	other mechanisation	mechanisation
Kadafur et al. (2020)	Nigeria	250	seeds	Inputs
Ojo et al. (2018)	Nigeria	52	other mechanisation	mechanisation
Kassahun (2021)	Ethiopia	293	other CSA	soil fertility
Abdoulaye et al. (2018)	Nigeria	1907	seeds	Inputs
Ahmed et al. (2016)	Ethiopia	301	seeds	Inputs
Belachew et al. (2020)	Ethiopia	150	terracing	erosion management
			Irrigation	mechanisation
			row planting	erosion management
Gebru et al (2021)	Ethiopia	1269	seeds	Inputs
Faturoti et al. (2006)	Nigeria	85	seeds	Inputs
Muluneh et al.(2022)	Ethiopia	420	fertilizer	soil fertility
Kassie et al. (2009)	Ethiopia	348	minimum tillage	soil fertility
			fertilizer	soil fertility
Tambo & Abdoulaye (2012)	Nigeria	200	seeds	Inputs
Habtewold (2021)	Ethiopia	2752	other CSA	soil fertility
Olagunju et al. (2020)	Nigeria	2216	seeds	Inputs
Amare et al. (2019)	Ethiopia	359	insurance	risk reduction/insurance
Budhathoki et al. (2019)	Nepal	350	insurance	risk reduction/insurance
Oyinbo et al. (2019)	Ethiopia	600	seeds	Inputs
Sertse et al. (2021)	Ethiopia	397	seeds	Inputs
Ali et al. (2022)	Ethiopia	278	other CSA	soil fertility
Dahal et al (2021)	Nepal	150	insurance	risk reduction/insurance
Tafere & Nigussie (2018)	Ethiopia	180	agroforestry	soil fertility
Ojiako et al (2007)	Nigeria	307	seeds	Inputs
Tesfay (2020)	Ethiopia	626	fertilizer	soil fertility
Dhakal et al. (2015)	Nepal	200	agroforestry	soil fertility
Ewunetu et al. (2021)	Ethiopia	414	terracing	erosion management
			fertilizer	soil fertility
			seeds	Inputs
			agroforestry	soil fertility

Aweke et al. (2021)	Ethiopia	248	seeds	Inputs
Manda et al. (2019)	Nigeria	1525	seeds	Inputs
Zegeye (2021)	Ethiopia	656	fertilizer	soil fertility
	Ethiopia	656	pesticides & herbicides	Inputs
Neway & Zegeye (2022)	Ethiopia	796	other mechanisation	mechanisation
Castellani et al. (2014)	Ethiopia	1872	insurance	risk reduction/insurance
Mihretie et al. (2022)	Ethiopia	224	other mechanisation	mechanisation
Mazvimavi & Twomlow (2009)	Zimbabwe	232	conservation farming	soil fertility
Gebremeskel et al. (2018)	Ethiopia	135	Irrigation	mechanisation
Zeweld et al. (2020)	Ethiopia	350	terracing	erosion management
Zeweld et al. (2019)	Ethiopia	350	fertilizer	soil fertility
Kassie et al. (2015)	Ethiopia	2540	diversification	soil fertility
			minimum tillage	soil fertility
			water management	mechanisation
			fertilizer	soil fertility
			seeds	Inputs
Mengistu (2021)	Ethiopia	270	water management	mechanisation
Nwaobiala et al. (2022)	Nigeria	60	intercropping	soil fertility
Tesfaye & Seifu (2016)	Ethiopia	296	diversification	soil fertility
			seeds	Inputs
			change in planting days	mechanisation
			water management	mechanisation
Awotide et al (2016)	Nigeria	600	seeds	Inputs
Diarra et al. (2021)	Mali	260	other CSA	soil fertility
Ghimire & Huang (2015)	Nepal	416	seeds	Inputs
Feleke et al. (2019)	Ethiopia	146	seeds	Inputs
Mujeyi et al. (2022)	Zimbabwe	386	other CSA	soil fertility
Gebru et al. (2020)	Ethiopia	485	water management	mechanisation
Yitbarek & Tesfaye (2022)	Ethiopia	2480	other CSA	soil fertility
Makate et al. (2017)	Zimbabwe	601	seeds	Inputs
Obayelu et al. (2016)	Nigeria	1663	pesticides & herbicides	Inputs
			fertilizer	soil fertility
			Irrigation	mechanisation
			minimum tillage	soil fertility
			other mechanisation	mechanisation
Verkaart et al. (2017)	Ethiopia	1212	seeds	Inputs
Somda et al (2002)	Burkina Faso	116	fertilizer	soil fertility
Wong et al. (2020)	Ethiopia	1100	insurance	risk reduction/insurance
Aizaki et al. (2021))	Myanmar	317	insurance	risk reduction/insurance
Jensen et al. (2014)	Timor-Leste	1511	seeds	Inputs
Zakari et al. (2022)	Niger	1783	Irrigation	mechanisation
			seeds	Inputs
			diversification	soil fertility
			agroforestry	soil fertility
Ngaiwi et al. (2023)	Cameroon	351	agroforestry	soil fertility
			intercropping	soil fertility
			cover cropping	erosion management
			crop rotation	soil fertility
			mulching	erosion management

			minimum tillage	soil fertility
Bayu (2020)	Ethiopia	250	water management	mechanisation
Mebrate et al (2022)	Ethiopia	270	fertilizer	soil fertility
			mulching	erosion management
Omonona et al (2006)	Nigeria	150	seeds	Inputs
Bedeke et al. (2019)	Ethiopia	252	seeds	Inputs
			fertilizer	soil fertility
			intercropping	soil fertility
			minimum tillage	soil fertility
			water management	mechanisation
Yifru & Miheretu (2022)	Ethiopia	304	water management	mechanisation
Geddafa et al (2021)	Ethiopia	167	Irrigation	mechanisation
Kifle et al. (2022)	Ethiopia	368	conservation farming	soil fertility
			fertilizer	soil fertility
			Irrigation	mechanisation
			agroforestry	soil fertility
			diversification	soil fertility
Orkaa & Ayanwale (2021)	Nigeria	552	other mechanisation	mechanisation
Tiruneh & Wassie (2020)	Ethiopia	2797	fertilizer	soil fertility
Tura et al. (2010)	Ethiopia	120	seeds	Inputs
Asfaw et al. (2019)	Ethiopia	384	fertilizer	soil fertility
			terracing	erosion management
			Irrigation	mechanisation
			seeds	Inputs
Emeru (2022)	Ethiopia	368	conservation farming	soil fertility
			fertilizer	soil fertility
			Irrigation	mechanisation
			agroforestry	soil fertility
			diversification	soil fertility
			seeds	Inputs
			water management	mechanisation
			other mechanisation	mechanisation
Chalak et al. (2017)	Lebanon	148	conservation farming	soil fertility
Abera et al. (2020)	Ethiopia	146	crop rotation	soil fertility
			fertilizer	soil fertility
			intercropping	soil fertility
Sertse et al. (2021)	Ethiopia	397	conservation farming	soil fertility
	Ethiopia	397	agroforestry	soil fertility
Ekemini-Richard et al. (2020)	Nigeria	202	Irrigation	mechanisation
			agroforestry	soil fertility
			conservation farming	soil fertility
			seeds	Inputs
Ajao & Ogunniyi (2011)	Nigeria	150	diversification	soil fertility
			seeds	Inputs
			other CSA	soil fertility
Betela & Wolka (2021)	Ethiopia	169	water management	mechanisation
Lawal et al . (2004)	Nigeria	64	seeds	Inputs
Oyawole et al. (2021)	Nigeria	1578	fertilizer	soil fertility
	Nigeria	1578	agroforestry	soil fertility
	Nigeria	1578	crop rotation	soil fertility
	Nigeria	1578	minimum tillage	soil fertility
(Kumar et al., 2020)	Nepal	1985	other CSA	soil fertility
	Nepal	1985	pesticides & herbicides	Inputs
	Nepal	1985	Irrigation	mechanisation
Shumetie & Alemayehu (2018)	Ethiopia	400	water management	mechanisation
			seeds	Inputs

			change in planting days	mechanisation
Sileshi et al (2019)	Ethiopia	408	terracing	erosion management
Alene & Manyong (2006)	Nigeria	480	seeds	Inputs
Gebrekidan et al. (2023)	Ethiopia	194	Irrigation	mechanisation
Kenee & Feyisa (2020)	Ethiopia	332	terracing	erosion management
			water management	mechanisation
			crop rotation	soil fertility
Kassa & Abdi (2022)	Ethiopia	213	other CSA	soil fertility
Tanimonure & Naziri (2021)	Nigeria	191	other CSA	soil fertility
Adesina & Chian (2002)	Nigeria	223	contour farming	erosion management
Adhikari et al. (2018)	Nepal	120	water management	mechanisation
Abebe et al. (2013)	Ethiopia	346	seeds	Inputs
Gebru et al. (2020)	Ethiopia	603	water management	mechanisation
Zegeye et a. (2022)	Ethiopia	2316	fertilizer	soil fertility
Gebre et al. (2019)	Ethiopia	560	seeds	Inputs
Yaméogo et al. (2018)	Burkina Faso	450	fertilizer	soil fertility
			change in planting days	mechanisation
			seeds	Inputs
			water management	mechanisation
			minimum tillage	soil fertility
			diversification	soil fertility
			agroforestry	soil fertility
Diro et al (2022)	Ethiopia	953	fertilizer	soil fertility
			minimum tillage	soil fertility
			intercropping	soil fertility
			seeds	Inputs
			water management	mechanisation
Cipriano et al. (2022)	DR Congo	192	conservation farming	soil fertility
Zeng et al. (2018)	Ethiopia	1300	seeds	Inputs
Ouédraogo et al. (2019)	Mali	300	seeds	Inputs
			Irrigation	mechanisation
			intercropping	soil fertility
			contour farming	erosion management
Abate et al. (2018)	Ethiopia	504	seeds	Inputs
Amare et al. (2019)	Ethiopia	260	row planting	erosion management
Jaleta et al. (2023)	Ethiopia	1088	seeds	Inputs

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