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Adoption of climate-smart agricultural technologies and practices in fragile and conflict-affected settings

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A major challenge for countries dealing with conflict and instability is promoting the use of climate-smart farming technologies and practices. In this meta-analysis, we assess determinants of farmers' adoption decisions for such innovations. We employ advanced machine learning-aided literature selection and review 112 papers selected from over 42,000 published papers covering countries in fragile and conflict settings. We categorized the technologies into five technology groups, including soil health, erosion management, mechanization, input use and risk reduction technologies and extract 1374 coefficients. Univariate and multivariate partial correlation coefficient analysis suggests that factors such as training, access to information, subsidies, and past experiences of using technologies predict technology adoption. However, there are significant differences across technology groups and most especially, a very low coverage of risk-reduction technologies such as insurance is recorded.

Increasing agricultural productivity and maintaining environmental sustainability are two important and complementary sustainable development goals[1,2]. In the face of conventional and conflict-related change and conflict-driven climate change The adoption of climate-smart innovations (such as sustainable intensification, conservation agriculture, improved seeds, organic and sustainable use of chemical fertilizer, agroforestry, and carbon farming among others) influences both agricultural productivity and environmental sustainability[3–5]. However, the adoption of these innovations has been extremely low and varying in many developing countries[6–8] and more so under different dimensions of fragility. Missing markets, market imperfections, productivity, and supply-side constraints have been identified as some of the constraints limiting their adoption[9–11]. Lack of profitability including heterogeneous profits with some farmers benefiting more than others also matters[10]. Also, poor rural infrastructure may lead to high transaction costs, lowering adoption[10]. Lack of adequate and timely information, education, and training further hinders adoption[12]. While there are a few reviews on adoption and impacts of climate-smart technologies[10,13,14], knowledge gaps remain regarding geographical coverage especially in regard to countries affected by violence and fragility (such as Ethiopia, Sudan, Nigeria, Syria, and Small Island States such as Micronesia, Tahiti, Kiribati among others) – an increasingly critical sub-group of vulnerable countries[2]. None of the existing reviews focuses on this critical sub-population and yet vulnerabilities that threaten agrarian livelihoods rise. For instance, the number of people living in proximity to conflict is increasing[2] while climate change continues to make Small Island States more fragile[1,3]. Moreover, the linkages between climate change and conflict[4,5] also underline why a renewed focus on this sub-group is important.

Our work builds on a few existing reviews[13–16] (See Supplementary Table 1 for a list of selected related reviews), while making a key contribution of focusing primarily on fragile and conflict-affected settings around the world, which none of the previous 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[17]. 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[18]. Conflict and climate-induced fragility might co-exist as it is the case in several Sahel and West

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African countries[19,20]. 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[21,22]. Moreover, in addition to this thematic gap in previous reviews, only one[23] focuses on sub-Saharan Africa. Indeed, the understanding of climate-smart technology adoption for "farmers in crises" is lacking. Methodologically, apart from Ruzzante et al.[16], none of the existing reviews implement a meta-analysis and therefore do not show how different determinants might influence adoption of innovations differently. And yet, for efforts and policies targeted at increasing adoption, knowing which determinants have the highest adoption-inducing potential, can be beneficial.

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 climate-smart agricultural technologies (innovations) captures both technologies and practices in line following Rosenstock et al.[24]. Agricultural innovations (technologies and practices) are therefore defined as agriculture and food systems technologies that sustainably increase food production, improve the resilience (or adaptive capacity) of farming systems, and mitigate climate change. These encompass 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 categorize these technologies into five groups, namely: (1) soil fertility improvement, (2) erosion management, (3) mechanization, (4) inputs, and (5) risk reduction technologies. Methodologically, we implement predictive meta-analysis using partial correlations and highlight how different determinants drive adoption decisions. Our focus is Fragile and Conflict-Affected (FCA) countries as defined by the World Bank between 2006 and 2022.

Results

Literature Description

Altogether, 112 studies are included in the final dataset, ranging from 2 studies in 2001 to 55 studies in 2022 (Supplementary Fig. 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 Fig. 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 38.8%. By level of representation, adoption rate was 27.5% for nationally representative studies ($n = 18$) and 40% for non-nationally representative studies ($n = 164$). Figure 1A shows the mean rates per technology category. The square brackets indicate the number of studies evaluated for each technology. The technology with the highest adoption levels was contour farming with an adoption rate of 58% followed by insurance with a 55% adoption rate. On the lower end of the adoption spectrum, crop rotation had an adoption level of only 13%, and using pests and herbicides were adopted by only 16% across the studies evaluated. Figure 1B shows the proportion of coefficients by technology type. About 44% were associated with the adoption of soil fertility-improving technologies. An additional 28% of the coefficients were associated with inputs, 15% with mechanization 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 5%.

We categorized all the 1374 coefficients into 38 determinants/ characteristics. Figure 2 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. 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 3 shows the relationship between all the 38 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 labor 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, 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[25–27]. However, what seems to be vivid here is the lack of capacity of poor, conflict-affected countries to provide subsidies to their farmers. Similarly, mechanization appeared in only 13 studies with only 24 coefficients.

Univariate Partial Correlation Coefficients of Technology Adoption

To assess the relationship between each determinant/characteristic on adoption of technologies, we first show univariate partial correlations. Univariate partial correlations show the linear relationship between each characteristic while holding all other characteristics to a constant, helping to isolate the relationships descriptively. Univariate partial correlations therefore simply summarize the relationships whether positive or negative, giving an average strength of the relationship in each direction.

Figure 4A–F and Supplementary Table 3 show results of univariate partial correlations. Figure 4 specifically shows divergent coefficient bar plots emanating from univariate partial correlation analysis to visualize the partial correlation of each of the 38 determinants across the technology types. Sub-figure (A) is for overall correlations and (B-F) corresponds to technology adoption for each of the five technology categories. All the coefficients are standardized 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 to assess the overall direction of influence. We return to this in the multivariate analysis in Section 2.3 under multivariate partial correlations. 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.[28] 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, (Fig. 4A), having other employment (PCC 0.27), market availability (PCC 0.26) and cost of technology acquisition (PCC 0.22) were more negatively associated with technology adoption. Moreover, for costs and markets, negative Partial Correlation Coefficients (PCCs) were larger than their positive PCCs suggesting that the absence of a characteristic was more influential in influencing technology uptake compared to the presence of the characteristic.

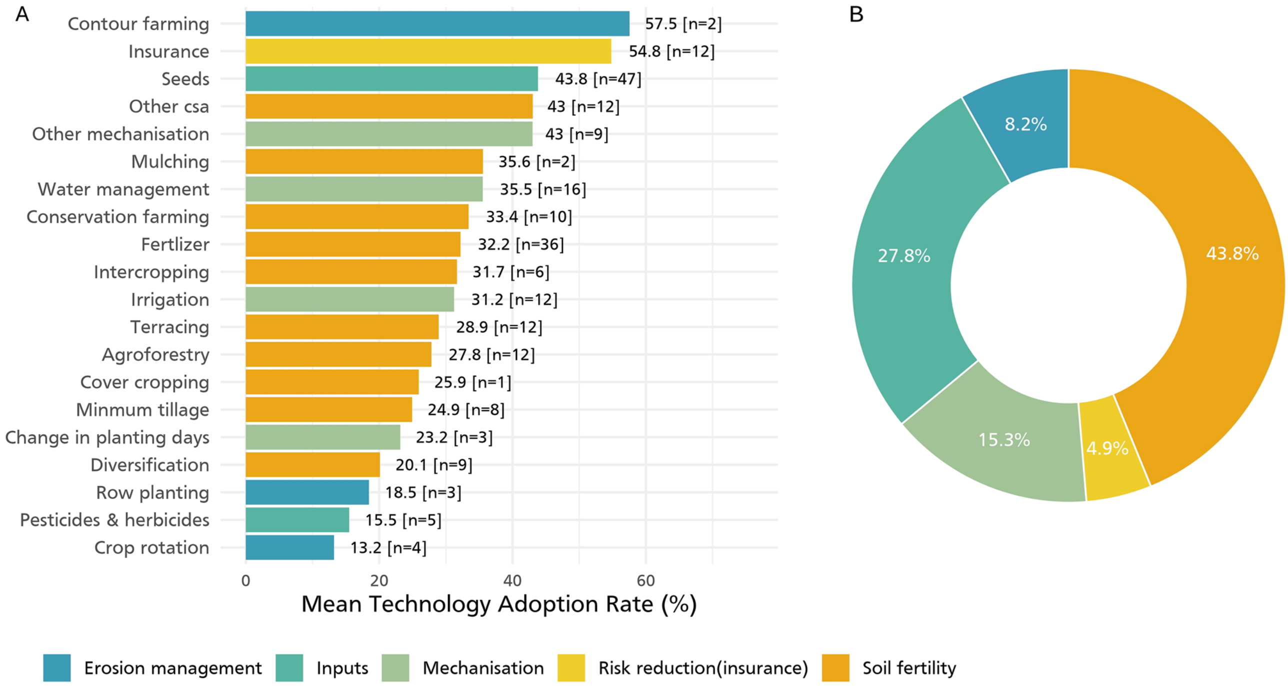

Fig. 1 | Technology adoption rates and coeffi cient frequencies. A Mean rates per technology category and **B** proportion of coefficients by technology type. The square brackets indicate the number of studies evaluated for each technology. **B** $n = 1374$ coefficients.

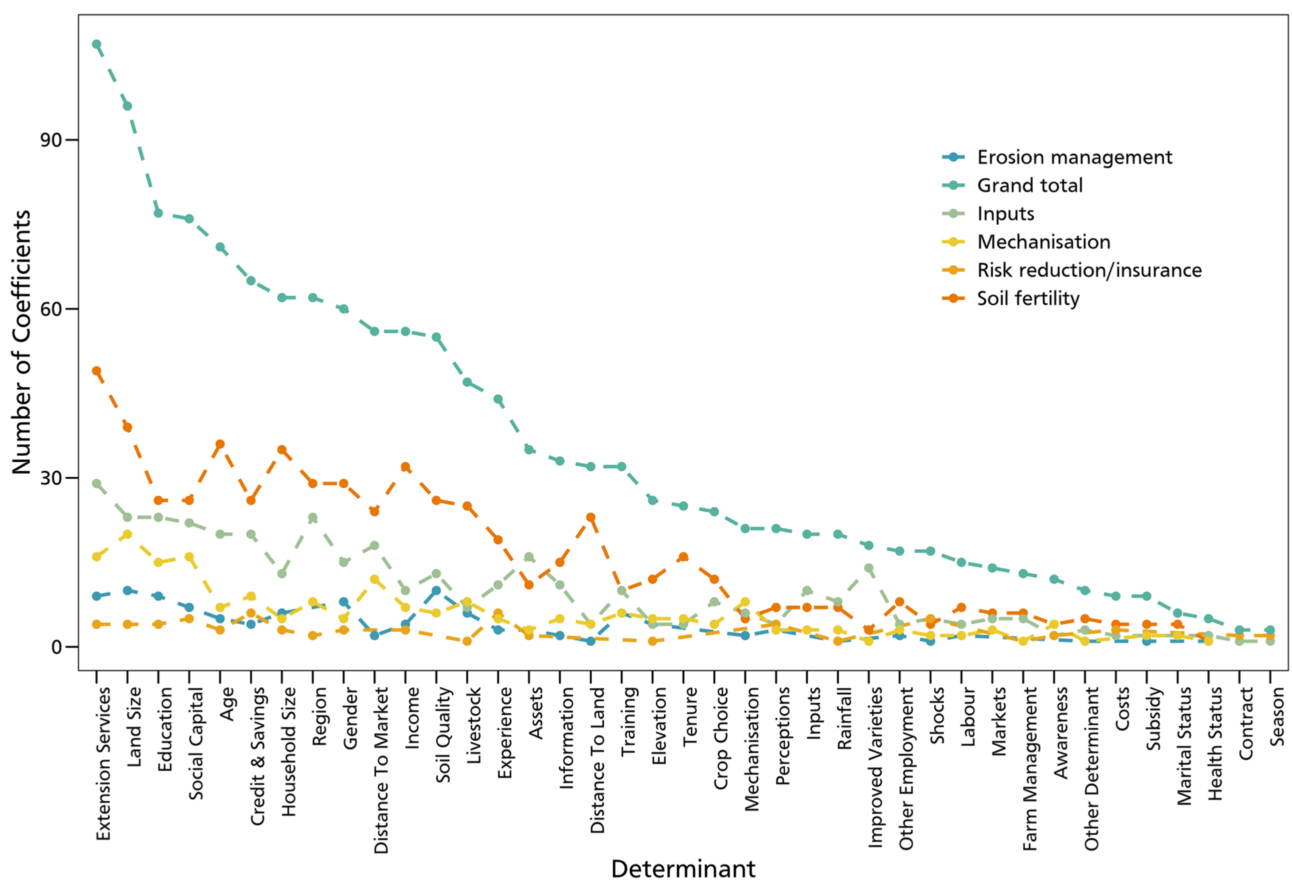

Fig. 2 | Frequency of coefficients by technology category.

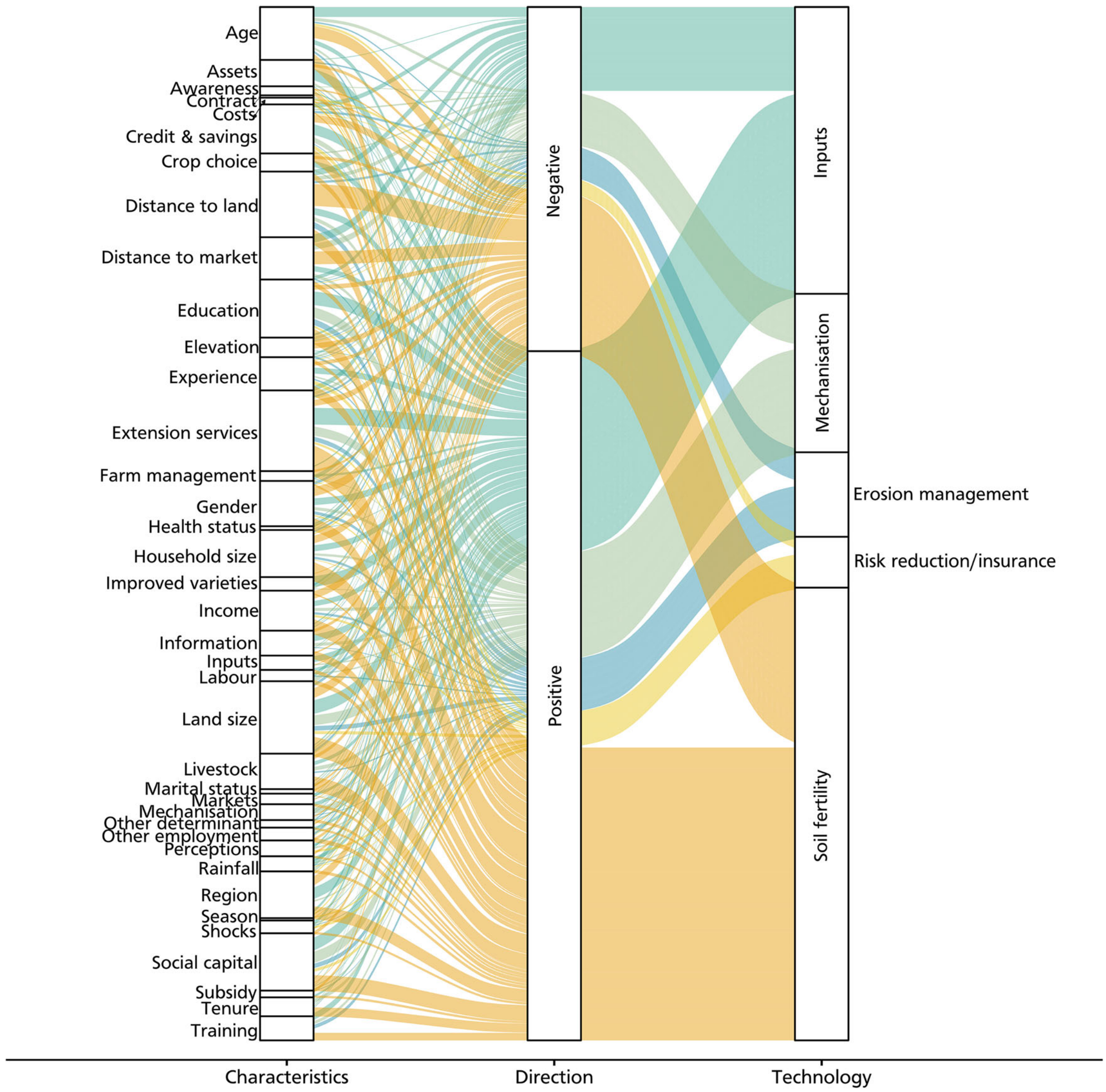

Fig. 3 | Links between determinants (characteristics) and technology category – colour coded by technology category.

Other characteristics with negative correlations were mechanization, labor availability, training, subsidy, education, and income. However, these characteristics also have generally higher positive PCCs. Indeed, from the positive side of the scale, labor 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.

We should make two caveats about this univariate analysis. First, it does not account for how other characteristics influence adoption but rather only consider how a single characteristic influences adoption. The characteristics might therefore be correlated and hence associations cancel out each other once regression analysis is conducted. Secondly, these correlations do not show the number of coefficients entering the correlational analysis. Therefore, they might be less nuanced and less representative given the limited number of observations that might be used. Next, we examine how different characteristics correlated with each of the five technology categories separately, showing the results in Fig. 4B–F and in Supplementary Tables 4.1 to 4.6.

Soil fertility management technologies

Figure 4B shows the PCC coefficients for soil fertility management technologies. The determinants with the largest univariate correlations with soil fertility management technologies were existing farmer experiences in farm management (PCC 0.3), subsidies (PCC 0.22) while inputs and rainfall also had higher adoption correlations (each with a PCC of 0.19). From a negative dimension, having other employment (PCC 0.41), presence of markets (PCC 0.36), presence of other mechanization technologies (PCC 0.28), farmer experience (PCC 0.24), farmer education (PCC 0.21) and availability of labor (PCC 0.20) were all strongly and negatively correlated with adoption of soil fertility management technologies. 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, labor, and rainfall had relatively higher PCCs with farm management and subsidies having PCCs greater than 0.2.

Erosion management technologies

Figure 4C shows the determinants of erosion management technologies. Credit and savings (PCC 0.37), other employment (PCC 0.21), assets (PCC 0.2) and health status (PCC 0.2) had negative and strong associations with lower technology uptake. In the positive direction, mechanization (PCC 0.20), social capital (PCC 0.22), livestock (PCC

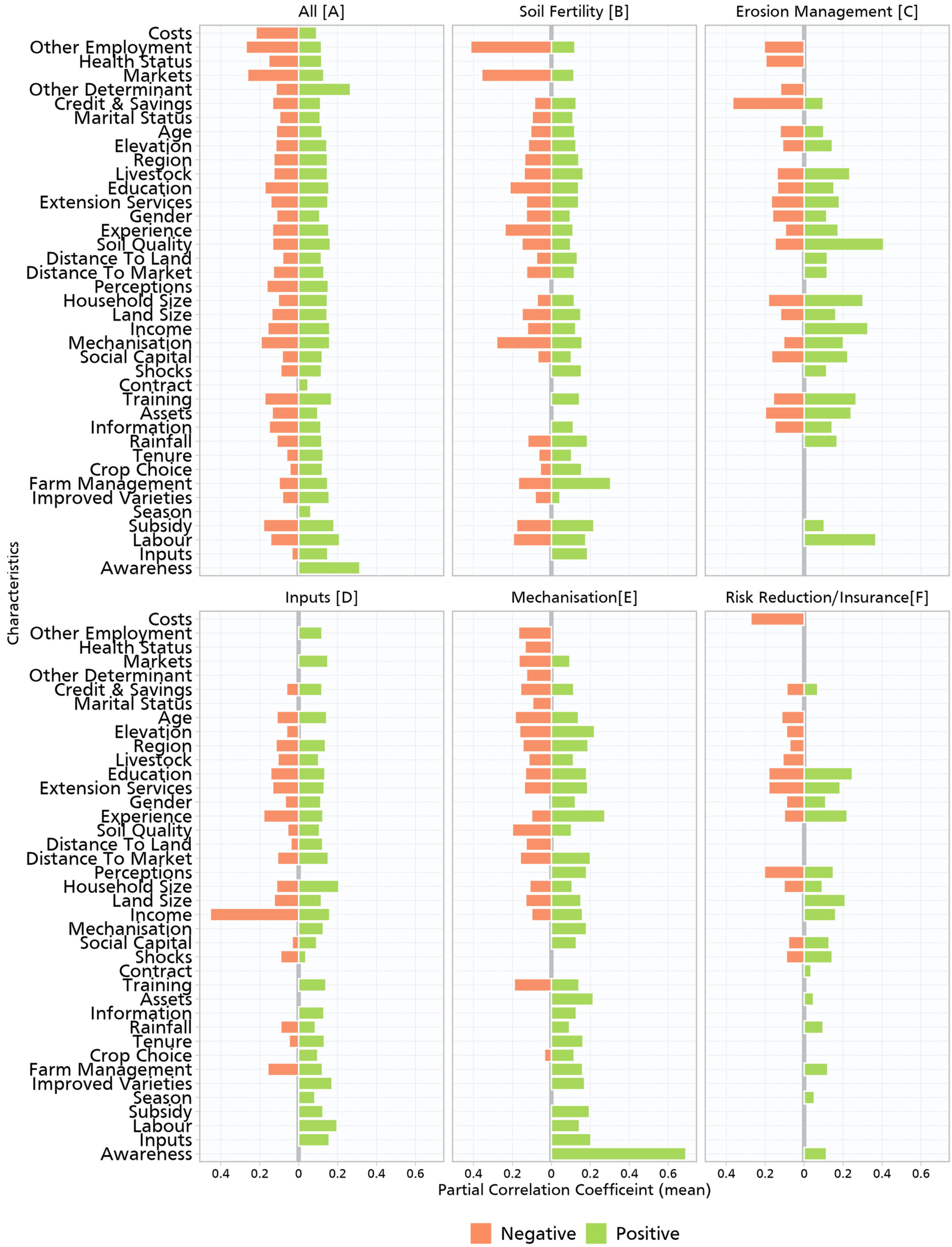

Fig. 4 | Univariate partial correlations by technology category. A All coefficients for all technology categories **B** Category: Soil fertility management. **C** Category: Erosion management. **D** Category: Inputs **E** Category: Mechanisation **F** Category: Risk reduction/insurance.

0.23), assets (PCC 0.24), training (PCC 0.27), household size (PCC 0.30), income (PCC 0.33), labor (PCC 0.37), soil quality (PCC 0.41) all have positive and strong associations with adoption of erosion management technologies. While erosion management technologies such as mulching and contour farming are generally not as costly, it is important to note that characteristics that proxy household wealth are very prominently associated with such technologies. More financially able households tend to adopt even the least costly technologies.

Input technologies

Figure 4D depicts the PCCs for input technologies, specifically chemical fertilizers 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 labor, other inputs, availability of markets, training, information provision, mechanization, subsidies, other employment, crop choices, and season of growing all had positive PCCs only. The coefficients for awareness (PCC 0.31) and labor (0.21) were particularly high in their positive association with adoption. From a negative dimension, availability of markets (0.26) and costs (0.22) were negatively associated with adoption of inputs. Among all the characteristics, income has only a positive PCC of 0.16. Increasing household income might likely offer households more economic options, which might include moving out of the agricultural sector – hence reducing technology adoption.

Mechanization technologies

Figure 4E shows the PCCs for mechanization technologies, specifically irrigation and the use of heavy equipment such as tractors. Regarding these technologies, we observe fewer characteristics that are negatively associated with adoption. Of the 30 characteristics correlated with the adoption of mechanization technologies, about 29% (9/30) had correlations of only positive PCCs. This was the highest proportion among the five technology categories studied. Of these, access to information/awareness stands out with a PCC 0.69. This was the highest correlation among all the determinants of mechanization technology adoption, whether from a positive or negative dimension. Farmer experience (PCC 0.27), elevation (PCC 0.22), household assets (PCC 0.22), inputs, distance to markets and availability of subsidies, all with correlations of 0.2 were strongly associated with adoption of mechanization technologies. Adoption of mechanization is correlated with more biophysical characteristics such as elevation and location (region) than other technologies. Farmers must evaluate the suitability of their land for the adoption of mechanization. Where the land is not suitable, for instance, elevation of soil stability, farmers are unlikely to make substantial investments. From a negative dimension, soil quality (PCC 0.20) was the characteristic with the strongest negative correlation. Farmers who perceive that their soil quality was better could be less likely to adopt mechanization technologies.

Insurance and risk management technologies

Finally, insurance and risk management technologies (Fig. 4F) had the least presentation in our review with only 4.3% coefficients featured in our dataset. This is also visible in the number of characteristics used entering the univariate correlations. Only 22 of the 38 determinants enter the analysis of risk management technologies. The main technology under this category is agricultural insurance (livestock and crop insurance) and related technologies such as risk contingent credit. Nine out of 109 studies were included in this technology category, coming from three countries (Ethiopia, Myanmar, and Nepal). Of these, we find that costs (PCC 0.27) and perception (PCC 0.20) were the strongest negative correlates to adoption. On the other hand, education (PCC 0.25), experience (0.22) and land size (PCC 0.21) were the strongest positive predictors of risk management technologies. The key risk management technology was agricultural insurance. In general, this technology, despite its promise and proven usefulness, has suffered both demand and supply-side bottlenecks in low-income countries thus keeping adoption rates very low[29]. 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[30].

Multivariate Partial Correlation Coefficients Meta-Regression for Technology Adoption

Figure 5, shows multivariate PCC regression results of all innovations together (Sub-Figure (a)) and the five innovation categories with five other corresponding sub-figures. 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). The numbers in the coefficient plots are the number of observations per characteristic. Tabular results from which the Fig. 5A–F are plotted are all shown in Supplementary Tables 4.1 – 4.6.

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 5A shows the results for the full model. Receiving a subsidy was positively correlated with overall adoption, (PCC 0.13; 95% CI: 0.027–0.223); having livestock (PCC 0.085; 95% CI: 0.031–0.140) and income (PCC 0.06; 95% CI: 0.006–0.112) were positively correlated with adoption. Households with more assets were associated with higher adoption levels corresponding to a PCC of 0.08 (95% CI 0.023–0.135) while farming experience had a positive PCC of 0.094 (95% CI 0.034–0.153). Of all the socio-economic determinants, awareness has the largest correlation of adoption, corresponding to 0.178 (95% CI 0.073–0.2819).

However, for the various technology types, there is wide heterogeneity in how various socioeconomic determinants interact with adoption. Of all the socioeconomic determinants included in the model, only livestock ownership was associated with adoption of soil fertility improving technologies (PCC 0.099, 95% CI 0.026–0.171). 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 correlated with erosion management technologies (PCC 0.339, 95% CI 0.082–0.598). Awareness was the only socioeconomic determinant associated with mechanization (PCC 0.544, 95% CI 0.244–0.844) while experience (PCC 0.261, 95% CI 0.046–0.476) and income (PCC 0.385, 95% CI 0.122–0.647) were also associated with risk management technologies. A larger number of socioeconomic determinants are associated with input adoption. Assets were correlated with increasing input adoption by 0.148 (95% CI 0.053–0.243) while cost of inputs was also positively associated with adoption by PCC 0.255 (95% CI -0.013–0.524). However, as we observe, only one observation enters this analysis and therefore this result should be considered with some context. Experience of the farmers (in using inputs before) was associated with adoption by PCC 0.175 (95% CI 0.064–0.286) while livestock was also correlated with adoption of inputs by PCC 0.14 (95% CI 0.013–0.267). Overall, households with more economic potential to purchase are likely to adopt inputs.

Demographic determinants. Age, education, gender, marital status, and household size were the determinants categorized 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 0.09, 95% CI 0.040–0.141) while gender of the farmer had a PCC correlation coefficient of 0.053 (95% CI −0.001–0.108) and household size was also correlated with overall adoption with a PCC coefficient of 0.048 (95% CI −0.006–0.102). Education was positively correlated with erosion management

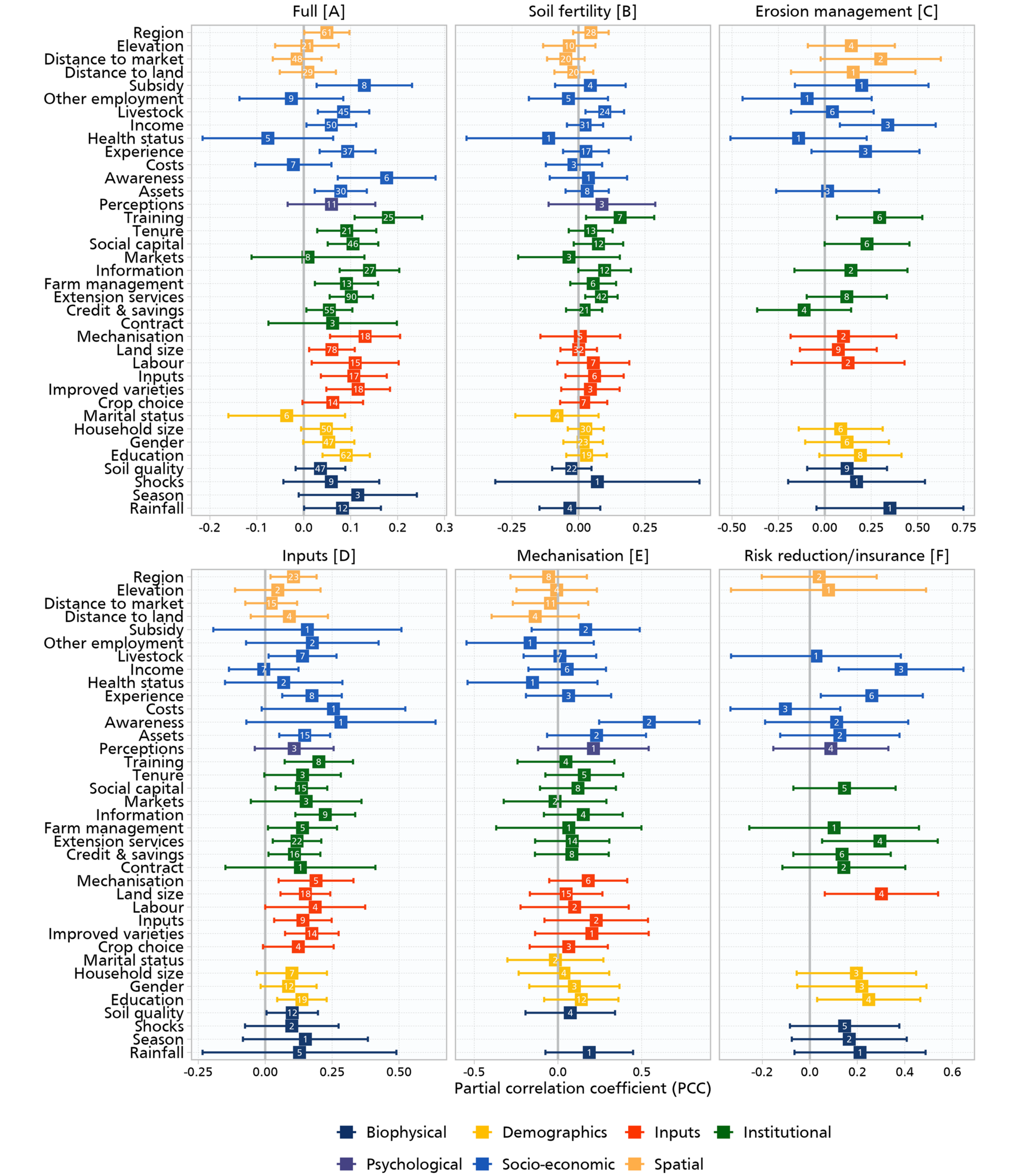

Fig. 5 | Multivariate partial correlations by technology category and determinant groups. Colour coding by determinant groups. Number in the whisker reflect the number of coefficients in each determinant by technology category. **A** All coefficients for all technology categories. **B** Category: Soil fertility management. **C** Category: Erosion management. **D** Category: Inputs. **E** Category: Mechanisation **F** Category: Risk reduction/ insurance.

technologies by a PCC of 0.192 (95% CI −0.029–0.414) and with input adoption with a PCC coefficient of 0.137 (95% CI 0.045–0.230). Education was also significantly correlated with risk reduction technologies (PCC 0.248, 95% CI 0.031–0.465) but none of the demographic characteristics were correlated with mechanization or soil fertility management technologies.

Biophysical determinants. We categorized weather shocks, rainfall, soil quality, and season of planting as the biophysical determinants. Of these, soil quality has the largest number of observations entering the model ($n = 47$), but was not a strong correlate in the overall analysis (Fig. 5A). Rainfall (PCC 0.083, 95% CI 0.001–0.165) and season (PCC 0.115, 95% CI -0.011–0.241) were the biophysical characteristics positively associated with overall technology adoption. Biophysical characteristics were not significantly associated with soil fertility management technologies but rainfall was associated with erosion management technologies (PCC 0.351, 95% CI -0.045–0.747). However, note that only one observation for rainfall enters the model therefore representativeness might be weak. Farmers are likely to adopt inputs considering their soil quality (PCC 0.101, 95% CI 0.005–0.197).

Spatial determinants. Regarding spatial characteristics and overall adoption, only regional differences show a positive correlation (PCC 0.049, 95% CI 0.001–0.097), all the other factors were not significantly associated with overall adoption. Longer distances to markets was positively correlated with erosion management technologies (PCC 0.302, 95% CI -0.022–0.625). Regional differences are also observed to positively correlate with input adoption (PCC 0.106, 95% CI 0.020–0.192). We observe a negative (though not significant) correlation of distance to markets with soil fertility but positive and strongly significant with erosion management technologies. The finding here implies some potential substitution of technologies. On the one hand, an increase in distance to markets is associated with lower adoption of inputs, but on the other hand, farmers tend to increase uptake of erosion management technologies (e.g., mulching, cover cropping etc.) when they are located further from markets. Of course, the recommendation is not to encourage farmers to live further from markets but rather to underline that farmers find cheaper alternative technologies when markets are inaccessible.

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 0.055 95% CI 0.006–0.104), extension services (PCC 0.101, 95% CI 0.055–0.148), farm management experience (PCC 0.091 95% CI 0.024 – 0.158), access to information (PCC 0.140, 95% CI 0.076–0.204), social capital (PCC 0.105 95% CI 0.051–0.159), land tenure (PCC 0.092, 95% CI 0.029–0.155) and training (PCC 0.180, 95% CI 0.108–0.253) all were correlated with technology adoption.

Regarding soil fertility technologies, availability of extension services (PCC 0.086, 95% CI 0.025–0.147), access to information (PCC 0.098, 95% CI -0.001–0.197) and receiving training (PCC 0.157, 95% CI 0.028–0.285) were all associated with adoption of soil fertility improving technologies. Training (PCC 0.296, 95% CI 0.066–0.526) and social capital (PCC 0.227, 95% CI -0.001–0.457) were associated with erosion management technologies, suggesting that both learning by formalized teaching and through informal social networks was influential in adoption of erosion management technologies.

Institutional factors were even more influential in input technologies adoption. Credit and savings (PCC 0.109, 95% CI 0.012–0.206), extension services (PCC 0.119, 95% CI 0.028–0.209), farm management experience (PCC 0.139, 95% CI 0.010–0.268), information (PCC 0.224, 95% CI 0.113–0.336), social capital (PCC 0.135, 95% CI 0.039–0.232), land tenure (PCC 0.140, 95% CI −0.003–0.283) and training (PCC 0.201, 95% CI 0.073–0.329) were all positively correlated with inputs adoption. Surprisingly, none of these determinants were associated with mechanization but access to extension services (PCC 0.295, 95% CI 0.052–0.539) was positively correlated with risk reduction technologies.

Inputs. Input technologies include land size, labor, 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 while they are categorized among inputs as a determinant. Assessing how these determinants influence overall technology adoption, we observe that all these inputs determinants are correlated with technology adoption. Improved crop varieties (PCC 0.116, 95% CI 0.048–0.184), inputs (in other words seeds and pesticides) (PCC 0.107; 95% CI 0.036–0.175), land size (PCC 0.06; 95% CI 0.011–0.109) and mechanization (PCC 0.131; 95% CI 0.056–0.205) as well as crop choice (PCC 0.062; 95% CI -0.003–0.126) were all significantly correlated with overall 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 in Fig. 5A–F. Looking at input technologies, we do not observe any statistically significant correlations with mechanization, soil fertility or erosion management technologies but we observe that input determinants were indeed strongly correlated with input technologies. Crop choice (PCC 0.124, 95% CI −0.008–0.256), improved varieties (PCC 0.174, 95% CI 0.074–0.274) previous inputs use (PCC 0.141, 95% CI 0.034–0.248), labor availability (PCC 0.187, 95% CI 0.000–0.374), land size (PCC 0.150, 95% CI 0.057–0.243) and mechanization (PCC 0.190, 95% CI 0.050–0.330) were all correlated with input technologies. We also observe that land size was positively correlated (PCC 0.302, 95% CI 0.063–0.540) with risk management technologies. Tabular results of all these multivariate partial correlations are in Supplementary Tables 4.1 to 4.6 in the online information.

Discussion and Conclusions

Discussion

Several reviews have recently assessed the adoption of climate-smart agricultural technologies and natural resource management practices in various dimensions[13,14,16,28]. However, none of them have so far been done with a focus on countries that are conflict-stressed or facing climate change-induced fragility. Following a pre-registered process, 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. Eighty-six percent of the studies are from two countries, namely Ethiopia and Nigeria and not a single study was found from any of the countries listed as fragile due to climate change.

Adoption of improved seeds, use of organic fertilizers, and use of inorganic fertilizers are the most frequent technologies, and the least frequent technologies were contour farming, row planting, cover crop and mechanization, and irrigation. The most adopted technologies are timely weeding (77%) and contour farming (67%) while the least adopted was cover cropping with an average adoption rate of only 11%. The mean adoption rate for all technologies was 40.1%. Overall, there is a difference between studies which are nationally representative and those which are not nationally representative. Nationally representative studies had a higher overall adoption rate of 34.6% compared to 40.62% with a difference in mean of 5.99% (p-value 0.012). The technologies were categorized into soil fertility improvement, erosion management, mechanization, inputs and insurance/risk reduction technologies, broadly following previous categorizations[24].

We collected 1374 coefficients and categorized 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 only two countries – Ethiopia and Nigeria. It is therefore not possible to assess these characteristics by country or region. 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 112 papers studying these technologies and only from 3 countries. Only 21 of the 38 characteristics entered 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[29,31]. 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[32] or multi-trigger insurance policies[33] or risk contingent credit[33,34]. 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[35]. More research is critically needed especially as policymakers increase their interest in agricultural insurance as a pathway for reducing climate and conflict-related vulnerability.

Directions and Recommendations for Future Research

In this review, we identify several gaps. First, while many Small Island Countries are increasingly affected by climate change effects such as rising sea levels, our review does not find any papers from many of these countries. From the list of countries as of 2022, the Small Island States included Timor Leste, Comoros, Kiribati, Marshall Islands, Federated States of Micronesia, Solomon Islands, Tuvalu and Papua New Guinea. This review hence observes the increasingly concerning phenomenon of research desserts and oasis[2], where some countries are over-studied while others are hardly studied. Future research and research funding needs to explicitly focus on these countries. Secondly, we note the rarity of certain technologies, especially risk management technologies. Previous studies show that demand and supply bottlenecks limit uptake of risk management technologies in low-income countries[29]. There is therefore a need for more research and policy tools to unlock uptake of these technologies. Thirdly, a substantial proportion of the coefficients extracted were not used. On the one hand, this reduced the number of studies that fully entered the analysis. On the other hand, we hope there can be a more standard scientific reporting system. It is possible that researchers can request for missing data from authors. However, that also depends on finding the correct contact information and even then, not all information can be provided. Instead, scientific publishers could implement uniform reporting rules such that meta-analytic data can be well extracted. Finally, our study, due to the limits in coverage that were selected, excludes regions with recent conflict and or climate vulnerability, for instance Ukraine. Future predictive studies and meta-analyses will therefore be useful to update scientific understanding on these themes.

Some limitations

Our results should be read with two considerations in hindsight. The first is the advantages and drawbacks of machine learning-aided literature search and selection process. While machine learning-aided techniques are evolving and drastically improving on the labor-intensive literature selection, they are not yet 100% failproof[36,37]. As van de Schoot and colleagues[38] mentioned, the labor savings of reducing human-aided data selection by as much as 95% might also carry the risk of missing 5% of relevant studies that would otherwise be included. More comprehensiveness can be achieved by executing a more relaxed stopping procedure[39]. In our case, we stopped at the 100th paper per theme. This is commonly referred to as the knee method[40]. We did not pre-register this stopping procedure. However, having discovered this error, we assigned two reviewers (EN-R and BHG) to manually proof read the abstracts 20 additional documents ranked between 101 and 120 to ascertain that our stopping strategy was valid. The number at which to stop is arbitrary but about one third of machine learning reviews use this heuristic[41]. Despite the advantages this method gives, there could still be a potential of missing useful papers though with a much lower rate of success (slope ratio)[40]. Overall, the opportunities, limitations and potential biases of machine learning-aided literature review continue to be assessed[42]. We acknowledge these drawbacks while also appreciating that they are not specific to our work but a general characteristic of a useful and evolving methodological innovation therefore these methodological limitations should be considered.

Another limitation is the potential bias that is apparent in small sample meta-analyses using partial correlation coefficients[43]. Our overall sample is 1374 coefficients with about 1130 used in partial correlation regressions. Therefore, we are more confident that the overall analysis is not threatened by small sample bias. However, in the heterogenous analysis of separate technology categories, some categories have fewer than 200 observations. These include erosion management (102 observations), risk management (67 observations), and mechanization (160 observations). While overall technology adoption is not threatened by bias, heterogenous analysis might suffer from small sample bias.

Methodology

Thematic scope of the review

We followed our Open Science Framework pre-registered protocol (https://doi.org/10.17605/OSF.IO/Z4HMW). Our definition of agricultural technologies follows Ruzzante et al.[16] who define agricultural technologies as "equipment, genetic material, farming techniques, and agricultural inputs that have been developed to improve the effectiveness of agriculture." Following Rosenstock et al.[24], we classify agricultural technologies into five categories. The first category is inputs, which include improved seeds (such as climate-resilient seeds, pest-resistant seeds, drought-resistant seeds, and genetically modified seeds) and pesticides and herbicides. The second category is soil fertility management technologies. Technologies assessed here include those that organically replenish soil fertility such as mulching, organic fertilizer use, crop residue use, inter-cropping, and agroforestry as well as chemical fertilizers. 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[44]. The fourth category is mechanization 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. The list of all technologies included in the study and their definitions based on Rosenstock et al.[24] are in Supplementary Table 2.

Scope

Our scope is limited to countries which are categorized as Fragile and Conflict-Affected (FCA). Fragility and Conflict are defined as per the World Bank[17]. Fragility is 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". Conflict is defined "as a situation of acute insecurity driven by the use of deadly force by a group — including state forces, organized non-state groups, or other irregular entities — with a political purpose or motivation. Such force can be two-sided — involving engagement between multiple organized, armed sides, at times resulting in collateral civilian harm — or one-sided, in which a group specifically targets civilians". The World Bank categorizes 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.

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. The definition of technologies is based on Rosenstock et al.[24] and therefore consistent with previous studies.[9,12]

Literature search and data extraction

We conducted an initial search of Web of Science and Scopus, from which we extracted 42,024 records. The literature search key terms, including the country list, are in Annex 1 of the Supplementary Information. To process all these data, we employed a machine learning-driven process to improve our efficiency in the literature selection process. Our machine learning data selection process was in two stages. First, we combined Scopus and Web of Science results into one sheet. We then used an R-script to remove duplicates by considering 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% (12,469) records due to the above reasons.

The second stage machine learning strategy is an iterative multi-stage training and literature selection[45] via ASReview[38], a Python-based open-source and transparent algorithm for literature selection.

For each technology category, we hand-selected (after reading their abstracts) between 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 6 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.

Data from the 112 studies were extracted and aggregated using a questionnaire (see Supplementary Materials) designed on SurveyCTO, a data computer-assisted 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 individually such that each sub-sample for each country represented a separate entry. We further collected the sample sizes of the studies, whether the study was nationally representative or not. We list the technology under study and its adoption rate. Technologies are categorized into five categories, namely: (1) soil fertility improvement, (2) erosion management, (3) mechanization, (4) inputs, and (5) risk reduction technologies. These categories are informed by Rosenstock's classification. We then extract data on determinants. From each selected study, we extract data where all the listed determinants were statistically significant predictors on both the negative and positive side. We extract the point estimates, standard errors, and p-values altogether collating 1374 coefficients. Seven of the 112 studies (6%) recorded point estimates without and miss p-values, t-stat or standard error. These are not included in the PCC regressions though they are included in the descriptive analysis.

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 categorize all the coefficients into 21 groups and summarize their mean effect to assess their contribution to adoption. We use Sankey diagrams to visualize 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[16,46], we estimate the partial correlation coefficients of the characteristics for overall technology adoption and each of the five technology categories. Technology adoption enters the modelling only as an extensive measure, a binary measure of whether respondents adopt or not. As such, we do not consider other intensive dimensions of adoptions such as the number of technologies adopted or the area size allocated to the technology. 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. However, the outcome variables (adoption) might be measured in metrics that are not directly comparable and therefore comparison across studies and inferring the overall prevalence (adoption) rates might be biased. To overcome this drawback, we use Partial Correlation Coefficients (PCC), a scale-free metric which provides a common interpretation across studies[46,47]. The PCC describes the strength of one linear relationship between two variables, holding constant all other factors that might drive the relationship. Therefore, Y^*_{ij}, which is the PCC for each individual technology, is

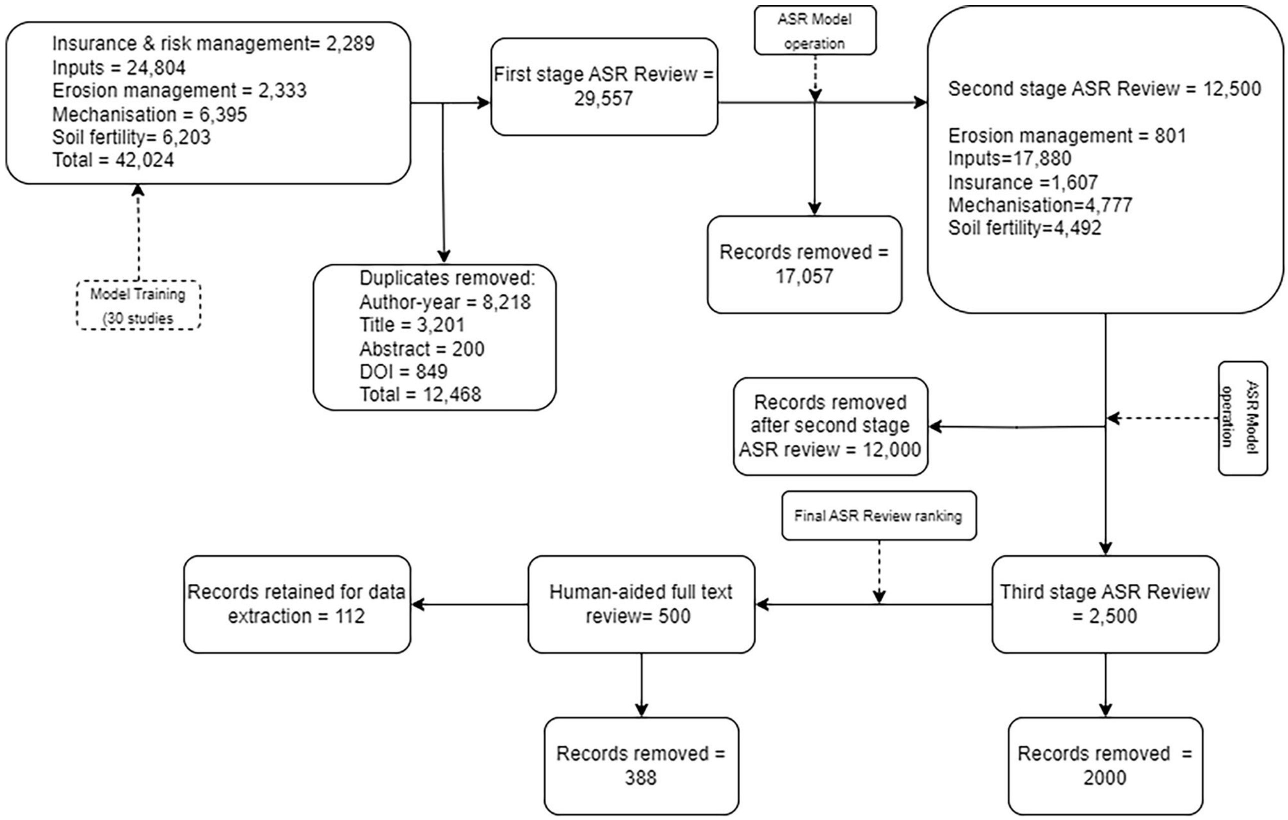

Fig. 6 | PRISMA flow chart showing the search and literature selection and inclusion/ exclusion process.

computed using the formula:

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

The standard error of the PCC is calculated as follows:

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

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 relative comparison of the strength between variables and an outcome given the presence of other variables (other determinants)[16,46]. 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[47]. 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[47]. For its advantages, PCC has been the preferred method for meta-analysis in technology adoption studies[16,46] and overall, in other applied disciplines. We used the R package *metafor*[48] 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. 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. Our meta-regression controls for various characteristics including year of publication, whether the paper was from Ethiopia, number of authors, sample size, age of the farmer, 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. Our list of controls is more or less consistent with Ruzzante et al., whose analysis is closely related to this.

Despite the advantages of PCC in meta-analysis, it is sensitive to small samples, especially under 200 observations[43]. Our sample size for the pooled estimates is more than 1000 observations. Therefore, this small sample size sensitivity does not threaten our results. Finally, we employ corrected standard errors following Stanley and Doucouliagos[49], a method that removes potential biases from standard errors in random effects PCC models.

Exploration of heterogeneity and publication bias. In our study, we use moderators to control for heterogeneity and publication bias. We use τ^2 and I^2 to compare the residue variance before and after using moderators. In both cases, the values were close to zero, indicating negligible between-study heterogeneity. Similarly, for the publication bias, we used funnel plots and Egger-type regression test[50,51] and provide these sensitivity results in the supplementary material. As shown in Supplementary Fig. 3, after including moderators, we observe that the plotting of the studies reveals a more symmetrical and balanced funnel, suggesting that the moderators helped control for potential publication bias.

Finally, we would like to highlight one deviation from our preregistered protocol. As show in our pre-registered protocol, we intended to both determinants and impacts in one paper. In hindsight, we realized that these two objectives would not fit into one paper. This paper therefore considers only determinants. A paper focusing on the impacts of agricultural technologies is the pipeline and will follow the same methodology as pre-registered.

Data availability

All data used in this study is publicly available through the repository: https://github.com/bsrthyle/CSA-adoption-FCAS.

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References

1. Cassman, K. G. & Grassini, P. A global perspective on sustainable intensification research. *Nat. Sustain.* **3**, 262–268 (2020).
2. Bennett, E. M. Changing the agriculture and environment conversation. *Nat. Ecol. Evol.* **1**, 1–2 (2017).
3. Lipper, L. et al. Climate-smart agriculture for food security. *Nat. Clim. Chang.* **4**, 1068–1072 (2014).
4. Tabe-Ojong, M. P. J., Aihounton, G. B. D. & Lokossou, J. C. Climate-smart agriculture and food security: cross-country evidence from West Africa. *Glob. Environ. Chang.* **81**, 102697 (2023).
5. Tabe-Ojong, M. P. J., Affognon, H. D. & Lokossou, J. C. Adoption of climate-resilient groundnut varieties increases agricultural production, consumption, and smallholder commercialization in West Africa. *Nat. Commun.* **14**, 5175 (2023).
6. Duflo, E., Kremer, M. & Robinson, J. How high are rates of return to fertilizer? Evidence from field experiments in Kenya. *Am. Econ. Rev.* **98**, 482–488 (2008).
7. Emerick, K., De Janvry, A., Sadoulet, E. & Dar, M. H. Technological innovations, downside risk, and the modernization of agriculture. *Am. Econ. Rev.* **106**, 1537–1561 (2016).
8. Sheahan, M. & Barrett, C. B. Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy* **67**, 12–25 (2017).
9. Ashraf, N., Giné, X. & Karlan, D. Finding missing markets (and a disturbing epilogue): Evidence from an export crop adoption and marketing intervention in Kenya. *Am. J. Agric. Econ.* **91**, 973–990 (2009).
10. Suri, T. & Udry, C. Agricultural technology in Africa. *J. Econ. Perspect.* **36**, 33–56 (2022).
11. Hanna, R., Mullainathan, S. & Schwartzstein, J. Learning through noticing: theory and evidence from a field experiment. *Q. J. Econ*. 1311–1353 https://doi.org/10.1093/qje/qju015.Advance (2014).
12. Kabunga, N. S., Dubois, T. & Qaim, M. Heterogeneous information exposure and technology adoption: the case of tissue culture bananas in Kenya. *Agric. Econ. (U. Kingd.)* **43**, 473–486 (2012).
13. Acevedo, M. et al. A scoping review of adoption of climate-resilient crops by small-scale producers in low- and middle-income countries. *Nat. Plants* **6**, 1231–1241 (2020).
14. Piñeiro, V. et al. A scoping review on incentives for adoption of sustainable agricultural practices and their outcomes. *Nat. Sustain.* **3**, 809–820 (2020).
15. Stathers, T. et al. A scoping review of interventions for crop postharvest loss reduction in sub-Saharan Africa and South Asia. *Nat. Sustain.* **3**, 821–835 (2020).
16. Ruzzante, S., Labarta, R. & Bilton, A. Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World Dev.* **146**, 105599 (2021).
17. World Bank. Classification of Fragility and Conflict Situations (FCS) for World Bank Group Engagement. *Brief* (2022). Available at: https://thedocs.worldbank.org/en/doc/fb0f93e8e3375803bce211ab1218ef2a-0090082023/original/Classification-of-Fragility-and-Conflict-Situations-FY24.pdf (Accessed: 20th December 2022).
18. Scandurra, G., Romano, A. A., Ronghi, M. & Carfora, A. On the vulnerability of small island developing states: a dynamic analysis. *Ecol. Indic.* **84**, 382–392 (2018).
19. Benjaminsen, T. A. Does Climate Change Lead to Conflicts in the Sahel? in *The End of Dessertification? Disputing Environmental Change in the Drylands* (eds. Behnke, R. H. & Mortimore, M.) 99–116 (Springer Earth Systems Sciences, 2016). https://doi.org/10.1007/978-3-642-16014-1_4.
20. Raleigh, C. Political marginalization, climate change, and conflict in african sahel states. *Int. Stud. Rev.* **12**, 69–86 (2010).
21. IFPRI. *Conflict and agricultural productivity: Evidence from Myanmar*. (2023).
22. Sanch-Maritan, M. & Vedrine, L. Forced displacement and technology adoption: an empirical analysis based on agricultural households in bosnia and herzegovina. *J. Dev. Stud.* **55**, 1325–1343 (2019).
23. Takahashi, K., Muraoka, R. & Otsuka, K. Technology adoption, impact, and extension in developing countries' agriculture: A review of the recent literature. *Agric. Econ. (U. Kingd.)* **51**, 31–45 (2020).
24. Rosenstock, T. S. et al. *The scientific basis of climate-smart agriculture A systematic review protocol*. (2015).
25. Jayne, T. S. & Rashid, S. Input subsidy programs in sub-Saharan Africa: A synthesis of recent evidence. *Agric. Econ. (U. Kingd.)* **44**, 547–562 (2013).
26. Jayne, T. S., Mason, N. M., Burke, W. J. & Ariga, J. Review: Taking stock of Africa's second-generation agricultural input subsidy programs. *Food Policy* **75**, 1–14 (2018).
27. Ricker-Gilbert, J., Jayne, T. & Shively, G. Addressing the " Wicked Problem" of Input Subsidy Programs in Africa. *Appl. Econ. Perspect. Policy* **35**, 322–340 (2013).
28. Arslan, A., Floress, K., Lamanna, C., Lipper, L. & Rosenstock, T. S. A meta-analysis of the adoption of agricultural technology in Sub-Saharan Africa. *PLoS Sustain. Transform.* **1**, e0000018 (2022).
29. Nshakira-Rukundo, E., Kamau, J. W. & Baumüller, H. Determinants of uptake and strategies to improve agricultural insurance in Africa: A review. *Environ. Dev. Econ*. 605–631 https://doi.org/10.1017/S1355770X21000085 (2021).
30. Janzen, S. A. & Carter, M. R. After the drought: the impact of microinsurance on consumption smoothing and asset protection. *Am. J. Agric. Econ.* **101**, 651–671 (2019).
31. Ali, W., Abdulai, A. & Mishra, A. K. Recent advances in the analyses of demand for agricultural insurance in developing and emerging countries. *Annu. Rev. Resour. Econ.* **12**, 411–430 (2020).
32. Ceballos, F., Kramer, B. & Robles, M. The feasibility of picture-based insurance (PBI): Smartphone pictures for affordable crop insurance. *Dev. Eng.* **4**, 100042 (2019).
33. Ndegwa, M. K., Shee, A., Turvey, C. G. & You, L. Uptake of insurance-embedded credit in presence of credit rationing: evidence from a randomized controlled trial in Kenya. *Agric. Financ. Rev.* **80**, 745–766 (2020).
34. Shee, A., Turvey, C. G. & You, L. Design and rating of risk-contingent credit for balancing business and financial risks for Kenyan farmers. *Appl. Econ.* **51**, 5447–5465 (2019).
35. Sakketa, T. G., Maggio, D. & McPeak, J. The protective role of index insurance in the experience of violent conflict: evidence from ethiopia. *J. Dev. Econ*. **174**, (2025).
36. Van Dijk, S. H. B. et al. Artificial intelligence in systematic reviews: promising when appropriately used. *BMJ Open* **13**, e072254 (2023).
37. Bolaños, F., Salatino, A., Osborne, F. & Motta, E. Artificial intelligence for literature reviews: opportunities and challenges. *Artif. Intell. Rev.* **57**, (Springer Netherlands, 2024).
38. van de Schoot, R. et al. An open source machine learning framework for efficient and transparent systematic reviews. *Nat. Mach. Intell.* **3**, 125–133 (2021).
39. Boetje, J. & van de Schoot, R. The SAFE procedure: a practical stopping heuristic for active learning-based screening in systematic reviews and meta-analyses. *Syst. Rev.* **13**, 1–10 (2024).

40. König, L. et al. An evaluation of the performance of stopping rules in AI-aided screening for psychological meta-analytical research. *Res. Synth. Methods* **15**, 1120–1146 (2024).
41. Burgard, T. & Bittermann, A. Reducing literature screening workload with machine learning. *Z. Psychol.* **231**, 3–15 (2023).
42. Siemens, W. et al. Opportunities, challenges and risks of using artificial intelligence for evidence synthesis. *BMJ Evid.-Based Med.* **0**, 1–4 (2025).
43. Stanley, T. D., Doucouliagos, H. & Havranek, T. Meta-analyses of partial correlations are biased: Detection and solutions. *Res. Synth. Methods* **15**, 313–325 (2024).
44. Rofikha, A. A., Saputra, Y. & Islami, F. A. Best management practices for erosion and sedimentation control of the Sermo Watershed. *IOP Conf. Ser. Earth Environ. Sci*. **930**, (2021).
45. Zimmerman, J. et al. Iterative guided machine learning-assisted systematic literature reviews: a diabetes case study. *Syst. Rev.* **10**, 1–8 (2021).
46. Ogundari, K. & Bolarinwa, O. D. Impact of agricultural innovation adoption: a meta-analysis. *Aust. J. Agric. Resour. Econ.* **62**, 217–236 (2018).
47. Stanley, T. D. & Doucouliagos, H. *Meta-Regression Analysis in Economics and Business*. *Meta-Regression Analysis in Economics and Business* https://doi.org/10.4324/9780203111710 (2012).
48. Viechtbauer, W. & Cheung, M. W. Outlier and influence diagnostics for meta-analysis. *Res. Synth. Methods* **1**, 112–125 (2010).
49. Stanley, T. D. & Doucouliagos, H. Correct standard errors can bias meta-analysis. *Res. Synth. Methods* **14**, 515–519 (2023).
50. Sterne, J. A. C. & Egger, M. Funnel plots for detecting bias in meta-analysis: guidelines on choice of axis. *J. Clin. Epidemiol.* **54**, 1046–1055 (2001).
51. Sterne, J. A. C. & Harbord, R. M. Funnel plots in meta-analysis. *Stata J.* **4**, 127–141 (2004).

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