FRONT MATTER

Title:

Determinants of the Adoption of Sustainable Intensification in Southern African Farming Systems: A Meta-Analysis

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Abstract:

Climate change and environmental degradation are major threats to sustainable agricultural development in Southern Africa. Thus, the concept of sustainable intensification (SI) i.e. getting more output from less input using certain practices such as agroforestry, organic fertilizer, sustainable water management etc. has become an important topic among researchers and policy makers in the region in the last three decades. A comprehensive review of literatures on the adoption of SI in the region identify nine relevant drivers of adoption of SI among (smallholder) farmers. These drivers include (i) age, (ii) size of arable land, (iii) education, (iv) extension services, (v) gender, (vi) household size, (vii) income, (viii) membership in farming organization and (ix) access to credit. We present the results of a meta-analysis of 21 papers on the impact of these determinants on SI adoption among (smallholder) farmers in Southern African Development Community (SADC) using random-effects estimation techniques for the true effect size. While our result suggests that variables such as extension services, education, age, and household size may influence the adoption of SI in SADC, factors such as access to credit is also of great importance. Decision-makers should therefore concentrate efforts on these factors in promoting SI across the SADC. This includes increasing the efficiency of public extension service as well as involvement of private sector in extension service. Furthermore, both public and private agriculture financing models should consider sustainability indicators in their assessment process.

Keywords: Climate change; sustainable intensification (SI); Adoption; smallholder; meta-analysis; random-effect model; effect size; Southern Africa Development Community (SADC).

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RESEARCH MANUSCRIPT SECTIONS

1. Introduction

Meeting the United Nations Sustainable Development Goal of eradicating hunger and guaranteeing food security by 2050 might entail a 69-110% increase in current global food production [1, 2]. Similarly, the global population is estimated to increase to from seven to nine billion by midcentury [3]. These projections puts a spotlight on agriculture, as food production must increase to meet rising food demand. However, meeting these challenge is complicated by the fact that several current agricultural practices degrade the environment; contributing about 19-29% of current global greenhouse gas (GHG) emissions, majority of which comes from land clearing and intensive farming needed to increase crop production [1, 4]. This has led to calls for a shift in current agricultural practices towards cultivation systems that accommodates both sustainability and increased productivity [3]. Several terminologically different, but conceptually similar production systems have been proposed to achieve this goal. One of which is Sustainable Intensification (SI).[1]

[5] define SI as agricultural practices that results in higher outputs from efficient use of available inputs, while simultaneously reducing environmental damage, building resilience and improving environmental services. According to [6] four principles supports SI. One, increasing food production. Two, increasing production through higher yields not land expansion. Three, equally prioritizing environmental sustainability and increased productivity to achieve food security. Four, a process that requires rigorous assessment of various sustainability approaches within different social and institutional contexts to ascertain the merits of each approach. Common agricultural SI practices include organic fertilizer use, improved crop cultivars, soil and water conservation methods, cereal-legume intercropping, crop rotation, contour ploughing, leguminous trees, and agroforestry [7, 8].

In sub-Saharan Africa (SSA), agricultural production per capita still lags behind production per capita in Asia and Latin America [9]. While farm yield has increased in previous years, these gains are typically from land expansion [10]. Opening up new arable lands however faces competition from other human activities [9]. High rates of food insecurity and projected population increases on the continent points to the need to intensify further agricultural production [11]. How to intensify agriculture, without the accompanying environmental degradation and increases in GHG emissions remains a challenge. SI has been touted as a solution to these challenges [12, 13].

[9] documents several benefits emerging from various projects that deploy SI practices in SSA countries between the 1990s and 2000s. These include on average a 2.13 fold increase in yield, improvements in soil carbon content and a 94.5% reduction in pesticide use. Several studies have also demonstrated the superiority of adopting SI practices to conventional agricultural practices in improving crop productivity and food security [see 14 and 15]. The fact that only direct benefits of adopting SI practices are often reported may also underestimate the true effect of SI. For example, [16] and [17] found that agroforestry payment for ecosystem schemes could promote financial inclusion among smallholder farmers and economically empower female smallholders. [18] also found that these schemes tend to be cost-effective for developers introducing SI practices and farmers alike.

Despite the benefits of SI, adoption of SI practices remains very low among farmers and pastoralists across the SSA sub-region [9, 11, 19]. This is in spite of several campaigns and initiatives aimed at promoting the adoption of SI practices in SSA [10]. Farmers must perceive adequate welfare gains from SI uptake before choosing to adopt SI [20]. However, tradeoffs between economic productivity and sustainability often prolong gains from adopting SI [21]. Consequently, incentivized interventions e.g.,

[1] Other systems include climate smart agriculture, agro-ecology, ecological intensification, organic agriculture and agro-ecology. See [22] for an exposition on these terminologies.

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financial, behavioral and institutional are often needed to ensure uptake of SI practices and promote sustainable agriculture [22, 23]. Designing interventions to encourage sustainable agricultural or identifying specific target groups first involves identifying and a better understanding of factors driving the adoption of SI practices.

In this study, we address this issue. We focus specifically on agricultural systems in the Southern African Development Community (SADC), comprising: Angola, Botswana, the Democratic Republic of Congo, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Namibia, Seychelles, South Africa, Swaziland, United Republic of Tanzania, Zambia and Zimbabwe. Agricultural production increases in Africa are less pronounced in SADC compared to Western or Northern Africa [9]. Moreover, climatic conditions in the SADC are mostly semi-arid or sub-humid climates and under threat from climate change [24]. The threat posed by climate change in the SADC are related to erratic rainfall patterns, changes in temperature and extreme weather condition such as reoccurring droughts and floods [25]. This exposes arable lands in the region to environmental degradation, biodiversity losses and unsustainable natural resource management; further threatening the livelihoods of smallholders in SADC unless concrete measures are taken to address the situation.

Given the potential benefits of adopting SI practices, the question that arise is - *What are the essential drivers or determinants of SI among smallholder farmers in regions most vulnerable to climate change such as the SADC?* Several empirical studies have investigated the determinants of adoption of SI practices and have focused on various human capital assets, farm assets, institutional factors, risks and economic factors, and climatic conditions that drive SI adoption.

Our aim is to collate results from empirical studies examining SI adoption in SADC to obtain an true effect size that depicts the importance of various drivers of SI adoption. This provides insights into the direction of relationship between different human, social, economic and institutional capital factors, and adoption of SI practices. From a policy perspective, we provide information useful to decision-makers interested in designing policy initiatives or intervention measures that encourage the adoption of SI practices in the SADC.

To the best of our knowledge, this is the first study to use meta-analytic methods to estimate the true effect size of the determinants or drivers of SI in SADC. The random-effects models, such as DerSimonian-Laird (DL) model, Maximum-likelihood (ML) model, Restricted Maximum-likelihood (REML) model, Profile-likelihood (PL) model, and Permutations (PE) model are used for this meta-analysis. The standardization of the effect size of the studies to ensure uniformity was followed by the evaluation of heterogeneity, resulting in between-study variance, and its mitigation in preparation for the meta-analysis. Our results, which is not only based on statistical significance but also the precision of estimation, indicate that access to credit, arable land, education, extension, gender, and household size mainly drive SI adoption in SADC.

The rest of paper is structured as follows. Section 2 outlines the materials and methods uses for the meta-analysis. Section 3 presents the results of the meta-analysis. Section 4 opens up some insightful discussion with regards to the result. Section 5 then concludes.

2. Materials and methods

Criteria for Selecting Studies

Choice of Studies: One of the first steps of the literature review in meta-analysis is retrieval and selection of studies [26]. Only studies that investigated determinants of smallholder’s decisions to adopt SI in SADC and those written in English were considered for this study. Furthermore, these studies must report quantitative data sufficient for computing weighted average effect sizes.

Search Method and Strategy

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We searched the following online social science database from September 2018 through March 2019: Google Scholar, PubMed, ISI Web of Science, ResearchGate, and ScienceDirect. The following keywords and descriptors were used as search criteria namely: *'sustainable intensification agriculture - SIA,' 'Sustainable Intensification Practice - SIP,' 'determinants, improved cultivar,' 'cereal-legume intercropping,' 'crop rotation,' 'organic fertilizer,' 'contour plough,' 'leguminous trees,' 'agroforestry,' 'soil conservation,' and 'pest management.'* The search was extended to the reference list of the relevant articles to ensure that relevant studies were not unintentionally neglected.

Data Collection and Analysis

The author(s) conducted the article selection process by initially screening those articles that matched the selection criteria by title and abstract. This was followed by data extraction from the studies that met the selection criteria. The data that was extracted from each article are as follows: title, author(s), study area, type of SI, characteristics of intervention(s), and outcome data. The outcome data extracted from each article included coefficients and standard errors from logistic- rather than probit regression as it would be impossible to find an effect size measure that simultaneously suits both methodologies. In the event the outcome data were missing or unclear the authors excluded such studies.

Logistic and probit regression are models often used in the adoption papers. The reason logistic and probit regression are widely used in studies investigating the determinants of technology adoption such as SI is because dependent variables representing technology adoption are often categorical [27]. In this case, categorical means a value of one for adopting a specific intervention and zero for non-adoption. 112 studies met the above requirements, among which 50 studies presented their results by using logistic regression. There were no duplicate studies within these 50 studies. However, 15 of the 50 studies presented only marginal effect instead of odds ratio (OR) and were dropped. Among the remaining 35 studies, 14 did not provide standard errors of coefficients and were removed from the database. From the remaining 21 studies, we extracted 33 estimates because some studies analyzed more than one SIPs. We illustrate this process in Figure 1.

[**Insert Figure S1 Here**]

Method of Meta-analysis

Since the purpose of meta-analysis is to combine study results, effect size statistics (regression) are tools for transforming different forms of results into a common form, to compute overall magnitude of a phenomenon across primary studies. In a meta-analysis, the overall effect size is a quantitative measure of the influence of a variable or factor on the outcome of interest [28]. It could be interpreted as an index to quantify the relation between an independent variable and a dependent variable in a function. It is however important that a common measure be calculated for different studies and then combined into an overall summary. Given that units of measurements included in primary study results are often different, a standardized effect size is more appropriate. In our case the standardized effect size is derived from the association-based family, *r*, which measures the size of variation between two (or more) variables observed in the same sample or in different samples [29]. Using the association-based family, *r*, estimation we opt for the odd ratios estimation as this is appropriate for logistic regression [29].

Fixed-effect model and random-effects model are the two models commonly used in meta-analysis in computing the weighted average effect sizes [30]. The fixed-effect model assumes the true effect to be the same (i.e. homogeneous) across studies, and the weighted average effect size is an estimate of this true effect size. In contrast, the random-effects model assumes distribution and variance in the true effect size across studies. A random-effects model is appropriate if (a) it is unlikely that all the studies are practically similar and (b) the research goal is to compute a weighted mean of true effect sizes, which would then be generalized for the entire population. In most cases, homogeneity has been found to be the exception rather than the rule, and some degree of true effect variability between studies is to be expected [31]. For instance, experiments or projects on SI in SSA are often conducted in different locations, recruit participants with different standards or adopt various SIPs. It is, therefore, plausible to assume a distribution of true effect sizes for each determinant. Thus, in this study we settle for the random effect models of estimating the effect sizes. The weighted average effect computed by random-effects model is an estimate of the weighted mean of a distribution of true effect sizes. The equation for the random-effects model [see 32] can be written as:

$$y_i = \mu_{RE} + \varepsilon_i + \delta_i \qquad [1]$$

Where y_i is the observed effect in the study i; μ_{RE} is the common true effect; $\varepsilon_i \sim N(0, v_i)$, and v_i is the within-study variance in the study i; while $\delta_i \sim N(0, \tau^2)$, τ^2 represents the between-study variance. In the random-effects model we assume the observed variation: $Var\ (y_i)$, is caused by within-study and between-study variance, illustrated in equation 2 as:

$$Var_{RE}\ (y_i) = v_i + \tau^2 \qquad [2]$$

The weighting method for the estimating of effect size computed by random-effects model, $\hat{\mu}_{RE}$, [see 33] is calculated as:

$$\hat{\mu}_{RE} = \frac{\sum y_i w_{i,RE}}{\sum w_{i,RE}} \qquad \text{where } w_i = \frac{1}{v_i + \tau^2} \qquad [3]$$

Where y_i is the estimated effect size for study i, and w_i is the weight for study i. It is important to note that when there is between-study variance, random-effect model gives less weights to study i and wider 95% confidence intervals (CIs) [34]. Another important thing to note from the equations above is the central role that between-study variance, τ^2, plays in the estimation of the overall effect using random-effects model. This estimation of between-study variance τ^2 can be done using the DerSimonian-Laird (DL) model, Maximum-likelihood (ML) model, Restricted Maximum-likelihood (REML) model and the Profile-likelihood (PL) model [32]. The Stata command *metaan* and *metan* can both can be used for meta-analysis given the pre-calculated effect estimates extracted from included primary studies with the *latter* providing statistical significance level for the estimated overall effect size. In this study we shall place some emphasis on the REML model because we have dichotomous outcome data and there may exists large between-study variance (τ^2). As for the estimation method of CI for between-study variance i.e. precision of effect, the PL method performs better than the Wald-type method in terms of coverage probability [35, 36][2] . The objective of the meta-analysis in this paper is to find the estimated overall effect size for each of the aforementioned determinants, which should be statistically significant and precise. Since the precision value i.e. CI is derived from the equation that generate the P value, there is essentially a relationship between both values [39, 40]. If the value of zero is reported at the 95% CI, then the null hypothesis (effect size=0) is rejected and this estimate is statistically significant at the 5 percent level [41, 42]. To this end, only statistically significant estimates close to the true value are relevant. The table 1 below provides an overview of the estimation methodology using the statistical tool Stata.

[**Insert Table S1 Here**]

Heterogeneity

The between-study variance stemming from differences in populations, interventions, outcomes or follow-up times is called heterogeneity [33, 34]. If the studies are very dissimilar on these factors, it may be preferable not to pool the results [43]. Heterogeneities among primary study results affects true effect. In this paper, the included primary study results have some similar characteristics, but also contain potential sources of heterogeneity. Similar characteristics shared by the primary studies include

[2] For more clarity on the usefulness and functionalities of the different models, see [37] and [38] for more information.

smallholders as participants living in the SADC member states, SI as trial interventions, and multivariate logistic regression equations as study outcomes containing regression coefficients and their standard errors. On the other hand, there are several potential sources of heterogeneity given that the domain of value for some variables differ between studies. For instance, the study by [44] on adoption of conservation agriculture measured education as an ordinal variable (2 = secondary level, 1 = primary, and 0 = illiterate), while [45] measured education in years of schooling. Furthermore, other factors such as duration of the experiments, disparity in the number of independent variables measured across primary studies, the reliability of outcome measures as well as correlation between independent variables may affect the accuracy of the estimation of the effects of determinants. Thus, it is necessary to also undertake a heterogeneity test to evaluate the extent of between-study variance. There are three default heterogeneity tests provided by the Stata command metan namely: Cochrane's Q, I^2, and τ^2 . In this study we shall restrict ourselves to I^2, which is the percentage of the total variability in a set of effect sizes due to true heterogeneity, i.e. between-study variability [46]. We cannot use τ^2 to compare the absolute value of heterogeneity across determinants, as most determinants are in different metrics. [33] classifies the values of I^2 as ranging from low (< 25%), moderate ($25\% \leq I^2 < 50\%$), high ($50\% \leq I^2 < 75\%$) to considerably high ($I^2 \geq 75\%$). If the value of I^2 is low then there is limited between-study variance and hence further analysis to explore the cause through subgroup analysis is not necessary. However, if the value of I^2 is large then subgroup analysis is essential as it can also help reduce the between study variance. In this study, we propose a subgroup analysis based on effect size and outliers. This is essentially eliminating the outliers i.e. dropping single effect sizes far away from the estimated overall effect size, to make the result more consistent. Such outlier observed in our sample may be due to variability in the measurement or experimental error. In this paper, the values falling out of a distance of half of the width of the 95% CI of estimated overall effect size is termed an outlier thus resulting in two subgroups with the single effect sizes within this interval termed as more consistent, while those out of this interval are less consistent.

3. Results

Table 2 summarizes the values of the of estimated overall effect sizes at the 95% CI and their statistical significance (at 5% significance level) computed by all the available models in Stata i.e. DL, ML, REML, and PL. The results of the DL model overall effect size suggest determinants such as *Age*, *Membership* and *Credit* have a positive effect on SI adoption while *Arable land* and *Gender* had negative effect on the adoption of SI in SADC (see table 2). If we look at the 5% significance level of the 95% CI, the estimated overall effects of *Gender* and *Credit* are the only valid results across all four models. From the result we can infer that farmers having access to credit were 1.2 ($e^{0.156}$) times more likely to adopt SI compared to those not having access to credit service, while male farmers were less likely 0.6 ($e^{0.509}$) to adopt SI compared to female farmers.

[**Insert Table S2 Here**]

Since the P value of significance test is not available in the ML, REML, or PL model, the range of 95% CIs are used to test the statistical significance of the result at 0.05 significance level. The narrower the width of the 95% CI, the more precise the estimation of the effect size is. In this respect, the DL model provided the most precise estimations for seven of the nine determinants namely: *Age, Arable Land, Education, Household Size, Income, Membership, and Credit* (see Table 2). We take a closer look at the precision level of the determinants in question within the DL model (see Figure 2). The sequence of order from the narrowest to the widest 95% CI of the estimated overall effect size, assuming a 0.2-point drop mark, is *Extension, Age, Education, Household Size, Credit, Income, Arable Land, Membership* and *Gender*. This implies *Extension* has the most precise overall effect size, although not statistically significant, while *Gender* has the least precise result.

[**Insert Figure S2 Here**]

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In order to get a good overview of the statistical significance and precision of estimation reported by the DL model we represent the results in table 3. The estimated overall effect size of *Membership* and *Credit* are highly statistically significant at 0.1%.

[**Insert Table S3 Here**]

In terms of precision, *Extension, Age, Education, Household Size,* and *Credit* are the top-five ranked determinants based on a 0.2 threshold. We can interpret from table 3 that *Age* and *Credit* play a significant role in SI adoption in SADC. That is to say, the estimated overall effect size of *Age* and *Credit* are the only two simultaneously significant and precise computed by the DL model.

Table 4 summarizes the value of I^2 computed by the DL, ML, REML, and PL model. We interpret the estimates based on the aforementioned classification of I^2 by [33]. The estimated overall effects for all the nine determinants, with the exception of *Extension* for ML, REML, and PL, are considerably heterogeneous across all the models.

[**Insert Table S4 Here**]

The results from table 4 imply we have to conduct a subgroup analysis to eliminate the causes of heterogeneity i.e. drop outliers. Table 5 show that after conducting the subgroup analysis there was substantially lower heterogeneity within the more convergent column compared to that of the less convergent and overall. The low level of heterogeneity means smaller between-study variance and more similar result for the more convergent. For the more convergence, the estimated overall effect size of *Age*, *Membership* and *Credit* displace a relative considerably heterogeneity. In contrast, the estimated overall effect sizes of *Extension*, *Gender*, *Arable Land*, *Education*, and *Income* range from homogenous to highly heterogeneous.

[**Insert Table S5 Here**]

We adopt a 5% significance level in the significance test and set I^2=75% as the limit for distinguishing heterogeneity. In other words, only results that are simultaneously statistically significant at 5% significance level and have value of I^2 less than 75% are viewed as valid results. In table 6, seven of the nine determinants statistically significant at 0.1% and 1% significance level in the more convergent subgroup. Seven of the nine determinants were statistically significant at 0.1% and 1% significance level in the more convergent subgroup. The results suggest that when the size of *Arable Land* increases by one unit, farmers are 1.096 ($e^{0.092}$) times more likely to adopt SI in SADC with similar results for *Education* which is in strong contracts to the results without the subgroup analysis presented in Table 2. Increasing *Extension, Household Size, Membership of cooperative* and *Access to credit* by one unit would likely increase the adoption of SI among farmers in SADC by units greater than 1. The result of *Gender* is consistent with the results from Table 2 that male farmers are 0.467 ($e^{-0.762}$) less likely to adopt SI compared female farmers.

[**Insert Table S6 Here**]

4. Discussion

This study sets out to analyze the true effect size of identified determinants (age, size of arable land, education, extension, gender, household size, income, membership in farming organization and access to credit) of SI adoption among smallholder farmers in SADC considering their vulnerability to climate change. Given that there is often no clear direction of the magnitude of some of the determinants, we revert to a comprehensive meta-analysis in this study. We estimated the effect size of the aforementioned determinants using random effect models specifically DL model, ML model, REML model, and PL model using a standardization approach. The DL model produced a high degree of statistical significant and precise results which to some extent align with conventional findings as well as others that were not necessarily plausible. For instance, in our study *Age*, *Membership* and *Credit* were found to have a positive and significant effect size on the adoption of certain SI practices among

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smallholder farmers in SADC which is also similar to the study by [47]. Conversely, the study by [48] was inconclusive on the effect of Membership in a farming organization on SI adoption, while Education and Extension was positive and significant which aligns with the study of [49]. However, some of the results of these previous studies appear not to align with our meta-analysis, at least at the initial stage, as it suggests that education and extension provide insignificant and negative value as effect size. Furthermore, our initial results of the effect size suggest that female smallholders are more likely to adopt SI compared to their male counterparts in SADC which contradicts the study by [48] who argue that women are resources constraint and do not have access to adequate extension service. However, one could also counter-argue that while asset is probably owned by male smallholders, the running of the day-to-day agricultural land activities in SSA remains in the hands of female smallholders [see 48] which would also hold for the SADC region. Our *somewhat* unconventional results of the overall effect sizes of some of the determinants of SI adoption among smallholder farmers requires further analysis on the precision of these determinants and their similarity across the different studies aside from the atypical statistical significance. We conclude that only access to *Credit* and *Age* can be ascertained to have produced valid results, given their significance and precision, from our initial stage meta-analysis. Our results from the initial stage meta-analysis can however be considered invalid according to the heterogeneity i.e. between-study variance analysis as none of the determinants across all models were in the ranges low to high, in other words $I^2 < 75\%$. In order to reduce heterogeneity in our dataset to an acceptable the level, a subgroup analysis was conducted resulting in two groups more- and less convergent. In the more convergent category, a number of determinants namely; *Arable Land, Education, Extension, Gender, Household Size* and *Income* have $I^2 < 75\%$ with *Credit* a little above this threshold. Given that the DL model reports statistical significance and is the most precise of all the models, another round of meta-analysis was conducted using this model. The results suggest that the effect size of *Arable Land, Education, Extension, Household Size and Credit* are positive and statistically significant while gender remains negative and also significant. These results have some immense implications for the spread of SI practices in SADC. While there are a number of large farms operational in the SADC which may help adoption of SI practices, micro- and small scale farming systems are prevalence and shape the agricultural land scape with some these farmer having limited or no education or access to credit [see 16]. This could explain the modest uptake of the SI especially among smallholder farmers. Our result strongly suggest that women smallholders are more likely to adopt SI practices compared to their male counterparts in SADC. This may be due to the aforementioned line of reasoning that women often actively partake in on-farm activities in SSA and our results align with those from other studies [see 51, 52].

5. Conclusion

This study sets out to answers to the question - *What are the essential drivers or determinants of SI in SSA sub-regions most vulnerable to climate change such as the SADC?* Our meta-analysis shows that *Arable Land Size, Education, Extension, Household Size and access to Credit* are key to the adoption of SI by smallholder farmers in the SADC while the role women smallholder farmers play in SI adoption remains unquestionable. Thus, policy makers in the SADC economic block esp. those located in vulnerable regions that would like to promote SI adoption among smallholder farmers should further develop some of these variables. This could take the form of turning fragmented small parcel of lands into a larger farm through a more proactive farmer's association. Smallholder farmers affected by climate change participating in such association can also acquire new skills and techniques related to SI practices through farmer schools, demonstration farms etc. while adequate provision should be made for content specific public as well as private extension services. There is also a need to develop novel models for sustainable agricultural financing for smallholder agribusiness adopting SI practices [see 53] given the prevalence of credit rationing to overall agricultural systems in SSA. This should involve the participation of different stakeholders ranging from private financial institutions to agricultural development intervention programs. The role of women should be taken more seriously in the spread of SI in the SADC region. There should be awareness campaigns to showcase some of the benefits that

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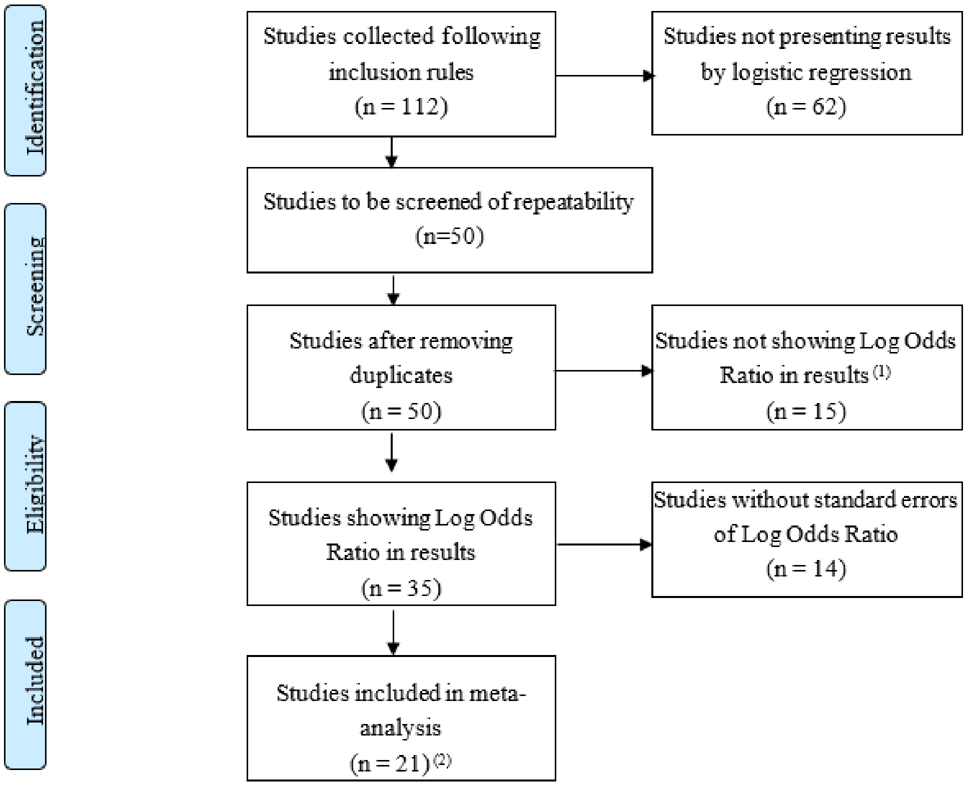
accrue to women smallholder who adopt some form of SI practices which according to [17] includes economic empowerment. Finally, there is a need for further research using meta-analysis to assess the true effect of the determinants of SI in SADC by expanding such study based on a more comprehensive climatic classification, improved methodology of estimation as well as inclusion of future studies.

BACK MATTER

Supplementary Materials:



(1) Some logistic regression coefficients were presents not in the form of log OR but marginal effect.
(2) The included 21 studies contain 33 study results, as some of them contain more than one results in one paper.

Source: Own illustration modified from the PRISMA flow diagram (2009).

Figure S1: Flow Diagram of Literature Review

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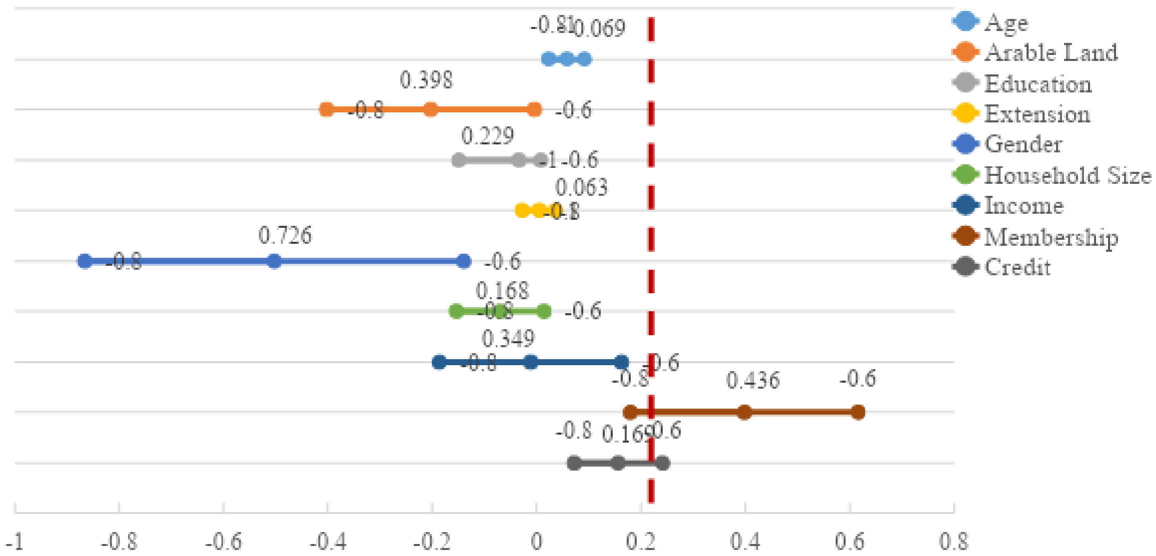

Figure S: Forest Plot to study distribution of the Estimated Overall Effect Sizes Computed by DL Model

Source: Authors

Table S1: Overview Stata Commands metan and metaan for Aggregate Data Meta-analysis

Stata Command	Estimation Methods for τ^2 (1)	Estimation Methods for CI of τ^2	Significance Test (P Value) for $\hat{\mu}$ (2)
metan	DL	Wald-type	Available
metaan	DL, ML, REML	Wald-type, PL	Not Available

(1) τ^2 denotes between-study variance.
(2) $\hat{\mu}$ denotes estimated overall effect size.

Source: Authors illustration modified from Kontopantelis & Reeves (2010) and Harris & Bradburn (2008).

Table S2: Estimated Overall Effect Sizes and their 95% CIs by DL, ML, REML, PL models

Determinants	DL model	ML model	REML model	PL model
	(1)	(2)	(3)	(4)
Age	0.058(1) * (3) (0.023, 0.092) (2)	0.119 (-0.075, 0.313)	0.119 (-0.079, 0.316)	0.119 (-0.082, 0.319)

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	(0.069) [(4)]	(0.388)	(0.395)	(0.401)
Arable Land	-0.203* (-0.402, -0.004) (0.398)	0.402 (-0.063, 0.867) (0.93)	-0.202 (-0.66, 0.256) (0.916)	-0.202 (-0.668, 0.266) (0.934)
Education	-0.034 (-0.149, 0.080) (0.229)	-0.033 (-0.44, 0.374) (0.814)	-0.032 (-0.447, 0.383) (0.83)	-0.033 (-0.451, 0.393) (0.845)
Extension	0.005 (-0.027, 0.036) (0.063)	003 (-0.011, 0.017) (0.028)	0.003 (-0.012, 0.019) (0.031)	0.003 (-0.014, 0.020) (0.034)
Gender	-0.503* (-0.866, -0.140) (0.726)	-0.509* (-0.844, -0.173) (0.671)	-0.507* (-0.849, -0.165) (0.684)	-0.509* (-0.852, -0.155) (0.697)
Household Size	-0.07 (-0.154, 0.014) (0.168)	-0.079 (-0.278, 0.12) (0.398)	-0.078 (-0.282, 0.125) (0.407)	-0.079 (-0.285, 0.132) (0.417)
Income	-0.011 (-0.186, 0.163) (0.349)	-0.009 (-0.192, 0.175) (0.367)	-0.005 (-0.199, 0.188) (0.387)	-0.009 (-0.200, 0.209) (0.409)
Membership	0.398* (0.180, 0.616) (0.436)	0.402 (-0.063, 0.867) (0.93)	0.402 (-0.078, 0.882) (0.96)	0.402 (-0.092, 0.896) (0.988)
Credit	0.156* (0.072, 0.241) (0.169)	0.159* (0.043, 0.276) (0.233)	0.16* (0.036, 0.283) (0.247)	0.159* (0.031, 0.290) (0.259)

(1) The estimated overall effect sizes are Log ORs computed by Stata.
(2) Width of 95% CI = lower and upper limit of 95% CI.
(3) Indicates effect size that this is statistically significant at 5% significance level.
(4) The bold represents the narrowest width of 95% CI in the row.
Source: Authors

Table S3: P Values and Widths of CIs of Estimated Overall Effect Sizes Computed by DL Model

Rankings of Significance (1)	**Determinants**	**P Values for Significance Test of ES=0**	**Rankings of Precision (2)**	**Determinants**	**Widths of 95% CI (3)**
1	Membership	0.000*** (4)	1	Extension	0.063
2	Credit	0.000***	2	Age	0.069
3	Age	0.001** (5)	3	Education	0.157
4	Gender	0.007**	4	Household Size	0.168
5	Arable Land	0.046* (6)	5	Credit	0.169
6	Household Size	0.102	6	Income	0.349
7	Education	0.556	7	Arable Land	0.398
8	Extension	0.778	8	Membership	0.436
9	Income	0.900	9	Gender	0.726

(1) Rankings of significance: sorted by P value of significance test (null hypothesis is ES=0), from the smallest value to the largest value.
(2) Rankings of precision: sorted by width of 95% CI of estimated overall effect size, from the smallest value to the largest value.
(3) Widths of 95% CI: calculated by subtracting lower limit of 95% CI from upper limit of 95% CI.
(4) *** indicates that this effect size is statistically significant at 0.1% significance level, i.e. P value≦0.001.
(5) ** indicates that this effect size is statistically significant at 1% significance level but not significant at 1% significance level, i.e. 0.001<P value≦0.01.
(6) * indicates that this effect size is statistically significant at 5% significance level but not significant at 5% significance level, i.e. 0.01≦P value<0.05.

Source: Authors.

Table S4: I^2 for Estimated Overall Effect Sizes by the DL, ML, REML, PL Model

Determinants	**DL model**	**ML model**	**REML model**	**PL model**
	(1)	**(2)**	**(3)**	**(4)**
Age	96.20%	99.91%	99.91%	99.91%
Arable Land	98.80%	99.51%	99.97%	99.76%
Education	97.50%	99.83%	99.83%	99.83%

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Extension	80.30%	34.45%	40.64%	34.45%
Gender	97.90%	97.51%	97.62%	97.51%
Household Size	94.30%	99.07%	99.11%	99.07%
Income	76.50%	79.03%	81.55%	79.03%
Membership	97.40%	99.51%	99.54%	99.51%
Credit	95.20%	97.72%	98.00%	97.72%

Source: Authors

Table S5: Subgroups analysis classified by Effect Size using DL model

Determinants	More convergent	Less convergent	Overall
Age	93.10%	98.50%	96.20%
Arable Land	*70.20%*[(1)]	99.60%	98.80%
Education	*64.30%*	99.30%	97.50%
Extension	*0.00%*	82.20%	80.30%
Gender	*0.00%*	98.40%	97.90%
Household Size	*50.00%*	99.00%	94.30%
Income	*69.40%*	75.30%	76.50%
Membership	90.30%	99.40%	97.40%
Credit	78.70%	96.30%	95.20%

(1) Italic indicates not considerably heterogeneous ($I^2 < 75\%$)

Source: Authors

Table S6: Estimated Effect Sizes in Subgroups by DL Model- classified by Effect Size

Determinants	More convergent	Less Convergent	Overall
Age	0.022 (-0.002, 0.046) (n=25)[(1)]	0.442 (-0.447, 1.331) (n=8)	0.058** (0.023, 0.092) (n=33)

Arable Land	0.092***(2) (0.048, 0.135) (n=18)	-1.233 (-3.416, 0.949) (n=5)	-0.203* (-0.402, -0.004) (n=23)
Education	0.083*** (0.051, 0.115) (n=21)	-0.139 (-2.084, 1.806) (n=8)	-0.034 (-0.149, 0.080) (n=29)
Extension	0.013**(3) (0.003, 0.022) (n=5)	0.038 (-0.107, 0.183) (n=15)	0.005 (-0.027, 0.036) (n=20)
Gender	-0.762*** (-0.915, -0.609) (n=7)	-0.404 (-0.867, 0.058) (n=18)	-0.503** (-0.866, -0.140) (n=25)
Household Size	0.053*** (0.022, 0.084) (n=22)	-0.446 (-1.297, 0.406) (n=5)	-0.07 (-0.154, 0.014) (n=27)
Income	-0.022 (-0.235, 0.191) (n=2)	0.005 (-0.232, 0.241) (n=13)	-0.011 (-0.186, 0.163) (n=15)
Membership	0.215** (0.081, 0.348) (n=12)	0.69 (-1.540. 2.919) (n=4)	0.398*** (0.180, 0.616) (n=16)
Credit	0.188** (0.054, 0.321) (n=12)	0.136*(4) (0.030, 0.243) (n=4)	0.156*** (0.072, 0.241) (n=16)

(1) n indicates the number of included primary study results.
(2) *** indicates that this effect size is statistically significant at 0.1% significance level, i.e. P value≦0.001.

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(3) ** indicates that this effect size is statistically significant at 1% significance level but not significant at 1% significance level, i.e. 0.001<P value≦0.01.
(4) * indicates that this effect size is statistically significant at 5% significance level but not significant at 5% significance level, i.e. 0.01≦P value<0.05.

Source: Author

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Conceptualization, Guo and Benjamin; Methodology, Guo and Benjamin; Software, Guo and Benjamin; Validation, Ola and Benjamin; Formal Analysis, Guo and Benjamin; Investigation, Guo, Ola and Benjamin; Data Curation, Guo; Writing – Original Draft Preparation, Guo and Benjamin; Writing – Review & Editing Ola; Supervision, Benjamin.

Conflicts of Interest:

The authors declare no conflict of interest.

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