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Nexus of agricultural informatisation and sustainable practices: Food security implications for drought-affected maize farmers in Zambia

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Abstract: Agricultural informatisation (AgI) is hailed as a 'game-changer' for farmers worldwide, even as climate change increases agriculture's vulnerability to climatic risks and threatens sustainable agrifood production. While AgI aspires to help alleviate hunger and poverty in smallholder farm households by improving on-farm productivity through the promotion of sustainable agricultural practices (SAPs), limited empirical evidence exists on the AgI–SAPs nexus, particularly under severe environmental stress such as drought. We analysed data from a survey of maize farmers in central Zambia – a country exemplifying the impact of severe drought, declared a national emergency and disaster – to explore whether and how AgI can optimise SAP adoption and improve crop yields. Given the potential endogeneity of AgI adoption, we employed a recursive bivariate probit (RBP) and endogenous-treatment regression (ETR) to estimate the former and the latter, respectively. We focused on adoption portfolios of three AgI tools – radio, television and mobile phones – and five SAPs: minimum tillage, residue retention, planting basins, improved seed varieties and irrigation. The results reveal that AgI adoption significantly influences SAP adoption, with varying impacts across different AgI and SAP portfolios. Importantly, the adoption of productivity-enhancing SAPs, particularly improved seed and drip irrigation, produced the largest yield effects (124.46 g/capita/day) for AgI adopters. This increase potentially contributes 43.21% towards daily maize-supply quantity, which is crucial for helping households meet the minimum recommended daily caloric intake. The study therefore underscores that AgI plays a critical role in improving yields through SAP adoption, serving as a compelling pathway for agricultural resilience, especially under adverse climatic conditions. These insights align with the United Nations Sustainable Development Goals (SDGs), particularly those aimed at zero hunger, climate action and poverty alleviation, which advocate re-thinking and transforming food-production strategies.

Keywords: information and communication technology; sustainable intensification;severe drought; maize yield; smallholder agrifood production

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The world is undergoing a digital agricultural revolution with the potential to significantly address global food security needs (Barrett 2021; Gouvea et al. 2022). In Africa, particularly in rural areas, the rapid development and penetration of information and communication technologies (ICTs) have spurred considerable interest among policymakers, researchers and development funding agencies in exploring their capacity to enhance extension and advisory services and contribute to rural development (Tossou et al. 2020; Ortiz-Crespo et al. 2021). In 2022, mobile subscriptions, SIM connectivity, and smartphone adoption in Sub-Saharan Africa (SSA) had penetration rates of 43%, 86%, and 51%, respectively, with projections reaching 50%, 99%, and 88% by 2030 (GSMA 2025). Similarly, radio remains a key medium for disseminating information, with an estimated 800 million radios in SSA, penetrating even the poorest communities (Hudson et al. 2017). Importantly for agriculture, over 390 digital service providers are active, and digital applications currently reach 33 million smallholder farmers, with projections of 200 million by 2030 (Tsan et al. 2019). Given this context, agricultural informatisation (AgI) – the use of ICTs to support agricultural processes – has been recognised as a 'game-changer' for farmers and communities in SSA (Agyekumhene et al. 2018; Duncan et al. 2021). Consequently, ICTs are seen as transformative for smallholders in Africa, with the potential to enhance access to knowledge, boost productivity, and improve food security (Goedde et al. 2021).

Despite the growth in ICTs, connectivity in rural areas remains limited, with access to technologies significantly trailing behind urban centres – hindering meaningful integration of innovation and deepening cycles of poverty (Cariolle 2021; Abdulqadir and Asongu 2022; Alabdali et al. 2023; FAO 2023; Choruma et al. 2024). This limitation constrains agricultural development, with low productivity partly due to the insufficient adoption of sustainable agricultural practices (SAPs) – which are environmentally friendly, resource-conserving, socially acceptable, technically appropriate, and economically viable. Notably, addressing these technology inequities and promoting the adoption of SAPs could significantly drive agricultural growth and enhance crop productivity (Nakasone and Torero 2016). Indeed, empirical evidence demonstrates that SAPs boost crop productivity, contributing to economic development and helping to reduce poverty and food insecurity (Mwalupaso et al. 2019a; Vatsa et al. 2023b).

Adopting SAPs is crucial, given agriculture's inherent vulnerability to climate change. Zambia serves as a pertinent example, having recently experienced a severe drought that was declared a national emergency and disaster. This crisis was aggravated by smallholder farmers' heavy reliance on rain-fed agriculture, leading to significant agricultural losses. Government crop assessments estimated that more than one million hectares of cropland were affected, resulting in either outright crop failure or substantial yield declines in the staple crop, maize (WFP 2024). These extreme weather events not only reduce agricultural productivity but also exacerbate food and nutrition insecurity, contributing to the increasing severity and prevalence of food insecurity. With only six years remaining until 2030, if these scenarios persist, achieving Sustainable Development Goals (SDGs) 1 (no poverty), 2 (zero hunger), and 13 (climate action) will be unattainable.

Consequently, to enhance resilience and foster the adoption of sustainable practices, agricultural extension and advisory services (EAS) were introduced to provide smallholder farmers with timely and relevant information. However, their impact is mixed despite decades of investment, primarily due to the untimeliness or irrelevance of the information provided, imperfect market data, and the high costs of face-to-face delivery (Norton and Alwang 2020). Given these challenges, confidence is growing in the potential of ICTs – such as mobile-enabled advisories, phones, radios, and televisions – to enhance agri-food systems (Aker et al. 2016; Giulivi et al. 2023). Specifically, these technologies facilitate real-time market data access, financial services, extension support, and input availability, offering more effective solutions for farmers.

However, the empirical exploration of the relationship between smallholders' engagement with ICTs and SAPs adoption remains limited. Most studies either focus on specific digital solutions in isolation, ignoring their potential interplay, or examine factors influencing adoption and intensity without incorporating SAPs considerations (Parlasca et al. 2022; Abdulai et al. 2023; Abate et al. 2023). Other research estimates the adoption or intensity of SAPs (Manda et al. 2016; Ehiakpor et al. 2021) or yield effects (Amadu et al. 2020a) without assessing the impact of digital tools. Although an emerging body of research has explored the potential of ICT in agriculture (Aker et al. 2016; Khanna et al. 2022; Quarshie et al. 2023), highlighting benefits related to agricultural smartness and sustainability, it often lacks empirical analysis especially in the context of severe environmental stress such as drought. This oversight limits actionable insights into the AgI–SAPs nexus, leaving policymakers and practitioners without evidence-based strategies for resilience-building in climate risk hotspots.

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Moreover, while the adoption of multiple SAPs is acknowledged (Kassie et al. 2013; Ehiakpor et al. 2021), the impact of AgI adoption portfolios on SAP decision-making is often overlooked.

To address this gap, the study draws on primary cross-sectional data from 568 randomly selected farm households in central Zambia to investigate the effect of AgI adoption on various SAPs adoption portfolios and crop yields, revealing important implications on sustainable agrifood production. Recognising that the adoption of AgI adoption is endogenous, we utilised the recursive bivariate probit (RBP) and endogenous treatment regression (ETR) to jointly estimate a pair of two equations: one pair sheds light on the impact of AgI on SAPs, and the other illuminates the effects of AgI adoption on maize yields.

Consequently, this study makes a three-fold contribution to the existing literature. First, it explores the nexus between AgI and SAPs within the context of smallholder farmers in a developing country, offering critical insights into how ICT-based agricultural solutions can enhance food production resilience. This is particularly relevant to achieving the SDGs. By focusing on smallholder agriculture – an area critical for policy interventions – the study provides a comprehensive understanding of how AgI can drive agricultural modernisation. Second, the study examines maize production during a severe drought, shedding light on the vulnerabilities of maize producing households. Maize, a staple crop with high per capita consumption, is extensively grown across Sub-Saharan Africa (SSA) and processed into various products such as starch, sweeteners, oil, and fuel ethanol. Its high energy density and nutritional content make maize strategically important for regional and global food security, especially in areas prone to micronutrient deficiencies (Mustafa et al. 2021). Lastly, the study offers significant scholarly and policy insights by calculating the yield effects associated with various SAP adoption portfolios. This analysis provides policymakers and development partners with targeted evidence on whether and how AgI–SAP nexus can enhance daily per capita food supply quantity (maize available for consumption) and caloric intake. Such insights are pivotal in light of the call by Barrett (2021) to pay attention to Africa , highlighting its rich potential for agricultural innovation, rapid population growth, rising food demand driven by income growth, and increasing urbanisation with the emergence of mega-cities. Overall, the study is essential for developing evidence-based policies that harness ICT-driven innovations to build resilience in climate-vulnerable farming systems.

MATERIAL AND METHODS

Data

The study employed a rigorous data collection methodology combining quantitative and qualitative approaches to ensure reliability and contextual relevance. Our empirical analysis is based on household survey data collected from maize farmers in central Zambia between March and May 2024. The survey design incorporated retrospective production data from the immediate past farming season (2023/2024), collected shortly after harvest to minimise recall error as well as ensure relevance to the drought period under analysis.

To ensure a representative sample, we employed a multistage sampling design. In the first stage, we randomly selected three districts in Central Zambia affected by the drought – Kapiri, Kabwe, and Chibombo. These districts were selected because they represent the dominant agroecological characteristics of the Zambian Central Plateau (Region IIa), which is one of the major maize-producing zones in Zambia. The area experiences moderate rainfall patterns and mixed farming systems, making it broadly reflective of smallholder farming conditions across much of the country's maize belt. Moreover, these districts were among those formally declared drought-affected during the 2023/2024 season, as per the Government of Zambia's disaster declarations. Their inclusion provides an analytically relevant proxy for national smallholder conditions where climate variability poses systemic food security risks.

In the second stage, we purposively selected 3–5 agricultural camps within each district based on their comparability in terms of agroecological conditions, cropping systems, and household socio-economic characteristics, as guided by expert recommendations from local agricultural officers. This purposive selection ensured that sampled areas shared broadly similar production and market contexts, minimising structural differences that could bias the analysis.

In the final stage, we randomly selected 50 households from each agricultural camp. This stage, conducted within agroecologically and socioeconomically comparable camps, ensured that any observed differences in farming outcomes could be attributed to household-level variation rather than structural disparities between locations. Consequently, the randomisation enhanced internal validity, facilitated meaningful comparisons across farm households, and minimised potential sampling bias. As the study focused on farmers who cultivated maize during the 2023/2024 farming season, and excluded those who did

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not provide information on maize production, the final sample comprised 568 maize-producing households.

A team of trained enumerators administered a structured, pre-tested household questionnaire to gather quantitative data on demographics, location, and production information. Farmers were asked about the amount of maize produced and the land area used for maize cultivation in the reference year, 2023/2024. The maize yield data – measured as total output in kilograms per hectare – was self-reported by respondents but cross-validated with enumerator field notes, consultations with local extension officers, and, where available, cooperative production records. This triangulation approach enhanced the internal consistency, credibility, and traceability of the yield information used in this study.

Notably, AgI adoption was assessed through the use of ICTs [radio, television, and mobile phones (MP)] – with a focus on their agricultural application. This approach recognises that, in smallholder farming systems within low-resource settings such as Zambia, advanced digital technologies like drones or artificial intelligence AI-based precision tools remain largely inaccessible due to digital illiteracy, affordability constraints, and weak ICT infrastructure (Ayim et al. 2022). Instead, farmers rely on more rudimentary but functional ICT tools to support key stages of the agricultural production cycle. To reflect this contextual reality, our measure of AgI captured the extent to which farmers used these ICT tools to inform agricultural decision-making processes, including (but not limited to): land preparation, seed variety selection, planting time decisions, pest and disease management, fertiliser application, irrigation scheduling, post-harvest handling, and market engagement. This focus on application-based use, rather than simple device ownership, aligns with the operational definition of agricultural informatisation as the integration of ICTs into agricultural processes for decision support and productivity enhancement (Zhang et al. 2016; Tian et al. 2022). In this sense, these ICT tools function as critical decision-support mechanisms – they are enabling farmers to pull, interpret, and apply that information in real time (Mwalupaso et al. 2019b; Domguia and Asongu 2021). This dynamic use reflects the essence of agricultural informatisation: the integration of ICTs into the production process, not just the communication process.

On the other hand, SAP adoption covered minimum tillage (MT), improved seed, planting basins, residue retention and drip irrigation The categories of the SAP adoption portfolios considered in this study, based on these five practices, are shown in Table 1.

To provide transparency and facilitate comparability, Table 2 presents key descriptive statistics on the socioeconomic and agronomic characteristics of the sampled households. On average, farm households comprised 6.68 members, with 86.6% male-headed and 83.5%

Table 1. Sustainable agriculturural practices (SAPs) adoption portfolio among smallholder farmers in the study area

Category	Primary function	Secondary benefits	Associated practices	Adopting households (%)	Indicative references
Water conservation	optimise water use efficiency	reduces erosion, enhances drought resilience	planting basins, drip irrigation	40.3	Sarvade et al. (2019); Rastogi et al. (2024)
Soil health	improve soil structure and fertility	enhances moisture retention, supports carbon sequestration	residue retention, minimum tillage	87.1	Sarvade et al. (2019); Cooper et al. (2020)
Nutrient management	sustain soil nutrient levels	improves crop nutrient uptake, stabilizes yields	residue retention, planting basins, minimum tillage	65.8	Bhattacharya et al. (2023); Kaduwal et al. (2023)
Productivity-enhancing	maximise crop productivity	supports climate adaptation, enhances pest resistance	improved seed varieties, drip irrigation	66.9	Ahmed (2022); Cao et al. (2022); Yang et al. (2023)
Operational efficiency	reduce manual labour & input costs	improves timeliness of operations, enhances resource use	minimum tillage, drip irrigation	18.1	Cao et al. (2022); Adam and Abdulai (2023)

Source: Authors' own elaboration

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Table 2. Definition and summary statistics of variables used in the models

Variable	Measurement	Mean (*n* = 568)	Mean (*n* = 499)	Mean (*n* = 69)	*t*-statistics
Yield	kg/ha	951.928	1 042.177	744.062	6.40***
Gender	1 if household head is male, 0 otherwise	0.866	0.876	0.797	1.80*
Marital	1 if household is married, 0 otherwise	0.835	0.848	0.739	2.28**
Education	1 if household head can read local language, 0 otherwise	0.798	0.81	0.71	1.93*
Hsize	number of people in a household	6.678	6.776	5.971	2.42**
Mland	size of land for maize cultivation	4.84	4.84	4.835	0.02
Ncrop	planned number of crops to grow in the survey year	2.273	2.311	2	2.71***
TLU	weighted index of tropical livestock per hectare	2.243	2.453	0.727	4.69***
Off farm	1 if household head has participated in off-farm activities, 0 otherwise	0.614	0.619	0.58	0.63
Extension	1 if household have access to extension service, 0 otherwise	0.826	0.858	0.594	5.54***
Market	the distance to the market in kilometres	25.886	26.096	24.362	1.44
Cooperative	1 if household head is a member of a cooperative	0.512	0.561	0.159	6.47***
Power	1 if household has access to electricity, 0 otherwise	0.713	0.733	0.565	2.91***
Knowledge	prior knowledge about NGO activities	0.186	0.170	0.304	–2.69***
Ownership	1 if household head owns any of the three devices as strong, 0 otherwise	0.745	0.792	0.406	7.18***

*, ** and ***significance at 10%, 5%, and 1% levels, respectively; TLU – tropical livestock units
Source: Authors' own elaboration

of household heads married. Approximately 79.8% of household heads were literate in the local language, reflecting moderate education levels among smallholder farmers in the study area. The average maize cultivation area was 4.84 hectares, and most households practiced mixed cropping systems, planting an average of 2.27 different crops during the survey year.

Households also kept an average of 2.24 tropical livestock units (TLU) per hectare, indicating moderate livestock ownership. About 61.4% of household heads participated in off-farm activities, and 82.6% reported access to extension services. The average distance to the nearest market was approximately 25.89 kilometres, underscoring the spatial constraints faced by many farmers in accessing inputs and output markets. Furthermore, 51.2% of households were members of agricultural cooperatives, and 71.3% had access to electricity, suggesting moderate infrastructure access across the sample. Regarding digital access, 74.5% of households reported ownership of at least one of the three ICT devices (radio, TV, or mobile phone) used to measure agricultural informatisation. Finally, 18.6% of farmers had prior

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knowledge of NGO activities related to agricultural development, reflecting exposure to external agricultural support programmes.

Importantly, to complement the quantitative data, qualitative methods – including key informant interviews (KIIs), in-depth interviews (IDIs), and focus group discussions (FGDs) – were conducted. The KIIs involved stakeholders such as government officials, media representatives, mobile network providers, farmers' unions, agribusiness traders, and NGOs. The IDIs provided deeper insights into farmers' experiences, while the FGDs explored climate adaptation challenges and collective solutions.

Econometric strategy

To evaluate the impact of AgI on SAP adoption and assess its subsequent effects on maize yields, the study applied the recursive bivariate probit (RBP) and endogenous treatment regression (ETR) model. These two-stage regression models are advantageous as they address selection bias associated with both observed and unobserved factors (Mabe et al. 2019). Moreover, the estimates derived from these models are efficient, as they involve the joint estimation of two equations. Additionally, Artificial neural networks (ANN) were employed as a robustness check, with validation conducted through the analysis of the normalised importance of factors influencing SAP adoption.

Modelling the effect of AgI adoption on farmers' decisions to adopt SAPs. Farmers' decisions to adopt specific practices are generally driven by the pursuit of maximising utility (Zheng et al. 2021). These decisions are typically dichotomous, meaning a farmer either adopts the practice or does not. Assuming farmers are risk-neutral, with the utilities of SAPs adopters and non-adopters denoted by U_1 and U_0 respectively, a rational and risk-neutral farmer will choose to adopt SAPs only if $U^* = U_1 - U_0 > 0$. Although U^* is unobservable, farmers' decisions to adopt SAPs can be modelled using a probit model. Given our focus on estimating the effect of AgI participation on SAPs adoption, the model specification is as follows:

$$SAPs_i = aAgI_i + \beta X_i + \varepsilon_i \tag{1}$$

where: $SAPs_i$ – a dummy variable where 1 represents the i^{th} household that has adopted at least one of the five SAPs portfolios during the survey year, and 0 otherwise; X_i – a vector of household socio-demographic and economic variables commonly referenced in agricultural innovation literature, these variables include the household and farm characteristics; AgI_i – AgI adoption, captured as a binary variable equal to 1 if a household member used any of the three ICTs to support agricultural processes during the survey year, and 0 otherwise; a and β – parameters to be estimated for AgI and vectors of household and farm characteristics; ε_i – the random error term.

Modelling the impact of AgI on crop yields and the possible mechanism. Since maize yield is a continuous variable, we followed Ma et al. (2022) and modelled the association between SAPs adoption and maize yield using the following linear regression:

$$Y_i = aAgI_i + \beta X_i + \mu_j \tag{2}$$

Where: Y_i – the maize yield for the i^{th} household; μ_j – the random error.

However, for the actual estimation of yield effects and the mechanism pathway analysis, the computation of the expected outcome values of the AgI adopters and non-adopters in real and hypothetical scenarios as guided by Lokshin and Sajaia (2004) was defined as follows:

$$\begin{aligned} ATT = {} & E\left(Y_{Adopter} \middle| AgI = 1, X\right) - \\ & - E\left(Y_{Non\text{-adopter}} \middle| AgI = 1, X\right) \end{aligned} \tag{3}$$

$$\begin{aligned} ATU = {} & E\left(Y_{Adopter} \middle| AgI = 0, X\right) - \\ & - E\left(Y_{Non\text{-adopter}} \middle| AgI = 0, X\right) \end{aligned} \tag{4}$$

The average treatment effect on the treated (*ATT*) and untreated (*ATU*) was calculated for both the pooled sample and the subset of SAPs adopters. While both analyses reveal the yield effect, the latter specifically assesses the impact of AgI on maize yield among SAPs adopters. Accordingly, if the yield effect among SAPs adopters is similar to that of the pooled sample, it suggests that SAP adoption could be the primary pathway. Conversely, if the pooled sample shows a higher yield effect than the subset of SAPs adopters, it indicates that AgI may have a direct impact on maize yield.

Controlling for potential endogeneity and model selection. A common challenge in estimating Equations (1 and 2) is the potential endogeneity of the AgI adoption variable, which could lead to biased estimates in the regression models. There are three primary sources of endogeneity. First, placement endogeneity arises from the non-random selection of AgI-adopting communities. If communities with a higher prevalence of SAP adopters or inherently higher yields were more

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likely to adopt AgI, the impact of AgI would be overestimated. Second, within these communities, farmers may self-select into AgI adoption, leading to systematic differences between adopters and non-adopters in unobserved characteristics, such as entrepreneurship and risk behaviour. This self-selection can result in biased estimates of the effect of AgI adoption on SAPs adoption and maize yield. Third, some covariates, such as access to extension services, may be endogenous, influencing both AgI adoption and the outcome variables – SAPs adoption and maize yield. Notably, these sources of endogeneity imply that AgI adopters and non-adopters are not directly comparable.

To address these issues, we exploited our sampling frame and employed robust two-stage regression approaches incorporating a control function with district fixed effects. First, to mitigate placement endogeneity, our sampling strategy involved selecting respondents from agricultural camps that agricultural stakeholders, such as the Ministry of Agriculture, recommended as having similar observed factors (e.g. gender, education, land size, off-farm participation, and market distance) and are within the same agro-ecological zone. By ensuring that these key factors are comparable across camps and applying random selection of SAP-adopting and non-adopting households within these camps, we aimed to reduce potential placement bias (Tambo and Wünscher 2018; Amadu et al. 2020a; Hughes et al. 2020). This approach ensures that the sample includes both adopters and non-adopters with similar observable characteristics. Secondly, we employed two-stage models, specifically RBP and ETR, to further address endogeneity concerns. Given that AgI adoption is not randomly assigned, and rural farmers' decisions to adopt AgI could be influenced by both observed factors (e.g. marital status, gender, education, access to extension) and unobserved factors (e.g. motivation, resilience, innate talent), it is likely that AgI adoption is endogenous. In such cases, standard probit regression and ordinary least squares (OLS) may produce biased estimates of AgI's impact on SAPs adoption and maize yield. Therefore, empirical strategies that explicitly account for endogeneity are crucial.

Previous studies have employed various empirical strategies to address endogeneity, including RBP (Tambo and Wünscher 2018), propensity score matching (PSM) (De Los Rios 2022), the augmented inverse probability weighted (AIPW) estimator (Ma et al. 2020), the inverse probability weighted regression adjustment (IPWRA) estimator (Zheng and Ma 2023), ETRs (Vatsa et al. 2023a), and the CMP model (Vatsa et al. 2023b). While PSM, AIPW, and IPWRA can address endogeneity due to observed factors, they do not account for unobserved factors. The ETR and RBP models, however, account for both observed and unobserved endogeneity and estimate the direct impact of treatment variables on the outcome. Given that the RBP and ETR models require the treatment variable to be dichotomous, we applied these models while incorporating district fixed effects (V_i) to account for unobservable heterogeneity between districts in estimating Equations (1 and 2). In both the RBP and ETR models, we first estimated a selection model, expressed as:

$$AgI_i = \beta X_i + \delta V_i + \gamma Z_i + \tau_i \tag{5}$$

where: τ_i – the random error; V_i – the district fixed effects; δ and γ – parameters to be estimated; Z_i – instrumental variables (IVs).

We included IVs to correctly specify the ETR and RBP models.

A valid IV must satisfy both the correlation and exogeneity assumptions: it should be correlated with the treatment variable (AgI adoption) and uncorrelated with the outcome variables (SAPs adoption and maize yield). Accordingly, access to a power source and ownership of any of the three devices were select IVs. This choice is supported by previous findings that access to power and ownership of digital tools significantly increase farmers' uptake of AI technologies (Tadesse and Bahiigwa 2015; Mwalupaso et al. 2019b). Based on this evidence, we expect the IVs to be positively associated with AgI adoption. Moreover, these IVs influence SAPs adoption and maize yield only through their effect on AgI adoption, meaning they are exogenous to the outcome variables. Access to power and possession of ICTs are unlikely to directly impact SAPs adoption and maize yield unless they lead to optimised AgI adoption, which in turn could increase SAPs adoption and yield.

We further confirmed the statistical validity of the IVs using IV validity tests [Underidentification Test (Anderson Canonical Correlation LM Statistic), Weak Identification Test (Cragg-Donald Wald F Statistic), Overidentification Test (Sargan Statistic)], the results of which are presented in Table S1 in Electronic Supplementary Material (ESM). The LM statistic is 40.833 with a *P*-value of 0.000, indicating that the instruments are not underidentified and strongly rejecting the null hypothesis of non-identification. The Wald-*F* statistic is 21.417, which exceeds the critical value of 19.93 for a 10% maximal IV size, thereby rejecting the null hypothesis of weak instruments. For the overidentification

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test – a necessary condition for assessing the exogeneity of the IVs – the Sargan statistic is 1.017 with a *P*-value of 0.3133. Since the *P*-value is greater than 0.05, we fail to reject the null hypothesis, suggesting that the instruments are valid and uncorrelated with the error term. Therefore, the selected IVs are statistically valid, strong, and reliable.

Finally, we addressed the potential bias from the endogenous covariate (access to extension) by applying a probit regression on determinants of the endogenous covariate plus its instrumental variable prior to the first stage [Equation (5)]. Following Amadu et al. (2020a), we used the number of prior knowledge of government and NGO activities as an instrument. This approach, known as the control function method, involves calculating the generalised residuals (GR) after applying this probit regression and including the GR in Equation (5) along with the endogenous covariate. If the GR is statistically significant, it indicates that access to extension is endogenous and the estimates are likely biased. Conversely, if the GR is statistically insignificant, the estimates are free from bias related to the endogenous covariate, and there is no need to use the predicted values of the access to extension. In our case, the effect of prior knowledge on AgI (coefficient = –0.002, $P = 0.206$) and extension (coefficient = 0.171, $P = 0.001$) confirms that access to extension is not endogenous.

Robustness checking. We utilised Artificial Neural Networks (ANNs) as a robustness check only on the impact of AI adoption on SAPs. ANNs are capable of learning intricate and nonlinear input-output interactions through a training process that maps data from input to output spaces (Kujawa and Niedbała 2021). The neural network models used in this study include the Radial Basis Function (RBF) and Multi-Layer Perceptron (MLP).

For the MLP model, we implemented a single hidden layer architecture with 10 neurons. The activation function used for the hidden layer was the ReLU (Rectified Linear Unit), while a sigmoid activation function was applied at the output layer to handle the binary classification task. For the RBF model, we used a Gaussian radial basis activation function with 15 hidden neurons. Both models were trained using a learning rate of 0.01, with a maximum of 500 training iterations (epochs). The training algorithm employed was the stochastic gradient descent (SGD) optimiser for the MLP and a *K*-means clustering algorithm for determining the RBF centres.

Seventy percent of the observations were used for training the classifiers, while the remaining 30% were reserved for testing (Sahoo et al. 2023). In our analysis, demographic and socioeconomic traits, along with AI adoption, served as input features in the ANN model. ANNs are particularly well-suited for capturing complex relationships in data, making them valuable for understanding the interactions between AI and SAPs adoption. The general equation governing ANNs is as follows:

$$q = f(\sum_{i=1}^{N} w_i p_i + b \qquad (6)$$

where: q – the predicted output (SAPs adoption); f – the transfer function; w – the weight of the i^{th} input; b – the bias; p – the inputs (variables).

RESULTS AND DISCUSSION

AgI adoption intensity and patterns. Figure 1 presents the AgI adoption portfolios, providing critical

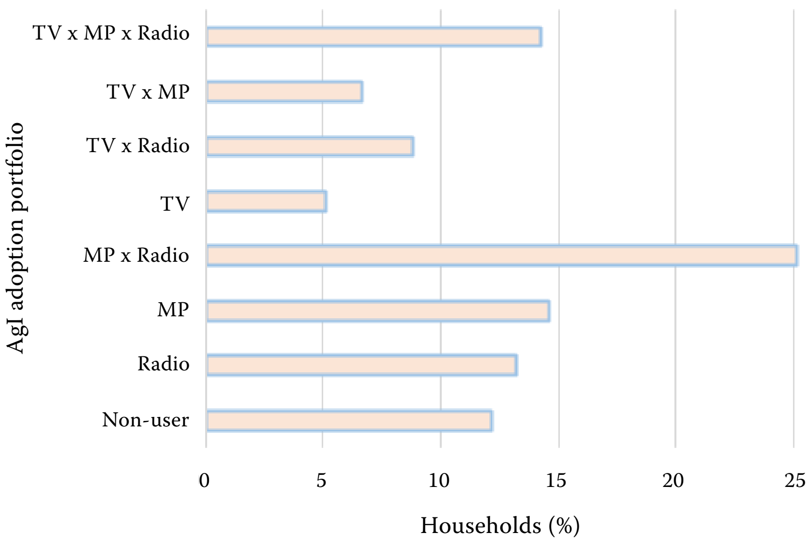

Figure 1. Distribution of AgI adoption portfolio

AgI – agricultural informatisation
TV – television
MP – mobile phone
Source: Authors' own elaboration

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insights into how drought affected smallholder maize farmers adapt their AgI usage to maximise resilience under climate stress. While 12.15% remain non-users – a concerning gap during crises – most farmers strategically combine channels to optimise information access. The MP × radio combination (25.18%) dominates, leveraging mobile phones for real-time weather alerts and market updates while relying on radio's resilience against power disruptions. This synergy proves more effective than single-channel use (MP 14.61%, radio 13.20%) and outperforms less adaptive pairings such as TV × radio (8.80%), which lacks interactive capabilities.

Television's low standalone usage (5.11%) suggests that it serves as a supplement rather than a primary tool, likely due to infrastructure limitations (e.g. electricity and signal reliability) in resource-constrained settings such as Zambia. Moreover, television has a limited role in urgent decision-making. Nevertheless, its inclusion in hybrid systems such as TV × MP × radio (14.26%) amplifies its utility, making it valuable for visual learning and extension services. These patterns highlight the need for practical, multi-channel AgI strategies that combine mobile interactivity with radio's wide reach, ensuring smallholders receive timely, actionable agricultural insights – a vital component of climate adaptation efforts.

Overall, farmers prioritise practicality over redundancy by selecting cost-effective and adaptable communication channels suited to local conditions. Their strategic preference for complementary rather than duplicative tools ensures maximised information access. This approach aligns with the findings in existing literature, which emphasizes the importance of multi-channel systems that can deliver comprehensive and actionable agricultural information in a manner that suits the farmers' unique circumstances and environmental constraints (Mtega 2018; Das et al. 2021; Mabula and Wema 2024).

Notably, our assessment goes beyond mere ownership or passive access to information. Figure 2 illustrates that 76.4, 59.1, and 81.2% of farmers used radio, TV, and mobile phones, respectively, to support at least one agricultural process. This metric provides a general indication of the reach and functional relevance of each ICT tool in facilitating agricultural decision-making among smallholder farmers. The findings demonstrate that these tools are not simply channels for information dissemination but are actively used to support specific agricultural processes – including land preparation, seed variety selection, planting schedules, pest and disease management, irrigation planning, and post-harvest handling. These processes are critical for enhancing productivity, particularly under drought conditions.

Insights from key informant interviews with district agricultural officers, meteorological officers, NGO staff working on climate adaptation and media personnel revealed that these ICTs have been instrumental in promoting drought-tolerant seed varieties and conservation agriculture practices. Similarly, IDIs and FGDs with farmers emphasised the role of these basic ICTs in communicating seasonal weather forecasts, delivering early warning messages, issuing pest outbreak

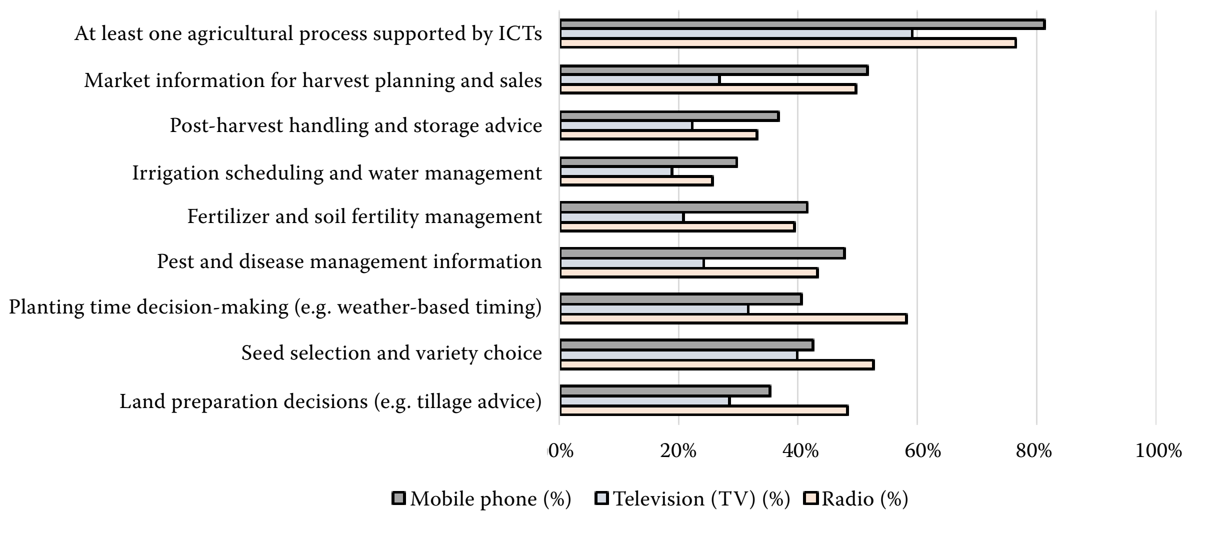

Figure 2. Farmer use of ICTs across various agricultural processes

Source: Authors' own elaboration

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alerts, and providing timely guidance on fertiliser use and soil fertility management.

Overall, the triangulation of quantitative survey data and qualitative insights underscores that these rudimentary ICTs are actively embedded in the agricultural production cycle. This provides empirical justification for framing their use within the broader concept of agricultural informatisation – defined not by the sophistication of the technology, but by its purposeful application to support agricultural processes (Zhang et al. 2016). Moreover, this level of engagement offers a critical foundation for scaling more advanced digital agriculture technologies in the future, as improvements in digital literacy, infrastructure, and localised content delivery continue to evolve in smallholder systems.

Impact of AgI on SAPs adoption. Table 3 presents the results of the RBP analysis on the influence of AgI on SAP adoption. First, the negative and statistically significant correlation coefficient between the error terms (Rho) in both models indicates the presence of negative selection bias, reinforcing the appropriateness of using the RBP to reliably estimate the effect of AgI on SAP adoption. Additionally, this result suggests that farmers' decisions to adopt AgI are linked to SAP adoption through unobserved factors, such as their ability to adapt quickly to changing agricultural conditions or their willingness to take risks. Moreover, the statistical significance of the extension residuals highlights that the estimates are susceptible to bias resulting from endogenous covariates. Failure to control for these factors would undermine the validity of the findings, further justifying the robustness of the estimation approach. Therefore, the results presented in Table 3 are methodologically sound and reliable.

Stage 1 of the RBP confirms that AgI adoption is influenced by both demand-side and supply-side factors consistent with Tadesse and Bahiigwa (2015). Importantly, the IVs are statistically significant, which strengthens the causal interpretation of AgI's effect on SAP adoption and further supports the robustness and reliability of our findings (Vatsa et al. 2023b).

Focusing on Stage 2, our results reveal a positive and statistically significant association between AgI and SAP

Table 3. Stage 1 and 2 of the RBP estimates

Variable	First stage (1)		Second stage (2)	
	Coef	SE	Coef	SE
Constant	–2.197	1.857	–0.816	0.602
AgI			3.712***	0.336
Gender	–0.122	0.276	–0.433	0.345
Marital	0.195	0.260	0.500*	0.255
Education	0.507*	0.261	0.351*	0.194
Hsize	0.032	0.053	–0.029	0.044
Mland	0.040*	0.024	–0.038	0.057
Ncrop	0.344***	0.097	–0.048	0.120
TLU	0.237***	0.066	0.209**	0.103
Off farm	0.070	0.178	–0.271	0.223
Extension	–0.336	0.772	–0.601**	0.265
Market	0.028***	0.009	0.027**	0.011
Cooperative	0.218***	0.073	0.711**	0.276
Village fixed Chibombo as reference category				
Kabwe	0.511**	0.204	0.466*	0.239
Kapiri	0.040	0.239	1.142***	0.347
IVs				
Ownership	0.824***	0.179		
Power	0.550***	0.167		
Extension residual	0.021***	0.001	0.158***	0.009

*, ** and *** significance at 10%, 5%, and 1% levels, respectively; AgI – agricultural informatisation; IVs – instrumental variables; RPB – Radial Basis Function; TLU – tropical livestock units

Source: Author's own elaboration

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adoption, confirming that farmers who engage with AgI are more likely to implement SAPs. This relationship can be explained through several key mechanisms. First, AgI enhances access to timely and relevant agricultural information, enabling farmers to make informed decisions regarding crop management, soil conservation, and resource allocation (Mwalupaso et al. 2019c). Participants in FGDs highlighted that real-time access to market information, extension advisory services, and input recommendations allows farmers to optimise their farming strategies, leading to the adoption of more sustainable and efficient agricultural practices especially amidst a drought. Second, AgI plays a critical role in climate adaptation and risk mitigation, particularly in regions vulnerable to extreme weather events. Insights from in-depth interviews further support this finding, as farmers unanimously emphasised that integrating AgI into their decision-making processes, farmers gain access to early warning systems, weather forecasts, and climate-resilient farming techniques, helping them adjust their practices in response to changing environmental conditions. This aligns with previous studies highlighting farmers' increased information-seeking behaviour during climate stresses, such as droughts or floods, to safeguard their crops and livelihoods (Amadu et al. 2020a, Malambo et al. 2023). Third, AgI strengthens access to financial and market resources, which are essential for sustaining SAP adoption. Key informants underscored that ICT platforms provide farmers with market price updates, direct market linkages, and financial services such as mobile banking, credit access, and crop insurance. These financial solutions reduce liquidity constraints and enable farmers to invest in sustainable inputs and technologies. Lastly, the behavioural aspect of AgI adoption must be considered consistent with the social learning theory (Bandura 1969; Akers and Jennings 2015). ICT-agricultural solutions not only provide technical information but also serve as platforms for peer learning and social influence, encouraging farmers to adopt SAPs through knowledge-sharing networks and extension interactions. The diffusion of digital agricultural innovations facilitates the spread of best practices within farming communities, reinforcing the transition towards sustainable farming models. Therefore, the content and sources of AgI-related information should be carefully evaluated and effectively communicated, as farmers may rely heavily on this information in desperate situations.

For robustness checking, we also used ANN to evaluate the performance of two models – MLP and RBF – in demonstrating the normalised importance of AgI on SAPs adoption. The reliability of these findings is supported by the area under the curve (AUC) (ESM, Figure S1) and the model summary (ESM, Table S2), which confirm that both models are well-calibrated and dependable. This validation ensures that the results are credible and that the conclusions are based on robust models. Having established the credibility of both the Multilayer Perceptron (MLP) and Radial Basis Function (RBF) models through their performance metrics, it is noteworthy that Figure 3 in both models reveals that AgI adoption achieves a score of 100% in normalised importance. This indicates that AgI's role

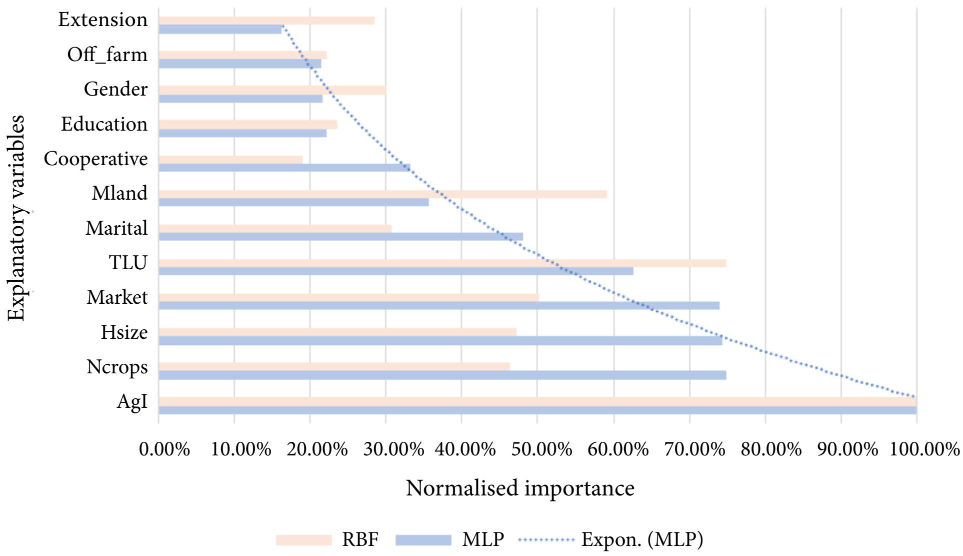

Figure 3. Normalised importance of explanatory variables in MLP and RBF

MLP – Multi-Layer Percepton; RBF – Radical Basis Function; TLU – Tropical Livestock Unit
Source: Authors' own elaboration

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is deemed crucial and highly influential in the adoption of SAPs, as assessed by both models.

Treatment effects of AgI adoption portfolios on SAPs adoption. In quantifying the impact of various AgI and SAP adoption portfolios, Table 4 presents the treatment effects from RBP following the procedure advanced by Coban (2021). For the pooled estimation, we find that AgI adoption significantly influences adoption of at least one SAP by 36.8%. Notably, among the AgI adoption portfolios, the use of mobile phones has the greatest impact at 43%. This significant influence can be attributed to the accessibility of mobile phones and their ability to quickly disseminate crucial information to farmers (Giulivi et al. 2023), especially during crises like drought. Mobile phones provide farmers with timely updates, enabling them to proactively adjust their farming strategies in response to changing conditions. Additionally, mobile phones facilitate mobile money transactions, enabling farmers to access financial services for purchasing inputs (Batista and Vicente 2020). This financial flexibility allows farmers to purchase necessary resources, further enhancing their ability to adopt and implement sustainable agricultural practices (Kikulwe et al. 2014, Sekabira and Qaim 2017).

Surprisingly, the adoption of all three ICTs under consideration (radio, mobile phone, and TV) has the lowest effect on optimising at least one SAP adoption at 24.4%. This suggests that while diversification of information sources can be beneficial, it may also introduce information overload or difficulties in processing and applying knowledge effectively. Farmers may struggle to synthesise information from multiple sources, particularly if they lack digital literacy or face time constraints. This was well acknowledged by key informants who highlighted that most smallholder farmers are digitally illiterate – a view echoed by participants in the focus group discussions. This underscores the importance of simplified, targeted, and user-friendly information dissemination in ensuring optimal AgI utilisation.

Examining specific SAP portfolios, all AgI adoption portfolios show an influence of more than 40% on the adoption of productivity-enhancing practices (improved seed and drip irrigation), with the highest being a combination of TV and radio at 79.6%. The high effectiveness of this combination suggests that traditional media played a crucial role in educating farmers on how to cope with the drought. The visual and auditory communication provided by TV and radio may have resonated more with farmers, particularly those with limited literacy or technical skills, helping them adopt critical SAPs during the crisis without requiring intensive hands-on involvement with the technology (Silvestri et al. 2021; Mabula and Wema 2024).

For the SAP portfolio comprising soil fertility and conservation practices, mobile phones again have the highest effect at 71.3%, while a combination of radio and TV has only a 22.2% effect. This reinforces the notion that immediate, actionable, and personalised advisory services, which mobile phones facilitate, play a crucial role in encouraging the adoption of practices soil health-oriented SAPs. Specifically, the direct and interactive nature of mobile-based agricultural advisory services likely enhances farmer engagement and application

Table 4. Treatment effect of AgI adoption portfolio on SAPs portfolio

AgI adoption portfolio	SAPs adoption portfolio											
	SAPs		productivity-enhancing		soil health oriented		water conservation		nutrient management		operational efficiency	
	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE	Coef	SE
AgI	0.368***	0.068	0.526***	0.101	0.529***	0.065	0.411***	0.109	0.524***	0.082	0.314***	0.066
Radio	0.426***	0.073	0.558***	0.169	0.681***	0.069	0.411***	0.119	0.375***	0.097	0.399***	0.073
MP	0.430***	0.078	0.401***	0.105	0.716***	0.172	0.623***	0.141	0.581***	0.076	0.348***	0.083
TV	0.374***	0.066	–	–	–	–	–	–	–	–	0.288***	0.058
MP × Radio	0.413***	0.074	0.568***	0.101	0.202	0.184	0.349	0.256	0.566***	0.105	0.337***	0.071
TV × Radio	0.288***	0.068	0.796***	0.208	0.222***	0.089	0.066	0.070	0.590***	0.126	0.264***	0.067
TV × MP	0.321***	0.076	–	–	–	–	–	–	0.286***	0.085	0.314***	0.074
TV × MP × Radio	0.244***	0.070	–	–	–	–	0.603**	0.247	0.156	0.114	0.242	0.069

***significance at 1% level

AgI – agricultural informatisation; MP – mobile phones; SAPs – sustainable agriculture practices

Source: Author's own elaboration

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of recommended soil conservation techniques. Likewise, in the case of water-saving practices, mobile phones remain the dominant tool, with a 62.3% effect, followed closely by the combination of all three AgI tools (60.3%). While multi-tool integration might provide comprehensive insights, the marginally lower effect than mobile phones alone suggests that complexity and integration challenges might hinder optimal utilisation.

Interestingly, for nutrient management practices, the combination of TV and radio has the highest effect (59%), while the combination of TV and mobile phones has the lowest effect (28.6%). This finding highlights the continued relevance of traditional media in promoting knowledge-intensive SAPs, particularly in reaching farmers in rural or underserved areas where mobile-based services may be less accessible or costly.

Lastly, although all AgI adoption portfolios have less than a 40% effect on the operational efficiency SAPs, the highest effect is observed with radio users at 39.9%, followed by mobile phone users at 34.8%, with the third being a combination of radio and mobile phone at 33.7%. This finding underscores the importance of targeted and easily accessible information sources like radio, which remains a trusted and widespread medium among farmers for easily implemented SAPs like drip irrigation and minimum tillage. The strong effect of radio in this category emphasises its role in disseminating simple, easy-to-follow best practices that do not require high levels of digital literacy or interactive engagement.

Yield effect of AgI and link to SAPs adoption. The yield effects from the endogenous switching regression are presented in Table 5, revealing that AgI adoption is a rational decision in both factual and counterfactual scenarios. Specifically, AgI-adopting households experienced a 257% increase in yield during the severe drought, while non-adopting households would have seen a yield increase of about 144% had they adopted AgI. Similarly, for SAP adopters, AgI adoption proves to be rational across both scenarios, with adopters experiencing a yield effect of approximately 253%, while non-adopters would have seen a yield increase of about 65% had they adopted AgI. This significant difference underscores the critical role that AgI plays in enhancing agricultural resilience, particularly during extreme weather events. However, it is important to interpret these findings with caution, as they are specific to the Zambian context and may not be generalisable to other regions or conditions. The severe drought in Zambia likely exacerbated the differences in yield between adopters and non-adopters, highlighting the necessity of context-specific analysis. Moreover, similar 'fantastic' yield effects were reported in Noltze et al. (2013) regarding the impact of natural resource management technologies on agricultural yield.

Notably, the relatively small decrease in yield effects – just 5% – between the pooled sample and the SAP adopter sample indicates that AgI's impact on yield is closely tied to its role in facilitating the adoption of SAPs. The consistent yield benefits observed across both samples reinforce the idea that AgI's primary contribution to yield improvement lies in its ability to support and enhance the adoption of these critical practices. Therefore, the yield improvements among AgI adopters can be attributed to several factors. First, AgI provides farmers with better access to timely and relevant information, enabling farmers to make informed decisions that directly impact their productivity (Lio and Liu 2006, Mwalupaso et al. 2019b). Second, AgI adoption often facilitates more effective and widespread adoption of SAPs, which are particularly essential under drought conditions when resources are scarce. The integration of AgI into farming practices thus provides a compelling pathway for improving yields, even under challenging environmental conditions.

Table 5. *ATT* and *ATU* from the ETR

Item	Pooled				SAPs			
	yield with AgI adoption	yield without AgI adoption	coef (SE)	change (%)	yield with AgI adoption	yield without AgI adoption	coef (SE)	change (%)
ATT	6.479	1.812	4.668*** (0.09)	257.6	6.484	1.840	4.645*** (0.091)	252.4
ATU	7.789	3.190	4.6*** (0.235)	144.2	8.111	4.892	3.218*** (0.215)	65.8

***significance at 1% level; prior estimation of stages 1 and 2 in Table S3; the yields shown are predictions based on the coefficients estimated with the endogenous switching regression model; as the dependent variables in the model are the logarithm of yields in kg/ha, the predictions are also given in logarithmic form

AgI – agricultural informatisation; *ATT* – average treatment effect on the treated; *ATU* – average treatment effect on the untreated; ETR – endogenous-treatment regression; SAP – sustainable agriculture practices

Source: Author's own elaboration

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Policy implications of AgI-SAP nexus for sustainable agrifood production. To contextualise these findings, we utilised FAOSTAT's maize supply data (2018–2022) (FAOSTAT 2018–2022) to relate the ATT across adoption categories to food availability. The FAO's food supply quantity metrics, measured in kilograms per capita per year (kg/capita/year), provide a critical indicator of food availability at the national and regional levels. These metrics offer insights into the physical quantity of food available for consumption by the average person and help assess whether the food supply meets dietary needs and preferences. Based on the FAO's five-year average, the maize supply in Africa, Southern Africa, and Zambia stands at 113.83, 225.56, and 287.99 g/capita/day, respectively.

Our calculations, as presented in Table 6, reveal that adopting at least one SAP potentially contributes an additional 40.73 g of maize per person per day, significantly boosting food supply. This increase equates to 82.73% of the global maize supply, 35.78% in Africa, 18.1% in Southern Africa, and 14.14% in Zambia. These contributions also indicate a meaningful improvement in caloric intake, with an estimated increase of 125.09 kcal per person per day in Zambia. This would meet approximately 5% of the daily caloric requirement for males and 6.25% for females, underscoring the critical role of SAP adoption in addressing food insecurity and malnutrition. This is particularly vital in climate-vulnerable regions such as Zambia, where maize is a staple crop and a primary source of dietary calories for farming households.

Among the various SAP portfolios, productivity-enhancing practices, particularly the use of improved seeds and irrigation, have the most substantial impact. These practices could increase maize availability by an additional 124.46 g per person per day, surpassing 100% of global and African food supply levels. However, in Southern Africa and Zambia, where maize consumption exceeds the global average, these practices potentially contribute 55% and 43.21% of the food supply, respectively. In caloric terms, this increase in Zambia could cover 15.29% of the daily caloric requirement for males and 19.11% for females, representing a significant step towards meeting the population's nutritional needs.

Interestingly, even at the lowest ATT among SAP portfolios, the potential contribution is equivalent to 62.90% of global maize supply, 27.21% in Africa, and 13.7% in Southern Africa. This underscores the transformative potential of SAP adoption, even at a modest scale, in enhancing food security in regions where

Table 6. Policy calculations based on the yield effect of each sustainable agricultural practice (SAP) portfolio

SAPs adoption portfolio	Yield effect			Potential contributions to food supply quantity (%)				Caloric intake	Minimum caloric requirements (%)	
	per household (kg)	capita/year (g)	capita/day (g)	global	Africa	Southern Africa	Zambia		male	female
Productivity-enhancing	317.98	45 426.24	124.46	252.79	109.33	55.2	43.21	382.22	15.29	19.11
Soil health oriented	248.14	35 448.82	97.12	197.27	85.32	43.1	33.72	298.27	11.93	14.91
Water conservation	109.51	15 644.04	42.86	87.06	37.65	19.0	14.88	131.63	5.27	6.58
Nutrient management	247.65	35 377.99	96.93	196.87	85.15	43.0	33.66	297.68	11.91	14.88
Operational efficiency	79.12	11 303.24	30.97	62.90	27.21	13.7	10.75	95.11	3.80	4.76
SAPs	104.06	14 866.20	40.73	82.73	35.78	18.1	14.14	125.09	5.00	6.25
Average				49.23	113.83	225.56	287.99	884.48		

Note: Average household size is 7 people. This number was used to find the yield effect per capita. Divided by 365, we obtain the yield per capita per day. The average food supply quantity and caloric intake is calculated from FAOSTAT (2018–2022). The National Health Service (NHS) general average of 2 500 and 2 000 calories for males and females respectively, was used to calaculate the minimum caloric requirement percentage

Source: Authors' own elaboration

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climate variability threatens agricultural productivity. Specifically, the additional maize supply can be utilised through two key pathways: (*i*) food consumption – increased maize availability improves household food security, ensuring that families have access to adequate calories and essential nutrients, (*ii*) commercialisation – surplus maize can be sold in local markets, providing smallholder farmers with an additional income stream and contributing to poverty reduction. While caution is required when extrapolating these findings to broader regions, this analysis underscores the relevance of the AgI-SAPs nexus as a strategic pathway for addressing food security challenges in similar contexts across Zambia, Southern Africa, and the African region.

Therefore, in developing robust policy frameworks for sustainable agrifood production and consumption, our findings have important policy recommendations. First, governments and key stakeholders must invest in robust AgI systems that effectively leverage traditional media, such as radio and television, to disseminate timely and relevant information on SAPs. This is particularly vital during periods of environmental stress, such as droughts, when access to real-time guidance can significantly enhance farmers' resilience and decision-making. Additionally, local radio and TV stations should be empowered with the necessary resources, funding, and training to effectively communicate SAP-related information (Das et al. 2021, Mabula and Wema 2024). Content must be tailored to local contexts and languages to maximise outreach and ensure practical application at the community level. Moreover, there is an urgent need to improve digital literacy, particularly regarding the use of mobile phones in disseminating agricultural information. Farmers must be equipped with the skills to effectively navigate digital tools, access climate-related information, and integrate it into their farming decisions. Governments should partner with private sector actors to enhance digital content and develop user-friendly platforms that are accessible even to low-literacy populations (Silvestri et al. 2021). Strengthening these information systems will ensure that even digitally marginalised communities can benefit from accessible and actionable agricultural knowledge.

Second, policy efforts should prioritise the promotion of productivity-enhancing practices, particularly the adoption of improved seeds and irrigation. These SAPs have demonstrated the greatest potential for increasing yields and caloric intake, especially in drought-prone regions where climate shocks threaten food security (Ahmed 2022; Akter et al. 2022). Governments should introduce targeted subsidies, financial incentives, and capacity-building programmes to facilitate widespread adoption of these high-impact practices, ensuring that smallholder farmers can effectively implement them.

Third, SAPs must be integrated into national emergency response strategies to enable their rapid adoption during climate-induced crises. Policymakers should establish contingency plans that make SAP-related interventions readily available in times of drought or extreme weather events, thereby minimising agricultural losses and enhancing food security.

Finally, prior exposure to AgI tools and incentives for ICT device ownership should be a policy priority. Governments and development partners should promote affordable access to mobile phones, radios, and televisions by subsidising costs or implementing financing schemes that allow smallholder farmers to acquire these essential tools. Without equitable access, the transformative potential of AgI on SAP adoption may remain unrealised, particularly in climate-vulnerable regions where timely agricultural information can mean the difference between food security and crisis (Tadesse and Bahiigwa 2015; Abdulai et al. 2023). While basic in form, these ICT tools are embedded within the broader framework of agricultural informatisation. Rather than serving merely as passive communication channels, they are leveraged by farmers as decision-support mechanisms – enabling them to apply information in ways that materially influence agricultural outcomes. This distinction is especially important in low-resource settings, where advanced technologies such as drones or AI-based applications are limited by digital illiteracy, poor infrastructure, and affordability constraints.

By implementing these recommendations, policymakers can create a resilient and adaptive agricultural sector capable of withstanding climate shocks, improving food security, and fostering sustainable agricultural growth across vulnerable regions.

CONCLUSION

This study examined the effects of AgI adoption on the uptake of various SAP portfolios and its impact on crop yields among smallholder maize farmers in Zambia, revealing crucial implications for sustainable agri-food production. By employing a rigorous methodology that accounts for selection bias, programme placement, and endogenous covariates, we found that AgI significantly influences SAP adoption. Specifically, AgI adoption portfolios exert varying effects on SAP portfolios. On average, AgI influences SAP adoption

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by 36.8%, while a combination of television and radio has a 79% impact on productivity-enhancing SAPs, underscoring their critical role in promoting sustainable practices – particularly in rural areas where digital literacy may be low, yet access to television and radio remains widespread. Furthermore, mobile phones were found to be instrumental in optimising the adoption of various SAP portfolios, highlighting their significance in the AgI-SAP nexus. Notably, SAP adoption serves as a vital mechanism through which AgI enables farmers to achieve significantly improved yields, even under adverse climatic conditions such as severe droughts. These findings demonstrate that AgI adoption not only leads to substantial yield improvements but also holds the potential to make a significant contribution to maize supply quantity, primarily through its influence on the adoption of SAPs. Importantly, this interpretation recognises that, once crops are established, yield outcomes remain largely contingent upon external factors such as prevailing weather conditions. Therefore, while the results should be interpreted with due caution, they nonetheless reinforce the notion that, even in the context of increasing climate variability, the nexus between AgI and SAPs presents a promising pathway for strengthening food security among smallholder farmers.

Finally, our study is not without limitations. First, the use of panel data would have allowed us to observe the mechanisms of the AgI-SAP nexus over time and how yields fluctuate, particularly under severe drought conditions. Additionally, nationwide data would have provided a more comprehensive understanding of the varied effects of AgI portfolios on SAP adoption. Second, capturing the agricultural content itself would have enriched the research by identifying its sources, availability, and effectiveness in optimising SAPs and enhancing maize yields. Furthermore, we did not account for the spillover and neighbourhood effects of these ICTs, which could have provided deeper insights into the AgI-SAP nexus. Therefore, future studies addressing these limitations could help validate and expand upon our findings. Nevertheless, given the limited empirical evidence on promoting sustainable agri-food production during severe droughts – often declared national emergencies – this study contributes to global development efforts by aligning with the SDGs, particularly zero hunger (SDG 2), climate action (SDG 13), and poverty alleviation (SDG 1).

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