Net Journal of Agricultural Science
Vol. 8(3), pp. 59-66, September 2020
DOI: 10.30918/NJAS.83.20.038
ISSN: 2315-9766
Full Length Research Paper

Determinants of smart valley technology adoption in lowland rice farming: Evidence from Burkina Faso

Adama Ouédraogo[1], Nati Aïssata Delphine Bama[1], Boureima Tassembédo[1], Aminou Arouna[2], Elliott Doussou Yovo[2] and Issa Wonni[1]

[1]Institut de l'Environnement et de Recherches Agricoles (INERA), BP 910 Bobo-Dioulasso, Burkina Faso.
[2]Africa Rice Center (AfricaRice).

Accepted 10 September, 2020

ABSTRACT

The overall objective of this study is to identify the major factors affecting smart valley new technologies in lowland by rice farmers in Burkina Faso. Managing flood and water retention in lowland rice farming is still the biggest challenge in West Africa particularly in Burkina Faso. In order to face this challenge Africa Rice funded a project to promote this technology in Burkina Faso during 2018 and 2020. Surveys on 145 rice farmers spread in 6 villages were carried out. A Probit model was used to analyse the key factors affecting the adoption decision. The results show that women are the highest adopters (76.36%) of smart valley technology. Also, about 92.19% of the adopters have access to technical support structures (extension services, research and NGOs) compared to 7.81% of the non-adopters. The analysis show also that schooling level, rice farming experience, contact with agricultural extension and research institutes, additional cost due to the technology and the yield are key factors influencing the farmers adoption decisions. The additional cost due to smart valley construction is affecting negatively the decision to adopt it. This factor is the key to enhance the adoption rate because all the beneficiaries recognize that smart valley is able to manage drought and flood effectively; but the cost still unreachable to lowland rice farmers.

Keywords: Smart valley, adoption, Probit, rice, Burkina Faso.

*Corresponding author. E-mail: damsleeser@gmail.com.

INTRODUCTION

Rice is the fourth crop in terms of areas, production and consumption in Burkina Faso (MAAH, 2020; FAOSTAT, 2020). Annual consumption per person increased from 16 kg in 2007 to 38 kg in 2017 and exceeds 50 kg per person in the urban centres like Ouagadougou and Bobo-Dioulasso (CNS, 2019). Currently the annual consumption greatly exceeded 400,000 MT in Burkina Faso. Also, the consumption rate grows about 5.6% in average per year (MAAH, 2020; FAOSTAT, 2020). After world food crisis occurred in 2007/2008, Agricultural policy in Burkina Faso comes up with strong response. These policies enhance rice production from 195,102 MT in 2008 to 350,322 MT in 2018 (CNS, 2019).

This production covers less than half of rice consumption needs (27 and 38% respectively in 2006 and 2017). To meet this demand, Burkina Faso relies on massive imports each year to meet the growing demand, which leads to significant foreign exchange outflows averaging CFA currency 41.6 billion per year between 2005 and 2013 (CNS, 2019). Average yields have remained practically stable and vary from 0.8 to 1.4 T/ha (MAAH, 2020; FAOSTAT, 2020). Thus the increase in production recorded in recent years is mainly due to the extension of the areas sown and not the improvement of productivity (Ouédraogo and Dakouo, 2017). Rice farming in Burkina Faso, like in other Sub-Saharan African countries, is marked by a low productivity, which is attributable to the level of production technologies (such as drought and flood management) used (Ouédraogo and Dakouo, 2017). In addition, rice-growing systems are characterized by low use of improved seeds, fertilizers and phytosanitary products in strict rainfed rice-growing, low control of technical itineraries in lowland rice-growing and intensification in irrigated rice-growing

(Adebiyi et al., 2019). However, Burkina Faso has a large potential of land not exploited yet in the domain of rice cultivation: about 500,000 hectares of lowland that can be developed, of which less than 10% is currently being put in value, and more than 233,500 hectares that can be irrigated, of which less than 5% is currently being developed Rice cultivation is practised in Burkina Faso in three (03) forms, including lowland rice, irrigated rice and strictly rainfed rice. Lowland rice cultivation is the most dominant. In fact, it concerns 67% of the total area under rice, with the undeveloped lowlands providing 42% of the national rice production (DGPER, 2011)[1]. The lowlands represent a huge potential for increasing rice production in the current context of climate change. However, the overriding priority for improving rice production remains effective and efficient water management, hence the introduction of smart-valley technology. Smart-valley technology is a lowland development approach for rice production systems in sub-Saharan Africa, based on a participatory, sustainable and low-cost approach. The Smart-valley approach was introduced in West Africa in 1997 and 2001 in Ghana and Nigeria respectively (AFRICARICE, 2017; Aminou et al., 2017). Smart-valley was developed by the Africa Rice Center (AFRICARICE) and its national research and development partners in Benin and Togo (Aminou et al., 2017). The Smart-valley approach is based on a multi-phases and multi-stages approach, focusing on exploration, prospecting, validation, design, and development of land drain plan and construction of water control infrastructures after sites selection based on socio-economic and biophysical factors and by exploiting farmers' experience. In fact, it refers to a plot of land that has been drained, ploughed, levelled and delimited by dykes and earth bunds for rice cultivation (Fashola et al., 2006). It has improved yields on rice farms, which are estimated to average between 4.5 and 5.2 tonnes per hectare (Wakatsuki et al., 2009). Therefore, Smart-valley technology is a godsend for rice intensification because of the good water control and soil fertility management in these developed lowlands. According to the same authors, thanks to the satisfactory results obtained and experiences acquired during its introduction in 2010 in Benin and Togo through the pilot project SMART-IV[2], Africa Rice has decided to extend it to Burkina Faso with the CSA-Rice project[3] started in 2017.

This study aims to analyse the determinants of the adoption of smart valley technology among small producers in Burkina Faso. Specifically, it consists of: (i) identifying the socio-economic and institutional factors of smart valley technology adoption in the rice lowlands and (ii) identifying the intrinsic factors of smart valley technology that could influence its adoption in the rice lowlands.

METHODOLOGY

Study area

The study was carried out in three regions selected by the project in Burkina Faso (Figure 1). These are the regions of the Haut-Basins with a Sudanian climate, the Cascades with a southern Sudanian climate and the Central Plateau with a Sudano-Sahelian climate. These regions were chosen by the coordination of the CSA-Rice project in collaboration with the Regional Directions of Agriculture and Hydraulic Installations to benefit from the introduction of smart valley technology according to the following criteria: (i) the importance of rice production in three (03) regions (29.43% of the total production, i.e. 102,464 T); (ii) the importance of the areas sown with rice (29.81% of the total area, i.e. 47,972 ha); (iii) the importance of the rice production in three (03) regions (29.43% of the total production, i.e. 102,464 T); (iv) the importance of the areas sown with rice (29.81% of the total area, i.e. 47,972 ha), (v) the availability of shallows, and (vi) the presence of INERA research stations such as Farako-Bâ, Banfora and Niangoloko and Kamboinsé. All this has made these regions a favourable zone for the dissemination of rice technologies, hence the choice of this zone for this study. Thus, in the Haut-Bassins region, the study villages are Banflaguè fon and Houndé. In the Cascades region, the villages selected are Sindou and Toumousséni. In the Central Plateau region, the villages of Tanseiga and Zantore are concerned. A total of six (06) villages were selected and surveyed. The map below illustrates the selected sites as well as the regions concerned by the study.

Theoretical framework

According to the diffusion of innovation theory, there are five adopter categories are: (1) innovators, (2) early adopters, (3) early majority, (4) late majority, and (5) laggards. Technology adoption is a process that follows several stages (observation, evaluation of the innovation). The decision to adopt is made after these stages of observation, evaluation of the potential adopter (Rogers, 1983). Each category of adopter has its own reasons and motivations for the technology presented. However, the common parameter for all adopters is the added value of innovation. At individual level, decisions to adopt an innovation are submitted to a bias arbitration by farmers and influenced by multiple factors endogenous or exogenous (observable or non-observable) to the farmers and the intrinsic characteristics of the innovation (Rogers, 1983). The adoption of a technology presupposes the knowledge of its existence by a potential adopter (Aminou et al., 2017). A producer is in a position to make the decision whether or not to adopt smart valley when he has all the information inherent in the technology. In microeconomic theory, any economic agent seeks to maximize its utility or profit under the constraint of income or technology. Indeed, the decision to adopt or not to adopt a technology also depends on the utility that the adopter hopes to drive from it. To formalize this decision, we suppose U_i^a and U_i^b, utility levels whether or not a rice producer i adopts smart valley technology. Indeed, any rice producer who adopts smart valley technology hopes to achieve maximum utility (U_i^a) contrary to a non-adopter (U_i^b); which means. $U_i^a > U_i^b$. In the literature, the linear model of the random utility function takes the following form:

$$U_i^a = \beta_a x_i + \varepsilon_{ai} \text{ and } U_i^b = \beta_b x_i + \varepsilon_{bi} \quad (1)$$

With β_a and β_b, parameters to be estimated x_i the vector of

---

[1] DGPER: Direction Générale de la Promotion de l'Economie Rurale (Rural Economy Promotion Office)
[2] SMART-IV: Sawah, Market Access and Rice Technologies for Inland Valleys.
[3] CSA : Climate Smart Approach.

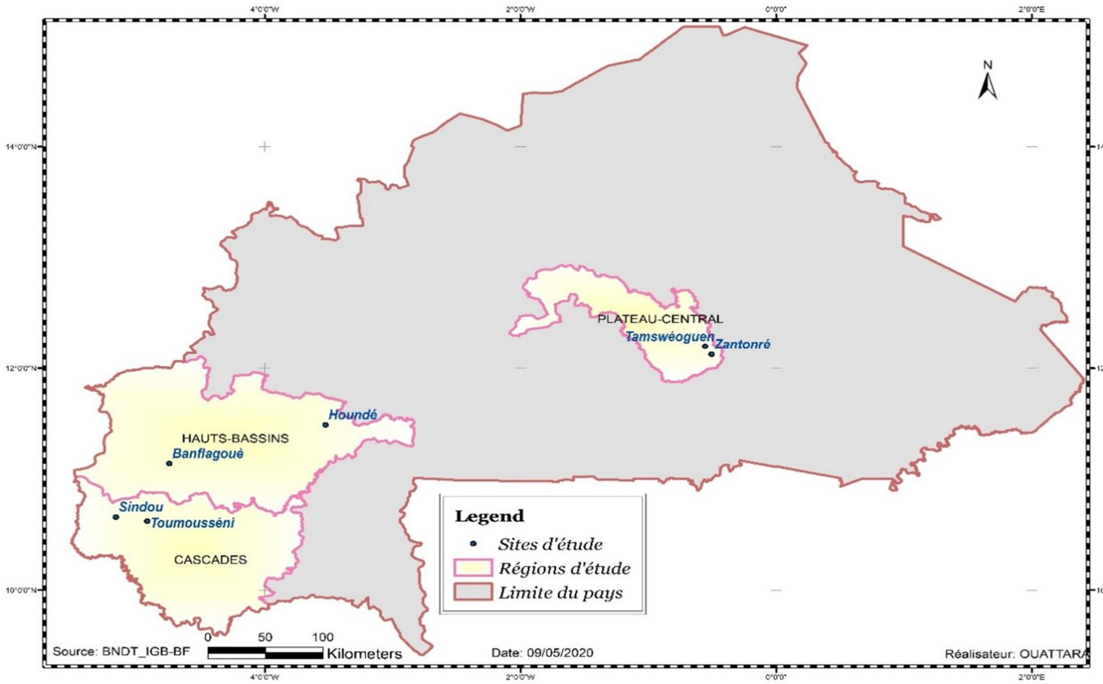

Figure 1. Mapping of study sites. Source: Field survey data, 2020.

producers and ε_{ai} and ε_{bi} the random error terms of the two functions, respectively

According to Greene (1951) for each producer i, the difference in the utility level of adoption and non-adoption of smart valley technology is a function of observable and unobservable characteristics. It is as follows:

$$T_i^* = U_i^a - U_i^b = \beta x_i + \varepsilon_i \qquad (2)$$

With

$\beta = \beta_a - \beta_b$ et $\varepsilon_i = \varepsilon_{ai} - \varepsilon_{bi}$;

T_i^* represents an unobservable dummy variable. It is a binary variable where T_i can only take the value 1 or 0. Indeed, T_i=1 represents the probability of a rice farmer to adopt smart valley technology, and and T_i = 0 or else. Thus, Equation 2 determines the probability that a rice farmer will adopt the smart valley technology or not. The economic literature indicates that the Probit and Logit models are the most commonly used for analysing the adoption of agricultural innovations, in particular the binary dependent variables. However, the choice of one of the two models proves difficult because their results are similar (Greene, 1951; Katchova, 2013). From the above, the probit model appears to be the most appropriate model for estimating the dependent variable for this study. In addition, authors such as (Issoufou et al., 2017; Ouédraogo and Dakouo, 2017; Teno et al., 2018; Adebiyi et al., 2019; Sanou et al., 2019), have used it successfully in their respective work on the adoption of agricultural innovations. This model is a prediction tool ‘par excellence’. It has the advantage of identifying the determining factors that need to be taken into account to achieve adoption. Thus, the probit model takes the following general theoretical form:

$$Prob\ (T_i = 1|x_i) = \int_{-\infty}^{x_i\delta} \emptyset(t)dt = \psi(x_i\beta) \text{with } \emptyset(t) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}t^2\right) \qquad (3)$$

Where

$\phi(.)$ and $\psi(.)$ are representing the density function and the cumulative distribution function of the normal distribution, respectively. The dependent variable y_i corresponds to the rice farmer's adoption decision, which takes the value 1 if the rice farmer has adopted Smart valley technology and 0 otherwise. The dependent variable y_i being binary, the maximum likelihood method is the most appropriate for model estimation (Greene, 1951; Katchova, 2013).

Specification of the model

The variable ADOPT in the probit study model corresponds to the adoption status of respondents and represents the dependent variable. Indeed, it takes the value 1 if the rice producer adopts smart valley technology and 0 otherwise. The categories of factors that may influence technology adoption depend on the type of technology (Katchova, 2013).

Two categories of factors are considered in this study. These are factors inherent to smart valley technology (technology attributes) and factors intrinsic to rice farmers (socio-economic and institutional factors).

Table 1 presents the explanatory variables selected in each category, their abbreviation, modality and expected impact of each variable are as follows:

Sex: The respondent's gender variable takes the value 1 if the rice farmer is male and 0 if it is a female one. In the literature, there are many studies that have addressed the gender issue. The work of (Aminou et al., 2017; Ouédraogo and Dakouo, 2017) show that men's gender has an effect on the adoption of agricultural technologies because they can have access to extension services and inputs more easily than women. In fact, the expected theoretical sign of this variable would be positive for men and negative for women.

Table 1. List of independent variables (by category), level of measurement and expected signs of Smart Valley technology adoption.

Category	Independent variables	Abbreviations (variable name)	Variable values	Expected sign
Socio-economic and institutional factors of the respondent	Gender	Sexe	1= male 0= female	+
	School level	N_Scolaire	1= Schooled, 0=No	+
	Head of household	Chef_mena	1=yes, 0=No	+
	Contact with another producer	Cont_aupro	1=yes, 0=No	+
	Contact with a technical support actor	Cont_aat	1=yes, 0=No	+
	Experience in rice farming	Exp_riz	Number of year in rice farming	+
Smart valley technology attributes (Intrinsic characteristics)	Maintaining water on the landscaped plot	M_eau	1=yes, 0=No	+
	Drainage of water from the plot	Drainage	1=yes, 0=No	+
	Realization of smart valley on all lowlands	Reasv_bf	1=yes, 0=No	+
	Yield	Rendement	Quantity harvested in 1 ha (MT/ha)	+
	Additional costs related to drainage	Coutsup	1=yes, 0=No	-
	Smart valley infrastructure maintenance	Entret_sv	1=yes, 0=No	-
	Nutrient maintenance on the plot	M_nutri	1=yes, 0=No	+

Source: Field survey data, 2020. Legend: + = Expected positive influence; –= Expected negative influence.

Schooled-people: This is a binary variable that takes the value 1 if the rice farmer is in school and 0 otherwise. Indeed, an educated farmer is inclined to seek out useful information on modern production technologies and can master them easily (Ouattara, 2017). In fact, the expected effect of this variable on the adoption of smart valley technology is positive.

Household-Head: this is a dichotomous variable which takes the value 1 if the producer is the head of household and 0 if he is not. The head of household is the guarantor of the household's well-being. Indeed, it is the one who decides on the household's agricultural production, and hence on the adoption of an agricultural innovation. A positive sign is expected for the coefficient of this variable.

Cont_aupro: This is a binary variable which takes the value 1 if the producer is in contact with another producer and 0 otherwise. Producers who are in contact with their peers using new agricultural technologies are able to use them on their farm. It is hoped that this variable will have a positive effect on smart valley adoption.

Cont_aat: This variable is binary and takes the value 1 if the producer is in contact with the technical support structures and 0 otherwise. It is hoped that this variable will have a positive influence on adoption since these structures are responsible for disseminating innovations to producers and facilitating their adoption. Indeed, producers with access to technical support services are more likely to adhere to agricultural innovations (Mabah Tene et al., 2013).

Exp_riz: The variable number of years in rice cultivation is a continuous variable, i.e. it is quantitative. The experience acquired in rice cultivation over the years by the farmer gives him a certain sensitivity to innovations, unlike the less experienced. A positive sign of the coefficient of this variable is expected.

M_eau: this is a binary variable that takes the value 1 if the producer perceives that smart valley allows rainwater to be maintained on the plot and 0 otherwise. It is hoped that this factor will have a positive sign because it is based on the attributes of smart valley technology. So it contributes to water efficient use.

Drainage: It is a binary variable that takes the value 1 if the producer perceives it as allowing drainage on the development and 0 otherwise. It is also an attribute of smart valley technology so its expected effect is positive.

Reasv_bf: This is a binary variable that takes the value 1 if smart valley technology can be on any lowland and 0 otherwise. The easy use of this type of land-drain on any lowland is an important criterion for wide adoption of the technology. A positive effect is expected from this factor.

Rendement: it is a continuous quantitative variable. It is expressed in tonnes per hectare. Yield is an important factor in the adoption of agricultural innovations. Indeed, yield in microeconomic theory positively affects the adoption of smart valley technology to the extent that it improves their gain. The expected sign is positive for adoption (Moya et al., 2004).

Coutsup: This variable is binary and takes the value 1 if there are additional costs for drainage in case of flooding and 0 otherwise. The expected effect is negative because additional investments tend to discourage potential adopters.

Entret_sv: It is a binary variable which takes the value 1 if it is necessary to regularly maintain the layout and 0 otherwise. Like the previous variable, the expected sign is negative because any maintenance requires labour force, time and investment.

M_nutri: Nutrient maintenance in the soil is a binary variable that takes the value 1 if the producer perceives it as such and 0 otherwise. It is an attribute of technology and is involved in soil fertility management. In fact, the positive effect of this factor is expected on the adoption of innovation (Delphine et al., 2019).

Sampling and data collection

The study used stratified sampling at two levels (villages and households). In the first stage, six (06) rice-producing villages concerned by the project intervention were selected from the village sampling frame. Then, 145 producers were randomly selected from the list of producers involved in the project. As a reminder, the households were selected from the list of the sample surveyed during the baseline study of the project conducted in 2018. This sample included rice-growing households. The sample is composed as follows: 40 producers in Banflaguè Fon, 40 in Sindou, 30 in Tanseiga, 10 in Zantore, 15 in Toumousseni and 10 in Houndé. This disparity in the number of respondents per village takes into account the level of involvement of producers in the smart valley technology demonstration activities. In addition, the health context (Covid-19 pandemic) at the time of the survey limited the participation of some producers.

The data collected were primary and secondary data. The secondary data were mainly derived from the literature review. The primary data were collected through the field survey of rice producers. The survey took place during the month of April 2020. These data were collected through an individual questionnaire. This questionnaire was digitized on the open access platform "ODK collect" and downloaded using smartphones. The primary data focused on the socio-economic and institutional characteristics of heads of households, rice farms and the characteristics of smart valley technology. This new collection method reduced costs and time and reduced data entry errors. It also made it possible to ensure the quality of the data through rigorous monitoring of the process and to have the data available at all times via the internet.

RESULTS AND DISCUSSION

This section presents the overall results of the study and their discussion.

Quantitative socio-economic characteristics of rice farmers

Table 2 shows that the average age of adopters (44.13 years) is relatively higher than that of non-adopters (43.62). The same applies to the yield of adopters (3.20 MT/ha) and non-adopters (2.93 MT/ha). Of course the yield difference adopters and non-adopter still low but in term of income, the 0.2 MT/ha means 30,000 FCFA/ha (60 USD/ha) additional for adopters. On the other hand, adopters have a relatively lower average number of years of experience (10.39 years) than non-adopters (11.35 years).

Table 2. Quantitative socio-economic characteristics of rice farmers by adoption status.

Variables	Adopters			Non-adopters		
	Mean	Max	Min	Mean	Max	Min
Age	44.13	65.00	27.00	43.62	79.00	25.00
Number of years in rice farming	10.39	30.00	2.00	11.35	30.00	2.00
Rice yield (MT/ha)	3.20	5.00	1.00	2.93	3.00	2.00

Source: Field survey data (2020).

Socio-economic quality characteristics of rice farmers and the characteristics of smart valley technology

The results in Table 3 indicate that women (76.36%) are the highest adopters of smart valley technology. This can be explained by the fact that in the Hauts-Bassins and Cascades regions, rice cultivation is predominantly practised by women. The same is true for female heads of households (78.43%) who have adopted it in majority as shown in Table 3. It also emerges from Table 3 that those who have adopted the smart valley technology are mostly rice farmers who have not attended school (66.09%). About 92.19% of the adopters have access to technical support structures (extension services, research and NGOs) compared to 7.81% of the non-adopters. It is the same concerning the contact with another producer, with adopters having access to another producer (92.19%). More than 80% of the adopters believe that smart valley technology makes it possible to maintain water on the plot in order to preserve the crop from water stress compared to 18.75% of the non-adopters as shown in Table 3. 81.69% of the producers believe that smart valley management facilitates drainage in case of flooding and have adopted it compared to 18.31% who have not adopted it. This is virtually the same proportion for those (81.08%) who believe that smart valley is feasible on any shoal and have adopted it as shown in Table 3. As for the option of additional costs for flood drainage, 70.59% of producers who have adopted the technology believe that there are no additional costs for drainage compared to 29.41% of non-adopters. The results in Table 3 also indicate that more than 75% of producers who have adopted the smart valley technology believe that it does not require maintenance compared to 21.05% of non-adopters who believe the opposite. More

Table 3. Quality characteristics of rice farmers and smart valley by adoption status.

Independant variables	Variable label	Adopters (%)	Non-adopters (%)
Gender	Male	56.67	43.33
	Female	76.36	23.64
School level	Schooled	56.67	43.33
	Non schooled	66.09	33.91
Head of household	Yes	55.91	44.09
	No	78.43	21.57
Contact with another producer	Yes	92.19	7.81
	No	41.98	58.02
Contact with a technical support actor	Yes	92.19	7.81
	No	41.98	58.02
Maintaining water on the landscaped plot	Yes	81.25	18.75
	No	6.06	93.94
Drainage of water from the plot	Yes	81.69	18.31
	No	47.30	52.70
Realization of smart valley on all lowlands	Yes	81.08	18.92
	No	5.71	94.29
Additional costs related to drainage	Yes	70.59	29.41
	No	96.61	3.39
Smart valley infrastructure maintenance	Yes	78.95	21.05
	No	97.06	2.94
Nutrient maintenance on the plot	Yes	84.76	15.24
	No	0.10	0.90

Source: Field survey data (2020).

than 84.76% of smart valley adopters believe that land-use development helps maintain nutrients in the soil compared to 15.24% of non-adopters as shown in Table 3. Indeed, it contributes to good soil fertility management.

Determinants of smart valley technology adoption

The estimation of the smart valley technology adoption model is based on the probit model. The results of the probit regression used to identify the determinants of Smart Valley technology adoption and their marginal effects are reported in Table 4. The likelihood ratio test is highly significant at the 1% threshold; this means that the model is well specified as well as the variables used to explain adoption. It is concluded that the alternative hypothesis that at least one coefficient is not zero is accepted at the expense of the null hypothesis that all coefficients are simultaneously zero. Table 4 shows that eight (8) factors influence the adoption of smart valley technology. These factors are: level of education, contact with a technical support actor, water retention, drainage, yield, additional costs related to the construction of drains, fertility maintenance, and the number of years of experience in rice cultivation. The educational level of rice farmers positively and significantly influences the adoption of Smart Valley technology at the 5% threshold. These results are in line with those obtained by Mabah Tene et al. (2013), Aminou et al. (2017) and Issoufou et al. (2017). The results also indicate that schooling status increases the probability of smart valley adoption by 18%. This means that focusing on the educated sub-population will improve the likelihood of Smart Valley technology adoption.

Table 4. Probit regression results of the determinants of Smart valley technology adoption.

Variables	Coefficients	Standard errors	Marginal effects
Sex	-8.822	735.4	-0.579
N_scolaire	2.754**	1.425	0.181**
Chef_mena	7.933	735.4	0.520
Con_aupro	-0.0670	1.080	-0.00440
Cont_aat	1.700*	0.960	0.112**
M_eau	2.198**	1.003	0.144***
Drainage	1.639**	0.836	0.108**
Reasv_bf	-2.071	1.781	-0.136
Rendement	1.659**	0.862	0.109**
Coutsup	-3.967***	1.523	-0.260***
Entret_sv	0.117	1.355	0.00765
M_nutri	3.072*	1.663	0.202**
Exp_riz	0.148*	0.0822	0.00970**
Constante	-6.500***	2.756	0.0184

Number of observation = 110; LR Chi^2 (13) = 68.24***; Prob > Chi^2 = 0.0000; Pseudo R^2 = 0. 7205; Log likelihood = – 13.2351
Source: Field survey data, 2020; Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The variables "Plot water retention" and "Plot drainage" are important factors in the decision to adopt Smart valley technology. Table 4 shows that they have a positive and significant influence on the adoption of Smart Valley technology at the 5% threshold. This could be explained by the fact that these factors are based on the intrinsic characteristics of the smart valley technology. Thus, the fact that smart valley has the capacity to maintain or drain water on the plot according to the needs of rice production, increases the probability of adoption by 14 and 11% respectively.

Yield is also an important factor in the adoption of agricultural technologies. Indeed, the model results indicate that yield has a positive and significant effect on Smart valley technology adoption at the 5% threshold. This result is similar to that obtained by Issoufou et al. (2017). The marginal effect of this variable indicates that an increase of one unit of return increases the probability of adoption by 11%. This means that performance is one of the factors that must be addressed to improve technology adoption. The results of the analysis show that the factors 'contact with a technical support agent', 'maintenance of nutrients (fertilizers) in the soil' and 'number of years of experience in rice production' have a significant and positive impact on the adoption of Smart valley technology at the 10% threshold. The marginal effects analysis argues that the factors 'contact with a technical support actor', 'maintenance of nutrients (fertilizers) in the soil' and 'number of years of experience in rice production' increase the probability of adoption of the Smart Valley technology by 11, 20 and 1% respectively. Indeed, the positive relationship between contact with a technical support agent and adoption can be explained by the fact that these technical support agents are channels of information on agricultural innovations. This result is consistent with that found by Mabah Tene et al. (2013), Aminou et al. (2017) and Issoufou et al. (2017). The result relating to the soil nutrient maintenance factor is explained by its contribution to good plant development and therefore to improved yields. Moreover, rice farmers who have a number of years of experience in rice production are more likely to adopt the technology, contrary to beginners in rice production (Moya et al., 2004; Ouattara, 2017; Ouédraogo and Dakouo, 2017; Marcellin et al., 2019).

The variable "additional cost due to plot drainage" is the only variable that negatively and significantly affects the 1% threshold. This means that an increase of one unit leads to a 26% decrease in the probability of adopting the smart valley.

CONCLUSION

This study analysed the determinants of the adoption of smart valley technology and assessed its impact on the yield and income of small-scale rice producers in Burkina Faso. It used the probit model to identify the determinants of the adoption of the new smart valley technology. The results obtained have thus made it possible to identify eight (08) factors that influence the adoption of the smart valley technology, which are: school level, contact with another agricultural actor, water retention, drainage, and yield, additional costs related to the construction of drains, maintenance of soil nutrients and the number of years of experience in rice growing. Out of these eight (8) factors, only the additional cost factor negatively influences the adoption of smart valley technology.

The results suggest that any policy aimed at promoting the smart valley technology should rely on "female" heads of household who are educated and in contact with technical support structures (extension, research, NGOs) to promote its adoption. Also, any reduction in smart valley acquisition costs will improve the rate of technology adoption among small-scale rice producers in Burkina Faso. All these actions combined, will undoubtedly ensure the sustainability and wide adoption of the smart valley technology. However, national dissemination of the smart valley technology should take into account the specificities of each agro-ecological zone for greater efficiency.

ACKNOWLEDGEMENT

The CSA-Rice project implemented by the Institute for Environment and Agricultural Research (INERA) and AfricaRice was funded by the German Cooperation through the University of Bonn/Germany. We would like to thank the German Cooperation, the project implementation sites and AfricaRice for the technical support.

REFERENCES

Adebiyi KD, Maiga-Yaleu S, Issaka K, Ayena M, Yabi JA, 2019. Déterminants de l'adoption des bonnes pratiques de gestion durable des terres dans un contexte de changement climatique au Nord Bénin : cas de la fumure organique. Int J Biol Chem Sci,13(2): 998. doi: 10.4314/ijbcs.v13i2.34.

AFRICARICE, **2017**. Smart Valley manuel du formateur-facilitateur.

Aminou A, Adégbola Ygué P, Akpa AK, **2017**. Impact de la technologie smart- pour l' amenagement riz au Benin Aristide.

CNS, **2019**. RAPPORT STATISTIQUE NATIONAL 2018.

Delphine BNA, Dial N, Mahama G, Ibrahima O, **2019**. Adaptation and Resistance of Smart Valleys Bunds in Sudanians ' Lowland : Experience in Four Lowlands in Burkina Faso. Amer J Water Resour, 7(2): 58–61, doi: 10.12691/ajwr-7-2-3.

DGPER, **2011**. Burkina Faso.

FAOSTAT, **2020**. http://www.fao.org/faostat/en/#home (Accessed Apr. 22, 2020).

Fashola OO, Hayashi K, Wakatsuki T, **2006**. Effect of water management and polyolefin-coated urea on growth and nitrogen uptake of indica rice. http://dx.doi.org/10.1081/PLN-120014069, doi: 10.1081/PLN-120014069.

Greene WH, **1951**. Econometric analysis. Seventh edition.

Issoufou O, Boubacar S, Adam T, Yamba B, **2017**. Determinants de l'adoption et impact des varietes ameliorees sur la p roductivite du mil au Niger. Afr Crop Sci J, 25(2): 207, doi: 10.4314/acsj.v25i2.6.

Katchova A, **2013**. Probit and Logit Models Ani Katchova.

MAAH, **2020**. "Ministère en charge de l'agriculture - Situation alimentaire et nutritionnelle : le comité de prévision valide les résultats définitifs". https://www.agriculture.bf/jcms/fra_100813/fr/situation-alimentaire-et-nutritionnelle-le-comite-de-prevision-valide-les-resultats-definitifs (Accessed May 28, 2020).

Mabah Tene GL, Temple L, Havard M, **2013**. Les déterminants de l ' adoption d ' innovations techniques sur maïs à l ' Ouest Cameroun , une contribution à la sécurisation alimentaire AGRAR 2013 Les déterminants de l ' adoption d ' innovations techniques sur maïs à l ' ouest Cameroun, une contribut.

Marcellin OO, Firmin AI, Jacob YA, **2019**. Impact Environnemental de L'adoption des Variétés Ameliorées de Soja dans le Département du Borgou au Nord du Bénin. Eur Sci J, 15(28): 11–20, doi: 10.19044/esj.2019.v15n28p148.

Moya P, Hong L, Dawe D, Chongd C, 2004. The impact of on-farm water saving irrigation techniques on rice productivity and profitability in Zhanghe Irrigation System, Hubei, China. Paddy Water Environ, 2(3): 207–215, doi: 10.1007/s10333-004-0063-2.

Ouattara M, **2017**. Les déterminants de l'adoption de certaines bonnes pratiques culturales avant récolte de la noix de cajou en Côte d'Ivoire. IOSR J Econ Financ, 8(3): 08–15, doi: 10.9790/5933-0803010815.

Ouédraogo M, **Dakouo** D, **2017**. "Evaluation de l'adoption des variétés de riz NERICA dans l'Ouest du Burkina Faso," Afr J Agric Resour Econ, 12(1): 1–16.

Rogers EM, **1983**. Diffusion of innovations. Third Edition.

Sanou L, Savadogo P, Ezebilo EE, Thiombiano A, **2019**. Drivers of farmers' decisions to adopt agroforestry: Evidence from the Sudanian savanna zone, Burkina Faso. Renew Agric Food Syst, 34(2): 116–133, doi: 10.1017/S1742170517000369.

Teno G, Kim L, Abdoulaye K, **2018**. Les facteurs de l'adoption des nouvelles technologies en agriculture en Afrique Subsaharienne: une revue de la littérature. Afr J Agric Resour Econ, 13(2): 140–151.

Wakatsuki T, Buri MM, Oladele OI, **2009**. West Mrican Rice Green Revolution by Sawah Eco-technology and the Creation of Mrican SA TOY Systems.

Citation: Ouédraogo A, Bama NAD, Tassembédo B, Arouna A, Yovo ED, Wonni I, 2020. Determinants of smart valley technology adoption in lowland rice farming: evidence from Burkina Faso. Net J Agric Sci, 8(3): 59-66.