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# Driving factors toward adoption of improved maize varieties in Mozambique. An approach based on generalized estimating equations for spatial structured data

# Determinantes da adopção de variedades melhoradas de milho: Uma abordagem baseada em equações de estimação generalizadas para dados com estrutura espacial

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**ABSTRACT**
Maize is one of the main economic crops and staple food in Mozambique. However, despite the importance of the crop in the country, maize productivity is still low due to several factors including low adoption of improved agricultural technologies. This paper aimed to identify the main factors driving adoption of improved maize varieties applying generalized estimating equations (GEE). The motivation for this class of models is due to the fact that adoption of improved maize varieties is a spatial auto correlated variable and the traditional probit and logit models widely applied in studies of adoption of agricultural technologies do not take into account the structure of correlation existing in the response variable. The study uses data from Integrated Agrarian Survey of 2012 (IAI 2012). The proportion of small farmers who adopted improved maize varieties per district was used as response variable and a set of nine variables were used as covariates classified in social, economic, institutional and technologic factors. The spatial auto correlation of the dependent variable was assessed by global and local Moran indexes. Two classes of models were fitted: The traditional logistic regression (logit model) and the generalized estimating equations approach. The inclusion of spatial auto correlation in GEE was carried out inserting the Moran's index in the working correlation matrix. The results have shown that the GEE approach for spatial lattice data was the best and all factors analysed in the

study including the spatial dependency are the main factors driving adoption of improved maize varieties in Mozambique.

**Key words**: Generalized estimating equations, spatial autocorrelation, adoption of maize varieties.

**RESUMO**
A cultura de milho é um dos mais importantes cereais e fonte de subsistência em Moçambique. Contudo, seus níveis de produtividade continuam baixos devido a vários factores incluíndo o baixo nível de adopção de tecnologias agrícolas melhoradas. Este trabalho tem como objectivo identificar os principais factores determinantes da adopção de variedade melhoradas de milho usando as equações de estimação generalizadas (EEG). A escolha desta classe de modelos está aliada ao facto de que a adopção de variedades melhoradas constitui um fenómeno espacialmente autocorrelacionado e os tradicionais modelos *probit* e *logit* amplamente usados em estudos de adopção de tecnologias agrícolas não preconizam a estrutura de autocorrelação existente na variável resposta. Foram usados dados do Inquérito Agrário Integrado de 2012 e como variável resposta foi considerada a proporção de produtores que usou variedades melhoradas de milho em cada distrito do país. Adicionalmente, um conjunto de nove variáveis classificadas em factores sociais, económicos, institucionais e tecnológicos foram consideradas como covariáveis. A ocorrência da autocorrelação espacial na variável resposta foi avaliada com base nos índices global e local de Moran. Duas classes de modelos foram ajustadas: o modelo *logit* e as EEG. A inclusão da autocorrelação espacial foi feita pela inserção do índice de Moran na matrix de correlação de trabalho. Os resultados mostraram que a abordagem das EEG apresentou os melhores resultados e que todos os factores do estudo incluíndo a interação entre os produtores avaliada através da dependência espacial constitiuem os determinantes da adopção de variedade melhoradas de milho no país.

**Palavras chave**: Equações de estimação generalizadas, Auto correlação espacial, Adoção de variedades de milho.

## 1 INTRODUCTION

Agriculture is one of the main key sectors for social and economic development in Mozambique. The agriculture sector employs more than 80% of people living in rural areas and it is the main source of income and livelihood for many families in such areas. According to INE (2017), the agriculture sector of Mozambique contributes in approximately 23% of the Gross Domestic Product (GDP).

Among the main cultivated crops in Mozambique, maize is the most important cereal in the country fallowed by rice, wheat and Sorghum (Dias, 2013). Maculuve (2011) claims that maize is the staple food for many Mozambicans accounting in 40% of the total calorie diet in nutrition. In urban areas, the contribution of maize in the consumption expenditures is estimated in 13.4% whereas for other cereals such as rice and wheat the expenditures accounted in 8.4% and 7.5%, respectively (Donavan and Tostão, 2010).

Despite the role that the crop represents for the country, maize productivity is still low (0.97 tonnes/ha) when compared to other southern African countries. For instance, the average maize yield in South Africa is estimated in 3.9 tonnes/ha (Renapri, 2017).

For developing countries like Mozambique, the adoption of improved agricultural technologies may increase the yields of many crops promoting more diversification of crops enhancing family income in rural areas. Uaiene (2009) claims that many improved agricultural technologies such as improved maize varieties are available in Mozambique. However, despite of the availability of such agricultural technologies, small famers have limited access to them.

Aiming to understand the main reasons of low levels of agricultural technologies adoption in developing countries, many authors tried to find out what factors drive farmers to adopt improved technologies. Some examples that may be cited are studies of Lambrecht *et al*. (2014); Cavane and Donavan (2011); Uaene (2009) and Zavale *et al*. (2005). The authors apply logit and probit models to study the relationship between adoption of agricultural technologies and several factors (covariates). These models were developed under the assumption of independence between observations of the response variable (McCullagh and Nelder, 1989). However, it is known that small farmers in developing countries usually share their agricultural experiences between them and strongly influence each other in the decision to adopt an improved agricultural technology. Thus, it is expected that in a given region, farmers in neighbour areas will exhibit spatial similarity between them in the pattern of adoption of any improved technology when compared to farmers located in distant areas. This spatial pattern can be assessed by the Moran's index which is the well known measure of spatial autocorrelation widely applied in spatial lattice data. Therefore, the application of logit and probit models widely used in adoption of agricultural technologies may not represent well the phenomena due to the fact that such models do not take into account the spatial dependency existing between observations of the response variable. Thus, in order to overcome the limitation of such models, in this paper we study the proportion of farmers who adopted improved maize varieties in Mozambique applying generalized estimating equations (GEE) which are more appropriate to spatial and temporal correlated data (Liang and Zeger, 1986; Lin and Clayton, 2005). The inclusion of spatial dependency between observations of the response variable in GEE is accomplished inserting the Moran's index in the working correlation matrix

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(Manuel and Scalon, 2020). We also compare the results of GEE approach with the results of the traditional methods (logit model).

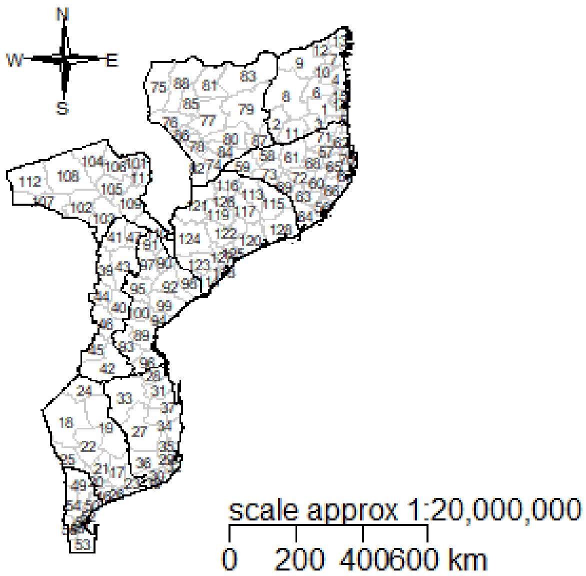
## 2 MATERIAL AND METHODS

This chapter describes the study area including the source of data and the variables used in the study. The spatial autocorrelation measure and the description of generalized estimating equations for spatial lattice data are presented as well.

### 2.1 STUDY AREA

The study was carried out using the shapefile of Mozambique, a southern African country bordered by the Indian Ocean at the east. Mozambique is divided in 10 provinces where each of the provinces is divided into several districts, resulting in 128 districts along the country. Figure 1 shows the study area exhibiting the 128 districts with the corresponding geographic code areas denoted by centroids.

Figure 2. Map of Mozambique divided in 128 districts




Source: CENACARTA (1997)

### 2.2 DATA SOURCE AND VARIABLES OF THE STUDY

The study was carried out using Mozambique´s data from 2012 Integrated Agrarian Survey. The proportion of smallholder farmers who adopted improved maize varieties per district was considered as response variable and a set of nine variables as covariates. These explanatory variables were classified as social, economic, technologic and institutional factors. The covariates considered as social factors were: (i) household size – defined as average number of family members per district; (ii) farmer's age - given by the average age of the household head per district; (iii) permanent labourers - a binary variable equal 1, if farmers hire permanent labourers and, equal 0, otherwise; (iv) temporal labourers – a binary variable equal 1, if farmers hire temporal labourers and, equal 0, otherwise. The economic factors were: (v) access to credit – a binary variable equal 1, if farmers have credit access, and equal 0, otherwise; (vi) ownership of improved storage grains system - a binary variable equal 1, if farmers have improved storage seeds system, and equal 0, otherwise. The Institutional factors considered in the study were: (vii) Access to agriculture extension services - a binary variable equal 1, if farmers have access to extension services, and equal 0, otherwise; (viii) Information access - a binary variable equal 1 if the farmers own a radio, and equal 0, otherwise. Only one technologic factor was used: (ix) animal traction - a binary variable equal 1 if farmers use animal traction, and equal 0, otherwise. All variables were measured at the district level depicted in Figure 3.

## 2.3 SPATIAL AUTOCORRELATION ANALYSIS

Spatial autocorrelation is a measure of association of a random variable observed in two locations such as municipalities, districts, provinces, etc. According to Rogerson and Yamada, there are several indexes used to depict the spatial autocorrelation between observations for spatial lattice data, being the global Moran's index the most popular. However, the application of this index depends on the definition of a spatial weight matrix **W** whose elements are given as following: $w_{ij} = 1$, if area $A_i$ and $A_j$ share the same border, for $i \neq j$ and $w_{ij} = 0$, otherwise (See: Waller and Gotway, 2004 for more details).

The global Moran's index is defined by:

$$\hat{I} = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,(Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}, \qquad (1)$$

where: $n$ is the number of areas (districts); $Y_i$ and $Y_j$ is the proportion of small farmers who adopted improved maize varieties in area $i$ and $j$ respectively; $\boldsymbol{\bar{Y}}$is the sample mean ($\boldsymbol{\bar{Y} = \sum_{i=1}^{n} Y_i / n}$); $w_{ij}$ are elements of the spatial weight matrix (Rogerson and Yamada, 2009).

Positive values of the Moran´s index indicates positive spatial autocorrelation, suggesting that values of a random variable in neighbour regions tend to be similar between them. While negative estimates of Moran indicate negative spatial autocorrelation which means that neighbour regions tend to be dissimilar between them. In the absence of spatial autocorrelation the Moran's index is zero which suggests that the random variable is spatially independent. Inference for the Moran's index is carried out constructing the distribution of the index under the hypothesis of independence using permutations or the normal distribution assumptions (See: Manuel and Scalon, 2020 for more details).

## 2.4 MODELLING

Let $\boldsymbol{Y_i} = (Y(s_1),\ldots, Y(s_{n_i}))$ a $n_i \times 1$ dimensional vector of a random variable denoting the proportion of small farmers who adopted an improved maize variety at the *i*th province of Mozambique, where $i = 1,2,\ldots,10$ and $n$ is the number of observation at each province, and $s_1, \ldots, s_{n_i}$ are spatial locations (districts in each province) denoted by centroids (Figure 1). The correspondent vector mean of $\boldsymbol{Y_i}$ is denoted by $\boldsymbol{\mu_i} = (\mu(s_1), \ldots, \mu(s_{n_i}))$. Furthermore, let $\mathbf{X_i} = (\mathrm{x}_{i1}(\mathrm{s}_1), \ldots, \mathrm{x}_{ip}(\mathrm{s}_{n_i}))$ a $n_i$ *x* $p$ dimensional matrix containing observations of $p$ covariates measured at districts $s_1, \ldots n, s_{n_i}$. The mean response $\boldsymbol{\mu_i} = \mathrm{E}(\boldsymbol{Y_i})$ is assumed to be associated with the measurements of explanatory variables $\boldsymbol{X_i}$ through the link function denoted by:

$$\mathrm{g}(\boldsymbol{\mu}_i) = \mathbf{X}_i\boldsymbol{\beta} \qquad (2)$$

where $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_p)$ is a $p \times 1$ dimensional vector of parameters to be estimated and $\mathrm{g}(\boldsymbol{\mu_i}) = \log\{\boldsymbol{\mu_i}/(1-\boldsymbol{\mu_i})\})$ is the link function.

The spatial lattice covariance structure of $\boldsymbol{Y}_i$ is denoted by:

$$\boldsymbol{\Omega}(\boldsymbol{Y}_i) = \phi^{-1}\mathbf{V}_i^{1/2}\mathbf{R}_i(\rho)\mathbf{V}_i^{1/2}, \qquad (3)$$

where $\mathbf{V_i} = \mathrm{diag}\{\mu_i(s_1)[1-\mu_i(s_1)], \ldots, \mu_i(s_{n_i})[1-\mu_i(s_{n_i})]\}$ is $n_i \times n_i$ dimensional diagonal matrix with the main diagonal defining a mean function or variance function in the *i*th province at spatial location $s_1, \ldots, s_{n_i}$; $\phi$ is the dispersion parameter which is assumed equal 1 ($\phi = 1$); $\mathbf{R_i}(\rho) = \rho\mathbf{W_i} + \mathbf{I}$, is $n_i \times n_i$ dimensional correlation matrix measuring the spatial correlation between observation of the random variable $\boldsymbol{Y_i}$ ; $\rho$ is the Moran´s index given by equation (1); **W** is the spatial weight matrix and **I** is the identity matrix.

Assuming that the first and second moments of the joint distribution of $\boldsymbol{Y_i}$ are depicted by equations (2) and (3), respectively, and applying the generalized estimating equation (GEE) approach for spatial lattice data, the model parameters are reached using the scoring fisher algorithm. Inference for parameters are obtained by the Wald test (See Manuel and Scalon, 2020 for more details).

Two types of models were fitted: logistic regression and GEE. The former was fitted assuming spatial independence between observations while the later was fitted considering the occurrence of spatial autocorrelation measured by the Moran's index.

All analyses were carried out using software R (R core team, 2019) packages s*pdep* (Bivand et al., 2011) and *geepack* (Halekoh, et al., 2006).

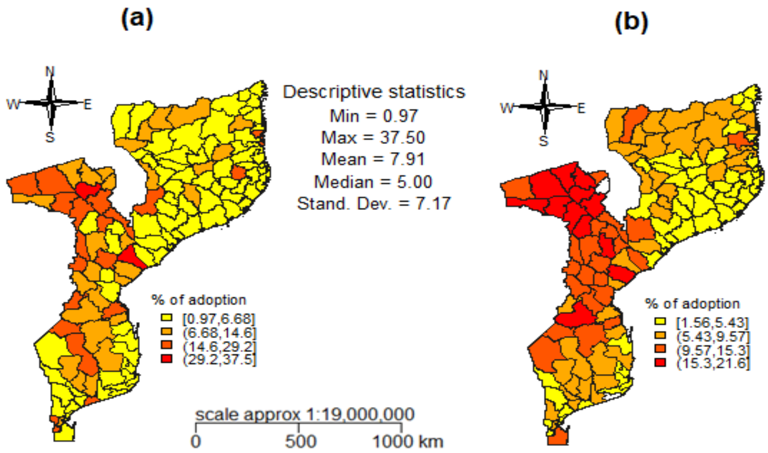
## 3 RESULTS AND DISCUSSION

This chapter presents results of exploratory analysis of the response variable and results of fitted models.

### 3.1 EXPLORATORY ANALYSIS OF ADOPTION OF IMPROVED MAIZE VARIETIES

Figure 2 depicts the thematic map of the proportion of farmers who adopted improved maize varieties along the 128 districts of Mozambique including the spatial smoothing of the variable using spatial moving average estimator. It is noticed that the proportion of adoption varies from approximately 1% up to 37.5% with an average estimate of 8% per district. The median equal 5% indicates that 50% of districts have adoption levels lower than 5% which means in general that most districts are characterized by low levels of adoption of improved maize varieties. The spatial smoothing map suggests that there are different spatial patterns of adoption of improved maize varieties along the country characterized by higher levels of adoption in districts of the centre region when compared to districts belonging to the south and north regions which are depicted by low levels of adoption. It is noticed that districts with higher levels of adoption pertain to Tete and Manica provinces. One possible reason for such adoption performance in those districts has to do with the strong influence from farmers of neighbour countries like Malawi and Zimbabwe.

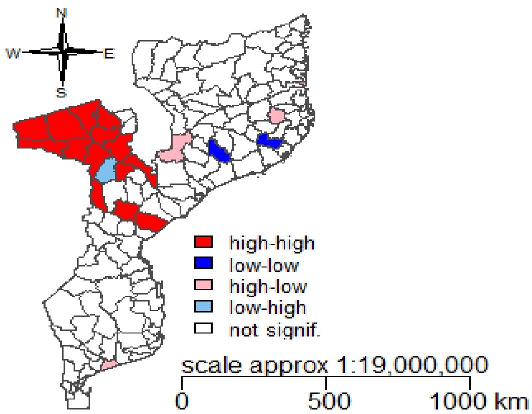
Figure 2. Thematic map of the proportion of small farmers who adopted improved maize varieties. (a) Observed data; (b) Spatial moving average




Source: From authors (2021)

The spatial autocorrelation analysis of the proportion of small farmers who adopted improved maize varieties in Mozambique has shown that there is a significant positive spatial association between observations of the response variable (*Moran* = 0.31, $p < 0.05$). This suggests that regions with high levels of adoption of improved maize varieties are likely to be surrounded by regions with high levels of adoption and areas characterized by low levels of adoption are surrounded by neighbours with low levels as well. Figure 3 depicts the Moran local index of spatial autocorrelation (LISA map) which indicates what type of spatial association exists between given district and its neighbours.

Figure 3. Moran local index of spatial auto correlation "LISA map"




Source: From authors (2021)

It is noticed that there are three types of spatial association between districts along the country. Firstly, districts characterized by "high-high" and "low-low" correspond to areas with significant positive spatial association for higher and lower levels of adoption of improved maize varieties, respectively. Secondly, districts classified by "low-high" and "high-low" represent significant negative spatial association meaning that districts of lower levels of adoption are surrounded by districts with high levels and vice versa. Finally districts whose spatial association is not significant are not spatially auto correlated with their neighbours.

Thus, the adoption of improved maize varieties is a variable that is spatially auto correlated across observational units. Once the spatial autocorrelation of this variable is not taken in account while modelling, the inferences may be questionable.

## 3.2 FITTED MODELS

Two models were fitted to the data, the logistic regression and the generalized estimating equations (GEE). The former is widely used in technology adoption studies which assumes that the proportion of small farmers who adopted improved maize varieties is not spatially auto correlated while the later takes into account the occurrence of spatial association between observations of adoption of improved maize varieties measured by the Moran's index. Table 1 reports the results of logistic regression model and the GEE approach.

Table 1: Estimates for Logistic regression model and generalized estimating equations (GEE)

| | | **Logistic regression** | | **GEE** | |
|---|---|---|---|---|---|
| **Covariates** | | **estimate** | **Stand. error** | **Estimate** | **Stand. error** |
| Intercept | | -2.82* | (0.70) | -4.14* | (0.19) |
| Household size | | 0.31* | (0.07) | 0.30* | (0.02) |
| Farmer's age | | -0.06* | (0.01) | -0.03* | (0.004) |
| Temporal labours | | 0.78* | (0.37) | 1.10* | (0.07) |
| Permanent labours | | 0.59* | (0.14) | 0.69* | (0.03) |
| Acesso to credit | | 0.19 | (0.10) | 0.16* | (0.02) |
| Improved storage grain system | | 0.34 | (0.21) | 0.46* | (0.05) |
| Access to extension | | 0.36* | (0.15) | 0.48* | (0.03) |
| Access to information | | 0.22 | (0.12) | 0.41* | (0.03) |
| Animal traction use | | 0.32 | 0.16* | 0.14 | 0.04* |
| Association parameter (λ) | | | | 0.33 | 0.11* |
| Working correlation criterions | QIC | 89.96 | | 82.94 | |
| | CIC | 10.00 | | 6.34 | |
| | RJC | 1.36 | | 1.00 | |

* Significant at 5%. QIC – quasi-likelihood information criterion; CIC – correlation information criterion; RJC – Rotnitzky and Jewell criterion.

Source: Manuel and Scalon (2020)

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The signals of the estimates of all covariates are positive excepting for the farmer's age variable which is negative. These signals converge to the expected results for all predictors. The logistic regression model has shown that among all covariates tested in the study, there are three without a significant effect in the model: the access to information, access to credit and the ownership of improved storage grains system. However, the logistic regression analysis assumes independence between observations in the response variable. This is not the case of the data of adoption of improved maize varieties, where there is a positive spatial autocorrelation as demonstrated by the Moran's index. Thus, any inference based on the logistic regression may be questionable. Therefore, the occurrence of spatial autocorrelation in the response variable was taken into account using the GEE approach proposed in this paper. The estimates of the covariates parameters applying GEE approach are similar with those obtained by logistic regression model due to the property of consistence of the estimators (Liang & Zeger, 1986).

Applying the GEE to reach the estimates of the model, it is noticed that all covariates have significant effect in the model due the increment of the efficiency of the parameters estimators which has influenced the power of the tests. Furthermore, the working correlation matrix selection criterions (QIC, CIC and RJC) have indicated the spatial working correlation matrix using the Moran's index as the best structure, when compared to its competitor with independent structure. Therefore, all inference is carried out using results of generalized estimating equations approach.

Table 2 depicts the results of marginal effects of each covariate given by odds ratio. This measure describes the odds of a given small farmer to adopt an improved maize variety when the covariate in analysis changes (increases) in one unit keeping constant all other factors.

Table 2 Marginal effect of each covariate

| **Covariate** | **Estimate($\widehat{\beta}$)** | **Odds ratio (exp($\widehat{\beta}$))** |
|---|---|---|
| Household size | 0.30 | 1.35 |
| Farmer's age | -0.03 | 0.97 |
| Temporal labours | 1.10 | 3.00 |
| Permanent labours | 0.69 | 1.99 |
| Acesso to credit | 0.16 | 1.17 |
| Improved storage grain system | 0.46 | 1.58 |
| Access to extension | 0.48 | 1.62 |
| Access to information | 0.41 | 1.51 |
| Animal traction use | 0.14 | 1.15 |
| Association parameter ($\lambda$) | 0.33 | 1.39 |

Source: From authors (2021)

Social factors regarding to availability of labour such as household size, temporal and permanent labours have shown a positive significant effect in adoption of improved maize varieties. For the former case it is expected that farmers with greater household sizes are more likely to adopt improved maize varieties in 35% than farmers with fewer household members. For both permanent and temporal labour it is expected that the use of such hired labour increase the odds of adoption of improved maize varieties in 99% and 200% for permanent and temporal labours, respectively. In fact the temporal labours which impacts most in the decision of adoption of improved maize varieties, characterize the agriculture sector of Mozambique which is majority rudimentary and depends mainly by human factor. Authors like Mignouna et al. (2011) & Bonana – Wabbi (2002) have also shown a positive impact of the labour availability in adoption of improved agricultural technologies due to the great role of the factor during introduction of new technologies.

Farmer's age is another social factor with significant effect in adoption of improved maize varieties in Mozambique. Among all factors considered in the study the farmer's age was the unique covariate with negative effect in the decision of adoption. The results suggest that older farmers are less likely to adopt improved maize varieties than younger farmers in 3%. Similar results are reported by Zavale (2005); Mauceri *et al*. (2005); Adesina and Zinnah (1993). The authors state that older famers are less likely to risk exposure and they tend to decrease their investment in agriculture in long term. On the other hand, younger farmers are more likely to risk exposure and to try new technologies. However, Kariyasa and Dewi (2011); Mwuangi and Kariuki (2015), report that the more experienced the farmer, the more accumulated knowledge he has. This allows old farmers to better analyze information regarding new agricultural technologies than young farmers.

The ownership of an improved storage grain system and access to credit, both related to economic factors, have shown positive effect in adoption of improved maize seeds. If the farmer owns an improved storage grain system he is more likely to adopt improved maize seeds in 58% compared to farmers without a storage grain system. In fact the availability and access of improved storage grain system guarantee a reliable maize storage in large scale. This has strong influence in market access and mostly impacts on the season of maize commercialization. Farmers with access to improved storage grain system are more likely to trade their products during seasons of high demand where prices are more attractive and therefore more profitable. For the second economic factor, the results suggest that if a farmer has access to credit his odds to adopt improved maize varieties is 17% higher than those without access to financial resource. Several empiric studies have shown that access to credit impacts positively in adoption of new agricultural technologies due to the role that financial resources exert in purchasing agriculture inputs ensuring high productivity. Uaiene (2009) also found a positive effect of access to credit in the study of agricultural technologies in Mozambique. However, Zavale *et al*. (2005) in a study of adoption of improved maize seeds have found an inverse relationship between access to credit and adoption of improved seeds. The authors justify the relationship claiming that financial institutions only provide credit to farmers with other sources of income beyond agriculture activity. In such cases, those farmers are more likely to make their investments is cash crops like tobacco and cotton or other profitable activities.

Concerning to institutional factors such as access to information and agriculture extension services, the results have also shown that these covariates impacted significant positively in the decision to adopt improved maize varieties in Mozambique. Farmers with access to information and agriculture extension services are more likely to adopt improved maize varieties in 51% and 62%, respectively when compared to those without access to such services. Uaiene (2009) reported that access to extension services had only impact in the use of animal traction. For all other technologies such improved maize seeds, fertilizers, pesticides and mechanizations, access to extension services had no significant effect in the fitted models. However, authors like Mignouna *et al*. (2011); Sserunkuama (2005); Akudugu *et al*. (2012) highlight the role of extension services as the driving force in agricultural technology adoption process. Furthermore, Mwuangi and Kariuki (2015) claim that extension services strongly impacts in adoption of new technologies because it overcomes the effect of illiteracy that characterize many farmers in developing countries.

Likewise all other variables, the technologic factor represented by animal traction, has shown a positive influence in the decision to adopt improved maize varieties. However, the impact of this covariate was lesser than all other variables considered in the study. It is noticed that the odds of farmers to adopt improved maize varieties when they plough land using animal traction is 15% higher compared to farmers without access to this technologic factor. Compared to all other factors the animal traction presented the lowest estimate of odds ratio.

Regarding to spatial association parameter which measures the influence between neighbour areas, this has also shown a positive impact in the decision to adopt improved maize varieties. Farmers located in neighbour districts are 39% more likely to adopt improved maize

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varieties than those located in distant districts. Therefore, neighbour farmers tend to exhibit spatial similarity in the pattern of adoption of improved maize varieties due to the interaction existing between them. The interaction highlights the effect of spatial dependency between observations of the proportion of small farmers who adopted improved maize varieties proved by the global and local Moran's indexes (Figure 3). In fact, the inclusion of spatial autocorrelation applying spatial generalized estimating equations allowed measuring the impact of spatial dependency in the decision to adopt improved maize varieties given by the odds ratio of spatial association parameter.

## 4 CONCLUSION

The results obtained in this paper have allowed to show that despite the fact that generalized estimating equations (GEE) are widely applied in longitudinal data, its application in spatial lattice data analysis is worthwhile. Using the neighbourhood spatial matrix and the Moran's index in GEE to account to the spatial autocorrelation between observations of adoption of improved maize varieties has reached the best model and allowed to show that all factors analysed in the study including the spatial dependency are determinants of adoption. This results is an indicative that policy makers should direct their attention in developing agricultural policies at district level in the country.

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