



Ordinal regression Assessment of orange Postharvest loss determinants among Orange Farmers in Konshisha Local Government Area of Benue State.

Dooga, M.Y.¹, Agada, P.O.² and Ogwuche, I.O.³

¹Statistics Department,

University of Calabar, Calabar, Cross River State, Nigeria.

²Mathematics/Statistics/Computer Science Department,
University of Agriculture, Makurdi, Benue State, Nigeria.

³Mathematics/Computer Science Department,

Benue State University, Makurdi, Benue State, Nigeria.

Corresponding author: innocent.ogwuche@yahoo.com

[doi:https://doi.org/10.46912/napas.243](https://doi.org/10.46912/napas.243)

Abstract

Orange wastage through postharvest losses has contributed to food scarcity, economic loss and massive importation of food items in Nigeria. The research was mainly carried out to investigate the determinants of orange postharvest losses among orange farmers in Konshisha Local Government of Benue State, North Central geopolitical zone of Nigeria. Primary data was collected from the orange farmers using structured questionnaires and key informant interviews. Descriptive statistics and Ordinal Regression model were used to analyse the data collected. The quantity lost was perceived at six (6) categories. The results revealed that most (63.7%) of the farmers were above 34 years of age. Also the majority (95.1%) were male, while 55.3% of the respondents' farm size was relatively large with 200 and above stands of orange. The farmers' literacy level was 73.6%. Those that belonged to farmers groups were 39.5. Further results established the use of probit link function in the ordinal regression modelling and that the significant factors affecting orange postharvest losses in the area are farmer's lack of education and farmers not belonging to any association or group. The only significant covariate with the postharvest loss quantity of orange is farm size. The test of parallel lines established that, the location parameters (slope coefficients) are the same across response categories.

Introduction

Agriculture is the science and art of cultivating plants and livestock. Agriculture was the key development in the rise of sedentary human civilization, whereby farming of domesticated species created food surpluses that enabled people to live in cities. The history of agriculture began thousands of years ago (Food and Agriculture Organisation [FAO], 2004). Agriculture has been the main stay of the Nigeria economy right from the time of independence (1960), but due to relevance of oil as a major contributor to the Gross Domestic Product (GDP) over the years led to its relegation by government. However, due to fall in international price of oil in the third quarter of 2014 resulting to a decline in revenue thereby, leading to contraction of economic activities which subsequently plunged the economy into recession (Tadesse *et al.*, 2018), non-oil sectors like agriculture became necessary in order to improve the country's GDP. In an attempt to revamp the economy from the devastating effects of recession, the government came up with an economic plan known as Economic Recovery and Growth Plan (ERGP). Agriculture being one of the key sectors of the economy has been outlined in the ERGP to help arrest the problem of food insecurity, generate employment, improve foreign exchange earnings and drive industrialization (Inusa *et al.*, 2018).

Orange fruit production as an important part in horticultural industry has emerged as a major economic activity in developing countries, especially those which were hitherto heavily dependent on agricultural production, often at subsistence levels. It is estimated that 10 to 20% of all farmers are producers of horticultural crops, sometimes in combination or rotation with field crops (FAO, 2011). Despite of the economic importance of horticultural crops including orange fruits, they are important sources of plant nutrients, vitamins and minerals that are essential for human health and well-being, particularly for children and pregnant or nursing women (World Health Organisation [WHO], 2006). One of the major challenges in meeting this high demand for fresh fruits is postharvest losses. Postharvest losses lower the gains of the effort that was put into production and negatively affects marketing efficiency (Babalola *et al.*, 2010). Minimizing postharvest losses of already produced food is more sustainable than increasing production to compensate for these losses (Kader, 2003).

A lot of works have been done in search of solutions to some of farmers' postharvest losses problems.

Oluwatusin (2017) used Descriptive statistics and fractional regression model and established that, the main significant determinants of postharvest loss management among the cassava farmers were age, farming experience, farm size, distance of farm to market and educational level. Based on the results of the study, it is recommended that the farmers should be trained formally on postharvest management practices and procedures involved in accessing loans from banks should be reviewed by Central Banks of Nigeria in such a way to attract farmers to bank loans.

According to Mbuk *et al.* (2011), over half of the quantity of tomatoes were already spoiled on purchase due to conditions the produce were subjected to en-route the market. They used the Tobit regression model; a hybrid of the discrete and continuous models, to determine the impact of explanatory variables on the probability of spoilage of tomatoes. The regression analysis also revealed that all management practises employed by retailers in the market to reduce loss, increased the probability of spoilage except for the practise of covering the tomatoes on the table with paper.

Aidoo *et al.* (2014) employed a multiple regression analysis to determine the main factors that influence postharvest losses in tomatoes. The Model was estimated using ordinary least squares method and the regression revealed that, gender (female) of the farmer, farm size and days of storage positively associate with losses incurred. While, household size, membership of farmer based organisations and cultivation of improved varieties were found to reduce postharvest losses.

Dekota *et al.* (2014) in their research Assessment of Fruit and Vegetable Losses at Major Wholesale Markets in Nepal Surveyed three major market centers namely; Narayangadh, Pokhara, and Kalimati fruit and vegetable wholesale market was conducted. Forty five wholesalers and 90 retailers were selected for the study. Data were collected using structured questionnaires. In order to identify the determinants of overall loss, multiple regression analysis was performed. The wholesalers were surveyed about the extent of percentage loss that may be due to poor packaging, lack of cold storage, improper transportation and handling and poor quality. In the analysis, the dependent

variable was overall loss and the independent Variables were losses due to poor packaging methods, losses due to the lack of cold storage facility, losses during transportation and handling and losses due to poor quality. The R^2 value, $R^2=0.341$ and F value, $F=10.98$, R^2 being statistically significant, indicated the fitness of equation for interpretation. It could be noticed from the equation that the lack of cold storage facility in the market centers is contributing more loss. Loss of the produce was also found to be influenced by the use of inappropriate packaging materials and for each unit increase in the poor packaging method the losses would increase by 0.35 units.

James *et al.* (2018) in their research, Determination of Causes of Post-Harvest Losses in Orange Marketing in Selected Markets in Kano State, Nigeria analysed the causes of post-harvest losses in orange marketing in selected markets in Kano state, Nigeria. They used Multistage sampling technique for sample selection in the study area. The first stage involved purposive selection of three major markets notable for orange marketing. The second stage was based on random selection of 30% of the traders from each of the markets targeting total of 124 orange marketers, 100 retailers and 24 whole sellers. Data for the study was analyzed using descriptive statistics, The result of the socio economics characteristics revealed that age of orange retailers in the study area was found to fall between 23 and 69 years, and that of wholesalers falls between 36 and 69, which is economically active age. The research established that, poor market patronage, poor transportation facility, inadequate storage facility, poor storage facility, physical damage, inadequate management skill, pest and diseases and weather condition were the major causes of post-harvest losses. The strategies adopted by the marketers to reduced post-harvest losses during orange marketing were through advertisement of the produce, good packaging and persuasion of customers.

Tadesse *et al.* (2018) used descriptive statistics, gross margin and ordinary least squares regression analysis to analyse data in their research, Assessment of postharvest loss along potato value chain: the case study of Sheka Zone, Southwest Ethiopia. The descriptive result indicated that the mean value of the amount of potato postharvest loss at producer level was 9.31 qt per year per household which means 21.72%. When we estimate it in ETB, one household lose

3683.11 Br per year due to potato postharvest loss. Next to producer, postharvest loss of potato was higher at retailer level. The postharvest loss assessment of local traders revealed that the quantity of potato lost in quintal per household was 3.34 qt which accounts 0.59%. It indicated that local traders lose 1324.64 ETB per household per year due to potato postharvest loss. Wholesalers lose 2.5 qt per household per year due to postharvest loss which estimated 0.65%. It indicated that one wholesaler lose 1630.1 ETB per year. Retail level losses were about 1.92 percent of the total produce of potato in the study area. The causes of loss were physical injury during harvest, rotting and disease infection, lack of storage area and poor handling area. The discarded potato fetched no economic value to the retailers. The aggregate postharvest loss from production (farm gate level) to consumption level is 24.88% Distance to the nearest market, area allocated for potato and total output determine postharvest loss positively, and sex, experience, family size of working age, selling price and access to credit determine postharvest loss negatively. Econometrically, multiple linear regression model was used to examine the relationship between postharvest loss of potato and explanatory variables

Babalola *et al.* (2010) In their study, determinants of postharvest losses in tomato production, used the linear regression form as the lead equation on the basis of coefficient of determination, F-ratio, number of significant variables, sign of the coefficients and economic expectation. They posited that, with respect to postharvest losses, large land holdings implies large volumes being produced and the higher the production volumes, the higher the losses since farmers face the constraints of poor handling practices and limited storage facilities.

Farming experience is an important characteristic in postharvest handling and management. Farming experience is thought to positively influence technology adoption.

Improper harvest and postharvest practices result in losses due to spoiling of the product before reaching the market, as well as quality losses such as deterioration in appearance, taste and nutritional value

Kisaka-Lwayo and Obi (2014) in their research, Analysis of Production and consumption of Organic Products in South Africa, 100 consumers were selected and interviewed. This

included 30 respondents from rural Cata, 40 urban respondents from the East London Suburbs and lastly 30 respondents drawn from the peri urban area of Kwezana and Tsathu villages in Eastern Cape of South Africa. A structured questionnaire was used that covered the respondent's socioeconomic and demographic background, consumer knowledge and awareness of organic products, perceptions, attitudes as well as consumption decisions. The ordered probit model was used to identify the determinants of farmers' decision to participate in organic farming. The dependent variable is the farmer's organic farming status and was placed in three ordered categories in the survey. The model is estimated as:

Organic farming status = $f(\text{age gender education household size farm size farm income off farm income input costs land tenure location land tenure livestock chicken ownership risk attitudes and assets})$

According to Garikai (2014), Cabbage postharvest losses were significantly influenced by gender of household head, farming experience, literacy, type of packaging used, distance to the market and attendance of postharvest handling training. Spinach postharvest losses were significantly influenced by gender of household head, farming experience, hand and equipment washing before harvesting, time of harvesting, storage duration before marketing and attendance of postharvest handling training. Variables that significantly influenced tomato postharvest losses were farming experience, farmers' group membership, farm size, hand and equipment washing, packaging used and distance to the market. The researcher achieved this using ordered probit econometric model.

Data on postharvest loss quantity of oranges produced in the study area are never tracked and kept by farmers. Relating postharvest loss quantity and its determinants becomes a challenge. This work succeeded in removing this challenge by considering six (6) quantified levels of losses obtained from farmers' responses and relating them to some identified postharvest loss determinants using the Ordinal Regression Modelling Approach.

METHODOLOGY

Primary data on postharvest loss quantity and its determinants were conveniently sourced from orange farmers across five (5) council wards in Konshisha Local Government namely;

Mbatem/Tse Agberagba, Mbatsen, Mbayegh/Mbakyer, Iwarinyam, Mbakyase using structured questionnaires and key informant interviews. The data was collected by five (5) enumerators who are very fluent in Tiv, the local language in the study area.

The Ordinal Regression Model

Many variants of regression model for analyzing ordinal response variables have been developed and described during the past years. Ordinal regression model is embedded in the general framework of generalized linear models (Javila & Pandit, 2010). Different models result from the use of different link functions.

The general ordinal regression model is given as;

$$\text{link}(\gamma_{ij}) = \theta_j - [\beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ij}] \quad (3.1)$$

Where;

$\text{link}(\)$ is the link function

γ_{ij} is the cumulative probability of the j^{th} category for the i^{th} case

θ_j is the threshold for the j^{th} category

p is the number of regression coefficient

$x_{i1} \dots x_{ij}$ are the values of the predictors for the j^{th} case

$\beta_1 \dots \beta_p$ regression coefficients. (Javila & Pandit, 2010)

Probit Link Functions.

The link function is the process of "linking" a transformation of the observed responses to the original data. The probit model is used in modeling dichotomous outcome variables. And is represented as;

$$f(\pi) = \varphi^{-1}(\pi) \quad (3.2)$$

Where;

φ is the cumulative distribution function of the standard normal distribution represented as;

$$\varphi(Z) = \int_{-\infty}^Z \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}t^2} dt \quad (\text{Razzaghi, 2013}) \quad (3.3)$$

Since "the probit model assumes that random errors have a multivariate normal distribution and it's used for modelling the relationship between one or more numerical or categorical predictor variables and a categorical outcome" (Razzaghi, 2013). These make the probit link function attractive and considerable.

b. Data Coding and Capturing

The data was coded and captured in Statistical Package for the Social Sciences (SPSS) Version 21. As shown in Table 1, descriptive statistical analysis was used to describe the socio-economic and demographic characteristics of the sample households. Descriptive statistical analysis (frequency, means, cross tabulations and Chi Square tests) was used in determining the knowledge, training and the respective postharvest handling practices.

c. Multicollinearity Test

The collinearity of the independent variables was tested using the SPSS Version 21 statistical package. The Variance Inflation Factor (VIF) was used to identify the correlation between independent variables and the strength of that correlation. The VIF is calculated by regressing each independent variable on all the others and calculating a score using the relation:

$$VIF = \frac{1}{1-R^2} \quad \text{Miraoui (2020)} \quad (3.4)$$

Where;

R^2 = the coefficient of determination that summarises the proportion of variance in the dependent variable associated with the predictor variables.

“As a rule of thumb, VIFs scores above 5 are generally indicators of multicollinearity (above 10, it can definitely be considered an issue)” Miraoui (2020). Multicollinearity can be fixed by performing feature selection: deleting one or more independent variables.

d. Ordinal Regression Analysis

The Ordinal Regression was also done using SPSS Version 21. The Regression model was used to establish the determinants of orange postharvest losses. Appendices B present the variables (Gender, Age, farm experience, educational level, farmer belonging to a farmers' group, farm size, availability of buyers, harvesting period, duration before transporting the product and orange training attended by farmer) that were used in the regression model. The predictors are sub-divided into two, namely;

1. Factors (gender, edu_lev, fam_grp, buyers, harv_prd and tranin_attded)
2. Covariates (age, fam_xp, fam_size and dbtpn)

e. Ordinal Regression Model Diagnostics

Testing for the overall significance of the regression models was done using Model Fitting Information, Chi-square Statistic, Pseudo R-squared Measures of fit and Test of Parallel Lines.

i. Model Fitting Information

The significant chi-square statistic was used to establish if the model gives better predictions than predictions based on the marginal probabilities for the outcome categories. Using the significance level (0.05). The hypothesis is given as;

$$H_0: \beta_i = 0$$

$$H_1: \beta_i \neq 0$$

ii. Goodness-of-Fit Table

The goodness-of-fit table contains Pearson's Chi-Square statistic for the model and another Chi-Square statistic based on the deviance. This statistic was used to test whether the observed data are inconsistent with the fitted model. Here, lack of significance is interpreted as indicating good fit. The test hypothesis is given as;

$$H_0: \text{model fits the data}$$

$$H_1: \text{model do not fit the data}$$

That is to say, the p-value should be greater than the established cut-off (generally 0.05) to indicate good fit.

iii. Test of Parallel Lines

This test compares the estimated model with one set of coefficients for all categories to a model with separate set of coefficients for each category (Yatskiv and Kolmakova, 2011). Therefore, the test was used to assess whether the assumption that parameters are the same for all categories of postharvest losses. The hypothesis is given as;

$$H_0: \beta_1, \dots, \beta_3 = \theta_1, \dots, \theta_5$$

$$H_1: \beta_1, \dots, \beta_3 \neq \theta_1, \dots, \theta_5$$

If the $p > 0.05$, this indicates that the location parameters are the same across response categories.

g. Variables Used in the Regression Model

Different socio-economic variables, knowledge indicators, training and postharvest handling variables such as Gender, Age, farm experience, educational level, farmer belonging to a farmers' group, farm size, availability of buyers, harvesting period, duration before transporting the product and orange training attended by farmer as presented in Appendix A were used as

independent variables in the Ordinal Regression model.

RESULTS AND DISCUSSION

Discussion on Household Demographic and Socio-economic Characteristics

Table 1: Summary descriptive statistics of some respondent variables

Variables		Percentage (%)
Age	< 45yrs	61.1
	≥ 35yrs	38.9
Gender	Male	95
	Female	5
Farm size	< 200 stands	44.7
	≥ 200 stands	55.3
Farm Experience	< 20yrs	42.9
	≥ 20yrs	57.1
Literacy	None/Pri. sch	26.4
	Post primary	73.6
Farmers' group membership	No	60.5
	Yes	39.5
Lost Quantity	< 20bags	52.7
	≥ 20bags	47.3

The results Table 1 revealed that the majority of the respondents were male. The male gender makes 95% of the study population while the remaining 5% is occupied by the female gender. These findings show that an investment in men would have a greater impact in orange postharvest loss reduction since they are actively involved in orange production.

More than 30% of the farmers are 45 years and above. The age statistics suggest an ageing farmer population in the study population, with the much younger generation getting a low 15%.

The results also show a farming community which is largely composed of a moderately experienced population. These years of experience in orange production suggests better knowledge and adoption of postharvest handling technology and practices among the farmers.

73.6% attended post-primary education while 26.4% have at most attended primary educational level. Meanwhile, education level is expected to exert a negative effect on the quantity that is lost. Babalola *et al.* (2010) argued that only farmers with post-primary education can appreciate and use most postharvest technology available hence the overall effect on quantity lost is negative.

Results on Farmers' group membership indicates that there is a low percentage of participation in farming groups. Key informant interviews disclosed that most of the members were not aware of the existence of farmers' groups. Similarly, farmers who belong to farmers'

groups or associations get information and ways of carrying out farm practices.

The results in Table 1 supports that over 60% of the farmers have a relatively large farm size. Farm size has a direct impact on the farm income; with the larger farm expected to generate more income and reduce the cost of production. Farm size is directly related with employment of labour. If the farm size is big and the household labour is not able to handle the farming activities, the employment of labour is necessary for income generation. However, in cases where the size of the farm is small coupled with costly labour, this will reduce the farm income. Large farm sizes can mean the need to rely on hired labour which has negative effects on postharvest losses. Hired labour may not carefully handle produce whilst harvesting resulting in high postharvest losses from mechanical damages induced by poor handling.

52.7% of farmers recorded postharvest loss of orange at the lower category of below 20bags while 47.3 % of the farmers experienced postharvest loss of orange at the above 20% category. Kader (2005) explained that overheating during transportation of fruits and vegetables leads to decay and increases the rate of water loss. Mechanical damage originates from poor postharvest handling practices (Mbuk *et al.*, 2011). According to FAO (2004), mechanical damage also occurs as a result of careless handling of packed produce, with packages often

squeezed into transporting vehicles in order to maximize revenue for transporters.

Multicollinearity Test

The multicollinearity test table below (see Table 2) shows that, all variables have tolerance greater than 0.1 and VIF of less than 10. This is an indication that, the independent variables were not highly correlated.

Table 2: multicollinearity test

Model	Tolerance	Collinearity Statistics	VIF
1 (Constant)			
hhd	.686		1.458
gender	.838		1.193
hh_size	.609		1.643
age	.408		2.450
fam_xp	.483		2.072
edu_lev	.575		1.739
occupatn	.687		1.457
fam_grp	.672		1.487
fam_size	.348		2.876
fam_ownshp	.701		1.428
fn_kind	.797		1.255
fn_mthd	.845		1.183
buyers	.782		1.278
harv_prd	.674		1.484
packg_mthd	.860		1.163
dbtpn	.757		1.320
dist_mkt	.747		1.339
tp_means	.679		1.473
harv_qty	.403		2.483
mloss_qtr	.771		1.297
eqmt_washd	.658		1.520
tranin_attded	.472		2.120
axtn_serv	.320		3.128
plnts_advo	.386		2.593
labr_shotage	.786		1.273
labrs_traind	.852		1.174

c. Test of Parallel Lines

Table 3 shows the test parameters, description and application points for the link functions used. It could be deduced from the results of the parallel line test that probit link functions makes the assumption valid for ordinal

regression analysis of the data ($p > 0.05$). This means that we can use the same set of regression parameters (that is β_0 's) in modelling each loss level of orange postharvest losses in the study area,

Table 3: The Test for Parallel Lines

Link Function	Model	-2 Log Likelihood	Chi-Square	df	Sig.
Probit	Null Hypothesis	864.235 ^b			
	General	805.359 ^b			58.875 ^c
Complementary log-log	Null Hypothesis				56
	General	860.091			.371
Negative log-log	Null Hypothesis	820.768 ^b			39.324 ^c
	General	871.446			56
Cauchit	Null Hypothesis	785.736 ^b			85.709 ^c
	General	863.633			56
logit	Null Hypothesis	774.147 ^b			89.487 ^c
	General	862.974			56
		794.229 ^b			68.745 ^c
					56
					.118

Discussion on Ordinal Regression and Model Interpretation

The data analysis involves the Parameter Estimates for the research which contains the outcome variable (loss_qty) and the predictors for the location model.

The parameter estimates table summarizes the effect of each predictor. The signs of the coefficients for covariates and relative values of the coefficients for factor levels give important insight into the effects of the predictors in the model.

Results from Table 4 below show that, fam_size covariate has positive relationship with outcome due to its positive coefficient status and statistical significance (p<0.05). This simply means, as fam_size increases, so does its probability of being in one of the higher categories of lost_qty increases. On the other hand, age, fam_xp and dbtpn covariates contributes less to the model (p>0.05).

On the factor levels, gender does not show a significant effect on the probability of being in one of the lost categories (p>0.05). Similarly, the availability of buyers at both levels, period of harvest of the produce at levels and orange training attended did not show a statistical significance effect on the probability of a farmer being in one of the orange postharvest lost categories.

While the 2nd, 3rd and 4th levels of education of an orange farmer do not significantly affect their probability chances of belonging to a postharvest loss group, educational level 1 (“no education”) significantly affects its probability chance of being in one of the orange postharvest lost categories. Going by the positive coefficient of 0.665 with respect to the educational level of 1, it affirms that, farmers

with no formal education were more likely to belong to the higher postharvest loss categories (i.e category 4 and 5).

These findings coupled with the absence of multicollinearity show that, the ordinal regression model’s estimated coefficients are therefore considerably unbiased, consistent and efficient.

The regression results in Table 4 shows that farm size (fam_size), none educational level (edu_lev=1) and do not belong to a farmers’ group (farm_grp=0) significantly influenced orange postharvest losses.

Since farm size, none educational level and farmer not belonging to any farmers’ group significantly influenced orange postharvest losses, and using (3.1), the model for the ordinal regression is then expressed as;

$$(\gamma_{ij}) = \theta_j - [\beta_1x_{i1} + \beta_2x_{i2} + \dots + \beta_px_{ij}] \tag{4.1}$$

Where $j = 1, \dots, 5 ; i = 1, \dots, 3$

Now, let;

$$farm\ size = x_1 \tag{4.2}$$

$$No\ educational\ level = x_2 \tag{4.3}$$

$$No\ farm\ group = x_3 \tag{4.4}$$

From the test of parallel lines analysis, it could be seen that, the parameters are the same for all categories of postharvest losses since the (p = 0.031 < 0.05 = α)

Therefore, the expression;

$$[\beta_1x_1 + \beta_2x_2 + \dots + \beta_3x_3]$$

Is significant for each category of lost quantity.

Hence, the models for the various category of lost quantity is expressed as follows taking into cognisance, the values for the expression parameters from Table 4.4.

For category 1.

$$\gamma_1 = \theta_1 - [\beta_1x_1 + \beta_2x_2 + \beta_3x_3] \tag{4.5}$$

$$\gamma_1 = -0.059 - [0.3x_1 + 0.665x_2 - 0.326x_3] \tag{4.6}$$

Table 4: Parameter Estimate

	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval		
						Lower Bound	Upper Bound	
Threshold	[lost_qty = 1]	-.059	.478	.015	1	.902	-.995	.877
	[lost_qty = 2]	.691	.479	2.082	1	.149	-.247	1.629
	[lost_qty = 3]	1.222	.481	6.457	1	.011	.279	2.165
	[lost_qty = 4]	1.582	.483	10.713	1	.001	.635	2.530
	[lost_qty = 5]	1.956	.487	16.139	1	.000	1.001	2.910
Location	Age	.080	.065	1.509	1	.219	-.048	.207
	fam_xp	-.080	.077	1.072	1	.301	-.231	.071
	fam_size	.300	.046	41.794	1	.000	.209	.391
	dbtpn	-.069	.099	.478	1	.489	-.263	.126
	[gender=0]	-.009	.307	.001	1	.977	-.610	.593
	[gender=1]	0 ^a	.	.	0	.	.	.
	[edu_lev=1]	.665	.329	4.098	1	.043	.021	1.309
	[edu_lev=2]	-.041	.187	.049	1	.824	-.408	.325
	[edu_lev=3]	-.230	.154	2.227	1	.136	-.532	.072
	[edu_lev=4]	0 ^a	.	.	0	.	.	.
	[fam_grp=0]	-.326	.149	4.774	1	.029	-.618	-.034
	[fam_grp=1]	0 ^a	.	.	0	.	.	.
	[buyers=0]	.246	.143	2.972	1	.085	-.034	.526
	[buyers=1]	0 ^a	.	.	0	.	.	.
	[harv_prd=1]	.146	.471	.097	1	.756	-.776	1.069
	[harv_prd=2]	.034	.189	.032	1	.857	-.336	.404
	[harv_prd=3]	.348	.803	.188	1	.664	-1.225	1.922
	[harv_prd=4]	0 ^a	.	.	0	.	.	.
	[tranin_attded=0]	-.143	.193	.550	1	.458	-.522	.235
	[tranin_attded=1]	0 ^a	.	.	0	.	.	.

Link function: Probit.

a. This parameter is set to zero because it is redundant.

For category 2.

$$\gamma_2 = \theta_2 - [\beta_1x_1 + \beta_2x_2 + \beta_3x_3] \tag{4.7}$$

$$\gamma_2 = 0.691 - [0.3x_1 + 0.665x_2 - 0.326x_3] \tag{4.8}$$

For category 3.

$$\gamma_3 = \theta_3 - [\beta_1x_1 + \beta_2x_2 + \dots + \beta_3x_3] \tag{4.9}$$

$$\gamma_3 = 1.222 - [0.3x_1 + 0.665x_2 - 0.326x_3] \tag{4.10}$$

For category 4.

$$\gamma_4 = \theta_4 - [\beta_1x_1 + \beta_2x_2 + \dots + \beta_3x_3] \tag{4.11}$$

$$\gamma_4 = 1.582 - [0.3x_1 + 0.665x_2 - 0.326x_3] \tag{4.12}$$

For category 5

$$\gamma_5 = \theta_5 - [\beta_1x_1 + \beta_2x_2 + \dots + \beta_3x_3] \tag{4.13}$$

$$\gamma_5 = 1.956 - [0.3x_1 + 0.665x_2 - 0.326x_3] \tag{4.14}$$

An increase in farm size, a change in educational level and a change in farmers' group status of a farmer, increases the farmer's probability of being in one of the higher categories of lost quantity when 4.6, 4.8, 4.10, 4.12 and 4.14 are applied.

e. Ordinal Regression model diagnostics

i. Model Fitting information

In Table 5 below, the -2 log likelihoods was used to compare model fit of the two models. The assumption as stated in the methodology is that all of the regression coefficients in the model are

equal to zero. The final -2 log likelihood for our model is 864.235 with a p-value = .000 ($p < .05$) which implies at least one of the regression coefficients in the model is not equal to zero. Hence, the final model is statistically significant and predicts the dependent variable better than the intercept only model.

Table 5: Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	953.199			
Final	864.235	88.964	14	.000

Link function: Probit.

ii. Chi-square fit Statistic.

The goodness-of-fit table contains Pearson's Chi-Square statistic for the model and another Chi-square statistic based on the deviance. This statistic test whether the observed data are inconsistent with the fitted model.

In Table 6, the significant values are large, indicating that the data and the model predictions are similar. This is an indicator that the model is good. That is, lack of significance is interpreted as indicating good fit. To be clear, the p-value should be greater than the established cut-off (generally 0.05) to indicate good fit.

Table 6: Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	1268.934	1316	.820
Deviance	847.599	1316	1.000

Link function: Probit.

Conclusions

The following conclusions could be made.

- i. The orange farmers' population in the study area is 95% dominated by male farmers.
- ii. An Ordinal Regression Model for assessing orange postharvest loss determinants has been developed in this work.
- iii. The test of parallel line established that, the location parameters (slope coefficients) are the same across response categories ($p > 0.05$).
- iv. It was ascertained that, farm size has a significant positive effect on farmer's probability of being in the higher orange postharvest loss category. Farmer's no educational level and a farmer not belonging to any farmers' group significantly influenced orange postharvest losses. While farmer's age, experience and their duration (days)

before transporting the oranges to the market do not have significant effect.

Recommendations

The identified determinants of postharvest losses in orange farming provide useful acumens for farmers, policy makers, advisers, developers and sellers of postharvest handling technologies. In view of this, the following recommendations are made.

- i. Farmers should be taught about the benefits of these cooperatives, associations or groups since key informant interviews disclosed that most of the members were not aware of neither the existence of farmers' groups nor the their importance to farmers. Since "no group" is a factor that affects orange postharvest losses positively, efforts should be made to get most farmers registered with a farmer's group.
- ii. Though it is evident that farm size positively affects orange postharvest loss in the study area, it would be counterproductive to advise farmers towards reduced orange farming. Hence, government interventions in the area of orange farming such as, provision of orange produce off-takers and orange farm inputs so as to augment the cost of orange farming
- iii. Formal or informal education opportunities should be made available to orange farmers in the study area since lack of education affects orange postharvest loss in the area.

References

- Aidoo, R., Danfoku, R. A. & Mensah J. O (2014). Determinants of postharvest losses in tomato production in the Offinso North district of Ghana. *Journal of Development and Agricultural Economics*, 6(8), 338-344. DOI:10.5897/JDAE2013.0545
- Aliber, M. & Hart, T.G.B. (2009). Should subsistence agriculture be supported as a strategy to address rural food insecurity? *Agrekon*, 48(4), 434-458. DOI: 10.1080/03031853.2009.9523835
- Babalola, D.A., Makinde, Y.O., Om-onona, B.T. & Oyekanmi, M.O. (2010). Determinants of post- harvest losses in tomato production: a

- case study of Imeko – Afon local government area of Ogun state. *Journal of Life and Physical Sciences*, 3(2), 14-18.
- Dekota A. R., Dhaka D. D. & Dutta J. P (2014). Assessment of Fruit and Vegetable Losses at Major Wholesale Markets in Nepal. *International journal of applied sciences and biotechnology*, 2(4), 559-562. DOI: <http://dx.doi.org/10.3126/ijasbt.v2i4.11551>
- Food and Agriculture Organisation (FAO) (2011). Appropriate food packaging solutions for developing countries. *Save Food Interpack Congress held on 16 – 17 May 2011 in Dusseldorf, Germany*. Rome.
- Food and Agriculture Organisation (FAO) (2004). *Socio-economic analysis and policy implications of the roles of agriculture in developing countries: Summary report for the Roles of Agriculture Project*. Rome.
- Garikai M. (2014). Assessment of Vegetable Postharvest Losses among Smallholder Farmers in Umbumbulu Area of Kwazulu-Natal Province, South Africa. Unpublished M. Agric. Thesis. University of KwaZulu-Natal, Pietermaritzburg.
- Inusa B. M., Daniel P. C., Dayagal D. F. & Chiya N. S. (2018). Nigerian Economic Growth and Recovery: Role of Agriculture. *Int J Econ Manag Sci* 7: 512. DOI: 10.4172/2162-6359.1000512
- James D., A. Abba., Aisha M., Shamsuddeen J., & Oni O. O. (2018). Determination of Causes of Post-Harvest Losses in Orange Marketing in Selected Markets in Kano State, Nigeria. *International Journal of Agriculture and Earth Science*, 4(5), 23-31. ISSN 2489-0081 2017
- Javali, S. B., & Pandit, P. V. (2010). A comparison of ordinal regression models in an analysis of factors associated with periodontal disease. *Journal of Indian Society of Periodontology*, 14(3), 155–159. doi:10.4103/0972-124X.75909
- Kader, A. A. (2005). Increasing food availability by reducing postharvest losses of fresh produce. *Acta Horticulture*, 682, 2169-2175. DOI: 10.17660/ActaHortic.2005.682.296
- Kader, A. A. (2003). Perspective on postharvest horticulture. *Horticultural Science*, 38, 1004-1008.
- Kisaka-Lwayo, M & Obi, A. (2014). Analysis of Production and consumption of Organic Products in South Africa. *Organic Agriculture Towards Sustainability*, 25-50, DOI:10.5772/58356
- Kisaka-Lwayo, M. (2012). *Risk preferences and consumption decisions in organic production: the case of KwaZulu-Natal and Eastern Cape provinces of South Africa*. Unpublished PhD Thesis. University of Fort Hare.
- Kostas, S., Casper, W. & Rikard, S. (2020) Perceived quality of products: a framework and attributes ranking method, *Journal of Engineering Design*, 31(1), 37-67, DOI: 10.1080/09544828.2019.1669769
- Liu, X., O'Connell, A. A. & Koirala, H. (2011). Ordinal Regression Analysis: Predicting Mathematics Proficiency Using the Continuation Ratio Model. *Journal of Modern Applied Statistical Methods*. 10(2), 512-527. DOI: 10.22237/jmasm/1320120600
- Mbuk, E. M., Bassey, N. E., Udoh, E. S. & Udoh, E. J. (2011). Factors influencing postharvest loss of tomatoe in urban market in Uyo, Nigeria. *Nigerian Journal of Agriculture, Food and Environment*, 7(2), 40-46.
- Michael Brannick, (d.n) Retrieved from <http://faculty.cas.usf.edu/mbrannick/regression/Part3/Reg2.html>
- Miraoui, Ilias (nd) Retrieved from <https://imiraoui.github.io/>
- Obasi, P.C., Henri-Ukoha, A., Ukwuihe, I.S. & Chidiebere-Mark, N.M. (2013). Factors affecting agricultural productivity among arable crop farmers in Imo State, Nigeria. *American Journal of Experimental Agriculture*, 3(2), 443-454.
- Oluwatusin, F. M. (2017). Analysis of Postharvest Losses Management among Cassava Farmers in Nigeria. *Nature and Science*, 15(1), 114-121.
- Razzaghi, M. (2013). The Probit Link Function in Generalized Linear Models for Data Mining Applications. *Journal of Modern Applied Statistical Methods*, 12(1), 163-169. DOI: 10.22237/jmasm/1367381880
- Sperandei, S. (2014). Understanding logistic regression analysis. *Biochemia medica*, 24(1), 12–18. doi:10.11613/BM.2014.003
- Tadesse, B., Bakala, F. & Mariam, L. W. (2018). Assessment of postharvest loss along potato value chain: the case of Sheka Zone, southwest Ethiopia. *Agric & Food Secur*, 7(18) doi:10.1186/s40066-018-0158-4

- Teddlie, C. & Fen Yu, F. (2007). Mixed methods sampling: A typology with examples. *Journal of Mixed Methods Research*, 1(1), 77-100. DOI: 10.1177/2345678906292430
- Ter Chris (n.d.) retrieved from <https://codemint.net/education/the-impact-of-girl-child-education-to-community-development-in-konshisha-lga/index.html#>.
- World Health Organisation (WHO) (2006). *Excreta and grey water use in agriculture: In WHO Guidelines for the safe use of wastewater excreta and grey water*. Switzerland: World Health Organization.
- Yatskiv I. & Kolmakova N. (2011), *Using Ordinal Regression Model to Analyze Quality of Service for Passenger Terminal*, Vilnius Gediminas Technical University Transport Engineering Faculty, J. Basanavičiaus g. 28, LT-03224, Vilnius, Lithuania; ISSN 2029-2384.