APPLYING ARTIFICIAL NEURAL NETWORK MODELING FOR PREDICTING POSTHARVEST LOSS IN SOME COMMON AGRIFOOD COMMODITIES

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ABSTRACT

This study was carried out to predict the extent of postharvest loss in three agrifood commodities namely rice, maize and yam along the food value chain in Delta State, Nigeria. The study considered famers, transporters, processors, marketers and consumers as the five principal actors in the value chain with farmers being the harvester. Sufficient relevant information was obtained from each of the actors with the aid of organized interviews and well-structured questionnaires. The questionnaires contain information relating to postharvest loss in each of the three commodities at every stage in the value chain - from harvest to consumption. 450 questionnaires were administered on each commodity, with 150 being handled by each actor in each commodity in each of the three senatorial districts in the state making a total of 2250 questionnaires that were administered altogether. Five types of Artificial Neural Network (ANN) topology were used for each commodity making a total of fifteen models that were used for three-layer feed-forward model (TL-FFM) with back-propagation multi-layer perception (BP-MLP) type of ANN. Data analysis was carried out by ANN-ALYUDA forecaster software under the TL-FFM with BP-MLP. Result obtained showed that transporters, processors and marketers contributed more to postharvest loss in rice, maize and yam compared with farmers and consumers. It can be inferred from this study that ANN using TL-FFM with the supervised training type BP-MLP is one of the best tools that can be used to predict postharvest loss in any agricultural commodity along the food value chain. This is due to its understanding in learning the pattern the input data followed and hence predict accurately the target output with little deviation and minimum error. Comparison between predicted values and the target output values in each of the fifteen models showed how good the ANN had been trained to predict losses that occurred along the value chain based on the five actors that contributed to postharvest loss in each commodity.

Keywords: ANN, agrifood commodities, postharvest losses, three-layer feed-forward model, backward propagation multi-layer perception

1. INTRODUCTION

Postharvest losses are losses along the food value chain, which includes handling, storage, processing, packing, transportation, marketing and consumption. Losses are measurable reduction in foodstuffs and may affect either quantity or quality (Tyler and Gilman, 1979). They arise from the fact that freshly harvested agricultural produce is a living thing that continues with its metabolic activities even after harvest and during postharvest handling. Loss should not be confused with damage, which is the visible sign of deterioration; for example, damage restricts the use of a product, whereas loss makes its use impossible.

Total crop loss is difficult to measure because it depends upon a variety of factors, including the type of crop, the weather, and the region. In under-developed or developing countries, most food is lost well before reaching the consumer. For instance, in Nigeria, it is estimated that nearly 20 percent of produce is lost and in sub-Saharan Africa, the annual value of grain loss is estimated at $4 billion – enough to feed 48 million people for one year (FAO, 2012).

The first distinction in agro-food losses is that between quantity and quality. Quantitative loss is a loss in terms of physical substance, meaning a reduction in weight and volume and can be assessed and measured. Qualitative loss, however, is concerned with the food and reproductive value of products and requires a different kind of evaluation. It should be noted that losses occurring during the production period and caused by various crop pests (insects, weeds, disease) will not be considered. However, they have a major influence on food preservation conditions and account in part for the nature and size of postharvest losses.

Several authors have presented a strong argument in favour of devoting more resources to postharvest research for development efforts in developing countries (Bourne, 1983; Mukai, 1987). Although minimizing postharvest losses of already produced food is more sustainable than increasing production to compensate for these losses, less than 5% of the funding for agricultural research is allocated to postharvest research areas (Kader, 2003).

Loss assessment can be time consuming and expensive, but in many instances it is necessary to prevent inefficient use of funds. The need to assess losses in large-scale storage is in general small. In most cases unacceptable losses are very obvious without assessment. For example, in Adaptive Research on Loss Prevention in Different Postharvest Systems - the traditional method of testing, insecticides or storage structures consists of first conducting experiments at the research station level.

Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. It is a natural proof that some problems that are beyond the scope of current computers are indeed solvable by small energy efficient packages. This brain modeling also promises a less technical way to develop machine solutions.

The exact workings of the human brain are still a mystery. Yet, some aspects of this amazing processor are known. In particular, the most basic element of the human brain is a specific type of cell which, unlike the rest of the body, does not appear to regenerate. Because this type of cell is the only part of the body that is not slowly replaced, it is assumed that these cells are what provide us with our abilities to remember, think, and apply previous experiences to our every action. These cells, all 100 billion of them, are known as neurons. Each of these neurons can connect with up to 200,000 other neurons, although 1,000 to 10,000 are typical.

These artificial neural networks try to replicate only the most basic elements of this complicated, versatile, and powerful organism. They do it in a primitive way. But for the software engineer who is trying to solve problems, neural computing was never about replicating human brains. It is about machines and a new way to solve problems (Strugholtz *et al*. 2006).

Yet, all natural neurons have the same four basic components. These components are known by their biological names - dendrites, soma, axon, and synapses. Dendrites are hair-like extensions of the soma which act like input channels. These input channels receive their input through the synapses of other neurons. The soma then processes these incoming signals over time. The soma then turns that processed value into an output which is sent out to other neurons through the axon and the synapses (Strugholtz *et al*, 2006).

2. MATERIALS AND METHODS

2.1. Validation and Reliability Procedure of Prepared Questionnaire

Structured Questionnaire were produced in order to reach out and get concise data on three (3) arable crops namely, rice, maize and yam, a necessary guide that enabled the five (5) actors namely, farmers, transporters, marketers, consumers and processors. This was done to have a record of their interaction and to encourage ease of data compilation. The validation and the reliability study of the questionnaire was done by contacting experts in the field of postharvest loss so as to be sure that the questionnaire will bring out the desired results that was needed to predicts the losses in the three arable crops.

2.2. Validation and Reliability Procedure of Prepared Questionnaire

In carrying out the postharvest loss survey experiment, the answer gotten depended very much on the questions asked. For the usefulness of the questionnaire, the data produced were trustworthy, i.e., the results were meaningful and can be applied more generally than to just the sample tested. Proving that trustworthiness for the questionnaire involved subjective experimental endpoints is not trivial, and ensuring that the resulting data reflected the “truth” has spawned an entire field of the survey experiment.

2.3. Sampling Procedure

In selecting the sampling technique for the experiment, it was virtually impossible to study every actor that contributed to postharvest losses in rice, maize and yam in Delta state. The targeted population was simply too large for the study when planning the research study. Collecting millions of questionnaires from every actor was presented with so many challenges.

2.4. Stratified Random Sampling

The sampling procedure used was stratified random sampling, the actors that contributed to postharvest losses was first identified and divided into groups based on their relevant characteristic and then the number of participant to be used was selected within those groups. Stratified random sampling was used so as to ensure that specific subgroups of the actors were adequately represented within the sample.

2.5. Method of Data Collection

Collection of data was done for three weeks in the Delta State; data collation was done for one week and data analysis using Artificial Neural Network was also done for another one week. The ANN software used to analyze and predict the data was ALYUDA forecaster using three layer feed-forward models with back-propagation multi-layer perceptron (MLP) type of neural network. Delta Central Senatorial District was taken care off for the first week, followed by Delta South for the second week, and lastly, Delta North. The ADP offices in each district were located and necessary information's on each actor was obtained from their staff.

2.6. Steps in Developing Artificial Neural Network Model

The following steps were followed in developing the Artificial Neural Network model used in this study: knowing a good model input to be used; determining the neural network type; pre-processing and partitioning of the collated data; determining network architecture to be used in running the program; defining model performance criteria to be used; training, testing and validating the model from the input data by optimizing the connection weights (Dawson and Wilby, 2001; Govindaraju, 2000; Maier and Dandy, 2000).

2.7. Inputs and Output Variables

The postharvest loss survey experiment was conducted for a period of three weeks. The five actors that contributed to postharvest loss were considered on each arable crop. In the selection of input and output variables, it was understood that in any postharvest loss, all the five aforementioned actors contributes to the losses. To achieve this, each actor was made an output variable and the other four serves as its input variables on a particular arable crop

2.8. Neural Network Topology

Five types of neural network topology were used for each of the three commodities (rice, maize and yam), making fifteen models in total for the three layer feed-forward model with back-propagation multi-layer perceptron (MLP) type of neural network . For rice, the neural network topology used for consumers, farmers, marketers, processors and transporters were 4-12-1, 4-18-1, 4-20-1, 4-24-1 and 4-24-1 as input, hidden and output layers respectively. For maize, the neural network architecture used was 4-16-1, 4-15-1, 4-18-1, 4-12-1 and 4-25-1 as input, hidden and output layers respectively. For yam, the neural network architecture used was 4-11-1, 4-17-1, 4-12-1, 4-13-1 and 4-17-1 as input, hidden and output layers respectively. This is in conformity with method Dawson and Wilby (2001) and Taylor (1979) used for determining input, hidden and output layers of neural topology.

3. RESULTS AND DISCUSSION

3.1. Rice Model Sensitivity Analysis

Figures 1 to 5 showed the sensitivity analysis result of rice consumers, rice farmers, rice marketers, rice processors and rice transporters respectively on rice crop. For rice consumers model, loss caused by processors on rice showed the highest sensitivity level with 36.673%. For rice farmers model, loss caused by processors in rice also showed the highest level of sensitivity with 44.212%. For rice marketers model, loss caused by processors in rice also showed the highest level of sensitivity with 40.524%. For rice processors model, loss caused by marketers on rice showed the highest level of sensitivity with 44.137%. Finally, for rice transporters model, loss caused by marketers on rice also showed the highest level of sensitivity with 39.425%. This implies that the major causes of postharvest loss in rice crop in Delta State are from two actors namely processors and marketers but more peculiar to processors because of inadequate processing equipments, poor road network and bad marketing structures. This is in-line with the report of Imonikebe (2013) and Talabi (1995) on methods of minimizing food losses and ensuring food security.

3.2. Maize Model Sensitivity Analysis

Figures 6 to 10 showed the sensitivity analysis result of maize consumers, maize farmers, maize marketers, maize processors and maize transporters respectively on maize crop. For maize consumers model, loss caused by processors on maize showed the highest sensitivity level with 52.166%. For maize farmers model, loss caused by processors on maize also showed the highest level of sensitivity with 33.614%.

For maize marketers model, loss caused by processors on maize also showed the highest level of sensitivity with 38.656%. For maize processors model, loss caused by marketers in maize showed the highest level of sensitivity with 28.241%. Finally, for Maize Transporters model, loss caused by processors in maize showed the highest level of sensitivity with 33.287%. This also implies that the major causes of postharvest in maize crop in Delta State are from two actors namely processors and marketers but more pronounced in processors. This is due to the attitudes of Delta State indigenes to maize crop compare with other crops which makes the processing of the produce to be less important compare to plantain. It is also due to poor road network and bad marketing structures. This is in conformity with the initial findings by Talabi (1995).

3.3. Yam Model Sensitivity Analysis

Figures 11 to 15 showed the sensitivity analysis result of yam consumers, yam farmers, yam marketers, yam processors and yam transporters respectively on yam crop. For yam consumers model, loss caused by processors in yam showed the highest sensitivity level with 29.045%. For yam farmers model, loss caused by processors in yam also showed the highest level of sensitivity with 42.367%. For yam marketers model, loss caused by processors in yam also showed the highest level of sensitivity with 34.725%. For yam processors model, loss caused by transporters in yam showed the highest level of sensitivity with 32.920%. Finally, for yam transporters model, loss caused by processors on yam showed the highest level of sensitivity with 56.126%. This also implies that the major causes of postharvest loss in yam crop in Delta State are from two actors namely processors and transporters but more prominent in processors due to lack of inadequate processing equipment in Ughelli where maize production is dominant and bad road network especially from Sapele market to Jege market which is the major market for yam tubers. This is in-line with the findings of Ebewore (2013) and Achoja (2013) on storage practices among arable farmers in Delta State, Nigeria

3.4 Implication of the Study

The study showed that majority of the respondents stated that postharvest looses in the Three (3) crops occurred mainly during processing. Other sources of losses are during transportation, and marketing. This is in conformity with the previous work done by Talabi (1995) that also identified these as the sources of postharvest losses. Poor methods of crop preservation, poor storage, processing methods and microbial attack were some of the causes of postharvest losses identified from the study. Ukoh-Aviomoh et al. (2005) had similar findings that Improvement in the processing and transportation of arable crops will drastically reduce postharvest losses. Other causes of losses in the state are careless handling of food crops during harvesting of immature food crops and marks of cutlass on yams that leads to bruises which causes marks/injuries and microbial attack on yam. Bruises or marks on crop could result in spoilage and consequently reducing the economic value of the foodstuffs. These can be prevented by teaching farmers as one of the five (5) actors of postharvest losses to recognize maturity index of various food crops and carefulness in harvesting of root crops e.g. yam, sweet potatoes and cocoyam. Some measures for minimizing postharvest crop losses were identified from the study to ensure food security. One of such measures is avoidance of over-stacking of arable crops like rice, maize and beans. Picha. (2002) stressed the need to avoid over-stacking of food crops during transportation and storage of the crops. This is because over-stacking leads to generation of heat and deterioration of food items. The avoidance of exposure of arable crops to direct sunlight, harvesting of tuber crops e.g. yam in the morning and evening to prevent exposure to sunlight could prevent postharvest crop losses. This is because such exposure to direct sunlight led to temperature increase and deterioration (Talabi 1995). Postharvest crop losses result in food shortage and consequently food insecurity in Delta state according to the findings. The various causes of food shortage need to be identified and addressed through teaching processors and farmers effective food processing and preservation methods especially in Ughara, Ughelli South and Warri North. If this is not done, food insecurity with its attendant problems of violence, stealing, morbidity and mortality mostly of infants, children, pregnant women and elderly people will be very rampant in the state.

4. CONCLUSIONS

The data generated from this study have been able to provide evidence that:

(i) The Artificial Neural Network using three layer feed- forward model with back propagation multi-layer perceptron were successfully used to predict postharvest losses on the three arable crops along the food value chain in Delta state.

(ii) The level of postharvest losses in rice in Delta State are from two actors namely processors with the highest sensitivity level of 36.673%, 44.212%, 40.524%, and marketers with highest sensitivity level of 44.137% and 39.425%. The level of postharvest losses in maize are from two actors namely processors with the highest sensitivity level of 52.166%, 33.614%, 38.656%, 33.287%, and marketers with highest sensitivity level of 28.241%.

(iii) The level of postharvest losses in yam are from two actors namely processors with the highest sensitivity level of 29.045%, 42.367%, 34.725%, 56.126%, and transporters with the highest sensitivity level of 32.920%.

(iv) Processors, marketers and transporters contributed immensely to the postharvest losses that occurred to rice, maize and yam in Delta state because of the aforementioned problems.

(v) Artificial Neural Network should be used to analyze postharvest losses on all major commodities grown in Delta state in particular and Nigeria in general so that the nation can have reliable information on postharvest loss on each of the commodities and proffer solutions.

(vi) Postharvest losses in perishable commodities such as fruits, vegetables and others should also be investigated using Artificial Neural Network to obtain information as well.

REFERENCES

Bourne M.C. 1983. Guidelines for Postharvest Food Loss Reduction Activities. United Nations Environment Programme, Industry & Environment Guidelines Series.

Dawson C.W., and Wilby R.L. 2001. Hydrological Modelling using Artificial Neural Networks. Progress in Physical Geography, 25 (1): 80–108.

Ebewore S.O., and Achoja F.O. 2013. Storage Practices among Arable Farmers in Delta state, Nigeria: Implication for Food Security.

FAO. 2012. High and Volatile Food Prices - FAO Support to Country Level Contingency Planning. Food andAgriculture Organisation of the United Nations, Rome, Italy.

Govindaraju R.S. 2000. Artificial Neural Networks in Hydrology I: Preliminary Concepts. Journal of Hydrologic Engineering, 5 (2): 115–123.

Kader A.A. 1983. Postharvest Quality Maintenance of Fruits and Vegetables in Developing Countries. p.455-570. In: Lieberman M. (ed.), Postharvest Physiology and Crop Preservation. Plenum Publ. Corp., New York, NY.

Maier H.R., and Dandy G.C. 2000. Neural Networks for the Prediction and Forecasting of Water Resources Variables: A Review of Modelling Issues and Applications. Environmental Modeling and Software 15, 1: 101–124.

Mukai M.K. 1987. Postharvest Research in a Developing Country: A View from Brazil. Horticultural Science, 22:7-9.

Picha D. 2002. Post Harvest Technology for Horticultural Crops. A Paper Presented at the USDA/CSREES/USAID/FMAARD Conference held in Agriculture/Extension Development Project at Abuja, Nigeria, pp 5-10.

Strugholtz S., Panglisch S., Gebhardt J, and Gimbel R. 2006. Modeling and Optimization of Ceramic Membrane Microfiltration using Neural Networks and Genetic Algorithms. Water Practice and Technology, 1 (4): 102-110.

Talabi A.E. 1995. Appropriate Storage Facilities for Promoting Economic Growth and Food Security. Proceedings of the 19th Annual Conference of the Nigerian Institute of Food Science and Technology, 5: 19-30.

Taylor R.W.D., and Webley D.J. 1979. "Constraints on the Use of Pesticides to Protect Stored Grain in Rural Conditions," Trop. Stored Prod. Inf., no. 38, pp. 1-9.

Ukoh-Aviomoh E.E., and Okoh F. 2005. Teaching Rural Families the Management of Postharvest Food Losses as a Strategy for Improving Household Food Security in Nigeria. Journal Home Economics Research, 6 (1):

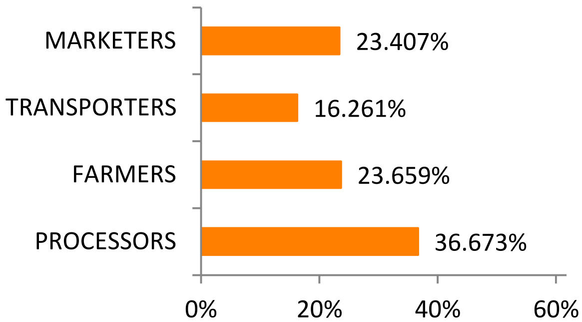

Figure 1: Sensitivity Analysis Result of Rice Consumers

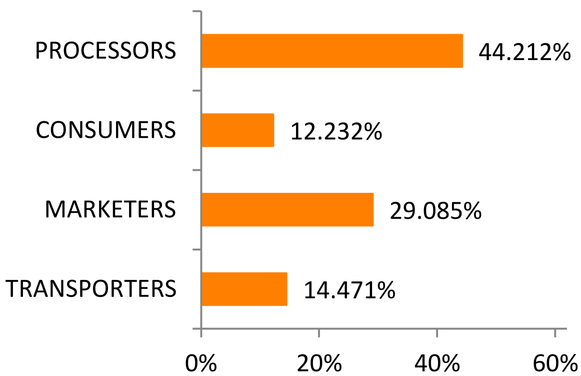

Figure 2: Sensitivity Analysis Result of Rice Farmers

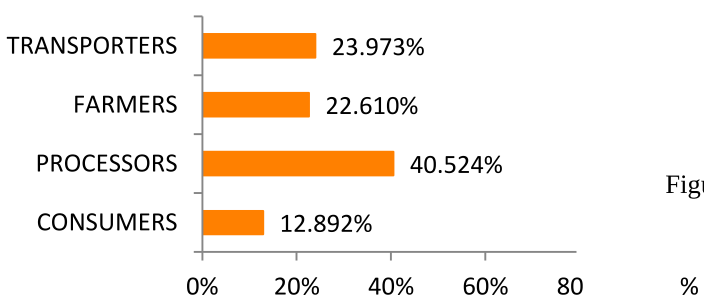

Figure 3: Sensitivity Analysis Result of Rice Marketers

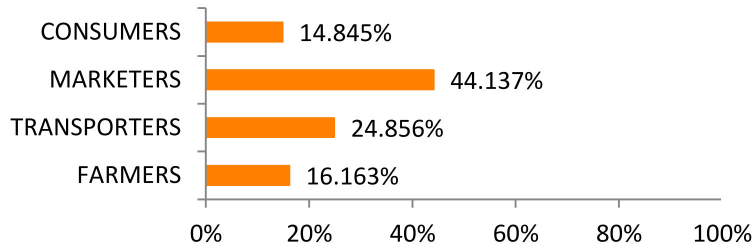

Figure 4: Sensitivity Analysis Result of Rice Processors

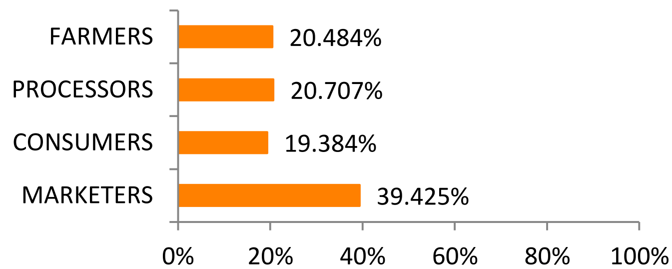

Figure 5: Sensitivity Analysis Result of Rice Transporters

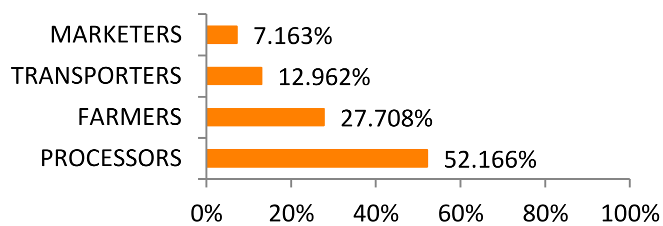

Figure 6: Sensitivity Analysis Result of Maize Consumers

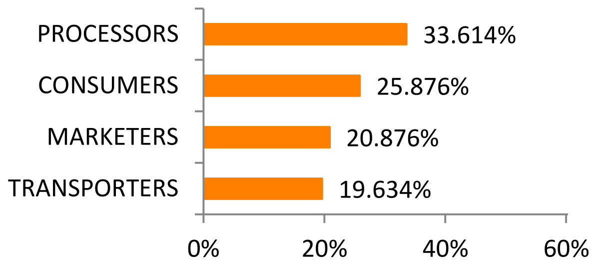

Figure 7: Sensitivity Analysis Result of Maize Farmers

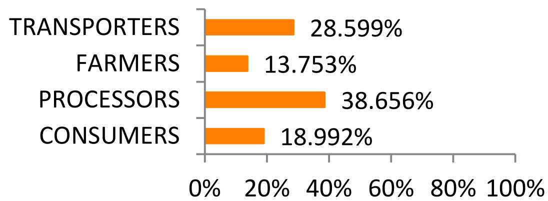

Figure 8: Sensitivity Analysis Result of Maize Marketers

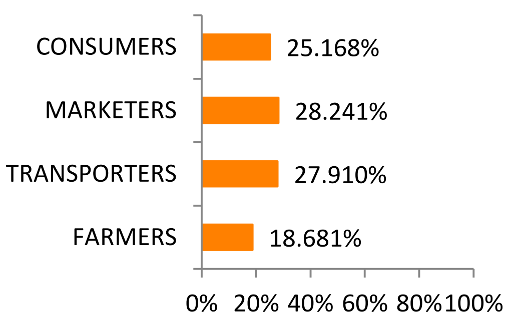

Figure 9: Sensitivity Analysis Result of Maize Processors

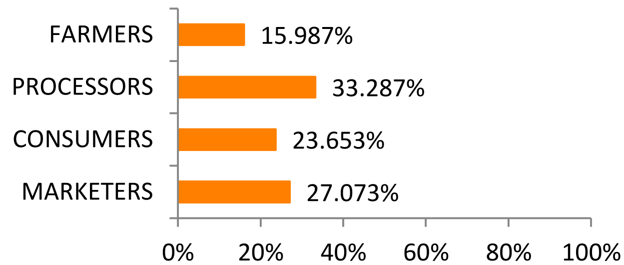

Figure 10: Sensitivity Analysis Result of Maize Transporters

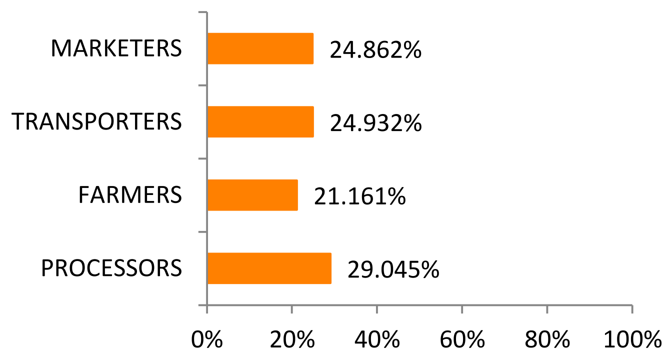

Figure 11: Sensitivity Analysis Result of Yam Consumers

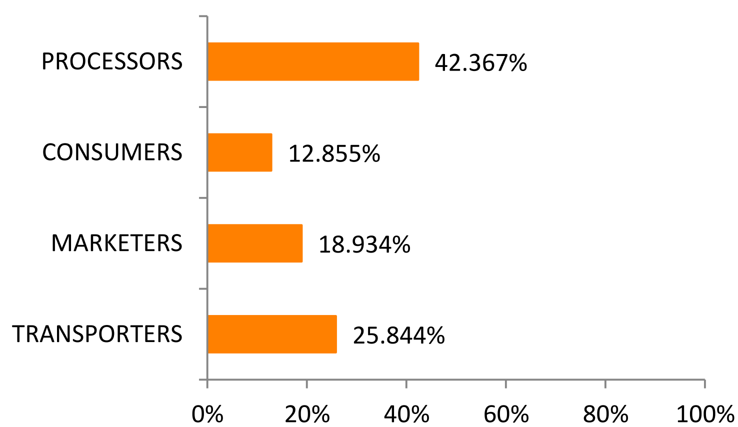

Figure 12: Sensitivity Analysis Result of Yam Farmers

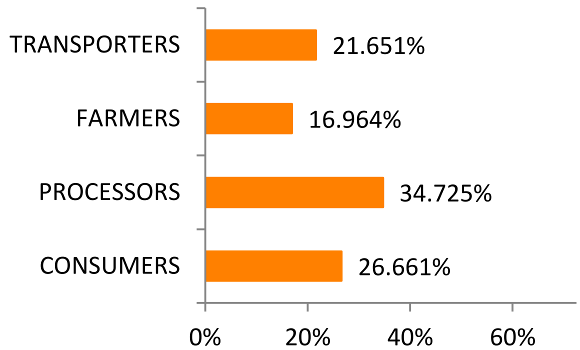

Figure 13: Sensitivity Analysis Result of Yam Marketers

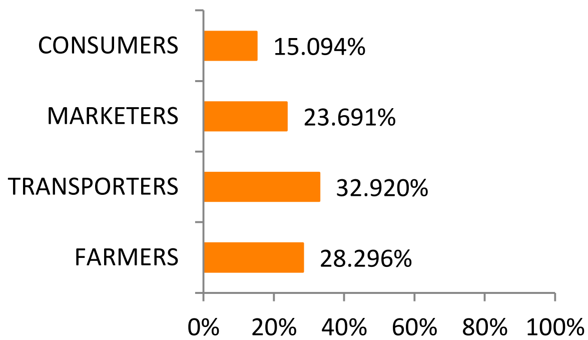

Figure 14: Sensitivity Analysis Result of Yam Processors

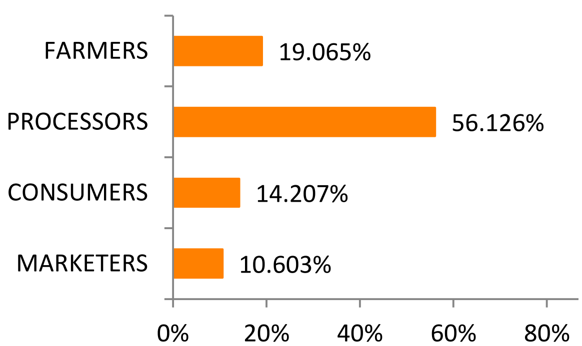

Figure 15: Sensitivity Analysis Result of Yam Transporters

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