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CHARACTERIZATION AND DETERMINANTS OF BAOBAB PROCESSING IN KENYA

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Abstract

Baobab is an iconic tree that is utilized as a source of food and income generation. While extant literature on baobab has focused on its morphological attributes and nutrient composition, there is a gap in literature in understanding the characteristics of processors and the factors that determine baobab processing. Using cross section data of 304 baobab processors in Kenya, we employ Principal Component Analysis and Cluster Analysis to characterize baobab processors and identify determinants of baobab processing. Results of processed volumes show that baobab processors are grouped in three clusters of high, average and low categories. Clusters of processors are shaped by number of years in processing, access to training, quantity processed, processing cost, income from other sources, access to land, and profit levels. The study suggests the need to train processors on baobab processing to increase their efficiency and returns. Through training, processors will be able to make informed decisions on input use, packaging and presentation of their products to the customers. Also, investment in baobab conservation, harvesting more trees and reducing the maturity rate of the baobab trees will increase baobab inputs thus lowering processing cost.
Keywords: *Baobab processing, processor characteristics, Kenya, cluster analysis, principal component analysis.*
JEL Codes: *Q1, Q10, Q13*

1. Introduction

Baobab is a deciduous tree originating from Central Africa. It belongs to the plant family *Bombacaceae* commonly found in the African savannas and India. It grows in the African tropical regions and some trees were exported and cultivated in other continents (Wicken & Lowe, 2008). The baobab fruit is known for its nutritional properties, which has increased its popularity not only in Africa but globally (Tembo, 2016). The fruit is made up of pulp and the seed; the fruit pulp is directly consumed as food while the seed can be processed into oil

(Muthai *et al*., 2017). Powder made from the pulp can be consumed as an additive in milk, porridge and water, and used as an ingredient for making wine. Baobab fruit contains high levels of vitamin C as well as other nutrients (potassium, magnesium) (Stadlmayr, Charrondiere, Eisenwagen, Jamnadass, & Kehlenbeck, 2013). It contains antimicrobial, antiviral, antioxidant, and anti-inflammatory features that are used for the treatment of numerous diseases in African medicine such as anemia, diarrhea, asthma, microbial infections, and fever among others (Kamatou, Vermaak, & Viljoen, 2011).

Apart from the fruit pulp, seeds, bark, roots, and fruit shells are can also be used for other purposes (Kaboré, Hagrétou, Diawaral, & Compaorél, 2011). For instance, fiber is extracted from the bark and used for manufacturing of clothes and ropes. Young leaves are used as fodder and as a source of water by animals and human beings. The leaves can also be dried and processed into leaf powder (Chadare, Hounhouigan, Linnemann, Nout, & van Boekel, 2009).

The multiple products of the baobab tree act as a buffer in times of need for people in the arid and semi-arid areas (ASALs), where it is mainly found, due to its ability to grow and produce fruits when other crops fail (Venter and Witkowski, 2013). It plays an important role in improving the livelihoods of the people, in the areas where it is grown, processed, and traded (Mwema, Lagat, & Mutai, 2013). Venter and Witkowski (2013) established that income from the sale of baobab fruits helps to reduce poverty. In Mali and Benin, cash from the sale of baobab dried leaves and fruits acts as a buffer to the household income (De Caluwé, 2011). Similarly, in Kenya, earnings from baobab processing and trade supplement household income (Jackering, Fischer, & Kehlenbeck, 2019; Kaimba, Kavoi, & Mithöfer, 2020).

There are over 300 uses of baobab in Africa (Buchmann, Prehsler, Hartl, & Vogl, 2010). Besides, in the year 2013 over 300 baobab processed products were available in the European markets (Gebauer, Whitney, & Tabuti, 2016). In Kenya, processing of baobab and value addition is at small scale with only with few exceptions of medium- to large-scale processing. Processed products available in Kenya are pulp as the first stage of processing, candy, juice, ice cream as the second stage of processing of pulp as well as, ropes, bowls, and rat traps made from other parts of the tree. Baobab candy is the main processed product (Jackering *et a*l., 2019).

Despite the economic and health benefits of baobab, its full potential remains untapped (Mullin & Kehlenbeck, 2015). This is attributed to challenges such as the seasonality of the baobab fruit, inadequate information on processing, limited markets, and poor access to training and credit facilities (Kaimba *et al*., 2020). Omotesho, Sola-Ojo, Adenuga, & Garba (2013) showed that utilization of baobab in Nigeria is hindered by negative cultural beliefs.

The acceptance of baobab pulp as a food ingredient by the European Commission (European Commission, 2008) and Food and Drug Administration (Food and Drug Administration, 2009) and the rising international market (Gebauer *et al.*, 2016) illustrates the growing significance of the baobab industry internationally but also nationally (Kaimba *et al*., 2020). However, the secret of unlocking its potential and its capture in the producing regions is embodied in the value addition and commercialization of the product in the countries of origin.

Existing studies have focused on the analysis of nutritional properties of baobab (Chadare et *al.*, 2009), marketing of baobab among collectors (Kaimba *et al.*, 2020), and consumer behavior towards baobab products (Kiprotich, Kavoi, & Mithöfer, 2019). However, there is scanty empirical evidence on characterization of baobab processors. Previous literature in Kenya has mainly focused on market channel choices of collectors (Kaimba *et al*., 2020) while Jackering *et al*. (2019) provided some information on the processor in their value chain analysis work showing that processing increased the value of the processed baobab products. Understanding the current status of processing in Kenya is key for the further development of the sector for the benefit of households in arid and semi-arid regions.

The present study aims to characterize baobab processors in Kenya and to analyze determinants of baobab processing. The study thus complements the study of Chadare *et al*. (2008) who noted that research on valorization and standardization of baobab products was crucial to improving benefits to the rural people involved in selling baobab products. Kiprotich *et al*. (2019) analyzed consumer attitudes towards baobab fruit and showed that product availability, packaging, labelling and certification are key to baobab utilization in Kenya. Kaimba *et al*. (2020) conclude that building capacity around market development, education and research, institutional services and road network are key to create more profitable channels in pulp marketing in Kenya. We contribute to these by a nuanced analysis at processor level in the baobab value chain. Our study further complements the study of Jackering *et al*. (2019) who conducted a value chain analysis of baobab products in Kenya by doing a more nuanced analysis of processors' characteristics and determinants of baobab processing. Overall, the study aims to provide insights on characterization and determinants of baobab processing in order to inform appropriate policies for the sector.

2. Design/Methodology/Approach

2.1 Study Area and Sampling

This study was conducted in Nairobi, Mombasa, Kilifi, Makueni, and Kitui counties, Kenya, which are characterized by a high concentration of baobab trade and processing activities. Kitui, Kilifi, and Makueni counties are rural counties within the baobab belt that produce a high amount of baobab fruits. Mombasa and Nairobi towns are urban areas with a high number of traders and consumers of baobab processed products. A cross-sectional survey design with multi-stage sampling involving purposive and snowball sampling techniques was used to select a sample of 304 baobab processors from the five counties in Kenya between January and June 2019. First, the five counties were purposively selected due to high presence of baobab trade and processing activities. Within the counties local guides helped to locate areas were baobab trade and processing took place. Then Snowball technique was used to select the processors. Snowball sampling was necessary to identify processors as processing is quite informal, with no data on the location of processors. A standardized questionnaire was administered through face-to-face interviews. It was structured to collect information on processed products, processor demographics, and their socio-economic attributes.

2.2 Analytical Model

In the first step data was analyzed descriptively and ANOVA was used to compare characteristics of baobab processors across counties. Then, a two-stage multivariate statistical technique, consisting of Principal component analysis (PCA) and cluster analysis (CA), were used to characterize baobab processors. PCA was used to reduce information from original interdependent variables to a smaller set of independent variables. The reduction thus shortens the dimensions while retaining the original information. The new set of independent variables know as components were used as input for CA, the second stage for identifying the typology of baobab processors. PCA describes the difference between the correlated variables using smaller sets of uncorrelated variables (Chatterjee, Goswami, & Bandyopadhyay, 2015). PCA is guided by the assumption of data interdependence normality, matrix factorability, and sampling adequacy. To uphold these assumptions, the data was subjected to Kaiser-Meyer-Olkin (KMO) and Bartlett Test of Sphericity (BTS) to validate data adequacy and matrix factorability, respectively. In the first stage 13 socio economic variables that described the attributes of baobab processors were used for PCA. PCA condensed all the interrelated variables to a set of interdependent factors called the principal components. The factors were rotated using the varimax method and highly correlated variables were put under each factor. Based on the Kaiser criterion, all factors with an eigenvalue of above one were retained and explained. This criterion is considered appropriate if the number of variables is less than 30 (Field, 2005).

In the second step, the retained factors in PCA were used in CA to characterize baobab processors according to similarities or dissimilarities of their presented attributes. A two-step clustering method was adopted namely: hierarchical and partitioning clustering to establish the number of clusters. The method was used due to its ability to automatically select clusters and ability to create clusters based both on categorical and continuous variables. Hierarchical agglomerative clustering schedule using Ward's method was employed to define the number of categories and then portioning was used to refine the K groups. Ward's Method produced a range of cluster solution where each observation started as its own cluster and was linked to a similar cluster until a singular cluster was left. In the hierarchical method, the k-cluster is formed by joining two clusters from the K+1 cluster while the partitioning method separates observations in various numbers of clusters. Agglomerative schedule and dendrogram helped in deciding on the meaningful and reasonable clusters.

Lastly, one-way Analysis of Variance (ANOVA) was used to identify the differences in variance between the clusters. This study tested the hypothesis, baobab processors do not differ in characteristics.

2.3 Description of Model Variables

Table 1 shows the various variables used in the model and their description.

Table 1. Description of Variables

Variable	Description	Variable Type
Age	Age of Processors (Years)	Continuous
Education Level	Years of Formal Schooling	Continuous
Other Source of Income	Annual Income (Kshs)	Continuous
Land Size	Size of The Land in Acres	Continuous
Access to baobab tree	(Yes=1, No=0)	Categorical
Access to land	(Yes =1, No=0)	Categorical
Baobab trees owned	Number of baobab trees owned	Continuous
Total Processing Cost	Annual Variable Cost (Kshs)	Continuous
Processing Revenue	Annual Revenue (Kshs)	Continuous
Household Size	Number of Individuals in a Household	Continuous
Experience	Years of Baobab Processing	Continuous
Profit	Annual Profit from Baobab Processing (Kshs)	Continuous

3. Findings

3.1 Socioeconomic Characteristic of Baobab Processors

Table 2 presents the socioeconomic characteristics of the baobab processors. The results reveal high level of involvement of women in baobab processing.

Table 2. Socioeconomic Characteristics of the Baobab Processors

Characteristic	Category	Kitui	Makueni	Kilifi	Mombasa	Nairobi	Overall
Gender	Female	90.5	91.7	99.1	79.5	96.9	92.4
Education of processor	None	9.5	25	15	21.9	7.8	14.8
	Primary	61.9	33.3	57.5	53.5	54.7	55.6
	Secondary	21.5	25	20.4	20.5	34.4	23.7
	Tertiary	7.1	16.7	5.3	2.7	3.1	4.9
	University	0.0	0.0	1.8	1.4	0.0	1.0
Other source of income	Full employment	7.1	16.7	7.1	4.1	0.0	5.3
	Business/trading	71.4	75	80.5	61.6	67.2	71.7
	Crop production	2.4	0	4.4	6.8	6.3	4.9
	Casual	7.2	0	2.7	4.1	18.8	6.9
	Part time job	0.0	0	0.0	1.5	3.0	1
	None	11.9	8.3	5.3	21.9	4.7	10.2
Access to land	Yes	76.2	66.7	66.4	57.5	37.5	59.5
Access to credit	Yes	35.7	25	46.9	43.8	67.2	48

Mombasa county had the highest percentage of male processors with 20.5% only, while the share of male processors was even less in the other counties with the smallest share found in Kilifi at not even 1%. The findings show that the majority (55.6%) of the processors had primary education or secondary education level (23.7%). Nearly 6% of the processors had the post-secondary qualification, with tertiary at 4.9% and University at 1%. The respondents with no formal qualification were 14.8%. The majority of the respondent (61.9%) in Kitui had primary school education, followed by Kilifi (57.5%), Nairobi (54.7%), Mombasa (53.4%), and Makueni (33.3%).

Further, the majority of the respondents (89.8%) were involved in other non-baobab processing activities, with only 10.2% recording that they didn't have other sources of income. The results show that most of the processors were involved in business or trade activities (71.7%) as an additional source of income. This is followed by casual employment (6.9%), full employment (5.3%), crop production (4.9%) and holding a part-time job (1%), respectively.

Mombasa County had the leading number of processors who practiced baobab value addition as the only source of income (21.9%), followed by Kitui (11.9%), Makueni (8.3%), Kilifi (5.3%), and Nairobi (4.7%). More than half of the respondents had access to land (59.5%). Kitui had the highest proportion (76.2%) of respondents with access to land followed by Makueni (66.7%), Kilifi (66.4), Mombasa (57.5%), and Nairobi (37.5%).

Overall, the majority of the respondents (52%) did not have access to credit. Nairobi county had the leading number of processors (67.2%) who had access to credit. On the other hand, Makueni processors had the least access to credit represented by 25%, Kilifi County (46.9%) was second, followed by Mombasa (43.8%), and Kitui (35.7%).

Table 3 presents the findings on household characteristics, baobab business decision-making, and steps on the operations of baobab processing. The results show candy to be the main (90.8%) processed product, while powder was the least (1%) processed. Ice cream (4.6%) and juice (3.6%) were second and third in terms of baobab processed products. In Kitui and Makueni counties candy was the only product that was processed. Female spouses were the main (70.8%) decision-makers on whether to venture into the baobab processing business.

Table 3. Household Characteristics, Decision Making and Operations on Baobab Processing

Characteristic	Category	Kitui (%)	Makueni (%)	Kilifi (%)	Mombasa (%)	Nairobi (%)	Overall (%)
Processed product	Candies	100	100	92.4	95.9	75	90.8
	Powder	0	0	1.8	0	1.6	1
	Juice	0	0	4.4	1.4	7.8	3.6
	Ice cream	0	0	1.8	2.7	15.6	4.6
The decision maker	Husband	7.1	0	7.1	16.4	6.3	8.9
	Wife	83.3	58.4	77.8	61.7	62.5	70.8
	Wife & husband	2.4	8.3	1.8	2.7	6.2	3.3
	Children	0	0	0.9	1.4	0	0.7
	Male processor	0	8.3	0	6.8	0	2
	Female processor	7.2	25	12.4	11	25	14.3
Processing pattern (similar)	Yes	54.8	50	32.7	28.8	57.8	40.8
Access to baobab tree	Yes	23.8	16.7	47	27.4	10.9	28.3
Target market	Rural Market	35.7	33.3	45.1	1.3	0	23.4
	Rural town	61.7	58.3	36.3	5.5	6.2	27
	Market	2.6	8.4	18.6	93.2	93.8	49.6
	Urban market						
Business registration	Yes	9.5	0	5.3	5.5	4.7	4.5

The majority (59.2%) of the respondents reported that their processing patterns were not similar throughout the year. Processors in Nairobi (57.8%) and Kitui (54.8%) reported that their processing patterns were similar throughout the year. While the majority of the processors in Kilifi (67.3%) and Mombasa (71.2%) reported varied processing patterns. Most (95.5%) of the baobab processing businesses were not registered with only 4.5% of baobab businesses being registered. Similarly, the majority (71.7%) of the processors did not have access to the baobab tree, with only 28.3% having access to the tree which is the source of baobab processing input. The findings also reveal that the main (50.4%) target markets by the processors were rural markets closely followed by the urban markets (49.6%).

Table 4 presents the ANOVA results used to identify differences between various household characteristics in the five study counties. The findings indicate that the mean age of baobab processors was 39 years. Processors in Makueni were significantly ($P<0.01$) older, with a mean age of 48 years compared to processors in Kitui, Nairobi, Kilifi, and Mombasa with mean ages of 42,41,38, and 38 years respectively. The results also reveal that the overall mean household size was 4 members. Processors in Nairobi were significantly ($P<0.01$) less experienced in baobab processing compared to other counties with a mean of 5.5 years.

In terms, of land ownership, the respondents had a mean land size of 1.9 acres. Households in Mombasa County significantly owned larger pieces of land with a mean size of 2.6 acres compared to those in Kilifi, Kitui, Makueni, and Nairobi Counties, whose average size of the land was 2, 1.8,1.4, and 1 acre respectively. Noticeably, there are significant differences among the five study counties across several characteristics including, other sources of income, annual processing revenues, processing cost, profits, and quantity processed.

Table 4. Mean Comparison of Key Household Characteristics of Baobab Processors

Characteristic	**Description**	**Overall mean N= 304**	**Kitui N=42**	**Makueni N=34**	**Kilifi N=91**	**Mombasa N=73**	**Nairobi N=64**	**F**	**P**
Age	No. of years	39	42	48	38	38	41	3.392	0.010
Years of schooling	No. of years	7	8	7	7	6	8	2.203	0.069
Household size	No. of individuals	4	6	5	4	4	4	2.842	0.024
Land Size	No. of acres	1.9	1.8	1.4	2	2.6	0.9	2.548	0.039
Other source of income	Amount in KShs	435,794	504,371	779,025	546,647	367,999	208,039	1.972	0.099
Experience	No. of years of processing	7	9	12	8	6	5	4.234	0.002
Total processing cost	Amount in KShs	133,119	194,312	71,109	62,022	263,337	81,591	6.122	0.000
Annual processing revenue	Amount in KShs	423,673	587,739	192,693	151,235	964,775	213,278	6.742	0.000
Annual profit	Amount in KShs	200,199	393,426	121,583	89,187	370,753	89,601	4.590	0.001
Annual processed quantity	In Kilograms (Kgs)	1,092	1,006	635	787	2,159	529	2.689	0.031

1$=KShs 100

3.2 Principal Components Analysis

The Kaiser-Meyer-Oklin (KMO) and Bartlett's Test of Sphericity were conducted before conducting PCA (Table 5). The results show a KMO of 0.66 meaning that each variable was sufficient. The BTS value was 660.60 with a P-value of 0.00 indicating that the data was appropriate for principal component analysis (Field, 2005).

Table 5. Kaiser-Meyer-Oklin and Bartlett's Test of Principal Components

Kaiser Meyer –Oklin Measure of Sampling Adequacy	0.66
Bartlett Test of Sphericity Chi-square	660.60
DF	78
P-value	0.000

Kaiser rule for principal component analysis provides that only factors with eigenvalues greater than 1 should be retained. Figure 1 shows the scree plots for the eigenvalues. In this analysis, 4 components met this criterion and were retained. The four components accounted for 57 % of the variance.

The first factor was named the baobab output factor. It accounted for 20.1% of the variance. The factor was made up of four items with their associated factor loading i.e., annual processed quantity, baobab profit, processing revenue, and annual processing cost. The second retained component was baobab input factor which accounted for 14.6% of the total variance.

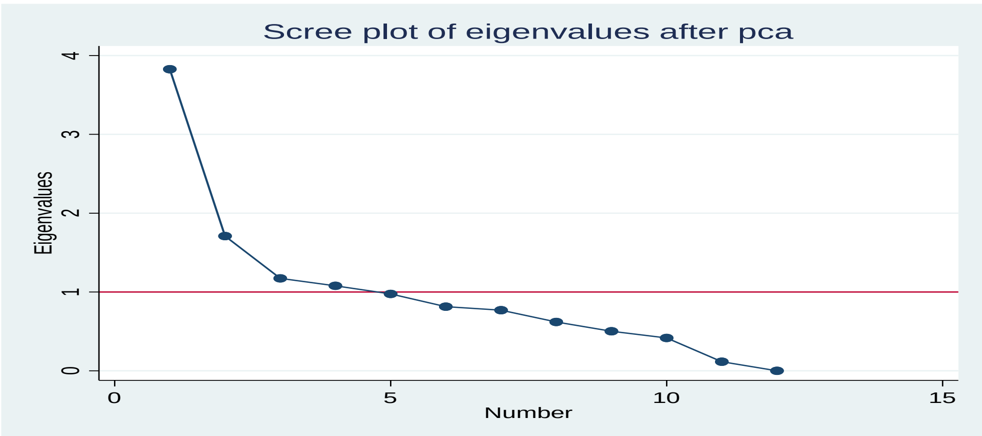

Figure 1. Scree Plot for the Eigenvalues

The input factors component was composed of items: access to baobab trees and the number of baobab trees owned. The third component was the socio-demographic factor which accounted for 12.7% of the total variance. The socio-demographic factors were composed of three items, i.e. age of the processor, years of schooling, and years of processing. The fourth component was the income factor which accounted for 9.5% of the total variance. It was composed of the income from other sources and credit access. Based on the factor loadings and the eigenvalues it is evident that - income, output, input, and socio-demographic factors are important factors in the characterization of baobab processors. Table 6 provides the results of the components selected and retained.

Table 6. Principal Component Factor Loadings

Factor and item description	Factor loading	% Variance explained
Factor1: baobab output factor		20.1
Annual processed quantity	0.4368	
Annual baobab profit	0.5189	
Annual baobab revenue	0.5169	
Annual processing cost	0.5045	
Factor 2: input factor		14.67
Access to baobab trees	0.6177	
No of baobab trees	0.5727	
Factor 3: socio demographics factor		12.72
Age of the processor	0.6496	
Years of schooling	0.4191	
Years of processing	0.5406	
Factor 4: Household income factor		9.54
Non processing income	0.4146	
Credit access	0.5565	

3.3 Cluster Analysis Results and Discussions

The four retained components in PCA were used as inputs for cluster analysis to characterize the processors. The processors were grouped in three clusters as shown by the dendrogram in figure 2.

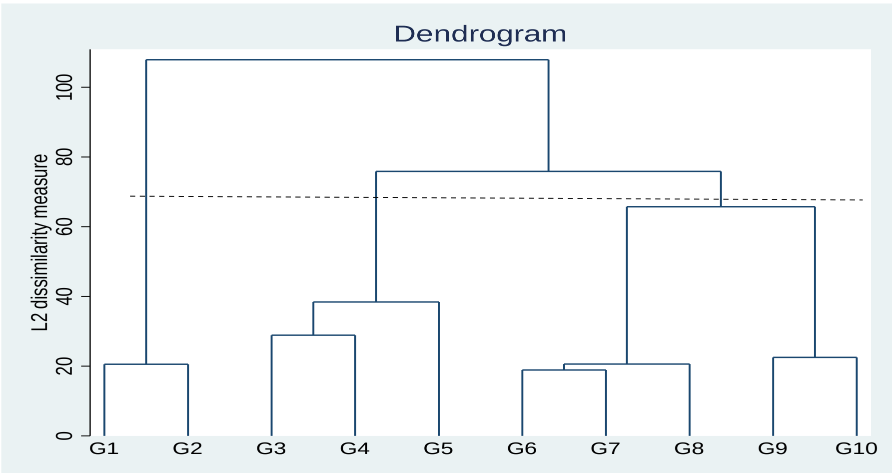

Figure 2. Cluster Dendrogram.

The results for the baobab processor typologies from the cluster analysis are presented in Table 7. The ANOVA analysis results reveal that three clusters were different based on various characteristics.

Table 7. Characteristics of the Clusters based on the Means

Socio economic characteristic	Cluster 1	Cluster 2	Cluster 3	F value	P value
Age of the processor (Years)	41	38	41	1.67	.191
Gender (1=male,0=female)	.06	.05	.04	0.22	.803
Years of schooling (Years)	8	6	7	1.85	.160
Household size (no.)	6	5	5	1.61	.203
Access to land (Yes=1, No=0)	0.58	0.93	0.44	23.88	.000
Size of land (Acres)	1.4	3.4	1.3	11.04	.000
Years of processing (Years)	11	6	7	7.48	.000
Credit Access (Yes=1, No=0)	.36	.44	.51	1.69	.187
Access to training (Yes=1, No=0)	.10	.14	.04	3.24	.041
Profit levels (KShs)	290,981	149,850	80,350	43.12	.000
Baobab Total revenue (KShs)	464,709	176,815	119,822	56.86	.000
Quantity processed (Kg)	1,203	407	372	30.14	.000
Income from other sources (KShs)	618,471	344,439	218,048	21.12	.000
Total variable cost (KShs)	174,199	69,050	59,548	42.19	.000
Frequency (No)	*52*	*59*	*135*		
Distribution (%)	*21%*	*24%*	*55%*		

Note: 1$=KShs100

3.3.1 Baobab Processor Typologies

Based on the baobab clusters identified in Table 7, the baobab processors fit three types 1, 2, and 3. Type 1 refers to high quantity processors. This group included 52 households representing 21% of the study sample. Households in this cluster are characterized by high quantity of baobab processed. Respondents in this group processed an annual average of 1,203 kg of baobab, were relatively educated with an average of 8 years of schooling, and their average land size was 1.4 acres. They had a mean annual profit of KShs 290,981. Similarly, their processing costs were high with an annual average of KShs 174,199. Households in this cluster were relatively wealthy with an annual average income of KShs 618,471 from other sources.

Type 2 refers to average processors. This group was made up of 59 households who represented approximately 24% of the study sample. Similar to type 1, they had low levels of education with an average of 6 years of schooling. The respondents in this cluster had an average household size of 5 individuals. The processors had a mean of 6 years of baobab processing hence, they were least experienced. In terms of land ownership, processor in this group, owned land with an average size of 3.4 acres, this being the highest among the groups. The production volume of this group was far lower than for the high quantity processors with an annual average quantity of 407 kg of processed baobab. Their annual average profit was KShs 149,850. Similarly, revenue from baobab processing was moderate with an annual average of KShs 176,815. They exhibited moderate annual average processing cost of KShs 69,050. Their mean annual income from other sources was KShs 344,439.

Type 3 refers to low quantity processors. This group is composed of 135 households which represented 55% of the respondents. Respondents in this cluster had an average of 7 years of schooling. The processors had a household size of 5 persons, had access to land, and owned an average of 1.3 acres. Processors in this group exhibited low profits with an annual average of KShs 80,350. This cluster produced lower volumes with an annual average of 372 Kg of processed baobab but with a wide spread in production volumes. They had lower processing cost with an annual average of KShs 59,548. Similarly, they exhibited low income from other sources averaging KShs 218,048 per year. Similar to land access, they also had low access to training.

3.3.2 Factors Influencing the Baobab Processors Typologies

The PCA and CA results presented in tables 6 and 7 identified factors that caused variations in baobab processing namely; years of processing, access to training, access to land, land size, profit levels, baobab total revenue, total quantity processed, income from other sources, and processing costs.

Years of processing considerably varies among the baobab processors. Processors in type 1 were more experienced compared to their counterparts in type 2 and 3. Experience caused differences in baobab processing under various economic environments. Processors with many years of processing managed their processing well in terms of acquiring and input use. This enabled them to realize more yields at lower cost and therefore receiving more income compared to those with less experience. Additionally, experience enables the processors to produce quality products due to the practical skills in baobab processing. Highly experienced processors have more information on the markets of the processed products therefore they are better placed to sell their products compared to processors with low experience.

Access to training facilities significantly varies among the clusters. Type 2 had more access to training compared to type 1 and 3. Training is an important factor in baobab processing. Training empowers processors with information on the baobab products, processing skill and processing regulations. Well informed processors make better decision on the input use to avoid wastage, thus lowering the processing cost. In terms of quality, trained processors produce high quality products compared to untrained processors. Quality products attracts more customers in the markets, in turn increasing sales. These findings are in agreement with the study by Adeyonu, Ajala, Adigun, Ajiboye, & Gbotosho (2016) who found out that training promoted sweet potato value addition in Nigeria.

Access to land significantly varies among the processor types. It is higher for the average as well as low for the low volume processors. Type 2 hand more access to land compared to type 1 and 3. Land is a key aspect of agricultural production and processing. In the case of baobab processing, some of the processors had access to land which had baobab trees. Having land with baobab trees reduced the cost of the baobab processing business, since it enabled the processor to readily access baobab input at relatively low costs. Additionally, the land was used for crop and livestock production which increased household income. Some proportion of the income received from farming was employed towards baobab processing, thus providing an advantage to the people with access to land. The land could also be used as collateral when applying for financial assistance to fund baobab processing.

The results show that the quantity of baobab processed to significantly differ between processor clusters. Type 1 produced highest amount of processed baobab while type 3 produced the lowest volume. The quantity processed was affected by seasonality of the baobab fruit. During the off-season baobab input is low in the market leading to higher prices while during the season there is a high supply of baobab leading to low prices of inputs. The quantity processed was also constrained by poor processing practices and the high cost of other inputs such as sugar and packaging materials.

Household income from other sources significantly ($P>0.01$) differs among the clusters. Cluster 3 registered the lowest amount of income from other sources while cluster 1 recorded the highest. Household income often determines the processor's ability to finance both processing and non-processing projects. Income from other sources could be used to buy baobab inputs and other inputs needed in baobab processing. This finding is in tandem with study by Musyoka *et al.* (2020), who revealed that access to off-farm income increased the monetary power of farmers to participate in the acquisition of value addition equipment. It enables the processors to buy inputs at affordable prices during the season, reducing processing costs. Additionally, the income could be crucial in the adoption of improved processing technology which seems risky. Improved technology increases the processor's efficiency in turn improving returns.

The processing cost significantly (P<0.01) varies as well. High quantity processor group had the highest processing cost while low quantity processor group had the lowest processing cost. This may be attributed to the quantity of baobab processed and the price of the inputs. The cost of input used in baobab processing was high due to the low supply in the market. Baobab inputs (pulp on seed, pulp, and fruit) were affected by the seasonality of baobab production. This increased their prices during the baobab off-season. The cost of packaging increased with the ban of plastic bags in Kenya forcing processors to shift from plastic bags to plastic containers. The prices of plastic containers were higher compared to the plastic bags in turn increasing the operation cost of the processors.

Types of baobab processors also differ in total revenue. Highest revenues were registered by the processors in cluster 1 while the lowest revenues were recorded by their counterparts in cluster 3. Baobab processors recorded better revenue during peak season and festive season due to the huge supply of baobab input and markets for the product respectively. Cluster 1 recorded higher revenue compared to other clusters due to their ability to process high quantities of baobab products thus enjoying economies of scale. Revenue from the baobab is limited by inadequate inputs and markets (Jackering *et al*., 2019).

4. Conclusion

This study investigated the baobab characterization and determinants of baobab processing using a sample of 304 baobab processors. Descriptive, principal component, and cluster analysis techniques were used in the analysis. From the study findings, it can be concluded that the majority of the baobab processors were female. A high number of processors did not have access to credit. The baobab processors would generally be categorized into 3 clusters namely high, average, and low quantity processors. The factors that caused variations in baobab processing are years of processing, access to training, access to the land, profit levels, baobab total revenue, quantity processed, income from other sources and processing costs

In line with the above conclusion, the study suggests the following recommendations. First, it is important to empower processor through training to increase their knowledge on baobab processing operations which improves their returns. As processing increases there is also a need for the government, research partners, community partners and other stakeholders to support conservation of the existing trees and to increase the number of baobab trees. Moreover, reducing the maturity period of baobab trees will encourage farmers to plant more trees thus increasing baobab input in turn reducing processing cost. Lastly, though it may seem far-fetched, reform of land policies to increase access to land and to streamline ownership would enable processors to use land as collateral when seeking credit.

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References

Adeyonu, A. G., Ajala, A. O., Adigun, G. T., Ajiboye, B. O., & Gbotosho, O. O. (2016). Determinants of sweet potato value addition among smallholder farming households in

Kwara state, Nigeria. Journal of Tropical Agriculture, Food, Environment and Extension 15 (1),17–22.

Buchmann, C., Prehsler, S., Hartl, A., & Vogl, C. (2010). The importance of baobab (Adansonia digitata L.) in rural West African subsistence - Suggestion of a cautionary approach to international market export of baobab fruits. *Ecology of Food and Nutrition,* 49(3):145-172.

Chadare, F. J., Linnemann, A. R., Hounhouigan, J. D., Nout, M. J. R. and Van Boekel, M. A. J. (2008). Indigenous Knowledge and Processing of *Adansonia Digitata* L. Food Products in Benin, Ecology of Food and Nutrition, 47:4, 338-362

Chadare, F. J., Linnemann, A. R., Hounhouigan, J. D., Nout, M. J. R. and Van Boekel, M. A. J. S. (2009). Baobab Food Products: A Review on their Composition and Nutritional Value', Critical Reviews in *Food Science and Nutrition*, 49:3,254 -274.

Chatterjee, S., Goswami, R., & Bandyopadhyay, P. (2015). Methodology of Identification and Characterization of Farming Systems in Irrigated Agriculture: case Study in West Bengal State of India. *Journal of Agricultural Science and Technology,* 17(5):1127-1140.

De Caluw´e, E. (2011). Market chain analysis of baobab (Adansonia digitata L.) and tamarind (Tamarindus indica L.) products in Mali and Benin. Ph.D. *thesis*, Faculty of Bioscience Engineering, Ghent University, Ghent, Belgium.

European Commission, (2008). Commission decision: Authorizing the placing on the market of baobab dried fruit pulp as a novel food ingredient under Regulation (EC) No. 258/97 of the European Parliament and of the Council. Official Journal of the European Union.

Field, A. (2005). Discovering statistics using SPSS: (and sex, drugs and rock ‘n’ roll), Sage, London.

Food and Drug Administration (FDA), (2009). Agency response letter GRAS, Notice No. GRN 000273, 25 July 2009. Silver Spring MD: US Food and Drug Administration.

Gebauer, J., Adam, Y.O., Sanchez, A.C. (2016) Africa’s wooden elephant: the baobab tree (*Adansonia digitata* L.) in Sudan and Kenya: a review. *Genet Resource Crop Evolution*, **63,** 377–399.

Jäckering, L., Fischer, S., & Kehlenbeck, K. (2019). A value chain analysis of baobab (Adansonia digitata L.) products in Eastern and Coastal Kenya. *Journal of Agriculture and Rural Development in the Tropics and Subtropics*, 120(1): 91-104.doi.10.17170/kobra-20191030732.

Kaboré, D., Hagrétou, S., Diawara, B., & Compaoré, S. (2011). A review of baobab (Adansonia digitata) products: Effect of processing techniques, medicinal properties and uses. *African Journal of Food Science*, 5(16): 833-844.

Kaimba G, Kavoi M, Mithöfer D (2020). Marketing of baobab pulp in Kenya: Collectors’ choice of rural versus urban markets. *African Journal of Agricultural and Resource Economics*, 15(3):194-212.

Kamatou, G., Vermaak, I., & Viljoen, A. (2011). An updated review of Adansonia digitata: A commercially important African tree. *South African Journal of Botany*, 77(4): 908–19.

Kiprotich, C., Kavoi, M., & Mithöfer, D. (2019). Determinants of intensity of utilization of Baobab products in Kenya. *Cogent Food Agriculture*, 5(1):1-12.

MC Mullin, S. & Kehlenbeck, K. (2015). Untapped potential of baobab. Miti, 26(1):16-17.

Mwema, C. M., Mutai, B. K., Lagat, J. K., Kibet, L. K., Maina, M. C., & Campus, N. (2012). Contribution of selected indigenous fruits on household income and food security in Mwingi, Kenya. *Current Research Journal of Social Sciences*, 4(6), 425–430.

Musyoka, J. K., Isaboke, H. N., & Ndirangu SN (2020). Farm-level value addition among small-scale mango farmers in Machakos County, Kenya. *Journal of Agricultural Extension*, 24(3):85-97.

Muthai, K. U., Karori, M. S., Muchugi, A., Indieka, A. S., Dembele, C., Mng’omba, S., & Jamnadass, R. (2017). Nutritional variation in baobab (Adansonia digitata L.) fruit pulp and seeds based on Africa geographical regions. *Food Science and Nutrition*, 5 (6):1116-1129.

Ngore, P. M., Mshenga, P. M., Owour, G., & Mutai, B. K. (2011). Socio economic factors influencing meat value addition by rural agribusiness in Kenya. *Current Research Journal of Social Sciences*, 3(6):453-464.

Omotesho, K., Sola-Ojo, F., Adenuga, A., & Garba, S. (2013). Awareness and usage of the baobab in rural communities in Kwara State, Nigeria. *Ethiopian Journal of Environmental Studies and Management*, 6(4): 412-418. doi:10.4314/ejesm. v6i4.10.

Stadlmayr B, Charrondiere R, Eisenwagen S, Jamnadass R, Kehlenbeck K (2013). Nutrient composition of selected indigenous fruits from sub-Saharan Africa. J*ournal of the Science of Food and Agriculture*, 93(1): 2627-2636.

Tembo, D. T. (2016). Optimization of Baobab (Adansonia digitata) fruit processing and handling techniques for increased human nutrition and commercialization in Malawi. PhD *thesis*, University of Leeds.

Venter, S. M., & Witkowski, E. T. (2013). Fruits of our labor: contribution of commercial baobab (Adansonia digitata L.) fruit harvesting to the livelihoods of marginalized people in northern Venda, South Africa. *Agroforestry Systems*, 187(1):159–172.

Wickens GE, & Lowe P (2008). *The baobabs: pachycauls of Africa, Madagascar and Australia*. Springer, Kew, UK.