Seasonality, food prices and dietary choices of vulnerable households: A case study of nutritional resilience in Tanzania

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Abstract

This study examines how food prices and related seasonality factors affect the dietary choices of low-income farm households in rural Tanzania. The Kishapu and Mvomero districts were selected based on contrasting rainfall patterns, farming practices and economic activities. Data were collected before and after harvest in 2014, using household surveys, focus group discussions, key informant interviews and monthly market-price surveys. A linear-programming solution provides a choice-diet bundle of food items, given model constraints. The cost of the choice diet was compared with household incomes to determine diet affordability. Cheaper, more energy-dense foods lacking other nutrients were consumed at lower budgets in both seasons. Policies and strategies to address problems of the high cost of nutritious foods should be considered to enable low-income households to consume affordable but nutritious diets. Moreover, strategies and interventions that can influence behaviour and promote awareness are important for better household nutrition through a suitably balanced diet of available foods.

Key words: agriculture; food prices, cost of diet, food security, rural Tanzania

1. Introduction

Tanzania, a low-income country largely dependent on agriculture, and with its rural population mostly vulnerable, is aiming for zero hunger and to end all forms of undernutrition in line with the Sustainable Development Goals. Efforts are being made to increase agricultural productivity, and interventions for affected individuals and households are in place. However, seasonality, price and price fluctuations affect household dietary choices and households' resulting nutritional resilience. Women are affected more by climatic and seasonal changes compared to male farmers, while men have more coping strategies then women (Nube & Van den Boom 2003; Nkengla-Asi *et al*. 2017). The poor spend a large part of their income on food and therefore are more vulnerable to price variability (Musgrove & Galindo 1988), and a linear programming model has demonstrated that, as income increases, the actual proportion spent on nutrition decreases (Silberberg 1985). There is high variability of food prices across seasons (Gilbert *et al*. 2017), which also translates into differences in caloric intake (Kaminski *et al*. 2016). High market prices have been associated with lower dietary diversity (Headey *et al*. 2019).

Empirical studies have consistently shown price effects on dietary choices, and this study revisits these findings in the context of resilience building and seasonality in Africa using a case study of

Tanzania. This study uses a linear programming approach, comparing two seasons in two economically distinct districts of Tanzania.

2. Background

Agriculture has remained a major source of income for most developing countries, especially for rural populations (FAO 2018). Smallholder agriculture is more common in Tanzania, where production is only enough to sustain food and a few basic needs, and smallholder farmers provide almost 70% of all food consumed in the country (FAO 2015). As consumers of marketed foods, households are affected by prices of the foods they consume (Aschemann-Witzel & Zielke 2017). It therefore is important to analyse the effect of prices on food choice (Herforth & Ahmed 2015; Hursh & Roma 2016; Privitera *et al*. 2019). Studies indicate that there are post-harvest losses (PHL) relating to food produced by households. In Tanzania, for most grains, up to 15% of the grain harvest is lost before consumption (Abass *et al*. 2014). Table 1 summarises the percentages of PHL for some food items in Tanzania.

Table 1: Percentage post-harvest losses for crops in Tanzania

Food Product	Post-harvest losses (%)
Cereals	15
Sweet potatoes	32.5
Cassava	52.3
Beans	25
Groundnuts	25
Tomatoes	50
Meat and fish	20
Chicken	38
Milk	5.66
Fruits and vegetables	50

Source: Affognon *et al*. (2015)

The theory of consumer behaviour postulates that every individual has a goal of maximising utility but is faced with time-specific budget constraints that limit the achievement of desired utility in each period (Alvino *et al*. 2018). People purchase less nutritious foods because they are cheaper (Cochrane & D'Souza 2015; Darmon & Drewnowski 2015; Mbegalo & Yu 2016). Animal products are not largely consumed by households in Tanzania, except for relatively cheaper animal-source foods (Baker *et al*. 2016). The seasonality of food crops significantly affects consumption patterns among food-secure and food-insecure families. More dietary diversity and food security were experienced in the post-harvest season compared to the pre-harvest season in Kilosa (Ntwenya *et al*. 2015).

Food security has been defined by the FAO as a situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life (FAO 2019). Policy makers in Tanzania have put forward several strategies, such as the provision of nutrition services, nutrients and supplements; promoting dietary interventions and practices; and intensifying awareness and public sensitisation, among others (United Nations 2017). All these are done to ensure that nutrition and healthy are improved. In addition, issues such as food shortages, low production of food crops, substandard imports, inadequate knowledge of nutrition, inappropriate food management and vulnerability of households and groups have been identified as challenges to achieving nutritional goals (United Republic of Tanzania [URT] 2013). To ensure that a sufficient quantity and quality of food is produced, accessible and utilised for enhanced food security and nutrition, the government intends to concentrate on the production of food crops according to agro-ecological zones, meet domestic demand and provide surplus for export, implement regulations to ensure that food imports are consistent with internationally acceptable safety and quality standards, focus on the production and utilisation of crops with high nutrient content in areas with nutritional problems, and promote nutritional knowledge and strengthen food storage and stability. However, there is no mention of how food prices affect types and amounts of foods consumed, the nutritional vulnerability of the rural poor, and seasonal variations in food prices. This paper examines how food prices affect the food choices of low-income farm households in rural Tanzania with respect to their daily diets in two seasons.

The problem of malnutrition in Tanzania is prominent among the majority of rural people. If this problem is not addressed, rural households will continue with practices that are not beneficial to them nutritionally and financially, and women and children in particular will suffer because they are more vulnerable (Brown *et al*. 2017; Mbwana *et al*. 2017). There are very few studies (Cochrane & D'Souza 2015; Yu & Shimokawa 2016; Masters *et al*. 2018) that have analysed the impact of food prices on household consumption of nutritious foods in Tanzania. It therefore is important to strengthen the literature on linkages between food prices and household nutrition while addressing specific issues of seasonality, household incomes, household size and location.

The main objective of this paper is to examine the effects of food costs on consumption of nutritious food for low-income rural households with the specific question: *How do food costs affect household consumption of nutritious food?* Knowledge about this is important because most households depend on markets to buy food and are affected by food costs. This analysis will help to understand household food choices and suggest better ways to achieve nutrition benefits.

3. Study area, data, and methods of analysis

3.1 Study area and sample

The study was conducted in two economically distinct districts in rural Tanzania: Kishapu District in Shinyanga Region, where households are more dependent on farm income, and Mvomero District in Morogoro Region, where households are more dependent on off-farm income. These were selected because of their high level of nutritional vulnerability (National Bureau of Statistics Tanzania and ICF Macro 2011; ICF and MUCHALI 2013), differences in economic activities (USAID 2008) and the absence of major nutrition interventions (TFNC and REACH 2015).

Morogoro and Shinyanga had stunting levels 44.4% and 43.3% respectively above national average (42%)(National Bureau of Statistics Tanzania and ICF Macro 2011; ICF and MUCHALI 2013). Shinyanga was a highly food-deficit region, with most of its districts being vulnerable, and Morogoro was food self-sufficient, but with two vulnerable districts, Morogoro Rural and Mvomero (ICF and MUCHALI, 2013).

Multi-stage clustered sampling was done in two purposely selected districts of Kishapu and Movomero (stage 1). Within each district, one ward was randomly selected (stage 2), from which two villages were randomly selected (stage 3): Lubaga and Mwakipoya villages from Kishapu, and Makuyu and Milama villages from Mvomero. Ethical approval was sought from St Augustine University of Tanzania and the University College Dublin; also, permission to conduct research was sought from the regional and district administrative offices. A list of all households and their members was collected from village officials and, after random sampling, data were collected from a total of 506 households, of which 255 were in Kishapu and 251 in Mvomero. Consent was sought from the respondents before beginning interviews.

3.2 Data collection

In 2014, quantitative data was obtained from structured questionnaires before and after harvest and monthly market price surveys for regularly consumed food and non-food items, while qualitative data comprised focus group discussions and key informant interviews. To understand the regular food consumptions of households, a 30-day food consumption recall was collected from households (Troubat & Grünberger 2017); for respondents whose memory was not that good, a three-day log was collected and estimated to 30 days. Energy and other nutrient contents of food items were obtained from the Tanzania Food Composition Tables (Lukmanji *et al*. 2008).

3.3 Data analysis

3.3.1 Determination of energy content

The amounts of food available in the households were reduced by their respective PHL percentages. The amounts of energy consumed were obtained by a multiplication factor of cooked foods from the consumption data of raw foods, considering common cooking and preparation methods in rural Tanzania (Lukmanji *et al*. 2008). Household energy consumption data were converted into individual adult equivalents (National Bureau of Statistics [NBS], 2014a), which were used in the place of household size to account for age and gender differences among household members (Hickey *et al*. 2016).

Due to resource sharing within households, adult equivalence units were adjusted for average cost economies of scale, since larger households spend less on average compared to smaller households (Newhouse *et al*. 2016). The economies of scale parameter was used, with $\theta = \frac{-\ln\left(1-\rho+\frac{\rho}{n}\right)}{1-n}$, where n is household size and ρ is household expenditure on goods consumed privately (ρ = 0.9 for an adult equivalent (Martin 2017)), while 1-ρ represents goods consumed publicly by the household. As n increases, ρ decreases. Household size is $n_{adj} = 1 + \left((n-1) \times \theta\right)$.

Seven food groups were used: cereals, roots and tubers, vegetables and fruits, meats, poultry and fish, legumes, oils and fats, and miscellaneous items. These are the most common food groups in Tanzania (Lukmanji *et al*. 2008), and are also used in this study. Lower limits and upper limits of energy from food items and food groups were obtained from a statistical distribution of data. For food items, the lower limit was the 5th percentile, while the upper limit was the 95th percentile of the distribution. For food groups, the lower limit was the 10th percentile and the upper limit was the 90th percentile of the distribution.

3.3.2 Household income determination

Data collected from the household survey provided the annual farm and non-farm income received by the households in the year prior to the interview (2013). The average exchange rate of the Euro and the Tanzanian Shilling (TZS) in 2013 was €1 = TZS2 140.98. A distribution of net annual household incomes was run in SPSS, generating four equal cut-off points (income quartiles): the poorest earned TZS707 271 (€330.35); the lower-middle earned between TZS707 271 (€330.35) and TZS1 424 969 (€665.57); the upper-middle earned between TZS1 424 969 (€665.57) and TZS2 991 930 (€1 397.46); and the wealthiest earned more than TZS2 991 930 (€1 397.46).

3.3.4 Linear programming

This study employed an optimisation approach to nutrition using linear programming (a mathematical technique used to optimise an objective function subject to a set of constraints). Decision variables were portions of 29 food items. The nutrient content of the target energy level from the linear programming solution was compared with the minimum required intake of 2 100 kcal (World Food Programme [WFP], 2017) to analyse whether, with that diet, the individuals consumed the desired nutrients and energy.

We adapted the methodology of Briend *et al*. (2003) and Darmon *et al*. (2006). Briend *et al*. (2003) do not mention how the absolute value of the objective function is considered by the linear programming solution in Excel Solver. This poses an effect of negative values of total deviation from mean intake (TDMI) cancelling out positive values. In this paper, the absolute value of the objective function is found by generating positive and negative values of TDMI so that Excel Solver chooses absolute values of TDMI. Optimal budgets were compared to household incomes to analyse affordability.

The hypotheses to be tested were the following:

Null: People's choices of diets were independent of food costs.
Alternative: People's choices of diets were dependent on food costs.

The objective was to minimise relative deviations from the mean diet in the population, calculated by subtracting the mean from the decision variable and divided by the mean. Hence,

Minimise: Sum of absolute values of relative deviations from mean diet
Subject to: Budget constraints, minimum and maximum energy, maximum portion size

Let Y = Objective function
E_d = Daily expenditure on food
P_i = Price per 100 kg of food item *"i"*
m_i = mean portion size (g/d) of food *"i" per person*
a_i = coefficients for food items
X_i = portion of food item *"i"*
G_j = total group energy
f_i = energy per gram of food item
$i = 1$ *to n (food item)*
$j = 1$ *to k (food group)*

3.3.5 Model assumptions

The following assumptions are made in the model:

i) Individuals are rational and choose a bundle of food items that maximises their utility (energy intake); ii) Proportionality: each decision variable was multiplied by a coefficient, such that when the variables change, the result is a proportionate change in that variable to the objective; iii) Divisibility: all decision variables were divisible – all food items were converted into metric weights, enabling divisibility; iv) Additivity: since the objective function is linear, the value of the objective is the sum of the contributions of each decision variable to the objective function; iv) Certainty: all coefficients/model parameters were known.

The coefficients for this analysis were derived from data collected in the field.

3.3.6 Model limitations

Model applicability was limited by: first, decision variables were limited to the common food items consumed by sampled households in the study areas. This does not mean that other food items were not consumed at all; rather, what was included was most representative of the population. Second, it is undeniable that palatability affects food choices; however a palatability scale was not measured during the quantitative data collection and therefore not included in the model. Nevertheless, the participants in the focus group discussions gave their perceptions of which foods were preferred. It is expected, however, that a food item that was more palatable was one that showed the highest mean despite its cost. Third, individuals may have made decisions to eat certain food items without knowledge of their energy or nutrient contents. This does not render the model unrealistic, however, because the individuals still make rational decisions based on what is available and the costs involved.

3.3.7 Optimisation problem

$$\boldsymbol{Y = a_0 + \sum_{i=1}^{n} a_i X_i} \tag{1}$$

Let total departure from mean intake (TDMI) be the sum of all absolute values of differences between each food variable portion size selected from the mean value of the diet.

Total departure from mean intake

$$\boldsymbol{TDMI = \sum_{i=1}^{n} \frac{|(m_i - X_i)|}{m_i}} \tag{2}$$

To standardise differences across food groups, the difference was divided by the mean and, because the TDMI function is non-linear, it was linearised with Z_i – the absolute value of TDMI:

$$\boldsymbol{Z_i \geq \left|\frac{(m_i - X_i)}{m_i}\right|} \tag{3}$$

Since Z_i is by definition greater than or equal to both the standardised values of the difference, this means the model selects the absolute (positive) values of Z_i. Then,

$$\boldsymbol{TDMI = \sum_{i=1}^{n} Z_i = \frac{(m_1 - X_1)}{m_1} + \frac{(m_2 - X_2)}{m_2} + \cdots + \frac{(m_n - X_n)}{m_n}} \tag{4}$$

$$\boldsymbol{= \left(1 - \frac{1}{m_1} X_1\right) + \left(1 - \frac{1}{m_2} X_2\right) + \cdots + \left(1 - \frac{1}{m_n} X_n\right)} \tag{5}$$

$$\boldsymbol{= n - \frac{1}{m_1} X_1 - \frac{1}{m_2} X_2 - \cdots - \frac{1}{m_n} X_n} \tag{6}$$

This follows the same format as the linear function, $Y = a_0 + a_1 X_1 + a_2 X_2 + \cdots + a_n X_n$, where a_0 is a constant $and\ a_i = -\frac{1}{m_i}$

Constraints

i. Budget constraint

Since the X_i's are decision variables, the cost constraint is:

$$\boldsymbol{E_d = \sum_{i=1}^{n} P_i X_i \leq TZS}, \tag{7}$$

where TZS is the shilling value of total food cost items in the diet.

ii. Total minimum energy intake constraint

Energy intake per day is constrained at the daily mean energy intake of the population distribution, and if f_i represents the food energy content of item i in 100 g of that food item, then optimal energy is expressed as:

$$\boldsymbol{\sum_{i=1}^{n} f_i X_i \geq \sum_{i=1}^{n} m_i^{energy}} \tag{8}$$

iii. Daily energy constraints

Minimum food item – Energy limit

$$\boldsymbol{f_i \geq f_i^{5^{th}}} \tag{9}$$

Maximum food item – Energy limit

$$\boldsymbol{f_i \leq f_i^{95^{th}}} \tag{10}$$

iv. Food group constraint

If *"j"* denotes food group, then X_{ij} is food item *"i"* belonging to group *"j"*. G_j indicates the energy limit of food groups. Only three food groups were constrained in this paper: cereals; vegetables and fruits; and meats, fish and poultry, because they were widely consumed in both seasons and survey areas.

Thus,

$$\boldsymbol{\sum_{i=1}^{n} X_{ij} \geq G_j^{10^{th}}} \tag{11}$$

and

$$\boldsymbol{\sum_{i=1}^{n} X_{ij} \leq G_j^{90^{th}}} \tag{12}$$

v. Food portions

Maximum food portion size in grams per day was constrained at the 75th percentile of population intake distribution.

$$\boldsymbol{X_i \geq X_i^{75^{th}}} \tag{13}$$

The linear programming optimisation results were matched with other nutritional content of the portions that were consumed to obtain how much of other nutrients was consumed by household members.

4. Results and discussion

4.1 Household profile

Numerous significant differences ($p < 0.05$) were observed between households in Kishapu and Mvomero, as outlined in Table 2.

Table 2: Household characteristics

Household characteristics	Kishapu	Mvomero
Average households size (number of members)	7.84	5.43
Average age of household head	46.4	42.6
Percentage of female-headed households	23.5%	20.9%
Average years of schooling of households head	5.08	4.99
Average number of rooms per household	4	3

Source: Survey data

The majority of households in both study districts were male headed, at 78% of households. Analysis of variance of the data above showed statistically significant differences for household size, age of household head and number of rooms per household between districts.

4.2 Household income and income distribution

Table 3 shows the analysis of variance run on household income data between Kishapu and Mvomero. This analysis revealed no statistically significant differences between household incomes in Kishapu and Mvomero; however, there were statistically significant differences in per capita (adult equivalents) household incomes. This could be due to larger household sizes in Kishapu than in Mvomero, making per capita incomes smaller in Kishapu than in Mvomero. Moreover, there were at least three months with no income at all in Kishapu, compared to at least two months in Mvomero; these were the same months that households faced food shortages during the rainy season.

Table 3: Analysis of variance – household incomes

ANOVA						
		Sum of squares	df	Mean square	F	Sig.
Net annual household income 2013 in Euros	Between groups	9 332 082.858	1	9 332 082.858	2.532	.112
	Within groups	1 857 659 297.000	504	3 685 831.938		
	Total	1 866 991 379.000	505			
Net annual household income 2013 per adult equivalent in Euros	Between groups	3 055 552.049	1	3 055 552.049	12.978	.000
	Within groups	118 662 141.300	504	235 440.757		
	Total	121 717 693.400	505			

4.3 Linear programming results

To generate budget points, a solution was initially found from linear programming without constraining the budget equation. The solution gave a choice-diet and energy level that could be consumed, and any further increase in budget did not change food choices. Furthermore, budgets were progressively decreased at intervals of TZS100 to assess how food choices varied when a person had less and less money at their disposal, and a minimum budget was reached when any further reductions in budget made the solution non-optimal. Prices were relatively lower in the post-harvest season than in the pre-harvest season in both areas. Solutions were obtained separately for the two seasons.

Apart from energy consumption, other macro- and micronutrients are also important for the body. According to the World Health Organization (WHO) (2019), nutrients are grouped into carbohydrates, fats and fatty acids, proteins, vitamins, minerals and water. Water is not included in this analysis, but was consumed independently and also contained in foods eaten.

4.4 Pre-harvest results

Figure 1 presents the results for the pre-harvest survey diet-optimisation problem. An individual may spend a minimum of TZS1 003.2 eating the required diet while meeting all constraints. When the budget was raised above TZS1 417.05, no further dietary changes occurred. As the budget gradually decreased, individuals increased their consumption of energy-dense foods, such as cereals (especially donuts and rice) and sugar. The consumption of sweet potatoes increased because they were widely available, while that of Irish potatoes decreased because these were not grown in the areas and were more expensive. Consumption of legumes decreased slightly, while that of meats, fish and poultry decreased notably, even with a slight decrease in budget.

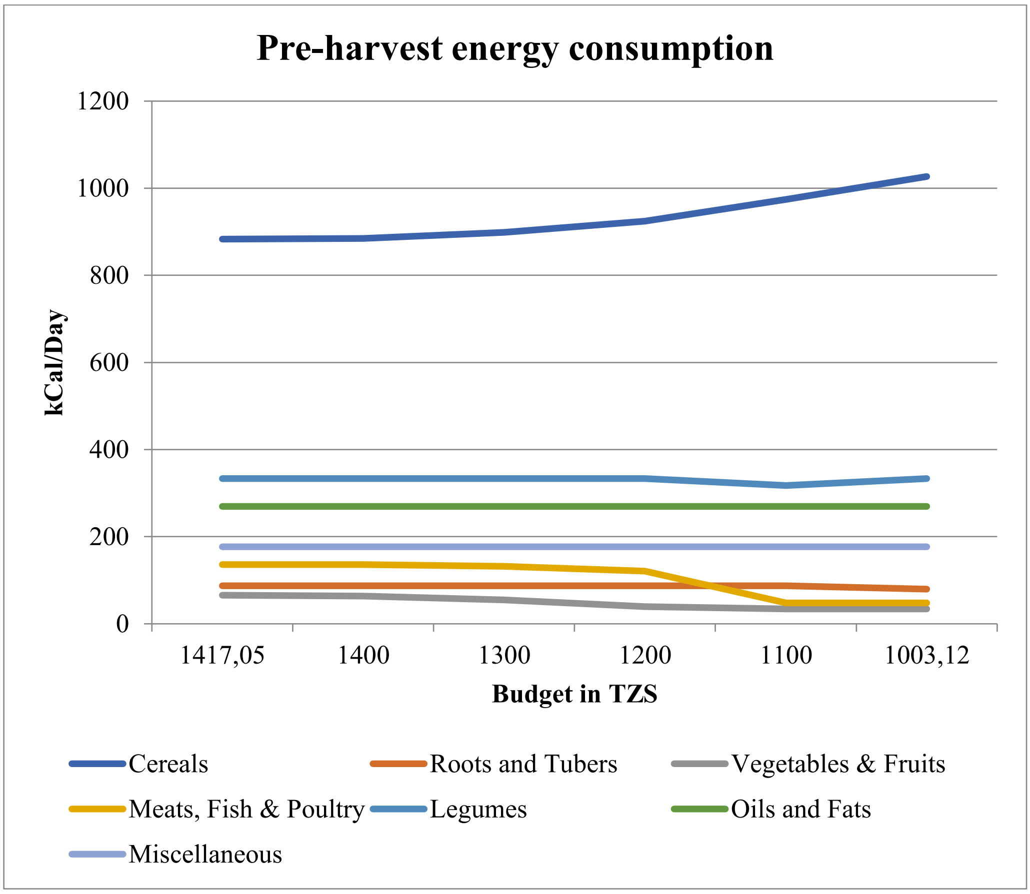
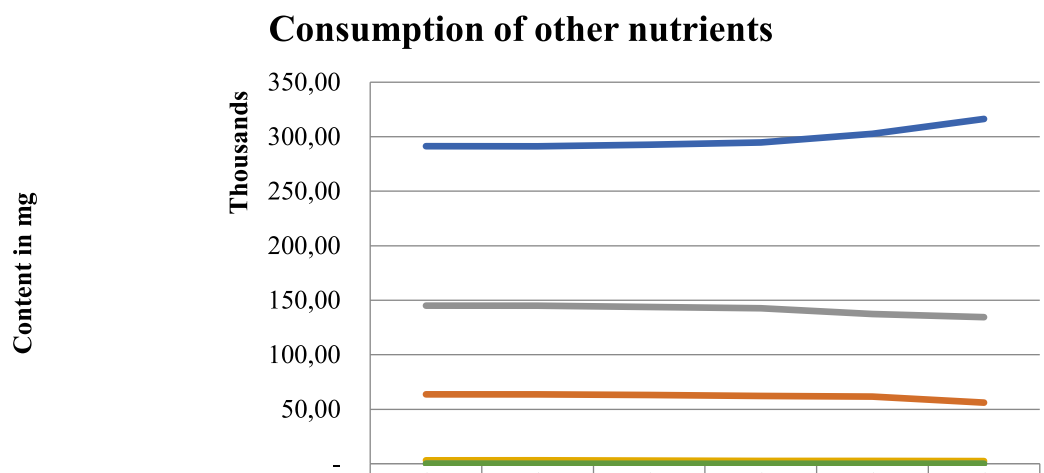


Figure 1: Linear programming results for the pre-harvest season
Source: Survey data

Figure 2 represents nutrients consumed from optimal food portion sizes. In the pre-harvest period, a decrease in budget increased consumption of carbohydrates and sugars, with a notable decline in the consumption of vitamin A. Further, there was a slight decline in the consumption of proteins, fats and fatty acids, minerals and other vitamins.

A daily budget of between TZS1 003.12 and TZS1 417.05 per person (adult equivalence) meant that it required a minimum food budget of approximately TZS30 096 and a maximum of TZS42 511.50 per person to meet the target energy level in a 30-day month during the lean season. Considering household sizes and household incomes, some households found it difficult to afford this diet.



	1 417,05	1 400,00	1 300,00	1 200,00	1 100,00	1 003,12
Carbohydrates and Sugars	291 306,2	291 350,1	292 544,2	294 695,6	302 710,8	316 309,1
Fats and Fatty Acids	63 654,82	63 657,23	63 063,61	62 333,17	61 757,94	56 093,98
Proteins	145 048,2	144 856,6	143 721,4	142 747,2	137 318,9	134 475,0
Minerals	3 143,53	3 091,30	2 821,00	2 676,73	2 627,53	2 449,89
Other Vitamins	106,06	105,15	99,87	85,39	78,56	59,16
Vitamin A	7,92	7,86	7,52	7,46	3,23	0,15

Figure 2: Post-harvest nutrient consumption

Table 4 compares feasible food budget, household size and household income. Even the minimum target energy level was not affordable by the poorest and lower-middle households. Even for the upper-middle and wealthiest households, and the overall sample, it still took a large part of their total annual income. The situation was even worse for the maximum budget.

The consumption of carbohydrates increased with a decrease in budget, while that of proteins and fats and fatty acids decreased slightly with a decrease in budget, and this was similar for minerals and vitamins.

Table 4: Comparison between feasible food budget, household size and household income for overall sample in the pre-harvest period

Quartile	Annual average household income (TZS)	Average household size	Amount needed to attain target energy level per year			
			Minimum		Maximum	
			TZS	% of household income	TZS	% of household income
1	< 707 272.74	3.98	1 461 224.84	206.60	2 064 188.39	291.85
2	< 1 424 972.06	4.04	1 483 253.36	104.09	2 095 306.81	147.04
3	< 2 991 933.91	4.00	1 468 567.68	49.08	2 074 561.20	69.34
4	> 2 991 933.91	4.62	1 696 195.67	56.69	2 396 118.19	80.09
Overall mean	2 755 227.16	4.15	1 523 638.97	55.30	2 152 357.25	78.12

Source: Survey data

4.5 Post-harvest results

In the post-harvest period, budgets were higher as individuals consumed more food varieties, even though food costs were lower, as shown in Figure 3 below.

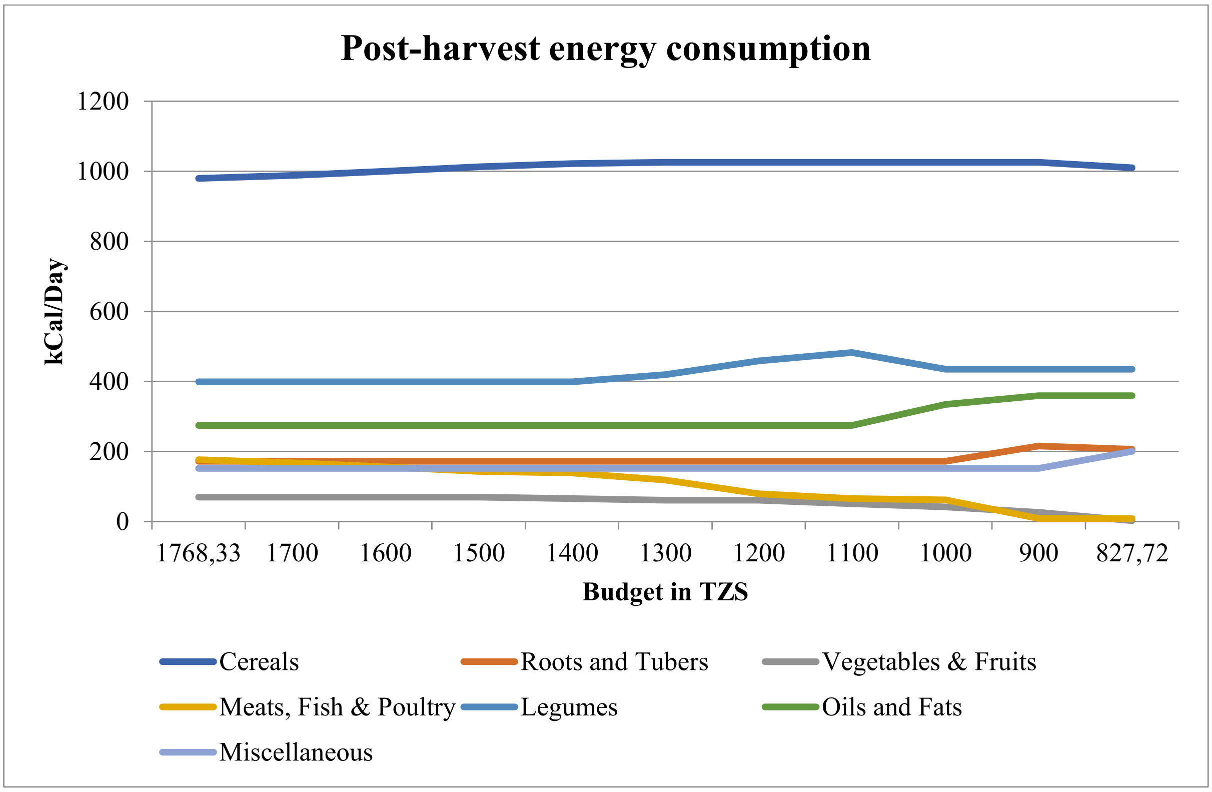


Figure 3: Linear programming results for the post-harvest season
Source: Survey Data

The consumption of cereals decreased compared to pre-harvest diets, whereas maize consumption increased with a decrease in budget. Consumption of roots and tubers increased because fresh sweet potatoes were harvested, while items in the fruits and vegetables, and meats, fish and poultry groups were reduced when budgets were lowered. With a minimum budget, there was very little consumption of fruits and vegetables, and no consumption of products from the meats, fish and poultry group, while the consumption of legumes (especially groundnuts), oils and sugar increased with budget decreases.

From Figure 4 it is clear that the consumption of carbohydrates and sugars, and other vitamins and minerals decreased only slightly when budget was decreased. However, the consumption of vitamin A shows a significant decline, while that of proteins and fats and fatty acids increased slightly.

One individual would have to spend between TZS827.72 and TZS1 768.33 per day, equivalent to TZS24 831.6 and TZS53 049.9 per month, in a plentiful season.

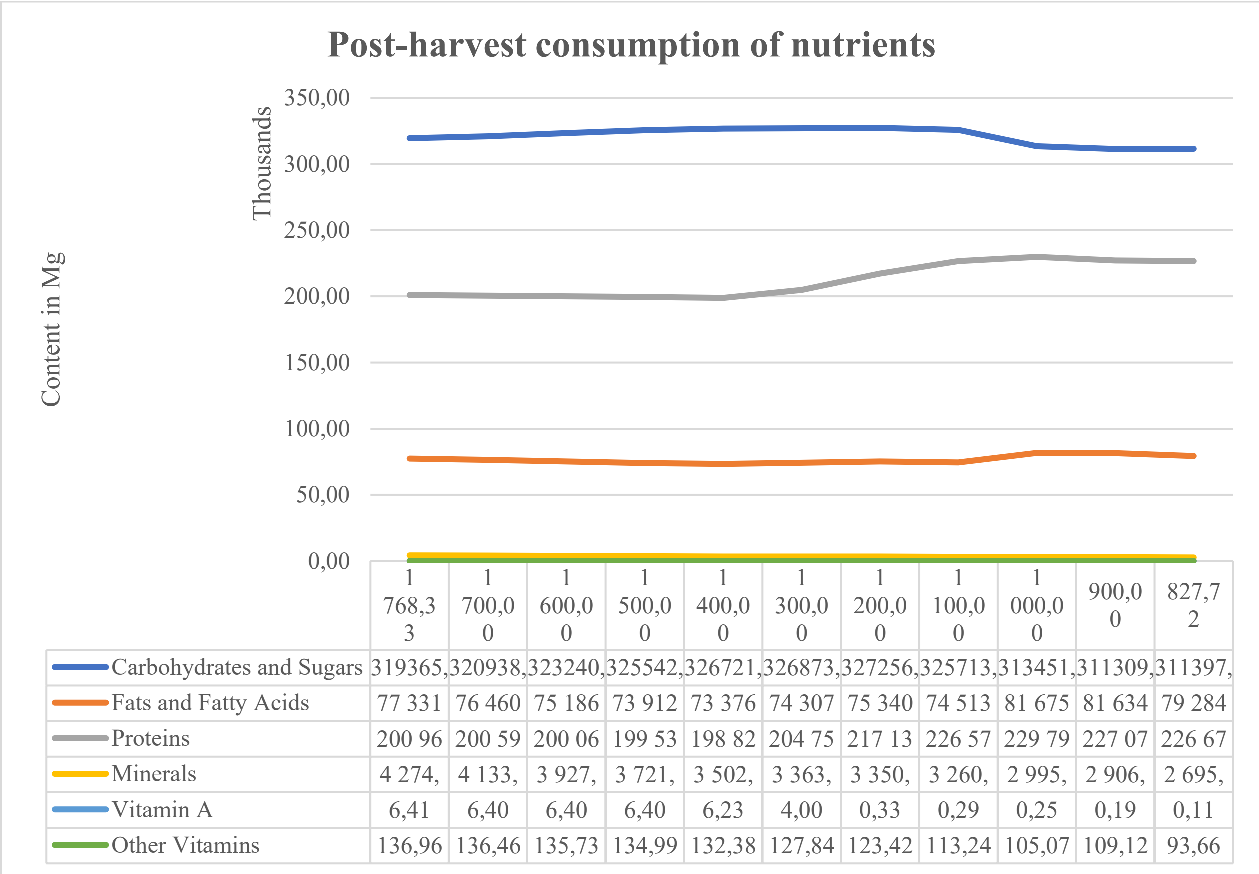


Figure 4: Post-harvest nutrient consumption

Table 5 shows that, even in the post-harvest period, when households had harvested and there was more income, the poorest could hardly afford even the minimum target energy level. Lower-middle households could afford the minimum target diet but not the maximum. The upper-middle and wealthiest households could afford both the minimum and maximum target diets, but they would need to spend a large part of their annual income on food alone.

Table 5: Comparison between food budget, household size and household income for overall sample in the post-harvest period

Quartile	Annual average household income (TZS)	Average household size	Amount needed to attain target energy level per year			
			Minimum		Maximum	
			TZS	% of household income	TZS	% of household income
1	< 707 272.74	3.98	1 205 723.17	2 575 890.94	170.47	364.20
2	< 1 424 972.06	4.04	1 223 899.90	2 614 723.47	85.89	183.49
3	< 2 991 933.91	4.00	1 211 782.08	2 588 835.12	40.50	86.53
4	> 2 991 933.91	4.62	1 399 608.30	2 990 104.56	46.78	99.94
Overall mean	2 755 227.16	4.15	1 257 223.91	2 685 916.44	45.63	97.48

Source: Survey data

5. Results and discussion

There were limited food choices during the pre-harvest season compared to the post-harvest season. At intervals of TZS100, only six combinations of budget points allowed for the optimisation of the objective function while staying within the constraints of the pre-harvest period compared to eleven budget points in the post-harvest period. Pre-harvest diets were less expensive, but also less energy was consumed compared to post-harvest diets. One person consumed up to 1 951.95 kcal per day in the pre-harvest period and spent between TZS1 417.05 and TZS1 003.12, while in the post-harvest period one person consumed up to 2 223.56 kcal and spent between TZS 765.33 and TZS 827.72. There was more energy intake in the post-harvest season than in the pre-harvest season, because food items were scarce and expensive during the pre-harvest season, which limited food choices compared to the post-harvest season. Progressive budget reductions increased the consumption of energy-dense rather than nutrient-dense foods, because most energy-dense foods were cheaper than nutrient-dense foods. Consequently, the recommended energy intake of 2 100 kcal was not met in the pre-harvest season. The participants in the focus group discussions revealed a food consumption pattern consistent with these findings, as many households could not afford energy- and nutrient-rich food items in the pre-harvest season and some households sometimes skipped meals or went the whole day without eating. Some households only consumed maize porridge, which contains nothing but maize flour and water, thus denying them important nutrients. Other nutrients also showed a decline as the budget decreased, except for carbohydrates and sugars in the pre-harvest season, as they were cheaper than other foods, and proteins, fats and fatty acids were cheaper in the in post-harvest season than pre-harvest.

In the focus group discussions, participants explained that households consumed a less than adequate diet in order to cater for other needs, such as school fees and other school needs for their children, along with rent, medical care and emergencies, and clothing. It was difficult even for those who were considered *well-off* to manage all these needs with the income they earned and with little to no alternative sources of income. On average, rural Tanzanians spend about 70% of their household budget on food (Kassie *et al*. 2014), as found in this study. The daily food cost poverty line in Tanzania in 2012 was TZS858 per adult equivalent (NBS, 2014b). This was below the budget requirements found by these linear programming results. However, as the Household Budget Survey (HBS) was based on the whole of Tanzania, food prices and other conditions may differ from this study. Nevertheless, as the pre-harvest season is a rainy season and rural households have the option of using forest foods, especially fruits and vegetables, this would lower the food burden on their incomes.

During the focus group discussions and interviews with leaders and elders, it was revealed that some food items were considered inferior and that only the poor would consume them. For example, sorghum, which is rich in calories and cheaper, grows well in an area like Kishapu with its little rain, but people do not like to grow it and, when they do, they would only consume it when there is no maize or rice. If sorghum was consumed largely, it could easily satisfy people's energy needs, even in the pre-harvest period. The linear programming solutions without a minimum energy constraint for all samples indicated that individuals might choose a diet that is lower in energy and lower in cost. Consequently, they would end up consuming inadequate nutrients.

These findings are also consistent with the findings of other studies, such as those by Darmon and Drewnowski (2015) in France; a review of more than 3 000 literature documents by Afshin *et al*. (2017); and a study that showed that decreases in food costs cause an increase in the consumption of nutritious foods (Ball *et al*. 2015). Moreover, low-income individuals consume higher complex carbohydrates and lower minerals and vitamin A (Si Hassen *et al*. 2016). However, Kaushal and Muchomba (2015) found that price subsidies intended to reduce food cost did not increase the consumption of nutritious foods, but rather increased the consumption of non-food items by poor households.

6. Policy implications

Food costs and seasonality are important in determining whether or not individuals consume nutritious foods. Therefore, policies to improve household incomes, reduce food costs and reduce seasonal variations in food availability could play an important role in improving dietary choices. Such strategies may include the improvement of transport infrastructure and rural markets, an increase in off-farm activities such as entrepreneurship education, and access to credit.

Cost of diet is an important consideration in policy contexts. While the poor spend most and sometimes more than 100% of income on food alone (Musgrove & Galindo 1988; Kassie *et al*. 2014; Beyer *et al*. 2016), it is important to design specific price-sensitive policies to help the rural poor. Since there are also differences in income among the rural poor, it is important to take into consideration the measuring of vulnerability for context-specific interventions, because it is not possibly to have a one-size-fits-all policy for all households. Policies and strategies to address problems of the high cost of nutritious foods should be considered to enable households with lower incomes to obtain affordable but nutritious diets.

Nutrition awareness could be an important approach to changing the eating habits of individuals in rural Tanzanian societies, but this should be supplemented by other approaches that may enhance food choices (Guthrie *et al*. 2015). Such policies could invest in strategies that would influence the behaviour and perceptions of communities towards nutritious foods (Ruel *et al*. 2013; Aunger & Curtis 2016; Celis-Morales *et al*. 2016). Other researchers have found that nutritional education starting at school level for children is more effective (Hawkes *et al*. 2015), but should also go together with enabling disadvantaged groups to afford nutritious diets (Hirvonen *et al*. 2017). Higher incomes should be accompanied by interventions such as investments in health, education and access to drinking water for better nutrition (Soriano & Garrido 2016). Even though individuals in developed countries might be consuming nutrient-rich expensive foods because they have enough income to do so, knowledge about nutrient content plays an important role in their decisions (Darmon *et al*. 2006; Si Hassen *et al*. 2016). Most foods in rural markets in Tanzania have no nutritional information attached, therefore, even with nutrition awareness, strategies to make sure that nutritional information is available can play a vital role in influencing the consumption decisions of rural Tanzanians.

The ability to recover from food security shocks caused by factors outside households' control, such as seasonality and price changes, will largely influence resilience in household food security and nutrition. There are unique behaviours that make some groups more resilient than others (Dufour *et al*. 2014; Aggarwal *et al*. 2016), and these should be identified and built upon for the benefit of others. Since indigenous forest foods contribute to dietary diversity and income (Ntwenya *et al*. 2017; Ochieng *et al*. 2018), strategies to domesticate and improve markets for such foods could also be important for rural communities.

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