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ORIGINAL PAPER

Estimation of nutritional postharvest losses along food value chains: A case study of three key food security commodities in sub-Saharan Africa

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Abstract

Postharvest losses (PHLs) amplify food insecurity and reduce the amount of nutrients available to vulnerable populations, especially in the world's Low and Middle Income Countries (LMICs). However, little is known about nutrient loss at the various postharvest stages. The objective of our study was to develop a methodology and a tool to estimate nutritional postharvest losses (NPHLs) along food value chains for three distinct food commodities in sub-Saharan Africa. The study used a combination of literature, laboratory and field data to investigate NPHLs caused by both changes in quantity and quality of food material (quantitative and qualitative NPHLs, respectively). The method can be expanded to various other food value chains. A user-friendly predictive tool was developed for case studies involving maize and cowpea in Zimbabwe, and for sweet potato in Uganda. Quantitative and qualitative NPHLs were combined and converted into predicted nutrient loss and nutritional requirement lost due to postharvest losses. The number of people who may not meet their daily nutritional needs, as a result of the food and nutrient losses at country level, was estimated. The estimates consider nutritionally vulnerable groups such as children under five years and pregnant women. The nutrient density of the harvested food material, the level of food production, the postharvest stages along the food value chain, the levels of pest damage along the value chain, and the susceptibility of the nutrients to degradation *e.g.* during storage, are all important factors that affect NPHLs. Our modelling work suggests that reducing PHLs along food value chains could significantly improve access to nutritious food for populations in LMICs.

Keywords Postharvest nutrient loss · Postharvest loss · Food system · Human nutritional requirements · Nutrient loss prediction

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1 Introduction

We realise, more than ever, the pressing need for food systems that are efficient and resilient to deliver safe and nutritious food (Fanzo et al., 2021; Heck et al., 2020). The EAT-Lancet Commission on healthy diets identified postharvest loss (PHL) reduction as an important way to make food systems more efficient (Willet et al., 2019). Increasing food production is limited by environmental concerns of agricultural land expansion and unavailability /or unaffordability of technologies to increase food productivity (FAO, 2017). Reducing PHLs is therefore considered a critical approach to preserve more of the harvested food along the food value chain, so that it is made available for human consumption (Willet et al., 2019).

Needs are especially critical in Low and Middle Income Countries (LMICs), where malnutrition widely occurs (Fanzo, 2012; Global Panel, 2018). Malnutrition constitutes a major health problem with knock-on effects on human and economic development. Malnutrition occurs as a result of: (1) undernutrition, (2) protein-energy malnutrition, and (3) deficiency in specific micronutrients, *i.e.* iron, zinc, and vitamin A, which are the most frequent in LMICs (Fanzo et al., 2018). PHLs can be high in LMICs as a result of attack by insect pests and micro-organisms, especially fungi (with potential mycotoxin contamination), favoured by poor storage conditions and marketing constraints (Chigoverah & Mvumi, 2018; Hodges et al., 2011; Mvumi et al., 1995; Shee et al., 2019; Stathers et al., 2020a, b; Tefera et al., 2011).

There is still a large knowledge gap regarding nutritional postharvest losses (NPHLs). Inadequate predictions of nutrient amounts in food could lead to public health problems in nutritionally vulnerable populations. Proper predictions, on the other hand, would open the way to prevention of (nutritional) losses, better investment guidance, and more effective national policies.

NPHLs occur along all postharvest stages of the food system where food may either be (1) physically lost (quantitative loss) or (2) its quality is degraded through spoilage by environmental conditions (*i.e.* temperature, humidity) and/or pest infestation (*i.e.* insects, mites, rodents, fungi) (qualitative loss). NPHLs have often been overlooked because of limited and costly techniques to correctly estimate these losses. Measurement evidence—accurately estimating the type and extent of nutrient losses—is therefore a necessary first step towards NPHL mitigation.

NPHL is often quantified at a single stage along the value chain, typically at the processing or storage stage. For example, the loss of a specific nutrient (*e.g.* provitamin A) in a food (*e.g.* sweet potato) may be predicted during home-cooking or commercial processing under certain processing and storage conditions (temperature, light, etc.) (Bechoff et al., 2010a, b). However, published information on NPHL across the broader food system is limited. Berners-Lee et al. (2018) developed commodity-based predictions of nutrient flow across the food system at a macro-level and recommended a plant-based diet to ensure healthy global nutrition. Alexander et al. (2017) examined nutrient loss predictions including dry matter, energy, protein and wet mass at a macro-level and pointed that excessive food consumption was found to be an important contributor to food system loss and waste. The Global Panel on Agriculture and Food Systems for Nutrition modelled data from FAO and concluded that PHL data were scant in LMICs and reducing PHLs in nutrient-dense foods should be prioritised (Global Panel, 2018).

2 The study approach

2.1 General approach

Our approach is derived from Ferruzzi (2016) who described nutritional qualitative changes in grains during storage. The idea was initially developed together with the African Postharvest Losses Information System (APHLIS), a global network to estimate postharvest weight loss of cereal crops from harvest to market in sub-Saharan Africa (SSA) (Hodges, 2013). APHLIS generates evidence-based estimates on PHL at a large geographical scale combining loss data from literature and experts' inputs (Hodges et al., 2014).

The current study was designed to develop a predictive model using a combination of literature, laboratory and field data (Bechoff et al., 2019). Two categories of NPHLs were considered:

(1) Quantitative NPHLs are nutrient *losses* due to physical loss of food along the value chain *e.g.* between harvesting and marketing. This assumes that the nutritional composition of the product remains constant and compartmentalised.

(2) Qualitative NPHLs are nutrient *changes* in the nutritional composition of food resulting from, e.g., storage duration, pathogen or pest infestation, and temperature This assumes that the nutritional composition of the product changes along the value chain. Qualitative NPHLs generally occur during intermediate and long-term storage of food commodities.

2.2 Case studies

NPHL prediction was considered in three case-studies, each of them dealing with an important food security commodities in SSA: sweet potato in Uganda; and cowpea and maize in Zimbabwe.

Sweet potato is an important food security commodity in Uganda as a source of carbohydrates and fibres. Biofortified orange-fleshed sweet potato contains significant amounts of provitamin A carotenoids. Uganda is amongst the largest producers of sweet potato in Africa behind Malawi, Nigeria, and Tanzania; with about 2 million tonnes per year (FAOStat, 2019).

Cowpea is a rich source of proteins with essential amino-acids. Although maize is known as the food security commodity *par excellence* in Zimbabwe, there is increasing interest in the cultivation of cowpea in Zimbabwe because of its nutritional value and its resilience to climate change (Jiri et al., 2017). Both grains and leaves are consumed.

Maize is a source of income to a large number of Zimbabwean farmers. It is an important source of carbohydrate but is poor in essential amino acids—lysine and tryptophan (Prasanna et al., 2001). Maize therefore needs to be complemented by legumes with a more balanced amino-acid composition. Quality protein maize (with higher lysine and tryptophan levels) and provitamin A biofortified orange maize are grown in very small quantities compared to white maize (Commercial Farmers Union of Zimbabwe, 2016). Maize national production is reported to be 1.7 million tonnes in 2017/18 (Ministry of Agriculture, 2018). Most households, especially in rural areas, grow and store their own maize and mill it when needed. Most of the grain in rural areas is milled into whole grain flour whilst in urban areas, consumers prefer ready refined flour produced by commercial grain processors or dehull the grain first before milling.

3 Methods

3.1 Baseline measurement of nutritional composition

Samples were collected in Uganda (sweet potato) and Zimbabwe (maize and cowpea) at baseline time (*i.e.* harvest time for sweet potato, and beginning storage for maize and cowpea). Sweetpotato samples were analysed at Beca Laboratories, International Livestock Research Institute (ILRI), Kenya. Grain (maize and cowpea) samples were analysed at the Standards Association of Zimbabwe Laboratories in Zimbabwe. These time baseline field samples were collected at two to three different locations and analysed in triplicate (Supplemental Table S1). Analyses were cross-verified with a UK-based laboratory (Kent Scientific Services, West Malling). Measurements on maize, cowpea, fresh sweet potato were expressed on a fresh weight basis while those on dried sweet potato were on a dried weight basis.

3.2 Calculation of weight loss data along the value chain

Four value chains were considered: one for maize and cowpea each, and two value chains for sweet potato. The stages of the value chain analysed were as follows (Fig. 1):

Maize and cowpea: harvest and field drying, transport from the field, further drying of grain, threshing and shelling, winnowing, farm-level storage, packing/sorting/grading, transport to market, and market storage.

Sweet potato (fresh and dried): harvest and handling, transport from the field, household storage of fresh harvest, slicing and drying, on-farm storage after drying, transportation to market, and market storage. Value chains for both fresh and dried sweet potato were selected based on different use of the fresh and dried form.

Weight losses at the different stages of the value chains were calculated as cumulative weight losses following Hodges (2013): the sum of the losses is not the sum of the individual *percentage* losses because the quantity of produce passing through each stage is different and losses are cumulative (Supplemental Table S2). This means that at each step, the previous loss is therefore taken into account.

3.3 Conversion of weight loss data into quantitative NPHLs

Weight losses at each stage of the value chain for each food commodity (as described in 3.2) were converted into NPHLs using the baseline nutritional composition (as described in 3.1).

3.4 Measurement of qualitative NPHLs

3.4.1 Sweet potato drying

Sweet potato was collected before and after drying under field conditions, using raised trays directly exposed to the sun for 2–3 days until dried at two farms in Koch, Omoro district, Uganda. Following collection, samples were kept frozen and sent to BecA Laboratories, ILRI, Kenya for nutritional analysis.

3.4.2 Storage

The storage trials are described in Table 1. Data were obtained from laboratory and field storage trials, where the same varieties were used. Two different predictive models were developed, based on laboratory data with artificial insect infestation and based on field data with natural insect infestation.

Cowpea and maize were artificially infested with common storage insect pests in a controlled laboratory experiment to mimic farm storage. The cowpea weevil, *Callosobruchus maculatus* (F.) was added to cowpea grain jars. The maize weevil, *Sitophilus zeamais* Motschulsky and the larger grain borer, *Prostephanus truncatus* (Horn) were added to jars containing maize grain. The artificially infested grains were stored for up to 6 months (Stathers et al., 2020a). Dried sweet potato was also infested with *S. zeamais* and stored for up to 4 months but the pest did not breed therefore the analysis accounted for non-infestation. Samples were analysed for nutritional composition at Kent Scientific Services, West Malling, UK, following methods described in the supplementary material in Stathers et al. (2020a).

Data were also obtained from field storage trials (at farm level) conducted in Guruve and Mbire districts of Zimbabwe using naturally infested cowpea and maize grains. The districts differ in climates. Two types of storage containers

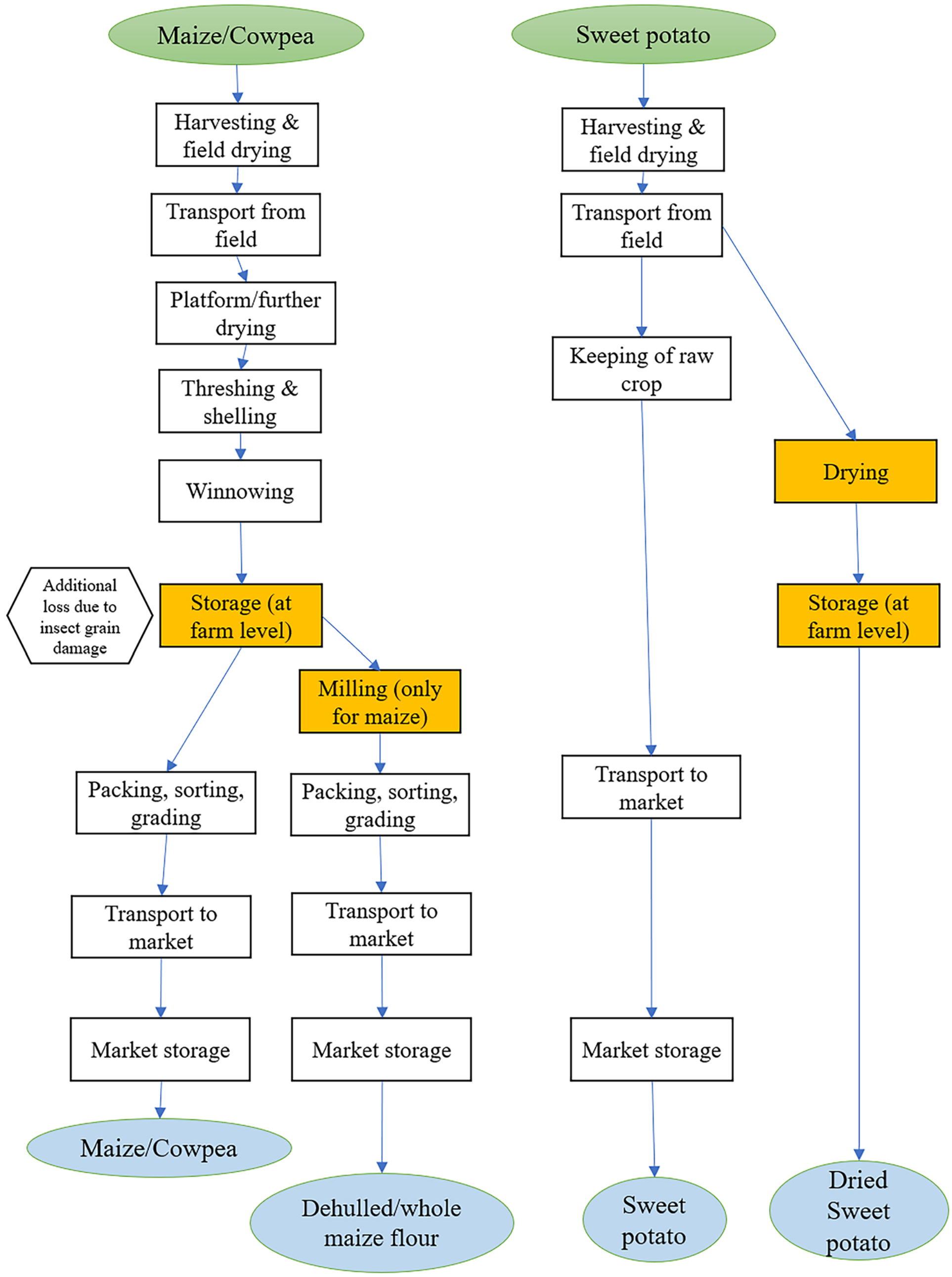

Fig. 1 Steps of the value chain for maize, cowpea, and sweet potato. Adapted from APHLIS + (www.aphlis.net) (APHLIS, 2021). In green colour: crops at time of harvest. In blue: crops at time of being sold. In orange: steps where qualitative NPHLs were modelled. In white, steps where quantitative NPHLs were calculated from weight losses

(conventional woven polypropylene and hermetic GrainPro Super Grain bag (SGBs) IVR™ bags; Ngwenyama et al., 2020) were tested in each district. Sampling was conducted for 8 months. The nutritional composition was analysed by the University of Zimbabwe through Standards Association of Zimbabwe Laboratories following Stathers et al. (2020a).

Based on empirical nutrient recovery data, predictive equations were generated using a multiple linear regression model in JMP Pro version 14 (SAS Institute Inc.). Storage duration, level of insect pest infestation, temperature, and percentage insect damaged grain along with their interaction terms were considered as factors in the regression. The content of each nutrient was regressed against these factors and their interaction, using standard least squares. Assumptions associated with linear regression were evaluated. When the assumption of normality were not met, data were transformed (Supplemental Table S3) and the regression model was compared against the non-transformed data. The coefficient of multiple determination (R^2) was used to assess the fraction of variance of the considered nutrient that was accounted for by the regression model. Significant effects of

Table 1 Trials to estimate qualitative NPHLs at the Storage step

Trial	Treatment/Infestation	Time points	Replication	Minimum storage time (weeks)	Maximum storage time (weeks)
Artificial infestation: Laboratory study (NRI, UK)[2]					
White maize (cv SC719[1])	No (control)	6	3	0	32
	S. zeamais (High infestation)	4	3	0	24
	S. zeamais + *P. truncatus* (Low infestation)	5	3	0	24
Orange maize (cv ZS242[1])	No (control)	3	3	0	16
	S. zeamais + *P. truncatus* (Low infestation)	2	3	0	16
Cowpea (cv CBC2[1])	No (control)	5	3	0	24
	C. maculatus (High infestation)	3	3	0	24
	C. maculatus (Low infestation)	4	3	0	24
Dried sweet potato (Vita)	No	4	3	0	16
Natural infestation: Field study (Zimbabwe) [3]					
White maize (cv SC719)	Natural infestation in polypropylene bags Natural infestation in hermetic bags	4	6[4]	0	32
Orange maize (cv ZS242)	Natural infestation in polypropylene bags Natural infestation in hermetic bags	4	6[4]	0	32
Cowpea (cv CBC2)	Natural infestation in polypropylene bags Natural infestation in hermetic bags	4	6[4]	0	32

cv = cultivar

[1]Raw data is the same as in Stathers et al. (2020a)

[2]Predictive factors are storage time; level of infestation Target nutrients are Energy, Moisture, Protein, Fat, Carbohydrate, Dietary fibre, Iron, Zinc, and Vitamin A only for orange maize and dried sweet potato

[3]Predictive factors are storage time; level of infestation; ambient temperature.Target nutrients are Energy, Moisture, Protein, Fat, Carbohydrate, Dietary fibre, Iron, Zinc and Vitamin A only for orange maize

[4]3 replicates × 2 locations (Guruve & Mbire districts)

each factor of the regression model on the considered nutrient levels were tested using analyses of variance (ANOVA). Predictive equations were developed as linear regressions:

$y = a + bx1 + cx2 + dx3$ where y = considered nutrient content in the commodity; x_1 = storage duration; x_2 = percentage damaged grain; x_3 = temperature (field data only) and *a, b, c, d* are parameters.

For each nutrient, NPHL was calculated as $\frac{y0-y}{y0}$ where y_0 is the initial considered nutrient content and y the considered nutrient content as in the preceding equation. Table 2 gives a description of the main variables.

Extech Instruments® Humidity/Temperature Data-loggers Model RHT10 (FLIR Systems, Inc., Nashua, USA) were installed under the roofs of selected representative storage facilities to measure and store temperature and relative humidity at 30-min intervals. Data were downloaded and saved at bi-monthly intervals. Storage time was the only factor incorporated in the prediction model for dried sweet potatoes as there had been no insect breeding in the experimental trials. We used a laboratory model previously developed by Bechoff et al. (2010a) to predict provitamin A degradation during storage of dried orange-fleshed sweet potato (OFSP). Estimated additional weight losses due to insects consuming the grains were modelled in the laboratory and in the field (grain weight loss vs. damaged grain) (Supplemental Fig. S1).

3.4.3 Maize milling

The influence of milling on the nutrient losses in maize was estimated after farm storage. Nutrient losses in maize (yellow and white) from whole grain to whole flour or refined (dehulled) flour were obtained from the United States Department of Agriculture database (Suri & Tanumihardjo, 2016).

3.5 Combination of quantitative and qualitative NPHLs

The final model combining quantitative and qualitative NPHLs was implemented in Microsoft Excel (Microsoft Office, 2010). The model involves fixed values – *i.e.* quantitative NPHLs, qualitative NPHLs after maize milling and sweet potato drying—and variable values, which are

Table 2 Table of variables and abbreviations

Variable	Description	Units
y	Considered nutrient content in the product[1] and outcome of predictive equations	Energy (Kcal), Protein (g), Carbohydrate (g), Fat (g), Dietary Fibre (g), Iron (mg), Zinc (mg), Provitamin A (mg)
NPHL	Nutritional postharvest loss (per 100 g of product[1])	
EAR	Estimated Average Requirement per day (this varies per group of nutritional interest[2])	
Population-weighted EAR (Pop_EAR)	Estimated Average Requirement adjusted for an average individual within the country[3]	Energy (10^6 kcal), Protein in metric tonnes (t), Carbohydrate (t), Fat (t), Dietary Fibre (t), Iron (kg), Zinc (kg), Provitamin A (kg)
NPHLc	Nutritional postharvest loss at country[3] level per year (based on the national production)	
NPHLcd	Nutritional postharvest loss at country[3] level per day	
N	Number of people in the country[3] having not met their daily EAR as a result of Nutritional postharvest loss. It is expressed as NPHLcd divided by Pop_EAR	-

[1]Sweet potato, maize, or cowpea

[2]Populations were categorised into groups of nutritional interest as follows: Children < 5 years, Children 5–15 years, Adolescent boys 15–19 years, Adolescent girls 15–19 years, Adolescent girls 15–19 years and pregnant, Adolescent girls 15–19 years and lactating, Men 20–49 years, Women 20–49 years and not pregnant/lactating, Women 20–49 years and pregnant, Women 20–49 years and lactating, Men 50 + years, Women 50 + years. The age categories 50 + were selected because there were few people over this age in the population pyramid

[3]Uganda or Zimbabwe

the qualitative NPHLs during storage that are predicted by equations.

3.6 Conversion of nutrient loss into nutritional requirement lost

First, NPHL (per 100 g of product) was converted into nutrient loss at country level ($NPHL_C$) as follows:

$NPHLc = NPHL \times P/100$ where $NPHL_C$ is the nutrient loss at the country level in the food commodity; $NPHL$ is the nutrient loss per 100 g of commodity; P is the national commodity production per year.

National commodity production data per annum (P) were obtained from- FAO(FAOStat, 2018) for sweet potato, and the Ministry of Agriculture of Zimbabwe (Ministry of Agriculture, 2018). The total production was estimated to be consumed in-country and the export part of the production was not considered here in order to simplify the calculations. Orange-fleshed sweet potato production in Uganda was estimated to be 10% of the white sweet potato production and the proportion of sweet potato that was dried estimated at 15% (Robert Mwanga, International Potato Center, Personal Comm.). National Orange maize production in Zimbabwe was estimated from an article of the Commercial Farmers Union of Zimbabwe (2016).

The daily amount of nutrient lost ($NPHLcd$) was calculated by dividing the nutrient lost at the country level ($NPHL_C$) by 365 days.

The Estimated Average Requirement (EAR) is the individual daily nutrient level estimated to meet the nutrient requirements of 50% of the population (healthy individuals) according to the Nutrient Reference Values from Australia and New Zealand (NHMRC, 2006). In order to estimate the loss in nutritional requirements at country level, we calculated the population-weighted EAR (also equivalent to the EAR of an average individual in Uganda or in Zimbabwe).

Population-weighted EAR (Pop_EAR) was calculated as a weighted average of the proportion of the groups of interest in these countries (p) multiplied by the daily EAR of each of the groups of nutritional interest:

$$\begin{aligned} Pop\_EAR = {} & p(children < 5years).EAR(children < 5years) \\ & + p(children5-15years).EAR(children5-15years) + \ldots \\ & + p(men50+).EAR(men50+) + p(women50+).EAR(women50+) \end{aligned}$$

Groups of nutritional interest were selected based on the Demographic Health Surveys (DHS) for Uganda and Zimbabwe and the population age pyramid of Uganda and Zimbabwe (Population Pyramid, 2019; Uganda DHS, 2016; Zimbabwe DHS, 2015). The number of pregnant women was calculated from the percentage of pregnant women given by the DHS Surveys for Uganda and Zimbabwe (respectively 6.3% and 10% of women 15–49 year-old) (Uganda DHS, 2016; Zimbabwe DHS, 2015). The number of lactating women was calculated from the birth rate (34.2 and 42.9

live birth per 1000 in Zimbabwe and Uganda, respectively; Index Mundi) minus the infant death rate (36 and 35 infant mortality per 1000 live birth in Zimbabwe and Uganda, respectively; UNICEF Zimbabwe, 2019, UNICEF Uganda, 2019). The number of live infants was made equal to the number of women giving birth and having a live infant (we did not consider twin or more births). The number of lactating women was calculated using the proportion of women breast-feeding from the DHS (98% and 97% in Zimbabwe and Uganda, respectively). The average weight gain of pregnant women was indicated to be on average 7.5 kg over the pregnancy period (NHMRC, 2006). For each nutrient, we calculated the average additional requirement of pregnant women over the 9 month-pregnancy period. The average weight of lactating women was estimated to be the same as before pregnancy. The nutritional requirements of lactating women was estimated to be for exclusive breast-feeding over the first 6 months and thereafter partial breast-feeding up to 12 months (NHMRC, 2006).

The number of people (*N*) having lost their daily nutritional requirement was calculated as follows: This calculation gave the estimated number of average individuals in the country who would have not fulfilled their daily nutritional requirement (EAR) as a result of the commodity PHL.

4 Results

4.1 Sweet potato

4.1.1 Fresh sweet potato

Retention and loss of nutrient at each stage of the value chain and cumulative nutrient losses are presented for sweet potato in Tables 3 and 4. In the case of fresh white fleshed sweet potato (WFSP) (Table 3), the same proportions of nutrients are lost at each stage of the value chain. In our example, the initial energy is 146.8 kcal per 100 g of sweet potato. Following harvest and handling, the energy decreases by 14% (126.2 kcal). Transport from the field results in a further decrease of 0.4% to 126.2 kcal because it is a cumulative loss, etc. The same calculation applies to each of the nutrients. The cumulative loss is 19.9%.

4.1.2 Dried sweet potato

With dried and stored orange-fleshed sweet potato (OFSP) (Table 4), the proportions of nutrient loss as a result of weight loss (quantitative NPHLs) at each stage of the value chain (harvesting and handling, transport from field, drying, farm-level storage) are independent of the type of nutrient (as with fresh sweet potato in 4.1.1). On the other hand,

Table 3 Predicted quantitative nutritional postharvest losses (NPHLs) along the white fleshed sweet potato (WFSP) value chain in Uganda for non-infested. Not stored. Nutritional composition is per 100 g of crop, on a fresh weight basis

		Retention at each step					NPHL at each step[2]					
	Baseline[1]	Harvesting and handling	Transport from field	Keeping of raw crop	Transport to market	Market storage	Harvesting and handling	Transport from field	Keeping of raw crop	Transport to market	Market storage	Cumulative loss
%	100.0	86.0	85.6	85.1	82.6	80.1	14.0	0.4	0.4	2.6	2.5	19.9
Energy Kcal)	146.8	126.2	125.6	125.0	121.2	117.6	20.5	0.6	0.6	3.7	3.6	19.9%
Protein (g)	1.07	0.92	0.91	0.91	0.88	0.85	0.15	0.00	0.00	0.03	0.03	19.9%
Carbohydrate (g)	33.1	28.4	28.3	28.2	27.3	26.5	4.6	0.1	0.1	0.8	0.8	19.9%
Fat (g)	0.4	0.3	0.3	0.3	0.3	0.3	0.1	0.0	0.0	0.0	0.0	19.9%
Dietary Fibre (g)	3.3	2.9	2.9	2.8	2.8	2.7	0.5	0.0	0.0	0.1	0.1	19.9%
Iron (mg)	0.6	0.5	0.5	0.5	0.5	0.5	0.1	0.00	0.0	0.0	0.0	19.9%
Zinc (mg)	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.00	0.0	0.0	0.0	19.9%

Table 4 Predicted quantitative and qualitative nutritional postharvest losses (NPHLs) along the orange fleshed sweet potato (OFSP) value chain in Uganda including drying and storage stages. Non-infested. Stored for 16 weeks at an average temperature of 26 °C. Nutritional composition is per 100 g of crop, on a dry weight basis

	Retention at each step					NPHL at each step					
						Quantitative NPHLs[2]				Qualitative NPHLs during drying & storage[3]	Cumulative loss
	Baseline[1]	Harvesting and handling	Transport from field	Drying>	Storage (at farm level)	Harvesting and handling	Transport from field	Drying	Storage (at farm level)		
%	100.0	86.0	85.6	83.0	77.2	14.0	0.5	3.0	7.0	variable	22.8
Energy (Kcal)	365.1	314.0	312.5	303.1	279.2	51.1	1.6	9.4	21.2	2.6	23.5%
Protein (g)	2.41	2.07	2.06	2.00	1.73	0.34	0.01	0.06	0.14	0.04	24.7%
Carbohydrate (g)	78.4	67.4	67.1	65.1	59.1	11.0	0.3	2.0	4.6	1.4	24.6%
Fat (g)	1.3	1.1	1.1	0.6	0.5	0.2	0.0	0.0	0.1	0.5	62.7%
Dietary Fibre (g)	15.1	13.0	12.9	12.5	14.0	2.1	0.1	0.4	0.9	-2.3	7.4%
Iron (mg)	2.0	1.7	1.7	1.6	1.6	0.3	0.0	0.1	0.1	0.0	20.6%
Zinc (mg)	0.3	0.2	0.2	0.2	0.2	0.0	0.0	0.0	0.0	0.0	20.6%
Provitamin A (mg)	8.2	7.0	7.0	1.1	-0.1	1.1	0.0	0.2	0.5	6.5	102.8%

[1]The baseline nutritional composition is provided in Supplemental Table 1

[2]The postharvest losses (PHLs) figures were provided by APHLIS + (see Supplemental Table 2)

[3]Predictive equations for qualitative NPHLs are in Supplemental Table 3

the proportions of nutrient loss due to quality change in the food commodity during drying and farm-level storage (qualitative NPHLs) are nutrient-dependent. The cumulative loss is highly variable from 7.4 to ~ 100%, depending on the nutrient. Dried and stored OFSP has an increased concentration of fibre and also slightly of iron/zinc minerals (respectively 7.4% and 20.6%) as compared with fresh OFSP. This mineral concentration could result from contamination for example from the soil. There is a sharp decrease in fat (62.7%) and no vitamin A was retained in the product as a result of drying and 16 weeks of farm-level storage (102.8 ≈100% loss).

4.1.3 Nutritional impact of sweet potato loss in Uganda

The percentage of the Ugandan population potentially losing their EAR as a result of sweet potato PHL are presented in Table 5. PHL in a year is equivalent to 1.4 million people (3.3%) and close to 70,000 people (1.7% of the population) losing their daily nutritional requirements in carbohydrate and energy, respectively if we sum up WFSP and OFSP and fresh and dried forms. This reflects that sweet potato is essentially a source of carbohydrate. The proportion of children affected by this loss is higher because children's needs are lower and therefore the same nutrient quantity loss would correspond to more children losing their EAR. Pregnant women's figures are close to that of the average population because their requirements are higher than that of the average person in the population, despite their number being smaller.

In spite of its low production (10% of that of WFSP), fresh and dried OFSP potentially represent a significant source of vitamin A to the diet. Sweet potato loss in production per annum corresponds to a loss in daily vitamin

Table 5 Predicted number of people (N) and percentage of the population missing their daily nutritional requirements[1] as a result of sweet potato postharvest loss in Uganda

	Fresh WFSP[2]	Dried & stored WFSP[2]	Fresh OFSP[1]	Dried & stored OFSP[3]
N				
Energy	544,193	95,921	44,555	7,960
Protein	275,175	50,854	20,417	3,828
Carbohydrate	1,093,950	201,597	85,366	15,932
Fat	63,347	30,052	6,866	3,278
Vitamin A [4]			388,482	309,064
% Population				
Energy	1.31%	0.23%	0.11%	0.02%
Protein	0.66%	0.12%	0.05%	0.01%
Carbohydrate	2.63%	0.48%	0.20%	0.04%
Fat	0.15%	0.07%	0.02%	0.01%
Vitamin A [4]	-	-	0.93%	0.74%
% Children under 5-year-old				
Energy	3.66%	0.65%	0.30%	0.05%
Protein	2.10%	0.39%	0.16%	0.03%
Carbohydrate	7.76%	1.43%	0.61%	0.11%
Fat	0.30%	0.14%	0.03%	0.02%
Vitamin A [4]	-	-	1.53%	1.22%
% Pregnant women				
Energy	1.05%	0.19%	0.09%	0.02%
Protein	0.41%	0.08%	0.03%	0.01%
Carbohydrate	2.11%	0.39%	0.16%	0.03%
Fat	0.13%	0.06%	0.01%	0.01%
Vitamin A [4]	-	-	0.80%	0.64%

[1]Expressed as population-weighted EAR and percentage of specific vulnerable groups. White fleshed sweet potato (WFSP); Orange fleshed sweet potato (OFSP). Calculations are based on an annual production of WFSP in Uganda of 1,529,608 tonnes (FAOStat, 2018). OFSP production in Uganda was estimated to 10% of the WFSP production, and the proportion of sweet potato being dried to 15%

[2]Non-infested. Not stored (fresh sweet potato is generally sold within a week)

[3]Non-infested. Storage time: 16 weeks, average temperature: 26 °C

[4]Bioconversion factor for provitamin A to retinol from OFSP is 12:1 Bechoff and Dhuique-Mayer, 2017

Population-Weighted EAR data are in Supplemental Table 5

A nutritional requirements for around 400,000 and 300,000 peoplefor fresh and dried OFSP, respectively. The nutritional impact is higher if children were considered. Loss of fresh and dried OFSP would translate into 1.5% and 1.2%, respectively of the nutrient loss of all children under 5 years old and 0.8% and 0.6%, respectively of all pregnant women, as a proportion of the Ugandan population. An increase in the production of OFSP and a decrease in PHLs therefore have a potentially positive nutritional impact on vitamin A intake at national level.

4.2 Cowpea and maize

4.2.1 Comparison of model predictions for stored cowpea and maize

Four predictive models are presented in Table 6. Model 1 is the quantitative NPHL model that does not include the qualitative NPHL prediction. Model 2 is based on laboratory data while Model 3 uses field data. Prediction equations of qualitative NPHL losses for Models 2 and 3 are in

Table 6 Predicted percentage of quantitative and qualitative nutritional postharvest losses (NPHLs) for insect-infested-cowpea and maize, using several different predictive models

Predictive model	1		2		3		4
	Quantitative NPHL only[1]		Lab. storage prediction[2]		Field storage prediction in Zimbabwe[3]		Calculated from Stathers et al. (2020a)[4]
Cowpea	-	Control (non-infested)	*C. maculatus* (high)	*C. maculatus* (low)	Polypropylene bags	Hermetic bags	*C. maculatus*
Cumulative loss [5]	28.4%	28.4%	30.9%	30.9%	39.6%	31.2%	43.4%
Energy	28.4%	30.2%	36.6%	37.0%	41.5%	31.5%	44.4%
Protein	28.4%	28.3%	27.4%	29.0%	36.8%	29.5%	9.7%
Carbohydrate	28.4%	28.4%	42.3%	42.3%	46.6%	31.5%	65.8%
Fat	28.4%	54.3%	19.8%	19.8%	29.2%	33.1%	-7.4%
Dietary Fibre	28.4%	30.5%	44.3%	44.3%	22.0%	40.7%	59.2%
Iron	28.4%	28.4%	25.3%	25.3%	34.4%	28.9%	19.9%
Zinc	28.4%	31.1%	33.9%	31.3%	34.3%	29.0%	31.8%
Maize	-	Control (non-infested)	*S. zeamais* (high)	*S. zeamais* + *P. truncatus* (low)	Polypropylene bags	Hermetic bags	*S. zeamais* + *P. truncatus* (low & high)
Cumulative loss [5]	25.9%	25.9%	32.4%	32.4%	29.0%	26.3%	38.5%
Energy	25.9%	25.6%	31.5%	32.9%	28.3%	26.7%	39.3%
Protein	25.9%	25.2%	24.9%	31.8%	-	-	35.5%
Carbohydrate	25.9%	25.5%	36.5%	34.5%	27.1%	26.7%	40.4%
Fat	25.9%	25.9%	27.9%	39.8%	37.9%	26.5%	-
Dietary Fibre	25.9%	25.9%	-	-	-	-	32.5%
Iron	25.9%	25.9%	-	-	91.6%	45.5%	44.6%
Zinc	25.9%	26.3%	27.4%	34.9%	-	-	-

[1]With no storage and no infestation

[2]Artificial infestation. Conditions selected are a storage time of 10 weeks and a percentage damaged grain (%DG) of 40% (except for control)

[3]Natural infestation. Insect species for cowpea reported are: *C. rhodesianus, Wasps*. Insect species for maize reported are: *S. zeamais, P. truncatus, S. cerealella, T. castaneum, R. dominica, Wasps, Cryptolestes*. Conditions selected are an average temperature of 26 °C, a storage time of 10 weeks and a %DG of 40% in Polypropylene bags, and a storage time of 10 weeks and a %DG of 10% in Hermetic bags in Guruve and Mbire districts in Zimbabwe

[4]Raw data are the same as the Model 2 (Laboratory). [5] Weight loss including weight lost due to insect grain damage during storage. Predictive equations used to estimate qualitative NPHLs for Models 2 and 3 are in Supplemental Table 3. Predictive equations for Model 4 are in Stathers et al. (2020a). Conditions selected are a %DG of 40%

Supplemental Table S3. Model 4 uses the same laboratory data as Model 2 but with different equations. Model 4 was developed by combining Model 1 with the purely qualitative NPHL model by Stathers et al. (2020a).

With cowpea, Models 2 and 4 (that use the same data) show a similar trend but nutrient variations in Model 4 are larger compared to Model 2. For example, fat and protein are concentrated, resulting in a negative loss of fat (-7.4%) while dietary fibre and carbohydrate are sharply reduced (59.2% and 65.8%, respectively). Levels of variability with Model 2 exceed possible ranges with no negative or extreme values. Model 3 with non-controlled infestation (polypropylene bags) follows the same variations as in Models 2 and 4 (i.e., sharp reduction of carbohydrate, concentration in protein, fat, and iron).

NPHLs are reduced with GrainPro hermetic bags (Model 3 with hermetic bags) that have lower insect damage than with standard polypropylene bags (Model 3 with polypropylene bags).

With maize, the variations in nutrients were not as large as with cowpea. The models were thus more difficult to compare. We were unable to model iron and dietary fibre using Model 2, and protein, dietary fibre and zinc using Model 3. In the presence of *P. truncatus* + *S. zeamais*, there was an additional consumption of fat, protein, and zinc whilst *S. zeamais* alone only led to a reduction in carbohydrate. In the field, on naturally infested grains, those selective feeding patterns were harder to detect. In Model 3 (field), the iron level was strongly reduced in both polypropylene and hermetic bags and this concurs with results from Model 4 (laboratory).

4.2.2 Influence of maize milling

Figure 2 shows predicted annual NPHLs in maize (whole grain, flour from whole grain, refined flour from dehulled grain) for Zimbabwe. Changes in maize composition after milling are presented in Supplemental

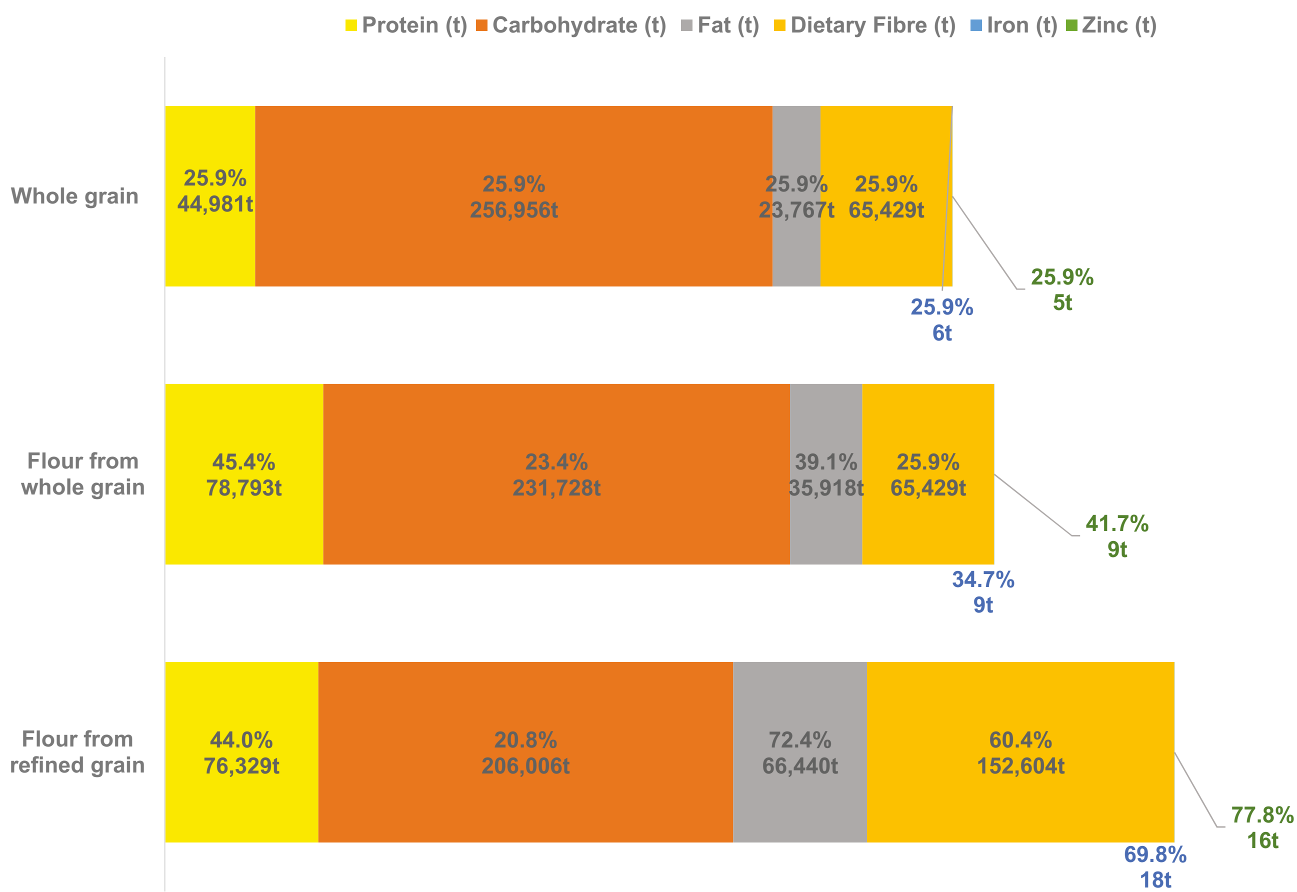

Fig. 2 Predicted annual nutritional postharvest loss (NPHLc) of white maize in Zimbabwe influenced by milling (in percentage and metric tonnes) without grain storage. Percentage change of the various nutrients following milling are in Supplemental Table 4

Table S4. Milling increases nutrient losses. On average, 25.9% of the maize produced is lost due to postharvest operations but when maize is milled into flour, the percentage of protein and zinc lost is almost doubled (45.4% and 41.7% loss over the whole value chain, respectively), and fat and iron loss is also increased by a third (39.1% and 34.7% loss). When maize is dehulled (during which degerming also occurs) and milled into flour, NPHL is much higher, with a loss of half the protein (44.0%), but also a loss of dietary fibre (60.4%), and over two third of fat, iron, and zinc (72.4%, 68.9%, and 77.8%, respectively).

4.2.3 Nutritional impact of cowpea and maize loss in Zimbabwe

The percentages of the Zimbabwean population potentially losing their EAR as a result of cowpea and white maize PHL are presented in Table 7 (details of the Population-weighted Estimated Average Requirement (EAR) calculations for Zimbabwe and Uganda are in Supplemental Table S5). The NPHLs were modelled based on the field grain storage study with natural insect infestation. Predictions were done for the grain with no storage (equivalent to a quantitative NPHL only – Model 1), and stored for 10 weeks with 40%

Table 7 Predicted number of people (N) and percentage of the population missing their daily nutritional requirements as a result of cowpea and maize loss postharvest loss in Zimbabwe

Crop	Cowpea			White Maize		
	Not stored[2]	Stored in polypropylene bags[3]	Stored in Hermetic bags[4]	Not stored[2]	Stored in polypropylene bags[3]	Stored in Hermetic bags[4]
N						
Energy	18,093	26,463	20,047	1,838,130	2,009,963	1,894,846
Protein	89,298	115,635	92,801	3,657,747	4,090,097	3,709,332
Carbohydrate	24,244	39,800	26,919	2,712,193	2,841,387	2,798,065
Iron	121,003	146,666	123,325	2,704,186	9,558,303	4,750,054
Zinc	64,247	77,583	65,573	2,070,016	2,314,694	2,099,209
% Population						
Energy	0.11%	0.16%	0.12%	11%	12%	12%
Protein	0.55%	0.71%	0.57%	22%	25%	23%
Carbohydrate	0.15%	0.24%	0.16%	17%	17%	17%
Iron	0.74%	0.90%	0.75%	17%	59%	29%
Zinc	0.39%	0.47%	0.40%	13%	14%	13%
% Children under 5-year-old						
Energy	0.32%	0.47%	0.35%	32%	36%	33%
Protein	1.81%	2.34%	1.88%	74%	83%	75%
Carbohydrate	0.45%	0.74%	0.50%	51%	53%	52%
Iron	0.84%	1.01%	0.85%	19%	66%	33%
Zinc	1.09%	1.32%	1.11%	35%	39%	36%
% Pregnant women						
Energy	0.09%	0.13%	0.10%	9%	10%	10%
Protein	0.35%	0.46%	0.37%	14%	16%	15%
Carbohydrate	0.12%	0.20%	0.14%	14%	14%	14%
Iron	0.22%	0.27%	0.23%	5%	18%	9%
Zinc	0.31%	0.37%	0.31%	10%	11%	10%

[1]Expressed as population-weighted EAR and percentage of specific vulnerable groups. Calculations are based on an annual production of cowpea and white maize in Zimbawe of 16,380 tonnes and 1,700,702 tonnes, respectively (Ministry of Agriculture, 2018)

[2]Non-infested. Not stored. Quantitative NPHL only (Model 1)

[3]Natural field infestation (Model 3). Storage time: 10 weeks. Percentage of damaged grain: 40%. Average temperature: 26 °C

[4]Natural field infestation (Model 3). Storage time: 10 weeks. Percentage of damaged grain: 10%. Average temperature: 26 °C

Predictive equations used to estimate qualitative NPHLs for Model 3 are in Supplemental Table 3

Population-Weighted EAR data are in Supplemental Table 5 and 10% grain damage in polypropylene bags and hermetic bags, respectively (Model 3). These levels of damage were selected based on an observation of the relationship between storage and damaged grain with these two types of storage containers. With levels of grain damage beyond 40–50%, grains tend to become unsuitable for human consumption (Tanya Stathers, Natural Resources Institute, Pers. Comm).

According to the models, PHL of white maize is equivalent to about 17% of carbohydrate and 22–25% protein lost for the Zimbabwean population per annum depending on the type of storage selected. If we consider specific vulnerable groups, NPHL could be equivalent to 51–53% and 14% of carbohydrate, and 74–83% and 14–16% of protein of children under five year-old and pregnant women's nutritional requirements lost, respectively.

Cowpea NPHL in protein would be equivalent to about 2% of the children under five year-old and 0.4% of pregnant women over the total population losing their daily requirements in protein. For iron, this will represent around 0.9% and 0.2%, respectively and for zinc, about 1.2% and 0.3% of children under five and pregnant women, respectively.

The predicted number of people who would not meet their EAR as a result of vitamin A loss in orange maize is described in Fig. 3. The loss of biofortified orange maize is about 10,000 tonnes per year (25.9% of production), a fraction of the production of white maize. However, the loss in vitamin A from orange maize could have a nutritional impact at the national level with tens of thousands of people affected. With longer storage periods, there is an increased vitamin A loss and therefore a predicted increased number of people affected. The model shows that before storage, NPHL would be equivalent to about 20,000 people losing their EAR (0.1% of the population in Zimbabwe) but after 32 weeks of storage, this would be equivalent to 50,000 and 70,000 people (0.4 and 0.5% of the population) losing their EAR in vitamin A, for orange maize storage in hermetic and polypropylene bags, respectively.

5 Discussion

5.1 Quantitative NPHLs

5.1.1 Development of the quantitative model

Quantitative NPHLs are obtained by converting weight losses into nutritional losses using weight loss data. Measuring weight loss is difficult because of the logistical challenges of analysing the food commodities' value chains, which might occur at different times in different households,

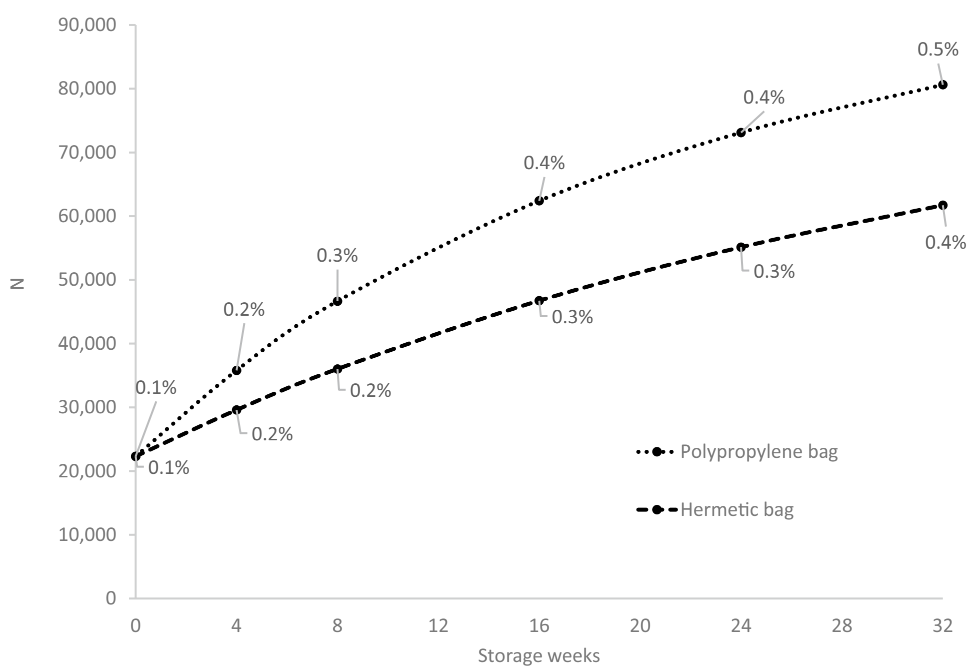

Fig. 3 Predicted number of people (N) and percentage of the population who could lose their daily nutritional requirement in vitamin A[1] as a result of storing orange maize in Zimbabwe: Storage (at farm level). Model 3 (Natural Infestation). Level of damaged grain: 20–70%, storage time: 0–32 weeks, average temperature: not included in the equation. [1]β-carotene content. The other carotenoids were not analysed. β-carotene in maize would represent only a third to half of the provitamin A of orange maize (Nkhata et al., 2019; Taleon et al., 2017). Bioconversion factor for provitamin A to retinol (vitamin A) from Orange Maize used was 4:1 (Bechoff and Dhuique-Mayer, 2017). Average percentage damaged grain (DG) in relation to storage time was estimated using a linear equation and calculated at each storage time (t) as follow: $DG = at + b$ where a = 1.56; b = 20.21 for polypropylene bags and a = 0.27 and b = 19.66 for hermetic bags

and all the possible scenarios leading to different levels of PHLs. Delgado et al. (2017), and Chaboud and Daviron (2017) explained that weight loss measurements found in literature are often inconsistent and imprecise. In our study, collecting weight loss from the field would have required extensive fieldwork and the data (for instance, obtained in a limited geographical area at a certain season) may still not reflect the entire variation in any single region. Therefore, weight losses for sweet potato, cowpea, and maize were obtained from APHLIS (Supplemental Table S2).

APHLIS uses various food composition tables to determine baseline nutritional data (APHLIS, 2021). We however used measured nutritional composition data at baseline (Supplemental Table S1). Databases can give more robust data prediction because the prediction is less sensitive to variations observed in the local context considering that: (i) it is not always possible to obtain data from the field, and (ii) nutritional analyses are generally costly and lengthy. On the other hand, nutritional data obtained from field samples could be considered more context-specific and therefore more accurate than that of global food composition tables (e.g. USDA; van Heerden and Schönfeld, 2004).

When nutritional loss is purely quantitative, the assumption is that the loss for various nutrients is the same. For fresh sweet potato, we made the assumption that there was little qualitative nutritional losses. Minor qualitative nutritional losses were observed in fresh sweet potato (sugars, carotenoids, starch) stored over long periods of time (over five months) (Ezell & Wilcox, 1952; Kósambo et al., 1999). In practice, fresh sweet potato in Uganda could be sold within a week after harvest. Additional variables could be included to refine the model in future. For example, sweet potato has a high moisture content that tends to decrease in storage. Parmar et al. (2017) showed that moisture content can significantly account for PHL in sweet potato during seven days of market storage. Although physical weight would be reduced, moisture loss would not normally result in nutrient loss because select nutrients would have their concentration increased in material with higher dry matter content. A simple measurement of weight loss could create a bias on the predictive model for NPHLs and the loss in moisture would need to be accounted for.

5.2 Qualitative NPHLs

5.2.1 Development of the qualitative model

Qualitative nutritional changes between harvest and market are losses that typically occur when food commodities are stored for long periods causing nutrient changes in the crop. These changes cannot be calculated using weight loss because they are not directly linked to the loss in weight of the product but to changes in the quality of the product itself. Estimation of qualitative NPHLs requires an understanding of the environmental factors and stages of the value chain that could influence nutrient degradation.

Literature data were sparse, inconsistent, or inaccurate. Hence, for qualitative NPHL, data were obtained from laboratory and field experiments. The qualitative model was generated to predict macronutrient and micronutrient losses during storage that may occur due to several factors including insect damage, high moisture, temperature, air oxidation, etc. Consumption of grains by insects results in a further weight loss in the product (Tefera et al., 2011).

We assumed that storage at the farm was the stage where qualitative NPHLs could mostly occur because the food commodity in its dried form (e.g. grain or dried sweet potato) could be stored for long periods of time (6–8 months) as compared to the market stage. We also selected drying of sweet potato and milling of maize as stages for estimating qualitative NPHLs. Drying can lead to significant degradation of provitamin A if carried out for several days (Bechoff, 2010). Our results concur with Suri and Tanumihardjo (2016) who showed that milling of maize into flour and degermination strongly modify the nutritional composition of maize, because minerals are contained in the germ. However, most carotenoids are found in the endosperm, and B vitamins are found either in the germ or endosperm. Therefore, degerming results in significant losses of minerals such as iron and zinc and some B vitamins but would concentrate vitamin A (carotenoids) (Suri & Tanumihardjo, 2016). This was also our observation.

The example of dried and stored OFSP shows that there are important differences in the retention of nutrients at postharvest stages, and qualitative NPHLs should be integrated as part of a model prediction of PHLs in relation to nutrition and food security. At the drying stage, there was a sharp loss in fat and provitamin A content from field samples in Uganda. This nutrient loss may have resulted from adverse field conditions *i.e.* high ambient temperatures, direct exposition to sun light, and extended traditional drying for several days as it is often practised in eastern parts of Uganda (Bechoff, 2010). Nutrients such as fat (i.e. highly unsaturated fat present in sweet potato) and provitamin A are sensitive to oxidation (air, light, temperature) and can be degraded through free radical reactions (Bechoff, 2010; Bechoff et al., 2010a, b). Macronutrients such as protein, carbohydrate and minerals are less sensitive to degradation due to adverse environmental conditions.

5.2.2 Development of predictive equations at the storage stage

Predictive equations of qualitative NPHL losses at the storage stage were developed through modelling of individual energy, macro and micronutrient content. Various models (Models 1 to 4) for cowpea and maize were compared (Table 6). Model 4 (from another publication—Stathers et al., 2020a) gave closer results to Model 2 that used the same insect infestations than to the other models (*C. maculatus* for cowpea and *P.truncatus* + *S. zeamais* for maize), as this was expected. According to Stathers et al. (2020a), *S. zeamais* preferentially feeds on the floury endosperm (rich in carbohydrate) whilst *P. truncatus* feeds on both the germ and endosperm (reducing the proportion of fat, protein, iron and zinc). The insect infestation data explain these nutrient trends during storage. In laboratory trials, Stathers et al. (2020a) demonstrated that there was a positive relationship between insect grain damage and iron reduction. However, it is difficult to explain why iron reduction was so high in maize stored under field conditions (Model 3 with polypropylene bags), It is possible that the trend could be associated with natural rather than artificial insect infestation or iron soil contamination. Additionally, in Model 3, there were many insect species, which made it difficult to model.

An attempt was made to reconcile these data through the models generated. This exercise proved challenging for several reasons: First, as described previously, there were limitations on the quantity and variability of empirical data collected; Second, additional factors were present in field-derived data that were not assessed in laboratory analyses. Additional factors such as geographic location and growing conditions can impact initial nutrient content. In addition to these agronomic/environmental factors, storage technology and conditions (use of hermetic bags, temperature and relative humidity) were factors that differed from laboratory conditions; Third, the laboratory and field models were set under different insect pest infestation levels and conditions (artificial or natural insect infestation). Natural infestation involved several insect species, especially in the case of maize. There were also insect-specific feeding habits with some being primary feeders while others were secondary feeders. Full reconciliation of these models could therefore not be completed. Two different predictive models with a complementary approach are thus put forward: one based on laboratory prediction and another on field data prediction.

While these findings provide a useful tool to predict nutritional changes during storage conditions in cowpea, maize, and sweet potato, there are limitations in using these models. This is reflected in the range of empirical data used in its development, and the relatively limited number of sites involved in the study.

5.3 Nutritional impact of NPHLs at country level

The quantitative NPHL calculator was initially developed by Stathers, Bush, de Bruyn, and Ferruzzi (APHLIS, 2021). Although the general approach used here is similar, the calculation of the conversion of nutritional loss into nutritional impact presented here for the tool (Supplemental Tool S6) was modified. We based our selection of groups of nutritional interest on the DHS classification for Uganda and Zimbabwe in order to follow more closely the nutritional recommendations, and we simplified the calculation of the number of pregnant and lactating women.

We chose to use EAR as a estimate of nutritional requirements and population-weighted EAR (for Uganda and Zimbabwe). According to Tarasuk (2006), EAR is a more appropriate estimate than Recommended Dietary Intake (RDI) (97.5% of the population's nutrient needs met) because there are fewer risks of overestimating the nutritional requirements in the former. EAR was based on a moderate Physical Activity Level (PAL) (PAL = 1.8) for all the groups because we hypothesised that manual jobs are common in Zimbabwe and Uganda and the country population pyramids indicate a young population. PAL is lower in urban populations where activities are more sedentary (PAL = 1.4 to 1.5), compared to rural populations where activities are more physical (PAL = 2.0 to 2.2). Carbohydrate requirements were not indicated in NHMRC (2006) for individuals older than one-year. We therefore used the USDA standard. Total fat requirements were not indicated in NHMRC (2006) for individuals older than one-year either. We therefore used 20 g/100 g. For orange maize and OFSP, we used conversion factors from provitamin A carotenoids to retinol of 4:1 and 12:1, respectively (Bechoff & Dhuique-Mayer, 2017). Population-weighed EAR has been used in previous studies (Beal et al., 2017) to determine nutritional impacts and predict inadequate intake of dietary micronutrient in the world.

Our model prediction estimates that processing has a restricted effect on macronutrients. A limitation is that the model does not include the details of macronutrients—type of fat, carbohydrates and proteins. For instance, it is well-established that maize is an inadequate source of proteins since it lacks essential amino-acids (lysine and tryptophan Prasanna et al., 2001). With respect to micronutrients, minerals are mostly unaffected by processing. Minerals may, however, be lost in cooking water for example, about 10% of iron and zinc are lost through boiling (Bechoff & Dhuique-Mayer, 2017). Provitamin A is sensitive to heat but the most common processes used in Uganda (steaming and boiling) have a limited effect (Van Jaarsveld et al., 2006; Bengsston et al. 2008). Drying and storage of OFSP would, however, result in significant provitamin A losses (Bechoff et al., 2010a, b). This may significantly hamper the expected impact of biofortified sweet potato on nutritional status of targeted populations (see, e.g., Table 5 for Uganda). The potential for OFSP as a target intervention against vitamin A deficiency was highlighted previously (Low et al., 2017). Our results suggest that provitamin A loss during drying and subsequent storage could be a major obstacle to impact.

Because of differing production levels, the nutritional impact of PHL depends on the food commodity considered. PHL in maize affects a larger proportion of the population of Zimbabwe than that in cowpea (Table 7). The PHL of white maize is estimated at 500,000 tonnes per year (i.e., 25.9% of the production). Using 2018 prices, this loss is equivalent to US$150 million (local price) to US$195 million (Zimbabwean Grain Marketing Board price) The nutritional impact figures may be over-stated, for example, if a significant fraction of the maize production (1.7 million tonnes) is exported to neighbouring countries and therefore the current maize PHL would be lower. However, the scale of the figures illustrates that PHL of maize has a significant nutritional impact corroborating that it is a major staple in the diet.

Storage duration and the type of storage container have a nutritional impact: using hermetic bags leads to better nutrient retention compared to polypropylene woven bags. The number of people losing their iron EAR is estimated to be much higher if maize were stored in polypropylene (9.5 million or 59% of the Zimbabwean population) than in hermetic bags (5 million or 29%). Insect infestation is higher in untreated polypropylene bags. This leads to increased NPHLs. Insect damage during maize storage is associated with an increased loss in iron (Stathers et al., 2020a). Our estimates (Supplemental Table S3) show that iron loss was correlated with insect damage and temperature. Costs of hermetic and polypropylene bags in Zimbabwe in 2019 were US$ 1.5 and US$ 0.3 a piece, respectively. Whilst the pesticides for use in polypropylene bags, as usually practiced, have to be purchased every year, hermetic bags may be re-used for two more storage seasons, if properly handled. Hermetic bags have the additional environmental, health and food safety benefits of being pesticide-free. Different brands of hermetic bags were found to be comparable in their performances against storage insects at on-station expriements in Zimbabwe (Chigoverah & Mvumi, 2018). In maize and other grains, nutrient losses mainly result from insect infestation. Nutrient loss may also be due to oxidation of fat and provitamin A carotenoids (Taleon et al., 2017). The equivalent of vitamin A requirements for 20,000 people could be saved if orange maize was stored in hermetic bags rather than usual polypropylene bags. Hermetic bags with an oxygen scavenger, which reduces internal oxygen concentration limited carotenoid degradation in orange maize stored for 8 months, compared to conventional polypropylene bags (Nkhata et al., 2019). However, PICS bags without oxygen scavengers did not significantly differ from polypropylene woven bags (Nkhata et al., 2019; Taleon et al., 2017). The study by Nkhata et al. (2019), however, did not have controlled infestation and was conducted in the US Midwest. The results of Nkhata et al. (2019) therefore may not reflect conditions prevailing in SSA. In our study, hermetic bags retained β-carotene significantly better than untreated polypropylene woven bags (Fig. 3), perhaps because of the significant level of insect infestation present, leading to rapid oxygen depletion in the bags. More research should be conducted to understand the relationships between insect infestation, oxygen level, and carotenoid degradation under controlled and natural conditions, and how this translates into a nutritional impact for nutrient-dense food commodities such as biofortified orange maize.

6 Conclusions

This study offers an original method to estimate nutritional postharvest losses (NPHLs) of food commodities that are important for food security. To our knowledge, our approach is the first to use a combination of quantitative and qualitative NPHL estimates. Predictive equations were developed to estimate qualitative NPHLs during storage. Reconciliation of the laboratory and field data were challenging, in part because of the limited data available and differences between controlled and field settings. However, both predictive models lead to similar conclusions in terms of nutritional implications at a broader scale. Hence, the complementarity of laboratory and field data strengthen the estimates generated by the NPHL predictive tool.

Qualitative NPHL losses are important because they can significantly increase the level of nutrient losses. Development of prediction models will require further work to improve the models' robustness through inclusion of new data and calculations of model error that are necessary to compare model estimates. Other aspects such as food safety of food commodities must be included in the prediction of PHLs. This includes mycotoxins which are produced by some fungal species pre- and postharvest, are a major problem in food commodities in LMICs and constitute threats to public health (Neme & Mohammed, 2017; Stathers et al., 2020b).

This work supports the development of PHL mitigation policy strategies for better food security, nutrition, and health. Results can be used to inform agriculture and food security decision-makers about NPHLs through the use of open-access tools and policy recommendations.

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Availability of data and material (Data transparency) Raw data will be available upon request.

Code availability (Software application or custom code). The model was developed in Microsoft Excel and is available in the supplementary material. There is no code.

Declarations

Ethics approval (Include appropriate approvals or waivers). Not applicable.

Consent to participate (Include appropriate statements). Not applicable.

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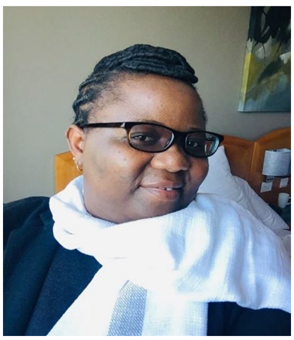

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