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Mango Postharvest Technologies: An Observational Study of the Yieldwise Initiative in Kenya

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Abstract: Several studies have evaluated the effects of postharvest technologies on postharvest loss (PHL) incurred at a single stage of a food value chain. However, very few studies have assessed the effect of multiple technologies on PHL incurred at various stages of a food value chain. This study evaluated the effect of five technologies (harvesting tools, cold stores, plastic crates, fruit fly traps, and ground tarps) promoted by the Rockefeller Foundation Yieldwise Initiative (YWI) in Kenya on PHL incurred at three mango value chain stages (harvest, transportation, and point of sale). After extensive screening of the YWI data, the Kruskal–Wallis statistical test was used to compare each YWI promoted technology to smallholder farmers (SHF) traditional practices. Results indicated that plastic crates used to transport or store mangos and fruit fly traps used to attract and kill fruit flies were statistically significant ($p < 0.05$) in reducing PHL at the point of sale. Meanwhile, no statistical evidence of PHL reduction was observed from SHF using harvesting tools, cold stores, and ground tarps. Cold stores were the least adopted of the promoted technologies due to their high costs of implementation and utilization. While this study asserts that increased technology adoption is associated with PHL reduction, further research is needed to identify additional factors that favor technologies' efficacy in reducing PHL in similar food value chains.

Keywords: postharvest technologies; mango postharvest loss; Yieldwise Initiative

Citation: Chikez, H.; Maier, D.; Sonka, S. Mango Postharvest Technologies: An Observational Study of the Yieldwise Initiative in Kenya. *Agriculture* **2021**, *11*, 623. https://doi.org/10.3390/agriculture11070623

Academic Editor: Isabel Lara Ayala

Received: 12 June 2021
Accepted: 29 June 2021
Published: 1 July 2021

1. Introduction

Rising incomes in low-income countries are driving changes in dietary patterns and increasing the demand for safe and nutritious food [1]. However, to equate future demand and supply of safe and healthy agricultural food, global food production will need to increase at a rate of 1.3 percent every year [2]. Sustainably achieving such a growth rate will require increasing plant-based food production. Such an effort will promote long-term food security without sacrificing nutrition [3] and will provide increased employment opportunities for farm workers [4].

The two commonly documented approaches for increasing plant-based food production are agricultural intensification and cropland expansion [5]. While both have contributed to global food security substantially, several limitations have also been reported. For example, the former has been challenging to achieve in geographic areas affected by climate change, especially as it pertains to increasing crop yield [6]. Meanwhile, the latter constitutes a potential threat to biodiversity by driving habitat loss. Additionally, cropland expansion impacts carbon storage through the loss of biomass and soil carbon [7].

Given these limitations, numerous studies have suggested postharvest loss (PHL) reduction as an essential and complementary approach to meeting the increasing demand for safe and nutritious food [8]. PHL can be defined as a measurable reduction in agricultural products that arise from changes these products undergo during postharvest handling [9]. Therefore, PHL reduction efforts, especially in sub-Saharan Africa (SSA), could be a catalyst for increasing profit for food value chain actors while at the same time improving food security [10]. Given the importance of PHL reduction, several PHL mitigation studies have been initiated over the last decade, focusing on improving food security in SSA, which remains the most food-insecure region in the world [11].

For example, notable PHL mitigation studies in SSA include introducing the Purdue Improved Crop Storage (PICS) hermetic bags, which prevent storage losses due to insects in maize and other grains without chemical pesticides [12]. The commercialization of this technology, funded by the Bill and Melinda Gates Foundation, led at least five other manufacturers to introduce hermetic storage bag technology products [13]. In 2016, the Rockefeller Foundation launched the Yieldwise Initiative (YWI), intending to provide smallholder farmers (SHF) access to markets, technologies, training, and financing [14] to reduce PHL of mangos in Kenya, maize in Tanzania, and tomatoes in Nigeria. More recently, the Consortium for Innovation in Postharvest Loss and Food Waste Reduction launched as a collaborative effort between the Foundation for Food and Agriculture Research (FFAR), the Rockefeller Foundation, Iowa State University (ISU), and several other academic and research institutions around the world (reducePHL.com (accessed on 2 June 2021)) to address social, economic, and environmental impacts from food loss and waste.

Over time several additional PHL mitigation projects have emerged [15], with a focus on either quantifying PHL by stages of a food value chain [16,17] or comparing the effect of postharvest interventions on PHL incurred at a single stage of a food value chain. However, relatively few PHL mitigation projects have compared the effect of several postharvest technologies on PHL incurred at several stages of a food value chain. Therefore, this study analyzed the YWI dataset generated within the Kenyan mango value chain to evaluate the effect of five YWI promoted technologies (harvesting tools, cold stores, plastic crates, fruit fly traps, and ground tarps) on PHL incurred at three value chain stages (harvest, transportation, and point of sale).

Over the past decades, mango farming in Kenya has expanded considerably, involving several value chain actors such as non-governmental organizations, farmer cooperative groups, aggregation centers, financial institutions, mango processors, and others [18]. Additionally, annual mango production in Kenya is estimated at 1,024,500 metric tons, with approximately 80% being sold to local markets [18]. Thus, mango farming is considered a major income earner for many SHF households in Kenya [19]. However, mango production is accompanied by major PHL estimated at 40–50%, which are mainly the result of a lack of suitable technologies for the postharvest handling and processing into a wide range of value-added mango products [18]. Therefore, comparing YWI promoted technologies and identifying the value chain stage at which they are most effective, is a key step in reducing PHL along the entire value chain and improving SHF livelihoods.

2. Materials and Methods

2.1. Data Collection

Following the launch of the YWI, the Rockefeller Foundation contracted Technoserve Kenya for implementation of the mango value chain study, whereby they conducted in-person surveys and collected field data from participating farmers and other value chain actors between June and July 2018 (The authors of this paper were neither involved in the survey design nor the data collection process.). Technoserve collected data from 920 SHF (*row entries*) who provided answers based on September 2017 to March 2018 mango harvesting season. For each respondent farmer, there were 697 recorded variables (*column entries*) grouped into 12 sections, including geography and socio-demographics, farm demographics, inputs and input costs, labor costs, production, production and PHL practices, harvesting, sales, grading and storage, training, top five sources of household income, and credit access. Finally, the YWI was performed in a quasi-experimental design. Its interventions were not randomly assigned to farmers, and farmers who benefited from the interventions were not randomly selected.

2.2. Data Review

Review of the mango dataset began by separating the dependent variables from the independent variables, also referred to as factors in this study. Thus, all numerical variables within the dataset are expressed in the unit of mango fruit, such as mangos consumed, mangos sold, and mangos losses in different ways, and were designated as potential dependent variables. Twenty-five (25) such potential dependent variables were determined from the dataset's 697 variables (total). The remaining 672 variables were designated as factors that potentially affect the dependent variables.

2.2.1. Independent Variables

The 672 potential factors were sorted by removing factors with one or more missing entries, except for the "production and PHL practices" factor. Following the removal of factors with missing entries, the resulting dataset was reduced to 61 factors.

Then, factors containing the respondent farmers' identification information, such as name, contact information, and survey starting and ending times were removed. Additionally, all factors containing "true and false" entries were removed from the dataset. Furthermore, several numerical factors were positively correlated, such as the "total number of mango trees" and "number of productive mango trees" owned by a farmer. In such cases, one (number of productive mango trees) of the two was removed to avoid collinearity [20].

Finally, a listwise deletion of rows within the factor "production and PHL practices" was performed. As mentioned in the first step, this factor was the only one that was not entirely removed from the dataset despite missing entries. The reason being that Technoserve experts suggested the "fruit fly traps," a subset of the "production and PHL practices" factor, played a crucial role in reducing insect infestations of mangos before harvest. Hence, by retaining this factor in the dataset, the importance of "fruit fly traps" in reducing insect infestations of mangos before harvest could be compared to its importance in preserving quality and reducing loss after harvest. The listwise deletion of rows was applied to remove any randomly missing entries of this factor. Although the listwise deletion of rows is a commonly used technique for handling missing data [21], it was only applied to the "production and PHL practices" factor and not to the entire dataset. Using such an approach to the entire raw dataset would have resulted in a 100% loss of information due to multiple missing entries.

The final dataset of factors consisted of nine sections and 21 factors (Table 1), where 19 factors were categorical (each containing at least two subsets), and two were numerical. Therefore, harvest methods, type of storage used after harvest, type of package for sale, and production PHL practices are the four identified factors that contain various technology subsets as specified in Table 1. Their effect on mango PHL will be evaluated in this study. Additionally, certain factors and subsets were renamed to provide more clarity, and some subsets were combined into fewer to facilitate the evaluation of their effect on PHL.

Following factor review and summarization, the four factors that contained postharvest technologies are listed in Table 2, along with their subsets, subset descriptors, and descriptions.

2.2.2. Dependent Variables

The 25 potential dependent variables were also sorted to identify the various types of mango losses along the value chain. The first step consisted of removing variables or columns with at least one missing entry. The second step consisted of identifying all mango PHL along the value chain. Though all 25 potential dependent variables were numerical data representing quantities of mango fruit sold, given to family, used as payment-in-kind, consumed by farmers, and lost along the value chain, not all were PHL variables. PHL variables are the hotspots of loss that form the entire PHL [22]. Therefore, in this study, mango losses that occurred during harvest and losses that occurred after harvest were the only types of losses considered to be PHL variables.

Table 1. A summary of the dataset showing sections, factors, subsets of factors, and respondent farmers: Column (a) lists the nine sections to which each factor belongs. Column (b) lists all 21 factors, including the 19 categorical ^{C}, two numerical ^{N}, and four containing postharvest technologies ^{T}. Column (c) expands each factor into subsets. Subsets with the superscript ^{PHT} are identified as postharvest technologies. Subsets with the superscript ^{PRHT} are identified as pre-harvest technologies. Numerical factors consist of numerical values estimated by each respondent farmer. Column (d) renames subsets and combines them into fewer categories to facilitate subsequent analysis. Subset descriptors with the superscript ^{YWI} are identified as technologies promoted by the YWI. Column (e) indicates the number of respondent farmers belonging to each subset. For each factor, respondent farmers who reported more than one subset were assigned the subset Other **.

(a) Sections	(b) Factors	(c) Subsets of Factors	(d) Subset Descriptors	(e) # Observations (Respondent Farmers)
A. Geography and socio-demographics	1. county ^{C}	Embu	eastern	159
		Garissa	north eastern	6
		Kilifi	coast	1
		Kirinyaga	central	1
		Lamu	coast	12
		Machakos	eastern	49
		Makueni	eastern	88
		Meru	eastern	86
		Muranga	central	12
		Tana river	coast	332
		Tharaka nithi	eastern	7
	2. treatment control ^{C}	control	non beneficiary	282
		treatment	yieldwise beneficiary	471
	3. farm ownership ^{C}	no	no	135
		yes	yes	618
B. Labor costs	4. labor costs ^{C}	no	no	468
		yes	yes	285
C. Harvesting	5. who harvested mango ^{C}	both	farmer and buyer	133
		buyer only	buyer	411
		self-family	farmer	181
		other **	other	28
	6. inform when to harvest ^{C}	days after blooming	days after blooming	5
		fruit color	fruit color	165
		fruit size or shape	fruit size or shape	49
		test for maturity	test for maturity	13
		other **	other	521
	7. frequency of harvest ^{C}	daily	daily	53
		fortnightly	fortnightly	231
		monthly	monthly	52
		weekly	weekly	308
		other **	other	109
	8. methods of harvest $^{C, T}$	handpicking	traditional practices	276
		harvesting tools ^{PHT}	harvesting tools ^{YWI}	48
		poles	traditional practices	67
		shaking trees or branches	traditional practices	11
		other **	other	350
D. Sales	9. how farmer identified buyer ^{C}	brokers	brokers	407
		farmer-based organization (FBO)	fbo	12
		own effort neighbor family or friend	own effort	253
		other **	other	81

Table 1. *Cont.*

(a) Sections	(b) Factors	(c) Subsets of Factors	(d) Subset Descriptors	(e) # Observations (Respondent Farmers)
E. Grading and storage	10. harvested mango graded [C]	no yes	no yes	346 407
	11. market destination [C]	export local market processing supermarket other **	export local market processing supermarket other	106 362 41 5 239
	12. storage after harvesting [C, T]	cold store [PHT] did not store shade store shed [PHT] other **	cold store [YWI] traditional practices traditional practices traditional practices other	18 386 212 88 49
	13. package for sale [C, T]	in crates cartons [PHT] in sacks [PHT] other **	plastic crates [YWI] traditional practices other	320 119 314
	14. mango price [N]	Ksh per mango	Ksh per mango	753
F. Training	15. receive production training [C]	no yes	no yes	534 219
G. Credit access	16. have bank account [C]	no yes	no yes	374 379
	17. have mobile money account [C]	no yes	no yes	95 658
	18. receive remittances [C]	no yes	no yes	467 286
	19. taken loan for farm [C]	no yes	no yes	695 58
H. Production and phl practices	20. production PHL practices [C, T]	fruit fly traps [PRHT] none scouting fruit fly tarp [PHT] other **	fruit fly traps [YWI] traditional practices traditional practices tarp [YWI] other	125 218 91 115 204
I. Farm demographics	21. total trees [N]	# of trees	# of trees	753

Following the selection of mango PHL variables, the resulting dependent variables consisted of nine types of mango PHL (Table 3) from the raw dataset's initial 25 potential dependent variables. The nine types of mango PHL were subsequently grouped based on the stages of the value chain at which they occurred (Table 3).

The third step consisted of identifying and removing outliers [23] from dependent variables. To identify outliers, mango gross production per farmer was calculated for each farmer. The calculation consisted of summing all variables that contributed to mango gross production, including mangos sold, given to family, used as payment-in-kind, consumed by farmers, and all PHL variables shown in Table 3. It was then observed that the calculated mango gross production distribution was skewed with outliers. Hence, removing the rows containing mango gross production outliers resulted in eliminating outliers from PHL distributions at each value chain stage.

The last step consisted of expressing mango PHL at all three value chain stages as percentages of gross production (Figure 1) for all 753 respondent farmers.

Table 2. Summarizing and describing factors containing postharvest technology subsets: Column (a) shows the four factors containing postharvest technologies. Column (b) shows the subset descriptors, which are renamed subsets; these were determined to reduce the raw data into fewer categories, to facilitate subsequent analysis. Column (c) shows the subsets of each factor as initially recorded in the raw data. Column (d) describes the purpose of each subset. The superscripts $^{\mathbf{YWI}}$ in Columns (b) and (c) refer to technologies that the YWI promoted.

(a) Factors	(b) Subset Descriptors	(c) Subsets	(d) Description
methods of harvest	harvesting tools ^{YWI}	harvesting tools ^{YWI}	Tools that reduce/eliminate the need for harvesting by hand and catch mangos in a soft fabric sack, thereby preventing bruising that may occur due to hard grips or when mangos fall on hard surfaces
	traditional practices	shaking trees or branches	Harvesting practice consisting of the farmer shaking the mango tree or branches, causing it to detach from the tree and fall on the ground
	traditional practices	handpicking	Not specified in the data
	traditional practices	poles	Not specified in the data
storage after harvesting	cold store ^{YWI}	cold store ^{YWI}	Cold stores consist of charcoal evaporative coolers, brick evaporative coolers, insulated air-conditioned containers powered by photovoltaic cells or by the electrical grid
	traditional practices	did not store	Not specified in the data
	traditional practices	shade	Trees shade
	traditional practices	store shed	Shed built to store mango
package for sale	plastic crates ^{YWI}	in crates ^{YWI}	Plastic rectangular containers that protect/preserve quality by reducing impact damage during transport, and each crate can hold up to 50 mangos
	traditional practices	in sacks	Not specified in the data
production phl practices	fruit fly traps ^{YWI}	fruit fly traps ^{YWI}	A container with chemicals like bactrolure or metarhizium anisopliae ICIPE 69 that attract fruit flies and eventually kills them, either directly by chemical exposure or through secondary transmission from other fruit flies
	tarp ^{YWI}	tarp ^{YWI}	Large plastic covers/surfaces mainly used to prevent bruising of mango during harvest by reducing the impact of mango. Mangos harvested by hand are thrown down on the tarp which acts as a cushion to reduce the mechanical impact force on the fruits. Tarps are also used after harvest to protect mangos from weather effects, including rain, moisture, or direct sunlight
	traditional practices	none	Not specified in the data
	traditional practices	scouting fruit fly	Not specified in the data

Table 3. Types of mango PHL within the dataset of dependent variables.

(A) Mango Value Chain Stages	(b) Types of Mango PHL (Dependent Variables)	(c) Description
Harvest	PHL during harvest	Mango fruit (quantity) discarded by the farmer as a result of bruises or injuries caused to the fruit during harvesting activities
	PHL during harvest other ways	Not specified in the data (unclear)
Transportation to the point of sale or aggregation site	PHL during transportation	Mango fruit (quantity) discarded by the farmer as a result of unspecified quality issues during transportation
Point of sale (off-takers, wholesaler or brokers)	PHL due to mangos being rejected by buyers	Mango fruit (quantity) discarded by the buyer as a result of unspecified quality issues
	PHL due to mangos being overripe	Mango fruit (quantity) discarded by the farmer as a result of the fruit being too overripe for sale
	PHL due to mangos physical damage	Mango fruit (quantity) discarded by the farmer as a result of bruises or injuries caused to the fruit after harvest
	PHL due to mangos being rotten	Mango fruit (quantity) discarded by the farmer as a result of the fruit being rotten
	PHL due to low-quality mangos being fed to livestock	Mango fruit (quantity) discarded by the farmer and fed to livestock as a result of the fruit being unfit for human consumption
	PHL other ways	Not specified in the data (unclear)

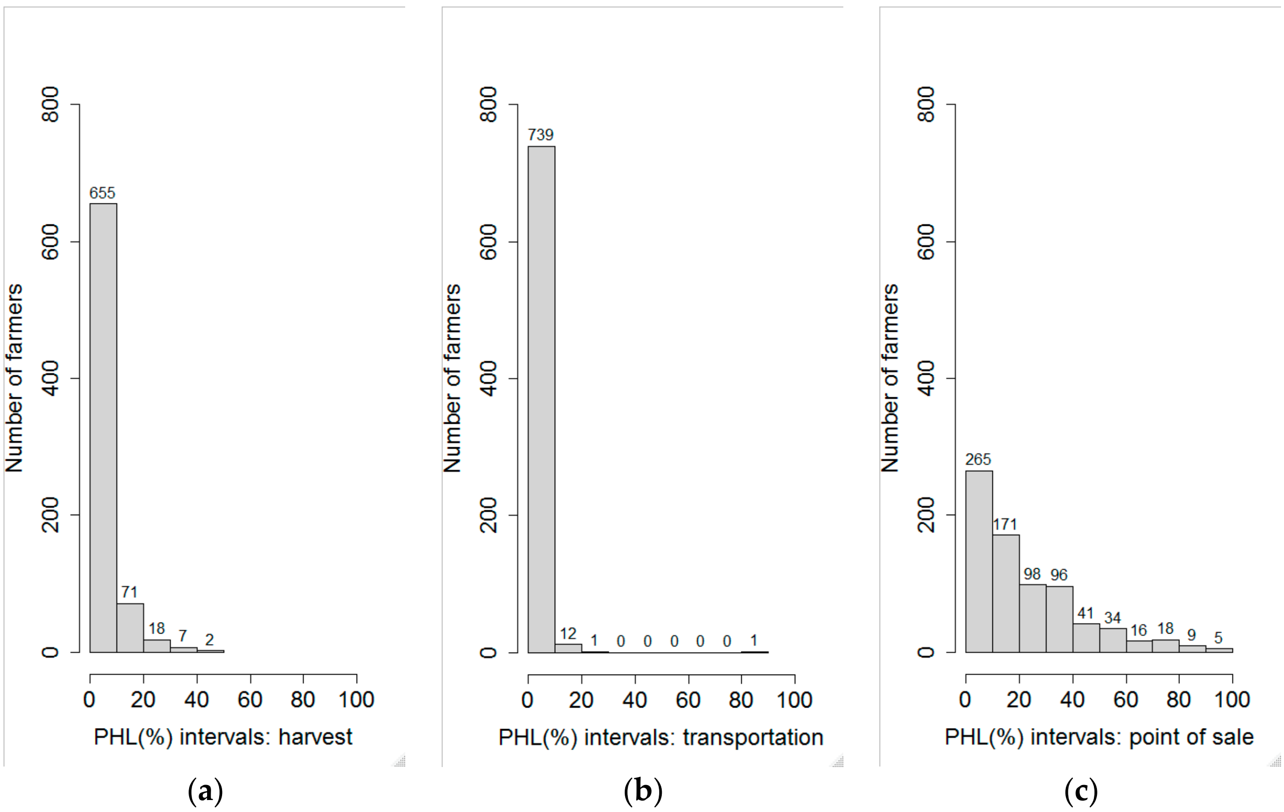

Figure 1. Distributions of mango PHL (%) during harvest (**a**), transportation (**b**), and at point of sale (**c**).

The PHL data summarized in Figure 1 were subsequently combined with the factors listed in Table 1. This combination resulted in creating the YWI mango dataset (summarized in Table 4) that formed the basis for the analysis and results presented in this study.

Table 4. Summary of all factors, subsets of factors, respondent farmers, and the seven types of mango PHL: Column (a) lists all 21 factors including the 19 categorical ^{C}, two numerical ^{N}, and four containing postharvest technologies ^{T}. Column (b) expands each factor into subsets that were previously referred to as subset descriptors in Table 1. The superscript ^{YWI} is used to identify technologies promoted by the YWI. "Other" refers to the combination of multiple subsets as reported by respondent farmers. Column (c) indicates the number of respondent farmers belonging to each subset. Column (d) encompasses mango PHL at harvest, during transportation, at point of sale, and as a total of all three value chain stages. PHL averages cannot be categorized by numerical factors, hence the n/a notation.

(a) Factors	(b) Subsets of Factors	(c) Observations (Respondent Farmers *n*)	(d) Average PHL (%) Per Farmer Per Value Chain Stage			
			Harvest	Transportation	Point of Sale	Entire Value Chain
1. county ^{C}	central	13	4	1	20	25
	coast	345	6	2	25	32
	eastern	389	4	1	20	25
	north eastern	6	3	0	15	18
2. treatment control ^{C}	non beneficiary	282	4	1	25	31
	yieldwise beneficiary	471	5	1	21	27
3. farm ownership ^{C}	no	135	5	1	22	28
	yes	618	5	1	23	28
4. labor costs ^{C}	no	468	5	1	25	30
	yes	285	5	1	19	25
5. who harvested mango ^{C}	buyer	411	4	0	22	27
	farmer	181	6	2	25	33
	farmer and buyer	133	5	1	21	27
	other	28	4	1	21	27
6. inform when to harvest ^{C}	days after blooming	5	6	2	5	14
	fruit color	165	5	1	24	30
	fruit size or shape	49	8	2	34	43
	test for maturity	13	3	2	24	29
	other	521	5	1	21	27
7. frequency of harvest ^{C}	daily	53	6	1	25	31
	fortnightly	231	5	1	23	29
	monthly	52	4	1	29	34
	weekly	308	5	1	20	26
	other	109	4	1	24	28
8. methods of harvest $^{C, T}$	harvesting tools ^{YWI}	49	6	1	19	25
	traditional practices	544	5	1	24	30
	other	160	4	2	19	25
9. how farmer identified buyer ^{C}	brokers	407	5	1	23	29
	farmer based organization	12	2	0	9	12
	own effort	253	4	2	20	26
	other	81	4	1	29	33
10. harvested mango graded ^{C}	no	346	4	1	25	30
	yes	407	6	1	20	27

Table 4. *Cont.*

(a) Factors	(b) Subsets of Factors	(c) Observations (Respondent Farmers *n*)	(d) Average PHL (%) Per Farmer Per Value Chain Stage			
			Harvest	Transportation	Point of Sale	Entire Value Chain
11. market destination C	export	106	3	0	15	19
	local market	362	5	1	23	29
	processing	41	7	2	26	34
	supermarket	5	6	0	20	25
	other	239	5	2	24	31
12. storage after harvesting C, T	cold store YWI	18	8	1	16	25
	traditional practices	686	5	1	22	28
	other	49	4	1	25	29
13. package for sale C, T	plastic crates YWI	320	5	1	18	24
	traditional practices	119	6	2	26	34
	other	314	5	1	25	31
14. mango price N	Ksh per mango	753	n/a	n/a	n/a	n/a
15. receive production training C	no	534	5	1	25	31
	yes	219	5	1	15	21
16. have bank account C	no	374	5	1	24	31
	yes	379	5	1	21	26
17. have mobile money account C	no	95	6	2	24	32
	yes	658	5	1	22	28
18. receive remittances C	no	467	5	1	22	28
	yes	286	5	1	23	29
19. taken loan for farm C	no	695	5	1	23	29
	yes	58	3	1	21	25
20. production phl practices C, T	fruit fly traps YWI	125	4	0	20	25
	tarp YWI	115	7	2	25	33
	traditional practices	310	4	1	24	29
	other	203	5	1	21	27
21. total trees N	# of trees	753	n/a	n/a	n/a	n/a

In addition to summarizing the YWI mango dataset in Table 4, each stage's PHL was expressed as a proportion of the total PHL (Figure 2) by dividing each stage's average by the average PHL of the entire value chain. Furthermore, an online interactive mango PHL dashboard was created (https://phldashboard.shinyapps.io/phldashboard/ (accessed on 2 June 2021)) to explore average mango PHL as a function of each factor in Table 4 Column (a) and as a function of a selected combination of factors.

2.3. Statistical Analysis

Identification of the four factors containing postharvest technology subsets (Table 2) and the subsequent quantification of mango losses associated with each subset (Table 4) provided a basis for comparing PHL averages per subset and quantifying the effect size among postharvest technology subsets. However, to ensure that the PHL averages are significantly different among subsets or technologies, a preliminary analysis of the subsets' data was conducted to identify an appropriate statistical tool for comparing means. The initial analysis consisted of verifying the main mathematical assumptions of normality, homogeneity of variance, and independence [24] required to use parametric statistical tools.

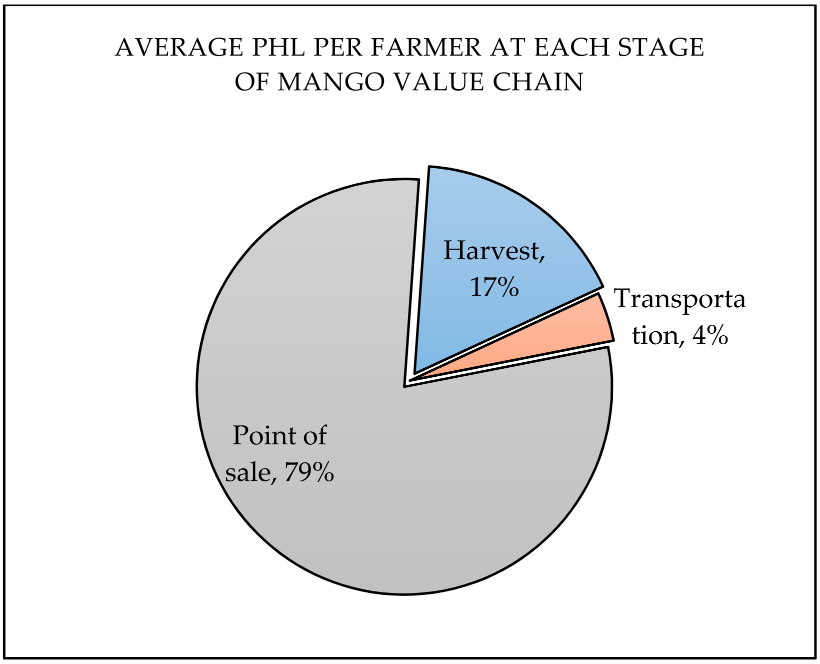

Figure 2. Proportion of PHL at each value chain stage.

The assumption of normality was considered violated as the distributions of PHL per subset were skewed, and the Shapiro–Wilk normality test results indicated that the skewed distributions were significantly different ($p < 0.05$) from a normal distribution curve. However, the assumption of homogeneity of variance was not violated as Levene's test results indicated a significant ($p > 0.05$) homogeneity of variance among subsets of all four factors. Similarly, the assumption of independence was not considered violated as PHL distributions per subset were identically distributed to the right for all four factors. Also, observations within each subset were assumed to be independent, although there could be a sampling bias owing to a lack of randomization during the YWI farmers selection process.

Consequently, the Kruskal–Wallis statistical test was identified as a suitable approach for evaluating the effect of the YWI promoted technologies on mango PHL incurred at the three stages of the value chain. The Kruskal–Wallis test is the nonparametric analog of a one-way ANOVA, which does not make assumptions about normality [25] and is robust when data contain outlying observations [24]. When the Kruskal–Wallis test showed significance, it was followed by a Dunn test with Benjamini–Hochberg adjustment.

In addition to performing the statistical tests mentioned above, the size of the reduction or increase in PHL was also calculated when PHL differences showed significance ($p < 0.05$). The method used for calculating the effect size of the Kruskal–Wallis test was the Epsilon-squared method [26]. Interpretation of the Epsilon-squared effect size was made using the measures of association rules [27]. However, since Epsilon-squared is a squared variable, the upper and lower bound of each bin mentioned were squared [27], yielding the following effect size rule: 0.00 and under 0.01 = negligible; 0.01 and under 0.04 = weak; 0.04 and under 0.16 = moderate; 0.16 and under 0.36 = relatively strong; 0.36 and under 0.64 = strong.

Lastly, knowing that interventions within the YWI were not randomly attributed to farmers and that farmers who benefited from the interventions were not randomly selected, causal inferences from statistical analysis results to a larger population of SHF can be somewhat speculative. However, thinking of the p-values as approximate p-values for permutation tests will lead to concluding that observed evidence of differences in the results is valid, more so than can be explained by chance [24].

3. Results

3.1. Harvesting Tools

Results indicate a PHL reduction at the point of sale from SHF using harvesting tools over traditional harvesting practices. However, this reduction was not statistically significant ($p < 0.05$) (Figure 3). Additionally, no PHL reduction was detected during harvest and transportation from SHF using harvesting tools over traditional harvesting practices (Figure 3). Furthermore, a moderate PHL increase ($p < 0.05$, Epsilon-squared = 0.096) during transportation was detected due to SHF combining traditional harvesting practices with harvesting tools (Figure 3).

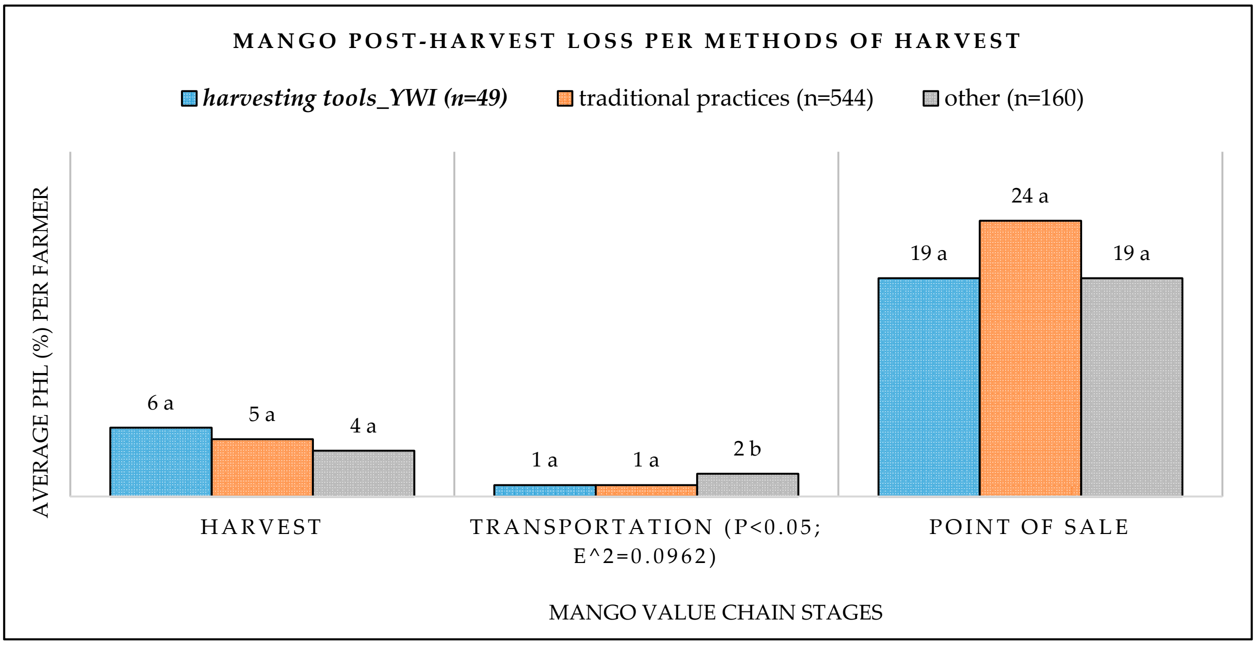

Figure 3. Comparing harvesting tools to traditional methods of harvest. Values with different letters are significantly different at $p < 0.05$ from the Kruskal–Wallis analysis, Dunn test, and Benjamini–Hochberg adjustment. E^2 = Epsilon-squared value for effect size. YWI refers to the technology that the Yieldwise Initiative promoted. (n) refers to the number of farmers who reported using a given practice or technology. 'Other' refers to practices that combined both YWI promoted technologies and traditional practices.

3.2. Cold Stores

Results indicate a PHL reduction at the point of sale from SHF using cold stores over traditional storage practices. However, this reduction was not statistically significant ($p < 0.05$). Additionally, no PHL reduction was detected during transportation and at the point of sales owing to SHF using cold stores over alternative traditional storage practices (Figure 4). Moreover, a weak PHL increase ($p < 0.05$, Epsilon-squared = 0.01) during harvest was detected due to SHF using cold stores (Figure 4).

3.3. Plastic Crates

Plastic crates were statistically significant ($p < 0.05$) in reducing PHL incurred at the point of sale (Figure 5), although the effect size of the reduction was weak (Epsilon-squared = 0.017). Additionally, PHL reductions were detected during harvest and transportation due to SHF using plastic crates over traditional packaging practices. However, these reductions were not statistically significant ($p < 0.05$) (Figure 5).

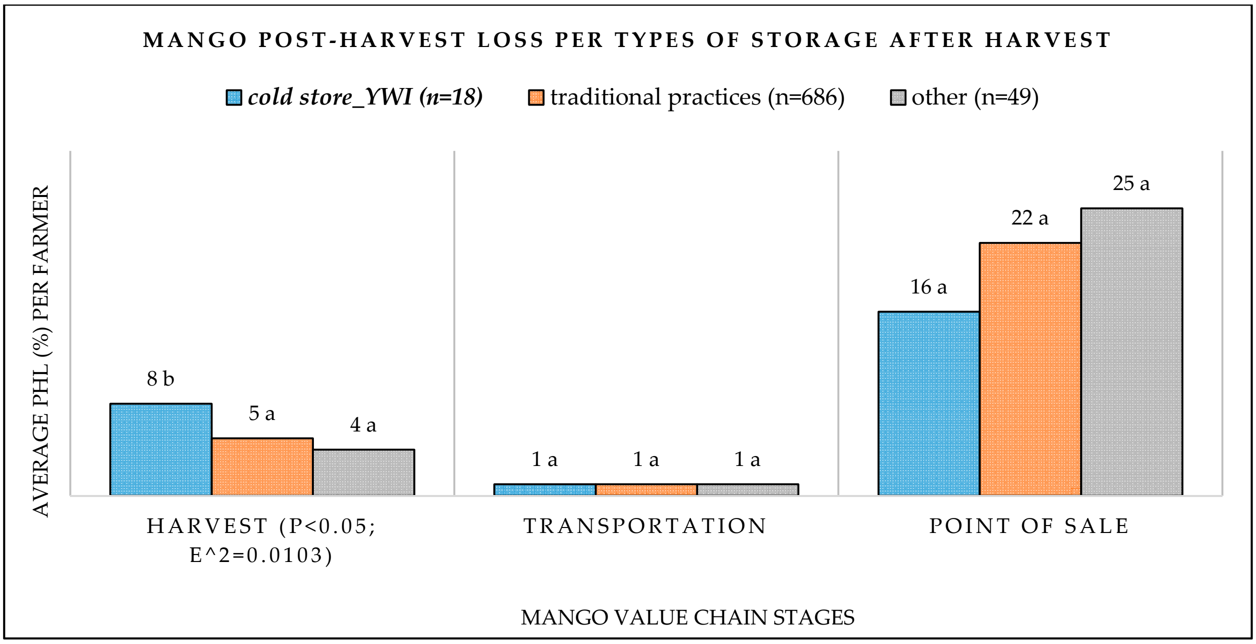

Figure 4. Comparing cold stores to alternative storage types after harvest. Values with different letters are significantly different at $p < 0.05$ from the Kruskal–Wallis analysis, Dunn test, and Benjamini–Hochberg adjustment. E^2 = Epsilon-squared value for effect size. YWI refers to the technology that the Yieldwise Initiative promoted. (n) refers to the number of farmers who reported using a given practice or technology. 'Other' refers to practices that combined both YWI promoted technologies and traditional practices.

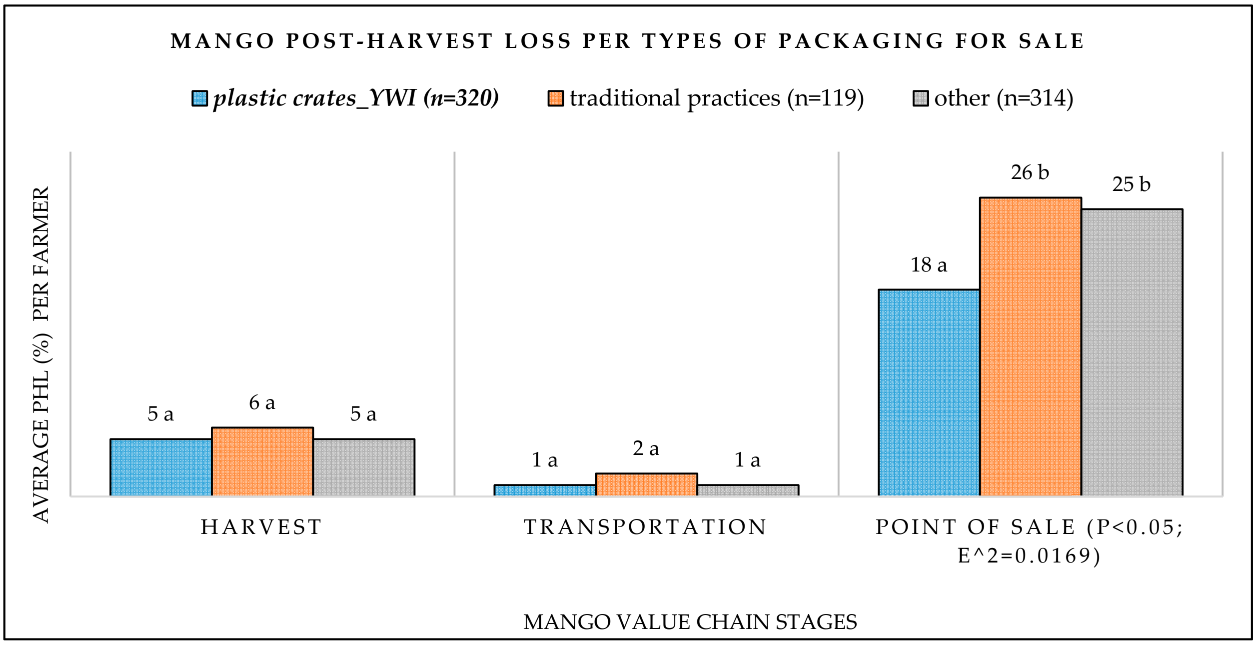

Figure 5. Comparing plastic crates to traditional practices. Values with different letters are significantly different at $p < 0.05$ from the Kruskal–Wallis analysis, Dunn test, and Benjamini–Hochberg adjustment. E^2 = Epsilon-squared value for effect size. YWI refers to the technology that the Yieldwise Initiative promoted. (n) refers to the number of farmers who reported using a given practice or technology. 'Other' refers to practices that combined both YWI promoted technologies and traditional practices.

3.4. Fruit Fly Traps and Ground Tarps

Fruit fly traps were statistically significant (p < 0.05) in reducing PHL incurred at the point of sale (Figure 6), although the effect size of the reduction was weak (Epsilon-squared = 0.017). Additionally, PHL reduction was detected during transportation due to SHF using fruit fly traps over traditional production practices. However, this reduction was not statistically significant (p < 0.05). Moreover, no PHL reduction was detected during harvest from SHF using fruit fly traps over traditional production practices (Figure 6). Meanwhile, moderate PHL increases during harvest (p < 0.05, Epsilon-squared = 0.04) and during transportation (p < 0.05, Epsilon-squared = 0.06), and a weak PHL increase (p < 0.05, Epsilon-squared = 0.017) at the point of sale were detected from SHF using ground tarps over any other harvest practice (Figure 6).

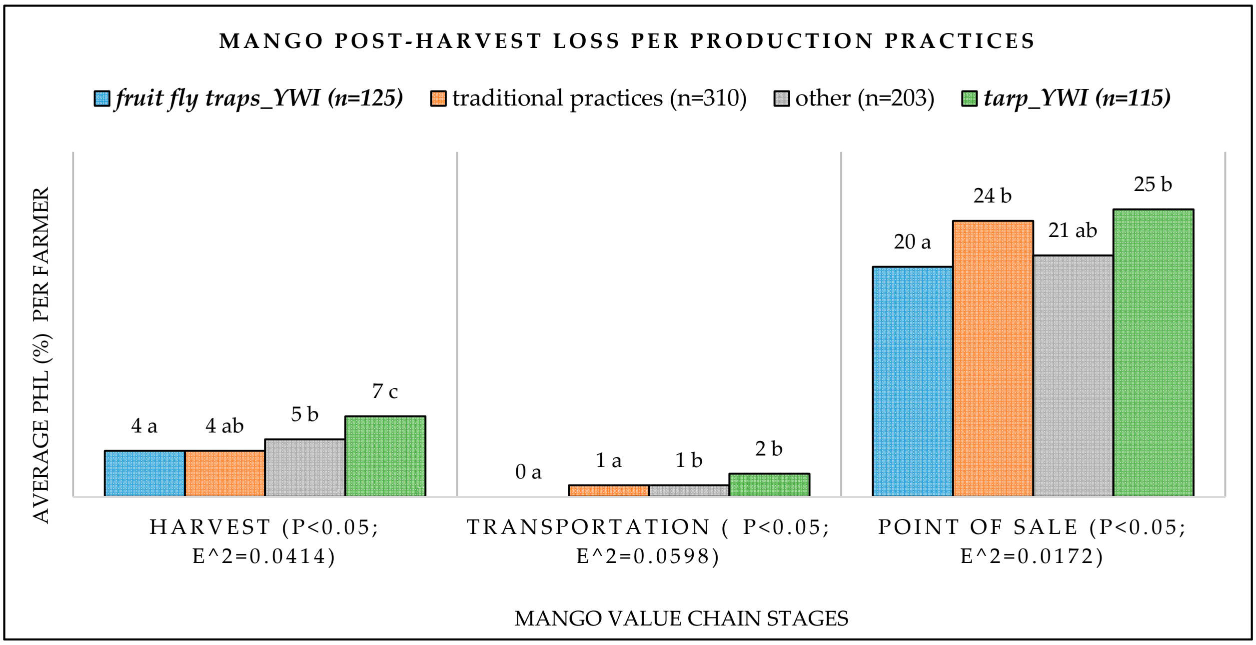

Figure 6. Comparing fruit fly traps to alternative production practices. Values with different letters are significantly different at p < 0.05 from the Kruskal–Wallis analysis, Dunn test, and Benjamini–Hochberg adjustment. E^2 = Epsilon-squared value for effect size. YWI refers to the technology that the Yieldwise Initiative promoted. (n) refers to the number of farmers who reported using a given practice or technology. 'Other' refers to practices that combined both YWI promoted technologies and traditional practices.

4. Discussion

While mango SHF have reported seeing a PHL reduction due to using harvesting tools [28,29], traditional harvesting practices such as handpicking can also reduce damage caused during harvest [30–32]. Hence, increasing the adoption of correct mango handpicking practices could be effective, if not more effective, than harvesting tools (Figure 3).

Cold stores utilized by SHF (photovoltaic-powered coolers, charcoal evaporative coolers, and brick evaporative coolers) effectively preserve mangos [33,34]. However, they are costly for individual farmers to own. Hence, most mango cold stores are owned by farmers' cooperatives [33], requiring farmers to inspect mangos during harvest and only store fruits that can be well preserved in the cold stores. Therefore, PHL increase during harvest from SHF using cold stores (Figure 4) can be attributed to large quantities of poor fruit quality set aside during the inspection process before storage.

Packaging mangos in plastic crates instead of sacks allows adequate packaging and storage of mangos [35] needed to preserve quality and provide greater wholesale value for the fruit [36,37]. Packaging mangos in crates can also reduce damage caused to the fruit during transportation (Figure 5), and by extension, reduces PHL at the point of sale

(Figure 5). Furthermore, plastic crates had the highest adoption (n = 320, Figure 5) of all the YWI promoted technologies as SHF and value chain actors saw value in using them.

Fruit fly traps were statistically significant in reducing PHL at the point of sale as their adoption was relatively higher (n = 125, Figure 6) than the other YWI promoted technologies, except for plastic crates. Two major factors were reported related to slowing the adoption of fruit fly traps. First, farmers' beliefs that fruit fly traps attract fruit flies from other farms caused the farmers to remove traps, leaving mangos susceptible to infestation and diminishing fruit fly traps' efficacy over traditional production practices [35]. Second, although farmers reported having fruit fly trap containers, without adequate financing, they could not refill the fruit fly trap containers with bait refills frequently enough for the traps to be effective [35]. Thus, overcoming these challenges could result in higher adoption of fruit fly traps.

Although essential, increased adoption and access to the technologies can be difficult to achieve. Cold stores, for example, are too expensive for SHF to own or utilize, especially without access to affordable credit [28,29]. Hence their adoption within the YWI was relatively low (n = 18, Figure 4). On the other hand, technologies easily accessible to farmers, such as plastic crates and fruit fly traps [38], had a relatively higher adoption rate. Hence, providing SHF easier access to affordable credit through innovative financing [35] or lower discount rates [39] could be an essential and initial step toward enabling increased adoption of preferred technologies. Alternatively, facilitating access to postharvest technologies through innovative subsidy programs could also increase the adoption of preferred technologies [40,41].

Lastly, discussions with Kenyan SHF revealed that buyers mainly do the harvesting and thus due to the informal and often hierarchal relationships between the two groups, farmers cannot intervene with the harvesting. Therefore, they do not have a say about whether or not ground tarps are used, increasing the chances of experiencing PHL during harvesting and, by extension, several other PHL types along the value chain (Figure 6). Moreover, training and promotion of ground tarps delivered through the YWI may lose their impact over time, and refresher training will be necessary [36].

5. Conclusions

This study quantitatively compared postharvest technologies and their effects on mango PHL in Kenya via the Rockefeller Foundation's YWI. Five YWI promoted technologies were compared to Kenyan SHF's traditional practices at three value chain stages. Subsequently, the following conclusions were inferred from analyzing the YWI mango dataset:

Efforts to reduce PHL in the mango value chain should prioritize adopting plastic crates and fruit fly traps. These technologies were statistically significant in reducing PHL incurred at the point of sale. In addition to preserving quality, plastic crates and fruit fly traps can be easily accessed and adopted by SHF compared to harvesting tools, cold stores, and ground tarps.

Harvesting tools as a YWI promoted technology and handpicking as a traditional practice to harvest mangos are similar in that both require careful handling of the fruit when picking. Therefore, PHL reduction from SHF using harvesting tools was not statistically significant because handpicking can effectively reduce mango PHL when done correctly. Further research is needed to determine factors other than increased adoption that increase the effectiveness of harvesting tools in reducing PHL.

PHL reduction from SHF using cold stores was not statistically significant. While several factors can contribute to this lack of statistical significance, this study posits that the low adoption of cold stores among SHF is due to their high cost of ownership or utilization.

The benefits of ground tarps should be further investigated because SHF are not always involved in the harvest and do not have a say about whether or not ground tarps are used, resulting in increased PHL. Additionally, training and promotion of technologies delivered through the YWI may lose their impact over time, and refresher training is recommended.

While this study asserts that increased technology adoption is necessary to obtaining better PHL reduction efficacy, further research is needed to identify additional factors of importance that favor technologies' efficacy in reducing PHL in similar food value chains.

Author Contributions: Conceptualization, H.C., D.M. and S.S.; data curation, H.C.; formal analysis, H.C.; investigation, H.C., D.M. and S.S.; methodology, H.C., D.M. and S.S.; software, H.C.; visualization, H.C. and D.M.; roles/writing—original draft, H.C.; writing—review and editing, H.C. and D.M.; funding acquisition, D.M. and S.S.; project administration, D.M. and S.S.; resources, D.M. and S.S.; supervision, D.M. and S.S.; validation, D.M. and S.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by The Rockefeller Foundation (Grant 2018 FOD 004), the Foundation for Food and Agriculture Research (Grant DFs-18-0000000008), and the Iowa Agriculture and Home Economics Experiment Station.

Data Availability Statement: An online interactive mango PHL dashboard was created at (https://phldashboard.shinyapps.io/phldashboard/ (accessed on 2 June 2021)) to support this study's results and to further explore average mango PHL as a function of several factors and combinations thereof.

Acknowledgments: Funding for this study was provided by The Rockefeller Foundation (2018 FOD 004), the Foundation for Food and Agriculture Research (DFs-18-0000000008), and the Iowa Agriculture and Home Economics Experiment Station. The authors would also like to thank the following individuals and their respective organizations for assistance in better understanding the YWI and data collection procedures: Amos Kioko at The Rockefeller Foundation (formally), Paul Ngugi, Isaiah Kirema, and Onesmus Kinene (formally) at Technoserve.

Conflicts of Interest: The funders had no role in the design of this study, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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