# DIFFERENCE IN DIFFERENCE METHOD TO IMPACT EVALUATION: A CASE STUDY OF FRUITING AFRICA PROJECT

BY
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# DECLARATION

This thesis is my own work and has not been presented for a degree award in any other institution.

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## DEDICATION

*I dedicate my project to all students pursing their career in the field of statistics and data science*

## ABSTRACT

Development programs designed to address particular global challenges are facing increasing pressure to demonstrate their impact on the targeted com munities. The method mostly used to measure impact of development programs is by comparing the changes in outcomes of the program participants over time commonly know as before-and-after comparison. However, in some cases, the treatment and control groups are usually heterogeneous at baseline, making the difference in difference (DiD) method the most appropriate as it accounts for the changes that would have occurred in the absence of the program. The aim of the project was to evaluate if 'Fruiting Africa Project (FAP)', an agroforestry project implemented by World Agroforestry Centre (ICRAF), made a difference in the livelihoods of beneficiaries. A sample of 300 households were randomly selected from the baseline sample of 600 households and questions of farm fruit tree diversity and abundances, food and nutrition security indicators, and knowledge on fruit tree grafting techniques. The Difference in Difference (DiD) method showed that there was significant change in the trend for the number of total and exotic fruit tree abundances from baseline to endline between the control and treatment groups for both Western and Lower Eastern Kenya. However, indigenous fruit tree abundances only had significant change in trend from baseline to endline only in Lower Eastern but not in Western Kenya. Total, exotic and indigenous fruit tree diversities had significant change in trend between control and treatment groups from baseline to endline in Lower Eastern, but not in Western Kenya. The percentage of respondents who had grafted a fruit tree significantly changed between control and treatment from baseline and endline in Western, however, not the same case for Lower Eastern Kenya. Regarding the dietary diversity variables, there was no significant change in dietary diversities between control and treat ment groups from baseline to endline. In summary, the impact of the projects' interventions were different across the different sites and the findings in this study could contribute towards developing better programs that enhance the livelihoods of smallholder farmers.

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# LIST OF ABBREVIATIONS AND ACRONYMS

## Acronyms

**AEZs** Agro-ecological zones

**CDD** Child Dietary Diversity

**CRA** Commission for Revenue Allocation

**DDS** Dietary Diversity Scores

**DFID** Department for International Development

**DiD** Difference in Difference

**EU** European Commission

**FAP** Fruiting Africa Project

**HDD** Household Dietary Diversity

**HHs** Households

**ICRAF** World Agroforestry Centre

**IE** Impact Evaluation

**IEG** Independent Evaluation Group

**IFAD** International Fund for Agricultural Development

**KNBS** Kenya National Bureau of Statistics

**MDGs** Millennium Development Goals

**ODK** Open Data Kit

**QGIS** Quantum Geographic Information System

**RCTs** Randomized Control Trials

**SDGs** Sustainable Development Goals

**SDSN** Sustainable Development Solutions Network

**WDD** Woman Dietary Diversity

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# CHAPTER ONE

# BACKGROUND OF THE STUDY

## 1.1 Introduction

Development programs are designed to address particular global challenges [47]. Those involved in development work are facing increasing pressure to demonstrate that the scarce resources given for development programs are actually improving the lives of people and communities they target, as well as the environment [47]. Experts for global development goals says that the experience from Millennium Development Goals (MDGs) showed the need to think through the indicators for Sustainable Development Goals (SDGs) as early as possible [81], either to measure impact connected to an intervention, or access performance of a development actor [28]. Increasing trend towards rigorous evidence while making policy decisions [20] has driven the need for impact evaluation.

Impact is widely described as a change that occurs due to a particular intervention given that the intervention as a cause has an effect [18]. The most commonly used definition of impact by international development players is that of [18], who define impact as:

**'Positive and negative, primary and secondary long-term effects produced by a development intervention, directly or indirectly, intended or unintended'**

IE on the other hand is defined as a type of evaluation designed to answer the question of whether the outcomes observed are as a result of the intervention or whether the observed outcomes would have happened anyway [13]. Basically, impact is the difference between the change observed among the individuals exposed to the programme interventions and counterfactual, what would have happened in the absence of the development programme [29]. For one to properly evaluate impact, identifying a group to participate in the program (treatment) and a group of non-participants (control) that are statistically identical is key [29]. One of the challenges evaluators face, is in estimating counterfactuals (what would have happened in the absence of the development programme). and the assumption is that the changes observed in treatment and control groups over time

should be the same in the absence of the program. In addition, the treatment and control groups should not be exposed to other interventions during the project's period. When these three conditions are met, then the program of interest can be said to explain any differences in the outcome [1].

The measure for impact evaluation can only be valid and credible if the control group for evaluation is valid [1]. There were two types of impact estimates of which were applied in this study. The first approach for impact estimate (before-and-after comparison) attempts to measure impact of a program by comparing the changes in outcomes for the program participants over time. The problem with this approach is that there are other unobservable factors that influence outcomes of development programs [28]. The second approach for impact estimate (treatment-and-control groups) attempts to measure impact by comparing the outcomes of the treatment group with outcomes of the control group. However, this method is not only prone to selection bias especially if there was no random allocation of participants to either treatment or control group [29] but also, the control group could have other external influences like a different intervention by a completely new program even in cases where there was random allocation of participants to the control group hence making it difficult to measure the counterfactual.

The two approaches of estimating impact are combined to produce a better estimate of the counterfactual [29], known as the difference-in-difference method which takes into account any difference between the treatment and control groups that are constant over time [29]. The difference in outcomes before-and-after for the treatment group controls for factors that are constant over time in the treatment group, the same group is compared to itself, the first difference. However, does not take into account the outside time-varying factors. To capture the time varying factors, the difference before-and-after outcomes are measured for the control group to account for the same set of environmental (natural) conditions, the second difference [29]. The difference between the first and the second difference eliminates the main source of bias that evaluators face in the simple before-and-after comparisons. This is known as the difference-in-difference method. This method is however used when the treatment group and the control group are heterogeneous at baseline [29].

Unlike experimental and quasi-experimental designs, participatory approach to impact evaluation entails involving the stakeholders right from the planning stages of the project, implementation of and measuring of the project impact [9]. Participatory approaches also assists in identifying impact indicators important to the beneficiaries [9] and provides a stronger context for impact evidence, however, the counterfactual is only hypothetical [71]. The hypothetical counterfactual is appropriate and credible if; it's predictable, key informants have extensive knowledge about usual outcomes and have no incentive to

present a particular view [71].

For the purpose of this study, the difference-in-difference method was used to estimate impact of the Fruiting Africa Project (FAP) in Kenya. FAP was an agroforestry project which sort to check the status quo of fruit tree cultivation and consumption in Kenya and Mali and implement impact oriented interventions. The project appreciated that cultivation of fruit trees diversifies crop production options for small-holder farmers while bringing significant health among the household members and ecological benefits. In addition, the various agro-ecological zones offered increased diversity for both cultivated and wild fruit species [53].

This particular study focused on the two study sites in Kenya. A total of 600 farming households were randomly selected across two levels of stratification; sampling groups ('GROUPS') and agro-ecological zones (AEZs). The first level of stratification used to design the sampling strategy was AEZ, to capture the influence of ecological diversity on farming activities and tree species on farms in the surrounding landscapes. A transect was used to cut across four AEZs in each of the study sites (Figure 3.1).

The second stratification was used to randomly select participating households (HHs) from three groups/strata. The first stratum 'FRUIT GROUP' was comprised of HHs from groups that had previously worked with World Vision Kenya in a project related to tree cultivation or tree nurseries. The second stratum 'WASH GROUP' was comprised of HHs from groups that had previously worked with World Vision Kenya in a project related to water and hygiene. The third and last stratum 'CONTROL GROUP' was comprised of HHs from villages where World Vision did not have any prior or ongoing projects in the area. From each study site, approximately 100 HHs were randomly selected from each stratum across the four agro-ecological zones. At the start of the FAP project, the assumption was that the treatment and control groups were heterogeneous, a key assumption in the difference-in-difference method of impact estimation.

Due to the complexity of the project design given by different interventions administered to different groups, a more elaborate impact estimation procedure has been explained in the methods section. Agroforestry has been defined as deliberate integration of trees with annual crop cultivation, livestock production and other farming activities [37]. Due to the enormous benefits of trees on farms and landscapes, there has been calls to effectively scale-up agroforestry to benefit more people [35]. Agroforestry projects have improved the livelihoods of the farmers adopting it [7]. Like many other project at ICRAF which are mainly research for development, FAP hoped that with evidence from the pilot studies and models, the interventions can be promoted to benefit more people, if the results are positive.

The y-axis represents the outcomes after a period of time (x-axis). Points B and D represented the observed outcomes of the Treatment and Control groups at the baseline of the Fruiting Africa Project. Points E and C represented the observed outcomes of the Treatment and Control groups at the end of the project. The first difference was measured by the difference in outcomes before-and-after for the treatment group which is given by O = D-E, while the second difference was measured by the difference in outcomes before-and-after for the control group given by W = B-C. The impact of the FAP was therefore estimated using I = O-W.

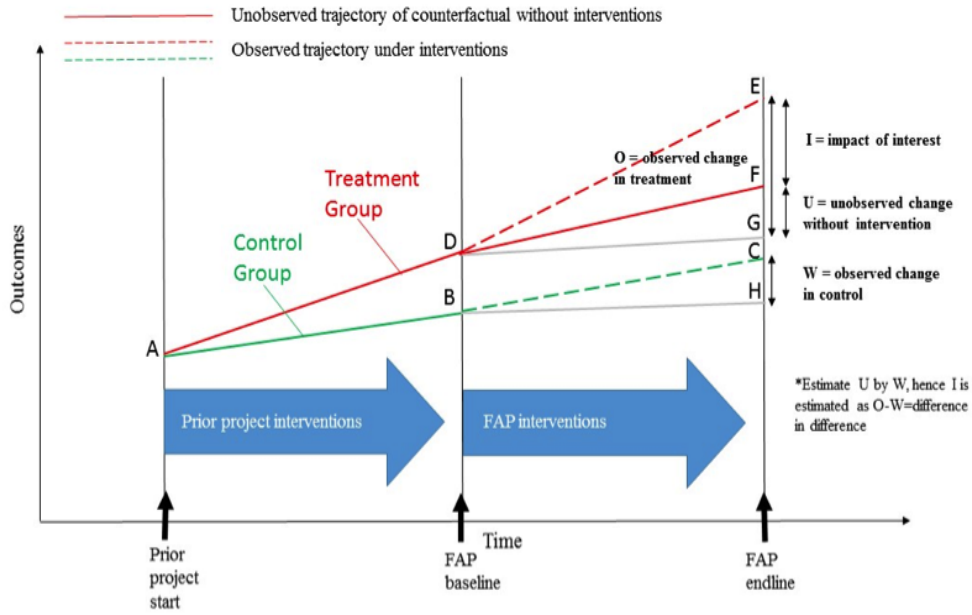



Figure 1.1: Conceptual diagram that was used for the difference-in-difference approach for impact estimation.

## 1.2 Statement of the problem

Despite billions of dollars having been spent on development assistance, very little is known about the actual effects of these development projects on the poor [1]. This may not necessary be as a result of no evidence of positive impact, but rather as a result of weak evaluation designs and methods (weak designs failure to produce convincing results) [5]. For example, these reviews that were specifically looking at evidence of impact of agricultural interventions on nutrition outcome concluded that rigorous evaluation designs are critically needed. Rigorous evaluation designs are also deemed as expensive in terms of money, time and skills required to carry them out [57], however, it is always not the

case [78]. Due to time and money constraints, single evaluation method becomes the obvious alternative [83].

## 1.3 Objectives

### 1.3.1 General Objective

To find out whether the FAP made a difference in the livelihoods of beneficiaries through the various interventions; training activities on diets, tree management and propagation, establishment and dissemination of tree portfolios, satellite nurseries and Rural Resource Centre, and distribution of quality nursery materials.

### 1.3.2 Specific Objectives

1. To find out whether the number of fruit tree abundance on smallholder farms increased as a result of the project
2. To find out whether the number of fruit tree diversity on smallholder farms increased as a result of the project
3. To find out if there was increased knowledge on diverse diets among the smallholder farm households as a result of the project.
4. To find out if there was increased knowledge on tree management and propagation among the smallholder farm households as a result of the project.

## 1.4 Hypotheses

1. Fruit abundance

   $$H_0 : E(Y_{f_a}|_T =_1, _t =_1) - E(Y_{f_a}|_T =_1, _t =_0) = E(Y_{f_a}|_T =_0, _t =_1) - E(Y_{f_a}|_T =_0, _t =_0)$$

   $$H_1 : E(Y_{f_a}|_T =_1, _t =_1) - E(Y_{f_a}|_T =_1, _t =_0) > E(Y_{f_a}|_T =_0, _t =_1) - E(Y_{f_a}|_T =_0, _t =_0)$$

2. Fruit diversity

   $$H_0 : E(Y_{f_d}|_T =_1, _t =_1) - E(Y_{f_d}|_T =_1, _t =_0) = E(Y_{f_d}|_T =_0, _t =_1) - E(Y_{f_d}|_T =_0, _t =_0)$$

$$H_1 : E(Y_{f_d}|_{T\,=1,\,t\,=1}) - E(Y_{f_d}|_{T\,=1,\,t\,=0}) > E(Y_{f_d}|_{T\,=0,\,t\,=1}) - E(Y_{f_d}|_{T\,=0,\,t\,=0})$$

3. Knowledge on diverse diets

$$H_0 : E(Y_{k_d}|_{T\,=1,\,t\,=1}) - E(Y_{k_d}|_{T\,=1,\,t\,=0}) = E(Y_{k_d}|_{T\,=0,\,t\,=1}) - E(Y_{k_d}|_{T\,=0,\,t\,=0})$$

$$H_1 : E(Y_{k_d}|_{T\,=1,\,t\,=1}) - E(Y_{k_d}|_{T\,=1,\,t\,=0}) > E(Y_{k_d}|_{T\,=0,\,t\,=1}) - E(Y_{k_d}|_{T\,=0,\,t\,=0})$$

4. Knowledge on tree management and propagation

$$H_0 : E(Y_{t_m}|_{T\,=1,\,t\,=1}) - E(Y_{t_m}|_{T\,=1,\,t\,=0}) = E(Y_{t_m}|_{T\,=0,\,t\,=1}) - E(Y_{t_m}|_{T\,=0,\,t\,=0})$$

$$H_1 : E(Y_{t_m}|_{T\,=1,\,t\,=1}) - E(Y_{t_m}|_{T\,=1,\,t\,=0}) > E(Y_{t_m}|_{T\,=0,\,t\,=1}) - E(Y_{t_m}|_{T\,=0,\,t\,=0})$$

**where:-**

$$H_0 = Null \quad Hypothesis$$

$$H_1 = Alternative \quad Hypothesis$$

$$Y_{f_a} = Fruit \quad Trees \quad Abundance$$

$$Y_{f_d} = Fruit \quad Trees \quad Diversity$$

$$Y_{k_d} = Knowledge \quad on \quad diets$$

$$Y_{t_m} = Knowledge \quad on \quad tree \quad management \quad practices$$

$$_{T\,=1,\,t\,=1} = Treatment \quad group \quad at \quad endline$$

$$_{T\,=1,\,t\,=0} = Treatment \quad group \quad at \quad baseline$$

$$_{T\,=0,\,t\,=1} = Control \quad group \quad at \quad endline$$

$$_T =_0, _t =_0 = Control \quad group \quad at \quad baseline$$

## 1.5 Significance of the study

This study is fundamental in determining if the approach used in FAP is sufficient to measure impact of the project, identified challenges faced and consequently how to improve on the design of similar projects. This will be important to ICRAF employees especially the principal investigators and project managers in determining if the project has the technical capacity not only to implement projects but also to measure the impact of those projects.The report created from this study is vital to donors in knowing whether development programs are improving the livelihoods of smallholder farmers involved in the project and also inform policy decisions.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.1 Introduction

Mixed methods approach refer to mixed data from different data collection processes ([86]). Quantitative and qualitative on the other hand refers to the type of data generated during the research process ([28, 55]). Interestingly, most methods can generate both quantitative and qualitative data ([86]), however, the type of data that is intended to be generated also influence the method used as some methods generate more quantitative data, while other methods generate more qualitative data ([28, 55, 79, 78]).

Other than the impact and evaluation method to be used, another challenge is in asking the right questions ([9]) which should be the highest priority and the basis for choosing the kind of method to be used. Actually, experts for global development goals said that the experience from Millennium Development Goals (MDGs) showed the need to think through the indicators for Sustainable Development Goals (SDGs) as early as possible ([81]).

Randomized Control Trials is an experimental design which can be used to collect both quantitative and qualitative data ([3, 57, 47, 79, 78]). While RCTs could be the most appropriate impact evaluation tool when feasible ([1, 9]), there are several misperceptions about RCTs. First, that these RCTs are a solution to all impact evaluation questions. Secondly, that the decision of measuring outcome (what to measure, how to measure it and who to include in the process) is independent of the decision to use RCTs. In addition, another grievous mistake is the perception that qualitative methodologies are an opposite of RCTs [9].

On the other hand, a difference in difference (DID) approach is a quasi-experimental design which is used to check for difference in group receiving an intervention, called treatment group (before and after) and comparing it with the difference in a group that

did not receive the intervention, called control group, given that the intervention had not been randomly assigned ([29, 42, 86]). The key strength of difference in difference approach is its ability to address the problem of selection bias as the difference between the control group and the treated group at baseline is factored in the estimation ([29, 86]). However, the assumption in the difference in difference estimate is that the background trend over time between the treatment and control group is the same. In addition, it's limited to quantitative impact estimate ([29, 86]).

Since, discussions on data collection strategies and measuring outcomes should be kept separate ([9]), then the inclusion of both quantitative and qualitative methods is acceptable in RCTs, however in difference in difference approach, it's limited to quantitative estimates. The use of quantitative methods to measure outcome makes it possible to establish statistical significance for program impact ([9]), hence allows the data to show whether an intervention made a difference or not.

In this study, the sampled households were perceived to be different due to the previous interventions that the households were subjected to and hence inappropriate to use the RCT approach to access impact of the Fruiting Africa project's interventions.

**CHAPTER THREE**

**METHODOLOGY**

## 3.1 Study Sites

The study took place in Machakos County, Eastern Kenya %(0 45'S 3645'E / 1 31'S 3745'E) and Siaya and Kakamega Counties, Western Kenya %(0 30'N 34 35'E / 0.500 N 34.583E and 005'S 3415'E / 0.083S 34.250E, respectively). This study was part of the FAP which was funded by IFAD and EU and implemented by ICRAF where a baseline survey (600 households) and other studies were done in both Eastern and Western Kenya, after which informed interventions were designed and implemented to increase fruit production and cultivation. Machakos County covers a total land area of about 6,208 km2 with a population of 1,098, 584 and population density of 177 people per km2 ([16, 45]) . The main farming system is mixed farming with maize, beans and peas being the main crops. It's inhabited mainly by the Kamba speaking community.

Kakamega County covers a total area of about 3,224.9 $km^2$ and has a population of about 1,660,651 with a population density of 515 people per $km^2$ while Siaya County covers a total area of about 2,496.1 km, population of about 842,304 and average population density of about 332km2 ([16, 45]). The main economic activity in Kakamega County farming where crops planted include maize, finger millet, cassava and sweet potatoes and fruit trees such as avocado, papaya and bananas. The area also practices dairy farming where cows, goats and sheep are reared for both milk production and meat. The area has the world famous equatorial rainforest known for its diversity of bird and insect life. The area is mainly inhabited by the Luhya speaking group. Siaya County on the other hand practices fishing, rice farming, livestock keeping and small scale subsistence farming. The area is mainly inhabited by the Luo community.

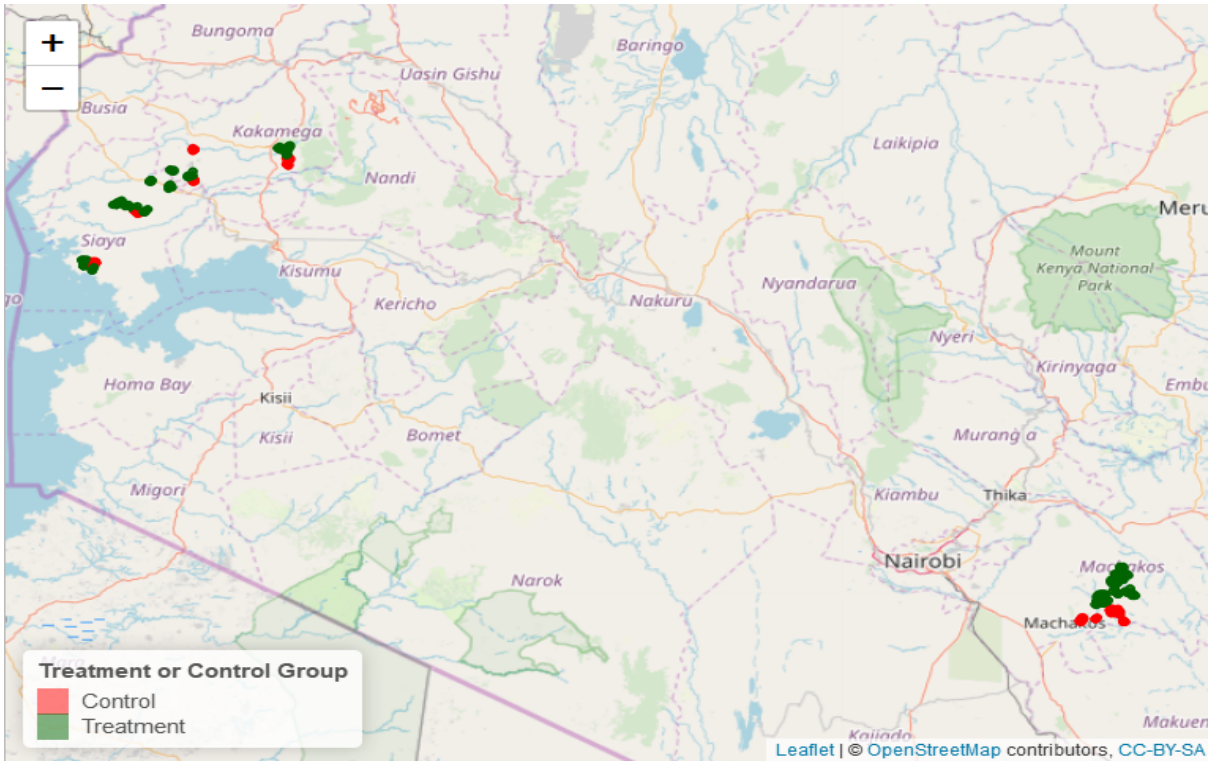



Figure 3.1: Maps of the study areas in Machakos, Siaya and Kakamega : Map by Ken Njogu using [68], packages: [12, 38, 14]

## 3.2 Description of the Fruiting Africa Project

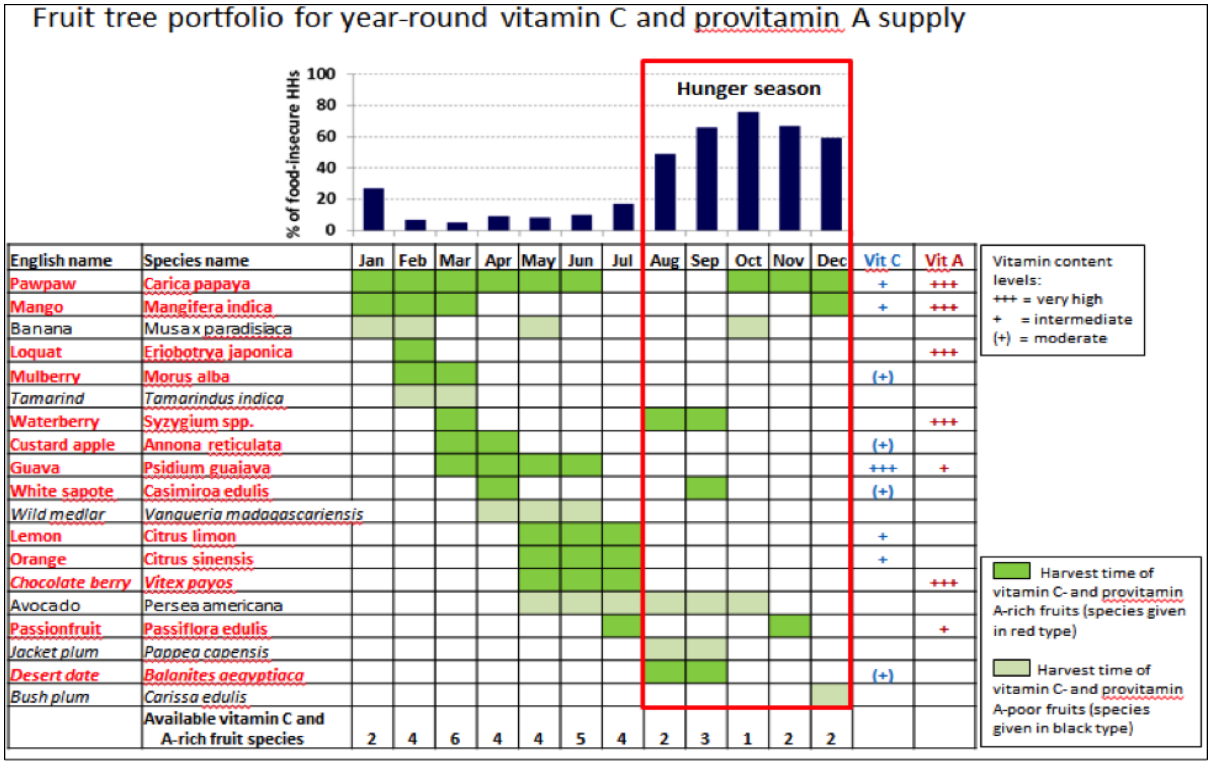
### 3.2.1 Overall Design of the FAP project

At the start of the project, a baseline survey was conducted in a total of 600 households randomly selected across two levels of stratification; sampling groups ('GROUPS') and agro-ecological zones (AEZs). The first level of stratification used to design the sampling strategy was AEZ, to capture the influence of ecological diversity on farming activities and tree species on farms in the surrounding landscapes. A transect was used to cut across four AEZs in each of the study sites (Figure 3.1). The second stratification was used to randomly select participating households (HHs) from three groups/strata. The first stratum 'FRUIT GROUP' was comprised of HHs from groups that had previously worked with World Vision Kenya in a project related to tree cultivation or tree nurseries. The second stratum 'WASH GROUP' was comprised of HHs from groups that had previously worked with World Vision Kenya in a project related to water and hygiene. The third and last stratum 'CONTROL GROUP' comprised of HHs from villages where World Vision did not have any prior or ongoing projects. From each study site, approximately 100 HHs were randomly selected from each stratum across the four agro-ecological zones. At

baseline social-economic and farm and fruit tree diversity and richness data was collected using a structured questionnaire by interviewing a responsible adult in the each of the household. In addition, a nutrition and consumption survey was done where data on household food security, 24-Hour recall, household and individual dietary diversity, fruit consumption and knowledge of nutrition and healthy diets was collected.

### 3.2.2 Programme Interventions

From the baseline results, interventions were designed and implemented. These interventions were only given to HHs from 'FRUIT' and 'WASH' groups and aimed at measuring impact of the interventions by finding out if the HHs would uptake the ideas. First was the Fruit Tree Portfolios ([41, 40, 54]) which were developed for Machakos County and disseminated to all the 'FRUIT' groups in Machakos County and demonstration plots set up in one of the group members in each of the eight groups. In addition these 'FRUIT' groups were supported through establishment of satellite nurseries where planting materials were made available to group members




| English name | Species name | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Vit C | Vit A |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pawpaw | Carica papaya | | | | | | | | | | | | | + | +++ |
| Mango | Mangifera indica | | | | | | | | | | | | | + | +++ |
| Banana | Musa x paradisiaca | | | | | | | | | | | | | | |
| Loquat | Eriobotrya japonica | | | | | | | | | | | | | | +++ |
| Mulberry | Morus alba | | | | | | | | | | | | | (+) | |
| Tamarind | Tamarindus indica | | | | | | | | | | | | | | |
| Waterberry | Syzygium spp. | | | | | | | | | | | | | | +++ |
| Custard apple | Annona reticulata | | | | | | | | | | | | | (+) | |
| Guava | Psidium guajava | | | | | | | | | | | | | +++ | + |
| White sapote | Casimiroa edulis | | | | | | | | | | | | | (+) | |
| Wild medlar | Vangueria madagascariensis | | | | | | | | | | | | | | |
| Lemon | Citrus limon | | | | | | | | | | | | | + | |
| Orange | Citrus sinensis | | | | | | | | | | | | | + | |
| Chocolate berry | Vitex payos | | | | | | | | | | | | | | +++ |
| Avocado | Persea americana | | | | | | | | | | | | | | |
| Passionfruit | Passiflora edulis | | | | | | | | | | | | | | + |
| Jacket plum | Pappea capensis | | | | | | | | | | | | | | |
| Desert date | Balanites aegyptiaca | | | | | | | | | | | | | (+) | |
| Bush plum | Carissa edulis | | | | | | | | | | | | | | |
| | Available vitamin C and A-rich fruit species | 2 | 4 | 6 | 4 | 4 | 5 | 4 | 2 | 3 | 1 | 2 | 2 | | |

Figure 3.2: Fruit tree portfolio developed for Machakos County, Kenya; Source: ([54])

These were designed to address the problem of low consumption of fruits ([37, 39]) and enable supply of vitamin-rich fruits throughout the year in each household by planting less than 10 fruits on each farm ([41, 54]). On the other hand, in Western Kenya, 'FRUIT'

groups were supported through the establishment of RRC and satellite nurseries where planting materials were made available to group members, expect for 'FRUIT' groups in AEZ– LM3, because the groups disintegrated before we could start the interventions and members showed no interest in participating in the FAP project. This was crafted to increase fruit diversity on their farms in Western Kenya where fruit tree diversity was low ([61]).

Figure 3.3: Photo of Ken Njogu, ICRAF staff, handing over Rural Resource Centre Materials to the Rambo nursery group members in Western Kenya

Lastly, were the trainings; tailor made trainings were carried out among the farmers from the 'FRUIT' and 'WASH' groups. All the 'FRUIT' groups in Machakos and Western Kenya were trained on tree management and propagation, tree nursery management, fruit processing and marketing, and nutrition and healthy diets. The 'WASH' groups received trainings on nutrition since being left out in the project would have potential to ruin the good relationship with World Vision, who were important partners in the project and would also 'further' the prior hygiene interventions received. These trainings were done with partners such as FEED THE CHILDREN, KALRO and JKUAT.

Figure 3.4: Photo of Valentine Gitonga, ICRAF staff, explaining how to set up the Rural Resource Centre to Rambo nursery group members in Western Kenya

## 3.3 Data Collection: Endline Survey

This study used data from the baseline survey (2014) and compared with results from the endline survey (2016). Given that the baseline had a sample of 600 households, using the ([46]) table, and Cochran equation the minimum sample size required for this study was 235 HHs ([34]). However, a total of 312 HHs were interviewed for the endline survey; 160 HHs were interviewed in Eastern Kenya (Machakos County) and 152 HHs were interviewed in Western Kenya (Kakamega and Siaya Counties) where data on key questions (indicator questions) were asked using a structured questionnaire. Those involved collecting data on socio-economic and farm and fruit tree diversity data of the HHs. Trained nutritionists were also used to assist in collection data on nutrition and consumption of HHs where data on HH food security, HH and Individual dietary diversity, fruit consumption amounts, household hunger scale and knowledge on nutrition and healthy diets were collected.

Most of the questions from the baseline questionnaire were asked in the endline survey including some key indicator questions which were compared with that from the baseline datasets. Before the actual field data collection, enumerator training was conducted to ensure that enumerators understand the questionnaires and that right questions were

being asked. Pre-test was done to check the validity and the reliability of the data collection tools. Mobile data collection, ODK ([32]) was used from which data was exported directly to Rstudio ([72]) for data cleaning and analysis ([31]).

Calculating sample size for large populations ([34])

$$\begin{aligned} n_0 &= \frac{Z^2 pq}{e^2} \\ &= \frac{1.96^2 \times 0.5 \times 0.5}{0.05^2} \\ &= 385 \quad farmers \end{aligned} \tag{3.1}$$

If the population is small, as in this study, then the sample size can be reduced ([34])

$$\begin{aligned} n &= \frac{n_0}{1 + \frac{(n_0 - 1)}{N}} \\ &= \frac{385}{1 + \frac{385 - 1}{600}} \\ &= 235 \quad farmers \end{aligned} \tag{3.2}$$

where;

$$Z^z = \text{ critical value of the normal distribution}$$

$$p = \text{sample proportion}$$

$$q = 1 - p$$

$$e^2 = \text{ margin of error}$$

## 3.4 Data Analysis

The data collected using tablets (ODK) ([32]) was exported to RStudio ([72]) for data cleaning and analysis ([31**?** , 89]), and the entire process documented using RMarkdown ([96, 95]) from which this thesis was produced a LaTeX document. Both simple descrip-

tive and inferential statistics were used to describe the data and check for significant differences among the groups ([87, 48, 52, 68]). Impact estimation was measured using key indicator variables using the difference-in-difference method using R and RStudio. The first step was to append the baseline dataset to the endline dataset with all variables of interest. Then a time variable 'time' was created with all cases/rows from baseline being coded as 0 and all cases from endline being coded as 1. A treatment variable 'treatment' was also created with all cases/rows from the control group being coded as 0 and all cases from the treatment group being coded as 1. Lastly, a variable 'did' was created which is the interaction of time and treatment variables given by time*treatment ([43]).

The first difference was used to estimate the unobservable change in outcomes for the control group at baseline and endline. The assumption was that this was the background trend of how the changes in outcome would have happened without the program, i.e. the counterfactual, which was used to estimate the unobserved change within the treatment group. The comparison group allows us to estimate the time tread given by ([29, 64, 80]);

$$\begin{aligned} D_1 &= E(Y_i|_T =_0, _t =_1) - E(Y_i|_T =_0, _t =_0) \\ &= E(Y_i|_T =_0) + \lambda_1 - E(Y_i|_T =_0) + \lambda_0 \\ &= \lambda_1 + \lambda_0 \\ &= \gamma \end{aligned}$$

The second difference was used to estimate the observable change in outcomes for the treatment group at baseline and endline survey given by;

$$\begin{aligned} D_2 &= E(Y_i|_T =_1, _t =_1) - E(Y_i|_T =_1, _t =_0) \\ &= E(Y_i|_T =_1) + \lambda_1 - E(Y_i|_T =_1) + \lambda_0 + \delta \\ &= \lambda_1 + \lambda_0 + \delta \\ &= \gamma + \delta \end{aligned}$$

The difference in difference estimator is given by;

$$\begin{aligned} DiD &= D_2 - D_1 \\ &= \big[\gamma + \delta\big] - \big[\gamma\big] \\ &= \delta \end{aligned}$$

One of the important coefficient of interest in the DiD regression framework is the treatment and comparison estimator, also known as the selection bias, given by $\beta$;

$$\begin{aligned} \beta &= E(Y_i|_{T\,=1}, {}_{t\,=1}) - E(Y_i|_{T\,=0}, {}_{t\,=1}) \\ &= \big[E(Y_i|_{T\,=1}) + \lambda_1\big] - \big[E(Y_i|_{T\,=0}) + \lambda_1\big] \\ &= E(Y_i|_{T\,=1}) - E(Y_i|_{T\,=0}) \end{aligned}$$

Therefore, to implement the DiD in a regression framework;

$$Y_i = \alpha + \gamma\big(time\big) + \beta\big(intervention\big) + \delta\big(time * intervention\big) + \xi$$

**where:-**

$$Y_i = variable \quad of \quad interest$$

$$\alpha = pre - program \quad mean \quad in \quad control \quad group$$

$$\gamma = time \quad tread \quad which \quad is \quad same \quad for \quad control \quad and \quad treatment \quad groups$$

$$\beta = selection \quad bias \quad or \quad pre - program \quad difference \quad between \quad control/treatment$$

$$\delta = true \quad impact \quad estimate$$

$$\xi = error \quad term$$

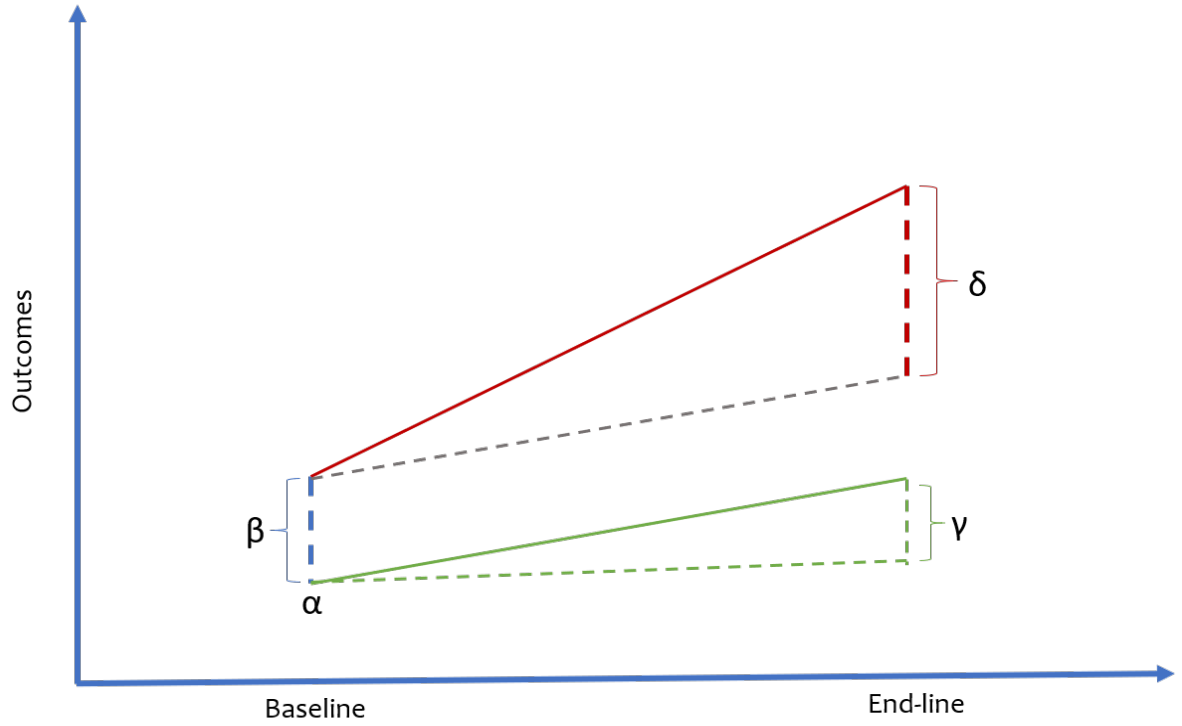



Figure 3.5: Simplified conceptual diagram that was used for the difference-in-difference estimation

### 3.4.1 Fruit Tree Diversity Indicators

Among the factors that were used to measure Fruit Tree Diversity were total, exotic and indigenous fruit tree individuals, species, and densities. In addition, Shannon diversity and evenness indices were calculated using BiodiversityR ([44]), and together with other fruit tree diversity variables significant differences between the baseline and endline data checked using the difference in difference estimation.

### 3.4.2 Food and Nutrition Security Indicators

The indicators that were used to measure food and nutrition security of participating HHs were; household, women and child dietary diversity, and amount of fruits consumed by woman and child. Dietary diversity were generated by summing up the different food groups consumed over a given period ([82, 8]), in this case 24 Hour Recall. The dietary diversity scores were computed separately for households, women and children.

# CHAPTER FOUR

# RESULTS AND DISCUSSIONS

## 4.1 Fruit Abundance

### 4.1.1 Total Fruit Trees Abundance

The Figure 4.1 above shows the median total tree abundance between control and treatment groups at baseline and endline. Regarding the total fruit tree abundance variable, the DiD estimate shows that there was sufficient evidence to conclude that the interventions for FAP had significant impact among our study sites in both Western and Lower Eastern Kenya (Table 4.1 and 4.2).

Table 4.1: Median for DiD estimation and significant differences for total fruit tree abundance

| | Treatment Group | | | Control Group | | | |
|---|---|---|---|---|---|---|---|
| Variable | Endline | Baseline | Difference | Endline | Baseline | Difference | Diff-in-Diff |
| Western Kenya | 20.0 | 14.0 | 6.0 | 12.0 | 12.0 | 0.0 | 6.0*** |
| L. Eastern Kenya | 37.0 | 28.5 | 8.5 | 38.0 | 45.0 | -7.0 | 15.5*** |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

Table 4.2: Coefficients for DiD estimator for the total fruit abundance for Western Kenya and Lower Eastern Kenya

| | Intercept | Intervention Group | Time Group | DiD | Null Hypothesis |
|---|---|---|---|---|---|
| Western Kenya | 2.94*** | 0.57*** | 1.01*** | -0.46*** | rejected |
| Lower Eastern Kenya | 4.45*** | -0.43*** | $0.005^{ns}$ | 0.18*** | rejected |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

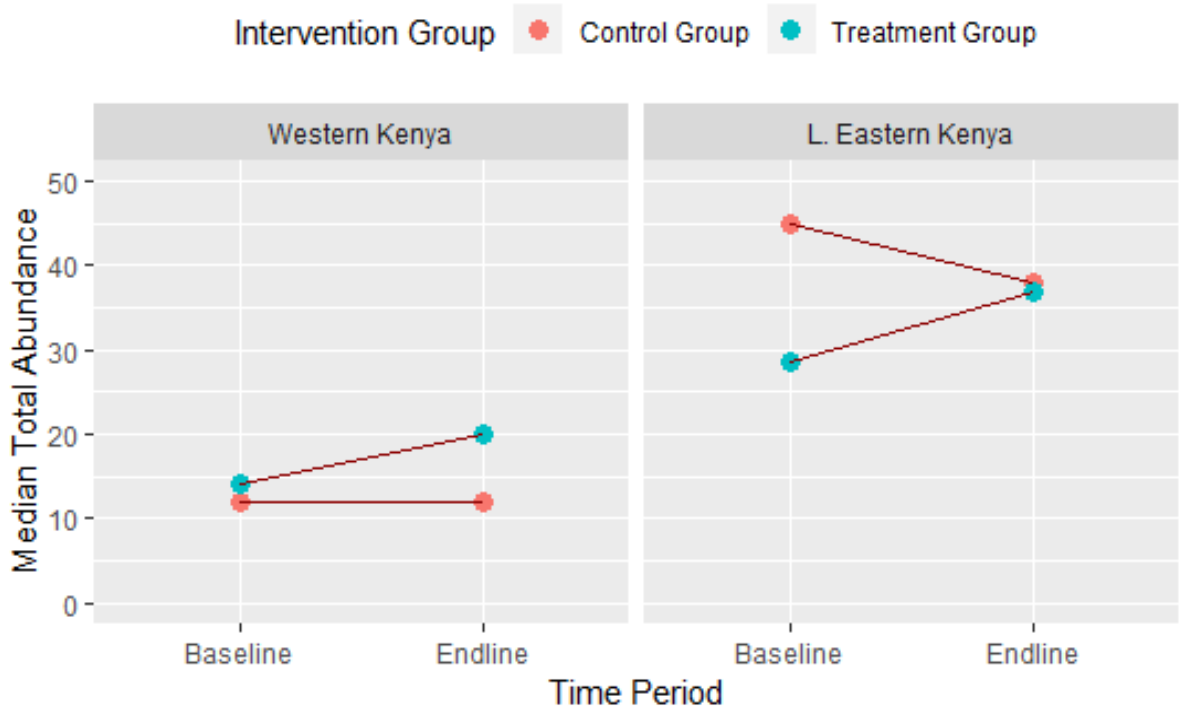



Figure 4.1: Median total fruit tree abundance between control and treatment groups at baseline and end-line

### 4.1.2 Exotic Fruit Trees Abundance

The Figure 4.2 below shows the median exotic tree abundance between control and treatment groups at baseline and endline. Regarding the exotic fruit tree abundance variable, the DiD estimate shows that there was sufficient evidence to conclude that the interventions for FAP had significant impact among our study sites in both Western and Lower Eastern Kenya (Table 4.3 and 4.4).

Table 4.3: Median for DiD estimation and significant differences for exotic fruit tree abundance

| | Treatment Group | | | Control Group | | | |
|---|---|---|---|---|---|---|---|
| Variable | Endline | Baseline | Difference | Endline | Baseline | Difference | Diff-in-Diff |
| Western Kenya | 19.0 | 13.0 | 6.0 | 11.0 | 12.0 | -1.0 | 7.0*** |
| L. Eastern Kenya | 33.0 | 23.0 | 10.0 | 36.0 | 36.0 | 0.0 | 10.0*** |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

Table 4.4: Coefficients for DiD estimator for the total fruit abundance for Western Kenya and Lower Eastern Kenya

| | Intercept | Intervention Group | Time Group | DiD | Null Hypothesis |
|---|---|---|---|---|---|
| Western Kenya | 2.88*** | 0.60*** | 1.04*** | -0.48*** | rejected |
| Lower Eastern Kenya | 4.39*** | -0.49*** | 0.05*** | 0.19*** | rejected |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

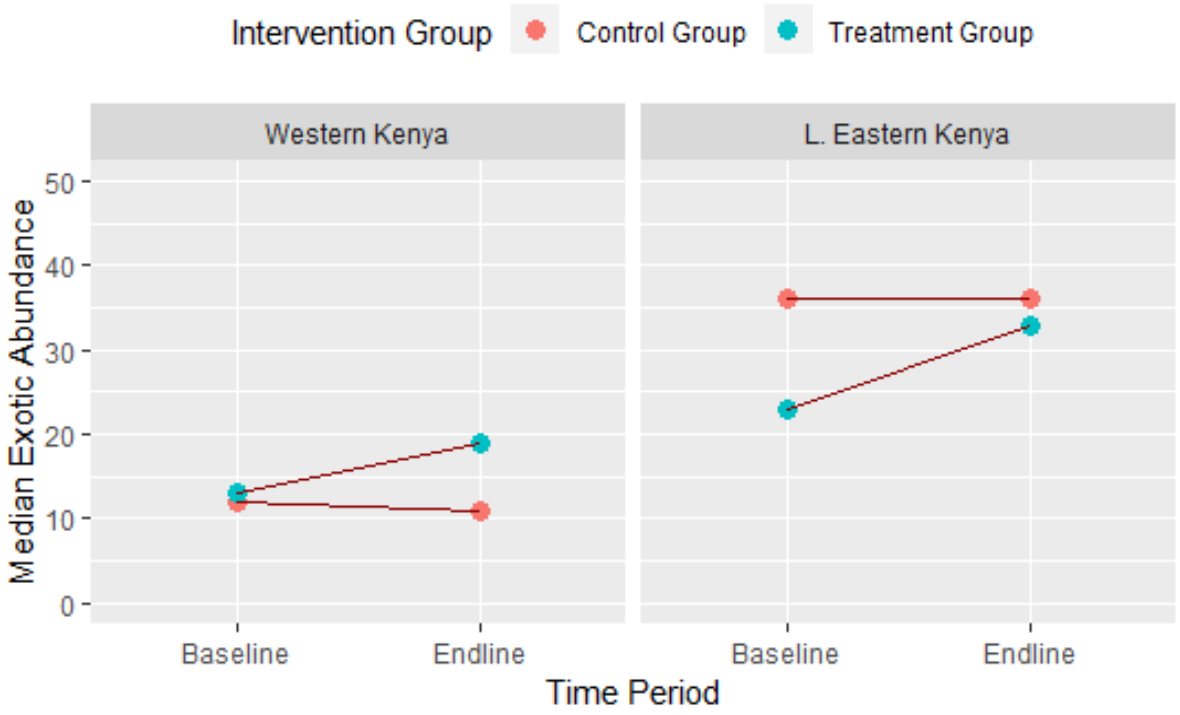



Figure 4.2: Median exotic fruit tree abundance between control and treatment groups at baseline and end-line

### 4.1.3 Indigenous Fruit Trees Abundance

The Figure 4.3 below shows the median indigenous tree abundance between control and treatment groups at baseline and endline. Regarding the indigenous fruit tree abundance variable, the DiD estimate shows that there was sufficient evidence to conclude that the interventions for FAP had significant impact among our study site in Lower Eastern Kenya, however, in Western Kenya, there were no significant changes (Table 4.5 and 4.6).

Table 4.5: Median for DiD estimation and significant differences for indigenous fruit tree abundance

| | Treatment Group | | | Control Group | | | |
|---|---|---|---|---|---|---|---|
| Variable | Endline | Baseline | Difference | Endline | Baseline | Difference | Diff-in-Diff |
| Western Kenya | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | $0.0^{ns}$ |
| L. Eastern Kenya | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | -1.0 | 1.0*** |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

Table 4.6: Coefficients for DiD estimator for the total fruit abundance for Western Kenya and Lower Eastern Kenya

| | Intercept | Intervention Group | Time Group | DiD | Null Hypothesis |
|---|---|---|---|---|---|
| Western Kenya | $-0.09^{ns}$ | $-0.20^{ns}$ | $-0.02^{ns}$ | $0.265^{ns}$ | not rejected |
| Lower Eastern Kenya | 1.59*** | 0.26*** | -1.45*** | 0.97*** | rejected |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

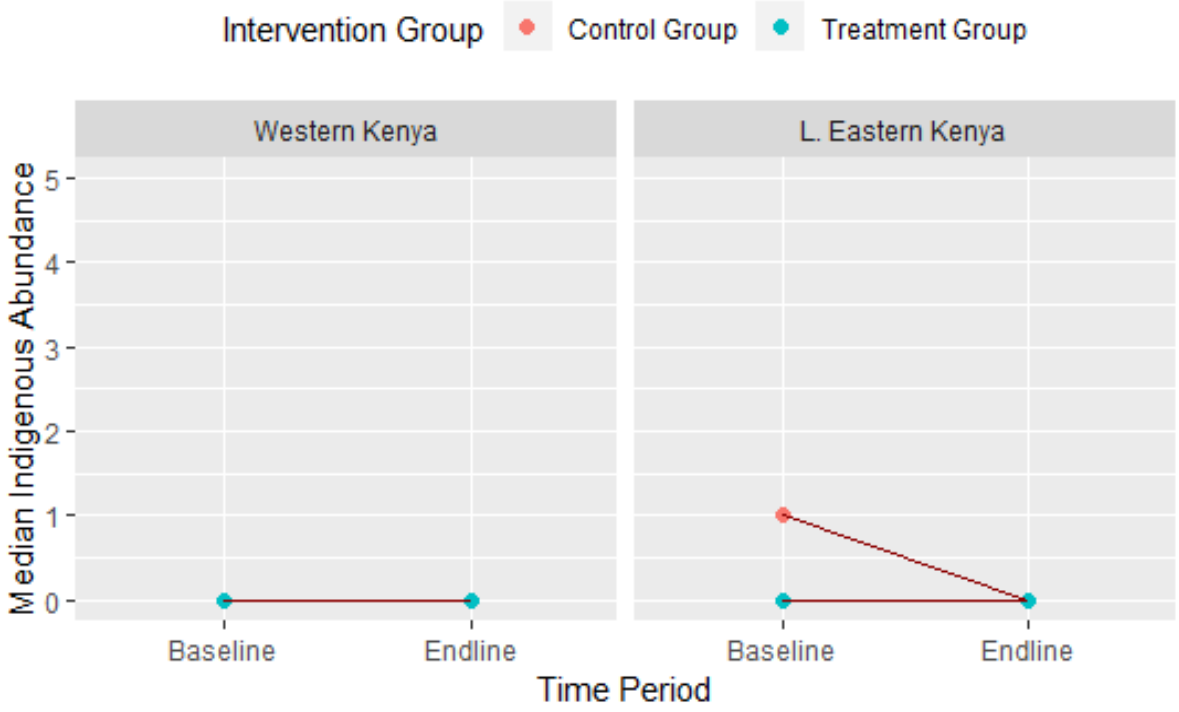



Figure 4.3: Median indigenous fruit tree abundance between control and treatment groups at baseline and end-line

### 4.1.4 Fruit Trees Abundance Summary

In summary, in regard to fruit trees abundances (section 4.1), in Lower Eastern Kenya, the null hypothesis that total, exotic and indigenous fruit trees abundances remained the same was rejected. In Western Kenya, the null hypothesis that total and exotic fruit

trees abundances remained the same was also rejected. However, in Western Kenya, there was no sufficient evidence to reject the null hypothesis that the indigenous fruit tree abundance remained the same.

## 4.2 Fruit Trees Diversity

### 4.2.1 Total Fruit Trees Diversity

The Figure 4.4 above shows the median total tree diversity between control and treatment groups at baseline and endline. The DiD estimator shows that there was sufficient evidence to conclude that the interventions for FAP had significant impact on total fruit tree diversity in Lower Eastern Kenya, however no the same case in Western Kenya (Table 4.7 and 4.8).

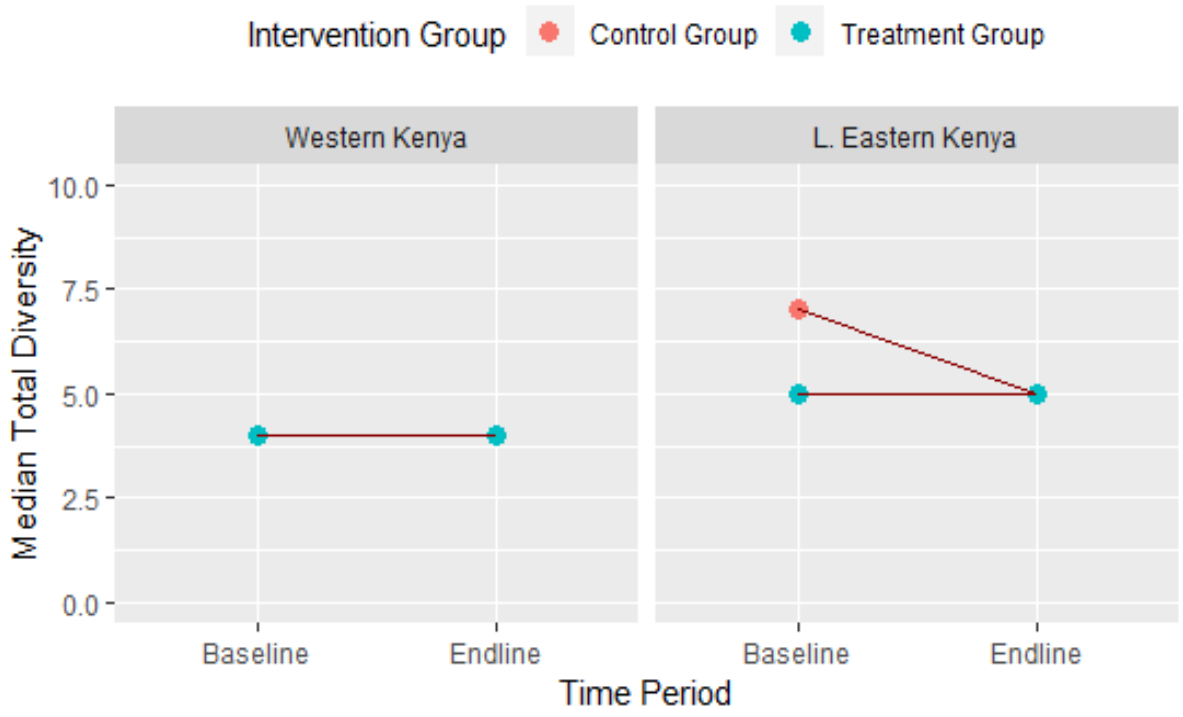



Figure 4.4: Median total fruit tree diversity between control and treatment groups at baseline and end-line

Table 4.7: Median for DiD estimation and significant differences for total fruit tree diversity

| | Treatment Group | | | Control Group | | | |
|---|---|---|---|---|---|---|---|
| Variable | Endline | Baseline | Difference | Endline | Baseline | Difference | Diff-in-Diff |
| Western Kenya | 4.0 | 4.0 | 0.0 | 4.0 | 4.0 | 0.0 | $0.0^{ns}$ |
| L. Eastern Kenya | 5.0 | 5.0 | 0.0 | 5.0 | 7.0 | -2.0 | 2.0** |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

Table 4.8: Coefficients for DiD estimator for the total fruit tree diversity for Western Kenya and Lower Eastern Kenya

| | Intercept | Intervention Group | Time Group | DiD | Null Hypothesis |
|---|---|---|---|---|---|
| Western Kenya | 1.31*** | $0.05^{ns}$ | $0.05^{ns}$ | $0.11^{ns}$ | not rejected |
| Lower Eastern Kenya | 1.97*** | -0.31*** | -0.21** | 0.25** | rejected |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

### 4.2.2 Exotic Fruit Trees Diversity

The Figure 4.5 below shows the median exotic tree abundance between control and treatment groups at baseline and endline. There was sufficient evidence to conclude that the interventions for FAP had significant impact on exotic fruit tree diversity in Lower Eastern Kenya, however, this was not the case with Western Kenya (Table 4.9 and 4.10).

Table 4.9: Median for DiD estimation and significant differences for exotic fruit tree diversity

| | Treatment Group | | | Control Group | | | |
|---|---|---|---|---|---|---|---|
| Variable | Endline | Baseline | Difference | Endline | Baseline | Difference | Diff-in-Diff |
| Western Kenya | 4.0 | 3.0 | 1.0 | 4.0 | 4.0 | 0.0 | $1.0^{ns}$ |
| L. Eastern Kenya | 5.0 | 5.0 | 0.0 | 5.0 | 6.0 | -1.0 | 1.0* |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

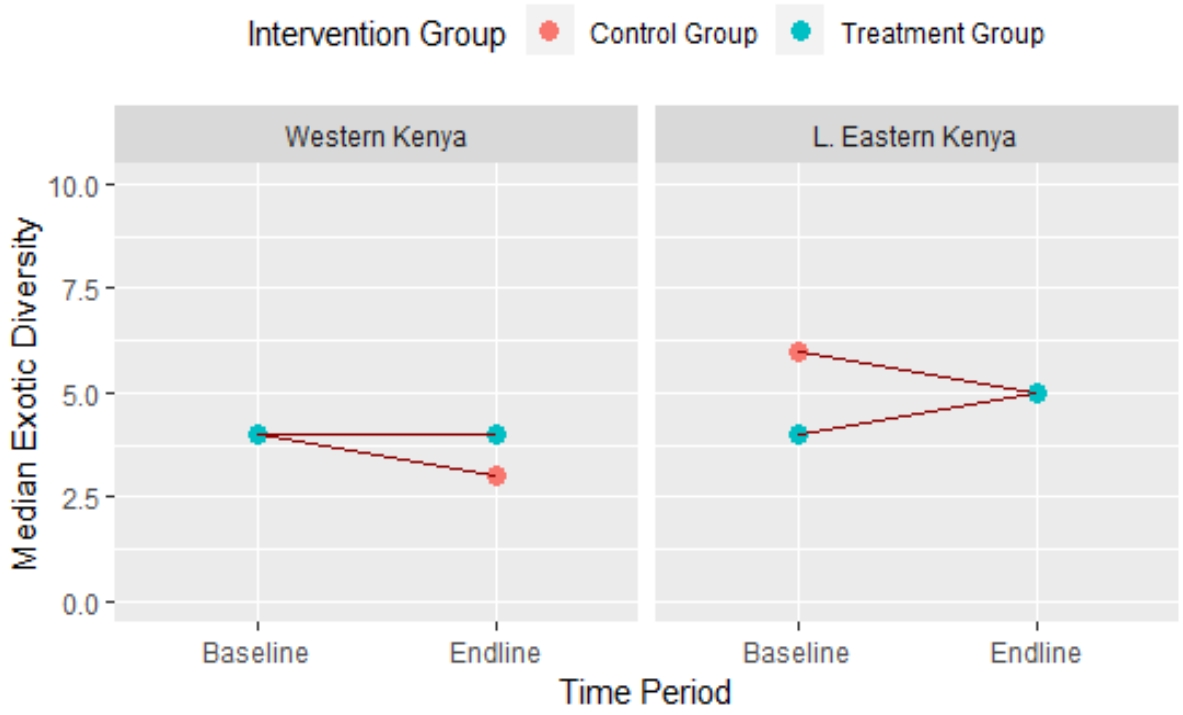



Figure 4.5: Median exotic fruit tree diversity between control and treatment groups at baseline and end-line

Table 4.10: Coefficients for DiD estimator for the exotic fruit tree diversity for Western Kenya and Lower Eastern Kenya

| | Intercept | Intervention Group | Time Group | DiD | Null Hypothesis |
|---|---|---|---|---|---|
| Western Kenya | 1.23*** | $0.07^{ns}$ | $0.06^{ns}$ | $0.11^{ns}$ | not rejected |
| Lower Eastern Kenya | 1.76*** | -0.33*** | $-0.11^{ns}$ | 0.22* | rejected |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

### 4.2.3 Indigenous Fruit Trees Diversity

The Figure 4.6 below shows the median indigenous tree abundance between control and treatment groups at baseline and endline. The DiD estimate showed that there was sufficient evidence to conclude that the interventions for FAP had significant impact on indigenous fruit tree diversity in Lower Eastern Kenya, however, not the same case with Western Kenya (Table 4.11 and 4.12).

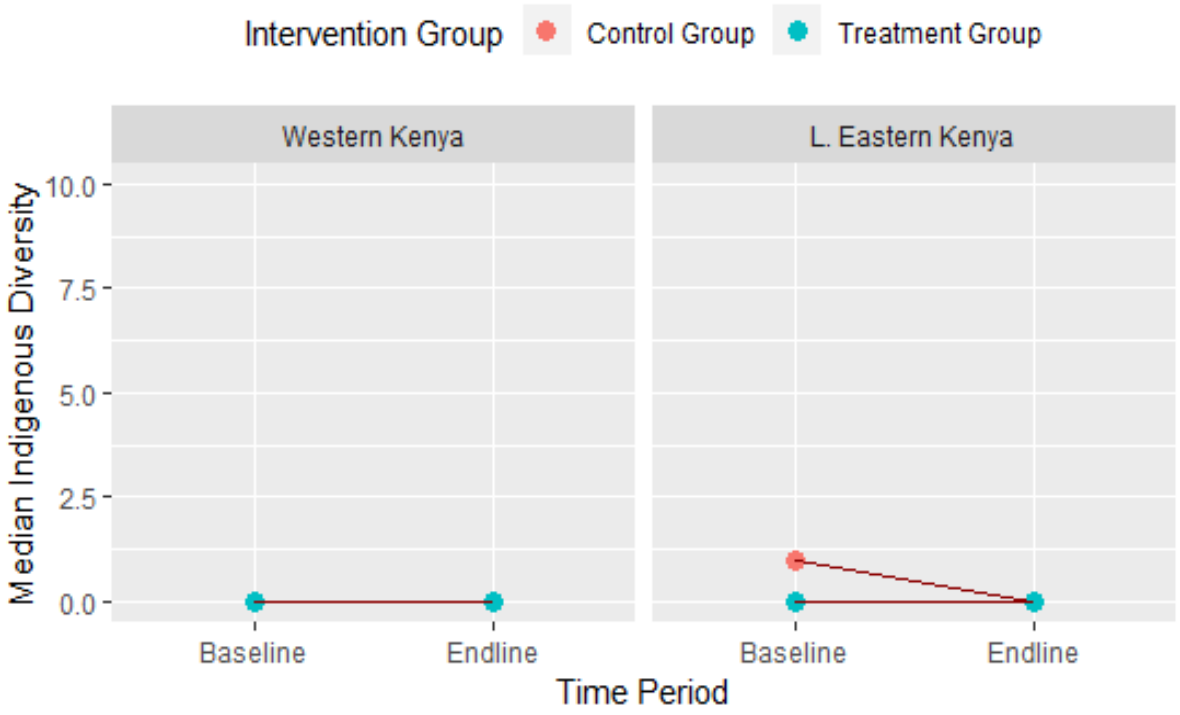



Figure 4.6: Median indigenous fruit tree diversity between control and treatment groups at baseline and end-line

Table 4.11: Median for DiD estimation and significant differences for indigenous fruit tree diversity

| | Treatment Group | | | Control Group | | | |
|---|---|---|---|---|---|---|---|
| Variable | Endline | Baseline | Difference | Endline | Baseline | Difference | Diff-in-Diff |
| Western Kenya | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | $0.0^{ns}$ |
| L. Eastern Kenya | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | -1.0 | 1.0* |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

Table 4.12: Coefficients for DiD estimator for the indigenous fruit tree diversity for Western Kenya and Lower Eastern Kenya

| | Intercept | Intervention Group | Time Group | DiD | Null Hypothesis |
|---|---|---|---|---|---|
| Western Kenya | -1.23*** | $-0.24^{ns}$ | $0.02^{ns}$ | $-0.06^{ns}$ | not rejected |
| Lower Eastern Kenya | 0.30*** | -0.21* | -0.89*** | 0.58* | rejected |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

### 4.2.4 Shannon Index

The Figure 4.7 below shows the mean shannon index between control and treatment groups at baseline and endline.

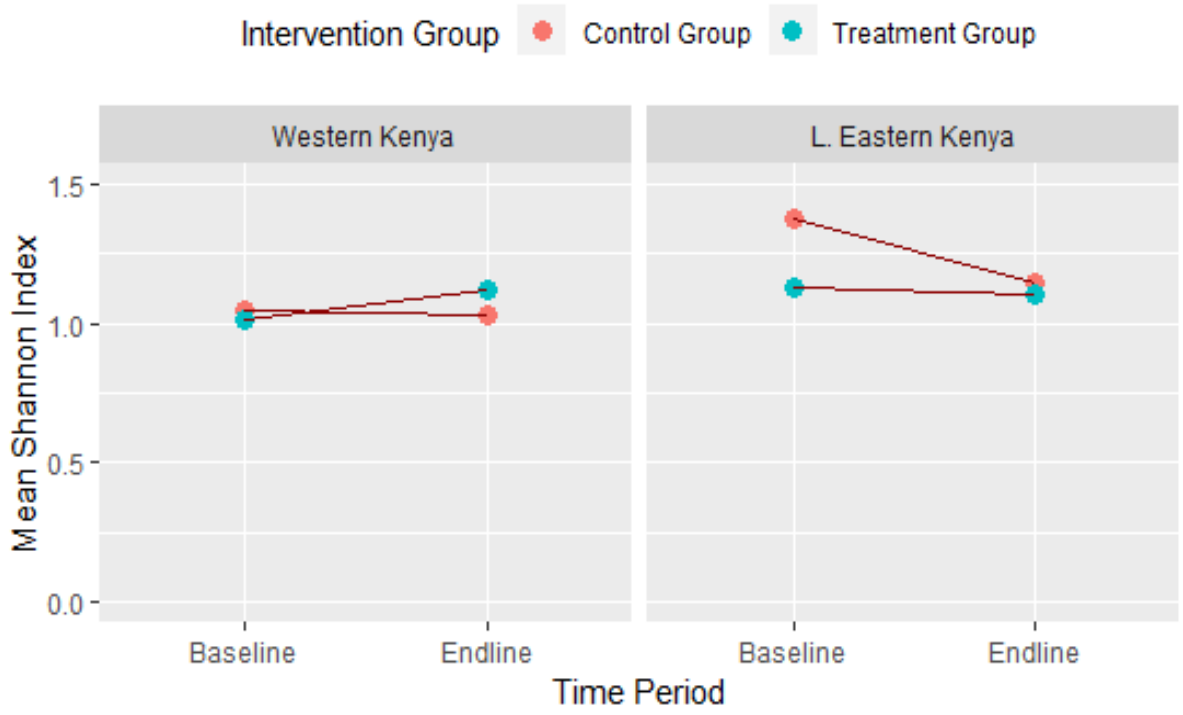



Figure 4.7: Mean shannon index between control and treatment groups at baseline and end-line

The DiD estimate showed that there was sufficient evidence to conclude that the interventions for FAP had significant impact on shannon index in Lower Eastern Kenya, however, not the same case with Western Kenya (Table 4.13 and 4.14).

Table 4.13: Mean for DiD estimation and significant differences for shannon index

| | Treatment Group | | | Control Group | | | |
|---|---|---|---|---|---|---|---|
| Variable | Endline | Baseline | Difference | Endline | Baseline | Difference | Diff-in-Diff |
| Western Kenya | 1.12 | 1.03 | 0.09 | 1.01 | 1.05 | -0.04 | $0.13^{ns}$ |
| L. Eastern Kenya | 1.11 | 1.15 | -0.04 | 1.13 | 1.38 | -0.25 | 0.21* |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

Table 4.14: Coefficients for DiD estimator for the shannon index for Western Kenya and Lower Eastern Kenya

| | Intercept | Intervention Group | Time Group | DiD | Null Hypothesis |
|---|---|---|---|---|---|
| Western Kenya | 0.29** | $-0.06^{ns}$ | $0.01^{ns}$ | $-0.02^{ns}$ | not rejected |
| Lower Eastern Kenya | 1.34*** | $-0.26^{ns}$ | -0.79*** | 0.58* | rejected |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

### 4.2.5 Fruit Trees Diversity Summary

In summary, in Lower Eastern Kenya, the null hypothesis that total, exotic, indigenous fruit tree diversities and Shannon index remained the same was rejected while, in Western Kenya, there was no sufficient evidence to reject the null hypothesis that total, exotic, indigenous fruit tree diversities and Shannon index remained the same for same period of time.

## 4.3 Knowledge on Grafting

The Figure 4.8 below shows the percentages of those who had heard about grafting, those who knew how to graft and those who had grafted a fruit tree.


Figure 4.8: Percentage of those who had heard about grafting, knew how to graft and had grafted a fruit tree

Regarding those who had heard of grafting techniques, there was no sufficient evidence to reject the null hypothesis that the percentage of those who had heard about grafting techniques remained the same for the same period of time for both Western Kenya and Lower Eastern Kenya (Table 4.15).

Regarding those who knew how to graft, there was no sufficient evidence to reject the null hypothesis that the percentage of those who knew how to graft remained the same for the same period of time for both Western Kenya and Lower Eastern Kenya (Table 4.15).

Regarding those who had grafted a fruit tree, there was sufficient evidence to reject the null hypothesis that the percentage of those who had grafted a fruit tree remained the same for the same period of time in Western Kenya, however not the same case with Lower Eastern Kenya (Table 4.15).

Table 4.15: Coefficients for DiD estimator for knowledge on grafting for Western Kenya and Lower Eastern Kenya

| | Region | Intercept | Intervention Group | Time Group | DiD | Null Hypothesis |
|---|---|---|---|---|---|---|
| Heard Grafting | Western Kenya | -0.27$^{ns}$ | 0.43** | -0.06$^{ns}$ | 0.28$^{ns}$ | not rejected |
| | Lower Eastern Kenya | 19.57$^{ns}$ | -16.71$^{ns}$ | -16.45$^{ns}$ | 17.61$^{ns}$ | not rejected |
| How to Graft | Western Kenya | -0.73** | 0.13$^{ns}$ | -0.36$^{ns}$ | 0.55$^{ns}$ | not rejected |
| | Lower Eastern Kenya | -1.10*** | -0.24$^{ns}$ | 0.09$^{ns}$ | 0.51$^{ns}$ | not rejected |
| Have Grafted | Western Kenya | 0.81$^{ns}$ | -0.41$^{ns}$ | -3.01*** | 0.93* | rejected |
| | Lower Eastern Kenya | -2.4*** | -0.27$^{ns}$ | -2.54*** | 0.31$^{ns}$ | not rejected |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

## 4.4 Knowledge on Diets

### 4.4.1 Amounts of Fruits Consumed

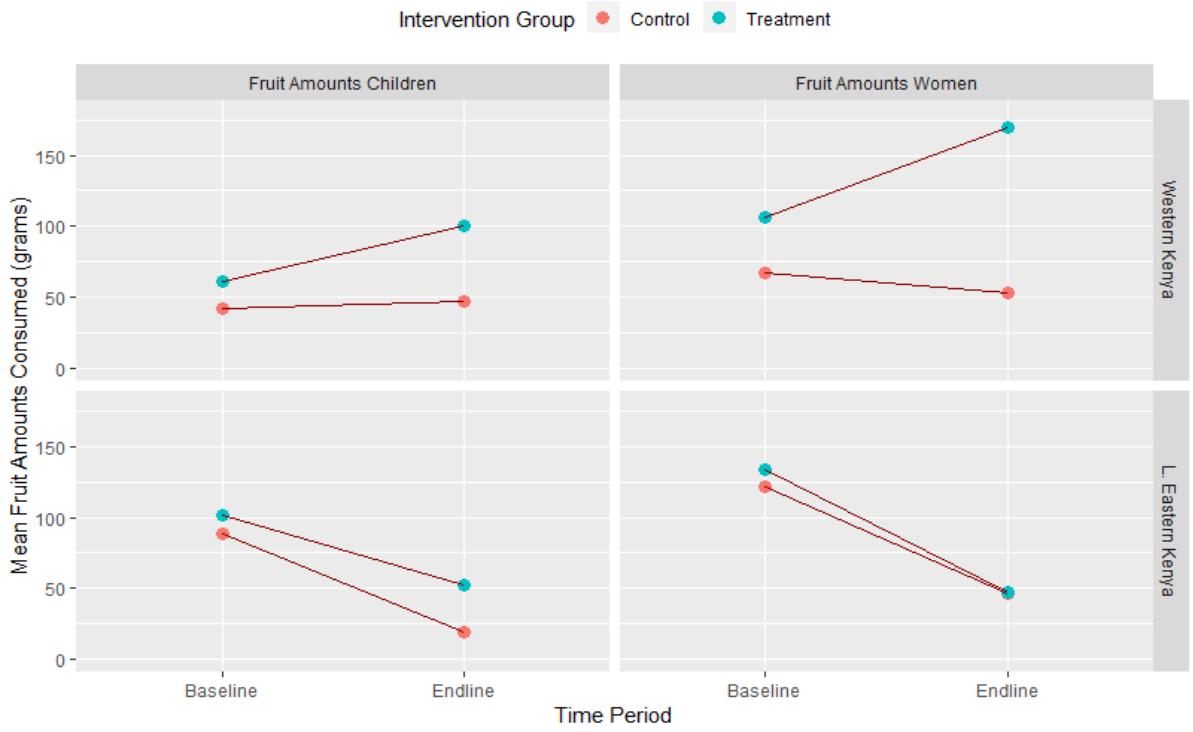



Figure 4.9: Mean amounts of fruits consumed between control and treatment groups at baseline and end-line

The Figure 4.9 above shows the mean fruit amounts consumed by women and children between control and treatment groups at baseline and endline.

There was sufficient evidence to reject the null hypothesis that the amounts of fruits (grams) consumed by women changed overtime due to our interventions in Lower Easter Kenya, however, a different case for Western Kenya. In regard to the amounts of fruits

consumed by children, there was no sufficient evidence to reject the null hypothesis that the amounts of fruits (grams) consumed by children changed overtime due to our interventions for both Western and Lower Eastern Kenya (Table 4.16 and 4.17).

Table 4.16: Coefficients for DiD estimator for fruit amounts consumed (grams)

| Region | | Intercept | Intervention Group | Time Group | DiD | Null Hypothesis |
|---|---|---|---|---|---|---|
| Western Kenya | Women | 66.9*** | 39.3* | -14.1$^{ns}$ | 77.3* | rejected |
| | Children | 41.8*** | 19.1$^{ns}$ | 4.9$^{ns}$ | 34.1$^{ns}$ | not rejected |
| L. Eastern Kenya | Women | 121.6*** | 12.1$^{ns}$ | -75.3* | -10.7$^{ns}$ | not rejected |
| | Children | 88.4*** | 13.3$^{ns}$ | -69.3* | 19.5$^{ns}$ | not rejected |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

Table 4.17: Mean for DiD estimation and significant differences for fruit amounts consumed (grams)

| | Treatment Group | | | Control Group | | | |
|---|---|---|---|---|---|---|---|
| Variable | Endline | Baseline | Difference | Endline | Baseline | Difference | Diff-in-Diff |
| Western Kenya - Women | 169.5 | 106.3 | 63.2 | 52.9 | 66.9 | -14.0 | 77.2* |
| Western Kenya - Children | 99.9 | 60.9 | 39.0 | 46.7 | 41.8 | 4.9 | 34.1$^{ns}$ |
| L. Eastern Kenya - Women | 47.8 | 133.8 | -86.0 | 46.4 | 121.6 | -75.2 | -10.8$^{ns}$ |
| L. Eastern Kenya - Children | 51.9 | 101.7 | -49.8 | 19.1 | 88.4 | -69.3 | 19.5$^{ns}$ |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

### 4.4.2 Dietary Diversity Scores (DDS)

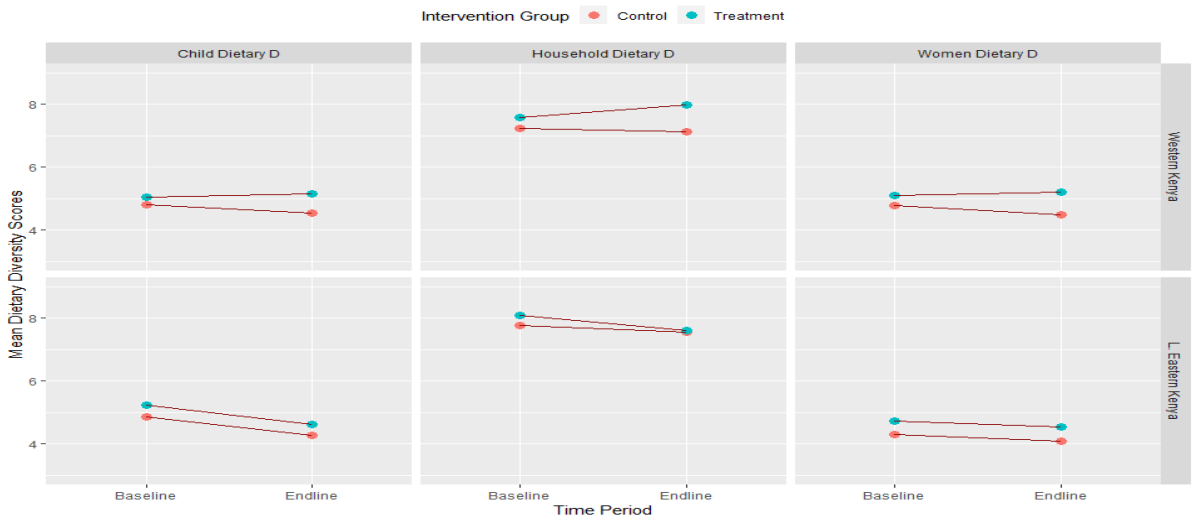



Figure 4.10: Mean dietary diversity scores control and treatment groups at baseline and end-line

The Figure 4.10 above shows the mean dietary diversity scores between control and treatment groups at baseline and endline.

There was no sufficient evidence to reject the null hypothesis that dietary diversity scores; child dietary diversity (cdd), household dietary diversity (hdd) and women dietary diversity changed overtime as a result of the project's interventions for both Western Kenya and Lower Eastern Kenya (Table 4.18 and 4.19).

Table 4.18: Mean for DiD estimation and significant differences for dietary diversity scores

| | Treatment Group | | | Control Group | | | |
|---|---|---|---|---|---|---|---|
| Variable | Endline | Baseline | Difference | Endline | Baseline | Difference | Diff-in-Diff |
| Western Kenya - cdd | 5.2 | 5.0 | 0.2 | 4.6 | 4.8 | -0.2 | $0.4^{ns}$ |
| Western Kenya - hdd | 8.0 | 7.6 | 0.4 | 7.1 | 7.2 | -0.1 | $0.5^{ns}$ |
| Western Kenya - wdd | 5.2 | 5.1 | 0.1 | 4.5 | 4.8 | -0.3 | $0.4^{ns}$ |
| L. Eastern Kenya - cdd | 4.6 | 5.2 | -0.6 | 4.3 | 4.9 | -0.6 | $0.0^{ns}$ |
| L. Eastern Kenya - hdd | 7.6 | 8.1 | -0.5 | 7.5 | 7.8 | -0.3 | $-0.2^{ns}$ |
| L. Eastern Kenya - wdd | 4.5 | 4.7 | -0.2 | 4.1 | 4.3 | -0.2 | $0.0^{ns}$ |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

Table 4.19: Coefficients for DiD estimator for dietary diversity scores

| Region | DDS | Intercept | Intervention Group | Time Group | DiD | Null Hypothesis |
|---|---|---|---|---|---|---|
| Western Kenya | cdd | 1.57*** | $0.05^{ns}$ | $-0.06^{ns}$ | $0.08^{ns}$ | not rejected |
| | hdd | 1.98*** | $0.05^{ns}$ | $-0.01^{ns}$ | $0.06^{ns}$ | not rejected |
| | wdd | 1.57*** | $0.06^{ns}$ | $-0.07^{ns}$ | $0.09^{ns}$ | not rejected |
| L. Eastern Kenya | cdd | 2.05*** | $0.04^{ns}$ | $-0.03^{ns}$ | $-0.03^{ns}$ | not rejected |
| | hdd | 1.58*** | $0.07^{ns}$ | $-0.13^{ns}$ | $-0.00^{ns}$ | not rejected |
| | wdd | 1.46*** | $0.09^{ns}$ | $-0.05^{ns}$ | $0.01^{ns}$ | not rejected |

Notes: *, **, *** denotes significance level at 5%, 1% & 0.1%, respectively.

# CHAPTER FIVE

# CONCLUSIONS AND RECOMMENDATIONS

The project timeline was only three years for interventions revolved around fruit consumption and production of high quality seedlings among the participating farmers.

Whereas in Lower Eastern Kenya there were significant differences between control and treatment groups at baseline and endline in fruit tree abundance and diversities, the other indicators for increased knowledge on tree propagation did not show any significant differences. In Western Kenya, exotic and total fruit tree abundances showed significant changes between control and treatment groups from baseline to endline, however, not the same case with indigenous fruit tree abundances. In addition, all diversity indicators did not show any significant changes between control and treatment groups from baseline to endline. Also, in regarding tree propagation indicators, the was significant change in the percentage of farmers who had grafted a fruit tree between control and treatment groups at endline .

Regarding food and nutritional security indicators, there was no significant differences between the control and treatment groups at baseline and endline for some of the nutrition indicators such ad dietary diversities. This could have be possible because food and nutritional security could have other 'stronger' factors influencing it than on farm fruit tree abundance and diversity.

In generally, such complex studies with unique challenges in different research sites are quite complex to design and even to evaluate. However, DiD method could be suitable for such studies when it comes to impact evaluation. Particularly in this type of studies, it is important to ensure that both the baseline and endline studies are done in the same months to take care of seasonal variations. Also, in agroforestry projects, it's a challenge to measure impact when project timelines are minimal such as three years.

## REFERENCES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## Appendix 1: Project's Repository

Repository for the following:

- Questionnaires used to collect data
- Endline Data for both sites
- Baseline Data for both sites
- Complete R ccript for documenting data cleaning and analysis

`https://data.worldagroforestry.org/dataverse/FruitingAfrica`

## Appendix 2: R Syntax for mapping study site

```
### mapping study sites

```{r study sites}
gps_data <- read.dta13(file = "EndlineSurveyFruitingAfrica.dta",
                       convert.factors = TRUE) %>%
  dplyr::select(farmid, county_name, Sampling_Strata, latitude, longitude) %>%
  dplyr::mutate(treatment_grp = ifelse(Sampling_Strata == "Control Group", "Control", "Treatment"),
                treatment_grp = ifelse(treatment_grp == "Control Group", "Control", "Treatment"))


factpal <- colorFactor(palette = c("Red", "Dark Green"),
                       gps_data$treatment_grp)

tudy_map <- leaflet(gps_data) %>%
  addTiles() %>%
  addCircleMarkers(lng = ~longitude,
             lat = ~latitude,
             popup = gps_data$farmid,
             radius = 1,
             weight = 4,
             opacity = 1,
             fill = TRUE,
             fillOpacity = 1,
             color = ~factpal(treatment_grp)) %>%
  addLegend("bottomleft",
            pal = factpal,
            values = ~ treatment_grp,
            title = "Treatment or Control Group")
```

Figure .1: R Syntax that developed study sites' map 3.1
```

## Appendix 3: R Syntax for plotting connected observations

```
### Dietary Diversity
```{r hdd}
## Dietary Diversity

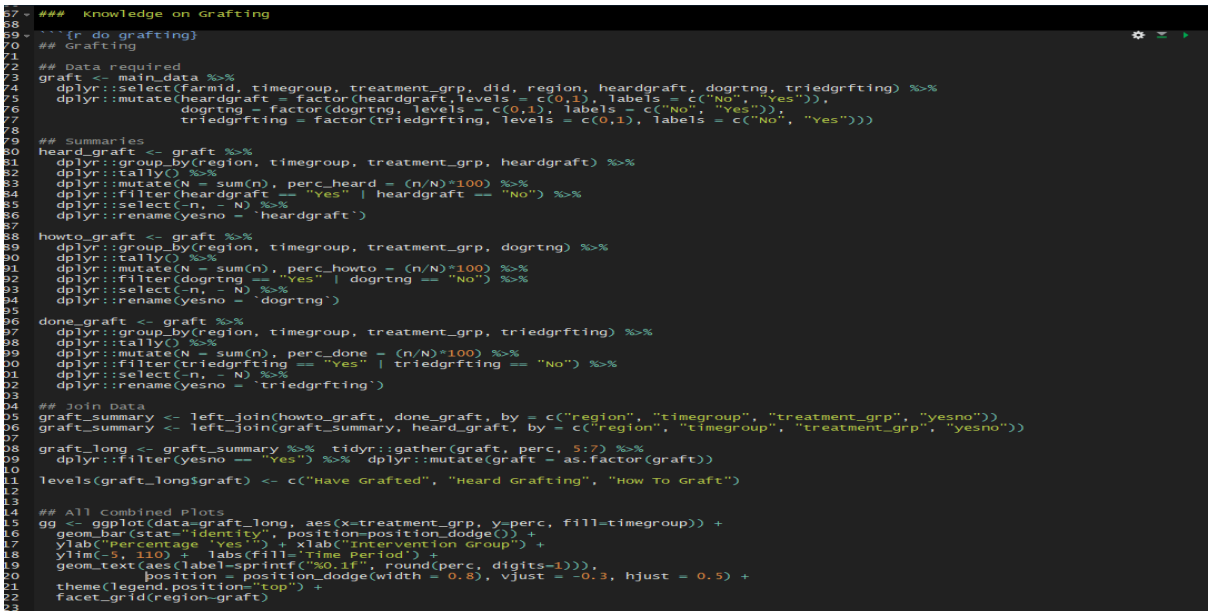
## Data required
dd <- diets %>%
  dplyr::group_by(timegroup, treatment_grp, region) %>%
  dplyr::summarise(hdd_median = mean(hdd, na.rm = TRUE),
                   wdd_median = mean(wdd, na.rm = TRUE),
                   cdd_median = mean(cdd, na.rm = TRUE)) %>%
  tidyr::gather(type_dd, dd, 4:6) %>%
  dplyr::mutate(type_dd = as.factor(type_dd))

levels(dd$type_dd) <- c("Child Dietary D", "Household Dietary D", "Women Dietary D")

##  fruit amounts graph
dd_g <- ggplot(dd, aes(x = timegroup, y = dd, group = treatment_grp)) +
  geom_point(aes(colour = treatment_grp), size = 3) +
  geom_line(colour= "dark red") +
  ylim(3, 9) +
  xlab("Time Period") +
  ylab("Mean Dietary Diversity Scores") +
  labs(color='Intervention Group') +
  theme(legend.position="top") +
  facet_grid(region~type_dd)
dd_g
```

Figure .2: R Syntax for plotting connected observations: a case of 4.10
```

## Appendix 4: R Syntax for plotting multiple bar graphs



```
###  Knowledge on Grafting

```{r do grafting}
## Grafting

## Data required
graft <- main_data %>%
  dplyr::select(farmid, timegroup, treatment_grp, did, region, heardgraft, dogrtng, triedgrfting) %>%
  dplyr::mutate(heardgraft = factor(heardgraft,levels = c(0,1), labels = c("No", "Yes")),
                dogrtng = factor(dogrtng, levels = c(0,1), labels = c("No", "Yes")),
                triedgrfting = factor(triedgrfting, levels = c(0,1), labels = c("No", "Yes")))

## Summaries
heard_graft <- graft %>%
  dplyr::group_by(region, timegroup, treatment_grp, heardgraft) %>%
  dplyr::tally() %>%
  dplyr::mutate(N = sum(n), perc_heard = (n/N)*100) %>%
  dplyr::filter(heardgraft == "Yes" | heardgraft == "No") %>%
  dplyr::select(-n, - N) %>%
  dplyr::rename(yesno = `heardgraft`)

howto_graft <- graft %>%
  dplyr::group_by(region, timegroup, treatment_grp, dogrtng) %>%
  dplyr::tally() %>%
  dplyr::mutate(N = sum(n), perc_howto = (n/N)*100) %>%
  dplyr::filter(dogrtng == "Yes" | dogrtng == "No") %>%
  dplyr::select(-n, - N) %>%
  dplyr::rename(yesno = `dogrtng`)

done_graft <- graft %>%
  dplyr::group_by(region, timegroup, treatment_grp, triedgrfting) %>%
  dplyr::tally() %>%
  dplyr::mutate(N = sum(n), perc_done = (n/N)*100) %>%
  dplyr::filter(triedgrfting == "Yes" | triedgrfting == "No") %>%
  dplyr::select(-n, - N) %>%
  dplyr::rename(yesno = `triedgrfting`)

## Join Data
graft_summary <- left_join(howto_graft, done_graft, by = c("region", "timegroup", "treatment_grp", "yesno"))
graft_summary <- left_join(graft_summary, heard_graft, by = c("region", "timegroup", "treatment_grp", "yesno"))

graft_long <- graft_summary %>%  tidyr::gather(graft, perc, 5:7) %>%
  dplyr::filter(yesno == "Yes") %>%  dplyr::mutate(graft = as.factor(graft))

levels(graft_long$graft) <- c("Have Grafted", "Heard Grafting", "How To Graft")


## All Combined Plots
gg <- ggplot(data=graft_long, aes(x=treatment_grp, y=perc, fill=timegroup)) +
  geom_bar(stat="identity", position=position_dodge()) +
  ylab("Percentage 'Yes'") + xlab("Intervention Group") +
  ylim(-5, 110) +  labs(fill='Time Period') +
  geom_text(aes(label=sprintf("%0.1f", round(perc, digits=1))),
            position = position_dodge(width = 0.8), vjust = -0.3, hjust = 0.5) +
  theme(legend.position="top") +
  facet_grid(region~graft)
```

Figure .3: R Syntax for plotting multiple bar graphs: a case of 4.8
```

## Appendix 5: R Syntax for glm models

```
###  Total Abundance Models

```{r ta models}
## a little data wrangling
main_data <- read.dta13(file = "FruitingAfricaIndicatorsBaselineEndlines.dta",
                                convert.factors = TRUE) %>%
  dplyr::mutate(treatment_grp = ifelse(Sampling_Strata == 3, 0, 1)) %>%
  dplyr::mutate(did = treatment_grp*timegroup) %>%
  dplyr::mutate(treatment_grp = factor(treatment_grp,
                                       levels = c(0,1),
                                       labels = c("Control", "Treatment"))) %>%
  dplyr::mutate(timegroup = factor(timegroup,
                                   levels = c(0,1),
                                   labels = c("Baseline", "Endline"))) %>%
  dplyr::mutate(region = factor(region,
                                levels = c(0,1),
                                labels = c("Western Kenya", "L. Eastern Kenya")))


##  ta DiD model for Western Kenya
ta_w <- main_data %>%
  dplyr::filter(region == "Western Kenya") %>%
  glm(formula = TotalAbundance ~ treatment_grp + timegroup + did,
              family = "poisson")
summary(ta_w)
tidy(ta_w)
glance(ta_w)
coef(ta_w)

##  ta DiD model for L. Eastern Kenya
ta_e <- main_data %>%
  dplyr::filter(region == "L. Eastern Kenya") %>%
  glm(formula = TotalAbundance ~ treatment_grp + timegroup + did,
              family = "poisson")
summary(ta_e)
tidy(ta_e)
glance(ta_e)
coef(ta_e)
```

Figure .4: R Syntax for glm models: a case of 4.1
```