# MONITORING AND EVALUATION PLAN

# WESTERN KENYA INTEGRATED ECOSYSTEM MANAGEMENT PROJECT

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# 1. Preamble

This manual for monitoring and evaluation of the Western Kenya Integrated Ecosystem Management Project (WKIEMP) has the objective to provide an orientation to project managers on the types of data that need to be collected, the manner in which these data are to be collected, analyzed, and interpreted to:

- Meet the needs for ongoing technical monitoring of implementation of the project; and

- Determine project baselines and attribute project impact.

The present manual was conceived and written as a practical guide with simple, straightforward instructions for use by the project coordination unit and the project partners. The manual provides the conceptual framework for the monitoring and evaluation activities and the practical instructions for data collection, analysis and interpretation.

This manual is also conceived to provide practical guidance of monitoring and evaluation for projects that are implementing an ecosystem approach to management of rural landscapes. IDA is in the process of developing three projects in Kenya and one in Ethiopia that will incorporate the principles of ecosystem management. This manual will serve as the basis for the development of monitoring and evaluation procedures for these projects and hopefully beyond.

Finally, this manual is conceived as a living document that will be updated and modified based on experience gained in the WKIEMP and hopefully in these other projects. Ultimately, we aspire to establishing rigorous monitoring and evaluation procedures that can be replicated and that facilitate learning replicable lessons from ecosystem management projects.

# 2. Context

The WKIEMP is part of the World Bank Country Assistance Strategy (CAS), which notes that poverty levels are increasing rapidly in Kenya and that poverty levels in rural areas are 46%. The CAS states that increasing poverty and the widening gap between rich and poor in Kenya pose the greatest threat to political stability. The strategy matrix specifically identifies actions to decrease poverty, which includes improvement of agricultural service delivery to farmers. The WKIEMP is an important component of the CAS, particularly with its focus on community-based initiatives in the fight against poverty. The National Poverty Eradication Plan (NPEP) places emphasis on the high and medium potential areas of Kenya, which characterize the Lake Victoria Basin. Priority is given to these areas because of their high population density, high incidence of rural poverty, and stagnant economic growth. Soil conservation and agroforestry are among the interventions specifically targeted as means for raising productivity, diversifying production, and raising farmers' incomes.

The WKIEMP is intended to assist rural communities in the Nyando, Nzoia and Yala River basins to understand and improve land management practices, largely through agroforestry interventions, in a way that provides a wide range of environmental services including biodiversity, watershed protection, land restoration, and carbon sequestration (climate change mitigation). While doing so, recognizable short-term benefits will serve as economic incentives to invest in land management practices that are associated with these longer-term environmental services. This Monitoring and Evaluation Plan (MEP) is a tool that guides information gathering and verification activities essential to the evaluation of the project. The MEP is built upon an accompanying Baseline Study, complies with the principles of the Clean Development Mechanism and is intended to serve as the technical component for the environmental services achieved within the community-based activities described within the WKIEMP Document.

One of the most important planned environmental benefits resulting from project activities will be the establishment of trees through agroforestry in a manner that is compliant with the Clean Development Mechanism, allowing for sequestered carbon to be traded to others requiring carbon offsets. Two particularly important elements of this compliance are that project activities not be established in areas with forests cleared after 1990 and that all C gains be related to afforestation and reforestation (as per the rules of the Clean Development Mechanism). The project will establish guidelines where C offset enterprises adhere with key principles of legal requirements, farmers' land use rights, fair payment, permanence and ecosystem health as established by The World Agroforestry Centre. This manual describes the process through which the carbon gains resulting from smallholder agroforestry may be monitored and evaluated in a cost and time-efficient manner. The monitoring protocols will be:

1. Conducted at least once per year at all locations and based upon the tree diameter at breast height measured by participants and supervised by project scientists;

2. Standardized across project locations and during repeated measures, and be appropriate for confirming baselines at the onset of the project;

3. Consider not only aboveground tree biomass C, but also estimates of root biomass C and soil C gains based upon conservative conversion factors;

4. Calculated as both "hard copy" data forms and through use of an "Excel Workbook" (spreadsheet) with options to either include or exclude below-ground C and to adjust key conversion factors as acceptable in carbon markets;

5. Sufficiently flexible to allow for the development of improved allometric equations and conversion factors during the course of the project; and

6. Used to calculate the C gains resulting from individual farm enterprises, participating grassroots groups and for the project as a whole during the project lifetime.

Impact assessment will be carried out on a 5-year time scale, where project impact will be evaluated against the baseline conditions.

# 3. Principal concepts

The **Monitoring System** is defined as the process of systematic collection and analysis of data in order to improve the management and implementation of the project through provision of information that is useful for assessing the state of achievement against objective indicators in a timely manner to project managers.

The **Evaluation System** is defined as the process of systematic collection and analysis of data in order to attribute project impact through provision of information that is useful for assessing the state of achievement against long-term performance indicators to project managers and evaluators. The Evaluation System is comprised of a baseline assessment and periodic assessments of impact. These periodic assessments are similar in form to the baseline assessment and are carried out in such a way as to assess departure from the baseline that are attributable to project activities.

The **objective** is the desired state that the project is supposed to achieve on the ground over its lifetime. The i**mpact** is the actual realization of this objective.

**BACIP** is the fundamental concept of our **Evaluation System**. BACIP stands for Before-After, Control-Impact Pairs and refers to different pairings of observations. Evaluating true project impact requires monitoring of a without-project baseline. This requires observations outside project intervention areas both before the initiation of project activities and after project activities have been undertaken to estimate the likely evolution of impact indicators in the absence of the project. To attribute project impact, before-after measurements on control areas are subtracted from before-after measurements on project impact areas. Spatial stratification and replication of before-after, control-impact pairs provides the primary means for partitioning the relevant random and project-related variance components, and thus these simple models can generally be expanded to accommodate different levels of scale. Pairing of observation plots is done to increase efficiency of sampling and to ensure comparability between the two sets of samples. A large number of replicates is useful in accurately representing the baseline in as much as implementation of the project in one area may influence non-participants outside the project area.

**Objectively verifiable indicators** are quantitative parameters, limited in time, that allow project managers and evaluators to determine the degree to which the project is approaching or missing designated objectives within the allotted timeframe.

An **intermediate result** indicates milestones that are achieved in the course of achieving an objective.

**Baseline** is the without-project situation on the ground and can be assessed for any of the objective indicators

**Baseline Survey** is the field survey in which the objectively verifiable indicators of the biophysical and socioeconomic condition are measured to determine the baseline situation.

A **Household Survey** is an instrument for gathering socioeconomic information from households.

A **Land Resource Survey** is an instrument for gathering biophysical information from the field.

A **Block** is the major organizational unit of the project. Project blocks are 100 square kilometers or 10, 000 ha (10 km on a side), and are located in the upper, middle and lower portion of each river basin in the project.

Each block is partitioned into sixteen $2.5 \times 2.5$ km, or 625 ha **survey units**. Within each survey unit, ten 1000 $m^2$ **plots** were established within a 1 $km^2$ circular area that is referred to as a **cluster**.

# 4. Objectives and approach

## *4.1. Project baselines for planning and impact assessment*

The aims of a baseline are twofold. The first is to synthesize a quantitative description of the baseline project situation along the ecological and socioeconomic dimensions that are relevant for project implementation. The second aim is to lay a foundation for monitoring, change detection and impact assessment that considers spatial variability explicitly.

The starting point for any project is to define the nature and extent of the problem that the project wants to address, and a baseline is the information that helps the project do this. The baseline is the situation at the start of a project before any work has been carried out. When the project is clear about the nature and extent of a problem it is going to address in a particular block, it can then set clear objectives.

Objectives are specific statements that can be measured and state exactly what is to be achieved. They must be written so that they can be measured. For this to take place they should be SMART, which means that they are:

- Specific – all objectives should have specific outcomes;
- Measurable – the outcome of an objective should be able to be measured;
- Achievable – within the timescale and resources set for the project;
- Realistic – objectives describe something that can actually be done; and
- Timebound – a timescale should be set for when the objective is to be achieved.

The other major aim of a baseline is to provide a starting point for reliable change detection and project impact assessment over time. Even the SMARTest objectives can go wrong and can have negative environmental or socioeconomic impacts that were not foreseeable at the start of the project. Conversely, the project could have spillover effects that amplify positive impacts. The baseline should thus provide an assessment of the initial conditions and their trajectory without the project, against which both positive and negative changes can be evaluated and attributed.

## *4.2. Monitoring & evaluation (M&E)*

Monitoring is the routine collection of information about a service or activity provided by the project. It allows the project to keep track of what is going on, and involves regular measurement of project progress toward SMART objectives. Monitoring is done by systematic collection and review of information on project inputs, outputs and milestones.

*Why Monitor?*

- To track progress toward SMART objectives;
- To enable project delivery to be adjusted if necessary;
- To help to plan, develop and deliver future projects; and
- To update donors and partners on the progress of the project.

Monitoring as such cannot assess either the quality of a project, or explain why a project succeeds or fails. This is established through evaluation. Monitoring data on SMART objectives provides the starting point for evaluations to which additional information and data is added and analyzed.

*Why Evaluate?*

- Evaluation is an invaluable tool for assessing if a project is achieving it's SMART objectives and if not, how service delivery can be improved.
- Evaluation can establish why a project has succeeded or failed, making it possible to assess whether the project is suitable for other areas or client groups.
- Evaluation is a useful mechanism for sharing good project practice.
- It is an important tool for establishing to what degree a project is delivering value for investment.

Evaluation identifies whether a project has achieved its objectives by identifying whether there is a link between the effects of the project and its stated outcome(s).

### 4.3. Impact assessment

Project-level impact assessment involves evaluating the magnitude of management responses and the beneficial and harmful changes in social and ecological systems that occur as a consequence of project interventions. Impact assessment involves using methods that compare the before project situation to the situation following project implementation using control-intervention pairing.

*Why assess impact?*

- To evaluate the efficacy of different project interventions, i.e. to what extent are the project's interventions achieving what it is they are meant to achieve.
- To evaluate if and under what circumstances project interventions result in negative (or positive) side effects on the environment or project beneficiaries.
- Generate lessons for other similar development projects.

## 5. Methodology and implementation

### 5.1. Sampling designs

WKIEMP's baseline assessments, monitoring and evaluation activities and impact assessment are build around a set of permanent **plots** and **household** locations that provide a sample of the populations of similar plots and households in each of nine, 100 $km^2$ ($10 \times 10$ km) **blocks** which have been selected for project implementation.

The blocks have been located in three of the five major river basins that drain the Kenyan portion of the Lake Victoria Basin, namely the Nyando, Yala and Nzoia River Basins (Figure 1). Block locations were stratified by landscape position, and one block was placed within the upper, middle and lower elevation zones of each basin and so as to focus on areas of the respective watersheds that appear to be severely degraded based satellite observations.

The overall sampling design follows a nested strategy in which, plots and households are randomly selected in spatially stratified manner. Each block is divided into sixteen, 625 ha **survey units** within which 10 plots and 10-15 households are surveyed and monitored over time. The main reason for following a randomized, spatially stratified sampling design is that the design provides for scale and time specific analyses described below.

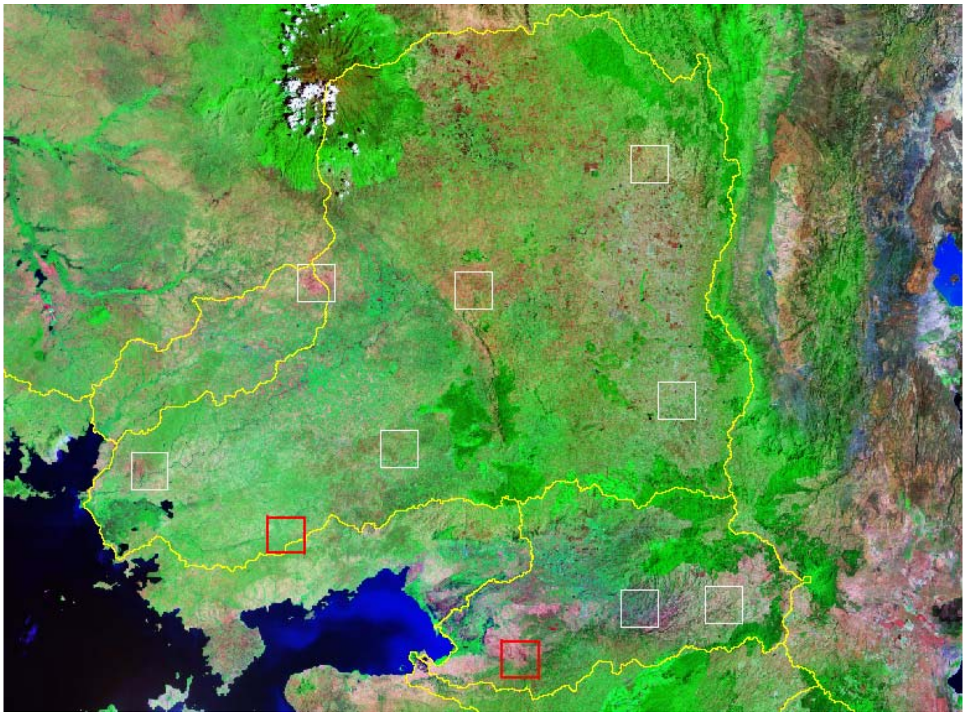


**Figure 1**. Block locations in the Nyando, Yala and Nzoia river basins in western Kenya. Note that the Yala and Nzoia basins (in yellow) appear to be combined due their common drainage outlet in the Yala swamp; however, higher resolution, SRTM-based watershed delineations are available. Block locations marked in red have been ground surveyed at the time of the writing of this report, block locations marked in white have not.

### 5.1.1. Land resource surveys

Plot locations are selected prior to initiating the field survey using a spatially stratified random sampling procedure. Blocks are initially partitioned into sixteen $2.5 \times 2.5$ km, or 625 ha survey units. Within each survey unit, ten 1000 $m^2$ plots are double randomized within a 1 $km^2$ circular area that is referred to as a **cluster**. Initially the cluster centroid is randomly selected within each survey unit. Plot locations are then randomized away from the cluster centroid using a polar coordinate conversion that ensures reasonably equal (circular) area coverage of the cluster. Each sampling location is subsequently labeled with a unique cluster and plot identifier (e.g., KO.1.1, referring to Katuk Odeyo Block, cluster 1, plot 1).

Details of this procedure as well as an MS-Excel procedure for generating the randomized coordinates are provided in an attached document (Field Sampling Procedures in Appendix II). The randomized locations are then loaded into a GPS unit, which the survey crew can use for locating the plots and field navigation. Typically, reasonably accurate navigation can be achieved to within < 10 m of the specified location ~95% of the time. The actual survey locations are then logged and recorded by averaging GPS position estimates for several minutes.

### 5.1.2. Household surveys

Household survey and monitoring locations are selected in a similar manner to those of the land resource survey plots; however the exact locations of households are generally not known prior to a field survey. Thus, field survey teams initially navigate to a given cluster centroid and then locate 10-15 households in proximity to this position. The actual household locations in which the survey is conducted are then logged by averaging the GPS position of the main dwelling for several minutes.

## *5.2. Land resource indicators*

### 5.2.1. Remote sensing

Nine, 0.6 meter resolution multi-spectral QuickBird satellite images[1] will be acquired in 10×10 km segments centered on project blocks at the time of the baseline surveys, as well as in year 5 of the project. All images will be georegistered using survey-grade differential GPS at prominent landmarks located in each image. Using standard image interpretation and supervised classification techniques, complete inventories of woody vegetation cover (tree and shrub density, crown cover and area) will be assessed at the time of image acquisition. Accuracy of the respective classification models will be determined by ground survey. Additionally, the images will be used to identify FAO Land Cover Classification System (LCCS) classes, housing units (thatch & modern roofs), the presence of soil conservation structures, roads, water sources including stock tanks, springs, boreholes, lakes and rivers, roads, tracks and physically degraded or barren areas such as rock outcrops, gullies, landslides and hardset areas.

Currently available digital terrain models (DTM's) for western Kenya were derived by digitizing ~20 m interval contour lines on 1: 50,000 topographic maps or from Shuttle Radar Topography Mission (SRTM) data. These datasets are not sufficiently accurate to "orthorectify"[2] the high-resolution satellite images that are a key component of our monitoring strategy. We will therefore construct DEM's using Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) images collected by the TERRA satellite. Band 3 nadir and back-looking radiance scenes will be processed with standard soft-photogrammetry techniques. One particular advantage of ASTER versus SPOT for DEM construction, particularly for large regions, is that imagery is collected along-track instead of across-track, thus reducing potential problems with changes in atmospheric conditions and/or radiation between passes. ASTER DEM's will also be used to derive watershed boundaries at different levels of stream order, and secondary terrain information such as slope, specific catchment area and plan and profile curvatures. We will also use the interpreted QuickBird images to calibrate ASTER scenes for broader-area coverage of woody vegetation cover inventories.

[1] http://www.digitalglobe.com
[2] Orthorectification is a terrain correction technique that is necessary for measuring true map distances and areas on aerial photographs and satellite images.

### 5.2.2. Land cover

Land cover will be assessed using the FAO Land Cover Classification System (LCCS), which has been developed in the context of the FAO-AFRICOVER project (DiGrigorio and Jansen, 2000, also see attached document LCCS.pdf). The "*binary phase*" of LCCS recognizes 8 primary land cover types, only 5 of which will be sampled in western Kenya including:

- Cultivated and managed terrestrial areas;
- Natural and semi-natural vegetation;
- Cultivated aquatic or regularly flooded area;
- Natural or semi-natural aquatic or regularly flooded vegetation; and
- Bare areas.

Artificial surfaces and associated areas, natural and artificial waterbodies, will not be formally surveyed, though their presence within sampling clusters will be noted and georeferenced. Surfaces covered by snow, or ice, do not occur in the study area.

The "*modular-hierarchical phase*" of LCCS further differentiates primary land cover systems on the basis of dominant vegetation life form (tree, shrub, herbaceous), physiognomy, cover, leaf phenology and morphology, and spatial and floristic aspect. All the associated features can be assessed visually and coded on either categorical or ordinal rating scales, and entered into a GIS compatible database. The ratings are subsequently converted to unique hierarchical identifiers of different landcover types.

The unique hierarchical identifiers of the different landcover types can subsequently be used to calculate an index of ecosystem richness (i.e., and indicator of biodiversity) at the block level as.

$$E_k = l + \left( \frac{n-1}{n} \right)^q \qquad (1)$$

Where:

$E_k$ = the jackknife estimator of ecosystem richness

$l$ = the total number of LCCS Level 2 land cover types present in the sample

$n$ = is the total number of plots per block (n = 160)

$q$ = is the number of unique LCCS Level 2 land cover types.

The variance of this estimate is given by Krebs (1990) as:

$$\mathrm{var}(E_k) = \left( \frac{n-1}{n} \right) \cdot \left( \sum_j j^2 f_j - \frac{q^2}{n} \right) \qquad (2)$$

Where:

var($E_k$) = the variance of the jackknife estimate of ecosystem richness

$f_j$ = the number of clusters containing $j$ unique landcover types ($j$ = 1 …, $l$)

$q$ = the number of unique LCCS Level 2 landcover types

$n$ = the total number of plots per focal area (= 160)

### 5.2.3. Soil surface condition

The field assessment soil surface condition involves observation of visible signs of accelerated soil erosion (i.e., sheet, rill and gully erosion), topsoil (0-20 cm) and subsoil (20-50 cm) texture classes, the presence of soil depth restrictions to 50 cm, the proportion of plot area covered by rocks, stones and gravel, and infiltration capacity. Details of the associated field observation and measurement procedures are provided in the Field Sampling Procedures (Appendix II). Also provided is are MS-Excel procedures for fitting field infiltration data to either the Phillips or Horton infiltration models (Infiltration.xls)

### 5.2.4. Soil reflectance

Diffuse reflectance spectroscopy (DRS) is an established technology for non-destructive characterization of the composition of materials based on the interaction of visible-infrared light (electromagnetic energy) with matter. Near-infrared spectroscopy is now routinely used for rapid analysis of a wide range of materials in many laboratory and process control applications in agriculture, food, geology and biomedicine. Both the visible–near-infrared (0.35-2.5 µm) and mid-infrared (2.5-25 µm) wavelength regions have been investigated for non-destructive analysis of soils and simultaneous prediction of a number of important soil properties. Primary properties of substances that significantly affect the shape of a soil spectrum generally calibrate well to soil reflectance. These include mineral composition, organic matter, water (hydration, hygroscopic, and free pore water), iron form and amount, carbonates, salinity, and particle size distribution. Importantly, these properties also largely determine the capacity of soils to perform various production, environmental and engineering functions. Indirect information can also often be obtained about secondary properties of soils (e.g. low concentrations of nutrients in soil extracts, potentially mineralizeable C and N, stable isotopes) because of their interactions with primary soil properties.

*Spectral calibration*

Extracting information about soil properties of interest from reflectance spectra requires specialized multivariate calibration and classification techniques. The general aim is to find relationships between measurements made in the laboratory or field that are expensive or labor intensive and the reflectance spectra, which are easy and inexpensive to acquire. To obtain robust calibrations one must minimize information in the spectra that is not relevant to predicting the target variable. Data transformations may be performed to minimize irrelevant information produced by light scattering, variation due to sample presentation (thickness, packing, particle size) and optical set-up, and statistical problems such as colinearity (correlation among wavelength bands) and non-linearity.

Optimal transformations depend on the individual data set, but first derivative transformation has been commonly used for visible–near-infrared soil spectra. Multivariate calibration methods are then used to relate the measured soil property to reflectance values in a number of different wavelength bands. Methods that include compression of the spectral data are common to reduce the problem of multicollinearity. The most common methods are principal components regression and partial least squares regression. However, non-linear parametric regression methods (e.g. multivariate regression splines), non-parametric regression methods (e.g. regression trees) and classification methods (screening tests using classification trees) have also been used.

This method of soil analysis has been extensively tested in western Kenya, and a large library of soil samples consisting of visible-near infrared spectra (0.35–2.5 μm) and associated soil properties has been compiled in the context of previous projects. Based on this library, spectral (pedo)transfer functions for predicting a number of important soil properties have been developed (e.g., soil organic carbon and nitrogen concentration, CEC, clay content among others).

### 5.2.5. Woody vegetation biomass

The main quantities for evaluating and monitoring the abundance and biomass of woody vegetation in the project area are aerial cover, density and biovolume. The field procedures for measuring these quantities are provided in the attached Field Sampling Manual (Appendix II). Conversion of these basic quantities to biomass estimates requires allometric equations that have currently not been validated for western Kenya.

*Woody biomass allometry*

Woody biomass is most often estimated by applying harvest-based allometric regressions to measurements of the diameters of all trees in a plot that are above a minimum size. As developing site-specific allometric equations is fairly labor intensive, equations adopted from previous work in similar ecological zones are frequently used for this purpose (*cf*. Brown et al., 1989). To our knowledge, no site-specific biomass equations currently exist for western Kenya, and thus relationships between above-ground biomass, diameter at breast height (*dbh*), and long-term average annual rainfall, developed by the FAO provide the best option for the short term. For sub-humid zones (<1500 mm $yr^{-1}$) the relationship between individual above-ground tree weight (*w*, kg dry matter) and *dbh* (cm) is given by:

$$w_i = 0.136\, dbh^{2.32} \tag{3}$$

and in humid zones (1500-4000 mm $yr^{-1}$) as,

$$w_i = 0.118\, dbh^{2.53} \tag{4}$$

Other equations are available for drier (<900 mm $y^{-1}$) and wetter zones (>4000 mm $y^{-1}$) from FAO. It is important to note that equations 3 & 4 have not been validated in western Kenya.

Because of the potential for inter-site variation in tree architecture and wood density, using generalized equations can introduce significant errors and biases in biomass estimates (see Clark et al., 2001). Thus, we will test the accuracy of existing equations, and alternatively develop and validate new regionally specific allometric relationships. Noting plant taxonomy, a suite of allometric measurements will be obtained for a large regional sample (300-500) of trees and shrubs. The following table summarizes all the relevant individual measurements that will be considered.

| **Variable** | **Units** | **Description** |
|---|---|---|
| **Allometric predictors:** | | |
| Plant height | m | Tree height measured either with a height pole (< 5 m) or with a clinometer (> 5 m). |
| Furcation index | m | Stem length to first internode. |
| *Dbh* | m | Stem diameter at 1.3 m above-ground-level |
| Crown projection | m | Average of longest and shortest crown diameter. |
| Apical dominance | - | Average ratio of the length of the longest twiglet at a node to the length of the next longest twiglet. |
| Growth deceleration | - | Average ratio of terminal twiglet length to the previous (parent) internode length. |
| Stem number | n | Number of stems at 1.3 m (a.g.l). |
| Branching order | n | Average number nodes from terminal node to main stem. |
| **Dependent variables:** | | |
| Shoot weight ($w_s$) | kg | Fresh weight of each component measured destructively in the field, sub-samples dried at 60° C, for 24-72 hrs to determine dry weight, sub-sampled again to determine carbon content by dry combustion. |
| Leaf weight ($w_l$) | kg | |
| Above-ground weight ($w_a = w_s + w_l$) | kg | |
| Coarse root weight ($w_r$) | kg | |
| Root : Shoot ($w_r / w_s$) | - | |
| Total plant weight ($w = w_a + w_r$) | kg | |

This large multivariate dataset will be subjected to standardized principal components analysis (PCA), to examine redundancies and clustering a taxonomic groupings. Typical for morphological data, we anticipate that the first principal component will correlate strongly with indicators of specimen size, whereas the residual components (2, 3, … no. variables) will correlate with differences in specimen shape that are unrelated to size (Somers, 1986). To ensure that a representative allometric calibration sample is collected, we will apply the PCA construct to group specimens into sampling strata using the central composite design shown in Figure 2.

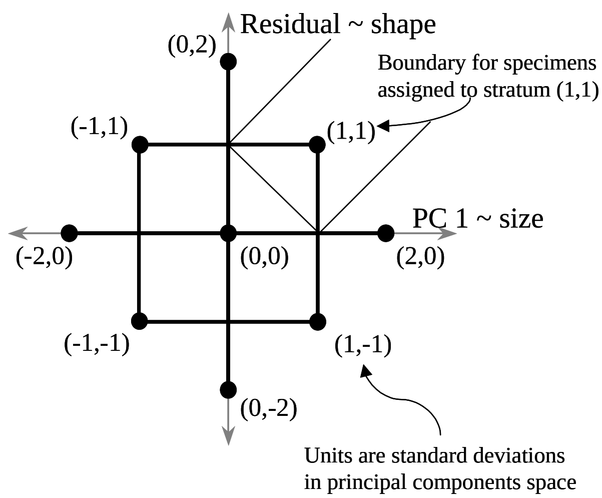
**Figure 2.** Central composite biomass sampling design using principal components analysis of allometric predictors (see Table 1) of trees and shrubs.

1. Compute principal components for correlation matrix morphologic measurements, and project specimens into the principal components space (e.g., PC 1 and its residual hyperplane).

2. The schematic below illustrates the placement of stratum centroids (nodes) in the central composite design.

3. The number of nodes (N) in this type of design depends on the number of principle components ($\Lambda$) used, given by $N = 2\times\Lambda + 2^{\Lambda} + 1$ (9 nodes for 2 components).

4. Assign each specimen to the nearest node based on minimum Euclidean distance.




Both the above- (stem and leaf) as well as the below-ground (roots > 2 mm) biomass of a smaller sample consisting of at least 20 representative specimens per stratum will subsequently be harvested and weighed. Woody biomass and excavated coarse root material will be passed through a wood chipper to facilitate determination of fresh-weight in the field. Representative subsamples for each stratum × biomass component will be dried at 60°C for 24-72 hours for moisture content determination, and further subsamples will be determined by dry combustion to $CO_2$ using a total element analyzer. In the case of stocking plots, for which detailed plant age and growth information will be available, species specific allometric equations will be developed along similar lines. A randomly selected sample of individuals at different ages will be destructively harvested from stocking plots. Relationships between allometric measurements (Table 2), latent variables (i.e., principal components) and individual biomass components will be explored through graphical and correlation analyses. We will develop predictive equations for biomass components as well as total individual biomass with generalized-additive and generalized linear models (McCullagh and Nelder, 1989). The standard error of prediction of selected models will be reported relative to a randomly withheld 25% validation segment of the data.

Individual plant weight estimates from allometric equations may be converted to plot biomass ($b_j$, kg dry matter ha$^{-1}$) as:

$$b_j = q \sum_n w_i \qquad (5.)$$

for which:

$n$ = Number of trees in the sampling unit,

$q$ = Area expansion factor (10,000 m$^2$ ha$^{-1}$ / m$^2$ sampling unit$^{-1}$); and

$w_i$ = The individual plant weight estimates.

*Root biomass*

The distribution of below-ground biomass and biomass production in forests and agroforestry systems remains poorly understood due to problems in the associated measurement methods. With the exception of coarse root biomass, there are currently no simple field methods for measuring this biomass component. Coarse roots, which we define as >2 mm in diameter, are thought to turn over relatively slowly in most ecosystems, and thus may constitute the most persistent below-ground carbon storage component. We will use a two-part strategy (after Bledsoe et al., 1999 and described in Clarke et al., 2001) that combines: (1.) sampling of coarse roots in replicated monoliths, and (2.) a biomass allometry approach based on excavation and harvesting of individual trees.

As coarse root distributions tend to be strongly influenced by above ground biomass of woody vegetation, location of pits will be stratified by woody vegetation density and height. We will use 11.28 m diameter circular sampling plots for this and tally the total number of trees in each plot and measure their average height. The combination of number of trees and the average height of these will then be used to stratify locations of pits. Each profile pit location with woody vegetation cover will be matched to a pit location within a < 50 m distance on which woody vegetation is absent. The table below summarizes the proposed stratification.

| **No. trees per plot** | **Average height** | **No. of Pits** |
|---|---|---|
| *absent* | - | 24 |
| *1 – 10* | *< 3 m* | 3 |
| | *> 3 m* | 3 |
| *10 – 20* | *< 3 m* | 3 |
| | *> 3 m* | 3 |
| *20 – 30* | *< 3 m* | 3 |
| | *> 3 m* | 3 |
| *> 30* | *< 3 m* | 3 |
| | *> 3 m* | 3 |

Roots will be collected by excavating a 0.3 × 0.3 m portion of the pit, at 20 cm depth increments to 2.4 m, using a narrow, flat-bladed shovel and hand saw. Four such excavations will be made in each pit (one on each pit wall). Coarse roots are then hand sorted and washed. The remaining sample will be dispersed in tap water, passed through a 2 mm sieve and roots collected without attempt to differentiate live and dead roots. Roots will be washed of gross mineral contamination, dried at 65$^o$ for 24-36 hrs and weighed.

The cumulative distribution of coarse root biomass for each profile ($b^r$) will be modeled as an asymptotically increasing function of soil depth and given by:

$$b^r = \phi_1 + (\phi_2 - \phi_1) \cdot \exp(-\exp(\phi_3) \cdot d) \quad (6)$$

for which $\phi_1$ (asymptote), $\phi_2$ (intercept) and $\phi_3$ (shape parameter) to be estimated by non-linear regression, and $d$ is soil profile depth. Note that the asymptote expresses the total root biomass in the profile. Including indicators for treatment and/or classification effects in the design matrix of this function is straightforward and can subsequently be used to derive conditional estimates for profiles under different aboveground woody biomass scenarios.

*Litter biomass and soil organic carbon*

Surface litter will be collected from 1 m diameter (0.785 $m^2$) circular sampling frames at the center and terminal positions of each radial line transect using a small hand rake (see Fig. 3). Surface litter is assumed to be necromass of identifiable origin (e.g. leaves, fine branches) although judgement is often necessary in differentiating it from the soil organic horizon in grasslands or under trees. Surface litter will be washed over a 2 mm sieve, dried at $65^o$ C to constant weight and corrected for moisture content.

Similarly, four topsoils (0-30 cm) and 4 subsoils (30-50 cm) will be sampled at the center of the plot at the terminal end of the radial line transects. All soil samples will be air-dried, weighed, crushed through a 2 mm sieve and adjusted for rock and gravel content. Coarse root biomass will be separated from soil by sieving. A randomly selected subset of 5 plot-level samples per cluster will be analyzed for total C, SOC (after acidification with dilute HCl), N, and $\delta^{13}C$ using element analysis coupled with ratio isotope mass spectrometry. All soil carbon stocks will be expressed on a soil mass (rather than volume) equivalent basis.

## 5.3. Household indicators

Household indicators of the social and economic dimensions of the project will be collected and analyzed in a number of ways to understand and document how the project impacts on different segments of the population. The Project will pay particular attention to capture gender dimensions of the baseline and project impact. The project will also work with communities to monitor progress in these areas as implementation proceeds.

### 5.3.1. Willingness to participate and adoption

There are two commonly observed empirical regularities with regard to the adoption of new land management practices. First, the adoption of new practices is anything but instantaneous. Second, once initial adoption occurs, the inter farm diffusion pathway tends to be nonlinear and asymptotic; i.e., some farmers adopt early, and others late (or never), with a potentially accelerating adoption process initially, followed by a decelerating process once most farmers have adopted. These processes are largely regulated by the arrival and perceived value of the new practice, as well as its strategic interaction in the overall farm-product market. Thus, prior information regarding who is willing to participate in which project activities is critical for planning delivery of targeted extension services, resource and market mobilization. Additionally, this assessment will provide information *ex ante* on adoption rates, which may subsequently be used in project baseline projections.

Household surveys will be used to quantitatively assess willingness to participate in the various interventions proposed during the focus group discussions. Respondents will initially be asked to identify in which of the priority activities identified in the respective focus group discussions they would be willing to participate. We further expect that most activities will require privately owned land allocations. Thus, farmers will also be asked what proportion of their land they would to allocate to activities in which they are willing to participate. This information will be synthesized by activity, at the level of survey units. As willingness to adopt is a binary variable we will use a mixed effects logistic model, in which covariates such as household type i.e.:

1 – Male-headed, single

2 – Male-headed, married

3 – Female-headed, single,

4 – Female-headed, married

5 – Child-headed

6 – Other

labor availability, expenditure-levels and resource endowments (see below) as well as biophysical variables can be included. Specifying $n_i$ households grouped within $i$ = 1, … $m$ survey units, the basic model for the probability of willingness to participate ($P$) is given by:

$$\log\left(\frac{P_i}{1-P_i}\right) = X_i\beta + Z_i b_i + \varepsilon_i \quad (7)$$

for which,

- $\beta$ – is a $p$ dimensional vector of unknown fixed regression parameters.
- $b_i$ – is a $q$ dimensional vector of unknown random effects normally distributed as $b_i \sim N(0, \sigma^2)$.
- $X_i$ – is a $n_i \times p$ dimensional matrix of covariates.
- $Z_i$ – is a $n_i \times p$ dimensional design matrix for the random effects.
- $\varepsilon_i$ – is a $n_i$ dimensional within-survey unit error vector that is assumed to be independently distributed as $\sigma^2\pi^2/3$.

Similar analyses will be conducted for potential household land allocation to project activities. This is essentially a rate variable for which observations are standardized by farm size. We will therefore use a mixed effects Poisson regression approach. The formulation of this is similar to equation 7, but (in Generalized Linear Model terminology) with a log link-function and Poisson error distribution. By including time in the model formulation, adoption rates may be estimated.

### 5.3.2. Agricultural labor

The availability of agricultural labor at the household level is often one of the critical constraints to adopting new land management practices. Labor inputs are also frequently used in econometric studies to assess the technical efficiency with which goods and services can be generated under a given activity requiring labor. It may therefore also be considered as an indicator of project impact. However, detailed farm labor allocation studies are difficult and time consuming to conduct, as frequent household follow up visits are required to establish the absolute amount of time spent on different activities.

We have developed a simpler approach to this, which is based on a simple self-assessment of the amount of time spent on agricultural activities. Household survey respondents are asked to rank the amount of time engaged in agricultural activities, for all members of their family. We use a 3-point ordinal rating-scale (0 – never, 1 – part time, 2 – full time). Concurrently, respondents are asked to specify the size of their farms and to identify the gender, age and years of education of all family members and whether or not they are currently engaged in off-farm employment. Finally, respondents are also asked if and how many non-family members are employed on their farms and for how long (see rating scale above).

We then use a mixed effects proportional odds model to estimate the contribution fixed effects – farm size, age, gender, education level and off-farm employment of family members etc. The basic model is as follows: Assuming $n_{ij}$ individual family members that are grouped within $j = 1 \ldots n_i$ households, which are in turn grouped within $i = 1 \ldots n$ survey areas, the cumulative probabilities ($L_{ij}$) for the $k = 1, \ldots \lambda$ ordered categories may then be defined for the ordinal outcome of time engaged in agricultural activities ($Y$) as:

$$L_{ij} = \Pr(Y \leq k \mid X_{ij}, Z_{i,j}, Z_{ij}) \qquad (8)$$

The mixed effects logistic regression model for these cumulative probabilities is then given given by:

$$\log\left(\frac{L_{ij}}{1-L_{ij}}\right) = \gamma_k + X_{ij}\beta + Z_{i,j}b_i + Z_{ij}b_{ij} + \varepsilon_{ij} \qquad (9)$$

for which,

$\gamma_k$ – are $\lambda$-1 strictly increasing model intercepts $\gamma_k$ ($\gamma_1 > \gamma_2 \ldots \gamma_{\lambda-1}$),

$\beta$ – is a $p$ dimensional vector of fixed regression parameters,

$b_i$ – is a $q_1$ dimensional vector of survey unit-level random effects, distributed as $b_i \sim N(0, \sigma_1^2)$

$b_{ij}$ – is a $q_2$ dimensional vector of household in block-level random effects, $b_{ij} \sim N(0, \sigma_2^2)$

$X_{ij}$ – is a $n_{ij} \times p$ dimensional matrix of covariates and time

$Z_{i,j}$ & $Z_{ij}$ – are $n_i \times q_1$ & $n_i \times q_2$ dimensional design matrices respectively

$\varepsilon_{ij}$ – is the within household error term assumed to be distributed as $\varepsilon_{ij} \sim \pi^2/3$.

Since the regression coefficients $\beta$, do not depend on $k$, the model assumes that the relationship between the explanatory variables and the cumulative logits also do not depend on $k$ and therefore identical odds ratios across the $\lambda$-1 cutoff can be assumed[3]. By estimating, the relevant fixed effects, focal areas, and households within focal areas may subsequently be ranked on a standardized scale relative to the sampled population. By including time in the model formulation changes in agricultural labor availability may be assessed.

[3] Hence the term proportional odds model.

### 5.3.3. Household expenditures

A similar approach will be used to model self-assessed household monetary expenditures. These will be taken as a proxy of the relative income levels of different households. Respondents will be asked to identify their sources of major expenditure as well as to estimate their total annual household expenditures. These estimates will be standardized using a linear mixed-effects model formulation, taking into account covariates such as family size, number of family members engaged in off-farm employment and the dependency ratio (*DR*) given by:

$$DR = \frac{n_{-14} + n_{65+}}{n_{15-64}} \tag{10}$$

for which $n_{-14}$ is the number of children (< 14 years of age) in the household, $n_{65+}$ is the number of seniors, and $n_{15\text{-}64}$ is the number of adults in the household. By including time in the model formulation changes in expenditure profiles may be evaluated.

### 5.3.4. Household well-being

Improvements to main household dwelling are an excellent indicator of household economic status and may be readily assessed through observation as well as by satellite remote sensing. Baseline studies indicate that the poorest households reside in thatch-roofed and mud-walled dwellings and the better-endowed families live in brick homes with metal or tile roofs (Swallow *et al*., personal communication).

Access and distance to potable water sources and access and diversity of energy sources are other important indicators of household well-being, which are easily quantified through either remote sensing or systematic ground survey. Household survey respondents will be asked to indicate if they apply sanitation treatments such as filtration, boiling and/or chemical treatment to their drinking water. Respondents will be asked about time allocation of labor to acquiring energy sources and the availability of different sources of energy.

Finally, household food sufficiency is an important indicator of household well-being, that is perhaps most proximally linked to proposed WKIEM project objectives and activities. While detailed food availability studies will not be undertaken in the context of this project, we will enquire for how many months per year people feel they have sufficient food. This will be done in focus group discussions, rather than through household interviews[4].

### 5.3.5. Household resource endowment

The level of household resource endowment may be considered as both a baseline condition for adoption of project activities and as an indicator of eventual project impacts. Shepherd and Soule (1998) have suggested that four criteria:

[4] Note that this can be a fairly sensitive topic in many communities in western Kenya.

1 – farm size,

2 – the proportion of land devoted to subsistence food crops,

3 – the diversity of farm enterprises and,

4 – the number and type (local, crossbred or grade) of cattle

which allow most farms in west Kenya to be assigned to one of three resource endowment categories (Low, Medium and Well-endowed). Well-endowed farms are >1.2 ha, that contain four or more enterprises with <40% of land devoted to household food production and own three or more cattle.

We will further refine Shepherd and Soule's (1998) classification through cluster analysis, with what will be a larger and more geographically distributed dataset than was used in their analysis. The objective of cluster analysis is to explicitly identify observations (in our case households) that have more in common with one another than they do with other observations, in terms of the indicator variables measured. There are a number of options in this regard but we will be using a finite-mixture formulation, which has been widely applied in socioeconomic and behavioral research (Titterington, 1985), and which does not depend on arbitrary decisions about similarity measures and clustering algorithm. The basic model is given by:

$$f(E) = \sum_{c} p_c \cdot N(\mu_c, \Sigma_c) \tag{11}$$

for which $E$ represents level of household resource endowment (as measured for example on the four dimensions above), $p$ is the proportion of households in resource endowment category ($c$), which in this case we assume to be rankable on an ordinal scale from, for example, low, medium and well endowed, and for which $N(\mu_c, \Sigma_c)$ designate multivariate normal probability densities of resource endowment indicators, with mean vectors $\mu_c$ and covariance matrices $\Sigma_c$[5]. All parameters are treated as unknown, and the model will be fit iteratively using an expectation maximization (EM) approach (Ripley, 2000). The result is a classification in which individual households are assigned to a resource endowment category corresponding to a specific mixture density, which can then be used both for targeting project activities to particularly resource poor households, and also for change detection.

### 5.3.6. Livestock ownership

In addition to being an important indicator of household resource endowments, the size and composition of household livestock herds is also an important component for developing baselines and monitoring of non-$CO_2$ greenhouse gases, assessing the effects of grazing pressure on soil condition. Therefore, household survey respondents will also be asked to enumerate livestock numbers (including cattle, equines, pigs, smallstock and poultry) in their possession. Per capita as well as per household livestock herd size,

[5] Note that multivariate densities other than the Normal may also be used were appropriate (Titterington, 1985).

stratified by elevation zone, will then be used to provide regional estimates of total herd size and composition using the most recent human population census (Kenya CBS, 1999).

# 6. Analytical methods

The analyses of the land resource and household survey data utilize linear, generalized linear and non-linear mixed model formulations extensively. In mixed model analyses, the random part of the model, or what is often referred as the "error", has structure. In the analyses presented here the structure arises from the spatially nested design in which, subplots are nested within plots, plots are nested within clusters, and clusters are nested within blocks. Each level represents a different spatial scale at which a given land resource or household indicator may be observed (or measured) as given in the tables below.

| **Level** | **Area (ha)** |
|---|---|
| *Block* | 10,000 |
| *Cluster* | 100 |
| *Plot* | 0.1 |
| *Subplot* | 0.01 |

The situation for households is similar, but does not involve area. Rather, the number of people involved is given in orders of magnitude in the table below.

| **Level** | **No. people** |
|---|---|
| *Block* | $10^{3-5}$ |
| *Cluster* | $10^{2-3}$ |
| *Household* | $10^{1}$ |
| *Individuals* | 1 |

Because levels (of scale) imposed by the sampling design do not represent fixed, repeatable factors like an experimental treatment; they are a sample drawn from a larger population of similar levels and are considered as random effects in the models. Ideally, we would like to generalize the limited observations and measurements to, the population of clusters in a given block, and ultimately to the population of blocks in the WKIEMP project area. Models are needed to achieve this because of the random variability that occurs at each level.

### 6.1. Baseline models

The most basic baseline linear mixed-effects model for a continuous, $n$-dimensional response vector $y_i$ with a single level of grouping can be written in matrix form as follows:

$$
\begin{aligned}
y_i &= X_i\beta + Z_i b_i + \varepsilon_i, \quad i = 1 \ldots n \\
b_i &\sim N(0, \Psi), \quad \varepsilon_i \sim N(0, \sigma^2)
\end{aligned}
\tag{12}
$$

where $\beta$ is a p-dimensional vector of fixed effects, $b_i$ is a q-dimensional vector of random effects, assumed to be normally distributed with mean 0 and variance-covariance matrix $\psi$ $X_i$ and $Z_i$ are know fixed-effects and random effects regressor matrices, and $\varepsilon_i$ is a normally distributed $n$-dimensional within-group error vector. Extended formulations can be derived for multi-level models that can include additional parameters for variance heteroscedasticity and correlated within-group errors, as well as for generalized linear (in which the structure of $\varepsilon$ varies depending on a link-function) and non-linear model forms[6].

The main advantages of this style of analysis are that: project baselines can be evaluated at different levels of spatial scale, providing a means for targeting interventions in different areas in the landscape, and the fact that the fixed-effects (i.e., the $X_i$ regressor matrix) can incorporate covariates and changes over time that provide the means for monitoring change detection and impact assessment at the whole project-level. In other words, the same basic analytical framework can be applied over the entire project cycle, integrating spatial scale, temporal variability and management impacts in one general analytic model.

### 6.2. Operational monitoring

Operational monitoring of project progress is largely concerned with the level of adoption of specific recommended interventions or management practices in order to keep track of SMART project objectives, and is related to either to the proportion of project area or the proportion of households within the project area that are adopting a particular intervention over time. In either case, the outcome is binary, i.e. the practice is adopted, or is disadopted over time. One reasonable model for describing the relevant dynamics is:

$$
\frac{dI}{dt} = aI(1 - U - I) - mI \tag{13}
$$

[6] For a more thorough description of these, readers should consult Diggle et al., 1994 and Pinheiro and Bates, 2002.

for which $I$ is the proportion of area (or proportion of households) that is receiving a particular intervention, $a$ is the annual adoption rate (in ha or no. of households per year), $m$ is the disadoption rate (in ha or no. of households per year), and $U$ is the proportion of area or households for which the intervention is inappropriate or unsuitable. Under these conditions the equilibrium proportion ($\hat{I}$) is:

$$\hat{I} = 1 - U - \frac{m}{a} \tag{14}$$

The main questions for operational monitoring are thus: What determines the adoption and disadoption rates of an intervention? What constitutes unsuitable areas (or households) for the intervention?

Specifying the most basic model of $n_i$ intervention areas grouped within ($i$ = 1, … $m$) survey units, the model for the binary outcome ($I$) is given by:

$$\log\left(\frac{I_i}{1-I_i}\right) = X_i\beta + Z_i b_i + \varepsilon_I \tag{15}$$

for which similar to equation 7,

$\beta$ – is a $p$ dimensional vector of unknown fixed regression parameters.

$b_i$ – is a $q$ dimensional vector of unknown random effects normally distributed as $b_i \sim N(0, \sigma^2)$.

$X_i$ – is a $n_i \times p$ dimensional matrix of fixed effects and covariates, including time and plots or households that are unsuitable for the intrevention.

$Z_i$ – is a $n_i \times p$ dimensional design matrix for the random effects.

$\varepsilon_i$ – is a $n_i$ dimensional within survey area error vector that is assumed to be independently distributed as $\sigma^2\pi^2/3$.

In this particular case $X_i$ contains a time dimension, as well as an assessment of whether an area (or household) is suitable or unsuitable (U) for the intervention being evaluated. For example, agronomic interventions such as improved tillage practices, and fertilizer applications are likely to be unsuitable on rangelands, which would subsequently constitute a portion of $U$ in the above model.

### *6.3. Evaluation of impact*

Reliable assessments of management responses across large project areas require field trials that use intervention-control pairing over time and space. Analyses of field trial data complicated by the fact that they are typically sampled in at least two stages. At the first stage measurements of responses are taken sequentially within experimental units and form a time series in which there may be autocorrelation. At the second stage experimental units are sampled from a population of similar units, which must be stratified by control impact pairing and/or associated with a number of covariates.

Traditional analysis of variance approaches are of limited value in this context, because of their restrictive assumptions concerning missing data and the variance-covariance structure of the repeated measures. Also these procedures focus on estimating group trends over time and are of little use in understanding how and why individual experimental units differ over time.

The appropriate model for impact assessment is again mixed effects, but includes covariates that now specify the before-after project dimensions as well as well as control-intervention pairing over time.

The simplest model for a continuous, normally distributed response variable with random intercepts at the cluster and plot within cluster level of observation is:

$$y_{ijk} = \beta_0 + \beta_t t_k + \beta_2 I + \beta_2 t_k I + b_i + b_{ij} + \varepsilon_{ijk}$$
$$b_i \sim N(0,\sigma_1^2), \quad b_{ij} \sim N(0,\sigma_2^2), \quad \varepsilon_{ijk} \sim N(0,\sigma^2) \tag{16}$$

This is a before-after, control-impact (or BACI) model which is a standard tool for impacts evaluations. The estimate of the interaction term parameter $\beta_2$ between time (or before and after project implementation), and the location term defining the control/impact (CI) pairing, provides the best linear unbiased estimate of the intervention's impact per unit area or household at the block level in this particular case.

# 7. Organization, roles and responsibilities

Monitoring and evaluation activities are the joint responsibility of ICRAF and KARI in the WKIEMP. The two institutions work together and contribute from their respective strengths in the project. ICRAF is internationally recognized for its work in carbon measurement through projects and through contributions to the IPCC. Whereas carbon trading and carbon sequestration are relatively new concepts in Africa, part of ICRAFs mandate is to build capacity within KARI in this area. Thus, the two institutions will:

- Create a joint M&E team to establish an M&E system;
- Hold periodic meetings for joint critical reflection on the qualitative and quantitative information generated by the project;
- Create a communication system to management on the discussions of the joint meeting so that the results of this work can be institutionalized; and
- Follow up on management decisions based on recommendations of the joint meeting.

## 7.1. Roles of KARI

KARI will have a primary responsibility in project implementation monitoring through the field work and implementation of project activities. Through the establishment of the Participatory Action Plans (PAPs), KARI will set objectives with the communities and establish community based monitoring mechanisms to allow communities to monitor their progress toward the objectives of the plans. These participatory monitoring activities will:

- Monitor social and economic impacts of project activities;
- Monitor environmental impacts of project activities;
- Assess willingness of individuals in the communities to participate in applying new technologies;
- To monitor project implementation and impact;
- Monitor on-farm and off-farm agrobiodiversity and on threatened/ endangered habitats within each block (see capacity building strategy);
- Organize community feedback on implemented project activities that support IEM approaches, combining local and global benefits; and
- Field officers will prepare regular progress reports – monthly, quarterly on the status of implementation of the annual work-plan incorporating information from the monitoring activities.

## 7.2. Roles of ICRAF

ICRAF will have primary responsibility for measuring baselines and project impact. ICRAF's activities in the blocks will be limited to supporting participatory testing of new technologies and monitoring species screening trials, so monitoring efforts will be centered around technology performance. ICRAF will primary responsibilities for:

- Data management, archiving and sharing (note all data will be jointly owned by KARI and ICRAF);
- Build capacity of KARI staff, other local institutions and communities to undertake actively M&E of change in carbon stocks (see capacity building strategy);
- Establishing the framework for net-net accounting of greenhouse gases for improved technologies (including non-$CO_2$ greenhouse gases);
- Train KARI scientists on methods of measuring carbon stocks and non $CO_2$ greenhouse gases including data collection, laboratory procedures, monitoring and statistical analysis (see capacity building strategy);
- Measure the baselines in all blocks and evaluate project impact at the end of the project according to this MEP; and

- Develop a manual for the project M&E procedures;

# Appendix I.
# Use of IR Spectroscopy in Landscape Analysis

## A SUMMARY ON DIFFUSE REFLECTANCE SPECTROMETRY (DRS)

Because DRS measurements will be central to our strategy to analyze landscapes to establish project baselines and to monitor and evaluate project accomplishments, and because this technique is relatively new, it is worth briefly reviewing the basis for its interpretation.

Many components of complex material mixtures (such as those contained in a soil sample) can be distinguished using of their spectral signatures in the solar reflective region. Spectral signatures of materials are defined by their reflectance or absorbance of light as a function of wavelength. Under controlled conditions, the signatures are due to electron state transitions in atoms and vibrational stretching and bending of groups of atoms that form molecules and crystals. Fundamental features (or modes) in reflectance spectra occur at energy levels that allow molecules to rise to higher vibrational states. The fundamental features related to various components of soil organic matter, for example, generally occur in the mid- to thermal-infrared range (MIR, 2,500-25,000 nm), but their overtones (at one half, one third, one fourth etc. of the wavelength of the fundamental feature) occur in the near- (NIR, 700-1,000 nm) and short wave infrared (SWIR, 1,000-2,500 nm) regions. Soil minerals such as different clay types have very distinct spectral signatures in the SWIR because of strong absorption of the overtones of $SO_4^{2-}$, $CO_3^{2-}$ and $OH^-$ radicals and combinations of fundamental features, for example, of $H_2O$ and $CO_2$. The visible (VIS, 400-700 nm) region has been widely used for color determinations in soil and geological applications as well as in the identification of iron oxides and hydroxides. Because of the close relationships between soil molecular/physical chemistry and soil reflectance it is possible to consolidate assessment and prediction numerous soil properties under one measurement.

Indeed, recent research has demonstrated the ability of DRS to provide non-destructive, rapid prediction of soil physical, chemical, and biological properties in the laboratory (Dalal and Henry, 1986; Coleman and Montgomery, 1987; Morra et al., 1991; Palmborg and Nordgren, 1993; Ben-Dor and Banin, 1995; Wander and Traina, 1996, Janik, et al., 1998; Ben-Dor et al., 1999). DRS has also been used in the field, for instance to determine soil organic matter content (e.g. Sudduth and Hummel, 1993). Our own work has shown that many different soil properties related to soil productivity and degradation may be reliably predicted using laboratory and field based DRS approaches (see Tables A1-1 to A1-3).

While there is a growing body of literature related to the application of DRS to soil science there has been little focus on examining the potential of soil reflectance as an <u>integrated</u> indicator of specific soil functions, such as those related to primary productivity and soil degradation. Our own research indicates that this may indeed be a promising area for further research. For example, we have analyzed a number of crop performance trials in Eastern and Southern Africa and found very good correlations between soil reflectance and soil productivity (see for example Figure 1).

Our experience has shown that spectral signatures can be successfully used to detect different land management systems on a same soil type and can be used to detect degradation. Figure 2 shows how the spectral signatures of soils that are cultivated differ from uncultivated soils and how spectral signatures differ between soils subjected to different types of erosion. Finally, to demonstrate the feasibility of application of DRS and remote sensing techniques to landscape scale analysis, in Figure 3 we present a landscape scale analysis of erosion in the Nyando River basin that drains into Lake Victoria.

**Table A1-1.** Prediction success in an 18-year soil management experiment in Kenya.

| Soil attribute | $r^2_{cal}$* | $r^2_{val}$* | SEP† | Min | Max |
|---|---|---|---|---|---|
| Exchangeable bases ($cmol_c$ $kg^{-1}$ soil) | 0.90 | 0.81 | 0.796 | 6.3 | 12.8 |
| Light fraction OM‡ (g $kg^{-1}$ soil) | 0.89 | 0.78 | 0.288 | 0.8 | 8.2 |
| Microbial biomass C (mg $kg^{-1}$ soil) | 0.90 | 0.80 | 11.8 | 40 | 133 |
| Bean yield§ (Mg grain $ha^{-1}$) | 0.91 | 0.82 | 0.092 | 0.22 | 1.01 |
| Maize yield§ (Mg grain $ha^{-1}$) | 0.88 | 0.77 | 0.535 | 1.65 | 5.39 |

*Coefficients of determination for observed versus fitted values for calibration (n=31) and full cross-validation sample sets. †Standard error of prediction. SEP for light fraction soil organic matter (SOM) is presented for $\log_e$ transformed data. ‡Light plus medium Ludox fraction of organic matter >250 µm size and <1.37 Mg $m^{-3}$ density. §Long-term average grain yields. Maize (*Zea Mays* L.) and beans (*Phaseolus vulgaris* L.) were grown once each year in rotation.

**Table A1-2.** Relationships between soil attributes and soil reflectance in soil management experiments. Coefficients of determination ($r^2$) are for observed versus expected values of soil attributes (0–15 cm depth) predicted from soil reflectance spectra convolved to Landsat 5 band-passes.

| Soil Attribute | Study | Method | n | $r^2$ | Min | Max |
|---|---|---|---|---|---|---|
| Total soil N (g $kg^{-1}$) | LTSM[#] | GM[†] | 31 | 0.66 | 1.4 | 2.2 |
| Macroorganic matter (g $kg^{-1}$) | LTSM | GM | 31 | 0.70 | 21 | 37 |
| Light fraction N (mg $kg^{-1}$) | LTSM | GM | 31 | 0.78 | 23 | 126 |
| Medium fraction N (mg $kg^{-1}$) | LTSM | GM | 31 | 0.71 | 4 | 75 |
| Heavy fraction N (mg $kg^{-1}$) | LTSM | GM | 31 | 0.71 | 9 | 31 |
| Microbial C (mg $kg^{-1}$) | LTSM | GM | 31 | 0.70 | 40 | 133 |
| Microbial N (mg $kg^{-1}$) | LTSM | GM | 31 | 0.74 | 8 | 24 |
| NaOH organic P (mg $kg^{-1}$) | STAF-1[*] | GM | 16 | 0.68 | 155 | 199 |
| NaOH organic P (mg $kg^{-1}$) | STAF-2 | GM | 16 | 0.62 | 62 | 113 |
| Resin inorganic P (mg $kg^{-1}$) | STAF-1 | GM | 16 | 0.34 | 2.3 | 4.4 |
| Resin inorganic P (mg $kg^{-1}$) | STAF-2 | GM | 16 | 0.77 | 5.7 | 18.7 |
| Light fraction P (mg $kg^{-1}$) | STAF-1 | GM | 16 | 0.33 | 0.1 | 2.2 |
| Light fraction P (mg $kg^{-1}$) | STAF-2 | GM | 16 | 0.39 | 0.1 | 1.6 |
| Macroorganic matter P (mg $kg^{-1}$) | STAF-1 | GM | 16 | 0.26 | 0.7 | 4.4 |
| Macroorganic matter P (mg $kg^{-1}$) | STAF-2 | GM | 16 | 0.52 | 0.5 | 4.4 |
| Soil C (g $kg^{-1}$) | MLAF[§] | CC[‡] | 114 | 0.76 | 6 | 32 |
| Soil nitrate (mg $kg^{-1}$) | MLAF | BR[&] | 114 | 0.63 | 0.01 | 16.5 |
| Exchangeable K ($cmol_c$ $kg^{-1}$) | MLAF | CC | 116 | 0.65 | 0.04 | 0.94 |
| Extractable P (mg $kg^{-1}$) | MLAF | BR | 116 | 0.82 | 1.3 | 72.5 |

[#] LTSM is a long-term soil fertility management experiment in Kenya
[*] STAF-1&2 are agroforestry experiments in Kenya (1) Oxisol, (2) Alfisol
[§] MLAF is a multilocation agroforestry trial from Southern Africa.
[†] Graphical model (Edwards, 1995)
[‡] Canonical correlation analysis
[&] Breakpoint regression analysis

**Table A1-3**: Prediction of basic soil properties using partial least-squares (PLS) regression of NIR soil reflectance in the Lake Victoria Basin of East Africa.

| Soil attribute | T (1) | # Comp (2) | Range (3) | $r^2_{cal}$ (4) | $r^2_{val}$ (5) | SEP (6) | SER (7) |
|---|---|---|---|---|---|---|---|
| PH (water) | none | 13 | 4.8 – 10 | 0.72 | 0.70 | 0.41 | 0.07 |
| Soil texture (8) | mix | 10 | – | 0.78 | 0.73 | – | – |
| Clay (%) (8) | none | 10 | 5.0 – 79 | 0.79 | 0.74 | 7.8 | 5.2 |
| Silt (%) (8) | none | 10 | 0.0 – 42 | 0.66 | 0.56 | 7.2 | 4.0 |
| Sand (%) (8) | none | 10 | 8.0 – 90 | 0.77 | 0.76 | 9.9 | 3.0 |
| CEC Clay (cmol $kg^{-1}$ clay) | sqrt | 5 | 4.0 – 188 | 0.81 | 0.78 | 0.80 | 0.10 |
| Sum of Exch. Bases (cmol $kg^{-1}$) | sqrt | 8 | 0.3 – 55 | 0.87 | 0.87 | 0.54 | 0.03 |
| Ca (cmol $kg^{-1}$) | sqrt | 10 | 0.6 – 48 | 0.91 | 0.88 | 0.45 | 0.02 |
| Mg (cmol $kg^{-1}$) | sqrt | 10 | 0.0 – 18 | 0.84 | 0.79 | 0.32 | 0.01 |
| K (cmol $kg^{-1}$) | ln(x+1) | 10 | 0.0 – 6.2 | 0.56 | 0.52 | 0.16 | 0.01 |
| Na (cmol $kg^{-1}$) (9) | none | 10 | 0.0 – 6.7 | 0.99 | 0.81 | 0.84 | - |
| Org. C (g $kg^{-1}$) | ln | 15 | 2.3 – 56 | 0.79 | 0.71 | 0.22 | 0.08 |
| Min. N (mg $kg^{-1}$ $d^{-1}$) | ln(x+3.8) | 13 | -2.8 – 45 | 0.64 | 0.53 | 0.43 | 0.07 |
| Ext. P (mg $kg^{-1}$) | ln(x+1) | 10 | 0.0 – 328 | 0.63 | 0.60 | 0.60 | 0.03 |

(1) type of transformation (indicated by Box-Cox test).

(2) number of significant spectral components in model.

(3) data range in original (untransformed) units

(4) Coefficient of determination for calibration set (n = 434, unless indicated as otherwise).

(5) Coefficient of determination for validation set (n = 217, unless indicated as otherwise).

(6) Standard error of prediction(in transformed units where applicable).

(7) Indicative standard error of replication in lab. data (in transformed units where applicable).

(8) PLS2 mixture model applied

(9) n = 32, full holdout cross-validation applied.

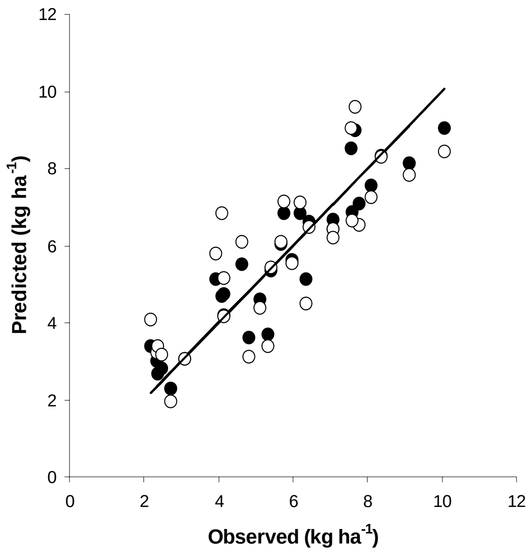



**Figure A1-1.** DRS prediction of bean yield from an 18-year old soil fertility management experiment in Kenya (solid circles are the calibration set, open circles are cross validated values).

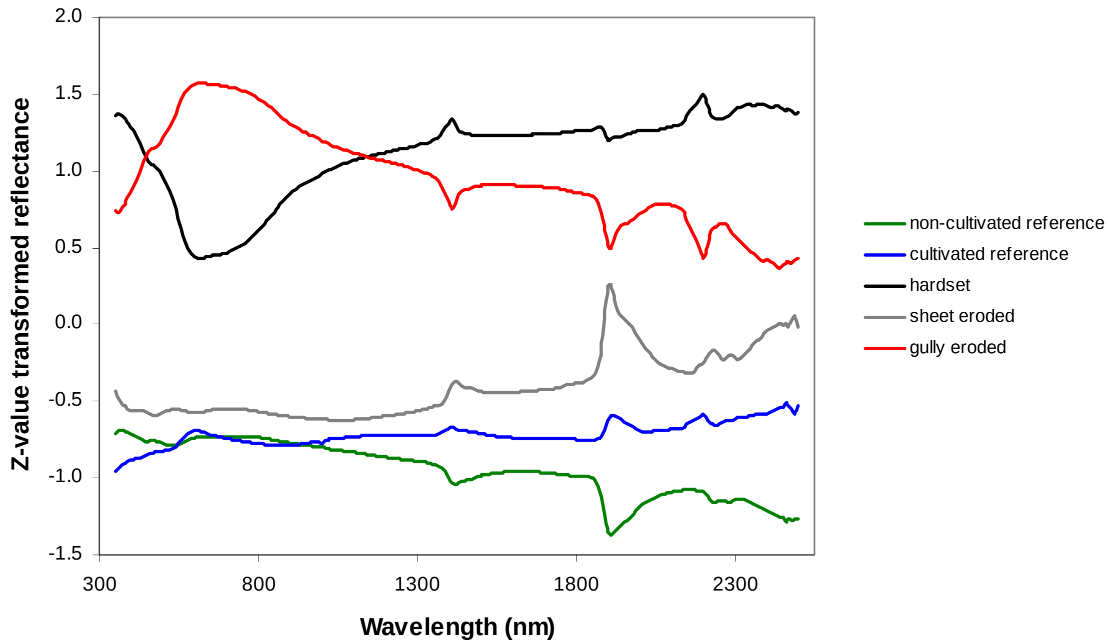
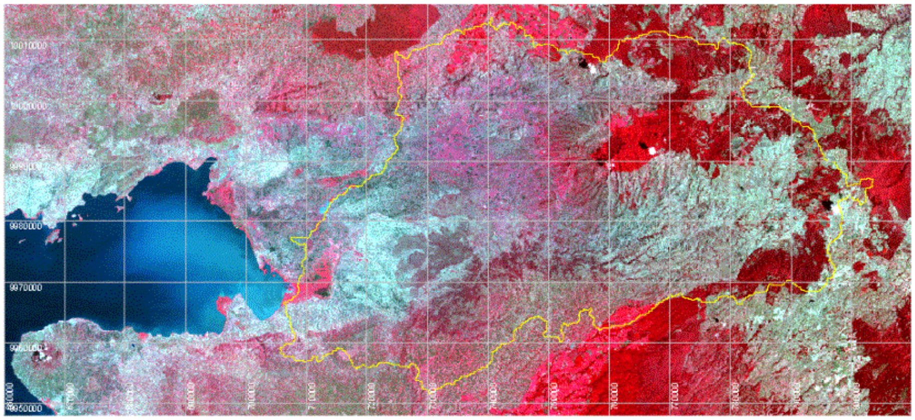



**Figure A1-2.** Reflectance signatures of physically degraded soils in Western Kenya, relative to "intact" non-cultivated and cultivated reference soils. This figure demonstrates the ability of DRS to distinguish between physically degraded soils and to distinguish between management practices on soils.



Landsat Thematic Mapper image of the Nyando River Basin (yellow outline) in Western Kenya.

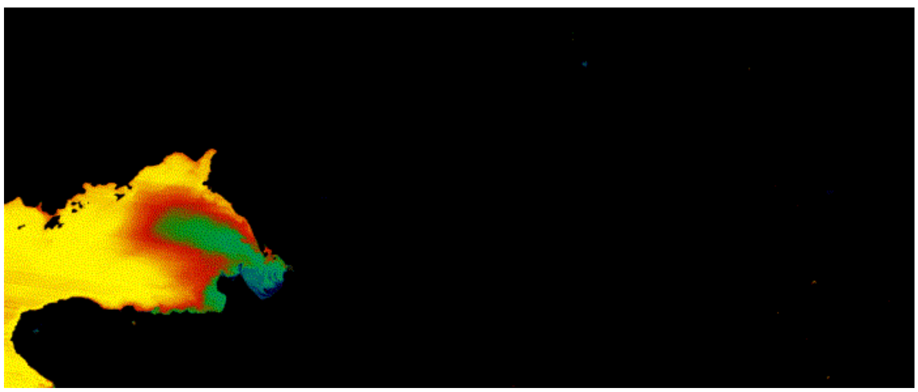


Image processed to highlight Nyando River sediment plume in Lake Victoria.

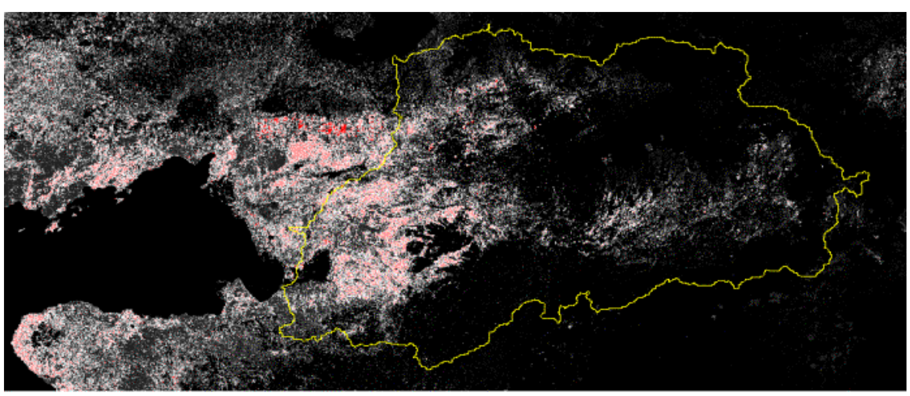


Image processed to highlight local sediment source areas.

**Figure A2-3.** Sample image analysis showing erosion/sedimentation at the level of a 3,500 $km^2$ size river basin draining into Lake Victoria in Western Kenya. Top panel shows the original image. The middle panel shows the image processed to characterize the sediment plume in Winam Gulf from the Nyando River. The bottom panel shows the area around Winam Gulf that is the likely source of the sediment in the lake.

# Appendix III

# Manual of Field Procedures

# Appendix III.
# Socioeconomic Survey

## Questionnaire for Contingent Valuation Study, Western Kenya

Serial No. ________

Date ____________________ Block ________________ Focal Area ______________

**GPS reading of the homestead** (Long.)_________ Lat ____________ Altitude __________

1. Name of the sub-location ______________________ 2. Name of the Village ___________________________

3. Name / Alias of the respondent __________________ 4. Sex (Male / Female) ______ 5. Age (Years) _____

6. Is the respondent the head of the household? (Yes / No) __________

7. If no, then name / alias of the head of the household __________________________________________

8. Is the head married (Yes / No / Widowed / Separated) ________ 9. Total No. of people in the household ____

10. Details of people in the household

| **No** | **Name / Alias** | **Relation with head of the hh** | **Sex** | **Age (Years)*** | | | **Education Status** |
|---|---|---|---|---|---|---|---|
| | | | **M / F** | **<15** | **15 - 65** | **> 65** | **L – literate, P – Primary<br>S – Secondary, U- University<br>I – Illiterate, Y - Young** |
| | | | | | | | |
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* Tick √ whatever is appropriate

11. What is the type of household?

| Female headed | Male headed | Orphan headed | Polygamous |
|---|---|---|---|
| | | | |

* Tick √ whatever is appropriate

12. Last year, did you incur expenses on your children's education? (Yes / No) ______

13. If yes, then how much (Ksh)? _____________

14. No. of shambas that you own ___________

15. Total area under all shambas (in acres) _________

16. Details of Shambas

| | Shamba area (in acres) | Last year, the area that was put under food crops (e.g. maize, sorghum, cassava etc.) in acres | Do you have land title for this shamba? Yes / No | Type of structure – indicate type of roof and semi/permanent structure |
|---|---|---|---|---|
| **Shamba 1** | | | | |
| **Shamba 2** | | | | |
| **Shamba 3** | | | | |
| **Shamba 4** | | | | |
| **Shamba 5** | | | | |
| **Shamba 6** | | | | |
| | | | | |

17. Involvement of the household members in agricultural practices (includes farming, raising cattle, selling the agricultural produce in market etc.

| No. | Name / Alias | Never | Part-time | Full-time |
|---|---|---|---|---|
| | | | | |
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18. Last year, did you employ non-household members on any of your shambas (Yes / No) ______

19. If yes, then please provide the following details:

| No. | Activity for which the labor was hired | Money Paid (Ksh) or in kind |
|---|---|---|
| | | |
| | | |
| | | |
| | | |
| | | |
| | Total | |

20. Last year were any of your household members employed outside your own shambas?

| No. | Name / Alias | Within Village on Someone's farm | Outside village (Part-time) | Permanent Job |
|---|---|---|---|---|
| | | | | |
| | | | | |
| | | | | |
| | | | | |
| | | | | |

21. Last year, did you spend any money on the following activities on your farm? (Yes / No) _______

| No. | Activity | Total Money Spent (Ksh) |
|---|---|---|
| | Improvement of the farms | |
| | Use of improved seeds | |
| | Use of manure (if yes, fill question 22.) | |
| | Use of artificial fertilizer (if yes, fill question 22.) | |
| | Purchasing / improvement of agricultural implements | |
| | Any other | |
| | ***Total*** | |

22. Please specify use of manure and fertilizer

| Type of fertilizer | Type of fertilizer used | Type of crop fertilized | Area fertilized (in acres) |
|---|---|---|---|
| Animal manure | | | |
| Green manure | | | |
| Artificial fertilizer | | | |
| Mix of manure & fertilizer | | | |

23. Present ownership of animals (write the number of animals in the blanks)

| | | | |
|---|---|---|---|
| **Cow local breed** | **Chicken local breed** | **Goats local breed** | **Bulls local** |
| **Cow high-breed** | **Chicken high-breed** | **Goats high-breed** | **Bulls high-breed** |
| **Sheep** | **Pigs** | **Donkey** | **Others** |

24. How do you utilize crop residue and animal waste? Please indicate below

| | **Crop residue** | **Animal waste** |
|---|---|---|
| **Unutilized** | | |
| **Fuel** | | |
| **Manure** | | |
| **Composting** | | |
| **Animal feed** | | |
| **Sold to neighbours** | | |
| **Other uses** | | |

25. If yes to owning livestock, please specify source of fodder, * Tick √ whatever is appropriate

| **Source of fodder** | | **Area used for fodder production (in acres)** |
|---|---|---|
| **Own farm** | **Crop residue** | |
| | **Grasses** | |
| **Off-farm** | **Communal land** | |
| | **Government land** | |
| **Artificial feed** | | |
| **Local market** | | |
| **Others** | | |

26. Are you facing any problems with your livestock? (Yes / No) _____, if yes please specify below

_______________________________________________________________________________

27. Do you practice free-grazing? (Yes / No) ______,
if yes, do you have sufficient land? (Yes / No) ______ and/or do your animals graze on communal land? (Yes / No) ______

28. Do you experience problems with free-grazing animals on your farm/shamba? (Yes / No) ______

29. Last year did you spend any money on your animals? (Yes / No) _____If yes then how much:

| | |
|---|---|
| **On buying new animals (Ksh)** | |
| **Health related expenditure on animals (Ksh)** | |
| **Buying of fodder for animals (Ksh)** | |
| **Any Other (Ksh)** | |

30. Kind of dwelling (thatch-roofed / metal or tile roofed) ______________________________

31. Last year, did you spend any money on improving your dwelling? (Yes / No) ___________

32. If yes, then how much (Ksh) _______________

33. Where do you bring your water from? _________ 34. How far is it? (Km) ______

35. How much water do you usually bring in a day (in terms of 20 litre cans)? _______________

36. How much money do you usually pay on water in a day? (Ksh) _________________________

37. Last year, did you buy any food-grains for your household? (Yes / No) __________

38. If yes, for how many months? ________

39. How much did you spend on buying food-grains? (Ksh) _____________

40. Last year, did you incur any other expenses apart from those discussed above? (Yes / No) ______

41. If yes, then please provide details:

| **No.** | **Nature of Expense** | **Money Spent (Ksh)** |
|---|---|---|
| **1** | Health | |
| **2** | Transportation | |
| **3** | Others | |
| **4** | | |
| **5** | | |
| | **Total** | |

42. Last year, did you take any loan? (Yes / No) _______

43. If yes, then how much (Ksh) __________ For how long (years) ______
How much money do you need to return ______________
And From where (within village, outside village, bank) ____________________________

44. What is/are your source of fuel at your farm?

(i) ______________________________
(ii) ______________________________

(iii) ______________________________

45. Are you self sufficient with fuel (Yes / No) ________

46. What are the three major problems that you face in managing your shambas?

(iii) ______________________________

(iv) ______________________________

(iii) ______________________________

47. Are there any Tree species that you have protected or planted on your shambas? (Yes / No) _____

48. If yes, then please provide the names of the three species that are most important to you?

(i) _________________________________

(ii) _________________________________

(iii) _________________________________

49. Are you planning to cut down some trees from your farm? (Yes / No) ___________

50. In case you want to cut down some trees from your farm, then which species do you want to remove and why?

| **No.** | **Trees Species** | **Purpose** |
|---|---|---|
| | | |
| | | |
| | | |

51. Would you like to plant additional trees on your shambas this year? (Yes / No) ___________

Please be frank if you want to say no. Many farmers say they do not want to plant any more trees on their farm, as they may not have enough land, time to look after the trees etc.
(If no then go to Q 52) (If yes, skip Q 52 and go to Q53)

52. If no, can you please tell us why you are not interested to plant any new trees? __________________________

53. Are there any cultural practices in your area which prohibits planting of trees? (Yes / No) ______
If yes, please specify ________________________________________________________________________
54. If you were given free seedlings, then how many new trees would you like to plant on your shambas this year? ________

55. In this case, which trees would you like to plant and why?

| No. | Trees Species | Purpose |
|---|---|---|
| | | |
| | | |
| | | |

56. If you had to pay 10 Ksh for each seedling, then how many new trees would you like to plant on your shamba this year ? _________

57. In this case, which trees would you like to plant and why?

| No. | Trees Species | Purpose |
|---|---|---|
| | | |
| | | |
| | | |

58. If you were given free seedlings and also paid 10 Ksh for each seedling that you plant, then how many trees would you like to plant on your shamba this year? Please remember that the money will be paid only on the basis of the actual number of trees that survive on your farm six months after you plant them. ____________

59. In this case, which trees would you like to plant and why?

| No. | Trees Species | Purpose |
|---|---|---|
| | | |
| | | |
| | | |

60. Can you please show us the place where you would start planting trees this year?
**GPS reading of the place** (Long.)__________ Lat ____________ Altitude __________

61. Do you practice soil and water conservation on your farm? (Yes / No) ______
If yes, in this case which conservation measures do you have on your farm?

| Type of conservation Measure (tick √) | Purpose of conservation measure | Tree/crop species used | Area under conservation (in acres) | Challenges |
|---|---|---|---|---|
| Grass/shrub strips | | | | |
| Contour lines | | | | |
| Terraces (indicate which type: fanya chini, fanya juu, etc. | | | | |
| Mulching | | | | |
| Minimum tillage | | | | |
| Trash lines | | | | |
| Other | | | | |
| | | | | |

62. Do you practice agroforestry on your farm? (Yes / No) ______, if yes please indicate use of agroforestry products

| | | | | | |
|---|---|---|---|---|---|
| **Food** | **Fodder** | **Fuel wood** | **Wind breaker** | **Aesthetics** | **Soil conservation** |
| **Fruits** | **Timber** | **Medicine** | **Soil fertility** | **Cash income** | **Water conservation** |

* Tick √ whatever is appropriate

63. Have you received any trainings in the past to improve your farm? (Yes / No) ______, if yes, please specify

| No. | Topic of training | Organization training/ sponsor | Have you applied the skills | If no, why not |
|---|---|---|---|---|
| | | | | |
| | | | | |
| | | | | |
| | | | | |

64. Are you a member of a farmer/community group? (Yes / No) ______, if yes, please specify below group name and what it focuses on

_______________________________________________________________________________

Any other comments that you would like to make?_______________________________________________

Thank you!

This interview was conducted by Name ________________________ Signature ______________________