BASELINE AND PROJECT MONITORING PLAN

Prepared For The Western Kenya
Integrated Ecosystem Management (WKIEM) Project

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1. INTRODUCTION

The principal development objective of the Western Kenya Integrated Ecosystem Management Project (WKIEMP) is to improve the productivity and sustainability of farming systems in the Nyando, Yala, and Nzoia watershed catchments of the Lake Victoria basin by pursuing an integrated ecosystem management approach to: 1) rehabilitate degraded lands through interventions focused on improving soil fertility, agroforestry, and introduction of value added cropping systems; and 2) improve capacity for local communities, farmer associations, and national institutions to identify, formulate, and implement sustainable land management activities capturing local and global environmental benefits. The global environmental objective of the project is to promote integrated ecosystem management so as to capture the benefits of reduced greenhouse gas (ghg) accumulation in the atmosphere, improved on and off farm biodiversity, and decreased erosion in watersheds that feed into the Nyando, Yala, and Nzoia watersheds. Project activities will be achieved through a community driven development process whereby communities direct and coordinate resources for improved land management investments, technical assistance and implementation of ecosystem management activities.

In contrast to purely technology-driven extension and development approaches, IEM attempts to reinforce positive or beneficial feedback mechanisms between biotic, soil, atmospheric and human/economic components of ecosystems (Fig. 1).

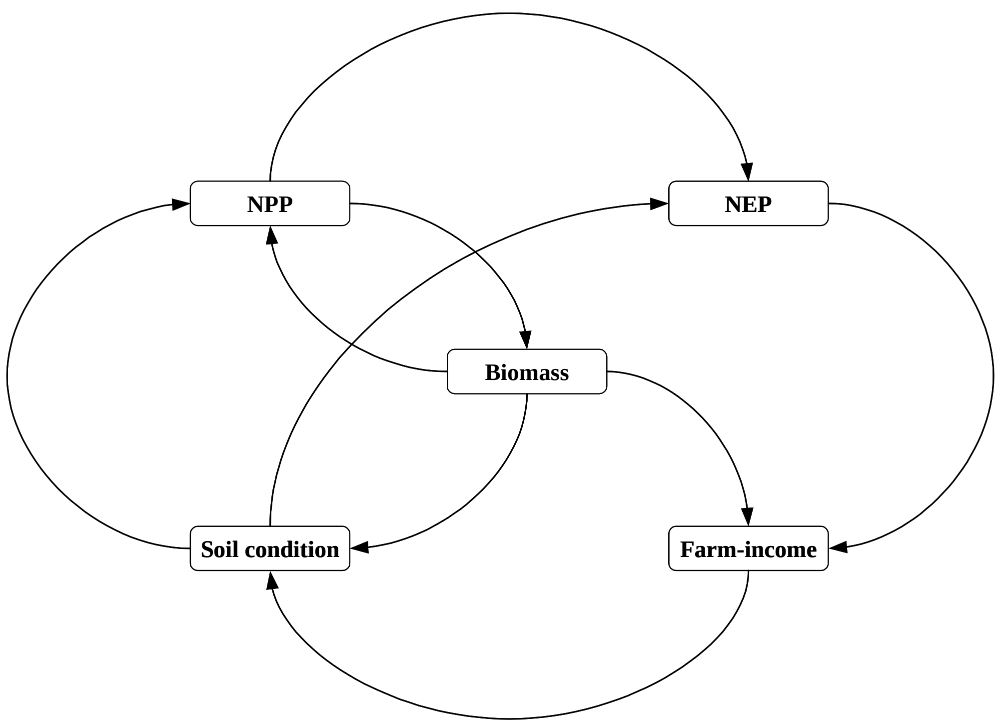

Figure 1. Causal loop diagram showing positive feedback relationships between net primary production (NPP), biomass, soil condition, net ecosystem production (NEP) and farm income.

Using a variety of land management interventions, ranging from afforestation and reforestation activities, soil conservation and fertility management, to dissemination of value added agronomic and agroforestry practices, which will be identified in collaboration with local land managers, WKIEMP seeks to increase net primary production in currently degraded cropping, and rangeland ecosystems in western Kenya.

Net primary production (*NPP*, kg C m^2 yr^{-1}) is defined as the product of standing crop (~ *Biomass*, kg C m^{-2}) and the relative growth rate (*RGR*, kg C kg^{-1} *Biomass* yr^{-1}) of vegetation as:

$$NPP = Biomass \times RGR \tag{1.}$$

Therefore, *NPP* represents the total new organic matter of an ecosystem that is produced over the period of one year. Biomass exerts the predominant influence over *NPP*, with forests (and presumably agroforests) being more productive than shrublands or grasslands, despite their relatively lower *RGR's* (Chapin, 1993). Individual plant traits such as mature size and growth rate influence *NPP* directly, and can be manipulated in plant communities through selection and species substitutions. Plant mortality is an inevitable consequence of *NPP*, and after plant litter is transferred to the soil, decomposition is the principal process determining carbon losses from ecosystems. Thus, carbon exchanges between land and atmosphere are largely controlled by the difference between *NPP* and heterotrophic respiration (R_h, kg C m^{-2} yr^{-1}). This balance, is most commonly expressed as net ecosystem production (*NEP*, kg C m^{-2} yr^{-1}) given by:

$$NEP = NPP - R_h \tag{2.}$$

NEP is important because it is a measure of the annual increment of carbon stored by ecosystems. *NPP* and *NEP* are ultimately constrained by soil conditions[1], which affect both resource availability for plant growth and the abundance and diversity of decomposer communities. In western Kenya rapidly declining soil condition over the last 100 years, as a consequence of continuous cropping in the absence of organic and inorganic inputs, nearly complete removal of woody vegetation, lack of soil conservation structures, poor and late land preparation and grazing of cattle on fragile soils is well documented (e.g., Buresh et al., 1997; Shepherd et al., 2001). These practices have led to downward spiraling system dynamics leading to declining *NPP* and *NEP* regionally, though this has never been quantified at a landscape scale. Moreover, though not shown in Fig. 1, soil condition, biomass and *NPP* also exert strong controls on water quality and quantity by regulating erosion/sedimentation, ground-water recharge and transpiration rates. Also important, economic returns to land, labor and/or capital from farming and livestock currently occur only as a function of biomass harvest. Therefore assessing change biomass has important agricultural as well as environmental implications.

WKIEMP will also evaluate the potential to increase farm incomes through environmental service payments for CO_2 and other greenhouse gas emission reductions. In turn, reinvestment of farm resources in labor and capital resources is expected to further enhance *NPP* in the region.

Direct field measurement of all the above-mentioned quantities and processes remains somewhat problematic. In some cases, such as for example for *NPP*, no direct field measurement is currently feasible because of difficulties associated with measuring all the above- and below-ground components of *RGR*. Instead, *NPP* is estimated based on a suite of indicators of various types and underlying assumptions (see Clarke et al., 2001). Similar situations exist in the context of measuring *NEP*, soil condition, and the various socio-economic dimensions of poverty, including farm income. As there currently are no globally accepted standards for monitoring these quantities, this document describes the underlying assumptions, associated measurements and statistical modeling approaches, which will be tested in the context of WKIEMP activities. The document is divided into three major sections including: (1.) definitions of the geographic scope and operational domain of the project, (2.) procedures for assessing initial site conditions and calculating biophysical and socioeconomic baselines, and (3.) procedures for monitoring change and project impact assessment.

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[1] Soil condition here is taken as a short-hand describing the properties and characteristics of soil that promote primary production (Swift and Palm, 2000).

2. PROJECT AREA

Forest cover (1990)

Forest cover estimates from Dec. 31rst, 1989 are required to demonstrate that works and plantings undertaken in the context of projects are consistent with international rules for carbon sink eligibility. To meet these criteria under the current agreements (i.e., COP7), forests (including agroforests) have been flexibly defined as having a minimum canopy cover of 10%, a minimum mature height of 2 meters, and a minimum spatial extent of 0.05 ha. Definitions of afforestation, reforestation and deforestation all use forest cover change criteria, with afforestation activities being located on lands that have not been forested for more than 50 years, and reforestation located on lands which have not been forested since Dec. 31rst, 1989. These definitions preclude inclusion of activities that involve clearing of forests after 1989 – to subsequently claim reforestation credits. Additionally, projects focusing on forest conservation and "forest buffer zone" agroforestry projects have to provide estimates of forest cover during the base year, against which subsequent changes can be evaluated.

The Kenyan portion of the Lake Victoria Basin covers a land area of ~3.9 million ha, and to our knowledge no comprehensive forest inventory was ever conducted in the region in 1989. However recently, NASA's Earth Science Applications Directorate has made a global dataset of Landsat Thematic Mapper 5 mosaics available to the public (see https://zulu.ssc.nasa.gov/mrsid). All acquired images date from an approximately six-month period between 1989-1990. Mosaics are provided in terrain corrected Universal Transverse Mercator (UTM) / World Geodetic System 1984 (WGS1984) projection and each cover a standard UTM zone of 6 deg. longitude, in three spectral regions (Band 7, Band 4 & Band 2), at 28.5 m spatial resolution. We extracted the relevant coverages for western Kenya and used spectral mixture analysis to estimate the ~1990 forest cover fractions for the region. An example, including a brief description of the applied methods, is shown in Fig. 2. We note that the forest cover estimates provided by this approach do not constitute a regional estimate of woody vegetation cover more generally, but appear to be valid for "evergreen broadleaf" forest types, based on what is known regarding their current distribution in western Kenya.

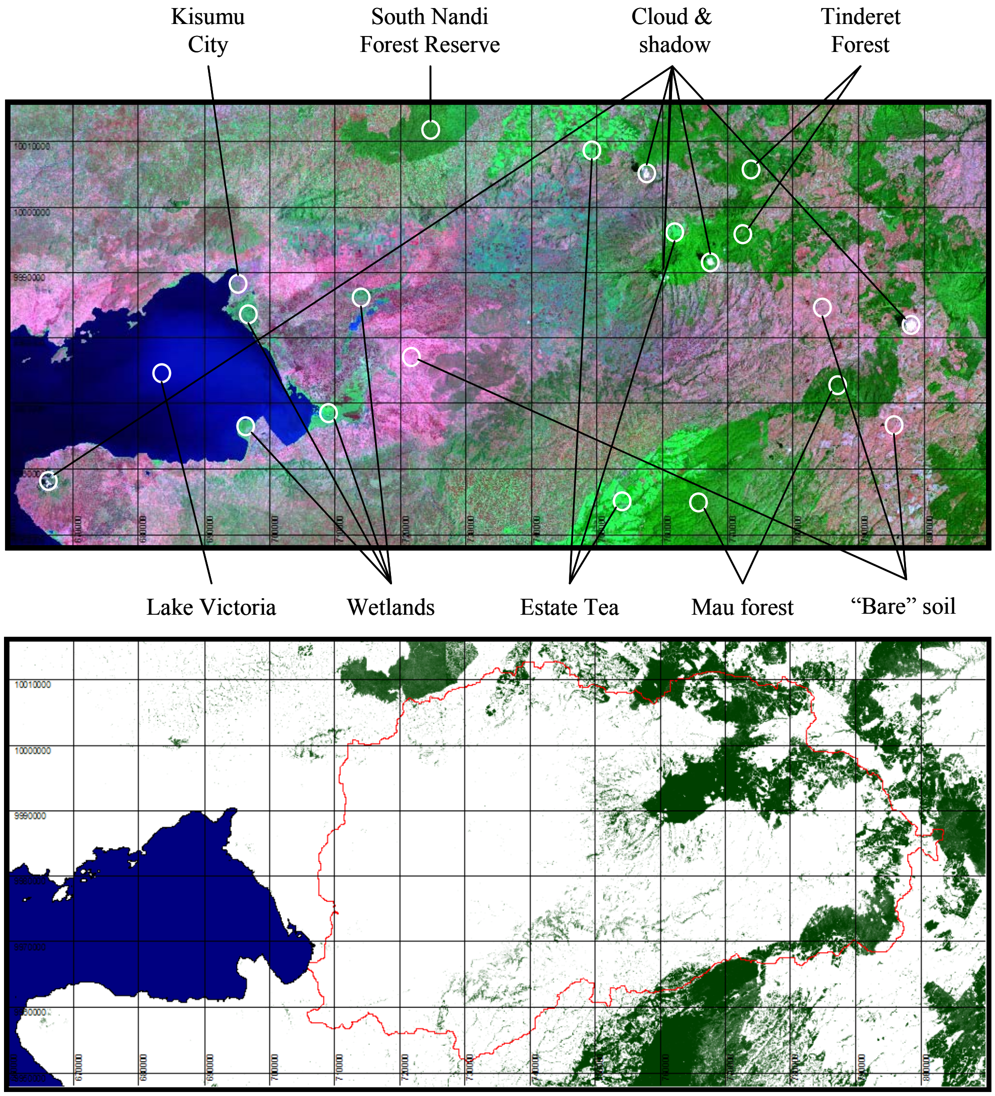


Figure 2. Extent of forest cover in the Nyando River Basin ~1990. Top image shows Landsat 5 composite (Band 7 = red, Band 4 = green, Band 2= blue). Bottom image shows estimated forest cover fraction based on partial spectral unmixing.

Methods:

Forest cover has a very distinctive signature in the Landsat 5 Band 2,4,7 spectral range, and particularly "closed broadleaf evergreen" forest canopies are easily distinguished from non-forest cover types upon visual inspection (see examples top panel). Image pixel signatures from a wide range of visually identified forest and non-forest land cover types were extracted and posted to a database for analysis. The separability of different forest/non-forest types was tested statistically using linear discriminant analysis. Based on a 50% hold-out validation sample of 492 visually classified pixels, 98.7% were correctly classified as "forest", and 97.5% were correctly classified as "non-forest". Incorrectly classified pixels in the validation set were subsequently screened from further analyses. Using the screened validation dataset, signature files were then created in the ENVI® image processing system (see www.rsinc.com), and the "Matched-Filtering Algorithm" was used to estimate the fraction of forest cover in each 28.5 × 28.5 m pixel in the image (results shown in bottom panel).

Gross project area

The gross project area will include the Nyando, Yala, and Nzoia basins of the Lake Victoria watershed. This large area, consisting of 19,898 km^2, will include specific monitoring focal areas (FA) which will receive detailed attention for monitoring and evaluation of project and environmental objectives, and the remainder of the area which will not receive the same degree of treatment but in which farmer/community associations have indicated that they also want to participate.

Net Project Area

The net project area, commonly called “the project area”, will consist of nine 10×10 km focal areas (FA’s) specifically designed for monitoring and evaluation. Because of the wide geographic dispersion and large area coverage within the region, a phased approach in implementing project activities is deemed necessary. The table below shows the timing for inclusion of FA’s in years 2004-2006.

Water-shed	**Area (km^2)**	**No. 100 km^2 FA’s** *2004*	*2005*
Nyando	3,550	3	
Yala	3,364	3	
Nzoia	12,984		3

To further ensure that the project area is regionally representative, allocation of FA’s within basins will be stratified by elevation zones including: *Lowlands*, 1134-1440 m, *Midlands*, 1440-1890 m and *Highlands* ≥1890 m a.s.l. Considering the size of each FA in each elevation zone, the FAs will represent 8.5% of the land area of Nyando, 8.9% of Yala a and 2.3 % of Nzoia.

Research conducted in the context of the TransVic and other projects has demonstrated strong associations between this zonation and variables related to population density, land use, soil condition and production ecology. Examples of these relationships are summarized in Table 1.

Focal area locations will be selected randomly, nested within basins and elevation zones, but subject to the following criteria: no part of any FA will impinge on 1990 baseline “*forested lands*” (as defined under section 2.1); FAs will not impinge on large-scale commercial agricultural areas (e.g., rice irrigation schemes, tea estates, and sugar cane plantations); FAs will not impinge on government lands such as protected areas and game parks; FAs will not impinge on large wetlands or urban areas.

The net project area (NPA) is the area in which improved land management treatments will be implemented, as selected by farmers, and in which the impacts of these treatments will be monitored. These areas will be consistent with current international rules for eligible greenhouse gas sinks. It is also the area over which baseline predictions are made and which will be monitored. In the context of this project, it is very likely that the NPA will evolve over time, as communities outside the NPA take benefit of the project and begin to participate.

Table 1. Indicative differences between elevation zones in western Kenya. Table reports 95% CI's of mean zonal values.

Variable	*Lowlands*	*Midlands*	*Highlands*
Housing units (no. km^{-2})[1]	111 – 142	62.3 – 85.1	23.3 – 33.5
Ave. tree cover (ha km^{-2})[1]	8.47 – 10.0	18.7 – 22.6	23.0 – 30.6
Tree cover on farms (ha km^{-2})[1]	2.58 – 3.39	2.30 – 3.52	0.72 – 1.13
Cropland (ha km^{-2})[1]	14.6 – 17.9	11.1 – 15.3	8.95 – 12.6
Commercial crops (ha km^{-2})[1]	1.12 – 1.66	1.43 – 2.04	1.51 – 2.25
Ave. annual NDVI[2]	0.29 – 0.33	0.38 – 0.43	0.52 – 0.61
pH (water)[3]	6.44 – 6.68	5.81 – 6.30	–
Clay (%)[3]	37.1 – 42.8	29.2 – 36.4	–
CEC[3]	17.3 – 21.6	11.5 – 16.8	–
SOC (g kg^{-1})[3]	12.6 – 15.1	17.8 – 23.0	*24.8 – 27.3*[5]
Steady-state infiltration (cm hr^{-1})[4]	1.67 – 3.05	5.28 – 13.0	–

[1] Data from Ecosystems Ltd (1986) regional low-altitude aerial survey interpretation.
[2] Normalized Difference Vegetation Index data from Africa Data Dissemination Service, GAC decadal time-series (1985 – 2002).
[3] Shepherd & Walsh (2002).
[4] Thine et al. (in press).
[5] Spectral library estimate.

To quantify these dynamics, it is necessary to define what will determine eligibility. In terms of above ground carbon, we define project eligible reforestation, afforestation and agroforestry activities to consist of areas with a minimum contiguous spatial extent of 0.05 ha (woodlots), and subject to the stocking guidelines presented in the table below.

	Minimum stocking level (trees ha^{-1})	
Stand age	*Total*	*Indigenous*
Initial planting	1600	800
3 months	1120	560
1 year	800	400
3 years	700	350

Areas excluded from the NPA are any patches of existing woody vegetation, large and dense enough to already be considered as "forests" under the IPCC definition, which are converted to "non-forested" areas over the course of the project. Due to spatial and spectral resolution constraints of the available Landsat satellite images, deciduous trees and shrubs, hedgerows and other scattered woody vegetation types were not captured in foregoing analyses. The distribution of other existing woody vegetation in focal areas will therefore be assessed using higher resolution satellite data and ground surveys (see section 3). Converted areas and will subsequently be "subtracted out" of any carbon sink credits claimed by WKIEMP participants.

Soil carbon qualifying activities will largely focus on improving soil condition through various agronomic and range management measures (e.g. cover cropping with (tree) legumes or green manures, grazing deferment and rangeland reseeding), conservation tillage (e.g. vegetated contours and/or zero/minimum till practices), and agroforestry boundary plantings, etc. These practices can potentially sequester and/or protect significant amounts of carbon in the soil, as well as reduce emissions of non-CO_2 greenhouse gases. However, the potential magnitude of these emission reductions is currently unknown and will therefore be monitored. For the most part, it will not be possible to determine the aerial extent or monitor the adoption of these activities using remote sensing data. Instead Section 4 discusses how this will be accomplished using systematic GPS surveys.

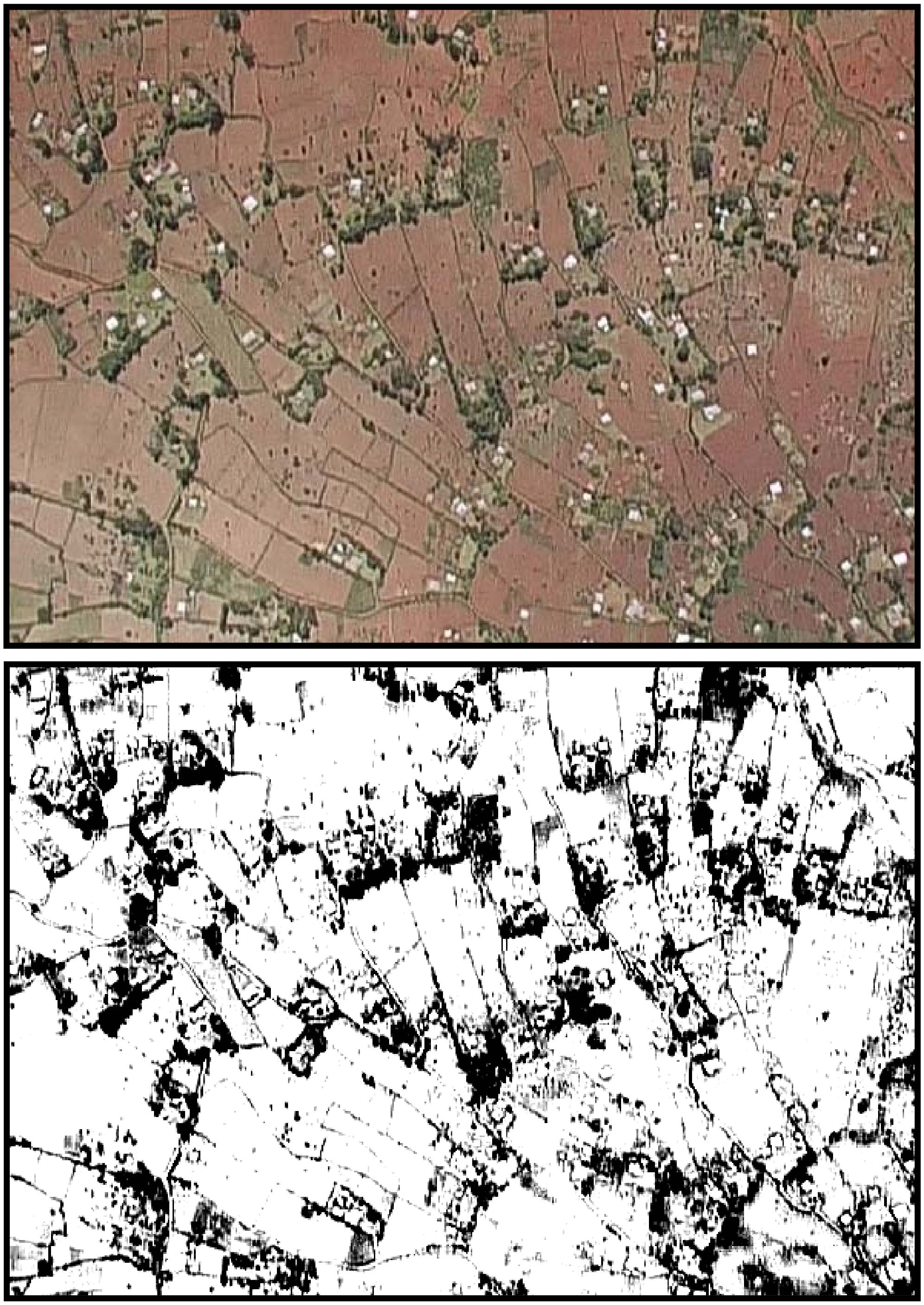


Figure 3: 0.7 m resolution true color aerial photograph of a portion of the Ebukanga catchment in western Kenya; below image processed to highlight the distribution of woody vegetation cover in the image.

3. INITIAL SITE CHARACTERIZATION AND REGIONAL BASELINES

The monitoring focal areas (FAs) described in section 2 will serve as the primary data collection sites for the project. All detailed site characterization and survey activities will be concentrated in these areas. The location of the FAs and all data collected therefrom will be georeferenced and entered into a project GIS data base.

Remote sensing

Fifteen, 0.7 meter resolution true-color QuickBird satellite images[2] will be acquired in 10×10 km blocks centered on focal areas. 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 existing, non-project woody vegetation cover (tree and shrub density, crown cover and area) will be completed prior to initiating ground surveys. Accuracies of the respective classification models will subsequently be determined by ground survey. A simulated example of this is shown in Figure 3. 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 elevation models (DEM's) for western Kenya were derived by digitizing ~20 m interval contour lines on 1: 50,000 topographic maps. These datasets are not sufficiently accurate to "orthorectify"[3] 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 (Toutin, 2002). 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 (Toutin and Cheng, 2002). 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 inventories.

Socio-economic indicators

Participatory rural appraisal

Participatory rural appraisal techniques will be used to capture socio-economic indicators in each FA. Attention will first be given to villages within the FAs, although additional villages may be included later. Initially, focus group discussions with local leaders and community members will be used to introduce the project to the area and to identify the major natural resource management constraints faced by the community. Copies of processed satellite images and other available materials describing the area will be distributed to community members and used to discuss the occurrence and distribution of specific natural resource management problems as well as perceptions of what would required to overcome these. Focus groups will then be asked to rank specific problems and possible interventions for these by consensus. Results from these discussions will be synthesized and compiled

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

as reference documents for each community (~ cluster). Results will then be further aggregated to identify communities with similar perceptions regarding the relative importance of different resource management activities that could be addressed by the project. This information may then be used for example to adjust the current definition of the net project area described under section *2.3* and to ensure that the project will be responsive to the needs of its participants.

Willingness to participate

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 and required resources. Additionally, this assessment will provide prior information on adoption rates which may subsequently be used for 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 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 allocate to activities in which they are willing to participate. This information will be synthesized by activity at the level of clusters (and levels beyond this), using mixed effects logistic regression (Gillespie et al., 1994) in which covariates such as household labor availability and resource endowments as well as biophysical variables can be included.

Agricultural labor profiles

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 efficiency with which goods and services can be generated under a given activity. 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 amount of time spent on different activities.

We have developed a simpler approach, 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 by all individual members of their family. We use a 4-point ordinal rating-scale (0 – never, 1 – occasionally, 2 – part time, 3 – full time). Concurrently, respondents are asked to specify the size of their farm, and to identify the gender, ages, number of years of education and whether or not the individual family member currently has off-farm employment. Finally, respondents are asked if and how many non-family members are employed on their farms and for how long.

We then use a random intercept proportional odds model (see Venables and Ripley, 1999) to remove the effects of the respective individual covariates – household and farm sizes, age, gender, education level and off-farm employment of family members as well as the employee effects. The remainder of unexplained variation in the model, is partitioned into assessment error and a random intercept household effect. The latter may be interpreted as a standardized measure of level of household agricultural labor input relative to the sampled population of households.

Household resources

The level of household resource endowment may be considered as both a baseline condition for adoption of project activities and as an indicator of project impacts. Shepherd and Soule (1998) have suggested that four criteria, farm size, the proportion of land devoted to subsistence food crops, the diversity of farm enterprises and the number and type of cattle allows for most farms in west Kenya can be assigned to 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. This classification can be used both for targeting project activities to particularly resource poor households but also for change detection on the constituent variables.

Livestock

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

Household well-being

Improvements to main household dwelling are an excellent indicator of household economic status and this is 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 is another indicator of household well-being which is easily quantified through either remote sensing or systematic ground survey. Finally, household food sufficiency is an important indicator of household well-being that is perhaps most proximally linked to proposed WKIEM project activities. While detailed food availability studies will not be undertaken in the context of this project we will assess for how many months per year people feel they have sufficient food largely through focus group (rather than household) interviews[4].

FAO Land Cover Classification

The pre-project land cover of all (reference, stocking and control) plots will be recorded using the FAO Land Cover Classification System (LCCS), which has been developed in the context of the FAO- AFRICOVER project (DiGrigorio and Jansen, 2000). 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 areas
- 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.

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

The "*modular-hierarchical phase*" of LCSS 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 will 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. A few examples of LCCS classes are presented in the table below.

Level 1	Level 2	Basic FAO classifier
Cultivated terrestrial areas	Small sized field(s) of graminoid crop (Maize) with fallow system.	A4B2B5C1D1D8
Cultivated terrestrial areas	Permanently cropped area with a sprinkler irrigated shrub crop (Tea)	A2B1B5XXD3D9
Natural or semi natural terrestrial vegetation	Semi-deciduous fragmented (cellular 40%) woodland with open short herbaceous layer	A3A11B2C2D1E2F2F4F7G4F1
Natural or semi natural terrestrial vegetation	Closed short perennial grassland, single layer	A6A10B4C1E5F1

Ecosystem richness and Agro-biodiversity

Two complimentary approaches for measuring biodiversity will be used. The first, called "ecosystem richness" is calculated at the level of focal areas (and subsequently higher levels aggregation) as:

$$E_k = l + \left(\frac{n-1}{n}\right)^q \qquad (3.)$$

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 focal area (= 345)
q = is the number of unique LCCS Level 2 land cover types.

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

$$\mathrm{var}(E_k) = \left(\frac{n-1}{n}\right) \cdot \left(\sum_j j^2 f_j - \frac{q^2}{n}\right) \qquad (4.)$$

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 = is the total number of plots per focal area (= 345)

The second, called "agrobiodiversity", employs a pair-wise plant checklist of 84 useful, common exotic and indigenous plants was prepared. The checklist is intended for use as a rapid approach to biodiversity assessment by surveyors lacking detailed taxonomic knowledge and operates at the plot level (see Appendix 1 for recording forms). The presence of plants may be weighed in terms of their abundance. Frequently encountered plants not appearing on the checklist may be "written in" for consideration. The density and relative frequencies of plant species may be calculated from the checklist, and indicators of the importance of traditional, indigenous plants calculated. Weedy species and those occurring in wastelands are not particularly well covered within the checklist. Because the plant species list is largely "close-ended", the indicative statistics collected from this approach cannot be readily compared to other, more open-ended and taxonomic procedures (Boulinier *et al*., 1998; Gotelli and Colwell, 2001). The approach may, however, be well suited to documenting the changed composition of useful plants between project locations and over the project lifetime.

The two approaches are complementary in that in each case the operational taxonomic units (OTU's) are 625 m^2 plots. Thus, for example, plot-level "useful" species richness (no. of species) may be aggregated by land cover types, and the corresponding conditional estimates may be generated using standard statistical approaches for calculating baselines, and for change detection. Moreover, because the distribution of the various landcover types may be mapped using high-resolution satellite images it may be possible to derive spatially explicit estimates of changes in both ecosystem richness and agro-biodiversity using this approach.

Measuring impacts of land degradation on Lake Victoria

Monitoring of deforestation, sediment and nutrient loads to lake Victoria will be achieved by integration of the WKIEMP with the SIDA funded project "Improved Land Management in the Lake Victoria Basin". Large scale diagnostics of land degradation will be done using spectral analyses of soil samples, based on a reference soil library (procedure described in other section of this report). This quantifies the areas as erosion sources, sediment deposition basins, and reasonably stable areas. Results are used to target land management interventions.

Deforestation is monitored along forest margins using remote sensing. Land degradation and sediment loads are monitored using the "Snowflake" approach. In this, focal areas consisting of 10 X 10 km^2 monitoring sites are located (as described in other sections of this report), within which more detailed sampling site are located to match TM, ASTER, and SPOT pixel resolution. Observations are matched with field data and socio-economic surveys collected at the monitoring sites. Interpretation are done for deforestation hot spots, sources of sediment, and impacts on soil fertility.

Sediment and nutrient loads in rivers are monitored by collecting water samples at 14 day intervals during the rainy season, and less frequently during the dry season. These are collected at the headwaters, midway, and the mouth of each river, and analyzed for normalized turbidity units (NTU). NTUs are calculated by measuring the dispersion of a light beam through the water sample. Results are interpreted for human consumption, recreation use, and impacts on aquatic life.

Measuring initial condition biomass

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 (1997) have been used in previous studies (e.g. Woomer et al., 2000). For Dry Zones (<1500 mm yr^{-1}) the relationship between individual above-ground tree weight (*w*, in kg dry matter) and *dbh* (cm) is given by:

$$w_i = 0.136\ dbh^{2.32} \qquad (5.)$$

and in Moist Zones (1500-4000 mm yr^{-1}) as,

$$w_i = 0.118\ dbh^{2.53} \tag{6.}$$

Other equations are available for drier (<900 mm y^{-1}) and wetter zones (>4000 mm y^{-1}) from FAO (1997). Notably, equations 5 and 6 have not been validated in western Kenya.

Using generalized equations can introduce significant errors and biases in biomass estimates (see Clark et al., 2001). Thus, at the outset of the project, 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 (~1000) of trees and shrubs. The following table summarizes all the relevant individual measurements that will be considered.

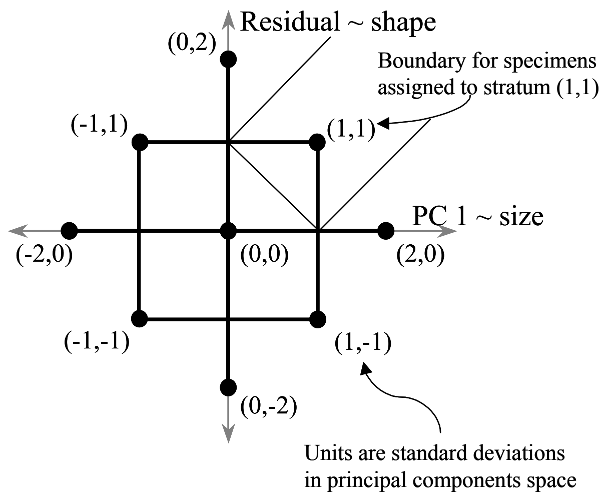
Variable	Units	Description
Allometric predictors:		
Height	m	Tree height measured with either a height pole (< 5 m) or with a ranging clinometer (> 5 m).
Furcation index	m	Stem length to first internode.
Dbh	cm	Stem diameter at 1.3 m above-ground-level (a.g.l.)
Crown projection	m	
Apical dominance	-	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 destruc-tively in the field, subsamples dried at 60° C, for 24-72 hrs to determine dry weight, subsampled again to determine carbon content by dry combustion.
Leaf weight (w_l)	kg	
Above-ground weight ($w_a = w_s + w_l$)		
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 among individual predictors and 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 Fig. 5.

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 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 graphic 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.

Figure 5. 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 (Λ) 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.



Plot biomass

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

$$b_j = q\sum_n w_i \tag{7.}$$

for which n is the number of trees in the sampling unit, q is an area expansion factor (10,000 m^2 ha^{-1} / m^2 sampling unit^{-1}), and w_i are the individual plant weight estimates. While traditionally all trees/shrubs in given sampling unit are enumerated, the effort and time required to achieve this in a 625 m^2 plot can be substantial, particularly in shrubland vegetation types. Thus, an alternative method that we have found to be particularly suited for rapid woody biomass and woody debris inventories in western Kenya, is line intercept sampling (LIS). A LIS sample consists of three 14.38 m radial line transects that originate at the plot center, and terminate at the plot edge (Fig. 4). Trees/shrubs are included in the sample if their crown projections intersect any portion of the line. Crown projections (c_i, meters) of all intercepted individuals are measured as:

$$c_i = \sqrt{c_l \cdot c_w} \tag{8.}$$

for which c_l and c_w are the largest and the smallest crown diameter of the i = 1 …,n^{th} intersecting crown projection, respectively (see Fig. 4). In addition to crown projection measurements, all necessary allometric predictors are then measured and converted to individual plant weight (w_i) using the relevant allometric equations. The LIS estimate of live biomass (B_j, kg 1000 m^{-2}) may then be calculated as (de Vries, 1986):

$$b_j = \frac{10^3}{L} \cdot \sum_n \frac{w_i}{c_i} \tag{9.}$$

for which L is transect length (L = 3 × 14.38 m). The variance of this estimate is approximated by:

$$\operatorname{var} b_j = \frac{1}{L} \cdot \frac{\sum_n \frac{w_i^2}{c_i}}{10^3} \tag{10.}$$

Where observations on plots may be considered as independent, the best linear unbiased estimate of biomass at the cluster level of observation (b_k, Mg km^{-2}) may be derived as:

$$b_k = \frac{10^6}{\sum_k L_j} \cdot \sum_j \sum_n \left(\frac{w_{ij}}{10^3 \cdot c_{ij}} \right) \tag{11.}$$

Based on previous experience however, the assumption of independence between plots at the cluster-level is fairly strong. Thus in section 4 we introduce the concept of multilevel mixed effects models to allow more precise scaling between different levels of observation.

Woody debris

Standing dead and intact fallen tree biomass will be measured using the allometric approach described above. Other coarse woody debris such as slash and fallen branches (>2 cm in diameter) is best measured using LIS. The corresponding general estimator is:

$$x_j = \frac{10^3 \pi}{2L} \cdot \sum_n \frac{x_i}{l_i} \tag{12.}$$

for which x_i and l_i are the characteristic of interest (number, volume or weight) and the needle length of the i^{th} intersecting element respectively, and π (= 3.1416). If x_i is the cubic volume (v_i, m^3) of the i^{th} element, given by (Hush et al., 2003),

$$x_i = v_i = \pi \left(\frac{d_i}{2} \right)^2 \cdot l_i \tag{13.}$$

for which d_i is the diameter of the element measured at the point of intersection, then eqn. 13 reduces to:

$$v_j = \frac{125}{L} \cdot \sum_n d_i^2 \tag{14.}$$

Multiplying by wood density (γ_i, kg DM m^{-3}) would subsequently yield a debris biomass (kg DM 625 m^{-2}) estimate for the plot as:

$$b_j = \frac{125}{L} \cdot \sum_n d_i^2 \cdot \gamma_i \tag{15.}$$

Coarse roots (> 2 mm)

The distribution of belowground 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 belowground 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.) the biomass allometry approach (described above) 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 6 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 then 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 is dispersed in tap water, passed through a 2 mm sieve and roots collected without attempt to differentiate live and dead roots. Roots are 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:

$$b^r = \phi_1 + (\phi_2 - \phi_1) \cdot \exp(-\exp(\phi_3) \cdot d) \qquad (16.)$$

for which ϕ_1 (asymptote), ϕ_2 (intercept) and ϕ_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.

Soil organic matter will be analyzed using standard procedures. Four topsoils (0-30 cm) and 4 subsoils (30-50 cm) will be sampled in at the center of the plot and 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. Carbon sequestration from annual crops (agricultural areas) will be reflected in soil organic matter.

Soil condition

Spectral library

Diffuse reflectance spectroscopy (DRS) is a 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.

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 cheap to acquire. To obtain robust calibrations one must minimize information in the spectra that is not relevant to prediction of the target variable. Various data transformations may be performed to minimize irrelevant information produced by effects of light scattering, variation due to sample presentation (thickness, packing, particle size) and optical set-up, and statistical problems such as multi-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 multi-colinearity. 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 transfer functions for predicting a number of important soil properties have been developed.

Figure 6 shows an example for predicting soil organic carbon (SOC). A sample of >10,000 (0-20 cm) topsoils collected across an extremely broad range of soil conditions in western Kenya was spectrally characterized using methods described by Shepherd and Walsh (2002). A subset of samples from 300 randomly selected sites (soil pH, 4.5 – 9, clay content, 20 – 83%, CEC, 11 – 117 cmol kg^{-1}) was subsequently analyzed for SOC (after acidification with dilute HCl) by total element analysis at the U.C Davies stable isotope laboratory in California. The 1[rst] derivative reflectance spectra of 70% of these samples (n=210) were then calibrated to SOC using the regression spline method described by Shepherd and Walsh (2002). A further 90 randomly selected samples, from as many sites, were held-out to assess model stability.

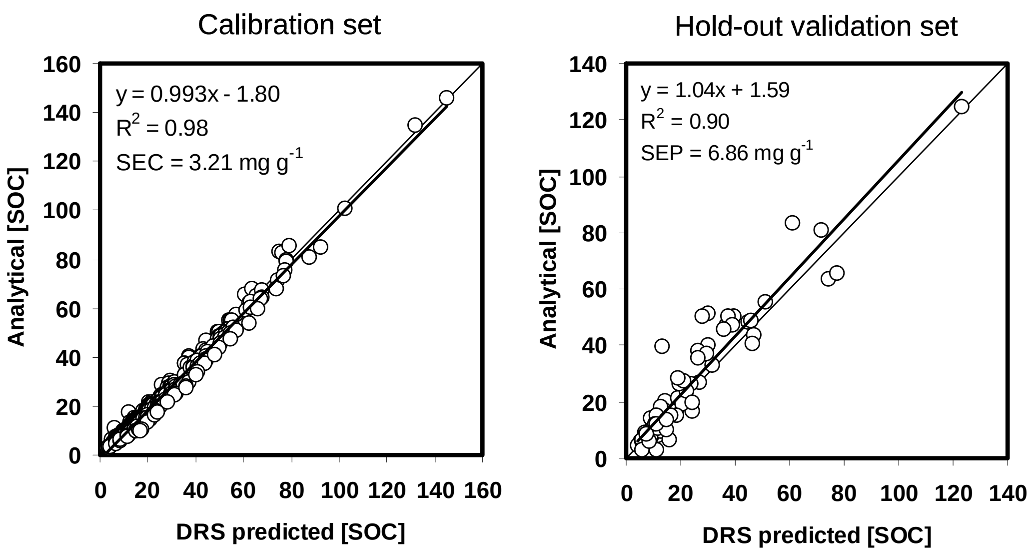


Figure 6. Prediction of soil organic carbon using diffuse reflectance spectrometry across a broad range of environmental conditions in western Kenya.

Notably, this particular calibration performed nearly as well as repeated dry-combustion measurements carried out on subsamples from the same location (Std. repeatability error, SER = 2.98 mg g^{-1}). Similarly encouraging results have been obtained for a number of other important physico-chemical soil properties in western Kenya. A selection of these is summarized in the following table.

Prediction of soil properties based on first derivative reflectance spectra using regression splines (Shepherd & Walsh, 2002). The coefficient of determination (r^2), bias and residual mean square error (RMSE) of a 30% hold-out validation sample are reported.

Soil property	n	Min	Max	r^2	Bias	RMSE
pH (water)	758	4.2	10.0	0.83	-0.02	0.34
Exchangeable Ca, $cmol_c\ kg^{-1}$	740	0.16	47.0	0.94	-0.11	2.2
Exchangeable Mg, $cmol_c\ kg^{-1}$	739	0.01	17.9	0.91	-0.06	0.8
CEC, $cmol_c\ kg^{-1}$	740	0.40	55.0	0.95	-0.11	2.6
Sand, g kg^{-1}	457	80	900	0.91	-2.3	61
Silt, g kg^{-1}	457	0	420	0.79	-1.9	39
Clay, g kg^{-1}	457	50	790	0.88	-1.9	54
N min. potential, mg kg^{-1} d^{-1}	604	0.1	30.1	0.74	-0.26	2.4

Exchangeable K, $cmol_c\ kg^{-1}$	768	0.02	5.74	0.66	-0.03	0.25

Clearly, soil spectral libraries can be used to generalize results of soil assessments that are conducted at a limited number of sites, and thereby increase the efficiency of otherwise expensive and time-consuming soil measurements. The variability of soils in a study area can be thoroughly sampled and spectrally characterized. Soil properties or attributes of soil functional capacity are then measured on only a selection of soils, designed to sample the variation in the spectral library, and then calibrated to soil reflectance. The soil functional attributes can then be predicted for the entire library and for new samples from the study area. New samples that classify as spectral outliers to the library are characterized by conventional soil analyses and added to the calibration library, thereby increasing the predictive value of the library.

Diffuse reflectance spectra of all collected soil samples (after sieving) will therefore be recorded using a FieldSpecTM FR spectroradiometer (Analytical Spectral Devices Inc, Boulder, Colorado) at wavelengths from 0.35 to 2.5 µm with a spectral sampling interval of 1 nm. Samples are placed into 7.4 cm diameter Duran glass petri dishes to give a sample thickness of about 1 cm, and will then be scanned through the bottom of the petri dishes using a high intensity source probe (Analytical Spectral Devices Inc, Boulder, Colorado). The probe illuminates the sample (4.5 W halogen lamp giving a correlated colour temperature of 3000 K; WelchAllyn, Skaneatles Falls, NY) and collects the reflected light from a 3.5 cm diameter sapphire window through a fibre-optic cable. To sample within dish variation, reflectance spectra will be recorded at two positions, successively rotating the sample dish through 90º between readings. The average of 25 spectra will then be recorded at each position to minimize instrument noise. Before reading each sample, ten white reference spectra will be recorded using calibrated spectralon (Labsphere®, Sutton, NH) placed in a glass petri dish. Reflectance readings for each wavelength band are subsequently expressed relative to the average of the white reference readings. The raw spectral reflectance data are then pre-processed prior to further analyses. Reflectance spectra will be resampled to 10 *n*m wavelength intervals by selecting every tenth–nanometer value from 350 to 2500 *n*m. This is done to reduce the volume of data for analysis. Reflectance values are then transformed with first derivative processing (differentiation with 2nd order polynomial smoothing with a window width of 20 *n*m) using a Savitzky-Golay filter. Derivative transformations are known to minimize variation among samples caused by variations in grinding and optical set-up. Using this method, a single operator can comfortably scan several hundred samples a day.

We will generate predictions and error estimates for the various management sensitive soil properties using this procedure. Spectral outliers will be screened and a subset of these will be analyzed using more conventional reference methods (e.g. element analyses). This ensures that accurate calibrations for regional prediction of soil properties can be maintained.

Soil erosion phase classification

Management of accelerated soil erosion is one of the key elements for increasing net primary production and reducing sediment loading of waterways in western Kenya. However, spatially explicit measurement of soil erosion patterns, rates and associated environmental impacts in large watersheds remains problematic, time consuming and expensive (Ritchie, 2001). Erosion plot, pin and sediment trap studies are impractical in situations where erosion rates are highly variable, are difficult to extrapolate to wider spatial settings, and generally require long-term investments in monitoring activities. Lake and reservoir surveys, while useful for reconstructing historical sediment export dynamics of watersheds, cannot resolve the attendant source and sink areas in the landscape (Walling, 1983). Spatially extensive field surveys and sediment budgeting approaches typically suffer from observer dependence, lack of repeatability and under-detection of emerging and/or visually cryptic erosion symptoms (Reid and Dunne, 1996). Erosion models based on the redistribution of atmospherically delivered radionuclides such as Cesium-137 (^{137}Cs) have been widely applied for estimating erosion rates and as watershed sediment tracers in small watersheds (Ritchie and Ritchie, 1998; Walbrinck et al., 1998). Nonetheless, application of radioisotopes in situations where large numbers (i.e., 10^2-10^4) of spatially distributed samples are required to separate management sensitive sources of variation in soil erosion processes from environmental background and/or for large-area erosion mapping, are limited by extremely long analysis times and high costs. Thus, new approaches for rapid quantification of landscape soil erosion patterns are needed to localize and monitor land, water and atmospheric degradation problems in large watersheds.

Diffuse reflectance spectrometry again offers a promising addition to conventional ground-based erosion measurement techniques in this regard and may also assist in bridging data and methodological gaps in interpreting erosion phenomena from remotely-sensed information. Based on our Kenyan spectral library we have developed a simple spectral index that is capable of differentiating eroded, reference (apparently intact) and depositional soil phases. Details of this approach are described in (Walsh et al., in press); however, the method essentially relies on comparing recorded soil reflectance to a reference sediment reflectance model. Values of the index, which we refer to as δ_{Sed} (deviation from sediment standard), theoretically vary between 0 and $+\infty$, with. We classify soils as being "eroded" if their $\delta_{Sed} \geq$ "reference" soils are classified between $0.6 > \delta_{Sed} < 2.8$, and "depositional" soils are classified as having values of $\delta_{Sed} \leq 0.6$.

We have extensively tested this index and the resulting classification relative to a suite of independently measured observational, radioisotope and physicochemical soil properties of western Kenya soils. Strong power law relationships between EDI, Cesium-137 ($R^2 = 0.73$) and Lead-210 ($R^2 = 0.75$) radionuclide inventories of topsoils were observed. Similarly, relationships between EDI, particle size distributions, extractable soil nutrients, soil organic carbon and field infiltration capacity were strongly consistent with erosion induced physicochemical depletion/accretion processes. The index is also strongly management sensitive, as indicated from chronosequence studies conducted across the Kakamega forest ecotone (Walsh et al., submitted).

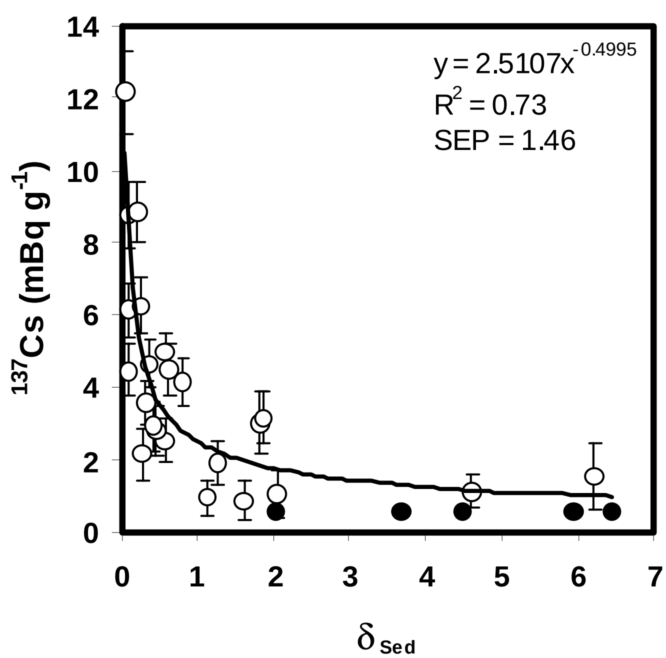


Figure 7: Relationship between δ_{Sed} index and Cesium-137 concentrations of western Kenya topsoils. Black dots indicate below detection level ^{137}Cs concentrations.

We have tested this index and the resulting classification extensively relative to a suite of independently measured observational, radioisotope and physicochemical soil properties of western Kenya soils. Strong power law relationships between δ_{Sed}, Cesium-137 ($R^2 = 0.73$) and Lead-210 ($R^2 = 0.68$) radionuclide concentrations of topsoils have been observed (see Fig 7.). Similarly, relationships between δ_{Sed}, particle size distributions, extractable soil nutrients, soil organic carbon and steady-state field infiltration capacity were strongly consistent with erosion induced physicochemical depletion/accretion processes. The index is also highly management sensitive and has been shown to decline in chronosequence studies conducted across the Kakamega forest ecotone (Walsh et al., submitted).

Infiltration Capacity

Knowledge of movement of water in soils is critical for assessment of soil erosion potential, water harvesting, aquifer recharge, and plant water and nutrient management. Movement of water in soils is principally determined by two factors; resistance of the soil to water flow and gravitational forcing (Faybishenko et al., 2003). At a watershed scale gravitational forcing is primarily determined by generation of groundwater and overland flow, which is in turn determined by factors such as upstream catchment area and soil infiltration capacity. Determination of resistance of soil to water flow may be obtained by estimating saturated soil infiltration capacity, as this represents the inverse of soil resistance to water flow (Tuller and Or**,** 2003).

Two single-ring infiltration cylinders per plot (each 16 cm inner diameter, 25 cm tall) will be used to measure surface infiltration (cylinders will be located at the center of each plot, see Fig. 1, and ~1 m apart). The cylinder rings will be carefully inserted into a pre-wetted soil surface according to the procedures reported in Dingman (2002), and infiltration capacities will be monitored as the change in water level in each cylinder for 2-3 hrs. Since determination of soil saturated hydraulic conductivity (K_s) from single-ring infiltrometers tests involves determination of soil alpha parameter (Reynolds & Elrick, 1990), undisturbed soil samples will also collected from every point-pair. These will be collected using 5.2 cm diameter and 5.2 cm high core rings according to the methods described by Klute (1986) and will be further analyzed for water retention characteristics in the laboratory using desorption methods with a pressure-membrane apparatus at 0.0, 0.1, 0.5, 1, 3, 5, 7, 10, and 15 bars (Reginato & van Bevel, 1962). Soil texture-structure indices can then be determined from water retention characteristics using the hydraulic parameter code RETC (van Genuchten *et al*., 1992).

As infiltration may be described as an asymptotically decaying function with respect to time (Chow *et al.*, 1988), we will use a slightly modified version of Horton's (1940) equation to model cylinder infiltration rates (I, cm min^{-1}) as a function of time (t):

$$\log(I(t)_{ij}) = \log\left(f_j + \left(s_j - f_j\right)\exp(-\exp(k_j)\cdot t_j)\right) + \varepsilon_{ij} \qquad (17.)$$

for which i and j index cylinders in plots, f is steady-state infiltration, q is starting infiltration, k is the decay rate parameter, and ε is a normally distributed error term.

Estimates of saturated hydraulic conductivity (K_s) from steady-state infiltration capacities are subsequently based on fluid flow analysis from a buried spherical cavity using the interaction between the flowing water, steady ponding depth of water in the cylinders, dimensions of the cylinder, soil texture-structure index, and insertion depth of the cylinder, as given by Reynolds & Elrick (1990):

$$K_s = \frac{g \cdot \alpha \cdot q}{\left(r(\alpha \cdot w + 1)\right) + g \cdot \alpha \cdot \pi \cdot r^2} \quad (18.)$$

where a is the radius of the cylinder used, α is the soil alpha parameter (defining the texture-structure index), w steady-state ponding depth of water in the cylinder, r is the radius of the cylinder, and q is the steady-state volumetric infiltration rate ($q = f\pi r^2$). The empirical estimate of g is given by (Reynolds & Elrick 1990) as:

$$g = 0.316 \cdot \left(\frac{d}{r} + 0.184\right) \quad (19.)$$

where d is the depth of insertion of the cylinder ring into the soil.

Site index and bio-assay

Since the concept of site quality most often refers to plant productivity, its most direct measurement is the quantity and allocation of biomass produced over a given time period. We have developed a simple, rapid procedure for assessing this variable under controlled greenhouse conditions using maize (*Zea mays* L. var. Kenya HB-8258) as an indicator species.

Topsoil (0-20 cm) samples recovered during the survey will be screened in pot-studies. Maize seeds will be weighed to the nearest mg prior to planting, and individual maize seedlings will subsequently be grown in 500 ml plastic pots for 14 days under controlled greenhouse conditions. Harvested biomass will be separated into root and shoot components, and both the fresh and dry matter (60°C, 24 hrs) weight components will be measured to the nearest mg. The root : shoot biomass ratio of harvested biomass can subsequently be modeled as:

$$\log_e\left(\frac{r}{s}\right)_{ij} = \mu + b_j + \varepsilon_{ij} \quad (20.)$$

for which r is root biomass (mg dry weight), s is shoot biomass (mg dry weight), μ is the mean root : shoot ratio of the population, b_j is a random effect describing the deviation of the jth plot in the sampled population, and ε_{ij} is a normally distributed error term.

The motivation for this simple model is that plants in water and nutrient limited environments will allocate a greater proportion of their biomass to root rather than shoot growth. In this particular case soils will be irrigated and grown under otherwise similar (light, temperature) greenhouse conditions. Differences in root : shoot partitioning are therefore expected to be largely due to differences in soil condition. Previously conducted experiments have shown close correlation of “site index” with land cover conversion, EDI, as well as the infiltration capacity of soils.

Non-CO_2 greenhouse gases

Tier 1 Level Assessment of Green house Gasses

The current emissions of non-CO_2 greenhouse gases from the project blocks will be estimated using the methods described in the IPCC “Revised 1966 Guidelines for National Greenhouse Gas Inventories” and “Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories”, also published by the IPCC. Non-CO_2 gases will only be accounted for in the project specific baseline. Although the IPCC methods are designed for national inventories, in the absence of approved methods for project-based estimations, we have adapted these national methods for the project area. However, the level of aggregation implicit in this method is not very applicable to the objectives of the project. We will attempt to develop a better approach to estimating these fluxes at the project level over the life of the project.

Our approach will use the so-called Tier 1 methods in all cases. In general, country specific factors have not been developed for Kenya in the agriculture sector, as this sector is not considered a significant[5] source. For our purposes, and given the large degree of variability between the different agroecological zones of the country, region specific factors will be required to improve the accuracy of the estimates based on default factors. Over the course of the project we will develop the emissions factors to allow us to estimate a baseline using Tier 2 methods for all significant sources. Tier 2 accounting will also be used for significant sources in the monitoring and evaluation of the project.

In general, we will present the decisions made at each node of the IPPC decision trees in the Good Practices Guidance. We then present the equation for the Tier 1 estimate, a table that summarizes the calculations, the source of the data to be used for the calculation and a description of the sources of uncertainty in the estimate. The relevant decision trees and tables are appended at the end of this document. The following sections describe methods that will be used to refine these estimates.

Targeted Research to Refine IPCC Coefficients.

The following sections describe methods which will be used to refine the IPCC estimates.

Soil Emission Factor Determination

To account for seasonal and interannual variability, we will use the he hole-in-the-pipe model (Firestone and Davidson 1989), which provides a conceptual framework to explain the variability of nitrogen oxide emissions, including the effects of deforestation and land-use change (Davidson, 1991). This model can easily be incorporated in ecosystem models such as CENTURY or NASA-CASA. This conceptual, mechanistic model is applicable to studies at various scales. The metaphor of fluid flowing through a leaky pipe (Figure 1) is used to describe two levels of regulation of N-oxide emissions from soils: (i) the amount of fluid flowing through the pipe is analogous to the rate of N cycling in general, or specifically to rates of NH_4^+ oxidation by nitrifying bacteria and NO_3^- reduction by denitrifying bacteria; and (ii) the amount of N that "leaks" out of the pipe as gaseous N-oxides, through one "hole" for NO and another "hole" for N_2O, is determined by several soil properties, but most commonly and most strongly by soil water content. This effect of soil water content, and in some cases acidity or other soil factors, determines the relative rates of nitrification and denitrification and, hence, the relative proportions of gaseous end products of these processes. The first level of regulation determines the total amount of N-oxides produced (NO + N_2O) while the second level of regulation determines the relative importance of NO and N_2O as the gaseous end products of these processes.

[5] A source is considered to be significant if it accounts for between 25-30% of the emissions from the source category.

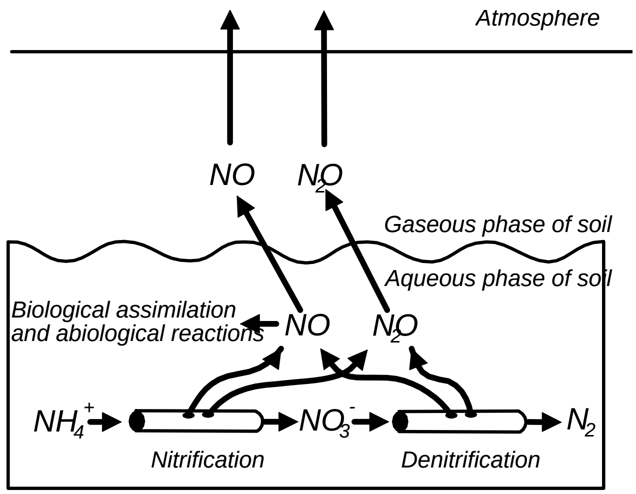


Figure 8. Hole-in-the-Pipe Conceptual Model

This mechanistic model is based, first, on the idea that emissions of N-oxides increase with increasing N fertility. The second level of regulation addresses the relative importance of NO and N_2O production. Both nitrification and denitrification produce both gases, but nitrification often produces greater quantities of NO relative to N_2O, and denitrification usually produces greater quantities of N_2O relative to NO (Davidson, 1993). Several factors have been shown to affect the ratio of N_2O to NO (Firestone and Davidson, 1989), but Davidson (1993) suggested that soil water content could be a useful predictor of the ratio at regional and global scales. At water content below field capacity (field capacity is often operationally defined as water content at 0.010 MPa tension), nitrification is often the predominant gas producing processes, so NO predominates. In wet soils, denitrification increases as O2 diffusion decreases and, as soils become more anaerobic, N_2O from denitrification becomes the predominant N-oxide. The water content effect is a continuum, although the response of the N_2O:NO ratio to soil water content may not be linear. Experimental evidence and field studies exist that support this hypothesized relationship (Davidson, 1993; Davidson et al., 1993; Keller and Reiners 1994; Riley and Vitousek, 1995).

Measurement of N_2O and NO Fluxes

Surface fluxes of N_2O and NO will be analyzed using chamber techniques in a subset of reference plots, stratified by spectral soil condition (erosion phase and hydraulic conductivity), that are representative of the variation encountered in the project landscape. Chambers will be made of a polyvinyl chloride (PVC) ring (20-cm diameter x 10-cm height) and a vented PVC cover made from an end-cap of a 20 cm diameter PVC pipe. PVC rings will be pushed into the soil to a depth of 2-3 cm to make the base of the chamber. An intensive sampling scheme involving monthly measurements will be made in plots representing project interventions and appropriate controls. A less intensive scheme will be used to capture variability associated with landscape variability.

NO fluxes will be measured using a dynamic chamber technique similar to Davidson et al. (1991). At the time of measurement, a vented cover will be placed over the base, making a chamber with approximately a 4 L head-space volume. Air will be circulated in a closed loop between a Scintrex LMA-3 NO_2 analyzer (Scintrex, Inc., Ontario, Canada) and the chamber through Teflon tubing using a battery operated pump, at a rate of 0.5 L min^{-1}. Inside the instrument, NO will be oxidized to NO_2 by reaction with CrO_3 and the NO_2 will be then mixed with Luminol solution to produce a luminescent reaction directly proportional to the mixing ratio of NO_2. Because of problems with humidity wetting the CrO_3 catalyst, we will dry the air stream entering the analyzer using a Nafion gas sample dryer (Perma Pure Inc., Toms River, NJ). NO concentrations will be recorded at 5 second intervals over a period of 3 to 4 minutes using a data logger. Fluxes will be calculated from the rate of increase of NO concentration using the steepest linear portion of the accumulation curve. The average length of time used for the calculation of fluxes is 1.9 min. The instrument will be calibrated 2-3 times daily in the field, by mixing varying amounts of a 1 ppm NO standard with NO- and NO_2-free air.

N_2O fluxes will be measured with a static chamber technique (Matson et al., 1990), using the same chamber bases as those used for the NO measurement. At the time of measurement, a PVC cover (20-cm PVC end-cap) will be placed over the base making a chamber with a head-space volume of approximately 5.5 L. Four 20mL headspace samples will be withdrawn at 10-minute intervals and returned to the laboratory for analysis with a gas chromatograph fitted with an electron capture detector.

N_2O fluxes will subsequently be calculated from the rate of concentration increase, determined by linear regression, based on the four samples. Occasionally, and particularly for very high fluxes, the accumulation curve may appear nonlinear, probably due to the reduction in the concentration gradient between the soil atmosphere and the head-space (Hutchinson and Livingston, 1993). In these cases, only points representing the linear portion of the accumulation curve will be used. In almost all cases, NO and N_2O flux measurements for a particular site will be made on the same day and within 90 minutes of each other.

CH_4 consumption by soils

Surface fluxes of CH_4 will be measured using chambers techniques similar to NO and N_2O. A conceptual model will be used to estimate consumption by soils under improved and traditional land use practices. The model is based upon the linkage between CO_2 in the soil atmosphere and CH_4 fluxes. Microbial and root respiration affects the availability of O_2 to microbial populations in the soil. Hence, the availability of O_2 is affected by both physical restraints on diffusion, which are determined by soil water content and soil texture, and by biological processes of O_2 consumption. Thus, the effect of high rates of soil respiration reinforces the effect of restricted diffusivity during the wet season by increasing the probability of occurrence of anaerobic microsites where methanogenesis can occur and by reducing the probability of well aerated microsites of CH_4 consumption. The combined effect either reduces the sink strength of CH_4 or results in the soil becoming a net source.

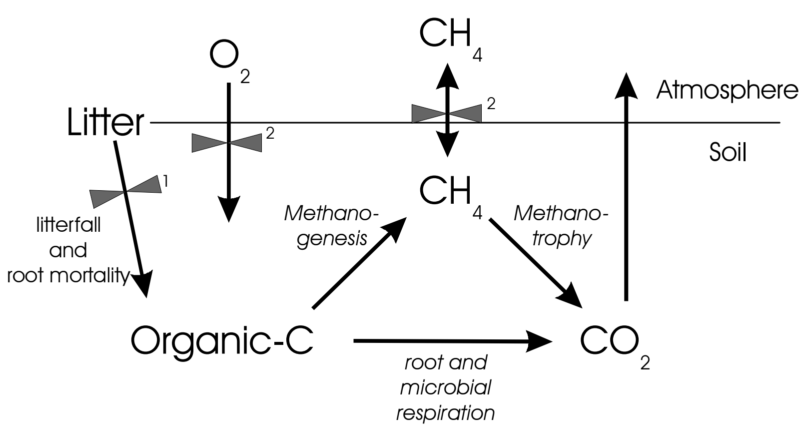


Figure 9. Conceptual model of CH_4 exchange between the atmosphere and the soil.

The significance of this is that seasonality of precipitation must be interpreted in terms of its effects both on diffusivity and on plant phenology and microbial activity. Furthermore, responses of plant communities to seasonal patterns of precipitation vary depending upon the land use and ecosystem type within the same climatic regime. Where agricultural ecosystems are very productive during the wet season and senescent during the dry season, CH_4 fluxes can vary from net emission to relatively high rates of uptake (Figure 9). Deeper rooted woody ecosystems, in contrast, maintain modest rates of soil respiration during the dry season, which results in lower rates of net CH_4 uptake. Parameterizing this conceptual model for the systems that will be part of this project will be straight forward and the model is easy to link with other ecosystem models such as CENTURY or NASA-CASA.

Calculating baselines (plot to region)

We will assess regional baselines using mixed-effects models. Mixed models provide a flexible extension of generalized linear models, intended specifically for analyses of grouped data including longitudinal data, repeated measures, blocked designs and multilevel data among others (Pinheiro and Bates, 2000). In this particular case grouped data structures occur as a consequence of sampling at multiple spatial scales across a large project area. Thus, plot-level measurements are grouped within clusters, which are in turn grouped within 10×10 km blocks. Each level is replicated several times, and is associated with specific length or area dimensions. The following linear mixed effects model represents the grouped structure as:

$$y_{ij} = \mathbf{X}_{ij}\beta + \mathbf{Z}_{i,j}b_i + \mathbf{Z}_{ij}b_{ij} + \varepsilon_{ij} \tag{21.}$$

where:

y_{ij} = a two-level grouped response variable (e.g., clusters within FA's), $i = 1 \ldots m$, $j = 1 \ldots m_i$

$\mathbf{X}_{ij}$ = a fixed effects design matrix,

β = unknown fixed effects coefficients,

$\mathbf{Z}_i$ = a $p_i \times r$ design matrix,

b_i = an unknown $r \times 1$ vector of random coefficients, assumed to be independently distributed across plots with distribution $\gamma_i \sim N(0, \sigma^2\mathbf{B})$, for which $\mathbf{B}$ is a *between* subject variance-covariance matrix,

ε_{ij} = within-group error term distributed as $\varepsilon_{ij} \sim N(0, \sigma^2\mathbf{I})$, where $\mathbf{I}$ is a *within* subject covariance matrix.

Generalizations to higher levels of grouping (e.g. plots / clusters / FA's / Elevation zones) are straightforward (see Pinheiro and Bates, 2000). Distributions for all the relevant levels of grouping will initially be assumed to be independently and normally distributed with zero mean, but these assumptions may be modified should they prove to be inappropriate[6]. Models of this type may be fit by different methods including, maximum likelihood (ML), restricted maximum likelihood (REML) and Markov chain Monte Carlo (MCMC) simulation, which under certain circumstances can provide qualitatively different results. Convergence between different methods is generally indicative of stable parameter estimates and will be assessed. Once a stable model formulation has been found, best linear unbiased predictions (BLUP's) of variations in response variable (incl. confidence intervals etc.) can be generated at any given level in the multilevel structure. This provides an explicit mechanism for scaling observations from plot-to-region.

[6] There are a variety of diagnostics available for checking this (see Pinheiro and Bates, 2000).

MONITORING AND IMPACT ASSESSMENT

Monitoring Focal Areas and Reference plots

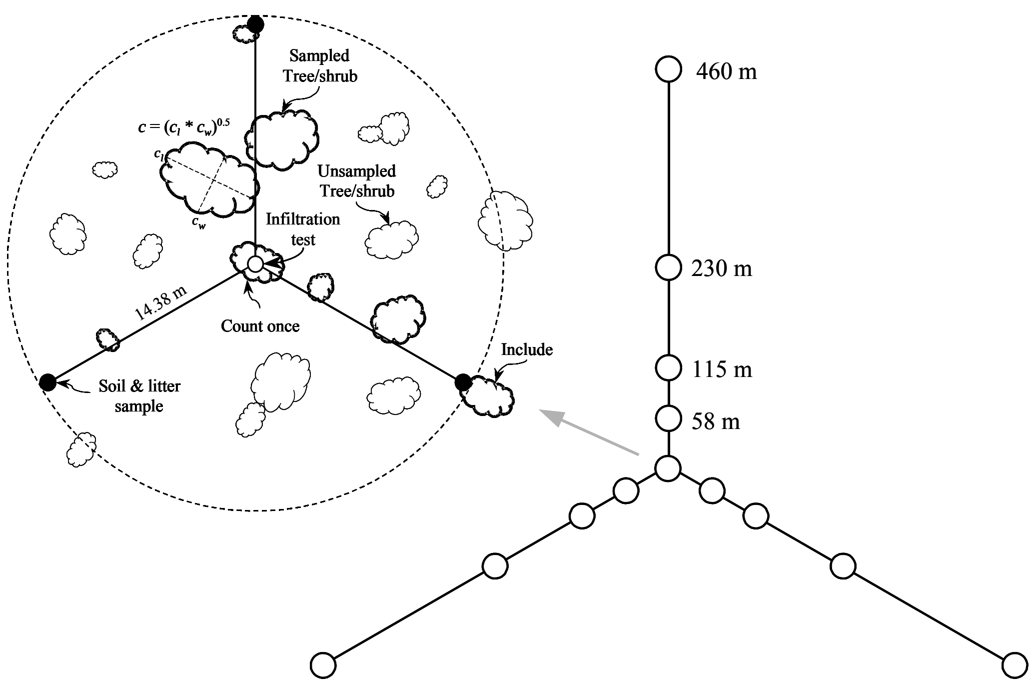
Section 2 describes the broad scale field monitoring system, based on 10 X 10 km monitoring focal areas (FA) one each for lowlands, midlands, and uplands in each basin. Ground measurements within each focal area will be carried out using a spatially clustered sampling plan. Fifteen plot clusters, based on QuickBird images, will be selected at spatially stratified, randomly located grid intersections in each image. Randomization at this level ensures that the collected data are as locally representative as possible.

Within each cluster, there will be 13 systematically located 625 m^2 (~28.8 m diameter) circular sampling plots. Plots are located at 2, 4, 8, 16 × plot diameter distances along 3 radial line transects placed at 120° angles to one-another. This scheme is designed to efficiently sample local ecosystem patterns across a ~64 ha area. All plots will be georeferenced with survey-grade GPS equipped with satellite broadcast correction. To absolutely ensure that plots can be relocated at a later point in time, a prominent local reference position will be selected within each cluster, from which navigation lines to individual plots will be established. All reference locations and plots will be documented with digital photographs that will contain the precise geographic coordinates of each plot. All georeferenced photographs will subsequently be entered into a GIS compatible database to facilitate validation of field observations, and assist in navigation during revisits.

The table below provides a summary of the proposed number of observations at each level. A schematic diagram of the cluster-level sampling pattern is shown below.

	FA's	Clusters	Plots
No. per sublevel		15	13
Total No.	9	135	1755

Note that positioning of plot locations within clusters is provided as a general guideline. Actual plot locations will vary somewhat, based on local land cover homogeneity criteria[7]



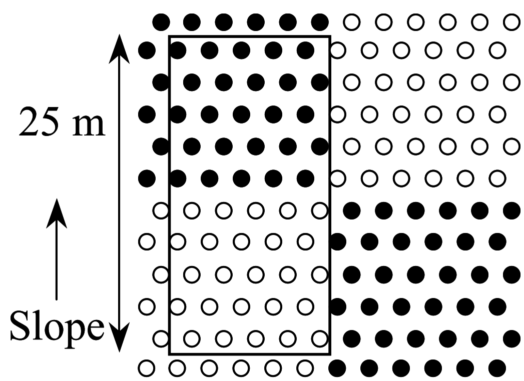
[7] i.e. plots will only be located in homogenous FAO Land Classification System Types (see section 3.4 for description). Thus, for areas near land cover boundaries actual plot locations may deviate slightly from the cluster pattern.

Figure 4. Ground sampling design at the cluster and plot levels of observation.

Data collected at each cluster will include all biophysical measures described in Section 3, including above and below ground biomass, site conditions, erosion observations, etc. Previous experience with this sampling plan has shown that a 5-person team consisting of 1 person for data recording GPS data collection and infiltration measurement, and 2 persons for soil augering and vegetation sampling respectively can comfortably complete 1 cluster in ~1 day depending on accessibility and local terrain conditions. Operational costs for implementing the approach are being monitored.

Farmer-selected stocking plots

Five additional 625 m^2 (25×25 m) square plots per cluster will be identified in collaboration with local communities and individual land-owners. These experimental plots will be stocked with a variety of farmer-selected tree species, as well as with a project-selected indigenous reference tree. These "stocking plots" are primarily intended to provide information about tree survival, growth performance, and carbon sequestration traits across differing site conditions in western Kenya. They will also be used as demonstration plots, and as seed orchards for supplying locally operated nurseries. Within each stocking plot, 325 m^2 rectangular livestock-proof exclosures will be established to assess the effects of tree performance vis-à-vis livestock browsing. This is necessary for monitoring NPP and NEP (see section 4.5). The layout of stocking plots is shown below.



Stocking plot layout. Stocking at 1600 trees ha^{-1} (2.5 m spacing = 100 individuals) on a 625 m^2 plot, with 1 reference species, and species per plot "farmers choice". In each case half of the plot will be fenced to assess the importance of livestock herbivory. A guard row of trees will be included to minimize edge effects on subsequent measurements.

Stocking plots will be matched with an equal number of "control plots" located immediately adjacent to stocking plots and under essentially identical pre-project site conditions[8], and on which no project facilitated interventions will be carried out. Both stocking and control plots will be monitored over the course of the project. This will provide information on shifts in non-project related baseline measurements. The following table summarizes the total number proposed stocking and control plots that will be established[9].

[8] Note that this assumption will be quantified prior to initiating plantings
[9] To ensure that stocking plots are managed in accordance to project guidelines, we anticipate the necessity of compensating farmers for incurred production losses and labor inputs. Compensation

	FA's	Clusters	Control	Stocking
No. per sublevel		15	5	5
Total No.	9	135	675	675

General impact assessment models

Conventionally, project impact attribution involves collection of baseline data prior to an intervention and comparing it to data collected after the intervention. For example, under current IPCC guidelines, all gains in CO_2 emission reductions above regional baseline-levels may be credited to project activities (Watson et al., 2000). The implied model for a given response variable (y), e.g., *NEP*, is:

$$y_i = \mu + p_i + \varepsilon_i \tag{22.}$$

for which μ is the population mean, p is the effect of period (i = before or after), and ε is a normally distributed error term. This is a reasonable approach in situations where projects are implemented as large, homogeneous, well-delineated projects, or for example for monitoring adoption dynamics. In situations where this is not the case, project impact attribution using simple before-and-after (BA) studies is more difficult, as the data would be collected without controlling for non-project related variations in impact indicators. Thus, measured changes would be confounded with sampling period and could not be reliably attributed to the project.

More rigorous impact assessment models therefore often use control-intervention pairing (CIP, Stewart-Oaten et al., 1986; Smith, 2002), in which before-after observations are paired with observations at control sites on which no project activities are implemented. Changes in target indicators can then be reliably assessed as the interaction between location (i.e., control vs intervention) and period (i.e., before vs after intervention) strata. In its most basic form, the implied model for response variable (y) is:

$$y_{ij} = \mu + p_i + l_j + (p.l)_{jk} + \varepsilon_{ij} \tag{23.}$$

for which, μ is the population mean, p is the effect of period (i = before or after), and l is location (j = control or intervention). With repeated measurements, nested within before-after periods, the model is given as:

$$y_{ijk} = \mu + p_j + t_{k(i)} + l_i + (p.l)_{ij} + \varepsilon_{ijk} \tag{24.}$$

for which t represents sampling times within periods (k = 1, 2 … t_B, for period i = before; and k= 1, 2 … t_A for i = after. Spatial stratification and replication of before-after, control-impact pairs (BACIP) 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. The following sections describe application of this general construct to monitoring and impact assessment of the various socio-economic and biophysical performance indicators described under section *3*.

Adoption

The appropriate model for assessing expansion of the net project area over the lifespan of the project can be described by a modification equation 22 given by:

$$\log_e\left(\frac{f_a}{1-f_a}\right) = p_i + e_i \tag{25.}$$

for which f_a is the proportion of the net relative to gross project area, p is period (before vs after) and e is a normally distributed error term. This basic model may be conditioned by grouping levels (e.g. clusters within FA's) which can then be included random effects as described under *section 3.10*.

Socio-economic indicators

The economic and social benefits accruing through this project are among its most important goals but may also the most difficult to quantify. Several indicators of project impacts that relate broadly to potential changes in household economic status can be assessed in a reasonably quantitative manner. The table below outlines these

Socio-economic response variable	Variable type
Labor:	
Family size	count
Standardized farm labor index	continuous
Expenditure:	
Major expenditure source	categorical
Weekly household expenditure	ordinal
Standardized household expenditure index.	continuous
Resources:	
Farm size (ha)	continuous
%age of land allocated to subsistence crops	ratio
No. of on farm enterprsies	count
No. of cattle	count
No. of equines	count
No. of pigs	count
No. smallstock	count
No. poultry	count
Endowment category	ordinal
Well-being:	
Dwelling type	categorical
Primary drinking water source	categorical
Quality of primary drinking water source.	continuous
Distance to water source	continuous

The impact assessment model described in equations 24 and 25 will be used to determine the impact of the project in the socioeconomic indicators.

The monitoring plan has not attempted to develop a standardized survey tools for the numerous other social benefits that may eventually be accrued by the project. Socio-economic surveys have a high degree of client-and-site specificity, and survey instruments that harbor inappropriate questions represent a disservice to the project scientists and goals. Furthermore, much of the most important information concerning the human dimension of project impacts is gained by experienced field workers using informal approaches. Nonetheless, it is extremely important that a detailed record of such results and observations be maintained. Ultimately, the success of this project will be viewed in terms of its social benefits derived by households undertaking environmentally-friendly land management practices, and it is extremely important that these benefits be precisely documented, insightfully interpreted and creatively communicated to a broad cross-section of interests. These challenging tasks must be undertaken in a responsive, iterative manner.

Land cover and agro-biodiversity change

Land cover change will be assessed qualitatively from remote sensing images acquired at the start and the end of the project. Any shifts in area in the FAO LCCS classification will be noted. Agrobiodiversity will be assessed according to changes in “species richness”, and also qualitatively from the field surveys that will be conducted at the beginning and end of the project. These surveys will be conducted in all project blocks. The BACIP evaluation approach involving equations 23 and 24, as given above will be employed to determine project impact on biodiversity. Results will be reported as trends.

Carbon sequestration

For reasons indicated in the introductory section we anticipate that the largest gains in net ecosystem production (hence carbon sequestration) will be largely determined by increased abundance of woody vegetation biomass in the in the western Kenya landscape.

Tree growth

Tree weight growth, like many other plant growth relationships, may be expressed in one of two ways, as cumulative growth, or as incremental growth. Cumulative growth is often an S-shaped curve when plotted against plant age. Alternatively, instantaneous growth rate curves, (increment curves) show the current rate of weight growth at any point in time. Plant weight (w, kg) at age (t) is therefore most often represented by growth functions such as the widely used Richards equation (Richards, 1959):

$$w(t) = s \cdot \left(1 - \exp(r \cdot t)\right)^{m} \qquad (26.)$$

Though considered an empirical model, the Richards-equation lends itself to biological interpretation with s representing asymptotic weight with r & m providing shape parameters that can accommodate Mitscherlich, exponential, Gompertz and/or logistic (von Bertalanffy) growth dynamics depending on values of m (see examples in Fig. 4). The first derivative of w with respect to t is biomass increment (kg yr^{-1}) given by:

$$\frac{dw}{dt} = s \cdot \left(1 - \exp(-r \cdot t)\right)^{m-1} m \cdot r \cdot \exp\left(-r \cdot t\right) \qquad (27.)$$

The 2nd derivative (or growth acceleration curve, not shown), indicates where w is increasing or decreasing over time. When the 2nd derivative is set to zero, solving for t yields t^*, the inflection point at which maximal biomass growth occurs,

$$t^* = \frac{1}{r} \log_e \left(\frac{1}{m}\right) \qquad (28.)$$

which is often useful for predicting the onset of canopy closure and density-dependent mortality in even-aged, self-thinning populations.

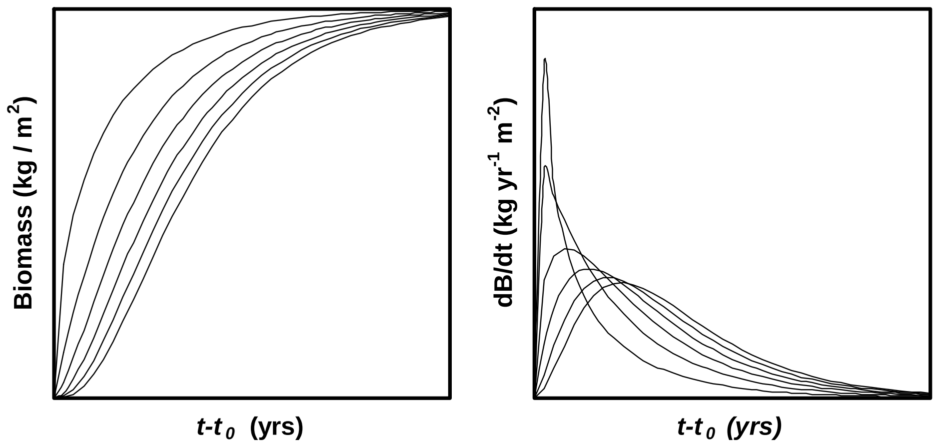


Figure . Example of simulated biomass and increment curves as a function of age

Populating equations (5.) and/or (6.) with data is straightforward (in principle), requiring repeated observations of biomass on individuals in the population. Model parameters can then be estimated using nonlinear regression techniques that can be adjusted to include site and/or population specific covariates. While it is reasonable to assume that the general form of the Richards-model will be common to all individuals in a stand, intra- as well as interspecific differences between individuals will determine the specific parameter values

$$\begin{gathered} \hat{w}_{ij} = \phi_{1i} \cdot \left(1 - \exp(\phi_{2i} \cdot t_{ij})\right)^{\phi_{3i}} + \varepsilon_{ij} \\ \phi_i = \begin{bmatrix} \phi_{1i} \\ \phi_{2i} \\ \phi_{3i} \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} + \begin{bmatrix} b_{1i} \\ b_{2i} \\ b_{3i} \end{bmatrix} = \beta + b_i \\ b_i \sim N(0,\psi), \quad \varepsilon_{ij} \sim N(0,\sigma^2) \end{gathered} \tag{29.}$$

Net Primary Productivity (NPP) and Net Ecosystem Productivity (NEP*)*

Extending the model for tree growth, we can estimate net primary productivity, which corresponds to the net amount of carbon fixed by the vegetation from

$$NPP^* = \hat{n} \cdot \frac{d\hat{w}}{dt} \tag{30.}$$

where n represents the number of trees growing.

Total carbon is that is fixed in the ecosystem can also be lost through heterotrophic processes. Thus it important to calculate the net carbon gain by the ecosystem. Net ecosystem productivity is calculated from the following:

$$NEP^* = \hat{n} \cdot \frac{d\hat{w}}{dt} + \hat{w} \cdot \frac{d\hat{n}}{dt} \tag{31.}$$

Calculating the Net Project Effect on Atmospheric GHGs

Non-CO_2 GHG's

The non-CO_2 gasses will be assessed according to Tier 1 accounting at the start of the project to establish the greenhouse gas baseline. However, targeted research during the course of the project will result in improved coefficients, and a move to Tier 2 accounting. In this case the baselines will be updated. At the end of the project, the baselines will be repeated to identify atmospheric forcing due to the non-CO_2 gasses, expressed as CO_2 equivalents. CH_4 has 21 times the forcing strength of CO_2, and N_2O has 310 times more forcing strength.

Calculating carbon equivalents

The effect of the project in terms of carbon equivalents will be calculated on the basis of net-net accounting. This will involve summing the carbon sequestered in the five key pools recognized by the IPCC (aboveground biomass, dead wood, belowground biomass, litter, and soil organic matter) under the agroforestry and soil management interventions (tonnes CO_2 equivalent) compared to the baseline condition where interventions were not applied. However, determining the net effect of the project on atmospheric GHGs must also account for changes in sources of N_2O and changes in both sources and sinks of CH_4. Thus, we will calculate the overall carbon benefits of the projcet to the atmosphere in terms of carbon equivalents as:

$$Ceq = NEP - C_{N2O} + C_{CH4\ sink} - C_{CH4\ source} \quad (32.)$$

Results will be expressed as tonnes CO_2 equivalents. The before-after control-impact procedure (BACIP) will be used, as described in earlier sections. This will identify the project impacts on atmospheric GHG loading.

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Appendix 1

Data Form: A rapid assessment of biodiversity in smallhold systems of west Kenya (1 of 4)

Household ______________________________ Location _____________________________

Division ________________________________ District ______________________________

Longitude _____________________ Latitude _____________________ Elevation ____________

Farm size _________________ ha Enterprise no. _________________ Cattle ______________

Enumerator ____________________________ Date ________________________________

1. Fruit trees

Exotic	few	some	many	Indigenous	few	some	many
Mango	[ ]	[ ]	[ ]	Wild custard apple	[ ]	[ ]	[ ]
Avocado	[ ]	[ ]	[ ]	Prunus africana	[ ]	[ ]	[ ]
Guava	[ ]	[ ]	[ ]	Tamarind	[ ]	[ ]	[ ]
Citrus	[ ]	[ ]	[ ]	Vanguaria	[ ]	[ ]	[ ]
other _____________	[ ]	[ ]	[ ]	other _____________	[ ]	[ ]	[ ]
total				total			
factor				factor			
weighted total				weighted total			

2. Trees with "needle" leaves

Exotic	few	some	many	Indigenous	few	some	many
Cypress/Pine	[ ]	[ ]	[ ]	Juniper	[ ]	[ ]	[ ]
Casuarina	[ ]	[ ]	[ ]	Podocarpus	[ ]	[ ]	[ ]
other _____________	[ ]	[ ]	[ ]	other _____________	[ ]	[ ]	[ ]
total				total			
factor				factor			
weighted total				weighted total			

3. Bamboo

Exotic	few	some	many	Indigenous	few	some	many
Golden bamboo	[ ]	[ ]	[ ]	Mountain bamboo	[ ]	[ ]	[ ]
other _____________	[ ]	[ ]	[ ]	other _____________	[ ]	[ ]	[ ]
total				total			
factor				factor			
weighted total				weighted total			

Data Form: A rapid assessment of biodiversity in smallhold systems of west Kenya (2 of 4)

4. Other trees (timber, fuel, ornamental and ceremonial)

Exotic	few	some	many	Indigenous	few	some	many
Prosopis	[ ]	[ ]	[ ]	Acacia (not wattle)	[ ]	[ ]	[ ]
Grevillia	[ ]	[ ]	[ ]	Albizia	[ ]	[ ]	[ ]
Jacaranda	[ ]	[ ]	[ ]	Erythrina	[ ]	[ ]	[ ]
Flamboyant	[ ]	[ ]	[ ]	Nandi flame	[ ]	[ ]	[ ]
Cassia	[ ]	[ ]	[ ]	Camel's foot	[ ]	[ ]	[ ]
Eucalyptus	[ ]	[ ]	[ ]	Cordia	[ ]	[ ]	[ ]
Monkeypod	[ ]	[ ]	[ ]	Sausage Tree	[ ]	[ ]	[ ]
Pepper tree	[ ]	[ ]	[ ]	*Markhamia* (luciola)	[ ]	[ ]	[ ]
Ficus (exotic)	[ ]	[ ]	[ ]	Ficus (native)	[ ]	[ ]	[ ]
Pithecellobium	[ ]	[ ]	[ ]	*Milicea (*murumba)	[ ]	[ ]	[ ]
Bottlebrush tree	[ ]	[ ]	[ ]	Croton	[ ]	[ ]	[ ]
Prickly pear cactus	[ ]	[ ]	[ ]	Euphorbia	[ ]	[ ]	[ ]
other ____________	[ ]	[ ]	[ ]	other ____________	[ ]	[ ]	[ ]

total
factor
weighted total

total
factor
weighted total

Subtotal for trees (Categories 1 to 4)

total
factor
weighted total

total
factor
weighted total

5. Shrubs, hedges and live fences

Exotic few some many Indig1
enous few some many

Exotic	few	some	many	Indigenous	few	some	many
Gliricidia	[ ]	[ ]	[ ]	Sesbania	[ ]	[ ]	[ ]
Leucaena	[ ]	[ ]	[ ]	Carissa	[ ]	[ ]	[ ]
Calliandra	[ ]	[ ]	[ ]	Moringa	[ ]	[ ]	[ ]
Lantana	[ ]	[ ]	[ ]	Euphorbia	[ ]	[ ]	[ ]
Tithonia	[ ]	[ ]	[ ]	Tephrosia	[ ]	[ ]	[ ]
Caesapinia	[ ]	[ ]	[ ]	Terminalia	[ ]	[ ]	[ ]
other ____________	[ ]	[ ]	[ ]	other ____________	[ ]	[ ]	[ ]

total
factor

total
factor

weighted total	weighted total

Appendix 2

DECISION TRESS AND WORKSHEETS FOR NON CO_2 GASSES

LIVESTOCK

CH_4 emissions from Enteric fermentation in domestic livestock

Decision tree: In the national accounting system, this category is not a significant source, but it may be significant in the project area. Furthermore, we do not have adequate data at this time to permit a Tier 2 estimate. The estimate that we are presenting at this point is a Tier 1 estimate.

$$\text{Emissions} = \text{EF} \bullet \text{population}/(10^6 \text{ kg/Gg})$$

Where ef is the emission factor and population is the number of animals (head). We used the emissions factors in ipcc guidelines tables 4.3 and 4.4

CH_4 emissions from manure management

Decision tree: The data are not available to do an 'enhanced' Livestock Population Characterization. This category is not considered a *key source category*[10] in the national inventory, so no country or region specific emission factors exist. Thus, we will use Tier 1 and IPCC default emission factors. The estimate that we will present at this point is a Tier 1 estimate. We will develop the factors to permit a Tier 2 estimate.

$$\text{Emissions} = \text{EF} \bullet \text{population}/(10^6 \text{ kg/Gg})$$

where EF is the emission factor, and population is the number of animals (head). We used the emissions factors in IPCC Guidelines tables 4.3 and 4.4

N_2O emissions from manure management

Decision tree: The data is not available to do an 'enhanced' Livestock Population Characterization. This category is not considered a *key source category*. No country or region specific N-excretion rates, manure management and usage data or emission factors exist. Thus, we used Tier 1 and IPCC default emission factors. We assumed that the principal manure management system practiced for penned cattle consisted of composting the manure and then spreading it on fields; for all other livestock we assumed that manure was essentially unmanaged.

$$N_2O\text{-}N = \Sigma_{(S)} \{[\Sigma_{(T)} (N_{(T)} \bullet Nex_{(T)} \bullet MS_{(T,S)})] \bullet EF_{3(S)}\}$$

[10] A *key source category* is one that is prioritized in the inventory system because it has significant influence on the total inventory of total direct greenhouse gases in terms of absolute level of emissions, trend in emissions, or both.

Where:

$N_{(T)}$ =	Number of head of livestock per category *T*
$Nex_{(T)}$ =	Annual average excretion per category *T*
$MS_{(T,S)}$ =	Fraction of total annual excretion for each livestock category *T* in management system *S*
$EF_3(S)$ =	N_2O emission factor for manure management system *S*

Worksheets:

MODULE	**AGRICULTURE**					
SUBMODULE	**METHANE AND NITROUS OXIDE EMISSIONS FROM DOMESTIC LIVESTOCK ENTERIC FERMENTATION AND MANURE MANAGEMENT**					
WORKSHEET	**4-1**					
SHEET	**1 OF 2 METHANE EMISSIONS FROM DOMESTIC LIVESTOCK ENTERIC FERMENTATION AND MANURE MANAGEMENT**					

	STEP 1			STEP 2		STEP 3
	A	B	C	D	E	F
Livestock Type	Number of Animals (1000s)	Emissions Factor for Enteric Fermentation (kg/head/yr)	Emissions from Enteric Fermentation (t/yr)	Emissions Factor for Manure Management (kg/head/yr)	Emissions from Manure Management (t/yr)	Total Annual Emissions from Domestic Livestock (Gg)
			C = (A x B)		**E = (A x D)**	**F = (C + E) / 1000**
Dairy Cattle		**36**		**1.00**		
Non-dairy Cattle		**32**		**1.00**		
Buffalo		**55**				
Sheep		**5**		**0.21**		
Goats		**5**		**0.22**		
Camels		**46**		**2.56**		
Horses		**18**		**2.18**		
Mules & Asses		**10**		**1.19**		
Swine		**1**		**2.00**		
Poultry		**--**		**0.023**		
Totals						

MODULE	**AGRICULTURE**				
SUBMODULE	**METHANE AND NITROUS OXIDE EMISSIONS FROM DOMESTIC LIVESTOCK ENTERIC FERMENTATION AND MANURE MANAGEMENT**				
WORKSHEET	**4-1 (SUPPLEMENTAL)**				
SPECIFY AWMS	**PASTURE, RANGE, AND PADDOCK**				
SHEET	**1 OF 2 METHANE EMISSIONS FROM DOMESTIC LIVESTOCK ENTERIC FERMENTATION AND MANURE MANAGEMENT**				

	A	B	C	D
Livestock Type	Number of Animals (1000s)	Nitrogen Excretion Nex (kg/head/yr)	Fraction of Manure Nitrogen per AWMS (%/100) (fraction)	Nitrogen Excretion per AWMS, Nex (kg/head/yr)
				D = (A x B x C)
Dairy Cattle		**60**	**83**	
Non-dairy Cattle		**40**	**96**	
Sheep		**12**	**99**	
Swine		**16**	**0**	
Poultry		**0.6**	**81**	
Others		**40**	**99**	

Total	

MODULE	**AGRICULTURE**
SUBMODULE	**METHANE AND NITROUS OXIDE EMISSIONS FROM DOMESTIC LIVESTOCK ENTERIC FERMENTATION AND MANURE MANAGEMENT**
WORKSHEET	**4-1**
SHEET	**2 OF 2 METHANE EMISSIONS FROM DOMESTIC LIVESTOCK ENTERIC FERMENTATION AND MANURE MANAGEMENT**

STEP 4			
Animal Waste Management System (AWMS)	A Nitrogen Excretion Nex $_{(AWMS)}$ (kg N/yr)	B Emission Factor For AWMS EF_3 (kg N_2O-N/kg N)	C Total Annual Emissions of N2O (Gg)
			C = (A x B)[44/28] x 10^{-6}
Anaerobic lagoons		**0.001**	
Liquid systems		**0.001**	
Daily spread		**0.0**	
Solid storage and drylot		**0.02**	
Pasture range and paddock		**0.02**	
Others		**0.005**	
Total			

Source Data: Data will be collected on animal populations by project block at the outset of the project. This data will be crosschecked using remote sensing data and census data held by ILRI and the Ministry of Agriculture.

Uncertainty assessment: The largest source of uncertainty in this submodule will be the estimation of the livestock population. We will use the livestock characterization procedures set out in the Good Practices Guidance to minimize this uncertainty. Using the Tier 1 method, there will also be uncertainty introduced by the generic emissions factors. Emission factors are unlikely to be known more accurately than ± 30%, and may be uncertain to ± 50%. Developing the emissions factors for a Tier 2 approach will minimize this uncertainty.

METHANE EMISSIONS FROM FLOODED RICE

Decision tree: As there is no flooded rice in the project blocks, we report that these emissions are not occurring.

Worksheet:

MODULE	**AGRICULTURE**
SUBMODULE	**METHANE EMISSIONS FROM FLOODED RICE FIELDS**
WORKSHEET	**4-2**
SHEET	**1 OF 1**

Water Management Regime			A Harvested Area	B Scaling Factor for Methane Emissions	C Correction Factor for Organic Amendment	D Seasonally Integrated Emission Factor for Continuously Floded Rice without Organic Ammendment	E CH_4 Emissions
							E = A x B x C x D
Irrigated	Continuously Flooded						
	Intermittently Flooded	Single Aeration					
		Multiple Aeration					
Rainfed	Flood Prone						
	Drought Prone						
Deep Water	Water depth 50 – 100 cm						
	Water depth > 100 cm						
Totals							

EMISSIONS FROM BURNING

Prescribed Burning of Savannas

Decision Tree: This category is not considered a *key source category*. No country or region specific activity data on the area burned, aboveground biomass density, aboveground biomass burned, aboveground biomass that is living, combustion efficiency or emission factors exist. Thus, we used Tier 1 and IPCC default emission factors. For default values, no IPCC values exist for East Africa. We use default values from West Africa for the South Sudan Zone.

Worksheets:

MODULE	AGRICULTURE
SUBMODULE	PRESCRIBED BURNING OF SAVANNAS
WORKSHEET	4-3
SHEET	1 OF 3

STEP 1					STEP 2		
A Area Burned by Category (specify) (k ha)	B Biomass Denisty of Savanna (t dm/ha)	C Total Biomass Exposed to Burning (Gg dm)	D Fraction Actually Burned	E Quantity Actually Burned	F Fraction of Living Biomass Burned	G Quantity of Living Biomass Burned (Gg dm)	H Quantity of Dead Biomass Burned (Gg dm)
		C = (A X B)		E = (C x D)		G = (E x F)	H = (E – G)
	3-6		0.25 – 0.50		0.85		
	3-6		0.25 – 0.50		0.85		
	3-6		0.25 – 0.50		0.85		
	3-6		0.25 – 0.50		0.85		

MODULE	AGRICULTURE		
SUBMODULE	PRESCRIBED BURNING OF SAVANNAS		
WORKSHEET	4-3		
SHEET	2 OF 3		
STEP 3			
I Fraction Oxidised of living and dead biomass	J Total Biomass Oxidised (Gg dm)	K Carbon Fraction of Living & Dead Biomass	L Total Carbon Released (Gg C)
	Living: J = G x I Dead: J = H x I		L = (J x K)
Living 0.80		0.45	
Dead 1.00		0.40	
Living 0.80		0.45	
Dead 1.00		0.40	
Living 0.80		0.45	
Dead 1.00		0.40	
Living 0.80		0.45	
Dead 1.00		0.40	
Living 0.80		0.45	
Dead 1.00		0.40	
Living 0.80		0.45	
Dead 1.00		0.40	
Living 0.80		0.45	
Dead 1.00		0.40	
Total			

MODULE	AGRICULTURE					
SUBMODULE	PRESCRIBED BURNING OF SAVANNAS					
WORKSHEET	4-3					
SHEET	3 OF 3					
STEP 4					STEP 5	
L Total Carbon Released (Gg C)	M Nitrogen-Carbon Ratio	N Total Nitrogen Content (Gg N)	O Emissions Ratio	P Emissions (Gg C **or** Gg N)	Q Conversion Ratio	R Emissions from Savanna Burning (Gg)
		N = (L x M)		P = (L x O)		R = (PxQ)
			0.004		16/12	CH_4
			0.06		28/12	CO
	0.006			P = (N x O)		R = (P x Q)
			0.007		44/28	N_2O
			0.121		46/14	NO_x

Field Burning of Agricultural Residues

Decision Tree: This category is not considered a *key source category*. No country or region specific activity data on the fraction of the area burned, aboveground biomass density, aboveground biomass burned, aboveground biomass that is living, combustion efficiency or emission factors exist. Thus, we used Tier 1 and IPCC default emission factors. For default values, no IPCC values exist for East Africa. We use default values from West Africa for the South Sudan Zone. We will enhance our ability to more accurately estimate this source through improved estimates of area burned annually in the project blocks.

Worksheets:

MODULE	AGRICULTURE							
SUBMODULE	BURNING OF AGRICULTURAL RESIDUES							
WORKSHEET	4-4							
SHEET	1 OF 3							
	STEP 1			STEP 2		STEP 3		
Crops (specify locally important crops)	A Annual Production (Gg crop)	B Residue to Crop Ratio	C Quantity of Residue (Gg biomass)	D Dry Matter Fraction	E Quantity of Dry Residue (Gg dm)	F Fraction Burned in Fields	G Fraction Oxidized	H Total Biomass Burned (Gg dm)
			C = (A X B)		E = (C x D)			H = (E x F xG)
Maize		1.0		0.4				
Millet		1.4						
Sorghum		1.4						
Bean		2.1						

MODULE	AGRICULTURE			
SUBMODULE	BURNING OF AGRICULTURAL RESIDUES			
WORKSHEET	4-4			
SHEET	2 OF 3			
STEP 4				
	I Carbon Fraction of Residue	J Total Carbon Released (Gg c)	K Nitrogen – Carbon Ratio	L Total Nitrogen Released (Gg N)

		J = (H x I)		L = (J x K)
Maize	.4709		0.02	
Millet			0.016	
Sorghum			0.02	
Bean				

MODULE	**AGRICULTURE**
SUBMODULE	**BURNING OF AGRICULTURAL RESIDUES**
WORKSHEET	**4-4**
SHEET	**3 OF 3**

STEP 6

	M Emission Ratio	N Emissions (Gg N)	O Conversion Ratio	P Emissions From Field burning of Agricultural Residues (Gg)
		N = (J x M)		P = (N x O)
CH_4	0.005		16/12	
CO	0.060		28/12	
		N = (L x M)		P = (N x O)
N_2O	0.007		44/28	
NO_x	0.121		46/14	

Source Data: Data will be collected on area burned, aboveground biomass density, aboveground biomass burned, aboveground biomass that is living, and combustion efficiency by project block at the outset of the project. Emission factors will be developed for the project area. This data will be crosschecked using remote sensing data and comparisons with results obtained in other similar environments in Latin America.

Uncertainty assessment: The largest source of uncertainty in this submodule will be the estimation of the area burned and the biomass density. We will conduct annual field surveys minimize this uncertainty. Using the Tier 1 method, there will also be uncertainty introduced by the generic emissions factors. Emission factors are unlikely to be known more accurately than ± 30%, and may be uncertain to ± 50%. Developing the emissions factors for a Tier 2 approach will minimize this uncertainty.

N_2O EMISSIONS FROM SOILS

Direct N_2O Emissions from Soils

Decision Tree: This category is likely to be a *key source category*. No country or region specific activity data on the fertilizer use or organic inputs exist. Dry pulse production is important in the project area, but no data exist to allow us to quantify production. Organic soils exist in the region, however mapping of these soils is only completed at a coarse scale and the types of corps grown on these soils are poorly quantified. Emissions factors do not exist for this region. Thus, we will use a Tier 1 and IPCC default emission factors initially and refine our estimates over the course of the project through a targeted research effort. The overall approach will be to estimate total N_2O emissions in the project area according to the following equation:

$$N_2O = N_2O_{DIRECT} + N_2O_{ANIMALS} + N_2O_{INDIRECT}$$

Worksheets:

MODULE	AGRICULTURE		
SUBMODULE	AGRICULTURAL SOILS		
WORKSHEET	4-5		
SHEET	1 OF 5 DIRECT NITROUS OXIDE EMISSIONS FROM AGRICULTURAL FIELDS, EXCLUDING CULTIVATION OF HISTOSOLS		
	STEP 1	STEP 2	
Type of N input to Soil	A Amount of N Input (Kg N/yr)	B Emission Factor for Direct Emissions EF_1 (kg N_2O-N/kg N)	C Direct Soil Emissions (Gg N_2O-N/yr)
			$C = (A \times B) \times 10^{-6}$
Synthetic fertilizer (F_{SN})		0.0125	
Animal Waste (F_{AW})		0.0125	
N-Fixing crops (F_{BN})		0.0125	
Crop Residue (F_{CR})		0.0125	
		Total	

MODULE	AGRICULTURE				
SUBMODULE	AGRICULTURAL SOILS				
WORKSHEET	4-5A (SUPPLEMEMNTAL)				
SHEET	1 OF 1 MANURE NITROGEN USED				
A Total Nitrogen Excretion	B Fraction of Nitrogen burned for Fuel	C Fraction of Nitrogen Excreted During Grazing $Frac_{GRAZ}$*	D Fraction of Nitrogen Excreted Emitted as NO_x and NH_3	E Sum	F Manure Nitrogen Used (corrected for NOx and NH3 emissions) F_{AW}

(kg N/yr)	(fraction)	(fraction)	(fraction)	(fraction)	(kg N/yr)
				E = 1-(B + C + D)	F = (A x E)
	0.25		0.2		
			0.2		
			0.2		

*$Frac_{GRAZ}$ will be calculated according to Annex 1 of the IPCC Guidelines

MODULE	**AGRICULTURE**
SUBMODULE	**AGRICULTURAL SOILS**
WORKSHEET	**4-5B (SUPPLEMEMNTAL)**
SHEET	**1 OF 1 NITROGEN INPUT FROM CROP RESIDUES**

A	B	C	D	E	F	G
Production of non – N – Fixing Crops	Fraction of Nitrogen of non – N – Fixing Crops	Production of Pulses and Soybeans	Fraction of Nitrogen in N – Fixing Crops	One minus the Fraction of Crop Residue Removed from Field	One minus the Fraction of Crop Residue Burned	Nitrogen Input from Crop Residues
(kg dm/yr)	(kg N/kg dm)	(kg dm/yr)	(fraction)	(fraction)	(fraction)	(kg N/yr)
						G = 2 x (A x B + C x D) x E X F
	0.015		0.03			

MODULE	**AGRICULTURE**
SUBMODULE	**AGRICULTURAL SOILS**
WORKSHEET	**4-5**
SHEET	**2 OF 5 DIRECT NITROUS OXIDE EMISSIONS FROM CULTIVATION OF HISTOSOLS**

	STEP 3			**STEP 4**
	D	E	F	G
	Area of Cultivated Organic Soils F_{OS}	Emissions Factor for Direct Emissions EF_2	Direct Emissions from Histosols	Total Direct Emissions of N_2O
	(ha)	(kg N_2O-N/ha/yr)	(Gg N_2O-N//yr)	(Gg)
			F = (D x E) X 10^{-6}	G = (C + F)(44/28)
		10		
		10		
		10		
		10		
		Total		

MODULE	**AGRICULTURE**		
SUBMODULE	**AGRICULTURAL SOILS**		
WORKSHEET	**4-5**		
SHEET	**3 OF 5 DIRECT NITROUS OXIDE EMISSIONS FROM GRAZING ANIMALS, PASTURE RANGD AND PADDOCK**		
	STEP 5		
Animal Waste Management System (AWMS)	A Nitrogen Excretion $Nex_{(AWMS)}$	B Emission Factor for AWMS EF_3 (kg N_2O-N/ha/yr)	C Emission of N2O from Grazing Animals
			$C = (A \times B)(44/28) \times 10^{-6}$
Pasture range and paddock		0.02	

Indirect N2O Emissions

MODULE	**AGRICULTURE**
SUBMODULE	**AGRICULTURAL SOILS**
WORKSHEET	**4-5**
SHEET	**5 OF 5 INDIRECT NITROUS OXIDE EMISSIONS FROM ATMOSPHERIC DEPOSITION OF NH_3 AND NO_x**
	STEP 6

Type of Deposition	A Synthetic Fertilizer N applied to soil, N_{FERT} (Kg N/yr)	B Fraction of Synthetic Fertilizer N Applied that volatilizes $Frac_{GASFS}$ (kg N/kg N)	C Amount of synthetic N applied to soil that volatilizes (kg N/kg N)	D Total N Excreted by Livestock N_{ex} (kgN/yr)	E Fraction of Total Manure N Excreted that Volatilizes $Frac_{GASM}$ (kg N/kg N)	F Total N Excretion by Livestock that Volatilizes (kg N/kg N)	G Emission Factor EF_4 (kg N_2O-N/kg N)	H Nitrous Oxide Emissions (Gg N_2O-N/kg N)
			C = (A x B)			F = D x E)		H = (C + F) x G x 10^{-6}
Total		0.1			0.2		0.01	

MODULE	**AGRICULTURE**
SUBMODULE	**AGRICULTURAL SOILS**
WORKSHEET	**4-5**
SHEET	**5 OF 5 INDIRECT NITROUS OXIDE EMISSIONS FROM LEACHING**
	STEP 7

Type of Deposition	I Synthetic Fertilizer N applied to soil, N_{FERT} (Kg N/yr)	J Total N Excreted by Livestock N_{ex} (kgN/yr)	K Fraction of N that Leaches $Frac_{LEACH}$ (kg N/kg N)	L Emission Factor EF_5 (kg N_2O-N/kg N)	M Nitrous Oxide Emissions from Leaching (Gg N_2O-N/kg N)	N Total Nitrous Oxide Emissions (Gg N_2O/kg N)	O Total Nitrous Oxide Emissions (Gg)

					$M = (I + J) \times K \times L \times 10^{-6}$	$N = (H + M)(44/28)$	O = G + C+ N (G from worksheet 4-5, sheet 2, step 4; C from worksheed 4-5 sheet 3, step 5; N from worksheet 4-5 sheet 5, step 8).
Total			0.3	0.025			

Source Data: Data will be collected on area of different crops, crop productivity, livestock population, manure management, by project block at the outset of the project. This data will be crosschecked using remote sensing data. Emission factors will be developed for the project area and compared with results obtained in other similar environments in Latin America.

Uncertainty assessment: The largest source of uncertainty in this submodule will be the estimation of the area under different crops, and annual crop productivity. We will conduct annual field surveys minimize this uncertainty. Methods to limit uncertainties regarding animal populations and manure management have been dealt with earlier. Using the Tier 1 method, there will also be uncertainty introduced by the generic emissions factors. Emission factors are unlikely to be known more accurately than ± 30%, and may be uncertain to ± 50%. Developing the emissions factors for a Tier 2 approach will minimize this uncertainty.

CH_4 UPTAKE BY SOILS

IPCC national reporting guidelines do not make a provision for accounting for the soil CH_4 sink. As part of this project, we will develop a system for this accounting that will parallel the IPCC system in accounting for soil emissions of N_2O