RESEARCH PROGRAM ON
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Assessing complex interactions between human and agro-ecosystem using Satellite Information

- A Case Study in Katuk Odeyo, Western Kenya

A CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) Technical Report

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Photos:
All photos in this working paper have been taken by Faisal Mohd Noor.
Picture of subsistence farming landscape in Kenya (closed range) and the Rift Valley (far range) during the afternoon haze condition. Photo: Faisal Mohd Noor.
Picture of crop types, corn field during stem elongation period (far left) and cotton field (middle) and immature sugar cane field (far right). Photo: Faisal Mohd Noor.
Picture of harvested/matured corn field (far left) and harvested sorghum field. Photo: Faisal Mohd Noor.
Picture of Water body, dam covered by water vegetation and surface water. Photo: Faisal Mohd Noor.
Picture of Fodder land, Napier grass field (left) and wild savanna grasses (right). Photo: Faisal Mohd Noor.
Pictures of short grasses and grazing lands. Photo: Faisal Mohd Noor.
Pictures of terrestrial primary vegetated areas. Photo: Faisal Mohd Noor.
Picture of Taminia tree canopy and mixed species. Photo: Faisal Mohd Noor.
Pictures of different bush land types. Photo: Faisal Mohd Noor.
Pictures of terrestrial primarily non-vegetated area expose bare soils not cover by vegetation. Photo: Faisal Mohd Noor.
Picture of the gully formation in Nyando. Photo: Faisal Mohd Noor.
Pictures of hedge plants, Euphobia plant (left) and Tavita plant. Photo: Faisal Mohd Noor.
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Picture of land cover types. Photo: Faisal Mohd Noor.
Picture of terrestrial permanent vegetated area in Nyando block. Photo: Faisal Mohd Noor.
Pictures of bare soils type within the block. Photo: Faisal Mohd Noor.
Pictures of grass cover types and bushes within the block. Photo: Faisal Mohd Noor.
Pictures of vegetation type within the block. Photo: Faisal Mohd Noor.

Abstract

The objective of this study is to integrate socioeconomic, biophysical, and remote-sensing information to enhance the understanding of climate change, agriculture and food security within and between CCAFS sites. The purpose is to assess the agricultural production system in the CCAFS site Katuk Odeyo, Nyando (Western Kenya) to explore potential indicators that can be long-term monitored. Ecosystem health determines energy supply and demand by sustaining the productive capacity of the landscape. The study uses a pixel-based RapidEye satellite image classification and assessment of agroecosystem health (for agricultural practices and landscape health relations) to characterise Katuk Odeyo into four functional agro-zones: highly intensive agro-zone condition (IAC), good agricultural condition (GAC), potential agricultural condition (PAC), and semi agricultural condition (SAC).

Different approaches for pixel and object based classification were evaluated. The accuracy assessment involved collecting ground truth data within the 10x10 km study location. The overall accuracy for the best classification, combining a pixel-based approach with digitization by hand, amounts to 48% for the ground truth data. Statistical analysis revealed that household locations had a significant effect on household innovativeness. Despite coarse input parameters, the variable functional agro-zones explained 7% of the variation in innovativeness. Land segmentation into functional agro-zones based on availability of farm resources provided reliable data for the subsequent farming system assessment. However, the main threat is the lack of imagery to show seasonal changes – e.g., ¾ of bare soils are shown on the dry season RapidEye image but did not match rainy season ground truth data. Results obtained between functional agro-zones and land size, transport assets, farmer adaptations for crops and animals, water resources, and innovativeness were significantly different.

Landscape health factors provided insights regarding the productive function of the farming system. The main threats are degradation and loss of forest to maintain the energy demand, which depends on optimal inputs from key environmental health factors such as woody biomass, water resources, and soil fertility. The choice of the functional agro-zones approach to assess the productive function of the farming system proved pertinent.

Keywords

Subsistence farming; Climate change; Food security; Integrated-analysis; Image processing; Remote sensing

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Acronyms

AFSIS	African Soil Information System
AOI	Area of Interest
CCAFS	Climate change agriculture and food security
DEM	Digital elevation model
FAZ	Functional agro-zone
FZ	Functional zone
GAC	Good agricultural condition
GIS	Geographic Information System
GT	Ground Truth
HEC	Healthy ecosystem condition
IAC	Intensive agricultural condition
ICRAF	International Centre for Research in Agroforestry
LTA	Long Term Average
SAC	Semi agricultural condition
PAC	Potential agricultural condition
RS	Remote sensing
SPIRITS	Software for the processing and Interpretation of Remotely sensed image Time Series

Introduction

This study has two dimensions: firstly, it explicitly addresses the complex interactions and feedback between human and natural systems. Secondly, it aims to integrate knowledge from ecological and social sciences, as well as other disciplines such as, remote sensing (RS) and geographic information system (GIS) for data collection, management and analysis, modelling, and integration of the datasets.

Healthy ecosystems are essential for resilient agricultural systems. Environmental services provided by healthy ecosystems are important assets for rural livelihoods and, at the same time, rural land use and environmental management change the functioning of these ecosystems and shape its environmental services (Farber et al., 2006; Palmer et al., 2005). Understanding how to manage feedback between ecosystems and humans is vital if one is to move towards more sustainable land use (Collins, 2010).

While the need for integrative research (Liu et al., 2003; Liu et al., 2007 Pickett et al., 2005; Robertson et al., 2004) has been widely accepted, the key question is how to do it. A fundamental problem of integrative research is to cross-link socio-economic and biophysical data that are often collected at the different scales. National census data may only be available at administrative units such as district level or country level, while panel data are often taken at household or village level. Agro-ecological data is typically taken at farm or plot level and matched with remotely sensed data with spatial resolutions as low as one meter. Even linking a farmer's household characteristics to the on-farm biophysical parameters can be difficult, especially when farmland is fragmented and not in direct vicinity of the house. Practical approaches and methodologies to link social and ecological data are urgently needed.

The purpose of this study is to a) investigate whether remotely sensed data can be used to derive information about the status of the agro-ecosystem that farmers depend on and to b) link this information to social-economic data in order to understand what makes some farmers and regions more vulnerable to the effects of climate change than others. The study hypotheses are; i) subsistence farming activities within an agro-ecological system cannot be sustained unless provided by sufficient farm supports from a healthy ecosystem, and ii) people and community adaptation strategies within an agro-ecological system can be better understood and predicated than social-ecological systems.

The overall aim of this study is to integrate and analyze socio-biophysical and RS information in order to have a good understanding of the interactions between climate change, agriculture and food security within CCAFS sites. The objectives of this study are:

- To use remote-sensing information as a tool to form critical linkages between social and biophysical domains within agro-ecological systems.
- To identify gaps in the methodological approach taken.
- To recommend appropriate data management solutions.

The CCAFS baseline data[1] was used for this study. Similar to Kristjansen et al. (2009), socio-economic household information consisted of 16 socio-economic indices that were calculated from the CCAFS household level baseline data. These were then analysed using functional agro-zones in order to draw conclusions about greenness (above ground biomass), soil organic carbon content, and farmers' adaptation, while taking key differences in poverty levels, trends, and environmental health factors into consideration.

[1] http://ccafs.cgiar.org/resources/baseline-surveys

Background

Remotely sensed data can be utilised using two different approaches: firstly by extracting information from remotely sensed images as continuous covariates or secondly by using spectral features of the image to partition an image space into a set of non-overlapping, meaningful, homogeneous regions, where the term 'meaningful' is problem-dependent.

There are advantages and disadvantages to both of these approaches. For example, the African Soil Information System (AFSIS) project at ICRAF is using the first approach to produce predicted soil degradation indicator maps for Africa. Spectral measurements of soil samples and visual ground sampling information at sentinel sites, combined with spectral information from satellite data allow for the prediction of soil and landscape characteristics at any location within the satellite image (Shephard K, Gunner Vågen, Gumbricht T., 2011 unpublished). This approach is useful if high-resolution imagery is available and it provides detailed information on soil biophysical and landscape information at a very large scale. The constraint of this approach is that it requires recalibration of the models if different satellite data are used. In addition, while continuous covariates provide very detailed information, sometimes it is difficult to match this information with household characteristics, especially in situations where only the exact location of the homestead is known, but not the locations of other parts of the farm. Smallholdings are more and more characterized by fragmented farmland, with individual plots or fields being considerable distances apart.

Remotely sensed images are normally poorly illuminated (Curran, 1981; Baumgardner et al., 1985; Heute and Jackson, 1987), highly dependent on environmental conditions, and often have very low spatial resolution. Often a scene contains many ill-defined and ambiguous regions. Extracting numeric values for each pixel to create continuous covariates or assigning unique class labels (land-use classification) with certainty is an inherent problem for remotely sensed images (Baumgardner et al., 1985; Foerster et al., 2010). Under these circumstances, segmentation, defined as the partitioning of an image space into a set of non-overlapping, meaningful, homogeneous regions, can be a better alternative (Gamanya et al., 2007). Segmentation refers to the process of assigning a label to every pixel in an image, such that each pixel in the same segment shares certain visual characteristics – say, color, intensity, texture. Adjacent regions are ideally expected to be significantly different with respect to these characteristics. This approach provides information about the dominant features in the image and makes interpretation easier but, only at the cost of fine resolution. The success of any subsequent image analysis depends on the quality of the segmentation. Segmentation of satellite images is the standard process used for land-cover and land-use classification. The drawback of this approach is that the commercial software available is often very expensive and that the segmentation process done automatically by the program follows a black box approach.

Given the size of the CCAFS sites – the CCAFS baseline was conducted in10km by 10km sampling frames in broader landscapes – and the lack of available high resolution imagery it was decided to test whether image segmentation could be a useful tool to simplify remotely sensed data into something that is more meaningful and easier to analyse in the context of smallholder farming systems. Rather than applying a black box approach, the present study tries to use the approach of image segmentation into different functional agro-ecological zones. Factors considered for this analysis include main land-cover types, infrastructure, soil carbon, topography, moisture, and greenness/biomass.

Following site-specific management criteria developed by Precision Farming concept (see Box 1) the CCAFS 10km by 10km sampling frame was divided into four agro-ecological zones depending on observations during the ground truth survey.

- Good Agricultural Condition (GAC) - Highly intensive to semi-intensive agro-landscape, with good support from a healthy ecosystem and farm resources/supports.

- Intensive Agricultural Condition (IAC) - Very intensive land use where farm resources (woody biomass, water, and soil nutrients) are depleting due to highly intensive human consumption. It must noted that IAC may be a non-agricultural area depending on the land use types but may also represent a kitchen garden, grazing areas around and within villages or crop lands.
- Potential Agricultural Condition (PAC) - Available land with good access for agricultural activity, but landscape is underutilised and/or still maintained in a good fallow condition with bushy vegetation or high-density biomass. Area does not have to be perfectly physically suitable for agricultural activity when considering topographic factors such as steep slope and wetlands.
- Semi agricultural condition (SAC) – Area is maintained for agricultural activity but has limited access to farm resources. The definition of SAC areas fits between GAC and IAC.

Box 1: Key considerations for the delineation of management zones, adopted from Ortiz, 2011

Key considerations when implementing a functional zone (FZ) delineation strategy:

•*Relationship between block (agroecosystem) characteristics and healthy ecosystem services within the block*: Look at factors that have the most direct impact on the agroecosystem that can be targeted for FZ delineation. Some examples include primary forest, healthy riparian and river ecosystems, and soil nutrient levels.

•*Level and amount of data required*: In depth ecosystem assessment and analysis allow the collection of data sets that provide discrimination of within-landscape features sufficient for FZ delineation. Some good examples of these are the high resolution aerial or satellite images, and terrain elevation measured with real-time kinematic differential GPS (RTK-DGPS)... In situations where there is no access to these data, county soil surveys and topographic maps provide a relatively coarse depiction of within-block variability that is often related to human practices.

•*Use of quantitative and time-series data*: Functional zones delineated from data that is in multi time-series or seasonals are might be the most cost efficient strategy. Terrain elevation/DEM, soil electrical conductivity patterns and soil physical properties are examples of the biophysical information that are best in FZ delineation of the agroecosystem landscape. In the case of two seasonal characteristics of the block landscapes, within block crops variability can be assessed with a single year of data; however, multi-year image data along with supplemental information (e.g., soil electrical conductivity or elevation) is recommended for FZ delineation in order to identify consistent crop patterns within the block.

•*Cost of the data*: The implementation of a FZ strategy should not require a high initial capital investment. However, FZ delineation requires time. Using spatial data that is free and available on the Web may be a good start. It is the aim of this study also to show to CCAFS what are others available data in the Web and provider, such as of the long term data, SPOT vegetation and RFE from the Estation can be far great support for the available data for delineation.

Materials and Methods

CCAFS Household Baseline data

The household level model integrates household demography (e.g. household size, ages, and highest schooling levels of each family member), household economy (land use activities, income, and expense sources, etc.), attitudes toward issues of interest (e.g., climate change and food security), and agricultural activities. In total there are fifteen CCAFS sites in three different regions of East Africa, West Africa and South Asia, representing twelve different countries[2]. CCAFS began collecting socioeconomic, demographic, and behavioural baseline data in September 2010, when 140 households were interviewed from each random chosen village within each of the sites, using standardised tools and approaches.

CCAFS Village Baseline data

In March 2011, CCAFS the village baseline tool was tested in Nyando. Implementation of the village baseline followed across all sites during late 2011 and early 2012. Since macro-level socioeconomic factors (i.e. contextual factors beyond the household level, such as roads, trade-centres/markets, administration buildings, bridges, dams, schools, and organisational landscapes) also influence population, land use, and environment interactions, CCAFS obtained these types of information by conducting different exercises with community groups during the village baseline.

Satellite images

The following satellite images have been utilised for this study:

- RapidEye, February, 2011 (5 bands, 6.5 m resolution; contain band 4 or Red-Edge band)
- SPOT-VGT for cumulative degree of greenness (CNDVI) 1km resolution (time-series February 1999 – May 2011), Kenya, Uganda, Somalia, Ethiopia, Tanzania and Rwanda
- NOAA-AVHRR satellite for rainfall estimate from 1km resolution (time-series February 1999 – May 2011), Kenya, Uganda, Somalia, Ethiopia, Tanzania and Rwanda
- Predicted soil carbon concentration based on Quickbird imagery (1m resolution) provided by AFSIS group ICRAF

Ground Truth data

For the case study of Nyando, additional ground-truth (GT) information on major land-use covers and features was obtained in October 2011. Table 1 provides a summary of data available and utilized for this report.

[2] http://ccafs.cgiar.org/where-we-work

Table 1. Overview of major variables and information available for this study.

CCAFS Baselines[3]	Remotely-Sensed Images[4]	Field Observations	Other sources	Additional information
• Household Baseline -140 household respondents interviewed from each village during the CCAFS baseline -Population structure: number of households, number of people and relationships in a household, occupation, marital status, education level, average economic income, age, gender, and education levels. -Human activities: agricultural practices, input and production, adaptation and changes in agricultural practices, livestock, amount of fuel wood consumed, location of fuel wood collection, amount of cropland, income sources and expenses. • Village Baseline -Understanding the landscape in relation to natural resources, infrastructure and facilities; organizational landscapes (in relation to food security, natural resources and food crisis); communication and networking and visioning. • Mitigation questionnaires at farmer level: Perceptions; attitudes; concerns; needs; understanding.	• CCAFS purchased RapidEye satellite images for all its 2011 sites (5 bands, 6.5m resolution; including band 4 or Red-Edge band). The image for the CCAFS site in Western Kenya: Nyando, Katuk Odeyo 10x10km sampling frame was used for this study,	• Household locations • Ground-truthed plot data • Ground control points • Forest types • Vegetation/ crop types • Species coverage • Road locations • Location of human activities • Elevation and slope aspects	• Cumulative degree of greenness (CNDVI), predicted rainfall (RFE), and average increase in vegetation index provided by MARS/JRC covering East Africa (Kenya, Uganda, Somalia, Ethiopia, Tanzania and Rwanda): - CNDVI from SPOT-VGT [1km resolution (time-series February 1999 - May 2011) - RFE (rainfall estimate) from NOAA-AVHRR satellite [1km resolution (time-series February 1999 – May 2011) • Predicted soil carbon concentration (Nyando) provided by AFSIS at ICRAF • DEM (ASTER data) freely available	• Western Kenya Integrated Ecosystem Management Project (WKIEMP) (KARI, 2006) • Baseline Surveys,WKIEMP (Verchot, BoyeZomer; ICRAF Nairobi, Kenya, April 5, 2008)

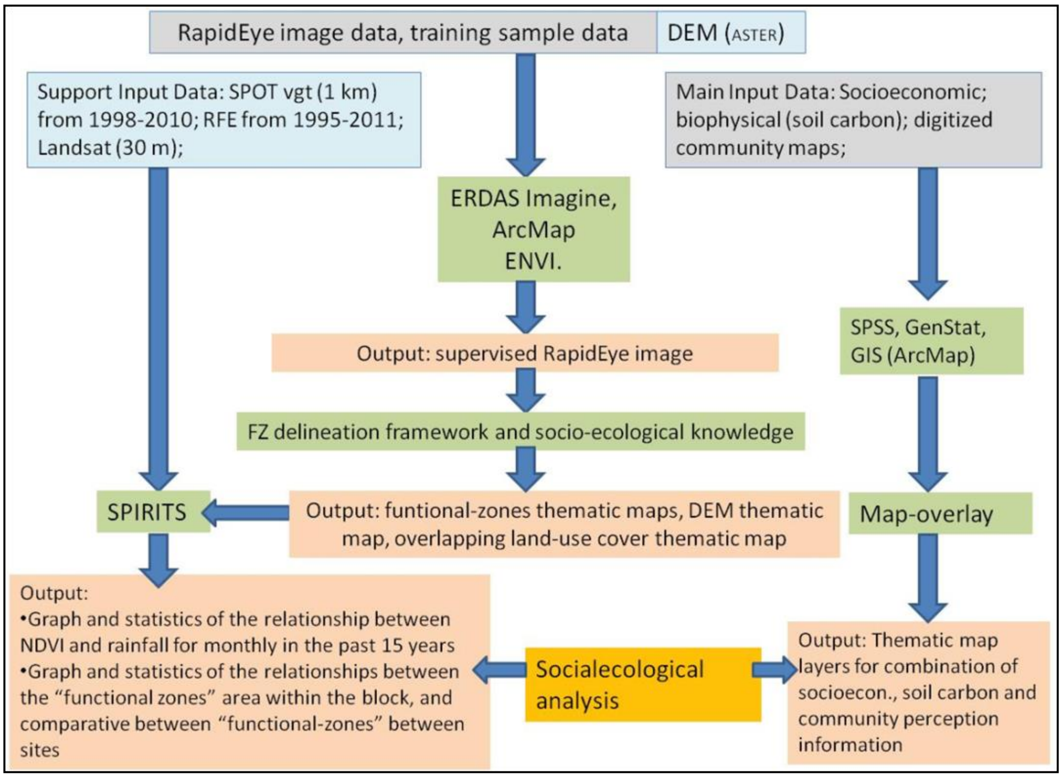
[3] More information on the CCAFS Baseline tools as well as data and reports is available through http://ccafs.cgiar.org/resources/baseline-surveys
[4]**NOTE**: *East Africa; ** West Africa and *** Indo-Gangetic plains

Methods

The delineation of the satellite image space into functional agro-zones is a 4-step procedure.

- Step 1: Pre-processing of RapidEye satellite image including atmospheric corrections and principal component analysis (PAC). This was conducted using ERDAS Imagine.
- Step 2: Image classification is an iterative process, which consists of unsupervised classification, collection of training sets during a ground survey, and a supervised classification.
- Step 3: Segmentation of study block into a set of non-overlapping, homogeneous functional agro-ecological zones based on:
    - Natural forest cover (woody biomass or tree counts)
    - Greenness (CNDVI)
    - Main land cover features
    - River networks
    - Topography - DEM (Aster data)
    - Soil organic carbon (Tor Vagen, 2011 unpublished data)
    - Infrastructure
- Step 4: Functional agro-zones were analysed for their differences in vegetation greenness (using the CNDVI index), and rainfall (using RFE data). The final results were then integrated with the socio-economic data from the CCAFS baseline and analysed using a statistical package (SPSS) to explore correlations between the landscape biophysical parameters and socio-economic parameters. Figure 1 provides an overview of the process. The next sections give a more detailed account of the different steps.

Figure 1. General work-flow and data involved and analyses.

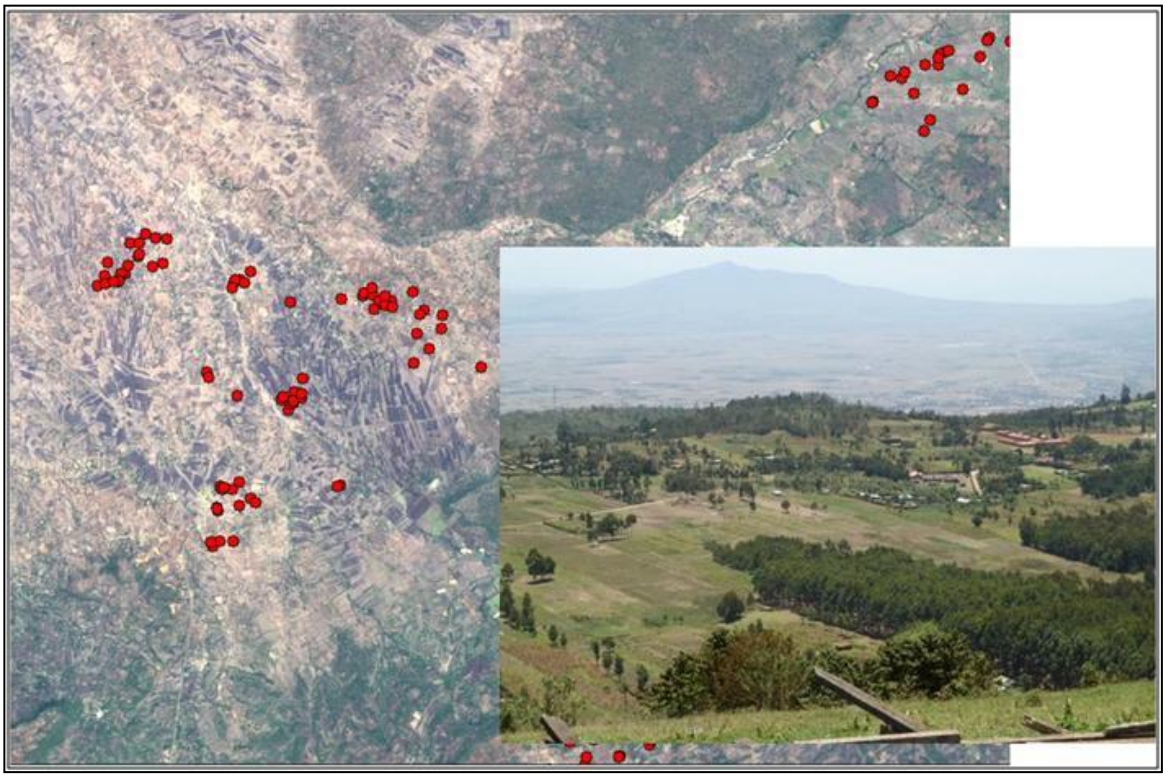


Atmospheric corrections of the RapidEye satellite image

Solar radiation reflected by the Earth's surface to satellite sensors is modified by its interaction with the atmosphere (Heute et al., 1984; Baumgardner et al., 1985; Hadjimitsis et al., 2010). Due to this, the RapidEye satellite image was processed for atmospheric corrections (ATCOR) using ERDAS imagine. This section provides a detailed description of the impact of atmospheric effects, examples of the satellite images before and after ATCOR, and comparisons between corrected images and non-corrected images from different sites.

ATCOR is the most important part of pre-processing remotely sensed data. The objective of ATCOR is to determine true surface reflectance values and to retrieve physical parameters of the Earth's surface by removing atmospheric effects from the satellite images (Heute et al., 1984; Curran, 1981). This is not only true for the extraction of spectral information from the data, but also for visual interpretation of images. Figure 2 illustrates the effect of hazy weather (i.e. high water vapour) on the spectral reflectance of the satellite image.

Figure 2. Water vapor in the air influencing the spectral reflectance of the RapidEye image and photo of a typical farming landscape in Kenya during afternoon haze (with the Rift Valley in the background).



ATCOR normally involves modelling by processing digital images to reduce the influence of errors or inconsistencies (usually referred to as "noise") in image brightness values that may limit one's ability to interpret or quantitatively process and analyse digital remotely sensed images (Van der Kwast, 2002). The algorithm accounts for horizontally varying atmospheric conditions and also includes the height dependence of the atmospheric radiance and transmittance functions to simulate the simplified properties of a three-dimensional atmosphere.

The Richter database, which contains the results of radiative transfer calculations (i.e. atmospheric transmittance, path radiance, direct and diffuse solar flux) for a wide range of weather conditions, was used to correct the RapidEye satellite images using the ATCOR-2/3 (Richter, 1998) function provided in ERDAS Imagine.

Initially, digital numbers (DN) values were converted to units of radiance by using standard calibration values specific for tropical African conditions. Secondly, to correct satellite imagery over mountainous or hilly terrain, these were overlaid on the Aster digital elevation model (DEM) to obtain information about surface elevation, slope, and orientation as well as to visualise steep slopes. Figures 3 to 6 show the visual sharpening of the RapidEye satellite images after ATCOR.

Figure 3. RapidEye images comparing before (left) and after ATCOR (right) for the CCAFS Nyando site in western Kenya

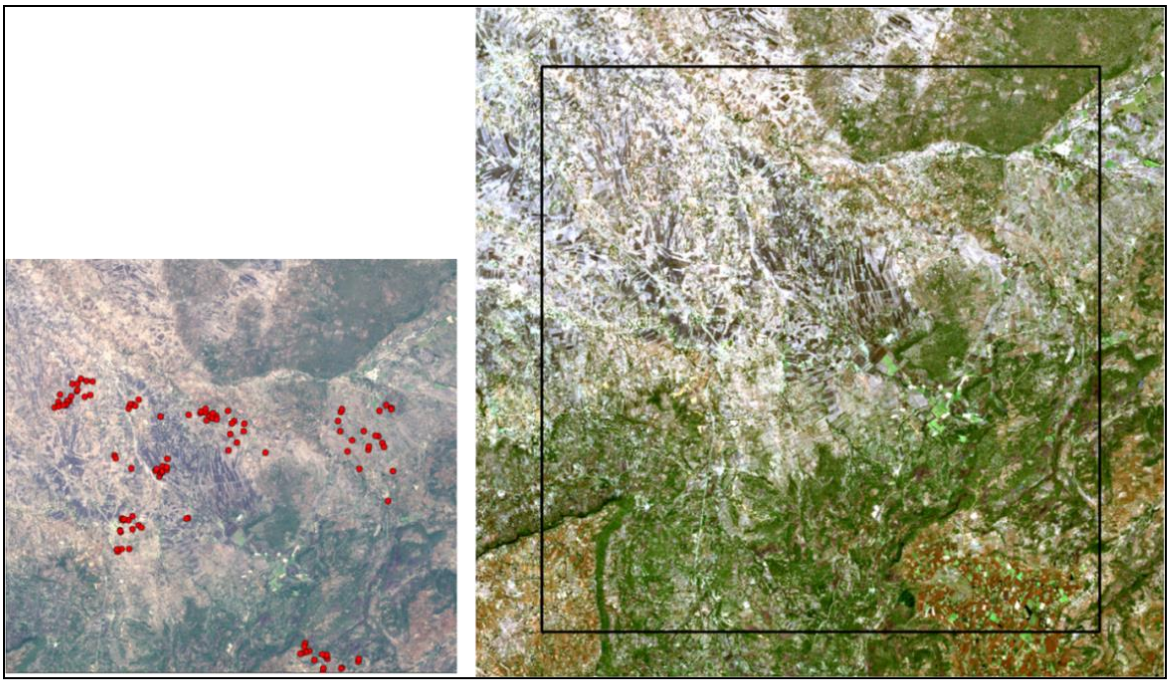


Figure 4. RapidEye image of the CCAFS Borana site in Ethiopia before (left) and after ATCOR (right)

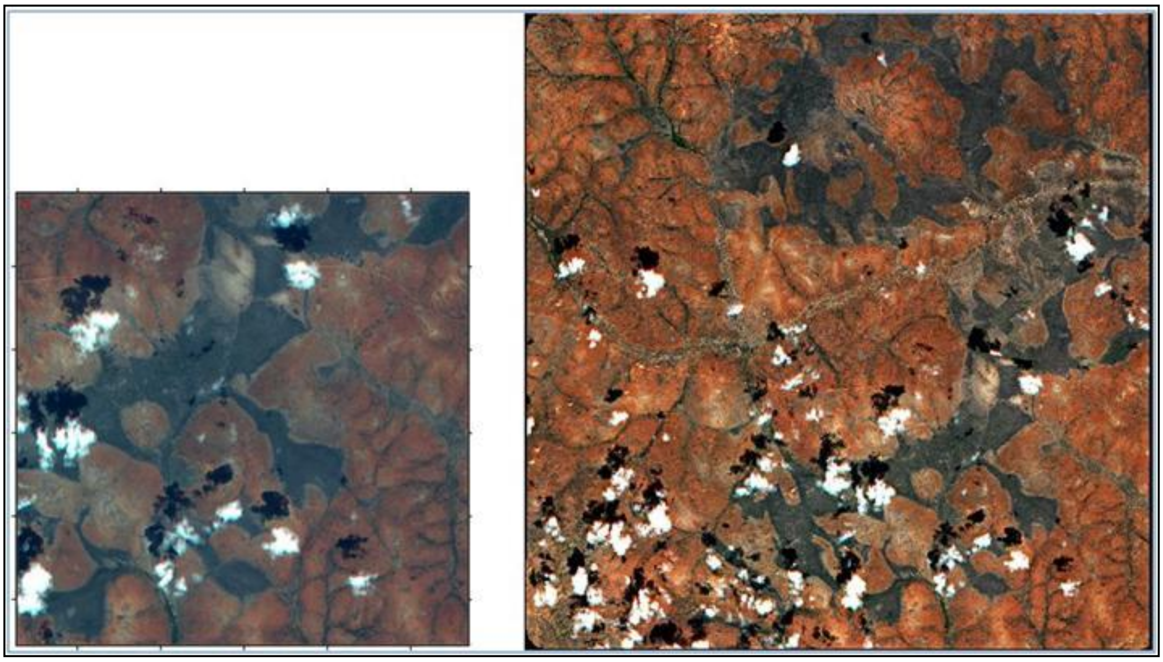


Figure 5. RapidEye image of the CCAFS Kaffrine site in Senegal before (left) and after ATCOR (right)

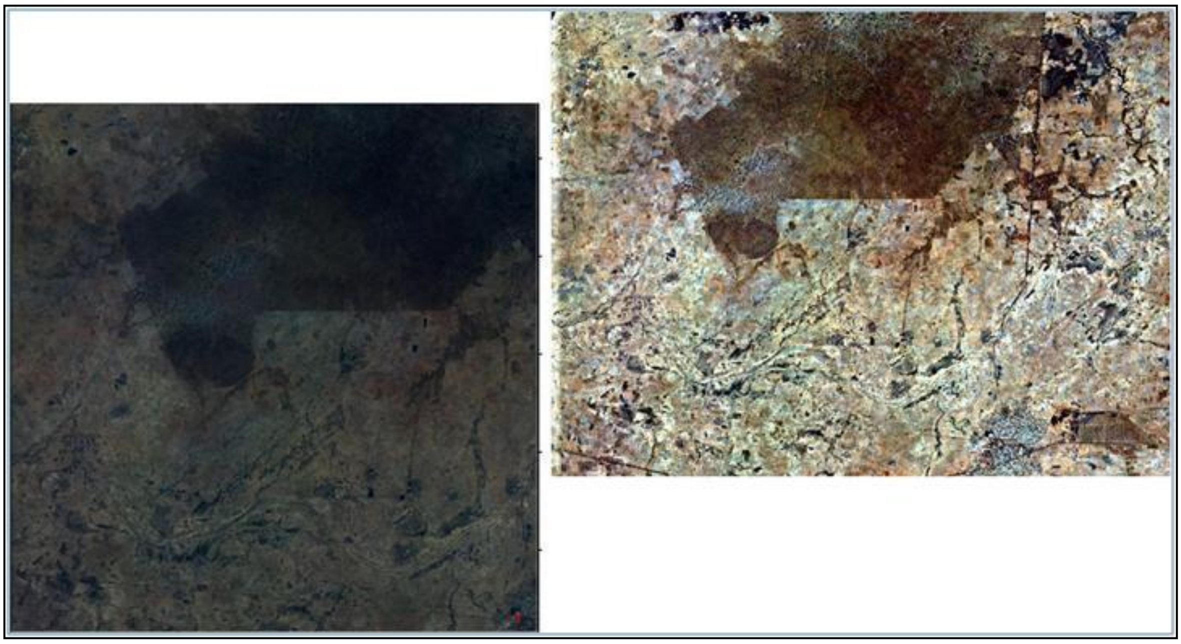
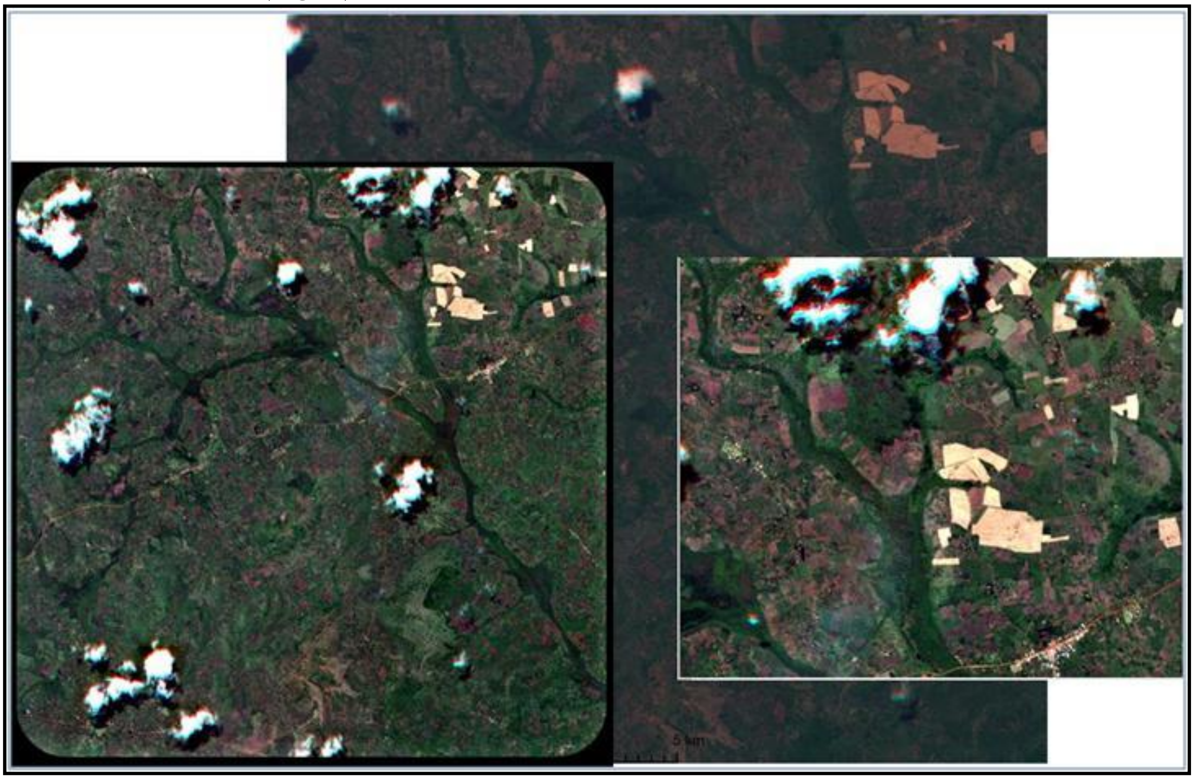


Figure 6: RapidEye image of the CCAFS site in Hoima, Uganda before (far back) and after ATCOR (right)

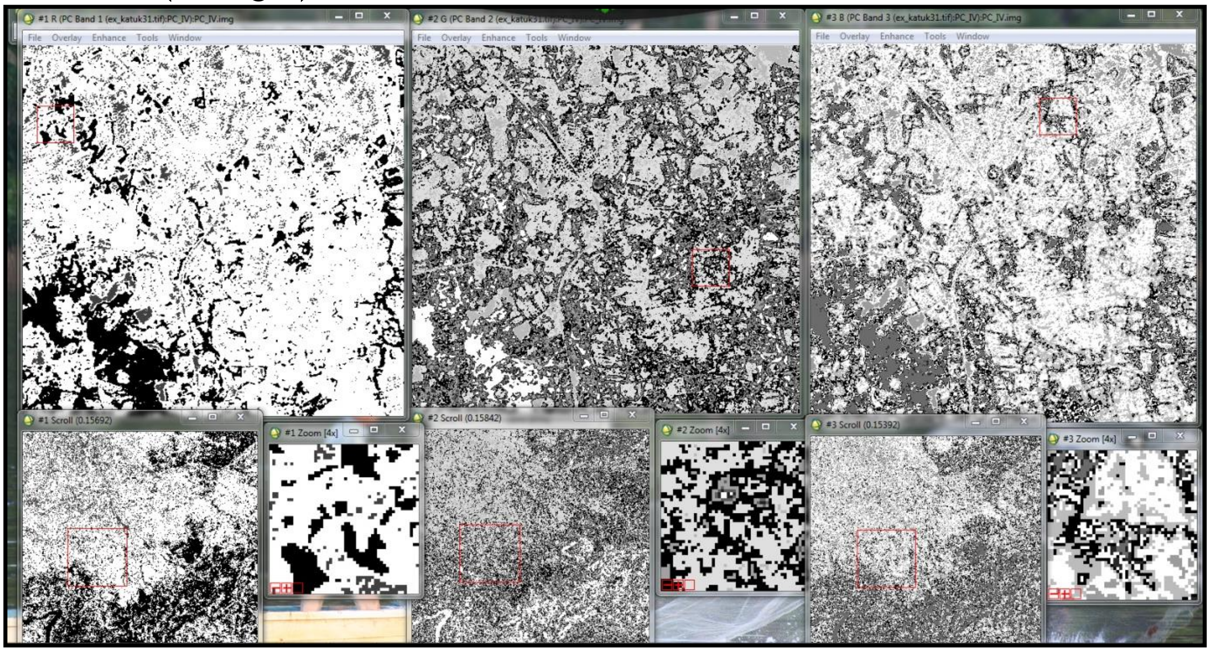


Principal Component Analysis

Principal component analysis (PCA) was used to extract linear combinations of available bands, and it is a prerequisite for image classification. Individual bands of hyperspectral images are spatially and spectrally correlated, therefore noise within one band affect information on other bands (Pandey et al., 2011). PAC transforms the image bands into orthogonal, and hence uncorrelated, principal components. During the classification procedure PCA generally results in a maximum of two bands due to distortions and noise recorded by the satellite within the bands.

The analysis shows that the first component eigenvalues explains 94.5% of the variation contained within the five bands, the second component with 0.2% and the third component with 5.2%. While Landsat satellite images usually require 3 PCA, just 2 PCA are needed with RapidEye (see Figure 7). Thus, bands 4 and 5 were omitted from the selection because of distortions, and the analyses was conducted with three bands.

Figure 7. The PCA demonstrates PC of band 1 (far-left) PC band 2 (middle) and PC band 3 (far-right)



Unsupervised Image Classification

Unsupervised image classification is a data exploration step that provides information about the inherent variation within the area of interest. Unsupervised image classification divides the area of interest into classes based on spectral and pattern similarity. Classes are chosen based on a mathematical function to ensure that pixels within one class have the smallest variation, whereas pixels between classes have the highest variation (Foerster et al., 2010). The actual relationship of the classes with land-cover features on the ground is not established.

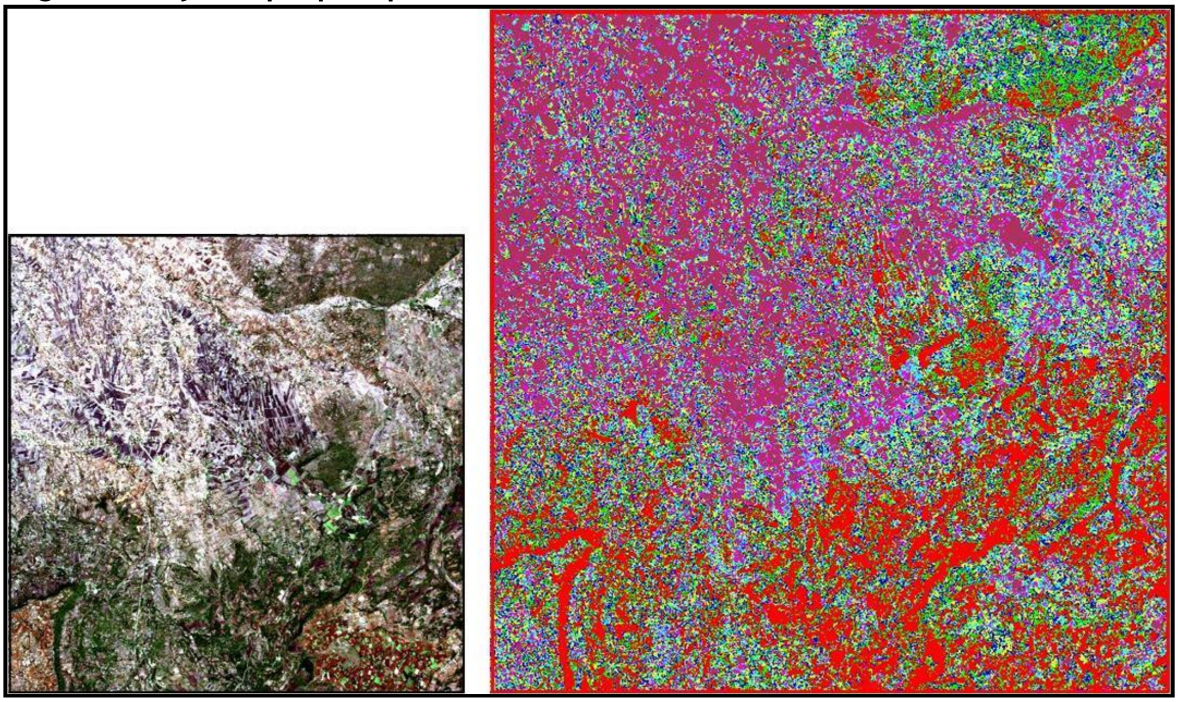
On the other hand, with supervised classification one identifies examples of land cover types within the area of interest, which are called 'training sites'. These have to be collected through a visual inspection of the site, whereby GPS positions of different land features are taken. This information is entered into the classification analysis to provide a direct connection between spectral characteristics of pixels and the land cover type. By identifying other pixels within the image with similar reflectance, the software is able to identify all regions within the image that belong to the same land cover type.

For the unsupervised classification, the NDVI[5] was calculated from the corrected RapidEye image. The NDVI values provide a good differentiation between vegetated and non-vegetated areas in the Nyando site (see Figure 8). However, NDVI does not allow for the differentiation between vegetation

[5] Normalized Difference Vegetation Index (NDVI): An index calculated from reflectance measured in the visible and near infrared channels. It is related to the fraction of photosynthetically active radiation

types. In addition, mining sites, fallow land parcels, dry grasslands, gully formations, roads, and compacted bare soils cannot be identified or differentiated with NDVI. Moreover, the river and road networks are almost entirely missing. It is important to note that an unsupervised image classification lacks important information on land-cover features and can therefore not be used for the delineation process. GT is crucial for any further analysis of the image.

Figure 8. Output from the unsupervised NDVI of the RapidEye image for Nyando, where high above ground biomass is represented by the red and non-vegetated by the purple spectral reflectance



Ground-truth survey

A GT survey was conducted in Nyando in October, 2011, with two main objectives:

i. To get a clear picture of the general land use cover and crop types within the sampling frame.
ii. To obtain the ground training samples for the supervised image classification analysis of the RapidEye image.

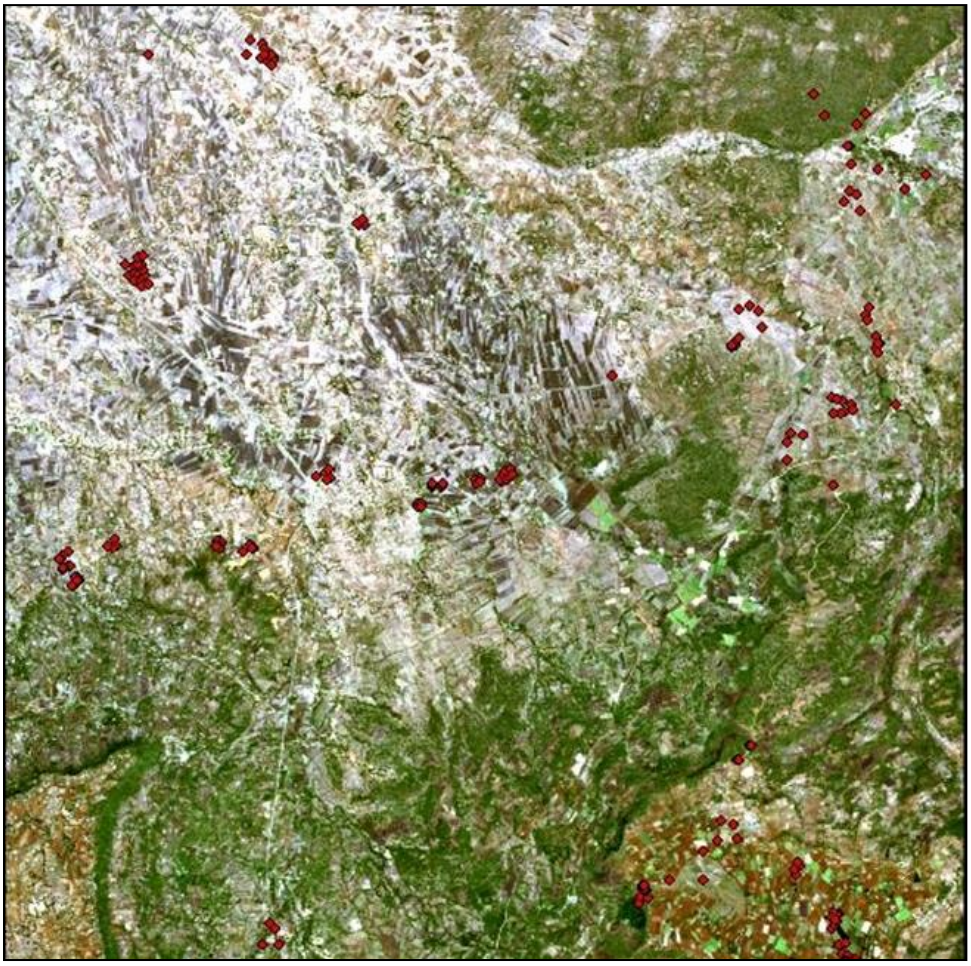
A total of 15 different land cover features were sampled (Pictures 15-17). The aim was to get at least three replicates for each feature class in order to achieve a good representation of the spectral variation between the main feature classes. In the end, a total of 54 GT points were sampled. The distribution of these points within the study area is shown in Figure 9.

Within the Nyando sampling frame, food crops are cultivated on regularly tilled fields and on a rotational basis. During the rainy season both fodder and short grasses are used for grazing. In the dry season forestland on the higher grounds is the main source for livestock feed. Forested areas are often located in undulating areas in the southern part of the sampling frame, whereas extensive pastures of short grass species are mostly located in the northeast.

Forested land and woodlands are used for the collection of fire and construction wood, whereas trees are maintained close to buildings to provide shade for livestock. Some species (e.g. Euphobia, Tavita, and Sisal) provide non-wood forest products and are planted as hedges along farm borders. The main building materials for houses are wood and stonewalls built with an emulsion of silt, dung, and water. Roofs are constructed with corrugated iron sheets. These surfaces, when older and highly weathered (rusted), can be misinterpreted as bare soil during image processing analysis. Some houses also use hay as roof cover. Both types of houses make the spectral classification of buildings challenging.

Bare soil comprises a range of different environmental conditions: rocky soil without vegetation from mining activities (often small boulder fields or rocky areas as a result of intensive run-off and soil erosion), bare soils not covered by vegetation, or tilled agricultural fields. The latter two conditions can be differentiated on the basis of moisture content. The co-existence of agricultural land left fallow, short grasses, dry pastures, and harvested crops during the dry season provide potential difficulties for land-use classification as all of these have similar spectral characteristics.

Figure 9. Points of the ground-truth survey in Nyando and photos of landscape and crop types



Corn during stem elongation period (left), cotton (middle) and immature sugar cane (right)

Mature corn (second row, left) and harvested sorghum (second row, right)

Water body, dam covered by water vegetation and surface water

Fodder land, Napier grass (left) and wild savanna grasses (right)

Short grasses and grazing lands

Forest and woodland areas: primary forest area (left), plantation forest (middle) and acacia forest

Taminia tree canopy and mixed species

Bushland types

Non-vegetated areas exposing bare soils

Gully formation in Nyando

Hedge plants, Euphobia plant (left) and Tavita (right)

Flooded area and high moisture vegetated area



Infrastructure and buildings

Results

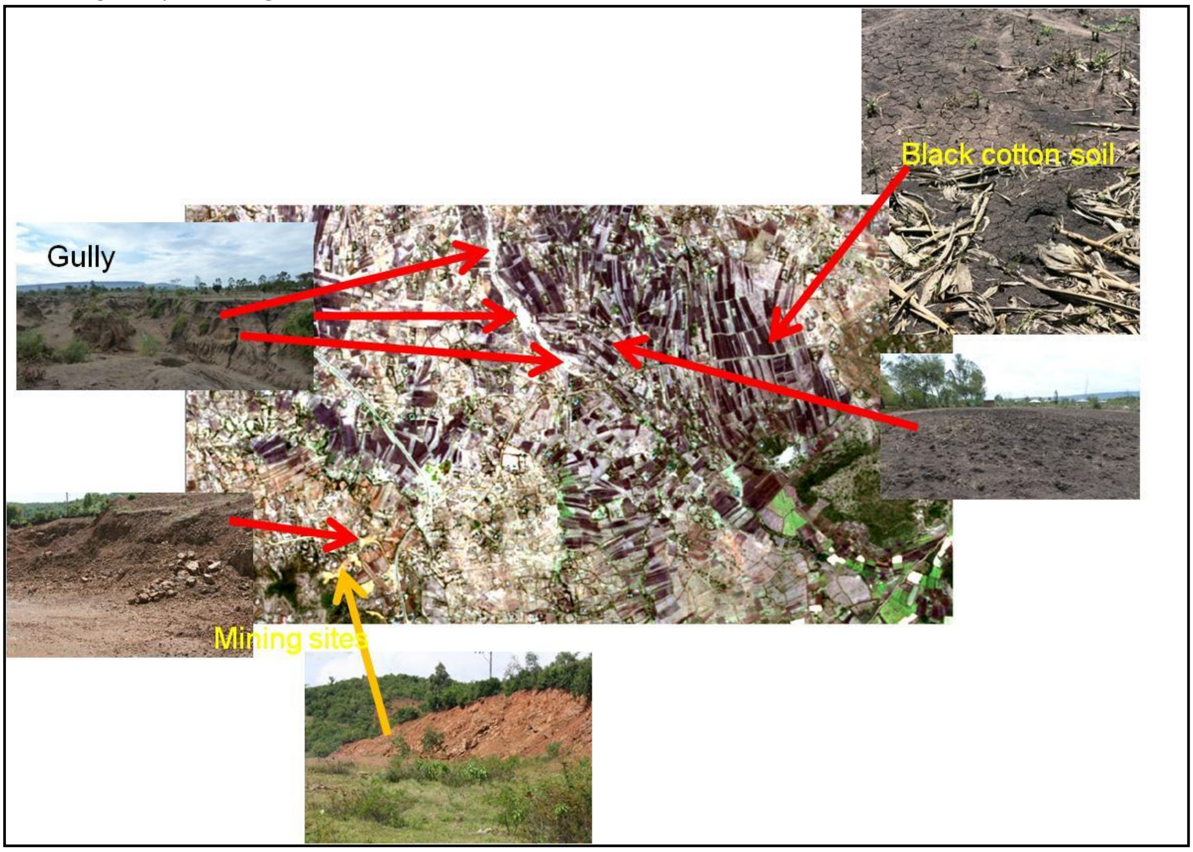
Spectral signature of land-cover features

This section discusses the reflectance of different land-cover features as obtained from the analysis of the Rapideye image of Nyando. A large source of error was found because dates of the GT survey and the RapidEye image did not coincide. The RapidEye scene was taken in February 2011 during the dry season, whereas the ground-truth survey was conducted in October 2011 just after the main rainy season.

Bare soils can be seen in several different reflections along with several other features (Figure 10). Gully formation is shown in bright white, light orange reflects exposed bare soils due to mining, dark brown is reflected from ploughed black cotton soils, and very light brown is reflected by dry areas and short grasses. Dry short grasslands display the same spectral signature as bare soils due to the strong reflectance of the soil background, especially during the dry season.

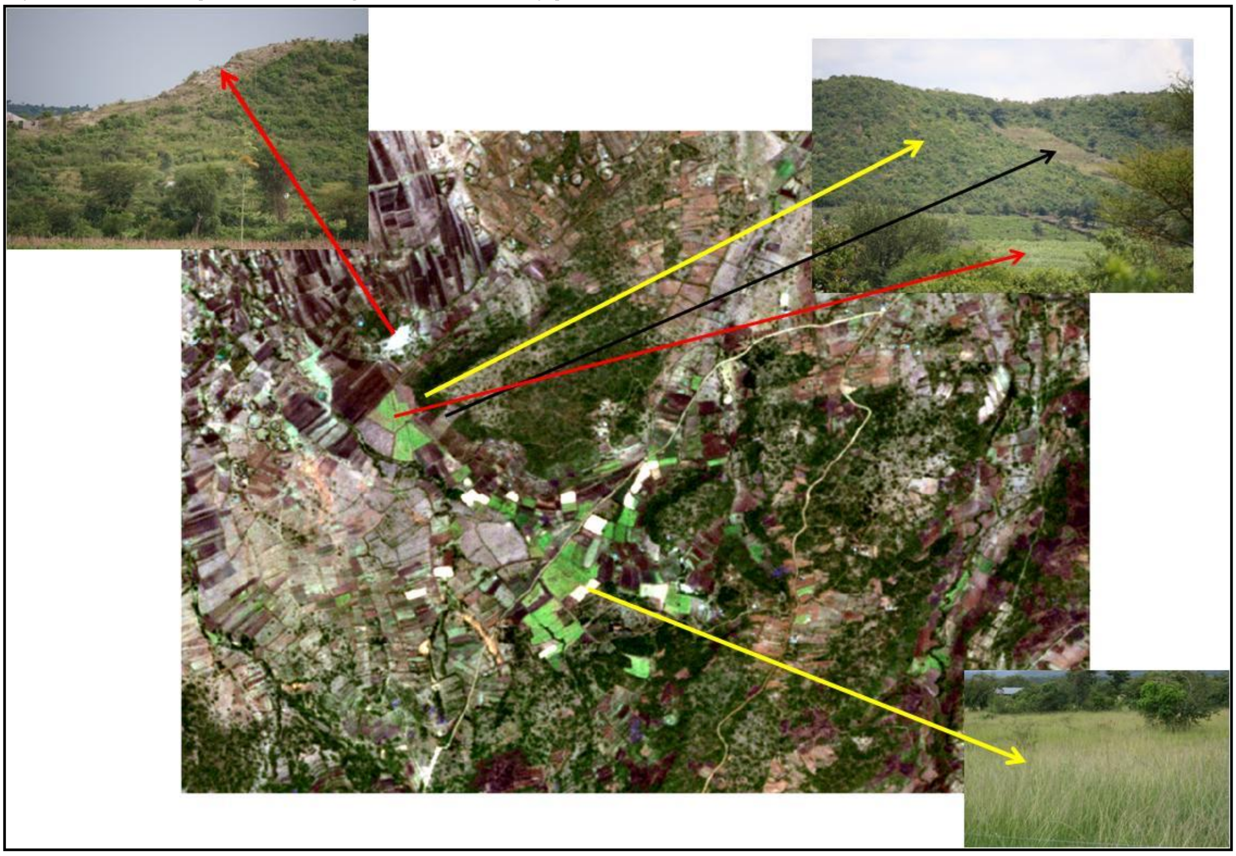
Diagnostic absorption features of soils are due to the inherent spectral behavior of the mineralogical composition, organic matter, and water (Baumgardner et al., 1985; Irons et al., 1989). Thus, the only way to differentiate fallow land from bare, degraded soil is a 'multi-temporal spectral analysis' of images from both dry and wet seasons (Vuolo et al., 2010).

Figure 10. Primarily non-vegetated areas in Nyando and spectral signatures of the RapidEye image



"Buffalo-grass" and open bare soils on courses and stony formations were found to have the same bright white spectral reflectance (Figure 11), which can result in a misclassification of these grass types as bare soil. From the GT points it was confirmed that tiller formation of the buffalo grass was responsible for this misclassification.

Figure 11. Overview of the RapidEye image spectra and ground features in Nyando with photos of grass cover types and bushes



Uncultivated land, however, can be clearly distinguished from agricultural areas. Bushy vegetation (uncultivated or non-agricultural lands) can be seen scattered with a coarse green spectral, while agricultural land areas are shown with a very light green spectral and are visible through clear land parcel demarcations. However, spectral reflections of different agricultural crops (and growth stages) are the same and thus impossible to distinguish. With the exception of a mature Eucalyptus plantation (black spectra), agricultural crops have the same light green spectra. However, the light green spectral from an immature Eucalyptus tree canopy is similar to other crop types such as sugar-cane, Napier grasses or corn – especially during the stem-elongation growth stages (Figure 12).

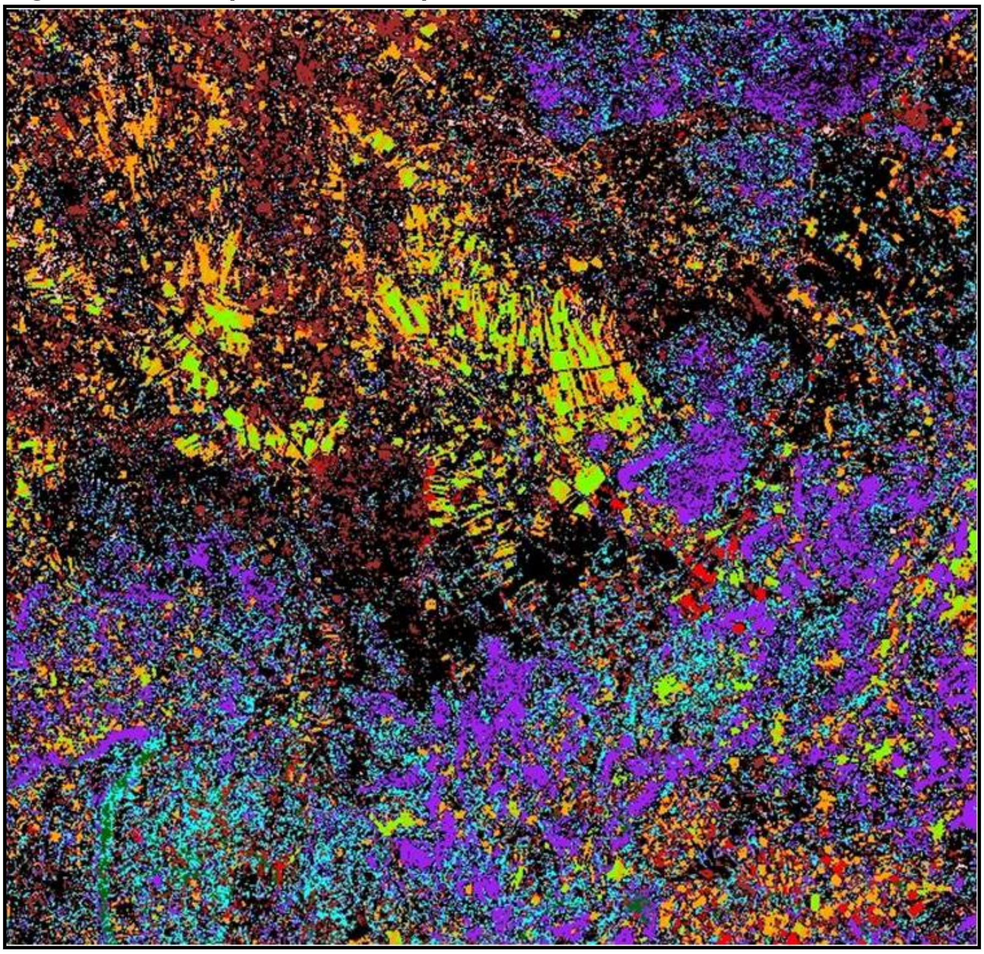
Figure 72. Primarily vegetated areas in Nyando and their spectral signatures of the RapidEye image

Supervised-image classification

The output of the supervised land cover use classification is shown in Figure 13. Overall classification accuracy of the supervised image was about 55%. The high error of the classification is attributed to the fact that the GT survey did not coincide with the date of the RapidEye image.

Image interpretation from the supervised image classification showed that the training sets collected during the GT survey provided enough information to separate dry bare soils (non-agricultural land) from higher moisture content soils (tilled fields) (Figure 14). Dry soil surfaces and erosion gullies have characteristic white spectral signatures on the ATCOR RapidEye image and dark brown spectral signatures on the supervised classified image, whereas high moisture tilled bare soils have a dark brown spectral signature on the ATCOR RapidEye image and a light green spectral signature on the supervised classified image.

Figure 13. Output of the supervised land cover use classification

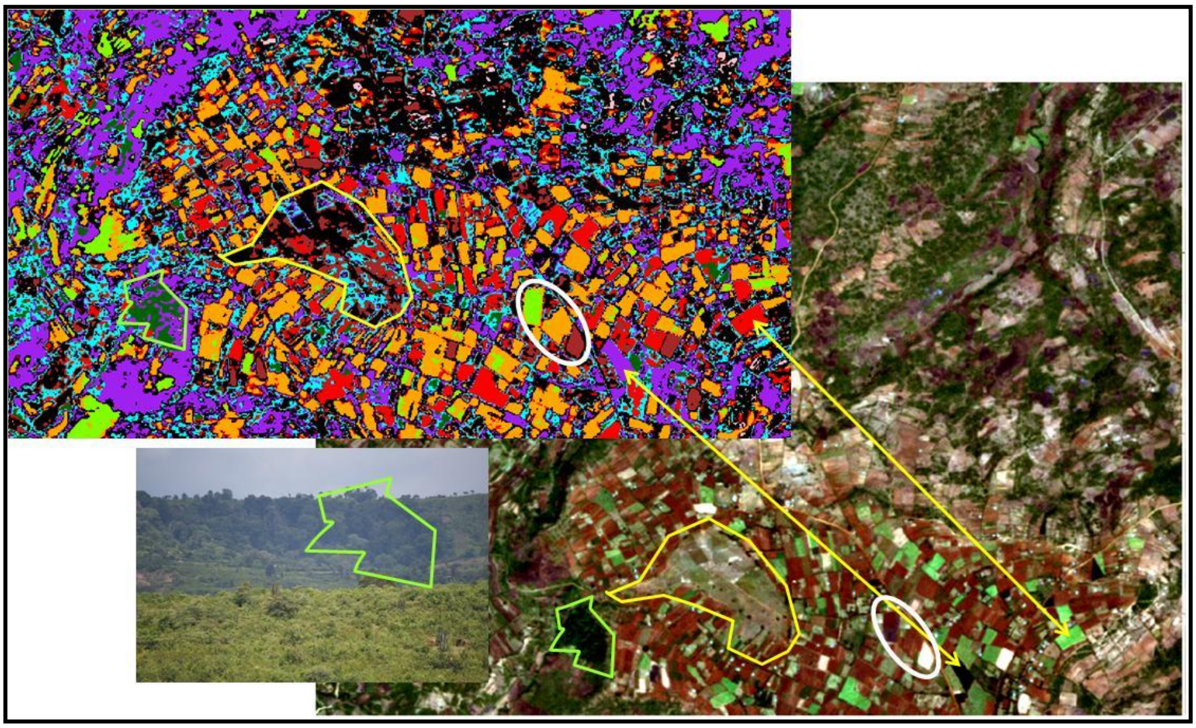


Given the scarcity of dense forest areas within the Nyando sampling frame, the primary forest area adjacent to cultivated areas was located during the GT. This was clearly distinguished as a feature class in the supervised image classification process (marked in green polyline) (Figure 14). A few more areas with a similar dark green signature can be seen in the image but they were confirmed as highly dense bushy vegetation on a steep slope instead of forested land.

The GT survey also showed that black spectral reflectance on the supervised image (yellow polyline) may represent mixed land cover, such as human settlement, grazing areas, kitchen gardens or even dry vegetation, which during the dry season may be exposing bare soils. This suggests the spectral representing dry above ground biomass or fallows, such as dry grasses, harvested corn or sorghum fields (with bare soil reflectance). The following pictures demonstrate some of these field observations.

However, the supervised image classification showed a clear improvement when compared to the unsupervised image. A clear differentiation of land cover features was achieved with the supervised image classification; primary forest and river networks (white circled polyline areas) and all major vegetation types were identified (high and low density bushy vegetation, primary forest, agricultural crops, and dry biomass) (Figure 14).

Figure 14. Comparison of spectral classes identified in the supervised image and ground features depicted in the ATCOR RapidEye image



Overall the supervised image showed a good differentiation of land cover types, especially for the cultivated land parcels represented with green, orange and red spectral, whereas bushy vegetation (purple and light blue), primary forest (in circled green polyline), and bare soils (dark brown spectral). What is also shown here is that the dark brown spectral reflectance may appear the same in the ATCOR image but, found also in light green spectral and the other is with orange spectral as shows in the supervised image. This indicates a difference between land cover types, suggesting that these differences may be caused by differences in moisture content or soil types but may also indicate fallow land with small amounts of plant residue still covering the ground. In this case, the light green spectral is representing tilled cultivated land.

Land cover types that may have bare soil spectral signatures during the dry season on the RapidEye image

A comparison to the SAVI[6]image shows an overall good correspondence between vegetated and non-vegetated areas. When compared to the NDVI image it is clear that the supervised image classification provided much more detail about the different land features and vegetation types (Figure 15). Overall, the supervised image classification identified the most important land cover features that are needed for the delineation process to derive the functional agro-zones segmentation (Figure 16).

[6]Soil-Adjusted Vegetation Index (SAVI): Vegetation index that accounts for, and minimises, the effects of soil background conditions

Figure 15. Comparison between the unsupervised and supervised RapidEye land cover classification, February, 2011 for Nyando. The features in white circles represent cultivated land parcels, except the smallest circle, which is the primary forest classified by the supervised image classification

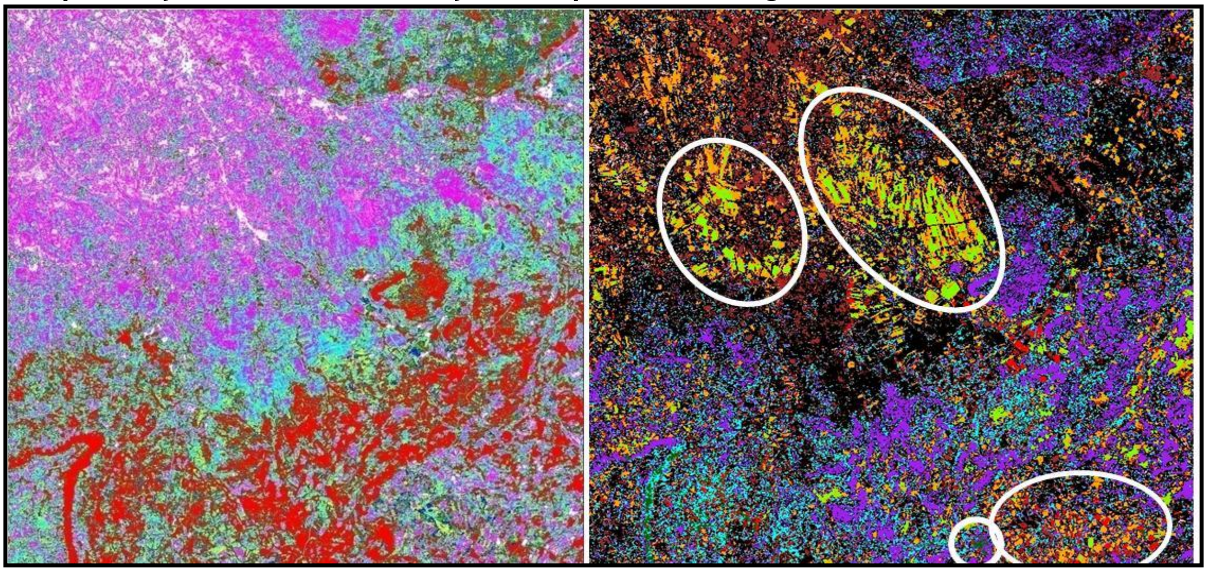
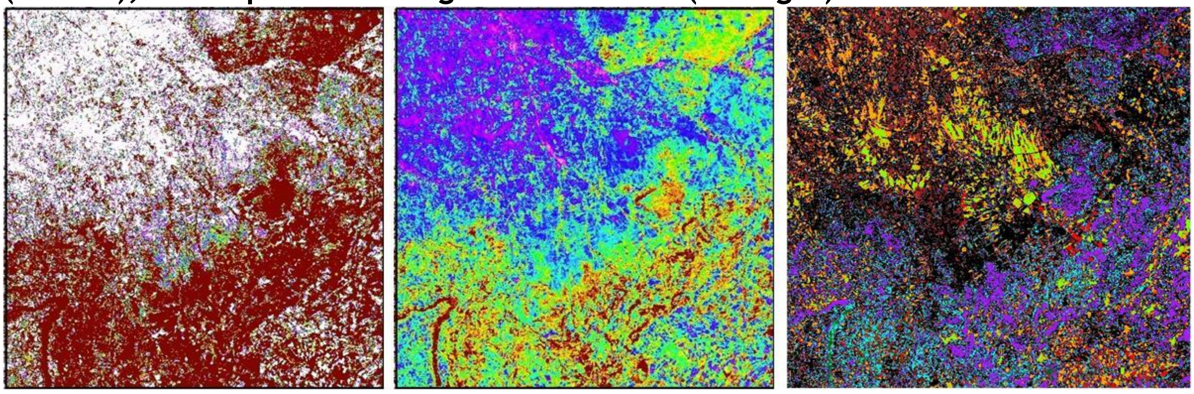


Figure 16. Comparing common vegetation indexes SAVI (far-left), NDVI (middle), and supervised image classification (far-right)

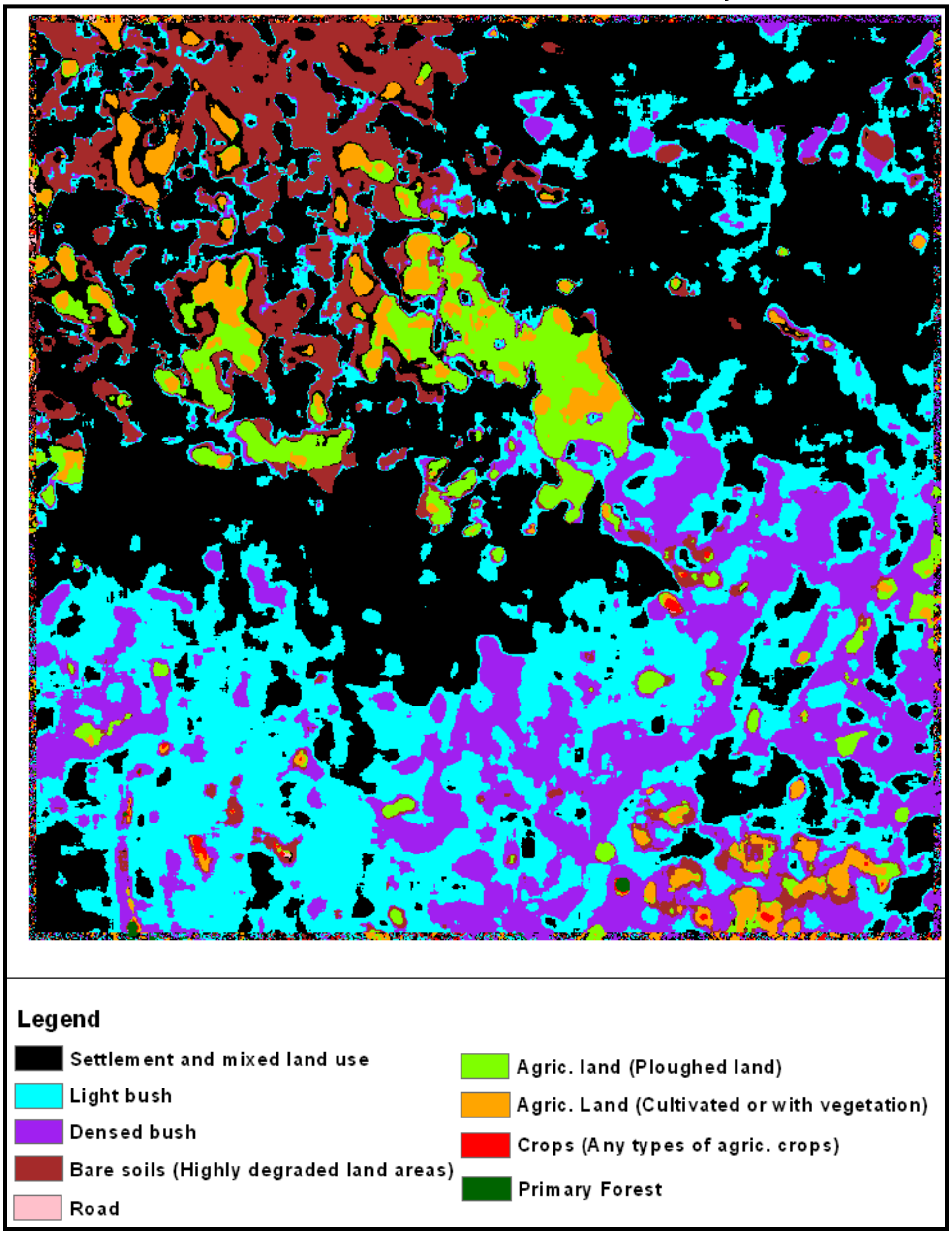


Segmentation of study area into functional agro-zones

The delineation process was based on visual interpretation of the supervised image. To sharpen the contrast between feature classes, the supervised image produced was filtered with Median (6x6) in ENVI., and further was smoothed in the same filter function (Figure 17). It is interesting that the primary forest cover on the block is still present, as seen on the image (dark green reflectance).

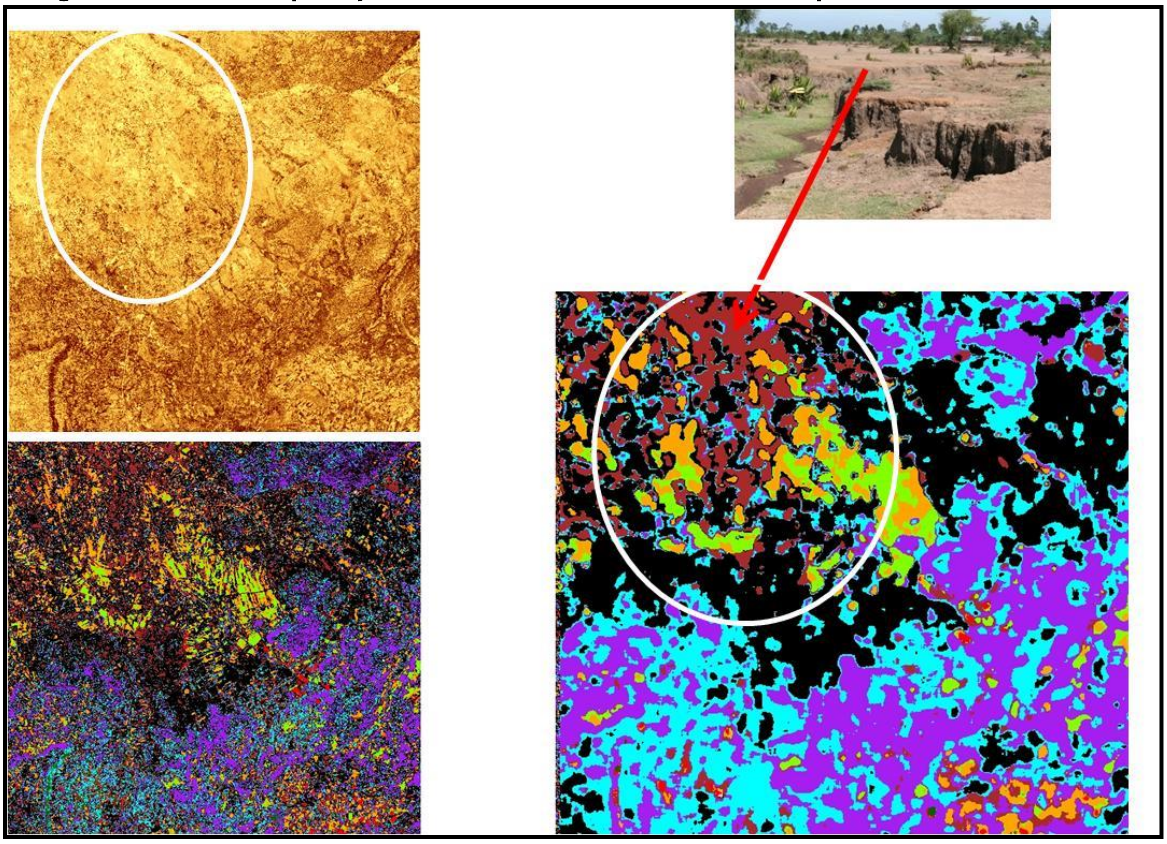
Additional and important information used to aid this process is the distribution of predicted soil organic carbon for Western Kenya, which has been produced by the Geoinformatic unit in ICRAF (Tor Vagen, 2011 unpublished data). This predicted soil organic carbon concentration was derived from a Quickbird satellite image with finer resolution (2.5 meters) as compared to the RapidEye image, thus was a valuable validation for this analysis. It is important to note that the delineation was only possible through the site-specific knowledge of the study block gained during the GT survey.

Figure 17. Output from the filtered supervised image shows distinct differences between land use cover within the Nyando block.



After application of the Median (6x6) filter, three distinctive agro-zones were clearly showed (Figure 18): a) highly intensive agro-zone area on low soil organic carbon concentration area (white circle), b) major forested areas (purple and light blue spectral), and c) good agricultural condition zone that provides support to productive farms in the form of good quality forests, sufficient amount of woody biomass, rivers, and other natural water sources.

Figure 18. Steps in delineation process of the functional agro-zones show patterns of the filtered image, soil organic carbon, and supervised classification images from the RapidEye as tools for the delineation procedure.



The delineated forestlands were further overlaid on topography (DEM, derived from ASTER data), which showed that more than 90% of the bushy land cover is located on the higher ground. This was also confirmed during the GT survey.

The picture taken during the GT survey revealed that even though the block was inspected during the rainy season, land on the top left corner of the study site was bare and exposed, thus is characterized as unhealthy or highly degraded.

Time-series analysis

Software for the processing and interpretation of remotely sensed image time series (SPIRITS) is designed for the post-processing of time series (ten-daily or monthly composites) derived from low resolution sensors such as SPOT-VEGETATION, NOAA-AVHRR, METOP-AVHRR, TERRA-MODIS and MSG-SEVIRI (Rembold, 2012). All maps generated by SPIRITS are directly compatible with other common image processing software like ENVI with [*.img] format.

SPIRITS provides summaries of seasonal variation of input parameters (Rainfall and NDVI) over a 10-year period, which includes climate factors (rain and temperature) integral to the CCAFS research agenda. The advantage of SPIRITS is its ability to do time-series analysis on vegetation using low-resolution satellite imagery. All data sets used in the analysis were rasterized in SPIRITS. CNDVI and RFE data sets were formatted and provided by eStation[7] (FAO Somalia, Nairobi).

The main input data sets used for SPIRITS analysis are:

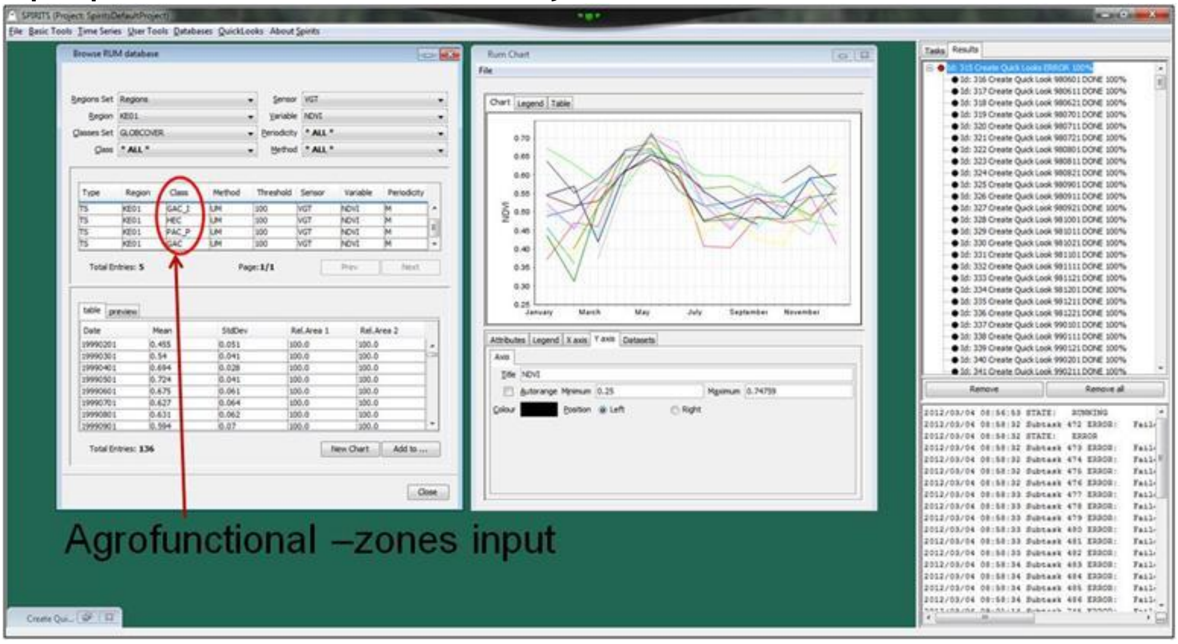
- CNDVI derived from SPOT-VGT (1km) [May 1998 – Feb 2011]
- RFE estimate derived from NOAA-AVHRR [Jan 2000 – Feb 2011]
- Functional agro-zones thematic map derived from the supervised image classification

The main outputs produce by the software are:

- Vegetation anomalies based on the comparison of the actual NDVI maps and the long- term average
- Extraction of regional unmixed means statistics for CNDVI and RFE for different areas within an image (such as agro-zones)

Figure 19 shows that the functional agro-zones developed for this study were used as input classes in further SPIRITS analysis. Each agro-zone was subsequently analysed for its temporal changes in CNDVI values and interactions to the rainfall estimates (RFE).

Figure 19. Clip from the SPIRITS analysis show the functional agro-zones as input parameter for time-series analysis.



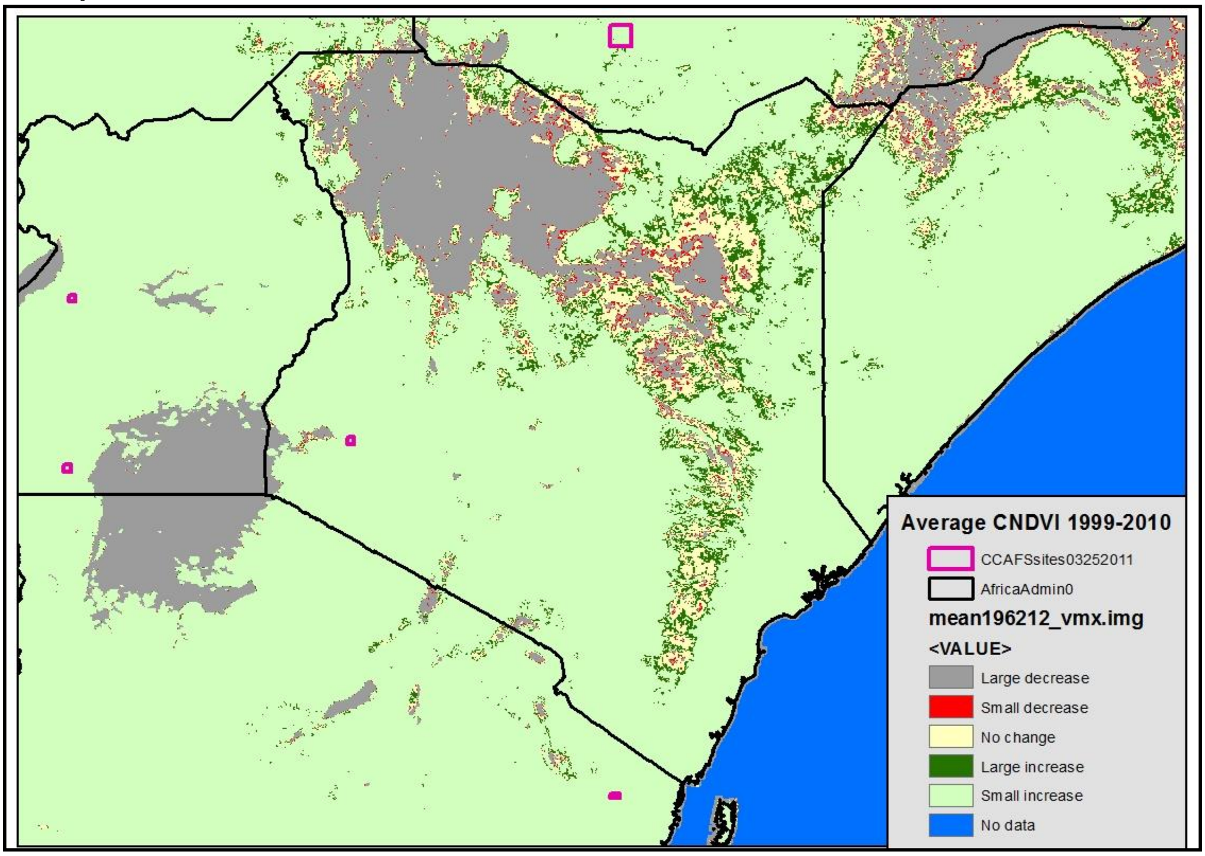
[7] http://estation.jrc.ec.europa.eu/

Time series analysis of vegetation changes in East African

To understand the overall health of the ecosystem of individual CCAFS sites, vegetation anomalies were calculated. Firstly, a long-term average of vegetation growth (CNDVI) was calculated for the period 1999 to 2010, whereby for each site the highest level of greenness (maximum CNDVI) within a year (usually the peak of the cropping season) was extracted. The calculated average is the average of the annual CNDVI maxima.

The distribution of the average maximum CNDVI value over the Eastern Part of Africa shows a strong decline of greenness started in Tsavo, East towards the North. Areas especially affected stretch from Lake Turkana to the Ethiopian border (Figure 20). In contrast the Northeast of Kenya to the Somali border has actually seen an increase of vegetation cover since 1999.

Figure 20. Average maximum CNDVI value 1999-2010 for East Africa representing five CCAFS sites in Western Kenya, two in Uganda, Tanzania and Ethiopia.



With the exception of Bohero, Ethiopia, all CCAFS study sites in East African were found to be located within areas with small increases in greenness or vegetation cover (maximum cumulative NDVI-CNDVI) (Table 2). From 1999 to 2010 Bohero, Ethiopia appeared to have a relative higher increase in greenness than other CCAFS sites.

Table 2. Groups of CCAFS sites showing the status of the land-health based on SPIRITS analysis.

CCAFS Study sites	Uganda (Hoima)	Uganda (Rakai)	Kenya (Nyando)	Tanzania (Lushoto)	Ethiopia (Yabero)
10 year maximum CNDVI level	Small increase	Small increase	Small increase	Small increase	Medium increases
Status	Low greening	Low greening	Low greening	Low greening	greening
Land-health	Good	good	good	good	good

To understand yearly conditions, the distribution of the maximum CNDVI for each year was compared to the average of maximum CNDVI in ten years (Figures 21 and 22). The years with the largest extent of decreasing greenness (vegetated areas) were in 2000, 2001, 2002, 2005, 2009, and 2010. In particular, 2000 and 2009 suggest a severe drought affected almost the entire Northern part of Kenya. However, even during these years of extreme drought, the Bohero block in Ethiopia showed to have a strong increase in vegetation cover, indicating that the rainy seasons were better in this area. For the years 1999, 2003, 2004, 2006, and 2007, a larger area represented a small increase in the CNDVI value, which indicates good cropping seasons for 2006 and 2007.

Figure 81. Maximum CNDVI values for each year compared to the average maximum CNDVI values for the period 1999-2010 for CCAFS sites in four East African countries (Kenya, Uganda, Ethiopia, and Tanzania).

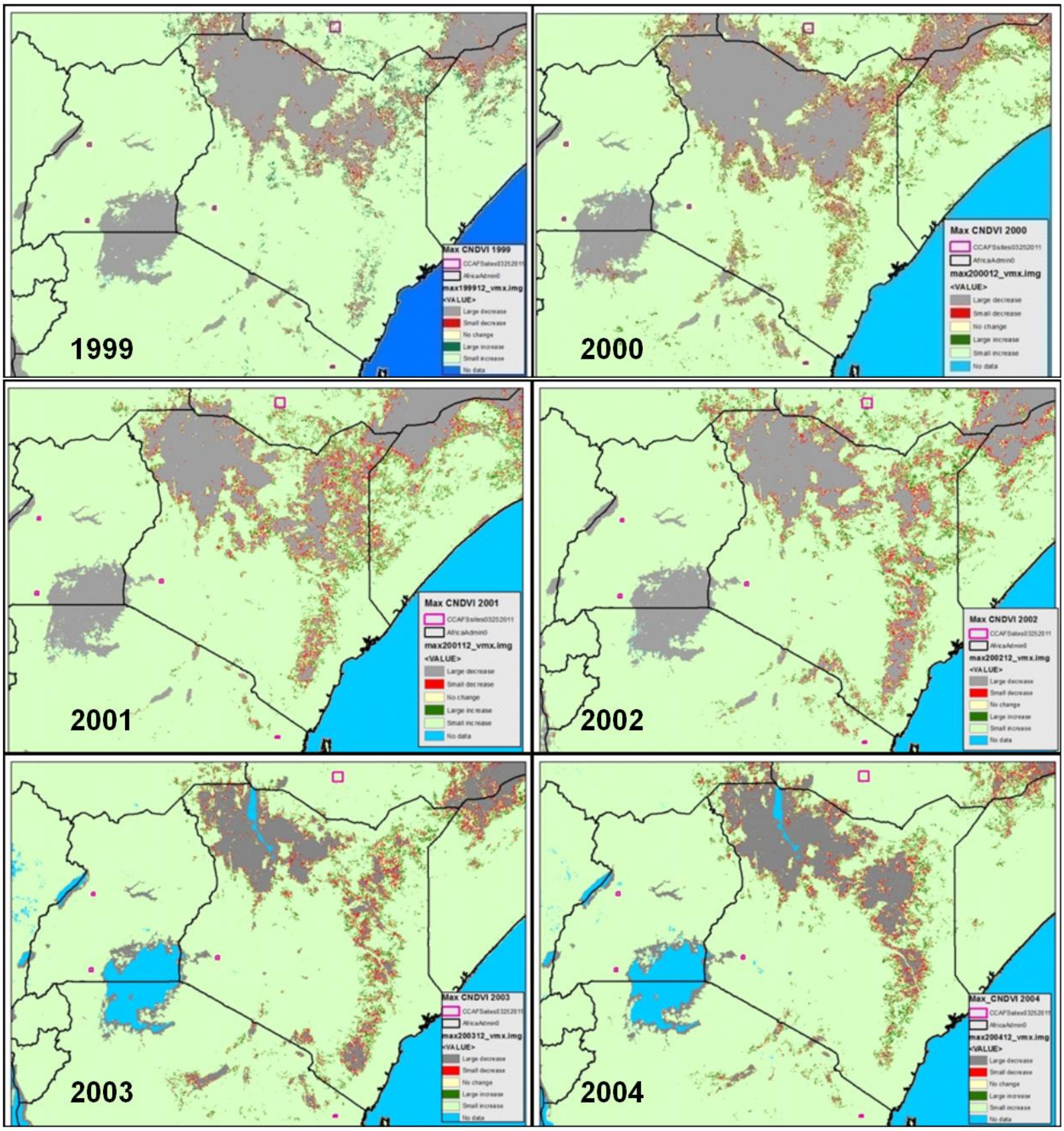
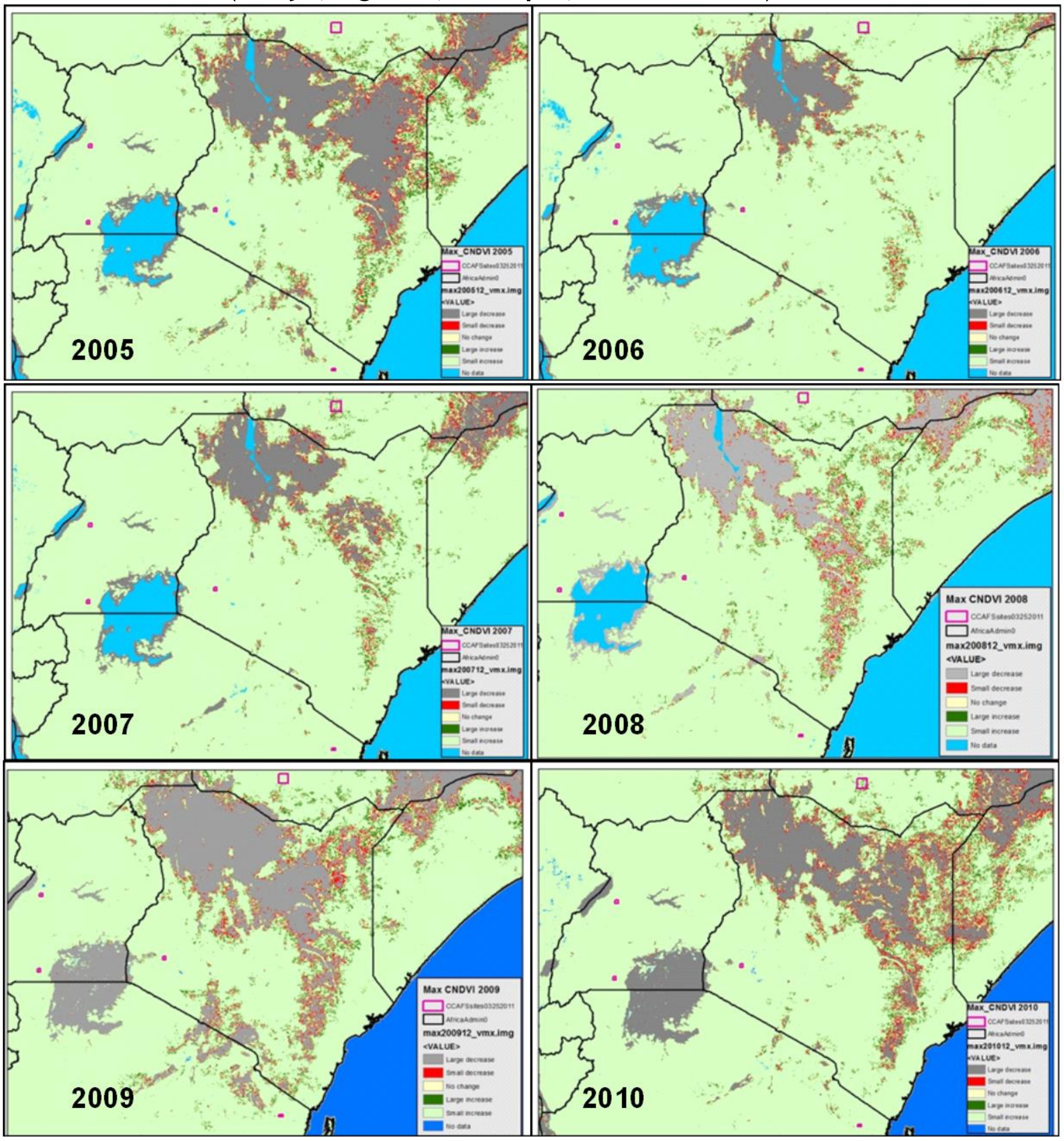


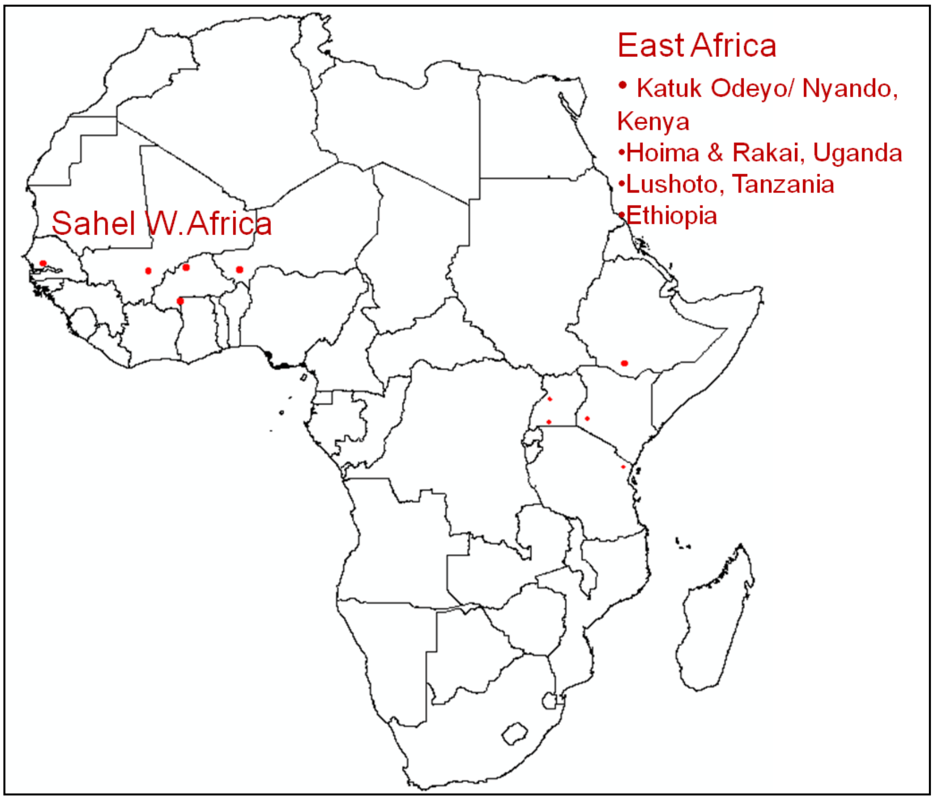
Figure 22. Maximum CNDVI values for each year compared to the average maximum CNDVI values for the period 1999-2010 for CCAFS sites in four East African countries (Kenya, Uganda, Ethiopia, and Tanzania).



The Nyando site of Western Kenya (Katuk-Odeyo block)

For the purpose of this case study, Katuk Odeyo, also known as Nyando block, in Western Kenya was particularly analysed due to the availability of data sets. This is also due to the requirements of this integrated analyses, which calls for optimal amounts of processed social-biophysical datasets, and especially processed satellite datasets that are the integral data in this study. In term of CCAFS research interests, this site provides a framework to improve the baseline study over the long-term within and between different CCAFS study areas.

Figure 23. Sentinel sites for CCAFS in East and West African

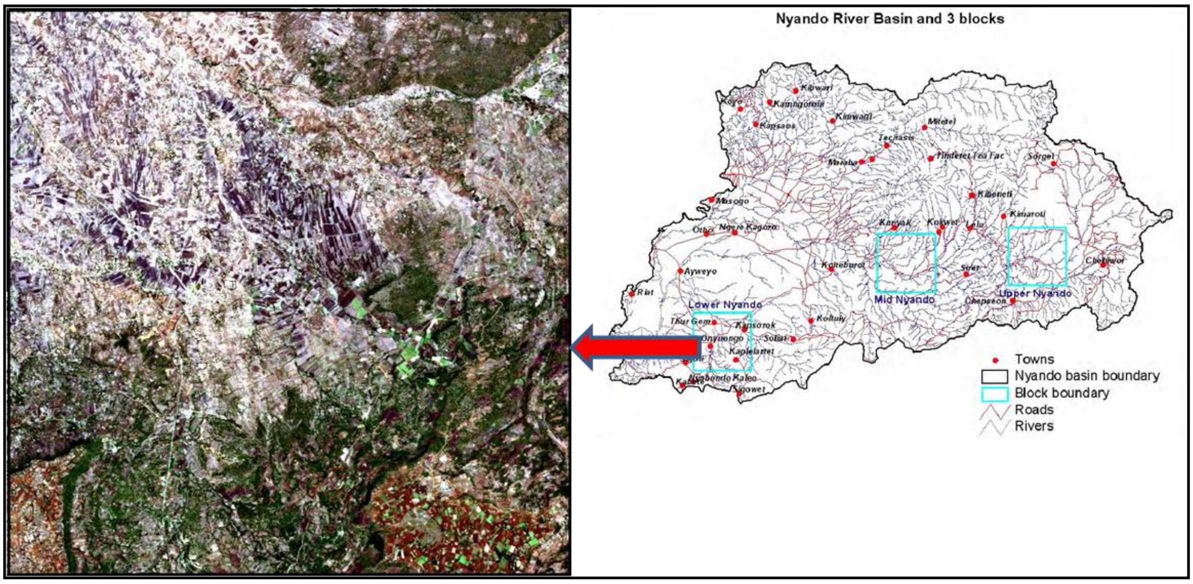


For the East African region, CCAFS sites consist of 10x10km locations in Katuk Odeyo in Kenya, two sites in Uganda at Hoima and Rakai, and Lushoto in Tanzania, as well as 30x30 km in Bohero, Ethiopia (Figure 23). The agro-landscape characteristics displayed by the spectral feature of the RapidEye images indicate similar land cover types of the 10x10km sites to Nyando. The Bohero landscape features are very different than the other East African sites and more similar with those in the West African region like Segou in Mali, Niger, Senegal and Burkina Faso that display a more semi-arid and desert types spectral.

The CCAFS study site in Katuk-Odeyo is located within the Nyando River basin. This river basin is one of the seven major river basins within the Kenyan side of Lake Victoria drainage basin and covers an area of approximately 3550 km^2 (KARI, 2006). Within the basin there are the Upper and Lower Nyando divisions and 16 sub-locations (Figure 24). The Lower Nyando block (CCAFS block) is located in the lake plain (Kano Plains) of Lake Victoria in Nyando and Kericho Districts.

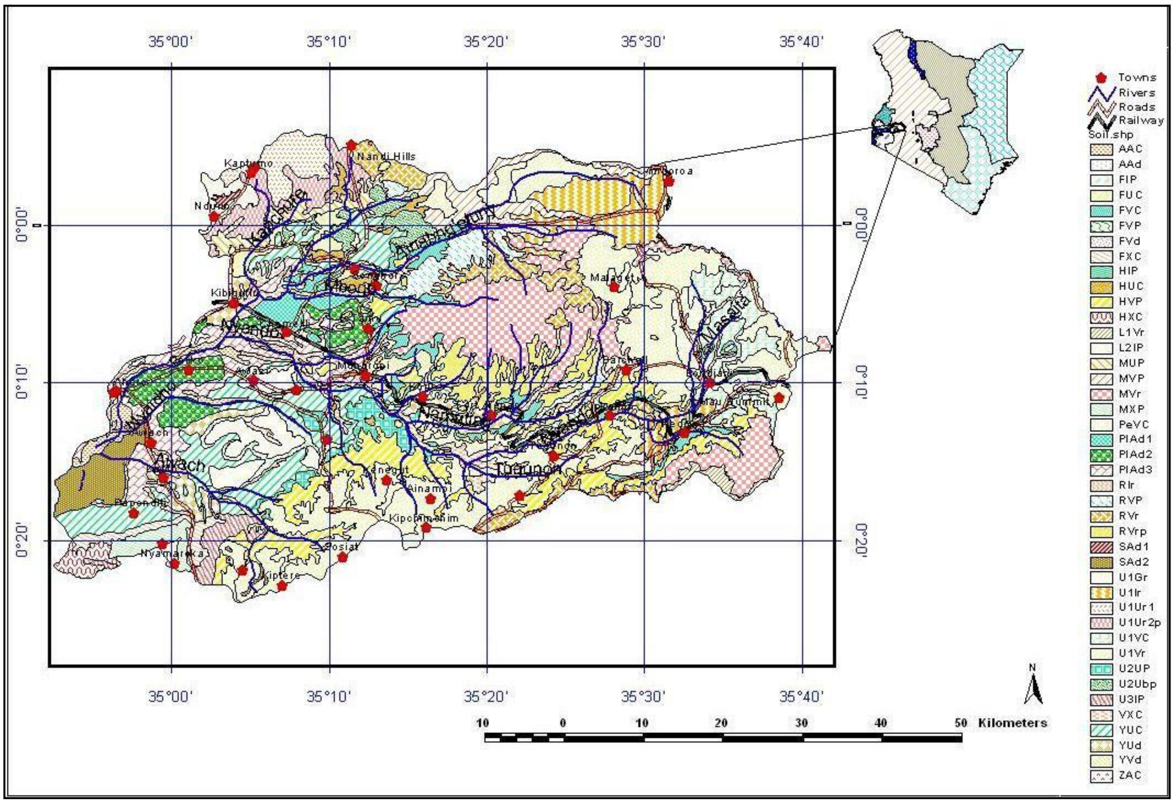
The population is predominantly Luo and Kalenjin. While the main land cover types are forestry and agriculture, the individual land-uses are as diverse as the basin's soil types (Van Der Kwast, 2002). As observed, the block is dominating by subsistence farming practices, with a mix of crops typical of the lower elevations in Western Kenya. Maize and sorghum are the major crops especially in the middle part of block; banana and cassava are also grown. The area is also important in the production of mangos (ICRAF/ NALEP Project). The crop type characteristics are more diverse in the highlands located on the Southeast of the study block, where crops like tea, sugar cane, and eucalyptus can be seen growing between food crops land parcels.

Figure 24. Location of the block within Nyando Basin and RapidEye satellite image of the study block.



Nyando experiences diverse climate ranging from humid to sub humid, which is mainly attributed to variation in altitude from the highlands to the shores of Lake Victoria. The mean annual rainfall varies from 1000 mm near Lake Victoria to about 1600 mm in the highlands (Njogu, 2000). The rainfall pattern shows no distinct dry season. Peaks occur during the long rains (March – May) and short rains (October – December). The proximity to the highlands and lakeshore causes a considerable spatial variation of rainfall. In the lowland zones, the short rains are unreliable, and sustain only drought tolerant crops like millet and sorghum.

Figure 95. Soil map of the Nyando River Basin (Waruru et al., 2003).



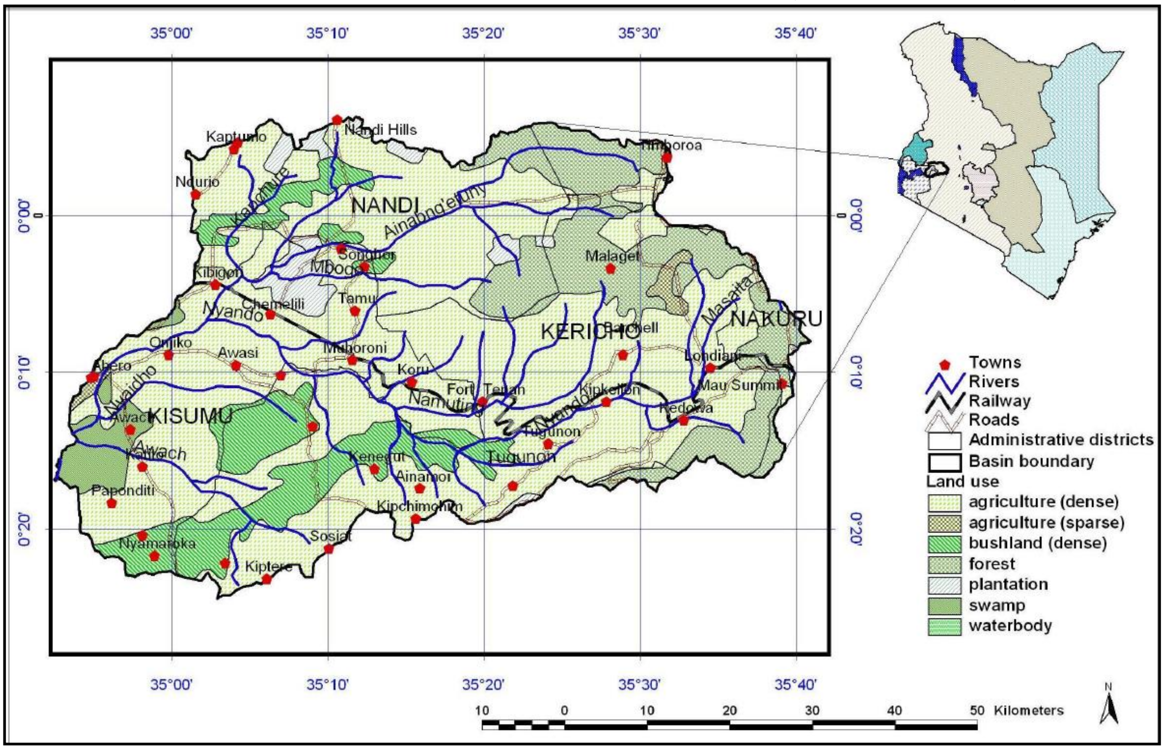
Soils in Nyando basin vary with changes in elevation and parent materials (Waruru et al., 2003). Soils in the highlands are well drained and deep to very deep (Figure 25). They are of moderate to low fertility and have shallow humic topsoil and subtle soil aggregates. These soils include: nitosols, alisols, luvisols and cambisols. The soils found in degraded hills and volcanic foot ridges, however, are shallow, rocky and boulder. These include: leptosols and cambisols. In the lowland or in the middle of the study block, soils are moderately deep to deep. They have impeded drainage, sodic subsoil and less stable aggregates. They include: luvisols, gleysols and fluvisols.

Forested land falls under government designated land. Some of the larger forests in the area are: Timboroa, Tinderet, Londiani, Western Mau and parts of South Nandi. Some of these are commercial timber plantations consisting of exotic species such as *Pinuspatula*, *Pinus radiate* and *Cupresses spp*. Timber is harvested legally and illegally for pulpwood and fuel (Wagate and Macharia, 2003). Encroachment into natural forests is common, indicated by agricultural fields inside forests, re-vegetated sites, grazing lands and abandoned charcoal production kilns.

Agricultural activities in the basin consist of subsistence and cash crop farming. In subsistence farming, which is the main agricultural activity, mixed farming is common, with cattle, goats, sheep and donkeys kept together with maize, sorghum, millet and vegetables (Figure 26).

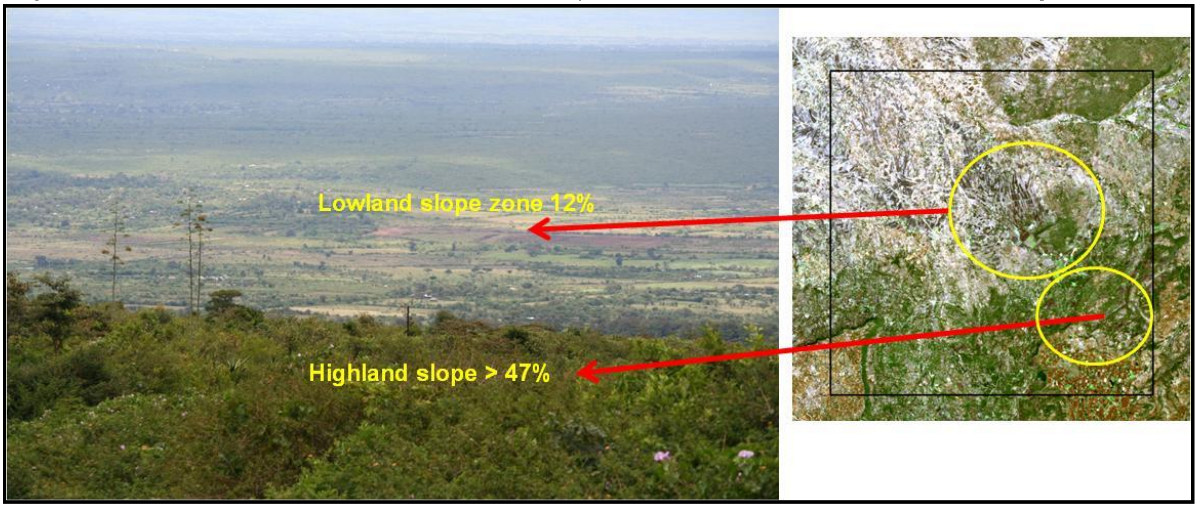
Generally, the main cash crops in the Nyando basin are tea and sugar cane. These crops are grown in large plantations under the management of multinational companies. The tea growing estates are Tinderet and Kapchorua. Sugar cane is grown in the nucleus estates of Muhoroni, Chemelil, Soin and Miwani. These companies have out growers, who grow and supply additional crops to the factories. Other land use/land cover types in the basin are permanent and seasonal swamps. These areas are mainly used for farming seasonable vegetables and are harvested for grasses such as papyrus and reeds, however they were only observed once within the block during the GT survey.

Figure 26. Land use map of the Nyando River Basin (WKIEMP, 2006).



There are various changes in land use in the basin. Akotsi and Gachanja (2003) reported that vegetation has changed considerably from the original woody types to the present shrub types. These changes are attributed to human activities such as overstocking, burning of charcoal, and clearing of vegetation. The intensity, type and extent of crops cultivated have changed considerabley over time due to population increases (Wagate and Macharia, 2003). The land uses/land cover map of the Nyando basin is shown in Figure 26 along with the stratification of the block landscape (Figure 27).

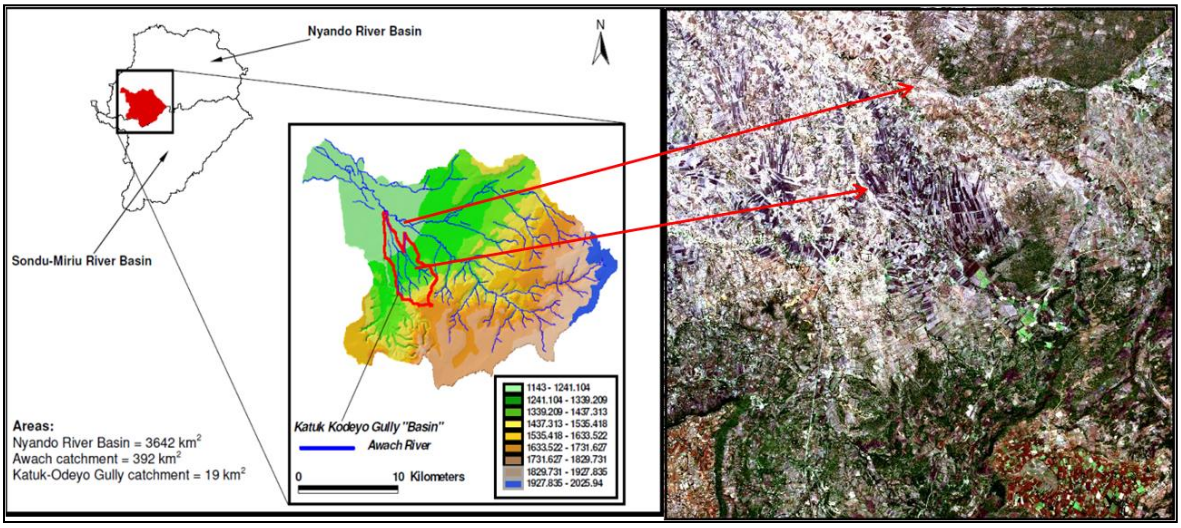
Figure 27. Stratification of Katuk-Odeyo Sub-watershed based on slope.



The lower Nyando block is characterized by a distinctive gully. The formation of the gully has been one of the main research focuses of both the government and NGOs. Most of the past works conducted in Nyando have addressed issues of conservation and preservation of the watershed, while attempting to halt land degradation and rehabilitate the gully area.

The gully itself has been considered a sub-watershed of approximately 20 km^2 within the 400 km^2 Awach-Kano watershed (Figure 28). The watershed extends from Sigowet Division of Kericho District to lower Nyakach Division of Nyando District.

Figure 28. Sub-watershed and the gully formation as seen from the RapidEye.



During the village March, 2011 baseline survey conducted in Komango village, the community expressed concern due to land lost from the gully's expansion yet also noted the gully provides basic materials and resources such as sand, rock, ballot for housing material, and cash income.

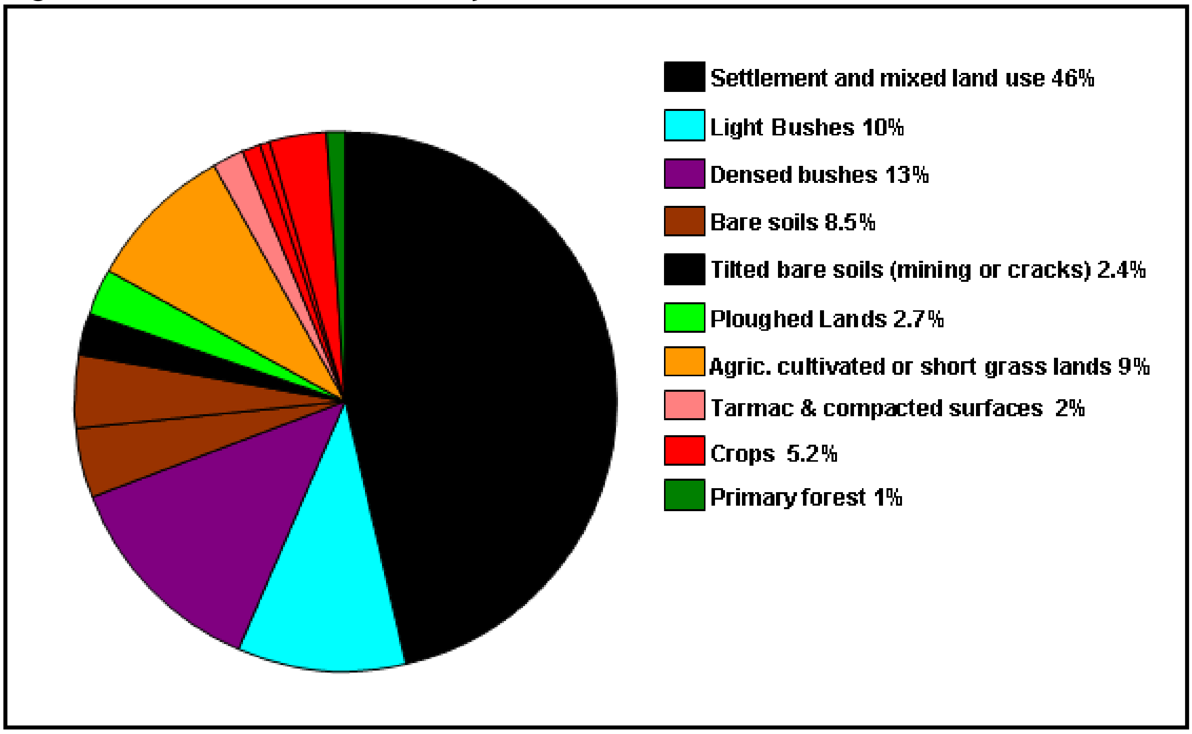
The water sources available to the community in Katuk Odeyo/Nyando basin are rainwater harvested in water pans, natural water holding depressions such as gullies, and a few roof catchment systems (WKIEMP, 2006). This surface water is generally of low quality due to poor methods of collection and low levels of system maintenance. Almost all the surface water sources dry up during the dry seasons resulting in severe water scarcity and stress. There are a few boreholes, shallow wells, and springs, however they dry up during the dry season (CCAFS village level baseline 2011, personnel communication).

Due to the rainfall pattern and catchment characteristics, there is a high potential for rainwater harvesting to meet local water requirements for irrigation, domestic use and environmental conservation. However, during the village baseline survey conducted in March, 2011 in Komango village, it was noticed that efforts to harvest rainwater in the area are scarce. Households rarely have basic water tanks and lack even gutters on roofs. Only schools and churches have water tanks, which are provided by NGOs like the World Vision.

Land Use Cover in Nyando Block

Based on the supervised image classification, the area categorized as settlement and/or mixed activity areas cover 46% of Nyando and represents the largest form of land use (Figure 29 and 30). However, the mixed activity within this area is not limited to only the main settlement area as it is also utilized for other human activities like farmland, kitchen gardens, and grazing fields. This area, which represent, as black spectral feature, is where human activity and utilisation are assumed the most intensive, therefore zoned as an Intensive functional agro zone (IAC).

Figure 29. Land cover use in Nyando block.

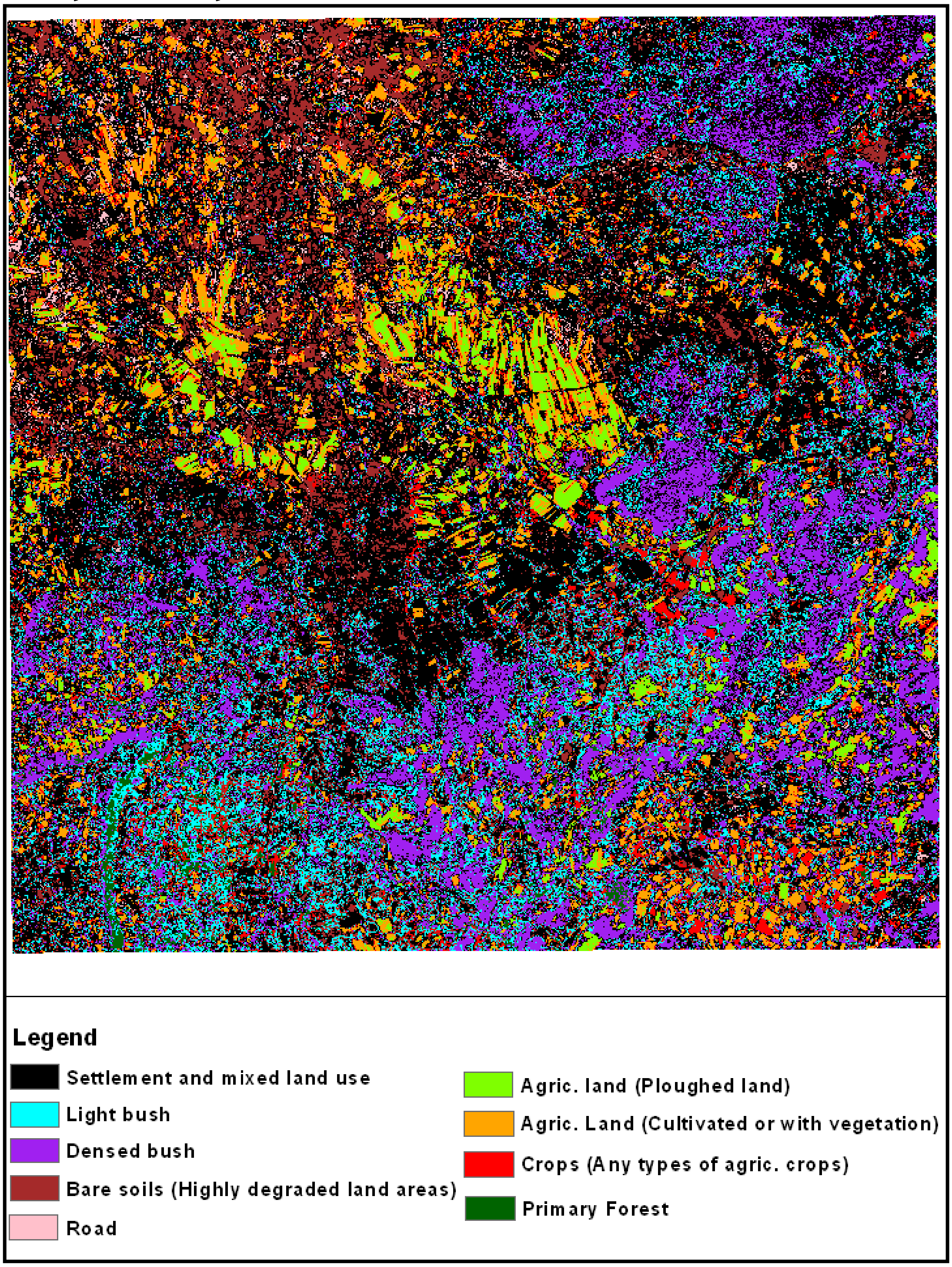


Forested land accounted for a total of 23%, with low density and high density covering 10% and 13%, respectively. The latter is mainly located on slopes (18 to > 25% steepness). The bare soils were represented with a dark brown spectral feature, which accounted for 8.5% of the total area. The area with no vegetated cover is mostly located on the upper left corner of the study block and is classified as highly degraded or non-agricultural land. This can be assumed since exposed bare soils located on the agricultural land parcels (lower right corner of the block) were classified as green spectral with the same condition of no biomass on the ground. However, since this finding was based on the dry season RapidEye image, some of these areas may be overestimated because of the vegetation changes that occur during the rainy season. Some of these areas are predicted as kitchen gardens and grass fields given they are mostly located together with settlement areas, but some of these areas may also be exposed bare soil agricultural lands with low water moisture content.

Only 5% of the image was classified as an agricultural crops area, while short grasses accounted for 9%. This is attributed to corn and sorghum having similar spectral signatures as sugar cane and Napier grass, especially during the early growth stage. It therefore assumed that some of the areas classified as short grasses are in fact food crops. A better differentiation could be achieved by a more in-depth spectra analysis of these areas utilizing the Red-Edge band (Band 4) from the RapidEye image (Heute, 1987; Curran, 1981).

The 1% primary forest can be mainly attributed to the area's geo-coded during the ground survey. Other mixed forest areas, such mature acacia forests, were classified in the same signature as highly dense bush vegetation.

Figure 30. Supervised image classification of the RapidEye satellite image of the Nyando study block.

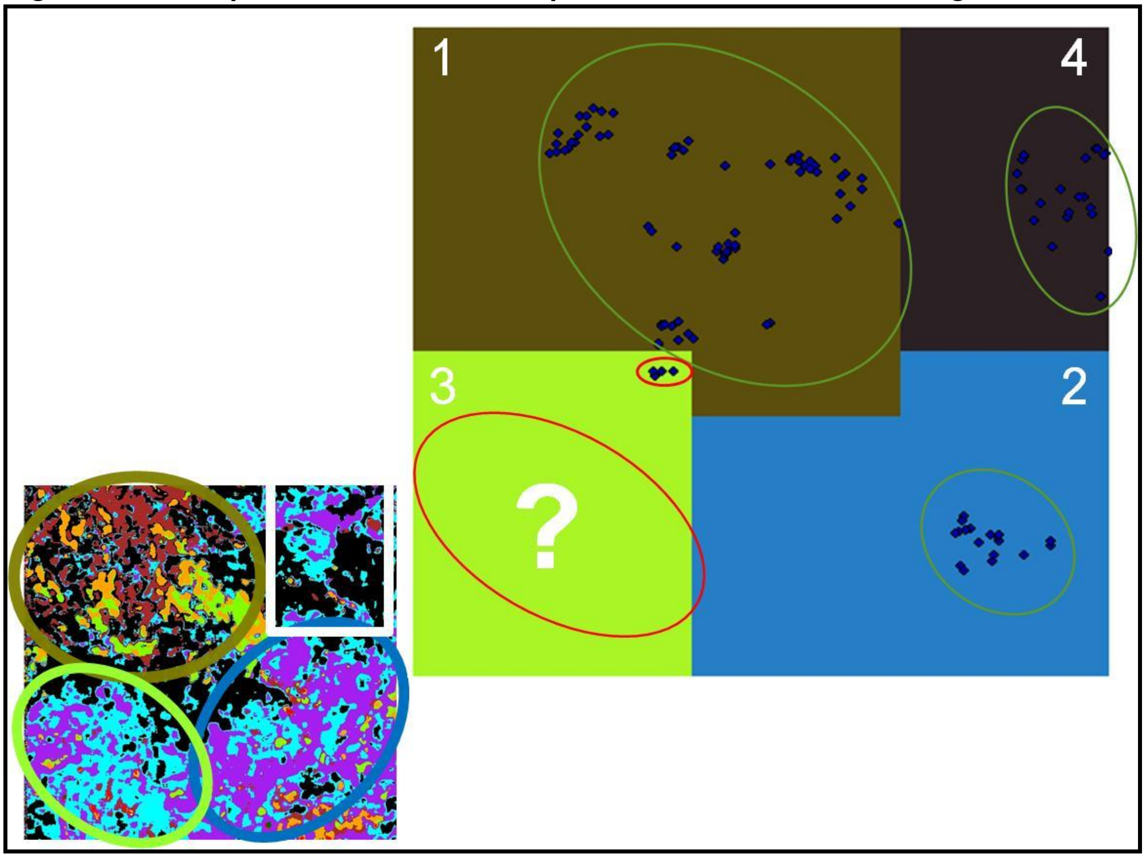


It is important to note that the size of the area is likely to be overestimated given the high classification error, due to the mismatch between acquisition of the RapidEye image and the time of the ground survey. It is likely that areas in the vicinity of houses, such as kitchen gardens, dry grazing fields, dry harvested crops, and bush lands were misclassified as bare soils not covered, where in the rainy season these particular areas would give a strong green signature and may be classified as Good agriculture condition (GAC) areas.

Four functional agro-zones within the block (Figure 31):

1. Dark green: IAC - functional agro-zone 1.
2. Blue: GAC as an agricultural area that still consists of healthy agro-ecological factors as farm supports - functional agro-zone 2.
3. Green: PAC as an agricultural area that still has available space for agricultural expansion (area may have obstacles due to geographical factors) - functional agro-zone 3.
4. Dark brown: SAC as an area which still has the capacity to carry out agricultural and farming practices, but below the GAC due to limited resources - functional agro-zone 4.

Figure 31. Output from delineation process of the functional agro-zones.



SAC is similar to PAC given its vegetated land consists of bush land and kitchen garden. However, it does have a much larger proportion of degraded land (see description in IAC) whereas with PAC there is an undulating and steeper landscape. At the same time, SAC has a better supply of water (river network) and a flat highland plateau, which is utilized for grazing especially during the dry season within the block. In addition, governmental acacia forest is located within this agro-zone. SAC accounts for 1010 hectares, where the IAC represents the largest area within the block with 5553 hectares respectively. Generally, it can be described that Nyando block is a highly fragmented landscape, severely altered by human activities. The main land use types are human settlements, mining, compacted and highly degraded land, tarmac and hard surfaces, and mixed with patches of forests (primary & secondary) that are protected by the authority or the community for its services and high value.

As discussed earlier, the limitation of this study is that the satellite image was taken during the dry period, showing an unclear separation of soil covered by dry vegetation, which could be fallow, grazing areas or bare soil, making the result of degradation difficult to determine. An analysis of multi-temporal RapidEye images taken during different seasons would overcome such limitations and improve the delineation process (Foerster et al., 2010; Tapsall et al., 2010).

Table 3 provides an overview of the different land use classes for each functional ago-zone. The GAC accounted for a total of 1633 hectare and consisted mainly of ploughed land (270 ha), short grasses (899 ha) and crops (400 ha). The PAC covers an area of 1750 hectare that consists mostly of forestland. These areas could be potentially converted into agricultural land or into GAC but are limited by the steepness of the landscape regardless for their high soil organic carbon concentration and biomass cover. Access to water is also a limiting factor to pursue agriculture within the PAC.

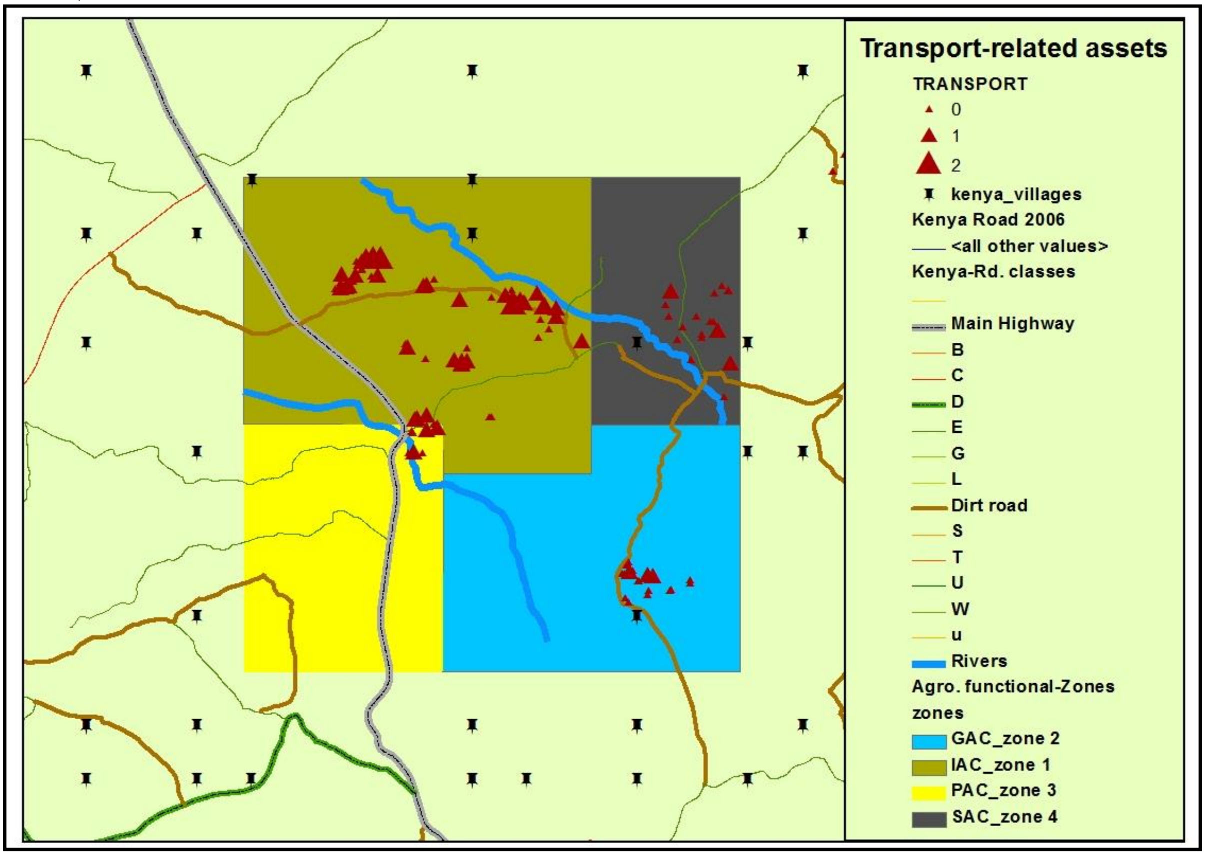
Table 3. Land cover classes in Nyando block and areas delineated for functional agro-zones.

Functional zone	Land cover classes	Area (ha)	Area (%)
GAC	Ploughed land	270	3
	Short grasses	899	9
	Crop1	119	1
	Crop2	70	1
	Crop3	325	3
Total		1683	17
PAC	Bushes & kitchen garden	747	7
	Dense Bushes	1003	10
Total		1750	18
IAC	Settlements	4140	41
	Bare soils (dry)	426	4
	Bare soils (moist)	452	5
	Mining sites & bare soil	242	2
	Tarmac roads and hard surfaces	186	2
	Primary forest	107	1
Total		5553	56
SAC	Bushes & kitchen garden	245	2
	Dense Bushes	253	3
	Settlements	512	5
Total		1010	10

Infrastructure differences between the functional agro-zones

The main highway connecting the study block with Kisumu town intersects both IAC (Zone 1) and PAC (Zone 3). GAC (Zone 2) and SAC (Zone 4) are disconnected from the main highway. The road network only consists of dirt roads, which require a 4x4 vehicle during rainy season, and exists in Zones 2 and 4. It was also observed that the number of villages noted by the Ministry of Public Works does not include the total number of existing villages within the block because there are so many villages that are not included especially within the study block (Figure 32).

Figure 102. Existing road network and villages (Ministry of Public Works, 2006).



RFE and NDVI

The long-term average from 2000 to 2011 for CNDVI and RFE show that on average the main rainy season coincided with the months of March and May, with a peak in April. The CNDVI follows this pattern with a lag of about 1 month. The short rains start in July, lasting until the end of the year, with a peak in October. The total rainfall intensity is much lower than that of the long rains, reflected in a very modest response of the NDVI (Figure 33).

Figure 33. Average CNDVI and Rainfall (RFE) relationships in Nyando block.

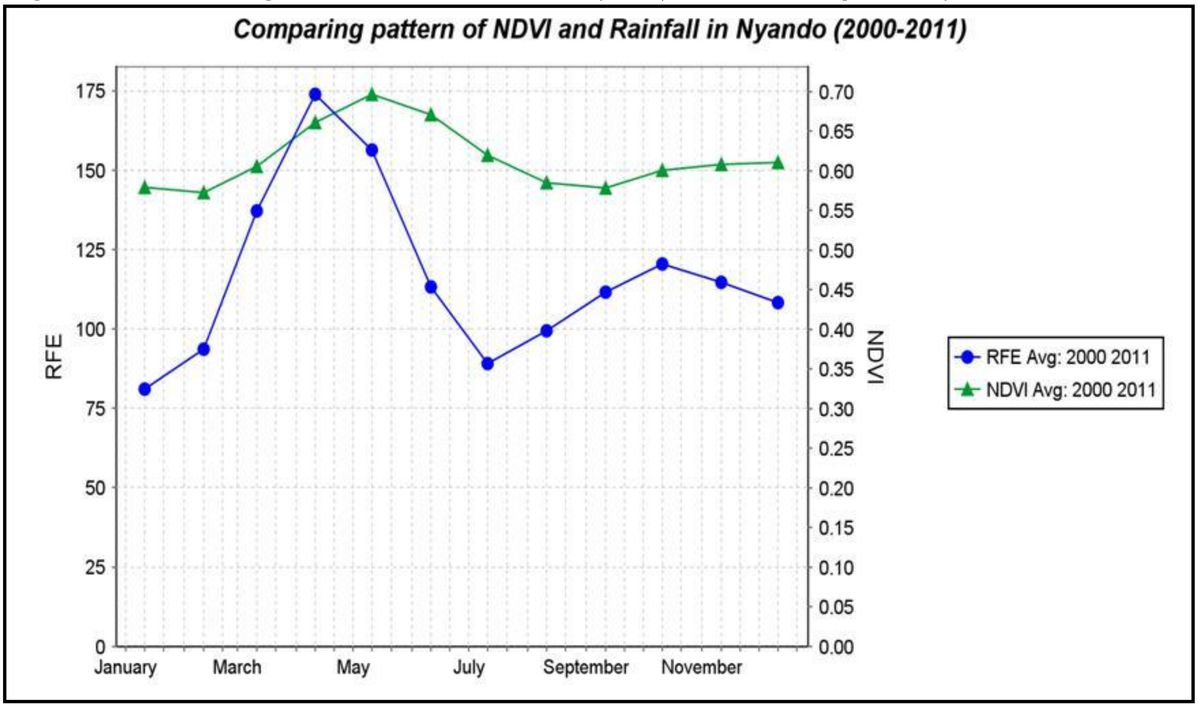
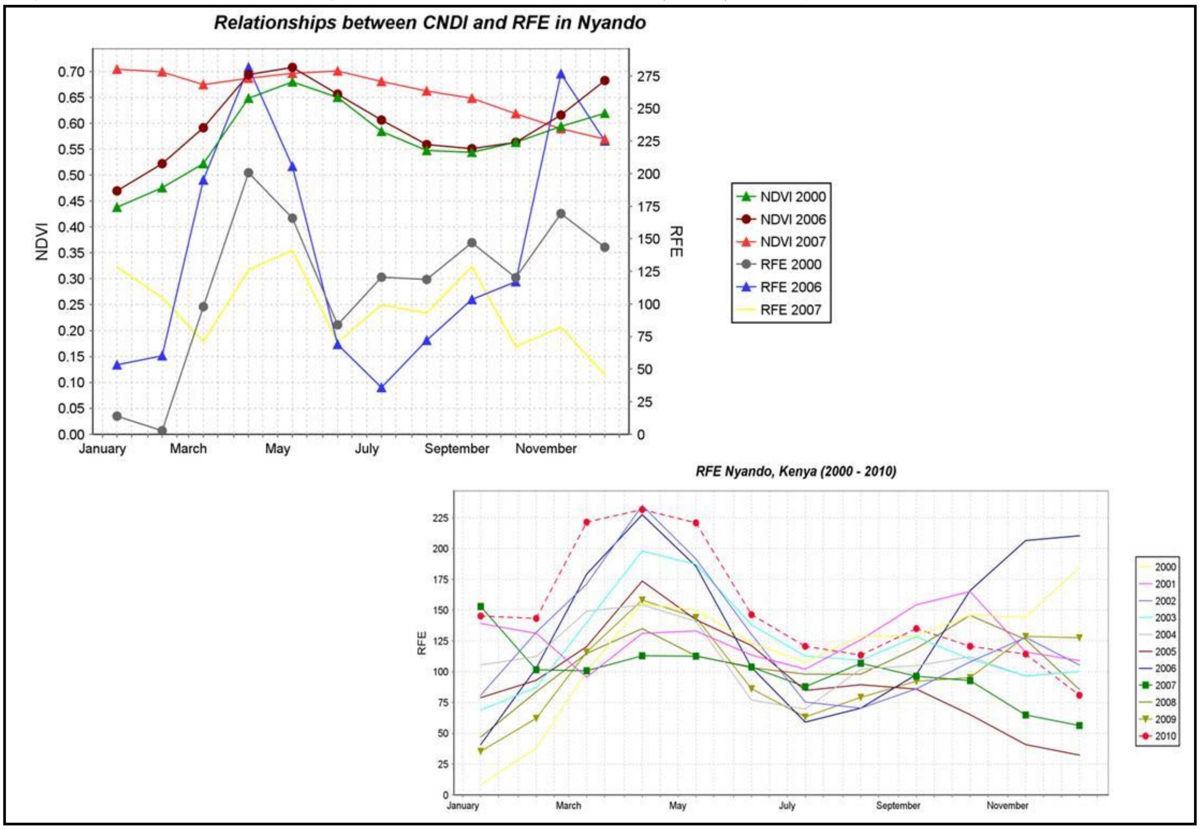


Figure 34. The average CNDVI and Rainfall (RFE) in Nyando block.



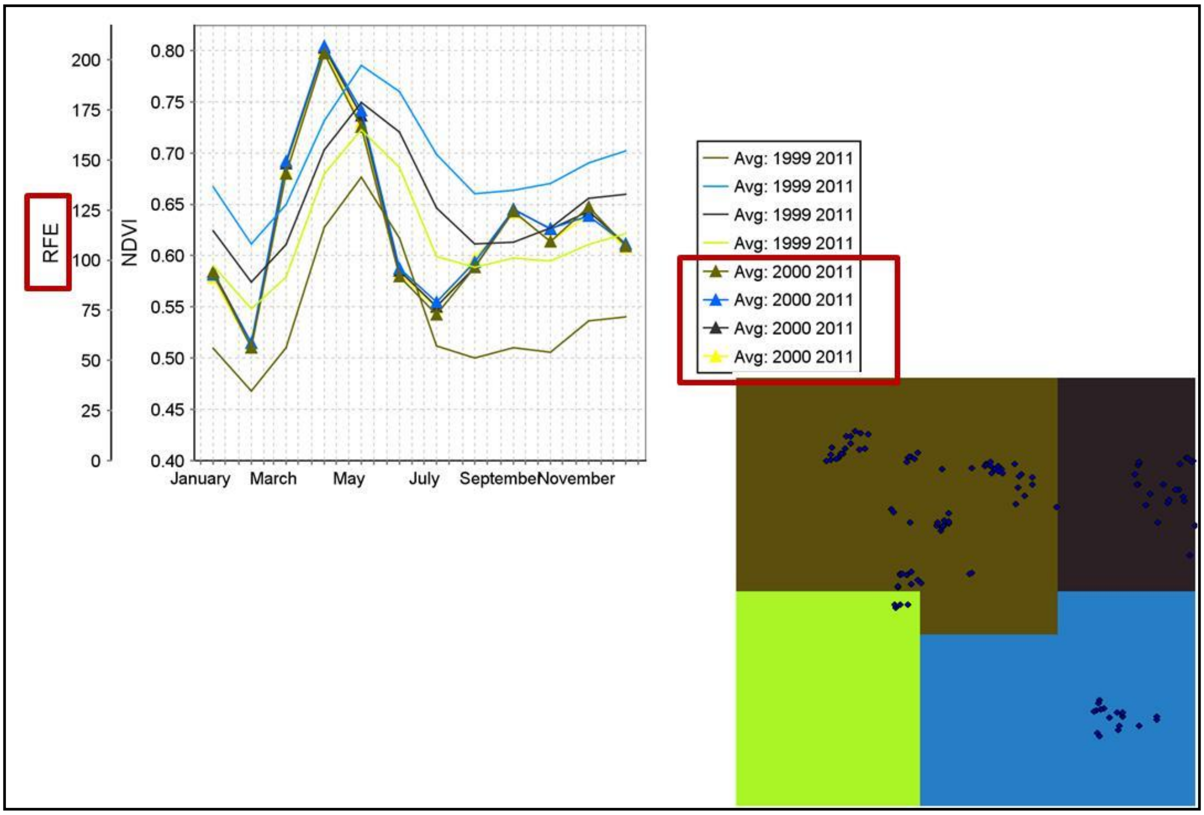
It also appears that inter annual variation is larger for the short rains than for the long rains. For the long rains the intensity was highly variable, whereas the timing of the onset and ending seem to be very predictable. It is the period of the short rains that not only varies in total amount of rainfall, but also in its timing. This makes planting during the short rainfall much more risky than planting during the long rains (Figure 34).

Figure 35 shows the long-term averages for rainfall and vegetation growth for the different functional agro-zones. There is no difference in rainfall as the resolution of the RFE data is much larger than 10x10 km^2. However, large differences in CNDVI values are shown. The NDVI is increasing in the following order:

IAC zone 1< PAC zone 3<SAC zone 4< GAC zone 2

Despite the problems of differentiating between fallow land and degraded land this result shows that the zones identified do represent different agro-ecological conditions within the study site.

Figure 35. Time-series of CNDVI and RFE/Rainfall for functional agro-zones.



Integrating Household Information to the Functional agro-zones

Socio-economic household information used in this analysis is derived from the CCAFS household level baseline (available at "CCAFS Baseline Household Survey 2010-11"); http://hdl.handle.net/1902.1/BHS-20102011UNF:5:0XcEhtcP4B97YHKkHNT9wA== V8 [Version]

The baseline survey describes its methodology in detail (Kristjanson et al., in press; Kristjanson et al., 2009). In addition, 16 socio-economic indices were calculated from the data collected during the baseline. The indices used were:

Food Deficit Months	Number of months households have insufficient food for their family in a typical (average rainfall) year
Innovativeness	Total number of crop, livestock and/or soil, land, water management changes made on their own farm in the last 10 years (see supplementary information for full list of possibilities)
Education	0 = Full-time resident of the household with no or primary education; 1 = Resident with more than primary education
Household size	Total number of people resident in the household
Household Non-Worker	% of people in the household below age 5 and over 60 years
Cash sources	Number of different sources of cash income
Land	Owned and rented land in hectares
Production Diversity	Number of different agricultural products produced on-farm, from list of: food crops, cash crops, fruit, vegetables, fodder, large livestock, small livestock, livestock products, fish, timber, fuel-wood, charcoal, honey, manure/compost, and other
Information	Number of information-related assets owned by household from list of: radio, television, cell phones, computer, and internet access
Transport	Number of agricultural transport-related assets owned by household from list of: bicycle, motorcycle, car or truck
Production assets	Number of agricultural production-related assets owned by household from list of: tractor, mechanical plough, mill, and thresher
Energy	Number of energy-related assets owned by household from list of: solar battery, generator, battery, and biogas digester
Functional agro-zones	1=IAC; 2=GAC; 3=PAC and 4=SAC developed in this analysis
On farm water	0= No on-farm source of water for agricultural use; 1=an on-farm source of water for agricultural use (water pond, tank/water harvesting, borehole, or irrigation)
Social	Number of different agriculture/natural resource management oriented groups of which someone in the household is a member

Credit 0=Not using credit; 1=Using credit

Distribution of Household Survey Points across the functional agro-zones

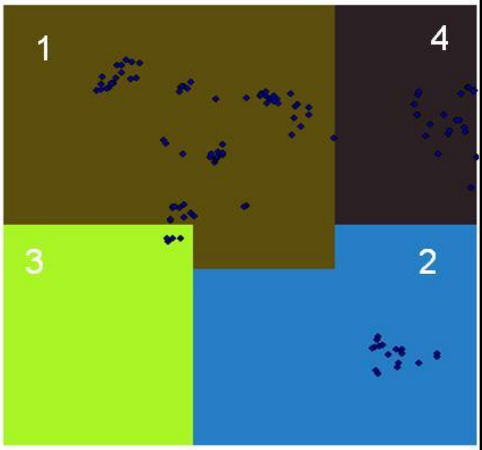
Figure 36 shows the distribution of households included in the 2011 baseline survey across the study block and on the different functional agro-zones. It is clear that the random sampling approach used for the survey did not result in an equal distribution of households across the different zones developed in this study. Most of the samples are located within IAC (Zone 1), with a total of 74 samples. For the GAC (Zone 2) and SAC (Zone 4), both have the same sampling density with 21 households and only 4 samples fall within zone 3.

This suggests that the household information obtained from the survey does not optimally represent the delineated four functional agro-zones developed in this study. While the IAC (Zone 1) is proportionally over represented, the survey has almost no information for the PAC (Zone 3).

Figure 36. Distribution of households sampled across the different functional zones.

Zone

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	74	53.2	61.7	61.7
	2	21	15.1	17.5	79.2
	3	4	2.9	3.3	82.5
	4	21	15.1	17.5	100.0
	Total	120	86.3	100.0	
Missing	System	19	13.7		
Total		139	100.0		



Demographic characteristics

Households across different functional agro-zones were found to be very similar in household size, number of young children and elderly. While households in SAC (Zone 4) did have on average one household member more than households from the other zones, the difference was not statistical significant (Table 4).

Table 4. Comparison of the functional agro-zones with respect to demographic variables.

Functional agro-zones	IAC Zone 1		GAC Zone 2		PAC Zone 3		SAC Zone 4		P value (F-test)
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
HHSIZE	5.19	2.30	4.95	2.84	4.75	2.63	6.14	2.13	0.332
HHLT5	1.01	1.04	0.90	0.77	1.25	0.96	1.33	1.35	0.550
HHGT60	0.31	0.52	0.29	0.56	0.50	0.58	0.38	0.59	0.849
HHNonWorkers	0.29	0.24	0.35	0.32	0.50	0.33	0.28	0.24	0.340

HH (household); LT5 (below age 5); GT60 (over 60 of age)

Only IAC (Zone 1) was found to have a large proportion of female-headed households, whereas male-headed households dominated in GAC (Zone 2) and SAC (Zone 4). Out of the four households interviewed in PAC (Zone 3) all were female-headed, however due to the small sample size this is not regarded as representative (Table 5). Interestingly, neither household size nor the proportion of very young or very old household members was found to differ between the zones. It is therefore suggested that there was a relationship between the type of household and the size of household.

Table 5. Frequency distribution of different household types across the functional agro-zones. 01=Male-headed, with a wife or wives, 02=Male-headed, divorced, single or widowed, 03=Female-headed, divorced, single or widowed, 04=Female-headed, husband away, husband makes most household/agricultural decisions, 05=Female-headed, husband away, wife makes most household/agricultural decisions, 06=Child-headed (age 16 or under)/Orphan, 96=Other, specify

Functional agro-zones			HHTYPE 1	2	3	4	5	96	Total
Zone	1	Count	39	0	29	1	4	1	74
		% within Zone	52.7%	.0%	39.2%	1.4%	5.4%	1.4%	100.0%
	2	Count	18	1	2	0	0	0	21
		% within Zone	85.7%	4.8%	9.5%	.0%	.0%	.0%	100.0%
	3	Count	0	0	4	0	0	0	4
		% within Zone	.0%	.0%	100.0%	.0%	.0%	.0%	100.0%
	4	Count	18	1	1	0	0	1	21
		% within Zone	85.7%	4.8%	4.8%	.0%	.0%	4.8%	100.0%
Total		Count	75	2	36	1	4	2	120
		% within Zone	62.5%	1.7%	30.0%	.8%	3.3%	1.7%	100.0%

The majority of households across the study site did have at least primary education; less than 3% of the households had no education at all. Secondary schooling accounted for about one third of the households interviewed in both SAC (Zone 4) and GAC (Zone 2); the proportion of households with secondary education was found larger in IAC (Zone 1) with 45%. Households from PAC (Zone 3) showed more respondents completed secondary school with 50% but, again, due to the small sample size this is not considered representative for this zone (Table 6).

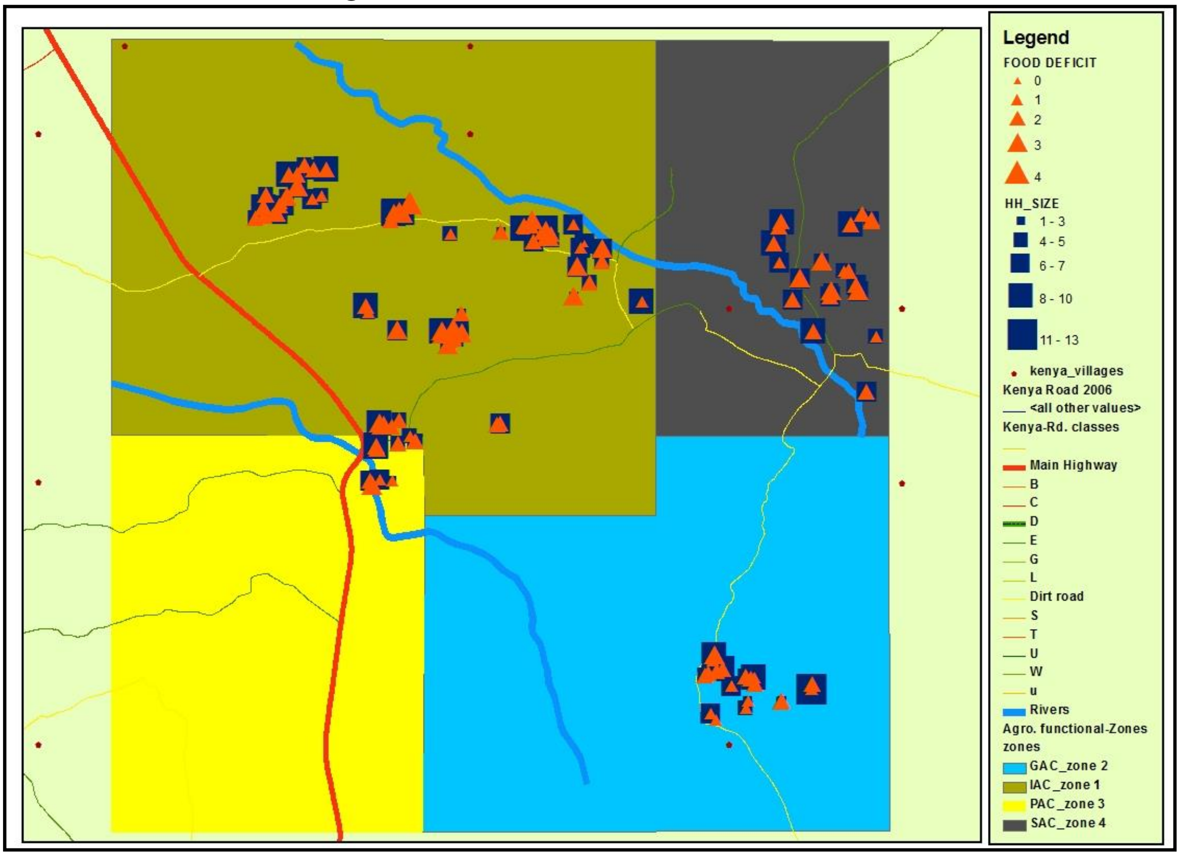
Table 6. Frequency distribution of the highest educational status of any one member in the household across the different functional agro-zones. (00=No formal education, 01=Primary, 02=Secondary, 03=Post Secondary).

Functional agro-zones			HHEDUC				
			0	1	2	3	Total
Zone	1	Count	2	34	33	5	74
		% within Zone	2.7%	45.9%	44.6%	6.8%	100.0%
	2	Count	0	13	7	1	21
		% within Zone	.0%	61.9%	33.3%	4.8%	100.0%
	3	Count	1	1	2	0	4
		% within Zone	25.0%	25.0%	50.0%	.0%	100.0%
	4	Count	0	14	5	2	21
		% within Zone	.0%	66.7%	23.8%	9.5%	100.0%
Total		Count	3	62	47	8	120
		% within Zone	2.5%	51.7%	39.2%	6.7%	100.0%

Assets, sources of cash income, food security

The household location did not seem to influence food deficiency. Both household size and food deficiency vary randomly within the study area (Figure 37). Within Nyando, the average food deficiency experienced by households ranged from 1.5 to 2 months. There was no significant difference between the functional agro-zones (Table 7).

Figure 37. Relationships between food deficit months and households size within the functional agro-zones.



For the wealth indices it was found that there was not much difference between households located in different functional agro-zones. Only transport related assets (bicycle, motorbike, car or truck) were found to be significantly higher in IAC (Zone 1) (Table 7). Households located in this zone also have access to a better road network and are closest to Kisumu town. Figure 38 shows the relationship between on-farm production diversity and the number of transport related assets. While some of the farms within IAC (Zone 1) seem to have higher on-farm production diversity than farmers in any other zone, the variance within IAC (Zone 1) is also very large.

Table 7. Comparison of assets, sources of cash income, and food security.

Functional agro-zones	IAC Zone 1		GAC Zone 2		PAC Zone 3		SAC Zone 4		P value (F-test)
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Energy	0.19	0.46	0.05	0.22	0.50	1.00	0.10	0.30	0.191
Information	1.51	0.69	1.48	0.68	1.25	0.96	1.38	0.67	0.791
Transport	0.49	0.58	0.19	0.40	0.25	0.50	0.14	0.36	**0.017**
Luxury	0.65	0.58	0.43	0.51	0.50	0.58	0.38	0.59	0.179
Cash	1.77	1.05	1.62	1.07	1.50	0.58	1.86	1.46	0.875
FSI	1.96	0.73	1.57	0.60	1.75	0.96	2.05	0.67	0.109

Table 8 provides details on the type of cash sources within each of the functional zones. Farmers within IAC (Zone 1) are also more active in business than any of the other zones. The PAC zone is also found to be high, but because of the small sample size this figure is seen as not representative for that zone.

Figure 38. Relationship between transport assets and farm produce diversity.

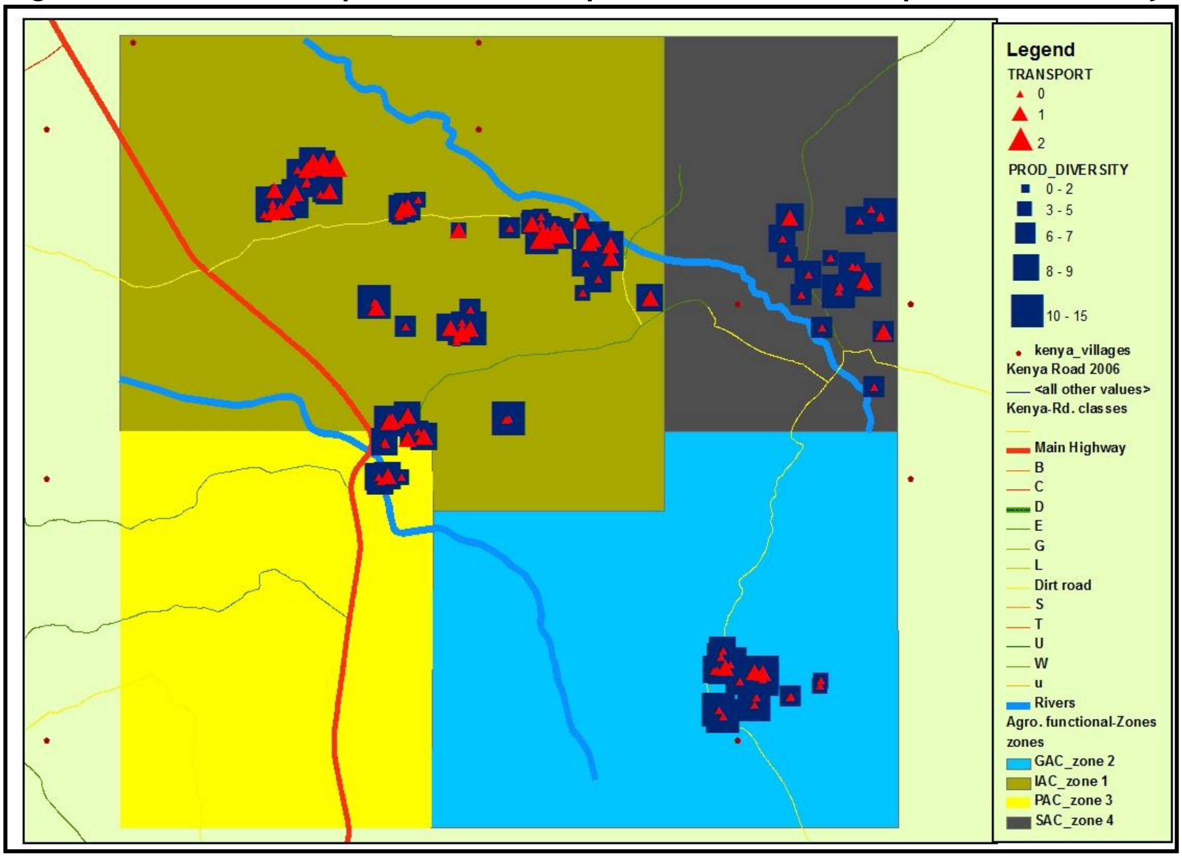


Table 8. Comparison of cash sources.

	Employment on someone else's farm	Other paid employment (e.g. salary)		Business (other than farm products)		Remittances or gifts		Payments for environmental services		Other payment from projects/ government including benefits in kind (e.g. pensions, aid, subsidies, etc.)		Renting out farm machinery (e.g. tractor, thresher, pump, etc.) or animals for traction		Renting out personal land	
		No	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**		
IAC	Count	40	34	61	13	47	27	31	43	70	4	69	5	72	2		
	%	54.1	45.9	82.4	17.6	63.5	36.5	41.9	58.1	94.6	5.4	93.2	6.8	97.3	2.7		
SAC	Count	11	10	19	2	9	12	16	5	21	0	20	1	19	2		
	%	52.4	47.6	90.5	9.5	42.9	57.1	76.2	23.8	100.0	.0	95.2	4.8	90.5	9.5		
PAC	Count	2	2	4	0	3	1	1	3	4	0	4	0	4	0		
	%	50.0	50.0	100.0	.0	75.0	25.0	25.0	75.0	100.0	.0	100.0	.0	100.0	.0		
GAC	Count	14	7	17	4	10	11	15	6	18	3	20	1	18	3		
	%	66.7	33.3	81.0	19.0	47.6	52.4	71.4	28.6	85.7	14.3	95.2	4.8	85.7	14.3		
Total	Count	67	53	101	19	69	51	63	57	113	7	113	7	113	7		
	%	55.8	44.2	84.2	15.8	57.5	42.5	52.5	47.5	94.2	5.8	94.2	5.8	94.2	5.8		

Farming characteristics

With respect to household demographic characteristics, assets, food security and number of cash sources, not many differences were found between the functional agro-zones. However, with respect to farming characteristics there were significant differences between these functional agro-zones.

In terms of access to on-farm water either by pond, tank, harvesting, borehole or irrigation it was found that there was a significantly ($\chi 2$, $p<0.005$) higher frequency of no water sources for PAC (Zone 3) and SAC (Zone 4) compare to IAC (Zone 1) and GAC (Zone 2). The frequency of access to on-farm water decreased from IAC<PAC<SAC<GAC (Table 9).

Table 9. Availability of on-farm water for the different functional agro-zones.

		Water		Total
		No	Yes	
IAC	Count	32	42	74
	% within Zone	43.2%	56.8%	100.0%
SAC	Count	14	7	21
	% within Zone	66.7%	33.3%	100.0%
PAC	Count	3	1	4
	% within Zone	75.0%	25.0%	100.0%
GAC	Count	17	4	21
	% within Zone	81.0%	19.0%	100.0%
Total	Count	66	54	120
	% within Zone	55.0%	45.0%	100.0%

Land size was found to be significantly larger in IAC (Zone 1) when compared to PAC (Zone 3). The numbers of changes made to either animal husbandry (adaptanimal) or field management (adaptcrop) were also found to be significantly different, with more changes made in GAC (Zone 2) and SAC (Zone 4) when compared to IAC (Zone 1) and PAC (Zone 3) (Figure 39). Farmers in GAC (Zone 2) were also found to have the highest production diversity, however the differences were also found to not be statistically significant (Table 10).

Figure 39. Distribution of total number of changes in both farm management (crop) and animal husbandry (animal) across the functional agro-zones.

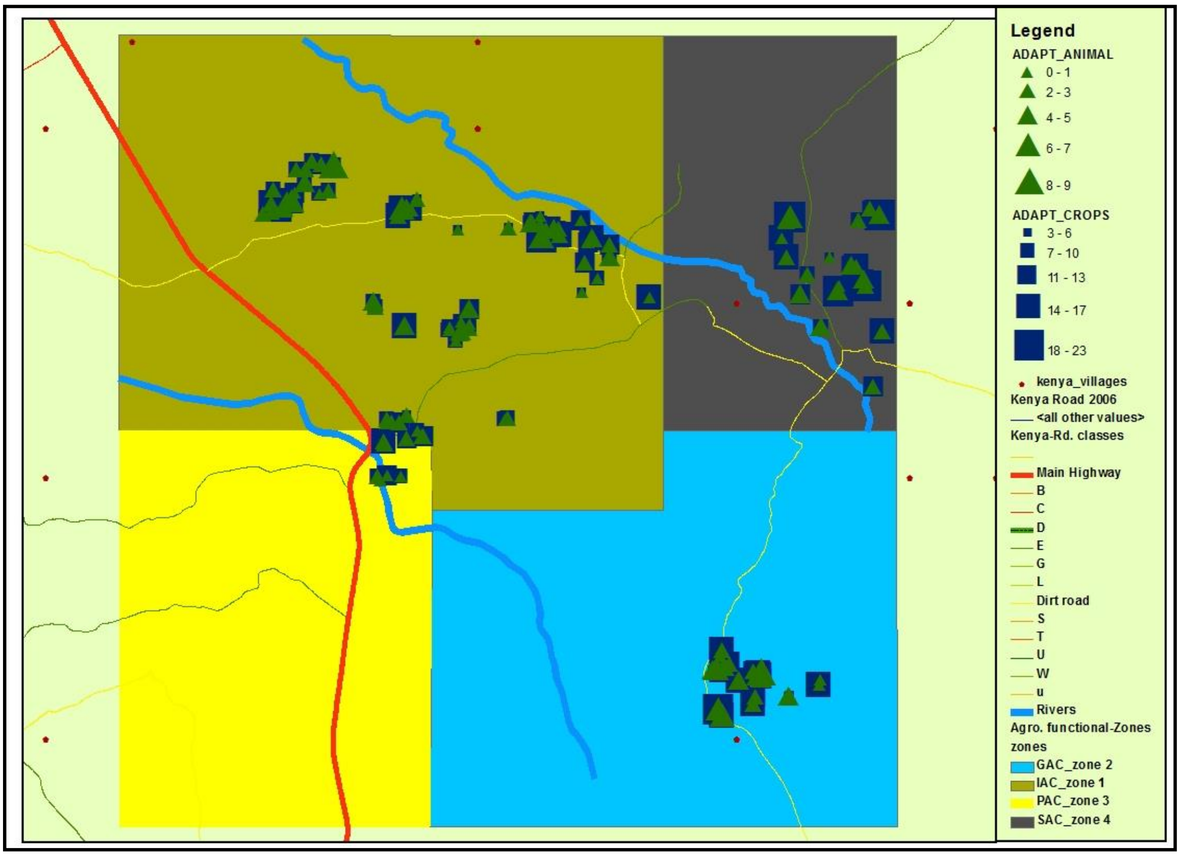


Table 10. Comparison of different socio-economic indices across the functional agro-zones.

Functional agro-z	IAC		GAC		PAC		SAC		P value (F
	Zone 1		Zone 2		Zone 3		Zone 4		
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Land size	2.78	2.09	5.05	4.59	2.56	1.36	6.71	5.12	**0.000**
Production Diver	6.79	2.31	8.15	2.78	7.50	2.38	7.47	3.15	0.188
Adapt crop	9.49	3.76	12.29	4.68	8.25	2.22	12.29	5.19	**0.006**
social	0.72	0.67	0.43	0.60	0.75	0.50	0.38	0.67	0.104
Adapt animal	2.35	1.71	3.48	2.48	1.25	0.50	2.90	1.55	**0.033**
Innovativeness	11.84	4.55	15.76	5.20	9.50	2.38	15.19	6.10	**0.001**

From the GT survey it was observed that there are large differences in farm types and crop varieties between these functional agro-zones. It was found that farmers in SAC (Zone 4) and GAC (Zone 2) have more livestock than in the other two zones. It is clear that GAC (Zone 2) has the most suitable farmland, however SAC (Zone 4) is also considered a good area for livestock within the block due to the availability of the flat highland plateau, which is utilized for grazing especially during the dry season, as well as the presence of a perennial river and a governmental Acacia forest. The more uniform pattern of the grazing areas in SAC (Zone 4) can also be easily identified from the black spectral signature in the supervised image in previous Figure 29. During the village baseline, farmers confirmed that the flat highland plateau (Kolango Forest) is an important source of feed for livestock, especially when the field grasses are dried during the dry period, and the Acacia government forest is an important source of fuel wood. From the evidence of the spectral reflectance of the soil and the lower predicted soil organic carbon content, the area is also expected to have sandier soils than GAC (Zone 2).

As previously noted that GAC (Zone 2) and SAC (Zone 4) had the highest average CNDVI over the last decade, it can thus be assumed that they are the areas with the least degraded and most fertile soils. From the soil carbon map (Figure 40), the average estimated soil carbon content for each agro-zone can be extracted. When plotting both CNDVI and soil carbon a strong correlation between these two can be found. In summary, the two zones (GAC and SAC) that have the best soil, both in terms of fertility (soil carbon) as well as vegetation performance (CNDVI) are also the two zones with the largest farm sizes (Figure 41).

Figure 40: Relationship between CNDVI and average estimated coil carbon. (Vagen 2011, unpublished data).

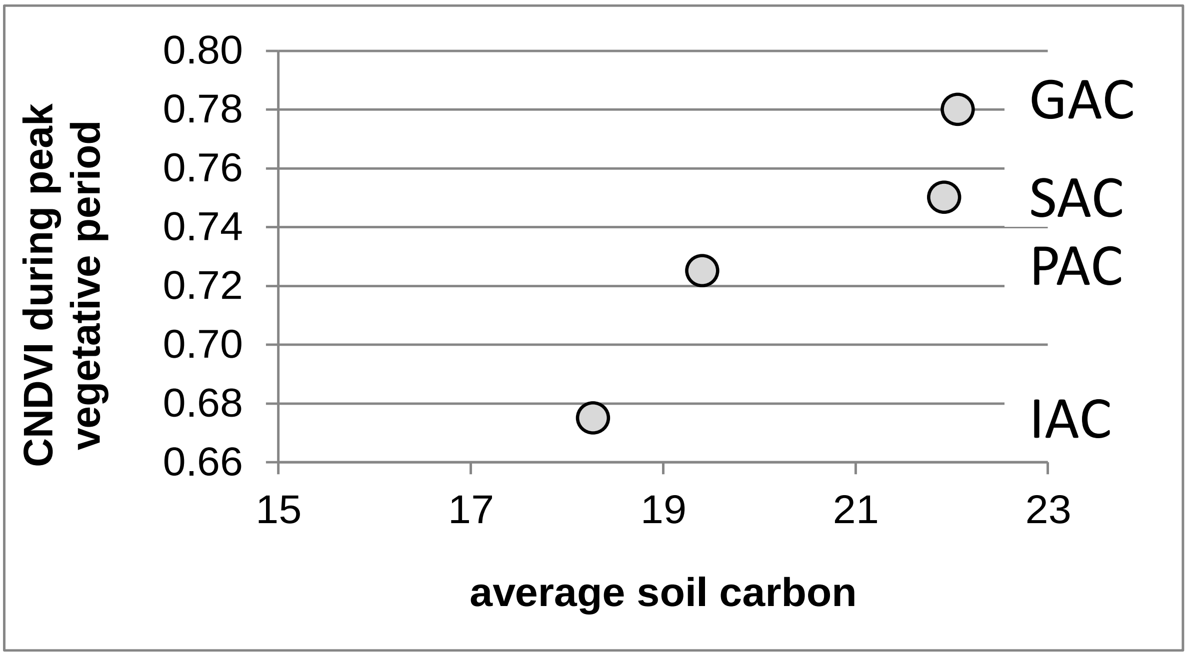
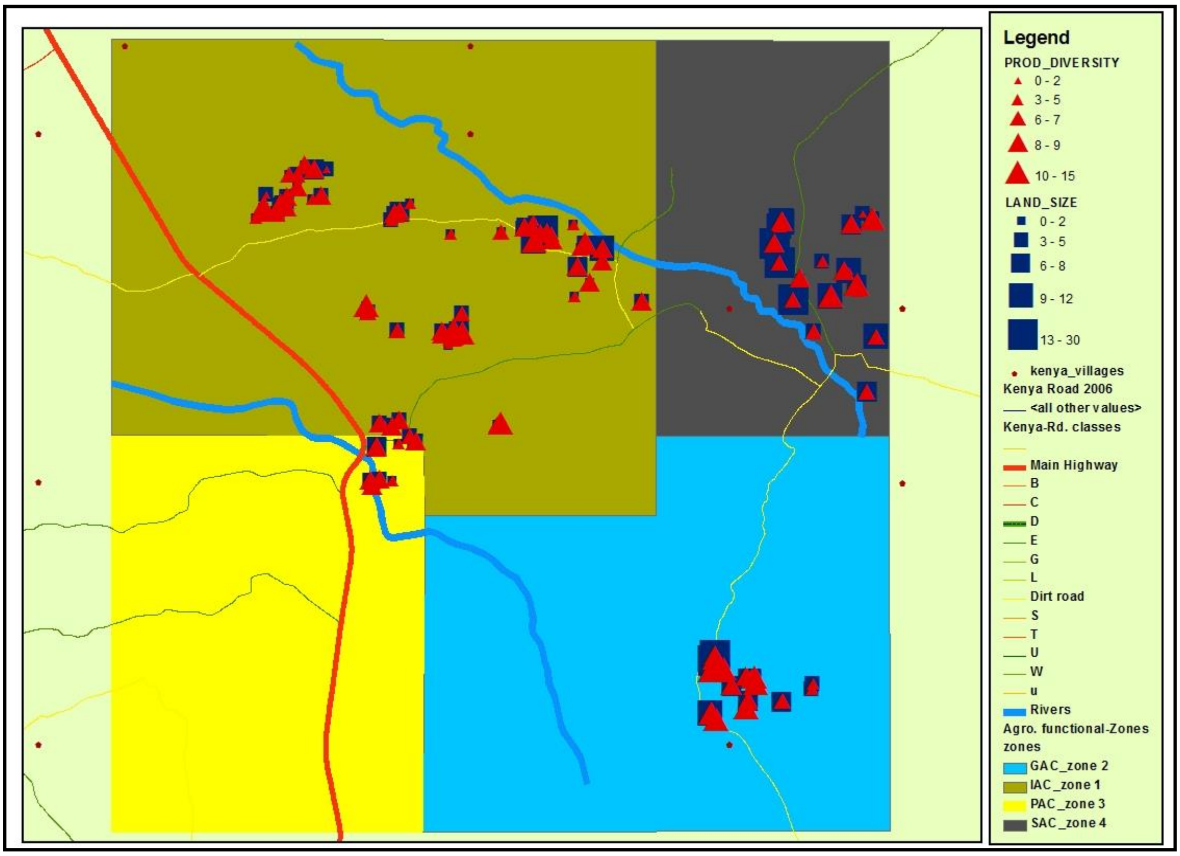


Figure 41. Distribution of farm sizes and farm production diversity across the functional agro-zones.



One of the main questions to be answered in this report was whether differences in the quality of natural resources households have access to have an effect on the way households farm. Also, how do farmers adapt to changing conditions, such as land degradation and population pressures?

The CCAFS baseline survey calculated an innovativeness index from questions regarding what changes households made over the last 10 years in practices such as crop type, variety type, land use and management practices, and farm animal/fish management. The total number of changes made was used as an indication of how much experimentation and adoption of new practices had been undertaken by each household and was thus used as a proxy for innovativeness.

From Figures 42 and 43, it is clear that farmers with larger farm sizes were more innovative than farmers with small farms. One could conclude that large farm size indicates wealth and is thus an enabling factor that allows farmers to be innovative. However, neither the assets table (Table 7) nor the sources of cash table (Table 8) provide any indication for this. Instead, based on the discussion above, it is suggested that the health of the farmland enables farmers to be more innovative.

Figure 42. Distribution of land-size and innovativeness of farmers across the functional agro-zones.

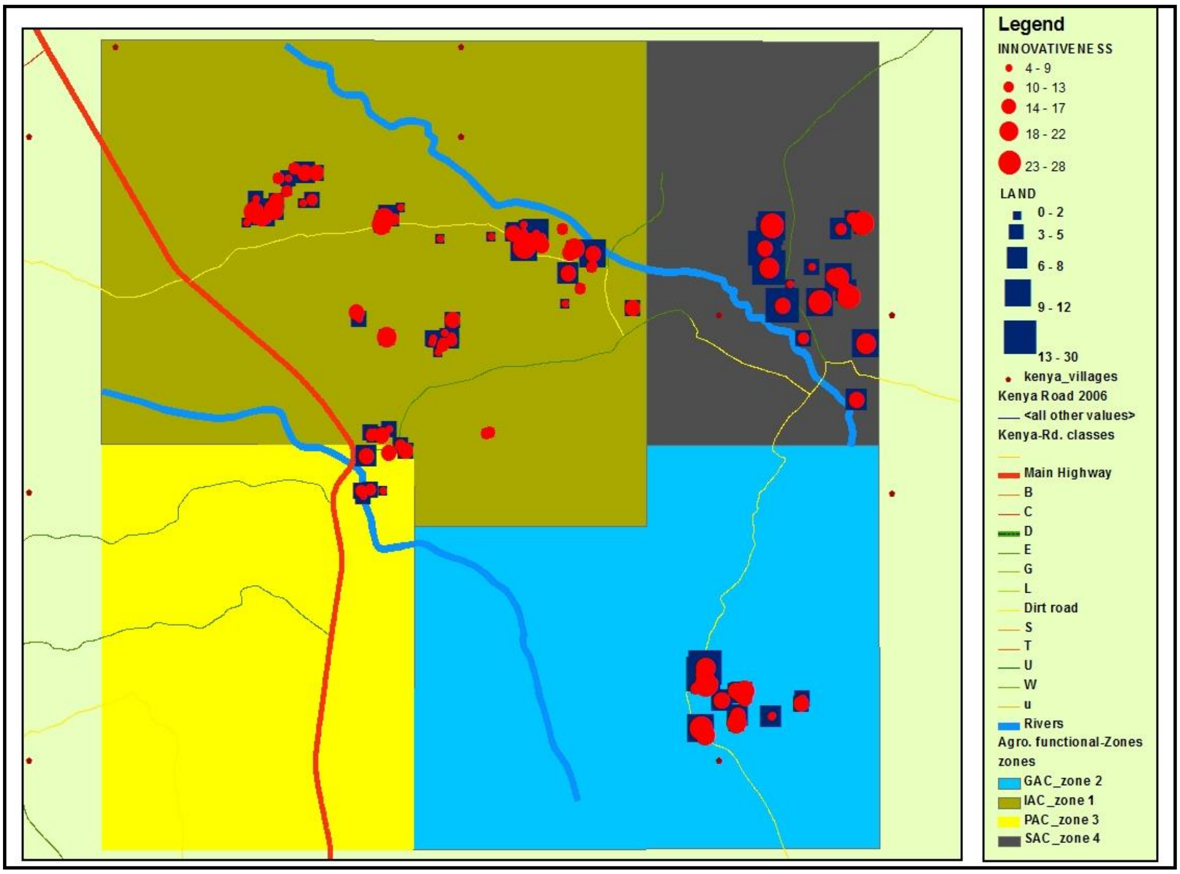


Figure 43: Comparison of farmers across functional zones with respect to farm size and innovativeness.

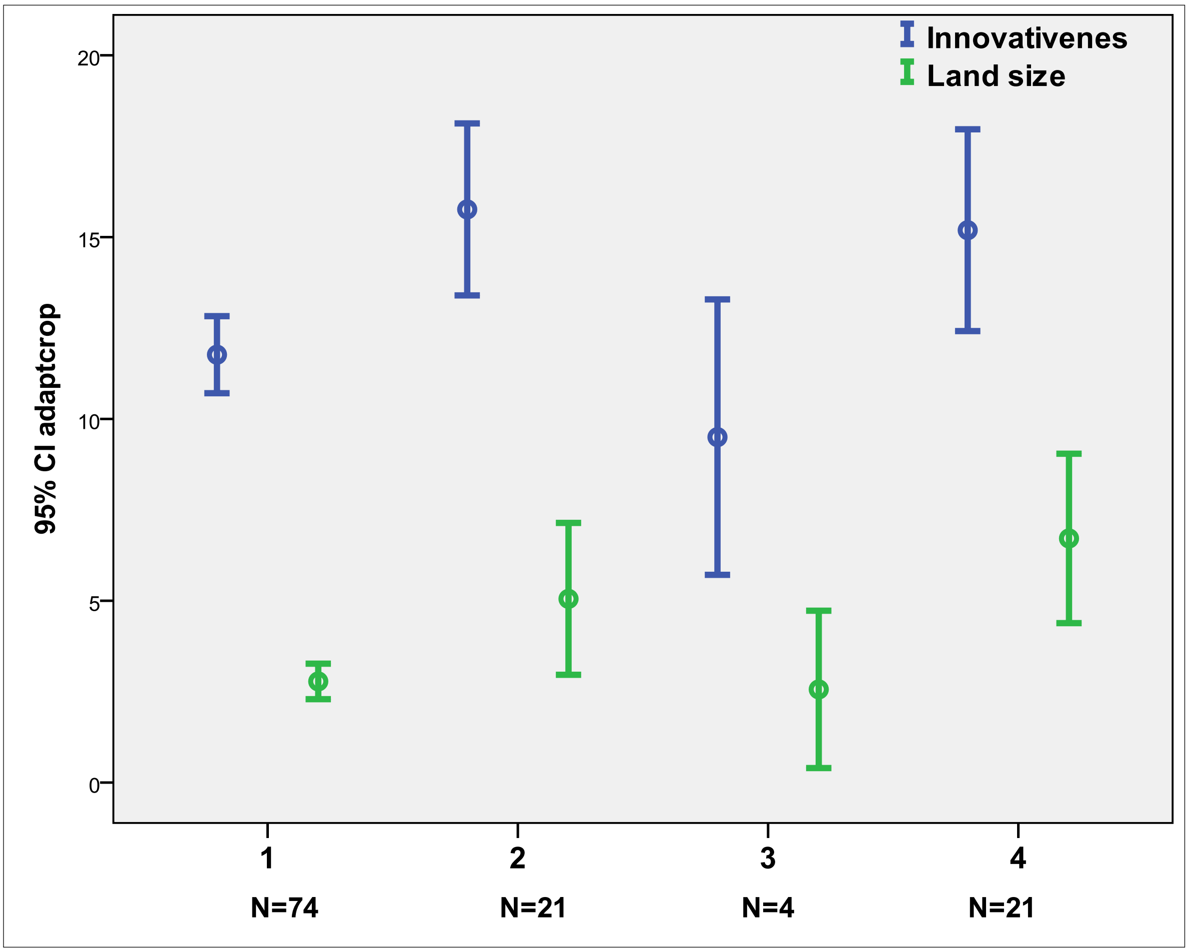
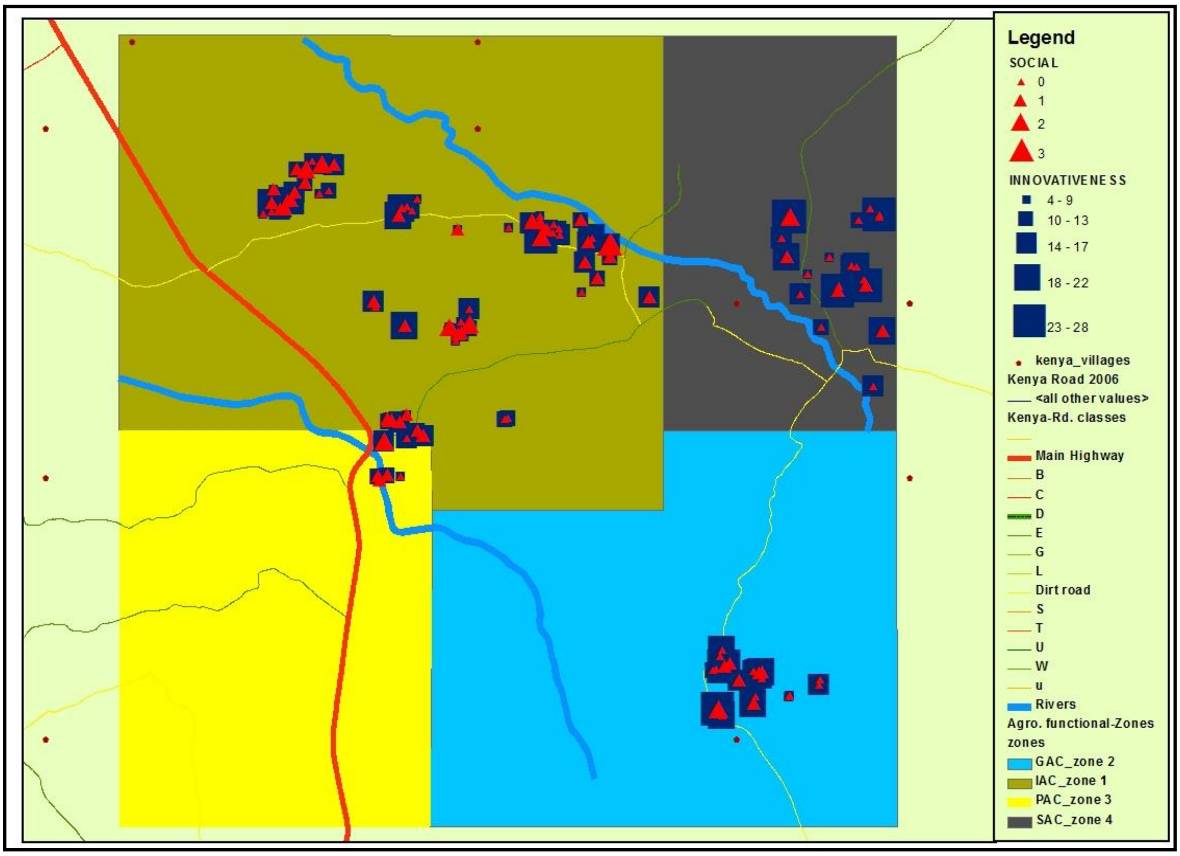
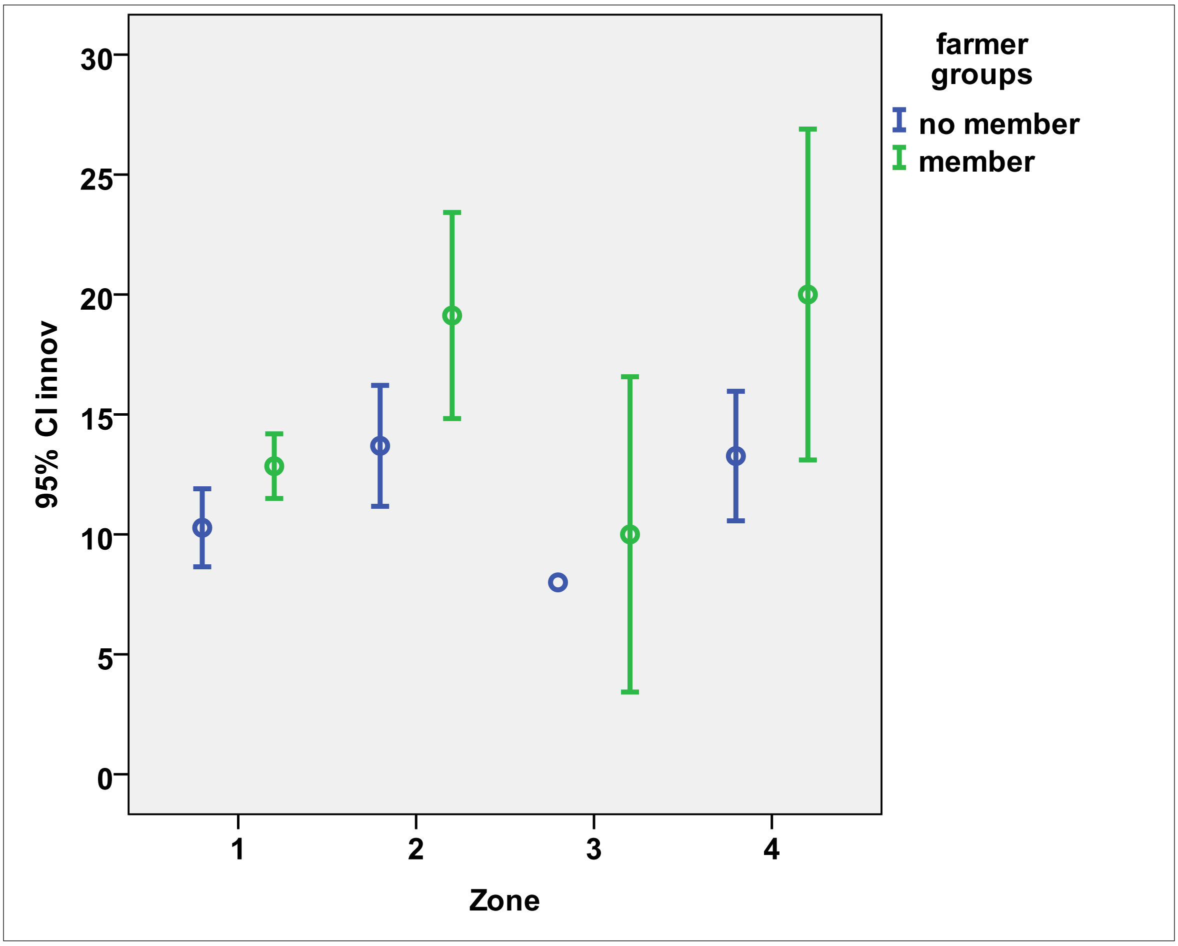


Figure 44: Distribution of social and innovativeness across the functional agro-zones.



Figures 44 and 45 further show that farmers that were engaged with group activities were more innovative than farmers that had no group membership. In addition, the road that was turned into the main highway, intersecting IAC (Zone 1), was most likely the first road access to the Nyando block. The villages in IAC (Zone 1) are most likely the oldest residential areas in the Nyando block, which is reflected in the high utilization of diverse land use types. It is also the area with the highest population density. Thus it can be concluded that strong differences in land health between IAC (Zone 1) and GAC (Zone 2) and SAC (Zone 4) are a result of the differences in population pressure and land management.

Figure 45: Comparison of farmers across functional zones with respect to farmer group membership and innovativeness.



To examine what enabling factors make farmers more innovative than others, a general linear regression model was fitted:

(Innovativeness): Constant + Energy + FSI + HHEDUC + Land + Luxury + Prod.Diversity + Functional Agro-Zones + social

The results of the final model are shown in Table 11. The model was found to explain 46% of the variation between households. The variables with the largest contribution to the model were land size and the total production diversity. Also food deficiency was found to be important. The functional agro-zone does account for 7% of the variation in innovativeness (Table 12). While this is a relative small contribution, it was found to be significant. Given the problems of unequal representation (sampling) of the different functional agro-zones within the socio-economic baseline survey, a contribution of 7% is a surprisingly high result.

Table 11. Correlation between innovativeness of farmer and other parameters including functional agro-zones. Parameters for factors are differences compared with the reference level: Factor reference level IAC (Zone 1).

Parameter	Estimate	s.e.	t (102)	t pr.
Constant	6.12	1.75	3.50	<0.001
Energy	0.80	1.01	0.80	0.426
FSI	-1.035	0.520	-1.99	0.049
HHEDUC	0.462	0.613	0.75	0.452
Land Size	0.341	0.114	2.99	0.004
Luxury	0.788	0.743	1.06	0.291
ProdDiv	0.670	0.161	4.17	<0.001
GAC (Zone 2)	2.89	1.07	2.70	0.008
PAC (Zone 3)	-2.95	2.01	-1.46	0.147
SAC (Zone 4)	2.35	1.12	2.09	0.039
Social	1.158	0.607	1.91	0.059

Table 12. Accumulated analysis of variance, correlation between farmer innovativeness and other parameters.

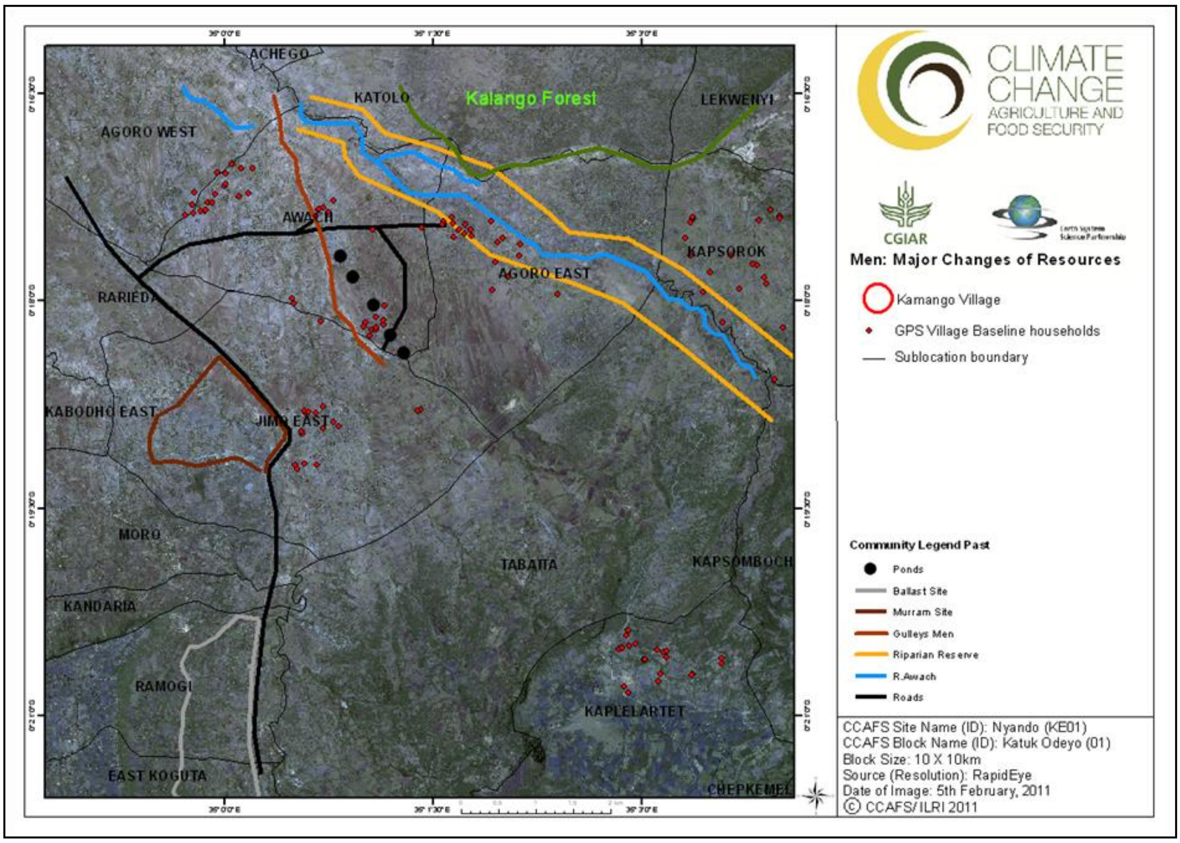
Change	d.f.	s.s.	Variance explained
+ FSI	1	262.46	17%
+ Land Size	1	569.21	37%
+ ProdDiv	1	509.23	33%
+ Functional agro-zones	3	106.19	7%
+ Social	1	99.61	6%
Residual	105	1550.98	
Total	112	3097.68	

This also suggests that in the absence of human-made water resources such as ponds, tank/water harvesting equipment, boreholes, and irrigation, the role of natural water resources such as rivers and streams located within GAC (Zone 2) and SAC (Zone 4) are imperative to maintain farm produce diversity at large. During the GT survey, the existence of a stream within the primary forest was pointed out by the local coordinator of GAC (Zone 2).

Migration within the Nyando block

From the village level baseline survey (March 2011), farmers stated that people are moving from IAC (Zone 1) into PAC (Zone 3) for mining activities (ballot, stone and murram) (Figure 46). This supports our findings that population pressure and degraded resources (soil, vegetation, and farm sizes) are forcing people to look for alternative livelihoods. Unfortunately the village level baseline was only conducted in a few villages and does not give a good representation of the entire block.

Figure 46. Community map showing men changes of resources.



The household baseline provides some information with respect to new farmers (Table 12), which could be both new generation farmers or newly migrated farmers. While the majority of farmer's interviewed had been living on the land for at least 10 years, 14% of households within SAC (zone 4) were found to be new farmers. Very few new farmers were found in IAC (zone 1) and GAC (zone 2). It is assumed that a larger percentage of new farmers settled in SAC (Zone 4) due to the continued availability of space and basic resources within SAC (Zone 4) such as rivers, vegetation and grasslands.

Table 13. Frequency distribution of long-term (longer than 10 years/ 10YR) and new (shorter than 10 years) farmers across the different functional agro-zones. (01=long-term; 00=short-term). Farmer refers both to households conducting farming and/or keeping animals.

Functional agro-zones			FARM10YR		Total
			0	1	
Zone	1	Count	3	71	74
		% within Zone	4.1%	95.9%	100.0%
	2	Count	1	20	21
		% within Zone	4.8%	95.2%	100.0%
	3	Count	0	4	4
		% within Zone	.0%	100.0%	100.0%
	4	Count	3	18	21
		% within Zone	14.3%	85.7%	100.0%
Total		Count	7	113	120
		% within Zone	5.8%	94.2%	100.0%

Conclusion

The random sampling approach over sampled the IAC (Zone 1) and under sampled the PAC (Zone 3). If we assume that innovative farmers are those that move from IAC (Zone 1) to PAC (Zone 3) than the baseline sampled more "*status quo*" farmers than entrepreneurs. The location of households had a significant effect on household innovativeness. Despite the very coarse input parameters used (NDVI ~ SPOT VGT 1km; RFE~ NOAA AVHRR 1km), the variable functional agro-zones explained 7% of the variation in innovativeness, which is considered good. It suggests that a stratified household sampling procedure will provide better representation for the functional agro-zones developed in this study, which may further improve correlations within and between functional agro-zones.

The subsistence agricultural production system is dependent on optimal inputs from key environmental health factors such as woody biomass (primary and pioneer forests), water resources (river and watersheds), and soil fertility in order to maximize farm production and crops (Deichmann, 1999). If soil organic carbon is a proxy for soil fertility (Tobler, 2011), which supports the production of biomass with adequate water and vice versa, it is therefore suggested that soil carbon content is a reliable indicator to monitor food security in relation to subsistence agricultural systems.

However, these key environmental health factors cannot stand alone, whereby other factors such as infrastructure (human made facility) and especially the accessibility to the main road and nearby towns are proven to have a powerful effect on the overall correlation to social ecological parameters. As shown, key factors (forest, water and soil carbon) have allowed farmers within GAC (Zone 2) and SAC (Zone 4) to better cultivate with larger land size, better innovativeness, and thus larger farm produce diversity. However, it is also found that regardless of these advantages, bad infrastructure (roads) conditions may hamper the good farming potential within GAC (Zones 2) and SAC (Zone 4); negative trends between the social network and land sizes combined with lower transport assets than the IAC (Zone 1) and PAZ (Zone 3) indicates bad transport. Poor infrastructure may have especially hampered their marketing strategy, as well as distance from being reached by any extension services (organizational landscape from govt. and NGO's agencies), which may bring important information and incentives to farmers. Perhaps it is the inability to market their crops that results in farmers in the SAC (Zone 4) and especially to GAC (Zone 2) remaining poor and food insecure despite available resources.

Regardless of difficulties encountered during the image classification analyses in this study, which is due to time-lap differences between the acquisition time of the RapidEye image and the GT survey date, results obtained between functional agro-zones with respect to the land size, transport related assets, farmer crop and animal adaptation, water, and innovativeness were significantly different. The same positive response was obtained when course image resolution from SPOT VGT and NOAA AVHRR satellite datasets were utilized and showed to match the site-specific characterizations of the developed functional agro-zones in this study. Whereas further demonstration of the vegetated anomalies between different CCAFS sites in East Africa using time series (1999-2011) have also explained and grouped the study sites in terms of their dynamic environmental health conditions, which is a very important, observation needs to be pursued with finer satellite datasets to show better accurateness.

As shown from the calculated vegetation anomalies between and within sites in East Africa, there were trends thru all the major parts of East Africa and mainly between CCAFS study sites that a small increase in greenness was experienced in the past ten years (1999-2011). Even though the RFE data has showed no difference in rainfall patterns between these developed functional agro-zones, GT survey observation noted that the GAC (Zone 2) is located on a higher flat plateau located close to Kericho tea plantation, which indicates a consistent rainfall pattern. On the other hand, drier zones (IAC zone 1) showed that the short rainy period not only varies in total amount of rainfall, but also in its timing which makes planting during the short rainfall much more risky than planting during the long rains, especially where soil fertility conditions are poor as in the IAC (Zone 1). This observation matched our findings during the GT survey within IAC (Zone 1) where sorghum and some cotton fields were found, highlighting crop selection based on very low specific requirements for soil quality as well as drought resistance (Glemnitz and Hufnagel, 2012). Sorghum in particular takes a shorter period to grow than maize and it only takes two months to mature in the area (Mango J., Personnel communication 2011). This suggests that crop type is another important indicator parameter to be monitored by CCAFS in order to understand land health and vigor, farming types, and thus the innovativeness of the farmers in the face of environmental changes to the agroecological system.

The pattern of migration within the Nyando block was found strongly influenced by natural resources (farm supports), topography, and infrastructures. It was shown that road access (infrastructure) plays a critical role in terms of the migration pattern of communities between the agro-zones, where innovative farmers have moved from IAC (Zone 1) to PAC (Zone 3) and small numbers may have moved from IAC (Zone 1) to SAC (Zone 4), even though more healthy areas are located within GAC (Zone 2) and data did not reveal any migration pattern from IAC (Zone 1) to GAC (Zone 2). It was assumed that the reasons are that GAC (Zone 2) is mainly represented by steep areas and is far from the main road, whereas IAC (Zone 1) and PAC (Zone 3) are vertically connected with the main highway. In addition, most villages are located within IAC (Zone 1) and are connected closely to SAC (Zone 4) by roads.

This integrated analysis built a framework to assess subsistence agricultural production systems or farming type practices towards farmer adaptation and mitigations strategies on agroecological landscape levels based on the assessment of ecosystem health services. This has led to the adoption of a “functional agro-zones” concept which has revealed that the status and characteristic of land use practices between these functional agro-zones are highly dependable on such environmental impacts and the quality of the agroecological system and farm particularly support three key factors: i) woody biomass, ii) water resources and iii) soil fertility. These factors are examined as indicators for environmental changes and food security to measure the capacity of an agroecological landscape to sustain human activity such as subsistence agricultural production system. It is believe that the absence of either one or two of these key factors will lead to further landscape degradation or land conversion resulting in people having to cope with their impact on the environment. The goal of this study is satisfactorily addressed. Nevertheless, the interpretation of results can only be regarded as preliminary, since further research is necessary to widen the application for other CCAFS sites.

Recommendations

What needs to be done within other CCAFS sites for rapid-supervised image classification in order to come up with a reliable "functional agro-zones" thematic map and better understand the health of the agroecological landscape is detailed through the following step recommendations.

Step 1: CCAFS image processing team has to improve the value of datasets by maximizing the utilization of the RapidEye image. The key environmental health factors/indicators (pictured below) covered in this study can be missed if the analysis is only based on satellite image processing. Therefore, the suggestions are:

Picture of terrestrial permanent vegetated area in Nyando block consisting of primary forest, plantation Eucalyptus forest, and pioneer or Acacia govt. forest (Kolango forest) species. Photo: Faisal Mohd Noor.

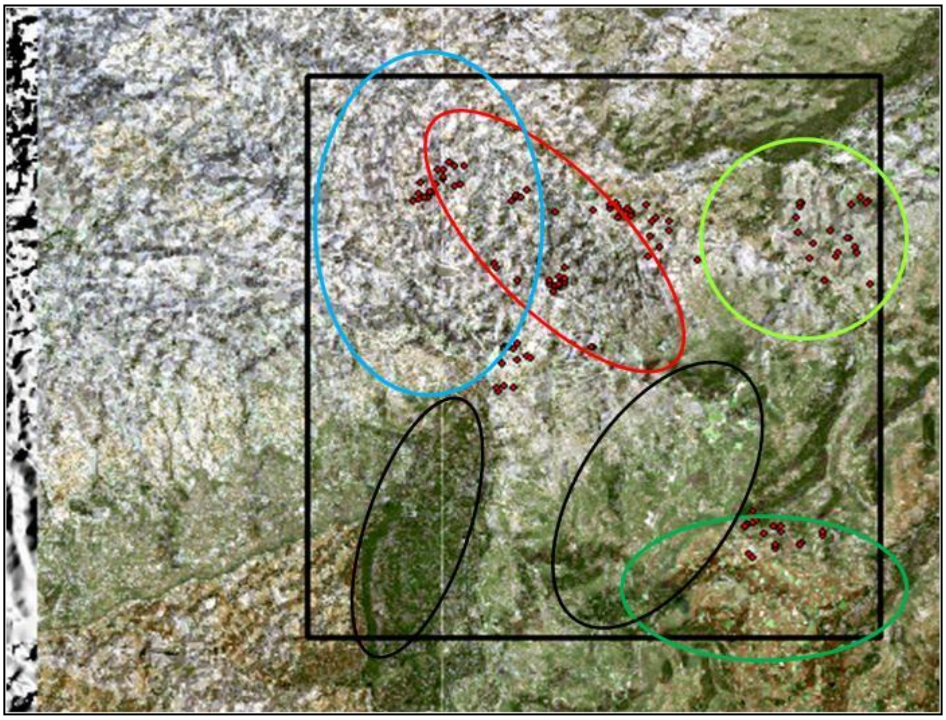
- Generate a woody-biomass (wood count) image from the RapidEye satellite imagery throughout all the CCAFS study blocks. The woody-biomass image will show tree counts from the study block (Tor Vagen, *personnel communication*) and most importantly the quality of the forest and function areas within the block. In addition, local coordinators can provide input from their knowledge to validate and confirm information obtained from the woody biomass image and vice-versa.
- The SPOT VGT (1km) provides a coarse resolution to derive the vegetation anomaly image, therefore not much difference was shown between CCAFS study sites in East Africa and between functional agro-zones within the Nyando study block. It is recommended that a finer LANDSAT 30 meter resolution (in time-series) must be provided in the next analysis for better greenness (CNDVI) estimates. This will allow a better measure for the landscape health within CCAFS study sites and especially for different farming practices between the agro-zones within the study block.

- Since the rainfall estimate (RFE datasets) showed no difference in the estimated rainfall patterns between Nyando block agro-zones, finer datasets for rainfall estimate such as the ones derived from the real weather stations are preferably suitable and have to be included in the next analyses.

Step 2: Multi-temporal satellite analysis information can supply valuable information about changing patterns of land-cover, especially for vegetation species (Foerster et al., 2010; Vuolo et al., 2010), when information about the seasonal development of different land-cover types is included. This is the only way that CCAFS can compare the types of changes farmers have done in different functional agro-zones within the block, since farmer innovativeness in this study is explained based on the total number of changes rather than the types of changes. It is recommended that CCAFS purchase two sets of RapidEye images from two different seasons (dry and crop season) to limit issues due to cloud cover.

Step 3: In-depth site-specific knowledge about the block’s biophysical characteristics and land-use cover by local coordinators are important assets in this analysis. This knowledge must be shared with image processor/soil and plant scientists so that image classification and interpretation of the study sites can be done efficiently. For an example, within the Nyando block it is rather easy for the local coordinator to identify basic farm resources/supports as well as general knowledge about landscape characteristics (Figure 47). Information about the topography will be provided from Aster or SRTM DEM data sets in this exercise, however having the local coordinator do a basic delineation process by providing the following basic information would be valuable.

Figure 4711. Overlay of RapidEye image with Aster DEM and areas that are potentially to be identified by the local coordinator (see description of areas).



BLUE - highly populated area, main highway in the block, many villages and few townships;

RED - highly populated, gully formation, intensive subsistence agricultural land parcels, and major crop types;

LIGHT GREEN - basic resources are available such as, pioneer/acacia government forest (Kolango forest), river, farming types and field grasses;

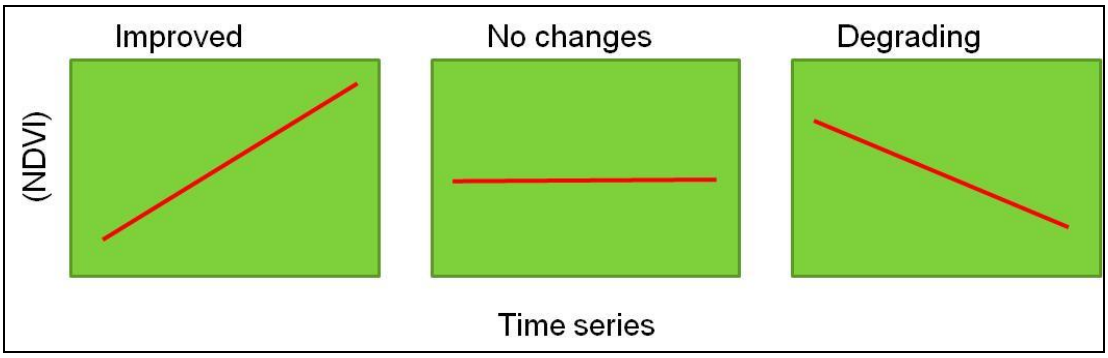
BLACK - undulating area to very steep areas, define greenness seen from the spectral signature of the RapidEye as vegetation types (dense bushes, coarse bushes, pioneer forest);

GREEN - highland with intensive crop cultivated area due to good farm resources such as a primary forest, and water resources to carry out best subsistence farming practice.

By getting this basic extra information, the pictures (village level baseline datasets) taken by the youth groups during the village baseline survey should help with the image processing procedure since they are geo-referenced. The limitation to fully utilize the information from the pictures in this process is that the type of landscape shown by the picture does not tell the scale on the ground or study site, which is easily provided by the local coordinators. This also provides a proper framework for CCAFS in dataset utilization and management. If the above procedure can be done in a controlled way, with the aid of soil organic carbon maps, the GT survey can be minimized or omitted, and should be explored by CCAFS.

Step 4: Create site groups representing the environmental health status. What indicators (NDVI) can be used to group the other fourteen CCAFS sites from healthy to degraded agroecological systems? The aim of the "*functional agro-zone*" concept is to be able to group the other fourteen CCAFS sites into three main groups as shown in Figure 48. If NDVI is a potential and reliable indicator to monitor changes between these different groups in time series, the recommendation above on utilizing the potential of Landsat 30 meter resolution in time-series is crucial given the size of the CCAFS study block is rather small to derive the best NDVI model.

Figure 48. Site groups representing improved landscape group, no changes landscape group and degrading landscape group.



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